Rising temperatures drive lower summer minimum flows across hydrologically diverse catchments in British Columbia

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Key Points:

- Summer low flows are highly sensitive to summer temperature and precipitation, with winter storage historically playing a secondary role
- Regression models outperform process-based hydrologic models for minimum summer flow prediction and enable valuable process understanding
- Precipitation variability historically drove low flows but rising temperatures are responsible for recent declines in warmer catchments

Supporting Information:

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

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Rising Temperatures Drive Lower Summer Minimum Flows Across Hydrologically Diverse Catchments in British Columbia

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Abstract Excessively low stream flows harm ecosystems and societies, so two key goals of low-flow hydrology are to understand their drivers and to predict their severity and frequency. We show that linear regressions can accomplish both goals across diverse catchments. We analyze 230 unregulated moderate to high relief catchments across rainfall-dominated, hybrid, snowmelt-dominated, and glacial regimes in British Columbia, Canada, with drainage areas spanning 5 orders of magnitude from 0.5 to 55,000 km^2. Summer low flows are decreasing in rainfall-dominated and hybrid catchments but have been stable in catchments that remain snowmelt or glacial-dominated. However, we find that since 1950 approximately one third of snowmelt-dominated catchments have transitioned to a hybrid rain-snow regime. The declines in rainfall-dominated and hybrid catchments are dominantly driven by summer precipitation and temperature, and only weakly influenced by winter storage. We apply this understanding to create regression models that predict the minimum summer flow using monthly temperature and precipitation data. These models outperform distributed process-based models for every common goodness-of-fit metric; the performance improvement is mostly a result of abandoning the requirement to simulate all parts of the annual hydrograph. Using these regression models we reconstruct streamflow droughts and low flow anomalies from 1901 to 2022. We reproduce recent drying trends in rainfall-dominated and hybrid catchments, but also show that present conditions are comparable to those seen one hundred years ago. However, anomalously low flows last century were caused by large precipitation deficits while current declines are driven by rising summer temperatures despite near-normal precipitation.

Plain Language Summary Late-summer streamflow in British Columbia, Canada, is essential for ecosystems and for water resources. We used statistical techniques to analyze and model the annual minimum summer flow in free-flowing streams across the province. We found that summer minimum flows across the province have decreased (become drier) since mid-20th century, particularly in warmer and coastal watersheds where precipitation mainly falls as rain. Summer streamflow drought in warmer watersheds is now more common and more severe than at any point since the early 20th century. Summer minimum flows are mainly controlled by precipitation but also by high summer temperatures, which increase evaporation and reduce water storage. Although there were dry periods during the 20th century, these were primarily caused by below-average rainfall, while recent declines in summer minimum flows in warmer watersheds are primarily a result of hotter summer temperatures. Summer flows in colder watersheds (where more precipitation falls as snow) have been relatively stable since mid-century but these snow-dominated watersheds are becoming less common.

1. Introduction

1.1. Environmental Flows and Streamflow Drought

Preserving environmental flows, and especially low flows, is critical to maintaining healthy riverine ecosystems and the societies that depend on them (Arthington et al., 2018; Bradford & Heinonen, 2008). Living things, including humans, can be harmed when rivers have less water than normal: low flows that are significantly below the natural envelope of variability have been shown to disrupt lifecycles of aquatic species and reduce biodiversity (Poff & Zimmerman, 2010), cause economic losses (Folkens et al., 2023), and disrupt cultural practices (Morgan, 2012; Tipa & Nelson, 2012). The more evocative term "streamflow drought" has also been coined, presumably to attribute some gravity to a concept that is defined drily as a "sustained period" of "below-normal river discharge" (Van Loon, 2015).

Climate change and human activity increasingly threaten environmental flows globally, resulting in severe and probably irreparable harm to riverine ecosystems (Porkka et al., 2022; Richardson et al., 2023; Virkki et al., 2022). Streamflow drought is driven by precipitation (P) and temperature (T) anomalies: in a process called drought propagation, these anomalies cause below-normal storage of groundwater, snow, and soil moisture, resulting in below-normal discharge (Van Loon, 2015). Land use and water abstraction can also affect low flow occurrence and severity (de Graaf et al., 2019; Guzha et al., 2018; Wada et al., 2016). Effective water management requires an understanding of the relative importance of human and climate drivers because land and water use can be managed at local scales, while climate change is a global challenge. Within the category of climate drivers, it is important to distinguish precipitation and temperature effects because climate model projections of temperature are considered highly reliable, while projections of precipitation are less robust (Ukkola et al., 2020).

The province of British Columbia (BC) in so-called Canada is a microcosm of the water resource challenges posed by low flows and the hydrologic uncertainties regarding their driving mechanisms. The ecosystems and communities of BC have acutely felt the impacts of streamflow drought. In the late summer and early fall, photographs of drying rivers and dead salmon regularly make national and international news (Cecco, 2022; Hernandez, 2023), and increasingly severe droughts are threatening Indigenous nations' ways of life that have existed for millennia (First Nations Fisheries Council of British Columbia, 2020).

British Columbia is the colonial name for the westernmost province of Canada. In this manuscript we use this name to refer to the extent of the study area (although the spatial unit of analysis is watersheds). We acknowledge that colonial boundaries and names do not reflect the traditional territories of the (at least) 194 distinct First Nations located within our study area (British Columbia Assembly of First Nations, 2024), whose inherent rights to the land are unceded and unsurrendered. Many Indigenous governments continue to assert and exercise their jurisdiction over land and resource decisions within their traditional territories. Indigenous communities throughout BC are acutely impacted by drought and other water-related disasters, and are at the forefront of many environmental restoration and adaptation efforts (Cruickshank, 2023; First Nations Fisheries Council of British Columbia, 2020; Page, 2007; Teegee, 2023; The Columbia River Salmon Reintroduction Initiative, 2023; Wood, 2021).

The public perception that summer low flows are getting lower in British Columbia is supported by empirical evidence. Around the year 2000 various authors analyzed streamflow data from the Reference Hydrometric Basin Network and found that September, October, and annual minimum flows had decreased in southern BC (Burn & Hag Elnur, 2002; Yue et al., 2003; X. Zhang et al., 2001). Ehsanzadeh et al. (2011) conducted another Canada-wide study and found that low flows in southern BC continued to decrease to 2008. However, these national studies provide little insight into the behavior of different hydrologic regimes within BC. Hernández-Henríquez et al. (2017) found persistent decreases in summer runoff to the year 2015 for catchments on the western side of the Coast Mountains. Stahl & Moore (2006) found that mean August flows were decreasing in most glacierized basins in BC, particularly between 1976 and 1996, but trends were inconsistent in non-glacierized basins, a pattern they attributed to glacial retreat. Other authors have found mixed trends in regional studies with smaller samples of catchments (Anderson, 2016; Najafi et al., 2017; Rayne & Forest, 2011, 2012). There is a need for an updated provincial-scale analysis of low flow trends that allows disaggregation by region and hydrologic regime.

The provincial government enacted, in 2016, legislation declaring their authority to prohibit water use for irrigation when streamflow falls below a critical threshold. This authority has been exercised nine times from 2016 to 2023, alleviating ecosystem stress at the cost of economic hardship for many farmers. Thus, debates about the drivers of low flows are politically charged: is human water use really to blame, or are climate drivers more consequential? If climate is responsible, are increasingly severe low flows primarily driven by rising temperatures (which will almost certainly continue to rise) or changing precipitation patterns (which may continue, or reverse, or stabilize)?

Unfortunately, in BC as in many parts of the world, there is a shortage of scientific evidence to answer these questions. Assessments of low flow drivers have usually been limited to a small number of catchments and, as we find in Section 3.2, may have placed outsized importance on the role of winter snow storage. Thus, there is a need to investigate the widely held view that streamflow drought is becoming more common across the province, and if so, why.

1.2. Limitations of Hydrologic Models

Hydrologic models often produce unsatisfactory low flow simulations and forecasts (Collins, 2020; Kim et al., 2021; Newman et al., 2015; Nicolle et al., 2014). One reason for these inaccuracies is that models are usually calibrated to all parts of the annual hydrograph. Low-flow generating mechanisms can differ from those that generate high and medium flows (Smakhtin, 2001), so parameters that are calibrated to reproduce high and medium flows may not accurately reflect hydrologic conditions nor accurately reproduce low flows (Cenobio-Cruz et al., 2023). In addition, since low flows are usually less variable than medium and high flows, low flows exert less influence on model calibration.

Various flow transforms can be used to force models to prioritize low flow estimation, but estimation of yearly minimum flows, or zero-flow days, remains challenging. For example, Aryal et al. (2020) achieved a median modified Kling-Gupta Efficiency of 0.5 and a median Nash-Sutcliffe Efficiency of about 0.35 for the prediction of zero-flow days in 595 Australian catchments. Using 9 hydrologic models in 10 major river basins worldwide, Huang et al. (2017) found percent bias values from −675% to 98% (median absolute value of 48%) for the flow duration curve low-segment volume and −83%–1,067% (median absolute value of 38%) for the 10 and 30-year low flow levels.

Studies in the Pacific Northwest region show the same limitations. Whitfield et al. (2003) modeled six watersheds around the Salish Sea (southwestern BC), and found that models produced biased 7-day low flow estimates for pluvial (rain-dominated) catchments. Various authors have used a distributed hydrological model (Variable Infiltration Capacity, or VIC) to model climate impacts in the Fraser River Basin, but found that simulated low flows were systematically lower than measured flows (Islam et al., 2017; Kang et al., 2016; Shrestha et al., 2012). We will return to these VIC simulations in Section 3.3. No comprehensive analysis of summer low flows across BC has been published.

1.3. Low Flow Drivers

We consider six climatic mechanisms that may influence summer low flows in BC, derived from previous work on low flows and streamflow drought (Smakhtin, 2001; Van Loon, 2015). We group these six mechanisms into three categories of driver: (a) below-normal winter storage, which includes groundwater and snowmelt drought (b) accelerated summer hydrograph recession, which includes rainfall deficits and storage depletion driven by evapotranspiration (ET), and (c) short-term anomalies caused by temperature fluctuation, which include transmission losses and glacier melt drought. These mechanisms are listed in Table 1.

Which mechanisms are most important? In 2005, Barnett et al. published a widely cited article showing that warming temperatures would induce snowmelt drought and decrease summer water availability across much of the northern hemisphere. It was thought that potential effects of warming on ET were small because actual evapotranspiration (related to temperature) is often much less than potential evapotranspiration in catchments that become water-limited in the summer. Much research over the last two decades has been focused on the effects of declining snowpack (Adam et al., 2009; Diffenbaugh et al., 2015; Godsey et al., 2014) and in the Pacific Northwest region (Ban et al., 2023; Chang et al., 2012; Clifton et al., 2018; Dierauer et al., 2018, 2021; Hale et al., 2023; Safeeq et al., 2014).

More recently, however, researchers have identified that, in some regions, summer ET may also be driving streamflow droughts. Teuling et al. (2013) showed that summer ET was amplifying European droughts; Woodhouse et al. (2016) and Udall and Overpeck (2017), working independently and using different methods, showed that air temperature is increasingly a driver of drought in the Colorado River basin. Floriancic et al. (2020) found that summer ET and precipitation controlled drought occurrence, and that winter snow storage had only minor effects on warm-season low flows in Switzerland. Then Brunner et al. (2021) and Floriancic et al. (2021) analyzed catchments across the United States and Europe and both found that the importance of temperature as a driver of low flows was increasing or likely to increase in many places. However, Brunner et al. found that the effect of summer temperature was increasing in the Pacific Northwest, while Floriancic et al. argued that summer temperature was not a driver in this region. Boeing et al. (2024) found that increasing evapotranspiration has contributed to water storage deficits in Germany over recent decades.

