

Responses to Reviewers' Comments on "Terrestrial Ecosystem Model in R (TEMIR) version 1.0: Simulating ecophysiological responses of vegetation to atmospheric chemical and meteorological changes" by Tai et al. (MS No.: EGUSPHERE-2023-1287)

We would like to thank the reviewers for the thoughtful and insightful comments. The manuscript has been revised accordingly, and our point-by-point responses are provided below. The reviewers' comments are *italicized*, our replies are in black font, and our new/modified text cited below is highlighted in **bold**.

Response to Referee #1

With a background in ecosystem modelling, I find this really appealing. Although I can not fully understand/buy into what you are talking about in the introduction regarding the use of R by ecologists. Sure, we in the ecosystem modelling community are using lower level computer language, but we are also using R, MATLAB or Python for our analysis. I suggest that you re-write that section.

We thank the reviewer for the comment and recognize the confusing phrasing. We were trying to emphasize most Earth system models are written in lower-level computer languages, making these models less accessible to ecologists who are more familiar with R, and certainly ecosystem modelers ourselves often use R, Python and other high-level languages for analysis. The paragraph is now rewritten to make these points clearer:

P4 L29: "Developing an ecosystem model in the R programming language is beneficial to various ends. **R is an increasingly popular tool** for ecological research (R Core Team, 2022), especially in population and community ecology. Lai et al. (2019) surveyed more than 60,000 peer-reviewed ecology journal articles, and found that the number of studies reported using R as their primary tool in data analysis increased from ~10% in 2008 to ~60% in 2017. **However, ecosystem and Earth system models are often written in low-level languages such as Fortran, because the field of ecosystem and Earth system modeling has close historical ties** with geoscientific research due to the importance of representing the land cover and biogeochemical cycles in climate **models, which are most often written in low-level languages that are less accessible to researchers outside of the field.** Having a terrestrial ecosystem model in R may help enhance the accessibility to ecosystem modeling for ecological researchers **who are more familiar with R**, generate a common modeling framework across population, community and ecosystem scales, and hopefully serve as a bridge between ecological and geoscientific fields to advance interdisciplinarity. Being an entirely free and open software as well as a highly versatile and relatively user-friendly programming language, it may also help promote **open science in environmental research and education**, allowing the model to be more widely used as a policy-relevant assessment tool for practitioners, **such as those who need to assess the carbon uptake potential of tree planting or reforestation as means to achieve carbon neutrality.**"

Generally, I like your model description, but there are two things that I believe needs a bit more attention. First of all, PFT:s (Plant Functional Types), are you really simulating PFT:s? From what I have read, it is more like you are simulating different land tiles with monocultures of PFT:s planted on them. There is a mix, in the text, between talking about a PFT as plant and PFT as a land-cover/vegetation type. For instance in section 2.2.1. For instance, bare ground can not be a PFT.

We thank the reviewer for raising these issues that may cause confusion. The plant functional types (PFT) description was brief and we agree it should be clarified. Indeed, PFTs should be discussed as broad vegetation types that are simulated individually (“monoculturally”) per “land tile” for each grid cell, which can consist of multiple such land tiles for such PFTs. We have now revised the relevant parts as follows:

P6 L7: “... The plant type categories consist of 14 natural vegetation types (including generic C3 crops) (Lawrence and Chase, 2007b) and 10 rainfed or irrigated crop types (Table S1), **giving a total of 24 different plant function types (PFTs), and one land type for unvegetated land or bare ground. Each model grid cell consists of a mosaic of natural or managed PFTs and/or bare ground**, where only the natural PFTs share a single soil column, allowing them theoretically to compete for soil water. **Each PFT or bare ground has a prescribed present-day fractional coverage in each grid cell**, derived from MODerate resolution Imaging Spectroradiometer (MODIS) satellite data (Lawrence and Chase, 2007b) according to climatic (temperature- and precipitation-based) rules (see table 3 of Bonan et al., 2002), **as well as managed crop distribution for non-generic crops (corn, temperate and winter cereals, soybean) (Portmann et al. (2010). Each PFT has their own characteristic structural and physiological parameters (Table S2), as detailed in Oleson et al. (2013). The parameters used to represent vegetation structure include LAI, stem area index (SAI) and canopy height (*h*). This version of TEMIR lacks a full carbon cycle, thus these structural parameters are prescribed as model input data.** Monthly PFT-level LAI is derived from MODIS using the deaggregation methods described in Lawrence and Chase (2007b); PFT-level SAI is derived from LAI with the methods of Zeng et al. (2002). PFT-level canopy heights are prescribed following Bonan et al. (2002). **Users can specify any gridded total LAI input data, whereby the PFT-specific LAI that TEMIR requires is then scaled accordingly. ...”**

Depending on your answer to the question above, if you are truly simulating different PFT:s in a tile, then competition needs to be presented. If not, then clearly state that you are not simulating competition between different strategies, and that the spatial extent of these strategies is fixed. Something that I was missing from the discussion as well. How is that affecting your results, that you have a fixed fraction of strategies?

I would claim that for instance having different sensitiveness to ozone would affect the composition if [O3] will change in the future.

We thank the reviewer for comments on competition, adaptation and composition, in particular the O₃-related composition changes (Calvete-Sogo et al., 2016; Fuhrer et al., 2016; Emberson, 2020). These are active research areas with many developing model implementations (Lawrence et al., 2019; Franklin et al., 2020; Franz and Zaehle, 2021). TEMIR v1.0 lacks a prognostic carbon cycle, and thus cannot simulate compositional or distributional changes (e.g., due to adaptation) at model timesteps. While model development for a full carbon cycle is ongoing, we focus here in this version the shorter-timescale biosphere-atmosphere interactions with prescribed plant type distribution and structure. Yet, at the capacity of TEMIR v1.0, we can address distributional changes by changing the input of PFT fractional coverage, which is currently updated in the simulations yearly and can be modified for higher frequencies. This has now been stated more clearly here:

P6 L20: “... **This version of TEMIR does not dynamically simulate PFT coverage and structural parameters, thus competition among different plant strategies or adaptation to environmental changes such as climate change and air pollution is not simulated. The effects of land use and land cover change (LULCC) or changing**

plant type distribution due to adaptation can only be included by user-modified prescribed PFT fractional coverage or LAI data obtained externally from other models or studies. These input data can however be updated every simulation year to represent continuous LULCC over interannual to multidecadal timescales. Model development for a full carbon cycle for both natural vegetation and crops (Tai et al. (2021) is actively ongoing.”

