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Climate Forcings Across Multiple Timescales Control Stream Drying and Wetting in a Headwater Catchment

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ABSTRACT

Hydrologists commonly use climate metrics to understand watershed function and streamflow response due to their widespread availability and effectiveness in hydrologic models used to predict streamflow. This is particularly true in research aimed at characterising how streamflow response varies under changing climate conditions. In semi-arid to arid environments, researchers typically hypothesise that in drier, warmer years, vegetation and streamflow are in direct competition for stored water. Conceptual models suggest that seasonal plant water use and evapotranspiration (ET) can ultimately cause stream drying (or non-perennial flow) in summer months. While past research has directly investigated links between riparian ET and stream drying, we have yet to explore the link between the climate conditions that drive ET and stream non-perenniality, particularly over longer and varying timescales. Here, we used commonly observed climate variables in combination with machine learning and explainable artificial intelligence techniques to identify drivers and their impacts on the wetting and drying characteristics in the semi-arid Dry Creek Experimental Watershed. Our results highlight that actual ET (AET) and precipitation are highly correlated to non-perennial behaviour. We found an inverse relationship between ET and drying: higher AET corresponds to less drying. This may suggest that watershed scale AET and streamflow might not be in direct competition; rather, AET is an indicator of overall water availability in this semi-arid climate. Finally, we found that wetting and drying behaviour is driven by climate processes on shorter (weekly) and longer (seasonal) timescales, respectively. Non-perennial streamflow processes rely on antecedent climate conditions active over a range of timescales. Therefore, it is not sufficient to use a singular temporal discretisation of climate metrics to determine hydrologic response. These results can be used to inform the design of interdisciplinary studies that link climate, hydrology and ecological function to climate change impacts.

1 | Introduction

Globally, models suggest that over half of all streams and rivers dry for at least 1 day of the year (Messager et al. 2021), but within the United States, only 10% of US Geological Survey stream gauges have ever observed one or more days of dry conditions (Zimmer et al. 2020). USGS gauge sites are biased towards larger drainage basins as opposed to small headwater catchments where stream drying is most commonly observed (Krabbenhoft et al. 2022). Stream drying in headwaters influences stream habitat, biodiversity (Malish et al. 2023) and water chemistry (Zimmer et al. 2022), and has implications for downstream water resource management and regulation (Datry et al. 2016; Dodds and Oakes 2008; Golden et al. 2025;

Larned et al. 2010; Zipper et al. 2021). Headwater streams are a critical drinking water source and set the initial water quality signature for downstream systems (Wohl 2017). Regulation and protection of these headwater systems is critical, yet models predict that 45% of previously regulated streams in the United States are no longer protected because they do not meet new, more restrictive standards of a 'connected waterway' (Greenhill et al. 2024). Models can aid in focusing efforts on protection of these at-risk areas, but they are ultimately only as good and accurate as our data and process understanding of the drivers of stream drying and disconnection from larger, more perennial stream systems. Further understanding of the controls on stream intermittency is critical to improve accuracy in predicting the timing and duration of stream drying in headwaters. To do so, the relatively few long-term climate and streamflow datasets in intermittent headwater streams must be leveraged to understand how climate controls the duration of stream drying.

Drivers of and differences in stream drying are primarily studied and compared at continental scales (Hammond et al. 2021; Messager et al. 2021; Price et al. 2021; Shanafield et al. 2021; Zipper et al. 2021). Those studies indicate that climate, along with geology, land cover and anthropogenic activities, impact when and where streams will dry. Climate explains when and for how long a stream will dry, while physiography explains where and how fast it dries (Godsey and Kirchner 2014; Hammond et al. 2021; Prancevic and Kirchner 2019; Price et al. 2021; Shanafield et al. 2021; Warix et al. 2021; Zimmer et al. 2020; Zipper et al. 2021). Large-scale statistical models can successfully capture general intermittency patterns integrated over large areas (Hammond et al. 2021; Jaeger et al. 2019; Zipper et al. 2021). Most regional and continental scale models integrate climatic processes over annual timesteps. Limited studies capture how seasonal or shorter-term climate variables control stream drying, though this is common practice in evaluating runoff ratios and storage dynamics in perennial systems (e.g., Aulenbach and Peters 2018; Grande et al. 2022; Nippgen et al. 2016; Penna et al. 2015; among others). Only recently have studies incorporated sub-annual climate metrics in stream drying predictive models (Sando et al. 2022). It is still unclear how climatic processes at finer temporal scales or across a range of scales influence stream drying in smaller catchments. Representation and analysis of climate drivers at multiple timescales, particularly finer ones, are very important in regions with strong climate and streamflow seasonality and/or when energy and water availability are out of phase, namely snowmelt dominated and semi-arid systems. Understanding the influence of these climate drivers in snowmelt driven catchments is even more critical considering how sensitive mountain environments are to climate change. Predicted changes to snowpack accumulation and melt (Klos et al. 2014; Marshall et al. 2019) will influence streamflow volumes and timing and therefore stream drying in complex ways (Barnhart et al. 2016; Berghuijs et al. 2014; Christensen et al. 2021; Newcomb et al. 2024).

The interactions of plant water use and interannual storage of water (Donaldson et al. 2024) are major confounding factors in predicting the drivers and timing of stream drying. Traditional lines of estimating plant water availability are via monitoring and modelling soil moisture, the water available in the shallow subsurface: the land surface to the saprolite (Wang et al. 2019). This shallow water storage is depleted and refilled annually in snowmelt dominated semi-arid environments (Harpold 2016; McNamara et al. 2005). Following this, any water that recharged deeper groundwater systems in the regolith was thought to be isolated from plant water use and supplied baseflow for streams in late summer (Tashie et al. 2019), that is, green and blue water (Falkenmark and Rockström 2006). However, additional critical zone studies now suggest that, particularly in more arid mountain environments, plants are more deeply rooted and can access much deeper water stores, utilising and potentially competing for the same water that supports baseflow (Donaldson et al. 2024, 2023; Dralle et al. 2018, 2020; Hahm et al. 2019; Rempe and Dietrich 2018). This implies that evapotranspiration (ET) may be an indicator of late summer flows and/or stream drying. Further, the zone of storage that supports ET and base flow is much deeper with multi-year residence times, but it is at least partially filled and drained on annual and seasonal timescales. This suggests that it is even more critical to evaluate potential climate drivers of stream drying across multiple timescales.

In this study we synthesised a long-term record (23+ years) of streamflow and climate observations in the 27-km^2 Dry Creek Experimental Watershed (DCEW) in southwestern Idaho to investigate how climate variables relate to the drying and wetting regimes of semi-arid snowmelt dominated headwater streams. We expected that increased snow in a given winter would result in less stream drying, while higher spring and summer temperatures with more ET would cause more drying. However, we found that ET was a good predictor of stream drying, where greater ET was related to less drying. The results of this analysis will provide insight into the timescales of climatic controls on stream drying and provide information on potential metrics that can be used to improve statistical models of stream drying and flow permanence.

