Response to Editor and Reviewer

Dear Editor and Reviewer,

First and foremost, we sincerely thank you for dedicating your valuable time to providing such rich, valuable, detailed, and highly constructive comments on our study (**Manuscript title**: Forest and bioenergy expansion amplifies climate warming by accelerating regional cloud loss; **Manuscript ID**: egusphere-2026-367). We were privileged to receive detailed and professional review comments from this expert; these insights further stimulated our interest in the potential role of cloud cover in large-scale land use and cover change (LUCC) and prompted us to reflect on the actual climate impacts of highly popular afforestation initiatives. These valuable comments have undoubtedly significantly enhanced the scientific rigor of the manuscript, the readability of the figures, and the reliability of the conclusions. We would like to express our most sincere gratitude to the editor and reviewer once again.

Now, we provide a comprehensive, point-by-point response to the specific comments raised by the reviewer.

Major comments

1. The interpretation of cloud reduction due to afforestation seems simplified and does not account for several competing land-atmosphere processes associated with afforestation. Forest expansion typically alters not only surface albedo, but also aerodynamic roughness, evapotranspiration, boundary-layer turbulence, and moisture recycling. Increased evapotranspiration may enhance local atmospheric moisture supply, while increased roughness can strengthen turbulent mixing and modify planetary boundary-layer structure. These processes may either promote or suppress low-level cloud maintenance depending on the regional background climate and circulation regime.

We are deeply honored to receive your valuable comments, and we are also very grateful for the huge role your valuable comments have played in improving our research work. We agree that our interpretation in the previous version regarding the mechanism underlying long-term cloud cover trends induced by large-scale LUCC (specifically referring to forest and bioenergy crop expansion in this study) was oversimplified, thereby ignoring several competing bio-geophysical processes. In fact, our interpretation of the mechanism driving cloud cover trend changes induced by forest and bioenergy expansion mainly derived from the well-trained (via 100 Bayesian hyperparameter searches to find the optimal machine learning parameters, as shown in Table S1) machine learning-driven mechanism analysis in the main text. Our initial focus was on using machine learning to reveal the dominant factors driving cloud cover trend changes caused by large-scale LUCC, thereby overlooking the competing processes of secondary factors; consequently, we failed to fully consider the contributions of multiple competing processes involved in forest or bioenergy expansion to cloud cover trends. We already know that, as reported in most previous observational or simulation studies, large-scale land cover expansion not only alters surface albedo (which is the primary surface physical property altered and the starting point for all bio-geophysical responses), but also affects aerodynamic roughness, evapotranspiration, boundary layer turbulent mixing, and the water cycle. These processes undoubtedly exhibit competing relationships; for instance, the increase in net surface radiation caused by the decrease in albedo due to forest expansion induces tropospheric warming, while forest expansion may also enhance evapotranspiration, thereby bringing more moisture to the atmosphere and favoring the maintenance of cloud cover. These similar competing processes may exert a more important impact on the maintenance of low-level clouds, because previous studies imply that the impact of large-scale LUCC on high-level atmospheric dynamics may be relatively weak, whereas the primary impacts exerted remain near the surface (King et al., 2024: King, J. A., Weber, J., Lawrence, P., Roe, S., Swann, A. L. S., and Val Martin, M.: Global and regional hydrological impacts of global forest expansion, Biogeosciences, 21, 3883–3902, https://doi.org/10.5194/bg-21-3883-2024, 2024). These potential competing processes may lead to changes in the final net cloud effect, for example, enhanced evaporation replenishing sufficient moisture to offset cloud cover loss induced by albedo warming. Obviously, our current analysis did not consider these competing processes; please forgive our incompleteness in mechanistic explanations, but these analyses undoubtedly make the content scientifically deeper. However, in the main text, our core objective is to reveal the dominant factors driving long-term cloud cover trend changes induced by large-scale LUCC through machine learning, which indirectly indicates that certain other factors are not that important; this can be seen from the contribution plots we generated. For example, regarding the contribution to the trend change in total cloud cover, the LUCC-induced trend change in TMQ is the most important, contributing 20.5%, 26.3%, and 23.1% in the three sensitivity simulations, respectively—in other words, this factor alone explains roughly one-fifth of the cloud cover trend changes—whereas the contributions of latent heat flux (LHFLX) and evapotranspiration (QFLX) ranked at the bottom, which indirectly demonstrates from the side that these factors are not the most critical and their competing effects are likely weak, making them unlikely to exert a huge impact on long-term cloud cover trends..

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In our results, we find significant increases in low cloud fraction over Argentina in Base relative to No LULCC in 2095. In Max Forest, there are small but significant increases (~ 5 %) in low-level cloud fraction (below 700 hPa) over the Congo Basin, northern Australia, Uruguay, and Colombia and Venezuela in 2095 (Fig. 5a) with smaller yet significant increases of the same spatial pattern in 2050. All of these are areas with significant increases in tree cover in Max Forest. Significant differences in oceanic low cloud of both positive and negative signs are seen in both scenarios relative to No LULCC (Fig. 5a). However, given the moderate nature of our land use change scenarios, attributing these changes directly to forestation is challenging. While low cloud cover is important for the surface radiation balance, changes to deep convective clouds over the tropical rainforest basins can have important consequences for regional and global climate. We find statistically significant but small (~ 0.2 %) increases in tropical convective cloud fraction over Africa in Max Forest relative to No LULCC in 2095 (Fig. 5b), but the significant differences are restricted to below 900 hPa, implying a limited effect of the land use change scenario on deep convection.

