ULUSLARARASI **İLİŞKİLER** | INTERNATIONAL **RELATIONS**

Volume 23, Number 89, 2026: 27-49
https://doi.org/10.33458/uidergisi.1853672

Analysis of Van Province's Migration from Iran by Geographically Weighted Regression Method

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Abstract

The ability of migrants to adapt to their new environment in a short period of time while establishing a new life is an important factor affecting the welfare of both individuals and societies. The process of adaptation can determine the quality of life of the individual, reflecting the migrant's ability to adapt socially, economically and culturally to their new environment. Adaptation in the new life after migration is usually associated with factors such as age, post-migration support from public institutions, post-migration support from relatives, post-migration support from neighbors, and inadequate educational opportunities. In this study, migration from Iran to Van province was analyzed using the geographically weighted regression (GWR) method. The analysis focused on identifying the factors that influence individuals' responses to the statement "I adapted to my new life in a short time after migration". According to the analysis results, it is observed that the GWR method gives stronger results. In comparison to the ordinary least squares (OLS) model, the GWR model demonstrates clear superiority across all evaluation criteria, indicating that the GWR model provides a substantially better fit to the data by capturing spatial variability more effectively.

Keywords: Spatial Heterogeneity, Local Modeling, Forced Migration, Integration Dynamics, Institutional Assistance

Research Article | Received: 22 October 2024, Last Revision: 31 December 2025, Accepted: 7 January 2026

Introduction

People have a strong connection with the places where they were born and raised or where they have lived for a long time. However, people may have to change these areas for various reasons. This change, which is expressed by the concept of migration, not only increases the dynamics of the person with the new settlement, but also increases the desire to preserve the strong bond with the land and society they left. Migration leads to significant changes in the relations between people and space (Dandy et al. 2019). These changes affect the migrant, the abandoned place, the new settlement and the resident population in different dimensions. The reason for migration, the process and post-migration experiences determine the direction, level and duration of this effect. In particular, necessity, massiveness and causality significantly affect what happens during and after the migration process. The potential and level of the settlement unit that accepts the migrant can also be effective on the migration process (Galinsky et al. 2015). In addition to these effects, each migration has a different meaning for each migrant and each member of the settled population. However, past migrations and similarities in these migrations have allowed generalizations to be made about migration (Beine et al. 2019). In this context, researchers have collected statistical data on migration, classified migration, predicted possible situations in migration processes and developed migration theories (Dumitru 2023). Research on migration helps to make the social structure and relationship in society more understandable, which further increases the value of migration research (Xiang and Lindquist 2014).

At the same time, these studies indicate that there are different reasons for migration, which brings the human relationship with space to a new stage (Lami et al. 2022). Economic, social, political and natural reasons have increased the repulsiveness of some settlements and the attractiveness of others. Economically motivated migration, which accelerated after geographical discoveries, entered a different phase after the industrial revolution. In this process, the repulsiveness of the countryside and the attractiveness of big cities led to rapid and mass internal migration movements in western countries. In later periods, there has been an uninterrupted global scale migration movement from the southern hemisphere to the north and from east to west (Kandel and Massey 2002). As mentioned, there is a necessity in mass migration in general. However, it can be said that voluntary and individual migration for economic purposes has a much greater negative impact on migrants and the settled population than forced mass migration for political purposes. While voluntary individual migrants with economic motives are expected to adapt to the new settlement faster, the adaptation of the masses forced to migrate for political reasons can be quite problematic. The geographical distance and the level of cultural proximity between the place of migration and the new settlement also significantly affect what happens after migration (Gemenne and Blocher 2017).

Although geographical distance and cultural proximity are important in this adaptation process, the level of economic development of the receiving country and the state of the social structure and network of relations are also of great importance in migrant adaptation. Countries that have the potential to successfully welcome and manage the migration they receive in socio-economic terms are less affected by the migration process. In countries that fail to manage the migration process successfully, migrants are left to the mercy of the market and the conscience of society (Musah-Surugu et al. 2018). This situation paves the way for the emergence of many complex new problems (Crush 2000). Managing the adaptation process well is of great importance for both the migrant and the individuals in the society of immigration. In order to manage this process well, the theories developed on the phenomenon of migration are of great importance to explain the integration process experienced by migrants while establishing a new life. In this context, the Assimilation Theory developed by Park and Burgess (1921) predicts that immigrants will move away from their own cultural identities by adopting the norms and values of the host society over time. Although this theory has been used to explain the integration process, especially when the host society has a homogenous cultural structure, it has been criticized for requiring immigrants to give up their own identities.

In contrast, Kymlicka's (1996) Multiculturalism Theory argues that different cultures can coexist and individuals can contribute to society by preserving their own identities. According to this theory, integration is possible when immigrants are able to maintain their own cultural values without having to fully adapt to the dominant culture. Today, many countries adopt this theory and develop multicultural policies and support the integration process of different ethnic groups. Another important model that explains the adaptation process of immigrants to their new societies is Berry's Acculturation Model. Berry (1997: 9-11) addresses the integration process of immigrants with four different strategies: integration (both preserving their own culture and adapting to the new society), assimilation (adopting the culture of the host society and distancing themselves from their own cultural identity), separation (adopting only their own culture and having limited interaction with the host society) and marginalization (having strong ties with neither their own culture nor the host society). This model provides an important framework for understanding the social and psychological adaptation processes of migrants. In addition, Portes and Rumbaut's (2006) Differential Integration Theory suggests that the integration process of migrants is not a homogeneous process and that individuals may follow different integration paths depending on their socio-economic conditions. For example, immigrants with higher levels of education and income may integrate into society faster, while individuals facing socio-economic difficulties may experience more difficulties in integration. This theory is widely used to explain the social and economic barriers faced by second-generation members of migrant communities in particular.

Research on migration and social integration provides important data for understanding the process of migrants' adaptation to new societies. Birgier and Cantalini (2025) examine the labor market integration and overeducation levels of immigrants in 17 countries in Western Europe, drawing attention to how immigrant integration patterns vary by gender and immigrant origin. Within the framework of integration theories, the study analyzes the education-job mismatch and employment levels of migrants. Furthermore, Fasani (2024), while addressing the barriers such as language barriers, education levels, discrimination that affect the integration of immigrants into the labor market in Europe, emphasizes that integration is a two-way process, that is, mutual adaptation of both immigrants and the host society is important. This finding suggests that economic integration of migrants is often slow and incomplete, with particularly low-educated and non-EU migrants experiencing more difficulties. Similarly, Tsindeliani et al. (2024) examine the effects of migrant amnesty on social integration in Russia and found that migrant amnesty can be an important tool in regulating the labor market and ensuring social integration. In another important study, Tibajev and Nygård (2023) investigate the labor market participation of immigrant women in Sweden in the context of gender norms and individual work experiences and examined how cultural adaptation and work experiences shape integration.

