MAPPING REGIONAL DIVERGENCE: NIGHT-TIME LIGHT SATELLITE IMAGERY IN DEFINING COASTALIZATION OF EUROPE

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ABSTRACT

Marine coasts have always been natural growth poles for all mankind attracting population, entrepreneurship, industrial agglomeration, financial flows to adjacent coastal zones. Contemporary research on integrated coastal management suggests that coastalization effect remains to be the catalyst factor of regional development throughout the world and will strengthen within the next quarter of a century. Increasing socio-spatial polarization and dispersion among countries against regional convergence policies puts the 'marine factor' on the research agenda of human geographers. The aim of this article is to test the applicability of remote sensing technologies in capturing the coastalization processes across Europe by undertaking a comparison of results obtained via statistical multivariate analysis and the night-time light satellite imagery. The study is based on analysis of population density and GRP in PPP per km^2 figures for 413 NUTS 2 level regions of Europe. The totality of regions is grouped into clusters depending on their socio-economic indicators. Coastal and inland types of territories are found to be evenly distributed within the allocated clusters – approximately 40 to 60 percentages on average, thus, not reflecting a clear coastalization effect. The juxtaposition of statistical data with nocturnal satellite imagery of emitted light enables to confirm the identified pattern, while featuring a number of particularities.

Keywords: *regional divergence, polarization, coastalization, coastal region, inland region, night-time lights, VIIRS, remote sensing*

INTRODUCTION

The influence of marine coasts over regional development has been at the forefront of geo-economic research since the middle of the XX century. The 'coastal revolution' in scholarly literature has started after the repeated registration of the uneven distribution of population, industrial agglomerations, financial flows, innovation activity, research output, et cetera in the maritime and adjacent coastal regions. At the same time the inference on the scope of the coastalization effect remains controversial, as most research designs are either limited to naturally marine-driven regions of southern coasts or neglect the regional segregation of the states whatsoever. Fairly modest estimations suggest that coastal areas constitute about 40% of the world's population, with a density being twice the global average [1], [2], [3]. Yet there are plenty of publications that advocate for a considerably higher disproportion on a global scale. Hinrichsen [4], for instance, found that 75%

of the world's population resides within 150 kilometer-limits of the coast. Similar inconsistency can be found on a macro-regional level, e.g. in the scope of Europe, where the findings on national disparities vary in dozens of times [5], [6], [7].

A significant limitation of social sciences research methodology on coastalization is caused by the narrowness of statistical data available as well as the inseparability of this data from administrative units' division it is pegged to, i.e. its strict bind to the administrative-territorial boundaries. As it is noted by Zeng et al. ([8], p. 9599), "…census data for any given area are neither always available nor adequately reflect the internal differences of thepopulation". A possible solution to this problem may be the research methodology based on advances in Earth remote sensing, e.g. the Visible Infrared Imaging Radiometer Suite (VIIRS) satellite system. This technology enables to detect foci of artificial illumination or the night-time lights (NTL), providing enhanced reliability of quantitative methods for assessing the unevenness of geo-space, including socio-economic data used in human geography research.

Suggested approach on utilization of natural sciences techniques in social sciences research has been tested by a number of recent studies [9], [10], [11], [12], [13], [14], [15]. Literature review suggests that NTL data based on Earth remote sensing technologies provide reliable data on the distribution of human activity, thus, can justifiably be applied to the assessment of the coastalization phenomenon. The present study examines this allegation by measuring the coastal (marine) factor in the performance of coastal regions as compared to inland territories using the population density and the Gross Regional Product (GRP) in Purchasing Power Parity (PPP) figures. The major focus of the article is to bring to discussion the research results on the comparability of the nocturnal satellite observations of emitted light with a number of set statistical parameters employed for coastalization analysis.

METHODOLOGY

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 the two partially recognized 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. 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. The methodology for delimitation of coastal regions is adopted from [6].

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 – 2014: population density and the relative values of GRP (PPP) in million euros per km2. 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.

The second stage includes a comparative analysis of the geo-location of the allocated clusters of regions and the satellite imagery that reflect NTL. The source for night-time light imagery is the joint database of the National Aeronautics and Space Administration (NASA) Earth Observatory and the National Geophysical Data Center (NGDC) of the National Oceanic and Atmospheric Administration (NOAA) of the USA. The data contains images of the Suomi National Polar-orbiting Partnership (NPP) satellite acquired in April and October 2012 using the Visible Infrared Imaging Radiometer Suite (VIIRS) sensor. Images provide a cloud-free view of Earth by combining the day-night band photos with next generation of 'blue marble' images. The juxtaposition of statistical data with NTL observations is implemented in a single map.

