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Influence of bias correction on simulated landcover changes

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[1] Vegetation responses to climate change will provide feedbacks that could amplify or moderate regional temperature and precipitation changes. However, systematic biases in the simulation of regional climate across general circulation models (GCMs) may lead to consistent misrepresentation of vegetation changes and associated ecological processes. This study uses Köppen classification driven by simulated climate with and without bias correction. Our results indicate that because climate biases lead to inaccuracies in land cover, corrected and uncorrected analyses result in distinct land cover changes in regions (the tropics and high-latitude Northern Hemisphere) that have strong climate feedbacks, even though the climate change is identical. While a more realistic biosphere may ameliorate some model biases, our results illustrate the potential for existing errors to influence feedbacks and suggest that, as models become more complex, nuanced understanding of bias propagation will be critical in assessing the uncertainty of projections and common downscaling techniques. **Citation:** McAfee, S. A., J. L. Russell, and R. S. Webb (2012), Influence of bias correction on simulated landcover changes, *Geophys. Res. Lett.*, *39*, L16702, doi:10.1029/2012GL052808.

1. Introduction

[2] The presence of regional climate biases in GCMs is well documented [*Intergovernmental Panel for Climate Change*, 2007], as is their potential to influence vegetation models [*Foley et al.*, 2000]. However, the impact of biases shared by multiple GCMs on projected ecosystem and climate change is not well understood. In light of the growing number of studies using of GCM projections with [e.g., *Gonzalez et al.*, 2010] and without [e.g., *Alo and Wang*, 2008] bias correction to assess climate change impacts, and given that incorporating dynamic vegetation into a model can enhance feedbacks [*Cook et al.*, 2008], it is critical that we understand how regional biases influence the results of vegetation models and how comparable results produced using differing methods are.

[3] Reviews by *Cramer et al.* [2001] and *Sitch et al.* [2008] compare different vegetation models run with the same climate. *Friedlingstein et al.* [2006] compare coupled climate-ecosystem models, while *Alo and Wang* [2008] run a single DGVM with the output from eight GCMs. Another line of inquiry investigates the role of vegetation on simulated climate [*Delire et al.*, 2002, 2004]. Individual modeling groups have explored the sources of bias in model components and how those biases respond to coupling [*Bonan and Levis*, 2006].

[4] However, to our knowledge, no study has evaluated the role of climate bias on vegetation change across a suite of GCMs. We are particularly concerned that biases common to large numbers of GCMs may introduce a consistent, yet potentially erroneous understanding of projected vegetation change. Here we perform a simple preliminary evaluation using the Köppen classification to determine how systematic biases influence land cover changes in relation to results from bias-corrected climate change, acknowledging that the incorporation of truly interactive vegetation may alter regional climate biases [*Delire et al.*, 2002], as well as the trajectory of climate change [*Delire et al.*, 2004], and that changes in bias with coupling may not be straightforward [*Bonan and Levis*, 2006].

2. Data and Methods

[5] We used output from 18 climate models included in the IPCC Fourth Assessment Report, listed in *McAfee et al.* [2011], and monthly precipitation and temperature from the 1°-resolution University of Delaware (UDEL) dataset [*Willmott and Matsuura*, 1995] to investigate the impact of regional biases in climate simulation on land cover classification. The Program for Climate Model Diagnosis and Intercomparison provided model output (http://www-pcmdi.llnl.gov/), which was regridded to match UDEL. To demonstrate potential impacts of regional climate biases on modeled land cover, we applied a simplified version of the Köppen classification in *Kottek et al.* [2006]. The Köppen system describes five major climate/vegetation types: tropical (A), arid (B), temperate (C), strongly seasonal (D), and polar (E), subdivided based on amount and seasonality of precipitation and/or by temperature extremes [*Kottek et al.*, 2006].

[6] Although the Köppen classification is not an exact analog for plant functional types used in vegetation models, it provides a straightforward way of evaluating the impact of regional temperature and precipitation biases in GCMs on simulated land cover change. The Köppen classification has a long history of use with GCMs to identify errors [*Gnanadesikan and Stouffer*, 2006; *Lohmann et al.*, 1993], and efficiently characterize vegetation-type changes with few climate variables and minimal computation [e.g., *Feng et al.*, 2012]. Individual DGVMs can contain biases of their own, irrespective of the GCMs used to force them [*Bonan and Levis*, 2006; *Gonzalez et al.*, 2010], and different models do not produce identical results from the same climate [*Sitch et al.*, 2008]. Using a simple classification removes the complication of vegetation model differences.

