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Land cover effects on runoff patterns in eastern Piedmont (USA) watersheds

Jason P. Julian[1]* and Robert H. Gardner[2]

[1] *Department of Geography and Environmental Sustainability, University of Oklahoma, Norman, OK 73019, USA*
[2] *Appalachian Laboratory, University of Maryland Center for Environmental Science, Frostburg, MD 21532, USA*

Abstract:

Physiography and land cover determine the hydrologic response of watersheds to climatic events. However, vast differences in climate regimes and variation of landscape attributes among watersheds (including size) have prevented the establishment of general relationships between land cover and runoff patterns across broad scales. This paper addresses these difficulties by using power spectral analysis to characterize area-normalized runoff patterns and then compare these patterns with landscape features among watersheds within the same physiographic region. We assembled long-term precipitation and runoff data for 87 watersheds (first to seventh order) within the eastern Piedmont (USA) that contained a wide variety of land cover types, collected environmental data for each watershed, and compared the datasets using a variety of statistical measures. The effect of land cover on runoff patterns was confirmed. Urban-dominated watersheds were flashier and had less hydrologic memory compared with forest-dominated watersheds, whereas watersheds with high wetland coverage had greater hydrologic memory. We also detected a 10–15% urban threshold above which urban coverage became the dominant control on runoff patterns. When spectral properties of runoff were compared across stream orders, a threshold after the third order was detected at which watershed processes became dominant over precipitation regime in determining runoff patterns. Finally, we present a matrix that characterizes the hydrologic signatures of rivers based on precipitation *versus* landscape effects and low-frequency *versus* high-frequency events. The concepts and methods presented can be generally applied to all river systems to characterize multiscale patterns of watershed runoff. Copyright © 2013 John Wiley & Sons, Ltd.

KEY WORDS watershed hydrology; power spectral analysis; hydrologic signatures; fluvial landscape ecology; hydrologic memory

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INTRODUCTION

The unique structure of each landscape – its topography, soils, hydrologic pathways, and land cover – defines the hydrologic response of watersheds to local weather events. This obvious relationship between structure and process should allow the determination of how landscape properties affect hydrology and therefore simplify the prediction of hydrologic response of watersheds to variable climatic conditions (Black, 1991). Although a variety of methods have been used to summarize patterns of water runoff, including statistical moments (Richter *et al*., 1996), geochemical/isotopic tracers (Brown *et al*., 1999), rainfall–runoff models (Beighley *et al*., 2005), wavelets (Smith *et al*., 1998), multifractals (Tessier *et al*., 1996), and spectral analysis (Fleming *et al*., 2002), a definitive relationship between landscape structure and runoff patterns over broad areas has yet to be established.

Two factors have complicated the assessment of pattern–process relationships at landscape scales. First, the frequency, duration, and magnitude of precipitation events – the drivers of watershed hydrology – vary greatly in time and space, requiring long-term records to define significant relationships. However, long-term hydrologic records rarely satisfy the statistical requirement of stationarity because both climate and land cover have been changing over the last century. These simultaneous trends can interact to produce effects that are neither independent nor additive. For instance, human development has tended to reduce the amount of wetlands and increase sealed surfaces in urbanized watersheds. Although wetlands retain water and reduce levels of peak runoff, sealed surfaces counter these effects by reducing storage and increasing overland flows (Eshleman, 2004). The construction of reservoirs, which retard water movement and reduce the variance and peak flows associated with climatic events (Singer, 2007), further complicates the establishment of pattern–process relationships at landscape scales.

Secondly, variation in the size of watersheds and the heterogeneity of landscapes makes direct comparisons problematic. Runoff patterns within small watersheds tend to be more responsive to precipitation inputs, whereas landscape features become more important as watershed size increases (Tessier *et al*., 1996; Sabo and Post, 2008); however, this issue of scale effects is still a matter of ongoing discussion (Shaman *et al*., 2004; Hrachowitz *et al*., 2010; Frisbee *et al*., 2012). The effects of land cover are easier to discern when land cover is relatively homogeneous (mostly forested *vs* highly developed), but more difficult to establish when there is a broad mix of land cover types, as

*Correspondence to: Jason P. Julian, Department of Geography and Environmental Sustainability, University of Oklahoma, Norman, OK 73019, USA.
E-mail: jjulian@ou.edu

most watersheds have (Poff *et al*., 2006; Oudin *et al*., 2008). Thus, the comparison of multiple watersheds of different sizes from diverse geographic regions, as many studies have attempted, produces results dominated by these scale-dependent effects (Beven, 2000).

This paper addresses these difficulties by using a multiscale approach to compare landscape structure and hydrologic properties of watersheds within the same physiographic region. The Piedmont physiographic province of the USA is situated between the Appalachian Mountains and the Atlantic Coastal Plain, extending from New Jersey in the north to Alabama in the south (Figure 1). Watersheds were selected for comparison in this region because of the following: (i) similar morphometry among watersheds (pear-shaped or oval-shaped basins with a dendritic channel pattern), (ii) moderate relief preventing runoff from being dominated by topography, yet not so flat that subsurface controls dominate, (iii) similar geology (thick clay-rich soils underlain by deeply weathered bedrock, and relatively few solid outcrops), (iv) similar climate (midlatitude, humid subtropical climate with no dry season; Köppen Cfa), (v) diversity of land cover types including large areas of urban development, extensive agriculture, and both large and small forested areas, (vi) numerous precipitation and flow gauges with long continuous daily records. By keeping physiography as constant as possible over such a large area, this experimental design maximizes the potential for identifying effects of land cover on watershed hydrology.

Power spectral analysis (PSA) was used to assess relationships between periodic patterns of precipitation and runoff for all watersheds. PSA provides an ensemble measure across all periods within the frequency domain, allowing patterns at multiple temporal scales to be evaluated (Fleming *et al*., 2002; Sabo and Post, 2008). The existence of linear relationships between spectral power and period (1/*f*, where *f* is frequency) indicates scale invariance over the temporal domain for which linearity holds (Gupta *et al*., 1994; Pandey *et al*., 1998). These properties have made PSA a useful tool for the analysis of a wide assortment of environmental data (Lovejoy and Schertzer, 1995; Halley, 1996; Hodell *et al*., 2001; Perron *et al*., 2008), with the most widespread application being for hydrological analyses (for recent examples, see Kirchner *et al*., 2000; Hrachowitz *et al*., 2009). The fine temporal resolution and long duration of discharge records from monitored stations provide data well suited for PSA. The combined analysis of measured precipitation and runoff data for each watershed also makes PSA useful for assessing the relationships between landscape structure and hydrologic patterns.

The first use of PSA comparing daily runoff time series for multiple watersheds was performed by Tessier *et al*. (1996) on 30 small watersheds (40–200 km^2) in France that had been minimally affected by anthropogenic change. They found that PSA of runoff data mirrored a parallel PSA of rainfall, the only difference being less variability in runoff spectra, which they attributed to watershed characteristics attenuating the rainfall signal. In both the rainfall and runoff spectra, Tessier and colleagues found two consistent features: (i) a change in spectral slope at 16 days (subsequently referred to as the cross-point) attributed to the frequency and duration of synoptic weather patterns and (ii) a distinct peak in spectral power at 1 year attributed to strong seasonal cycles in water budgets (e.g. winter–spring wet periods *vs* summer–fall dry periods). Other studies from a variety of

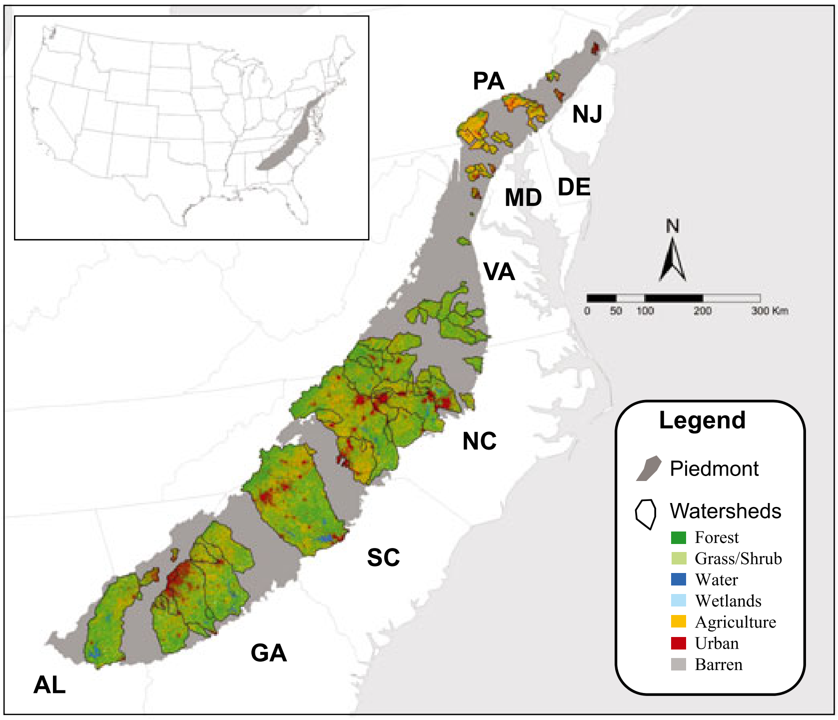

Figure 1. Locations and land cover (NLCD 2001) of the study's 87 watersheds within the Piedmont physiographic province in the USA. State abbreviations are included for reference

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watersheds have produced similar results: a spectral peak at 1 year and a cross-point that varies between 3 and 24 days (Pandey *et al*., 1998; Sauquet *et al*., 2008).

