Evolving Land–Atmosphere Interactions over North America from CMIP5 Simulations

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ABSTRACT

Long-term changes in land–atmosphere interactions during spring and summer are examined over North America. A suite of models from phase 5 of the Coupled Model Intercomparison Project simulating preindustrial, historical, and severe future climate change scenarios are examined for changes in soil moisture, surface fluxes, atmospheric boundary layer characteristics, and metrics of land–atmosphere coupling.

Simulations of changes from preindustrial to modern conditions show warming brings stronger surface fluxes at high latitudes, while subtropical regions of North America respond with drier conditions. There is a clear anthropogenic aerosol response in midlatitudes that reduces surface radiation and heat fluxes, leading to shallower boundary layers and lower cloud base. Over the Great Plains, the signal does not reflect a purely radiatively forced response, showing evidence that the expansion of agriculture may have offset the aerosol impacts on the surface energy and water cycle.

Future changes show soils are projected to dry across North America, even though precipitation increases north of a line that retreats poleward from spring to summer. Latent heat flux also has a north–south dipole of change, increasing north and decreasing south of a line that also moves northward with the changing season. Metrics of land–atmosphere feedback increase over most of the continent but are strongest where latent heat flux increases in the same location and season where precipitation decreases. Combined with broadly elevated cloud bases and deeper boundary layers, land–atmosphere interactions are projected to become more important in the future with possible consequences for seasonal climate prediction.

1. Introduction

A large number of studies with regional and global models and observed datasets over the last three decades have demonstrated that the state of the land surface has a significant influence on the atmosphere. Soil moisture is the most important land surface state variable affecting the global atmosphere on intraseasonal to interannual time scales (Dirmeyer 2011a). Climate modeling and observational studies have shown that a large portion of North America demonstrates a feedback of the land surface onto the atmosphere during summer (e.g., Koster et al. 2004; Findell et al. 2011). Guo et al. (2011) showed that potential predictability from soil moisture is high over North America. North America also demonstrates the strongest improvement in prediction skill from the realistic initialization of the land surface for seasonal forecasts (Koster et al. 2011). The location of maximum land–atmosphere coupling can vary in space (Koster et al. 2011), and its strength can vary from year to year (Guo and Dirmeyer 2013) depending on the pattern of the climatology of soil moisture and the fluctuation of its anomalies.

These results raise questions. Have the interactions between land and atmosphere on intraseasonal to interannual time scales changed since preindustrial times?
when atmospheric composition, aerosol loading, and global vegetation cover were different? More importantly, will land–atmosphere interactions change in the future? Phase 5 of the Coupled Model Intercomparison Project (CMIP5) (Taylor et al. 2012) provides an opportunity to address these questions in a multimodel framework.

This study has been conducted under the aegis of the “CMIP5 Task Force” coordinated under the Modeling, Analysis, Prediction, and Projection (MAPP) program of the National Oceanic and Atmospheric Administration Climate Program Office. The overall goal of the task force is to evaluate CMIP5 simulations of the twentieth-century climate specifically over North America, as well as the character of long-term predictions and projections of future climate. This study focuses specifically on the evolving role of the land surface and land–atmosphere interactions in a changing climate over North America. We focus on the spring and summer seasons because previous research indicates these are the most crucial for land–climate interactions in this region and their impact on predictability and prediction on subseasonal to seasonal time scales (e.g., Dirmeyer et al. 2009; Guo et al. 2012).

Section 2 describes the data used and the techniques for estimating metrics and indices of land–atmosphere interaction from the model simulations. Results and synthesis are given in sections 3 and 4. A discussion and conclusions are presented in section 5.

2. Data and techniques

Monthly-mean output fields from land and atmospheric datasets from 15 models are used. Table 1 lists all models examined in this study. The choice of models was predicated on several factors. Most important was the availability of a complete set of necessary model output variables from a single ensemble member for each of three simulations: the preindustrial experiment (past), the historical experiment (present), and the 8.5 W m$^{-2}$ representative concentration pathways (RCP85) experiment (future). Table 1 also shows the horizontal resolution of each model and whether land use changes as described by Hurtt et al. (2011) are implemented. No metadata was supplied that describe the external forcings specified for the INM model. Otherwise, 11 of the remaining 14 models indicate that land use changes have been represented, which are major over the central United States and southern Canada from preindustrial to historical climate but fairly limited in the future scenario.

