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Key Points:

- We evaluate patterns of intermittent stream drying and identify variables that influence surface water presence and variability across years
- We developed models to characterize streams based on their sensitivity to climate variability
- Physical watershed characteristics and precipitation at multiple time scales controlled the spatial and temporal variation of intermittency

Supporting Information:

Supporting Information may be found in the online version of this article.

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Spatial Patterns and Sensitivity of Intermittent Stream Drying to Climate Variability

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Abstract Intermittent streams comprise much of the global river network, and are expected to become more prevalent with climate change. Characterizing the expansion and contraction of intermittency in stream networks, and understanding how sensitive these dynamics are to climatic variability, is critical for predicting the trajectory of hydrologic regimes in a changing climate. Here, we consider the spatial patterns of stream intermittency, focusing on wetted channel conditions at the end of the dry season, and identify land cover, physiographic, and climate variables that influence surface water presence and variability across years. We trained statistical models with wetted channel mapping data from 25 streams over 7 years to predict both the spatial and interannual variability of the wetted channel network. We then used the models to assess intermittent stream dynamics across the Russian River watershed in northern California, USA. We found that an average of 3.7% of the stream network was reliably dry, while 16.1% was reliably wet at the end of the dry season, with the remainder of the network exhibiting variability in wetted conditions in response to antecedent precipitation. Both climatic and landscape characteristics controlled the extent of the wetted network, particularly antecedent precipitation at seasonal and annual time scales, highlighting the role of hydrologic memory in this system. Given predictions of increased climate volatility, an improved understanding of the spatial patterns and stability of dry season conditions in intermittent streams can inform climate risk assessments and strategies for protecting biodiversity and the ecosystem services that intermittent streams support.

1. Introduction

Intermittent streams are common throughout the world, and are characterized as having variable cycles of wetting and flow cessation (Busch et al., 2020). Though intermittency is a natural phenomenon, projected changes in temperature and precipitation patterns are expected to prolong the dry season and increase the frequency of multi-year droughts in many parts of the world (Dai, 2011). This, in turn, is predicted to intensify the low-flow period and exacerbate the duration and severity of intermittent conditions (Grimm & Fisher, 1992; Larned et al., 2010). Changes to streamflow patterns can profoundly influence ecological functioning of streams by disrupting evolutionary cues (Heim et al., 2016), altering nutrient cycles (von Schiller et al., 2011), and increasing the risk of invasion by nonnative species (Larson et al., 2009). Many endemic and imperiled species that are adapted to natural intermittency may be placed at risk of extirpation from these shifts (Jaeger et al., 2014). Furthermore, changes to hydrological regimes may reduce the ecosystem services provided by intermittent streams, such as drinking water resources (Marshall et al., 2018) and nutrient cycling (Datry, Foulquier, et al., 2018), which may exacerbate stressors faced by human populations (Datry, Boulton, et al., 2018). Understanding the drivers of intermittent stream dynamics, as well as their sensitivity to climate variability, is critical for predicting how functioning of these systems may change under a volatile climate future.

Previous studies on temperate and arid intermittent stream dynamics have shown that as the dry season progresses, the wetted channel contracts from the full extent of the geomorphic channel network in response to declining stream discharge (Godsey & Kirchner, 2014). The spatial and temporal patterns of intermittency are affected by meteorologic, geologic, and land cover conditions (Costigan et al., 2016), with topographic relief and lithology playing a particularly important role in influencing the spatial patterns of wetted channel contraction in intermittent stream networks (Jensen et al., 2017; Lovill et al., 2018; Prancevic & Kirchner, 2019). Growing insight into the mechanisms that control wetted channel dynamics has led to attempts to model and predict intermittent stream expansion and contraction (Pate et al., 2020; Ward et al., 2018; Yu et al., 2019). These studies have explored both seasonal or subseasonal expansion and contraction of the channel network, showing that both climatic and geologic setting can predict the wetted portion of networks. These efforts have ranged in spatial scale, from small headwater catchment studies (Ward et al., 2018) to large regional analyses (Yu et al., 2019), but have rarely considered the interannual variability (IAV) in patterns of intermittency.

The extent of stream drying can vary greatly depending on antecedent precipitation conditions, which are expected to be more variable with climate change (Pendergrass et al., 2017). There is evidence that intermittent streams are especially sensitive to climate fluctuations and, compared to perennial streams, are predicted to be the most at risk of hydrologic regime shifts (Dhungel et al., 2016). Yet, relatively little attention has been given to documenting and evaluating the factors that influence IAV in intermittent stream drying. The consideration of interannual hydrological variation in intermittent streams has largely been devoted to characterizing its effect on ecosystem processes such as nutrient cycling (Bernal et al., 2004), fish behavior (Hwan & Carlson, 2016), and food chain length (Sabo et al., 2010). The few studies that have captured the IAV in hydrologic condition (Allen et al., 2019; Datry et al., 2016; Hammond et al., 2021; Lapides et al., 2021; Lovill et al., 2018) highlight the dynamism of wetted extents, but none have included a spatially explicit understanding of how river networks may respond to climate variability and change. With increasing precipitation volatility and rising temperatures (Swain et al., 2018), there is an urgent need to characterize where and when intermittent streams will be buffered from, or vulnerable to, climate change.

The overall goal of this study is to characterize intermittent stream drying patterns and their stability in relation to climate variability and physical setting. We mapped dry season wetted channel extent between 2012 and 2019 at 25 streams in the Russian River watershed in northern California, USA. We used these data to develop a statistical model for wetted channel condition at the end of the dry season to evaluate the influence of a suite of land cover, physiographic, and climate variables (hereafter, the end-of-season model). Using a similar approach, we developed a model to identify factors that influence interannual variation in end-of-season wetted conditions (hereafter, the IAV model). Finally, the end-of-season and IAV models were applied across the watershed to predict extent and stability of wetted channel condition throughout the entire network.

2. Study Site

The Russian River watershed (3,850 km^2; Figure 1) encompasses parts of both Mendocino and Sonoma counties in northern California, USA. The mainstem flows 175 km from north to south and drains into the Pacific Ocean (Opperman et al., 2005). The basin is mostly underlain by Franciscan Complex, a Jurassic-Cretaceous age terrane (Berkland et al., 1972). There are also large swaths covered by hillslope deposits or alluvium. Vegetation consists of a mixture of hardwood forests, conifer stands, oak woodlands, and chaparral. The region has a legacy of timber harvesting, which peaked in the 1950s and subsequently declined rapidly due a depletion of resources (Osward, 1972). Currently, the predominant land-use change stems from the conversion of many valleys and surrounding hillslopes in the basin to vineyards and residential development (Merenlender, 2000).

The region has a Mediterranean climate, with a highly seasonal precipitation regime. Much of the rainfall occurs from November to March, with the remainder of the year being fairly hot and dry (Gasith & Resh, 1999). Relatively few storms account for the total annual precipitation, which is highly variable year-to-year, ranging from 690 to 2,160 mm (Opperman et al., 2005). Streamflow reflects this seasonal and IAV in rainfall (Sumargo et al., 2020), with discharge peaking in the winter wet season and then receding through the summer dry season, and varying between years relative to antecedent precipitation. Most of the tributaries of the Russian River cease to flow in the dry season, contracting into reaches that contain a series of disconnected pools or are completely dry (Deitch et al., 2009). While recession in many watersheds begins in the low-order headwaters (Biswal & Marani, 2010), drying in the tributaries of this system tends to begin in the lower alluvial reaches and proceeds upstream, with headwater reaches often remaining wetted through inputs from groundwater and springs (Grantham, 2013), as has been reported in other arid landscapes (Stanley et al., 1997). Despite the harsh environmental conditions of these intermittent streams, remnant pools within these tributaries are important habitats for native aquatic species, including endangered

