

Land-Atmosphere Interactions: The LoCo Perspective

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1 **ABSTRACT**

2 Land-atmosphere (L-A) interactions are a main driver of Earth’s surface water and energy budgets;
3 as such, they modulate near-surface climate, including clouds and precipitation, and can influence
4 the persistence of extremes such as drought. Despite their importance, the representation of L-A
5 interactions in weather and climate models remains poorly constrained, as they involve a complex
6 set of processes that are difficult to observe in nature. In addition, a complete understanding of
7 L-A processes requires interdisciplinary expertise and approaches that transcend traditional
8 research paradigms and communities. To address these issues, the international Global Energy and
9 Water Exchanges project (GEWEX) Global Land-Atmosphere System Study (GLASS) panel has
10 supported ‘L-A coupling’ as one of its core themes for well over a decade. Under this initiative,
11 several successful land surface and global climate modeling projects have identified hotspots of
12 L-A coupling and helped quantify the role of land surface states in weather and climate
13 predictability. GLASS formed the Local L-A Coupling (‘LoCo’) project and working group to
14 examine L-A interactions at the process level, focusing on understanding and quantifying these
15 processes in nature and evaluating them in models. LoCo has produced an array of L-A coupling
16 metrics for different applications and scales, and has motivated a growing number of young
17 scientists from around the world. This article provides an overview of the LoCo effort, including
18 metric and model applications, along with scientific and programmatic developments and
19 challenges.

24

CAPSULE

25 Metrics derived by the LoCo working group have matured and begun to enter the mainstream,
26 signaling the success of the GEWEX approach to foster grassroots participation. In this article,
27 LoCo's researchers discuss past, present and planned efforts.

28

29 **1. Background**

30 The role of land-atmosphere (L-A) interactions in weather and climate prediction has
31 emerged over the last two decades as important but inherently challenging and complex. One
32 reason is that L-A interaction research has proceeded ‘in reverse’ compared to most science.
33 Typically in Earth system sciences, observations inform theory, which then leads to the
34 development and gradual refinement of conceptual and numerical models based on elucidated
35 physical processes. The benchmark for such models' success, and the progress of the underlying
36 science, is when they begin to consistently outperform purely statistical approaches inherently not
37 based in the representation of physical processes (Best et al. 2015).

38 Conversely, coupled L-A (i.e. weather and climate) models arose well before the
39 theoretical basis for L-A interactions had begun to mature, driven by the pressing need to supply
40 accurate lower boundary conditions to atmospheric models as their use was extended from weather
41 time scales to seasonal and longer periods. Demand for closure of surface energy and water
42 budgets in atmospheric models led to the development of the first land surface models (LSMs; e.g.
43 Manabe 1969) that were internally consistent, but not necessarily well-behaved when coupled to
44 atmospheric models that often have strong precipitation or radiative energy biases over continents.

45 As was the case with early coupled ocean-atmosphere models, strong climate biases
46 developed when LSMs were coupled to GCMs. But unlike the ocean, for which fairly
47 comprehensive measurements of sea surface temperatures were available to expose the symptoms
48 of coupled model biases, the land surface lacked routine observations of states like soil moisture
49 and temperature, vegetation water content, and snow mass. In addition, key LSM parameters and
50 state variables can be difficult to observe routinely, or are unmeasurable (e.g. soil moisture in
51 models vs. observations as discussed in Koster et al. 2009). As a result, LSMs traditionally have

52 lacked a full representation of components such as water transport (e.g. groundwater) and
53 vegetation dynamics, and the method for correcting meteorological biases in weather and climate
54 forecast models often falls to tuning relatively unconstrained LSM parameters, such as vegetation
55 rooting depth, to compensate for atmospheric model shortcomings (Kleidon and Heimann 1988).

56 Over time, separate atmospheric and land surface model development communities have
57 emerged. Although working towards related goals, the two communities have operated in parallel
58 and have been largely unsuccessful in addressing coupled process representation via joint
59 modeling efforts. As a result, the development and evaluation of traditional LSMs and hydrological
60 models has occurred predominantly in an offline (uncoupled) mode (van den Hurk et al. 2011).
61 The study of L-A interactions has emerged from a need to explore system feedbacks to improve
62 process understanding and model performance. In this paper, we first outline the broader context
63 of L-A interactions over time and the emergence of the GEWEX international community-based
64 Local L-A Coupling (LoCo) initiative. The following sections discuss the evolution of LoCo over
65 time and its contributions to the research community.

66

67 **2. A Brief History of L-A Interaction Research**

68 It is widely accepted that realistically representing coupled processes in models is a
69 prerequisite for surface climate predictability (Betts 2004). However, the necessary spatial and
70 temporal coverage of observations to underpin coupled L-A model evaluation and development
71 has been lacking (Guillod et al. 2014). The prototypical 2-week field campaigns that have been
72 the backbone of developing atmospheric process understanding have proved too short to provide
73 the necessary data, and longer campaigns are costly. With few exceptions (e.g. FIFE; Hall and
74 Sellers 1995, CASES; Yates et al. 2001; Moeng et al. 2003), the majority of campaigns are also

75 lacking in terms of addressing the full suite of measurements (across the soil-vegetation-
76 atmosphere system) required for L-A studies, focusing on observations in one or two of these
77 compartments only. The new Land-Atmosphere Feedback Experiment (LAFE) which was
78 conducted in August 2017 was designed to close these observational gaps (Wulfmeyer et al. 2017).

79 Additionally, land surface properties (e.g., land cover, terrain and soil texture) are highly
80 heterogeneous across a wide range of spatio-temporal scales, hampering generalization of
81 measurements from one location to another. As a result, the multivariate and multiscale coupled
82 L-A processes remain *poorly observed and incompletely understood* (e.g., Betts et al. 1996, Betts
83 2000, Betts 2004, Ek and Holtslag 2004, Guo et al. 2006, Jimenez et al. 2014, Teuling et al. 2017).
84 Standard model outputs, especially those from climate model intercomparison projects such as
85 CMIP, are often insufficient to diagnose coupled sensitivities at the L-A interface.

