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Importance of land use versus atmospheric information verified from cloud simulations from a frontier region in Costa Rica

Deepak K. Ray,[1] Roger A. Pielke Sr.,[2] Udaysankar S. Nair,[3] Ronald M. Welch,[4] and Robert O. Lawton[5]

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[1] Land-use/land-cover (LULC) change has been recognized as a key component in global climate change, and numerous climate modeling studies at regional to global scales document this. The research strategies have invariably been to first conduct baseline simulations of current conditions to evaluate model performance. Then simulation of regional climate with land cover changes (LCC) implemented within the model allows differences with the baseline simulation to be used as evidence of global to regional-scale climate impacts of LCC. However, even state-of-the-art regional climate models require two data sets to conduct reasonable baseline simulations. These are representative current land cover and atmospheric information over the study region. In frontier and developing areas (where most of the rapid land-use conversion is taking place), these data sets are frequently unavailable and the errors in simulations are due to either inaccurate land cover, insufficient atmospheric information, nonrepresentative model physics, or a combination of one or more of the above. This study shows that in one frontier region, that surrounding the Cordillera de Tilarán of Costa Rica, the accuracy of simulating clouds decreases by 1% to 3% if default model land cover information is used. If the atmospheric data sets used are the ones usually available to researchers (with land cover information held constant), then the model accuracy is reduced by 21% to 25%. Model runs without updated land cover or atmospheric information reduce model accuracy slightly further. Precipitation comparisons also provide similar results. This study thus shows that the critically important data set for conducting accurate simulations is not land cover information but atmospheric information. Researchers may similarly get significant increase in the accuracy of their baseline simulations elsewhere by using radiosondes/rawinsondes over their study region. Finally, since atmospheric information is not available for different landscape scenarios, assessments of the relative role of LULC change will have to continue to rely on using the standard atmospheric data set and the acceptance that the use of more detailed atmospheric data to initialize and provide lateral boundary conditions would have reduced the uncertainties in such landscape sensitivity studies.

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1. Introduction

[2] Human activities are transforming the surface of the Earth to enhance the proportion of primary productivity for human consumption [*Rojstaczer et al.*, 2001; *Vitousek et al.*, 1986]. This results in decreasing the proportion remaining to perform other ecosystem services such as regulation of floods, climate, disease, and habitats for other species [*DeFries et al.*, 2004].

[3] The current rate of forest conversion is extremely high in most tropical regions of the world and these changes are known to have an important impact on ecosystems felt at local and regional scales through atmospheric changes [*Laurance et al.*, 2004]. Land cover conversion from one type to another type results in atmospheric changes because

[1]Forestry and Natural Resources, Purdue University, West Lafayette, Indiana, USA.
[2]Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, Colorado, USA.
[3]Earth System Science Center, National Space Science and Technology Center, University of Alabama, Huntsville, Alabama, USA.
[4]Department of Atmospheric Sciences, University of Alabama in Huntsville, Huntsville, Alabama, USA.
[5]Department of Biological Sciences, University of Alabama in Huntsville, Huntsville, Alabama, USA.

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the dynamic, thermodynamic, and radiative processes that couple the Earth's surface with the atmosphere are land cover specific. When LCC occur, the unique coupling process associated with a specific land cover pattern changes [*Chase et al.*, 1999; *Houghton et al.*, 1999; *Pielke*, 2001]. However, land-atmosphere coupling being a nonlinear process, the impact of LCC on climate can be most effectively estimated through numerical modeling.

[4] Many numerical modeling experiments have investigated land-atmosphere coupling [*Charney*, 1975; *Xue*, 1997; *Zheng and Eltahir*, 1997; *Pielke et al.*, 1999; *Chase et al.*, 2000; *Pielke et al.*, 2007]. These experiments often used the National Centers for Environmental Prediction (NCEP) Reanalysis data [*Kalnay et al.*, 1996] to provide the initial and lateral boundary conditions [e.g., *Marshall et al.*, 2004; *Pielke et al.*, 2007]. Numerical modeling experiments have also been performed to estimate potential future climate changes by using projected possible future LCC in the numerical simulations [*Feddema et al.*, 2005]. However, even with good representation of the physics of land-atmosphere coupling, a numerical model may not be able to accurately simulate atmospheric changes due to LCC in the absence of accurate atmospheric and land cover data sets. Detailed and accurate data sets are, however, difficult to obtain in frontier and developing areas where the lack of infrastructure precludes the launching of regular radiosondes and development of high-quality land cover information through major land cover classification efforts. Therefore, nearly all studies that look at the impacts of LCC on regional climate in frontier and developing areas lack these data sets to varying degrees of accuracy. For example, if the land covers are coarsely classified, a given land cover type may be assigned a single Leaf Area Index (LAI) despite significant site to site variations. Another example is numerical simulation for a site using the radiosondes from another site several hundreds of kilometers away owing to a lack of nearby radiosondes. *Pielke et al.* [1989] have shown for example that the placement of atmospheric soundings is critically important in accurately defining the initial atmospheric structure.

[5] Early studies were also done at coarse resolution [e.g., *Shukla et al.*, 1990; *Nobre et al.*, 1991] often using standard data sets that necessarily had inaccurate representation of the land surface and atmospheric information. These studies provided a good indication of the sensitivity of regional climate to LCC, but the inaccuracies in land cover and atmospheric data produced inaccuracies in the baseline runs, and hence, any projections were suspect. With the increase in computing power three things have happened: (1) high-resolution modeling studies are now possible which allow validation against high-resolution observations; (2) site specific projections are now possible; and (3) multiple model simulations can be performed to estimate the errors in simulations that occur owing to inaccuracies of input land cover and atmospheric data sets in frontier and developing areas if accurate validation data sets are available.

[6] This study conducts high-resolution model simulations using the Regional Atmospheric Modeling System (RAMS) [*Pielke et al.*, 1992] such that each model cell exactly overlaps each satellite observation which is also time coincident. We also compared daily simulated and observed rainfall from 92 locations. Furthermore, we also compared model profiles of temperature and dewpoint temperature with nearly time coincident and spatially collocated rawinsonde information to: (1) evaluate the errors in simulations from incomplete land cover and/or atmospheric information in a frontier region; and (2) evaluate the relative importance of land cover and atmospheric information for model simulation accuracy.

2. Study Region and Experiment Design

[7] The RAMS modeling domain in this study was centered on the Monteverde cloud forest (10.25°N, 84.7°W), situated along the crest of the Cordillera de Tilarán, one of the northwest-southeast trending ranges comprising the continental divide in Costa Rica. The northeasterly trade wind blows inland from the Caribbean Sea, crosses the lowlands of Costa Rica and then encounters these mountains that separate Costa Rica into the Atlantic (or Caribbean) side and the Pacific side. The trade winds are forced up these mountains to form orographic clouds on the windward Caribbean side [*Lawton et al.*, 2001; *Nair et al.*, 2003; *Ray et al.*, 2006]. Immersion of forests in clouds along the slopes of the continental divide is responsible for one of the richest cloud forest ecosystems in the world.

[8] There are four reasons for choosing this particular site for conducting our modeling experiments. First, we had high-quality atmospheric data sets that were obtained during a National Center for Atmospheric Research (NCAR) supported intensive field campaign called Land Use Cloud Interaction Experiment (LUCIE) in March 2003. Second, our modeling group has more than 3 decades of experience with the land cover of the study region. Third, we have an extensive validation data set available for this region. Fourth, this region is at the center of biodiversity in Central America and it has been suggested that regional climate changes could have resulted in the observed species extinction in the Monteverde cloud forests [*Pounds et al.*, 1999].

[9] Four different combinations of input data sets with and without extra land cover and/or atmospheric data sets are possible and accordingly four simulations were conducted for the period 1–14 March, 2003: (1) model run with advanced land cover information and extra (i.e., besides the standard) atmospheric information derived from the LUCIE experiment (Model O); (2) model run with the extra LUCIE atmospheric data set but default land cover information (Model LU); (3) model run with advanced land cover information but atmospheric information provided to the numerical model are standard inputs based on the NCEP Reanalysis since this is the data set used for many land use change sensitivity experiments (which in reality is a data set without any LUCIE rawinsondes from this frontier region; see section 3 for further description (Model ATM)); and (4) model run with default model land cover and standard atmospheric information (Model LUATM). We acknowledge that this short-term simulation can only provide an indication of the relative importance of atmospheric and land cover data sets and our results, of course, apply only for the period simulated. A more detailed investigation for different seasons and different years is needed. This is not possible for the current study area since special radiosondes were not launched for an extended period in this, or other similar locations.

