Dear Editor and Referees:

We are particularly grateful for your careful reading, and for giving us many constructive comments on this work. According to the comments and suggestions, we have tried our best to improve the previous manuscript ESSD-2022-142 (An improved global land cover mapping in 2015 with 30 m resolution (GLC-2015) based on a multi-source product fusion approach). The modified words or sentences are marked as blue color in the revised manuscript. We are providing an item-by-item response to all questions and recommendations.

Thanks very much for your time.

Best regards,

Xiaoping Liu and all co-authors

Reviewer #1:

General comment:

This study developed a 30m resolution GLC product by integrating multiple products using the DSET method. Accuracy assessment with two validation datasets demonstrates the high quality of the GLC-2015. The comparison between GLC-2015 and other GLC products (Globeland30, FROM_GLC, GLC_FCS30) is comprehensive and the analysis is reasonable. This data is valuable and can provide accurate information for many applications. Some improvements are needed before publication.

Response: Thanks for the comment. These comments are very helpful for revising and improving our paper. The manuscript has been improved according to your and another reviewer's comments. The point-by-point responses are listed below in **blue**. The changes in our manuscript are marked with red.

Comment #1-1. The authors used three national-scale products to improve the quality of the GLC-2015 in China and America. However, it is unknown that whether the GLC-2015 performed better than these national-scale products. It is advised that the authors quantitatively compared the GLC-2015 with NLCD, CLCD and CLUD. Also, area difference for various LC classes in GLC-2015 and national-scale data can be analyzed.

Response: Thanks for the comment. Based on your suggestion, we have compared the accuracy of GLC-2015 with three national-scale products. Also, we quantified the area difference for each land cover class in our revised manuscript.

"**4.4 Inter-comparison with national-scale products**

Except for comparison with the existing GLC products, the GLC-2015 was also compared with three national-scale products (CLCD, CLUD, and NLCD 2016 over CONUS). We first compared the accuracy of the GLC-2015 with NLCD, CLCD, and CLUD using the point-based samples (Tables S5-S6). It can be found that the GLC-2015 obtained an overall accuracy of 88.8% in China, higher than CLCD (78.3%) and CLUD (70.2%). Specifically, the GLC-2015 achieved the highest PA and UA in all LC classes except wetland. In the CONUS, the GLC-2015 outperformed NCLD 2016 with an OA improvement of 13.2%. Additionally, the GLC-2015 exhibited better mapping performance in nearly all LC classes." (Revised manuscript, Line 684-692)

"**Table S5. Comparison of mapping accuracy for the GLC-2015, CLCD, and CLUD via point-based samples.**

		Cropland	Forest	Grassland	Shrubland	Wetland	Water bodies	Impervious surfaces	Bare land	Permanent snow and ice	OA (Kappa coefficient)
GLC-2015	PA	0.844	0.965	0.968	0.316	0.598	0.896	0.905	0.891	0.793	0.888
	UA	0.930	0.928	0.803	0.923	0.870	0.741	0.899	0.962	0.958	(0.864)
CLCD	PA	0.812	0.893	0.939	0.079	0.009	0.742	0.671	0.767	0.737	0.783
	UA	0.812	0.874	0.635	0.600	1.000	0.857	0.793	0.907	0.808	(0.734)
CLUD	PA	0.715	0.590	0.793	0.158	0.704	0.691	0.759	0.763	0.439	0.702
	UA	0.779	0.800	0.604	0.062	0.864	0.807	0.782	0.753	0.893	(0.639)

Table S6. Comparison of mapping accuracy for the GLC-2015 and NLCD 2016 via point-based samples.

		Cropland	Forest	Grassland	Shrubland	Wetland	Water bodies	Impervious surfaces	Bare land	Permanent snow and ice	OA (Kappa coefficient)
GLC-2015	PA	0.890	0.958	0.917	0.869	0.903	0.935	0.867	0.911	1.000	0.910
	UA	0.944	0.932	0.815	0.972	0.878	0.977	0.903	0.689	1.000	(0.893)
NLCD 2016	PA	0.824	0.760	0.617	0.862	0.873	0.830	0.800	0.446	0.750	0.778
	UA	0.849	0.982	0.594	0.641	0.899	0.902	0.714	0.439	1.000	(0.736)

” (Supplementary material with change)

“An accuracy comparison between the GLC-2015 and three national-scale products was also performed using the patch-based samples (Tables S7-S8). Overall, the GLC-2015 achieved a better OA of 85.7% in China, with respect to CLCD (83.6%) and CLUD (75.4%). In terms of PA and UA, the GLC-2015 ranked first or second in most LC classes. In the CONUS, the GLC-2015 possessed an OA of 84.5% and a kappa coefficient of 0.787, outperforming NLCD 2016. Although the GLC-2015 had lower PAs in wetland and impervious surfaces, and lower UAs in cropland and forest compared to NLCD 2016, the GLC-2015 outperformed NLCD 2016 in most LC classes.” (Revised manuscript, Line 693-699)

