ESTIMATING REGIONAL GDP PER CAPITA IN TÜRKİYE: INSIGHTS FROM NIGHTTIME LIGHTS AND LANDUSE DYNAMICS

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ABSTRACT

ESTIMATING REGIONAL GDP PER CAPITA IN TÜRKİYE: INSIGHTS FROM NIGHTTIME LIGHTS AND LANDUSE DYNAMICS

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This study investigates nighttime light (NTL) data integrated with land use and population dynamics to estimate regional GDP per capita in Türkiye. Using high-resolution satellite imagery and geospatial datasets, it analyzes the relationship between economic activity and nighttime intensity at the provincial level from 2004 to 2020. The framework overlays NTL data with land use classifications—urban, rural, and other—while incorporating grid-based population data. Results reveal a positive, significant relationship between NTL intensity and GDP per capita in a convex trajectory. Urban areas show stronger associations, reflecting industrial and service sector dominance. Error analyses highlight regional disparities: highly urbanized regions show relatively narrower error margins, whereas provinces in the Eastern part of Türkiye show a more dispersed error distribution. Alternative indicators like lit pixel counts and electricity consumption are assessed, with electricity consumption proving the most robust proxy. NTL data remain valuable for regions with sparse economic data. This research highlights geospatial data's role in economic modeling while noting limitations like data noise, endogeneity, and regional variations in light usage. Future studies could refine these methods and explore sector-specific dynamics.

Keywords: Nighttime Lights, GDP Estimation, Land Use, Geospatial Analysis, Türkiye.

ÖZ

TÜRKİYE’DE BÖLGESEL KİŞİ BAŞINA GSYİH TAHMİNİ: GECE IŞIKLARI VE ARAZİ KULLANIMI DİNAMİKLERİNDEN ÇIKARIMLAR

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Bu çalışma, Türkiye'de kişi başına düşen bölgesel GSYH'yi tahmin etmek için arazi kullanımı ve nüfus dinamikleri ile entegre edilmiş gece ışık (NTL) verilerini incelemektedir. Yüksek çözünürlüklü uydu görüntüleri ve jeo-uzamsal veri setleri kullanılarak, 2004-2020 yılları arasında il düzeyinde ekonomik faaliyet ve gece ışığı yoğunluğu arasındaki ilişki analiz edilmektedir. Çalışmanın çerçevesi, NTL verilerini arazi kullanım sınıflandırmaları (kentsel, kırsal ve diğer) ile örtüştürürken, grid tabanlı nüfus verilerini de içermektedir. Sonuçlar, NTL yoğunluğu ile kişi başına düşen GSYH arasında dışbükey bir eğri izleyen pozitif ve anlamlı bir ilişki olduğunu göstermektedir. Kentsel alanlar, sanayi ve hizmet sektörlerinin baskınlığını yansıtarak daha güçlü ilişkiler sergilemektedir. Hata analizleri ise bölgesel farklılıkları ortaya koymaktadır: Yüksek oranda şehirleşmiş bölgeler daha dar hata marjları gösterirken, Türkiye'nin doğusundaki iller daha geniş ve dağınık hata marjlarına sahiptir. Aydınlatılmış piksel sayıları ve elektrik tüketimi gibi alternatif göstergeler değerlendirilmiş ve elektrik tüketiminin en sağlam vekil olduğu görülmüştür. Ancak, NTL verileri, özellikle seyrek ekonomik verilere sahip bölgeler için değerli olmaya devam etmektedir. Bu araştırma, veri gürültüsü, endojenlik ve ışık kullanımındaki bölgesel farklılıklar gibi sınırlamalara dikkat çekerken, coğrafi verilerin ekonomik modellemedeki rolünü vurgulamaktadır. Gelecekteki çalışmalar, bu yöntemleri geliştirebilir ve sektöre özgü dinamikleri araştırabilir.

Anahtar Kelimeler: Gece Işıkları, GSYH Tahmini, Arazi Kullanımı, Jeo-uzamsal Analiz, Türkiye

To my Family

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LIST OF ABBREVIATIONS

AIC	Akaike Information Criteria
BIC	Bayesian Information Criteria
DMSP-OLS	Defence Meteorological Satellite Program
FAO	Food and Agriculture Organization
GDP	Gross Domestic Product
HDF	Hierarchical Data Format
IGBP	International Geosphere-Biosphere Program
LCCS	Land Cover Classification System
MODIS	Moderate Resolution Imaging Spectroradiometer
NTL	Nighttime lights
PWT	Penn World Tables
RMSE	Root Mean Squared Error
TIF	Tagged Image File Format
TURKSTAT	Turkish Statistical Institute
UMD	University of Maryland
VIIRS	Visible Infrared Imaging Radiometer Suite

CHAPTER 1

INTRODUCTION

Gross Domestic Product (GDP) is the core variable in economic analyses. It is one of the most important variables used to measure the economic performance and living standards of countries and regions. Nevertheless, there are some challanges in the way of accurately measuring economic growth. Especially in developing countries, these challenges can be serious. The inability to accurately estimate the informal economy, inadequate data collection capabilities of countries and rapid price changes are among the main reasons for these challenges. The possibility that GDP, which is the most important variable showing the production power of countries, may not be measured accurately due to these reasons can lead to the inability to accurately assess the economic performance of countries and the inefficiency of the policies implemented in the country.

The use of nighttime lights (NTL) data has emerged as a promising alternative for measuring economic activity. Using nighttime lights for economic measurement and forecasting is based on the idea that regions with high levels of development and high incomes are able to consume and produce more and, as a reflection of this, emit more artificial light into the sky at night.

This study aims to measure Türkiye's GDP per capita by province using high-resolution nighttime lights data, and to investigate the dynamics of the GDP per capita nighttime light per capita relationship for the Türkiye example.

The novelty of this study lies in its innovative approach to estimating economic activity by integrating nighttime lights data, land-use classifications, and population distributions. This is achieved by overlaying geospatial population data onto disaggregated nighttime lights data, segmented by land-use categories, providing a more granular and insightful analysis of economic patterns. In the study, landuse types are classified as urban, rural and other, and the differentiation in the relationship between nighttime lights emitted from these regions and GDP per capita is examined.

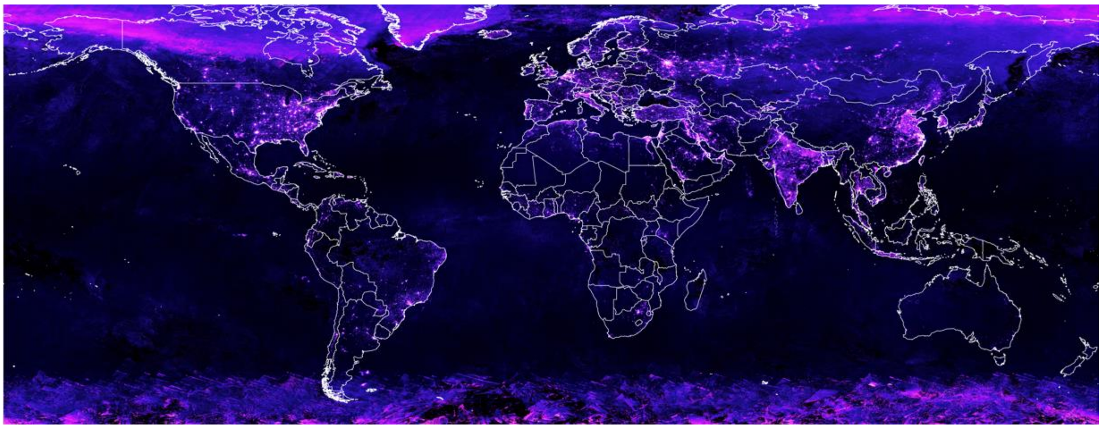

Figure 1: Nighttime lights of the World, 2020
Source: Chen et al., 2021

Two main findings were obtained in this study. First, there is a positive relationship between nighttime light intensity per capita and GDP per capita. This relationship exhibits generally a convex trajectory, thus reflects an increasing elasticity in regions with higher levels of light intensity. Furthermore, rural and urban areas exhibit distinct patterns, with urban areas generally showing a stronger association.

According to the results, the distribution of estimation errors varies across regions, with a narrower concentration observed in areas such as Istanbul, Western Marmara, and Western Anatolia, while higher variability is noted in regions such as Northeastern Anatolia, Central Eastern Anatolia, and Southeastern Anatolia.

The Root Mean Squared error (RMSE) generally decreases from east to west but remains high in provinces like Zonguldak, Bartın, Karabük, and Çankırı in the Western Black Sea region. In the Mediterranean Region, particularly in Antalya, estimation errors increased due to the COVID-19 pandemic's impact on tourism. When the ratio of estimated GDP per capita to official values is examined, the ratios are found to be high in eastern provinces such as Van, Ağrı, and Şanlıurfa, while they are lower in large cities and industrial centers in the west.

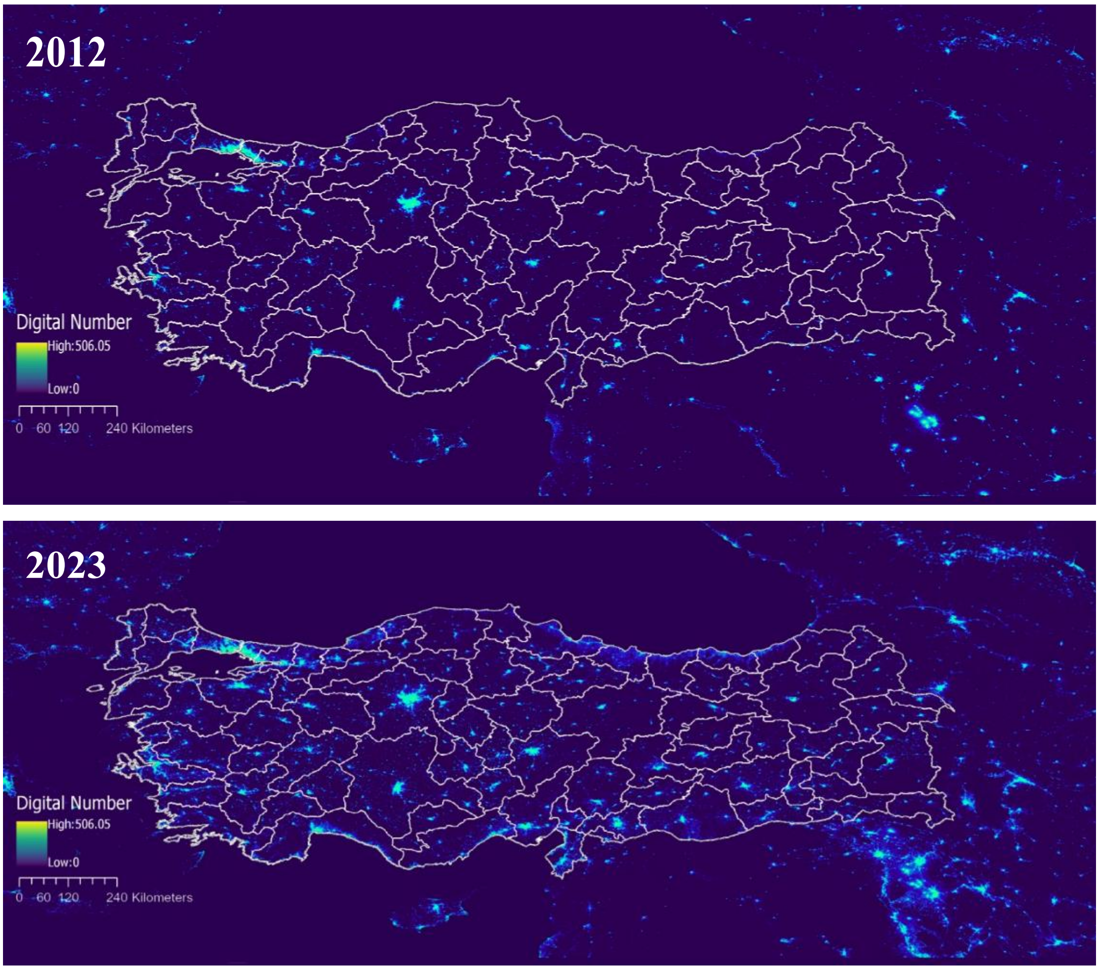

Figure 2: Nighttime lights of Türkiye, 2012-2023

Source: Chen et al., 2021

As Hu and Yao (2019) state, it would be wrong to assume that there is a direct relationship between nighttime lights and GDP. First of all, there is an endogeneity problem in the relationship between these two variables. Nighttime lights can be a predictor of GDP, just as GDP can be a predictor of nighttime lights. Moreover, light usage habits may vary from region to region and from culture to culture. This can complicate the relationship between these two variables. Finally, not all economic developments in regions may be reflected positively or negatively on nighttime lights. Furthermore, nighttime light analyses are not a substitution for GDP and, as with GDP, there are various shortcomings and limitations in this method. For example, errors in satellite data, miscalculations, and atmospheric conditions affecting nighttime light intensity may limit the reliability of this method. Such methods can only be used for supplementary or complementary analysis to GDP.

In the rest of the study, Chapter 2 presents the literature review. Chapter 3 explains the methodology of the study, Chapter 4 presents descriptive statistics and descriptions of the data used in the study. Finally, explanations of the results are presented in Chapter 5 and conclusion is given in Chapter 6.

CHAPTER 2

LITERATURE REVIEW

Geospatial data are used in economics to understand the relationship between spatial dynamics and economic activity. By examining spatial data such as satellite imagery, landuse or a variety of other datasets, researchers have studied regional development, urbanization, measuring inequality and, as in this study, GDP estimation. The ability to model and visualize economic processes and outputs makes geospatial datasets important in economic studies.

Recoding images of the Earth's surface were first publicly archived in 1973 and it was not until 1978 that Croft (1978) conducted a study using these data for the first time. It was only after the Defense Meteorological Satellite Program Operational Linescan System (DMSP-OLS[1]) nighttime light data became available in 1992 that studies using nighttime light data gained momentum. In 2002, the first paper using nighttime lights was published in an economics journal. The article found that GDP is correlated with the total light emission of countries (Sutton and Costanza, 2002; Gibson, Olivia, and Boe-Gibson, 2020).

The use of geospatial data in the social sciences, and especially in economics, can be useful in analyzing informal economies estimated by traditional methods. Ghosh et al. (2009) worked measuring Mexico's informal economy by the regression parameters of the United States calculated by DMSP nighttime light dataset, by assuming United States has a stronger and more reliable statistical capability, and observed that the informal economy and remittances in Mexico are 150% higher than the official estimates.

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[1] DMSP-OLS is referred as DMSP hereafter.

In his work Elvidge et al. (2013) argues that Visible Infrared Imaging Radiometer Suite (VIIRS) is superior to DMSP data for the nighttime lights as it performs better in resolution, dynamic range, quantization and calibration. Mathen et al. (2024) in their study on economic activity and regional inequality in India using DMSP and VIIRS nighttime light data, reported that utilizing VIIRS dataset yields more accurate results than utilizing DMSP dataset due to former one's higher resolution and relatively lower computational error capabilities.

Nighttime light data of DMSP (1992-2013) and VIIRS, after 2012, are inconsistent due to the differences in satellite systems. Therefore, some efforts have been made to combine these two to enhance the temporal coverage of nighttime light data. Li et al. (2020) combined DMSP and VIIRS data to create a harmonized nighttime light dataset at 1km resolution. Chen et al (2021) developed a high-resolution dataset using DMSP and VIIRS data using deep learning methods. This dataset developed by Chen et al. is also used in this study.

In 2012, Henderson et al. (2012), the most cited study in this partly new literature, uses the example of the quality grading of countries' income in the Penn World Tables (PWT) datasets to address the problem of inaccurate measurements of GDP espicially in low income countries. In the study, they developed a method to produce an adjusted GDP series by weighting the results obtained using official statistics, nighttime lights data and statistical quality rankings of the countries, provided by the IMF and World Bank. Bickenbach et al. (2013) analyzed regional GDP across Brazil, India, the United States and Western Europe using nighttime lights. However, they found that the elasticity between nighttime lights and GDP is unstable and that nighttime lights are often an unreliable proxy for subnational economic activity.

The method developed by Henderson et al. (2012) has also been applied in other studies in GDP per capita (Hu and Yao, 2019) and GDP growth adjustments (Beyer, Hu, and Yao, 2022). In their 2022 study, they found that the correlation between quarterly nighttime light growth and GDP growth in Emerging Market and Developing Economies is higher than in advanced economies. Furthermore, the study of Hu and Yao (2019) showed that the elasticities of nighttime lights with respect to GDP have a quadratic relationship. It is important to note that in the same study, they emphasized that although countries in Africa are growing rapidly, their economic growth is not reflected in nighttime lights as expected because they have low income levels and limited access to electricity.

Nighttime lights are also widely used in the literature to examine the effects of disasters and the COVID 19 pandemic. Lin and Rybnikova (2023) examined the impact of the COVID-19 pandemic on the relationship between nighttime light and GDP at the subnational level, and stated that the relationship weakened during th COVID-19 period, however the shock-induced effects of the relationship can be corrected with appropriate adjustments, and emphasized that the reliability of nighttime lights as a proxy may fall during such unusual periods. Elliott et al. (2015) conducted a disaster impact analysis in coastal areas of China using historical typhoon track and nighttime light data. They calculated that total economic output decreases by 20% in a scenario where total property is damaged by 50%.

Many regional estimation studies have been conducted using nighttime lights and the efficiency of these estimates is widely discussed. Chen and Nordhaus (2019) examined the performance of the VIIRS nighttime light dataset in GDP estimation at the state and metropolitan level in the US and stated that cross-sectional GDP estimates are more accurate than GDP growth estimates. Also they stated that the relationship between GDP and nighttime lights is stronger in urban areas (metropolitan areas). Similarly, Zhang and Gibson (2022) concluded in their study at the county level that nighttime lights are effective in estimating cross-sectional GDP, but have limited accuracy in estimating the temporal movements.

McCord and Rodriguez-Heredia (2022) estimated Paraguay's subnational level GDP using nighttime lights and suggested that nighttime light estimation may be useful, especially where there is a lack of detailed data collection. Ehsan et al. (2024) developed a methodology to predict district-level GDP for Bangladesh's 64 districts from 1992 to 2020 using nighttime light data, building on Henderson et al.'s (2012) approach. They differentiated between productive nighttime light emissions for agricultural, industrial, and service sectors to refine GDP estimates at the district level.

Finally, Chen et al. (2024) constructed pooled-OLS, between and within estimator models using landuse and sectoral GDP breakdowns for Türkiye. They find that the highest GDP-nighttime light intensity elasticity is in the industrial sector (1.14%), indicating that industrial economic activities are better captured by nighttime lights.

CHAPTER 3

METHODOLOGY

The study is based on the approach that nighttime lights are an indicator for the economic development of a region and the theoretical framework is centered on interpreting the economic relationship through nighttime light data derived from high-resolution satellite imagery and it attempts to develop a tool to estimate province-based GDP in Türkiye using nighttime light data.

The models are constructed using a random coefficients specification, allowing for the relationship between variables to vary across units, capturing heterogeneity with limited number of parameters.[2] The general form of the model is expressed as:

$$y_{it} = (\beta_0 + b_{0i}) + (\beta_1 + b_{1i})x_{it} + (\beta_2 + b_{2i})x_{2it} + \varepsilon_{i,t} \qquad (1.1)$$

where $\beta_0,\ \beta_1,\ \beta_2$ represent the fixed (average) coefficients, while $b_{0i},\ b_{1i},\ b_{2i}$ denote the random deviations that vary across units. These random effects are assumed to follow normal distributions with zero mean and variances τ_0, τ_1, and τ_2 respectively. The error term, $\varepsilon_{i,t}$, accounts for idiosyncratic noise in the model.

In the standard random coefficients model, the random effects (b_{0i}), (b_{1i}), (b_{2i}) are assumed to be mutually independent, implying no correlation between the random deviations in the intercept and slopes. Mathematically, this assumption is captured as:

$$cov(b_{ji,} b_{ki}) = 0, \qquad \forall\, j,k \text{ such that } j \neq k \qquad (1.2)$$

where $j,k = 0,1,2$. This independence simplifies the covariance structure, ensuring that heterogeneity in one coefficient does not influence the variability in others. In

[2] For comparison, the results from the fixed effects models are provided in the appendices.

contrast, the correlated random coefficients model allows for correlations between the random effects. In this case:

$$cov\left(b_{ji,}b_{ki}\right) = \tau^2{}_{jk}, \qquad \forall\, j,k \text{ such that } j \neq k \qquad (1.3)$$

where τ_{jk} represents the covariance between the random effects $b_{\mathrm{j}i}$ and $b_{\mathrm{k}i}$.

In all models below, lowercase notation represents the per capita form of the variables. This flexibility when allowing for correlated coefficients provides a better representation for the complex relationship, though at the cost of increased model complexity.

3.1. The Linear Model

The linear models are constructed in logarithmic form to correct the effect of outliers and to treat the coefficients obtained as elasticities. The basic equation is as follows:

$$\ln\left(gdp_{i,t}\right) = \alpha + \beta ln\left(ntl_{i,t}\right) + \gamma_t + \varepsilon_{i,t} \qquad (2.1)$$

In the equation, i represents provinces and t denotes the year. β is the random coefficients parameter for the linear term. $gdp_{i,t}$ is the GDP per capita of province i at time t, while $ntl_{i,t}$ is the nighttime light intensity per capita of province i at time t. α is intercept, γ denotes the year specific fixed effect, and ϵ is the error term.

3.2. The Quadratic Model

This model incorporates the quadratic form of nighttime light intensity per capita to test and examine the characteristics of non-linear relationships between nighttime light intensity per capita and GDP. This specification allows us to analyze whether the relationship between nighttime lights and GDP follows an increasing or decreasing quadratic pattern.

$$\ln\left(gdp_{i,t}\right) = \alpha + \beta ln\left(ntl_{i,t}\right) + \delta(ln(ntl_{i,t}))^2 + \gamma_t + \varepsilon_{i,t} \qquad (2.2)$$

where $(\ln(\mathrm{ntl}_{i,t}))^2$ is the square of the logarithm of per capita nighttime light intensity and δ is the random coefficients parameter for the quadratic term.

3.3. Models with Landuse Specifications

Here unlike previous models, the relationship between rural and urban nighttime lights and GDP is analyzed separately, since different economic activities take place in different landuses and the effects of them on nighttime lights consequently differs.

$$\ln\left(GDP_{i,t}\right) = \alpha + \sum_{k} \beta_k ln\left(ntl_{i,t,k}\right) + \gamma_t + \varepsilon_{i,t} \qquad (2.3)$$

$$\ln\left(GDP_{i,t}\right) = \alpha + \sum_{k} \beta_k ln\left(ntl_{i,t,k}\right) + \sum_{k} \delta_k (\ln(ntl_{i,t,k}))^2 + \gamma_t + \varepsilon_{i,t} \qquad (2.4)$$

The subscript k in equations (3) and (4) denotes the landuse type. Therefore, $ntl_{i,t,k}$ is the per capita light intensity of province i in year t and by landuse type k.

In order to control for the variance of the regression error term, model parameters are estimated using heteroscedasticity robust standard deviations.

The relationship between nighttime light intensity per capita and GDP per capita is compared with the variables of the number of lit pixels per capita and electricity consumption per capita. In addition, Akaike Information Criteria (AIC) and Bayesian Information Criteria (BIC) metrics were used for model selection.

CHAPTER 4

DATA, VARIABLES AND DESCRIPTIVE STATISTICS

4.1 Official Dataset

This study incorporates data from the Turkish Statistical Institute (TURKSTAT) alongside various geospatial datasets to be mentioned below. The province level GDP data is drawn from TURKSTAT's national accounts database. To align with the study's temporal focus, chained volume values are applied. Electricity consumption data from TURKSTAT is also provided by detailing usage by various categories from 1995 to 2021 and presenting total electricity consumption in Mwh units.

4.2. Nigttime Lights dataset: NPP-VIIRS-like NTL

Nighttime light data are widely used to understand the intensity and spatial distribution of economic activity, especially with imagery from satellite systems such as the DMSP and the VIIRS (Henderson et al., 2012; Hu & Yao, 2019). DMSP-OLS, which was operational from the early 1990s until 2013, has a resolution of approximately 1km at the equator. The fact that the maximum value each pixel can take in the images presented in this dataset is limited to 63 leads to the problem of underestimating the total light intensity, especially in urban centers, in which the nighttime light intensities are expected to much higher than the average. VIIRS, which became operational in 2012, has a resolution of about 500m at the equator. Due to its high resolution compared to DMSP-OLS and the fact that it is radiometrically calibrated unlike DMSP-OLS, noise and glare in the data set have been significantly reduced, resulting in a data set that is more sensitive to changes in light intensity. In addition, the fact that the maximum nighttime light values in pixels are not limited as in DMSP-OLS allows for a more accurate calculation of nighttime light emissions, especially in places such as city centers where nighttime lights are intensively emitted (Elvidge, Baugh, Zhizhin, & Hsu, 2013).

