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Research papers

Relationships among forest type, watershed characteristics, and watershed ET in rural basins of the Southeastern US

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ABSTRACT

Evapotranspiration (ET) typically accounts for 60–70% of precipitation in rural basins of the Southeastern United States. Since 1930, substantial reforestation of former croplands has occurred in the Piedmont and Appalachian Highlands in this area, leading to an expected increase in ET and reduction in baseflow. This study examines relationships between basin vegetative cover, abiotic factors, and water-budget partitioning in 45 USGS-gaged rural basins in the Southeastern US. Data are for the 1982–2014 water years with watersheds having ≥40% forest cover, crystalline-rock aquifers, minimal basin water export, and no large reservoirs. Long-term annual ET is calculated using the water-budget equation (ET = P-Q), which ranges from 641 to 971 mm/yr. (median 824). Vegetative cover and other basin variables are regressed against ET to quantify the effects of vegetative and forest types. Budyko analysis is employed to compare the watersheds and to evaluate factors affecting residuals. Regression analysis indicates that ET behavior is best explained by abiotic factors (i.e., precipitation and temperature) but forest-cover type also has some effect. Evergreen forest cover is less common than deciduous or mixed forest but has a positive relationship with ET, while deciduous and total forest have negative relationships with ET. Comparison of water-balance and Budyko-estimated ET indicates that deciduous and total forest are associated with negative residuals while evergreen is not significant. These results show that: forest cover effects on basin ET are complicated; forest-cover type is important for water-yield management in this region, and abiotic basin characteristics exert stronger control than forest cover on ET.

1. Introduction

Whether and how to mitigate the hydrologic effects of climate change are pressing questions for hydrologists requiring better understanding of how rural vegetation management affects water budgets and streamflows. Because of higher leaf area indices, higher interception, and somewhat deeper rooting, forest cover increases ET and reduces average streamflows relative to croplands, pastures, and lawns in the same hydroclimatic region according to water budget studies (Teuling, 2018).

Syntheses of paired watershed experiments shows forests are the most water-use intensive land-cover type and that afforestation of grassland reduces water yield by 44–75% (Andréassian, 2004; Farley et al., 2005; Filoso et al., 2017; Hibbert, 1967; Teuling, 2018). Paradoxically, global synthesis of eddy-flux estimates of ET suggest an opposite relationship between forest and grassland ET; that grassland ET as a fraction of precipitation is 9% higher that of forests (Williams et al., 2012). However, lysimeter measurements match the results of water-budget studies and indicate that eddy flux underestimates latent-heat flux from forest canopies (Teuling, 2018).

Paired-watershed studies typically focus on first- or second-order basins with species diversity limited by management, thus ignoring confounding factors associated with larger scale, mixed-land use watersheds that cannot independently account for ET variability driven by abiotic factors such as watershed elevation and latitude.

Regardless, water-budget measurements are subject to substantial uncertainty, and accurate and precise measurement of ET is difficult and expensive. A better understanding of the role of forests and forest type on the variability of water budgets across a region is needed to develop policies for maintaining hydrologic ecosystem services in the face of climate change and expanding human populations.

In humid environments, annual evapotranspiration (ET) typically accounts for half or more of precipitation (P) inputs, and the amount of ET partly depends on the composition and condition of vegetation types in a watershed. Watershed responses to afforestation or deforestation are not linear and are dependent upon watershed specific factors including soil depth and water holding capacity, climate factors such as temperature, precipitation, and vapor-pressure deficit and

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physiological factors such as plant rooting depth and hydraulic traits (Andréassian, 2004).

Water-budget responsiveness to vegetation change varies with annual precipitation and temperature and these abiotic factors are often more important than biotic ones (Sahin and Hall, 1996; Stednick, 1996; Sanford and Selnick, 2013; Teuling et al., 2019). Globally, vegetative management influences watershed water budgets (Oudin et al., 2008), but the relative effects of forest types and the scale of vegetative effects to abiotic effects are less clear.

Forests are the dominant land cover in rural basins of the Piedmont and Appalachian highlands of the Southeastern United States (Sanford and Selnick, 2013; Wear and Greis, 2013). These forests are comprised of two broad functional groups, deciduous and evergreen, of which deciduous forest area is more than twice that of evergreen (Wear and Greis, 2013). Southeastern evergreen forests are dominated by several pine species, most notably loblolly pine (*Pinus taeda L.*) that are highly productive and commonly grown for wood products (Washlenberg, 1960; Wear and Greis, 2013). Some high-elevation watersheds in the Appalachian Highlands also contain eastern white pine (*P strobus*) and spruce-fir communities (Wear and Greis, 2013). Southeast deciduous species are far more numerous than evergreen species and exhibit a broader range of traits (Wear and Greis, 2013). Some deciduos species, such as chestnut oak (*Quercus montana*) and northern red oak (*Quercus rubra),* have lower ET than evergreens (*Pinus strobus*) (Ford et al., 2010), whearas american sweet gum (*Liquidambar styraciflua)* have higher ET than evergreen loblolly pines (Caldwell et al., 2018).

Understanding the relative effects of forest types on water use is important for forest and stream flow management. Evergreen forests transpire more water than deciduous forests (Swank and Miner, 1968; Swank and Douglass, 1974, Bosch and Hewlett, 1982), which is explained by biological and physiological factors that contribute to different water use behavior (Ford et al., 2010). Evergreens maintain canopy cover, interception (I), and transpiration (T) throughout the year while deciduous forests lose their leaves in winter or in dry seasons.

Evergreen and deciduous species also conduct water differently, evergreens typically have higher stomatal conductance although hardwoods exhibit a wide range of conductance (Ford et al, 2010; Carlquist, 2001; Sperry et al., 2006). In the Southeast, deciduous species are more dominant in riparian areas that have more available water than upland areas (Bosch and Hewlett, 1982; Ford et al., 2010). Evergreen forests have a lower albedo and reflect less incoming solar radiation than deciduous forests, and this increases evergreen ET potential (Rosenberg, 1986). However, Bosch and Hewlett (1982) found that watersheds with evergreen forests occurred in more humid environments than deciduous forested watersheds, thus confounding the relationships between ET, climate, and land cover.

