Groundwater Responses to Deluge and Drought in the Fraser Valley, Pacific Northwest

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Abstract

Extreme weather events are reshaping hydrological cycles across the globe, yet our understanding of the groundwater response to these extremes remains limited. Here we analyze groundwater levels across the South Coast of British Columbia (BC) in the Pacific Northwest with the objective of determining groundwater responses to atmospheric rivers (ARs) and drought. An AR catalogue was derived and associated to local rainfall defining extreme precipitation. Droughts were quantified using dry day metrics, in conjunction with the standardized precipitation index (SPI). From September to January, approximately 40% of total precipitation is contributed by ARs. From April to September, more than 50% of days receive no precipitation, with typically 26 consecutive dry days. We used the autocorrelation structure of groundwater levels to quantify aquifer memory characteristics and identified two distinct clusters. Cluster 1 wells respond to recharge from local precipitation, primarily rainfall, and respond rapidly to both ARs during winter recharge and significant rainfall deficits during summer. Cluster 2 wells are also driven by local precipitation, and are additionally influenced by the Fraser River’s large summer freshet, briefly providing a secondary recharge mechanism to South Coast aquifers. Accordingly, groundwater recessions are offset to later in the summer, contingent on the Fraser River, mediating drought. The results suggest that groundwater memory encapsulates multiple hydrogeological factors, including boundary conditions, influencing the response outcome to extreme events.

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Key Points:

- Two distinct styles of groundwater response to atmospheric rivers and drought occur in coastal valley aquifers
- Meltwater transported via the Fraser River to the coast mediates drought in hydraulically connected aquifers
- Groundwater memory reflects intrinsic aquifer hydraulic properties and encodes the effects of physical boundary conditions
Abstract

Extreme weather events are reshaping hydrological cycles across the globe, yet our understanding of the groundwater response to these extremes remains limited. Here we analyze groundwater levels across the South Coast of British Columbia (BC) in the Pacific Northwest with the objective of determining groundwater responses to atmospheric rivers (ARs) and drought. An AR catalogue was derived and associated to local rainfall defining extreme precipitation. Droughts were quantified using dry day metrics, in conjunction with the standardized precipitation index (SPI). From September to January, approximately 40% of total precipitation is contributed by ARs. From April to September, more than 50% of days receive no precipitation, with typically 26 consecutive dry days. We used the autocorrelation structure of groundwater levels to quantify aquifer memory characteristics and identified two distinct clusters. Cluster 1 wells respond to recharge from local precipitation, primarily rainfall, and respond rapidly to both ARs during winter recharge and significant rainfall deficits during summer. Cluster 2 wells are also driven by local precipitation, and are additionally influenced by the Fraser River’s large summer freshet, briefly providing a secondary recharge mechanism to South Coast aquifers. Accordingly, groundwater recessions are offset to later in the summer, contingent on the Fraser River, mediating drought. The results suggest that groundwater memory encapsulates multiple hydrogeological factors, including boundary conditions, influencing the response outcome to extreme events.

Plain Language Summary

Heavy rainfall events and drought are becoming more commonplace around the world. Their effects are immediately observable to us; we see the devastating impacts of floods and the drying of river beds. But we often forget about what happens underground. We sought to shed light on how extremes affect groundwater, the largest accessible freshwater reservoir on Earth. We combined real world observation data on groundwater levels, rainfall, and streamflow within the Pacific Northwest to determine groundwater response to extremes. We found that aquifers connected to large rivers that carry summer snowmelt are more resistant to drought than unconnected aquifers. However, both aquifer groups still depend on heavy rainfall events to recover from drought. As we continue to rely on groundwater for crop irrigation and clean drinking water, climate change will challenge how we manage this resource.

1 Introduction

Anthropogenic climate change will continue to lead to global increases in the intensity, duration, and frequency of extreme weather events (Cook et al., 2022; Dai, 2013; Fowler et al., 2021; Intergovernmental Panel on Climate Change (IPCC), 2023; Kirchmeier-You & Zhang, 2020; Min et al., 2011; Seneviratne et al., 2012; Zhang et al., 2013; Zhao et al., 2020). These events are reshaping global, regional, and local hydrological cycles and landscapes (Gleeson et al., 2020; Meixner et al., 2016; Peterson et al., 2021; Thomas et al., 2016). Within the terrestrial water cycle, groundwater is the largest accessible freshwater resource reservoir. As such, groundwater is increasingly being relied upon as a source of freshwater (de Graaf et al., 2019; Famiglietti, 2014) for food and water security (Dalini et al., 2019; Taylor et al., 2013), so much so that abstracted groundwater likely accounts for 70% of global irrigation demand (Wood & Cherry,
2021). Yet only 20% of all groundwater on Earth, several hundred metres deep, is actively in
flux with the water cycle (Ferguson et al., 2023). Therefore, extreme events disproportionately
affect easily accessible shallow groundwater. However, groundwater responses to these extremes
remains somewhat unclear.

Extreme precipitation and drought can lead to different responses in groundwater systems
depending on the prior series of recharge events and the hydrogeological context (Nygren et al.,
2022; Schuler et al., 2022). Mechanistically, recharge is primarily controlled by the antecedent
water content, thickness, and infiltration capacity of the vadose zone (de Vries & Simmers, 2002;
Fetter & Kreamer, 2021). The vadose zone effectively acts as a reservoir that can store extreme
event water (Corona & Ge, 2022), functioning as a recharge signal filter. In many cases, extreme
precipitation is an important contributor to groundwater recharge (Corona et al., 2023; Thomas et
al., 2016). Unconfined aquifers can respond to infiltration from within several hours to days
(Wittenberg et al., 2019), depending on the vadose zone thickness (Schuler et al., 2022).

Consistently maintaining a moist vadose zone year-over-year tends to favour groundwater
recharge, especially for deeper aquifers (Shao et al., 2018). In temperate climates, Gu et al.
(2022) show that total precipitation amounts more strongly influence groundwater levels than
event duration. Notwithstanding, events that exceed the infiltration capacity of the vadose zone
can trigger overland flow, leading to a reduction in net recharge (Rathay et al., 2018). Reductions
in recharge lead to storage depletion, which in turn controls the degree of groundwater drought
(Van Loon, 2015).

Drought is a complex and multi-faceted process that can affect—and propagate to—different
components of the hydrological cycle (e.g., soil moisture, groundwater, streamflow), contingent
on the extent and length of sustained meteorological moisture deficits (Van Lanen, 2006; Van
Loon, 2015; W. Wang et al., 2016). During severe droughts, groundwater is usually the last line
of defence, maintaining supply to surface water bodies, before ultimately being exhausted
(Hellwig et al., 2020). Evapotranspiration (ET) tends to accelerate drought propagation,
especially as the atmospheric moisture demand increases (Teuling et al., 2013), increasing
temperatures, and establishing a positive feedback loop (Bartusek et al., 2022). While
groundwater droughts are primarily driven by precipitation deficits, increases in ET due to
anthropogenic warming are likely to become the main driver of groundwater drought
(Bloomfield et al., 2019), with the capacity to push hydrologic regimes into new stable states
(Peterson et al., 2021).

