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Remote-sensing technology in mapping socio-economic divergence of Europe

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Abstract. Marine and ocean coasts traditionally act as natural growth poles for humankind. Recent studies conducted by scholars from both natural and social sciences suggest that coastal zones accumulate population, agglomerate industries, attract entrepreneurs, and pull investments. The coastalisation effect remains one of the defining factors of regional development around the globe and is projected to strengthen over the next quarter century. Deepening socio-economic inequality and polarisation between countries and regions despite efforts taken with convergence policies put the “marine factor” on the research agenda. The study contains a comparative evaluation of coastalisation processes across the regions of Europe using remote-sensing technology and statistical multivariate analysis for testing the correlation level of results. The research is based on a dataset for 413 regions of Europe featuring indicators for population density and Gross Regional Product (GRP) in Purchasing Power Parity (PPP) per sq. km. The regions are grouped into clusters depending on their socio-economic indicators and the intensity of nocturnal illumination. The results suggest that coastal and inland region types evenly distribute between clusters, with an average of 40% coastal. Observations of nocturnal illumination clearly indicate an extensive anthropogenic impact on European coasts, both northern and southern. However, their overall luminosity is inferior to inland territories. The study concludes with four patterns derived from a combined methodology of socio-economic indicators and remote-sensing of night-time lighting.

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1. Introduction

Since the mid-1950s, the impact of the marine factor on regional socio-economic development has been at the forefront of geo-economic research. The scholarly literature has experienced a boom of studies on coastal territories after the continual registration of asymmetries in population settlements, industrial agglomerations, investment flows, R&D and innovative activity in favour of coastal areas. With that, the scope of the coastalisation effect remains controversial for being based on arbitrary estimations obtained from a limited range of maritime-dominant economies of southern coasts or for neglecting regional-level assessments. Modest estimations suggest that approximately 40% of the global population live in coastal areas, with the density being twice the worldwide average (Barbier et al., 2008; Burke et al., 2001; Cohen et al., 1997; Crossland et al., 2005; Pak and Majd, 2011). Numerous researchers advocate for a considerably higher share (e.g. Cetin et al., 2008; Cracknell, 1999; El-Sabh et al., 1998; Vallega, 1998; Vitousek et al., 1997). For instance, Hinrichsen (1996) found that three quarters of the population of the Earth reside within 150 km of the shoreline. Studies held on a macro-regional level display similar inconsistency, indicating extreme inter-regional disparities on a national scale (Baztan et al., 2015; Fedorov et al., 2017; Kurt, 2016; Makhnovsky, 2014; Salvador et al., 2015; Valev, 2009).

Considerable limitations in the variety of statistical data available and its inseparability from administrative–territorial boundaries restrict the applicability of social science research methodologies. Zeng et al. (2011: 9599) follow that "census data for any given area are neither always available nor adequately reflect the internal differences of population". Recent studies suggest that a research methodology based on advances in Earth remote-sensing adopted from natural sciences can enhance data reliability. For instance, the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite system enables the detection of foci of artificial nocturnal illumination or night-time lights (NTL), thereby providing an additional input of data for assessing spatial divergence, including the unevenness of socio-economic activity. A number of recent studies have successfully tested these techniques in human geography research (Banzhaf et al., 2009; Bennett and Smith, 2017a; 2017b; Chen and Nordhaus, 2011; Ghosh et al., 2009; Rybnikova and Portnov, 2014; 2016; Ryznar and Wagner, 2001; Zhao et al., 2017). Elvidge et al. (2001) have analysed the spatial distribution of human settlements and infrastructure using the Operational Line-scan System (OLS) – the predecessor technology of VIIRS technology that is capable of detecting natural (e.g. fires, lightning, the aurora) and artificial lights. After examining the worldwide data, the authors conclude that the NTL data could be one of the most precise tools for tracing the process of urban sprawl on a global scale. Their proceeding research has resulted in the Night Light Development Index (NLDI) as an inexpensive, annually collectible, legitimate and explicit measure on the spatial distribution of wealth based on nocturnal satellite observations of emitted light (Elvidge et al., 2012).

However, the capabilities of the NTL data based on OLS technology should not be overestimated. Zhang and Seto (2013) have designed research on urbanisation processes based on a random sample of 240 locations distributed across the globe in order to test the validity of NTL data. The results of the study indicate a considerable distortion of results due to over-glow from proximate light sources. This predominantly affects the inaccuracy of results for identifying urbanisation in less developed regions of the world – up to 42% of error, while featuring high reliability in developed countries where urban sprawl has taken place. Research on economics, demographics and environmental issues conducted by Cauwels et al. (2014) using NTL data for 160 different countries worldwide concludes that NTL images can be used as a veracious tool for monitoring the global change in light centralisation, which is assumed to be equated to the density of socio-economic activity. Those authors argue that the suggested methodology can be used to track the expansion of inhabited territories in developing countries (e.g. Brazil, India), the growth rates of urban sprawl in major new agglomerations (e.g. Shanghai in China or the Nile delta in Egypt), and regression and spatial divergence in countries suffering from demographic decline (e.g. Russia and Ukraine). A strong correlation between NTL and economic activity was also found in a recent study by an international team of scholars using a dataset for Sweden (Mellander et al., 2015). This conclusion is drawn from a study based on a combination of geographically weighted regression and correlation analysis that was conducted in order to test whether the relationship between statistical data on economic activity and night-time lights is strong enough to build the evidence base.

A review of prior studies focusing on settlement patterns and industrial clustering based on observations over nocturnal illumination advocates for its accuracy. Thus, remote-sensing technology is expected to be a reliable source of data in evaluating the coastalisation phenomenon. Our study is designed to examine the extent of thalasso-attractiveness in Europe – that is, the impact of marine coasts (coastal factor) on regional performance, and to test the two research methods traditionally applied in social sciences and the natural sciences. In the course of the research, we will first compare coastal and inland regions by two widely used development indicators – Gross Regional Product (GRP) and population figures. The next step will be to compare the standard statistical parameters of coastalisation to the nocturnal satellite observations of emitted light. The comparability of the results obtained will be evaluated and patterns discussed.

2. Materials and research methods

The study area covers the total territory of Europe, featuring 413 regions of NUTS 2 level (i.e. nomenclature of territorial units for statistics corresponding to the EU administrative geocoding system) from 48 countries, including Cyprus, Turkey and two partially recognised states – the Republic of Kosovo and the Pridnestrovian Moldavian Republic, in view of the actual isolation of their socio-economic systems and the maintenance of independent statistical records. The following demarcation assumptions are made for analytical purposes: firstly, no regional divide is made for seventeen states – Andorra, Cyprus, Estonia, Iceland, Kosovo, Latvia, Liechtenstein, Lithuania, Luxembourg, Macedonia, Malta, Moldavia, Monaco, Montenegro, Pridnestrovian Moldavian Republic, San Marino and the Vatican. The total territory of each of these countries is equated to the NUTS 2 level as suggested by the Statistical Office of the European Union (Eurostat). Secondly, only the European part of Russia is taken for analysis, which is limited by the Central, North Caucasus, North-western, Southern, and Volga Federal Districts.