In the Southeastern U.S., streamflow (Q) has been declining (Gotvald, 2016). Stephens and Bledsoe (2020) found that over the last 25–50 years the majority of Southeast watersheds had decreases in average annual 7-day low flows of 4–16 mm and understanding the drivers of these decreases is important. Observed trends of decreasing total streamflow could be due to recurring droughts (Stephens and Bledsoe, 2020), changes in precipitation distribution, reforestation, increasing consumptive use, changes in forest composition, increasing temperatures and longer growing seasons due to climate change (Pourmokhtarian et al., 2017; Vadeboncoeur et al., 2018) or a combination of these factors (Gotvald, 2016). The region has seen an increase in forest cover since approximately 1940 when a trend of agricultural land abandonment began (Auch et al., 2015; Jackson et al., 2005a; Jacksonet al., 2005b; Ramankutty et al., 2010; Trimble et al., 1987). The Southeast is predicted to see a continued conversion of deciduous forests to evergreen due to increased demand for softwood timber production (Wear and Greis, 2013).

Trimble et al. (1987) attempted to determine if water yield decreased due to afforestation of cropland from 1919 to 1967 across ten USGS-gaged watersheds in the piedmont of Alabama, Georgia, and South Carolina. This small set of watersheds included some with large reservoirs and some with substantial urbanization, and the analysis suffered from low-resolution land-cover estimates, data gaps, and confounding simultaneous increases in urbanization and afforestation (Auch et al., 2015; Trimble et al., 1987). Nonetheless, Trimble et al. (1987) determined that increases in forested areas were associated with decreases in water yield and that watershed land cover modifications of < 20% could be detected. This is inconsistent with findings by Bosch and Hewlett (1982), who suggested that changes would need to be larger to be detectable.

In the Southeast, Lu et al. (2003) calculated water balance ET for 36 watersheds and attempted to determine if forest cover type was important for predicting ET. They found slight but non-significant model improvements by considering forest type (Lu et al., 2003). However, many of the watersheds were in the coastal plain and underlain with high conductivity aquifers with the potential for leakiness (Fan, 2019) which can allow water to exit the basins through regional groundwater flow paths and bias water balance estimates. In a nationwide analysis of water balance ET, abiotic factors including temperature and precipitation had the most influence on ET, but including total forest cover provided slight significant improvements to model evaluations (Sanford and Selnick, 2013), these authors did not report forest type effects.

Our objective in this study is to examine how average annual watershed ET is influenced by land cover distribution, including forest type, and other geographic variables including latitude, elevation, drainage area, population, mean annual air temperature, average vapor pressure deficit, the dryness index, and available soil water storage. Specifically, we sought to answer three questions: 1) Does average annual water balance ET increase as the fraction of forest cover in the basin increases; 2.) Does the type of forest (evergreen versus deciduous) affect the answer to the first question; and 3) To what degree do pertinent geographic variables influence the variation of ET across these basins. Our approach was to use a large set (45) of undammed, rural, Southeastern watersheds underlain by crystalline rock with long-term USGS streamflow records, available climatic data, and small amounts of urbanization and irrigation. Confining the watersheds to crystalline rock aquifers reduces the effects of storage changes and the potential for significant cross-basin groundwater movement (Fan, 2019; McGuinness, 1963).

2. Methods

2.1. Watershed selection

We selected all Southeastern watersheds meeting the following criteria: 1) located over Piedmont and Blue Ridge crystalline rock aquifers; 2) precipitation (P) and USGS discharge (Q) data available from Water Years 1982–2014; 3) mean forest cover greater than or equal to forty percent; 4) reservoir surface area less than one percent of total watershed area (calculated from the National Inventory of Dams database (Goteti, 2014)); 5) located outside of metropolitan areas; and 6) no substantial changes in land cover through time (see Mahalanobis distance details in Section 2.2). The final dataset consisted of 45 watersheds (Fig. 1, Table S1).

We limited our study to crystalline rock aquifers which have low conductivity and well productivity (McGuinness, 1963) and thus reduce the potential for water-balance errors associated with groundwater pumping, leakage to regional flow paths, or long storage-discharge lags. We limited the basins to those with ≥40% in order to have enough forest cover to separate the effects of evergreen, deciduous, and total forest.

The defined study area (Fig. 1) includes most of the water supply watersheds for the rapidly growing cities of the developing Interstate 85 megapolitan corridor from Atlanta, GA, to Raleigh, NC (Terando et al., 2014). Population growth and development in these cities is expected to adversely affect aquatic health and reduce assimilative capacity for

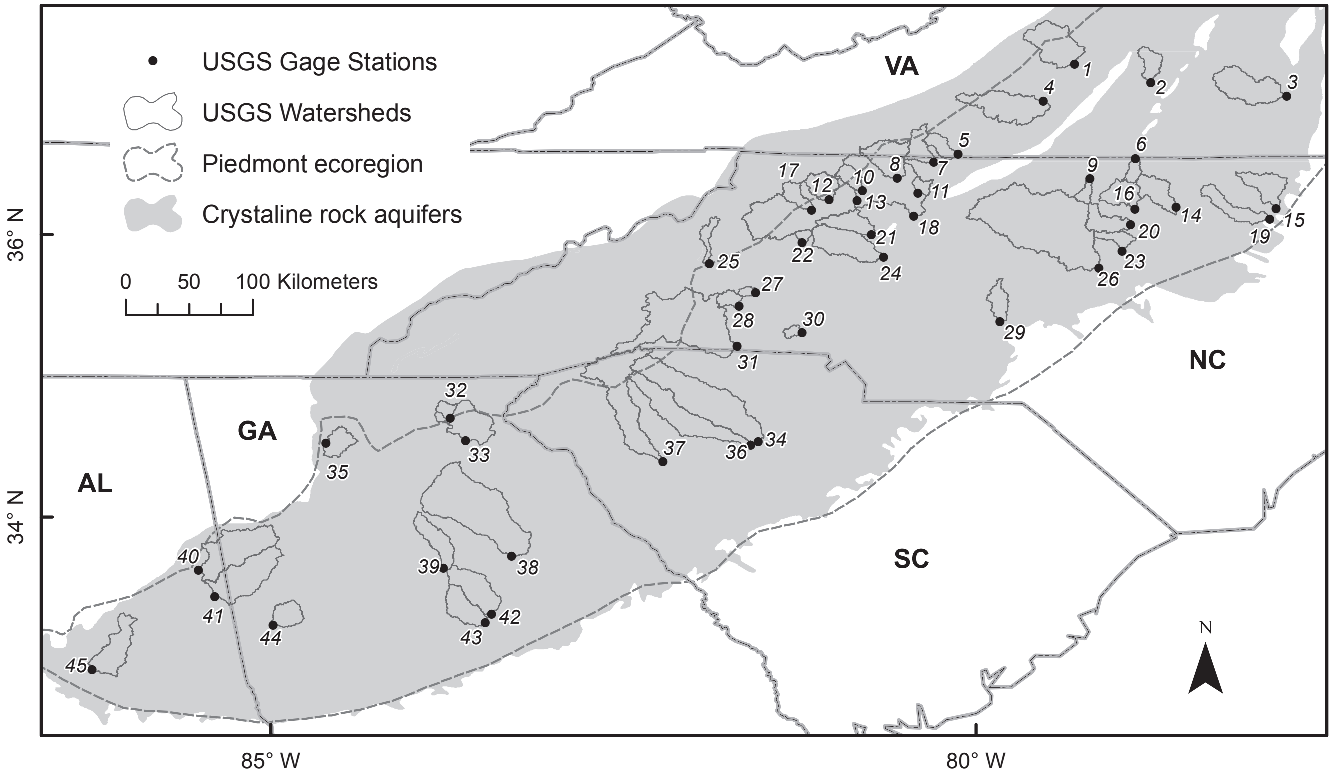

Fig. 1. Study area in the Southeastern US that includes 45 USGS-gaged watersheds with daily precipitation and streamflow data from 1982 to 2014, total forest cover ≥40%, and crystalline-rock aquifers.

pollutants (Van Metre et al., 2019).

