Changes in built-up areas and population in a typical mountainous region—a case study of Liping County, Southwest China

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Abstract: Mountainous regions surrounded by various natural environments are sensitive to anthropogenic disturbances. This study aims to investigate recent changes in built-up areas and population in Liping County, a typical mountainous region in Southwest China since 2000 by Landsat time series and township-level census data. We found that built-up areas have continuously expanded whereas the population has decreased, which may imply excessive human impacts on this region.

Keywords: Spatio-temporal analysis, LandTrendr, Random Forests, land development, depopulation

1. Introduction

The developing world has experienced rapid urbanization in recent decades, accompanying drastic changes in land use and land cover. In order to support effective land management with environmental conservation, monitoring built-up areas is undoubtedly essential. However, the expansion of built-up areas might not be accordance with the increase of population in some less populated regions (Bai et al., 2014), which would imply an excessive human impact on such regions. In particular, mountainous regions, often with less population, are sensitive to the impact of the expansion of built-up areas as they have complicated fragile ecosystems consisting of a large proportion of natural resources. As such, it is essential to investigate changes in built-up areas and population in mountainous regions.

Unlike cities with large urban extents in plain areas, built-up areas in mountainous regions are likely to be found in scattered patterns with small agglomerations due to the complex landform, resulting in the difficulty of the mapping. Hence, researchers often attempt to map the built-up areas by remotely sensed imagery. A supervised classification approach is often employed as analysts can train the model with ground-truth reference data. Particularly, Random Forests (RF) classifier gets popular in mapping land covers due to the ability of being less sensitive to the quality of training samples and to overfitting (Belgiu & Drăguţ 2016). Such approach can be applicable to the static land cover classification, however, it may not be an appropriate means to detect changes in land cover. Recently, Landtrendr, a robust change detection algorithm from temporal trajectories of spectral data on a pixel basis, has been developed (Kennedy et al., 2018). It helps capture both the trends and events of the land cover changes and tells when and where such changes happened.

This study aims to detect changes in built-up areas in Liping County, a typical mountainous region in China, from time-series Landsat imagery by the combined approach with RF and Landtrendr. We then compare the results of built-up areas with population changes to explore excessive human impacts in this area.

2. Methods

We applied an integrated algorithm of LandTrendr and RF to map and calculate built-up areas across the study area from 2000 to 2017. LandTrendr only detects changes in built-up areas and does not map the spatial distribution of them. Thus, we produced

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built-up area maps for 2013 and 2017 by RF. The map for 2013 was served as the base map while the map for 2017 was used for comparison. With the base map by RF and the change areas by LandTrendr, we mapped the spatial distribution of annual built-up areas from 2000 to 2017. The built-up changes were compared to population data collected from Liping Statistical Yearbooks (Statistics Bureau of Liping, 2017).

2.1. Study area

Liping County, covering approximately 4433 km^2, is located in a typical mountainous region in southwest China. Most of the towns and villages are located in relatively lower flat areas in valleys.

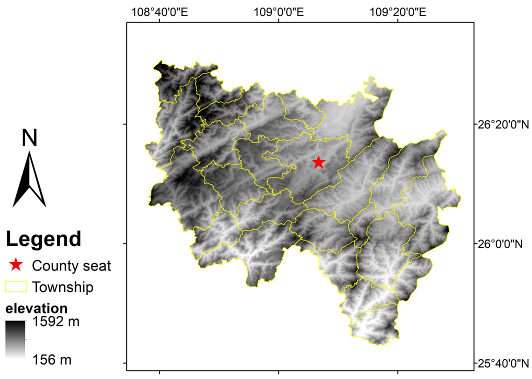

Figure 1. Study area, Liping County in Southwest China.

2.2. LandTrendr

To explore continuous built-up area changes from 2000 to 2017, we employed LandTrendr that analyzes temporal configuration of data based on the idea of "each pixel in an image time series has a story to tell" (Kennedy et al., 2018). It extracts the spectral history of pixels and specifies when and where the change occurred. We calculated the changed pixels in the first year that change is detectable (yod). Figure 2 gives an example of pixel time series changes by LandTrendr.

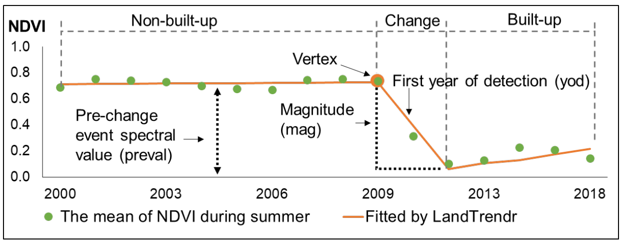

Figure 2. LandTrendr pixel time series changes.

