A simple framework to characterize land aridity based on surface energy partitioning regimes

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Abstract

Land aridity is often characterized by the aridity index (AI), which does not account for land surface water-energy interactions that are crucially important in determining regional climate. Such interactions can be captured by the evaporative fraction (EF, ratio of evapotranspiration to available energy) regimes. As EF is subject to energy and water limitations in humid and dry areas, respectively, EF regimes may be used to characterize land aridity to account for the influence of complex land characteristics and their impact on water availability. Here, we propose a simple framework to characterize land aridity by statistically ranking the coupling strength between EF and surface energy and water terms. The framework is demonstrated using gridded data and compared with AI over the U.S. and China. Results show that regionalization of aridity zones based on EF regimes and a two-tiered classification scheme may provide information such as surface energy and water variability complementary to the background aridity depicted by AI, with implications for extreme events.

1. Introduction

Land aridity is an important index to depict regional water and energy conditions [1–3]. By definition, land aridity is characterized by the total available water and energy received by the land surface within a certain period. Therefore the ratio of atmospheric water demand and land precipitation supply has been investigated in early studies since Schreiber [4–9]. Later aridity index (AI) (AI = P/PET, with P the annual mean precipitation, and PET the annual mean potential evapotranspiration) was proposed as a benchmark to assess regional aridity conditions [10, 11] and to predict aridity conditions in the future [12, 13].
Short-term water and energy interactions can be represented by the energy partitioning between surface latent heat flux (LE) and sensible heat flux (H), which is captured by the evaporative fraction (EF), the ratio of LE to total available energy (LE + H). The energy partitioning can be conceptually described by two broad EF regimes: an energy-limited regime common in humid areas (e.g. AI > 0.65) and a water-limited regime typical in arid areas (e.g. AI < 0.65) [6, 16-18]. Similarity between the broad spatial distributions of EF regimes and AI implies that EF regimes may be used to indicate the long-term aridity conditions underpinned by AI. In addition, since EF regimes encode the information of surface energy-water feedbacks, they may further provide complementary information of land-atmosphere interactions that influence shorter-term variations in energy and water availability, with potential implications for extreme events. As such, using EF regimes to characterize regional aridity can offer an opportunity for joint assessment of regional aridity conditions and the potential risks for climate extremes.

However, estimating the EF regimes at large spatial scales is challenging since concurrent observations of surface variables (e.g. soil moisture (SM) and evapotranspiration (ET) observations) are uncommon and uneven [17, 19]. Another difficulty in estimating EF regimes is the requirement of various information from the heterogeneous land surface, e.g. the ecosystem conductance (gs) in the widely-used Penman-Monteith equation [20, 21] of ET. A recent study (surface flux equilibrium theory, SFE theory) has shown that ET could be estimated solely from meteorological information (i.e. air temperature (Tair) and specific humidity (qair)) [22]. Evaluated at 76 eddy covariance sites globally, the SFE method performs accurately across a diverse range of climates with errors comparable to those of eddy covariance measurements [23]. Applying the SFE theory with meteorological observations provides a unique opportunity to estimate EF regimes with extended spatial and temporal coverage.

In this study, we propose a simple framework to characterize land aridity considering the effects of land-atmosphere interactions. The framework is demonstrated by using meteorological and remote sensing soil moisture datasets. Specifically, the EF regimes are first estimated by calculating the coupling strength between EF and surface energy and water terms. An aridity scheme including surface energy partitioning effects is then developed by comparing the spatial distribution of the mapped EF regimes and AI. Interpretations and illustrations for the new scheme are finally given over two study areas (U.S. and China). Our study provides a new and complementary framework to AI to characterize land aridity conditions, highlighting the importance of energy and water coupling effects in regulating regional climate at shorter time scales (e.g. daily).

