1   **Land Surfaces at the Tipping-Point for Water and Energy Balance Coupling**

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7

8   **Abstract**

9   The surface water and energy balances can be coupled or uncoupled depending on whether the
10   evaporation regime is water-limited or energy-limited. As the landscape loses soil moisture
11   during drydowns, a transition between the regimes may occur, which signifies a nonlinear
12   change in water-energy-carbon coupling. Regions that switch often between these two regimes,
13   i.e., are dominated by neither regime, are particularly vulnerable to climate variability and
14   change. To robustly identify these tipping points, we identify drydown events based on global
15   soil moisture data sets from remote sensing. The event identification does not rely on
16   precipitation information and is robust with respect to measurement noise. Then, the soil
17   moisture thresholds delineating the evaporation regime transitions are determined by
18   Sequential Monte Carlo Sampling and a two-stage parametrization strategy. Based on the
19   estimated soil moisture thresholds across the globe, we estimate observation-based water
20   availability indices which quantify the nonlinear controls of soil moisture on evaporation. This
21   framework is tested and applied globally using Soil Moisture Active Passive (SMAP) soil moisture
22   retrievals. Combined with a new tippling-point metric that describes the frequency of
23   evaporation regime transitions, we identify regions that switch often between different
24   evaporation regimes at the global scale. Given unit shifts in soil moisture, these regions will
25   experience the most change in how their surface water and energy are coupled.

26   1. **Introduction**

27   Evaporation flux couples the water, energy and carbon balances over land surfaces
28   (Biederman et al. 2018; Crow et al. 2019; Entekhabi et al. 1996; Santanello Jr et al. 2019).
29   During drydowns and depending on the availability of volumetric soil moisture (θ), microclimate

30 and landscape attributes, evaporation can be classified to be in energy- (Stage-I) or
31 water-limited (Stage-II) regimes (Gallego-Elvira et al. 2016; Greve et al. 2015; Seneviratne et al.
32 2010).

33   Transitions between Stage-I and II evaporation regimes determine the degree of coupling
34 between the water, energy and carbon fluxes and states (Feldman et al. 2019, 2020; Miralles et
35 al. 2019). Specifically, soil moisture's control on evaporation abruptly increases once it drops
36 below a critical value θ_* (denotes the onset of Stage-II evaporation), which will subsequently
37 elevate local air temperature via land-atmosphere coupling (Orth 2021). For some extreme
38 cases, this mechanism can increase air temperature to soil moisture sensitivity by four times –
39 leading to exacerbated local heatwaves (Dirmeyer et al. 2021). Likewise, such mechanisms are
40 also often responsible for local drought intensification and global carbon uptake variability
41 (Humphrey et al. 2021; Seneviratne et al. 2010; Zhou et al. 2019). Therefore, landscapes with
42 frequent evaporation regime transitions (or land surface tipping-points) are more sensitive to
43 climate change/variability, since dry anomalies can be amplified via land-atmosphere coupling
44 (Schwingshackl et al. 2017).

45   However, existing physical models contain substantial uncertainties in capturing the
46 tipping-point locations and the associated regime change frequencies (Schwingshackl et al.
47 2017). This is because model representations of soil moisture's control on evaporation are
48 highly uncertain (Crow et al. 2015; Dirmeyer et al. 2000; Lorenz et al. 2016). For example, Dong
49 et al. (2020b) demonstrates that most land surface model schemes preferentially classify the
50 central US into water-limited evaporation regimes, leading to overestimated evaporation water
51 stress and biases in screen-level air temperature estimates (Crow et al. 2020). Likewise,
52 modeled evaporation and soil moisture correlations (higher for water-limited dominated
53 evaporation regimes) are typically biasedly higher than that of observations (Crow et al. 2015;
54 Dirmeyer et al. 2018; Dong et al. 2022b; Lei et al. 2018), which may be a key source of projected
55 air temperature uncertainty in atmospheric models (Berg and Sheffield 2018; Dong et al. 2022b;
56 Seneviratne et al. 2013). Therefore, observed land tipping-point distributions and the associated
57 evaporation changes are of paramount importance for improving and diagnosing large-scale
58 modeling frameworks.

59   Although evaporation regimes and land tipping points can be identified using observed
60 evaporation and soil moisture data pairs (Buitink et al. 2020; Dirmeyer et al. 2018; Williams and

61   Torn 2015), flux tower based evaporation observations have limited spatial availability (Holmes

62   et al. 2018). Remotely sensed evaporation has been used for diagnosing large-scale soil

63   moisture – evaporation relationships and the associated critical soil moisture thresholds

64   (Denissen et al. 2020; Hain et al. 2009; Miralles et al. 2012). However, algorithmic and retrieval

65   uncertainties in these evaporation estimates can mask soil moisture and evaporation

66   relationships (Crow et al. 2015; Lei et al. 2018). More importantly, remote sensing based

67   evaporation products may involve pre-defined evaporation and soil moisture relationships

68   (Martens et al. 2017) – making them difficult to be used as an objective reference (Qiu et al.

69   2020). Evaporation regimes can also be identified using the diurnal amplitude of land surface

70   temperature and air temperature changing rates (Feldman et al. 2020; Gallego-Elvira et al.

71   2016). However, the evaporation and land surface temperature relationship is complicated by a

72   multitude of factors (Bateni et al. 2014; Lu et al. 2016).
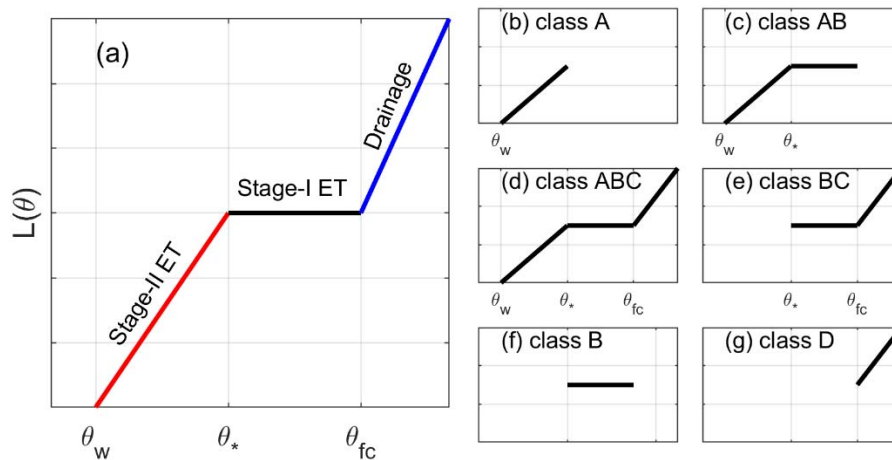
73

74   **Figure 1**. Key hydrological regimes dominating soil moisture losses during interstorm periods (a).
75   The black, red and blue solid lines represent stage-I and II evaporation and drainage hydrological
76   regimes, respectively. The presence of different hydrological regimes is driven by microclimate
77   and landscape attributes, and the potential combinations of hydrological regimes are shown in
78   parts b to g – representing soil loss function $L(\theta)$ shapes vary from dry to wet conditions. θ_w,
79   θ_* and θ_{fc} represent the wilting point, critical evaporation regime transition point and field
80   capacity, respectively, which are used for characterizing $L(\theta)$.

81   Alternatively, the large scale signature of different evaporation regimes can be identified

82   using remote sensing soil moisture interstorm drydown patterns, without evaporation

83   observations or proxies (Akbar et al. 2018; Sehgal et al. 2021b). Specifically, on

84   non-precipitation days, soil moisture loss (i.e., the rate of soil moisture temporal change during

85   drydowns) is dominated by water- and energy-limited evaporation and drainage regimes. The
86   transition of different evaporation regimes can be identified when soil moisture crosses the
87   critical value θ_* – see Figure 1 (Akbar et al. 2018). However, such methods typically require
88   high-quality precipitation data or (arbitrarily) defined thresholds to identify soil moisture
89   drydown time series. Additionally, numerous free parameters need to be optimized from a
90   single soil moisture drydown time series, which undermines the robustness of the results.

91   This study seeks to further advance large-scale soil moisture drydown analysis, and we aim
92   to provide observation-based identification of tipping-points that represent landscapes with
93   frequent switches between different evaporation regimes. To do so, we first present an
94   improved soil moisture drydown identification and parameterization framework. Then, an
95   observation-based measure of land evaporation water availability index (Π) is introduced and
96   evaluated using flux tower observations. Based on Π, we further propose a new tipping-point
97   metric (Φ), which quantifies the frequency of a landscape switching between water- and
98   energy-limited evaporation regimes. Our main result is the observation-based identification of
99   surface water, energy and carbon balance tipping-points, which identify regions likely to be
100 more vulnerable to climate variability and change.

101 2. **Methods and Data**

102 The shifts in evaporation regimes occur during interstorm periods where soil moisture is
103 persistently decreasing. To determine the critical soil moisture value θ_* that marks the
104 evaporation regime change, interstorm soil moisture drydown periods need to be isolated first.
105 Therefore, a robust interstorm drydown identification method is first presented in Section 2.1.
106 After the isolation of drydowns, five parameters (three soil moisture thresholds and two loss
107 rates, Figure 1a) need to be determined. Based on Sequential Monte Carlo Sampling (SMCS;
108 (Jeremiah et al. 2012)), we propose a two-stage optimization framework in Section 2.2. This
109 framework can robustly determine $L(\theta)$ forms and the associated parameters – see Section 1
110 of the Supporting Information.

