Response to comments

Paper #: essd-2022-180
Title: GWL_FCS30: global 30 m wetland map with fine classification system using multi-sourced and time-series remote sensing imagery in 2020
Journal: Earth System Science Data

Reviewer #1

In terms of the whole workload, there is no doubt that this paper carried out a lot of data processing and analysis. The submitted MS also has good writing. However, I still have some concerns about the method and accuracy of classification results. My major comments are as below.

Great thanks for the positive comments. The manuscript has been greatly improved based on your and two other reviewers' comments and suggestions.

1. Besides the mangrove, how did you consider other coastal swamp in the classification system?

Great thanks for the comment and this great question. I am sorry we do not consider the coastal swamp in the manuscript because: 1) Ramsar convention only defines the coastal wetlands into: unvegetated tidal flats, saltmarshes, coastal deltas, mangroves, seagrass beds and coral reefs, it can be found that the **coastal tree-related wetlands** only include mangrove forest and **no other coastal swamp**. 2) We currently defined coastal wetlands into mangrove, saltmarsh and tidal flat **because there is almost no global/regional coastal swamp products can be used**. And the coastal wetland system of three subcategories (mangrove, salt marsh and tidal flat) is also widely recognized in many previous studies (Murray et al. 2022, Zhang et al., 2022).

Murray, N. J., Worthington, T. A., Bunting, P., Duce, S., Hagger, V., Lovelock, C. E., ... & Lyons, M. B. (2022). High-resolution mapping of losses and gains of Earth's tidal wetlands. Science, 376(6594), 744-749.

Zhang, Z., Xu, N., Li, Y., & Li, Y. (2022). Sub-continental-scale mapping of tidal wetland composition for East Asia: A novel algorithm integrating satellite tide-level and phenological features. Remote Sensing of Environment, 269, 112799.

2. As mentioned, the wetlands have clear seasonal changes within a year?

Great thanks for the comment. After carefully checking our manuscript, the manuscript didn't state that **the wetland have clear seasonal changes**, instead, we emphasize that the spectra variability of wetlands is simultaneously affected by the **water-level and phenology changes**. Therefore, we use time-series Landsat and Sentinel-1 to generate the lowest and highest water-levels:

The spectral characteristics of the wetlands would quickly change along with the seasonal or daily water levels of the underlying surface. For example, the tidal flat was the status of seawater at the high tidal stage and mud or sand flats at low tidal stages (Wang et al., 2021); therefore, it was necessary to **extract the highest and lowest water-level composites to completely capture these inundated wetlands**. Over the past several years, the time-series compositing strategy has been widely used to capture phenological and cloud-free composites.

Derived the phenological features from time-series Landsat imagery as:

Many studies also demonstrated that a multi-temporal phenology was also essential for classifying the vegetated wetlands and excluding these non-wetland land-cover types (Li et al., 2020; Ludwig et al., 2019). There were usually two options for capturing phenological features from time-series Landsat imagery. These included seasonal-based compositing (Zhang et al., 2021a; Zhang et al., 2022a) and percentile-based compositing (Hansen et al., 2014; Zhang and Roy, 2017; Zhang et al., 2021b). The former used the phenological calendar for selecting time-matched imagery. It then adopted the compositing rule to capture the seasonal features, while the latter directly used the statistical distributions to select various percentiles. Azzari and Lobell (2017) quantitatively analyzed the performance of two compositing methods and found that both of them had similar mapping accuracy for land-cover mapping. Meanwhile, the seasonal-based compositing method needed the prior phenological calendar, while the percentile compositing method did not require any prior knowledge or explicit assumptions regarding the timing of the season; therefore, the percentile compositing method was more suitable to generate phenological features. This study composited time-series Landsat reflectance bands and four spectral indexes into five percentiles (15th, 30th, 50th, 70th and 85th). It should be noted that the minimum and maximum percentiles were excluded because they were usually affected by residual clouds, shadows, and saturated observations.

How did you define the final date for the wetland product?

