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Calculating Digital Transformation Index with Geographically Weighted Regression

Coğrafi Ağırlıklı Regresyon ile Dijital Dönüşüm Endeksinin Hesaplanması

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ABSTRACT

The purpose of this study is to examine the factors affecting the regional digitalization processes of information and communication technologies with the spatial regression method in Türkiye. In the research, separate models were created for the regions where 81 provinces are located from the data obtained from the household information technologies usage survey covering the years 2017, 2018, and 2019 by the Turkish Statistical Institute, and an index related to the factors affecting digital transformation was calculated. As a result of the study, according to the digital transformation index, significant differences were observed between regions depending on the factors telecommunication infrastructure, education, labor force, employment opportunities, and the ability to use electronically provided services. As a result, this research will serve as a road map for what needs to be done to develop digital transformation in cities.

Keywords: Digital transformation, digital transformation index, geographically weighted regression, geographic information systems, digital divide

ÖZ

Bu çalışmanın amacı, Türkiye'de bilgi ve iletişim teknolojilerinin bölgesel dijitalleşme süreçlerine etki eden faktörlerin mekânsal regresyon yöntemi ile incelenmesidir. Araştırmada Türkiye İstatistik Kurumu tarafından 2017, 2018, 2019 yıllarını kapsayan hane halkı bilgi teknolojileri kullanım anketinden elde edilen verilerden 81 ilin bulunduğu bölgeler için ayrı modeller oluşturulmuş ve dijital dönüşümü etkileyen faktörlere ilişkin bir endeks hesaplanmıştır. Çalışma sonucunda, dijital dönüşüm endeksine göre, telekomünikasyon altyapısı, eğitim, iş gücü, istihdam olanakları ve elektronik olarak sağlanan hizmetleri kullanma becerisine bağlı olarak bölgeler arasında önemli farklılıklar gözlemlendi. Sonuç olarak bu araştırma, kentlerde dijital dönüşümü geliştirmek için yapılması gerekenler için bir yol haritası görevi görecektir.

Anahtar Kelimeler: Dijital dönüşüm, dijital dönüşüm endeksi, coğrafi ağırlıklı regresyon, coğrafi bilgi sistemleri, dijital uçurum

Introduction

The development of digital technologies has greatly changed and affected our lives, needs, and expectations. Digital transformation is the deep and accelerating transformation of business activities, processes, competencies, and models by integrating technology to take full advantage of their impact on society in a strategic and priority way (Demirkan et al., 2016, p. 14). Because of the diversity of digital technologies and their applications, digital transformation is present in almost every field such as healthcare, education, manufacturing, retail, automotive, mining, and telecommunications (Lerch & Gotsch, 2015, pp. 48–50; Rachinger et al., 2018, pp. 1154–1157).

The ideas of digital products and services started the digital transformation at the end of the twentieth century. Digital transformation got placed in every single detail of our life with the increment of smartphones and social media usage (Schallmo & Williams, 2018, pp. 3–8). Public services are delivered to citizens quickly through a portal, shopping is carried out simply in an electronic environment, education is provided electronically, new business areas are developed, and bureaucratic obstacles are reduced by the realization of digital transformation.

Despite of the advantages of information and communication technologies (ICT) in digital transformation, not all regions have been able to adopt digital transformation immediately and directly. The reason for this is the differences in the level of development, external environments and basic conditions between regions. Due to get the most out of information and communication technology, countries must reduce the digital divide because it is one of the most challenging problems facing the information society (Aissaoui, 2021, p. 4). The digital divide is the difference between those who have access to new forms of information technologies and those who do not (Dijk, 2006, pp. 221–222).

At this time of globalization and digital age, access to ICTs shows significant inequalities between countries and regions (Çapar & Vural, 2013, p. 1676). The fact that there are developed countries that use ICT and that have this infrastructure makes these countries advantageous in the globalization process and widens the gap with other underdeveloped and developing countries (Kılıç, 2011, p. 84). Therefore, countries and some people are excluded from the digitalization process.

Numerous studies have analyzed the impact of ICT at the individual (Fernández-Gutiérrez et al., 2020, pp. 11–12) or country level (Niebel, 2018, pp. 199–200) and have confirmed its positive impact on personal life (Fu, 2020, p. 102), financial development (Cheng et al., 2021, p. 662), and organizational operations (Yunis et al., 2018, p. 345). Based on these studies, this study aims to extend existing research by analyzing the impact of ICT on urbanization.

This study aims to examine and reveal the factors influencing digital transformation, as well as to calculate the digital transformation index of Türkiye's regions using the geographically weighted regression (GWR) method. In the study, a separate model was established for each region and the map was shaped according to the factors that most affected this index with the parameters obtained. Solutions were offered to the regions with a low digital transformation index based on the data received from the map.

Methods

The Scope of the Research

In this study, separate models will be established for the regions where 81 cities are located. The research consists of 12 regions at level 1 of the Classification of Territorial Units for Statistics (NUTS). These regions are TR1 (Istanbul), TR2 (Western Marmara), TR3 (Aegean), TR4 (East Marmara), TR5 (Western Anatolia), TR6 (Mediterranean), TR7 (Central Anatolia), TR8 (Western Black Sea), TR9 (East Black Sea), TRA (Northeast Anatolia), TRB (Middle East Anatolia), and TRC (Southeast Anatolia).

Data Set and Variables

The study includes NUTS level 1 data. This geocoding system is used to obtain statistics on a regional basis. The data of the regions in NUTS level 1 were obtained from the Turkish Statistical Institute (TURKSTAT). In this context, TURKSTAT Household Information Technologies usage survey data was used.

