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
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Reviewer #3

The manuscript presents a new 10 m global land cover product, developed using a hierarchical methodology. This is a valuable and well-constructed contribution to global land cover mapping. The product is validated with over 56,000 samples and the LCMAP_Val dataset, which strengthens the credibility of the reported accuracy. However, several questions need further clarification to enhance the methodological rigor:
Great thanks for your positive comment, the manuscript has been further improved based on your and another reviewer's constructive and useful comments.

1. Line 152: Why are impervious surfaces and wetlands treated separately from other land cover classes? While it is understandable that impervious surfaces are structurally different from natural land covers, the rationale for treating wetlands separately is less clear. Wetlands typically consist of a mix of vegetation and soil types, which may overlap with other land cover categories. Could this separation introduce additional uncertainty or classification confusion by inadvertently including other vegetation types? Please provide a clearer justification for this decision, especially compared to classifying all types together.
Great thanks for the comment. Yes, the reason why the impervious surface was treated separately from other land cover classes because impervious surfaces are structurally different from natural land covers.
In terms of wetlands, we have made wetlands independent for the following reasons: 1) a large amount of works have demonstrated that the spatial distributions of wetlands were simultaneously affected by the variations of water-levels and phenological information, and wetlands usually reflected more complicated spectral characteristics and spatiotemporal heterogeneities (Mao et al., 2020; Zhang et al., 2023;); 2) wetland distributions have strong locational characteristics (Gong et al., 2010), e.g., wetlands are mainly concentrated in low-lying areas and coastal wetlands are mainly distributed within 50 km of the coastal zone; 3) the existing land cover products, mixing wetlands with other natural surfaces, have been demonstrated to have poor performance in wetland mapping (Zhao et al., 2023).
Gong, P., Niu, Z., Cheng, X., Zhao, K., Zhou, D., Guo, J., Liang, L., Wang, X., Li, D., Huang, H., Wang, Y., Wang, K., Li, W., Wang, X., Ying, Q., Yang, Z., Ye, Y., Li, Z., Zhuang, D., Chi, Y., Zhou, H., and Yan, J.: China's wetland change (1990–2000) determined by remote sensing, Science China Earth Sciences, 53, 1036-1042, https://doi.org/10.1007/s11430-010-4002-3, 2010.
Mao, D., Wang, Z., Du, B., Li, L., Tian, Y., Jia, M., Zeng, Y., Song, K., Jiang, M., and Wang, Y.: National wetland mapping in China: A new product resulting from object-based and hierarchical classification of Landsat 8 OLI images, ISPRS Journal of Photogrammetry and Remote Sensing, 164, 11-25, https://doi.org/10.1016/j.isprsjprs.2020.03.020, 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.
Zhao, T., Zhang, X., Gao, Y., Mi, J., Liu, W., Wang, J., Jiang, M., and Liu, L.: Assessing the Accuracy and Consistency of Six Fine-Resolution Global Land Cover Products Using a Novel Stratified Random Sampling Validation Dataset, Remote Sensing, 15, 2285, https://doi.org/10.3390/rs15092285, 2023.

Based on the comment, the necessities of why impervious surfaces and wetlands are treated separately from other land cover classes have been added as:
To achieve high quality with detailed categorizations in global 10-m land-cover mapping, a hierarchical land-cover mapping methodology has been proposed. It leverages prior land-cover products and time-series satellite observations, **and gives more attention to impervious surfaces and wetlands by importing more prior knowledge and adding sufficient high-confidence training samples. Notably, the reasons why we separated impervious surfaces and wetlands from other land cover types include: 1) impervious surfaces are structurally different from natural land covers (Huang et al., 2022; Zhang et al., 2022); 2) wetlands are a highly zonal land cover type (concentrating in low-lying areas) with extremely complex spectra and heterogeneities due to changes in phenology and water-levels (Mao et al., 2020; Zhang et al., 2023b); 3) previous studies have demonstrated that many existing global land-cover products suffered poor performance on these complicated land-cover types (Zhao et al., 2023).**

2. Line 167: In the context of 10-meter resolution imagery, how are closed forests and open forests defined and differentiated?
Great thanks for the comment. The definitions of 30 fine land-cover types have been added in the Table S1 as:

Table S1. The detailed definitions of 30 land-cover types in the fine classification system.