2 | Study Site

Research was completed in the DCEW, a 27-km^2 semi-arid watershed located in Southwest Idaho ranging in elevation from 1000 to 2200 m.a.s.l. (Figure 1). DCEW spans the rain–snow transition, where higher elevations receive as much as 55% of annual precipitation as snow while lower elevations receive as little as 16% of annual precipitation as snow (McNamara et al. 2018). Soils are loam and sandy loam and are underlain by fractured Cretaceous granodiorite bedrock (Rember et al. 1979; Tesfa et al. 2009). Vegetation below 1500 m.a.s.l. is primarily grasses and sagebrush (*Artemisia tridentata*), transitioning to douglas-fir (*Pseudotsuga menziesii*) and ponderosa pine (*Pinus ponderosa*) at higher elevations. Riparian areas are densely vegetated with cottonwoods (*Populus fremontii*), water birch (*Betula occidentalis*), mountain alder (*Alnus viridis*), mountain maple (*Acer spicatum*) and yellow willow (*Salix lutea*; Graham et al. 2013).

DCEW has several permanent sites for measuring streamflow, however for this study we only use the gauge located at the watershed outlet where the stream dries in most years, referred to as 'Lower Gauge' or 'LG' (Figure 1; Aishlin and McNamara 2011). A Natural Resources Conservation Service (NRCS) SNOTEL site

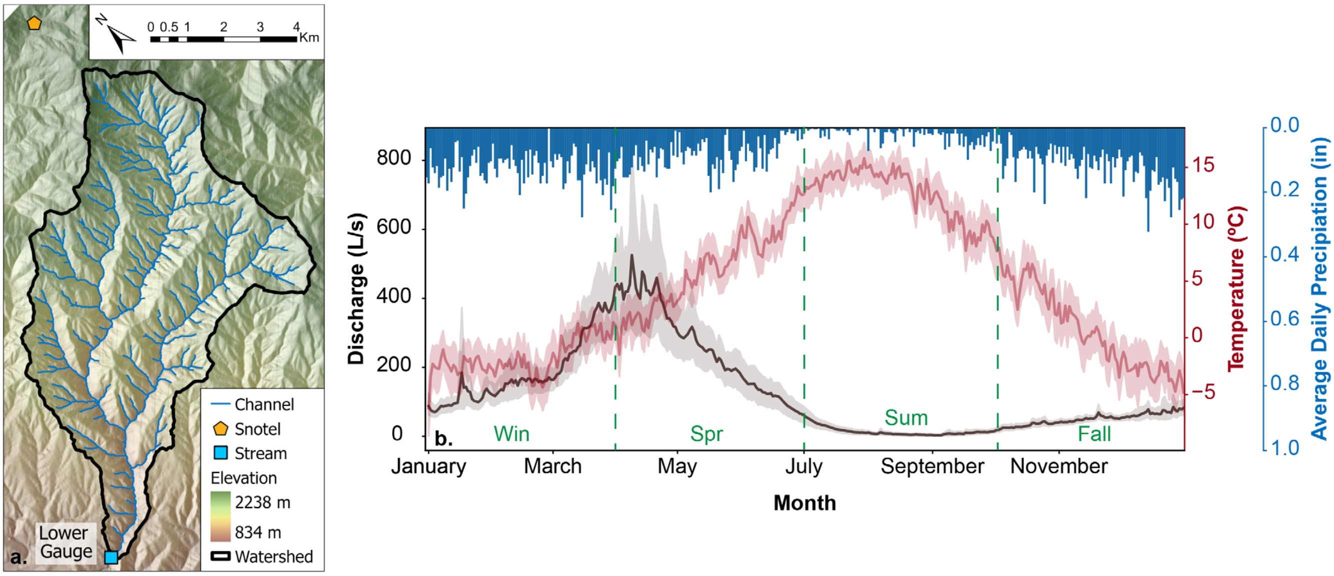

FIGURE 1 | (a) Map of Dry Creek Experimental Watershed (DCEW) with Lower Gauge (LG) and Bogus Basin SNOTEL. (b) Average climate and hydrograph of DCEW over the period of record (2000–2023). Mean daily discharge at LG (black), mean daily air temperature and precipitation (red and blue, respectively) is measured at Bogus Basin SNOTEL. Shaded area around discharge and temperature is the 5th and 95th percentiles of the distribution of flow. Green dashed lines indicate seasonal breaks.

is located ~1.5 km north of DCEW at 1932 m.a.s.l., and measures snow water equivalent (SWE), precipitation, air temperature and many additional hydrometeorological proxies (Figure 1, site 978 Bogus Basin).

3 | Methods

3.1 | Filtering for Drying and Climate Metrics

3.1.1 | Drying Metrics

Streamflow data for each year was visually quality checked to identify dry and wet conditions. For each hourly time step in the discharge time series, streamflow below 1 L/s was determined to be dry. Additionally, streamflow was manually designated as dry when it reached a minimum (1–4 L/s) and diel changes in streamflow were not observed (> 12 h of drying in a day). These assumptions are supported by field observations that disconnected pools form in this range of observed flows. We calculated drying metrics over the period of record from 2001 to 2022, removing years that had missing streamflow data during the summer low-flow period, which removed the years 2000, 2003, 2006, 2010 and 2021. The resulting dataset contained 14 years that drying was observed and 4 years where drying was not observed at LG.

Using this drying dataset, drying metrics were identified for each year that describe the natural flow regime (sensu Hammond et al. 2021; Poff et al. 1997; Price et al. 2021; Zipper et al. 2021):

1. No-flow duration: total number of days that drying was observed for at least 1 h during that day.
2. No-flow start date: first Julian day the stream dries within a given water year.
3. Wetting start date: first Julian day streamflow returns and where flow remains continuous for the remainder of the water year (i.e., there are no dry days later in the season).
4. Peak to no-flow: number of days from spring peak streamflow to no-flow start date, the drying duration.

We evaluate drying on a water year basis (Oct–Sept), but for simplicity of analysis, we use Julian day for no-flow start and wetting start dates (Jan 1 = 1). No-flow duration and peak to no-flow are a number of days and are not associated with a specific date.

3.1.2 | Climate Metrics

A total of 138 climate metrics were calculated using observed and modelled datasets. Annual and seasonal climate metrics of snowpack, precipitation and air temperature were calculated using the Bogus Basin SNOTEL site. Actual evapotranspiration (AET) was calculated using Terra Moderate Resolution Imaging Spectrometer Net Evapotranspiration Gap-Filled 8-Day data at 500 m resolution (MOD16A2GF; data were retrieved from the Application for Extracting and Exploring Analysis Ready Samples AρρEEARS; Running et al. 2013). ET data were extracted for DCEW for years 2000–2022 and was processed by spatially averaging ET data over each time step. Temporal averages were then taken to determine the monthly mean, seasonal mean and annual mean ET values for the entire DCEW.

3.1.3 | Variable Time Windows

All climate metrics are cumulative or average values taken over weekly, seasonal or annual timesteps. Based on the climatology of DCEW, we established seasonal breaks based on climatic characteristics of precipitation and temperature (Figure 1b). We grouped months into seasons as defined in Table 1, which are 1 month offset from a traditional meteorological or astronomical season. In DCEW, summer is most accurately defined as the period of minimal precipitation, warmest temperatures and the snowpack has melted entirely, all of which occur in the months of July, August and September (Figure 1b). In DCEW and southwest Idaho in particular, substantial snowpack development does not commonly occur until January, building to its maximum in March, making these months the most representative of winter conditions at DCEW. The months of October, November and December are left as a reasonable definition of fall for this system (also aligning with the water year). We defined spring to align with the historical period of snowmelt, with April being the broadly accepted date to measure peak SWE before its decline, and full melt commonly occurring in May and June (Table 1).