More specifically regarding the competition due to O₃ (Agathokleous et al., 2020), we have now extended the discussion here:

P34 L4: “O₃ influences in the current version of TEMIR are limited to vegetation physiological and productivity responses. Intra- and interspecies differential sensitivity to O₃ can cause competition (Agathokleous et al., 2020), affecting some species more than others in terms of biomass, flowering and seed development, and thus impacting community composition, PFT fractional coverage and biodiversity (Calvete-Sogo et al., 2016; Fuhrer et al., 2016; Emberson, 2020). This can also be seen among functional groups; e.g., perennial species retains more aboveground biomass than annuals, and angiosperms are more prone to O₃ damage than gymnosperms, thus giving possible long-term biodiversity effects (Agathokleous et al., 2020). Such effects are further also complicated by soil conditions (e.g., water and nitrogen content), and spatial heterogeneity whereby regional strategies might differ within functional groups requires more studies to obtain observation-based parameterization.”

Some specific corrections:

line 10, page 2; there is a missing "is" on that line.

Eq. 14 is missing something

We thank the reviewer for noticing the places in need of corrections, and changes are made accordingly as shown:

P2 L9: “... About a third of the total cumulative CO₂ emission to date **that is due to anthropogenic land cover change** could have been emitted before the time of industrialization (Pongratz et al., 2009). ... ”

P8 L13: “ $\Theta_{\text{PSII}} J^2 - (I_{\text{PSII}} + J_{\text{max}}) J + I_{\text{PSII}} J_{\text{max}} = 0$ ”

Response to Referee #2

(1) Is the spatial distribution and fractional coverage of PFTs fixed during the simulation period? Does it mean that the model doesn't consider land use change effect? If so, it is necessary to discuss the effect of lacking LULCC change on GPP estimation.

We thank the reviewer for the comments. We have now clarified the representation of land use and land cover change in this version of TEMIR here:

P6 L11: “... **Each PFT or bare ground has a prescribed present-day fractional coverage in each grid cell**, derived from MODerate resolution Imaging Spectroradiometer (MODIS) satellite data (Lawrence and Chase, 2007b) according to climatic (temperature- and precipitation-based) rules (see table 3 of Bonan et al., 2002), as well as managed crop distribution for non-generic crops (corn, temperate and winter cereals, soybean; Portmann et al. (2010)). **Each PFT has** their own characteristic structural and physiological parameters (Table S2), as detailed in Oleson et al. (2013). The parameters used to represent vegetation structure include LAI, stem area index (SAI) and canopy height (h). **This version of TEMIR lacks a full carbon cycle, thus these structural parameters are prescribed as model input data.** Monthly PFT-level LAI is derived from MODIS using the deaggregation methods described in Lawrence and Chase (2007b); PFT-level SAI is derived from LAI with the methods of Zeng et al. (2002). PFT-level canopy heights are prescribed following Bonan et al. (2002). **Users can specify any gridded total LAI input data, whereby the PFT-specific LAI that TEMIR requires is then scaled accordingly. This version of TEMIR does not dynamically simulate PFT coverage and structural parameters, thus competition among different plant strategies or adaptation to environmental changes such as climate change and air pollution is not simulated. The effects of land use and land cover change (LULCC) or changing plant type distribution due to adaptation can only be included by user-modified prescribed PFT fractional coverage or LAI data obtained externally from other models or studies. These input data can however be updated every simulation year to represent continuous LULCC over interannual to multidecadal timescales. Model development for a full carbon cycle for both natural vegetation and crops (Tai et al. (2021) is actively ongoing.”**

Land use and land cover change (LULCC) would undoubtedly have large regional effects on vegetation, soil and thus GPP, especially in the productive tropical regions (Hou et al., 2022). As the reviewer rightly noticed, LULCC is mostly represented by PFT fractional changes; our study does not dynamically simulate LULCC effects as PFT coverage inputs are fixed, as explained above. As studies mostly found that LULCC reduces GPP for the 2010s (due to urbanization, agricultural expansion, and deforestation (Hou et al., 2022), it is likely that our results may overestimate GPP; however, under CO₂ effect, global influences of LULCC may be small (~2%) for the coming century. We now discuss these aspects more here:

P33 L3: “... The nondynamic representation of vegetation cover and parametrization is a shortcoming of TEMIR, thus **simulations overlook intricate and transient impacts of LULCC on land-atmosphere exchange (Ganzeveld et al., 2010; Pongratz et al., 2010; Prescher et al., 2010; Chen et al., 2018; Bastos et al., 2020; Hou et al., 2022).** **With the capacity of the current version of TEMIR, our simulations address these aspects by changing the input data of LAI and PFT fractions derived from LULCC, for yearly and higher frequencies. LULCC can drive large regional changes, though recent LULCC mostly reduces GPP (due to urbanization, agricultural expansion, and deforestation), counteracted partly by CO₂ fertilization effects (Wu et al., 2023), thus the validity of our results is likely unchanged.** The assumption of sufficient nitrogen availability is a limitation...”

(2) Please elaborate what MODIS product did you use to derive PFTs distribution maps. And how did you separate C3 and C4 crops, since MODIS products don't have such information.