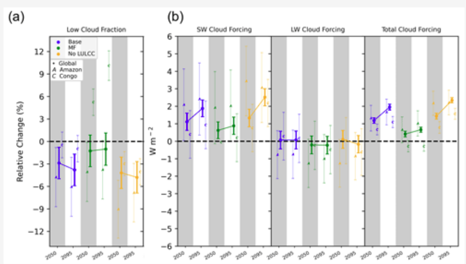
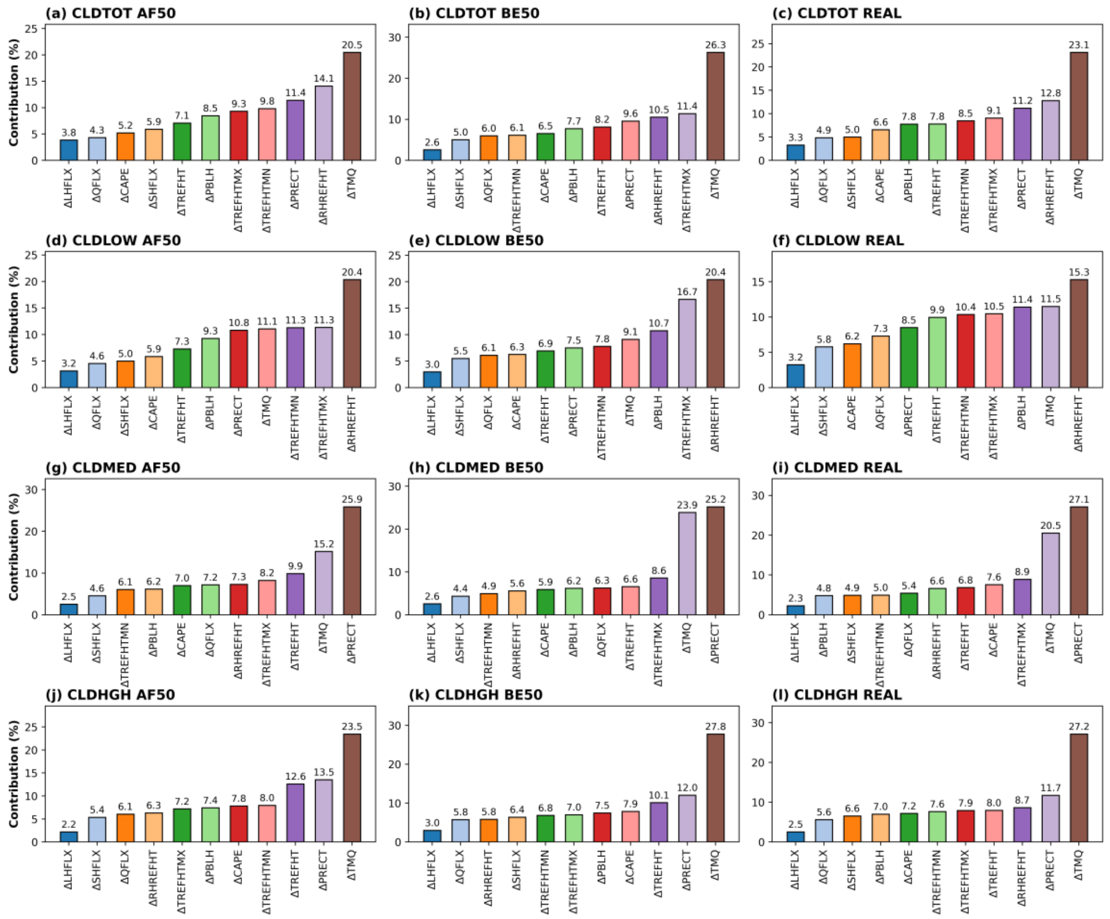
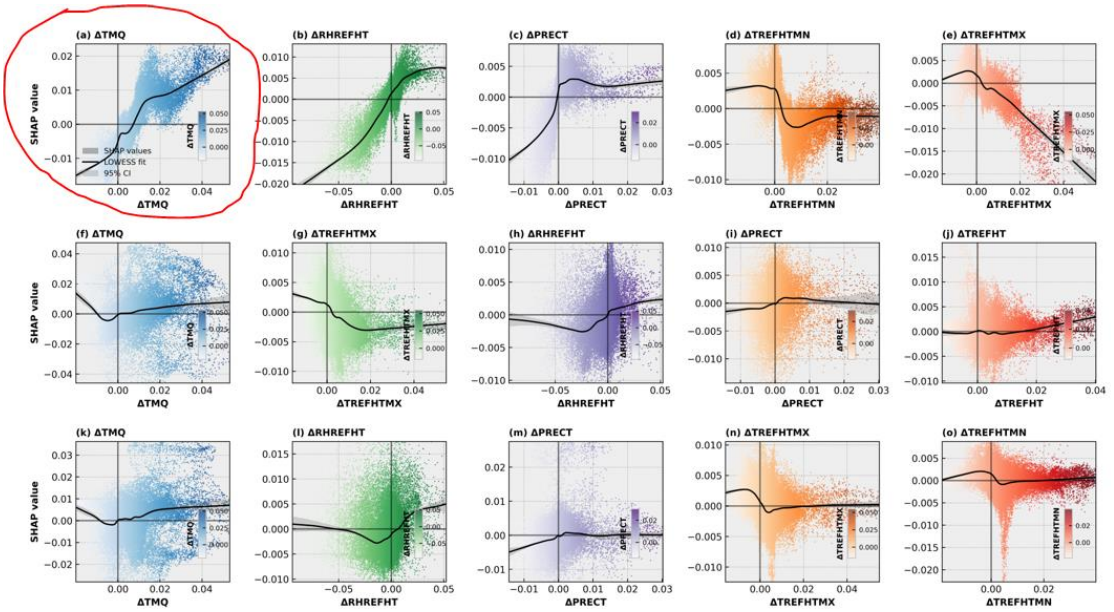
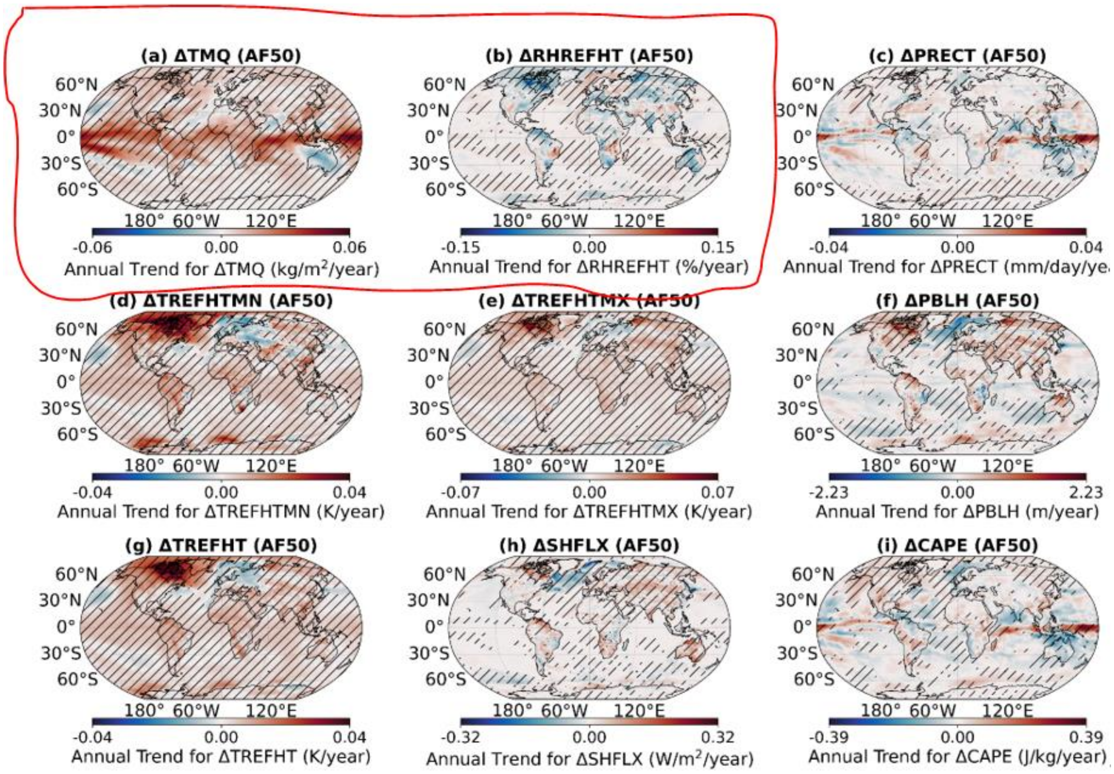


Figure 7 As Fig. 2b but showing differences in cloud cover integrated between 1200–700 hPa **(a)** and differences in clean-sky shortwave cloud radiative forcing, clean-sky longwave cloud radiative forcing, and total clean-sky cloud radiative forcing **(b)**.



However, to lend greater scientific depth and comprehensiveness to our analysis, we still chose to adopt your valuable suggestion to elaborate in the Discussion section on how these competing processes respond to cloud cover trend changes, but we chose not to discuss driving factors of lower importance. Instead, our approach was to select the dominant factor and the next three most important driving factors based on variable importance for analysis; for instance, in the trend driving factor analysis of total cloud cover in the AF50 simulation, the dominant factor is TMQ, so when analyzing competitive relationships, we paired them one-by-one—namely, TMQ paired with RHREFHT, TMQ paired with PRECT, and TMQ paired with TREFHTMN (Figure S38). As another example, for low-level cloud cover, the dominant factor is RHREFHT, which was similarly paired with the next three factors for analysis. We first learned from the partial dependence plots provided by machine learning that the LUCC-induced decreasing trend in TMQ would lead to a reduction in the total cloud cover trend—that is, producing a negative effect; however, in reality, idealized afforestation leads to a slight increasing trend in TMQ in the mid-to-high latitudes of the Northern Hemisphere, but this increase is clearly masked by a sharp decreasing trend in relative humidity, which explains why TMQ is the primary controlling factor for long-term trend changes in total cloud cover, whereas the total cloud cover loss trend in northern mid-to-high latitudes is mainly manifested through the decreasing trend in relative humidity. We consider this to be within expectations, because in these moisture-limited northern regions, the increase in transpiration brought about by converting grassland or shrubland to forest is relatively limited, thereby constraining the positive benefit of moisture supply for cloud cover maintenance, which also explains why machine learning failed to identify evaporation as a more important driving factor. Competitive regions (regions where the paired factors have opposite SHAP value signs, displayed as black scatter points) exist widely, indicating that changes in net cloud cover trends are the result of interactions between the dominant factor and multiple secondary factors. Total cloud cover under the AF50 scenario is consistently dominated by TMQ as the primary factor, but its positive contribution is often offset by the opposite effects of RHREFHT and PRECT, especially in terrestrial regions of the northern mid-to-high latitudes, which happen to be the primary regions for grassland- or shrubland-to-forest conversion, whereas competition is weaker over tropical oceanic regions, reflecting the differences of these competing driving factors across different background climate.




(a) ΔTMQ (AF50)
Annual Trend for ΔTMQ (kg/m2/year)
-0.06 0.00 0.06
(b) ΔRHREFHT (AF50)
Annual Trend for ΔRHREFHT (%/year)
-0.15 0.00 0.15
(c) ΔPRECT (AF50)
Annual Trend for ΔPRECT (mm/day/ye
-0.04 0.00 0.04
(d) ΔTREFHTMN (AF50)
Annual Trend for ΔTREFHTMN (K/year)
-0.04 0.00 0.04
(e) ΔTREFHTMX (AF50)
Annual Trend for ΔTREFHTMX (K/year)
-0.07 0.00 0.07
(f) ΔPBLH (AF50)
Annual Trend for ΔPBLH (m/year)
-2.23 0.00 2.23
(g) ΔTREFHT (AF50)
Annual Trend for ΔTREFHT (K/year)
-0.04 0.00 0.04
(h) ΔSHFLX (AF50)
Annual Trend for ΔSHFLX (W/m2/year)
-0.32 0.00 0.32
(i) ΔCAPE (AF50)
Annual Trend for ΔCAPE (J/kg/year)
-0.39 0.00 0.39
60°N
30°N
0°
30°S
60°S
180° 60°W 120°E