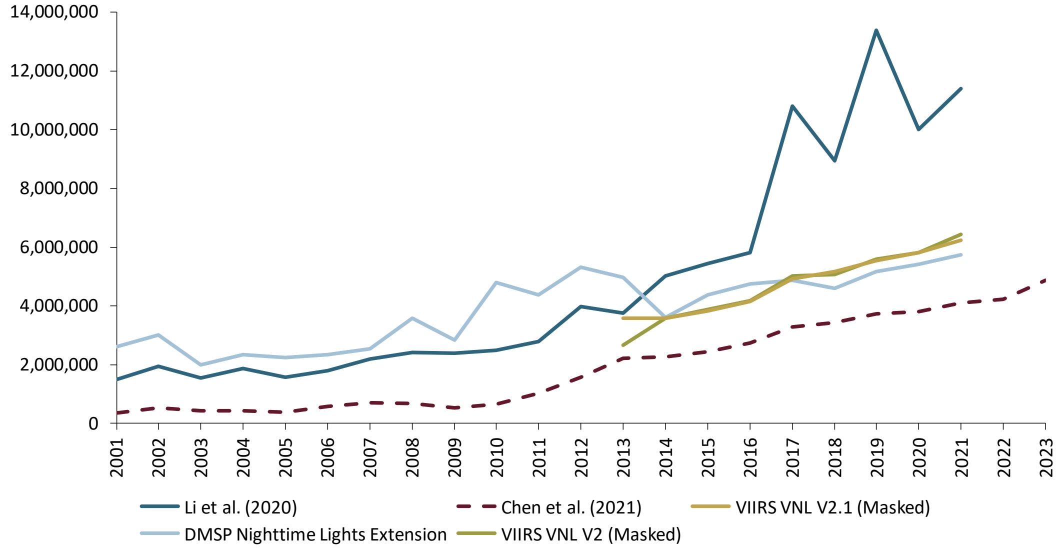

Figure 3: Nighttime lights of Türkiye from different datasets, 2001-2023

As can be seen in Figure 3, different satellites and data collection methods provide different values for Türkiye's total nighttime light intensity by year. The different sensor and resolution characteristics of DMSP-OLS (1992-2013) and VIIRS (from 2012 onwards) do not allow for a direct combination of these two datasets to form a continuous time series. Therefore, in order to correct this time-dependent mismatch an extended nighttime light dataset (Chen et al., 2021) similar to VIIRS is used in this study.[3] The dataset utilized in this study employs a cross-sensor calibration technique that integrates DMSP-OLS data (2000–2012) with VIIRS data (2013 onwards), creating a consistent VIIRS-like time series (Chen et al., 2021). The extended spatial nighttime light data provided by Chen et al. (2021) has created an important opportunity for long-term spatial studies. The dataset covers the period 2000-2023 and provides nighttime light intensity values at pixels with at 500-500m radius. Nighttime light from oceanic sources such as ships and oil rigs are not included in the dataset to avoid possible inconsistencies during model training.

[3] Li et al. (2020) also provides an extended nighttime lights dataset however, as Chen et al. (2021) provides a more advanced dataset that retains the VIIRS benefits and it does not inherit weaknesses present in the older DMSP data.

Therefore, this limits the use of the dataset for the study of maritime activities. However, this limitation does not affect this study since the scope of this study is to make sense of the relationship between economic size and nighttime light from terrestrial areas in Türkiye.

In this study, the NPP-VIIRS-like NTL imageries were divided by the provincial boundaries given in the Turkish Provincial Administrative Boundaries classification provided by the General Directorate of Mapping of the Ministry of National Defense of the Republic of Türkiye, and the total nighttime light intensity of the provinces was calculated by summing the pixel values within the boundaries of each province for the years 2000-2023. Similarly, the total number of pixels with values greater than zero within the borders of the provinces is utilized to calculate the total number of lit pixels of the provinces.

4.3. Landuse Dataset

This study also examines the variation of the elasticity of the nighttime light data with respect to GDP per capita depending on the land type from which the nighttime lights being emitted. Therefore, the Terra and Aqua combined Moderate Resolution Imaging Spectroradiometer (MODIS) Land Cover Type (MCD12Q1) Version 6.1 dataset was used to distinguish landuse types in Türkiye (LP DAAC, 2024). This landuse dataset consists of global land cover types at annual intervals from 2001 to 2023. The dataset was derived using supervised classifications of MODIS Terra and Aqua reflectance data with land cover types based on various classification schemes, including the International Geosphere-Biosphere Program (IGBP) and the University of Maryland (UMD) system. The dataset also includes land cover assessment layers provided by the Food and Agriculture Organization (FAO) Land Cover Classification System (LCCS), which add more detail on land cover, landuse and surface hydrology.

Land use data files in Hierarchical Data Format (HDF), provided in six separate segments per year to cover Türkiye's borders, were downloaded. These files were then converted into Tagged Image File Format (TIF) files[4] and merged based on Türkiye's borders to produce comprehensive land use maps for the country. There are 17 landuse types in MODIS landuse data. These are evergreen coniferous forests (1), evergreen broadleaf forests (2), deciduous coniferous forests (3), deciduous broadleaf forests (4), mixed forests (5), closed shrublands (6), open shrublands (7), woody savannas (8), savannas (9), grasslands (10), permanent wetlands (11), croplands (12), urban and built-up areas (13), field/natural vegetation mosaics (14), permanent snow and ice (15), barren areas (16) and water bodies (17).

These 17 land types have been reclassified according to the author's own classification. According to the landuse numbers mentioned above, landuse types 1, 2, 3, 4, 5 were regrouped as natural forests; landuse types 6, 7 as shrublands; landuse types 8, 9, 10 as grasslands; landuse types 12, 14 as agricultural areas; landuse type 13 as urban areas; landuse types 11, 17 as wetlands and water bodies; and landuse types 15, 16 as barren lands.

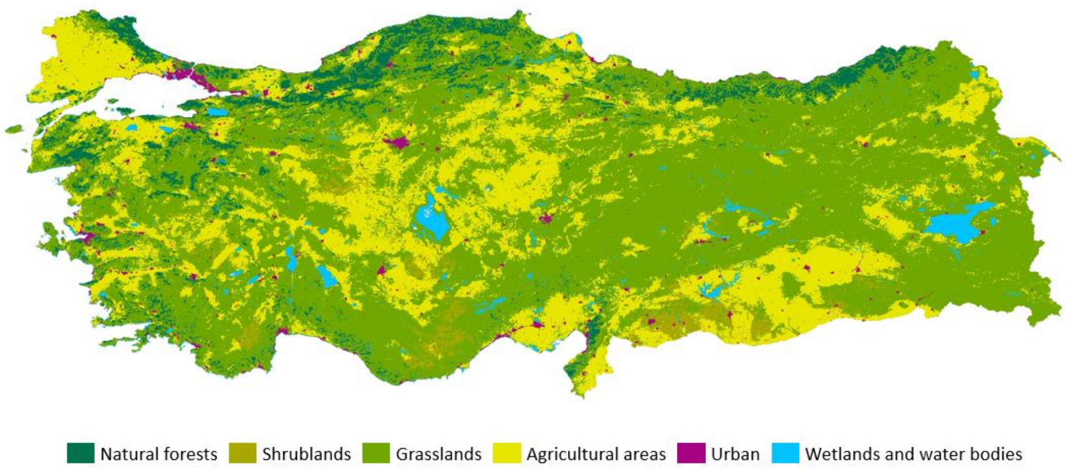

Figure 4: Landuse map of Türkiye

Note: Natural Forests: (1, 2, 3, 4, 5), Shrublands: (6, 7), Savannas/Grasslands: (8, 9, 10), Agricultural Areas: (12, 14), Urban Areas: (13), Wetlands and Water Bodies: (11, 17), Barren and Snow/Ice: (15, 16)
Source: LP DAAC

[4] TIF (Tagged Image File Format) files are raster image files commonly used for geospatial or satellite imagery, offering high-quality, detailed visuals and support for spatial metadata.

Figure 4 shows the landuse classification of Türkiye for 2020, based on MODIS landuse data reclassified by the author into broader categories. The green tones dominating most of the map indicate the prevalence of natural forests, shrublands and grasslands. Yellow areas represent agricultural land, which is spread across the country. Small purple spots indicate urban areas, while blue dots highlight wetlands and water bodies.

As a second meta-grouping, natural forests, heathlands, grasslands and agricultural areas are grouped under rural land, and those outside rural and urban lands are classified as other. The reason for such a grouping is that the service and industrial sectors are generally located in urban areas, while the agricultural sector is located in rural areas. Therefore, it is aimed to capture more nuanced results in GDP per capita nighttime light modeling.

4.4. Population Dataset

Since the province-based population data provided by TURKSTAT cannot provide the required spatial detail, The WorldPop dataset was used in the study. This dataset provides high-resolution, gridded population data between 2000 and 2020 (WorldPop, 2024). The data were generated using advanced spatial modeling techniques that combine census data, satellite imagery and ancillary datasets to estimate population distribution at a detailed level. The dataset provides population counts and densities in $100m^2$ grid cells, enabling detailed spatial analysis of demographic changes over time.

The population density map of Istanbul, Figure 5, shows the spatial distribution of population across the city. The maroon and purple zones represent the highest population densities concentrated in the urban core, particularly in districts characterized by dense residential and commercial activity, such as Beyoğlu, Şişli, Fatih and Kadıköy. Dark blue areas represent medium-density areas on the outskirts of the city where suburban areas are expanding. Blue areas reflect lower population densities and are likely to represent rural or industrial areas in the northern and peripheral districts.

Figure 6 shows the comparison of the population data of TURKSTAT, and Türkiye's grid-based population data described above. On the Y-axis are the logarithmic values

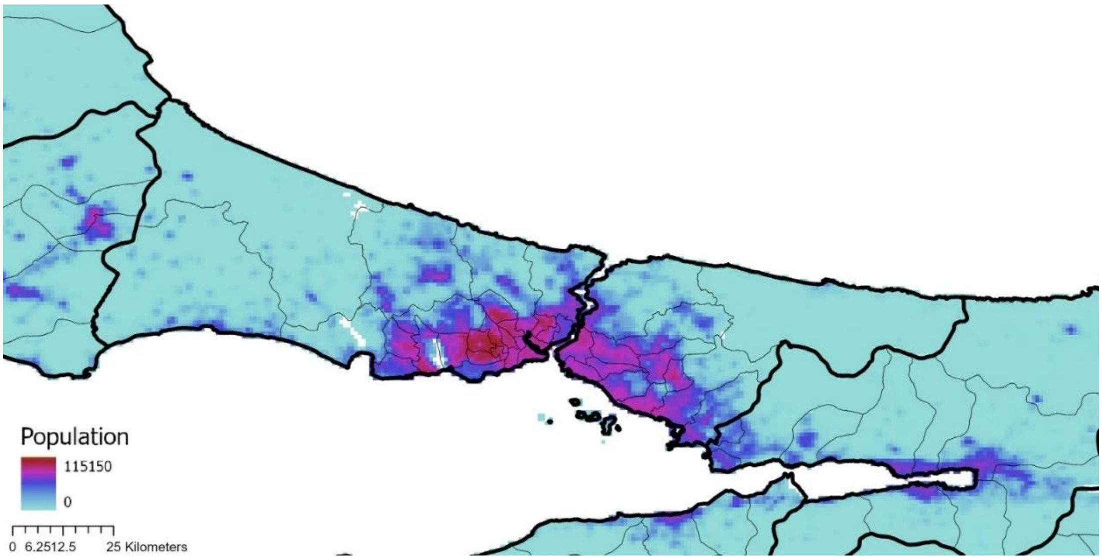

Figure 5: Grid based population of Istanbul, 2020

Source: WorldPop

of the official population data provided by TURKSTAT and on the X-axis are the logarithmic values of the grid-based population data. The correlation coefficient between the two population data is 0.9986 showing that official statistics adjusted grid based population data can be used as an alternative in the rest of the study.

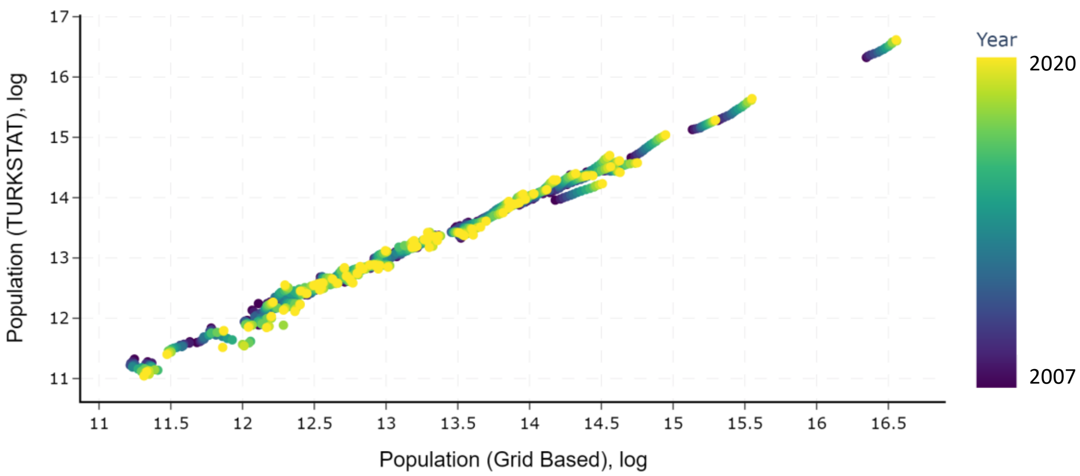

Figure 6: Population of Türkiye, 2007-2020

Source: TURKSTAT, WorldPop

Figure 7 illustrate the three geospatial datasets described above. The nighttime light intensites and the number of lit pixels, calculated based on the landuse distribution of each province, were divided by grid-based population data to obtain nighttime light variables on a per capita basis. Likewise, GDP per capita values were calculated by dividing the chained volume GDP figures from TURKSTAT by the grid-based population values.

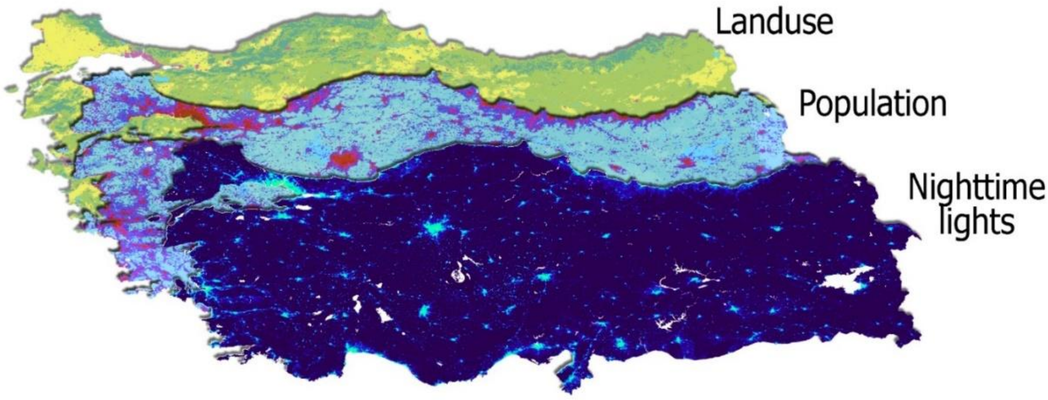

Figure 7: Landuse, population and nighttime lights

The correlation table below (Table 1) illustrates the extent of relationships between the variables used in the study.[5] It is seen that GDP has a high correlation with total nighttime light intensity. This correlation is particularly higher in urban areas. The fact that advanced economic activities such as manufacturing and services take place especially in urban areas and at the same time have a high population density compared to rural areas strengthens the relationship between economic activity and nighttime light intensity in the region. One of the important points here is that agriculture, which has the most important place in the economy of rural areas, is mostly not carried out at night and therefore we see relatively lower correlation coefficients between rural areas and the GDP. This may lead to an underestimation of the economic activity in rural areas using nighttime light intensity. The 94.8% correlation of total nighttime light intensity with urban nighttime light intensity indicates that urban areas are the main regions influencing total nighttime light intensity.

[5] Correlation tables for total, per capita, logarithmic per capita, and growth variables are provided in the annex.

Lit pixel count shows the spatial distribution of nighttime lights without taking intensity into account and gives us a clue about the distribution of economic activity. As street lighting is one of the main elements of urbanization, lit pixel count in urban

	GDP	NTL intensity	Urban NTL intensity	Rural NTL intensity	Other NTL intensity	Lit cell count	Urban lit cell count	Rural lit cell count	Other lit cell count	Electricity consumption
GDP	1									
NTL intensity	0.8167	1								
Urban NTL intensity	0.9423	0.9481	1							
Rural NTL intensity	0.4445	0.8671	0.6643	1						
Other NTL intensity	0.4615	0.6003	0.5364	0.5407	1					
Lit cell count	0.4827	0.8602	0.6724	0.9687	0.5786	1				
Urban lit cell count	0.8857	0.8649	0.9153	0.5975	0.5613	0.6626	1			
Rural lit cell count	0.3673	0.7935	0.5739	0.9672	0.5265	0.9891	0.5455	1		
Other lit cell count	0.4055	0.5659	0.4866	0.5398	0.9447	0.5908	0.5474	0.5418	1	
Electricity consumption	0.9175	0.8418	0.9113	0.5499	0.5345	0.6046	0.9332	0.4936	0.5024	1

Table 1: Correlation table of nighttime lights and TURKSTAT variables

areas has a much stronger correlation with GDP than lit pixel count in rural areas. Finally, total electricity consumption has also a strong correlation with GDP. This is because electricity consumption directly reflects many economic activities in urban regions, such as manufacturing, services and residential energy use.

Figure 8 displays the logarithmic values of GDP per capita, based on the chained volume index, alongside the logarithmic values of nighttime light density per capita.

This analysis yields two key insights. First, the graph clearly demonstrates a positive relationship between nighttime light intensity per capita and GDP per capita. Second, and more notably, it reveals a quadratic relationship between these two variables. Accordingly, as nighttime light intensity increases, the elasticity of nighttime lights with respect to real GDP per capita gradually increases. As highlighted by Hu and Yao (2019), this relationship suggests that the region or province has begun transitioning from infrastructure investments to economic activities that yield higher technical and economic returns. The significant rise in per capita nighttime light intensity, particularly in less developed provinces, coupled with the comparatively slower growth in per capita income, suggests that low-income and developing regions focuses on strengthening their infrastructure. In contrast, in provinces that have moved beyond this phase, the relationship appears to have shifted, with per capita income growth outpacing the increase in nighttime light intensity.

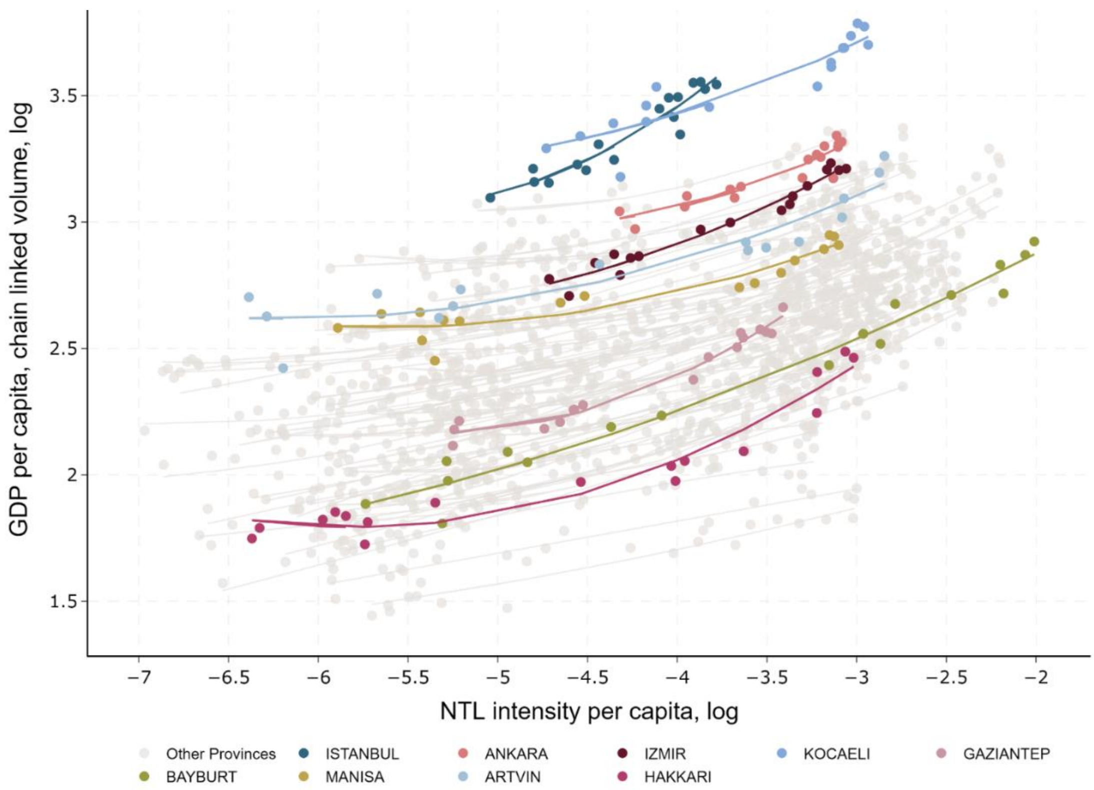

Figure 8: Nighttime light intensity and GDP per capita, log, 2004-2020

As an alternative to the widely used nighttime light intensity indicator in the literature, the number of lit pixels and electricity consumption can serve as complementary data sources. These measures not only provide valuable insights into regional economic development but also allow for meaningful comparisons across different metrics to better understand the nuances of economic activity.

Figure 9 displays the relationship between the number of lit pixels and GDP per capita across provinces. It shows a positive relationship between the number of lit pixels and economic output, as is the case for nighttime light intensity, suggesting more lights per capita is associated with higher GDP per capita. Notably, the quadratic relationship observed in the previous figure diminishes in developed cities but remains evident in low-income cities. In developed cities, increasing lit areas at night—driven by factors such as industrialization and urbanization beyond city centers—does not exhibit as strong a relationship with economic activity as it does in low-income provinces. This illustrates the scenario where production facilities established in rural areas may contribute more significantly to the provincial economy compared to those located in highly urbanized regions.

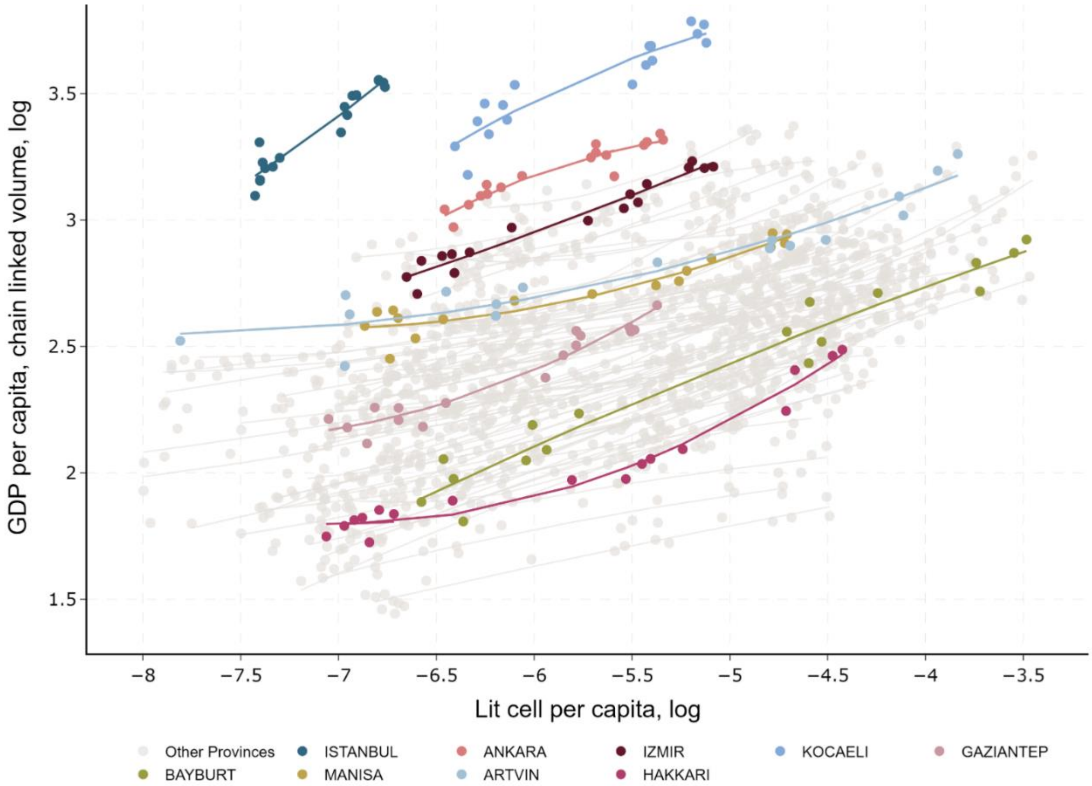

Figure 9: Lit cell count per capita and GDP per capita, log, 2004-2020

Figure 10 displays the nighttime light maps of the Akkuyu Nuclear Power Plant region, illustrating the area both before and after the construction of the facility. The gray rectangles on the maps highlight the area in the Gülnar district of Mersin where the Akkuyu Nuclear Power Plant is being constructed, shown for the years 2012 and 2023. Key milestones in the plant's development include the foundation of its marine structures and harbor in 2015, the first reactor unit in 2018, the second unit in 2020, the third unit in 2021, and the fourth unit in 2022. While, in the specified area, the degree of light intensity was near zero in 2012, by 2023, light intensity levels exceeding the average were observed.