Regional studies focused on the Pacific Northwest do not resolve this inconsistency. Kormos et al. (2016) found that low flows in the Pacific Northwest were more sensitive to precipitation than to temperature. Cooper

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Table 1
Data Used to Assess Sensitivity to Climate and Anthropogenic Drivers

Driver	Mechanism/drought type	Variable	Description	Data set	Dates
Below-normal winter storage	Snowmelt drought	SWE_{max}	Maximum Snow Water Equivalent	ERA5 Land Hourly (Muñoz Sabater, 2019)	1950-present
	Groundwater drought	BF_{winter}	Average baseflow for 30 days prior to SWE_{max}	Eckhardt baseflow separation of discharge time series	Same as discharge
Accelerated summer recession	Rainfall deficit	P_{summer}	Total Precipitation from May to the low-flow month	North American gridded monthly historical climate (~2 km resolution) (MacDonald et al., 2020)	1900–2022
	ET-driven storage depletion	T_{summer}	Average Temperature from May the low-flow month		
Short-term anomalies	ET-driven transmission losses Glacier melt drought	T_7	7-day mean temperature, concurrent with $Q7_{min}$	Canadian gridded daily historical climate (~10 km resolution) (Hutchinson et al., 2009)	1949–2020
Direct Human Interventions	Water Abstraction	Abstraction	Estimated annual water use	Estimated based on water licenses, well construction records, and land use data. See Appendix B in Supporting Information S1	1863–2023
	Forest Harvesting	ECA_{I}	Fraction of watershed harvested or burned within 9 years	Calculated from BC Consolidated Cutblocks (Province of BC, 2024b) and Fire Perimeters (Province of BC, 2024a)	1900–2023
		ECA_{III}	Fraction of watershed harvested or burned between 24 and 80 years ago		1900–2023

et al. (2018) found the opposite: that low flows in the western US are more sensitive to ET than to precipitation, but that sensitivity to both climate variables decreases towards the northern end of their study range. Georgiadis and Baker (2023) argued that both temperature and precipitation exert important controls on low flows in the Puget Sound.

In addition to climatic drivers, water and land use can alter low flows. In some watersheds, surface and groundwater use substantially reduces low flow discharge. The main land use and land cover disturbance throughout most of British Columbia is forest harvesting, which has been observed to both increase and decrease warm-season low flows (Moore, Gronsdahl, & McCleary, 2020; Moore, Pelto, et al., 2020). Coble et al. (2020) reviewed 25 small catchment studies in the Pacific Northwest and found that there tends to be an increase in low flows following harvesting, sometimes followed by low flows similar to pre-harvest conditions, and then low flows below pre-harvest conditions. However, they also reviewed 19 large-catchment studies from around the world and found that long-term reductions in low flows were observed at large scales. Hou et al. (2024) analyzed 20 catchments in British Columbia and did not find consistent increases or decreases in summer flows.

With this study we aim to improve the understanding and prediction of low flows in a well-gauged but under-studied region, and in so doing develop novel approaches that can be applied in other regions. Our first objective is to quantify the drivers of low flows in diverse hydroclimatic regimes and whether these drivers are changing over time (Section 3.2). This will contribute to the debate about the importance of winter storage, summer ET, and summer precipitation as drivers of low flows. Second, we aim to extend the statistical analysis of drivers to create predictive regression models, enabling the reconstruction of low flows since 1901 (Sections 3.3 and 3.4). This modeling strategy will be of interest to the hydrologic modeling community, as it demonstrates a data-driven approach that improves the simulation of low flows by avoiding many of the challenges posed by traditional process-based hydrologic models, while also providing valuable process understanding by attributing low-flow trends to climate drivers. Our final objective is to apply these methods to produce locally relevant information about low flow trends and drivers for British Columbia. These results will be of interest to a local audience as well as researchers focused on similar hydrologic environments.

2. Data and Methods

2.1. Study Location

British Columbia occupies an area of almost 1 million km^2 on the western coast of Canada between 48.3° and 60° latitude. The province is endowed with a rich climatic diversity, ranging from Mediterranean climates in the southwest of the province (southern Vancouver Island) to polar climates at high elevations, with cold arid steppe climates in parts of the Interior (Beck et al., 2018). The geography is dominated by mountains, which rise up to 4,653 m above the Pacific.

We focus on the part of the province west of the continental divide (approximately 663,000 km^2, roughly the size of Myanmar, or 20% larger than metropolitan France). This excludes the northeast of the province, where most precipitation falls in the summer months, leading to high flows in the summer. Also, since one of the chief concerns regarding low flows in British Columbia is the threat to Pacific salmon spawning habitat, it makes sense to focus on the Pacific drainage basin.

2.2. Catchments

We examine records from 230 hydrometric stations in British Columbia, maintained by the Water Survey of Canada. Of the 2235 operational and discontinued stations in British Columbia that measure Pacific-draining streams, 1477 measure unregulated flows. We filter these records for data completeness and recency criteria: at least 20 years of data (from August to October), at least 1 year of continuous year-round operation, and a data record not ending before 1 January 2000. 240 stations met the completeness and recency criteria. We then removed 8 intermittent streams, which recorded a zero flow in more than 1 year, and 2 streams for which urban land use accounted for more than 20% of the catchment area.

We designed an algorithm to classify the catchments as rainfall-dominated, snowmelt-dominated, hybrid, or glacial regimes based on average annual hydrographs for the years 1991–2020. Rainfall regimes are those with a single low flow period in late summer, snowmelt regimes are those with a single low flow period in late winter, while hybrid regimes show two distinct low flow periods (Fleming et al., 2007; Wade et al., 2001). The algorithm

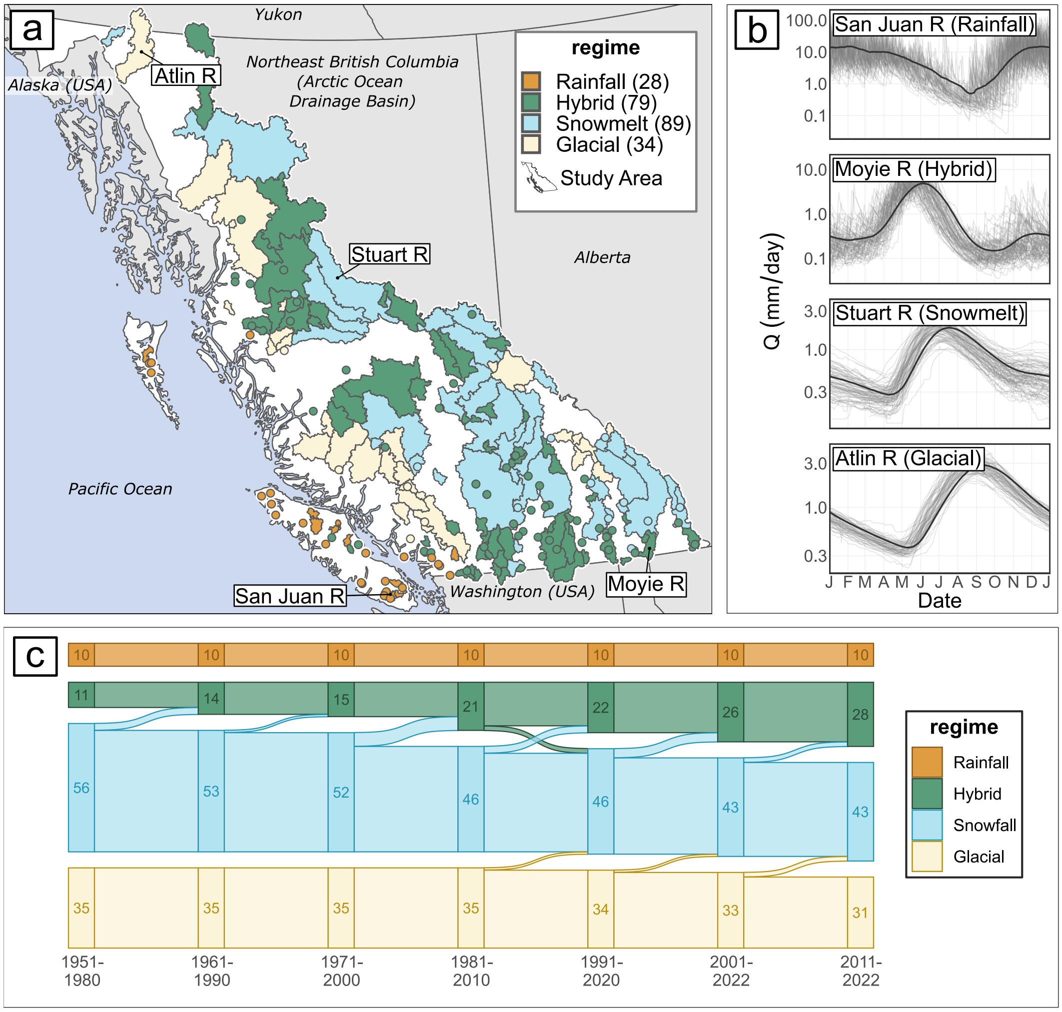

Figure 1. (a) Regime classification for catchments in our sample, for 1991–2020. Circles represent catchments of less than 200 km^2. (b) Example hydrographs are shown for four catchments. San Juan River Near Port Renfrew (rainfall-dominated, gauge ID 08HA010), Moyie River at Eastport (hybrid, gauge ID 08NH006), Stuart River near Fort St James (snowmelt-dominated, gauge ID 08JE001) and Atlin River Near Atlin (glacial, gauge ID 09AA006). The thick black line in each graph is the 30-day mean flow, averaged across all years. Areas outside of study are shown in gray. (c) The evolution of catchment classification since 1951, for 112 catchments with enough data to classify the regime in each interval.

to identify flow minima is described in Appendix A of the Supporting Information S1. Glacial regimes are those where glaciers occupied more than 5% of the catchment area, which is a threshold used by previous researchers to identify basins most affected by glacial processes (Brighenti et al., 2023; Moore, Gronsdahl, & McCleary, 2020; Moore, Pelto, et al., 2020; Stahl & Moore, 2006).

Figure 1, panel A shows the catchment classification based on data from 1991 to 2020. Example annual hydrographs for each regime are shown in panel B. There are 28 rainfall, 79 hybrid, 89 snowmelt, and 34 glacial catchments.

Although the classification used throughout this paper is static in time, we found that many formerly snowmelt-dominated catchments have transitioned to a hybrid regime. We ran our classification algorithm on data from 30-year intervals between 1951 and 2022 (see Appendix A in Supporting Information S1 for details). 112 stations had enough data in each interval to run the algorithm (at least 10 years or glacial cover >5%). Of 56 stations classified as snowmelt-dominated in 1951, 18 transitioned to a hybrid regime by 2022, more than doubling membership in the hybrid regime. Four formerly glacial catchments lost enough glacial cover to be reclassified as snowmelt-dominated. Overall the combined membership in the snowmelt-dominated and glacial regimes fell from 82%

to 66% of the 112 catchments. Appendix A in Supporting Information S1 provides more detail on the regime classifications through time.

Throughout the rest of the paper, the regimes correspond the period 1991–2020 (Figure 1 panel A).

