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Citizen scientists document long-term streamflow declines in intermittent rivers of the desert southwest, USA

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Abstract: Intermittent rivers are spatially dynamic, expanding and contracting in response to changes in water availability, but studies that explicitly examine spatial drying patterns are scarce. We used long-term data produced by citizen scientists to map wet and dry reaches of 3 different river systems to investigate mechanisms producing temporal variation in drying patterns. We quantified the total wetted river length in each survey, and calculated ecologically scaled landscape indices that indicate the carrying capacity (population size) and habitat connectivity of large and small fish metapopulations in these systems. We found that the spatial extent of perennial water decreased over the study period in 2 of the 3 study rivers: ~26% in the Agua Fria River from 2008 to 2016, and ~14% in Cienega Creek from 2006 to 2016. We also observed an ~8% decline in habitat connectivity for large fish in the Agua Fria River. We used multivariate structural equation models to infer causal relationships between spatial drying patterns and temperature, precipitation, streamflow, and drought conditions. These models explained 85% of year-to-year variation in the total length of wet reaches, and 63 and 55% of year-to-year variation in habitat connectivity for large and small fish, respectively. With the US Southwest shifting to an even more arid climate, our results suggest that this may reduce habitat connectivity of fish populations in this region.

Key words: citizen science, intermittent river, drought, streamflow, river drying, fish, habitat connectivity, climate change

Intermittent rivers (fluvial landforms that cease to flow at some point in space or time) are globally widespread and occur in all climates and terrestrial biomes. Despite comprising up to 50% of total river length and being equally common as perennial (continuously flowing) rivers, intermittent rivers are understudied relative to perennial rivers (Nadeau and Rains 2007, Datry et al. 2014). Researchers are beginning to understand that intermittent rivers are ecologically and hydrologically different from perennial systems,

but considerable knowledge gaps remain (Boulton 2014, Datry et al. 2014, Costigan et al. 2016). Moreover, intermittent rivers are among the types of water bodies that are most likely to experience hydrological changes as a result of climate change (Dhungel et al. 2016). Yet, we have little understanding of how spatial drying patterns in intermittent rivers vary over time, or how tightly this variation is linked to concomitant changes in streamflow, drought severity, temperature, or precipitation.

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At the landscape-scale stream networks exhibit expansion and contraction cycles in response to variation in water availability (hereafter 'landscape drying patterns'; Stanley et al. 1997, Datry et al. 2016). Under the driest conditions only the perennial portions of intermittent streams are wetted, and all intermittent reaches are dry. Hydrologic and geomorphologic properties, such as proximity of the stream channel to the water table, control which reaches dry in a given river network (Konrad 2006, Larned et al. 2010, Goulsbra et al. 2014), whereas regional climate and recent weather history should control when and for how long intermittent reaches dry (Costigan et al. 2016). Nevertheless, few studies have investigated long-term drying patterns within intermittent river systems, so in many cases we lack even a basic understanding of how much temporal variability in drying patterns exists in intermittent rivers, much less what factors are responsible for such temporal variation.

Changes in landscape drying patterns have strong implications for habitat connectivity of aquatic taxa that require perennial water, such as fish. Dewatering of streams in the Great Plains, US, has led to shifts in fish communities towards the dominance of benthic- vs pelagic-spawning species in regions where zero-flow days and drying events are more common (Perkin et al. 2014, Perkin et al. 2015). Jaeger et al. (2014) found that increased drying events as a result of projected climate change are likely to decrease connectivity for native fish during spawning periods when upstream migrations are common. Thus, changes in landscape drying patterns have strong implications for fish populations, as some species may require long stretches of unfragmented river reaches to successfully reproduce.

Streamflow monitoring in intermittent rivers is difficult because intermittent rivers are not as likely as perennial rivers to have gages that continuously record water levels or discharge (Costigan et al. 2016). Citizen science programs that monitor the locations and extent of perennial water in intermittent river systems (hereafter 'wet/dry mapping') can provide long-term datasets to address basic questions about temporal variation in landscape drying patterns. Turner and Richter (2011) used 12 y of citizen science-collected wet/dry mapping data in the San Pedro River, Arizona, USA, to show that ~32% of the river length surveyed had perennial water across all years. Datry et al. (2016) analyzed 9 y of citizen scientist-collected wet/dry mapping data from 5 river networks in Poitou–Charentes, France, and found that during the driest portions of the year ~20% of the network had perennial water. Thus, citizen scientists have already demonstrated their potential to play important roles as primary data collectors in studies that investigate long-term trends of landscape drying patterns in intermittent rivers.

The southwestern US has experienced large droughts over the past several decades. Analyses of weather and streamflow data in this region have shown significant decreases in precipitation (Prein et al. 2016) and increases in the frequency of anomalous low-flow events (Ruhí et al. 2016).

Further, studies project that the spatial and temporal extent of river drying will increase as a result of climate change (Jaeger et al. 2014). We are aware of 3 different rivers in Arizona with long-term citizen science wet/dry mapping programs, and wanted to use these data to investigate how yearly variation in weather, streamflow, and drought conditions might influence landscape drying patterns. We hypothesized that streamflow is a causal factor of spatial drying patterns throughout a river, as it is the quantity of surface water present in a river and is one of several first order controls on what length of a river is dry versus wet; the other factors being geomorphological and hydrologic (i.e., groundwater inputs, depth of alluvium, and channel morphology; Costigan et al. 2016). Increases in drought severity might separately influence drying patterns by reducing the availability of groundwater inputs or increasing evapotranspiration throughout the watershed. Further, we expect that temporal variation in streamflow and drought severity is caused by variation in weather (short-, medium-, and long-term temperature and precipitation history).

Here we present the results of a study where we aimed to: 1) describe landscape drying patterns in desert intermittent rivers, 2) investigate temporal variation in these landscape drying patterns, and 3) test the hypothesis that temporal variation in landscape drying patterns can be predicted by temperature, precipitation, and streamflow history, in addition to metrics that describe overall drought conditions. To do so we compiled 3 long-term wet/dry mapping datasets produced by citizen science river monitoring programs to describe landscape drying patterns, examine how they have varied over time, and used structural equation models to test causal hypothesis networks between spatial metrics that quantify landscape drying patterns and temperature, precipitation, streamflow, and drought metrics.

