AN EMPIRICAL ASSESSMENT OF HUMAN DEVELOPMENT THROUGH REMOTE SENSING: EVIDENCES FROM ITALY

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An Empirical Assessment of Human Development through Remote-Sensed Night Light Development Indexes: Evidences from Italy

Abstract

The Human Development Index (HDI) based on life expectancy, education and per-capita income, is one of the most used indicators of human development. However, undeniable problems in data collection limit between-countries comparisons reducing the practical applicability of the HDI in official statistics. Elvidge et al. (2012) proposed an alternative index of human development (the so called Night Light Development Index, NLDI) derived from nighttime satellite imagery and population density, with improved comparability over time and space. The NLDI assesses inequality in the spatial distribution of night light among resident inhabitants and has proven to correlate with the HDI at the country scale. However, the NLDI presents some drawbacks when applied to smaller analysis' spatial domains, since similar NLDI values may indicate very different levels of human development. A modified NLDI overcoming such a drawback is proposed in this study to assess human development at 3 spatial scales (the entire country, 5 geographical divisions and 20 administrative regions) in Italy, a country with relevant territorial disparities in various socioeconomic dimensions. The original and modified NLDI were correlated with 5 independent indicators of economic growth, sustainable development and environmental quality. The spatial distribution of the original and modified NLDI is not coherent with the level of human development in Italy being indeed associated with various indexes of environmental quality. Further investigation is required to identify in which socioeconomic context (and at which spatial scale) the NDLI approach correctly estimates the level of human development in affluent countries.

Key-Words: Satellite imagery, Population density, Composite index, NLDI, Italy.

1. Introduction

About 40% of the 1,100 satellites currently orbiting earth contribute to weather forecasting, national defense, science and agriculture (de Araujo et al., 2015). The Earth Resources Technology Satellite (re-named as LANDSAT), one of the most used satellites in the world, was launched in 1972 (Seto et al., 2002) and has provided multi-temporal information to a number of applications in the field of cartography, geology, forest, hydrology and agriculture (e.g. Bajocco et al., 2015). Land cover/land-use mapping and change detection is a typical application of LANDSAT imagery in the field of environmental monitoring (Salvati et al., 2012; Smiraglia et al., 2014; Dörnhöfer and Oppelt, 2016; Lawley et al., 2016). Urbanization trends and urban sprawl patterns have been successfully assessed through remote sensing in both developed and developing countries (Sudhira et al., 2004; Wu et al., 2006; Ceccarelli et al., 2013; Behling et al., 2015). Official statistics have implemented the use of satellite imagery for surveying socioeconomic phenomena and mapping variables that are hardly estimated with traditional surveys (Elvidge et al., 2012). For instance, the Australian Bureau of Statistics proposed a methodological approach to estimate agricultural land-use and crop yield (Marley et al., 2014). The Italian National Institute of Statistics used satellite imagery to support agricultural censuses (Benedetti and Ciovatella, 2006). Using satellite data in official statistics contributes to overcome survey and data collection problems (e.g. difficulty in gathering data in remote places, lack of homogeneous information, approximation of measures, non-response). Moreover, satellite data are low-cost, spatially explicit, available globally, and regularly updated (Dörnhöfer and Oppelt, 2016).

While advantages in the use of satellite imagery are clear and intuitive in environmental sciences (Kerr and Ostrovsky, 2003), the implementation of remote sensing techniques to monitoring socioeconomic variables of relevance for official statistics still requires in-depth investigation. Doll et al. (2000) have demonstrated that nighttime satellite data can be used to estimate global urban population, gross domestic product, total carbon dioxide and the level of economic activity. In fact, these variables are correlated with brightness of night lights (Doll et al., 2006). Elvidge et al. (2012) derived an empirical measure of human development from nighttime satellite imagery and population density, the so called Night Light Development Index (NLDI) assessing inequality in the spatial distribution of night light among resident inhabitants. The NLDI was demonstrated to be significantly correlated with the Human Development Index (HDI), an official statistic produced at the global scale by United Nations and disseminated every year since the early 1990s. Taken as a basic tool to analyze the developmental path of countries, the HDI goes beyond the simple idea of development measured in terms of domestic income (UNDP, 2011) by introducing a linear composition (equal weighting) of three indicators of life expectancy, education and per-capita income. However, the HDI is affected by problems in data collection and variable homogeneity that reduce spatial and temporal comparability (Wolff et al., 2011). By contrast, the NLDI is based on satellite maps that can be produced in a consistent and repeatable manner. The NLDI presents some drawbacks when applied to smaller analysis' spatial domains, since similar values of the index may reflect vastly different levels of human development.