Groundwater is often considered as possessing a “memory” effect (Brooks et al., 2021; Delbart
et al., 2014; Jukić & Denić-Jukić, 2004), because of its ability as a reservoir to store water.
Mangin (1984) was among the first to formally quantify the memory characteristics of
groundwater, which has been linked to aquifer hydraulic properties (Duy et al., 2021; Van Lanen
et al., 2013), the recharge signal (Bloomfield & Marchant, 2013), rates of groundwater discharge
(Imagawa et al., 2013), and vadose zone thickness (Schuler et al., 2022). Groundwater memory
is being increasingly used as an indicator of aquifer response to drought (Nygren et al., 2022;
Schuler et al., 2022; Sutanto & Van Lanen, 2022). The autocorrelation characteristics of
groundwater level timeseries attempt to quantify and represent the responsiveness and rate at
which external factors (e.g., recharge) are retained by an aquifer, hence the attribution of
memory. The theory supposes that a higher memory aquifer will respond more slowly to
externals forcings and retain these input signals for longer. Conversely, lower memory aquifers
will respond more quickly and dissipate input signals, leading to a less resilient and more vulnerable aquifer. In this study, we examine groundwater levels from the Pacific Northwest (PNW), along the South Coast of British Columbia (BC) at the outlet of the Fraser River Basin (FRB). Observation wells are clustered into groups based on the shape of their autocorrelation structure. These clusters are then used to infer recharge mechanisms and memory characteristics. Groundwater responses to ARs and drought are explored by considering the effects of total precipitation, the fraction of AR precipitation, dry days, and consecutive dry days. We hypothesize that aquifer-stream interactions significantly influence aquifer memory characteristics, thereby altering the groundwater response to extremes.

2 Study Area and Methods

2.1 Study Area

The study area is situated in the Pacific Northwest (PNW) and encompasses the Fraser Valley, extending from Hope to the mouth of the Fraser River in the Georgia Strait (Figure 1). The valley is bordered to the north by the Coast Mountains and to the southeast by the Cascade Mountains. An important hydrological feature of the Fraser Valley is the Fraser River, which drains the Fraser River Basin (FRB; inset map in Figure 1) from its Rocky Mountain headwaters, through the Interior Plateau, and down into the Pacific Ocean through the Coast Mountains (Martins et al., 2023). The 1,400 km-long Fraser River is predominantly driven by snow- and glacial melt, with substantial rainfall contribution near the coast, reflecting the collective hydrological input of nearly a third of the province of BC (Déry et al., 2012). Climate across the FRB is diverse with precipitation ranging from 350 mm/yr (<30% as snow) in the Interior Plateau, to about 1000 mm/yr (>50% as snow) in the Rocky Mountains, and over 3000 mm/yr (<15% as snow) in the Coast Mountains (Moore et al., 2010). Snow accumulation typically begins in October, peaks in early April, and melts by early August (Curry & Zwiers, 2018). In contrast, the Fraser Valley features a characteristically temperate ocean climate (Köppen-Geiger: Cfb bordering Csb (Beck et al., 2018)), receiving on average 1525 mm/yr (range: 1186–1994 mm/yr) of precipitation (1991-2020 climate normals). Snowfall constitutes only 3.3%, or 51 mm/yr (range: 8–200 mm/yr), of precipitation. The mean annual temperature is 10.8 °C, with summer highs around 25 °C, and winter lows just above 0 °C (Figure S1). The Fraser River tends to be event-driven near the coast, where extreme rainfall events can promptly triple the river’s discharge (Pawlowicz et al., 2017). The Fraser River can exceed 10,000 m$^3$/s during freshet peak flows in late June, while low flows (~1,500 m$^3$/s) persist from December to April (Figure 2b). Peak flows are primarily controlled by the annual maximum snow water equivalent (SWE), and secondarily, by the rate of spring- and summer-time warming (Curry & Zwiers, 2018).

The contemporary physiography of the Fraser Valley is characterized by low relief and flat gently rolling hills (<150 masl) with isolated bedrock outcrops, and bounded by the high relief Coast and Cascade Mountain (Figure 1). This landscape has evolved over hundreds of thousands of years of Quaternary glacial and interglacial processes, largely shaped by the most recent Fraser Glaciation (Clague et al., 1983; Clague & Ward, 2011). Glacio-isostatic adjustment, eustatic sea level change, and successive glacial advances and retreats, have favoured the emplacement of a complex succession of alternating marine, glacial, and non-glacial sediments,
Consequently, the spatial distribution and stratigraphy of aquifers and aquitards within the valley can be quite complex. Aquifers, up to 60 m thick, are predominantly sand and gravel of colluvial, fluvial, and glaciofluvial origin (Armstrong, 1984). Aquitards, exceeding 80 m of thickness, are predominantly basal and lodgement tills, and clay and silt of marine, lacustrine, glaciomarine, glaciolacustrine, and glacial origin (Armstrong, 1984).

Groundwater levels in aquifers throughout British Columbia (BC) are monitored by observation wells (OW) through the Provincial Groundwater Observation Well Network (PGOWN) (BC Ministry of Environment and Climate Change Strategy (ECCS), 2023). Figure 1 shows the distribution of OW used in this study. In this study, we broadly classify aquifers as: fractured bedrock, confined sand and gravel (S&G), and unconfined S&G associated with alluvial, glacial outwash or large river systems (Figure 1).

Figure 1. Hydrogeological setting of the Fraser Valley showing the distribution of aquifers (S&G: Sand and Gravel) and provincial observation wells (numbered) along with their associated ACF cluster (see Section 2.5). The Fraser River is the large stream flowing through the valley from east to west. The small provincial inset map shows the Fraser River Basin (FRB) outlined in white with the Fraser River in blue, and the study area is outlined in red. The large inset map shows the underlying bedrock geology (BCGS, 2019) and the extent of unconsolidated
fill deposited during the Quaternary. Map created with QGIS v3.26.3 (QGIS Development Team, 2022).

2.2 Extreme Climate in the Pacific Northwest

Atmospheric Rivers (ARs) are the main mechanism for extreme precipitation events in the PNW (Eldardiry et al., 2019; Sharma & Déry, 2020; Tan et al., 2022) and have been an integral component of Western North America’s hydrological cycle for at least 600 years (Borkotoky et al., 2023). ARs are prolonged, extensive, and concentrated bands of enhanced water vapour sourced from tropical or extratropical regions (Neiman et al., 2008; Ralph et al., 2018; Zhu & Newell, 1998). ARs making landfall along the PNW are typically sourced from the northeastern Pacific (20°N–50°N), with more extremes sourced from the tropics (Nusbaumer & Noone, 2018). While ARs do not always result in extreme precipitation events (Collow et al., 2020), they are important drivers of both flooding and—in their absence—drought persistence (Berghuijs & Slater, 2023; Paltan et al., 2017). The amount of precipitation contributed from landfalling ARs depends heavily on orographic uplift (Ralph et al., 2016; S. Wang et al., 2023), which causes successive depletion in water vapour, controlling the inland penetration (Tan et al., 2022). ARs are important snowpack building events during the winter and at higher altitudes along the North American Cordillera (Eldardiry et al., 2019; Goldenson et al., 2018; Neiman et al., 2008; Paltan et al., 2017; Payne et al., 2020). However, as ARs are transported via warmer moisture circulations, lower elevations can be subject to substantial snowmelt and rain-on-snow events (Chen et al., 2019; Eldardiry et al., 2019; Guan et al., 2016; Spry et al., 2014). In the PNW, higher AR frequency is associated with lower seasonal snowpacks (Goldenson et al., 2018).