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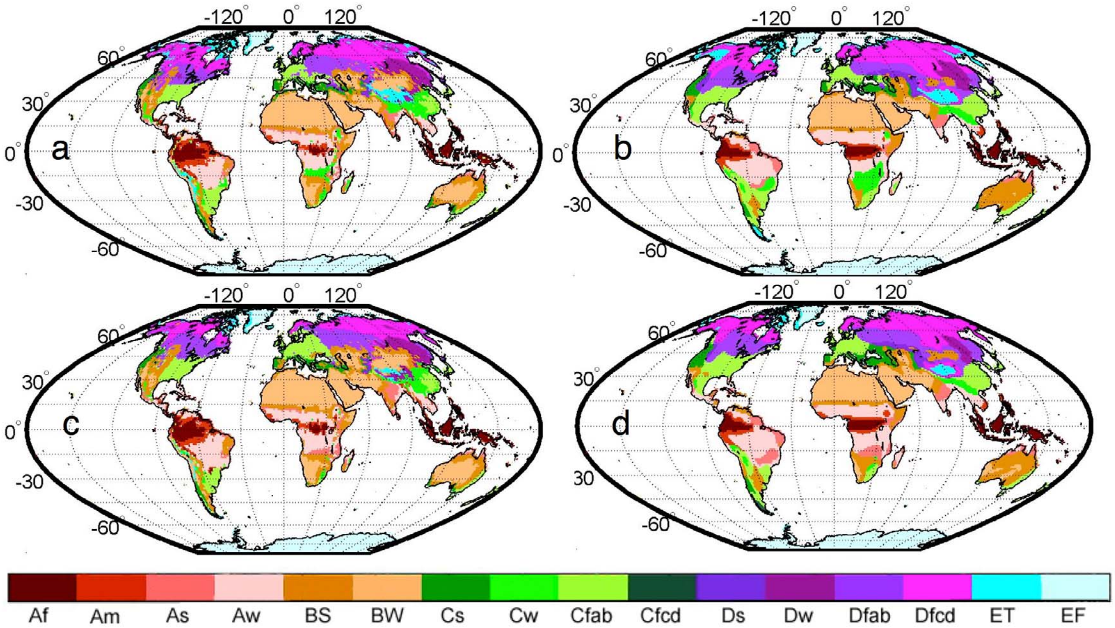

Figure 1. Köppen classification maps produced using (a) University of Delaware temperature and precipitation (1979–99), (b) the ensemble of 18 models (1979–99), using (c) adjusted 2079–99 ensemble climate and (d) unadjusted 2079–99 ensemble projections. See Table 1 for Köppen type descriptions.

[7] To investigate climate-driven changes in land cover by the end of the 21st century (2079–99) under the A1B scenario, we created Köppen classifications based on: 1) late 20th century (1979–99) UDEL observations (Figure 1a); 2) late 20th century simulated climate (ensemble mean shown in Figure 1b); 3) late 21st century (2079–99) climate derived by adding absolute changes in temperature and percent changes in precipitation projected by each model to the UDEL dataset (bias-corrected or adjusted, Figure 1c); and 4) directly simulated late 21st century climate (uncorrected or unadjusted, emulating coupled runs, Figure 1d).

[8] We calculated the area covered by each Köppen type and the projected change in area of each class for all the models individually and for the ensemble mean climate. Although maps display ensemble results, the statistical analyses do not include the ensemble. We used two-tailed one-sample t-tests to characterize differences in the areas of different land cover types produced by simulated and observed climate. To compare changes in land cover from adjusted and unadjusted experiments, we used paired t-tests (or the Wilcoxon signed rank test), pairing by model (Table 1). This analysis focuses on the role of shared biases across GCMs in influencing vegetation change, while controlling for the fact that different models project somewhat different changes in climate.

