

Interactive comment on “Multi-scale assessment of a grassland productivity model” by Shawn D. Taylor and Dawn M. Browning

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Referee 2 Comments are in plain text, with Author responses in bold

Using the observed data at the sites of phenoCam network, the authors evaluated the performance of a productivity model, PhenoGrass at different ecosystem types. They identified the ‘optimal spatial extent’, in which the model performed the best. I have several major concerns on the manuscript, which I think are very important before the publication of this paper.

1. Apparently, this study just evaluated the performance of a model, identifying which

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ecosystem types the model perform best. However, this evaluation did not fill any knowledge gap on the way of improving our capability of forecasting.

The original model was already used for long term projections of grassland productivity in the highly cited Hufkens et al. 2016 paper. We feel that re-evaluating that model with newer and more extensive data (featuring 89 sites and 463 site-years) to examine performance and identify limitations on where it is applicable is a valid contribution.

2. The model results suggest that the model perform best in grassland ecosystems. I can guess that is within expectation, because it is likely that the model was originally developed for grassland ecosystems according to its name, PhenoGrass. No explanation was provided on how the model has been updated on simulating productivity in other ecosystem types.

Despite its name the PhenoGrass model has no component which is specific to grass. The primary response variable, fractional vegetation cover, can theoretically apply to any vegetation type. The original formulation derived in Ogle Reynolds 2004 was used, with hypothetical parameters, on several plant functional types including annual and perennial grasses, cacti, and shrubs. Choler et al. 2010, 2011 modified this formulation and modeled grasslands using NDVI, since grasslands are a homogenous functional type which have a distinct NDVI signal and a well studied relationship with precipitation. Hufkens et al. 2016 expanded on the Choler 2011 model by adding temperature and daylength constraints, but again nothing specific to grasslands. Because PhenoCams allow us to isolate the annual growth of specific vegetation types at a daily scale, it was worth evaluating the PhenoGrass model on other vegetation types.

We will revise text in the methods to include the following clarification on this:

“Despite its name the PhenoGrass model can theoretically apply to any vegeta-

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tion type with a distinct growth signal in response to precipitation, as hypothesized in the original threshold-delay model (Ogle Reynolds 2004). Here we use two other vegetation types, shrubs and agricultural plots, to test how applicable it is beyond grasslands.”

3. Here the evaluation focus on primary productivity. Why not use the GPP data observed at fluxnet sites by eddy covariance towers, but the fcover at phenoCam sites?

The PhenoGrass model is designed to work with fractional vegetation cover, the proportion of ground covered by live vegetation. Flux tower measurements cannot quantify this, thus they could not be used.

4. More text is needed to elaborate the principle of the model. Key equations are needed as appendix.

The model is fully described in Hufkens et al. 2016 and we made no modifications to it for this study. On revision we will include the full equations in the appendix for clarity.

5. How the parameters of the model were determined? How the parameters varied across ecosystem types?

We will include the following main text in the method to clarify this.

“Parameterization was done using differential evolution, a global optimization algorithm, to minimize the mean coefficient of variation of the mean absolute error (F), which accounts for variation among average Gcc values among sites (Choler et al. 2011).

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$$F = \frac{1}{N} \sum_{j=1}^N CVMAE_j$$

$$CVMAE_j = \frac{\frac{1}{i} \sum_{i=1}^n |fCover_{i,obs} - fCover_{i,pred}|}{fCover_{obs}}$$

Where N is the number of sites, i is the number of daily values in each site, $fCover_{i,obs}$ and $fCover_{i,pred}$ are observed and predicted values, respectively. $fCover_{obs}$ is the average fCover at each site.”

We will also include the following table in the appendix describing the final parameter values for the two models which met the threshold.

parameter	Great Plains	E. Temperate Forests
b2	0.0021756	0.0143214
b3	0.0607134	0.0269089
b4	0.2630305	9.8632117
Phmax	48.1106340	49.6940973
Phmin	25.5471298	33.1345876
Topt	29.7376494	35.6335041
L	3.0685254	3.1769617
h	10.3601586	949.5914722
mean_cvmae	0.3882550	0.2734598

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6. How to use the image data (RGB) to estimate fcover? Is there some uncertainty at this step?

Phenocam images are subset to a region of interest (ROI) which isolates a specific vegetation type in the camera field of view. RGB values from within each ROI are converted to the green chromatic coordinate (Gcc):

$$Gcc = G / (R + G + B)$$

Where R,G, and B are the average digital number values of the respective color within the ROI. This produces a daily normalized greenness index which tracks vegetation extremely well (Richardson et al. 2018). Gcc values are converted to fCover via asymptomatic transfer function

$$fCover = Gcc * S$$

$$S = MAP / (MAP + h)$$

Where MAP is the mean annual precipitation at a site and h is a parameter estimated along with the rest of phenogross model parameters (Hufkens et al. 2016).

We will include these details in the appendix along with the full model description. Uncertainty around the Gcc is minimized by using the 90th percentile of the 3-day moving average, which reduces the effects of different lighting conditions.

References:

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