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Insights for empirically modeling evapotranspiration influenced by riparian and upland vegetation in semiarid regions

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A B S T R A C T

Water resource managers aim to ensure long-term water supplies for increasing human populations. Evapotranspiration (ET) is a key component of the water balance and accurate estimates are important to quantify safe allocations to humans while supporting environmental needs. Scaling up ET measurements from small spatial scales has been problematic due to spatiotemporal variability. Remote sensing products provide spatially distributed data that account for seasonal climate and vegetation variability. We used MODIS products [i.e., Enhanced Vegetation Index (EVI) and nighttime land surface temperatures (LST_n)] to create empirical ET models calibrated using measured ET from three riparian-influenced and two upland, water-limited flux tower sites. Results showed that combining all sites introduced systematic bias, so we developed separate models to estimate riparian and upland ET. While EVI and LST_n were the main drivers for ET in riparian sites, precipitation replaced LST_n as the secondary driver of ET in upland sites. Riparian ET was successfully modeled using an inverse exponential approach ($r^2 = 0.92$) while upland ET was adequately modeled using a multiple linear regression approach ($r^2 = 0.77$). These models can be used in combination to estimate ET at basin scales provided each region is classified and precipitation data is available.

1. Introduction

A common goal for water resource managers in the southwestern United States and arid and semiarid regions worldwide is to ensure long-term water supplies for increasing human populations. In these regions, evapotranspiration (ET) is a substantial component of the water budget (Dahm et al., 2002; Glenn et al., 2010; Nichols, 1994) and has important implications for water resources management (Jackson et al., 2001; Newman et al., 2006). Therefore, estimates of ET at watershed or basin scales that are relevant to water resource managers are central for quantifying how much water can be allocated safely for human use while supporting environmental needs (Commission for Environmental Cooperation, 1999; Congalton et al., 1998; Hansen and Gorbach, 1997; U.S. Department of Interior 2002).

Because reliable estimates of ET at watershed and basin scales are difficult to obtain due to heterogeneous patterns of land cover that include mixed riparian and upland vegetation (McDonnell et al., 2007; Scott et al., 2008), ET estimates tend to be available only at local site-specific scales. These site-specific ET estimates are typically made using Bowen ratio and eddy covariance techniques (e.g., Cleverly et al., 2002; Coonrod and McDonnell, 2001; Dahm et al., 2002; DeMeo et al., 2003; Devitt et al., 1998; Goodrich et al., 2000; Scott et al., 2004). At scales of hundreds to thousands of square meters, the eddy covariance technique has been regarded as the best and most reliable method for estimating ET (Rana and Keterji, 2000), and many studies have confirmed reasonable estimates of ET using this approach (Barr et al., 2000; Kosugi and Katsuyama, 2007; Schume et al., 2005; Wilson et al., 2001). However, the eddy covariance technique can only provide measurements representative of a single ecosystem type that is of an extensive, uniform area immediately upwind of the tower (Baldocchi, 2003; Unland et al., 1998). Therefore, directly extrapolating site-specific ET to larger landscapes may lead to biased

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regional estimates because towers may not adequately represent larger areas.

Recent studies have demonstrated the potential to combine site-specific eddy covariance data with remotely sensed and other data sources to develop empirical models for making regional scale estimates (e.g. Glenn et al., 2010; Wylie et al., 2003). Using this approach, an empirical equation that incorporates remotely sensed data products such as the normalized difference vegetation index (NDVI), the enhanced vegetation index (EVI), or nighttime land surface temperature (LST_n) is developed to predict site-specific eddy covariance ET; the resulting equation is then assumed to be a predictive ET model for the particular ecosystem that the eddy covariance tower represents (Nagler et al., 2005a, Scott et al., 2008). This vegetation index (VI) approach has been used to estimate ET in a variety of semiarid landscape types across the globe including agricultural districts (Gonzalez-Dugo et al., 2009; Kim and Hogue, 2008), riparian zones and desert phreatophyte communities (Barz et al., 2009; Groeneveld et al., 2007; Guerschman et al., 2009; Murray et al., 2009; Nagler et al., 2005a, b, 2009; Scott et al., 2008), grasslands and savannahs (Alfieri et al., 2009; Cleugh et al., 2007; Guerschman et al., 2009; Nagler et al., 2009), and water-limited shrublands (Nagler et al., 2007).

Notably, these empirical ET models are derived for single ecosystem types, rather than entire watersheds or river basins. However, if an empirical ET model can be derived for each ecosystem type within a watershed and the watershed can be discretized into pixels of individual ecosystems that align with remotely-sensed data cells, then an ET estimate based on the weighted contribution from each ecosystem type could be made for the entire watershed. Unfortunately, digital images used for these types of analyses inherently include pixels that combine upland vegetation or bare soil and riparian vegetation. In semiarid ecosystems, this is especially problematic because riparian ecosystems are influenced by shallow groundwater (e.g. Busch et al., 1992; Snyder and Williams, 2000) whereas upland ecosystems depend exclusively on pulses of moisture from precipitation events (e.g. Kurc and Small, 2004; Scott et al., 2006; Williams et al., 2006). As an example, an empirical ET model developed by Scott et al. (2008) was calibrated using eddy covariance towers located in riparian ecosystems influenced by relatively shallow groundwater (≤10-m depth) near the San Pedro River, AZ. In practice, empirical ET models calibrated using riparian ecosystems will generally over-predict ET when the region of interest consists of mosaic vegetation (e.g., mixed riparian and upland vegetation) because of the presence of upland vegetation and/or bare soil within the pixel (Scott, pers. comm. 2011). As a result, water lost via ET at the watershed or basin scale is over-estimated as a function of upland area or bare soil present in region of interest (Scott et al., 2008). For this reason, calibrating empirical ET models developed for riparian ecosystems using additional data from adjacent, upland ecosystems is likely to improve watershed and basin scale ET estimates.

The objective of this study is to provide insights for improving watershed or basin scale estimates of ET in mosaic semiarid regions that include water-limited upland vegetation. To do this, we incorporate data from two upland and three riparian eddy covariance tower sites to (1) recalibrate an empirical ET model using information from both riparian and upland sites, (2) develop and calibrate a modified empirical ET model that uses a multiplicative approach which may better represent the interaction between LST and EVI than in previous empirical models, and (3) develop and calibrate a modified empirical ET model that incorporates moisture for large scale applications in semiarid regions. Specifically, we quantify whether models developed using data combined from upland and riparian eddy covariance sites improve predictions of ET for combined datasets, riparian datasets, upland datasets and individual sites. Further, we provide insights on which techniques and variables are most appropriate for developing empirical ET models for specific semiarid ecosystems that can be used to improve predictions of ET in spatially explicit applications that scale from the ecosystem to the watershed or basin.

