This development and technical paper concerns the development of a new model to simulate GPP which does not directly use soil moisture as limit to carbon assimilation, but rather uses aridity to account for soil moisture stress on carbon assimilation.

The reviewer has misunderstood our method. We do indeed use soil moisture directly as a limitation on carbon assimilation. However, the function relating the degree of assimilation reduction due to low soil moisture is empirically shown to vary systematically as a function of climatic aridity. As this is a fundamental point, we have tried to make this logic clear already in the revised Abstract:

> "The coupling between carbon uptake and water loss through stomata implies that gross primary production (GPP) can be limited by soil water availability through reduced leaf area and/or reduced stomatal conductance. Vegetation and land-surface models typically assume that GPP is highest under well-watered conditions and apply a stress function to reduce GPP with declining soil moisture below a critical threshold, which may be universal or prescribed by vegetation type. It is unclear how well current schemes represent the water conservation strategies of plants in different climates. Here eddy-covariance flux data are used to investigate empirically how soil moisture influences the light-use efficiency (LUE) of GPP. Well-watered GPP is estimated using a first-principles LUE model driven by atmospheric data and remotely sensed green vegetation cover, the P model. Breakpoint regression is used to relate the daily value of the ratio $\beta(\theta)$ (flux-derived GPP/modelled well-watered GPP) to soil moisture, which is estimated using a generic water-balance model. Although the soil moisture is used directly as a limitation on carbon assimilation the function relating the degree of assimilation reduction due to low soil moisture is empirically shown to vary systematically as a function of climatic aridity. Maximum LUE, even during wetter periods, is shown to decline with increasing climatic aridity index (AI). The critical soil-moisture threshold also declines with AI. Moreover, for any AI, there is a value of soil moisture at which $\beta(\theta)$ is maximized, and this value declines with increasing AI. Thus, ecosystems adapted to seasonally dry conditions use water more conservatively (relative to well-watered ecosystems) when soil moisture is high, but maintain higher GPP when soil moisture is low. An empirical non-linear function of AI expressing these relationships is derived by non-linear regression, and used to generate a $\beta(\theta)$ function that provides a multiplier for well-watered GPP as simulated by the P model. Substantially improved GPP simulation is shown during both unstressed and water-stressed conditions, compared to the reference model version that ignores soil-moisture stress, and to an earlier formulation in which maximum LUE was not reduced… Our results demonstrate (a) how climatic aridity modulates the response of GPP to soil moisture independently of plant functional types and (b) that this modulation satisfies an optimality criterion: i.e. that for any aridity value there is a soil moisture value at which the associated GPP response is maximal. These lessons are transferable to any LUE-based model, with re-calibration of the functions as required. These results point the way towards a better approach to the simulation of soil moisture stress in different models and a better-founded representations of carbon-water cycle coupling in any vegetation or land-surface model."

And we added the following sentence in the last paragraphs of the introduction:

"…These relationships are used to generate a family of $\beta(\theta)$ functions, dependent on AI, which can serve as multipliers of the modelled, well-watered GPP. We used the P model to simulate GPP, and soil moisture directly as limitation on carbon assimilation, when we apply the new empirical function. The performance of the resulting…"

We have also modified the text in section 2.4 (Breakpoint regression analysis):

"….

$$\beta(\theta) = \min [y, (y/\psi) \times \theta] \quad (1)$$

where $\beta(\theta)$ is equal to its maximum level (y) when $\theta \geq \psi$ while it is equal to the ratio between its maximum level and the critical threshold (y/ψ) when $\theta < \psi$. "

Major comments:

- Following GMD paper conventions, a development and technical paper should be clear on which model/code it is improving. I assume in this case it is the "P model"? That should be emphasized in the title. It also lacks details on the "technical aspects of running models and the reproducibility of results", or "a significant amount of evaluation against standard benchmarks, observations, and/or other model output", see https://www.geoscientific-model-development.net/about/manuscript_types.html#item2. Discussing how the code can be used is a feature distinct to GMD papers, which is not provided in this preprint.

