Simulated Changes in Northwest U.S. Climate in Response to Amazon Deforestation*

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ABSTRACT

Numerical models have long predicted that the deforestation of the Amazon would lead to large regional changes in precipitation and temperature, but the extratropical effects of deforestation have been a matter of controversy. This paper investigates the simulated impacts of deforestation on the northwest United States December–February climate. Integrations are carried out using the Ocean–Land–Atmosphere Model (OLAM), here run as a variable-resolution atmospheric GCM, configured with three alternative horizontal grid meshes: 1) 25-km characteristic length scale (CLS) over the United States, 50-km CLS over the Andes and Amazon, and 200-km CLS in the far-field; 2) 50-km CLS over the United States, 50-km CLS over the Andes and Amazon, and 200-km CLS in the far-field; and 3) 200-km CLS globally. In the high-resolution simulations, deforestation causes a redistribution of precipitation within the Amazon, accompanied by vorticity and thermal anomalies. These anomalies set up Rossby waves that propagate into the extratropics and impact western North America. Ultimately, Amazon deforestation results in 10%–20% precipitation reductions for the coastal northwest United States and the Sierra Nevada. Snowpack in the Sierra Nevada experiences declines of up to 50%. However, in the coarse-resolution simulations, this mechanism is not resolved and precipitation is not reduced in the northwest United States. These results highlight the need for adequate model resolution in modeling the impacts of Amazon deforestation. It is concluded that the deforestation of the Amazon can act as a driver of regional climate change in the extratropics, including areas of the western United States that are agriculturally important.

1. Introduction

Many numerical models have predicted that Amazon deforestation would lead to local increases in surface temperature and decreases in precipitation (Henderson-Sellers et al. 1993; Lean and Rowntree 1993; Gash and Nobre 1997; Hahmann and Dickinson 1997; Costa and Foley 2000; Gedney and Valdes 2000; Werth and Avissar 2002; Avissar and Werth 2005; Findell et al. 2006; Sampaio et al. 2007; Hasler et al. 2009; Medvigy et al. 2011). Using numerical models, some studies have concluded that Amazon deforestation can impact extratropical climate (Gedney and Valdes 2000; Werth and Avissar 2002; Medvigy et al. 2012); however, other modeling studies have not found a statistically significant response (Findell et al. 2006). Using observations to directly assess extratropical impacts of deforestation is

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extremely difficult because large-scale deforestation has only been occurring for a few decades and thus any signal would be obscured by natural climate variability. Furthermore, the total deforested area in the Amazon may increase by a factor of 2–3 in the next few decades to 40%–60% (Soares-Filho et al. 2006; Walker et al. 2009), and this may lead to a very different climatic response than that arising from the pattern of deforestation that exists today (Ramos da Silva et al. 2008).

It is possible that other climate anomalies can be used to gain insights on the ultimate impacts of Amazon deforestation. El Niño events, for example, arise from the natural variability of tropical climate and bring increased near-surface temperatures and increased convective activity to the eastern tropical Pacific. This situation results in the strengthening and contraction of the Hadley cell and an equatorward shift of the tropospheric zonal jets (Seager et al. 2003, 2005). Midlatitudes are affected by changes in transient eddy momentum fluxes and in the eddy-driven mean meridional circulation that results from changes in the jet (Seager et al. 2005). The northwest United States, including northern California and western Oregon and Washington, is particularly strongly affected. Composite maps show an intensified Aleutian low and ridging high pressure in the Pacific Northwest, which results in warm dry weather in this sector (Ropelewski and Halpert 1987, 1989; Redmond and Koch 1991; Wallace et al. 1992; Cayan 1996). This warm and dry anomaly has important societal and ecological implications, affecting drought, snowpack, and fires (Dai et al. 1998; Enfield et al. 2001; McCabe et al. 2004; Seager et al. 2010).

Previous studies have considered the potential similarities and differences between El Niño and Amazon deforestation. Eltahir and Bras (1993) pointed out that, for both El Niño and Amazon deforestation, near-surface temperature increases might be expected to lead to convergent circulations. In the case of El Niño, increased precipitation leads to increased latent heat release aloft, and this heating reinforces the convergent circulation. In the case of Amazon deforestation, many GCMs have simulated large decreases in precipitation, suggesting reduced latent heat aloft and a competing divergent circulation. This putative difference in latent heat release would distinguish El Niño from Amazon deforestation. However, recent high-resolution modeling studies (Ramos da Silva et al. 2008; Walker et al. 2009; Medvigy et al. 2011) have simulated much smaller precipitation reductions in the Amazon resulting from deforestation. In particular, Medvigy et al. (2011) simulated the Amazon with a 25-km characteristic length scale (CLS) grid mesh and found that reductions in evapotranspiration were nearly balanced by increases in moisture convergence. If this balancing holds, precipitation changes may be small and Amazon deforestation may be more similar to El Niño than previously expected.

Amazon deforestation and El Niño differ in other ways, including the obvious fact that the Amazon is situated to the east and somewhat to the south of the eastern tropical Pacific. However, different historical El Niño events having differences in equatorial sea surface temperature (SST) anomalies have consistently been associated with drying in the northwest United States (Hoerling and Ting 1994; Yu and Zou 2013). This motivates the idea that there will be important similarities between the extratropical responses to El Niño and Amazon deforestation, although we do not necessarily expect them to be exactly the same. This study will focus on the northwest United States because this region is known to be highly sensitive to El Niño.