Istanbul Airport is located in Aranavutköy district in the north of Istanbul (Figure 11). Its construction began in 2015 and it was inaugurated on October 29, 2023. It has an area of approximately 76.5 square kilometers. The size of the airport also allows the nighttime lights to be captured. Increased nighttime light intensity in the marked area indicates that infrastructural and economic activity in the region has also increased with the construction of the airport.

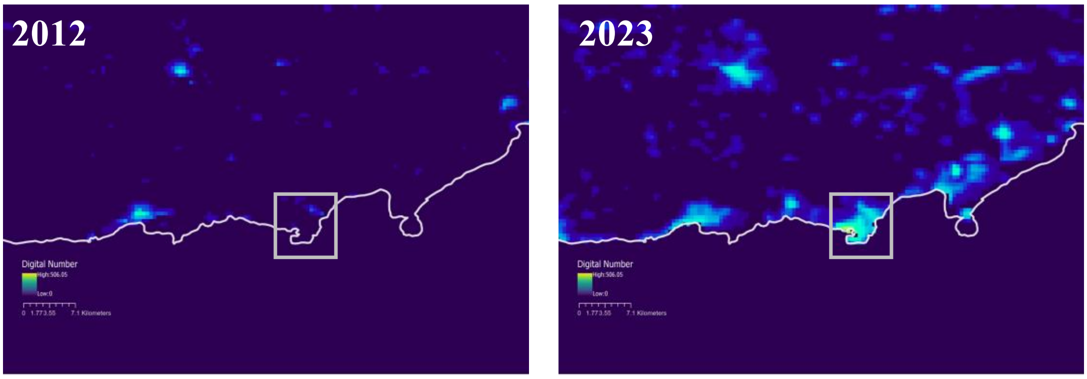

Figure 10: Akkuyu Nuclear plant by nighttime lights

Source: Chen et al., 2021

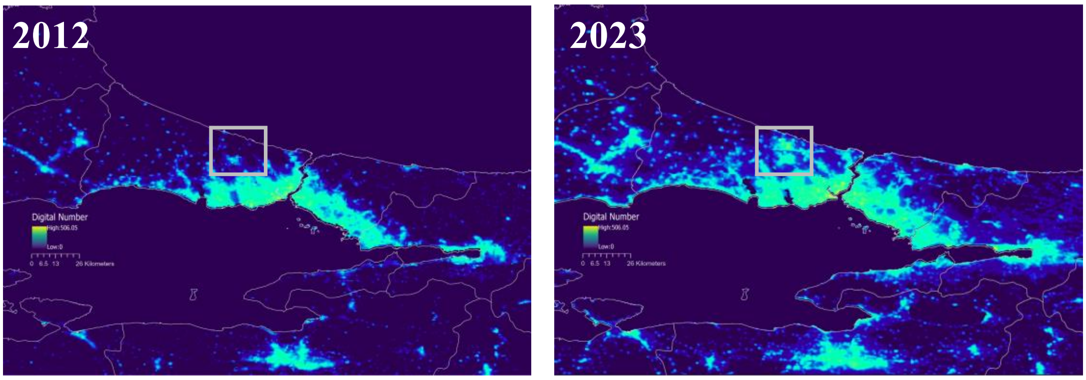

Figure 11: Istanbul Airport by nighttime lights

Source: Chen et al., 2021

Finally, when electricity consumption and GDP per capita variables are observed in Figure 12, it is noticable that the quadratic relationship observed before is only partially present. It is evident that the quadratic relationship is not valid for all provinces. It can be seen that the convex relationship, which is mostly seen in the figures above, albeit to different degrees, turns into a concave relationship in electricity consumption.

Table 2 provides a comprehensive overview of the nighttime light intensity, number of lit pixels, electricity consumption and GDP per capita. The table is organized into three main sections: total values, per capita values and first differences of natural logarithms, i.e. growth rates.

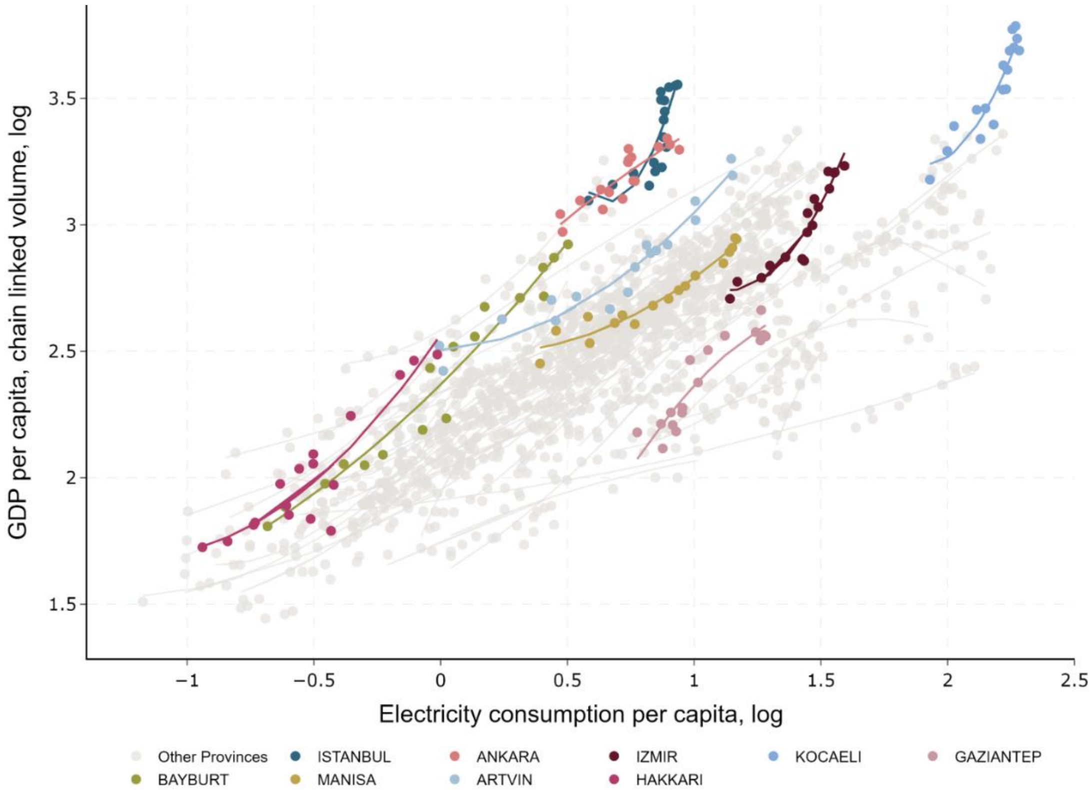

Figure 12: Electricity consumption per capita and GDP per capita, log, 2004-2020

The first section contains total values. The "sum_NTL" variable in the table shows the total nighttime light intensity of the provinces. The average light intensity value of the provinces is 22,139.27 with a standard deviation of 38,957.38. This indicates that there is a high variation in the total light intensity values of the provinces and thus high differences in the level of development. The "sum_LIT" variable refers to the number of pixels with values higher than one and the "electricity_total" variable refers to the total electricity consumption of the provinces, finally the "gdp_2009" variable refers to the GDP of the province. In parallel to the nighttime light intensity, these variables also have high standard deviations compared to their averages. Naturally, these differences between provinces are directly related to their surface area, therefore, by dividing these variables by provincial populations, we can get a better idea about the dynamics between GDP and the other variables in the regions.

The second part of the table presents the summary statistics of the above-mentioned variables converted to per capita terms. The variable “NTL_pp” represents the average nighttime light intensity per capita. The fact that the mean value of this variable is 0.026 and the maximum value is 0.134 highlights the persistence of economic disparities between provinces. The mean value of the variable “dif_ln_NTL_pp”, which shows the change in nighttime light intensity per capita, is 0.158, and the minimum and maximum values of -1.288 and 1.658, respectively, indicate that some regions have seen significant declines over certain periods, while others have experienced rapid growth.

	Observations	Mean	Standard Deviation	Minimum	Maximum
sum_NTL	1377	22139.27	38957.38	87.84	369266.29
sum_LIT	1377	3622.88	4219.32	54.00	29276.00
electricity_total	1377	2395313.07	4496814.35	44188.00	40425644.00
gdp_2009	1377	16323562.52	48957992.24	533450.94	560599692.37
NTL_pp	1377	0.026	0.023	0.000	0.134
LIT_pp	1377	0.006	0.005	0.000	0.032
electricity_total_pp	1377	2.359	1.654	0.309	9.799
gdp_2009_pp	1377	13.431	5.728	4.235	44.097
dif_ln_NTL_pp	1296	0.158	0.349	-1.288	1.658
dif_ln_LIT_pp	1296	0.141	0.255	-0.841	1.655
dif_ln_electricity_total_pp	1296	0.051	0.095	-0.537	0.710
dif_ln_gdp_2009_pp	1296	0.038	0.051	-0.283	0.260

Table 2: Summary statistics for the nighttime lights and TURKSTAT variables

Figure 13 displays the distribution of nighttime light intensity and spatial population by landuse type. The horizontal axis shows the landuse categories and the vertical axis shows the percentage distribution of the variables within these categories.
Grasslands, agricultural lands and urban areas stand out as the landuse types with the highest share in total nighttime light intensity and population. Urban areas stand out as the regions with the highest share in nighttime light intensity and population. Additionally, grasslands and agricultural lands emerge as the most significant landuse

types, accounting for notable shares of both total nighttime light and population. In 2020, the share of grasslands, agricultural land, natural forests and urban areas in Türkiye's total land area were 61.8%, 26.06%, 6.08% and 1.3%, respectively.

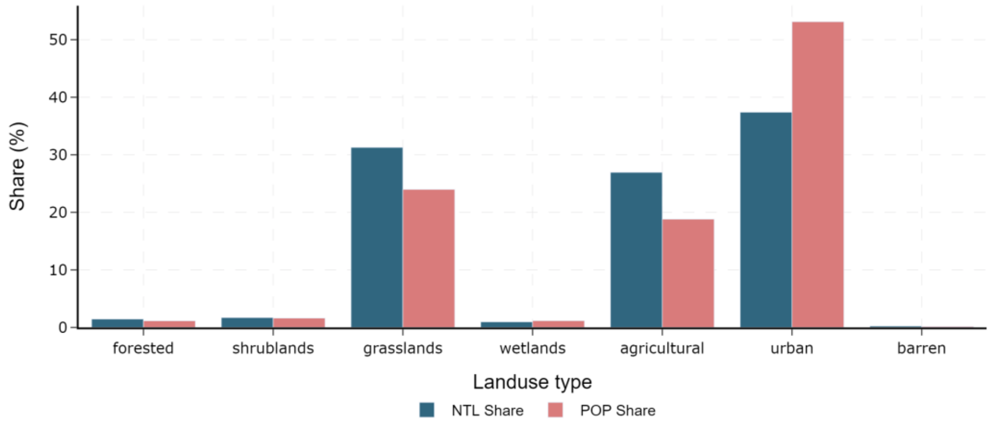

Figure 13: Nighttime light intensity and population distribution by landuse types, 2020

The figures below examines the relationship between nighttime light intensity per capita and GDP per capita in logarithms for different landuse types. The Y-axis shows GDP per capita and the X-axis shows nighttime light intensity across land types.

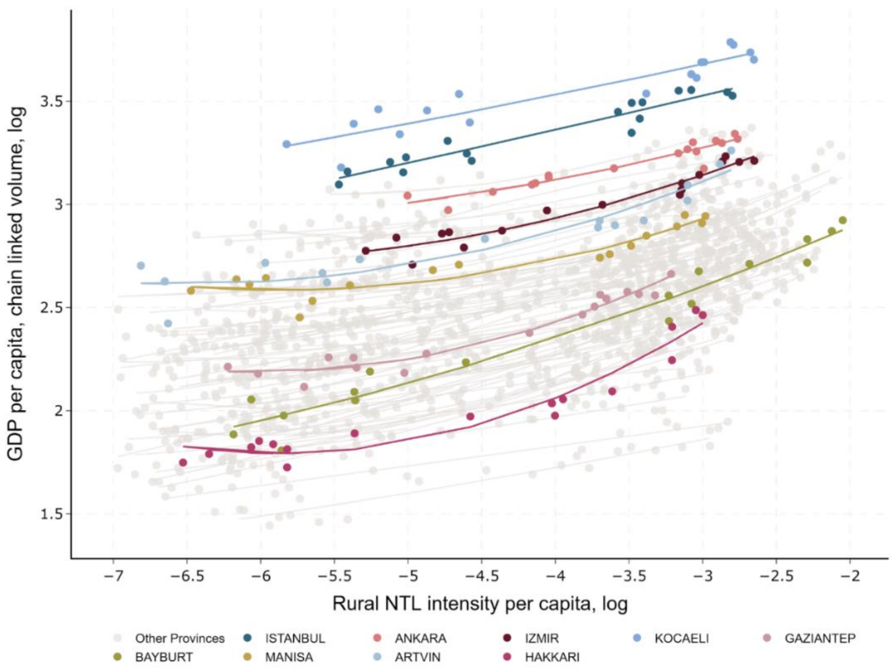

Figure 14: Rural nighttime light intensity per capita and GDP per capita, log, 2004-2020

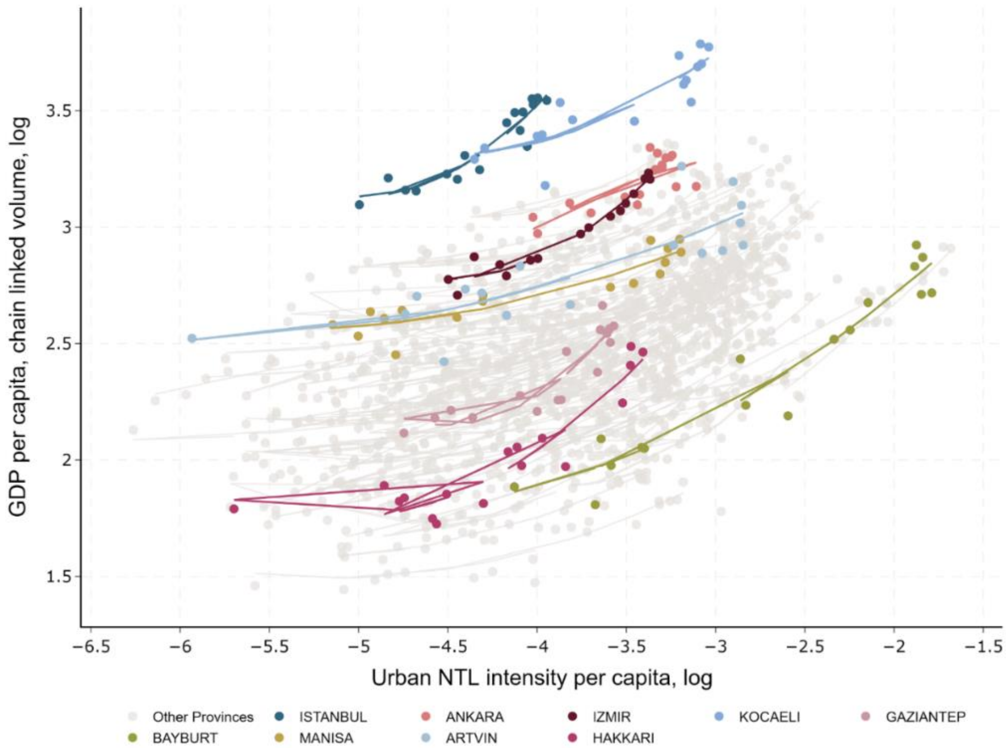

Figure 15: Urban nighttime light intensity per capita and GDP per capita, log, 2004-2020

There is a positive relationship between GDP per capita and nighttime light intensity per capita for both landuse types. When we compare the two landuse types, the curves in urban areas are steeper than the curves in rural areas. This may be due to the fact that the agricultural sector, which does not emit nighttime light, has a high intensity in rural areas, while in urban areas, the industrial and services sectors, which have much higher value added than agriculture, are more active. As the nighttime light intensity per capita increases, GDP per capita increases at different rates in urban and rural areas. In rural areas, this relationship tends to follow a more linear pattern. However, in urban areas, where light intensity is already high, the stronger and more gradual reflection of increases in light intensity on GDP through economic activities could explain this difference.

CHAPTER 5

RESULTS

The main results of the study are presented under three main sections. The first section examines the elasticity of nighttime light intensity per capita with respect to GDP per capita. Subsequently, the relationships between per capita lit pixel count, per capita electricity consumption, and per capita GDP are analyzed to provide a comprehensive comparison framework and to validate robustness of the models. The second part takes the main findings of the first part to the next level and re-examines the relationship between nighttime light intensity per capita and GDP per capita within the author's landuse specification as defined above. Finally the last section evaluates the selected model predictions and their error structures. This approach provides us the province level variations of the results and helps us to understand the regional dynamics of the nighttime light and GDP dynamics better.

5.1. Results of Base and Alternative Models

Table 3 presents the results of random coefficients regression models and its random effects parameters examining the relationship between nighttime light intensity per capita and GDP per capita, where model (1.2) and (2.2) allows for correlating coefficients specification. These models present the characteristics of the linear and nonlinear relationship between the two variables. “ln_NTL_pp” is the natural logarithm of nighttime light intensity per capita and ‘ln_NTL_pp_squared’ is the square of this variable. The logarithm of GDP per capita is expressed as “ln_gdp_2009_pp”.

	(1.1) NTL linear	(1.2) NTL linear	(2.1) NTL quadratic	(2.2) NTL quadratic
ln_NTL_pp	0.030***	0.031***	0.140***	0.116***
	(0.008)	(0.008)	(0.036)	(0.037)
ln_NTL_pp_squared			0.012***	0.009**
			(0.003)	(0.004)
Observations	1,377	1,377	1,377	1,377
Year FE	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES
AIC	-3832	-3842	-3849	-3931
BIC	-3722	-3727	-3729	-3795
Number of groups	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES
Robust standard errors in parentheses				
*** p<0.01, ** p<0.05, * p<0.1				

Table 3: Results for the base models

Model	Random-effects parameters	Estimate	Robust std. err.	95% conf. interval	
(1.1)	var(ln_NTL_pp)	0.003	0.001	0.002	0.004
	var(_cons)	0.131	0.024	0.092	0.186
	var(Residual)	0.002	0.000	0.002	0.002
(1.2)	var(ln_NTL_pp)	0.003	0.001	0.002	0.005
	var(_cons)	0.134	0.024	0.094	0.190
	cov(ln_NTL_pp,_cons)	0.008	0.002	0.004	0.012
	var(Residual)	0.002	0.000	0.002	0.002
(2.1)	var(ln_NTL_pp)	0.0031	0.0005	0.0022	0.0044
	var(ln_NTL_pp_squared)	0.0000	0.0000	0.0000	6.9440
	var(_cons)	0.1218	0.0236	0.0833	0.1782
	var(Residual)	0.0019	0.0002	0.0016	0.0022
(2.2)	var(ln_NTL_pp)	0.0390	0.0119	0.0215	0.0709
	var(ln_NTL_pp_squared)	0.0004	0.0001	0.0002	0.0007
	var(_cons)	0.2919	0.0558	0.2007	0.4246
	cov(ln_NTL_pp, ln_NTL_pp_squared)	0.0037	0.0012	0.0012	0.0061
	cov(ln_NTL_pp,_cons)	0.0838	0.0208	0.0431	0.1246
	cov(ln_NTL_pp_squared,_cons)	0.0079	0.0021	0.0037	0.0121
	var(Residual)	0.0017	0.0001	0.0014	0.0020

Table 4: Random-effects parameters for the base models

Random-effects parameters for the base models

In (1.1) and (1.2) the natural logarithm of nighttime light intensity per capita is the only independent variable. Regardless of the covariance structure both models give statistically significant coefficients for “ln_NTL_pp”. In both linear models the coefficients are very similar, namely, 0.03 for (1.1) and 0.031 for (1.2), which means 1% increase in nighttime light intensity per capita is associated with a nearly 0.03% change in GDP per capita. The similar coefficients in (1.1) and (1.2) suggests that allowing correlations in random effects does not substantially change the outcomes.In models (2.1) and (2.2) the quadratic term of per capita nighttime light intensity is introduced. This allows us to examine the possible nonlinear relationship between these two variables. Quadratic terms in both models are statistically significant which supports the nonlinear relationship mentioned in descriptive statistics section. The addition of the quadratic term also leads to an increase in the coefficient of the linear terms of the models (1.1) and (1.2) to 0.14 and 0.116 respectively.

It is worth taking into account that the quadratic models have lower AIC and BIC compared to the linear ones. Also the AIC and BIC values in the results suggest that allowing the models for correlating coefficients fits the data slightly better than those without.

In the linear models the choice of allowing for coeffient correlations has minimal impact on the coefficients and the fit. However in quadratic models (2.1) and (2.2) it improves the model fit relatively more (AIC and BIC). In summary, quadratic models, specifically model (2.2) is the most preferable, since the both independent variables have significant coefficients and it has the lowest AIC and BIC values compared to the others.

In the tables below (Table 5 and Table 6) the model results with alternative variables and their variance/covariance structure are shown respectively. Both linear and quadratic specifications of the models are constructed and tested with the alternative variables namely logarithm lit pixel count per capita, “ln_LIT_pp”, and logarithm of electricity consumption per capita, “ln_electricity_total_pp”.

	(3.1)	(3.2)	(4.1)	(4.2)	(5.1)	(5.2)	(6.1)	(6.2)
	LIT	LIT	LIT	LIT	Electricity consumption	Electricity consumption	Electricity consumption	Electricity consumption
	linear	linear	quadratic	quadratic	linear	linear	quadratic	quadratic
ln_LIT_pp	0.026**	0.023*	0.168***	0.134**				
	(0.012)	(0.012)	(0.051)	(0.062)				
ln_electricity_total_pp					0.201***	0.191***	0.277***	0.272***
					(0.034)	(0.035)	(0.040)	(0.033)
ln_LIT_pp_squared			0.012***	0.009*				
			(0.004)	(0.005)				
ln_electricity_total_pp_squa							-0.034**	-0.027**
							(0.015)	(0.013)
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377
R-squared								
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES	YES	YES	YES	YES
Adjusted R-squared								
AIC	-3881	-3923	-3907	-3989	-3893	-3913	-3924	-3942
BIC	-3771	-3808	-3786	-3853	-3783	-3798	-3804	-3806
Number of groups	81	81	81	81	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year fixed effects is set to 2020.

Table 5: Results for the alternative models

Models (3.1), (3.2), (4.1) and (4.2) examine the lit pixel count as an alternative measure of nighttime light intensity. The linear and quadratic terms for per capita lit pixel count are positive and statistically significant across all models, albeit with varying levels of significance. When unconstructed covariance specification is introduced in both linear and quadratic models, the coefficients and statistical significances of independent variables are reduced slightly.

Since electricity consumption is related to GDP, it is incorporated into this study as a robustness check. The electricity consumption variables evaluated in models (5.1), (5.2), (6.1) and (6.2) consistently outperforms the models with nighttime light intensity and lit pixel count per capita variables. Both linear and quadratic terms' coefficients of the electricity consumption models are higher than the models with nighttime light intensity and lit pixel count models. When allowing for correlating coefficients the magnitudes and statistical significances of coefficients reduces slightly. Comparatively, among the all models the ones with electricity consumption emerge as the strongest one in terms of coefficient magnitude and model fit. The quadratic lit pixel count per capita model outperforms the quadratic nighttime light model in model selection terms, however, although the lit pixel count variable stands out as a key indicator of the spatial distribution of economic activities, it is acknowledged that nighttime light intensity is a more widely recognized and utilized independent variable in the literature. Unlike the number of lit pixels variable, it provides a deeper understanding of regional economic activities by reflecting the intensity of luminosity rather than merely the number of illuminated cells.

Finally quadratic specifications and the allowance for correlating coefficients should be favored to enhance the accuracy and flexibility of the models in capturing complex dynamics. Thus, the model with correlating coefficients and the quadratic term for nighttime light intensity emerges as the preferred one among the other nighttime light models.