Watershed population densities (population/km^2) range from 35 to 987, averaging 176 with a standard deviation of 160 (Table 2). Basin drainage areas range from 66 to 4,389 km^2, averaging 772 km^2, with a standard deviation of 910 km^2. Watershed mean elevations above mean sea level (amsl) range from 100 to 1,009 m, averaging 315 m, with a standard deviation of 182 m. Watershed outlet latitudes range from 32.9168 to 37.2085°N, averaging 35.4526°N, with a standard deviation of 1.1925°.

2.2. Data acquisition

Publicly available land cover, hydrologic, and meteorological datasets were used in this study as listed below. Temporal data were aggregated from daily or monthly timesteps to annual totals that were averaged for Water Years 1982–2014 (October 1, 1981 through September 30, 2014). Spatial data were aggregated to the watershed scale (McManamay et al., 2012). GIS overlays were performed in ArcGIS, database development and statistical analyses were performed in R 3.6.1 (Grolemund and Wickham, 2011; Hirsch and De Cicco, 2015; R Core Team, 2019; Wickham and Francois, 2015).

Mean daily discharges (Q, ft^3/s) from the US Geological Survey were converted to runoff depth (mm/day). Area-weighted averages of total monthly precipitation (P, mm) and mean monthly temperature (T, °C) were from the PRISM dataset (4 km resolution) (PRISM, 2012, Blodgett et al., 2011). Daily maximum and minimum temperature and relative humidity were from the University of Idaho gridMET dataset (Abatzoglou, 2013, Blodgett et al., 2011). Watershed boundaries were from the US Geological Survey (USGS, 2011). Land cover was from 30-m National Land Cover Datasets (NLCD) for 2001, 2006, and 2011 (Homer et al., 2015).

The 1992 NLCD dataset was not used because of inconsistencies with subsequent classifications. Land cover types include Water, Developed, Barren, Deciduous Forest, Evergreen Forest, Mixed Forest, Shrubland, Herbaceous, Grassland, Pasture, Crops, and Wetlands. Pasture and grass were grouped together as grass, all other cover types were combined to 'Other cover'. Total forest was calculated as the sum of Deciduous, Evergreen and Mixed forest. Mahalanobis distances were calculated for each watershed between the three landcover datasets (2001, 2006, and 2011) for evergreen, deciduous, mixed forest and grass cover proportions (Mahalanobis, 2015). Watersheds with non-normal Mahalanobis distances were excluded interactively using qq plots using the R stats package (R Core Team, 2019).

Land cover from the three datasets was averaged by watershed and class then logit transformed prior to regression analysis. Average basin elevation was calculated using 30-m data from the National Elevation Dataset (NED) (NED, 1999). Populations densities (population/km^2) were estimated using 2010 block-level census data and watershed areas (Walker, 2018). Potential evapotranspiration (PET, mm) was determined using the Priestley-Taylor formulation and gridMET meteorological variables (Guo et al., 2016; Priestley and Taylor, 1972).

Vapor pressure deficits (VPD, millibars) were calculated using daily maximum and minimum relative humidity and temperature from the gridMET dataset (Abatzoglou, 2013; Alien, 1998). Available soil water storage (AWS) from 0 to 150 cm was extracted from the SSURGO database and an area-weighted average was calculated for each watershed (SSURGO, 2016).

2.3. Screening of land cover and basin Regression variables

VPD was excluded from multivariate models because of strong covariance with elevation and temperature (correlation coefficient = -0.85). Population density and drainage area were not significant factors based on bivariate linear regressions and were excluded from further analysis.

2.4. Water balance

Direct measurement of ET is difficult and expensive, making indirect techniques necessary. The long-term watershed water-balance is a common indirect method for estimating ET and is calculated for gaged watersheds with long records of available P and Q. Eq. (1):

$$ET = P - Q - \left(\frac{dS}{dt}\right) \tag{1}$$

where: changes in storage over a long record $\left(\frac{dS}{dt}\right)$ are assumed to be negligible.

Long periods reduce the effects of interannual changes in watershed storage (Bosch and Hewlett, 1982; Rice and Emanuel, 2019) and memory effects (Nippgen et al., 2016). The water balance does not allow for separation of canopy interception (I) or soil evaporation (Es) from total ET. Any biases in the precipitation or runoff measurements bias ET estimates.

2.5. Temporal changes in water budgets

Because we analyzed water budgets using long-term averages of Q and P, we wanted to screen each watershed for temporal shifts in hydrology. Temporal changes were evaluated by comparing Q to P using double-mass analysis (Searcy et al., 1960). Cumulative Q was graphed against cumulative P for each watershed. Temporal changes were evaluated by visually inspecting each timeseries for an inflection point when Q increased or decreased relative to P. No significant changes through time are indicated if the double-mass curve is near-linear. Minor changes are to be expected due to annual variations in climate and other conditions (Searcy et al., 1960).

2.6. Budyko analysis

We employed the Budyko framework to compare the influence of climate on ET. Budyko (1974) hypothesized a functional relationship between P, ET, and PET based on the assumption that ET is limited whenever water or energy are insufficient to support PET. The Budyko framework extends the water-balance method by using both mass- and energy-balance equations to constrain the physical system (Sposito, 2017). The Budyko method assumes that long-term changes in water and energy fluxes across the land surface can be neglected; P entering a watershed exits as Q or ET, and incoming shortwave radiation is balanced by outgoing longwave radiation plus latent-heat losses due to evapotranspiration. The Budyko method relies on a nonlinear empirical relationship between the dryness index (PET/P) and the evaporative index (AET/P), which has the effect of normalizing by P.