“**Table S7. Comparison of mapping accuracy for the GLC-2015, CLCD, and CLUD via patch-based samples.**

		Cropland	Forest	Grassland	Shrubland	Wetland	Water bodies	Impervious surfaces	Bare land	Permanent snow and ice	OA (Kappa coefficient)
GLC-2015	PA	0.915	0.914	0.512	0.002	0.000	0.915	0.837	0.397	0.841	0.857
	UA	0.929	0.922	0.075	0.005	0.000	0.770	0.805	0.953	0.700	(0.789)
CLCD	PA	0.916	0.914	0.497	0.000	0.000	0.846	0.742	0.280	0.856	0.836
	UA	0.900	0.925	0.065	0.000	0.000	0.873	0.757	0.930	0.633	(0.755)
CLUD	PA	0.831	0.782	0.478	0.002	0.385	0.823	0.703	0.280	0.875	0.754
	UA	0.892	0.906	0.041	0.000	0.023	0.733	0.686	0.900	0.652	(0.647)

Table S8. Comparison of mapping accuracy for the GLC-2015 and NLCD 2016 via patch-based samples.

		Cropland	Forest	Grassland	Shrubland	Wetland	Water bodies	Impervious surfaces	Bare land	OA (Kappa coefficient)
GLC-2015	PA	0.924	0.514	0.788	0.905	0.024	0.911	0.747	0.691	0.845
	UA	0.873	0.718	0.840	0.916	0.019	0.916	0.686	0.683	(0.787)
NLCD 2016	PA	0.871	0.369	0.787	0.686	0.054	0.906	0.796	0.676	0.769
	UA	0.879	0.809	0.788	0.847	0.001	0.913	0.395	0.361	(0.690)

” (Supplementary material with change)

“We further performed an areal comparison for each LC class of GLC-2015 and three national-scale products (Figures S12-S13). Generally, the GLC-2015, CLCD, and CLUD exhibited similar areas in most classes. Notably, the areas of cropland, shrubland, and wetland in GLC-2015 were very close to CLCD but different from CLUD. In the CONUS, the areas of cropland, water bodies, and bare land in the GLC-2015 and NLCD 2016 were close. In contrast, the areas of the remaining LC classes in the GLC-2015 showed a large difference from NLCD 2016. The area differences in forest, grassland and shrubland between GLC-2015 and NLCD 2016 were mainly related to different LC definitions. For example, the minimum fraction of tree cover in the forest is 10% in GLC-2015, whereas NLCD 2016 used a minimum fraction of 20%. NCLD 2016 had higher area of impervious surfaces than the GLC-

2015 because open urban in NLCD 2016 includes too much vegetation." (Revised manuscript, Line 700-709)

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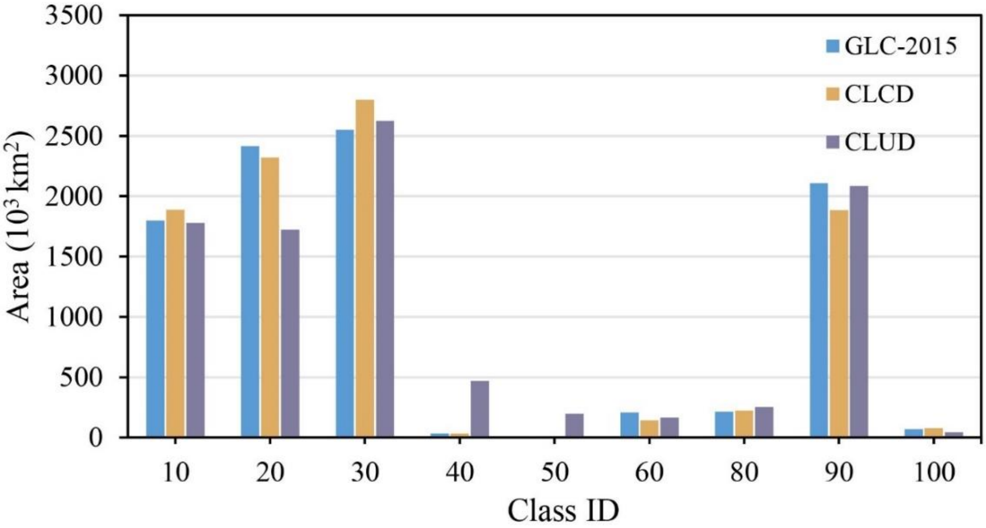

Figure S12. Areal comparison of various land cover classes among the GLC-2015, CLCD and CLUD. Class IDs 10, 20, 30, 40, 50, 60, 80, 90, and 100 denote cropland, forest, grassland, shrubland, wetland, water bodies, impervious surfaces, bare land, and permanent snow and sea ice, respectively.

