2015


Jozsef Szilagyi
University of Nebraska - Lincoln, jszilagyi1@unl.edu

Follow this and additional works at: http://digitalcommons.unl.edu/natrespapers

Part of the Natural Resources and Conservation Commons, Natural Resources Management and Policy Commons, and the Other Environmental Sciences Commons

http://digitalcommons.unl.edu/natrespapers/615

This Article is brought to you for free and open access by the Natural Resources, School of at DigitalCommons@University of Nebraska - Lincoln. It has been accepted for inclusion in Papers in Natural Resources by an authorized administrator of DigitalCommons@University of Nebraska - Lincoln.

Jozsef Szilagyi1,2

1Department of Hydraulic and Water Resources Engineering, Budapest University of Technology and Economics, Budapest, Hungary, 2School of Natural Resources, University of Nebraska-Lincoln, Lincoln, Nebraska, USA

Abstract
Thirty year normal (1981–2010) monthly latent heat fluxes (ET) over the conterminous United States were estimated by a modified Advection-Aridity model from North American Regional Reanalysis (NARR) radiation and wind as well as Parameter-Elevation Regressions on Independent Slopes Model (PRISM) air and dew-point temperature data. Mean annual ET values were calibrated with PRISM precipitation (P) and validated against United States Geological Survey runoff (Q) data. At the six-digit Hydrologic Unit Code level (sample size of 334) the estimated 30 year normal runoff (P–ET) had a bias of 18 mm yr$^{-1}$, a root-mean-square error of 96 mm yr$^{-1}$, and a linear correlation coefficient value of 0.95, making the estimates on par with the latest Land Surface Model results but without the need for soil and vegetation information or any soil moisture budgeting.

1. Introduction
With a changing climate and an expected intensification of the global hydrologic cycle, accurate determination of the latent heat fluxes (ET) between the land surface and the ambient atmosphere over extended time intervals and/or extensive areas is crucial for, e.g., hydroclimatological predictions and simulations, as well as long-term and/or large-scale water management operations including drought monitoring and flood alleviation. While remote-sensing based ET estimation methods are evolving fast (for a review, see Wang and Dickinson [2012]), reanalysis-based methods [Chen et al., 1997; Koster and Suarez, 1996; Liang et al., 1994; Mesinger et al., 2006] are also important because of their longer temporal coverage, their insensitivity to cloud cover, and because they may form part of remote-sensing based ET estimation techniques [Szilagyi et al., 2011; Wu et al., 2014]. Reanalysis data are considered as the best representation of reality for spatially distributed, long-term applications, since they combine measurements with modeling results by taking into account the errors in both. The North American Regional Reanalysis (NARR) data [Mesinger et al., 2006] are an improvement on continental-scale reanalyses due to its finer resolution (i.e., 32 km), its state-of-the-art Land Surface Model (LSM) component, and the assimilation of observed precipitation for the North American continent and adjacent oceans over the past 35 years [Sheffield et al., 2012]. The LSMS provide sensible (H) and latent heat fluxes typically employing variations of the Penman-Monteith equation [Monteith, 1965] for the latter, requiring soil and vegetation information to perform soil moisture budgeting. Considering the typically large heterogeneity in soil type, thickness, layering, vegetation-cover, and rooting depth, the ensuing ET fluxes may contain a relatively high degree of uncertainty, resulting in noticeable differences in ET values among LSM versions [Sheffield et al., 2012], giving rise to the need for an alternative formulation of the ET fluxes not requiring soil, land surface or vegetation information.