In the PNW, drought onset and intensity have increased (Iglesias et al., 2022; Kormos et al., 2016). Moreover, summer baseflow contributions have been in decline (Murray et al., 2023), and likely to deteriorate with continued aridification (Overpeck & Udall, 2020) and increased ET (Liu et al., 2013). Berghuijs et al. (2022) show that climatic aridity imparts a first-order control on whether precipitation recharges groundwater. Notably, the decline in overall precipitation, and winter precipitation arriving as snow, under a warming climate is expected to significantly affect mountain system recharge (Meixner et al., 2016). This is particularly concerning for coastal catchments that oscillate above and below the freezing point both diurnally and seasonally. Coastal groundwater systems relying on snowpack melt for recharge and baseflow supply during summers face heightened risk (Islam et al., 2017; Mote et al., 2005), which is well documented in the mountainous regions of the PNW (Dierauer et al., 2018). Overall, mountainous aquifers are particularly sensitive to region-specific climate and hydrological variables (Gullacher et al., 2023).

The El Niño–Southern Oscillation (ENSO) is the main driver of interannual precipitation variability in the PNW, with less impactful effects from the Pacific Decadal Oscillation (PDO) (Brigode et al., 2013; Fleming & Whitfield, 2010; Lopez & Kirtman, 2019). ENSO can influence extreme precipitation (Brigode et al., 2013) and drought occurrence across the PNW (Vicente-Serrano et al., 2011). During an El Niño, the subtropical jet stream strengthens and shifts equatorward (Payne & Magnusdottir, 2014; Seager et al., 2005), redirecting tropical moisture down into southern California (Young et al., 2017). This causes the PNW to be quite dry and warm during the summer season. Accordingly, these climate teleconnections can significantly influence drought occurrence, and are reflected in the frequency characteristics of groundwater (Malmgren et al., 2022; Rust et al., 2019; Velasco et al., 2017). ARs also tend to be less frequent...
during an El Niño summer and winter (Mundhenk et al., 2016). Conversely, the La Niña phase tends to shift storm tracks towards the PNW, increasing winter precipitation (Fleming & Whitfield, 2010) at a time when ARs tend to also be more frequent (Mundhenk et al., 2016; Xiong & Ren, 2021).

2.3 Hydroclimatological Data

AR and integrated vapour transport (IVT) data were obtained from an online catalogue (http://sioftp.ucsd.edu/) maintained by the Center for Western Weather and Water Extremes (CW3E), following the AR detection algorithm described in Rutz et al. (2014). The algorithm constraints for AR detection are: atmospheric water vapour feature length >2000 km and IVT >250 kg m⁻¹ s⁻¹. This AR catalogue, as part of the Atmospheric River Tracking Method Intercomparison Project (ARTMIP) (Rutz et al., 2019), identifies the occurrence (or non-occurrence) of landfalling ARs using MERRA-2 gridded climate reanalysis data (Gelaro et al., 2017). AR detection is sensitive to more complex mountainous topography and has been shown to be best resolved by ERA-5 due to a finer spatial resolution (0.25° × 0.25°) (Collow et al., 2022). However, the slightly coarser MERRA-2 (0.5° × 0.625°) AR catalogue was chosen as it was the most up-to-date catalogue (1980–2022). AR data were cropped to an extent of two grid cells (49.0°N, 49.5°N, 121.875°W, 123.125°W) covering the Fraser Valley study region (Figure 1). Then, AR count and mean IVT were converted from three-hourly time steps to daily, if five or more of the eight timesteps were AR occurrences. If an AR was detected in at least one of the grid cells within the study region, then the entire extent was considered to have had an AR occur. This yielded a daily timeseries of AR occurrence and mean IVT. Our derived AR counts in the same region compared well (Figure S2) to both the SIO-R1 AR catalogue by Gershunov et al. (2017) and the distribution of landfalling ARs from CW3E (2022).

Climate data (1980–2022) were obtained from the Abbotsford Airport Climate Station (EC1100030/31) (Figure 2a) operated by Environment and Climate Change Canada (ECCC, 2023) and used to associate precipitation amounts to AR occurrence on any given day. Based on the coarse spatial resolution of the AR catalogue (approx. 45 × 56 km pixels) and the drawbacks of gridded climate data in preserving key features of extreme precipitation (Hu et al., 2018; King et al., 2013; Sun et al., 2018), station-based climate data was deemed appropriate in being able to capture more accurate precipitation associated with ARs.

Given the relatively short record of about two decades for groundwater, we chose to focus on ENSO rather than on the PDO, as the latter tends to highlight interdecadal patterns (15-to-25 years) of climate variability (Mantua & Hare, 2002). The Oceanic Niño Index (ONI) is used to identify the positive (El Niño) and negative (La Niña) phases of ENSO (available from the National Oceanic and Atmospheric Administration’s (NOAA) Climate Prediction Center CPC, https://origin.cpc.ncep.noaa.gov/products/analysis_monitoring/ensostuff/ONI_v5.php). The ONI is a three-month running average of sea surface temperature anomalies in the Niño-3.4 region of the Pacific where anomalies above (below) 0.5°C are considered as El Niño (La Niña) events.

2.4 Deluge and Drought Indicators

To investigate the effects of discrete deluge events, first we separated the contribution of AR precipitation to monthly (annual) precipitation by considering the AR fraction of precipitation. The AR fraction was obtained by dividing the total monthly (annual) AR precipitation by the
total monthly (annual) precipitation to isolate any distinct effects ARs might have on groundwater levels.

To quantify discrete drought events, we considered two precipitation-based metrics, consecutive dry day (CDD) and number of dry day (NDD). The CDD fraction was computed by taking the longest run of dry days (precipitation < 1 mm) in a month (year) and dividing by the number of days in a month (year). The NDD fraction is simply a count of dry days (precipitation < 1 mm), divided by the number of days in a month (year).

For determining wet and dry periods, the Standardized Precipitation Index (SPI) (McKee et al., 1993) was computed for precipitation at the Abbotsford Airport Climate Station, using the SCI package (Gudmundsson & Stagge, 2022) in R 4.1.3 (R Core Team, 2022). Several accumulation periods for the SPI were explored (3, 6, 9, 12, and 24), but ultimately, an accumulation period of 6 months was chosen to best represent meteorological drought or deluge at an appropriate temporal scale (Barker et al., 2016). The Pearson type-3 distribution was used for the SPI (see Figure S3, for selection choice). SPI values less (more) than -1 (+1) represent dry (wet) periods (McKee et al., 1993). Therefore, we used the SPI as a metric of classifying wet or dry (meteorological drought) periods, acting as a measure of antecedent wetness or dryness. Linear regression lines are fit between points for SPI less (more) than -1 (+1). This adds more flexibility to exploring groundwater responses in the context of multivariate extremes (Brunner, 2023) over different time scales, where there may be a high CDD or NDD fraction in a positive SPI (wet) period, or conversely, a high AR fraction in a negative SPI (dry) period.