We experimentally chose Normalized Difference Vegetation Index (NDVI) for the spectral index and set Magnitude of Change Event (mag) as 400, indicating the change of NDVI values are greater than 0.4. Pre-change Event Spectral value (preval) was set as 300, indicating the NDVI value before the pre-event vertex should greater than 0.3. The study period ranged from 2000 to 2017 and the spectral values were based on the mean of the summer season, from June to September. We assumed that all of the detected changes by Landtrendr under the setting above were associated with built-up expansion in this study. The LT-GEE function available in Google Earth Engine (GEE) environment (Kennedy et al., 2018) was used in this study.

2.3. Supervised classification—Random Forests

The satellite images in 2013 and 2017 were collected from USGS Landsat 8 Surface Reflectance Tier 1. These datasets are the atmospherically corrected 8 surface reflectance (band 1-7, and 10) of Landsat 8 OLI/TIRS data. We processed annual composite images for 2013 and 2017 with the annual mean of each band after masking cloud covers on GEE.

RF is developed from Decision Tree classifier by randomly selecting a subset of variables through replacement (Breiman, 2001). The RF was applied to the annual composite images with approximately 635 training sample polygons, 200 for built-up and 435 for non-built-up, visually recorded from the CNES Airbus imagery found in Google Earth for 2013 and 2017. Stratified random validation samples, consisting of 401 points (200 for built-up and 201 for non-built-up), were also visually confirmed by using CNES Airbus imagery on Google Earth. These data were used for the calculation of overall accuracy, precision, and recall for the accuracy assessment.

3. Results

Figure 3 illustrates the changes in built-up areas from 2000 to 2017 and the static built-up areas in 2013 for Liping County. The change map by LandTrendr suggests built-up areas had been expanded from 2000 to 2017. In general, the built-up areas were distributed at lower and flat terrains. The spatial distribution of built-up areas for 2013 was estimated by RF with an overall accuracy of 0.93 and precision of built-up class of 0.88. As LandTrendr depicted only changes in land covers from the temporal profile of Landsat time series, a static reference map is required to estimate dynamics of built-up areas.

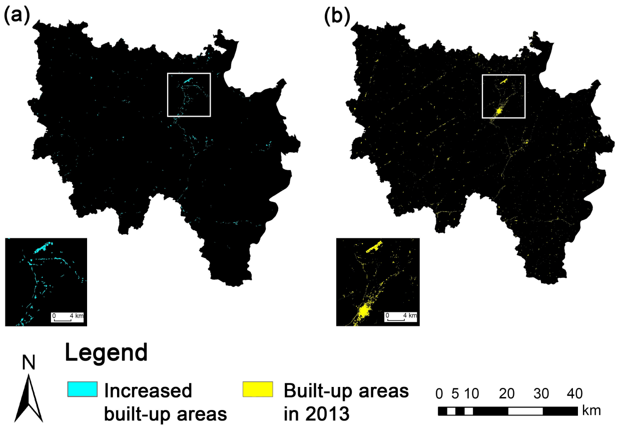

Figure 3. (a) Built-up change map by LandTrendr between 2000 and 2017 and (b) built-up area base map by RF in 2013.

The total built-up areas in each year were estimated from the spatio-temporal analysis combined with LandTrendr and RF (Figure 4). The built-up areas have been increasing since 2000 and moreover, the development has been accelerated after 2010. Compared to the expansion of built-up areas, the total population in Liping County showed a different trend. The population had a drastic decline between 2005 and 2010 while did not increase after 2010. It implies unwilling temporal relations between population and built-up areas. The estimated built-up areas per capita shown in Figure 5 also indicates the differences between population and built-up areas. Ten townships, approximately half of Liping County, exceeded 100 m^2 in built-up areas per capita in 2017, which implies that the developments in Liping County might be excessive.