For each model and experiment, we use 95 years of model output for calculation of statistics and land–atmosphere coupling metrics. For the historical run, that corresponds to the period 1911–2005 in the simulation. For the preindustrial and RCP85 simulations, we chose the last 95 years of the time series of data from each model simulation. The length of preindustrial and RCP85 simulations varies among models from exactly 95 years to several centuries. The data within each 95-yr time series is detrended so that statistics such as interannual standard deviations and temporal correlations between variables emphasize the short-term (interannual) variability characteristic of land–climate interactions. This also ensures the comparisons between experiments are consistent since the historical run likely has an inherently significant trend that the other two experiments should not. The RCP85 projection is chosen over other less severe climate change scenarios with the rationale that signals not evident in this run will also be absent from the other projections, although individual forcings in other projections may be stronger than in RCP85 (van Vuuren et al. 2011). This case may provide a sort of “upper bound” for radiative forcing on coupled land–atmosphere responses in the CMIP5 dataset. RCP85 is characterized by high ongoing anthropogenic CO$_2$ emissions, a severe curtailment of aerosols, and ongoing land use change, particularly in low latitudes and the Southern Hemisphere (Riahi et al. 2011). The variables used in this study are the soil wetness in the top 10 cm of the soil column, surface sensible and latent heat fluxes, near-surface temperature, and relative humidity (nominally 2 m above ground level). We do not analyze precipitation, as we are concerned here with what may be considered the upward branch of the hydrologic feedback loop between land and atmosphere. Precipitation is the principal hydrologic input to the land surface at the opposite end of the “cycle” from the land surface feedback to the atmosphere. Because of the complex and nonlinear nature of convective processes, it is very difficult to discern the effect of the land surface on precipitation without carefully constructed sensitivity studies (cf. Koster et al. 2006; Guo et al. 2006) that are beyond the scope of CMIP5.

Our use of monthly data and focus on anomalies relative to mean annual cycles (for correlations, variances, etc.) constrains the scope of this analysis to interactions on intraseasonal to interannual time scales. All statistics are calculated separately for each month over a 95-yr period and then averaged to seasonal values. All calculations are performed on each model’s native grid for only ice-free land points based on each model’s land–sea ice mask. The data from each model are then interpolated bilinearly onto the operational grid of the European Centre for Medium-Range Weather Forecasts operational forecast model, which is T1279 or a regular longitude–latitude grid of $2560 \times 1280$ grid.
This is a much higher resolution than any of the CMIP5 models, thus ensuring that information content is not lost in the process of interpolation through smoothing, either to a lower-resolution grid than some models or between grids of a similar resolution that are offset horizontally (Lam 1983). We retain only the grid points on the high-resolution grid that overlay land grid boxes of more than 80% of the CMIP5 models.

In addition to basic means and interannual standard deviations of the model output variables, we calculate several derived terms to investigate land–atmosphere interactions in the CMIP5 simulations. These include one-month lagged autocorrelations for soil moisture (soil moisture memory), unlagged correlation between variables, and the terrestrial coupling index of Dirmeyer (2011b):

\[ I(w_m, \phi_m) = \frac{\sum(w'_{m,y}\phi'_{m,y})}{\sqrt{95\sum(w'_{m,y})^2}} \]

where \( w \) is the soil moisture and \( \phi \) is either the sensible or the latent heat flux. Primes denote anomalies from the mean annual cycle, and correlations are calculated for each month \( m \) across the 95 years \( y \) of available data. This index is mathematically equivalent to the product
of the standard deviation of the flux and the correlation between soil moisture and the flux (Guo et al. 2006), and has the same units as the flux (W m$^{-2}$). Variables relevant to the atmospheric boundary layer are also derived, including the height of the lifting condensation level:

$$Z_{LCL} = (T_{2m} - T_{D2m})/\left(\Gamma_{Dry} - \Gamma_{Dew}\right)$$

$$\cong 125(T_{2m} - T_{D2m}),$$

(2)

where the 2-m dewpoint $T_{D2m}$ is estimated from near-surface relative humidity, temperature $T_{2m}$, and the mean surface pressure. Standard lapse rates $\Gamma$ are used. Relative humidity is converted to specific humidity $q_{2m}$ for several of our analyses as well. Finally, we estimate the local mean value of the Priestley–Taylor coefficient based on the formulation of Betts (2004):

$$\alpha = \left(\frac{\lambda M}{H + \lambda M}\right)\left(\frac{1 + \varepsilon}{\varepsilon}\right), \quad \varepsilon = \frac{\lambda dq}{C_p dT} \frac{1}{T_{LCL}}.$$

(3)

When combined with information from the other calculations, variations in $\alpha$ can suggest how entrainment at the top of the growing daytime boundary layer may be changing relative to bulk aerodynamic and canopy resistances at the surface (Lhomme 1997).

It should be noted that we are using monthly-mean model output to estimate quantities initially derived and applied on instantaneous ($Z_{LCL}$), daily ($I_{LH}$) and 5-day mean ($\alpha$) data. Virtually all important land–atmosphere interactions are strongly tied to the diurnal cycle, but time-averaged data can be used conscientiously to tease out these processes (e.g., Betts et al. 1996; Betts 2004). Given the large spatial scales and long time series of this study, gross features and changes should be discernible from monthly data (Dirmeyer 2006). We verified this by comparing estimates of the terrestrial coupling index calculated with daily and monthly mean data for current and future climate from a single model (cf. Dirmeyer et al. 2012) and found that the magnitude of the index was slight weaker when estimated from monthly data, but the pattern and magnitude of changes were nearly identical.

A problem that cannot be ignored is the issue of spurious change signals in multimodel means, where a single model that is an extreme outlier can dominate the average. Figure 1 gives an example from our current analysis. The difference in soil moisture between historical and preindustrial experiments for June–August (JJA) is shown. The results from the 15 individual models are shown anonymously in Fig. 1a and their unweighted average is given in Fig. 1b. Certain features of the multimodel mean are not robust across models,

Fig. 1. (a) JJA individual model projections of historical minus preindustrial change in soil moisture, (b) 15-model mean change with equal weighting of each model, (c) intermodel standard deviation of JJA change in soil moisture, and (d) degree of consensus quantified as the number of models that agree on a change in soil moisture of the indicated sign.
such as the wetter conditions over the far western continental United States or the drying in the central Great Plains. The intermodel standard deviation (Fig. 1c) indicates that these two areas have the least agreement among models. For instance, it appears that the wet signal over California and Nevada is almost entirely due to the bottom model in the center column.

As a result, we choose to use the degree of consensus among models for the sign of the change (Fig. 1d) as the primary indicator of climate change responses. The coloring shows the number of models out of 15 that agree on a change of a given sign. We see that the drying signals over Mexico, the St. Lawrence Valley, the northern Great Plains, and the Northwest Territories of Canada are indeed robust, but the drying over the north-central United States does not have widespread consensus.

The consensus approach also lends itself to straightforward estimation of statistical significance. We can treat each model’s projected change at each location as having equal probability of an increase or decrease. Under this null hypothesis, the expected probability of any particular number of models agreeing, or more than a certain number agreeing, follows directly (see Table 2). For instance, the likelihood of 11 or more models randomly agreeing on a positive or a negative change is 11.84% (2 × 5.92%).

