Dry, drier, driest: Differentiating flow patterns across a gradient of intermittency

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Abstract

Intermittent streams exhibit regular patterns of drying and are widespread, but the patterns of drying between geographically close streams are not fully understood. We compared annual patterns of flow and drying among ten intermittent streams within a single drainage basin and determined how traditional hydrologic metrics described variation between streams. We installed stream intermittency sensors and evaluated stage height using low-cost methods. We evaluated landscape factors as potential drivers of flow patterns. Intermittent streams varied based on both high and low flow metrics, driven by a variety of landscape level factors, especially watershed size. Additionally, we compared the observed flow regimes within our system with an established soil and water assessment tool, finding that modeled streamflow patterns generally underrepresented observed drying within the system.

INTRODUCTION

Intermittent streams are closely tied to local climate and geology and reflect the hydrologic cycle within their watershed (Baker et al. 2004). Intermittent streams are naturally dynamic systems that often follow periodic cycles of drying and wetting (Arthington et al. 2014). Intermittent streams may fully dry, but often retain isolated pools during low flow periods (Busch et al. 2020). Intermittent streams are common and critical components of aquatic ecosystems that occur across most biomes and are estimated to account for up to 60% of the length of all defined stream channels (Larned et al. 2010; Datry et al. 2014; Costigan et al. 2016; Messager et al. 2021). Due to climate change, intermittent streams will likely become more widely distributed and many will likely dry for longer periods of time as precipitation patterns shift (Larned et al. 2010; Jaeger et al. 2014; Costigan et al. 2016; Zipper et al. 2021; Datry et al. 2022).

Despite drying for parts of the year, intermittent streams support diverse and complex community assemblages (Meyer et al. 2007, Datry et al. 2016), are valuable components of aquatic ecosystems (Colvin et al. 2019), play a role in the persistence of fishes by providing seasonal habitats (Vander Vorste et al. 2020), transport nutrients and material (von Schiller et al. 2017) and support terrestrial biodiversity (Sánchez-Montoya et al. 2022). The availability of habitats and resources provided by intermittent streams is variable within and between water years, influencing community dynamics (Fausch and Bramblett 1991) and driving patterns of community structure (Olden and Kennard 2010). Moreover, intermittent streams provide valuable habitat for native species and contain variable community compositions compared to perennial streams (Rogosh and Olden 2019). For example, wet season habitats can provide complementary habitats for different life stages of aquatic organisms (Labbe and Fausch 2000) and increase connectivity and therefore colonization rates (Franssen et al. 2006). In contrasts, during summer drying, fish communities shift as intermittent systems reduce to isolated pools, whether by reducing as conditions harshen, or by as available habitat shrinks (Capone and Kushlan 1991; Pires et al. 1999; Taylor and Warren 2001; Hopper et al. 2020). The longer a no-flow period persists, the more potential exists for long-lasting impacts on the aquatic community, as no-flow periods represent a significant disturbance (Poff et al. 1997).

While both high- and low-flow conditions are integral aspects of the flow regime (Poff et al. 1997), low-flow conditions such as no-flow duration, dry-down period and no-flow timing drive intermittent stream ecology (Poff et al. 1997; Olden and Poff 2003; Zipper et al. 2021). Ecologically relevant low-flow conditions can also be described by simple classifications such as whether or not a stream fully dries or dries to isolated pools, and what proportion of time the stream spends in each state (Gallart et al. 2017). The temporal and spatial components of low flow hydrology are closely linked and require understanding of both physical and anthropogenic factors (Smakhtin 2001). Climatic patterns, ground water, water table interactions, geology, and watershed shape, structure and size are all key components influencing low flow periods (Smakhtin 2001, Snelder and Biggs 2002, Hammond et al. 2020). At relatively fine spatial scales, geology and land use characteristics may be stronger drivers of flow patterns than climate (Snelder and Biggs 2002, Ssegane et al. 2012). Geology can impact stream flow through groundwater storage, recharge characteristics and flow capabilities (Mwakalila 2003). Anthropogenic alterations may also influence stream intermittency patterns, with changes in land cover influencing timing and magnitude of flow patterns, especially in regard to flow variability and low flow periods (Ficklin et al. 2018; Datry et al. 2022).

