

Large-scale Imperviousness Mapping and Detection of Urban Land Changes

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Summary

The paper aims to introduce a remote sensing method to quantify urban land take, which can be used to support the quantitative objectives for limiting land take in Europe. Taking Germany as a case study, we carried out a nationwide imperviousness mapping and change detection. Based on Sentinel-2 satellite images and cloud computing platform, we applied a sub-pixel analysis approach to retrieve the imperviousness layer. This approach enables us to improve the mapping accuracy and also reduce random noise in the change detection results.

KEYWORDS: Large-scale mapping, Imperviousness, Change detection, Spectral unmixing, Big data

1. Introduction

Rapid urbanization has led to more and more natural land being converted into artificial surfaces. The fast land take has been a concern in Europe, therefore, the EU has set a clear target to achieve no net land take by 2050. Member states have pledged to integrate the targets into their land-use strategies and urban planning. For example, the German sustainable development strategy has set up the goal of reducing land consumption for settlement and transportation infrastructure to 30 ha per day by 2030 and no land take by 2050. Such quantitative objectives have the merit of being clear and simple, however, it remains challenging to retrieve a consistent measurement of land consumption on a yearly basis. Data sources on the European level such as Copernicus Urban Atlas, Imperviousness and CLC land cover maps are frequently used for monitoring urban land changes. However, these data sets feature a low update frequency (every 3 or 6 years), coarse mapping units, or incomplete spatial coverage, limiting their usefulness for mapping urban land changes in line with land take objectives. Nation-wide land use data from the real estate cadastre information system has changed and will change again its nomenclature, resulting in unreliable time series.

The remote sensing technique has been an attractive tool for consistently and regularly mapping landcover changes. The current development of big data and cloud computing techniques has revolutionized our ability to map at a large scale and monitor urban land dynamics in a long time series. However, the often-used methods such as image classification and post-classification comparison encounter many problems in the change detection products. Firstly, these products contain many random noises caused by the differences in atmospheric conditions, sun angle, vegetation phenology change, etc. Secondly, these methods do not take an insight into the mixed pixels problem: Since urban land is a heterogeneous surface with spatial variation at a fine scale, the urban image pixels are often mixtures of different land covers. Therefore, our study aims to take a sub-pixel analysis approach to retrieve an imperviousness layer that represents the urban surface, use cloud computing techniques to realize a Germany-wide mapping and detect the changes of imperviousness layers to quantify annual urban land consumption.

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2. Workflow and Method

Sentinel-2 satellite data was chosen as our main data source, due to its high revisit frequency, high spatial resolution and free accessibility. We use Google Earth Engine as the computing platform to process big remote sensing data. The overall workflow is illustrated in Figure 1, and it mainly includes four steps.

Firstly, we aggregated more than 4000 Sentinel 2 image scenes from a single year into 27 composites based on a two-week time interval. These 27 composites enable us to capture the temporal characteristics of different land covers. Based on the temporal metric, urban land featuring the lowest temporal variation can be well separated from other land covers. Then, these 27 composites were further aggregated into a yearly composite that is a Germany-wide mosaic with spectral bands and spectral indices. Afterward, the spectral and temporal information was integrated into the linear spectral unmixing algorithm. Spectral unmixing considers a pixel on a remote sensor image as a composition of distinct materials, and the unmixing process is to decompose each mixed pixel by estimating the fraction of each component. We used a three-component model and one of the components is imperviousness. Finally, change detection was applied to the yearly imperviousness layers. As any newly built structure converts a natural surface to a sealed surface, leading to an increase in imperviousness degree, image pixels with increased imperviousness were collected to quantify urban land take.

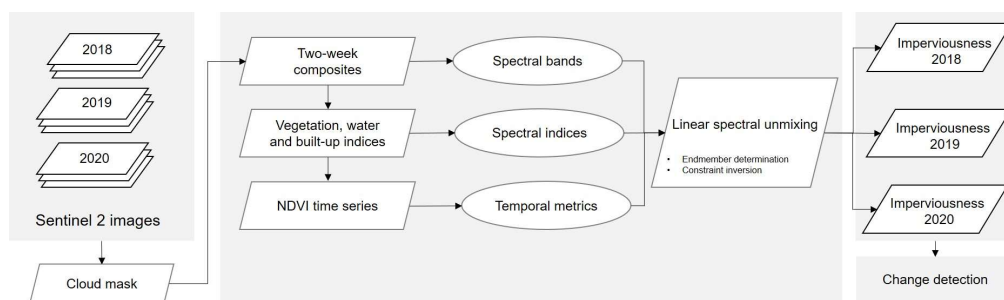


Figure 1 Workflow of Imperviousness mapping and change detection based on Sentinel-2 data.

3. Result

Based on the three-component model, spectral unmixing produces three layers, including imperviousness, greenness and temporal variation. Each layer has a continuous fraction index, ranging from 1 to 100 percent. With red, green and blue representing imperviousness, greenness and temporal variation respectively, figure 2a illustrates the spectral unmixing results in 2018, 2019 and 2020.

The change detection was retrieved by subtraction of two status Imperviousness layers. Pixels with imperviousness increases of more than 70% in the change layers were taken as new built-up areas. The threshold value was set up to filter out noise caused by irrelevant changes. The change detection result was able to detect various kinds of newly built areas, such as residential houses, industrial factories and transportation infrastructure, see figure 2b. It is remarkable that it also detected new structures with small sizes, such as single houses, bases of wind turbines and gas pipelines.

