

1 Projections of Leaf Area Index in Earth System Models

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1 **Abstract**

2 The area of leaves in the plant canopy, measured as leaf area index (LAI), modulates
3 key land-atmosphere interactions, including the exchange of energy, moisture,
4 carbon dioxide (CO₂), and other trace gases and aerosols, and is therefore an
5 essential variable in predicting terrestrial carbon, water, and energy fluxes. Here
6 our goal is to characterize the LAI projections from the latest generation of Earth
7 system models (ESMs) for the Representative Concentration Pathway (RCP) 8.5 and
8 RCP4.5 scenarios. On average, the models project increases in LAI in both RCP8.5
9 and RCP4.5 over most of the globe, but also show decreases in some parts of the
10 tropics. Because of projected increases in variability, there are also more frequent
11 periods of low LAI across broad regions of the tropics. Projections of LAI changes
12 varied greatly among models: some models project very modest changes, while
13 others project large changes, usually increases. Modeled LAI typically increases with
14 modeled warming in the high latitudes, but often decreases with increasing local
15 warming in the tropics. The models with the most skill in simulating current LAI in
16 the tropics relative to satellite observations tend to project smaller increases in LAI
17 in the tropics in the future compared to the average of all the models. Using LAI
18 projections to identify regions that may be vulnerable to climate change presents a
19 slightly different picture than using precipitation projections, suggesting LAI may be
20 an additional useful tool for understanding climate change impacts. Going forward,
21 users of LAI projections from the CMIP5 ESMs evaluated here should be aware that
22 model outputs do not exhibit clear-cut relationships to vegetation carbon and
23 precipitation. Our findings underscore the need for more attention to LAI

1 projections, in terms of understanding the drivers of projected changes and
2 improvements to model skill.

3

4 **1.0 Introduction**

5 Providing future projections of climate change feedbacks and impacts is one of the
6 goals motivating the development of Earth system models (ESMs). The latest
7 generation of ESMs includes land models that simulate the temporal evolution of
8 carbon and vegetation (Friedlingstein et al., 2006). To do so, these models predict
9 leaf area index (LAI) and other carbon cycle variables. LAI represents the amount of
10 leaf area per unit land area, and is an important land carbon attribute. Many ESMs
11 calculate leaf-level carbon and water fluxes, which are then scaled regionally and
12 globally based on LAI (e.g. Oleson et al., 2013). The surface energy budget, as well as
13 plant-based emissions and deposition of aerosols and chemically or radiatively
14 important gases, are also sensitive to predicted LAI (e.g. Oleson et al., 2013).
15 Therefore, small errors in simulated LAI can become large errors in many ESMs'
16 biophysical and biogeochemical processes, and changes in LAI alone can change
17 climate (e.g. Bounoua et al., 2000; Ganzeveld et al., 1998; Lawrence and Slingo, 2004;
18 Oleson et al., 2013; Kala et al., 2014). Unlike many biophysical attributes, LAI can be
19 observed from satellite (Zhu et al., 2013), and thus represents one of the few land
20 carbon or vegetation variables that can be directly evaluated in coupled models (e.g.
21 Randerson et al., 2009; Luo et al., 2012, Anav et al., 2013b). Finally changes in LAI,
22 and the related normalized difference vegetation index (NDVI), can indicate
23 ecosystem health and natural resource availability. As such, LAI is used within the

1 famine prediction community (Funk and Brown, 2006; Groten, 1993) and
2 represents a variable that is easy to use in climate impacts studies. Thus it is
3 important to consider the 21st century projections for LAI in Earth System Models.

4 The current generation of ESMs has prepared historical and future scenario
5 simulations within the Coupled Modeling Intercomparison Project (CMIP5) (Taylor
6 et al., 2009). There have been extensive evaluations and comparisons of the future
7 projections of the land, ocean, and atmospheric carbon cycle in the ESMs in the
8 CMIP5 (e.g. Arora et al., 2013a; Friedlingstein et al., 2013; Jones et al., 2013). There
9 has also been comparison of ESM-simulated seasonal variability in LAI against
10 satellite-based observations for the high latitudes (Anav et al., 2013a; Murray-
11 Tortarolo et al., 2013), as well as comparisons of LAI and other variables in ESMs
12 across the globe (Anav et al., 2013b). Additionally, Shao et al. (2013), Mao et al.
13 (2013), and Sitch et al. (2015) evaluated the relationship between the carbon cycle
14 and other variables, such as temperature, or LAI, over decadal and longer time
15 scales. These ESM-based comparisons build on the long history of evaluation of
16 model simulations of vegetation properties and carbon balance (e.g. Cramer et al.,
17 1999).

18 Here, our goal is to characterize the ESM projections of future LAI in order to
19 better understand how LAI is projected to change. Most of our analysis emphasizes
20 the Representative Concentration Pathway (RCP) 8.5, the most extreme future
21 scenario, and we contrast it with RCP4.5, a less extreme scenario (van Vuuren et al.,
22 2011) (Section 3). We characterize both the model mean LAI projected change, as
23 well as the model mean divided by the standard deviation (e.g. Meehl et al., 2007;

1 Tebaldi et al., 2011). In addition, we consider whether LAI projections can help the
2 climate impact community anticipate regions that may experience increased climate
3 exposure and increased risk of food insecurity in the future. Changes in LAI
4 variability are also important for understanding the impact of climate change, since
5 they can lead to an increase in the length and frequency of low LAI events, even as
6 mean LAI increases. We consider, therefore, both changes in the mean and the
7 frequency of low LAI events, and how this information compares to precipitation
8 projections, which are commonly used for climate impact studies (e.g. Field et al.,
9 2014). We also consider what model traits may be related to the spread in the future
10 model projections (Section 3). We use evaluations of LAI, based on satellite-based
11 observations (e.g. Zhu et al., 2013; Anav et al. 2013b; Sitch et al. 2015), to
12 characterize the relationship between model skill and projections (e.g. Steinacher et
13 al., 2010; Cox et al., 2013; Flato et al., 2013; Hoffman et al., 2014) (Section 4).
14 Section 5 presents our summary and conclusions.

15

16 **2.0 Methods and datasets**

17

18 **2.1 Model datasets**

19 Coupled carbon model experiments were included as part of the CMIP5
20 experiments (e.g. Arora et al., 2013; Taylor et al., 2009). The historical simulations
21 and Representative Concentration Pathway for 8.5 (RCP8.5; van Vuuren et al., 2011;
22 Riahi et al., 2011), using prescribed carbon dioxide concentrations, were analyzed
23 here (Table 1). We chose to focus on the RCP8.5 scenario as it has the largest

1 changes in carbon dioxide and climate. Analysis of the RCP4.5 scenario (Wise et al.
2 2009; van Vuuren et al., 2011) is also included for comparison for the models which
3 included the RCP4.5 simulations at the CMIP5 archive (all models except BNU-ESM
4 and CESM-BGC).

5 Model variables analyzed included monthly-mean precipitation, near surface
6 air temperature, vegetation carbon stock and LAI. Only models which had data for
7 all these variables for both historical and RCP8.5 scenarios were included in this
8 study. Some models submitted multiple versions, at different resolutions or with
9 slightly different physics (Table 1). Even though some of the models are closely
10 related (e.g. CESM1-BGC and NorESM-ME), we include different configurations of
11 the same model.

12 **2.2 Model future projection analysis**

13 This analysis examines model mean changes between the current climate (1981-
14 2000) and future climate time periods (2011-2030, 2041-2060 and 2081-2100). To
15 identify the location where models project statistically significant changes, we
16 analyze the ratio of the mean change to variability; this is accomplished by dividing
17 the mean changes over 20 year time periods by the standard deviation over the
18 current climate (1981-2000) and shown in terms of standard deviation units (e.g.
19 Mahlstein et al., 2012; Tebaldi et al., 2011). Previous studies have shown that the
20 spatial and temporal scale used to define these changes can determine whether
21 these signals are statistically significant (Lombardozzi et al. 2014). We focus on
22 three time periods throughout the twenty-first century because the change in LAI
23 can potentially switch between positive and negative in these different time periods

1 (e.g. Lombardozzi et al. 2014), and we want to identify whether the changes through
2 time are gradual, or if there is a tipping point.

3 Changes in LAI variability are also important for understanding the impact of
4 climate change. To estimate the periods of low LAI and low precipitation, we
5 calculate the fraction of the time during which the variable is one standard deviation
6 (evaluated in the 1981-2000 time period) below the current mean (1981-2000). By
7 definition, if the variables have a Gaussian distribution, each gridbox would be
8 considered having a “Low LAI” for $1/6$ (16%) of the time, and this is approximately
9 true at most grid points (not shown). We use this metric to estimate the fraction of
10 the time in the future that this condition exists, and specifically whether it increases
11 in the future.

12

13 **2.3 Observational data**

14 LAI data derived from satellite over the 30-year period 1981-2010 is used to
15 evaluate the CMIP5 model skill in the current climate. This observational dataset is
16 derived using neural network algorithms using the Global Inventory Modeling and
17 Mapping (GIMMS) Normalized Difference Vegetation Index (NDVI3g) and the Terra
18 Moderate Resolution Spectroradiometer (MODIS) LAI (Zhu et al., 2013). The
19 satellite data are only available over regions with green vegetation, and thus are
20 lacking over desert and arid regions. A detailed description of the algorithm and
21 comparison to ground-truth observations are shown in Zhu et al. (2013). Compared
22 with field-measured LAI, Mean Squared Errors (RMSE) in the satellite LAI estimates
23 are estimated to be approximately 0.68 LAI, for spanning LAI ranges from < 1 to

1 almost 6 (Zhu et al., 2013). Comparisons with ground-based observations confirm
2 that the new LAI product also seems to capture observed interannual variability
3 patterns (Zhu et al., 2013).

4 Gridded temperature data for the period 1981-2010 were derived from the
5 Global Historical Climatology Network and Climate Anomaly Monitoring System
6 (GHCN_CAMS) 2m temperature dataset (Fan and Dool, 2008). Estimates of the
7 uncertainty in temperature gridded datasets suggest that the uncertainty in
8 temperatures at a grid box level is estimated to be between 0.2 and 1°C (Jones et al.,
9 1997; Fan and Dool, 2008).

10

11 **2.4 Methodology for evaluation of current climate LAI simulation**

12 Several recent studies have used the same new satellite-derived LAI dataset
13 (GIMMS LAI3g) in land model evaluation (e.g. Murray-Tortarolo et al 2013; Anav et
14 al. 2013a; 2013b, Mao et al. 2013, Sitch et al. 2015), including some of the same land
15 models used here. Thus we do not repeat a complete evaluation of model LAI
16 compared to satellite LAI. We use the satellite LAI dataset to consider whether there
17 is a relationship between the models' ability to simulate LAI in the current climate
18 and the models' climate projections. We use a few basic metrics in this study (Table
19 2), which are described briefly below.

20 Results for the model and observations are evaluated on a 2.5°x2.5° grid
21 based on the observed temperature data grid (see Section 2.3). For the metric
22 analysis here, the averages shown are grid-box means, not areal averages. This
23 allows us to use similar weighting for both the averages and the rank correlation

1 coefficients, and tends to weight the global analysis towards high latitudes. However,
2 most of the analysis focuses on regional areas (tropical ($<30^\circ$), mid-latitudes ($>30^\circ$
3 and $<60^\circ$) and high-latitudes ($>60^\circ$), where the differences between weighting by
4 area and weighting by grid box are reduced.

5 We compare the satellite-based observed (LAI3g) and model-simulated mean
6 LAI for the current climate (similar to previous studies e.g. Randerson et al., 2009;
7 Luo et al., 2012; Anav et al., 2013b). The period 1981-2010 is used for this
8 comparison. To examine regional differences in LAI simulations, the annual mean
9 LAI in the models and observations are averaged and compared over different
10 areas: global, tropical ($<30^\circ$), mid-latitudes ($>30^\circ$ and $<60^\circ$) and high-latitudes
11 ($>60^\circ$) (Table 2: mean LAI: model/obs.). A second metric evaluates the models'
12 ability to capture spatial variations in LAI, using the spatial correlation across the
13 grid-boxes of the annual mean LAI in the model compared to the observations (e.g.
14 Anav et al., 2013b; Table 2: Mean: Corr.).