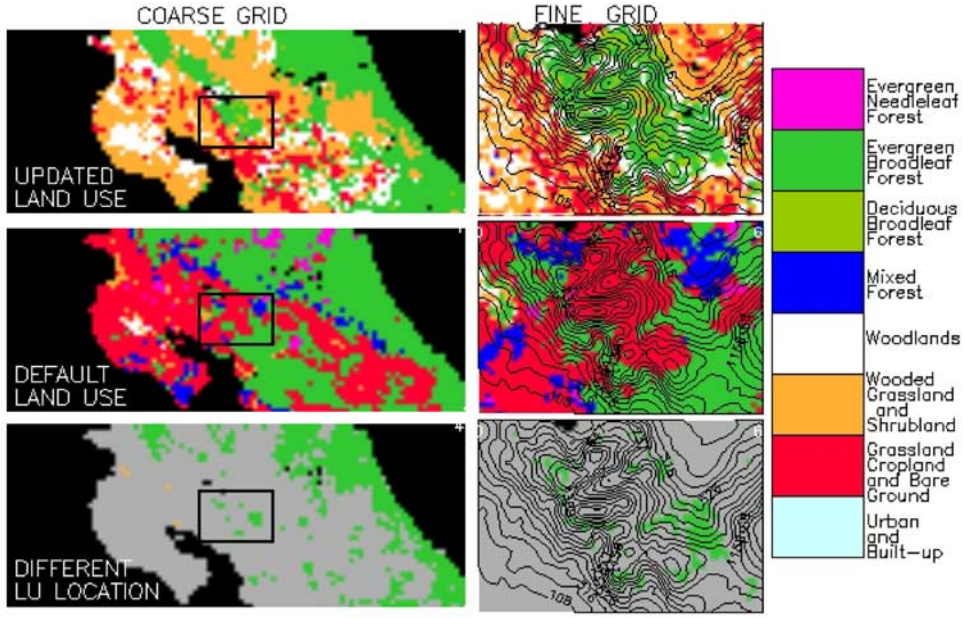

Figure 1. Comparison of the differences in LU information due to updated LU and model default LU. Gray areas in the bottom panels correspond to those areas where there are differences in the land cover between the updated and default land use prescription.

[10] The simulations used a two nested grid configuration (Figure 1) with the outer grid having a 4-km grid spacing covering a domain of 400 by 160 km extending into the ocean and insulating the finer grid from lateral boundary effects and at the same time providing inputs of larger-scale atmospheric flow into it. The finer nested grid had 1-km spacing covering 62 by 42 km without any coverage of the ocean. In the vertical a stretched grid with a grid stretch ratio of 1.2 and grid spacing that varied from 20 m near the surface to 750 m higher up in the atmosphere was used. Only five points along the lateral boundaries were nudged with a time scale of 900 s and nudging strength exponentially decreasing toward the domain interior. The *Klemp and Wilhelmson* [1978] lateral boundary conditions were applied to the coarse grid, to allow disturbances to propagate out of the model domain without strongly reflecting back into the interior. The explicit microphysical parameterization [*Walko et al.*, 2000] and the atmospheric radiative transfer scheme of *Harrington and Olsson* [2001] that accounts for the effects of clouds and water species in the atmosphere was utilized. In the horizontal a deformation based scheme was used to represent diffusion, while in the vertical, diffusion was parameterized using the *Mellor and Yamada* [1982] scheme.

[11] An average of 2.5 m was chosen as the depth of the soil layer though the soils prescribed were themselves spatially heterogeneous as determined from the FAO soil database for the study region [*Webb et al.*, 1992; *Food and Agriculture Organization*, 1971; *Gerakis and Baer*, 1999]. In situ observations collected from the study area during March 2003 do not show significant differences of soil saturation as a percent of field capacity up to a depth of 1 m for forested and deforested regions [*Ray et al.*, 2006] and varies between 10 and 15%, 10–20% and 25–30% at 20-, 50- and 100-cm soil depth. However, field observations suggest pasture grasses are more stressed during the dry season than are trees, as might be the case if trees have access to water stored in deeper soil layers, a phenomenon also observed in the Amazon [*Huete et al.*, 2006]. Consequently, the initial soil saturation prescribed in the simulations varied from 0.1 at the surface, 0.2 at 50 cm depth, to 0.3 at 1.0 m depth and linearly increased to 0.8 at 2.5 m soil depth to represent a soil moisture profile where the forest vegetation has access to deep soil moisture and is less water stressed compared to deforested areas, consistent with the field observations. The sea surface temperature prescribed was a constant value of 300 K as determined from the Moderate Resolution Imaging Spectroradiometer (MODIS) overpass scenes for the simulation time frame.

[12] Figure 1 shows the differences in the updated versus the default land cover. 52.08% of the outer grid has identical land cover. The presence of Evergreen Needleleaf Forest (pink colors in the default land use panel of Figure 1) is an error. These forests are not found in Costa Rica. Perhaps the misclassification was due to spectral signatures similar to those of Evergreen Needleleaf Forests found elsewhere. In fact, even the updated land cover maps had this misclassification, which we corrected and changed to Evergreen Broadleaf Forest. The rectangular box in the coarser grid (Figure 1, left) shows the location of the inner high-resolution grid and is enlarged in Figure 1 (right). Only 8.14% of the inner grid has land cover identical to the default land cover (Figure 1, inner grid default land use panel). The locations of identical land cover are plotted in Figure 1 (bottom) and are mostly composed of Evergreen Broadleaf Forests.

3. Data and Method

[13] The models were initialized and nudged forward in time using a variety of data sets. The quality of the simulations depends critically on the quality of these data

Table 1. List of the Rawinsonde Location and Time of Launch for Those That Were Utilized in This Study

Rawinsonde Number	Day	UTC Time	Latitude	Longitude
1	1	1800	10.453	−83.704
2	1	1500	10.453	−83.704
3	2	1500	10.468	−84.457
4	2	1800	10.454	−83.704
5	2	1800	10.473	−84.469
6	2	2100	10.454	−83.704
7	2	2100	10.473	−84.469
8	3	0000	10.454	−83.704
9	3	0000	10.473	−84.469
10	3	1200	10.453	−83.704
11	3	1200	10.473	−84.469
12	3	1500	10.454	−83.705
13	3	1500	10.473	−84.469
14	3	1800	10.454	−83.704
15	3	1800	10.473	−84.469
16	3	2100	10.454	−83.704
17	3	2100	10.473	−84.469
18	4	0000	10.454	−83.705
19	4	0000	10.473	−84.469
20	4	1200	10.454	−83.704
21	4	1200	10.473	−84.469
22	4	1500	10.454	−83.704
23	4	1500	10.473	−84.469
24	4	1800	10.454	−83.704
25	4	1800	10.473	−84.469
26	4	2100	10.454	−83.704
27	4	2100	10.473	−84.469
28	6	1200	10.728	−84.556
29	6	1500	10.728	−84.556
30	6	1500	10.540	−84.020
31	6	1800	10.728	−84.557
32	6	1800	10.540	−84.020
33	6	2100	10.728	−84.557
34	6	2100	10.540	−84.020
35	7	1500	10.728	−84.557
36	7	1200	10.728	−84.557
37	7	0000	10.728	−84.557
38	7	0000	10.540	−84.020
39	7	1800	10.728	−84.557
40	7	1800	10.540	−84.020
41	7	2100	10.728	−84.557
42	7	2100	10.540	−84.020
43	8	0000	10.728	−84.557
44	8	1500	10.728	−84.557
45	8	1500	10.540	−84.020
46	8	1800	10.728	−84.557
47	8	1800	10.540	−84.020
48	8	2100	10.728	−84.557
49	8	2100	10.540	−84.021
50	9	0000	10.728	−84.557
51	9	0000	10.540	−84.020
52	10	1200	10.688	−84.180
53	10	1200	10.362	−84.591
54	10	1500	10.688	−84.180
55	10	1500	10.362	−84.591
56	10	1800	10.688	−84.180
57	10	1800	10.362	−84.591
58	10	2100	10.688	−84.180
59	10	2100	10.362	−84.591
60	11	0000	10.688	−84.180
61	11	0000	10.362	−84.591
62	11	1200	10.688	−84.180
63	11	1200	10.362	−84.591
64	11	1500	10.688	−84.180
65	11	1500	10.362	−84.591
66	11	1800	10.688	−84.180
67	11	1800	10.362	−84.591
68	11	2100	10.688	−84.180
69	11	2100	10.362	−84.591
70	12	0000	10.688	−84.180
71	12	0000	10.362	−84.591
72	12	1500	10.688	−84.18
73	12	1500	10.362	−84.591
74	12	1800	10.688	−84.180
75	12	1800	10.362	−84.591
76	12	2100	10.687	−84.180
77	12	2100	10.362	−84.591
78	13	1500	10.687	−84.180
79	13	0000	10.687	−84.180
80	13	0000	10.362	−84.591
81	13	1800	10.687	−84.180
82	13	1800	10.362	−84.591
83	13	2100	10.687	−84.181
84	13	2100	10.362	−84.591
85	14	0000	10.687	−84.180
86	14	0000	10.362	−84.591

sets. In frontier and developing areas such as northern Costa Rica site-specific high-quality climate simulations may be desired for conservation and development purposes but a lack of high-resolution land cover and atmospheric data sets hinders accurate simulation. The usual atmospheric data sets available such as the NCEP Reanalysis [*Kalnay et al.*, 1996] (data available from: http://dss.ucar.edu/datasets/ds090.0/), upper air (data available from: http://dss.ucar.edu/datasets/ds351.1/), and surface observations (data available from: http://dss.ucar.edu/datasets/ds461.0/) have serious shortcomings. The problem is that, owing to a lack of weather stations, upper air and surface observations are often not available. This shortcoming is also present with other reanalyses such as the North American Regional Reanalysis (NARR), since the data it uses to construct the analysis fields are essentially the same as in the NCEP Reanalysis. Thus for frontier and developing areas, most standard atmospheric data sets can be considered as low quality.