Whereas the previous authors emphasized the similarity of PSA results among watersheds, Sabo and Post (2008) examined PSA differences among watersheds due to differences in physiographic properties. Although Sabo and Post did not make direct comparisons between landscape attributes and PSA metrics, they did find a trend in one PSA metric: the spectral slope ($-\beta_0$), which is a direct reflection of the composite pattern of timescales of the dominant processes active in the watershed, or in other words, a reflection of the hydrologic response function according to which precipitation signals are routed through the watershed (Kirchner *et al*., 2000). Sabo and Post (2008) found that the value of $-\beta_0$ (commonly referred to as spectral colour or $1/f$ noise) increased (or reddened) from low $-\beta_0$ for flashy streams to high $-\beta_0$ for less responsive, groundwater-dominated streams. Because higher spectral slopes indicate greater temporal autocorrelation, watersheds with high $-\beta_0$ will have a longer system memory of previous hydrologic events, which we henceforth refer to as hydrologic memory (Halley, 1996; Mudelsee, 2007). It is important to note that spectral slopes are not a direct measure of water transit time as they do not take into account actual particle transport (for recent research on water travel time scaling, see McGuire *et al*., 2005; Hrachowitz *et al*., 2010); however, they do reflect the response of runoff to precipitation and landscape attributes (Tessier *et al*., 1996; Godsey *et al*., 2010).

This paper uses long-term records from 87 Piedmont watersheds to more fully explore relationships between PSA and landscape structure, with special emphasis on the effects of variation in land cover. We first summarize the statistical attributes of PSA and landscape structure variables and then use canonical correlation to test the overall hypothesis that significant dependencies between land cover and runoff exist. Multiple statistical tests are then used to define those variables that best explain changes in runoff patterns. The changes in relationships across stream orders, from first-order headwater streams to large seventh-order streams are also examined. Throughout the manuscript, we address the general question as to whether land cover has a detectable influence on the hydrologic memory of watersheds and, in particular, how development has affected this memory. Finally, we identify a subset of spectral runoff metrics that can be used to summarize hydrologic signatures of watersheds. By characterizing relationships between landscape structure and hydrology, this work provides a basis for predicting future runoff patterns produced by changing weather and human alterations of the landscape.

METHODS

Watersheds

Landscape and hydrologic data were assembled from watersheds with at least 90% of their area within the Piedmont physiographic region of the eastern USA (defined using the ecoregion classification of Omernik, 1987) and with 40 years of continuous daily discharge data for the water year (1 Oct–30 Sep) from 1969 to 2008 (Figure 1). The requirement of 40 years insured a sufficient time-series length for PSA to characterize low-frequency events but not so long that there would be an insufficient number of watersheds for comparison. The same record length (1969–2008) was used for all analyses to minimize temporal differences in climate and land cover among watersheds. Daily mean discharge (m^3/s) records were obtained from the US Geological Survey, and daily total precipitation (cm/day) records were collected from the US Historical Climatology Network using the station closest to the centre of the watershed. Precipitation data were used to illustrate differences in spectral properties between runoff and precipitation at a station, and thus, we did not attempt to characterize the spatial distribution of precipitation across watersheds.

In five of the 87 datasets, missing daily discharge values (always < 30 days) were filled by linear interpolation. A Monte Carlo sensitivity analysis was performed ($n = 100$) by randomly replacing continuous 30-day records by linear interpolation for ten different watershed datasets (a total of 1000 data alterations). The results showed that the average change in PSA variables was generally $<1\%$ with only four of 70 contrasts exceeding this criterion, but in all cases, the maximal change remained $<2\%$. Missing daily precipitation values were replaced by values from the next nearest US Historical Climatology Network station, usually within 60 km.

Landscape variables

A series of landscape variables that have been identified as having important effects on hydrologic processes (Black, 1991; Buttle, 2006) were assembled to characterize the structure of each watershed (Table I). These variables were organized into morphometric, geologic, hydrologic, and land cover variables. After deriving watershed boundaries associated with each flow gauge using a 30-m flow direction grid, we calculated watershed morphometrics using the National Elevation Dataset and National Hydrography Dataset. Mean silt-clay percentage (*SC%*; upper 10 cm) and mean depth to bedrock (Z_{br}) were calculated from the 1-km CONUS-SOIL dataset (Miller and White, 1998), which is a derivation of the US Department of Agriculture's State Soil Geographic Data Base. Reservoir storage (*RS%*) was calculated as the percentage of total watershed runoff (average annual flow volume measured at the outlet gauge plus reservoir storage) stored in reservoirs within the watershed. We calculated precipitation effectiveness (R_{pe}) by dividing average annual precipitation by average annual temperature (1961–1990), using the 10′ dataset of New *et al*. (2002).

Anderson level I classification of the 30-m 2001 National Land Cover Database (NLCD; Multi-resolution Land Characteristics Consortium, 2001) was used to characterize the proportional land cover types in each watershed. Water and wetlands were combined because of their indistinguishable effect on water storage. Temporal changes in land cover over the 40-year study period were approximated and assessed by comparing the

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Table I. Landscape variables characterizing the 87 watersheds within the Piedmont of the eastern USA

Variable	Definition (units)	Source (resolution)
Morphometric variables		
Area (A)	Total watershed area above stream gauge (km^2)	National Elevation Dataset (30 m)
Stream order (O_{HS})	Stream order of watershed using Horton–Strahler classification	National Hydrography Dataset (1 : 24 000)
Drainage density (D_d)	Total length of streams per watershed area (km/km^2)	National Hydrography Dataset (1 : 24 000)
Mean channel slope (S_c)	Slope of the main stem channel measured from its source to watershed outlet (m/m)	National Elevation Dataset (30 m) with National Hydrography Dataset (1 : 24 000)
Basin form ratio (R_f)	Basin area divided by the square of the maximum basin length, as measured from its outlet (km^2/km^2)	National Elevation Dataset (30 m) with National Hydrography Dataset (1 : 24 000)
Geologic variables		
Silt-clay percentage ($SC\%$)	Proportion of surface soil (upper 10 cm) that is below 63 μm in texture (%)	Miller and White (1998) (1 : 250 000)
Depth to bedrock (Z_{br})	Mean depth to bedrock (cm)	Miller and White (1998) (1 : 250 000)
Hydrologic variables		
Reservoir storage percentage ($RS\%$)	Proportion of average annual runoff normally stored in reservoirs (%)	National Inventory of Dams, 2007 (normal storage > 6.17 Gl)
Precipitation effectiveness ratio (R_{pe})	Average annual precipitation over average annual temperature (cm/°C)	New *et al*. (2002)) (10′ lat/long)
Land cover variables		
Percent water–wetland ($\%WW$)	Portion of area that is open water and wetland (%)	National Land Cover Dataset, 2001 (30 m)
Percent urban ($\%UR$)	Portion of area that is urban (%)	National Land Cover Dataset, 2001 (30 m)
Percent forest ($\%FO$)	Portion of area that is forest (%)	National Land Cover Dataset, 2001 (30 m)
Percent agriculture ($\%AG$)	Portion of area that is agriculture (%)	National Land Cover Dataset, 2001 (30 m)

1975 NLCD (Mitchell *et al*., 1977; US Geological Survey, 1998) with the 2001 NLCD. Given the coarser resolution of the 1975 NLCD and its potential limitations (Jawarneh and Julian, 2012), we did not incorporate temporal land cover changes in our statistical analyses.

Although other variables than those listed in Table I may have been used, we limited our selection to first-order hydrologic controls (*sensu* Buttle, 2006) that displayed minimal collinearity (Wang and Malanson, 2007). For example, basin relief ratio and mean channel slope (S_c) are both expressions of elevation and are thus highly correlated. For this and other similar cases, the variable exhibiting the strongest relationship with the dependent variables was retained.

