Response to comments
Paper #: essd-2025-73
Title: GLC_FCS10: a global 10-m land-cover dataset with a fine classification system from Sentinel-1 and Sentinel-2 time-series data in Google Earth Engine
Journal: Earth System Science Data

Reviewer #2

This study developed a novel global 10-m land-cover dataset with a fine classification system. The data performs well and is of great value to high-resolution land-cover applications. Here are some of my concerns:

Great thanks for your positive comment, the manuscript has been further improved based on your and another reviewer's constructive and useful comments.

1. As highlighted in previous studies (Wang et al, 2023; Xu et al, 2024), Imp-ESRI_LC exhibits extensive patches of the impervious surface and lacks spatial details, which can also be found in Figure 6. This raises concerns about the MaxBound_imp (the union of several impervious surface products), which appears to include substantial areas of inner-city vegetation. If all training samples for natural land cover types are collected outside the MaxBound_imp, could this lead to the omission of inner-city vegetation types like grass and avenue trees?

See: Wang, Y., Xu, Y., Xu, X., Jiang, X., Mo, Y., Cui, H., Zhu, S., and Wu, H.: Evaluation of six global high- resolution global land cover products over China, International Journal of Digital Earth.

Xu, P., Tsendbazar, N.-E., Herold, M., de Bruin, S., Koopmans, M., Birch, T., Carter, S., Fritz, S., Lesiv, M., Mazur, E., Pickens, A., Potapov, P., Stolle, F., Tyukavina, A., Van De Kerchove, R., and Zanaga, D.: Comparative validation of recent 10 m-resolution global land cover maps, Remote Sensing of Environment.

Great thanks for the comment. Yes, we agree that the Imp-ESRI_LC exhibits extensive patches of the impervious surface and lacks spatial details. In terms of the concerns about the MaxBound_imp affects the omission error of inner-city vegetation types like grass or avenue trees, actually, these inner-city vegetations can be comprehensively captured because 1) we imported the vegetated training samples when identifying the impervious surfaces; 2) there are significant spectral and phenological differences between impervious surfaces and vegetations; 3) the high spatial resolution of Sentinel-1 and 2 can help us accurately identify these grass or avenue trees.

To intuitively understand the performance of GLC_FCS10 on the inner cities, Figure S3 gave the enlargements of three mega-cities in the Shanghai and Beijing as examples, we can clearly find that these vegetations within the cities can be finely identified, e.g., street trees on both sides of the road and green belts in some neighborhoods.