Input data and classifications are based on the Community Land Model version 4.5 (Lawrence et al., 2019), with more specifics in Bonan et al. (2002) and Lawrence and Chase (2007a). Generic crops are all C3, and otherwise specific crops are separate PFTs; this is now clarified in the text:

P6 L7: “... The plant type categories consist of 14 natural vegetation types (including generic C3 crops) (Lawrence and Chase, 2007b) and 10 rainfed or irrigated crop types (Table S1), **giving a total of 24 different plant function**

types (PFTs), and one land type for unvegetated land or bare ground. Each model grid cell consists of a mosaic of natural or managed PFTs and/or bare ground, where only the natural PFTs share a single soil column, allowing them theoretically to compete for soil water. Each PFT or bare ground has a prescribed present-day fractional coverage in each grid cell, derived from MODerate resolution Imaging Spectroradiometer (MODIS) satellite data (Lawrence and Chase, 2007b) according to climatic (temperature- and precipitation-based) rules (see table 3 of Bonan et al., 2002), as well as managed crop distribution for non-generic crops (corn, temperate and winter cereals, soybean) (Portmann et al., 2010). Each PFT has their own characteristic structural and physiological parameters (Table S2), as detailed in Oleson et al. (2013). The parameters used to represent vegetation structure include LAI, stem area index (SAI) and canopy height (h). This version of TEMIR lacks a full carbon cycle, thus these structural parameters are prescribed as model input data. Monthly PFT-level LAI is derived from MODIS using the deaggregation methods described in Lawrence and Chase (2007b); PFT-level SAI is derived from LAI with the methods of Zeng et al. (2002). PFT-level canopy heights are prescribed following Bonan et al. (2002). Users can specify any gridded total LAI input data, whereby the PFT-specific LAI that TEMIR requires is then scaled accordingly. ...”

(3) *MERRA-2 has a native resolution of $0.5^\circ \times 0.625^\circ$, why didn't you conduct simulations at this relative high resolution?*

We thank the reviewer for pointing this out. Modeling time and computing costs will be a lot higher if the model is run at the said native resolution for global simulations, and therefore for the current version the inputs are consistently restricted to $2^\circ \times 2.5^\circ$, which is also the commonly used resolution for GEOS-Chem global simulations. As a primary goal of this model development is to couple with GEOS-Chem output, $2^\circ \times 2.5^\circ$ was first used, but the model is in essence resolution-independent; as long as the input data all share the same resolution, the model can be easily modified to run at a higher resolution. In fact, we have run at said MERRA-2 native resolution and much higher with assimilated local meteorology for regional studies (e.g., Hong Kong), which are currently in preparation (e.g., Figure 1, Tao et al., in prep; Lam et al., in prep). More on this is now discussed:

P15 L24: “... We also note that as the model mechanisms are essentially resolution-independent, the model can be straightforwardly modified to conduct simulations at higher resolutions as long as the corresponding input data are provided.”

P32 L29: “... This highlights that generalization and the coarse resolution of the MERRA-2 dataset used (due to computational limitation and necessary consistency with other input datasets) can drastically overlook regional and small-scale nuances. ...”

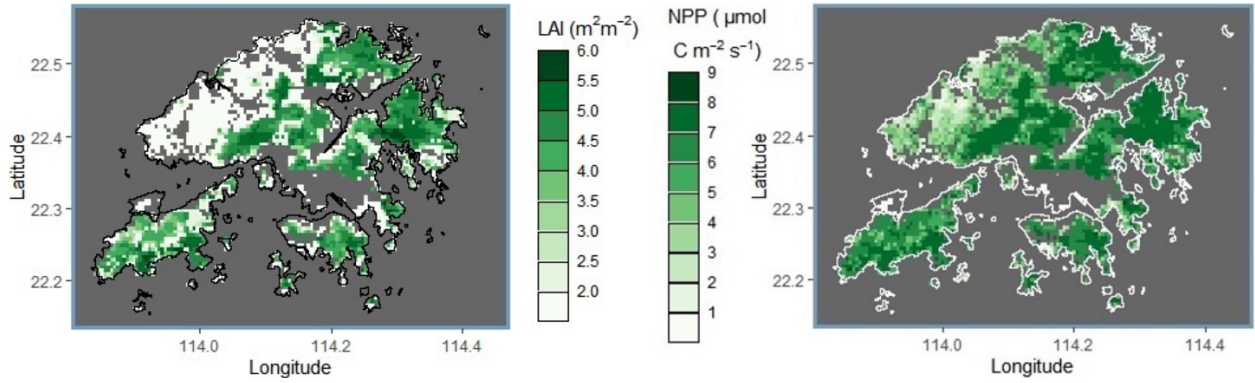


Figure 1: MODIS LAI (left panel) and TEMIR simulated annual NPP (right panel) averaged over 2009–2015 for Hong Kong.

(4) Please elaborate how is the dark respiration (R_d) rate calculated in the model.

We thank the reviewer for the comment, and have now added to the model description accordingly in P9 L1:

“... ”

$$R_d = \begin{cases} 0.015 V_{cmax} \frac{f_{R_d}(T_v)}{f_{V_{cmax}}(T_v)} & \text{for C3 plants} \\ 0.025 V_{cmax} \left(\frac{(1 + \exp[s_1(T_v - s_2)])(1 + \exp[s_3(T_v - s_4)])}{1 + \exp[s_5(T_v - s_6)]} \right) & \text{for C4 plants} \end{cases}$$

where R_d ($\mu\text{mol CO}_2 \text{ m}^{-2} \text{ s}^{-1}$) is the dark respiration rate; s_1 , s_3 and s_5 are 0.3, 0.2 and 1.3 K, respectively; s_2 , s_4 , and s_6 and 313.15, 288.15, and 328.15 K^{-1} , respectively; T_v is leaf temperature (K); and $f_{R_d}(T_v)$ and $f_{V_{cmax}}(T_v)$ are functions to adjust for variations due to temperature (Bonan et al., 2011). All of the parameters (V_{cmax} , J_{max} , T_p , R_d , K_c , K_o , Γ^* , k_p) are temperature-dependent and scale with their respective PFT-specific standard values at 25°C by different formulations. Temperature acclimation of V_{cmax} and J_{max} from the previous 10 days as well as daylength dependence of V_{cmax} is implemented as default options. These are all detailed in Sect. 8.2 and 8.3 of Oleson et al. (2013).”

(5) The TEMIR contains a two-layer soil model. Does this soil model have carbon cycling and water transport processes?

