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Research paper

Analysis of the energy justice in natural gas distribution with Multiscale Geographically Weighted Regression (MGWR)

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ABSTRACT

Energy justice is violated when particular customers and locations are excluded from a variety of urban energy service distribution. This study explores energy justice in terms of natural gas distribution by providing empirical evidence from 356 neighborhoods of Izmir Metropolitan Area (IMA). The aim is to reveal driving factors of natural gas investment and the spatial reflections of the relationships between investment, and socio-economic and physical characteristics. A global regression model, OLS, and two local spatial regression models, GWR and MGWR, are conducted. Population, income, employment and disadvantaged areas are the significant determinants of natural gas investments. Due to the presence of spatial autocorrelation in OLS residuals, GWR and MGWR are utilized to account for spatial variation in the response variable. Local models are superior to the global model according to AICc values, which are 607.3, 586.7, and 558.5, in OLS, GWR, and MGWR, respectively. MGWR further improves the overall fit with higher R-sq and lower AICc values. The local R-sq values indicate at least 70% variability is explained in 85% of the study area in MGWR, and in 73% of IMA in GWR. Parameters are slightly overestimated in GWR at the mean level. None of the local models are subject to multicollinearity according to local condition numbers, but local variance decomposition proportions indicate the effects of multicollinearity in some observations. Spatial modeling of investments helps to demonstrate local variations of energy injustice and to develop site-specific policies. Population and employment are related to potential customers, which lead to higher investments. Income depends on purchasing power, and there are economic barriers that need to be regulated through subsidies and incentives for the low-income households. Awareness raising policies can also be developed to better inform households about energy alternatives. Disadvantaged areas, either declared as urban transformation areas or currently under urban transformation, lack the natural gas service in general, while the investments can be considered in those areas along with the new development plans.

1. Introduction

Energy justice is strongly associated with spatial, socio-economic, and political structures of societies, while injustice can be embedded in particular locations, communities and administrative framework. The issue becomes more critical in emerging economies such as Turkey, which have increasing energy demand but are heavily dependent on imported energy. The extent of socio-economic inequalities further exacerbates the problem. This study aims to provide insight into energy justice in natural gas distribution in Izmir, Turkey, through discussing the factors affecting the natural gas investments, and the spatial dimension of the relationship between investments, socio-economic and physical characteristics. In order to address this issue, it is important to first clarify the concept of energy justice, characteristics of natural gas as an urban energy network, the sector profile in Turkey and natural gas distribution in the study area, İzmir.

1.1. Energy Justice: A literature review

Energy justice is achieved through fair, sustainable and secure energy for all. The concept addresses various issues related to energy provision and consumption, energy policy, energy security, climate change and environmental problems. UN defines ensuring access to affordable, reliable, sustainable and modern energy for all as one of the sustainable development goals; while setting the target of expanding and upgrading technology for supplying modern and sustainable energy services for everyone (United Nations, 2015). Energy is not a need, but an essential source to deliver adequate living conditions (Najam and Cleveland, 2003), and the provision of modern energy services is critical for sustainable development (Nussbaumer et al., 2012). Network providers consider various factors when making investment decisions, based

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on their priorities. The investments may bypass the non-valued users or places in cities (Graham and Marvin, 2001), when the energy provider is a profit-oriented company. Such local bypasses result in social and/or spatial injustice in energy provision, since some communities have access to variety of fuel choices for their energy needs, whereas some others are deprived of modern, efficient and clean alternatives.

Conceptualization of energy justice is important in the recognition of the issue and developing sustainability-oriented policies. The main tenets of energy justice are conceptualized as distributional, recognition, and procedural, which refer to the distribution of physical and associated responsibilities of injustice, affected and ignored groups, and the fairness of the process and participation, respectively (Walker, 2009; McCauley et al., 2013; Heffron and McCauley, 2014; Jenkins et al., 2016; Lacey-Barnakle, 2020; Moniruzzaman and Day, 2020). There are no clear distinctions between these principles, while they can be co-existing and mutually reinforcing (Gillard et al., 2017). Calver and Simcock (2021) indicate that the three-tenet approach has a limitation of prescribing normative principles regarding what constitutes injustice regarding each dimension. Sovacool et al. (2016) suggest an alternative framework which addresses to real world problems by focusing on availability, affordability, due process, transparency and accountability, sustainability, intragenerational equity, intergenerational equity, and responsibility. Both conceptualizations are revisited in this study, particularly in terms of distributional justice and availability.

Energy justice literature revolve around energy poverty and energy vulnerability in general. Energy poverty can be understood as the inability of a household to secure a socially and materially necessitated level of energy services in the home (Bouzarovski, 2014, p. 276) and generally conceived of and measured at the household level (Moniruzzaman and Day, 2020, p. 1). Energy vulnerability, on the other hand, puts the emphasis on the unbearable dimension of an energy supply (Percebois, 2007, p. 51), and the coping capacity of adverse events, such as supply disruptions (Gnansounou, 2008). Energy justice presents a useful decision-making tool that can assist energy planners and consumers in making more informed energy choices (Sovacool and Dworkin, 2015, p. 435), and deals with where the injustices observed, who are the affected ones, and how to remedy and reduce the injustice (Jenkins et al., 2016). Energy injustice can be more common and inherent in particular areas which have either no access to sustainable and modern energy services or low levels of affordability, indicating spatial dimension and geographical embeddedness of energy justice. Spatial differences in energy poverty and vulnerability result from structural geographical inequities that are engrained in various stages of energy systems, and, moreover, in the fundamental infrastructural, economic, and cultural make-up of societies (Bouzarovski and Simcock, 2017, p. 645).

It is important to determine communities benefiting or loosing from access to the energy, while energy justice is about fair distribution of cost and benefits across communities no matter what their income, location and race are (Sarkodie and Adams, 2020). Although there are studies regarding environmental and economic dimensions of natural gas distribution, the factors underpinning the amount of natural gas investments, and their spatial correspondences leading to energy injustice have been overlooked in the literature. This article aims to fill this gap by providing empirical evidence from the Metropolitan Area of Izmir, Turkey, by analyzing the relationship between natural gas investments and socio-economic and physical characteristics. Following the arguments of Bouzarovski and Simcock (2017), it is attempted to explore the spatial dependence of energy justice in natural gas distribution and investigate driving factors affecting natural gas investments. Socio-economic and spatial analyses of natural gas distribution allow to identify problem areas and to reveal the source of the problem in these areas. In this study, energy justice is considered as a decision-making tool that will ultimately help develop policies regarding location-specific priorities, as suggested by Sovacool and Dworkin (2015).

1.2. Natural gas: General characteristics, and the sector profile in Turkey

Natural gas is one of the most preferred forms of energy in residential consumption. Although being a fossil fuel, it has many qualities in terms of being an efficient, relatively clean burning, and economical energy source (EIA, 2020). Natural gas is also expected to support the transition to a low-carbon energy system through reducing the fast-growing emerging economies' dependency on coal, and providing a source of low-carbon energy when combined with carbon capture, use and storage (BP, 2022). Apart from the environmental concerns, natural gas provision has various socio-economic impacts. Modern energy services support economic development, while income inequality adversely affect access to these services (Sarkodie and Adams, 2020). The study of Balvin et al. (2020) shows that bringing natural gas service to the disadvantaged parts of the city of Lima is expected to provide socio-economic and environmental benefits, while eradicate energy poverty.

Market characteristics determine the provision of the service in terms of the investment decisions. Natural gas, once a public utility, is now supplied by private companies. Liberalization of the natural gas market was realized in the 1990s in the US and in Europe, although the deregulation attempts started in late 1970s in the US with the Natural Gas Policy Act of 1978 (Pierce, 1982). Order 636 released in 1993 in the US (Gorak and Ray, 1995) and several directives released in 1996 and in 1997 in Europe (Percebois, 1999) paved the way for the liberalization in natural gas provision. The transition to a new natural gas market in Turkey was realized almost a decade later. Natural gas service had been provided by a BOTAS, a public company, until 2001. Series of legislations were enacted from 2001 to 2007, which framed the new regime deregulating the natural gas market (TEPAV, 2009). Deregulations inevitably had socio-economic and environmental repercussions.

