Thank you for the comments and suggestions. These comments were very helpful for revising and improving our paper. We have responded to the comments point by point and made the detailed revisions embedded in the manuscript with the line numbers indicated in the responses.

Comment 1: The manuscript provides the China's 30-m UISA and UGS fraction datasets based on the urban area in CLUDs by logistic regression and linear calibration using NDVI from Landsat data. I would suggest the authors reorganize the sections, give more details on the samples and mapping algorithm, discuss more about the accuracy of the maps and comparison with various datasets, add a discussion part and resubmit this paper.

Response: Thank you for the comments. We considerably rewrote the sections in Method, Results, and Discussion. In this revision, we proposed a new mapping strategy to acquire the multitemporal and fractional information of the essential urban land cover types at national scale through synergizing the advantage of both big data processing and human interpretation in aid of geoknowledge. We developed a set of new algorithms to acquire the UIS and UGS fractions using random forest algorithm in GEE platform. And then the UIS and UGS fractions with 30 m X 30 m resolution were mapped through overlaying the urban boundaries of CLUD.

Here we added five sections to elucidate the mapping strategy and technological flow on developing the new version CLUD-Urban product, including the strategy of developing CLUD-Urban product, data sources and preprocessing, extraction of urban boundaries from CLUD, method of mapping UIS and UGS fractions using GEE platform, accuracy assessment of the CLUD-Urban product and comparison of different products.

In discussions, “8.1 The mapping advantages integrated with human-computer interpretation and GEE platform; 8.2 The potential implications in promoting habitat environment and sustainability of cities; 8.3 Limitations of the method and dataset and future prospect” were added to address those issues.

Changes in manuscript: We conducted a major revision on the method, results and discussions in L105-330.

Comment 2: Figures:

1. For Figure 5 and 8, it would be better to remove the other land cover types and only show the fraction of UISA. The color is confusing among the vegetation types and the lower percentage of UISA.

Response: We revised the legend of Fig. 9.

Comment 3: Introduction:

2. There are quite a few existing dataset/report that are providing information about urban green spaces and urban land use categories of China. For examples, (1) https://www.mdpi.com/2072-4292/10/10/1569/htm, (2)

https://www.sciencedirect.com/science/article/pii/S2095927319307054?via%3Dihub

Response: We citied the above references, and added the reviews on those researches.

Changes in manuscript: We added the reference in L385-550

Comment 4: Method

3. I feel the methodology section can be written to make it clearer (e.g., sample selection, the retrieval of UGS fraction)

Response: Thank you for your suggestions. We rewrote the method parts, including the strategy of developing CLUD-Urban product, data sources and preprocessing, extraction of urban boundaries from CLUD, method of mapping UIS and UGS fractions using GEE platform, accuracy assessment of the CLUD-Urban product and comparison of different products.

Changes in manuscript: We rewrote the method on the extraction of urban boundaries from CLUD and the retrieval of UIS and UGS fractions below in L130-205.

5 Mapping UIS and UGS fractions using GEE platform

5.1 Collection of training samples

The training samples of UIS and UGS fractions are a pivotal input parameter in random forest model for mapping national settlement and vegetation fraction. In light of large discrepancies among UIS and UGS composites in different climate zones with various geographical and social economic conditions, we collected a total of 2,570 samples from randomly selected cities in different climate zones (Schneider et al. 2010) (Fig. 5). Here we also refer to the existing UIS dataset to acquire samples with 10% intervals of the ISA fraction, and those samples primarily distributed in the homogeneous UIS or UGS areas, which might provide more effective samples and decrease the impact of imagery mismatch. The samples of UIS and UGS covered with diversified types, including buildings, roads and squares, and grass, trees from parks, road and residential green spaces. The UIS and UGS percentages were interpreted within each sample using Google Earth images (Fig. 5b1-b4). Finally, the training samples in 2000, 2005, 2010, 2015 and 2018 were used for training the random forest model, respectively.