TEMIR v1.0 of this study does not have soil carbon cycling, nor soil water transport. Soil water is prescribed from MERRA-2; this is now described in in P10 L5: “... consistent with and constrained by the input soil moisture and model structure of MERRA-2. ... ”

Soil carbon cycling is under development, which compliments the corresponding carbon cycling in natural vegetation. Currently, a newer version of TEMIR has carbon cycling for crops (Tai et al., 2021). We thank the reviewer for the comment, and have now explained this more clearly:

P6 L20: “... This version of TEMIR lacks a full carbon cycle, thus these structural parameters are prescribed as model input data. ... Model development for a full carbon cycle for both natural vegetation and crops (Tai et al., 2021) is actively ongoing.”

(6) *The canopy decay coefficient for nitrogen K_n is 0.30 in the model. How was this number determined? Shouldn't it vary with leaf nitrogen content or nitrogen availability? It seems that the current version of TEMIR doesn't have an explicit nitrogen cycle. If so, it is necessary to discuss how does lack of considering nitrogen cycle affect GPP estimation.*

We thank the reviewer for the comments. TEMIR v1.0 does not have dynamic nitrogen cycle. The canopy decay coefficient $K_n = 0.30$ is calculated and calibrated to match an explicit multi-layer canopy, following exactly the formulation in CLM4.5 (Bonan et al., 2012; Oleson et al., 2013). For the effect of a lack of nitrogen cycle, the discussion is now modified as follows:

P36 L3: "... The changing nitrogen deposition due to anthropogenic activities may likewise influence the interactions between vegetation, CO₂ and O₃ (Zhao et al., 2017; Liu et al., 2021), **whereby nitrogen can limit CO₂-promoted growth (Wang et al., 2020) or modify vegetation responses (e.g., for g; Hu et al., 2021) with further implications on soil and nutrient cycling (Terrer et al., 2021).** As atmospheric composition rapidly changes in the next century, these interactive mechanisms should be considered for modelers to more representatively and accurately model the future Earth system (e.g., Bytnerowicz et al., 2007; Pu et al., 2017; Sicard et al., 2017; Franz and Zaehle, 2021; Leung et al., 2022)."

(7) *The model doesn't perform well at several crop sites. Could you add one paragraph discussing the potential measures to improve model performance for crops?*

Crop type simulations underperform in comparison to other vegetation types, and we agree very much that more discussion is needed, as now included in the following:

P32 L16: "**Simulating crops in ecosystem modeling remains particularly challenging (Deryng et al., 2016; Chopin et al., 2019; Muller and Martre, 2019; Boas et al., 2021), as it combines the nuances in phenology, physiology, coverage, and active human management with high spatiotemporal variations (Monfreda et al., 2008; Emberson et al., 2018; Ahmed et al., 2022; Gleason et al., 2022; Corcoran et al., 2023), which already exist for natural vegetation to a lesser degree. One particular crucial aspect for improvement is to get crop LAI correct, which is typically more challenging to measure than trees with large canopies and often varies to greater extents with leaf orientations for different crops. More long-term ground-based and/or remote-sensing measurements of crop LAI for different crop types across the world are particularly recommended, not only as input data but also for model validation in future development. For especially site-level simulations, locally relevant crop physiological and structural parameters should also be measured and used. Ongoing development has already been attempting to enhance crop representation in a version of TEMIR with active crop biogeochemistry (Tai et al., 2021) to improve and reconcile model inaccuracies.**"

(8) *For the site-level simulation, why did you fix CO₂ concentration at the level of 390 ppmv, rather than using the actual CO₂ concentration during the study period?*

The reviewer has correctly pointed out that we only used a constant CO₂ concentration of 2010 (Dlugokencky and Tans, 2022; Lan et al., 2023). We recognize the possible inaccuracy as modelled productivity is sensitive to CO₂

concentrations, which has been explored using TEMIR in another study (Yung et al, in prep). We also note that spatial variability of CO₂ concentration can also contribute to this issue (Cheng et al., 2022), though it is generally found to be minor (Lee et al., 2018; Tian et al., 2021). Moreover, as similar modeling studies often treated CO₂ concentration as spatially and temporally uniform, and for direct comparison with literature, this study followed such practice. We now note these limitations more extensively, which we believe do not interfere with the utility of the model (since CO₂ can easily be adjusted) for this model development paper:

P32 L31: “... Furthermore, CO₂ concentration was kept constant and spatially uniform in all simulations, which enables direct comparison with other modeling studies, but ignores possible spatiotemporal variability of CO₂ concentration (Cheng et al., 2022). Though such effects are usually minor on simulated GPP magnitudes (Lee et al., 2018; Tian et al., 2021), uncertainties should be minimized anyhow, thus users are recommended to use the measured CO₂ concentration, if available, as input for especially site-level simulations. Users are also recommended to recalibrate relevant model parameters with site observations and available datasets (e.g., of higher resolutions), such as LAI, V_{cmax} , PFT fractional coverage, etc., to yield the most accurate results. ...”

(9) *For the site CH-Cha, can you explain why the model performance is good using reanalysis meteorological input data?*

We thank the reviewer for astutely noticing and raising the issue of the site CH-Cha. We revisited all our site simulation results and noticed issues only with CH-Cha. The relative humidity provided by FLUXNET is incredibly low (mostly 0%) for July 2012 and the whole 2012. This is unrealistic and simulations should have used gap-filled (i.e., MERRA2) relative humidity instead. Hence, graphs for site CH-Cha are updated with new results, and analysis and discussion are edited accordingly, as in:

P20 L4: “... Overestimation of CH-Cha (Error! Reference source not found.(d)) is similar under FLUXNET meteorology, which is likely due to disturbances from intensive site management (i.e., cutting, slurry application and grazing, Imer et al., 2013; Merbold et al., 2014), which is a shortcoming of simplistic model representation for crops. ...”

