Evaluating Error Propagation in Coupled Land–Atmosphere Models

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Received 15 September 2010; accepted 30 July 2011

ABSTRACT: This study examines how land-use errors from the Land Transformation Model (LTM) propagate through to climate as simulated by the Regional Atmospheric Model System (RAMS). The authors conducted five simulations of regional climate over East Africa: one using observed land cover/land use (LULC) and four utilizing LTM-derived LULC. The study examined how quantifiable errors generated by the LTM impact typical land–climate variables: precipitation, land surface temperature, air temperature, soil moisture, and latent heat flux. Error propagation was not evident when domain averages for the land–climate variables of the yearlong simulation were examined.

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DOI: 10.1175/2011EI380.1
However, the authors found that spatial errors from the LTM propagate through in complex ways, temporally affecting the seasonal distributions of rainfall, surface temperature, soil moisture, and latent heat flux. In particular, rainy seasons exhibited greater precipitation in LTM-RAMS simulations than in the reference simulation and less precipitation occurred during the dry season. Complex interactions of precipitation and soil moisture were also evident. Overall, results indicate that small errors from a land change model could grow as a “coupling drift” if both are used to forecast into the future; these couplings could create larger combined errors of land–climate interactions because of time-scale differences into the future. Thus, although land-use change projection is necessary for a more accurate climate projection, existing errors from a land change model will likely amplify through the climate simulation. This finding affects interpretation of large-scale versus land-use/land-cover feedbacks on climate projections.

KEYWORDS: Land-use and land-cover change; Regional climate models; Error propagation; Precipitation; Soil moisture; Latent heat flux; Land surface temperature

1. Introduction

There is growing evidence that land-use change has an important impact on regional and global climate (Cox et al. 2000; Cramer et al. 2001; Pielke et al. 2002; Xue et al. 2004; Feddema et al. 2005a; Bonan 2008; Pielke and Niyogi 2010; Mahmood et al. 2010). Current efforts in developing strategies for adapting to and mitigating future climate change, however, have focused primarily on reducing greenhouse gases related to radiative forcings (Pielke et al. 2002; Boko et al. 2007). Efforts at prioritizing investments for adaptation and mitigation in places such as Africa have largely neglected the nonradiative forcings on climate associated with land-use/land-cover (LULC) change (Conway 2004; Lobell et al. 2008; Moore et al. 2010; Moore et al. 2011). Similarly, with the Intergovernmental Panel on Climate Change (IPCC) Fifth Assessment, there is growing understanding that climate projections need to include a spectrum of LULC (Pielke et al. 2007). For example, LULC prescription affects surface energy partitioning, hydroclimatology, and landscape greening/senesce. LULC heterogeneities also create mesoscale atmospheric boundaries that can affect regional convergence, convection, and rainfall patterns (Kabat et al. 2004; Pielke and Niyogi 2010).

In East Africa, the land surface can have a significant influence on the simulated spatiotemporal distribution of rainfall and temperatures (Moore et al. 2010). Uncertainty in land-cover characteristics like leaf area index (LAI) and albedo can impact model performance as well as validation (Ge et al. 2009). Ultimately, these land surface parameters influence the surface energy budget through partitioning of incident radiation into sensible heat flux (SHF), latent heat flux (LHF), reflected shortwave radiation, and emitted longwave radiation (Alapaty et al. 1997; Niyogi et al. 1999). Changes in the land surface have been shown to drastically alter local and large-scale atmospheric dynamics around the world (Pielke et al. 2002; Werth and Avissar 2005; Ray et al. 2003; Ray et al. 2006), including East Africa (Moore et al. 2010; Moore et al. 2011).

It is well known in the LULC change modeling community that errors are common in LULC models (Veldkamp and Lambin 2001; Pijanowski et al. 2002; Pijanowski et al. 2005; Pontius et al. 2008). Errors are typically of two types: 1) location, which is
the error in placement of a land-use cell within the simulation domain, and 2) quantity, the error from a model that exists when the incorrect number of cells is predicted for any LULC category. Pijanowski et al. (Pijanowski et al. 2011, manuscript submitted to *Int. J. Geogr. Inf. Sci.*) have shown that, in coupled land–climate interaction modeling for East Africa using the Land Transformation Model (LTM), as much as 35% of the cells were incorrectly placed at a 1-km scale when assessed during validation. However, the LULC model is often run at finer spatial resolutions (~30–1000 m) than that of regional climate models (~10 000 m); coupling of these models requires that output from an LULC model be aggregated and presented to climate models as fractional quantities. Thus, it is possible that the placement errors from an LULC model may “cancel out” when aggregating to the climate model resolution, eliminating the LULC model errors when coupled to climate models.

The errors in LULC have the potential to affect regional surface fluxes and other regional variables, such as temperature and precipitation (PCP). It can be hypothesized that errors in surface heat fluxes can lead to changes in rainfall through modified boundary layer and mesoscale convection. Errors in simulated precipitation can result in long-term changes in soil moisture (SM), which in semiarid regions can persist for months in the form of soil moisture “memory” (Eltahir and Gong 1996; Niyogi et al. 2002). Thus, it is also possible that, over time, small uncertainties in land surface parameterizations can lead to larger cumulative divergences in a region’s climate projection. This sensitivity is important, but in most studies the uncertainty of the landscape parameterizations is not explored beyond simple statistical reporting.