Local probabilities have limited meaning without a concept of the field significance. Dirmeyer et al. (2013) determined that, for the land surface variables considered here, there are about 200 spatial degrees of freedom across all ice-free land points. The entirety of North America, displayed in all plots in this study, constitutes approximately 17% of the global ice-free land area as depicted in the high-resolution grid used for these analyses. Assuming the spatial scale of variability is relatively uniform between continental and global scales, we estimate 34 spatial degrees of freedom for North America. With this estimate, we can calculate the field significance based on a set of 34 events where the outcome of each is based on the “cumulative probability” row of Table 2. The cumulative probability is progressively less than 50% as one approaches the extremes and is analogous to an unfair coin that is tossed 34 times to test field significance (Livezey and Chen 1983). In this way we determine how much we must exceed the expected areal coverage of a given change at a given level of consensus to have confidence of a certain degree. The last row shows the thresholds that need to be met for areal coverage to be significant at the 99% confidence level. The fractional area required to pass a test for field significance is determined iteratively from

\[ f = \sum_{x=0}^{X} \binom{n}{x} P^x (1 - P)^{n-x}, \]

where \( n \) is the assumed number of spatial degrees of freedom (34), \( \binom{n}{x} \) is the number of possible combinations of \( n \) things taken \( x \) at a time, \( P \) is the probability of a given number of models agreeing (from the cumulative probability row of Table 2), and \( f \) is our target confidence level (0.99). We solve iteratively for \( X \) where \( 0 \leq X \leq n \), and the percentage of area in Table 2 is estimated as \( X/n \), where we interpolate linearly between integer values of \( X \) to hit our target value of \( f \).

Based on these statistics, 71% or more of North America would have to be covered by at least a minimum (8:7) model consensus change of the same sign to be considered significant. We only check for significance of exceedance on the tails of the probability distribution—one could also test the likelihood of being significantly below the expected fraction of area as well. Last, sensitivity to the exact number of degrees of freedom is not great. Decreasing the number of degrees of freedom by half, for example, increases the significant areal coverage for the 7, 8 count (Table 2) to 81.7% and the 3, 12 count to 16.5%.

3. Results

Calculations and significance testing have been performed on all fields and metrics for both past (historical minus preindustrial) and future (RCP85 minus historical) cases. However, the results presented here will focus more on future changes than the past, which are stronger
and more significant in most cases. Where past changes suggest significant or interesting results and where they have some bearing on our interpretation of future projections, they are also shown. Keep in mind that degrees of model consensus are shown for all changes, not the model-estimated magnitudes of the change.

Figure 2 shows the multimodel mean soil moisture from the historical run for March–May (MAM) and JJA (top) and the past (middle) and future (bottom) changes, represented as the sign of the change and the degree of consensus among models. The right middle panel is the same as Fig. 1d. The mean fields show clearly the climatological drying from spring to summer over most of North America, with the principal exception over much of Mexico where the North American monsoon brings seasonal rains during JJA. The models indicate that soil moisture has decreased over much of North America in both seasons since preindustrial conditions, with especially robust signals during both seasons over most of Mexico and much of Canada. The models suggest spring has become drier over the western Great Plains and eastern Rockies of the United States but wetter along the West Coast. Table 3 shows that the consensus decreases of soil moisture in both seasons cover a significantly large portion of the continent. The same is true for the percentage of area with moderately high (≥12 models) agreement on drying soils and during JJA for very high (≥14 models) consensus.

Similar statistics for future changes are shown in Table 4. For soil moisture, corresponding to the bottom panels of Fig. 2, agreement on drying is significant at all thresholds of consensus and is nearly complete during JJA. During MAM there is a region of agreement near the Arctic coast for wetter soils. However, over most well-populated and cultivated areas, soil moisture is projected to decrease.
Past changes in surface heat fluxes and net radiation are shown in Fig. 3. The preindustrial simulations of the models are free of anthropogenic aerosols, whereas the time evolution of such emissions is provided as a boundary condition for the historical experiment (Taylor et al. 2012). The signal of aerosols is very clear over much of the land area from southern Canada southward. The reduced net surface radiation is mainly a product of the increased shortwave optical depth in the CMIP5 models from the preindustrial to the historical run, whose effect is evident during winter as well (Dirmeyer et al. 2013). However, in regions of expanding agriculture like the Great Plains, there is a warm season surface albedo change that appears to have some impact on surface climate as well (Kumar et al. 2013). At higher latitudes, the present-day warming signal is apparent as increased net surface radiation, which during the warmer seasons is likely radiatively driven rather than dynamically driven (Wallace et al. 2012). These changes in net radiation suggested by the models appear to partition between both heat fluxes, favoring consensus in sensible heat slightly in