3. Results and Discussion

[9] The late 20th century ensemble mean climate displays systematic dry biases over portions of South and Central America and wet biases in many of the world's arid and semi-arid regions. (Figures 2a and 2b). During the summer, there are cool biases across much of the Arctic (Figure 2d), but individual models display a wide range of errors (not shown). Associated with regional climate biases are miscategorizations of late 20th century land cover. Dry biases over South America are associated with contracted tropical forests (Af and Am) and expansion of the savanna-like As type (cf. Figures 1a and 1b). The presence of wet biases in many of the world's arid and semi-arid lands leads to statistically significant ($p < 0.05$) underestimation of the late 20th century area in steppe (BS) and desert (BW) land cover types and significant over-representation of the Cs and Ds types globally (Figures 1b and 3a and Table 1). The variety of regional temperature biases over the Arctic translates into a variety of landscape configurations, though the ensemble simulates excess tundra (ET, Figure 3a).

[10] Despite identical climate shifts, there are notable differences in the changes in tropical forest (Af), desert (BW) and cold boreal forest (Dfcd) areas between the adjusted and unadjusted analyses. The adjusted analysis predicts larger changes in the areas of tropical savannah and forest (A types) related to contraction of the Amazon forest in a number of models. There is no change in the area of Af in the unadjusted analysis, likely because 20th century simulations produce so little tropical forest in the region that losses are minimal. Only the unadjusted analysis projects statistically significant desertification (increasing BW). Late 20th century simulations underestimate the area of desert, allowing for expansion of desert into areas that are already classified as BW in the bias-corrected simulations. The overall decrease in cold boreal forest (Dfcd) is much smaller in the unadjusted analysis, largely because initial cool biases limit the northern extent of Dfcd in the late 20th century (Figure 3b and Table 1).

[11] *Alo and Wang* [2008] find consistent shifts in vegetation across a number of climate models in two geographic regions – the tropics and the boreal Northern Hemisphere, areas identified in other studies [*Sitch et al.*, 2008] and known to have strong climate feedbacks [*Bonan*, 2008; *Betts et al.*, 2004]. However, they are also the very regions in which we find that consistent biases in simulated climate

Table 1. Description of Modified Köppen Classification Used in This Study [*Kottek et al.*, 2006] and Summary of Statistical Analysis Associated With Figure 3[a]

	Classification	Late 20th Century Area	Late 21st Versus Late 20th Century Area		Change in Area
			Bias-Corrected	Uncorrected	
Af	Rainforest	0.102	0.040	0.612	0.031
Am	Monsoonal forest	<0.001	0.025	<0.001[b]	0.865
As	Savannah, winter wet	0.001	<0.001	<0.001	0.005
Aw	Savannah, summer wet	0.003	0.035	0.040	0.420[b]
BS	Semi-arid scrub or grassland	0.011	<0.001	<0.001	0.129
BW	Desert	0.001	0.104	<0.001	0.028
Cs	Mediterranean	<0.001	0.001[b]	<0.001	0.286[b]
Cw	Temperate, wet summers	0.075	<0.001	<0.001	0.005
Cfab	Temperate, warm summers	0.668	0.330	0.598	0.652
Cfcd	Temperate, cool summers	0.617[b]	0.112[b]	0.983[b]	0.472[b]
Ds	Boreal, wet winters	<0.001	0.073	0.007	<0.001
Dw	Boreal, wet summers	0.446[b]	0.003	<0.001[b]	0.003[b]
Dfab	Boreal, warm summers	0.515	<0.001	<0.001	0.305
Dfcd	Boreal, cool summers;	0.744[b]	<0.001	0.007[b]	<0.001
ET	Tundra	0.634	<0.001	<0.001	0.557[b]
EF	Polar desert/ice	0.008[b]	<0.001	<0.001[b]	0.005

[a]The column Late 20th Century Area shows the p-values from a two-tailed one-sample t-tests (Wilcoxon tests) evaluating whether simulated areas were equivalent to areas derived from observed climate. In the adjusted analysis, areas covered by each Köppen type in the late 21st century were compared to observed late 20th century areas with two-tailed t-tests (Wilcoxon signed rank tests) to determine whether there had been an overall change in the area of that land cover type. For the unadjusted analysis, we compared the areas covered by each Köppen type in the late 21st century to the corresponding simulated late 20th century areas, using a two-sided paired t-test (Wilcoxon signed rank test). Finally, we compared changes in area of each Köppen type from the adjusted analysis to those in the unadjusted analysis, pairing by model to account for the fact that the climate change in a given model were the same in both analyses. Köppen type descriptions modified from *Gnanadesikan and Stouffer* [2006] and *Kottek et al.* [2006].