Analysis of this problem in the context of numerical models is difficult. Many climate models give large underestimates of the climatological precipitation in the Amazon (Randall et al. 2007), and it is uncertain if this would compromise their ability to simulate the impacts of Amazon deforestation. In one recent study, it was shown that simulation of the Amazon hydroclimate markedly improved when the model resolution of the Andes became finer, and that the model captured interannual variability of precipitation in the Amazon only when the Andes were simulated at <100-km resolution (Medvigy et al. 2008). Furthermore, in the United States, the impacts of El Niño are highly regional and may be challenging to resolve with current GCMs. Previous work has shown that adequate resolution of topography is critical for correctly simulating precipitation in the northwest United States (Leung and Qian 2003; Leung et al. 2003a,b; Zhang et al. 2012). For example, Leung et al. (2003a,b) carried out sensitivity analyses and found that a 40-km resolution was adequate for simulating seasonal and interannual precipitation variability in the region. Leung and Qian (2003) compared simulations at 40 and 13 km and found that the simulation of snowpack was greatly improved at the higher resolution, but differences in precipitation biases were small.

The computational problem of carrying out high-resolution simulations becomes more tractable by using a variable-resolution GCM. Variable-resolution GCMs allow for fine resolution in the region of interest with a coarser, more computationally efficient resolution in the far-field. This enables the simulation of regional-scale circulations without the need for lateral boundary conditions, while maintaining a reasonable computational cost (Medvigy et al. 2008, 2010, 2011). In this study, we use the Ocean–Land–Atmosphere Model (OLAM; Walko and Avisser 2008a,b, 2011) variable-resolution GCM to
investigate the impacts of Amazon deforestation on the United States. Unlike past studies, we use locally fine-resolution grid spacing over both North America and South America. Because El Niño has particularly large effects over the United States during winter (e.g., Harrison and Larkin 1998), by analogy our focus is on the December–February (DJF) season. The objectives of this work are to identify the impacts of Amazon deforestation on the northwest United States during DJF, identify relevant mechanisms, and assess the sensitivity of the mechanisms to model resolution.

2. Model simulations

We used the OLAM model (Walko and Avisar 2008a,b, 2011) run as an atmospheric GCM with prescribed SSTs. The model’s ability to simulate Amazon precipitation has already been evaluated by us for different grid configurations (Medvigy et al. 2008, 2010, 2011), interannual variability (Medvigy et al. 2008), decadal averages (Medvigy et al. 2010), and the frequency and intensity of daily rainfall (Medvigy et al. 2011). Amazon deforestation has also previously been simulated with OLAM (Medvigy et al. 2011, 2012). In this study, we carried out multiple pairs of simulations. The pairs of simulations differed only in their grid mesh, whereas the pair members differed in their land cover specification. In our first pair (FINE), the grid mesh had a 50-km CLS over the Andes, most of the Amazon, and also over the contiguous United States (Fig. 1a). This 50-km CLS was previously shown to be adequate for OLAM to simulate South American hydroclimate (Medvigy et al. 2008). The grid mesh gradually expanded to 200 km away from North and South America. Second, we carried out a pair of simulations with the same horizontal grid mesh as FINE but with enhanced vertical resolution (FINEV). Third, we carried out a pair of simulations with the same vertical resolution as FINE but with a more refined horizontal mesh. This pair (XFINE) had a 50-km CLS over the Andes and most of the Amazon and a 25-km CLS over most of the contiguous United States (Fig. 1b). The purpose of the FINEV and XFINE pairs was to evaluate and challenge the conclusions stemming from the FINE pair. Finally, we carried out a coarse pair of simulations (COARSE), in which the entire globe was simulated with a uniform 200-km CLS, which is a typical GCM resolution (Fig. 1c). This pair would be most comparable to previous investigations of the extratropical impacts of Amazon deforestation.

The FINE, XFINE, and COARSE simulations used a Cartesian vertical grid consisting of 53 levels, with the grid spacing stretching from 200 m near the surface to 2 km near the model top at 45 km. The FINEV simulations also used a Cartesian vertical grid but in this case there were 74 levels, with the grid spacing stretching from 100 m near the surface to 2 km near the model top at 45 km. As a postprocessing step, upper-air variables were interpolated to pressure levels. For the convective parameterization, we used the Eta version of the Kain–Fritsch scheme (Kain 2004). All other parameterizations are the same as those used in Medvigy et al. (2011). (The “namelist” file that contains all the necessary information to configure our simulations is available as supplemental material at the Journals Online website: http://dx.doi.org/10.1175/JCLI-D-12-00775.s1.)

In each pair, the two pair members correspond to two land cover scenarios, tagged as forested (FOR) and deforested (DEF). These land cover scenarios are described in detail in Medvigy et al. (2011) and are only briefly described here. In our FOR runs, each land grid

![OLAM grid mesh and topography (m) for the different simulations. All simulations were global, but the panels show only the Americas for clarity.](http://dx.doi.org/10.1175/JCLI-D-12-00775.s1)
cell is assigned a single land cover classification according to the Olson Global Ecosystem framework (Olson 1994a,b), which was based on satellite imagery from 1992/93. About 10% of the Amazon sector is classified as agriculture or short grass in FOR. Our corresponding DEF runs are identical to the corresponding FOR runs in every way except land cover classification. The DEF runs, meant to represent the total deforestation of the Amazon, classes all land grid cells between 15°S–0° and 75°–49°W (boxed areas in Fig. 1) as deforested land cover. The land surface and vegetation properties of these deforested grid cells are prescribed according to in situ measurements at pasture sites (Gash and Nobre 1997) and have been tested in previous studies (Gandu et al. 2004; Avisar and Werth 2005; Ramos da Silva et al. 2008; Hasler et al. 2009; Medvigy et al. 2011). A more sophisticated treatment might distinguish between pasture, soy, and cultivation of other crops, but we expect differences between these types to be much smaller than the differences between tropical forest and pasture (Sampaio et al. 2007). The naming convention that we use for our simulations combines the grid mesh identifier (FINE, FINEV, XFINE, or COARSE) by itself, as well as for the ensemble consisting of the FINE, FINEV, and the XFINE pairs (note that the COARSE pair was excluded for reasons that will become evident later). All statistical