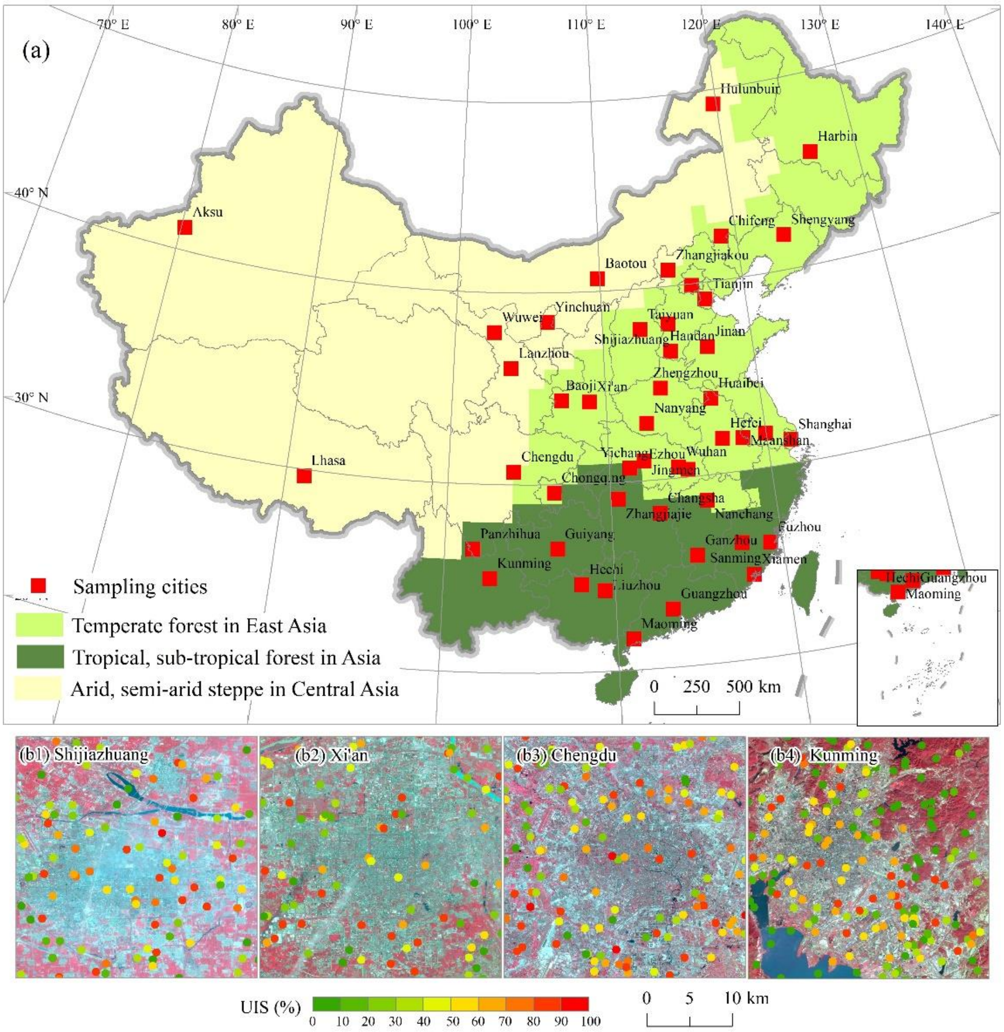

Figure 5: Distribution of sampling cities in China and training samples in selected cities. (The images were provided by Geospatial Data Cloud site, Computer Network Information Center, Chinese Academy of Sciences (http://www.gscloud.cn). The administrative boundaries were provided by National Geomatics Center of China (http://www.webmap.cn))

5.2 Retrieval of settlement and vegetation fractions using random forest model

Many previous studies have indicated that random forest is more effective and accurate in classifying urban land types than other machine learning approaches such as support vector machine (SVM) and artificial neural network (ANN) (Zhang et al., 2020). Random forest exhibits a strong capacity in processing high-dimensional datasets and has been successfully applied to mapping global ISA at 30-m resolution (Zhang et al., 2020). In this research, we proposed a strategy to acquire the settlement and vegetation percentage at pixel scale using the advantage of random forest and big-data processing based on GEE platform.

