Ecological Indicators 166 (2024) 112486

Contents lists available at ScienceDirect

Ecological Indicators

journal homepage: www.elsevier.com/locate/ecolind

Original Articles

Assessing urbanization dynamics using a pixel-based nighttime light indicator

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ARTICLE INFO

Keywords:
Nighttime light
Urbanization
Territorial sustainability
Coastal proximity
Tourism

ABSTRACT

Nighttime light (NTL) is a reliable indicator for measuring urban development, population density, and economic activities. This study sets out to explain the spatio-temporal pattern of urbanization and population distribution using pixel-based NTL data. Changes in NTL intensity in Puglia (Italy) were evaluated from 2014 to 2023, and how NTL is affected by various spatial metrics was investigated. Summer–winter differences at the pixel level were monitored utilizing the Normalized Nighttime Light Index (NNLI), and the relationship between this indicator and tourism was assessed. A consistent increase in NTL across the region in both summer and winter was measured, with variations among provinces. Urban areas with high population density showed greater NTL values, while inland areas showed low NTL intensity. The study also revealed that proximity to urban areas was the most influential factor in predicting NTL intensity. The analysis revealed that differences between summer and winter correlated with tourist activity, especially in coastal municipalities. Leveraging NTL images can support decision-making across various sectors and aid in developing evidence-based urban strategies tailored to local needs and challenges.

1. Introduction

Urbanization is a process which facilitates collaboration of individuals, reduces land dependence through technological advancements, and enables easier access to services like healthcare and education. (Barkan, 2011). In 2020, nearly half the global population lived in cities, while 29 % resided in towns and semi-dense areas (United Nations Human Settlements, 2022). By 2070, it is predicted that 58 % of the global population will live in cities, with a decrease in the share of the population residing in towns and semi-dense areas (United Nations Human Settlements, 2022). The rapid trend of urbanization has raised concerns among researchers and policymakers regarding the minimization of externalities such as land conversion and habitat disruption (Zhang and Seto, 2011). Traditional urban research faces difficulties in grasping the complexities of the relentlessly changing interaction between the human and physical component of the territory (Mouratidis, 2021). The dynamics of human behavior are often ignored, including short-term use of an area for different activities, temporary residents, and non-resident students (Brollo and Celata, 2022).

Among the tools used to overcome certain limitations mentioned above is satellite imagery (Nash et al., 2018). Research has shown that Nighttime Light (NTL) remote imagery was initially used to map urbanization (Levin et al., 2020) by analyzing urban land use expansion and defining the border between the urban and agricultural or natural land use types (Lafortezza et al., 2007; Lafortezza and Giannico, 2019; Marziliano et al., 2013; Imhoff et al., 1997). Methodologies concerned with these objectives are improving, but the difficulty resides in the inability to be universally applied (Zhou et al., 2015). NTL has also been employed as an indicator to estimate economic development. It has been discovered that the luminosity of an area is strongly linked to both Gross Domestic Product (GDP) and electric power consumption (Elvidge et al., 1997). More than a decade later, the economic literature widely accepted the use of NTL as a proxy for economic growth in countries with limited available data at a granular scale (Henderson et al., 2012). A growing body of research has consistently demonstrated that NTL is a viable proxy of population density (Chen et al., 2019a), economic

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https://doi.org/10.1016/j.ecolind.2024.112486
Received 27 May 2024; Received in revised form 26 July 2024; Accepted 7 August 2024
Available online 22 August 2024

vitality (Bickenbach et al., 2016), urban development (Stokes et al., 2021), urban sprawl (Sanesi et al., 2007; Bergantino et al., 2020), and even building height (Kazawa et al., 2022).

Chen et al. (2019b) established a clear correlation between NTL and human activity intensity. The authors divided the Shanghai greater city area into two parts based on the number of points of interest (POIs): high activity area and low activity area. A significant difference had been observed across seasons and types of POIs between these two areas. Spring and autumn resulted in higher overall NTL due to the weather conditions encouraging people to spend more time outdoors (Chen et al., 2019b).

One of the factors driving urbanization is tourism, since it involves continuous influx of individuals. Its impacts are as significant as to lead researchers into coining the term "tourism urbanization" (Mullins, 1991). Following Anton Clavé's (2022) characterization, we define "tourism urbanization" as the type of city growth occurring as a response to increasing tourist demand. Tourism urbanization generally involves new infrastructure development (i.e. roads, railways, utilities network) and land use/land cover change which may result in a number of environmental impacts, e.g. water and air pollution, biodiversity loss (Aretano et al., 2017). Therefore, it is necessary to understand the impact of tourism urbanization on the environment, society, and economy to establish a development plan that promotes long-term sustainable goals (Bergantino et al., 2021). A cross-European study has confirmed a clear relationship between NTL emissions and tourism (Krikigianni et al., 2019). Using "total nights spent" as the metric for tourism at country level during the 2012–2013 period, a strong correlation was demonstrated, particularly in southern European countries.

The overarching goal of this study is to develop a modeling approach explaining the spatio-temporal pattern of urbanization and population distribution using pixel-based NTL data in the Puglia region, Southern Italy. To this end, we relied on NTL capability to act as a proxy of urbanization and concentration of human activity, as confirmed by many studies (Operti et al., 2018; Stathakis et al., 2015; Wang et al., 2020; Zhang and Seto, 2011; Zhang and Gibson, 2022). We specifically set out to address the following objectives: (1) understand to what extent NTL intensity has changed in the past 10 years in the region; (2) assess how this change could be explained by spatial variables such as distance from various types of urban areas (e.g., internal) and coastline proximity, and (3) monitor the seasonal difference in NTL intensity (i.e., summer-–winter yearly change) and how this difference could explain the change in population increase due to tourist influx. The Puglia region was used as a testbed for developing and evaluating our modeling approach given its diverse landscape, cultural attractions, and initiatives to increase tourism industry competitiveness and innovation (Buongiorno and Intini, 2021; Del Vecchio and Passiante, 2017). The region is characterized by a high seasonality of tourist influx (i.e. more intense tourist activities during summer) as a result of a combination of natural and cultural factors (Petrosillo et al., 2006). Tourism is a growing sector in Puglia (Bergantino et al., 2023), and the region continues to attract foreign visitors. According to Regione Puglia, in 2023 the number of tourist arrivals increased by 8 % and the overnight stays by 3 %, with the figures for 2022 climbing even higher at 20 % and 14 %, respectively (Pugliapromozione, 2024).

