Environ Monit Assess (2020) 192: 790
https://doi.org/10.1007/s10661-020-08735-y

Determination of the nighttime light imagery for urban city population using DMSP-OLS methods in Istanbul

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Received: 9 October 2020 / Accepted: 10 November 2020 / Published online: 26 November 2020

Abstract Demography researchers and scientists have been effectively utilizing advanced technologies and methods such as geographical information systems, spatial statistics, georeferenced data, and satellite images for the last 25 years. Areal interpolation methods have also been adopted for the development of population density maps which are essential for a variety of social and environmental studies. Still, a good number of social scientists are skeptical about such technologies due to the complexity of methods and analyses. In this regard, a practical intelligent dasymetric mapping (IDM) tool that facilitates the implementation of the statistical analyses was used in this study to develop the population distribution map for the Istanbul metropolitan area via night light data provided by the Defense Meteorological Satellite Program's Operational Linescan System (DMSP-OLS) and the census records of the study area. A population density map was also produced using the choropleth mapping method to enable to make a comparison of the traditional and intelligent population density mapping implementations. According to the dasymetric population density map, 38.5% of the study area fell into sparse density category while low, moderate, high, and very high population density class percentages were found to be 9.4%, 5.5%, 2.9%, and 0.1% respectively. On the other hand, the percentages of the same population density classes ranking from sparse to very high in the choropleth map were determined to be 90.7%, 7.3%, 1.7%, 0.3%, and 0%. In the change analysis made as a result of the classification, the changes between the city area and the population were revealed. During this period, the city area and population grew. Spatial change has also been interpreted by comparing it with population changes. There appears to be a remarkable increase in both surface area and population. It is observed that the increase is especially in the south and northwest of the city. With the population increase, the number of new residential areas has increased. It is thought that behind this growth, there are different reasons besides the effect of the increase in residential areas. When the environmental awareness of people has increased more than in the past centuries, new solutions should be produced in order to

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be more controlled, smart, and sustainable while planning the cities of the future. Considering that the development of technology and remote sensing techniques is progressing in parallel with this technology, this study in which GIS technologies integrated with satellite images are used, it is thought that it will contribute positively to the studies in this area in terms of regular development of urban areas, increasing the opportunity to make fast and correct decisions, and creating infrastructure for studies such as monitoring and prevention of illegal housing.

Keywords Areal interpolation · Intelligent dasymetric mapping (IDM) · Night light data · Population density

Introduction

Today, new-generation geographical information sciences (GIS) and technologies, which present practical and easy-to-handle tools for everyone, have facilitated and disseminated the utilization of the spatial analyses in a range of fields in social sciences. Especially for the last 25 years, researches and studies with comprehensive spatial context have become even more popular amongst social scientists (Voss 2007). Goodchild et al. (2000) explain that easy mapping, spatial analysis, and spatial modeling techniques enabled by GIS capabilities have increased the interest in the "spatial social science," and social scientists have discovered that continuously advancing GIS technologies help them generate innovative ideas.

Social sciences mainly focus on the examination of the human relations in a diverse context and therefore comprise a wide range of disciplines adopting different goals and methods. Though social sciences have varying fields of research and studies, still, there are common goals such as describing and interpreting human behaviors; prediction and analysis of commercial, administrative, and social processes; and solution of predicted problems via scientific data and behavioral approach (Goodchild and Janelle 2004). One of the significant phenomena within this process is the "space" context, since it is not possible to examine the interaction/relation between human behaviors and the natural and built-up environments. From this perspective, GIS is a unique asset to comprehend and associate these major concepts with one another. Consequently, the utilization of GIS, as well as a variety of advanced technologies have improved the quality and quantity of the researches aimed at the spatial analysis of the social rules and anomalies. In social sciences, space functions as a framework in which different social processes and social domains are integrated (Goodchild et al. 2000).

The increase in spatial researches in social sciences has also attracted the demographers. Advancements in spatial statistics design, diversity of georeferenced databases, and their availability encouraged the formation of spatial thinking approaches in demography studies (Weeks 2004). In the early 1990s, spatial thinking–based demography studies were rather scarce. However, the emergence of diverse GIS technologies and tools provided noticeable progress in this field (Matthews and Parker 2013).

The early spatial researches in demography in Europe are closely related to the advancements in the field of cartography. The "moral statistics" thematic map (demographic characteristics such as education, crime, poverty, etc.) developed in France by Michel Guerry in 1833 is an example of this. Later on, utilization of advanced technologies and micro data has also become available in demography researches, and enabled sociologists and demographers to frequently benefit from these opportunities (Voss 2007).

Demographic researches comprise the examination of the complex models of interrelated social, behavioral, economic, and environmental events (Matthews and Parker 2013). These multidisciplinary examinations embrace the processes of gathering, manipulating, and analyses of a good number of data required for planning, management, administrative, and political questions and problems. Especially for the last decade, new spatial perspectives have been developed so as to better comprehend and analyze the relations of the human lives with the social and environmental factors. Amongst the spatial data used by the sociologists and the demographers are the remotely sensed ones. Satellite images are beneficial for a good number of interdisciplinary studies such as urbanization, disaster management, demography, archaeology, war and conflict, and environmental management. Nevertheless, according to Hall (2010), utilization of satellite imagery in social sciences is rather limited as also underlined in Blumberg and Jacobsan's "New Frontiers: Remote Sensing in Social Science Researches (Blumberg and Jacobson 1997)," although they are widely used data resources in most of the disciplines of natural sciences since the 1950s. In Blumberg and Jacobsan's study, the authors emphasized that remote sensing capabilities were substantially ignored in social and political researches. Definitely, a good number of social studies supported with remote sensing methodologies have been presented to the literature since then.

The most remarkable demographic studies using remotely sensed data are the population distribution modeling. Currently, global gridded population maps, such as Gridded Rural-Urban Mapping Project (GRUMP), Gridded Population of the World (GPW), and Global Human Settlements Layer (GHLS), are available for the users. Besides, there are several population studies in the literature focusing on the utilization of the satellite images. Kugler et al. (2019) explained the advantages of remote sensing data as well as the widely used data products and methods. Weber et al. (2018) also used satellite images to produce population maps in their study area. Amaral et al. (2005) benefited from DMSP nighttime satellite data to analyze and evaluate the relation between the electric consumption and spatial distribution of the population in Brazilian Amazonia and discussed the socioeconomic outcomes.

