Global-Scale Benchmarking of TRENDY Dynamic Vegetation Model Spatiotemporal Estimates of Dryland Productivity using a Dryland-Specific, Ecohydrologically-Informed GPP Product

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1 INTRODUCTION

Drylands are hotspots of land-atmospheric coupling and are thought to play a dominant role in global carbon cycle variability. Given dryland ecosystem functioning is extremely sensitive to future changes in water availability, it is essential that the dynamic global vegetation models (DGVMs) that form the land component of earth system models used for climate change projections can accurately simulate dryland carbon and water fluxes. However, several recent studies have documented that DGVMs perform poorly in capturing dryland carbon dynamics (Fawcett et al., 2022; MacBean et al., 2021; Teckentrup et al., 2021). Thus, a global scale assessment of model dryland productivity using a data product specifically developed for dryland ecosystems is needed. In this study, we evaluated the ability of the TRENDY v10 suite of DGVMs in capturing global spatiotemporal patterns in dryland gross CO_2 uptake (or gross primary productivity, GPP) using the newly developed 'DryFlux' GPP product (Barnes et al., 2021). DryFlux is an upscaled eddy covariance flux product developed using machine learning methods that was designed to capture ecohydrologic controls on dryland carbon dynamics.

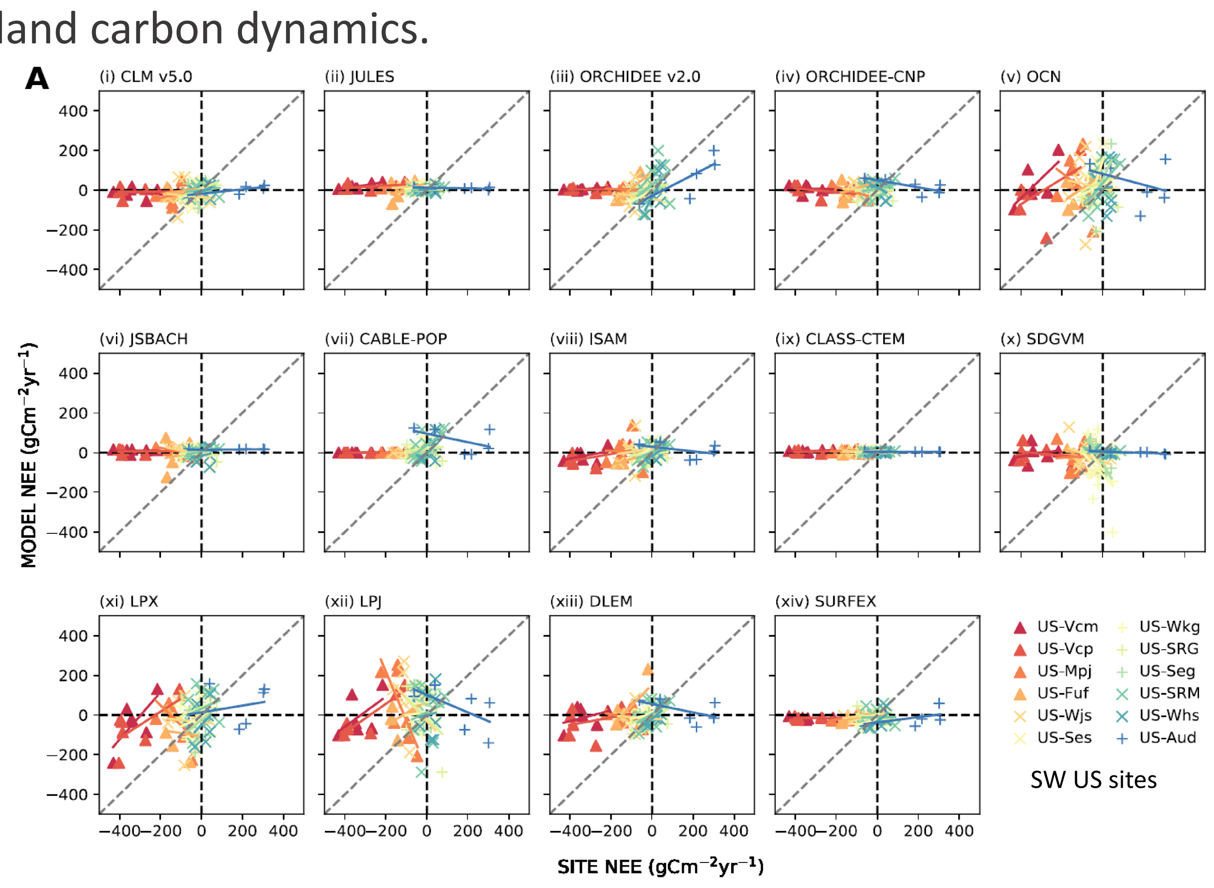

Figure 1: DGVMs perform poorly in capturing dryland carbon dynamics (MacBean et al. (2021))