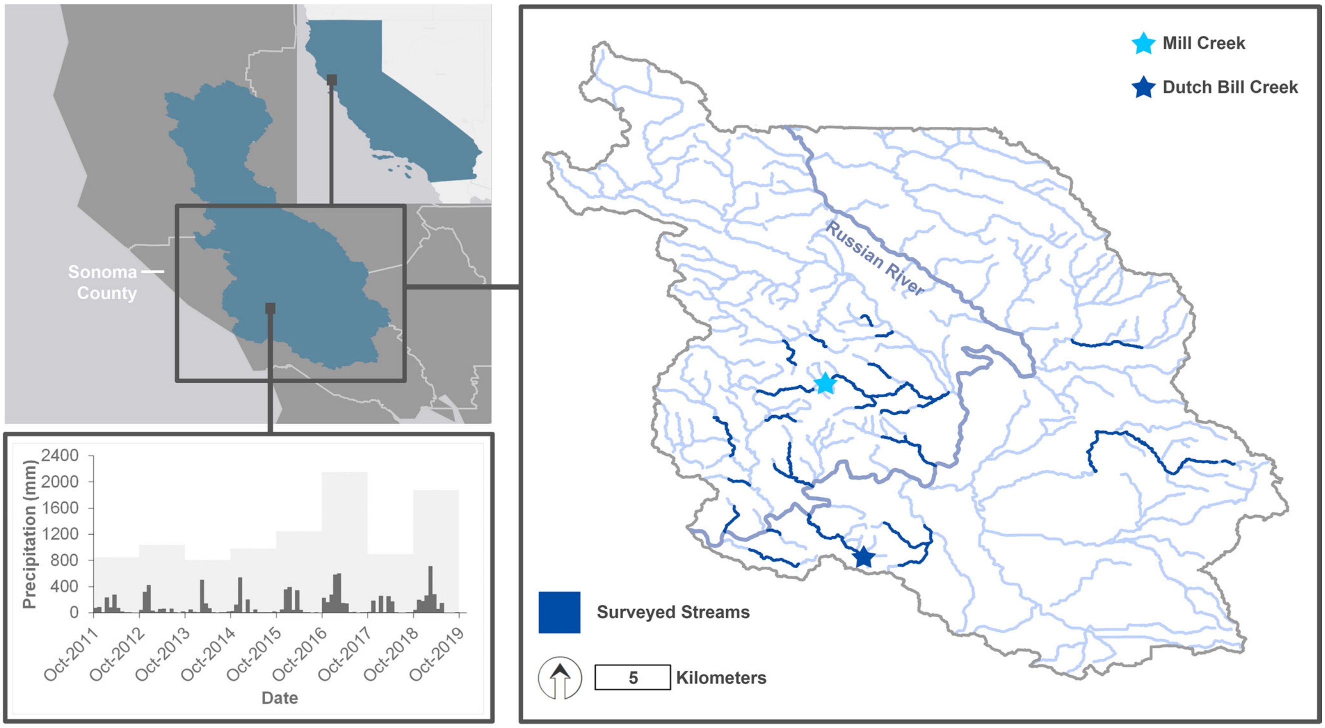

Figure 1. Map of the Russian River watershed in northern California, USA. Right inset shows the spatial distribution of the streams included in the study. Bottom inset shows the water year precipitation (gray) and monthly (black) precipitation.

Coho salmon (*Oncorhynchus kisutch*), and threatened Steelhead trout (*Oncorhynchus mykiss*; Grantham et al., 2012; Obedzinski et al., 2018; Vorste et al., 2020).

3. Methods

3.1. Wetted Channel Mapping

Surveys of wetted channel conditions were conducted between 2012 and 2019 in 25 stream reaches (Table S1 of Supporting Information S1), ranging in length 0.46–22.04 km, for an average total surveyed length of 84.89 km each year. Most streams were surveyed at the end of the dry season (September–October), when the extent of stream drying is greatest, while a few focal streams (Figure 2b) were surveyed biweekly to capture the change in condition during the summer dry-down period (May–October). For many streams, surveys were completed in one day, but surveys for longer streams were surveyed on consecutive days. Study streams were selected for their potential to support endangered salmon, and represent the broad range of land cover, physiographic, and climate conditions found in the Russian River watershed. For some streams, the extent of the channel that was surveyed depended on landowner access, which was subject to change yearly. The timespan within which surveys were conducted encompassed extreme low and high precipitation years (Figure 1).

To document wetted channel condition, field crews walked the length of the geomorphic channel of each stream, using a Bad Elf GPS (±1 m accuracy) connected to ArcCollector on a digital tablet to map the presence of surface water. A “wet” classification was defined as visible surface water presence. Following data collection, the survey data was aggregated and delineated into 100 m long reaches. The proportion of the reach length that was classified as dry along the 100 m reach was calculated for each year. IAV was calculated as the coefficient of variation of the end-of-season wetted reach proportion across years. Not all streams or reaches were surveyed each year and only streams with at least 3 yr of mapping were included in this analysis (Table S1 in Supporting Information S1).

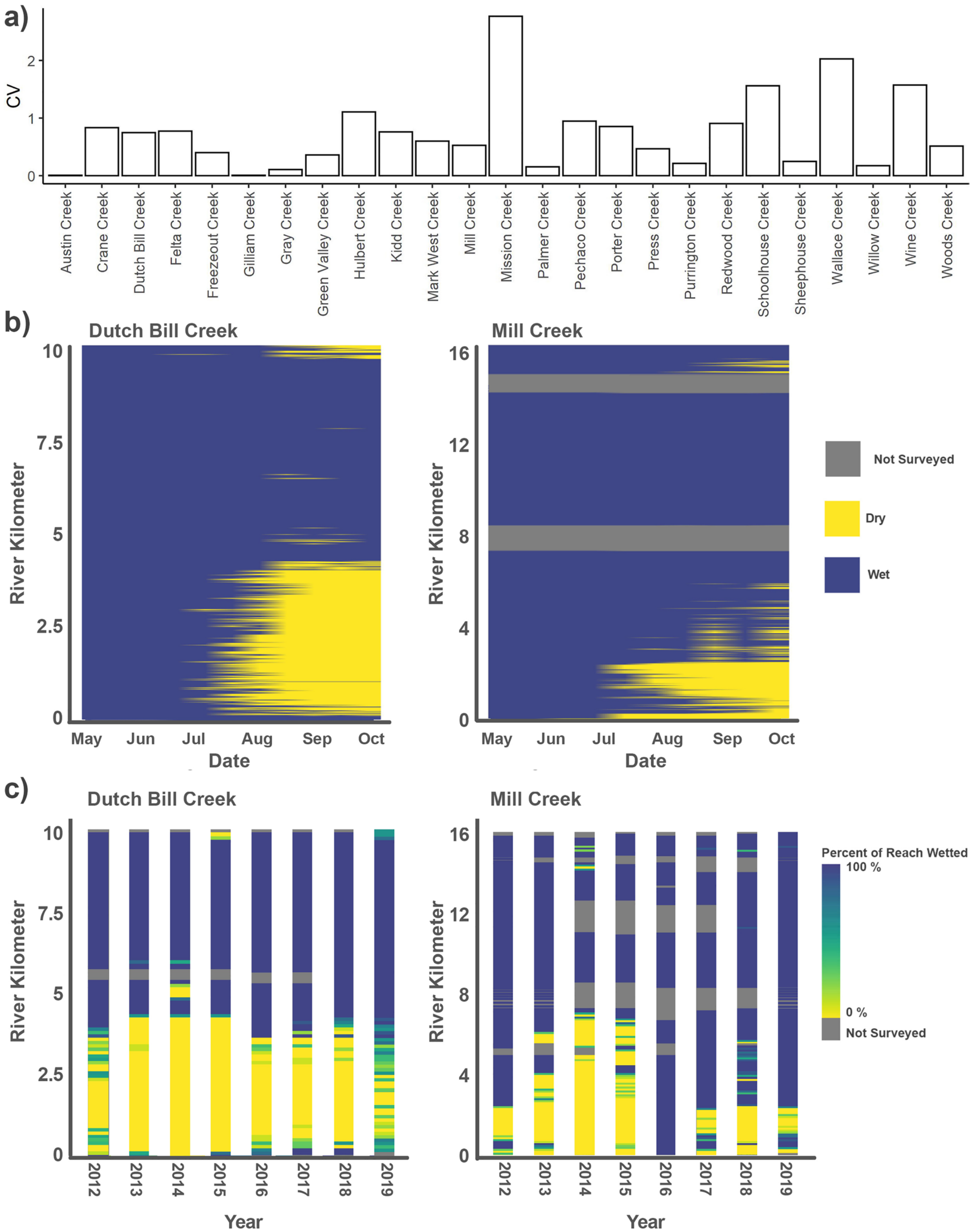

Figure 2. Variability of end-of-season condition within the watershed. (a) It shows overall variability in end-of-season condition for each stream surveyed, calculated by taking the coefficient of variation. (b) It shows the change in condition over the summer dry-down period (May–October) for two representative streams, Dutch Bill Creek and Mill Creek in 2018. (c) It shows the end-of-season condition in September from 2012 to 2019 for the same streams. For both (b and c), the vertical axis is river kilometer in upstream order, with 0 denoting the most downstream point. Gray denotes regions that were not surveyed due to inaccessibility.