Fine classification system	**Definition**
Herbaceous rainfed cropland	Herbaceous cropland with no irrigation facilities and crops grown by natural precipitation
Tree or shrub covered rainfed cropland (orchard, oil palm…)	Tree or shrub covered rainfed cropland, mainly including orchard, oil palm, etc.
Irrigated cropland	Cropland with guaranteed water sources and irrigation facilities that can be irrigated normally in a typical year
Closed evergreen broadleaved forest	Evergreen broadleaved tree cover, tree height > 3 m, tree-cover percentage > 40%
Open evergreen broadleaved forest	Evergreen broadleaved tree cover, tree height > 3 m, 15%< tree-cover percentage < 40%
Closed deciduous broadleaved forest	Deciduous broadleaved tree cover, tree height > 3 m, tree-cover percentage > 40%
Open deciduous broadleaved forest	Deciduous broadleaved tree cover, tree height > 3 m, 15%< tree-cover percentage < 40%
Closed evergreen needleleaved forest	Evergreen needleleaved tree cover, tree height > 3 m, tree-cover percentage > 40%
Open evergreen needleleaved forest	Evergreen needleleaved tree cover, tree height > 3 m, 15%< tree-cover percentage < 40%
Closed deciduous needleleaved forest	Deciduous needleleaved tree cover, tree height > 3 m, tree-cover percentage > 40%
Open deciduous needleleaved forest	Deciduous needleleaved tree cover, tree height > 3 m, 15%< tree-cover percentage < 40%
Closed mixed-leaf forest	Mixed broadleaved and needleleaved forests, tree height > 3 m, tree-cover percentage > 40%
Open mixed-leaf forest	Mixed broadleaved and needleleaved forests, tree height > 3 m, 15%< tree-cover percentage < 40%
Evergreen shrubland	Vegetation communities dominated by low cover and evergreen dwarf and scrub woodlands
Deciduous shrubland	Vegetation communities dominated by woody shrubs that lose their leaves in winter or the dry season
Grassland	Refers to land where herbaceous plants predominate
Lichens and mosses	Lichens and moss-covered areas
Swamp	The forest or shrubs which grow in the inland freshwater

Marsh	Herbaceous vegetation (grasses, herbs and low shrubs) grows in the freshwater
Lake/river flat	The non-vegetated flooded areas along the rivers and lakes
Saline	Characterized by saline soils and halophytic (salt tolerant) plant species along saline lakes
Mangrove forest	The forest or shrubs which grow in the coastal brackish or saline water
Salt marsh	Herbaceous vegetation (grasses, herbs and low shrubs) in the upper coastal intertidal zone
Tidal flat	The tidal flooded zones between the coastal high and low tide levels including mudflats and sandflats
Urban impervious surfaces	Land covered with buildings and other man-made structures within the urban boundary
Rural impervious surfaces	Land covered with man-made structures outside the urban boundary, mainly including rural residential land, transportation land, etc.
Sparse vegetation	Areas covered by woodland, shrubs and grasses, vegetation-cover percentage < 15%
Bare areas	Refers to land that is largely devoid of vegetation cover
Water	Lakes, rivers and streams that are always flooded
Permanent ice and snow	Areas covered by snow and ice all year round

Given the spatial resolution, the criteria used to distinguish these two types may significantly influence classification reliability.

In this study, the criteria used to distinguish the open forest and closed forest is the tree-cover percentage. And we agree that there may be significant mixing problems for forested areas with moderate tree cover. Thus, one of our ongoing works is retrieving the fraction of tree-cover (FTC), and then import the annual maximum FTC to better distinguish the open forest and closed forest.

3. Line 191: Regarding the use of MaxBound, does it only constrain the region from which training samples are selected, or does it also limit the area where land cover classification is applied? Please clarify its role in both processes.