Atmospheric and soil initial conditions were prescribed from the National Centers for Environmental Prediction (NCEP) reanalysis from 0000 UTC 1 October 1996 (Kalnay et al. 1996). All simulations were forced with weekly 1° SSTs (Reynolds et al. 2002) and sea ice extent from the NCEP reanalysis (Kalnay et al. 1996). The CO2 and other greenhouse gas concentrations were held fixed throughout all the simulations at current-day levels to enable us to isolate the effects of deforestation. We simulated the period from 1 October 1996 to 1 April 2012. To estimate the amount of time required to spin up the soil moisture, we carried out preliminary simulations similar to FINE-FOR and FINE-DEF but driven with climatological SSTs. We computed the average soil moisture in the top 50 cm of soil in the deforested sector (15°S–0°, 75°–49°W). The time series of this quantity is shown in Fig. 2a. Soil water in this layer increases for the first ~180 days of the simulation, but then it oscillates about 20–21 cm. The maxima occur near the end of the wet season, and the minima occur near the end of the dry season. The amplitude of the oscillation is about 2 cm. A similar pattern is seen in the deforested simulation, except that the amplitude of the seasonal oscillation is greater. In addition, deforestation induces an anomalous spatial pattern (Fig. 2b). The soil in the northwest and central Amazon is somewhat drier in the deforested simulation than in the forested simulation, and the soil in the northeast and southeast Amazon is somewhat wetter.

Based on these spinup results, we discarded the first 26 months of each simulation (October 1996–November 1998), leaving 14 years for analysis. The 1998–2012 period includes a wide variety of sea surface temperature configurations (though by no means all possible configurations). This period includes moderate El Niños in 2002 and 2009 based on the Oceanic Niño index (ONI; obtained at http://www.cpc.ncep.noaa.gov/products/analysis_monitoring/ensoyears.shtml), moderate-to-strong La Niñas in 1999, 2007, and 2010 based on the ONI, positive and negative anomalies of the Pacific decadal oscillation (data obtained from http://jisao.washington.edu/pdo/), and sea surface temperature variability in the Atlantic (Fig. 8 of Zeng et al. 2008). In this paper, we limited our analysis to DJF, though output variables from the other months were saved to disk and are available for future analyses.

We performed a series of statistical tests to evaluate the significance of differences between the DEF and FOR simulations. The 95% confidence level is taken as the threshold for the statistical significance throughout this paper. Tests were performed for each pair (FINE, FINEV, XFINE, or COARSE) by itself, as well as for the ensemble consisting of the FINE, FINEV, and the XFINE pairs (note that the COARSE pair was excluded for reasons that will become evident later). All statistical
tests are conducted in R (R Development Core Team 2008). A t test can be used to test the null hypothesis that the means from the DEF and FOR simulations are equal, provided that the DEF and FOR samples are independent and normally distributed. If the normality assumption does not hold, a nonparametric test such as the Wilcoxon signed-rank test (wilcox.test in R; Hollander and Wolfe 1999) may be used instead of the t test. The null hypothesis of the Wilcoxon signed-rank test is that the median difference between the DEF and FOR samples is zero. We used the Shapiro–Wilk test (shapiro.test in R; Royston 1982) to test for normality. We found that the normality assumption was violated for as many as 15%–20% of the grid cells, and so we conservatively adopted the Wilcoxon signed-rank test as our test of choice in this paper. We used the Ljung–Box test (Box.test in R; Ljung and Box 1978) to test for independence. In no case did we find that the assumption of independence was violated for more than 5% of the grid cells, and so we adopted independence as a generally reasonable assumption.

3. Results

a. Model evaluation for North America

We limited our model evaluation to North America because model evaluation for South America has already been carried out (Medvigy et al. 2008, 2010, 2011, 2012). Precipitation and near-surface temperature are evaluated using the Princeton Global Forcings (PGF) dataset at 0.5° resolution (Sheffield et al. 2006). This dataset blends surface and satellite observations with reanalysis and is available for 1948–2008. Because our study focuses on DJF quantities and our post-spinup begins in December 1998, we defined a climatological winter daily precipitation rate and daily temperature by averaging the daily values of these quantities over all days in December, January, and February within the period December 1998 through December 2008. We constructed climatological averages for our FINE-FOR, FINEV-FOR, XFINE-FOR, and COARSE-FOR simulations for this same time period. For consistency with the PGF dataset, we excluded our simulations of 2009–12 from these comparisons to the PGF dataset. However, our subsequent analyses do correspond to the full post-spinup period (1 December 1998 through 1 April 2012).

The PGF precipitation dataset (Fig. 3a) is generally well represented by the FINE-FOR (Fig. 3b) simulation. The model captures such features as the rainfall maxima along coastal British Columbia, Washington, northwest California, and the Sierra Nevada. Precipitation is generally overestimated in the rain shadow on the eastern side of the Rockies and is underestimated along the east coast of North America. The FINEV-FOR simulation is very similar to FINE-FOR in the western United States but gives slightly improved precipitation estimates in the Midwest (Fig. 3c). The XFINE-FOR simulation (Fig. 3d) is a slightly better match to the PGF data than FINE-FOR in the Appalachian Mountain region. The COARSE-FOR simulation generally gives lower rainfall amounts than the other simulations, leading to underprediction of the rainfall maximum on the west coast and exacerbating the underprediction on the east coast (Fig. 3e). However, it gives a better simulation of the low precipitation values in the rain shadow of the Rockies.
The PGF temperature dataset (Fig. 4a) was also well simulated by FINE-FOR (Fig. 4b) for most of the United States. However, one notable bias occurred for parts of the Great Basin, where the model was too cool. This is potentially related to biases in the 1° SST data, especially near relatively small-scale features like the Gulf of California. Most of the nearby offshore temperatures were also lower in the simulations than in the PGF, and advection of this relatively cool air may be biasing the model over land. A second bias was that the model was too warm in eastern Canada. Temperature biases in FINEV-FOR (Fig. 4c), XFINE-FOR (Fig. 4d), and COARSE-FOR (Fig. 4e) were similar to those in FINE-FOR.