  A key point here is that our results have relevance beyond the P model; they point the way towards a better approach to the simulation of soil moisture effects in different models, including LUE models, land-surface schemes and DGVMs. Therefore, it does not seem appropriate that the title should include the specific version name. However, we have included the version name in the revised subsections of the method part of the MS and, importantly, we have revised the text to make the wider relevance of the work more apparent. The amended text in the abstract, introduction, and discussion on the general utility of this approach is given in the response to the reviewer 1 (point 2). We have also commented on the general utility of this approach in the new conclusion, provided in response to comment 9 of reviewer 1.

  We believe that the structure of the Methods allows readers to understand the steps required to reproduce our work. However, we have added a new final paragraph in the Methods, in response to point 2 raised by the reviewer 1, which provides information on the settings used to run the model.

  Regarding how the code should be used, we followed the journal guidelines and included a section (*Code and data availability*) in the original manuscript to document the different sources of code and data. Specific details are given in the readme files on the Zenodo/GitHub repositories. The revised text for this section is given in the response to reviewer 1.

The original manuscript included evaluation against observations, and other models. In response to a comment by the first reviewer, we have now added a comparison of our model with the latest version of MODIS GPP. Please see response to reviewer 1 (comment 3) for the added figures and text supporting this new evaluation.

- Code availability: it is not entirely clear whether the provided code is an improved version of the "P model" or a standalone module that can be attached to the "P model".

  We used the sub-daily version of the P model, which is an enhanced version of the P model v1.0 (Stocker et al. 2020, GMD) adapted to work at a sub-daily timescale. The sub-daily version is a stand-alone model that only needs meteorological and satellite input data to simulate GPP. The new function for the soil moisture response, presented here, is an external module that can be applied to the subdaily model output directly. This new module, and its application, have been deposited and are publicly available in the GitHub channel cited in the MS. There are readme files for all the codes provided. Specific modifications to the text which clarify which version of the model we use and how it is run have been made in response to comment 2 by reviewer 1.

- An impression from reading this manuscript is that it reads like an report, rather than an academic paper. It only discusses work that are immediately related to the approach taken, but hasn't provided a survey of the full suite of other work that has contributed to the field.
  In response to a similar comment by reviewer 1 (comment 5), we have expanded the introduction to provide a fuller coverage of other work in this area.

- The sensitivity of the model parameters should be investigated, especially since the new model basically relies on a single scaling parameter beta. Also, a potential issue with using aridity index is that it is an long-term average, which may not capture changing aridity under changing climate.

  The first point, as we understand it, addresses the issue of uncertainty in the values of $\beta(\theta)$ derived using our empirical functions. In other words: to what extent does this uncertainty influence the resulting simulations of GPP? We therefore performed a simple sensitivity test to show the order of magnitude of this effect in arid versus humid climates. We describe the results of this sensitivity analysis in the results section as follows:

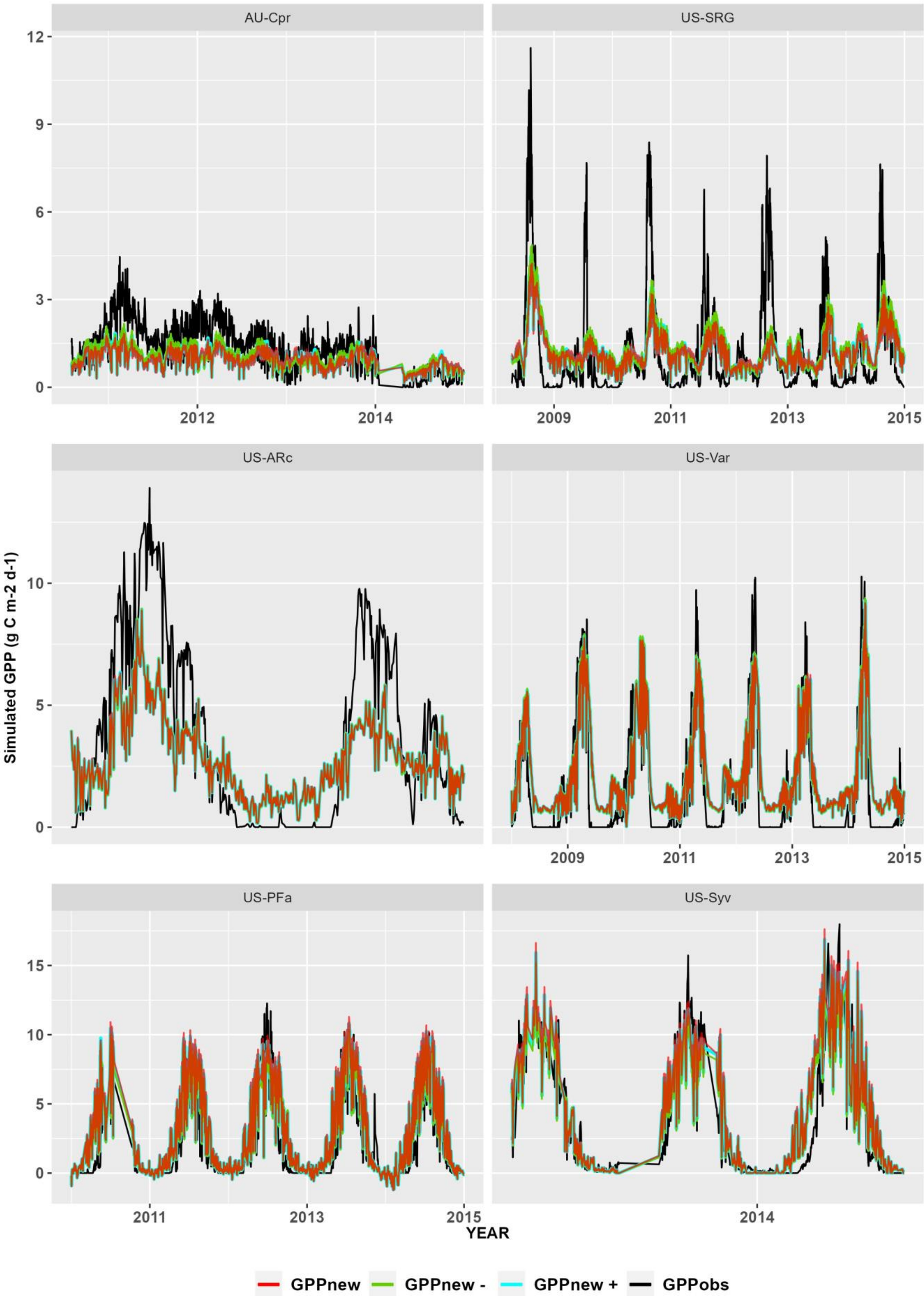
  "We performed a sensitivity test to assess the impact of uncertainty in the estimated parameters on GPP, by substituting the upper and lower value of the standard errors on the fitted parameters in equation (4) and (5). This test showed that these uncertainties had little impact on $\beta(\theta)$ and did not change the simulated GPP (Figure 5)."

  The caption for the new figure (displayed at the end of this comment) is:

Figure 5: Sensitivity of the model to parameter uncertainty. The plot shows gross primary production (GPP) using the new soil-moisture stress function (GPPnew) at six sites representing the range of climatological aridity compared to the simulated GPP resulting from the adding the upper (GPPnew +) and lower (GPPnew -) standard error to the canonical fitted parameters in equation 4 and 5. The flux-derived values (GPPobs) are also shown. Note that the scale varies between the rows.

The second point is also a good one. Aridity index (AI) is a long-term average. Its use here reflects the finding (see also the cited papers by Fu et al.) that the "fast" soil-moisture response of plant function (whether evaporative fraction or GPP) differs between climates – indicating that the vegetation in climates differing in aridity is differentially adapted to cope with low soil moisture. (This is not a controversial idea in itself, but current land surface models capture it – if at all – only through distinctions among plant functional types, each of which is allowed to exist over a wide range of aridity values.) Global environmental change then poses two practical questions. First, if aridity changes, on what time scale will it be necessary to update it? Second, will the response to aridity be modified by changes in atmospheric CO_2? These are non-trivial questions. We included an extra final paragraph addressing these questions in the Discussion as follows:

"We have developed an empirical soil-moisture stress function that improves the performance of the P model but could also be applied in the context of other models. This research therefore represents a step towards an empirically well-founded representation of the interactions between carbon and water cycling, where the next step would involve the interactive coupling of transpiration and GPP in a land-surface modelling framework. However, we have used a long-term average of climate parameters to calculate the aridity index (AI). Under a changing climate, the AI will change along with changes in vegetation properties such as rooting depth and hydraulic strategy. This poses two practical questions about how to implement our approach under future climate change. First, what is the appropriate timescale at which to update the AI calculation? Second, how will the response to aridity be modified by changes in atmospheric CO_2? Both questions are likely related to trait plasticity, plant lifespan, and the speed and magnitude of climate change. Further research is required to address these two crucial issues."


AU-Cpr
US-SRG
US-ARc
US-Var
US-PFa
US-Syv
Simulated GPP (g C m-2 d-1)
YEAR
GPPnew
GPPnew -
GPPnew +
GPPobs

Specific comments:

- L71: while you have given some empirical evidence of photosynthesis levels under drought stress, it should be properly introduced in the introduction section.

As noted in this response above and to the reviewer 1 (comment 5), we have now revised the introduction including more information on this point.

- L103: I think an expanded introduction of the P model is necessary somewhere in the paper.

As mentioned in our response to the first reviewer, both the original P model and the subdaily version have already been published in full. Furthermore, our findings are relevant to all GPP models. We have now revised the text in the abstract, introduction and in the conclusion to emphasize the more general applications of these findings. Please see response to reviewer 1 for the revised text is presented in the response to the second point of the first reviewer.

- L120: so what is the version number of this new model?

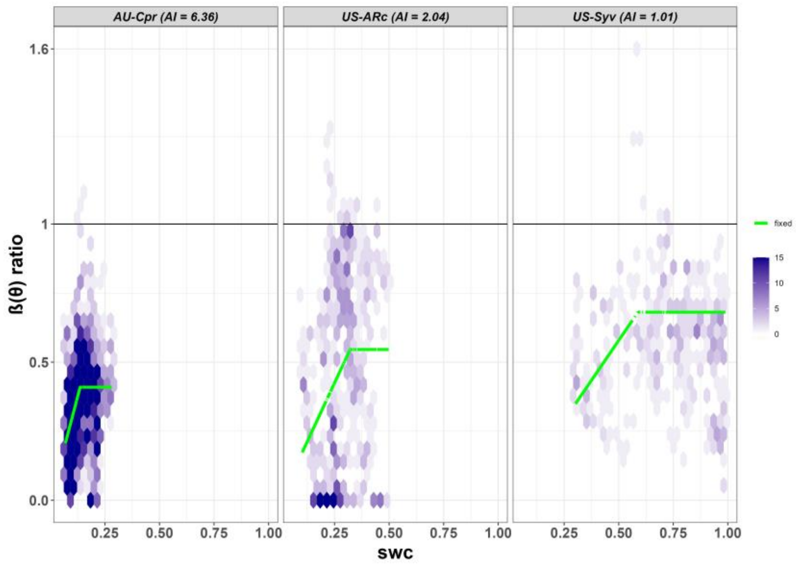
We have provided a version number and the full name of the new model (P-model subDaily v1.0.0) in the revised manuscript.

- L360: this concluding paragraph seems quite short and incomplete.

We have provided a new conclusions section in response to comment 9 by reviewer 1.