A wide range of metrics have been developed and used to characterize the flow regime and compare variations in hydrologic patterns across space and time. Many of these metrics are simple calculations that correspond to ecologically important aspects of flow, are often highly correlated (Smakhtin 2001), and serve to represent the complexity of a riverine system (D'Ambrosio et al. 2017). Olden and Poff (2003) examined 171 hydrologic indices to evaluate informativeness, redundancy and ecological importance and concluded intermittent flow regimes are best characterized by unique indices in comparison to more stable systems. The time scale at which flow patterns exist is highly variable, from hours to years, potentially requiring long-term observation to fully quantify variability (Poff et al. 1997; Richter et al. 1997; Leasure et al. 2016). Many streams have established, long-term monitoring in the form of gauging stations, such as those maintained by the United States Geological Survey (USGS), providing accurate discharge data (Falcone 2011). However, stream gauges are often not suitable for highly dynamic stream systems, and alternate data collection techniques have met varying levels of success (Blasch et al. 2004). Additionally, most intermittent streams are not gauged (Eng et al. 2015), limiting readily available long-term flow data.

Evaluating flow conditions in the absence of stream gauge data can be analytically and conceptually difficult, but is important given the increased interest in intermittent streams (Sivapalan 2003; Datry et al. 2016; Zipper et al. 2021) and in understanding how hydrology and hydrologic indices predict ecological patterns and processes (Clausen and Biggs 2000; Meyer et al. 2007; Booth and Konrad 2017). One approach to quantify dry periods of intermittent streams is to use water temperature data, which can be subject to interpretation (Blasch et al. 2004; Sowder and Steel 2012). Another technique is to model streamflow using nearby gauged streams, a data intensive methodology that may miss inherent variation between stream segments (Black 1972; Mwakalila 2003; Zimmer et al. 2020). Spatial scale is an integral aspect of flow modeling, as conditions between nearby streams can be highly variable, often as a result of local precipitation (Yuan 2013). The Soil and Water Assessment Tool (SWAT) is a widely used model for evaluating streamflow characteristics and potential changes in flow regime, predicting streamflow patterns and soil or nutrient transport from various processes including climate, hydrology, vegetation, management and precipitation (Cibin et al 2014; Gassman et al. 2014; Jajarmizadeh et al. 2015). In ungauged systems, SWAT models may not represent flow patterns accurately (Qi et al. 2020) and can be difficult to calibrate and validate due to a lack of empirical data (Sivalapalan et al. 2003; Beven and Smith 2015). Regardless, there is a need for low-cost techniques to monitor ungauged intermittent streams (Blasch et al. 2004; Chapin et al. 2014) to better understand the link between stream drying and ecological responses.

Our objective was to describe patterns of drying, rewetting, and flow variability across a gradient of intermittency at ungauged streams. We used two low-cost techniques to identify drying extent (*e.g.,*completely dry, isolated pools, or retain connectivity) and quantify metrics describing the flow regime of intermittent streams (timing, duration, magnitude, rate of change, and frequency of high and low flow events). In addition to describing ecologically relevant flow metrics that can be derived from low-cost field methods, we also identified landscape and geophysical drivers of stream intermittency and hydrologic variability. We hypothesized watershed size and slope would be primary drivers of intermittency, with smaller and steeper watersheds exhibiting earlier and more frequent periods of no-flow. We aim for the field methods, hydrologic metrics, and observed variability in stream drying described in this paper to help initiate larger efforts to monitor hydrologic variability of intermittent streams.

METHODS

Study Area and Site Selection

We quantified attributes and drivers of stream drying in the Ouachita highlands of southeastern Oklahoma. We chose this ecoregion because the hydrology remains relatively unaltered (Fox and Magoulick 2019). Ouachita highland streams are generally high gradient and clear, with rocky substrates and riffle-pool morphology (Geise et al. 1987). Within the Ouachita mountains, more than 58% of total stream length is made up of headwater streams and 17-81% of total stream length is intermittent, as streams may be simultaneously classified as both intermittent and headwater (Nadeau and Rains 2007). Hydrology is driven by precipitation runoff with little groundwater influx and streams typically dry in the summer (Giese et al. 1987; Williams et al. 2002; Leasure et al. 2016). The Oklahoma Mesonet site located in Mt. Herman reports 1310.64 mm of average annual precipitation over the 30-year period from 1991-2020 (Oklahoma Climatological Survey, Mt. Herman, OK, 2023).