2. Methods

2.1. Study sites

Five flux tower sites were used for this research including three riparian-influenced (i.e., all sites have access to shallow groundwater during at least part of any given year) sites (CM, LM, LS) and two water-limited (i.e., neither site has access to groundwater reserves) upland sites (KG, SR) in southeastern Arizona, US (Table 1, Fig. 1). Our study region extends from the Santa Cruz River Watershed in the west to the San Pedro River Watershed in the east. All sites are considered to be semiarid with cool winters and warm summers where rainfall varies spatially and temporally with mean annual precipitation (MAP) ranging from 250 mm to 390 mm (McClaran et al., 2002; Nagler et al., 2007; Scott et al., 2008). Precipitation is characterized by bimodal patterns in which 50–60% of the total annual rainfall arrives during the summer (July–Sept) as part of the North American Monsoon (Adams and Comrie, 1997). MAP was documented at each of the five sites during the study period (2003–2007; Table 1).

The three riparian sites are located in the San Pedro River Natural Conservation Area (SPRNCA) within the San Pedro Basin and are influenced by relatively shallow groundwater supported by intermittent San Pedro River streamflow. Soils consist of sandy loam alluvium with interspersed layers of gravel and clayey materials (Scott et al., 2008). The Charleston Mesquite Woodland riparian site (CM, N 31.6636 −110.1778) is adjacent to the main river channel and had a mean annual temperature of 16.8 °C during the study period. CM is a dense mesquite woodland dominated by velvet mesquite (*Prosopis velutina*) with an understory consisting of perennial sacaton bunchgrass (*Sporobolus airoides*), greythorn (*Zizyphus obtusifolia*), and various summer annuals. The Lewis Springs Mesquite riparian site (LM, N 31.5658 W−110.1344) is located within one kilometer of the main channel and had a mean annual temperature of 16.2 °C during the study period. LM is a mesquite shrubland with sparsely distributed *P. velutina*, scattered patches of *S. airoides*, and other various shrubs within the tree

Table 1
Locations and descriptions for five study sites.

Site	Long. (W)	Lat. (N)	Elev. (m)	MAP[a] (mm)	Dist. to San Pedro River (km)	Dominant veg. type and species
Charleston Mesquite Woodland (CM)	−110.178	31.664	1200	244	0.22	Riparian: *Prosopis velutina*
Lewis Springs Mesquite Shrubland (LM)	−110.134	31.566	1230	294	0.76	Riparian: *Prosopis velutina*
Lewis Springs Giant Sacaton Grassland (LS)	−110.14	31.562	1230	298	0.14	Riparian: *Sporobolus airoides*
Kendall Grassland (KG)	−109.942	31.737	1531	250	22.25	Upland: *Eragrostis lehmanniana*
Santa Rita Mesquite Savannah (SR)	−10.866	31.821	1116	310	58.00	Upland: *Prosopis velutina*

[a] Mean annual precipitation (MAP).

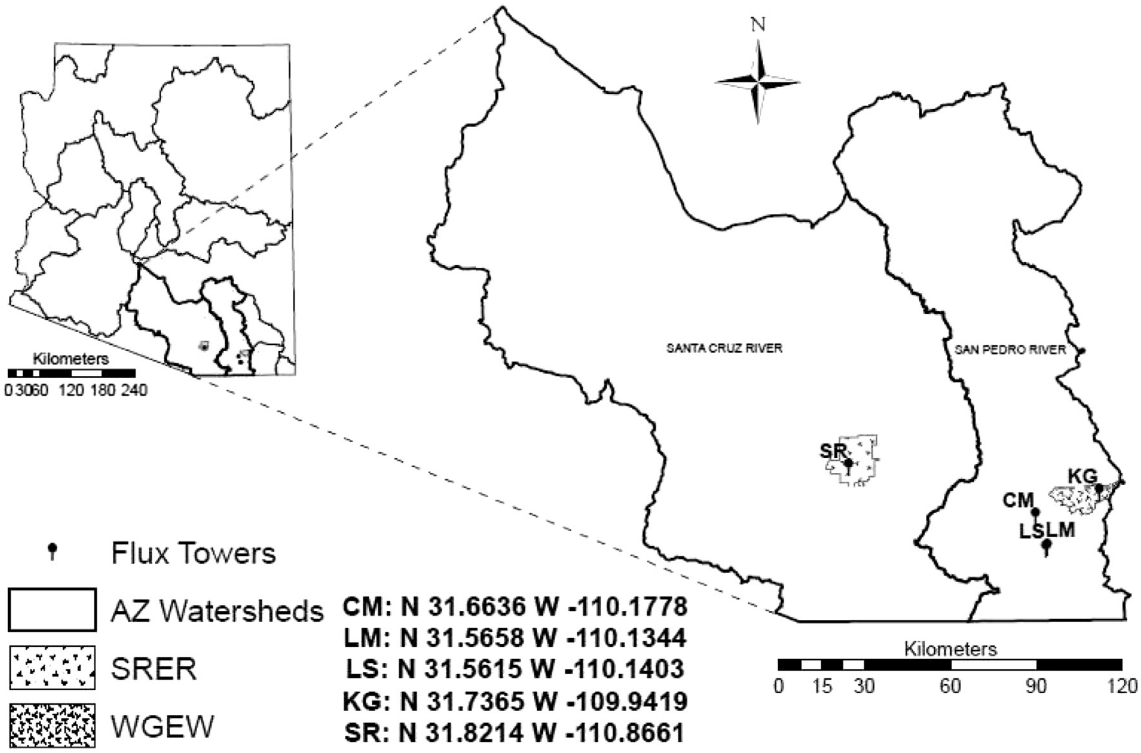

Fig. 1. Locations of the five study sites, including one in the Santa Cruz River Watershed (Santa Rita Mesquite Savannah, SR). and four in the San Pedro River Watershed (Charleston Mesquite Woodland, CM; Lewis Springs Mesquite, LM; and Lewis Springs Sacaton, LS; and Kendall Grassland, KG) in Arizona, USA.

interspaces. The Lewis Springs Sacaton riparian site (LS, N 31.5615 W−110.1403) is adjacent to the main river channel and had a mean annual temperature of 15.4 °C during the study period. Dominant vegetation includes dense *S. airoides* with occasional summer annuals.

The two upland sites include a grassland and a mesquite savannah. The Kendall Grassland upland site (KG, N 31.7365 W−109.9419) lies in the northwest portion of the Walnut Gulch Experimental Watershed and is located over 20 km from the San Pedro River. The mean annual temperature during the study period was 17.4 °C. Surface soils are generally very gravelly with sandy to fine sandy loams with some silty clay to clay loams at depth. Historically, vegetation consisted of diverse patches of native bunchgrasses including black grama (*Bouteloua eriopoda*), hairy grama (*Bouteloua hirsuta*), curly mesquite grass (*Hilaria belangeri*), and hook three-awn (*Aristida hamulosa*). Following the peak of the drought (2003–2006), the dominant vegetation has been replaced by non-native Lehmann love grass (*Eragrostis lehmanniana*). The Santa Rita Mesquite Savannah upland site (SR, N 31.8214 W−110.8661) is located in the Santa Rita Experimental Range approximately 65 km west of the San Pedro River and 45 km south of Tucson, AZ. The mean annual temperature during the study period was 19.2 °C and dominant vegetation includes *P. velutina* and *S. airoides*.