3.2. Model Development

The wetted channel observations were combined with a suite of geospatial variables to train models for end-of-season condition and IAV. Predictor variables were compiled for each 100 m reach of all study streams using land cover, physiographic, and climate characteristics that have been previously reported to influence stream expansion and contraction (Costigan et al., 2016; Prancevic & Kirchner, 2019). Climatic variables were obtained for each reach from the PRISM data set (Daly et al., 2008) and included mean annual temperature, total annual precipitation, and total seasonal precipitation, which was calculated from monthly averages for winter (December, January, and February), spring (March, April, and May), summer (June, July, and August), and fall (September, October, and November). We also calculated precipitation totals from the antecedent year, antecedent 3 years, and antecedent 5 years to explore legacy effects of precipitation. Physiographic variables included upstream area, slope, elevation, planform curvature, and surficial properties. The drainage density scaling exponent (Prancevic & Kirchner, 2019), quantifying how drainage area increases nonlinearly with downstream distance, was calculated for each subwatershed. The dominant geologic unit class, obtained from the State Geologic Map Compilation (Horton, 2017), and soil properties, such as texture and runoff potential, obtained from the Gridded Soil Survey Geographic Database (Soil Survey Staff, 2016), were calculated at the local (from a 10 m buffer along each 100 m reach) and watershed scale (contributing area to each reach). Finally, percent land use/land cover obtained from the National Land Cover Database (Homer et al., 2012) and canopy density from the Sonoma County Vegetation Mapping and LiDAR Program (Dubayah & Hurtt, 2014) were calculated at the local- and watershed-scale. An extended description of the variables included can be found in the Table S2 in Supporting Information S1. We calculated a correlation matrix and removed variables that were highly correlated (Pearson correlation coefficient ≥0.80; Figure S1 in Supporting Information S1). The variables that were highly correlated were annual precipitation with winter, spring, and fall precipitation; spring precipitation with fall precipitation; antecedent 3 years' precipitation with antecedent 5 years' precipitation; medial soil with agriculture; and loam soil with high soil runoff potential and skeletal soil. For each group of highly correlated variables, we identified and removed the one that was more correlated with other variables. This process removed the annual precipitation, spring precipitation, antecedent 3 years' precipitation, medial soil, and loam soil variables from model development.

The predictor variables were combined with the wetted channel survey observations in two statistical models using the random forest method (Cutler et al., 2007; Prasad et al., 2006): one to predict the end-of-season condition and one to predict the IAV. For the end-of-season (EOS) model, the wetted channel was quantified as the proportion of each reach that was dry, ranging from 0% to 100%. For the IAV model, the coefficient of variation of the end-of-season condition across the years surveyed (2012–2019) was calculated for each reach.

3.3. Model Evaluation and Application

The random forest models were implemented using the caret 6.0-86 package in R 3.4.2 (Kuhn, 2011). Random forests are a robust decision tree model, where predictions from hundreds of individual decision trees are aggregated to compute a mean predicted value. Partitioning the dataset into independent decision trees reduces variance and limits the risk of overfitting (Liaw & Wiener, 2002). A leave-one-out cross-validation method was used to assess model performance, in which models were iteratively trained with subsets of the data that randomly excluded five streams. The omitted sites were then returned to the training class for the next iteration, with a different subset of streams being reserved as the validation class. In each iteration, model predictions were made for the streams that were excluded from the dataset and performance was assessed by comparing observed and predicted values using R^2 and mean square error (MSE). A range of tuning parameters were tested to find optimal values for the model (Table S3 in Supporting Information S1). We found a marginal increase in model performance with an increase in number of trees or tree depth, with 100 trees and tuning length of 5 resulting in a model with both high performance and lower processing time. Variable selection was done by using a recursive feature elimination method (Gregorutti et al., 2017) to identify a subset of variables to train a model with comparable accuracy as when all variables are included. The importance of each predictor variable was determined using increase in MSE in predictions when a variable is permuted and node purity, which is a measure of the variance of the predictions when a given variable is a node of a decision tree. For example, if reach observations are consistently wet when "clay soil" is a node, then the "clay soil" variable would have a high purity value. If observations have a large variance in their predicted outcome when "clay soil" is a node, then the variable would have a lower purity value. Individual conditional expectation (ICE) plots, which isolate the effect of a variable on the predicted outcome, were used to determine the direction of each variable's influence on wetted condition or variability.

The trained models were then used to predict EOS wetted conditions and IAV in all streams in the lower Russian River watershed (Figure 1). The upper section of the Russian River watershed was not included due to lack of LiDAR data used for topography and canopy variables. We calculated the same predictor variables used in the model for all 100 m stream reaches in the NHD data set. Meteorologic variables were calculated from a 10-yr climate record from 2009 to 2019 (PRISM). Since model predictions cannot be reliably made outside of the domain of the training data set, we removed the stream reaches for which the predictor variable value fell outside the maximum and minimum bounds of the training data domain. This excluded 1.5% of the stream network, located in the lower Russian River watershed. We determined stability of intermittent stream drying patterns by relating the EOS wetted channel predictions with the IAV model predictions for each reach. "Reliably dry" reaches were defined as those with a low proportion of wetted extent (<20% of the reach) and low IAV (CV < 20%), while "reliably wet" reaches were defined as those with a high proportion of wetted extent (>80% of the reach) and low IAV (CV < 20%).

4. Results

4.1. Wetted Channel Mapping Patterns

While nearly all streams in the watershed are intermittent, the extent and interannual variation of end-of-season wetted habitat varies among streams, with some streams exhibiting consistent end-of-season conditions, regardless of antecedent precipitation, while others differ greatly across years (Figure 2a). Two representative streams, Dutch Bill Creek and Mill Creek (Figure 1), show similar temporal patterns of wetted channel contraction over the summer months of 2018 (Figure 2b), with the lower reaches of both creeks becoming dry around August, but to a greater spatial extent in Dutch Bill. The creeks also exhibit distinct interannual variation in end-of-season wetted conditions (Figure 2c), with Dutch Bill Creek showing consistent drying patterns in the lower reaches between 2012 and 2019, while Mill Creek varies more in the lower reaches across years. Given that both watersheds share the same climate regime, this suggests that differences in hillslope routing and subsurface properties may cause this difference in wetted channel conditions between years. This pattern is consistent across the Russian River watershed; where each stream varies such that there is no unifying signal of channel contraction.

4.2. End-of-Season Predictive Model

The EOS model accurately predicted the spatial extent of wetted channel conditions, with the best performing model having an R^2 of 76.7% (Figure 3a). A recursive feature elimination analysis determined 15 variables (Figure 3b) that improved model accuracy, with an R^2 of 82.2%. When comparing the predicted wetted channel extent to the observed channel extent in streams excluded from model training, we found that 77% of the predictions were within 20% of the observed condition. The EOS model was trained using data from a range of water years, including extreme wet and extreme dry years, which allowed us to understand how the watershed responds to anomalous conditions. In the wettest year surveyed (2019), 65% of the study reaches were predicted to be wet (>80% of the reach wetted at the end of the season), while 13% of the reaches were predicted to be dry (<20% of the reach wetted at the end of the season) at the end of the season. In contrast, in the driest year surveyed (2013), 51% of the study reaches were predicted to be wet compared to 18% of the reaches predicted to being dry. On average, 58% of the reaches were predicted to be wet, while 18% were predicted to be dry at the end of the season.

Climate variables were the most influential in the EOS models, as determined by rankings in both MSE and node purity (Figure S2 in Supporting Information S1). Long-term precipitation (LTP), including antecedent year and 5-yr totals, as well as seasonal precipitation metrics, were among the top important variables. All precipitation metrics had a positive influence on reach wettedness, while mean annual temperature had a negative influence (Figure 3c). Physical variables were also influential, particularly the soil runoff potential,

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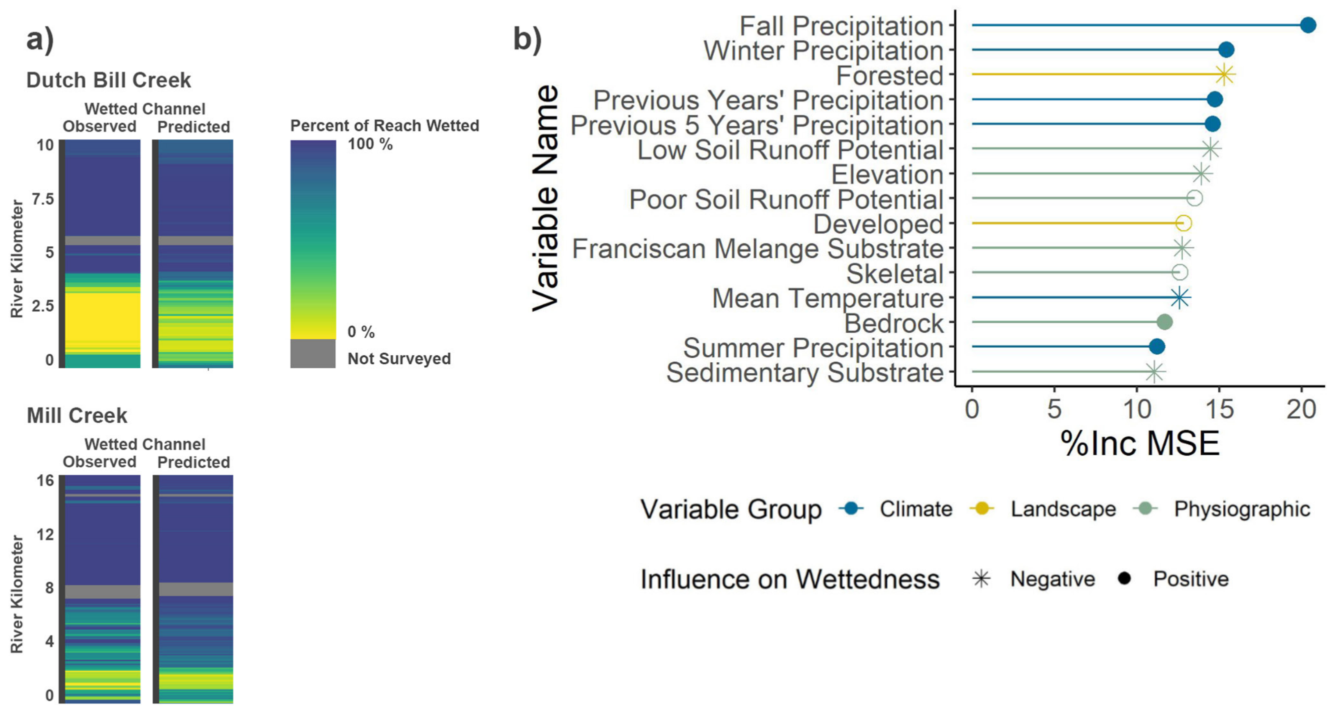