Recent flow classification schemes described headwater streams in the Ouachita Mountains as being dominated by intermittent flashy and intermittent runoff regimes, where stream flows closely mirror precipitation events and exhibit regular no-flow days, thus allowing for predictions of local flow characteristics (Leasure et al. 2016; Fox and Magoulick 2019). Intermittent flashy flow regimes are predicted to exhibit drying for 1 to 3 months annually and occur in small drainage areas, while intermittent runoff regimes are predicted to have 14-50 no-flow days annually and occur in slightly larger drainage areas (70-622 km^2) (Leasure et al. 2016). Streams generally exhibit drying patterns from early summer through the fall and have a period of elevated baseflow during the wetter winter months (Eng et al. 2015).

We selected 10 sites on 10 unique stream segments within the Glover River basin, a north-south free-flowing (undammed) tributary of the Little River in McCurtain County, Oklahoma (Figure 1). Each site consisted of a representative riffle and pool (in sequence). We selected sites along a hypothesized intermittency gradient based in part on the flow regime classifications of Leasure et al. (2016), watershed area, and stream slope to capture a range of intermittency. The USGS maintains a stream gauging station on the mainstem Glover River (no. 07337900) downstream of the study area, and there are no other gauges within the basin.

Intermittency Evaluation

We modified Onset HOBO Pendant temperature and light data loggers (Model UA-002-64, Onset Computer Corp, Bourne, MA, USA) per the methods described by Chapin et al. (2014) to allow loggers to detect presence or absence of water. The modifications repurpose the light intensity circuitry to record a non-standardized conductivity measurement, which serves as a proxy for water presence. These modifications retain the original capacity of the logger to record temperature. One logger was placed in the deepest pool to capture potential periods of complete stream drying, while the other was placed a riffle to capture timing and duration of periods when the stream was at a no-flow state with limited connectivity among isolated pools.

We additionally measured stream depth in the same riffle as our data logger. A t-post marked at 0.1 m intervals was installed in the riffle, and a trail camera was placed nearby and set to take hourly photos of the t-post. Data loggers and camera data were collected from April 2022 through March 2023 to capture a complete annual cycle of the drying and rewetting stages of intermittency. We inspected sensors and cameras approximately every two months over the survey period, downloading data, replacing batteries, and repairing equipment as necessary.

Riverscape and Geophysical Drivers

Physical and geologic covariates we hypothesized drove variation in flow regimes were collected for each watershed (Table 1). We used the National Hydrography Database Plus Version 2 data layer in ArcGIS Pro (ESRI Redlands, CA) to obtain the slope of each stream segment, and the area and mean slope for the watershed upstream of each site. We used the USDA Web Soil Survey (NRCS 2023) for McCurtain County to calculate geological metrics for each watershed, including mean depth to water table and depth to impermeable layer, because groundwater inputs and geologic permeability exert influences on streamflow (Costigan et al. 2015; Bourke et al. 2021). Additionally, we calculated the percentage of each watershed that is forested, because vegetative type and cover influence water movement, water use and evapotranspiration patterns (Chappell and Tych 2012; Ellison et al. 2012). We imported a 2020 land cover type dataset from the LandFire database (LANDFIRE 2020) into ArcGIS Pro and determined the cumulative percentage of each watershed that was covered by any category of forest.

Analysis

We removed any days with missing data, which generally occurred because of equipment malfunctions, such as dead batteries or water damage. When possible, we used the redundancy of the stream sensors or camera data to fill in missing data gaps. Camera photos were used to measure stream flow depth to 0.05 m increments on an hourly time scale. We summarized each measurement on the daily scale, for example mean daily stage height, as an input in our calculations.

We selected five ecologically relevant and informative flow metrics encapsulating all five major components of a flow regime (Poff et al. 1997): (1) skew in daily stage or the mean daily stage divided by the median daily stage (magnitude), (2) Julian date of first no-flow day (timing), (3) number of no-flow days (duration), (4) high pulse count, where a pulse is defined as a flow event greater than 3 times the median stage (frequency), and (5) number of reversals, or when flow rates change from rising to falling or vice versa, (rate of change). For all flow metrics, we substituted stream stage, or the depth of water present as a suitable proxy for discharge (Booth and Konrad 2017). All metrics were calculated with the camera stream stage data and compared for consistency with sensor data where applicable. We considered a no-flow day to be any calendar day in which there was no flow observed (i.e., the riffle was dry, for the entire 24-hour period).

