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Improving predictions of summer climate change in the United States

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[1] Across vast, agriculturally intensive regions of the United States, the spread in predictions of summer temperature and soil moisture under global warming is curiously elevated in current climate models. Some models show modest warming of 2–3C° and little drying or slight moistening by the 22nd century, while at the other extreme are simulations with warming as large as 7–8C° and 20–40% reductions in soil moisture. We show this region of large spread arises from differences in simulations of snow albedo feedback. During winter and early spring, models with strong snow albedo feedback exhibit large reductions in snowpack and hence water storage. This water deficit persists in summer soil moisture, with reduced evapotranspiration yielding warmer temperatures. Comparison of simulated feedback strength to observations of the feedback from the current climate's seasonal cycle suggests the inter-model differences are excessive. At the same time, the multi-model mean feedback strength agrees reasonably well with the observed value. We estimate that if the next generation of models were brought into line with observations of snow albedo feedback, the unusually wide divergence in simulations of summer warming and drying over the US would shrink by roughly one third to one half. **Citation:** Hall, A., X. Qu, and J. D. Neelin (2008), Improving predictions of summer climate change in the United States, *Geophys. Res. Lett.*, *35*, L01702, doi:10.1029/2007GL032012.

1. Spread in Summer Climate Predictions

[2] The future evolution of summer temperature and hydrology is a particularly critical aspect of climate prediction in the United States (US) for three reasons. First, a warming climate would result in an increase in frequency and intensity of summer heat waves [*Stott et al.*, 2004]. Second, farming is most productive in summer, so climate change in this season will have significant effects on agriculture, particularly if it involves changes in moisture availability. And finally, water resources are most limited at this time of year relative to needs of urban areas, agriculture, and ecosystems, intensifying impacts of any future drying trend. Concern about these critical climate change impacts is further heightened by the fact that large continental regions have been identified as zones of elevated drying and warming in response to increases in greenhouse gases since nearly the beginning of the climate change modeling era [*Manabe and Stouffer*, 1980; *Manabe and Wetherald*, 1987; *Gregory et al.*, 1997; *Douville et al.*, 2002], although there has long been uncertainty among climate models on the extent of this effect [*Mitchell and Warrilow*, 1987; *Meehl and Washington*, 1988; *Kellogg and Zhao*, 1988; *Seneviratne et al.*, 2002] and validation of contributing factors against existing observations has been challenging [*Henderson-Sellers et al.*, 1995; *Foster et al.*, 1996; *Slater et al.*, 2001; *Mahanama and Koster*, 2003; *Reichle et al.*, 2004; *Robock et al.*, 2005; *Li et al.*, 2007]. In an ensemble-mean sense, the models used in the most recent Intergovernmental Panel on Climate Change (IPCC) Fourth Assessment report (AR4) continue to predict large warming and drying in the US by the 22nd century in response to anthropogenic forcing [*Wang*, 2005; *Meehl et al.*, 2007].

[3] Unfortunately, confidence in current projections for the US remains limited by large intermodel spread. Figure 1a shows the standard deviation of 22nd-century summer warming in the AR4 models when the SRES 1AB scenario is imposed. Over much of the US, the standard deviation is curiously elevated compared to surrounding areas, reaching values of over 1.5°C (compared to an ensemble mean of 5°C). The spread in the soil moisture change also exhibits a puzzling relative maximum in a band across the US, where the standard deviation of the soil moisture reduction exceeds 20% (Figure 1b), larger than the ensemble mean drying of 10%. This implies an uncertainty in the predictions ranging from slight moistening to strong drying. Here we demonstrate that the elevated spread in simulated summer temperature and hydrologic response to anthropogenic forcing over the US can be traced in large part to widely varying simulations of snow albedo feedback (SAF) during spring.

2. Link to Snow Albedo Feedback

[4] SAF occurs when surface air temperature (T_s) increases in response to anthropogenic forcing and surface albedo (α_s) decreases significantly, mainly because of a retreat of snow cover [*Randall et al.*, 1994, 2007]. This results in a large increase in absorbed solar radiation—and enhanced warming—especially in spring because insolation is relatively large at this time of year. In this case, we can quantify SAF strength by calculating the ratio of the change in α_s averaged over North America poleward of 30°N to the change in T_s averaged over the same region. This ratio contains almost all information about intermodel variations in SAF strength [*Qu and Hall*, 2007]. When we calculate it based on differences between 22nd and 20th century spring climate states, we find it exhibits nearly a three-fold spread.