2. Methods

2.1. EF estimated from SFE theory

The SFE theory models water and energy budget near the surface driven by incoming available energy. Surface moistening and heating modulated by relative humidity are balanced by atmospheric drying (e.g. dry air entrainment from the upper layer atmosphere) and cooling (e.g. radiative cooling), yielding an equilibrium qair, specific humidity and temperature in the box [22]. The SFE theory calculates the Bowen ratio (B) as:

$$B \approx \frac{R_s C_p T_a^2}{\lambda^2 q_a}$$  \hspace{1cm} (1)$$

where, qa is screen-level specific humidity (–), T_a is screen-level air temperature (K), λ = 2.5 × 10^5 J kg^-1, is the latent heat of vaporization of water, ε_p = 10^3 J kg^-1 k^-1 is the specific heat capacity of air at constant pressure, and R_s = 461.5 J kg^-1 k^-1 is the gas constant for water vapor. EF can therefore be estimated as EF_{SFE} = \frac{1}{1+B}.

2.2. Proxy for the EF regime

At short time scales (e.g. daily), surface air temperature (Tair) is strongly correlated with solar radiation (figure S1 available online at stacks.iop.org/ERL/17/034008/mmedia), therefore Tair is used to indicate the energy-limitations on EF regimes. Specifically, we calculate the temporal correlation between EF_{SFE} and Tair at the daily time scale to indicate the response of EF_{SFE} to surface energy variability. Similarly, the correlation between EF_{SFE} and SM is used to indicate the variability of surface water effects on EF_{SFE}. We chose to use the Spearman’s correlation here since the relationships for both EF_{SFE} and Tair, and EF_{SFE} and SM can be non-linear [24]. The difference between EF_{SFE} response to energy and water is then used as a proxy of the EF regime:

$$\Delta \text{Corr} = \text{Corr}(T'_{air}, \text{EF}^{'}_{SFE}) - \text{Corr}(\text{SM}^{'} , \text{EF}^{'}_{SFE})$$ \hspace{1cm} (2)$$

where superscript (′) denotes the residuals after subtracting the seasonal cycle from the time series of the variables.

By definition, ΔCorr > 0 indicates that EF correlates more strongly with Tair than SM, so surface energy plays a larger role in limiting EF, which is more common with ‘humid’ surface conditions (mean state). Although mathematically, we note there could be cases when SM plays the dominant role whereas ΔCorr is still positive (i.e. Corr(SM′, EF_{SFE}) < 0 but its magnitude is larger than that of Corr(T′_{air}, EF_{SFE})); however in real world these situations rarely happen since the negative correlation of EF and SM itself indicates the area is subject to energy-limited. In contrast, ΔCorr < 0 occurs in areas where EF is more sensitive to SM, implying
Table 1. A two-tiered scheme and associated criteria for redefining aridity in this study. The first tier category denotes the background mean aridity condition at grid $(i,j)$, with $\Delta \text{Corr}_{i,j} > 0$ indicates wet (W) climate and $\Delta \text{Corr}_{i,j} < 0$ indicates dry (D) climate, respectively. The second tier category indicates the surface energy and water variability, and is classified based on $\Delta \text{Corr}$ thresholds (75 and 25 percentiles), with each indicates high (h), moderate (m), and low (l) potential for climate extremes. Details are described in section 2.3.

| First tier (background mean state) | Second tier (variability) | Criterion |
|-----------------------------------|---------------------------|------------|
| W                                 | $\Delta \text{Corr}_{i,j} > 0$ | Wh, Wm, WI |
| D                                 | $\Delta \text{Corr}_{i,j} < 0$ | Dh, Dm, DI |

a ‘dry’ background mean condition. The correlation difference $\Delta \text{Corr}$ is similarly applied in a previous study to estimate the water- and energy-limitation thresholds over Europe [25].

In addition to the background aridity condition indicated by the sign, the magnitude of $\Delta \text{Corr}$ can also serve to indicate surface energy and water variability. For example, for $\Delta \text{Corr} < 0$ with large magnitude (i.e. approaching unity), a small change of surface water deficit could significantly reduce atmospheric humidity, with other related effects; similar effects of energy terms on EF can be found when $\Delta \text{Corr} > 0$ (also see the sensitivity of EF to SM described in [26–29]). As such, $\Delta \text{Corr}$ with higher absolute magnitude should imply strong land–atmosphere coupling and higher potential for climate extremes. Such land–atmosphere feedbacks could exacerbate atmospheric aridity and soil drought [30], heat extremes [14, 15], ecosystem water stress, and terrestrial $\text{CO}_2$ fluxes [31].