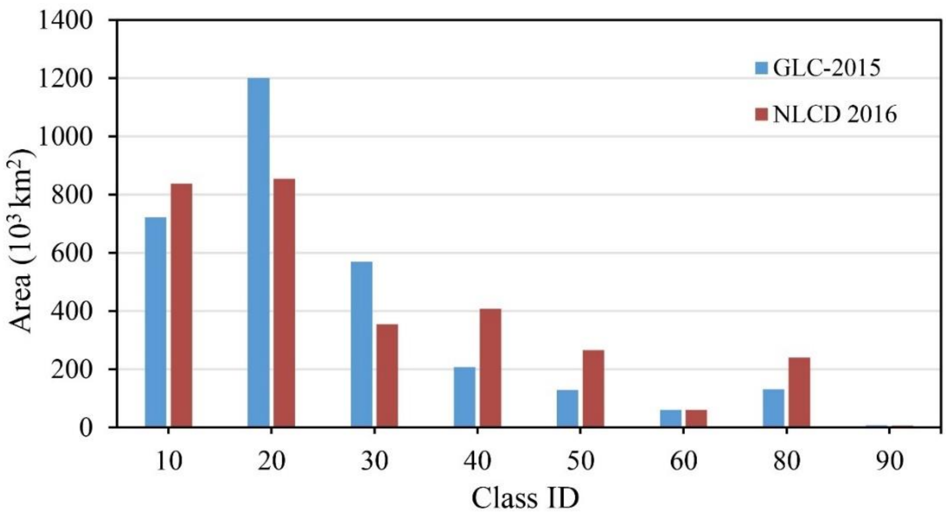

Figure S13. Areal comparison of various land cover classes among the GLC-2015 and NLCD 2016. Class IDs 10, 20, 30, 40, 50, 60, 80, 90 denote cropland, forest, grassland, shrubland, wetland, water bodies, impervious surfaces, and bare land, respectively." (Supplementary material with change)

Comment #1-2. National-scale land cover products, such as CLUD, NLCD 2016, have a two-level classification system, how did you transform these classification systems into the adopted classification system? This should be explained in the study.

Response: Thanks for the comment. The harmonization of different classification systems is the critical pre-process for the fusion. Based on the similarity of LC definition, a translation table (see Table S3) was made to converse the classification system of CLUD and NLCD 2016 to the target classification system.

Table S3. Classification systems of three national-scale LC products and the translation table.

Id	GLC-2015	CLCD	CLUDs	NLCD 2016
10	Cropland	Cropland	Rice paddy Bare farmland Orchard	Pasture Cropland
20	Forest	Forest	Wooden land	Deciduous forest Evergreen forest Mixed forest
30	Grassland	Grassland	Grassland, highly-covered Grassland, medium-covered Grassland, lowly-covered	Grassland
40	Shrubland	Shrub	Shrubland	Shrubland
50	Wetland	Wetland	Marshland Tidal flat Salt marsh Flooded flat	Woody wetlands Herbaceous wetlands
60	Water bodies	Water	Rivers Lakes Reservoir and ponds	Water
70	Tundra			
80	Impervious surfaces	Impervious	Urban Rural Other construction sites	Urban, open space Urban, low intensity Urban, med. Intensity Urban, high intensity
90	Bare land	Barren	Sandy land Gobi desert Barren Bare rocky land	Barren

100	Permanent snow and ice	Snow/ice	Permanent snow and ice	Ice/snow

Correspondingly, we have added how we translated level-2 classification systems of CLUD and NLCD into the target classification system in the revised manuscript.

"According to the LC translation tables (Tables S2-S3), the original LC classes of FROM_GLC and GLC_FCS30, CLUD for 2015, and NLCD 2016 for 2016 were converted into the 10 target land cover classes based on the similarity of LC definition." (Revised manuscript, Line 309-311)

Comment #1-3. The national-scale land cover datasets, such as CLCD for 2015, were used in the fusion, why these products were not listed in the framework (Figure 4)?

Response: Thanks for the comment. We have updated the framework in our revised manuscript.