The Pacific Northwest relies heavily on winter snowfall to provide water for the summer months because there is relatively little summer precipitation. To measure snow water equivalent (SWE), the U.S. Department of Agriculture’s Natural Resources Conservation Service maintains a network of snow courses throughout Oregon, Washington, Idaho, and other western states. The earliest records go back to 1915. The California Department of Water Resources has an independent network of snow courses. Details on the measurements have been previously published (Clark et al. 2001; McCabe and Dettinger 2002). Mote (2003) reported that SWE on 1 April has typically ranged from 40 to 50 cm for the past ~25 years for a region that includes mountainous areas of Oregon, Washington, and Idaho. In California, Howat and Tulaczyk (2005) found a peak SWE of about 120 cm along much of the central spine of the Sierra Nevada.

We compared these observation-based numbers to values simulated by OLAM. Our intentions here are to explore the effects of model resolution and compare typical simulated values to the observations. A detailed spatiotemporal analysis may require simulations at finer characteristic length scales than those simulated here, as previous studies with other models have shown that snowpack was underestimated at 40- (Leung and Qian 2003) and 27-km (Pavelsky et al. 2011) resolution. However, at equivalent resolution, we expected the “shaved cell” method in OLAM (Walko and Avissar 2008b) would represent terrain features better than the terrain-following coordinates that have typically been used in previous studies, and it is not known exactly how this will affect simulations of snowpack.
We consider the higher-resolution simulations first. The corresponding 1 April SWE simulated in XFINE-FOR averaged over 1999–2012 is shown in Fig. 5a. Values in the northwest United States are generally consistent with the observed values and ranged from about 65 cm in the southern Cascades to about 20 cm in northwest Oregon to about 50 cm in western Idaho. Peak values along the Sierra Nevada reached 100–120 cm and are also consistent with observations. The simulation with enhanced vertical resolution, FINEV-FOR, also gave reasonable results for central California (Fig. 5b) but gave less SWE than XFINE-FOR in other sectors. In contrast, simulated values from FINE-FOR were much lower (Fig. 5c), which is unsurprising given its coarser representation of topography (Leung and Qian 2003; Pavelsky et al. 2011). Peak SWE in southern Oregon and the Sierra Nevada reached only 50 cm in FINE-FOR. Finally, in COARSE-FOR simulated SWE was less than 35 cm throughout the western United States and was negligible in California (Fig. 5d). These results show that the quality of the simulation of snowpack degrades sharply with coarsening model resolution.

To summarize, we find that the simulated SWE was dramatically larger (and closer to observations) for XFINE-FOR and FINEV-FOR than for FINE-FOR. In contrast, precipitation differences between these three simulations were modest. We therefore focus our analysis on the FINEV and XFINE simulations of SWE but consider the FINE, FINEV, and XFINE simulations for precipitation and other hydroclimatic variables.

b. Impacts of deforestation on surface climate

We found that FINE-DEF had a large, statistically significant precipitation deficit relative to FINE-FOR throughout the northwest United States (Fig. 6a). Precipitation differences were typically 10%–20% (or 1–2 mm day$^{-1}$) and reached up to 30%. There was also a comparable precipitation deficit along the western slopes of the Sierra Nevada range, but this difference was not statistically significant at the 95% confidence level. Statistically significant precipitation reductions occurred in other locations (e.g., off the east coast of the United States), but the magnitudes of these reductions are much smaller than the reductions in the northwest United States.

With any significance test, it is expected that some percentage of the field will pass the test merely by chance (in our case 5%). It is therefore critical to check for consistency by comparing the results of the FINE simulation pair to the other simulation pairs. In the XFINE pair, XFINE-DEF had large precipitation
deficits relative to XFINE-FOR in the northwest United States, and these precipitation deficits were statistically significant near the Sierra Nevada as well as in Oregon and Washington (Fig. 6b). Differences between FINEV-DEF and FINEV-FOR (not shown) were very similar to the differences between FINE-DEF and FINE-FOR. Finally, in the combined ensemble consisting of FINE, FINEV, and XFINE, there is a region with statistically significant precipitation deficits encompassing Washington, Oregon, Idaho, northern California, and Nevada (Fig. 6c). That the northwest United States signal is present in all simulation pairs as well as in the combined ensemble provides evidence that Amazon deforestation impacts precipitation in the northwest United States. The combined ensemble also has statistically significant precipitation changes in other locations, including just north of Minnesota. However, this signal is much smaller in magnitude than the signal in the northwest United States, and we will not consider it further.

Our analysis of the COARSE simulation pair led to very different results (Fig. 6d). In this case, COARSE-DEF actually had more precipitation than COARSE-FOR in the northwest United States, although this difference was not statistically significant. The effects of model resolution will be discussed in more detail below.
We also computed changes in other important hydroclimatic variables, including evapotranspiration, moisture convergence, and temperature. The precipitation deficits in the western United States occurred almost entirely because of changes in moisture convergence in the FINE simulation pair (Fig. 7a), and changes in evapotranspiration were small for all grid cells (Fig. 7b). Similar results held for the FINEV and XFINE simulation pairs (not shown). In the northwest United States, FINE-DEF was generally about 0.5°C cooler than FINE-FOR (Fig. 7c). However, these changes were generally not statistically significant in the locations where the largest precipitation changes occurred, including western Washington, western Oregon, and California. Temperature differences between XFINE-DEF and XFINE-FOR were small, generally having a magnitude of less than 0.2°C in the western United States (Fig. 7d). Temperature differences from this simulation pair were statistically significant only in the southeast United States. Temperature differences between FINEV-DEF and FINEV-FOR
and between COARSE-DEF and COARSE-FOR were also small and generally not statistically significant (not shown).