To better understand the nature of the error propagation from coupling an LULC model to a regional climate model, we conducted an error propagation study using the LTM (Pijanowski et al. 2001) calibration land projections, which are input into the Regional Atmospheric Modeling System (RAMS; Pielke et al. 1992). By using a combination of a land-use prediction model and a corresponding coupled land–atmosphere regional climate modeling system, we intend to assess the propagation of the uncertainty in land-use prediction on corresponding meteorological simulations.

### 2. Study area, models, and methods

#### 2.1. Study area

The study area for the coupled simulation is located in East Africa (see Figure 1), enclosing five countries wholly (Kenya, Uganda, Rwanda, Burundi, and Tanzania) and a number of other countries partially (Sudan, Ethiopia, Somalia, Mozambique, Malawi, Zambia, and Zaire). Rain-fed crops compose 15.6% of the land cover in the study area. The study area also contains a number of rift valley lakes such as Lakes Victoria and Tanganyika with the Indian Ocean to the east; these bodies of water significantly influence the regional climate. The northern part of the area is dominated mostly by desert and arid savanna. A number of complex orographic features, such as Mt. Kenya, Mt. Elgon, and Mt. Kilimanjaro, as well as the African Rift Valley, are also present. All of these affect the climate patterns in this area (Hughes et al. 2009).

This study builds from a National Science Foundation (NSF)-sponsored Climate Land Interaction Project (CLIP) (Olson et al. 2008), which assesses the relationship
between land uses and climate in East Africa. A summary of the coupling of different models in CLIP can be found in Olson et al. (Olson et al. 2008). The development of the LULC map used as input to the LTM is detailed in Torbick et al. (Torbick et al. 2006); an assessment of errors from the LTM is in Pijanowski et al. (Pijanowski et al. 2011, manuscript submitted to Int. J. Geogr. Inf. Sci.); Ge et al. (Ge et al. 2009) and Moore et al. (Moore et al. 2010) discuss using Moderate Resolution Imaging Spectroradiometer (MODIS)-based LAI for inputs to a regional atmospheric model; and Moore et al. (Moore et al. 2011) discuss the results of coupling RAMS, LTM, and a crop production model on local and regional food security.

2.2. The LTM

The LTM combines geographical information systems (GIS) with an artificial neural network (ANN) to predict spatial distributions of land uses in one time period or changes in land use learned from maps separated in time (Pijanowski et al. 2001). Socioeconomic (e.g., transportation corridors) and biophysical factors (e.g., soils) that have an influence on spatial distributions of land uses are input to
the LTM using GIS routines (Shellito and Pijanowski 2003; Ray and Pijanowski 2010). The model employs a raster (e.g., grid of cells) modeling environment.

The ANN within LTM is a multilayered perceptron based on the Stuttgart Neural Network Simulator (SNNS; http://www.ra.cs.uni-tuebingen.de/SNNS/). The ANN learns about patterns of LULC changes in relation to spatial maps of driver surrogates (e.g., distance to a road, slope) prepared using a GIS. The ANN contains three layers (Figure 2a): an input (containing the surrogate driver values), a hidden (with nodes that connect to all other nodes), and an output (map of the location of an LULC class or transition class). The weights for input, hidden, and output nodes (also called neurons) are determined by ANN algorithms in a “feed-forward, back propagation manner” in the following way: The ANN starts with a set of randomly assigned weights at each node (Figure 2b). Weights are then applied to a nonlinear activation function at each node (Figure 2c), which is then integrated across all nodes to estimate the output. A root-mean-square error (RSME) of the estimate and observed output value for all locations is then calculated (Figure 2a); a full pass forward using weights and then back-propagating errors is called a cycle and the process of learning about patterns in data is called training. The RSME is then compared to the previous cycle and a delta rule (an ANN algorithm that adjusts weights within the neural network) is then applied to adjust the weights. An ANN is generally run many times and stopped after a global RSME minimum is reached.

We use a two-step process to run the LTM for our simulations. The first step is training of input maps and an output map containing the presence (value = 1) and absence (value = 0) of rain-fed agriculture. The GIS was used to create the following 10 input maps: distance to three classes of roads (primary tarmac, secondary tarmac, and nontarmac roads), distance to towns and villages less than 500,000, distance to regional cities (more than 50,000 but less than 1 million people), distance to major cities, distance to major cities, distance to lakes, distance to rivers, and slope.

Figure 2. The ANN configuration used in the LTM illustrating the structure of (a) a network, (b) a node with weights and input values, and (c) an activation function.
cities with population over 1 million, distance to lakes, distances to rivers and streams, distance to parks, and slope. A pattern file representing a random selection of 10% of all locations in these maps with 10 inputs, one hidden layer with 10 nodes (following procedures of Pijanowski et al. 2002), and one output node was constructed using the createpat routine in the LTM. Training of the pattern file using SNNS occurred through 100,000 cycles, saving RMSE and network files every 100 cycles.