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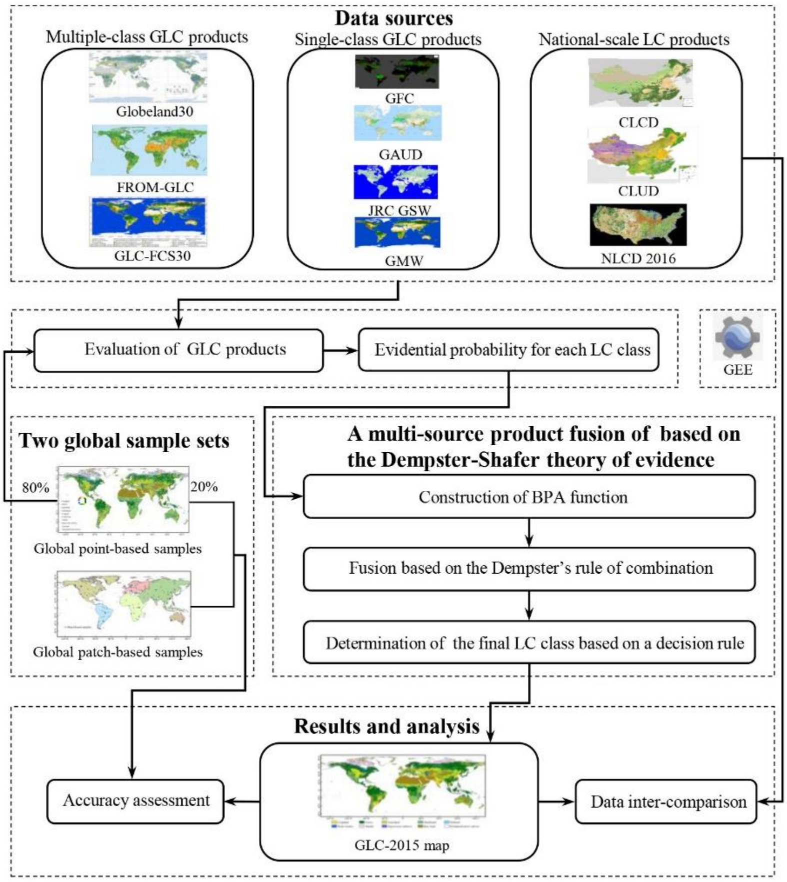

Figure 4. The framework for generating the GLC-2015 map using a multi-source product fusion approach based on DEST." (Revised manuscript, Line 292-294)

Comment #1-4. Figures S8-S11 exhibit visual comparisons for various land cover classes at local scale. However, the detailed locations of examples were not clearly showed. It would be better to tell readers the specific locations with graticules or central point as well as area size.

Response: Thanks for the comment. We have added the scale bar as well as the latitude and longitude of the center for each example in the revised manuscript.

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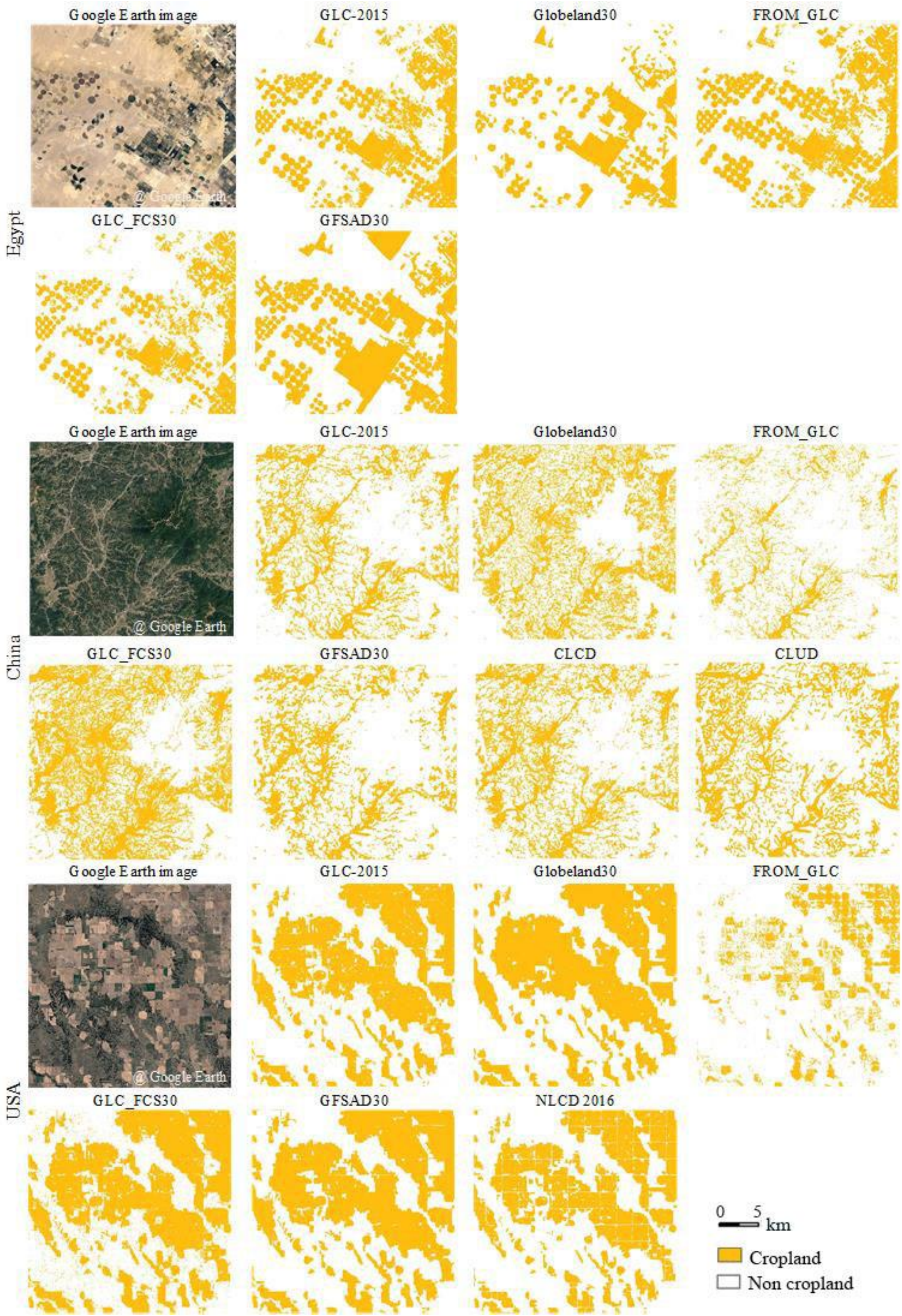