111 Combined with metrics proposed in Section 2.3, the soil moisture drydown analysis is used
112 to quantify global evaporation water availability and land surface tipping points. All the data
113 used in our analysis is described in Section 2.4.

114

2.1 Soil moisture drydown identification

116 Surface volumetric soil moisture content (θ) temporal dynamics during interstorms are
117 dissipative and exhibit a Markovian behavior (Crow et al. 2009; Dong and Crow 2018; Short
118 Gianotti et al. 2019b) so that during the entire time-series:

$$\theta_t = \lambda^\tau \theta_{t-\tau} + \varsigma_t \tag{1}$$

$$\varsigma_t = I_t + \epsilon_t \tag{2}$$

119 where τ denotes the temporal difference of two consecutive soil moisture observations in
120 days (overpasses); $I_t \geq 0$ is infiltration due to precipitation addition (zero for non-precipitation
121 days); λ is a dimensionless temporal constant describing the θ decorrelation at daily time
122 scales; ϵ_t is zero-mean random error.

123 According to (1), ς_t represents the error of approximating θ_t with $\lambda^\tau \theta_{t-\tau}$, which is a
124 combination of random errors (in non-precipitation days) and positive outliers (i.e., $I_t > 0$, in
125 precipitation days) – see Figure 2a for demonstration. Days in which θ is strongly affected by
126 I_t can be identified as positive outliers of ς_t, which can be iteratively removed.

127 An illustrative example of this drydown identification procedure based on in-situ soil
128 moisture observations from Oklahoma is shown in Figure 2, in which 20% of days experience
129 precipitation. To start, we directly fit the observed θ time series as $\lambda^\tau \theta_{t-\tau}$, which yields
130 contrasting errors (ς_t) in precipitation and non-precipitation days (see the blue and red
131 histograms in Figure 2a). Assuming the error ς_t is zero-mean and normally distributed and
132 based on its standard deviation, we can identify (via one-sample t-test) and filter out days that
133 ς_t realizations are outliers to the expected distribution. By repeating the above procedure, θ
134 observations that are significantly affected by precipitation are iteratively removed and only
135 drydowns remain (Figure 2b, c and d). The approach is tested and is reasonably robust to the
136 choice of confidence level for identifying the positive ς_t outliers. Higher t-test confidence
137 levels require more iterations to converge on the appropriate drydown identification. In this
138 study, we use a confidence level of p = 0.90, which yields clear $d\theta/dt$ vs. θ relationships with

139   efficient algorithmic convergence.
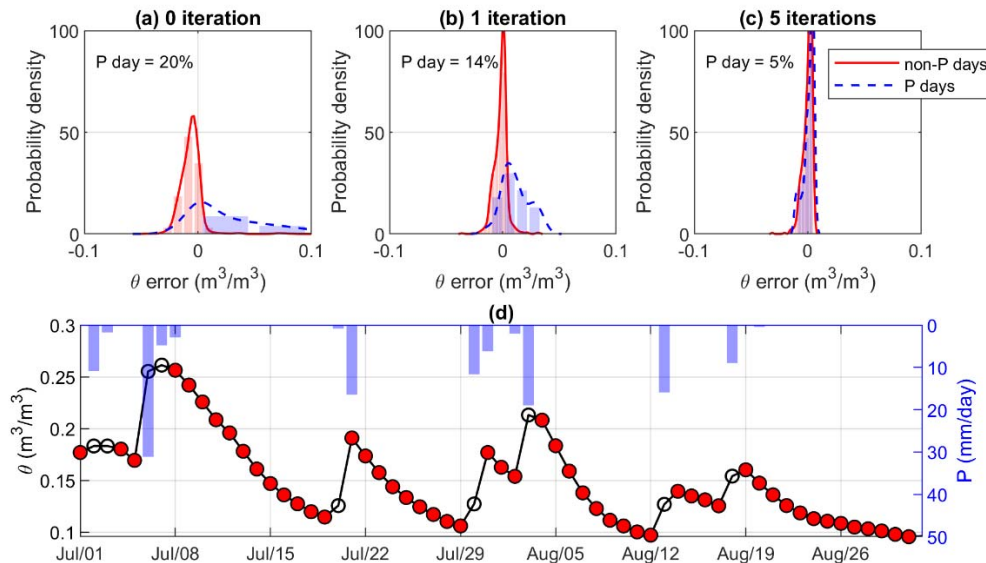
Figure 2. The distribution of θ estimation error (ς_t) using $\theta_t = \lambda^\tau \theta_{t-\tau}$ for different iterations of outlier removal (a to c), with text denoting the observed portion of precipitation days in the remaining time series. The resulting drydown time series (red circles) is shown in (d). Note that gauge-based precipitation is only used for demonstrating the contrasting error statistics in parts (a) to (c) and verification of the selected drydown time series (d). In-situ-based soil moisture (θ) from Agricultural Research Service (ARS) Little Washita (Oklahoma, $34^o35'$N, $97^o53'$W) during the 2016 June-July-August months is used here for demonstration.

2.2 Soil loss function determination

2.2.1   Soil loss function parameter optimization

The overall strategy for $L(\theta)$ identification is to fit each of the six possible forms shown in Figure 1b to 1g to the observed soil moisture losses on pixel-by-pixel bases. Either cross validation (Akbar et al. 2018) or information criteria can be used to avoid over-fitting. The infrequent sampling of locally-rare environmental states, however, can weaken the power of cross-validation of $L(\theta)$ models. We therefore directly analyze $L(\theta)$ based on all available drydown data using the small-sample biased-corrected Akaike information criterion (AICc, Burnham and Anderson (2004)) to perform parsimonious model selection.

158   Taking the most complex ABC form of $L(\theta)$ for illustration, the loss function can be

159   expressed as:

$$y_A = \alpha_1(\theta - \theta_w), \qquad \text{if } \theta < \theta_* \tag{3}$$

$$y_B = c, \qquad \text{if } \theta_* \leq \theta < \theta_{fc} \tag{4}$$

$$y_C = \alpha_2(\theta - \theta_{fc}) + c, \quad \text{if } \theta \geq \theta_{fc} \tag{5}$$

160   where y_A, y_B and y_C are the estimated $d\theta/dt$ for the three different phases of $L(\theta)$ – see

161   Figure 1; α_1 and α_2 are the slopes for Stage-II ET and drainage, respectively; and c is a

162   constant estimated as $\alpha_1(\theta_* - \theta_w)$ by setting $\theta = \theta_*$ in (3). As with Akbar et al. (2018), the

163   possible $L(\theta)$ forms in Figure 1 reflect the general landscape soil moisture state impact on

164   hydrologic fluxes. However, a constant, low-rate, stage III evaporation regime (when $\theta < \theta_w$) is

165   not included in this study. This is because the stage III evaporation rate is generally lower than

166   0.005 (for arid to semi-arid regions) and 0.01 $m^3/(m^3$ day) (for semi-humid and humid regions) –

167   see Figure 9 of Sehgal et al. (2021b). These rates are much lower than the retrieval error of

168   SMAP and hence, this evaporation stage is not considered in this study.

169   For a given combination of θ_w, θ_*, θ_{fc}, the slope parameters (i.e., α_1 and α_2) can be

170   explicitly determined via linear regression. In effect, we first optimize only three (i.e., θ_w, θ_*,

171   θ_{fc}), instead all five parameters with SMCS. By reducing the dimensionality of the estimation

172   problem, it is more robust to parameter equifinality and local optima problems (Dong et al.

173   2015; Dong et al. 2016; Moradkhani et al. 2005).

174   At first, SMCS is initialized with *n* particles (i.e., parameter combinations, $\mathbf{\theta}^j = [\theta_w^j, \theta_*^j, \theta_{fc}^j]$,

175   with *j* ranging from 1 to *n*) randomly drawn from the entire parameter space. For each $\mathbf{\theta}^j$,

176    $L(\theta)$ can be estimated using linear regression – see (3) to (5). The fitting error for this particle is

177   calculated as the quadratic mis-fit:

$$e^j = \sum(y - y_{obs})^2 \tag{6}$$

178   where *y* and y_{obs} are estimated and observed $d\theta/dt$, respectively. Based on e^j, the likelihood

179   (l) of $\boldsymbol{\theta}_j$ can be quantified as:

$$l_j = \frac{1}{(2\pi\sigma^2)^{m/2}} \exp\left(-0.5\frac{e^j}{\sigma^2}\right). \tag{7}$$

180   Where σ is the standard deviation of the observation error, m is the number of observations.

181   As shown in Dong et al. (2015), σ is essentially a parameter controlling the convergence speed

182   of SMCS. The likelihood is positively correlated to the accuracy of $\boldsymbol{\theta}_j$, irrespective to the choice

183   of σ. However, extremely low σ values may lead to severe particle degeneracy problems

184   (Dong et al. 2016). Based on these considerations, a default value of 0.02 m^3/(m^3 day) is used

185   for σ and if the maximal likelihood of the particles is lower than 10^{-99}, σ will be set to 0.2

186   m^3/(m^3 day) to prevent particle degeneracy.