2.3. Definitions

We define the warm season as the snow-free season, based on the monthly average snow-water-equivalent (SWE) for the period 1991–2020, using data from the ERA-5 Reanalysis (Muñoz Sabater, 2019). We include months with a catchment-average SWE of less than 1 mm. For catchments with perennial snow or ice cover we defined the warm season as months for which SWE is within the bottom 10% of the annual range.

We define the *low-flow month* based on the timing of the minimum warm-season flow on the average annual hydrograph of 30-day mean discharge. This minimum is also constrained to occur after the spring freshet. We define the *low-flow season* as the low-flow month plus the month before and the month after, if the neighboring months are within the previously defined warm season.

The 7-day flow, Q7, is the 7-day running mean of discharge. The 7-day low flow, $Q7_{min}$, is the minimum value of Q7, and can be defined for each month or for the entire low-flow season (the *overall* low flow).

2.4. Historical Trends

First, we analyze historical trends in low flows. We analyze overall low flows as well as low flows for July, August, September, and October separately. We use Sen's slope on the log-transformed values, $\log(Q7_{min})$, from 1950 to 2022. Using the logarithm allows the estimated trend coefficient b to be interpreted as a percentage change per decade:

$$\%\Delta_{10} = (\exp(10 \dot{\times} b) - 1) \times 100\% \tag{1}$$

We assess significance at $p < 0.05$ using the modified Mann-Kendall trend test for autocorrelated data (Hamed & Ramachandra Rao, 1998), implemented in R by Patakamuri and O'Brien (2021).

2.5. Climate and Anthropogenic Drivers

We assess stream sensitivity to the mechanisms discussed in Section 1.3 using several ancillary data sets. For each catchment, we create a linear regression model with $\log(Q7_{min})$ as the dependent variable (Equation 2). All variables are standardized to mean 0 and unit variance.

$$\begin{aligned}\log(Q7_{\text{min}}) \sim \beta_1 \text{SWE}_{\text{max}} + \beta_2 \text{BF}_{\text{winter}} + \beta_3 P_{\text{summer}} + \beta_4 T_{\text{summer}} + \beta_5 T_7 + \beta_6 \text{Abstraction} + \beta_7 \text{ECA}_{\text{I}} \\ + \beta_8 \text{ECA}_{\text{III}}\end{aligned} \tag{2}$$

β_i are the standardized regression coefficients and the independent variables are defined in Table 1. For gridded data sets (SWE, P, T, ECA_{I}, and ECA_{III}) we took the arithmetic average of all grid cells within each catchment. For Abstraction data we took the sum of values for all points of use within each catchment. The regression models are fit using all years with streamflow data from 1950 to 2020, which is the common subperiod for which all the ancillary data sets (Table 1) are available.

Since the objective here is to test a theory, we fit the regression models using forced simultaneous entry of the predictor variables (we enter all eight variables at once rather than using stepwise regression or any other data-driven variable selection techniques). We refer to these models as *explanatory* regressions.

The log transformation is used here to increase the influence of the lowest annual low flows and because log ($Q7_{min}$) meets Shapiro-Wilk and Anderson-Darling tests for normality much more frequently than the untransformed values.

Large β coefficients indicate that the mechanism is responsible for a large portion of historical interannual variability in $\log(Q7_{min})$. This contrasts with the elasticities reported by Cooper et al. (2018), which express the % change in y related with % change in x. Low flows are more variable from year to year in warmer catchments than in colder catchments, so elasticities will tend to be greater in rainfall-dominated and hybrid catchments. However, we think sensitivities are better understood in the context of historical variability than in absolute terms, so we prefer to use the correlation coefficient.

We assess below-normal winter snow storage using ERA5-Land reanalysis snow water equivalent (SWE) data (Muñoz Sabater, 2019). Shao et al. (2022) found that these data performed better than other published gridded snow data products, and we also found that this data set provided a much better match to snow survey data (Vionnet et al., 2021), than a Canadian data product (Environment and Climate Change Canada, 2021). SWE_{max} is the maximum catchment-averaged SWE for each year. We tested two alternatives: an alternative variable definition SWE_{fixed}, which is the average SWE for the median peak accumulation month, and the snow disappearance date calculated from daily ERA5-Land SWE.

We estimate groundwater drought based on spring baseflow (BF_{winter}). British Columbia's monitoring well network is very sparse (Curran et al., 2023), precluding an analysis based on groundwater levels. We estimate baseflow using an Eckhardt filter, implemented in R in the FlowScreen package with parameters $\alpha = 0.97$ and $BFI_{max} = 0.8$ (Dierauer & Whitfield, 2019). These parameters are considered typical for perennial streams with porous aquifers (Eckhardt, 2012). We also test the Eckhardt filter with parameters suitable for hard rock aquifers and 5 other baseflow filtering algorithms. BF_{winter} is the average estimated baseflow for 30 days prior to SWE_{max}, and we also test using a fixed timing (the same timing as SWE_{fixed}).

To estimate the impact of accelerated summer recession, we use the average summer temperature T_{summer} and the total summer precipitation P_{summer}. The summer season is defined as May–August, May–September, or May–October, depending on the low flow month. We use the interpolated, gridded, monthly data produced using the ANUSPLIN algorithm by MacDonald et al. (2020).

We investigate ET-driven transmission losses and glacier melt drought using T_7, 7-day mean temperature for the same 7 days used to calculate $Q7_{min}$. We cannot, unfortunately, separate the drying effects of ET-driven transmission losses from the wetting effects of increased meltflow. However, we may expect that glacial catchments will exhibit more positive (or less negative) streamflow-temperature correlations (Stahl & Moore, 2006). We use the interpolated, gridded, daily data produced using the ANUSPLIN algorithm by Hutchinson et al. (2009).

The ANUSPLIN monthly and daily data are derived from unadjusted precipitation records (Hutchinson et al., 2009; MacDonald et al., 2020), so changes to operating procedures, instrumentation, and station locations over time may introduce non-stationarity to the precipitation data (MacDonald et al., 2021; Werner & Cannon, 2016). We compared the ANUSPLIN data to Adjusted and Homogenized Canadian Climate Data (AHCCD: see Mekis & Vincent, 2011; Vincent et al., 2020) from climate stations within our study region (Appendix G in Supporting Information S1). Surprisingly, we found that the ANUSPLIN data set was as temporally consistent (the bias did not change over time) as two data sets developed using adjusted precipitation data and homogenized temperature data: ANUSPLIN-adjusted (MacDonald et al., 2021) and PNWNAmet (Werner et al., 2019). We also found that ANUSPLIN was more temporally consistent than ERA5-Land reanalysis data (Muñoz Sabater, 2019). We chose the ANUSPLIN data set for the main analyses in this study because it offers the longest temporal coverage and finest resolution of available data sets for the region. We also repeat our sensitivity analyses using the PNWNAmet gridded data set, which is available from 1945 to 2012 and the ERA5-Land reanalysis, which is available from 1950-present.

Water abstraction is estimated following the strategy in Barroso and Wainwright (2020). For licensed water use, we converted yearly and daily allocations to m^3/s. Although surface water licensing is thorough in BC, most groundwater use is unlicensed. We spatially joined well construction records to BC Assessment parcels and determined the most likely well use based on the intended well use from the well record (where available) and the property description from the BC Assessment. For most well uses we assigned a representative water use value, but for irrigation wells we estimated water demand based on the size of the property. More details are provided in Appendix B of the Supporting Information S1. Abstraction is only included for catchments in which the estimated mean annual water use is greater than 10% of the low-flow discharge in any individual year.

We include two variables related to forest disturbance: ECA_I and ECA_{III}. These correspond to hydrological periods I and III as described by Coble et al. (2020). Hydrologic period I is expected to be a period of increased low flow discharge, lasting between up to 40 years after the disturbance; the median length in the studies reviewed by Coble et al. was 9 years. ECA_I is defined here as the fraction of the catchment with a stand age of 9 years or less. Hydrologic period III is expected to be a period of reduced low flow discharge, beginning some years after the disturbance. The onset of period III has been found to be highly variable, with a median onset timing of 24 years following the disturbance. We defined ECA_{III} as the fraction of the catchment with stand age between 24 and 80 years old. These variables are only included if more than 10% of the catchment area has ever been logged and if less than 10% of the catchment area is privately held (where logging records are not public).

2.5.1. Nonlinearity in Temperature Effects

A common argument is that temperature (or potential evapotranspiration) does not drive droughts because actual evapotranspiration becomes water limited rather than energy-limited as the landscape dries (Barnett et al., 2005). As temperature increases, there may be thresholds above which no water is available for evaporation, or when plants close their stomata to regulate transpiration. Thus, we may expect a nonlinear relationship between temperature and $Q7_{min}$.

Our linear regression models assume that the effect of temperature on $Q7_{min}$ is loglinear. This means that a unit increase in temperature will produce a fractional reduction in $Q7_{min}$, which is consistent with the expectation that the ratio of actual evapotranspiration to potential evapotranspiration decreases as water availability decreases. This is a reasonable assumption, but the real relationship could be either concave up or down on a loglinear plot, and we can statistically test the assumption in two ways.

First, we add a squared term in the linear regressions, $\beta_9(T_{summer})^2$. If the effect of temperature is diminished at high temperatures, we expect that β_9 will be positive. For each regime we use a binomial test to compare the number of positive coefficients to a binomial distribution with probability = 0.5 as a test for field significance, which is the extent to which the distribution of results for several catchments differs from a random distribution (Burn & Hag Elnur, 2002). We also test whether the number of positive or negative significant coefficients exceeds the number expected by chance, by using a binomial test with probability = 0.05.

Second, we can substitute space for time and test whether temperature is a weaker driver in warmer catchments. For each regime, we evaluate the correlation between β_4 (the T_{summer} coefficient) and the mean summer temperature.

2.5.2. Stationarity

The trends that will be shown in Section 3.1 are evidence of non-stationary time series, which could be due to non-stationary drivers and/or non-stationarity in low-flow generating mechanisms. The latter, which we term "mechanistic non-stationarity" has been variably described as parameter instability, model non-stationarity, rainfall-runoff non-stationarity, and non-stationarity in catchment characteristics (Beven, 2016; Niel et al., 2003; Westra et al., 2014). If part of the trend in low flows is related to mechanistic non-stationarity, then inferences drawn from analyzing historical data will be less useful for making predictions about the future or simulating years before the calibration period.

We can evaluate whether low-flow generating mechanisms have been stationary in the past by repeating the sensitivity analysis over early and late (recent) time frames. For this analysis we choose 153 catchments that have at least 20 years of data up to 1997 and at least 20 years from 1998 onwards (this split maximizes the number of catchments meeting the criterion). We fit the explanatory regression models (Equation 2) to the early (up to 1997) and late (1998 onwards) data sets.

If there is mechanistic non-stationarity, β_{early} and β_{late} will differ. We tested agreement between the two sets of coefficients for each catchment by comparing the test statistic, $\Delta\beta = \beta_{late} - \beta_{early}$, to an empirical distribution generated by a Monte Carlo permutation test with 10,000 random assignments of the data to the early and late periods. For this analysis we exclude the Abstraction, ECA_I, and ECA_{III} variables because (a) they are less consistently measured through time, which could lead to erroneous findings of non-stationarity, (b) this would also reduce the statistical power to correctly detect non-stationarity in the climate variables, and (c) these variables are strongly autocorrelated by construction, which violates the independence assumption necessary for the Monte Carlo permutation test.