Many alternate non-linear formulations have been developed, some with parameters to improve the fit for watersheds with varying land cover or other properties (Zhang et al., 2001; Wang and Tang, 2014). We first compare different Budyko-type formulations for our watershed in the complementary space (Budyko, 1974; Zhanget al., 2001) then calculate residuals between the estimates from Zhang et al., 2001 (with w = 2.0 for forest and w = 0.5 for non-forest) and water balance evaporative indices (AET/P) to evaluate forest-cover type. We acknowledge that this linear scaling of w is an approximation which introduces some error. However, we checked the relationships between empirical and water balance ET with fixed w values (0.5, 1, and 2) and using the parameter free Budyko (1974) all of which show the same significance.

Following Oudin et al. (2008), land-cover accounting models were parameterized to evaluate the influence of land cover on ET. Land-cover accounting models had no more than five parameters with each tied to the proportion of a land-cover class in each watershed (Oudin et al., 2008). The included parameters were Ti = Total forest, Ei = evergreen forest, Di = deciduous forest, Mi = mixed forest, Gi = grass, and Oi = all other covers not explicitly represented. As a sensitivity analysis, one model contained a free parameter (*sigma*) not tied to a land-cover variable. Land-cover is not important if *sigma* performed as well as the land-cover parameters, (Oudin et al., 2008). Preliminary comparisons of common Budyko type models with our watersheds indicated that the Zhang et al. (2001) method provided the best ET prediction (Zhang et al., 2001; Oudin et al., 2008). Thus, we used the landcover accounting Zhang et al. (2001) model from Oudin et al. (2008) to estimate the effects of land cover on watershed ET.

2.7. Regression analysis – land cover and basin characteristics

Regression models were constructed to evaluate the effects of land-cover and non-land-cover variables on watershed ET. Bivariate regressions were fit between ET and every variable of interest. Variables that were strongly correlated (correlation coefficient > 0.7) were excluded from further analysis by selecting the variable from correlated pairs with the highest predictive power (R^2). Variables with non-significant relationships were also excluded from further analysis.

Multivariate models were constructed from the remaining variables and their interactions, the multivariate models were evaluated using AIC from the R package stats (R Core Team, 2019). Regression models were evaluated to ensure that the assumptions were met, including independence between variables, linear relationships between independent and dependent variables, as well as independent and normally distributed residuals (Michael and Patrick, 1971).

3. Results

Within the selected watersheds, deciduous forest is the most common vegetation type, followed by grass, then evergreen forest, and then mixed forest. Other land cover includes small amounts of low- and medium-intensity development (median 6%), shrub (median 2%), barren, crops, emergent herbaceous wetland, and woody wetland (medians $<$ 1% each) (Table 1).

Total forest cover ranges from 43 to 95% (median 60%), with deciduous forest cover ranging from 23 to 80% (median 45%), and evergreen ranging from 3 to 34% (median 10%) (Table 1). Grass cover ranges from < 1 to 40% (median 21%). Other land covers, including developed, barren, crops, herbaceous wetland, water, and woody wetland, range from < 1 to 30% (median 4%). Overall, land cover proportions of the entire region, as defined by the crystalline rock aquifer polygon, have a similar central tendency to the 45 study watersheds but deciduous forests are more common and evergreen forests are less common in the study watersheds than regionally (Fig. 2, Table 1).

Mean annual precipitation for the 32-year period range from 1,124 to 1,847 mm across the watersheds, averaging 1,252 mm with a standard deviation of 136 mm (Table 3, Fig. 3). Mean annual discharges range from 217 to 998 mm, averaging 434 mm with a standard deviation of 147 mm (Table 3, Fig. 3). Water balance ET is less variable and normally distributed (Shapiro-Wilk p-value = 0.4733), ranging from 640 to 971 mm, with mean and median of 817 and 824 mm, and a

Table 1
Summary statistics of land-cover characteristics for 45 study watersheds in the Southeastern US.

Statistic	Forest Type				Grass	Other
	Total (%)	Deciduous (%)	Evergreen (%)	Mixed (%)	(%)	(%)
Maximum	94.7	80.6	34.2	8.3	39.9	45.5
Mean	62.8	46.4	13.0	3.3	22.7	14.5
Median	60.1	45.1	10.3	3.2	21.5	13.1
Minimum	43.5	22.9	3.3	0.3	0.7	4.6
Std Dev	12.7	14.3	8.2	2.0	10.0	7.9

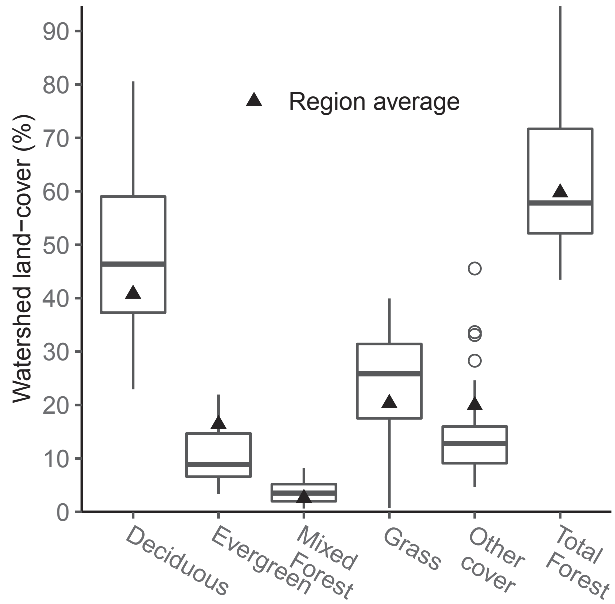

Fig. 2. Land-cover distribution for the forty-five selected watersheds. Boxplots show the media, the 25th and 75th percentiles, whiskers at 1.5 * IQR and open circles are outliers. Black triangles indicate the average land cover for the crystalline rock aquifer region.

Table 2
Statistical summary of basin characteristics of 45 study watersheds in the Southeastern US. AWS = Available Soil-Water storage.

Statistic	Population (per km^2)	AWS (mm)	Area (km^2)	Elevation (m amsl)	Latitude (°N)
Maximum	987	205	4,390	1,009	37.21
Mean	176	166	772	315	35.45
Median	131	167	428	269	35.89
Minimum	35	122	67	100	32.92
Std Dev	160	24	910	182	1.19

Table 3
Statistical summary of annual water-budget components for 45 study watersheds in the Southeastern US. P = precipitation, Q = discharge, ET = evapotranspiration, PET = potential evapotranspiration, VPD = vapor pressure deficit, T = temperature.

