

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 ($\sim 5\%$) 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 ($\sim 0.2\%$) 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.

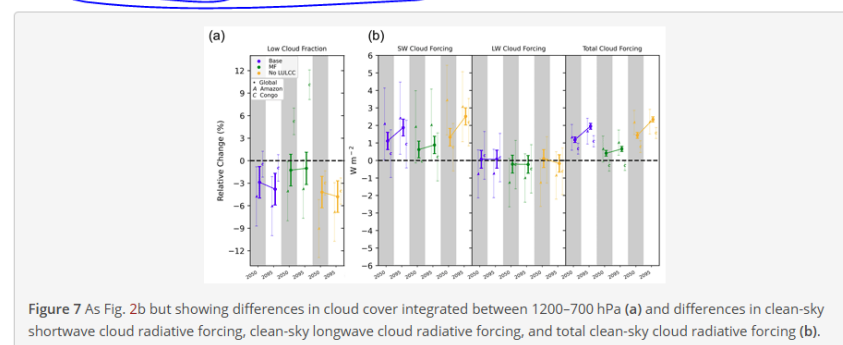
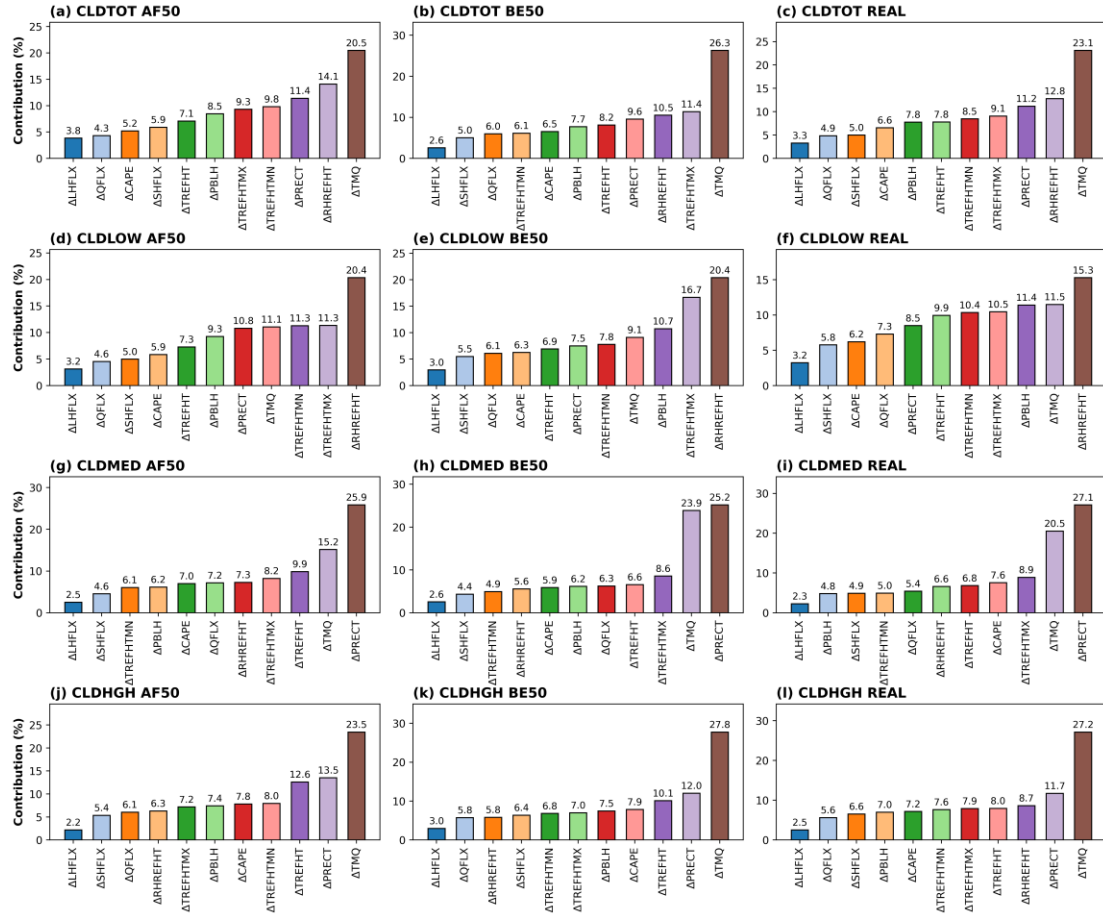
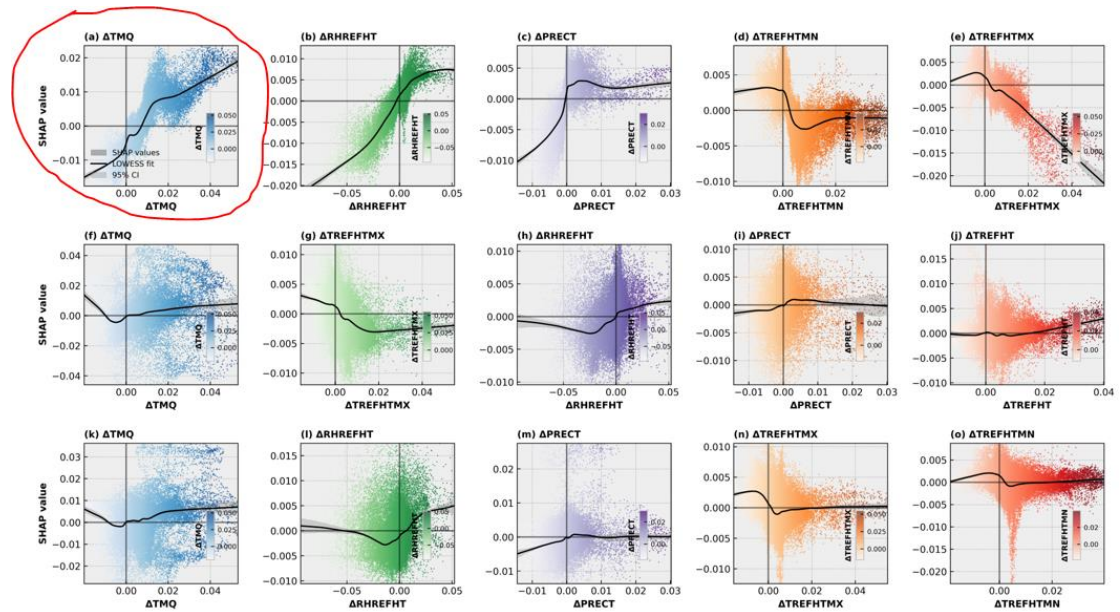


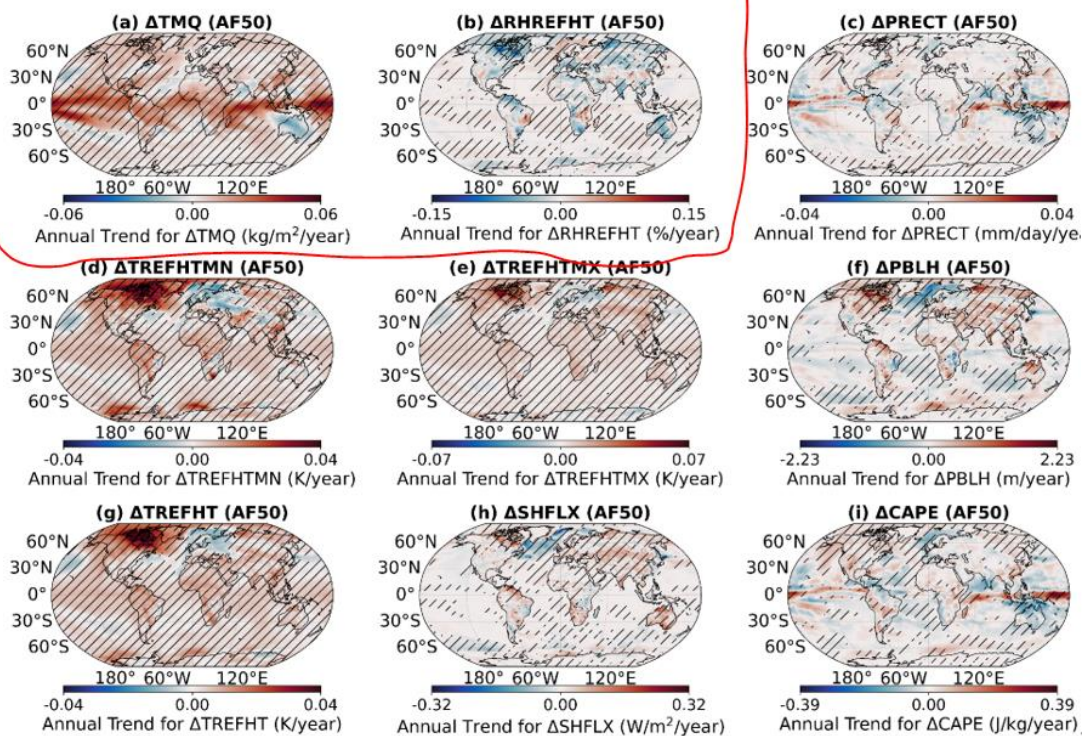
Figure 7 As Fig. 2b but showing differences in cloud cover integrated between 1200–700 hPa (a) and differences in clean-sky shortwave cloud radiative forcing, clean-sky longwave cloud radiative forcing, and total clean-sky cloud radiative forcing (b).



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.





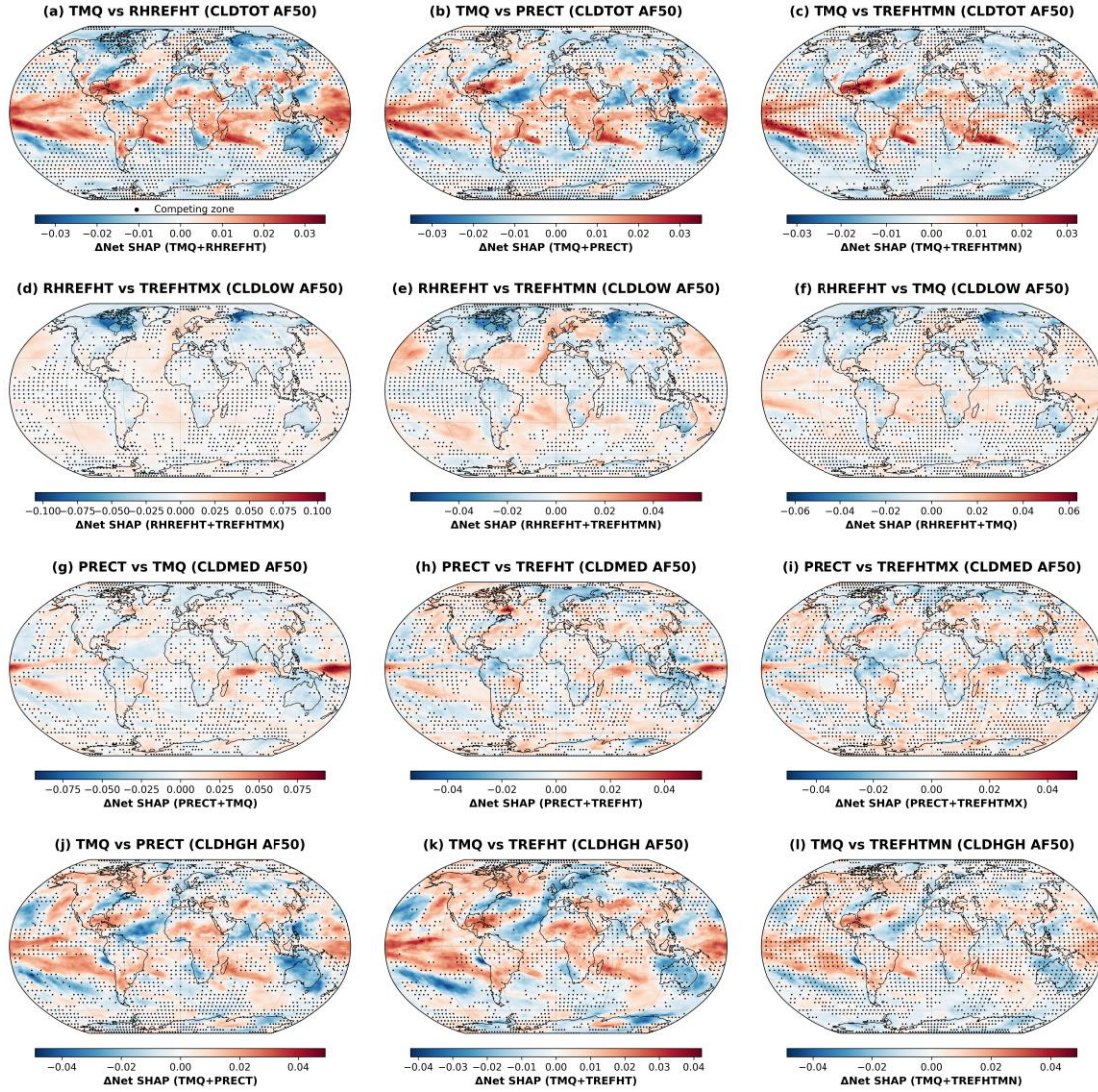


Figure S38. Spatial competitive patterns of key meteorological drivers for cloud cover changes induced by the idealized afforestation (AF50) scenario. Rows from top to bottom correspond to total (CLDTOT), low (CLDLOW), mid (CLDMED), and high (CLDHGH) cloud cover. The background color shading represents 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. 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

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

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.