2.3. Redefine aridity by ranking $\Delta \text{Corr}$

The above analyses motivate the use of EF regimes in a two-tiered scheme to redefine surface aridity to account for the influence of land processes. In the first tier, the climatological aridity condition is first defined by the signs of $\Delta \text{Corr}$, with $\Delta \text{Corr} > 0$ defining wet region (W) and otherwise, dry region (D). In the second tier, $\Delta \text{Corr}$ at each grid is then rescaled to subject to magnitude of $[0, 1]$ within each climatological bin. The 75% and 25% percentiles within each wet or dry bin ($Q_{75}$ and $Q_{25}$ hereafter, with $i$ indicating wet or dry classes) are calculated separately to define the thresholds of potential for extreme conditions. Offset factors of $\pm 5\%$ are further imposed to test the dependence of the regional boundaries on the choice of the $\Delta \text{Corr}$ percentile thresholds. $\Delta \text{Corr}$ values above $Q_{75}$ are labeled as high potential (h) for climate extremes (e.g. droughts/floods for severe surface water deficit/excess), between $Q_{25}$ and $Q_{75}$ are moderate potential (m), and the rest are low potential (l), as shown in table 1.

- The potential for climate extremes emphasized as the absolute magnitude of $\Delta \text{Corr}$ ($|\Delta \text{Corr}|$) is an indication of the sensitivity of EF to perturbations of air temperature and soil moisture, which has implications for climate extremes as discussed in section 2.2. With this classification, negative $\Delta \text{Corr}$ with larger magnitude denotes climatologically dry with high potential for climate extremes caused by surface water anomaly. Although positive $\Delta \text{Corr}$ denotes climatologically wet regions, such regions with large $|\Delta \text{Corr}|$ may still be prone to large climate anomalies due to the high sensitivity of EF to variations of the incoming energy.

2.4. Datasets

To demonstrate the use of EF regimes to define land aridity, we limit our analysis to China and North America due to the availability of long-term and high-quality meteorological forcing datasets. Collocated daily surface meteorological variables ($T_a$, $q_a$, and precipitation, Prec) from 2002 to 2018 from the China Meteorological Forcing Datasets [32] and Princeton Hyper-Resolution Surface Meteorological Forcing Dataset [33] are the major input datasets used to estimate EF over China and North America based on the SFE theory, respectively. Surface SM data are from the Soil Moisture from Neural Networks (NNSM) dataset [34]. Daily averaged meteorological variables are upscaled to 36 km as in NNSM. Our analysis focuses on the summer season (June–July–August, JJA) when land–atmosphere interactions tend to be most intensive [27, 35]. The performance of large-scale meteorological and SM datasets are evaluated against 124 in-situ observations, with 115 sites from the U.S. Climate Reference Networks [36], and nine publically available sites from China Ecosystem Reference Networks (part of the ChinaFlux database; www.chinaflux.org/enn/index.aspx).

AI is calculated as the ratio of seasonal mean precipitation over PET, as suggested by Food and Agriculture Organization of the United Nations and United Nations of Environment Programme (UNEP) [11]. A detailed description of these datasets as well as calculation of AI and PET can be found in supplementary materials.
The analyses of EF regimes are conducted at the daily time scale to indicate land–atmosphere interactions at shorter time scales. Additional analyses at time scales of weekly, monthly, and JJA-mean are also provided to ensure reasonable comparison of the spatial distribution between $\Delta$Corr at multiple time scales and AI results, all representing the background mean aridity condition, while regional differences between $\Delta$Corr at different time scales highlight differences in variability of aridity across time scales (supplementary materials).

3. Results and discussion

3.1. Mapped EF regimes

Figure 1 shows the EF regime defined by the difference in correlation ($\Delta$Corr) estimated using meteorological and NNSM datasets at the daily time scale. The energy- and water-limitations on the EF regimes derived using gridded datasets are comparable to the corresponding values estimated based on in-situ observations (figure S2). The binned $\Delta$ Corr – SM curves derived from the gridded and in-situ data are also comparable, both showing $\Delta$Corr $\geq$ 0 occurring mostly in SM bins with higher values and vice versa (figure S3), consistent with previous studies [16–18, 37]. In terms of spatial patterns (figures 1(a) and (b)), $\Delta$ Corr shows a significant spatial gradient, where positive $\Delta$Corr occurs in the humid regions (e.g. southern and eastern in China, and eastern North America) while negative $\Delta$Corr tends to be found in the arid northwestern China and western U.S. Results at longer time scales (i.e. weekly to JJA-mean) show similar spatial distribution (figure S4), which agree with that of the AI (figures 1(c) and (d)), or the precipitation of summer season (figure S5) showing demarcation of the broad humid and arid/semi-arid regions [38–43].

