

EOSC 510 - Term Project: A Probabilistic Evaluation of the
Predictive Power of Weather Radar Data for Runoff Estimation
in Ungauged Watersheds in Western Canada

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Contents

1	Abstract	1
2	Introduction	1
3	Data	1
3.1	Historical Weather Radar	1
3.2	Daily Average Streamflow (Runoff)	1
3.3	Catchment Boundaries	3
4	Methodology	4
4.1	Anomaly Detection	4
4.1.1	AD Algorithm	4
4.1.2	Hydrograph Reconstruction	7
5	Results and Discussion	7
6	Conclusions	7
	References	7

1 Abstract

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2 Introduction

The characterization of water resources is a critical step in support of natural resource project proposals in Canada. Hydrological analysis is critical to the planning, design, permitting, and operation of mines and hydropower facilities in particular. The standard of resource engineering practice in assessing precipitation is limited to quantifying seasonal or annual total volumes due to the limitations in the resolution of available data—precipitation gauges measure a single point in space, while spatial distribution of precipitation is highly variable. As a result, there is considerable uncertainty associated with applying precipitation measurements to a basin of interest for analytical purposes, and derivative metrics such as runoff ratio and evapotranspiration are accordingly highly uncertain. Rules of thumb for physiography are applied to crudely adjust long-term estimates from one location to ungauged locations of interest some distance away, combining precipitation and runoff estimates from different sources to develop a reasonable picture of expected values. In other words, good practitioners make the most of information available.

Despite its own inadequacies, weather radar data uses low frequency radio waves to measure the density of water droplets in the air. The calibration of radar sensing to precipitation intensity has its own limitations and uncertainty, but weather radar has the benefit of providing a spatial projection of precipitation intensity within some sensor radius. The goal of this research is to develop a probabilistic estimate of the uncertainty in using weather radar data for predicting runoff in ungauged locations. Historical weather radar data and concurrent streamflow data at 144 hydrometric stations in British Columbia (BC) and Alberta (AB) are used in conjunction with weather radar data from five stations in BC and AB to compare estimated precipitation to the resultant runoff.

3 Data

3.1 Historical Weather Radar

Environment Canada (EC) provides free access to historical weather radar data as far back as 2007 for some radar stations, though programmatic access is not provided at the time of writing. Historical weather radar as a result was obtained by a web-crawling script on specific time periods corresponding to summer and fall runoff events. Five stations in BC and Alberta were used based on coverage of mountainous basins. Weather radar coverage encompasses a circular area described by a radius of 250km from the radar station. An example radar image is shown in Figure 1

The resolution of radar imagery corresponds to 1 pixel for every 1kmx1km, and the image is centred on the station. It is these two pieces of information that allow a reasonable projection of a coordinate system onto an unreferenced image. The algorithm behind the extraction of radar data is discussed in greater detail in Section X. Note the information layers, such as place names and concentric circles are embedded in the image and cannot be removed, causing issues for some catchments.

3.2 Daily Average Streamflow (Runoff)

The Water Survey of Canada (WSC) provides open, programmatic access to historical daily average streamflow records for over 8000 active and inactive hydrometric stations across Canada. A database file (HYDAT) containing all historical WSC streamflow data is maintained and updated quarterly, and the October 2019 HYDAT database file is used in this study. An example streamflow time series is shown in Figure 2. Figure 2 and subsequent figures are plotted using the Bokeh Data Visualization library (Bokeh Development Team 2020) for Python.

