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Brief article

An empirical assessment of human development through remote sensing: Evidences from Italy

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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, since similar NLDI values may indicate very different levels of human development. A modified NLDI overcoming such a drawback is proposed and applied to assessment of 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.

1. Introduction

About 40% of the 1100 satellites currently orbiting earth contribute to weather forecasting, national defense, science and agriculture (de Araujo Barbosa 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 Ciavatella, 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).

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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 extensive 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 may reduce spatial and temporal comparability (Wolff et al., 2011). Conversely, the NLDI is based on satellite maps that can be produced in a consistent and repeatable manner. Nevertheless, the NLDI presents some drawbacks since similar values of the index may reflect vastly different levels of human development (Elvidge et al., 2012). Drawbacks should be considered when developing a diachronic assessment of human development levels ranking countries uniquely according to the value of the index (Doll et al., 2006). Integration with additional, background indicators is useful to improve ranking reliability and estimate precision (Sudhira et al., 2004).

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 Fig. 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. Fig. 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:

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

where $R = NLDI$, n is the number of the grids, $Q_i = \sum_{j=1}^{i} x_j / \sum_{j=1}^{n} x_j$ is the proportion of lights corresponding to the grid with the proportion P_i of inhabitants in which x_j is the value of radiance class. Furthermore, $P_i = \sum_{j=1}^{i} x_j / n$. Values of the NLDI close to 0 indicate a developed area. In the example of Fig. 1, NLDI = 0.672 denotes a middle-low development level (Elvidge et al., 2012).

3. A modified NLDI

The NLDI 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 1 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:

$$NLDI^{*} = \left(\frac{((x_i)}{255}\right)NLDI + \left(1 - \frac{(x_i)}{255}\right), \quad 0 \leq \mathrm{NLD}I^{*} \leq 1$$

where (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 (x_i) and his maximum value (255). Therefore, the weaker the light is, less important the inequality in the lights distribution is. Furthermore, a term that takes into account the brightness level in the area is added. In this way, cases 1 in Fig. 1 can be discriminated from cases