In this study, a modification of the NLDI was presented with the aim to overcome the above mentioned drawbacks and to produce regional figures of the index with relevance for official statistics. An empirical exercise was carried out for Italy, an European country with important disparities in the spatial distribution of income and wealth, by computing the original and modified NLDI at 3 spatial levels (country (NUTS-0), geographical divisions (NUTS-1) and administrative regions (NUTS-2) scale) with the aim to verify if the NLDI may provide a comprehensive outlook of socioeconomic disparities in a divided country. Values and maps of selected indicators of socioeconomic development were provided for Italy in Supplementary Materials, Table 1 and Figure 1. Original and modified NLDI were finally correlated with indicators of economic growth, sustainable development and environmental quality to test spatial coherence and reliability of the proposed approach. The paper is organized as follows. The rationale of the NLDI is presented in section 1. Approaches aimed at overcoming limitations in the NLDI are introduced in section 2, and data needed to built-up a modified NLDI are illustrated in Section 3. The spatial distribution of the modified NLDI in Italy is commented in section 4 and compared with independent indicators in section 5. Section 6 provides some concluding remarks and suggestions for future studies in the field of remote sensing applied to official statistics.

2. The Night Light Development Index (NLDI)

The Night Light Development Index (NLDI) has been introduced by Elvidge et al. (2012). Although being correlated with the Human Development Index (HDI) at country level, the NLDI does not consider monetary measures of wealth, including only nighttime satellite and population density data. The rationale behind the NLDI is grounded on the evidence that nocturnal lights are proxy of public goods, services, pavements, built infrastructures and economic activities. It has been assumed that people living in brightly lit areas have easier access to goods and services than people living in “dark” areas, possibly displaying better conditions of life (Doll et al., 2000). The more brighter and diffused the light (in respect with the number of “lit inhabitants”), the greater will be the level of human development (Doll et al., 2006). More recently, Elvidge et al. (2012) have assumed that an equal distribution of outdoor lighting among inhabitants based on the NLDI, is a proxy of the level of human development.

The inputs of the NLDI are two geo-referenced grids organized into cells with the same size and geographical coordinates: (i) the nighttime light raster including the radiance level for each cell derived from satellite images and (ii) the population count in each cell derived from the national census of population and household. Figure 1 illustrates a typical urban context where brightness and population density decrease linearly from the inner city to suburbs (Elvidge et al., 2012, p. 25). Grid

(a) is related to the radiance level with values ranging between 0 (minimum radiance) and 255 (maximum radiance). Grid (b) represents the number of inhabitants in each cell. Grid data are aggregated into tables associating radiance level and population count. Data are sorted by brightness light level and aggregated in radiance classes (Table 1). To measure equality in the spatial distribution of lights, the Gini index has been finally applied to the statistical distribution in Table 1 according to the formula:

$$R = 1 - \frac{2\sum_{i=1}^{n-1} Q_i}{n-1}, \qquad 0 \leq R \leq 1 \tag{1}$$

where $R = NLDI$, $Q_i = \sum_{j=1}^{i} x_j \,/\, \sum_{j=1}^{n} x_j$ is the proportion of lights corresponding to cells with the proportion P_i of inhabitants, and $P_i = \sum_{j=1}^{i} x_j \,/n$. Values of the NLDI close to 0 indicate a developed area. In the example of Figure 1, NLDI = 0.672 denotes a middle-low development level (Elvidge et al., 2012).