2.2. Eddy covariance flux data

The eddy covariance technique was used to estimate daily ET (Moncrieff et al., 1997). At each of our sites, typical instruments included three-dimensional sonic anemometers to measure wind speed and infrared gas analyzers to measure CO_2 and H_2O fluxes. Additional instrumentation included net radiometers, ground heat flux plates, and tipping bucket rain gauges. Methods specific to the San Pedro sites can be found in Scott et al. (2004, 2008) while the upland sites are described in Scott et al. (2009) and Scott et al. (2010).

Daily ET values were estimated by averaging the original half-hourly flux tower ET measurements. A 16-day average was then computed to match 16-day composites offered by remote sensing products. Likewise, precipitation was summed for each 16-day window to match remote sensing products. Eddy covariance data used for this study included five years of riparian site data (2003–2007) and four years of upland site data (2004–2007).

2.3. Remotely sensed data

Pre-processed MODIS products are available through the Oak Ridge National Laboratory Distributed Active Archive Center (ORNL-DAAC; http://daac.ornl.gov/MODIS/). For this study, we obtained vegetation indices (MOD13Q1 products) as 16-day composites with 250-m resolution and land surface temperatures (LSTs, MOD11A2 products) as 8-day composites with 1-km resolution. MOD13Q1 products include calculations of both NDVI and EVI while the MOD11A2 products include measurements of both daytime (LST_d) and LST_n. We extracted all data for our study period for each MODIS pixel inside which our eddy covariance towers were located, i.e. data from 5 total MODIS pixels.

Empirical ET models using pre-processed MODIS data acquired from the ORNL-DAAC have a temporal resolution limited by the 16-day VI products. As such, the 8-day LST data were averaged up temporally to meet the resolution of the 16-day MODIS data and were interpolated spatially onto the 250-m EVI pixels (e.g. Scott et al. 2008). The Regression analyses were conducted to compare relationships of ET among selected variables across each site as well as each year of the study period (Table 2). To examine potential issues arising from multicollinearity, tolerance and variation

Table 2
Relationships of evapotranspiration to selected variables.[a]

	EVI	NDVI	LST_n	LST_d	LST_{n-d}	T_{avg}	PPT	VPD	W_{spd}	R_n	G	LE	H	SW_{inc}	ET_{oAZMET}	ET_{oSW}
CM	0.89	0.84	0.92	0.73	0.015	0.89	0.46	0.59	−0.33	0.68	0.39	1.00	−0.41	0.50	0.48	0.67
LM	0.83	0.80	0.90	0.63	0.006	0.85	0.53	0.44	−0.27	0.61	0.27	1.00	−0.41	0.13	0.43	0.59
LS	0.85	0.80	0.92	0.73	0.027	0.90	0.42	0.56	0.01	0.75	0.36	1.00	−0.19	0.59	0.55	0.67
Riparian	0.86	0.80	0.91	0.69	0.012	0.87	0.46	0.53	−0.17	0.66	0.33	1.00	−0.35	0.32	0.48	0.63
KG	0.72	0.73	0.48	0.19	0.102	0.39	0.59	−0.04	−0.49	0.54	−0.09	1.00	−0.08	0.13	0.04	0.16
SR	0.82	0.75	0.54	0.24	0.067	0.46	0.75	0.05	−0.46	0.44	0.00	1.00	−0.17	0.09	0.06	0.17
Upland	0.76	0.72	0.52	0.22	0.084	0.43	0.64	0.03	−0.37	0.50	0.00	1.00	−0.12	0.10	0.04	0.17
2003	0.85	0.79	0.90	0.67	0.001	0.86	0.51	0.54	−0.22	0.58	0.21	1.00	−0.38	0.43	0.45	0.56
2004	0.84	0.79	0.64	0.63	0.260	0.65	0.01	0.42	−0.34	0.73	0.47	1.00	−0.03	0.46	0.30	0.54
2005	0.85	0.82	0.66	0.45	0.003	0.62	0.52	0.29	−0.41	0.64	0.20	1.00	−0.30	0.30	0.22	0.51
2006	0.86	0.81	0.71	0.43	0.053	0.65	0.59	0.16	−0.42	0.66	0.12	1.00	−0.37	0.03	0.15	0.47
2007	0.89	0.83	0.68	0.50	0.001	0.65	0.46	0.31	−0.42	0.70	0.32	1.00	−0.27	0.26	0.24	0.53

[a] A multivariate analysis reported coefficients of determination (r^2) for ET versus selected independent variables: enhanced vegetation index (EVI), normalized difference vegetation index (NDVI), nighttime land surface temperature (LST_n), daytime land surface temperature (LST_d), difference between daytime and nighttime LST (LST_{d-n}), average daily temperature (T_{avg}), precipitation (PPT), vapor pressure deficit (VPD), wind speed (W_{spd}), net radiation (R_n), ground heat flux (G), latent heat flux (LE), sensible heat flux (H), incoming shortwave radiation (SW_{inc}), potential ET computed by The Arizona Meteorological Network (ET_{oAZMET}), and potential ET computed using the Shuttleworth approach (ET_{oSW}). Regressions were analyzed to determine which variables explained most of the variation in ET among each site while regressions across each year determined overall variations among years during the study period.

inflation factors (VIFs) between explanatory variables were examined (Table 3). The only variables approaching critical thresholds of concern (i.e., tolerance < 0.2; VIF > 5; Haan, 2002) were EVI and LST_n at the CM site. By restricting the equation to the strongest two inputs, a VI and a LST variable, a parsimonious model was created to limit inflations in standard error. Excluding the KG site, EVI explained more variation in ET than NDVI at each site. Similarly, MODIS LST_n was a stronger predictor of ET than average daily temperature (T_{avg}) or MODIS LST_d at all sites.

2.4. Empirical ET models

2.4.1. Combined upland/riparian recalibration approach

While many empirical ET models have been created (see Murray et al., 2009; Nagler et al., 2005a, 2005b, 2007), the Scott et al. (2008) model was selected for this study because inputs can be acquired solely from remote sensing products. This makes it a valuable approach for researchers and managers limited by data acquisition. Additionally, results from our regression analysis (see Section 2.3) were consistent with the input variables for the Scott et al. 2008 empirical ET model. The empirical ET model introduced in Scott et al. (2008) is:

$$ET = a\left(1 - e^{-b\mathrm{EVI}}\right) + c\left(e^{dT_s}\right) + e \tag{1}$$

where a, b, c, d, and e are calibration coefficients, and T_s is LST_n. Scott et al. (2008) calibrated the empirical ET model using three years of data from three eddy covariance towers located in three different riparian ecosystems along the San Pedro River, AZ.