To sum up, recent studies show that the need to determine the spatial distribution of the population as well as the dissemination of such kind of data and implementations increase in a good number of fields of social sciences. Areal interpolation methods, which can be classified under two main categories depending on whether ancillary data is used (Wu et al. 2005), such as dasymetric and intelligent dasymetric mapping (IDM) methods, are amongst the mostly preferred ones for modeling population distribution over an area. Nevertheless, despite the advancements, Langford (2007) underlined the fewness of the evidences showing the widespread utilization of intelligent areal interpolation methods amongst the GIS users and emphasized the necessity to develop more simple procedures rather than depending on complex information extraction applications from satellite images. Actually, satellite images are good data inputs and can be used as ancillary data for areal interpolation processes. For example, besides land use and land cover datasets, night light data have recently become one of the most beneficial ancillary data to produce areal population distribution maps. Night light data are based on the experimental observations of the relations between the size of the settlement area and population (Hall 2010). Correspondingly, due to its strong correlation with the population distribution, night light data at varying scales (global or regional) have been used for population distribution mapping studies (Cheng et al. 2007; Elvidge et al. 1999; Sutton et al. 2001). Defense Meteorological Satellite Program's Operational System (DMSP-OLS) has been sharing digital night light data since 1992, and digital DMSP-OLS data have been used as significant inputs for developing global human settlement maps (Elvidge et al. 1997), national urban extent maps (Imhoff et al. 1997), and population and energy consumption studies at national levels (Elvidge et al. 1997). It is also noted that night light data are beneficial for the estimation of the population densities especially in urbanized settlement areas (Sutton 1997). Nevertheless, Tan et al. (2018) explained that using night light imagery as the sole source of ancillary data decreases the accuracy and the consistency of the population mapping works due to some specific problems such as reflections resulting in high light values, differences in characteristics of built-up environments, and spatial resolutions. Therefore, combining light emission and land use/cover data is proposed by the authors to overcome this problem.

Within this context, the main goal of this study is to produce the areal population distribution maps of Istanbul, Turkey, one of the largest and most crowded metropolises in the world, using IDM technique based on the utilization of the night light data as an ancillary dataset. Thus, both an areal population modeling method will be practiced using a new and practical IDM tool enabling fast and simple spatial analyses and outcomes, and a sample study focusing on the use of night light data as ancillary datasets will be presented, especially for the social scientists to encourage the community to adopt and use GIS techniques and remote sensed data. To fulfill the aim of the study, gridded population distribution of Istanbul in 2000 was determined using the IDM method and the tool provided by the US Environmental Protection Agency (EPA). As GIS technologies and remotely sensed data become available and practicable for users, it is no doubt that they will easily be applicable in wider areas of interest.

Dasymetric mapping and IDM

Population is one of the most significant factors to better understand, plan, design, and manage the rural and urban landscapes. Today, inhabited areas change and develop rapidly resulting in a continuous increase in the human population, especially in the cities (Lu and

Guldmann 2012; Lu et al. 2011). A growth by 2–4 billion individuals in the population and an increase in the number of highly urbanized cities are estimated by 2050 (Cohen 2003). Therefore, information related to population is one of the major inputs for a good number of studies. Some authors have investigated the effects of the human population densities on the environmental issues such as biodiversity, species (Cardillo et al. n.d.; Cincotta et al. 2000; Luck 2007a; Spear et al. 2013; Thompson and Jones 1999), and wildfires (Bistinas et al. 2013; Guyette and Spetich 2003; Knorr et al. 2014). Some authors examined the correlation between the population and land use changes (Luck 2007b; Vačkář et al. 2012). Accordingly, determination of the population and its spatial distribution plays an important role for the realization of a wide range of processes.

Census tracts are the main data sources used for the determination of the population distribution. The demographic datasets are usually aggregated to areal units and mapped to represent the population of a whole administrative unit (province, district, town, etc.). This approach is mostly inadequate to determine the spatial distribution of the population over specific areas, since the population is not actually homogeneously distributed within the areal zones, resulting in inaccuracies and failures in particular kinds of studies. One example of this can be the risk and disaster management works, in which risky region boundaries do not overlap with the administrative boundaries at all (Mennis 2003; Wang et al. 2018). Recently, a variety of methods have been used for the determination of the grid-based distribution of the population. The areal interpolation method, which deals with the reallocation of a variable in a source zone to the overlapping targets zones (Kallio et al. 2019), is amongst the most common ones (Bhaduri et al. 2007; Goodchild 1993; Goodchild and Siu-Ngan Lam 1980). Nevertheless, areal interpolation still ignores the potential changes in the population and therefore limits the accuracy of the results (Holt et al. 2004). Moreover, in the population density map produced with the areal interpolation method, sharp changes can be observed throughout the administrative boundaries. Therefore, dasymetric mapping methods, in which high-resolution spatial data (land use, land cover, etc.) are used as ancillary data, are widely used to obtain more accurate and realistic analysis results. For example, Sarkissian et al. (2019) used the dasymetric method to produce accurate population maps from the administrative population and land use and land cover data for disaster risk reduction works in Lebonan. Maroko et al. (2019) benefited from cadastral, building footprint, and building height data to realize a 3D dasymetric mapping study to more accurately determine the locations of the population in São Paulo, Brazil, in a study focusing on exposure to air pollution. The dasymetric mapping method originally developed by Wright (1936) was considered a complex and difficult process in the past. However, the advancements in the GIS technologies and overlaying processes facilitated its implementation (Wu et al. 2005), and increased the benefits of this method in the enhancement of the population data. Still, some uncertainties in the dasymetric modeling resulting from the uncertainty of the census data itself or the connection between the population and the ancillary data are underlined (Nagle et al. 2014). Wu et al. (2005) explained that although dasymetric mapping promises a good number of advantages when compared with the traditional choropleth mapping techniques, there are yet deficiencies, such as the ignorance of the differences between the subzones of the ancillary data. In the IDM method, on the other hand, classified ancillary datasets help overcome such problems and increase the accuracy of the interpolation. This is because level-zone interpolation is used in dasymetric mapping, while IDM is based on pixel-level interpolation providing more accurate results.

Materials and method

Study area

The study area is Istanbul, the most populated and developed metropole of Turkey, located between the coordinates of 41° 0′ 29.52″ N and 29° 58′ 42.24″ E. The province lies on the northwest part of the country and encloses the Bosphorus and Golden Horn. The overall area of the province is 5712 km^2 including the islands on the Marmara Sea. There are 39 districts, 782 neighborhoods, and 152 villages within the province (Fig. 1).

According to the 2019 records of the Turkish Statistical Institute (TUIK), 18.66% of the country population, which is 15,519,267 inhabitants, resides in Istanbul. The increase in 2018 recorded 451,543 inhabitants. Due to its geopolitical position, Istanbul offers a wide range of opportunities in terms of employment, education, and health and cultural facilities that have resulted