Figure 3. Performance of the end-of-season (EOS) predictive model. (a) Comparison of observed and predicted wetted channel for Dutch Bill Creek and Mill Creek, displaying EOS condition averaged across years along the stream length. The vertical axis is river kilometer, with 0 denoting the most downstream point. (b) The 15 variables selected from the recursive feature elimination with the sign of each variable's influence on channel wettedness, determined using individual conditional expectation plots.

as well as different land cover metrics. Partial dependence plots (Figure S3 and S4 in Supporting Information S1) illustrate the influence of physical surface and near-subsurface variables relative to LTP. They show that reaches were more likely to be wet when the LTP was higher, but that physical properties mediate the influence of LTP. For example, the positive effect of LTP on wetted conditions is dampened in watersheds predominantly underlain by metamorphic rock (Figure S3 in Supporting Information S1), but is amplified in those underlain by sedimentary rock (Figure S4 in Supporting Information S1).

4.3. IAV Model

The IAV model was trained on the observed interannual variance of each reach's EOS condition, along with the variables outlined in Table S2 in Supporting Information S1. Unlike the EOS model, the IAV model did not include time-varying climatic data, and instead included long-term variables of precipitation and temperature variance to characterize each stream reach. The best performing IAV model had an R^2 of 68.3% and highlighted differences within and among the study streams. For example, Dutch Bill Creek and Mill Creek (Figure 4a) have a very different wetted channel pattern, but the IAV model is able to capture the degree and distribution of IAV for both. For regions that show low IAV, the IAV model is able to predict both reliably wet and reliably dry sections.

Important predictor variables (Figure S5 in Supporting Information S1) were determined using both percent increase in MSE and node purity. A recursive feature elimination analysis (Figure 4b) determined 15 variables that were sufficient in maintaining model accuracy, with an R^2 of 63.9%. These variables primarily relate to the physical surface or near-subsurface conditions, including geologic classes, soil permeability, and some land cover metrics. Geologic classes, including Franciscan Melange and sedimentary substrate, as well as low soil runoff potential, upstream, area, and elevation had a negative influence on end-of-season condition variability. In contrast, fine soil, clay soil, high soil runoff potential, and metamorphic substrate had a positive influence on variability.

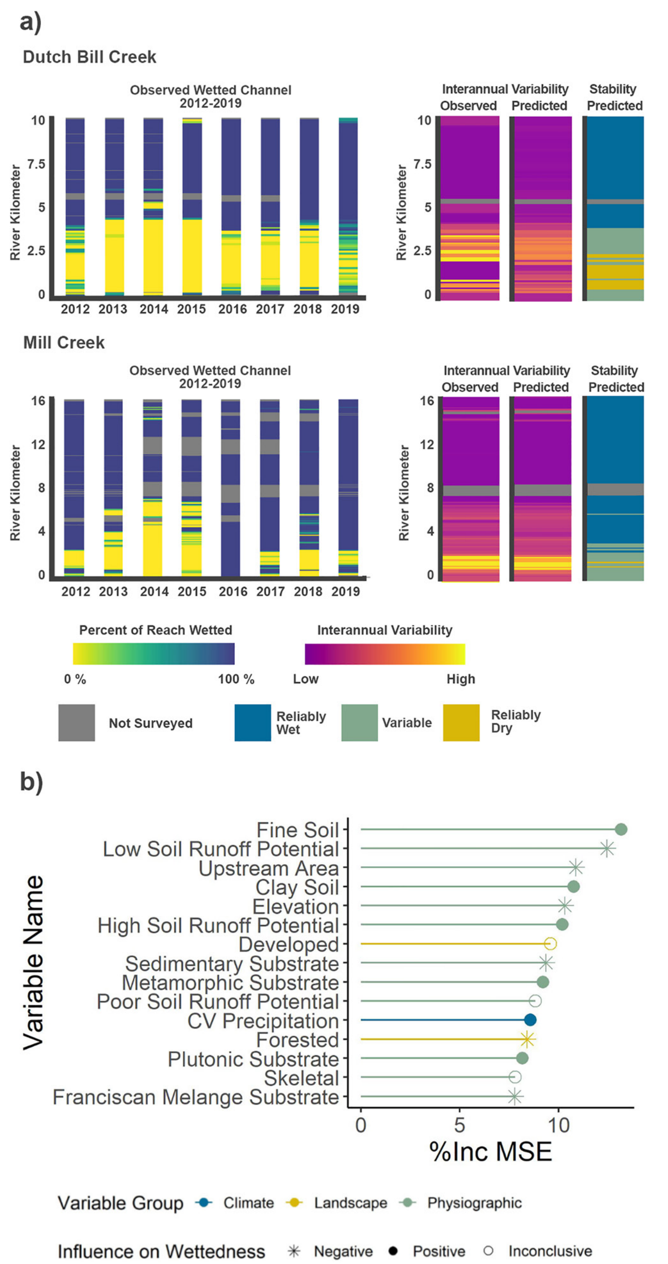

Figure 4. Performance of the interannual variability (IAV) model. (a) Comparison of observed wetted channel for Dutch Bill Creek and Mill Creek between 2012 and 2019 with the observed and predicted IAV, as well as streamflow stability, along the stream length. Streamflow stability is characterized through "reliably dry" reaches, which are defined as those with a low proportion of wetted extent (<20% of the reach) and low IAV (CV < 20%), while "reliably wet" reaches are defined as those with a high proportion of wetted extent (>80% of the reach) and low IAV (CV < 20%). The vertical axis is river kilometer, with 0 denoting the most downstream point. (b) The 15 variables selected from the recursive feature elimination with the sign of each variable's influence on variability, determined using individual conditional expectation plots.

4.4. Stability of Intermittent Stream Drying Patterns to Climate Variability

Applying our models to the whole watershed provides insights into the sensitivity of the wetted stream network to climate variability. For the driest year included in this analysis (2013), 9.8% of the entire stream network in the study area was predicted to be dry (<20% of reach wetted) and 46.7% of the stream network wet (>80% of reach wetted) at the end of the season. In contrast, for the wettest year (2017), 6.5% of the stream network was dry, compared to 71.1% of the stream network being wet.

Application of the results from the EOS model and the IAV models to predict stability of streams within the lower and middle Russian River watershed indicate that 3.7% of the watershed can be classified as reliably dry, while 16.1% of the watershed is classified as reliably wet at the end of the dry season (Figure 5). The remaining reaches in the watershed are more variable in their EOS condition, either due to high variance in surface water presence, or because the response is neither strongly wet nor dry. In terms of the spatial distribution of reliably wet and reliably dry regions, 51% of the reliably dry reaches are located in the lower sections of tributary streams, within a distance of 3 km from the Russian River, compared to only 10% of the reliably wet reaches.

5. Discussion

We developed two models to characterize intermittent stream drying patterns in relation to climate variability, using dry season wetted extent surveys for 25 streams in the Russian River watershed, across a range of water years. Our results show that end-of-season condition of streams vary both spatially and temporally, depending on physical setting and antecedent climatic conditions, with precipitation in prior seasons and years having a particularly influential effect. The models we developed to predict the end-of-season condition and the IAV both had strong predictive accuracy, with an R^2 of 76.7% and 68.3%, respectively. The trained models were applied across all streams in the lower Russian River watershed to characterize the stability of intermittent stream drying patterns to interannual climate variability. Accordingly, we were able to characterize streams based on their sensitivity to climate and identify stream reaches predicted to be reliably dry, those responsive to antecedent precipitation, and those predicted to be reliably wet and thus buffered to climate variability.