Using data concatenated from all five of our study sites, which included three riparian and two upland sites and spanned the time period 2003–2006, we recalibrated the Scott et al. (2008) model using the surface fitting tool in MATLAB (The Mathworks, Inc., Natick, MA). With the recalibrated coefficients, the empirical ET model took the form:

$$ET = -14.45\left(1 - e^{-0.622\mathrm{EVI}}\right) + 0.197\left(e^{0.089T_s}\right) - 1.028 \tag{2}$$

To validate this recalibrated model, Eq. (2) ($r^2 = 0.78$, RMSE = 0.57; Table 4) was used to compute ET predictions for 2007 at each of the five sites individually and collectively. Predicted ET was then compared to measured ET in 2007. Root mean square error (RMSE) was used to compare model performance for

Table 3
Tolerance and variation inflation factors (VIF), where a tolerance of less than 0.20 and/or a VIF above 5 indicates a potential multicollinearity problem.

		Tolerance (1-r^2)			VIF (1/Tolerance)		
		EVI	LST_n	PPT	EVI	LST_n	PPT
All Sites	EVI	0	0.58	0.86	x	1.72	1.16
	LST_n		0	0.88		x	1.14
	PPT			0			x
Riparian	EVI	0	0.35	0.81	x	2.86	1.23
	LST_n		0	0.83		x	1.20
	PPT			0			x
Upland	EVI	0	0.83	0.94	x	1.20	1.06
	LST_n		0	0.83		x	1.20
	PPT			0			x
CM	EVI	0	0.23	0.82	x	4.35	1.22
LM		0	0.44	0.79	x	2.27	1.27
LS		0	0.38	0.8	x	2.63	1.25
SR		0	0.83	0.77	x	1.20	1.30
KG		0	0.85	0.96	x	1.18	1.04
CM	LST_n		0	0.82		x	1.22
LM			0	0.81		x	1.23
LS			0	0.83		x	1.20
SR			0	0.92		x	1.09
KG			0	0.95		x	1.05

Table 4
Evapotranspiration model statistics reported after parameterization.[a]

Training set	Statistical test	Eq. (1) model[b]	Eq. (3) model[c]	Eq. (8) model[d]
		Eq. (2)	Eq. (5)	Eq. (9)
All	r^2	0.78	0.85	0.74
	RMSE	0.57	0.47	0.62
		Eq. (2.1)	Eq. (6)	Eq. (10)
Riparian	r^2	0.92	0.92	0.75
	RMSE	0.37	0.37	0.66
		Eq. (2.2)	Eq. (7)	Eq. (11)
Upland	r^2	0.62	0.67	0.77
	RMSE	0.40	0.37	0.31

[a] Each model was trained by all five sites combined (ALL), riparian sites only (CM, LM, LS), and upland sites only (KG, SR).
[b] Original Scott et al. (2008) model.
[c] Modified multiplicative model.
[d] Multiple linear regression model.

predicting ET at each study site individually. The location of predicted ET values with respect to the 1:1 line provided insight as to whether a particular model tended to under- or over-predict ET.

2.4.2. Modified multiplicative approach

Eq. (1) takes the form of an additive and inverse exponential function to account for lower and upper ET thresholds (see Nagler et al., 2005a; Scott et al., 2008). This equation assumes that riparian ET approaches zero when winter LST_n and EVI values reach a minimum, while summer ET reaches full potential, stabilizing when LST_n and EVI reach optimal levels. Theoretically, ET should be dependent on temperature (e.g., LST) multiplied by a scaling factor to account for the amount of light intercepted by the canopy (e.g., EVI) (Nagler et al., 2005b). A multiplicative approach may be more realistic for estimating ET at riparian sites because it accounts for an interaction between LST_n and EVI rather than having additive terms. Furthermore, this approach is analogous to traditional crop coefficient approaches that multiply potential ET of a reference crop by a crop coefficient (e.g. Farahani et al., 2007). Replacing crop coefficients with VIs has been explored on a theoretical basis because VIs give a measure of the actual state of a crop canopy, instead of a crop coefficient produced by expert opinion (Choudhury et al., 1994; Glenn et al., 2010). Therefore, we altered Eq. (1) to take a multiplicative form in an effort to further improve riparian ET predictions specifically:

$$\mathrm{ET} = a\left(1 - e^{-b\mathrm{EVI}*}\right)*\left(e^{cT_s}\right) + d \tag{3}$$

Eq. (3) simplifies Eq. (1) from five to four parameter and scales EVI between an $\mathrm{EVI_{min}}$ (averaged value from three bare soil sites = 0.059) and an $\mathrm{EVI_{max}}$ (averaged value from three fully vegetated sites = 0.704). The three bare soil sites included an area under construction and two mine tailings and the three fully vegetated sites included a golf course, a fully vegetated park, and a grass lawn, all located within the study region. As in Nagler et al. (2005b), the following equation was used to scale EVI:

$$\mathrm{EVI}* = 1 - \frac{(\mathrm{EVI_{max}} - \mathrm{EVI})}{(\mathrm{EVI_{max}} - \mathrm{EVI_{min}})} \tag{4}$$

Scaled EVI (EVI^*) allows ET to reach a minimum (i.e., the intercept) when EVI^* approaches 0.0 and allows ET to reach full potential when EVI^* approaches 1.0 (Nagler et al., 2005b). Eq. (3) was calibrated with all sites combined, riparian sites only, and upland sites only to obtain and compare three new empirical ET models, respectively:

$$\mathrm{ET} = 2.587\left(1 - e^{-1.218\mathrm{EVI}*}\right)*\left(e^{0.064\mathrm{LST}}\right) + 0.016 \tag{5}$$

$$\mathrm{ET} = 1.109\left(1 - e^{-3.464\mathrm{EVI}*}\right)*\left(e^{0.075\mathrm{LST}}\right) + 0.062 \tag{6}$$

$$\mathrm{ET} = 294.5\left(1 - e^{-0.001\mathrm{EVI}*}\right)*\left(e^{0.164\mathrm{LST}}\right) + 0.318 \tag{7}$$

To validate this modified model, Eq. (5) ($r^2 = 0.85$, RMSE = 0.47; Table 4), Eq. (6) ($r^2 = 0.92$, RMSE = 0.37; Table 4), and Eq. (7) ($r^2 = 0.67$, RMSE = 0.37; Table 4) were used to compute ET predictions for 2007 at each of the five sites individually and collectively. Predicted ET was then compared to measured ET in 2007. Root mean square error (RMSE) was used to compare model performance for predicting ET at each study site individually and collectively. The location of predicted ET values with respect to the 1:1 line provided insight as to whether the model tended to under- or over-predict ET.