2.5 Hydrogeologic and Hydrometric Data

Streamflow (1965–2022) for the Fraser River at the City of Mission hydrometric station (08MH024) (Figure 2b) was obtained from the Water Survey of Canada (Water Survey of Canada (WSC), 2023). Hourly (upscaled to daily and monthly) groundwater level data for 34 monitoring wells (Figure 2c) were obtained from PGOWN (ECCS, 2023). Care was taken to remove wells with obvious trends or pumping signals; however, there is likely some anthropogenic signal in all monitoring wells. We filtered for well data from 2004 onwards (Figure S4), due to the higher data quality of hourly observations, which prior to, were monthly.

Information for 23 aquifers (Table S1) associated to each monitoring well was obtained from the mapped aquifer registry maintained by the BC Ministry of Water, Land and Resource Stewardship (WLRS, 2023). Unfortunately, none of the observation wells have had hydraulic tests performed. Therefore, transmissivity (T) and storativity (S) values were assigned (Table S1) as best estimates (for 26 wells) from various pumping tests conducted around the Fraser Valley (Carmichael, 2013; Cox & Kahle, 1999; Gibbons & Culhane, 1994; Golder Associates Ltd., 2005; Piteau Associates Engineering Ltd., 2012; Ricketts, 1998, 2000; Scibek & Allen, 2005). Fractured aquifer T and S were estimated from literature (Kuang et al., 2020) and well completion reports (ECCS, 2023). We used T, in dimensions of [L²/T], and S, dimensionless, to determine the hydraulic diffusivity, $D = T/S$, in dimensions of [L²/T].
Figure 2. (a) Boxplot and kernel density distributions of monthly precipitation at the Abbotsford Airport Climate Station (EC1100030/31). (b) Fraser River discharge at the Mission hydrometric station (08MH024). See Figure 1 for station locations. (c) Groundwater level hydrographs.

2.6 Memory Metrics and Autocorrelation Clustering

Autocorrelation measures the linear relationship, or degree of similarity, between subsequent values of the same timeseries lagged over time (Maity, 2018). The autocorrelation function (ACF) of groundwater levels has been widely used in the literature to quantify aquifer memory.
in karst and fractured bedrock systems (Bloomfield & Marchant, 2013; Delbart et al., 2016;
Lafare et al., 2016; Mangin, 1984; Massei et al., 2006; Schuler et al., 2020), and porous alluvial
systems (Duvert et al., 2015; Duy et al., 2021; Imagawa et al., 2013; Nygren et al., 2022; Schuler
et al., 2022). The source of this autocorrelation has been linked to autocorrelation in the recharge
signal itself, and intrinsic aquifer characteristics (Bloomfield & Marchant, 2013; Duy et al.,
2021). Mangin (1984) used an ACF threshold of 0.2 to extract the decorrelation lag time to
quantify this memory effect. Massei et al. (2006) emphasized the importance of considering the
shape of the ACF in characterizing memory, by fitting a logarithmic function to the ACF at early
lag times, to determine a decay rate. This method is often applied to karst systems (Delbart et al.,
2016), but has also been used in alluvial systems (Duvert et al., 2015; Duy et al., 2021).
Alternatively, a linear fit, to determine decay (slope), can also be applied to early lag times
(Delbart et al., 2016; Imagawa et al., 2013).

We used three different ACF-derived metrics to attempt to quantify aquifer memory (Figure 3,
summarized in Table S1). First, we considered the traditional decorrelation lag time by threshold
(ACF = 0.2). Second, we considered the linear decay rate at early lag times (<150 days) by
iteratively fitting a straight line to an optimal fit window of lag times (by maximizing the fit R²).
Finally, we introduce an approach to characterizing the progressive attenuation of the oscillatory
ACF pattern. We fit an exponentially decaying (damped) sinusoid function (lag < 1000 days) to
determine a decay rate of the ACF oscillation pattern:

\[ y(t) = Ae^{-\lambda t} \cos(\omega t - \varphi) \]  

(1)

where \( A \) is the amplitude [-], \( \lambda \) is the exponential decay rate [T⁻¹], \( \omega \) is the angular frequency [T⁻¹], and \( \varphi \) is the phase shift [-]. See Figures S5, S6, and S7 for the memory metrics mapped to
each well.

Exploring memory characteristics revealed distinct ACF shapes (Figure 3). Agglomerative
hierarchical clustering, which performs well with groundwater data (Giese et al., 2020; Yin et al.,
2022), was applied to groundwater level (GWL) ACFs and optimized two clusters. We applied
the Ward Linkage method implementing Euclidean distance as the dissimilarity metric, which
tends to result in more distinct and homogenous clusters (Haaf & Barthel, 2018). Clustering was
performed using the factoextra R package (Kassambara & Mundt, 2020), and the optimal
number of clusters was confirmed using the NbClust R package (Charrad et al., 2014).

2.7 Groundwater Level Adjustments

Groundwater may not immediately respond to ARs or drought. This delay was accounted for by
considering a forward lead observation (e.g., considering the following month). Interestingly,
GWL rates-of-change (ROC), by successive differencing, cross-correlated with precipitation rate
suggest that in nearly all wells, the initial groundwater response can be on the order of days
(Figure S8). However, GWL cross-correlated with precipitation reveals that the full response, or
total amount of recharge from a precipitation event, is differentially delayed on the order of
months (Figure S9). To determine an appropriate lead time adjustment, we checked the cross-
correlation lag time (at maximum correlation) between GWLs and precipitation. Lead
adjustments range from 2–4 months in confined aquifers, 0–2 months in fractured aquifers, and
0–4 months in unconfined aquifers. Cluster 2 GWLs were unadjusted because of aquifer-stream
interactions (discussed below). We assume minimal snow storage acting as lagged recharge
based on the snowfall fraction.
2.8 Wavelet Analysis

The Continuous Wavelet Transform (CWT) was used to determine time-averaged frequency spectrums (wavelet spectra) for GWLs, and SPI, using the WaveletComp R package (Roesch & Schmidbauer, 2018). The Wavelet Coherence (WTC) is a measure of coherency (ranging from 0 to 1), or synchronicity in the time-frequency domain, between two signals from the Cross-Wavelet Transform (XWT). The XWT is a time-frequency analogue to cross-correlation, (Torrence & Compo, 1998). The CWT and WTC are advantageous for elucidating changes in frequency over time in non-normal and non-stationary hydrological data (Grinsted et al., 2004; Sang, 2013), and have been effectively applied to groundwater levels (Duvert et al., 2015; Kuss & Gurdak, 2014; Malmgren et al., 2022; Rust et al., 2019). The CWT can be thought of as consecutive band-pass filters (Grinsted et al., 2004) wherein a mother wavelet, here, the Morlet wavelet, is convolved with a timeseries signal. The average wavelet power spectra were min-max normalized to allow for direct comparison between each well, as done in Rust et al. (2019). The time-averaged WTC was used to determine the correlation, in time-frequency space, between GWLs and ENSO (via the ONI), as well as between ENSO and SPI. The significance (α = 0.05) of wavelet power, and coherence, were tested via Monte Carlo simulations (n = 100), against a null hypothesis that the time series are being driven by a lag-1 autoregressive process (Torrence & Compo, 1998).