The various aspects of social integration have been further deepened by the effects of community participation (Zhang 2023), which suggests that it helps migrants to cope with inequalities and strengthen their relationship with the local community. On the other hand, Ekhtiari and Aysan (2023) link the integration of Iranian migrants in Türkiye to factors such as geographical and cultural proximity, visa-free travel and economic opportunities, noting that language barriers and difficulties in legal procedures make integration difficult. In the light of this information, in order to better understand the phenomenon of migration, it is of great importance to address the factors affecting migration, the results of migration and the integration process in detail.

Located in the eastern part of Türkiye, Van is an open door for migration movements as well as natural and cultural interactions due to its border with Iran (Erdoğan et al. 2022). This border has historically been an important transit point for trade, cultural exchange and human mobility, with a strategic location on the Silk Road. Economic, social and political factors are among the main reasons for migration between Van and Iran. Iran is known as a country struggling with economic hardship, unemployment and limited opportunities. Therefore, Iranian migrants turn to Van in search of better economic conditions, employment opportunities and living conditions. Moreover, factors such as political and religious pressures, ethnic and linguistic conflicts also encourage migration from Iran to Van. Migration between Van and Iran creates various problems for both sides: including the demographic and population structure of the province, especially with regard to its ethnic and cultural mosaic. This has led to the emergence of diversity in urban life and increased cultural exchange.

This migration is also of great importance for migrants to adapt to their new lives in a short time while building a new life. The adaptation process can determine the quality of life of the individual by reflecting the ability of the migrant to adapt to the new environment in social, economic and cultural terms. Adaptation in the new life after migration can generally be associated with factors such as age, post-migration support from public institutions, post-migration support from relatives, post-migration support from neighbors, and inadequate educational opportunities. As already mentioned, Berry's (1997) acculturation model explains the adaptation processes of immigrants to the new society through assimilation, integration, separation and marginalization strategies. The adaptation processes of Iranian immigrants in Van can be evaluated especially within the framework of integration and separation strategies. Individuals who adopt an integration strategy may adapt faster by taking advantage of public institutions and social support mechanisms in Van, whereas individuals who adopt a disengagement strategy may remain more attached to their own communities and have more limited interaction with the wider society. In addition, Portes and Rumbaut's (2006) differential adjustment theory suggests that migrants' adjustment processes are not homogeneous and individuals may follow different adjustment paths depending on their socio-economic conditions. For example, it has been observed in our study that immigrants with higher levels of education and income can integrate into the society faster, whereas individuals with low income and low education levels may experience more difficulties in integration.

In this study, the migration of Van province from Iran is analyzed using the Geographically Weighted Regression (GWR) method, which has not been used in this field before. The main purpose of this study is to examine the integration processes of individuals migrating from Iran to Van, to accurately identify the reasons why migrants prefer Van and to provide concrete suggestions for developing strategies to facilitate integration. The findings reveal that the support provided by public institutions plays an important role in the integration processes of migrants, but the impact of neighborhood relations on integration has a more complex structure. In this framework, the study is expected to contribute to the development of Van and provide an innovative method to the migration literature.

Material and Method

In the study, snowball sampling method was used to survey individuals who migrated from Iran to Van. Since sample selection is difficult especially due to security concerns, this method facilitated healthier data collection. Data was collected regionally for Iran and face-to-face surveys were conducted with a total of 629 individuals.[1] The surveys were conducted in the presence of a sworn translator, two interviewers and a PhD student.

The sample selection from the research population was made with reference to the Sample Size According to the Margin of Error developed by Bartlett et al. (2001). According to the TurkStat (2021) report, the total number of foreign nationals who migrated to Van province between 2016-2019 is 5,081 people. After face-to-face interviews during the pilot data collection process conducted before the start of the survey, it was observed that in addition to this data, there were individuals who migrated and settled in Van long ago and that this was the majority. Therefore, there are individuals who migrated before 2016. For this reason, more samples were collected than the required number of samples. Accordingly, taking into account the sampling error of 0.05, it is sufficient to sample between 357-370 people. A total of 629 individuals from 31 provinces of Iran were surveyed. Although more individuals were interviewed for this study, only 629 individuals agreed to participate in the survey.

Geographically Weighted Regression

GWR treats behaviors differently across regions or individuals and draws conclusions based on these differences. Unlike Ordinary Least Squares (OLS) analysis, GWR analysis looks at geographical differences and looks for spatial variations in the relationship between the dependent variable and independent variables (Fotheringham et al. 2002). Equation 2.1 below represents the OLS model.

$$Y_i = \beta_0 + \sum_{k=1}^{p} \beta_k X_{ik} + \varepsilon_i, \quad i = 1, \dots, n, \tag{2.1}$$

1 Due to the nature of the data, all replication material including data, codes, and raw output are available upon request directly from the authors.

where Y_i is the dependent variable, β_0 is the constant term, β_k is the independent variable coefficients, X_{ik} is the value of the kth independent variable of the ith observation, p is the number of independent variables, n is the number of observations and ε_i is the independent random error. Equation (2.1) is adapted to the coordinate system to obtain the GWR model in equation (2.2) (Fotheringham et al. 2002; Hu et al. 2024; Herawati et al. 2024; Wang et al. 2024).

$$Y_i = \beta_0(u_i, v_i) + \sum_{k=1}^{p} \beta_k(u_i, v_i) X_{ik} + \varepsilon_i. \tag{2.2}$$

where Y_i is the dependent variable at location i in a two-dimensional space; X_{ik} is the value of the kth independent variable at location i; p is the number of independent variables; $\beta_0(u_i, v_i)$ is the intercept parameter at location i; $\beta_k(u_i, v_i)$ is the local regression coefficient for the kth independent variable at location i; (u_i, v_i) is the spatial coordinates of location i; and ε_i is the independent random error at location i (Fotheringham and Oshan 2016; Hu et al. 2024; Herawati et al. 2024; Wang et al. 2024; Jia and Guo 2025).

Equation (2.2) measures the relationships inherent in the model around each location i. Thus, the OLS provides an insight into how GWR works. In GWR, an observation is weighted according to its proximity to location i, so that the weight of an observation is no longer fixed in the calibration but varies with i. Data from observations close to i are weighted more than data from observations further away. The parameter estimation equation is then as in (2.3);

$$\widehat{\boldsymbol{\beta}}(u_i, v_i) = (\boldsymbol{X}^T \boldsymbol{W}(u_i, v_i) \boldsymbol{X})^{-1} \boldsymbol{X}^T \boldsymbol{W}(u_i, v_i) \boldsymbol{Y}, \tag{2.3}$$

where $i = 1, \dots, n$ is the matrix row, $\widehat{\boldsymbol{\beta}}$ is an estimate of $\boldsymbol{\beta}$, $\boldsymbol{X}$ is the matrix of explanatory variables, $\boldsymbol{Y}$ is the vector of dependent variables and $\boldsymbol{W}(u_i, v_i)$ is the $n \times n$ spatial weight matrix. When only the diagonal axis is calculated using Gaussian or two-square functions, $\boldsymbol{W}(u_i, v_i) = diag[w_{i1}, w_{i2}, \dots, w_{in}]$ (Fotheringham and Oshan 2016; Hu et al. 2024; Herawati et al. 2024; Wang et al. 2024; Jia and Guo 2025).

