Responses to CC #1

General Comments:

This article used deep learning methods to produce a refined distribution of global Plastic-covered greenhouse in 2020. The methodology of the paper is sound and the data is novel. Although there are some global PCG data in the current study, the data set has some value in terms of resolution. There is some value for global agricultural macro-management.

Specific Comments:

There are some problems and deficiencies that need to be corrected as follows:

1. Plastic-covered greenhouse can divided into daylight greenhouses and plastic greenhouses. Is there a significant difference in the spectra of the two kinds.

Response:

Thank you for your thoughtful question. To address this, we selected Weifang in Shandong Province as a representative region and analyzed the seasonal spectral reflectance differences between Daylight Agricultural Greenhouses (sunlight greenhouses) and Normal Agricultural Greenhouses (conventional greenhouses). A comparative reflectance plot illustrating these seasonal differences is provided below.

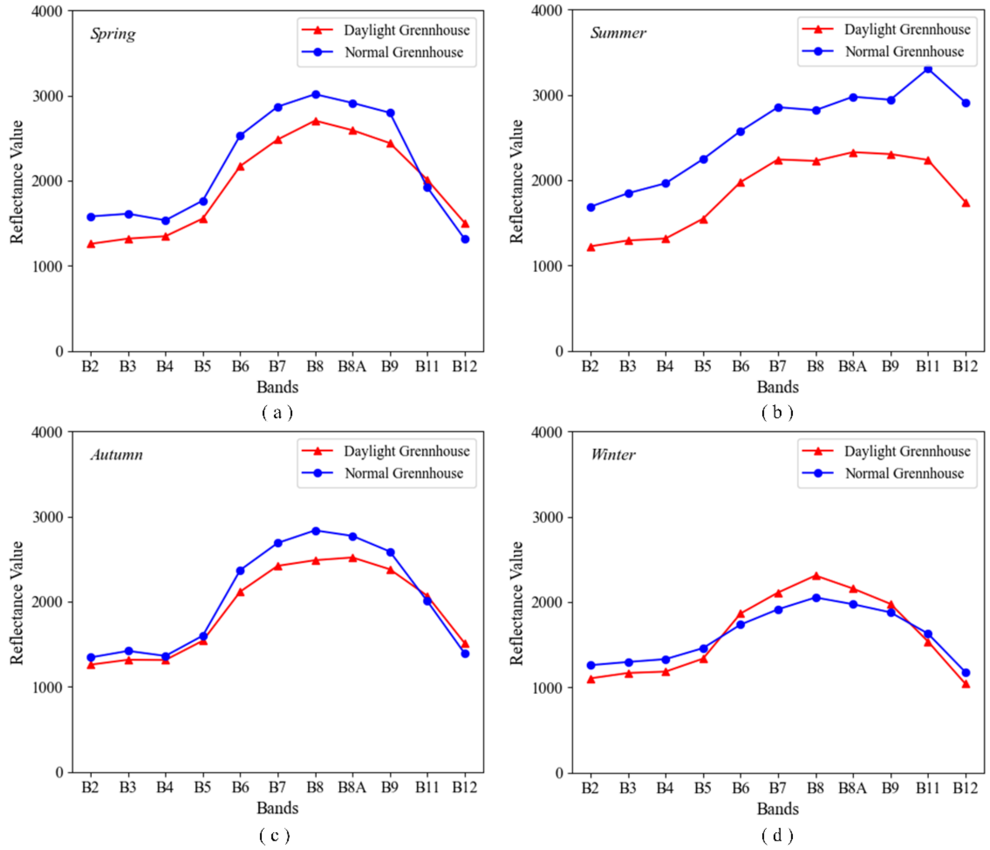

Figure CC1-1. Comparison of Spectral Reflectance Between Two Types of Greenhouses

As shown in the figure, the two types of agricultural greenhouses exhibit noticeable spectral differences, particularly during the summer months (June to September), when the distinction is most pronounced. Therefore, summer-season remote sensing imagery is essential for distinguishing between Daylight Agricultural Greenhouses and Normal Agricultural Greenhouses. In addition, the spectral differences are also relatively evident in spring, making spring imagery the second best alternative when summer data are unavailable. In contrast, the spectral differences during autumn and winter are relatively small, making it difficult to effectively differentiate between the two types of greenhouses during those seasons. These findings indicate that while Daylight and Normal greenhouses can be spectrally distinguished, this separability is season-dependent and varies significantly across different times of the year.

In future studies, we will further explore the fine-scale classification of agricultural greenhouses (AG), including distinguishing between daylight greenhouses, conventional plastic greenhouses, glass greenhouses and small arch sheds to improve the accuracy and application value of PCG dataset.

2. Line 150-155, authors generated initial PCGs labels via RFM and GEE. Did the authors use some manually labeled data to validate the results?

