# 1 Reduction of tropical land region precipitation variability2 via transpiration

<sup>3</sup> Jung-Eun Lee,<sup>1</sup> Benjamin R. Lintner,<sup>2</sup> J. David Neelin,<sup>3</sup> Xianan Jiang,<sup>1</sup> Pierre Gentine,<sup>4</sup>

4 C. Kevin Boyce,<sup>5</sup> Joshua B. Fisher,<sup>1</sup> J. Taylor Perron,<sup>6</sup> Terence L. Kubar,<sup>1</sup> Jeonghoon Lee,<sup>7</sup> 5 and John Worden<sup>1</sup>

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7 [1] Tropical rainforests are known to exhibit low intrasea-8 sonal precipitation variability compared with oceanic areas 9 with similar mean precipitation in observations and models. 10 In the present study, the potential role of transpiration for 11 this difference in precipitation variability is investigated 12 using the National Center for Atmospheric Research 13 (NCAR) atmospheric general circulation model. Comparing 14 model results with and without transpiration shows that in 15 the absence of transpiration, mean precipitation decreases as 16 may be expected. However the incidence of both higher 17 daily total column water and more intense precipitation 18 increases without transpiration; consequently the variability 19 of precipitation increases substantially. These results can be 20 understood in terms of the complex interplay of local near-21 surface and remote moist dynamical processes with both 22 local positive (boundary-layer drying) and large-scale neg-23 ative (increased large-scale convergence) feedbacks when 24 transpiration is disabled in the model. It is also shown that 25 surface turbulent fluxes over tropical rainforests are highly 26 correlated with incoming solar energy but only weakly cor-27 related with wind speed, possibly decoupling land precipi-28 tation from large-scale disturbances like Madden-Julian 29 Oscillation. Citation: Lee, J.-E., et al. (2012), Reduction of trop-30 ical land region precipitation variability via transpiration, Geophys. 31 Res. Lett., 39, LXXXXX, doi:10.1029/2012GL053417.

# 32 1. Introduction

33 [2] The heavy reliance of many tropical societies on the 34 availability of seasonal rainfall for food, agriculture, and 35 drinking water renders such societies particularly vulnerable 36 to rainfall variability. Recently, *Lintner et al.* [2012] have

<sup>5</sup>Department of Geophysical Sciences, University of Chicago, Chicago, Illinois, USA.

<sup>6</sup>Department of Earth, Atmospheric and Planetary Sciences, Massachusetts Institute of Technology, Cambridge, Massachusetts, USA. <sup>7</sup>Polar Research Institute, Incheon, South Korea.

Corresponding author: J.-E. Lee, Jet Propulsion Laboratory, California Institute of Technology, 4800 Oak Grove Dr., MS 233-200, Pasadena, CA 91109, USA. (jung-eun.lee@jpl.nasa.gov)

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shown that the distribution of monthly-mean precipitation **45** statistics over tropical land regions may already be changing 46 in response to anthropogenic warming. In addition, a mod-47 eling study by *Lee et al.* [2011] indicates that ongoing 48 changes in vegetation associated with anthropogenic land 49 use and land cover change may contribute to the recent 50 increase in drought occurrence over tropical South America. 51

[3] Precipitation variability on intraseasonal timescales 52 poses an especially pronounced risk to human systems, as, 53 for example, the timing and occurrence of wet-season 54 precipitation are critical to agriculture. For example, the 55 Madden-Julian Oscillation (MJO) [Madden and Julian, 56 1994], an intraseasonal mode of eastward propagating plan- 57 etary scale disturbances originating over the Indian and 58 western Pacific Oceans with a period of 30-90 days, is 59 known to impact regional rainfall over many tropical land 60 regions [Zhang, 2005]. An interesting feature of MJO events 61 is the apparent suppression of precipitation variability over 62 tropical rainforests compared with adjacent oceanic regions 63 [Sobel et al., 2008]. More generally, tropical rainforests 64 exhibit lower precipitation variability than nearby oceanic 65 regions with similar mean precipitation. 66