### Table 3.

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<tr>
<th>Models decreasing</th>
<th>% land increase</th>
<th>Models increasing</th>
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<tr>
<td>≥14</td>
<td>≥12</td>
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<tr>
<td>Mean soil moisture</td>
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<td>Mean sensible heat flux</td>
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<tr>
<td>Mean latent heat flux</td>
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<td>8.5%</td>
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<tr>
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<tr>
<td>Priestley–Taylor coefficient (\alpha)</td>
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<td>8.1%</td>
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### Table 4.

<table>
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<th>Models increasing</th>
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<tr>
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<td>Mean latent heat flux</td>
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<td>88.2%</td>
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<td>Mean latent heat flux</td>
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<tr>
<td>Lifting condensation level (Z_{LCL})</td>
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<td>0.1%</td>
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<tr>
<td>Priestley–Taylor coefficient (\alpha)</td>
<td>62.2%</td>
<td>93.4%</td>
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spring and latent heat in summer. The changes in net radiation in the midlatitudes are reflected strongly in the sensible heat flux field. In the subtropics, consensus on changing latent heat flux follows the pattern and evolution of net radiation. Field significance statistics for these variables are listed in Table 3. During MAM the percentage area under various portions of the negative tail of the distribution is usually significantly large. In summer, the area where at least 12 models agree on increases in net radiation and latent heat flux is significant, as are matching degrees of agreement for decreases in both net radiation and sensible heat flux. The significant areas with changes of both signs for net radiation show that the distributions do not merely shift in one direction, with extremes of different signs emerging over large but separate areas of the continent.

Figure 4 shows the consensus for projected future changes in surface energy terms. We omit the net radiation plots here—they are almost uniformly positive except over the desert Southwest and North American monsoon region, where consensus is weak or moderately negative (refer to Table 4 for the field significance statistics). The features can be summarized as follows. The combination of strong warming and greatly reduced aerosols in the RCP85 experiment appears to lead to a strong increase in available energy at the surface in most regions. There are broad bands where a strong consensus increase in latent heat flux corresponds to a weak-to-moderate consensus decrease in sensible heat flux. The bands align along the margin marking the accelerated snowmelt margin that follows the southern edge of the retreating snowpack through the season (northern United States and southern Canada in MAM, northern Canada and Alaska in JJA). Otherwise, there is a persistent signal of increased sensible heat fluxes in both seasons, agreement on reduced latent heat fluxes over Mexico and far southwestern United States in MAM extending into the lower Mississippi Valley and Great Plains in JJA, and increasing
latent heat flux in boreal regions. The dominance of areas of positive trends is evident in Table 4, although the southern decreases in latent heat flux are able to cross the 99% confidence threshold for certain ranges of model consensus.

As surface fluxes are the channel by which anomalies in soil moisture are translated to the atmosphere, the changes that we have shown set the stage for determining trends in land–atmosphere interactions from past to future. Figure 5 shows the multimodel mean

Fig. 4. As in Fig. 3, but for RCP85 minus historical experiments (net radiation not included).

Fig. 5. (top) Seasonal multimodel mean of the terrestrial coupling index from the historical experiment and (bottom) sign and degree of consensus among the models for RCP85 minus historical.
distribution of the terrestrial coupling index between soil moisture and latent heat flux for the historical experiment (top) and the change going forward to the RCP85 experiment (bottom). The climatological distribution in current climate shows that regions of land–atmosphere coupling are confined to Mexico and the southwestern United States in spring but expand northward and eastward in summer to encompass all of the Great Plains, the Gulf Coast, and some of the intermountain West, with a maximum over Texas.