In the second step, the weights from the ANN are then applied to the input data (all locations) to estimate the output, which produces a continuous value between 0 and 1. Several steps are required to create a simulated map of rain-fed agriculture that is composed of 1 = rain-fed agriculture and 0 = all other land uses. First, a rank order sort is performed on all cells in the output map. Next, the quantity of rain-fed agriculture cells in the original map is calculated. Those cells that match the quantity of rain-fed agriculture above a critical threshold value (Pijanowski et al. 2002) are then used to create a binary map with 1 = rain-fed agriculture and 0 = all other land uses. Models from network files from 100, 1000, 10,000, and 100,000 cycles were built following Pijanowski et al. (Pijanowski et al. 2002). A map of cropland was then created in the GIS for each of the four neural network models and the fractional cover for each LULC class then calculated for each climate grid based on the predicted fraction of cropland. The output from each of these simulation steps is then compared to the observed land-use map following the procedures of Pijanowski et al. (Pijanowski et al. 2005; Pijanowski et al. 2006) and errors quantified using several metrics (described in section 2.5).

The land cover for rain-fed agriculture was obtained by merging Africover, a land-cover map derived from Landsat Thematic Mapper imagery with a resolution of 90 m for circa 1999, and the Global Land Cover Characterization [GLC2000; obtained using preprocessed vegetation sensor on the Satellite pour l’Observation de la Terre-4 (SPOT-4) satellite, which is also circa 1999] datasets (for details, see Torbick et al. 2006). These two datasets were merged because Africover had a better resolution for human and agricultural land uses, whereas GLC2000 had a better resolution for natural land categories (Torbick et al. 2006). Using GIS, the dataset was resampled to obtain land use at 1000 m. Rivers and streams were obtained from a regional database developed by the International Livestock Research Institute in Nairobi, Kenya. Roads were digitized from paper maps for Kenya, Tanzania, Rwanda, Burundi, and Uganda. We used the digital elevation model from the Shuttle Radar Topographic Mission (SRTM) scaled to 1000 m (originally at 90 m). Soils were determined from the Food and Agriculture Organization (FAO) soils series (1000 m), and they were placed into four classes based on crop suitability (0 = none, 1 = poor, 2 = good, and 3 = excellent). A mask including the rift lakes, Indian Ocean, and national parks was created, and these locations were set to “no data” in the GIS.

### 2.3. RAMS

We employed RAMS version 4.4 (Pielke et al. 1992; Cotton et al. 2003), including the Land Ecosystem-Atmosphere Feedback version 2 (LEAF-2) model module for the representation of surface-vegetation processes (Walko et al. 2000). RAMS is a fully three-dimensional, nonhydrostatic, atmospheric simulation system, which
solves the equations of motion, heat, and mass continuity using finite difference schemes. RAMS utilizes terrain following a coordinate system in the vertical and a polar stereographic coordinate system in the horizontal. We used the Mellor–Yamada closure for turbulence (Mellor and Yamada 1982), a calibrated Kain–Fritsch scheme (Kain 2004) for convective parameterization, and the Chen–Cotton radiative transfer parameterization (Chen and Cotton 1987). Soil properties from Clapp and Hornberger (Clapp and Hornberger 1978) were used in conjunction with a soil model that handles temperature and moisture (Deardorff 1978; Tremback and Kessler 1985). The model used a grid at 36-km spacing. Top and lateral boundary conditions were specified using National Centers for Environmental Prediction (NCEP) reanalysis data (Kalnay et al. 1996) at 6-hourly intervals for the year 2000, a relatively normal rainfall year for East African countries. The model was initialized for soil moisture using two layers (shallow and deep) of resampled soil moisture data at the simulation start date from the National Oceanic and Atmospheric Administration (NOAA)/National Climatic Data Center, and LAI and fractional cover were prescribed from simple spline functions constructed from MODIS data following Moore et al. (Moore et al. 2010). Lateral boundary nudging is driven for six points deep from the grid edge at a time scale of 1200 s. Additional details on model configuration and surface-vegetation parameterization are found in Moore et al. (Moore et al. 2010). For this study, we used the observed land use (CLIP) in the reference model run, which we refer to as CLIP-RAMS, and the simulated output from the LTM as input LULC to RAMS for the error propagation experiments, which we refer to as LTM-RAMS.

2.4. Experiments

Five experiments (Figure 3) were run: 1) CLIP-RAMS, using existing land cover, which we refer to as the reference simulation, and coupled LTM-RAMS for 2) 100, 3) 1000, 4) 10 000, and 5) 100 000 cycles. Previous work (e.g., Pijanowski et al. 2005; Pijanowski et al. 2006) has shown that maps created by the LTM using different training cycles produce different spatial distributions of land uses. Determining which training cycle to use is part of the calibration of the LTM (Pijanowski et al. 2006). Thus, these experiments assist us in determining how short (e.g., 100 cycles) versus long (e.g., 100 000 cycles) training sessions affect the coupled simulation and what, if any, different spatial distributions produced by the different LTM simulations affect RAMS. The RAMS model was executed using these LTM simulated maps as inputs, and PCP, land surface temperature (LST), surface air temperatures (SAT), LHF, and SM values were saved daily for PCP, LHF, SM, and SAT (Temp_{min} and Temp_{max}) and 8 days for LST for each RAMS grid for a yearlong simulation. The simulations for land use/cover and regional climate represent the year 2000.