[4] How the differences in the physical characteristics of 67 land versus ocean impact or modulate climate represents an 68 important issue in interpreting both observed and simulated 69 climate system variability. The finite land surface moisture 70 capacity and the heterogeneity of available surface moisture 71 are thought to play some role in modulating the spatiotem-72 poral variability of land region climate. In this regard, the 73 distribution of vegetation is especially critical. As a conse-74 quence of photosynthesis, water leaves plants through open 75 stomata: this process (transpiration) cools the plant and 76 facilitates transport of nutrients from the soil. Moreover, 77 plants may extract soil water that has infiltrated to depths 78 only accessible to roots and thus make such "hidden" sub- 79 surface water available to the atmosphere [Lee et al., 2005; 80 Seneviratne et al., 2006; Teuling et al., 2006]. The surface 81 moisture flux from transpiration can modulate the surface 82 energy budget and the atmospheric stability [Findell and 83 Eltahir, 1997]. It has also been suggested that transpiration 84 may exert control on the triggering of deep convection [see, 85] e.g., Findell et al., 2011]. 86

[5] The role of soil moisture and vegetation on the mean 87 precipitation has been extensively studied in the past [e.g., 88 *Shukla and Mintz*, 1982; *D'Odorico and Porporato*, 2004; 89 *Juang et al.*, 2007]. In this study, we consider the role of 90 transpiration as a potential explanation of the lower pre- 91 cipitation variability observed over tropical rain forests 92 compared with over ocean. Using a climate model, we 93 examine differences in precipitation statistics between a pair 94

<sup>&</sup>lt;sup>1</sup>Jet Propulsion Laboratory, California Institute of Technology, Pasadena, California, USA.

<sup>&</sup>lt;sup>2</sup>Department of Environmental Sciences, Rutgers, State University of New Jersey, New Brunswick, New Jersey, USA.

<sup>&</sup>lt;sup>3</sup>Department of Atmospheric and Oceanic Sciences and Institute of Geophysics and Planetary Physics, University of California, Los Angeles, California, USA.

<sup>&</sup>lt;sup>4</sup>Department of Earth and Environmental Engineering, Columbia University, New York, New York, USA.

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**Figure 1.** (a and b) Differences between the no-transpiration and transpiration cases in intraseasonal variance of 30–90 day band-pass-filtered daily precipitation and (c and d) the changes in the number of high-intensity precipitation days at each grid point. Figures 1a and 1c are for May through October and Figures 1b and 1d are for November through April. The cutoff in precipitation intensity is determined from the transpiration run as the most intense 3% daily precipitation, and the changes in number of days that exceed the cutoff precipitation in the no transpiration run is calculated. The general pattern does not change when we used different % of precipitation as the cutoff for the intense precipitation.

95 of simulations, a control simulation and a simulation in 96 which transpiration is disabled.

#### 97 2. Method

#### 98 2.1. Model

99 [6] To assess the role of transpiration on precipitation 100 statistics, we analyze simulations from the National Center 101 for Atmospheric Research Community Atmosphere Model 102 (CAM) version 3 [Collins et al., 2006] coupled to the 103 Community Land Model (CLM) version 3.5 with transpira-104 tion (transpiration or control run) and without transpiration 105 (no-transpiration run). In the no-transpiration run, transpi-106 ration alone is suppressed, while other characteristics of the 107 land surface, e.g., biomass, roughness and soil type, are 108 identical to the control. In particular, evaporation of water 109 from bare soil and from canopy surfaces (i.e., rainfall inter-110 ception) still occurs in the no-transpiration case. We note 111 that CLM3.5 also includes a simple groundwater model for 112 determining water table depth. Over ocean regions, the 113 simulations assume a Slab Ocean Model (SOM) with pre-114 scribed climatological oceanic q-flux and mixed layer 115 depths, with these quantities calculated using the CAM 3 116 tool provided by NCAR. Each simulation consists of 117 40 years of output, although we restrict our analysis below to 118 the last 10 years to avoid spin-up effects. The simulation is 119 performed at T42 resolution  $(2.8125^{\circ} \times 2.8125^{\circ})$  with 26 120 atmospheric layers and 10 soil layers up to  $\sim$ 3.5 m.

