

1 **An idealized prototype for large-scale land-atmosphere coupling**

2
3 Benjamin R. Lintner^{1*}, Pierre Gentine², Kirsten L. Findell³, Fabio D’Andrea⁴, Adam H.
4 Sobel^{5,6,7}, and Guido D. Salvucci⁸

5
6 *Revised for Journal of Climate*
7 *4 September 2012*

8
9 ¹*Department of Environmental Sciences, Rutgers, The State University of New Jersey, New*
10 *Brunswick, NJ, USA*

11 ²*Department of Earth and Environmental Engineering, Columbia University, New York, NY,*
12 *USA*

13 ³*Geophysical Fluid Dynamics Laboratory, Princeton, NJ, USA*

14 ⁴*Laboratoire de Météorologie Dynamique, Ecole Normale Supérieure, Paris, France*

15 ⁵*Department of Applied Physics and Applied Mathematics, Columbia University, New York, NY,*
16 *USA*

17 ⁶*Department of Earth and Environmental Sciences, Columbia University, New York, NY, USA*

18 ⁷*Lamont-Doherty Earth Observatory, Columbia University, New York, NY, USA*

19 ⁸*Department of Earth and Environment, Boston University, Boston, MA, USA*

20 _____
21 *Corresponding author: Benjamin R. Lintner, Department of Environmental Sciences, Rutgers,
22 The State University of New Jersey, 14 College Farm Road, New Brunswick, NJ 08901-8551,
23 USA

24 Email: lintner@envsci.rutgers.edu

25 Telephone: (732) 932-9800 ext. 6223

26

27 **Abstract.** A process-based, semi-analytic prototype model for understanding large-scale land-
28 atmosphere coupling is developed here. The metric for quantifying the coupling is the sensitivity
29 of precipitation (P) to soil moisture (W), $\frac{\Delta P}{\Delta W}$. For a range of prototype parameters typical of
30 conditions found over tropical or summertime continents, the sensitivity measure exhibits a
31 broad minimum at intermediate soil moisture values. This minimum is attributed to a tradeoff
32 between evaporation (or evapotranspiration) E and large-scale moisture convergence across the
33 range of soil moisture states. For water-limited, low soil moisture conditions, $\frac{\Delta P}{\Delta W}$ is dominated by
34 evaporative sensitivity $\frac{\Delta E}{\Delta W}$, reflecting high potential evaporation (E_p) arising from relatively
35 warm surface conditions and a moisture-deficient atmospheric column under dry surface
36 conditions. By contrast, under high soil moisture (or energy-limited) conditions, $\frac{\Delta E}{\Delta W}$ becomes
37 slightly negative as E_p decreases. However, because convergence and precipitation increase
38 strongly with decreasing (drying) moisture advection, while soil moisture slowly saturates, $\frac{\Delta P}{\Delta W}$ is
39 large. Variation of key parameters is shown to impact the magnitude of $\frac{\Delta P}{\Delta W}$, e.g., increasing the
40 timescale for deep convective adjustment lowers $\frac{\Delta P}{\Delta W}$ at a given W , especially on the moist side of
41 the profile where convergence dominates. While the prototype applicability's for direct
42 quantitative comparison to either observations or models is clearly limited, it nonetheless
43 demonstrates how the complex interplay of surface turbulent and column radiative fluxes, deep
44 convection, and horizontal and vertical moisture transport influences the coupling of the land
45 surface and atmosphere that may be expected to occur in either more realistic models or
46 observations.

47

48 **1. Introduction**

49 Although coupling between land surface and atmospheric processes is regarded as a significant
50 modulator of climate system variability, isolating land-atmosphere coupling pathways in
51 observations and models, such as potential feedbacks between soil moisture and precipitation,
52 remains a significant challenge. Incomplete knowledge of the mechanisms of land-atmosphere
53 interactions, not to mention how such mechanisms are ultimately represented in numerical
54 weather prediction and climate models, limits forecast and predictive skill across multiple
55 timescales. Several factors contribute to the difficulty of assessing land-atmosphere interactions
56 in observations and models. Some, such as limited data or coarse resolution, may be mitigated
57 through increased sampling or finer resolution; others require more careful consideration. For
58 example, the inherent heterogeneity of both the land surface and atmosphere, particularly at
59 small spatial scales, may obscure the relationship between soil moisture and subsequent
60 precipitation (Li and Avissar, 1994; Pielke et al., 1998).

61 The feedback of soil moisture onto subsequent precipitation is postulated to depend on
62 three necessary conditions (Koster and Suarez, 2003). First, a sufficiently large soil moisture
63 perturbation must be present. Second, evaporation (or evapotranspiration) must be sensitive to
64 soil moisture, and finally, precipitation must be sensitive to evaporation. Much of the
65 contemporary research on land-atmosphere interactions has emphasized hotspots where soil
66 moisture-precipitation coupling appears to be especially pronounced (Koster et al., 2004;
67 D'Odorico and Porporato, 2004), that is, where all three conditions are likely to be met. Model
68 simulations show that such coupling hotspots often occur in transitional hydroclimatic regimes
69 characterized by intermediate values of soil moisture and precipitation. An argument for hotspot
70 occurrence under such conditions hinges on the tradeoff between, on the one hand, the weak

71 dependence of evapotranspiration on soil moisture in the saturation limit for humid, high rainfall
72 conditions and, on the other hand, a tropospheric environment unfavorable to moist deep
73 convection in too dry environments. Together, these suggest maximization of the potential for
74 land surface-atmosphere feedbacks between the driest and wettest extremes.

75 Of course, it is well known that models exhibit wide variation in how they simulate
76 hotspots (Guo et al., 2006). Intermodel discrepancies may reflect differences in model
77 parameterizations and the fidelity of model simulations in producing spatially consistent
78 distributions of precipitation and soil moisture, although even within a given model, hotspots
79 may not occur in all transition regimes. Moreover, the simple argument for the existence of
80 localized hotspots is qualitative rather than quantitative: while this argument provides guidance
81 for anticipating conditions under which to anticipate hotspots, it does not offer quantitative
82 predictions of hotspots and how these depend on hydroclimatic variables. In the context of the
83 three necessary ingredients for producing coupling, models may differ in the details of their soil
84 moisture variability, their evaporation sensitivity to soil moisture, and/or the precipitation
85 sensitivity to evaporation.

86 In the present study, we focus on the two sensitivity components in the soil moisture-
87 precipitation feedback. To do this, we employ a steady state, semi-analytic prototype based on
88 some simplifying assumptions for the atmospheric and land surface components of the climate
89 system. In our view, closing the gap between theoretical understanding of land-atmosphere
90 coupling and its applicability to observed or simulated behavior requires use of idealized
91 modeling. The prototype employed couples an idealized atmosphere derived from an
92 intermediate level complexity model to a simple bucket land surface model; it can be viewed as
93 representing a 1D spatial transect across a hydroclimatic gradient between nonconvecting, dry

94 surface conditions on one side and strongly-convecting, saturated conditions on the other.