86 Broadly speaking, the potential linkages between land surface variables such as soil
87 moisture (*SM*), and atmospheric variables, such as temperature or precipitation (*P*) are rather
88 intuitive, and have been highlighted in recent studies and review articles (e.g. Seneviratne et al.
89 2010, Betts and Silva Dias 2010). The importance of the land surface has been demonstrated not
90 only in terms of predictability on daily to seasonal timescales (e.g., Koster et al. 2010, Hirsch et
91 al. 2014, Dirmeyer and Halder 2016, Betts et al., 2017), but also in terms of influencing extremes
92 such as drought and heatwaves (Roundy et al. 2013ab, Miralles et al. 2014, Wang et al. 2015,
93 PaiMazumder and Done 2016), PBL evolution and cloud formation (Milovac et al. 2016) and
94 afternoon convection (Findell et al. 2003a,b, Gentine et al. 2013, Guillod et al. 2015), and tropical
95 cyclone re-intensification (Andersen and Shepherd, 2013). Other linkages, such as the role of *SM*
96 or vegetation heterogeneity in mesoscale circulations (e.g., Taylor et al. 2012, Hsu et al. 2017) and
97 planetary waves (Koster et al. 2014), and those driven by land use and land cover change or

98 management (e.g. Findell et al. 2007, Pitman et al. 2009, de Noblet-Ducoudre et al. 2012,
99 Mahmood et al. 2014, Lejeune et al. 2015, Hirsch et al. 2015, Findell et al. 2017) are topics of
100 active research. The fact that coupling studies are carried out across a range of time and space scale
101 perspectives tends to also confound community thinking and consensus building (Guilod et al.
102 2015, Knist et al. 2016). For example, assessment of the coupling within GCMs may vary
103 significantly from local, diurnal scales to large and seasonal to inter-annual time scales (e.g., Wei
104 et al., 2010, Ferguson et al. 2012, Green et al. 2017).

105 Understandably, the focus of the climate community in terms of L-A interactions has been
106 on large scale *SM-P* relationships and causality. Most notably, the Global Land Atmosphere
107 Coupling Experiment (GLACE; Koster et al. 2004, Koster et al. 2006, Guo et al. 2006) highlighted
108 potential regions where GCMs indicate the influence of antecedent *SM* on *P*, and the degree to
109 which GCMs differ in describing that relationship (Dirmeyer et al. 2006). The GLACE studies
110 highlighted the potential role of the land surface in climate predictability and served to galvanize
111 community interest in L-A interactions, especially toward global hotspots of L-A coupling in many
112 semi-arid and agricultural areas. Since then, numerous studies have pursued the notion of coupling
113 hotspots (e.g., Notaro 2008, Zhang et al. 2008, Anderson et al. 2009, Dirmeyer et al. 2009, Wei et
114 al. 2010, Zeng et al. 2010, Zhang et al. 2011, Ferguson et al. 2012, Mei and Wang 2012). GLACE
115 also exposed the need to revisit the complex interactions, controls, and feedbacks inherent to SM-
116 P feedbacks that are indiscernible using metrics that rely on large-scale ensemble statistics rather
117 than observable features.

118

119 **3. Evolution of LoCo**

120 Over the last decade, the importance of L-A coupling for weather and climate model
121 development has become more apparent under the GEWEX Imperatives

122 (<http://www.gewex.org/about/science/seven-gewex-imperatives>) and the World Climate Research
123 Program (WCRP) Grand Challenges ([https://www.wcrp-climate.org/grand-challenges/grand-](https://www.wcrp-climate.org/grand-challenges/grand-challenges-overview)
124 [challenges-overview](https://www.wcrp-climate.org/grand-challenges/grand-challenges-overview)). The overarching goals of these programs suggest that science must integrate
125 approaches to evaluate atmospheric or land models to achieve further breakthroughs in model
126 development, and that comprehensive coupling metrics (rooted in observable process-level scales)
127 should be integral to the model development cycle.

128 GLACE was an early element of the GEWEX Global Land-Atmosphere System Study
129 (GLASS; van den Hurk et al. 2011), which was conceived as a voluntary, community-based panel
130 under GEWEX in the late 1990s and focused on coordinating research efforts to evaluate and
131 compare L-A models in four modes: (1) local-scale offline (i.e., uncoupled LSMs at the point
132 scale); (2) large-scale offline (which has evolved into continental and global land data assimilation
133 systems); (3) local-scale coupled (LSMs coupled to single-column models); and (4) large-scale
134 coupled (LSMs coupled to GCMs) models. These have been addressed through community-
135 supported model inter-comparison projects (MIPs), including the Project for the Inter-comparison
136 of Land Surface Parameterization Schemes (PILPS; Henderson-Sellers et al. 1993, 2002), the
137 Global Soil Wetness Project (GSWP; Dirmeyer 2011a), and the aforementioned GLACE (Koster
138 et al. 2006, 2010, Guo et al. 2006, Seneviratne et al. 2013, van den Hurk et al. 2012). However,
139 formation of a local-scale coupled MIP (mode 3) has lagged, initially due to the difficulty both in
140 selecting sufficiently holistic metrics and designing an experiment that incorporates the full
141 complexity of local L-A interactions (Fig. 1). Note that PILPS and GSWP were performed in
142 offline mode without atmospheric feedbacks (i.e. uncoupled), while GLACE, despite being a
143 multi-model coupled experiment, lacked process-level diagnosis.

144 To address this, a GLASS-supported working group, coined ‘LoCo’ for ‘local coupling’,
 145 was established in the mid 2000s to coordinate and promote process-level, local L-A coupling
 146 research and develop integrative metrics to quantify these complex relationships and feedbacks.
 147 Over the years, LoCo has grown to facilitate integrated model development and identify
 148 observational needs to better understand the complex nature of L-A interactions and their role in a
 149 changing climate.