We assess field significance for this test statistic in with three tests: Test 1 is a binomial test with an expected probability of 0.5 to evaluate if the proportion of catchments with $\Delta\beta > 0$ is more or less than expected. Test 2 is a binomial test with an expected probability of 0.05 to test whether the proportion of catchments with individually significant positive differences is greater than expected. Test 3 is the same as Test 2 but for negative significant differences. Each binomial test is applied 20 times (4 regimes and 5 variables), so we assess significance using the Holm-Bonferroni method to control the family wise error rate (Holm, 1979).

2.6. Predictive Regression Models

We build on the analysis of low flow drivers to create ordinary least squares regression models that predict the yearly minimum flow, $Q7_{min}$ for each catchment.

Despite its simplicity, regression is an appropriate model to simulate summer low flows. In the 20th century multiple regression models were often used for streamflow simulation and forecasting (e.g., Cayan et al., 1993; Garen, 1992; US Soil Conservation Service, 1972; Vogel et al., 1999). Process-based computer models, though first proposed in the 1960s (Freeze & Harlan, 1969), became more popular in the late 1990s and 2000s with improvements in computer technology (Grayson et al., 1992; Todini, 2007). More recently, data-driven approaches have made a comeback in the form of machine learning models, with some authors showing that data-driven approaches can outperform process-based models in a wide variety of settings (Arsenault et al., 2023; Kim et al., 2021). Regression is a simple form of machine learning, and its use is thus neither particularly new nor out of step with current practices.

We ruled out more complex machine learning models because of limitations in the size of the data set. We have chosen to predict only the minimum yearly summer/fall low flow, in contrast to many previous low-flow and hydrologic drought studies that analyze flow percentiles or spell durations. The minimum flow has relevance for fish survival, passage, and spawning, has regulatory implications for British Columbia, and is also commonly the portion of the hydrograph that is most poorly predicted by process-based hydrologic models. By abandoning the requirement to simulate all parts of the annual hydrograph, we can more accurately represent the flow-generating mechanisms that are most relevant to low flows. However, we also reduce the size of our calibration data to one observation per year, so a high-order machine learning model would likely be overfit. Regression works well with small data sets and produces models that are straightforward to interpret, whose properties have been studied over more than a century.

We choose to make bespoke models for each catchment, rather than to create one model for the region with catchment characteristics as covariates, because the one-model approach did not perform well in our preliminary tests (results not shown). Our approach allows us to accurately simulate the unique response of each catchment to climate variability and change. We are then able to analyze how these responses across the four hydrologic regimes.

2.6.1. Model Selection

For each catchment we develop three regression models to predict $\log(Q7_{min})$: one for each of the 3 months comprising the low-flow season. We use all available years of streamflow data up to 2022 to build these regression models. In our sample of 230 catchments the longest record begins in 1903.

For each catchment-month combination, we construct the best model using 5-fold cross-validation, which is repeated 10 times with random partitions of the data into folds. We evaluate the models using the Kling-Gupta Efficiency (KGE), evaluated jointly on the predicted $Q7_{min}$ of the five folds. Due to the known problems with using the KGE on log-transformed flow values (Santos et al., 2018), we use the square root of $Q7_{min}$.

We start with 15 physically plausible variables and train models for all subsets of variables ($2^{13} = 32{,}768$ models). The model with the highest average KGE for each catchment-month is selected. We then evaluate the models using 10 new random partitions of the data into folds.

The 15 candidate variables are chosen to represent climate variables and water abstraction (Equation 3). We only use precipitation (P) and temperature (T) as predictor variables because they are uniformly available in the historical climate data from 1900 to 2022. We chose to include mean T and total P variables over seven averaging times (1, 2, 3, 4, 6, 8, and 12 months prior to the month being predicted). This allows the cross-validation routine to select the most appropriate lag times, or combinations thereof, for each catchment. Using overlapping averaging times ensures that the model will include more recent months, which prevents the construction of physically implausible models.

For month k the full model with all 15 variables is:

$$\begin{aligned}\log(Q\,7_{\min})_k \sim\ & b_1 T_{[k-11,k]} + b_2 T_{[k-7,k]} + b_3 T_{[k-5,k]} + b_4 T_{[k-3,k]} + b_5 T_{[k-2,k]} + b_6 T_{[k-1,k]} + b_7 T_{[k]} \\ & + b_8 P_{[k-11,k]} + b_9 P_{[k-7,k]} + b_{10} P_{[k-5,k]} + b_{11} P_{[k-3,k]} + b_{12} P_{[k-2,k]} + b_{13} P_{[k-1,k]} + b_{14} P_{[k]} \\ & + \text{Abstraction} \end{aligned} \tag{3}$$

b_i are the regression coefficients and the subscripts $[k-m,k]$ indicates the period ending on month k and beginning m months before. For each year, the predicted minimum summer low flow is the lowest prediction of the 3 months comprising the low-flow season.

We construct our models based on ANUSPLIN data. For comparison, we also construct predictive regression models using the same process with PNWNAmet and ERA5-Land data.

We can compare the model fits to published models for some of the catchments. The Pacific Climate Impacts Consortium (2020) has created distributed, physically based hydrologic models for 56 of the 230 catchments studied here, using a Variable Infiltration Capacity model with a glacier model (VIC-GL). These 56 models include 21 hybrid, 26 snowmelt, and 9 glacial regimes. No rainfall-dominated catchments are included. To enable comparison of low-flow predictions between the VIC-GL models and the regression models developed in this study, we fit the regression models to the same time period (1945–2012) using the same gridded meteorological data (PNWNAmet, Werner et al., 2019). Only the final calibrated model data are available for the VIC-GL models, so we compare the performance to our final regression models, trained and evaluated on all years of data. These performance statistics are referred to as "in-sample" statistics, in contrast to the "out of sample" statistics derived from cross-validation. One catchment had less than 20 years of data between 1945 and 2012 so we compare the remaining 55.

We evaluate our models for residual autocorrelation and stationarity. We used the Breusch-Godfrey test for lag-1 autocorrelation (Breusch, 1978; Godfrey, 1978), and evaluated the critical value of the test statistic using Monte Carlo randomization of the lagged residuals with 10,000 draws. We evaluated residual stationarity by subjecting the residuals to the same trend analysis as described in Section 2.4. We applied the same binomial tests for field significance as described in Section 2.5.1.

2.7. Environmental Flow Thresholds

We compare the predicted low flows with two flow thresholds. The BC government has the authority to set a Critical Environmental Flow Threshold (CEFT) for any stream, which is defined as the discharge "below which significant or irreversible harm to the stream's aquatic ecosystem is likely to occur" (Water Sustainability Act, 2016). The presumptive CEFT is often set using a modified Tennant method, at 5% of the long-term mean annual discharge (McCleary & Ptolemy, 2017). However, for rainfall-dominated catchments, flows are frequently less than 5% long-term mean annual discharge. As such, the interim CEFT for the Xwulqw'selu (Koksilah) Watershed (a typical rainfall-dominated catchment) was set close to 2% long-term mean annual discharge. We follow this strategy and set the presumptive CEFT at 2% long-term mean annual discharge for rainfall regimes and 5% for other catchments.

British Columbia has a separate drought classification framework, which is based on flow percentiles calculated for each day of the year. The most severe drought level (5) corresponds to flows below the 2nd percentile (a 1-in-50-year event), while level 4 corresponds to flows below the 5th percentile, and Level 3 to the 10th percentile. At level 5 "adverse impacts to socio-economic or ecosystem values are almost certain," regulatory action to limit water use is "highly likely," and the province prepares for "emergency response where risk of failure or loss of [water] supply exists" (BC Ministry of Water, Land and Resource Stewardship, 2023). The North American Drought Monitor classifies events below the 10th, 5th, and 2nd percentiles as "Severe," "Extreme," and "Exceptional" droughts.

We calculate the 10th, 5th, and 2nd percentiles of $Q7_{min}$, based on available data from 1950 to present. Compared to British Columbia's drought monitoring this is somewhat conservative (less likely to classify events as drought), since the province calculates percentiles for each day of the year.

2.8. Historical Reconstruction

We reconstruct low flows from 1901 to 2022 using the optimized regression models (Section 2.6) and the historical monthly temperature and precipitation data. We compare the simulated low flows to the thresholds described in Section 2.7.

We also assess what has driven decadal changes in low flows over the last century. To answer this question, we estimate the yearly anomaly in $Q7_{min}$ for each catchment, relative to the average simulated $Q7_{min}$ from 1950 to 1999 (in the absence of any effect of water abstraction). This "total anomaly" is composed of anomalies driven by winter and summer temperature and precipitation, as well as water abstraction.

We estimate the $Q7_{min}$ anomalies and their components using the regression model for the low-flow month for each catchment. First, we find the temperature and precipitation anomaly for each month, year, and catchment. We construct the predictor matrix for each regression model using these anomalies, considering temperature and precipitation separately and winter (November–April) and Summer (May–October) separately and setting all other values to 0. We run these predictor matrices through each regression model; the predicted values, minus the model intercept, are the anomalies in $\log(Q7_{min})$ associated with each driver.

3. Results

3.1. Dissecting Past Trends in Low Flows

Figure 2 shows the trends in summer to fall low flows, from 1950 to 2022. Overall low flows have decreased in 174 of 230 (76%) watersheds. There has been a significant ($p < 0.05$) decrease in 50 watersheds, and only five watersheds have seen a significant increase.

Rainfall and hybrid regimes have seen strong drying trends. Low flows in 27 of 28 rainfall-dominated catchments have decreased, with 16 statistically significant trends. 74 of 79 hybrid catchments have seen declines, with 22 significant drying trends.

Snowfall and glacial regimes show weaker evidence of regional trends. 61 of 89 snowfall-dominated catchments show drying trends, with 11 significant drying trends and three significant wetting trends. Over half of glacial catchments (22 of 34) have seen increases in summer low flows, with only one significant increase and one significant decrease.

Only two catchments have seen statistically significant increases of more than 10% per decade. Further inspection revealed that these are small (<100 km^2) catchments located very near to the two largest open-pit copper mines in Canada, which were operating since before hydrometric monitoring began. Although a detailed investigation of these sites is beyond the scope of this study, we hypothesize that historical mining operations (water use and/or mine dewatering) have induced a non-natural streamflow response.

July, August, September, and October trends are shown individually in Appendix C of the Supporting Information S1. Drying trends are strongest in August (210/230 drying, 104 significantly), and weakest in October (121/228 drying, 21 significantly). Glacial regimes have seen more increases than decreases in September and October but across the three other regimes drying trends are more common in all months.