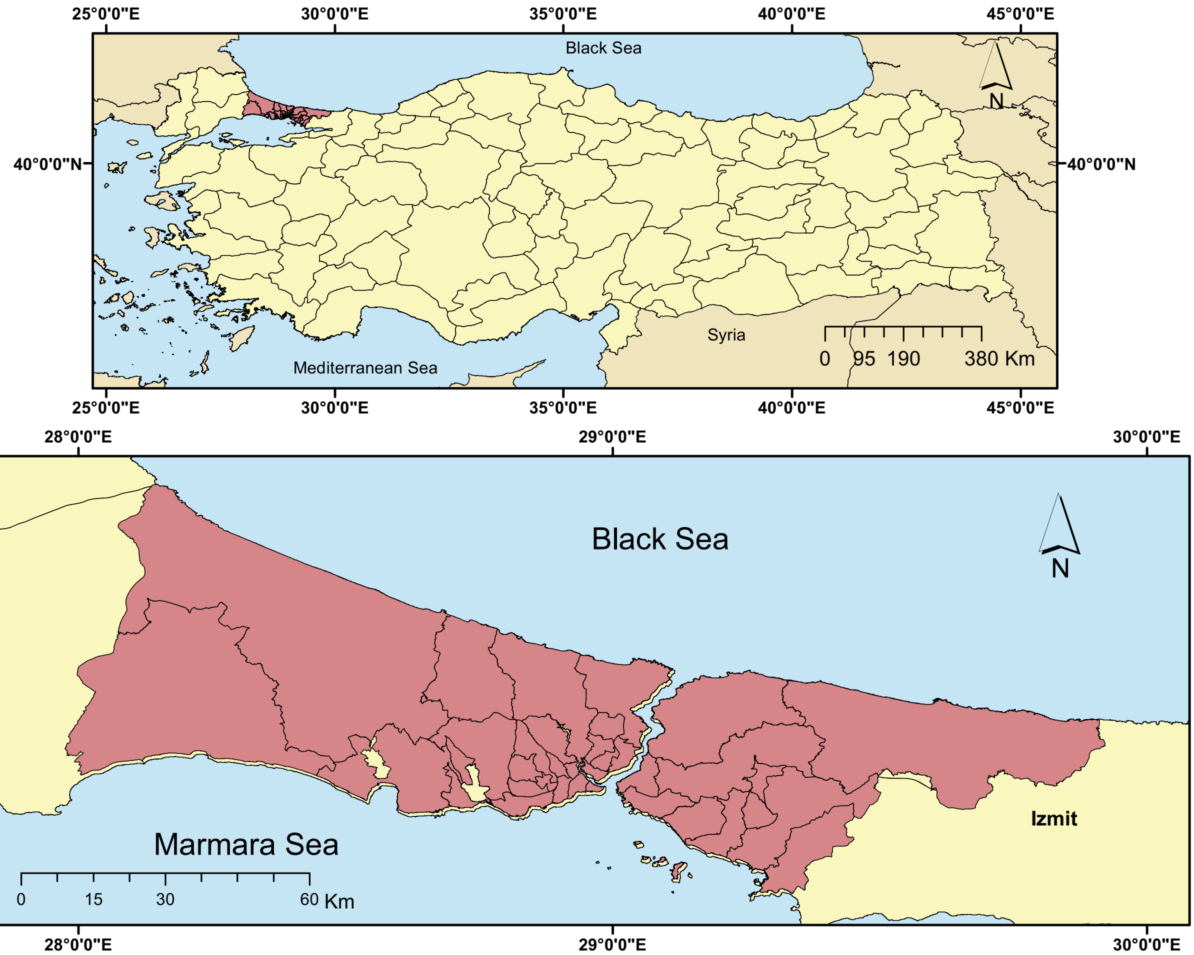


Fig. 1 Location of the study area

in dense immigration and ranked the province amongst the most populated cities in the world. The number of inhabitants living in Istanbul is even above the total population of a good number of countries.

Uncontrolled rapid population growth, especially in the developing countries like Turkey, leads to a diversity of environmental and social problems such as pollution, environmental degradation, increased pressure on resources, destruction of ecosystems, informal settlement, unemployment, etc. (Uysal et al. 2018). Therefore, demographic studies and researches play an important role for the future of the city. The current demographic studies on Istanbul mostly focus on urbanization problems and immigration. For example, Tandoğan (1989) highlighted the place and significance of Istanbul in terms of population activities in the country. Gürel and Balta (2011) studied the migration potential and population ethnicity of Istanbul. Menteşe et al. (2019) evaluated the social vulnerability in Istanbul against natural disasters. However, the studies including the utilization of spatial demographic analyses methods mostly concentrate on issues and fields such as environmental factors, land use, landscape architecture, and city planning (Çakir et al. 2008; Geymen and Baz 2008; Kaya and Curran 2006). Unfortunately, spatial analyses and mapping techniques have been scarcely used in social and economic studies related to population movements in Istanbul.

Yet, it is of great significance to examine and evaluate the demographic structure of the city using current advanced technologies and spatial analysis methods, since demography is directly and indirectly linked with a good range of factors such as economic, cultural, and social developments and physical planning activities. Therefore, this study aims to produce the spatial population distribution map of Istanbul using GIS technologies and spatial data, which has recently become widespread amongst the social scientists and demographers worldwide.

Materials

The main materials of the study are the night light images, settlement area maps, and census data of Istanbul province. The spatial and non-spatial data related to the study area were provided from various sources (Table 1).

In the study, 2000 census data was used, since it was the last traditional census (on-site counting) work, before switching to the national address–based population register system in 2007, in the country. Despite providing efficient and fast census operations, the address-based population register system has also brought some inaccuracies and deficiencies (false or incomplete address declaration of individuals) in the population records resulting from actions such as temporary address information changes/updates prior to the elections and school registrations. Therefore, by using year 2000 data, it was aimed to obtain more consistent results for accuracy analysis. Census data was provided from TUIK on a district basis. In 2000, Istanbul was administratively divided into 32 districts; therefore, the data of the study represents population information for 32 districts.

The night light data for Istanbul captured by DMSP-OLS and produced by NOAA-NGDC were downloaded from https://www.ngdc.noaa.gov/eog/dmsp/downloadV4composites.html. In this study, a year 2000 stable night light composite for Turkey/Istanbul was used. The values of the dataset including the digital values varying between 0 and 63 (DN) represent the brightness of the night lights. DMSP-OLS data have been indicated as a valuable information source to distribute the population into density surfaces (Turner and Openshaw 2001). Considering its nature and the spatial resolution, the DMSP nighttime light is the most suitable data source to represent the urban concentration and extension at continental and global scales (Sutton et al. 2001). The night light composites, which have been used for a variety of demography studies, are made up of the lights detected by sensors from highly urbanized areas with high amounts of brightness as well as from less lightened rural regions (Lowe 2012). The night light data are then classified in accordance with light levels. Figure 2 shows the year 2000 night light data for Istanbul City.

The global settlement area datasets produced by the European Commission are accessible from https://ghsl.jrc.ec.europa.eu/data.php. Estimations were performed with GHLS-Build Up, and GHS-Population Grid data were used for accuracy tests. Figure 3 shows the classified population density grid map (GHS-Population Grid) for Istanbul in 2000.

Methods

The main method of this study is the IDM method which was used for the development of the areal population density in ArcGIS environment. Linear correlation was calculated in SPSS (Statistical Package for the Social Sciences) for the determination of the accuracy of the results.