Power spectral analyses

PSA is a form of analysis of variance of a Fourier-transformed time series that partitions the variances at frequencies (f) that are harmonics of the dataset (Platt and Denman, 1975; Fleming *et al*., 2002). A plot of spectral power, or variance, against $1/f$ illustrates the periodic nature of precipitation and runoff (Fleming *et al*., 2002; Sauquet *et al*., 2008). Excellent texts (Brockwell and Davis, 1991; Bloomfield, 2000) and reviews (Platt and Denman, 1975) describing the theory and methods of PSA and its application to hydrologic data (McLeod and Hipel, 1995; Fleming *et al*., 2002) are widely available. Therefore, we focus here on the methods used to extract PSA statistics from the 87 study watersheds.

We examined both precipitation and discharge records for each watershed with leap days discarded to create complete, continuous records of exactly 365 days for all years. Daily discharges were normalized by watershed area so that spectral power would be comparable among watersheds of different sizes. The *spectrum* routine of R (R Development Core Team, 2008) was used to perform PSA on the area-normalized discharge (henceforth runoff) and precipitation time series. Because stationarity of the time series is required by spectral analysis, *spectrum* removes linear trends via regression before performing PSA (Venables and Ripley, 2002). Examination revealed that slopes associated with the time-dependent trends were small: -2.97×10^{-4} for runoff (m^3/s/km^2) and 1.10×10^{-7} for precipitation (cm/day). Because daily values for precipitation and runoff were time averaged, an aliasing filter was not needed (Kirchner, 2005). Smoothed periodograms of the logarithms of spectral power *versus* $1/f$ were produced for each analysis (Figure 2), and the statistical attributes of PSA (described later) were obtained. Smoothing of the periodograms was performed by *spectrum* using three Daniell smoothers of lengths 7, 9, and 15 (Venables and Ripley, 2002, p. 409) to remove noise and improve the clarity of the spectral plots. Smoothing does reduce estimates of power and slope but had minimal effect (<2%) on the PSA statistical parameters reported here.

The statistical parameters extracted from each PSA (Table II; Figure 2) include daily power (P_d), which is the day-to-day variance of runoff (or rainfall); annual power (P_a), which is the degree of variance associated with year-to-year differences in runoff; spectral slope ($-\beta_0$), which is the rate of change in spectral power across all periods (also an overall measure of temporal

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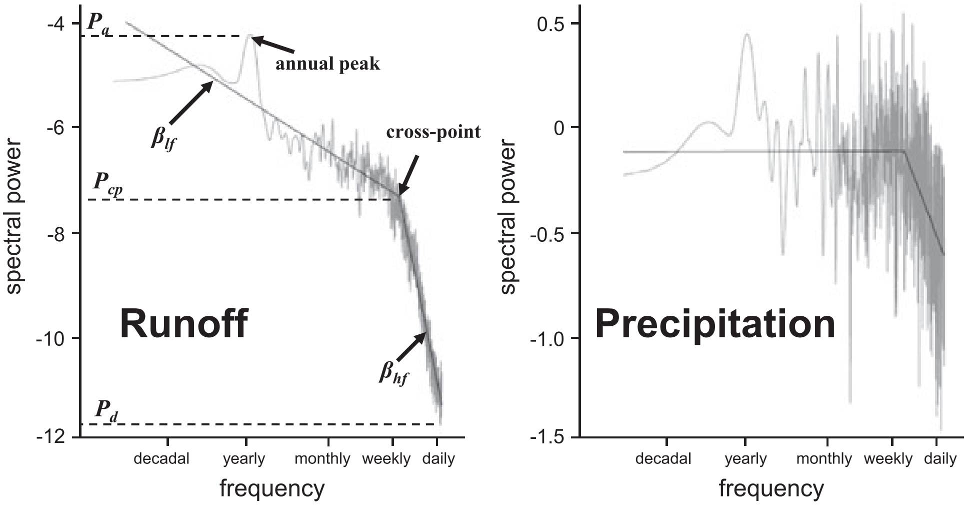

Figure 2. An example periodogram for runoff (left) and precipitation (right) from the Meherrin River basin (US Geological Survey 2051500). The Meherrin River basin represents the average watershed in terms of area (1432 km^2), contains a mixture of land cover (69 *%FO*, 17 *%AG*, 4 *%UR*, 2 *%WW*), and has little reservoir storage (0.07%). For simplicity, β_0 is not illustrated. See text and Table II for the definition of spectral variables. Notice that the low-frequency spectral slope (β_{lf}) is essentially 0 for precipitation (white noise) but is much steeper for runoff (pink noise). Also note the differences in magnitude for spectral power (y-axis) between plots

Table II. Statistical variables produced by PSA of runoff and precipitation data (i.e. spectral variables)

Variable	Definition
Daily power (P_{d})	Spectral power at 1 day
Annual power (P_{a})	Spectral power at 1 year
Spectral slope (β_0)	Least squares regression slope for the entire spectrum
Cross-point (f_{cp})	The period (in days) at which the break in scale occurs between regression lines of low and high frequencies
Cross-point power (P_{cp})	Spectral power at the cross-point
Spectral slope for low-frequency domain (β_{lf})	Least squares regression slope for low-frequency spectra as defined by the cross-point
Spectral slope for high-frequency domain (β_{hf})	Least squares regression slope for high-frequency spectra as defined by the cross-point

autocorrelation with steeper slopes indicating greater hydrologic memory within watersheds); cross-point (f_{cp}), which marks the change in slope separating high-frequency from low-frequency periods; and cross-point power (P_{cp}), which is the spectral power associated with f_{cp}. The $-\beta_{\mathrm{hf}}$ and $-\beta_{\mathrm{lf}}$ are the spectral slopes associated with these high-frequency and low-frequency domains, respectively.

The presence of a cross-point in the spectral plots and the parameters associated with the linear relationships above and below this cross-point were estimated by segmented linear regression methods provided by the *segmented* procedure in R (Muggeo, 2008). The *segmented* procedure employs generalized linear models via an iteration procedure starting from an initial estimate and then fits piecewise linear relationships above and below this cross-point value. Using the intermediate value from the range of previous studies (Tessier *et al.*, 1996; Pandey *et al.*, 1998; Sauquet *et al.*, 2008), we chose 10 days as our initial estimate for all plots. Because the expected cross-point occurs over a limited time span, the final estimate provided by *segmented* was not sensitive to the initial estimate. Maximum likelihood methods were used to obtain final estimates of all parameters, including the location and confidence estimates of cross-points (Muggeo, 2008).

Statistical analyses

Canonical correlation was used to test the overall hypothesis that landscape attributes were related to precipitation and runoff patterns within the Piedmont watersheds. Canonical correlation analysis (CCA) estimates correlations through linear combinations of the multivariate dependent and independent variables subject to the constraint that each set of linear factors and corresponding correlations are independent of one another (Shumway and Stoffer, 2000). We performed CCAs (González and Déjean, 2009) in R using ten landscape descriptors (D_{d}, S_{c}, R_{f}, Z_{br}, *RS%*, R_{pe}, *%WW*, *%UR*, *%FO*, and *%AG*) as independent variables and seven PSA variables (P_{d}, P_{a}, P_{cp}, f_{cp}, $-\beta_0$, $-\beta_{\mathrm{lf}}$, and $-\beta_{\mathrm{hf}}$) as response variables. The Wilks' likelihood ratio (Friederichs and Hense, 2003) was used to test the significance of each canonical correlate.

Stepwise regression, performed in SAS JMP® (v9), was then used to rank-order the relative contributions of multiple landscape variables associated with each spectral variable. Stepwise regression was used because it accounts for correlations among the independent landscape variables. The order of variables in the stepwise regression model provides an objective measure of the unique contribution of each landscape variable to the hydrologic response of these Piedmont watersheds. The level of entry into the model was set to $p = 0.05$. Bivariate comparisons were also examined for the following: (i) the level of significance of bivariate correlations between landscape and spectral variables, (ii) the existence of nonlinear trends between variables, and (iii) departures from normality and homoscedasticity.

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To test hypotheses from previous studies on the effect of landscape attributes on runoff patterns, we conducted two additional analyses: one to examine how spectral runoff properties change with landscape position (i.e. stream order) and one to examine threshold responses with urban coverage (i.e. a sudden change in linear regression). Mudelsee (2007) hypothesized that hydrologic memory increases with watershed area. We tested this hypothesis by comparing means and standard deviations of spectral properties among watersheds of different stream orders (O_{HS}), using the Horton–Strahler classification. This classification has weaknesses due to dependency on mapping scale and inconsistency among physiographic regions (Julian *et al.*, 2012); but with the use of a hydrography dataset mapped at the same scale (National Hydrography Dataset; 1 : 24 000) and from the same physiographic region (Piedmont), O_{HS} is a relevant variable that can be used to functionally group watersheds according to their position in the landscape. That is, first-order watersheds are headwater catchments with no tributaries, second-order watersheds are formed by two headwater catchments and are thus lower in the landscape, and so on. For comparative purposes, we also characterized watershed area across stream orders. The second hypothesis we tested was that urban land cover thresholds exist, above which urban land cover becomes the dominant influence on runoff (*sensu* Wang *et al.*, 2001). In the same fashion as f_{cp} (Section on Power Spectral Analysis), urban thresholds were identified using segmented linear regression, but this time comparing the spectral runoff variables to urban coverage (%*UR*).