The research includes 32 parameters affecting digital transformation. These parameters are as follows: Information equipment in households: desktop computer, portable computer, tablet computer, mobile phone, game console, TV connected to the internet; household internet access status, household internet usage status, types of internet connections used at home; fixed broadband connection, mobile broadband connection, dial-up connection, dial-up connection or ISDN connection, narrowband connection over the mobile phone; household monthly total income, literacy status, education level, internet usage, portable devices used to connect to the internet; mobile phone, portable computer, wireless network, other devices; obtaining information from public institutions' websites, downloading forms from e-government platforms, sending forms, purchasing goods or services via e-commerce, downloading over the internet; movies-music, books, magazines-newspapers, computer software; transferring files between computers and other devices, installing software or mobile applications, copying files and folders, using ready-made programs, editing photos, videos, or audio files using the software.

The dependent variable in the analysis was calculated by taking the weighted average of 32 parameters affecting the digital transformation index. First, the weighted averages of the parameters were calculated according to the formula:

$$W = \frac{\sum_{i=1}^{n} \omega_i . x_i}{\sum_{i=1}^{n} \omega_i}$$

where W is the weighted average; n is the number of terms; w_i is the weights to be applied to x values, and; x_i is the data values to be averaged.

Each year's digital transformation index is calculated using the parameters of the relevant year. Furthermore, the index of the relevant year is included in the dependent variable column in the analysis.

Data Analysis

The GWR model was used to model spatial data in the research. The GWR method is one of several spatial regression techniques that are increasingly used in geography and other disciplines. Geographically weighted regression provides a local model of the variable or process we are trying to predict by fitting a regression equation to each feature in the data set (Zhou et al., 2019, pp. 843–844).

The regression equation is a mathematical formula applied to the independent variables to best predict the dependent variable that we try to model. The dependent variable used in the regression equations is always represented by the letter y. Also, the independent or explanatory variables are always symbolized by the letter *x*. Each independent variable is associated with a regression coefficient that describes the strength and sign of that variable's relationship with the dependent variable. This relationship is not uniform across regions because of differences in attitudes, preferences, or other contextual influences. These differences can be estimated using GWR analyses. The classical regression model showing that this relationship is constant for each unit is as follows (Scott & Pratt, 2009, pp. 41–43).

$$Y_i = \alpha_0 + \sum \alpha_k \cdot X_k + U_i$$

In the equation, the dependent variable (*y*) is the variable that represents the process that we try to predict or understand. The independent variable (*x*) is the variable used to model the dependent variable value. The regression coefficient (*a*) is the value that represents the strength and type of the relationship between the independent variable and the dependent variable. The number of observations is represented with *n* and the margin of error with U_i. This model is estimated using the output least square method. The sum of the squares is minimized according to the distance of the *n* values to the regression line. This model, in which local parameters are used instead of global parameters in GWR models, is as follows:

$$Y_i = \alpha_{i0} + \sum \alpha_{ik} \cdot X_{ik} + U_i$$

In the GWR model, an observation is weighted according to its proximity to the point "*I*," so the weight of it varies with "*i*." Data from observations closer to "*i*" are weighted more than data from observations further away (Fotheringham et al., 2001, pp. 51–52). Spatial regression calculated with this formula is a technique that models and analyzes spatial data in which spatial autocorrelation between regression parameters is considered and helps to explain the factors between models.

There are many methods to measure spatial autocorrelation in GWR models. One of these methods is the autocorrelation tool developed by Patrick Alfred Moran in 1950 and expressed as Moran's *I* (Moran, 1950, p. 22). This tool measures spatial autocorrelation and allows similar or different values to be clustered rather than randomly positioned on a map. When given a set of features and an associated feature, it evaluates whether the model is clustered, scattered, or random (Griffith, 1992, p. 266). Spatial weight matrices w_{ij} is created to show the degree of interaction between the analyzed regions. These weight matrices show that regions that are close to each other interact more than those that are far apart. The spatial autocorrelation formula is as follows (Zhang et al., 2017, p. 1461):

$$I = \frac{n^* \sum_i^n \sum_j^n \omega_{ij} * (x_i - \bar{x})(x_j - \bar{x})}{\left(\sum_i^n \sum_j^n \omega_{ij}\right)^* \sum_i^n (x_i - \bar{x})}$$

In the formula, *n* represents the sum of the number of pixels, x_i is the observation value, ω_{ij} is the spatial weight index of neighboring observation points, $\bar{x}$ is the average scalar property value for all observation points (Özçelik & Barut, 2018, pp. 102–103).

The formula for the expected value is

$$E(I) = -1/(n+1).$$

The tool calculates both a *Z*-score and a *p*-value by evaluating the index value of Moran's *I* and the significance of this index. The *Z* value tests whether the difference is statistically significant. In general, a Moran's index value near +1.0 implies clustering (positive autocorrelation), whereas an index value near –1.0 shows negative autocorrelation (Goodchild, 1986, pp. 16–17). In the geographical distribution of the examined variable, positive autocorrelation indicates similarity between nearby objects, while negative autocorrelation means no similarity between objects. In the Spatial Autocorrelation tool, the null hypothesis (the Moran *I* value being equal to zero) points that there is no spatial clustering of values associated with geographical features in the study area. The null hypothesis can be rejected when the *p* value is small and the absolute value of the *Z*-score is large enough to exceed the desired confidence level ($z > 1.96$ or < -1.96). If the index value is greater than zero, the feature set exhibits a clustered pattern. On the contrary, if the value is less than zero, the feature set shows a dispersed pattern (Fu et al., 2014, p. 2403). As a result of the spatial analysis, R^2 and the Akaike Information Criterion (AIC) values are also calculated. The R^2 value is obtained depending on the regression model and is the power of the independent variables to explain the dependent variable. If the R^2 value is close to zero, the model is incompatible. Conversely, if it is close to one, the model is compatible. The AIC allows testing how well the studied model fits the dataset. The AIC value should be low in the analyzed regression model. A lower AIC value indicates a better model fit.