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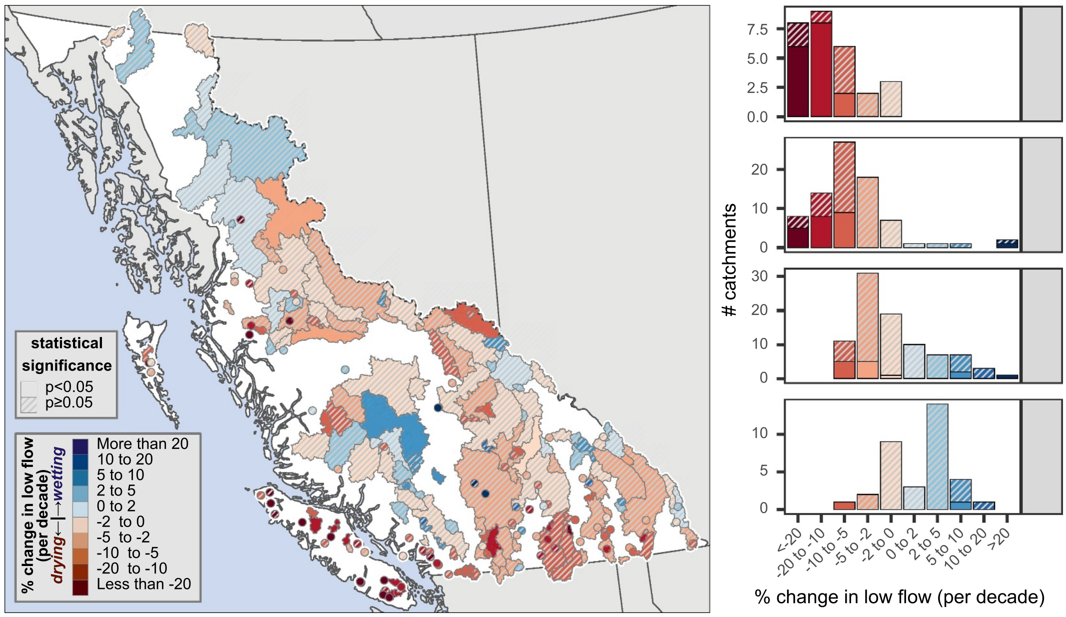

Figure 2. Trends for the overall (August–October) low flow in the 230 study catchments, using available data from 1950 to 2022. Hatched polygons denote non-significant trends. Red denotes drying trends and blue denotes wetting trends. 174 of 230 catchments are drying, and 50 of these decreases are statistically significant. Rainfall-dominated and hybrid catchments are drying much more than snowmelt-dominated and glacial catchments. Only five catchments show statistically significant increases (wetting trends).

3.2. Examining Sensitivity to Key Climate Variables

Figure 3 shows the standardized regression coefficients for regression models with each the variables listed in Table 1. Figure D1 in Supporting Information S1 shows bivariate (Pearson) correlation coefficients for each of the variables for comparison.

Below-normal winter storage has historically had a minor influence on summer low flows. For winter snow storage, the median coefficient is less than 0.2 across all regimes, with one third being significant. We found no meaningful differences in the strength of the correlations when using a fixed timing for the SWE variable (Figure D2 in Supporting Information S1). The snow disappearance date was a slightly stronger predictor than SWE_{max}, probably because the snow disappearance date includes information about both winter snow accumulation and summer melting rates. The bivariate correlation coefficients (Figure D1 in Supporting Information S1) were only slightly larger than the standardized coefficients in Figure 3 (median of 0.249 with 43% being significant).

Winter snow accumulation also does not necessarily prevent severe low flows. Across the 230 catchments, 35% of the catchment-years in the bottom decile (10th percentile) of $Q7_{min}$ had above-median winter snow accumulation; 210 of 230 catchments had at least 1 year with above-median snow accumulation and $Q7_{min}$ in the bottom decile, and 52 catchments had at least 1 year with exceptionally high snow accumulation (top decile) that nevertheless had $Q7_{min}$ in the bottom decile, including 6 rainfall-dominated, 17 hybrid, 21 snowmelt-dominated, and 8 glacial catchments.

Correlations with end-of winter baseflow (BF_{winter}) are small in all hydroclimatic regimes. The median coefficient is 0.08. Only 12% are significant and positive, which is slightly more than the 5% that would be expected by chance. The bivariate correlation coefficients (Figure C1 in Supporting Information S1) were similar to the standardized coefficients in Figure 3 (median of 0.11 with 14% being significant). We tested six other baseflow filtering algorithms (Figure D3 in Supporting Information S1). Although the baseflow time series were considerably different, we did not find meaningful differences in the correlations with $\log(Q7_{min})$. We also tried holding the timing constant and calculating the average baseflow over the same month for each year (the median peak SWE accumulation month) and found even weaker correlations.

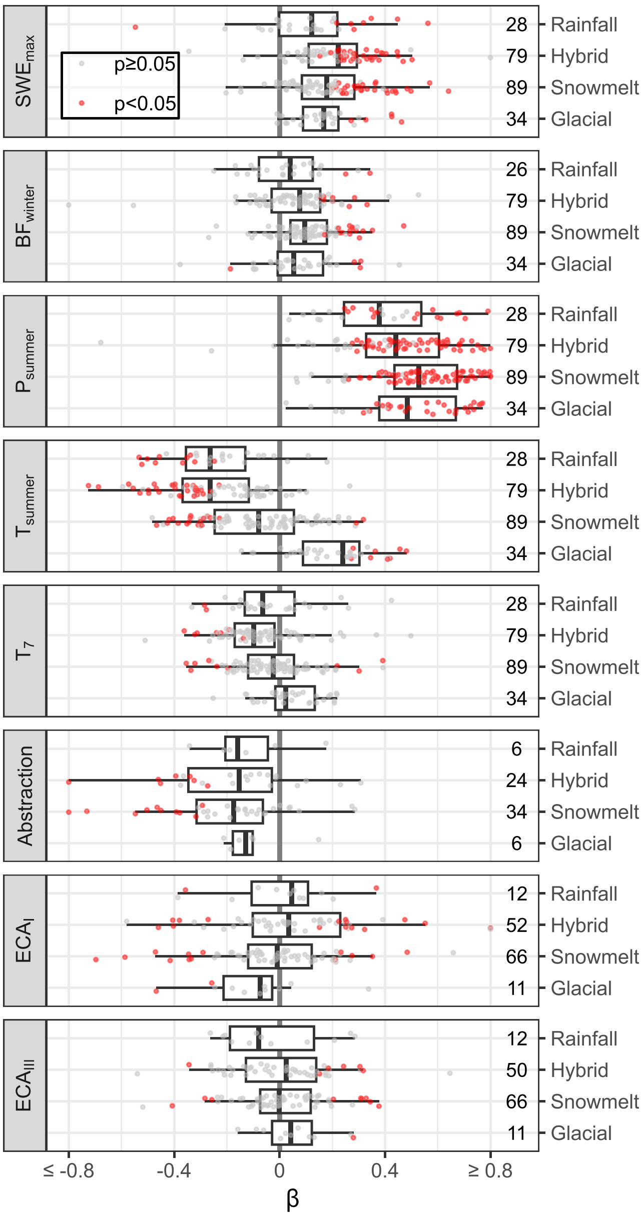

Figure 3. Standardized regression coefficients for log-transformed summer low flows with 8 explanatory variables. Analogous graphs with bivariate Pearson correlation coefficients are shown in Figure D1 of the Supporting Information S1. The numbers indicate the number of catchments.

As another robustness check on our conclusions about the importance of winter storage, we tried including winter (November–April) T and P in place of SWE$_{max}$ and BF$_{winter}$ (Figure D4 in Supporting Information S1). The coefficients of T_{winter} and P_{winter} were similar in magnitude to the correlations with SWE$_{max}$, indicating that these variables serve as reasonable proxies for snow accumulation.

Summer precipitation, P_{summer}, shows large positive correlations for most catchments across all regimes (median of 0.48), and 79% of these correlations are statistically significant. Summer temperature, T_{summer}, shows negative coefficients for most rainfall-dominated and hybrid catchments, with median coefficients of −0.26 for both regimes, and 36% and 39% significant, respectively. In snowmelt-dominated catchments the median coefficient for T_{summer} is close to zero and in glacial catchments it is positive.

We note that bivariate correlation coefficients (Figure D1 in Supporting Information S1) for T_{summer} are considerably more negative than the coefficient from the multiple linear regression. For rainfall-dominated and hybrid catchments, the median bivariate correlations for T_{summer} are −0.54 and −0.55, respectively, which are approximately equal and opposite to the correlations for P_{summer}. The discrepancy between the bivariate correlations and the coefficients of the multiple linear regression occurs because T_{summer} tends to be correlated with many of the other predictor variables, especially P_{summer}, T_7, Abstraction, ECA$_I$ and ECA$_{III}$.

The results are similar when we specify an alternate regression model with potential evapotranspiration and precipitation from the ERA5-Land model instead of T_{summer} and P_{summer} from the observational ANUSPLIN data (Figure D5 in Supporting Information S1). However, the correlations with potential evapotranspiration are slightly stronger (more negative) than those with temperature, probably because the potential evapotranspiration data accounts for the effects of humidity, wind speed and radiation, and the nonlinear shape of the saturation vapor pressure curve. The correlations with precipitation are slightly weaker, probably because the ERA5-Land precipitation data are less accurate than the ANUSPLIN data and because there is some collinearity between precipitation and potential evapotranspiration.

There are both positive and negative coefficients with T_7, but most of these relationships are weak. The coefficients are more likely to be negative in rainfall and hybrid catchments, which is similar to the pattern for T_{summer}.

Abstraction tends to reduce low flows, as expected. However, the magnitude of the effect varies widely, probably because the magnitude of water use varies. Most catchments in our sample had very little water use.

The two forest harvesting variables, ECA$_I$ and ECA$_{III}$, do not show the expected behavior of low flow increases in period I and decreases in period III. Both positive and negative coefficients are common for ECA$_I$ and ECA$_{III}$ and the median is near zero in all regimes.

We replicated Figure 3 using PNWNAmet data (Werner et al., 2019) for T_{summer}, P_{summer}, and T_7. We found that results were very similar to those using ANUSPLIN (Figure D6 in Supporting Information S1).

We also performed a more detailed analysis of the effect of forest disturbances on low flows (Appendix E in Supporting Information S1), using four different Equivalent Clearcut Area functions and the pre-whitening strategy applied by M. Zhang and Wei (2012) and various other authors. This analysis also showed mixed and mostly non-significant results for most regimes. We found that pre-whitening resulted in extremely low statistical power to detect even large effects, so we also conducted an analysis without pre-whitening. There was some evidence that forest disturbance lowers low flows in snowmelt-dominated and glacial catchments, but we were unable to detect effects in rainfall or hybrid regimes.

We note that the standardized regression coefficients, β, measure the effect of each explanatory variable as a fraction of the standard deviation of $\log(Q7_{min})$. However, this variance tends to be smaller in cold catchments: the average coefficient of variation of $Q7_{min}$ is 0.53 in rainfall, 0.49 in hybrid, 0.34 in snowmelt and 0.30 in glacial regimes. This means that, all else being equal, the same β indicates a greater effect on the magnitude of the low flow in rainfall-dominated catchments than in colder catchments.

3.2.1. Nonlinearity of Temperature Effects

The first test for non-linearity in the effect of temperature was to include $(T_{summer})^2$ in our explanatory regression models. The coefficient for $(T_{summer})^2$ is positive in 57%, 77%, 74%, and 65% of rainfall, hybrid, snowmelt, and glacial catchments; these rates are field-significant (greater than would be expected by chance) for hybrid and snowmelt catchments and not significant for rainfall-dominated and glacial catchments. The rate of positive *significant* coefficients is significant only for the hybrid regime. These results suggest that the effect of temperature on $\log(Q7_{min})$ may be slightly nonlinear, and that the effect of temperature diminishes at high temperatures for hybrid and snowmelt-dominated catchments.

The second test for nonlinearity was to examine whether the effect of temperature was weaker in warmer catchments. We found the opposite: for all regimes, the coefficient for T_{summer} was larger (more negative) in warmer catchments; this relationship was statistically significant for the snowmelt-dominated regime, not significant for the rainfall-dominated regime, and marginally significant ($p < 0.1$) in hybrid and glacial catchments.