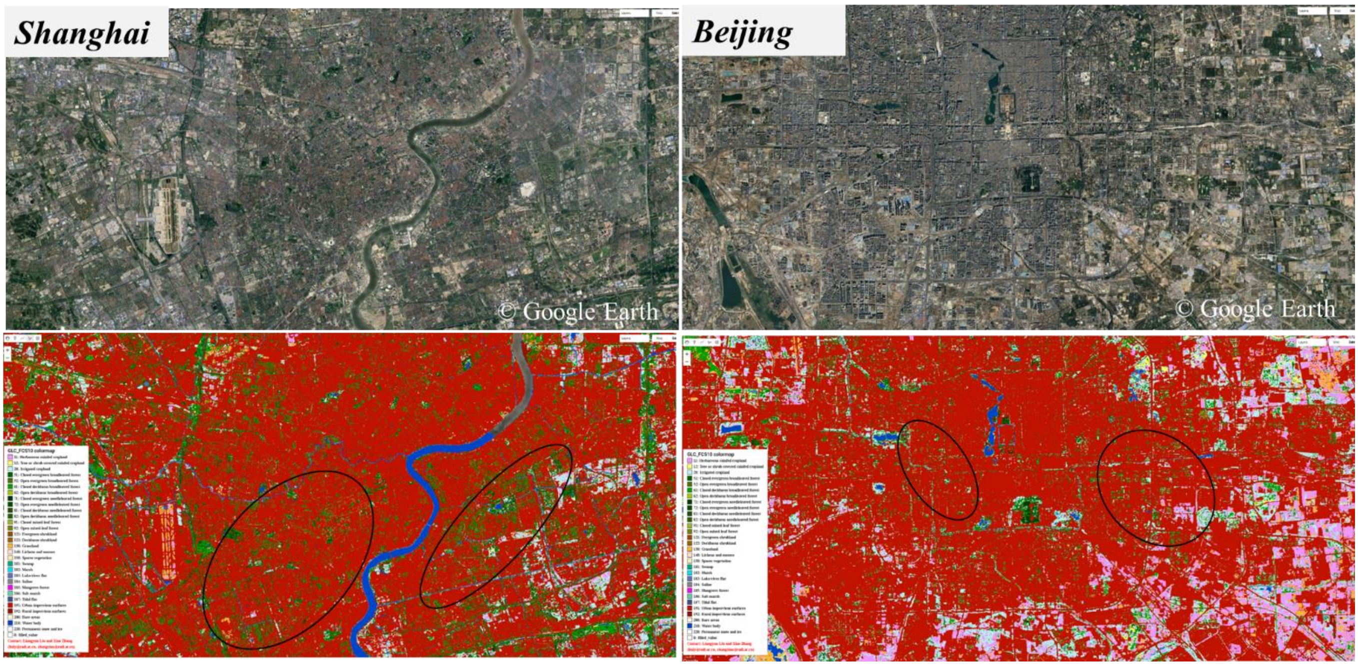

Figure S3. The enlargements of three mega-cities in the Shanghai and Beijing, and the black circles illustrates the vegetations within the cities. The high-resolution imagery came from © Google Earth.

The problem of Imp-ESRI_LC also has been added in the manuscript as:

Beyond the confident impervious surface areas, it is equally important to identify high-quality natural land-cover types (Zhang et al., 2024a). To avoid confusion between natural land-cover types and impervious surfaces, the maximum impervious surface boundary (MaxBound_imp) is also generated. **The training samples for natural land-cover types should be located outside of the MaxBound_imp, i.e., some inner-city areas, easily misclassified or confused with impervious surfaces, will be excluded because Imp-ESRI_LC exhibits extensive patches of the impervious surface and lacks spatial details (Wang et al., 2024; Xu et al., 2024).**

2. Line 307, how many the samples for urban, rural and natural surfaces? The author just mentioned the ratio of these three land cover types.

Great thanks for the comment. The sample sizes of urban, rural and natural surfaces were selected as 5000, and the corresponding description has been added in the manuscript as:

Specifically, because we divide impervious surfaces training samples into rural and urban samples and design the equal distribution to enhance the training samples' ability to characterize impervious surfaces. The ratio of urban samples, rural samples, and natural surfaces is 1:1:1 for each 5×5 geographical tile. **Meanwhile, in terms of the sample size of each class, some previous studies have quantified the relationship between sample size and mapping accuracy (Foody, 2009; Li et al., 2014), and suggested a minimum size of 600 and maximum size of 8000 for these sparse and abundant land-cover types (Zhu et al., 2016). In this study, after considering the trade-off between sample representativeness with mapping efficiency, the sample size of each class was selected as 5000, which was also consistent with the work of Zhang et al. (2022) in monitoring the impervious surface dynamics.**

3.Line 330, why divide the non-wetlands into water body, forest, grassland, bare land, and others but not the remaining 8 basic land cover types?