15 Important for this study is the consideration of the temporal variability
16 simulated in the model. The magnitude of the seasonal cycle is calculated as the
17 standard deviation of the climatological monthly means at each grid box. This metric
18 is slightly different than how LAI has previously been evaluated in some studies (e.g.
19 Anav et al., 2013a; Murray-Tortarolo et al. 2013; Sitch et al. 2015), but is more
20 similar to analyses of other climate variables (Glecker et al., 2008), facilitating
21 inclusion of LAI within climate model evaluations. Metrics for the seasonal cycle
22 were computed using a spatial average over each region (Table 2: Std. Dev.
23 Seasonal: Model/obs.). For the seasonal cycle, the ability to capture the timing of

1 phenology can be important (e.g. Anav et al., 2013a, Zhu et al., 2013). To analyze this
2 ability, we computed the temporal correlation of observed and model-simulated
3 monthly means at every grid box, and then averaged over each region (Table 2:
4 Seasonal Avg. Corr.).

5 To evaluate the models' ability to simulate LAI interannual variability (IAV),
6 we consider the magnitude of the interannual variability, which is calculated as the
7 standard deviation of annual mean LAI across years at each grid box (e.g. Zhu et al.,
8 2013). The IAV is then spatially averaged and compared between the model and
9 satellite observations (Table 2: Std. Dev. IAV: Model/obs.). We focus our study on
10 IAV, based on the inter-annual means, but there may be important changes in the
11 seasonal cycle or length of growing season on an interannual time basis, which our
12 simple approach does not consider (e.g. Murray-Tortarolo et al. 2013).

13 Previous studies have examined correlations between temperature and
14 satellite- derived LAI (e.g. Anav et al., 2013a; 2013b, Zhu et al., 2013) or the closely
15 related normalized difference vegetation index (NDVI; Zeng et al. 2013). Observed
16 variations of LAI at high latitudes tend to be dominated by changes in temperature,
17 while the tropics are more dominated by moisture (Anav et al., 2013a; 2013b, Zeng
18 et al., 2013), which is also seen in coupled-carbon climate models for carbon cycle
19 variables (e.g. Fung et al., 2005). In order to understand what may be driving the
20 IAV in the LAI, we calculate metrics to examine the rank correlation between
21 anomalies in LAI and anomalies in temperature and trends with time. Although
22 correlations do not identify causation, they can help identify the strength of
23 relationships among various driving factors.

1 This analysis focuses on the relationship between temperature and LAI for
2 comparing interannual variability in the modeled and observed datasets. Sensitivity
3 studies have indicated that the grid-box level relationship between temperature and
4 LAI is a good indicator of features intrinsic to the model, rather than to the
5 meteorology forcing the model (supplemental material Figure S1; as seen also in
6 Anav et al., 2013a; Murray-Tortarolo et al., 2013). This was not the case for the
7 relationship between precipitation and LAI. In sensitivity studies conducted as part
8 of this study, we forced the Community Land Model (Lawrence et al., 2012; Lindsay
9 et al., 2014), which is the land model used in the CESM (Table 1), with reanalysis
10 derived data data (Qian et al., 2006; Harris et al., 2013) instead of model derived
11 winds. The LAI-precipitation relationship across IAV was very sensitive to the
12 meteorology used, and thus is not shown or used to evaluate the current climate
13 simulations of LAI (supplemental material; Figure S1). This implies that errors in
14 the simulations of the mean and variability in precipitation in the current climate,
15 which are very difficult for ESMs to simulate well (e.g. Flato et al., 2014), are very
16 important for the simulation of IAV in LAI.

17 Land use, especially the conversion from natural vegetation to agricultural
18 use, can heavily perturb the mean and evolution of the seasonal cycle and
19 interannual variability in current climate LAI. To determine whether this changes
20 our model evaluation, we exclude grid boxes with more than 50% of agricultural
21 land use based on Ramankutty et al. (2008). Results of the model evaluation with
22 and without agricultural grid-box were quantitatively and qualitatively similar to
23 those presented here, and thus we include all grid-boxes in this analysis. Future

1 simulations are unlikely to be more sensitive than the historical simulations to land
 2 use and land cover change, because the scenarios include less future land cover
 3 change than has occurred historically (Hurtt et al., 2011; Van Vuurden et al., 2011).

4 For ease of interpretation, we present the metrics described above in Figure
 5 9, in which higher numbers represent a better simulation. For correlations, this
 6 representation is straightforward: 1 is a perfect correlation and lower values
 7 represent a worse simulation. For the other metrics that are not correlations, we
 8 convert the statistics to values similar ranges to facilitate ease of display. The mean
 9 model bias metric (model/obs) is normalized to a value that varies between 0 and 1,
 10 with 1 being close to the observed data. This approach penalizes models which have
 11 too high of a mean equally with model that have too low of a mean, using the
 12 following formula (Figure 9):

$$14 \text{ Model Evaluation Value} = \frac{2}{\left\{ \frac{\text{Model Mean}}{\text{Observed Mean}} + \frac{\text{Observed Mean}}{\text{Model Mean}} \right\}} \quad (1)$$

15 We use this method to convert mean biases and standard deviation biases to a
 16 model evaluation value (MEV). This is a slightly different method than used in
 17 previous studies (e.g. Gleckler et al., 2008), as the MEV does not square the standard
 18 deviations. Since we use ranks and rank correlations, the difference between these
 19 methods is unlikely to be important, and allows us to use a similar ranking method
 20 for mean and standard deviation comparisons.

21

22 **3.0 Results**

23 **3.1 Future projections**

1 First we consider the model mean projections of change in LAI for RCP8.5, similar to
2 analyses for other standard model variables, and show their evolution through the
3 21st century (e.g. Meehl et al., 2007). Across most of the globe, LAI is projected to
4 increase through 2081-2100, with small decreases projected for parts of Central and
5 South America and Southern Africa (Figure 1). The increases in LAI are largest in
6 high latitudes, mountainous regions (e.g. Tibetan plateau) and some parts of the
7 mid-latitudes and tropics (Figure 1; for reference, mean satellite observed LAIs in
8 the current climate are presented in Figure S2). Notice that in this study we use
9 projections of human land use based on the RCP8.5 or RCP4.5, and thus an
10 important human role in future land cover change is driven by the assumptions of
11 the scenario chosen for these studies. Generally, for all the RCPs, there is less land
12 use and land cover change projected in the future than occurred in the past (e.g. van
13 Vuuren et al., 2011; Ward et al., 2014).

14 In order to isolate the changes that are statistically significant, for each model
15 we divided the change in LAI by the IAV standard deviation. Values over 1 are
16 considered statistically significant (e.g. following Tebaldi et al. 2011; Mahlstein et al.
17 2012). Using this approach, statistically significant changes in LAI start over the
18 high latitudes, and spread over much of the globe with time (Figure 2). By 2081-
19 2100, the increases in LAI are 8 times as large as IAV over large parts of high
20 latitude regions, as well as the Tibetan plateau and some desert regions, indicating
21 large changes (Figure 2c). Part of the reason for these very large normalized LAI
22 values is that they have low IAV in the current climate. A few isolated tropical

1 regions are projected to have statistically significant reductions in mean LAI, such as
2 in Central America and the Amazon basin.

3 Examination of the RCP4.5 shows a similar pattern of an increase in LAI over
4 most of the globe, although lower in magnitude, based on either the mean change in
5 LAI, or the normalized LAI change (Figure S3a and S3b). This result suggests that
6 the pattern of change in LAI, as seen in the literature for temperature or even to a
7 lesser extent for precipitation, is similar across different climate change scenarios,
8 with the magnitude dependent on the magnitude of the forcing (e.g. Mitchell, 2003;
9 Moss et al., 2010). There is a consistent relationship between changes in LAI and
10 temperature across the different time periods for each model; that is, most models
11 and regions show a constant slope between changes in LAI and temperature (Figure
12 3). Most models even show a similar slope between LAI and temperature for the
13 RCP4.5 as the RCP8.5 (Figure S4). Recognize that the change in temperature scales
14 with the change in CO₂ forcing from carbon dioxide fertilization as well as other
15 physical variables such as precipitation (e.g. Mitchell, 2003; Moss et al., 2010). This
16 similarity in slope for each model across RCPs and time periods breaks down in the
17 tropics for a few of the models, as some show steeper increases in LAI at warmer
18 temperatures and others shift from LAI increases to declines as warming continues
19 (GFDL, IPSL, MIROC and MPI models) (Figure 3b). Across the tropics, LAI is
20 projected to increase in some regions and decrease in others, so small changes in
21 the relative area of these changes can lead to large shifts in the regional net mean
22 LAI change. The value of spatial correlations between the RCP4.5 and RCP8.5 mean
23 LAI change at each gridbox for the 2081-2100 time period is 0.81, 0.70, 0.79 and

1 0.89, for the globe, tropics, mid-latitudes and high-latitudes, respectively (averaged
2 across the models), showing the spatial coherence in the LAI projections between
3 these two RCPs. Even the models with the lowest spatial correlations between the
4 two RCPs (GFDL, IPSL, MIROC and MPI) have statistically significant correlation
5 coefficients of 0.45 or higher in the tropics, where correlations are the lowest.

6 The models project a wide range of future changes in LAI (Figure 3). One
7 model (BNU-ESM) projects a large global mean increase of over 1 m²/m² by 2081-
8 2100. For the other models, projected global mean increases in LAI amounted to 0.5
9 m²/m² or less. Some models (inmcm4, IPSL, MIROC and MPI model versions)
10 projected small net decreases in LAI in the tropics (Figure 3). Inter-model
11 differences become even more apparent at the grid-box level, with very different
12 changes in LAI projected by the different models (Figure S5). The spread in model
13 projections is discussed further below (section 4.0) in relation to whether there is a
14 relationship between model skill at predicting LAI in the current climate and future
15 model projections (e.g. Steinacher et al., 2010; Flato et al., 2013; Cox et al., 2013;
16 Hoffman et al., 2014).

17

18 **3.2 Identifying regions at risk due to climate change**

19 In addition to being important for land-atmosphere biophysical and biogeochemical
20 interactions, LAI is also one of the few ESM model variables that is directly usable by
21 the climate impacts community, along with temperature and precipitation. This is
22 because LAI and the closely related variable, NDVI, are used for identification and
23 forecasting of drought and famine (e.g Funk and Brown, 2006; Groten, 1993) as well

1 as a general indicator of ecosystem health (e.g. Field et al., 1998). Thus LAI
2 projections that identify the regions that are most at risk can help guide and
3 motivate climate adaptation by identifying emergent areas of vulnerability. The
4 model mean view of the future projections of LAI is quite optimistic (Figure 1, 2 and
5 3), however, if variability also increases, some regions may experience years with
6 lower LAI more frequently than in current climate, despite having a constant or
7 higher mean LAI. In fact, many regions, especially in the tropics, are at risk for
8 more Low LAI years (Figure 4). Here we define % Low LAI as the % of years when
9 the annual average is one standard deviation below the current mean (Section 2.2).
10 If the variability and mean stayed constant, the % Low LAI would remain at 16%.
11 More Low LAI years are projected for large areas of the tropics and subtropics
12 where projected increases to mean LAI are small in magnitude or negligible (Figure
13 1c vs 4c, for example). Model mean changes between the current climate (1981-
14 2000) and future climate time periods indicate substantial (>2x) increases in the
15 frequency of low LAI in important agricultural areas (South America, Australia,
16 Southeast Asia, and parts of Southern Africa) (Figure 4). Increased risk areas in Fig.
17 4 also coincide, in some cases, with some of the most food insecure regions of the
18 world (e.g. Brown and Funk, 2008; Field et al., 2014). Similar to mean changes in LAI,
19 the %Low LAI for the RCP4.5 at 2081-2100 is similar in pattern and magnitude to
20 that seen earlier in the century for the RCP8.5 scenarios (Figure S3c vs. Figure 4).