All of the 413 regions under study are differentiated according to the availability of the marine coast into two groups: regions with direct access to sea, ocean or gulf coast – coastal regions, and other non-coastal regions – inland regions (Fig. 1). A number of assumptions are made for this delimitation: 1) Warmian-Masurian region (voivodeship) of Poland is referred to as a coastal region, as it has access to the Vistula (Kaliningrad) gulf; 2) all islands (e.g. Balearic) and island states (e.g. Cyprus) are referred to as coastal; 3) islands of France (Guadeloupe, Martinique, La Réunion, Mayotte), Portugal (Madeira, Azores), Canary islands of Spain are excluded from the study due to their considerable distance from mainland Europe; 4) micro-enclaves, such as Jungholz (Austria), Baarle-Hertog (Belgium), Büsingen am Hochreihn (Germany), Livia (Spain), Campione d'Italia (Italy), Baarle-Nassau (Netherlands), Dubrovnik (Croatia), Medvezhye-Sankovo (Russia) are not considered individually, while overseas enclaves of Spain in Africa (Ceuta, Melilla) and France in South America (Guyana) are excluded from the study; 5) the sub-regions of Greater

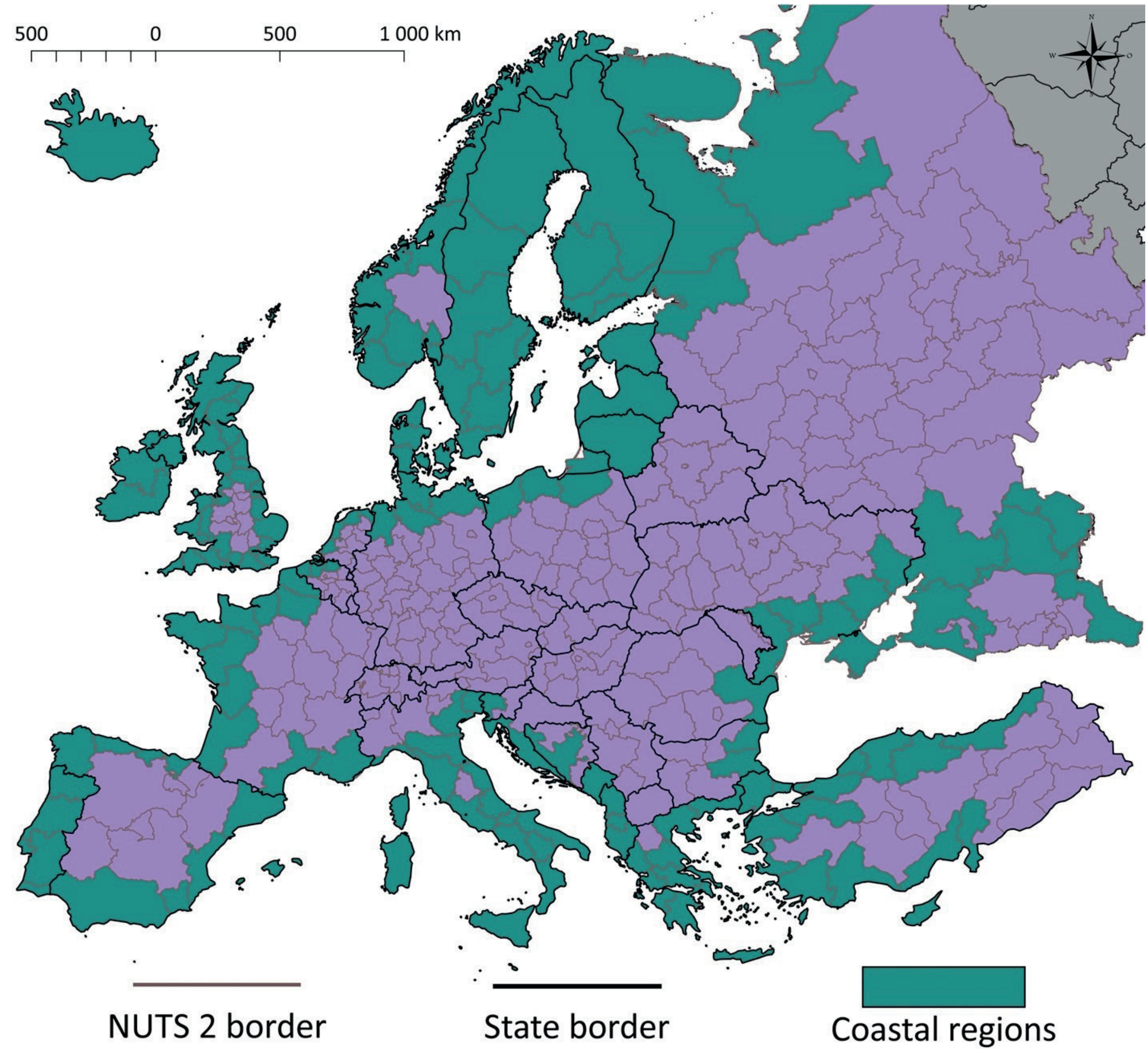

Fig. 1. Coastal and inland regions of Europe

London are combined and considered as a single region; 6) the Bremen and Hamburg urban agglomerations of Germany are considered as coastal.

The research methodology is composed of two stages. The first stage includes cluster analysis of regions on socio-economic development indicators for the period 2010–14: population density and the relative values of GRP (PPP) in million euros per sq. km. Average values of the indicators for each region over the five-year period are applied in the clustering. The cluster analysis is performed using the k-means method in IBM SPSS Statistics software 24. The priority sources for the statistical data are: Statistical Office of the European Union (Eurostat) for the 28 countries of the European Union and the national statistical offices for other countries. The databases of the United Nations, the World Bank, and the International Monetary Fund are used as complementary sources of information. A number of assumptions are made with regard to data collection: 1) population figures for Slovenia of 2014 are transposed for 2010–13, for Albania the 2013 data is transposed for 2014 (Note: total population share of these countries is 0.64%); 2) Gross Domestic / Regional Product (PPP) data transposition is made for Albania (2014 is replaced by the data for 2013), Liechtenstein (2013 by 2014), Monaco (2012–14 by 2011), Norway (2010 by 2011 and 2014 by 2013), and Serbia (2010–12 by 2013) (Note: national share of these states in the total amount of