Model	Random-effects parameters	Estimate	Robust std. err.	95% conf. İnterval	
(3.1)	var(ln_LIT_pp)	0.005	0.001	0.004	0.007
	var(_cons)	0.188	0.031	0.136	0.259
	var(Residual)	0.002	0.000	0.001	0.002
(3.2)	var(ln_LIT_pp)	0.005	0.001	0.004	0.007
	var(_cons)	0.196	0.032	0.142	0.269
	cov(ln_LIT_pp,_cons)	0.021	0.004	0.013	0.029
	var(Residual)	0.002	0.000	0.001	0.002
(4.1)	var(ln_LIT_pp)	0.0010	0.0008	0.0002	0.0044
	var(ln_LIT_pp_squared)	0.0000	0.0000	0.0000	0.0001
	var(_cons)	0.1188	0.0249	0.0788	0.1791
	var(Residual)	0.0018	0.0002	0.0015	0.0021
(4.2)	var(ln_LIT_pp)	0.1077	0.0432	0.0491	0.2363
	var(ln_LIT_pp_squared)	0.0007	0.0003	0.0003	0.0016
	var(_cons)	1.0048	0.3033	0.5561	1.8155
	cov(ln_LIT_pp, ln_LIT_pp_squared)	0.0087	0.0036	0.0017	0.0157
	cov(ln_LIT_pp,_cons)	0.3098	0.1135	0.0874	0.5322
	cov(ln_LIT_pp_squared,_cons)	0.0246	0.0094	0.0062	0.0429
	var(Residual)	0.0015	0.0001	0.0013	0.0018
(5.1)	var(ln_electricity_total_pp)	0.034	0.006	0.024	0.048
	var(_cons)	0.103	0.020	0.071	0.151
	var(Residual)	0.002	0.000	0.002	0.002
(5.2)	var(ln_electricity_total_pp)	0.038	0.007	0.026	0.055
	var(_cons)	0.114	0.022	0.077	0.167
	cov(ln_electricity_total_pp, _cons)	-0.034	0.011	-0.056	-0.012
	var(Residual)	0.002	0.000	0.002	0.002
(6.1)	var(ln_electricity_total_pp)	0.0186	0.0040	0.0122	0.0284
	var(ln_electricity_total_squared)	0.0102	0.0040	0.0047	0.0220
	var(_cons)	0.0820	0.0150	0.0573	0.1173
	var(Residual)	0.0018	0.0002	0.0015	0.0022
(6.2)	var(ln_electricity_total_pp)	0.0153	0.0031	0.0102	0.0228
	var(ln_electricity_total_squared)	0.0073	0.0033	0.0030	0.0179
	var(_cons)	0.0800	0.0144	0.0563	0.1139
	cov(ln_electricity_total_pp, ln_electricity_total_squared)	0.0047	0.0025	-0.0002	0.0096
	cov(ln_electricity_total_pp, _cons)	0.0008	0.0070	-0.0130	0.0145
	cov(ln_electricity_total_squared, _cons)	-0.0190	0.0056	-0.0299	-0.0080
	var(Residual)	0.0018	0.0002	0.0015	0.0023

Table 6: Random-effects parameters for the alternative models

5.2. Landuse Spesification

The regression analyses so far have been kept simple to provide a baseline for understanding the relationship between nighttime lights and GDP. In this section, the relationship is analyzed across different landuse categories which enables us a more detailed examination.

	(7.1)	(7.2)	(8.1)	(8.2)	(9.1)	(9.2)	(10.1)	(10.2)	(11.1)	(11.2)	(12.1)	(12.2)
	Rural NTL	Rural NTL	Rural NTL	Rural NTL	Urban NTL	Urban NTL	Urban NTL	Urban NTL	Other NTL	Other NTL	Other NTL	Other NTL
	linear	linear	quadratic	quadratic	linear	linear	quadratic	quadratic	linear	linear	quadratic	quadratic
ln_rural_NTL_pp	0.013	0.013*	0.051*	0.045								
	(0.008)	(0.008)	(0.027)	(0.032)								
ln_urban_NTL_pp					0.014	0.013	0.231***	0.077				
					(0.009)	(0.009)	(0.057)	(0.054)				
ln_other_NTL_pp									-0.007	-0.007	0.000	-0.021
									(0.005)	(0.005)	(0.016)	(0.017)
ln_rural_NTL_pp_squared			0.004	0.003								
			(0.002)	(0.003)								
ln_urban_NTL_pp_squared							0.026***	0.007				
							(0.007)	(0.006)				
ln_other_NTL_pp_squared											0.001	-0.001
											(0.001)	(0.001)
Constant	2.830***	2.832***	2.909***	2.891***	2.830***	2.828***	3.253***	2.951***	2.780***	2.781***	2.798***	2.746***
	(0.044)	(0.044)	(0.070)	(0.074)	(0.045)	(0.046)	(0.117)	(0.118)	(0.039)	(0.039)	(0.056)	(0.058)
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,361	1,361	1,361	1,361
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AIC	-3894	-3899	-3895	-3979	-3427	-3448	-3454	-3549	-3153	-3152	-3151	-3253
BIC	-3785	-3784	-3775	-3843	-3317	-3333	-3334	-3413	-3044	-3038	-3031	-3117
Number of groups	81	81	81	81	81	81	81	81	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year fixed effects is set to 2020.

Table 7: Landuse model results

	(13.1)	(13.2)	(14.1)	(14.2)	(15.1)	(15.2)
	U-R landuse NTL linear	U-R landuse NTL linear	U-R landuse NTL quadratic	U-R landuse NTL quadratic	Reduced Landuse	Reduced Landuse
ln_rural_NTL_pp	0.000	-0.012	0.028	0.004	0.004	-0.008
	(0.008)	(0.009)	(0.029)	(0.037)	(0.009)	(0.009)
ln_urban_NTL_pp	0.013*	0.025***	0.084**	0.093**	0.099***	0.086**
	(0.007)	(0.007)	(0.041)	(0.046)	(0.038)	(0.037)
ln_other_NTL_pp	0.001	0.001				
	(0.001)	(0.001)				
ln_rural_NTL_pp_squared			0.002	0.001		
			(0.002)	(0.003)		
ln_urban_NTL_pp_squared			0.008*	0.009*	0.010**	0.007*
			(0.005)	(0.005)	(0.004)	(0.004)
ln_other_NTL_pp_squared						
Observations	1,361	1,361	1,377	1,377	1,377	1,377
Year FE	YES	YES	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES	YES	YES
AIC	-3917	-3954	-3899	-4021	-3901	-3956
BIC	-3786	-3792	-3758	-3828	-3770	-3794
Number of groups	81	81	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year fixed effects is set to 2020.

Table 8: Landuse combined model results

The tables above examines the relationship between nighttime light intensity per capita and GDP per capita in the author's broadly defined landuse categorization. Here, "ln_rural_NTL_pp" represents the logarithm of nighttime light intensity per capita in rural areas, "ln_urban_NTL_pp" in urban areas, and "ln_other_NTL_pp" in the remaining landuse types.

Model	Random-effects parameters	Estimate	Robust std. err.	95% conf. İnterval	
(7.1)	var(ln_rural_NTL_pp)	0.002	0.000	0.002	0.003
	var(_cons)	0.124	0.022	0.087	0.176
	var(Residual)	0.002	0.000	0.001	0.002
(7.2)	var(ln_rural_NTL_pp)	0.002	0.000	0.002	0.003
	var(_cons)	0.125	0.023	0.088	0.178
	cov(ln_rural_NTL_pp,_cons)	0.005	0.002	0.001	0.008
	var(Residual)	0.002	0.000	0.001	0.002
(8.1)	var(ln_rural_NTL_pp)	0.0023	0.0004	0.0017	0.0031
	var(ln_rural_NTL_pp_squared)	0.0000	0.0000	0.0000	0.0000
	var(_cons)	0.1191	0.0222	0.0826	0.1717
	var(Residual)	0.0018	0.0002	0.0015	0.0021
(8.2)	var(ln_rural_NTL_pp)	0.0218	0.0072	0.0114	0.0416
	var(ln_rural_NTL_pp_squared)	0.0002	0.0001	0.0001	0.0004
	var(_cons)	0.1925	0.0337	0.1366	0.2714
	cov(ln_rural_NTL_pp, ln_rural_NTL_pp_squared)	0.0019	0.0007	0.0004	0.0033
	cov(ln_rural_NTL_pp,_cons)	0.0414	0.0112	0.0195	0.0633
	cov(ln_rural_NTL_pp_squared, _cons)	0.0034	0.0011	0.0013	0.0055
	var(Residual)	0.0016	0.0001	0.0013	0.0018
(9.1)	var(ln_urban_NTL_pp)	0.007	0.001	0.005	0.010
	var(_cons)	0.149	0.026	0.105	0.211
	var(Residual)	0.003	0.000	0.002	0.003
(9.2)	var(ln_urban_NTL_pp)	0.007	0.001	0.005	0.010
	var(_cons)	0.157	0.028	0.111	0.222
	cov(ln_urban_NTL_pp,_cons)	0.018	0.004	0.009	0.026
	var(Residual)	0.003	0.000	0.002	0.003
(10.1)	var(ln_urban_NTL_pp)	0.0066	0.0139	0.0001	0.3989
	var(ln_urban_NTL_pp_squared)	0.0000	0.0000	0.0000	.
	var(_cons)	0.1353	0.1671	0.0120	1.5220
	var(Residual)	0.0026	0.0002	0.0022	0.0031
(10.2)	var(ln_urban_NTL_pp)	0.1437	0.0316	0.0934	0.2211
	var(ln_urban_NTL_pp_squared)	0.0015	0.0004	0.0009	0.0024
	var(_cons)	0.6887	0.1530	0.4455	1.0646
	cov(ln_urban_NTL_pp, ln_urban_NTL_pp_squared)	0.0146	0.0034	0.0079	0.0213
	cov(ln_urban_NTL_pp,_cons)	0.2862	0.0653	0.1582	0.4141
	cov(ln_urban_NTL_pp_squared, _cons)	0.0288	0.0070	0.0151	0.0425
	var(Residual)	0.0024	0.0002	0.0020	0.0029
(11.1)	var(ln_other_NTL_pp)	0.001	0.000	0.001	0.002
	var(_cons)	0.112	0.020	0.078	0.160
	var(Residual)	0.003	0.000	0.002	0.004
(11.2)	var(ln_other_NTL_pp)	0.001	0.000	0.001	0.002
	var(_cons)	0.113	0.021	0.079	0.163
	cov(ln_other_NTL_pp,_cons)	0.002	0.002	-0.002	0.005
	var(Residual)	0.003	0.000	0.002	0.004
(12.1)	var(ln_other_NTL_pp)	0.0013	0.0004	0.0007	0.0023
	var(ln_other_NTL_pp_squared)	0.0000	0.0000	0.0000	0.0000
	var(_cons)	0.1103	0.0204	0.0768	0.1584
	var(Residual)	0.0031	0.0005	0.0023	0.0043
(12.2)	var(ln_other_NTL_pp)	0.0082	0.0018	0.0053	0.0127
	var(ln_other_NTL_pp_squared)	0.0000	0.0000	0.0000	0.0000
	var(_cons)	0.1589	0.0305	0.1090	0.2316
	cov(ln_other_NTL_pp, ln_other_NTL_pp_squared)	0.0005	0.0001	0.0002	0.0007
	cov(ln_other_NTL_pp,_cons)	0.0186	0.0061	0.0065	0.0306
	cov(ln_other_NTL_pp_squared, _cons)	0.0010	0.0004	0.0003	0.0017
	var(Residual)	0.0029	0.0005	0.0021	0.0040

Table 9: Random – effects parameters for the landuse models

In models (7.1) and (7.2), different covariance specifications are implemented for only linear rural nighttime light intensity per capita variables. The model restricting correlating coefficients does not yield statistically significant results whereas the coefficients in the model which allows for correlating coefficients show only limited statistically significance. In models (8.1) and (8.2) the quadratic rural nighttime light intensity per capita variables are found to be statistically insignificant (at the 10%

level), where only the linear term of the model (8.1) is statistically significant at 0.1 significance level.

Model	Random-effects parameters	Estimate	Robust std. err.	95% conf. İnterval	
(13.1)	var(ln_rural_NTL_pp)	0.0025	0.0005	0.0017	0.0036
	var(ln_urban_NTL_pp)	0.0002	0.0003	0.0000	0.0023
	var(ln_other_NTL_pp)	0.0001	0.0000	0.0000	0.0002
	var(_cons)	0.1210	0.0223	0.0843	0.1736
	var(Residual)	0.0016	0.0001	0.0013	0.0019
(13.2)	var(ln_rural_NTL_pp)	0.0044	0.0007	0.0031	0.0061
	var(ln_urban_NTL_pp)	0.0017	0.0007	0.0008	0.0038
	var(ln_other_NTL_pp)	0.0001	0.0000	0.0000	0.0002
	var(_cons)	0.1282	0.0252	0.0872	0.1885
	cov(ln_rural_NTL_pp, ln_urban_NTL_pp)	-0.0024	0.0007	-0.0038	-0.0010
	cov(ln_rural_NTL_pp, ln_other_NTL_pp)	-0.0001	0.0001	-0.0003	0.0001
	cov(ln_rural_NTL_pp,_cons)	0.0013	0.0031	-0.0047	0.0073
	cov(ln_urban_NTL_pp, ln_other_NTL_pp)	0.0000	0.0001	-0.0002	0.0002
	cov(ln_urban_NTL_pp,_cons)	0.0023	0.0032	-0.0041	0.0087
	cov(ln_other_NTL_pp,_cons)	-0.0001	0.0008	-0.0016	0.0014
	var(Residual)	0.0015	0.0001	0.0013	0.0018
(14.1)	var(ln_rural_NTL_pp)	0.0023	0.0005	0.0016	0.0034
	var(ln_rural_NTL_pp_squared)	0.0000	0.0000	0.0000	0.0000
	var(ln_urban_NTL_pp)	0.0003	0.0003	0.0001	0.0021
	var(ln_urban_NTL_pp_squared)	0.0000	0.0000	0.0000	0.0000
	var(_cons)	0.1151	0.0219	0.0792	0.1671
	var(Residual)	0.0017	0.0002	0.0014	0.0021
(14.2)	var(ln_rural_NTL_pp)	0.0308	0.0077	0.0188	0.0504
	var(ln_rural_NTL_pp_squared)	0.0002	0.0001	0.0001	0.0004
	var(ln_urban_NTL_pp)	0.0615	0.0296	0.0240	0.1578
	var(ln_urban_NTL_pp_squared)	0.0006	0.0004	0.0002	0.0019
	var(_cons)	0.2676	0.1010	0.1278	0.5606
	cov(ln_rural_NTL_pp, ln_rural_NTL_pp_squared)	0.0023	0.0007	0.0009	0.0037
	cov(ln_rural_NTL_pp, ln_urban_NTL_pp)	-0.0276	0.0118	-0.0507	-0.0045
	cov(ln_rural_NTL_pp, ln_urban_NTL_pp_squared)	-0.0027	0.0014	-0.0054	0.0000
	cov(ln_rural_NTL_pp,_cons)	0.0060	0.0163	-0.0259	0.0379
	cov(ln_rural_NTL_pp_squared, ln_urban_NTL_pp)	-0.0017	0.0009	-0.0036	0.0001
	cov(ln_rural_NTL_pp_squared, ln_urban_NTL_pp_squared)	-0.0002	0.0001	-0.0004	0.0000
	cov(ln_rural_NTL_pp_squared, _cons)	0.0012	0.0013	-0.0014	0.0039
	cov(ln_urban_NTL_pp, ln_urban_NTL_pp_squared)	0.0062	0.0032	-0.0001	0.0126
	cov(ln_urban_NTL_pp,_cons)	0.0687	0.0439	-0.0174	0.1548
	cov(ln_urban_NTL_pp_squared, _cons)	0.0069	0.0046	-0.0020	0.0159
	var(Residual)	0.0014	0.0001	0.0012	0.0017
(15.1)	var(ln_rural_NTL_pp)	0.0024	0.0005	0.0016	0.0035
	var(ln_urban_NTL_pp)	0.0003	0.0003	0.0000	0.0026
	var(ln_urban_NTL_pp_squared)	0.0000	0.0000	0.0000	.
	var(_cons)	0.1173	0.0221	0.0811	0.1697
	var(Residual)	0.0017	0.0002	0.0015	0.0021
(15.2)	var(ln_rural_NTL_pp)	0.0041	0.0007	0.0029	0.0059
	var(ln_urban_NTL_pp)	0.0355	0.0240	0.0094	0.1334
	var(ln_urban_NTL_pp_squared)	0.0004	0.0002	0.0001	0.0013
	var(_cons)	0.2912	0.1181	0.1316	0.6446
	cov(ln_rural_NTL_pp, ln_urban_NTL_pp)	-0.0027	0.0029	-0.0085	0.0030
	cov(ln_rural_NTL_pp, ln_urban_NTL_pp_squared)	0.0000	0.0004	-0.0007	0.0007
	cov(ln_rural_NTL_pp,_cons)	-0.0005	0.0064	-0.0129	0.0120
	cov(ln_urban_NTL_pp, ln_urban_NTL_pp_squared)	0.0035	0.0024	-0.0011	0.0082
	cov(ln_urban_NTL_pp,_cons)	0.0776	0.0499	-0.0202	0.1755
	cov(ln_urban_NTL_pp_squared, _cons)	0.0081	0.0049	-0.0015	0.0177
	var(Residual)	0.0016	0.0002	0.0013	0.0019

Table 10: Random – effects parameters for the landuse models (continued)

Models (9.1) to (10.2) examines the urban nighttime light intensity per capita. Introducing correlating coefficient specification does not make much difference in the linear urban nighttime light intensity models in terms of coefficients and their statistical significances. When correlated coefficients are allowed in quadratic urban model (10.2), both the linear and quadratic terms lose their statistical significance (at the 10% level). The correlated coefficients model improves the model fit (as seen in the AIC and BIC) but also increases standard errors of coefficient estimates, and reduces the (mean) size of coefficients. This makes confidence intervals wider and reduces statistical significance.

The models from (11.1) to (12.2) includes only nighttime light intensities emitted from other landuse areas. In the models the coefficients of independent variables are found to be statistically insignificant (at the 10% level), which is due to other landuse areas' lower nighttime light and population shares.

The models (13.1) to (14.2) combines the landuse variables in linear and quadratic specifications. In all models, it is seen that urban landuse variables are the only ones with statistically significant coefficients.

In summary, allowing for correlating coefficients province level nighttime light intensity (2.2) and urban nighttime light intensity (10.1) models stand out as the most prominent ones, however their implications differ. Model (2.2) allows for correlated coefficients providing greater reliability in capturing the relationship between nighttime light intensity. However, although model (10.1) coefficients demonstrate statistical significance it does not allow for correlated coefficients. Furthermore, model (2.2) outperforms (10.1) in model selection criterias. Thus, in the next section, as model (2.2) is decided as the best performing model its regional results and error structures is examined.

5.3. Regional Differences

Figure 16 shows the distribution of the residuals of Model (2.2) by regions. The lower and upper edges of each box are drawn to cover the interquartile range, the line in the middle of the boxes is the median, and the whiskers of the boxes are drawn to cover values within 1.5 times the lower and upper quartiles of the data so the points outside the whiskers represent outliers. The distribution of error terms varies across regions. Istanbul (TR1), Western Marmara (TR2), Western Anatolia (TR5), have relatively narrower boxes. However, Northeast Anatolia (TRA), Central East Anatolia (TRB), Southeast Anatolia (TRC), Western Black Sea (TR8), Eastern Black Sea (TR9), and, Central Anatolia (TR7), stand out as provinces with much higher quartile spacings of the error terms compared to other regions.

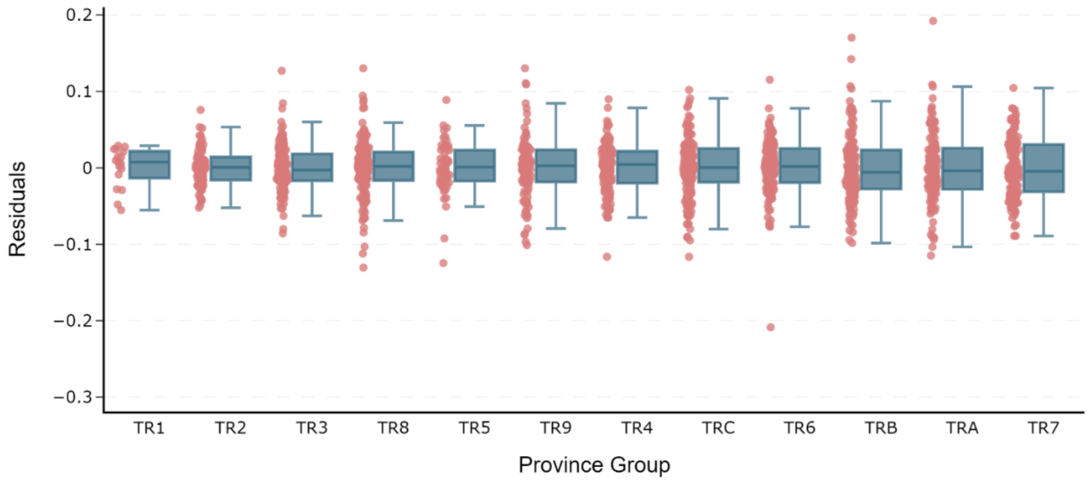

Figure 16: Regional distribution of residuals, Quadratic NTL Model (2.2)

Figure 17 below displays the values of RMSE of model (2.2) by provinces. In the map, it is seen that the RMSE values of the eastern provinces from north to south are generally high. However, Zonguldak, Bartın, Karabük, Çankırı are the provinces with large RMSE values in the West Black Sea Region. In the Mediterranean, Antalya stands out due to the relativelty larger estimation error of the model in 2020 due to the impact of the COVID-19 pandemic on tourism.

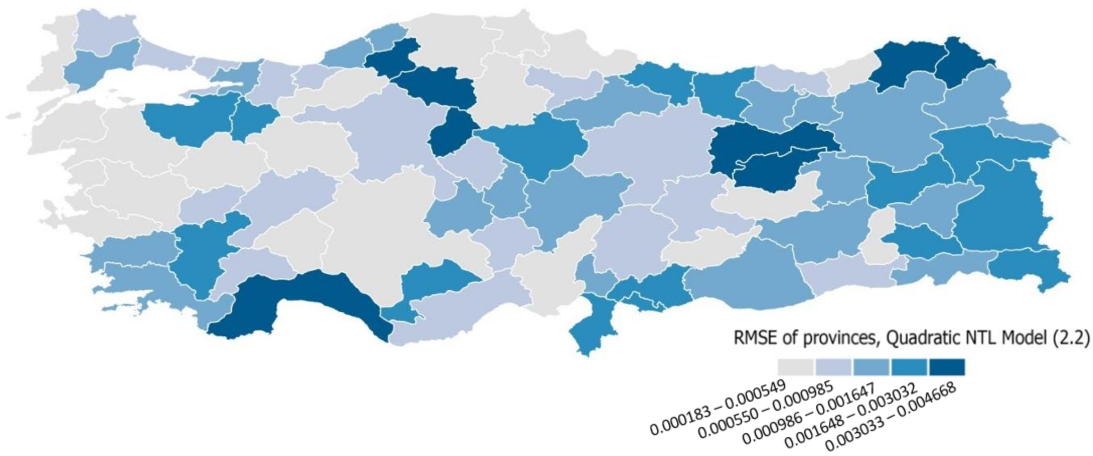

Figure 17: RMSE of provinces, Quadratic NTL Model (2.2)

Figure 18 below shows the ratio of GDP per capita values predicted using model (2.2) to official GDP per capita values by province. Dark blue regions show where this ratio is high and dark red regions show where this ratio is low. The Eastern Anatolia region, specifically Van, Ağrı, Şanlıurfa, has the highest ratio. The west of Türkiye, including large urban and industrial centers, shows lower rates. Light colored areas close to white indicate regions where the predicted values are relatively closer to the official data.

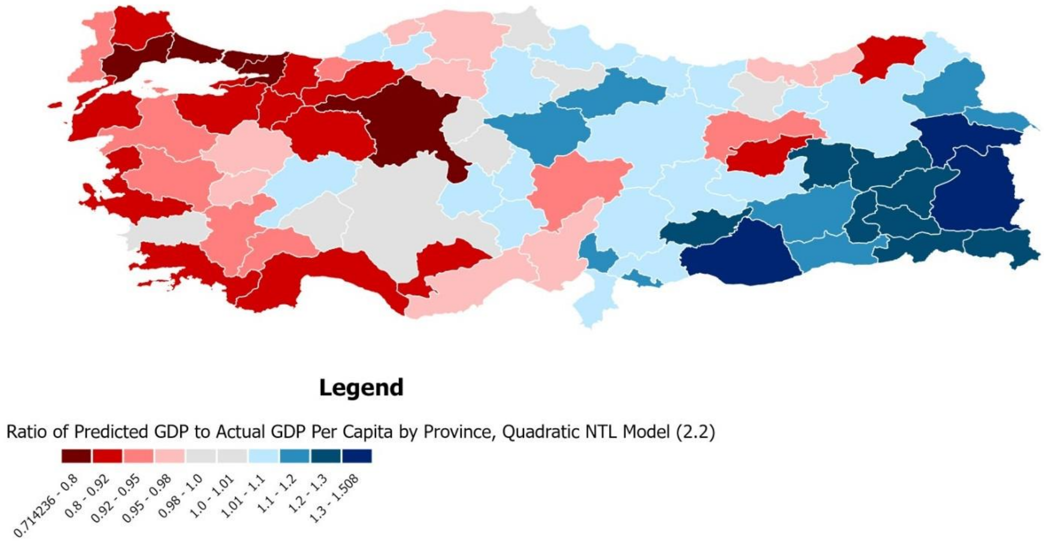

Figure 18: Ratio of predicted GDP to actual GDP per capita by province (2004-2020 average), Quadratic NTL Model (2.2)

CHAPTER 6

CONCLUSION

This study presents a comprehensive analysis of the relationship between night lights and provincial GDP in Türkiye. Using geospatial population and land use data on night lights, the study examines the relationship between GDP per capita and night light intensity at the provincial level. The outputs reveal that per capita night light values are a statistically significant positive indicator of GDP per capita. Moreover, consistent with prior research (Hu and Yao, 2019), the results confirm the quadratic nature of this relationship.