3.2.2. Testing Stationarity

We did not find evidence of significant non-stationarity in most of the correlations. Tests 2 and 3 (the number of positive and negative significant differences) were non-significant for all variables and regimes, even before applying the Holm-Bonferroni method.

Test 1 (the ratio of positive to negative differences) was significant for T_{summer} in hybrid and snowmelt-dominated regimes (for most catchments the coefficients were less negative in the late period), indicating that the influence of summer temperature may be decreasing. However, the influence of T_7 appears to be increasing in snowmelt-dominated regimes (most catchments had more negative coefficients in the later period), although this was non-significant after applying the Holm-Bonferroni method. Test 1 was also significant for SWE_{max} in hybrid and snowmelt-dominated regimes, indicating that the influence of winter snow accumulation may be decreasing. P_{summer} and BF_{winter} were not significantly non-stationary in this analysis.

We tested the robustness of our analysis by splitting the data at years 1995, 1996, and 1998. All results are included in Appendix D of the Supporting Information S1.

3.3. Parsimonious Predictive Regression Models

Figure 4 shows the modeled response (change in low flow as a percentage) to temperature and precipitation anomalies, based on the predictive regression models (Section 2.6). The x-axis indicates the lag time between the anomaly and the low-flow month. The top row shows the response to 10 mm of additional precipitation, and the bottom row shows the response to a 1°C increase in temperature over a single month.

All regimes show increases in $Q7_{min}$ related to precipitation events over a period of about 4 months. The lag-0 effect is smaller for some catchments because low-flow events can occur early in the month, before large precipitation events. Some hybrid and snowmelt-dominated catchments have longer lag times (up to 11 months) which is probably related to winter snow accumulation that persists into the summer.

The response to temperature for the low-flow month (lag 0) is strongly negative in rainfall regimes and variable in hybrid regimes. For snowmelt and glacial regimes, increased temperature leads to higher flows over the short term (up to a lag of 1 month) probably because of increased meltflow, but lower flows over the longer term (3–6 months) because of storage depletion. The short term increase could also be partly related to catchments where low-flow month precipitation falls as snow in particularly cold years.

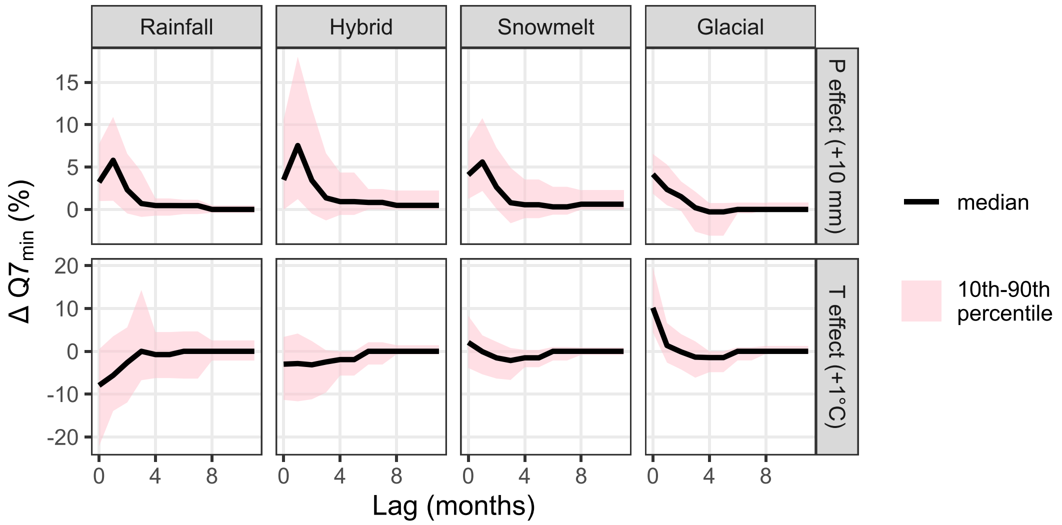

Figure 4. The modeled response to precipitation and temperature anomalies occurring 0–11 months before the month for which the low flow is predicted. The top row shows responses to 10 mm of additional precipitation and the bottom row shows responses to a 1°C increase in temperature over a single month.

Table 2 shows the KGE, NSE, and R^2 statistics for the predictive regression models, derived from 10 repeated 5-fold cross-validations. The median KGE for the overall low-flow prediction is 0.64, with a range from 0.18 to 0.92. All the models perform significantly better than the benchmark KGE of −0.41 (Knoben et al., 2019). Three models have negative NSEs. We also tested the modeling framework using three other data sets: ANUSPLIN-adjusted (MacDonald et al., 2021), ERA5-Land (Muñoz Sabater, 2019) and PNWNAmet (Werner et al., 2019); we found that performance was very similar across ANUSPLIN, ERA5-Land, and PNWNAmet, but the ANUSPLIN-adjusted models performed slightly worse (see Appendix H in Supporting Information S1).

Based on the R^2 values, the models explain a median of 48% of the historical variance. The residual error may be due to unobserved variables (e.g., land use change) and measurement errors in streamflow, climate, and water use variables. Some of the error can also be attributed to variability in the timing of precipitation events during the month of interest.

In terms of predicting the overall summer low flow, the regression models presented here generally outperform the VIC-GL models (Pacific Climate Impacts Consortium, 2020). KGE($Q7_{min}$) and NSE($Q7_{min}$) for the regression models are better in 96% and 98% of the catchments, respectively. Evaluated on transformed flow values, KGE($Q7_{min}^{1/2}$) and NSE(log($Q7_{min}$)) are better in 95% and 98% of the catchments. Table 3 shows the median and range of NSE and KGE for the regression and VIC-GL models. Strikingly, NSE(log($Q7_{min}$)) is negative for 40 of 55 of the VIC-GL models but none of the regression models.

We also evaluated 27 common goodness-of-fit statistics included in the hydroGOF R package (Zambrano-Bigiarini, 2024) under square-root, log, and identity transformations (81 statistics total). The regression models

Table 2
Median Goodness of Fit Statistics for Best Regression Models Selected for the 230 Catchments

	Rainfall	Hybrid	Snowfall	Glacial
N	28	79	89	34
KGE($Q7_{min}^{1/2}$)	0.68 (0.28, 0.77)	0.72 (0.28, 0.91)	0.66 (0.12, 0.88)	0.57 (0.26, 0.77)
NSE(log($Q7_{min}$))	0.47 (−0.07, 0.6)	0.55 (−0.19, 0.8)	0.46 (−0.08, 0.8)	0.36 (−0.07, 0.63)
R^2($Q7_{min}$)	0.49 (0.08, 0.74)	0.54 (−1.8, 0.86)	0.47 (−0.15, 0.78)	0.39 (−0.04, 0.63)
PBIAS($Q7_{min}$)	−4.14 (−24.15, 3.78)	−1.04 (−19.38, 8.22)	−0.37 (−18.08, 7.27)	−0.69 (−5.17, 6.51)

Note. Minimum and maximum values are provided in brackets.

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Table 3
Median Nash-Sutcliffe and Kling-Gupta Efficiencies for Regression and VIC-GL Models

	Regression	VIC-GL	Regression outperforms VIC-GL
KGE($Q7_{min}$)	0.80 (0.42, 0.93)	0.43 (−1.71, 0.86)	53/55 catchments
KGE($Q7_{min}^{1/2}$)	0.80 (0.46, 0.92)	0.45 (−0.48, 0.88)	52/55 catchments
NSE($Q7_{min}$)	0.71 (0.29, 0.91)	−0.22 (−70.6, 0.75)	54/55 catchments
NSE(log($Q7_{min}$))	0.71 (0.38, 0.88)	−0.56 (−44.74, 0.7)	54/55 catchments
PBIAS($Q7_{min}$)	−0.3 (−3.2, 5.8)	−12.8 (−88, 129.1)	52/55 catchments

Note. Minimum and maximum statistics are provided in brackets.

outperformed the VIC-GL models for every one of these statistics; on average for the 81 statistics, the regression models outperformed VIC-GL in 52 of 55 catchments.

The efficiency statistics in Table 3 are evaluated using in-sample statistics to ensure a like-with-like comparison. However, the regression models outperform the VIC-GL models even if we give the regressions an artificial disadvantage by using their cross-validated efficiency statistics (Table 2). The cross-validated regression KGE ($Q^{1/2}$) scores are better than the in-sample scores for VIC-GL in 43 of 55 (78%) catchments, and the cross-validated Regression NSE(log(Q)) are better than the in-sample VIC-GL scores of 53 of 55 (96%) catchments.

The VIC-GL models are not poorly calibrated overall. When calculated on daily flows for the entire time series, the median NSE(log(Q)) and KGE($Q^{1/2}$) for these models are 0.76 and 0.84. Only one VIC-GL model has a negative KGE($Q^{1/2}$), and only five have a negative NSE(log(Q)). However, the models clearly perform poorly for low-flow prediction. The VIC-GL models were not calibrated with the sole purpose of predicting low flows, so general conclusions about the relative suitability of regression versus process-based models for predicting low flows may not be appropriate. It is possible that process-based models calibrated to optimize low-flow prediction could outperform the regression models presented here, but a rigorous benchmarking of different models and calibration techniques is out of the scope of the current work.

We found little evidence of residual autocorrelation. Overall, the Breusch-Godfrey test was significant for 8% of the catchments. Hybrid regimes were most likely to be autocorrelated (13%), followed by rainfall and snowmelt-dominated catchments (7% each), glacial catchments (0%). Based on binomial tests, these rates of significant results are field-significant (greater than expected by chance) for the hybrid regime but not field-significant for the other regimes. Despite the finding of field-significance for the hybrid regime, the proportion of catchments with significant autocorrelation is low. This indicates that ignoring interannual catchment storage in the models is a reasonable choice.

We also found little evidence of non-stationarity in the model residuals. We found individually significant trends in 13% of the catchments (18% of rainfall catchments, 14% of hybrid catchments, 10% of snowmelt catchments and 15% of glacial catchments). Approximately half (48%) of all catchments had positive trends in the residuals. Based on binomial tests, none of the regimes had an abnormal number of positive/negative trends nor an abnormal number of significant positive/negative trends.

3.4. Hindcasted Low-Flow Conditions

We use the regression models to simulate past low flows from 1901 to 2022 and compare low flows to the Critical Environmental Flow Threshold (CEFT) and drought thresholds. Figure 5 shows the percentage of catchments within each regime that transgress these thresholds smoothed using a running mean of 10 years.

Rainfall-dominated catchments are, in general, more likely to transgress the CEFT than hybrid catchments, even though the CEFT for these catchments is set at 2% of long-term mean annual discharge for rainfall-dominated catchments and 5% for hybrid catchments. This is because low flows in these catchments are more variable from year to year than low flows in colder catchments, as was noted in Section 3.2. This larger envelope of variability means that low flows transgress the CEFT more frequently.