This study proposes a new method of assessing urbanization dynamics. Unlike similar studies, the analysis was based on a period of 10 consecutive years and included various levels of spatial resolution: from the pixel to the regional level. This sort of analysis in the future can be tested and used in other regions or in larger territories (e.g. countries). The models developed allow the evaluation of the state of urbanization with almost real-time data. This approach can help policymakers assess the urbanization patterns in a very up-to-date fashion, thus limiting the need for land use maps or other data sources that require substantially more time to access. We considered the assessment of touristic activity using a NTL-based indicator as an added value to the current body of literature. The indicator used makes it possible to rapidly spot emerging touristic hotspots and address environmental or public service concerns.

The paper is organized as follows. In Section 2 we give a general description of the study area, some insights regarding the nature of the dataset we used, and a detailed clarification of the two statistical models utilized to establish the relationship between (1) NTL and selected spatial metrics, and (2) the Normalized Nighttime Light Index (NNLI) and tourism. In Section 3 we provide the main results of our analysis, i.e. the annual and decadal NTL variation, the spatial distribution of NTL and the results of the two regression analyses. In Section 4, the findings are interpreted, and the usefulness of the methods employed outside of this particular study is stated. In Section 5, we provide the main conclusions.

2. Materials and methods

2.1. Study area

Puglia is one of 20 regions in Italy, situated in the southeastern part of the Apennine peninsula (Fig. 1a). It covers a surface area of 19,541 km^2, and as of 2022 the population has reached approximately 3.9 million (ISTAT, 2023). The region is made up of 6 provinces and 257 municipalities. Bari serves as the capital and is the most populous city of the region, with 316,736 inhabitants (ISTAT, 2024). Puglia has the longest coastline (1,224 km) of any Italian peninsular region and is also the longest region in terms of length (348 km). The territory is characterized by a low average altitude comprised of hilly areas (45 %) and plains (53 %), making it a unique feature of the region (Contillo et al., 2022). Forty-nine municipalities, which make up 16.9 % of the total surface area, have been designated as "internal areas" under the Strategia Nazionale delle Aree Interne, a policy designed by the Italian Agency of Territorial Cohesion to support the municipalities (Fig. 1b). They do not have direct access to healthcare facilities, schools, or major infrastructural nodes, and are often located far from major urban centers. These municipalities typically face significant demographic and economic challenges because they are not considered appealing to residents and businesses.

2.2. Data analysis and processing

The dataset exploited in this study is the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB). VIIRS contains images captured by the Suomi National Polar-orbiting Partnership satellite, jointly set in orbit by NASA and NOAA. The dataset is a successor of the Defense Meteorological Satellite Program (DMSP) Operational Linescan System (OLS) for global low-light imaging of the Earth at night. Its low-light sensor captures imagery with a 505–890 nm spectral response and nominal band-center wavelength of 705 nm (Lee et al., 2006). VIIRS outperforms the OLS in spatial resolution, dynamic range, quantization, calibrations, and the availability of spectral bands, which are ideal for discriminating thermal sources of light emissions (Elvidge et al., 2013). Images of this dataset are preprocessed to eliminate certain "contaminations" such as moonlight, light stray, volcanoes, and fires, although the final images are not entirely immune to such elements (Elvidge et al., 2017). The spatial resolution of the images is 500 m, amounting to 77,379 pixels for the Puglia region (Fig. S1 contains the mapped values of summer NTL for the Puglia region from 2014 to 2023). The images are clean and preprocessed, but a few pixels were found with abnormally high and low values. Abnormally high values were considered to be those exceeding the maximum value of the urban core. Abnormally low values in our dataset were those showing a negative value due to forest fires, after being recognized as light pollution by the algorithm. These pixels were located in Gargano National Park, in the province of Foggia. In both cases, the values of the pixels were recalculated as the mean of the neighboring pixels in a grid of 3x3 pixels. It is worth noting that the number of such pixels did not exceed 200, and only in one year it reached this figure. The distribution of the NTL data, be it summer

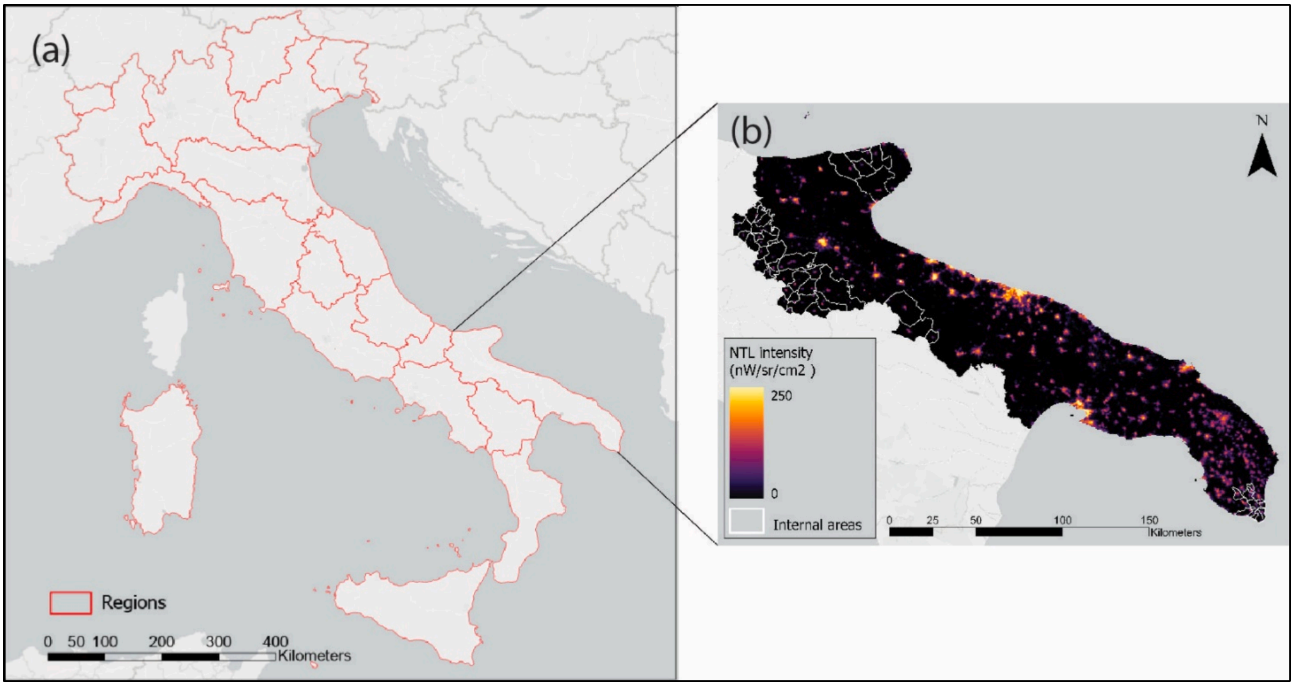

Fig. 1. Geographic location of the Puglia region (a); Nighttime Light (NTL) in summer (June-September) 2023 (b).

