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RESEARCH ARTICLE

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Key Points:

- We offer an objective, consistent, and reproducible way of detecting streamflow response to earthquakes
- Bayesian piecewise regression reveals credible and previously unrecognized increases in post-seismic discharge variability
- The variance in thus detected post-seismic streamflow changes exceeds by far the discharge variability following rainstorms

Supporting Information:

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

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Bayesian Detection of Streamflow Response to Earthquakes

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Abstract Detecting whether and how river discharge responds to strong earthquake shaking can be time-consuming and prone to operator bias when checking hydrographs from hundreds of gauging stations. We use Bayesian piecewise regression models to show that up to a fifth of all gauging stations across Chile had their largest change in daily streamflow trend on the day of the M_w 8.8 Maule earthquake in 2010. These stations cluster distinctly in the near field though the number of detected streamflow changes varies with model complexity and length of time window considered. Credible seismic streamflow changes at several stations were the highest detectable in eight months, with an increased variance of discharge surpassing the variance of discharge following rainstorms. We conclude that Bayesian piecewise regression sheds new and unbiased insights on the duration, trend, and variance of streamflow response to strong earthquakes, and on how this response compares to that following rainstorms.

Plain Language Summary Strong earthquakes can abruptly change the discharge or rivers. Detecting this streamflow response mostly depends on visually checking data from gauging stations, and may be prone to bias. We test an alternative approach that estimates the most probable date of the largest change in daily river discharge. We test the approach with data from over 200 Chilean stations to see which responded to the 2010 magnitude 8.8 Maule earthquake. We find that dozens of stations near the epicenter had their largest jumps in streamflow on the day of the earthquake. This response lingered for up to four months at some stations, also raising the variability of discharge much above that following rainstorms. These findings are consistent with the idea of an earthquake-driven increase in vertical permeability underground, and show how data-driven models can usefully augment visual checks of river data.

1. Introduction

Pliny the Elder lived in the 1st century CE and was among the first to report in writing that the amount of water discharged at Earth's surface can change following earthquakes. Following the Great Lisbon Earthquake in 1755, Immanuel Kant described sudden changes in surface hydrology that occurred "in the same minutes as the earthquake devastated the coasts of Portugal." He noted that "in just (...) minutes, the mineral water at Töplitz in Bohemia (Czech Republic) suddenly stopped and returned to blood red," while "in the Kingdom of Fez (Morocco) in Africa, a subterranean force split a mountain and poured blood-red streams out of its mouth" (Kant, 1756). Many other similar observations show that streamflow can increase or decrease following strong seismic shaking and thus reflects responses of groundwater being supplied to streams (Mohr et al., 2017). Earthquakes modify crustal stresses, hydraulic heads, and physical properties such as the permeability of the subsurface that all control water flux (Wang & Manga, 2014). Altered river discharges following earthquakes have been reported in the near- and intermediate-field, that is, within one or a few rupture lengths away from the earthquake source (Rojstaczer et al., 1995). The magnitude of streamflow responses can involve the release of >1 km^3 of excess water into streams (Mohr et al., 2017) and sustain enhanced streamflow for months (Ishitsuka et al., 2017; Muir-Wood & King, 1993; Rojstaczer et al., 1995). Even dry streams may begin to flow (Wang & Manga, 2014) or flowing streams disappear (Cucci & Tertulliani, 2015). Earthquakes may also change the hydrochemistry of streamflows, which in turn may impact aquatic biota (Galassi et al., 2014), and modify the water available to plants (Bekker et al., 2018; Mohr et al., 2015).

Seismically triggered changes in discharge allow us to explore how the hydrological cycle reacts to, and recovers from, short-lived disturbances. The mechanisms responsible for increased stream discharge are uncertain. Proposed hypotheses include squeezing water out of aquifers from static contraction (Muir-Wood & King, 1993); breaking subsurface hydraulic barriers to allow new fluids to reach the surface (Wang, Manga, Dreger, & Wong, 2004); consolidating saturated surface (Montgomery et al., 2003) and subsurface (Mohr et al., 2012) material; mobilizing soil water by ground shaking (Mohr et al., 2015); and increasing hydraulic permeability (Briggs, 1991; Rojstaczer & Wolf, 1992; Sato et al., 2000; Tokunaga, 1999; Wang, Wang, & Manga, 2004). All mechanisms may be valid for specific local conditions. However, they often compete with, or even exclude, each other in a more general view. Recent modeling studies have favored changes in vertical permeability as the probable mechanism in most cases (Ishitsuka et al., 2017; Mohr et al., 2017; Petitta et al., 2018), triggering a streamflow response once seismic ground velocity exceeds roughly 0.1 m s^{-1} (Mohr et al., 2018).