2 DATA AND GLOBAL DRYLAND

- Reference data: Monthly mean DryFlux GPP from 2001 -2016
- Yearly mean TRENDY v10 GPP from 1970 – 2020 from 18 models (Friedlingstein et al., 2021)
- Global aridity index (AI) data were used for dryland masking

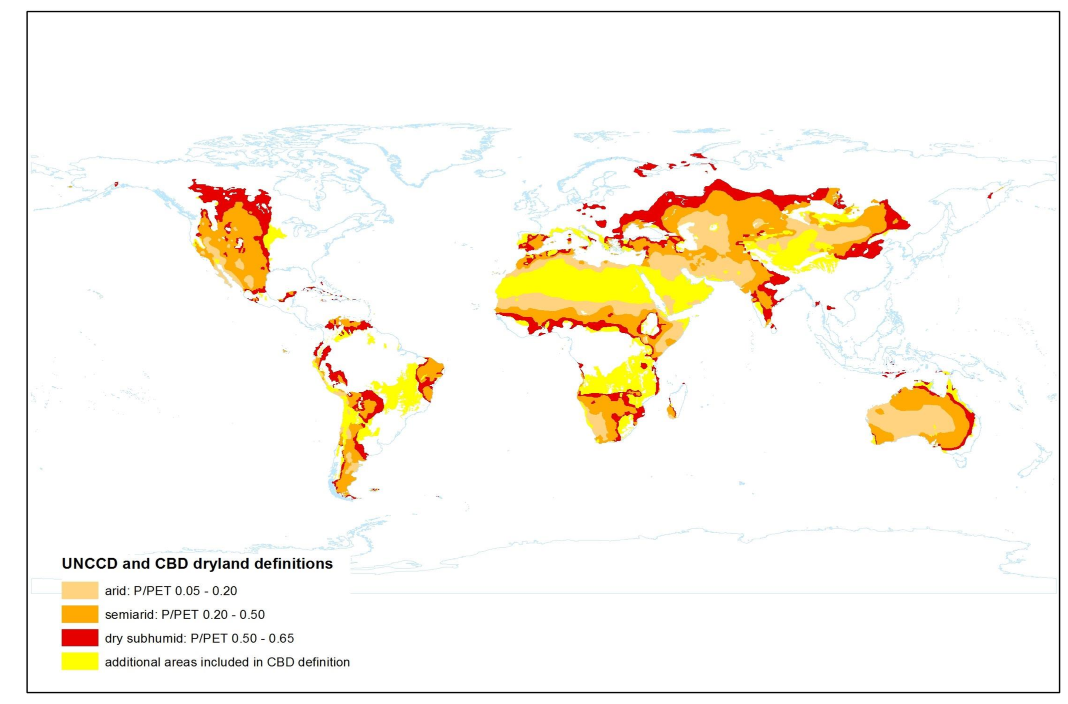

Figure 2: Dryland based on Aridity Index (precipitation/potential evapotranspiration). Source: https://resources.unep-wcmc.org/products/789fcac8959943ab9ed7a225e5316f08

3 METHOD

- Both 0.5° resolution DryFlux and TRENDY GPP datasets were converted to same unit ($KgCm^{-2}y^{-1}$) to calculate the mean annual GPP over a 16-year time period (2001-2016)
- The coefficient of variance (CV) was calculated by dividing standard deviation in annual GPP by the mean
- Global AI data were downscaled to 0.5° to match DryFlux and TRENDY data
- Only arid (AI range 0.05-0.20) and semi-arid (AI range 0.20-0.50) areas are masked out for dryland model GPP evaluation