150 When referring to water and energy cycle research, LoCo defines ‘local coupling’ as: “the
 151 impact of land surface states on the evolution of surface fluxes, the PBL and free atmosphere,
 152 including clouds and precipitation, as well as positive and negative feedback mechanisms that
 153 modulate extremes”. This incorporates the notion that all interactions between land and
 154 atmosphere begin locally through the interface of the land surface and PBL (see Fig. 1). The ‘LoCo
 155 Process Chain’, a simplification of the complexities illustrated in Fig. 1, is shown schematically in
 156 Fig. 2 and written as:

$$\begin{array}{ccccccc}
 \Delta SM & \longrightarrow & \Delta EF & \longrightarrow & \Delta PBL & \longrightarrow & \Delta Ent \longrightarrow \Delta T_{2m}, Q_{2m} \Rightarrow \Delta P, Cloud \\
 \text{(a)} & & \text{(b)} & & \text{(c)} & & \text{(d)} & \qquad \qquad \qquad (1)
 \end{array}$$

158 (Santanello et al., 2011). The links (arrows a-d) in the current process chain describe the
 159 sensitivities of: (a) surface sensible (H) and latent (LH) heat flux partitioning [i.e. evaporative
 160 fraction; $EF = LH/(LH + H)$],) to SM, (b) PBL height evolution to surface fluxes, (c) entrainment
 161 fluxes to PBL height evolution, and (d) the collective feedback of the free atmosphere (through
 162 the entrainment zone) on PBL thermodynamics. Taken in full, these interactions (a-d) contribute
 163 towards the development of convective cloud and precipitation, outlining the pathways that define
 164 the SM-P relationship (Fig. 2). The importance of these processes and interactions have been
 165 documented individually (e.g. Pan and Mahrt 1987, Oke 1987, Diak 1990, Brubaker and Entekhabi
 166 1996, Dolman et al. 1997, Peters-Lidard and Davis 2000, Betts and Viterbo 2005, Santanello et al.

167 2005, 2007, LeMone et al. 2010ab, Gentine et al. 2013a,b). Within this chain, there are also
168 numerous positive and negative feedback loops, which have been detailed by Santanello et al.
169 (2007), van Heerwaarden et al. (2009), and Seneviratne et al. (2010).

170 The LoCo process-chain is far from being all-inclusive, and can be augmented in the future
171 to account for terms such as radiation, snow, landscape type (e.g. desert, grassland, and tundra),
172 canopy interception, large-scale convergence, and additional feedbacks such as those related to
173 clouds (Fig. 1). In addition, the focus to date has been on daytime process and interactions with
174 the convective PBL. Nevertheless, it provides a framework for simplifying the myriad of process
175 interactions into a manageable and measurable series of quantities. Within this definition and
176 scope, LoCo has been working to develop metrics and global mappings that quantify the
177 components of Eq. 1. Voluntary contributors to LoCo span several continents, government and
178 academia, and research interests including regional to global modeling and weather to climate
179 prediction scales.

180

181 4. **LoCo Contributions**

182 Arguably the most prominent contribution of LoCo has been the continued development
183 and promotion of quantifiable L-A coupling metrics to diagnose the land and PBL/precipitation
184 coupling. Rather than common single-variable factors such as bias, root-mean-square-error or skill
185 scores, where compensating errors are often hidden and causality is obscured, multivariate metrics
186 can be used to quantify critical aspects of the L-A coupled system in models and observations,
187 allowing for the exposure of model differences and deficiencies in a systematic fashion.

188 Metrics and their diagnostic nature can be categorized in several ways. Figure 3 illustrates
189 the suite of LoCo-relevant metrics defined by their temporal scales of application (x-axis), by the

190 link(s) within the LoCo process chain (Eq. 1) they encapsulate (y-axis), and by their statistical vs.
191 process-based nature (grey solid and dashed outlines). Some metrics, such as those quantifying
192 soil moisture effects on surface fluxes, cover two-component interactions and others, such as those
193 connecting soil moisture to precipitation, capture the totality of interactions. LoCo metrics can
194 shed light on systematic model biases in coupled processes that might otherwise have been
195 overlooked in a classical model calibration-validation paradigm. Table 1 lists the metrics from Fig.
196 3 along with more of their characteristics, including the nature of input requirements (states vs.
197 fluxes, and land vs. atmosphere), spatial and temporal scale characteristics, and primary foundation
198 for the metrics in terms of variables included. A selection of LoCo metrics and approaches,
199 highlighted in Fig. 3, are now described in more detail below.

200 **a. Process-Level Metrics**

201 *I. Mixing Diagrams and Thermodynamics*

202 One diagnostic approach that incorporates components of the LoCo process chain is
203 concept of thermodynamic 'mixing diagrams', demonstrated for LoCo applications by Santanello
204 et al. (2009). This approach, first introduced by Stommel (1947), relates the daytime co-evolution
205 of 2-meter potential temperature (θ) and humidity (q) to the full energy and water budgets and
206 growth of the PBL. Mixing diagrams break down the evolution of θ and q into vector components
207 that represent the flux contributions of surface heat (sensible) and moisture (latent) versus those
208 from the atmosphere (including PBL entrainment and advection; see Betts, 1992, Freedman and
209 Fitzjarrald, 2001). Mixing diagrams require only near surface or mixed-layer temperature and
210 humidity, surface fluxes, and PBL height information to infer entrainment fluxes that are
211 notoriously difficult to observe (Lenschow and Stankov 1985, Grossman and Gamage 1995).
212 Fortunately, to overcome the expense and difficulties of aircraft measurements, a new generation

213 of ground-based active remote sensing systems permits the measurement of water-vapor,
214 temperature, and wind turbulence and flux profiles from the mixed to the entrainment layer
215 (Muppa et al. 2016, Behrendt et al. 2016, Wulfmeyer et al. 2016, Bonin et al. 2017, Wulfmeyer et
216 al. 2017).