[5] This large spread in SAF strength is tightly associated with the intermodel spread in the spring temperature response to anthropogenic forcing over North America, as one might expect. The multi-model correlations between SAF strength and temperature response reach values of 0.6 (not shown). Less intuitive is the tight association between

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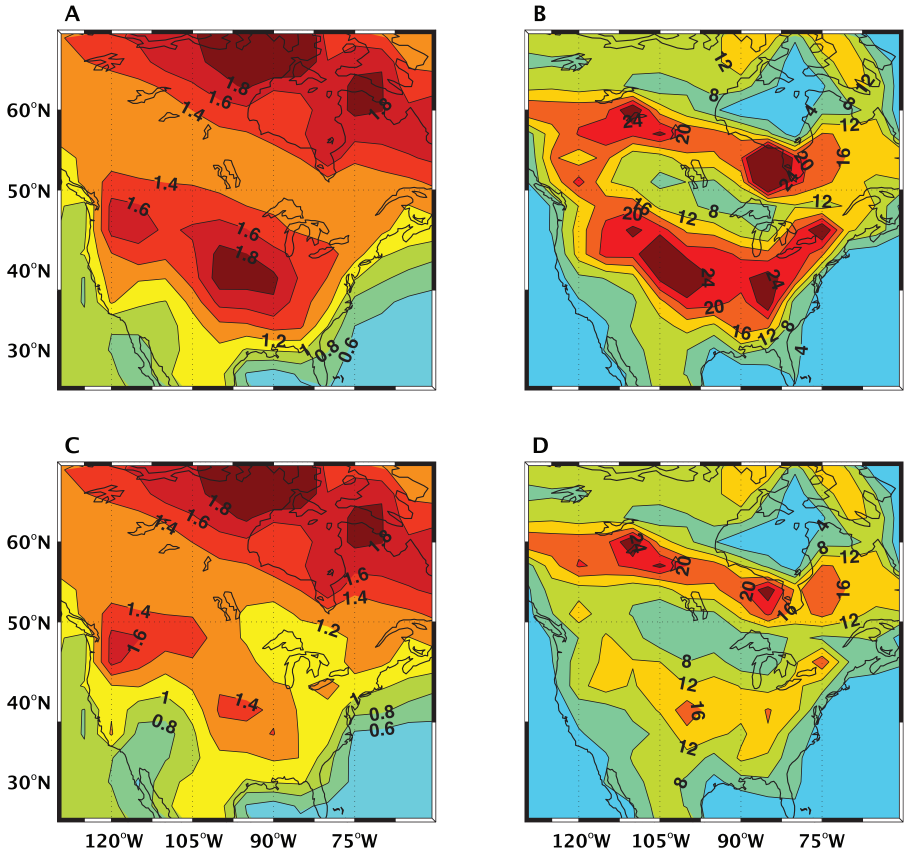

Figure 1. (a) Intermodel standard deviation of the change in summer temperature (°C) over the U.S. and Canada in 18 AR4 models. (b) Standard deviation of fractional change in summer soil moisture. The fractional change in soil moisture is here defined as the change in soil moisture at any particular location divided by the continental-mean soil moisture. (c) Standard deviation of the change in summer temperature when the component that can be linearly related to SAF is removed. (d) Standard deviation of fractional change in summer soil moisture when the component that can be linearly related to SAF is removed. Changes are defined as the differences between 22nd century and 20th century averages from the '720 ppm stabilization experiment,' where historical 20th century forcing was imposed, followed by the SRES A1B emission scenario for the 21st century, followed by fixed anthropogenic forcings from year 2100 to 2200. Summer averages are over June–September.

variations in spring SAF strength and summer temperature and hydrologic response. The correlations between SAF strength and summer warming in Figure 2a reach values of 0.5 to 0.6 over much of the US, well above the 95% significance level. The correlations between SAF strength and summer soil moisture changes are even more striking, reaching values as low as −0.8 (Figure 2b). Models having strong SAF during spring also consistently exhibit a large drying during summer. Conversely, models with very weak SAF exhibit little drying or, in some cases, slight moistening.