ArcGIS 10.3 analysis program was utilized for the spatial analysis of the research. The Moran *I* value was calculated using the tools from the Spatial Statistics Toolset.

Findings

Density Maps for 2017, 2018 and 2019

The density maps (Figure 1) colored according to the digital transformation index values in Türkiye cover the years 2017, 2018, and 2019. The maps in the left column show the year 2017, the maps in the middle column show the year 2018, and the maps in the right column show the year 2019. The colors red, yellow, green, blue, and dark blue used on the maps represent the lowest, low, medium, high, and highest values of the coefficients, respectively.

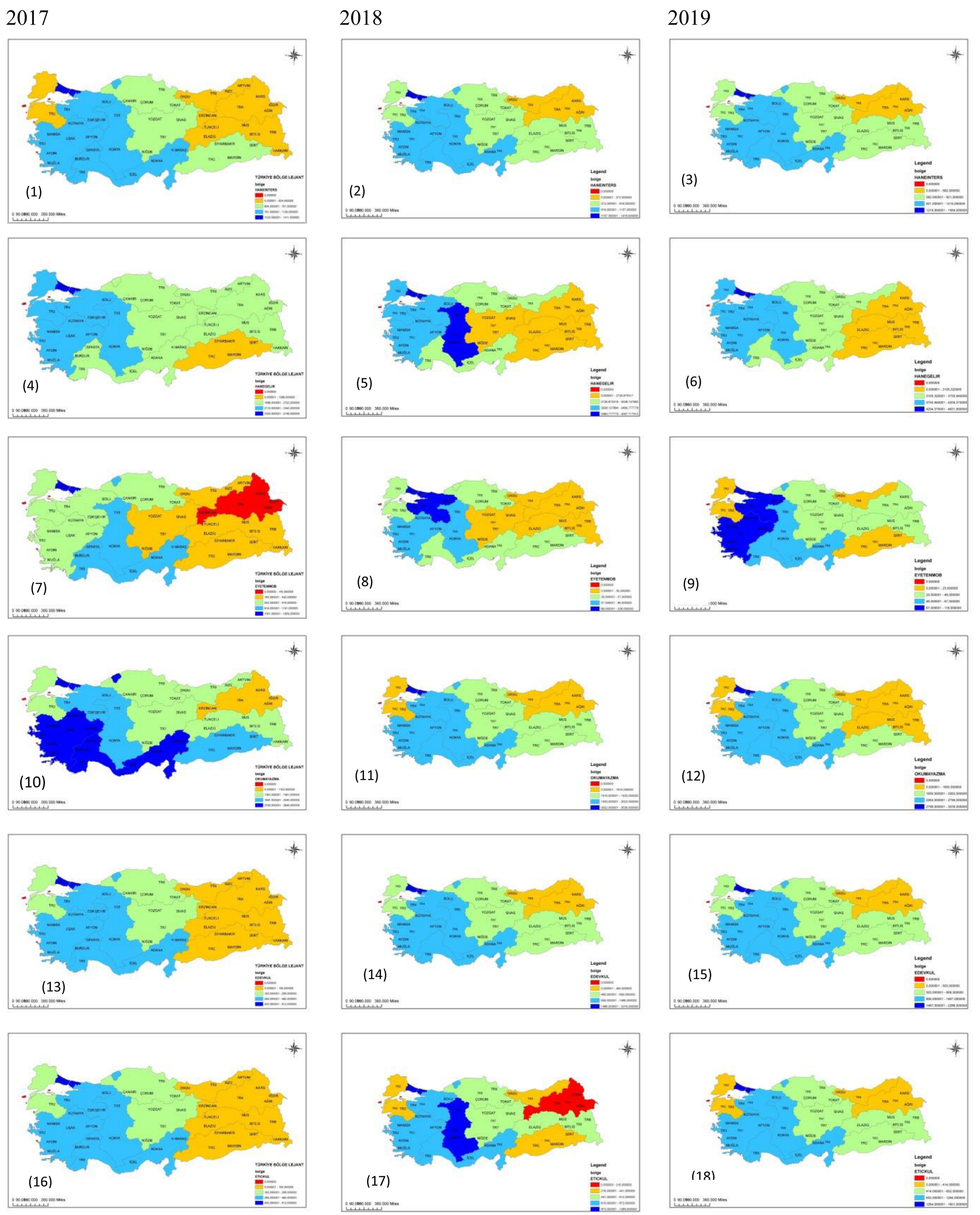
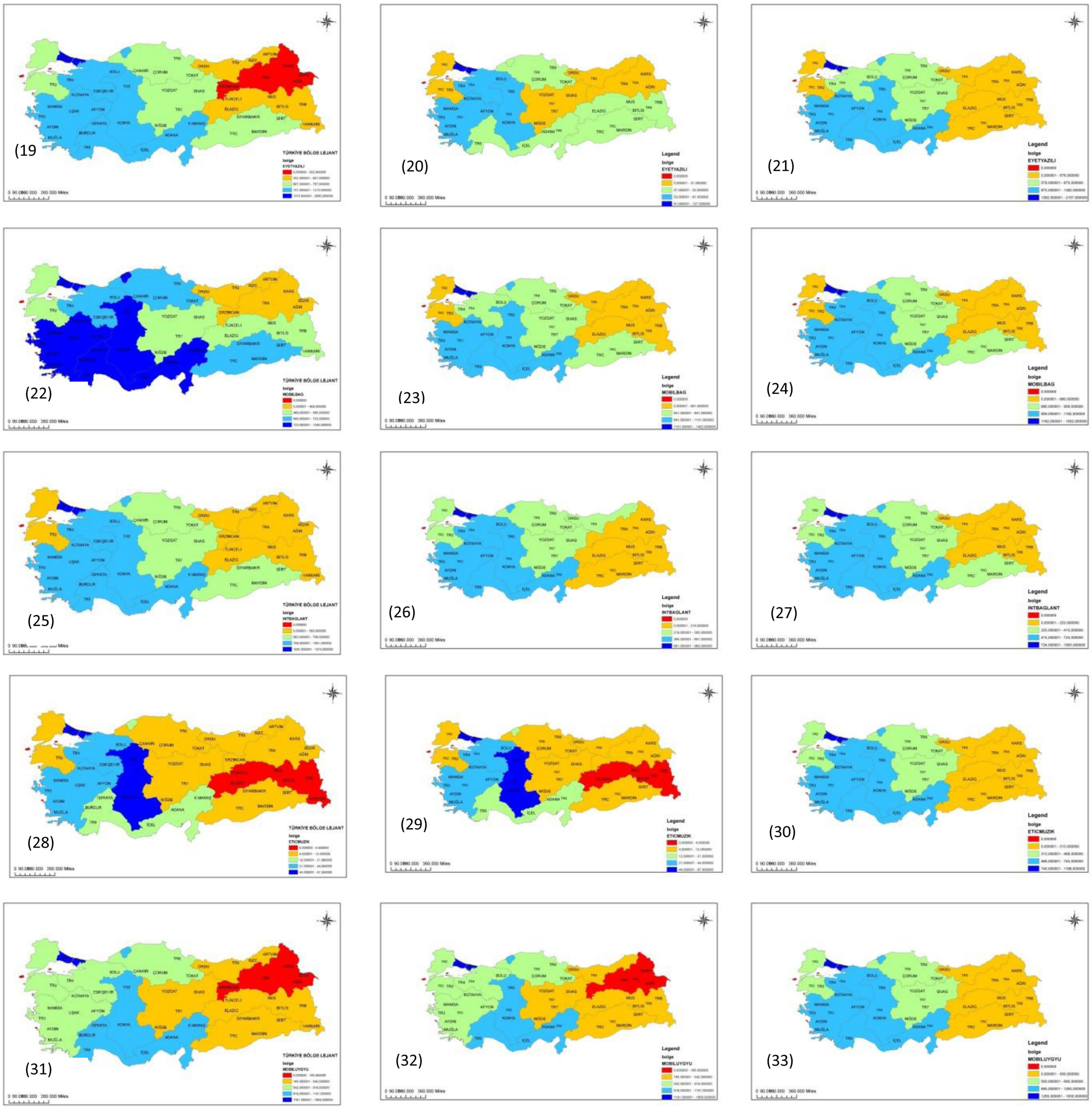