217 Furthermore, the spread in model results due to different physics scheme combinations
218 (e.g. LSM + PBL) can be evaluated directly against observations. Other well-known metrics like
219 the Bowen ratio and lifting condensation level are inherent in this approach and can be used in
220 complimentary fashion to pinpoint weaknesses in the land and atmospheric components of coupled
221 models (Santanello et al. 2009, 2011a,b, 2013a,b, 2015).

222 The co-evolution of θ and q (as energy variables, J kg^{-1}) simulated by three different
223 versions of a coupled mesoscale model (WRF-ARW w/Noah LSM) is shown for dry and wet soil
224 moisture locations over the Southern Great Plains (Fig. 4; from Santanello et al. 2011a).
225 Simulations were run with varying LSM-PBL combinations in WRF, and allowed for the model
226 to evolve in response to L-A interactions generated by each combination as compared with
227 observations (using flux tower, radiosonde, and meteorological data). Overall, the results show
228 that different soil moisture states lead to distinct diurnal patterns of θ and q evolution throughout
229 the day. In this mixing diagram, vectors are defined for the daytime surface and atmospheric
230 (advection + entrainment) flux contributions to the PBL budget. Over drier soils, significant
231 warming and drying occurs due to strong surface heating (sensible heat flux) that leads to deep
232 PBL growth and aggressive warm, dry air entrainment at the PBL top. Over wetter soils, there is
233 strong surface moistening due to evaporation and little warming and drying throughout the day
234 due to limited PBL growth and entrainment. Overall, these diagrams also demonstrate that in order
235 to further constrain the causes of model errors it is desirable to have observing systems (such as

236 that available at the SGP site shown here) that can measure a full suite of L-A variables including
237 vertical profiles and sensible and latent heat and entrainment fluxes.

238 *II. CTP- HI_{low}*

239 The convective triggering potential (CTP) – low-level humidity index (HI_{low}) framework
240 (see Findell and Elthair 2003a,b for details) was developed to better characterize the circumstances
241 in which LoCo could influence afternoon convection: when positive feedbacks (moist surface
242 conditions increasing the chances of rain) or negative feedbacks (dry surface conditions increasing
243 the chances of rain) were more likely to prevail, or when large-scale atmospheric conditions would
244 dictate the occurrence or absence of rain. It is built on the idea that early-morning atmospheric
245 profiles of temperature and humidity can provide information on whether boundary layer
246 moistening or boundary layer deepening would be more likely to lead to convective triggering
247 during the course of the day, or if the fluxes from the surface are unlikely to influence convective
248 conditions. For example, if HI_{low} indicates that the early-morning lower atmosphere is extremely
249 dry, moisture evaporated into the PBL from the surface cannot increase the PBL's moist static
250 energy enough to allow for convection to occur. Such days are termed atmospherically controlled
251 as rain cannot be triggered by local surface processes (Fig. 5).

252 The CTP assesses the stability of the lower troposphere by measuring the departure of the
253 temperature profile from moist adiabatic conditions in the region between 100 and 300 hPa above
254 the ground surface. This is important because deep convection is triggered when the growing
255 daytime PBL reaches the level of free convection (LFC). The lowering of the LFC during this
256 period of BL growth is impacted by the moist static energy within the boundary layer and the
257 temperature lapse rate of the air through which the LFC falls: the LFC falls faster when the
258 temperature profile is close to moist adiabatic. For convective triggering, high sensible heat flux

259 accompanied by rapid PBL growth is more effective when the low-level atmospheric profile is
260 near dry adiabatic and the CTP is high (a negative feedback), while PBL moistening accompanied
261 by rapid LFC fall is a more effective mechanism when the lower atmosphere is close to moist
262 adiabatic and CTP is low (a positive feedback). A negative CTP indicates the local atmosphere is
263 too stable to convect; any rainfall would likely come from large-scale systems moving into the
264 area during the course of the day.

265 Findell and Eltahir (2003b) used one-dimensional PBL modeling with U.S radiosonde data
266 to map regions with frequent positive and negative feedback days (Fig. 5). Ferguson and Wood
267 (2011) used satellite data sources to generate global maps of CTP, HI_{low} , and regional convective
268 regime classifications of four types: local atmospheric conditions favoring convection over wet
269 soils, over dry soils, and either supporting or suppressing convection, independent of land surface
270 conditions. They developed a methodology to derive dataset-specific threshold values in CTP-
271 HI_{low} parameter space that compensates both for biases in the satellite-derived datasets and for
272 limitations of the original thresholds. Roundy et al. (2013a) extended the work of Ferguson and
273 Wood (2011) and developed the Coupling Drought Index (CDI), which allows for day-to-day
274 diagnosis of wet-soil advantage, dry-soil advantage, or atmospherically controlled conditions,
275 given a long historical record to establish “climatological” joint probabilities between surface soil
276 moisture, CTP and HI_{low} . This allows for real-time assessment of convective sensitivity to local
277 land-surface conditions, and has been used to better understand the role of the land surface in
278 modulating drought events (Roundy et al. 2013a,b, Roundy and Santanello 2017).

279 *III. Heated Condensation Framework*

280 The Heated Condensation Framework (HCF; Tawfik and Dirmeyer 2014, Tawfik et al.
281 2015a,b) diagnoses the contribution of surface fluxes to convective initiation based on atmospheric

282 profiles of temperature and humidity. The HCF differs from traditional convective diagnostic
283 approaches; rather than lifting an isolated air parcel to quantify convective instability due to
284 sensible heating and moisture flux, the HCF quantities are calculated by considering the well-
285 mixed turbulent growth of the PBL. This construction emphasizes local buoyancy forced motions
286 rather than large-scale mechanical parcel lifting, and diagnoses a critical atmospheric level referred
287 to as the buoyant condensation level (BCL). The BCL is the height where clouds would form atop
288 a developing PBL through surface buoyancy fluxes alone. To find the BCL, the surface
289 temperature is increased incrementally with the resulting heat mixed into the atmosphere
290 producing an adiabatic temperature profile that intersects the original temperature profile at some
291 height above the ground. The moisture within that depth is also mixed to a constant specific
292 humidity. This incremental heating is repeated until saturation occurs at the top of the adiabatically
293 mixed temperature profile, determining the BCL height. Locally triggered convection is initiated
294 when no further surface heating is required (e.g. the PBL height equals the BCL height).