One aspect of testing these mechanistic hypotheses is that researchers identify sudden streamflow changes mostly by visually inspecting time series of discharge with knowledge about the exact timing of the earthquake (Mohr et al., 2012; Montgomery et al., 2003; Wang, Wang, & Manga, 2004). Such expert assessment may be difficult to compare between studies, however. Ideally, we prefer more objective evidence to decide whether an observed streamflow change is causally linked to seismic shaking, so that we can avoid a wrong or biased interpretation. Checking hydrographs visually to establish a marked coseismic (i.e., during the earthquake) change in discharge may be prone to confirmation bias, and ignores the possibility that sudden increases or decreases in streamflow coincided randomly with seismic shaking. An alternative is to learn the timing of the largest streamflow change directly from the data with models that express these uncertainties in a probabilistic framework. To explore this alternative, we use a Bayesian approach to track the largest daily change in streamflow trends and variances with minimal prior knowledge. We test whether these changes happened on the day of the M_w 8.8 Maule earthquake that struck central Chile in 2010. This earthquake triggered some of the most pronounced streamflow changes reported, releasing >1 km^3 of water from below the surface into the drainage network (Mohr et al., 2017). Yet this and other studies largely left unexplored how reliably, and for how long, this hydrologic response to seismic shaking is detectable in streamflow trends and variances. Here we demonstrate how we can capture these central aspects of earthquake hydrology in a Bayesian framework.

2. Materials and Methods

We use freely available gauging data from more than 800 stations of the Chilean hydrological network maintained by the Dirección General de Aguas and collated in the CAMELS-CL data set by Alvarez-Garreton et al. (2018) (http://camels.cr2.cl/). To test the applicability of our approach for raw streamflow data, we refrain from pre-preprocessing these hydrographs such as correcting for precipitation or checking for systematic or instrumental errors. Instead we test whether various Bayesian change-point models can efficiently and reliably screen this large number of stations and pick those with a sudden and pronounced change in daily discharge on the day of the Maule earthquake.

Bayesian change-point models can detect major changes in trends in geophysical time series, such as rates of regional or global seismicity (Touati et al., 2016). Change-point models have been used, for example, in the context of objectively tracking the onset of induced earthquakes in Oklahoma (Fiedler et al., 2018). Hydrological time series are also amenable to change-point analysis, and Jo et al. (2016) used a Bayesian extreme-value model with a Markovian structure to detect changes in maximum yearly precipitation. These and other Bayesian models based on piecewise regression (Gallagher et al., 2011) have the advantage of explicitly handling the uncertainties in parameters and previous knowledge.

Here we use both analytical and numerical solutions to Bayesian change-point problems to systematically flag the day that streamflow trend and variance had their most credible change. Our strategy is to search a given time series of daily discharge measurements for the day that is the most likely candidate for having the largest change in both the mean and the variance of streamflow. We consider daily measurements of $\log_{10}$-transformed, standardized discharge that we left uncorrected for instrumental effects or antecedent precipitation. These measurements at time t are separated into two intervals either side of a single, unknown change point t_c. We prefer this approach over alternative models accommodating multiple change points, because we wish to detect whether the single most largest change in streamflow trend and variance happened on a single day with a sufficiently high probability.

Assuming a Gaussian data noise, the likelihood of observing N discharge data $\mathbf{Q} = \{Q_1,\ldots Q_N\}^\top$ generated by this piecewise model is:

$$p(\mathbf{Q} \mid f(t,\mathbf{w}),\boldsymbol{\sigma}^2,\mathbf{n}) = \prod_{\nu=1}^{2}\prod_{i=1}^{n_\nu}\frac{1}{\sqrt{2\pi\sigma_\nu^{\,2}}}\exp\left[-\frac{1}{2\sigma_\nu^2}\left(Q_\nu(t_i) - f(t_i,\mathbf{w}_\nu)\right)^2\right], \tag{1}$$

where the subscript ν identifies the intervals before (I_1) and after (I_2) the change point, and the daily subscript i recycles at the start of I_2. The number of data in these intervals is $n_1 + n_2 = N$, stored in a column vector $\mathbf{n} = \left\{n_1, n_2\right\}^\top$ whose entries vary with t_c. We use the same subscript notation for the data noise $\boldsymbol{\sigma}^2 = \left\{\sigma_1^2, \sigma_2^2\right\}^\top$, assuming that it differs before and after the change point. We model mean daily discharge with a function $f(t, w)$, where $\mathbf{w} = \{\mathbf{w}_1, \mathbf{w}_2\}^\top$ is a stacked vector whose entries are the parameter vectors for either side of the change point. The number of entries in w_1 and w_2 specifies the complexity of the piecewise mean function. Following Bayes' Rule, we multiply the likelihood function in Equation 1 by a joint prior distribution $p(w, \sigma^2)$, and renormalize this product to obtain a marginal posterior distribution of the change point. For sufficiently broad, finite support on independent and very weakly informed priors $p(w, \sigma^2) = p(w)p(\sigma^2)$, we can derive analytical solutions of the posterior change-point location for polynomial basis functions $f(t, w) = w^\top\phi(t)$, where $\phi(t) = \left\{1, t^1, t^2, \ldots, t^D\right\}^\top$, and D is the order of the polynomial; see Equations 24.14–24 in Van der Linden et al. (2014). We test these analytical solutions of Bayesian piecewise continuous polynomials of order 0, 1, 2, and 3, and record the posterior daily change-point probabilities $P_c \sim p(t_c|t, Q, n)$ for a given gauging station. We focus on those stations at which the largest change in both discharge trend and variance credibly focus on a single day, defining "credible" as $P_c > 0.95$ (Figure S1). If this threshold probability is exceeded on the day of the Maule earthquake, we refer to the streamflow as having a "credible response to the earthquake." The downside of these analytical solutions is that they rely on integrating out w and σ^2, so that these parameters elude any inference; the model solely reports a posterior distribution of daily change-point probabilities without any information on how streamflow trends or their variance changed.