We compared the metrics among the nine sites to characterize variation across intermittent streams. We converted date of first no flow period to a Julian date and centered and scaled each of the flow metrics prior to analysis. To visualize differences among sites and the relative importance of each metric in describing variation across sites, we constructed a Principal Component Analysis (PCA) in the vegan package of R (Oksanen et al. 2022; R Core Team Version 4.2.2, 2022).

To explore the role of physical watershed characteristics on flow classifications (completely dry, isolated pools, or connected), we evaluated how four environmental covariates related with whether streams fully dried or dried to isolated pools. Stream segment slope and depth to restrictive layer were highly correlated (>0.65) with other covariates and were removed from all analyses. We evaluated the group means for this analysis, constructing boxplots to visualize differences among groups. We used a Mann-Whitney U Test to compare medians among groups.

We next explored the relationships between physical predictor variables (watershed area, mean slope, percent forested, and mean depth to water table) and flow metrics. Because this is an exploratory analysis and due to small sample sizes, we evaluated relationships among flow metrics and landscape variables by calculating correlation correlations for all combinations of metrics and covariates. When data was available, we used all ten sites to evaluate correlations, however only 9 sites had complete data for some variables.

HAWQS Models

We compared observed flow data to flow predictions obtained from the Oklahoma Hydrologic and Water

Quality System (HAWQS) model, a web-based tool using the Soil and Water Assessment Tool (SWAT) modeling framework, using standard settings for three drainages in the Glover River (EPA 2017). We selected only three drainages because their predetermined boundaries roughly aligned with our study sites (Figure 1). No data was available when field sampling occurred (2021-2022), so we used data from the Mt. Herman Mesonet site (Mesonet 2023) to select ten years (April through March) with similar (within 15%) total precipitation as our study period and ran the HAWQS model for each of those periods. We compared four hydrologic metrics (skew, number of no-flow days, high pulse count, and number of reversals) from the HAWQS output to our observed field data. We considered any day where the predicted flow was less than $0.01\mathrm{m}^3/\mathrm{s}$ to be a no-flow day and required a change of more than 10% of mean daily flow to be considered a reversal, in order to minimize the impact of negligible variation resulting from modeling processes.

RESULTS

The combination of intermittency sensors and images of stream stage allowed us to successfully characterize broad classifications of drying (completely dry, isolated pools, or connected; Figure 2). We captured a full gradient of stream drying, including one site that maintained connectivity, five sites that dried to isolated pools, and four sites that fully dried. The extent of drying was variable across a gradient of watershed area (stream size), with one intermediate sized watershed maintaining connectivity, while the two largest watershed areas dried to isolated pools. Due to a damaged camera, we were unable to calculate flow metrics associated with stage height at one site.

Variation in Hydrologic Metrics

PCA analysis indicated the five flow metrics were highly variable across the observed intermittency gradients (Figure 3). Because we were focused on describing the broad patterns of variation between hydrologic metrics and sites, we opted to primarily interpret the first two PCA axes (Table 3). The first PCA axis explained 47.97% of variation, and was predominately driven by skew and pulse count, while the second PCA axis explained 39.13% of variation, and was driven by reversals, number of no-flow days, with some influence of reversals and the date of the first no-flow day. Sites that fully dried were negatively associated with reversals, pulse count and skew, and sites that dried to isolated pools were more positively correlated with these metrics. Each site had a relatively unique hydrologic signature, as evidenced by the variable impact of each flow metric on the locations of sites within the PCA. The relationships between drying regime (fully dry, drying to isolated pools, or remaining flowing) and the variability of our selected hydrologic metrics, underscores the variability of intermittent streams at small spatial scales.

Associations between Landscape Factors, Intermittency Classes, and Hydrologic Metrics

We observed moderate associations among environmental covariates and whether streams fully dried, or only dried to isolated pools (Figure 4), although none exhibited statistically significant differences (Table 4). Streams that fully dried had generally smaller watershed areas and lower slopes, and higher forested cover ratios.

Similarly, hydrologic metrics were only moderately associated with landscape factors (Table 5). Watershed area was correlated with metrics of skew (0.61), reversals (0.73) and pulse count (0.52). Reversals were correlated with watershed slope and water table depth, while pulse count was correlated with percent forest cover. Interestingly, low flow metrics were less correlated with landscape factors than metrics associated with flow variability and high flow.

