A time-series study of two cities: the built-up areas change between 1995 and 2015 in London and Shanghai

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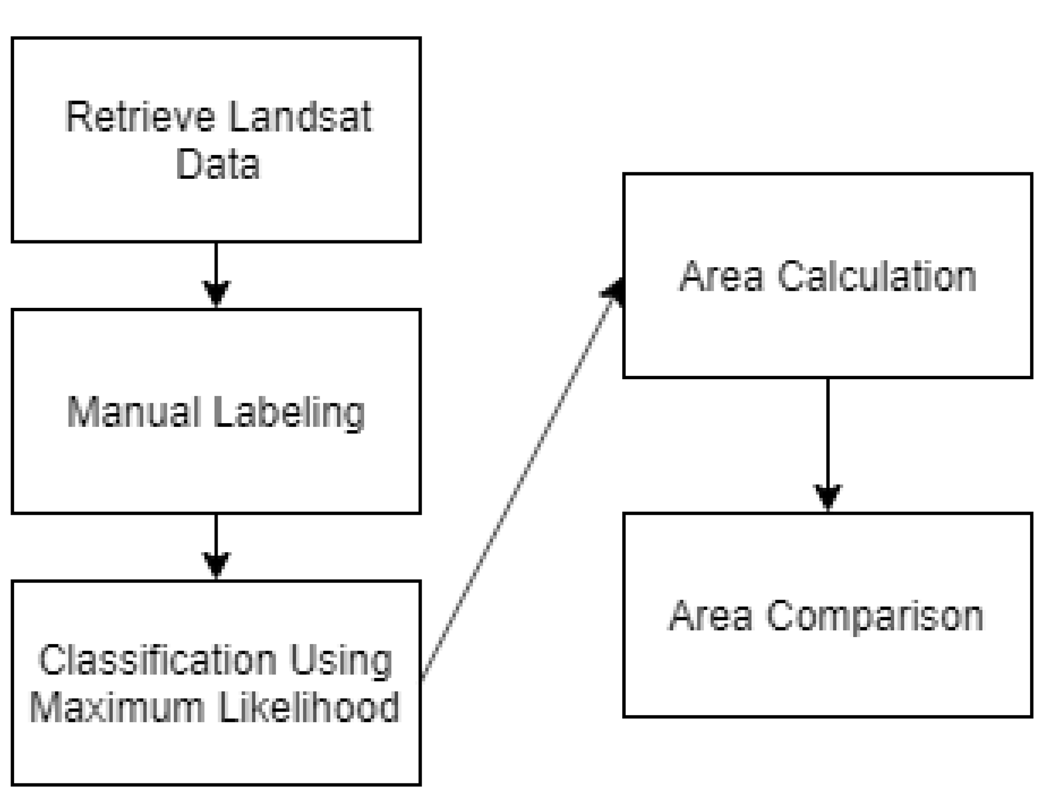
Introduction

Prosperous built-up areas are a sign of city growth. Up to 2015, the number of megacities triple that of 1990 (United Nations, 2014). We are interested in seeing the change of built-up areas of pre-existed megacity and a megacity that started to develop from 1990. With the free availability of Landsat data, we are able to study city changes using remote sensing methods. In this project, London and Shanghai are chosen to study the change of built-up areas over an approximate of 25-year range.

Methodology

Level 1 data from Landsat 5, 7, and 8 were downloaded from the USGS Earth Explorer. City boundaries shapefiles downloaded from the Greater London Authority Datastore and the ArcGIS data portal are used to crop the extent of the Landsat data. Manual labelling was applied to the Landsat data to distinguish three features: built-up areas, green lands, and water. The Maximum Likelihood Algorithm is then used to study 20% randomly selected pixels for each image to classify the pixel into one of the three categories.