Figure 1.
Distribution of GWR Analysis Results of Local R^2, and Its Coefficients by Years: Household Internet Access (1-2-3), Household Income (4-5-6), Software or Mobile Application Download (7-8-9), Household Literacy (10-11-12), E-Government Usage (13-14-15), E-Commerce Usage (16-17-18), E-Talent Software Usage (19-20-21), Mobile Connection (22-23-24), Internet Connection (25-26-27), E-Commerce Music Acquisition (28-29-30), and Mobile Application Installation Ability (31-32-33). GWR = geographically weighted regression.



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Distribution of GWR Analysis Results of Local R^2, and Its Coefficients by Years: Household Internet Access (1-2-3), Household Income (4-5-6), Software or Mobile Application Download (7-8-9), Household Literacy (10-11-12), E-Government Usage (13-14-15), E-Commerce Usage (16-17-18), E-Talent Software Usage (19-20-21), Mobile Connection (22-23-24), Internet Connection (25-26-27), E-Commerce Music Acquisition (28-29-30), and Mobile Application Installation Ability (31-32-33). GWR = geographically weighted regression.

According to the Household Internet Access Density Maps (1-2-3), in comparison to 2017, internet access increased in the Middle East Anatolia region in both 2018 and 2019.

According to the Household Income Density Maps (4-5-6), household income raised in the West Anatolia region in 2018 compared to 2017, whereas it decreased in the Central Anatolia, Northeast Anatolia, and Middle East Anatolia regions. Moreover, in 2019, household income rose in the Central Anatolia region compared to 2018, whereas it lowered in the Western Anatolia region.

According to the E-Talent Mobile Density Maps (7-8-9), software or mobile application installation increased in the Aegean, East Marmara, Northeast Anatolia, and Southeast Anatolia regions in 2018 compared to 2017. Also, the Aegean, Mediterranean, Central Anatolia, Northeast Anatolia, and Middle East Anatolia regions saw an increase in software or mobile application installation in 2019 compared to 2018, while the West Marmara and Southeastern Anatolia regions saw a fall.

According to the Household Literacy Density Maps (10-11-12), literacy decreased in the West Marmara, Aegean, Mediterranean, Eastern Black Sea, and Southeastern Anatolia regions in 2018 compared to 2017. Furthermore, literacy declined in the Middle East Anatolia region in 2019 compared to 2018.

According to the E-Government Usage Density Maps (13-14-15), e-government usage rose in the Middle East Anatolia and Southeastern Anatolia regions in 2018 compared to 2017. Nevertheless, it remained unchanged from 2018 to 2019.