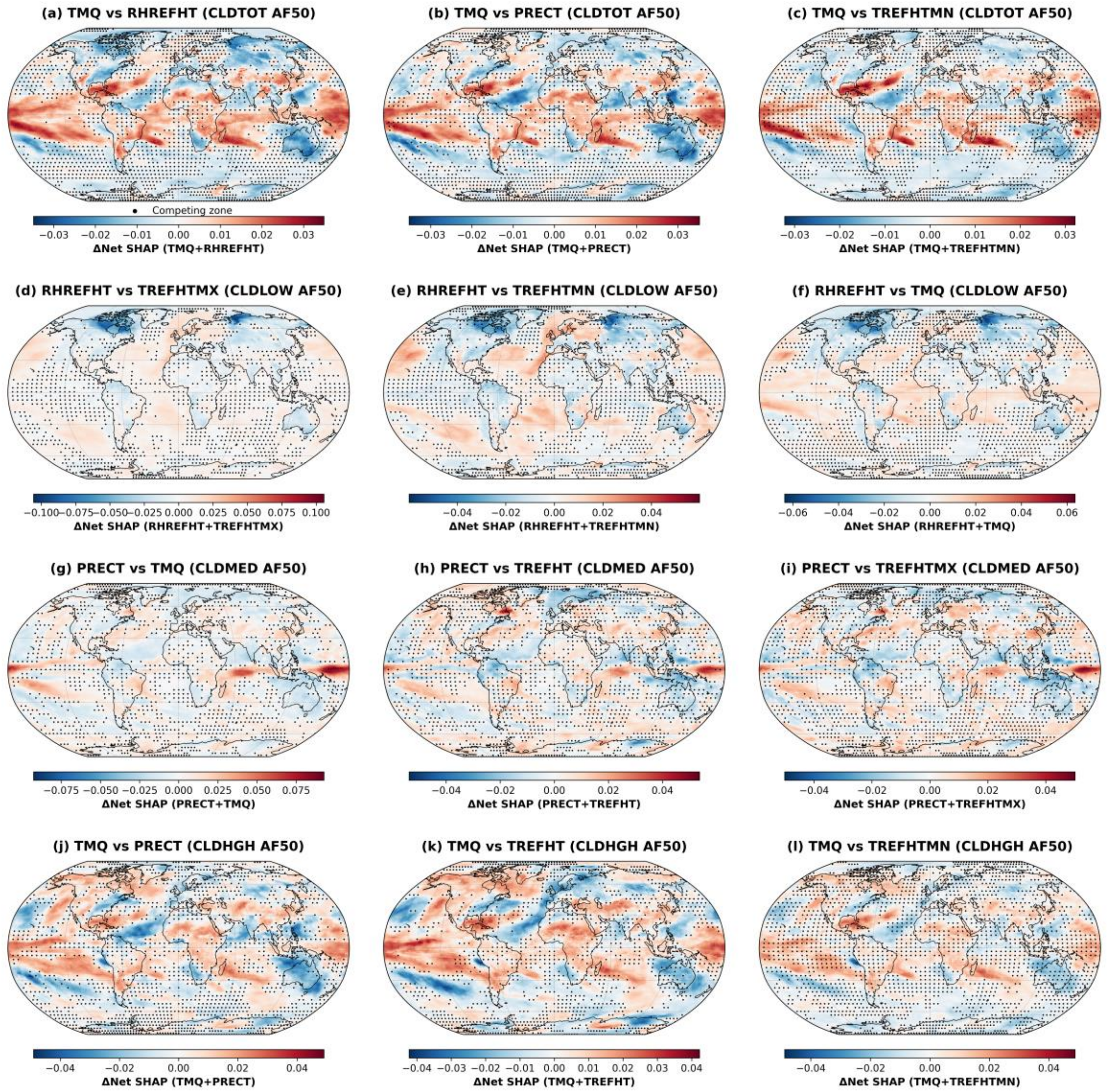


Figure S38. Spatial competitive patterns of key meteorological drivers for cloud cover changes induced by the idealized afforestation (AF50) scenario. Rows from top to bottom correspond to total (CLDTOT), low (CLDLOW), mid (CLDMED), and high (CLDHGH) cloud cover. The background color shading represents the net SHAP contribution (Net SHAP) of the specific paired dominant and secondary drivers. The stippled areas highlight the "competing zones," defined as regions where the two paired drivers have opposite impacts on cloud formation (i.e., one driver promotes cloud cover while the other suppresses it, indicated by opposite signs of their SHAP values).

2. <u>Cloud responses may involve substantial non-local influences, including large-scale circulation adjustments, changes in moisture transport pathways, downwind moisture recycling, and land-ocean thermal contrasts. However, the current mechanism explanations remain largely qualitative and focused primarily on local</u>

<u>thermodynamic effects, without sufficiently disentangling the relative contributions of competing local and remote processes</u>.

We sincerely thank you for this crucial and constructive comment. We fully agree that the cloud response induced by large-scale land-use change involves both local biophysical processes and significant non-local dynamical impacts, such as large-scale circulation adjustments, moisture transport pathways, and downwind moisture recycling. Our initial manuscript mainly focused on local thermodynamic mechanisms (such as albedo-driven warming, boundary layer drying, and decreases in relative humidity and precipitable water); although these local thermodynamic mechanisms are crucial in explaining cloud cover changes, the original draft failed to fully discuss the contributions of local versus remote processes. We reviewed research literature in relevant fields, and in fact, we did not find any suitable diagnostic method to decompose cloud cover changes into local and non-local components as is done for surface temperature changes. In the surface energy balance equation, we can decompose surface temperature into direct (local) and indirect (non-local) physical terms, but there seems to be no method that can decompose cloud cover changes in this way. Therefore, to parse the non-local changes in cloud cover induced by large-scale LUCC, we approached the analysis through another method—namely, by analyzing temperature advection—because temperature is one of the core factors in cloud formation. Through the temperature advection diagnostic method, we can determine which remote regions contribute to warming in a specific area or where local cooling originates remotely; if remote transport brings cooling, it obviously provides a favorable environment of condensational cooling for cloud formation, whereas non-local warming may accelerate cloud cover loss.

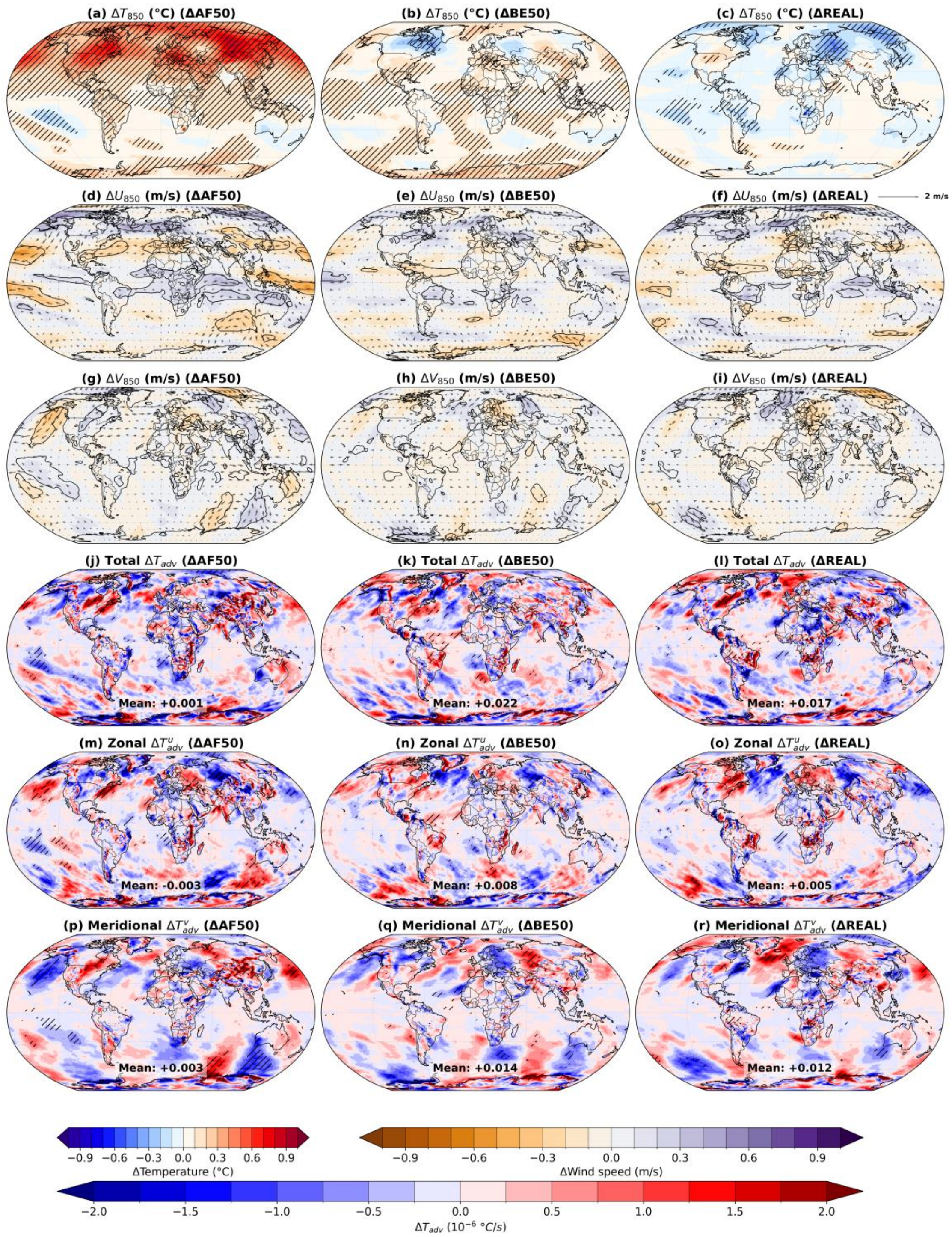


Figure S41. Spatial distributions of lower-tropospheric temperature, horizontal wind, and temperature advection anomalies. Climatological mean differences for the three sensitivity experiments (AF50, BE50, and REAL) relative to the CTL experiment averaged over the 2015–2100 period. Rows from top to bottom display: (1st row) 850 hPa temperature anomalies (ΔT_{850}; units: °C); (2nd row) 850 hPa zonal wind anomalies (ΔU_{850}; units: m/s); (3rd row) 850 hPa meridional wind anomalies

(ΔV_{850}; units: m/s); (4th row) total temperature advection anomalies (Total ΔT_{adv}; units: °C/s); (5th row) zonal component of temperature advection anomalies (Zonal ΔT^{u}_{adv}; units:°C/s); and (6th row) meridional component of temperature advection anomalies (Meridional ΔT^{v}_{adv}; units:°C/s). In the 2nd and 3rd rows, black vectors represent the combined horizontal wind anomaly field, with a reference vector of 2 m/s shown at the top right of panel (f). Statistical significance at the 95% confidence level (p<0.05) is indicated by hatching in the 1st, 4th, 5th, and 6th rows, and by solid black contours in the 2nd and 3rd rows.