Streamflow Models

For our small, highly variable intermittent streams, HAWQS models had moderate success at predicting flow patterns (Figure 5). Given the variability in annual precipitation between the modeled years and the field collected data, the HAWQS models predicted annual skew and high flow pulses reasonably well despite both variables being sensitive to precipitation patterns. However, the models underestimated the number of no-flow days and overpredicted the number of reversals.

DISCUSSION

Our low-cost field methods allowed us to calculate five flow metrics corresponding with potentially ecologically relevant aspects of the flow regime (Poff et al. 1997; Clausen and Biggs 2000). Demonstrating the capability of using low-cost and robust techniques in flashy systems is an important step towards monitoring and understanding the flow regime of intermittent streams. The use of redundant methods of stream flow measurement allowed us to collect variations in data inherent to each method, such as when sensors sat in small, isolated pools of water at substrate level, had residual water on the electrodes, or from high humidity levels. Additionally, the initial dates of first noflow period varied slightly between methods, likely for the same reasons. The sensor data produced significant advantages: data processing time was faster and less prone to error because no manual evaluation of stage height was required. The sensors also provided stream temperature data, which can be of high biotic importance, especially in intermittent streams experiencing extreme temperatures during drying. The methods presented in this study can be used to quantify variation in intermittent flow at other ungauged sites.

Current modeling strategies may not accurately or fully depict the flow regimes of small, highly variable watersheds. Predictions by the Oklahoma HAWQS model were within the range of what we observed in the field for some metrics but underestimated the number of no-flow days. The number of no-flow days is a simple, but ecologically and conceptually important metric describing stream drying (Poff et al. 1997; Olden and Poff 2003; Zipper et al. 2021). Prior calibrations of hydrologic models have reported varying success in calculations of hydrologic metrics, often overestimating low flow conditions (Kiesel et al 2017; Pool et al. 2017), a direct contrast to our observations, wherein the HAWQs models underestimated low flow conditions. Other observations in the region report levels and durations of stream drying consistent with our observations (Homan et al. 2005). Generally, our streams exhibited higher numbers of no-flow days than predicted in a localized framework developed by Leasure et al. (2016), implying that environmental conditions may be harsher than anticipated in Ouachita streams.

Watershed area, a measure of stream size, is often considered to be one of the defining variables in flow patterns. Larger streams typically have less extreme variations in flow, with lower relative extremes of both high and low flows (Chiang et al. 2002). Slope is also frequently regarded as an important driver of flow, given that slope plays a role in determining the speed at which water moves through a system, with steeper slopes more likely to shed water faster (Harr 1977; Paznekas and Hayashi 2016). We observed some of our strongest correlations between watershed area and slope with our flow metrics, however these relationships were surprisingly variable. Because the gradient of stream sizes included in our study was relatively narrow, other variables may be exerting strong influences on streamflow patterns, such as watershed and ecological processes (Snelder and Biggs 2002). The impact of the relatively fine spatial scale of this study may have also influenced the lack of significant links between land use or geological features and flow patterns. Landscape factors typically used to predict hydrology may not have varied enough within our study area to predict flow dynamics, however variability and high flow conditions may be better explained at the landscape level than drying trends. Our observed variability in hydrologic metrics and the relatively weak observed relationships among landscape factors and metrics highlight the challenge of predicting ecologically meaning measures of stream drying in small streams. However, we acknowledge the exploratory nature and small sample size in this study limited our ability to statistically detect strong relationships among landscape variables and hydrologic metrics. There is a need for more field observations of stream drying to understand drivers of variation in stream drying dynamics at intermediate spatial scales relevant to ecological process and land management.

In addition to watershed characteristics, climate maintains a well-established link with flow regime (Poff et al. 1997; Snelder and Biggs 2002; D'Ambrosia et al. 2017). Within runoff driven systems, such as the Glover River basin, local variation in precipitation likely serves as a driver of variation in stream drying, a pattern seen in other intermittent systems (Costigan et al. 2015). Southeastern Oklahoma is characterized by high intensity and short duration precipitation events, with two primary rainy seasons (Oklahoma Climatological Survey 2023). During the sampling period, we observed variation in local precipitation between adjacent drainages.

Variation in rainfall and hydrograph responses can shift within a storm, based upon storm direction, speed, movement patterns and watershed shape (Roberts and Klingeman 1970; Jensen 1984; Singh 1997). Given the relatively small area of our study extent, the scale of precipitation variability is somewhat surprising and difficult to account for. Measuring site-specific precipitation would be beneficial to further inform and understand the drivers of small intermittent streams.