Statistic	P (mm)	Q (mm)	ET (mm)	PET (mm)	VPD (mBar)	Temp (°C)
Maximum	1,847	998	970	1,167	0.97	13.7
Mean	1,252	434	817	1,066	0.85	11.4
Median	1,224	425	824	1,056	0.85	11.4
Minimum	1,124	217	640	1,000	0.57	8.1
Std Dev	136	147	60	48	0.07	1.2

standard deviation of 61 mm (Table 3, Fig. 3). Most of the basins' average ET falls between 725 and 900 mm while three basins (35, 6, 44) have ET above 900 mm, and three basins (25, 10, 27) are below 725 mm. PET ranges from 1,001 mm to 1,167 mm, averaging 1,067 mm, with a standard deviation of 48 mm.

3.1. Temporal variation in hydrologic behavior

Double-mass curve analysis of Q versus P indicates that the large majority of the 45 watersheds exhibited no changes or very gradual changes in these relationships through time (Fig. S1). Seven watersheds (2, 6, 15, 19, 29, 30, 34) had a decrease in Q near the end of the 32-year period. This decrease was likely due to a recurring drought that

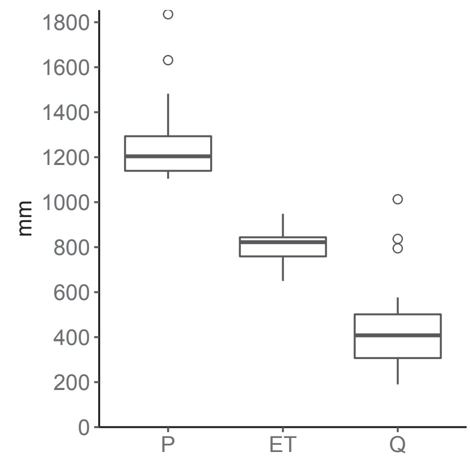

Fig. 3. Distribution of median annual precipitation (P), water-budget evapotranspiration (ET), and streamflow (Q) for the study watersheds over the 32-year period of record. Boxplots show the media, the 25th and 75th percentiles, whiskers at 1.5 * IQR and open circles are outliers.

appeared to affect a band of Piedmont watersheds from SC to central NC (Stephens and Bledsoe, 2020). Given the small number of watersheds affected and the limited amount of time, this drought effect should not alter the interpretation of the overall results, but we report it here since it may be a source of estimated ET variability.

3.2. Budyko analysis

Most watersheds were tightly clustered in the complementary space (Fig. 4), reflecting the similarity of the climate, geology, and ET across the study area. The plurality of basins fall along the Budyko (1958) curve, with forty-two percent of the studied basins falling between the Zhang et al. (2001) curves defined by $w = 1.15$ and $w = 1.95$, scattering across these lines in the vertical (AET/P) axis. Thus, the difference between water balance AET/P and Zhang et al. (2001) AET/P for each watershed reveals differences in AET processes across watersheds (Fig. 4).

The distance between the water-balance estimated AET/P ratio and the Zhang et al. (2001) estimated AET/P ratio is negatively related to the percentage of both total and deciduous forest and unrelated to evergreen-forest percentage. A 1% increase in deciduous or total forest cover corresponds to a 0.27% or 0.29% decrease, respectively, in the difference between the two estimates in AET/P space (Fig. 5). Consequently, many of the water-balance estimates of AET/P fall below the empirical predictions for watersheds where deciduous and total forest cover exceeded 50% and 70%, respectively (Figs. 4 and 5).

Including land cover (Zhang et al., 2001) in the model improves the fit, although different combinations of land-cover parameters produce similar results (Table 4). Each of the models accounting for forest type had a slightly better fit ($R^2 = 0.18$) than the total forest model ($R^2 = 0.15$). The sensitivity analysis with a free parameter not tied to land cover performed the worst ($R^2 = 0.09$) indicating that land-cover parameters are significant (Table 4). While forest cover type improved Budyko type ET estimates, total forest had similar support.

3.3. Regression analysis of ET as a function of land cover and basin variables

Bivariate, linear-regression analysis indicates ET has significant relationships with both evergreen and deciduous forest cover, but with opposite signs (Table 5, Fig. 6). An increase in evergreen forest cover is associated with an increase in ET and an increase in deciduous land cover is associated with a decrease in ET. Both relationships are noisy with low correlations ($R^2 = 0.159$ and 0.107, respectively). Mixed

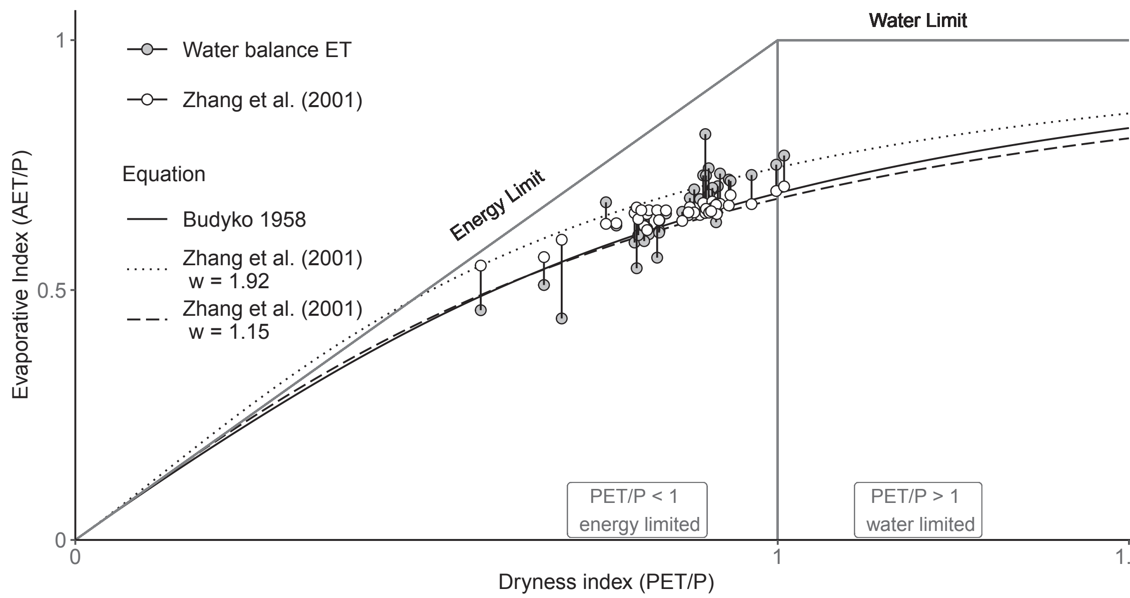

Fig. 4. The Budyko space provides a precipitation (P)-normalized view of evapotranspiration (ET) in two-dimensions, constrained by available water and energy. The evaporative index for each watershed is calculated using water-balance ET (open points) and the Zhang et al. (2001) equation (grey points). Differences between the two estimates are shown as vertical lines. The dryness index is calculated using Priestley-Taylor PET methods. Curves are shown for the Budyko (1958) equation and Zhang et al. (2001) equation with w values approximating the high and low ends of watershed landcover.

forest cover has a significant negative trend with ET ($R^2 = 0.107$). Interestingly, total forest cover was not significantly related to ET (Table 5). Regression analysis suggests that the type of forest cover is more meaningful than total forest cover.