TABLE 1 | Time groupings, naming conventions and statistical groupings for predictor variables.

Groupings	Naming conventions	Description
Temporal	Fall	Oct, Nov, Dec
	Win	Jan, Feb, Mar
	Spr	Apr, May, Jun
	Sum	Jul, Aug, Sep
	ant	Antecedent (prior) water year
	Month	Entire month
	doy	Julian day of year
	#-week	Number of weeks prior
Predictor	Precip	Precipitation at SNOTEL (in)
	ET	Evapotranspiration from MODIS ($kg\,m^{-2}\,day^{-1}$)
	Temp	Air temperature at SNOTEL (°C)
	Rain	Precipitation as rain at SNOTEL (in)
	Snow	Precipitation as snow at SNOTEL (in)
	%snow	Percent precipitation as snow at SNOTEL (%)
	%rain	Percent precipitation as rain at SNOTEL (%)
	Melt_day	Day of year SWE = 0 at SNOTEL (doy)
	Q_Max	Maximum streamflow discharge at Lower Gauge in DCEW ($ft^3\,s^{-1}$)
	Q_Vol	Total volume of water passed through Lower Gauge in DCEW in water year (ft^3)
Statistics	$Pred_{\mu}$	Mean value over time period
	$Pred_{cum}$	Cumulative value over time period

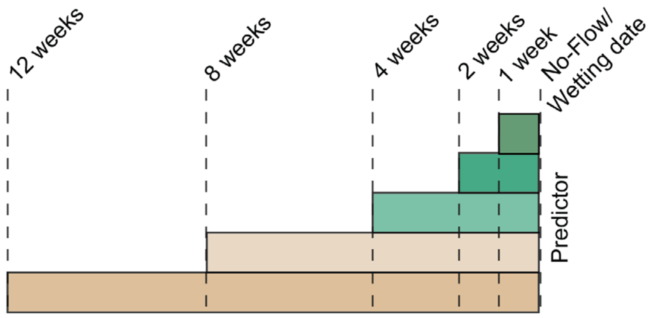

FIGURE 2 | Conceptual diagram explaining how predictor variables are calculated using time lags from the no-flow and wetting start dates. From the date of wetting or no-flow, predictor variables are calculated for a window 1, 2, 4, 8 and 12 weeks prior.

To describe the impact of shorter time scale climate processes (i.e., meteorological conditions) on drying and wetting regimes in DCEW, we calculated lagged ET, temperature and precipitation relative to the timing of no-flow start and wetting start dates. We calculated the 1-, 2-, 4-, 8- and 12-week mean values of each of these climate variables prior to the date of drying and wetting (Figure 2, Table 1).

3.2 | Statistical Correlation and Machine Learning

To test our expectations that climate proxies with varied timescales impact stream drying, we applied random forest analysis, a commonly applied machine learning technique, to identify predictors of stream drying. In addition to the random forest analysis, we filtered climate variables to reduce multicollinearity and improve parameter identifiability in statistical models using commonly used approaches (sensu Hammond et al. 2021; Price et al. 2021; Zipper et al. 2021) and used a new explainable artificial intelligence method called 'Shapley value analysis'. Parameter engineering in combination with random forest will allow us to identify the top predictors of non-perennial flow characteristics, while Shapley value analysis lends insights into how predictor variables (climate proxies) impact the predictive skill of the random forest model. We highlight the specifics of parameter engineering, random forest parameter tuning and Shapley value analysis in the following sections.

3.2.1 | Feature Selection

To better fit and inform our random forest machine learning models, we used a feature selection technique that utilised the *f*-score between the predictor (climate variables) and response (streamflow metrics) variables. Using the 'sklearn' python package (Pedregosa et al. 2011) we used the univariant f_regression function for feature selection for the regression type and f_classif function for classification type random forest models. The *f*-function is based on analysis of variance (ANOVA) and utilises the *f*-test, which compares the variances between two variables (predictor and response variables in our case) and returns an *f*-statistic (−1 to 1) and a *p* value that can be used to accept or reject the null hypothesis. In our variable selection workflow, we selected the top four most informative predictors for annual and seasonal streamflow response variables and the top 10 most informative predictors for weekly streamflow response variables (no-flow start date and wetting start, only). We preferentially removed variables that have the highest correlation with multiple climate variables. We also removed antecedent year climate variables and annual timescale variables to focus on current water year variables with a seasonal temporal resolution. Additionally, variables that integrate multiple processes or are derivative of multiple variables (i.e., timing of snowpack melt, which integrates air temperature, snowpack depth, solar radiation, etc.) were preferentially removed from analysis before variables that integrate fewer processes (i.e., summer air temperature).

3.2.2 | Random Forest and Shapley Values

Using the filtered data set, we constructed seven random forest models; four regression random forest models for each drying metric on a seasonal or greater time scale, two regression random forest models for wetting and drying on lagged weekly time scales and one classification random forest model for annual perennial versus non-perennial classification. Hyperparameter tuning was performed for each random forest model to determine the best model performance given the different combinations of response and predictor variables. In combination with the hyperparameter tuning, each random forest was run with 100 *k*-fold cross-validation and used a 75/25 split of training versus testing data, respectively. We used mean squared error (MSE) and Gini impurity for regression and classification random forest model split criteria, respectively. We also calculated training and testing out-of-bag errors as well as variable importance for each predictor in the model and averaged over each *k*-fold validation to report the mean variable importance for each set of model predictors.

For each observation and iteration of the random forest models, we used an explainable artificial intelligence technique called a 'Shapley value analysis' to complement the random forest analysis, objectively identify the influence of predictor variables on the outcome of the model and elucidate our process understanding of the drivers of drying (Park et al. 2022). Shapley values (Shapley 2016) compute the relative importance of input variables to the prediction of the response variable of the random forest. Shapley values can also interpret the directionality of influence of a predictor variable in adding or detracting from the predictive capacity of the random forest model (Husic et al. 2024).

4 | Results

4.1 | Streamflow Metric Distribution

Streamflow metrics for DCEW showed a range of behaviours across years. During years that dried, LG experienced a mean no-flow duration of 55 days (77 max, 14 min) and the mean peak to no-flow of 121 days (151 max, 78 min; Figure 3a). The occurrence of these dry events showed high variability in no-flow start date with a mean Julian date of 210 (late-July), earliest no-flow start at Julian date 182 (late-June) and latest at Julian date 246 (early-September). However, the dates that flow returned to the system had less variability, with a mean wetting start Julian date of 258 (mid-September), earliest wetting occurring at Julian date 230 (late-August) and latest occurrence at Julian date 270 (late-September; Figure 3c). Spearman rank correlation of streamflow metrics showed that no-flow start date and no-flow duration have a high degree of inverse monotonicity (more no-flow days, earlier no-flow start doy) as well as wetting start doy and no-flow duration have a high degree of monotonicity (more no-flow days, later wetting start doy; Figure 3b). The remaining streamflow metrics all showed weak Spearman correlations to one another.