High-resolution land use data is used in this study to highlight how differences in land use influence the relationship between nighttime lights and GDP. A stronger link between nighttime lights and GDP is observed in urban areas, where industries and services are more active. This highlights the role of economic centers in shaping this connection. In contrast, rural areas, where agriculture is the dominant activity and typically does not occur at night, show a more straightforward and linear relationship.

Through the econometric evaluations of the models, it was determined that the most robust model using nighttime light data is the one where total nighttime light intensity per capita at the provincial level is represented in quadratic form. Error analyses conducted on the forecasts obtained from this model allowed for the examination of regional dynamics in the relationship between nighttime light per capita and GDP per capita. It was observed that regions with dense urbanization, such as Istanbul, have narrower error margins, indicating a stronger relationship in these areas. In contrast, less developed regions, such as TRA (Northeast Anatolia) and TRB (Central East Anatolia), show official GDP per capita values lower than the estimates. This variation may be attributed to factors such as the informal economy, sectoral differences, or other unobservable region-specific factors. Since this study focuses solely on empirically examining the relationship between nighttime light per capita and GDP per capita, the factors influencing this relationship could be explored in future research.

In addition to night light intensity, the relationship between GDP and alternative data such as the number of illuminated pixels and electricity consumption is also analyzed. In particular, electricity consumption models are found to be the most robust. However, the broader applicability of nighttime lights, especially in regions with sparse economic data, highlights its value as a supplementary tool for economic analysis.

The study also acknowledges limitations, including potential endogeneity in the NTL-GDP relationship, regional and cultural variations in light usage, and data noise from atmospheric conditions. These factors necessitate cautious interpretation and emphasize the need for complementary indicators.

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APPENDICES

	(1.1)	(1.2)	(2.1)	(2.2)
	NTL	NTL	NTL	NTL
	linear	linear	quadratic	quadratic
ln_NTL_pp	0.030***	0.031***	0.140***	0.116***
	(0.008)	(0.008)	(0.036)	(0.037)
ln_NTL_pp_squared			0.012***	0.009**
			(0.003)	(0.004)
Constant	2.877***	2.879***	3.100***	3.044***
	(0.043)	(0.044)	(0.084)	(0.084)
year = 2004	-0.514***	-0.512***	-0.477***	-0.491***
	(0.031)	(0.031)	(0.032)	(0.031)
year = 2005	-0.429***	-0.427***	-0.399***	-0.413***
	(0.032)	(0.032)	(0.033)	(0.032)
year = 2006	-0.392***	-0.390***	-0.355***	-0.367***
	(0.029)	(0.030)	(0.031)	(0.030)
year = 2007	-0.365***	-0.363***	-0.325***	-0.338***
	(0.028)	(0.028)	(0.030)	(0.029)
year = 2008	-0.368***	-0.367***	-0.328***	-0.340***
	(0.027)	(0.027)	(0.029)	(0.028)
year = 2009	-0.404***	-0.402***	-0.364***	-0.379***
	(0.026)	(0.027)	(0.029)	(0.028)
year = 2010	-0.332***	-0.330***	-0.290***	-0.303***
	(0.022)	(0.023)	(0.026)	(0.025)
year = 2011	-0.263***	-0.261***	-0.221***	-0.232***
	(0.020)	(0.020)	(0.023)	(0.022)
year = 2012	-0.249***	-0.248***	-0.215***	-0.223***
	(0.016)	(0.017)	(0.019)	(0.019)
year = 2013	-0.201***	-0.201***	-0.178***	-0.183***
	(0.013)	(0.013)	(0.014)	(0.014)
year = 2014	-0.170***	-0.169***	-0.147***	-0.151***
	(0.013)	(0.013)	(0.014)	(0.014)
year = 2015	-0.130***	-0.130***	-0.110***	-0.114***
	(0.012)	(0.012)	(0.013)	(0.013)
year = 2016	-0.111***	-0.110***	-0.096***	-0.098***
	(0.010)	(0.010)	(0.011)	(0.011)
year = 2017	-0.060***	-0.060***	-0.053***	-0.054***
	(0.009)	(0.009)	(0.009)	(0.009)
year = 2018	-0.039***	-0.039***	-0.034***	-0.034***
	(0.008)	(0.008)	(0.008)	(0.008)
year = 2019	-0.040***	-0.040***	-0.039***	-0.038***
	(0.006)	(0.006)	(0.006)	(0.006)
Observations	1,377	1,377	1,377	1,377
Year FE	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES
AIC	-3832	-3842	-3849	-3931
BIC	-3722	-3727	-3729	-3795
Number of groups	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year fixed effects is set to 2020.

Table 11: Random coefficients base model results, including constant variable dummy coefficients

	(3.1)	(3.2)	(4.1)	(4.2)	(5.1)	(5.2)	(6.1)	(6.2)
	LIT	LIT	LIT	LIT	Electricity consumption	Electricity consumption	Electricity consumption	Electricity consumption
	linear	linear	quadratic	quadratic	linear	linear	quadratic	quadratic
ln_LIT_pp	0.026**	0.023*	0.168***	0.134**				
	(0.012)	(0.012)	(0.051)	(0.062)				
ln_electricity_total_pp					0.201***	0.191***	0.277***	0.272***
					(0.034)	(0.035)	(0.040)	(0.033)
ln_LIT_pp_squared			0.012***	0.009*				
			(0.004)	(0.005)				
ln_electricity_total_pp_squared							-0.034**	-0.027**
							(0.015)	(0.013)
Constant	2.899***	2.884***	3.289***	3.187***	2.626***	2.639***	2.594***	2.602***
	(0.065)	(0.066)	(0.153)	(0.177)	(0.043)	(0.044)	(0.043)	(0.041)
year = 2004	-0.526***	-0.532***	-0.514***	-0.517***	-0.408***	-0.413***	-0.409***	-0.413***
	(0.033)	(0.035)	(0.035)	(0.035)	(0.032)	(0.032)	(0.034)	(0.033)
year = 2005	-0.446***	-0.453***	-0.439***	-0.442***	-0.355***	-0.359***	-0.357***	-0.360***
	(0.034)	(0.035)	(0.036)	(0.035)	(0.030)	(0.030)	(0.031)	(0.031)
year = 2006	-0.403***	-0.410***	-0.391***	-0.393***	-0.325***	-0.329***	-0.328***	-0.331***
	(0.032)	(0.033)	(0.034)	(0.033)	(0.027)	(0.027)	(0.028)	(0.028)
year = 2007	-0.376***	-0.382***	-0.360***	-0.364***	-0.312***	-0.315***	-0.315***	-0.317***
	(0.031)	(0.032)	(0.032)	(0.032)	(0.024)	(0.024)	(0.025)	(0.025)
year = 2008	-0.380***	-0.386***	-0.363***	-0.367***	-0.323***	-0.326***	-0.326***	-0.327***
	(0.029)	(0.030)	(0.031)	(0.030)	(0.023)	(0.023)	(0.024)	(0.023)
year = 2009	-0.420***	-0.426***	-0.404***	-0.408***	-0.371***	-0.374***	-0.373***	-0.375***
	(0.028)	(0.029)	(0.030)	(0.029)	(0.021)	(0.021)	(0.022)	(0.022)
year = 2010	-0.342***	-0.347***	-0.323***	-0.327***	-0.303***	-0.305***	-0.306***	-0.307***
	(0.024)	(0.025)	(0.027)	(0.026)	(0.019)	(0.020)	(0.020)	(0.020)
year = 2011	-0.270***	-0.275***	-0.249***	-0.253***	-0.239***	-0.240***	-0.241***	-0.242***
	(0.021)	(0.022)	(0.024)	(0.023)	(0.017)	(0.017)	(0.018)	(0.018)
year = 2012	-0.256***	-0.259***	-0.236***	-0.240***	-0.215***	-0.217***	-0.218***	-0.218***
	(0.016)	(0.016)	(0.018)	(0.018)	(0.015)	(0.015)	(0.016)	(0.016)
year = 2013	-0.200***	-0.202***	-0.184***	-0.186***	-0.155***	-0.157***	-0.158***	-0.158***
	(0.013)	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.015)	(0.014)
year = 2014	-0.168***	-0.169***	-0.151***	-0.154***	-0.138***	-0.139***	-0.140***	-0.141***
	(0.013)	(0.013)	(0.014)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)
year = 2015	-0.127***	-0.129***	-0.112***	-0.114***	-0.101***	-0.102***	-0.103***	-0.102***
	(0.012)	(0.012)	(0.013)	(0.014)	(0.011)	(0.011)	(0.012)	(0.012)
year = 2016	-0.106***	-0.108***	-0.093***	-0.095***	-0.089***	-0.089***	-0.090***	-0.089***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.010)	(0.010)	(0.010)	(0.010)
year = 2017	-0.059***	-0.060***	-0.054***	-0.054***	-0.047***	-0.047***	-0.047***	-0.046***
	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)	(0.009)
year = 2018	-0.038***	-0.038***	-0.033***	-0.033***	-0.032***	-0.032***	-0.032***	-0.032***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
year = 2019	-0.038***	-0.039***	-0.036***	-0.036***	-0.030***	-0.031***	-0.031***	-0.031***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377
Year FE	YES	YES	YES	YES	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES	YES	YES	YES	YES
AIC	-3881	-3923	-3907	-3989	-3893	-3913	-3924	-3942
BIC	-3771	-3808	-3786	-3853	-3783	-3798	-3804	-3806
Number of groups	81	81	81	81	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year fixed effects is set to 2020.

Table 12: Results of the random coefficients model with alternative variables, including constant variable dummy coefficients

	(7.1)	(7.2)	(8.1)	(8.2)	(9.1)	(9.2)	(10.1)	(10.2)	(11.1)	(11.2)	(12.1)	(12.2)
	Rural NTL	Rural NTL	Rural NTL	Rural NTL	Urban NTL	Urban NTL	Urban NTL	Urban NTL	Other NTL	Other NTL	Other NTL	Other NTL
	linear	linear	quadratic	quadratic	linear	linear	quadratic	quadratic	linear	linear	quadratic	quadratic
ln_rural_NTL_pp	0.013	0.013*	0.051*	0.045								
	(0.008)	(0.008)	(0.027)	(0.032)								
ln_urban_NTL_pp					0.014	0.013	0.231***	0.077				
					(0.009)	(0.009)	(0.057)	(0.054)				
ln_other_NTL_pp									-0.007	-0.007	0.000	-0.021
									(0.005)	(0.005)	(0.016)	(0.017)
ln_rural_NTL_pp_squared			0.004	0.003								
			(0.002)	(0.003)								
ln_urban_NTL_pp_squared							0.026***	0.007				
							(0.007)	(0.006)				
ln_other_NTL_pp_squared											0.001	-0.001
											(0.001)	(0.001)
Constant	2.830***	2.832***	2.909***	2.891***	2.830***	2.828***	3.253***	2.951***	2.780***	2.781***	2.798***	2.746***
	(0.044)	(0.044)	(0.070)	(0.074)	(0.045)	(0.046)	(0.117)	(0.118)	(0.039)	(0.039)	(0.056)	(0.058)
year = 2004	-0.553***	-0.551***	-0.531***	-0.547***	-0.573***	-0.574***	-0.552***	-0.558***	-0.603***	-0.603***	-0.599***	-0.609***
	(0.035)	(0.035)	(0.039)	(0.038)	(0.028)	(0.028)	(0.028)	(0.028)	(0.031)	(0.031)	(0.035)	(0.036)
year = 2005	-0.474***	-0.472***	-0.455***	-0.473***	-0.495***	-0.495***	-0.479***	-0.482***	-0.534***	-0.533***	-0.530***	-0.540***
	(0.038)	(0.038)	(0.041)	(0.039)	(0.027)	(0.027)	(0.027)	(0.027)	(0.031)	(0.031)	(0.035)	(0.036)
year = 2006	-0.430***	-0.428***	-0.408***	-0.422***	-0.452***	-0.453***	-0.430***	-0.436***	-0.486***	-0.486***	-0.482***	-0.491***
	(0.035)	(0.035)	(0.039)	(0.038)	(0.026)	(0.026)	(0.026)	(0.027)	(0.029)	(0.030)	(0.034)	(0.034)
year = 2007	-0.399***	-0.397***	-0.376***	-0.391***	-0.420***	-0.421***	-0.395***	-0.406***	-0.452***	-0.452***	-0.448***	-0.456***
	(0.033)	(0.033)	(0.037)	(0.036)	(0.025)	(0.025)	(0.025)	(0.026)	(0.028)	(0.028)	(0.032)	(0.033)
year = 2008	-0.403***	-0.402***	-0.380***	-0.393***	-0.420***	-0.421***	-0.396***	-0.404***	-0.451***	-0.451***	-0.447***	-0.454***
	(0.031)	(0.031)	(0.036)	(0.035)	(0.024)	(0.024)	(0.024)	(0.025)	(0.027)	(0.027)	(0.032)	(0.032)
year = 2009	-0.445***	-0.443***	-0.421***	-0.436***	-0.454***	-0.455***	-0.436***	-0.443***	-0.498***	-0.498***	-0.494***	-0.501***
	(0.030)	(0.030)	(0.035)	(0.033)	(0.023)	(0.024)	(0.023)	(0.024)	(0.026)	(0.026)	(0.031)	(0.031)
year = 2010	-0.365***	-0.364***	-0.341***	-0.354***	-0.380***	-0.381***	-0.356***	-0.366***	-0.417***	-0.417***	-0.412***	-0.419***
	(0.025)	(0.025)	(0.031)	(0.030)	(0.020)	(0.020)	(0.021)	(0.021)	(0.023)	(0.024)	(0.028)	(0.029)
year = 2011	-0.291***	-0.289***	-0.267***	-0.278***	-0.298***	-0.299***	-0.274***	-0.285***	-0.315***	-0.315***	-0.311***	-0.319***
	(0.022)	(0.022)	(0.027)	(0.027)	(0.018)	(0.018)	(0.019)	(0.020)	(0.020)	(0.020)	(0.025)	(0.025)
year = 2012	-0.267***	-0.267***	-0.249***	-0.255***	-0.271***	-0.272***	-0.251***	-0.260***	-0.281***	-0.281***	-0.277***	-0.284***
	(0.017)	(0.018)	(0.021)	(0.022)	(0.016)	(0.016)	(0.017)	(0.017)	(0.015)	(0.015)	(0.019)	(0.019)
year = 2013	-0.211***	-0.211***	-0.199***	-0.202***	-0.214***	-0.214***	-0.202***	-0.206***	-0.228***	-0.228***	-0.225***	-0.230***
	(0.014)	(0.014)	(0.015)	(0.016)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)
year = 2014	-0.180***	-0.179***	-0.167***	-0.170***	-0.186***	-0.186***	-0.178***	-0.179***	-0.198***	-0.198***	-0.195***	-0.199***
	(0.013)	(0.013)	(0.015)	(0.016)	(0.012)	(0.012)	(0.012)	(0.013)	(0.013)	(0.013)	(0.015)	(0.015)
year = 2015	-0.139***	-0.138***	-0.127***	-0.130***	-0.144***	-0.144***	-0.139***	-0.138***	-0.153***	-0.153***	-0.151***	-0.155***
	(0.012)	(0.012)	(0.015)	(0.015)	(0.011)	(0.011)	(0.011)	(0.011)	(0.012)	(0.012)	(0.013)	(0.013)
year = 2016	-0.116***	-0.116***	-0.107***	-0.109***	-0.122***	-0.122***	-0.122***	-0.119***	-0.130***	-0.130***	-0.128***	-0.132***
	(0.011)	(0.011)	(0.012)	(0.013)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.010)	(0.011)	(0.011)
year = 2017	-0.062***	-0.062***	-0.058***	-0.058***	-0.066***	-0.066***	-0.072***	-0.066***	-0.071***	-0.071***	-0.070***	-0.072***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)	(0.009)	(0.010)	(0.009)	(0.009)	(0.010)	(0.010)
year = 2018	-0.041***	-0.041***	-0.037***	-0.038***	-0.045***	-0.045***	-0.050***	-0.045***	-0.048***	-0.048***	-0.048***	-0.049***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)	(0.008)	(0.008)	(0.009)	(0.009)	(0.009)	(0.009)
year = 2019	-0.040***	-0.040***	-0.039***	-0.039***	-0.041***	-0.040***	-0.044***	-0.041***	-0.047***	-0.047***	-0.046***	-0.048***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Observations	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,377	1,361	1,361	1,361	1,361
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
AIC	-3894	-3899	-3895	-3979	-3427	-3448	-3454	-3549	-3153	-3152	-3151	-3253
BIC	-3785	-3784	-3775	-3843	-3317	-3333	-3334	-3413	-3044	-3038	-3031	-3117
Number of groups	81	81	81	81	81	81	81	81	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year fixed effects is set to 2020.

Table 13: Random coefficients landuse model results, including constant variable dummy coefficients

	(13.1)	(13.2)	(14.1)	(14.2)	(15.1)	(15.2)
	U-R landuse NTL linear	U-R landuse NTL linear	U-R landuse NTL quadratic	U-R landuse NTL quadratic	Reduced Landuse	Reduced Landuse
ln_rural_NTL_pp	0.000	-0.012	0.028	0.004	0.004	-0.008
	(0.008)	(0.009)	(0.029)	(0.037)	(0.009)	(0.009)
ln_urban_NTL_pp	0.013*	0.025***	0.084**	0.093**	0.099***	0.086**
	(0.007)	(0.007)	(0.041)	(0.046)	(0.038)	(0.037)
ln_other_NTL_pp	0.001	0.001				
	(0.001)	(0.001)				
ln_rural_NTL_pp_squared			0.002	0.001		
			(0.002)	(0.003)		
ln_urban_NTL_pp_squared			0.008*	0.009*	0.010**	0.007*
			(0.005)	(0.005)	(0.004)	(0.004)
ln_other_NTL_pp_squared						
Constant	2.837***	2.845***	3.033***	3.008***	3.015***	2.974***
	(0.042)	(0.043)	(0.088)	(0.089)	(0.083)	(0.086)
year = 2004	-0.574***	-0.597***	-0.542***	-0.579***	-0.553***	-0.577***
	(0.034)	(0.035)	(0.037)	(0.039)	(0.035)	(0.035)
year = 2005	-0.499***	-0.525***	-0.468***	-0.506***	-0.477***	-0.503***
	(0.036)	(0.037)	(0.039)	(0.040)	(0.037)	(0.038)
year = 2006	-0.454***	-0.478***	-0.420***	-0.456***	-0.431***	-0.457***
	(0.034)	(0.034)	(0.038)	(0.039)	(0.034)	(0.035)
year = 2007	-0.422***	-0.448***	-0.389***	-0.429***	-0.401***	-0.430***
	(0.032)	(0.032)	(0.036)	(0.037)	(0.032)	(0.033)
year = 2008	-0.422***	-0.443***	-0.390***	-0.425***	-0.402***	-0.427***
	(0.030)	(0.031)	(0.035)	(0.036)	(0.031)	(0.031)
year = 2009	-0.462***	-0.481***	-0.428***	-0.464***	-0.441***	-0.462***
	(0.028)	(0.028)	(0.033)	(0.035)	(0.029)	(0.029)
year = 2010	-0.383***	-0.399***	-0.348***	-0.380***	-0.361***	-0.381***
	(0.024)	(0.024)	(0.030)	(0.032)	(0.025)	(0.025)
year = 2011	-0.302***	-0.320***	-0.274***	-0.305***	-0.286***	-0.307***
	(0.021)	(0.021)	(0.026)	(0.028)	(0.022)	(0.022)
year = 2012	-0.272***	-0.282***	-0.252***	-0.272***	-0.262***	-0.275***
	(0.017)	(0.017)	(0.021)	(0.022)	(0.018)	(0.018)
year = 2013	-0.217***	-0.224***	-0.203***	-0.215***	-0.209***	-0.218***
	(0.013)	(0.013)	(0.015)	(0.016)	(0.014)	(0.014)
year = 2014	-0.186***	-0.194***	-0.174***	-0.187***	-0.181***	-0.190***
	(0.013)	(0.013)	(0.015)	(0.017)	(0.013)	(0.014)
year = 2015	-0.145***	-0.152***	-0.135***	-0.146***	-0.141***	-0.149***
	(0.012)	(0.012)	(0.015)	(0.016)	(0.012)	(0.013)
year = 2016	-0.123***	-0.129***	-0.116***	-0.124***	-0.121***	-0.127***
	(0.010)	(0.010)	(0.012)	(0.013)	(0.011)	(0.011)
year = 2017	-0.067***	-0.072***	-0.065***	-0.070***	-0.068***	-0.072***
	(0.009)	(0.009)	(0.010)	(0.010)	(0.009)	(0.009)
year = 2018	-0.046***	-0.050***	-0.044***	-0.048***	-0.047***	-0.049***
	(0.008)	(0.008)	(0.008)	(0.009)	(0.008)	(0.008)
year = 2019	-0.043***	-0.045***	-0.042***	-0.043***	-0.043***	-0.044***
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)
Observations	1,361	1,361	1,377	1,377	1,377	1,377
Year FE	YES	YES	YES	YES	YES	YES
Random Coefficients	YES	YES	YES	YES	YES	YES
AIC	-3917	-3954	-3899	-4021	-3901	-3956
BIC	-3786	-3792	-3758	-3828	-3770	-3794
Number of groups	81	81	81	81	81	81
Correlated Coefficients	NO	YES	NO	YES	NO	YES

Robust standard errors in parentheses
*** $p<0.01$, ** $p<0.05$, * $p<0.1$
The base constant for year fixed effects is set to 2020.