In the IDM method, source data and classified ancillary data are used as inputs. During the IDM process, source data is redistributed in accordance with the combinations of the areal weight and relative density of the ancillary data (Mennis 2003). This type of mapping is used for a variety of studies where users want to increase the precision of the spatially gathered data, for example,

Table 1 Data sources of the study

Data name	Data type	Data source
Administrative boundaries	Vector	The Database of Global Administrative Areas (GADM)
Night lights	Raster ($1\ km^2$)	NOAA-NGDC (National Oceanic and Atmospheric Administration-The National Geophysical Data Center) F142000.v4b_web.stable_lights.avg_vis.tif
Settlement areas	Raster ($1\ km^2$)	European Commission Global Human Settlements GHS_SMOD_POP2000_GLOBE_R2016A_54009_1k_v1_0.tif (2000) GHS_BUILT_LDS2000_GLOBE_R2016A_54009_1k_v1_0.tif (2000)
Population	Text	Turkish Statistical Institute (2000)

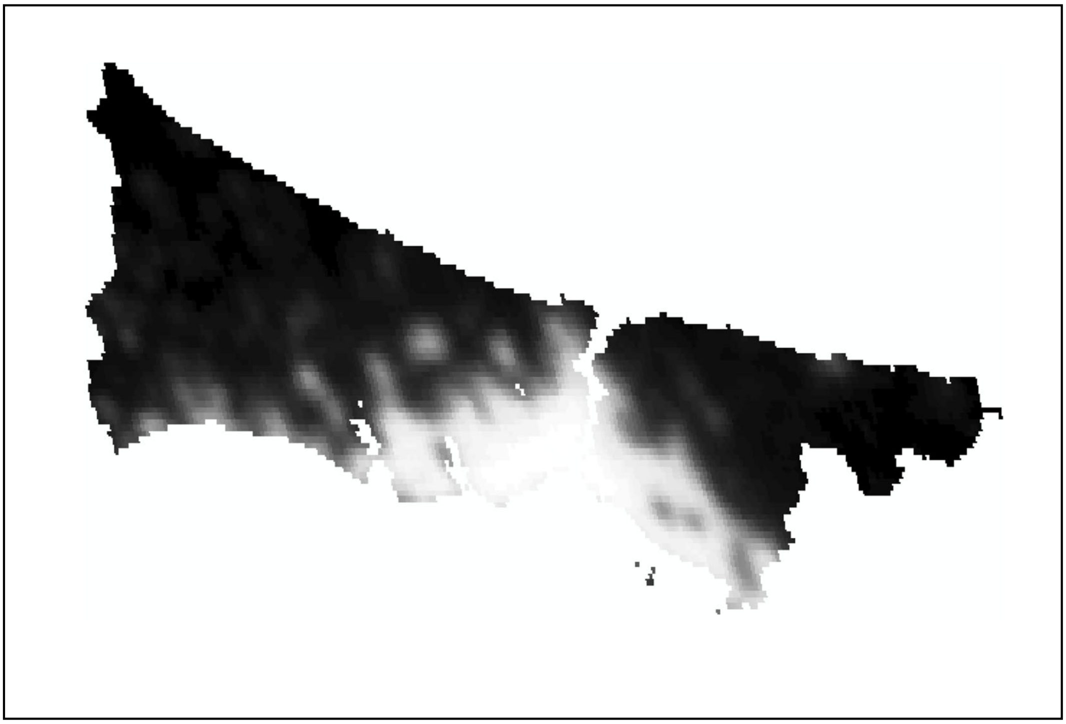


Fig. 2 The nighttime light data for Istanbul in 2000

estimating the local population characteristics in areas where only regional census data are available. The IDM tool provides the design, application, and validation of a new "intelligent" dasymetric mapping technique which supports numerous methods for characterization of the relation between the ancillary data and the underlying statistical surface. The technique is referred to as "intelligent," since users can subjectively determine this relation depending on their own expertise/knowledge, use an experimental sampling technique to conclude on the relation, or combine the technique with subjective or experiment-based methods.

In the IDM method, population data is distributed to the intersection of the source and ancillary areas using source boundaries and classified data. Given that the source area is s, ancillary area is z, ancillary data class is c, and estimation of ancillary data class is $\widehat{D}_C$, then the source area, where s and z are overlapped, is t. In this case, the estimated count of the target area can be calculated with the below formula:

$$\hat{y}_t = y_s\left(\frac{A_t\widehat{D}_C}{\sum\left(A_t\widehat{D}_C\right)}\right) \quad (1)$$

The $\widehat{D}_C$ value can be either determined by the user or sampled as a subset of the total source areas (Mennis and Hultgren 2006). At the end of the IDM process, a dasymetric polygon and a table of values such as estimated density for the source area are created. Besides, a summary table containing supporting information is also created. Figure 4 shows the basic process flow of the IDM method.

In this study, a practical IDM tool provided by US EPA (https://www.epa.gov/enviroatlas/dasymetric-toolbox) was used to perform the IDM process. This tool was integrated in ArcGIS using a Visual Basic for Applications (VBS) script. With the use of a number of communication boxes, the tool guides the user to determine the source area, ancillary data layers, and sampling strategy. Various sampling strategies can be applied using basic overlay processes of ArcGIS.

Within the pre-processing stage of the study, night light, GHLS-Build Up, and GHS-Population Grid data were clipped regarding Istanbul province boundaries. The projection system for GHS data was set to WGS-1984, cell sizes were resampled 1 km^2, and GHLS-Build Up data were classified into two classes, inhabited and uninhabited areas. The inhabited areas then were overlaid with the night light data so as to crop the lit

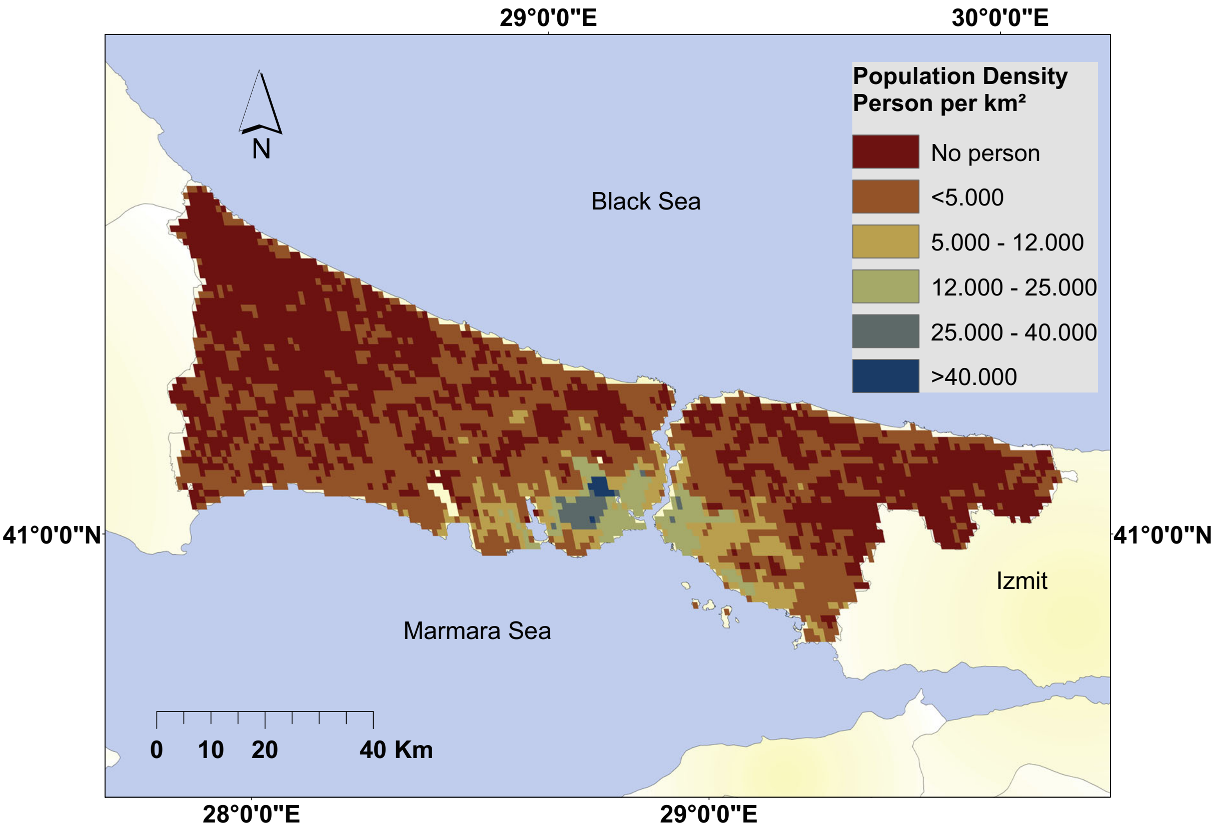


Fig. 3 Population density map for the settlement areas in Istanbul in 2000.Source: GHS-Population Grid (2000)

areas in the study area which were actually uninhabited. In the first step of IDM, vector data for Istanbul district boundaries were used and district census data was utilized as population future input. In the next steps of the process, tool use guides were followed to obtain the final dasymetric raster.