Given the large decreases in precipitation and relatively small changes in temperature in the XFINE simulation pair, we expected that SWE would decrease in the mountains of the northwest United States and the Sierra Nevada. The 1 April SWE averaged over 1999–2012 from XFINE-FOR and XFINE-DEF are shown in Figs. 5a and 5e, respectively. SWE from XFINE-DEF was much lower than in XFINE-FOR. Values over the central Sierra Nevada were reduced by about half, with values in XFINE-DEF generally ranging from 30 to 90 cm. In XFINE-DEF, the snowpack was eliminated from parts of northern California and was reduced by over 50% in southern Oregon, but areas farther north and east were not strongly affected. Similar results were obtained for the FINEV simulation pair, with FINEV-FOR (Fig. 5b) having much more snowpack than FINEV-DEF (Fig. 5f).
c. Comparison to El Niño

The simulated reductions in precipitation in the northwest United States resulted from Amazon deforestation, but similar precipitation anomalies are commonly observed during El Niño events (Redmond and Koch 1991). We now pursue this analogy a bit further. During DJF, precipitation in the northwest United States is strongly controlled by the jet stream position. In El Niño years, the jet has a tendency to split into two branches, with one over the Queen Charlotte Islands and the other over the southern tier of the United States (Yu and Zou 2013). This directs storms away from the northwest United States and toward British Columbia and the southwest United States. In addition, a deepened Aleutian low and warm SSTs off the coast of California facilitate low-level advection of warm moist air to southern California and the southwest United States (Seager et al. 2005). Recent work has distinguished between different types of El Niños depending on the longitude of the tropical heating anomaly (e.g., Ashok et al. 2007), but the northwest United States is relatively dry regardless of whether the warm anomaly is over the central tropical Pacific or eastern tropical Pacific.

In our FINE simulations, deforestation resulted in positive anomalies of 1–3 m s\(^{-1}\) in the 250-hPa zonal winds for northern British Columbia and northern Mexico, while negative anomalies of 2–4 m s\(^{-1}\) were evident over the northwest United States (Fig. 8a). These changes were statistically significant, but hatching was omitted from the figure to reduce visual clutter. Thus, as with El Niño, deforestation modifies the jet stream so as to divert storms away from the northwest United States. In the XFINE simulation pair, deforestation also causes a reduction in 250-hPa zonal wind speed over the western United States (Fig. 8b). However, the magnitudes of the changes are about 1 m s\(^{-1}\) smaller and are shifted to the south relative to the FINE simulation pair. The FINEV simulation pair (not shown) was very similar to the FINE simulation pair.

Unlike typical El Niño events, deforestation does not result in a wet anomaly over the southwest United States (Figs. 6a–c). Our simulations show a decrease in convergence of the 800-hPa horizontal wind over the northwest United States resulting from deforestation and very little change in low-level convergence over the southwest United States (Fig. 9a). In addition, the northwest United States and California both have negative anomalies in low-level humidity (Fig. 9b). In contrast, during a typical El Niño, there are often positive humidity anomalies over the southwest United States due to anomalously warm SSTs off the coast (Zhang et al. 2012). Because our simulations used the same SSTs for forested and deforested runs, we were unable to determine how SSTs off the

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Fig. 8. The 250-hPa winds and wind differences. (a) The arrows show the mean DJF winds from FINE-FOR and the colors show the zonal wind anomalies (DEF minus FOR; m s\(^{-1}\)). (b) As in (a), but for the XFINE simulations.
North American coast would be affected by Amazon deforestation. The negative humidity anomalies that we simulated in response to deforestation were associated with strong midlevel subsidence over the western United States (Fig. 9c). However, in the eastern subtropical Pacific at about 10°N, positive vertical velocity and low-level humidity anomalies are simulated. Mo and Higgins (1998) pointed out that enhanced convection in this sector can lead to subsidence and suppressed precipitation over California, even during El Niño years.

It has also been suggested that the southeast United States experiences relatively cool and wet conditions during El Niño winters (Ropelewski and Halpert 1986, 1987). If this is the case, then we might expect similar anomalies in our deforestation simulations. We found that deforestation did result in slightly reduced temperatures in the southeast United States, but this signal was not significant in all simulations (Figs. 7c,d). Furthermore, in part of Florida only, we also found a statistically significant precipitation decrease in our combined (FINE, FINEV, and XFINE) ensemble (Fig. 6c).

These small anomalies are consistent with the idea that there are factors besides El Niño that exert strong controls on southeast United States winter climate. Katz et al. (2003) investigated the correlations between southeast United States climate and the El Niño–Southern Oscillation, the Pacific–North America pattern, the North Atlantic Oscillation, and the Bermuda high, and concluded that the Bermuda high (Davis et al. 1997) had the strongest correlation with winter temperature and precipitation in the southeast United States. As an index for the Bermuda high, Katz et al. (2003) used the seasonally averaged Bermuda minus New Orleans pressure difference, which indicates the approximate position of the western edge of the Atlantic subtropical high. Deforestation produced very small changes in this index (less than 0.4 hPa in all simulation pairs).

d. Planetary-scale impacts

Previous modeling experiments have demonstrated how a tropical heating anomaly can act as a source of Rossby waves that can propagate from the tropics to the extratropics. Hoskins and Karoly (1981) used linearized vorticity and potential temperature equations to argue that a thermal forcing in the tropics would generate strong poleward velocity anomalies. This was confirmed in their model simulations, which showed height perturbations that arced across great circle paths from the tropics into higher latitudes. Because the mean absolute vorticity and the associated stretching increase as the heating and divergence anomalies are moved poleward, the amplitude of the wave train can also increase as it moves poleward (Held et al. 2002). Subsequent studies have obtained similar results; see Held et al. (2002) for a review. Furthermore, GCM studies have found that extratropical responses to tropical heating tend to be enhanced in the North Pacific and over North America (Ting and Yu 1998; Hoerling and Kumar 2002).