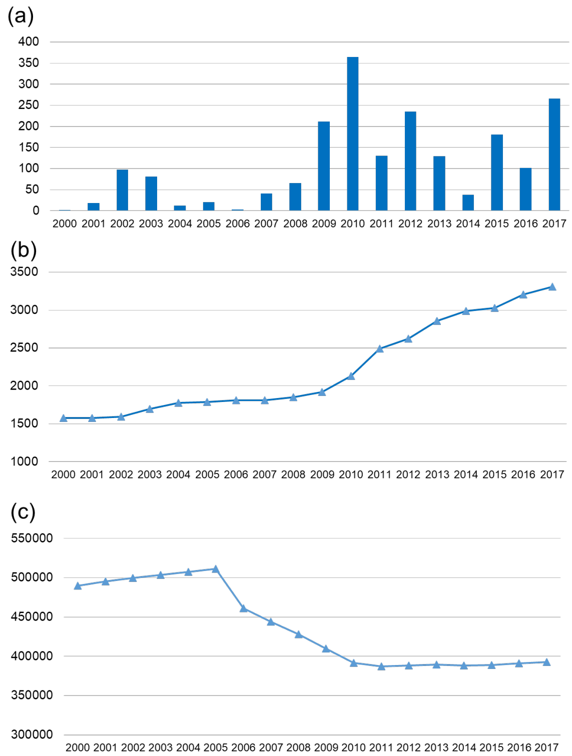

Figure 4. Changes in Built-up areas (ha) and population. (a) Annual changed built-up areas by LandTrendr, (b) the total built-up areas estimated by LandTrendr and RF, (c) population

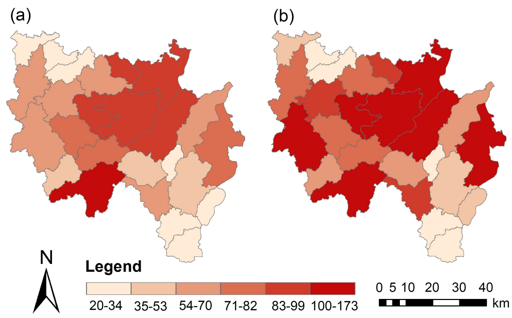

Figure 5. Built-up area per capita at township level in (a) 2010 and in (b) 2017 (m^2).

4. Discussion

The results may imply excessive developments in the study area with different backgrounds in the following three phases. In the first phase (2000-2005), positive natural increase and small population mobility suggest a slight population growth, whereas built-up areas kept stable. During the second phase (2005-2010), numerous young people migrated to big cities, leading to drastic depopulation and the built-up areas had a slight increase. In the third phase (2010-2017), the out-migration was decelerated and population has become stable. Meanwhile, a policy, “Building New Countryside” was widely implemented in rural China, which may accelerate the expansion of rural housing (Long et al., 2010). However, more evidence are needed to support these discussions in future studies. In the perspective of environmental conservation, the regional planners and policy-makers should pay attention to the unbalanced development of built-up areas.

Changes in built-up areas by LandTrendr and RF are considerably different (Figure 6). LandTrendr demonstrates the increase of built-up areas as 715 ha between 2013 and 2017 whereas RF indicates 1465 ha increase. LandTrendr is designed for time-series analysis and land change detections. However, it is sensitive to the parameter settings (Kennedy et al., 2018), which may lead to fitting errors. Also, as this approach is not a classification tool, some other thematic changes such as deforestation may be overlooked. The changes detected by LandTrendr were not validated in this study due to the limited reference data. RF captured the spatially static distribution of built-up areas in 2013 and 2017 and the results from RF were also validated. However, the static maps were classified separately and this post-classification comparison approach is criticized as classification errors in each map will be neglected (Boucher et al., 2006). This on-going study will overcome such issues mentioned above in the next step and develop a novel spatial-temporal analysis to identify land cover changes so as to quantify the anthropogenic pressure in Liping County.

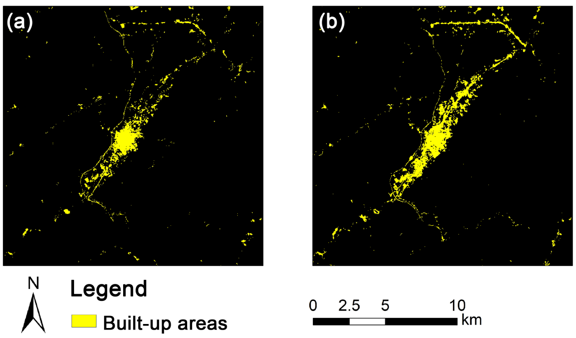

Figure 6. Comparison of estimated built-up areas of the year 2017 by (a) LandTrendr and RF and by (b) RF only.

5. Conclusion

We applied a spatio-temporal approach combined with LandTrendr and RF to extract changes in built-up areas from satellite imagery and compared them with the township-level population census data between 2000 and 2017. With the comparison of built-up areas and population, we found an excessive human impact on Liping County, a typical mountainous region in Southwest China. This study will attempt to assess this unusual and unsustainable development in the next step.

Acknowledgement

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