To learn more about the nature of streamflow response, we modify Equation 1 to learn a discontinuous piecewise model from the streamflow data. We consider only linear regression curves and allow them to be more robust and unconnected at the change point to capture the largest changes in streamflow that appear discontinuous in daily data. This modification offers posterior distributions of the offset of stepwise increase or decrease in discharge; the sign of streamflow response (whether discharge increased or decreased); the trends in mean discharge; and changes in its variance from a single model. The likelihood function of our refined model is:

$$p(\mathbf{Q} \mid \boldsymbol{\mu}(t),\boldsymbol{\sigma}^2,\mathbf{n},\eta) = \prod_{\nu=1}^{2}\prod_{i=1}^{n_\nu}\mathcal{T}\left(Q_\nu(t_i) \mid \mu_\nu(t_i),\sigma_\nu^2,\eta\right), \tag{2}$$

where the piecewise linear mean function is:

$$\mu_\nu(t_i) = \begin{cases} \mu_1(t_i) = \mathbf{w}_1^\top t_i, & \text{for } t_i < t_c \\ \mu_2(t_i) = \mathbf{w}_2^\top t_i, & \text{for } t_i \geq t_c. \end{cases} \tag{3}$$

We use two linear model segments with $\mathbf{w}_1 = \{w_{1_a}, w_{1_b}\}^\top$ and $\mathbf{w}_2 = \{w_{2_a}, w_{2_b}\}^\top$, but refrain from using higher-order polynomials because their generally poorer fits at the boundaries of the data range may unduly exaggerate streamflow changes at the change point. The model assumes a robust (Student-t) distributed noise σ^2 that is constant for the data subsets either side of t_c; here $\mathcal{T}(\cdot \mid \cdot)$ is the Student-t distribution that is less sensitive to outliers such as distinct peaks in discharge. We fix the degrees of freedom at $\eta = 5$ in order to compare the models consistently. We choose independent standard Gaussian priors ($\mathcal{N}(0,1)$) for

