**Responses to Editor and Referee's comments**

First of all, we would like to thank the Editor and Referee for their comments and suggestions, which improved greatly the presentations and interpretations in our revised manuscript. In the revised article, we have addressed all comments and suggestions from the Editor and Referee. Our point-by-point responses to the Referee's comments are outlined below. The Referee's original comments are shown in italics and our responses are given in normal fonts.

**Referee #2**

**Comments:**

*The manuscript egusphere-2024-1497 introduces a satellite-derived historical land cover product to a climate model, recalculates the radiative forcing (RF) of land use change (LUC) from 1983 to 2010, and demonstrates that satellite-derived results show weaker LUC RF compared to the original model's coarse-resolution LUC input. This study is well designed, and the results sufficiently support the conclusions. I have some questions regarding the interpretation of the results, and I believe that addressing these concerns will strengthen the manuscript and facilitate its publication in ACP.*

**Response:** We thank the Referee's positive and encouraging comments, which help us to improve this article considerably.

**Major Comments**

*1. Inter-Annual Variability of Satellite Land Cover Product*

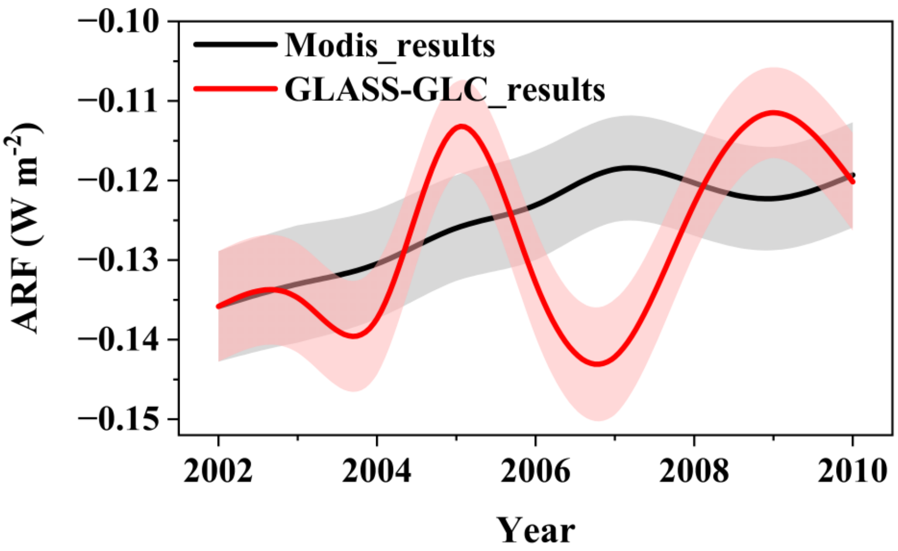
*My main concern is the excessive annual variability in the satellite-derived land cover product, particularly when it is claimed to represent land use change. Typically, land use change reflects human activities. However, Figure 1 shows significant fluctuations in the global average of LUC-derived RF between the late 1980s and early 1990s, with increases and decreases that nearly double the overall magnitude observed since the industrial era. Similar abrupt changes are noted in South Asia and Russia in the late 1990s (Figure 2). These fluctuations seem unrealistic and undermine the reliability of the input satellite data. I recommend exploring additional satellite datasets, if available, and comparing the results for inter-validation.*

**Response:** Following Reviewer's comment, we compared GLASS-GLC and MODIS LUC data, of which, the GLASS-GLC used satellite multi-source fusion approach and MODIS used direct MODIS sensor to derived their respective LUC inventories. The GLASS-GLC dataset spanning 1982-2015 but MODIS data is only available from 2000 onward. So, we replaced the GLASS-GLC by MODIS LULC data from 2002 to 2010 in the OSCAR model. The figure below shows annual fluctuations of the OSCAR simulated annual RF under global forestland changes using GLASS-GLS and MODIS from 2002 to 2010, respectively. Both RF results show annual fluctuations, though the

RFs from the CLASS-GLC illustrate somewhat stronger oscillations. However, during this period, accumulated RFs subject to the global forestland changes driven by GLASS-GLC and MODIS LUC are 0.0165 $Wm^{-2}$ and 0.0157 W $m^{-2}$, respectively, indicating only a 5% difference between the two satellite remote sensing derived LUC datasets.

Sun et al. (2022) compared the applications of six LULC products in the identification of LUCs in Northwestern China. Their results indicated, while the GLASS-GLC and MODIS (MCD-12Q1) were not superior to other four products (developed only for China), these two datasets were of most temporal and spatial consistency. This paper has been cited in the revised paper.

These discussions have been summarized in a new paragraph in section 2.2 (third paragraph).




The GLASS-GLC dataset was further compared temporally and spatially with the LUH1 dataset in Supplementary Figures S1 and S2. While the GLASS-GLC is superior to the LUH1, the magnitude of GLASS-GLC is comparable to LUH1 dataset. Eq. S1 defines the principle of the OSCAR model to predict ARF, which is closely related to the area of LUC, and therefore, the fluctuation of the ARF results is also reflected by the land use conversion data of the dataset, which is well reflected by Figure 3 and Figs. S3-S13 of this paper.

The result has been added to the revised Supplementary Text 2 (the last paragraph).

Sun, W. et al. Land use and cover changes on the Loess Plateau: A comparison of six global or national land use and cover datasets. Land Use Policy 119, 106165 (2022).