Bivariate linear regression between ET and basin characteristics indicate that temperature ($R^2 = 0.402$), elevation ($R^2 = 0.237$), latitude ($R^2 = 0.175$), and AWS ($R^2 = 0.152$) each significantly affect basin water budgets. ET relationships with temperature, elevation, and latitude were stronger and better supported than any of the vegetative-cover relationships (Table 5). ET increases with temperature, VPD, and AWS and decreases with elevation and latitude. Drainage area, precipitation, and population density were not significant when examined individually (Table 5, Fig. 7). Temperature, elevation, VPD, AWS, and latitude explain more of the ET relationship than evergreen, deciduous, or mixed forest. Correlations between evergreen, deciduous, and mixed forest types with ET are significant and explain more of the variation than total forest alone, for which the correlation is not significant.

Multivariate regressions with ET as the response indicate that precipitation and temperature together offer the best explanatory power, and together their adjusted R^2 is 0.408. These two variables also had the only significant interactions. For simplicity, non-significant interactions are not shown in Table 6. The best models with three or more variables all included precipitation and temperature. The addition of

Table 4
Model comparison using land-cover to predict the runoff ratio following Oudin et al. (2008). Land cover parameters are deciduous (Di), evergreen (Ei), other cover (Oi), grass (Gi), mixed forest (Mi) and total forest (Ti).

Model	param.	Estimate	p value		R^2	AIC
Oudin-Zhang 3	Di	0.63	0.0055	**	0.18	−148.2
Oudin-Zhang 3	Ei	2.40	0.0772	*		
Oudin-Zhang 3	Oi	2.80	0.0008	***		
Oudin-Zhang 4	Di	0.63	0.0061	**	0.18	−146.3
Oudin-Zhang 4	Ei	2.36	0.0898	*		
Oudin-Zhang 4	Oi	2.99	0.0912	*		
Oudin-Zhang 4	Gi	2.68	0.0213	**		
Oudin-Zhang 2	Ti	0.90	0.0001	***	0.18	−145.0
Oudin-Zhang 2	Gi	2.57	0.0240	**		
Oudin-Zhang 2	Oi	4.26	0.1256			
Oudin-Zhang 1	Ei	2.41	0.1197		0.18	−144.3
Oudin-Zhang 1	Di	0.61	0.0595	*		
Oudin-Zhang 1	Mi	3.87	0.7410			
Oudin-Zhang 1	Gi	2.70	0.0271	**		
Oudin-Zhang 1	Oi	2.90	0.1331			
Sensitivity analysis	sigma	−2.01	0.0000	***	0.09	−51.0

Note: Significance shown using *($p < 0.1$), **($p < 0.05$), ***($p < 0.01$). Number of observations = 45. AIC = Akaike Information Criterion.

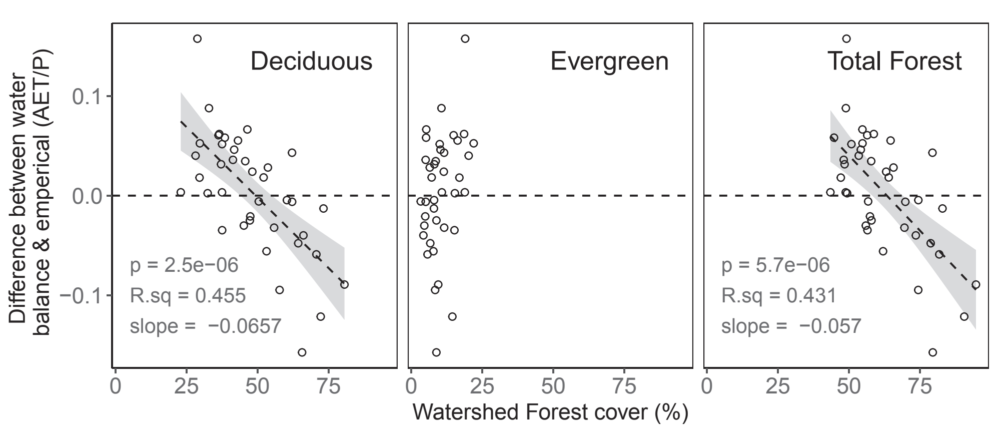

Fig. 5. Difference between water-balance and empirically estimated evaporative index (vertical lines in Fig. 4) using the proportion of evergreen, deciduous, and total forest in each watershed. Negative values indicate that water-balance estimates are less than empirical estimates. The empirical method overpredicts ET relative to the water-balance as deciduous and total forest cover increase beyond 50 and 70%, respectively. Trend lines, 95% confidence intervals, and summary statistics are shown for significant relationships.

Table 5
Bivariate regressions between water-budget estimated evapotranspiration (ET) and land cover or watershed variables.

Variable	Type	df	Estimate	*p-value*		Adj. R^2	AIC
Evergreen	Landcover	2	35.89	0.004	**	0.156	493.4
Deciduous	Landcover	2	−34.95	0.017	**	0.105	496.0
Mixed forest	Landcover	2	−25.62	0.017	**	0.104	496.0
Total forest	Landcover	2	−16.29	0.243		0.009	500.6
Grass	Landcover	2	3.32	0.761		−0.021	501.9
Temperature	Watershed	2	32.53	0.000	***	0.402	477.9
Elevation	Watershed	2	−0.17	0.000	***	0.237	488.8
Latitude	Watershed	2	−22.37	0.002	**	0.175	492.3
AWS 150 cm	Watershed	2	1.05	0.005	**	0.152	493.6
Population	Watershed	2	−0.05	0.413		−0.007	501.3
Drainage	Watershed	2	−0.01	0.649		−0.018	501.8
Precipitation	Watershed	2	0.02	0.801		−0.022	502.0

Note: Significance shown using *($p < 0.1$), **($p < 0.05$), ***($p < 0.01$). Number of observations = 45. df = degrees of freedom, AIC = Akaike Information Criterion.

land cover variables to the models that include precipitation and temperature did not improve model fits. Although the univariate regressions indicate that forest cover type is important, it is less important than several abiotic factors, particularly the combination of temperature and precipitation (Table 6).