5.1. Controls on End-of-Season Channel Dynamics

Results from the EOS model suggest that climatic variables have a dominant influence on wetted channel conditions. In addition to wet season precipitation, cumulative precipitation from the previous year and previous 5 yr all had a significant influence on EOS wetted conditions. This points to the importance of hydrologic memory, and the legacy effects of antecedent precipitation in controlling wetted channel conditions. Hydrologic memory has been described as the phenomenon of the landscape retaining the effects of a hydroclimatic event long after the atmosphere does (Jacobs et al., 2020). In areas with highly variable precipitation, such as Mediterranean climates, watersheds exhibiting hydrologic memory can buffer stream hydrologic responses to climate variability. For example, an unusually dry year may not exhibit the same

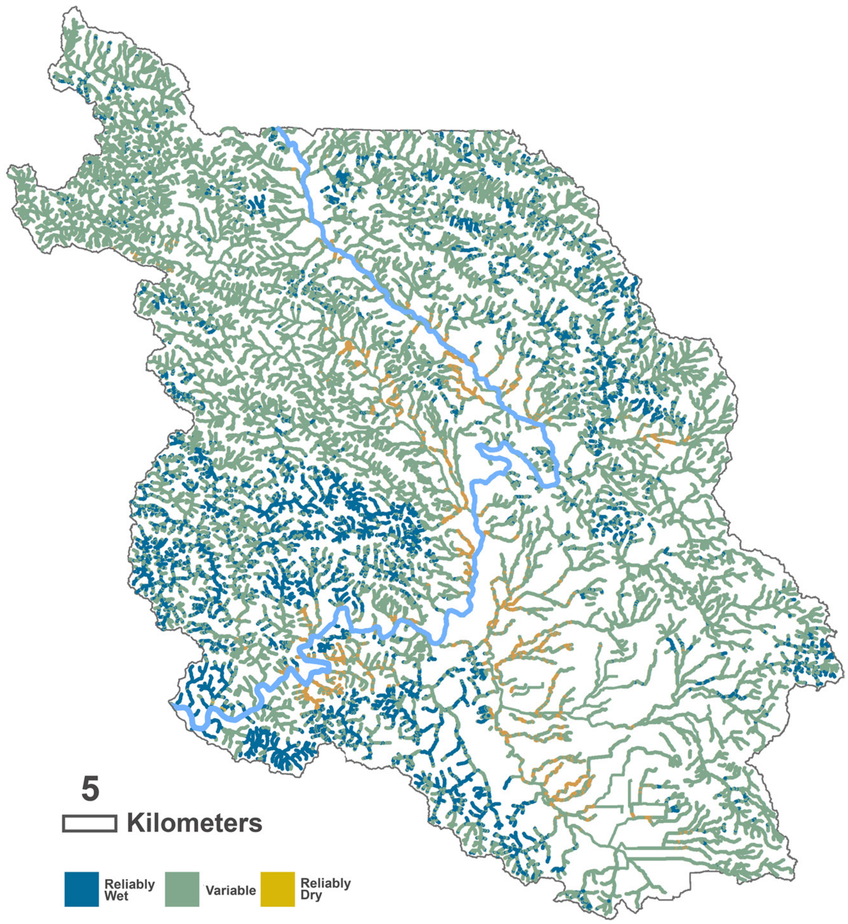

Figure 5. Stability of tributaries in the Lower and Middle Russian River watershed. "Reliably dry" reaches are defined as those with a low proportion of wetted extent (<20% of the reach) and low interannual variability (IAV; CV < 20%), while "reliably wet" reaches are defined as those with a high proportion of wetted extent (>80% of the reach) and low IAV (CV < 20%).

degree of stream drying if there was high precipitation in previous years. This has been expressed in the literature; looking at this potential influence of past precipitation, Nippgen et al. (2016) used 21 years of daily streamflow and precipitation data from five watersheds in North Carolina to show that the previous year's precipitation was as important as that year's precipitation for streamflow. We found that surface water presence is affected by precipitation record at even longer time scales, which could buffer the stream network from interannual precipitation variability.

The expression of hydrologic memory is spatially heterogeneous, and depends largely on the physical variables that affect subsurface, or near-surface, storage. Results from partial dependence plots show that physical variables like geology can either amplify or diminish antecedent precipitation effects. Areas underlain with sedimentary rock augment the influence of previous years' precipitation on end-of-season wetness, while areas underlain with metamorphic rock dampen the influence of previous years' precipitation. The importance of the underlying physical structure in water storage and streamflow response has been considered by others (Hahm, Rempe, et al., 2019; Katsuyama et al., 2005; Tague & Grant, 2004), who have shown that storage capacity is largely dependent on properties like bedrock geology, soil depth, or degree of weathering. Recent work has shown that "rock moisture," water held within weathered bedrock, can hold significant proportions of annual rainfall, thus regulates the timing of streamflow (Rempe & Dietrich, 2018) and extent of the wetted channel (Lovill et al., 2018). Indeed, regions underlain by more permeable bedrock have been shown to have higher storage and baseflow (Pfister et al., 2017), as well as higher transit times and different flow paths (Tetzlaff et al., 2009). Recent modeling work on intermittent stream hydrology has also shown that soil type is a major control on the spatial distribution of flow generation, and that unsaturated storage dynamics largely mediated the thresholds and pathways of flow (Gutiérrez-Jurado et al., 2019). Furthermore, the mechanisms that underpin the timing and extent of streamflow are in part due to the depth and permeability of the underlying soil, leading to spatiotemporally varying surface water presence during the dry season (Gutierrez-Jurado et al., 2021). This interplay between long term climate patterns and the highly localized influence of the underlying physical structure results in a heterogeneous wetted channel response, as is shown by our findings.

The importance of the critical zone moisture storage on subsurface moisture storage and surface water presence cannot be discounted, and the growing body of work on the subject (Brooks et al., 2015) has shown how these physical characteristics can decouple environmental responses from precipitation variability (Hahm, Dralle, et al., 2019). This understanding translates to wetted channel dynamics, with regions underlain by deeply weathered bedrock shown to sustain surface water flow much longer than nearby regions with a shallow critical zone (Lovill et al., 2018). Similarly, results from this study show that longer term precipitation can buffer regions from anomalous climatic conditions depending on the subsurface storage characteristics.

5.2. Variability and Stability of Streams in a Non-Stationary Climate

While it is important to understand factors that control the extent of the wetted channel in a given year, the factors that predict the IAV of stream responses provide valuable insight as well. Current climate models predict a shifting climate regime, with already variable regions expected to become even more volatile (Horne et al., 2019). For example, in California, which experiences a Mediterranean climate with strong IAV, future climate is projected to have an exacerbated seasonal cycle, with rapidly alternating drought and flood periods (Swain et al., 2018). This increase in anomalous and extreme events will likely intensify intermittent stream conditions, and may shift systems from perennial to intermittent (Datry et al., 2014; Döll & Schmied, 2012; Larned et al., 2010). Given that a river's flow regime acts as a first order control on its ecological and biogeochemical processes (Power et al., 1995), changes to a system's flow regime can alter its integrity and capacity to support specific biotic communities (Cid et al., 2020; Grimm et al., 2013). Understanding how the river network responds to precipitation variability can provide insight into its stability under a non-stationary climate and help predict changes in streamflow patterns.

The variability model developed in this paper can be used to characterize the river network and allows us to understand its long-term functioning. Streams within the Russian River watershed all fall within the same Northern Coast Ranges hydrogeologic province, but we see a large variation in stream drying dynamics across space and time. Our results show that in an extreme wet year, the predicted proportion of wet reaches is nearly double that in an extreme dry year, while the predicted proportion of dry reaches is half. By applying the end-of-season and IAV models to the whole watershed, we can identify where these wet and dry reaches persist regardless of antecedent conditions. For example, regions of high variability, which respond proportionally to antecedent conditions, are vulnerable to a volatile climate and are at risk of increasing in severity of intermittent condition and habitat fragmentation. These changes can have profound effects on ecosystem functioning and species survival, where suitable habitats may become ecological traps in highly responsive systems (Vorste et al., 2020). Though many species are adapted to intermittent conditions, increased severity of drying has been found to influence the persistence (Jaeger et al., 2014) and genetic composition of populations (Golden et al., 2021). In all likelihood, projected climate change will alter conditions faster than some species can respond (Lytle & Poff, 2004; Morrongiello et al., 2011). In contrast, regions of low variability, which are stable in their EOS condition regardless of the antecedent conditions, are buffered from anomalous climate events. From an ecological perspective, we can use this understanding to identify wet reaches with low variability as candidates for climate refuges, with reliable habitat year-to-year.

5.3. Implications for Management

Understanding where viable habitat exists within a stream network is a key management challenge, but existing strategies are often based on static conditions. Tonkin et al. (2019) recently called for novel strategies to adaptively manage river ecosystems, with a focus on models that incorporate increasing climatic variability. We address this directly by developing models that build in the nonstationarity of climate projections. The tools developed from these models can be applied to identify reaches of relative stability and concern, as well as determine areas that are vulnerable to increased intermittency. The ability to predict where the wetted channel will persist through the dry season is critically important for sustaining aquatic biodiversity in arid and semi-arid regions, and can be used to target conservation and restoration decisions. Conversely, regions that are vulnerable to increased intermittency can be targeted for further monitoring and habitat recovery strategies. That said, a distinction must be made that the models and results presented here are with respect to the end-of-season condition. Regions identified as "reliably dry" may not provide suitable habitat for aquatic organisms at the end of the summer, but may be important habitat during earlier phases of species' life cycle, such as spawning or rearing (Erman & Hawthorne, 1976; Hooley-Underwood et al., 2019; Meyer et al., 2007).