[14] During the LUCIE field campaign coincident rawinsonde launches were conducted over several paired forested and deforested sites in the Caribbean lowlands of northern Costa Rica at 3-h intervals starting at 0600 local time (LT) to 1800 LT [*Ray et al.*, 2006]. Eighty-six of these rawinsonde observations were included in the current study (Table 1). When these rawinsondes were (1) included together with the standard atmospheric profile data sets from NCAR and then (2) the Barnes objective analysis scheme used to objectively analyze the combined data it resulted in superior initial as well as lateral boundary conditions for model runs. This data set is what we are referring to as high-quality atmospheric data sets. Quantification of the impact of not using high-quality atmospheric data sets for conducting model simulations can then be determined by conducting a numerical simulation with the standard low-quality atmospheric data set but retaining the high-quality land cover. This ensures that the error signal is from the usage of lower-quality atmospheric data.

[15] On the contrary, we would also like to quantify the impact of using/not using high-quality land cover information to contrast the importance between atmospheric and land cover information. In RAMS, the land-surface processes are represented by the submodel called the Land Ecosystem Atmosphere Feedback-2 (LEAF-2). The LEAF-2 submodel accounts for the energy and moisture transfers between atmosphere and soil, water, snow, and vegetation

and allows for specification of multiple types of land use at individual model cells. LEAF-2 has a default land-surface type database which is a 30-s resolution cross-referenced Olson Global Ecosystems (OGE) data set [*Walko et al.*, 2000]. The values of the biophysical variables such as emissivity, LAI, and roughness length of each land cover type in this default database is represented by a table in LEAF-2. The seasonality of these biophysical variables in LEAF-2 is computed from the information of latitude, longitude, and time of the year during the model run. The OGE data set was derived from the Global Land Cover Characterization (GLCC) database, which was based primarily on continental-scale unsupervised classification of 1-km monthly Advanced Very High Resolution Radiometer (AVHRR) data spanning from April 1992 through March 1993 [*Loveland et al.*, 2000]. Since each land cover category has specific land surface parameters prescribed in the model, each land cover type has nearly identical biophysical properties when the study region is of regional scales. This obviously is not true. Using this default land cover for the RAMS simulations would then be similar to the use of low-quality land cover information.

[16] RAMS however allows the user to specify realistic land cover characteristics derived from other sources such as satellite data. High-quality land cover information was derived from the global land-use categorization at 1-km spatial intervals developed by the University of Maryland (UMD) [*Hansen et al.*, 2000] using MODIS imagery. This was transferred to the RAMS land cover category and the misclassification of the Monteverde cloud forests as Evergreen Needleleaf was corrected to Evergreen Broadleaf. Moreover LAI, a crucial input characteristic for the vegetation parameterization within RAMS, is also specified using MODIS derived LAI at 1-km increments [*Myneni et al.*, 1997; *Knyazikhin et al.*, 1998] available at 8-day intervals. The LAI values used in this study are based on MODIS imagery acquired over the study area during the time period 6–13 March 2003. Rooting depth was corrected to be representative of the study area [*Ray et al.*, 2006]. This combination of heterogeneous LAI, rooting depths and land use classes in turn creates spatial variations of soil moisture and energy fluxes.

[17] Since we have the model default land cover as well as the more recently updated land cover information, we can now quantify the simulation errors due to inaccurate land cover prescription in the numerical simulation. We can then compare and quantify whether land cover or atmospheric information leads to larger errors in the numerical simulations in frontier and developing areas. Note that all previous studies in frontier and developing areas had errors of both types and the relative importance of each error type is as yet unknown.

[18] Finally, we also need a consistent method for quantifying the simulation accuracies and errors. First, we compared the simulated precipitation against observed precipitation. We had 92 rainfall locations over the entire simulation domain and thus 92 cells out of the total 4000 cells (4-km spatial resolution) over the outer domain were collocated for the comparisons. For the inner grid the comparison was possible with a very small sample size (8 cells out of 2604) as can be expected owing to the remoteness of the inner grid and smaller spatial extent, thus preventing any robust statistical conclusions for the inner grid. We used the root mean square error (RMSE) for estimating the simulation accuracies of the four model types in each case which is defined as

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n} (O^i - S^i)^2}{n}}, \quad (1)$$

where O^i is the observed precipitation at location i, S^i is the model simulated precipitation at this location and n (92 for outer and 8 for inner grid, respectively) is the number of comparisons. Robustness of the comparisons would however increase if we could conduct a complete point-to-point comparison. Comparison of simulated clouds with observed clouds at 1-km spatial resolution provides such a possibility and thus only for the inner grid we conducted a complete point-to-point comparison of simulated clouds with those detected from the Geostationary Operational Environmental Satellite (GOES) 8 imagery using the structural thresholding algorithm [*Nair et al.*, 1999; *Ray et al.*, 2003]. Previous studies have conducted both subjective validation [*Pielke*, 1974; *Baidya Roy and Avissar*, 2002], and point and pattern quantitative validation [*Segal and Pielke*, 1981; *Shaw et al.*, 1997; *Ray et al.*, 2006] to prove that RAMS accurately simulates the atmospheric dynamics. This point-to-point quantitative validation is rigorous as both possibility of spatial and temporal displacement of the predicted and observed clouds are removed which according to *Pielke* [2002] could yield a poor verification of model simulation.

[19] For each cloud comparison one can get two possible prediction errors and two possible prediction accuracies. A false positive (FP) occurs when according to the simulation, the model cell has a cloud, but observations (i.e., GOES) show that there was no cloud. A false negative (FN) conversely is the case when there is a GOES observed cloud but the simulation for the model cell produces no cloud. Similarly, two prediction accuracies are possible: true positive (TP) when both the simulation and observation matches, i.e., both have clouds, and true negative (TN) when both model cell and GOES observation show that there are no clouds. The sum of FN and TP is then the real positive (RP), the actual number of times there is a GOES observed cloud. The performance of presence/absence is normally summarized in an error matrix [*Fielding and Bell*, 1997]. Using the error matrix tabulation of FP, FN, TP, TN, and RP, a variety of error or accuracy measures can be calculated. We use the Percent Correct Metric (PCM) to estimate the accuracy of the simulations in each case (equation (2)).

$$PCM = 100\left(\frac{TP}{RP}\right). \quad (2)$$

[20] We also determined the threat score (TS) [*Giorgi and Bates*, 1989; *Olson et al.*, 1995; *Zhao and Carr*, 1997; *Pielke*, 2002], which is a measure of the accuracy of the model in simulating clouds for any given comparison (equation (3)). It varies from 0 to 1. A TS score of 1 indicates a perfect simulation and the simulation accuracy decreases as the TS score decreases. The TS score is thus a

Table 2. RMSE Associated With Simulating Precipitation for the Four Models

Day	Model O	Model LU	Model ATM	Model LUATM
2 Mar	3.42	2.57	9.73	8.29
3 Mar	4.90	3.74	6.02	7.64
4 Mar	4.77	3.97	3.13	3.11
5 Mar	3.11	2.64	8.14	11.93
6 Mar	6.25	5.40	2.05	1.88
7 Mar	4.08	5.12	2.31	2.38
8 Mar	5.74	7.03	8.36	6.79
9 Mar	4.99	6.60	5.67	11.19
10 Mar	4.70	4.86	10.94	9.89
11 Mar	5.36	4.04	0.85	0.87
12 Mar	8.30	11.59	14.40	17.97
13 Mar	8.46	14.19	10.67	8.64

measure of both spatial and temporal forecast skill and is defined as

$$TS = \frac{C}{(F + O - C)}, \tag{3}$$

where C is the number of grid cells where the simulated clouds was confirmed by GOES observation, F is the number of grid cells where clouds were simulated, and O is the number of cells where the GOES satellite observed clouds. The model comparisons with clouds were excluded for the 3 days of 5, 9, and 14 March when rawinsondes were not launched during the LUCIE field campaign.

4. Results

[21] Previously, all numerical experiments dealing with LCC and regional climate changes used hypothetical data sets (see papers cited by *Kabat et al.* [2004] and *Cotton and Pielke* [2007]). With the availability of satellite derived land cover information, the baseline simulations now have access to better land cover representation [e.g., *Baidya Roy and Avissar*, 2002; *Pitman et al.*, 2004; *Ray et al.*, 2006; *Ge et al.*, 2007]. Detailed atmospheric information however is generally still lacking in the frontier and developing areas. Moreover, validation data is either missing or validation is conducted against data sets that may themselves have errors (for example comparing simulated rainfall with coarse resolution, temporally inconsistent and/or empirically derived rainfall from satellite cloud top radiances). In this section we summarize the results of our quantitative comparisons of model simulations with observations. The result is a quantification of inaccuracies researchers may expect when they know that their prescribed land cover and/or atmospheric information is deficient. Since the soil vegetation atmosphere transfer (SVAT) process could also impact model performance [*Pitman et al.*, 1999; *Henderson-Sellers et al.*, 2002; *Matsui et al.*, 2007] in a follow-up paper we will evaluate the impact of SVAT processes on the quality of model simulations, i.e., conduct simulations with LEAF3 RAMS [*Walko and Tremback*, 2005] instead of LEAF2 RAMS [*Walko et al.*, 2000].