In this study, Bisquare function, one of the Kernel functions, was used to determine the weighting function w_{ij}in the GWR method;

$$w_{ij} = \begin{cases} \left[1 - \left(d_{ij}/b^2\right)\right]^2 & \text{if } j \text{ is one of the closest points to } i \\ 0 & \text{if not} \end{cases}$$

where d_{ij} is the Euclidean distance between location i, where the parameters are estimated, and location j, where the data are observed (Fotheringham and Oshan 2016; Hu et al. 2024; Herawati et al. 2024; Wang et al. 2024; Jia and Guo 2025).

A criterion used for the appropriate bandwidth is the Akaike information criterion (AIC) value. When the AIC value is low, we can say that the model is less complex and provides a better trade-off. AIC plays an important role as a benchmark for model selection because it takes into account both the explanatory power and the complexity of the model (Shi and Tsai 2002; Akaike 1974).

While the OLS assumes that the relationships between variables in spatial data are constant across the entire study area, the GWR model recognizes that these relationships may vary with location and estimates separate parameters for each location. This approach allows us to analyze spatial heterogeneity and the spatial distribution of variability in more detail (Fotheringham and Oshan 2016; Hu et al. 2024; Herawati et al. 2024; Wang et al. 2024; Jia and Guo 2025). Especially in migration studies, the use of GWR allows us to conduct more precise analyses at the local level, as migration movements have spatially varying dynamics. In this way, we can reach more in-depth conclusions about the determinants and impacts of migration that take into account regional differences. Moreover, GWR's ability to model spatial heterogeneity helps policymakers and researchers to develop more effective strategies at the regional level (Jia and Guo 2025). For these reasons, the migration analyzed in this study is analyzed with the GWR method.

Analysis and Findings

Post-migration adaptation is a complex process that requires individuals and communities to adapt to a new cultural, social, and economic environment. While challenges such as language barriers and unemployment stand out in this process, the support of public institutions and social networks are important factors that accelerate the integration of migrants. Research shows that supportive policies and social integration efforts facilitate integration (Berry 1997; Portes and Rumbaut 2006). In particular, supports such as language training, employment services, and housing assistance provided by public institutions contribute to the faster adaptation of migrants to society (Bloemraad 2006). In addition, the emotional and financial support provided by family and relatives enables migrants to cope with stress and feel safe in the new environment (Boyd 1989). Moreover, the role of local communities in this process is particularly significant. The literature strongly emphasizes that support from the native population is a key determinant in the adaptation process of migrants (Berry 1997; Portes and Rumbaut 2001). In fact, there is strong evidence in the literature that support from local communities plays a critical role in the adaptation process of migrants (Putnam 2000; Berry 1997). On the other hand, inadequate educational opportunities also stand out as an important reason for migration, individuals see migration as a way out to access better education and opportunities (Todaro 1980). Many studies on migrant adaptation also highlight interaction with local communities and the strength of social support networks as primary variables shaping integration outcomes (Portes and Rumbaut 2001; Putnam 2000). Evaluating these factors together is critically important in understanding the adaptation processes of migrants. In the light of this information, the variables considered in the study are given in Table 1.

Table 1. Information on the Variables Used

Variables	Explanations
IAMNLST	I adapted to my new life in a short time after migration (Dependent Variable)
AGE	Age
IFSPI	I felt the support of public institutions after the migration
IFSMR	After the migration, I felt the support of my relatives
IFSMN	After the migration, I felt the support of my neighbors
MDTIE	Migration due to inadequate educational opportunities

While the abbreviations of the variables are given in Table 1, descriptive statistics of the variables are given in Table 2. While evaluating the survey questions in the study, 10 was coded as strongly agree and 1 as strongly disagree. Thus, it can be said that the higher the score of any Likert-scale question in the questionnaire, the higher the degree of agreement of the participant's opinion with the question asked.

Table 2. Descriptive Statistics

Variables	Min.	1. Quar.	Median	Mean	3. Quar.	Max.
IAMNLST	1.000	1.550	2.000	2.010	2.200	4.000
AGE	32.00	34.740	36.900	36.900	38.850	41.000
IFSPI	2.000	3.300	3.800	3.716	4.068	5.000
IFSMR	4.000	4.500	5.000	4.956	5.268	6.000
IFSMN	5.000	6.361	6.800	6.760	7.150	8.000
MDTIE	4.000	4.950	5.265	5.222	5.500	6.000