2.4.3. Modified moisture-based approach

Models in the form of Eq. (1) and Eq. (3) are sensitive to temperature and greenness but do not sufficiently account for near surface soil moisture. However, if ET is strongly coupled to pulses of moisture in upland ecosystems (e.g. Kurc and Small, 2004; Scott et al., 2006; Williams et al., 2006), then empirical ET models should incorporate a variable that explains how soil moisture affects upland ET. Changes in moisture content can be related to temporal fluctuations in apparent thermal inertia (Van Doninck et al., 2010), which can be derived from the difference between day and nighttime LST (LST_d−LST_n; Zhang et al. 2003). Relating LST_d−LST_n to measured ET showed stronger relationships at upland sites when compared to riparian sites, but, unfortunately because averaged 8-day MODIS-DAAC data used in this research does not represent consecutive days, relationships were not sufficient for use as a proxy to soil moisture (Table 2). Because precipitation data was available at the study sites, a new model was created in an effort to improve upland site ET, specifically, using a multiple linear regression approach with precipitation replacing LST_n as a new model input, i.e.:

$$\mathrm{ET} = a\mathrm{EVI} + b\mathrm{PPT} + c \tag{8}$$

where PPT ($\mathrm{mm}^{-16\ \mathrm{day}}$) is precipitation summed over each 16-day window at each flux tower. Eq. (8) was calibrated with all sites combined, riparian sites only, and upland sites only to obtain three additional empirical ET models, respectively:

$$\mathrm{ET} = 12.00\mathrm{EVI} + 0.013\mathrm{PPT} - 0.956 \tag{9}$$

$$\mathrm{ET} = 12.43\mathrm{EVI} + 0.011\mathrm{PPT} - 0.900 \tag{10}$$

$$\mathrm{ET} = 6.93\mathrm{EVI} + 0.017\mathrm{PPT} - 0.507 \tag{11}$$

Notably, in this current approach PPT is local and site-specific, limiting its application in basin-scale applications. However, while remotely sensed data products with a moisture component are available (e.g. Kerr et al., 2001; Njoku et al., 2003), the processing of these data was beyond the scope of this study. Therefore, we consider our contribution as providing results that point in the direction of the future use of those products in the development of empirical ET models in semiarid regions that include upland ecosystems.

To validate this modified model, Eq. (9) ($r^2 = 0.74$, RMSE = 0.62; Table 4), Eq. (10) ($r^2 = 0.75$, RMSE = 0.66; Table 4), and Eq. (11) ($r^2 = 0.77$, RMSE = 0.31; Table 4) were used to compute ET predictions for 2007 at each of the five sites individually and collectively. Predicted ET was then compared to measured ET in 2007. Root mean square error (RMSE) was used to compare model performance for predicting ET at each study site individually. The location of predicted ET values with respect to the 1:1 line gave insight to whether a particular site tended to under- or over-predict ET.

3. Results

3.1. ET estimates using combined upland/riparian recalibration approach

Our recalibrated empirical ET model, i.e. Eq. (2), successfully predicted 2007 ET (Fig. 2; Table 5; RMSE = 0.62). However, when evaluated by site, predicted ET values were not evenly distributed along the 1:1 line (Fig. 2), suggesting a bias. The majority of predicted ET values for upland sites fell above the 1:1 line, which suggests the model tended to over-predict ET for those sites (Fig. 2).

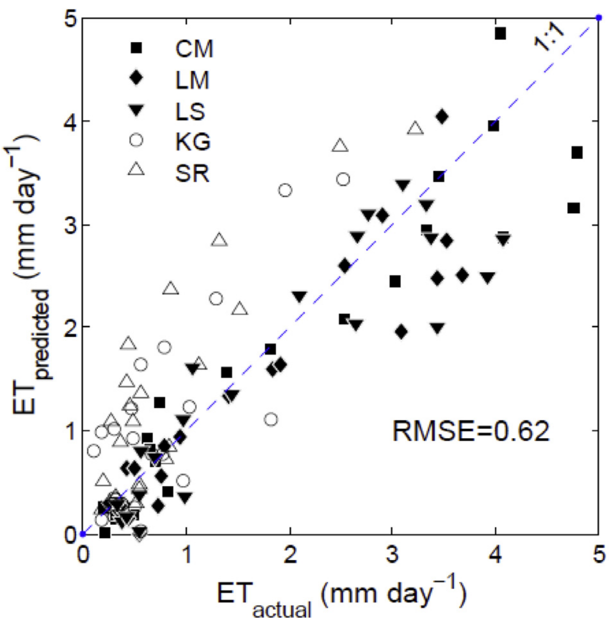

Fig. 2. Predicted 2007 ET ($ET_{predicted}$) versus measured ET (ET_{actual}) plotted for all sites along the 1:1 line by calibrating Eq. (1) using all sites combined to yield Eq. (2). Locations include three riparian influenced sites (filled symbols): Charleston Mesquite Woodland (CM), Lewis Springs Mesquite (LM), and Lewis Springs Sacaton (LS); and two upland, water-limited sites (hollow symbols): Kendall Grassland (KG) and Santa Rita Mesquite Savannah (SR).

For riparian sites, the majority of predicted ET values below the 1:1 line, which suggests the model tended under-predict ET for those sites (Fig. 2). Plotting residuals shows an even distribution when all sites are combined; however, when examining residuals by vegetation association, it is evident that riparian sites have a positive skew while upland sites have a negative skew. If this model were to be used in practice, ET would be systematically under- or over-estimated depending on the dominant vegetation association and plant water status in the scene.

When examined qualitatively with precipitation, eddy covariance ET showed a much different trend at riparian sites than upland sites (Fig. 3). Whereas riparian site ET often more than doubled values observed at upland sites and tended to follow a typical growing season trend, upland site ET responded strongly to moisture inputs, having peaks that just lagged the precipitation events (Fig. 3). While coefficients of determination (r^2) showed that EVI and LST_n were the strongest predictors of ET for all three riparian sites, EVI and precipitation explained most of the variation in ET at the two upland sites (Table 2). Therefore, these findings suggest that Eq. (2) is better suited for predicting riparian ET than upland ET or combined upland/riparian ET.

Table 5
Root mean square error (RMSE) reported for each model.[a]

Training set	Site	Eq. (1) model[b]	Eq. (3) model[c]	Eq. (8) model[d]
		Eq. (2)	Eq. (5)	Eq. (9)
All	CM	0.59	0.47	0.65
	LM	0.48	0.46	0.52
	LS	0.58	0.53	0.70
	KG	0.66	0.71	0.49
	SR	0.78	0.89	0.48
	combined	0.62	0.63	0.58
		Eq. (2.1)	Eq. (6)	Eq. (10)
Riparian	CM	0.49	0.38	0.62
	LM	0.35	0.35	0.49
	LS	0.48	0.46	0.68
	combined	0.44	0.40	0.60
		Eq. (2.2)	Eq. (7)	Eq. (11)
Upland	KG	0.38	0.40	0.22
	SR	0.33	0.52	0.24
	combined	0.36	0.46	0.23

[a] RMSE was used to determine overall closeness of fit where lower values represent empirical ET models that provide the closest 2007 ET predictions compared to measured ET.
[b] Original Scott et al., (2008) model.
[c] Modified multiplicative model.
[d] Multiple linear regression model.