95 While our prototype is clearly a simplified representation of land-atmosphere coupling, it
96 can be used to demonstrate how key atmospheric and land surface parameters may be anticipated
97 to impact the coupling. Thus, one objective here is to emphasize how large-scale conditions
98 modulate the coupling. In contrast to many studies that adopt a *de facto* local view of land-
99 atmosphere coupling, i.e., relating the land surface conditions and atmosphere at a particular
100 point or observation site, we explicitly address local as well as nonlocal effects, the latter
101 reflecting (large-scale) moisture advection and convergence. We further use our prototype to
102 illustrate potential sources of discrepancy between models and observations and within the
103 models themselves.

104

105 **2. Land-atmosphere coupling strength inferred from the GFDL AM2.1**

106 To motivate our study, we present results from the Geophysical Fluid Dynamics Laboratory
107 (GFDL) AM2.1 GCM (GAMDT, 2004). Applying a methodology similar to Findell et al. (2011),
108 we estimate metrics of tropical land surface-atmosphere coupling for December-January-
109 February (DJF) from a 25-year simulation forced by observed sea surface temperatures (Fig. 1).
110 These metrics represent the sensitivity of 10-day mean daily precipitation to 10-day mean 9
111 am—noon evaporative fraction (EF ; panel a) and root-zone soil water (WTR ; panel b), denoted
112 as $\frac{\Delta P}{\Delta EF}$ and $\frac{\Delta P}{\Delta WTR}$, respectively. EF is related to the partitioning of surface turbulent fluxes, i.e.,
113 $EF = \frac{E}{H+E} = (1 + B)^{-1}$, where B is the Bowen ratio, $B = HE^{-1}$, with H the sensible heat flux
114 (H and E are in the same units; throughout this paper the units are mm day^{-1}). Fluctuations in EF
115 may be driven by soil moisture fluctuations (Gentine et al., 2007, 2010, 2011).

116 Consideration of 10-day means, as opposed to the daily means in Findell et al. (2011), is

117 motivated by the assumptions of the prototype discussed below. Of course, the use of 10-day
118 means introduces some ambiguity in the implied directionality of the relationship between P and
119 either EF or WTR , as soil moisture clearly responds to precipitation. However, in what follows,
120 we are not directly interested in isolating the response of soil moisture (or surface conditions) to
121 precipitation from the more subtle effect of surface conditions feeding back onto precipitation.
122 Rather, we aim to assess the coupled behavior as a whole, i.e., given an incremental change in
123 the surface state, how much is precipitation changed?

124 The functional relationship between the mean $\frac{\Delta P}{\Delta EF}$ curve and EF reflects increased
125 sensitivity at higher EF , consistent with the findings of Findell et al. (2011). However, the large
126 spread in the 5th to 95th percentile values, estimated from 20 bootstrap samples of the original
127 data, indicates substantial noise in the mean and even includes negative values of $\frac{\Delta P}{\Delta EF}$. For
128 $\frac{\Delta P}{\Delta EF} > 0$, a positive excursion of morning EF (e.g., induced by increased soil moisture under
129 constant radiative conditions at the surface; see Gentine et al., 2007) would be expected to
130 increase rainfall. It is of interest to note that the tropical gridpoints for which $\frac{\Delta P}{\Delta EF} < 0$ in AM2.1
131 are typically those for which convective precipitation is most intense (not shown). The reason for
132 this negative sensitivity is not immediately clear.

133 Relating $\frac{\Delta P}{\Delta WTR}$ to WTR (Fig. 1b) shows the mean, 5th, and 95th percentile values to be
134 positive everywhere. However, in contrast to the $\frac{\Delta P}{\Delta EF}$ versus EF relationship, $\frac{\Delta P}{\Delta WTR}$ versus WTR
135 exhibits a distinct sensitivity *minimum* in the mid range of soil water values, both in its mean and
136 5th-95th-percentile spread. In other words, the GFDL-simulated tropical land region precipitation
137 increases less strongly in the mid-range of soil water (~80 mm) than it does at somewhat lower
138 and higher values of WTR . For $WTR < 40$ mm, where the probability distribution function

139 (pdf) of WTR has its largest values, the sensitivity again decreases, which we suspect reflects
140 conditions too dry for the GFDL model to trigger significant deep convection in DJF. Above
141 ~ 120 mm, there are too few observations per WTR bin used to estimate the sensitivities, so $\frac{\Delta P}{\Delta WTR}$
142 is not calculated there. For now we note that a mid-range sensitivity minimum appears at first to
143 be at odds with the study of Koster et al. (2004), in which their soil moisture-precipitation
144 coupling metric is argued to maximize at intermediate soil moisture values. However, the
145 metrics considered here and in Koster et al. (2004) are substantively different, as their metric
146 includes the variability in soil moisture. In the analysis below, we address the genesis of this
147 minimum and discuss its potential implications for interpreting the soil moisture-precipitation
148 feedback.

149 In the next section, we outline an analytic prototype for interpreting the precipitation
150 sensitivity to soil moisture. The objective of this analysis is not to provide an encompassing
151 quantitative explanation for the sensitivity but rather to develop a framework for diagnosing
152 models and observations. The utility of this framework, in our view, is that it demonstrates, in a
153 straightforward and physical manner, why the observed or simulated soil moisture-precipitation
154 relationship may vary in magnitude across a well-defined hydroclimatic spatial gradient, or more
155 generally, over distinct atmospheric and land surface states.

156

157 **3. Semi-analytic prototype overview**

158 *a. Governing equations*

159 The prototype is distilled from a model of intermediate level complexity of the tropical
160 atmosphere, the Quasi-equilibrium Tropical Circulation Model 1 (QTCM1; Neelin and Zeng,
161 2000; Zeng et al., 2000). Briefly, implementation of QTCM1 is guided by the postulate of quasi-

162 equilibrium (QE), which provides a set of constraints for relating tropical deep convection,
 163 temperature, and circulation. Applying the QE constraints leads to a reduced vertical structure,
 164 which greatly diminishes the model's computational load, and for our purposes, facilitates
 165 diagnosis and interpretation of the model.