(June–September) or winter (November–February), is non-normal (Fig. S2). The density curve shows a heavily right-skewed distribution, with most values stacked close to zero. This finding was expected since most of the territory is represented by agricultural land and natural landscape which exhibit very low values of NTL intensity, while human settlements occupy a tiny portion of the total.

2.3. Analyzing the annual and decadal change in NTL intensity in the past 10 years

To analyze the annual change in NTL intensity, a Kruskal-Wallis test was conducted, given the distribution type of our data, followed by the Dunn post-hoc test (Dunn, 1964), with the Bonferroni method to correct for possible multiple comparison errors (Bonferroni, 1936). From the Kruskal-Wallis test, the chi-squared (χ^2), p value, and epsilon-squared ordinal ($\varepsilon^2_{ordinal}$) parameters are provided. The Dunn post-hoc test which compares the differences between all possible pairs of years showed which years are similar in values to one another. Those pairs of years which exhibited a “Bonferroni” p-adjusted value of more than 0.05 were not considered statistically significant (Fig. 3).

To quantify the decadal change, we calculated the relative difference in NTL intensity, which would represent the change over the 10 years expressed as a percentage for every pixel. We selected only the pixels located within the urban areas according to 2018 Corine Land Cover land use map to isolate the human settlements from agricultural or uncultivated areas in the analysis.

2.4. Assessing the spatial variation in NTL intensity

We considered three variables closely associated with NTL and our study area to analyze how the NTL intensity changes across various parts of Puglia. In our model, these variables are distance from the nearest built-up area (Dist_built), distance from the nearest city or town (Dist_city), and coastline proximity (Dist_coast). The distance from urban areas and important cities was selected considering that NTL is a known proxy of urbanization. Coastline proximity was deemed important because of two prominent features of Puglia: firstly, the three large cities, Bari, Brindisi, and Taranto, are located along the coastline, and secondly, the coastal areas of the region function as holiday destinations for the local population and tourists. As the reference layer for measuring distance from the nearest built-up area, we used the Copernicus Imperviousness Built-up dataset (Copernicus Land Monitoring Service, 2018), while for isolating city and town footprints on the map, we employed the Continuous Urban Fabric class of the 2018 Corine Land Cover dataset (Copernicus, 2018). We calculated these distances using the “Euclidean distance” tool in ArcGIS, generating raster images with the same number of pixels as our NTL images to secure perfect overlapping. The three variables were fed to a hyperbolic model as follows:

$$NTL = a + \frac{b}{Dist_{urb} + c} + \frac{d}{Dist_{city} + e} + \frac{f}{Coast_{dist} + g} \tag{1}$$

where $Dist\_built$ = distance from the nearest built-up area, $Dist\_city$ = distance from the nearest city or town, and $Dist\_coast$ = distance from the coastline.

This type of regression was considered the most suitable due to the relationship between the considered variables exhibiting a hyperbolic shape. To better illustrate the influence of coastal proximity on NTL, we categorized the pixels of the distance layer into 1-km intervals (Fig. 5). A linear regression analysis was conducted to assess the annual variation in light intensity in internal areas and compare it with the rest of the region. This involved grouping municipalities and considering the average NTL values in summer (June-September) and winter (November-February) for each year.

2.5. Monitoring the seasonal difference in NTL intensity

A standardized indicator was developed to quantify the difference between summer and winter NTL, thus assessing the seasonal patterns of urbanization. Specifically, we designed the Normalized Nighttime Light Index (NNLI) as shown in Eq. (2):

$$\mathrm{NNLI} = \frac{(\mathrm{NTL\,summer} - \mathrm{NTL\,winter})}{(\mathrm{NTL\,summer} + \mathrm{NTL\,winter})} \tag{2}$$

The NNLI values range from −1 to 1, with values closer to 1 signifying that summer is brighter than winter in a certain year and vice-versa