Natural gas is an imported fuel in Turkey, of which usage started in the 1970s in industry. The first residential use of natural gas was in Ankara, in 1992, and later the distribution was extended to Istanbul and Bursa (Natural Gas Market in Turkey, 2021). Today natural gas is supplied to all 81 provinces. Annual natural gas consumption was 48.26 billion Sm^3 in 2020, and housing was the leading sector having 32.35% of total consumption followed by power plants with 28.27%, industry with 26.31%, and services with 8.89% (Republic of Turkey Energy Market Regulatory Authority, 2021). It is the most preferred energy source in residentials having the highest shares in home heating, water heating, and cooking with 53.7%, 51.8, and 48.8%, respectively, followed by coal in home heating with 24.9%, electricity in water heating with 26%, and oil and petroleum products in cooking with 43.3% (Ediger et al., 2018).

Switching from coal to natural gas in residential use has had several outcomes, but the environmental benefits are the most discussed ones in the literature. Genc et al. (2010, p.11) states that use of natural gas in residential heating resulted in a significant improvement of air quality in most of the Turkish cities, although coal consumption in low-income districts are still a concern. Tayanç (2000) mentions switching from low-quality lignite coal to natural gas usage for heating in residential and commercial buildings had an impact on the decrease of air pollution levels

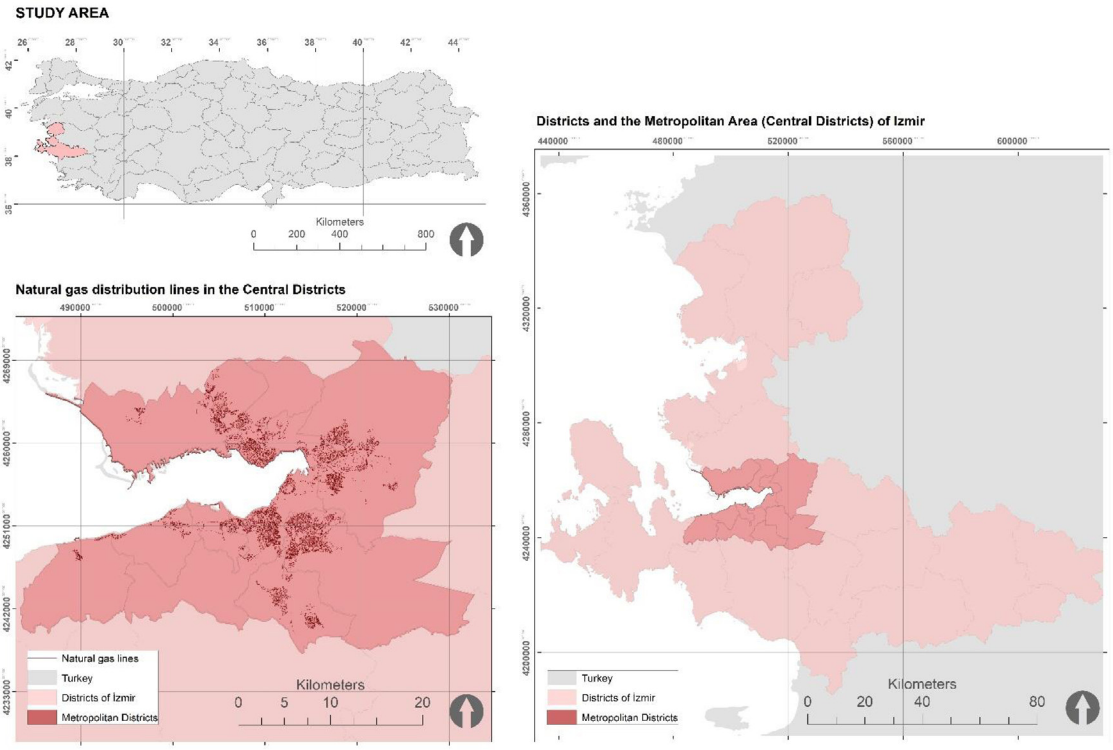

Fig. 1. Study area (IMA).

in Istanbul, while Ilten and Selici (2008) suggest the encouragement of natural gas usage in residential heating to improve air quality. Özdilek (2006, p.203) discusses the topic from a different perspective and states that around 212 to 350 million US dollars per annum could be saved with the use of natural gas in urban centers just by reducing health related problems caused by outdoor air pollution.

Considering the intensity of natural gas use in residential sector, it is clear that the issue needs to be discussed beyond the environmental framework. Social and spatial outcomes of natural gas distribution, including equity and justice issues, are waiting to be discovered and discussed in the literature.

1.3. Natural gas distribution in Izmir, the study area

İzmir is the third largest province in Turkey with 4.3 million population. It is located in the Western part of the country, on the Aegean cost. The province has 30 districts, 11 of which are the central districts (Balçova, Bayraklı, Bornova, Buca, Çiğli, Gaziemir, Güzelbahçe, Karabağlar, Karşıyaka, Konak, Narlıdere) constituting the İzmir Metropolitan Area (IMA) (Fig. 1). The population is concentrated in the IMA with around 3 million inhabitants, constituting approximately 70% of the province's total population. The city faced with rural-to-urban migration starting from the 1950s, which resulted in an unexpected population increase and unauthorized housing. Today, due to its natural and cultural values as well as the diversified and strong economy, İzmir is still a center of attraction, as can be understood from its ever-increasing population. Industrial and commercial activities as well as the high population result in high levels of energy demand. Per capita electricity consumption in İzmir is 1.65 times more than the national averages (İzmir Greater Municipality, 2016). Coal, natural gas, geothermal, and electricity are the main energy alternatives, although, geothermal is available only in a limited area in Narlıdere and Balçova serving to 23,210 customers by the end of 2017 (Jeotermal, 2019).

Natural gas is a relatively new energy alternative in the province, of which investment started in 2005. The gas network was extended to all IMA districts by 2013 (İzmirGAZ, 2020), but still not all neighborhoods have received the service. In the neighborhoods lacking access to natural gas service, domestic heating is met from coal and electricity, in general. However, coal is a fossil fuel emitting a great deal of greenhouse gases, besides being inconvenient and expensive. Electricity can be polluting in the generation phase, particularly when produced in thermal plants. Besides, it is expensive and the system losses are high. The share of renewables other than geothermal, is limited particularly in residential heating, although solar and wind energy potentials are considerably high in the area. İzmir was able to utilize only 2.5% of its wind energy potential by 2012, while it is aimed to increase the share to 10% by 2023 (İzmir Greater Municipality, 2016, p. 79). There were approximately 11MW installed solar power by 2016, which is considerably lower than its potential, yet it is aimed to increase this amount to 190MW by 2023 (İzmir Solar Energy Sector, 2016). Negative externalities of other fossil fuels and the limited availability of renewables have encouraged customers to switch to natural gas throughout time. The use of natural gas has become more widespread and preferable, while the investments and the number of customers increased gradually (Fig. 2).

İzmirGAZ, an incorporated company, is the only provider of the service. İzmir Greater Municipality is 10% shareholder of the company. IMA districts started to receive natural gas investments as early as 2005 and today all central districts receive the service lines. Nevertheless, some neighborhoods still lack natural gas distribution network, while 77 of the 356 neighborhoods in the study area had not received any service lines by the end of 2018. Households living in the neighborhoods lacking natural gas service have been left with two fuel options, coal (lignite or imported) and electricity, when geothermal is ruled out due to the limited geographic availability. Therefore, while energy justice appears to be violated in terms of access to a variety of convenient, modern and relatively cleaner fuel alternatives, the

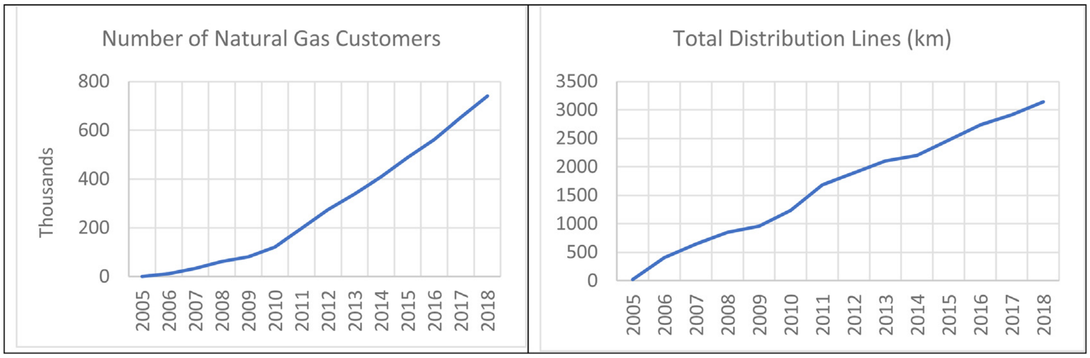

Fig. 2. The number of customers and total distribution lines from 2005 to 2018 in İzmir.
Source: IzmirGAZ.