4.1. Comparisons Against Observed Rainfall

[22] For the outer grid (4-km spatial grid increment) Model O has lower RMSE compared to the model ATM on 8 days whereas model LU had lower RMSE than model LUATM on 7 days (Table 2). The RMSE for total precipitation over the entire simulation period was 31.3 mm and 39.3 mm for models O and LU respectively and 40.6 mm and 49.8 mm, respectively, for models ATM and LUATM. Since the only difference was atmospheric information it appears that improving atmospheric information leads to better precipitation simulations. On the other hand when models O and LU are compared on 6 days precipitation simulations improved owing to better LU information but on another 6 days it was worse. Similarly when models ATM and LUATM were compared on 4 days improved land cover improved precipitation simulations, but on 4 days it was worse and on another set of 4 days they were comparable. While the precipitation comparisons appear to show that improving atmospheric information improves precipitation simulations whereas improving land cover information may not always improve precipitation simulations we would like to point out that the sample size is quite small. Precipitation comparisons often suffer from comparisons conducted with a small set of validation data. For the inner grid the comparisons were even more tenuous as only 8 comparisons were available and thus not pursued any further. Cloud cover comparisons however provided a comparison against independent observations for each of the 2604 cells and can be considered a robust indicator of model performance.

4.2. Comparisons Against Cloud Cover

4.2.1. Accuracy of Model O

[23] Model O gave an entire range of PCM accuracy for the 110 distinct times when a GOES scene was available to conduct our accuracy assessment. The values ranged from 2% to 100% with a mean and median of 69.90% and 74.31%, respectively (Table 3). Over cloud forests (CF) the range was 5.6% to 100% (Figure 2a) with a mean of 77.51% and a median of 82.36% (Table 3). Over noncloud forest (NCF), the range was 1.6% to 100% with mean and median values of 69.16% and 73.84%, respectively (Table 3). Figure 2b shows the performance of model O for each comparison. Out of 11 days, the model generally performed well, except for 6 March between 1215 UTC (0615 LT) to 1715 UTC (1115 LT) when the model simulated few clouds over the study domain though GOES imagery shows that there were, in fact, more clouds. Table 4 shows the corresponding TS averaged over the 110 comparisons. Over the entire region the averaged TS was 0.46, whereas over CF and NCF the values were 0.55 and 0.45, respectively.

4.2.2. Accuracy of Model LU

[24] Model LU used default model land cover and in-built information of land cover properties such as LAI. However, the initial soil moisture and soil type information was updated to reflect those of the study region. Thus with respect to initial soil moisture, soil types, and soil depths, this model run was identical to model O differing with it only in its land cover. A hypothetical distribution of soil moisture profiles could have been used but we chose to conduct the simulation using default land cover with observed soil moisture and soil texture information to get the impact of only the land cover differences. Our reasoning is that soil moisture and texture impacts the accuracy of simulations [*Niyogi et al.*, 1999] and is particularly hard

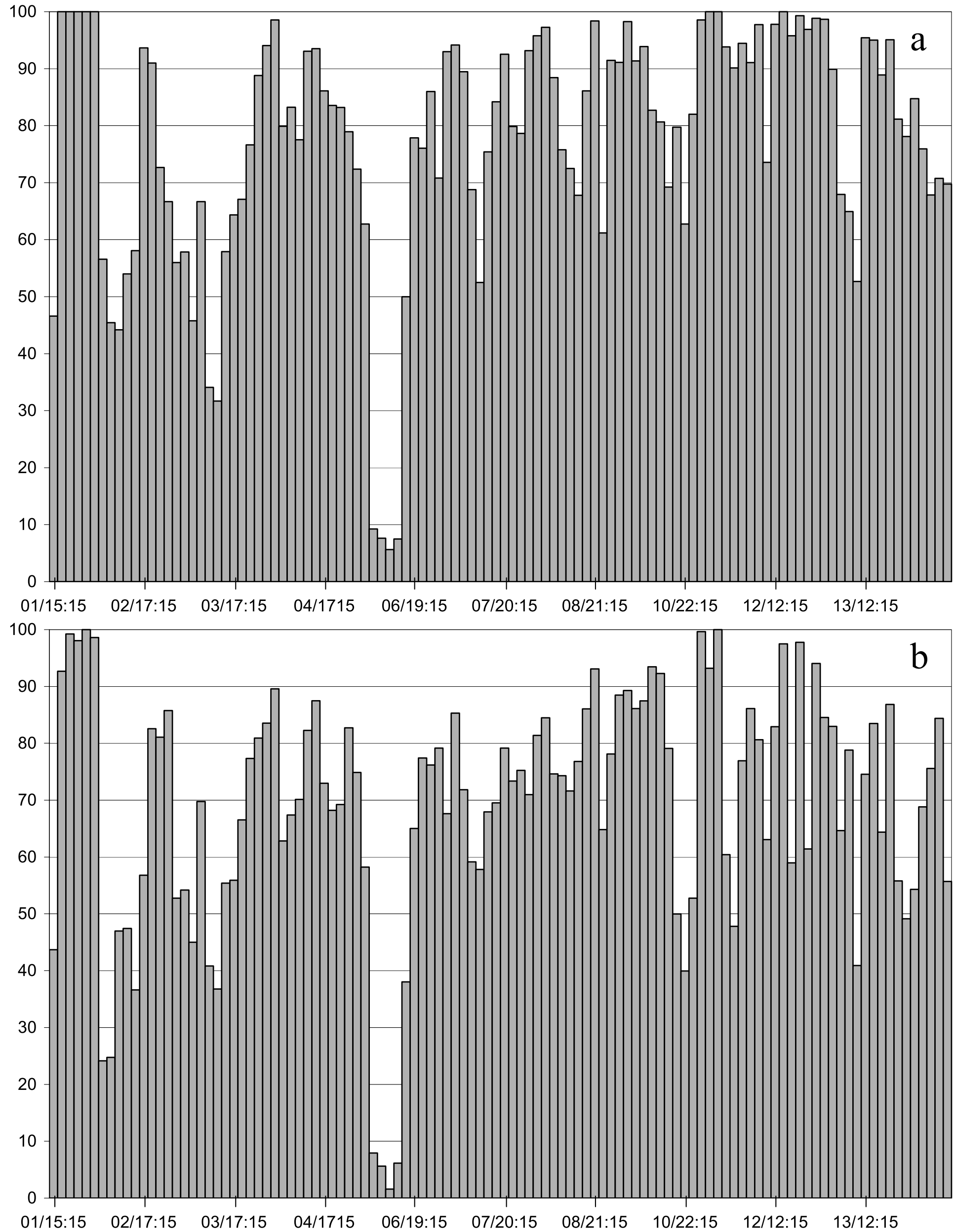

Figure 2. Model O (model with updated LU and extra rawinsonde information) performance over (a) cloud forest locations as identified in the updated LU and (b) noncloud forest location.

to obtain in frontier regions. On the contrary, it is easier to obtain LAI information and accurate land cover classification from analysis of higher-resolution satellite imageries. Thus in general, models can be run with updated land cover information but not the observed soil moisture values so one needs to compare model runs that differ simply in this information. Several studies such as those by *Ge et al.* [2007] in East Africa and *Xue et al.* [2004] in East Asia and West Africa have shown the importance of prescribing accurate land cover information for rainfall simulations.

Table 3. Mean and Median Accuracy of Models O, LU, ATM, and LUATM Over the Entire Study Region, Cloud Forest Locations, Noncloud Forest Locations, and Regions With Identical LU Among the Four Models

	Mean				Median			
	O	LU	ATM	LUATM	O	LU	ATM	LUATM
Entire region	69.90	67.49	45.91	44.56	74.31	71.31	46.75	47.12
Over cloud forests locations	77.51	76.32	51.74	51.26	82.36	81.75	56.22	53.01
Over noncloud forests locations	69.16	66.63	45.35	43.90	73.84	70.86	46.53	46.70
Over common land cover locations	71.68	68.28	43.44	42.35	77.32	72.62	43.74	35.65

Table 4. Same as Table 3 but for Threat Score

	Mean				Median			
	O	LU	ATM	LUATM	O	LU	ATM	LUATM
Entire region	0.46	0.44	0.35	0.34	0.48	0.47	0.35	0.32
Over cloud forests locations	0.55	0.54	0.41	0.41	0.53	0.55	0.43	0.39
Over noncloud forests locations	0.45	0.43	0.35	0.33	0.47	0.46	0.35	0.31
Over common land cover locations	0.48	0.46	0.34	0.34	0.50	0.48	0.31	0.26

[25] Model LU had a mean simulation accuracy of 67.49%, i.e., 2.41% decrease in simulation accuracy from model O. Over CF, the simulation accuracy ranged between 3.5% to 100% with a mean of 76.32% and a median of 81.75% (Table 3), i.e., 1.2% lower accuracy than model O. Over NCF locations, the range was 0.1% to 100% with a mean of 66.63% and median of 70.86% (Table 3), i.e., a 2.5% lower accuracy than model O.