Because of the difficulty of accounting for temporal changes in land cover, a *post hoc* test was conducted to test differences in spectral runoff variables among dominant land covers of watersheds, where watersheds with >50% urban coverage would be grouped as UR (AG: >50% agriculture; FO: >50% forest). Watersheds where no land cover exceeded 50% were labelled as mixed (MX). The Steel–Dwass test was performed on all pairs of dominant land cover. The significance of difference among ranks was based on a quantile value (q^*) of 2.569 and an alpha level (α) of 0.05.

RESULTS AND DISCUSSION

We compared the landscape properties of 87 watersheds in the Piedmont of the eastern USA (Section on Landscape Characterizations) with their periodic responses of precipitation/runoff using PSA (Section on Spectral Flow Regimes) to define broad-scale statistical relationships between precipitation/runoff and landscapes (Section on Relationships between Landscape and Spectral Hydrologic Variables). CCA confirmed a strong and significant relationship between spectral properties of runoff and their watershed attributes, but a weaker relationship between PSA for precipitation and landscape descriptors. A detailed examination of relationships between runoff spectra and landscape properties provided a quantitative summary of land cover effects on runoff patterns (Section on Land Cover Effects on Spectral Runoff Patterns), threshold responses in runoff with urbanization (Section on Runoff Pattern Responses to Urban Thresholds), changes in spectral properties across stream order (Section on Runoff Patterns across Stream Orders), and spectral metrics for a hydrological signature (Section on Spectral Metrics for a Hydrologic Signature).

Landscape characterizations

The 87 study watersheds ranged from a small first-order watershed with an area of 8 km^2 to a large seventh-order one with an area of 20 294 km^2 (Table III, Figure 1). Stream order (O_{HS}) followed a normal-like distribution with most watersheds (27 of 87) being of the fourth order. Mean daily runoff for all watersheds ranged from 0.09 to 251 m^3/s. With the use of the 16 watersheds with no reservoir storage, the mean rainstorm recurrence interval (calculated from unique flood peaks) for the Piedmont was 6.1 ± 0.7 days (mean standard deviation).

Land cover varied widely among the watersheds (Table III, Figure 1), with forest (%*FO*), agriculture (%*AG*), and urban (%*UR*) being the three dominant coverages, respectively. Water–wetland coverage (%*WW*) never exceeded 11%. The summed coverage of barren, grassland, and shrubland was 3%, on average. Given the

Table III. Statistical description of landscape variables, spectral runoff variables (from area-normalized daily discharge values), and spectral precipitation variables (from nonnormalized daily values)

Variable	Minimum	Maximum	Mean ± SD
Landscape variables			
A	8	20 294	1466 ± 3307
O_{HS}	1	7	4 ± 1
D_d	0.39	1.04	0.81 ± 0.15
S_c	0.0004	0.0112	0.0032 ± 0.0020
R_f	0.20	0.70	0.39 ± 0.11
$SC\%$	31	83	58 ± 12
Z_{br}	87	151	138 ± 15
$RS\%$	0.0	47.3	6.5 ± 10.8
R_{pe}	5.95	10.93	7.12 ± 0.89
$\%WW$	0.2	11.0	2.7 ± 2.2
$\%UR$	0.9	96.6	17.5 ± 23.1
$\%FO$	2.9	90.4	45.8 ± 19.5
$\%AG$	0.2	74.0	29.6 ± 20.3
Spectral runoff variables			
P_d	−13.38	−6.74	−9.42 ± 1.72
P_a	−5.25	−3.06	−4.23 ± 0.48
$-\beta_0$	0.28	1.90	0.86 ± 0.45
P_{cp}	−9.39	−5.73	−7.31 ± 0.76
f_{cp}	3.0	10.8	6.0 ± 1.2
$-\beta_{lf}$	0.16	1.17	0.44 ± 0.16
$-\beta_{hf}$	0.32	4.63	1.82 ± 1.16
Spectral precipitation variables			
P_d	−0.64	−0.08	−0.43 ± 0.13
P_a	−0.32	0.88	0.28 ± 0.24
$-\beta_0$	0.07	0.20	0.13 ± 0.02
P_{cp}	−0.67	0.46	0.11 ± 0.25
f_{cp}	4.7	7.3	5.6 ± 0.6
$-\beta_{lf}$	−0.03	0.06	0.02 ± 0.02
$-\beta_{hf}$	0.35	0.55	0.42 ± 0.05

Measures of power (P_d, P_a, and P_{cp}) are log values (Figure 2). A and O_{HS} were not used in multivariate analyses because spectral variables were already normalized by A, whereas O_{HS} is not a continuous variable.

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large ranges of the three dominant land cover types, many possible combinations were represented (Appendix A). Among all watersheds, 40 were forest dominated (FO), 19 were agriculture dominated (AG), and nine were urban dominated (UR). There were 19 mixed watersheds (MX), where no land cover exceeded 50%. From 1975 to 2001, *%UR* and *%WW* increased by $3.6\% \pm 7.8\%$ and $2.1\% \pm 1.8\%$, respectively (Appendix A). Conversely, *%AG* and *%FO* decreased by $7.9\% \pm 7.6\%$ and $1.7\% \pm 10.0\%$, respectively. Again, these changes are only broad estimates because of the shortcomings of the 1975 NLCD (Jawarneh and Julian, 2012). There were few large reservoirs in our study area, and 90% of the watersheds had less than a quarter of their average annual volume of water stored behind dams (*RS%*). Average *RS%* was $6.5\% \pm 10.8\%$. With all watersheds lying within the Piedmont physiographic province, the other landscape variables were constrained (Table III) when compared with global ranges (Knighton, 1998 and references within).

Spectral flow regimes

The statistical variables produced by PSA (Table II) provide a synoptic description of a watershed's flow regime. In all spectral runoff periodograms (Figure 2 as an example), spectral power decreased with frequency, with the overall spectral slope ($-\beta_0$) ranging from 0.28 to 1.90 (Table III). The coefficient of determination around this regression line ranged from 0.51 to 0.92, with variance increasing in the lower $1/f$ ranges. The break in spectral slope (f_{cp}) between high-frequency and low-frequency runoff events is determined by watershed response to synoptic weather conditions (i.e. the characteristic intervals of rainstorms). The period at which f_{cp} for runoff occurred did not vary greatly among watersheds, averaging 6.0 ± 1.2 days with a range of 3.0–10.8 days. This value matches the 6.1-day mean rainstorm recurrence interval of this region and is similar to f_{cp} for precipitation (5.6 ± 0.6). Pandey *et al.* (1998) found virtually the same f_{cp} (~6 days) for 19 random watersheds across the USA. Tessier *et al.* (1996) estimated f_{cp} for watersheds in France, finding that the shift in spectral slopes matched regional rainstorm recurrence intervals with a mean value of 16 days. This cross-point, however, depends on the temporal resolution of data, with finer temporal data allowing additional cross-points to be defined. For instance, Sauquet *et al.* (2008) found a median cross-point of 27 h using hourly discharge data from 34 French watersheds.

Whereas f_{cp} was similar for precipitation and runoff, all other spectral properties were quite different between precipitation and runoff (Table III): precipitation had much higher spectral power (i.e. more variance) and much lower spectral slopes (i.e. less memory). The most striking difference was the spectral slope for the low-frequency domain ($-\beta_{lf}$), which was essentially 0 for precipitation (white noise, which indicates a random process) but 0.44 ± 0.16 for runoff (pink noise; Figure 2).