295 If some surface energy goes into moisture flux instead of sensible heat flux, the PBL
296 specific humidity would increase and the BCL would descend. However, that latent heat energy
297 would be at the expense of sensible heat flux, and the lower BCL may not be reached as easily
298 depending on the atmospheric profile. An optimum partitioning between sensible heat and
299 moisture flux will trigger convection with the minimum total energy input. Surface soil moisture
300 conditions and available energy (net surface radiation) may determine whether the PBL will grow
301 to the BCL height. It should also be made clear that the HCF does not quantify the intensity of
302 convection but rather whether convection is initiated locally.

303 Using the HCF, the atmospheric and land surface conditions leading up to any convective
304 initiation can be quantified in models, reanalysis, or observations, elucidating emergent land-

305 convection relationships. Figure 6 shows the percent chance of convective initiation given a
306 morning convective inhibition (as defined by the HCF variable θ_{def} , which represents the
307 temperature inputs needed in order for saturation to occur at the top of the mixed layer) and
308 morning 10-cm soil moisture using 34-years of summer (June -August) reanalysis data from the
309 North American Regional Reanalysis (NARR; Mesinger et al. 2006) over the contiguous United
310 States, and indicates that these regions have between a 15-35% probability of local convective
311 cloud initiation.

312 Starting from the regional average of soil moisture and θ_{def} over the Southeastern United
313 States (indicated by the SE in Fig. 6) the sensitivity of convective initiation to morning states of
314 soil moisture and θ_{def} can be determined. For example, decreasing soil moisture from the 0.28 m^3
315 m^{-3} average to $0.15 \text{ m}^3 \text{ m}^{-3}$ would increase the likelihood of local convective initiation by roughly
316 10%. Overall, Fig. 6 shows that the likelihood of convective initiation is more sensitive to the
317 morning state of θ_{def} , and soil moisture provides a secondary control on convective initiation. In
318 addition to this emergent soil moisture-convective initiation relationship, the HCF also contains a
319 set of other diagnostic quantities (not covered here) that quantify the most efficient surface energy
320 partitioning needed to achieve convective initiation (Tawfik et al. 2015a).

321 **b. Statistical Metrics**

322 *I. Soil Moisture Memory*

323 As the first link of the process-chain (Eq. 1), soil moisture has the ability to influence the
324 L-A processes over time, and has been the focus of a number of quantitative metrics (e.g.,
325 Schlosser and Milly 2002, Betts et al. 2004, Notaro et al. 2008, Orlowsky and Seneviratne et al.
326 2010, Mei and Wang 2012, Miralles et al. 2012, Roundy et al. 2013a,b). Soil moisture memory
327 (SMM) is a measure of the persistence of SM anomalies, which may then affect coupled feedbacks

328 (e.g. McColl et al., 2017a,b). This is important because the soil accumulates and retains past
329 precipitation and other weather anomalies (e.g., heat waves). This memory extends the impact of
330 weather and climate events forward in time and can provide additional predictability of future
331 weather and climate, improving predictions.

332 Delworth and Manabe (1988, 1989) showed that the time evolution of the surface water
333 budget can be represented as a first-order Markov process such that the lagged autocorrelation of
334 soil moisture (defined as $r(\tau) = \exp(-\lambda\tau)$) has an e-folding time scale of $1/\lambda$ that can redden the
335 spectrum of atmospheric variability where feedbacks are present. This time scale is typically
336 defined as the SMM and is sensitive not only to the time spectrum of precipitation but also
337 terrestrial hydrologic processes (e.g., infiltration, runoff, evapotranspiration), making it a tool to
338 validate LSM simulation of these processes. SMM is generally calculated from long time series of
339 data as a seasonally-varying climatological characteristic of local hydrology (cf. Koster and Suarez
340 2001). SMM has been estimated in observational studies (e.g., Vinnikov and Yesserkepova 1991,
341 Koster et al. 2003, Dirmeyer et al 2016) and applied as a robust metric for verifying soil moisture
342 persistence in both uncoupled and coupled LSMs and across observational datasets from in-situ to
343 satellite instruments (e.g., Robock et al. 1995, Koster and Suarez 2001, Seneviratne and Koster
344 2012, Dirmeyer et al. 2013, Hagemann and Stacke 2015). It should be noted that the frequency of
345 data (observations or model output) affects the estimation so care must be taken when comparing
346 results; longer periods between samples (weekly instead of daily, or monthly instead of weekly)
347 act as a low-pass time filter, removing higher frequencies from consideration.

348 *II. Two-legged metrics*

349 The most common multi-variate statistic is the correlation $r(v_1, v_2)$, where high correlations
350 between variables can hint at causality. However, high correlations within the LoCo process chain

351 do not guarantee important feedbacks are acting. For instance, in the Sahara there are very strong
352 correlations between soil moisture and evapotranspiration (ET), but there is rarely enough soil
353 moisture to contribute to meaningful evaporation. To have an impact on the atmosphere, there
354 must be sufficient variability in the terms over time. Guo et al. (2006) recognized this and presented
355 a metric combining correlation and standard deviation σ . Dirmeyer (2011b) generalized this as a
356 “terrestrial coupling index” I , noting the relationship:

$$357 \quad I = \sigma_{\phi} r(SM, \phi) = \sigma_{SM} \frac{d\phi}{dSM} \quad (2)$$

358 where the linear regression slope of surface flux ϕ on SM , $\frac{d\phi}{dSM}$, is a measure of the sensitivity of
359 ϕ to SM . Like CTP-HI_{low}, coupling indices are calculated from large time series of daily (or longer)
360 data.

