

Interactive comment on “Aboveground biomass in Inner Mongolian temperate grasslands decreases under climate warming” by Guocheng Wang et al.

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Reviewer #1: The work by Wang and co-authors viewed the above-ground biomass (AGB) over Inner Mongolian temperate grasslands, and analyzed the relationships of many climate, soils, grazing intensity, and grassland type variables to plants using combine biomass measurements from six long-term experiments and data in existing literatures. They found that under future climate warming, AGB in the study region could continue to decrease. On average, compared with the historical AGB (i.e., average of 1981-2019), the AGB at the end of this century (i.e., average of 2080-2100) would decrease by 14% under RCP4.5 and 28% under RCP8.5, respectively. The paper is of interests to the broad readership of Atmospheric Chemistry and Physics. The finding may also help advance our understanding how global climate change influence

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the temperate grasslands. Yet there are several limitations in the current version that need to be addressed before the publication.

Authors' Response: We greatly appreciate the reviewer's positive comments and understandings of our study.

There are several concepts in the manuscript that are not easy to understand, including 'temperate grasslands', 'meadow steppe', 'typical steppe', and 'desert steppe'.

Authors' Response: Thanks to the reviewer's comments. The study region (i.e., Inner Mongolian grasslands) is characterized mainly by a temperate climate (Zhang et al., 2020) and thus is also called Inner Mongolian temperate grassland. The grasslands in the study region can be generally classified into three categories, i.e., meadow steppe, typical steppe and desert steppe (National Research Council, 1992). In brief, meadow steppe is distributed mainly in the eastern steppe zones, typical steppe locates mostly in the central Inner Mongolia, and desert steppe is found mainly to the west of the typical steppe (Fig. 1). We have clarified this information in the revised MS (Line 83 – 87).

Introduction. The novelty of your work should be emphasized and explained in a better way.

Authors' Response: Thanks to the reviewer's suggestions. In the revision, we have modified the Introduction section in a more logic flow (Line 41-45; 53-55; 63-72; 79-80). Specifically, we have emphasized that we aim to explicitly take into account the seasonality of climate, soil, grassland type and grazing intensity in assessing the spatiotemporal variations of AGB. Moreover, we also highlight that we aim to predict the future AGB dynamics under climate change characterized mainly by warming. The possible promoting effect of CO₂ enrichment on AGB is also included in the revision as recommended by another reviewer and emphasized in the Introduction. Please see details in the Introduction of the revision, we hope these modifications can satisfy the concerns of the reviewer.

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Materials and Methods. Lines 125-126, identifying the root mean square error (RMSE) is not clear here, please add its calculations (equations) and units (% or kg ha⁻¹?).

Authors' Response: Added accordingly (Line 141-143).

Results. Lines 172-175, that is, Figure 4. Correlation matrix cannot indicate environmental drivers of Inner Mongolian grassland biomass. Thus, maybe you could employ that correlation matrix combined with structural equation modelling analysis of the environmental factors effect on AGB.

Authors' Response: Thanks to the reviewer for her/his constructive suggestions. We have added a path analysis on relationship between the environmental factors and AGB in the revised MS (Line 154-161, 210-218, Fig. 4b). Specifically, the path modelling analysis suggests that AGB shows small correlations with climate (using the 10 climatic indicators identified by the analysis to exclude the environmental covariates with high multicollinearities, hereafter the same for soil) and soil (reflected by the five edaphic properties) while significantly and positively correlates with grazing (Fig. 4b). We also found that climate can indirectly affects AGB via its influence on soil (Fig. 4b). It should be noticed that the small average magnitude with large variabilities of the loadings for climate (Fig. 4b) suggests the corresponding indicators for climate may distinctly affect AGB dynamics. It should also be noted that the overall performance of the fitted path model ($R^2=0.22$, Fig. 4b) in explaining the variability of AGB is much smaller than those of the machine learning models (Fig. 3), which indicates that more complex and non-linear relationships of the environmental drivers may exist in regulating AGB dynamics. We have clarified these in the revision (Line 154-161, 210-218, Fig. 4b).

In that way, in Supplementary Figures S2-S4, AGB in Inner Mongolian temperate grasslands decreases, who is major driver? Climate change (e.g., temperature) or human activities (e.g., grazing intensity)?

Authors' Response: The major drivers of the simulated temporal changes in AGB (Fig. 6) can vary during different periods due to data availability particularly for grazing in-

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tensity. For example, AGB dynamics over 1981-2019 is co-regulated by both changes in climates and grazing activities (Fig. S2, S3 and S5) and grazing intensity has a higher influence on AGB dynamics (Fig. 4b). In the future scenario simulations (e.g., 2020-2100, Fig. 6), however, AGB dynamics are predominantly controlled by climate changes since a constant grazing intensity was adopted over time in the future predictions. We admit that the actual grazing intensity can vary over time in the future depending on RCP scenarios, simply assuming a stable grazing intensity over time can lead to substantial biases in AGB estimations. We have clarified these in the revised MS (Line 277-284).

Lines 182-184, i.e., Figure 6. You need to increase the segmentation fitting lines to ensure the description more clearly in Figure 6s.

Authors' Response: We have updated the Fig. 6 by more clearly presenting the temporal variations in AGB. Besides, we have also revised the MS by more clearly describing the results associated with Fig. 6 (Line 225-227).

Discussion. Lines 219-223, I do not understand the argument that's being made here. I think, a better work could be finished to set up the questions here in the rest of the introduction-talking more about how climate warming (major driver?) linked to soil conditions and livestock (positive feedback?) might affect AGB, and so on?

Authors' Response: We have clarified these sentences in the revision (Line 273-277). Briefly, we intend to inform that, apart from climatic factors, soil conditions and livestock also co-regulate the dynamics of grassland AGB, which is indicated by the machine learning models (Fig. S4) and the path analysis model (Fig. 4b). Such findings have seldom been assessed on large scales in the study region. These findings are consistent with several findings highlighting the importance of soil physical and chemical characteristics (Griffiths et al., 2012; Yang et al., 2009) and grazing intensity (El-dridge and Delgado-Baquerizo, 2017) in controlling grassland biomass changes. As mentioned above, we have also summarized that the major drivers of the simulated

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temporal changes in AGB (Fig. 6) can vary during different periods due to data availability particularly for grazing intensity (Line 277-284). We hope these clarifications can satisfy the reviewer's concerns.

Minor comments: P2, L41-42, L49, L57, in many cases, citations of references are not arranged systematically. Either it should be chronologically or alphabetically arranged.

Authors' Response: In the revision, we have updated all the citations by alphabetically arranging the references in the main text. P14, L364-367, model calibration (80% samples) does not need to enumerate R2 and RMSE? Why the proportion for model calibration and validation is 80%:20%? Why not 50%:50%?

Authors' Response: We have added the R2 and RMSE for the model calibrations in Figure 3 (Line 471-472). For the proportion of train-test split, there is no universal or best split option, however, the representativeness of both train set and test set is required. In this study, we used the stratified to ensure the dataset representativeness. A training set with the percentage size of 80% and a remainder percentage of 20% for testing set (e.g., that in this study) is one of the most commonly used split percentages in machine learning approaches (Brownlee, 2016). We have clarified this in the revision (Line 137-138).

I wish the above suggestions or comments can help improve the quality of this manuscript. Thanks in advance.

Authors' Response: We highly appreciate the reviewer's constructive comments, which significantly contribute to the improvement of this study.

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