4.2 | Random Forest Results

4.2.1 | Annual and Seasonal Timescales

AET in the summer (ET_Sum) was the top-ranked predictor for the random forest classification model of perennial versus non-perennial as well as regression models for no-flow duration and no-flow start date (Figure 4a–c). The Shapley value analysis showed that high values of ET_Sum resulted in a decreased probability of non-perennial classification, a decrease in the no-flow duration, and a later no-flow start date (Figure 4f–h). Precipitation in the spring (P_Spr) as well as cumulative annual AET (ET_Cum) were also among the Top 4 predictors of non-perennial versus perennial and no-flow duration (albeit different ranks), with higher values in both predictors resulting in decreased non-perennial prediction probability and shorter no-flow durations. Top predictors for drying duration (peak to no-flow) were annual maximum discharge (Q_max), annual volume of discharge (Q_Vol), percent of precipitation that was rain in the preceding winter (%rain_win) and winter precipitation (P_Win). Shapley value analysis showed that the higher values of Q_Max and lower values of Q_Vol, %rain_win and P_Win all resulted in fewer days from peak to no-flow (Figure 4d,i). Finally, the random forest model for the wetting start day showed the top predictors were all related to antecedent conditions in the prior water year. Percent spring precipitation as snow (%snow_Spr_ant), percent fall precipitation as rain (%rain_Fall_ant), total summer precipitation (P_Sum_ant) and percent summer precipitation as rain (%rain_Sum_ant) all in the previous water year were the top predictors, respectively (Figure 4e). The Shapley analysis for wetting start day showed that a singularly high value of %snow_Spr_ant contributed the most to the earlier prediction of wetting start date, with the other values of %snow_Spr_ant contributing very little to model prediction. The leverage of a single point may mean that this analysis does not accurately represent the most important predictors for timing of flow return. Low values of all other predictors resulted in an earlier prediction of wetting date (Figure 4j).

Random forest regression models all showed slight increases in out-of-bag error between the training and testing data splits respectively, signalling that the model is not overfitting the data. Additionally, the root mean square error for each of the random

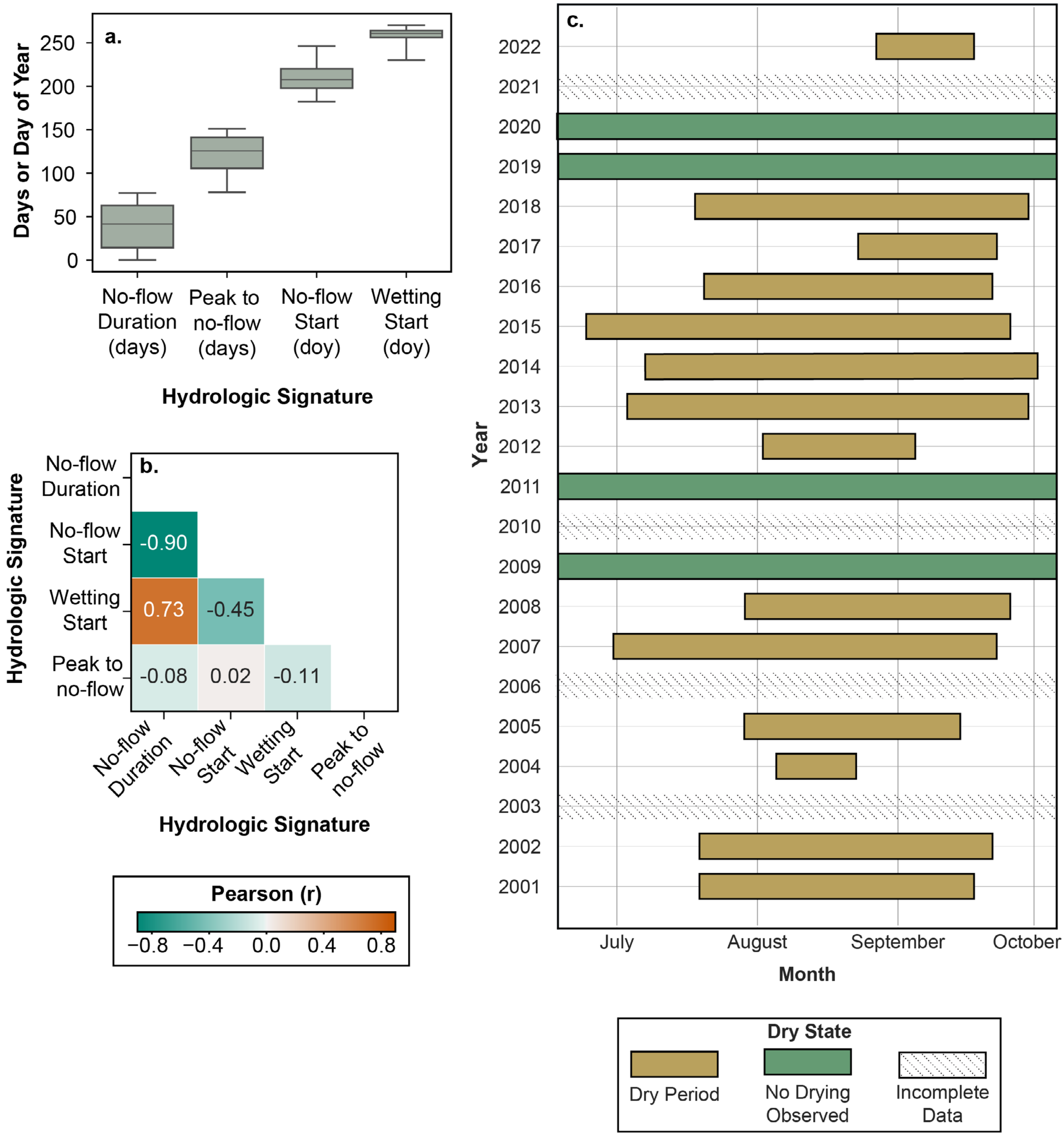

FIGURE 3 | (a) Boxplot of streamflow metric where *y*-axis represents number of days or the day-of-year depending on streamflow metric and (b) correlation heatmap based on Pearson correlation coefficient between streamflow metrics where orange represents higher positive correlation and blue higher negative correlation. (c) Annual occurrence of drying observed at DCEW with dry years represented with yellow bars where length corresponds to no-flow duration, green bars represent years with no drying observed and stippled bars with incomplete data to delineate drying occurrence.

forest regression models were well within the range and standard deviation of the predictors. Root mean squared errors were 20 days for no-flow duration, 15 days for no-flow start date, 10 days for wetting date and 19 days for drying duration. The classification random forest (perennial versus non-perennial) had an *F*1-score, which is the harmonic mean of precision and recall, of 0.7 for perennial years and 0.9 for non-perennial years.