Great thanks for the comment. Yes, the non-wetlands should contain the remaining 8 basic land cover types, however, the snow and ice and shrubland usually belong to the sparse land-cover types at their co-existence areas, and some land-cover types share similar spectral characteristics are also merged into a common land-cover type. The specific descriptions about why we import non-wetland samples and

Wetlands are divided into four inland and three coastal wetland subcategories (in Table 2), and equal-distribution sampling is used to enhance the training samples' ability to characterize wetlands. **Additionally, since some non-wetland land-cover types also reflected the similar spectral characteristics with the wetlands, for example, the swamp and the forest/shrubland shared similar vegetation spectra during the peak growth period, while the marsh and cropland/grassland exhibited the characteristics of herbaceous vegetations, and the river flats also performed the spectral characteristics of bare land during the dry seasons (Zhang et al., 2023b).** Thus, the approximate ratio of inland wetlands, coastal wetlands, and non-wetlands (including **water body, forest/shrubland, cropland/grassland, bare land, and others**) is 4:3:5 in areas where they coexist.

4. Line 356 and Line 357, the manuscript references both "LCMAP_V" and "LCMAP_AL", are these two distinct datasets?

Great thanks for pointing out this mistake. Both of them belong to the same dataset, and it has been revised as "LCMAP_Val" in our revised manuscript.

5. Line 436, P.A. is complementary to the omission error, not the commission error.

Great thanks for pointing out this issue. It has been revised as

"Barren land has the lowest P.A. value of 31.93%, indicating a high omission error of 68.07%."

6. Why was the land cover type "Impervious surface" written as "Developed" in Table 5? These two have different definitions.

Great thanks for the comment. The reason why we use the "Developed" in the Table 5 because the third-party validation dataset (LCMAP_Val) contains the 634 **developed** points, and **one of the important guidelines for using the third-party validation points is not to artificially modify them**. To make the confusion matrix in Table 5 more intuitive, the column name of 'developed' has been changed as 'impervious' as:

	Cropland	**Forest**	**Grass/Shrub**	**Wetland**	**Impervious**	**Barren**	**Water**	**Ice & Snow**	**Total**	**U.A.**
Cropland	3445	28	393	6	0	9	2	0	3883	88.72
Forest	7	4621	133	92	0	0	2	0	4855	95.18
Grass/Shrub	368	358	3440	21	1	272	1	0	4461	77.11
Wetland	37	260	30	522	1	0	5	0	855	61.05
Developed	44	69	164	3	344	9	1	0	634	54.26
Barren	1	0	0	10	0	137	1	0	149	91.95
Water	0	2	1	63	2	1	1173	0	1242	94.44
Ice & Snow	0	0	0	0	0	1	0	2	3	66.67
Total	3902	5338	4161	717	348	429	1185	2	16082	
P.A.	88.29	86.57	82.67	72.80	98.85	31.93	98.99	100.00		
O.A.					85.09					
Kappa					0.804					

Meanwhile, the accuracy analysis about the different definition between ‘developed’ with ‘impervious surface’ was also discussed in our Discussion Section as:

In addition, to objectively understand the accuracy performance of GLC_FCS10, we introduced the LCMAP_Val third-party validation dataset, but the differences in the definition of the classification system still affect the accuracy metrics, such as the higher P.A. and the lower U.A. for the impervious surfaces in Table 5. Therefore, one of the ongoing works would take some measures (such as: semantic similarity (Gao et al., 2020)) to more comprehensively and objectively assess the third-party accuracy metrics of GLC_FCS10.

7. The confusion matrix (Table 5) shows that GLC_FCS10 misclassifies a large proportion of actual vegetation types as developed land (44 cropland, 69 forest and 164 grass/shrub reference samples are misclassified as developed land by GLC_FCS10), resulting in low UA for developed land, while only 4 developed land reference samples are misclassified elsewhere. This contradicts the statement in Line 433-435.

Great thanks for the comment. We are very sorry that the expression about the confusion matrix is not very clear, in fact, **the row direction represents the true value of LCMAP_Val and the column direction represents the predicted value of GLG_FCS10**. Namely, some vegetated developed pixels in the inner-city are excluded as impervious surfaces in the GLC_FCS10, so the GLC_FCS10 achieves the lowest U.A. of 54.26% with high P.A. of 98.85%.