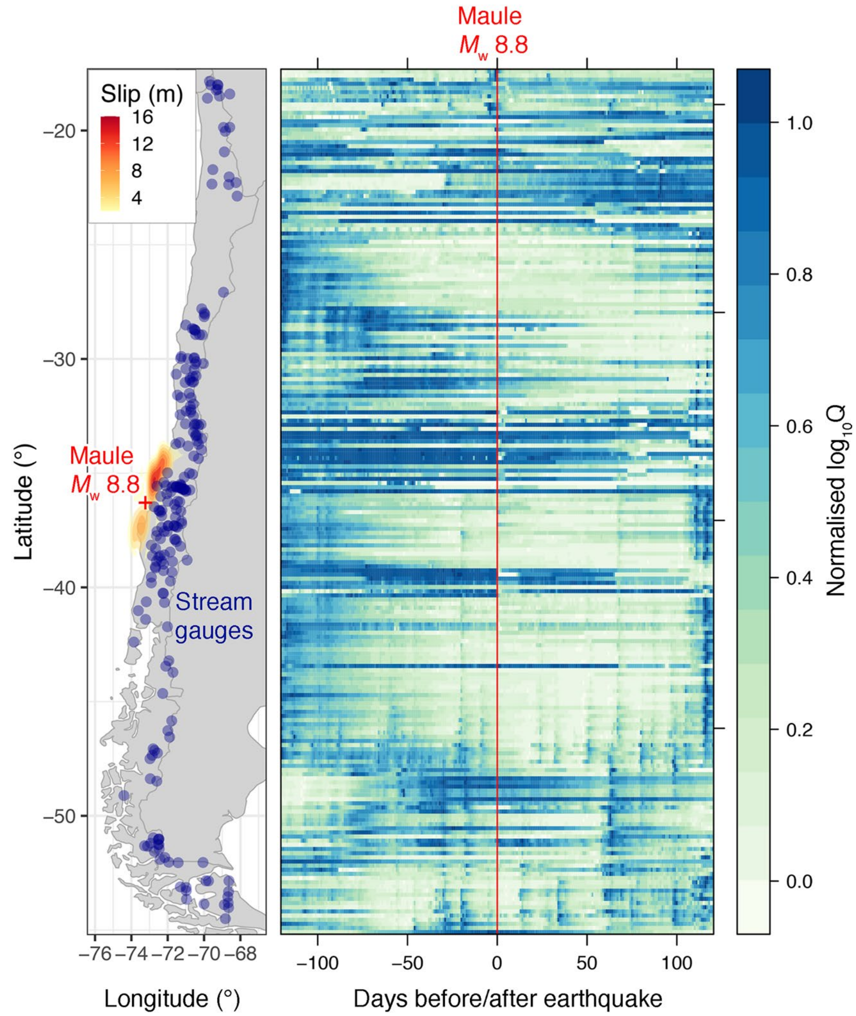

Figure 1. Left: Map of Chile with the distribution of slip during the 2010 M_w 8.8 Maule earthquake (Lorito et al., 2011) and 212 stream gauges (blue bubbles, slightly transparent to highlight spatial clusters) with complete daily records spanning 120 days before and after the earthquake; red cross marks epicenter. Right: Normalized and $\log_{10}$-transformed river discharge of the 212 gauges arranged by geographic latitude and centered around the day of the main earthquake shock; each row contains the time series of a single station.

w, half-Cauchy priors ($\mathcal{C}(0, 2.5)$) for $\boldsymbol{\sigma}$, and a uniform distribution for t_c. Multiplied by the product of these independent priors, Equations 2 and 3, the resulting (unnormalized) posterior distribution is analytically intractable and requires numerical approximation. To this end we use a Hamiltonian Monte Carlo-driven numerical solution to Bayesian piecewise polynomial models on standardized data to increase sampling efficiency (Betancourt et al., 2017). We approximate the posterior distributions with sampling algorithms implemented in the STAN programming language (Carpenter et al., 2017), using five parallel chains that we check for autocorrelation and successful convergence. We use 50,000 simulations (excluding warm-up) per chain to obtain stable posterior estimates and repeated sampling where the chains converged insufficiently. We maintain the prior belief that the change-point location is uniformly distributed, and run the model on five intervals of Δt of ± 7, ± 30, ± 60, ± 90, and ± 120 days centered around the day of the earthquake. We considered $n = 212$ stations that had complete daily discharge readings for $\Delta t = \pm 120$ days, and were between 40 and 2,070 km away from the epicenter of the 2010 Maule earthquake (Figure 1). Again, we focus on the credible posterior daily change-point probabilities with the added advantage that we now also obtain posterior estimates of w and σ^2, as $P_c \sim p\,(t_c | t, Q, w, \sigma^2, n)$.

10.1029/2020WR028874

Table 1
Percentages of n = 212 Chilean Stream Gauging Stations With Credible Changes in Discharge for Five Different Bayesian Piecewise Regression Models for Intervals Centered on the Date of the 2010 Maule earthquake

	Interval Δt (days)				
Piecewise model	±7	±30	±60	±90	±120
Discont. constant[a]	29% (7%)	17% *(2%)*	10% *(1%)*	9% (2%)	8% (1%)
Discont. Robust linear[b]	–	24% (8%)	16% (3%)	11% (1%)	*7% (0.5%)*
Linear[a]	25% (8%)	28% (7%)	19% (3%)	18% (2%)	12% *(0.5%)*
Quadratic[a]	–	28% (6%)	29% (6%)	30% (5%)	19% (4%)
Cubic[a]	–	29% (8%)	28% (5%)	34% (4%)	28% (5%)

Note. Listed here are stations for which the posterior daily probability for the largest change is > 0.95 (Figure S1). Percentages in parentheses refer to this credible change occurring on the day of the earthquake. *Italics* indicate that the percentage of stations may have arisen from random coincidence (see Figures S7 and S8, and text for details); "–" refers to overparameterized models.
[a]Analytical solution. [b]Numerical approximation.

3. Results

Our computations show that the number of detected changes in streamflow at all stations increases with model complexity, but decreases with longer intervals. We find that 8%–34% of the 212 stations had credible changes in mean daily streamflow in up to four months both before and after the 2010 Maule earthquake, based on the analytical solutions of the Bayesian regression models by Van der Linden et al. (2014). In the interval of $\Delta t = \pm 30$ days, for example, we find that 5 to 16 stations had their highest credible posterior changes in daily streamflow on the day of the earthquake (Figure S2). The piecewise quadratic and cubic models detected credible jumps or drops in discharge at over 60 stations for up to 90 days before and after the earthquake. About a third of these largest changes were on the day of the earthquake, or at 4%–6% of all stations (Table 1). Integrating over all stations, we observe that the highest marginal daily change-point probability was on the day of the earthquake for up to four months before and after, except for the most complex (piecewise cubic) model (Figure S3). The geographic pattern of these detected streamflow changes is distinctly clustered around the earthquake region. Stations with credible streamflow responses on the day of the earthquake had a median distance of nearly 160 km from the epicenter, as opposed to some 500 km for all stations together (Figure 2).

