Earth Syst. Sci. Data Discuss.,
https://doi.org/10.5194/essd-2019-65-AC3, 2019

Interactive comment on "A 30-meter resolution national urban land-cover dataset of China, 2000–2015" *by* Wenhui Kuang et al.

Wenhui Kuang et al.

kuangwh@igsnrr.ac.cn

Received and published: 8 November 2019

General Comment:
This study proposed a method to provide multi-year urban land cover maps for China. However, the proposed method suffers from several critical issues and uncertainties remain for the resulted maps. Thus, I do not recommend this manuscript to be accepted for publication in the journal.
Response:
Thanks for your comments. In the original version, we did not clearly describe the methods and results; thus, the true values of these products cannot be effectively evaluated. In the revised manuscript, we provided more detailed explanation of the methods and results, including accuracy assessment. Thanks for your comments and suggestions,

as well as from other reviewers, we believe the new version is considerably improved. Detailed response and changes in manuscript were listed in the PDF file in the supplement.

Paragraph 1
Paragraph 1, Point 1: First, my main concern is the accuracy of these maps to detect urban land cover changes. It is more important for readers to know the accuracy of change detection than merely mapping accuracy of each year because this is the reason why we need maps at multiple time points.
Response:
Yes, accuracy of the maps is very important. We did not pay sufficient attention in the original manuscript. Thanks for your suggestions, we conducted accuracy assessment and added tables (Tables 2 and 3) to explain this issue. The accuracy of the urban land-cover changes has been validated in CLUD (Liu et al., 2005, RSE; Zhang et al., 2014, RSE; Ning et al., 2018, JGS). The accuracies of urban land change in 2000-2005, 2005-2010, 2010-2015 were 97.01%, 95.93% and 94.99%, respectively. The accuracy of urban land for each period has range between 91.9% and 98.9%. The intra-urban land-cover dataset is derived from CLUD. The validation results showed that the RMSE values of ISA for 2000, 2005, 2010, and 2015 were 0.12, 0.11, 0.10, and 0.10, respectively. The RMSE values of UGS for 2000, 2005, 2010, and 2015 were 0.18, 0.17, 0.16, and 0.14, respectively.
We also performed the validation for change detection results for different period products of ISA and UGS fraction. We chose 741 samples (90m$\times$90m) within urban area for validation. We used medium relatively error (MRE) to examine the accuracy. The MRE for ISA in 2000-2005, 2005-2010, and 2010-2015 were 5.69%, 5.33%, and 6.83%, respectively. The MRE values for UGS in 2000-2005, 2005-2010, and 2010-2015 were 5.69%, 5.33%, and 6.83%, respectively.
Changes in manuscript:

The validation results of ISA and UGS changes were also added in the validation section (4.1.2) of the manuscript. We revised Table 3 in the manuscript (Table 1, shown in Fig.1 below) to add the accuracy of urban land-cover types for 2000, 2005, 2010 and 2015.
We added a new table in the revised manuscript to delineate the accuracy of urban land and its intra land-cover change (Table 2, shown in Fig.2 below).

Paragraph 1, Point 2: Meanwhile, CLUD was created by visual interpretation and ignored small urban clusters and human settlements as indicated by Fig. 8. Thus, the maps generated in this study seem to loss the details that the 30-m resolution Landsat images can provide.
Response:
Yes, we agree with you that the CLUD loss the details in the urban landscape, because one objective of producing CLUD was to obtain the urban extent, not spatial details in the urban landscape. However, the CLUD has accurate urban boundary through visual interpretation and this research just used this advantage. This research aims to making use of advantages of different data sources to produce accurate and detailed urban components. Therefore, we used CLUD to provide the accurate urban boundary and urban pixels, then used other data sources (such as NDVImax, fractional ISA reference data) to establish models to estimate fractional ISA, as well as green spaces, so that we can provide the detailed urban components, which other individual data sources do not have.