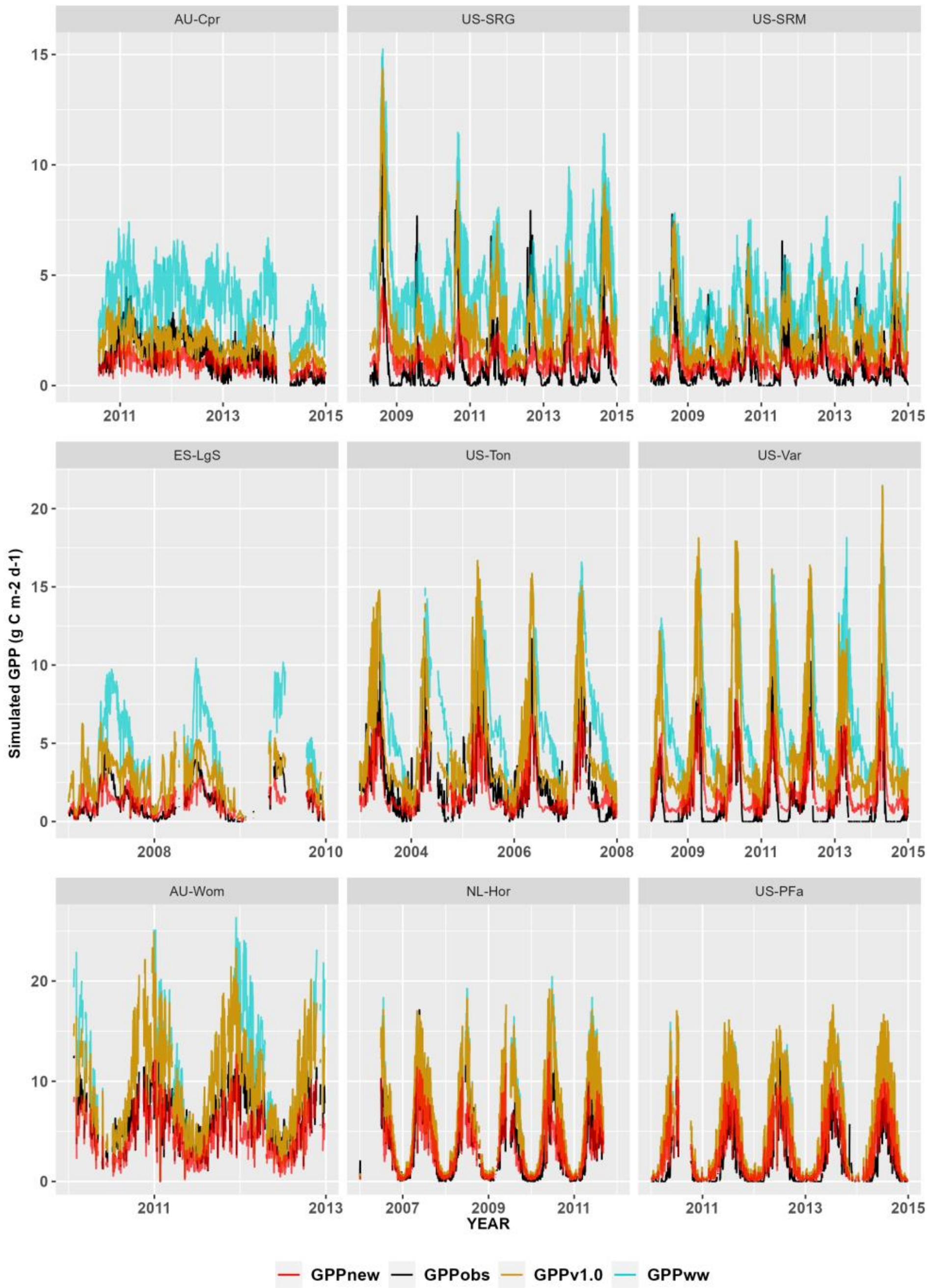
- Figure 1: perhaps a hexbin plot can show the density of points better than a scatter plot

We thank the reviewer for this suggestion. We have generated a new hexbin plot (see below).



- Figure 5,6: much of them are presenting the same information and can be combined.

We thank the reviewer for this suggestion. We have now combined the two figures. The resulting figure (see below) is now Fig. 6 in the revised manuscript.



The revised caption is:

Figure 6. Examples of how the new soil-moisture stress function modifies simulated gross primary production (GPPnew) at nine sites representing the range of climatological aridity compared to how the original stress function, when applied in the sub-daily model, affects simulated GPP (GPPv1.0). The new model is compared to the simulated level of GPP under well-watered conditions (GPPww), and to flux-derived values (GPPobs). Note that the scale varies between the rows. Plots for all the flux tower sites are given in Supplementary Figures 6–8 & 9-11.