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 five clusters of regions are identified (Table 1).

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

No.	Number of regions			Population density, people per km^2			GRP in PPP, million Euro per km^2		
	total	coastal regions							
		units	%	max.	median	min.	max.	median	min.
1	**6**	**2**	**33**	**18474.2**	**5817.5**	**4177.9**	**2205.5**	**237.0**	**105.1**
2	**7**	**3**	**43**	**3779.7**	3061.9	**2579.2**	**124.9**	**87.5**	**52.2**
2.1.	3	1	33	3779.7	2622.2	2297.5	124.9	118.5	115.1
2.2.	4	2	50	3575.0	3223.5	2579.2	87.5	68.0	52.2
3	**20**	**9**	**45**	**2116.0**	**977.9**	**664.0**	**65.7**	**29.2**	**0.0**
3.1.	9	5	56	2116.0	1564.5	1040.1	65.7	36.7	0.0
3.2.	11	4	36	993.2	809.6	664.0	47.0	26.8	0.9
4	**120**	**48**	**40**	**624.9**	**231.8**	**131.9**	**28.1**	**6.2**	**0.1**
4.1.	42	17	40	624.9	431.1	326.7	25.0	11.8	0.5
4.2.	78	31	40	311.1	189.7	131.9	28.1	4.9	0.1
5	**260**	**110**	**42**	**130.6**	**61.5**	**0.2**	**4.1**	**0.7**	**0.0**
Total	413	172	42	18474.2	96.3	0.2	2205.5	1.6	0.0

Regions are distributed between the five clusters in descending order, with the regions featuring the highest indicator values being included in the first cluster. The number of regions in the defined clusters is unequal and increases from the first to the fifth cluster. The proportion of coastal regions in each cluster fluctuates from 33 to 45%, which is evaluated as an individual criterion of coastalization assessment. The allocation of sub-clusters for the second, third and fourth clusters is justified by strong heterogeneity in the totally of regions studied. These sub-clusters demonstrate different groups of regions within each cluster by population and GRP figures. For all clusters and sub-clusters, the maximum, median and minimum indicator values are calculated. The median value enables to obtain objective average values given the strong differences in the sampling elements.

Average performance of regions in the second cluster is 1.9 times inferior to the fist cluster in terms of population density and 2.7 times in GRP (PPP) per km^2. Regions of the sub-cluster 2.1 show higher average GRP (PPP) per km^2 values than the sub-cluster 2.2 regions with comparable population density values for both sub-clusters. The distribution of coastal regions shows minor difference – one region has entered the sub-cluster 2.1 and two – the sub-cluster 2.2. Statistical values of the third cluster regions are three times lower than of the second cluster. The sub-cluster 3.1 is characterized by higher values of both indicators applied in comparison with the sub-cluster 3.2. Over half of the regions of the sub-cluster 3.1 are coastal. In general, both sub-clusters of the third cluster have high values of the studied indicators in comparison with most regions of Europe. Their nominal values are greater than of 380 other European regions. Regions of the fourth cluster are inferior to regions of the third cluster by 4.2 times in population density and by 4.7 times in GRP (PPP) per km^2. The sub-cluster 4.1 has higher values of both statistical indicators used in comparison with the sub-cluster 4.2. This cluster is the second largest in terms of the number of regions (second only to cluster 5). It includes economically developed regions, which are regional and national growth nodes for their countries. The fifth cluster is very heterogeneous in its composition. It includes more than half of all regions of Europe – 260, of which 42% are coastal. Regions of the fifth cluster on the average are inferior to regions of the fourth cluster by 3.8 times in terms of population density and by 8.9 times in GRP (PPP) per km^2. The gap between the first and last cluster is immense: by 95 times in terms of the population density and by 339 times for the GRP (PPP) per km^2.

A total of 172 regions of the NUTS 2 level of Europe are classified as coastal regions in accordance with the presented methodology, which is 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 isolated clusters is similar and on average equates to 40 and 60% respectively (Table 1). The fewest coastal regions are found to be in clusters 1 and 2.1 – 33% each. The largest share of coastal regions is found to be in clusters 2.2 and 3.1 – 50 and 56% respectively.

Based on the results of the cluster analysis, the mapping of selected clusters of regions is performed with the imposition of NTL (Fig. 1).