Spectral slopes ($-\beta$) are determined by the temporal autocorrelation inherent in runoff data and, consequently, an indication of hydrologic memory. Godsey *et al.* (2010) showed that spectral slopes reflect the response of runoff to precipitation and landscape attributes, as determined 'by the heterogeneity of the flow path lengths and velocities'. Values of $-\beta$ near 0 occur when all periods of runoff are equally represented, indicating a system with little memory (white noise). The low-frequency domain for precipitation spectra (Figure 2) is an excellent example of white noise. Steep spectral slopes, on the other hand, correspond to long retention times and thus greater hydrologic memory (red noise) of previous storm events (Halley, 1996; Sabo and Post, 2008). Most watersheds tend to have intermediate levels of memory with pink noise ($-\beta \approx 1$; characteristic of low-frequency flow events) or red noise ($-\beta \approx 2$; characteristic of high-frequency flow events) evident (Sabo and Post, 2008). Results showed that runoff from the 87 Piedmont watersheds followed these patterns with values of $-\beta_{lf}$ that averaged 0.44, never exceeding 1 (pink noise), and values of $-\beta_{hf}$ that averaged 1.89 (red noise; Table III). Both $-\beta_{hf}$ and $-\beta_{lf}$ varied widely (coefficient of variation of 64% and 36%, respectively), which we examine in subsequent sections to determine if differences in runoff patterns between watersheds can be attributed to landscape structure.

Daily power (P_d) reflects day-to-day variance of flows, where spring-fed rivers tend to have low (more negative) values of P_d and ephemeral rivers tend to have higher values of P_d (for additional examples, see Sabo and Post, 2008). Because our data were based on daily flows, P_d defines the endpoint for the linear regressions from which $-\beta_{hf}$ was estimated, which explains why these variables were strongly correlated ($r = -0.83$). P_{cp} and $-\beta_{lf}$ were also strongly correlated ($r = -0.83$). Given that f_{cp} is similar for all watersheds, it appears that short-term hydrologic memory ($-\beta_{hf}$) is dictated by day-to-day flow variance (P_d), and long-term hydrologic memory ($-\beta_{lf}$) is dictated by week-to-week flow variance (P_{cp}).

All watersheds showed a characteristic peak in variance at annual scales (P_a). Year-to-year differences in weather have been consistently shown by spectral analysis to be a dominant periodic response (Tessier *et al.*, 1996; Pandey *et al.*, 1998; Sauquet *et al.*, 2008). Most Piedmont watersheds also exhibited a smaller peak at 6-month intervals that may be related to seasonal precipitation regimes but, given the region's relatively minimal seasonality in precipitation, might be a simple harmonic of the peak in variance at 1-year intervals. There was relatively little deviation in P_a among all the watersheds (Table III), suggesting that these 87 Piedmont watersheds were experiencing similar year-to-year variability in interannual precipitation regimes. P_a and f_{cp} were not strongly correlated with other spectral runoff variables, including each other. None of the spectral precipitation variables were strongly correlated. There were no obvious latitudinal or longitudinal trends for any of the spectral runoff or precipitation variables.

Relationships between landscape and spectral hydrologic variables

Distributional properties. Inspection of distributional properties of dependent and independent variables showed only minor departures from normality, homoscedasticity, or

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linearity. The greatest departures were in homoscedasticity for S_c, Z_{br}, R_{pe}, *%FO*, and *%UR*; however, transformations to correct for heteroscedasticity resulted in increased nonlinearity or nonnormality. The only landscape variable that displayed possible nonlinear trends with spectral variables was S_c; however, log-transformations of S_c did not improve correlations significantly (16% at most) or consistently. Some log-transformations of S_c decreased the correlation coefficient. Consequently, transformations were not considered for statistical analyses.

Canonical correlation analysis. The results of the CCAs, contrasting separately the PSA variables for runoff and precipitation with landscape descriptors, showed that three of seven canonical correlations were significant for runoff (Table IVA) whereas two of seven were significant for precipitation (Table IVB). The levels of significance of the canonical correlations for precipitation were higher than expected, especially because of the greater variance associated with precipitation data (Figure 2) and overall lower values for spectral slopes (Table III). The higher than expected canonical correlations for precipitation may be due to an overfit by CCA (Friederichs and Hense, 2003) and/or the climate properties that jointly produce landscape features and precipitation regimes such as drainage density (D_d) and precipitation effectiveness (R_{pe}) – two landscape variables with high weights on the first canonical correlate.

The results for runoff are more easily interpreted: The weight of PSA variables on the first canonical correlate was related to the slopes ($-\beta_0$ and $-\beta_{lf}$) and power (P_d) of the spectral response, whereas the second correlate was related to higher-frequency spectral properties (P_{cp} and $-\beta_{hf}$). The corresponding weights for the landscape variables indicate that the first canonical correlate for runoff is related to predominant subsurface processes (S_c, *%WW*, and *%FO*) and the second to predominant overland runoff (*%UR* and Z_{br}). Notably, P_a and f_{cp} were not significantly related to any of the canonical correlates, indicating that these variables are relatively independent of landscape attributes.

Table IV. Canonical correlation relating ten landscape descriptors against seven spectral variables for runoff (A) and precipitation (B)

Dimension	Canonical correlation	F	df_1	df_2	p
A: runoff					
1	0.818	3.22	70	391.7	<0.0001
2	0.726	2.27	54	346.2	<0.0001
3	0.540	1.57	28	299.2	0.02
4	0.493	1.28	18	250.2	0.07
B: precipitation					
1	0.730	2.45	70	391.7	<0.0001
2	0.689	1.96	54	346.2	0.002
3	0.506	1.34	40	299.2	Ns
4	0.426	1.11	28	250.2	Ns

Dimension refers to the sequential numbering from most to least important of the canonical correlations (only the first four of seven dimensions are shown). The canonical correlations are the estimated linear relationships between landscape and spectral variables. The F ratios were estimated by Wilks' likelihood ratio, testing the null hypothesis of no relationship; df_1 and df_2 are the degrees of freedom for the F ratio, and p is the level of significance.

Stepwise and bivariate regressions. A level of entry into the stepwise model of $p < 0.05$ was selected to minimize the inclusion of variables with low explanatory power, which lowered the overall coefficient of determination (r^2) for each model. Nevertheless, the identified dominant landscape attributes explained much of the variability in the spectral variables (Table V) with two exceptions: P_a ($r^2 = 0.18$) and f_{cp} ($r^2 = 0.20$), which was also shown by CCA to be not strongly correlated to landscape attributes. Of the remaining five spectral runoff variables, land cover was the only landscape attribute that appeared in every stepwise model. *%WW* was the primary independent variable for three of the five regression models. The landscape variables *%FO*, *%UR*, *%AG*, S_c, and *RS%* also appeared in stepwise models. The landscape variables that did not appear in any of the five stepwise models (P_a and f_{cp} excluded) were D_d, R_f, *SC%*, Z_{br}, and R_{pe}.

Land cover effects on spectral runoff patterns

Rivers respond to global climatic forcing that result in common seasonal hydrologic responses for rivers in the same physiographic region (Tessier *et al*., 1996; Sabo and Post, 2008). However, the local environmental conditions of the watershed will also influence hydrologic responses and, in some cases, can be the dominant control (Phillips, 2007). In this study, we analysed hydrologic responses of watersheds from the same physiographic province in an attempt to minimize variation in climatic and geomorphic factors and thus maximize our ability to evaluate the effect of land cover on hydrologic patterns.

When watersheds were separated into dominant land cover, distributions varied considerably for five of the

Table V. Stepwise regressions (forward selection, $p < 0.05$) and bivariate correlations of spectral runoff variables on landscape descriptors

Spectral variable	Step	Landscape variable	Multivariate sequential r^2	Bivariate r
P_d	1	*%WW*	0.22	−0.47***
	2	*%FO*	0.35	−0.41***
	3	S_c	0.40	0.38***
	4	*%UR*	0.44	0.34**
	5	*%AG*	0.48	0.15
P_a	1	*%WW*	0.18	0.42***
$-\beta_0$	1	*%WW*	0.32	0.56***
	2	S_c	0.42	−0.49***
	3	*%FO*	0.51	0.38***
P_{cp}	1	*%UR*	0.21	0.45***
	2	*RS%*	0.29	−0.33**
f_{cp}	1	R_{pe}	0.15	−0.39***
	2	*RS%*	0.20	0.23*
$-\beta_{lf}$	1	*RS%*	0.21	0.46***
	2	*%UR*	0.34	−0.41***
	3	*%WW*	0.40	0.37***
$-\beta_{hf}$	1	*%WW*	0.33	0.57***
	2	S_c	0.43	−0.50***
	3	*%FO*	0.49	0.33**

Level of significance for bivariate relationships is indicated as follows: $^*\alpha < 0.05$; $^{**}\alpha < 0.01$; $^{***}\alpha < 0.001$.

spectral runoff variables (P_d, $-\beta_0$, $-\beta_{hf}$, $-\beta_{lf}$, and P_{cp}), but only minimally for P_a and f_{cp} (Figure 3). The Steel–Dwass test ($q^* = 2.569$, $\alpha = 0.05$) showed that the only significant difference among dominant land covers for P_a was a marginal one where UR ranked less than MX ($p = 0.045$) and FO ($p = 0.047$). For f_{cp}, AG ($p = 0.008$) and UR ($p = 0.026$) ranked slightly less than FO. Overall, UR had significantly higher values of P_d and P_{cp} than all other dominant land covers, with p-values less than 0.004 for all tests. UR significantly differed from FO for all spectral runoff variables and differed from MX for all variables except f_{cp}. UR and AG had significantly different values for P_d ($p < 0.001$), $-\beta_0$ ($p = 0.045$), P_{cp} ($p < 0.001$), and $-\beta_{lf}$ ($p < 0.001$), but not for $-\beta_{hf}$. AG and FO were significantly different for P_d ($p = 0.036$), $-\beta_0$ ($p = 0.001$), and $-\beta_{hf}$ ($p < 0.001$). AG and MX were also significantly different for $-\beta_0$ ($p = 0.017$) and $-\beta_{hf}$ ($p = 0.001$), but not P_d. FO and MX were not significantly different for any of the spectral runoff variables.