Figure S8. Comparing the crop extent from GLC-2015 and other widely used products in three agricultural regions of Egypt (30.365°N, 30.189°E), China (27.508°N, 110.976°E), and USA (41.449°N, 99.934°W).

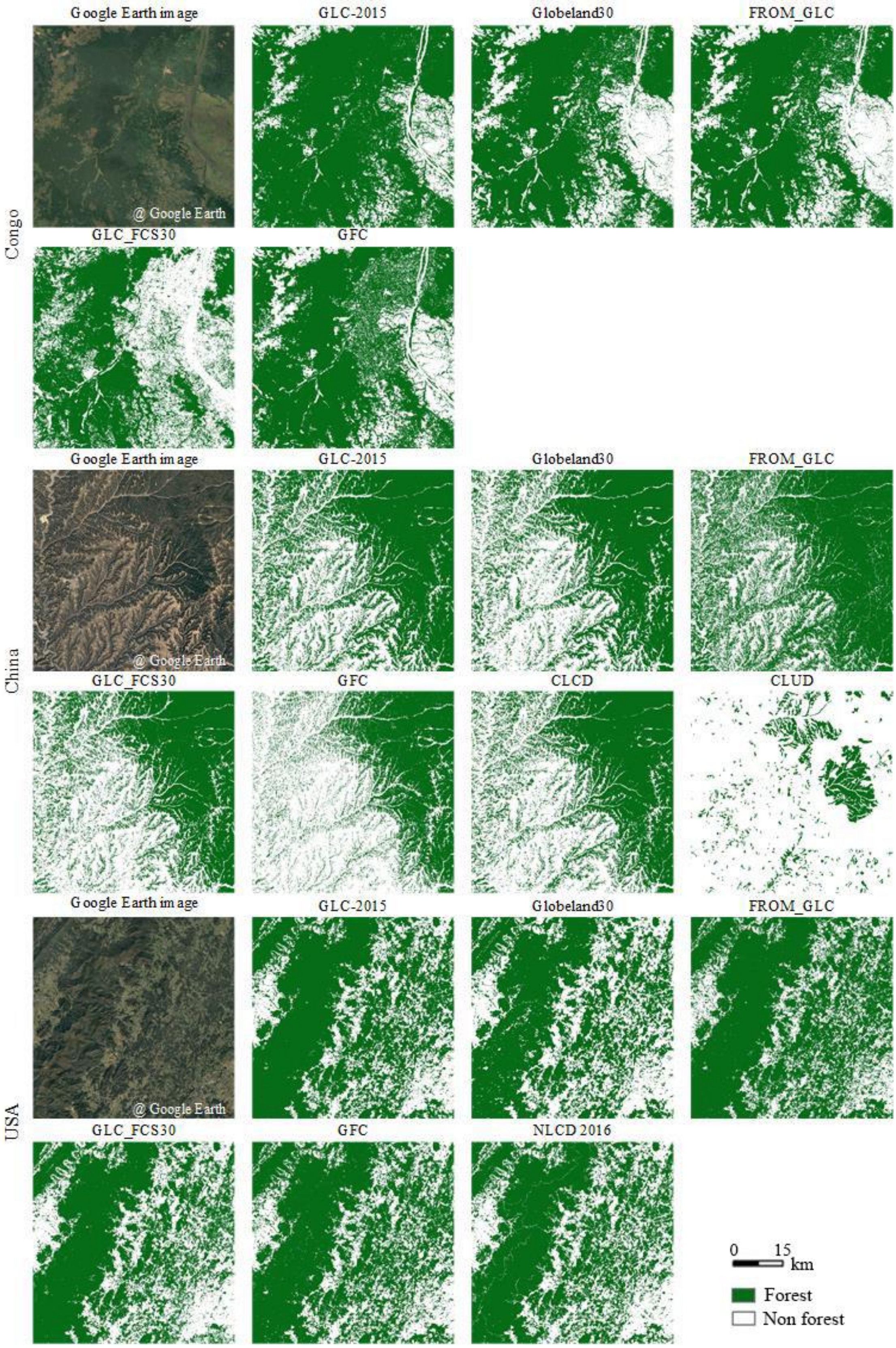

Figure S9. Comparing the forest extent from GLC-2015 and other widely used products in three forest-dominated regions of Congo (4.044°S, 25.851°E), China (35.791°N, 109.594°E), and USA (38.626°N, 78.189°E).