On each scene, the classified built-up pixels would be divided by the total selected pixels to obtain the fraction of the built-up pixels. This fraction was then applied to the total pixels of the region. In combination of the fraction and the total area of the city, which is calculated by multiplying the number of pixels by 900 m^2 for each pixel, the built-up area is obtained for each scene.



Results

London

According to the classification, the built-up area is 1696 km^2, taking up 64.8% of the total area in 1995 in London. In 2014, the built-up area is 1367 km^2, occupying 54.2% of the total area. It can be seen from the line graph that there is a slight decrease of 1.72% per year in the built-up area from 1995 to 2015.

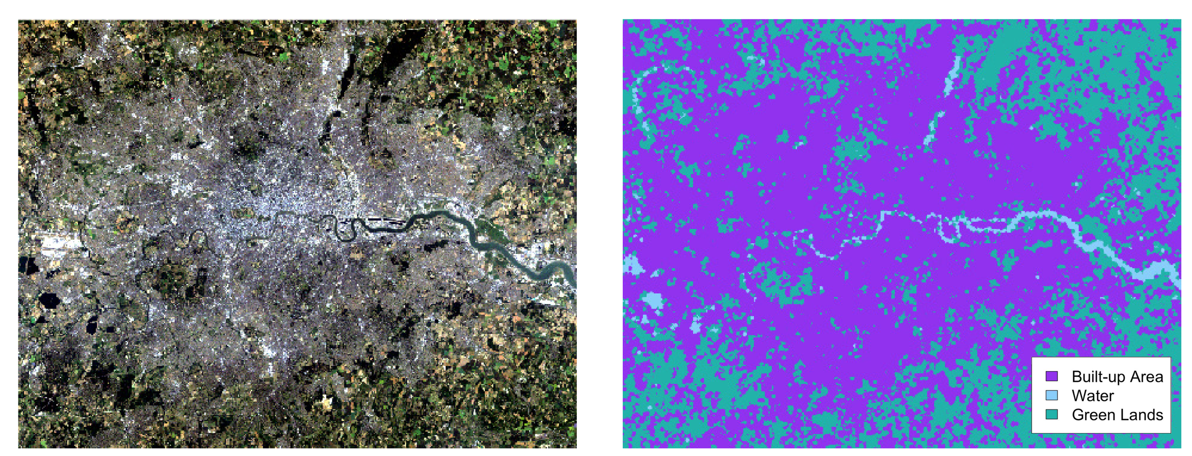


Figure 1 The RGB composite image of the Greater London Area (Up Left) and the classification results of the image (Bottom Right). Image date: May 11th, 1995