361 Progressing along the process chain in Eq. 1 to the response of atmospheric states to surface
362 fluxes, coupling indices for the atmospheric leg can also be generated using the same formulation
363 in Eq. 2 but substituting the surface fluxes for soil moisture, and atmospheric properties for the
364 surface fluxes. When atmospheric leg indices are paired with indices from the terrestrial leg, we
365 have “two legged” coupling metrics showing the potential link from land surface states to
366 atmospheric responses. Separate pathways in the process chain through the heat and moisture
367 cycles can be examined, e.g., noting the strong relationships between surface sensible heat flux
368 and daytime PBL growth (Betts 2004).

369 Two-legged metrics are easily applied to model output, provided that the necessary
370 variables are saved and complete in time and space. Figure 7 shows the global distribution of
371 terrestrial (through the moisture variables, SM and latent heat flux) and atmospheric (through the
372 thermal variables, sensible heat flux and PBL height) legs for boreal and austral summers estimated

373 from multi-decade simulations of the operational coupled L-A model from ECMWF (Dirmeyer et
 374 al. 2012). Application to observed data can be more challenging as surface flux measurements are
 375 not widespread nor typically long-term. For the terrestrial leg, co-located soil moisture and surface
 376 flux measurements are necessary. For the atmospheric leg, co-located surface flux and
 377 meteorological or profile measurements are necessary. There is also a seasonality in coupling that
 378 is made evident using these metrics, as seen in Fig 7.

379 *III. Triggering and Amplification Feedback Strength (TFS/AFS)*

380 Findell et al. (2011) evaluated the sensitivity of afternoon rainfall to morning EF using 25
 381 years of data from the North American Regional Reanalysis dataset (NARR; Mesinger et al. 2006).
 382 The EF-dependence on rainfall was assessed using two statistical metrics: triggering feedback
 383 strength (TFS), which reflects how afternoon rainfall frequency changes with EF, and
 384 amplification feedback strength (AFS), which quantifies how accumulated rainfall varies with EF
 385 on those afternoons when rainfall occurs. They are defined as:

$$386 \quad TFS = \sigma_{EF} \frac{\partial \Gamma(r)}{\partial EF} ; AFS = \sigma_{EF} \frac{\partial E[r]}{\partial EF} \quad (3)$$

387 where σ_{EF} is the standard deviation of evaporative fraction, $\Gamma(r)$ is the probability of afternoon
 388 rainfall occurrence, and $E[r]$ is the expected value of rainfall amount when rainfall does occur ($>$
 389 1 mm).

390 To limit the analysis to local conditions when large-scale forcing was not dominant, TFS
 391 was calculated using data from only summertime days with no rain in the morning and with
 392 CTP $>$ 0. Days contributing to the AFS calculation were further limited to those when afternoon
 393 rainfall occurred. This work showed that high evaporation enhances the probability of afternoon
 394 rainfall over the U.S. primarily east of the Mississippi River (Fig. 8). Variations in surface fluxes
 395 were shown to lead to 10-25% changes in afternoon rainfall probability in these regions (Fig 8a).

396 The intensity of rainfall, by contrast, was largely insensitive to surface fluxes (Fig 8b). These
397 results indicate that while surface flux partitioning can shift the local atmosphere from non-
398 convecting to convecting in non-moisture-limited regions, other controls such as free tropospheric
399 moisture content or large scale moisture convergence largely determine how much rainfall occurs.

400 Findell et al. (2011) suggest that local surface fluxes represent an important trigger for
401 convective rainfall in the eastern United States during the summer, leading to a positive
402 evaporation–precipitation feedback. This focus on the impact of surface fluxes on subsequent
403 rainfall does not include the soil moisture portion of the process chain in Fig 2 (arrow a), but is a
404 statistical assessment of the net sensitivity of ΔP to ΔEF (arrows b, c, and d). Berg et al. (2013)
405 showed results from a GCM with similar TFS and AFS signatures as the NARR model data, but
406 demonstrated that the GCM’s TFS resulted from a weaker sensitivity of rainfall to EF than the
407 NARR model data yet showed enhanced variability of EF, highlighting the complexity of
408 characterization of interdependent processes. In addition, Guillod et al. (2014) showed that the
409 TFS patterns are sensitive to the choice of observational data, highlighting the need for better
410 constrained observations of surface turbulent fluxes.

411

412 **5. Resources and Outreach**

413 In addition to the GEWEX, GLASS, and LoCo websites (<http://www.gewex.org/loco/>),
414 there have been a number of resources developed by the LoCo Working Group to help support
415 community involvement.

416 **a. The Coupling Metrics Toolkit (CoMeT)**

417 The Coupling Metrics Toolkit (CoMeT; <http://www.coupling-metrics.com/>) is an open
418 source code package for calculating selected LoCo coupling metrics. Specifically, CoMeT is a set

419 of portable FORTRAN 90 modules with thorough in-line documentation currently available via a
420 Git repository. The modules are designed to be easily wrapped into existing Python or NCAR
421 Common Language (NCL) code using the *f2py* and *WRAPIT* commands respectively.
422 Development of CoMeT was motivated by the growing need from the broader research community
423 to examine L-A coupling and interactions and the lack of a standard code package to facilitate
424 calculation. Currently CoMeT contains six metrics, five of which are discussed in this article: 1)
425 soil moisture memory (SMM), 2) the variables from the mixing diagram approach, 3) CTP-HI_{low},
426 4) the two-legged coupling indices, 5) HCF, and 6) the relative humidity (RH) tendency (Ek and
427 Mahrt 1994, Ek and Holtslag 2004, Gentine et al. 2013). Future plans for CoMeT include a Python-
428 based wrapper that would allow users to specify the path to data and desired metrics, where CoMeT
429 would return an output file with the results. This will enable a friendlier interface that does not
430 require the user to write wrapping code. Because this resource is intended for broad use,
431 community input and requests regarding additional metrics are highly welcome.