2.5. Land-use model error metrics

We used several error metrics (following Pontius and Schneider 2001; Pijanowski et al. 2005; Ray and Pijanowski 2010) to assess the performance of each of the four LTM simulations. We used the area under the receiver operating characteristic
(AROC) curve (Fielding and Bell 1997) to assess how well the LTM simulations fit observed data. AROC is a threshold-independent measure (Pontius and Schneider 2001) of how well a simulation that produces values between 0.0 and 1.0 fit to binary (0,1 only) observed data.

Several contingency table metrics were also employed to quantify location and quantity errors per simulation (Fielding and Bell 1997). We used the quantity of observed agricultural cells to fix the number of expected cells in each simulation map. These two binary maps were then compared using a GIS. Table 1 illustrates these two kinds of errors. Location errors (Table 1a) are of two types: a false positive (FP; i.e., incorrectly placing an agriculture cell, which in the simulation is coded as 1) error and a false negative (FN; i.e., incorrectly placing a non-agriculture, or 0, coded cell) error. Correctly placing an agricultural cell or non-agricultural cell is referred to as true positive (TP) and true negative (TN). We used

![Figure 3. Experimental design of the five simulations and the ways in which they are compared.](Image)

**Table 1.** Confusion matrices that show (a) how cross-tabulated maps of observed (CLIP) and simulated (LTM) generate positive (correct) and negative (not correct) values and (b) how totals for positives and negatives are calculated for each map. (a) Cross-tabulation matrix and terms.

<table>
<thead>
<tr>
<th>Observed</th>
<th>Simulated</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>True positive</td>
</tr>
<tr>
<td>0</td>
<td>False positive</td>
</tr>
</tbody>
</table>

(b) Cross-tabulation matrix totals with notation.

<table>
<thead>
<tr>
<th>Observed</th>
<th>Simulated</th>
<th>Observed totals</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>$N_{TP}$</td>
<td>$N_{FN}$</td>
</tr>
<tr>
<td>0</td>
<td>$N_{FP}$</td>
<td>$N_{TN}$</td>
</tr>
<tr>
<td>Simulated totals</td>
<td>$S_{positives}$</td>
<td>$S_{negatives}$</td>
</tr>
</tbody>
</table>

$O_{positive}$ $O_{negatives}$
the percent positive correct (PPC) metric to determine the goodness of fit for the placement of rain-fed agricultural cells,

\[ \text{PPC} = \frac{TP}{TP + FP}. \]  

(1)

To determine how location errors impacted the coarser 36-km grid spacing RAMS model, we employed the scalable window technique of Pijanowski et al. (Pijanowski et al. 2002). Briefly, FN and FP errors that occurred in the same window size were considered to cancel out because the RAMS model uses fractional amounts per climate simulation grid as inputs. For every FN and FP cell pair that occurs in a simulation, the number of TP cells is incremented by one. Once all of the FN and FP pairs are accounted for, the window is then shifted and the process is repeated. The PPC is then calculated across the entire simulation area. Window sizes of \(3 \text{ km} \times 3 \text{ km}, 5 \text{ km} \times 5 \text{ km}, 7 \text{ km} \times 7 \text{ km}\), and so on, through \(79 \text{ km} \times 79 \text{ km}\), are used and the PPC for each window size calculated and then plotted as a function of window size. In particular, we are interested in the goodness of fit for the model at \(36 \text{ km} \times 36 \text{ km}\) size, because this is the size of the climate simulation grid.

We also compared the spatial distribution of all predicted agricultural cells by summing the binary simulation maps in GIS and then mapping the locations of TP and FN for all four LTM simulations. The locations where all models predicted the correct location of rain-fed agriculture was then mapped.

We also assessed quantity errors. Quantity errors (for an excellent overview of these kinds of errors, see Pontius 2002) occur when there are too many or too few agricultural cells; quantity errors (Table 1b) are calculated by comparing row (for observed) and column totals (for simulated) for the simulated area in each of the four cells in the contingency table. Note that quantity errors can be positive (overpredicting the number of agricultural cells) or negative (underpredicting the number of agricultural cells) in amount. We expressed quantity errors simply as the total area of rain-fed agriculture that differed from observed; we made this calculation for each climate simulation grid.