Paragraph 1, Point 3: In addition, the created maps should also be compared. to more existing urban maps with higher spatial resolution than the ones used in this study (Fig. 8), such as the Global Human Settlement Layer and Global Urban Footprint.
Response:

Good suggestion. Thanks a lot. We conducted the comparison of our results with existing urban land datasets, as shown in Fig. 8 (in the manuscript). A list of urban land datasets includes MODIS land cover, ESA land cover, Global Human Settlement Layer (GHSL), GlobaLand 30 and other products were compared (Table 3, shown in Fig.3 below). As shown in Figure 8 in the manuscript (Figure 1, shown in Fig.4 below), our product provided more details of urban spatial patterns than other products (note: both of the GHS Built and GlobaLand 30 products only have two years).
Changes in manuscript:
We revised Fig. 8 in the manuscript and added more urban land products at 30 m or higher spatial resolution. The manuscript was revised to add a more detailed comparison in section 4.2.

Paragraph 2
Paragraph 2, Point 1: The method that used NDVI as the single indicator to estimate surface imperviousness is problematic due to the confusion between bare land and impervious surfaces. This is especially true for China where a large amount of bare land existed due to rapid urbanization during the study period. Although the authors used EBBI to extract bare land, the capability of this index to differentiate impervious surfaces and bare land across biomes is uncertain.
Response:
We completely agree with you that bare land is a big problem in ISA mapping, especially in arid/semiarid regions. This is a common problem and there is lack of suitable approaches to solve this problem yet. This problem can be ignored in tropical and subtropical regions as we used NDVImax, but cannot be ignored in arid and semiarid regions. In this research, we explored use of EBBI bare land index to remove bare land (As-syakur et al., 2012, Remote Sens.). More research should be conducted in the future to explore suitable approach to separate bare land and ISA. If high spatial resolution thermal images or nighttime light data are available in the future, proper

integration of these types of data may be a solution. We added some texts in the Discussion section to discuss this issue.
Changes in manuscript:
We added texts in Discussion section (section 4.6) to discuss the methods or data which can be improved in further research.

Paragraph 3
Paragraph 3, Point 1: The method used to temporally adjust multi-year ISA is also questionable because urban redevelopment (e.g., convert high ISA urban villages to high residential buildings with vegetation) is very common in Chinses cities. Thus, the inversible assumption of urban development is problematic, especially for this study that aimed to detail intra-urban land cover change.
Response:
Good comments. We agreed with you on this concern. If we directly conduct the temporal adjustment, the redevelopment area has problem. However, we used NDVImax to do the calibration. In the redevelopment region, if ISA was replaced with greenness (such as park), this kind of problem is solved. When we conducted the calibration, we assume that the generally increasing trend of impervious density inside Chinese cities is mainly in the urban greening area. We modified the manuscript to stress this assumption.
Changes in manuscript:
We stressed that the temporal adjustment between multi-year ISA data was conducted. The related change can be found in page 6, line 33, page 7, line 2.

Paragraph 3, Point 2: Additionally, the authors mentioned that the 2015 map was the most accurate so that it was used as reference to temporally adjust ISA in previous years. Quantitative results were needed to support this decision and whether the 2015

map was the most accurate across regions should be addressed.
Response:
We added the accuracy assessment results in the revised manuscript. The RMSE values for 2000, 2005, 2010, and 2015 were 0.12, 0.11, 0.11, and 0.10, respectively. The dataset in 2015 has the lowest error.
Changes in manuscript:
In page 7 lines 3-4, we added the RMSE values for 2000, 2005, 2010, and 2015 in the revised manuscript.

Paragraph 4
Paragraph 4, Point 1: Line 2, Page 3: 30-m resolution is not “high-resolution”
Response:
We replaced“high-resolution” as “30-m resolution”.
Changes in manuscript:
We replaced “high-resolution” as “30-m resolution” in page 3, line 12.

Paragraph 4, Point 2: Line 15, page 5: not just“JavaScript”.
Response:
As Python can be used in GEE, it could be better not to emphasize a particular language. We revised the manuscript.
Changes in manuscript:
We deleted “JavaScript” in this sentence.

Please also note the supplement to this comment:
https://www.earth-syst-sci-data-discuss.net/essd-2019-65/essd-2019-65-AC3-supplement.pdf

Interactive comment on Earth Syst. Sci. Data Discuss., https://doi.org/10.5194/essd-2019-65, 2019.