Figure 5 shows the comparisons of the lit-unlit and uninhabited-inhabited areas. As seen in the figure, some parts of the land have varying reflection/light values in the night light data resulting from a number of reasons, although they are uninhabited. Thus, the overlay process

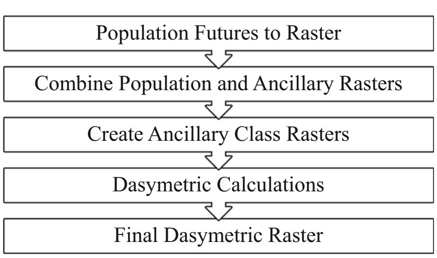


Fig. 4 IDM process flow

was performed to acquire more precise results. Besides, Wang et al. (2018) and some other researches underlined that night light data alone were not sufficient and overlaying night light data with land use data enabled to achieve more precise results. In the mentioned studies, authors aimed to overcome the blooming effect with this approach. Therefore, the night light data was overlaid with the GHLS-Build Up data in this study. Thus, the blooming effect was removed. Figure 6 shows the Istanbul nighttime light DN values produced via overlaying night light data with the settlement areas.

The resulting data given in Fig. 6 was used as the ancillary data of the IDM method in this study for the production of the areal population density distribution maps in Istanbul province. However, a second map, in which night light data was not overlaid with the settlement areas, was also produced. For both output maps, linear correlations between GHS-Population Grid data and areal population density maps were determined in terms of direction, degree, and statistics, for detecting the accuracy of the results. During the study, a traditional

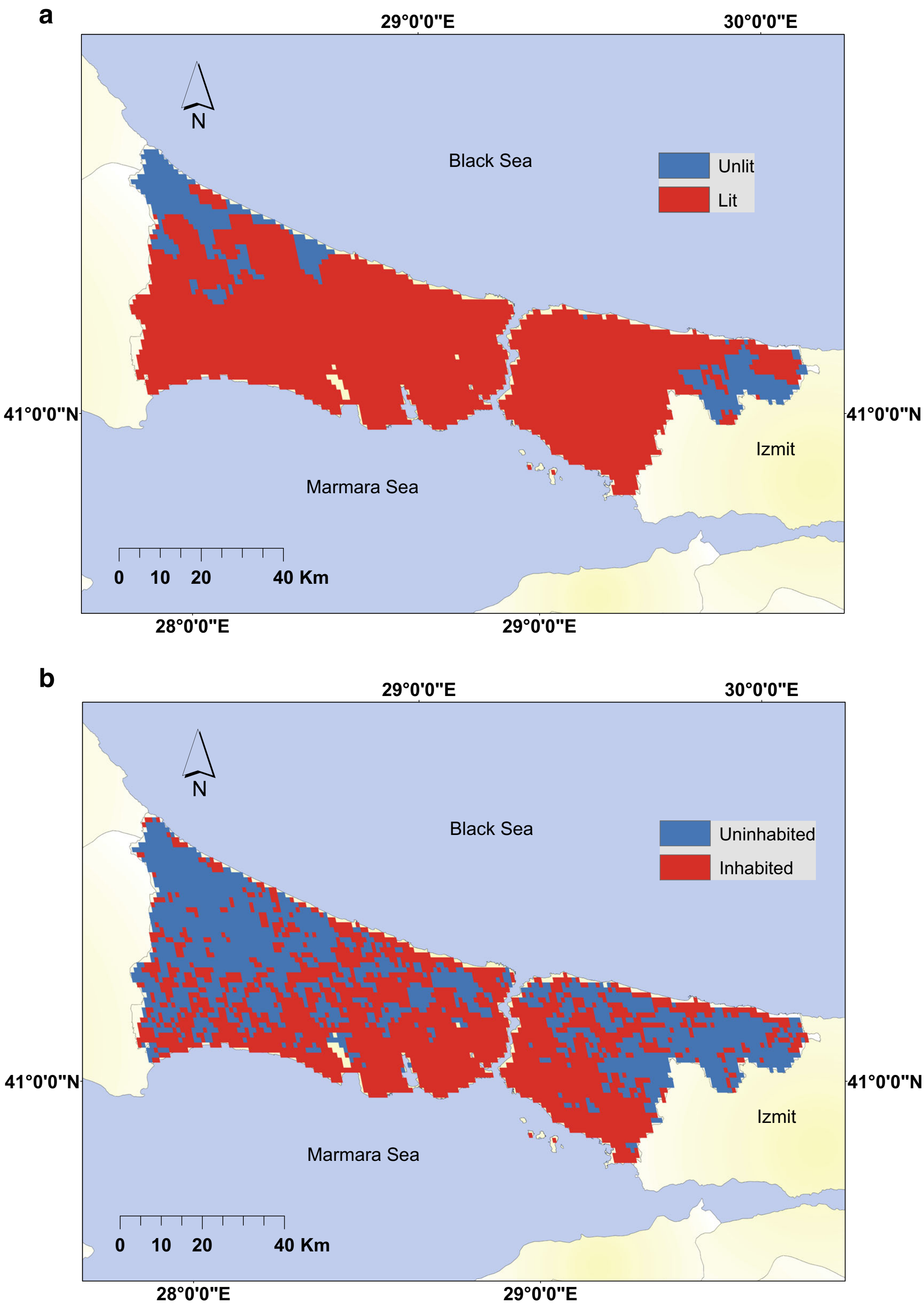


Fig. 5 Comparisons of the lit-unlit and inhabited-uninhabited areas. **a** Lit-unlit areas derived from night light images. **b** Inhabited-uninhabited areas in GHS-Population Grid datasets