5.4. Limitations and Further Research

The results from this study show that empirical observations of wetted channel conditions coupled with readily available climatic and physical features of the stream network can provide valuable insights into the temporal and spatial dynamics of intermittent stream drying. However, limitations in the availability, resolution, and accuracy of geospatial variables constrained our ability to represent all the physical factors likely to influence wetted conditions. For example, geological variables were only available as coarse resolution classes, which only represented surficial components and not the subsurface structure. Previous studies have shown that subsurface geology (Day, 1980), depth to bedrock (Svec et al., 2005), and thickness of alluvium (Lovill et al., 2018) all affect the distribution of wetted channels but could not be incorporated into our analysis. Another limitation of our approach is the difficulty in distinguishing controls on stream drying from anthropogenic influences. Many of the reaches surveyed to calibrate the models presented here reflect a legacy of land use change in the watershed, which includes a history of intensive logging, agriculture, and water withdrawals. While we included some variables in the models to account for land use change, there were no data available to represent water-use pressures and alteration in stream channel morphology, which could significantly influence stream drying patterns. Nevertheless, the omission of these factors did not appear to substantially affect the models, given their high overall predictive performance.

Given that our models were calibrated to a single watershed in a coastal Mediterranean climate system, the utility of the approach in modeling wetted conditions in other intermittent stream contexts requires further exploration. Because performing field-based wetted channel surveys over multiple years require significant time and resources, wetted condition information obtained from remotely sensed observations may offer an alternative, cost-effective, means of building a model training data set. Future studies using remote sensors should be able to replicate the wetted channel condition data used in this study, at least in stream systems with limited canopy cover and high visibility of the stream channel. This analytical framework could also be adapted for predicting other relevant hydrological metrics, including timing of disconnection or rewetting, which would advance our understanding of how intermittent stream ecosystems may respond to climate change.

Furthermore, research is needed to expand on these findings and clarify the mechanistic connections between climate and physical variables. We found that precipitation at multiple timescales was important in predicting channel wetness, but it is unclear how these different precipitation metrics then translate to surface water presence. Of the few studies that have considered the response of precipitation at multiple timescales, Spencer et al. (2019) found that the discharge response to multi-year precipitation was controlled by bedrock storage, which regulated the baseflow, whereas event-scale rainfall response was controlled by soil and glacial till storage. However, this work was characterizing perennial streams, and more work is needed for intermittent streams in regions with seasonal precipitation. Future research focusing on the mechanisms by which both multi-year and event-scale precipitation translate to wetted channel dynamics and how the underlying physical properties that facilitate both short- and long-term water storage would greatly shape our understanding of these dynamic systems.

6. Conclusion

Understanding the spatial and temporal distribution of stream intermittency and variability is of fundamental importance for hydrology and freshwater ecology, with implications for sustaining imperiled and endemic species. By combining field observations of wetted channel extent with land cover, physiographic, and climate variables, we developed two models to predict both the extent and variability of the wetted network. We expanded this model to the entire watershed to further understand network dynamics and explore the stability of end-of-season conditions to climate variability. Climatic variables largely controlled the extent of the wetted network at the end of the season, with an emphasis on LTP, pointing to the importance of hydrologic memory. The degree to which hydrologic memory contributed to the condition of a reach was dependent on the underlying physical structure. Regions underlain by sedimentary rock tend to amplify hydrologic memory, while regions underlain by metamorphic rock tend to diminish hydrologic memory. These surficial characteristics also strongly influenced the variability of the wetted network. Given that climate predictions are calling for increased precipitation volatility, understanding the spatiotemporal drying dynamics of intermittent streams can inform climate risk assessments and strategies for protecting biodiversity and the ecosystem services that intermittent streams support.

Data Availability Statement

Sampling data are available at http://www.hydroshare.org/resource/b7973d7df99b4f719098d959078ef4c3.

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References

Allen, D. C., Kopp, D. A., Costigan, K. H., Datry, T., Hugueny, B., Turner, D. S., et al. (2019). Citizen scientists document long-term streamflow declines in intermittent rivers of the desert southwest, USA. *Freshwater Science*, *38*(2), 244–256. https://doi.org/10.1086/701483

Berkland, J. O., Raymond, L. A., Kramer, J. C., Moores, E. M., & O'day, M. (1972). "What is Franciscan?" *AAPG Bulletin*, *56*(12), 2295–2302. https://doi.org/10.1306/819A421A-16C5-11D7-8645000102C1865D

Bernal, S., Butturini, A., Riera, J. L., Vázquez, E., & Sabater, F. (2004). Calibration of the INCA model in a Mediterranean forested catchment: The effect of hydrological inter-annual variability in an intermittent stream. *Hydrology and Earth System Sciences Discussions*, *8*(4), 729–741. https://doi.org/10.5194/hess-8-729-2004

Biswal, B., & Marani, M. (2010). Geomorphological origin of recession curves. *Geophysical Research Letters*, *37*(24). https://doi.org/10.1029/2010GL045415

Brooks, P. D., Chorover, J., Fan, Y., Godsey, S. E., Maxwell, R. M., McNamara, J. P., & Tague, C. (2015). Hydrological partitioning in the critical zone: Recent advances and opportunities for developing transferable understanding of water cycle dynamics. *Water Resources Research*, *51*(9), 6973–6987. https://doi.org/10.1002/2015WR017039

Busch, M. H., Costigan, K. H., Fritz, K. M., Datry, T., Krabbenhoft, C. A., Hammond, J. C., et al. (2020). What's in a name? Patterns, trends, and suggestions for defining non-perennial rivers and streams. *Water*, *12*(7), 1980. https://doi.org/10.3390/w12071980

Cid, N., Bonada, N., Heino, J., Cañedo-Argüelles, M., Crabot, J., Sarremejane, R., et al. (2020). A metacommunity approach to improve biological assessments in highly dynamic freshwater ecosystems. *BioScience*, *70*(5), 427–438. https://doi.org/10.1093/biosci/biaa033

Costigan, K. H., Jaeger, K. L., Goss, C. W., Fritz, K. M., & Goebel, P. C. (2016). Understanding controls on flow permanence in intermittent rivers to aid ecological research: Integrating meteorology, geology and land cover. *Ecohydrology*, *9*(7), 1141–1153. https://doi.org/10.1002/eco.1712

Cutler, D. R., Edwards, T. C., Beard, K. H., Cutler, A., Hess, K. T., Gibson, J., & Lawler, J. J. (2007). Random forests for classification in ecology. *Ecology*, *88*(11), 2783–2792. https://doi.org/10.1890/07-0539.1

Dai, A. (2011). Drought under global warming: A review. *WIREs Climate Change*, *2*(1), 45–65. https://doi.org/10.1002/wcc.81

Daly, C., Halbleib, M., Smith, J. I., Gibson, W. P., Doggett, M. K., Taylor, G. H., et al. (2008). Physiographically sensitive mapping of climatological temperature and precipitation across the conterminous United States. *International Journal of Climatology*, *28*(15), 2031–2064. https://doi.org/10.1002/joc.1688

Datry, T., Boulton, A. J., Bonada, N., Fritz, K., Leigh, C., Sauquet, E., et al. (2018). Flow intermittence and ecosystem services in rivers of the Anthropocene. *Journal of Applied Ecology*, *55*(1), 353–364. https://doi.org/10.1111/1365-2664.12941

Datry, T., Foulquier, A., Corti, R., von Schiller, D., Tockner, K., Mendoza-Lera, C., et al. (2018). A global analysis of terrestrial plant litter dynamics in non-perennial waterways. *Nature Geoscience*, *11*(7), 497–503. https://doi.org/10.1038/s41561-018-0134-4

Datry, T., Larned, S. T., & Tockner, K. (2014). Intermittent Rivers: A Challenge for Freshwater Ecology. *BioScience*, *64*(3), 229–235. https://doi.org/10.1093/biosci/bit027

Datry, T., Pella, H., Leigh, C., Bonada, N., & Hugueny, B. (2016). A landscape approach to advance intermittent river ecology. *Freshwater Biology*, *61*(8), 1200–1213. https://doi.org/10.1111/fwb.12645

Day, D. G. (1980). Lithologic controls of drainage density: A study of six small rural catchments in New England, N.S.W. *CATENA*, *7*(4), 339–351. https://doi.org/10.1016/0341-8162(80)90018-1

Deitch, M. J., Kondolf, G. M., & Merenlender, A. M. (2009). Surface water balance to evaluate the hydrological impacts of small instream diversions and application to the Russian River basin, California, USA. *Aquatic Conservation: Marine and Freshwater Ecosystems*, *19*(3), 274–284. https://doi.org/10.1002/aqc.1012

Dhungel, S., Tarboton, D. G., Jin, J., & Hawkins, C. P. (2016). Potential effects of climate change on ecologically relevant streamflow regimes. *River Research and Applications*, *32*(9), 1827–1840. https://doi.org/10.1002/rra.3029

Döll, P., & Schmied, H. M. (2012). How is the impact of climate change on river flow regimes related to the impact on mean annual runoff? A global-scale analysis. *Environmental Research Letters*, *7*(1), 014037. https://doi.org/10.1088/1748-9326/7/1/014037

Dubayah, R. & Hurtt, G. UMD-NASA carbon mapping/Sonoma county vegetation mapping and LiDAR program. *Data provided and funded by the Sonoma county vegetation mapping and lidar program, and the University of Maryland under grant NNX13AP69G from NASA's Carbon Monitoring System*.