166 The basis for our prototype is the simplest QTCM1, which comprises a single vertical
 167 temperature mode and barotropic and first baroclinic momentum modes; a single moisture mode
 168 is also invoked. The vertically-averaged tropospheric temperature (T) and moisture (q) equations
 169 are given by:

$$170 \quad \frac{\partial T}{\partial t} = -Ms\nabla_H \cdot \mathbf{v} + P + R_{net} + H - \mathbf{v}_T \cdot \nabla_H T, \quad (1)$$

$$171 \quad \frac{\partial q}{\partial t} = Mq\nabla_H \cdot \mathbf{v} - P + E - \mathbf{v}_q \cdot \nabla_H q, \quad (2)$$

172

173 where ∇_H is the horizontal gradient operator; R_{net} is the net column (top of the atmosphere
 174 minus surface) radiative heating; M_s and M_q are the dry static stability and moisture
 175 stratification (which are related to integrals over the vertical structures of temperature and
 176 moisture with momentum) and $\nabla_H \cdot \mathbf{v}$ is signed positive for low-level convergence; and \mathbf{v}_T and
 177 \mathbf{v}_q are vertically-averaged horizontal wind vectors weighted by the prescribed temperature and
 178 moisture vertical structures assumed in QTCM1. In the formulation of the vertically-averaged
 179 equations, the terms in P in (1) and (2) represent the net convective (condensational) heating and
 180 moistening, respectively; the negative sign in (2) indicates that P is a tropospheric moisture sink.
 181 Moreover, all terms appearing in (1) and (2) are implicitly scaled to units of mm day^{-1} by
 182 absorbing constants such as specific heat capacity, latent heat of fusion, and $\frac{\Delta p}{g}$, where Δp is the
 183 tropospheric pressure depth. A balanced surface flux constraint, neglecting ground surface heat
 184 flux, is also assumed:

$$185 \quad R_{surf} - E - H = 0 \quad (3)$$

186

187 where R_{surf} is signed positive downward. Equations (1)-(3) are evaluated assuming horizontal
188 temperature gradients are small (as in the tropics). Assuming flow in the zonal direction only, we
189 consider moisture advection as in Sobel and Bellon (2009), i.e., $u_q \frac{\partial q}{\partial x} = -\tau_{adv}^{-1}(q - q_u)$, where
190 the τ_{adv} is an advective timescale and q_u is an upstream moisture value. We consider τ_{adv} to be
191 fixed and treat q_u as an adjustable parameter, though it is also possible to adjust τ_{adv} for fixed
192 q_u . The system of equations (1)-(3) is solved for q , $\nabla_H \cdot \mathbf{v}$, and surface temperature T_s (see
193 Appendix). These quantities depend parametrically on the evaporative efficiency $\beta = \beta(W)$. A
194 closed-form, self-consistent solution can be obtained by invoking a steady soil moisture budget:

$$P - E - Q = 0 \quad (4)$$

195
196

197 where Q is the net runoff. For simplicity, $\beta(W) = W$ and Q is represented as a simple power law
198 $Q = PW^\alpha$.

199 We note that Schaepli et al (2012) have recently developed an analytic framework that
200 shares some similarities with our prototype, e.g., consideration of advection along an “inflow”
201 path into a region. One difference is that our prototype obtains moisture convergence as part of
202 the solution rather than specifies it. The model of Schaepli et al (2012) also contains a more
203 detailed treatment of the land surface.

204
205 *b. Forcing and comparison to QTCM1*

206 In what follows, we consider the behavior of the prototype as the advection term is varied
207 between 0 and a value such that moisture convergence precisely balances advection; for
208 advection larger than this value, the prototype is in a nonconvecting regime with moisture
209 convergence balancing advection and $P = 0$ (see Section 6). Solutions are obtained for a

210 prescribed value of T .

211 Comparing the prototype solutions for P , E , and W from output of a QTCM1 simulation
212 reveals broad agreement, particularly in the limit of small advection (Fig. 2). The QTCM1
213 results shown here are from a configuration comprising a tropical zonal strip with one land and
214 one ocean region, as described in Lintner and Neelin (2009; c.f. Fig. 2 of that paper for a
215 schematic overview of the model configuration). For the parameter values chosen, this
216 configuration produces a single convecting center over the midpoint of the land region. Because
217 the horizontal moisture advection is monotonic in the zonal coordinate, i.e., its magnitude
218 decreases inward toward the center of the convection zone, the large advection values to the right
219 in Fig. 2, which here reflect drying advection that tends to suppress precipitation, occur at the
220 edge of the convection zone. In this region, the agreement is much less satisfactory given the
221 time-dependence of soil moisture, a point to which we return later. The offset between the
222 prototype estimate of E at relatively high soil moisture and E from the full QTCM1 arises from
223 the windspeed feedback on evaporation present in the latter, i.e., horizontal windspeed decreases
224 inward from the edge of the convection zone, which reduces the drag coefficient in the bulk
225 formulation of potential evaporation.

226

227 *c. Prototype caveats*

228 We briefly remark here on a few limitations of the semi-analytic model. Most significantly, the
229 prototype lacks an explicit atmospheric boundary layer (ABL), owing to its use of single vertical
230 temperature and moisture basis functions. The limited vertical degrees of freedom may be very
231 important to manifestation of soil moisture-precipitation relationship in our prototype, e.g., Betts
232 et al. (2007) note the importance of boundary layer clouds to land-atmosphere coupling.

233 Moreover, some studies, including Findell et al. (2011), posit the feedback's operation in terms
 234 of convection triggering, which may ultimately depend on factors such as diurnal ABL growth
 235 with time-dependent solar heating. Our purpose is to emphasize how the coupling might be
 236 expected to impact the intensity of precipitation, assuming the state of the system can support
 237 deep convection, i.e., deep convection is already triggered. In related work (Gentine et al., *in*
 238 *progress*), we are developing a coupled boundary layer-convection model that will explicitly
 239 address the role of triggering. Our analytic solutions also assume steady-state conditions, so that
 240 for a prescribed T , the prototype provides the fully-adjusted behavior, similar to Entekhabi et al.
 241 (1992).

242

243 **4. Sensitivity of precipitation to soil moisture and its dependence on prototype parameters**

244 Using the solutions summarized in the Appendix, we can estimate $\frac{\Delta P}{\Delta W}$ directly:

$$\begin{aligned}
 \frac{\Delta P}{\Delta W} = [P + \tau_c^{-1} q_c(T)] & \left[\Delta \ln(MsMq^{-1}(\epsilon_{Ts}^{Ts} G_q - \epsilon_{Ts}^q G_{Ts})) + \epsilon_{Ts}^{Ts} G_T - \epsilon_{Ts}^T G_{Ts} \right. \\
 & \left. - \Delta \ln(MsMq^{-1}(\epsilon_{Ts}^q \epsilon_q^{Ts} - \epsilon_q^q \epsilon_{Ts}^{Ts})) + \epsilon_{Ts}^T \epsilon_q^{Ts} - \epsilon_{Ts}^{Ts} \epsilon_q^T \right] / \Delta W
 \end{aligned}
 \tag{5}$$

245

246

247 In writing (5), the moisture stratification has been taken as a constant, leading to a solution linear
 248 in q . However, a more general solution, with moisture stratification expressed as a linear
 249 function of q , is quadratic in moisture, although one root is nonphysical (i.e., $q < 0$) for the
 250 parameter values considered here.