According to sixteen global urban ecoregions based on temperature, precipitation, topographic conditions and social economic factors (Schneider et al. 2010), China has three urban ecoregions. In each urban ecoregion, the annual maximum NDVI, and spectral bands in Landsat TM/ETM+/OLI, and the slope index derived from SRTM DEM with 30-m resolution were selected as the input parameters to run random forest model. The Landsat images were from January 1 to December 31 of each baseline year. The annual maximum NDVI ($NDVI_{max}$) was retrieved using equation (1):

$$NDVI_{max} = \max(NDVI_1, NDVI_2, \cdots, NDVI_i) \quad (1)$$

where $NDVI_i$ is the NDVI value of the i^{th} image. Individual NDVI was calculated from Landsat images in the period between January 1 to December 31 and all images were collected using GEE (Gorelick et al., 2017).

In GEE platform, the settlement and vegetation fractions were calculated for each urban ecoregion through using the training parametrizations. The lawn, forest or their mosaicked areas were selected as input samples in mapping UGS. A post-processing was implemented to remove the pixels with NDVI values of greater than 0.5 or DEM slope values of greater than 15^{o}. In arid and semi-arid areas, the enhanced bare soil index (EBSI) was utilized to separate UIS from bare soils (As-syakur et al., 2012; Li et al., 2019). As a result, the settlement and vegetation fractions with 30 m $\times$ 30 m in 2000, 2005, 2010, 2015 and 2018 were generated for developing CLUD-Urban product (Fig. 6).

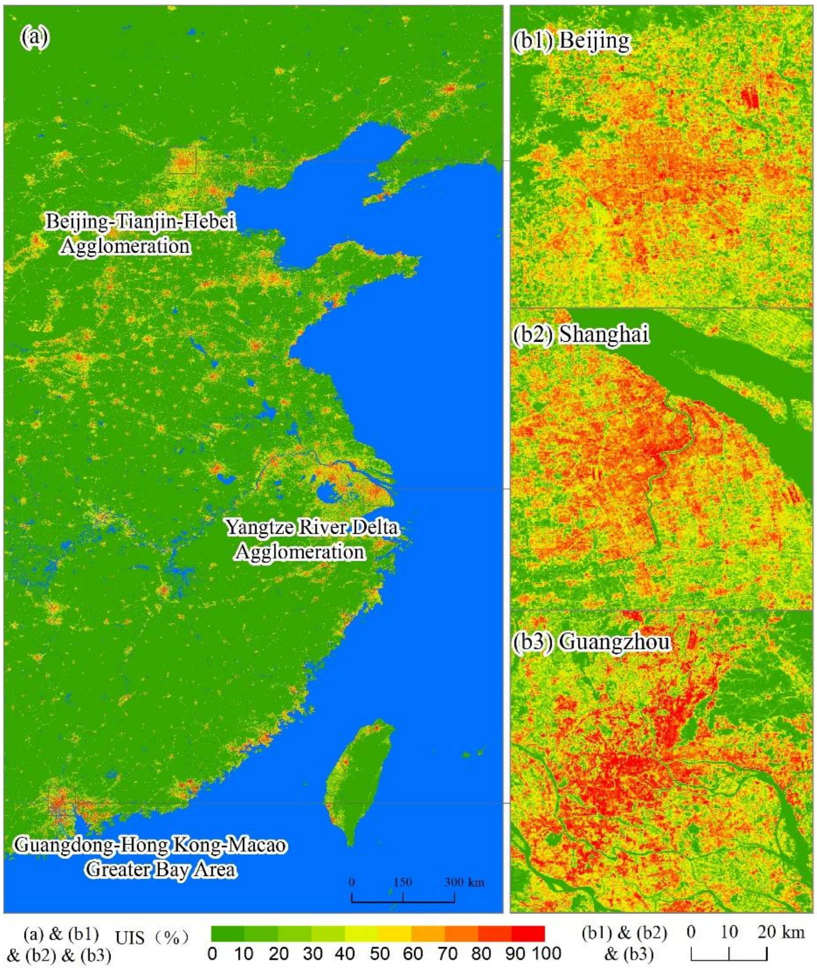

Figure 6: **Distribution of sampling cities in China and training samples in selected cities. (The administrative boundaries and residential points information were provided by National Geomatics Center of China (http://www.webmap.cn))**