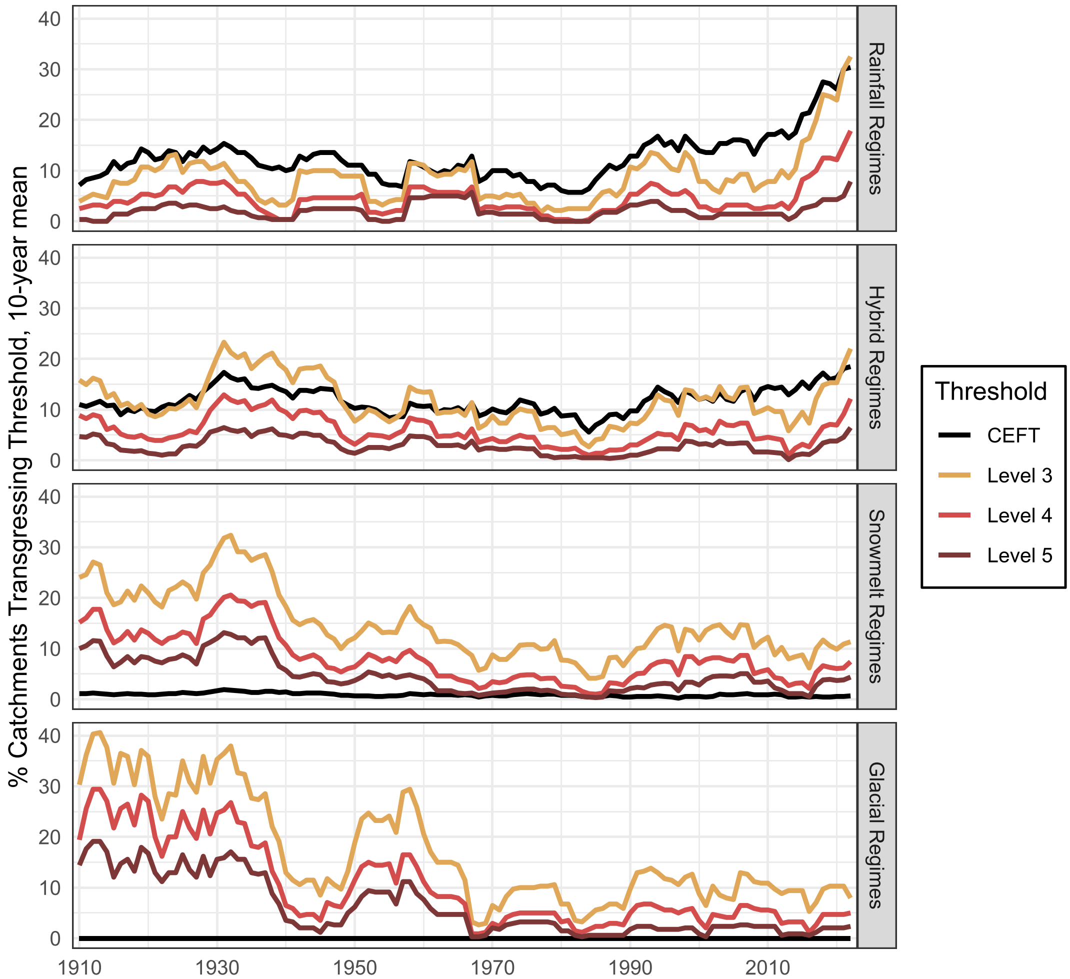

Figure 5. The simulated percentage of catchments transgressing the Critical Environmental Flow Threshold (CEFT) as well as Drought Levels 3, 4, and 5. A 10-year rolling mean (beginning in 1901) is used to smooth the data.

Warm-season low flows in snowmelt-dominated and glacial catchments almost never fall below the CEFT because these catchments tend to see their lowest flows in the winter months. However, drought thresholds were defined on a seasonal basis, and these catchments do experience warm-season droughts.

Drought and CEFT transgressions in rainfall-dominated catchments have risen erratically but persistently since the 1980s. There has also been a recent increase in transgressions for hybrid regimes over the same period, although it has been less dramatic than the trend in rainfall regimes. These simulated trends are consistent with the declining trends in measured $Q7_{min}$ observed in Figure 2.

Another remarkable detail in Figure 5 is that, for hybrid, snowmelt, and glacial regimes, streamflow drought was more common 100 years ago than it is currently. Although CEFT transgressions are rising in hybrid regimes, they are currently no more common than they were throughout the warm and dry 1920s and 1930s.

Figure 6 shows the total anomaly in $Q7_{min}$ (black line) and the components of this anomaly that can be attributed to winter and summer temperature and precipitation. Low flows in the early 20th century were considerably below-average in hybrid, snowmelt, and glacial regimes, and this was mostly related to a long-term precipitation deficit. Variability in precipitation drove most of the overall low-flow variability throughout the 20th century.

In recent years temperature has begun to play a much larger role. Since 1990, warm summer temperatures have led to large negative low-flow anomalies associated with temperature in rainfall-dominated and hybrid regimes (dark brown in Figure 6). This, in combination with slightly below-average precipitation, has led to large negative

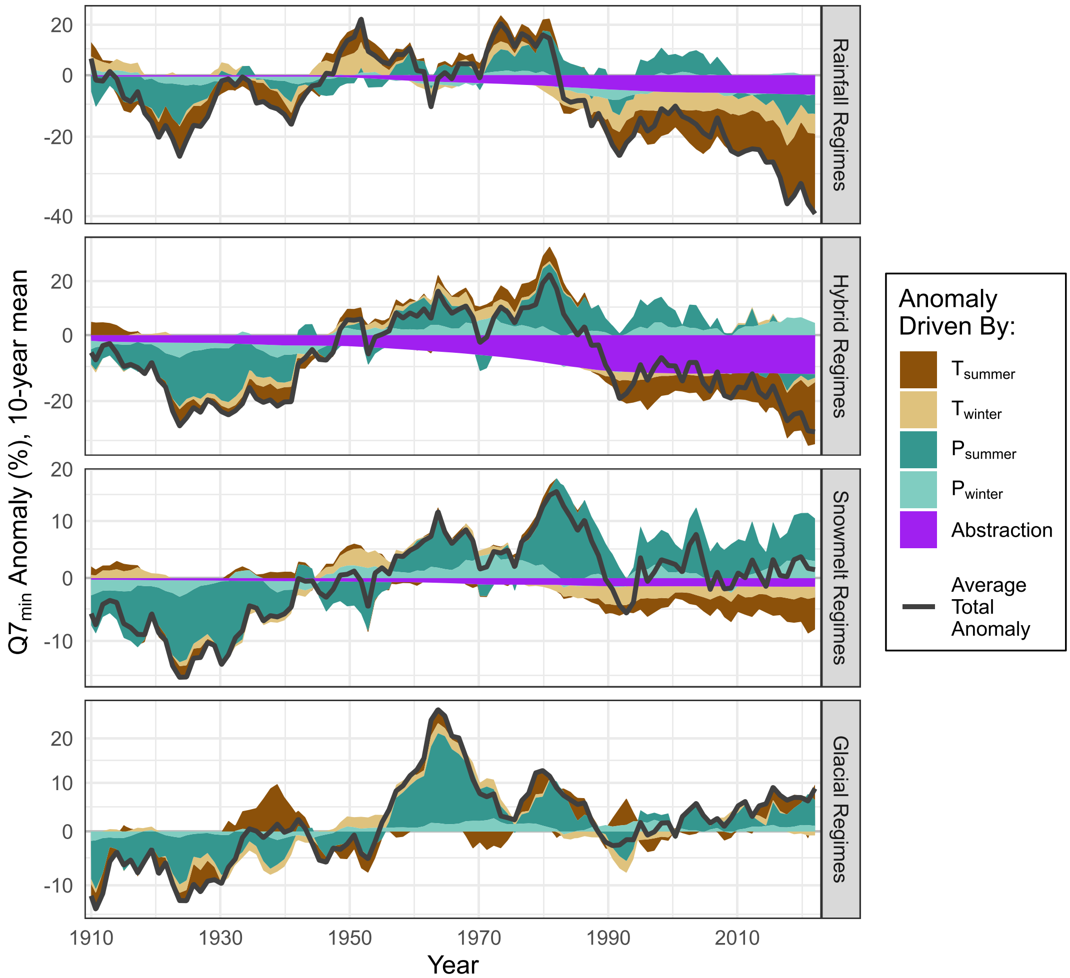

Figure 6. The average total anomaly in $Q7_{min}$ (relative to the period 1950–1999, with no water abstraction) is shown as a black for each catchment. The total anomaly is composed of anomalies driven by winter and summer temperature and precipitation, as well as abstraction. The *y*-axis is log-scaled so the width of the colored ribbons can be directly compared.

anomalies which continue to trend downwards. Hotter summers are continuing to increase the size of the negative anomaly driven by temperature.

Increasing water abstraction began in earnest around 1950 and the effect on low flows has grown ever since. On average, in 2022 abstraction is estimated to have reduced flows by 7%, 13%, and 1% in rainfall, hybrid, and snowmelt-dominated catchments. Note that this is an average across all studied catchments, many of which have little or no water use; the effect on some catchments is much larger.

We created similar plots of $Q7_{min}$ anomalies using models trained and applied to the ANUSPLIN-adjusted, ERA5-Land, and PNWNAmet data sets, and found similar patterns (Appendix H in Supporting Information S1). All data sets show a large and growing deficit associated with summer temperatures in rainfall and hybrid catchments, and all data sets show similar patterns precipitation-dominated variability in the 20th century. The ANUSPLIN-adjusted data set depicts much drier conditions for the first half of the 20th century, so models created using this data set show larger negative anomalies prior to 1950. However, the ANUSPLIN-adjusted data set produces annual runoff ratios much greater than one between 1900 and 1950, particularly in coastal, rainfall-dominated catchments, so we believe that these data underestimate precipitation prior to 1950 (Appendix G in Supporting Information S1). The hindcasts created using the unadjusted ANUSPLIN data are probably more reliable.

4. Discussion

In the introduction we acknowledged that the extent of our study area was determined by colonial boundaries, which do not reflect the traditional territories or jurisdictions of the many First Nations located within this region. We start this discussion by acknowledging that in the future it could be useful to reframe the methods and results to explicitly consider Indigenous rights, jurisdictions, and priorities, if this would be of interest to Indigenous governing bodies. This could include considering the colonial roots of climate change, taking an environmental justice lens to consider disproportionate impacts on Indigenous and other marginalized communities, or remapping and synthesizing results for specific Indigenous territories.

Regarding our first objective, we found that low flows in rainfall-dominated catchments are currently lower than at any point during the 20th century, and there are strong drying trends over the last few decades. There are similar drying trends in hybrid catchments, but drought was probably as common during the 1920s and 1930s as it is now. We did not find strong trends in snowmelt or glacial catchments since 1950, but our hindcasts indicate that summer flows in the early 20th century were probably substantially lower than they are now. However, these hindcasts should be interpreted with caution as the ANUSPLIN data are less accurate prior to 1950.

Our second objective was to analyze the drivers of low flows, with particular attention to the impact of changing winter snow accumulation (Barnett et al., 2005) and recent work indicating that the impact of evapotranspiration and summer temperature may be increasing (Boeing et al., 2024; Brunner et al., 2021).

We found low flows have not been very sensitive to winter storage of snow and groundwater. In Section 3.2 we found small correlations between winter maximum snow water equivalent and near-zero correlations with end-of-winter baseflow. We also found some evidence that the effect of snowpack has been non-stationary (the correlations have shrunk in recent years) in hybrid and snowmelt-dominated catchments. Low flows below the 10th percentile occur regularly in years with above-average snowpack and have even been observed in years with snowpack above the 90th percentile. In Section 3.4 we found that winter precipitation and temperature anomalies have not contributed substantially to decadal variability in $Q7_{min}$. These findings are consistent with some past sensitivity analyses, including Cooper et al. (2018) who found low sensitivities to snow in the northwestern United States, and Floriancic et al. (2020) who found similar results in Switzerland.