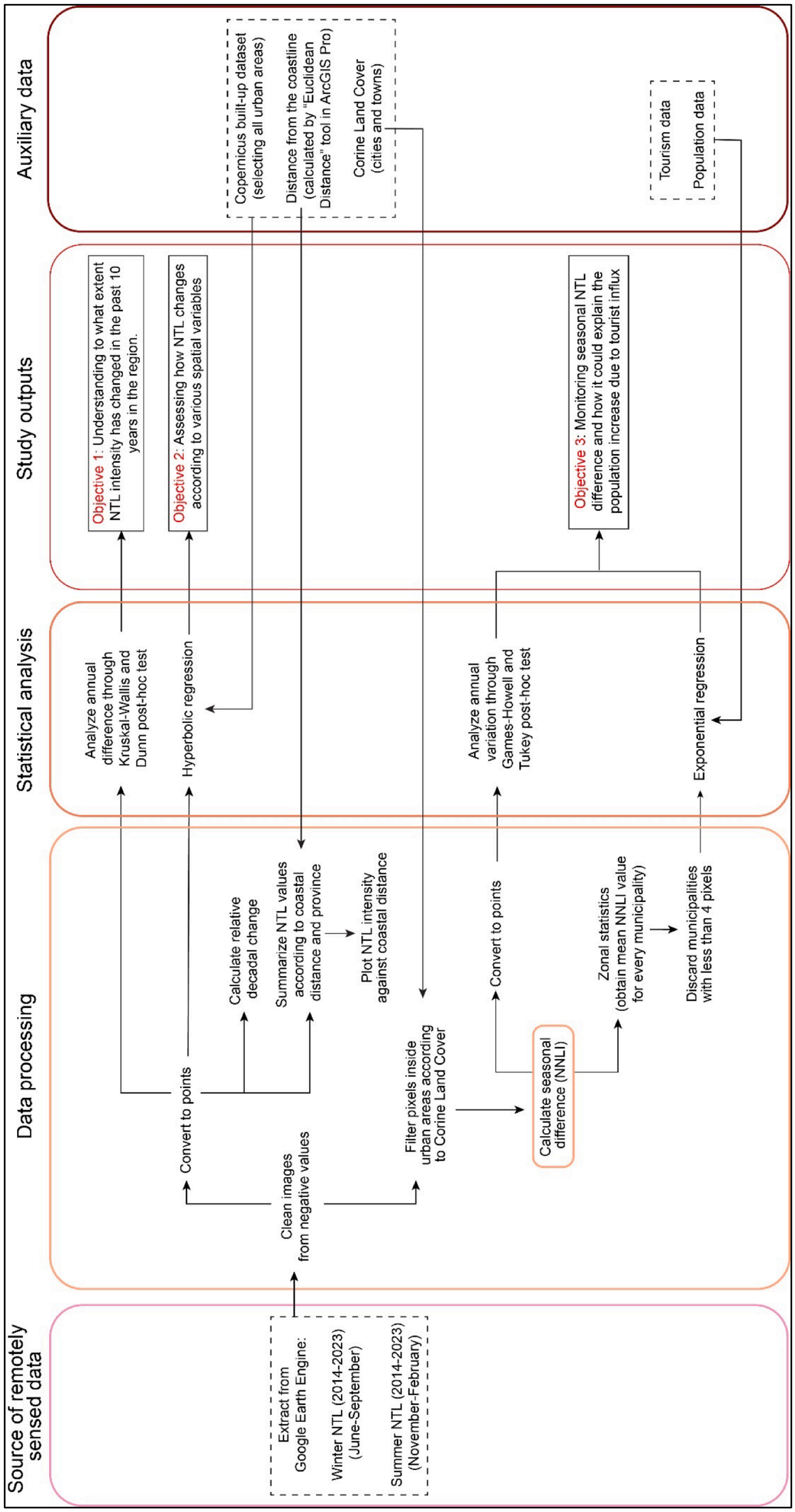

Fig. 2. Flowchart synthesizing the methodological process.

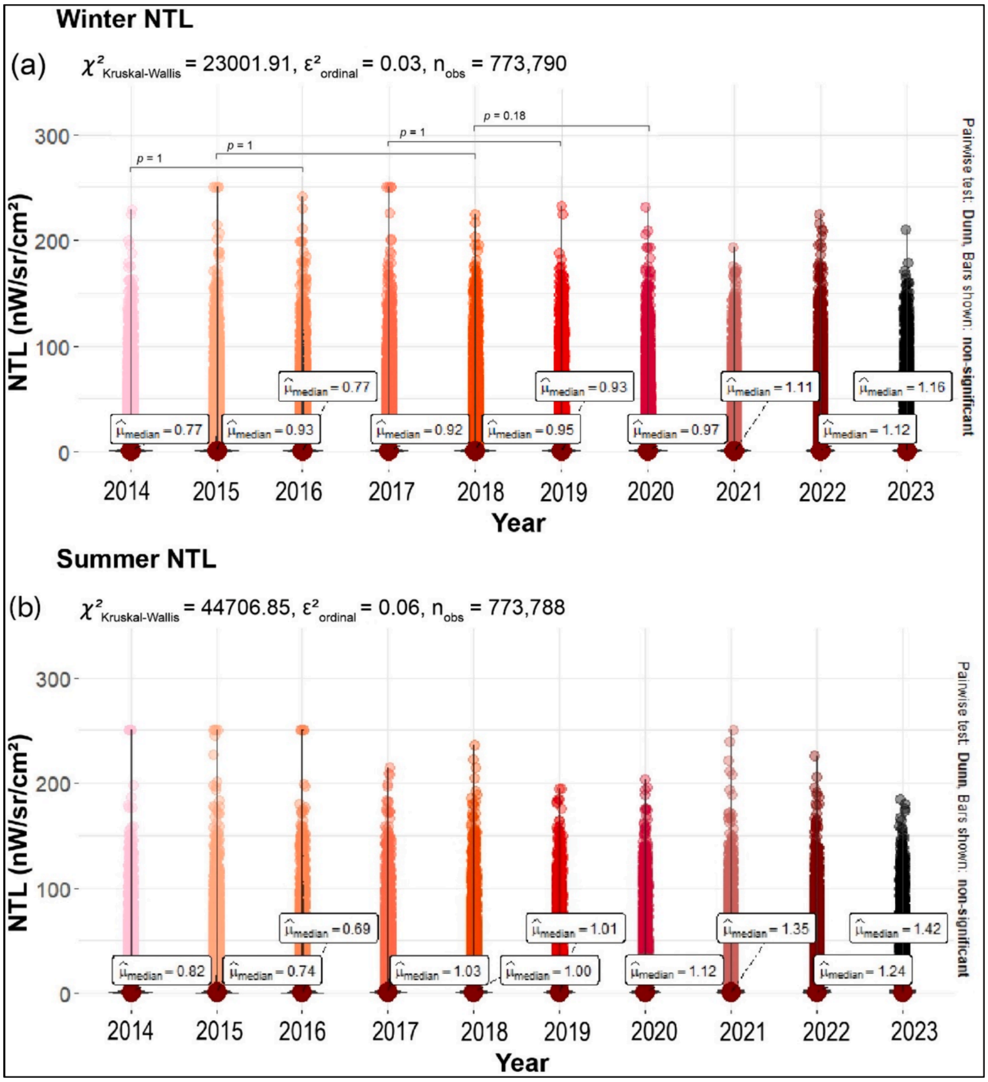

Fig. 3. Distribution plots with Kruskal-Wallis and Dunn post-hoc test results of winter (a) and summer (b) Nighttime Light (NTL) from 2014 to 2023 for the Puglia region. Segments connect similar years identified by the Dunn test.

(Fig. S3). The values of this indicator were calculated at pixel level using the raster calculator tool in ArcGIS Pro. To understand how the NNLI values have changed in the past decade, we conducted the Games-Howell test (Games and Howell, 1976), based on the distribution characteristics of NNLI (Fig. S4), and then ran the Tukey HSD post-hoc test to determine which year differed significantly from the others.

Furthermore, we aimed to clarify the connection between NNLI and tourist traffic. By running an exponential model to analyze tourist numbers and the average NNLI values at the municipal level, we were able to assess the effectiveness of NNLI as a proxy for tourism. The fitted model is expressed in the following equation:

$$\text{pop\_change} = \beta 0 * \text{mean\_NNLI}\, \beta 1 \tag{3}$$

where *pop_change* = (tourist presences – resident population)/resident population, *tourist presences* = number of tourists * nights spent

During the data preparation step, we maintained only pixels situated inside the border of urban areas according to the 2018 Corine Land Cover classification to remove uninhabited areas. Subsequently, the NNLI was calculated only for municipalities with at least 4 pixels (1 square kilometer) to avoid potential outliers. This was deemed as the appropriate threshold considering that 1 km^2 is the unit used by Eurostat in its classification of urban areas (Eurostat, 2022). We also excluded the capital cities of the provinces from the list of municipalities because their NTL is very stable throughout the year, and tourism is spread more evenly across the seasons. Fig. 2 summarizes the methods utilized in this paper.