251 Despite the idealized formulation of the prototype, the behavior of equation (5) is
 252 nontrivial. We can speculate on some of the properties of $\frac{\Delta P}{\Delta W}$. First, the leading term in brackets
 253 on the RHS depends on the total precipitation and the threshold moisture value. This indicates
 254 that, in the limit as $P \rightarrow 0$, the sensitivity is nonzero: for our prototype, moisture advection

255 balances moisture convergence in the limit $P \rightarrow 0$ (or $E \rightarrow 0$), so $P \rightarrow E$ and $\frac{\Delta P}{\Delta W}$ is dominated
 256 by the sensitivity of evapotranspiration, $\frac{\Delta E}{\Delta W}$, in this limit. Also, in obtaining the prototype
 257 solution, we assume turbulent and radiative fluxes to be linearized about their mean values
 258 (which are dependent on large-scale T) and deviations from the mean are expressed in terms of q
 259 and Ts . The mean values appear in the functions G_i while deviations from the mean are reflected
 260 in the ϵ_i^j (as defined in the Appendix). The W -dependence enters explicitly through E , so each
 261 of the G_i and ϵ_i^j associated with evapotranspiration depends on β . Thus, except for the terms
 262 $\epsilon_{Ts}^{Ts} G_T$, $\epsilon_{Ts}^T \epsilon_q^{Ts}$, and $\epsilon_{Ts}^{Ts} \epsilon_q^T$, all other terms in the arguments of the logarithms in (5) are quadratic
 263 in W .

264 Plotting $\frac{\Delta P}{\Delta W}$ as estimated from equation (5) as a function of W (Fig. 3, black curve)
 265 indicates positive curvature across the entire range of soil moisture states, with a *minimum*
 266 sensitivity in mid range of soil moisture values, consistent with the GFDL model results
 267 presented in Fig. 1b. In the next subsection, we address the source of this functional dependence.
 268 One notable difference with respect to the GFDL results is that large $\frac{\Delta P}{\Delta W}$ persists even down to
 269 $W = 0$; we interpret this difference in terms of the steady-state nature of the prototype and the
 270 assumption that moisture is sufficiently high to trigger deep convection. We further point out
 271 that the behavior of $\frac{\Delta P}{\Delta EF}$ plotted against EF (not shown) is also consistent with the GFDL AM2.1
 272 results, namely $\frac{\Delta P}{\Delta EF}$ increases with increasing EF . The simple convective boundary layer model
 273 of de Ridder (1997) was found to produce qualitatively similar behavior, although that model
 274 was explicitly time-dependent.

275

276 *a) Tropospheric moisture budget analysis*

277 To understand the variation in $\frac{\Delta P}{\Delta W}$ across the range of surface moisture conditions, it is instructive
 278 to examine the sensitivities of the other terms (evapotranspiration, moisture convergence, and
 279 horizontal advection) on the RHS of (2), the sum of which balance P in steady-state. For low
 280 soil moisture (water-limited) conditions, $\frac{\Delta P}{\Delta W}$ largely mirrors the sensitivity of evapotranspiration
 281 to soil moisture $\frac{\Delta E}{\Delta W}$ (blue curve), as anticipated from the discussion above. With increasing W ,
 282 $\frac{\Delta E}{\Delta W}$ decreases while the sensitivities of moisture convergence (red), and to a lesser extent,
 283 horizontal advection (green) increase. At sufficiently large W , the sensitivity associated with
 284 moisture convergence dominates, with $\frac{\Delta P}{\Delta W}$ increasing, and interestingly, $\frac{\Delta E}{\Delta W}$ becomes small and
 285 even slightly negative, since the humidity deficit near the surface is reduced, i.e., E is reduced
 286 with increasing soil moisture through the reduction of potential evaporation induced by moisture
 287 convergence (see below). This behavior is of course anticipated from Fig. 2, which has P
 288 increasing with decreasing (dry) moisture advection, with E (slightly) decreasing. W also
 289 increases, although it does so proportionally much less than P .

290 We can further consider decomposition of $\frac{\Delta E}{\Delta W}$ itself:

$$291 \quad \frac{\Delta E}{\Delta W} = \frac{\Delta}{\Delta W}(\beta E_p) = E_p + W \frac{\Delta E_p}{\Delta W} \quad (6)$$

292 which is depicted in Fig. 4. The first term on the RHS of (6), which is simply the potential
 293 evaporation, decreases with increasing soil moisture. This decrease can be understood by noting
 294 that, on the low soil moisture side, the surface is relatively warm while the overlying atmosphere
 295 is relatively dry, which corresponds to a relatively large gap between the saturation specific
 296 humidity (at the surface temperature) and the actual specific humidity (Bouchet 1963; Brutsaert
 297 and Sticker 1979). As the surface moistens, the equilibrium surface temperature decreases and
 298

299 column moisture increases. In other words, as the Bowen ratio drops, latent heating increases
 300 (because of higher W) and sensible heating decreases: the shift toward latent heating and away
 301 from sensible heating results in T_s decreasing and q increasing. The second term on the RHS is
 302 negative over the range of W since E_p decreases monotonically with soil moisture.

303 While the physical pathway connecting soil moisture to precipitation through evaporation
 304 may be clear, how do we interpret the apparent linkage of soil moisture and moisture
 305 convergence? It is instructive here to consider the moisture convergence as the product of
 306 moisture and mass convergence; by combining equations (1) and (2) for the assumptions applied
 307 in the prototype, the mass convergence is just:

$$308 \quad \nabla_H \cdot \mathbf{v} = M^{-1} (R_{toa} - u_q \frac{dq}{dx}) \quad (7)$$

309
 310 where $M = Ms - Mq$ is the gross moist stability. From this expression, the mass convergence is
 311 seen to comprise top-of-the-atmosphere net radiative heating and horizontal moisture advection.
 312 Thus, as drying advection (the second term on the RHS) decreases in magnitude, mass
 313 convergence increases. Combining (7) and (2) and computing a first-order perturbation gives:

$$314 \quad \delta P \approx \delta E + \delta M q \nabla_H \cdot \mathbf{v} + M q M^{-1} \delta R_{toa} + M s M^{-1} \delta (-u_q \frac{dq}{dx}) \quad (8)$$