187   Based on the likelihood function, the normalized importance weight (denoted as w_j) of

188   each particle is calculated as:

$$w_j = l_j / \sum l_j. \tag{8}$$

189   The particles are then resampled to discard particles with low importance weights (at a

190   probability of $1 - w_j$), using the procedure shown in Smith and Gelfand (1992). After

191   resampling, each particle is perturbed to enhance the sampling power of the parameter

192   posterior:

$$\boldsymbol{\theta}_j = \beta\boldsymbol{\theta}_j + (1 - \beta)\boldsymbol{\theta}_k + \varepsilon \tag{9}$$

193   where β is a temporal constant and ε is white noise. Given the most complicated class-ABC

194   form of $L(\theta)$ only has three free parameters, our algorithm is generally insensitive to the

195   choice of β and ε. Therefore, $\beta = 0.95$ and ε with standard deviation of 5% of the

196   posterior distribution are used in this study.

197   Figure 3 provides an illustrative example of the SMCS optimization. We start by initializing

198   the SMCS with particles randomly drawn from the entire parameter space (Figure 3a). Based on

199   the importance weights of each particle (calculated using (8)), inaccurate particles are discarded

200   by resampling, and the resulting particles are randomly perturbed using (9) – leading to

201   significantly improved (likelihood) parameter posteriors (Figure 3b). By repeating the above

202   processes, the mean of the particles gradually converges to the true parameters (Figure 3c and

203   d).
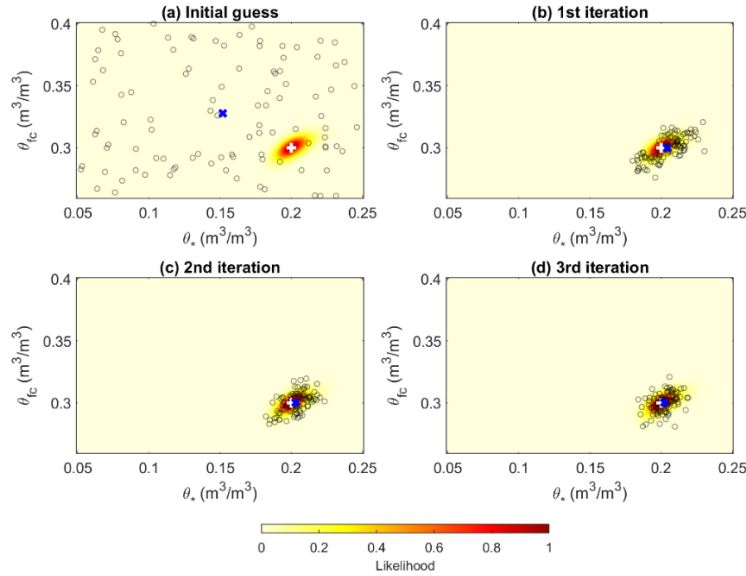
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205   **Figure 3**. An illustrative example of the SMCS parameter optimization procedure using 100
206   particles (grey open circles). Parts (a) to (d) show the evolution of particles after each iteration
207   (or resampling). The synthetic "truth" is generated using the class-ABC form of $L(\theta)$ with
208   pre-defined parameters (white plus sign). Each gray open circle represents the parameter
209   combinations of a particle and the mean of all particles is denoted as the blue cross. For
210   simplicity, only θ_* and θ_{fc} are shown here for demonstration.

211

212   *2.2.2 Soil moisture loss functional form determination*

213   The SMCS algorithm is applied for all the six candidate forms of $L(\theta)$ (see Figure 1). Based

214   on the optimized parameters (i.e., θ_w, θ_*, θ_{fc}), AICc is used to compare the performance of

215   different $L(\theta)$ forms, i.e., model selection. For each $L(\theta)$ form, AICc is calculated as:

$$\text{AICc} = Nln\left(\frac{e}{N}\right) + 2K + \frac{2K^2 + 2K}{n - K - 1} \qquad (10)$$

216   where K is the number of parameters of the $L(\theta)$, N is the number of observations, and e is

217   the fitting error of a specific $L(\theta)$ form based on SMCS optimized parameter, which is

218   calculated analogously using (6) (Burnham and Anderson 2004).

219   To further enhance model selection, physical and statistical constraints are also applied. For

220   example, θ should not limit evaporation when it is above 0.40 m³/m³ and hence, class-A has to

221   be rejected – given the field capacity of clay is approximately 0.37 m³/m³ (Zhang and Schaap

222   2017). Therefore, in addition to AICc, we also include physical and statistical constraints in the

223   loss function determination: i) if the maximum θ value exceeds 0.40 m³/m³, class-A is rejected;

224   ii) if θ_* is lower than the 5th percentile of the θ time series, class-AB and ABC are rejected; iii)

225   if θ_{fc} is higher than the 95th percentile of the θ time series, class-BC is rejected; iv) if the

226   drainage slope (α_2) is smaller than the slope of stage-II evaporation (α_1), class-ABC is rejected.

227   Although four physical constrains are implemented, $L(\theta)$ is mainly determined by AICc. These

228   constraints are typically triggered at locations with strong dry-wet transitions and relatively

229   poor data quality.

230   Synthetic experiments demonstrate that the two-stage strategy is robust to variations in

231   sample size and observation errors. In addition, synthetic tests show that 300 particles are

232   sufficient to provide satisfactory results, with 100% $L(\theta)$ classification accuracy and

233    $R^2 > 0.95$ for low observation error scenarios, and with some reduced accuracy for increased

234   observation error levels (Figure S1). The detailed synthetic experiment design and results are

235   shown in Section 1 of the Supporting Information.

236   *2.3 Quantification of evaporation water availability and hydrologic tippling points*

237   We use soil moisture thresholds estimated from Section 2.2 to estimate the evaporation

238   water availability index (denoted as Π):

$$\Pi = \min\left(1, \frac{\theta - \theta_w}{\theta_* - \theta_w}\right). \tag{11}$$

239   This Π metric has traditionally been used in physically-based hydrological models (Mintz

240   and Walker 1993) and remote sensing evaporation retrievals (Martens et al. 2017) to evaluate

241   evaporation water stress. It is worth noting that Π is insensitive to multiplicative and additive

242   soil moisture retrieval biases – see demonstrations in Section 2 of the Supporting Information –

243   which makes it particularly suitable for our analysis, given the remote sensing soil moisture

244   biases are relatively unknown at the global scale (Dong et al. 2020a).

245   Based on Π, we seek to highlight regions influenced by both evaporation regimes, or those

246   at land surface tipping points. Over these regions, climate change/variability is more likely to

247   cause evaporation regime transitions. Therefore, this metric should leverage the time of a

248   landscape spent in both Stage-I and II evaporation regimes. Here, we propose a tipping point

249   metric (Φ) which is calculated as:

$$\Phi = 1 - |2\mathrm{Prob}(\Pi < 1) - 1| \tag{12}$$

250   As shown in equation (12), humid regions constantly dominated by Stage-II ET (i.e., Π is

251   constantly 1, leading to $\mathrm{Prob}(\Pi < 1) = 0$) have a Φ value of 0 – meaning no transitions in

252   evaporation regimes. Likewise, arid regions with Π constantly lower than 1 will also have

253     $\Phi = 0$. In contrast, Φ will approach 1 over dry-wet transitional climate zones, which

254   experience frequent transitions in Stage-I and II ET regimes. For instance, regions with 50% of

255     $\Pi < 1$ and 50% of $\Pi = 1$ will have the maximum Φ value of 1.

256   Note that regions with $\Phi \approx 0$ are not insensitive to hydroclimatic variability or change. For

257   example, evaporation strongly depends on the variability of precipitation and atmospheric

258   evaporative demand in arid regions (Feldman et al. 2022; Short Gianotti et al. 2020), but such

259   responses are mostly linear (see Figure 1b). In contrast, areas with high Φ values tend to

260   present nonlinear transitions between evaporation regimes, which may lead to abruptly

261   increased hydroclimate extremes (Zhang et al. 2020), once soil moisture drops below θ_*.

262   Additionally, Φ reflects multi-year evaporation regime statistics, which may not be applicable

263   to short time scale analyses. Finally, Φ closer to 1 indicates a higher likelihood of transitions,

264   but does not directly indicate frequent transitioning across the critical soil moisture threshold.

265   *2.4 Data*

266   Surface soil moisture estimates from the NASA Soil Moisture Active Passive (SMAP) mission

267   are used to quantify the global soil moisture drydown patterns (O'Neill et al. 2020). The global

268   level-3 36-km SMAP data from 1 April 2015 to 1 April 2021 are acquired from the National Snow

269   and Ice Data Center archive (Entekhabi et al. 2010). SMAP data collected from 6 AM overpasses

270   and based on the single channel algorithm are used in this study (Entekhabi et al. 2014).

271   Retrievals affected by snow, ice, frozen ground, complex topography, or high vegetation density

272   (vegetation water contented higher than 7kg/m^2) are excluded. Note that SMAP is mostly

273   sensitive to the top 5 cm surface soil moisture conditions (Njoku and Entekhabi 1996). However,

274   our recent study demonstrates that surface and deeper rootzone soil moisture are consistent in

275   identifying evaporation regime transitions (Dong et al. 2022a). The soil moisture retrieval error

276   impacts on our estimates are comprehensively discussed in Sections 1 and 2 of the Supporting

277   Information. The number of valid SMAP observation after drydown identification is shown in

278   Figure S2.

279   In some tests and analyses, we use flux tower observations of daily latent heat (LE) and

280   sensible heat (H) fluxes collected from the AmeriFlux network (Novick et al. 2018). Land surface

281   energy partitioning is quantified based on the commonly used evaporation fraction, or EF =

282   LE/(LE + H). These EF observations are used to evaluate the effectiveness of SMAP-based

283   drydown analysis in quantifying the land surface energy partition. Only sites with at least 5

284   years of available data during April 2015 to April 2021 are used. The spatial distribution of the

285   resulting 37 flux tower observations is shown in Figure S3.