3. The study points out that the idealized forest expansion leads to a reduction in low-level clouds and an enhancement in high-level clouds. Some papers the authors cited, such as Teuling et al., 2017 and Duveiller et al., 2021, show an enhancement of low-level clouds due to afforestation. It is recommended that the authors discuss the discrepancies. Here, studies reported that deforestation increases cloud cover may be a good option to discuss, such as Xu et al., 2022 and Leung et al., 2024. The authors should also clarify more precisely: is the observed reduction in cloud cover driven by a local biophysical process, or is it dominated by changes in large-scale atmospheric circulation?

Teuling, A., Taylor, C., Meirink, J. et al. Observational evidence for cloud cover enhancement over western European forests. Nat Commun 8, 14065 (2017). https://doi.org/10.1038/ncomms14065

Duveiller, G., Filipponi, F., Ceglar, A. et al. Revealing the widespread potential of forests to increase low level cloud cover. Nat Commun 12, 4337 (2021). https://doi.org/10.1038/s41467-021-24551-5

Xu, R., Li, Y., Teuling, A.J. et al. Contrasting impacts of forests on cloud cover based on satellite observations. Nat Commun 13, 670 (2022). https://doi.org/10.1038/s41467-022-28161-7

Leung, G. R., Grant, L. D., & van denHeever, S. C. (2024). Deforestation-driven increases in shallow clouds are greatest in drier, low-aerosol regions of Southeast Asia. Geophysical Research Letters, 51, e2023GL107678. https://doi.org/10.1029/2023GL107678.

We are very grateful to you for pointing out this important issue regarding the apparent discrepancy between our simulated cloud responses and previous observational studies. In fact, through past studies, we also know that such contradictory conclusions are very common, especially contradictions between observational and simulation results—so we consider this to be a normal phenomenon. However, we must admit that our previous manuscript indeed did not discuss the comparison with previous studies in depth; for example, studies by Teuling et al. (2017) and Duveiller et al. (2021) reported an increase in low-level cloud cover over forests (especially in Europe), whereas our idealized afforestation experiment (AF50) showed a decrease in low-level and mid-level cloud cover. To address this issue, we have explored this discrepancy in the "Discussion" section and incorporated the studies you suggested referencing.

We believe this discrepancy stems from multiple factors. First, there is a fundamental difference in the spatial scale and homogeneity of the land-use forcing: our AF50 experiment is a large-scale, idealized, and relatively homogeneous afforestation implemented at the continental scale, whereas the studies by Teuling et al. (2017) and Duveiller et al. (2021) were based on existing, patchily distributed forest patterns in temperate Europe. Second, there is a significant dependence on latitude and background climate. In our simulations, the regions with the most pronounced reductions in cloud cover are located in the mid-to-high latitudes of the Northern Hemisphere, where moisture supply is limited and the increase in transpiration brought about by converting grassland to forest is relatively small. In contrast, many European observational studies focus on temperate regions, where the enhancement of evapotranspiration may more effectively increase boundary layer humidity. Third, our results derive from long-term, fully coupled CESM simulations under strong idealized forcing, whereas observational studies reflect current, more slowly changing land-cover patterns (For example, we incorporated realistic afforestation scenarios into our study). Furthermore, regarding whether the cloud cover reduction is explicitly driven by local biophysical processes or primarily influenced by large-scale atmospheric circulation changes, we currently have not found a tool similar to decomposing surface temperature changes into local and non-local physical terms; nevertheless, we are still very grateful to you for providing new inspiration for our future research, namely, considering how to develop equations like those for surface temperature decomposition to directly analyze changes in cloud cover into local and non-local processes. Therefore, we adopted a temperature advection diagnostic method used to parse non-local variations in temperature, which serves to diagnose non-local factors contributing to regional temperature increases; the prerequisite for using this method is that we already know, through the surface energy balance method, that the changes in surface temperature are dominated by non-local processes. Consequently, we can clarify that the cloud cover reduction induced by large-scale LUCC is dominated by non-local atmospheric circulation.

4. The reported increase in high clouds requires a more careful physical explanation, as high clouds are generally considered weakly coupled with local surface perturbations and are primarily controlled by large-scale dynamical and thermodynamic conditions in the upper troposphere. In this context, the manuscript does not sufficiently clarify the pathway through which afforestation can systematically influence high-level cloud fraction. If the simulated high-level cloud response is robust, it likely reflects indirect mechanisms rather than local surface forcing.

We are very grateful for your important comment regarding the high-level cloud cover response. We agree that high-level clouds are typically weakly coupled with local surface perturbations—as mentioned in previous studies (King et al., 2024: King, J. A., Weber, J., Lawrence, P., Roe, S., Swann, A. L. S., and Val Martin, M.: Global and regional hydrological impacts of global forest expansion, Biogeosciences, 21, 3883–3902, https://doi.org/10.5194/bg-21-3883-2024, 2024), and are mainly controlled by large-scale dynamical and thermodynamic conditions in the upper troposphere. We previously attributed the increase in high-level clouds to enhanced moisture supply, a conclusion that mainly derived from the results of interpretable machine learning modeling; this statement may indeed be somewhat oversimplified and failed to fully elucidate its physical mechanism. In order to present our results on the increase in high-level clouds more cautiously, we have refined the explanation of the high-level cloud response mechanism in the revised manuscript. We view the simulated increase in high-level clouds as an indirect response mediated by non-local dynamical adjustment, rather than a direct result of local surface forcing. The core stance we ultimately convey is that the increase in high-level clouds is an indirect, non-local dynamical response, rather than a direct result of local surface forcing.

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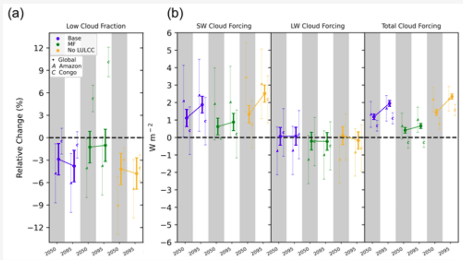

Figure 7 As Fig. 2b but showing differences in cloud cover integrated between 1200–700 hPa **(a)** and differences in clean-sky shortwave cloud radiative forcing, clean-sky longwave cloud radiative forcing, and total clean-sky cloud radiative forcing **(b)**.

5. <u>This study relies on CESM simulations; however, cloud representation remains one of the largest sources of uncertainty in contemporary climate models. It would be valuable to acknowledge that uncertainties in cloud parameterizations may affect both the magnitude and even the sign of simulated cloud feedback.</u>

We are very grateful for your valuable comments on CESM model uncertainty. In Earth system models, the representation of cloud processes remains one of the largest sources of uncertainty in the current generation of climate models, which is also the primary reason why models maintain high equilibrium climate sensitivity, and uncertainties in cloud parameterization schemes can affect both the magnitude and the sign (positive or negative direction) of the simulated cloud response. Although CAM6 used in our CESM simulations adopts improved cloud microphysics (the Morrison-Gettelman 2 scheme, MG2) and turbulence parameterization schemes compared to earlier versions, we recognize that caution should be exercised regarding the results from a single model. The cloud cover trends and quantitative values of cloud radiative effects reported in this study are subject to uncertainties arising from cloud parameterization schemes. Future multi-model intercomparisons or perturbed parameter ensemble simulations will help to further evaluate the robustness of these findings. We have added relevant discussions in the manuscript to provide a more comprehensive and objective perspective on the research results.

Specific comments

6. Lines 88-93: It is recommended to discuss recent studies, for example, Tom and Graham, 2026 and Luo et al., 2024, that quantify the relationship between forest loss and changes in cloud albedo, as these are directly relevant to the current study.

Tom Dror, Graham Feingold, Amazon forest loss: An all-sky biophysical top-of-atmosphere cooling feedback. Science 392, 429-432 (2026). DOI:10.1126/science.adz8296

Luo, H., Quaas, J. & Han, Y. Decreased cloud cover partially offsets the cooling effects of surface albedo change due to deforestation. Nat Commun 15, 7345 (2024). https://doi.org/10.1038/s41467-024-51783-y

We sincerely thank the reviewer for recommending these two highly relevant and insightful studies (Dror & Feingold, 2026; Luo et al., 2024). We completely agree that quantifying the interplay between land cover change, surface albedo, and cloud radiative/albedo feedback is crucial for contextualizing our work.

In accordance with the your valuable suggestion, we have incorporated a detailed discussion of these recent findings into the Introduction (Lines 88-93) to strengthen the background logic regarding cloud-mediated biophysical feedback. Furthermore, we discuss the implications of our findings for recent research; this is indeed closely related to the study, and we highlight the role of cloud feedback in the context of large-scale land-use changes. We believe that policymakers should give serious consideration to this feedback when developing future nature-based solutions (Nbs)—treating it with the same level of importance as albedo, as suggested by previous studies (Wang et al., 2024: K. Wang, D. Zhao, Y. Zhu, X. Gao, S. Deng, Z. Chen, S. Wang, Y. Cui, Albedo-dominated biogeophysical warming effects induced by vegetation restoration on the Loess Plateau, China. Ecol. Indic. 154, 110690). In fact, we have also recently paid attention to the study by Tom Dror and Graham Feingold (2026). Before this study was published, we were already carrying out our own research work, but ultimately, we both convey a core idea: under large-scale land use change (such as the very popular afforestation), it is necessary to incorporate cloud-mediated biophysical feedback into future schemes for addressing climate warming.