Response:

Thank you for your good question. Actually, we employed multiple strategies to ensure the accuracy of initial PCG labels during the training sample collection process. Firstly, field investigations were conducted in typical greenhouse distribution regions in China, such as Weifang (Shandong), Kunming (Yunnan) and Lishu (Jilin), where we consulted with local farmers to confirm the types and spatial distribution of greenhouses. Considering that agricultural PCG generally has a long lifespan and stable structures (Ou et al., 2020), we conducted systematic manual visual interpretation of high-resolution historical imagery from Google Earth across various regions, both in China and abroad, to obtain high-confidence samples. For international regions, we supplemented the sampling process with literature review, meta-analysis and information from online sources, followed by manual verification using Google Earth. All manually interpreted samples were subsequently cross-validated using Sentinel-2 imagery to confirm their presence in the year 2020.

Based on these manually annotated samples, we constructed the training dataset with the Google Earth Engine (GEE) platform. The samples were split into training and validation subsets using standard practices widely adopted in the LULC (land use/land cover) domain. We then used these datasets to evaluate the initial classification results generated by the Random Forest model in GEE through confusion matrix analysis. Therefore, both the training and validation samples were derived from manual interpretation, ensuring the accuracy and reliability of the labeling process.

3. Line 100-105, this paper mentioned a case which used commercial satellite data to extract the PCGs. What's its resolution? And what's different from that research? The authors point that the scientific problem is how to use open access data to generate PCGs map. I think this was not the true scientific problem.

Response:

Thank you for your insightful comment. Regarding the study you mentioned that uses commercial satellite data to extract PCG, we have addressed this in the manuscript **(see Line 99 ~ 100)**. That study employed PlanetScope imagery with a spatial resolution of 3 meters, which provides stronger texture representation due to its higher spatial detail. However, commercial satellite data are typically expensive, subject to access restrictions, and often lack globally consistent coverage within a single time period. Therefore, we argue that a key scientific challenge in the current context is to develop a low-cost, scalable and replicable methodology for global PCG mapping based on open and accessible data sources.

We also observed from the dataset released by Tong et al. that their 2019 global PCG product incorporates imagery from 2021 to supplement the 2019 data. While this approach may be feasible for greenhouse identification tasks, it inevitably introduces temporal inconsistency. In contrast, our study utilizes multi-temporal Sentinel-2 imagery strictly from the year 2020, which allows for temporally consistent large-scale mapping and reduces potential errors caused by temporal mismatches.

Moreover, compared to manual annotation based on 3-meter resolution imagery, our approach enables automated large-scale PCG extraction using 10-meter resolution data, significantly reducing labor costs. The grid-based data organization strategy adopted in this study also improves data processing efficiency.

In summary, we believe that our research not only proposes a practically applicable method but also addresses the scientific challenges of global-scale PCG mapping under the constraint of open-access remote sensing data. The proposed approach provides a reliable technical framework for future studies with similar objectives.

4. Figure 4 illustrated the multiple-temporal NDVI profile of bareland, PCGs and PMFs in a representative sub-region of Gansu Province, China. There are PMFs in some southern area. Farmer used plastic much earlier than the northern area, which would induce the difference of multiple-temporal NDVI.

Response:

We sincerely thanks for your detailed observation. We agree with your point that in Southern China, the mulching period of PMF (Plastic-Mulched Farmland) typically begins earlier than in northern regions, and this temporal difference is indeed reflected in the fluctuation patterns of the NDVI time series. Based on our constructed 2020 PMF distribution dataset of China (Niu et al., 2025), we observed that the spatial extent of PMF in Southern China is relatively limited. However, agricultural systems in this region are mainly characterized by a double-cropping pattern, which results in shorter cultivation cycles and more rapid vegetation changes. In contrast, PCG exhibit more stable and long-term coverage characteristics, leading to more consistent and regular NDVI patterns. It is precisely this marked difference in the multi-temporal NDVI curves that facilitates the effective differentiation between PMF and PCG in our classification model.

As illustrated in **Figure CC1-2**, for example, in the case of Shandong Province, Ou et al. (2021) constructed NDVI curves for various land cover types using Landsat-8 imagery. The cropping system in this region follows a double-cropping schedule, which is comparable to that in most parts of Southern China. Their data clearly show significant spectral differences between PCG, cropland and PMF during two key temporal windows, from day 73 to 136, and from day 165 to 248. Consequently, their study also focused on spring and summer imagery when analyzing regions with a double-cropping system.