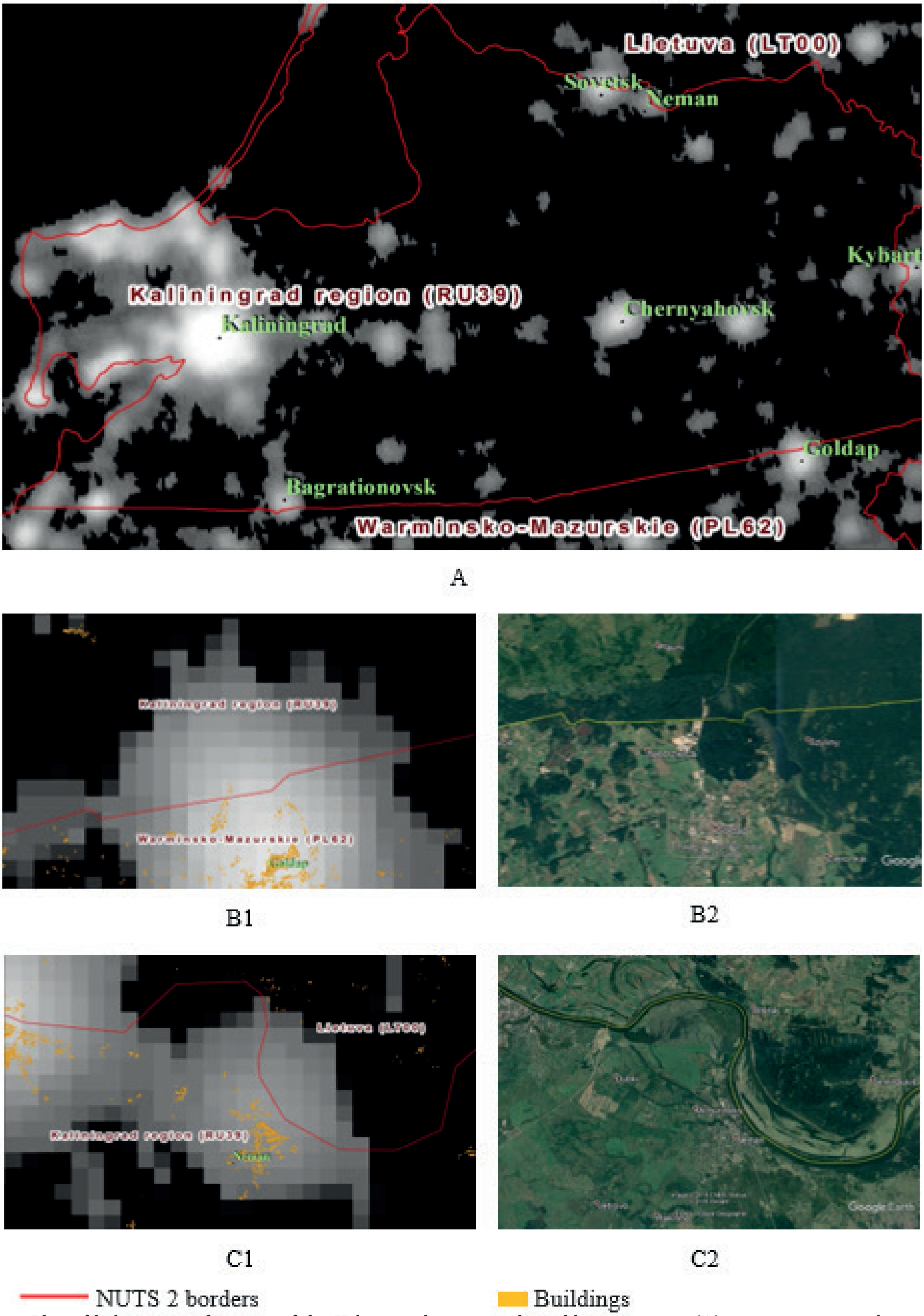

Fig. 2. Blur of light sources for cities of the Kaliningrad region and neighbouring states (A) in comparison with satellite images of the Google Earth program: Goldap, Poland (B1 – NTL, B2 – Google Earth); Neman, Russia (C1 – NTL, C2 – Google Earth).

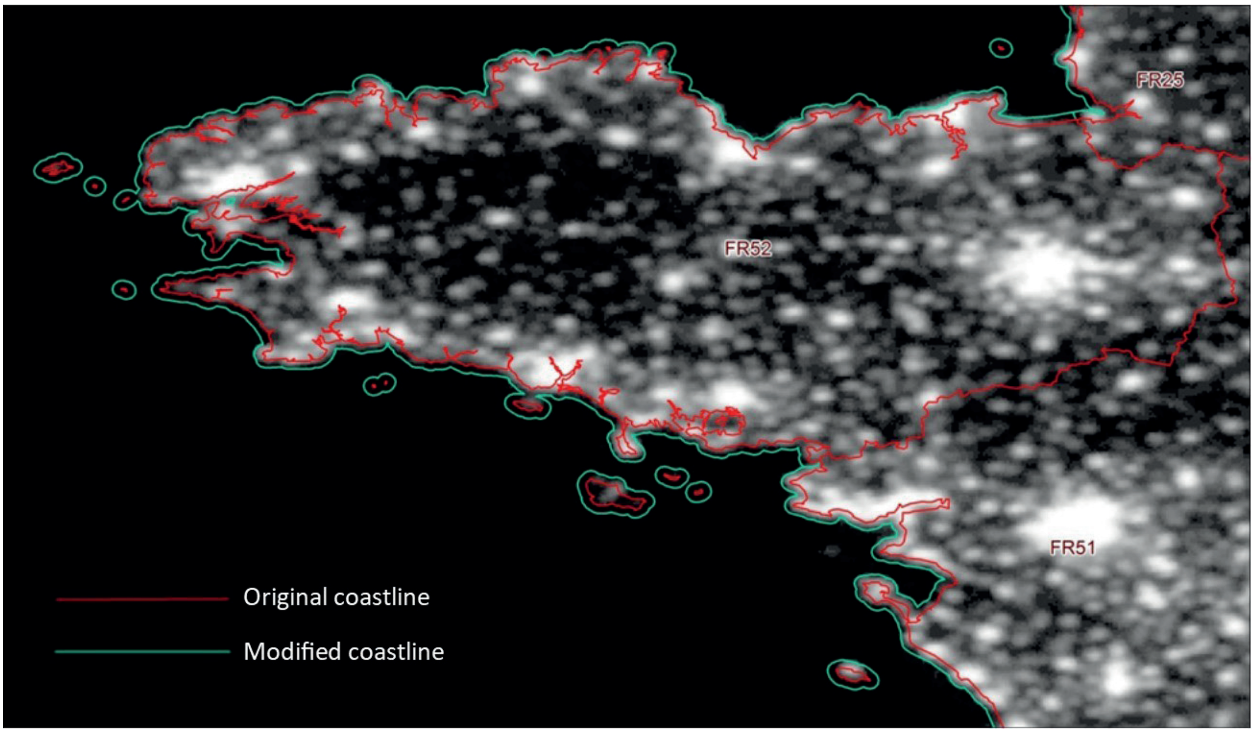

Fig. 3. Modification of coastline due to overglow effect

GRP (PPP) is 1.47%); 3) data for the total area of regions is taken for 2014, for Slovenia it is 2015; 4) statistical data for Crimea and Sevastopol for the period 2010–13 is provided by the State Statistics Service of Ukraine, and for 2014 the data source is the Federal Service of State Statistics of the Russian Federation.

The second stage includes a comparative analysis of the geo-location of the allocated clusters of regions and the satellite imagery that reflects the total luminosity of each region. The source for luminosity data is the database of the Defense Meteorological Satellite Program (DMSP) project for 2013 (Version 4 DMSP-OLS Nighttime Lights Time Series), featuring the normalised composite of constant NTL, where the luminosity of each pixel in the original image is in the range from 0 to 63 units. The image is given in the geographic coordinate system WGS-84, which is essentially a cylindrical projection. To ensure minimal distortion in the recalculation of projections, the evaluation is carried out in the original projection for the given image. Taking into account the extension in a given linear dimension with increasing values of geographical latitude, the image is modified by multiplying the value of each pixel by a factor compensating for this extension – the cosine of the latitude in radians.

As topographic layers, NUTS maps of the Eurostat database (scale 1:1 million) and administrative division maps from the Environmental Systems Research Institute (ESRI) collection are used. An expanded NUTS 2 map includes the territories of Albania, Belarus, Bosnia and Herzegovina, Moldova, Serbia, Ukraine, and a 1:1 million map of the European part of Russia. High-precision maps of the Open Street Map project are used for analysing individual cities. To ensure topological correctness, the borders are corrected using the countries layer (1:1 million) from the Eurostat database. The selected scale of the maps and the detailed elaboration of the original image provide an adequate overlap of these two spatial factors.

It should be noted that the boundaries of nocturnal illumination near the coast do not coincide with the boundaries of the land. This is due to several reasons, the main one of which is the diffraction of light in the Earth's atmosphere. Figure 2 illustrates the blurring of light from settlements. The cities of Neman (Russia) and Goldap (Poland) have historically been located in such a way that they are closely adjacent to the state border, and for geographical and political reasons, there are practically no light sources across the state border. However, the radiation spot is partially located on both sides of the border.

Thus, calculating the total luminosity of each coastal region requires accounting for the glow of the water surface adjacent to the coast. For this, the outlines of each coastal region are modified so that a strip of the sea surface is added to the land area. A strip of width 3 km is expertly selected as this width is able to capture the diffraction of light over the sea surface in most cases (Fig. 3). Further assessment of this factor will require considering the "erosion" of light spots on land as well, which is technically quite difficult and not applied in the current study. It should be noted that the calculation errors for the luminescence sources of a certain region are on average compensated by the "erosion" of border sources in neighbouring regions. The spatial data and NTL are prepared using ArcGIS and QGIS software.

3. Research results

According to the multivariate classification of regions based on population density and GRP (PPP) data processed using the method of cluster analysis, the following four clusters of regions are identified (Table 1).