7. <u>Line 227: A wording issue here. Only the CRE in the atmosphere evaluates the influence of clouds on the atmosphere. TOA CRE measures the influence on the Earth-atmosphere system, while surface CRE measures the influence only on the surface</u>.

We sincerely thank the reviewer for pointing out this conceptual precision in wording. We completely agree with the reviewer's distinction. We have revised the sentence in the manuscript to accurately specify the distinct physical domains evaluated by CRE at the top of the atmosphere (TOA), within the atmosphere, and at the surface, respectively. Additionally, we have added the results for TOA CRE and included them in the supplementary materials (Figure S20, Figure S21).

8. <u>Line 230: Change “LwCRE” to “lwCRE”.</u>

We greatly appreciate your careful review; we have corrected the issue in the revised version.

9. <u>Line 231: Change “SwCRE” to “swCRE”.</u>

We greatly appreciate your careful review; we have corrected the issue in the revised version.

10. <u>Line 272: Change “LW” to “LW↓”. Change “from the surface” to “at the surface”.</u>

We greatly appreciate your careful review; we have corrected the issue in the revised version.

11. <u>Line 302: 1037 should be 0.1037.</u>

We are very grateful for your careful checking. The sentence in the original text is “While CLDTOT exhibited a moderate negative trend in both CTL (-0.0083±1037%/year)…”. Indeed, the correct value here should be 0.1037, please forgive our carelessness. At the same time, we checked the calculation code and found that a calculation error existed in the old version of the code, resulting in a relatively large calculation error. In the old code, the error of the *absolute value* of cloud cover at the first timestamp was mistakenly represented as the error of the time-series *trend* over the entire simulation period. In the new version, we have corrected it.

```python
import xarray as xr
import matplotlib.pyplot as plt
import numpy as np
import scipy.stats as stats
import cmaps
import matplotlib.ticker as mticker
from matplotlib.colors import BoundaryNorm
from matplotlib.lines import Line2D
import matplotlib.patches as mpatches

# ====================== 1. Trend calc ======================
def calculate_trends(data):
    years = np.arange(len(data))
    slope, intercept, r_value, p_value, std_err = stats.linregress(years, data)
    return slope, intercept, r_value, p_value

# ====================== 2. Bootstrap 95% CI ======================
def calc_bootstrap_ci(years, data, n_boot=1000, ci=95):
    x = np.arange(len(years))
    slope, intercept, _, _, _ = stats.linregress(x, data)
    fitted = intercept + slope * x
    resid = data - fitted

    boot_slopes = []
    boot_intercepts = []
    rng = np.random.default_rng()
    for _ in range(n_boot):
        boot_resid = rng.choice(resid, size=len(resid), replace=True)
        boot_y = fitted + boot_resid
        s, i, _, _, _ = stats.linregress(x, boot_y)
        boot_slopes.append(s)
        boot_intercepts.append(i)


    boot_slopes = np.array(boot_slopes)[:, np.newaxis]          # (n_boot, 1)
    boot_intercepts = np.array(boot_intercepts)[:, np.newaxis]  # (n_boot, 1)
    boot_trends = boot_slopes * x + boot_intercepts            # (n_boot, n_years)
    # -------------------------------

    lower = np.percentile(boot_trends, (100 - ci) / 2, axis=0)
    upper = np.percentile(boot_trends, 100 - (100 - ci) / 2, axis=0)
    return lower, upper

# ====================== 3. File path ======================
base_path_cldtot = 'C:/JupyterXPC/Cloud_Analysis_AF_BE_Cloud_Trend/CLDTOT/'
cldtot_files = [
    base_path_cldtot + 'merged_CLDTOT_CTL_h0.nc',
    base_path_cldtot + 'merged_CLDTOT_AF50_h0.nc',
    base_path_cldtot + 'merged_CLDTOT_BE50_h0.nc',
    base_path_cldtot + 'merged_CLDTOT_REAL_h0.nc'
]
titles = [
    '(a) Annual CLDTOT in CTL',
    '(b) Annual CLDTOT in AF50',
    '(c) Annual CLDTOT in BE50',
    '(d) Annual CLDTOT in REAL'
]
```

OLD

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import scipy.stats as stats
import cmaps
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    resid = data - fitted

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    boot_intercepts = []
    rng = np.random.default_rng()
    for _ in range(n_boot):
        boot_resid = rng.choice(resid, size=len(resid), replace=True)
        boot_y = fitted + boot_resid
        s, i, _, _, _ = stats.linregress(x, boot_y)
        boot_slopes.append(s)
        boot_intercepts.append(i)

    boot_slopes = np.array(boot_slopes)[:, np.newaxis]          # (n_boot, 1)
    boot_intercepts = np.array(boot_intercepts)[:, np.newaxis]  # (n_boot, 1)
    boot_trends = boot_slopes * x + boot_intercepts            # (n_boot, n_years)


    lower_line = np.percentile(boot_trends, (100 - ci) / 2, axis=0)
    upper_line = np.percentile(boot_trends, 100 - (100 - ci) / 2, axis=0)

    slope_lower = np.percentile(boot_slopes, (100 - ci) / 2)
    slope_upper = np.percentile(boot_slopes, 100 - (100 - ci) / 2)