3. Results

3.1. Annual change in NTL intensity (2014–2023 study period)

Over the last decade, the median NTL intensity generally increased during the summer season in Puglia (Fig. 3b). Some drops in values were observed for 2015 and 2016. Subsequently, NTL intensity increased considerably, reaching its peak in 2023. Meanwhile, similarities were found in the winter season between 2014 and 2020. However, the last 5 years (2019–2023) showed a clear trend of increasing NTL, with 2023 being again the brightest year (Fig. 3a). The variation in NTL values in the 10 years considered in the analysis ranged from 1 to 29 % in winter and from 1 to 49 % in summer.

When analyzing the individual provinces of Puglia some differences in NTL intensity were observed. During the summer, Taranto and Brindisi showed a decrease in NTL from 2014 to 2016, followed by higher values from 2017 to 2019, and increasing values thereafter. Lecce displayed a grouping pattern of values, with the first three years and the second three years showing similar values, followed by a continuous

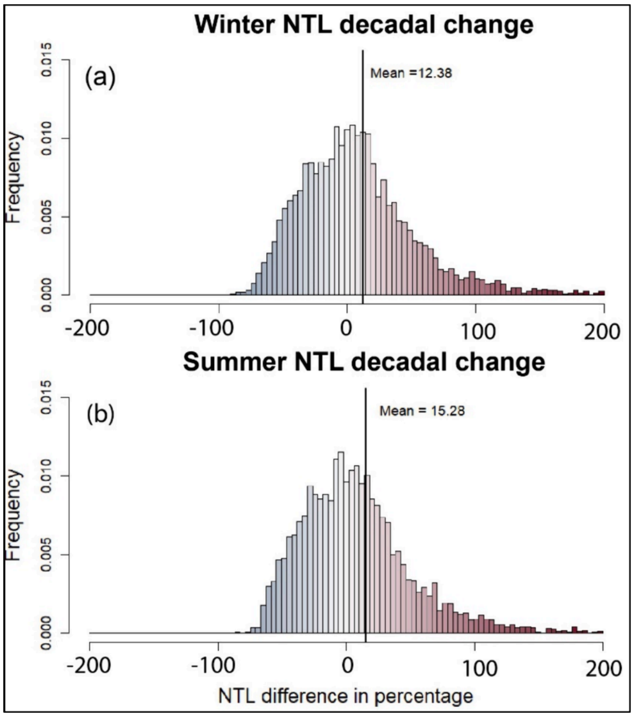

Fig. 4. Histogram of decadal change in Nighttime Light (NTL) intensity in winter (a) and summer (b). Values express the relative change in NTL intensity as a percentage.

increase in the following years. In Bari and Barletta-Andria-Trani (BAT), the situation was very similar to Taranto and Brindisi, with the sole difference being the similarity in values between 2021 and 2023 (Fig. S5). In winter, the province of Taranto followed quite closely the pattern of the Puglia region. From 2014 to 2020, Brindisi and Bari showed many similarities, while the subsequent years displayed higher values. In Lecce, the grouping pattern (of values per 3-year groups) continued. Lastly, in Foggia and BAT, few similarities were observed in values among the years of the first half of the decade, while the values of the remaining years constantly increased (Fig. S6).

The analysis of decadal changes revealed a rise in NTL values during both summer and winter seasons. However, the increase in light intensity was more pronounced during the summer months (15.28 % compared to 12.38 %, see Fig. 4). Every province exhibited an uptick in NTL intensity during both seasons. BAT registered the most substantial increase in NTL intensity during the winter, while Taranto revealed the smallest. In summer meanwhile, Foggia experienced the most significant increase in NTL intensity, with Taranto still ranking last (see Table S1).

3.2. Assessing the impact of spatial metrics and variability on NTL

A hyperbolic regression analysis was conducted to investigate the spatial variability of NTL considering the distance from the nearest urban area, distance from the nearest city, and proximity to the coastline as explanatory variables. The results indicated that these spatial metrics could serve as effective explanatory variables for NTL intensity. Our model was able to account for approximately 60 % of the variability in NTL, with minor variations observed when considering different years and seasons (Table 1). The most significant variable of our model was the distance from urban areas, accounting alone for about 40 % of NTL variability. The distances from major cities and proximity to the coastline were complementary to some extent. The former could explain the high NTL values for pixels located in densely populated urban areas, while the latter could account for pixels situated along the coastline.

3.2.1. Impact of coastal proximity on NTL in different provinces

The coastal proximity analysis of Puglia provinces (Fig. 5) revealed that the decrease in NTL was often gradual in areas like Bari and Taranto, while in other areas such as Brindisi and BAT noticeable spikes were found. Conversely, in some cases, no discernible trend was observed. For instance, in Bari and Taranto (Fig. 5a,f) NTL was intense within a few kilometers from the coastline due to the cities located there. As the distance from the coastline increased, the intensity of the light diminished. In the case of Bari, NTL intensity remained high from the fourth to the eighth kilometer from the coastline due to the high population density of satellite towns like Modugno, Valenzano, and Triggiano. In the province of Brindisi (Fig. 5b), a noticeable increase was observed in light intensity at the seventh and eighth kilometer, attributed to the relatively dense town of Ostuni. Regarding Lecce, no clear correlation between NTL and coastal proximity was found; the light intensity decreased significantly only in the farthermost kilometers from the coastline. Although the city of Lecce itself is not situated along the coast (approx. 11 km away), the coastal areas showed higher light intensity compared to the inner part of the province. The limited change in NTL intensity is attributed to the high urban polycentricity which characterizes the Lecce province (Fig. 5d). In the province of Foggia, NTL intensity increased only at the 25th km distance from the coastline; this is explained by the presence of the city of Foggia and a lack of additional dense urban centers. The three spikes of NTL values in the BAT province are represented in Fig. 5g: the first by Barletta, Trani, and Bisceglie, which are located along the coastline; the second by Andria; and the third by Canosa di Puglia.