METHODS

Study rivers

The Agua Fria River, Cienega Creek, and the San Pedro River in the Arizona, USA, have long-term wet/dry mapping data from yearly citizen science surveys (Fig. 1). These rivers historically contain both intermittent and perennial reaches, though the extent of perennial reaches in these rivers is likely much greater in the past than at present (Turner and Richter 2011). These rivers are unregulated and their flow regimes are unmodified by dams in the portions studied, but they are subject to unknown amounts of groundwater withdrawals in their watersheds. These rivers also vary in physical and hydrological characteristics (Table 1), and in geographic location, but they all drain into the Gila River in the Lower Colorado River Basin. The San Pedro River has the largest watershed area and the lowest watershed slope, Cienega Creek has the smallest watershed area, and the Agua Fria River has the highest watershed slope. The mean elevation in each watershed is similar, as are an-

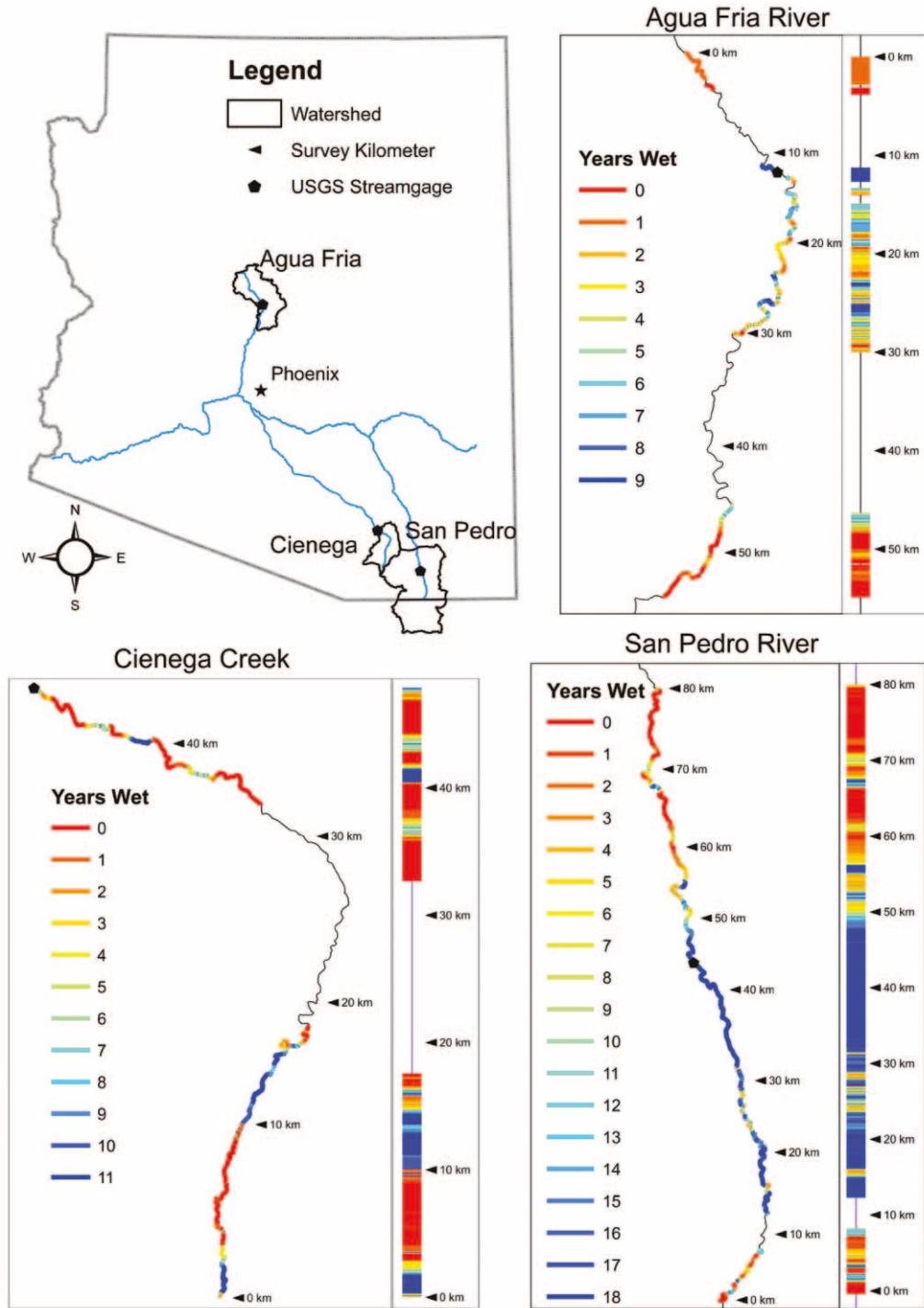


Figure 1. Maps showing locations of the study rivers and watersheds (delineated from the most downstream surveyed reach) in Arizona and reaches within each study river. Pentagons show locations of US Geological Survey gages used in our study (Agua Fria River, 09512500; Cienega Creek, 09484600; San Pedro River, 09471000). Study periods for the study rivers: Agua Fria River, 2008 to 2016; Cienega Creek, 2006 to 2016; San Pedro River, 1999 to 2016. The reaches are color coded to show the number of wet years.

nual precipitation and temperature. However, the Agua Fria receives nearly 2× the precipitation in the winter than Cienega Creek and the San Pedro River, which receive nearly 50% more precipitation than the Agua Fria during the North

American Monsoon season in mid-to-late summer. This leads to these rivers showing different seasonal hydrographs, as the Agua Fria has peak flows driven by winter rains, the San Pedro has peak flows driven by monsoon rains, while

Table 1. Summary of physical and hydrological characteristics of the study rivers. Watershed area was calculated from the most downstream surveyed point. Discharge data were obtained from US Geological Survey gaging stations in or near the surveyed reaches (Agua Fria River [AFR], 09512500; Cienega Creek [CC], 09484600; San Pedro River [SPR], 09471000). Precipitation (precip) and air temperature (temp) data were derived from PRISM gridded climate data, and elevation and slope data were derived from digital elevation maps (30-m resolution) of the watersheds.

River	Surveyed length (km)	Watershed area (km ²)	Mean discharge (m ³ /s)	Annual, monsoon, and winter precip. (mm)	Mean temp. (°C)	Mean elevation (m)	Slope (%)
AFR	31.11	2124	0.573	389.4, 153.4, 147.3	15.15	1420.9	10.49
CC	32.74	1179	0.147	364.5, 220.9, 72.2	16.88	1407.6	8.36
SPR	76.49	4951	0.895	362.3, 225.8, 61.9	16.78	1476.6	5.29

Cienega Creek has peak flows more frequently in the monsoon but also experiences peak flows during the winter (Figs S1–S3). Nevertheless, these rivers represent the variation in size, physical characteristics, and hydrological regime typical of unregulated intermittent rivers in the southwestern USA.