    return lower_line, upper_line, slope_lower, slope_upper

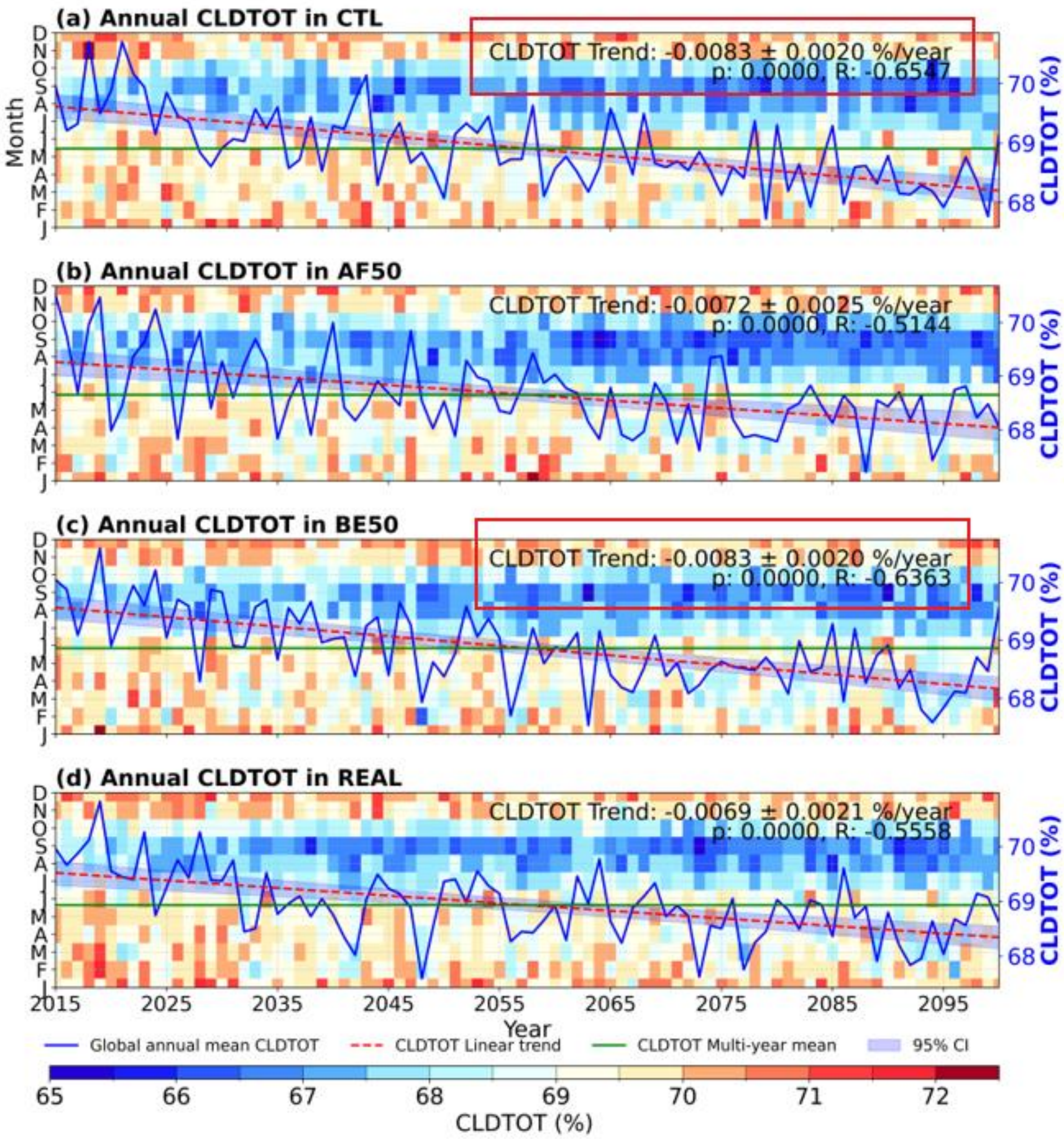
# ====================== 3. File path ======================
base_path_cldtot = 'C:/JupyterXPC/Cloud_Analysis_AF_BE_Cloud_Trend/CLDTOT/'
cldtot_files = [
    base_path_cldtot + 'merged_CLDTOT_CTL_h0.nc',
    base_path_cldtot + 'merged_CLDTOT_AF50_h0.nc',
    base_path_cldtot + 'merged_CLDTOT_BE50_h0.nc',
    base_path_cldtot + 'merged_CLDTOT_REAL_h0.nc'
]
titles = [
    '(a) Annual CLDTOT in CTL',
    '(b) Annual CLDTOT in AF50',
    '(c) Annual CLDTOT in BE50',
    '(d) Annual CLDTOT in REAL'
]
```

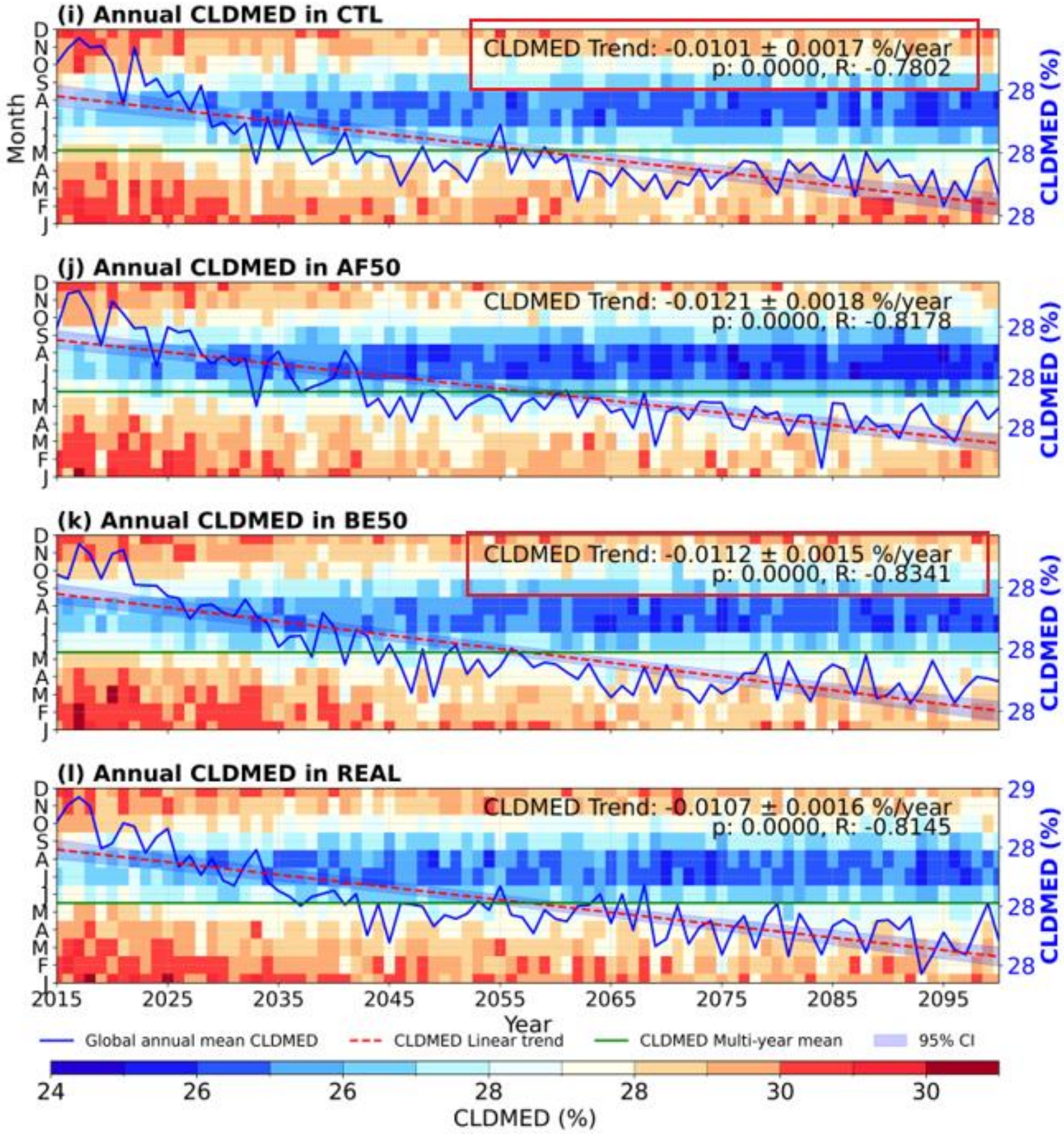
NEW

12. <u>Line 303: BE50 and CTL have the same decline trend for CLDTOT.</u>

We are very grateful for your careful checking. We checked the code for reading the data and plotting and have ensured that this is correct. In fact, although the trend is the same when retaining four decimal places, the regression coefficient (R) is very different, where R in CTL is -0.6547, while in BE50 it is -0.6363, which indirectly proves that the plotted results are correct. As for why the trends are the same, this may be because the expansion of bioenergy has a smaller impact on the trend of total cloud cover, but has a larger overall negative impact on low-and-middle-level clouds and a larger positive impact on the trend of high-level clouds, ultimately resulting in mutual compensation. For example, in the low-level cloud response, the trend in CTL is -

0.0153±0.0030%/year, while in BE50 it is -0.0157±0.0032%/year. The performance in mid-level clouds shows an even larger difference; for the response of mid-level clouds, the trend in the CTL simulation is -0.0101±0.0017%/year, while in BE50 it is -0.0112±0.0015%/year. For high-level clouds, the performance is that BE50 induces an increase in the high-level cloud trend. Therefore, the final result may be reflected in very little change in the trend of total cloud cover, but mainly imposing an impact of accelerated loss on mid-level clouds.





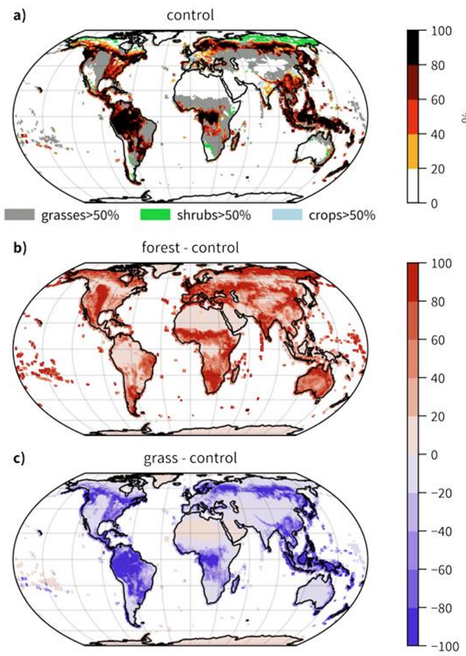
13. <u>Line 314: Does "downward response" refer to a "decreasing trend"?</u>

Yes, it conveys the same meaning: the LUCC-induced decrease or downward trend in cloud cover.

14. <u>Fig. S23: Could the authors show the differences between the experiments and the original data? It is currently difficult to identify the tree-cover changes from the maps. In particular, it is unclear whether the REAL and AF50 experiments exhibit distinct changes across different latitudes. Since afforestation at different latitudes can lead to substantially different albedo and surface energy responses, a clearer comparison would help readers better interpret the results.</u>