3.2.2. Differences in NTL intensity between internal and non-internal areas

Significant variations in NTL intensity were observed between internal and non-internal areas (Fig. 6). After conducting a *t*-test, a 3.23 $nW/sr/cm^2$ difference was discerned in absolute values during summer, and a 3.12 $nW/sr/cm^2$ difference was found during winter. These results indicate that, on average, non-internal areas are 3.34 and 3.32 times brighter than internal areas in summer and winter, respectively. The findings further support the notion that NTL serves as an effective proxy for measuring human activity levels, given that the internal areas of Puglia have a significantly lower population density (4.7 times less) compared to the rest of the region and lack major urban centers. Furthermore, the test revealed that the NTL increase rate in internal areas is lower than that of non-internal areas (slope coefficient: 0.0467 vs 0.0729 in summer and 0.0216 vs 0.0343 in winter). Additionally, light emissions from both internal and non-internal areas generally increased in both summer and winter. However, the intensity of summer light emissions increased at a faster rate than in winter, indicating a greater contrast between both seasons in the future.

3.3. Seasonal difference of NTL: Normalized Nighttime light Index (NNLI)

The NNLI values were shown to have increased over the past decade in Puglia (Fig. 7), indicating a rise in NTL intensity during summer compared to winter. In the years 2015 and 2016 the most significant decreases in NNLI values were monitored across the region, attributed to a substantial increase in winter values. The years 2021 and 2023 recorded the highest NNLI values, contributing significantly to the upward trend (see Fig. S7).

Even in the case of this indicator, the situation was not the same across the entire territory. Overall, we monitored values close to 0 in large cities, i.e., no major difference between the summer and winter seasons. The NNLI decrease in values for 2015 and 2016 was more pronounced in the Foggia, Bari, and BAT provinces, due to relatively high numbers of tourist arrivals during the winter season (Pugliapromozione, 2017). On the other hand, the Brindisi and Lecce provinces showed a milder decrease in values for those two years, with a noticeable increasing trend in the last three years influenced by a

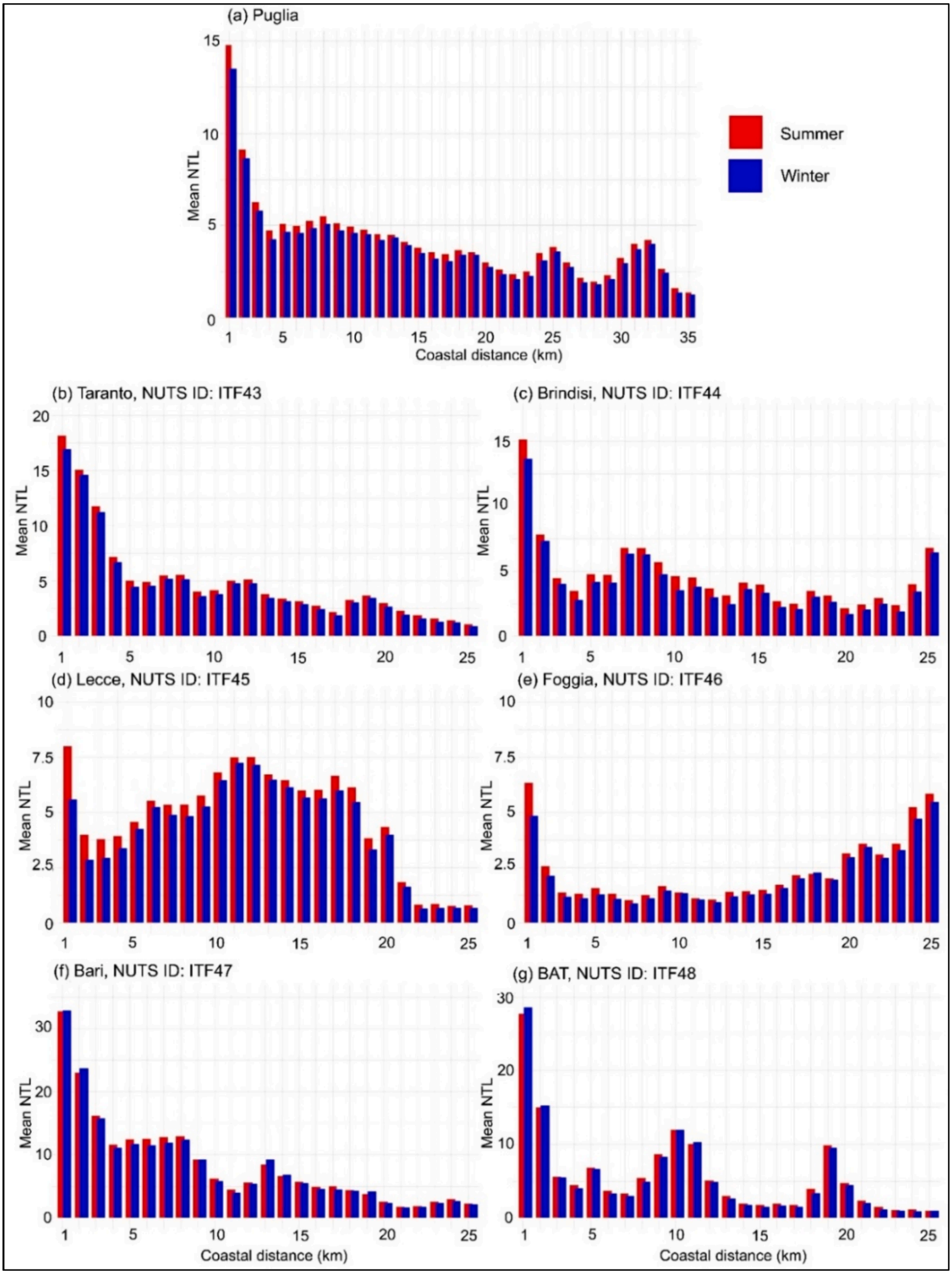

Fig. 5. Nighttime Light (NTL) vs coastal distance for the Puglia region (a) and provinces (b-g) in summer and winter 2023. NUTS, Nomenclature of territorial units for statistics.

Table 1
Hyperbolic regression analysis of spatial NTL variability.

Year	Summer R^2	RMSE	Winter R^2	RMSE
2014	0.561	7.099	0.574	6.988
2015	0.564	7.284	0.576	7.189
2016	0.581	7.423	0.580	7.434
2017	0.599	7.274	0.579	7.458
2018	0.602	7.199	0.583	7.364
2019	0.633	6.635	0.593	6.981
2020	0.624	6.751	0.587	7.069
2021	0.551	6.986	0.586	6.706
2022	0.640	6.873	0.584	7.395
2023	0.624	6.223	0.597	6.437

R squared and Root Mean Square Error (RMSE) considering summer and winter Nighttime Light (NTL) from 2014 to 2023; other spatial variables remained constant.

marked increase in overnight stays (10.5 and 8.5 % respectively, Pugliapromozione, 2024). The index was also affected by coastal proximity. The provinces in which proximity to the coast significantly impacted NNLI were Foggia, Taranto, and Lecce.