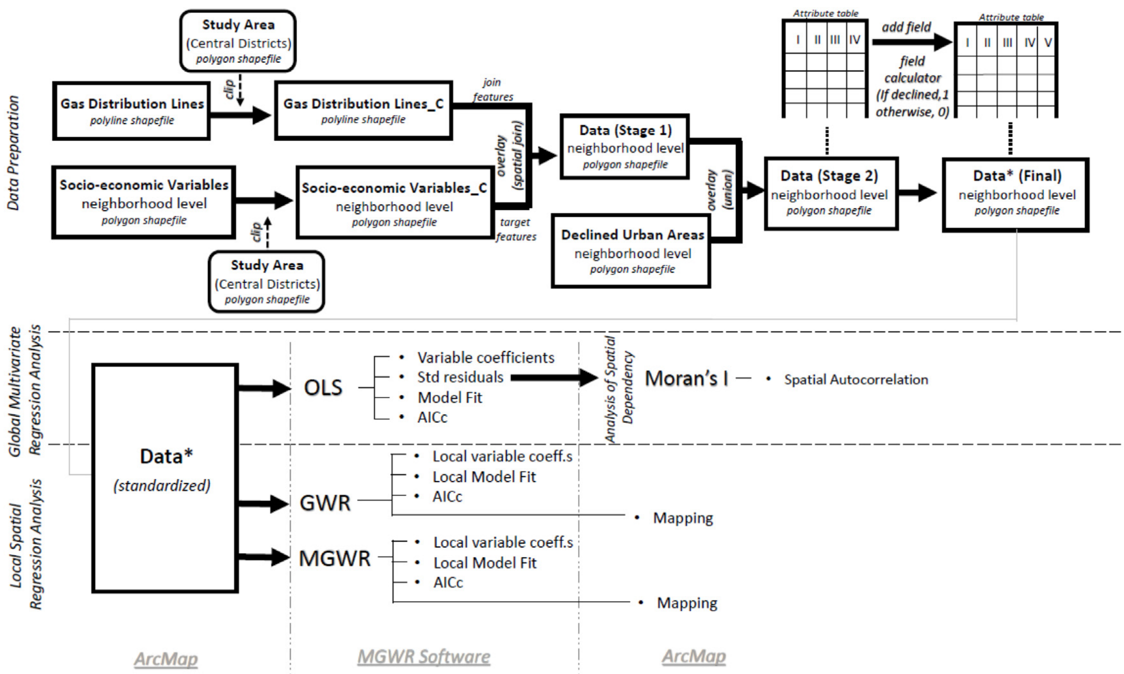

Fig. 3. Summary of the method.

factors driving the injustice and their spatial correspondences need to be explored.

The rest of this article is organized as follows. Section 2 describes the study materials and the method. Section 3 analyzes the relationship between natural gas investments and socio-economic and spatial characteristics in IMA using multiple regression and local spatial regression techniques. Section 4 provides the comparative discussion of the results, and Section 5 gives the conclusions and recommendations.

2. Materials and method

Multiple datasets and techniques are employed in the study. Data obtained from different sources were processed and brought together to create a single dataset that can be used in the regression analyses. First, Ordinary Least Squares (OLS), a multivariate regression analysis technique, is utilized to reveal the socio-economic and physical characteristics affecting the amount of natural gas investments. Then, spatial autocorrelation is investigated through Moran's I. In the following step, two local spatial regression techniques, Geographically Weighted Regression (GWR) and Multiscale Geographically Weighted Regression (MGWR), are conducted. The results of OLS, GWR and MGWR models are interpreted and compared to find out the best fitting one. Furthermore, maps are produced to visualize the outputs and demonstrate spatial distribution of the findings. ArcMap 10.7 (ESRI) is utilized in data preparation, spatial autocorrelation analysis and mapping. MGWR 2.2 software (Oshan et al., 2019) is utilized in OLS, GWR and MGWR analyses. Fig. 3 summarizes the process in three stages: data preparation, global multivariate regression analysis, and local spatial regression analyses.

2.1. Data

Three datasets are used in this study: (1) natural gas distribution lines, (2) socioeconomic characteristics, and (3) disadvantaged urban areas. Data preparation is conducted in Geographic Information Systems (GIS), using ArcMap 10.7. Geographic Information Systems (GIS) are designed to store, retrieve, manipulate, analyze, and map geographical data (Church, 2002, p. 541), and it has a wide range of applications in various fields. Natural gas distribution lines shapefile is provided by İzmirGAZ, of which attribute table includes investment year, diameter, length and the investment area fields. The investments cover 2005–2018

Table 1
Descriptive statistics of the variables.

Variable (unit)	N	Minimum	Maximum	Mean	Std. Deviation
INV (m)	356	.00	46982.63	7002.61	7977.07
POP (#)	356	273	34467	8248.20	6653.78
INC (TL)	356	675.00	5693.10	2065.31	739.70
EMPL (#)	356	.00	29003.40	1592.87	2644.36
DISADV	356	.00	1.00	.11	.31

period. Natural gas investment is the total pipeline length in kilometers in each neighborhood. The second dataset covering socio-economic variables is provided by İzmir Greater Municipality, Department of Transportation (DoT). DoT conducted a survey in 2015 which provides socio-economic information of the neighborhoods such as population, average household income, total employment, industrial employment, employment other than industry, average household size, car ownership, number of students in the household, etc. The third dataset, disadvantaged urban areas, includes either physically declining areas or the areas with unauthorized housing. The data of disadvantaged urban areas is derived from the Ministry of Environment and Urbanization İzmir Directorate of Infrastructure and Transformation documents (Varan, 2016), and İzmir Greater Municipality 1/25000 scale Development Plan Revision Plan Notes (İzmir Greater Municipality, 2009, p. 103). A polygon shapefile is produced for the disadvantaged neighborhoods covering a dummy variable, 1 representing disadvantaged areas and 0 others.

Natural gas distribution lines shapefile and DoT neighborhood survey polygon shapefile are clipped with regard to the Metropolitan Area boundaries. Then, the two shapefiles are overlaid to get the total natural gas investment in each neighborhood. Then, the final dataset is produced by overlaying the shapefile covering socio-economic characteristics and the natural gas investments with the disadvantaged areas shapefile (refer back to Fig. 1). The final data covers a total of 356 features, including information on total natural gas investments and socio-economic characteristics, and whether the feature is a disadvantaged neighborhood.

Model variables are natural gas investment (INV), population (POP), income (INC), employment (EMPL) and disadvantaged areas (DISADV). The dependent variable, investment, is the total natural gas lines in meters in a neighborhood. Population is the total inhabitants living in the neighborhood and employment refers to the number of people working in that neighborhood. Both variables are expressed in terms of the total number of people. Income variable refers to the monthly average income in a neighborhood, and its unit is Turkish Liras (TL). A dummy variable is used for the disadvantaged neighborhoods, where 1 is the disadvantaged areas and 0 is others. Descriptive statistics of the model variables are given in Table 1. Spatial distribution of the model variables demonstrates the variation of each variable in IMA (Fig. 3).