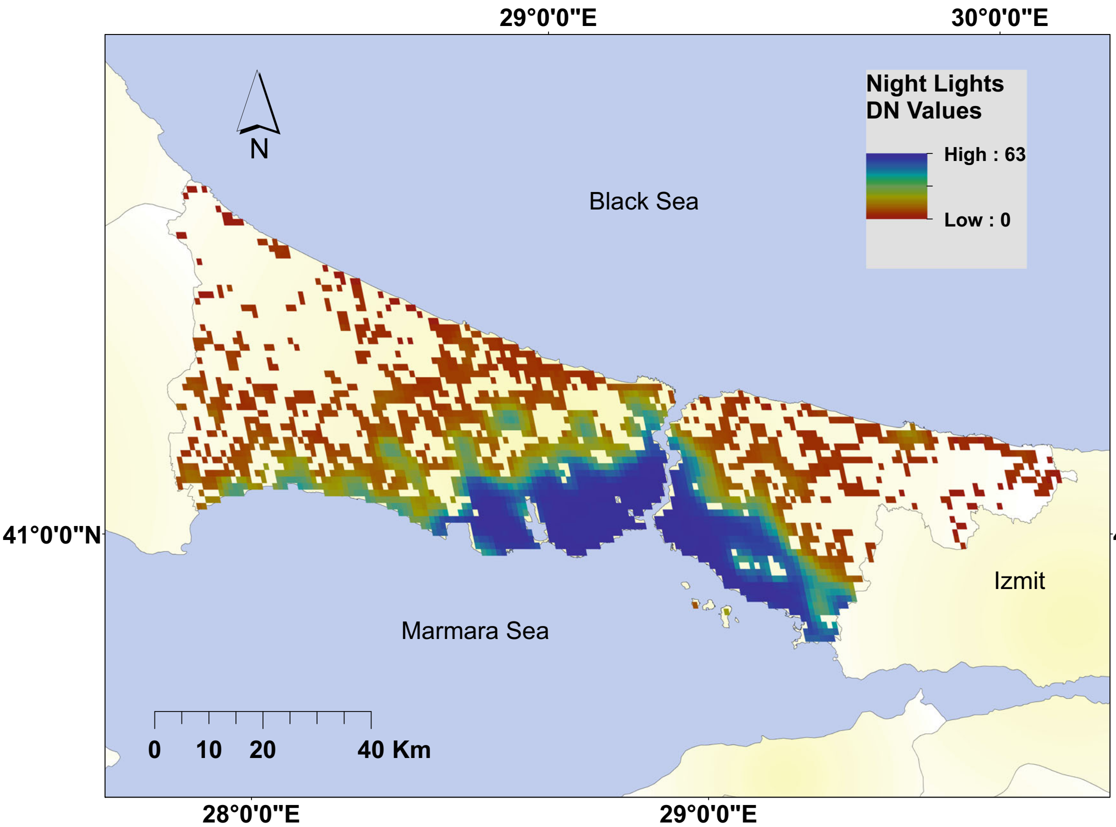


Fig. 6 Year 2000 Istanbul nighttime light DN values produced via overlaying night light data with the settlement areas

choropleth map for Istanbul in 2000 was also prepared and compared with the intelligent dasymetric map.

Results

Areal population density maps

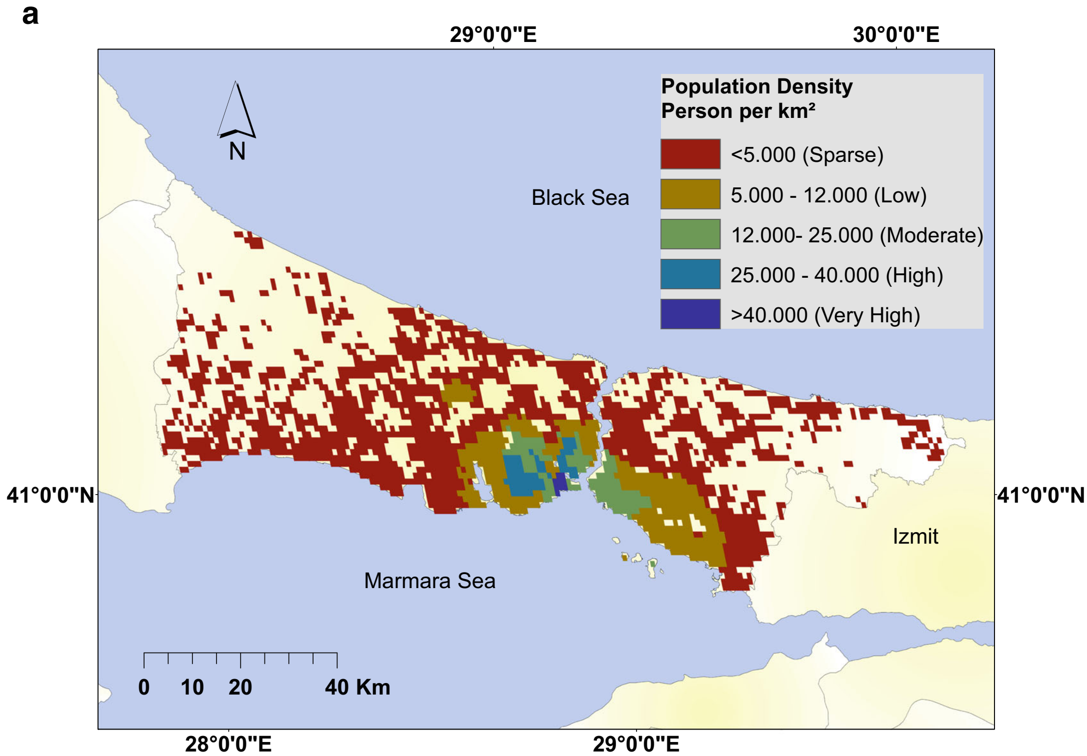
In this study, two major outputs (population density maps) were produced for Istanbul province in 2000, using night light data as the ancillary input of the IDM process. The first population density map was produced using cropped night light data boundaries according to the settlement areas, while the second was developed without this overlay process. The population density that was produced in accordance with 1-km^2 grid datasets was divided into 5 classes, in accordance with the settlement area gross population density categories determined for the development plans in the Physical Plans Development Regulation. Figure 7 shows the areal population density maps.

Gridded population density maps provide precious resources for researches and decision-makers. Moreover, they enable users to detect the anomalies in the area. For example, on both sides of the Bosphorus, the highest population densities are observed in the map (Fig. 7a). However, toward the northern parts of the province, the population density considerably decreases.

In Fig. 7a, the areas covered by sparse, low, moderate, high, and very high population density classes were determined, 74.8%, 9.1%, 2.3%, 1.4%, and 0.1%, respectively. 13.3% of the study area was accepted uninhabited. In Fig. 7b, on the other hand, the results were 38.5% sparse, 9.4% low, 5.5% moderate, 2.9% high, and 0.1% very high (Table 2).

Accuracy Analysis Results

Accuracy tests were made via the calculation of the linear correlations between the GHS-Population Grid data and areal population density maps. The correlations