Erman, D. C., & Hawthorne, V. M. (1976). The quantitative importance of an intermittent stream in the spawning of rainbow trout. *Transactions of the American Fisheries Society*, *105*(6), 675–681. https://doi.org/10.1577/1548-8659(1976)105<675:TQIOAI>2.0.CO;2

Gasith, A., & Resh, V. H. (1999). Streams in Mediterranean climate regions: Abiotic influences and biotic responses to predictable seasonal events. *Annual Review of Ecology and Systematics*, *30*(1), 51–81. https://doi.org/10.1146/annurev.ecolsys.30.1.51

Godsey, S. E., & Kirchner, J. W. (2014). Dynamic, discontinuous stream networks: Hydrologically driven variations in active drainage density, flowing channels and stream order. *Hydrological Processes*, *28*(23), 5791–5803. https://doi.org/10.1002/hyp.10310

Golden, H. E., Holsinger, K. E., Deegan, L. A., MacKenzie, C. J. A., & Urban, M. C. (2021). River drying influences genetic variation and population structure in an Arctic freshwater fish. *Conservation Genetics*. https://doi.org/10.1007/s10592-021-01339-0

Grantham, T. E. (2013). Use of hydraulic modelling to assess passage flow connectivity for Salmon in streams. *River Research and Applications*, *29*(2), 250–267. https://doi.org/10.1002/rra.1591

Grantham, T. E., Newburn, D. A., McCarthy, M. A., & Merenlender, A. M. (2012). The role of atreamflow and land use in limiting oversummer survival of juvenile steelhead in California streams. *Transactions of the American Fisheries Society*, *141*(3), 585–598. https://doi.org/10.1080/00028487.2012.683472

Gregorutti, B., Michel, B., & Saint-Pierre, P. (2017). Correlation and variable importance in random forests. *Statistics and Computing*, *27*(3), 659–678. https://doi.org/10.1007/s11222-016-9646-1

Grimm, N. B., Chapin, F. S., Bierwagen, B., Gonzalez, P., Groffman, P. M., Luo, Y., et al. (2013). The impacts of climate change on ecosystem structure and function. *Frontiers in Ecology and the Environment*, *11*(9), 474–482. https://doi.org/10.1890/120282

Grimm, N. B., & Fisher, S. G. (1992). Responses of arid-land streams to changing climate. In P. Firth & S. G. Fisher (Eds.), *Global climate change and freshwater ecosystems* (pp. 211–233). Springer. https://doi.org/10.1007/978-1-4612-2814-1_10

Gutiérrez-Jurado, K. Y., Partington, D., Batelaan, O., Cook, P., & Shanafield, M. (2019). What triggers streamflow for intermittent rivers and ephemeral streams in low-gradient catchments in Mediterranean climates. *Water Resources Research*, *55*(11), 9926–9946. https://doi.org/10.1029/2019WR025041

Gutierrez-Jurado, K. Y., Partington, D., & Shanafield, M. (2021). Taking theory to the field: Streamflow generation mechanisms in an intermittent Mediterranean catchment. *Hydrology and Earth System Sciences*, *25*(8), 4299–4317. https://doi.org/10.5194/hess-25-4299-2021

Hahm, W. J., Dralle, D. N., Rempe, D. M., Bryk, A. B., Thompson, S. E., Dawson, T. E., & Dietrich, W. E. (2019). Low subsurface water storage capacity relative to annual rainfall decouples Mediterranean plant productivity and water use from rainfall variability. *Geophysical Research Letters*, *46*(12), 6544–6553. https://doi.org/10.1029/2019GL083294

Hahm, W. J., Rempe, D. M., Dralle, D. N., Dawson, T. E., Lovill, S. M., Bryk, A. B., et al. (2019). Lithologically controlled subsurface critical zone thickness and water storage capacity determine regional plant community composition. *Water Resources Research*, *55*(4), 3028–3055. https://doi.org/10.1029/2018WR023760

Hammond, J., Zimmer, M., Shanafield, M., Kaiser, K., Godsey, S., Mims, M., et al. (2021). Spatial patterns and drivers of nonperennial flow regimes in the contiguous United States. *Geophysical Research Letters*, *48*(2), e2020GL090794. https://doi.org/10.1029/2020GL090794

Heim, K. C., Wipfli, M. S., Whitman, M. S., Arp, C. D., Adams, J., & Falke, J. A. (2016). Seasonal cues of Arctic grayling movement in a small Arctic stream: The importance of surface water connectivity. *Environmental Biology of Fishes*, *99*(1), 49–65. https://doi.org/10.1007/s10641-015-0453-x

Homer, C. H., Fry, J. A., & Barnes, C. A. (2012). *The national land cover database (Fact Sheet 2012-3020)*. U.S. Geological Survey, p. 4. https://doi.org/10.3133/fs20123020

Hooley-Underwood, Z. E., Stevens, S. B., Salinas, N. R., & Thompson, K. G. (2019). An intermittent stream supports extensive spawning of large-river native fishes. *Transactions of the American Fisheries Society*, *148*(2), 426–441. https://doi.org/10.1002/tafs.10141

Horne, A. C., Nathan, R., Poff, N. L., Bond, N. R., Webb, J. A., Wang, J., & John, A. (2019). Modeling flow-ecology responses in the Anthropocene: Challenges for sustainable riverine management. *BioScience*, *69*(10), 789–799. https://doi.org/10.1093/biosci/biz087

Horton, J. D., (2017). *The state geologic map compilation (SGMC) geodatabase of the conterminous United States*. U.S. Geological Survey. https://doi.org/10.3133/ds1052

Hwan, J. L., & Carlson, S. M. (2016). Fragmentation of an intermittent stream during seasonal drought: Intra-annual and interannual patterns and biological consequences. *River Research and Applications*, *32*(5), 856–870. https://doi.org/10.1002/rra.2907

Jacobs, E. M., Bertassello, L. E., & Rao, P. S. C. (2020). Drivers of regional soil water storage memory and persistence. *Vadose Zone Journal*, *19*(1), e20050. https://doi.org/10.1002/vzj2.20050

Jaeger, K. L., Olden, J. D., & Pelland, N. A. (2014). Climate change poised to threaten hydrologic connectivity and endemic fishes in dryland streams. *Proceedings of the National Academy of Sciences of the United States of America*, *111*(38), 13894–13899. https://doi.org/10.1073/pnas.1320890111

Jensen, C. K., McGuire, K. J., & Prince, P. S. (2017). Headwater stream length dynamics across four physiographic provinces of the Appalachian Highlands. *Hydrological Processes*, *31*(19), 3350–3363. https://doi.org/10.1002/hyp.11259

Katsuyama, M., Ohte, N., & Kabeya, N. (2005). Effects of bedrock permeability on hillslope and riparian groundwater dynamics in a weathered granite catchment. *Water Resources Research*, *41*(1). https://doi.org/10.1029/2004WR003275

Kuhn, M. (2011). *Contributions from Jed Wing, Steve Weston, Andre Williams, Chris Keefer and Allan Engelhardt. Caret: Classification and regression training* [R package version 4.98]. Retrieved from http://CRAN.R-project.org/package=caret

Lapides, D. A., Leclerc, C. D., Moidu, H., Dralle, D. N., & Hahm, W. J. (2021). Variability of stream extents controlled by flow regime and network hydraulic scaling. *Hydrological Processes*, *35*(3), e14079. https://doi.org/10.1002/hyp.14079

Larned, S. T., Datry, T., Arscott, D. B., & Tockner, K. (2010). Emerging concepts in temporary-river ecology. *Freshwater Biology*, *55*(4), 717–738. https://doi.org/10.1111/j.1365-2427.2009.02322.x

Larson, E. R., Magoulick, D. D., Turner, C., & Laycock, K. H. (2009). Disturbance and species displacement: Different tolerances to stream drying and desiccation in a native and an invasive crayfish. *Freshwater Biology*, *54*(9), 1899–1908. https://doi.org/10.1111/j.1365-2427.2009.02243.x

Liaw, A., & Wiener, M. (2002). Classification and regression by randomForest. *R News*, *2*, 18–22.