2.2. Method

The study aims to reveal the variables affecting the natural gas investments, and their varying effects on space. Comparison of different techniques allows not only the selection of the best fitting model, but also spatialization of the model variables to see which factors are more influential at the local scale. In that respect, first a global multivariate regression analysis is conducted. Then, spatial autocorrelation is investigated in the model residuals to find out if spatial dependence exists. Considering the parameters varying across space, two local spatial regression techniques, GWR and MGWR, are conducted in the following stage, and comparative analyses are done. Model variables have been standardized to have comparable results.

2.2.1. Ordinary least squares (OLS)

Ordinary Least Squares (OLS) is one of the most well-known multivariate analysis techniques. It is used to predict values of a continuous response variable using one or more explanatory variables and can also identify the strength of the relationships between these variables (Hutcheson, 2011, p. 228). The relationship between the variables are modeled as follows:

$$\mathrm{Y_i} = \mathrm{b_0} + \mathrm{b_1 X_{1i}} + \mathrm{b_2 X_{2i}} + \ldots . \mathrm{b_k X_{ki}} + \varepsilon_\mathrm{i} \quad (1)$$

where $\mathrm{Y_i}$ is the ith observation of the dependent variable, $\mathrm{X_{ji}}$ is the ith observation of the jth explanatory variable, ε_i is the error term of the ith observation, $\mathrm{b_0}$ is the intercept and $\mathrm{b_j}$ is the slope coefficient of each explanatory variable. Although OLS is a practical and straightforward method, it fails to account for the spatial heterogeneity in data relationships. Thus, spatial dependence should be explored in model residuals.

2.2.2. Spatial autocorrelation

Regression models applied to spatial data frequently contain spatially autocorrelated residuals, however, indicating a misspecification error (Thayn and Simanis, 2012, p. 47). If the residuals from the model exhibit significant positive autocorrelation, the standard errors of the parameter estimates will be underestimated leading to potential problems with inference (Fotheringham et al., 2002, p.112). Spatial pattern turns out to be worth interpreting and information can be obtained from the mapping of the distribution of the phenomenon (Cliff and Ord, 1981; Getis, 2007). Therefore, first, the presence of spatial autocorrelation in the residuals should be tested. Moran's I is the best-known statistics (Getis and Ord, 1992) to show the presence of spatial autocorrelation. The index, I, is expressed as follows:

$$I = \frac{N \sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}(x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_{i=1}^{n} \sum_{j=1}^{n} w_{ij}\right) \sum_{i=1}^{n} (x_i - \bar{x})^2} \quad (2)$$

Where N is the number of observations, x_i and x_j are the observations in i and j, $\bar{x}$ is the mean variable, and w_{ij} is the spatial weight matrix. Statistical significance of I indicates spatial dependency.

2.2.3. Geographically weighted regression (GWR) and multiscale geographically weighted regression (MGWR)

Techniques accounting for spatial dependency better represent the relationship among the variables that geographically vary. OLS provides a global model, but overlooks the site-specific variations. Local spatial regression techniques, on the other hand, take site-specific variations into account and produce a model for each location through a distance parameter.

Geographically weighted regression (GWR) demonstrates patterns in the data and the underlying processes by allowing for spatial variations in relationships, whereas global values provide spatial averages on the expense of hiding information about such processes (Fotheringham et al., 2002). GWR extends OLS linear regression models by accounting for spatial structure and estimates a separate model and local parameter estimates for each geographic location in the data based on a local subset of the data using a differential weighting scheme (Matthews and Yang, 2012, pp. 2–3). It allows for the investigation of spatial non-stationarity. GWR is also considered as a useful tool for visualizing the spatial dimensions of the dependent and explanatory variables (Lysek et al., 2020).

GWR is expressed in Fotheringham et al. (2017) as follows:

$$y_i = \sum_{j=0}^{m} \beta_j(u_i, v_i) x_{ij} + \varepsilon_i \quad (3)$$

Where y_i is the response variable, $\beta_j(u_i, v_i)$ is the jth coefficient, (u_i, v_i) is the center location of the feature in coordinates, x_{ij} is the jth predictor, and ε_i is the error term. The parameters, (β_i), are derived by matrix algebra, incorporating a weight matrix, W_i. In technical terms, with GWR, a continuous surface of parameter values is estimated under the assumption that locations nearer to ith (e.g. within the scope of the bandwidth) will have more influence on the estimation of the parameter $\hat{\beta}_1$ for that location (Siordia, 2013, p. 52).

GWR attempts to capture spatial variation by calibrating a multiple regression model which allows different relationships to exist at different points in space (Brundson et al., 1996, p.281). Hence, GWR produces locally linear regression estimates for every point in space (Wang et al., 2012, p. 2). Since GWR technique calculate the relationship between variables with a different coefficient for each geographic unit, it is possible to map where the relations are weak and strong, significant and insignificant (Özbil Torun et al., 2020, p. 5). In order to calculate estimates in each location, it borrows data from the neighboring locations, down-weighing these data according to how far away they are located from a regression point (Sachdeva et al., 2022).

However, GWR considers a single bandwidth for all parameters, and operates at that single spatial scale. In order to overcome this limitation, a Multiscale Geographically Weighted Regression (MGWR) is modeled by Yang (2014) in the PhD thesis supervised by A. S. Fotheringham, which suggests varying bandwidths across parameter surfaces instead of a single bandwidth. This multi-bandwidth approach generates a more accurate and useful representation of the real world (Yu et al., 2020), and the model considers different spatial scales allowing conditional relationships between the response variable and the explanatory variables. By allowing multiple bandwidths in MGWR, the model accounts for an optimal number of neighbors for each parameter estimate, thus allowing better predictions for the response variables, theoretically (Shabrina et al., 2021, p. 697). MGWR is formulated in Fotheringham et al. (2017) as follows:

$$y_i = \sum_{j=0}^{m} \beta_{bwj}(u_i, v_i)x_{ij} + \varepsilon_i \tag{4}$$

Where β_{bwj} is the bandwidth used in the jth location.

MGWR 2.2 software, developed by Oshan et al. (2019) to conduct MGWR analysis, is used in this study.

Various studies in the literature comparing global and local regression models indicate that local models (GWR and MGWR) perform better than global models (OLS) in case of spatial dependence. When local models are compared, MGWR appears to be superior to GWR. Mansour et al. (2021) modeled the socio-demographic determinants of Covid-19 incidences using OLS, spatial lag model (SLM), spatial error model (SEM), GWR and MGWR, and found that MGWR had a better model representation according to the model fit than the other models. Chen et al. (2021) compared GWR and MGWR when analyzing the driving forces of urban resilience in China, and concluded that MGWR is superior to GWR according to model fit criteria. Fotheringham et al. (2019) compared six models – OLS, GWR, MGWR, and the three models with spatially lagged dependent variables –, in their study of air quality in China. They found that MGWR models are superior to others and also do not exhibit spatial autocorrelation of residuals. Yuan et al. (2021) analyzed pollutant emissions in Chinese cities using OLS, GWR and MGWR, and concluded that MGWR better represents the data while different bandwidths indicate different effects on identification of the predictors. Liu et al. (2021) analyzed the driving factors of industrial green development efficiency with MGWR, and discussed the impact of each variable with regard to their spatial distribution and bandwidths. Chien et al. (2020) investigated the relationship between crowdsourced landscape perceptions and landscape physical characteristics, and concluded that MGWR better performs than the standard regression and GWR, and suggested that spatially aware techniques such as MGWR can be used in decision making. Li et al. (2022) analyzed driving factors of residential electricity expenditure using OLS, GWR and MGWR, and concluded that socio-economic, housing-type and demographic indicators affect the expenditures, while climate zones are influential on the expenditures, as well. The study also demonstrated that the performance of MGWR is better than the other models. Similar to these studies, global and local regression models are conducted and compared to reveal the driving factors of natural gas investments in this research.

Table 2
Model diagnostics for OLS, GWR and MGWR.