315
 316 We have seen that δE is small in the limit of high W . Assuming that top-of-the-atmosphere
 317 radiative heating varies most strongly with the cloud-radiative feedback, the 3rd term on the RHS
 318 can be expressed in terms of δP itself. The 2nd term can also be expressed in terms of δP from
 319 the Betts-Miller formulation of precipitation (see equation A5): under fixed T , $\delta P = \tau_c^{-1} \delta q$.
 320 Thus, from equation (8):

$$321 \quad \delta P \propto \delta (-u_q \frac{dq}{dx}) \quad (9)$$

322 This shows that precipitation responds more-or-less directly to advection for very wet surface

323 conditions; the response is similar to what has been recently noted for a cloud-resolving model
324 over the ocean (Wang and Sobel, 2012). On the other hand, soil moisture itself varies relatively
325 little as the surface approaches saturation. As a consequence, $\frac{\Delta P}{\Delta W}$ appears to be large. However,
326 this should not be interpreted as indicating that small soil moisture increases drive large
327 precipitation increases; rather horizontal moisture advection—the imposed external control
328 parameter in these calculations—influences precipitation strongly but soil moisture only weakly,
329 due at least in part to the saturation limit that constrains soil moisture but not precipitation.

330

331 *b) Sensitivity of $\frac{\Delta P}{\Delta W}$ to prototype parameters*

332 As an example of the dependence of $\frac{\Delta P}{\Delta W}$ on the prototype parameters, we examine what happens
333 as the convective adjustment time scale τ_c is varied. Our consideration of this parameter is
334 motivated by the fact that τ_c , or its analogues of this timescale in other types of convection
335 schemes, is currently poorly constrained: the range of potential values for this parameter is 2-16
336 hours (Jackson et al., 2008). Given this spread, it is worthwhile to assess what impact varying
337 this parameter may have on the prototype’s precipitation sensitivity to soil moisture. We also
338 note that this parameter is clearly on the “atmospheric-side” of the coupled system, i.e., it is
339 independent of land surface formulations that are often viewed as the principal determinants of
340 model discrepancy with respect to the soil moisture-precipitation feedback (Guo et al., 2006). It
341 is therefore of interest to see how a change in such a parameter is reflected in the land-
342 atmosphere coupling.

343 Increasing τ_c from its standard value of 2 hours up to 16 hours leads to a progressive
344 lowering of the sensitivity at a given soil moisture value (Fig. 5a). However, greatest impact of
345 changing the convective adjustment timescale occurs at high soil moisture conditions. This is

346 consistent with the strong relationship between convergence and precipitation on the moist side
347 of the profile. Another aspect of increasing τ_c is flattening of the region of minimum $\frac{\Delta P}{\Delta W}$: thus
348 while the sensitivity curves all exhibit the general U-shaped profile, the profiles widen at longer
349 adjustment timescales.

350 Another highly uncertain process in current generation models is the radiative impact of
351 clouds (Bony et al., 2004; IPCC 2007). In our prototype, cloud-radiative feedback is associated
352 solely with precipitating deep convective conditions and encompasses surface and column
353 radiative effects from both deep cumulonimbus and high anvil clouds. The radiative forcing
354 associated with such clouds is expressed in terms of net surface and top-of-the-atmosphere
355 feedback parameters c_{surf} and c_{toa} (see Appendix), for which respective baseline values of 0.18
356 and -0.08 (based on QTCM1) are assumed. Sobel et al. (2004) considered a range of values for
357 c_{surf} between 0 and 0.2: halving c_{surf} is found to increase $\frac{\Delta P}{\Delta W}$, but as with changes to τ_c , the
358 effect is largely confined to high soil moisture conditions (Fig. 5b). Based on the observed
359 cancellation of shortwave and longwave radiative cancellation for tropical deep convective
360 clouds (Kiehl 1994; Hartmann et al. 2001), it may in fact be reasonable to set the top-of-the-
361 atmosphere forcing parameter c_{toa} to zero. Changing the value of c_{toa} has little impact on the
362 sensitivity (not shown).

363 A final parameter we highlight briefly here pertains to the vertical structure of specific
364 humidity. As noted above, the prototype is formulated in terms of vertically-averaged moisture
365 (and temperature). However, the bulk formula for E_p depends on the surface moisture
366 (parameter b_{1s} in the Appendix). By varying the value assigned to b_{1s} , the relative weighting of
367 moisture can be shifted: assuming the vertical mean profile averaged over the entire depth of the
368 troposphere remains unchanged, increasing b_{1s} requires decreased weight in the layers above.

369 We note that increasing b_{1s} decreases sensitivity over the entire range of soil moisture, although
370 the effect is small (not shown). This implies that, for two states with the same column water
371 vapor but different boundary layer-free troposphere partitioning, the one with the moister
372 boundary layer will exhibit (slightly) enhanced precipitation sensitivity to soil moisture.
373 Whether similar sensitivity should hold in the presence of explicit boundary layer dynamics is
374 uncertain.

375

376 **5. Sensitivity for “uncoupled” evapotranspiration**

377 We have thus far not explicitly addressed what role the coupling of the land-atmosphere system
378 plays in the precipitation sensitivity. In fact, precipitation sensitivity to soil moisture similar to
379 our Fig. 3 has been previously demonstrated in an uncoupled stationary soil moisture balance
380 model (Salvucci 2001). Using observed precipitation and other meteorological measurements to
381 drive a soil-vegetation-atmosphere transfer (SVAT) model to estimate soil moisture and surface
382 fluxes, Salvucci (2001) constructed conditional averages of P , E , and Q on soil moisture and
383 obtained a U-shaped profile of $\frac{\Delta P}{\Delta W}$.

384 The interpretation offered in Salvucci (2001) is that, under the assumption of stationarity,
385 conditional averaging of P on W must reflect evapotranspiration at low soil moisture and runoff
386 at high soil moisture, so consistent with equation (4), $\frac{\Delta P}{\Delta W} = \frac{\Delta E}{\Delta W} + \frac{\Delta Q}{\Delta W}$. Such results do not
387 necessarily imply that coupling with the atmosphere is not playing a role: assuming the SVAT
388 model simulations reflect what would be measured, the soil moisture and surface fluxes
389 produced by the model would reflect land-atmosphere interaction. On the other hand, similar
390 sensitivities have been obtained in an even simpler statistical model framework with
391 evapotranspiration and runoff resembling those in the present study and forced by random

392 perturbations to both P and E_p . In this case, no land-atmosphere coupling is present.