121 [7] Like other models, NCAR CAM underestimates pre-122 cipitation variability [e.g., *Dai*, 2006]. The model convec-123 tion parameterization is based on quasi-equilibrium theory 124 [*Zhang and McFarlane*, 1995]. Schemes based on quasi-125 equilibrium often fail to exhibit the entire temporal spectrum 126 of deviations from equilibrium [*Neelin et al.*, 2008]: in par-127 ticular, intraseasonal variability is often weaker than in the 128 observations [*Zhang et al.*, 2006]. Moreover, because the 129 runs are performed at relatively coarse resolution, potentially 130 important impacts of terrain or small-scale heterogeneity are 131 not resolved. [8] Although CAM precipitation amounts do not match 132 the observed amounts precisely in all regions, e.g., too much 133 precipitation is simulated over the Indian Ocean, the broad 134 features, such as the relative partitioning of precipitation 135 between land and ocean, are captured (Figure S1 in the 136 auxiliary material).<sup>1</sup> For our purposes, we note that CAM 137 does simulate the key feature of interest here, namely, the 138 intraseasonal variance over tropical land regions is typically 139 smaller than over oceanic with comparable mean precipita-140 tion. Although consistent with observations, the simulated 141 precipitation variance is smaller than observed because convection is triggered too often in the model [*Lee et al.*, 2009]. 143 This deficiency may influence the magnitude of precipitation 144 response to transpiration. 145

## 3. Results and Discussion

[9] Removal of transpiration obviously reduces tropical 147 latent heat flux over land regions (Figure S2). Total evapo-148 transpiration decreases in all seasons when transpiration is 149 shut down, but the percent decrease is largest late in the local 150 dry season (e.g., September–October–November for Ama-2015) to forest in Figure S2). In terms of mean precipitation, 152 the reduced surface moisture flux in the absence of transpiration is associated with reduced rainfall, as may be expected [*Shukla and Mintz*, 1982]. The reduction of mean precipi-155 tation over the continents in the absence of transpiration can be viewed in terms of positive land-atmosphere coupling [*Seneviratne et al.*, 2010], with water captured from earlier rain events recycled into subsequent precipitation. 159

[10] In contrast to the mean precipitation changes, the sta-160 tistics of daily precipitation change in a more complicated 161 way with transpiration disabled. Indeed, the incidence of the 162 most intense daily precipitation rates actually increases in the 163 no-transpiration case (Figures 1c and 1d). While the fre-164 quency of precipitation rates in the range of  $3-18 \text{ mm day}^{-1}$  165

<sup>&</sup>lt;sup>1</sup>Auxiliary materials are available in the HTML. doi:10.1029/2012GL053417.



**Figure 2.** The distribution of daily (a) evaporation, (b) surface air temperature, (c) total column water vapor and (d) precipitation (left axis) precipitation count difference (right axis) between no-transpiration and control runs from model simulations for all land grid points with precipitation greater than 2000 mm/year. Error bar in Figure 3d depicts 95% significance interval as estimated from bootstrap sampling.

166 drops when transpiration is removed, the occurrence of driest 167 days (rainfall < 3 mm day<sup>-1</sup>) increases. Thus, the removal of 168 transpiration in the NCAR model is seen to amplify the 169 extremes of the simulated daily precipitation distribution.

170 [11] To place these results in some context, we note that the 171 onset of the rainy season has been both observed and simu-172 lated to occur earlier with high surface latent heat flux, as 173 water vapor supplied by the surface makes convection more 174 favorable around the onset of the wet season [*Fu and Li*, 175 2004; *Boyce and Lee*, 2010; *Lee and Boyce*, 2010]. In other 176 words, without transpiration, the dry season is lengthened: 177 indeed, Figure 2d indicates a substantial increase in the 178 number of days with little precipitation in the no-transpira-179 tion case. Thus, both the days without precipitation and days 180 with intense precipitation are less numerous in the presence 181 of transpiration because of the buffering of atmospheric 182 moisture content by transpiration.