We now illustrate how this plays out in our simulations. In our FINE simulation pair, deforestation resulted in reduced precipitation of about 2 mm day\(^{-1}\) toward the north of the deforested region (Fig. 10a). This precipitation reduction was partially balanced by precipitation increases in the southwestern part of the deforested region and just to the northeast of the deforested region. There was little impact on the easternmost portion of the deforested region. Medvigy et al. (2011) also found spatial shifts in the Amazon precipitation in response to
deforestation. The corresponding spatial pattern in the XFINE simulations was similar, although the strength of the signal was somewhat weaker (Fig. 10b). The precipitation changes in FINEV were also similar to those of FINE, except that there were larger reductions in precipitation near 5°S, 60°W and smaller reductions near 0°S, 70°W (Fig. 10c). However, the differences between FINE, FINEV, and XFINE were much smaller than the differences between any of these pairs and the COARSE simulation pair (Fig. 10d). In the COARSE simulations, there were more widespread precipitation reductions in the north and northwest of the deforested area. There were also stronger and more widespread precipitation increases, but these fell more toward the southeast of the deforested area than in the other simulation pairs.

These precipitation changes were accompanied by changes in the dynamics. In all simulation pairs, we found negative 500-hPa vertical velocity anomalies in the northern part of the Amazon that experienced precipitation reductions and positive 500-hPa vertical velocity anomalies in the southern part of the Amazon that experienced precipitation increases (Fig. 11). However, this circulation was modulated by the prevailing easterlies. The easterlies have relatively strong vertical shear, especially in the western part of the basin, because of topography. This is illustrated in Fig. 12 for FINE-FOR.
for simplicity, we will illustrate the remainder of our results for the FINE simulation pair only, except where prominent differences between simulation pairs exist. Combined with the latitudinal gradients in vertical velocity, the wind shear generates relative vorticity anomalies that can then propagate poleward according to the mechanism of Hoskins and Karoly (1981). In our FINE simulation pair, examination of the deforestation-induced changes in the 250- (Fig. 13a) and 850-hPa (Fig. 13b) wind fields indeed reveal that wave trains were excited in both hemispheres, with the higher-amplitude wave train in the Northern (winter) Hemisphere.

We also found changes in the thermodynamics. As reported in many previous studies, we found that deforestation acted to increase the sensible heat flux and the near-surface temperature in the deforested region (Figs. 14a,b). Tropospheric diabatic heating rates are also of interest, but they are not written to disk in the default version of OLAM. To investigate these, we repeated our simulation of December 2000 through February 2001 for the FINE-DEF and FINE-FOR. This period was chosen because the Amazon precipitation anomaly during this interval was more highly correlated \( (r = 0.52) \) with the 14-yr DJF average anomaly than that of any other single DJF period. During this period, changes in column-integrated diabatic heating (Fig. 14c) were strongly collocated with changes in precipitation and were most influenced by contributions from the
cumulus parameterization and from sensible heating at the surface. Changes in the vertical distribution of diabatic heating were generally positive near the surface over the deforested region (due to changes in sensible heating) and negative between 500 and 1500 m. At higher levels, the spatial pattern of diabatic heating was very similar to the spatial pattern of the column average (Fig. 14c).

These changes bear marked similarities to the GCM experiments of Jin and Hoskins (1995), who analyzed the quasi-steady extratropical response to a thermal source over the Amazon. In particular, they found an upper-level negative vorticity anomaly in the northern vicinity of their heating source and a positive vorticity anomaly in the southern vicinity of their heating source. The reverse configuration was realized at low levels. These anomalies generated Rossby wave trains that propagated into both hemispheres, and North America in particular was affected. We obtained very similar results in our simulations. Our corresponding southern upper-level anomaly is located south of the deforested region and spans approximately from 90° to 40°W (Fig. 13a). Our corresponding lower-level northern anomaly is evident in the northern part of the deforested area, though our corresponding lower-level southern anomaly, just south of the deforested area, is weak (Fig. 13b). Results from the XFINE simulation pair (Figs. 13c,d) are broadly similar, with the main differences being slightly stronger lower-level anomalies and slightly weaker upper-level anomalies in the deforested sector.

In the COARSE simulation pair, deforestation also generated wave trains (Fig. 15). However, over South America the 250-hPa velocity anomalies (Fig. 15a) were different from the other simulation pairs (Figs. 13a,c). And in the extratropics, the wave trains from COARSE were nearly 180° out of phase with those from FINE, XFINE, and FINEV. To facilitate quantitative comparison of simulations on different grid meshes, we interpolated the DEF minus FOR changes in the 250-hPa meridional winds from FINE, XFINE, FINEV, and COARSE simulation pairs onto a common 3° longitude by 3° latitude grid. We then computed the Spearman’s ρ correlation coefficients between FINE and XFINE and between FINE and COARSE for all grid cells between 30° and 48°N. We found a positive correlation (ρ = 0.27; $p < 1 \times 10^{-5}$) between FINE and XFINE and a negative correlation (ρ = −0.28; $p < 1 \times 10^{-5}$) between FINE and COARSE. Unsurprisingly then, the COARSE simulation pair gave a (not statistically significant) increase in precipitation for northwestern North America, rather than a decrease (Fig. 6d). These differences between COARSE and FINE are consistent with previous work that underlined the importance of a high-resolution representation of topography for the simulation of Amazon precipitation (Medvigy et al. 2008) and local impacts of deforestation (Ramos da Silva et al. 2008; Medvigy et al. 2011).