Our piecewise robust linear model (Equations 2 and 3) identified between one and 16 stations with credible streamflow changes on the day of the earthquake (Figure 3). This prediction is similar to that of the piecewise constant model with Gaussian noise, and detects fewer stations as the interval Δt increases. For a $\Delta t = \pm 120$ days, only one station (or 0.5% of all stations) remained with a credible streamflow change on the day of the earthquake (Table 1). The robust model further reveals that the detected changes involved both up- and downward shifts in mean daily discharge (Figure 4). Yet roughly two thirds of the credible changes on the day of the earthquake were sudden drops in discharge, locally by $>2\sigma$. These drops accentuated the overall decreasing trend in discharge recorded at most stations in the months before the earthquake. The model also highlights that credible streamflow changes on the day of the earthquake were followed by higher average (t-distributed) data noise, which more than doubled in the first month after the earthquake (Figure S4). This variance in discharge increased much more following credible streamflow changes on the day of the earthquake than for any other days (Figure S5).

4. Discussion

Our Bayesian approach offers several insights that augment the expert-based, though subjective, checking of hydrographs for sudden streamflow responses to the Maule earthquake. We begin by discussing how our methods performed before proceeding with what we learned about the possible earthquake effects.

One way to assess the performance of our models is to look at how they compare with independent approaches to detecting changes in streamflow. Mohr et al. (2017) reported that 25% of the stations with

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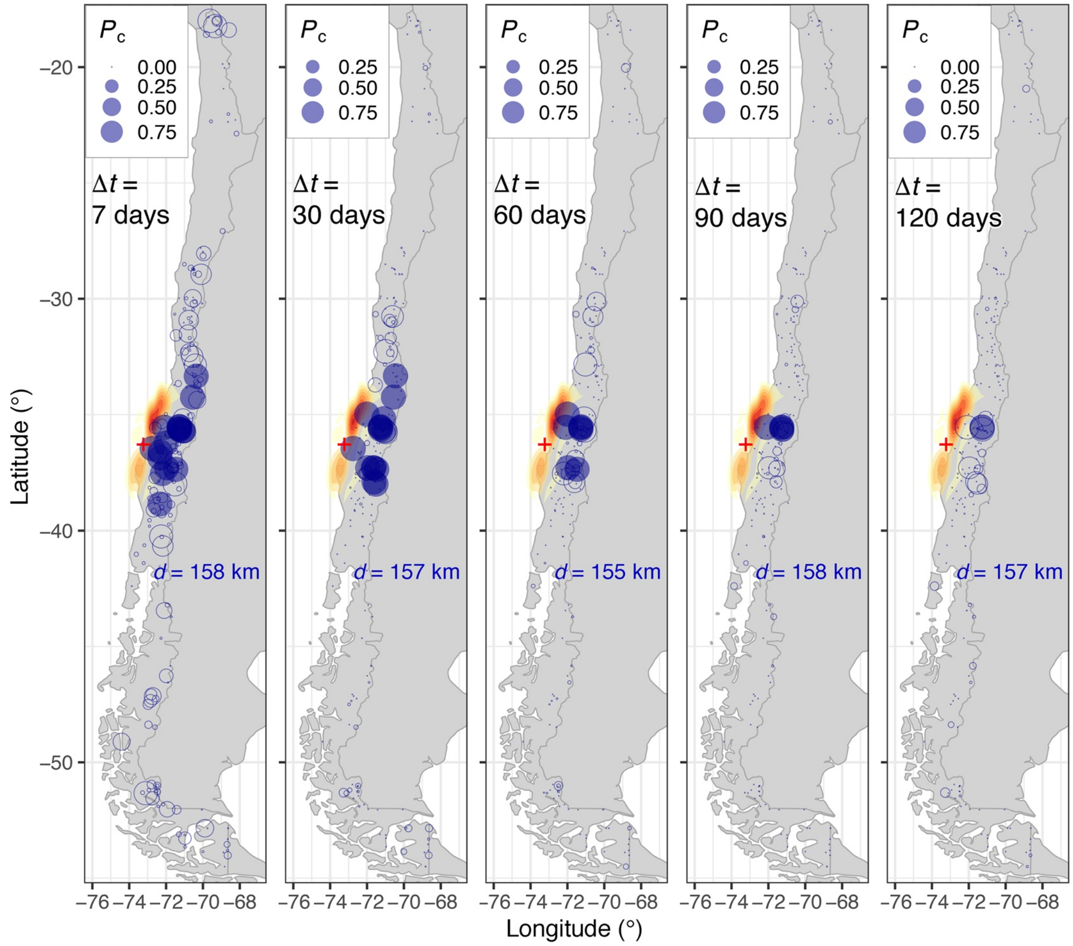

Figure 2. Distribution of slip (Lorito et al., 2011) and posterior probabilities P_c (blue bubbles) of change points in streamflow on the day of the Maule earthquake; see Figure 1 for amount of slip. Filled blue bubbles are stations where $P_c > 0.95$ on the day of the earthquake, estimated from a Bayesian piecewise linear regression (based on Equation 1) with daily discharge data covering intervals Δt of ±7, 30, 60, 90, and 120 days centered around the day of the earthquake; d is the median distance of blue filled bubbles from the epicenter (red cross); the median distance of all 212 stations is nearly 500 km.