4 RESULTS

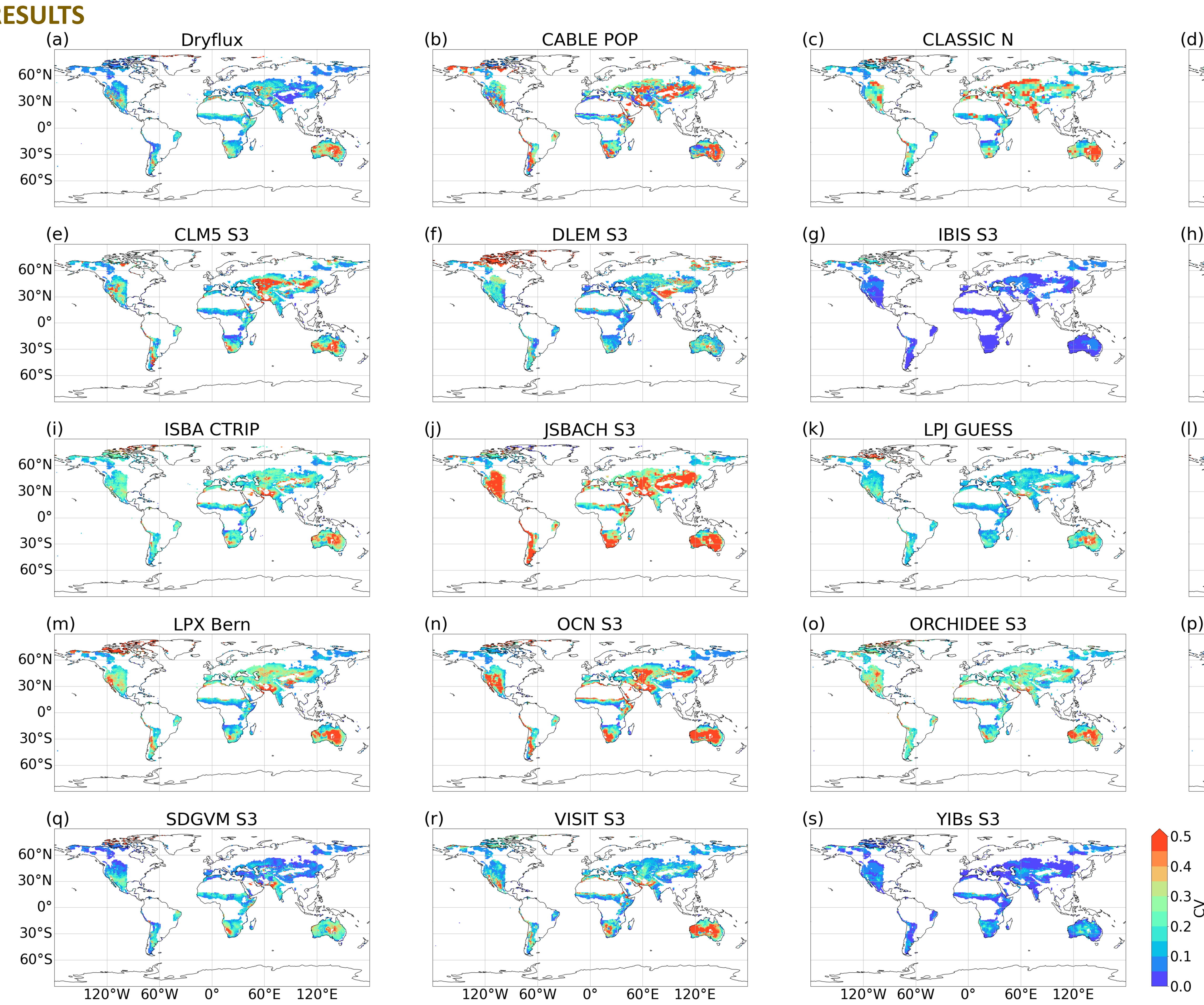

Figure 3: Evaluation of mean annual GPP of 18 TRENDY models in comparison with Dryland mean annual GPP

- High CV means inter-annual variability in GPP is high for that model (and vice versa)
- For DryFlux CV, yearly GPP variability is lower in northern hemisphere compared to southern hemisphere and only ORCHIDEEv3 S3 captured this spatial pattern
- Within sub-Saharan regions, semi-arid region GPP variability is lower than arid regions variability and this patterns are well captured by several models.
- DryFlux GPP variability is highest Australia and very few models captured this spatial pattern
- IBIS S3 and YIBs S3 perform worst in terms of underestimating the GPP variability in global drylands

5 SUMMARY

- We identified spatial patterns of inter-annual GPP variability in global dryland regions using the DryFlux product and assessed if the TRENDY models were able to capture these pattens
- However, further research is needed to answer why some models are performing better or worse in capturing spatial patterns of interannual variability in GPP.

References: Fawcett et al. (2022); Friedlingstein et al. (2021); MacBean et al. (2021); Teckentrup et al., (2021).