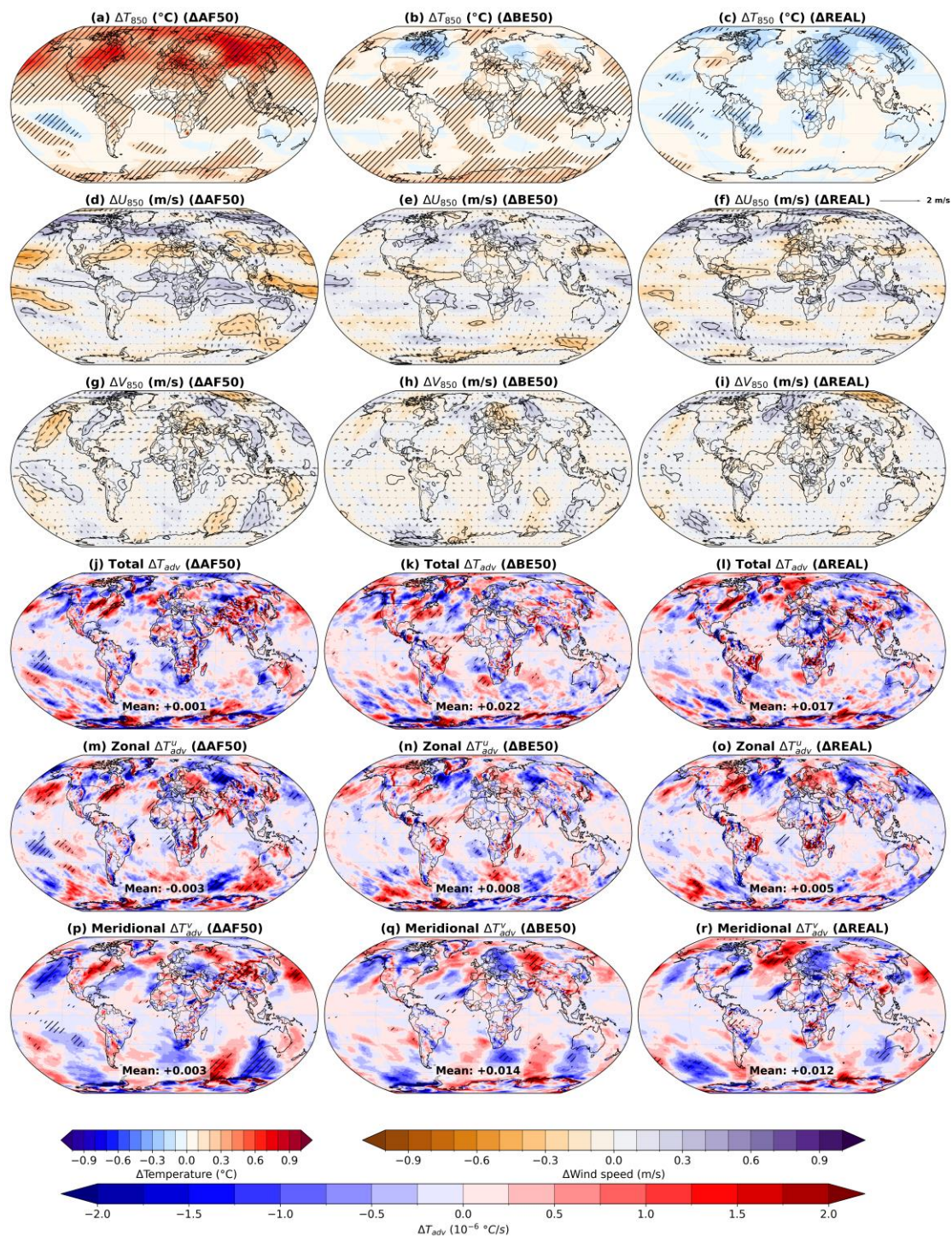


Figure S41. Spatial distributions of lower-tropospheric temperature, horizontal wind, and temperature advection anomalies. Climatological mean differences for the three sensitivity experiments (AF50, BE50, and REAL) relative to the CTL experiment averaged over the 2015–2100 period. Rows from top to bottom 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: $^{\circ}\text{C/s}$); (5th row) zonal component of temperature advection anomalies (Zonal ΔT_{adv}^u ; units: $^{\circ}\text{C/s}$); and (6th row) meridional component of temperature advection anomalies (Meridional ΔT_{adv}^v ; units: $^{\circ}\text{C/s}$). 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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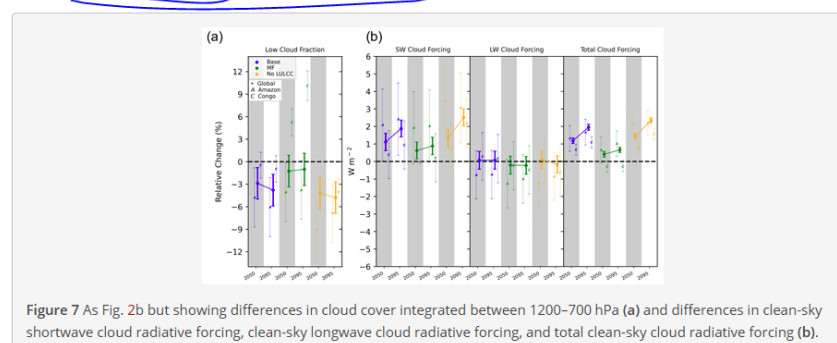


Figure 7 As Fig. 2b but showing differences in cloud cover integrated between 1200–700 hPa (a) and differences in clean-sky shortwave cloud radiative forcing, clean-sky longwave cloud radiative forcing, and total clean-sky cloud radiative forcing (b).

5. 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.

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. 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.

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. Line 230: Change “LwCRE” to “lwCRE”.

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

9. Line 231: Change “SwCRE” to “swCRE”.

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

10. Line 272: Change “LW” to “LW↓”. Change “from the surface” to “at the surface”.

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

11. Line 302: 1037 should be 0.1037.

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 ($-0.0083 \pm 1037\%/year$)...”. 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.

```

1  import xarray as xr
2  import matplotlib.pyplot as plt
3  import numpy as np
4  import scipy.stats as stats
5  import cmaps
6  import matplotlib.ticker as mticker
7  from matplotlib.colors import BoundaryNorm
8  from matplotlib.lines import Line2D
9  import matplotlib.patches as mpatches
10
11 # ===== 1. Trend calc =====
12 def calculate_trends(data):
13     years = np.arange(len(data))
14     slope, intercept, r_value, p_value, std_err = stats.linregress(years, data)
15     return slope, intercept, r_value, p_value
16
17 # ===== 2. Bootstrap 95% CI =====
18 def calc_bootstrap_ci(years, data, n_boot=1000, ci=95):
19     x = np.arange(len(years))
20     slope, intercept, _, _ = stats.linregress(x, data)
21     fitted = intercept + slope * x
22     resid = data - fitted
23
24     boot_slopes = []
25     boot_intercepts = []
26     rng = np.random.default_rng()
27     for _ in range(n_boot):
28         boot_resid = rng.choice(resid, size=len(resid), replace=True)
29         boot_y = fitted + boot_resid
30         s, i, _, _ = stats.linregress(x, boot_y)
31         boot_slopes.append(s)
32         boot_intercepts.append(i)
33
34     boot_slopes = np.array(boot_slopes)[: , np.newaxis]
35     boot_intercepts = np.array(boot_intercepts)[: , np.newaxis]
36     boot_trends = boot_slopes * x + boot_intercepts
37     # (n_boot, 1)
38     # (n_boot, 1)
39     # (n_boot, n_years)
40
41     lower = np.percentile(boot_trends, (100 - ci) / 2, axis=0)
42     upper = np.percentile(boot_trends, 100 - (100 - ci) / 2, axis=0)
43     return lower, upper
44
45 # ===== 3. File path =====
46 base_path_cldtot = 'C:/JupyterXPC/Cloud_Analysis_AF_BE_Cloud_Trend/CLDTOT/'
47 cldtot_files = [
48     base_path_cldtot + 'merged_CLDTOT_CTL_h0.nc',
49     base_path_cldtot + 'merged_CLDTOT_AF50_h0.nc',
50     base_path_cldtot + 'merged_CLDTOT_BE50_h0.nc',
51     base_path_cldtot + 'merged_CLDTOT_REAL_h0.nc'
52 ]
53 titles = [
54     '(a) Annual CLDTOT in CTL',
55     '(b) Annual CLDTOT in AF50',
56     '(c) Annual CLDTOT in BE50',
57     '(d) Annual CLDTOT in REAL'
58 ]

```

```

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2  import matplotlib.pyplot as plt
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6  import matplotlib.ticker as mticker
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24
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26     boot_intercepts = []
27     rng = np.random.default_rng()
28     for _ in range(n_boot):
29         boot_resid = rng.choice(resid, size=len(resid), replace=True)
30         boot_y = fitted + boot_resid
31         s, i, _, _ = stats.linregress(x, boot_y)
32         boot_slopes.append(s)
33         boot_intercepts.append(i)
34
35     boot_slopes = np.array(boot_slopes)[:, np.newaxis] # (n_boot, 1)
36     boot_intercepts = np.array(boot_intercepts)[:, np.newaxis] # (n_boot, 1)
37     boot_trends = boot_slopes * x + boot_intercepts # (n_boot, n_years)
38
39     lower_line = np.percentile(boot_trends, (100 - ci) / 2, axis=0)
40     upper_line = np.percentile(boot_trends, 100 - (100 - ci) / 2, axis=0)
41
42     slope_lower = np.percentile(boot_slopes, (100 - ci) / 2)
43     slope_upper = np.percentile(boot_slopes, 100 - (100 - ci) / 2)
44
45     return lower_line, upper_line, slope_lower, slope_upper
46
47 # ===== 3. File path =====
48 base_path_cldtot = 'C:/JupyterXPC/Cloud_Analysis_AF_BE_Cloud_Trend/CLDTOT/'
49 cldtot_files = [
50     base_path_cldtot + 'merged_CLDTOT_CTL_h0.nc',
51     base_path_cldtot + 'merged_CLDTOT_AF50_h0.nc',
52     base_path_cldtot + 'merged_CLDTOT_BE50_h0.nc',
53     base_path_cldtot + 'merged_CLDTOT_REAL_h0.nc'
54 ]
55
56 titles = [
57     '(a) Annual CLDTOT in CTL',
58     '(b) Annual CLDTOT in AF50',
59     '(c) Annual CLDTOT in BE50',
60     '(d) Annual CLDTOT in REAL'
61 ]

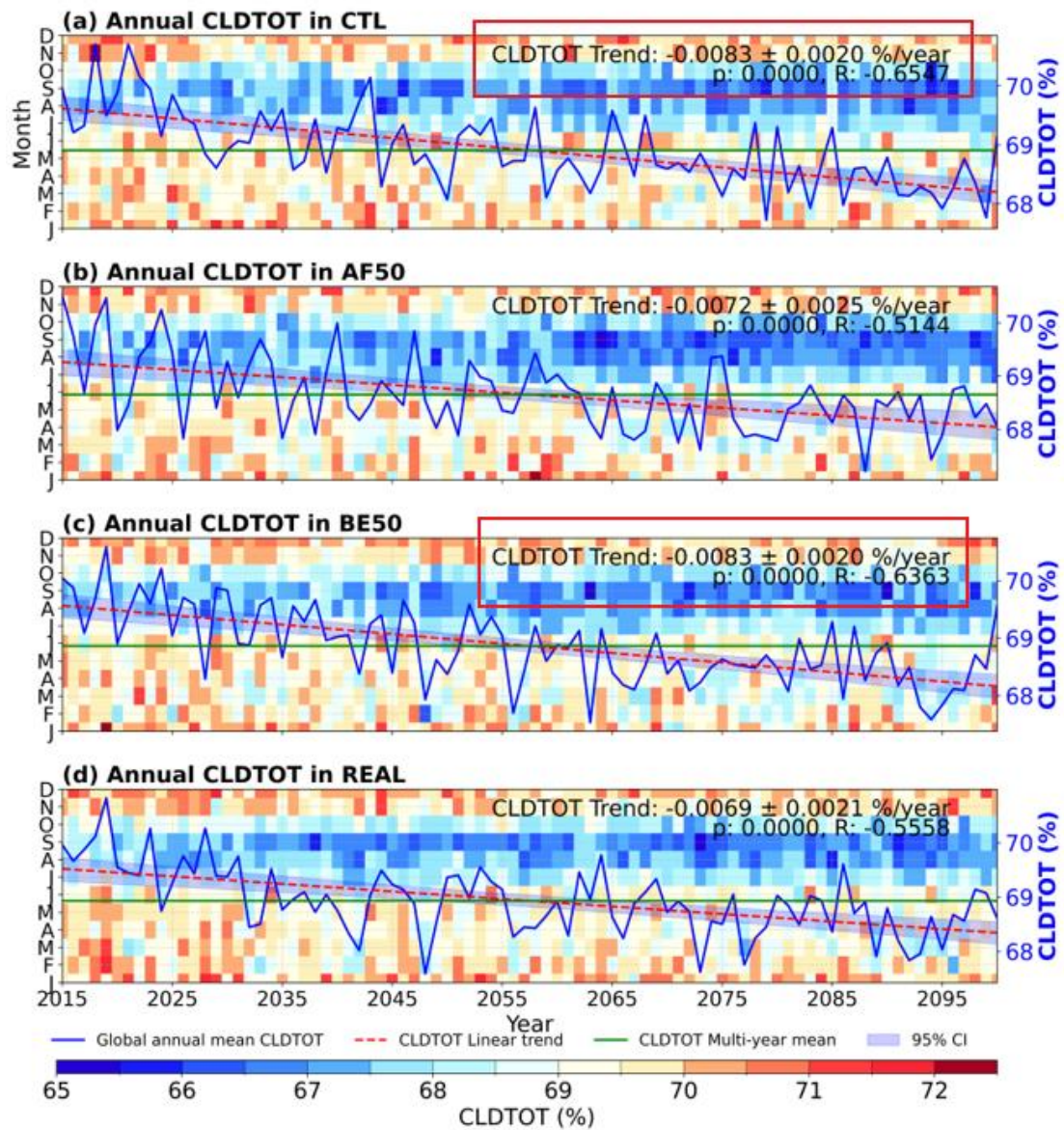
```

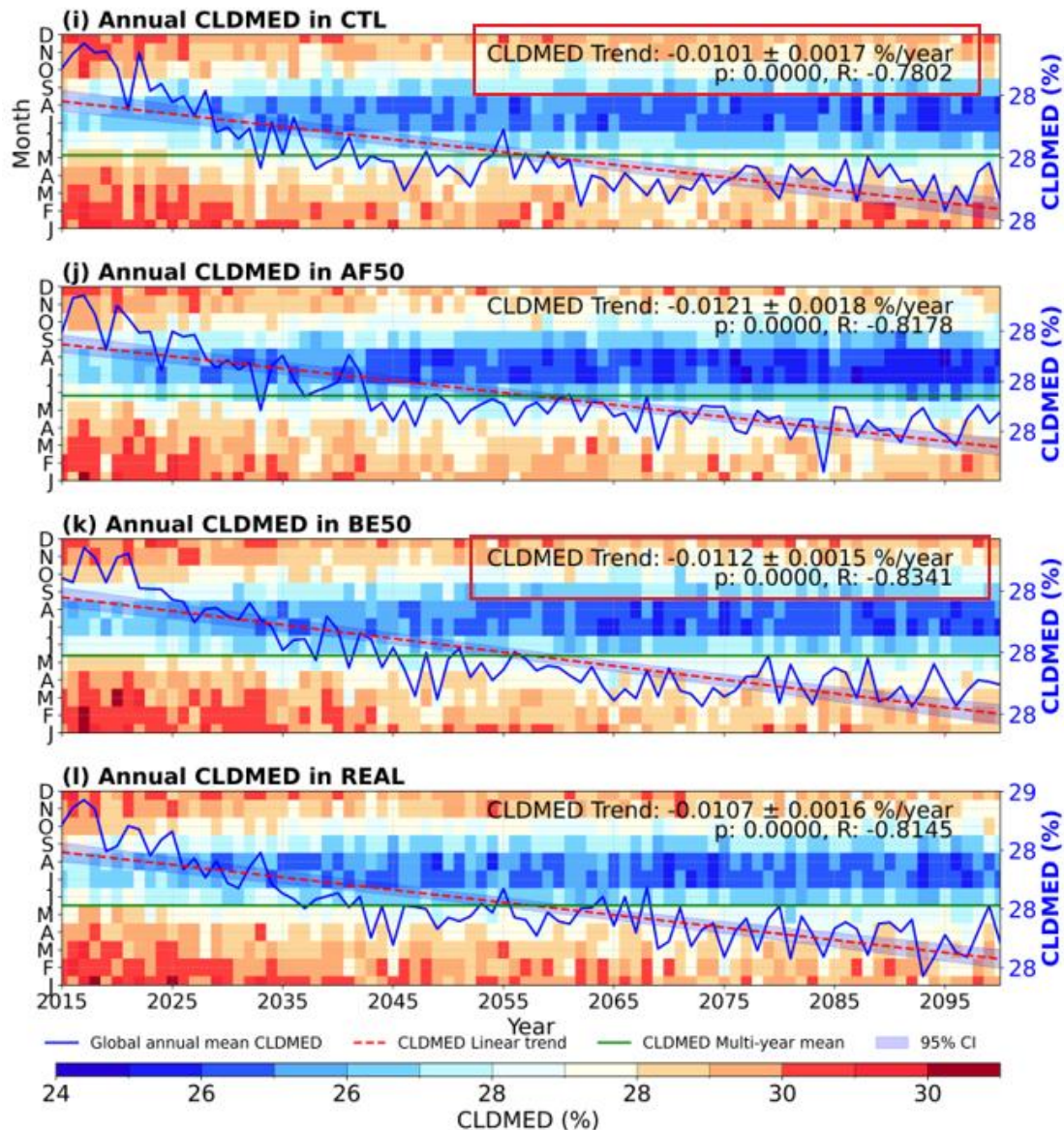
NEW

12. Line 303: BE50 and CTL have the same decline trend for CLDTOT.

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. Line 314: Does “downward response” refer to a “decreasing trend”?