According to the E-Commerce Usage Density Maps (16-17-18), e-commerce usage increased in the Western Anatolia and Middle East Anatolia regions in 2018, compared to 2017, but fell in the West Marmara and Northeastern Anatolia regions. Also, in 2019, the Northeast Anatolia and Southeastern Anatolia regions witnessed a rise in e-commerce usage, whereas the West Anatolian region saw a reduction.

According to the E-Talent Software Usage Density Maps (19-20-21), software usage rose in the Northeast Anatolia and Middle East Anatolia regions in 2018 compared to 2017, while it fell in the West Marmara, Mediterranean, and Central Anatolia regions. Moreover, in comparison to 2018, software usage raised in the Mediterranean and Central Anatolia regions and lowered in the East Marmara, Middle East Anatolia, and Southeastern Anatolia regions in 2019.

According to the Mobile Connection Density Maps (22-23-24), in comparison to 2017, mobile connection decreased in the West Marmara, Aegean, East Marmara, West Anatolia, Mediterranean, West Black Sea, Middle East Anatolia, and Southeastern Anatolia regions in 2018. However, mobile connection rose in the East Marmara region in 2019 compared to 2018.

According to the Internet Connection Density Maps (25-26-27), internet connection raised in the West Marmara and East Black Sea regions in 2018 compared to 2017, while it declined in the Southeastern Anatolia region. In addition, in comparison to 2018, internet connection increased in the Southeastern Anatolia region while it fell in the Eastern Black Sea region in 2019.

According to the E-Commerce Music Acquisition Intensity Maps (28-29-30), there is no change in music acquisition via e-commerce in 2018 compared to 2017. On the other hand, in comparison to 2018, the West Marmara, Mediterranean, Central Anatolia, West Black Sea, and Middle East Anatolia regions saw a rise in music acquisition through e-commerce in 2019, while the West Anatolia region saw a reduction.

According to the Mobile Application Installation Ability Density Maps (31-32-33), mobile application installation ability remained unchanged in 2018 compared to 2017. However, this ability increased in the Aegean, East Marmara, Central Anatolia, and Northeast Anatolia regions in 2019 compared to 2018.

Geographically Weighted Regression Analysis Findings

The maps obtained by analyzing the digital transformation index in Türkiye with the GWR method are shown in Figure 2.

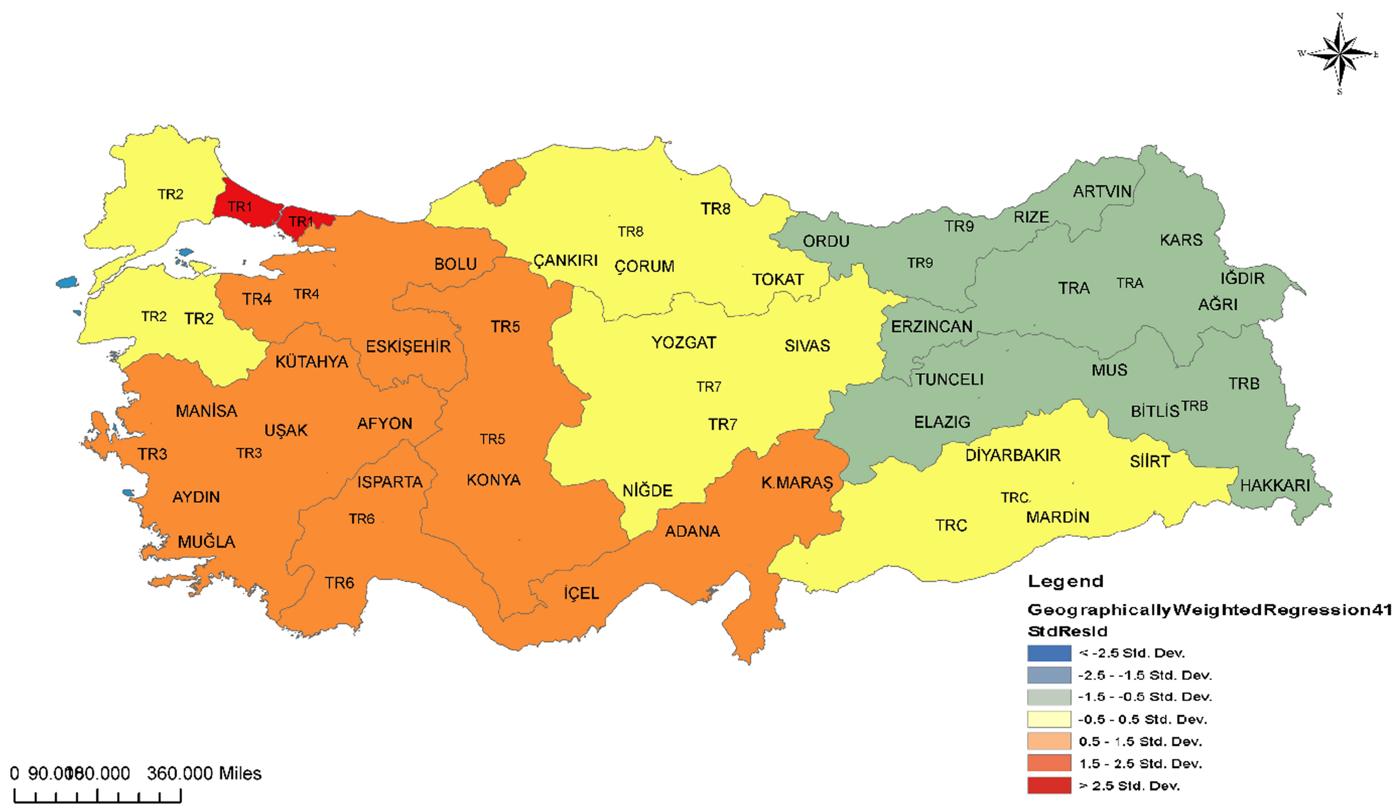

Figure 2.
Türkiye Digital Transformation Index Spatial Regression Analysis Map and Outputs for 2017.