286   Finally, the aridity index (AI, calculated as the ratio of precipitation and potential ET) is used

287   to evaluate microclimate influence on hydrological regime transition frequencies. The global

288   and daily 0.1-degree precipitation data from Multi-Source Weighted-Ensemble Precipitation

289   (Beck et al. 2019) and the 0.25-degree and daily potential evaporation estimates from the

290   Global Land Evaporation Amsterdam Model (Martens et al. 2017) are used to define pixel-wise

291   AI values. Both products are resampled onto 36-km SMAP grids through bilinear interpolation.

292

293   **3   Results and Discussions**

294   *3.1 Influence of climate and seasons on the distribution of evaporation regimes*

295   Loss function $L(\theta)$ forms are estimated using the framework described in Section 2. Using

296   the SMAP soil moisture product alone, the global land regions are categorized into

297   water-limited (class-A), transitional (class-AB and ABC) and energy-limited (class-B, BC and D)

298   evaporation regimes, according to their soil moisture thresholds (i.e., θ_w, θ_* and θ_{fc}, see

299   Figure 1). Note that these thresholds may be affected by both climate and vegetation phenology

300   – making them potentially seasonally variable (Haghighi et al. 2018). Hence, we perform our

301   analysis separately for each season (Figure 4).

302   As expected, arid and semi-arid regions are dominated by water-limited regimes, e.g., such

303   as in the western US, the North Africa, central Asia and central Australia (Figure 4a). These

304   findings are qualitatively confirmed by Figure 4b, which shows that more than 90% of land

305   pixels within arid regions display water-limited evaporation regimes.
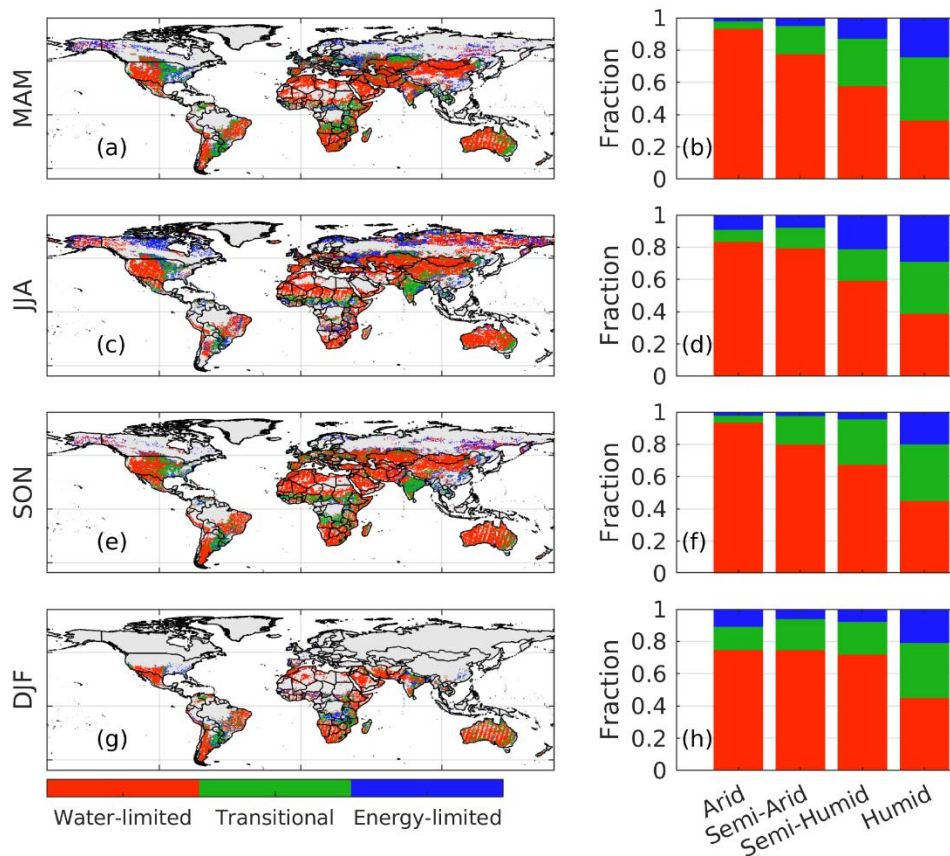
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307   **Figure 4**. Global distribution of evaporation regimes for different seasons (first column) and the
308   fraction of each regime for different climate zones (second column). Arid, semi-arid, sub-humid
309   and humid regions are corresponding to pixels with AI values of 0 - 0.2, 0.2 - 0.5, 0.5 - 0.65 and >
310   0.65, respectively. Water-limited cases are pixels constantly dominated by Class-A $L(\theta)$, while
311   energy-limited regimes are pixels with the absence of Class-A $L(\theta)$. Transitional ET regimes are
312   cases containing both stage-I and stage-II evaporation, e.g., Class-AB and -ABC $L(\theta)$.

313

314   A significant fraction of land pixels within arid and semi-arid regions shows transitional or
315   energy-limited evaporation regimes. This situation applies for approximately 2% of land pixels
316   within the arid region. This is particularly noticeable in India during DJF, in response to
317   large-scale winter irrigation (Douglas et al. 2006). Relative to arid regions, the portion of
318   transitional regimes substantially increases in semi-arid and semi-humid regions (Figure 4b, d
319   and f). Fluctuations of dry and wet conditions within these climate regions lead to more
320   frequent switching between evaporation regimes. Likewise, energy-limited regimes are
321   primarily shown in humid areas – suggesting the overall water supply (i.e., P) exceeds the
322   evaporative demand. Overall, the seasonal transitions of hydrological regimes shown in Figure 4
323   are mainly due to seasonal variability in microclimate and human activities.

324

325   *3.2 Factors influencing soil moisture thresholds*

326   In our parameter estimation, all pixel-wise soil moisture thresholds are estimated separately
327   for each season. However, seasonal variations in soil moisture thresholds are usually small. We
328   acknowledge that soils with clay content higher than 50% may exhibit stronger seasonal
329   variability in soil moisture thresholds (Sehgal et al. 2021b). However, such cases are only
330   applicable for less than 1% of global land grids, according to SMAP soil texture map, which is
331   derived based on multiple commonly used global soil texture datasets. Because of this low
332   temporal variability, we only focus on the seasonal mean of these soil moisture thresholds for
333   the remainder of this study.

334   Seasonally averaged soil moisture thresholds, θ_w, $\theta_\star$, and θ_{fc} are shown in Figure 5.
335   While Monte Carlo or bootstrapping based uncertainty analysis of Figure 5 is computationally
336   expensive, synthetic experiments on a case with error statistics comparable to SMAP
337   observations demonstrate that the coefficient of determination of soil moisture threshold
338   estimates is above 0.84 (see Figure S1). In addition, Figure 5 is consistent with those derived
339   based on independent methods (Akbar et al. 2018; Sehgal et al. 2021b). These results suggest
340   the general robustness of our parameter estimates in Figure 5.
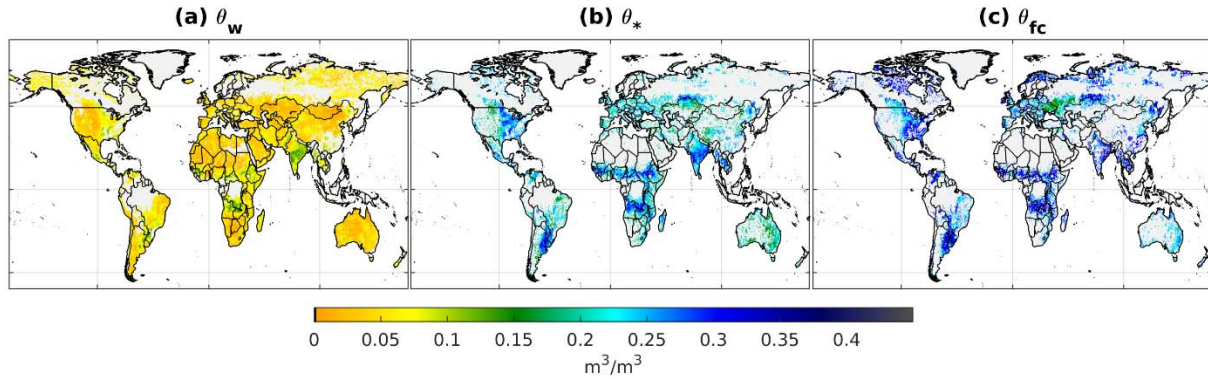
Figure 5. Global distribution of all-season-mean θ_w (a), θ_* (b) and θ_{fc} (c). Gray shadings represent land areas that soil moisture drydown analysis cannot be performed or the soil moisture thresholds cannot be estimated using the corresponding $L(\theta)$.