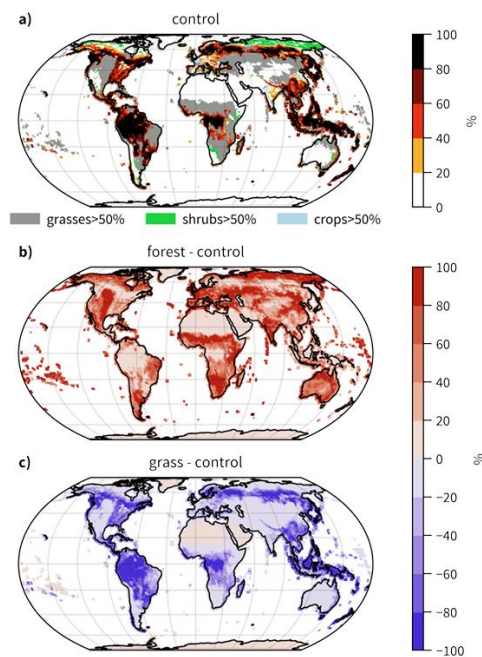
Yes, it conveys the same meaning: the LUCC-induced decrease or downward trend in cloud cover.

14. 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.

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



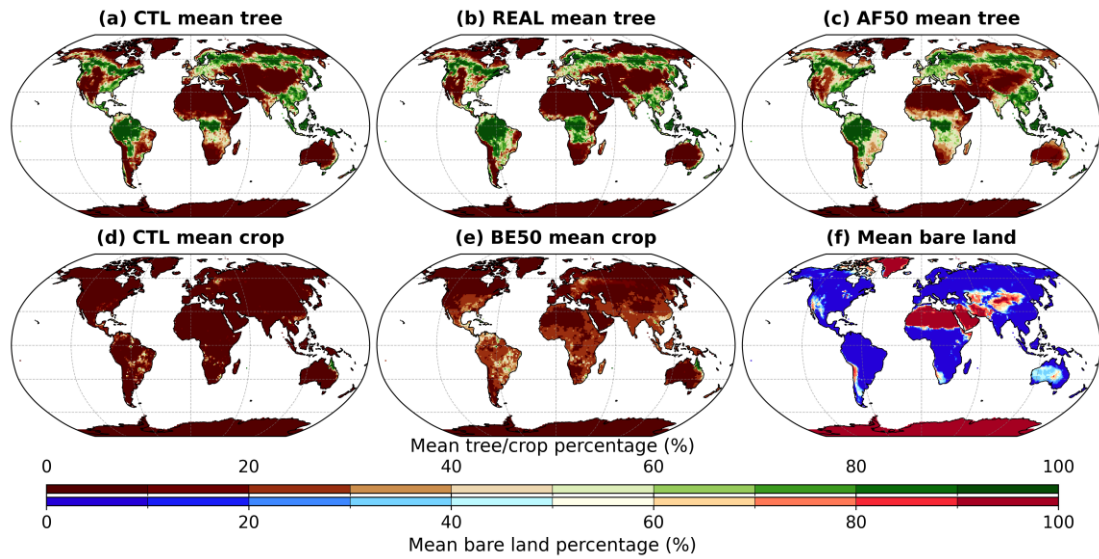


Figure S7. Spatial distribution of forest and bioenergy crop under different land use and land cover scenarios. (a and d) Spatial distribution of forests and bioenergy crops in the original land-use data (CTL run). (b) Spatial distribution of forests in the realistic afforestation scenario (REAL). (c 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.

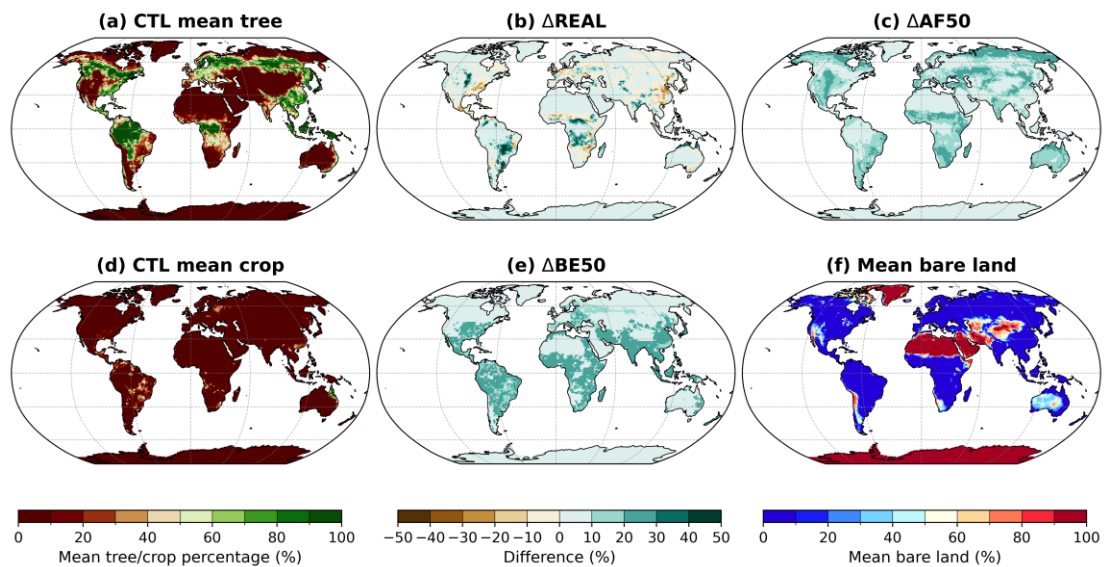


Figure S8. Spatial distribution of mean tree, crop, and bare land percentages and their differences under different land-use scenarios averaged over 2015-2100. (a and d) Mean tree and crop percentage in the CTL scenario. (b, c) Differences in tree percentage for the REAL and AF50 scenarios relative to CTL (Δ REAL and Δ AF50,

respectively). (e) Difference in crop percentage for the BE50 scenario relative to CTL (Δ BE50). (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.

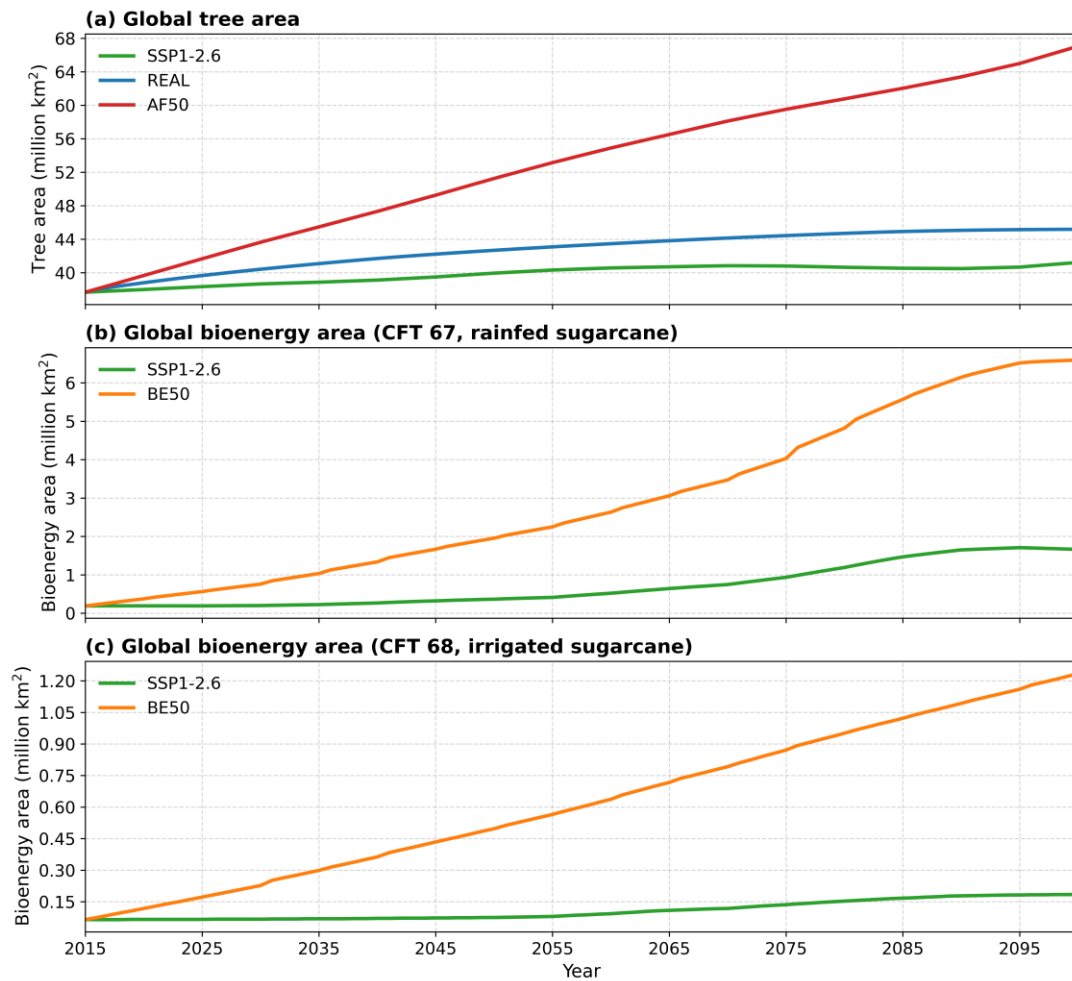


Figure S9. Area change of forest and bioenergy crops under different land-use scenarios (unit: million km²). In the Community Land Model Version 5 (CLM5), indices 67 and 68 correspond to rainfed and irrigated sugarcane, respectively, among bioenergy crops.

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).

The screenshot shows a GitHub repository for the HPSC TerrSys/CLM5.0 project. The file `PatchType.F90` is selected in the file explorer. The code defines a module `PatchType` with a list of patch types and their corresponding values. A red circle highlights the value 0, which is labeled "not vegetated". A red line connects this value to the list of vegetated patch types below.

```
1 module PatchType
2
3 !-----
4 ! !DESCRIPTION:
5 ! Patch data type allocation
6 ! -----
7 ! patch types can have values of
8 ! -----
9 ! 0 => not vegetated
10 ! 1 => needleleaf_evergreen_temperate_tree
11 ! 2 => needleleaf_evergreen_boreal_tree
12 ! 3 => needleleaf_deciduous_boreal_tree
13 ! 4 => broadleaf_evergreen_tropical_tree
14 ! 5 => broadleaf_evergreen_temperate_tree
15 ! 6 => broadleaf_deciduous_tropical_tree
16 ! 7 => broadleaf_deciduous_temperate_tree
17 ! 8 => broadleaf_deciduous_boreal_tree
18 ! 9 => broadleaf_evergreen_shrub
19 ! 10 => broadleaf_deciduous_temperate_shrub
20 ! 11 => broadleaf_deciduous_boreal_shrub
21 ! 12 => c3_arctic_grass
22 ! 13 => c3_non-arctic_grass
23 ! 14 => c4_grass
24 ! 15 => c3_crop
25 ! 16 => c3_irrigated
26 ! 17 => temperate_corn
27 ! 18 => irrigated_temperate_corn
28 ! 19 => spring_wheat
29 ! 20 => irrigated_spring_wheat
30 ! 21 => winter_wheat
31 ! 22 => irrigated_winter_wheat
32 ! 23 => temperate_soybean
33 ! 24 => irrigated_temperate_soybean
34 ! 25 => barley
35 ! 26 => irrigated_barley
36 ! 27 => winter_barley
37 ! 28 => irrigated_winter_barley
38 ! 29 => rye
39 ! 30 => irrigated_rye
40 ! 31 => winter_rye
41 ! 32 => irrigated_winter_rye
42 ! 33 => cassava
43 ! 34 => irrigated_cassava
```

github.com/HPSTerrSys/clm5_0/blob/tsmp-pdaf/src/main/PatchType.F90

Files

tsmp-pdaf

Go to file

- GetGlobalValuesMod.F90
- GridcellType.F90
- LandunitType.F90
- PatchType.F90**
- TopoMod.F90
- abortutils.F90
- accumulMod.F90
- atm2IndMod.F90
- atm2IndType.F90
- clm_driver.F90
- clm_initializeMod.F90
- clm_instMod.F90
- clm_varcon.F90
- clm_varctl.F90
- clm_varpar.F90
- clm_varsur.F90
- column_varcon.F90
- controlMod.F90

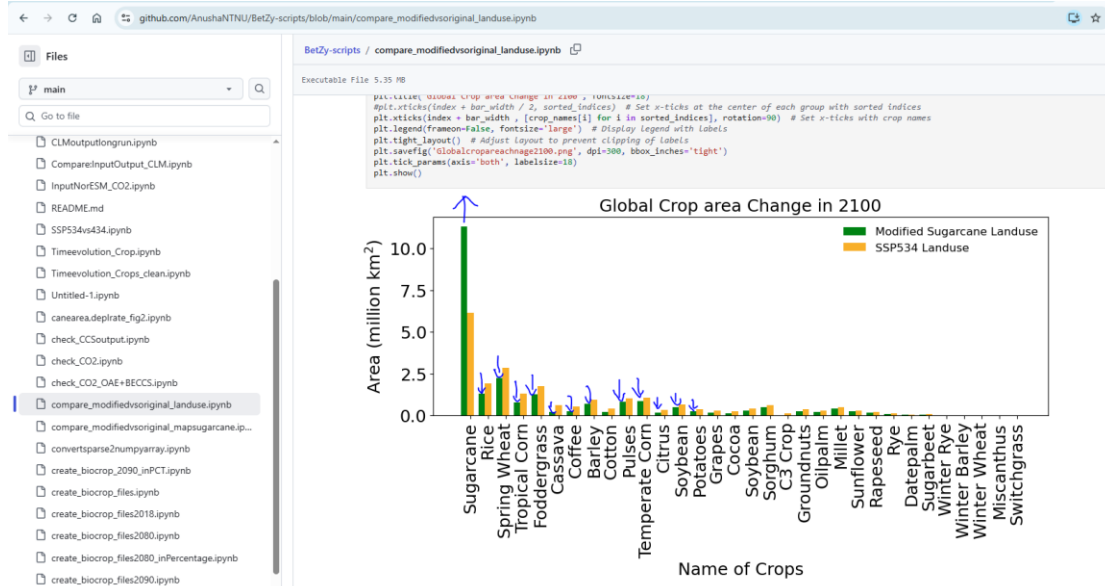
clm5_0 / src / main / PatchType.F90

Code Blame 207 lines (180 loc) · 6.87 KB

```

56 ! 47 => grapes
57 ! 48 => irrigated_grapes
58 ! 49 => groundnuts
59 ! 50 => irrigated_groundnuts
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61 ! 52 => irrigated_millet
62 ! 53 => oilpalm
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66 ! 57 => pulses
67 ! 58 => irrigated_pulses
68 ! 59 => rapeseed
69 ! 60 => irrigated_rapeseed
70 ! 61 => rice
71 ! 62 => irrigated_rice
72 ! 63 => sorghum
73 ! 64 => irrigated_sorghum
74 ! 65 => sugarbeet
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76 ! 67 => sugarcane
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83 ! 74 => irrigated_switchgrass
84 ! 75 => tropical_corn
85 ! 76 => irrigated_tropical_corn
86 ! 77 => tropical_soybean
87 ! 78 => irrigated_tropical_soybean

```



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 study interest in the potential role of cloud cover in large-scale land use and cover change (LUCC) and prompted us to reflect on the 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 sincerest gratitude once again to the editors and reviewers for their valuable time and effort.

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

Major comments

1. LUCC Maps: In the main text (e.g., Lines 192-197), different land-use simulations are described, but the spatial distribution of the LUCC forcing is relegated to the supplement (Fig. S23). Because the cloud response depends on the specific latitude bands and local background conditions (e.g., Duveiller et al. (2021), Xu et al. (2022)), understanding exactly where the afforestation and bioenergy expansion occur is critical to interpreting the paper's core findings. I strongly recommend moving the LUCC maps to the main text (perhaps as a new Fig. 1) and addressing two main limitations of the current Fig. S23. First, the terminology is inconsistent with the main text (e.g., is "ORI" essentially the "CTL" simulation?). Second, the figure plots absolute mean percentages rather than the difference relative to the control, which makes it visually challenging to identify where the land cover changes actually occur, particularly for the REAL

scenario (comparing panels 'a' and 'c'). Crucially, these maps should be replotted as difference maps from CTL using standardized terminology, so the reader can immediately identify the geographic locations and magnitude of the land cover forcing driving the cloud responses.