Table 1.
GWR on the Impact of Dependent Variables on the Digital Transformation Index for 2017

Geographically Weighted Regression				
Residual Squares	Sigma	AIC	R^2	Adapted R^2
1107.712	11.777	120.738	.98777	.97868

Note: AIC = Akaike Information Criterion; GWR = geographically weighted regression.

Table 2.
Spatial Autocorrelation Analyses for 2017

Spatial Autocorrelation Analysis of Geographically Weighted Regression Residues			
Spatial Weight Matrix	Moran's *I* Index	*Z*-Value	*P*
First Degree Polygon Neighborhood	.2124	3.1766	.0414

According to the map in Figure 2, the region with the highest digital transformation index is Istanbul. It has the highest R^2 value. In the digital transformation index map, the Aegean, East Marmara, West Anatolia, and Mediterranean regions are in the second rank, while West Marmara, Central Anatolia, West Black Sea, and Southeastern Anatolia regions are in the third rank. The regions with the lowest digital transformation index are the East Black Sea, Northeast Anatolia, and Middle East Anatolia regions. These regions have the lowest R^2 value.

The results of the model's GWR analysis tested by considering the digital transformation index as the dependent variable are given in Table 1. According to this table, the value of R^2 is .98777. To the analysis results, the AIC value is 120.738.

According to Table 2, the Moran *I* value for the 2017 digital transformation index is .2124. This value means that there is positive autocorrelation between the variables. To the analysis results, the *Z* value is 3.176. It is seen that the value is greater than the desired confidence level. This value shows the significance of the general model of the digital transformation index map obtained.

In line with the map in Figure 3, Istanbul is the region with the greatest digital transformation index. It has the highest R^2 value. In the digital transformation index map, the Aegean and Western Anatolia regions are ranked second, the Eastern Marmara and Mediterranean regions are ranked third, the Western Marmara, Central Anatolia, Western Black Sea, Central Anatolia, and Southeastern Anatolia regions are ranked fourth, and the Eastern Black Sea region is ranked fifth. The Northeast Anatolia region has the lowest digital transformation index of all the regions.

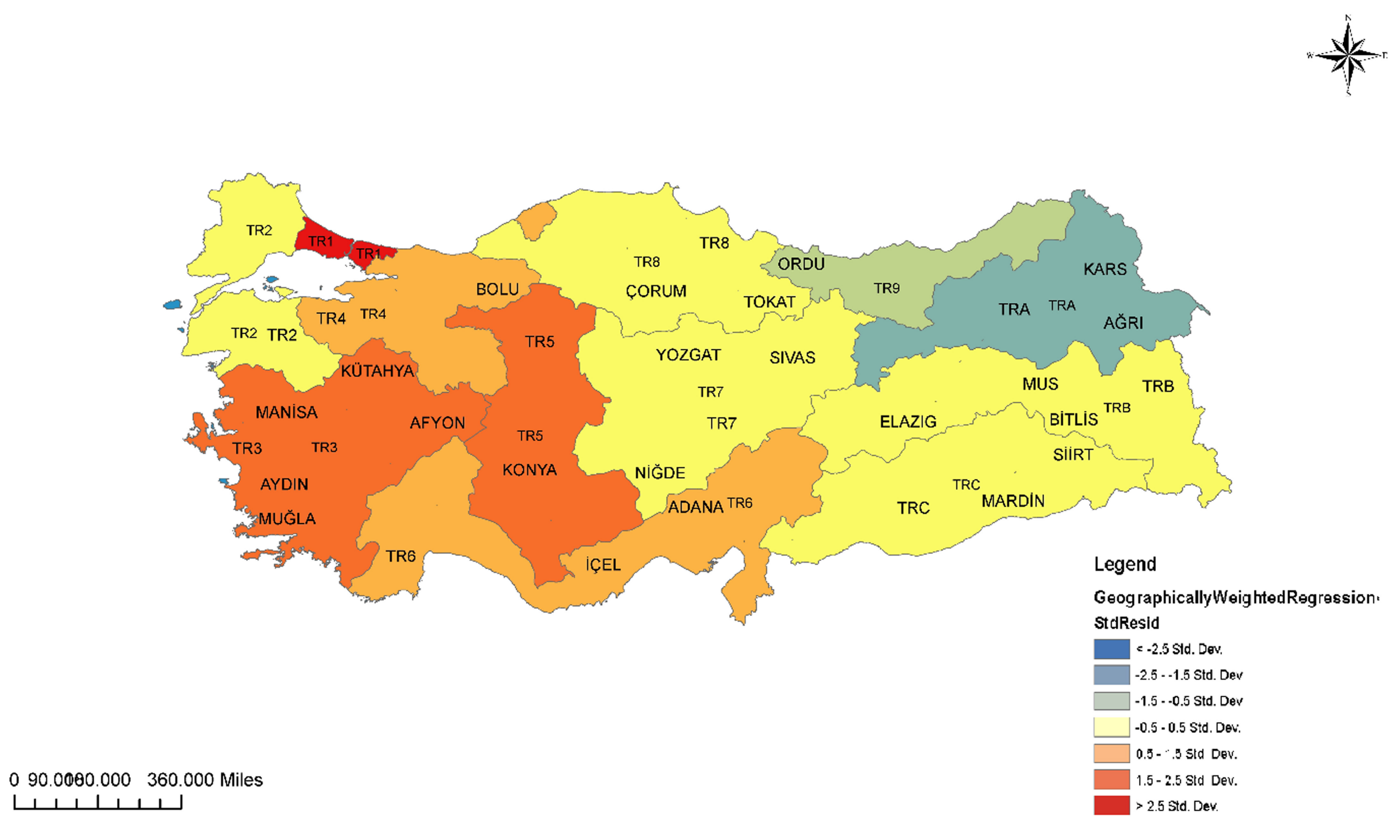

Figure 3.
Türkiye Digital Transformation Index Spatial Regression Analysis Map and Outputs for 2018.