Regions are distributed between the four clusters in descending order, with the regions featuring the highest indicator values being included in cluster I. The number of regions in the defined clusters is unequal and increases from cluster I to cluster IV. The proportion of coastal regions in each cluster fluctuates from 38 to 45%, which is evaluated as an individual criterion of coastalisation assessment. The allocation of two clusters with average performing regions is justified by strong heterogeneity in the totality of regions studied. These clusters demonstrate different groups of regions by population and GRP (PPP) figures. For all clusters, the maximum, median and minimum indicator values are calculated. The median value allows objective average values to be obtained given strong differences in the sampling elements.

Table 1. Cluster distribution of regions on socio-economic development indicators

Cluster	Number of regions	Population density, people per km²			GRP in PPP, million euro per km²		
		max	median	min	max	median	min
I – strong	13	18474.2	3779.7	2579.2	2205.5	118.5	52.2
inland regions	8	7202.3	3978.8	2503.7	400.0	116.8	66.0
coastal regions	5	18474.2	3575.0	2579.2	2205.5	124.9	52.2
II – average	20	2116.0	977.9	664.0	65.7	29.2	0.0
inland regions	11	2116.0	962.5	759.0	50.8	26.7	0.0
coastal regions	9	1703.9	1040.1	664.0	65.7	29.9	12.6
III – average	120	624.9	231.8	131.9	28.1	6.2	0.1
inland regions	72	609.9	230.2	131.9	28.1	6.2	0.1
coastal regions	48	624.9	237.8	144.2	23.0	6.1	1.2
IV – weak	260	130.6	61.5	0.2	4.1	0.7	0.0
inland regions	150	130.6	60.7	2.1	4.1	0.5	0.1
coastal regions	110	129.9	65.0	0.2	4.0	0.9	0.0
Total	413	18474.2	96.3	0.2	2205.5	1.6	0.0
inland regions	241	7202.3	95.8	2.1	400.0	1.3	0.0
coastal regions	172	18474.2	97.0	0.2	2205.5	2.0	0.0

Cluster I includes the smallest number of regions, but they show the highest concentrations of population and GRP (PPP). Cluster II follows behind the leader with 3.9 times lower average population density and 4.1 times lower GRP (PPP) per sq. km, which did not allow these regions to be attributed to the strong cluster, but they are also national growth nodes for their countries. Between clusters of regions with average values of the characteristics of clusters II and III there is also a strong gap in median values of population density and GRP (PPP) per sq. km – the gap being a factor of 4.2 and 4.7, respectively. However, their aggregate statistical values are higher than those of most European regions, which allows us to attribute them as economically developed. The most numerous is cluster IV, which includes 62.9% of all the regions studied. It is very heterogeneous in its qualitative composition, but quantitatively these regions have shown the lowest indicators of socio-economic development. Cluster IV lags behind cluster III in terms of population density by a factor of 3.8, and in terms of GRP (PPP) by a factor of 8.9. In general, the gap between cluster I and cluster IV in terms of medi-

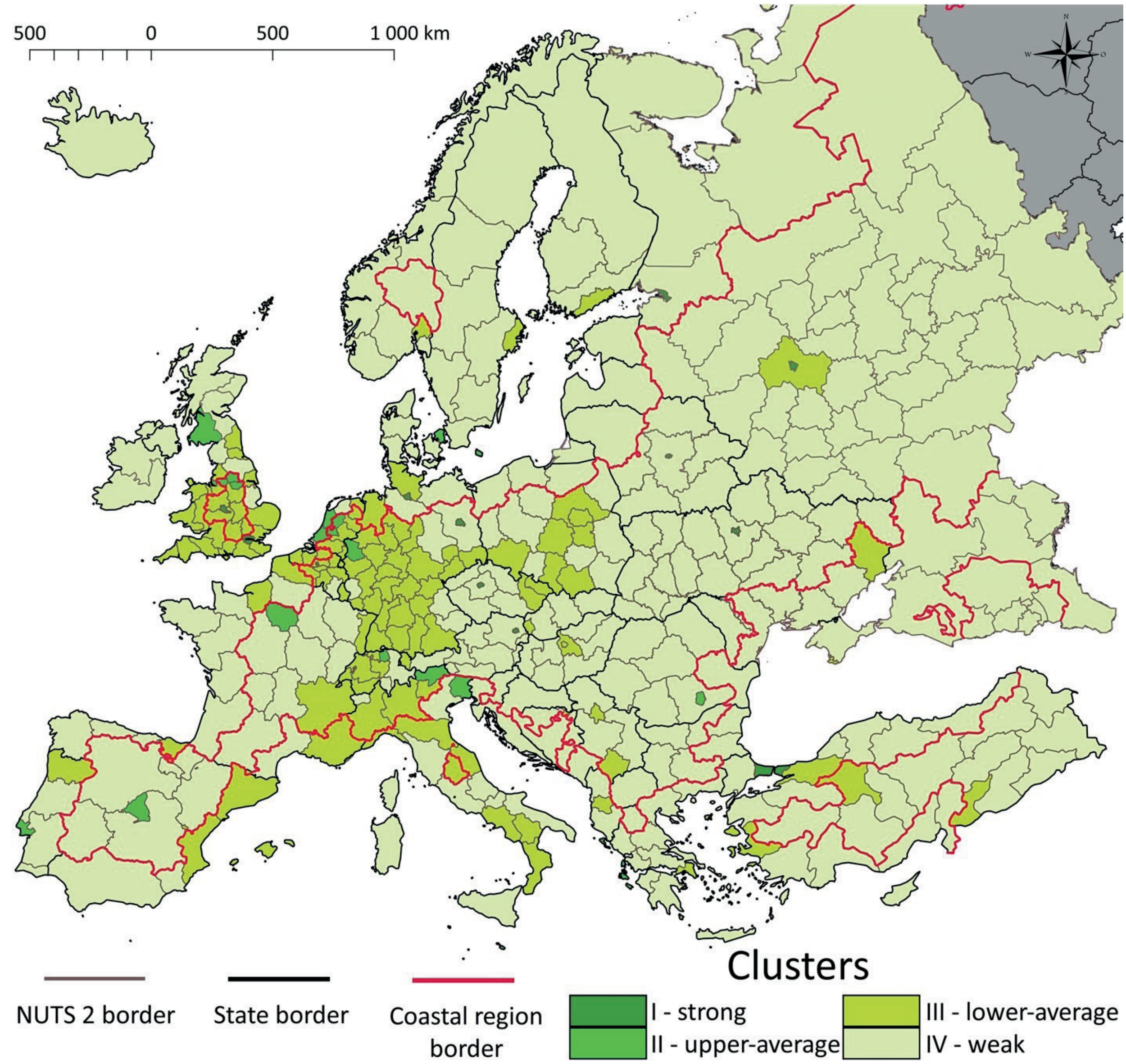

Fig. 4. Clusters of regions by socio-economic development indicators

an population density and GRP (PPP) is enormous – at respective factors of 61.5 and 169.3, which indicates a high degree of heterogeneity of spatial development at the level of NUTS 2. The distribution of coastal regions between the four allocated clusters is fairly even – at the level of 42%, which does not allow us to draw an unambiguous conclusion about the superiority of coastal regions over intracontinental rgions in terms of socio-economic development. The spatial distribution of statistically defined clusters by population density and GRP (PPP) is presented in Fig. 4.

Cluster I is the smallest in the number of affiliated regions. It includes major metropolitan cities of Europe – Brussels, London, Minsk, Moscow, Vienna, Berlin, Prague, Kyiv, and large economically-developed non-capital cities (St Petersburg [Russia], Hamburg [Germany], Istanbul [Turkey]), as well as the micro-state of Monaco and the West Midlands agglomeration (the United Kingdom). The regions of this cluster are characterised by the highest values of population density and the level of GRP creation per sq. km. The leader in these indicators is Monaco, featuring the highest density rate.