Survey methods

Trained citizen scientists conducted the wet/dry surveys on each of these rivers. The Friends of the Agua Fria National Monument organize the Agua Fria River surveying effort (2008–present). The Nature Conservancy and the US Bureau of Land Management organize the upper Cienega Creek surveys (2006–present), and the Pima County Association of Governments organize surveys of the lower reaches of Cienega Creek (1999–present). The Nature Conservancy and the US Bureau of Land Management organize surveys on the San Pedro River (1999–present). Some of the San Pedro River data (1999–2010) has been published (Turner and Richter 2011). Here, we use the 1999 to 2016 data from the San Pedro River, the 2008 to 2016 data from the Agua Fria River, and the 2006 to 2016 data from Cienega Creek (38 years of wet/dry mapping data across all 3 rivers).

Each river was surveyed using the same methods in the middle of June. Water levels in June are typically at their lowest as weather conditions are usually driest and warmest just before the North American Monsoon rains begin (typically last week of June or 1st week of July). The Agua Fria and the San Pedro Rivers were surveyed on the 3rd Saturday of June each year. Cienega Creek was surveyed either the week before or after the 3rd Saturday of June, because many of the same citizen scientists conduct surveys on both the San Pedro River and Cienega Creek. Surveyors used handheld global positioning system (GPS) units to record the beginning and endpoint of all surface water (either standing or flowing) reaches ≥ 9.1 m (30 ft) in length. Surveyors disregarded any wet or dry gaps < 9.1 m to account for potential geolocation errors inherent in handheld GPS units. Ignoring these unsurveyed reaches could result in small, ecologically important stagnant pools being represented as dry, but overall this method gives a robust, repeatable, and generalizable understanding of large-scale drying patterns through-

out a given river at a given point in time. We used the beginning and endpoint coordinates of each reach with surface water and linearly referenced ('snapped') them to the closest points on US Geological Survey National Hydrography Dataset flow lines (<http://nhd.usgs.gov>) to generate maps of wet and dry reaches of a river at a point in time. We manually corrected any errors in location caused by river meanders. If there were gaps in the data between the most upstream and downstream surveyed reaches, we did not include the unsurveyed reaches in our analysis. Reaches that had data in some years but not others were treated as unsurveyed.

Landscape intermittency indices

We used the maps of wet and dry river reaches to calculate a suite of spatial metrics to describe landscape river drying patterns (hereafter collectively referred to as "landscape intermittency indices"). First, we calculated the total length of wet river reaches from each survey, expressed as a percent of the total river length surveyed. We then calculated Ecologically Scaled Landscape Indices (ESLIs, Vos et al. 2001) which have an advantage over traditional landscape metrics by explicitly accounting for ecological processes underlying metapopulation persistence (local extinction and regional dispersal), thus giving a more accurate interpretation of how landscape structure and organism traits influence metapopulation dynamics. Datry et al. (2016) recently developed ESLIs tailored for intermittent river systems, and we follow their approach here. We focused on 2 different ESLIs, one that describes the average patch carrying capacity, $ESLI_K$, and another that describes the average patch connectivity, $ESLI_C$. $ESLI_K$ is based on the inverse relationship between the likelihood of a population becoming extinct and its size, where the population size present in a given patch i is the area of that patch, A_i , multiplied by the population density of the species, N . Thus, $ESLI_K$ is the average population size per patch, calculated across the total number of patches, n :

$$ESLI_K = \sum_{i=1}^n N \times \frac{A_i}{n}. \quad (\text{Eq. 1})$$

$ESLI_C$ represents the connectivity between individuals residing in isolated wet reaches if all dry reaches were to be-

come immediately rewetted, but it depends on the number of individuals in a given patch and their dispersal ability. Here, an uncolonized wet patch i can only be colonized from an occupied patch j , and the probability of successful colonization in patch i increases with the number of colonists that reach it from occupied patch j . The number of colonists from patch j that reach patch i depends on the number of individuals in patch j available for colonization, which is a function of the area of patch j , A_j , and the distance between the 2 patches, d_{ij} . A dispersal kernel describes successful dispersal between patches i and j , which is parameterized by the average dispersal distance, D , of the species of interest. Assuming that a constant fraction of a population are emigrants, the connectivity of patch i , C_i , is given by:

$$C_i = \sum_{j=1}^n A_j \times e^{(-D \times d_{ij})} \text{ for } i \neq j, \quad (\text{Eq. 2})$$

and ESLI_C is then given by:

$$\text{ESLI}_C = \sum_{i=1}^n \frac{C_i}{n}. \quad (\text{Eq. 3})$$

We obtained fish species presence data in these rivers from species distribution maps and locality information provided by the Arizona Fish and Game Department Fish Database, which is a compilation of fish locality records documented from current and historical fish surveys (Table S1). We obtained maximum fish lengths for each species from the fish traits database (www.fishtraits.info). We calculated ESLI_C and ESLI_K for both small (~ 6 cm in length) and large native fish (~ 30 cm in length) common in these rivers following methods from Datry et al. (2016). These species include 2 US federally endangered fish: the Gila Topminnow (*Poeciliopsis occidentalis*) that is ~ 6 cm in length, and the Gila Chub (*Gila intermedia*) that is ~ 22 cm in length. The largest native fish in these rivers, the Sonoran Sucker (*Catostomus insignis*) is ~ 80 cm in length, but only occurs in the San Pedro River. Historically, the San Pedro River also supported 2 much larger native fish and 11 small native fish (Minckley and Marsh 2009). The fish survey data in the Arizona Fish and Game Department Fish Database were not quantitative estimates of fish density, and instead were qualitative catch-per-unit-effort (CPUE) data. Accordingly, we followed Datry et al. (2016) in using the inverse of home-range size as a surrogate measure for density, where home-range size is estimated from allometric relationships between body size and home-range size and dispersal distance, based on equations in Minns (1995) and Radinger and Wolter (2014), respectively.

Temperature, precipitation, and drought indices

We obtained weather and streamflow data during the surveyed years for the 3 study rivers. We first delineated watersheds upstream of the most downstream surveyed reach. We calculated the monthly mean air temperature and pre-

cipitation from the years surveyed for each watershed from the Parameter-elevation Relationships on Independent Slopes Model (PRISM), which interpolates observed weather data collected throughout the conterminous US (Daly et al. 2008). We used these data to calculate the cumulative precipitation 3, 6, and 12 mo prior to each yearly survey and during the previous monsoon (July–August) and winter (December–March) rains. We also calculated the mean temperature 3, 6, and 12 mo prior to each survey.