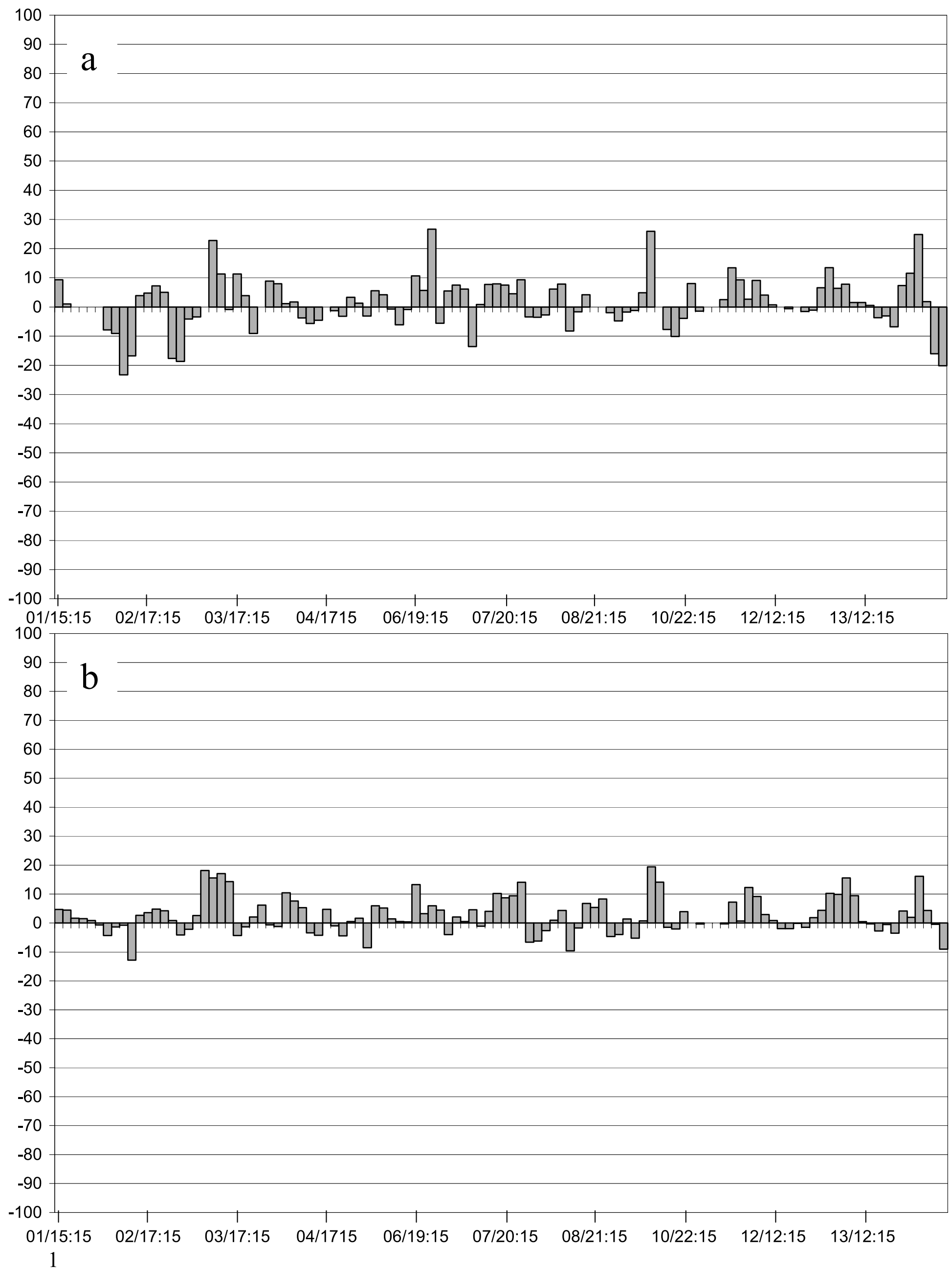

Figure 3. Difference in PCM accuracy of model simulated clouds. (a) Difference in PCM over cloud forest regions as identified in the correct LU map. (b) Difference over noncloud forest regions. PCM for the model run with accurate LU and accurate ATM information when subtracted from the PCM of model run with default RAMS LU information but accurate ATM gave the differences as plotted.

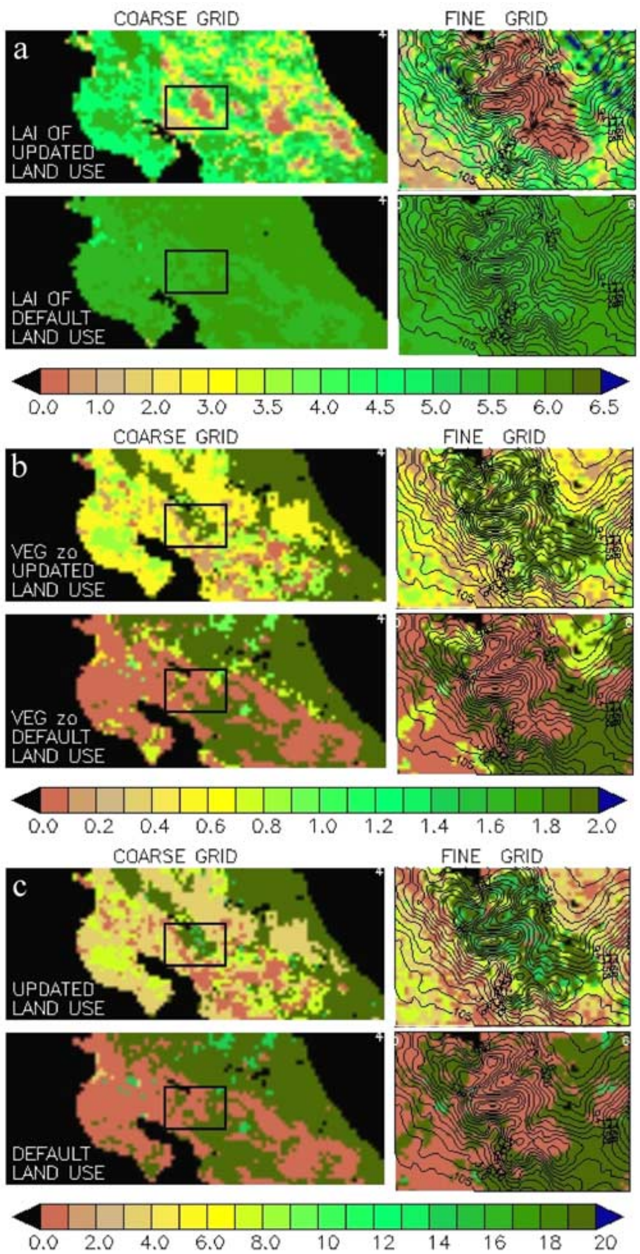

Figure 4. (a) Comparison of LAI between simulations with updated LU for Models O and ATM, and simulations without spatially explicit LAI for Models LU and LUATM. (b) Similar to Figure 4a but for vegetation roughness height (meters). (c) Similar to Figure 4a but for vegetation displacement height (meters). Note that over identical LU (see Figure 1), the vegetation roughness and displacement heights are identical, as we did not update these biophysical parameters and allowed the default values associated with land cover category to be used.

[26] The actual differences in simulation accuracy over CF locations (Figure 3a) shows an absence of any consistent positive differences that would have indicated that model O had better performance due to accurate land cover information. In fact there were 42 comparisons when model LU had better performance, 14 times when both models had identical performance, and in 53 cases model O had better simulations over CF. Over NCF locations (Figure 3b) there appears to be more consistent differences (positive differences) between models O and LU which means that better land cover representation improves the simulations over NCF (mean difference was 2.5%).

[27] Similar to the PCM, the TS scores (Table 4) of model LU had small decreases over all the comparison areas when compared to model O. The results from these analyses show that better land cover representation results in small gains in model performance. Note that a simulation with different soil moisture may have led to larger differences but we wanted to simply quantify the effect of land cover representation and not the combined effect of land cover representation and soil moisture.

[28] In RAMS, each land cover type is represented by a suite of biophysical variables: albedo, leaf area index (LAI), fractional vegetation cover, etc. These biophysical variables determine energy and moisture exchange between the land surface and overlying atmosphere. Thus the effect of land cover classification accuracy on simulated clouds is ultimately controlled by the changes in the biophysical variables. Therefore the effect of classification accuracy relies on how the surface scheme (LEAF-2 in this study) defines these biophysical variables for each type. As the biophysical parameters of different land cover types become more differentiated, the effect observed will be more pronounced. In the hypothetical case when all land cover has exactly the same biophysical characteristics, classification accuracy will not have any effect on the simulations differentiating the effects of land cover specification accuracy.