Great thanks for the comment. Yes, the MaxBound_imp was not only use to generate the training samples but also used in subsequent classification. The role of MaxBound_imp has been added in the subsequent classification as (Section 3.4.1):

When building the training model for each 5 × 5 geographical tile, we also import training samples within their spatial neighborhood of 3 × 3 tiles to ensure spatial consistency over the adjacent tiles. **Since the $MaxBound_{imp}$ (Eq. (2)) provides the maximum potential areas of impervious surfaces because of the overestimation problem of Imp-ESRI_LC (**Wang et al., 2024**;** Xu et al., 2024**), all identified impervious surfaces should be within the $MaxBound_{imp}$.** Afterward, we can produce 984 5 × 5 impervious surface and natural land cover maps using the local adaptive modeling strategy.

4. Lines 277 and 289: It appears that you apply a percentile-based compositing method to mitigate the impact of clouds and shadows, thereby avoiding the direct use of full time series satellite data. However, this method does not fully eliminate inter-tile differences, particularly in areas with high cloud frequency. Consequently, mosaic seams may still be visible. Could the authors clarify whether any additional techniques were applied to address these residual seams?

Great thanks for the comment. Yes, we completely agree that the percentile-based method does not fully eliminate inter-tile differences, particularly in areas with high cloud frequency. In terms of our land-cover classifications, these influences are minimized through the integration of Sentinel-1 and Sentinel-2 imagery and the import of spatial textures from the gray level co-occurrence matrix.

However, as for these persistent-cloudy areas, the lack of efficient optical observations still affects the continuity of land-cover maps, and causes the mosaic seams. Recently, some previous works have explained that the harmonization of Landsat and Sentinel-2 can increase the likelihood of clear observations, and some researches used the deep learning models to improve the land-cover mapping performance on these cloudy areas. Thus, this limitation is also discussed on the Section 4.5 as:

Meanwhile, although the combination of time-series Sentinel-1 and Sentinel-2 can minimize the effect of clouds and shadows, some high cloud-contaminated areas might be still affected, i.e., mosaic seams may be visible in these special areas. Many previous studies have demonstrated that the harmonization of Landsat and Sentinel-2 can increase the likelihood of clear observations (Claverie et al., 2018), and the advances of deep learning models also improve the land-cover mapping performance on these cloudy areas (Xu et al., 2024a). Thus, how to combine the Landsat imagery and deep learning techniques to further improve the quality of GLC_FCS10 in the persistent cloudy areas will be one of the future works.

5. Line 345: What happens if a specific land cover type is absent from the training samples within a 3×3 tile region due to limited sample size? Would this omission lead to that type being entirely excluded from prediction in the region? If so, how does the method ensure completeness of classification in regions with rare or underrepresented classes?

Great thanks for the comment. Actually, we have built a backup global training sample library, storing the typical training features of all land-cover types over the globe, to avoid missing training samples of these sparse or underrepresented land-cover types.

However, after using the training samples from neighboring 3 × 3 geographical tiles, the missing training samples in the central tile almost were supplemented by neighboring 3 × 3 tiles, which caused the backup library to lose its function.

6. Line 408: Why is the confusion matrix reported for only 16 land cover types, while the final product contains 30 classes? Please explain the rationale behind this evaluation subset and whether accuracy metrics for the remaining classes are available.

Great thanks for the comment. This is a good question, the reason why we only give the confusion matrix for 16 land-cover types because of **the limitations of the global validation dataset**. If the validation points are further refined, we cannot guarantee the authenticity and reliability of the validation points through visual interpretation and auxiliary information. Thus, this limitation has been discussed on the Section 4.5 as:

We collected a globally distributed validation dataset and one third-party validation dataset (LCMAP_Val) for the purpose of quantifying the performance of the GLC_FCS10. However, **the accuracy metrics of GLC_FCS10 for the fine classification system (containing 30 land-cover types) is still unknown. Actually, some previous studies have emphasized that collecting a large-area validation dataset is quite challenging (Tsendbazar et al., 2021; Xu et al., 2020), especially as this study also needed to focus on 30 fine land-cover types.** Fortunately, over the past decades, many previous works have collected high-quality validation points at global or regional scales (d'Andrimont et al., 2020; Li et al., 2017; Stanimirova et al., 2023; Stehman et al., 2012; Zhao et al., 2023). **Making full use of these prior knowledge bases to refine the globally distributed validation points into 30 fine land-cover types will be another focus for ongoing work.**