Despite the overall similarity between the spatial distributions of $\Delta$Corr and AI, regional differences are noticeable. For example, two patches of areas in northwestern China (black boxes with locations E, F, G in figure 1(a)) and two patches of areas in the southern U.S. (black boxes with locations B and H in figure 1(b)) stand out as strong water-limited EF regime although they receive relatively abundant precipitation (figure S5) and they are identified as relatively humid regions by the AI index (figures 1(c) and (d)). Similarly, two patches of the area in the northwestern U.S. (gray boxes with locations C and D in figure 1(b)) show strong energy limitations amidst broad areas of water-limited EF regime. Noticeable differences between the EF regimes and AI can also be found in the southeastern U.S., southwestern China, and patches scattered in central China. What could have caused the obvious differences in aridity defined using EF regime vs. AI?

It is important to note that AI considers only the total availability of water and energy (i.e. seasonal mean precipitation and net radiation) at the land–atmosphere interface. However, total availability may not indicate the readily available water or energy contributing in land–atmosphere interactions. Surface processes such as rapid SM drydown, replenishment from streamflow, or access to belowground water by plant roots could all influence surface water and energy variability. This indicates that while AI indicates the mean state land aridity at long timescales, EF regimes provide useful information of the surface water and energy variability shorter terms.

In figure 2 we display the probability density function (PDF) of surface SM and their drydown characteristics at three pairs of locations, each pair within the same selected subregion. We show that two of the pairs present contrasting EF regimes although they receive similar precipitation supply (figures 2(a) and (c), second column). Another pair receives different precipitation but exhibits similar EF regimes (figure 2(b)). Their geographical locations are shown in the left column of figure 2 overlaid on the $\Delta$ Corr values. In southwestern China (locations A and A’), the PDF of SM is more symmetrical for Yunnan (location A) compared to the positively skewed distribution in Hunan (location A’), despite comparable total water availability (i.e. precipitation). Below-normal SM conditions are encountered more frequently in Yunnan than in Hunan, even though the mode of surface SM in Yunnan is only slightly drier. The more frequent drier-than-normal SM in Yunnan is likely caused by the larger and more rapid water loss during the surface SM drydown compared to Hunan (figure 2(a), 4th column), since southwestern China is reported to exhibit karst topography [44]. The surface drying effect on total water availability is more significant in southwestern North America (figure 2(b), locations B and B’). Drier-than-normal SM conditions are noticeably more frequent in northwestern Mexico (location B) than in southwestern U.S. (figure 2(b), 3rd column). Northwestern Mexico (location B) receives abundant precipitation during the North American summer monsoon, however, it is subject to the water-limited regime, analogous to the southwestern U.S. (location B’) that receives much less precipitation. This is because the land surface of location B is covered by leptosols, which contain large amounts of gravel (e.g. [45]). Hence precipitation can drain rapidly to the subsurface, resulting in rapid drydown (figure 2(b), 4th column); and EF is prone to be limited by water availability due to relatively dry SM. Similar analyses in southern Tibet (locations E and F in figure 1), Loess Plateau (location G), and central U.S. (location H) are shown in supplementary materials (figure S8).

Similar surface replenishing effects on EF regimes are observed in the Rocky Mountains. For example, location C (western Montana) and C’ (Wyoming) receive equivalent precipitation in the summer season (figure 2(c), 2nd column). However, they
Figure 1. (a), (b) Mapped EF regimes defined by the difference in energy partitioning ($\Delta Corr$) with EF estimated based on the SFE theory ($\Delta Corr$ is displayed only when it is significant, i.e. within 90% confidence interval, similar to [25]). Blue colors indicate energy-limited ($\Delta Corr > 0$) and red colors indicate water-limited ($\Delta Corr < 0$). The estimation of $\Delta Corr$ is robust to retrieval errors of the NNSM dataset (figure S7) and comparable to estimation using in-situ data (circles). (c), (d) Spatial distribution of AI during the JJA season. Lower values indicate higher land aridity. Boxes of dashed lines denote areas of interest for further discussion or analysis. Triangles labeled by alphabets (A)–(H) indicate the locations analyzed in figures 2 and S6. Missing pixels in (a), (b) are masked areas of coastal zones and water bodies and in (c), (d) are grids with missing values of MODIS albedo products. AI distribution with different colorbars is shown in figure S6.