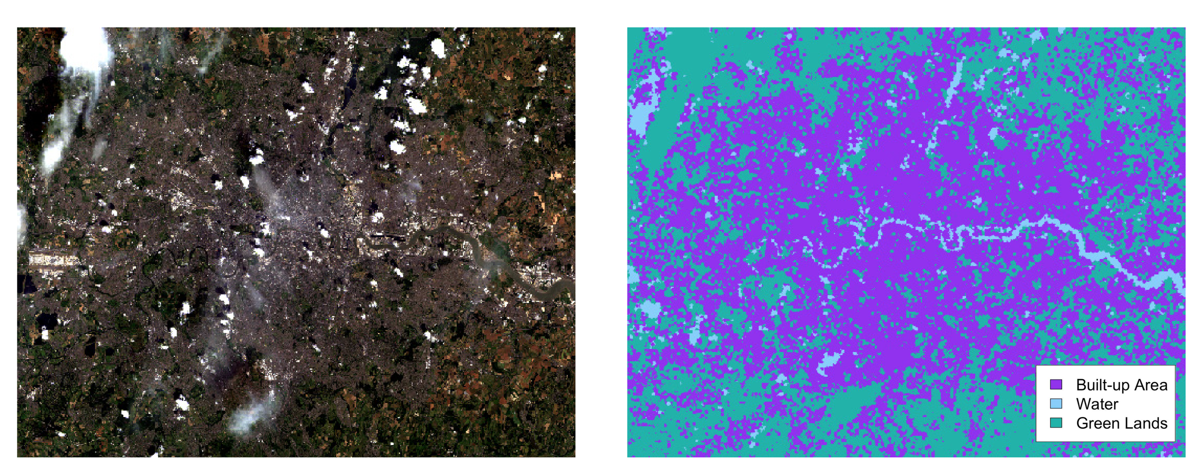
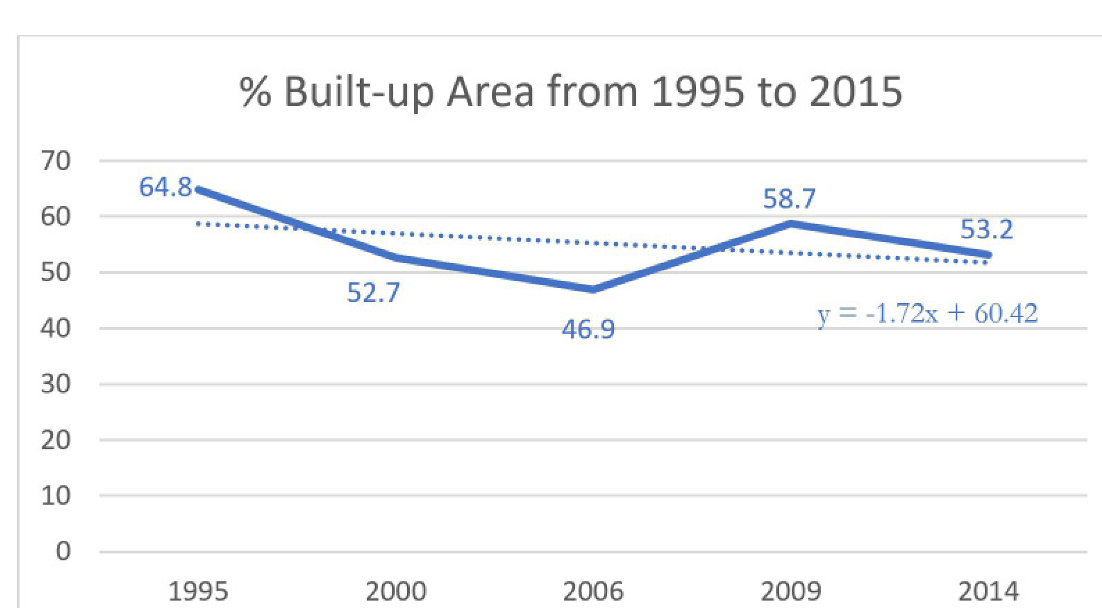


Figure 2 The RGB composite image of the Greater London Area (Up Left) and the classification results of the image (Bottom Right).Image date: July 4th, 2014

Figure 3.
Line Graph of Build-up Area Percentage Variation over 20 years in London