First and foremost, we sincerely appreciate the valuable time and effort you dedicated to helping us improve our study, and we are also very grateful for the issue you raised regarding improving the visualization of land use and land cover change (LUCC) maps. Indeed, as you mentioned, the response of cloud cover to large-scale LUCC depends heavily on the specific locations where land cover changes occur, because those specific locations often exhibit widely varying background climate, which happen to serve as the foundational conditions influencing how LUCC impacts cloud cover. Therefore, presenting the precise locations where changes in forest and bioenergy crops occur is critical for interpreting the cloud cover responses of interest in our study. To address this issue, we generated land use and land cover difference maps between the three sensitivity experiments (idealized afforestation AF50, idealized bioenergy expansion BE50, and realistic afforestation REAL) and the control experiment (CTL), as has indeed been standard practice in many previous studies, making such an improvement necessary. We still placed the newly drawn land use difference maps in the Supplementary Material rather than in the main text (this is because there are already enough figures in the main text, which are the most important ones retained after screening, whereas secondary figures or those used for auxiliary explanations were all placed in the Supplementary Information, and also to reduce the length of the main text). Regarding the land use difference maps, the new figure label is Figure S8; as for why it is not Figure S1, this is because prior to this, we also evaluated the simulation performance of the Community Earth System Model (CESM) for key atmospheric variables (cloud cover directly relevant to this study, temperature, and the newly added cloud cover trend comparison), which is a necessary step to ensure the accuracy of the CESM simulation results, whereas the land use simulation setup comes after the CESM simulation performance evaluation, so the land-use-related

result figures were naturally placed further behind, which was also done to ensure that the figures appear in sequential order during the analysis of results in the main text. We also retained the original absolute land cover percentage maps (Figure S7) to intuitively view the geographic distribution of global forests or crops. Furthermore, we newly added Figure S9 to show the temporal changes in tree and bioenergy crop areas in the three sensitivity experiments relative to the control experiment (we simultaneously corrected ORI to CTL to avoid confusion); doing so allows readers to see more clearly how much tree area increased by the end of the 21st century relative to 2015 under the realistic afforestation scenario (approximately 7.5 million km²), as well as how much tree area increased by the end of the 21st century under the idealized afforestation scenario (approximately 29 million km²). While 29 million km² appears to be a large number, especially compared with the realistic afforestation scenario, previous studies have already shown that global grassland area is sufficient to support such idealized land-use conversion; more importantly, converting grassland or shrubland to forest aligns better with the Food and Agriculture Organization (FAO) definition of afforestation, namely a fundamental conversion of land type (e.g., from grassland to forest). Therefore, strictly speaking, our realistic afforestation sensitivity experiment does not qualify as afforestation. Such confusing usage of concepts is not uncommon, so categorizing it as forest enhancement or reforestation might actually be more appropriate, a point we also mentioned in the manuscript, but for formal consistency in the analysis of results, we still refer to it as afforestation.

We once again thank you for your valuable comments and please forgive our initial oversight. We initially thought that readers would be able to directly discern the areas of forest or bioenergy expansion through the maps of absolute percentages of forest or grassland, as such differences could be partially displayed through the shading of the color bar. However, to demonstrate the differences in land cover more intuitively, we decided to adopt your valuable suggestion and make improvements.

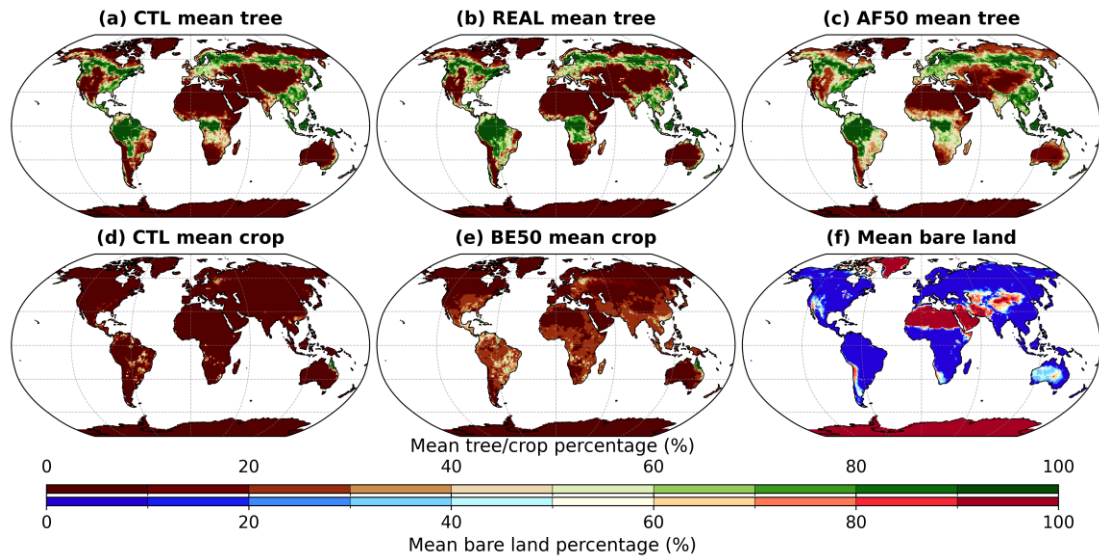


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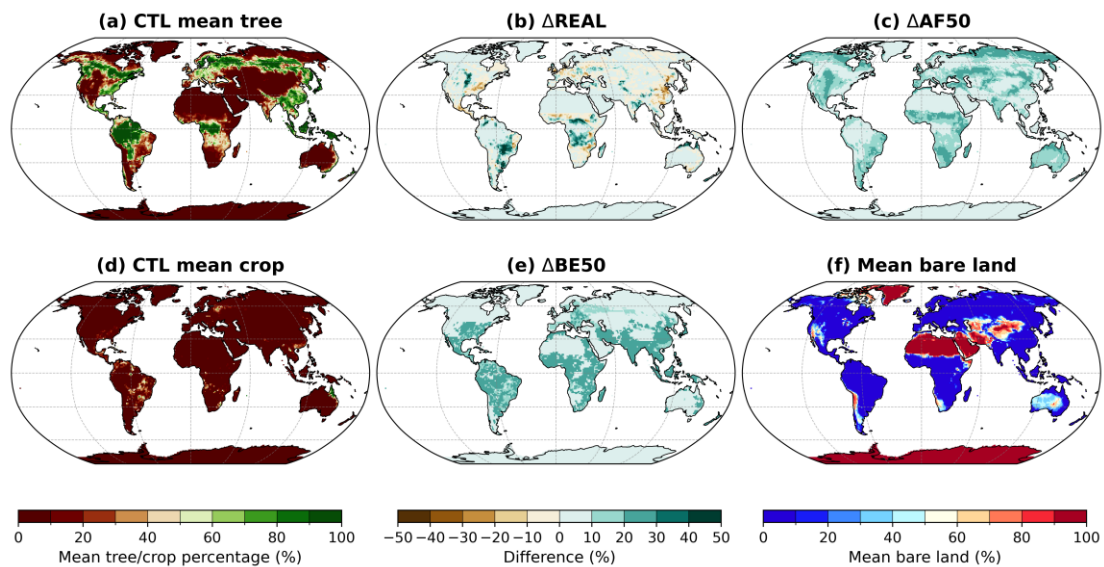


Figure S8. Spatial distribution of mean tree, crop, and bare land percentages and their differences under different land-use scenarios averaged over 2015-2100. (a and d) Mean tree and crop percentage in the CTL scenario. (b, c) Differences in tree percentage for the REAL and AF50 scenarios relative to CTL (Δ REAL and Δ AF50,

respectively). (e) Difference in crop percentage for the BE50 scenario relative to CTL (Δ BE50). (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.

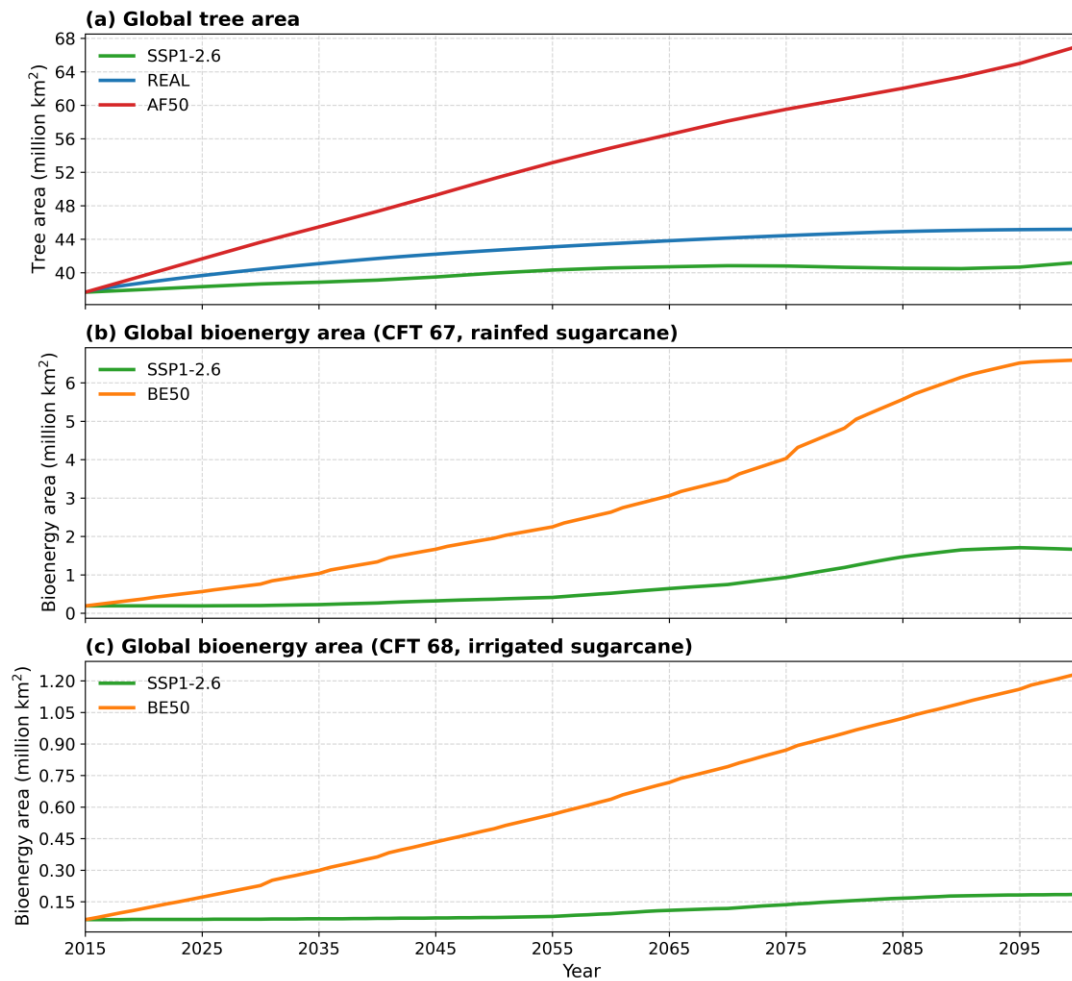


Figure S9. Area change of forest and bioenergy crops under different land-use scenarios (unit: million km²). In the Community Land Model Version 5 (CLM5), indices 67 and 68 correspond to rainfed and irrigated sugarcane, respectively, among bioenergy crops.

In CLM5, sugarcane is subdivided into rainfed sugarcane and irrigated sugarcane, with indices 67 and 68, respectively. Meanwhile, index 0 is bare ground; indices 1–8 are trees; and indices 9–14 are shrubs and grasslands, which are precisely the land sources for forest expansion in our study, conforming to the strict FAO definition of

afforestation. In the bioenergy crop expansion simulation experiment, the land for sugarcane (rainfed and irrigated sugarcane) expansion originated from the land of remaining crops, as demonstrated by other researchers (https://github.com/AnushaNTNU/BetZy-scripts/blob/main/compare_modifiedvsoriginal_landuse.ipynb), which represents a trade-off state to ensure area conservation. Just as the land used in idealized afforestation comes from grasslands or shrublands, which is likewise to ensure area conservation, CESM strictly requires that land type modifications at the sub-grid level (patch-level) must ultimately sum to 100% at the grid level (grid-level).

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7  ! patch types can have values of
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39 ! 30 => irrigated_rye
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42 ! 33 => cassava
43 ! 34 => irrigated_cassava
```

github.com/HPSTerrSys/clm5_0/blob/tsmp-pdaf/src/main/PatchType.F90

Files

tsmp-pdaf

Go to file

- GetGlobalValuesMod.F90
- GridcellType.F90
- LandunitType.F90
- PatchType.F90**
- TopoMod.F90
- abortutils.F90
- accumulMod.F90
- atm2IndMod.F90
- atm2IndType.F90
- clm_driver.F90
- clm_initializeMod.F90
- clm_instMod.F90
- clm_varcon.F90
- clm_varctl.F90
- clm_varpar.F90
- clm_varsur.F90
- column_varcon.F90
- controlMod.F90

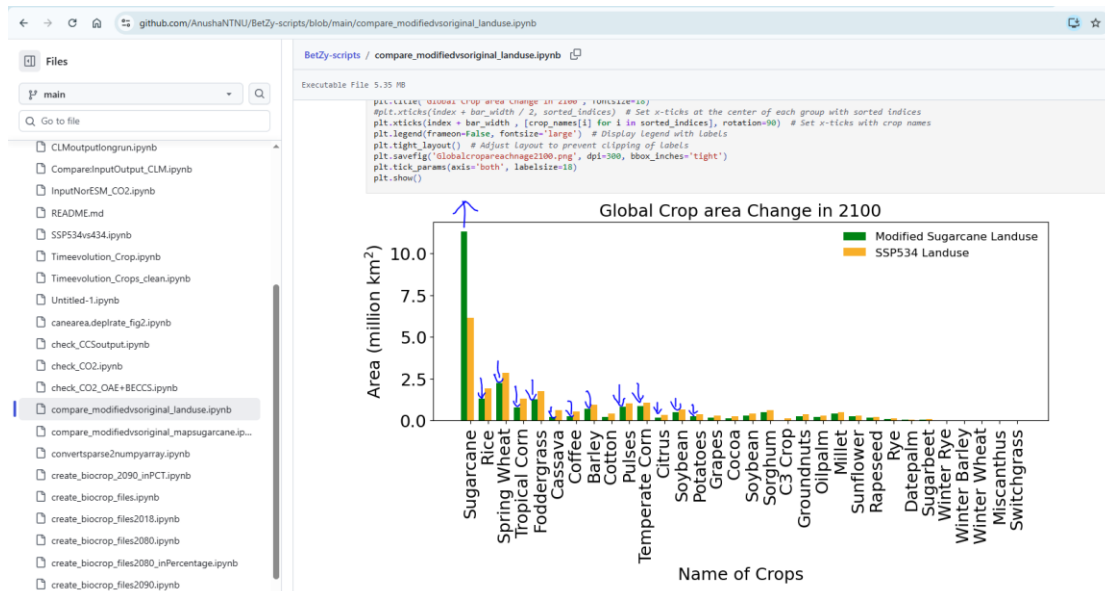
clm5_0 / src / main / PatchType.F90

Code Blame 207 lines (180 loc) · 6.87 KB