3.2. ET estimates using modified multiplicative approach

Although Eq. (5) produced favorable 2007 ET predictions (Table 5; RMSE 0.63) and was an improvement from Eq. (2) (Table 5; RMSE 0.62), the model still produced bias and skewed residuals (Fig. 4). As expected, Eq. (6) produced the best 2007 riparian ET predictions (Table 5; RMSE = 0.40) and values among each riparian site were evenly distributed along the 1:1 line (Fig. 5a), suggesting that the model is unbiased. Furthermore, plotted residuals were randomly dispersed, validating this approach for estimating riparian ET. Not surprisingly, Eq. (7) calibrated with upland sites only, did not predict 2007 upland ET as well (Fig. 5b; Table 5; RMSE = 0.46), suggesting that this empirical model may not be the most appropriate for estimating ET at water-limited sites.

3.3. ET estimates using a modified moisture-based approach

Because changes in ET in arid and semiarid ecosystems are often coupled with growing season moisture inputs that wet upper soil layers (Kurc and Small, 2004; Scott et al., 2006; Williams et al., 2006), we wanted to examine an approach that included a moisture input, i.e. Eq. (8). Eq. (9) predicted overall 2007 ET well (Table 5; RMSE = 0.58; Fig. 6), but at similar performance to Eq. (2) (Table 5; RMSE = 0.62) and Eq. (5) (Table 5; RMSE = 0.63). However, this model also shows a reversed bias in which upland sites tend to over-predict and riparian sites tend to under-predict 2007 ET. Furthermore, unevenly dispersed residuals among each site suggest that combining all sites together does not create a robust multiple regression model. Eq. (10) did not improve 2007 riparian ET predictions (Table 5; RMSE = 0.60; Fig. 7a) compared to Eq. (6) (Table 5; RMSE = 0.40), suggesting that including moisture into an empirical ET model does not improve riparian ET predictions at these sites. As expected, Eq. (11) greatly improved 2007 upland site ET predictions (Table 5; RMSE = 0.23, Fig. 7b) compared to Eq. (7) (Table 5; RMSE = 0.46). Eq. (11) also produced evenly distributed values along the 1:1 line and residuals were not skewed. Furthermore, this approach reduced RMSE at both upland sites suggesting that using a multiple linear regression approach for an empirical ET model that incorporates a moisture input provides the best estimates of ET at water-limited sites.

4. Discussion

4.1. Influence of riparian vegetation on empirical ET models

Our modified multiplicative model represented by Eq. (6) is a good predictor of riparian ET specifically because meteorological (e.g., temperature) and vegetation conditions (e.g., leaf area) control ET when soil moisture is not limiting. Our riparian sites are composed of phreatophytic vegetation with extensive root systems that access groundwater reserves. Phreatophytic vegetation in this region is known to derive 80–100% of its transpiration water from groundwater and is minimally impacted by monsoon rain events (Horton et al., 2001; Snyder and Williams, 2000; Yepez et al., 2003). Because vegetation is not limited by soil moisture at these sites, the

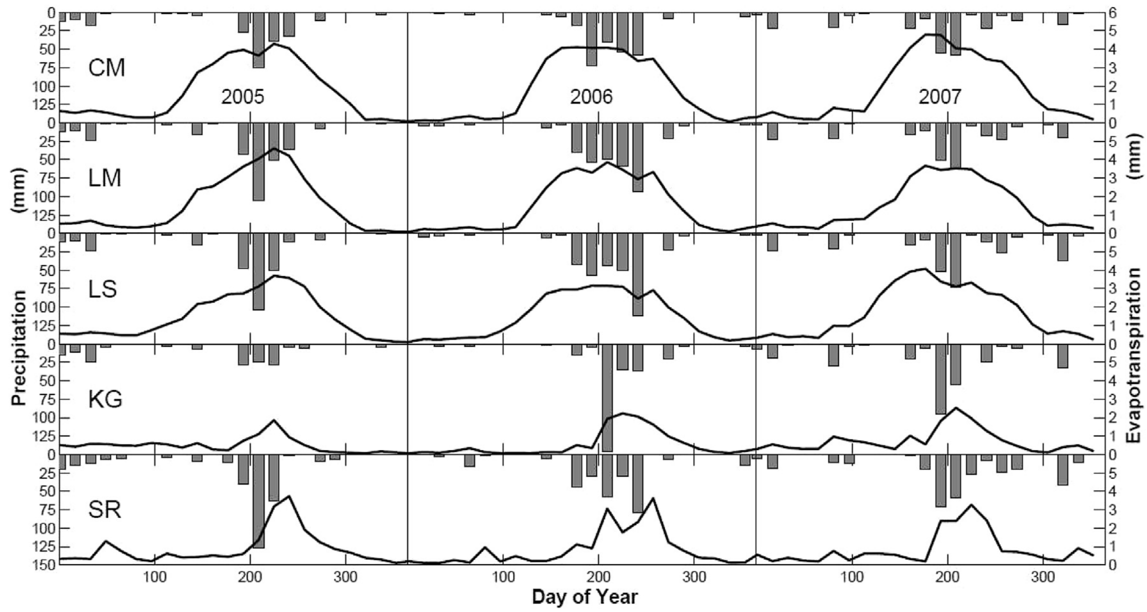

Fig. 3. Precipitation and evapotranspiration (ET) plotted over time for all study sites [Charleston Mesquite Woodland (CM), Lewis Springs Mesquite (LM), and Lewis Springs Sacaton (LS), Kendall Grassland (KG), and Santa Rita Mesquite Savannah (SR)] during a 3-yr period. Precipitation was summed over 16-day windows measured using tipping-bucket rain gauges at each flux tower site and ET was calculated using the eddy covariance technique and averaged over each 16-day window.

amount of available energy, for which LST_n can be a proxy (Scott et al., 2008), becomes the limiting factor driving ET during the growing season (Gazal et al., 2006; Moore and Heilman, 2011; Williams et al., 2006;).

4.2. Influence of upland vegetation on empirical ET models

In contrast to riparian vegetation, upland vegetation often depends on pulses of water for productivity (Huxman et al., 2004; Noy-Meir, 1973; Potts et al., 2006; Sala and Lauenroth, 1982; Scott et al., 2000). ET in arid and semiarid regions dominated by upland vegetation is not limited by available energy, but by near-surface soil moisture supplied by seasonal rainfall (Kurc and Small, 2004; Moore and Heilman, 2011; Serrat-Capdevila et al., 2011). In fact, ET in upland ecosystems has been shown to rapidly increase following rainfall events (Kurc and Small, 2004; Sala and Lauenroth, 1982; Scott et al., 2006), which in part explains how >90% of precipitation in semiarid regions can be returned to the atmosphere via ET (Wilcox et al., 2003). This is not accounted for, however, in our modified empirical models represented by Eq. (1) and (3) because ET is driven by increased temperature and greenness, independent of moisture. Consequently, these empirical ET models based solely on temperature and greenness will lead to overpredictions in overall ET in watersheds or basins where upland vegetation encompasses the majority of pixels in the scene.