4.2.2 | Weekly and Seasonal Timescales

Out of the Top 10 dry date start predictors, five were ET and three were temperature, with the most influential predictor being the 12-week mean temperature prior to drying (Figure 5a). These longer timescale climate predictors had a higher influence on the results of the random forest than did shorter timescale predictors,

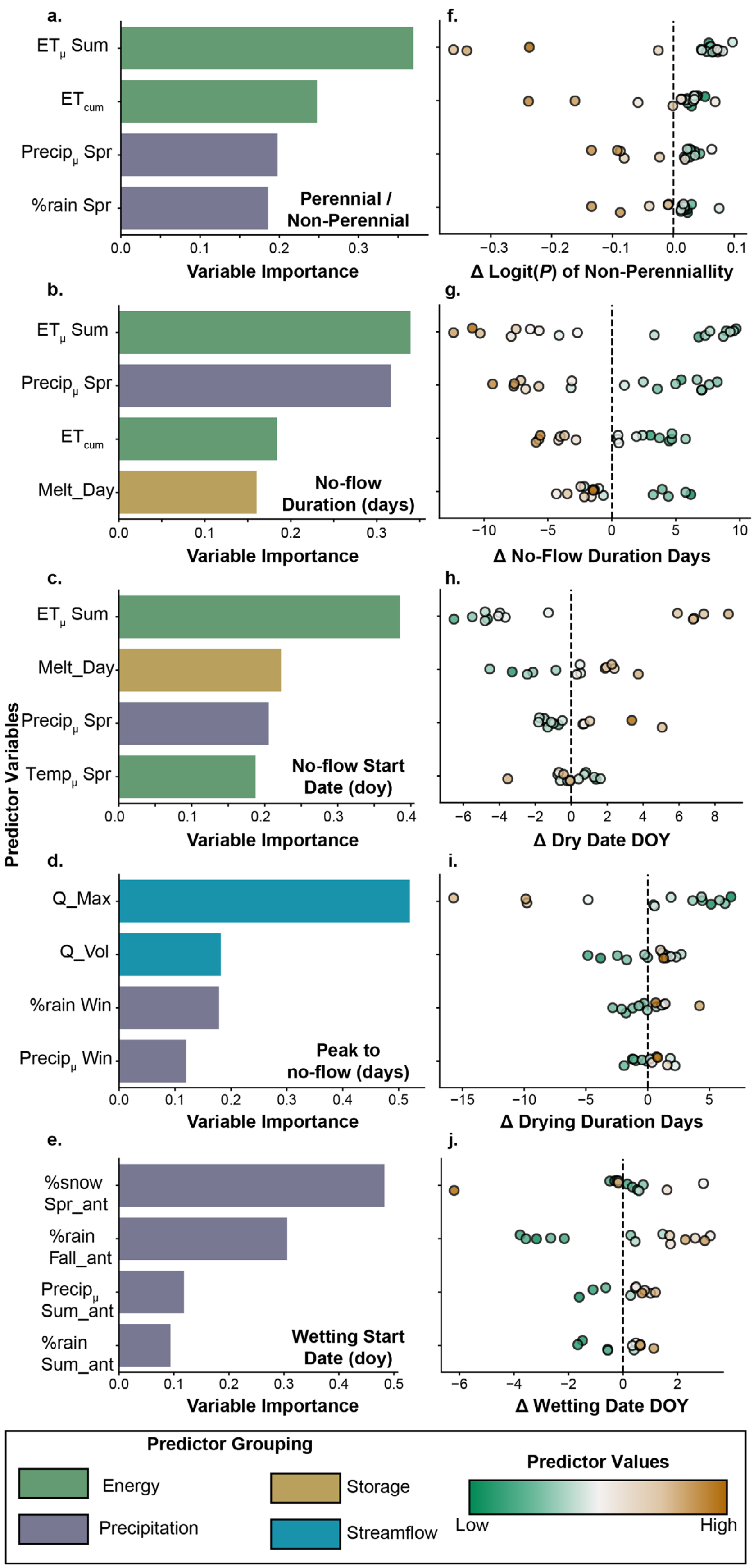

FIGURE 4 | Variable importance plots (a–e) for random forest analysis of streamflow metrics where colours of bars represent predictor groupings evapotranspiration (green bars), precipitation (purple bars), storage (yellow bars) and streamflow (blue bars). Shapley value results from random forest analysis for each streamflow metric (f–j). Points are coloured by the value of the predictor with green being lower values and orange being higher values. The dashed line represents the mean of the response variable.

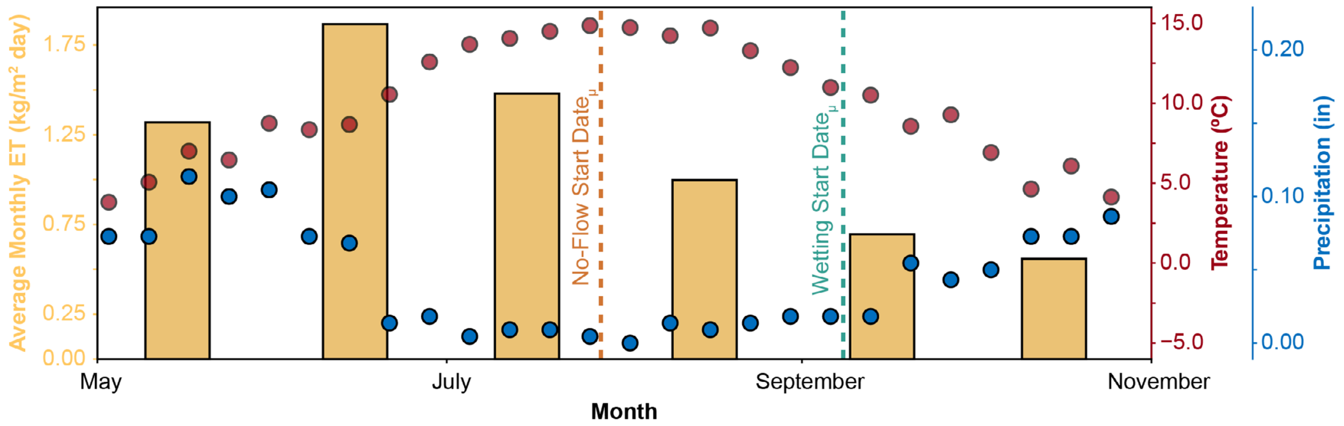

FIGURE 5 | Variable importance plots for (a) no-flow start date and (c) wetting date for random forest analysis where colours of bars represent predictor groupings evapotranspiration (green bars), precipitation (purple bars), storage (yellow bars) and streamflow (blue bars) and Shapley values for (b) no-flow start date and (d) wetting date from random forest analysis. Points are coloured by the value of the predictor with a gradient of green being lower values and orange being higher values.

with the Top 4 predictors being ≥ 8 weeks prior to the no-flow start date (three of the Top 4 being 12-week means). Shapley value results for no-flow start date showed inconsistent behaviour across predictors, where lower values of longer timescale predictors (≥ 8 weeks) resulted in an earlier no-flow start date, and higher values of shorter timescale predictors (< 8 weeks) also resulted in an earlier no-flow start date (Figure 5b).

Similar to the random forest predictors of no-flow start date, of the Top 10 climate predictors of wetting start date, eight were either ET or temperature (Figure 5c). However, the most influential predictors for wetting start date were much shorter than no-flow start date predictors, with most wetting date predictors being on timescales < 8 weeks and only one predictor being ≥ 8 weeks (Figure 5c). Additionally, Shapley value analysis for wetting start date contrasts that of drying in that the behaviour of all predictors is similar and leads to similar outcomes in the random forest model. Both higher values of temperature and ET led to an earlier wetting start date, with the shorter timescale variables being more influential in the prediction of that date (Figure 5d). Furthermore, random forest classification models all showed slight increases in out-of-bag error between the training and testing data splits, respectively, similar to the regression models. However, root mean squared errors were significantly lower at 8 days for no-flow start date and 7 days for wetting start date.