21 Next we consider whether using LAI adds information compared to
22 precipitation, which is more traditionally used in climate change impacts
23 assessments (e.g. Stocker et al. 2013; Field et al. 2014). General correlations

1 between precipitation and LAI will be discussed in the next few sections, but here
2 we consider the spatial distribution of at-risk regions as defined by LAI or
3 precipitation changes. To do this, we first consider the mean change in normalized
4 precipitation (Figure 5a) and the % Low Precipitation (Figure 5b), both defined
5 equivalently to the LAI values (Section 2.2; Figure 2c and Figure 4c, respectively) for
6 the model simulations considered here. Broadly speaking, the changes in
7 precipitation seem to occur in similar regions as the changes in LAI, with large
8 increases in precipitation over the high latitudes, and decreases over the subsidence
9 zones of the tropics, as seen previously (e.g. Meehl et al., 2007; Tebaldi et al., 2012).
10 Note that requiring the mean change to be statistically significant is a much stricter
11 criteria than just an increase in low LAI, and thus the area identified in the two
12 methods is quite different (Figure 5a vs. 5b). Overlaying the regions from LAI and
13 precipitation which are either one standard deviation below the mean on average in
14 the models (Figure 5c) or see an increase in % Low values (Figure 5d) suggests that
15 LAI and precipitation largely show similar areas being at risk due to climate change,
16 but there are significant regions which do not overlap. This suggests that there is
17 potentially additional information for climate impact studies using LAI projections
18 than using precipitation alone (Figure 5c and 5d). One of the most noticeable
19 differences between LAI and precipitation projections is in the Mediterranean
20 region where precipitation is projected to decrease, but LAI is not. Conversely, LAI
21 projections suggest that some parts of South America and southern Africa are likely
22 to experience more stress, which are not identified using precipitation. Future

1 studies should consider whether the results of the LAI projections are useful for
2 impact studies specifically in these regions.

3

4 **3.3 Drivers of LAI projections**

5 Next we consider what drives the differences in model projections for LAI, using the
6 example of RCP8.5 at 2080-2100. Here we use different model output attributes to
7 characterize the future projections, and focus on the following variables:
8 temperature, precipitation, and vegetation carbon. We also characterize the
9 relationship of carbon dioxide fertilization as simulated in the models to the model
10 projections. Note that there are many other potential drivers of the projected LAI
11 changes that are likely to be important, and thus our study only seeks to consider
12 the most obvious interactions, and highlights the uncertainties in the model-specific
13 drivers of LAI projections.

14 By correlating temperature and LAI projections at each grid box for each
15 model we can look for potentially causal relationships between model projections of
16 temperature and LAI (Figure 6). This is analogous to using a ranked correlation
17 coefficient to summarize the scatter in RCP8.5 points in Figure 3, but at each grid
18 box instead of the regional average. There are strong positive correlations between
19 model simulated changes in temperature and LAI in some regions, especially in
20 parts of the northern high latitudes (Figure 6a), suggesting that models with a
21 projected larger warming in the high latitudes also simulate larger increases in LAI.
22 Higher temperatures may drive higher LAI; higher LAIs may also be driving higher
23 temperatures because of the importance of LAI in changing surface energy fluxes

1 (e.g. Lawrence and Slingo, 2004; Kala et al. 2014). By contrast, there are strong
2 negative correlations across most of the tropics and subtropics (Figure 6a).

3 The projected changes in precipitation are strongly correlated with projected
4 changes in LAI across different models in many locations (Figure 6b). This is
5 consistent with the model mean analysis (Section 3.2) that showed that for most
6 locations changes in LAI occur in the same locations as changes in precipitation
7 (Figure 5). Again, because LAI changes the surface energy fluxes, there may be a
8 feedback from LAI changes to precipitation (e.g. Lawrence and Slingo, 2004; Kala et
9 al. 2014). The correlations seen in this analysis for RCP 8.5 are similar for the
10 RCP4.5 (Figure S6).

11 Next, we examine the correlation across models between the modeled
12 changes in vegetation carbon stocks and change in LAI between current conditions
13 and 2081-2100 (Figure 6c). The relationship between LAI and vegetation carbon is
14 not straightforward, and depends on the specific biophysics and biogeochemistry
15 algorithms used in the models. Many ESMs calculate photosynthetic rates per unit
16 leaf area; these rates are then extrapolated to canopy-level gross primary
17 production using LAI and other variables (e.g., light, nitrogen and CO₂ availability
18 and leaf physiological parameters) (e.g., See Bonan et al., 2011, Piao et al., 2013).
19 The simulated increases in LAI are correlated across models with simulated
20 increases in plant carbon stocks in many low-LAI regions, including many deserts,
21 grasslands, and tundra ecosystems (Figure 6c). Leaves compose most or all of the
22 aboveground plant biomass in these ecosystems (e.g., Friedlingstein et al. 1999),
23 such that increases in LAI relate directly to increases in plant carbon stocks.

1 Changes in LAI correlate more poorly with simulated changes in plant carbon stocks
2 in other regions, with small or negative correlations in many boreal, temperate, and
3 tropical forested regions (Figure 6c). Leaves typically compose only 3-5% of
4 aboveground plant biomass in forests (Friedlingstein et al. 1999), and closed-
5 canopy forests can contain widely variable stocks of woody biomass that typically
6 depend more on successional status than LAI or growth rate. Differences in the
7 fractional composition and turnover of these leaf- and woody tissues should
8 decouple changes in LAI from changes in carbon stocks in woody biomass. As an
9 example, in the CLM, the land model for the CESM-BGC, CO₂ fertilization causes a
10 larger increase to wood allocation (62%) than to leaf allocation (21%) in the
11 Southeastern US (Lombardozzi, personal communication, 2015). Thus, the issue of
12 how LAI responds in different models is interesting and should be considered in
13 future studies.

14 Another important potential contributor to the future projections of LAI is
15 the effectiveness of carbon fertilization in the models (e.g. Arora et al., 2013). Using
16 the carbon dioxide fertilization factor (β -land) from the Arora et al. (2013) study we
17 use a rank correlation to explore the importance of the carbon dioxide fertilization
18 strength for predicting future vegetation carbon and LAI across the models. Naively,
19 we might expect models that respond more strongly with increased carbon uptake
20 under higher CO₂ conditions (i.e. larger β -land) to have greater vegetation carbon
21 and LAI in the future. Globally the correlation with β -land is 0.46 for vegetation
22 carbon and -0.21 for LAI, suggesting that while some of the differences in future
23 vegetation carbon projections across models are due to differences in the model

1 simulation of CO₂ fertilization, LAI changes are not necessarily related to CO₂
2 fertilization. The β -land correlation for vegetation carbon is 0.29, 0.47 and 0.60 for
3 tropical, mid-latitude and high latitude, regions, respectively, while for LAI these
4 values are -0.18, -0.09 and 0.21. Thus for high latitudes, especially, the projections
5 of LAI appear to be dependent on the way the models' simulate the carbon dioxide
6 fertilization in the different models. This could also be, however, an artifact that the
7 two models with the lowest carbon dioxide effect (CESM-BGC and NOR-ESM) use
8 the same land carbon model (Thornton et al., 2009), which predicts low values of
9 LAI in high latitudes for present day and does not tend to increase LAI much in the
10 future. These models also have low carbon dioxide fertilization effects, because of
11 the inclusion of nitrogen limitation, which could be driving the weak positive
12 correlation between model projections of LAI and carbon dioxide fertilization in the
13 high latitudes.

14 It is interesting that in the tropics the carbon dioxide fertilization is
15 negatively correlated to future LAI changes, and only slightly correlated with
16 vegetation carbon. Again, this could be an artifact of having only two related low
17 carbon fertilization models, as these models see a strong increase in nitrogen
18 mineralization in the tropics in a warming climate, which allows an increase in
19 productivity in the future tropics (Thornton et al., 2009). In other words, the
20 negative correlation in the tropics between LAI projections and CO₂ fertilization
21 could be due to the smaller temperature impact on carbon cycle (γ -land from Arora
22 et al. 2013) in the N-limited models (i.e. the β -land and γ -land are negatively
23 correlated in Table 2 of Arora et al., 2013).

1 Across these simulations, whether or not the model includes dynamic
2 vegetation does not significantly correlate with changes in LAI in any of the regions.

3 Overall, the relationship of land model characteristics and LAI is not
4 straightforward, which argues that more analysis of the complicated interactions
5 between the details of the land biophysics and biogeochemistry, as well as
6 biogeography changes is required in order to better understand and improve model
7 projections

8

9 **4.0 The relationship between model skill and future projections**

10 There are large differences between the different models' projections of
11 future LAI (e.g. Figure 3; Figure S5; Figure 7b). Previous studies have hypothesized
12 that they could reduce the uncertainty in future projections by looking for
13 relationships between model metrics and future projections of climate, and then
14 choosing the models which best match the observations in the current climate (e.g.
15 Cox et al., 2013; Hoffman et al., 2014) or by subsampling models for different regions
16 by their performance (e.g. Steinacher et al., 2010). In this section we explore both
17 approaches. In essence, we are looking for a correlation between current model
18 performance and future projections, this correlation has been used in some studies
19 to argue for a more correct answer, and to reduce the uncertainty in the future
20 projections. In many cases in climate modeling and projections, there is no
21 correlation between model skill in current climate conditions and projections (e.g.
22 Cook and Vizzy, 2006), however in some limited cases there is a correlation between
23 metric score and a projection, and one is able to constrain future projections (e.g.

1 Cox et al., 2013; Steinacher et al., 2010). Here we consider whether such a case
2 applies. In doing this type of analysis, we are making an assumption that model skill
3 in the current climate translates into better model projections, which may be a
4 product of real model differences or a statistical error. The advantages and
5 disadvantages of using this type of approach are discussed in more detail in Flato et
6 al. (2013). Here we do not advocate that such an approach leads to a better
7 projection, but rather simply use this approach to characterize the future model
8 projections.

9

10 **4.1 Evaluation of model LAI**

11 Several recent studies have evaluated the land models in ESMs using the LAI
12 satellite records (e.g. Anav et al. 2013a; 2013b; Mao et al. 2013; Sitch et al. 2015).
13 Thus we do not repeat those assessments, but rather briefly summarize the results
14 of the comparisons here.

15 Most models tend to overestimate the mean LAI compared to the
16 observations (Figure 8a), and this is true at all latitudes (Figure 8a, Table S2).
17 Several models have a large overestimates (>50% too high), including bcc-csm1,
18 bcc-csm1-1, BNU-ESM, GFDL-ESM2G, GFDL-ESM2M, MIROC-ESM. The over-
19 prediction relative to the satellite data tend to be larger in tropical regions for most
20 models, but the GFDL model estimates are also larger in the high latitudes (Figure
21 8a, Table S2). However, the satellite derived LAIs have biases; for example, they
22 underestimate high LAIs due to being unable to see all the leaf layers in closed
23 canopies or overestimate LAIs in more arid regions, and thus there may also be an

1 error in the observational dataset (see discussion in Anav et al. 2013b; Pfeifer et al.
2 2014 or Forkel et al., 2015, for example).

3 Some models also tend to over predict the strength of the seasonal cycle (e.g.
4 bcc-csm1, BNU-ESM, MIROC-ESM) (Figure 9b; Table S1), where the strength of the
5 seasonal cycle is measured by the globally averaged standard deviations of the
6 monthly mean climatology. But the region in which they over-predict the strength of
7 the seasonal cycle differs between models. Of course, there is not a strong seasonal
8 cycle in the tropics, where the lowest standard deviations tend to occur (Figure 8e;
9 Table S2a). Again, because of the difficulties of retrieving accurate LAI from
10 satellites in closed canopies, the observations may underestimate the seasonal cycle
11 in tropical forests.