Figure 1. Violin Plots for Descriptive Statistics

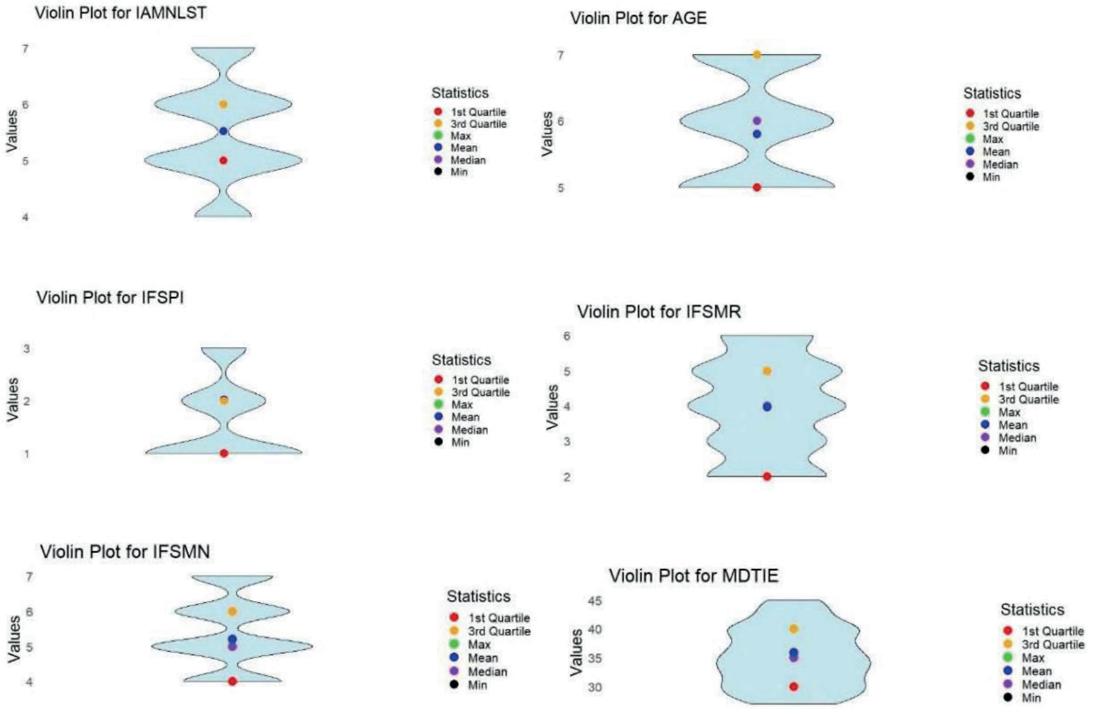


Table 2 and Figure 1 summarize the descriptive statistics (Min. 1st, Quartile, Median, Mean, 3rd Quartile and Max.) for all variables. The IAMNLST variable varies within a narrow range between a minimum of 1 and a maximum of 4, with two different points of intensity in the violin plot. The median (2,000) and mean (2,010) values are quite close to each other, indicating that the distribution is symmetric. The AGE variable exhibits a wide spread, ranging between a minimum of 32 and a maximum of 41. The median and mean are 36.900, indicating a symmetric distribution, while the moderate distance between quartiles indicates that there are no extreme outliers. The IFSPI variable ranges between 2 and 5, with median (3.800) and mean (3.716) values close to each other, indicating a symmetrical distribution. The distance between quartiles is low, indicating that the data is concentrated in the middle values. The IFSMR variable ranges between 4 and 6 and exhibits a multimodal structure in the violin plot. The median (5,000) and mean (4,956) are close, indicating that the data is largely concentrated between quartiles. The IFSMN variable ranges between 5 and 8, with a symmetric distribution concentrated in the midpoints. The median (6.800) and mean (6.760) are very close to each other, with most of the data distributed close to the mean. The MDTIE variable ranges between 4 and 6 and shows a symmetric and narrow distribution. The median (5.265) and mean (5.222) are very close, with most of the data concentrated around the mean. Overall, most of the variables are symmetrically distributed and concentrated in the middle rather than the extremes. Violin plots and descriptive statistics largely overlap, indicating that the data are reliably distributed.

The demographic information of the individuals who participated in the surveys is given in tables 3, 4, 5 and 6 in detail.

Table 3. Demographic Information of the Individuals Who Participated in the Surveys

Gender		Age				Marital Status		
Female	**Male**	**18-30**	**30-40**	**40-50**	**50-60**	**Single**	**Married**	**Widowed**
244	385	199	273	104	53	200	395	34

Table 4. Education Information of the Individuals Who Participated in the Surveys

Education Status	Number
Not literate	25
Literate but not school	63
Graduated from primary school	47
Secondary School Graduate	73
High school graduate	206
Vocational high school graduate	5
Associate degree graduate	31
Bachelor's degree	158
Post-graduate degree	21

Table 5. Occupational Information of the Respondents and ODDS Ratio Results

What were you doing before you migrated to Van?							
Unemployed	**Farmer**	**Student**	**Officer**	**Tradesmen**	**Construction**	**Private**	**Others**
69	45	79	18	136	36	68	178
Occupation after migration?							
Unemployed	**Farmer**	**Student**	**Officer**	**Tradesmen**	**Construction**	**Private**	**Others**
30	1	26	6	214	28	51	273
ODDS RATIO							
Estimate				**95% Confidence Interval**			
2.46				(1.578, 3.835)			

Table 5 presents the results of the ODDS Ratio by comparing the occupational distribution of individuals before and after migration (Bilder and Loughin 20224). In this analysis, the employment status of individuals before and after migration was classified into two groups: unemployed and employed. The unemployed group consisted of individuals who reported being without a job before and after migration. The employed group included individuals who transitioned into any occupation category (e.g., farmer, student, officer, tradesmen, construction, private sector, and others) after migration. The estimated odds of unemployment before migration are 2.46 times as high as after migration. Since the confidence interval (1.578, 3.835) does not include 1, there is sufficient evidence to suggest that unemployment significantly decreases after migration. This result indicates that migration to Van has a potential impact on employment status, reducing the likelihood of being unemployed.

Table 6. Descriptive Statistics of Reasons for Migration

	N	Mean	Median	S. Deviation
Access to a better life	629	6.519	6	1.938
Economic (unemployment, poverty, etc.) inadequacy	629	4.779	5	2.195
I don't have land etc.	629	2.949	2	2.231
Inefficiency in agricultural activities	629	2.965	2	2.246
Inadequate opportunities for education (my own education or children's education)	629	5.519	6	1.670
Inadequacy of health services	629	5.238	5	1.250
Inadequacy in social life	629	7.295	8	1.614
Security concerns	629	8.017	8	1.468
Challenging geographical conditions and adverse climatic conditions	629	4.888	5	1.473
Marriage	629	2.163	1	2.788
Positive encouragement from our relatives who migrated	629	3.298	3	2.114
Previous migration of one or more of my family members	629	3.910	4	2.346
Political and policy pressures	629	7.777	8	1.953
Pressure from social environment	629	7.821	8	1.588
For my work	629	1.887	1	2.127

Table 6 presents descriptive statistics on reasons for migration. According to the table, the factors with the highest mean values among the reasons why individuals migrate are security concerns (8.017), inadequate social living conditions (7.295) and social environmental pressure (7.821), indicating that individuals are in search of a safer and more socially favorable living space. On the other hand, reasons such as the need for work (1.887) and marriage (2.163) seem to be less effective in the decision to migrate. When the standard deviation values are analyzed, it is seen that the incentives of relatives who migrated (2.783) and marriage (2.718) have the highest variability and are evaluated differently among individuals, whereas inadequate health services (1.250) and lack of educational opportunities (1.670) show a more homogeneous distribution. In general, migration decisions are strongly influenced by security, social life and economic factors, while some reasons are perceived differently among individuals, suggesting that individual and environmental factors should be considered together in understanding migration movements.

Table 7. Breusch-Pagan test was used for the problem of variance and Kolmogorov-Smirnov test was used for normality.

Table 7. Assumptions

Tests	Values	p-values
Breusch-Pagan Test (Heteroscedasticity)	6.708	0.243
Kolmogorov-Smirnov Test (Normality)	0.537	0.581

When Table 7 is analyzed; it is concluded that there is no problem of varying variance according to the probability value of Breusch-Pagan test ($p > 0.05$) and normal distribution is obtained with the probability value of Kolmogorov-Smirnov Test ($p > 0.05$). In addition, Variance Inflation Factor (VIF) values were used for the multicollinearity problem and the results are given in Table 8. Table 8 also summarizes the coefficients of the OLS model.