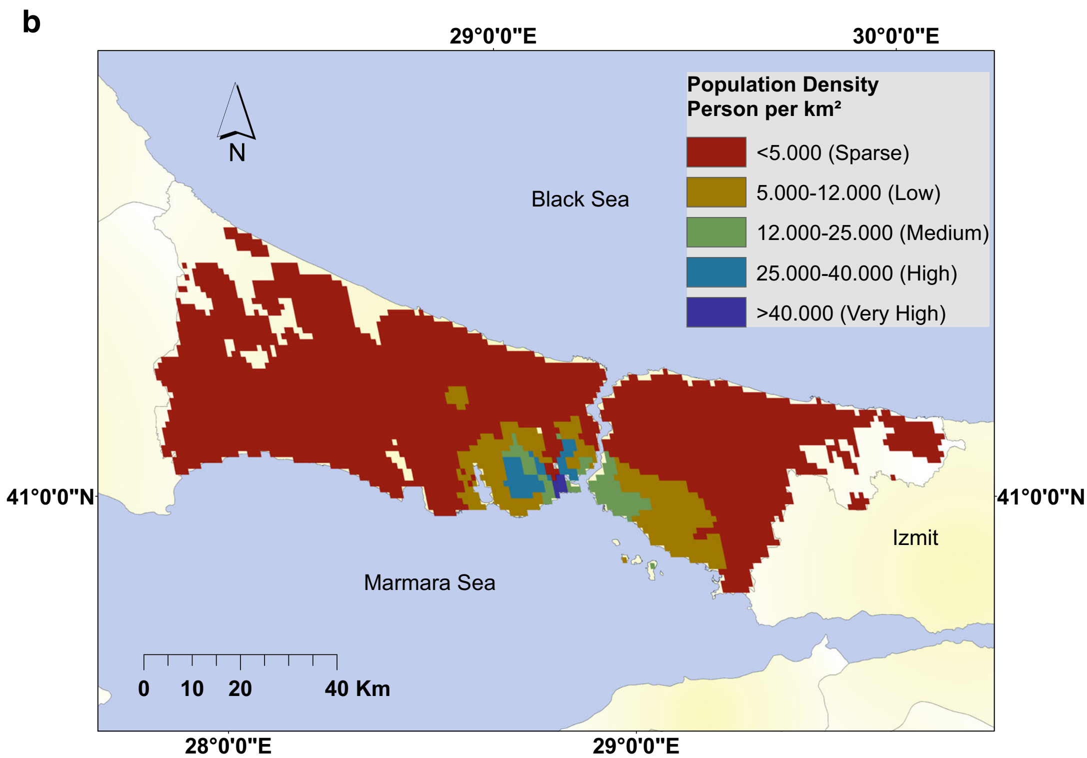


Fig. 7 Areal population density maps of Istanbul province in year 2000 (person/km^2) . **a** Areal population density map produced with cropped night light data. **b** Areal population density map produced without cropped night light data

Table 2 Population density percentages in the study area

Population density (person per km^2)	Areal population density map produced with cropped night light data (Fig. 7a)	Areal population density map produced without cropped night light data (Fig. 7b)
Uninhabited	13.3%	43.6%
< 5000 (sparse)	74.8%	38.5%
5.000–15.000 (low)	9.1%	9.4%
15.000–30.000 (moderate)	2.3%	5.5%
30.000–60.000 (high)	1.4%	2.9%
> 60.000 (very high)	0.1%	0.1%

between the GHS-Population Grid data and the areal population density maps produced with and without (whole night light data) the overlaid night light data were, respectively, 94% and 90% (Fig. 8). Both rates correspond to a very strong relation. Still, the results achieved when the night light data was overlaid with the settlement areas are even more precise.

Comparison of choropleth and dasymetric maps

Dasymetric mapping methods provide diverse advantages when compared to traditional choropleth mapping techniques as supported by a good number of studies in the literature (Bielecka 2005; Crampton 2004; Lwin and Murayama 2010). The use of ancillary data in dasymetric mapping applications helps create smaller geographic units, which is significant for analyses of the demography, economy, disaster risks, crime, etc. In order to understand the differences between these methods, a choropleth map of the study area was also developed. In Fig. 9, the choropleth population density map of Istanbul in 2000 is illustrated. Table 3 gives the comparison of the results obtained from the areal population density map and the choropleth population density map of Istanbul.

There is a considerable difference in the population density results obtained from choropleth and dasymetic maps, as summarized in Table 2. This shows that dasymetric mapping methods are important for the determination of the areal population density to conduct accurate researches and implementations for a variety of fields.

Conclusions

Night light data produced by DMSP are amongst the remote sensing data used for dasymetric mapping

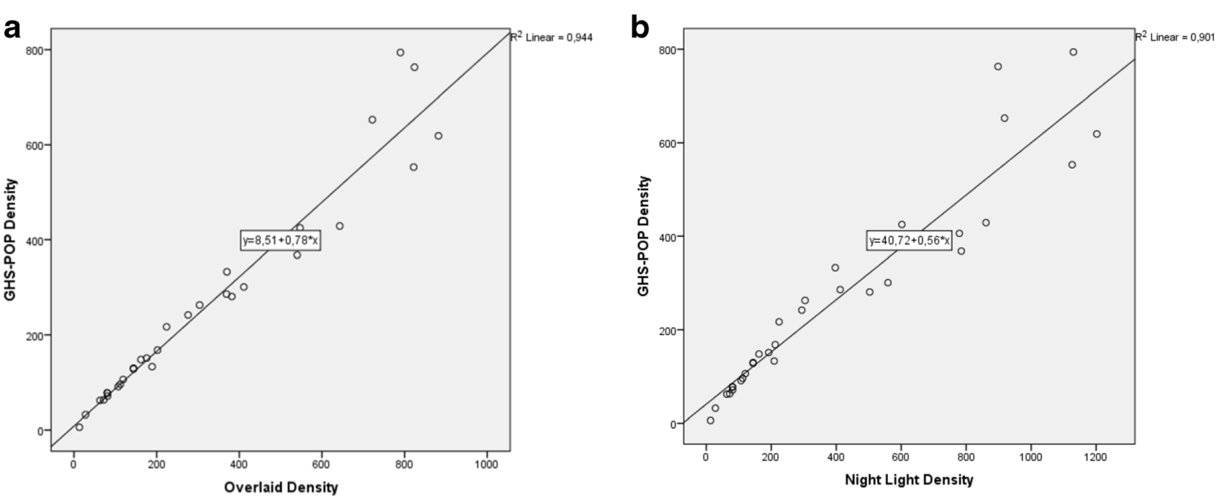


Fig. 8 Linear correlation results for areal population density maps of Istanbul in 2000. **a** Linear correlation results for map produced with overlaid night light data. **b** Linear correlation results for areal population density maps of Istanbul from night light data