3 Results

3.1 Groundwater Clustering and Memory Metrics

Groundwater level responses cluster into one of two groups based on their hydrograph shape (Figure 2), reflected in their autocorrelation structure (Figure 3). Cluster 1 wells are interpreted to respond to recharge from local from precipitation, which is predominantly rainfall within the Fraser Valley. The autocorrelation structure of this cluster oscillates with a periodicity of 365 days (Figure 3a). Some wells display a weak semi-annual signal (Figure 3b, e.g., OW474, 440, 462, 406). The strongest semi-annual signal within cluster 1 is from OW474, which likely reflects a snowmelt contribution to recharge from the adjacent local mountains. The average decorrelation lag time for cluster 1 is about 80 days, but ranges from 65 to 97 days. The linear decay rate, averages -0.012 days⁻¹. The dampening of the sinusoidal oscillation of the ACF is represented by he exponential decay rate which can be converted to a half-life. The half-life for cluster 1 is about 954 days. That is, approximately every 3 years, the ACF oscillation amplitude is diminished by half. Overall, cluster 1 wells are a group of relatively high memory aquifers.

Cluster 2 wells not only exhibit a groundwater response that is driven by recharge from local rainfall but are also significantly influenced by the Fraser River due to the strong hydraulic connectivity. Cluster 2 wells are typically low lying and adjacent to the Fraser River (Figure 1), and can be strongly influenced by the Fraser River, which is best observed during the summer freshet (Figure 2). The hydraulic gradient between the Fraser River and OW485 confirms this (Figure S10). During the brief summer freshet, hydraulic gradients are reversed, whereby the Fraser River contributes to adjacent aquifers. For a brief period during the summer, remote, upcatchment mountains in the FRB provide recharge to aquifers in the Fraser Valley. Otherwise, aquifers contribute baseflow to the Fraser River, with gradients reaching their maximum during January (Figure S10). The sole exception is OW349 which has no hydraulic connection to the
Fraser River but mimics its snowmelt response during the summer from the adjacent mountains. While many cluster 1 wells are situated near mountains, snowmelt seems to have little effect on summer groundwater levels.

Cluster 2 wells exhibit an autocorrelation structure that is markedly different than that of cluster 1 wells (Figure 3a), showing twice the ACF oscillation with dual frequency response in annual and semi-annual periodicities (Figure 3b). The additive nature of precipitation seasonality and aquifer-stream interactions with the Fraser River causes this dual signal. The average decorrelation lag time for cluster 2 is about 51 days, but ranges from 40 to 56 days. This average is significantly less than cluster 1 by about 30 days. The linear decay rate at early lag times is about -0.018 days$^{-1}$. The half-life for cluster 2 is about 392 days, whereby, approximately every year, the ACF oscillation amplitude is diminished by half, dampened much more rapidly than in cluster 1.

**Figure 3.** (a) Groundwater ACF clusters and cluster-averaged memory metrics including the linear decay rate, the decorrelation lag time, and the damped sinusoid. (b) Frequency characteristics for each ACF cluster based on the normalized average wavelet power.

In determining appropriate groundwater level lead adjustments (see Section 2.6), the cross-correlation between precipitation with GWLs, and GWL ROCs, shed some insight into response times (Table S1). The average GWL-precipitation cross-correlation lag time for confined aquifers (in cluster 1) is 77 days, ranging from 50 to 110 days. Fractured and unconfined aquifers
(in cluster 1) average 58 days, ranging from 2 to 132 days. Cluster 2 wells tend to average 14.3 days, ranging from 2 to 53 days.

3.2 Intra-annual Variability in Deluge and Drought

The majority of ARs make landfall from October to January, but are focused to October and November (Figure 4a), when they are the most intense and likely to result in extreme precipitation events (Figure S11). Expressed as an amount contributed, ARs make up on average more than half of all precipitation received in October (Figure 4b); Gershunov et al. (2017) reported that October to December AR contribution averaged around 50%. Generally, between September and January, ARs contribute around 40% of total precipitation. ARs are generally insignificant contributors to total, or extreme, precipitation during the spring to summer months (Figure 4b), as they are weaker in intensity and carry less moisture (Figure S11).

From April to October, on average, over 50% of the month will receive no precipitation, and over 80% of days in August and July receive no precipitation (Figure 4c). Of those days in August and July, at least two weeks will be continuously dry (Figure 4d). Late summer to early autumn represents a significantly dry and drought-prone period. The transition between significantly dry and significantly wet is relatively rapid; August might be significantly dry but can transition to being significantly wet by October.
Figure 4. Deluge indicators as monthly averages of AR counts (a) and AR fraction of precipitation (b). Drought indicators as average number of dry days (NDD) (c) and consecutive dry days (CDD) (d), as a fraction of total days in a month.

Monthly groundwater responses reveal a contrast between clusters and their relationship with intra-annual variability in wet and dry periods (Figure 5). GWLs in cluster 1 wells increase as precipitation amounts increase, regardless of SPI (column 1 – Figure 5a). Graphs for all wells are provided in Figure S12. During dry periods (brown) the slope of groundwater levels is steeper, when total precipitation is generally lower. This suggests that aquifers are more responsive to precipitation events during dry periods compared to wet periods. Conversely, during wet periods, the groundwater level response slope is shallower, suggesting that more precipitation does not necessarily result in higher groundwater levels (column 1, Figure 5a). In this case, the infiltration capacity may be reached, as soils are continuously wetted, leading to overland flow and hence, less recharge. For cluster 1 wells, as more precipitation is contributed by ARs (i.e., the AR fraction increases), groundwater levels increase regardless of wet or dry conditions (column 2, Figure 5a). Generally, groundwater level variability in response to higher AR fraction of precipitation is quite high (Figure S13).

Cluster 2 wells tend to show a diverging pattern whereby, during a dry period (negative SPI), the GWL slope is negative (column 1, Figure 5b). During a dry period, as precipitation amounts increase, GWLs seem to decrease. Cluster 2 wells also show a diverging pattern as the AR fraction of precipitation increases (column 2, Figure 5b). AR maximum event intensity follows a similar response; greater intensity ARs are associated with higher groundwater levels, except during dry periods (Figure S14). More intense events are likely to contribute a greater amount to the fraction of precipitation, leading to a greater recharge potential. For example, of the 541 mm of precipitation in November 2021, 153 mm fell in only two days, substantially raising GWLs across the Fraser Valley (Figure 5c). Some cluster 1 wells (e.g., OW406 and OW450 in Figure S13) show a diverging pattern of lower groundwater levels with greater AR fractions of precipitation. We believe this to be a weak influence from the Fraser River, given their relative position to the river (Figure 1), but that the climate signal is stronger, placing them in cluster 1. Overall, this dichotomy between cluster response stresses the adage of correlation versus causation. Greater precipitation does not cause lower groundwater levels. Rather, cluster 2 GWLs are higher in the summer than in early autumn, opposite to cluster 1. This shifts the summer GWL mean to be higher than the autumn mean (Figure 5c), resulting in the diverging patterns observed in Figure 5b.
Figure 5. Mean monthly groundwater levels for OW299 (a) and OW448 (b) as a function of total monthly precipitation, monthly AR fraction, monthly CDD fraction, and monthly NDD fraction. (c) Temporal variations in hydraulic heads and stage at Mission (08MH024). The annotated rectangles (teal and purple), mapped in (a) and (b), highlight extreme events. Note that the hydrometric station is ~42 km downstream of OW448; therefore, the Fraser River stage is ~10 masl lower than it would be beside OW448.