We obtained drought index data from the US National Oceanic and Atmospheric Administration (NOAA) North American Drought Monitor (<https://www.ncdc.noaa.gov/climate-monitoring/>), and calculated the average Palmer Modified Drought Index (PMDI), Palmer Hydrological Drought Index (PHDI), and Palmer Z Drought Index (ZNDX) values for the month of each survey, and for the 3-, 6-, and 12-mo periods prior to each survey. These drought indices are calculated from meteorological data and other parameters related to soil and vegetation, but they differ in their meaning and interpretation. PMDI assesses the severity of dry or wet periods. PHDI is indicative of long-term changes in moisture supply and thus, measures drought on a longer time span than PMDI. ZNDX is indicative of short-term changes in precipitation relative to normal levels, and measures drought on a shorter time span than PMDI. ZNDX can, therefore, indicate a brief period of abnormal wetness during an extended drought that would not be captured by PMDI and ZNDX. For all of these indices, values between -1.5 and 1.5 indicate normal conditions; values between -1.5 and -3 or 1.5 and 3 indicate mild-to-moderate drought or wetness; values between -3 and -4 or 3 and 4 indicate severe drought or wetness; and values <-4 or >4 indicate extreme drought or wetness. We were unsure which drought index would be the best predictor and which amount of time prior to the wet/dry mapping would be most useful in predicting landscape intermittency indices, so we generated this suite of variables to use as potential predictors in our data analyses that we describe below. We obtained daily mean discharge data from USGS gaging stations (Aguia Fria River, 09512500; Cienega Creek, 09484600; San Pedro River, 09471000) during the years surveyed. We then used these data to calculate the following streamflow indices following Richter et al. (1996): 1-, 3-, 7-, 30-, and 90-d minimum discharges, overall mean discharge, and the base flow index (7-d minimum flow/mean flow) observed during the 180- and 365-d periods prior to each survey.

Data analyses

First, we tested for changes in landscape intermittency indices (wet length and ESLIs) over time using univariate general linear mixed-effects models, where a given landscape intermittency index was the response variable, year was a fixed predictor variable, and we used river as a random effect on the intercept to account for between river varia-

tion. We used a Gaussian error structure and examined residual errors of each model to confirm that they were normally distributed. We also used simple linear regressions to analyze data from each river individually to investigate relationships between landscape intermittency indices and year in each river.

We used structural equation modeling to investigate how weather and streamflow history might explain year-to-year variation in landscape intermittency metrics (Grace 2006). We generated specific hypotheses as graphical networks of interaction paths (Fig. 2) about how relationships between

temperature, precipitation, drought, and streamflow might influence landscape drying patterns, and we then used structural equation models to analyze them as a set of linked equations. We had many potential variables that could represent each predictor (3 temperature, 5 precipitation, 20 streamflow, and 6 drought variables), but we wanted to generate a reasonable number of candidate models to evaluate each of landscape intermittency index. To determine the best set of starting variables to include in the preliminary structural equation models, we ran a series of AICc model selection analyses with these variables (Burnham and Anderson 2002).

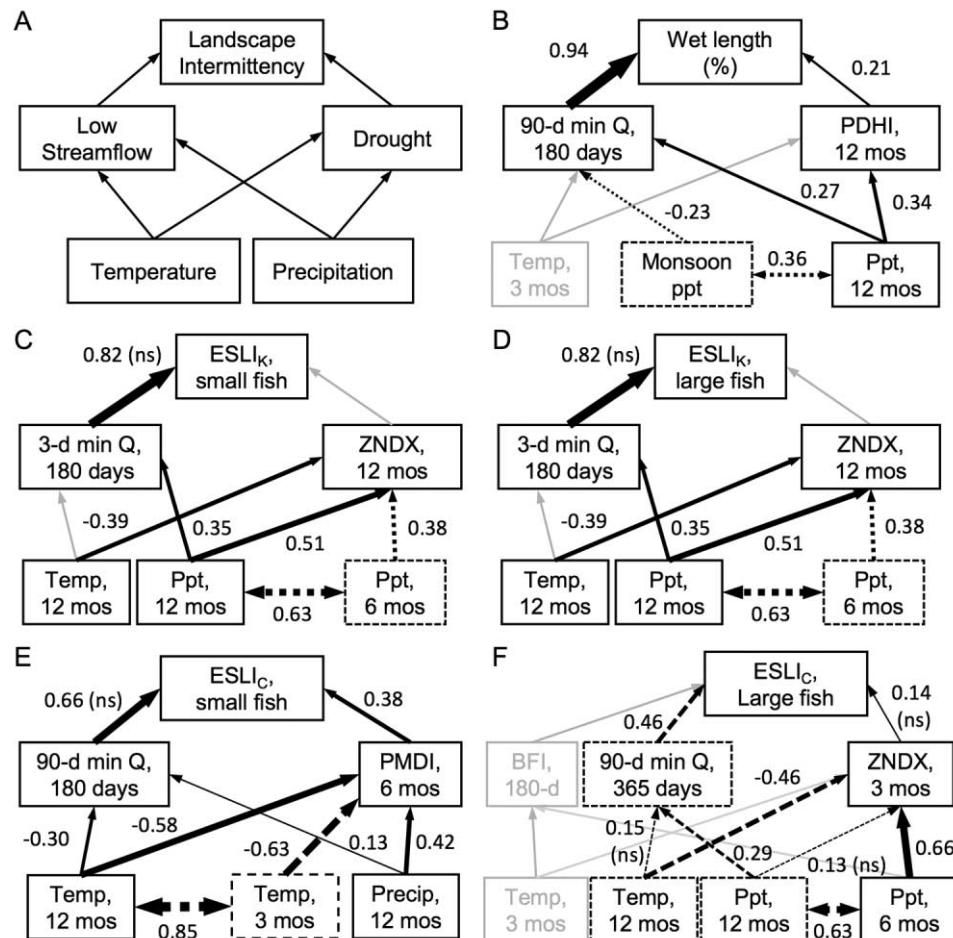


Figure 2. Summary of structural equation models. Schematic representation of hypothesized relationships between variables included in preliminary structural equation models (A). Here, temperature and precipitation variables are exogenous (not caused by other variables in the network) and have causal effects on streamflow and drought metrics, which have causal effects on intermittency metrics (streamflow, drought, and intermittency metrics are endogenous, being caused by other variables in the network). Final structural equation models (B–F) for each landscape intermittency index show standardized path coefficients next to each path, path/arrow size is proportional to path coefficient magnitude, and paths are statistically significant ($p < 0.05$) unless denoted by 'ns'. Double-headed arrows indicate correlated errors between variables rather than a causal path. Gray boxes/arrows indicate variables and paths present in the preliminary model that were not present in the final model, and dashed boxes/arrows indicate variables present in the final model that were not present in the preliminary model. Summary of model fit analyses for structural equation models (higher p -values indicate better fit): Fisher's $C = 5.81$, $df = 8$, $p = 0.669$ (B); Fisher's $C = 2.15$, $df = 14$, $p = 1.000$ (C); Fisher's $C = 2.15$, $df = 14$, $p = 1.000$ (D); Fisher's $C = 4.61$, $df = 12$, $p = 0.970$ (E); Fisher's $C = 8.07$, $df = 6$, $p = 0.622$ (F). Abbreviations: d = day, mos = months, temp = temperature, ppt = precipitation, and Q = discharge.