(10) *You explained that the underestimation of GPP at the FR-Fon site is most likely due to inaccurate parameterization overcompensating for the uncertainties of satellite derived LAI. Have you tried to quantify how uncertainties in LAI affect GPP estimation. Maybe you can compare the difference using tow simulations: one use MODIS LAI as input, one use observed LAI as input.*

We thank the reviewer for the suggestions, which is particularly relevant for site simulations. Undeniably, the choice of LAI product to use can affect GPP predictions and variability (Lin et al., 2023; Wu et al., 2023), yet investigations are limited by local data availability. We have conducted a sensitivity study by perturbing LAI on sites FR-Fon and CA-TP4 to investigate the uncertainty of LAI on evergreen needleleaf forests (ENF) and deciduous broadleaf forests (DBF) respectively. Site-level sensitivity simulations have shown, in Figure 2, that small perturbations around a given LAI gives an almost linear response of GPP (e.g., a 10% increase in LAI gives a roughly 2–4% increase in GPP). Nonlinear responses start to kick in for larger perturbations (e.g., more than 20%), especially at a high given LAI due to canopy shading effect, resulting in diminishing returns. Indeed, we are currently using TEMIR to investigate how interannual changes in LAI may affect global GPP (Yung et al, in prep), which essentially serves the same purpose.

We would like to reserve the results of the ongoing study for inclusion in a future scientific paper. Here we have discussed more extensively how LAI changes and biases may contribute to uncertainties of the estimated GPP:

P32 L7: “... For instance, there is a systematic underestimation for deciduous broadleaf forests, though it can be explained by the uncertainties of LAI datasets (Liu et al., 2018; Yang et al., 2023), and some regions show distinctive physiology and phenology of grasses and shrubs. Particularly for semiarid regions where the range of productivity is large, the model shows variable accuracy. **In general, variability in prescribed LAI can be an important source of uncertainty of the model results. Single-site sensitivity simulations show that GPP generally linearly increases with LAI at low LAI, but as LAI becomes larger, GPP would increase less than proportionately due to canopy shading effect. Such nonlinearity of GPP responses to LAI changes is less important for small perturbations of LAI (e.g., less than 20%).**”

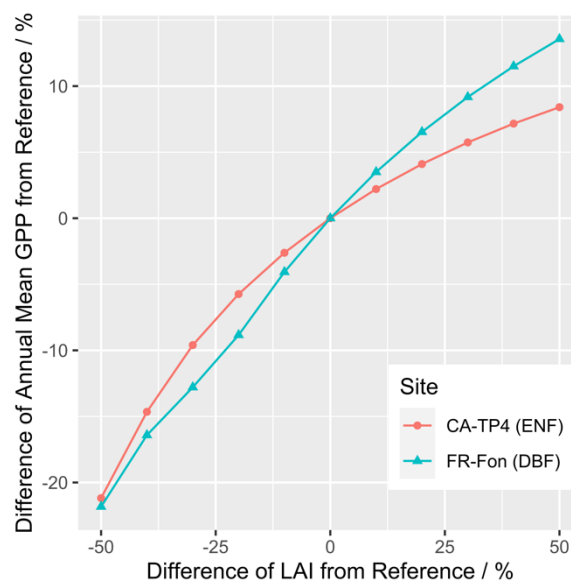


Figure 2: Changes of simulated annual mean gross primary product (GPP) under perturbation of leaf area index (LAI) for sites CA-TP4 and FR-Fon.

(11) I suggest the author add a paragraph describing what meteorological variables are needed to drive the TEMIR.

For better comprehension, we have now included the full list of MERRA-2 surface meteorological variables required to drive TEMIR in the supplementary materials (Table S5), and referred to accordingly in the text:

P15 L10: “... Global simulations from 2010 to 2015 are conducted under the same general setup as the site-level simulations, with ambient CO₂ concentration fixed at 390 ppmv and driven by 2°×2.5° MERRA-2 **surface meteorology. A full list of MERRA-2 variables required for running gridded simulations of TEMIR is shown in Table S5. ...**”

(12) Please add one table listing the key parameters for different PFTs.

A table is now added to the supplementary materials (Table S2) and mentioned here:

P6 L14: "... Each PFT has their own characteristic structural and physiological parameters (Table S2), detailed in Oleson et al. (2013). ..."