Great thanks for the comment. The global wetland product is developed for the nominal year of 2020, because the time-series Landsat imagery and Sentinel-1 SAR observations, used in this study, are mainly around 2020. It has been explained in the manuscript as:

First, all available Landsat imagery, including Landsat 7 ETM+ and Landsat 8 OLI missions, **during 2019–2021 was obtained for the nominal year of 2020 via the Google Earth Engine platform** for minimizing the influence of frequent cloud contamination in the tropics and snow and ice in the high latitudes.

The description of Sentinel-1: All the **time-series Sentinel-1 imageries archived on the GEE platform in 2020** in Interferometric Wide Swath mode with a dual-polarization of VV and VH were used.

3. Besides the time-series feature? Did you consider other features

Thanks for the comment. In this study, we used the time-series Landsat imagery to generate the lowest and highest water-level composites and multiple phenological features, used the time-series Sentinel-1 imagery to generate the lowest and highest water-level features, and used the ASTER GDEM to derive elevation, slope and aspect. To intuitively understand all training features, the 77 multisourced training features were listed in a table as:

In summary, a total of 77 multisource training features (listed in Table 3), including 70 optical features from Landsat imagery, 4 SAR features from Sentinel-1 imagery and 3 topographical features from ASTER GDEM.

Table 3. The multisourced and multitemporal training features for wetland mapping.

Data	**Derived training features from multisource remote sensing imagery**
Landsat	**Water-level features**: the lowest and highest composites with Blue, Green, Red, NIR, SWIR1, SWIR2, LSWI, NDWI, NDVI and EVI bands **Phenological features:** 5th, 30th, 50th, 70th and 85th percentiles with Blue, Green, Red, NIR, SWIR1, SWIR2, LSWI, NDWI, NDVI and EVI bands
Sentinel-1 SAR	**Water-level features**: the lowest and highest composites using 5th and 95th percentiles for VV and VH bands.
ASTER GDEM	**Topographical features**: elevation, slope and aspect.

4. How did you training the model? One model for the global wetland or one model per grid? There are distinctly phenological differences for the different wetland types and even the same wetland type. Please clarify it.

Great thanks for the comment. We used 961 local adaptive classification models in 961 5° × 5° geographical tiles after considering the phenological differences for the different wetland types and even the same wetland type at spatial dimension. The local adaptive modeling has been strengthen as:

Since we have simultaneously extracted the maximum coastal and inland wetland extents when deriving training samples from prior wetland datasets, the stratified classification strategy was adopted to fully use the maximum extent constraint. If a pixel was classified as a coastal wetland outside the maximum coastal wetland extents, it would be identified as a misclassification. Furthermore, there were two ideas for the large-area land-cover mapping including global classification modeling (using one universal model for the whole areas) and local adaptive modeling (using various models for different local zones) (Zhang et al., 2020). For example, Zhang and Roy (2017) demonstrated that local adaptive modeling outperformed the global classification modeling strategy. Therefore, the global land surface was first divided into 961 5° × 5° geographical tiles illustrated in Figure 5, which were inherited from the global 30 m land-cover mapping by (Zhang et al., 2021b). Then, **we trained the local adaptive classification models using derived training samples in Section 3 and multisource and multitemporal features (the highest, lowest water-level and phenological composites and topographical variables) at each 5° × 5° geographical tile.** It should be noted that we used the training samples from neighboring 3 × 3 geographical tiles to train the classification model and classify the central tile for guaranteeing the spatially continuous transition over adjacent regional wetland maps. Namely, we trained 961 local adaptive classification models and then produced 961 5° × 5° wetland maps. Finally, we spatially mosaiced these 961 regional wetland maps into the global 30 m wetland map in 2020.