12 Interannual variability tends to be over-predicted in some of the models (e.g.
13 bcc-csm1, bcc-csm1_1, BNU-ESM, CESM1-BGC, GFDL-ESM2G, GFDL-ESM2M, MIROC-
14 ESM, MIROC-ESM_CHEM) (Figure 8c, Table S1). For this calculation, the interannual
15 variability (IAV) is calculated as the standard deviation of the annual average across
16 multiple years. Generally, the models do a decent job simulating the spatial
17 variability in the annual mean LAI (Figure 8d; Table S1), with the correlations being
18 strongest in the tropics, and weakest in the high latitudes (Figure 8d; Table S2). This
19 is likely partly due to the strength of the LAI differences in tropics and the limitation
20 of LAI primarily by moisture alone (with low LAI in arid regions and high LAI in
21 tropical forests). The timing of the seasonal cycle (Figure 8e; Table S1) is less well
22 simulated in the models, with several models not having an average statistically
23 significant correlation (~ 0.5 for 95% significance for 12 month seasonal cycle) on

1 the global scale, or in the mid- and high latitudes (e.g. GFDL, MPI-ESM-MR on global
2 scale, GFDL, inmcm4 and MPI-ESM-MR for various regions).

3 Next we explore the observed and modeled relationship between LAI and
4 temperature, and the observed and modeled trend in LAI (e.g. Anav et al., 2013a;
5 Anav et al., 2013b; Ichii et al., 2002; Zeng et al., 2013; Mao et al., 2013; Zhu et al.,
6 2013). As previously shown, there are positive relationships between modeled and
7 measured LAI and temperature in high latitudes (Figure 6a; Figure S5; e.g. Anav et al.
8 2013a; Ichii et al., 2002; Zeng et al. 2013; Zhu et al. 2013). In the tropics (<30°), the
9 relationship can be positive or negative but some regions tend towards a negative
10 relationship (Figure S5; Figure 6a). This is consistent with our understanding that
11 many places in the tropics are close to the optimal growing temperature already,
12 and increases may lead to reduced productivity (Lobell et al., 2011), although this
13 also could be related to moisture stress (Fung et al., 2005). Compared to the
14 observed correlations, most models have too strong of a negative relationship
15 between LAI and temperature in the tropics, and too strong of a positive
16 relationship in the high latitudes (Figure 8f, Table S2a-c). In the tropics, the BNU-
17 ESM model has a weakly positive impact of temperature, while in the high latitudes,
18 especially the CanESM2, HadGEM2-CC, HadGEM2-ES, MPI-ESM-MR models have a
19 much stronger correlation than observed. The model and observations show
20 similarly weak correlations between the temperature and LAI in the mid-latitudes.

21 Some regions show substantial trends over time (1981-2010) in measured
22 LAI (Figure S7b), especially in high latitudes in the Northern Hemisphere (e.g. Zhu et
23 al., 2013; Mao et al. 2013). This could be associated with the longer growing season

1 due to warming (e.g. Lucht et al., 2002; Zeng et al. 2013). It is also possible that this
2 trend is due to CO₂ fertilization effects (e.g. Friedlingstein and Prentice, 2010). For
3 high latitudes, we find a rank correlation of 0.58 across the models between the CO₂
4 fertilization factor on land for the Earth system models (called the β -land in Arora et
5 al., 2013, as discussed above) and the average correlation of observed LAI with time,
6 suggesting that there may be a component of carbon dioxide fertilization in the
7 models' temporal trends. These trends are stronger in the models than the
8 observations, which may be related to an overestimate of the fertilization effect.

9 With regard to LAI interannual variability correlations with temperature or
10 time, there are also strong correlations among temperature, precipitation and time
11 themselves (e.g. IPCC, 2007). Here we do not attempt to differentiate these signals
12 because of the statistical complexity and the shortness of the time record. The
13 shortness of the record considered could also lead to aliasing of the real variability,
14 especially in regions like the Sahel that have strong decadal scale variations (e.g.
15 Loew, 2014). The observational datasets also contain measurement noise, while
16 the model values do not. We expect the measurement noise to reduce the
17 correlations of LAI with the environmental variables in the observations relative to
18 the true values, as seen compared to many models (Figure 8f). Thus, our metrics for
19 interannual variability are likely to be more impacted by uncertainty in the
20 observations than for the annual mean or seasonal cycle, and thus they may be less
21 useful for evaluation of the models, although potentially interesting. For this study,
22 we consider the IAV in the annual mean, but there may be important changes in the
23 seasonal cycle or length of growing season on an interannual time basis, which our

1 simple approach does not consider (e.g. Murray-Tortarolo et al. 2013). In addition,
2 the regional or global average of some of these correlations may be difficult to
3 interpret, as not statistically significant (e.g. Figure 8f), thus making the LAI IAV
4 correlations less helpful.

5 Figure 9 summarizes our comparisons of the models with the observations
6 for LAI for the different metrics in Table 2 (Tables S1, S2). In order to show both
7 correlations and model mean biases in the same figure, we have converted the
8 model-data comparisons into Model Evaluation Values using equation (1) in Section
9 2.3, where 1 is a perfect model simulation and lower values represent worse model
10 simulations. Overall, none of the models does a perfect job, and improving
11 simulation of LAI for all models will be important. In addition, as discussed above,
12 some models perform better in some regions than others. In order to more easily
13 see how the models compare, we also show the ranking of the different models in
14 each region (Table 3). For this comparison, we exclude the magnitude and
15 correlations in the IAV, because the observational estimates for this are more likely
16 to be in error than for the annual mean and seasonal analysis, as discussed above.
17 Thus our overall evaluation of LAI in the models includes the following metrics:
18 annual mean LAI, spatial correlation of annual mean, standard deviation of seasonal
19 cycle and temporal correlation of the seasonal cycle. In the tropics the top three
20 models are the INMCM4, the IPSL-CM5A-LR and the IPSL-CM5B-LR. For the mid-
21 latitudes the top models are the CanESM2, IPSL-CM5A-MR and the HADGEM2-ES.
22 For high-latitudes the top models are the BNU-ESM, bcc-csm1 and the MIROC-
23 ESM_CHEM (Table 3; Figure 9).

1

2 **4.2 Future projections constrained by current model performance**

3 Across broad regions, we evaluate which metrics are the most useful for potentially
4 constraining future climate projections by considering how the metric is correlated
5 with the projections (Figures 8 and 9; Tables S1; S2). We consider 4 regions: the
6 globe, tropics (latitudes < 30°), mid-latitudes (latitudes between 30 and 60°), and
7 high latitudes (latitudes > 60°). For the first approach, we look for the metrics that
8 have the highest correlation coefficient to constrain the future estimate of change in
9 LAI (similar to Cox et al., 2013) (Figure 10a and 10b). Using this approach, we look
10 for the model metrics (from Table 2) which have the highest correlations with
11 future projections across the models, for each of the regions. If we choose the
12 models which do the best job with the metrics, this reduces the number of models
13 included in the projections, and may reduce model spread in projections.

14 As an example, for the globe, there are two metrics that correlate the highest
15 with future projections: the average correlation of IAV in LAI with date (i.e. the
16 trend), and the global mean LAI ratio of model to observation. This analysis
17 suggests that models with the largest relative change in LAI over the last 30 years
18 (1980-2010) will have the largest change in LAI in the future (Figure 10a). It also
19 suggests that models with higher LAI in the current climate, will have a larger
20 change in the future (Figure 10b). In Fig 10a and 10b, the observation-based
21 estimates are indicated by the gray vertical bar. Notice that the projected change in
22 LAI given by models that match best with the observations differs for different
23 metrics, and thus it does not allow us to uniquely constrain the future projections

1 (although it does suggest that the highest values are the least likely). There is one
2 model with a very large change in LAI in the future (BNU-ESM). We use Spearman
3 rank correlations instead of Pearson correlations, so that these results are largely
4 insensitive to the removal of one model.

5 For both the tropical region and in the global analysis, the change with time
6 (LAI IAV correlation with date) and the mean model/observation have the largest
7 correlations (Figure 10c and 10d). Thus models that predict high LAIs in the current
8 climate and/or currently have large trends with time, tend to project higher LAI
9 changes in the future. Again, these two metrics would constrain our future
10 projections to two different LAI values, as they grey lines intersect with the slope at
11 different LAI changes (Figure 10c and 10d). For mid-latitudes, the highest
12 correlation (and only statistically significant correlation) is between the model
13 predicted change in precipitation and LAI (Figure 10e). Thus mid-latitude
14 projections of LAI are difficult to constrain based on model metrics, but are sensitive
15 to modeled changes in precipitation (as seen also in Figure 5). For high latitudes
16 there are three metrics with similar correlation coefficients: the average temporal
17 correlation in the seasonal cycle, the size of the interannual variability and the size
18 of the seasonal cycle in LAI (Figure 10f., 10g, 10h). Unfortunately again, these three
19 metrics suggest a different projected change in LAI when the observed value is used
20 to identify the models that are most realistic (grey line in Figure 10f, 10g and 10h).

21 Overall, this analysis of multiple metrics suggests that there is no single
22 metric available that is the most important in all circumstances for improving our
23 estimates for the changes in LAI. Thus, deduction of a more probable future LAI

1 projection is not available to us in this case (as opposed to Cox et al., 2013, where
2 only one metric is presented).

3 The second approach for characterizing the relationship between model
4 simulations in the current climate and future climate projections, and potentially for
5 reducing spread in the future projections follows the ideas of Steinacher et al.
6 (2010). Here for each region, we chose the models that performed the best for
7 several metrics (i.e. using the rankings in Table 3), instead of just one metric at a
8 time (as above). For this study, we chose to use the top half of the models, based on
9 their performance for each region (Table 3), so we include 9 models out of the
10 available 18 models for each region. Using this approach does change the mean
11 future projections, especially for the tropics and high latitudes (Table 4; Figure 7a vs.
12 7b), and does reduce the spread in the model values in the tropical region, but does
13 not reduce the mean spread in mid-latitudes or high latitudes (Table 4; Figure 7c vs.
14 7d). In the tropics, the top models tend to have lower future projections of LAI than
15 the average of all the models ($0.07 \text{ m}^2/\text{m}^2$ instead of $0.16 \text{ m}^2/\text{m}^2$). This is actually
16 consistent with the analysis in Figure 10, since the models with the higher skill
17 (close to grey line) would tend to have lower or middle values of future LAI
18 projections (Figure 10a,b). For the mid-latitudes, there is not as much difference
19 between using all models or the top performing models (Table 6), while for high
20 latitudes, the top models tend to project slightly higher LAI in the future, also
21 consistent with Figure 10 (f,g,h), where the observations tend to suggest higher LAI
22 projections are more consistent for the metrics with the highest correlation.

1 The spatial distribution of the change in the future projections using the all
2 models in comparison to the top models is consistent with the mean over the
3 regions, with the largest change being seen across the tropics, with a reduction in
4 both the mean LAI projection (Figure 7a vs. 7b) as well as the standard deviation
5 (Figure 7c vs. 7d). The changes in mid-latitudes and high latitudes from
6 subsampling only the top performing models are not very large in most locations
7 (Figure 7a vs. 7b). Only in the tropics is the spread in the models reduced in the
8 future projections (Figure 7c vs. 7d). The fraction of the time in drought in the
9 future is increased in the tropics, if we only consider the top models (Figure 7e vs.
10 7f).

11 Our results suggest that the better performing models tend to project lower
12 LAIs in the future in the tropics in contrast to Cox et al. (2013), which focused on
13 carbon-temperature relationships in the Amazon and which showed that
14 observational constraints on the models tend to suggest less loss in carbon under
15 higher temperatures. However these results may not be inconsistent as they
16 consider different metrics in different regions, and LAI is not necessarily linearly
17 related to vegetative carbon or carbon uptake in the models (see discussion in
18 Section 3.4), suggesting that more analysis of how allocation is parameterized in the
19 land carbon models is warranted.

20 Our analysis suggests that using multiple metrics does provide information
21 that allows us in some cases (especially the tropics) to change our mean future
22 projection, and potentially reduce the spread between models predictions. Overall,
23 including only the top models in the tropics project a more pessimistic future, with

1 small increases in mean LAI, and an expansion in the regions at risk for a low LAI,
2 while at high latitudes, it tends to increase the already large increase in mean in LAI.