Diagnostic Information	OLS	GWR	MGWR
Log-likelihood	−298.568	−266.218	−233.055
AICc	607.307	586.713	558.520
R-sq	0.687	0.739	0.783
Adj. R-sq	0.684	0.720	0.756
RSS	111.542	93.006	77.197

2.2.4. Model fit

Model fit criteria, such as R squared (R-sq), the Akaike information criterion (AICc) and residual sum of squares (RSS), give information about the performance of a model in the representation of the data. R-sq refers to the variation explained by the model. AICc and RSS, on the other hand, address to the prediction errors. The higher the R-sq the better the model, whereas smaller values of AICc and RSS indicate a better fit. Different models can be compared with regard to these criteria. Oshan et al. (2019) argue that AICc is a better criterion than R-sq due to accounting for model complexity, thus the evaluation of the model fit is be based on AICc in this study.

3. Results

Initially, an OLS model is run and spatial autocorrelation in the residuals is investigated. Moran's I results confirm that residuals are spatially autocorrelated, with $I = 0.089$, z-score=2.559, p=0.01. Based on the evidence for spatial dependency, spatial regression techniques, GWR and MGWR, are utilized to better represent the data.

A comparison is provided for OLS, GWR and MGWR model results (Table 2). The outputs indicate that MGWR model is superior to the others with lower AICc and Residual Sum of Squares (RSS), and higher log-likelihood and R-sq. R-sq and Adj-R-sq represent the model fit, while the higher values indicate that model explains a larger amount of variability in the dependent variable. AICc value provides a more accurate diagnostic for the model fit, and a lower value refers to a better fit. Here MGWR provides an AICc value 5.05% lower than GWR model, and 8.73% lower than OLS model. RSS results, which refers to the unexplained variation, are in accordance with the other findings, since MGWR performs the best with the lowest RSS value.

In the following step, model variables are investigated. The outputs of the OLS model (Table 3) show that population (POP), average income (INC), total employment (EMPL), and disadvantaged areas (DISADV) have statistically significant effects on the total amount of natural gas investment (INV) at the neighborhood level. The first three variables are positively related to the investment, whereas disadvantaged areas variable has an inverse relationship with the line investments. Population appears to have the highest impact on natural gas investments followed by income, employment and disadvantaged areas, while unit increase in population increases investments by 0.71 units.

Table 3
Summary statistics for OLS parameters.

Variable	Est.	SE	t-value	p-value
Intercept	−0.033	0.032	1.032	0.302
POP	0.717	0.033	21.878	0.000
INC	0.124	0.032	3.903	0.000
EMPL	0.120	0.032	3.732	0.000
DISADV	−0.096	0.031	−3.139	0.002

Table 4
Summary statistics for GWR parameters.

Variable	Mean	STD	Min	Median	Max	Bandwidth
Intercept	−0.088	0.288	−0.780	−0.102	0.583	157
POP	0.691	0.114	0.345	0.701	0.893	157
INC	0.127	0.073	−0.061	0.154	0.241	157
EMPL	0.091	0.067	−0.196	0.099	0.311	157
DISADV	−0.077	0.071	−0.308	−0.073	0.040	157

Then, GWR models are run with two kernel types: fixed and adaptive. Fixed type uses a fixed distance for the spatial context of the solution of local regression, whereas adaptive type is defined as a function of a set of neighbors which adapts the spatial context with regard to the density of the feature distribution. In this study, features are more densely distributed at the central locations and relatively sparser in the periphery. Consistent with the variation in the spatial distribution of the features, adaptive type gives better results than the fixed type. AICc value is 31.23 units (5.32%) lower and Adj. R-sq is 0.043 units (5.97%) higher in adaptive mode than the fixed mode. Thus, the outputs of the adaptive modes are considered in GWR model (Table 4).

A MGWR model, which allows the geographic variation of the relationship between dependent and explanatory variables considering multiple bandwidths, is conducted in the following step. In addition to the descriptive statistics, the corresponding bandwidths of the variables are presented in Table 5.

At the mean level, MGWR generates lower estimates for the population and the income variables, the same estimate for the employment variable and a higher estimate for the disadvantaged areas variable, when compared to GWR results. The impact of population appears to be the highest in both models at the mean level. The local effect of disadvantaged areas on natural gas investment is generally negative. The universal bandwidth of GWR model is 157. MGWR, on the other hand, provides individual bandwidths for each parameter estimate. The bandwidths of population and disadvantages areas can be considered as micro-scale, which indicates higher spatial heterogeneity. Employment is a global scale variable, having a bandwidth of 230, thus exhibits a low degree of spatial heterogeneity. Income is also a global scale variable with a bandwidth of 354, which has a constant association with investments in almost all IMA and reflects no spatial heterogeneity. This may be due to the relatively little variation in income variable (refer back to Table 1).

In addition to the comparison of the model fit, maps are produced and compared for GWR and MGWR results (Figs. 5–8). These maps demonstrate local variations in both models, as well as their difference in absolute values.

Local R-sq values are higher in MGWR than in GWR. MGWR computes that 301 neighborhoods (84.5% of the observations) have a local R-sq greater than 0.7, and in 330 neighborhoods (92.6% of the observations) the local R-sq values are greater than 0.5. Only 26 neighborhoods, which are clustered in the south-west, have R-sq values lower than 0.5. In GWR model, the local R-sq values of 259 neighborhoods (72.7% of the observations) greater than 0.7, and in 325 neighborhoods (91.2% of the observations) the local R-sq. values are greater than 0.5. 31 neighborhoods have local R-sq values less than 0.5 and are also clustered in the south-west, similar to MGWR results. The differences of local R-sq values between MGWR and GWR are more prominent in the south-west and in the north-west where both models have poor fits. In the rest of the area, however, the results are quite similar (Fig. 5).

Multicollinearity is also investigated and compared in the model results. Fotheringham and Oshan (2016) state that GWR is robust to the effects of multicollinearity. Yet, it would be informative to compare the results in terms of multicollinearity according to local condition number (CN) and local variance decomposition proportions (VDP). Local CN is a single value at the aggregate level for all variables and is expected to be lower than 30; whereas local VDP provides a diagnostic for each variable and is expected to be lower than 0.5. The results show that MGWR performs better than GWR with CN values of 1.89 and 2.16, respectively (Fig. 6). The difference map demonstrates that local CN values of the two models are quite similar, while in 197 neighborhoods the difference is less than 1. In any case, neither GWR nor MGWR has a multicollinearity issue according to CN criterion, since the values are far less than 30. High local VDP values are observed at the outskirts, particularly for the population and the employment variables (Fig. 7). MGWR appears to perform slightly better than GWR in population variable, yet both models have high values of local VDP at the average. MGWR handles multicollinearity in income variable better than GWR. The observations having a local VDP greater than 0.5 in MGWR and in GWR are 31 and 153, respectively. The VDP outputs of the employment variable are quite similar in both models, while GWR performs slightly better since the number of neighborhoods local VDP greater than 0.5 is 133 in GWR and 142 in MGWR. Lastly, when disadvantaged areas are considered, GWR handles multicollinearity better than MGWR since the mean local VDP value is 0.22 in GWR and 0.39 in MGWR. The number of neighborhoods with local VDP values greater than 0.5 in GWR and in MGWR are 59 and 144, respectively. The relatively poor representation of MGWR may result from the issues regarding the dummy variable.

Mapping of the parameter estimates provide insight for future policies and decision making, since the results show the local effects of variables in each neighborhood (Fig. 8). Difference maps demonstrate whether GWR and MGWR produce similar or different estimates for each variable and their geographic distribution. Different bandwidths of MGWR present a higher capacity of representing the data in terms of varying effects of the estimators. Population variable is significant in all observations in GWR model and 94% of the observations in MGWR model, while the coefficient values are higher in the central and eastern parts where the existing population is also high (refer back to Fig. 4). The difference of GWR and MGWR is high only in the areas where population is insignificant in MGWR model. Therefore, it can be concluded that parameter estimates are quite similar in both models. Income variable is significant in 53% of the neighborhoods in GWR model, whereas it is significant everywhere in MGWR model. When the difference map is considered, the coefficient estimates of the two models do not give similar results mostly in the center and in the eastern periphery. Employment is significant in 50% of the observations in GWR and 78% of the observations in MGWR models. The coefficients are significant and higher in the south, where Ege Free Zone and Industrial areas are located. The difference between two models is quite small, when the significant neighborhoods are considered, particularly. Disadvantaged areas have the lowest local significance in both models. In GWR 32% of the neighborhoods, and in MGWR 31% of the neighborhoods have significant estimates for disadvantaged areas. The relatively small number of significant observations in parameter estimates of disadvantaged areas is a potential limitation of this study, although 109 neighborhoods provide significant

Table 5
Summary statistics for MGWR parameters.