393 To obtain some insight into the role of coupling in our prototype, we consider a
394 configuration of the model for which the factors γ and b_{1s} in the linearized expansion of
395 evapotranspiration (equation A2) are set to zero. In this configuration, E is simply dependent on
396 soil moisture, while the effect of the atmospheric state on evapotranspiration is suppressed.
397 Disabling the direct atmospheric impact on E dramatically alters $\frac{\Delta P}{\Delta W}$ (Fig. 6, red curve) compared
398 to Fig. 3: the sensitivity in this configuration increases monotonically over the range of soil
399 moisture values. We suggest that the difference between this sensitivity curve and $\frac{\Delta P}{\Delta W}$ in Fig. 3
400 (dashed gray line) may be interpreted as the effect of the two-way coupling through
401 evapotranspiration. At low W , this coupling enhances precipitation sensitivity to soil moisture,
402 while at high W , it reduces it.

403

404 **6. Multiple equilibria and the bimodality of soil moisture probability distribution functions** 405 **(pdfs)**

406 The results presented above have assumed a convectively triggered state, i.e., the moisture
407 balance is solved for moisture values such that $q \geq q_c(T)$. In fact, as discussed in Lintner and
408 Neelin (2009), the prototype also supports a nonconvecting solution. Vertical mean moisture
409 values for convecting and nonconvecting states are depicted in Fig. 7 as functions of the
410 advective forcing. It can be seen that for a given value of moisture advection, the prototype
411 admits both a low moisture/nonconvecting and high moisture/convecting state. Fig. 7 also
412 depicts the solution for c_{toa} set to zero. Interestingly, the convecting solution for this case (red
413 curve) is double valued for a small region near the convecting/nonconvecting transition value of
414 moisture advection, which corresponds to convecting states with both low and high values of

415 precipitation.

416 In prior work, convecting and nonconvecting solutions have been obtained in both single
417 column and cloud-resolving model simulations in weak temperature gradient mode for tropical
418 oceans (Sobel et al., 2007; Sessions et al., 2010), with the principal difference being that for the
419 steady-state land region, the nonconvecting latent heat flux is identically zero. Even for nonzero
420 evaporation (and soil moisture) in the dry equilibrium over land, the surface temperature will
421 change significantly with soil moisture, with the former increasing as the latter decreases, as
422 under arid or semi-arid conditions. Over oceans, surface conditions may not differ dramatically
423 between the convecting and nonconvecting equilibria.

424 Under certain conditions, soil moisture pdfs have been shown to exhibit bimodality
425 (D’Odorico and Porporato, 2004; Teuling et al., 2005; D’Andrea et al., 2006), although the
426 mechanisms for such bimodal behavior remain unclear. For example, it has been speculated that
427 soil moisture bimodality represents a signature of the positive feedback between soil moisture
428 and precipitation (see, e.g., D’Odorico and Porporato, 2004). While the determination of such
429 pdfs is obviously time-dependent, the presence of convecting and nonconvecting solutions in our
430 prototype could be envisioned to give rise to bimodal behavior in soil moisture, if one considers
431 a “succession” of steady-state solutions. In this case, the shape of the pdf would depend on the
432 relative frequency of occurrence of the nonconvecting, $W = 0$ state and the convecting, nonzero
433 soil moisture states.

434

435 **7. Summary and conclusions**

436 In this study, we develop an idealized, semi-analytic prototype for understanding large-scale
437 land-atmosphere coupling. Using this prototype, we show that the sensitivity of precipitation (P)

438 to soil moisture (W), defined as $\frac{\Delta P}{\Delta W}$, is characterized by a broad U-shaped profile, with the
439 highest sensitivities at both extremes of W . From simple atmospheric moisture budget
440 considerations, we illustrate how the shape of the $\frac{\Delta P}{\Delta W}$ profile reflects a tradeoff between
441 evapotranspiration, which dominates the sensitivity at low W , and moisture convergence, which
442 dominates at high W . A key point here is that the large $\frac{\Delta P}{\Delta W}$ values at high W are attributable to
443 direct forcing of P by moisture advection (the control parameter in simulations) but with W itself
444 changing little. One conclusion here is that the apparent discrepancy with Koster et al. (2004)
445 need not be one. As noted in Section 2 may simply reflect that their study relied directly on soil
446 moisture as the control variable: to construct their metric, Koster et al. (2004) compared
447 variances for simulations with and without interactive soil moisture.

448 A related difference with respect to the Koster et al study is that we have considered here
449 only the sensitivity, such that for a prescribed perturbation in soil moisture, we could estimate
450 how much precipitation might be expected to change. This obviously bypasses how such soil
451 moisture perturbations would occur in the first place. In broadly qualitative terms, we suggest
452 that the convolution of our sensitivity with a measure of the soil moisture perturbations (e.g., the
453 soil moisture standard deviation) should give something akin to the Koster et al metric (see Fig.
454 7). For dimensionless soil moisture, which is bounded by 0 and 1 [or some $W_{max} < 1$], the
455 distribution of soil moisture variance will approach zero at the endpoints, precisely where the
456 sensitivity is largest.

457 Our study further suggests how $\frac{\Delta P}{\Delta W}$ may depend on parameters of interest in models, such
458 as the convective adjustment timescale, cloud-radiative feedback strength, and vertical moisture
459 distribution. These parameters are shown to impact the shape of $\frac{\Delta P}{\Delta W}$, which may help to explain

460 (at least in a qualitative way) why models disagree in terms of where areas of strong or weak
 461 land-atmosphere coupling occur. For this reason, we suggest that examination of land-
 462 atmosphere coupling under systematic changes to parameters such as those used in convection
 463 schemes would be diagnostically useful.

464

465 **Acknowledgements**

466 The authors thank Alan K. Betts for discussion about this work and two anonymous reviewers
 467 for their comments. This work was supported by National Science Foundation (NSF) grant
 468 AGS-1035968 and New Jersey Agricultural Experiment Station Hatch grant NJ07102. AHS
 469 acknowledges support from NSF AGS-1008847.