Table 8. Summary of OLS Model Coefficients

Variables	Coefficients	Std.Error	t-statistics	p-values	VIF values
CONSTANT	2.067	1.977	1.046	0.305	-
AGE	-0.024	0.038	-0.634	0.531	1.266
IFSPI	0.593	0.176	3.362	0.002*	1.411
IFSMR	-0.102	0.181	-0.567	0.575	1.287
IFSMN	-0.363	0.158	-2.301	0.029*	1.684
MDTIE	0.306	0.250	1.222	0.232	1.233

*: p<0.05

VIF values less than 10 indicate that there is no multicollinearity problem (Demir, 2020). When Table 8 is examined, it is concluded that the VIF values of all variables are below 10, confirming the absence of multicollinearity among the independent variables. According to the OLS model probability values, a significant relationship is observed between the independent variables “I felt the support of public institutions after migration” and “I felt the support of neighbors after migration” with the dependent variable $(p > 0.05)$. Specifically, an increase in “I felt the support of public institutions after migration” is correlated with an increase in the post-migration adaptation process. Conversely, an increase in “I felt the support of neighbors after migration” is associated with a decrease in the post-migration adaptation process. Table 9 presents the spatial autocorrelation values of the variables.

Table 9. Global Moran’s I for Dependent and Independent Variables

Variables	Moran’s I values	Pattern	p-values
IAMNLST	0.346	Clustered	0.037*
AGE	0.173	Clustered	0.041*
IFSPI	0.160	Clustered	0.002*
IFSMR	0.273	Clustered	0.026*
IFSMN	0.536	Clustered	0.008*
MDTIE	0.301	Clustered	0.031*

*: p<0.05

According to the Global Moran’s I analysis presented in Table 9, both the dependent variable (IAMNLST) and all independent variables (AGE, IFSPI, IFSMR, IFSMN, MDTIE) show statistically significant positive spatial autocorrelation $(p > 0.05)$. This suggests that these variables are not randomly distributed in space, but rather similar values are geographically clustered. The significantly positive Moran’s I values indicate that the assumption of independent and homogeneous error term, which is one of the basic assumptions of the classical OLS model, is violated. Therefore, in this context, the GWR model, which calculates local regression coefficients for each location taking into account spatial heterogeneity and autocorrelation, is a more appropriate and explanatory approach that should be preferred over OLS in the analysis. Table 10 shows the comparison of the OLS and GWR models.

Table 10. Comparison of OLS and GWR Models

Model Selection Criteria	OLS	GWR
R^2	0.403	0.669
$Adjusted\ R^2$	0.284	0.417
AIC	51.720	32.978
AICc	56.589	52.963
BIC	54.796	25.447
RSS	6.128	4.007

Table 10 shows that R^2 (0.403) and $Adjusted\ R^2$ (0.284) values of OLS are lower than R^2 (0.669) and $Adjusted\ R^2$ (0.417) values of GWR. Moreover, the AIC value of OLS

(51.720) is higher than the AIC value of GWR (32.978). The same is true for AICc, BIC and OLS. These values are calculated as 56.589, 54.796 and 6.128 for AIC and 52.963, 25.447 and 4.007 for GWR, respectively. According to these results, all criteria used in this study indicate that GWR has a better fit to the empirical data than OLS. Therefore, it can be said that GWR provides stronger results than OLS. Table 11 shows the Global Moran I statistics for the OLS and GWR residuals.

Table 11. Global Moran's I Statistics of OLS and GWR Residuals

Model	Moran's I	Variance	z-score	p –values
OLS	0.193	0.011	1.872	0.037*
GWR	-0.197	0.011	-1.271	0.964

*: $p<0.05$

The Global Moran's I statistics presented in Table 11 comparatively reveal the level of spatial autocorrelation in the residuals of the OLS and GWR models. The residuals of the OLS model show a positive and statistically significant Moran's I value (0.193; p = 0.037), suggesting that this model does not adequately remove spatial dependence. In contrast, the residuals of the GWR model show a negative (-0.197) and non-significant (p = 0.964) Moran's I value, indicating that the GWR model successfully removes spatial autocorrelation and the error terms are randomly distributed across space. These results clearly show that the GWR model, which takes into account the spatial structure, produces more spatially consistent and reliable results than the classical OLS model, thus justifying the use of GWR. Table 12 presents the results of Leung's F-test, which examines the improvement factor of the OLS (Leung et al. 2000). Leung's F-test is calculated using three different techniques (F_1, F_2 and F_3).

Table 12. OLS and GWR Model Performance Comparison

Leung et al. (2000) F_1 test				
F-value	RSS for OLS	RSS for GWR	df	p-value
0.673	8.128	15.007	33.319	0.041*
Leung et al. (2000) F_2 test				
F-value	RSS for OLS	GWR RSS optimization	df	p-value
2.165	8.128	10.120	18.352	0.046*
Leung et al. (2000) F_3 test				
Variables	F statistics	Numerator d.f.	Denominator d.f.	p-values
CONSTANT	8.581	11.739	23.319	0.001*
AGE	2.807	11.496	23.319	0.016*
IFSPI	4.252	9.935	23.319	0.001*
IFSMR	5.043	5.499	23.319	0.002*
IFSMN	4.193	6.615	23.319	0.004*
MDTIE	2.704	4.534	23.319	0.049*

*: $p<0.05$

The ratio between the RSSs of OLS and GWR is evaluated using F_1, the first test for a set of degrees of freedom. According to Table 12, the F_1 test statistic value is 0.673, the OLS RSS value is 8.128 and the GWR RSS value is 15.007. A low F_1 statistic value indicates that GWR model fit is superior to OLS. Therefore, according to the probability value calculated for F_1 $(p < 0.05)$, the null hypothesis H_0 is rejected and the alternative hypothesis is accepted. In this case, it is concluded that GWR model fit is superior to OLS. For the F_2 test, the F test statistic is 2.165, the OLS RSS is 8.128 and the GWR RSS improvement is 10.120. According to the probability value of the F_2 test $(p < 0.05)$; there is a statistically significant difference between the OLS and GWR models, thus the null hypothesis H_0 is rejected and the alternative hypothesis is accepted. In this case, it is concluded that GWR model fit is superior to OLS. The F_3 test includes a dispersion analysis for each variable coefficient. If the F_3 value is high, regional differences are statistically significant for the questioned coefficient. When Table 12 is examined, it can be said that there are regional differences in variables since the probability values calculated separately for all variables are < 0.05. Therefore, the null hypothesis H_0 is rejected and the alternative hypothesis is accepted. In this case, it is concluded that GWR model fit is superior to OLS. GWR parameter summary results for the variables are given in Table 13.