The soil moisture thresholds that distinguish different hydrologic regimes are themselves a function of vegetation characteristics and soil hydraulic properties and hence, persistent geographic patterns of these variables are expected. As evident in Figure 5, the thresholds demonstrate strong dependency on the dominant climate zones. For example, θ_* in the semi-humid central US (lightly vegetated) is approximately 0.15 m^3/m^3 and sharply increases to 0.3 m^3/m^3 in the humid eastern US (densely vegetated, Figure 2b). Such strong climate-vegetation-soil links are expected, given climate is a major determinant of vegetation and the vegetation rooting system that can also significantly affect the soil hydraulic properties (Hao et al. 2019). Furthermore, θ_* is dependent on the process of roots extracting water from the unsaturated soil matrix and there it will depend on vegetation traits, soil hydraulic properties, lower atmosphere winds, and potential evaporative demand (Feldman et al. 2019; Haghighi et al. 2018). These findings are qualitatively confirmed by Figure S4, and are also consistent with previous soil moisture drydown analysis (Akbar et al. 2018; Sehgal et al. 2021a, b).

In addition to climate and vegetation dependencies, soil hydraulic properties are also known to be a strong function of soil texture (Zhang and Schaap 2017), which defines vegetation and evaporation water availability (Kramer and Boyer 1983). Figure 6 further shows SMAP-based soil

363　moisture thresholds as a function of clay content. This depiction of soil moisture thresholds as a
364　function of soil texture appears as a conceptual diagram in many hydrology textbooks, based on
365　laboratory hydraulic test data (Kramer and Boyer 1983). Here we use the global SMAP soil
366　moisture product to re-visit this classic diagram but based on global and landscape scale data.
367　We show that θ_* and θ_w demonstrate a strong increasing trend with increased clay content.
368　However, a slightly more complicated θ_{fc} and clay content relationship is evident in Figure 6,
369　which may be related to limited sample size of some soil classes, e.g., limited number of pixels
370　with sandy soils are available for a robust detection of the drainage process. Additionally, SMAP
371　overpass intervals are 2 to 3 days which is longer than typical drainage time to field capacity
372　after rainstorms. Therefore, the drainage hydrologic regime is more difficult to capture from
373　remote sensing data. Nevertheless, our thresholds as a function of clay content largely reflect
374　that of known soil hydraulic diagrams.

375　　We note that samples within each clay class of Figure 6 may contain significant variability in
376　vegetation and microclimate conditions, as well as sub-grid heterogeneity of land surface
377　conditions. Therefore, Figure 6 is aimed at linking the landscape-scale soil texture impacts to soil
378　moisture thresholds, and is not directly comparable to classic laboratory-based sample
379　conditions.

380　　Figure 6 also provides direct insights into evaporation water availability (denoted as Π). The
381　soil water component above θ_{fc} (blue shaded area) percolates quickly to deep sub-layers,
382　which is less likely to be used by evaporation or vegetation. In contrast, soil water potential is
383　too negative to be effectively used for evaporation when soil moisture drops below θ_w.
384　Evaporation water supply is bracketed by soil moisture dynamics when it is between θ_{fc} and
385　θ_w. This storage can be further divided as un-stressed and stressed water according to θ_*
386　(white and red shadings). This figure directly illustrates the physical link of Π (calculated using
387　(11)) and evaporation water viability. Specifically, $\Pi = 1$ means that soil moisture content is
388　above θ_* and evaporation is not limited by soil moisture – see the white and blue shadings in
389　Figure 6. In contrast, $\Pi < 1$ suggests that soil moisture availability starts to become a limiting
390　factor of evaporation (see the red shadings in Figure 6).

391
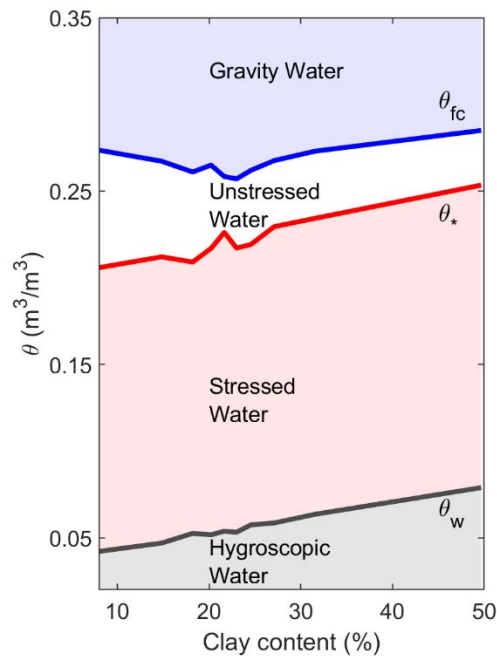
Figure 6. Soil water conditions as a function of clay content. Solid lines are averaged soil moisture thresholds sampled across different clay contents based on Figure 5.

394

3.3 SMAP-based Evaporation water availability and land-surface energy partition

The metric Π can be estimated on a pixel-by-pixel basis using SMAP-based soil moisture thresholds (again using seasonally-averaged values of the soil moisture thresholds). The Π time series at the US-ARM site (Raz-Yaseef et al. 2015) in Oklahoma is shown in Figure 7 for demonstration.

The consistency between the SMAP-based Π and flux tower-based EF temporal dynamics is evident in Figure 7b, which is particularly noticeable in JJA months (warm season). For example, a consistent decrease of Π is observed in the middle of August, leading to a similar reduction in EF. The water stress is alleviated by precipitation events in late August (Figure 7a). As a result, the US-ARM site shifts to energy-limited regimes, as Π approaches 1, which yields sharply increased EF (Figure 7b).

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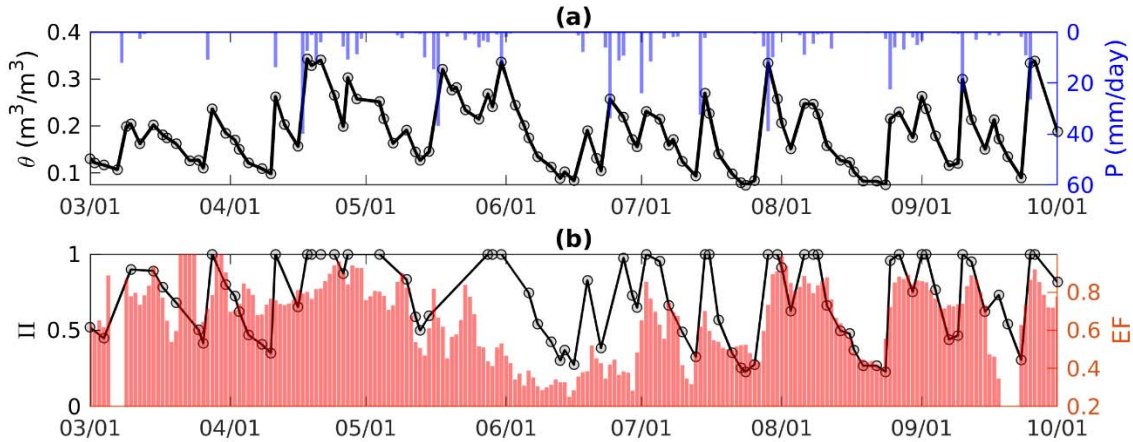
Figure 7. Evaluation of Π at US-ARM site located in Oklahoma (36.6N^o, 97.4^{o}W). (a):
MSWEP-based P and SMAP observed soil moisture time series during March to September 2016.
(b): Flux tower observed EF and SMAP-based Π during the period. The red bars are US-ARM
observed EF and black line is the SMAP-based Π.

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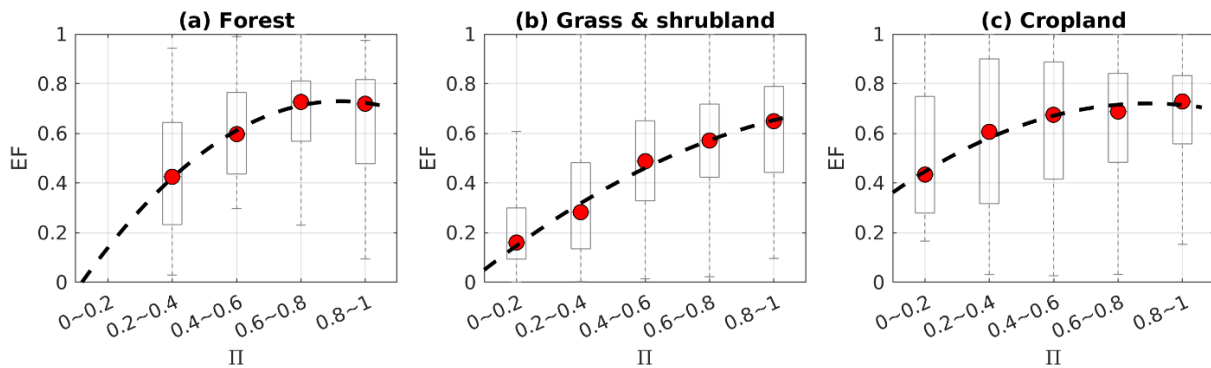
Figure 8. EF as a function of Π sampled from AmeriFlux sites under different land cover types.
Estimates from all seasons are used, with 1, 23 and 13 sites available for forest, grass and
shrubland, and cropland, respectively. The box and the whiskers represent the interquartile and
5th – 95th percentile range of EF values, respectively, which are sampled across all the available
sites. The red circle is the median EF value of each bin.