432 **b. Quick Reference for Metrics**

433 A growing reference catalog of L-A coupling metrics is maintained at:
434 http://cola.gmu.edu/dirmeyer/Coupling_metrics.html. Some two-dozen metrics are listed, with
435 links to single page PDF documents on each that give a basic description, input/variable
436 requirements, applicability, caveats and references for further information. The catalog also
437 outlines to which portion of the LoCo process chain each metric is relevant, the applicable space
438 and time scales of the metric, and whether it can be estimated from observational data (cf. Table 1
439 for a subset). As with CoMeT, this is a community resource that can expand to accommodate new
440 metrics, and user input is welcome.

441 **c. Community Connections**

442 LoCo Working Group members serve to facilitate and advocate for L-A coupling
443 considerations in several science communities. As with the LoCo metrics, these connections span
444 a wide range of scales and applications, and aim to increase awareness of the role of L-A
445 interactions in weather and climate. This includes the subseasonal-to-seasonal (S2S) prediction
446 community (Vitart et al. 2017), where LoCo has been utilized to elucidate how global models
447 should initialize their LSMs. This also includes strong involvement in the planning and execution
448 of field campaigns and dataset production like those led by the Department of Energy's
449 Atmospheric Radiation Measurement (DOE-ARM) program's Southern Great Plains (SGP)
450 testbed. Over the past 20 years, the ARM community has utilized observations of the PBL to
451 investigate L-A interactions from a mostly atmospheric perspective (e.g. Berg and Stull 2004,
452 Zhang and Klein 2010), and the SGP site has recently undergone significant reconfiguration to
453 better monitor L-A interactions, including new soil moisture sensors and an overall instrument
454 synergy that spans the LoCo process chain. LoCo efforts have helped lead to development of 'best
455 estimate' products of land surface (ARMBE-Land; Xie et al., 2010) and additional PBL profile
456 measurements (ESLCS; Ferguson et al., 2016) complementing the traditional suite of atmospheric
457 measurements to more fully assess coupled processes and utilize LoCo metrics. Ongoing and
458 future campaigns over the SGP are focused on the surface layer (< 100 meters above surface)
459 (Cheng et al. 2017). L-A interactions including the observation and theoretical derivation of key
460 variables in the PBL such as variance and flux profiles as well as entrainment fluxes have recently
461 become available, e.g. within the Land-Atmosphere Feedback Experiment (LAFE; Wulfmeyer and
462 Turner 2016, Wulfmeyer et al. 2017) which can be applied for testing new similarity relationships
463 (Wulfmeyer et al. 2016) and extended analyses of LoCo metrics.

464 LoCo is supporting the organization of a North American regional hydroclimate project
465 ([http://www.gewex.org/panels/gewex-hydroclimatology-panel/regional-hydroclimate-projects-
467 rhps/north-american-regional-hydroclimate-project-initiative/](http://www.gewex.org/panels/gewex-hydroclimatology-panel/regional-hydroclimate-projects-
466 rhps/north-american-regional-hydroclimate-project-initiative/)) under GEWEX's water
468 availability grand challenge, and convenes or contributes to numerous conference sessions,
469 Decadal Survey by identifying gaps in our observational suite, especially from space, that are
470 needed to utilize LoCo metrics to further improve understanding of L-A coupling.

471 **6. Challenges and the Future of LoCo**

472 It is evident that the scope of LoCo, defined by Eq. 1, captures only a subset of L-A
473 processes and types of coupling that exist in nature. However, the LoCo paradigm serves as a
474 foundation, rooted in water and energy exchanges, from which to expand upon in terms of breadth
475 and complexity. As the second decade of LoCo begins, the Working Group has broadened its scope
476 to consider cold processes (snow, ice), radiation and cloud feedbacks, spatial SM-P feedbacks,
477 human land and water management impacts (drainage, irrigation, land use/land cover change,
478 dams), soils and groundwater, biogeochemistry (carbon), vegetation state (e.g. Williams et al.
479 2015) and stress (solar-induced fluorescence, transpiration), and to extend to phenomena such as
480 monsoons and landfalling tropical cyclones. There is also a strong push to extend to
481 nighttime/stable coupling assessment and interactions with the PBL community. The expanding
482 themes are reflective of science steering at higher levels within GEWEX and WCRP, as well as
483 new areas of expertise represented within the LoCo working group. There is also work to quantify
484 the relative contribution of local versus external forcing to event- and seasonal-scale L-A coupling
485 strength, in the midst of internal variability (e.g., Song et al. 2016, Ford et al. 2015, Berg et al.
486 2017). This evolution coincides with, and contributes to, the evolution of Earth System models

487 that encapsulate additional processes, but at the same time require more complex and quantitative
488 metrics to employ in their development.

489 In terms of recent community-based projects, there are direct connections that are being
490 made to the GEWEX Diurnal land/atmosphere Coupling Experiment (DICE;
491 <http://appconv.metoffice.com/dice/dice.html>) and the Protocol for the Analysis of Land Surface
492 Models (PALS) Land Surface Model Benchmarking Evaluation Project (PLUMBER; Best et al.
493 2015, Haughton et al. 2016); the latter can provide a paradigm for extending model benchmarking
494 vertically into the atmosphere. LoCo is also connected to the GLACE modeling community via
495 the GLACE-CMIP5 project (Seneviratne et al. 2013), which seeks to evaluate SM-atmosphere
496 coupling and its impact on climate change in models using idealized GCM simulations with and
497 without interactive SM (e.g., Berg et al. 2016, 2017a, 2017b), and LoCo approaches have been
498 used to find coherency in trends as part of the IPCC AR5 (van Heerwaarden et al. 2010). Likewise,
499 as the CMIP6 exercise comes to fruition, LoCo will look to support and inform the analysis of
500 climate model simulations, in particular modeling experiments focusing on the role land surface
501 processes, such as soil moisture and snow feedbacks (LS3MIP; van den Hurk et al. 2016).