Variable	Mean	STD	Min	Median	Max	Bandwidth	Bandwidth CI (95%)
Intercept	−0.106	0.274	−0.597	−0.137	0.610	44	[43, 53]
POP	0.682	0.206	0.002	0.719	0.961	43	[43, 60]
INC	0.104	0.007	0.074	0.106	0.125	354	[236, 355]
EMPL	0.091	0.035	0.003	0.090	0.254	230	[208, 282]
DISADV	−0.058	0.260	−0.916	−0.045	0.694	43	[43, 53]

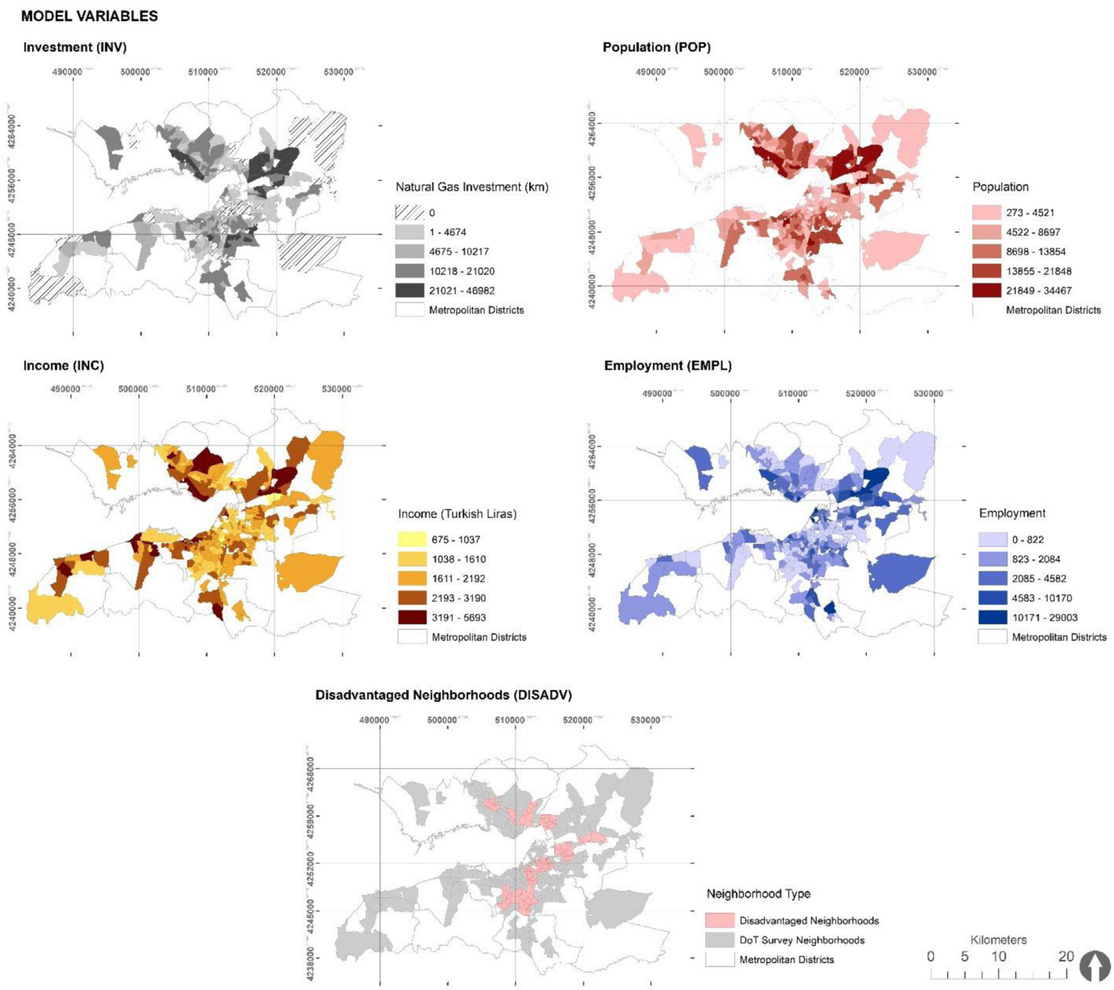

Fig. 4. Spatial distribution of model variables.

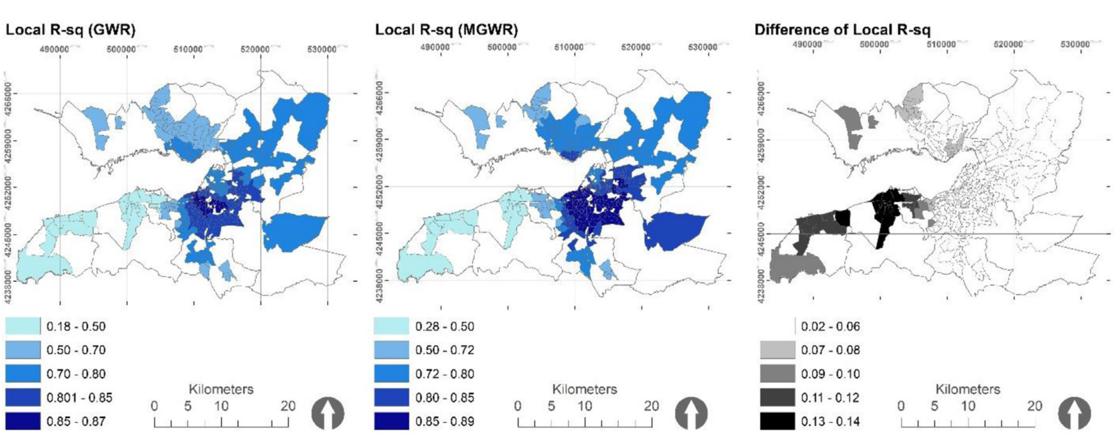

Fig. 5. Spatial distribution of the local R-sq values for GWR, MGWR, and the difference map.

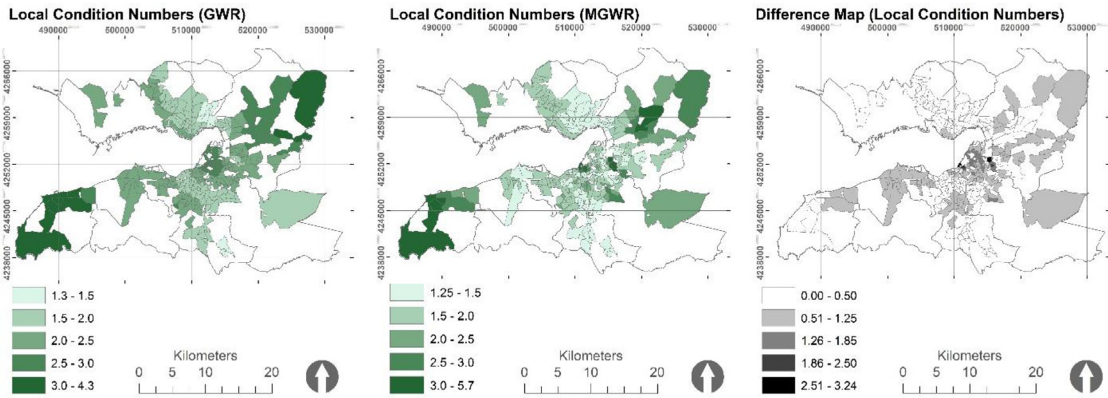

Fig. 6. Spatial distribution of local condition numbers for GWR, MGWR, and the difference map.