3

4 **5.0 Summary and Conclusions**

5 LAI is an important term for scaling leaf-level biogeophysical and biogeochemical
6 processes to regional and global areas, and thus it is vital to consider its change in
7 future projections. Here for the first time we consider LAI projections across the
8 CMIP5 models and find that over much of the globe in the future, the models project
9 an increase in mean LAI in the RCP8.5 scenario over the 21st century. Decreases are
10 projected in the limited regions where there is also a projected decrease in mean
11 precipitation; these regions are constrained primarily to the tropics. The change in
12 LAI appears to grow with carbon dioxide and temperature increases across regions
13 over the 21st century (Figure 3). Changes in LAI projected in the RCP4.5 are largely
14 consistent with changes in RCP8.5, but have a reduced amplitude due to the smaller
15 carbon dioxide and climate forcing.

16 For assessing climate change impacts, we propose that both mean LAI and
17 LAI variability are important in identifying vulnerable regions in future projections.
18 The models project an increased incidence of Low LAI conditions despite higher
19 mean LAIs, especially in the tropics (Figure 4). While much of the variability in LAI
20 is driven by changes in precipitation, projections of lower mean LAI or Low-LAI
21 incidence can identify a slightly different set of vulnerable regions (Figure 5), and
22 add to the information that precipitation projections provide.

1 In order to characterize the model projections and evaluate whether we can
2 potentially use model skill in the current climate to reduce the spread in the future
3 projections (e.g. Flato et al., 2013), we conducted a brief comparison of the models
4 to available satellite-derived LAI data (Zhu et al., 2013), similar to previous analyses
5 (e.g. Anav et al., 2013a; 2013b; Mao et al., 2013; Sitch et al., 2015). Our results
6 support the previous conclusions that the modeled LAI could be improved in many
7 aspects of the mean, seasonal and interannual variability, although difficulties in the
8 observational data may preclude definitive assessment (Figure 8).

9 We use two different methods for relating current model skill to model
10 projections, and find that combining multiple metrics to choose better models (e.g.
11 similar to Steinacher et al., 2010) seems to work more robustly than simply
12 correlating one metric against future projections (e.g. Cox et al., 2013; Hoffman et al.,
13 2014), because the different metrics suggest different future projections (Figure
14 10). Overall, the top-performing models (top half of the models from Table 4)
15 suggest smaller future increases in LAI in the tropics, and more regions with more
16 incidences of low-LAI conditions than assessments that include all the models. This
17 approach also reduces the spread among models in the tropics. However, using only
18 the top models did not make a large difference in projections in the mid- and high
19 latitudes (Figure 7). Realize, however, that it is not clear that the models that
20 perform best in the current climate have more accurate projections, as discussed in
21 more detail in Flato et al. (2013).

22 Finally, the spread among the models' projections of LAI was correlated with
23 the models' projections of precipitation (Figure 6b, and Figure 5). Thus our

1 projections of LAI ultimately rest on the ability of models to project future
2 precipitation. Unfortunately, in many regions the projected changes in precipitation
3 are not large enough to be statistically significantly outside natural variability (e.g.
4 Tebaldi et al., 2011) and there are discrepancies between climate model and
5 statistical model predictions (e.g. Funk et al., 2014 vs. Tebaldi et al., 2011). In
6 addition to precipitation affecting the future projections of LAI, increasing
7 temperatures are likely to stress systems, even if there is additional rainfall (e.g.
8 Lobell et al., 2011), expanding the regions at risk to increased drought (Figure 5).
9 Because of the importance of LAI for biophysical and biogeochemical interactions,
10 as well as the potential for LAI to be useful to the impacts community, we encourage
11 more analysis of the drivers of LAI variability and changes in the future, as well as
12 improvements in the model mechanisms responsible for the simulation of LAI.

13

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9

10

1 **Table 1** Model simulations from the Climate Modeling Intercomparison Projection
 2 (CMIP5) included in this study. All models listed here were available for the RCP8.5
 3 analysis, while the all models except BNU-ESM and CESM-BGC were available for the
 4 RCP4.5 analysis.

Model	Land Model	Land Resolution	N-Cycle	Dynamic Veg.	Citation
BCC-CSM1	BCC-AVIM1.0	2.8°x2.8°	N	Y	(Wu et al., 2013)
BCC-CSM1-M	BCC-AVIM1.0	1.1°x1.1°	N	Y	(Wu et al., 2013)
BNU-ESM	CoLM + BNU-DGVM	2.8°x2.8°	N	Y	(BNU-ESM, http://esg.bnu.edu.cn/BNU_ESM_web/htmls/index.html)
CanESM2	CLASS2.7+CTEM1	2.8°x2.8°	N	N	(Arora et al., 2011)
CESM1-BGC	CLM4	0.9°x1.2°	Y	N	(Lindsay et al., 2014)
GFDL-ESM2G	LM3	2.5° x 2.5°	N	Y	(Dunne et al., 2013)
GFDL-ESM2M	LM3 (uses different physical ocean model)	2.5° x 2.5°	N	Y	(Dunne et al., 2013)
HadGEM2-CC	JULES+TRIFFID	1.9° x 1.2°	N	Y	(Collins et al., 2011)
HadGEM2-ES	JULES+TRIFFID (includes chemistry)	1.9° x 1.2°	N	Y	(Collins et al., 2011)
INM-CM4	Simple model	2° x 1.5°	N	N	(Volodin et al., 2010)
IPSL-CM5A-LR	ORCHIDEE	3.7° x 1.9°	N	N	(Dufresne et al., 2013)
IPSL-CM5A-MR	ORCHIDEE	2.5° x 1.2°	N	N	(Dufresne et al., 2013)
IPSL-CM5B-LR	ORCHIDEE (improved parameterization)	3.7° x 1.9°	N	N	(Dufresne et al., 2013)
MIROC-ESM_	MATSIRO+SEIB-DGVM	2.8° x 2.8°	N	Y	(Watanabe et al., 2011)
MIROC-ESM-CHEM	MATSIRO+SEIB-DGVM (adds chemistry)	2.8° x 2.8°	N	Y	(Watanabe et al., 2011)
MPI-ESM-LR	JSBACH+BETHY	1.9° x 1.9°	N	Y	(Raddatz et al., 2007)
MPI-ESM-MR	JSBACH+BETHY (ocean model higher resolution)	1.9° x 1.9°	N	Y	(Raddatz et al., 2007)
NorESM1-ME	CLM4	2.5° x 1.9°	Y	N	(Bentsen et al., 2013)

5

6

- 1 Table 2: Table of Metrics for LAI comparisons between model and observation used in the following
 2 tables. More description of these metrics are provided in Section 2.4.

Metrics		Description
Mean	Model /obs	Ratio of mean LAI from the model and observations
	Corr.	Spatial correlation of Mean LAI
Std. Dev. Seasonal	Model /obs	Ratio of seasonal cycle strength: Ratio of standard deviation of the climatological monthly mean LAI from the model and observations
	Avg. Corr.	Avg. Corr. of the temporal evolution of the climatological seasonal cycle in the model vs. observations at each grid box
Std. Dev. IAV	Model /obs	Ratio of IAV strength: ratio of standard deviation of the annual mean LAI from the model and observations
IAV LAI vs. T	Avg. Corr.	Avg. Corr. between LAI and temperature in IAV
IAV LAI vs date	Avg. Corr.	Avg. Corr. between LAI and date in IAV

3
4

1 **Table 3: Model ranking based on performance on mean annual and seasonal**
 2 **cycle metrics for each region (see description in section 2.1).**
 3

	Tropical	Midlatitude	High latitude
bcc-csm1	10	10	2
bcc-csm1-1	9	8	11
BNU-ESM	18	18	1
CanESM2	17	1	16
CESM1-BGC	6	11	17
GFDL-ESM2G	14	15	17
GFDL-ESM2M	16	17	6
HadGEM2-CC	10	5	7
HadGEM2-ES	14	3	11
inmcm4	1	8	13
IPSL-CM5A-LR	2	5	13
IPSL-CM5A-MR	4	1	9
IPSL-CM5B-LR	3	4	5
MIROC-ESM	12	15	4
MIROC-ESM-CHEM-	13	14	2
MPI-ESM-LR	5	7	9
MPI-ESM-MR	7	12	15
NorESM1-ME	8	13	7

4

1 **Table 4: Mean and standard deviation across models for future projections**
2 **(LAI change in m^2/m^2) (2081-2100) for all models and for the top half of the**
3 **models**

	Tropics	Mid-latitude	High-latitude
Mean Change (all models)	0.16	0.35	0.31
Mean Change (top models)	0.07	0.31	0.37
Standard Deviation across models (all models)	0.35	0.23	0.20
Standard Deviation across models (top models)	0.25	0.24	0.24

4

1 **Figure captions**

2 **Figure 1:** Mean of all models for the annual mean change in LAI (m^2/m^2) over time
 3 relative to current (1981-2000) for 2011-2030 (a), 2041-2060 (b) and 2081-2100
 4 (c) for RCP8.5.

5

6 **Figure 2:** Mean of all models for the annual mean change in LAI over time relative to
 7 current (1981-2000), normalized by each model's current (1981-2000) standard
 8 deviation at each grid point, for 2011-2030 (a), 2041-2060 (b) and 2081-2100 (c)
 9 for RCP8.5.

10

11 **Figure 3:** Scatter plot of the change in annual average surface temperature (T_s C)
 12 (x-axis) against the change in annual average LAI (m^2/m^2) (y-axis) for the global (a),
 13 tropics (b), mid-latitudes (c) and high-latitudes (d). Averages over four time periods
 14 are shown: 1981-2000 (with 0 changes), 2011-2030, 2041-2060 and 2081-2100,
 15 connected by a line. The final point (2081-2100) for RCP8.5 is a triangle. The
 16 temperatures increase in all simulations with time, so increases in the x-axis
 17 indicate an increase in time. Note that there are 4 points along each line, and thus if
 18 there is no inflection point, the slope of the line is constant across the 21st century. A
 19 similar plot including RCP4.5 is included in Figure S4.

20

21 **Figure 4:** Mean of the models for the fraction of the time during which the annual
 22 mean LAI is considered "Low" (model projected annual mean LAI is less than one
 23 standard deviation of the current mean at each gridbox) is shown for 2011-2030 (a),

1 2041-2060 (b) and 2081-2100 (c) for RCP85, where the current mean and standard
2 deviation are defined for each grid box for 1981-2000. For the current climate, the
3 fraction of time below one standard deviation will be 0.16, which is colored in grey,
4 so all colors represent an increase in low LAI.

5

6 **Figure 5:** Mean of all models for the change in annual mean precipitation for 2081-
7 2100 compared to current (1981-2000), normalized by the model standard
8 deviation for RCP8.5 (similar to Figure 2c, but for precipitation) (a). Mean of the
9 models % of the time during which the annual mean precipitation is one standard
10 deviation below current values (similar to figure 5c, but for precipitation) for 2081-
11 2100 in RCP8.5 (b). Grid-boxes identified as statistically significantly decreasing in
12 LAI (green) or precipitation (blue) or both (red) (i.e. the blue regions in Figure 2a
13 and Figure 6a contrasted) (c). Grid-boxes identified as having an increase in the
14 amount of time with Low LAI (green) or precipitation (blue) or both (red) (i.e. the
15 blue regions in Figure 5c and Figure 6b contrasted) (c).

16

17

18 **Figure 6:** Rank correlation across models at every grid box of the mean model
19 change in LAI (2081-2100 minus 1981-2000) for RCP8.5 against the model change
20 over the same time period of temperature (a), precipitation (b) and vegetation
21 carbon stock (c).

22

1 **Figure 7:** Mean of all models for the annual mean change in LAI over time (2081-
2 2100) relative to current (1981-2000), normalized by each model's current (1981-
3 2000) standard deviation at each grid point (a) for all models (same as Figure 1c)
4 and (b) for the top models, defined as the models performing in the top half (Table
5 4) for each region, tropical, mid-latitude or high-latitude. Because different models
6 are included in different regions, there can be discontinuities at the boundaries in
7 Figure 8b (e.g. 30 and 60 degrees latitude). The standard deviation in the mean
8 future projection at 2081-2100 across the models at each grid point are shown for
9 (c) all models and (d) top models. Indication of "Low" LAI is the model mean
10 fraction of the time that LAI is more than one standard deviation below the current
11 mean LAI and is shown for (e) all models (same as figure 5c) and (f), top models for
12 the period 2081-2100, where the current mean and standard deviation are defined
13 for each grid box for 1981-2000. For the current climate, the fraction of the time
14 below one standard deviation will be 0.16, which is colored in grey, so all colors
15 represent an increase in drought.