Shanghai

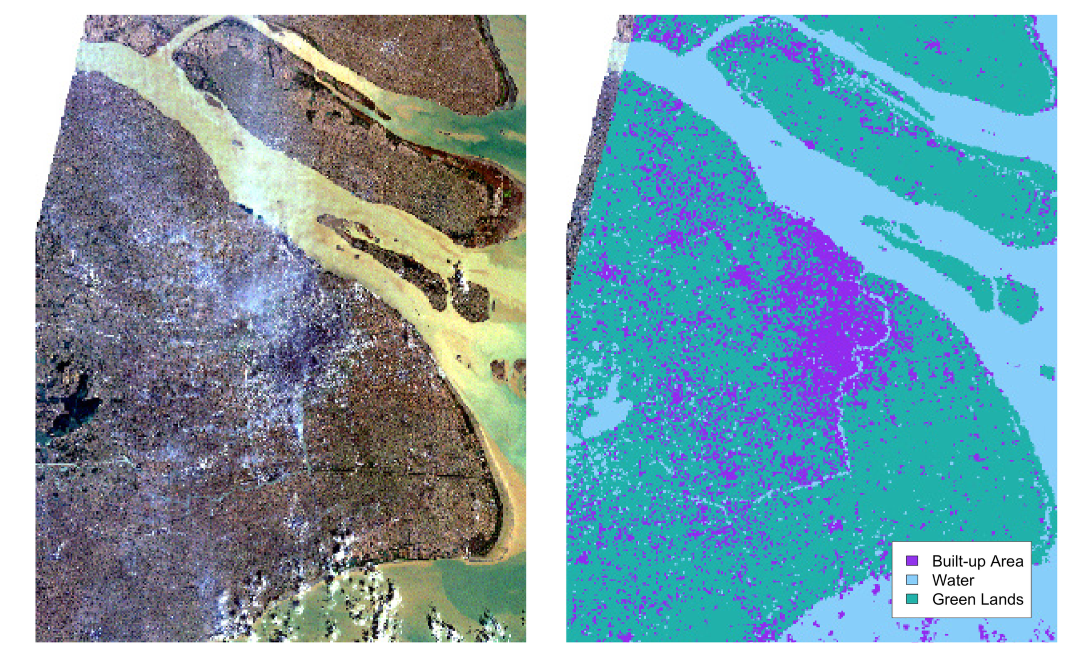


Figure 4 The RGB composite image of Shanghai City (Left) and the classification results of the image (Right). Image date: November 16th, 1995