[b]Prior to statistical analysis, we evaluated the normality of the data. If the distribution was determined to be non-normal by the Lilliefors test (α = 0.05), we used the non-parametric Wilcoxon signed-rank test.

have the greatest impacts on land cover changes. Models that are initially too dry to support tropical forest in the Amazon cannot simulate forest conversion there, whereas in the HadCM3LC model, loss of tropical forest in the Amazon exacerbated projected decreases in precipitation, driving further mortality [*Betts et al.*, 2004]. Expansion of coniferous boreal forests into tundra would likely decrease albedo – a positive feedback on temperature that could instigate further, possibly rapid, encroachment of forest into tundra [*Bonan*, 2008; *Cook et al.*, 2008]. Thus GCMs with dynamic vegetation that are initially too cool might experience more vegetation change and greater regional warming than unbiased models. Bias-correction related differences in land cover changes in arid and semi-arid regions, where many models display wet biases, might not have significant influence on the global climate. However, the transition from woodlands to steppe or desert in the sub-tropics seen in the uncorrected analysis imply a host of local ecological and meteorological changes that would seem unrealistic given that much of the region is, in fact, already in these dry ecosystem classes.

[12] Bias may not have a strong impact on general studies such as *Alo and Wang* [2008] that describe broad-scale

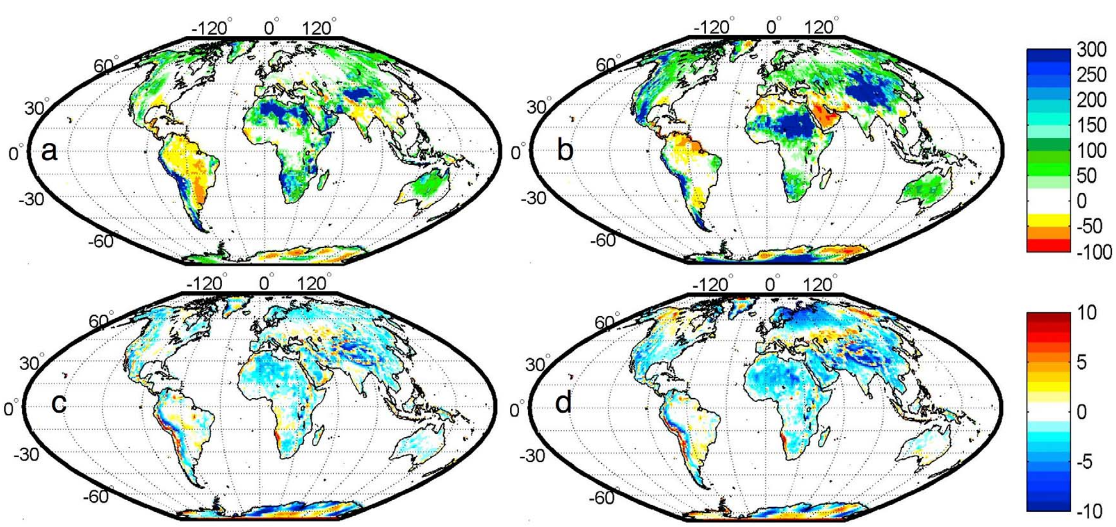

Figure 2. (a, b) Percent precipitation error and (c, d) absolute temperature error of the ensemble average of 18 models in relation to the University of Delaware climate data (1979–99). Figures 2a and 2c show the mean error for May to October; Figures 2b and 2d show November to April.