16

17 **Figure 8:** Comparison of model metrics for the LAI comparisons from Table 2
18 across the models, for each region (global, tropical, mid-latitude and high latitude)
19 for a) Mean model/observations, b) seasonal std deviation model/observations, c)
20 IAV standard deviation model/observations, d) spatial correlation of model to
21 observed LAI, e) average temporal correlation for seasonal variability, f) average
22 IAV LAI correlation with temperature (* indicates observed value), g) average IAV
23 LAI correlation with time (* indicates observed value).

1

2 **Figure 9:** Comparison of model metrics for the annual mean and seasonal metrics
3 from Table 2 across the models for a. global, b. tropical, c. mid-latitude and d. high-
4 latitude regions. Similar information is shown in Table S1 and S2, but here
5 converted to the Model Evaluation Value (equation 1) so that 1 is a perfect model
6 simulation and lower values indicate worse simulations. Models are shown in Table
7 1, and listed in the figure. Metrics are mean annual (+), spatial correlation of mean
8 annual (*), seasonal cycle standard deviation(diamond), mean seasonal cycle
9 correlation (triangle) and interannual variability (IAV) standard deviation (square).

10

11 **Figure 10:** Scatterplot of the metrics with the highest absolute value of the
12 correlation between the metric and future LAI changes across the globe (LAI IAV
13 correlated with date (a) and mean LAI model/obs (b)) tropics (<30°) (LAI IAV
14 correlated with date (c) and mean LAI model/obs (d)), mid-latitudes (between 30°
15 and 50°) projected change in precipitation (e)) and high-latitudes (>50°) (seasonal
16 cycle average correlation (f), strength of IAV model/obs (g), and seasonal cycle
17 strength model/obs (h). The symbols are in the shown colors for each model. The
18 grey represents the value an ideal model would have based on the observations.
19 The black line is the line that results from a linear regression of the x and y-axis.

20

21

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8

Figure 1

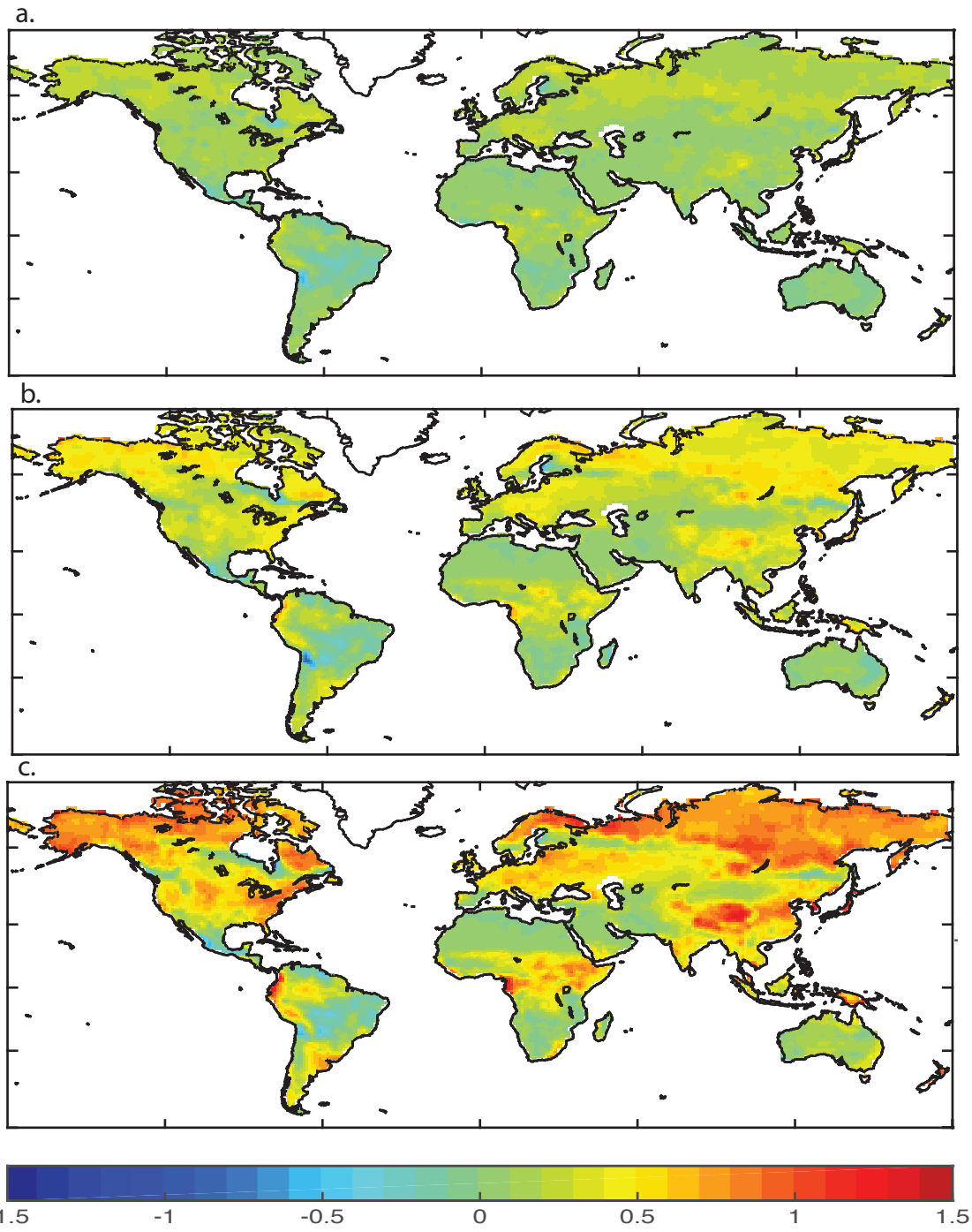
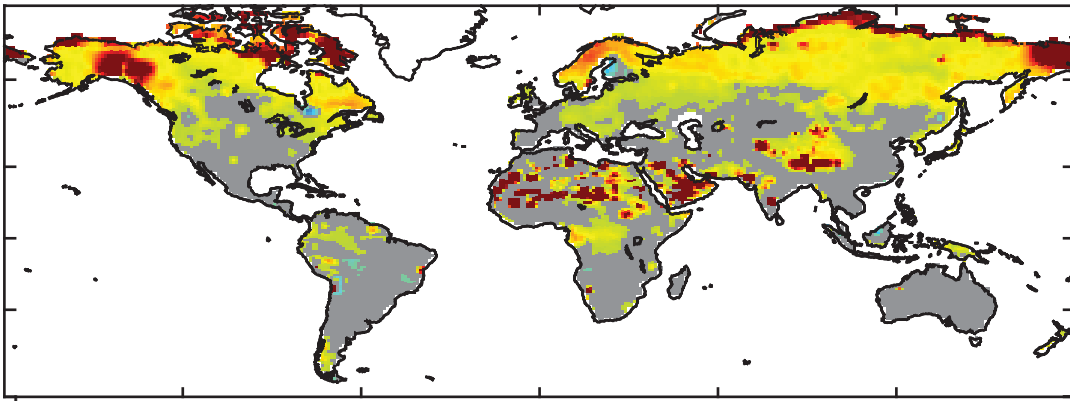
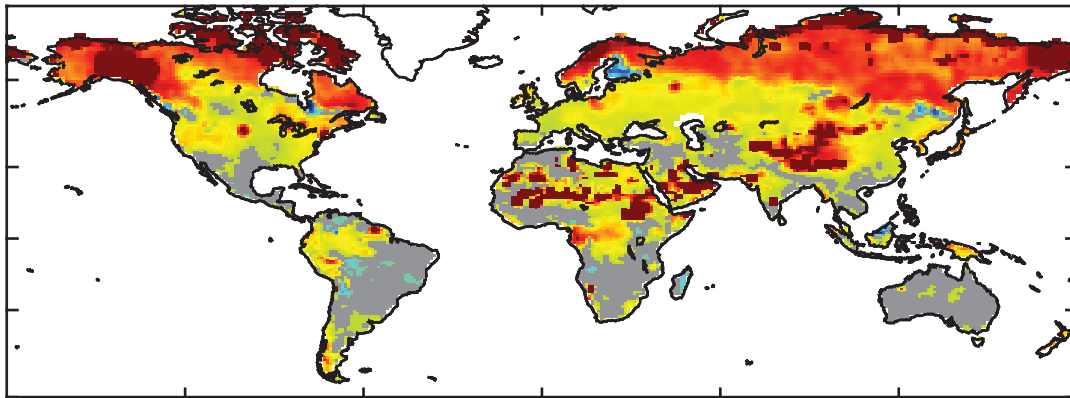


Figure 2

a.



b.



c.

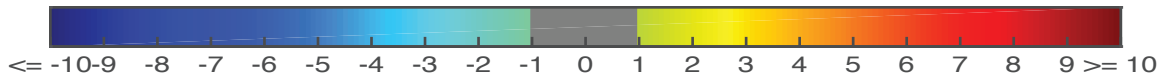
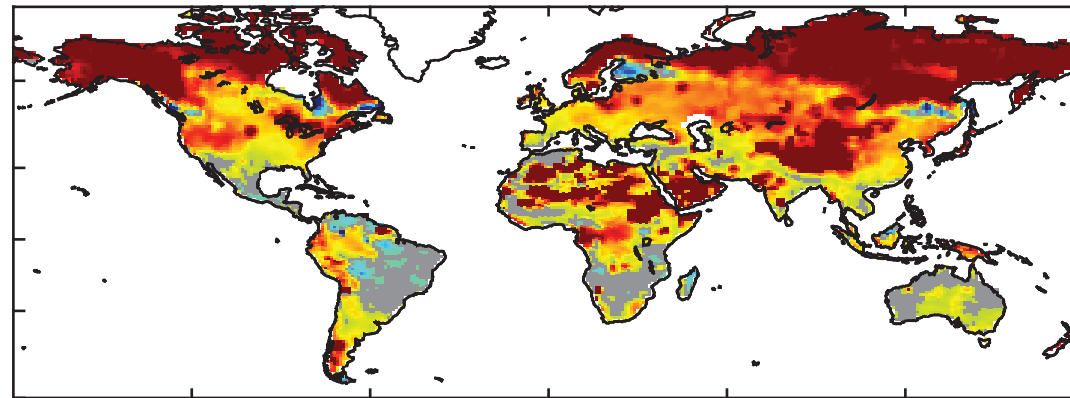
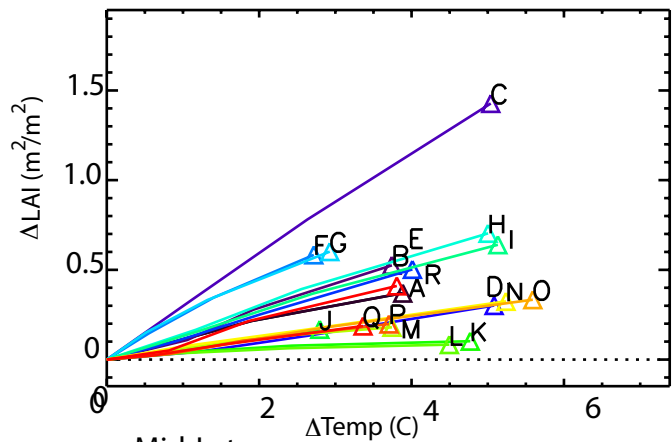
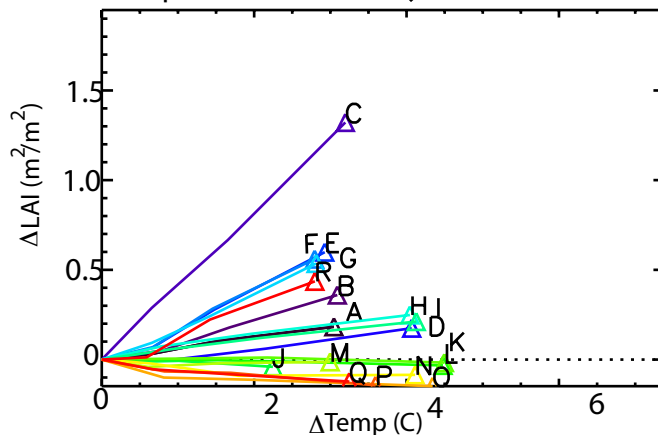