The ranking of importance between spectral–landscape relationships produced by stepwise regressions showed that the coverage of wetlands (%WW) and urban areas

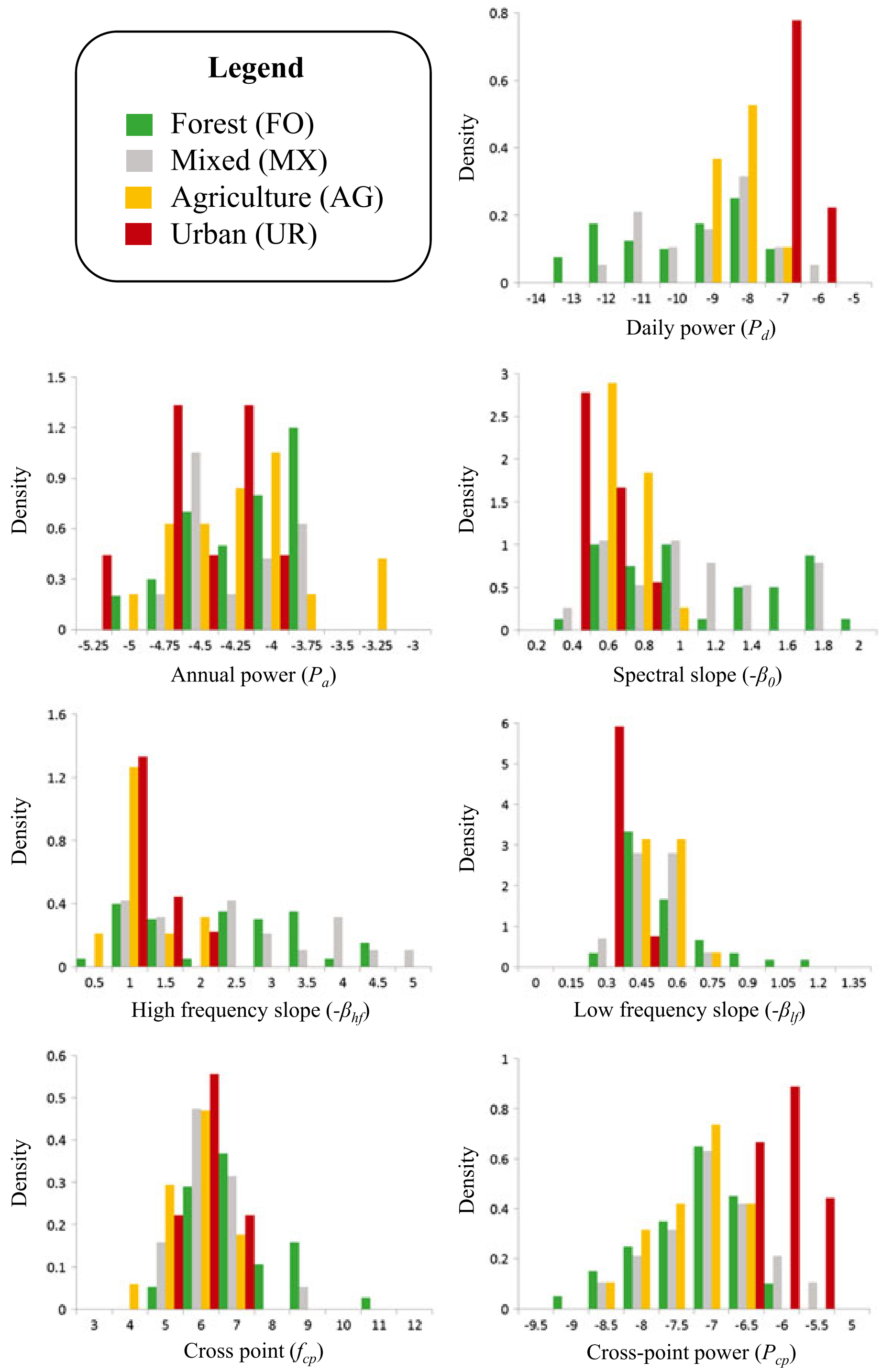

Figure 3. Distributions of spectral runoff variables among watersheds grouped by dominant land cover (>50% coverage). Watersheds without a dominant land cover are labelled mixed

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(*%UR*) had the strongest association with patterns of runoff (Table V). These two land cover types have competing hydrological effects because wetlands and other surface water features increase hydrologic storage whereas the sealed surfaces of urban areas decrease water storage (Eshleman, 2004; Schoonover *et al.*, 2006). Indeed, watersheds with high values of *%WW* displayed greater hydrologic memory whereas watersheds with high values of *%UR* had the opposite effect, as shown by strong positive correlations between *%WW* and $-\beta_{\mathrm{hf}}$ ($r = 0.57$) and strong negative correlations between $-\beta_{\mathrm{lf}}$ and *%UR* ($r = -0.41$). In sum, urbanization increased flow variance and decreased watershed hydrologic memory.

In addition to land cover, two other landscape variables had strong relationships with short-term hydrologic memory ($-\beta_{\mathrm{hf}}$), both of which are directly related to the immediate transport of water runoff: As channel slope (S_{c}) increased, $-\beta_{\mathrm{hf}}$ decreased (i.e. steeper slopes carry away runoff faster, and thus less storage); and, as soil silt-clay content (*SC%*) increased, $-\beta_{\mathrm{hf}}$ decreased (i.e. lower infiltration capacity leads to greater surface runoff, and thus less subsurface storage). The respective order of these two landscape variables in bivariate relationships matches the order of influence these factors tend to have on short-term runoff patterns (Black, 1991).

Given that long-term memory in river runoff is influenced by the spatiotemporal aggregation of high-frequency events (Mudelsee, 2007), one may question why $-\beta_{\mathrm{lf}}$ and $-\beta_{\mathrm{hf}}$ were not equally affected by similar landscape attributes. Because PSA estimates the power associated with each period independently, the spectral slope for the low-frequency domain is only partially determined by the spectral slope for the high-frequency domain ($-\beta_{\mathrm{lf}}$ *vs* $-\beta_{\mathrm{hf}}$: $r = 0.49$). Therefore, factors that influence immediate transport of runoff following a rain event, such as S_{c} and *SC%*, do not have as strong of an influence on long-term hydrologic response estimated by $-\beta_{\mathrm{lf}}$. The three most important landscape variables affecting long-term hydrologic memory, as identified by the stepwise model for $-\beta_{\mathrm{lf}}$, were those related to long-term water storage: *RS%*, *%UR*, and *%WW*. For heavily urbanized watersheds (values of *% UR* > 40), $-\beta_{\mathrm{lf}}$ averaged only 0.22 – a value approaching that of white noise. The separate assessment of short-term and long-term memory of watersheds, made possible by the use of segmented regression methods, provides important insights into the change in hydrologic response associated with climatic *versus* landscape change.

It is surprising that reservoir storage (*RS%*) was not strongly related to the spectral slope for the high-frequency domain, $-\beta_{\mathrm{hf}}$. A possible explanation is that most dams in the Piedmont are small and did not alter hydrographs considerably (*RS%* averaged only $6.5\% \pm 10.8\%$). In watersheds with many and/or large dams, such as the Sacramento River basin (Singer, 2007), *RS%* becomes a dominant control on spectral hydrologic patterns, affecting both low-frequency and high-frequency measures. Similarly, Z_{br} and *SC%* were relatively homogeneous across the Piedmont watersheds and therefore did not emerge as dominant controls in any of the stepwise models. Because soil depth and composition have been shown to greatly affect water residence times (Sayama and McDonnell, 2009; Tetzlaff *et al.*, 2009b), these landscape variables can be important determinants of spectral hydrologic patterns of more physiographically diverse watersheds. Further, the moderate relief of the Piedmont constrains the range of topographic effects, resulting in S_{c} playing a relatively minor role in shaping hydrologic patterns. In more mountainous regions, such as the nearby Ridge and Valley province, topographic controls will likely emerge as dominant controls on hydrologic patterns (McGuire *et al.*, 2005; Tetzlaff *et al.*, 2009a).