4. Discussion

Watershed scale ET in the southeastern U.S. is sensitive to the type of forest cover (deciduous, evergreen, mixed) and even more sensitive to abiotic factors, including precipitation, temperature and available water storage together as well as temperature, elevation, and latitude individually. Vegetative effects on ET are mediated by climatic and geologic variation, so that vegetative signals are noisy when viewed across a broad geographic region (e.g. Freund et al., 2020; Teuling et al., 2019) and in the small basins (< 50,000 km^2) that were included in our study (Li et al, 2013).

Bosch and Hewlett, (1982) found evidence for higher ET in evergreen basins but results were confounded by generally higher precipitation in these basins. Where precipitation was comparable, evergreen forests transpired more water than deciduous forests. Vadeboncoeur et al. (2018) examined ET relationships across a larger, more climatically-variable region, and found that the dominant controls of ET vary systematically with increasing ET in the most energy limited part of the region and decreasing ET in the less energy limited parts of the region. Variations in the abiotic template along with variations in functional diversity of species affect our ability to detect effects of vegetation type.

Here, watershed-scale sensitivity to land cover was detectable at a lower threshold than the 20% suggested by Bosch and Hewlett (1982) but was in line with the suggestion of Trimble et al. (1987) that forest cover changes less than 20% can be detected. In short, vegetation composition partly controls watershed-scale ET, but variations in abiotic controls such as elevation, latitude, precipitation, temperature, lithology, and aspect often matter more (Sanford and Selnick, 2013; Fan et al., 2019, Metzen et al., 2019; Teuling et al., 2019).

Our analysis indicates that increasing total forest cover does not necessarily increase basin ET. Forest type matters. In these watersheds, increasing deciduous and mixed forest cover was associated with lower ET, while increasing evergreen forest cover was associated with higher ET. Regression analysis indicated that watersheds with more evergreen forest had higher ET and those with more deciduous forest had less. Budyko residuals also suggested that watersheds with more deciduous cover had less ET, but Budyko residuals did not identify the effects of evergreen cover as statistically significant. Taken together, the analysis argues for considering forest type to improve predictions of the effects of forest cover on ET.

The study region is currently dominated by deciduous forests, but there is some potential for loblolly pine afforestation by conversion from marginal agricultural (Wear and Greis, 2013). The data indicate that conversion of other cover types to fast-growing loblolly pine would increase ET and reduce stream baseflow. The impact of forestry operations on water budgets is critical to understand, particularly given

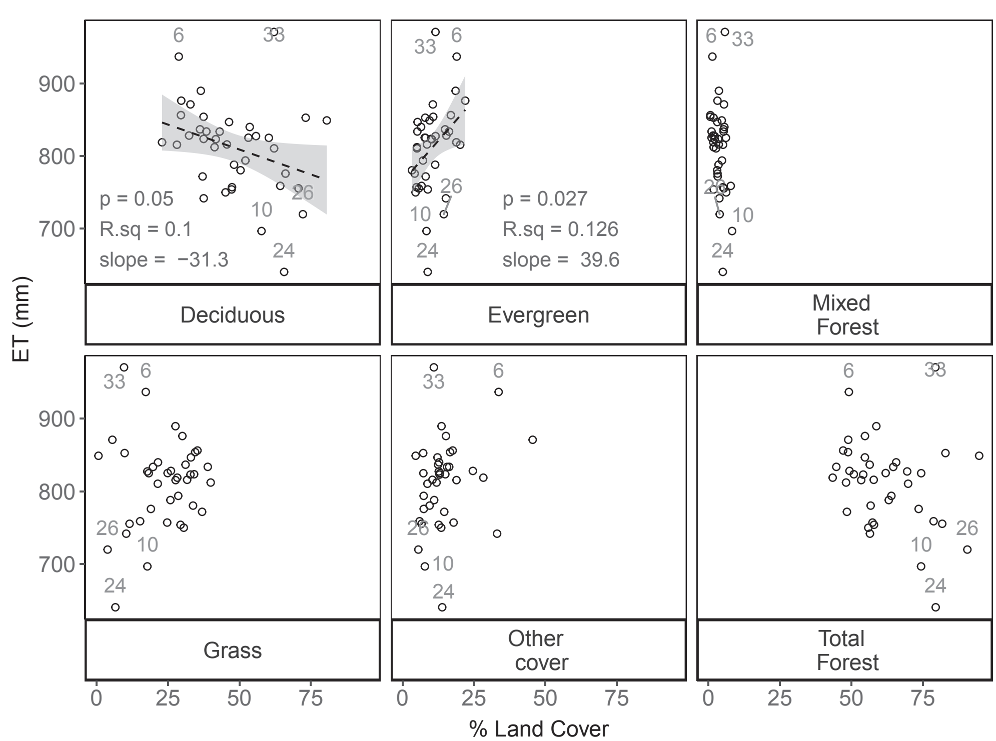

Fig. 6. Bivariate regressions between evapotranspiration (ET) and land-cover types. Watersheds IDs are shown when ET > 900 and ET < 725 mm, which correspond to identifiers in supplemental tables. Trend lines, 95% confidence intervals, and summary statistics are shown for significant relationships.