Geographically weighted regression analysis results of the model are presented in Table 3. According to Table 3, the value of R^2 is .99465. To the analysis results, the AIC value is 137.681.

According to Table 4, Moran *I* value for the 2018 Digital transformation index is .1932. To the analysis results, the *Z* value is 2.9587.

According to the map in Figure 4, the regions with the highest digital transformation index are Istanbul, Aegean, East Marmara, West Anatolia, and the Mediterranean. The West Marmara, Central Anatolia, West Black Sea, Middle East Anatolia, and Southeastern Anatolia regions are ranked second in the digital transformation index map. The regions with the lowest digital transformation index are the Eastern Black Sea and Northeastern Anatolia. Geographically weighted regression analysis results are given in Table 5. Accordingly, the R^2 value is .9978. To the analysis results, the AIC value is 131.8512.

Table 6 illustrates that the Moran *I* value for the 2019 Digital Transformation Index is .3012. According to the analysis results, the *Z* value is 4.7841.

According to the analyses obtained by examining the maps showing the digital transformation index distribution, the R^2 value is .9877 for 2017, .9946 for 2018, and .9978 for 2019. These values present that the model is compatible.

The AIC value is 120.738 for 2017, 137.681 for 2018, and 131.851 for 2019. A lower AIC value indicates a better model fit. On the other hand, the Moran *I* value is .2124 for 2017, .1932 for 2018, and .3012 for 2019. These values mean that there is a positive autocorrelation between the variables.

Table 3.
GWR on the Impact of Dependent Variables on the Digital Transformation Index for 2018

Geographically Weighted Regression				
Residual Squares	Sigma	AIC	R^2	Adapted R^2
4076.626	22.599	137.681	.99465	.99133

Note: AIC = Akaike Information Criterion; GWR = geographically weighted regression.

Table 4.
Spatial Autocorrelation Analyses for 2018

Spatial Autocorrelation Analysis of Geographically Weighted Regression Residues			
Spatial Weight Matrix	Moran's *I* Index	*Z*-Value	*P*
First Degree Polygon Neighborhood	.1932	2.9587	.0325