Figure 3

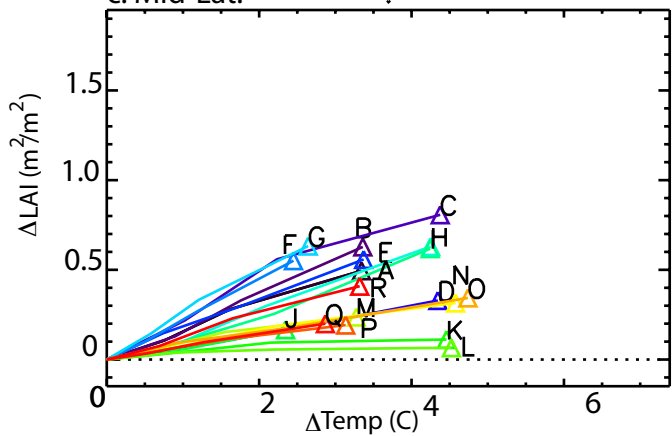
a. Global



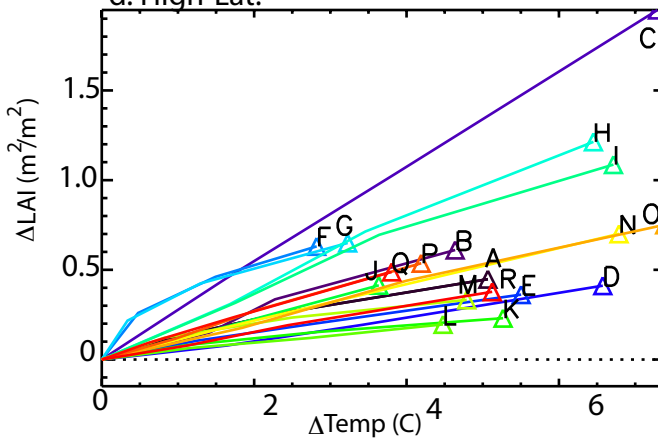
b. Tropics



c. Mid-Lat.



d. High-Lat.



A bcc-csm1-1
 B bcc-csm1-1-m
 C BNU-ESM
 D CanESM2
 E CESM1-BGC

F GFDL-ESM2G
 G GFDL-ESM2M
 H HadGEM2-CC
 I HadGEM2-ES
 J Inmcm4

K IPSL-CM5A-LR
 L IPSL-CM5A-MR
 M IPSL-CM5B-LR
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 O MIROC-ESM-CHEM

P MPI-ESM-LR
 Q MPI-ESM-MR
 R NorESM1-ME

Figure 4

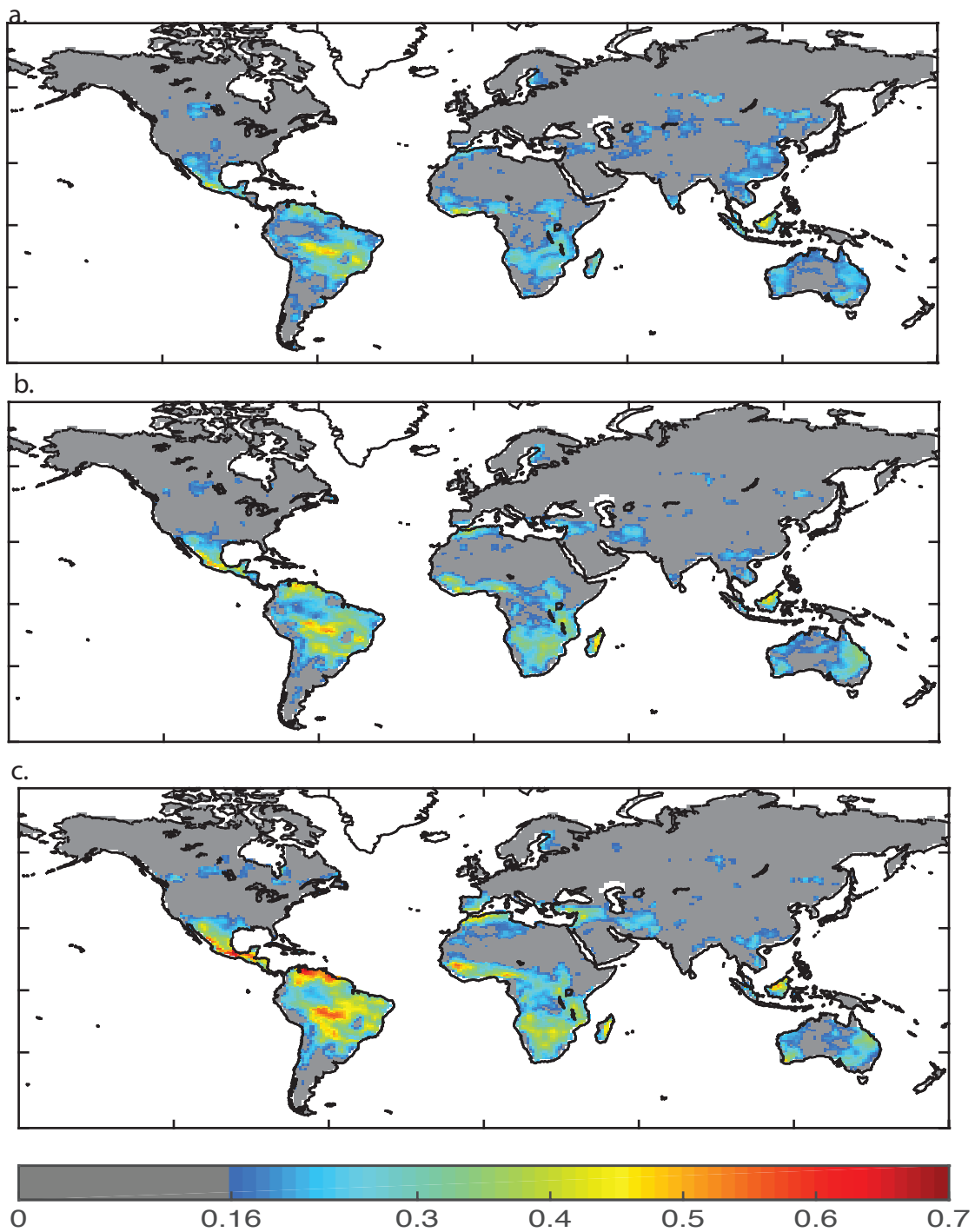


Figure 5

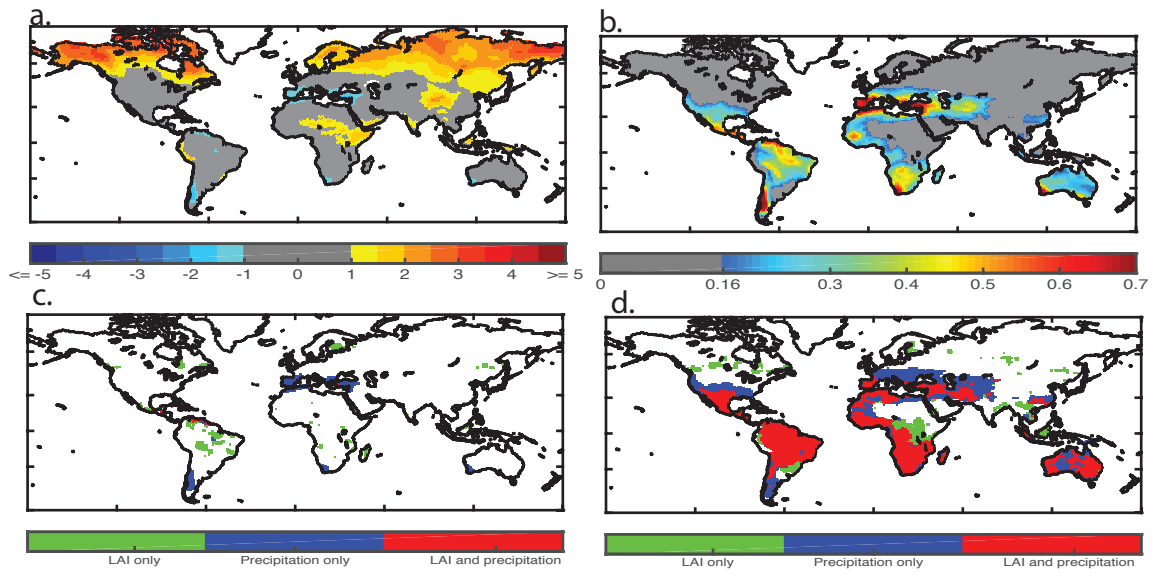
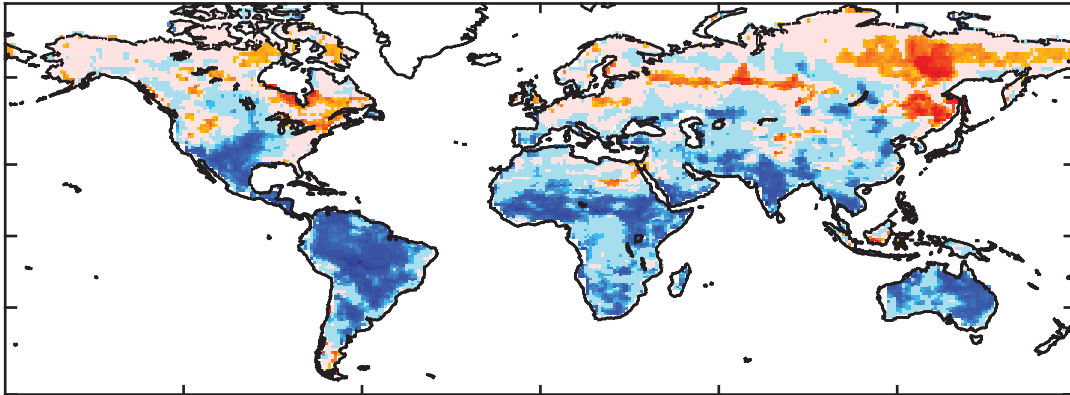
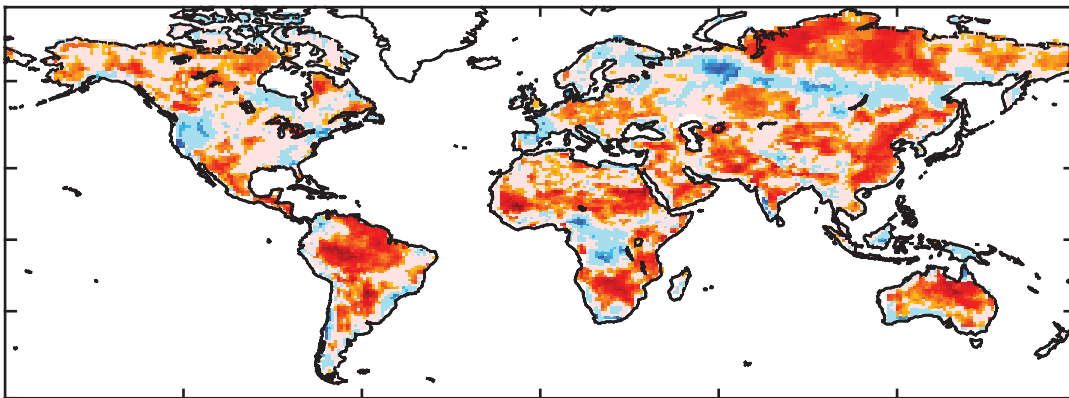


Figure 6

a.



b.



c.