Cluster II includes the developed regions of Denmark, France, Germany, Italy, the Netherlands, Portugal, Romania, Spain, Switzerland and the United Kingdom. It also includes the states of Malta and the Vatican. The concentration of population and GRP in these regions is also significant, although it is several times lower than the regions of cluster I.

Clusters III and IV are the most numerous: they include 120 and 260 regions, respectively. The level of population concentration and GRP in these regions is medium and below average. The lowest density of population and the level of GRP (PPP) creation per sq. km are noted for the regions included in cluster IV. This is 93% of all regions of Russia, 92% of Ukraine, 88% of Sweden and Romania, 86% of Belarus, Norway and Hungary, 81% – Turkey, 80% – Finland and Denmark, 78% – Austria, 77% – Greece, 75% – Serbia and Slovakia, 73% – France, 69% – Spain and Poland, 67% – Bosnia and Herzegovina and Albania, 63% – the Czech Republic, 60% – Portugal, 43% – Italy, 29% – Switzerland, 19% – the United Kingdom, 18% – Germany, 17% – the Netherlands, 9% – Belgium, as well as the entire territory of the Baltic countries (Estonia, Latvia, Lithuania), Iceland, the Pridnestrovian Mol-

Table 2. Cluster distribution of regions by the average illumination of the territory

Cluster	Number of regions	Average luminosity of the territory *		
		max	median	min
A – strong NTL	25	239.7	64.0	50.3
inland regions	13	73.3	65.0	50.3
coastal regions	12	239.7	58.9	50.3
B – medium-strong NTL	73	47.5	28.4	20.0
inland regions	41	47.5	28.9	20.0
coastal regions	32	45.7	27.4	21.5
C – medium-weak NTL	111	19.9	14.5	11.0
inland regions	58	19.9	14.4	11.0
coastal regions	53	19.7	14.5	10.9
D – weak NTL	204	10.9	5.08	0.1
inland regions	129	10.9	4.9	0.9
coastal regions	75	10.8	5.6	0.1
Total	413	239.7	11.0	0.1
inland regions	241	73.3	9.6	0.9
coastal regions	172	239.7	11.5	0.1

* The average luminosity of the territory is the ratio of the total illumination of regions taking into account the water area to the total area of these regions

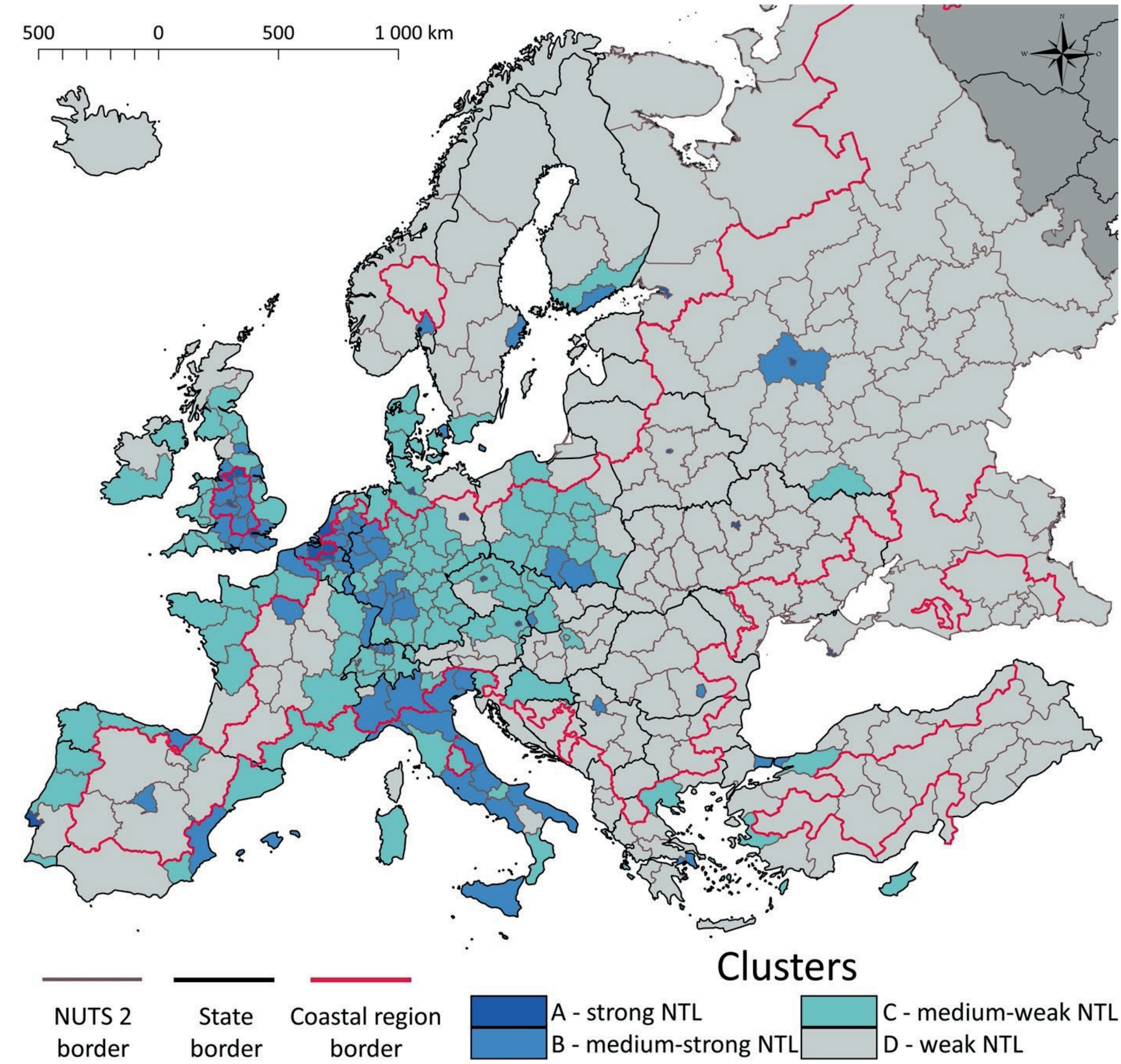

Fig. 5. Average intensity of nocturnal luminosity by regions

davian Republic, Montenegro, Macedonia, Moldova, Cyprus, Bulgaria, Ireland, Croatia and Slovenia.

A total of 172 NUTS 2 level regions of Europe are classified as coastal regions in accordance with the presented methodology, representing 42% of the total number of regions considered. Coastal regions occupy 45% of the total terrestrial area of Europe. They account for 42% of its population and 43% of the total GRP. The distribution of regions to coastal and inland (i.e. continental) in each of the defined clusters is similar and on average equates to 40 and 60%, respectively (Table 1). The fewest coastal regions are found to be in cluster I – 38%, while the largest share is found to be in cluster II – 45%.

According to the results of the analysis of data on the illuminance of the territory, all NUTS 2 regions are divided into four clusters according to luminous intensity (Table 2).

Several areas with strong NTL clusters are identified, which are formed by glow in the territory of 25 regions, including 48% coastal – Monaco, Malta, United Kingdom (Merseyside, London), Russia (St Petersburg, Sevastopol – Ukraine at the time of the study), Germany (Bremen, Hamburg), Portugal (Área Metropolitana De Lisboa), Belgium (Prov.