2. Application of the Complementary Relationship
The complementary relationship (CR) of regional evaporation [Bouchet, 1963] scales the wet-environment ET rate, $ET_w$, to actual ET rate by comparing the spatially averaged latent heat fluxes of wet surfaces differing only in size: that of a small wet patch (e.g., a wet meadow) with a horizontal extent of $\sim$100 m to one with an extent in excess of $\sim$1 km, the scale $ET_w$ in fact is valid at. The more the small wet patch ET rate, $ET_w$...
The latent heat flux (in mm d\(^-1\)) of the small wet patch is defined by the Penman [1948] equation:

\[ ET_p = \frac{\Delta(T_a)}{\Delta(T_a) + \gamma} R_n + \frac{\gamma}{\Delta(T_a) + \gamma} f_u (e^* - e_a), \]  

where \( T_a \) is the air temperature over the drying land surface, \( e_a \) is the actual vapor pressure in hPa, \( e^* \) is the saturation vapor pressure at \( T_a \), \( f_u \) is the (so-called Rome) wind function, traditionally expressed [Brutsaert, 1982] as:

\[ f_u = 0.26(1+0.54u_2), \]  

where \( u_2 \) is the wind speed (m s\(^-1\)) at 2 m above the ground.

The CR obtains actual \( ET \) as:

\[ ET = ET_w - (ET_p - ET_w)/b, \]  

where \( b \) is a proportionality coefficient [Kahler and Brutsaert, 2006; Szilagyi, 2007]. When the time-rate of change in \( ET_p \) is similar to the one in \( ET \) (but with an opposite sign) during wetting/drying of the environment, \( b \) becomes a constant unity, and the CR symmetric [Brutsaert and Stricker, 1979], otherwise \( b \) depends on the aridity of the environment [Szilagyi, 2007].

Notice that the air temperatures are different in (1) and (2) when the environment is not wet, which is typical. Therefore, it is necessary to estimate \( T_a \) from drying conditions. Szilagyi and Jozsa [2008] recommended an implicit formula based on the Bowen ratio \( (B_o) \) written for the small wet patch with daily sums of the fluxes as:

\[ B_o = \frac{H}{ET_p} \approx \frac{R_n - ET_p}{ET_p} \approx \gamma \frac{T_{ws} - T_{a}}{e^*(T_{ws}) - e(T_a)} \]  

making use of the assumptions that \( R_n \), \( T_a \), and \( e_a \) over the drying and wet surfaces are about the same due to the small extent of the latter. \( T_{ws} \) is the estimated air temperature at the wet surface, which has recently been shown to be constant [Szilagyi and Schepers, 2014] in space and time under constant (temporally and spatially) \( R_n \) and wind conditions during drying of the environment around the wet patch. Since the equilibrium air temperature profile over wet surfaces has a mild gradient with height above the ground [Szilagyi and Jozsa, 2009], the \( T_{ws} \) value estimated from (5) can be taken for \( T_w \) as long as \( T_{ws} < T_o \), otherwise \( T_w \) can be replaced by \( T_o \) [Huntington et al., 2011; McMahon et al., 2013a,b; Szilagyi, 2014a].
Table 1. List of Functions (After Fenicia et al. [2011]) Applied for $b^{-1}$

<table>
<thead>
<tr>
<th>Functional Form of $b^{-1}$</th>
<th>Name</th>
<th>Parameter ($p$, $q$) Range</th>
</tr>
</thead>
<tbody>
<tr>
<td>$RH = \text{const.}$</td>
<td>Constant</td>
<td>$p = 0.7$–1</td>
</tr>
<tr>
<td>$RH$</td>
<td>Identity function</td>
<td>$p = 0.13$–1.5, $q = 0.1$–1</td>
</tr>
<tr>
<td>$(RH)^p$</td>
<td>Power function</td>
<td>$p = 1$–3</td>
</tr>
<tr>
<td>$1 - (1 - RH)^p$</td>
<td>Reflected power function</td>
<td>$p = 0.4$–0.6</td>
</tr>
<tr>
<td>$(1 + p)RH/(RH + p)$</td>
<td>Monod-type kinetics</td>
<td>$p = 1$–20, $q = 0.1$–1</td>
</tr>
<tr>
<td>$(1 + e^{-p1\cdot q}(e^{-p1\cdot q} - 1))/\left(e^{-p1\cdot q} - 1\right)$</td>
<td>Modified logistic curve</td>
<td>$p = 0.5$–2</td>
</tr>
<tr>
<td>$\left(E_{\text{Rome}}(f_{\text{pu}})/E_{\text{pan}}(f_{\text{pu}})\right)^p$</td>
<td>Pan coefficient</td>
<td>$p = 1$</td>
</tr>
<tr>
<td>$p:/(\Delta T_d)$</td>
<td>Szilagyi [2007]</td>
<td>$p = 0.1$–1</td>
</tr>
</tbody>
</table>