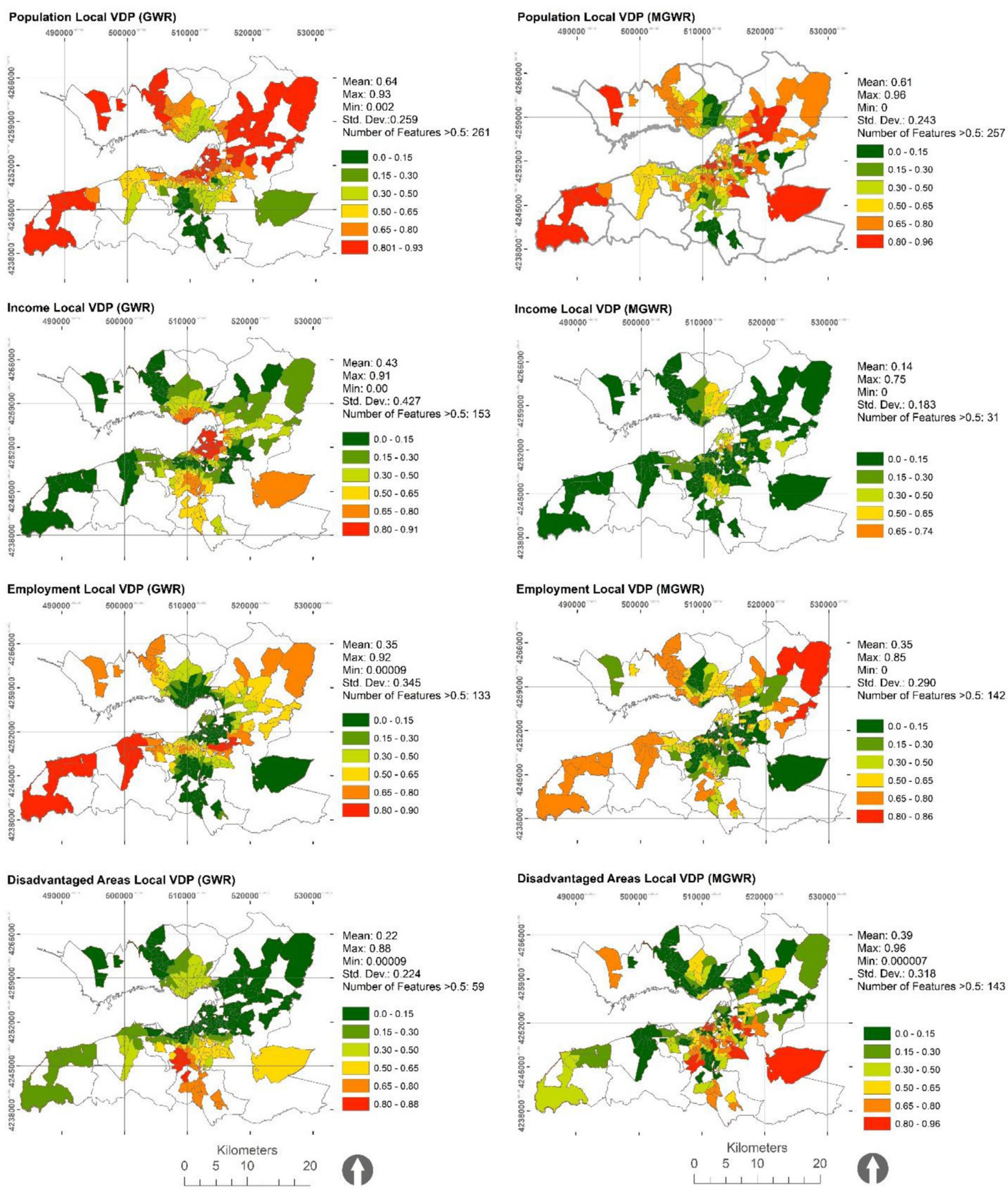

Fig. 7. Spatial distribution and the descriptive statistics of local variance decomposition proportions (VDP) for GWR and MGWR.

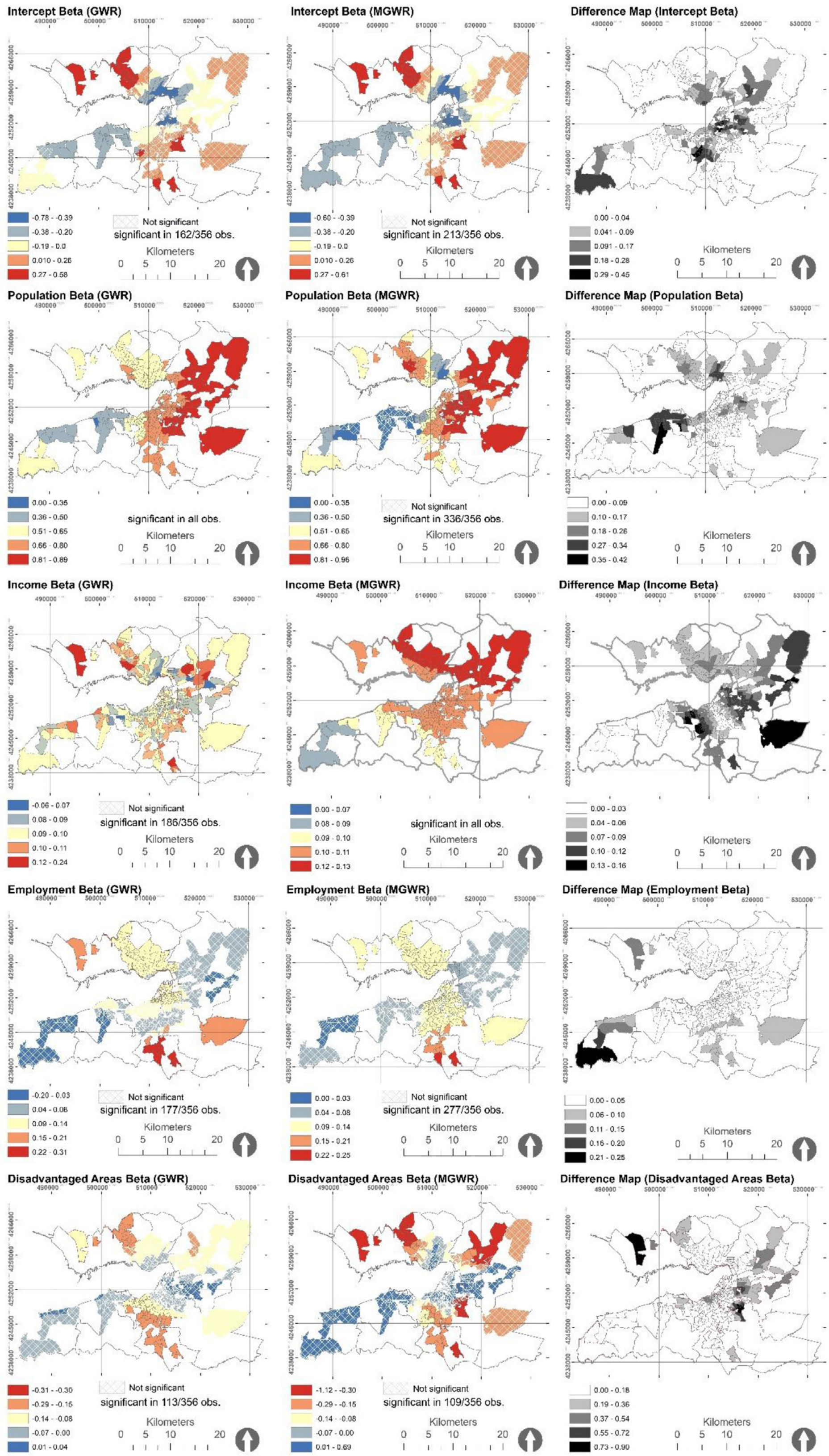

Fig. 8. Spatial distribution of parameter estimates for GWR and MGWR.

results. The variable appears to have an impact on natural gas investments in the southern and the northern periphery, the areas close to the existing squatter settlements (refer back to Fig. 4). Similar to the population and the employment variables, the difference of the GWR and MGWR estimates is quite small and both models provide similar estimates for disadvantaged areas except for the peripheral neighborhoods in the northern and the eastern parts of the study area.