Moreover, this index effectively identified coastal tourist areas (Fig. 8). Using an exponential regression model, NNLI explained a large portion of the population increase attributed to tourist influx ($R^2 = 0.65$, RMSE=15.75 when considering all the years in the model; refer to Table S2). Municipalities such as Vieste, Peschici, and Otranto were ranked on top for population change and NNLI values. These municipalities not only had high tourist arrival numbers, but also a relatively longer residing period (Agenzia Regionale del Turismo, 2024). In contrast, municipalities such as Terlizzi and Bitetto ranked almost at the bottom of the list for both indicators. Furthermore, the municipalities with the highest growth rate in tourist presences in the past three years were Polignano a Mare and Monopoli, likely to be favored by their proximity to Bari, where the region's main airport is located (Pugliapromozione, 2024).

4. Discussion

This study assessed the changes in the dynamics of urbanization and human activity in the Puglia region over the past decade using NTL as indicator. Additionally, we examined the spatial variation of NTL intensity in Puglia, considering key factors such as urbanization (section 3.2), proximity to the coastline (section 3.2.1), and tourist attractiveness (section 3.3). The pixel-based analysis of NTL images enabled the territory to be seen at different scales, from regional to municipal.

Our analysis revealed that the NTL intensity in Puglia increased from 2014 to 2023. This increase could be potentially attributed to higher population numbers, urbanization, or economic growth. However, in the case of the Puglia region, there has been only a negligible change in population over the past decade, making economic growth the most plausible explanation. The GDP in Puglia has steady increased over the past decade, with 2020 being the only exception. It was observed that the intensity of NTL increased during both summer and winter. However, the rate of increase was shown to be higher in summer compared to winter. This finding can be attributed, to some extent, to the rise in tourist numbers. Considerable spatial heterogeneity was observed in NTL intensity and trend (Fig. S8). Distance from urban areas, important cities, and the coastline were used in a hyperbolic regression to explain NTL variability. The internal areas of Puglia were found to be significantly less bright than the rest of the region. This difference results mainly from the lower population density in these areas and the lack of activities that would attract residents to stay during the holiday season.

We developed the Normalized Nighttime Light Index (NNLI) as an indicator which quantifies the difference in NTL intensity between summer and winter. Our analysis revealed that in coastal areas, particularly popular holiday destinations, high NNLI values are monitored while major cities display minimal differences in NTL between the two seasons (Figs. S9 and Fig. S10). Considering that Puglia attracts a significant number of tourists (17 % more than the resident population), especially during the summer season (Agenzia Regionale del Turismo, 2024), we also examined whether NNLI could help explain the population increase due to tourism. An exponential regression model was developed to show that NNLI is a reliable estimator of the population surplus resulting from tourism. However, the model's inability to fully predict the population increase can be attributed to various factors, such as type of tourism, building characteristics, and hotel booking behaviors (e.g., number of nights spent in accommodation facilities).

Compressing the data of the 10-year study period, visualization helped to identify four coastal areas in the Puglia region exhibiting higher NNLI values: the coasts of Gargano, Monopoli-Ostuni, Otranto-Melendugno, and southern Salento, all of which are popular tourist destinations during the summer. While the overall trend shows an increase in the NNLI values across the Puglia region, differences exist between municipalities. Lastly, we observed that the increase in the values of this indicator throughout the past decade was not a result of a decrease in winter NTL intensity but rather of an increase in NTL intensity in summer. Our investigation of the years 2021 and 2023, during which we monitored the highest NNLI values of the past decade,

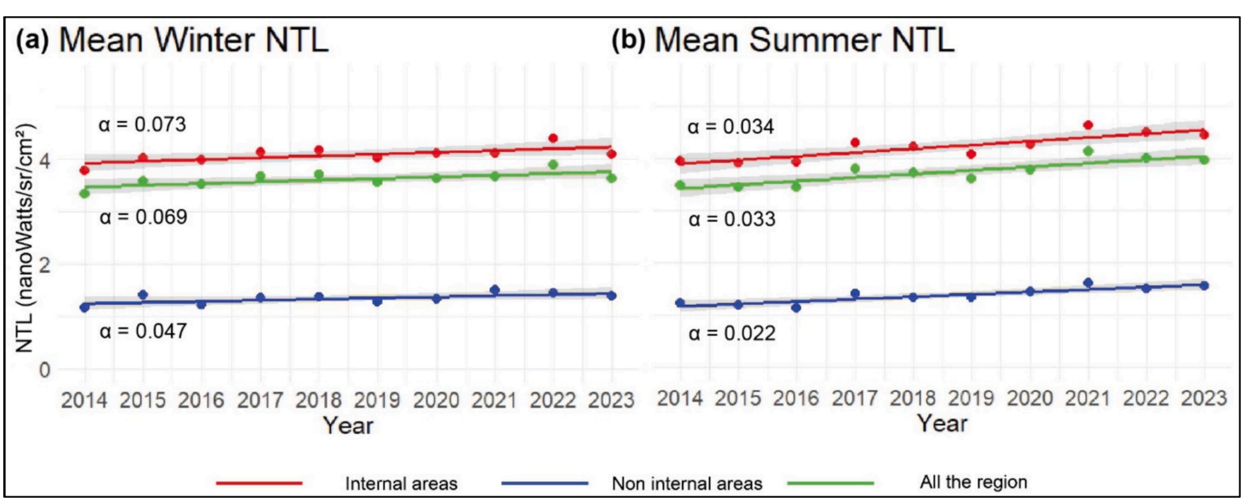

Fig. 6. Differences in Nighttime Light (NTL) intensity between internal and non-internal areas in winter (November – February) (a) and summer (June – September) (b) from 2014 to 2023. Confidence intervals are highlighted in gray.