3. A modified NLDI

The NDLI respectively assumes the lowest value when the lights are evenly distributed among inhabitants and the highest value when one person has light and the rest of population lives "in the dark". Table 2 illustrates the behavior of the NLDI in some extreme cases. The NLDI assumes the same value (0 or 1) in very different conditions, independently of light brightness. In cases 1 and 2, grids 1a-2c have different spatial distribution of light and population with the same development level (NLDI = 0). Cases 1a and 2a, 1b and 2b, 1c and 2c, respectively represent a high, intermediate and low development level. To overcome this drawback, we introduced a penalization that takes account of the average light brightness. The modified NLDI (NLDI*) is defined as:

$$NLDI^* = \left(\frac{\mu\,(x_i)}{255}\right) NLDI + \left(1 - \frac{\mu\,(x_i)}{255}\right) \qquad 0 \leq NLDI^* \leq 1 \tag{2}$$

where $\mu(x_i)$ is the weighted mean of radiance measured in the study area (in respect with population count in each cell); the NDLI* modifies the NLDI by considering the ratio between $\mu(x_i)$ and his maximum value (255). In this way, cases 1 in Figure 2 can be discriminated from cases 2: NLDI* is respectively 0 for scenario 1a, 0.5 for scenario 1b and 1 for scenario 1c. The same pattern is observed for cases 2: case 2a (NLDI* = 0) refers to a better development condition than case 2b (NLDI* > 0). Cases 1c and 2c have the same NLDI*. NLDI* is equal to 1 for cases 3a and 3b. NLDI* assumes values ranging between 0 and 1 (maximum dispersion of lights or $\mu\,(x_i) = 0$).

4. Data and variables

We calculated NLDI and NLDI* in Italy using nighttime light and population density data. Nighttime light data were derived from freely available images collected by Suomi NPP satellite between April and October 2012 (Figure 2a) and disseminated by NASA (http://earthobservatory.nasa.gov/Features/NightLights/page3.php). The satellite is equipped with a VIIRS (Visible Infrared Imaging Radiometer Suite) detecting photons of light in 22 wavelength bands and filtering them to distinguish even isolated highway lamps, fishing boats, faints and nocturnal atmospheric lights. The use of VIIRS allowed to improve 10 to 15 times the images' spatial resolution. For each pixel, corresponding to a square of 742 meters (0.46 miles), the outdoor lights have been isolated and the radiance light level has been derived. A 1 km² grid covering the whole of Europe and reporting the amount of resident population was disseminated by EUROSTAT (http://ec.europa.eu/eurostat/web/gisco/geodata/reference-data/populationdistribution-demography) after elaboration on elementary data collected within the national censuses of population and households at the enumeration district scale (Figure 2b).

According to the methodology illustrated in section 3, grids were properly overlaid using QGIS software and the joint distribution of radiance and population in each cell was calculated to derive the NLDI and NLDI* in Italy at three spatial scales: (i) the entire country (NUTS-0), (ii) 5 geographical divisions (NUTS-1), and (iii) 20 administrative regions (NUTS-2). A graphical analysis of the statistical distribution of both variables using frequency histograms was proposed in Supplementary Materials, Figure 2. Descriptive statistics of both variables were also presented in Supplementary Materials, Table 2. The spatial distribution of the original and modified NLDI at the regional scale in Italy was compared with independent indicators of economic growth, sustainable development and environmental quality, including per-capita income (PCVA), HDI (UNDP, 2011), QUARS environmental quality index (Sbilanciamoci!, 2012), Sustainable Development Index, SDI (Salvati and Carlucci, 2014), Environmentally Sensitive Area Index, ESAI (Salvati et al., 2015, 2016a), an accessibility index (ACC) formulated by Istat (2012), percent share of agriculture in total value added (SHA), land productivity (LAN, euros per hectare) and labor productivity in agriculture (LAB, euros per workers). All these indicators were based on official statistics produced by the Italian National Institute of Statistics. Maps for selected indicators were provided in Supplementary Materials, Figure 3.