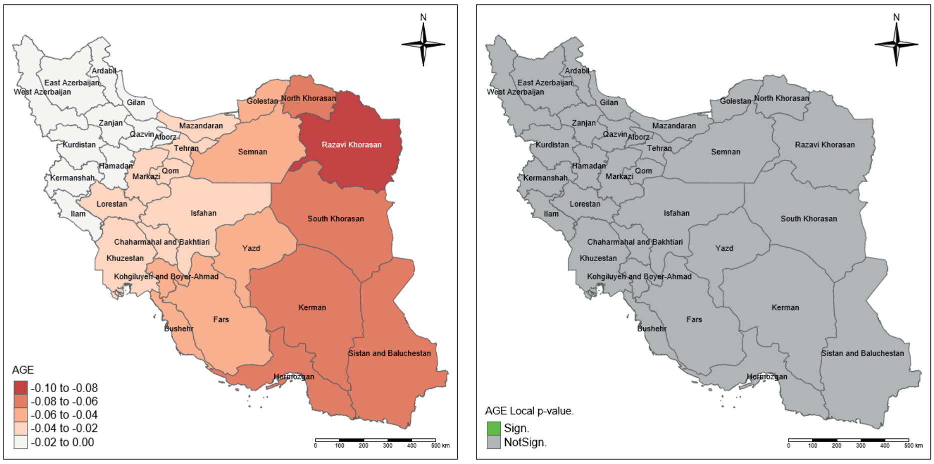
Table 13. GWR Parameter Summary Results

Variables	Min.	1. Quar.	Median	3. Quar.	Max.
CONSTANT	-0.969	-0.302	0.356	3.296	5.770
AGE	-0.087	-0.052	-0.023	-0.014	-0.005
IFSPI	0.446	0.682	0.816	0.865	1.005
IFSMR	-0.320	0.094	0.187	0.211	0.229
IFSMN	-0.724	-0.643	-0.618	-0.510	-0.230
MDTIE	0.106	0.298	0.498	0.564	0.619

When Table 13 is analyzed, it is seen that the highest median value (0.816) belongs to the IFSPI variable and the lowest median value (-0.618) belongs to the IFSMN variable. The minimum and maximum values reveal that the parameters vary in different regions. When the table is analyzed; the age variable negatively affects the post-migration adjustment process. The coefficient change of the age variable by region is (-0.087, -0.005). The IFSPI variable positively affects the post-migration adjustment process. The coefficient change of the IFSPI variable by regions is (0.446, 1.005). While the IFSMR variable positively affects the post-migration adjustment process in some regions, it is observed to affect it negatively in some regions. The coefficient change of the IFSMR variable by regions is (-0.320, 0.229). The IFSMN variable negatively affects the post-migration adjustment process. The coefficient change of the IFSMN variable by region is (-0.724, -0.230). The MDTIE variable positively affects the post-migration adjustment process. The change in the coefficient of the MDTIE variable by region is (0.106, 0.619). Unlike the GWR model, the global model shows only average data and does not describe the context of local labor markets. According to the results of the GWR analysis, the effects of the independent variables on the dependent variable by region are presented in the figures below.

Figure 2 shows the distribution and significance of the relationship between the independent variable "age" and the dependent variable "I adapted to my new life in a short time after migration" according to the results of GWR analysis by Iranian regions.

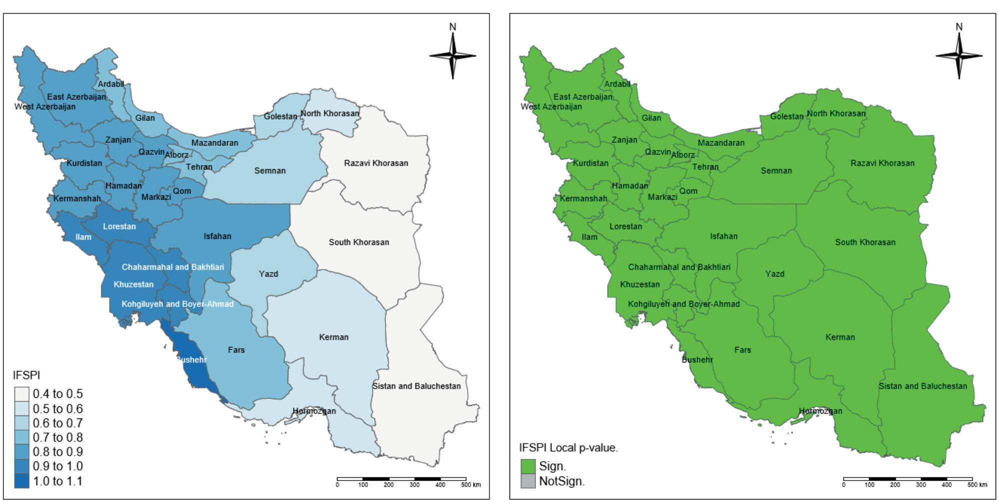
Figure 2. Coefficient and Significance Distribution of AGE Variable by Iranian Regions



When the local significance of the relationship between the independent variable age and the dependent variable I adapted to my new life in a short time after migration is analyzed in Figure 2 (map on the right); there is no significant relationship in any region. Therefore, the interpretation of the relationship between variables by region does not carry any meaning.

Figure 3 shows the distribution and significance of the relationship between the independent variable "I felt the support of public institutions after migration" and the dependent variable "I adapted to my new life in a short time after migration" according to the results of GWR analysis according to Iranian regions.

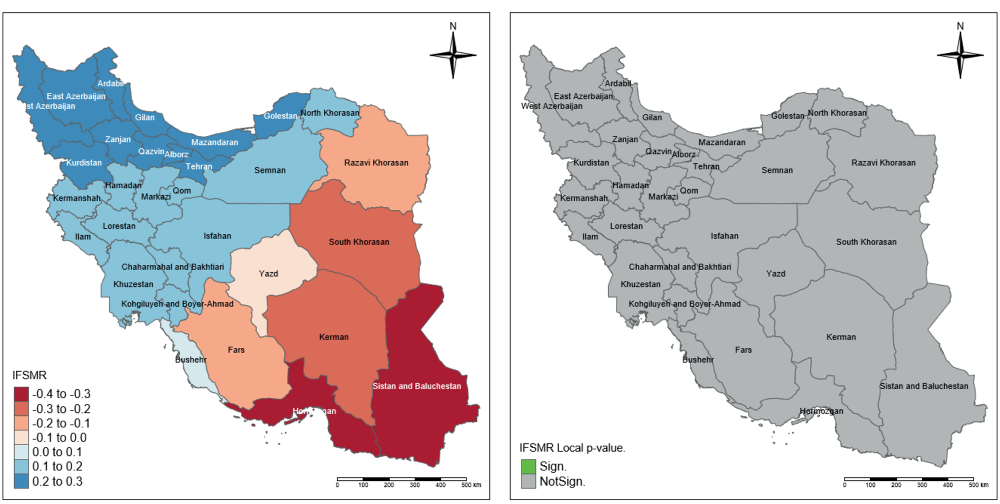
Figure 3. Coefficient and Significance Distribution of IFSPI Variable by Iranian Regions