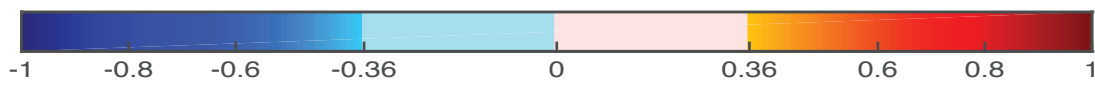
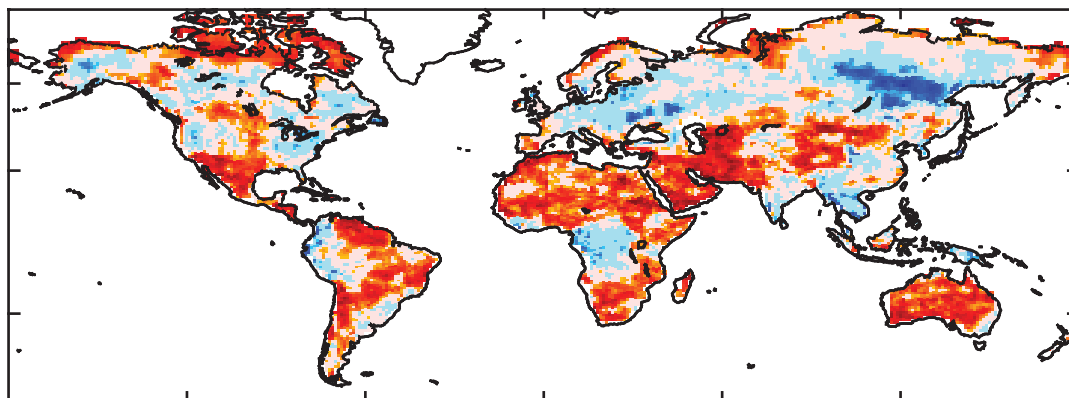
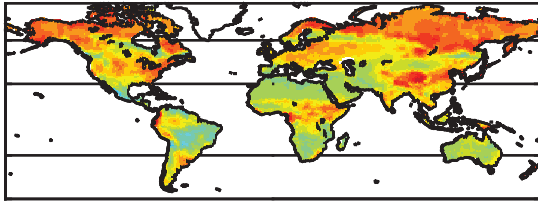
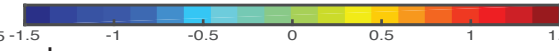
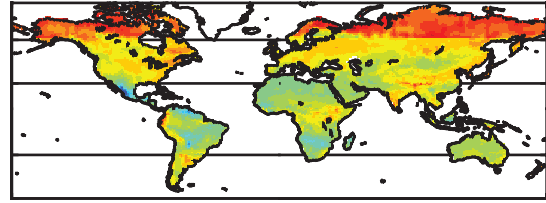


Figure 7

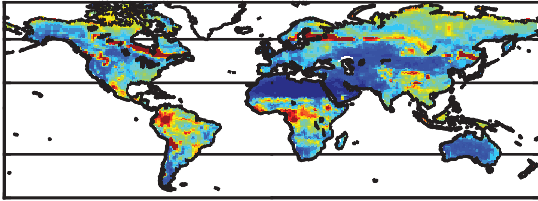
a.



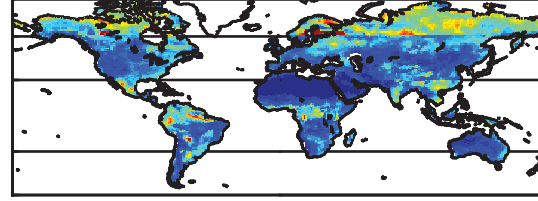
b.



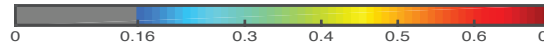
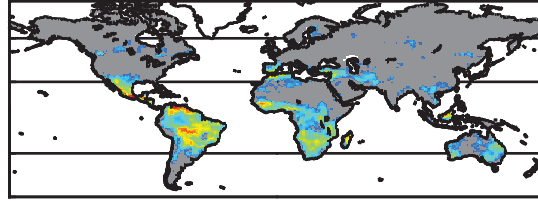
c.



d.



e.



f.

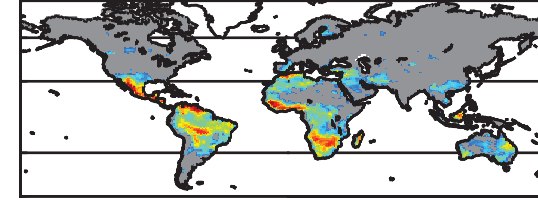


Figure 8

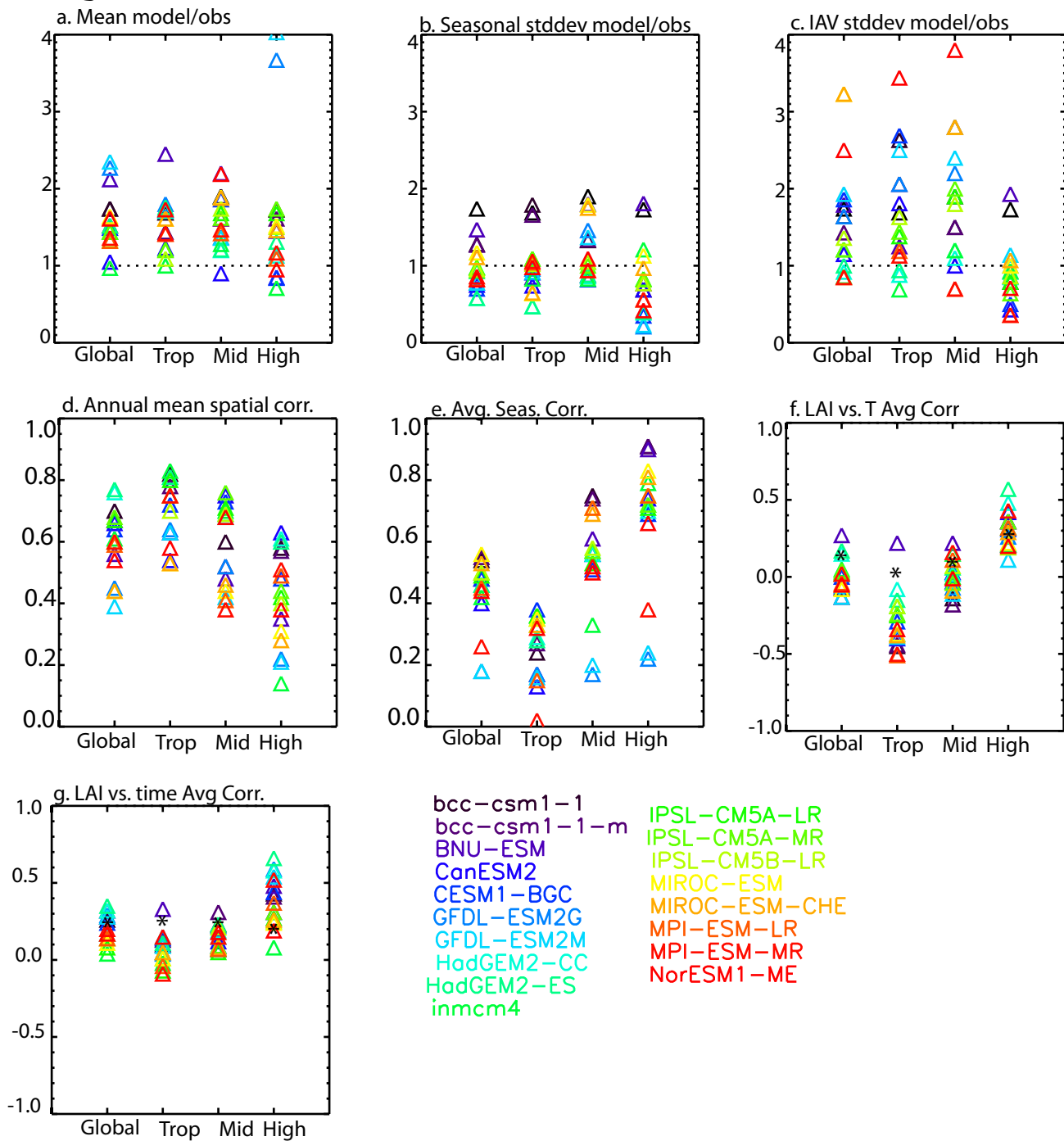


Figure 9

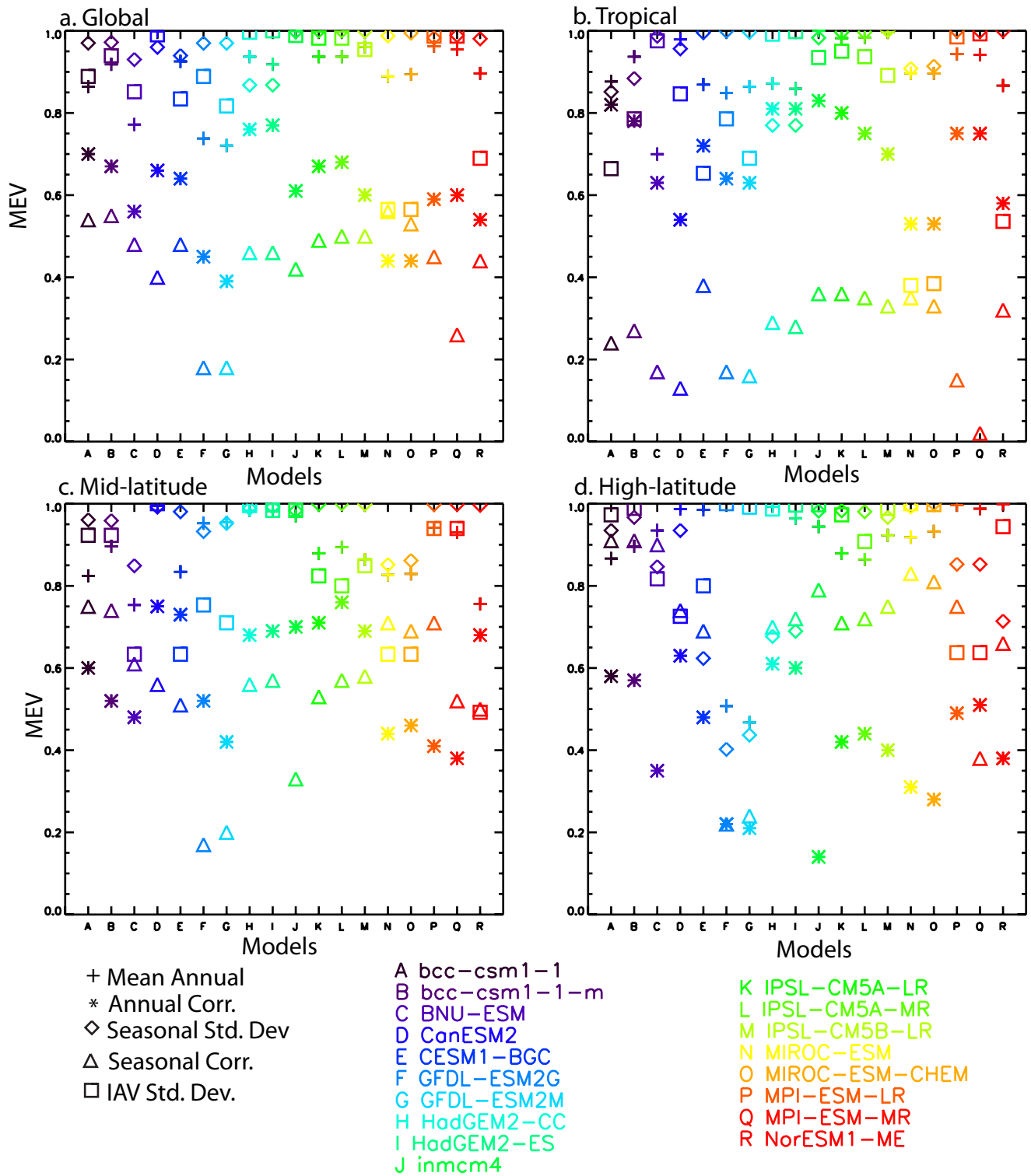


Figure 10