Changes from the preindustrial experiment are not shown—they are mostly small and noisy for JJA, but there is some coherent tendency for a decline in spring across the northern United States in alignment with the reduced net radiation seen in Fig. 3. None of the past changes pass field significance (Table 3). Figure 5 shows a seesaw pattern of future change for MAM. Along the northern edge of positive values of the coupling index, across the southern United States, there are positive changes that extend northward into southern Canada. The implication, since this is a season of northward expansion of land–atmosphere feedbacks, is that the coupling is being established earlier in the year in the RCP85 scenario. The reductions at high latitudes are small in magnitude, albeit well agreed across models, and do not suggest a significant change to land–atmosphere feedbacks in that area. During JJA the extensive range of robust terrestrial coupling (values greater than about 9 W m$^{-2}$) is largely unaffected, but all around the northern and eastern margins there is consensus for future increases, suggesting the range of territory of the so-called hot spot of land–atmosphere coupling over North America could expand. Continental field significance for these changes is strong (Table 4).

A similar index can be constructed using sensible heat flux in place of latent heat flux. The correlation between soil moisture and sensible heat flux is generally negative during spring and summer, and is associated with the control of soil moisture on the growth of the PBL (Betts 2004). As with the correlation between soil moisture and latent heat flux, the relationship between sensible heat flux and soil moisture during MMA is strong, although inverse, over Mexico and the southern United States, dropping to uncorrelated at high latitudes (not shown). During JJA strong negative correlations are present across North America. The changes in the RCP85 experiment for MAM indicate a widespread strengthening of the negative correlation over most of the continent north of 30°N (not shown). This hints again at a stronger role for soil moisture as a control on the overlying atmosphere: the growth of the boundary layer in this case. We can quantify further the evolving connection between the land surface and atmospheric boundary layer by investigating the derived quantities in Eqs. (2) and (3).

Figure 6 shows the historical multimodel mean and changes (past to present and present to future) for the height of the lifting condensation level. In both seasons $Z_{LCL}$ is largest over the Sonoran Desert, but north of about 40°–45°N the highest values are over the latitudes corresponding with the high plains east of the Rockies. The cloud base is lowest at high latitudes in spring and over Alaska, northeastern Canada, and the mid-Atlantic region of the United States during summer. The $Z_{LCL}$ represents the depth to which the atmospheric boundary layer must grow to trigger clouds. Values shown here, based on monthly-mean data, are not representative of specific synoptic conditions but give a good idea of the amount of heating needed to spawn convection in the absence of a dynamical process in the atmosphere.

The CMIIP5 models concur that $Z_{LCL}$ has increased over much of the continent since industrialization, except over the characteristic region of increased aerosols where the cloud base has dropped. Consensus changes for JJA are generally weak, except over the monsoon areas of Mexico and Central America where $Z_{LCL}$ has increased. Future projections are for higher cloud bases across North America in both seasons. The overwhelming field significance for this increase is evident in Table 4.

Last, we show the changes to the Priestley–Taylor coefficient $\alpha$ in Fig. 7. There is an inverse correspondence between $Z_{LCL}$ and $\alpha$. The Priestley–Taylor coefficient is a measure of the efficiency of surface evaporation into the boundary layer, and one controlling factor is the gradient of humidity across the entrainment zone at the top of the boundary layer. This gradient weakens as the atmospheric boundary layer deepens so that entrainment becomes less effective at reducing the moisture content within the boundary layer. As a result, the humidity gradient at the bottom of the well-mixed boundary layer, between the land surface and the air above it, is not as effectively maintained by the mixing within the boundary layer, thus hampering evaporation. However, because $\alpha$ also contains a factor representing the evaporative fraction, controls of surface and near-surface properties (e.g., aerodynamic resistance and stomatal conductance) are also represented.

The mean field of $\alpha$ shows a gradient from low values over warm dry regions to high values over cool moist regions where entrainment is most effective at maintaining surface evaporation by drying the atmospheric boundary layer. Changes from preindustrial to historical experiments show areas of both positive and negative changes, especially during spring. The increases over the
United States and southern Canada again correspond to the region of increased aerosols. However, only the decreases during summer pass field significance thresholds (Tables 3 and 4). Future changes are uniformly negative with strong consensus among models. The match with increasing height of the lifting condensation level suggests that this shift is dominated by the reduced humidity gradient across the elevated entrainment zone.