complete data had a coseismic response based on visual checks for $\Delta t = \pm 7$ days. The more complex Bayesian change-point models that we use have too many parameters to meaningfully learn from this short interval (Figure S1). Still, our simpler models detect that up to 7% of the stations had credible changes in discharge coincident with the earthquake. Model and visual checks agree for two thirds of all complete hydrographs, though mainly concerning true negatives, that is in assigning no streamflow response (Table S1). One reason for this moderate agreement (other than large coseismic streamflow changes being rare) may be that a visual check may include in its assessment more minute and autocorrelated details in hydrographs than the daily change-point models can. Mohr et al. (2017) also used a larger set of stations after having conducted several quality checks and filtering of the data that we omitted here to see how well the Bayesian model would aid a first screening. Moreover, they also considered co-seismic changes in discharge that were less prominent than those several days before or after the earthquake. We also recall that the models presented here are probabilistic as opposed to expert judgement using fixed categories of streamflow response. Hence we caution against over-interpreting this rough comparison between our Bayesian model and the operator-picked changes. For $\Delta t = \pm 30$ days, all models detect a fraction of credible station responses similar to that of the visual checks for the much shorter interval, despite using fewer complete hydrographs (Table 1).

The earthquake occurred in the dry season, likely accentuating large hydrological changes that might be more difficult to detect during the rainy season (Figure S6). Nonetheless, from the Bayesian models we can

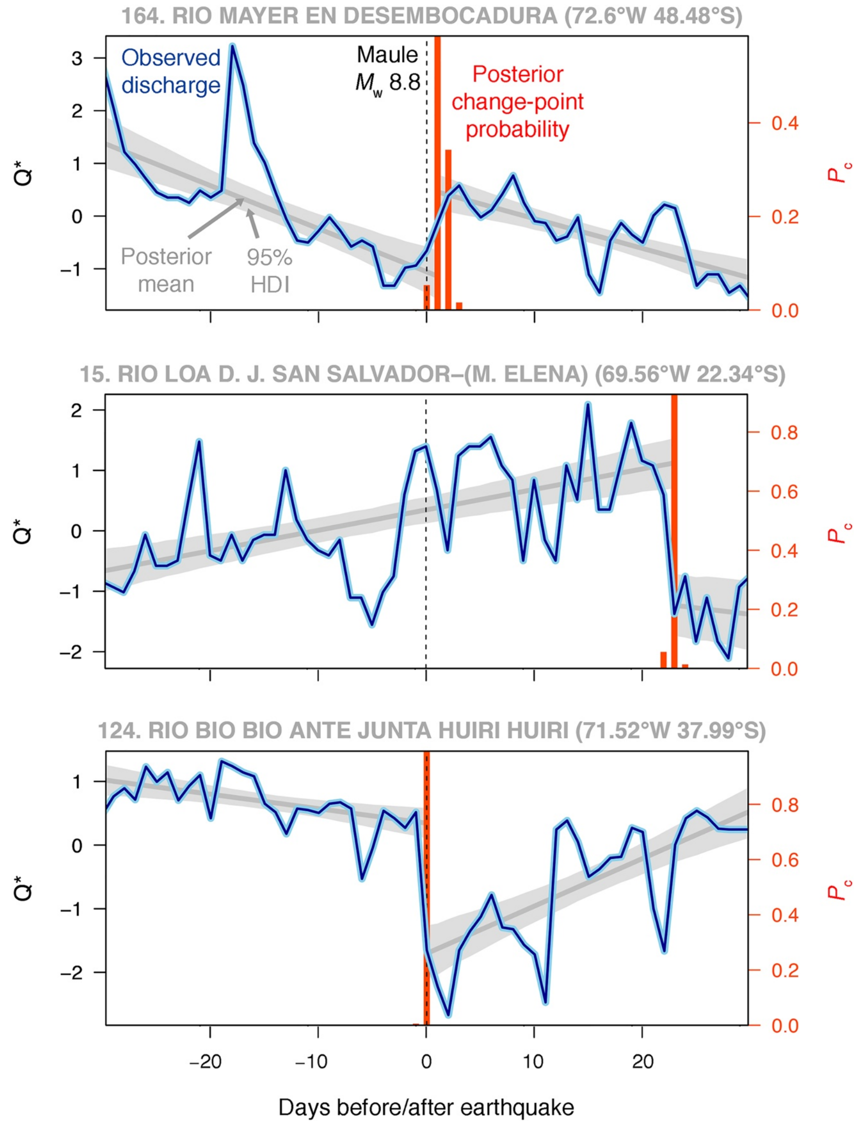

Figure 3. Bayesian robust piecewise linear fits to streamflow data from three representative examples of gauging stations (Equations 2 and 3); Q^* is standardized, $\log_{10}$-transformed daily discharge in an interval Δt of ±30 days centered around the day of the Maule earthquake (dashed line). Dark gray lines are posterior means and light gray shades their 95% highest density intervals (HDI). Station 164 had daily posterior changepoint probabilities $P_c < 0.95$ throughout, and thus lacked credible changes in Q^* on any single day; station 15 had a marginally credible change in streamflow 23 days after the earthquake; station 124 had a credible streamflow response on the day of the earthquake.