We compared all possible univariate and multivariate models in sets of comparisons in a stepwise manner to identify: 1) the streamflow and drought variables that best predicted each intermittency metric, and 2) the temperature and precipitation variables that best predicted streamflow and drought variables. We assessed the best performing models for multicollinearity and did not consider models with a variance inflation factor >10 . We then used general linear mixed-effects models to construct preliminary structural equation models for each intermittency metric in a piecewise manner, using river as a random effect on the intercept in each model.

After developing the preliminary structural equation model, we allowed all variables (even those not included in the preliminary model) to be explored as ways to improve overall model fit based on model modification indices. When we added variables that were likely to be correlated (e.g., 2 temperature variables, etc.) to the model, we also added their covariance to the model. Once we achieved the best possible model fit, we explored if pruning paths with insignificant path coefficients would further improve model fit, dropping those with the smallest standardized path coefficients first. We restricted our final structural equation models to a maximum of 7 paths (to generate structural equation models with ≥ 5 data points per path, Grace 2006), pruning models as necessary. Finally, we evaluated the ability of the final structural equation model to predict the landscape intermittency indices by assessing the marginal (fixed-effects only) and conditional (fixed-effects plus random effect) R^2 values (following Nakagawa and Schielzeth 2013).

All statistical analyses were run with R software (version 3.3.3; available from: www.r-project.org). General linear mixed models were run with the *lme4* and *lmerTest* packages, versions 1.1–13 and 2.0–33, respectively. AICc model selection analyses were run with the *MuMin* package, version 1.15.6. Structural equation models were run with the *piecewiseSEM* package, version 1.2.1. Data and code files for this project are open-access at the Open Science Framework (available from: <https://doi.org/10.17605/OSF.IO/A7VCE>; Allen et al. 2018).

Table 2. Summary of landscape intermittency variables of the study rivers over time. Values for wet length (%), $ESLI_K$ large fish, $ESLI_K$ small fish, $ESLI_C$ large fish, and $ESLI_C$ small fish are means. Values in parentheses are standard deviations (SDs) and ranges (max–min), respectively, for each river. ‘Total’ represents the total values pooled across all 3 rivers, and here we list SDs and coefficients of variation in parentheses, respectively. $ESLI_K$ and $ESLI_C$ are ecologically scaled landscape indices representative of carrying capacity and connectivity, respectively. Values are log-transformed and were calculated for a small fish (6 cm in body length) and a large fish (22 cm) based on fish species present in these systems. Some raw $ESLI_K$ large fish values were negative, so we transformed these data by adding the absolute value of the minimum observed value for all data within each river to generate coefficients of variation that were comparable with other variables in other rivers.

River	Years surveyed	Wet length (%)	$ESLI_K$ large fish	$ESLI_K$ small fish	$ESLI_C$ large fish	$ESLI_C$ small fish
Agua Fria River	9	35.8 (11.3, 32.9)	0.59 (0.50, 1.37)	2.22 (0.50, 1.37)	7.63 (0.33, 0.89)	5.76 (0.61, 1.89)
Cienega Creek	11	32.2 (6.4, 20.6)	0.45 (0.22, 0.62)	2.17 (0.22, 0.62)	7.34 (0.25, 0.74)	5.29 (0.51, 0.80)
San Pedro River	18	55.0 (8.4, 7.8)	0.95 (0.33, 0.30)	2.89 (0.33, 0.29)	8.44 (0.39, 0.81)	6.27 (0.54, 0.64)
Total	12.33	41.0 (8.7, 0.22)	0.66 (0.35, 0.56)	2.42 (0.35, 0.15)	7.80 (0.32, 0.04)	5.77 (0.55, 0.10)

RESULTS

Temporal variation in landscape drying patterns

The San Pedro River had a greater length of wet reaches than the other rivers, as well as the highest $ESLI_K$ and $ESLI_C$ values for both large and small fish (Table 2). The Agua Fria River, however, tended to show the greatest raw magnitude of temporal variation with the greatest ranges of these metrics. We observed the greatest coefficient of variation for $ESLI_K$ for large fish and the smallest coefficient of variation for $ESLI_C$ for large fish. General linear mixed-effects models indicated no change over time in the wet length of surveyed reaches or in any of the ESLIs we calculated when all rivers were included in the models. However, we observed changes over time in at least one river when we analyzed data from each river individually for 3 of these variables (Fig. 3, Table 3). We observed significant declines in total wet length in both the Agua Fria River, which declined by $\sim 26\%$ from 2008 to 2016, and in Cienega Creek, which declined by $\sim 14\%$ from 2006 to 2019 (Fig. 3A). There was an $\sim 8\%$ decline in $ESLI_C$ for large fish in the Agua Fria River (Fig. 3C), and an $\sim 15\%$ increase in $ESLI_C$ for small fish in the San Pedro River (Fig. 3E). $ESLI_K$ did not change over time for either small or large fishes. Throughout our study, the focal rivers had annual drought index values (PMDI, PHDI, ZNDX) in the normal (-1.5 to 1.5) to mild/moderate (-1.5 to -3.0) drought range (Table 4). However, drought index values during the month of the surveys were more extreme, and had values in the mild/moderate, extreme (-3 to -4), or severe (less than -4) drought ranges for 6 of the 9 study years for the Agua Fria River, 9 of the 11 study years for Cienega Creek, and 14 of the 18 years in the San Pedro River.

Mechanisms producing landscape drying patterns

We used an iterative model development process to make structural equation models for each landscape intermittency index and used these models to develop a causal hypothesis network to determine which mechanisms pro-

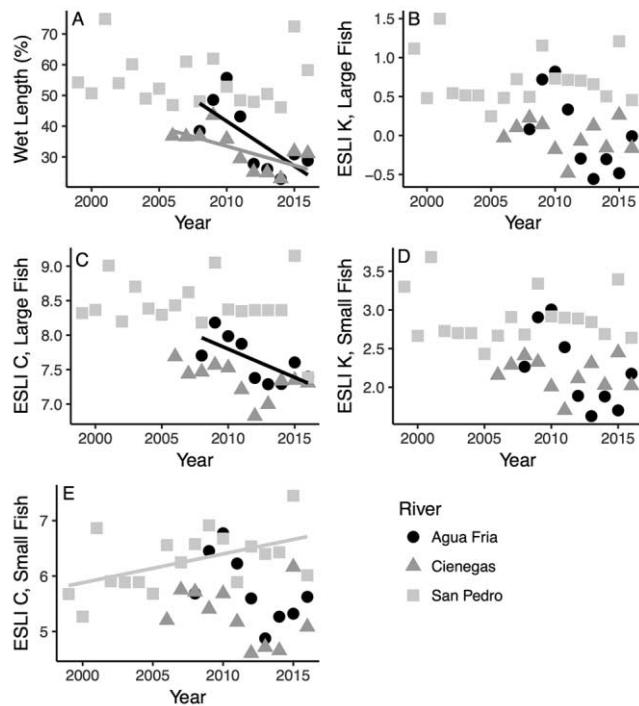


Figure 3. Summary of temporal trends in wet length of surveyed reaches (%), panel A), and ESLI_C and ESLI_K calculated for small and large fish species (6 and 30 cm, respectively; panels B–E). Solid lines in panels A, B, D, and E represent statistically significant ($p < 0.05$) linear regressions analyzed separately for each river (black = Agua Fria River, gray = Cienega Creek, light grey = San Pedro River).