4. Synthesis

We attempt here to integrate the results found in the projected changes of land surface state variables, fluxes, and derived metrics. Figure 8 shows a set of maps like those in the previous figures, defining broad areas of prevalent behavior for the two seasons and periods of simulated change by the CMIP5 models. As with previous figures, all changes shown are based on high degrees of model consensus and not necessarily an extraordinary magnitude of change.

The changes from preindustrial to historical experiments are largely defined by specific regions of unitary response, such as the high-latitude warming that results in increased available surface energy, latent heat flux, and, in summer, drier soils and a deeper boundary layer. Spring shows many smaller regions of specific responses to increasing aerosols in midlatitudes. The west coast of the conterminous United States becomes rainier and soils wetter, but latent heat flux drops as this is an energy-limited regime. Across Mexico, where there is a positive feedback in the terrestrial water cycle, reduced latent heat flux accompanies drier soils and decreasing rainfall. Reduced net radiation over much of the United States and southern Canada has different manifestations in different areas. Across the core of the industrial belt around the Great Lakes, sensible heat is reduced and the cloud base drops. Farther south around the Ohio Valley, the boundary layer changes little despite the changes in surface heat flux.
The central Great Plains is a particularly interesting region of change. The model consensus is that precipitation has decreased since preindustrial conditions, but latent heat flux and atmospheric boundary layer properties remain largely unchanged. In particular, $\alpha$ fails to increase in this area (see Fig. 7). This may be an example of land use change having a direct impact, as the spread of agricultural crops into the prairies may have lowered the bulk aerodynamic and canopy resistances to moisture fluxes in this region. This signal is more evident when we exclude from the calculation the four models not indicating land use changes; however, as in the modeling experiment of Land-Use and Climate, Identification of Robust Impacts (LUCID) (Pitman et al. 2009), the change to crops does not have the same impact on surface fluxes and local climate in each model (not shown).

The summertime changes from preindustrial to historical conditions are more large scale and homogeneous. There are basically three zonal bands: the high-latitude warming band with increased net radiation, the mid-latitude band of reduced net radiation and sensible heat flux where anthropogenic aerosols have increased, and the subtropical band of drying and deepening of the boundary layer.

Changes from historical to RCP85 projections seem to be defined by broad north–south dipoles in a number of fields, each with a node at a different latitude. During spring, most of North America has drier soils except along the Arctic coast. However, the line between increasing and decreasing rainfall lays much farther to the south. Approximately midway between the zero lines for precipitation change and soil moisture change is a band where consensus for an increase in latent heat flux is maximum. This is also the only region of the continent where sensible heat flux is not increasing, and here the cloud base is not higher. The line dividing increasing latent heat flux to the north from decreasing latent heat flux to the south lies near the United States–Mexico border. Between that line and the zero-change
line for rainfall is the region where the coupling index between land and atmosphere has its maximum consensus for increase, along the northern edge of the strongest springtime coupling. However, the area over which the CMIP5 models suggest the land–atmosphere coupling will increase extends from southern Mexico to southern Canada.

During summer the nodes retreat poleward and become less zonal in orientation. Soil moisture decreases prevail over the entire continent. The line between increasing and decreasing rainfall extends from British Columbia to Hudson Bay, across Quebec and down the East Coast to the mid-Atlantic. The line between increasing and decreasing latent heat flux remains south of the precipitation node, and the greatest consensus for increasing land–atmosphere coupling is again between them, most prevalent over the Ohio Valley and parts of the Canadian Shield. Coupling increases over most of North America north of a line a couple hundred kilometers north of the United States–Mexico border and is largely unchanged south of that line.

5. Summary and conclusions

Results of past and future projected changes to climate variables relevant to land–atmosphere interactions on intraseasonal to interannual time scales over North America have been presented, based on consensus among the 15 CMIP5 models. Because of possible vagaries in the changes simulated by specific models for specific variables, which are very difficult to ameliorate in an objective fashion, all assessments are made in terms of the degree of consensus among models for either a positive or negative change in each term at each location. We focus on the spring and summer seasons and assess changes in a representation of past climate change (the historical experiment minus the preindustrial experiment) and extreme future climate change (RCP85 minus historical).