Szilagyi and Jozsa [2008] demonstrated that by prescribing a suitable (pan) wind function:

$$f_u = 0.49(1 + 0.35u_2),$$

(2) can be applied for estimating monthly class-A pan evaporation rates in moderately dry regions. As was shown by Kahler and Brutsaert [2006], class-A pan evaporation is more sensitive to changes (i.e., drying) in the surrounding environment than a small wet patch, therefore better poised for detecting small changes in actual $ET$, provided the proportionality/aridity function, $b^{-1}$, is well defined. While the CR, (4), with the original Penman equation (i.e., (2) with the Rome wind function, (3)) tends to be symmetric ($b^{-1} \approx 1$) [Brutsaert and Stricker, 1979; Hobbs et al., 2001a;b; Ramirez et al., 2005; Szilagyi et al., 2009; Huntington et al., 2011; Szilagyi, 2014a], it becomes highly asymmetrical with class-A pan evaporation rates [Ramirez et al., 2005; Kahler and Brutsaert, 2006; Szilagyi and Jozsa, 2008].

In this study an asymmetric CR, i.e., (2) with (6), is applied to estimate the 30 year normals (1981–2010) of monthly $ET$ rates across the contiguous United States, making use of the North American Regional Reanalysis (NARR) radiation and 10 m wind ($u_{10}$) as well as Parameter-Elevation Regressions on Independent Slopes Model (PRISM) precipitation ($P$), air and dew-point temperature ($T_d$) data [Daly et al., 1994] at a spatial resolution of 4 km. The monthly mean PRISM $T_d$ values are only available as 30 year normals therefore the ensuing $ET$ estimation could not be performed on a continuous month-by-month basis, but rather as 30 year normals using similar averages of the input variables. Monthly $u_{10}$ values were transformed to $u_2$ via $u_2 = u_{10} (2/10)^{1/7}$ [Brutsaert, 1982].

3. Calibration of the CR

Hobbs et al. [2001b] demonstrated that the CR-based AA model [Brutsaert and Stricker, 1979] improves with local calibration of its wind function. Similar local calibration of Morton’s CR model [1983] is not easily viable because of its several globally optimized empirical parameters (e.g., the air stability function). While locally calibrating the wind function may lead to better AA-model performance, a more general approach that does not need such calibration is preferable, as data for local calibration may often be lacking. Szilagyi et al. [2009] demonstrated that AA-model performance improves, especially in hot and dry climates, by simply accounting for the changes in air temperature between (1) and (2). Therefore $ET$ rates at the 4 km PRISM resolution are estimated here by substituting the $T_{\text{arc}}$ estimates (as a proxy of $T_d$) of (5) into (1) and employing (2) and (6) in (4) through the calibration of the proportionality coefficient, $b^{-1}$, as a function of aridity [Szilagyi, 2007].

While aridity can be defined in several ways, the relative humidity, $RH = e^*(T_d)/e^*(T_{\text{arc}})$, as a proxy measure of aridity is used here in order to avoid introducing additional input variables to the model. Table 1 lists the types of the aridity functions considered during calibration. They all increase with $RH$ (except the first one, while the last one in its tendencies, since with wetting of the environment $RH$ increases while $T_d$ tends to decrease) in accordance with the CR and yield values between zero and unity. The objective function of calibration consisted of minimizing the following two quantities for the 30 year normal annual values: (a) the number of cells with $ET > P$; and; (b) the number of cells with $ET = 0$. Notice that (a) no other information (e.g., runoff for water balancing) was used for the calibration; (b) the two conditions somewhat counteract each other (the first depresses, while the second inflates $ET$), pressing the modeled $ET$ rates into a realistic interval in most parts of the study area. Note also that calibration does not prevent the resulting values to exceed precipitation rates as indeed $ET > P$ occurs on a long-term basis even at a regional scale [Szilagyi, 2013, 2014b].
During the trial-and-error calibration the value of $a$ in (1) was also changed systematically between 1.1 and 1.3 for each parameter value of Table 1. Eventually, the modified logistic curve (Figure 1) provided the best ET estimates (shown below) with $p = 13.5$, $q = 0.25$, and $a = 1.23$. It shows that in humid to mildly humid conditions ($RH > 0.5$) the CR is near-symmetric, a property that progressively breaks down with increasing aridity. Figure 2 displays the sensitivity of several model performances to changes in calibrated parameter values, proving the value of $a$ to be the most critical.