2.6. Evaluating impact of LTM errors on RAMS simulations

We examined departures from the four LTM-RAMS simulations from the reference CLIP-RAMS simulation for the land–climate interaction variables. We calculated domain averages for the four LTM-RAMS simulations and compared these to the reference simulation using a percent departure value (PDV),

\[ (\bar{r} - \bar{s}) \times 100/\bar{r} = \text{PDV}, \]

(2)

where \(\bar{s}\) and \(\bar{r}\) are the simulation (i.e., LTM-RAMS) and reference (i.e., CLIP-RAMS) domain averages for five regional climate variables: PCP, SAT, LST, LHF, and SM. A spatial and temporal analysis of departures from reference simulation was also conducted, and the results were plotted as time series and spatial maps. In particular, we examine patterns of departure relevant to long (March–May) and short (October–November) rainy seasons, because these periods impact crop production and food security for people in East Africa (Moore et al. 2011).
3. Results

3.1. LTM goodness of fit

A summary of the LTM goodness of fit statistics for each of the four simulations is contained in Table 2. Note that, for the AROC and PPC, small differences exist in each of the simulations. Surprisingly, 1000 training cycles proved to give the best fit compared to more training cycles. Pijanowski et al. (Pijanowski et al. 2005; Pijanowski et al. 2006) found that training of urban change improved considerably over the first 10,000 cycles, where it leveled off thereafter (i.e., reached a global minimum). Indeed, the ANN did very well even after only 100 training cycles.

We also compared the PPC for each LTM simulation over different window sizes (Figure 4). Note that FNs and FPs cancel each other out because the window size increases such that, at 36 km × 36 km, the model predicts rain-fed agriculture cells with a greater than 73% success. The 1000-cycle LTM performed the best at all window sizes, whereas the 100-cycle LTM produced the poorest goodness of fit. A map of TP, TN, FN, and FP for the 100,000-cycle LTM simulation is shown in Figure 5a. Note that the model correctly predicts the location of rain-fed agriculture in west-central Kenya, much of Uganda, northwest Tanzania, most of Rwanda, Burundi, northern Malawi, southern Sudan, and northwest Democratic Republic of Congo. Areas in gray show where the model correctly predicts non-rain-fed agriculture. FPs are located most along the coast of Kenya and Tanzania, in northwest Mozambique, and in central Uganda. Some of the FPs are also located along the edges of current rain-fed agriculture, especially in western Kenya and western Congo. FNs, locations where it occurs in the observed map but the model did not predict rain-fed agriculture to occur, are located in central Tanzania; in central–east Kenya; along valleys in the Congo; and in small patches in Mozambique, Malawi, and Zambia. In general, the model did well in areas where rain-fed agriculture was located in very large patches but did poorly in areas where rain-fed agriculture was scattered in small, complex shaped patches.

The co-occurrence of TPs and FPs for the four simulations is mapped in Figure 5b. All four LTM simulations placed rain-fed agriculture correctly in many of the same locations. The models also placed FPs in the same locations as well. A histogram (Figure 6) of the number of cells (each cell is 1 km × 1 km) for TP and FP locations derived from the map in Figure 5b shows that the models most often got the same locations correct or incorrect. Also note that, in Figure 6, there are large areas where none of the four simulations was able to correctly predict non-rain-fed agriculture (shown in yellow in Figure 5b). In other words, the area in

<table>
<thead>
<tr>
<th>No. of training cycles</th>
<th>AROC from LTM</th>
<th>PPC</th>
</tr>
</thead>
<tbody>
<tr>
<td>100</td>
<td>0.769</td>
<td>60.6</td>
</tr>
<tr>
<td>1000</td>
<td>0.815</td>
<td>62.8</td>
</tr>
<tr>
<td>10,000</td>
<td>0.785</td>
<td>61.7</td>
</tr>
<tr>
<td>100,000</td>
<td>0.798</td>
<td>61.8</td>
</tr>
</tbody>
</table>
yellow was rain-fed agriculture in the observed map, but all four LTM simulations missed these.

Quantity errors by climate simulation box are summarized in Figure 7. Of the 1989 of the 36 km \( \times 36 \) km climate simulation grids, approximately 37% (about 700) of the grid cells in the RAMS domain have a perfect match of the number of rain-fed agriculture cells produced by the LTM simulations and contained in the observed. The 1000-cycle LTM simulation produced the most number of climate simulation grids, with a perfect match of rain-fed agricultural cells. A moderate number of climate simulation grids (250 or fewer) have LTM simulations that either overpredicted or underpredicted quantity by 1–49 cells. Fewer than 100 climate simulation grids have more than 500 cells of rain-fed agriculture that were overpredicted by the LTM; this quantity represents a situation where the climate simulation grid has a fractional cover error that approaches or exceeds 50% of the area of one climate simulation grid. Also note that, across all four LTM simulations, the distribution of overprediction and underprediction appears rather similar.

### 3.2. Precipitation departures from coupled LTM-RAMS simulations

We averaged the annual precipitation across all climate simulation grids for each of the four LTM-RAMS simulations and the reference CLIP-RAMS simulation (Table 3). Precipitation averaged between 619 and 626 mm per climate simulation grid for all five land–climate simulations with standard errors around 9 mm per simulation.