*2. Land Cover and Land Use Classification*

*How do the authors reconcile the differences between the satellite-derived land cover classifications and the land use classifications in the original model input (LUH1)? Land cover and land use are distinct concepts, and their categories differ. For example,* *LUH1 includes "pasture" as a category, while GLASS-GLC uses "grassland," which are not equivalent. Clarification on the mapping or harmonization process is needed.*

**Response:** The Reviewer raised an important question! Land Cover refers to the physical and biological cover over the surface of the Earth, including vegetation, water bodies, urban areas, and bare soil. For example, land cover categories include forest, grassland, water, built-up areas, and bare soil. Land Use refers to how land is used by humans, including agricultural practices, urban development, forestry activities, and conservation. Land use categories may include crop land, pasture, urban, and nature reserves.

The key differences partly come from terminological differences, namely, different datasets might use different terminologies for similar land cover types (e.g., “pasture” in LUH1 vs. “grassland” in GLASS-GLC). These terms may have specific implications in the context of land use and ecology. Dynamically, land use might change more rapidly due to socio-economic factors than land cover, leading to discrepancies between the two categories over time.

In the revised paper, we have inserted a new Table S1 in Supplementary and referred it in the second paragraph in section 2.2.

*3. Sensitivity Analysis Methodology*
*The sensitivity analysis is a critical foundation for this study. Is the method employed here commonly used for quantifying LUC radiative forcing? If not, how does it compare with approaches used in previous studies? Providing context and justification for this methodology is essential.*

**Response:** The reviewer's comment raises a good point about the sensitivity analysis method. We used the normalized marginal attribution method in the sensitivity analysis (Supplementary Text 8). This approach has been applied previously to assess sensitivity of OSCAR simulated radiative forcing (Li et al., 2016; Fu et al., 2020). Table S5 provides detailed analysis results, which are referred to in the end of section 3.5 and revised section 2.3.

1. Li, B. G. et l. The contribution of China’s emissions to global climate forcing. *Nature* **531**, 357–361 (2016).
2. Fu, B. et al. Short-lived climate forcers have long-term climate impacts via the carbon–climate feedback. *Nat. Clim. Chang.* **10**, 851–855 (2020).

**Other Comments**

*1. Abstract: Clarify the apparent contradiction between "Sub-Saharan Africa made the largest net contribution" and "East and Southeast Asia dominated the changes in global ARF."*

**Response:** Here, the former refers to sub-Saharan Africa, which has the largest proportion of ARF to the value of global ARF, and the latter refers to East and Southeast Asia, which has the largest contribution to the change in global ARF, as showed in Figure 2. We have rewritten "*contribution*" as "*proportion*".

*2. Lines 55–57: Elaborate on the distinction between the well-investigated "LUC on climate balance" and the research gaps in "LUC-induced climate forcing."*

**Response:** **LUC on climate balance** refers to understanding how changes in land use (such as deforestation, urbanization, or land restoration) affect the climate system's energy balance through biogeochemical and biogeophysical processes. These processes drive **carbon sequestration and emissions and surface albedo change and interactively affects climate balance. The LUC-induced climate forcing** focuses on understanding how changes in land use generate direct climate forcing effects, which is an area that still requires significant exploration and has several research gaps, including mainly the lack of the long-term effects of LUC-induced climate forcing prediction. Immediate impacts may be different from those observed over decades or centuries.

Corresponding text has been added to the first and second paragraphs in revised Introduction.

*3. Lines 74–75: Suggest investigating multiple satellite products, rather than relying on a single dataset.*

**Response:** Please refer to our response to the Reviewer's major comment 1 and discussions in revised Supplementary Text 2 (last paragraph).

*4. Section 2.1: Provide an introduction to how OSCAR converts land use types into albedo values and their subsequent effects on radiative forcing and climate.*

**Response:** Thanks to Reviewer 1 for the suggestion. We provide a thorough description of how OSCAR converts land-use types into albedos in the simulation of the ARF. We have added a new ($2^{nd}$) paragraph in Supplementary Text 1, which provides a detailed introduction to the issue raised by the Reviewer.

*5. Line 188: Explain the rationale for using a 20% threshold in the analysis.*

**Response:** For many satellite-derived land-use classification products, overall classification accuracies range between 70% and 90%. This implies misclassifications can lead to an uncertainty of 10% to 30% in land-use area estimates. So, we took 20% in our sensitivity experiments.

Corresponding text has been added to the first paragraph of revised section 2.3. We also added a reference (Gong et al., 2013) to the corresponding text.

Gong, P. et al. Finer resolution observation and monitoring of global land cover: first

mapping results with Landsat TM and ETM+ data. *Int. J. Remote Sens*. **34**, 2607–2654 (2013).

*6. Figure 1(b): Indicate the time periods covered by other studies for better comparability.*

**Response:** Done, thanks!

*7. Figure 2: Justify the chosen regional separations and clarify whether latitude weighting was applied to calculate the regional means.*

**Response:** The OSCAR model already separated the world into 114 countries and regions and this study further divided the globe into nine regions, each includes certain number of countries and regions (Table S3). The mean ARF value in each of the nine regions was obtained by averaging ARFs over those countries and regions grouped in each of the nine regions, not from latitude weighting. The corresponding text have been added to the first paragraph of section 3.2.

*8. Lines 347–349: This statement is unnecessary and could be removed to streamline the manuscript.*

**Response:** Done, thanks!

*9. Supplementary Table S2: Explain why the values for "Rest of East Asia" are notably larger than those for other regions.*

**Response:** Firstly, the parameters are provided by the OSCAR model, and secondly, the “*Rest of East Asia*” mainly indicates Mongolia, and the relevant albedo data also indicate that the surface albedo is high in this region (https://www.geodata.cn/).