Application of Remote Sensing for the Estimation of the Human Population

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Accurate and up to date population estimation is crucial for including but not limited for governance, policy making, planning, public health, and researches. Population counts and distribution are also key to any future planning and resource allocation. Population estimation is available from the censuses in most of the part of the world. However, censuses are usually performed once per decade because of the costly, tedious and time-consuming process (Stathakis and Baltas, 2018; Weber et al., 2018). Moreover, population estimation for a small area or an area without formal administrative boundaries may not be available since census data are aggregated or disaggregated for an administrative unit. Accurate population estimation in between census years is often an essential parameter in many studies such as ambient population study, population migration pattern, seasonal population movement, and public health studies. Population estimation of a delineated region (without formal administrative boundary) for a specific purpose is also required in many cases. To fill up the gaps between the census and population data demand, scientists are trying to estimates population using various remote sensing data. Population estimation through remote sensing data is relatively cost-effective, convenient, and available at any time.

Methods for population estimation in GIS and remote sensing field can be broadly grouped into two types: areal interpolation and statistical modeling (Wu et al., 2005). The first group is mainly involved population estimation over an area in grid format interpolated from census data represented by a point location. This study aims to explore and discuss the second group where remote sensing data are used for population estimation. Although there is no direct approach to count the population from any remote sensing data, many proxy variables derived from remote sensing and their relationship with population distribution have been used for population estimation.

One very simple and straightforward approach is the functional relationship between the built-up area and population size. In this functional relationship, total population = a × (total built-up area)^p. The coefficient (a) and the exponent (p) depend on geographic location, urban functionality, and types of cities (Lo and Welch, 1977; Tobler, 1969). The correlation coefficient 0.82 is found by Lo and Welch (1977) for large Chinese cities. They calculated the built-up area by processing Landsat images.

Tobler (1969) concluded that the coefficient and exponent for cities in the United States are similar for cities in Europe, Japan, and Nile Delta. A gross population number is usually estimated for an area in this approach. The built-up area can easily be extracted from remote sensing images of any sensor operating in the optical or microwave spectrums. Likewise, urban nightlight intensity can also be used as a proxy variable instead of the urban built-up area for population estimation. Yearly composite of nightlight intensity data is available since 1992 from Defense Meteorological Satellite Program (DMSP). Nightlight intensity is direct measurement whereas built-up area is a derived thematic product. Thus, nightlight intensity has the benefit over the built-up area as a proxy for population estimation, since there is no variation among pixels in the homogenous built-up area, but nightlight intensity varies across pixels. The correlation between nightlight volume and population is very high. Prosperie and Eyton (2000) investigated 254 Texas counties and found very high R^2 of 0.974 between nightlight volume and population size. Likewise, Lo (2002) found this correlation coefficient is 0.91 for Chinese cities. As DMSP nightlight intensity data are yearly composite, seasonal population estimation is not possible with DMSP data. Nightlight monthly composite data are now available from Infrared Imaging Radiometer Suite (VIIRS) sensor onboard the SUOMI satellites. Stathakis and Baltas (2018) estimate the seasonal population size of Greek cities using VIIRS nightlight data. It is not possible to distinguish between residential land use and industrial land use from nightlight alone, which is one of the major drawbacks of nightlight data.

Another approach of residential population estimation from remote sensing derived proxy is the correlation between land use types and population density. This approach captures the variation of population concentration in different land use types instead of uniform consideration of built-up area. The total population can be estimated using the following mathematical expression:

$$\text{Total Population} = \sum_0^n Area\ of\ n^{th}\ Landuse\ \times Population\ Density\ of\ n^{th}\ Landuse$$

The population estimation with this approach required information on land use types and corresponding population density. Land use types can be extracted from remote sensing data in many ways depending on the desired level of details. Population density can be estimated from a physical survey of the small area of each land use types (Kraus et al., 1974; Weber et al., 2018). Another approach for population density estimation can be the regression analysis between population counts and the spatial extent of land use types (Lo, 2003; Weber, 1994). Weber et al. (2018) estimate census-independent population in northern Nigeria for Global Polio Eradication Initiative (GPEI) using this approach. They divided the built-up area into eight different categories using the visual interpretation of high-resolution satellite images. Micro-census of each class estimates population densities of each settlement categories. They found a very high correlation of 0.942 between land use categories and population density. Weber (1994) classified six types of urban land use from SPOT HRV XS images for the City of Strasbourg, France; he found a correlation coefficient of 0.91 between land use types and population density. The success of this approach relies on the accuracy of land use mapping and density estimation.

The total population can also be estimated by multiplying the total number of the dwelling unit and the average size of the population in a dwelling unit. The number of dwelling units can be counted from fine spatial resolution remote sensing imageries. Counting dwelling units are very challenging in urban centers which have dense high-rise residential buildings. Person to floor area ratio can also serve the purpose. Therefore, information on a number of story and units per floor also need to be estimated for accurate population count. Average person per dwelling unit also varies with the dwelling types and the locality. Therefore, dwelling units need to be categorized based on person per dwelling unit ratio. A straightforward approach could be manual counting of a residential building from fine resolution images, which is very time consuming and tedious. The recent development of automatic feature extraction from fine spatial resolution imageries aided population estimation with this approach (Haverkamp, 2004; Mayunga et al., 2005; Theng, 2006). Lo (1995) used SPOT images to extract population and dwelling unit high population densities and mixed land uses setting. LiDAR remote sensing, more advanced technology for accurate extraction of building object and their height, is also aiding population estimation with dwelling unit (Haverkamp, 2004; Morgan and Habib, 2002; Oda et al., 2004). Silvan-Cardenas et al. (2010) estimate the population for a high dense small urban setting using building volume and types extracted from LiDAR point clouds.

Researchers also find the relation between spectral reflectance value and population density at the pixel level (Harvey, 2002; Iisaka and Hegedus, 1982). Lo (1995) find the correlation coefficient of 0.91 between spectral values of SPOT band-3 images and population density in Hong Kong. Likewise, Iisaka and Hegedus (1982) estimate population in Japan using the relation between population distribution and reflectance of Landsat MSS bands. Wu and Murray (2007) estimate the population at pixel level through the regression approach between population density and reflectance of different bands of Landsat ETM+ images. Transformation measures, from Landsat TM bands such as the band-to-band ratio and difference-to-sum ratio, have also been utilized in the stepwise regression model for population estimation. Azar et al., (2013) produced gridded population dataset for Pakistan based on per-pixel built-up area fraction using regression tree. They found R^2 of 0.92 between estimated population and census population. Similar to reflectance value nightlight intensity can also be used for population density estimation at the pixel level. Pixel-based population estimation is helpful for administrative boundary independent population estimation.

Finally, multiple socio-economic variables –transport network, topography, land cover, information on business and industrial concentration – can be incorporated for population estimations (Dobson et al., 2000). Many of these variables again can be extracted from remote sensing imageries. The total population of an area may also correlate with distance to city center, transport network accessibility, slope and age of the residential community (Liu and Clarke, 2002).

Although population estimation using remote sensing is not replacing the census population estimation, remote sensing is aiding inter-census population estimation at local to regional scale. These above-discussed approaches for population estimation using remote sensing data have been developed over time. Availability of data from various remote sensing sensors and the development of remote sensing technologies will bring more opportunities for more accurate population estimation.

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