```

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86 ! 77 => tropical_soybean
87 ! 78 => irrigated_tropical_soybean

```



2. Building on the previous comment regarding the LUCC maps, The authors claim in Line 442 that the high Gini index is "...suggesting amplified local land use impacts." Without showing where the LUCC forcing actually occurred relative to

these trends, a "local" interpretation remains speculative. To my understanding, highly concentrated cloud trends do not necessarily indicate local forcing; they could equally be driven by non-local effects. More generally, utilizing a fully coupled model like CESM provides an excellent opportunity to account for both local and non-local LUCC effects, but this capability is underutilized in the current analysis. To address this, the authors should explicitly map the LUCC forcing areas and physically link them to the cloud trends to clearly differentiate local impacts from large-scale dynamical responses.

We are very grateful for the analysis you provided regarding leveraging CESM fully coupled simulations to gain insight into the local and non-local effects of climate responses to large-scale LUCC; we believe this is important, and this is also the core that distinguishes it from observational analyses, which lack exploration of non-local effects (observational analyses often employ space-for-time substitution methods to analyze the difference between a certain grid cell and surrounding grid cells to represent climate responses, thus rendering them powerless to evaluate non-local effects). In response to the first valuable suggestion, we explicitly added new maps to represent the differences in land use change across temporal and spatial scales. Then, regarding the issue of distinguishing local and non-local long-term cloud cover trends in response to large-scale LUCC, it may not be possible to decompose them into direct (local) and indirect (non-local) physical terms like decomposing surface temperature changes based on the surface energy balance (SEB) decomposition equation; at least at present, we have failed to find a similar method to decompose changes in cloud cover into local and non-local responses. In fact, in SEB, cloud feedback is already a non-local effect (as the SEB formula in the main text demonstrates, the meaning expressed by indirect is exactly non-local). However, we still have not currently discovered a suitable method directly applicable for decomposing cloud cover, which might be developed in future studies just like decomposing surface temperature into physical processes such as albedo, turbulent fluxes, and atmospheric feedbacks; therefore, to a large extent, what we can do currently is only to complete this part of the analysis by plotting land cover

difference maps, but we chose to deepen the non-local effects of cloud cover in the discussion, especially why large-scale forest and bioenergy expansion occurs in terrestrial regions, yet changes also occur over the ocean. Obviously, the setup of a fully coupled model is merely the basic tool to explain this phenomenon, and this content has been placed in the discussion section. In addition, we added an analysis of temperature advection; this is because temperature is one of the key factors affecting cloud cover, and by analyzing temperature advection, we can know where the temperature increases are caused by remote temperature advection, thereby illustrating the non-local response of cloud cover. Regarding the spatial concentration of LUCC-induced cloud cover trends, we can observe it through the newly drawn land cover difference maps. Specifically, in the control experiment, the Gini index for the decreasing trend in total cloud cover in the Northern Hemisphere is 0.36, whereas it increased to 0.44 in the large-scale idealized afforestation experiment; similarly, the Gini index for low-level cloud loss in the Northern Hemisphere in the control experiment is 0.41, whereas it increased even further to 0.50 in idealized afforestation. As mentioned in the main text, a Gini index closer to 1 indicates greater inequality, signifying that fewer latitudinal bands contributed to a stronger cloud cover loss trend. The two sets of sharply contrasting data directly indicate the spatial aggregation of total cloud cover and low-level cloud losses in the Northern Hemisphere; when compared with the land cover maps of idealized afforestation, it can be found that these are precisely the regions of large-scale conversion from grassland or shrubland to forest.

We once again deeply thank you for your scientific insights into the non-local effects of cloud cover, which is indeed something we had not thought of previously; we never thought that cloud cover could also be decomposed into different physical processes like surface temperature changes. We believe that the issue of decomposing changes in cloud amount into local and non-local driving factors is full of scientific value, and we may maintain further investigation in future research, rather than merely analyzing it indirectly through methods such as temperature advection.

3. Ambiguous Trend Reporting: The discussion of cloud-cover trends (Lines 298–

336) is difficult to follow. For example, the use of "respectively" in Line 303 when describing CLDTOT trends is ambiguous, making it unclear how the AF50 and REAL simulations compare with CTL and BE50. Furthermore, expressions like "1.14 times increase in loss rate" and "1.52 times" are confusing. I suggest reporting straightforward percentage changes and/or the actual trend values for each experiment.

We are very grateful for your valuable comments. We have decided to check the full text to resolve similar issues, and adopt the valuable suggestion you provided where necessary, namely, directly providing specific percentage changes or actual trend values. However, in some places, we will still choose to provide multiples; doing so is to intuitively compare the intensity of the changes in cloud cover trends.

4. High-Cloud Response Clarification: The discussion of the high-cloud response (Lines 326–332) requires significant clarification. The manuscript argues that afforestation amplifies the positive trend in CLDHGH, enhancing climate warming. However, it is unclear which cloud populations contribute to this diagnostic. Line 161 states that the classification is based on cloud-top pressure thresholds. Is the classification based solely on cloud-top pressure/height? If so, deep convective clouds (rooted in the boundary layer) extending aloft could be classified as high clouds alongside thin cirrus. Because deep convection could respond to surface fluxes while cirrus may not do so directly, the physical mechanism linking LUCC to CLDHGH is ambiguous. Please clarify how CESM defines these cloud types and provide targeted mechanistic support for the high-cloud response.

We sincerely thank you for this highly insightful comment, which astutely points out a subtle nuance in the representation of cloud cover types in climate models. We completely agree that distinguishing between isolated cirrus clouds and deep convective clouds is crucial for establishing robust mechanistic connections. As you mentioned, the response of high-level clouds to large-scale land-use change was not clearly explained in our manuscript, particularly the fact that the positive response of

high-level clouds is opposite to the negative response of low- and mid-level clouds. This contrasting response may stem from the fact that large-scale land-use change exerts a predominantly greater impact on low- and mid-level clouds (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). In CESM, high-level cloud fraction (CLDHGH) is diagnostically defined as the vertically integrated cloud fraction strictly located above the 400 hPa pressure level, meaning that different cloud types are classified based on cloud-top pressure (https://github.com/ESCOMP/CAM/blob/14ad2a03080e727e45e2e1c18f865a90f28a76e1/src/physics/cam/cloud_cover_diags.F90). However, this classification purely based on cloud-top pressure means that CLDHGH inherently encompasses both in situ generated thin cirrus clouds and the high-altitude portions of deep convective clouds rooted in the boundary layer (e.g., convective cloud tops and detrained anvil clouds). Although isolated cirrus clouds may not directly respond to surface fluxes, deep convection undoubtedly does. Our machine learning attribution framework identified atmospheric water vapor and precipitation as the primary drivers of the LUCC-induced long-term trends in CLDHGH, indicating that the physical mechanisms linking LUCC to the high-level cloud response are intrinsically tied to these deep convective processes. Specifically, idealized afforestation fundamentally alters surface energy partitioning, moderately increasing local surface temperatures and moisture supply. This enhanced surface buoyancy forcing destabilizes the boundary layer, triggering more intense deep convective updrafts, which can be observed in the enhanced trends of convective available potential energy (CAPE). These changes induced by large-scale idealized afforestation transport excess water vapor from the boundary layer to the upper troposphere. Upon reaching altitudes above 400 hPa (particularly around 200 hPa), the subsequent detrainment of this water vapor, coupled with local cooling and increased relative humidity, collectively catalyzes the formation and extensive horizontal expansion of high-level clouds. This phenomenon is evident in both the idealized and realistic afforestation scenarios, whereas it is weaker in the bioenergy expansion

experiment. This indirectly confirms that bioenergy expansion struggles to trigger the intense tropospheric atmospheric perturbations characteristic of forest expansion.

Therefore, the increasing trend in CLDHGH observed in our study is, in fact, a secondary dynamical consequence arising from the direct response of boundary layer convection to LUCC-driven surface flux anomalies. The increasing trend in high-level clouds and the decreasing trend in low- and mid-level clouds synergistically accelerate warming. Although their respective trends are in opposite directions, this indicates that large-scale idealized afforestation does not accelerate warming solely through the accelerated loss of low- and mid-level clouds. Notably, even realistic afforestation enhances the trend in high-level clouds, implying that even carefully planned realistic afforestation could generate positive radiative forcing at the top of the atmosphere. This contrasts starkly with the lower atmosphere and emphasizes that future research must adopt a whole-atmosphere perspective.

<https://bg.copernicus.org/articles/21/3883/2024/>

Global and regional hydrological impacts of global forest expansion
James A. King et al.



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 ($\sim 5\%$) 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 ($\sim 0.2\%$) 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.

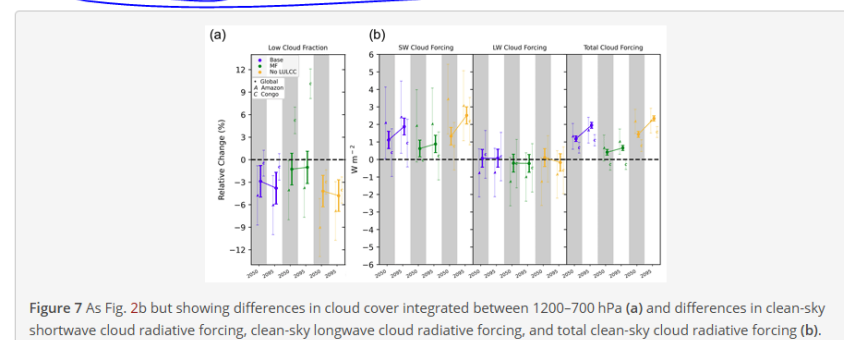


Figure 7 As Fig. 2b but showing differences in cloud cover integrated between 1200–700 hPa (a) and differences in clean-sky shortwave cloud radiative forcing, clean-sky longwave cloud radiative forcing, and total clean-sky cloud radiative forcing (b).

← → ↻ 🏠 🔍

github.com/ESCOMP/CAM/blob/14ad2a03080e727e45e2e1c18f865a90f28a76e1/src/physics/cam/cloud_cover_diags.F90

Files

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🔍 Go to file T

aoa_tracers.F90

beljaars_drag.F90

beljaars_drag_cam.F90

boundarydata.F90

cam_diagnostics.F90

cam_snapshot.F90

carma_diags_mod.F90

carma_flags_mod.F90

carma_intr.F90

carma_model_flags_mod.F90

check_energy.F90

chem_surfvls.F90

cldfrc2m.F90

cldwat2m_macro.F90

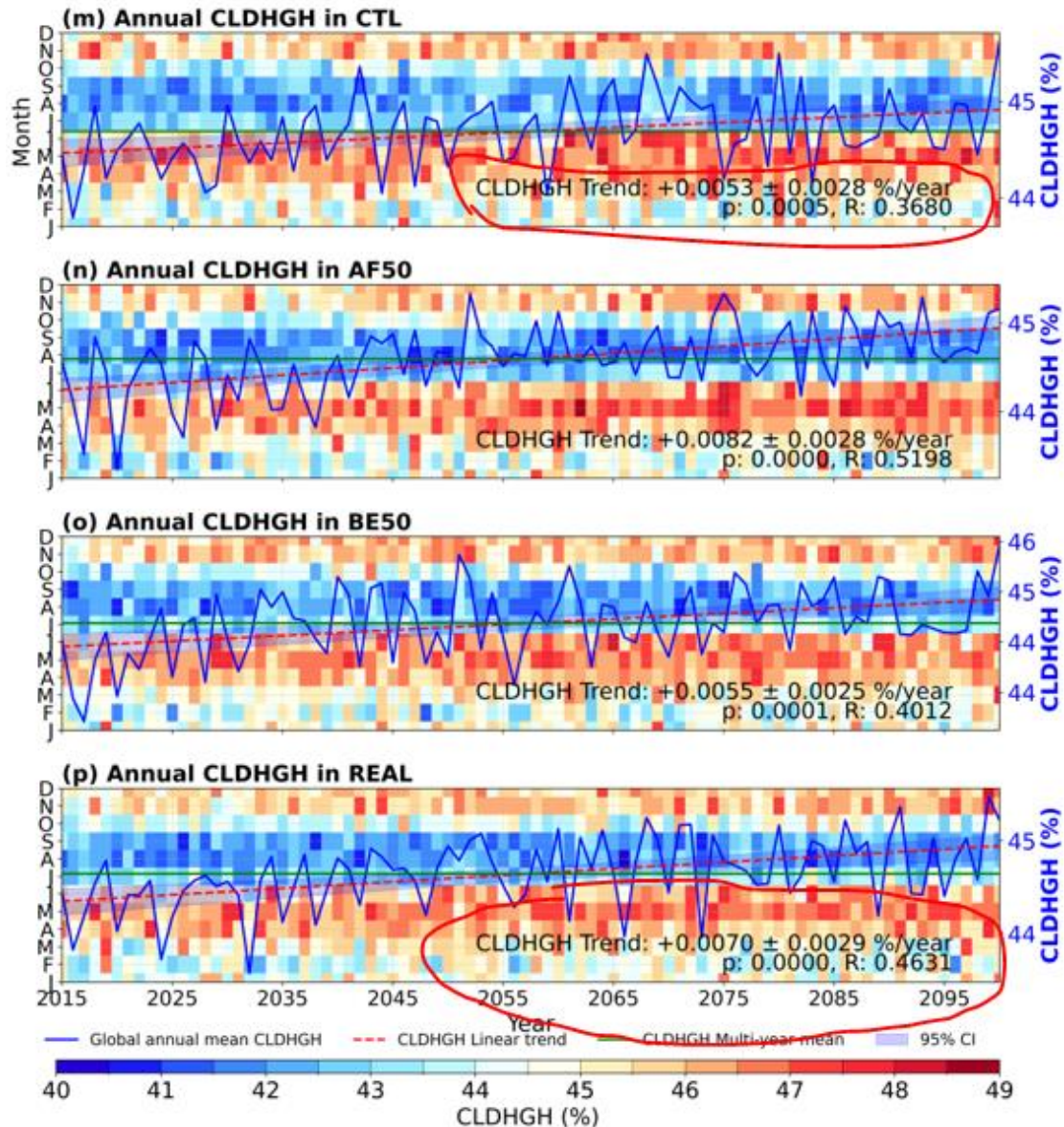
cloud_cover_diags.F90

cloud_diagnostics.F90

cloud_fraction.F90

Code Blame 201 lines (168 loc) · 7.71 KB