Climate change projections for the region predict an increase in short duration, high intensity precipitation events, potentially less overall annual precipitation (Karl et al. 2009; Marion et al. 2013; USGCRP 2018), and increased drought potential (Strzepek et al. 2010). These projections will likely result in more frequent no-flow periods, interspersed with large high-flow events. Beyond the obvious risk of more streams completely drying in response to longer no-flow periods, longer drying events also stress aquatic organisms where isolated pools remain. In isolated pools, increased temperatures and decreased dissolved oxygen levels can pass lethal thresholds for aquatic organisms, leading to mortality for less tolerant species (Capone and Kushlan 1991; Hopper et al. 2020). More intense precipitation events may increase the intensity of disturbance, potentially impacting reproductive success of resident organisms (Humphries et al. 1999) or influencing community structure (Bernardo et al. 2003).

Long-term field observations of stream drying are needed to understand drivers of variation in stream intermittency. This study documents the ability to measure ecologically relevant hydrologic metrics, however long-term data would serve to smooth the inherent year to year variability in precipitation, both annually and between sites, and more accurately represent between-site variability in flow patterns (Poff 1997). Without long term flow data, hydrologic dynamics can be difficult to predict or model, limiting the applicability of environmental flow standards (Zhang et al. 2016). Our comparison of HAWQS model predictions to observed data support previous observations that current long-term stream gauges in the US can provide potentially misleading or flawed information about no-flow periods, highlighting the need for increased data collection of streamflow data in smaller, intermittent streams (Zimmer et al. 2020).

Both stream intermittency sensors and trail cameras can serve to provide valuable information about stream flow regimes. We successfully evaluated the five major aspects of the flow regime for a gradient of intermittent streams. These techniques readily allow for classification of flow regimes into three ecologically relevant categories, but given the small sample size, both temporally and spatially, identification of watershed level impacts on flow regime remains less clear. Within the Glover River basin, our ten streams exhibited flashy intermittent flow patterns, with variable signatures among systems. Although we found some evidence of watershed characteristics correlating with flow patterns, many of the other drivers of local flow regime remained elusive, potentially due to highly variable precipitation patterns. Evaluation of the selected hydrologic indices serves to underscore the highly variable nature of intermittent streams in Southeastern Oklahoma, and the difficulty in linking watershed scale factors with local flow regime.

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TABLES

Table 1: Variation in landscape variables for 10 intermittent streams in the Glover River basin, OK.

	Landscape Variable	**Landscape Variable**	**Landscape Variable**	**Landscape Variable**
Site	**Watershed Area (km^2)**	**Segment Slope**	**Watershed Slope**	**Forested Cover Ratio**
Jones Ranch	3.63	1.20	2.55	0.91
Beeman	4.32	1.27	1.54	0.90
Lebow Hollow	5.14	1.32	3.32	0.79
Shorty Cox	5.33	1.55	2.36	0.85
Rock	5.43	1.42	1.80	0.82
Whisky Branch	6.60	1.11	1.87	0.91
Shell Rock	8.36	1.31	1.89	0.99
South Carter	14.53	0.83	2.91	0.89
Middle Carter	27.37	0.45	2.56	0.76
Pine	36.25	0.48	1.46	0.74

Table 2: Calculated flow metrics for 10 intermittent streams in the Glover River basin of Southeastern Oklahoma, including data from both cameras and stream intermittency sensors. Due to missing data, only metrics that could be calculated using a combination of both methods were included for Rock Creek.

	Flow Metric	**Flow Metric**	**Flow Metric**	**Flow Metric**	**Flow Metric**
Site	**Dry Days**	**No-Flow Days-Camera**	**No-Flow Days-Sensor**	**Reversals**	**Pulse Count**
Jones Ranch	41	95	87	54	5
Beeman	77	105	94	60	7
Lebow	16	112	117	54	16
Shorty Cox	0	30	56	60	17
Rock	0	N/A	128	N/A	N/A
Whisky Branch	101	102	102	54	7
Shell Rock	0	119	145	58	15
South Carter	0	0	4	60	8
Middle Carter	0	90	104	64	16
Pine	27	106	117	44	5

Table 3: Eigenvalues and proportions of explained variance from a Principal Component Analysis (PCA), of five hydrologic indices describing the flow patterns of nine intermittent streams within the Glover River basin, OK.