5 | Discussion

Stream intermittency is a growing area of focus across hydrology: however, to-date, the current body of literature characterising local to regional climate controls on stream drying is relatively small and falls into two broad categories: (1) statistical methods that have been used to examine drivers, characteristics and trends of drying at continental (Hammond et al. 2021; Kar et al. 2024; Price et al. 2021; Zipper et al. 2021) or regional scales (Jaeger et al. 2019, 2023; Sando et al. 2022) and (2) mechanistic models that have been applied at the reach, watershed and regional scale (Jung et al. 2019; Malish et al. 2023; Shanafield and Cook 2014; Ward et al. 2019). Conventional catchment hydrological studies have focused on specific hydrologic processes of stream drying (e.g., Dohman et al. 2021; McNamara et al. 2005; Warix et al. 2021; Zimmer and McGlynn 2017). However, due to the intensity and spatial scale of the field data collection, these studies used only a few seasons of data and are focused at the small catchment or reach scale. This study occupies a unique position within the current research of controls on stream drying because it is focused on the headwater watershed scale (27 km^2) but utilises long-term climate and streamflow data sets coupled with statistical methods to infer climatic controls on stream drying. Using this approach, we were able to quantify or relate streamflow observations to localised watershed scale processes and describe how sub-annual climate and process variability relate to drying.

5.1 | Seasonal Variability in Evapotranspiration and Precipitation Best Predict Stream Drying

Studies suggest that the increase in low- and no-flow is very sensitive to the amount of winter and spring precipitation as snow versus rain (e.g., Clifton et al. 2018). Rain is transferred episodically to and stored in the subsurface, whereas, a persistent snowpack produces a more consistent delivery of water to the subsurface during spring melt (Kiewiet et al. 2022). This more uniform water transfer to the subsurface by snowmelt is hypothesised to produce more runoff due to higher antecedent soil moisture (Hammond et al. 2019). We expected this would also result in later stream drying (e.g., Berghuijs et al. 2014) as previous research has suggested that peak SWE is an important predictor for summer low flows (Boisramé et al. 2024; Godsey et al. 2014; Jenicek et al. 2016). Interestingly, peak SWE and the percent of precipitation as snow were not significant predictors of any drying metric in this analysis (Figure 2). However, day of full snowpack melt (melt_day) was a significant predictor for no-flow duration and no-flow start date, where a later melt day produces later no-flow date and fewer dry days (Figure 4b,c). The persistence but not the magnitude of the snowpack is a strong predictor of the timing and duration of drying in DCEW. Kiewiet et al. (2022) found similar results in the nearby Reynolds Creek Experimental Watershed. When snowmelt is faster, it quickly brings soils to field capacity and promotes more streamflow (Seyfried et al. 2009). Snowmelt rates are typically faster later in the season due to available energy (Trujillo and Molotch 2014) so a later melt date in this analysis may relate to a higher snowmelt rate and more water available later in the season to sustain streamflow. Additionally, peak to no-flow did not share any of the top climate predictors with other drying metrics. Peak to no-flow, or drying duration, is highly influenced by the varying timescales of flow generation processes. Our results are supported by prior studies on drying regimes that highlight that land cover is the best predictor of drying rates, as they serve to modulate connectivity across the landscape (Price et al. 2021; Zipper et al. 2021; Hammond et al. 2021).

Total precipitation regardless of type, but particularly spring precipitation, is a strong predictor of drying dynamics (Figure 4). Spring precipitation occurs at a critical time for groundwater recharge and filling of storage. While multi-year carryover of deep groundwater storage can occur (i.e., Brooks et al. 2021; Wolf et al. 2023), later snowpack melt coupled with additional inputs from rain on already saturated soils is likely more effective at recharging deep groundwater stores (Carroll et al. 2020) and alluvial aquifers (Huntington and Niswonger 2012) and maintaining late season baseflows (Barnhart et al. 2016; Dierauer et al. 2018; Hammond et al. 2019). These results highlight that spring precipitation plays an important role in refilling subsurface storage and leads to later and less severe drying. While precipitation metrics were important predictors, they were not as important as summer ET (Figure 4a–c). Both precipitation and AET may be indicators of water availability, but precipitation metrics are a more direct indicator of water inputs to the system. The strong seasonality in precipitation in this watershed means that the bulk of water inputs occur in the winter and spring, several months before drying (Figure 1b). This offset results in a long period of time where storage depletion occurs, controlled by other hydroclimatic factors such as energy availability and additional water inputs. Summer ET may be a better predictor for drying due to temporal alignment between the two.

In this study, we found that summer AET was the strongest predictor for if the stream would dry, the number of days drying occurred and the timing of no-flow (Figure 4a–c), where higher summer ET was correlated with lower likelihood of drying, fewer days dry and a later no-flow start date (Figure 4f–h). We hypothesise that summer ET is a proxy for water availability and/or the degree and persistence of hydrologic connectivity across the watershed (e.g., Jencso et al. 2009). This is counter to what many studies suggest, including those that focus on climate change impacts on low flows (Barnhart et al. 2020; Dierauer et al. 2018; Harrison et al. 2021), diel changes in stream baseflow (Cadol et al. 2012; McLaughlin and Cohen 2014; Wondzell et al. 2009) and specifically on non-perennial stream systems (Lupon et al. 2018; Newcomb and Godsey 2023; Warix et al. 2023). Studies that have focused on the role of ET in non-perennial systems have concluded that ET is in direct competition for streamflow, that is, more ET leads to increased drying. Warix et al. (2023) found that the onset of diel wetting and drying occurred when ET exceeded groundwater inputs. While we use the number of days the stream is completely dry (i.e., >12 h dry in a day), we also calculated the amount of time dry or fractional dry days (i.e., accounting for sub-daily wetting and drying dynamics, days with ≤ 12 h dry) and found that it was not particularly different and produced similar results as using the number of dry days. However, other reach-scale studies focused specifically on riparian ET (Newcomb and Godsey 2023; Warix et al. 2023). This study used a remote sensing-based, watershed scale ET estimate, which incorporates riparian and upland ET. While riparian vegetation may have been drawing from water that would otherwise become streamflow, this signal is abstracted by upland ET, which makes up a greater proportion of the overall watershed area and potentially, total watershed ET. Upland ET is likely greater when overall water availability or catchment wetness is greater, later into the summer (Trujillo et al. 2012).

One critical aspect of this study is that we are focused on a semi-arid, relatively small watershed ($27\,km^2$) which spans the rain– snow transition. The highest elevations, particularly north aspects of the watershed, develop a ~1 m snowpack, but the lower elevations and south-facing aspects experience regular snowmelt over the winter (Poulos et al. 2021). Many studies that focus on total snowpack accumulation and melt timing impacts on summer low flows have been conducted in watersheds that have a persistent seasonal snowpack with a single melt period (e.g., Barnhart et al. 2020; Godsey and Kirchner 2014). Watersheds with a seasonal snowpack are much more efficient at runoff generation, and the entire watershed is thought to contribute to streamflow more uniformly, while watersheds with ephemeral snowpacks have much lower runoff efficiency and there is much more spatial heterogeneity in runoff contribution (Harrison et al. 2021). Stream drying at the watershed outlet integrates elevations with a seasonal and ephemeral snowpack, so it is likely that the watershed is not contributing uniformly to streamflow generation or the persistence of flow in summer. These differences are driven by elevational gradients in precipitation and temperature and also carry into energy availability for ET. Integration across seasonal and ephemeral snow regimes may be why snowpack development and depletion metrics were not strong predictors in this analysis.