418

A more comprehensive evaluation of Π is shown in Figure 8, which samples the
SMAP-based Π and flux tower observed EF relationship from different land cover types. Note
that EF is affected by multitude factors, e.g., microclimate, land cover, soil properties,
observation error, etc. These factors may all inflate the interquartile ranges of the EF values
presented in Figure 8. Nonetheless, for all three land cover types, EF is a monotonically

424 increasing function of Π. It is also noticeable that EF is relatively more sensitive to Π at dry

425 conditions, and this sensitivity decreases with increased Π. These findings are consistent with

426 previous modeled (Dirmeyer et al. 2000; Lu et al. 2016) and observation-based (Short Gianotti

427 et al. 2019a) EF and soil water availability relationships.

3.4 Frequency of evaporation regime transition at the global scale

429 Based on Π, we estimate the frequency of global evaporation regime changes using the Φ

430 metric – see (12) for metric definition. The spatial distribution of Φ shows regions of the global

431 land surface that can potentially experience water and energy balance regime changes as a

432 result of climate variability and change. They span the central US, Europe, the Pampas region in

433 South America, Sahel in Africa, the Indian subcontinent and the east coast of Australia (Figure 9).

434 Geographically, they cover vast regions that separate persistently water-limited areas (arid and

435 hyperarid areas) and forested humid areas. In addition, it is noteworthy that Φ tends to

436 increase in the summer and autumn, i.e., JJA and SON for Northern Hemisphere, and MAM and

437 DJF for the Sothern Hemisphere – see boxplots in Figure 9. These months represent a temporal

438 transition between evaporation and vegetation phenological regimes in many land regions of

439 the globe. Thus, these regions regularly switch between regimes, and climate variability or

440 change can prolong or contract the evaporation regime dominance from one season to the

441 next.

442 These findings add an observation-driven perspective to previous global classification of

443 land-atmosphere coupling strength based on models (Dirmeyer 2011; Koster et al. 2004;

444 Mueller and Seneviratne 2012; Seneviratne et al. 2006). The strength of the coupling between

445 local water and energy balances affects how closely the surface moisture state and the

446 near-surface air temperature are linked. In turn, this reflects how influential the land surface

447 dynamics are on the evolution of the near-surface atmosphere and ultimately, land-atmosphere

448 coupling.

449 Importantly, Φ seasonality and global distributions in Figure 9 are entirely

450 observation-based which means that they are not affected by process parameterizations in

451 models. Thus, they can be used to assess models and guide model development.

452 We recognize that extreme regional climate change and land use change may have significant

453 impacts on soil moisture thresholds and by extension, the global distribution of Φ. This may

454   lead to a different vulnerability map as that shown in Figure 9. For such cases, Φ estimates
455   should be sampled during the period that is representative of these environmental changes.

456

Φ (Hydrological regime tipping-point): Vulnerability to climate variability and change
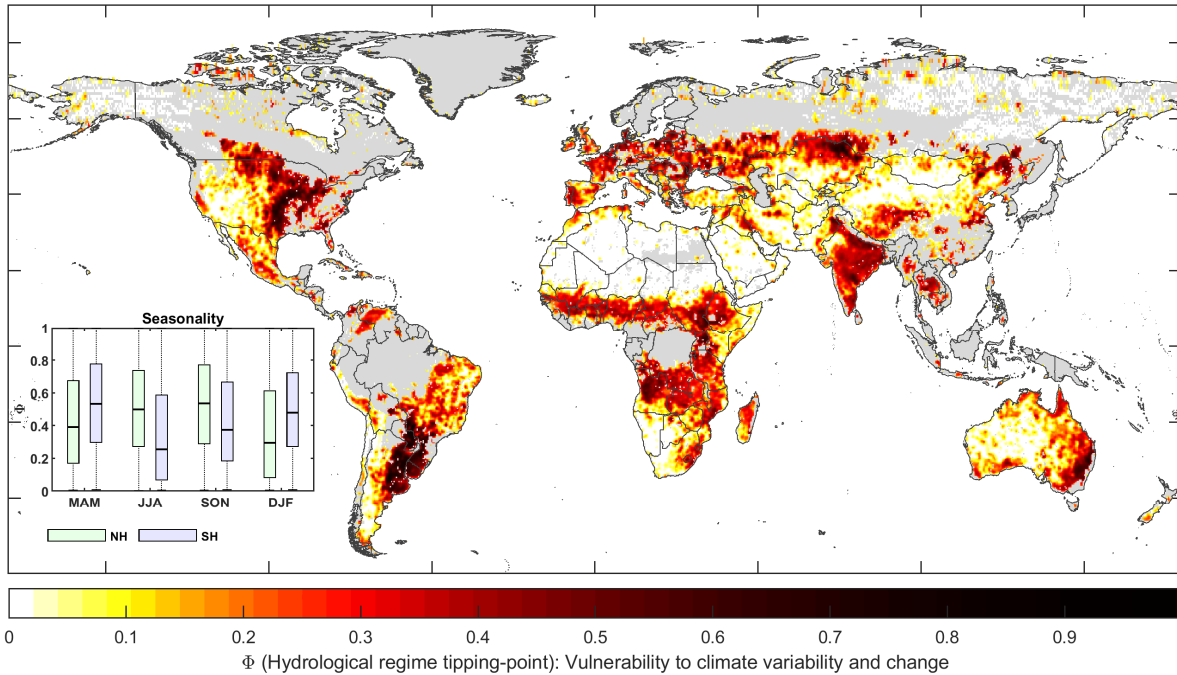
457
458   **Figure 9.** The global and annual mean distribution of land regions at the tipping-point between
459   water-limited and energy-limited evaporation regimes. The metric Φ captures how vulnerable
460   the landscape is to climate variability and change. Given unit shifts in soil moisture, regions with
461   Φ approaching one will experience the most change in how their surface water and energy are
462   coupled. Seasonal variations of Φ over the Northern (NH) and Southern Hemisphere (SH) are
463   shown in the inset boxplots. The metric is based on satellite observations only. The transitional
464   conditions between the evaporation regimes are at their peak during the summer and autumn
465   seasons (i.e., JJA and SON for NH, and DJF and MAM for SH) and span large areas in the
466   semi-arid to semi-humid landscapes.

467
468
469   **4. Conclusion**

470   Land evaporation switches between energy- and water-limited regimes that signify the
471   coupling and decoupling of water, energy and carbon cycles across landscape. The transition
472   point is dependent on environmental factors, the primary one being the soil moisture state
473   variable. Therefore, regions that are characterized by soil moisture distributions closer to this
474   soil moisture threshold, i.e., with frequent energy- to water-limited evaporation regime
475   transitions, are likely to be more vulnerable to climate variability and change. However, such

476 nonlinear evaporation regime transitions are typically identified using model-based approaches,
477 which is subject to model-specific assumptions and errors.

478   In this study, we use multi-year SMAP surface soil moisture observations to identify the
479 frequency of landscape changes between energy- and water-limited regimes. We first identify
480 soil moisture drydown time series. Then we estimate the soil moisture threshold value that
481 delineates the transitions between evaporation regimes. Based on this framework, an
482 observation-based index of evaporation water availability (Π) is developed and assessed using
483 37 flux-tower sites across the CONUS. As determined by θ_*, Π is expected to be influenced by
484 multiple factors, such as microclimate, vegetation cover and soil properties (Figure S4). A key
485 advantage of our approach is that it implicitly integrates all the environmental information and
486 provide large-scale estimates of evaporation regime transitions in a data-driven manner.

487   Based on the Π estimates, we further define an index of land surface vulnerability to
488 climate variability and change (the index Φ). Conceptually, the Φ index quantifies the
489 frequency of evaporation regime changes, which is associated with transitions from or to
490 coupled versus uncoupled land surface water and energy balance. This in turn affects the
491 sensitivity of the lower atmosphere to soil moisture changes, which has direct implications for
492 investigating the onset and the development of hydroclimate extremes, e.g., heatwaves and
493 flash droughts. The new tipping-point metric is based only on observations which allows it to be
494 used to assess land surface components of Earth System models. The observation-based metric
495 also adds to the suites of existing (mostly model-based) metrics for identifying critical regions
496 for land-atmosphere coupling.

497   Finally, we would like to note that global Φ distribution in Figure 9 is sampled over a
498 6-year period, which may not reflect the impact of historical long-term microclimate trends,
499 abrupt land use changes and climate cycles like El Niño-Southern Oscillation (ENSO). However,
500 except for extreme cases, the six years of soil moisture observations are generally
501 representative of long-term landscape wetness climatology (Dong et al. 2020a). Nonetheless,
502 applying our analysis on long-term European Space Agency Climate Change Initiative (ESA CCI)
503 soil moisture product (Dorigo et al. 2017) may provide insights into long-term global Φ
504 variations. However, ESA CCI soil moisture uses sensors with temporally varied soil moisture
505 error and sampling depth, and algorithms that can isolate these impacts are required.

Data Statement

The SMAP data are acquired from https://smap.jpl.nasa.gov/data/. MSWEP and GLEAM data are accessible at http://www.gloh2o.org/mswep/ and https://www.gleam.eu/, respectively.

Codes for the drydown analysis is available at: https://github.com/dongjianzhi/Soil-moisture-drydown-analysis

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718

Figure 1.

(a)
L(θ)
Stage-II ET
Stage-I ET
Drainage
θ_w θ_* θ_{fc}

(b) class A
θ_w

(c) class AB
θ_w θ_*

(d) class ABC
θ_w θ_* θ_{fc}

(e) class BC
θ_* θ_{fc}

(f) class B

(g) class D

Figure 2.