We deeply apologize for failing to show the comparison of differences between the sensitivity experiment data and the original data in the original manuscript; this was indeed where our consideration was not thorough enough when plotting. At the same time, we are very grateful for your valuable comments. In order to see the regions of forest or bioenergy crop expansion more intuitively, similar to that in the previous study by Portmann et al., 2022 (https://static-content.springer.com/esm/art%3A10.1038%2Fs41467-022-33279-9/MediaObjects/41467_2022_33279_MOESM1_ESM.pdf), we decided to adopt your valuable advice, but on the basis of retaining the original figure (Figure S7), we supplemented a difference map (Figure S8). Meanwhile, we also supplemented time-series plots of area changes for different land use and land cover (Figure S9).

Portmann et al., 2022



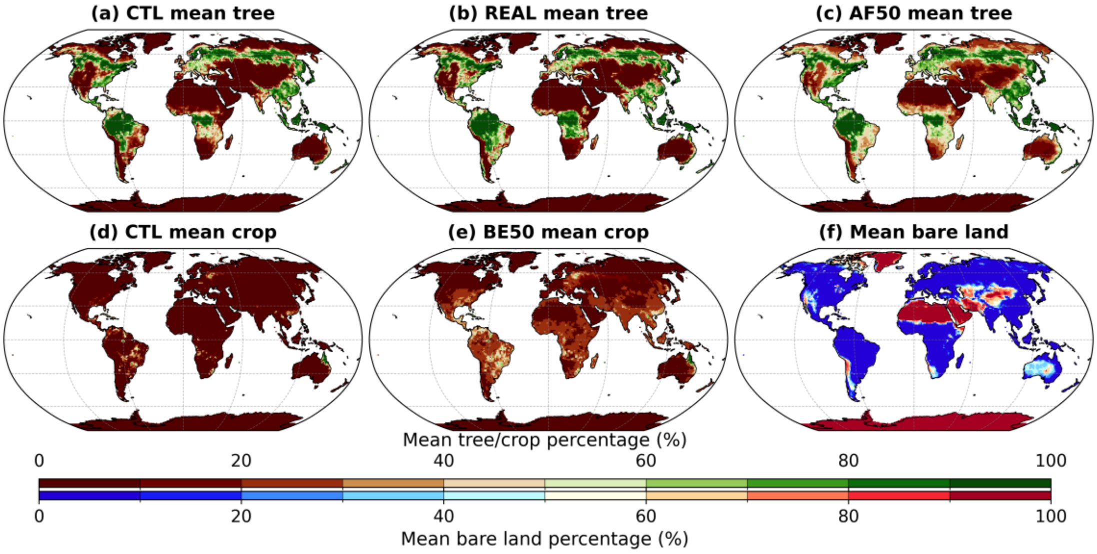


Figure S7. Spatial distribution of forest and bioenergy crop under different land use and land cover scenarios. (a and d) Spatial distribution of forests and bioenergy crops in the original land-use data (CTL run). (b) Spatial distribution of forests in the realistic afforestation scenario (REAL). (c and e) Spatial distribution of forests and bioenergy crops in the 50% idealized linear afforestation (AF50) and bioenergy crop expansion (BE50) scenarios. (f) Spatial distribution of bare land.

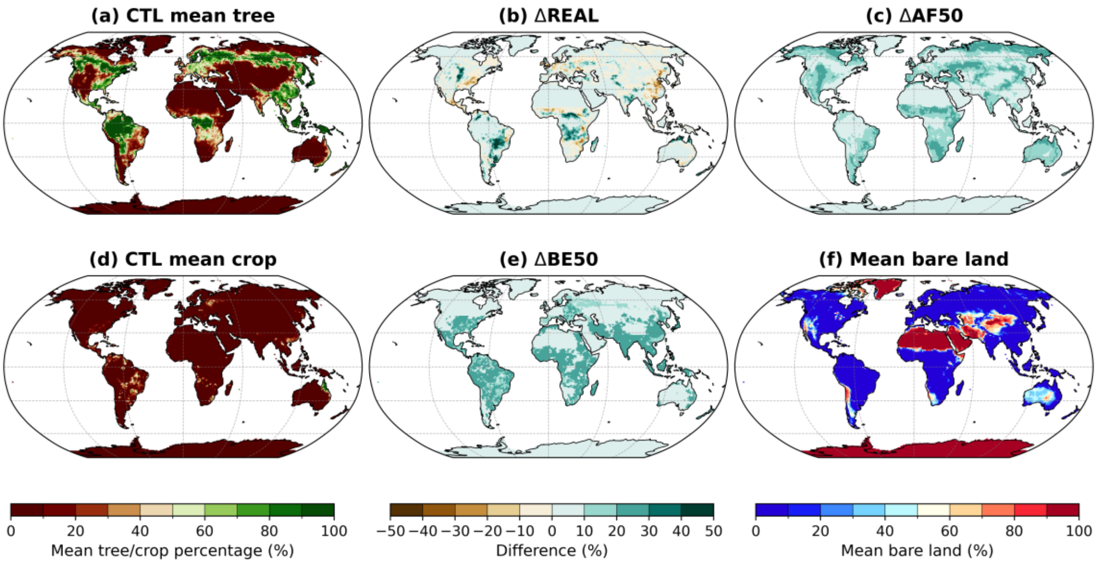


Figure S8. Spatial distribution of mean tree, crop, and bare land percentages and their differences under different land-use scenarios averaged over 2015-2100. (a and d) Mean tree and crop percentage in the CTL scenario. (b, c) Differences in tree percentage for the REAL and AF50 scenarios relative to CTL (ΔREAL and ΔAF50, respectively). (e) Difference in crop percentage for the BE50 scenario relative to CTL (ΔBE50). (f) Mean bare land percentage. The left and right color bars indicate the absolute percentages for vegetation (a, d) and bare land (f), respectively, whereas the middle diverging color bar represents the percentage differences between the forest and bioenergy expansion experiments and CTL scenario.

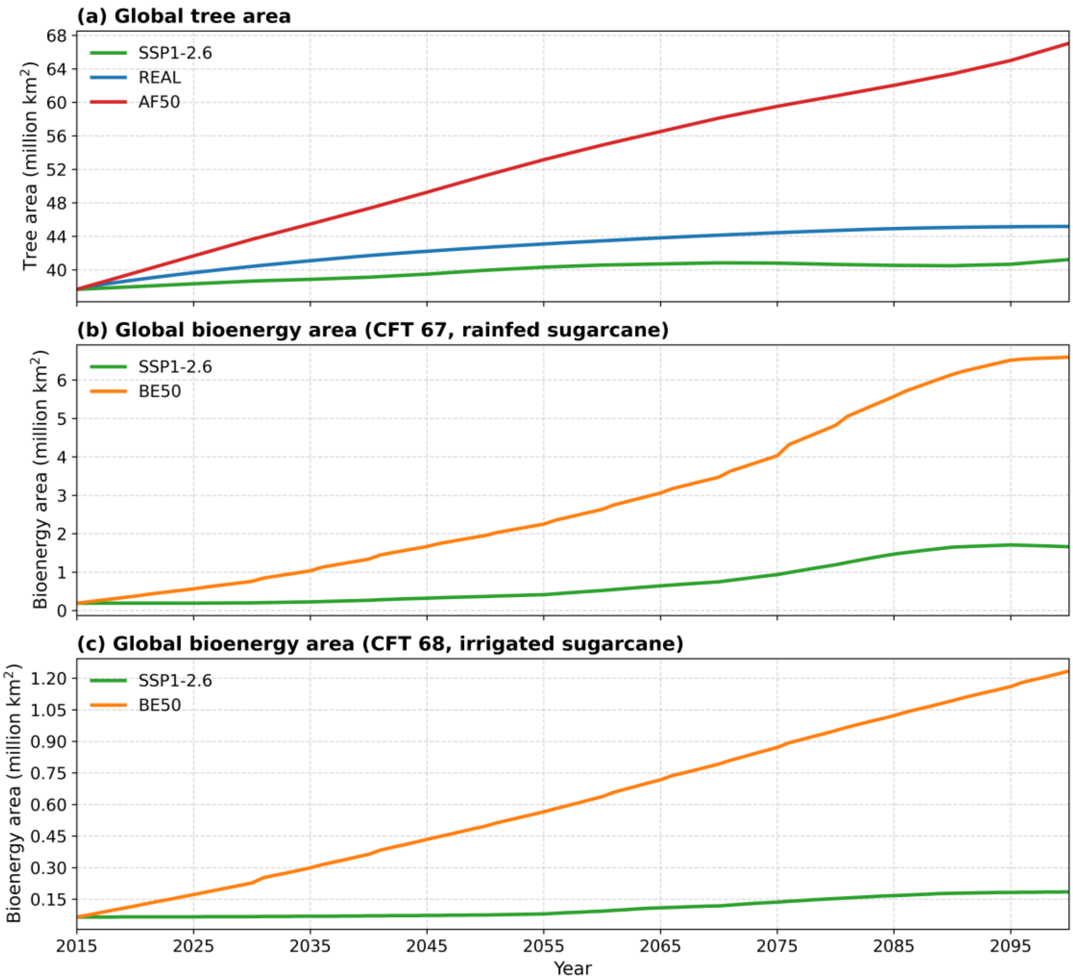
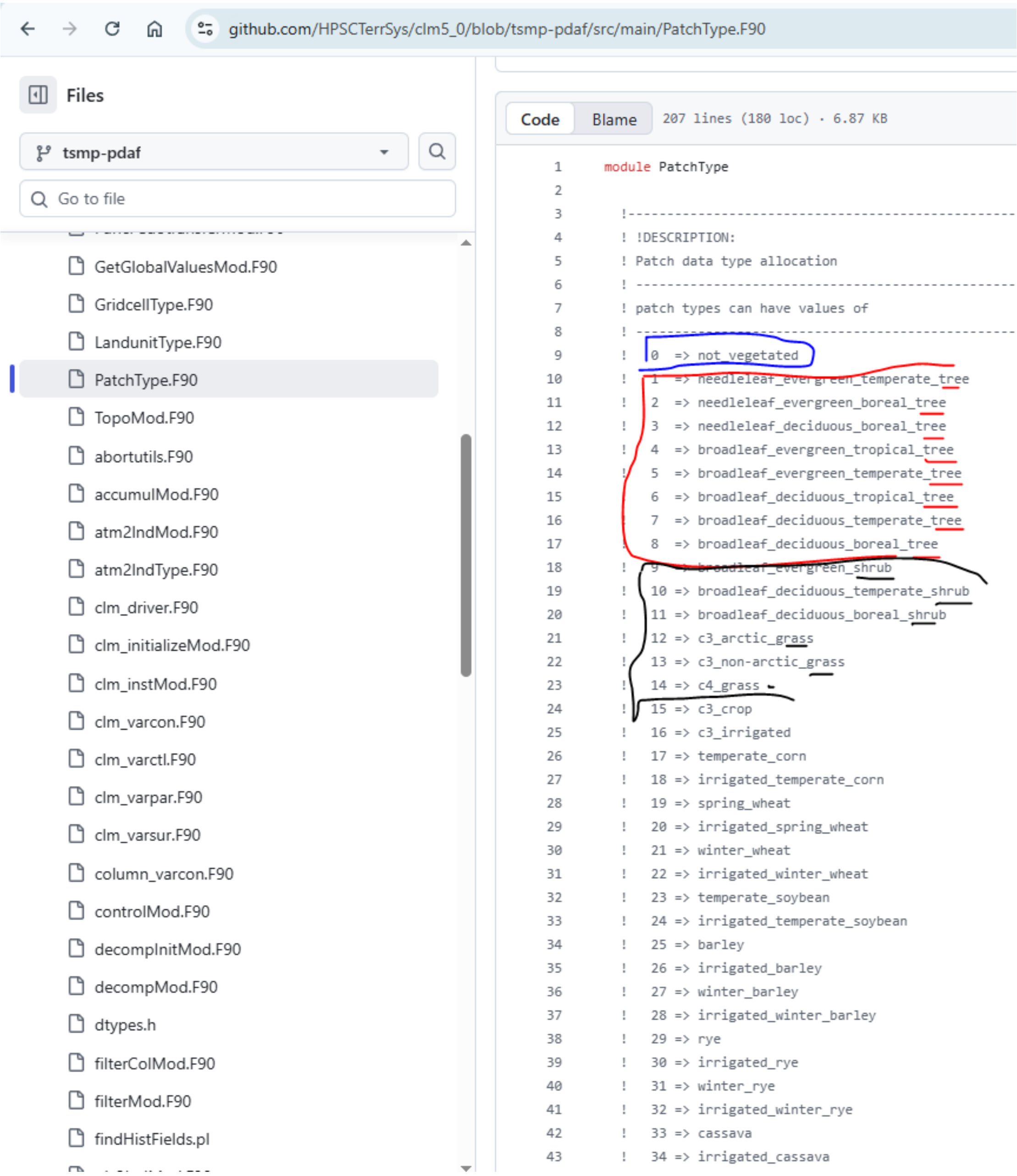
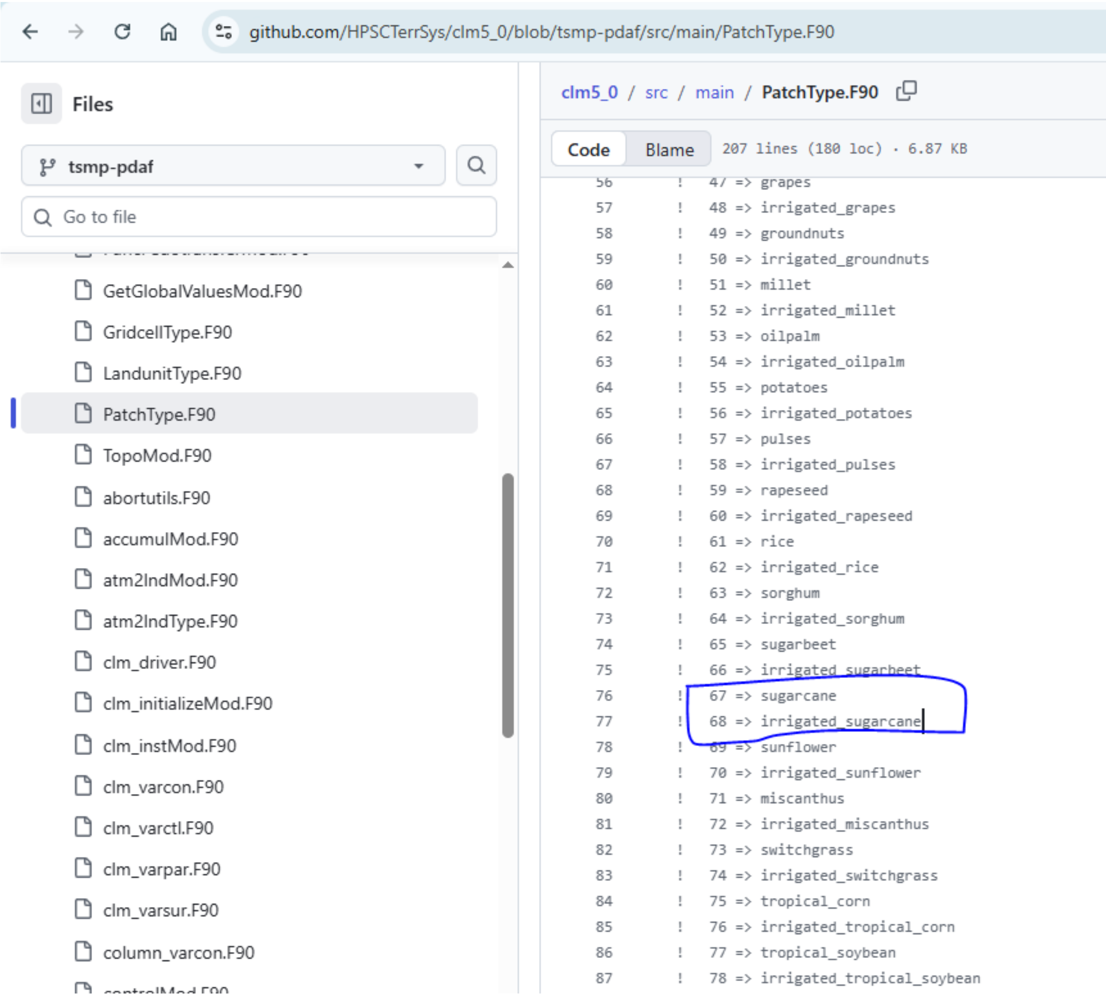
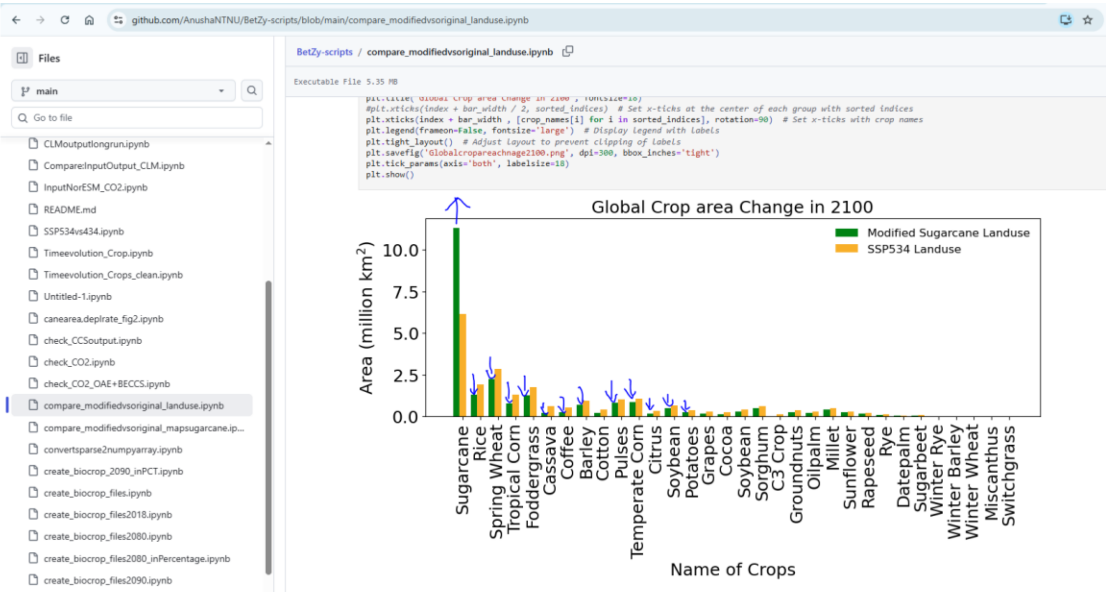