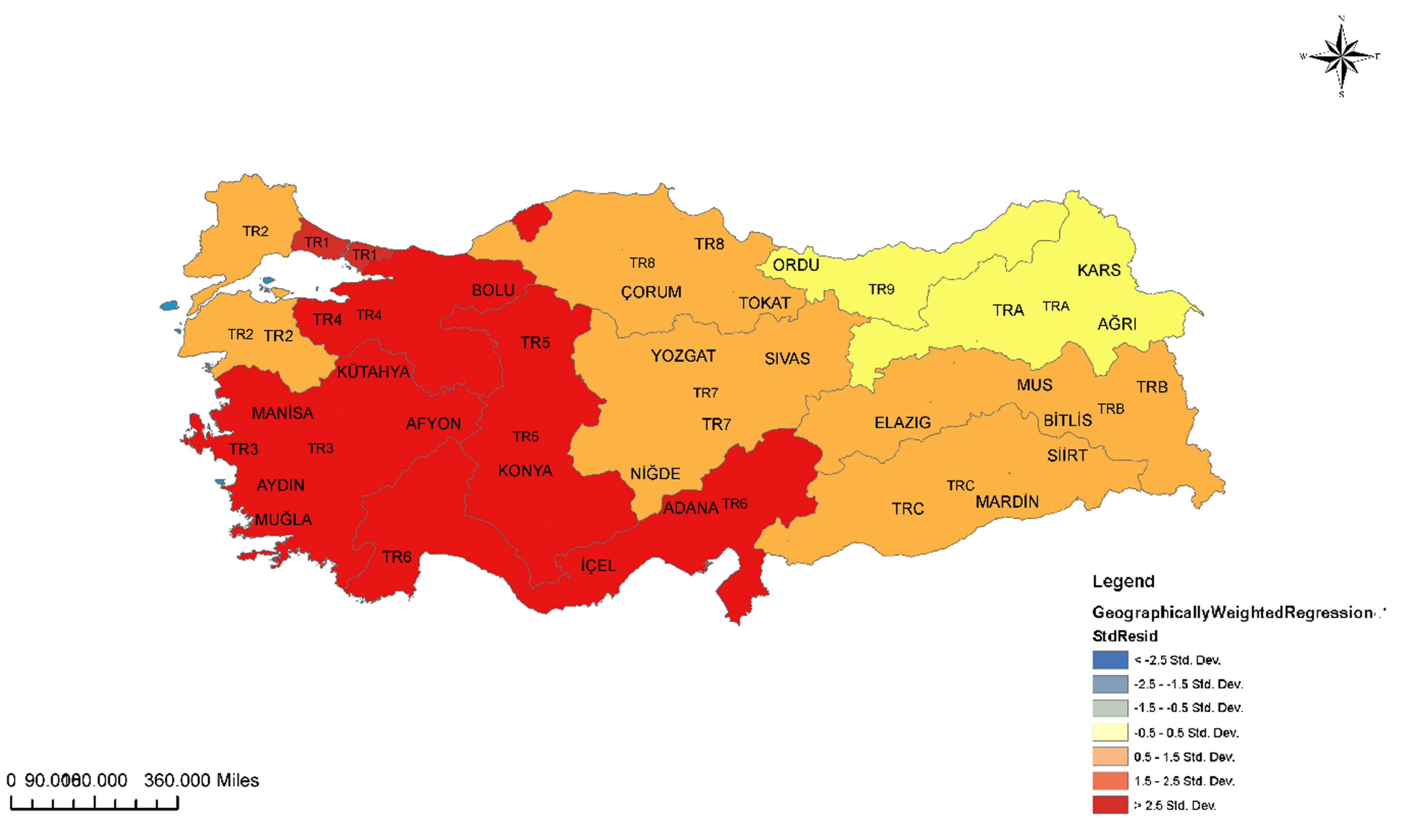

Figure 4.
Türkiye Digital Transformation Index Spatial Regression Analysis Map and Outputs for 2019.

Table 5.
GWR on the Effect of Dependent Variables on the Digital Transformation Index for 2019

Geographically Weighted Regression				
Residual Squares	Sigma	AIC	R^2	Adapted R^2
2604.336	18.085	131.851	.9978	.9968

Note: AIC = Akaike Information Criterion; GWR = geographically weighted regression.

Table 6.
Spatial Autocorrelation Analyses for 2019

Spatial Autocorrelation Analysis of Geographically Weighted Regression Residues			
Spatial Weight Matrix	Moran's *I* Index	*Z*-Value	*P*
First Degree Polygon Neighborhood	.3012	4.7841	.0214

The *Z* value is 3.1766 for 2017, 2.9587 for 2018, and 4.7841 for 2019. The fact that the *Z* values are greater than the desired confidence level shows the significance of the general model of the digital transformation index map obtained.

Discussion

This study examined the calculation of the digital transformation index in Türkiye using the spatial regression method and observed that the differences between the regions change over the years. Aydın et al. (2018, pp. 31–32), in their study, performed the display, research, and modeling of spatial data using economic and sociocultural variables to determine the total fertility rate in Türkiye. The research results showed that the relationship between the total fertility rate and sociodemographic co-variables could be explained by using spatial data analysis methods. When the mobile connection densities calculated by the spatial regression method between 2017 and 2019 are examined, it was seen that the regions with the highest level of mobile connectivity are compatible with the regions in which negative autocorrelation was detected in the study.

In their research, Ferronato et al. (2020, p. 929) aimed to evaluate the selective collection systems for urban wastes using the Geographic Information System in La Paz city of Bolivia. As a result of the study, they determined that the costs decreased by 10%, the recycling rate increased by 3%, and the distance covered by the compactor trucks decreased by 7%. Similarly, according to the household income density map discussed in the findings section of this study, there was no change in the top ranks between 2017 and 2019, but there was a year-on-year change in the remaining rankings.

In their research, Zhang et al. (2017, p. 1461) aimed to examine the relationship between e-commerce development and geographical features by using e-commerce, economy, internet, express, delivery, and population data between 2011 and 2015. As a result of the study, they determined that the spatial clustering of e-commerce development complies with certain rules and reflects a strong imbalance feature. Similar to the research done by Zhang et al. (2017, p. 1465), according to the E-commerce Usage Intensity Maps of this study, in comparison to 2017, e-commerce usage increased in the Western Anatolia and Middle East Anatolia regions in 2018, while it decreased in the West Marmara and Northeastern Anatolia regions. Also, e-commerce usage raised in the Northeast Anatolia and Southeastern Anatolia regions in 2019, compared to 2018, while it decreased in Western Anatolia.

This research, in which the digital transformation index in Türkiye is calculated by the spatial regression method, first revealed which elements must be together to fully realize digital transformation in a country. It utilized the factors included in the Digital Roadmap report published by the Ministry of Science, Industry, and Technology of the Republic of Türkiye, the United Nations E-Government Survey study, where the e-government development index is calculated, NRI report published by the World Innovation, Technology and Services Alliance (WITSA), and the Global Competitiveness Index 4.0 report published by the World Economic Forum (WEF) to determine the elements that make up the framework of digital transformation. Accordingly, these elements are technology, human, and process.

In conclusion, the study calculated the digital transformation index of the regions in Türkiye and revealed the regions with high and low indexes. According to the digital transformation index, significant disparities were detected between regions based on the factors which are telecommunications infrastructure, education, workforce, employment opportunities, and the ability to utilize electronically offered services. While Istanbul, which has the greatest digital transformation index of all years, has these factors, the Northeast Anatolia, East Black Sea, and Middle East Anatolia regions, which have the low index, do not.

With digital transformation, it is possible to improve the quality of life in the Northeast Anatolia, East Black Sea, and Middle East Anatolia regions, where the index is low. Especially with digitization, technology is directly infused into life, and problems in daily life are solved. This transformation cannot be accomplished merely by incorporating digital interfaces into existing traditional infrastructure. It is also of great importance to have qualified human resources and the ability to use technology. In this regard, training in the field of ICTs should be given by investing in human resources in regions with a low digital transformation index.

To realize digital transformation effectively, problems should be handled geographically, not in general, and the problems of each geography should be emphasized. By increasing the number of science centers, environments for the reciprocal exchange of ideas should be created, and this awareness among young people should be improved. Countries that have progressed in digital transformation should be used as models, and a digital ecosystem should be built by prioritizing digital investments. The reports prepared by organizations such as WEF and WITSA should be utilized, and opportunities should be assessed. The state should support the low-income regions with funds and try to boost the use of the internet and digital technologies there.

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