Figure 13 also suggests interesting differences between the FINE and XFINE configuration in the Southern Hemisphere extratropics. To assess whether there were robust changes in the 250-hPa meridional wind in both hemispheres, we combined the FINE, XFINE, and FINEV
simulation pairs into a single ensemble. Each ensemble member consisted of the 250-hPa meridional wind difference (DEF minus FOR) for a particular year and grid configuration. Because each simulation had 14 years of post-spinup output, this led to a total sample size of 42 configuration years for each grid cell. Next, we used the Wilcoxon signed-rank test for each grid cell to determine the statistical significance that its median difference was different from zero. The resulting $p$ values (Fig. 16) suggest two wave trains emanating out of the Amazon, one in the Northern Hemisphere and one in the Southern Hemisphere. As expected, there is a clear

![Diagram](image_url)
feature over North America. Based on these results, we conclude that there are robust wave train signals in both the Northern and Southern Hemispheres in our FINE, XFINE, and FINEV sets of simulations.

4. Discussion and conclusions

a. Comparison to previous deforestation and El Niño studies

This work has focused on some potential extratropical responses to the complete deforestation of the Amazon. We found that precipitation in the northwest United States and in parts of California was strongly reduced during DJF because of deforestation. Such an effect has not been seen in previous analyses (Gedney and Valdes 2000; Werth and Avissar 2002; Avissar and Werth 2005; Findell et al. 2006; Hasler et al. 2009). Model resolution is a critical difference between our simulations and previous simulations. Whereas previous work was carried out at resolutions of about 200 km, we studied simulations that used a mesh with a characteristic length scale (CLS) of 25–50 km for much of North and South

![Diagram](image1)

**FIG. 14.** Changes in heating (FINE-DEF minus FINE-FOR) resulting from deforestation. (a) Change in sensible heat flux (W m$^{-2}$), averaged over 14 DJF periods. (b) Change in near-surface temperature (°C), averaged over 14 DJF periods. (c) Change in column-integrated diabatic heating rate (W m$^{-2}$), December 1999–March 2000 only. The region of Amazon deforestation is boxed.

![Diagram](image2)

**FIG. 15.** Deforestation-induced wind changes (DEF minus FOR) in the COARSE simulation pair. The arrows show the changes in the wind vector and the colors show the changes in the meridional component of the wind (m s$^{-1}$): (a) 250 and (b) 850 hPa.
America. This permitted the simulation of regional-scale circulations in the Amazon that are important for the propagation of waves from the tropics to the extratropics. When we ran simulations at a CLS typical of previous studies, the wave trains resulting from deforestation had a different phase and their impacts on the northwest United States were strongly reduced. This study supports the suggestion made by Avissar and Werth (2005) that substantial similarities may exist between the extratropical effects of Amazon deforestation and of El Niño. A conceptual diagram illustrating our mechanism is given in Fig. 17. Like El Niño, we find that Amazon deforestation generates vorticity and diabatic heating anomalies, and these factors generate Rossby wave trains in both hemispheres. The implication of this for western North America is that the jet shifts south and negative vertical velocity anomalies develop. Western Washington and Oregon receive much less precipitation. However, the extratropical signature of deforestation extends farther south than that of El Niño, and consequently the Sierra Nevada are also strongly impacted by deforestation. Furthermore, because temperatures do not drastically change, the snowpack on the Sierra Nevada is markedly reduced.

b. Benefits and costs associated with different resolutions

Although there were some differences between the FINE, XFINE, and FINEV simulation results, we emphasize that the basic concepts in Fig. 17, including the precipitation reduction in the northwest United States in response to Amazon deforestation, held for all 3 simulations pairs. When compared to precipitation and temperature observations, the distinctions between FINE, FINEV, and XFINE were relatively small, though FINEV did a slightly better job of simulating precipitation in the Midwest (Figs. 3, 4). However, for snow water equivalent, FINEV and XFINE were both more realistic than FINE. In response to Amazon deforestation, large reductions in snow water equivalent were simulated in both the XFINE and FINEV pairs (Fig. 5).

Our results also highlight some advantages of a variable-resolution model. The FINE and FINEV configurations include only 21% of the number of grid cells that would be required in a simulation that used 50-km CLS globally (Table 1), representing substantial computational savings while still achieving fine resolution in regions of interest. In terms of the total number of grid
points, XFINE is 17% more computationally expensive than FINE (Table 1). However, it also requires a shorter time step, so that the total cost of XFINE is 1.76 times that of FINE. In contrast, the total cost of FINEV is only 1.23 times that of FINE. This suggests that FINEV may be the best computational bargain of the three, especially if one is interested in snow water equivalent. However, these results include only a small number of grid configurations, and further analysis should be done at different combinations of finer horizontal and vertical resolution.

c. Broader implications of this study

To the extent that our simulations are consistent with reality, the deforestation of the Amazon will have enormous consequences for the irrigation-fed agriculture in California. In the United States, agriculture and food sectors contribute 4.8% of the gross domestic product and are the source of 15.8 million jobs nationwide. California has been the nation’s number one state for food and dairy production during the past 50 years. The ability of California to maintain its large output is directly related to the availability of irrigation water (Draper et al. 2003). Our work complements the many previous studies that have investigated the impact of climate warming on California hydrology (Lettenmaier and Gan 1990; Kim et al. 2002; Maurer 2007). In response to increases in greenhouse gases, climate models have consistently simulated a warmer, slightly wetter California, with overall reduced end-of-winter snowpack. Our simulations indicate that Amazon deforestation would likely exacerbate this snowpack reduction.