```
1  !=====
2  ! cloud cover output
3  !=====
4  module cloud_cover_diags
5
6      use shr_kind_mod, only: r8=>shr_kind_r8, shr_kind_CS
7      use ppgrid,        only: pcols, pver, pverp
8      use cam_history,   only: addfld, add_default, outfld, horiz_only
9      use phys_control,  only: phys_getopts
10
11     implicit none
12
13     private
14
15     public :: cloud_cover_diags_init
16     public :: cloud_cover_diags_out
17
18     real(r8) plowmax      ! Max prs for low cloud cover range
19     real(r8) plowmin      ! Min prs for low cloud cover range
20     real(r8) pmedmax      ! Max prs for mid cloud cover range
21     real(r8) pmedmin      ! Min prs for mid cloud cover range
22     real(r8) phghmax      ! Max prs for hgh cloud cover range
23     real(r8) phghmin      ! Min prs for hgh cloud cover range
24
25     !
26     parameter (plowmax = 120000._r8, plowmin = 70000._r8, &
27                pmedmax = 70000._r8, pmedmin = 40000._r8, &
28                phghmax = 40000._r8, phghmin = 5000._r8)
29
30     contains
31
```



5. Significance and Uncertainty: A discussion of statistical significance and model uncertainty is largely missing from the core results and should be included to validate the claimed trends.

We are very grateful for your valuable comments, and we fully agree with conducting an objective discussion on the uncertainties in the presented research results. Particularly in Fig. 1, when calculating global mean trends, the uncertainty range was relatively large; however, when computing the land and ocean regions separately, the uncertainty narrowed significantly (Fig. S10). Upon inspection, this issue was caused by an error in the calculation code, which is addressed in our response to Comment 6.1.

On the other hand, in the discussion section, we further elaborated on the parametric uncertainties inherent in cloud parameterization within CAM6, the atmospheric component of CESM, as well as the limitations of our single-model experimental design. Regarding the machine learning driver attribution analysis, we strictly constrained the XGBoost model through 100 Bayesian hyperparameter optimization iterations to prevent overfitting, thereby rigorously mitigating uncertainties associated with machine learning; thus, the parameters presented in Table S1 represent the optimal parameter set. We deeply appreciate your kind reminder, as these additions regarding uncertainties and limitations have clearly substantially enhanced the rigor of our study.

6.1. Figure Presentation and Interpretability: Figure 1: The shading representing the uncertainty is almost invisible, and the $\pm$ error bounds listed in the legend are massive (please see my separate major comment regarding the missing discussion on uncertainty). Furthermore, the text for the p-values and R-values is unreadable in several panels (e.g., Fig. 1n). Finally, the caption fails to explain what the different curves represent physically.

We highly appreciate the reviewer's valuable comments. The issues raised regarding the excessively large uncertainty and the visual presentation in Fig. 1 are crucial for clarifying the underlying reasons and improving the figures. Furthermore, concerning the issue of where text labels in subfigures (such as Fig. 1n) were unclear or obscured, we have redrawn the figures and adjusted the positions of the text annotations to prevent any overlap. Initially, we considered placing the text inside a rectangular box with a white background; however, this approach risked obscuring the underlying heatmap. Therefore, we chose to reposition the text annotations to display them as clearly as possible. Additionally, we have included legends to explain the physical meanings of the different curves, and similar improvements have been applied to all subsequent figures.

Regarding the problem of the excessively wide confidence interval in Fig. 1, we reviewed the previous old calculation code and identified a computational error that led

to this issue. In the old code, the lower and upper bounds returned by the user-defined function *calc_bootstrap_ci* represented the fluctuation range of the Y-values (absolute cloud fraction in %) corresponding to the entire fitted regression line for each year. Moreover, the step $ci_half=(ci_upper-ci_lower)/2$ mistakenly extracted the uncertainty of the global cloud baseline at the very first timestamp of the sequence (year in 2015). Consequently, it addressed the uncertainty interval of the global mean cloud fraction specifically for the year 2015. In the revised new code, percentiles are calculated directly from the distribution of the regression slopes obtained through 1000 bootstrap resamples via *slope_lower* and *slope_upper*. Thus, it correctly addresses the uncertainty interval of the rate of change in cloud fraction over the simulated 85-year period (2015–2100). In the revised manuscript, we have corrected this statistical method. We now explicitly extract the 95% confidence interval directly from the distribution of the bootstrapped regression slopes. The updated trend ensures strict dimensional alignment and an accurate representation of the trend's statistical significance. The text and corresponding figures have been revised accordingly. Additionally, we have checked the code used to calculate the trends separated by land and ocean (Fig. S10), and confirmed that this section contains no errors.

To evaluate the performance of CESM in simulating cloud cover trends, we have added a spatial trend comparison plot (Fig. S3) to the previously generated difference plots (Figs. S1 and S2). Since trends are the primary focus of this study, visualizing trend comparisons allows for a more direct illustration of the uncertainties in the simulation results. Fig. S3 reveals that the CESM-simulated trends for total cloud cover and low-level clouds show good overall agreement with reanalysis data over land areas, specifically indicating a widespread decrease at comparable rates. This comparison reinforces our confidence in the cloud cover simulated by CESM.

```

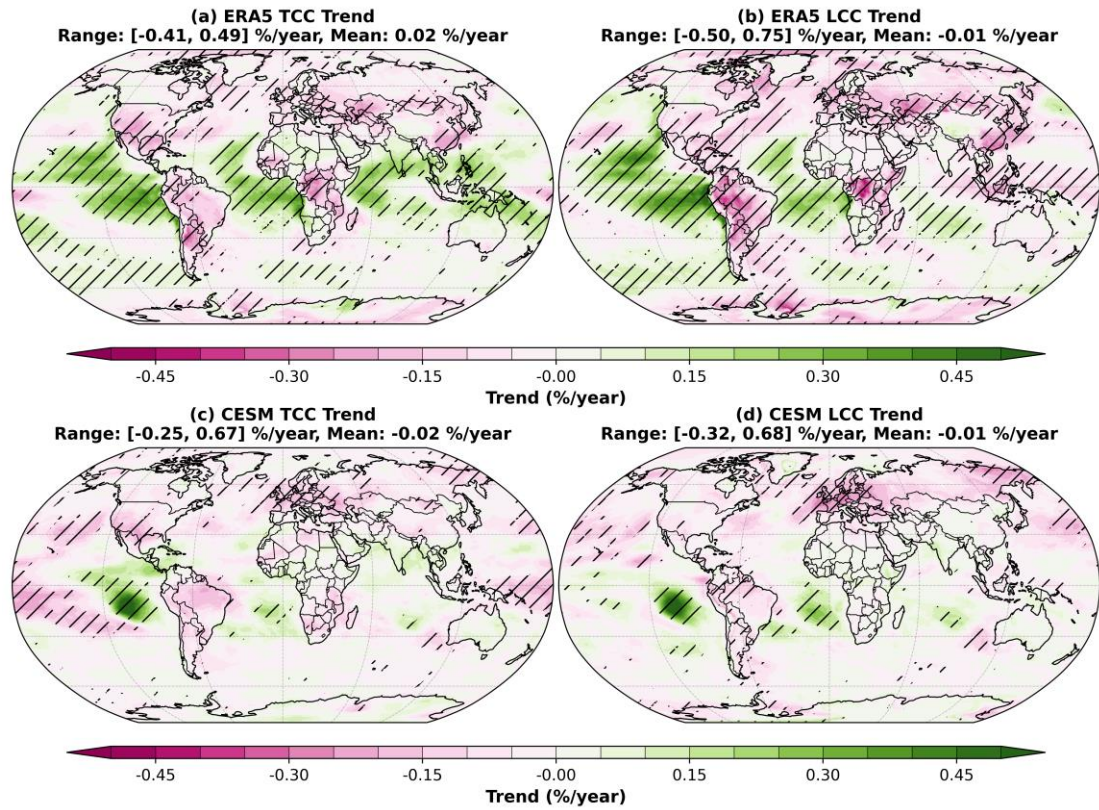
1  import xarray as xr
2  import matplotlib.pyplot as plt
3  import numpy as np
4  import scipy.stats as stats
5  import cmaps
6  import matplotlib.ticker as mticker
7  from matplotlib.colors import BoundaryNorm
8  from matplotlib.lines import Line2D
9  import matplotlib.patches as mpatches
10
11 # ===== 1. Trend calc =====
12 def calculate_trends(data):
13     years = np.arange(len(data))
14     slope, intercept, r_value, p_value, std_err = stats.linregress(years, data)
15     return slope, intercept, r_value, p_value
16
17 # ===== 2. Bootstrap 95% CI =====
18 def calc_bootstrap_ci(years, data, n_boot=1000, ci=95):
19     x = np.arange(len(years))
20     slope, intercept, _, _ = stats.linregress(x, data)
21     fitted = intercept + slope * x
22     resid = data - fitted
23
24     boot_slopes = []
25     boot_intercepts = []
26     rng = np.random.default_rng()
27     for _ in range(n_boot):
28         boot_resid = rng.choice(resid, size=len(resid), replace=True)
29         boot_y = fitted + boot_resid
30         s, i, _, _ = stats.linregress(x, boot_y)
31         boot_slopes.append(s)
32         boot_intercepts.append(i)
33
34     boot_slopes = np.array(boot_slopes)[:n_boot, np.newaxis]
35     boot_intercepts = np.array(boot_intercepts)[:n_boot, np.newaxis]
36     boot_trends = boot_slopes * x + boot_intercepts
37     # (n_boot, n_years)
38     # -----
39
40     lower = np.percentile(boot_trends, (100 - ci) / 2, axis=0)
41     upper = np.percentile(boot_trends, 100 - (100 - ci) / 2, axis=0)
42     return lower, upper
43
44 # ===== 3. File path =====
45 base_path_cldtot = 'C:/JupyterXPC/Cloud_Analysis_AF_BE_Cloud_Trend/CLDTOT/'
46 cldtot_files = [
47     base_path_cldtot + 'merged_CLDTOT_CTL_h0.nc',
48     base_path_cldtot + 'merged_CLDTOT_AF50_h0.nc',
49     base_path_cldtot + 'merged_CLDTOT_BE50_h0.nc',
50     base_path_cldtot + 'merged_CLDTOT_REAL_h0.nc'
51 ]
52 titles = [
53     '(a) Annual CLDTOT in CTL',
54     '(b) Annual CLDTOT in AF50',
55     '(c) Annual CLDTOT in BE50',
56     '(d) Annual CLDTOT in REAL'
57 ]

```