5.3 Mapping of UIS and UGS fractions

The settlement and vegetation fractions with 1ºX1ºgrid of each period were downloaded from GEE platform. In ARCGIS 10.0 software, the settlement and vegetation layers were merged respectively at provincial scale with 30 m X 30 m. The national UIS and UGS fractions with 30 m X 30 m resolution in 2000, 2005, 2010, 2015 and 2018 were produced through overlaying the urban boundaries of CLUD with settlement and vegetation fractions, respectively (Fig. 7, Fig. 8 and Fig. 9).

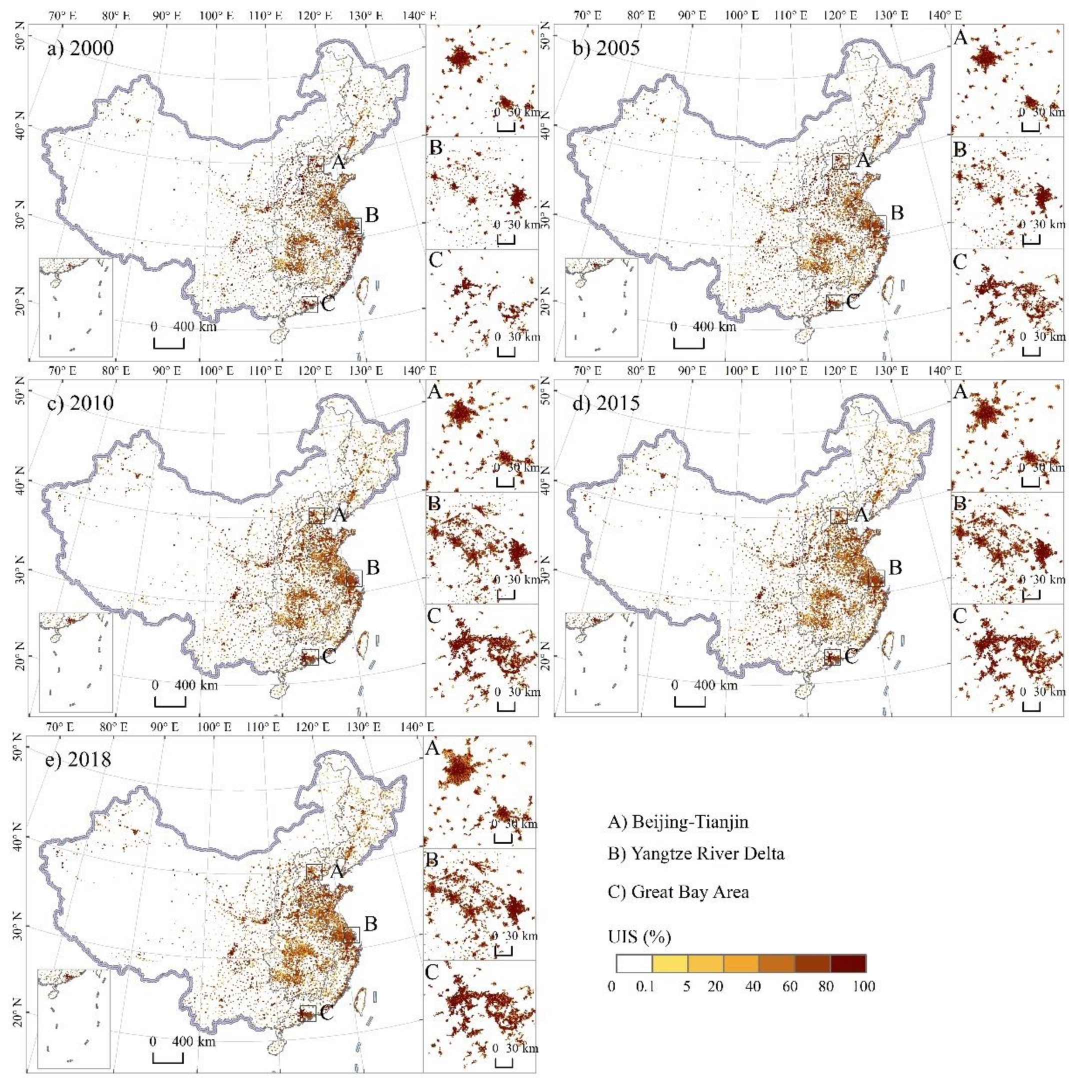

Figure 7: **Spatial distribution of urban impervious surface (UIS) in 2000–2018 across China. (The administrative boundaries were provided by National Geomatics Center of China (http://www.webmap.cn))**