Figure S9. Area change of forest and bioenergy crops under different land-use scenarios (unit: million km^2). In the Community Land Model Version 5 (CLM5), indices 67 and 68 correspond to rainfed and irrigated sugarcane, respectively, among bioenergy crops.

In CLM5, sugarcane is subdivided into rainfed sugarcane and irrigated sugarcane, with indices of 67 and 68, respectively. While index No. 0 is bare ground; Nos. 1–8 are trees; Nos. 9–14 are shrubs and grasslands, which is exactly the land source for the idealized forest expansion in our study, and this forest expansion complies with FAO's strict definition of afforestation. In the bioenergy crop expansion simulation experiment, the land for the expansion of sugarcane (rainfed and irrigated sugarcane) comes from the land of the remaining crops, as demonstrated by other researchers (https://github.com/AnushaNTNU/BetZy-scripts/blob/main/compare_modifiedvsoriginal_landuse.ipynb), which is a trade-off state to ensure area conservation. Just as the land used in idealized afforestation comes from grasslands or shrubs, which is also to ensure area conservation, CESM strictly requires that changes in land types at the sub-grid level (Patch-level) must ultimately sum to 100% at the grid level (Grid-level).







Finally, we would like to take this opportunity to express our sincere gratitude to the editor and reviewers of Atmospheric Chemistry and Physics (ACP) for their valuable time, effort, and highly constructive feedback in improving our work. Without a doubt, these comments have significantly enhanced the objectivity, scientific rigor, and linguistic precision of our manuscript, as well as the overall clarity of our figures. Furthermore, it has been a privilege to engage in this meaningful scientific dialogue with the reviewers, which has further stimulated our research interest in the climate and ecological consequences of large-scale land-use change, particularly afforestation practices, which are currently, and will likely continue to be, widely pursued. We must emphasize that evaluating the potential climate consequences of highly favored afforestation efforts necessitates taking cloud feedback processes into account (for instance, in our simulations, even realistic afforestation induced a significant increasing trend in high-level clouds, which exert positive radiative forcing and can induce a top-of-atmosphere energy imbalance; conversely, an increasing trend in low-level cloud cover might lead to the overly optimistic belief that realistic afforestation consistently yields cooling), just as previous studies have highlighted the equal importance of accounting for surface albedo.