Figure 1. The optimized logistic curve-type aridity function, $b^{-1}$, of Table 1.

Figure 2. Sensitivity of model performance to changes in calibrated parameter values. RMSE is the root-mean-square error of the 30 year normal annual ET rates averaged over the 334 United States Geological Survey (USGS) six-digit (HUC6) watersheds that cover the conterminous US.
4. Results and Discussion

Estimated long-term mean annual ET (Figure 3) is zero in only 59 PRISM grid-points (in California and south-western Arizona) from a total of 481,631 grid point values over the contiguous US, with a sample mean, \( \langle ET \rangle = 522 \pm 228 \text{ mm yr}^{-1} \). Estimated ET exceeds precipitation in 55,519 (\( \sim 12\% \) of the total) grid points (Figure 4).
4), but rarely by more than 20% of the PRISM precipitation value, typically in valleys and basins of the western states. The area-weighted sample \( (n = 334) \) mean of the simplified water-balance approach, i.e., the difference between the PRISM \( P \) values averaged over the HUC6 watersheds and the corresponding runoff, \( Q \) (source: waterwatch.usgs.gov), yields \( 537 \pm 228 \text{ mm yr}^{-1} \), a departure of less than 3% from the CR-based value.

Note that the watershed drainage area values contain varying portions of the Great Lakes surface areas therefore the HUC6 area-weighted 30 year normal of annual PRISM \( P \) becomes 786 instead of the original spatial average of \( 791 \pm 448 \text{ mm yr}^{-1} \) due to the absence of \( P \) values over the lakes.

Figure 5 displays the spatial distribution of the CR- and water-balance-derived mean annual \( ET \) ratios and their histogram. The CR-derived and HUC6-averaged \( ET \) is within 20% of the water-balance obtained value over 80% of the catchments.

![Figure 5](image1.png)

**Figure 5.** Distribution of the ratios of HUC6-averaged CR-(\( ET_{AA} \)) and simplified water-balance-derived (\( ET_{wb} \)) 30 year normal annual \( ET \) and their histogram (\( n = 334 \)).

Figure 6 displays the spatial distribution of the HUC6-averaged 30 year normal annual USGS runoff (\( Q \)) rates (\( \text{mm yr}^{-1} \)). \( \langle Q \rangle = 249 \pm 270 \text{ mm yr}^{-1} \).

![Figure 6](image2.png)

**Figure 6.** Spatial distribution of the HUC6-averaged 30 year normal annual USGS runoff (\( Q \)) rates (\( \text{mm yr}^{-1} \)).
The CR underestimates water-balance ET the most significantly in south-western Arizona, and overestimates it in the Mojave Desert of California and in Washington State, locations with the two extremes (i.e., driest and wettest) of precipitation within the conterminous US (Figure 4). Even within the driest region, runoff varies significantly, from less than 5 mm yr$^{-1}$ (south-western Arizona) to over 100 mm yr$^{-1}$ in the Mojave Desert (Figure 6) while corresponding catchment-averaged precipitation (not displayed) remains between 140 and 170 mm yr$^{-1}$.

Figure 7. Spatial distribution of the difference in the HUC6-averaged CR-derived ($Q_{est} = P - ET_{AA}$) and USGS-measured ($Q$) 30 year normal annual runoff rates (mm yr$^{-1}$) and their histogram ($n = 334$).