References

- Agathokleous, E., Feng, Z., Oksanen, E., Sicard, P., Wang, Q., Saitanis, C. J., Araminiene, V., Blande, J. D., Hayes, F., Calatayud, V., Domingos, M., Veresoglou, S. D., Peñuelas, J., Wardle, D. A., Marco, A. D., Li, Z., Harmens, H., Yuan, X., Vitale, M., and Paoletti, E.: Ozone affects plant, insect, and soil microbial communities: A threat to terrestrial ecosystems and biodiversity, *Science Advances*, 6, eabc1176, 10.1126/sciadv.abc1176, 2020.
- Ahmed, Z., Gui, D., Qi, Z., Liu, Y., Liu, Y., and Azmat, M.: Agricultural system modeling: Current achievements, innovations, and future roadmap, *Arabian Journal of Geosciences*, 15, 10.1007/s12517-022-09654-7, 2022.
- Bastos, A., O'Sullivan, M., Ciais, P., Makowski, D., Sitch, S., Friedlingstein, P., Chevallier, F., Rödenbeck, C., Pongratz, J., Lujikx, I. T., Patra, P. K., Peylin, P., Canadell, J. G., Lauerwald, R., Li, W., Smith, N. E., Peters, W., Goll, D. S., Jain, A. K., Kato, E., Lienert, S., Lombardozi, D. L., Haverd, V., Nabel, J. E. M. S., Poulter, B., Tian, H., Walker, A. P., and Zaehle, S.: Sources of uncertainty in regional and global terrestrial CO₂ exchange estimates, *Global Biogeochemical Cycles*, 34, 10.1029/2019gb006393, 2020.
- Boas, T., Bogena, H., Grünwald, T., Heinesch, B., Ryu, D., Schmidt, M., Vereecken, H., Western, A., and Hendricks Franssen, H.-J.: Improving the representation of cropland sites in the community land model (clm) version 5.0, *Geoscientific Model Development*, 14, 573-601, 10.5194/gmd-14-573-2021, 2021.
- Bonan, G. B., Levis, S., Kergoat, L., and Oleson, K. W.: Landscapes as patches of plant functional types: An integrating concept for climate and ecosystem models, *Global Biogeochemical Cycles*, 16, 5-1-5-23, 10.1029/2000gb001360, 2002.
- Bonan, G. B., Lawrence, P. J., Oleson, K. W., Levis, S., Jung, M., Reichstein, M., Lawrence, D. M., and Swenson, S. C.: Improving canopy processes in the community land model version 4 (clm4) using global flux fields empirically inferred from fluxnet data, *Journal of Geophysical Research*, 116, 10.1029/2010JG001593, 2011.
- Bonan, G. B., Oleson, K. W., Fisher, R. A., Lasslop, G., and Reichstein, M.: Reconciling leaf physiological traits and canopy flux data: Use of the TRY and fluxnet databases in the community land model version 4, *Journal of Geophysical Research: Biogeosciences*, 117, n/a-n/a, 10.1029/2011jg001913, 2012.
- Bytnerowicz, A., Omasa, K., and Paoletti, E.: Integrated effects of air pollution and climate change on forests: A northern hemisphere perspective, *Environmental Pollution*, 147, 438-445, 10.1016/j.envpol.2006.08.028, 2007.
- Calvete-Sogo, H., Gonzalez-Fernandez, I., Sanz, J., Elvira, S., Alonso, R., Garcia-Gomez, H., Ibanez-Ruiz, M. A., and Bermejo-Bermejo, V.: Heterogeneous responses to ozone and nitrogen alter the species composition of mediterranean annual pastures, *Oecologia*, 181, 1055-1067, 10.1007/s00442-016-3628-z, 2016.
- Chen, L., Dirmeyer, P. A., Guo, Z., and Schultz, N. M.: Pairing fluxnet sites to validate model representations of land-use/land-cover change, *Hydrology and Earth System Sciences*, 22, 111-125, 10.5194/hess-22-111-2018, 2018.

Cheng, W., Dan, L., Deng, X., Feng, J., Wang, Y., Peng, J., Tian, J., Qi, W., Liu, Z., Zheng, X., Zhou, D., Jiang, S., Zhao, H., and Wang, X.: Global monthly gridded atmospheric carbon dioxide concentrations under the historical and future scenarios, *Sci Data*, 9, 83, 10.1038/s41597-022-01196-7, 2022.

Chopin, P., Bergkvist, G., and Hossard, L.: Modelling biodiversity change in agricultural landscape scenarios - a review and prospects for future research, *Biological Conservation*, 235, 1-17, 10.1016/j.biocon.2019.03.046, 2019.

Corcoran, E., Afshar, M., Curceac, S., Lashkari, A., Raza, M. M., Ahnert, S., Mead, A., and Morris, R.: Current data and modeling bottlenecks for predicting crop yields in the united kingdom, *Front. Sustain. Food Syst.*, 7, 10.3389/fsufs.2023.1023169, 2023.

Deryng, D., Elliott, J., Folberth, C., Müller, C., Pugh, T. A. M., Boote, K. J., Conway, D., Ruane, A. C., Gerten, D., Jones, J. W., Khabarov, N., Olin, S., Schaphoff, S., Schmid, E., Yang, H., and Rosenzweig, C.: Regional disparities in the beneficial effects of rising co₂ concentrations on crop water productivity, *Nature Climate Change*, 6, 786-790, 10.1038/nclimate2995, 2016.

Dlugokencky, E., and Tans, P.: Trends in atmospheric carbon dioxide, national oceanic and atmospheric administration, global monitoring laboratory (noaa/gml), <http://www.gml.noaa.gov/gmd/ccgg/trends/global.html>, 2022.

Emberson, L.: Effects of ozone on agriculture, forests and grasslands, *Philos Trans A Math Phys Eng Sci*, 378, 20190327, 10.1098/rsta.2019.0327, 2020.

Emberson, L. D., Pleijel, H., Ainsworth, E. A., van den Berg, M., Ren, W., Osborne, S., Mills, G., Pandey, D., Dentener, F., Büker, P., Ewert, F., Koeble, R., and Van Dingenen, R.: Ozone effects on crops and consideration in crop models, *European Journal of Agronomy*, 100, 19-34, 10.1016/j.eja.2018.06.002, 2018.

Franklin, O., Harrison, S. P., Dewar, R., Fariior, C. E., Brannstrom, A., Dieckmann, U., Pietsch, S., Falster, D., Cramer, W., Loreau, M., Wang, H., Makela, A., Rebel, K. T., Meron, E., Schymanski, S. J., Rovenskaya, E., Stocker, B. D., Zaehle, S., Manzoni, S., van Oijen, M., Wright, I. J., Ciais, P., van Bodegom, P. M., Penuelas, J., Hofhansl, F., Terrer, C., Soudzilovskaia, N. A., Midgley, G., and Prentice, I. C.: Organizing principles for vegetation dynamics, *Nat Plants*, 6, 444-453, 10.1038/s41477-020-0655-x, 2020.

Franz, M., and Zaehle, S.: Competing effects of nitrogen deposition and ozone exposure on northern hemispheric terrestrial carbon uptake and storage, 1850–2099, *Biogeosciences*, 18, 3219-3241, 10.5194/bg-18-3219-2021, 2021.

Fuhrer, J., Val Martin, M., Mills, G., Heald, C. L., Harmens, H., Hayes, F., Sharps, K., Bender, J., and Ashmore, M. R.: Current and future ozone risks to global terrestrial biodiversity and ecosystem processes, *Ecol Evol*, 6, 8785-8799, 10.1002/ece3.2568, 2016.

Ganzeveld, L., Bouwman, L., Stehfest, E., van Vuuren, D. P., Eickhout, B., and Lelieveld, J.: Impact of future land use and land cover changes on atmospheric chemistry-climate interactions, *Journal of Geophysical Research*, 115, 10.1029/2010JD014041, 2010.