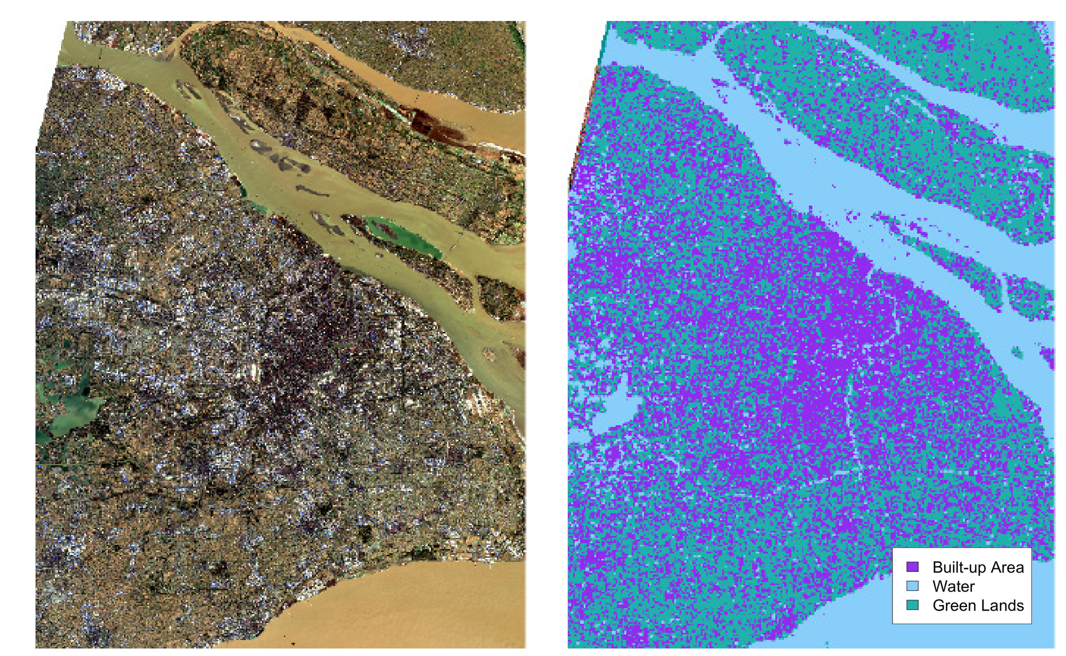
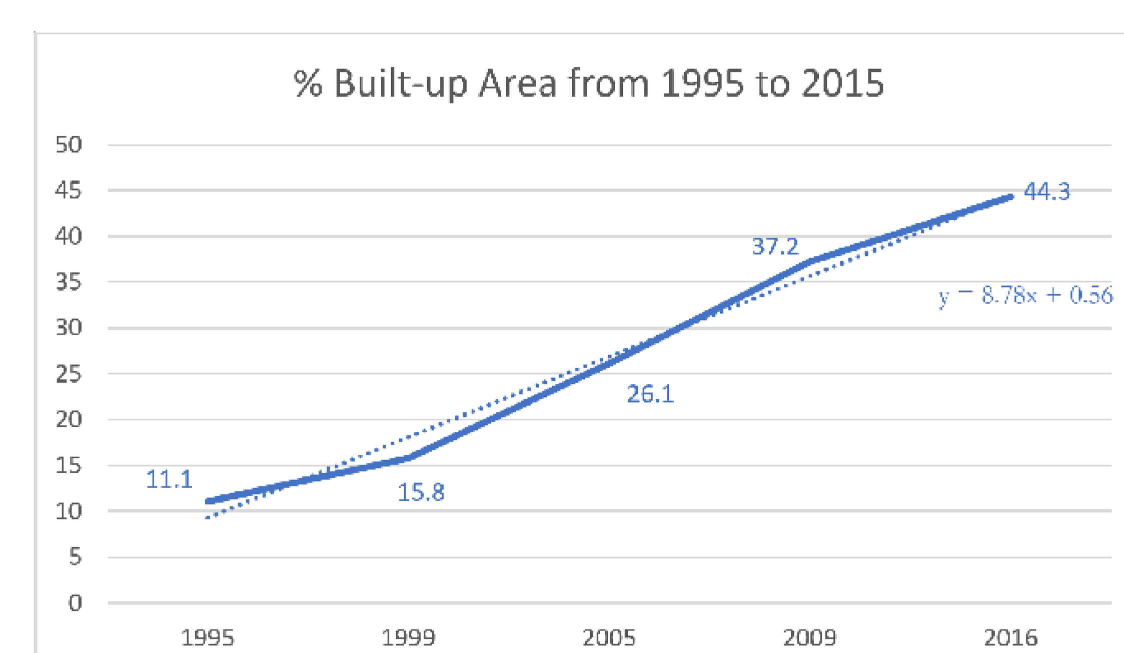


Figure 5 The RGB composite image of Shanghai City (Left) and the classification results of the iage (Right). Image date: January 26th, 2016

Figure 6.
Line Graph of Build-up Area Percentage Variation over 20 years in Shanghai



According to the classification, the built-up area is 1443 km^2, taking up 11.1% of the total area in 1995 in Shanghai. In 2016, the built-up area is 4403 km^2, occupying 44.3% of the total area. It can be seen from the line graph that there is a linear increase rate of 8.78% per year between 1995 and 2016.

Conclusion

Using the Maximum Likelihood Maximum classification method, we were able to delineate the built-up area from a city by manually labeling sampled extents. It can be concluded from the area calculation that from 1995 to 2014, a span of 19 years, there is a slight decrease of built-up area in London.

The built-up area change is apparent in Shanghai from 1995 to 2016. In 1995, the built-up area is 1443 km^2. In 2016, the built-up area tripled at 4403 km^2. The overall results justify the hypothesis of this research that London would not have an obvious change as it had developed before 1990 while Shanghai would have seen a dramatic increase because of the policy in China.

One drawback of this research is that although the Landsat data are available, a large portion of the data could not be used because of cloud coverage. Scenes coming with more clouds would affect the results of classification. Higher-resolution and cloud-free data, if available, would be useful for checking the quality of the classification results.

Acknowledgement

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