When the coefficient distributions of the variable "I felt the support of public institutions after migration" are analyzed in Figure 3 (map on the left), a positive relationship is observed between "I felt the support of public institutions after migration" and "I adapted to my new life in a short time after migration" across all regions. This indicates that higher levels of perceived institutional support are associated with a higher degree of post-migration adaptation. This relationship is particularly pronounced in the darker regions (western and northwestern regions of Iran). When the local significance of the relationship between the independent variable "I felt the support of public institutions after migration" and the dependent variable "I adapted to my new life in a short time after migration" is examined (map on the right), a statistically significant relationship is observed in all regions (green areas). The variation in this relationship across regions may be influenced by factors such as cultural similarities that facilitate adaptation, as well as the size, diversity, economic structure, social dynamics, education and healthcare systems, and overall cultural composition of the settlement areas. Additionally, the characteristics of the migrated region may also contribute to these differences. Moreover, it was found that there is a positive relationship between the support of public institutions and the integration process of migrants.

Figure 4 shows the distribution and significance of the relationship between the independent variable "I felt the support of my relatives after migration" and the dependent variable "I adapted to my new life in a short time after migration" according to the results of GWR analysis.

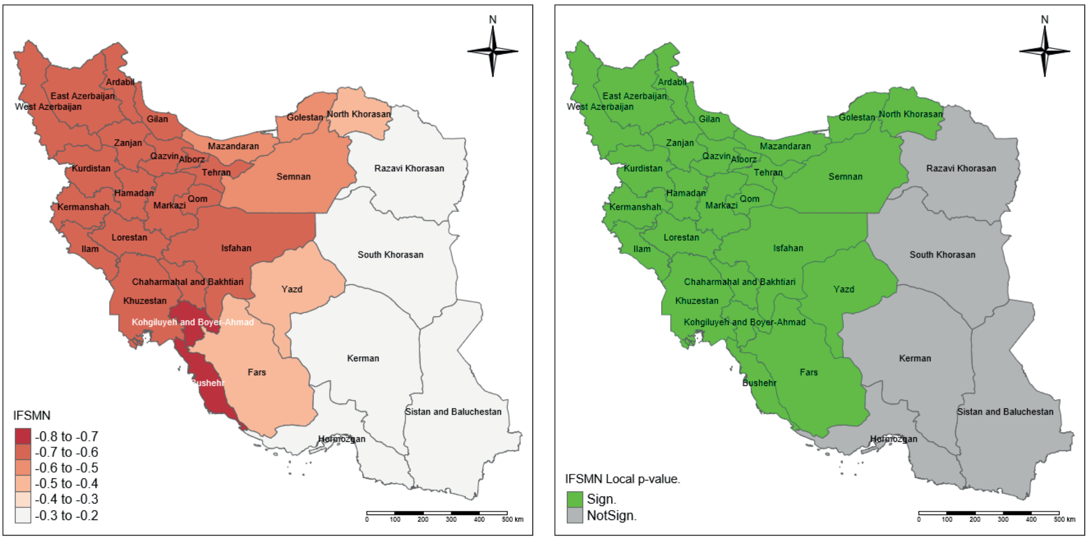
Figure 4. Coefficient and Significance Distribution of IFSMR Variable by Iranian Regions



When the local significance of the relationship between the independent variable I felt the support of my relatives after migration and the dependent variable I adapted to my new life in a short time after migration is analyzed in Figure 4 (map on the right); there is no significant relationship in any region. Therefore, the interpretation of the relationship between variables by region does not carry any meaning.

Figure 5 shows the distribution and significance of the relationship between the independent variable “I felt the support of my neighbors after migration” and the dependent variable “I adapted to my new life in a short time after migration” according to the results of GWR analysis according to Iranian regions.

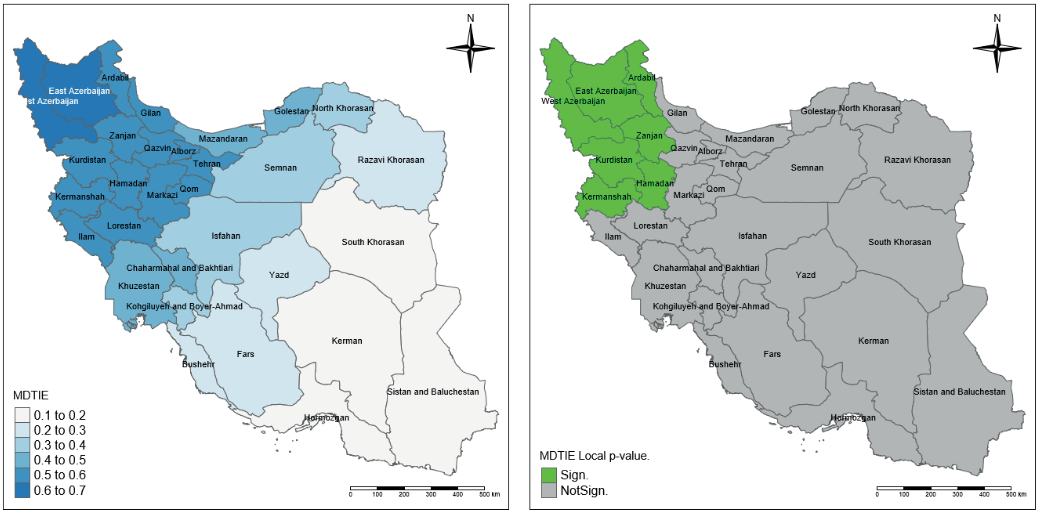
Figure 5. Coefficient and Significance Distribution of IFSMN Variable by Iranian Regions



When the coefficient distributions of the variable “I felt the support of my neighbors after migration” are examined in Figure 5 (map on the left), a negative relationship is observed between “I felt the support of my neighbors after migration” and “I adapted to my new life in a short time after migration” across all regions. This suggests that higher levels of perceived neighbor support are associated with lower levels of post-migration adaptation. This relationship is particularly pronounced in the darker regions (western and northwestern regions of Iran). When the local significance of the relationship between the independent variable “I felt the support of my neighbors after migration” and the dependent variable “I adapted to my new life in a short time after migration” is examined (map on the right), a statistically significant relationship is observed in the western and northwestern regions of Iran (green areas). The variation in this relationship across regions may be influenced by factors such as cultural similarities that facilitate adaptation, as well as the size, diversity, economic structure, social dynamics, education and healthcare systems, and overall cultural composition of the settlement areas. Additionally, the characteristics of the migrated region may also contribute to these differences.

Figure 6 shows the distribution and significance of the relationship between the independent variable “migration due to insufficient educational opportunities” and the dependent variable “I adapted to my new life in a short time after migration” according to the results of GWR analysis by Iranian regions.