The effect of temporal changes in land cover on runoff patterns was not assessed in this study, although 'modest' changes did occur (Appendix A). The changes in our 87 Piedmont watersheds roughly matched those of other analyses in the region (Griffith *et al.*, 2003), which found that between 1973 and 2000, *%UR* increased by 5%, accompanied by a 4% decrease in *%FO* and a 1% decrease in *%AG*. Water and wetland coverage remained virtually unchanged during this period. These temporal changes likely accounted for some of the variability in our relationships. By combining the techniques described in this paper (including PSA) with ones that incorporate changing flow regimes (e.g. Richter *et al.*, 1996), perhaps we will be able to understand both spatial and temporal consequences of land cover change on hydrologic patterns.

Runoff pattern responses to urban thresholds

There were clear and statistically significant thresholds of change (as identified by segmented linear regression) in three of the spectral runoff variables when regressed against *%UR* (Figure 4). The most distinct threshold was in the relationship between P_{d} and *%UR* at 10.6 ± 6.8 *% UR*. Above this threshold, P_{d} was highly correlated to *% UR* ($r = 0.67$) but weakly correlated below ($r = -0.20$). Thresholds also existed for P_{cp} (13.2 ± 4.7 *%UR*) and $-\beta_{\mathrm{lf}}$ (14.4 ± 3.5 *%UR*). These thresholds over the range of 10–15 *%UR* indicate that low levels of urban development had little effect on runoff properties, but further increases in urbanization caused predictable increases in spectral power (P_{d} and P_{cp}) and a predictable decrease in long-term hydrologic memory ($-\beta_{\mathrm{lf}}$), which approached white noise levels (i.e. no memory) near 100 *%UR*. A similar but inverse relationship existed between these three spectral variables (P_{d}, P_{cp}, and $-\beta_{\mathrm{lf}}$) and *%FO*: 55.9 ± 4.3, 46.6 ± 4.5, and 46.1 ± 3.6 *%FO*, respectively. Once watersheds lost half of their forest, runoff became flashier, and hydrologic memory decreased in a predictable fashion.

The consistency of these urban thresholds suggests that once a Piedmont watershed exceeds 10% urban coverage, runoff patterns become progressively dominated by the watershed's impervious surface coverage. Stream ecosystem studies have also reported that stream biota exhibit threshold responses at 10–15% levels of watershed imperviousness (Paul and Meyer, 2001; Wang *et al.*, 2001; Roy *et al.*, 2003; Utz *et al.*, 2009), possibly linked

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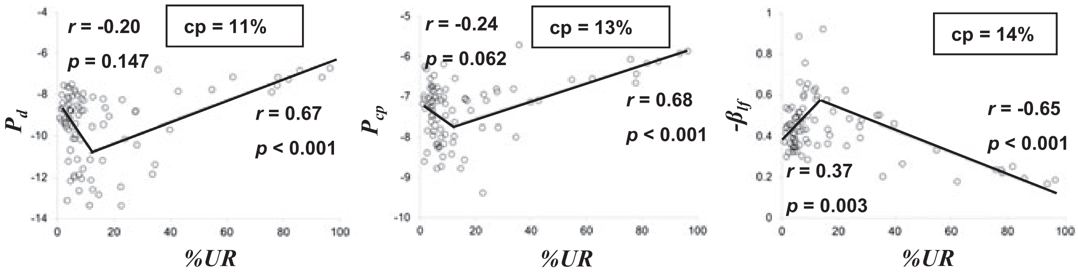

Figure 4. Urban land cover thresholds in spectral runoff variables. Thresholds (i.e. cross-points, cp) were identified using segmented linear regression. Correlation coefficients (r) and p-values are given for linear regressions below and above the cross-point

to hydrological responses. Indeed, hydrogeomorphic thresholds have also been found at 10% watershed imperviousness (Booth and Jackson, 1997). Threshold responses in runoff processes, like those illustrated earlier, are a common occurrence (Zehe and Sivapalan, 2009). If land cover threshold effects were incorporated into hydrologic models, a considerable amount of uncertainty may be reduced. Further, the increasing levels of global deforestation and urbanization makes the estimation of land cover thresholds for hydrological responses a priority.

Runoff patterns across stream orders

None of the spectral precipitation variables varied significantly with stream order (Figure 5), which is expected given that all of our watersheds were within the same physiographic province and precipitation records are point measurements. Conversely, all of the spectral runoff variables assessed in this study, except f_{cp} and P_a (the two variables least affected by landscape attributes), displayed trends with stream order (Figure 6). Of the remaining five spectral runoff variables, all displayed a similar trend where they remained approximately equal for stream orders 1 through 3. After the third order, runoff variance (P_d and P_{cp}) decreased and hydrologic memory ($-\beta_0$, $-\beta_{lf}$, and $-\beta_{hf}$) increased, all fairly linearly. A combination of Wilcoxon (between orders 1–3 and orders 4–7) and Steel–Dwass (among all pairs) tests confirmed all of the aforementioned relationships.

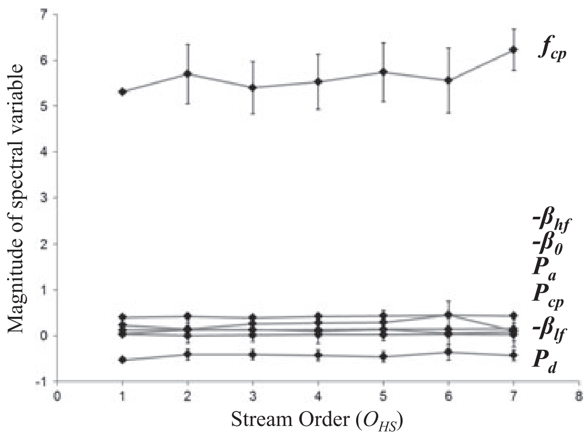

Figure 5. Trends in spectral precipitation variables with stream order for all 87 watersheds. Points represent mean values for the respective stream order, with error bars representing one standard deviation. Variable names are listed in order of their mean value at the seventh order. Note that none of the variables have a trend with stream order

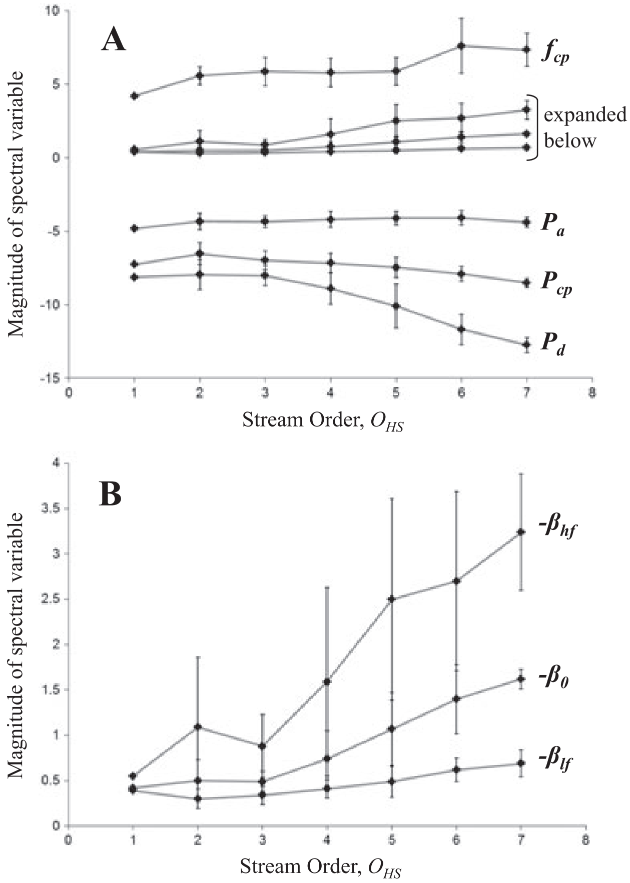

Figure 6. Trends in spectral runoff variables with stream order for all 87 watersheds (A) and expanded axis for spectral slope variables (B). Points represent mean values for the respective stream order, with error bars representing one standard deviation

Watershed area was highly correlated to O_{HS} ($r = 0.94$; $\log A = 0.904 + 1.188 * O_{HS}$). Accordingly, the watershed area that corresponds to the third-order landscape threshold in the Piedmont is approximately 87 km^2.