502 The theme of the 2017 AMS Annual Meeting – “Observations Lead the Way” – is also
503 highly relevant to the success of LoCo. Advanced metrics are only as good as the observations
504 applied to confront models. While tremendous progress has been made in retrieving components
505 of the water cycle (e.g. soil moisture, clouds, precipitation) from space, the layer of interaction
506 between the land and atmosphere (i.e. the PBL and its diurnal evolution) remains largely
507 undersampled, and thus the full suite of variables needed to assess the process-chain in Eq. 1 has
508 been very difficult to observe completely at the necessary spatial or temporal scales (Findell et al.
509 2015). It is also clear that the metrics most useful in terms of characterizing L-A feedback include

510 variables which include the characteristics of the PBL from which entrainment fluxes and ABL
511 depth are most important and which can also be observed. In particular, the lack of continuous
512 monitoring of the lower troposphere (the PBL ‘gap’) has become quite evident. Therefore, the
513 community must also support 1) the development and application of suitable observing systems to
514 address L-A coupling, 2) the design and the application of a suitable sensor synergy to directly
515 measure the required components of coupling metrics without any use of model data.

516 To this end, there is now increasing activity in ground-based PBL profiling using active
517 remote sensing techniques that will likely lead to methods that can be applied to future satellite
518 missions (Wulfmeyer et al. 2015). Efforts to produce long- (Liu et al. 2012), medium- (Kolassa et
519 al. 2016, 2017) and short-term (R. Bindlish, pers. communication) global and spatially and
520 temporally homogenous satellite-based soil moisture records, a surface flux record (e.g.
521 WECANN; Alemohammad et al. 2016) and within GEWEX to enhance the accessibility and
522 quality of sub-daily precipitation records (e.g., Blenkinsop et al. 2016) will further enable
523 observationally-based LoCo studies in the future.

524 Finally, the ultimate utility of improved understanding of the physical processes driving
525 the L-A system should be felt in advancing our community models, improving weather and climate
526 predictions, and ultimately enhancing decision making capabilities that protect life and property.
527 This will require a change in model development philosophy, where parameterizations in GCMs
528 and LSMs are not developed in separation but as linked parts of a coupled system, calibrated,
529 validated and diagnosed together. Closer connections between research and operational
530 communities, including joint development of benchmarks for coupled L-A modeling, will greatly
531 aid progress, and we invite interested readers to contact the authors and/or refer to the LoCo

532 website for more information. These are the ultimate aims of the LoCo community – building
533 effective scientific linkages that mirror the links we are recognizing in nature.

534

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Table 1: Land-atmosphere coupling metrics portrayed in Fig 3. A more thorough list of metrics and their descriptions is available at http://cola.gmu.edu/dirmeyer/Coupling_metrics.html.

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Figure 1: A schematic of local land-atmosphere interactions in a quiescent synoptic regime, including the SM-P feedback pathways. Solid arrows indicate a positive feedback pathway, and large dashed arrows represent a negative feedback, while red indicates radiative, black indicates surface layer and PBL, and brown indicates land surface processes. Thin red and grey dashed lines with arrows represent also represent positive feedbacks. The single horizontal gray-dotted line (no arrows) indicates the top of the PBL, and the seven small vertical dashed lines (no arrows) represent precipitation. *Fig. 1 is courtesy of Michael Ek; embellished from earlier versions appearing in Ek and Mahrt, 1994 and Ek and Mahrt, 2004.*

Figure 2: Schematic of the LoCo process-chain describing the components of L A interactions linking soil moisture to precipitation and ambient weather (T2m, Q2m), where SM represents soil moisture, EFsm is the evaporative fraction sensitivity to soil moisture, PBL is the PBL characteristics (including PBL height), ENT is the entrainment flux at the top of the PBL, T2m and Q2m are the 2-meter temperature and humidity, and P is precipitation.

Figure 3: LoCo metrics (see Table 1) across temporal scales (x-axis), relationship to the LoCo process-chain (Eq. 1) along the y-axis, and statistical vs. process-based nature (elliptical outlines). Green background shading indicates land surface related states and fluxes, while blue indicates PBL and atmospheric variables.

Figure 4: Mixing diagrams showing coupling behavior of three different modeling schemes vs. observations for dry and wet soil locations on 12 June 2002 over the U.S. SGP, as indicated by the diurnal (7am-7pm), hourly co-evolution of 2-meter temperature (y-axis) and humidity (x-axis) for a range of model simulations (green, red, blue representing different PBL schemes in the WRF model), observations (dashed black), and the derived surface and atmospheric flux vectors (black

arrows). The x- and y-axes are in units of J kg^{-1} after multiplying humidity by the latent heat of vaporization and temperature by the specific heat, respectively. *Source: Figure 1 from Santanello et al. (2011a) based on experiments in Santanello et al. (2009)*

Figure 5: Regional categorizations (panel a) based on the distribution of daily CTP- HI_{low} values at radiosonde stations (+) through the contiguous US given the CTP- HI_{low} framework shown in panel (b). *Source: Findell and Eltahir (2003b)*

Figure 6: Percent probability of triggering convection as a function of θ_{def} (a measure of convective inhibition) and 10 cm soil moisture derived from 34-years of daily NARR summer data. Average morning soil moisture and conditions are shown for four different regions over the United States: the Southeastern (SE), Southern Plains (SP), Northern Plains (NP), and Southwest (SW). *Source: Figure 11b from Tawfik et al. (2015b)*

Figure 7: Terrestrial (left) and atmospheric (right) coupling indices based on the formulation in Eq (2) for the indicated seasons; SM=soil moisture, LHF=latent heat flux, SHF=sensible heat flux, PBL is height of the planetary boundary layer. Positive values indicate coupling, insignificant correlations are masked. *Based on Fig. 8 of Dirmeyer et al. (2012)*

Figure 8: The sensitivity of convective triggering and rainfall amount to evaporative fraction. (a) Triggering feedback strength (TFS; units of probability of afternoon (noon-6 pm) rain) and (b) amplification feedback strength (AFS; units of mm of afternoon rain) during June-July-August, derived from 25 years of NARR data. *Source: Findell et al. (2011).*