Figure 6. Coefficient and Significance Distribution of MDTIE Variable by Iranian Regions



When the coefficient distributions of the variable "migration due to insufficient educational opportunities" are analyzed in Figure 6 (map on the left), a positive relationship is observed between "migration due to insufficient educational opportunities" and "adaptation to my new life in a short time after migration" across all regions. This suggests that migration driven by insufficient educational opportunities is associated with a higher level of post-migration adaptation. This relationship is particularly pronounced in the darker regions (western and northwestern regions of Iran). When the local significance of the relationship between the independent variable "migration due to lack of educational opportunities" and the dependent variable "I adapted to my new life in a short time after migration" is analyzed (map on the right), a statistically significant relationship is observed in the northwestern region of Iran (green areas). The regional variation in this relationship may be influenced by factors such as the role of cultural similarities in facilitating adaptation, as well as the size, diversity, economic structure, social dynamics, education and healthcare systems, and overall cultural composition of the settlement areas.

Discussion and Conclusion

The province of Van is a city that receives migration due to its relatively high level of development, historical and cultural heritage and tourism potential in the Eastern Anatolia Region. However, its border with Iran has provided an advantage in terms of trade and economic mobility, and has been a determining factor in migration flows from Iran to Van.

In this study, the adaptation processes of individuals who migrated from Iran to Van to their new lives were analyzed using OLS and GWR models. As a result of the analysis, it was found that the GWR model gave better results in explaining the adaptation processes of migrants. According to the findings, it was determined that migrants who felt the support of public institutions adapted to their new lives in a shorter time. However, the negative relationship between the support of neighbors and the adaptation process stands out as a striking finding. While social support mechanisms are expected to facilitate the adaptation process of migrants in line with generally accepted theories, in this study, it was observed that neighborhood relations can negatively affect adaptation. Although this finding may seem unexpected at first glance, similar examples can be found in the migrant studies literature. In the specific case of Van, the fact that Iranian migrants live together intensively in some neighborhoods ensures that neighborly relations are predominantly directed towards their own in-group, which may limit the social integration of the individual instead of facilitating adaptation. Moreover, the perception of neighborly support may vary from individual to individual; some individuals may experience it not as supportive but as social pressure or surveillance. This may explain why higher levels of perceived neighbor support correlate with lower adaptation outcomes. These findings point to the complex, and sometimes ambivalent, role of social networks in shaping integration-support is not universally positive, and its effects are deeply contingent on group structure, individual perception, and local context. This can be interpreted as neighborhood relations may create social isolation, cause migrants to stay more within their own groups and delay integration into the wider society. In particular, the fact that certain groups form closed social networks and interact only with their own communities can be associated with the segregation strategy within the scope of Berry's (1997) acculturation model. Portes and Rumbaut's (2006) differential integration theory also suggests that migrant groups may integrate into mainstream society at different speeds due to different social and economic factors. Accordingly, the results of the analysis should be analyzed not only in terms of individual but also structural and social dynamics.

In the study, it was found that there are differences between the geographical regions where migrants come from in terms of the integration process. While the integration process of migrants from the western, northern and northwestern regions of Iran was found to be faster, the integration process of those from the southern regions took longer. One of the reasons underlying this difference may be that the socio-economic structure of the western regions of Iran is relatively closer to Van province. In addition, it is known that some regions in western Iran have dense Turkish populations. This may explain why migrants from western Iran have fewer linguistic difficulties and integrate into the society faster due to cultural similarities. In particular, Azerbaijani Turks living in provinces such as West Azerbaijan, Ardebil and Zanjan are likely to establish social ties more easily in Van province and communicate faster with the local population. In this context, factors such as linguistic and cultural proximity may play an important role in the adaptation process of migrants. In the specific case of Van province, it is important that public institutions develop supportive policies for migrants and increase services to accelerate socio-economic integration.

One of the key methodological limitations of this study stems from the inability to use geographically identifiable data within Van province for spatial modeling. Due to ethical sensitivities, legal restrictions, and security concerns regarding migrant data privacy, it was not possible to geocode the current residential addresses of participants within Van. Instead, migrants' provinces of origin in Iran were used to assign spatial references, enabling the application of the GWR model. While this approach allowed for meaningful spatial analysis based on origin-specific patterns, it inherently limits the ability to assess spatial heterogeneity within the host region. This limitation should be considered when interpreting the spatial results of this study. Additionally, the study population is limited to Iranian migrants who currently reside in Van province. As such, the findings should be interpreted within the context of this specific local setting. The integration patterns, socio-economic dynamics, and support mechanisms observed in Van may not be reflective of the experiences of Iranian migrants residing in other Turkish provinces.

The originality of this study lies in analyzing the migration phenomenon with the GWR model, which is rarely used in Van province (Görür and Yüzbaşı 2024; Yüzbaşı and Görür 2023). When the studies on migration in the national literature are examined, it is seen that analyses based on real data are generally preferred and methods such as regression analysis, OLS, spatial analysis, panel data analysis and GWR are used (see Özgür and Aydın 2012; Yakar 2013; Öz and Çelebioğlu 2015; Aral and Oğuzlar 2021). However, it has been determined that the GWR method has been used to a limited extent in migration studies and its applications supported by survey data offer an innovative approach. Migration studies in Türkiye have long concentrated on Balkan migrants and, more prominently, on Syrian refugees. Within this body of literature, research has largely been shaped around issues such as host-society perceptions, integration processes, and narratives of threat (Danış Şenyüz et al., 2009; Özen et al., 2023). Migrant groups other than Syrians, as illustrated by the case of Ukrainian forced migrants, have begun to receive scholarly attention only in recent years and remain relatively underrepresented (Köşer Akçapar and Aydın, 2025). In contrast, migration from Iran to Türkiye continues to constitute a comparatively neglected field of research (Ekhtiari and Aysan, 2023). In this context, our research fills an important gap in terms of addressing the integration processes of Iranian immigrants with the GWR method.

Despite the noted limitations, this study offers a novel methodological contribution by demonstrating how GWR can be effectively applied using origin-based geospatial identifiers when post-migration geographic data are unavailable. In contexts where sensitive data collection within host locations is restricted, leveraging migrants' regions of origin provides an alternative way to explore spatial variation in integration outcomes. This approach expands the methodological toolkit for migration researchers working in data-constrained environments.

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Acknowledgment

The authors sincerely thank the editor and the two anonymous reviewers for their valuable comments and constructive suggestions, which greatly improved the quality of this manuscript. This study is derived from the second author's PhD thesis, and both authors were supported by the Scientific and Technological Research Council of Türkiye (TÜBİTAK) under the 3005 - Innovative Solutions in Social Sciences and Humanities Research Program (Project No. 122G128). The authors gratefully acknowledge the support of TÜBİTAK.