[29] In Figure 4a, the default RAMS LAI is compared to the satellite-observed LAI product [*Myneni et al.*, 2002] for March 2003. It is evident that the LAI in RAMS is unrealistically uniform over most of the domain with several regions poorly represented. Other biophysical parameters in RAMS, such as vegetation roughness height (Figure 4b), vegetation displacement height (Figure 4c), and albedo, while not being homogeneous, are nevertheless identical in regions where the land cover types are identical. This is because we did not update the values for any of these biophysical parameters and therefore only the patterns appear different. *Ge et al.* [2007] have speculated that these differences may impact simulation accuracy and thus the impact of land cover on simulating clouds might be greater than those described in this study. Unfortunately, there are no global data sets for these parameters currently available except albedo where methods to incorporate MODIS black and white sky albedo [*Schaaf et al.*, 2002; *Moody et al.*, 2005] into the land surface models is still under investigation [e.g., *Matsui et al.*, 2007].

4.2.3. Accuracy of Model ATM

[30] Model ATM compares the importance of accurate atmospheric profile information. The simulation was identical to model O in terms of land cover information but utilized standard atmospheric information generally available to researchers, i.e., NCEP Reanalysis, upper air profiles, and surface information from NCAR.

[31] The mean simulation accuracy over the entire high-resolution model domain decreased to 45.91% with a median of 46.75% (Table 3). This was a decrease of 24% from Model O and 21.58% from model LU. Over CF locations, the decreases were 25.8% from model O and

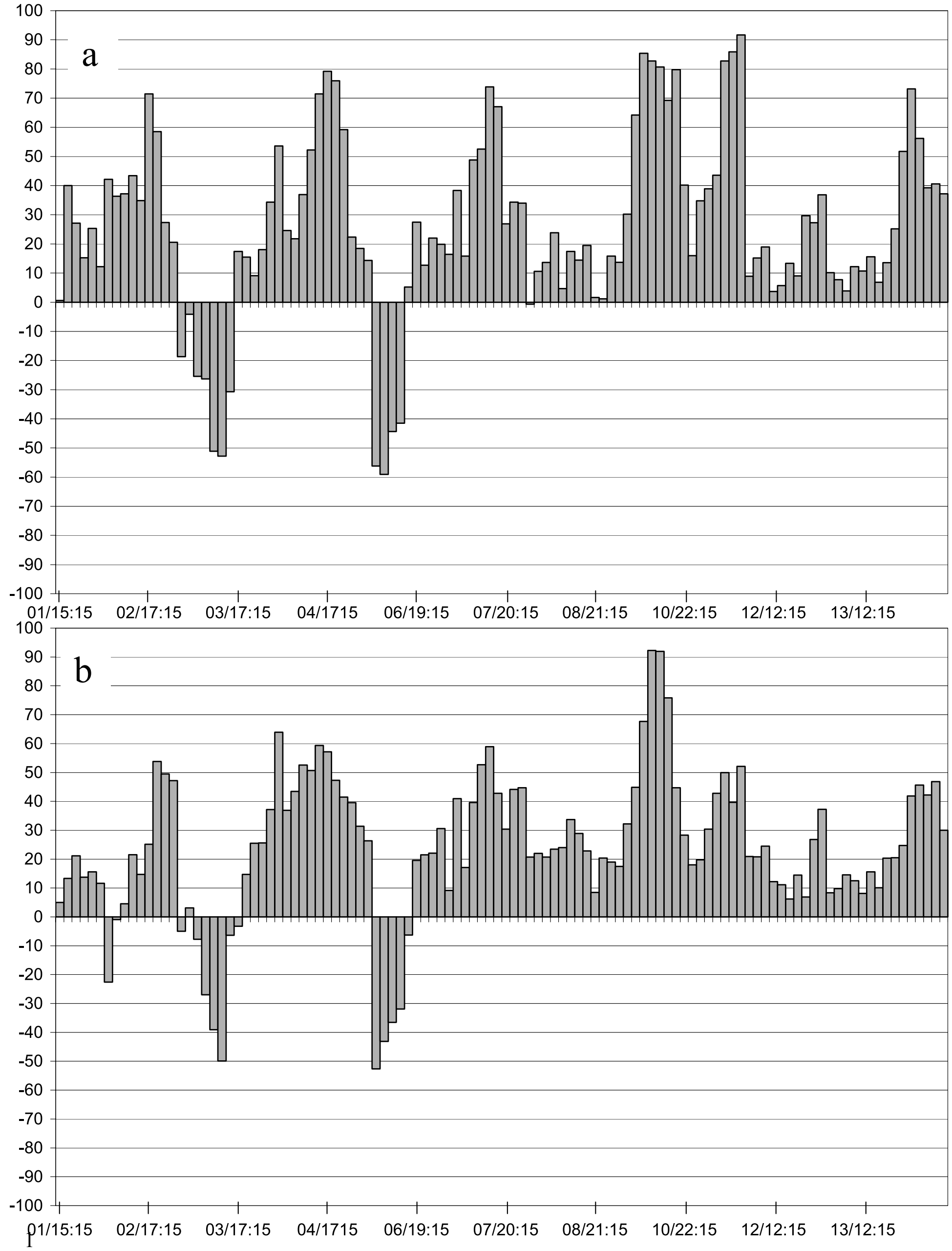

Figure 5. Difference in PCM accuracy of model simulated clouds. (a) Difference in PCM over cloud forest regions as identified in the correct ATM map. (b) Difference over noncloud forest regions. PCM for the model run with accurate LU and accurate ATM information when subtracted from the PCM of model run with default accurate LU but standard ATM information gave the differences as plotted.

24.6% from model LU. Over NCF the decreases were 23.81% and 21.35% respectively. Figure 5a shows the actual differences in the PCM between model O and this model for each comparison. It is quite clear from Figure 5a that, in general, the extra atmospheric information of model O led to substantially better simulations over the CF locations. There were only 12 cases when model ATM performed better than model O, while 98 times model O performed better than model ATM. Similarly over NCF locations model O performed better on 96 of the 110 comparisons. Default atmospheric information also decreased the TS scores by 0.1 (Table 4: TS comparisons of models O and ATM). These results clearly show that in frontier regions, better atmospheric information can lead to substantial improvements in model simulations.

4.2.4. Accuracy of Model LUATM

[32] Model LUATM utilized the same land cover as in model LU but atmospheric boundary and initial condition information as in model ATM. It is clear from the results presented in sections 4.2.2 and 4.2.3 that when simulations are conducted with standard atmospheric information (but updated land cover) there is a greater decrease in model accuracy than simulations that are done with model default land cover (but good atmospheric representation). Thus it

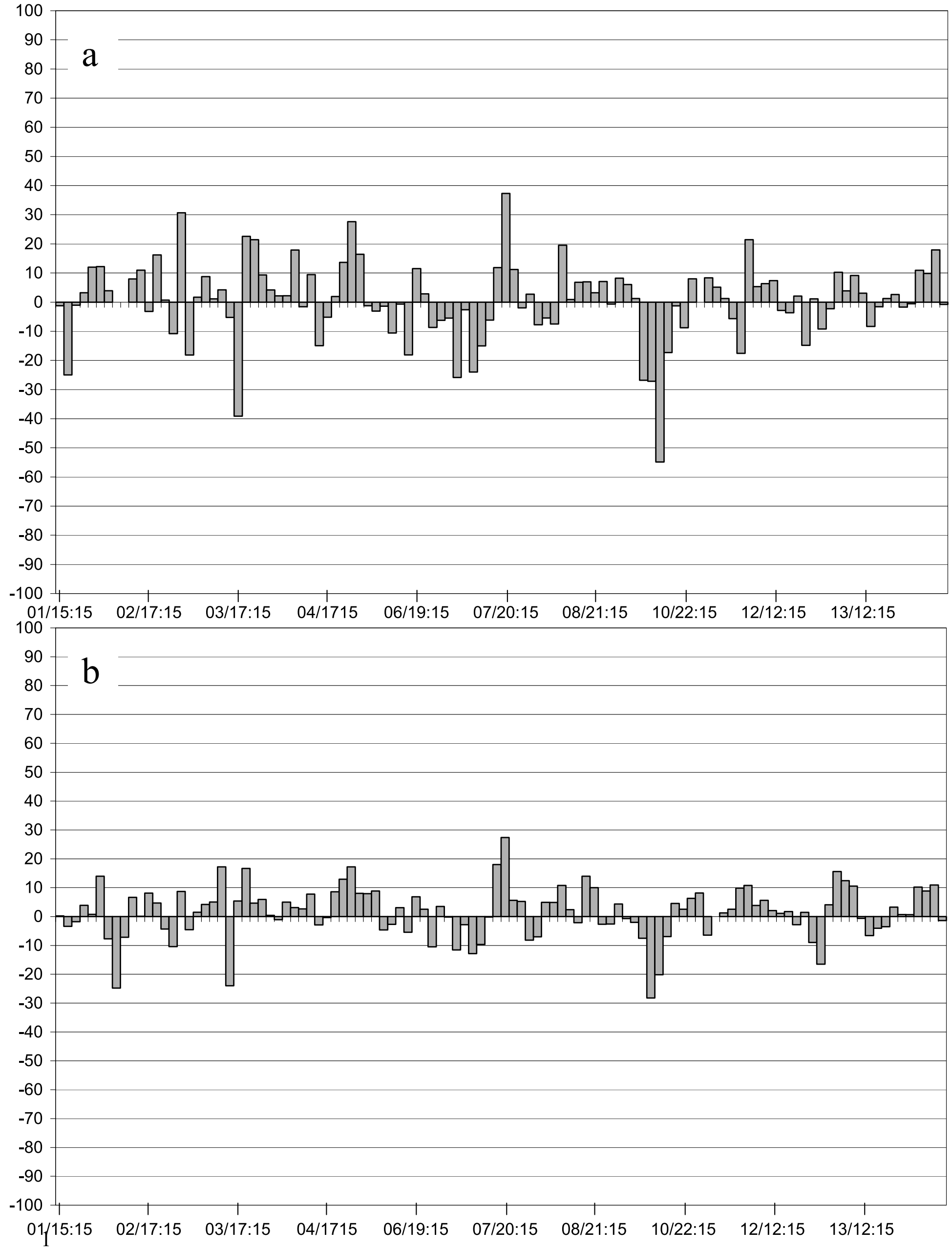

Figure 6. Impact of LU accuracy on simulations over (a) cloud forest regions and (b) noncloud forest regions when only standard atmospheric information is provided.