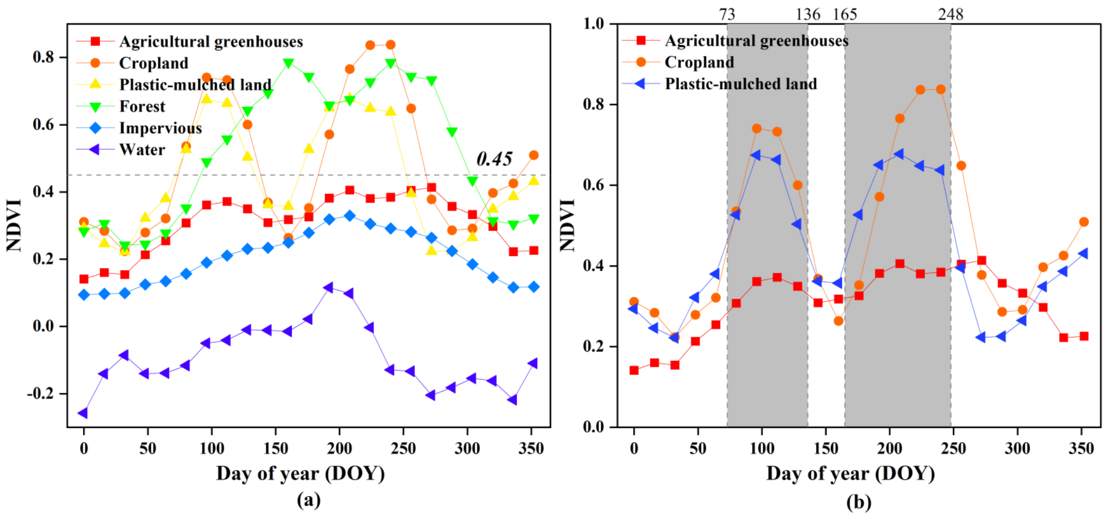

Figure 6. (**a**,**b**) Mapping window selection based on vegetation growth.

Figure CC1-2. Time-Series NDVI of Different Land Cover Types

In addition, we conducted sampling of PCG and cropland in the Yangtze River Delta region of Eastern China, and constructed NDVI time series curves for both land cover types in 2020 based on Sentinel-2 imagery. The results in Figure **CC1-3** indicate that although the period of separability between PCG and cropland may occur slightly earlier in this region compared to Northern China, the two classes still exhibit clear separability during the key seasonal windows of spring (March–May) and summer (June–September). This pattern further confirms the rationality and applicability of using spring and summer imagery in our classification model.

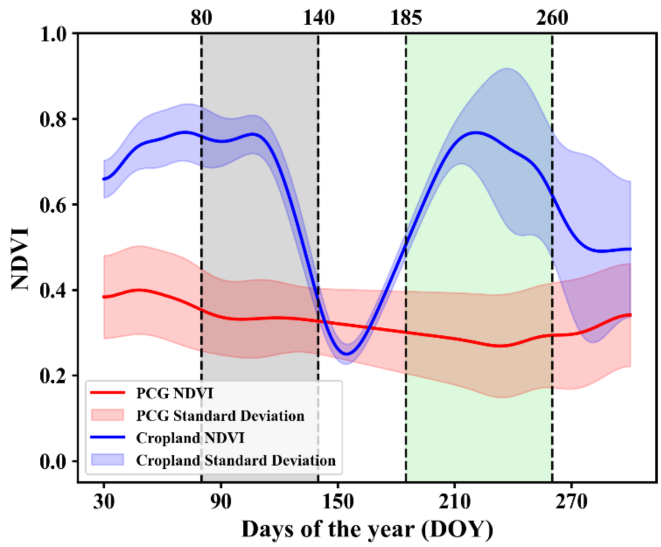

Figure. CC1-3. Time-Series NDVI of PCGs and Cropland

In fact, PMF (Plastic-Mulched Farmland) is essentially a form of cropland, and its overall phenological pattern does not change significantly due to the use of plastic mulch. Therefore, using spring and summer remote sensing imagery is an effective strategy to enhance the separability between PMF and PCG, as well as between general cropland and PCG. This choice is also well supported by our previous research findings and practical experience.

Reference:

Niu, B., Feng, Q., Zhang, X., Qiu, B., Zeng, Y., Su, S., Xu G., Gong J., Yan X., Huang J., Yin G., Liu J., Yang J., Zhu D. China-PMF-10: a 10-m national map of plastic-mulched farmlands in China of 2020 using deep semantic segmentation. 2025. figshare. Dataset.

5. Line 420-425, the PCGs dataset from the university of Copenhagen is the year of 2019. Differences between the two data years may result in discrepancies. Of course, it would be better if the data include a few more years.

Response:

Thank you for your valuable suggestion. We fully acknowledge that the PCG dataset provided by the University of Copenhagen corresponds to the year 2019, while the target year of our study is 2020, and thus there is indeed a temporal discrepancy between the two. To minimize the potential impact of this difference, all manually labeled samples and model validation efforts in our study were strictly based on Sentinel-2 imagery and historical Google Earth images from 2020, ensuring consistency between the data used and the target year of analysis.

Moreover, considering that PCG typically have long usage cycles and relatively stable spatial distributions over short periods, we believe that the 2019 dataset still holds substantial reference value in terms of spatial distribution and can serve as a useful auxiliary resource. In future studies, we plan to incorporate multi-year remote sensing data to further enhance the temporal adaptability and robustness of our model, thereby supporting long-term agricultural monitoring and change detection.

Thank you again for your comments. They are valuable and very helpful for revising and improving our paper, as well as the important guiding significance to our studies.

Yours sincerely,
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on behalf of all the co-authors