(a) 0 iteration   **(b) 1 iteration**   **(c) 5 iterations**

P day = 20%   P day = 14%   P day = 5%

non-P days
P days

(d)
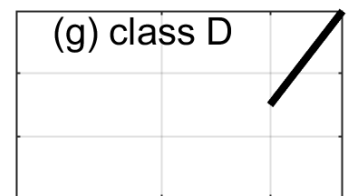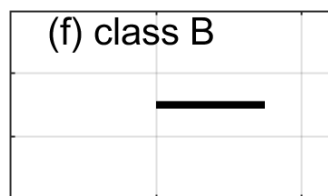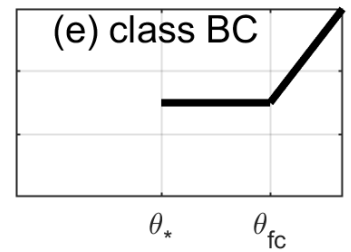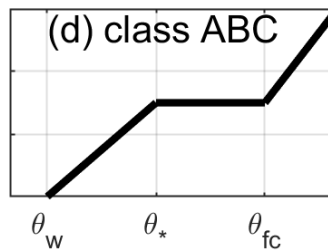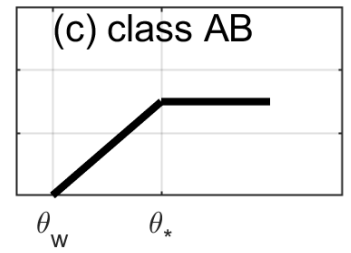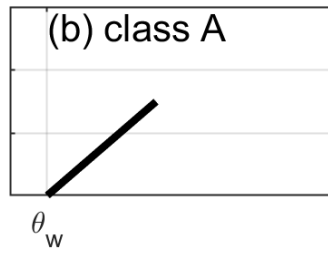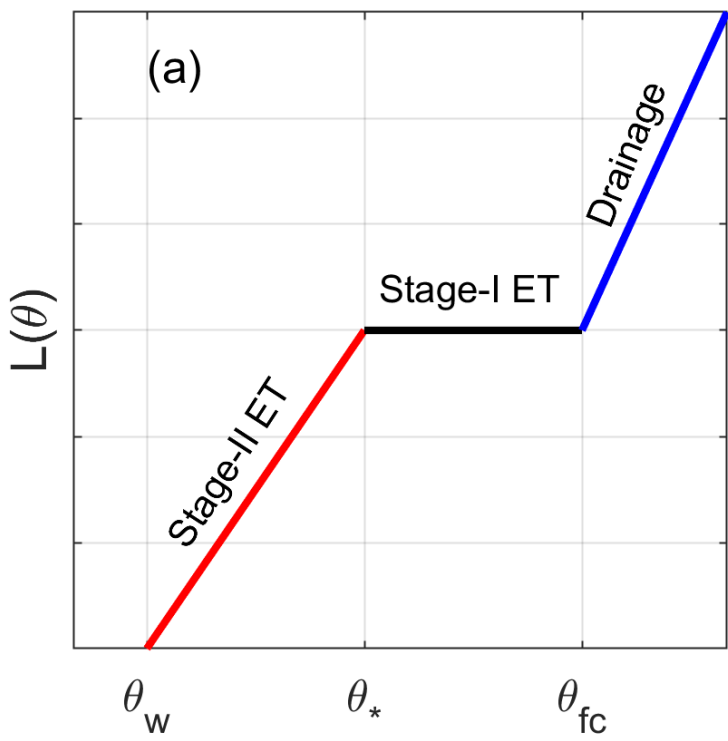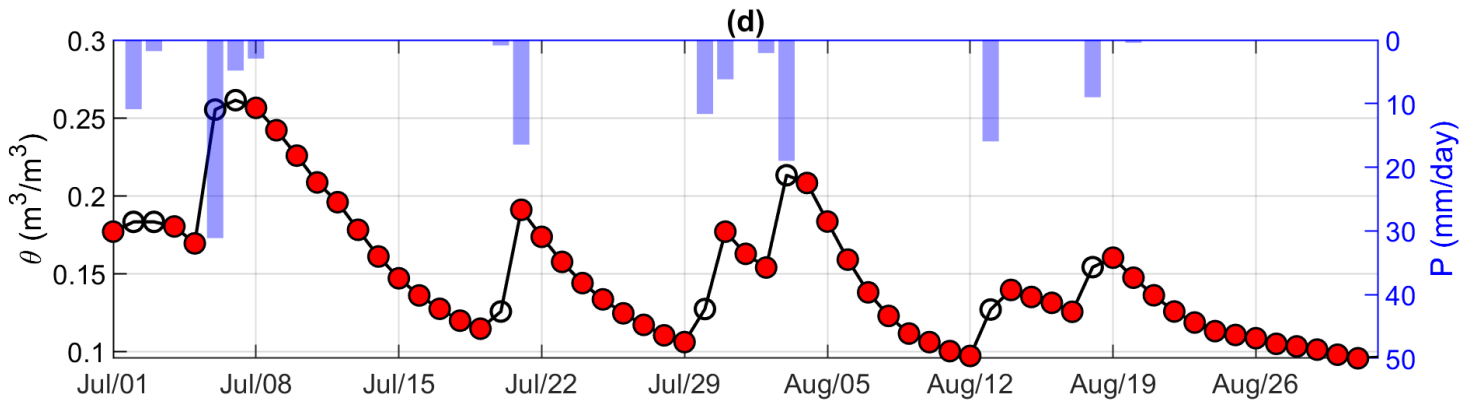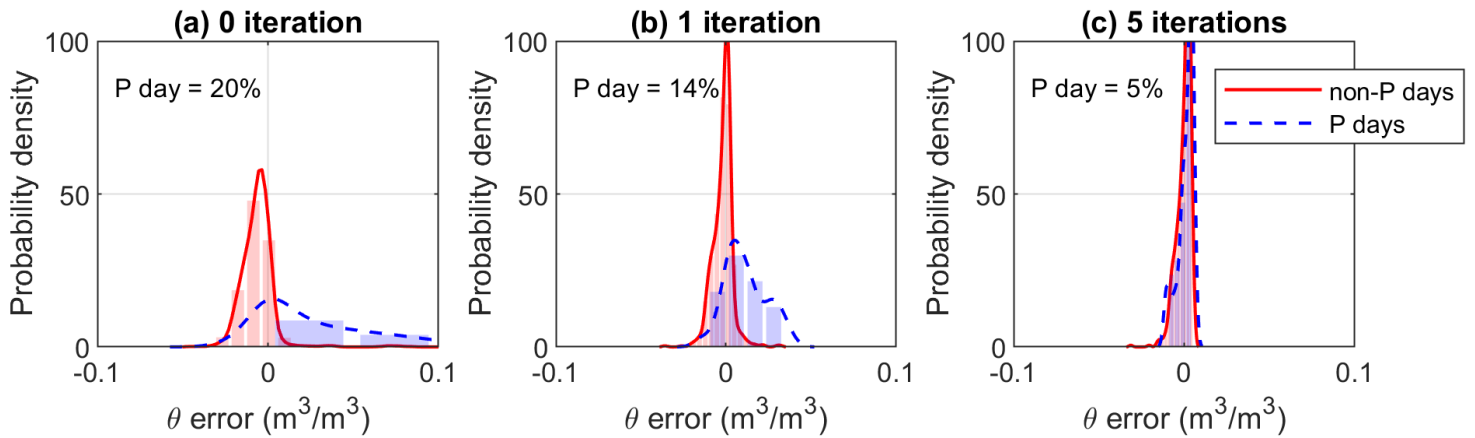
Figure 3.

Figure 4.

MAM

JJA

SON

DJF

Water-limited Transitional Energy-limited

Fraction

(a) (b)

(c) (d)

(e) (f)