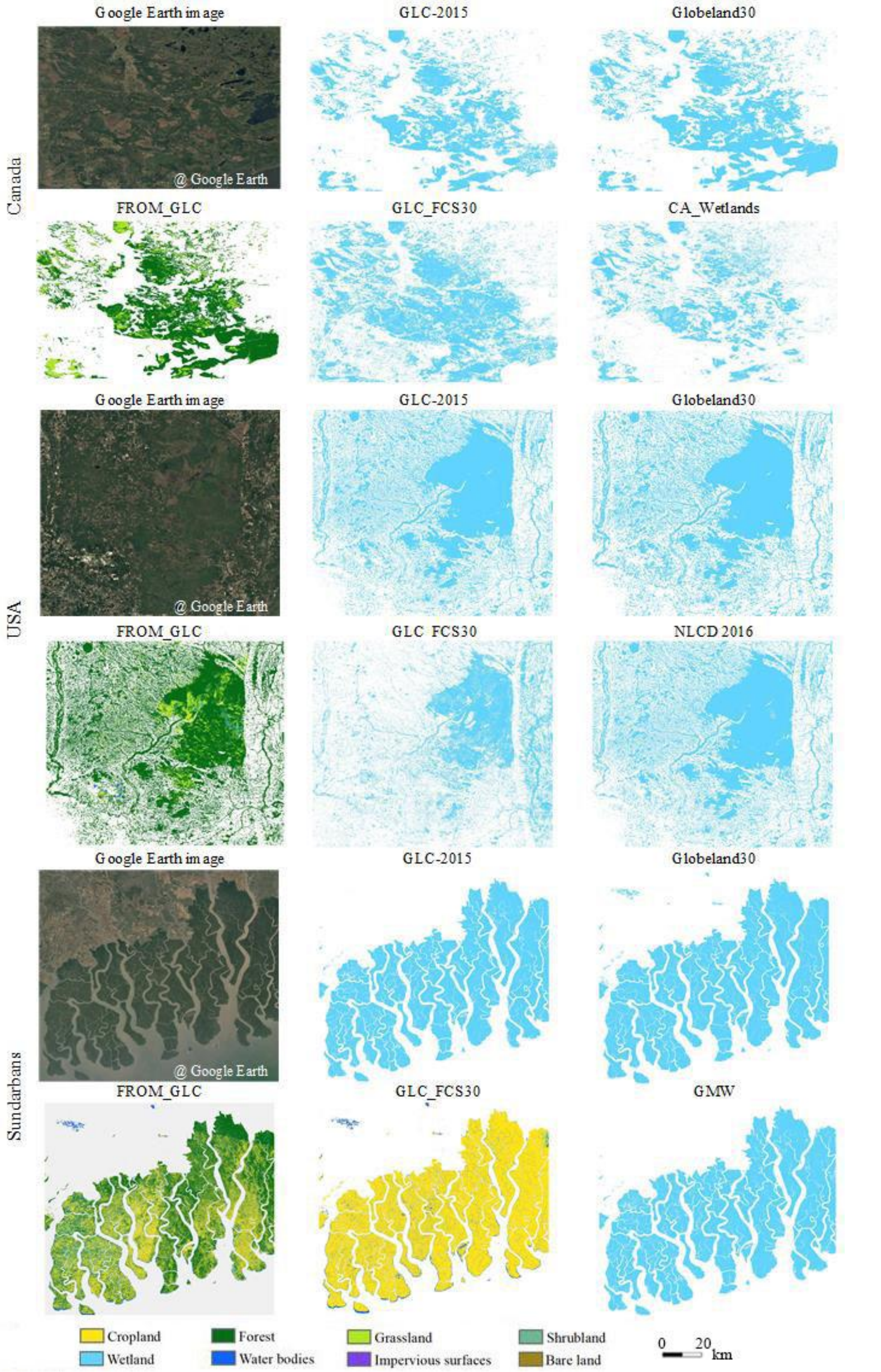

Figure S10. Comparing the wetland extent from GLC-2015 and other widely used products in three wetland-dominated regions of Canada (49.549°N, 95.701°W), USA (30.647°N, 82.5201°W), and Sundarbans (22.044° N, 89.203°E).