[6] Spring SAF strength and summer climate response are so tightly linked because of SAF's impact on the change in water stored in the snowpack and soil during winter and spring [*Manabe and Wetherald*, 1987; *Wetherald and Manabe*, 1995]. This is seen in multi-model correlations between spring SAF strength and the change in zonal-mean total water storage. We show these correlations as a function of latitude and season (Figure 3). During winter and early spring, models with strong SAF exhibit large reductions in total water stored, mostly because of reductions in snowpack size and the subsequent loss of this water through runoff. This occurs in mid-latitudes where the snowpack coincides with relatively large insolation values and SAF is most operative. These anomalies in water storage persist into the summer, as demonstrated by the fact that the correlation between SAF strength and water storage is preserved throughout the summer months. At this time of year, almost all water in mid-latitudes is stored as soil moisture, leading to the tight association between spring SAF strength and summer soil moisture changes seen in Figure 2b. Soil moisture reductions can contribute to increases in summer temperatures because of the decrease in evapotranspiration, and warm temperatures can also feedback on the soil moisture [*Manabe and Wetherald*, 1987; *Manabe et al.*, 2004; *Seneviratne et al.*, 2002; *Diffenbaugh et al.*, 2005; *Diffenbaugh et al.*, 2007], yielding the correlations between SAF strength and summer temperature response seen in Figure 2a. Atmospheric dynamical effects involving clouds and advection of atmospheric temperature anomalies may spread this effect to surrounding regions or modify it in particular models [*Gregory et al.*, 1997; *Cubasch et al.*, 2001].

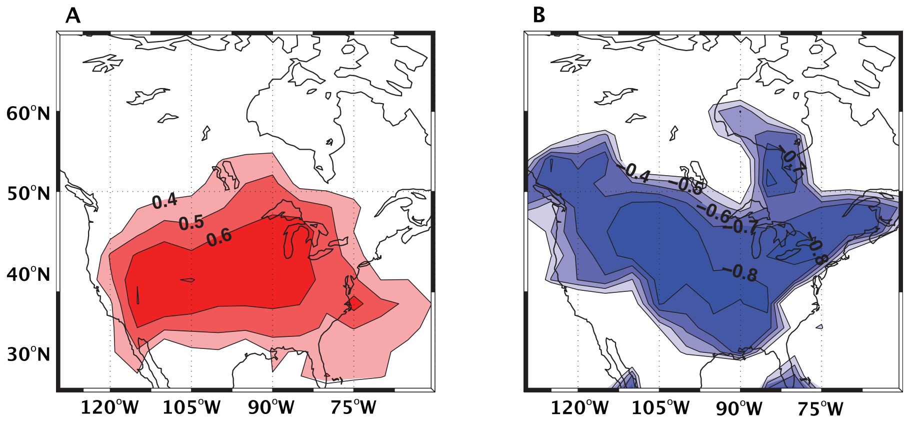

Figure 2. (a) Correlation between simulated spring SAF strength and the summer change in temperature over the U.S. and Canada. (b) Correlation between simulated spring SAF strength and the summer fractional change in soil moisture. Shaded areas indicate 90% significance; correlations exceeding 0.47 in magnitude are significant at the 95% level. SAF strength is defined as $-\Delta\alpha_s/\Delta T_s$, so that positive (negative) correlation indicates strong SAF strength is associated with an increase (a decrease) in temperature (soil moisture). Soil moisture is normalized by its North American mean for each model.

[7] The tight link between spring SAF strength and summer climate response in the US implies that if SAF could be constrained observationally, there would be a substantial reduction in the spread in summer climate response. To illustrate this, we removed the component of the spread in summer temperature and soil moisture changes that can be linearly related to intermodel variations in SAF strength, and recalculated the standard deviation of the intermodel spread (Figures 1c and 1d). Comparing Figures 1a and 1b, the spread is reduced by roughly one third for temperature and by almost half for soil moisture across much of the U.S, and the relative maximum in spread in this region largely disappears.