	PC1	**PC2**	**PC3**	**PC4**	**PC5**
Eigenvalue	2.3984	1.9565	0.49913	0.10695	0.039034
Proportion Explained	0.4797	03913	0.9983	0.02139	0.007807
Cumulative Proportion	0.4797	0.8710	0.97080	0.99219	1.00000

Table 4: Group means and standard errors of hydrologic metrics for sites that dried to isolated pools or

fully dried, of intermittent streams in the Glover River basin, OK. Additionally included are results of a Mann-Whitney U Test comparing landscape metrics for intermittent streams that dried to isolated pools or fully dried, represented as p.

Landscape Variable	**Isolated Pools**	**SE**	**Fully Dry**	**SE**	**p**
Watershed Area (km^2)	16.49	14.39	5.00	1.30	0.18
Watershed Slope (%)	2.32	0.70	1.94	0.43	0.39
Forested Cover Ratio	0.83	0.10	0.88	0.04	0.71
Water Table Depth (cm)	102.79	41.35	98.83	43.03	0.27

Table 5. Correlation coefficients between five hydrologic metrics and landscape factors for intermittent streams in the Glover River basin of southeastern Oklahoma. Models with an asterisk were calculated with nine sites due to missing data, and the other correlations were calculated with ten sites. Bolded values indicate an absolute value above 0.50.

Hydrologic Metric	**Watershed Area**	**Watershed Slope**	**Forested Cover Ratio**	**Water Table Depth**
*Annual Skew**	**0.61**	-0.05	-0.47	0.10
*Reversals**	**0.73**	**-0.50**	-0.25	**0.73**
*Pulse Count**	**0.52**	0.13	**-0.61**	<-0.01
First No-Flow Day	0.21	0.38	-0.01	0.09
Total No-Flow Days	-0.48	-0.38	0.21	-0.08

FIGURES:

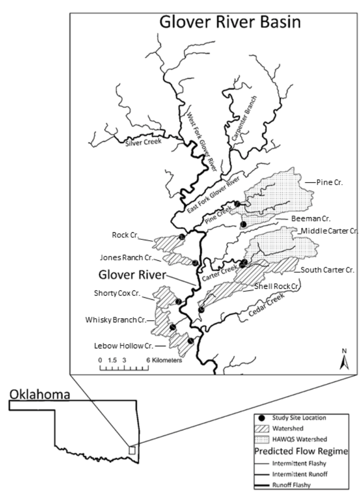

Figure 1: Map of the study area within the Glover River basin. Each study site and the associated watershed are depicted, and line thickness represents the predicted flow regime for each stream segment based on a regional scale (Interior Highlands) classification scheme (Leasure et al. 2016). Watersheds included in the HAWQS model are also included.

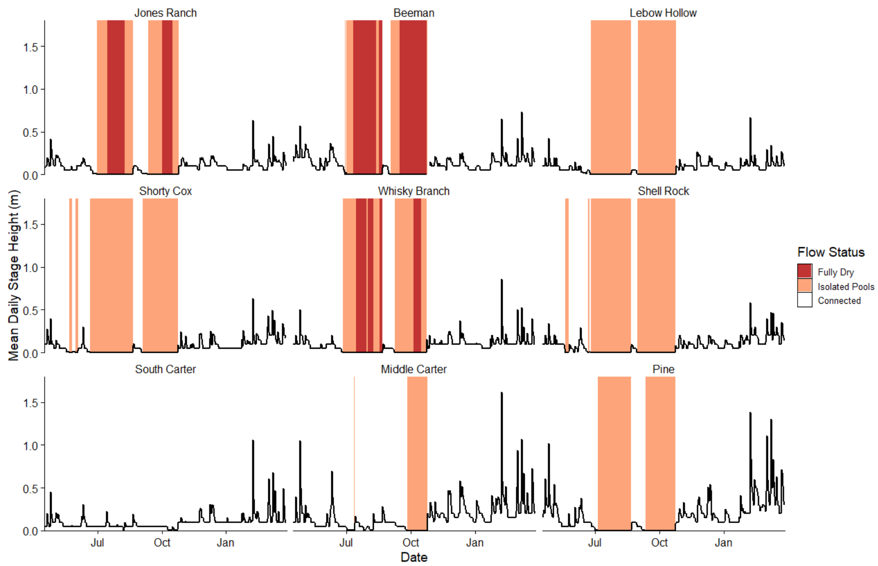

Figure 2: Hydrographs of measured stage height for nine intermittent streams in the Glover River basin, OK, showing periods of flow, no-flow, and fully dry stages for the period of April 2022 through March 2023. Sites are ordered from the smallest (Jones Ranch) to largest (Pine) watershed area.