Table 14: Random coefficients combined landuse model results, including constant variable dummy coefficients

	(1.3)	(2.3)	(3.3)	(4.3)	(5.3)	(6.3)
	NTL	NTL	LIT	LIT	Electricity consumption	Electricity consumption
	linear	quadratic	linear	quadratic	linear	quadratic
ln_NTL_pp	0.066*** (0.007)	0.274*** (0.029)				
ln_NTL_pp_squared		0.020*** (0.003)				
ln_LIT_pp			0.075*** (0.007)	0.458*** (0.040)		
ln_electricity_total_pp					0.233*** (0.019)	0.297*** (0.016)
ln_LIT_pp_squared				0.032*** (0.003)		
ln_electricity_total_pp_squared						-0.075*** (0.007)
Constant	3.836*** (0.025)	4.293*** (0.070)	4.081*** (0.046)	5.145*** (0.122)	3.359*** (0.024)	3.370*** (0.021)
prov_name = 11, AYDIN	-0.811*** (0.017)	-0.836*** (0.020)	-0.912*** (0.019)	-0.899*** (0.023)	-0.759*** (0.014)	-0.765*** (0.013)
prov_name = 12, BALIKESIR	-0.648*** (0.021)	-0.669*** (0.024)	-0.759*** (0.022)	-0.746*** (0.026)	-0.632*** (0.017)	-0.633*** (0.016)
prov_name = 13, BARTIN	-0.715*** (0.022)	-0.760*** (0.024)	-0.849*** (0.026)	-0.898*** (0.031)	-0.725*** (0.015)	-0.722*** (0.012)
prov_name = 14, BATMAN	-1.332*** (0.017)	-1.342*** (0.018)	-1.421*** (0.019)	-1.411*** (0.019)	-1.151*** (0.022)	-1.147*** (0.023)
prov_name = 15, BAYBURT	-1.008*** (0.040)	-1.069*** (0.034)	-1.118*** (0.043)	-1.147*** (0.036)	-0.767*** (0.041)	-0.756*** (0.033)
prov_name = 16, BILECIK	-0.481*** (0.034)	-0.518*** (0.038)	-0.584*** (0.035)	-0.579*** (0.039)	-0.667*** (0.035)	-0.541*** (0.032)
prov_name = 17, BINGOL	-1.258*** (0.022)	-1.268*** (0.027)	-1.376*** (0.024)	-1.362*** (0.028)	-0.995*** (0.026)	-0.949*** (0.021)
prov_name = 18, BITLIS	-1.364*** (0.023)	-1.390*** (0.026)	-1.476*** (0.027)	-1.472*** (0.030)	-1.115*** (0.028)	-1.081*** (0.021)
prov_name = 19, BOLU	-0.359*** (0.015)	-0.385*** (0.019)	-0.470*** (0.017)	-0.458*** (0.022)	-0.421*** (0.014)	-0.389*** (0.011)
prov_name = 20, BURDUR	-0.649*** (0.021)	-0.688*** (0.027)	-0.770*** (0.022)	-0.773*** (0.028)	-0.658*** (0.021)	-0.641*** (0.018)
prov_name = 21, BURSA	-0.402*** (0.024)	-0.413*** (0.023)	-0.473*** (0.024)	-0.445*** (0.023)	-0.489*** (0.019)	-0.452*** (0.019)
prov_name = 22, CANAKKALE	-0.517*** (0.011)	-0.536*** (0.014)	-0.633*** (0.016)	-0.624*** (0.021)	-0.756*** (0.023)	-0.597*** (0.025)
prov_name = 23, CANKIRI	-0.753*** (0.039)	-0.803*** (0.035)	-0.882*** (0.041)	-0.913*** (0.035)	-0.674*** (0.031)	-0.667*** (0.033)
prov_name = 24, CORUM	-0.965*** (0.012)	-0.989*** (0.016)	-1.063*** (0.016)	-1.051*** (0.020)	-0.834*** (0.014)	-0.845*** (0.014)
prov_name = 25, DENIZLI	-0.682*** (0.022)	-0.715*** (0.027)	-0.777*** (0.023)	-0.763*** (0.026)	-0.706*** (0.016)	-0.688*** (0.014)
prov_name = 26, DIYARBAKIR	-1.234*** (0.014)	-1.240*** (0.016)	-1.324*** (0.016)	-1.310*** (0.019)	-1.053*** (0.022)	-1.048*** (0.024)

Table 15: Results of fixed effect base and alternative models, including constant variable dummy coefficients

	(1.3)	(2.3)	(3.3)	(4.3)	(5.3)	(6.3)
	NTL	NTL	LIT	LIT	Electricity consumption	Electricity consumption
	linear	quadratic	linear	quadratic	linear	quadratic
prov_name = 27, DUZCE	-0.671***	-0.696***	-0.789***	-0.782***	-0.652***	-0.652***
	(0.014)	(0.017)	(0.016)	(0.021)	(0.011)	(0.010)
prov_name = 28, EDIRNE	-0.640***	-0.670***	-0.750***	-0.747***	-0.641***	-0.632***
	(0.016)	(0.020)	(0.020)	(0.025)	(0.011)	(0.010)
prov_name = 29, ELAZIG	-0.980***	-1.001***	-1.076***	-1.064***	-0.935***	-0.938***
	(0.010)	(0.014)	(0.014)	(0.018)	(0.011)	(0.010)
prov_name = 30, ERZINCAN	-0.664***	-0.713***	-0.774***	-0.791***	-0.518***	-0.512***
	(0.035)	(0.031)	(0.037)	(0.034)	(0.025)	(0.024)
prov_name = 31, ERZURUM	-1.048***	-1.087***	-1.140***	-1.133***	-0.858***	-0.862***
	(0.024)	(0.024)	(0.026)	(0.028)	(0.025)	(0.021)
prov_name = 32, ESKISEHIR	-0.415***	-0.449***	-0.498***	-0.481***	-0.444***	-0.417***
	(0.011)	(0.015)	(0.015)	(0.020)	(0.010)	(0.011)
prov_name = 33, GAZIANTEP	-0.974***	-0.983***	-1.039***	-1.012***	-1.015***	-0.998***
	(0.015)	(0.019)	(0.016)	(0.022)	(0.013)	(0.012)
prov_name = 34, GIRESUN	-0.911***	-0.949***	-1.049***	-1.096***	-0.810***	-0.814***
	(0.016)	(0.020)	(0.018)	(0.022)	(0.020)	(0.017)
prov_name = 35, GUMUSHANE	-0.807***	-0.843***	-0.943***	-0.969***	-0.710***	-0.676***
	(0.030)	(0.030)	(0.032)	(0.030)	(0.012)	(0.013)
prov_name = 36, HAKKARI	-1.311***	-1.325***	-1.430***	-1.421***	-1.024***	-0.968***
	(0.023)	(0.024)	(0.023)	(0.026)	(0.033)	(0.027)
prov_name = 37, HATAY	-1.029***	-1.044***	-1.118***	-1.099***	-1.115***	-1.078***
	(0.030)	(0.031)	(0.032)	(0.031)	(0.026)	(0.024)
prov_name = 38, IGDIR	-1.146***	-1.166***	-1.267***	-1.262***	-0.880***	-0.846***
	(0.013)	(0.017)	(0.016)	(0.020)	(0.026)	(0.024)
prov_name = 39, ISPARTA	-0.825***	-0.857***	-0.922***	-0.916***	-0.781***	-0.784***
	(0.015)	(0.020)	(0.019)	(0.023)	(0.010)	(0.010)
prov_name = 41, IZMIR	-0.391***	-0.418***	-0.451***	-0.424***	-0.493***	-0.430***
	(0.010)	(0.014)	(0.012)	(0.018)	(0.012)	(0.014)
prov_name = 42, KAHRAMANMARAS	-1.019***	-1.029***	-1.125***	-1.109***	-1.098***	-1.071***
	(0.013)	(0.015)	(0.015)	(0.019)	(0.012)	(0.010)
prov_name = 43, KARABUK	-0.875***	-0.900***	-0.976***	-0.965***	-0.993***	-0.931***
	(0.023)	(0.025)	(0.024)	(0.027)	(0.028)	(0.020)
prov_name = 44, KARAMAN	-0.629***	-0.663***	-0.734***	-0.727***	-0.602***	-0.593***
	(0.016)	(0.019)	(0.021)	(0.024)	(0.013)	(0.013)
prov_name = 45, KARS	-1.249***	-1.266***	-1.358***	-1.347***	-1.018***	-1.010***
	(0.016)	(0.019)	(0.018)	(0.022)	(0.023)	(0.019)
prov_name = 46, KASTAMONU	-0.767***	-0.793***	-0.884***	-0.891***	-0.717***	-0.721***
	(0.014)	(0.018)	(0.019)	(0.024)	(0.012)	(0.012)
prov_name = 47, KAYSERI	-0.725***	-0.762***	-0.797***	-0.773***	-0.672***	-0.674***
	(0.025)	(0.026)	(0.027)	(0.028)	(0.024)	(0.023)
prov_name = 48, KILIS	-1.126***	-1.158***	-1.219***	-1.214***	-0.994***	-0.992***
	(0.018)	(0.020)	(0.021)	(0.024)	(0.019)	(0.019)
prov_name = 49, KIRIKKALE	-0.869***	-0.911***	-0.973***	-0.972***	-0.798***	-0.798***
	(0.025)	(0.025)	(0.029)	(0.030)	(0.019)	(0.021)
prov_name = 50, KIRKLARELI	-0.384***	-0.416***	-0.496***	-0.495***	-0.581***	-0.454***
	(0.016)	(0.021)	(0.019)	(0.025)	(0.021)	(0.022)
prov_name = 51, KIRSEHIR	-0.864***	-0.906***	-0.990***	-1.004***	-0.772***	-0.775***
	(0.017)	(0.018)	(0.024)	(0.024)	(0.012)	(0.012)
prov_name = 52, KOCAELI	0.147***	0.109***	0.087***	0.115***	-0.122***	0.097***
	(0.013)	(0.017)	(0.016)	(0.020)	(0.027)	(0.035)

Table 16: Results of Fixed effect base and alternative models, including constant variable dummy coefficients (continued)

	(1.3)	(2.3)	(3.3)	(4.3)	(5.3)	(6.3)
	NTL	NTL	LIT	LIT	Electricity consumption	Electricity consumption
	linear	quadratic	linear	quadratic	linear	quadratic
prov_name = 53, KONYA	-0.820***	-0.851***	-0.910***	-0.893***	-0.821***	-0.807***
	(0.019)	(0.022)	(0.022)	(0.025)	(0.016)	(0.019)
prov_name = 54, KUTAHYA	-0.794***	-0.821***	-0.908***	-0.905***	-0.748***	-0.750***
	(0.011)	(0.015)	(0.016)	(0.022)	(0.011)	(0.010)
prov_name = 55, MALATYA	-1.047***	-1.073***	-1.149***	-1.140***	-0.971***	-0.980***
	(0.015)	(0.017)	(0.018)	(0.022)	(0.017)	(0.016)
prov_name = 56, MANISA	-0.624***	-0.639***	-0.727***	-0.712***	-0.632***	-0.627***
	(0.016)	(0.018)	(0.018)	(0.021)	(0.015)	(0.013)
prov_name = 57, MARDIN	-1.128***	-1.151***	-1.239***	-1.233***	-1.009***	-1.013***
	(0.027)	(0.028)	(0.029)	(0.030)	(0.028)	(0.028)
prov_name = 58, MERSIN	-0.766***	-0.785***	-0.845***	-0.827***	-0.724***	-0.725***
	(0.016)	(0.019)	(0.017)	(0.023)	(0.011)	(0.013)
prov_name = 59, MUGLA	-0.411***	-0.448***	-0.526***	-0.530***	-0.439***	-0.417***
	(0.020)	(0.025)	(0.023)	(0.029)	(0.016)	(0.014)
prov_name = 60, MUS	-1.339***	-1.351***	-1.457***	-1.447***	-1.092***	-1.057***
	(0.020)	(0.024)	(0.022)	(0.026)	(0.027)	(0.021)
prov_name = 61, NEVSEHIR	-1.028***	-1.078***	-1.147***	-1.164***	-0.933***	-0.941***
	(0.013)	(0.018)	(0.020)	(0.023)	(0.011)	(0.011)
prov_name = 62, NIGDE	-0.897***	-0.943***	-1.012***	-1.026***	-0.894***	-0.881***
	(0.014)	(0.020)	(0.019)	(0.026)	(0.010)	(0.010)
prov_name = 63, ORDU	-1.011***	-1.038***	-1.134***	-1.176***	-0.939***	-0.947***
	(0.021)	(0.026)	(0.018)	(0.025)	(0.026)	(0.024)
prov_name = 64, OSMANIYE	-1.163***	-1.176***	-1.261***	-1.253***	-1.246***	-1.150***
	(0.015)	(0.018)	(0.016)	(0.022)	(0.038)	(0.027)
prov_name = 65, RIZE	-0.686***	-0.720***	-0.816***	-0.853***	-0.673***	-0.681***
	(0.011)	(0.014)	(0.014)	(0.018)	(0.011)	(0.011)
prov_name = 66, SAKARYA	-0.598***	-0.620***	-0.699***	-0.689***	-0.619***	-0.604***
	(0.012)	(0.016)	(0.016)	(0.021)	(0.011)	(0.009)
prov_name = 67, SAMSUN	-0.864***	-0.883***	-0.961***	-0.957***	-0.820***	-0.827***
	(0.018)	(0.019)	(0.020)	(0.022)	(0.015)	(0.014)
prov_name = 68, SANLIURFA	-1.446***	-1.453***	-1.552***	-1.544***	-1.354***	-1.360***
	(0.018)	(0.019)	(0.022)	(0.023)	(0.024)	(0.024)
prov_name = 69, SIIRT	-1.281***	-1.299***	-1.397***	-1.396***	-1.138***	-1.142***
	(0.022)	(0.022)	(0.023)	(0.024)	(0.022)	(0.022)
prov_name = 70, SINOP	-0.779***	-0.816***	-0.904***	-0.926***	-0.706***	-0.713***
	(0.022)	(0.021)	(0.023)	(0.024)	(0.016)	(0.017)
prov_name = 71, SIRNAK	-1.273***	-1.282***	-1.390***	-1.375***	-1.020***	-0.987***
	(0.015)	(0.017)	(0.017)	(0.021)	(0.024)	(0.022)
prov_name = 72, SIVAS	-0.954***	-0.984***	-1.060***	-1.057***	-0.854***	-0.863***
	(0.014)	(0.017)	(0.018)	(0.021)	(0.015)	(0.014)
prov_name = 73, TEKIRDAG	-0.195***	-0.217***	-0.293***	-0.271***	-0.440***	-0.269***
	(0.017)	(0.019)	(0.018)	(0.022)	(0.024)	(0.027)
prov_name = 74, TOKAT	-1.118***	-1.142***	-1.228***	-1.228***	-0.950***	-0.947***
	(0.013)	(0.016)	(0.016)	(0.021)	(0.018)	(0.014)
prov_name = 75, TRABZON	-0.686***	-0.707***	-0.804***	-0.843***	-0.633***	-0.638***
	(0.014)	(0.021)	(0.012)	(0.023)	(0.015)	(0.013)
prov_name = 76, TUNCELI	-0.628***	-0.699***	-0.757***	-0.811***	-0.420***	-0.423***
	(0.022)	(0.024)	(0.027)	(0.028)	(0.021)	(0.018)
prov_name = 77, USAK	-0.786***	-0.820***	-0.897***	-0.893***	-0.838***	-0.809***
	(0.011)	(0.015)	(0.016)	(0.020)	(0.011)	(0.013)
prov_name = 78, VAN	-1.581***	-1.595***	-1.676***	-1.662***	-1.302***	-1.258***
	(0.020)	(0.021)	(0.021)	(0.023)	(0.029)	(0.030)

Table 17: Results of Fixed effect base and alternative models, including constant variable dummy coefficients (continued)

	(1.3)	(2.3)	(3.3)	(4.3)	(5.3)	(6.3)
	NTL	NTL	LIT	LIT	Electricity consumption	Electricity consumption
	linear	quadratic	linear	quadratic	linear	quadratic
prov_name = 79, YALOVA	-0.552***	-0.572***	-0.654***	-0.633***	-0.667***	-0.619***
	(0.012)	(0.015)	(0.016)	(0.023)	(0.021)	(0.021)
prov_name = 80, YOZGAT	-1.082***	-1.115***	-1.205***	-1.211***	-0.930***	-0.935***
	(0.021)	(0.021)	(0.025)	(0.025)	(0.021)	(0.018)
prov_name = 81, ZONGULDAK	-0.995***	-1.019***	-1.109***	-1.127***	-1.147***	-1.086***
	(0.027)	(0.027)	(0.031)	(0.031)	(0.018)	(0.018)
year = 2004	-0.434***	-0.331***	-0.434***	-0.365***	-0.413***	-0.418***
	(0.023)	(0.026)	(0.022)	(0.023)	(0.020)	(0.017)
year = 2005	-0.338***	-0.242***	-0.347***	-0.289***	-0.357***	-0.367***
	(0.024)	(0.026)	(0.023)	(0.023)	(0.018)	(0.016)
year = 2006	-0.311***	-0.208***	-0.309***	-0.240***	-0.326***	-0.339***
	(0.022)	(0.025)	(0.022)	(0.022)	(0.017)	(0.016)
year = 2007	-0.296***	-0.193***	-0.290***	-0.215***	-0.314***	-0.329***
	(0.021)	(0.024)	(0.021)	(0.021)	(0.016)	(0.015)
year = 2008	-0.294***	-0.191***	-0.293***	-0.217***	-0.324***	-0.342***
	(0.021)	(0.024)	(0.021)	(0.021)	(0.016)	(0.014)
year = 2009	-0.323***	-0.216***	-0.332***	-0.253***	-0.368***	-0.388***
	(0.021)	(0.025)	(0.020)	(0.021)	(0.015)	(0.014)
year = 2010	-0.268***	-0.161***	-0.267***	-0.183***	-0.305***	-0.324***
	(0.019)	(0.023)	(0.019)	(0.020)	(0.014)	(0.013)
year = 2011	-0.211***	-0.113***	-0.205***	-0.121***	-0.240***	-0.257***
	(0.017)	(0.020)	(0.017)	(0.018)	(0.013)	(0.013)
year = 2012	-0.214***	-0.138***	-0.218***	-0.150***	-0.216***	-0.231***
	(0.015)	(0.017)	(0.015)	(0.015)	(0.013)	(0.012)
year = 2013	-0.187***	-0.139***	-0.177***	-0.120***	-0.156***	-0.169***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)
year = 2014	-0.156***	-0.108***	-0.145***	-0.087***	-0.138***	-0.151***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.013)	(0.012)
year = 2015	-0.119***	-0.077***	-0.106***	-0.051***	-0.102***	-0.112***
	(0.015)	(0.014)	(0.015)	(0.015)	(0.013)	(0.013)
year = 2016	-0.102***	-0.071***	-0.088***	-0.042***	-0.090***	-0.096***
	(0.015)	(0.014)	(0.015)	(0.014)	(0.013)	(0.012)
year = 2017	-0.058***	-0.044***	-0.055***	-0.037***	-0.050***	-0.053***
	(0.015)	(0.014)	(0.015)	(0.013)	(0.013)	(0.012)
year = 2018	-0.037**	-0.026*	-0.033**	-0.015	-0.035**	-0.037***
	(0.016)	(0.015)	(0.016)	(0.014)	(0.014)	(0.013)
year = 2019	-0.039**	-0.038**	-0.036**	-0.030**	-0.029**	-0.033**
	(0.017)	(0.015)	(0.017)	(0.015)	(0.015)	(0.014)
Observations	1,377	1,377	1,377	1,377	1,377	1,377
R-squared	0.970	0.971	0.970	0.973	0.976	0.979
Province FE	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES
Random Coefficients	NO	NO	NO	NO	NO	NO
Adjusted R-squared	0.967	0.969	0.967	0.971	0.974	0.977
AIC	-3177	-3255	-3184	-3325	-3489	-3661
BIC	-2664	-2737	-2672	-2808	-2977	-3143
Number of groups						
Unstructed Covariance						

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year and province fixed effects is set to 2020 and İstanbul respectively

Table 18: Results of Fixed effect base and alternative models, including constant variable dummy coefficients (continued)

	(7.3)	(8.3)	(9.3)	(10.3)	(11.3)	(12.3)	(13.3)	(14.3)	(15.3)
	Rural NTL	Rural NTL	Urban NTL	Urban NTL	Other NTL	Other NTL	All landuse NTL variables	All landuse NTL variables	Reduced Landuse
	linear	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	
ln_rural_NTL_pp	0.032***	0.174***					0.023***	0.075**	0.036***
	(0.006)	(0.028)					(0.007)	(0.031)	(0.008)
ln_urban_NTL_pp			0.042***	0.291***			0.020**	0.258***	0.305***
			(0.007)	(0.037)			(0.010)	(0.043)	(0.036)
ln_other_NTL_pp					0.005***	0.012	0.005***	0.004	
					(0.001)	(0.008)	(0.001)	(0.007)	
ln_rural_NTL_pp_squared		0.011***						0.003	
		(0.002)						(0.002)	
ln_urban_NTL_pp_squared				0.029***				0.030***	0.034***
				(0.004)				(0.005)	(0.004)
ln_other_NTL_pp_squared						0.000		-0.000	
						(0.000)		(0.000)	
Constant	3.715***	4.016***	3.791***	4.299***	3.647***	3.664***	3.774***	4.350***	4.372***
	(0.021)	(0.064)	(0.032)	(0.082)	(0.017)	(0.026)	(0.032)	(0.087)	(0.082)
prov_name = 11, AYDIN	-0.790***	-0.785***	-0.822***	-0.839***	-0.803***	-0.805***	-0.806***	-0.811***	-0.817***
	(0.017)	(0.018)	(0.018)	(0.019)	(0.017)	(0.017)	(0.018)	(0.019)	(0.019)
prov_name = 12, BALIKESIR	-0.634***	-0.625***	-0.665***	-0.683***	-0.645***	-0.645***	-0.647***	-0.650***	-0.660***
	(0.021)	(0.021)	(0.023)	(0.023)	(0.021)	(0.021)	(0.021)	(0.022)	(0.023)
prov_name = 13, BARTIN	-0.700***	-0.710***	-0.764***	-0.795***	-0.724***	-0.726***	-0.711***	-0.721***	-0.741***
	(0.020)	(0.020)	(0.017)	(0.019)	(0.016)	(0.016)	(0.024)	(0.028)	(0.027)
prov_name = 14, BATMAN	-1.323***	-1.305***	-1.352***	-1.360***	-1.312***	-1.313***	-1.297***	-1.294***	-1.330***
	(0.020)	(0.019)	(0.017)	(0.014)	(0.018)	(0.018)	(0.020)	(0.019)	(0.017)
prov_name = 15, BAYBURT	-0.969***	-0.988***	-1.035***	-1.117***	-0.930***	-0.930***	-0.967***	-1.041***	-1.090***
	(0.043)	(0.037)	(0.045)	(0.037)	(0.048)	(0.048)	(0.050)	(0.040)	(0.035)
prov_name = 16, BILECIK	-0.451***	-0.458***	-0.496***	-0.535***	-0.419***	-0.420***	-0.446***	-0.477***	-0.513***
	(0.034)	(0.035)	(0.036)	(0.039)	(0.038)	(0.038)	(0.038)	(0.041)	(0.039)
prov_name = 17, BINGOL	-1.261***	-1.240***	-1.282***	-1.294***	-1.268***	-1.271***	-1.257***	-1.256***	-1.273***
	(0.024)	(0.027)	(0.023)	(0.026)	(0.020)	(0.020)	(0.022)	(0.029)	(0.029)
prov_name = 18, BITLIS	-1.352***	-1.340***	-1.396***	-1.416***	-1.377***	-1.380***	-1.372***	-1.372***	-1.381***
	(0.026)	(0.026)	(0.027)	(0.026)	(0.028)	(0.028)	(0.028)	(0.027)	(0.026)
prov_name = 19, BOLU	-0.339***	-0.336***	-0.376***	-0.397***	-0.329***	-0.331***	-0.342***	-0.353***	-0.375***
	(0.015)	(0.015)	(0.017)	(0.018)	(0.019)	(0.019)	(0.020)	(0.020)	(0.018)
prov_name = 20, BURDUR	-0.630***	-0.640***	-0.653***	-0.683***	-0.603***	-0.603***	-0.616***	-0.646***	-0.673***
	(0.019)	(0.022)	(0.022)	(0.023)	(0.022)	(0.021)	(0.023)	(0.025)	(0.022)
prov_name = 21, BURSA	-0.383***	-0.371***	-0.407***	-0.412***	-0.392***	-0.390***	-0.388***	-0.382***	-0.391***
	(0.028)	(0.027)	(0.028)	(0.025)	(0.028)	(0.028)	(0.027)	(0.025)	(0.025)
prov_name = 22, CANAKKALE	-0.499***	-0.493***	-0.531***	-0.544***	-0.508***	-0.510***	-0.516***	-0.517***	-0.523***
	(0.011)	(0.011)	(0.013)	(0.013)	(0.012)	(0.013)	(0.012)	(0.013)	(0.013)
prov_name = 23, CANKIRI	-0.730***	-0.747***	-0.766***	-0.802***	-0.723***	-0.727***	-0.739***	-0.770***	-0.784***
	(0.042)	(0.037)	(0.043)	(0.040)	(0.043)	(0.042)	(0.041)	(0.037)	(0.039)
prov_name = 24, CORUM	-0.938***	-0.930***	-0.985***	-1.005***	-0.923***	-0.923***	-0.934***	-0.939***	-0.972***
	(0.014)	(0.014)	(0.014)	(0.014)	(0.016)	(0.016)	(0.019)	(0.020)	(0.017)
prov_name = 25, DENIZLI	-0.656***	-0.665***	-0.680***	-0.698***	-0.654***	-0.654***	-0.667***	-0.680***	-0.686***
	(0.023)	(0.025)	(0.025)	(0.025)	(0.023)	(0.023)	(0.023)	(0.024)	(0.024)
prov_name = 26, DIYARBAKIR	-1.222***	-1.194***	-1.266***	-1.274***	-1.233***	-1.230***	-1.222***	-1.208***	-1.233***
	(0.016)	(0.016)	(0.016)	(0.015)	(0.017)	(0.017)	(0.018)	(0.019)	(0.017)
prov_name = 27, DUZCE	-0.656***	-0.653***	-0.680***	-0.698***	-0.670***	-0.671***	-0.667***	-0.674***	-0.679***
	(0.014)	(0.015)	(0.015)	(0.014)	(0.013)	(0.013)	(0.013)	(0.013)	(0.014)
prov_name = 28, EDIRNE	-0.612***	-0.612***	-0.652***	-0.676***	-0.602***	-0.603***	-0.618***	-0.631***	-0.652***
	(0.017)	(0.018)	(0.018)	(0.020)	(0.019)	(0.019)	(0.020)	(0.023)	(0.021)
prov_name = 29, ELAZIG	-0.969***	-0.964***	-0.991***	-1.007***	-0.974***	-0.974***	-0.977***	-0.984***	-0.993***
	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)	(0.012)	(0.011)	(0.011)	(0.011)
prov_name = 30, ERZINCAN	-0.635***	-0.653***	-0.672***	-0.705***	-0.626***	-0.628***	-0.645***	-0.672***	-0.686***
	(0.036)	(0.032)	(0.038)	(0.034)	(0.036)	(0.036)	(0.036)	(0.031)	(0.033)
prov_name = 31, ERZURUM	-1.011***	-1.008***	-1.078***	-1.148***	-1.002***	-1.005***	-1.029***	-1.080***	-1.114***
	(0.024)	(0.025)	(0.025)	(0.022)	(0.021)	(0.021)	(0.027)	(0.026)	(0.023)
prov_name = 32, ESKISEHIR	-0.385***	-0.394***	-0.413***	-0.431***	-0.390***	-0.396***	-0.405***	-0.416***	-0.417***
	(0.010)	(0.011)	(0.012)	(0.011)	(0.011)	(0.013)	(0.012)	(0.014)	(0.012)
prov_name = 33, GAZIANTEP	-0.955***	-0.937***	-0.986***	-0.989***	-0.963***	-0.964***	-0.961***	-0.950***	-0.964***
	(0.016)	(0.017)	(0.016)	(0.016)	(0.016)	(0.016)	(0.016)	(0.018)	(0.017)
prov_name = 34, GIRESUN	-0.920***	-0.916***	-0.954***	-0.974***	-0.955***	-0.953***	-0.925***	-0.927***	-0.936***
	(0.017)	(0.018)	(0.017)	(0.022)	(0.020)	(0.020)	(0.019)	(0.022)	(0.021)
prov_name = 35, GUMUSHANE	-0.799***	-0.802***	-0.827***	-0.858***	-0.782***	-0.783***	-0.789***	-0.815***	-0.842***
	(0.034)	(0.032)	(0.032)	(0.034)	(0.035)	(0.035)	(0.035)	(0.037)	(0.036)
prov_name = 36, HAKKARI	-1.318***	-1.298***	-1.343***	-1.350***	-1.309***	-1.309***	-1.299***	-1.295***	-1.325***
	(0.025)	(0.025)	(0.024)	(0.025)	(0.025)	(0.025)	(0.025)	(0.027)	(0.026)
prov_name = 37, HATAY	-1.010***	-0.996***	-1.044***	-1.053***	-1.027***	-1.027***	-1.024***	-1.016***	-1.025***
	(0.032)	(0.032)	(0.032)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
prov_name = 38, IGDIR	-1.132***	-1.120***	-1.170***	-1.189***	-1.140***	-1.141***	-1.132***	-1.134***	-1.155***
	(0.014)	(0.015)	(0.013)	(0.013)	(0.014)	(0.014)	(0.016)	(0.018)	(0.016)