5. Results and discussion

Although producing different absolute values, the spatial distribution of the original and modified NLDI was substantially similar, evidencing comparable rankings for regions situated in northern, central and southern Italy (Table 3). Regions with the lowest NLDI* and the largest difference with the original NLDI were concentrated in central and southern Italy (Campania, Latium, Marche, Abruzzo and Apulia). Northern Italian regions, and especially those situated along the Alps, such as

Aosta valley and Trentino-Alto-Adige, were characterized by a higher level of the NDLI* in respect with the neighboring flat and accessible regions of Lombardy and Veneto. This pattern was observed also in central and southern Italy irrespective of their development level, with the highest scores of the NLDI* assigned to regions having less populated areas and the lowest scores assigned to flat, coastal and accessible regions. Taken together, the NLDI* assumes the lowest values in regions with scattered population and diffused settlements and the highest values in regions with population concentrated in medium and small cities.

NLDI and NLDI* in Italy were not correlated with measures of economic growth (per-capita value added, percent share of agriculture in total product, land productivity, labor productivity in agriculture) or local development (human development index, sustainable development index, accessibility index) at the regional scale (Table 4). By contrast, NLDI and especially NLDI* were significantly correlated with two indicators of environmental quality (QUARS, ESAI), suggesting that an increase in the NLDI is reflected in a high environmental quality, irrespective of the level of human development. This finding suggests that both the NLDI and the NLDI* can be unreliable indicators of human development in countries with high electrification rate (equal to 100% in Italy). In this regard, the NLDI is related to the spatial distribution of urban centers in Italy, possibly discriminating regions with polycentric and spatially-balanced settlements (e.g. Lombardy, Veneto, Piedmont, Emilia Romagna, Campania, Apulia) from regions with compact and mono-centric cities concentrating the largest part of the population (e.g. Valle d'Aosta, Trentino Alto Adige, Basilicata). In other words, the NLDI and the modified NLDI* may represent, in developed countries like Italy, candidate indicators of settlement distribution (concentrated, clustered, scattered) and polycentric development at aggregated spatial scales (regions, economic districts, agricultural homogeneous areas). Based on the results of the correlation analysis, we assumed that NLDI and especially NLDI* estimate the environmental impact of human activities as a result of concentrated or dispersed settlement patterns.

6. Conclusions

Elvidge *et al.* (2012) proposed the Night Light Development Index (NLDI) with the aim to assess differences in the level of human development among countries, and to overcome problems of data collection that may affect standard indexes such as the HDI (Wolff et al., 2011). This paper has demonstrated that the NLDI assumes comparable values for background conditions that refer to different development levels. A mathematical transformation that takes account of the average level of brightness lights was proposed to overcome drawbacks in the NLDI, producing a modified index (NLDI*) with scores ranging in the same interval of the NLDI. The two indexes were used to assess the level of human development in Italy, a country with a marked north-south divide in several socioeconomic variables and the most developed areas concentrated in northern and central Italy (Salvati et al., 2016a). The spatial distribution of both indexes for Italian regions has evidenced a complex geography which is not reflected in the level of human development (Salvati and Carlucci, 2016), as the low correlation rates of NLDI and NLDI* with independent indicators have clearly evidenced. These results outline drawbacks in the NLDI when applied to developed countries with high electrification rate and spatial disparities in the distribution of human settlements.

Further investigations are needed to identify adequate spatial scales for a correct assessment of human development using the NLDI, or modified forms of the NLDI correcting for the average electrification rate. At the same time, based on our evidences, the NLDI can be considered a proxy of dispersed or compact spatial distribution of settlements, indirectly assessing the environmental impact of human activities (e.g. Salvati et al., 2016b). Further investigation is required to evaluate in which socioeconomic context (and at which spatial scale) the NDLI is (i) a reliable indicator of urbanization-driven pressure on the environment and (ii) a proxy of polycentric development and spatially-balanced settlements, a condition which is hard to measure with objective and comparable approaches at either global or continental scale (Salvati, 2014). These findings contribute to improve indicators' theory applied to urban sustainability and environmental surveillance.

7. References

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