4. Discussion

Investigation of energy justice in natural gas distribution in IMA has a number of notable findings. The global regression shows that population, average income, and employment are positively related to the natural gas investments, whereas disadvantaged areas have negative relationship with the amount of investments. In line with other studies in the literature that conduct comparative analysis, GWR and MGWR provide improved results than OLS in terms of the model fit (Fotheringham et al., 2019; Chien et al., 2020; Chen et al., 2021; Liu et al., 2021; Mansour et al., 2021; Shabrina et al., 2021; Yuan et al., 2021; Li et al., 2022). When the local spatial regression models are compared, MGWR is better than GWR, which further brings AICc down. Moreover, similar to the findings of Shabrina et al. (2021) MGWR provides slightly better results than GWR where the data is sparse, still both models outperform OLS.

An optimum bandwidth is defined in GWR in terms of a single value, whereas individual values for each parameter estimate in MGWR. The use of 157 nearest neighbors as the unique bandwidth, accounting for 44.1% of the total sample, correctly classifies 72% of the observations in GWR model, whereas multiple bandwidths defined for each variable increase the model fit to 75.6% in MGWR, at the mean level (refer back to Table 5). The local R-sq values indicate that at least 70% variability is explained in almost 85% of the study area in MGWR, while only the south-western outskirts have poor model fits. Smaller bandwidths of population and disadvantaged areas refer to high spatial heterogeneity. Once the scale is exceeded, the coefficient will change dramatically (Chen et al., 2021). Employment and income are global scale variables which have little spatial heterogeneity, so that they tend to be relatively stable in space. Multicollinearity results are in accordance with the findings of Oshan et al. (2019), since some observations are subject to the effects of multicollinearity according to local VDP values, whereas multicollinearity is not evident in GWR and MGWR according to CN results.

Discussion of each parameter estimate would help to reveal the local impacts of the drivers of energy justice in terms of natural gas distribution line investments. Population is a positive estimator for natural gas investments. Higher population means more customers, which is expected to create investment motivation for the service provider. Those living in populated areas in central locations would likely have variety of urban energy choices, including natural gas. Increasing unit population in low populated areas, on the other hand, results in relatively less impact on the amount of investments, meaning that the natural gas service favors compact settlements considering economic feasibility. Employment is significant only in the south and in the west parts of the IMA. The parameter estimates are high in the neighborhoods close to industrial areas, particularly in the south where Ege Free Zone and other industrial clusters are located, and in the north-west of the gulf around the Ataturk Organized Industrial Zone. Thus, it can be concluded that natural gas provision is more feasible in industrial clusters where additional employment would lead to higher levels of investments.

Income and disadvantaged areas should be considered in terms of affordability and ignored groups, since the low-income households and the ones living in disadvantaged areas are likely receive limited or no natural gas service. At that point, Sovacool and Dworkin's (2015) understanding of energy justice, which considers each individual as an end, while presenting them a set of opportunities and freedoms of choice are essential without any discrimination or marginalization, is not met in low-income and disadvantaged neighborhoods. In fact, the findings are in line with Graham and Marvin's (2001) discussion of network bypassing undervalued areas and customers.

Income has higher parameter estimates where the model fits are also high, and it has a positive relationship with investments. It is more likely for the high-income customers have natural gas service. From the demand side, low-income customers prefer more accessible fuels, particularly coal, although they are highly polluting and inefficient. The results imply Sovacool et al.'s (2016) definition of environmental burdens due to the lack of access to modern types of energy as well as the findings of Xu and Chen (2019) indicating that the inequality dimension of energy prevents the low-income households from improving their financial, health and other social situations. İzmir Greater Municipality has included strategies about replacing coal with natural gas to decrease air pollution and provide a more efficient and a modern fuel alternative in their master plan documents and sustainable energy action plans (İzmir Greater Municipality, 2012, 2016). High installation costs, security deposits and subscription fees may further prevent low-income customers switch to natural gas, so particular incentives and subsidies can be provided by the service providers and the local government. The system becomes economically more efficient when the household installation costs are compensated over time. The total combustion efficiency of natural gas is higher than many other types of energy while the system losses are quite negligible. The system is also more convenient than coal for being used in heating, hot water, cooking and production activities with a single subscription. Besides the incentives and subsidies, awareness raising policies can be developed to introduce the environmental and economic benefits of the system, while leaving the choice to the customers which urban energy network they would like to use, considering their economic and environmental impacts. Sharifi and Yamagata (2016) mentions the importance of raising awareness of citizens by urban authorities and utilities in improving energy resilience.

Disadvantaged areas are inversely related to investments, and are significant only around 31% of the observations in both models. The significant estimates are observed in the south and in the northern periphery, where the squatter settlements and urban transformation areas are located. In disadvantaged areas, the issue is related to the supply side in general. The service provider is likely to refrain from investing in the areas that have been either declared as urban transformation areas or currently undergoing urban transformation. Transformation requires an urban development plan with a new street layout. Therefore, constructing natural gas pipelines prior to the plan is not economically rational, since energy network investments are high-cost and hard to reverse, so it is costly to modify the system after they are constructed. In the squatter settlements, that are neither declared as urban transformation areas or currently under transformation, the problem turns out to be chronic. Those neighborhoods are generally located in unfavorable and risky areas in terms of topographic and ground conditions, so it is unlikely for them to receive the service. In such areas, planning and urban transformation can be prioritized. Infrastructure plans including natural gas network can be provided along with the implementation plans and the service provider can be encouraged to invest in such areas during the implementation of new development plans.

5. Conclusion

Natural gas distribution exhibits energy injustice in IMA in terms of the amount of investments, since some neighborhoods have little or no line investments, which prevents customers receiving a modern, efficient and relatively clean fuel alternative. Such an exclusion refers to distributional and recognition injustice in terms of the service provision and recognized/ignored groups and places, as well as availability principles. Spatial dependence that is discussed in the study also puts the emphasis on geographic embeddedness of energy justice. Within the energy justice framework, this article explores the relationships between natural gas investments, and socio-economic and physical characteristics to reveal the driving factors of natural gas distribution.

It is observed that population, average income, employment and disadvantaged areas are influential on the amount of natural gas investments. Considering the presence of spatial autocorrelation, a comparative analysis among global regression, OLS and local spatial regression models, GWR and MGWR, is conducted. Local models provide improved results than the global model, while MGWR is superior to both OLS and GWR in terms of the overall fit. MGWR handles multicollinearity better than GWR at the average, according to VDP values; yet multicollinearity is not evident in any models according to CN results. MGWR, which defines individual bandwidths for influencing factors, is found to better represent the features which have uneven spatial distribution. Therefore, that it can be considered as a useful tool in demonstration of the local-specific conditions.

Population and employment variables are positive estimators of natural gas investments. It can be concluded that compact urban forms with relatively high densities and industrial clusters are favorable in terms of investment decisions. Low-populated, scattered urban forms, on the other hand, have less possibility to receive natural gas investments. Low income and disadvantaged areas, on the other hand, inversely affect the amount of investments. The reasons for little or no investment in low-income and disadvantages areas are related to both the demand-side and supply-side conditions. Low-income households prefer more affordable and readily available fuel alternatives, such as coal. However, the fact that coal is highly polluting, inefficient and inconvenient, affects the quality of life negatively. Local government has already included strategies suggesting transformation from coal to natural gas in its energy documents. Incentives and subsidies particularly covering the initial installation costs and subscription fees would encourage households switch to natural gas. Moreover, economic and environmental advantages of natural gas, especially over coal, can be better explained to customers to enable them to make more informed choices. Disadvantaged areas, on the other hand, are not preferable for the service provider in terms of the legal and physical status of the neighborhoods. Planning can be considered as a means of eliminating energy injustice through the provision of infrastructure facilities along with the urban transformation through the development plans in those areas.

In conclusion, modeling of energy justice through revealing the drivers of the issue and demonstrating their spatial correspondences can be considered as a useful tool in defining the problem areas, sources of the problem and developing policies, while MGWR provides a useful tool in natural gas investment analysis.

CRediT authorship contribution statement

Muzeyyen Anil Senyel Kurkcuoglu: Conception and design of study, Acquisition of data, Analysis and/or interpretation of data, Drafting the manuscript, Revising the manuscript critically for important intellectual content.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

Data will be made available on request.

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