```

1 import xarray as xr
2 import matplotlib.pyplot as plt
3 import numpy as np
4 import scipy.stats as stats
5 import cmmaps
6 import matplotlib.ticker as mticker
7 from matplotlib.colors import BoundaryNorm
8 from matplotlib.lines import Line2D
9 import matplotlib.patches as mpatches
10
11 # ===== 1. Trend calc =====
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13 def calculate_trends(data):
14     years = np.arange(len(data))
15     slope, intercept, r_value, p_value, std_err = stats.linregress(years, data)
16     return slope, intercept, r_value, p_value
17
18 # ===== 2. Bootstrap 95% CI =====
19 def calc_bootstrap_ci(years, data, n_boot=1000, ci=95):
20     x = np.arange(len(years))
21     slope, intercept, _, _, _ = stats.linregress(x, data)
22     fitted = intercept + slope * x
23     resid = data - fitted
24
25     boot_slopes = []
26     boot_intercepts = []
27     rng = np.random.default_rng()
28     for _ in range(n_boot):
29         boot_resid = rng.choice(resid, size=len(resid), replace=True)
30         boot_y = fitted + boot_resid
31         s, i, _, _, _ = stats.linregress(x, boot_y)
32         boot_slopes.append(s)
33         boot_intercepts.append(i)
34
35     boot_slopes = np.array(boot_slopes)[:n_boot, np.newaxis] # (n_boot, 1)
36     boot_intercepts = np.array(boot_intercepts)[:n_boot, np.newaxis] # (n_boot, 1)
37     boot_trends = boot_slopes * x + boot_intercepts # (n_boot, n_years)
38
39     lower_line = np.percentile(boot_trends, (100 - ci) / 2, axis=0)
40     upper_line = np.percentile(boot_trends, 100 - (100 - ci) / 2, axis=0)
41
42     slope_lower = np.percentile(boot_slopes, (100 - ci) / 2)
43     slope_upper = np.percentile(boot_slopes, 100 - (100 - ci) / 2)
44
45     return lower_line, upper_line, slope_lower, slope_upper
46
47 # ===== 3. File path =====
48 base_path_cldtot = 'C:/JupyterXPC/Cloud_Analysis_AF_BE_Cloud_Trend/CLDTOT/'
49 cldtot_files = [
50     base_path_cldtot + 'merged_CLDTOT_CTL_h0.nc',
51     base_path_cldtot + 'merged_CLDTOT_AF50_h0.nc',
52     base_path_cldtot + 'merged_CLDTOT_BE50_h0.nc',
53     base_path_cldtot + 'merged_CLDTOT_REAL_h0.nc'
54 ]
55
56 titles = [
57     '(a) Annual CLDTOT in CTL',
58     '(b) Annual CLDTOT in AF50',
59     '(c) Annual CLDTOT in BE50',
60     '(d) Annual CLDTOT in REAL'
61 ]

```



6.2. Figure Presentation and Interpretability: Figs. 2, 3: The captions are currently quite brief and would greatly benefit from more detail to guide the reader. Please describe the panels more explicitly. For instance, are these long-term trends or Δ values? If they are Δ values, what is the reference run (e.g., CTL)? It would also be helpful to clarify what positive and negative values represent physically.

We are very grateful for your valuable comments. Indeed, our current figure captions were overly brief, which might prevent readers from accurately understanding the meaning represented by each subplot. Therefore, in the revised manuscript, we have comprehensively rewritten and expanded these figure captions to ensure clarity of expression.

Regarding whether the presented results represent changes or absolute values, we explicitly define the control experiment (CTL) as the reference baseline run, and all difference values are calculated as sensitivity experiments (AF50, BE50, and REAL) minus the CTL experiment, as demonstrated in Equation 3 of the main text. However, in certain places, such as Fig. 1, we chose not to display difference values, particularly

when presenting overall global trends, as expressing them as differences might instead impair clarity (because small difference values can be less intuitive and make comparing fold-changes less straightforward). On the contrary, directly showing the trend values within each experiment (including CTL) is more intuitive (for instance, in Fig. 1, the trend of low-level cloud cover in the CTL simulation is $-0.0153 \pm 0.0030\%/year$, whereas in AF50 it is $-0.0175 \pm 0.0036\%/year$, which very directly identifies that AF50 exacerbates the rate of low-level cloud loss). Furthermore, we have supplemented the color bar with clear physical interpretations, including the meanings of positive and negative values.

6.3. Figure Presentation and Interpretability: Figure 6: The application of the Lorenz curve and the Gini coefficient to cloud trends is innovative, but the current presentation lacks physical context and can be misleading. By isolating positive (+) and negative (–) trends into separate panels that are normalized to 100% on the y-axis, the reader cannot tell which trend direction actually dominates the hemisphere. For instance, if a hemisphere is overwhelmingly dominated by cloud loss, a high Gini coefficient calculated for a smaller area showing a positive (+) cloud trend would be physically minor but visually overemphasized as being equally important. I strongly suggest adding a table or text annotations within each panel showing the relative area fraction or the integrated absolute magnitude of the (+) vs. (–) grid cells. Additionally, the monochromatic orange/blue continuous colormaps make it highly challenging to distinguish between the latitudinal bands referenced in the text. I suggest replacing these smooth gradients with a discrete, stepped colormap that clearly delineates distinct zones (e.g., separate color steps for Tropical, Mid-latitude, and Polar regions).

We are very grateful for your highly insightful and constructive comment, and we also deeply appreciate your affirmation of our innovative application of the Lorenz curve and Gini index to cloud cover research. We believe that introducing this method allows for an intuitive evaluation of whether LUCC-induced cloud cover trends are broadly distributed in space or concentrated in a few latitudes. These two contrasting

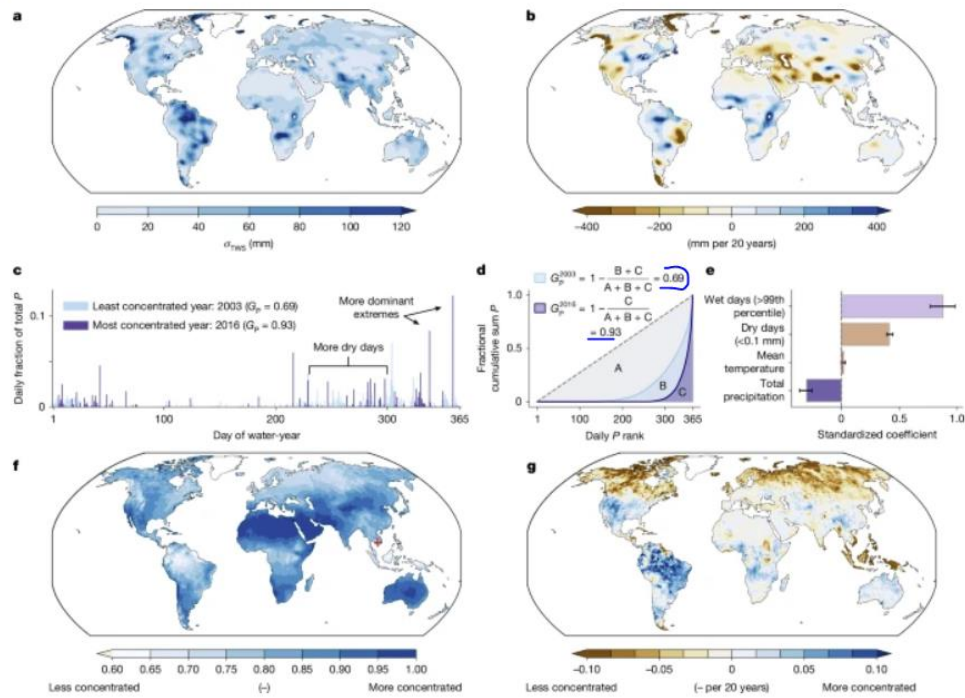
distributional directions are crucial for studying cloud cover trends, as it usually implies that if LUCC-induced cloud loss trends are concentrated in a few latitudinal bands (a Gini index closer to 1), the potential climatic and ecological consequences could be severe, much like recent research on precipitation concentration suggests—where Gini-index-based evaluations similarly demonstrated that regional precipitation concentration exacerbates droughts and terrestrial water storage deficits (Lesk and Mankin, 2026: Lesk, C. S., Mankin, J. S. More concentrated precipitation decreases terrestrial water storage. *Nature* 653, 425–432 (2026). <https://doi.org/10.1038/s41586-026-10487-7>). This offers important insights for our focus on cloud loss trends.

More importantly, we completely agree with your critique that normalizing both positive and negative trends to 100% without physical context visually overemphasizes secondary trends and could potentially mislead readers. Your suggestions for improvement are excellent, and we have adopted them in the revised figures. Specifically, we made the corresponding modifications: Adding physical context (grid cell area proportions of positive vs. negative cloud trends between hemispheres): To ensure readers can immediately discern the dominant trend direction within a hemisphere, we added clear text annotations to each subplot. These annotations display the relative grid-area proportions of positive (+) versus negative (–) grid cells, thereby placing the calculated Gini indices into proper physical perspective. Furthermore, regarding the display of the Gini index colorbar, we chose to adopt your valuable suggestion, as this approach has been utilized in recent research to provide a standard template and indeed employs a discrete colorbar for representation (Zhao et al., 2025: Haipeng Zhao et al., Greener green and bluer blue: Ocean poleward greening over the past two decades. *Science* 388, 1337–1340 (2025). DOI: 10.1126/science.adr9715).

More concentrated precipitation decreases terrestrial water storage

Greenland and Antarctica because of the dominant influence of their ice caps.

Fig. 1: Trends and variability in TWS and rainfall concentration.



limits phytoplankton biomass (18) in the high nutrient–low chlorophyll Southern Ocean.

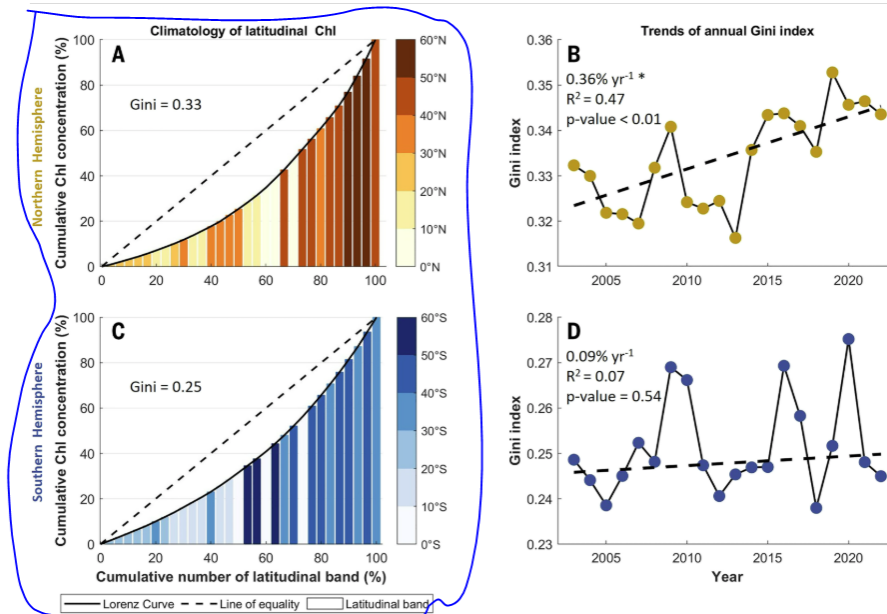
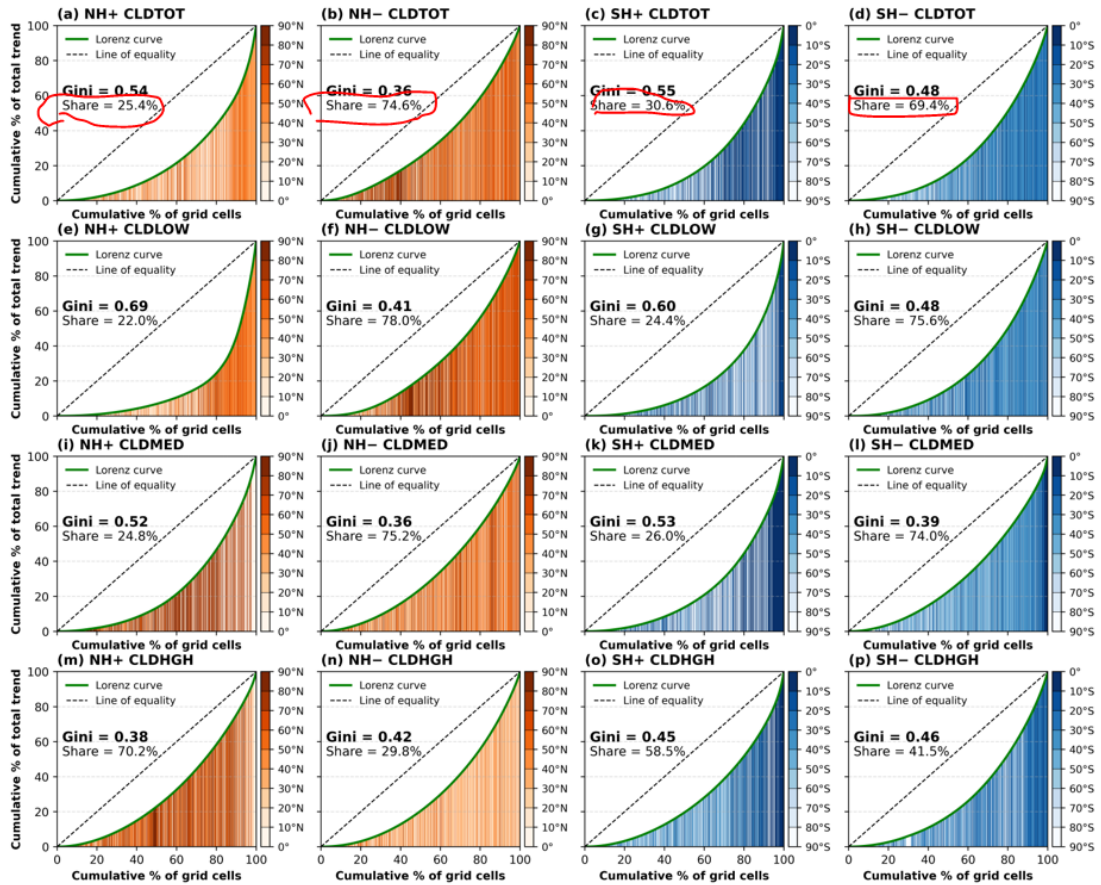


Fig. 2. Latitudinal disparity in area-integrated surface Chl concentration.

(A and C) Lorenz curves of climatological Chl area-integrated over 2° latitudinal bands in the Northern (0° to 60°N) and Southern Hemispheres (0° to 60°S) during the 2003–2022 period. Bars represent the cumulative percentage of surface Chl integrated over 2° latitudinal bands, ordered in ascending contribution of Chl to the total. (B and D) Interannual variability of the Gini index from 2003 to 2022, with significant trends ($P < 0.05$) indicated by an asterisk.



6.4. Figure Presentation and Interpretability: Figure 7, SHAP Analysis: The use of SHAP values needs to be more accessible. Please explain the intuition of the color bar (“Feature value: High vs. Low”) in relation to the x-axis (SHAP value) in the text or caption. Furthermore, the inset bar charts in Fig. 7 are currently too small and unreadable. To save space, panels sharing variables (a, b, c) should share a single y-axis and color bar, allowing the insets to be enlarged or moved to the supplement. Finally, please state in the caption if the features on the y-axis are ranked by overall importance.

We are very grateful for your suggestions regarding the improvement of figure readability. Indeed, the SHAP plot (Fig. 7) in the original manuscript appeared somewhat crowded, and the embedded bar charts were difficult to read, making them legible only upon zooming in on the page; please forgive our oversight in this regard. To enhance the readability and interpretability of the figure, we have completely reorganized Fig. 7. Specifically, we removed the inset bar charts representing

contributions from the original Fig. 7 and relocated them to Fig. 8 for clear display. Furthermore, to make the SHAP analysis more accessible and easier to understand, we added explicit explanations in the figure caption. We clarified the relationship between the color bar (feature value level) and the x-axis: the color bar indicates high versus low feature values, where feature values refer to the long-term trend of the difference between each sensitivity experiment and the control experiment. Because our modeling targets LUCC-induced cloud cover trends, the names of the drivers on the y-axis of the SHAP plot are preceded by the difference symbol (Δ). It should also be noted that these variables were already ranked by feature importance—a point we did not explain in the earlier version, but in the revised manuscript, we explicitly specify that the SHAP plot is sorted by feature importance. When purple (high feature value) is distributed along the positive x-axis, it indicates that a LUCC-induced increase in this climate feature drives an increase in the predicted cloud cover trend (i.e., making a positive contribution), consistent with standard SHAP visualizations in most studies (

1. Andrea K. Tokranov et al. ,Predictions of groundwater PFAS occurrence at drinking water supply depths in the United States. *Science*. 386,748-755(2024).DOI:10.1126/science.ad06638;

2. M. Berdugo, J. J. Gaitán, M. Delgado-Baquerizo, T. W. Crowther, V. Dakos, Prevalence and drivers of abrupt vegetation shifts in global drylands. *Proc. Natl. Acad. Sci. U.S.A.* 119, e2123393119 (2022);

3. Wang, Y., Liu, D., Wang, H., Shi, S., Hu, Q., Wang, Z., Liu, Z., Zhao, T., and Shen, L.: Synchronization of source and sink by boundary layer evolution: a key to new particle formation under varying ozone pollution, *Atmos. Chem. Phys.*, 26, 7827–7842, <https://doi.org/10.5194/acp-26-7827-2026>, 2026.).

Editor's summary

Abstract

Results and discussion

Conclusions

Acknowledgments

Supplementary Materials

References and Notes

eLetters (2)

ance reduction. However, both variables are important to the model, indicating that population density provides additional information to the model that further reduces variance. This is also the case for other correlated variables in the final model (fig. S13).

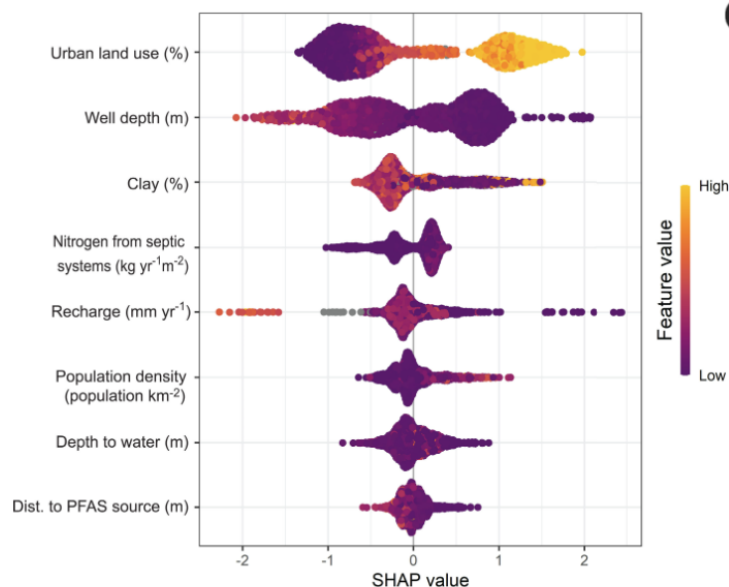


Fig. 3. SHAP plot for model training data for detection of PFAS.

Variables are organized from most to least important (fig. S11) from top to bottom of the figure. Positive SHAP values correspond to an increased probability of detection and vice versa (SHAP value units are in log odds). SHAP values are computed relative to the average prediction, indicated as zero on the x axis. Colors on the SHAP plot range from low (purple) to high (yellow) values of the predictor variable. Missing values are shown in gray.

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Significance

Abstract

Results and Discussion

Materials and Methods

Data, Materials, and Software Availability

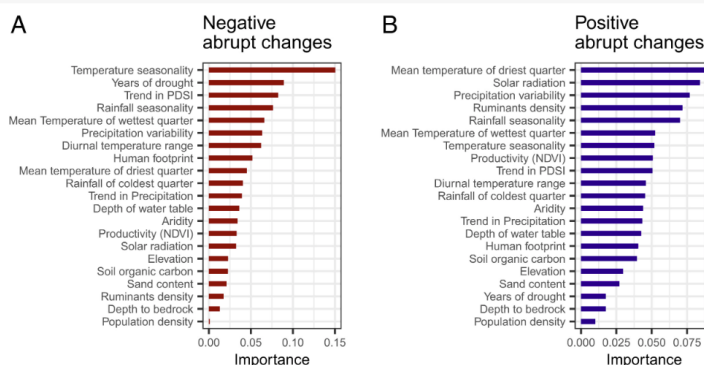
Acknowledgments

Supporting Information

References

seasonality on ecosystem productivity (30), e.g., monsoonal climates in India (31).

Fig. 2.



Drivers of abrupt changes have contrasting importance depending on the trend of NDVI analyzed. Ranked importance for negative (A) and positive (B) abrupt changes. Importance is measured as gain and represents the improvement in accuracy of the RF model when a factor is included. The model fitted is a RF algorithm confronting abruptness (1 if abrupt, 0 otherwise) with 21 uncorrelated environmental factors summarizing climatic, soil, topographical, and human-related drivers. Total number of instances used to train/validate the model is 1955/839 for negative abrupt changes and 9135/3915 for positive abrupt changes.

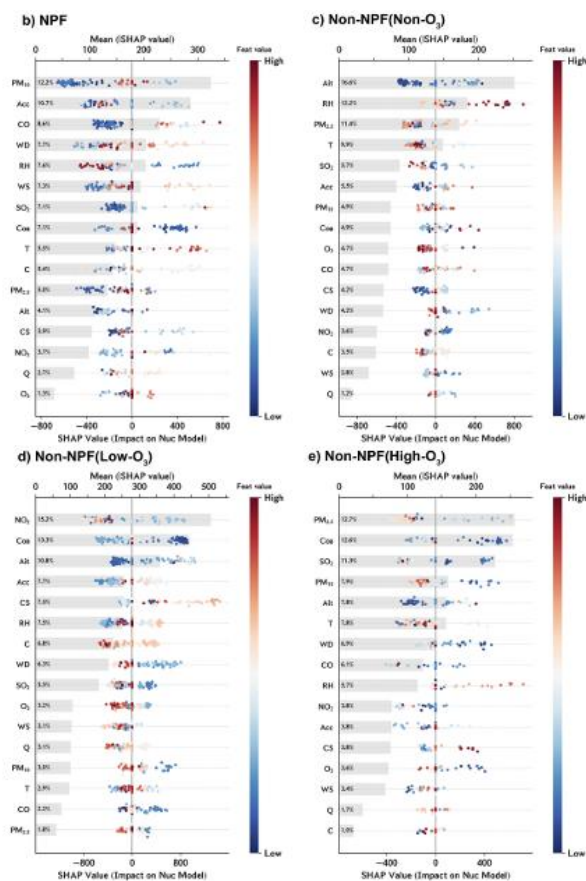


Figure 6. SHAP-based analysis of drivers for particle number concentrations in the Nuc mode. (a) Mean SHAP values across the four scenarios, with red, yellow, blue, and black bars represent the NPF, Non-NPF (Non-O₃), Non-NPF (Low-O₃) and Non-NPF (High-O₃) scenarios, respectively. (b–e) Feature importance and summary plots for (b) NPF, (c) Non-NPF (Non-O₃), (d) Non-NPF (Low-O₃), (e) Non-NPF (High-O₃) scenario. The bar charts indicate the mean absolute SHAP values, while the scatter plots show the distribution of SHAP values, with colors transitioning from blue (low feature values) to red (high feature values).

Specific comments

7. Title: The title in the preprint contains a typo (“amplifiers”) and does not match the corrected title in the online EGU sphere version.