470

471 **Appendix: Formulation of the semi-analytic prototype**

472 To derive the prototype solution from equations (1)-(3), we first expand the turbulent and
 473 radiative fluxes as functions of T , q , and Ts about flux offsets (0 subscripts):

$$474 \quad H = H_0 + \epsilon_H(Ts - a_{1s}T) \quad (A1)$$

$$475 \quad E = \beta(W)[Ep_0 + \epsilon_H(\gamma Ts - b_{1s}q)] \quad (A2)$$

$$476 \quad R_{surf} = R_{surf0} + \epsilon_{Ts}^{R_{surf}} Ts + \epsilon_T^{R_{surf}} T + \epsilon_q^{R_{surf}} q + c_{surf}P \quad (A3)$$

$$477 \quad R_{toa} = R_{toa0} + \epsilon_{Ts}^{R_{toa}} Ts + \epsilon_T^{R_{toa}} T + \epsilon_q^{R_{toa}} q + c_{toa}P \quad (A4)$$

478 The ϵ coefficients represent linear sensitivity of various fluxes to changes in T , q , and Ts .
 479 Precipitation (convective heating and drying) is formulated in terms of a Betts and Miller (1986)-
 480 type relaxation scheme:

$$481 \quad P = \tau_c^{-1}[q - q_c(T)] \quad (A5)$$

482 Here, $q_c(T)$ is a temperature-dependent moisture threshold, τ_c is the convective adjustment

483 timescale, and it is necessary that $P \geq 0$. c_{surf} and c_{toa} are cloud-radiative forcing coefficients
 484 associated with the presence of deep convective cloudiness and related anvil cirrus. Default
 485 values for the various parameters are summarized in Lintner and Neelin (2009). Solutions to
 486 equations (1)-(3) can then be written in the following format:

$$487 \quad q = \frac{[Ms(\epsilon_{Ts}^{Ts}G_q - \epsilon_{Ts}^qG_q) + Mq(\epsilon_{Ts}^{Ts}G_T - \epsilon_{Ts}^T G_{Ts})]}{[Ms(\epsilon_{Ts}^q\epsilon_q^{Ts} - \epsilon_{Ts}^{Ts}\epsilon_q^q) + Mq(\epsilon_{Ts}^T\epsilon_q^{Ts} - \epsilon_{Ts}^{Ts}\epsilon_q^T)]} \quad (A6)$$

$$488 \quad Ts = -\epsilon_{Ts}^{Ts}(G_{Ts} + \epsilon_q^{Ts}q) \quad (A7)$$

$$489 \quad \nabla_H \cdot \mathbf{v} = Ms^{-1}(G_T + \epsilon_{Ts}^T Ts + \epsilon_q^T q) \quad (A8)$$

490 Here, quantities of the form ϵ_j^i represent the net impact on variable i ($i = T, q, Ts$) of those
 491 components of the linearized turbulent and radiative fluxes or the convective heating and drying
 492 rates depending on variable j . The quantities G_i reflect the offset values as well and the T -
 493 dependent components of the fluxes.

494
 495

496 **References Cited**

497 Betts, A.K., and M. J. Miller, 1986: A new convective adjustment scheme. Part II: Single column
498 tests using GATE-wave, BOMEX, ATEX, and Arctic Airmass data sets. *Quart. J. Roy. Meteor.*
499 *Soc.*, *112*, 693—710.

500
501 Betts, A.K., R. Desjardins, and D. Worth, 2007: Impact of agriculture, forest and cloud feedback
502 on the surface energy balance in BOREAS. *Agric. Forest Meteorol.*, *142*, 156—169,
503 doi:10.1016/j.agrformet.2006.08.020

504
505 Bony, S., J.-L. Dufresne, H. Le Treut, J.-J. Morcrette, and C. Senior, 2004: On dynamic and
506 thermodynamic components of cloud changes. *Clim. Dyn.*, *22*, 71—86, doi:10.1007/s00382-
507 003-0369-6.

508
509 Bouchet, R.J., 1963: Evapotranspiration réelle et potentielle, signification climatique. *Int. Assoc.*
510 *Sci. Hydrol. Pub.*, *62*, 134—142.

511
512 Brutsaert, W., and H. Stricker, 1979: An advection aridity approach to estimate regional
513 evaporation. *Water Resour. Res.*, *15*, 443—450.

514
515 D'Andrea, F., A. Provenzale, R. Vautard, and N. De Noblet-Decoudré, 2006: Hot and cool
516 summers: Multiple equilibria of the continental water cycle. *Geophys. Res. Lett.*, *33*, L24807,
517 doi:10.1029/2006GL027972.

518
519 De Ridder, K., 1997: Land surface processes and the potential for convective precipitation. *J.*
520 *Geophys. Res.*, *102*, 30,085—30,090.

521
522 D'Odorico, P. and A. Porporato, 2004: Preferential states in soil moisture and climate dynamics.
523 *Proc. Nat. Acad. Sci.*, *101*, 8848—8851.

524
525 Entekhabi, D., I. Rodriguez-Iturbe, and R.L. Bras, 1992: Variability in large-scale water balance

526 with land surface-atmosphere interaction. *J. Clim.*, 5, 798—813.
527

528 Entekhabi, D., I. Rodriguez-Iturbe, and F. Castelli, 1996: Mutual interaction of soil moisture
529 state and atmospheric processes. *J. Hydrol.*, 184, 3–17.
530

531 Findell, K.L., P. Gentine, B.R. Lintner, and C. Kerr, 2011: Probability of afternoon precipitation
532 in eastern US and Mexico enhanced by high evaporation. *Nat. Geosci.*, 4,
533 doi:10.1038/ngeo1174.
534

535 Gentine, P., D. Entekhabi, A. Chehbouni, G. Boulet, and B. Duchemin, 2007: Analysis of
536 evaporative fraction diurnal behaviour. *Agric. Forest Meteorol.*, 143, 13—29.
537

538 Gentine, P., D. Entekhabi, and J. Polcher, 2010: Spectral Behaviour of a Coupled Land-Surface
539 and Boundary-Layer System. *Bound. Lay. Meteor.*, 134, 157–180. doi:10.1007/s10546-009-
540 9433-z
541

542 Gentine, P., D. Entekhabi, and J. Polcher, 2011: The diurnal behavior of evaporative fraction in
543 the soil-vegetation-atmospheric boundary layer. *J. Hydrometeorol.*, 12, 1530—1546.
544

545 The GFDL Global Atmospheric Model Development Team (GAMDT), 2004: The new GFDL
546 global atmosphere and land model AM2-LM2: Evaluation with prescribed SST simulations. *J.*
547 *Clim.*, 17, 4641—4673.
548

549 Guo, Z. and the GLACE Team, 2006: GLACE: The global land-atmosphere coupling
550 experiment. Part II: Analysis. *J. Hydrometeorol.* 7, 611—625.
551

552 Hartmann, D.L., L.A. Moy, and Q. Fu, 2001: Tropical convection and the energy balance at the
553 top of the atmosphere. *J. Clim.*, 14, 4495–4511.
554

555 Jackson, C. S., M.K. Sen, G. Huerta, Y. Deng, and K.P. Bowman, 2008: Error reduction and
556 convergence in climate prediction. *J. Clim.*, 21, 6698–6709, doi:10.1175/2008JCLI2112.1.