Figure 2. Regional water and energy characteristics at four selected subregions: (a) Southwestern China; (b) Southern U.S.; and (c) Rocky Mountains. From left to right, the columns present: (1st) $\Delta Corr$; (2nd) precipitation in the summer; (3rd) PDF (unitless) of surface SM; and (4th) median drydown curves. Vertical dashed lines in the PDFs indicate the SM mode values. Drydown curves are smoothed by moving average with a window width of 4 d. Shaded area indicate the range between the 75% and 25% quantiles of SM on each drying day. Within each region, letters with and without prime ($'$) indicate paired samples with contrasting EF regime behaviors. Detailed information of these samples including latitudes and longitudes, values of $\Delta Corr$, AI and precipitation are displayed in table S3. Gray bars in the right column denote precipitation events.

exhibit contrasting EF regimes and the modes of SM in C are notably higher compared to that of C'. If the total water availability is similar, what could contribute to the additional part that is readily available for EF at C'? Compared to the surrounding mountains, the surface elevation in locations C is less than 500 m above sea level (see e.g. www.yellowmaps.com/maps/img/US/elevation/USA-elevation-map-242.jpg). The inflows from the surrounding mountains can largely recharge the surface
Figure 3. Regionalization of surface aridity based on (a), (b) EF regimes and (c), (d) AI. Map of EF regimes is regionalized to five groups of areas based on the energy partitioning, defined as dry or wet climatology with high potential to extremes (Dh or Wh), dry or wet climatology with moderate potential (Dm or Wm), dry (wet) climatology with low potential (D(W)m). Regionalization map based on varied thresholds are shown in figure S7. The classical aridity regionalization based on AI also classifies aridity into five groups of areas defined as hyper arid (HypArid), arid (Arid), semiarid-semihumid (SubReg), humid (Humid) and hyper humid (HyphHumid) with UNEP classification rules. White pixels in (a), (b) are due to data masking and missing values, the same as in figure 1. Warnings should also be given to areas within 250 km to coastlines and to areas with extreme wet/dry areas since in these regions the SFE theory may contain large estimation uncertainties \[23\].

SM, and the groundwater recharge driven by the geothermal activities \[46\] in location C can also replenish the SM deficit. As such, it shows much higher mode values of SM (figure 2(c), 3rd column), and wetter SM initial and final values during their drydown processes compared to locations C’ (although the shapes of their drydown curves are similar). The streamflow and groundwater recharges can rapidly remove surface SM deficit, leading to relatively wet states and a stronger dependence of EF on energy.

These results suggest that using proxies such as AI based only on seasonal mean state of surface energy and water conditions may be insufficient for characterizing surface water/energy varibilities at short terms. Instead, the EF regime contains information of both the background mean state and short-term varibilities. Such information is important to evaluate the sensitivity of near-surface state to energy or water anomalies, with implications for the risks of extreme events such as heatwaves, floods, and droughts.

3.2. Regionalization of surface aridity based on EF regimes

The redefined map of aridity is compared with the aridity map based on AI, with the former showing larger spatial variability reflecting the effects of land surface heterogeneity (figure 3), although the boundaries of EF based classifications slightly vary with the choice of the ΔCorr thresholds (figure S9). Areas in southern North America traditionally classified as subhumid regions (humid in summer monsoon region) are instead labeled as region of dry climatology, and are highly prone to drought when severe surface water deficit occurs. This agrees with several studies reporting concurrence of droughts and heatwaves in the southern U.S \[14, 47, 48\]. Similar differences are also found in southwestern and northwestern China, where a higher frequency of droughts often occur \[49, 50\]. Similarly, areas in northeastern China and the northeastern U.S. traditionally classified as subhumid is instead identified by the EF regimes as regions with wet climatology, with
high potential for climate extremes (e.g., floods for the overabundance of surface water and otherwise droughts). These regions are therefore prone to water deficit induced by high variability of surface energy (e.g., sharp rise of $T_{\text{air}}$), although these regions usually receive sufficient water.