Gleason, S. M., Barnard, D. M., Green, T. R., Mackay, S., Wang, D. R., Ainsworth, E. A., Altenhofen, J., Brodribb, T. J., Cochard, H., Comas, L. H., Cooper, M., Creek, D., DeJonge, K. C., Delzon, S., Fritschi, F. B., Hammer, G., Hunter, C., Lombardozzi, D., Messina, C. D., Ocheltree, T., Stevens, B. M., Stewart, J. J., Vadez, V., Wenz, J., Wright, I. J., Yemoto, K., and Zhang, H.: Physiological trait networks enhance understanding of crop growth and water use in contrasting

- environments, *Plant Cell Environ*, 45, 2554-2572, 10.1111/pce.14382, 2022.
- Hou, H., Zhou, B. B., Pei, F., Hu, G., Su, Z., Zeng, Y., Zhang, H., Gao, Y., Luo, M., and Li, X.: Future land use/land cover change has nontrivial and potentially dominant impact on global gross primary productivity, *Earth's Future*, 10, 10.1029/2021ef002628, 2022.
- Hu, Y., Schäfer, K. V. R., Zhu, L., Zhao, P., Zhao, X., Ni, G., Zhang, Y., Ye, H., Zhao, W., Shen, W., and Fu, S.: Impacts of canopy and understory nitrogen additions on stomatal conductance and carbon assimilation of dominant tree species in a temperate broadleaved deciduous forest, *Ecosystems*, 24, 1468-1484, 10.1007/s10021-020-00595-4, 2021.
- Imer, D., Merbold, L., Eugster, W., and Buchmann, N.: Temporal and spatial variations of soil CO₂, CH₄ and N₂O fluxes at three differently managed grasslands, *Biogeosciences*, 10, 5931-5945, 10.5194/bg-10-5931-2013, 2013.
- Lai, J., Lortie, C. J., Muenchen, R. A., Yang, J., and Ma, K.: Evaluating the popularity of *r* in ecology, *Ecosphere*, 10, 10.1002/ecs2.2567, 2019.
- Lan, X., Tans, P., and Thoning, K. W.: Trends in globally-averaged CO₂ determined from NOAA global monitoring laboratory measurements, <https://doi.org/10.15138/9N0H-ZH07>, 2023.
- Lawrence, D. M., Fisher, R. A., Koven, C. D., Oleson, K. W., Swenson, S. C., Bonan, G., Collier, N., Ghimire, B., van Kampenhout, L., Kennedy, D., Kluzek, E., Lawrence, P. J., Li, F., Li, H., Lombardozzi, D., Riley, W. J., Sacks, W. J., Shi, M., Vertenstein, M., Wieder, W. R., Xu, C., Ali, A. A., Badger, A. M., Bisht, G., van den Broeke, M., Brunke, M. A., Burns, S. P., Buzan, J., Clark, M., Craig, A., Dahlin, K., Drewniak, B., Fisher, J. B., Flanner, M., Fox, A. M., Gentine, P., Hoffman, F., Keppel-Aleks, G., Knox, R., Kumar, S., Lenaerts, J., Leung, L. R., Lipscomb, W. H., Lu, Y., Pandey, A., Pelletier, J. D., Perket, J., Randerson, J. T., Ricciuto, D. M., Sanderson, B. M., Slater, A., Subin, Z. M., Tang, J., Thomas, R. Q., Val Martin, M., and Zeng, X.: The community land model version 5: Description of new features, benchmarking, and impact of forcing uncertainty, *Journal of Advances in Modeling Earth Systems*, 11, 4245-4287, 10.1029/2018ms001583, 2019.
- Lawrence, P. J., and Chase, T. N.: Representing a new MODIS consistent land surface in the community land model (CLM 3.0), *Journal of Geophysical Research: Biogeosciences*, 112, 10.1029/2006jg000168, 2007a.
- Lawrence, P. J., and Chase, T. N.: Representing a new MODIS consistent land surface in the community land model (CLM 3.0), *Journal of Geophysical Research*, 112, G01023, 10.1029/2006JG000168, 2007b.
- Lee, E., Zeng, F.-W., Koster, R. D., Weir, B., Ott, L. E., and Poulter, B.: The impact of spatiotemporal variability in atmospheric CO₂ concentration on global terrestrial carbon fluxes, *Biogeosciences*, 15, 5635-5652, 10.5194/bg-15-5635-2018, 2018.
- Leung, F., Sitch, S., Tai, A. P. K., Wiltshire, A. J., Gornall, J. L., Folberth, G. A., and Unger, N.: CO₂ fertilization of crops offsets yield losses due to future surface ozone damage and climate change, *Environmental Research Letters*, 17, 074007, 10.1088/1748-9326/ac7246, 2022.
- Lin, S., Hu, Z., Wang, Y., Chen, X., He, B., Song, Z., Sun, S., Wu, C., Zheng, Y., Xia, X., Liu, L., Tang, J., Sun, Q., Joos, F., and Yuan, W.: Underestimated interannual variability of terrestrial vegetation production by terrestrial ecosystem models, *Global Biogeochemical Cycles*, 37, 10.1029/2023gb007696, 2023.
- Liu, X., Tai, A. P. K., and Fung, K. M.: Responses of surface ozone to future agricultural ammonia emissions and

subsequent nitrogen deposition through terrestrial ecosystem changes, *Atmospheric Chemistry and Physics*, 21, 17743-17758, 10.5194/acp-21-17743-2021, 2021.

Liu, Y., Xiao, J., Ju, W., Zhu, G., Wu, X., Fan, W., Li, D., and Zhou, Y.: Satellite-derived lai products exhibit large discrepancies and can lead to substantial uncertainty in simulated carbon and water fluxes, *Remote Sensing of Environment*, 206, 174-188, 10.1016/j.rse.2017.12.024, 2018.

Merbold, L., Eugster, W., Stieger, J., Zahniser, M., Nelson, D., and Buchmann, N.: Greenhouse gas budget (co₂, ch₄ and n₂o) of intensively managed grassland following restoration, *Glob Chang Biol*, 20, 1913-1928, 10.1111/gcb.12518, 2014.