557
558 Kiehl, J.T., 1994: On the observed near cancellation between longwave and shortwave cloud
559 forcing in tropical regions. *J. Clim.*, 7, 559–565.
560
561 Koster, R.D., and M.J. Suarez, 2003: Impact of land surface initialization on seasonal
562 precipitation and temperature prediction. *J. Hydrometeor.*, 4, 408–423.
563
564 Koster, R.D., and the GLACE Team, 2004: Regions of strong coupling between soil moisture
565 and precipitation. *Science*, 305, 1138–1140.
566
567 Li, B., and R. Avissar, 1994: The impact of spatial variability of land-surface characteristics on
568 land-surface heat fluxes. *J. Clim.*, 7, 527–537.
569
570 Lintner, B.R., and J.D. Neelin, 2009: Soil moisture impacts on convective margins. *J.*
571 *Hydrometeor.*, 10, 1026–1039, doi: 10.1175/2009JHM1094.1.
572
573 Neelin, J.D., and N. Zeng, 2000: A quasi-equilibrium tropical circulation model—formulation.
574 *J. Atmos. Sci.*, 57, 1741–1766.
575
576 Pielke, R.A., R. Avissar, M. Raupach, A.J. Dolman, X. Zeng, and A.S. Denning, 1998:
577 Interactions between the atmosphere and terrestrial ecosystems: influence on weather and
578 climate. *Global Change Biol.*, 4, 461–475.
579
580 Salvucci, G.D., 2001: Estimating the moisture dependence of root zone water loss using
581 conditionally averaged precipitation. *Water Resour. Res.*, 37, 1357–1365.
582
583 Schaeffli, B., R.J. van der Ent, R. Woods, and H.H.G. Savenije, 2012: An analytical model for
584 soil-atmosphere feedback, *Hydrol. Earth Syst. Sci.*, 16, 1863–1878, doi:10.5194/hess-16-1863-
585 2012.
586
587 Sessions, S.L., S. Sugaya, D.J. Raymond, and A.H. Sobel, 2010: Multiple equilibria in a cloud-

588 resolving model. *J. Geophys. Res.*, *115*, D12110, doi:10.1029/2009JD013376.
589

590 Sobel, A.H., C.S. Bretherton, H. Gildor, and M.E. Peters, 2004: Convection, cloud-radiative
591 feedbacks and thermodynamic ocean coupling in simple models of the Walker circulation. In
592 *Earth's Climate: The Ocean-Atmosphere Interaction*, C. Wang S.-P. Xie, and J.A. Carton, Eds.,
593 American Geophysical Union Geophysical Monograph 147, 393—405.
594

595 Sobel, A.H., G. Bellon, and J. Bacmeister 2007: Multiple equilibria in a single-column model of
596 the tropical atmosphere. *Geophys. Res. Lett.*, *34*, L22804, doi:10.1029/2007GL031320.
597

598 Sobel, A. H. and G. Bellon 2009: The effect of imposed drying on parameterized deep
599 convection. *J. Atmos. Sci.*, *66*, 2085—2096.
600

601 Teuling, A.J., R. Uijlenhoet, and P.A. Troch, 2005: Bimodality in warm season soil moisture
602 observations. *Geophys. Res. Lett.*, *32*, L13402, doi:10.1029/2005GL023223.
603

604 Wang, S., and A. H. Sobel 2012: Impact of imposed drying on deep convection in a cloud-
605 resolving model. *J. Geophys. Res.-Atmos.*, *117*, doi:10.1029/2011JD016847.
606

607 Zeng, N., J.D. Neelin, and C. Chou, 2000: A quasi-equilibrium tropical circulation model—
608 Implementation and simulation. *J. Atmos. Sci.*, *57*, 1767–1796.
609

610 **Figure Captions**

611 **Fig. 1:** Precipitation sensitivity as functions of (a) evaporative fraction ($\frac{\Delta P}{\Delta EF}$) and (b) soil water
612 ($\frac{\Delta P}{\Delta WTR}$) as simulated by GFDL AM2.1. The sensitivities, expressed in units of mm day⁻¹ per *EF*
613 increment in (a) and mm/day⁻¹ per mm soil water in (b), are calculated as in Findell et al. (2011)
614 using a binning procedure applied to 10-day averages of daily rainfall, including only those 10
615 day periods in the calculation for which precipitation exceeds a 1 mm threshold. The results
616 shown are for 20 bootstrap samples generated from a 25-year model integration for all model
617 land gridpoints between 30°S-10°N for December-January-February (DJF). The dark blue lines
618 represent means of the 20 bootstrap samples, the dashed blue lines represent the $\pm 1\sigma$ level, and
619 the tan shading corresponds to the range between the 5th and 95th percentiles. The dashed black
620 lines (scaled along the right y-axes) are the pdfs of DJF mean *EF* or *WTR* values.

621
622 **Fig. 2:** Prototype solutions of precipitation (*P*; black line), evapotranspiration (*E*; red line) and
623 soil moisture (*W*; blue line) as functions of the horizontal advection (here rescaled by a minus
624 sign). Also shown are steady-state values of *P*, *E*, and *W* from a time-dependent QTCM1
625 simulation (see Lintner and Neelin, 2009) configured in the same way as the prototype.

626
627 **Fig. 3:** Sensitivity of the steady-state prototype precipitation budget to soil moisture. Here, the
628 sensitivity is estimated as the ratio of the incremental change in the budget term, *X*, and soil
629 moisture, *W*, i.e., $\frac{\Delta X}{\Delta W}$. Also shown [in units of mm/day x 4] is the total precipitation as a function
630 of *P* (gray line).

631

632 **Fig. 4:** Decomposition of evaporative sensitivity to soil moisture, $\frac{\Delta E}{\Delta W}$. Component terms are
633 discussed in the text.

634

635 **Fig. 5:** Sensitivity of $\frac{\Delta P}{\Delta W}$ for varying (a) convective adjustment timescales (τ_c) and (b) the surface
636 cloud-radiative feedback parameter.

637

638 **Fig. 6:** Sensitivity of $\frac{\Delta P}{\Delta W}$ to decoupling E from tropospheric moisture and surface temperature.
639 Here, the “No E-coupling” configuration (red line) has $E = E(W)$, i.e., evapotranspiration as a
640 function of soil moisture only. The difference between the baseline configuration and the No E-
641 coupling configuration is also shown (dashed gray line).

642

643 **Fig. 7:** Vertical mean moisture versus horizontal moisture advection for the nonconvecting
644 solution of the prototype (dashed black line) and the convecting solution (solid black line). Also
645 shown is the convecting solution for a configuration with top-of-the-atmosphere cloud-radiative
646 feedback set to zero (red line).

647

648 **Fig. 8:** Schematic illustration of precipitation sensitivity to soil moisture $\frac{\Delta P}{\Delta W}$ (dashed blue line),
649 standard deviation of soil moisture σ_W (gray shading), and their convolution $\frac{\Delta P}{\Delta W} * \sigma_W$ (solid
650 black line).

651

652