(g) (h)
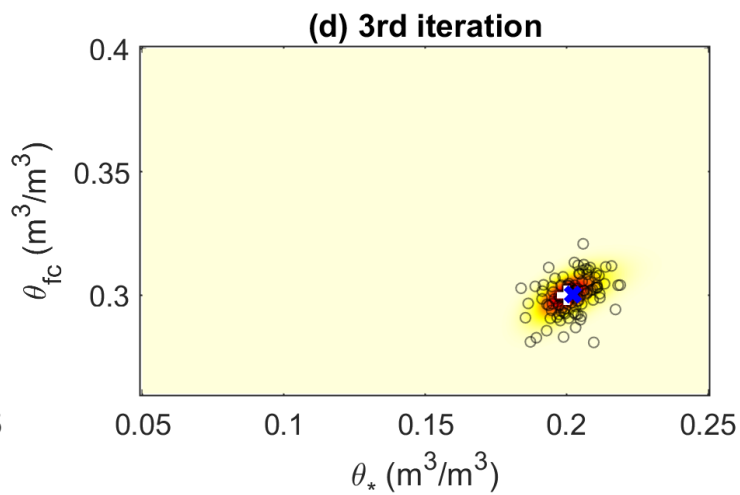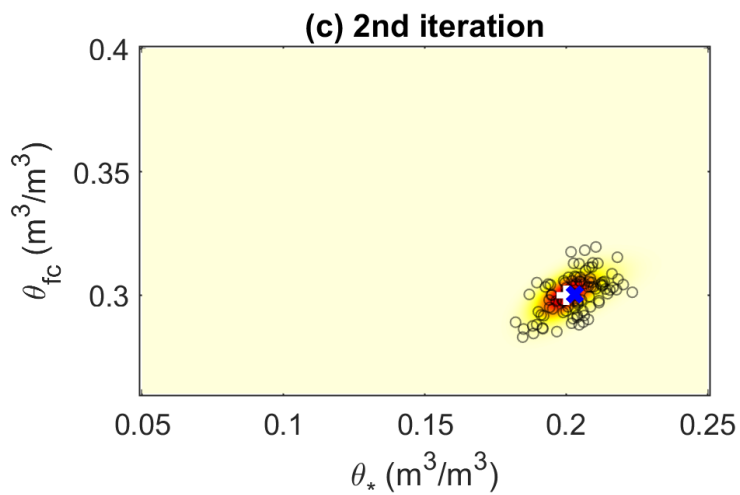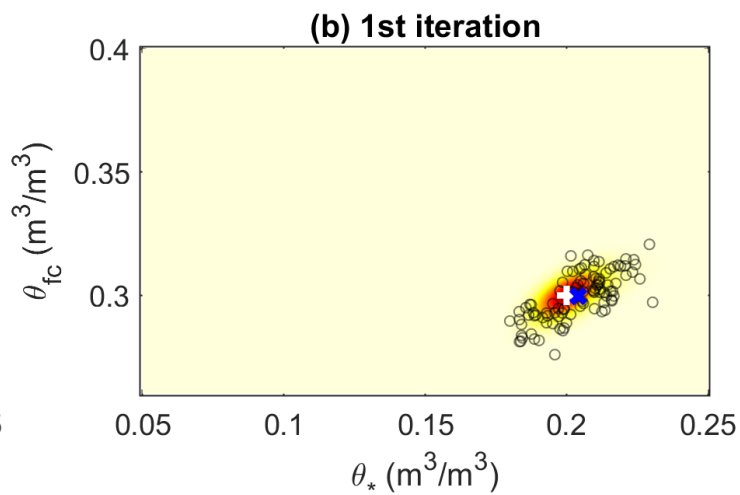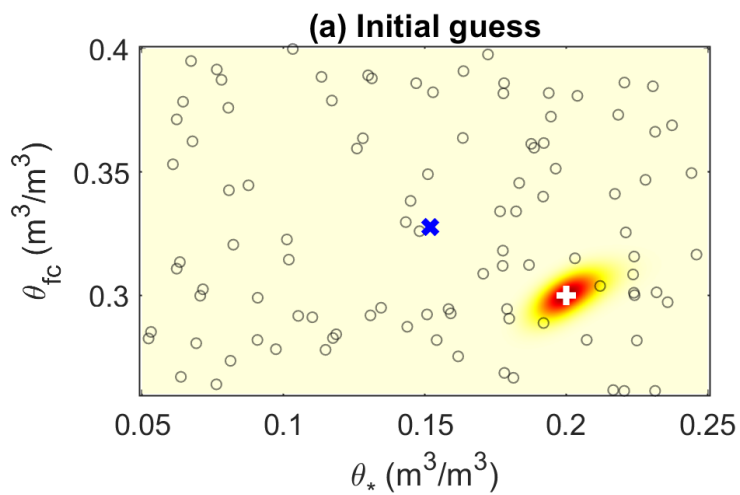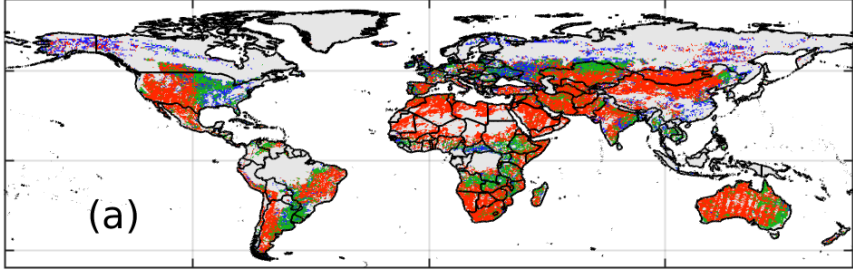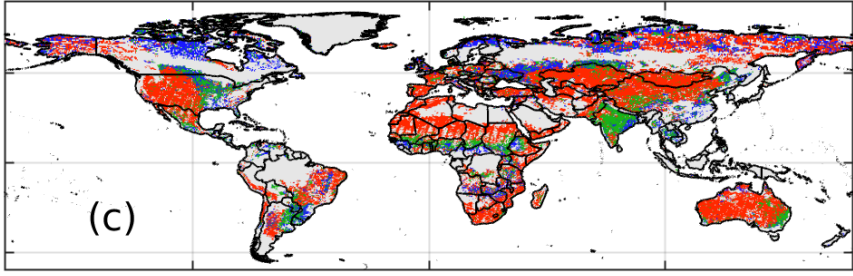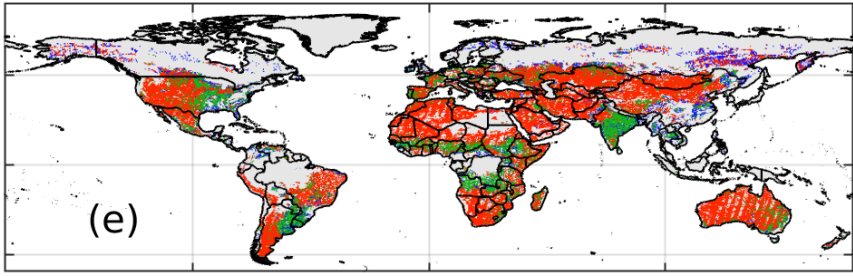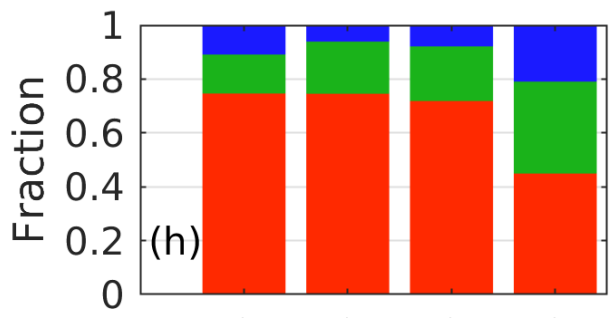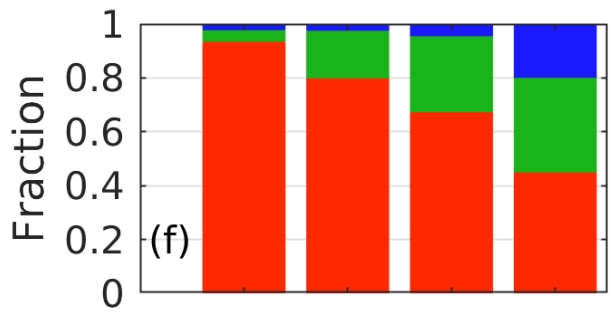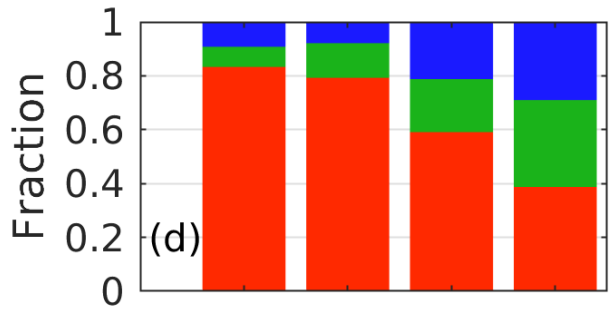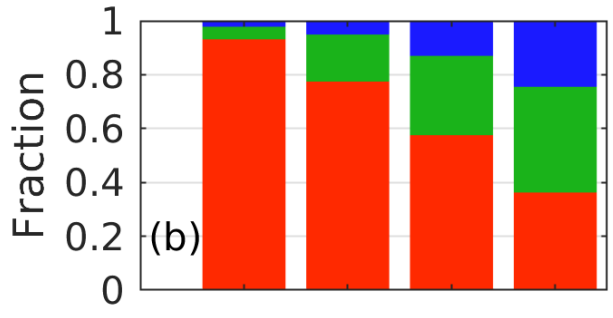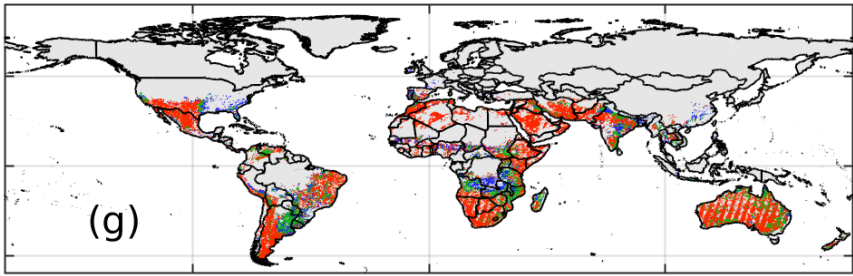
Arid Semi-Arid Semi-Humid Humid

Figure 5.

Figure 6.

Figure 7.

(a)

(b)

Figure 8.

(a) Forest

(b) Grass & shrubland

(c) Cropland

Figure 9.

Φ (Hydrological regime tipping-point): Vulnerability to climate variability and change