was not surprising that model LUATM only had a 44.56% (Table 3) simulation accuracy for clouds (i.e., 25.34%, 22.93%, and 1.35% worse simulation than models O, LU, and ATM, respectively). While the results clearly show that this model had the worst simulation accuracy, note the large difference in simulation accuracy between this model and models with extra atmospheric information, and the much smaller difference between this model and the model with standard atmospheric information but updated land cover, (i.e., model ATM). The difference with models O and LU is 17 to 19 times larger than the difference with model ATM.

[33] Figure 6 shows the differences in model LUATM and model ATM. Model LUATM has a mean performance accuracy of 51.26% over cloud forests and 43.90% over noncloud forest locations (Table 3) and corresponding median values were 53.01% and 46.70%. Thus over CF locations model LUATM had 0.5% reduced accuracy from model ATM but a much larger reduction when compared to models O and LU. Over NCF locations, model LUATM had a 1.46% reduced accuracy compared to model ATM. Figure 7 shows the difference in performance between models O and LUATM, i.e., between the model with the best land cover and atmospheric information and the model with the default land cover and standard atmospheric information. Table 4 displays the TS scores for model LUATM which were in general the least among all the simulations.

[34] The last set of cloud cover comparisons performed was over locations that had identical land cover (Figure 1) across all the models. At these locations the models performed as expected, with model O performing the best,

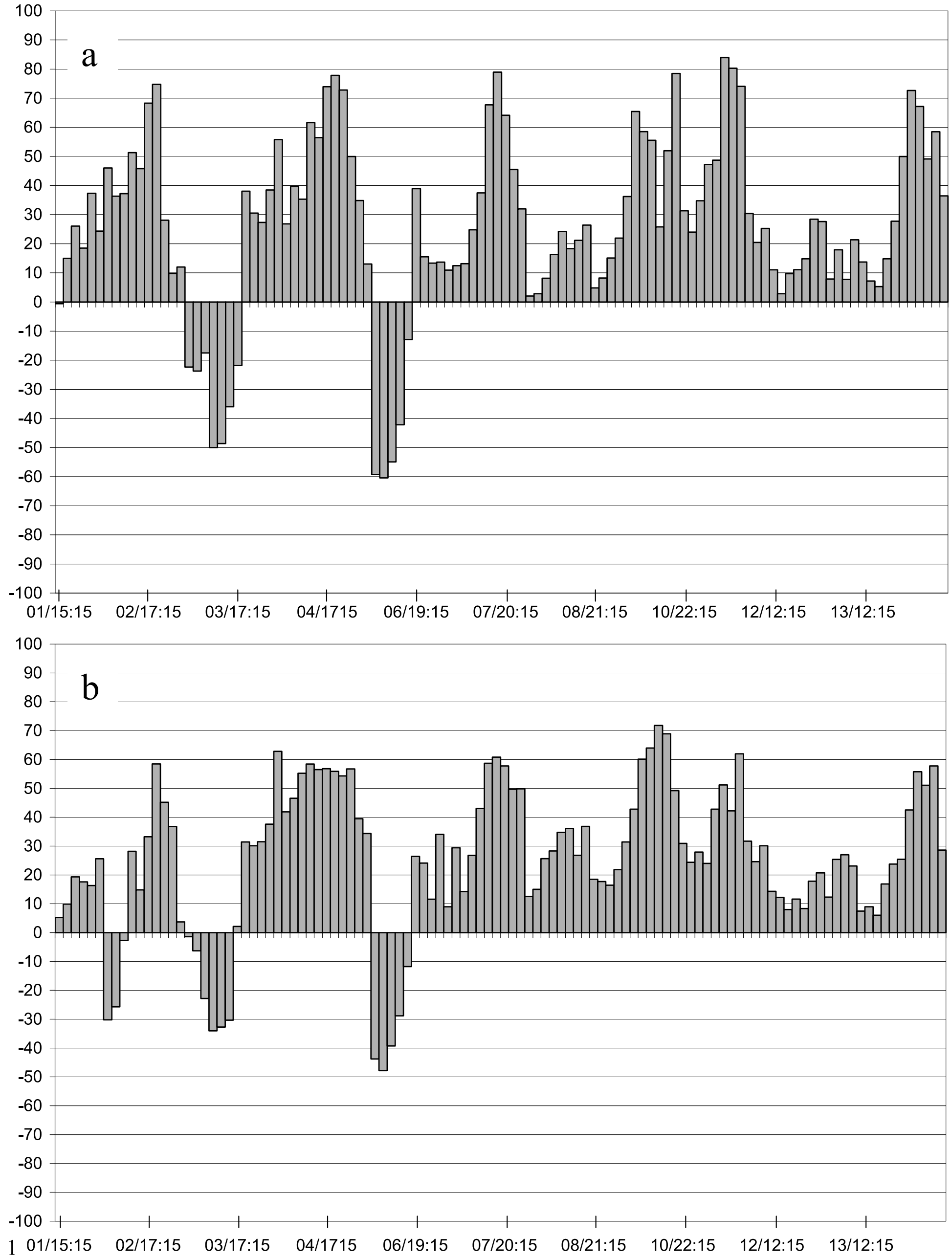

Figure 7. Impact of the combined effect of LU and ATM accuracy on PCM over (a) cloud forests and (b) noncloud forest locations.

followed by model LU, model ATM, and model LUATM. Interestingly, since the land cover is identical at these locations, if the atmosphere information is identical, one would expect nearly identical simulation accuracy but results suggest otherwise. Atmospheric information appeared to be the primary criterion for accurate simulations. Land cover appeared to be the secondary criterion. For example, model O and model LU both used updated atmospheric information and differed only in land cover (Figure 1). Simulation accuracy assessment in these locations of common land cover shows that model O performed 3.4% better than model LU. Since all other parameters are identical, the only explanation is that incorrect land cover at other locations led to the decreased simulation accuracy. Similarly when both models had standard atmospheric information (i.e., models ATM and LUATM), the model with better land cover representation over the entire study region (i.e., model ATM) had a 1.09% better simulation accuracy than model LUATM over the common land cover locations (Figure 1). However, when models O and LU (as a group) are compared with models ATM and LUATM (again as a group), the difference in accuracy is 24.85% to 29.33% over locations where all four model have identical land cover. Identical results are seen from the TS scores as well (Table 4). This clearly shows the overwhelming importance of accurate initial and lateral boundary atmospheric infor-

Table 5. Average Deviation of Model Simulated Atmospheric Profile From Observed Rawinsonde Values for Four Atmospheric Layers for Two Parameters[a]

	Temperature				Dew Point Temperature			
	O	LU	ATM	LUATM	O	LU	ATM	LUATM
Surface to 850 hPa	1.15	1.28	1.73	2.21	1.45	1.38	1.77	1.60
850 to 700 hPa	1.40	1.38	1.36	1.47	4.99	4.39	4.19	5.21
700 to 550 hPa	0.95	0.92	1.12	1.06	5.35	5.35	11.39	11.69
Above 550 hPa	0.98	0.97	0.78	0.80	8.33	8.34	11.82	11.43

[a]Parameters are temperature and dewpoint temperature at pressure levels that were matched to less than 0.1 hPa difference. The number of comparisons performed for each atmospheric layer and for each model is given within the temperature columns. A similar number of comparisons was performed for dewpoint temperature.

mation compared to accurate land cover information for accurate model simulations.