duce drying patterns. The final version of each structural equation model fit the data well enough to warrant interpretation (wet length: Fisher's $C = 5.81$, $df = 8$, $p = 0.669$; ESLI_K small fish: Fisher's $C = 2.15$, $df = 14$, $p = 1.000$; ESLI_K large fish: Fisher's $C = 2.15$, $df = 14$, $p = 1.000$; ESLI_C small fish: Fisher's $C = 4.61$, $df = 12$, $p = 0.970$; ESLI_C large fish: Fisher's $C = 8.07$, $df = 6$, $p = 0.622$).

Our final structural equation model indicated significant linkages between precipitation and the total wet length of surveyed reaches, mediated through effects on low streamflow and drought severity, and explained a large amount of variation in wet length (marginal- $R^2 = 0.79$, conditional- $R^2 = 0.85$, Fig. 2B). This model had a negative effect of previous monsoon precipitation (standardized path coefficient = -0.23) and a positive effect of precipitation over the previous year (0.27) on the 90-d minimum discharge observed in the previous 180 d. Further, precipitation over the previous year was positively related (0.34) to the mean Palmer Hydrological Drought Index (PHDI) over the previous year. In the next level of this model, both the 90-d minimum discharge and the mean PHDI were positively related (0.94 and 0.21, respectively) to the wet length of surveyed reaches.

Our final structural equation models did not show clear linkages between temperature, precipitation, drought metrics, and the ESLI_K of either small or large fish (Fig. 2C–D). The models for large and small fish were nearly identical. They showed no significant path between Palmer Z Drought Index (ZNDX) and 3-d min discharge on ESLI_K (despite a large-magnitude path coefficient of 0.82), even though they showed significant effects of temperature and precipitation on the PZDI over the previous year and the 3-d min discharge over the previous 180 d.

Finally, our structural equation models for ESLI_C of small and large fish produced models with different interpretations. For connectivity of small fish, our structural equation model demonstrated linkages between temperature, precipitation, drought, and ESLI_C, but not streamflow (marginal- $R^2 = 0.55$, conditional- $R^2 = 0.55$, Fig. 2E). Temperature over the previous 3- and 12-mo period had negative effects (-0.58 and -0.63) on the Palmer Modified Drought Index over the previous 6 mo, whereas precipitation appeared to cause PMDI to increase (0.42). PMDI then had a positive effect on ESLI_C (0.38). For connectivity of large fish, however, our structural equation model showed significant linkages between precipitation, streamflow, and ESLI_C, but not drought and temperature (marginal- $R^2 = 0.31$, conditional- $R^2 = 0.63$, Fig. 2F). Precipitation over the previous 12 mo had a positive effect on the 90-minimum discharge over the previous year (0.29), which then had a positive effect on ESLI_C (0.66).

DISCUSSION

Temporal variation in landscape drying patterns

Here we present one of the first long-term datasets of landscape drying patterns in multiple intermittent river systems, and we show that spatial and temporal drying patterns can vary greatly among rivers in the same region. For example, ~33% of the surveyed reaches were wet in the Agua Fria River and Cienega Creek across the 9 and 11 y of surveys there, respectively, whereas the San Pedro River averaged >50% of wet reaches surveyed in the almost 18 y of surveys there. We caution that the areas chosen for surveying in each river were designed to include wet reaches due to interest in monitoring their length over time, so these estimates are influenced by the survey design and may not represent the entirety of each river system. The wet length of the San Pedro was the least variable over time, and both the Agua Fria River and Cienega Creek showed much greater variation in wet length over the study period. The ESLI indices we generated for each river mirrored these patterns, with the Agua Fria River showing the greatest range of ESLI values and the San Pedro River showing a greater magnitude of ESLI values. These results support the ideas presented by Datry et al. (2016), that intermittent rivers can be viewed as dynamic mosaics of wet and dry habitats, characterized by strong spatial patterning and heterogeneity.

Table 3. Summary of general linear mixed models (GLMMs) investigating temporal trends in drying patterns across all rivers (with year as fixed effect and river as a random effect) and simple linear regressions (LRs) investigating temporal trends in drying patterns in each of the 3 rivers individually. For GLMMs, we use the Satterthwaite approximation for degrees of freedom (df) in calculating the *F*-statistic and *p*-value. For GLMMs we report both the marginal-*R*² (fixed effect only, listed 1st) and the conditional-*R*² (fixed effect plus random effect, listed 2nd). For statistically significant models (*p* < 0.05, in bold font), we report the equation (*y* = response variable, *x* = year), and the 95% confidence interval for the β in the GLMM.

Response variable	River(s)	Model type	<i>F</i> _{df1, df2}	<i>p</i>	<i>R</i> ²	Equation	95% CI for β
Wet length (%)	All rivers	GLMM	3.26 _{1,34.6}	0.080	0.039, 0.634		
	Agua Fria River	LR	6.91 _{1,7}	0.034	0.496	$y = -2.91x + 5892.24$	(-5.53, -0.29)
	Cienega Creek	LR	6.65 _{1,9}	0.030	0.425	$y = -1.25x + 2541.65$	(-2.34, -0.15)
	San Pedro River	LR	0.06 _{1,16}	0.802	0.004		
ESLI _K , Large Fish	All rivers	GLMM	1.84 _{1,34.9}	0.184	0.029, 0.524		
	Agua Fria River	LR	4.99 _{1,7}	0.061	0.417		
	Cienega Creek	LR	0.22 _{1,9}	0.652	0.024		
	San Pedro River	LR	0.10 _{1,16}	0.756	0.006		
ESLI _C , Large Fish	All rivers	GLMM	3.76 _{1,34.47}	0.061	0.035, 0.717		
	Agua Fria River	LR	6.47 _{1,7}	0.039	0.480	$y = -0.08x + 173.26$	(-0.159, -0.006)
	Cienega Creek	LR	3.66 _{1,9}	0.088	0.289		
	San Pedro River	LR	0.48 _{1,16}	0.498	0.029		
ESLI _K , Small Fish	All rivers	GLMM	1.84 _{1,34.9}	0.184	0.029, 0.524		
	Agua Fria River	LR	5.00 _{1,7}	0.060	0.417		
	Cienega Creek	LR	0.22 _{1,9}	0.652	0.024		
	San Pedro River	LR	0.10 _{1,16}	0.756	0.006		
ESLI _C , Small Fish	All rivers	GLMM	0.56 _{1,35.1}	0.456	0.010, 0.464		
	Agua Fria River	LR	3.88 _{1,7}	0.090	0.357		
	Cienega Creek	LR	0.72 _{1,9}	0.420	0.074		
	San Pedro River	LR	0.05 _{1,16}	0.028	0.265	$y = 0.05x - 98.16$	(0.006, 0.098)

With respect to the individual systems we studied, however, we note that our results are for the entire river and may thus mask patterns occurring in individual river reaches. For example, previous analyses at finer spatial scales within the San Pedro River show that certain reaches in the river are very dynamic, with very high year-to-year variation in being wet or dry (Turner and Richter 2011, Lacher et al. 2014).