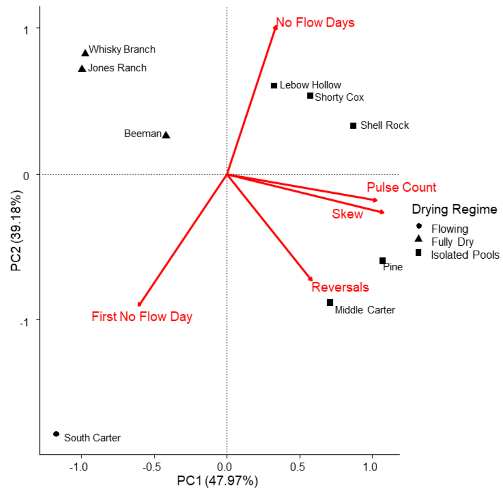

Figure 3: Principal Component Analysis (PCA) of nine intermittent streams within the Glover River basin, OK, and their relationships to five hydrologic indices.

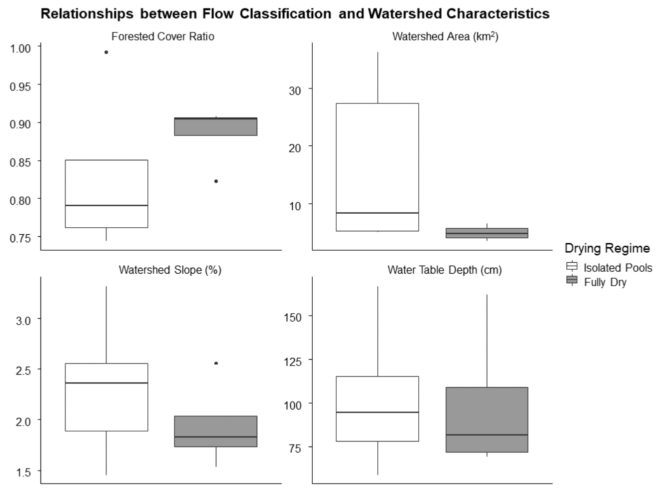

Figure 4: Boxplot displaying the variation in landscape factors for streams that fully dried or dried to isolated pools within the Glover River basin of Southeast Oklahoma (N=9).

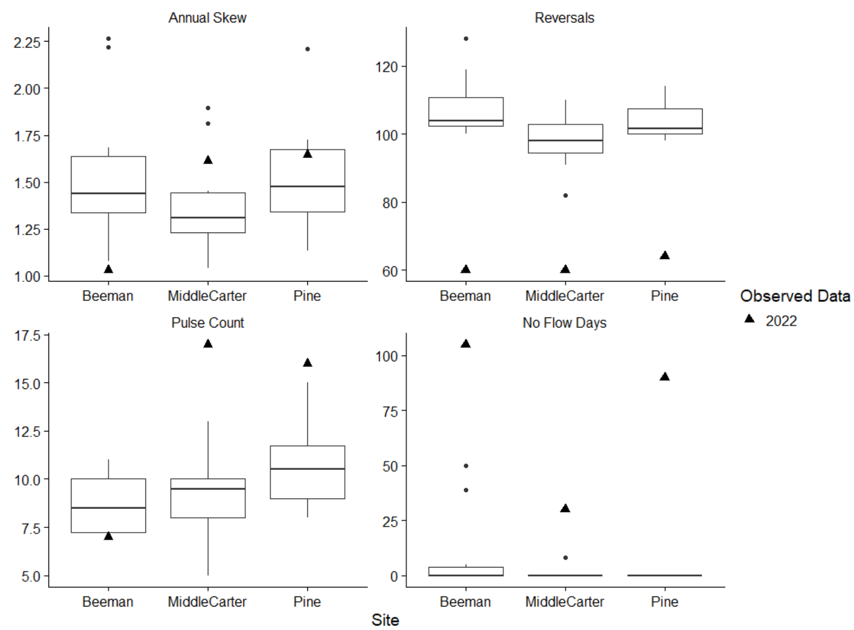

Figure 5: Comparison of SWAT model predictions based on 10 historic years with similar precipitation levels (boxplots) with observed field data (triangles) from three intermittent watersheds within the Glover River basin, OK.