Year	Urban land	ISA		UGS		Water body	Bare land
	Overall accuracy	RMSE	R	RMSE	R	Overall accuracy	Overall accuracy
2000	98.92%	0.12	0.89	0.17	0.85	95.97%	73.96%
2005	97.01%	0.11	0.89	0.17	0.87	96.98%	73.72%
2010	93.99%	0.1	0.91	0.16	0.87	98.66%	76.19%
2015	91.98%	0.09	0.93	0.02	0.89	98.32%	70.01%

Note: The validations of urban land were obtained from Zhang et al.(2014), Kuang et al. (2016) and Zhang et al.(2019)

Fig. 1. Table 1: Accuracy assessments of CLUD-Urban.

Period	Overall accuracy of Urban land	MRE of ISA	MRE of UGS
2000-2005	97.01%	5.69%	7.09%
2005-2010	95.93%	5.33%	5.86%
2010-2015	94.99%	6.83%	6.68%

Note: The validations of urban land were obtained from Zhang et al.(2014) and Ning et al.(2019)

Fig. 2. Table 2: Accuracy assessments of urban land-cover change.

Name	Spatial resolution	Abbreviation	Method	Reference
China's Urban Land use/cover Dataset	30 m	CLUD-Urban	Visual interpretation	-
Land Cover from Moderate-resolution Imaging Spectroradiometer	500 m	MODIS LC	Decision tree classification	(Friedl et al., 2010)
European Space Agency global land-cover data	300 m	ESA LC	Unsupervised classification and change detection	(Bontemps et al., 2011)
Global Land Cover at 30 m resolution	30 m	GlobaLand 30	Pixel-Object Knowledge (POK)-based classification	(Chen et al., 2015)
Built-up grid of the Global Human Settlement Layer	30 m	GHS Built	Symbolic machine learning	(Pesaresi et al., 2013, 2016)
Multi-temporal Global Impervious Surface	30 m	MGIS	Normalized urban areas composite index	(Liu et al., 2018)

Fig. 3. Table 3: List of urban land products for comparison.

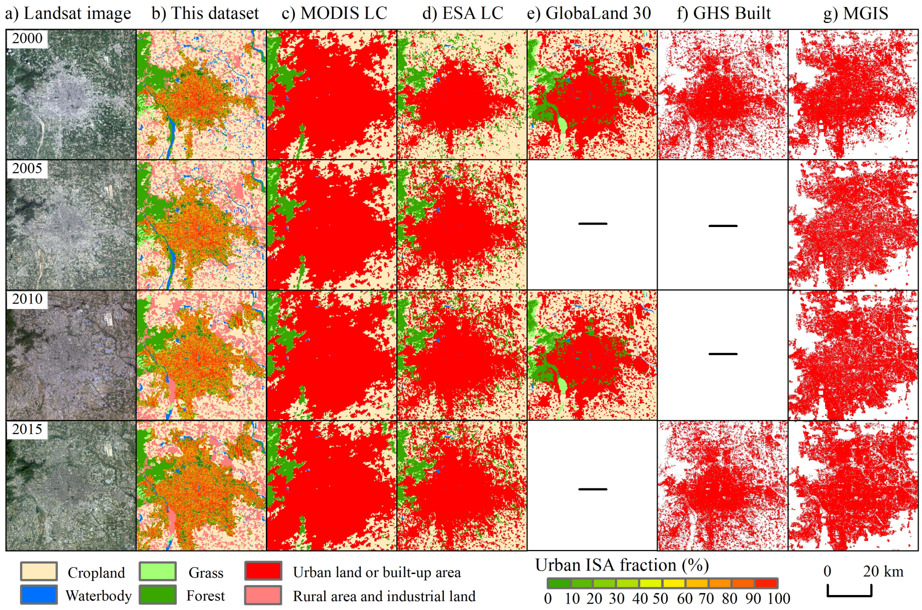

Fig. 4. Figure 1: Comparison of urban land distribution in Beijing, China, from different urban products.