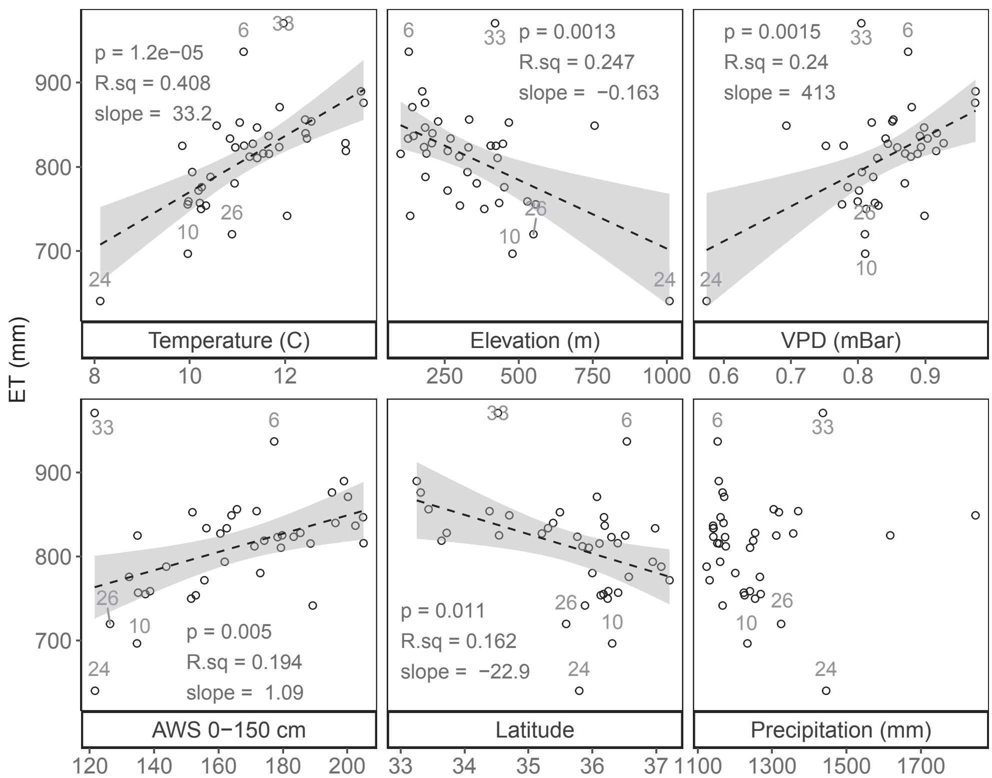

Fig. 7. Bivariate regressions between ET (mm) and watershed elevation, drainage area, latitude, mean-annual air temperature, vapor-pressure deficit (VPD) and available soil–water storage (AWS). Watersheds IDs are shown when ET > 900 and ET < 725 mm, which correspond to identifiers in supplemental tables. Trend lines, 95% confidence intervals, and summary statistics are shown for significant relationships.

Table 6
Multivariate regressions between water-budget estimated evapotranspiration and climate and forest cover variables.

Term	df	estimate	*variable p*		*model p*		Adj. R^2	AIC
Precipitation	3	0.06	0.229		0.000	***	0.408	478.3
Temperature	3	33.67	0.000	***				
Precipitation	4	0.08	0.163		0.000	***	0.405	479.5
Temperature	4	30.20	0.000	***				
AWS 150 cm	4	0.32	0.396					
Precipitation	4	0.08	0.228		0.000	***	0.396	480.1
Temperature	4	31.68	0.000	***				
Deciduous	4	−7.349	0.682					
Precipitation	4	0.063	0.244		0.000	***	0.396	480.2
Temperature	4	32.15	0.000	***				
Evergreen	4	4.352	0.728					
Precipitation	6	0.085	0.255		0.000	***	0.369	483.9
Temperature	6	32.12	0.001	***				
Evergreen	6	3.46	0.804					
Deciduous	6	−7.71	0.707					
Mixed forest	6	4.40	0.697					
Precip:Temp	2	0.02	0.000	***	0.000	***	0.277	486.4
Evergreen	4	21.98	0.146		0.015	**	0.165	494.7
Deciduous	4	−14.99	0.363					
Mixed forest	4	−12.54	0.284					
Dryness index	3	81.13	0.456		0.013	**	0.147	494.8
Evergreen	3	32.97	0.012	**				
Dryness index	4	−8.40	0.956		0.026	**	0.141	496.0
Evergreen	4	27.40	0.062	*				
Deciduous	4	−19.15	0.405					
Dryness index	3	−46.57	0.766		0.057	*	0.086	497.9
Deciduous	3	−39.50	0.064	*				

Note: Significance shown using *($p < 0.1$), **($p < 0.05$), ***($p < 0.01$). Number of observations = 45. df = degrees of freedom, AIC = Akaike Information Criterion.

predictions of increased atmospheric CO_2, temperature, growing season length, and precipitation variability due to climate change (Hwang et al., 2018; Pourmokhtarian et al., 2017; Vose et al., 2011).

Higher CO_2 levels generally increase water-use efficiency (Tyree and Alexander, 1993; Battipaglia et al., 2013), but Jaramillo et al. (2018) found that increased forest biomass increased regional ET and masked any potential reduction in ET due to increase water use efficiency. Additional plot-scale data nested in gauged watersheds should provide useful insights to help understand the dynamics of watershed-scale ET where multiple land-cover types and management strategies may act together to contribute to total ET (Boggs et al., 2015; Caldwell et al., 2018). In addition, reanalysis of the global datasets for forest type effects may be of value since the last review evaluating the effects of forest type was Bosch and Hewlett (1982), which focused on paired-watershed experiments rather than mixed-use basins.

In this study, we calculate long-term watershed-scale water budgets to address changing stream flows relative to land cover. The watershed water balance is prone to errors from land-cover uncertainty, unaccounted basin water losses or gains, consumptive uses (irrigation), shifts in forest-management practices, and forest succession. The focus on large, rural, undammed, crystalline bedrock, and mostly forested basins helps control for these factors. We could not account for effects of forest-age distributions, functional diversity among species within our forest type categories, or tree sizes and ages, although it is likely that deciduous forests are on average older than evergreen forests in the region, given that the rotation length of commercial pine plantations is generally 25–30 years. It is possible that such unaccounted-for effects contribute to the noisy character of ET relationships presented here.

5. Conclusions

Abiotic landscape variables and vegetative-cover types and abiotic variables interact to affect the variation in water-balance estimated evapotranspiration (ET) across 45 rural, mixed land-cover watersheds in the Southeastern U.S. Water balance ET is highly variable across the region, ranging from 641 to 971 mm. Results indicate that ET is most sensitive to abiotic watershed characteristics, primarily the combination of temperature and precipitation, but also including elevation, VPD, AWS, and latitude, all of which explain more variation in ET than any individual vegetative metric. Yet, we can also show that basin-scale average ET is sensitive to forest cover and forest type, specifically the relative mix of deciduous and evergreen forest. The vegetative cover relationships with ET are noisy and vegetative metrics individually explain less than a third of the variation explained by average watershed air temperature. While evergreen forest cover is less common than deciduous cover, it explains more of ET variability than does total forest cover alone and is associated with greater ET. While deciduous and mixed forests are associated with lower ET than evergreen forests. Thus, increasing evergreen forest cover in the region would decrease water yields.

Contrary to prior syntheses of global paired-watershed experiments (Andréassian, 2004; Farley et al., 2005; Filoso et al., 2017; Bosch and Hewlett, 1982), total forest cover in these watersheds appears to have little effect on water balances, and residuals from the Zhang curve suggest that ET decreases with increasing total forest cover, although this result is likely an effect of forest composition, specifically the relative dominance of deciduous forest. While biotic factors are the most important for controlling ET and streamflow, forest type influences water yield; the response to afforestation or deforestation in the Southeastern US depends upon the type of forest vegetation that is grown or harvested.

6. Data availability

All raw data are publicly available from the cited sources. Data generated by this study are available in the supplemental information.

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CRediT authorship contribution statement

Seth E. Younger: Data curation, Investigation, Formal analysis, Visualization, Writing - original draft. **C. Rhett Jackson:** Conceptualization, Supervision, Formal analysis, Writing-review & editing. **Todd C. Rasmussen:** Formal analysis, Software, Writing-review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jhydrol.2020.125316.

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