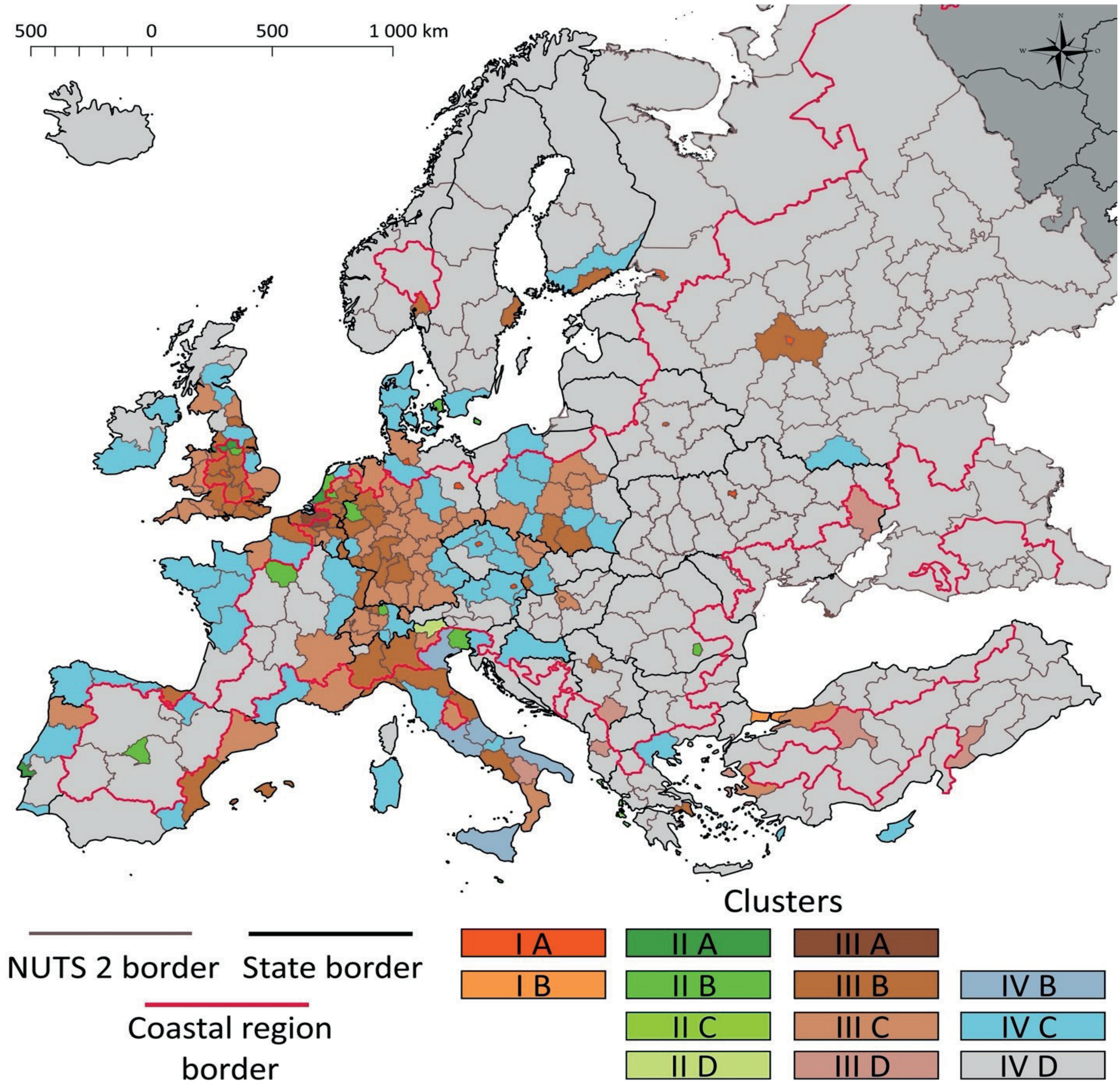

Fig. 6. Typology of European regions by nocturnal luminosity and socio-economic development statistics

Antwerpen, Prov. Oost-Vlaanderen) and the Netherlands (Zuid-Holland). In general, the distribution of coastal regions by illumination clusters is evenly distributed: 44–48%. The share of coastal regions is lower only in the cluster of less illuminated areas with a majority of regions – 37%. Figure 5 shows the spatial distribution of nocturnal illumination by NTL density.

Based on the results of the cluster analysis, the mapping of selected clusters of regions is performed with the imposition of NTL (Fig. 6).

Correlating the concentration of night-time artificial illumination and the distribution of identified clusters of regions evidently verifies the statistical clustering approach. Data reveals that the highest concentration of NTL is observed in regions with the highest population density and GRP (PPP) per sq. km. Some concentration of lights can be observed in the regions of clusters II and III, while the regions of cluster IV are predominantly characterised by weak scattered single lights, without pronounced aggregation.

Table 3. Matrix for distribution of NUTS 2 level regions by NTL and socio-economic development

Clusters		Socio-economic development				
		Cluster I	Cluster II	Cluster III	Cluster IV	*Total regions*
Nocturnal luminosity	Cluster A	12	8	5	0	*25*
	Cluster B	1	10	56	6	*73*
	Cluster C	0	1	52	58	*111*
	Cluster D	0	1	7	196	*204*
	Total regions	*13*	*20*	*120*	*260*	*413*

4. Discussion and interpretation of findings

The research findings suggest a number of combinations allocated resulting from comparative assessment of the two methods applied (Table 3): 1) strong NTL and cluster I; 2) strong NTL and clusters II–III; 3) medium-strong NTL and cluster I; 4) medium-strong NTL and clusters II–III; 5) medium-strong NTL and cluster IV; 6) medium-weak NTL and clusters II–III; 7) medium-weak NTL and cluster IV; 8) weak NTL and clusters II–III; 9) weak NTL and cluster IV.

In total, 92.3% of the regions of cluster I have strong NTL, 85% of the regions of clusters II and III have medium NTL, and 75.4% of the regions of cluster IV have weak NTL. The results obtained lead us to the conclusion that the level of socio-economic development is closely interlinked with the level of nocturnal illumination. Economically developed regions for the most part have a strong level of NTL and, conversely, regions with a lower level of economic development have weak NTL. Three general patterns can be distinguished as combining most regions within the framework of possible combinations (Table 3): strong NTL and strong development – 12 regions, medium NTL and average development – 119 regions, weak NTL and weak development – 196 regions. A number of patterns are more likely to be deviations from the general trend: cluster A vs. clusters II–III; cluster B vs. cluster I; cluster B vs. cluster IV; cluster C vs. cluster IV; cluster D vs. clusters II–III. These deviations combined account for 20.8% of all regions.

The first general pattern: cluster A and cluster I. A strong glare of nocturnal illumination and high values of statistical indicators are typical for the regions of cluster I, with NTL being centred on capital cities and large metropolitan agglomerations. Of the 12 regions of cluster I with strong NTL, four regions (33.3%) are coastal: Monaco, London, St Petersburg and Hamburg are large port cities where large transport and logistics complexes and port infrastructure provide additional luminosity. Often, they represent relatively small inner regions of NUTS 2 classification surrounded by a less developed territory. In the case of Moscow (Russia), Greater London and Birmingham (West Midlands, the UK), the adjacent territories show a higher level of development and an observable overglow as compared to the national average. By contrast, Berlin (Germany), Kyiv (Ukraine), Minsk (Belarus), Prague (Czech Republic), Vienna (Austria) and a few other major cities defined as individual NUTS 2 units showing no considerable effect in contributing to the socio-economic development of bordering regions, both in terms of NTL and statistics.

The first pattern is supplemented by two secondary models, which are dominated by coastal regions.

1.1. *Cluster A and cluster II.* This pattern is repeated for eight regions, including five coastal (62.5%). The coastal regions include Malta, the United Kingdom (Merseyside), Germany (Bremen), Portugal (Área Metropolitana de Lisboa), the Netherlands (Zuid-Holland), and the inland regions include the Vatican and the United Kingdom (Greater Manchester, West Yorkshire). These are urbanised densely populated areas and metropolises of developed European countries, where the concentration of infrastructure that provides NTL is a consequence of their high economic development. In the coastal regions, there are also large port and logistics complexes. The regions of this pattern have a fairly high level of development in comparison with most others, but it is lower than in the capital regions, which are included in cluster I.