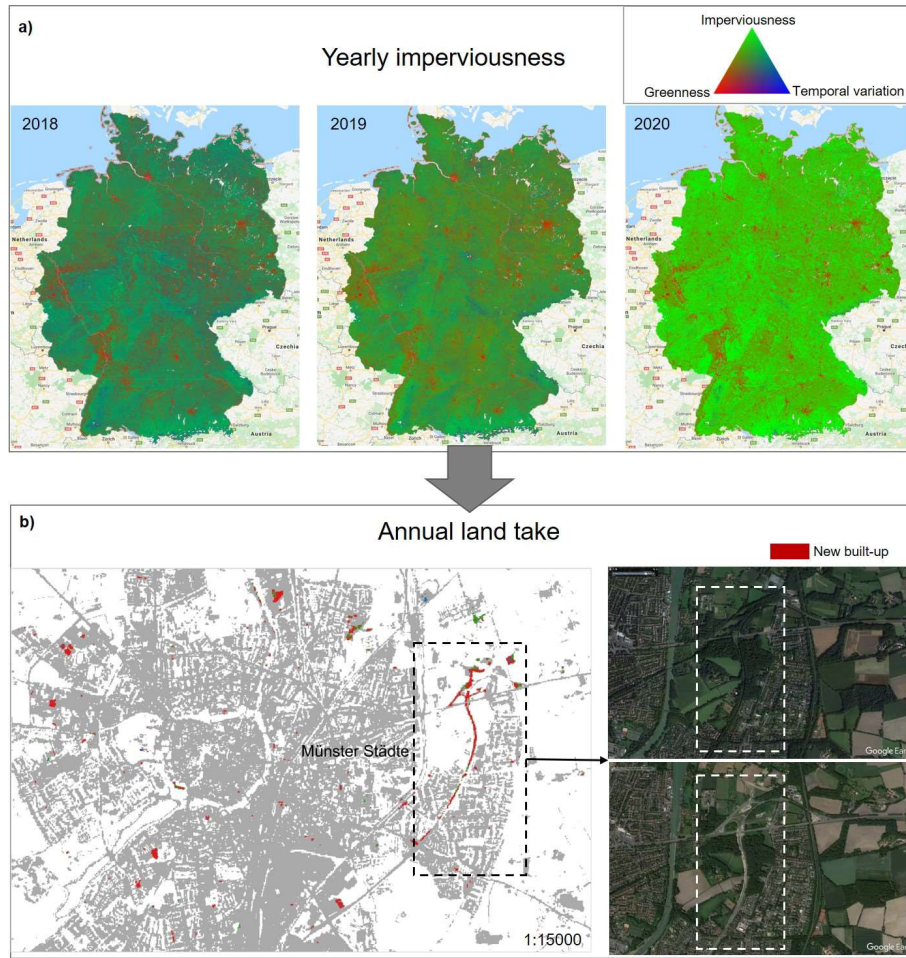


Figure 2 (a), Imperviousness mapping result for the years 2018, 2019 and 2020. (b), Change detection of newly built areas based on comparison of imperviousness layers.

The validation of change detection was then done by overlaying the sample points with high-resolution images from different years, including historical aerial photos and historical imagery from Google Earth Pro. We took two aspects to validate the change layers. Firstly, from the view of detection of urban land take, we only investigated whether the samples have been turned into built-up areas for urban use. In this way, it results in an overall accuracy of 87%, seen in the error matrix **Table 1**. Secondly, from the view of change detection itself, we examined whether the land surface of these samples has changed, and it results in an accuracy of 98%, sees **Table 2**. This is much higher than the detection of new built-up areas in reference datasets. The reason for such a difference is that part of the sample points shows changes on the surface where mining or deforest activity turn high vegetation into bare ground, where new greenhouses agricultural use are erected, or where plastic sheets for horticulture were installed on farmland. Such cases are correct change detection but were considered as false detection of built-up, as the changes were not for urban use.

Table 1 Accuracy assessment of detection of new built-up

Change layer	Reference map		
	Non-built-up	New built-up	Total
Non-built-up	0.50	0.00	0.50
New Built-up	0.13	0.37	0.50
Total	0.63	0.37	1
Accuracy = 0.87			

Table 2 Accuracy assessment of change detection

Change layer	Reference map		
	No change	Change	Total
No Change	0.50	0.00	0.50
Change	0.02	0.48	0.50
Total	0.52	0.48	1
Accuracy = 0.98			

4. Conclusion and Outlook

Based on big remote sensing data and Google Earth Engine, we carried out a nationwide annual imperviousness mapping and annual change detection. We found that data mining and cloud computing are not replaceable in large-scale mapping. Cloud computing enables us to reduce data volume and realize image aggregation. Data mining is a key approach to extract spectral and temporal information for the Germany-wide mosaic.

We applied spectral unmixing to retrieve the imperviousness layer. This sub-pixel approach has improved our mapping accuracy in urban areas. Newly built structures including those within mixed pixels can be identified. This explains why tiny structures such as single houses and the base of wind turbines can be detected in the change detection products.

Due to the continuous map index, imperviousness represents urban areas as continuous and gradually varied surfaces. With a continuous index as a basis of comparison, we could set up a threshold value to remove irrelevant changes and reduce the random noise to 2% in the change detection products.

Future work might focus on the two by-products of the spectral unmixing result: Greenness and the temporal variation layer. Further improvement on these two layers can make them useful for quantifying land change in natural surfaces.

Biographies

Dr. Shaojuan Xu received her doctoral degree in remote sensing and geoinformatics at the Osnabrueck University, Germany. She worked for an EU-funded project for three years before joining the current urban research institute. Her research interests lie in the application of big data for sustainable urban studies.

Prof. Dr. Stefan Fina currently is the head of the Geoinformation and Monitoring group in the Research Institute for Regional and Urban Development. He teaches Analysis and Monitoring of Urban Areas at the RWTH Aachen University. His research focuses on methods of spatial analysis in geography, spatial and environmental planning.