The redefined aridity map compares qualitatively well with the Köppen–Geiger climate classification [51, 52], which defines sub-climate zones within the main climate group based on land cover. The redefined map also compares reasonably with a newly developed AI considering vegetation fertilization effects [53], and a drought index considering joint effects of climate and land surface change [54]. These studies highlight the importance of specifying land characteristics in depicting land aridity conditions, however both of them address one-sided topic in land–atmosphere interaction studies (e.g. either land water availability or extreme events). By interpreting the EF regimes in terms of the mean state and variability, our study may provide a more synthesized reference for regional assessment on regional water and energy conditions and their implications for climate risks.

4. Conclusions and implications

This study develops a method to regionalize surface aridity based on observation-driven data from a simple approach with minimal data requirement. The redefined map of surface aridity shows broad agreement with the spatial pattern of the background aridity defined using AI. However, in areas with particular land types such as Karst topography and riverheads, classical proxies such as AI cannot properly characterize surface water variability, which is strongly modulated by land processes such as drydown, highlighting the land–atmosphere interaction effects on regional aridity. Moreover, aridity defined at relatively short time scales (i.e. daily) is more reflective of the extreme conditions induced by strong land–atmosphere coupling, since these events often occur within a relatively short time period. Hence our redefined aridity map should be viewed as providing complementary information to AI to include short-term surface water and energy variabilities, as reflected in EF regimes, to be considered along with the background climate for addressing environmental challenges related to water, ecosystems, and extreme events.

Our analysis also reveals some limitations in characterizing land aridity using the EF regimes. The metric we used here measures the magnitude of how much does EF change given a change in energy as compared to how much does it change given a change in SM, such that some unusual situations would bias the classification scheme. For example, a heavy rainstorm in a desert could lead to positive $\Delta \text{Corr}$, in which case this place would be unfairly classified as Wet background climate. However, such events do not persist or rarely occur in the real-world conditions. In this light, credible dataset with a rather long duration are expected to ensure the background aridity state will not be misrecognized by these exceptional events. In addition, there are many other advanced methods to more comprehensively estimate the land–atmosphere coupling strength, e.g. analyzing solely the EF or SM distribution may be more easily to be addressed compared to the coupled metric used in this study. However, these methods often need more superior modeling functions (usually imposed with extended hypothesis) [37, 55], which may introduce artificial errors. The aim of this study is to provide a complementary perspective on how land aridity can be defined based on land–atmosphere feedbacks. Hence we would expect a method as simple as possible. Future studies to more explicitly and quantitatively relate absolute surface conditions and climate extremes are expected to more rigorously define land aridity at short terms. Efforts to evaluate uncertainty associated with data quality in characterizing aridity are important to demonstrate the robustness of the new aridity metric.

Our study provides complementary information in characterizing land aridity conditions by considering land–atmosphere interaction effects at short-terms. Although this framework is only demonstrated at continental scales, our results address notable implications for broad environmental studies. First, distinctive characteristics of aridity conditions at short time scales suggest that land–atmosphere processes may be more reasonably resolved by incorporating measurements with higher temporal resolution. Recent studies have highlighted this not only in terms of land–atmosphere interactions [56], but also in studies of hydrology [55], plant water uptake strategies [57], and drought detections. Together with our work, these studies provide a more complete picture of geophysical processes happening on Earth. In addition, land aridity characterized by EF regimes indicates readily available water for ET. This opens an opportunity for improving understanding of how vegetation is influenced by water availability and for improving agricultural managements such as decisions on crop types, irrigation strategies, and harvest time at large spatial scales. Furthermore, this framework offers a new approach for future climate assessment. There is an ongoing debate on whether aridity conditions would be exaggerated in future climate [30, 53, 58], and how would their spatial distribution and temporal trends influenced by climate change [3, 41, 43]. Our approach could offer a complementary perspective on how water and energy interactions change in future, with implications for climate extremes, and with high simplicity.
Data availability statement

All data that support the findings of this study are included within the article (and any supplementary files).

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