We also created scatterplots of the departures in annual precipitation totals between the reference simulation (i.e., CLIP-RAMS) and the four LTM-RAMS simulations against the quantity departures in annual totals of rain-fed agriculture for each of the four LTM-RAMS simulations (Figure 8). Overall, the departure in
Figure 5. (a) A map illustrating TP, TN, FN, and FP for one LTM simulation (100 000 cycles). The 36 km $\times$ 36 km climate simulation domain is placed over this map. National parks and water are not counted in the location and quantity error assessment. (b) A map of all four LTM simulations showing the location of correct (green) and incorrect (red) placement from the LTM. The locations in yellow are where no LTM correctly predicted the occurrence of rain-fed agriculture.
simulated precipitation from the reference simulation does not show any systematic correspondence to departures in areal extent of rain-fed agriculture predicted by the LTMs. A majority of the positive and negative departures in projected areal extent of rain-fed agriculture are associated with near-zero simulated precipitation departures (indicated by dashed red ovals in Figure 8). However, for a specific few grid points, positive departure in projected areal extent of rain-fed agriculture is associated with large positive departures in simulated rainfall (>400 mm) and vice versa.

Maps of the largest precipitation departures, calculated as a percent of change from the LTM-RAMS simulation from the reference simulation, are illustrated in Figure 9a. Note that most of the positive PDVs (orange) in rainfall for LTM-RAMS simulations occur in the northwest corner of the domain; this means that the LTM-RAMS simulations produce less rainfall than the CLIP-RAMS simulation. The LTM-RAMS simulations contain negative PDVs (green) from the reference CLIP-RAMS simulations in central and northwest Tanzania, north of the central rain-fed agricultural belt of Kenya, and in northern Malawi.

Cumulative precipitation domain-average values are shown in Figure 10. Cumulative precipitation domain-average departures increase for all simulations until Julian day 130; the 10 000-training-cycle LTM-RAMS coupled simulation reaches 8-mm total departure in rainfall by this date. Over the next 150 days, departures decrease, although the 1000-cycle LTM-RAMS departure reaches less than 3 mm by Julian day 260; at 10 000 cycles, the coupled simulation does not fall below 5 mm during this time of the year. Anomalies steadily increase for all LTM-RAMS simulations in the last 80–90 days in the simulation year. Thus, although domain averages for precipitation are nearly identical between the five simulations, differences do exist in the spatial (Figure 9a) and temporal (Figure 10) distributions of rainfall.
3.3. Departures of land surface temperature, surface air temperature, soil moisture, and latent heat flux

Surface daily maximum air temperature departures (Figure 11a) for all LTM-RAMS simulations are 1°–3°C warmer than the CLIP-RAMS simulations for the first half of the year. During the latter half of the year, LTM-RAMS simulations exhibited slightly warmer (~1°C) maximum daily air temperatures with several days having maximum air temperatures 1°–2°C cooler than the CLIP-RAMS simulations. Daily minimum surface air temperatures (Figure 11b) for the LTM-RAMS simulations were considerably lower throughout the year, with most days 2°–3°C cooler compared to the CLIP-RAMS reference simulation. The 100-cycle LTM-RAMS simulation exhibited greater departures from the 1000, 10 000, and 100 000 LTM-RAMS reference simulations. These changes are closely related to changes in rain-fed agriculture in semiarid regions.

Domain-averaged 8-day LST anomalies for each of the LTM-RAMS simulations were calculated and plotted by Julian day over the entire year (Figure 12). The largest departures for LST occur early in the year, across all LTM-RAMS simulations, by

<table>
<thead>
<tr>
<th>Simulation</th>
<th>Mean</th>
<th>Standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>CLIP</td>
<td>619.0</td>
<td>9.40</td>
</tr>
<tr>
<td>100</td>
<td>623.6</td>
<td>9.12</td>
</tr>
<tr>
<td>1000</td>
<td>622.3</td>
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<td>100 000</td>
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as much as $-0.2^\circ$C. At midyear, the departures are still negative but are close to $0.0^\circ$C (i.e., they are close to those of the reference CLIP-RAMS simulations). Larger departures occur again during October (around Julian day 300).

We also plotted PDVs for surface layer soil moisture for each of the LTM-RAMS simulations (Figure 13a). All four LTM-RAMS simulations produce the same departure patterns, with increased soil moisture occurring throughout the year but mostly in the first half of the year. The 10 000-cycle LTM-RAMS simulation produced the largest departure consistently over the year; the 1000-cycle LTM-RAMS simulation produced the smallest departure from the CLIP-RAMS simulation in the latest two-thirds of the year. The largest departures of LTM-RAMS simulations from the reference CLIP-RAMS simulation occurred during the long rainy season (February), with departures of 2.5%–3.0% more than the reference simulation.
The PDVs for LHF, plotted over the year, are shown in Figure 13b. PDVs are frequently larger than 2% (in the positive direction) for LHF for the early part of the year, midyear, and some weeks near Julian days 290–306. PDVs that are negative include the first few days during the simulation, midyear, and year’s end. One +11% departure and one −6% departure occurred. However, nearly all of the simulations followed the same anomalous pattern over the year.