Monfreda, C., Ramankutty, N., and Foley, J. A.: Farming the planet: 2. Geographic distribution of crop areas, yields, physiological types, and net primary production in the year 2000, *Global Biogeochemical Cycles*, 22, 10.1029/2007gb002947, 2008.

Muller, B., and Martre, P.: Plant and crop simulation models: Powerful tools to link physiology, genetics, and phenomics, *J Exp Bot*, 70, 2339-2344, 10.1093/jxb/erz175, 2019.

Oleson, K. W., Lawrence, D. M., Bonan, G. B., Drewniak, B., Huang, M., Levis, S., Li, F., Riley, W. J., Swenson, S. C., Thornton, P. E., Bozbiyik, A., Fisher, R., Heald, C. L., Kluzek, E., Lamarque, F., Lawrence, P. J., Leung, L. R., Muszala, S., Ricciuto, D. M., Sacks, W., Sun, Y., Tang, J., and Yang, Z.-L.: Technical description of version 4.5 of the community land model (clm), 434, 2013.

Pongratz, J., Reick, C. H., Raddatz, T., and Claussen, M.: Effects of anthropogenic land cover change on the carbon cycle of the last millennium, *Global Biogeochemical Cycles*, 23, GB4001, 10.1029/2009GB003488, 2009.

Pongratz, J., Reick, C. H., Raddatz, T., and Claussen, M.: Biogeophysical versus biogeochemical climate response to historical anthropogenic land cover change, *Geophysical Research Letters*, 37, 10.1029/2010GL043010, 2010.

Portmann, F. T., Siebert, S., and Döll, P.: Mirca2000-global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modeling, *Global Biogeochemical Cycles*, 24, n/a-n/a, 10.1029/2008gb003435, 2010.

Prescher, A.-K., Grünwald, T., and Bernhofer, C.: Land use regulates carbon budgets in eastern germany: From nec to nbp, *Agricultural and Forest Meteorology*, 150, 1016-1025, 10.1016/j.agrformet.2010.03.008, 2010.

Pu, X., Wang, T. J., Huang, X., Melas, D., Zanis, P., Papanastasiou, D. K., and Poupkou, A.: Enhanced surface ozone during the heat wave of 2013 in yangtze river delta region, china, *Science of The Total Environment*, 603-604, 807-816, 10.1016/j.scitotenv.2017.03.056, 2017.

R Core Team: R: A language and environment for statistical computing, in, Vienna, Austria, 2022.

Sicard, P., Anav, A., De Marco, A., and Paoletti, E.: Projected global ground-level ozone impacts on vegetation under different emission and climate scenarios, *Atmospheric Chemistry and Physics*, 17, 12177-12196, 10.5194/acp-17-12177-2017, 2017.

Tai, A. P. K., Sadiq, M., Pang, J. Y. S., Yung, D. H. Y., and Feng, Z.: Impacts of surface ozone pollution on global crop yields: Comparing different ozone exposure metrics and incorporating co-effects of co₂, *Front. Sustain. Food Syst.*, 5,

534616, 10.3389/fsufs.2021.534616, 2021.

Terrer, C., Phillips, R. P., Hungate, B. A., Rosende, J., Pett-Ridge, J., Craig, M. E., van Groenigen, K. J., Keenan, T. F., Sulman, B. N., Stocker, B. D., Reich, P. B., Pellegrini, A. F. A., Pendall, E., Zhang, H., Evans, R. D., Carrillo, Y., Fisher, J. B., Van Sundert, K., Vicca, S., and Jackson, R. B.: A trade-off between plant and soil carbon storage under elevated CO_2 , *Nature*, 591, 599-603, 10.1038/s41586-021-03306-8, 2021.

Tian, J., Zhang, Y., and Zhang, X.: Impacts of heterogeneous CO_2 on water and carbon fluxes across the global land surface, *International Journal of Digital Earth*, 14, 1175-1193, 10.1080/17538947.2021.1937352, 2021.

Wang, S., Zhang, Y., Ju, W., Chen, J. M., Ciais, P., Cescatti, A., Sardans, J., Janssens, I. A., Wu, M., Berry, J. A., Campbell, E., Fernández-Martínez, M., Alkama, R., Sitch, S., Friedlingstein, P., Smith, W. K., Yuan, W., He, W., Lombardozzi, D., Kautz, M., Zhu, D., Lienert, S., Kato, E., Poulter, B., Sanders, T. G. M., Krüger, I., Wang, R., Zeng, N., Tian, H., Vuichard, N., Jain, A. K., Wiltshire, A., Haverd, V., Goll, D. S., and Peñuelas, J.: Recent global decline of CO_2 fertilization effects on vegetation photosynthesis, *Science*, 370, 1295-1300, 10.1126/science.abb7772, 2020.

Wu, Q., Wang, X., Chen, S., Wang, L., and Jiang, J.: Land surface greening and CO_2 fertilization more than offset the gross carbon sequestration decline caused by land cover change and the enhanced vapour pressure deficit in Europe, *Remote Sensing*, 15, 10.3390/rs15051372, 2023.

Yang, X., Chen, X., Ren, J., Yuan, W., Liu, L., Liu, J., Chen, D., Xiao, Y., Song, Q., Du, Y., Wu, S., Fan, L., Dai, X., Wang, Y., and Su, Y.: A gridded dataset of a leaf-age-dependent leaf area index seasonality product over tropical and subtropical evergreen broadleaved forests, *Earth System Science Data*, 15, 2601-2622, 10.5194/essd-15-2601-2023, 2023.

Zeng, X., Shaikh, M., Dai, Y., Dickinson, R. E., and Myneni, R.: Coupling of the common land model to the near community climate model, *JOURNAL OF CLIMATE*, 15, 23, 2002.

Zhao, Y., Zhang, L., Tai, A. P. K., Chen, Y., and Pan, Y.: Responses of surface ozone air quality to anthropogenic nitrogen deposition in the northern hemisphere, *Atmospheric Chemistry and Physics*, 17, 9781-9796, 10.5194/acp-17-9781-2017, 2017.