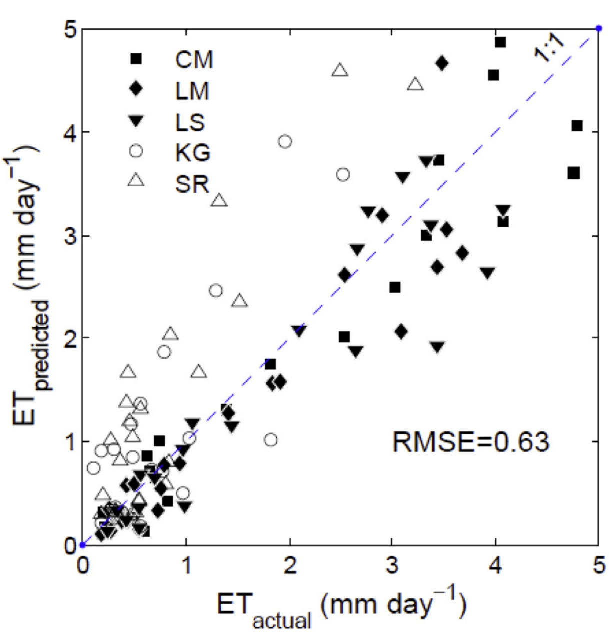

Fig. 4. Predicted 2007 ET ($ET_{predicted}$) versus measured ET (ET_{actual}) plotted for all sites along the 1:1 line by calibrating Eq. (3) using all sites combined to yield Eq. (5). Locations include three riparian influenced sites (filled symbols): Charleston Mesquite Woodland (CM), Lewis Springs Mesquite (LM), and Lewis Springs Sacaton (LS); and two upland, water-limited sites (hollow symbols): Kendall Grassland (KG) and Santa Rita Mesquite Savannah (SR).

4.3. Incorporating moisture into empirical ET models of upland ecosystems

As a first iteration for examining the influence of moisture on the performance of empirical ET models, we developed a modified empirical ET model that incorporates site-specific precipitation as an input (see Section 2.4.3). While EVI, as an indicator of greenness, captures the variation and contribution of transpiration to total ET, we make the assumption that precipitation accounts for rapid evaporation following rainfall events. We eliminated the energy input because LST_n did not improve the predictive power of the model. This multiple regression approach represented by Eq. (11) predicted upland ET adequately ($r^2 = 0.77$) with similar performance to other studies (Nagler et al., 2007 ($r^2 = 0.74$)).

This approach can estimate water lost from upland vegetation along river reaches where weather stations or rain gauges are available. When precipitation data is not available, however, the ability to accurately estimate ET is not likely unless rainfall can be interpolated from nearby rainfall gauges or forecasted using a suitable method or model for predicting rainfall at the site of interest. Remotely sensed data products with a moisture component

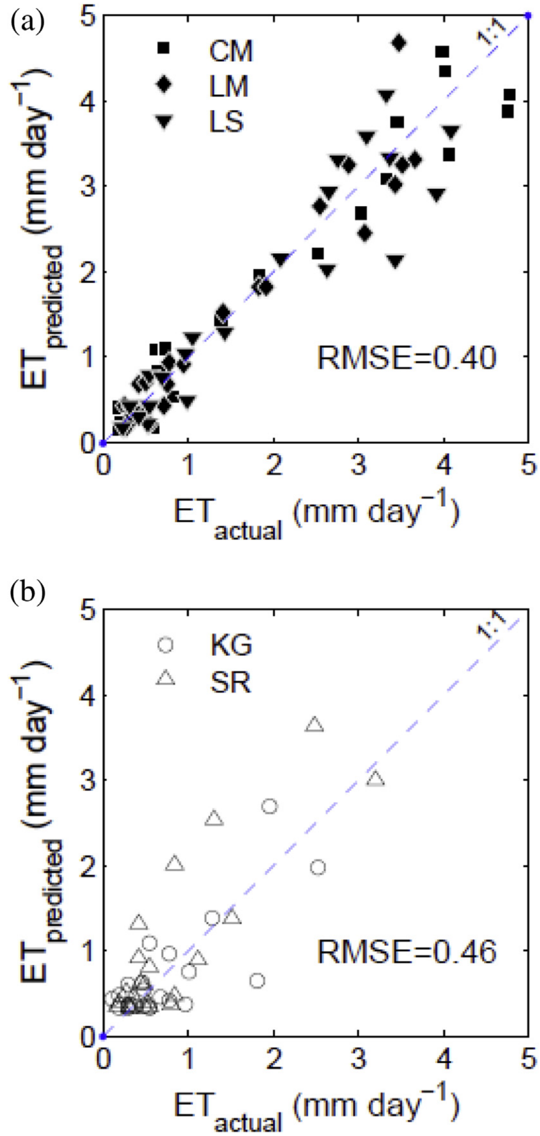

Fig. 5. Predicted 2007 ET ($ET_{predicted}$) versus measured ET (ET_{actual}) plotted along the 1:1 line by calibrating Eq. (3) using: 5a) (above) riparian sites only to yield Eq. (6), and 5b) (below) upland sites only to yield Eq. (7). Locations include three riparian influenced sites (filled symbols above): Charleston Mesquite Woodland (CM), Lewis Springs Mesquite (LM), and Lewis Springs Sacaton (LS); and two upland, water-limited sites (hollow symbols below): Kendall Grassland (KG) and Santa Rita Mesquite Savannah (SR).

are available (e.g. Kerr et al., 2001; Njoku et al., 2003), however, the processing of these data is intensive, and was beyond the scope of this study. Therefore, we consider our contribution as providing results that point in the direction of the future use of those products in the development of empirical ET models in semiarid regions that include upland ecosystems. Incorporating these moisture products are expected to improve models of ET by understanding how pulses of moisture at small scales affect ET across different regions.

4.4. Using an integration of upland and riparian empirical ET models to estimate watershed or basin ET

While a single predictive equation is desired to estimate ET at basin scales, our study suggests that differences in plant function (e.g., the ability or inability to access and use groundwater) and

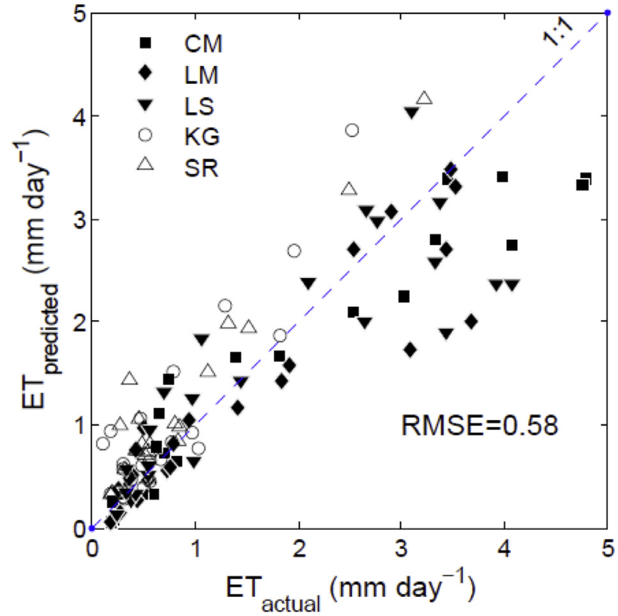

Fig. 6. Predicted 2007 ET ($ET_{predicted}$) versus measured ET (ET_{actual}) plotted for all sites along the 1:1 line by calibrating Eq. (8) using all sites combined to yield Eq. (9). Locations include three riparian influenced sites (filled symbols): Charleston Mesquite Woodland (CM), Lewis Springs Mesquite (LM), and Lewis Springs Sacaton (LS); and two upland, water-limited sites (hollow symbols): Kendall Grassland (KG) and Santa Rita Mesquite Savannah (SR).