At high elevation with deep seasonal snowpacks, total annual ET is typically limited by growing season length and energy availability (Christensen et al. 2008) while at low elevation in the ephemeral snow zone, total annual ET is typically limited by water availability (Flerchinger et al. 2019; Kraft and McNamara 2022). The strong topographic controls on ET, particularly in a semi-arid rain–snow transition site like Dry Creek, result in extreme spatial heterogeneity in ET (Kraft and McNamara 2022). We think that the MODIS estimate of ET in this system suffers from error introduced by the extreme variability; however, it is likely a good metric of relative wetness and water availability integrated across the entire watershed, as indicated by the strong predictive power in stream drying metrics (Figure 4). In general, the community still lacks the ability to link point and station-based ET and plant water use estimates to watershed scale and remotely sensed estimates of ET and water availability. Future studies should compare station-based and remotely sensed ET estimates in these environments with attention to the spatial variation with position on the hillslope or in the riparian zone.

5.2 | Streamflow Wetting and Drying May Be Related to Processes Occurring at Variable Timescales

Climate is an important driver of watershed processes across scales and is a central driver of streamflow intermittency in larger non-perennial stream networks (Hammond et al. 2021). Many investigations on climate drivers of non-perennial streamflow dynamics use fixed time windows over which statistics are calculated (i.e., annual, seasonal, monthly; Hammond et al. 2021; Zipper et al. 2021). This has resulted in improved insight into overarching climate indicators of non-perennial regime types across ecoregions (e.g., Price et al. 2021). However, we found that when we focused on how interannual climate variability impacted drying dynamics in a single headwater watershed, fixed longer timescale climate metrics were imperfect predictors, particularly for the wetting start date. In our initial variable selection and random forest modelling, we included monthly, seasonal (3 months), annual, antecedent seasonal and antecedent annual climate metrics as potential predictor variables (Table S1). Seasonal and annual variables were the most important predictors in our random forest models, particularly for drying (Figure 4). The wetting date was best predicted by climate variables up to roughly 1.5 years prior to the wetting date (e.g., % snow in the spring prior; Figure 4e). While there is some research that may support the idea that very long timescale processes influence mountain streamflow dynamics (Brooks et al. 2021; Wolf et al. 2023), we expected that if they were very important here, these metrics would appear as important predictors for both wetting and drying (Figure 4). This prompted us to examine climatic conditions around the time of wetting and drying each year to explore if potentially shorter timescale processes may be contributing to streamflow regimes.

At the mean no-flow start date, air temperature has reached an annual maximum and is above 10°C on average for the preceding month. Precipitation is also very low for over a month, and ET is declining (Figure 6). This follows findings from our random forest models that spring conditions, particularly those that prolong water availability for streamflow and ET, are strong predictors for a later no-flow start date (Figure 4c) and shorter drying duration (Figure 4b), if it dries at all (Figure 4a). When using shorter timescale climate variables (1–12 weeks) in our random forest models, we found that longer timescale variables were still the most important predictors of drying (Figure 5a). While mean temperature for the 12 weeks prior to the date of drying was the most important predictor, mean ET across a range of timescales appeared as important predictors of drying (Figure 5a) and Shapley value results were consistent with the initial random forest analysis (Figure 5b, Figure 4h), giving confidence that in this semi-arid watershed, spring and early summer conditions are very important for stream drying.

We found different results when assessing variable timescale controls on wetting. The date of stream wetting is much less variable than drying and is not particularly correlated with drying metrics (Figure 3) suggesting that wetting and drying may be controlled by different climate factors. Around the mean time of wetting, mean air temperature tends to drop, precipitation increases and ET continues to decline heading into the fall (Figure 6). Variable timescale random forest analysis suggests that conditions several weeks prior to the time of wetting are the most important predictors of when flow in Dry Creek resumes in the fall (Figure 5c). These results—higher ET is related to earlier resumption of flow—are now aligned with those associated with stream drying (Figure 5b,d). ET is a good indicator of total catchment wetness, where longer timescale moisture state matters for drying, but if higher moisture carries later into the summer, it is a strong predictor for when streamflow can resume. Longer timescale variables, % rain in the preceding fall and % snow in the preceding spring, still appear in this random forest model, but are much less important than shorter timescale temperature and ET metrics (Figure 5c). This highlights the complicated feedbacks of storage (shallow and deep) and the associated catchment memory in flow generation in this non-perennial system. Perhaps both very short and very long timescales are important indicators of the storage deficits that must be overcome for flow to resume.

It is much easier to conceptualise the physical hydrologic mechanisms leading to stream drying at a given point: there is not enough water in the system to maintain streamflow due to the physical characteristics of the channel and insufficient inputs of water (Godsey and Kirchner 2014; Prancevic and Kirchner 2019; Shanafield et al. 2021). However, with stream wetting, a storage deficit must be overcome to produce streamflow, and the way in which this is achieved can be the result of a number of mechanisms (e.g., Price et al. 2024) and has received considerably less attention. This lack of study may partially be because quantifying the degree of storage deficit within a watershed is an incredibly hard problem, particularly when there is no baseflow to use as a metric. Our findings suggest that shorter timescale indicators of water availability and therefore the degree of the storage deficit are the best predictors of wetting. Therefore, it could be that storage in this watershed is depleted every summer similar to what is described by Hahm et al. (2019). We need more direct investigations of the nature of storage in this climate and underlying rock type to make more conclusive inferences about storage dynamics and how they relate to ET and stream drying.

The connection between storage dynamics and streamflow is particularly important in non-perennial systems due to their strong connection with and reliance on groundwater. While groundwater tends to have a damped and lagged response to climate, this is variable as a function of the recharge mechanism, climate and aquifer/subsurface physical properties (e.g., Hellwig et al. 2020). This implies that longer timescale climate metrics are most relevant for groundwater response, storage and stream drying, which is the focus of most studies (Boisramé et al. 2024; Hahm et al. 2019; Hammond et al. 2021; Jaeger et al. 2019; Wolf et al. 2023). However, it is apparent that variable timescale processes control the dynamics of stream drying (Moidu et al. 2021) and we should also consider shorter timescale lags to ensure we capture all potential drivers and relevant indicators of drying and wetting dynamics. We also note that this analysis was possible due to the availability of high-quality long-term data, and all efforts should be made to continue to collect these types of datasets across ecoregions and in headwater watersheds.