Lovill, S. M., Hahm, W. J., & Dietrich, W. E. (2018). Drainage from the critical zone: Lithologic controls on the persistence and spatial extent of wetted channels during the summer dry season. *Water Resources Research*, *54*(8), 5702–5726. https://doi.org/10.1029/2017WR021903

Lytle, D. A., & Poff, N. L. (2004). Adaptation to natural flow regimes. *Trends in Ecology & Evolution*, *19*(2), 94–100. https://doi.org/10.1016/j.tree.2003.10.002

Marshall, J. C., Acuña, V., Allen, D. C., Bonada, N., Boulton, A. J., Carlson, S. M., et al. (2018). Protecting U.S. temporary waterways. *Science*, *361*, 856–857. https://doi.org/10.1126/science.aav0839

Merenlender, A. (2000). Mapping vineyard expansion provides information on agriculture and the environment. *California Agriculture*, *54*(3), 7–12. https://doi.org/10.3733/ca.v054n03p7

Meyer, J. L., Strayer, D. L., Wallace, J. B., Eggert, S. L., Helfman, G. S., & Leonard, N. E. (2007). The contribution of headwater streams to biodiversity in river networks. *JAWRA Journal of the American Water Resources Association*, *43*(1), 86–103. https://doi.org/10.1111/j.1752-1688.2007.00008.x

Morrongiello, J. R., Beatty, S. J., Bennett, J. C., Crook, D. A., Ikedife, D. N. E. N., Kennard, M. J., et al. (2011). Climate change and its implications for Australia's freshwater fish. *Marine and Freshwater Research*, *62*(9), 1082–1098. https://doi.org/10.1071/MF10308

Nippgen, F., McGlynn, B. L., Emanuel, R. E., & Vose, J. M. (2016). Watershed memory at the Coweeta Hydrologic Laboratory: The effect of past precipitation and storage on hydrologic response. *Water Resources Research*, *52*(3), 1673–1695. https://doi.org/10.1002/2015WR018196

Obedzinski, M., Pierce, S. N., Horton, G. E., & Deitch, M. J. (2018). Effects of flow-related variables on oversummer survival of juvenile Coho Salmon in intermittent streams. *Transactions of the American Fisheries Society*, *147*(3), 588–605. https://doi.org/10.1002/tafs.10057

Opperman, J., Lohse, K., Brooks, C., Kelly, M., & Merenlender, A. (2005). Influence of land use on fine sediment in salmonid spawning gravels within the Russian River Basin, California. *Canadian Journal of Fisheries and Aquatic Sciences*, *62*, 2740–2751. https://doi.org/10.1139/F05-187

Osward, D. D. (1972). *Timber resources of Mendocino and Sonoma counties. Resource Bulletin PNW-RB-040* (p. 89). U.S. Department of Agriculture, Forest Service. Pacific Northwest Research Station. Retrieved from https://www.fs.usda.gov/treesearch/pubs/26205

Pate, A. A., Segura, C., & Bladon, K. D. (2020). Streamflow permanence in headwater streams across four geomorphic provinces in Northern California. *Hydrological Processes*, *34*(23), 4487–4504. https://doi.org/10.1002/hyp.13889

Pendergrass, A. G., Knutti, R., Lehner, F., Deser, C., & Sanderson, B. M. (2017). Precipitation variability increases in a warmer climate. *Scientific Reports*, *7*(1), 17966. https://doi.org/10.1038/s41598-017-17966-y

Pfister, L., Martínez-Carreras, N., Hissler, C., Klaus, J., Carrer, G. E., Stewart, M. K., & McDonnell, J. J. (2017). Bedrock geology controls on catchment storage, mixing, and release: A comparative analysis of 16 nested catchments. *Hydrological Processes*, *31*(10), 1828–1845. https://doi.org/10.1002/hyp.11134

Power, M. E., Sun, A., Parker, G., Dietrich, W. E., & Wootton, J. T. (1995). Hydraulic food-chain models. *BioScience*, *45*(3), 159–167. https://doi.org/10.2307/1312555

Prancevic, J. P., & Kirchner, J. W. (2019). Topographic controls on the extension and retraction of flowing streams. *Geophysical Research Letters*, *46*(4), 2084–2092. https://doi.org/10.1029/2018GL081799

Prasad, A. M., Iverson, L. R., & Liaw, A. (2006). Newer classification and regression tree techniques: Bagging and random forests for ecological prediction. *Ecosystems*, *9*(2), 181–199. https://doi.org/10.1007/s10021-005-0054-1

Rempe, D. M., & Dietrich, W. E. (2018). Direct observations of rock moisture, a hidden component of the hydrologic cycle. *Proceedings of the National Academy of Sciences of the United States of America*, *115*(11), 2664–2669. https://doi.org/10.1073/pnas.1800141115

Sabo, J. L., Finlay, J. C., Kennedy, T., & Post, D. M. (2010). The role of discharge variation in scaling of drainage area and food chain length in rivers. *Science*, *330*(6006), 965–967. https://doi.org/10.1126/science.1196005

Soil Survey Staff. (2016). Natural Resources Conservation Service, United States Department of Agriculture. In *Agricultural and forest meteorology*. Soil Survey Geographic (SSURGO) Database for Eastern US. Retrieved from https://data.nal.usda.gov/dataset/gridded-soil-survey-geographic-database-gssurgo

Spencer, S. A., Silins, U., & Anderson, A. E. (2019). Precipitation-runoff and storage dynamics in watersheds underlain by till and permeable bedrock in Alberta's Rocky Mountains. *Water Resources Research*, *55*(12), 10690–10706. https://doi.org/10.1029/2019WR025313

Stanley, E. H., Fisher, S. G., & Grimm, N. B. (1997). Ecosystem expansion and contraction in streams. *BioScience*, *47*(7), 427–435. https://doi.org/10.2307/1313058

Sumargo, E., Wilson, A. M., Ralph, F. M., Weihs, R., White, A., Jasperse, J., et al. (2020). The hydrometeorological observation network in California's Russian rver watershed: Development, characteristics, and key findings from 1997 to 2019. *Bulletin of the American Meteorological Society*, *101*(10), E1781–E1800. https://doi.org/10.1175/BAMS-D-19-0253.1

Svec, J. R., Kolka, R. K., & Stringer, J. W. (2005). Defining perennial, intermittent, and ephemeral channels in Eastern Kentucky: Application to forestry best management practices. *Forest Ecology and Management*, *214*(1), 170–182. https://doi.org/10.1016/j.foreco.2005.04.008

Swain, D. L., Langenbrunner, B., Neelin, J. D., & Hall, A. (2018). Increasing precipitation volatility in twenty-first-century California. *Nature Climate Change*, *8*(5), 427–433. https://doi.org/10.1038/s41558-018-0140-y

Tague, C., & Grant, G. E. (2004). A geological framework for interpreting the low-flow regimes of Cascade streams, Willamette River Basin, Oregon. *Water Resources Research*, *40*(4). https://doi.org/10.1029/2003WR002629

Tetzlaff, D., Seibert, J., McGuire, K. J., Laudon, H., Burns, D. A., Dunn, S. M., & Soulsby, C. (2009). How does landscape structure influence catchment transit time across different geomorphic provinces? *Hydrological Processes*, *23*(6), 945–953. https://doi.org/10.1002/hyp.7240

Tonkin, J. D., Poff, N. L., Bond, N. R., Horne, A., Merritt, D. M., Reynolds, L. V., et al. (2019). Prepare river ecosystems for an uncertain future. *Nature*, *570*(7761), 301–303. https://doi.org/10.1038/d41586-019-01877-1

von Schiller, D., Acuña, V., Graeber, D., Martí, E., Ribot, M., Sabater, S., et al. (2011). Contraction, fragmentation and expansion dynamics determine nutrient availability in a Mediterranean forest stream. *Aquatic Sciences*, *73*(4), 485–497. https://doi.org/10.1007/s00027-011-0195-6

Vorste, R. V., Obedzinski, M., Pierce, S. N., Carlson, S. M., & Grantham, T. E. (2020). Refuges and ecological traps: Extreme drought threatens persistence of an endangered fish in intermittent streams. *Global Change Biology*, *26*(7), 3834–3845. https://doi.org/10.1111/gcb.15116

Ward, A. S., Schmadel, N. M., & Wondzell, S. M. (2018). Simulation of dynamic expansion, contraction, and connectivity in a mountain stream network. *Advances in Water Resources*, *114*, 64–82. https://doi.org/10.1016/j.advwatres.2018.01.018

Yu, S., Bond, N. R., Bunn, S. E., & Kennard, M. J. (2019). Development and application of predictive models of surface water extent to identify aquatic refuges in Eastern Australian Temporary Stream Networks. *Water Resources Research*, *55*(11), 9639–9655. https://doi.org/10.1029/2019WR025216