Long-term trends in landscape drying patterns

Of the 3 rivers where citizen scientists documented the extent of perennial water in Arizona, 2 experienced declines in perennial reach length over our study period. While we did not find a significant trend when we combined data from all 3 rivers together, we did find that interannual variation was important when we investigated each river individually.

Table 4. Summary of meteorological variables and drought index values for the study period of each river. For each variable we report the mean value for the 12-mo period prior to the survey, followed by the minimum and maximum annual value in parentheses.

River	Annual Air Temp. (°C)	Annual Precip. (mm)	Annual Palmer Modified Drought Index (PMDI)	Annual Palmer Hydrological Drought Index (PHDI)	Annual Palmer Z Drought Index (ZNDX)
Agua Fria	15.3 (14.5, 15.7)	381 (282, 521)	-1.71 (-3.00, -0.494)	-1.90 (-3.39, -0.43)	-0.63 (-1.28, 0.05)
Cienega Creek	17.0 (16.4, 17.6)	354 (241, 496)	-1.88 (-3.28, -0.39)	-2.21 (-3.45, -0.83)	-0.77 (-1.75, 0.25)
San Pedro River	16.9 (16.0, 17.5)	368 (234, 615)	-1.71 (-3.31, 0.35)	-1.94 (-3.50, 0.63)	-0.69 (-1.75, 0.92)

ally. The percentage of wet reaches declined by ~26% in the Agua Fria River and ~14% in Cienega Creek, since surveying began in those rivers (2008 and 2006, respectively). We also observed declines in ESLI_C for large fish in the Agua Fria River, which indicates that habitat connectivity for larger fish is being degraded in this river. Other studies have found that extreme low-flow events in southwestern US rivers favor the dominance of nonnative fish over native fish (Ruhí et al. 2015, 2016), which suggests that native fish species in the Agua Fria River, particularly larger ones, may be threatened because of declining perennial habitat. We did not find any significant change in the overall extent of perennial river length in the San Pedro River over the past 18 y, echoing results from analysis of the first 12 y of these data (Turner and Richter 2011). Further, we observed a 15% increase in habitat connectivity for small fish (ESLI_C calculated for fish of 6 cm in body length) over time, though the small federally endangered Gila topminnow that historically occurred in this river may have been extirpated due to the introduction of nonnative vertebrates now present in the river (bluegill [*Lepomis macrochirus*], largemouth bass [*Micropterus salmoides*], mosquitofish [*Gambusia affinis*], and the American bullfrog [*Lithobates catesbeianus*]). Finally, we did not observe any significant temporal trends in changes in habitat carrying capacity (ESLI_K) for large or small fish. This may be because we estimated fish density with allometric relationships with fish body size, as quantitative fish density data to use in the calculation of this metric was not available.

There are several different mechanisms that may explain the different patterns we observed among our study rivers. The first is related to differences in groundwater and water management within each basin. Base flows in the San Pedro River are supported by groundwater, and between 2002 and 2012 a combination of water conservation, reuse, recharge, and augmentation projects in the Sierra Vista subwatershed of the Upper San Pedro river (implemented by the Upper San Pedro Partnership and its member agencies) have reduced groundwater consumption by about 6.3 million m³/y (Gungle et al. 2016). Our results in this study indicate that this program may have helped the San Pedro River avoid the decline in perennial stream length we observed in the other 2 rivers. However, a groundwater use deficit remains in the watershed (Gungle et al. 2016). Population growth and human demand for water has increased in the region over the past 18 y, and hydrologic models indicate decreases in perennial reach length are highly likely if this deficit is maintained or grows in the future (Brand et al. 2010). Conversely, other modeling studies indicate that if groundwater recharge is increased, then base flows in the San Pedro River could be maintained until the year 2100 even if groundwater use increases in the watershed (Lacher et al. 2014, Richter et al. 2014). The San Pedro River is of critical conservation value because of the importance of its riparian areas as a bird migration pathway (Brand et al. 2011), which was one

impetus for the groundwater management plans that were implemented in the watershed.

The lack of a coordinated effort to recharge groundwater in the Agua Fria River and Cienega Creek watersheds may explain why we observed declines in perennial stream length in these rivers over the past decade. However, we were unable to test this hypothesis specifically because we did not quantify human water use in these watersheds over our study period. We are not aware of any direct surface water withdrawals from these rivers, but groundwater pumping does occur in all watersheds for agricultural, municipal, and other uses. Unfortunately, groundwater consumption is not accurately monitored in Arizona. Many wells do not require withdrawals to be reported, and many of those that do only require self-reporting that is rarely verified. Accurate data on groundwater use in our study watersheds are, therefore, largely unavailable. However, remote sensing studies have detected large declines in groundwater throughout the Colorado River Basin from 2004 to 2013, a period of sustained drought (Castle et al. 2014). Thus, increased human use of groundwater to compensate for reduced precipitation or surface water drought periods could have contributed to our results.

A 2nd explanation for the differences among our study rivers is that climatic and physical differences among the watersheds created the observed differences in the spatial drying patterns. The San Pedro River watershed receives more summer precipitation than either the Cienega Creek watershed, which is influenced by both summer and winter precipitation, or the Agua Fria watershed, which primarily receives winter precipitation. The drought data presented in this study indicate that the San Pedro river experienced less extreme drought over the course of our study relative to the other 2 rivers (mean PMDI value was -1.50 for the San Pedro River, -2.1 for Cienega Creek, and -1.7 for the Agua Fria River). Hydrologic and physiographic differences also exist between these rivers, which could influence how drying patterns vary over time. The San Pedro is the largest of these 3 rivers, with a watershed area 2× that of Agua Fria River and 4× that of Cienega Creek. Large watersheds should have relatively less variation in discharge over time than small watersheds (Gordon et al. 2004), as smaller basins are more susceptible to being influenced by the small-scale high-intensity rainfall events typical of the summer monsoon rains in the Sonoran Desert (Fisher et al. 1982). Additionally, aquifer recharge dynamics also differ between these rivers, which could explain some of the patterns we found. Studies of water chemistry, including water isotope analyses, may be able to tease apart some of these dynamics in the future. We are just beginning to address questions about what factors influence spatiotemporal drying patterns in intermittent river systems (Costigan et al. 2016), and long-term wet/dry mapping projects such as those presented here are well-suited to inform such research.