Longer dry spells (CDD) are associated with lower groundwater levels in both clusters, although cluster 2 wells show a flat response during negative SPI periods (column 3 – Figure 6). CDD fractions less than around 0.5 (two weeks without precipitation) show considerable variations in
groundwater level, regardless of dry or wet periods (Figure S15). A greater NDD is associated with lower GWLs (column 4, Figure 5a); but the dry period response from cluster 2 is opposite (column 4, Figure 5b). The Fraser River freshet coincides with the local climatological dry period of the Fraser Valley, where groundwater levels increase during precipitation deficits (Figure S16). This may not prevent the propagation of drought but can certainly delay its onset. A severe heat wave in June 2021 marked the beginning of significant drought across the Fraser Valley. By mid-July, cluster 2 wells maintained average levels while cluster 1 wells were well below (Figure 5c).

3.3 Inter-annual Variability in Deluge and Drought

The Fraser Valley averages 34 ARs (range: 16–53) per year (1980-2022), contributing to over a third (AR fraction: 37%), or about 571 mm, of total annual precipitation (1542 mm) (Table S2). These results agree with AR studies that include the PNW (Borkotoky et al., 2023; Collow et al., 2022; Gershunov et al., 2017; Tan et al., 2022). Typically, about 60% of the year receives no precipitation, leaving only 40% of the year for potential recharge. Every year averages nearly a full month that receives no precipitation, typically during late summer.

Figure 6b plots the last decade of GWLs for both OW299 (cluster 1) and OW448 (cluster 2), which have similar depths to water table and median GWLs. The interquartile range (IQR) for OW299 is much wider than for OW448, displaying a greater variability in groundwater level throughout a given year. Low GWLs occur around September, while highs are reached around December (Figure 6b).
Figure 6. (a) Four decades of hydroclimatology (b) Latest decade of water table variations in both clusters as a response to precipitation, ARs, and max CDDs. September (blue) and December (brown) monthly means typify average dry period lows and wet period highs, respectively. April 1st snow water equivalent (SWE) percentage of normal snowpack averaged across the entire FRB is sourced from the BC Snow Survey and Water Supply Bulletin (available from [https://www2.gov.bc.ca/gov/content/environment/air-land-water/water/drought-flooding-dikes-dams/river-forecast-centre/snow-survey-water-supply-bulletin](https://www2.gov.bc.ca/gov/content/environment/air-land-water/water/drought-flooding-dikes-dams/river-forecast-centre/snow-survey-water-supply-bulletin)). *The 2017 boxplot for OW299 is included for completeness despite missing data from August to November.

Aside from total precipitation, the most influential driver of intra-annual GWL variation seems to be in the timing and distribution of precipitation events. For example, despite an above average snowpack in 2022, nearly three months (end-July to mid-October) without precipitation affected both clusters significantly, resulting in December GWLs well below the annual median (Figure 6b). Warmer winters result in substantially lower snowpacks in the PNW, even if precipitation amounts are within a normal range, as evidenced in 2015 (Mote et al., 2016). Accordingly, cluster 2 wells show lower median groundwater levels during below average snowpack seasons (Figure 6b). These results also support the importance of ARs as significant contributors to
snowpack accumulation, as above average April 1st SWE in 2020 and 2021 were also years that experienced over 50 ARs (Figure 6a). Despite the second highest CDD run in over 40 years, 2021 GWLs across the Fraser Valley were at record highs after receiving 56% of precipitation as ARs (Figure 5c and Table S2).

The cyclicity in dry (SPI < -1) and wet (SPI > 1) periods tends to follow on average a 2-year cycle, with the CWT of SPI-6 (Figure S17) showing a dominant periodicity of 1 to 3 years. Cyclicities in extremes tend correlate more broadly with cycles of ENSO based on the WTC between SPI and ONI, although this is confined to select time periods (Figure S18). SPI and ONI show strong coherence in the 2-year periodicity from 1980 to 1990, 1- to 4-year periodicity from 1998 to 2002, and 3-year periodicity from 2015 to 2020 (Figure S18). This is broadly reflected in interannual GWL variations in the last decade (Figure 6b). Looking at the WTC between GWLs and ENSO cycles, there is significant coherence in the 1- and 2-to-7-year periodicities for cluster 1 wells (Figure S19). The variations in dry-wet periods with ENSO cycles highlights the inter- and intra-annual temporal complexities in climate and weather over the decades: flash droughts can occur during wet winter La Niña (see 2021), while intense ARs can occur dry winter El Niño (see 2015).

4 Discussion

4.1 Groundwater Response to ARs and Drought

Clustering was key in being able to systematically differentiate aquifer responses to extremes, highlighting the complexities of the temporal synchronization of hydrological signals. These signals, and groundwater responses for one representative well from cluster 1 (OW299) and cluster 2 (OW448), are summarized in Figure 7. During winter (1), precipitation (SPI) and the fraction of ARs are both high, while the Fraser River stage (discharge) is low. Both wells have high groundwater levels in response to recharge from autumn and winter precipitation and ARs. Interestingly, Siirila-Woodburn et al. (2023) find that ARs provide less recharge than non-AR precipitation, in a large mountainous catchment in Northern California.

Cluster 2 wells begin to recede earlier, and have much lower GWLs in the spring. During the summer, cluster 1 wells show a decrease in GWLs proportional to decreased precipitation and increased CDDs. Conversely, cluster 2 well GWLs begin to rise, synchronized with the Fraser River, despite precipitation deficits. Both clusters reach a minima in early autumn (2), around October, as precipitation and AR fraction increase. The Fraser River influence on cluster 2 wells is relatively brief, and by early autumn, these wells revert to responding to the availability of diffuse recharge from precipitation, matching cluster 1.

Cluster 2 wells are more drought resilient (to local climate) over nearly the entirety of the summer. The snowpack built up across the FRB can sustain the Fraser River during local meteorological droughts (high fraction of NDD and CDD). However, a low snowpack (snow drought) or a rapid rise in spring temperatures across the FRB generally results in lower summer cluster 2 groundwater levels. Both clusters are particularly sensitive to the number of CDD, which is the main driver for summer and autumn groundwater declines.
Figure 7. Integrated plot of normalized hydrological signals summarizing the controls of the Fraser River stage, AR fraction of precipitation, CDD fraction, and Precipitation, on the groundwater level response. (1) Concurrent periods of high AR precipitation fractions and positive SPI, associated with higher GWLs, present in both clusters. (2) GWL minima driven by local climate, in both clusters.