[12] In the absence of transpiration and the associated 183184 decrease in latent heat, the near-surface atmosphere warms 185 and dries (Figure S3). The near-surface warming propagates 186 into the upper atmosphere because convection centers are 187 located over tropical rainforests, and the increasing near-188 surface temperatures over rainforests warm the whole trop-189 ical troposphere through efficient tropical wave dynamics 190 that propagate the localized heating anomaly throughout the 191 tropical belt [Chiang and Sobel, 2002]. Even as the total 192 local surface water flux and near-surface moisture content 193 are decreased, total column moisture may actually attain 194 higher daily values (Figures 2c) in the no-transpiration run 195 because of increased temperature [Neelin et al., 2008] and 196 increased moisture convergence [Lintner and Neelin, 2009]. 197 Concurrently more intense precipitation is observed in the 198 no-transpiration case, corresponding to build up of convection 199 available potential energy (CAPE) and increased convective 200 inhibition (CIN). A negative land-atmosphere feedback is 201 thus created through large-scale atmospheric modifications.

202 [13] Over tropical oceans, precipitation intensity exhibits 203 a power-law dependence on total column water vapor 204 [*Bretherton et al.*, 2004; *Peters and Neelin*, 2006], with a temperature-dependent critical moisture threshold that must 205 be overcome for deep convection to occur [*Neelin et al.*, 206 2008]. To the extent that a similar relationship holds 207 over land, it is plausible that increasing temperature in the 208 no-transpiration simulation raises the critical amount of 209 atmospheric water vapor required for land region deep con-210 vection to occur. Plotting daily-mean land region total col-211 unn water vapor against mean precipitation intensity 212 (Figure S4) indicates lower precipitation intensity at a given 213 water vapor for the no-transpiration case compared with the 214 control case, indicating that a similar moisture-precipitation 215 relationship holds for land regions in NCAR CAM. 216

[14] Moisture budget analyses for tropical ocean regions 217 suggests that much of the precipitation is balanced by large-218 scale moisture convergence [Bretherton and Sobel, 1996]. 219 During wetter periods, when large-scale conditions favor 220 low-level moisture convergence, higher temperatures in 221 the no-transpiration case promote moister conditions and 222 more precipitation, which in turn induce more convergence 223 through convection-convergence feedbacks (Figure 3). 224 Figures 1a and 1b and Figure 3 (bottom) clearly show that the 225 intraseasonal signal is attenuated in the control simulation 226 relative to the no-transpiration simulation. Such behavior is 227 broadly compatible with observational studies showing the 228 most intense thunderstorms to occur over dry forests of 229 Africa or the Midwest of the US [Zipser et al., 2006], where 230 transpiration is expected to be low compared to everwet 231 tropical rainforests. 232

[15] During drier periods, with weakened large-scale 233 convergence, temperatures in the no-transpiration case are 234 even higher because the surface dries out, so turbulent sur-235 face flux partitioning favors more sensible heating, which in 236 turn favors surface warming. The increase in temperatures 237 raises the threshold of deep convection, so during drier 238 periods with the less convectively favorable large-scale 239 conditions, the likelihood of overcoming the convective 240 threshold is diminished without transpiration [*Neelin et al.*, 241 2008; *Muller et al.*, 2009]. This points to the operation of a 242



Transpiration from plants decreases precipitation extreme events over tropical rainforest

**Figure 3.** The role of transpiration from plants on decreasing precipitation variability over tropical rainforests. Plants can extract available soil moisture, making a larger reservoir of subsurface water available to the atmospheric vapor. During wetter periods, higher temperatures in the no-transpiration case promote more moisture and precipitation, which induces higher convergence. During drier periods, much higher temperatures increase the threshold of deep convection, so there is less precipitation and a slower recovery from drier to wetter conditions when transpiration is absent. Bottom panel shows the 10-day running average of precipitation over Borneo (latitude  $1.4^{\circ}$ S; longitude  $113^{\circ}$ E) from model simulations as an ideal example. The transpiration case (control) shows weak intraseasonal variations relative to the run without transpiration.