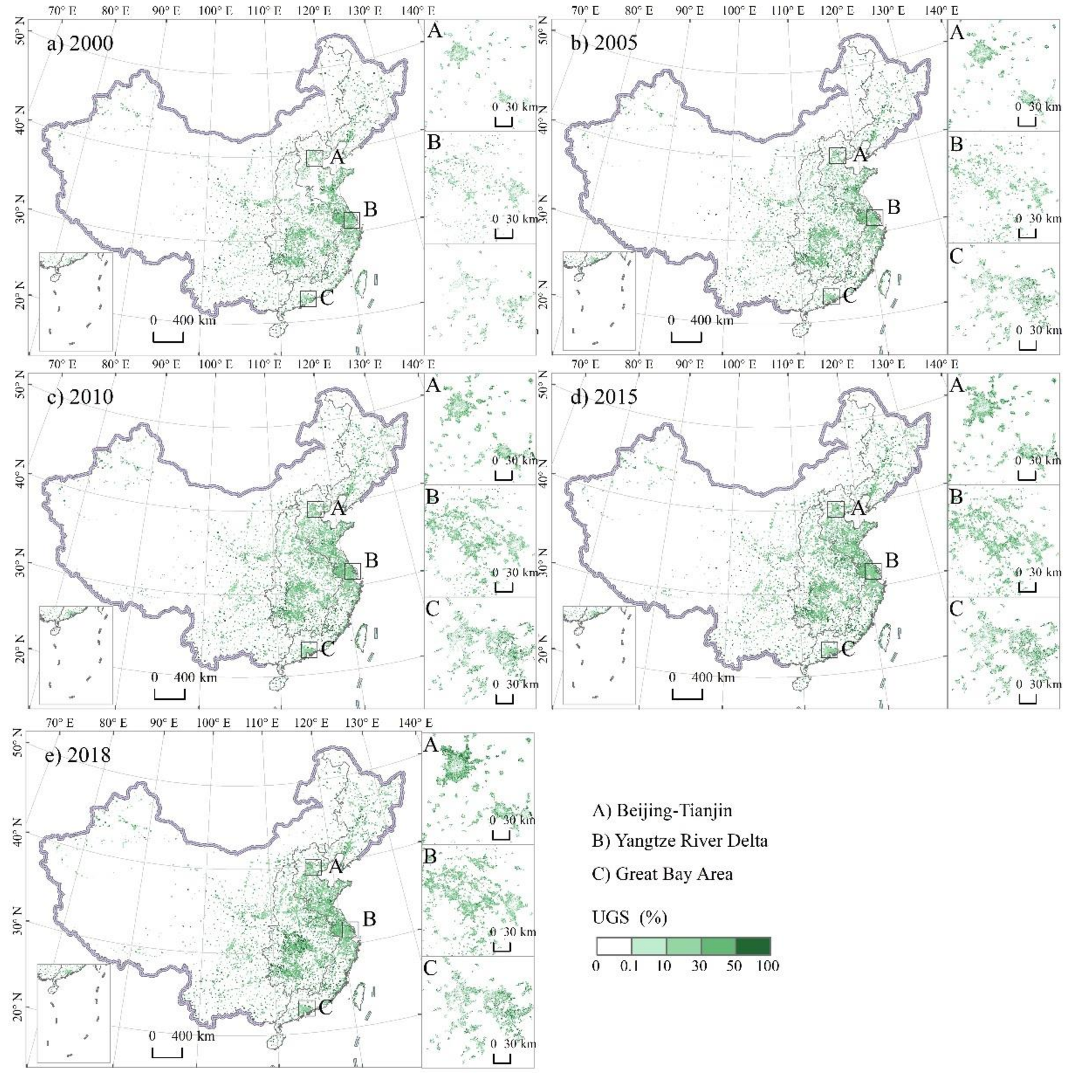

Figure 8: **Spatial distribution of urban green space (UGS) in 2000–2018 across China. (The administrative boundaries were provided by National Geomatics Center of China (http://www.webmap.cn))**