4.2 Groundwater Memory Characteristics

The decorrelation lag times for porous aquifers ranged from 40 to 97 days, in good agreement with other groundwater studies across the globe. Schuler et al. (2022) report decorrelation lag times between 45 and 154 days in porous aquifers across Ireland, whilst Duy et al. (2021) report values from 35 to 199 days in porous aquifers across the Mekong Delta in Vietnam.

While the ACF is an important technique for deriving groundwater memory characteristics, our results suggest broader implications for elucidating the influence of boundary conditions on groundwater response. We show that physical hydrogeological boundaries (aquifer-stream connectivity) can significantly influence the autocorrelation structure of groundwater levels. As expected, the hydraulic properties of an aquifer do not fully explain the variance in ACF-derived memory metrics (Figure 8). To explain why, we focus on the damped decay rate half-life and the decorrelation lag time. The linear decay rate is log-correlated with decorrelation lag time and therefore is redundant (Figure S20).

Estimating aquifer hydraulic properties is challenging and often highly uncertain (Kuang et al., 2020), yet is imperative in accurately characterizing groundwater memory. Hydraulic diffusivity, $D$, which acts to dampen hydraulic head responses (H. F. Wang, 2020), integrates $T$ and $S$ into a single property that represents the efficiency in signal propagation. We therefore argue that $D$ is
a fundamental property in governing aquifer memory. Higher diffusivity aquifers have a more rapid GWL recession (Corona et al., 2023), because the response can be propagated more efficiently. Of the wells with hydraulic property data (26), D spans over five orders of magnitude ranging from 0.007 to 260.7 m²/s. Cluster 2 wells have the greatest D values with a geometric mean of 168.1 m²/s (range: 101.3–260.7 m²/s), while cluster 1 wells have a much greater range of D values with a geometric mean of 0.5 m²/s (range: 0.007–205.9 m²/s). Generally, a lower D is correlated with higher values of both memory metrics. This relationship is stronger ($R^2 = 0.51$) when considering D as a function of decorrelation lag time (Figure 8a). While the damped decay rate half-life tends to decrease with decreasing D, the relationship is weaker ($R^2 = 0.25$) (Figure 8b). As more than half of the total variation in decorrelation lag time is explained by D, this suggests that the damped decay rate half-life reflects a more complex set of factors influencing the ACF.

Figure 8. Hydraulic diffusivity as a function of (a), the decorrelation lag time, and (b), the damped decay rate half-life. Points are colour coded by cluster while point shapes represent the
aquifer type. A linear regression is fit to all points (‘lm’ function in R) and reported with the coefficient of determination, $R^2$. Note the log axes.

The disparity in cluster memory metrics raises an important question: do cluster 2 wells really have lower memory than cluster 1 wells? Or would both clusters have similar memory metrics had the Fraser River been absent? We can tease out the answer by observing the relationship between the linear decay rate and the distance of the well to the Fraser River (Figure S21). Cluster 2 wells do tend to be more diffusive by nature of their location and fluvial depositional environment. However, their linear decay rate increases logarithmically with increasing distance away from the Fraser River, approaching cluster 1 decay rates (Figure S21). The linear decay rate for cluster 1 wells seems independent of distance to the Fraser River, despite also including aquifers that are relatively highly diffusive. We posit that cluster 2 wells have lower memory metrics, in part due to higher $D$, but also because of how effective the Fraser River is at behaving as a boundary condition to groundwater in these aquifers.

4.3 Implications for Groundwater Management

Nearly all Fraser Valley aquifers support agricultural activity, primarily used for irrigation. Peak water use in the South Coast generally occurs from June to September, concomitant with low precipitation. We suggest that cluster 1 wells should be at a higher priority for drought monitoring, as these aquifers respond only to local climate. Groundwater abstraction in cluster 2 wells could be focused during the Fraser River freshet, typically May to June, and minimized closer to the Fraser River autumn minima, in October (Figure 7). Agricultural activities have been linked to increased flood risks because of higher water tables from intense irrigation (Houspanossian et al., 2023). Abstraction during the peak while irrigating during the recession might mitigate this risk. However, during the autumn and winter where ARs can lead to rapid rises in the water table, groundwater flooding is a significant risk. The November 2021 ARs caused widespread flooding (Figure 5c), especially in the old Sumas Lake bed (Figure 1). Unsurprisingly, as cluster 2 associated-aquifers coincide with the Fraser River floodplain, they have been mapped as high flood risk potential (Fraser Basin Council, 2023). Extreme precipitation events in North America, have, and will continue to increase in frequency (Du et al., 2022) and intensity (Li et al., 2019; Prein et al., 2017; Sun et al., 2021). As atmospheric water vapour concentrations increase under continued climate change, ARs at midlatitudes are projected to become stronger and more frequent (Espinoza et al., 2018; S. Wang et al., 2023), especially in the PNW (Gershunov et al., 2019; O’Brien et al., 2022), resulting in less snowfall and more rainfall at mid-elevations (Payne et al., 2020). Presumably, groundwater flooding across the Fraser Valley is likely to become more frequent, especially during late autumn.

The FRB has been shifting from a snow-dominated regime to a hybrid nival-pluvial regime over the past decades (Kang et al., 2014), with future climate warming projected to lead to decreased and earlier peak summer melt (Islam et al., 2019). Climate warming has already begun to affect snow droughts and winter snowpack accumulation across the PNW (Mote et al., 2016). Islam et al. (2017) show that the fraction of precipitation falling as snow across the FRB is projected to significantly decrease, up to 50% by 2050, in addition to an earlier freshet. Although autumn streamflow extremes might be more likely with the projected increase in landfalling ARs across the FRB (Curry et al., 2019).
AR-laden moisture can continue to be transported inland, all the way to central and eastern Canada causing additional rainfall events within 12 days of making landfall on the coast (Vallejo-Bernal et al., 2023). Within a single day of making landfall on the coast, these ARs can contribute significantly to snowpack accumulation in the Rocky Mountains, the headwaters of the Fraser River, even recharging groundwater (Figure S22). However, warming AR circulations have contributed to an overall decrease in AR-related snowfall, even at higher elevations (Sharma & Déry, 2020), which will continue to shift the FRB regime.

5 Conclusions

Extreme events, in both the occurrence and magnitude of ARs and droughts, will continue to increase under a warming climate, shifting groundwater behaviour across the PNW. We analyzed groundwater levels across the Fraser Valley in the South Coast of British Columbia (BC) with the objective of determining groundwater responses to atmospheric rivers (ARs) and drought. On average, 34 ARs make landfall in the Fraser Valley every year, contributing to, on average, 37% of annual precipitation. During peak winter recharge (October to January), around 40% of total precipitation is contributed by ARs, concentrated to October and November. During drought-prone periods (April to September), more than 50% of days receive no precipitation, with typically 26 consecutive dry days. Annual average precipitation, 1542 mm, is concentrated to only about 40% of the year, indicating a concentrated recharge period.