However, sensitivity analyses rely on historical data, and the magnitude of future declines in snow accumulation may be much larger than the variability in the historical record. A very large decline multiplied by a small sensitivity could still result in a large impact to low flows, as predicted by Barnett et al. (2005) and Dierauer et al. (2021). We also found that sensitivities to groundwater storage were usually smaller than sensitivities to snow storage, suggesting that groundwater will not adequately buffer against the effects of declining snowpack. We propose that studies that investigate low flow drivers should consider both historical sensitivities and the magnitude of projected changes in each driver.

Across all regimes, accelerated summer recession has been the most important driver of summer low flows. In Section 3.2 we found that on average, a 1 standard deviation-increase summer precipitation leads to half a standard deviation increase in $\log(Q7_{min})$. The opposite is probably true for T_{summer} in hybrid and rainfall regimes, although this relationship is obscured by collinearity with several other predictors. The correlations with T_{summer} are weaker in snowmelt-dominated catchments, probably because these regimes are more water-limited than energy-limited: the average mean annual precipitation in snowmelt-dominated catchments is only 840 mm, compared to 2,191 mm in rainfall-dominated, 1,145 mm in hybrid, and 1,163 mm in glacial catchments. In glacial catchments correlations with T_{summer} are often positive, probably because increasing meltflow contributions at higher temperatures offset losses due to increased ET.

Our predictive regression models tell a similar story. These models predict that low flows are most influenced by temperature and precipitation over a period of about 4 months (Figure 4). Temperature generally exerts a negative influence on low flows, except for short-term temperature (up to 1 month) in snowmelt-dominated and glacial catchments, where it tends to increase flows.

We hindcasted anomalies in $Q7_{min}$ from 1901 to 2022 and found that these anomalies were primarily driven by precipitation variability except in rainfall-dominated catchments where temperature has also played a dominant role. Warmer temperatures over the last 30 years have also exerted negative pressures on $Q7_{min}$ in hybrid and snowmelt-dominated catchments (Figure 6). This finding is robust across four climate data sets (Appendix H in Supporting Information S1).

These results align with those of Brunner et al. (2021) and Kormos et al. (2016), who studied the US portion of the Pacific Northwest. However, our finding that summer temperature is an important driver of low flows stands in contrast to the conclusion of Floriancic et al. (2021) who argued that summer ET was not a driver of low flows in this region. Their argument relied on the fact that low flow timing in this region (late August–October) is not coincident with the timing of maximum ET (July or August). However, their analysis did not consider that precipitation often remains low across the region until mid-Autumn, so the water balance typically remains in deficit even though ET is not at a maximum in September and October. We have shown here that temperature over a period of about 4 months (not just the 30-day windows used by Floriancic and colleagues) strongly influences the severity of low flows in the late summer and early autumn.

The effect of temperature on low flows may be changing, but the evidence is mixed. By including $(T_{\mathrm{summer}})^2$ in our explanatory regressions, we found some evidence of nonlinearity (that the effect of summer temperature dissipates at high temperatures) in colder catchments. This is corroborated by the finding that the effect of summer temperature in hybrid and snowmelt-dominated catchments has been nonstationary, and has decreased in more recent (warmer) years. These findings are physically plausible if evapotranspiration in these catchments is becoming more water-limited, rather than energy-limited (Barnett et al., 2005). On the other hand, when substituting space for time, we found that the effect of temperature tends to be stronger in warmer catchments within each regime: this is opposite to the expected behavior if the warmest catchments are the most water limited. We also did not find evidence of non-stationarity in the residuals of the predictive regression models, so we conclude that any mechanistic non-stationarity has probably had minor effects on overall low-flow behavior.

Importantly, in rainfall-dominated catchments, which have seen the most severe declines in low flows, and where rising summer temperatures have had the largest effect, the effect of temperature does not appear to dissipate at high temperatures and has remained robust in recent years.

Transmission losses appear to play a secondary role in controlling low flows. We found mostly negative but small correlations of T_7 with $\log(\mathrm{Q7}_{\mathrm{min}})$, particularly in rainfall and hybrid catchments. These represent transmission losses: when temperatures are high, ET from open water and from riparian zones increases. This leads to a temporary reduction in streamflow that may rebound once temperatures decrease. On the other hand, in snowmelt-dominated and glacial regimes temporary increases in temperature can lead to increased meltflow (Stahl & Moore, 2006).

We note that our catchment classification was defined using data from 1991 to 2020, but many catchments are transitioning from snowmelt-dominated to hybrid regimes. From 1951 to 2022 approximately one third of snowmelt-dominated catchments transitioned to the hybrid regime and the hybrid regime more than doubled in size. Due to glacial retreat, some catchments also transitioned from the glacial regime to a snowmelt-dominated regime. With further warming these shifts are likely to continue, and many currently snowmelt-dominated catchments may behave more like hybrid catchments. They may begin to see more negative trends in low flows, and may become more sensitive to summer temperature.

Beginning in earnest around 1950, surface and groundwater abstraction has reduced summer low flows in many parts of the province. We estimate that total water use has exceeded 10% of low flow discharge in 30% of the catchments studied. Although the regime-average anomalies in $\mathrm{Q7}_{\mathrm{min}}$ associated with abstraction are estimated to be small (0% in glacial catchments, up to 13% in hybrid catchments), many individual catchments have seen much larger reductions.

We were unable to find strong evidence of the impact of harvesting on low flows, although several of our analyses did point toward reduced low flows for 5–20 years post-harvest in snowmelt-dominated catchments. This is the opposite of the typical response reported in the literature, but several reviews have shown that responses are highly heterogeneous and difficult to predict (Coble et al., 2020; Goeking & Tarboton, 2020; Moore, Gronsdahl, & McCleary, 2020; Moore, Pelto, et al., 2020). Moore, Gronsdahl, and McCleary (2020) and Moore, Pelto, et al. (2020) point out that longitudinal analyses of streamflow in disturbed catchments (as presented here) are less robust and statistically powerful than paired catchment studies. The issues they raised are compounded here by the gradual nature and low levels of disturbance in most of the studied catchments as well as the uncertain quality and completeness of historical forestry and fire data.

Our third objective was to build regression models to predict and hindcast low flows from 1901 to 2022. Our predictive regression models predict low flows much more accurately than models currently being used for climate change impact assessment (Pacific Climate Impacts Consortium, 2020). We found that the regression models had low levels of residual autocorrelation and non-stationarity. Some caveats do apply to our historical reconstructions. Land use changes over the past century may have led to other forms of mechanistic non-stationarity. Our analysis of stationarity was based on a before/after analysis split at 1997; we do not have enough data to evaluate stationarity at the time scale of a century. The climate data on which the models are based are less accurate for the early 20th century because meteorological stations were more sparsely distributed (MacDonald et al., 2020), and we found that there may be temporal inconsistencies in the ANUSPLIN data. Nevertheless, streamflow records from the few hydrometric stations with continuous records throughout the 1920s and 1930s largely confirm very low flows in these decades. Long-term records for some select stations are shown in Appendix F of the Supporting Information S1. See, for example, Figure F14 in Supporting Information S1 (South Thompson River, a tributary of the Fraser), or Figure F20 in Supporting Information S1 (the Columbia River).

We can also look to anecdotal evidence to confirm historical droughts. In our reconstruction, 1929 was the year with the highest number of hybrid catchments experiencing Level 5 drought. Newspaper records show that the region was so dry in 1929 that Vancouver and Seattle's hydroelectric reservoirs almost ran out of water ("Capilano Flow Hits New Low," 1929), water was rationed ("Water and Power Famine Spreads Over All Coast," 1929), wells ran dry, and Catholic clergy appealed for divine intervention ("Prayers for Rain Ordered by Archbishop," 1929). In those years newspapers also regularly ran headlines with dire warnings that salmon stocks were disappearing ("B.C. Salmon Run Tends to Decline," 1933; "Says Salmon Runs Facing Destruction," 1922; "What is a Poor Fish to do?"; Malloy, 1921; "Preservation of Salmon Problem for Authorities"; Y. E. M., 1920). Most Canadian articles from the time blamed dwindling salmon stocks on overfishing, American traps, seals, and dam construction, but in 1929 the Washington State Supervisor of Fisheries, Charles Pollock, identified that "Drought is imperiling the fish industry of the Pacific northwest" (Associated Press, 1929).

For rainfall-dominated catchments, the most drought-stricken year in our reconstruction was 1958 which, according to tree-ring data from Vancouver Island, may have been the driest year for 350 years (Coulthard et al., 2016). In snowmelt-dominated and glacial catchments 1928 and 1919 take the top spots; 1928 was the start of a 5-year drought in the Quesnel Basin (Brice et al., 2021) but 1919 does not stand out in paleohydrological studies. In snowmelt and glacial catchments 1904 and 1905 each take 2nd place in our reconstruction; 1905 took 4th place in the reconstruction presented by Coulthard et al. (2016), 1904 took 6th place since 1789 in the Stikine River (Welsh et al., 2019), and 1904–1905 was the second worst drought in a separate 300-year tree-ring reconstruction of snow droughts in Southwestern BC (Mood et al., 2020).

5. Conclusions

We have shown that linear regression provides a simple, highly interpretable, and surprisingly accurate way of analyzing and predicting low flows across a diverse range of hydrologic regimes. First, we assessed low-flow sensitivities to various climate and anthropogenic drivers and examined whether these sensitivities were changing. We then developed predictive regression models that outperformed process-based models on every standard goodness-of-fit metric. These regression models require just monthly temperature, precipitation, and water abstraction data, so we were able to hindcast droughts, environmental flow transgressions, and low flow anomalies to 1901. Due to the additive nature of the models, we were able to disaggregate these anomalies by driving mechanism, and so corroborate our sensitivity analysis. We propose that these regression techniques could be useful for explaining and predicting low flows and droughts in other regions.

Rainfall-dominated and hybrid catchments have seen large and statistically significant decreasing trends in the annual summer minimum flow. Rainfall-dominated catchments are now experiencing streamflow drought and environmental flow transgressions more often than at any point over the past 122 years. Hybrid catchments, on the other hand, are experiencing conditions about as dry as the 1930s. However, negative low flow anomalies through the Great Depression were caused by lack of precipitation while present-day low flows are being driven by warming temperatures, despite above-average precipitation.

Summer low flows in snowmelt-dominated and glacial catchments have not shown strong trends since the 1950s but seem to be substantially higher than flows during the early 20th century. We found that these catchments are primarily sensitive to summer rainfall. Sensitivity to temperature is low, probably because high temperatures induce melting which offsets increased evaporative losses in glacial catchments and because snowmelt-dominated catchments tend to be more water-limited than energy-limited. However, we note that our catchment classification indicated that about one third of previously snowmelt-dominated catchments have become hybrid. If this shift continues then many catchments currently classified as snowmelt-dominated may become more sensitive to temperature and summer low flows may begin to decline.

We found that winter conditions and annual snow accumulation have historically only weakly driven variability in low flows. However, climate-change-induced reductions in snowpack and glacial extent will probably be large compared to historical variability, and this large change combined with a weak sensitivity could still result in large reductions in low flow (Dierauer et al., 2021; Schnorbus et al., 2014).

Conflict of Interest

The authors declare no conflicts of interest relevant to this study.

Data Availability Statement

The R code developed for this project is archived on Zenodo along with the intermediate data files required to reproduce the statistical analyses (Ruzzante, 2024).

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