Correlating the concentration of night-time artificial illumination and the distribution of identified clusters of regions evidently verifies the statistical clustering approach. Figure 1 reveals that the highest concentration of NTL is observed in regions with the highest population density and GRP (PPP) per 1 km^2

– these are the first, second and third clusters. Some concentration of lights can be observed in the regions of the fourth cluster, while the regions of the fifth cluster are predominantly characterized by weak scattered single lights, without pronounced aggregation.

The research findings suggest a number of patterns allocated resulting from comparative assessment of the two methods applied: 1) strong NTL and strong cluster; 2) medium-strong NTL and medium cluster; 3) medium-strong NTL and weak cluster; 4) medium-weak NTL and medium cluster; 5) medium-weak NTL and weak cluster; 6) weak NTL and weak cluster.

The first pattern: strong NTL and strong cluster. A strong glare of nocturnal illumination and high values of statistical indicators is typical for the regions of the first and second clusters with NTL being centered on capital cities and large metropolitan agglomerations. 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 (Western Midlands, the UK), the adjacent territories show a higher level of development and an observable overglow as compared to the national average. Whereas Berlin (Germany), Kiev (Ukraine), Minsk (Belarus), Prague (Czech Republic), Vienna (Austria) and a few other major cities defined as separate territorial units show no considerable effect in contributing to the socio-economic development of bordering regions, both in terms of NTL and statistics.

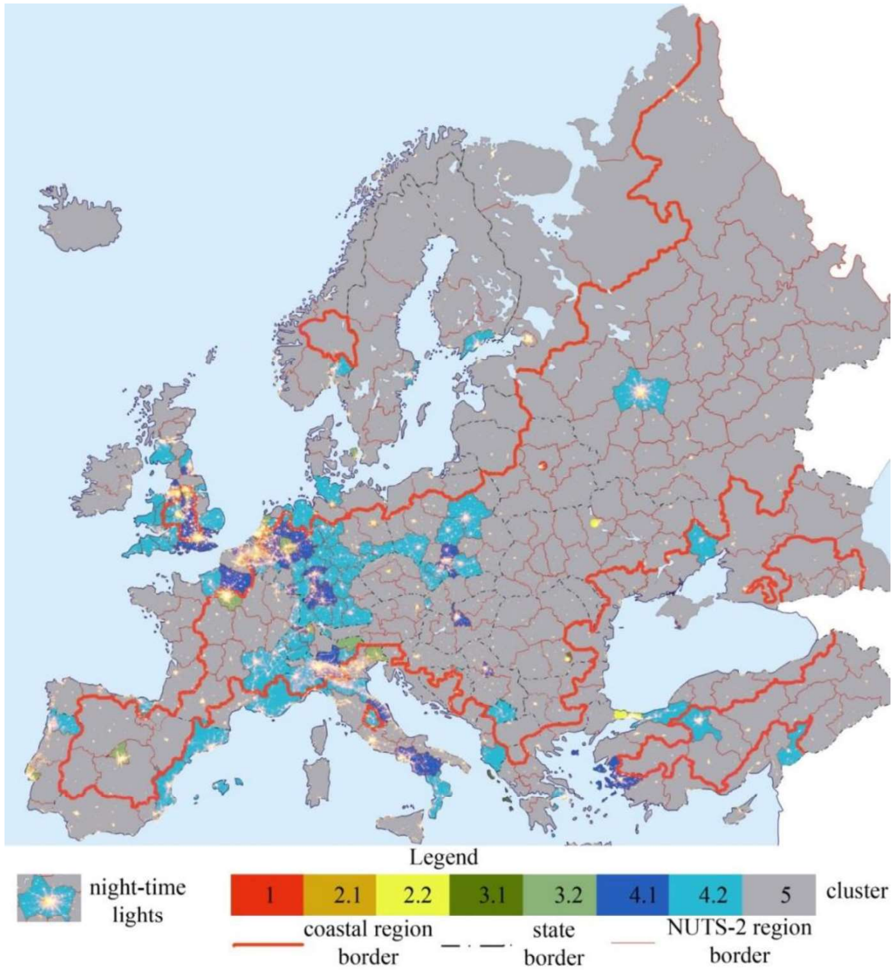

Figure 1. Comparative analysis of the geo-location of the allocated clusters of regions and night-time light satellite imagery

The second pattern: medium-strong NTL and medium cluster. The combination of a substantial cluster of NTL and moderate indicator values corresponding to statistical clusters 3 and 4 is often observed in cases when a capital or another major city of the country is an inseparable part of the larger territorial unit of the NUTS 2 classification, such as Athens (Greece), Copenhagen (Denmark), Helsinki (Finland), Lisbon and Porto (Portugal), Madrid (Spain), Oslo (Norway), Paris (France), Stockholm (Sweden). In terms of statistics, increased potential of the growth pole is being disseminated within the boundaries of the entire region. However, the NTL data suggests that in most cases this beneficial effect is nominal, featuring high spatial density. Another remarkable observation is NTL clusters falling beyond the boundaries of a single region, covering interregional and even international dimensions. This includes large interregional cluster of nocturnal illumination generated by the urban agglomerations in northern Italy (Turin, Milan, Bologna), as well as the NTL mega-cluster covering an area around Lille (France), Antwerp, Brussels, Gent (Belgium), Amsterdam, Den Haag, Rotterdam (the Netherlands), Bonn, Dortmund, Dusseldorf, Essen, and Koln (Germany).