Table 19: Results of fixed effect landuse models, including constant variable dummy coefficients

	(7.3)	(8.3)	(9.3)	(10.3)	(11.3)	(12.3)	(13.3)	(14.3)	(15.3)
	Rural NTL	Rural NTL	Urban NTL	Urban NTL	Other NTL	Other NTL	All landuse NTL variables	All landuse NTL variables	Reduced Landuse
	linear	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	
prov_name = 39, ISPARTA	-0.799***	-0.814***	-0.822***	-0.832***	-0.801***	-0.803***	-0.812***	-0.819***	-0.819***
	(0.017)	(0.021)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.018)	(0.017)
prov_name = 41, IZMIR	-0.366***	-0.378***	-0.379***	-0.386***	-0.361***	-0.363***	-0.376***	-0.383***	-0.382***
	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)
prov_name = 42, KAHRAMANMARAS	-1.017***	-0.999***	-1.036***	-1.046***	-1.018***	-1.017***	-1.008***	-1.007***	-1.026***
	(0.014)	(0.014)	(0.014)	(0.011)	(0.016)	(0.015)	(0.015)	(0.014)	(0.012)
prov_name = 43, KARABUK	-0.848***	-0.839***	-0.888***	-0.911***	-0.867***	-0.867***	-0.866***	-0.871***	-0.879***
	(0.024)	(0.026)	(0.024)	(0.024)	(0.027)	(0.027)	(0.030)	(0.031)	(0.026)
prov_name = 44, KARAMAN	-0.604***	-0.615***	-0.630***	-0.651***	-0.583***	-0.583***	-0.605***	-0.624***	-0.641***
	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)	(0.018)	(0.019)	(0.018)
prov_name = 45, KARS	-1.225***	-1.210***	-1.284***	-1.321***	-1.215***	-1.215***	-1.233***	-1.249***	-1.284***
	(0.015)	(0.018)	(0.017)	(0.017)	(0.014)	(0.014)	(0.021)	(0.022)	(0.019)
prov_name = 46, KASTAMONU	-0.751***	-0.742***	-0.798***	-0.825***	-0.752***	-0.752***	-0.757***	-0.767***	-0.791***
	(0.014)	(0.015)	(0.015)	(0.018)	(0.015)	(0.015)	(0.019)	(0.022)	(0.020)
prov_name = 47, KAYSERI	-0.684***	-0.689***	-0.721***	-0.744***	-0.684***	-0.687***	-0.705***	-0.719***	-0.726***
	(0.030)	(0.029)	(0.030)	(0.030)	(0.032)	(0.032)	(0.029)	(0.029)	(0.029)
prov_name = 48, KILIS	-1.106***	-1.106***	-1.135***	-1.161***	-1.049***	-1.049***	-1.064***	-1.089***	-1.142***
	(0.019)	(0.018)	(0.019)	(0.019)	(0.024)	(0.024)	(0.025)	(0.026)	(0.019)
prov_name = 49, KIRIKKALE	-0.831***	-0.834***	-0.909***	-1.009***	-0.806***	-0.807***	-0.845***	-0.927***	-0.976***
	(0.025)	(0.025)	(0.028)	(0.028)	(0.027)	(0.028)	(0.033)	(0.032)	(0.028)
prov_name = 50, KIRKLARELI	-0.363***	-0.369***	-0.397***	-0.419***	-0.350***	-0.351***	-0.368***	-0.383***	-0.401***
	(0.015)	(0.017)	(0.016)	(0.018)	(0.018)	(0.018)	(0.019)	(0.020)	(0.018)
prov_name = 51, KIRSEHIR	-0.838***	-0.854***	-0.867***	-0.894***	-0.829***	-0.832***	-0.852***	-0.875***	-0.883***
	(0.018)	(0.017)	(0.018)	(0.018)	(0.017)	(0.017)	(0.019)	(0.019)	(0.018)
prov_name = 52, KOCAELI	0.186***	0.176***	0.156***	0.138***	0.191***	0.191***	0.172***	0.160***	0.153***
	(0.014)	(0.014)	(0.015)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.015)
prov_name = 53, KONYA	-0.786***	-0.785***	-0.831***	-0.858***	-0.787***	-0.787***	-0.806***	-0.818***	-0.833***
	(0.017)	(0.018)	(0.019)	(0.019)	(0.017)	(0.016)	(0.021)	(0.021)	(0.020)
prov_name = 54, KUTAHYA	-0.774***	-0.772***	-0.813***	-0.835***	-0.766***	-0.768***	-0.781***	-0.793***	-0.812***
	(0.012)	(0.012)	(0.013)	(0.014)	(0.015)	(0.014)	(0.015)	(0.016)	(0.014)
prov_name = 55, MALATYA	-1.034***	-1.033***	-1.051***	-1.073***	-1.031***	-1.030***	-1.033***	-1.051***	-1.063***
	(0.017)	(0.016)	(0.014)	(0.015)	(0.017)	(0.017)	(0.016)	(0.019)	(0.018)
prov_name = 56, MANISA	-0.613***	-0.600***	-0.639***	-0.652***	-0.611***	-0.612***	-0.607***	-0.609***	-0.630***
	(0.016)	(0.017)	(0.018)	(0.016)	(0.019)	(0.019)	(0.019)	(0.018)	(0.016)
prov_name = 57, MARDIN	-1.110***	-1.103***	-1.152***	-1.174***	-1.127***	-1.129***	-1.140***	-1.146***	-1.146***
	(0.028)	(0.028)	(0.028)	(0.025)	(0.028)	(0.028)	(0.029)	(0.028)	(0.026)
prov_name = 58, MERSIN	-0.736***	-0.725***	-0.773***	-0.785***	-0.756***	-0.757***	-0.753***	-0.748***	-0.756***
	(0.015)	(0.015)	(0.016)	(0.015)	(0.017)	(0.017)	(0.017)	(0.018)	(0.016)
prov_name = 59, MUGLA	-0.384***	-0.396***	-0.411***	-0.437***	-0.382***	-0.384***	-0.400***	-0.422***	-0.427***
	(0.019)	(0.021)	(0.023)	(0.025)	(0.020)	(0.020)	(0.020)	(0.022)	(0.023)
prov_name = 60, MUS	-1.338***	-1.315***	-1.385***	-1.398***	-1.341***	-1.340***	-1.335***	-1.328***	-1.358***
	(0.021)	(0.024)	(0.021)	(0.021)	(0.020)	(0.021)	(0.023)	(0.026)	(0.023)
prov_name = 61, NEVSEHIR	-0.996***	-1.024***	-1.018***	-1.044***	-0.970***	-0.972***	-1.000***	-1.031***	-1.042***
	(0.013)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.015)	(0.016)	(0.015)
prov_name = 62, NIGDE	-0.866***	-0.887***	-0.894***	-0.914***	-0.859***	-0.860***	-0.881***	-0.900***	-0.903***
	(0.013)	(0.017)	(0.015)	(0.015)	(0.014)	(0.014)	(0.015)	(0.017)	(0.016)
prov_name = 63, ORDU	-1.011***	-1.005***	-1.054***	-1.066***	-1.054***	-1.054***	-1.021***	-1.013***	-1.019***
	(0.023)	(0.025)	(0.026)	(0.030)	(0.027)	(0.027)	(0.025)	(0.028)	(0.027)
prov_name = 64, OSMANIYE	-1.156***	-1.146***	-1.175***	-1.185***	-1.161***	-1.163***	-1.148***	-1.149***	-1.165***
	(0.015)	(0.016)	(0.015)	(0.017)	(0.016)	(0.016)	(0.015)	(0.017)	(0.018)
prov_name = 65, RIZE	-0.690***	-0.686***	-0.732***	-0.751***	-0.721***	-0.719***	-0.698***	-0.698***	-0.709***
	(0.012)	(0.012)	(0.010)	(0.012)	(0.012)	(0.013)	(0.013)	(0.015)	(0.013)
prov_name = 66, SAKARYA	-0.567***	-0.552***	-0.626***	-0.653***	-0.585***	-0.584***	-0.589***	-0.591***	-0.609***
	(0.014)	(0.014)	(0.014)	(0.016)	(0.013)	(0.013)	(0.017)	(0.020)	(0.019)
prov_name = 67, SAMSUN	-0.845***	-0.835***	-0.883***	-0.898***	-0.869***	-0.868***	-0.855***	-0.852***	-0.862***
	(0.020)	(0.020)	(0.018)	(0.016)	(0.016)	(0.016)	(0.019)	(0.020)	(0.019)
prov_name = 68, SANLIURFA	-1.439***	-1.416***	-1.474***	-1.480***	-1.446***	-1.447***	-1.436***	-1.424***	-1.446***
	(0.019)	(0.019)	(0.018)	(0.016)	(0.021)	(0.021)	(0.021)	(0.021)	(0.018)
prov_name = 69, SIIRT	-1.287***	-1.266***	-1.320***	-1.337***	-1.302***	-1.303***	-1.282***	-1.282***	-1.304***
	(0.021)	(0.021)	(0.021)	(0.019)	(0.022)	(0.022)	(0.024)	(0.022)	(0.020)
prov_name = 70, SINOP	-0.785***	-0.774***	-0.827***	-0.871***	-0.819***	-0.819***	-0.798***	-0.821***	-0.835***
	(0.019)	(0.018)	(0.019)	(0.018)	(0.014)	(0.014)	(0.020)	(0.020)	(0.019)
prov_name = 71, SIRNAK	-1.270***	-1.248***	-1.304***	-1.312***	-1.258***	-1.258***	-1.252***	-1.245***	-1.280***
	(0.015)	(0.016)	(0.015)	(0.014)	(0.019)	(0.019)	(0.020)	(0.021)	(0.016)
prov_name = 72, SIVAS	-0.930***	-0.936***	-0.959***	-0.973***	-0.929***	-0.929***	-0.942***	-0.948***	-0.956***
	(0.014)	(0.014)	(0.016)	(0.016)	(0.014)	(0.014)	(0.016)	(0.016)	(0.016)
prov_name = 73, TEKIRDAG	-0.174***	-0.173***	-0.199***	-0.209***	-0.174***	-0.175***	-0.186***	-0.187***	-0.193***
	(0.019)	(0.018)	(0.019)	(0.018)	(0.020)	(0.020)	(0.018)	(0.017)	(0.017)
prov_name = 74, TOKAT	-1.098***	-1.084***	-1.147***	-1.172***	-1.116***	-1.118***	-1.108***	-1.111***	-1.130***
	(0.015)	(0.016)	(0.015)	(0.014)	(0.016)	(0.016)	(0.017)	(0.018)	(0.016)
prov_name = 75, TRABZON	-0.678***	-0.683***	-0.718***	-0.729***	-0.721***	-0.719***	-0.683***	-0.677***	-0.683***
	(0.014)	(0.018)	(0.018)	(0.023)	(0.019)	(0.019)	(0.016)	(0.019)	(0.018)
prov_name = 76, TUNCELI	-0.591***	-0.636***	-0.600***	-0.642***	-0.555***	-0.558***	-0.588***	-0.644***	-0.654***
	(0.022)	(0.024)	(0.021)	(0.020)	(0.020)	(0.020)	(0.021)	(0.023)	(0.021)
prov_name = 77, USAK	-0.770***	-0.777***	-0.788***	-0.811***	-0.758***	-0.763***	-0.768***	-0.789***	-0.803***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.013)	(0.012)	(0.013)	(0.012)
prov_name = 78, VAN	-1.572***	-1.556***	-1.600***	-1.609***	-1.589***	-1.588***	-1.578***	-1.572***	-1.582***
	(0.021)	(0.021)	(0.020)	(0.017)	(0.020)	(0.020)	(0.020)	(0.019)	(0.018)

Table 20: Results of fixed effect landuse models, including constant variable dummy coefficients (continued)

	(7.3)	(8.3)	(9.3)	(10.3)	(11.3)	(12.3)	(13.3)	(14.3)	(15.3)
	Rural NTL	Rural NTL	Urban NTL	Urban NTL	Other NTL	Other NTL	All landuse NTL variables	All landuse NTL variables	Reduced Landuse
	linear	quadratic	linear	quadratic	linear	quadratic	linear	quadratic	
prov_name = 79, YALOVA	-0.542***	-0.536***	-0.561***	-0.574***	-0.555***	-0.555***	-0.548***	-0.552***	-0.558***
	(0.012)	(0.012)	(0.012)	(0.013)	(0.014)	(0.014)	(0.013)	(0.014)	(0.014)
prov_name = 80, YOZGAT	-1.065***	-1.071***	-1.101***	-1.133***	-1.039***	-1.040***	-1.060***	-1.086***	-1.115***
	(0.023)	(0.022)	(0.023)	(0.021)	(0.022)	(0.022)	(0.025)	(0.023)	(0.022)
prov_name = 81, ZONGULDAK	-0.982***	-0.976***	-1.020***	-1.037***	-1.015***	-1.015***	-0.995***	-0.994***	-1.000***
	(0.028)	(0.027)	(0.025)	(0.022)	(0.021)	(0.021)	(0.026)	(0.026)	(0.026)
year = 2004	-0.498***	-0.363***	-0.546***	-0.515***	-0.577***	-0.573***	-0.479***	-0.385***	-0.428***
	(0.025)	(0.035)	(0.020)	(0.020)	(0.020)	(0.020)	(0.026)	(0.035)	(0.026)
year = 2005	-0.409***	-0.276***	-0.464***	-0.439***	-0.504***	-0.499***	-0.390***	-0.298***	-0.341***
	(0.027)	(0.036)	(0.020)	(0.020)	(0.019)	(0.020)	(0.028)	(0.036)	(0.028)
year = 2006	-0.371***	-0.235***	-0.425***	-0.393***	-0.455***	-0.450***	-0.355***	-0.258***	-0.301***
	(0.025)	(0.034)	(0.019)	(0.019)	(0.018)	(0.019)	(0.025)	(0.035)	(0.027)
year = 2007	-0.349***	-0.215***	-0.405***	-0.373***	-0.424***	-0.419***	-0.335***	-0.239***	-0.284***
	(0.023)	(0.033)	(0.018)	(0.018)	(0.017)	(0.018)	(0.024)	(0.034)	(0.025)
year = 2008	-0.349***	-0.218***	-0.395***	-0.363***	-0.418***	-0.413***	-0.332***	-0.241***	-0.283***
	(0.022)	(0.033)	(0.018)	(0.018)	(0.017)	(0.018)	(0.023)	(0.033)	(0.024)
year = 2009	-0.392***	-0.256***	-0.421***	-0.394***	-0.460***	-0.455***	-0.365***	-0.281***	-0.324***
	(0.022)	(0.033)	(0.019)	(0.019)	(0.016)	(0.017)	(0.022)	(0.033)	(0.023)
year = 2010	-0.324***	-0.196***	-0.358***	-0.322***	-0.383***	-0.378***	-0.304***	-0.216***	-0.255***
	(0.020)	(0.031)	(0.017)	(0.017)	(0.016)	(0.017)	(0.021)	(0.031)	(0.022)
year = 2011	-0.256***	-0.140***	-0.285***	-0.254***	-0.302***	-0.297***	-0.237***	-0.160***	-0.197***
	(0.018)	(0.027)	(0.016)	(0.016)	(0.015)	(0.016)	(0.019)	(0.027)	(0.019)
year = 2012	-0.244***	-0.159***	-0.261***	-0.235***	-0.274***	-0.270***	-0.233***	-0.175***	-0.198***
	(0.016)	(0.021)	(0.015)	(0.015)	(0.015)	(0.015)	(0.016)	(0.021)	(0.016)
year = 2013	-0.202***	-0.149***	-0.216***	-0.201***	-0.219***	-0.217***	-0.198***	-0.162***	-0.178***
	(0.015)	(0.017)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.017)	(0.015)
year = 2014	-0.170***	-0.114***	-0.189***	-0.179***	-0.189***	-0.186***	-0.168***	-0.135***	-0.153***
	(0.015)	(0.017)	(0.015)	(0.014)	(0.015)	(0.015)	(0.015)	(0.018)	(0.015)
year = 2015	-0.130***	-0.080***	-0.149***	-0.143***	-0.145***	-0.143***	-0.128***	-0.101***	-0.119***
	(0.016)	(0.017)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.017)	(0.015)
year = 2016	-0.109***	-0.070***	-0.126***	-0.127***	-0.121***	-0.119***	-0.110***	-0.093***	-0.108***
	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)
year = 2017	-0.059***	-0.039**	-0.072***	-0.079***	-0.067***	-0.066***	-0.064***	-0.060***	-0.068***
	(0.016)	(0.015)	(0.016)	(0.015)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)
year = 2018	-0.038**	-0.021	-0.050***	-0.057***	-0.046***	-0.045***	-0.043**	-0.041**	-0.047***
	(0.017)	(0.016)	(0.017)	(0.016)	(0.017)	(0.017)	(0.017)	(0.016)	(0.016)
year = 2019	-0.039**	-0.034**	-0.044**	-0.048***	-0.042**	-0.042**	-0.042**	-0.044***	-0.045***
	(0.018)	(0.017)	(0.018)	(0.017)	(0.018)	(0.018)	(0.018)	(0.017)	(0.017)
Observations	1,377	1,377	1,377	1,377	1,361	1,361	1,361	1,361	1,377
R-squared	0.968	0.969	0.968	0.969	0.968	0.968	0.969	0.971	0.970
Province FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES
Random Coefficients	NO	NO	NO	NO	NO	NO	NO	NO	NO
Adjusted R-squared	0.965	0.966	0.965	0.967	0.965	0.965	0.966	0.968	0.968
AIC	-3096	-3139	-3095	-3170	-3054	-3053	-3093	-3179	-3202
BIC	-2584	-2622	-2583	-2653	-2543	-2537	-2572	-2642	-2679
Number of groups									
Unstructed Covariance									

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
The base constant for year and province fixed effects is set to 2020 and İstanbul respectively

Table 21: Results of fixed effect landuse models, including constant variable dummy coefficients (continued)

A. TURKISH SUMMARY / TÜRKÇE ÖZET

Gayri Safi Yurtiçi Hasıla (GSYH) ekonomik analizlerin temel değişkelerinin başında gelmektedir. Ülkelerin ve bölgelerin ekonomik performansını ve yaşam standartlarını ölçmek için kullanılan en önemli değişkenlerden biridir. Bununla birlikte, ekonomik büyümenin doğru bir şekilde ölçülmesinin önünde bazı zorluklar bulunmaktadır. Özellikle gelişmekte olan ülkelerde bu zorluklar ciddi boyutlarda olabilmektedir. Kayıt dışı ekonominin doğru tahmin edilememesi, ülkelerin veri toplama kapasitelerinin yetersizliği ve hızlı fiyat değişimleri bu zorlukların başlıca nedenleri arasında yer almaktadır. Ülkelerin üretim gücünü gösteren en önemli değişken olan GSYH'nin bu nedenlerden dolayı doğru ölçülememesi ihtimali, ülkelerin ekonomik performansının doğru değerlendirilememesine ve ülkede uygulanan politikaların etkinsizliğine yol açabilmektedir.

Gece ışıkları (NTL) verilerinin kullanımı ekonomik faaliyetlerin ölçümünde umut verici bir alternatif olarak ortaya çıkmıştır. Gece ışıklarının ekonomik ölçüm ve tahmin için kullanılması, gelişmişlik düzeyi ve geliri yüksek olan bölgelerin daha fazla tüketip üretebildiği ve bunun bir yansıması olarak geceleri gökyüzüne daha fazla yapay ışık yaydığı düşüncesine dayanmaktadır.

Bu çalışma, yüksek çözünürlüklü gece ışıkları verilerini kullanarak Türkiye'nin il bazında kişi başına düşen GSYH'sini ölçmeyi ve Türkiye örneği için kişi başına düşen GSYH gece ışığı ilişkisinin dinamiklerini araştırmayı amaçlamaktadır.

Bu çalışmanın yeniliği, gece ışıkları verilerini, arazi kullanım sınıflandırmalarını ve nüfus dağılımlarını entegre ederek ekonomik faaliyeti tahmin etmeye yönelik yaklaşımıdır. Bu, coğrafi nüfus verilerinin arazi kullanım kategorilerine göre ayrıştırılmış gece ışıkları verilerinin üzerine bindirilmesiyle elde edilmiş ve ekonomik modellerin daha ayrıntılı ve anlayışlı bir analizini sağlamıştır. Çalışmada arazi kullanım türleri kentsel, kırsal ve diğer olarak sınıflandırılmış ve bu bölgelerden yayılan gece ışıkları ile kişi başına düşen GSYH arasındaki ilişkideki farklılaşma incelenmiştir.

Yapılan hesaplamaların hata düzeyi genellikle doğudan batıya doğru azalmakta, ancak Batı Karadeniz bölgesinde Zonguldak, Bartın, Karabük ve Çankırı gibi illerde yüksek kalmaktadır. Akdeniz Bölgesi'nde, özellikle Antalya'da, COVID-19 salgınının turizm üzerindeki etkisi nedeniyle tahmin hataları artmıştır. Tahmin edilen kişi başına GSYH'nin resmi değerlere oranı incelendiğinde, Van, Ağrı ve Şanlıurfa gibi doğu illerinde oranların yüksek olduğu, batıdaki büyük şehirlerde ve sanayi merkezlerinde ise daha düşük olduğu görülmektedir.

Hu ve Yao'nun (2019) belirttiği gibi, gece ışıkları ile GSYH arasında doğrudan bir ilişki olduğunu varsaymak yanlış olacaktır. Öncelikle, bu iki değişken arasındaki ilişkide bir içsellik sorunu vardır. GSYH gece ışıklarının bir belirleyicisi olabileceği gibi, gece ışıkları da GSYH'nin bir belirleyicisi olabilir. Dahası, ışık kullanım alışkanlıkları bölgeden bölgeye ve kültürden kültüre değişebilir. Bu da bu iki değişken arasındaki ilişkiyi karmaşık hale getirebilir. Son olarak, bölgelerdeki tüm ekonomik gelişmeler gece ışıklarına tam olarak olumlu ya da olumsuz yansımayabilir. Ayrıca, gece ışık analizleri GSYH'nin yerine geçmez ve GSYH'de olduğu gibi bu yöntemde de çeşitli eksiklikler ve sınırlamalar vardır. Örneğin, uydu verilerindeki hatalar, yanlış hesaplamalar ve gece ışık yoğunluğunu etkileyen atmosferik koşullar bu yöntemin güvenilirliğini sınırlayabilir. Bu tür yöntemler yalnızca GSYH'ye ek veya tamamlayıcı analizler için kullanılabilir.

Mekansal veriler, mekansal dinamikler ve ekonomik faaliyetler arasındaki ilişkiyi anlamak için ekonomi biliminde sıkça kullanılmaya başlanmıştır. Araştırmacılar uydu görüntüleri, arazi kullanımı veya diğer çeşitli veri setleri gibi mekansal verileri inceleyerek bölgesel kalkınma, kentleşme, eşitsizliğin ölçülmesi ve bu çalışmada olduğu gibi GSYH tahmini üzerinde çalışmışlardır. Ekonomik süreçleri ve çıktıları modelleme ve görselleştirme yeteneği, coğrafi veri setlerini ekonomik çalışmalarda önemli kılmaktadır.

Elvidge ve diğerleri (2013) çalışmalarında, Visible Infrared Imaging Radiometer Suite'in (VIIRS) çözünürlük, dinamik aralık, niceleme ve kalibrasyon açısından daha iyi performans göstermesi nedeniyle gece ışıkları için DMSP verilerinden daha üstün olduğunu savunmaktadır. Mathen ve diğerleri (2024), DMSP ve VIIRS gece ışığı verilerini kullanarak Hindistan'daki ekonomik faaliyet ve bölgesel eşitsizlik üzerine yaptıkları çalışmada, VIIRS veri setini kullanmanın, birincisinin daha yüksek çözünürlüğü ve nispeten daha düşük hesaplama hatası yetenekleri nedeniyle DMSP veri setini kullanmaktan daha doğru sonuçlar verdiğini bildirmiştir.