3. Constraining Snow Albedo Feedback

[8] Having shown SAF contributes strongly to uncertainty in current US climate predictions via a clear physical pathway, we turn to a means of constraining the feedback. Recently, a method was proposed to constrain SAF observationally by calculating it in the context of the current climate's annual spring T_s increase and α_s reduction in the northern hemisphere [*Hall and Qu*, 2006]. (This contrasts with calculating SAF in climate change based on differences between 22nd and 20th century spring climate states, the basis of the analysis of section 2.) The method works because simulated feedback strength in the seasonal cycle context is an excellent predictor of its strength in climate change. Observed estimates of $\Delta\alpha_s/\Delta T_s$ in the seasonal cycle (Figure 3b) were calculated using International Satellite Cloud Climatology Project (ISCCP) α_s [*Zhang et al.*, 2004] and T_s monthly climatologies from two sources: National Center for Environmental Prediction Reanalysis (NCEP) [*Kalnay et al.*, 1996], and the shorter ERA40 reanalysis [*Simmons and Gibson*, 2000]. The statistical error in these two estimates was also calculated

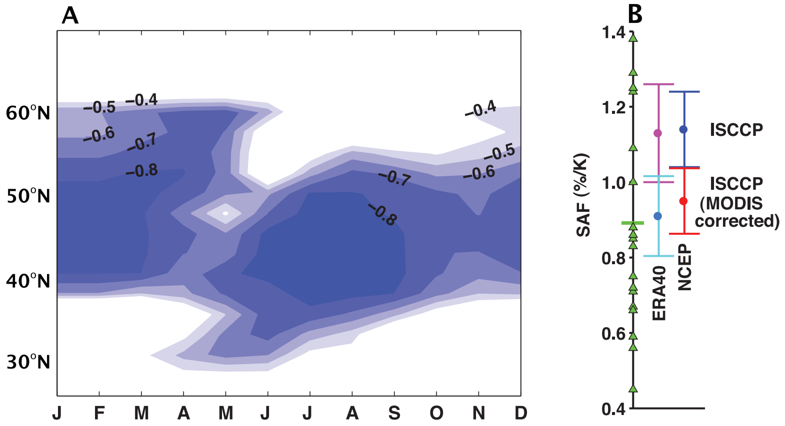

Figure 3. (a) Correlation between simulated spring SAF strength and the change in water storage (zonally averaged across North America) for each latitude and calendar month. Water storage is defined as the sum of snow mass and soil moisture, normalized by the continental-mean summer soil moisture in the 20th century climate (significance levels as in Figure 2). (b) Spring SAF from the 18 models (triangles) and multi-model ensemble mean (horizontal bar on SAF axis) compared to observational estimates from ISCCP and a hybrid calculation using a MODIS based correction to ISCCP data set (see text) for albedo, and surface temperature from NCEP and ERA40. Here SAF for both models and observations are estimated from the seasonal cycle. Error bars on the observed are 95% confidence intervals based on the variations in the 21 year NCEP record (19 years for ERA40 T_s), but do not include instrumental/retrieval errors.

based on the number of years of available data (21 for NCEP, 19 for ERA40), giving a 95% confidence range. The observational estimates of SAF strength are also subject to poorly quantified systematic errors, principally because ISCCP α_s values are based on reflectivity measurements at only two channels. A more sophisticated and reliable estimate of the α_s climatology is forthcoming from the Moderate Resolution Imaging Spectroradiometer (MODIS), which measures reflectivity at 36 channels. While the MODIS time series is still short, and direct calculation of SAF would involve nontrivial technical issues particularly in the computation of diffuse radiation contributions, we use the ISCCP to MODIS comparison relationships calculated by *Zhang et al.* [2007] for different snow cover conditions to recompute the ISCCP-based SAF values, giving two additional SAF values, one for each temperature data set. This provides an estimate of how much the observed SAF might shift due to ISCCP systematic errors. The correction is about 20%, much smaller than the range of SAF among the models.

[9] Eight models are within the range spanned by the error bars on these four estimates; eight are weaker than it; and two are stronger. The multi-model ensemble mean lies within the observed range, providing a physical basis for increased confidence in ensemble-mean changes in summer temperature and soil moisture in current models. Although we cannot assign a formal probability, SAF values in models at the high and low ends of the range in SAF strength appear unlikely. SAF values in the three weakest models are just over half the lower (mean MODIS-corrected) observed estimate, while SAF values in the two strongest models are more than 40% greater than this (20% greater than ISCCP estimate). This implies that the high and low ends of the range in projections of summer climate are less likely than would have been assumed without the benefit of information about SAF, helping to eliminate both the worst-case and best-case scenarios. Furthermore, Figures 1c and 1d suggest that if SAF in the models were brought into line with present and forthcoming observations [*Lawrence and Chase*, 2007], the simulated range in summer climate change projections would shrink by one third to one half—greatly increasing confidence in predictions of changes in heat waves, agriculture, and water resources in the US.

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