The spatial distribution of latent heat flux PDV is shown in Figure 9b. There are several differences with those of precipitation (in Figure 9a). First, positive and negative PDVs for LHF are distributed in the same locations across the simulation domain as those for positive and negative PDVs for precipitation, although they are more scattered in the LHF. Second, fewer large PDVs are located in the southern extent of the simulation domain.

4. Discussion

At coarser resolutions (i.e., the scale of the entire domain and over the entire year of simulation), errors in the LULC specification do not appear to propagate onto the regional climate simulation. Domain averages for precipitation are about the same as the CLIP-RAMS reference simulation (Table 3).
The changes in the spatial distribution of precipitation (Figure 9) were largest in areas of the largest LTM rain-fed agriculture errors. The largest negative departures of rainfall occurred in areas where the LTM underpredicted rain-fed agriculture (Figure 5a). Conversely, where the LTM overpredicted rain-fed agriculture, the largest positive rainfall departures occurred. From an LULC modeling standpoint, overprediction occurred in areas with complex spatial patterns. Underprediction was in unique areas of the simulation (e.g., northeast Congo) where LULC change drivers were possibly poorly represented. Because patterns were similar across all four LTM simulations, it is likely that the land-use change drivers for the Africa region need to be improved.

When each of the four climate variables (Figures 10–13) were examined temporally (as domain averages), differences from the LTM-RAMS simulations with the CLIP-RAMS reference simulation were apparent. For example, domain-average precipitation increases for all LTM-RAMS simulations in the early part of the year; cumulative precipitation difference was at its maximum during the long rainy season. Decreases in the amount of divergence were observed at its maximum during the dry season.

Apparent “drifts” in error propagation were noticed in the time series plots. For example, precipitation departures for the LTM versus observed land-cover prescription within RAMS increased over time through the rainy season (Figure 10). This propagation can be thought of as a feedback between land use affecting surface energy balance and regional hydroclimatology, which ultimately affects regional convection and precipitation. For example, as precipitation departures
increased through the rainy season, the accumulated soil moisture differences start to cause further divergence within coupled simulations run into the future. Thus, seasonal differences depending on land-cover errors and the propagation of those errors triggered a drift of between 3 and 7 mm yr\(^{-1}\) across the domain. This amount

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**Figure 11.** Daily (a) maximum and (b) minimum surface air temperature for each of the four LTM-RAMS simulation departures from the reference CLIP-RAMS simulation. Daily values represent domain averages.
is relatively small. However, given the unequal amounts and distributions of FP and FN (Figure 5a), the magnitudes of these excursions are significantly larger locally.

The magnitude of the errors from the LTM in this simulation is modest compared to errors reported for other land-use/land-cover change models and for past

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**Figure 12.** Daily land surface temperature departures for each LTM-RAMS simulation from the CLIP-RAMS reference simulation. Departures are given in °C.

**Figure 13.** Daily (a) soil moisture and (b) latent heat flux for each of the LTM-RAMS simulations from the CLIP-RAMS reference simulation. Departures for both are given in percentage differences from the reference simulation.
simulations using the LTM. Pontius et al. (Pontius et al. 2008) conducted a comparison of several models used to simulate urban change, deforestation, or agricultural expansion and found that most did not perform better than a rigorous null model of change. An urbanization version of the LTM was part of that study (reported in more detail in Pijanowski et al. 2005), where it was used to predict (during calibration) 2% change in urban at a fairly fine resolution (100 m × 100 m). There, it performed equally as well as a null model. However, the rain-fed agricultural expansion application presented here performed approximately twice as well as those simulations (as reflected in both PCM and AROC values as reported in Pijanowski et al. 2005). What we also found here is that short (e.g., 1000 cycles) training performed as well as long (e.g., 100 000 cycles) training sessions. Even 100 cycles performed remarkably well with goodness-of-fit values for predicting rain-fed agriculture larger than most urban expansion models (cf. Pijanowski et al. 2005). In previous urban expansion modeling (Pijanowski et al. 2005), stopping a training session early produced models with poor goodness-of-fit values. Training to 100 000 cycles or even 1 000 000 cycles was needed to reach a global minimum. It is quite possible that predicting the placement of agriculture in East Africa is easier for the artificial neural networks than is urban placement in the United States. This seems reasonable because agriculture in East Africa is driven by a few predictable drivers, such as rainfall patterns, soils, and topography; urban change in the United States is driven by individual preference, which is quite unpredictable. Therefore, it is likely that the length of training will be dependent on 1) the type of land-use transition that is being simulated and 2) the nature of the drivers of these transitions.

There are a limited number of studies that have diagnosed the effects of land change model errors on climate dynamics [cf. Dirmeyer 2001 with a global/general circulation model (GCM); Stott and Kettleborough 2002; Feddema et al. 2005b; Ray et al. 2010]. Regional climate models are currently too computationally intensive to run at the decadal (or longer) time scales required to fully couple back to land-use models as GCMs can. Because land change models are fully coupled to regional climate models, these errors could have the potential to create a cumulative impact whereby the initial condition errors from the land change model force moisture into another part of the simulation domain; the land change model, if climate inputs are used, would then react to this moisture change and allow for rain-fed agriculture to alter in response over the region. These positive feedback loops could continue with each time step. In probably the closest study to date to ours, Dirmeyer (Dirmeyer 2001) conducted a study of the nature of error propagation from a coupled land–atmosphere model. He focused on the behavior of soil moisture in ensemble runs of a coupled model and found that two different kinds of drift were evident. One such drift was observed in seasonal departures; this was labeled as systematic drift. The second occurred in fast-growing models that are present in the first few days of the simulation. This “incremental drift” was due to the nature of either model or a coupled model system.