DMSP (1992-2013) ve VIIRS'in 2012 sonrası gece ışık verileri, uydu sistemlerindeki farklılıklar nedeniyle tutarsızdır. Bu nedenle, gece ışık verilerinin zamansal kapsamını geliştirmek için bu ikisini birleştirmek için bazı çabalar gösterilmiştir. Li ve diğerleri (2020) DMSP ve VIIRS verilerini birleştirerek 1 km çözünürlükte uyumlu bir gece ışık veri seti oluşturmuştur. Chen ve diğerleri (2021) derin öğrenme yöntemlerini kullanarak DMSP ve VIIRS verilerini kullanarak yüksek çözünürlüklü bir veri kümesi geliştirmiştir. Chen ve diğerleri tarafından geliştirilen bu veri seti bu çalışmada da kullanılmıştır.

Henderson ve diğerleri (2012) tarafından geliştirilen yöntem, kişi başına düşen GSYH (Hu ve Yao, 2019) ve GSYH büyüme düzeltmeleri (Beyer, Hu ve Yao, 2022) ile ilgili başka çalışmalarda da uygulanmıştır. 2022 yılında yaptıkları çalışmada, Yükselen Piyasa ve Gelişmekte Olan Ekonomilerde üç aylık gece ışık büyümesi ile GSYH büyümesi arasındaki korelasyonun gelişmiş ekonomilere göre daha yüksek olduğunu bulmuşlardır. Ayrıca, Hu ve Yao'nun (2019) çalışması, gece ışıklarının GSYH'ye göre esnekliklerinin ikinci dereceden bir ilişkiye sahip olduğunu göstermiştir. Aynı çalışmada, Afrika'daki ülkelerin hızla büyümesine rağmen, düşük gelir seviyeleri ve elektriğe sınırlı erişimleri nedeniyle ekonomik büyümelerinin gece ışıklarına beklendiği gibi yansımadığını vurguladıklarını belirtmek önemlidir.

McCord ve Rodriguez-Heredia (2022) gece ışıklarını kullanarak Paraguay'ın ulus-altı düzeydeki GSYH'sini tahmin etmiş ve özellikle ayrıntılı veri toplama eksikliğinin olduğu durumlarda gece ışığı tahmininin faydalı olabileceğini öne sürmüştür. Ehsan ve diğerleri (2024), Henderson ve diğerlerinin (2012) yaklaşımını temel alarak, Bangladeş'in 64 ilçesi için 1992'den 2020'ye kadar gece ışık verilerini kullanarak ilçe düzeyinde GSYH'yi tahmin etmek için bir metodoloji geliştirmiştir.İlçe düzeyinde GSYH tahminlerini iyileştirmek için tarım, sanayi ve hizmet sektörleri için üretken gece ışık emisyonları arasında ayrım yapmışlardır.Son olarak, Chen ve diğerleri (2024) Türkiye için arazi kullanımı ve sektörel GSYH kırılımlarını kullanarak havuzlanmış-OLS, tahminciler arası ve tahminci içi modeller oluşturmuştur. En yüksek GSYH-gece ışık yoğunluğu esnekliğinin sanayi sektöründe (%1,14) olduğunu ve bunun da endüstriyel ekonomik faaliyetlerin gece ışıkları tarafından daha iyi yakalandığını gösterdiğini bulmuşlardır.

Çalışma, gece ışıklarının bir bölgenin ekonomik kalkınması için bir gösterge olduğu yaklaşımına dayanmakta ve teorik çerçeve, yüksek çözünürlüklü uydu görüntülerinden elde edilen gece ışığı verileri aracılığıyla ekonomik ilişkiyi yorumlamaya odaklanmakta ve gece ışığı verilerini kullanarak Türkiye'de il bazında GSYH'yi tahmin etmek için bir araç geliştirmeye çalışmaktadır.

Modeller, değişkenler arasındaki ilişkinin birimler arasında değişmesine izin veren ve sabit etkiler modellerinin ele alamadığı heterojenliği yakalayan rastgele katsayılar spesifikasyonu kullanılarak oluşturulmuştur.

Kişi başına düşen gece ışık yoğunluğu ile kişi başına düşen GSYH arasındaki ilişki, kişi başına düşen aydınlatılmış piksel sayısı ve kişi başına düşen elektrik tüketimi değişkenleri ile karşılaştırılmıştır. Ayrıca model seçimi için Akaike Bilgi Kriteri (AIC) ve Bayesian Bilgi Kriteri (BIC) metrikleri kullanılmıştır.

Bu çalışmada Türkiye İstatistik Kurumu (TÜİK) verilerinin yanı sıra çeşitli coğrafi veri setleri de kullanılmıştır. İl düzeyindeki GSYH verileri TÜİK'in ulusal hesaplar veri tabanından alınmıştır. Çalışmanın zamansal odağıyla uyumlu olması için zincirlenmiş hacim değerleri uygulanmıştır. TÜİK'ten alınan elektrik tüketimi verileri de 1995'ten 2021'e kadar çeşitli kategorilere göre kullanımı detaylandırarak ve toplam elektrik tüketimini Mwh birimlerinde sunarak sağlanmaktadır.

Gece ışığı (NTL) verileri, özellikle DMSP ve VIIRS gibi uydu sistemlerinden elde edilen görüntüler aracılığıyla ekonomik faaliyetlerin yoğunluğunu ve mekansal dağılımını analiz etmek için önemli bir araç haline gelmiştir. 1990'ların başından 2013 yılına kadar faaliyet gösteren DMSP-OLS uydusu ekvatorda yaklaşık 1 km çözünürlüğe sahipti. Bununla birlikte, veri setinin maksimum piksel değeri 63 ile sınırlıydı ve bu da ışık yoğunluklarının ortalamadan önemli ölçüde yüksek olduğu şehir merkezlerinde toplam ışık yoğunluğunun düşük tahmin edilmesine yol açıyordu. 2012'den beri faaliyette olan VIIRS uydusu, ekvatorda yaklaşık 500 m çözünürlük ve radyometrik kalibrasyon ile DMSP-OLS'yi geliştirdi. Bu geliştirmeler gürültü ve parlamayı azaltırken, özellikle gece ışık emisyonlarının yoğunlaştığı kentsel alanlarda daha hassas ışık yoğunluğu ölçümlerine olanak sağlamıştır.

İl gece ışık yoğunluğu, Türkiye'nin İl İdari Sınırları sınıflandırmasında tanımlandığı gibi il sınırları içindeki piksel değerlerinin toplanmasıyla hesaplanmıştır. Ayrıca, her ilin sınırları içindeki toplam yanan piksel sayısı da hesaplanmıştır. Bu hesaplamalar 2000-2023 yıllarını kapsamakta ve ekonomik büyüklük ile gece ışık emisyonları arasındaki ilişkiyi analiz etmek için kapsamlı bir veri seti sağlamaktadır.

Bu çalışma, gece ışık verilerinin kişi başına düşen GSYH'ye göre esnekliğini, ışığı yayan arazi türünü hesaba katarak incelemektedir. Türkiye'deki arazi kullanımını sınıflandırmak için Terra ve Aqua kombine Orta Çözünürlüklü Görüntüleme Spektroradyometresi (MODIS) Arazi Örtüsü Tipi (MCD12Q1) Sürüm 6.1 veri seti kullanılmıştır. Bu veri seti, MODIS yansıma verilerinin denetimli sınıflandırmaları yoluyla elde edilen 2001'den 2023'e kadar yıllık küresel arazi örtüsü türlerini sağlar. Arazi örtüsü sınıflandırma şemaları, diğerlerinin yanı sıra Uluslararası Jeosfer-Biyosfer Programı (IGBP) ve Maryland Üniversitesi (UMD) sistemini içermektedir. Türkiye için kapsamlı arazi kullanım haritaları üretmek amacıyla MODIS HDF dosyaları TIF formatına dönüştürülmüş ve Türkiye'nin sınırları temel alınarak birleştirilmiştir.

MODIS arazi kullanım verileri, araziyi 17 tipe ayırmaktadır ve bu tipler çalışmanın yazarı tarafından daha geniş kategorilere ayrılmıştır: doğal ormanlar, çalılıklar, otlaklar, tarım alanları, kentsel alanlar, sulak alanlar ve su kütleleri ve çorak araziler.

Örneğin, arazi kullanım tipleri 1-5 doğal ormanlar, tip 6-7 çalılık alanlar ve tip 13 kentsel alanlar olarak gruplandırılmıştır. Ek bir meta-gruplandırma doğal ormanları, çalılıkları, otlakları ve tarım alanlarını kırsal arazi olarak sınıflandırırken kentsel alanlar ayrı olarak kategorize edilmiştir. Bu gruplandırma, sanayi ve hizmet sektörlerinin kentsel alanlarda, tarım sektörünün ise kırsal alanlarda yoğunlaşması nedeniyle kişi başına düşen GSYH ve gece ışık modellemesinde farklı sonuçlar elde etmeyi amaçlamıştır.

TÜİK'in il bazlı nüfus verilerinin coğrafi detay açısından sınırlılıkları göz önüne alındığında, çalışmada 2000-2020 yılları arasında yüksek çözünürlüklü mekansal nüfus dağılımı verileri sağlayan WorldPop veri seti kullanılmıştır. Bu veri seti, nüfus sayımı verilerini, uydu görüntülerini ve yardımcı veri setlerini birleştirerek 100m²'lik mekansal tabanlı nüfus verisi hücrelerinde nüfus dağılımını tahmin etmektedir. Ayrıntılı mekansal çözünürlük, zaman içindeki demografik değişikliklerin derinlemesine analiz edilmesini sağlar.

TÜİK'in resmi nüfus verileri ile WorldPop'un mekansal nüfus dağılımı verileri karşılaştırıldığında 0,9986 gibi yüksek bir korelasyon katsayısı ortaya çıkmakta ve mekansal nüfus verilerinin bu çalışma için geçerliliği teyit edilmektedir. Nüfus verileri, kişi başına düşen değişkenleri hesaplamak için gece ışığı ve GSYH verileri ile entegre edilmiştir. Gece ışık yoğunluğu ve aydınlatılan piksel sayısı mekansal nüfus verilerine bölünerek kişi başına düşen değerler elde edilirken, kişi başına düşen GSYH TÜİK'in zincirleme hacim GSYH rakamlarının mekansal nüfus değerlerine bölünmesiyle hesaplanmıştır.

Özellikle kentsel alanlarda GSYH ile toplam gece ışık yoğunluğu arasında güçlü bir korelasyon vardır. Bu gözlem, imalat ve hizmetler gibi gelişmiş ekonomik faaliyetlerin kentsel bölgelerde yoğunlaşması ve kırsal alanlara kıyasla daha yüksek nüfus yoğunluğu ile uyumludur. Buna karşılık, kırsal kesimde gece ışıkları ile GSYH arasındaki nispeten daha düşük korelasyon, ağırlıklı olarak gündüz gerçekleşen tarımsal faaliyetlere bağlanabilir. Bu farklılık, gece ışıklarını bir vekil olarak kullanırken kırsal ekonomik faaliyetin potansiyel olarak düşük tahmin edildiğinin altını çizmektedir. Ayrıca, kentsel ve toplam gece ışık yoğunluğu arasındaki %94,8'lik korelasyonun da gösterdiği gibi, kentsel alanlar toplam gece ışık yoğunluğunu önemli ölçüde etkilemektedir.

Yoğunluktan bağımsız olarak gece ışıklarının mekansal dağılımının bir göstergesi olan aydınlık piksel sayısı, ekonomik faaliyetlerin dağılımına ilişkin bilgiler sağlar. Kapsamlı sokak aydınlatması ile karakterize edilen kentsel alanlar, kırsal alanlara kıyasla yanan piksel sayısı ile GSYH arasında daha güçlü bir korelasyon sergilemektedir. Buna ek olarak, elektrik tüketimi de GSYH ile güçlü bir korelasyon göstermektedir.

Kişi başına düşen gece ışık yoğunluğu ile kişi başına düşen GSYH arasında pozitif ve ikinci dereceden bir ilişki ortaya çıkmaktadır, çünkü daha yüksek gece ışık yoğunluğu, GSYH'ye göre gece ışıklarının artan esnekliğine karşılık gelmektedir. Bu durum, özellikle az gelişmiş illerde altyapı yatırımlarından daha yüksek getirili ekonomik faaliyetlere doğru bir geçişe işaret etmektedir. Buna karşın, gelişmiş illerde kişi başına gelir artışının gece ışık yoğunluğundaki artışı aştığı bir değişim görülmektedir. Aydınlatılan piksel sayısı ve elektrik tüketimi tamamlayıcı veri kaynakları olarak bölgesel ekonomik kalkınmanın anlaşılmasını geliştirmekte ve metrikler arası karşılaştırmalara olanak sağlamaktadır.

Özet istatistikler iller arasında gece ışık yoğunluğu, aydınlatılmış piksel sayısı, elektrik tüketimi ve GSYH açısından önemli farklılıklar olduğunu ortaya koymaktadır. Değişkenlik kısmen yüzölçümündeki farklılıklardan kaynaklanmaktadır, ancak kişi başına düşen ölçümler bölgesel dinamikler hakkında daha net bir görüş sağlamaktadır. Kişi başına ortalama gece ışık yoğunluğu (NTL_pp) ekonomik eşitsizlikleri vurgularken, gece ışık yoğunluğundaki değişiklikler (dif_ln_NTL_pp) hem hızlı büyüme hem de düşüş yaşayan bölgeleri göstermektedir.

Gece ışık yoğunluğu ve nüfusun arazi kullanım türüne göre dağılımı incelendiğinde, kentsel alanların her iki ölçütte de baskın olduğu görülmektedir. Otlaklar ve tarım arazileri de kırsal bölgelerdeki önemlerini yansıtan önemli paylara sahiptir. Kişi başına düşen GSYH ile kişi başına düşen gece ışık yoğunluğu arasındaki pozitif ilişki, arazi kullanım türleri arasında belirgindir ve kentsel alanlar kırsal alanlardan daha dik eğriler sergilemektedir. Bu durum, kırsal bölgelerde tarımın aksine kentsel alanlarda yüksek değerli sanayi ve hizmet sektörlerinin baskın olmasından kaynaklanıyor olabilir. Kırsal alanlarda ilişki daha doğrusal iken, kentsel alanlarda artan ışık yoğunluğunun GSYH'ye yansıması daha kademeli ancak daha güçlüdür.

Çalışmanın bulguları, gece ışık yoğunluğu ve GSYH arasındaki ilişkinin kapsamlı bir analizini sağlamak üzere sistematik olarak üç ana bölümde düzenlenmiştir. İlk bölümde kişi başına düşen gece ışık yoğunluğunun kişi başına düşen GSYH'ye göre esnekliği incelenmektedir. Net ve pozitif bir korelasyon ortaya çıkmakta ve ilişki ikinci dereceden olarak nitelendirilmektedir. Bu durum, gece ışık yoğunluğu arttıkça, kişi başına düşen GSYH ile ilgili esnekliğinin de arttığını göstermektedir. Bu olgu, bölgelerde altyapı odaklı yatırımlardan daha yüksek getiri sağlayan ekonomik faaliyetlere geçişi yansıtmaktadır ve özellikle az gelişmiş illerde belirgin bir dinamiktir. Buna karşılık, gelişmiş illerde bu ilişki değişmekte ve kişi başına düşen GSYH büyümesi gece ışık yoğunluğundaki artışı geride bırakmaktadır. Bu bulgular, gece ışık verilerinin ekonomik faaliyet için bir vekil olarak çok yönlülüğünün ve bölgesel kalkınmanın incelikli modellerini ortaya çıkarma kapasitesinin altını çizmektedir.

İkinci bölüm, farklı arazi kullanım kategorilerinde kişi başına düşen gece ışık yoğunluğu ile kişi başına düşen GSYH arasındaki ilişkiyi analiz ederek ilk bölümdeki bulguları temel almaktadır. Arazi kullanımını kentsel, kırsal ve diğer alanlar olarak kategorize eden bu bölüm, bölgeler arasındaki keskin zıtlıkları vurgulamaktadır. Kentsel alanlar, önemli ölçüde ışık üreten sanayi ve hizmet faaliyetlerinin yaygınlığı nedeniyle gece ışık yoğunluğu ile GSYH arasında çok daha güçlü bir ilişki sergilemektedir. Buna karşılık, tarımsal faaliyetlerin baskın olduğu kırsal alanlar, bu tür faaliyetler tipik olarak gece ışığı yaymadığı için daha zayıf bir korelasyon göstermektedir. Analiz, kentsel gece ışık yoğunluğu değişkenlerinin en önemli belirleyiciler olduğunu, kırsal ve diğer arazi kullanım kategorilerinin genel ilişkiye daha az katkıda bulunduğunu ortaya koymaktadır. Bu farklılaşma, bölgeler arasında değişen ekonomik faaliyet dinamiklerini yakalamak için verilerin arazi kullanımına göre ayrıştırılmasının önemini vurgulamaktadır.

Üçüncü ve son bölüm, seçilen modellerin tahmin kabiliyetlerini ve hata yapılarını değerlendirerek bölgesel farklılıklara ilişkin içgörüler sunmaktadır. İkinci dereceden özellikler içeren ve korelasyonlu katsayılara izin veren modeller, doğruluk ve sağlamlık açısından diğerlerinden daha iyi performans göstermektedir. Bunlar arasında, kişi başına düşen gece ışık yoğunluğuna odaklanan Model (2.2) en güvenilir model olarak ortaya çıkmaktadır. Bu model doğrusal olmayan ilişkiyi etkili bir şekilde yakalamakta ve gözlemlenen ekonomik modellerle iyi uyum sağlamaktadır. Bununla birlikte, tahmin doğruluğunda önemli bölgesel farklılıklar görülmektedir. Özellikle Batı ve Orta bölgelerdeki yüksek ekonomik faaliyete sahip iller daha dar hata marjları sergilerken, Doğu ve Güneydoğu bölgelerindeki iller daha geniş varyanslar sergilemektedir. Bu farklılıklar, ekonomik faaliyetlerin eşit olmayan dağılımını ve gece ışık verilerini kullanarak daha az gelişmiş bölgelerde GSYH'yi modellemenin zorluklarını vurgulamaktadır.

Çalışmada ayrıca, GSYH'nin modellenmesindeki etkinliklerini değerlendirmek için yanan piksel sayısı ve elektrik tüketimi gibi alternatif değişkenler de incelenmiştir. Elektrik tüketimi hem katsayı büyüklüğü hem de model uyumu açısından gece ışık yoğunluğu ve yanan piksel sayısından daha iyi performans göstermektedir. Bu üstünlük, elektriğin imalat, hizmetler ve konutlarda enerji kullanımı dahil olmak üzere ekonomik faaliyetlerle doğrudan ilişkili olmasına bağlanabilir. İkinci dereceden özellikler, özellikle de korelasyonlu katsayılara izin verenler, karmaşık dinamikleri yakalama ve model esnekliğini artırma yetenekleri nedeniyle tavsiye edilmektedir.

Çalışmanın arazi kullanımına özgü analizleri, gece ışığı ve GSYH ilişkilerinin anlaşılmasını daha da geliştirmektedir. Kırsal, kentsel ve diğer arazi kullanım kategorilerinin regresyon modellerine dahil edilmesiyle yapılan analiz, kentsel alanların gözlemlenen ilişkinin birincil itici gücü olduğunu ortaya koymaktadır. Kentsel gece ışık yoğunluğu değişkenleri, bu alanlarda yüksek değerli sanayi ve hizmet faaliyetlerinin yoğunlaşmasını yansıtan istatistiksel olarak anlamlı katsayılar sergilemektedir. Buna karşılık, tarımın hakim olduğu kırsal alanlar daha zayıf ilişkiler göstermektedir.Bu ayrımları içeren modeller, bölgesel ekonomik dinamiklerin daha ayrıntılı bir görünümünü sunarak gece ışık verilerinin ekonomik etkilerini anlamada bağlama özgü analizlerin önemini ortaya koymaktadır.

Model değerlendirmesinde, artıkların dağılımı bölgeler arasında incelenmiştir. Artıkların dağılımı önemli ölçüde farklılık göstermekte, İstanbul ve Batı Anadolu gibi iller daha geniş varyanslar sergileyen Doğu ve Güneydoğu bölgelerine kıyasla daha dar aralıklar sergilemektedir. Bu örüntüler, iller arasındaki ekonomik kalkınmanın heterojenliğini ve gece ışık verilerinin, özellikle sanayileşmenin veya kentleşmenin daha az olduğu bölgelerde, ekonomik faaliyetin tüm yönlerini yakalamadaki sınırlılıklarını yansıtmaktadır.

Çalışma, gece ışık verilerinin ekonomik faaliyet için değerli bir gösterge sağlarken, tahmin gücünün bölgeler ve arazi kullanım kategorileri arasında farklılık gösterdiği sonucuna varmaktadır. Korelasyonlu katsayılara sahip ikinci dereceden modeller, özellikle Model (2.2), gece ışığı ve GSYH ilişkilerinin karmaşık dinamiklerini yakalamak için en etkili araçlar olarak tanımlanmaktadır. Elektrik tüketimi ve aydınlatılmış piksel sayısı gibi alternatif değişkenlerin dahil edilmesi analizi zenginleştirmekle birlikte, birincil ölçüt olarak gece ışık yoğunluğunun belirgin avantajlarını da vurgulamaktadır. Bulgular, bölgesel ve sektörel farklılıkları hesaba katarak daha doğru ve bağlama duyarlı ekonomik analizler yapılmasını sağlayacak özel modelleme yaklaşımlarına duyulan ihtiyacı vurgulamaktadır.

Bu çalışma, Türkiye'de gece ışıkları ile il GSYH'si arasındaki ilişkinin kapsamlı bir analizini sunmaktadır. Gece ışıklarına ilişkin coğrafi nüfus ve arazi kullanım verilerini kullanan çalışma, il düzeyinde kişi başına düşen GSYH ile gece ışığı yoğunluğu arasındaki ilişkiyi incelemektedir. Sonuçlar, kişi başına düşen gece ışığı değerlerinin kişi başına düşen GSYH'nin istatistiksel olarak anlamlı pozitif bir göstergesi olduğunu ortaya koymaktadır. Ayrıca, önceki araştırmalarla tutarlı olarak (Hu ve Yao, 2019), sonuçlar bu ilişkinin ikinci dereceden olduğunu doğrulamaktadır.

Bu çalışmada, arazi kullanımındaki farklılıkların gece ışıkları ve GSYH arasındaki ilişkiyi nasıl etkilediğini vurgulamak için yüksek çözünürlüklü arazi kullanım verileri kullanılmıştır. Sanayi ve hizmetlerin daha aktif olduğu kentsel alanlarda gece ışıkları ile GSYH arasında daha güçlü bir bağlantı gözlenmektedir. Bu durum, ekonomik merkezlerin bu bağlantıyı şekillendirmedeki rolünü vurgulamaktadır. Buna karşılık, tarımın baskın faaliyet olduğu ve tipik olarak geceleri gerçekleşmediği kırsal alanlar daha basit ve doğrusal bir ilişki göstermektedir.

Modellerin ekonometrik değerlendirmeleri sonucunda, gece ışık verilerini kullanan en sağlam modelin, il düzeyinde kişi başına düşen toplam gece ışık yoğunluğunun karesel formda temsil edildiği model olduğu tespit edilmiştir. Bu modelden elde edilen tahminler üzerinde yapılan hata analizleri, kişi başına düşen gece ışığı ile kişi başına düşen GSYH arasındaki ilişkide bölgesel dinamiklerin incelenmesine olanak sağlamıştır. İstanbul gibi şehirleşmenin yoğun olduğu bölgelerin hata paylarının daha dar olduğu ve bu bölgelerde ilişkinin daha güçlü olduğu görülmüştür. Buna karşılık, TRA (Kuzeydoğu Anadolu) ve TRB (Orta Doğu Anadolu) gibi daha az gelişmiş bölgeler, kişi başına düşen resmi GSYH değerlerini tahminlerden daha düşük göstermektedir. Bu değişkenlik kayıt dışı ekonomi, sektörel farklılıklar veya bölgeye özgü diğer gözlemlenemeyen faktörler gibi etkenlere bağlanabilir. Bu çalışma yalnızca kişi başına düşen gece ışığı ile kişi başına düşen GSYH arasındaki ilişkiyi ampirik olarak incelemeye odaklandığından, bu ilişkiyi etkileyen faktörler gelecekteki araştırmalarda incelenebilir.

Gece ışık yoğunluğunun yanı sıra, GSYH ile aydınlatılan piksel sayısı ve elektrik tüketimi gibi alternatif veriler arasındaki ilişki de analiz edilmiştir. Özellikle elektrik tüketimi modellerinin en sağlam modeller olduğu görülmüştür. Bununla birlikte, özellikle ekonomik verilerin seyrek olduğu bölgelerde gece ışıklarının daha geniş uygulanabilirliği, ekonomik analiz için tamamlayıcı bir araç olarak değerini vurgulamaktadır.

Çalışma aynı zamanda NTL-GSYH ilişkisindeki potansiyel içsellik, ışık kullanımındaki bölgesel ve kültürel farklılıklar ve atmosferik koşullardan kaynaklanan veri gürültüsü gibi sınırlamaları da kabul etmektedir. Bu faktörler ihtiyatlı bir yorumlama gerektirmekte ve tamamlayıcı göstergelere duyulan ihtiyacı vurgulamaktadır.

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