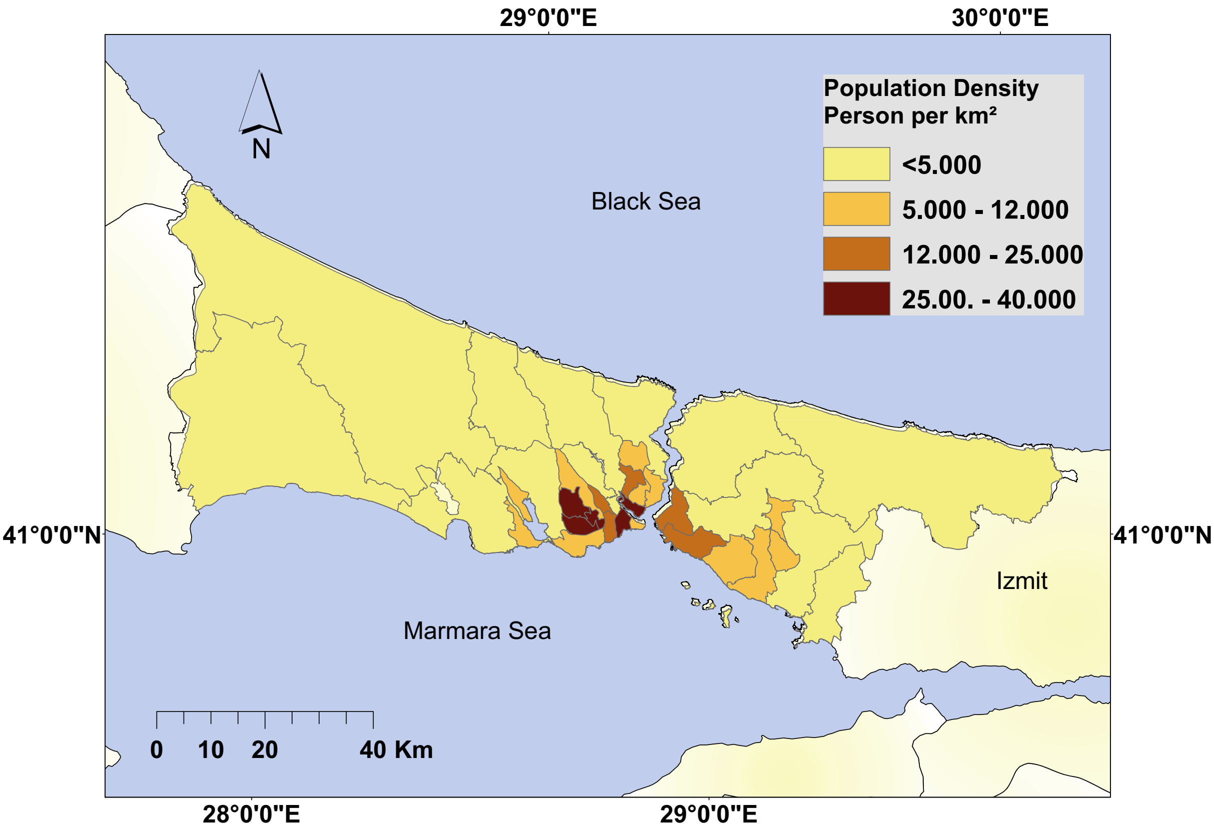


Fig. 9 Choropleth population density map of Istanbul in 2000

studies. Though night light data may vary depending on the socioeconomic characteristics of the territories, they are still reliable sources for the estimation of the areal population density. There are a number of studies in the literature emphasizing the strong relations between the night light data and the population (Small et al. 2005; Townsend and Bruce 2010; Zhou et al. 2014). Besides the estimation of population density over an area, night light data are also used for the realization of social and economic analyses. A good number of researchers therefore have used night light data as ancillary datasets in a variety of studies. However, in most of these works, besides night light data, secondary ancillary datasets such as land cover are also used since the utilization of night light data is not considered reliable enough for the accurate estimation

Table 3 Comparison of the population densities in choropleth and dasymetric maps

Population density (persons per km^2)	Choropleth map (Fig. 9)	Dasymetric map (Areal population density map) (Fig. 7a)	Dasymetric map (Areal population density map) (Fig. 7b)
Uninhabited	–	13.3%	43.6%
<5000 (sparse)	90.7%	74.8%	38.5%
5.000–15.000 (low)	7.3%	9.1%	9.4%
15.000–30.000 (moderate)	1.7%	2.3%	5.5%
30.000–60.000 (high)	0.3%	1.4%	2.9%
> 60.000 (very high)	–	0.1%	0.1%

of the population density. For instance, Wang et al. (2018) used second ancillary datasets to decrease the amount of the errors while increasing the precision. Regarding the literature review, it is observed that more advanced dasymetric models and perspectives have been developed and adopted in a wide range of studies since the 2000s. Yet, none of these models are practical and encouraging enough to convince the social scientists to use remotely sensed data, GIS technologies, and complex methodologies. Therefore, the method and approach explained in this study are believed to offer an insight into the necessity of the areal demographic analyses in social sciences and the utilization of advanced technologies and data.

In this study, an easy-to-use IDM tool developed by US EPA was used for producing the areal population density maps of Istanbul province for the year 2000. Therefore, a series of statistical operations and calculations were realized automatically, which facilitated the process. Within the context of the study, two maps were created. The first map was developed via the overlay of the night light with the settlement areas within the study, and in the second map, the night light data were used without the overlaying process. The linear correlation analysis revealed that the method used for the production of the first map had a higher correlation percentage (94%) compared to the correlation of the second one (90%). The results of this study also enabled the comparison of the different population density distribution results obtained via choropleth mapping and IDM.

The first map, which is the major output of the study, showed that both sides of the Bosphorus had the highest population densities, and the population density in the northern parts of Istanbul was rather low. This information is especially significant for the comprehensive strategic and physical planning works in a diversity of ways such as disaster risk analysis and management, urban planning, recreational planning, environmental protection, transportation and infrastructure planning and investment, implementation of sustainable development goals, social and economic advancements, etc. No doubt that this information is also substantially necessary for social and economic researches. Remote sensing data are also of great significance for the socioeconomic and demographic analyses of rural area planning processes especially for mega cities like Istanbul.

The results of this study also showed that traditional methods such as developing choropleth maps for population density calculations fail to provide accurate results and inputs for implementations for which population data is of great significance.

It is necessary to emphasize that the population density classification can be made in a variety of different ways regarding the national legislation, regional dynamics, and other type of classification approaches. Besides this, higher-resolution data and inclusion of different ancillary datasets would be preferred for specific purposes and implementations. Therefore, higher-resolution night light data are utilized for more precise socioeconomic and demographic analyses (Levin and Zhang 2017; Ma et al. 2014; Yu et al. 2015). Similarly, globally produced population products mainly those of remote sensing data with a diversity of resolutions are widely used by the researches.In the future, remote sensing data will be more effectively and easily used by more and more people from different disciplines thanks to advancements and newly developed tools in both image processing and geographical information technologies.

In the change analysis made as a result of the classification, the changes between the city area and the population were revealed. During this period, the city area and population grew. It shows that the city area and population increased 2.35 times and grow at an annual average rate of 3.45%. Spatial change has also been interpreted by comparing it with population changes. There appears to be a remarkable increase in both surface area and population. With the increase in population, a spatial growth in the city area is considered to be inevitable.

In our study about night images, night images and population are used. The population density of urban areas was determined by classifying them according to the classification method. According to the results, it is seen that the city area grows with the population and includes the city center with night images.

It is seen that the increase is especially in the south and northwest of the city. With the population increase, the number of new residential areas has increased. It is thought that behind this growth, there are different reasons besides the effect of the increase in residential areas. As a result of the newly built buildings in the places between the towns close to the center and the city center, these disconnections were removed and these areas were seen as a whole in the night view. The construction of the new airport in the southern part of the city and the settlements in this area explain the growth of the city area in the southern parts of the image.

The reason for the expansion in the west and northwest parts of the city area can be explained by the passing of the university campus area and the ring road built in that area.

Today, how cities will respond to the problems brought about by uncontrolled growth and the needs of individuals and society within this framework constitutes one of the most fundamental questions. Today, when the environmental awareness of people has increased more than in the past centuries, new solutions should be produced in order to be more controlled, smart, and sustainable while planning the cities of the future. Considering that the development of technology and remote sensing techniques is progressing in parallel with this technology, and this study in which GIS technologies integrated with satellite images are used, it is thought that these will contribute positively to the studies in this area in terms of regular development of urban areas, increasing the opportunity to make fast and correct decisions, and creating infrastructure for studies such as monitoring and prevention of illegal housing.

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