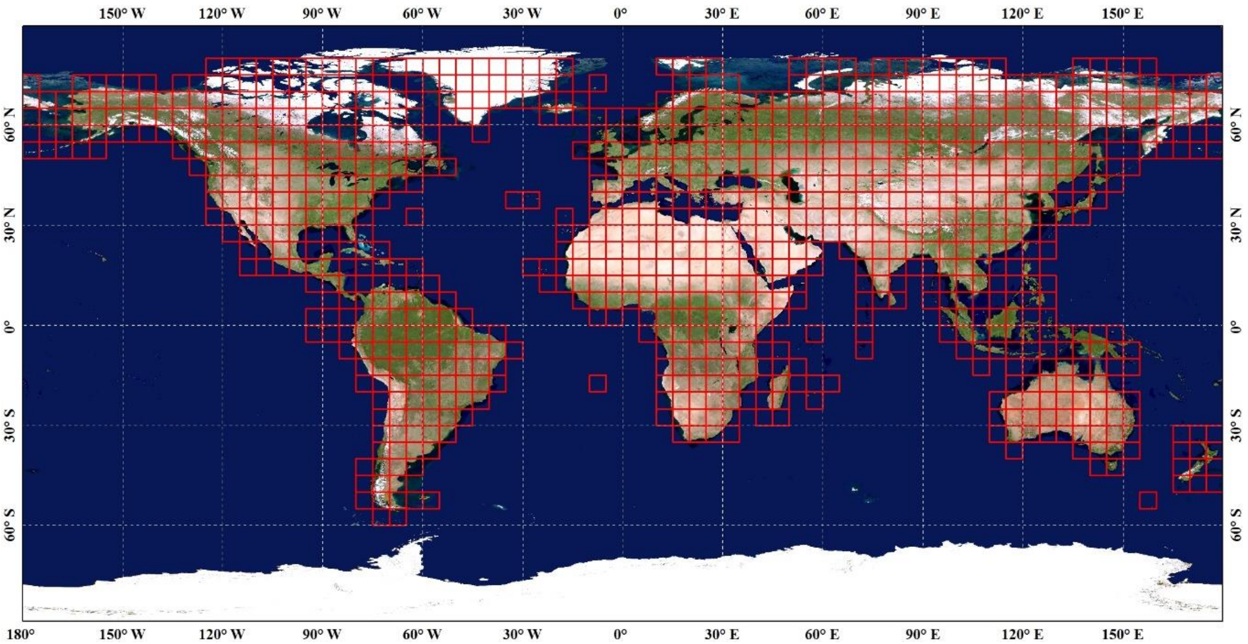

Figure 5. The spatial distribution of 961 5° × 5° geographical tiles used for local adaptive modeling, which was inherited from the global 30 m land-cover mapping by (Zhang et al., 2021b). The background imagery came from the National Aeronautics and Space Administration (https://visibleearth.nasa.gov, last access: 10 Nov 2022).

5. The authors used Sentinel SAR data, why do not produce the 10 m resolution product based on Sentinel 2?

Great thanks for the suggestion. Yes, we can combine the time-series Sentinel-1 and Sentinel-2 to develop the global 10m wetland maps, however, the reasons why we developed the global 30m wetland products are the following:

1) The spatial resolution of most prior global wetland products in Table 1 is 30 m, the derived training samples can be directly applied in the Landsat imagery for wetland mapping. If we used the derived training samples to Sentinel-1 and Sentinel-2, we must consider the spatial scale matching problem.
2) Compared to the Landsat imagery, the Sentinel-2 preprocessing method is not yet mature, namely, these bad quality (cloud, shadow, snow and ice) cannot be completely identified. It might be transferred to the wetland mapping especially in the tropics (cloudy regions) and high latitudes areas (frequent snow and ice covering).
3) The global 10-m wetland mapping also means 10 times the amount of computation when comparing to the global 30 m wetland mapping. Although the GEE provides free computation and storage ability, the time consumption is also a factor that cannot be ignored in global wetland mapping
4) Our further works would focus on the spatiotemporal dynamics of global wetlands over long time spans, which is also a hot spot in wetland monitoring today, however, the Sentinel-2 has shorter time span than the Landsat (since 1984).

Based on the above factors, we choose the Landsat imagery as our main data to develop the global 30 m fine wetland mapping.