ecohydrology introduce complications that curtail that possibility. However, we suggest that an approach using multiple empirical ET models could be integrated with a spatially explicit model in a gridded framework based on vegetation maps to estimate watershed or basin ET. Independent ET models appropriate for each vegetation association could then be applied to each land surface classification. Unland et al. (1998), for example, estimated ET from a riparian system in a semiarid environment by classifying five different surfaces and attributing multiple approaches to best estimate ET for each surface. A similar approach using multiple empirical ET models to represent the different riparian and upland vegetation classified along a river reach could be used to improve overall ET estimates along an entire reach or catchment of interest.

This approach would require adequate flux tower data, both spatially and temporally, to calibrate models for each vegetation association and assumes that classifying vegetation along a mosaic corridor into riparian-influenced versus upland, water-limited vegetation is feasible and sufficient for documenting all vegetation within the river reach. By combining functional groups, this method follows the assumption observed in many studies that riparian vegetation such as cottonwood, willow, tamarisk, and mesquite have similar transpiration rates on a leaf area basis and therefore could be combined into one riparian class (Anderson, 1982; Busch and Smith, 1995; Glenn et al., 1998; Nagler et al., 2008; Sala et al., 1996).

4.5. Considerations in the applications of empirical ET models

A degree of uncertainty is inherent when modeling watershed and basin scale ET due to errors propagating through subsequent steps (Devitt et al., 1998). Due to the empirical nature of the approach represented here, we caution that this method requires model re-calibration using accurate ground measurements of ET representing the vegetation captured in the satellite products. This study used free MODIS products to avoid pre-processing raw

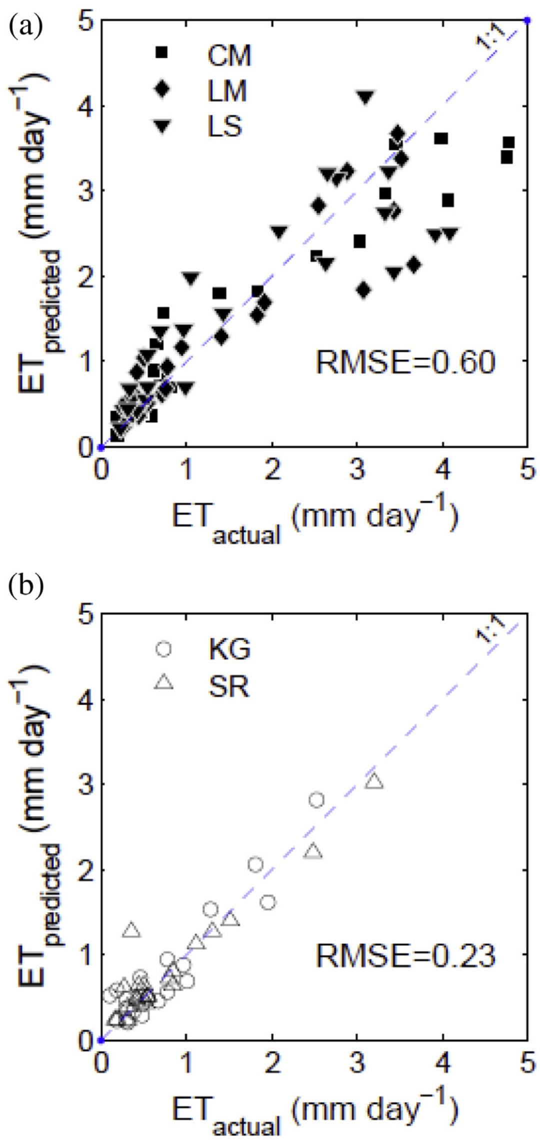

Fig. 7. Predicted 2007 ET ($ET_{predicted}$) versus measured ET (ET_{actual}) plotted along the 1:1 line by calibrating Eq. (8) using: 7a) (above) riparian sites only to yield Eq. (10), and 7b) (below) upland sites only to yield Eq. (11). Locations include three riparian influenced sites (filled symbols above): Charleston Mesquite Woodland (CM), Lewis Springs Mesquite (LM), and Lewis Springs Sacaton (LS); and two upland, water-limited sites (hollow symbols below): Kendall Grassland (KG) and Santa Rita Mesquite Savannah (SR).

satellite data. While MODIS data is available almost daily, the available ORNL-DAAC composites used in this research reduce the temporal resolution to 8 or 16-day products. ET models can be improved by using remotely sensed products with better temporal resolution. Likewise, remote sensing products with finer spatial resolution (e.g., Landsat, 15–30 m) would improve empirical methods of modeling ET, but may sacrifice the temporal resolution necessary to account for seasonal fluctuations in ET. With the advent of longer-term in situ ET measurements and high-frequency repeat-overpass remote-sensing data, there is great potential for improving empirical methods for estimating ET in the future.

5. Conclusions

Our modified empirical models that combine riparian and upland vegetation provide reasonable estimates of overall ET ($r^2 = 0.78, 0.85, 0.74$) and perform similar to other empirical models in which VIs were used in combination with temperature inputs to estimate ET in riparian zones (Nagler et al., 2005a ($r^2 = 0.82$); Nagler et al., 2005b ($r^2 = 0.76$); Nagler et al., 2009 ($r^2 = 0.80$); and Murray et al., 2009 ($r^2 = 0.80$)). Statistics were tabulated for all empirical ET models after parameterization (Table 4). The highest r^2 was 0.92 which shows that models in the form of Eq. (1) and Eq. (3) calibrated by riparian sites only are the best for estimating riparian ET. Upland site ET, on the other hand, is best estimated by using multiple linear regression with a moisture input such as precipitation calibrated with upland sites only ($r^2 = 0.77$). RMSE for all validations (i.e., 2007 ET model predictions vs. 2007 measured ET) were broken down among sites (CM, LM, LS, KG, SR) and vegetation associations (riparian, upland) to observe site-specific trends (Table 5). Smaller RMSE values show the best riparian site (CM, LM, LS) ET predictions were made using a model in the form of Eq. (3) while upland site (KG, SR) ET predictions were consistently better using a model in the form of Eq. (8). Therefore, our study suggests that a single predictive equation for estimating ET at basin scales is not reasonable in semiarid regions because of differences in plant function (e.g., the ability or inability to access and use groundwater) for different ecosystems. However, we suggest that an approach using multiple empirical ET models could be integrated with a spatially explicit model in a gridded framework based on vegetation maps to estimate watershed or basin ET.

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