We are very grateful for your thorough check. Regarding this issue present in the title, we have corrected it in the revised manuscript, and the corrected result is also displayed in the preprint following the EGU technical check. In the original version, the word "amplifiers" contained an extra letter "r"; we have removed the letter "r" in the revised version. We once again express our most sincere gratitude for your valuable time and meticulous review.

8. Abstract: The relative numbers provided are unclear. Relative to what baseline?

We are very grateful for your valuable feedback. Indeed, in the current version, we failed to clearly explain the relevant numerical values. In fact, when presenting differences, all of our data are calculated relative to the control experiment, that is, the sensitivity experiment minus the control experiment. To address this issue, we have thoroughly re-examined the numbers mentioned in the Abstract and revised the text to ensure clearer expression.

9. Acronyms & Variables: The paper has a lot of acronyms, making it difficult to read. I suggest using far fewer acronyms and wherever possible use conventional acronyms some readers might already be familiar with.

We sincerely thank you for pointing out this issue. We completely agree that the excessive use of abbreviations in the previous version (e.g., FAO, CESM, AF50, BE50, REAL, CLDTOT, CLDLOW, CLDMED, CLDHGH, etc.) could easily disrupt the reading flow, making the manuscript difficult to follow. In response to your valuable feedback, we have thoroughly reviewed and revised the main text to minimize the use of abbreviations, thereby enhancing overall readability.

However, certain abbreviations are necessary to retain—such as CESM, as well as the names of each experiment (CTL, AF50, BE50, and REAL)—though we have ensured that their full names are explicitly defined upon their first occurrence. Similarly, we needed to retain standard output variable names from the CESM model, such as cloud cover variables (CLDTOT, CLDLOW, CLDMED, and CLDHGH) and related climate factors. Other abbreviations were also preserved, such as SHAP and XGBoost, as this conforms to standard practice in numerous studies and maintains the conciseness of proper technical terminology.

10. The term "bioenergy": currently reads a bit like jargon and would benefit from a brief functional explanation. I recommend adding a short definition around Line 93 in the introduction, and perhaps including a few clarifying words in the abstract as well to ensure it is clear to all readers.

We thank you for your valuable comment. We agree that the term "bioenergy" might be perceived as jargon by a broader audience, and thus providing a clear functional explanation is necessary to significantly enhance the readability of the paper. Therefore, following your suggestion, we have added clarifying definitions in both the Abstract and the Introduction—specifically noting that bioenergy refers to the large-scale cultivation of dedicated energy crops for renewable electricity generation or biofuel production, the widespread deployment of which represents a major driver of future land-use and land-cover change. Indeed, while we had detailed this land-use change pathway involving bioenergy crops in the experimental design section, we fully agree that presenting it clearly in the Abstract is beneficial.

11. Line 171: The first reference to a Supplementary Information (SI) figure jumps to Figs. S24–S27. Might be better to reorder the SI figures so they appear sequentially as mentioned in the main text.

We thank you for your valuable comment. Indeed, our previous manuscript failed to account for the alignment between the supplementary figures and the narrative in the main text, resulting in substantial jumps that disrupted reading continuity. We are very

grateful for your insightful feedback. To address this issue, we have reordered the figures in the Supplementary Information to strictly follow the sequence in which they are cited in the main text.

12. Line 180: "landuse.timeseries" – Typo?

We thank you for your valuable comment. The term "landuse.timeseries" is not a typo. Therefore, we have retained this usage in the main text, as this expression intuitively reflects that our simulations are transient simulations, that is, the land-use forcing varies on an annual basis over time. This usage has also been adopted in previous studies (e.g., Cheng et al., 2022: Future bioenergy expansion could alter carbon sequestration potential and exacerbate water stress in the United States. *Sci. Adv.* 8, eabm8237 (2022). DOI: 10.1126/sciadv.abm8237). On the other hand, this phrasing also corresponds to the official naming convention of CESM input data (https://svn-ccsm-inputdata.cgd.ucar.edu/trunk/inputdata/lnd/clm2/surfdata_map/), which we speculate was intended by the official repository to highlight that the land-cover dataset is dynamic and time-evolving.



CLM5 can simulate transient LULCCs through a prescribed landuse.timeseries dataset (47). Changes in areas of PFTs are performed annually on 1 January of the year. Fertilizer and irrigation (53) are applied only to crop PFTs and are applied depending on rules from the crop module. Fertilizer application rates and irrigation areas are also set annually. Fertilization and irrigation affect the water quality and water availability, as fertilizer is an input for nitrogen leaching and irrigation could alter energy fluxes. For a full overview of CLM5 and the process of leaching, interested readers are referred

- Revision 70792: /trunk/inputdata/lnd/clm2/surfdata_map

- ..
- [NEON/](#)
- [README_c130529](#)
- [README_c130927](#)
- [README_c141219](#)
- [README_c141229](#)
- [ctsm1.0.dev094-2.g633be0eb/](#)
- [ctsm5.1.dev030/](#)
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- [ctsm5.1.dev120/](#)
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- [landuse.timeseries_0.9x1.25_hist_16pfts_Irrig_CMIP6_simyr1850-2015_c170824.nc](#)
- [landuse.timeseries_0.9x1.25_hist_16pfts_simyr1850-2015_c170428.log](#)
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- [landuse.timeseries_0.9x1.25_hist_78pfts_simyr1850-2015_c170112.nc](#)
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- [landuse.timeseries_0.9x1.25_hist_78pfts_simyr1850-2015_c170428.nc](#)
- [landuse.timeseries_0.9x1.25_hist_simyr1860-2013_c140818.nc](#)

13. Line 183: "FAO" appears here for the first time but is not defined until Line 603. Please ensure it is defined upon its first use in the text.

We are very grateful for your valuable comment. Please forgive our oversight in failing to explicitly define the abbreviation FAO upon its first occurrence. In the revised manuscript, we have corrected this issue by spelling out its full name: the Food and Agriculture Organization of the United Nations (FAO). This organization defines not only the concept of forests but also that of afforestation (<https://openknowledge.fao.org/server/api/core/bitstreams/531a9e1b-596d-4b07-b9fd-3103fb4d0e72/content>). Furthermore, we have conducted a full audit of all abbreviations upon their first appearance throughout the manuscript to ensure that similar issues are avoided.

OTHER PLANTED FOREST

Planted forest which is not classified as plantation forest.

1c ANNUAL FOREST EXPANSION, DEFORESTATION AND NET CHANGE

FOREST EXPANSION

Expansion of forest on land that, until then, was under a different land use, implies a transformation of land use from non-forest to forest.

AFFORESTATION (Sub-category of FOREST EXPANSION)

Establishment of forest through planting and/or deliberate seeding on land that, until then, was under a different land use, implies a transformation of land use from non-forest to forest.

NATURAL EXPANSION OF FOREST (Sub-category of FOREST EXPANSION)

Expansion of forest through natural succession on land that, until then, was under a different land use, implies a transformation of land use from non-forest to forest (e.g. forest succession on land previously used for agriculture).

DEFORESTATION

The conversion of forest to other land use independently whether human-induced or not.

Explanatory notes

1. Includes permanent reduction of the tree canopy cover below the minimum 10 percent threshold.
2. It includes areas of forest converted to agriculture, pasture, water reservoirs, mining and urban areas.
3. The term specifically excludes areas where the trees have been removed as a result of harvesting or logging, and where the forest is expected to regenerate naturally or with the aid of silvicultural measures.
4. The term also includes areas where, for example, the impact of disturbance, over-utilization or changing environmental conditions affects the forest to an extent that it cannot sustain a canopy cover above the 10 percent threshold.

14. Line 230+: Please include units for all variables discussed in the text, including those related to Equation 6.

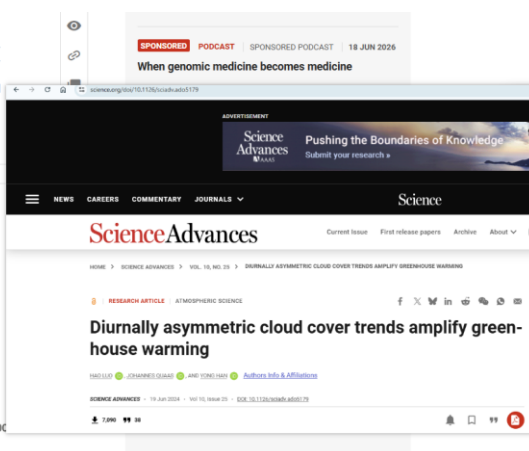
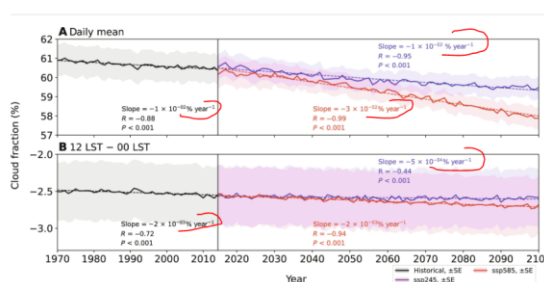
We sincerely thank you for pointing out this oversight. We have carefully checked the entire manuscript and added standard units for all physical variables in the text, almost all of which are derived from the default units in CESM (e.g., the unit for sensible heat flux is W/m^2). For dimensionless variables or ratios, we have also explicitly stated that they are dimensionless. We believe these additions will significantly enhance the clarity and rigor of our methodology.

15. Line 301: There appears to be a typo in the error bounds: “-0.0083 ± 1037%/year”. Additionally, it would be much more intuitive to present these trends per decade rather than per year.

We sincerely thank you for taking the valuable time to conduct such a rigorous review of our study, which has truly reinforced the importance of maintaining scientific rigor in our future work. Please forgive our oversight during manuscript preparation. In addition, we have corrected the code used for calculating confidence intervals, as detailed in our response to Comment 6.1. Regarding the presentation of trends, we have opted to retain our current approach of reporting annual trends rather than decadal trends. Expressing trends on an annual basis is a well-established convention in previous literature (e.g., Luo et al., 2024: Diurnally asymmetric cloud cover trends amplify greenhouse warming. *Sci. Adv.* 10, eado5179 (2024). DOI: 10.1126/sciadv.ado5179). We believe annual rates are more intuitive and tangible to interpret than decadal scales, which can feel somewhat abstract. Furthermore, because the land-use forcing dataset varies on an annual basis, presenting the simulated cloud cover and associated atmospheric response trends on an annual timescale provides a more consistent alignment with the underlying forcing.

Fig. 1. Trends in diurnal cloud fraction.

(A) Interannual variations in diurnal cloud fraction as a function of time of day from the “historical” simulations of the CMIP6 (1970–2014). (B) As (A) but for ERA5 (1970–2022). (C) As (A) but for MERRA-2 (1980–2022). (D) As (A) but for the projected period (2015–2100) under esp245. (E) As (D) but under esp585. (F) Interannual variations in diurnal difference (12 LST minus 00 LST) of cloud fraction. All the data are annual averages of the area-weighted near-global (60°S and 60°N) average. A standardized anomaly index (see Materials and Methods) is derived to eliminate the interference caused by the interannual decrease in the daily average cloud fraction (Fig. 2, A and B). The flipping of signs near the midpoint of the time series is due to the processing of the standard anomaly index and the approximately linear signal changes.



16. Lines 364 & 373: I suggest avoiding subjective phrases like “climate damage” or “negative impacts on the climate.” Maintain scientific descriptive, objective scientific language (e.g., “amplified warming”).

We are deeply grateful for your valuable comment. Indeed, we should avoid overly subjective language; maintaining objective and strictly descriptive scientific language is essential for this manuscript. In the revised version, we thoroughly audited the entire text to eliminate any subjective or value-laden phrasing. We once again express our

most sincere gratitude for the valuable time and effort you have invested. These insightful comments have not only improved the present study, but more importantly, will guide us to consciously maintain an objective description of research findings in our future work.

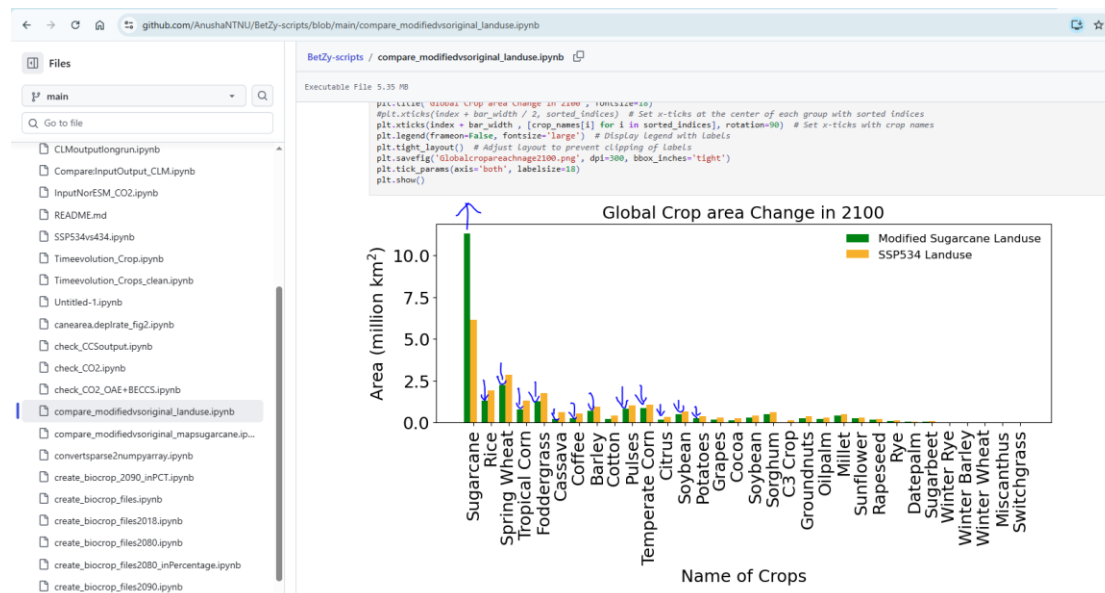
17. Lines 493–497: The “Mesosphere clouds” – is this a terminology error? The authors discuss the loss of “mesosphere clouds” due to boundary layer changes suppressing moisture supply. The CESM variable CLDHGH represents upper tropospheric clouds. Please clarify.

We are very grateful for your rigorous review. Fortunately, your thorough check helped us identify and correct this scientific inaccuracy, and we have fully addressed this issue in the revised manuscript.

18. Lines 596–597: The phrasing “the land comes from the land of other bioenergy crops” is awkward and should be rewritten for clarity.

We are very grateful for your valuable comment. Regarding this sentence, what we intended to convey is that the land utilized for bioenergy crop expansion in our simulations is converted from other crop lands, which differs from idealized afforestation (where land is derived from grasslands or shrublands). In fact, this point is closely related to your first comment. In CLM5, sugarcane is explicitly categorized into rainfed sugarcane and irrigated sugarcane, corresponding to indices 67 and 68, respectively. Meanwhile, Index 0 represents bare ground; indices 1 – 8 represent tree types; and indices 9 – 14 represent shrubs and grasses, which serve as the source lands for forest expansion in our study. This mode of forest expansion strictly adheres to the FAO definition of afforestation. In the bioenergy crop expansion experiment, the land area required for sugarcane expansion (both rainfed and irrigated) is reallocated from other crop lands. As demonstrated in existing repositories (https://github.com/AnushaNTNU/BetZy-scripts/blob/main/compare_modifiedvsoriginal_landuse.ipynb), bioenergy crop expansion operates as a zero-sum trade-off to ensure area conservation. Similarly, in

idealized afforestation, deriving land from grasslands or shrublands is likewise designed to preserve total land area, fulfilling CESM's strict requirement that patch-level land-cover alterations must sum to 100% at the grid-cell 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.