An enduring question in hydrologic theory that has yet to be answered is at what spatial scale do watershed processes become dominant over precipitation patterns (Sivapalan, 2003; McDonnell *et al*., 2007; Hrachowitz *et al*., 2010). Keeping in mind that PSA measures the effect of each period independently and that we used area-normalized discharge in our analyses, we show in our results (Figure 6) that the scale where watershed processes begin to dominate hydrologic patterns (at least for the Piedmont) exists between stream orders 3 and 4. If the influence of watershed processes on spectral runoff patterns was negligible, then

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spectral properties would be solely related to precipitation patterns and would not change appreciably with stream order, as was the case for the first to third orders and as evidenced by Figure 5. We contend that these trends are not just artefacts of fast-responding processes (overland flow, preferential flow, etc.) *versus* slow-responding processes (groundwater flow). If this was the case, the longitudinal trends would have been gradual and would not have exhibited a 'switch' after the third order, and this 'switch' would have only occurred for spectral variables characterizing short-term (<6 days) events.

We do acknowledge, however, that runoff becomes more serially correlated in the downstream direction simply because water in larger watersheds takes longer to move through the system compared with that in smaller watersheds, a result supported by previous studies (Gupta *et al.*, 1994; Chetelat and Pick, 2001; Mudelsee, 2007). The difference in rates of change with stream order between P_{d} and P_{cp} is evidence of this effect and suggests that weekly flow variability (P_{cp}) is less scale dependent than daily flow variability (P_{d}). Similarly, the higher rate of change with stream order for $-\beta_{\mathrm{hf}}$ compared with that for $-\beta_{\mathrm{lf}}$ supports the conclusion that hydrologic memory for high-frequency flow events is more scale dependent.

The change in spectral runoff properties with stream order supports Mudelsee's (2007) hypothesis that hydrologic memory increases in the downstream direction; however, we caution that such relationships may only apply when land cover and reservoir storage do not change greatly across the watershed. In watersheds where the spatial distribution of land cover and reservoir storage vary considerably, these longitudinal trends may not be evident. Consequently, the arrangement of land cover within a watershed can have considerable influence on hydrologic patterns (Sayama and McDonnell, 2009; Mejia and Moglen, 2010). The design of this study did not allow us to assess the effects of spatial heterogeneity, which for some of the larger watersheds was relatively high (Figure 1).

Spectral metrics for a hydrologic signature

The following criteria were used to select a subset of spectral variables to represent the hydrologic signature (i.e. metrics that characterize runoff patterns): (i) two variables that characterize low-frequency events, one dictated by precipitation and the other more influenced by landscape attributes; (ii) two variables that characterize high-frequency events, one dictated by precipitation and the other more influenced by landscape attributes; and (iii) selected variables that were minimally correlated with one another. Of the seven spectral variables analysed, the variables that best satisfied these conditions were P_{a}, f_{cp}, $-\beta_{\mathrm{lf}}$, and $-\beta_{\mathrm{hf}}$ (Figure 7). P_{a} reflects interannual precipitation consistency (low frequency), and f_{cp} indicates rainstorm recurrence interval (high frequency). Both of these variables were minimally correlated to landscape attributes. The variables $-\beta_{\mathrm{lf}}$ and $-\beta_{\mathrm{hf}}$, which reflect watershed hydrologic memory of low-frequency and high-frequency events, respectively, were both significantly correlated to landscape features, particularly those responsible for water storage.

	Precipitation-influenced	Landscape-influenced
Low frequency	P_a	$-\beta_{lf}$
High frequency	f_{cp}	$-\beta_{hf}$

Figure 7. Spectral runoff metrics to characterize hydrologic signatures of watersheds. None of the four variables are strongly correlated

The usefulness of f_{cp} for hydrologic signatures is that it characterizes rainstorm frequency (without needing precipitation data) and thus is a first-order indicator of hydrologic variability over short timescales, whereas P_{a} is an indicator of hydrologic variability over longer timescales. The spectral slopes, $-\beta_{\mathrm{lf}}$ and $-\beta_{\mathrm{hf}}$, summarize the effects of landscape attributes on runoff regimes over the entire flow record (both long and short terms) and thus provide a measure not only of runoff variability but also of runoff magnitude, intensity, and duration. When all four spectral variables are considered, precipitation–landscape interactions can be assessed over a wide range of scales.

CONCLUSIONS

Rivers are integrators of landscape processes, with the quantity and quality of water released at the watershed outlet reflecting all that has happened within the watershed. Although the effects of geomorphology and land cover on watershed runoff are generally understood (Oudin *et al.*, 2008), clear quantitative relationships between watershed structure and hydrologic patterns have yet to be established for large heterogeneous watersheds. Moreover, physics-based hydrological models that work at small scales have been of limited use for predicting broad-scale dynamics of large watersheds (McDonnell *et al.*, 2007). Consequently, 'our ability to make predictions at the watershed scale has advanced relatively little' (Sivapalan, 2003).

Despite the fact that each landscape has an inherent uniqueness (Phillips, 2007), there remains a need to develop macroscale laws for watersheds (Dooge, 1986; McDonnell *et al.*, 2007). PSA is a useful tool in this regard as it captures both periodic and stochastic variability of stream flow. By combining hydrologic and landscape data for 87 watersheds over a wide range of sizes, we were able to identify significant relationships between the spectral properties of runoff and landscape descriptors, including threshold behaviours and trends across seven orders of watersheds. Limiting the assessment of watersheds to the Piedmont of the eastern USA minimized variations in physiography, which allowed a more precise analysis of the effects of land cover on hydrologic patterns.

Dooge's (1986) vision of multiscale hydrologic laws that describe the relationship between landscape properties and watershed response is still unfulfilled. However, this study has made several important steps towards this goal. First, we found a characteristic frequency (6 days in this case) below which synoptic weather conditions dominate runoff patterns (Figure 2). Other studies in vastly different systems have found similar cross-point frequencies (Tessier *et al*., 1996; Pandey *et al*., 1998). Second, we were able to show that land cover has important, and predictable, effects on runoff patterns across all periods (Tables IV and V; Figure 3) – an effect that was only revealed by consideration of watersheds within a single physiographic region. Third, we identified urban coverage thresholds that produced significant changes in runoff patterns (Figure 4). Fourth, we found the watershed scale (third order) at which watershed processes likely become dominant over precipitation regime in determining runoff patterns (at least for the Piedmont physiographic province), as evidenced by the change in trend of spectral runoff variables after the third order (Figure 6). Finally, we present a matrix that characterizes the hydrologic signatures of rivers on the basis of precipitation *versus* landscape effects and low-frequency *versus* high-frequency events (Figure 7).

The concepts and methods presented in this manuscript can be generally applied to all river systems to characterize temporal patterns of watershed runoff, especially those associated with climatic and land cover change. We suggest that further studies use these concepts and methods to aid in the development of a greatly needed broad-scale watershed classification (McDonnell and Woods, 2004). Indeed, many of the questions we addressed are those that have been proposed to develop an effective watershed classification (Wagener *et al*., 2007; Sawicz *et al*., 2011).

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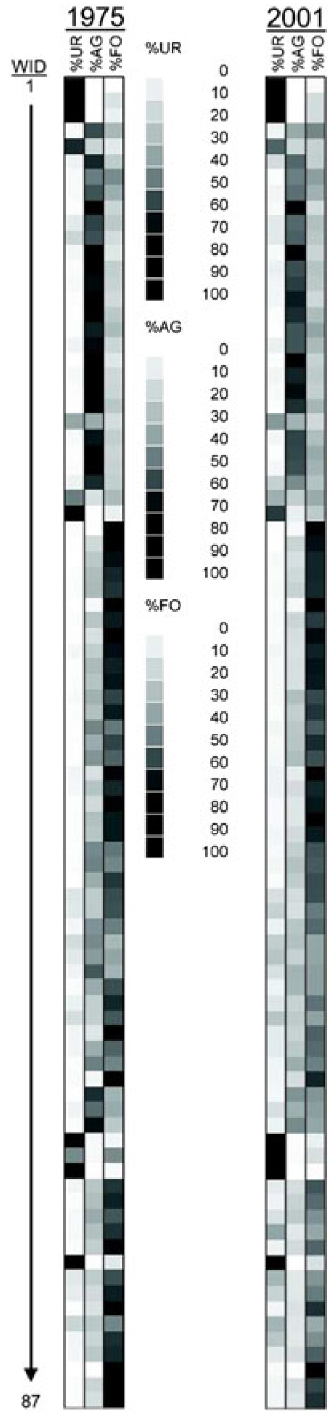
APPENDIX A



Land cover changes among the 87 study watersheds 1975–2001. Watershed ID increases from north to south, where 1 is the northernmost watershed (Figure 1). Dominant land cover is the one that exceeds 50%, or mixed when none exceed 50%.

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