Figure 8. Regression plots of HUC6-averaged a) CR-derived and simplified water-balance derived 30 year normal annual ET; (b) CR-derived ($P - ET_{AA}$) and measured ($Q$) runoff values ($n = 334$).
The situation is even more interesting in the West Texas and Oklahoma panhandle watersheds, displaying less than 5 mm yr\(^{-1}\) runoff while enjoying 344–572 mm of precipitation annually, resulting in runoff ratios of only a few percent. With this significant spatial variability in runoff, the AA-derived ET rates yield runoff rates that are within 100 mm of the measured value in more than 75% of the catchments (Figure 7) or within 50–200% of measured Q in 75% of the watersheds. From the 334 value pairs of Figure 8, water-balance ET and the corresponding runoff rate are under/overestimated by only 18 mm yr\(^{-1}\) on average, with a root-mean-square error (RMSE) of 96 mm yr\(^{-1}\) and a linear correlation coefficient (Corr) value of 0.92 and 0.95, respectively. The latter means that the present AA-model can explain about 90% of the variation found in the HUC6 30 year normal annual runoff rates, indicative of a robust model. These performance indicators are similar (or better than) to the ones reported by recent LSMs [Sheffield et al., 2012].

While at a long-term annual basis the estimated ET rates can be verified with simplified water-balance data, the monthly values cannot (Figure 9). Still some interesting patterns emerge from the estimated 30 year normal monthly ET rates. Some examples: (a) US-wide ET is not symmetrical over the year. ET is larger in general in the first part of the year, reaching a peak in June/July (106 and 105 mm, respectively). (b) In February, the largest ET contributor in the West is the Central Valley of California, due to mild climate conditions.

Figure 9. Spatial distribution of the AA-estimated 30 year normal monthly ET rates (mm mo\(^{-1}\)). The months are row-continuous (i.e., first row: January–February–March).
temperatures and winter rains. (c) Over the Rockies in general, ET rates in March shoot up first in the mountains, probably due to enhanced precipitation year round. (d) Dry out in the West starts first in Southern California and Arizona in July and spreads northward. (e) The large wetland area in Northern Minnesota stands out of its surroundings with its elevated ET rates during the entire warm season (April–September). (f) From April to August, ET rates are not the highest in Florida, but in different other Southern states, varying by month. (g) From June to August, ET is the largest in Nebraska among the prairie states along the 100th meridian (the north-south borderline between Texas and Oklahoma), even though annual precipitation is not. Nebraska, however, is the most intensively irrigated state (by irrigated area) within the US [United States Department of Agriculture (USDA), 2014] with peak water use in June and July. The effect of irrigation is reported [Kustu et al., 2011] to be felt as far as Ohio in the form of increased summer rain and streamflow.

Figure 10 displays the monthly 30 year normals of the P, ET and RH values by two-digit HUC regions (row continuous).
5. Summary and Conclusions

The Complementary Relationship of evaporation, after more than half a century of its inception [Bouchet, 1963] and undeniable success [McMahon et al., 2013a,b] is still a widely overlooked and underemployed tool in hydrology, climatology, and in the general area of water resources management. To this day, it is the only method that considers the complex interplay between soil moisture, vegetation, evapotranspiration, and water vapor content of the air and derives the corresponding ET rate from standard meteorological measurements only, without the need of information on the interacting land-soil-vegetation components. It is believed by this author that its application in LSMs as a calibration/verification tool would greatly improve the predictive capacity of such models.

Here a modified version of the CR-based AA model [Brutsaert and Stricker, 1979; Szilagyi et al., 2009] was employed for mapping 30 year (1981–2010) normals of monthly and annual latent heat fluxes across the contiguous US. Modifications included the choice of the wind function to increase the sensitivity of the CR, and the formulation as well as calibration of an aridity-based (relative humidity used as a proxy measure of aridity) proportionality function of the CR. Calibration was performed employing only precipitation measurements while validation was achieved by the help of watershed-averaged measured runoff.

The resulting long-term mean annual ET estimates explain 90% of the spatial variation found in measured HUC6 watershed-averaged runoff, with a bias of 18 mm yr\(^{-1}\) and RMSE of 96 mm yr\(^{-1}\), making the estimates on par with latest LSM results [Sheffield et al., 2012].

Future research could explore how different input data sets affect the shape of the aridity function, as it is not expected to be universal, but rather dependent on the data source employed.

References