1.2. *Cluster A and cluster III*. This pattern is observed in five regions, including three coastal regions (60%). The coastal regions include territories in Russia (Sevastopol, former Ukraine), Belgium (Prov. Antwerpen, Prov. Oost-Vlaanderen), and the intracontinental ones include San Marino and Belgium (Prov. Vlaams-Brabant). These are the urbanised areas of Belgium, as well as San Marino and the city of Sevastopol, where the creation of infrastructure that causes NTL is part of a national development strategy and not a direct consequence of their sustainable economic strength.

The second general pattern: cluster B–C and cluster II–III. It is subdivided into cluster B – cluster II – 10 regions (30% coastal), cluster B – cluster III – 56 regions (39.3% coastal), cluster C – cluster II – 1 coastal region, cluster C – cluster III – 52 regions (37.5% coastal). In general, 85% of average performing regions have medium NTL. However, as can be seen from the presented distribution, cluster III regions prevail, featuring only 38% of coastal regions.

The second general pattern is supplemented by three secondary patterns dominated by coastal regions:

2.1. *Cluster B and cluster I*. This pattern includes 1 coastal region of Turkey (İstanbul). It is a metropolitan urbanised region with the highest level of economic development and infrastructure among other Turkish regions. However, on a Europe-wide scale, Turkey's infrastructure is less developed (even of its most developed regions), which did not allow İstanbul to enter a group with strong NTL.

2.2. *Cluster B and cluster IV*. This pattern includes six coastal regions located in the Netherlands (Zeeland) and Italy (Veneto, Lazio, Puglia, Abruzzo, Sicilia). These are relatively large administrative–territorial units of statistics with a high level of intra-regional divergence being polarised towards major urban agglomerations and public infrastructure, such as roads. Despite the bright glow of NTL, these regions are attributed to the group of underperforming regions. The most vivid examples are the Italian regions of Lazio and Veneto, and all fall into cluster IV – the least developed regions by selected indicators. The illumination of artificial light in these regions follows the main motorways as well as outlining the area around the global urban tourist destinations – the cities of Rome (incl. the Vatican), Florence, Pisa, Verona and Venice. The census data for population figures neglect the immense tourist flows typical of these areas, while the GRP (PPP) figures evaluated per sq. km of the total area are low.

2.3. *Cluster C and cluster IV*. This pattern includes 58 regions, including 33 coastal regions (56.9 %). Coastal regions are found in 15 countries: Cyprus (Kypros), Denmark (Sjælland, Syddanmark, Midtjylland, Nordjylland), Finland (Etelä-Suomi), France (Picardie, Basse-Normandie, Pays De La Loire, Bretagne, Poitou-Charentes, Languedoc-Roussillon), Germany (Lüneburg), Greece (Notio Aigaio, Kentriki Makedonia), Ireland (Southern and Eastern), Italy (Molise, Sardegna, Toscana), the Netherlands (Friesland), Poland (Pomorskie), Portugal (Algarve, Centro), Slovenia (Zahodna Slovenija), Spain (Galicia, Principado de Asturias, Cantabria, Región de Murcia), Sweden (Sydsverige) and the United Kingdom (North Yorkshire, Lincolnshire, Eastern Scotland, Northern Ireland). This pattern is partly justified by the aforementioned specifics of the cluster analysis, when high indicator values of a limited number of highly developed regions boost the overall threshold level (Table 1). Thus, the category is dominated by either less well performing regions of highly developed countries, e.g. the United Kingdom, Germany, Spain, France and Italy, or strongly performing regional territorial socio-economic systems of less well developed ones – e.g. Poland, Croatia and the Czech Republic.

The third pattern: cluster D and cluster IV. This model is typical for 196 regions, including 71 coastal (36.2%). This category includes regions that show low performance in statistical cluster analysis and feature a few scattered single lights that are often too poorly visible to positively discern. Most of these regions are located in Eastern Europe, the Balkan Peninsula and Scandinavia. The availability of NTL does not per se reflect the socio-economic development of the territory. For example, the glow of northern Norway is less related to the population density or industrial agglomeration, but largely reflects temporal economic activities for exploiting natural resources. This includes marine oil extraction at the continental shelf (note 1). Another example is the Murmansk region of the Russian Federation, where artificial nocturnal illumination of the Murmansk city – the administrative centre and the largest city within the Arctic Circle, generates equal glow as does the mining industry of the mineral deposits close to Khibiny and Apatity.

The third general pattern is further differentiated into two modes with half of regions being coastal.

3.1. *Cluster D and cluster II*. This pattern is characteristic of only one inland region of Provincia Autonoma di Bolzano / Bozen, located in Italy. This is a developed agricultural region, the specialisation of the economy of which does not imply a high concentration of luminous infrastructure. Therefore, with sufficiently high economic indicators in the region, its position in terms of average luminosity is low. This suggests certain limitations in using NTL for mapping socio-economic divergence.

3.2 *Cluster D and cluster III*. This pattern is found in seven regions, including 57.1% coastal. These coastal regions are found in Italy (Basilicata), Albania (Qender), Ukraine (Donetsk), Greece (Voreio Aigaio), and inland regions include Turkey (Ankara and Gaziantep-Adıyaman-Kilis) and Serbia (Kosovo-Metohija). Despite the relatively low NTL values in these regions, they have an average level of socio-economic development due to developed traditional industries: agriculture (Basilicata, Qender, Ankara, and Gaziantep-Adıyaman-Kilis,), mining (Donetsk, Kosovo-Metohija), and tourism (Voreio Aigaio, Gaziantep-Adıyaman-Kilis). In addition, a significant part of the territory of the majority of the regions that fall into this group is mountainous, which complicates the development of electric power, transport and other infrastructure that can be registered using the NTL method.

The NTL data clearly presents an extensive anthropogenic impact on the marine coasts. All of the European shoreline, both northern and southern, is outlined by nocturnal illumination of human activity – residential, industrial, infrastructural, transport (incl. marine), etc. Most often is it presented as a narrow strip of light with the coastal towns and cities being interlinked by a seaside highway. The average width of this luminous stream does not exceed a 30 km distance from the coast. Despite an observable concentration of NTL in the coastal zone of Europe, it is not statistically dominant, since a significant part of the NTL is located in the continental zone – i.e. inland regions. Thus, the global effect of coastalisation described as the prevailing factor of spatial divergence is neither confirmed by the cluster analysis nor by the NTL observations in Europe.

5. Conclusion

Each of the 413 NUTS 2 regions of Europe considered herein features a visible cluster of NTL. Night-time light observations largely coincide with the highly developed clusters of regions defined using the statistical data on population density and the relative values of GRP (PPP) in million euros per sq. km. The brightest clusters of lights correspond to the most developed regions by selected indicators – clusters I and II. These are large metropolitan areas dominated by the urban sprawl of capital cities. However, the availability of a NTL cluster does not per se reflect the socio-economic development of the territory. As described in the three patterns identified from the comparative assessment of the two methods applied, there can be an asymmetry. In our study, supplementary patterns are identified in addition to each general scheme, which to a greater extent represent exceptions.

The share of coastal regions in the three general patterns identified is below 50%, while in supplementary ones it is above 50%. This shows that coastal regions exhibit unique development patterns. Research results suggest that some coastal regions of southern Europe do gravitate towards the coastline, reflecting an observable bind of NTL. However, it can hardly be labelled as a European pattern. Neither the results of the statistical cluster analysis nor the nocturnal light observations support the allegation of a pan-European trend of coastalisation.