The third pattern: medium-strong NTL and weak cluster. An intensive NTL and low values of statistical indicators are typical for regions of the cluster 5. These are relatively large administrative-territorial units of statistics with a high level of intra-regional divergence being polarized towards major urban agglomerations and public infrastructure. Despite a bright glow of NTL cluster of the region of this type it is statistically attributed to the group of underperforming regions. Most vivid examples are the Italian regions of Lazio, Tuscany, and Veneto, all of which fall into cluster 5 – the least developed regions by selected indicators. The illumination of artificial light in these regions follows the main motorways as well as outlines the area around the global urban tourist destinations – the cities of Rome (incl. Vatican), Florence, Pisa, Verona, and Venice. The census data for population figures neglect the immense tourist flows typical for these areas, while the GRP (PPP) figures evaluated per 1 km2 of the total area is low. Another notable example of this type is the Leningrad region (Russia) that falls under the overglow of the city of St. Petersburg – the second largest city of the country.

The fourth pattern: medium-weak NTL and medium cluster. This combination is typical for strong industrial and financial centers attributed to statistical clusters 3 and 4. These are, for instance, Poznan and Lodz in Poland, Donetsk in Ukraine, Frankfurt am Main, Leipzig, and Stuttgart in Germany. Most regions within this type are German, as high European average values of the indicators applied in cluster analysis have shifted the regions of most other countries to the cluster 5.

The fifth pattern: medium-weak NTL and weak cluster. 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 (see table 1). Thus, the category is dominated by either less performing regions of highly developed countries, e.g. Aragon and Seville in Spain, Aquitaine, Midi-pyrenees, and Pays de la Loire in France, Lazio, Tuscany, and Veneto in Italy, or strongly performing regional territorial socio-economic systems of less developed ones – e.g. Pomeranian and Wielkopolska Voivodeships in Poland, Kontinentalna Hrvatska in Croatia, the Republic of Tatarstan, Nizhny Novgorod and Samara regions in Russia, to name just a few.

The sixth pattern: weak NTL and weak cluster. This category includes regions that show low performance in statistical cluster analysis and feature a few scattered single lights, often not being ponderable. Most of these regions are located in Eastern Europe and Scandinavia. The availability of NTL per se does not reflect the socio-economic development of the territory. For example, the glow of the northern Norway is less related to the population density or industrial agglomeration, but largely reflects the temporal economic activities for the development of natural resources. This includes the marine oil extraction at the continental shelf (note 1). Another example is the Murmansk region of the Russian Federation, where artificial illumination of the Murmansk city – the administrative center 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 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 30 km. Despite an observable concentration 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 effect of coastalization described as the prevailing factor of spatial divergence is neither confirmed by the cluster analysis nor by the NTL observations.

CONCLUSION

Each of the 413 NUTS 2 regions of Europe considered is featuring a visible cluster of NTL. Night-time light observations largely coincide the highly developed clusters of regions defined using the statistical data on population density and the relative values of the GRP (PPP) in million euros per km^2. The brightest clusters of lights correspond to the most developed regions by selected indicators – clusters 1-3. These are large metropolitan areas dominated by the urban sprawl of capital cities. However, the availability of a NTL cluster per se does not reflect the socio-economic development of the territory. As described in the six patterns identified from the comparative assessment of the two methods applied, there can be an asymmetry. For instance, a region corresponding to the fifth cluster – the lowest values of statistical indicators, can emit an intensive NTL.

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 labeled as a nationwide pattern. Neither the results of the statistical cluster analysis nor do the nocturnal light observations support the allegation for the pan-European trend of coastalization. It is suggested that coastalization effect should be further studied using NUTS 3 level of regions, with the proposed methodology of combining the statistical data and the NTL observations. Most effective would be the country-level studies supplemented by qualitative information unveiling the rationale behind the results found (e.g. industry clusters, urbanization, cross-border regionalization, infrastructure, terrain features).

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