Natural ecosystems would also be strongly affected by the rainfall reductions simulated here. In the relatively wet forests of western Oregon and Washington, fires are relatively rare. However, fuel accumulations are high, and when fires do occur, they can lead to complete stand replacement (Mote et al. 2003). In California, the California Floristic Province has been designated as 1 of 33 global biodiversity hotspots as a result of its large number of native and endemic species (Myers et al. 2000). Drawdown of freshwater resources is one of the principal threats facing the area.

d. Future research needs

This study represents an initial effort at using a locally high-resolution GCM to investigate intercontinental effects of Amazon deforestation. Limits on computational resources required us to balance many factors in determining our simulation design; including grid resolution, simulation length, and land cover scenarios. Previous modeling studies of Amazon deforestation can generally be characterized as long term (more than a decade) at coarse resolution (>150 km) or short term (less than a year) at fine resolution (<50 km). Our study fills an important niche because critical regions of North and South America were simulated at <50-km resolution and the simulation length also exceeded a decade. However, the SST configurations realized in 1998–2012 are still limited, and future work should include longer-term simulations that include a wider range of SST configurations.

The extratropical response to tropical forcing depends on the magnitude, location, and vertical distribution of the forcing, and so it is important to consider how errors in simulating the forcing might affect the response. In terms of magnitudes, it is expected that the response would simply scale in proportion to the source (Held et al. 2002). Previous studies of responses to El Niños can help inform the sensitivity to location of the source. Notably, the northwest United States is anomalously dry both for El Niño events corresponding to heating in the central Pacific and for El Niño events corresponding to heating in the eastern Pacific (Yu and Zou 2013). In this study, we find that the Northwest also becomes anomalously dry when a deforested Amazon acts as a heat source.
The vertical distribution of the source also affects the response; for example, a source confined near the surface is not expected to generate Rossby waves capable of propagating out of the tropics (Hoskins and Karoly 1981). In our simulations, we find broadly similar impacts in the tropics and extratropics for our FINE, XFINE, and FINEV simulations, suggesting that our results are robust within the context of our model and not particularly sensitive to vertical resolution. However, like most GCMs, our model uses parameterizations for cumulus convection, turbulence, radiation, and microphysics. Errors in these parameterizations can potentially affect the magnitude of the upper-level source and hence the Rossby wave generation. One can envision several ways to further test the robustness of our results. First, it would be relatively straightforward (but computationally expensive) to rerun the simulations with perturbed values for key parameters in the physics parameterizations. Second, it would be possible—but again, computationally expensive—to run OLAM at much finer resolutions. Ideally, we would like to simulate the deforested sector with resolution sufficient to adequately resolve convection in the Amazon (~1 km; Ramos da Silva and Avissar 2006). Although it is not obvious that it would be feasible to run decadal-scale simulations at this fine of a resolution in the near future, seasonal simulations at this resolution may be possible. An alternative way forward would be to run OLAM with a multiscale modeling system or superparameterization (Tao et al. 2009). We have run some preliminary tests of this (Walko et al. 2011) and work is ongoing.

Future work should also investigate other mechanisms whereby deforestation can affect climate. For example, the fires that frequently accompany deforestation affect aerosol concentrations. Aerosols can intensify updrafts (Williams et al. 2002; Andreade et al. 2004) and potentially increase the vigor of individual convective events even if annual average rainfall decreases. In an analysis of satellite-based data over partially deforested areas of the Amazon, Ten Hoeve et al. (2011) found that cloud fraction more strongly increased aerosol optical depth over deforested land than over deforested land. Aerosol absorption of radiation may also be important, and this effect is expected to reduce cloud fraction and cloud height, especially for small shallow clouds (Koren et al. 2008).

Our experimental design was simplified in that it considered the complete deforestation of the Amazon. Presumably, this would lead to the strongest extratropical signal and would be the easiest to detect given the constraints of limited computational resources. However, now that this work has demonstrated a reason to suspect a signal in the northwest United States, it will be important to carry out new simulations including less aggressive deforestation scenarios. About 40% of the Brazilian Amazon is in some form of a protected area (Walker et al. 2009), and deforestation may be less severe in these areas. Furthermore, actual future spatial patterns of deforestation may be complex (Soares-Filho et al. 2006) and induce local- or regional-scale circulations. Thus, future analyses should consider more realistic spatial patterns of deforestation.

Our study raises several other questions that should be explored in future research. First, our simulations used a relatively coarse resolution over most of the world outside of the Americas. Pursuing the analogy of Amazon deforestation with El Niño, additional Amazon deforestation experiments should be carried out using model grid meshes with fine resolution over other areas known to be sensitive to El Niño. Second, our model simulations were designed to isolate the impacts of Amazon deforestation, and so they did not consider the effects of changes in greenhouse gases. Assessing the combined effect of Amazon deforestation and greenhouse gas increases on the northwest United States and California should be a priority. Third, there are a number of physical processes that were either parameterized, like cumulus convection, or not represented at all, like fires, aerosol effects, and the dynamic responses of terrestrial ecosystems. These are all processes that merit future attention. Fourth, our simulations were driven by historical SSTs and so they did not account for ocean feedbacks. Coupled atmosphere–ocean GCMs should be used to assess the extent to which the ocean can buffer (or exacerbate) the changes simulated here. Fifth, although our precipitation changes were statistically significant, additional runs, especially those carried out with independent models, would bolster this assessment.

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