learn for how long the coseismic streamflow response remains the most dominant change in the trends and variances of the hydrographs; at a few stations this response signal lingered for up to eight months ($\Delta t = \pm 120$ days). Our results are consistent with the idea that longer observation intervals increase the likelihood that rainstorm-derived floods, controlled flushing of reservoirs or water withdrawal caused marked changes in these streamflow characteristics.

We also observe that the more complex models detect more stations with credible change points, and a handful of stations had a streamflow response that stood out for up to four months after the earthquake (Table 1). Some of this apparent model skill may arise from a poor fit of polynomials near the boundaries of the data, and especially at the change point where the two fit segments are discontinuous by design. Hence, some of the change points could be artefacts of model complexity.

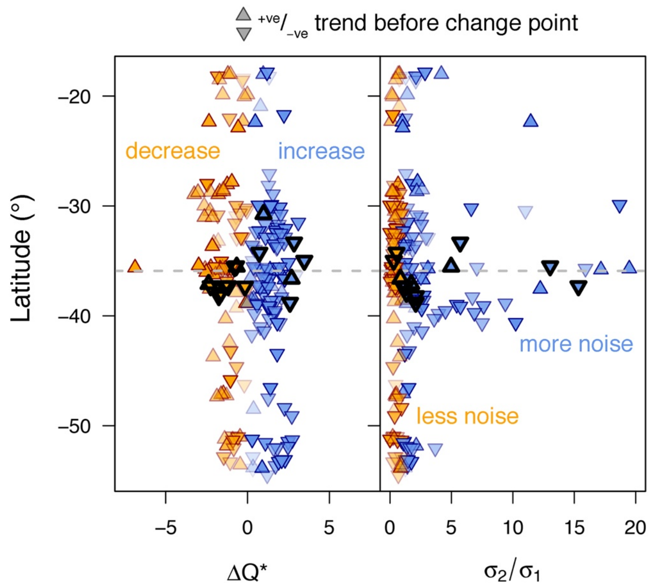

Figure 4. Changes in streamflow trend and noise from Bayesian robust piecewise linear model (based on Equations 2 and 3) at 212 gauging stations (triangles with opacity scaled to posterior estimate of P_c); ΔQ^* is decrease (orange) or increase (blue) in standardized, $\log_{10}$-transformed daily discharge for the maximum daily change-point probability in an interval $\Delta t = \pm 30$ days centered around the day of the 2010 Maule earthquake; σ_2/σ_1 is the (root) ratio of t-distributed noise after and before the change point: blue (orange) means that the variance has increased (decreased) after the change point; thick black outlines mark credible changes on the day of the earthquake. Upward (downward) pointing triangles show positive (negative) streamflow trends before the learned change point at each station; dashed line is epicenter latitude; Figure S4 summarizes these trends for all Δt.

One advantage of the Bayesian treatment is that we can measure what we have learned from the data by comparing the posterior daily change-point probabilities with their priors (Figures 3 and S3). Our choice of priors for the change-point location t_c concerned only uniform distributions with support over nearly the entire length of the intervals Δt except for their boundaries, where a minimum of data points is needed for fitting polynomials. Using $\Delta t = \pm 120$ days, for example, the prior probability of observing a streamflow response on the day of the earthquake by chance is $P_p = 1/(241 - 2)$ or about 0.4%, if excluding the first and last day as change-point candidates. This random success rate means that the probability of having exactly one out of the 212 stations we studied with a coseismic response signal that is random coincidence is about 37%, assuming a Binomial distribution; this probability drops to <5% for three stations showing this signal. Based on this reasoning, the number of detected stations with credible streamflow changes exceeds, except for a few cases, the number that we would expect due to mere chance (Table 1).

Uniform change-point priors favor modes of posterior distributions that are close to a maximum likelihood solution. One refinement of our model could feature a hierarchical level with a hyperprior distribution on the change-point location that could be informed by taking into account several or all gauging stations. Yet even credible changes in daily discharge on the day of the earthquake may be coincidental and only point to a possible coseismic streamflow response. Our definition of "credible" response can be modified easily. For example, if we believed that streamflow can also change gradually within several days of the earthquake, we could identify responses via a sufficiently high cumulative posterior probability spread out over several days.

In summary, Bayesian change-point models can systematically reveal important details about earthquake-affected hydrographs in a reproducible manner, and thus usefully complement visual expert analyses. Which of the five model variants one should prefer, depends on the objective. The analytical models (Equation 1) are easier to handle especially for longer time intervals, but mask any information about the magnitude and direction of changes in streamflow trends and variances. The robust model (Equations 2 and 3) provides this information, but requires numerical approximation and more parameters (especially if one wishes to include additional trends in streamflow variance), which limits its use for short intervals.