This paper builds on an earlier investigation by Ge et al. (Ge et al. 2007) in the same study area where propagation of errors from LULC maps to a regional climate model (e.g., were assessed using an experimental design that was similar but inputs to RAMS are different). Ge et al. (Ge et al. 2007) introduced different levels (10%, 30%, and 50%) of LULC class errors (classes were assigned at random) in
LULC maps forced into RAMS and then assessed spatial and temporal patterns of precipitation compared to a reference simulation with no errors. They found that precipitation increased at the center of the domain and decreased along the edges, particularly over the Democratic Republic of Congo in the western part of the domain, where evergreen forests with low surface albedo exist. Our simulation experiments also demonstrated that errors from a land-use change model could impact several important regional climate simulation results, including precipitation, soil moisture, surface air temperature, and latent heat flux. However, errors from the land-use change model on regional climate precipitation on domain averages were not detected, suggesting that more detailed analyses of spatial and temporal patterns are necessary to determine if error propagation occurs. Spatial distributions of rainfall were different, however, than those of Ge et al. (Ge et al. 2007); in our simulations, increased precipitation occurred in the northwest corner of our simulation, as opposed to the center. This is likely due to the large land change modeling errors that occurred in this area of the simulation domain. This area is unique from the other areas of the simulation domain in that broadleaf forests dominate the landscape: rain-fed agriculture is located only along valley corridors. Failure to predict rain-fed agriculture results in a larger proportion of the landscape being in forest. However, we failed to detect local land–climate interactions because no correlations between land change errors and precipitation deviations by climate simulation grid existed (Figure 8). Thus, more complex, larger-scale interactions between land and climate are likely.

We also detected temporal shifts in precipitation amounts when four coupled LTM-RAMS simulations were compared to a reference CLIP-RAMS simulation. Rainfall amounts during rainy and dry seasons were altered, in many cases reducing precipitation amounts during dry seasons. Reducing precipitation during dry seasons could negatively impact food production (Moore et al. 2011). In general, our results are consistent with those of Ge et al. (Ge et al. 2007) that errors from a land-use map (generated as either random errors or errors from a land change model) can impact precipitation patterns. Ge et al. (Ge et al. 2007) further explored the nature of these interactions by comparing three convection schemes using a nudging experiment. They found that convection schemes and interior nudging can mitigate precipitation differences brought about by any surface boundary forcings on the regional climate model.

Aspects of model configuration like nudging time scales, number of nudging boundary points (Castro et al. 2005), and lateral boundary condition source (Beltrán 2005) can strongly suppress internal dynamics. Spectral nudging (Miguez-Macho et al. 2004) can be used to ameliorate the damping of simulated mesoscale processes, and Weaver et al. (Weaver et al. 2002) have illustrated the primacy of configuring models to address the scales of the processes of interest. This study does not specifically include an exploration of whether nudging effects could subdue or eliminate these processes and feedbacks, but lateral boundary forcings have the capability to suppress error propagation effects within the nudging points and likely within the model interior as well.

It should be noted that errors from a land change model are never randomly dispersed but occur in clumped spatial arrangements (cf. Pontius et al. 2011). Therefore, our analysis and experimental design more explicitly examines the ramifications of error propagation from a land change model to a regional climate model than the design employed by Ge et al. (Ge et al. 2007) does.
In conclusion, errors from a land change model affect the resulting surface energy partitioning, which in turn affects the surface moisture and heat availability, including the entropy through moist static energy and the convective potential energy. These changes within the boundary layer instabilities help trigger convective clouds and convective rainfall, which alters the mount and distribution of rainfall across the domain.

Current modeling efforts (i.e., Earth system models; cf. Clausen et al. 2002) are headed toward increasing complexity along with introducing dynamic landscapes as integral components. Researchers using these models will have to contend with the initial condition of landscape errors as well as additional errors in the updated landscapes from land-use/land-cover change models. We hypothesize that “coupling drift” could locally become a significant source of error in land–climate projections.

Acknowledgments. This study was partially supported by NSF III-XT Grant (0705836), NSF Biocomplexity Grant (0308420), NSF CAREER (ATM 0847472; L. Zhou, A. Bumzai, and E. DeWeaver), NASA LCLUC (G. Gutman), a Department of Education GAANN Fellowship, a Purdue Doctoral Dissertation Completion Grant, and the Department of Forestry and Natural Resources. We thank Amelie Davis, Deepak Ray, and Konstantinos Alexandridis for help in processing the LTM simulations and Burak Pekin for editorial suggestions.

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