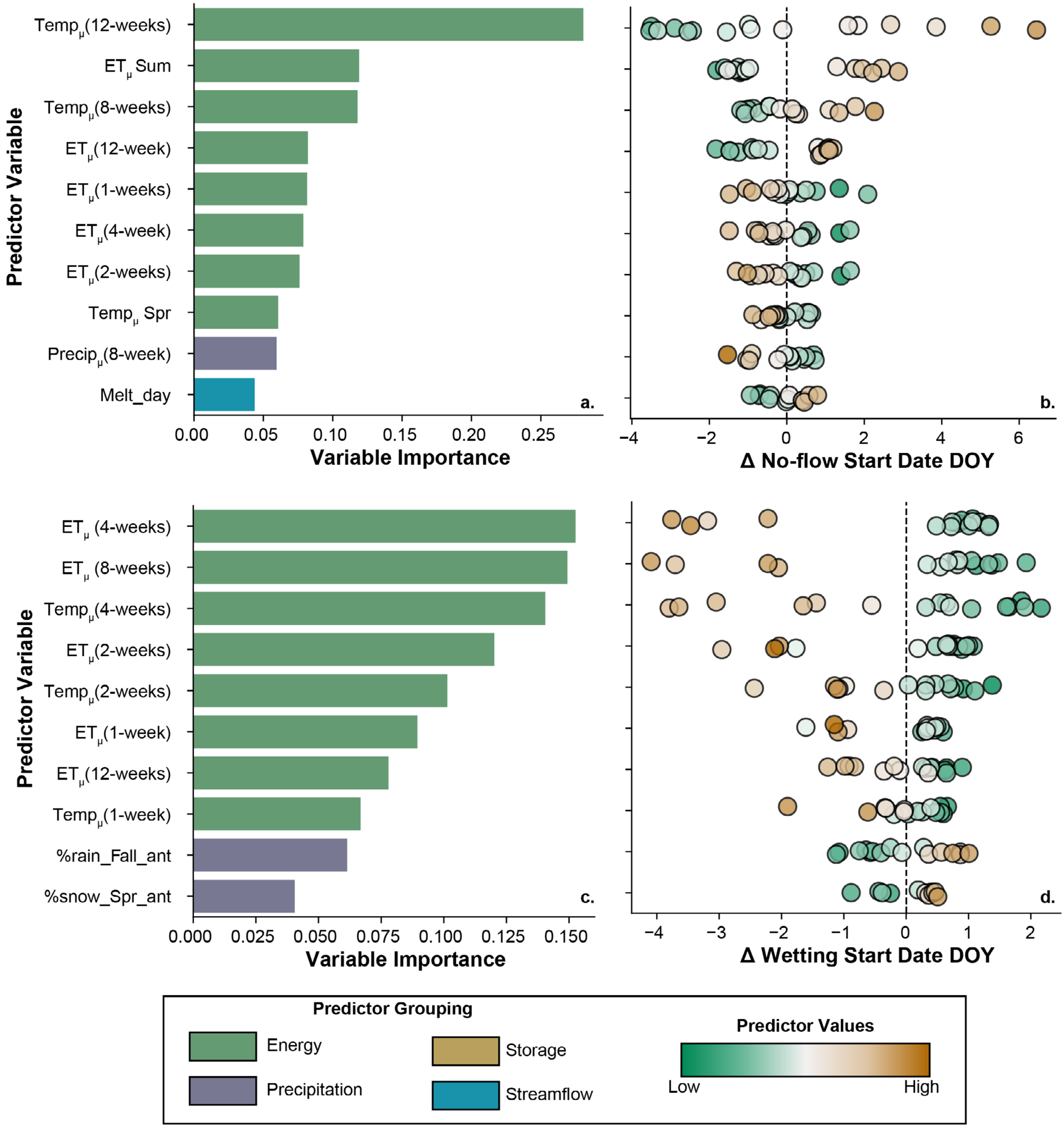

FIGURE 6 | Mean annual climate of DCEW from May to November with mean monthly evapotranspiration (yellow bars), mean weekly temperature (red dots) and mean weekly precipitation (blue dots). Vertical lines represent the timing of mean no-flow start date (orange dashed line) and mean wetting start date (teal dashed line).

5.3 | Stream Drying Under Continued Climate Change

Altered precipitation patterns as a result of climate change feed back into altered streamflow regimes, including the timing and duration of drying (Brunner et al. 2020). In most ecoregions of the United States, more streams are drying earlier in the year and for longer periods of time, which is associated with increasing aridity (Zipper et al. 2021). As summers become hotter and drier in many regions, streams will have increased reliance on stored subsurface water recharged during cooler, wetter months and/or during snowmelt, highlighting the need for further study on watershed storage properties and recharge and release mechanisms. In many historically snow-dominated regions, winters are becoming shorter, persistent snowlines are rising and there are increased mid-winter rain and melt events

(Siirila-Woodburn et al. 2021). Areas where precipitation is predicted to increase may make up for declining snowpack via cold season recharge to groundwater, however, there is not enough information to make confident predictions on changes to recharge rates (Meixner et al. 2016). In this specific instance, we found that the presence of spring precipitation rather than the form and the date of snow disappearance or the amount of water in the snowpack were most critical for delaying drying at the watershed outlet. This may be partly because the majority of the watershed is in the rain–snow transition zone and does not maintain a persistent snowpack. Watersheds that span the rain–snow transition have complex and variable balances in energy and water limitation (Kraft and McNamara 2022). It is therefore unlikely that the entire watershed is hydrologically connected and contributing runoff or recharging groundwater evenly over the water year. More detailed studies should focus on runoff generation and streamflow persistence in watersheds spanning the rain–snow transition, particularly because they have received less study (Harrison et al. 2021; Hinckley et al. 2014) and are especially sensitive to climate change in the near future as the elevation of persistent snowpack increases (e.g., Seyfried et al. 2018) and a larger proportion of the watershed is rain-dominated over the winter.

6 | Conclusion

Studies modelling climate change impacts on summer low flows suggest that semi-arid mountain watersheds will have an increased magnitude of low flow events, likely including stream drying (Clifton et al. 2018; Hasan et al. 2023; Kormos et al. 2016; Safeeq et al. 2014). This work supports existing research that shows climate is an important predictor of stream drying duration and timing (Hammond et al. 2021; Jaeger et al. 2019; Zipper et al. 2021). Here we show that the timing and magnitude of seasonal climate variables are important for controlling the no-flow duration, no-flow start date, wetting start date and peak to no-flow in a semi-arid watershed spanning the rain–snow transition. Specifically, this work highlights that summer ET is an indicator of water availability in the DCEW and is strongly correlated with no-flow duration. Greater spring precipitation and later day of full snowmelt (partially driven by spring temperatures) increase water availability in the summer and reduce no-flow days. We also show that the timing of the return of streamflow is more strongly influenced by shorter timescale climate variables as opposed to seasonal; the return of streamflow is coincident with declining temperatures and precipitation events in the fall. The wetting date also has a smaller standard deviation than the no-flow start date, and flow always returns by the end of September. Together, these results highlight the importance of including variable timescale climate variables when trying to identify controls on hydrologic regimes. Further, the strong relationships we found between ET and stream drying imply that ET is a potential indicator of catchment wetness in this semi-arid watershed at the rain–snow transition. Further work is needed to explore this relationship across climate regimes. Finally, we suggest that additional research is needed to understand how climate change will impact storage recharge in mountain watersheds and how this impacts stream intermittency.

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Conflicts of Interest

The authors declare no conflicts of interest.

Data Availability Statement

All datasets used in analysis are publicly available at the following sources: Lower Gauge Streamflow in Dry Creek Experimental Watershed (https://www.boisestate.edu/drycreek/dry-creek-data/lower-gauge/#historical-data), USDA Natural Resource Conservation Service SNOTEL climate data (https://wcc.sc.egov.usda.gov/nwcc/site?sitenum=978), AppEARS MOD16A2GF evapotranspiration (https://lpdaac.usgs.gov/products/mod16a2gfv061/).

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Supporting Information

Additional supporting information can be found online in the Supporting Information section.