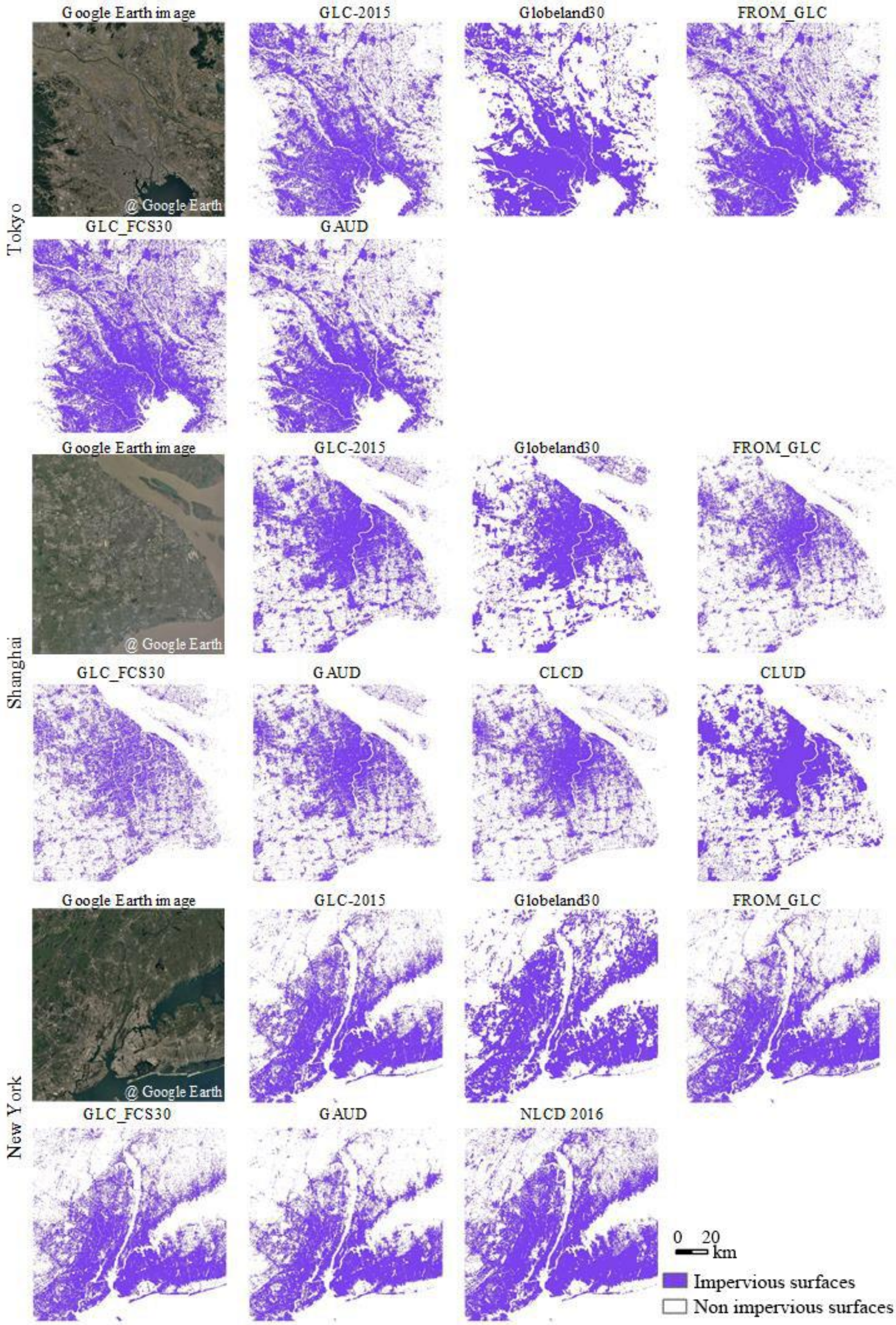

Figure S11. Comparing the impervious extent from GLC-2015 and other widely used products in three megacities: Tokyo (35.925°N, 139.716°E), Shanghai (31.148°N, 121.451°E), and New York (40.907°N, 73.936° W)." (Supplementary material with change)

Comment #1-5. In abstract, “LC” should be fully spelled.

Response: Thanks for the comment. We have fully spelled “LC” as “land cover” in the revised manuscript.

Comment #1-6. Line 116: do you mean “the final fused results based on the DSET method”?

Response: Thanks for the comment. We are sorry for this mistake. We have corrected it.

Comment #1-7. Line 128: “are” should be “were”. And line 211: “resulted” should be “result”.

Response: Thanks for the comment. We have revised the manuscript according to the suggestions. In addition to that, we have carefully checked the expression of the article sentence by sentence.

Comment #1-8. Some relevant papers may be reviewed in the references:
Mapping 10 m global impervious surface area (GISA-10m) using multi-source geospatial data. Earth System Science Data, 2022, 14: 3649–3672.
30-m global impervious surface area dynamics and urban expansion pattern observed by Landsat satellites: from 1972 to 2019. SCIENCE CHINA Earth Sciences, 2021, 64(11): 1922-1933.

Response: Thanks for the comment. We think these two papers are very useful. Correspondingly, we have cited them in the Introduction.