We now turn to what the model results might reveal about earthquake effects. Our models reveal that only stations close to the epicenter (~160 km or <25% of the estimated rupture length) had credible changes in streamflow on the day of the earthquake (Figure 2). This result is consistent with previous observations of coseismic streamflow response largely being limited to the near field; the extent of the rupture surface is roughly approximated by the dense pattern of earthquake epicenters (Figures 1 and 2).

A negligible part of this pattern may mimic the clustering of gauging stations in central Chile, with most stations located close to the 2010 epicenter (Figure S7). Yet we can exclude a chance occurrence for most of the detected streamflow responses with 95% confidence, especially for stations located 100–200 km from the epicenter (Figure S8).

The robust piecewise model adds another important aspect to the longevity of this signal by highlighting that the post-seismic (i.e., following the earthquake) variability of discharge was higher than that for any other sudden changes unrelated to the earthquake. This increased variance in the wake of strong ground motion is unrelated to absolute discharge, so that we can exclude that we observed spurious measurements tied to very low discharges. We infer that the credible coseismic streamflow responses that our model picked involve a higher, sustained discharge variability than did, for example, rainstorms (Figure S5).

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The increased variance of discharge after the earthquake is a hydrological response that has not previously been noted and highlights the value of objective methods. High discharge variability implies faster groundwater recharge and groundwater flow, in turn requiring higher vertical permeability. Previous studies of the streamflow response to the Maule earthquake also concluded that streamflow changes resulted from increased vertical permeability (Mohr et al., 2017). Permeability enhancement by transient stresses has been documented experimentally (Candela et al., 2014). Although groundwater recharge may have increased after the earthquake, by mostly a few tens of mm (Mohr et al., 2017), the overall contribution is small compared to that from annual precipitation. We thus expect a higher variability in post-seismic streamflow compared to pre-seismic conditions.

Estimating the variances σ^2 in our models yet serves another purpose. These variances represent unspecified noise in our models and may thus contain both measurement errors and variability of streamflow. A more refined model to analyze streamflow variance separately might feature an additional noise term for measurement errors or a time-dependent noise. Still, some of the excessive daily changes in discharge or noise help to identify several hydrographs that appear to have systematic errors. These large changes may reflect instrumental errors, readjustment or damage rather than a hydrological response to strong seismic shaking. Natural dams formed by earthquake-triggered landslides upstream of a gauging station may also cause a sudden decrease in discharge. Several of the detected streamflow responses were at stations nested in the same catchment and may thus depend on each other. However, the daily discharge data are too coarsely resolved to disclose whether these responses occurred independently of each other or simply as a result of a single response moving downstream. Either way, the extent and hydrological and ecological consequences of these streamflow changes remain unchanged.

5. Conclusions

We use Bayesian change-point models to objectively detect both abrupt and sustained streamflow response to the 2010 Maule megathrust earthquake at 212 candidate gauging stations across Chile. While models of higher complexity (ranging from constant to linear to polynomial) generally identify more numbers of stations that had their highest changes in discharge on the day of the earthquake, the mean proportion of stations thus flagged is similar to that identified by subjective checks of hydrographs. Stations that our methods detected as having a credible streamflow response on the day of the earthquake clustered in the near field exclusively and within a quarter rupture length from the epicenter. At these stations, daily discharge mostly dropped, whereas its variability more than doubled on average.

The number of stations with their highest credible change in streamflow on the day of the earthquake decreases as we increase the length of the inspected hydrograph before and after. For up to eight months we find that the number of these responding stations remains above the average of what we would expect by chance. These likely seismically triggered daily streamflow changes are the highest in up to four months before and after the earthquake. Our model is the first to objectively quantify this long-lasting earthquake hydrological signal, which may owe its strength partly to the dry season during with the earthquake happened.

Overall, our objective method enriches the subjective screening of hydrographs for a possible coseismic response, and offers metrics to rule out chance coincidences. Our models also reveal whether the changes in mean streamflow trends, the magnitude of changes, and accompanying changes in streamflow variance are credible in that they rise above the data noise. We also present evidence that the variance of post-seismic discharge is on average higher than that following major rainstorms, at least at the scale of several weeks to months. We conclude that Bayesian change-point models are flexible tools to filter a large number of hydrographs (or any other time series) to identify those that deserve more consideration.

Data Availability Statement

Model codes will be made available at a dedicated GitHub site. Streamflow data are freely available as part of the CAMELS-CL data set by Alvarez-Garreton et al. (2018) (http://camels.cr2.cl/).

Acknowledgments

We ran all computations using the statistical environment **R** (https://www.r-project.org/) and its graphical interface *RStudio* (https://www.rstudio.com/). We used the STAN programming language (https://mc-stan.org/) to run samples for the Bayesian analyses.

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