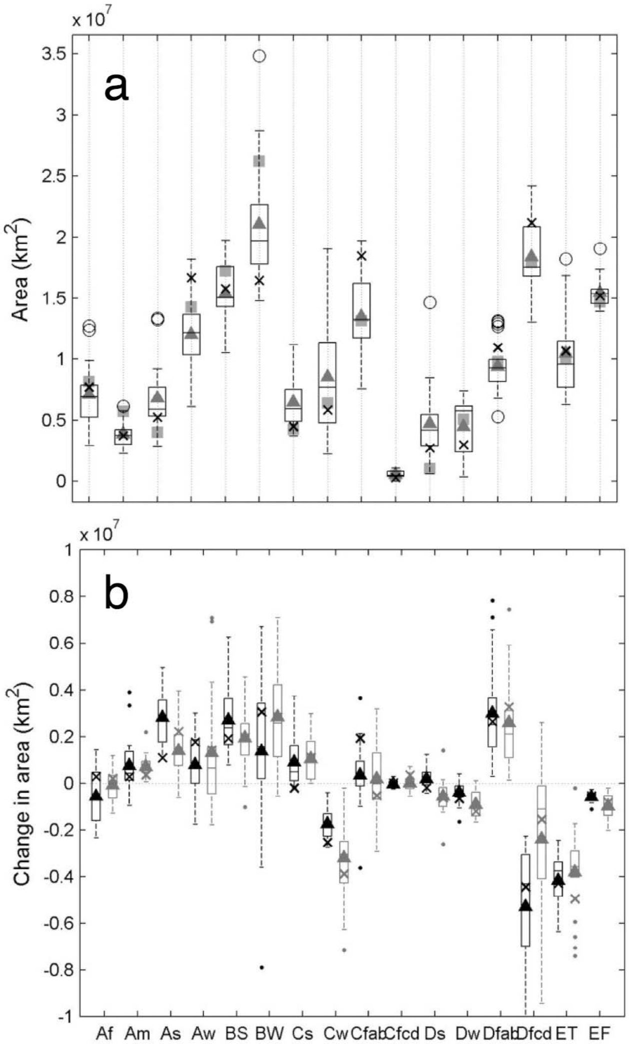

Figure 3. (a) Area covered by each Köppen type in the late 20th century (1979–99). Boxes show first and third quartiles and the median. Outliers are shown by small circles. Light gray squares indicate area derived from observed climate; black x's the area derived from the ensemble mean climate; dark gray triangles the mean area of the ensemble members. Köppen types for which models simulate areas significantly ($p < 0.05$) different from the observations are marked with an asterisk. (b) Change in area between the late 20th and late 21st (2079–99) centuries simulated by the adjusted (black) and unadjusted (gray) methods. Box plots are as in Figure 3a. X's show the change calculated when the 18-model ensemble climatology is used, and triangles the average change across all of the models. Statistically significant ($p < 0.05$) changes in area for each method are shown by filled black and gray circles; differences between the two methods are indicated by asterisks. See Table 1 for Köppen type definitions.

climate-driven ecosystem trends without explicitly considering feedbacks. However, bias may have more consequence in two rapidly expanding areas of study: vulnerability analyses and coupled climate-ecosystem simulation. With the proliferation of studies like *Gonzalez et al.* [2010], which aim to identify areas at risk of vegetation change using a small number of GCMs and one vegetation model, it will become more difficult to separate the effects of differing climate model bias, bias-correction choices, climate scenarios and vegetation models.

[13] As the use of fully coupled DGVMs and Earth System Models (ESMs) becomes more common, it will be essential to understand how regional climate biases influence the results, particularly when models display consistent biases. One strength of coupled models is simulation of vegetation that is consistent with modeled atmospheric conditions and provides appropriate feedbacks on climate. However, as shown here, errors in the simulation of regional climate can result in specifying incorrect land cover that may not only misrepresent regional vegetation responses to projected climate change, but may also amplify these errors through feedbacks that are not reasonable in the context of observed conditions.

4. Conclusions

[14] Although our analysis does not consider iterative and coupled feedbacks between the atmosphere and biosphere, our results strongly support the need for further research into how model bias should be treated in the context of fully coupled DGVMs and ESMs and into methods for the

comparison of off-line models run with or without bias-corrected climate to more complex models where vegetation both responds to and influences climate, particularly as these models may not share identical climate biases. We believe that systematic investigation of bias propagation, an occult source of uncertainty, will be needed to adequately evaluate results from the rapidly proliferating suite of ESMs and to assess sources of uncertainty in ecosystem vulnerability analyses.

[15] **Acknowledgments.** University of Delaware data (Matsuura and Willmott, climate.geog.udel.edu/∼climate/) was downloaded from the University of Washington Joint Institute for the Study of the Atmosphere and Oceans (jisao.washington.edu/data_sets/ud/). We would like to thank the anonymous reviewers whose comments improved the paper. Portions of this work were completed while S. McAfee was a National Research Council Research Associate at the NOAA Earth System Research Laboratory.

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