4.3. Differences in the Simulated Profiles of Temperature and Dewpoint Temperature

[35] We also determined the average absolute difference between the simulated and observed atmospheric temperature (equation (4)) and dewpoint temperature (equation (5)) profiles in four different atmospheric layers for the four model simulations. These four layers are: (1) surface to 850 mb which is the normal height of the trade wind inversion in Costa Rica; (2) 850 mb to 700 mb; (3) 700 mb to 550 mb; and (4) above 500 mb. These divisions were done simply to make it easier to analyze the data and to have a simple progression of heights. For example, 700 mb is around 3 km above ground level whereas 550 mb is around 5 km above sea level.

$$\frac{1}{n}\sum_{1}^{n}\left|T^{observed} - T^{simulated}\right| \tag{4}$$

$$\frac{1}{n}\sum_{1}^{n}\left|Td^{observed} - Td^{simulated}\right|. \tag{5}$$

[36] The deviations were computed in the following manner: starting with the first rawinsonde observed values (i.e., lowest atmospheric levels), we did a quality check on whether the observation had any fill value for pressure, temperature, dewpoint temperature, latitude, longitude, wind speed and wind direction. Next, using the information of latitude and longitude, we identified which RAMS cell this layer would fall into. The logic behind this is that while at the lowest layer the rawinsonde would be profiling within the same RAMS cell, as the rawinsonde would reach higher atmospheric layers it would deviate more from the original cell from where it was launched. In fact, our calculations show that for the surface to 850 mb layer, 32.63% of the observations collocated to cells other than those from where they were launched. At higher levels, 100% of the rawinsonde information came from cells other than those from which they were launched. Once the correct RAMS cell is identified, we next collocated the rawinsonde and the cell's pressure to within 0.1 hPa. The temperature and dewpoint temperature of the observations and simulations that collocated in this manner were then used to determine the average absolute temperature and dewpoint deviations. Since we had 4 models, 4 atmospheric layers, and two variables being compared, we had a total of 32 deviations that were averaged and are shown in Table 5.

[37] There are distinct differences in the amount of deviation in simulation of temperature and dewpoint temperature between the four models and at the different atmospheric levels. We also believe this partly accounts for the difference in the accuracy of cloud simulations using the four models. First, at each of the atmospheric layers, the deviations for dewpoint temperatures were always higher than for temperature. This simply means that whether we provided the model with standard atmospheric profiles or otherwise, and whether we provided the model with the default land cover or otherwise, simulating the dewpoint temperature correctly is more difficult than simulating the temperature profiles. Second, we cross-compared the four model performance for temperature and dewpoint temperature at these four atmospheric levels. At all the layers, model O (our best-performing model from the cloud comparisons) had errors in correctly simulating the temperature and dewpoint temperature. There is no consistent pattern in the errors of simulating temperature with the largest deviation present in the 850- to 700-hPa layer, and the least at 700- to 550-hPa layer. The dewpoint temperature deviations systematically increased with decreasing pressure and the errors in dewpoint temperature simulation were also larger than the errors in temperature simulation. Similar results were obtained for the other models.

[38] When the deviations are cross-compared across the models and for each meteorological variable at each model layer, the following was found. Model O had the least temperature deviation at the surface to 850-hPa layer, followed consecutively in increasing order models LU, ATM, and LUATM. In the 850- to 700-hPa layer, there was no trend but model LUATM had the maximum average deviations from observations. In the 700- to 550-hPa layer, models O and LU had lower deviations than models ATM and LUATM. Above 550 hPa, models ATM and LUATM had lower deviations than models O and LU. This shows that only at lower atmospheric layers models ATM and LUATM may have larger errors in simulating temperature. Next we compared the dewpoint temperature deviations in a similar manner. First, the deviations for all models systematically increased with elevation, but in general, at all atmospheric levels, models O and LU had lower deviations than models ATM and LUATM. The differences in the deviations were around 0.15 K to 0.39 K at the surface to 850-hPa layer. This means models O and LU had 0.15 K to 0.39 K less errors in simulating dewpoint temperature. In the 700- to 550-hPa layer these values ranged from 6.04 K to 6.34 K which again means that models O and LU had 6.04 K to 6.34 K less error in simulating the dewpoint temperature. These sets of comparisons also show that atmospheric information is more important for model simulations than land cover information.

5. Discussion and Conclusion

[39] Frontier and developing areas are the hot spots of LCC where several past studies [*Charney*, 1975; *Xue*, 1997; *Zheng and Eltahir*, 1997; *Pielke et al.*, 1999; *Chase et al.*,

2000; *Feddema et al.*, 2005; *Pielke et al.*, 2007] have shown local, regional, and global climate changes as a result of LCC using numerical model simulations. Very few studies have been performed to help understand the importance of accurate land cover representation to simulate the current regional climate [e.g., *Ge et al.*, 2007]. Even less common are studies comparing and contrasting the importance of atmospheric and land cover information in frontier and developing areas where most of the land cover transitions occur but where both these data sets are difficult to obtain.

[40] This study shows that in the dry season in the area surrounding the Cordillera de Tilarán in northern Costa Rica while accurate land cover information is important for simulating current conditions, atmospheric information is an order of magnitude more important. We ran, validated, and intercompared four model simulated precipitation, clouds and atmospheric profiles against independent observations. We selected clouds as the intercomparison metric for the four models because cloud cover simultaneously incorporates the nonlinear effects of LU and atmospheric structure and provides a point-to-point comparison that precipitation comparisons cannot provide as they are measured only in some select locations.

[41] Our results show that model O (which had updated land cover and extra atmospheric information), simulated precipitation and clouds best. Model LU had the next best simulation of precipitation and cloud cover, followed by model ATM and then model LUATM. Between models O and LU (as a group) and models ATM and LUATM (as a group) the difference in cloud simulation accuracy averages between 21% and 25%. Note that models O and LU had good atmospheric information whereas models ATM and LUATM had standard atmospheric information. Within the models O and LU (where the difference was only the land cover) the simulation accuracy of clouds differed by 1% to 3% whereas between models ATM and LUATM (where again the only difference was land cover), this value was between 1% and 2%. This result shows that detailed atmospheric information is more crucial in increasing simulation accuracy than land cover information. Similar results were obtained from the TS analyses.

[42] We found that similar to the cloud simulation accuracy the deviations tend to fall into two groups with models O and LU having lower deviations and models ATM and LUATM having larger deviations. The deviations were larger for dewpoint temperature than for temperature and it appears that dewpoint temperature deviations systematically increased with decreasing pressure (i.e., increasing altitude) for all 4 models. However, at lower pressures (higher altitudes) the model pairs O and LU and model pairs ATM and LUATM diverged in terms of their deviations. The latter model pair had 3 K to 6 K larger deviations compared to the former model pair. At lower elevations the latter model pair had a few tenths of Kelvin larger deviations. This also shows that models with better atmospheric information performed better.

[43] Our results thus show that in this frontier region, accurate and detailed atmospheric information is more critical than accurate and detailed land cover information for conducting accurate atmospheric simulations. There were small gains in simulation accuracy from updating land cover information compared to the larger gains from better atmospheric representation. However, even with updated land cover and extra atmospheric information, our simulations only had an overall accuracy of 70% and significant deviations from observed temperature and dewpoint temperatures. This shows that there are at least 4 opportunities for further model improvement. (1) A more substantial and close-knit network of radiosondes to provide information to the model; (2) further improvement in the land cover representation such as better land cover classification, observed albedo and roughness information; (3) improved model microphysics of land atmosphere interactions, cloud formation, and soil-vegetation-atmospheric transfer; and (4) a minor impact could simply be from the model configuration such as horizontal grid spacing and multiple nested grids.

[44] There are several aspects of this work that can be explored further. For example, an entire range of sensitivity analyses could be performed to evaluate the effects of accuracy in the land cover representation. Similarly, the impact of increasing or decreasing the number of rawinsondes to the model to determine the critical number of rawinsondes required to conduct simulations without compromising the accuracy. Systematic biases in the simulation as contrasted with the rawinsonde data, such as for the upper-level dewpoint temperature, can also be used to nudge the models toward the actual values. Also note that this since this study consists only of short time model integrations which are constrained by lateral boundary conditions, ensemble forecasting would not add to our assessment of the relative role of LU and atmospheric information on this time scale.

[45] From this study, however, it is quite clear that changes in land cover and atmospheric information will result in changes in simulation accuracy. The critical result that we have shown in this paper is that providing a state-of-the-art regional model with extra rawinsonde information improved the model accuracy by over an order of magnitude using the validation metrics analyzed in this paper. The same benefits for simulations conducted using the WRF or some other numerical model should also occur at other frontier regions.

[46] With respect to assessing the relative role of land-use change on the climate system, the improved simulation accuracy with better atmospheric structure information has an important implication. Since atmospheric information, of course, is not available for different landscape scenarios, (i.e., simulations are one-way nested regional model integrations in which there is no interaction from the regional to the large scales through the lateral boundaries) assessments of the relative role of LULC change will still have to rely on either using the standard atmospheric data set or on the use of more detailed atmospheric data over the current landscape even though it is affected by the current landscape for initial and lateral boundary conditions. The latter approach will reduce the simulation differences expected in such landscape sensitivity studies since the initial atmospheric conditions with a different landscape would in reality, of course, be different. This conclusion is independent of whatever larger-scale reanalysis product is used, even if the field data were assimilated into it, as well is independent of the particular climate metrics (e.g., orographic clouds) that are evaluated in this study.

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R. O. Lawton, Department of Biological Sciences, University of Alabama in Huntsville, Huntsville, AL 35899, USA.

U. S. Nair, Earth System Science Center, National Space Science and Technology Center, University of Alabama, Huntsville, AL 35805, USA.

R. A. Pielke Sr., Cooperative Institute for Research in Environmental Sciences, University of Colorado, Boulder, CO 80309, USA.

D. K. Ray, Forestry and Natural Resources, Purdue University, West Lafayette, IN 47907, USA. (dkray@purdue.edu)

R. M. Welch, Department of Atmospheric Sciences, University of Alabama in Huntsville, Huntsville, AL 35805, USA.