Past changes over North America as rendered by the CMIP5 models appear to be driven by a combination of main factors—high-latitude warming from changing atmospheric composition, the increase of anthropogenic aerosols over populated regions with the onset of industrialization, the aggressive expansion of agriculture over the center of the continent, and other regional precipitation changes that appear to be occurring as the general circulation of atmosphere and ocean respond to the global radiative changes. The models concur that a reduction in precipitation has taken place across subtropical North America since preindustrial conditions. There is also evidence for a response over the middle of the continent in spring that is consistent with the effect that the expansion of agriculture over the Great Plains would have on surface properties. A more focused and thorough evaluation of land cover change impacts in CMIP5 simulations is conducted by Kumar et al. (2013).

Anthropogenic aerosols appear to have delayed slightly the transition over much of the continent from wintertime conditions, when the atmosphere is the main controller of surface fluxes, to the summertime situation, when soil
moisture drives the partitioning of net radiation between sensible and latent heat flux. This shows as a general reduction in the terrestrial coupling index during MAM (see Table 3), which does not pass field significance at the 99% confidence level but would at the 90% level. By summer, there appears to be little change in land-atmosphere coupling, but a reduction in sensible heat flux and cloud base over much of the midlatitudes hints at the possibility that convective precipitation may have been inhibited somewhat with industrialization. It would be reasonable to speculate that recent indications of increasing convective rainfall and severe storms over the United States could be linked to cleaner air as well as increasing greenhouse gas concentrations. Sensitivity studies with climate models could examine this point further.

Future changes suggest that the springtime onset of land-atmosphere feedbacks will come earlier and penetrate farther north and east into the center of the continent. This has implications for climate predictability and prediction as anomalies in the land surface properties, such as soil moisture, can be a source of skill for forecasts on weekly to seasonal time scales. As the continent warms, subseasonal climate forecasts could draw more skill from land surface initialization. The growing role of land-atmosphere feedbacks could also be a contributing factor to the increased propensity toward extremes in the hydrologic cycle (e.g., more frequent and longer droughts) seen in most climate projections. This would make careful monitoring of soil moisture and other aspects of the land surface even more crucial.

The “rebound” in land-atmosphere predictability (Guo et al. 2012) that seems to set in around the first of June over the central Great Plains may begin earlier in the future. Again, it would be straightforward to test whether this would be the case using one or more climate models in properly designed experiments.

Changes in the atmospheric boundary layer during spring and summer are generally toward warmer and drier conditions (in terms of specific humidity deficit or dewpoint depression) and deeper development to reach a rising convective cloud base. These changes reduce the impact on the boundary layer humidity of entrainment. This occurs at the same time that the impact of surface fluxes and land-atmosphere feedbacks enhance the impact of the land surface on the boundary layer. Thus, both absolute and relative roles of the land surface in modifying the atmosphere over North America are projected to increase. In terms of local coupling between land and atmosphere (Santanello et al. 2011; Dirmeyer et al. 2012), the importance of the land surface is increasing.

A few caveats about this analysis should be noted. The past changes simulated by the models cannot be interpreted in terms of trend because we represent them as a degree of consensus among models for a certain binary change (either increase or decrease) in each quantity examined. Furthermore, we use 95-yr means from each experiment so we do not emphasize the later part of the historical climate record where observed trends are strongest. For the future changes, we chose the most extreme of the scenarios on the basis that, if we find no significant impacts in the most severe case, there is little chance to find effects in the more moderate projections. However, some changes such as future land use projections (cropland, pasture, and urbanized lands) are quite variable between the various scenarios. It would be worthwhile to examine results from other representative concentration pathways to see whether the responses vary linearly with the strength of the radiative signal or if responses to land use change are more prominent in other scenarios. Finally, as alluded to earlier in this section, the changes found tend to implicate certain processes to a greater or lesser degree, but further sensitivity studies with climate models are necessary to establish cause-effect relationships with confidence.

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