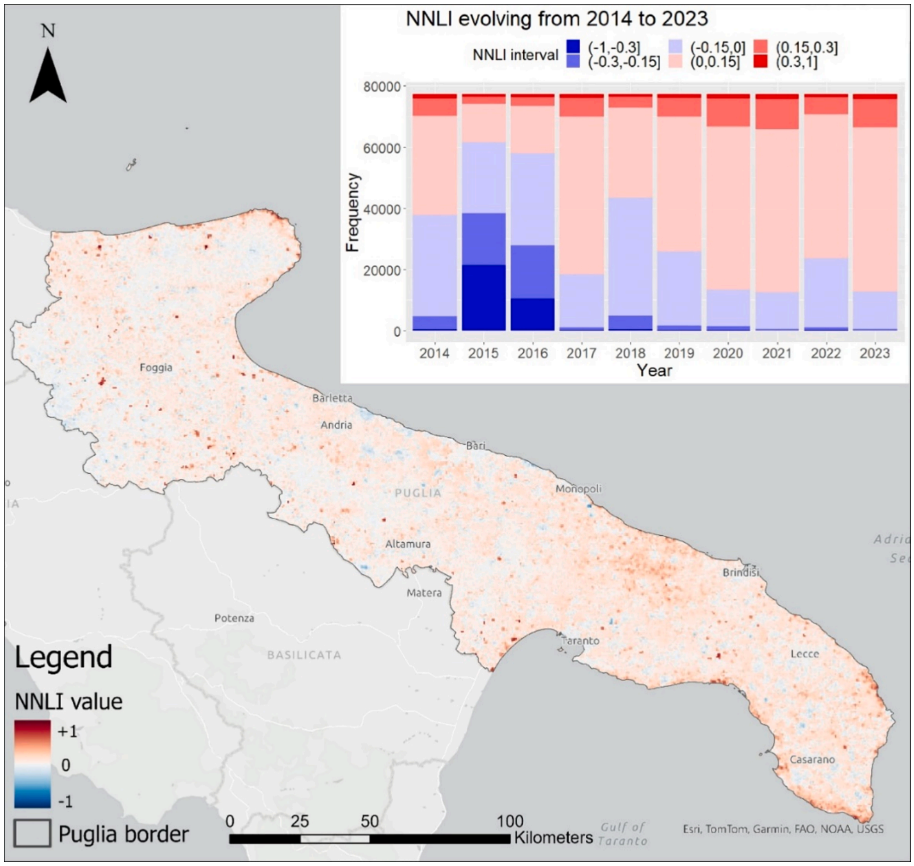

Fig. 7. Normalized Nighttime Light Index (NNLI) of the Puglia region from 2014 to 2023 and the annual change in frequency of NNLI intervals.

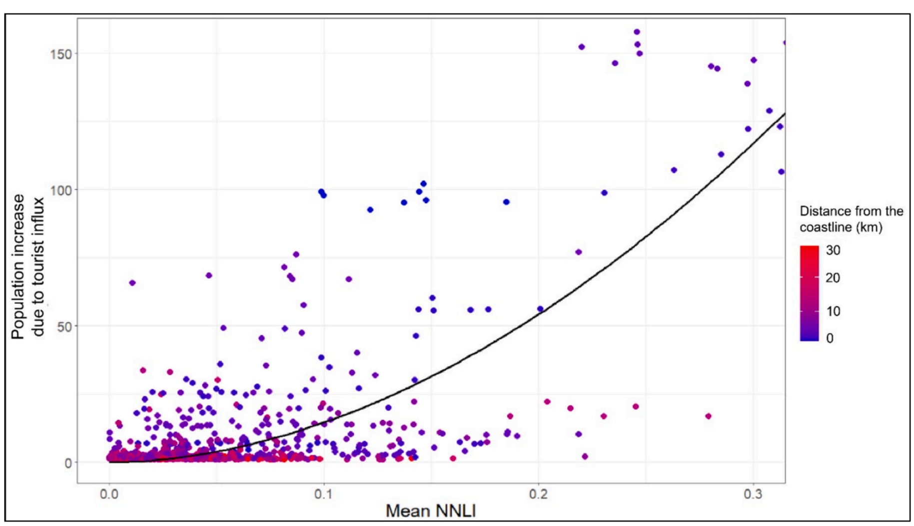

Fig. 8. Exponential regression showing the correlation between Normalized Nighttime Light Index (NNLI) and population increase due to tourist influx.

suggests that in the future Puglia could become even more attractive during the summer due to a greater variety of human activities.

5. Conclusions

Due to the ever-changing nature of urbanization, the techniques utilized in this study have the potential to enhance our comprehension of development trends in a specific area and their impact on the territory. The reliability, spatial scalability, and periodicity of NTL can provide valuable insights for decision-makers at various levels when formulating policies related to public services, environmental conservation, and local economic development. Furthermore, understanding the impact of artificial light on vegetation is crucial for ecological impact assessment (Gaston et al., 2013) and urban landscape design (Massetti, 2018).

Coastal regions in Europe, especially those in the Mediterranean, could benefit from methods similar to those proposed in this study. These regions, like Puglia, experience seasonal tourism spikes, and monitoring NTL variations could provide valuable insights into tourism trends and urbanization trajectories. Beyond coastal areas, urban centers globally can utilize NTL data to understand urbanization dynamics. Cities experiencing rapid growth, in the absence of high-quality ground data, could apply our methods to track urban sprawl and mitigate its environmental impacts. These findings can help policymakers make data-driven decisions, ensuring that territorial strategies are more sustainable, evidence-based, and tailored to the specific needs and challenges of the region.

CRediT authorship contribution statement

Arsid Pambuku: Writing – original draft, Methodology, Investigation, Formal analysis, Data curation. **Mario Elia:** Writing – original draft, Formal analysis, Conceptualization. **Alessandro Gardelli:** Writing – review & editing, Formal analysis. **Vincenzo Giannico:** Writing – review & editing, Formal analysis. **Giovanni Sanesi:** Writing – review & editing, Formal analysis. **Angela Stefania Bergantino:** Writing – original draft, Supervision, Funding acquisition, Formal analysis, Conceptualization. **Mario Intini:** Writing – original draft, Formal analysis, Conceptualization. **Raffaele Lafortezza:** Writing – original draft, Supervision, Methodology, Investigation, Formal analysis, Conceptualization.

Declaration of competing interest

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

Data availability

Data will be made available on request.

Acknowledgments

This study was carried out within GRINS – Growing Resilient, INclusive and Sustainable and received funding from the European Union Next-GenerationEU (NATIONAL RECOVERY AND RESILIENCE PLAN (NRRP), MISSION 4, COMPONENT 2, INVESTMENT 1.3 – D.D. 1558 11/10/2022, PE00000018, CUP: H93C22000650001, Spoke 7 Territorial sustainability). This manuscript reflects only the authors' views and opinions; neither the European Union nor the European Commission can be considered responsible for them. The authors wish to thank Yole DeBellis for her contribution in reviewing this work.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.ecolind.2024.112486.

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