By examining the autocorrelation structure of groundwater levels, a common approach to characterizing aquifer memory, we demonstrated that aquifers in the South Coast region of BC can be influenced by both local and non-local drivers of recharge, mediated by the hydraulic connectivity to the Fraser River. Two distinct clusters are identified using autocorrelation characteristics. Cluster 1 wells respond to recharge from local precipitation, and are quick to respond both ARs during winter recharge season and significant rainfall deficits during the summer. Predictably, cluster 1 groundwater levels increase as the total amount of precipitation or the fraction of AR precipitation increases, regardless of wet or dry season. Similarly, cluster 1 wells respond predictably to dry conditions, with groundwater levels declining with longer dry spells. Cluster 2 wells also respond to recharge from local precipitation during the winter, but are substantially influenced by the Fraser River, which acts as a hydraulic boundary. This hydraulic connectivity between cluster 2 wells and the Fraser River leads to a shift in the timing of groundwater hydrographs relative to local climate conditions. Summer groundwater drought is mediated by the Fraser River’s summer freshet, by shifting the recession in cluster 2 wells.

Despite experiencing the same climate, the differentiation in the dominant recharge mechanism (local recharge versus a hydraulic boundary condition) ultimately controls the groundwater response to extremes. Therefore, in this hydrological setting, groundwater memory is controlled by the intrinsic hydraulic properties of an aquifer and encodes the effects of hydraulic boundary conditions. The identification of different drivers of groundwater response can aid in more effective groundwater management strategies in dealing with the effects of climate change, as the hydrological regime of the Fraser River Basin and similar basins across the Pacific Northwest shift from being snow- to rain-dominated.

Acknowledgments
We thank Brian Kawzenuk from the Center for Western Weather and Water Extremes (CW3E) for help accessing the AR catalogue. This project was funded by the Pacific Institute for Climate Solutions (PICS) as a PICS Opportunity Project.

**Conflict of Interest**

The authors declare no conflicts of interest.

**Data Availability Statement**

The up-to-date AR catalogue (Rutz et al., (2014) method), used to derive the AR catalogue for the Fraser Valley, is available via file transfer protocol (FTP) at [http://sioftp.ucsd.edu/](http://sioftp.ucsd.edu/). The derived Fraser Valley AR catalogue, well and aquifer information including memory metrics (Table S1), PGOWN observation well data, and code used in the analysis, are available at [http://www.hydroshare.org/resource/d77f11c4ff8245d498fa17b924fe028a](http://www.hydroshare.org/resource/d77f11c4ff8245d498fa17b924fe028a). Open data from the government of British Columbia for provincial groundwater observation well data and aquifer information are available from [https://catalogue.data.gov.bc.ca/dataset/57c55f10-cf8e-40bb-aae0-2eff311f1685](https://catalogue.data.gov.bc.ca/dataset/57c55f10-cf8e-40bb-aae0-2eff311f1685) and [https://catalogue.data.gov.bc.ca/dataset/099d69c5-1401-484d-9e19-c121cc87c977](https://catalogue.data.gov.bc.ca/dataset/099d69c5-1401-484d-9e19-c121cc87c977), respectively. Meteorological data for BC are available at [https://services.pacificclimate.org/met-data-portal-pcds/app/](https://services.pacificclimate.org/met-data-portal-pcds/app/). Hydrometric data are available at [https://wateroffice.ec.gc.ca/search/real_time_e.html](https://wateroffice.ec.gc.ca/search/real_time_e.html).

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Supporting Information for

**Groundwater Responses to Deluge and Drought in the Fraser Valley, Pacific Northwest**

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Table S2

**Additional Supporting Information (Files uploaded separately)**

Table S1 is provided as an Excel spreadsheet in the linked hydroshare repository,  
http://www.hydroshare.org/resource/d77f11c4ff8245d498faf7b924fe028a.

**Introduction**

This document contains supplemental figures (S1 to S22) and Table 2 as referred to in the paper.
**Figure S1.** Climate normals at the Abbotsford Airport Climate Station EC1100030/31 (ECCC, 2023) from 1991 to 2020. Monthly maximum (red line), mean (beige line), and minimum (blue line) temperatures. Monthly mean precipitation (blue bars) and snow (dark blue bars).

**Figure S2.** Annual count of landfalling ARs in the study area (see Figure 1) from three AR catalogues: (1) Center for Western Weather and Water Extremes (CW3E) observations, (2) Cropped and resampled Rutz et al. (2014) catalogue, and (3), cropped and resampled Gershunov et al. (2017) SIO-R1 catalogue.
Figure S3. Kolmogorov-Smirnov goodness-of-fit D-statistic for select distributions used in computing the SPI. The Pearson Type-3 (PE3) is selected in this study as it is the most consistent distribution with a low variability in the D-statistic. The dashed grey line represents the D-critical statistic (0.18) for which the empirical data no longer fit the tested distribution.
Figure S4. Groundwater monitoring well level data with a loess smoothing line in teal.
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Figure S6. Linear decay rate (red line) at early lag times of the ACF for each well.
Figure S7. Damped decay sinusoid function fit to the ACF for each well.
Figure S8. Daily groundwater level rates of change (ROC) cross-correlated with daily precipitation to a maximum lag of 365 days.
Figure S9. Daily groundwater level cross-correlated with daily precipitation to a maximum lag of 365 days. The red dot shows the lag time for the minimum correlation values.
Figure S10. Top: Hydraulic gradient between the Fraser River and OW485. A negative (positive) gradient denotes stream (aquifer) to aquifer (stream) exchange; hence, groundwater is being recharged (discharged). Bottom: Head and stage elevation for OW485 and the Fraser River, respectively. Precipitation is split into AR and non-AR events.
**Figure S11.** Maximum AR intensity averaged by month.
Figure S12. Total monthly precipitation as a function of mean monthly groundwater levels.
Figure S13. AR fraction of precipitation as a function of mean monthly groundwater levels.
Figure S14. Maximum monthly AR IVT as a function of mean monthly groundwater levels.
**Figure S15.** The fraction of consecutive dry days (CDD) in a month as a function of mean monthly groundwater levels.
Figure S16. The fraction of number of dry days (NDD) in a month as a function of mean monthly groundwater levels.
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Figure S18. WTC between ONI and SPI-6. Significant periods outlined in white. Black arrows represent the phase lag between both signals.
Figure S19. Wavelet coherence between the GWLs and ONI. Grey rectangles mark areas of significant coherence at a 5% significance level.
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Figure S21. The linear decay rate fitted to the ACF as a function of well distance to the closest reach of the Fraser River. Linear and logarithmic regressions are fit to cluster 1.
and 2 aquifers, respectively. OW349 is omitted, as it is not hydraulically connected to the Fraser River.

Figure S22. Headwaters of the Fraser River Basin (FRB) and the groundwater response in OW 502 and snow water equivalent (SWE) during the historic November 2021 ARs.
Table S2. Hydrometeorological summary of drought and deluge in the last decade. The long-term average is computed from 1980 to 2022. *Major drought year. **Major drought year interrupted by the strongest recorded AR in the Fraser Valley. ***Very wet winter.

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<td>217 (0.59)</td>
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