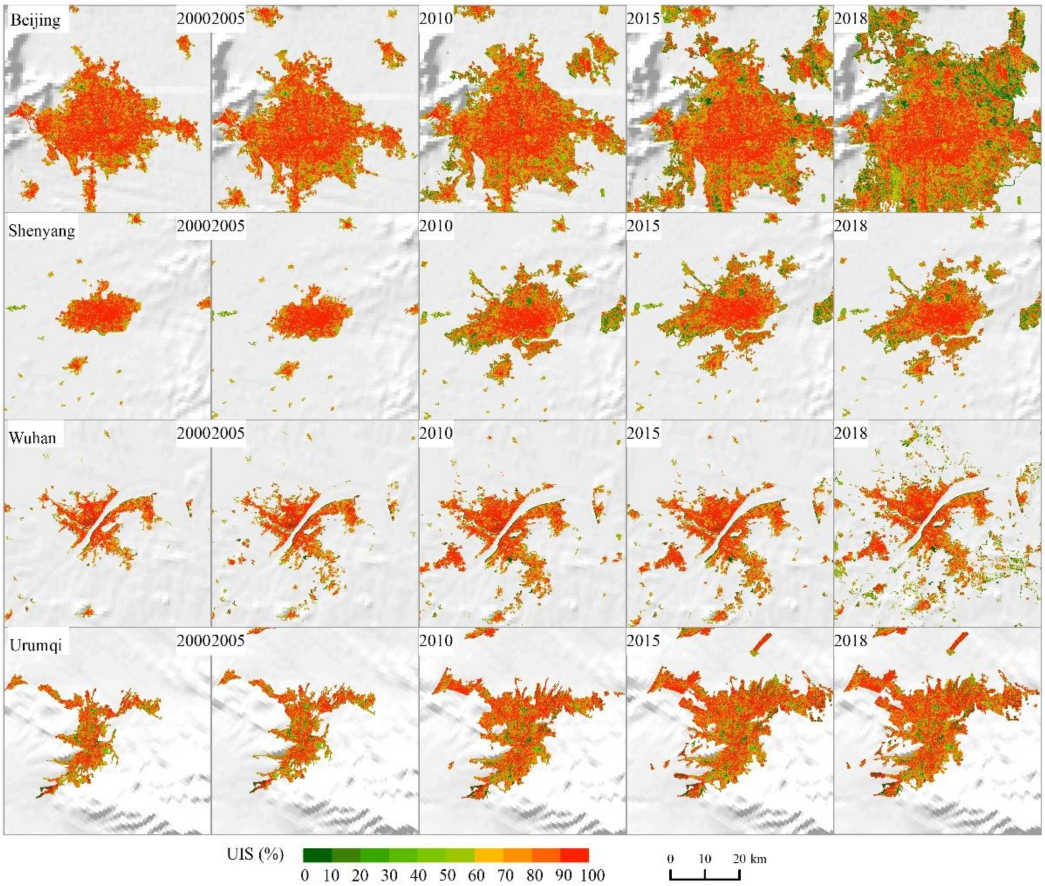

Figure 9: The change of urban impervious surface (UIS) in selected cities from coastal, central, eastern and western zones from 2000 to 2018. (DEM dataset was downloaded from SRTM 90 m Digital Elevation Data (http://srtm.csi.cgiar.org/))