We suggest that the coastalisation effect should be further studied using the NUTS 3 level of regions, with the proposed methodology of combining statistical data and NTL observations. Particular attention should be given to the country-level studies supplemented by qualitative information unveiling the rationale behind the research results (e.g. industry clusters, urbanisation, cross-border regionalisation, infrastructure, terrain features). The overglow effect of light diffraction in the Earth's atmosphere should be further addressed when approaching NTL observations at the municipal level.

Note 1: Norwegian Petroleum Directorate. FactMaps. URL: http://gis.npd.no/Factmaps/html_21 (accessed 15.09.2017)

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References

Banzhaf, E., Grescho, V., Kindler, A. (2009). Monitoring Urban to Peri-Urban Development with Integrated Remote Sensing and GIS Information: A Leipzig, Germany Case Study. *International Journal of Remote Sensing*, 30(7), 1675-1696.

Barbier, E.B. Koch, E. Silliman, B. Hacker, S. Wolanski., E. Primavera, J. Granek, E. Polasky, S. Aswani, S. Cramer, L.A. Stoms, D.M. Kennedy, C.J. Bael, D. Kappel, C. Perillo, G. and Red, D (2008). Coastal Ecosystem-Based Management with Nonlinear Ecological Functions and Values. *Science*, 319, 321-323. DOI: http://dx.doi.org/10.1126/Science.1150349

Baztan, J., Chouinard, O., Jorgensen, B., Tett, P., Vanderlinden, J.-P., Vasseur, L. (2015). Coastal Zones: Solutions for the 21st Century. 1st Edition. Amsterdam: Elsevier.

Bennett, M.M., Smith, L.C. (2017a). Advances in Using Multitemporal Night-Time Lights Satellite Imagery to Detect, Estimate, and Monitor Socioeconomic Dynamics. *Remote Sensing of Environment*, 192, 176-197.

Bennett, M.M., Smith, L.C. (2017b). Using Multitemporal Night-Time Lights Data to Compare Regional Development in Russia and China, 1992–2012. *International Journal of Remote Sensing*, 38(21), 5962-5991.

Burke, L. Kura, Y. Kassem, K. Revenga, C. Spalding, M. McAllister, D. (2001). Pilot Analysis of Global Ecosystems: Coastal Ecosystems. Washington: World Resources Institute.

Cauwels, P., Pestalozzi, N., Sornette, D. (2014). Dynamics and Spatial Distribution of Global Nighttime Lights. *EPJ Data Science*, 3(2). URL: http://www.epjdatascience.com/content/3/1/2

Cetin, M., Musaoglu, N., Tanik, A. (2008). Multitemporal Assessment of Land-Use Change in a Rapidly Urbanizing Coastal Region in Turkey Using Remote Sensing. *Environmental Engineering Science*, 25(6), 917-928.

Chen, X., Nordhaus, W.D. (2011). Using Luminosity Data as a Proxy for Economic Statistics. *Proceeedings of the National Academy of Sciences*, 108(21), 8589-8594.

Cohen, J.E., Small. C., Mellinger, A., Gallup, J., Sachs, J., Vitousek, P.M., Mooney, H.A. (1997). Estimates of Coastal Populations. *Science. New Series,* 278(5341), 1211-1212.

Cracknell, P. (1999). Remote Sensing Techniques in Estuaries and Coastal Zones an Update. *International Journal of Remote Sensing*, 20(3), 485-496.

Crossland, C.J., Kremer, H.H., Lindeboom, H.J., Marshall Crossland, J.I., Le Tissier, M.D.A. (2005). Coastal Fluxes in the Anthropocene: The Land-Ocean Interactions in the Coastal Zone Project of the International Geosphere-Biosphere Programme. Berlin: Springer.

El-Sabh, M., Demers, S., Lafontaine, D. (1998). Coastal Management and Sustainable Development: From Stockholm to Rimouski. *Ocean and Coastal Management,* 39, 1-24.

Elvidge, C.D., Baugh, K.E., Anderson, S.J., Sutton, P.C., Ghosh, T. (2012). The Night Light Development Index (NLDI): A Spatially Explicit Measure of Human Development from Satellite Data. *Social Geography*, 7, 23-35.

Elvidge, C.D., Imhoff, M.L., Baugh, K.E., Hobson, V.R., Nelson, I., Safran, J., Tuttle, B.T. (2001). Night-Time Lights of the World: 1994-1995. ISPRS *Journal of Photogrammetry and Remote Sensing*, 56(2), 81-99.

Fedorov, G.M., Mikhaylov, A.S., Kuznetsova, T.Yu. (2017). The Influence of the Sea on the Development of the Economy and the Resettlement of the Baltic Region Countries. *Baltic Region*, 9(2), 4-18.

Ghosh, T., Anderson, S., Powell, R.L., Sutton, P.C., Elvidge, C.D. (2009). Estimation of Mexico's Informal Economy and Remittances Using Nighttime Imagery. *Remote Sensing*, 1, 418-444.

Hinrichsen, D. (1996). Coasts in Crisis. *Issues in Science and Technology*, 12(4), 39-47.

Kurt, S. (2016). Analysis of Temporal Change Taking Place at the Coastline and Coastal Area of the South Coast of the Marmara Sea. Gaziantep *University Journal of Social Sciences,* 15(3), 899-924.

Makhnovsky, D. (2014). The Coastal Regions of Europe: Economic Development at the Turn of the 20th Century. *Baltic Region*, 4(22), 59-78.

Mellander, C., Lobo, J., Stolarick, K., Matheson, Z. (2015). Night-Time Light Data: A Good Proxy Measure for Economic Activity? *Plos ONE*, 10(10). DOI: http://dx.doi.org/10.1371/Journal.Pone.0139779

Pak, A., Majd, F. (2011). Integrated Coastal Management Plan in Free Trade Zones, *A Case Study. Ocean and Coastal Management,* 54, 129-136.

Rybnikova, N.A., Portnov, B.A. (2014). Mapping Geographical Concentrations of Economic Activities in Europe Using Light at Night (LAN) Satellite Data. *International Journal of Remote Sensing*, 35(22), 7706-7725.

Rybnikova, N.A., Portnov, B.A. (2016). Estimating Geographic Concentrations of Quaternary Industries in Europe Using Artificial Light-At-Night (ALAN) Data. *International Journal of Digital Earth*, 10(9), 861-878.

Ryznar, R.M., Wagner, T.W. (2001). Using Remotely Sensed Imagery to Detect Urban Change: Viewing Detroit from Space. *Journal of the American Planning Association*, 67(3), 327-336.

Salvador, R., Simões, A., Soares, C.G. (2015). Features of the European Maritime Clusters. 55th Congress of the European Regional Science Association: World Renaissance: Changing Roles For People and Places, 25-28 August 2015, Lisbon, Portugal.

Valev, E.B. (2009). The Problems Of Development and Interaction of Seaside Territories in Europe. *Regionalnie Isslegovania*, 1(22), 11-23.

Vallega, A. (1998). Agenda 21 of Ocean Geography. In: A. Vallega Et Al. (Eds.), Geography, Oceans and Coasts Towards Sustainable Development (pp. 17-116). Angeli, Milano.

Vitousek, P.M., Mooney, H.A., Lubchenco, J., Melillo, J.M. (1997). Human Domination of Earth's Ecosystems. *Science*, 277(5325), 494-499.

Zeng, C., Zhou, Y., Wang, S., Yan, F., Zhao, Q. (2011). Population Spatialization in China Based on Night-Time Imagery and Land Use Data. *International Journal of Remote Sensing*, 32(24), 9599-9620.

Zhang, Q., Seto, K.C. (2013). Can Night-Time Light Data Identify Typologies Of Urbanization? A Global Assessment of Successes And Failures. *Remote Sensing*, 5(7), 3476-3494.

Zhao, N., Hsu, F.-C., Cao, G., Samson E.L. (2017). Improving Accuracy of Economic Estimations with VIIRS DNB Image Products. *International Journal of Remote Sensing*, 38(21), 5899-5918.