243 positive land-atmosphere feedback through boundary-layer 244 modulation [*Findell and Eltahir*, 1997].

# 245 4. Summary and Conclusion

246 [16] Over tropical rainforests, observations from TRMM 247 indicate that intraseasonal precipitation variability is lower 248 than over ocean [*Sobel et al.*, 2008]. Hypothesizing that 249 consistently high evapotranspiration over tropical rainforests 250 is related to low precipitation variability, we compare precipitation statistics from a pair of NCAR climate model 251 simulations with and without transpiration. In the absence 252 of transpiration, mean precipitation decreases while sim-253 ulated daily precipitation variability rises substantially, with 254 increasing incidence of both dry and wet extremes of the 255 daily precipitation distribution. Thus, it appears plausible that 256 transpiration dampens the impact of propagating, large-scale 257 disturbances such as those associated with active MJO peri-258 ods by modulating temperature and moisture content in the 259 planetary boundary layer [e.g., *Findell and Eltahir*, 1997]. 260

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-0.7 -0.5 -0.3 -0.1 0.0 0.1 0.3 0.5 0.7

**Figure 4.** Correlation between surface latent heat flux and wind speed (a) for the control run and (b) for the no transpiration run and between surface latent heat flux and incident solar energy at the surface (c) for the control run and (d) for the no transpiration run. All variables are 30–90 day band-pass filtered daily values.

261 These model-based indications of the role of transpiration in 262 modulating tropical intraseasonal precipitation variability 263 raise intriguing questions that could serve as potential targets 264 for observational assessment and evaluation in other models. [17] It is worth mentioning that other differences between 265266 land and ocean may contribute to the contrasting MJO 267 behavior between tropical rainforests and oceans. For exam-268 ple, Sobel et al. [2008] suggest that the lower land surface 269 heat capacity reduces the impact of wind induced surface heat 270 exchange (WISHE) over land because of finite land surface 271 moisture holding capacity. Indeed, land region surface heat 272 fluxes tend to be highly correlated with incoming solar 273 energy but only weakly correlated with wind speed (Figure 4) 274 [see also Araligidad and Maloney, 2008]. As a consequence 275 the surface heat fluxes over land are not strongly coupled to 276 the large-scale dynamics on intraseasonal timescales. In the 277 absence of transpiration, the simulated surface latent heat flux 278 dependence on incoming solar energy decreases while its 279 dependence on wind increases (Figures 1b and 1d), making 280 land area more coupled to the MJO-like disturbances (e.g., 281 Figure 3).

282[18] In a broader sense, the buffering of rainfall extremes via 283 transpiration could have substantial implications for land sur-284 face and ecosystem changes since erosion rates are thought to 285 be higher where rainfall is more variable [Molnar, 2001]. 286 Vegetation reduces land surface erodibility by supplying root 287 cohesion [Schmidt et al., 2001], promoting infiltration [Viles, 288 1990], adding roughness that slows overland flow, and pro-289 viding a canopy that intercepts and attenuates rainfall reaching 290 the surface. Thus, regional reductions of vegetation cover 291 could have a compounding impact on landscapes, accelerating 292 erosion both by promoting more intense rainfall and by mak-293 ing the land surface more vulnerable. Moreover, since plant 294 productivity increases when variations in precipitation and 295 temperature decrease [Medvigy et al., 2010], the suppression 296 of precipitation variability by transpiration may augment the 297 effects of transpiration capacity on assimilation capacity 298 [Boyce et al., 2009], in turn leading to increased biomass 299 production.

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