Streamflow and drought as causal agents of landscape drying patterns

Here, we also show that yearly variation in landscape intermittency indices can be a direct result of temporal variation in surface flow and drought conditions. We hypothesized that temperature and precipitation would influence intermittency indices through mediating effects on streamflow and drought. Our structural equation models broadly supported this hypothesis, even though we observed differences when comparing our final structural equation models for the different intermittency indices we investigated. We found clear linkages between wetted river length and precipitation mediated through effects on low streamflow and drought. Streamflow was the most important factor that caused variation in the amount of wetted river length, but long-term hydrologic drought was also important. Interestingly, this model had 2 precipitation variables in it with opposing effects on minimum discharge, negative effects of precipitation from the previous monsoon season coupled with a positive effect of precipitation from the previous 12 mo. These opposing effects could indicate that quantity of more recent precipitation (in the fall, winter, and spring) is a more important determinant of base flows in these rivers.

The results of this study are consistent with other studies showing increases in the prevalence and duration of droughts in the southwestern US, and decreases in streamflow, in past decades. Prein et al. (2016) conducted a weather type analysis across the conterminous US from 1979 to 2014, and found that changes in weather type frequency in the southwestern US led to decreases in precipitation of up to 25%. In an analysis of streamflow data from 120 stream gages across the Colorado and Rio Grande Rivers in the southwestern US, Ruhí et al. (2016) found that the magnitude of anomalous low-flow events increased between 1938 and 2012. These results are important within the context of climate change, leading some authors to argue that the arid southwestern US climate has already become drier as predicted by many climate change models (Prein et al. 2016).

Other studies have suggested that a shift towards a drier climate resulting from global climate change will have implications for habitat connectivity for fish in intermittent river systems in the southwestern US. In an analysis of the Verde River, Arizona, Jaeger et al. (2014) used hydrologic models to show that stream drying events are projected to increase with climate change, in ways that will decrease habitat connectivity during spring spawning seasons. Our results complement these studies, showing that in 2 of our study rivers perennial reach length is declining over time, reducing habitat connectivity for fish in one of these rivers. These effects can be attributed to effects of streamflow and drought caused by decreased precipitation and increased temperatures. Our final structural equation models on habitat connectivity differed depending on whether they were calculated for small or large fish. For small fish,

temporal variation in habitat connectivity was caused by droughts, which were caused by lower precipitation coupled with higher temperatures. For large fish, however, temporal variation in habitat connectivity was caused by variation in streamflow, which was primarily influenced by precipitation. These differences may be related by the differences in home-range size, abundance, and dispersal ability of large versus small fish used to calculate this metric (Datry et al. 2016). In general, smaller fish are more abundant but do not disperse as far, whereas large fish are less abundant but have larger home ranges and dispersal abilities. Thus, larger fish may rely on large perennial areas being present that are further apart but rarer, whereas a landscape with perennial habitats that are small but close together may still result in high connectivity for a smaller fish species. Nevertheless, we found no significant relationship between streamflow and drought for the average patch carrying capacity for large or small fish. This metric represents the average carrying capacity of a given patch rather than the total carrying capacity across all patches (Datry et al. 2016), so it may be unaffected by variation in streamflow or drought if the average area of wet patches is unaffected.

Role of citizen science in this project

This study relied on data collected by citizen scientists. Wet/dry mapping data collected by citizen scientists of the San Pedro River has been published on its own previously (Turner and Richter 2011). These data have also been used in other studies to project the effects of groundwater recharge on future San Pedro River streamflow in hydrological models (Lacher et al. 2014), and in studies of riparian plant and animal ecology conducted along the San Pedro River (Stromberg et al. 2006, Allen et al. 2014). Moreover, data from another citizen science driven wet/dry mapping program in Europe have been used to study intermittent river ecology (Datry et al. 2016). Thus, these wet/dry mapping programs are part of a growing trend of relying on citizen scientists to collect freshwater monitoring data (Clavero et al. 2017, Lévesque et al. 2017, Vincent et al. 2017). We used citizen science data in our study to find that landscape intermittency indices produced by wet/dry mapping data can be predicted by streamflow metrics derived from discharge data collected on the same river. Thus, once a long-term monitoring project is established and relationships developed between wet/dry mapping and streamflow data, research efforts could be lessened and distributed to other rivers.

The data collected by citizen scientists that we present here is considerable and of high quality, leading us to believe that there is potential for citizen scientists to play a crucial role in intermittent streamflow monitoring. Streamflow data of any type (e.g., discharge, water presence/absence) are notoriously difficult to collect in intermittent river systems. Intermittent rivers are not as well represented

as perennial systems in stream gage networks, but even if a stream is gaged important aspects of an intermittent flow regime (i.e., stagnant water vs dry river bed) may not be measured (Costigan et al. 2016). Here we show that citizen scientists can produce reliable data on water presence/absence through wet/dry mapping. We think citizen scientists could also be trained to collect additional information on the wetness of sediments in dry river channels, the presence/absence of fish or tadpoles, or other features of interest. Finally, we note that the specific monitoring methods used should be tailored for the particular drying patterns of each system. In some intermittent systems there are small, isolated, and permanent pools that may be ecologically important as refugia (Bogan et al. 2015), but our method of only counting wet/dry stretches >9.1 m could miss these localities.

Conclusions

We found that data collected by citizen scientists shows the extent of perennial river length has decreased in 2 of the 3 rivers in Arizona that have wet/dry mapping programs, but many more intermittent river systems in the southwestern US provide critical habitats for plants, birds, fish, and insects, all of which are influenced by the presence or absence of water (Merritt and Bateman 2012, Bogan et al. 2013, Bateman et al. 2014, Jaeger et al. 2014). Here, we showed that citizen science programs focused on mapping wet and dry sections of rivers and streams are valuable, and suggest that these citizen science programs should be expanded to currently unmonitored intermittent river systems of interest. New technologies, such as citizen science-oriented smartphone applications, are being developed that could improve current efforts and aid in integrating data collected by different programs. If such programs were expanded across the USA, we could study how the relationship between streamflow, drought, and spatiotemporal river drying patterns might vary under different climates and under different intensities of human water use. Answers to these questions would provide valuable information about how to best manage our water resources under a changing climate.

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