Comment 5: 4. Effect of urban boundary. How to define the urban area and extract the urban boundary are not clear? There are some other datasets providing the urban extent using different algorithms and data sources, e.g.: Gong P, Li X C, Zhang W. 40-Year (1978-2017) human settlement changes in China reflected by impervious surfaces from satellite remote sensing. Science Bulletin, 2019, 64, https://doi.org/10.1016/j.scib.2019.04.024

Zhou, Y., Li, X., Asrar, G. R., Smith, S. J., & Imhoff, M. (2018). A global record of annual urban dynamics (1992–2013) from nighttime lights. Remote Sensing of Environment, 219, 206-220.

Li, X., Gong, P., Zhou, Y. et al. 2020. Mapping global urban boundaries from the global artificial impervious area (GAIA) data. Environmental Research Letters.

https://iopscience.iop.org/article/10.1088/1748-9326/ab9be3/meta

Response: Thank you for your comments. We added a definition on urban boundary in sub-section "4.1 The classification system and interpretation symbols". Meanwhile "4.2 Land use and dynamic polygon interpretation" and "4.3 Retrieval of multitemporal urban boundaries" were supplemented to elucidate the method on extracting the urban boundaries. Thanks for your recommendation of these references and they were cited in the revised version.

Changes in manuscript: We revised the section in L130-160. We added the reference in L385-550.

Comment 6: 5. In model training, 28 capital cities were selected to extract samples for LRM model input. Are these capital cities capable to represent other cities in China? As is mentioned, the UISA is related with economic and geographic conditions, but the capital cities are commonly the better developed region than the other cities.

Response: We used the new algorithm and method to map the UIS and UGS. Therefore, the issues have been addressed in this new CLUD-Urban product.

Changes in manuscript: We added a sub-section "5.1 Collection of training samples" to elucidate the issue in L170-180.

Comment 7: 6. Does the urban land changes area refer to the area with land conversion between urban area and other land cover types (cropland to urban) or the changes within urban area (from built-up to greenspace)?

Response: The urban land changes refer to the area with land conversion between urban area and other land cover types (cropland to urban).

Changes in manuscript: We revised this sentence.

Comment 7: 7. Why not use samples in 90 m × 90 m for validation?

Response: Yes, we validated the datasets with pixels of 90 m×90 m.

Changes in manuscript: We revised this sentence in L220-225.

Comment 8: 8. Would you please provide the details of validation samples, e.g., spatial distribution, types.

Response: We added a paragraph to elucidate the detail methods on accuracy assessment of urban boundaries, UIS and UGS fractions of CLUD-Urban. We added the Fig. 10 to descript the distribution of validation samples.

Changes in manuscript: We revised the method on accuracy assessment of CLUD-urban product and results of assessment in L210-245.

Comment 9: Results

9. Currently, there is no discussion part. What is the potential application and the uncertainty of this datasets? And the results are too short and simplified. Please add more details such as comparisons with other UGS, UISA dataset, line graphs of the temporal changes of UISA in different regions to support the conclusion of "high in east and low in west".

Response: We added a discussion part, which includes three sub-sections: "8.1 The mapping advantages integrated with human-computer interpretation and GEE platform; 8.2 The potential implications in promoting habitat environment and sustainability of cities; 8.3 Limitations of the method and dataset and future prospect". We revised the sub-section of results, including 7.1 The accuracy of CLUD-urban, 7.2 Patterns and dynamics of UIS and UGS since the beginning of the 21th century, and 7.3 Comparisons of the CLUD-Urban product with other datasets. In results part, we added texts to explain the distribution of UIS of "high in east and low in west".

Changes in manuscript: We added a discussion part in L285-330. We also revised the results part in L250-255.