“In addition to these multiple-class GLC products, GLC products for individual LC classes, such as cropland (Yu et al., 2013; Lu et al., 2020), forest (Hansen et al., 2013; Shimada et al., 2014; Zhang et al., 2020), wetland (Hu et al., 2017; Zhang et al., 2023), water bodies (Liao et al., 2014; Pekel et al., 2016; Pickens et al., 2020), and **impervious surfaces** (Gong et al., 2020; **Huang et al., 2021; Huang et al., 2022;** Liu et al., 2020b), have been successfully generated.” (Revised manuscript, Line 74-78)

References:

Gong, P., Li, X., Wang, J., Bai, Y., Chen, B., Hu, T., Liu, X., Xu, B., Yang, J., Zhang, W., and Zhou, Y.: Annual maps of global artificial impervious area (GAIA) between 1985 and 2018, Remote Sens. Environ., 236, 111510, https://doi.org/10.1016/j.rse.2019.111510, 2020.

Hansen, M. C., Potapov, P. V., Moore, R., Hancher, M., Turubanova, S. A., Tyukavina, A., Thau, D., Stehman, S. V., Goetz, S. J., Loveland, T. R., Kommareddy, A., Egorov, A., Chini, L., Justice, C. O., and Townshend, J. R. G.: High-resolution global maps of 21st-century forest cover change, Science, 342, 850-853, https://doi.org/10.1126/science.1244693, 2013.

Hu, S., Niu, Z., Chen, Y., Li, L., and Zhang, H.: Global wetlands: Potential distribution, wetland loss, and status, Sci. Total Environ., 586, 319-327, https://doi.org/10.1016/j.scitotenv.2017.02.001, 2017.

Liao, A., Chen, L., Chen, J., He, C., Cao, X., Chen, J., Peng, S., Sun, F., and Gong, P.: High-resolution remote sensing mapping of global land water, Science China Earth Sciences, 57, 2305-2316, https://doi.org/10.1007/s11430-014-4918-0, 2014.

Huang, X., Li, J., Yang, J., Zhang, Z., Li, D., and Liu, X.: 30 m global impervious surface area dynamics and urban expansion pattern observed by Landsat satellites: From 1972 to 2019, Science China Earth Sciences, 64, 1922-1933, https://10.1007/s11430-020-9797-9, 2021.

Huang, X., Yang, J., Wang, W., and Liu, Z.: Mapping 10 m global impervious surface area (GISA-10m) using multi-source geospatial data, Earth Syst. Sci. Data, 14, 3649-3672, https://essd.copernicus.org/articles/14/3649/2022/, 2022.

Liu, X., Huang, Y., Xu, X., Li, X., Li, X., Ciais, P., Lin, P., Gong, K., Ziegler, A. D., and Chen, A.: High-spatiotemporal-resolution mapping of global urban change from 1985 to 2015, Nature Sustainability, 3, 564-570, 2020b.

Lu, M., Wu, W., You, L., See, L., Fritz, S., Yu, Q., Wei, Y., Chen, D., Yang, P., and Xue, B.: A cultivated planet in 2010 – Part 1: The global synergy cropland map, Earth Syst. Sci. Data, 12, 1913-1928, https://essd.copernicus.org/articles/12/1913/2020/, 2020.

Pekel, J. F., Cottam, A., Gorelick, N., and Belward, A. S.: High-resolution mapping of global surface water and its long-term changes, Nature, 540, 418-422, https://doi.org/10.1038/nature20584, 2016.

Pickens, A. H., Hansen, M. C., Hancher, M., Stehman, S. V., Tyukavina, A., Potapov, P., Marroquin, B., and Sherani, Z.: Mapping and sampling to characterize global inland water dynamics from 1999 to 2018 with full Landsat time-series, Remote Sens. Environ., 243, 111792, https://doi.org/10.1016/j.rse.2020.111792, 2020.

Shimada, M., Itoh, T., Motooka, T., Watanabe, M., Shiraishi, T., Thapa, R., and Lucas, R.: New global forest/non-forest maps from ALOS PALSAR data (2007–2010), Remote Sens. Environ., 155, 13-31, https://doi.org/10.1016/j.rse.2014.04.014, 2014.

Yu, L., Wang, J., Clinton, N., Xin, Q., Zhong, L., Chen, Y., and Gong, P.: FROM-GC: 30 m global cropland extent derived through multisource data integration, Int. J. Digit. Earth, 6, 521-533, https://doi.org/10.1080/17538947.2013.822574, 2013.

Zhang, X., Long, T., He, G., Guo, Y., Yin, R., Zhang, Z., Xiao, H., Li, M., and Bo, C.: Rapid generation of global forest cover map using Landsat based on the forest ecological zones, J. Appl. Rem. Sens., 14, 022211, https://doi.org/10.1117/1.JRS.14.022211, 2020.

Zhang, X., Liu, L., Zhao, T., Chen, X., Lin, S., Wang, J., Mi, J., and Liu, W.: GWL_FCS30: a global 30 m wetland map with a fine classification system using multi-sourced and time-series remote sensing imagery in 2020, Earth Syst. Sci. Data, 15, 265-293, https://doi.org/10.5194/essd-15-265-2023, 2023.