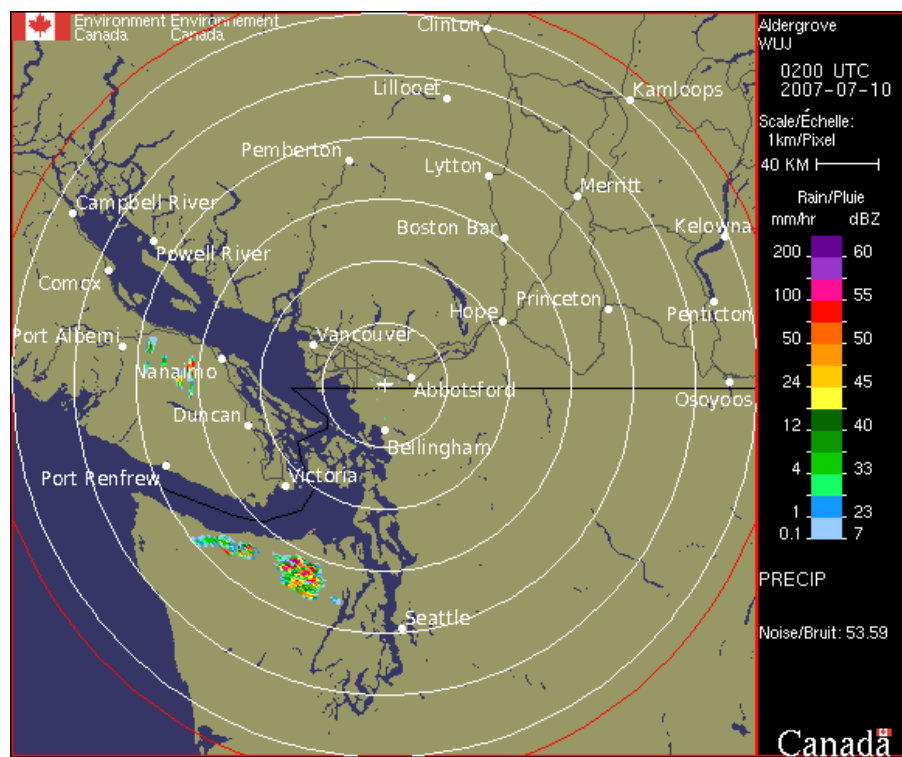


Figure 1: Example Radar Image (Aldergrove, BC Radar Station)

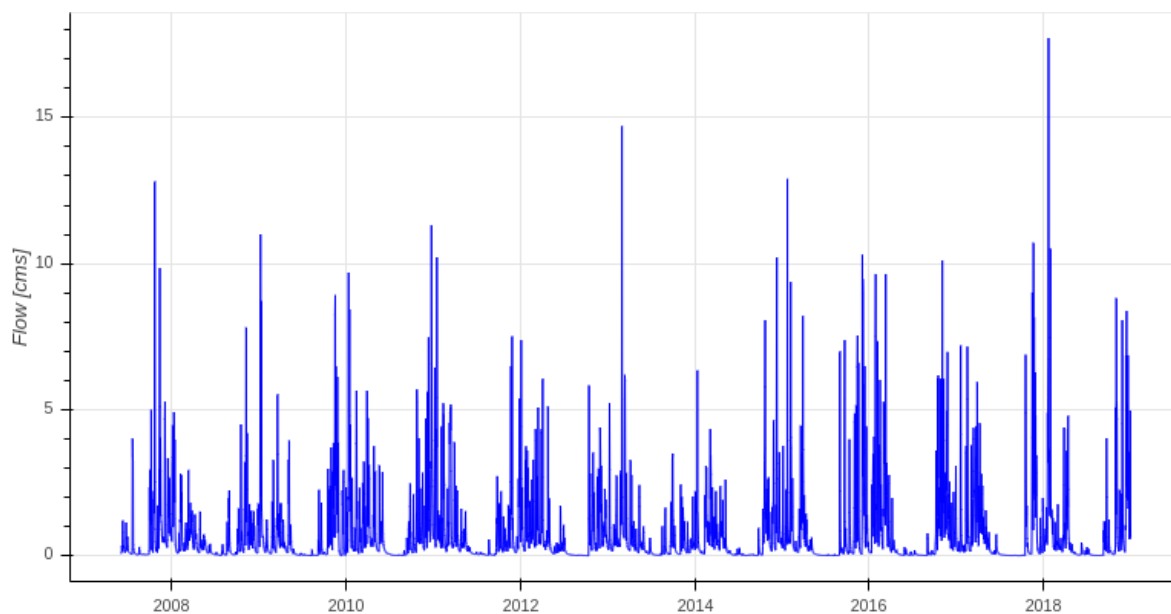


Figure 2: Example Daily Average Flow Timeseries (WSC 08HB048: Carnation Creek at the Mouth)

The HYDAT database is filtered to include stations in BC and Alberta, to include stations with historical record concurrent with the weather radar stations, to include stations falling within a 200km radius of the nearest radar station. Since the radar coverage has a radius of 250 km, and also because of the obstruction of some pixels due to overlaid information layers, the WSC stations were also filtered to include stations capturing a drainage area of less than 1000km^2 . The smallest WSC catchments are in the order of 10km^2 which correspond to a mere ~ 10 pixels of the radar image. As a result, the accuracy of the smallest and largest catchments is expected to be the poorest. The WSC stations satisfying the above criteria are plotted on Figure 3

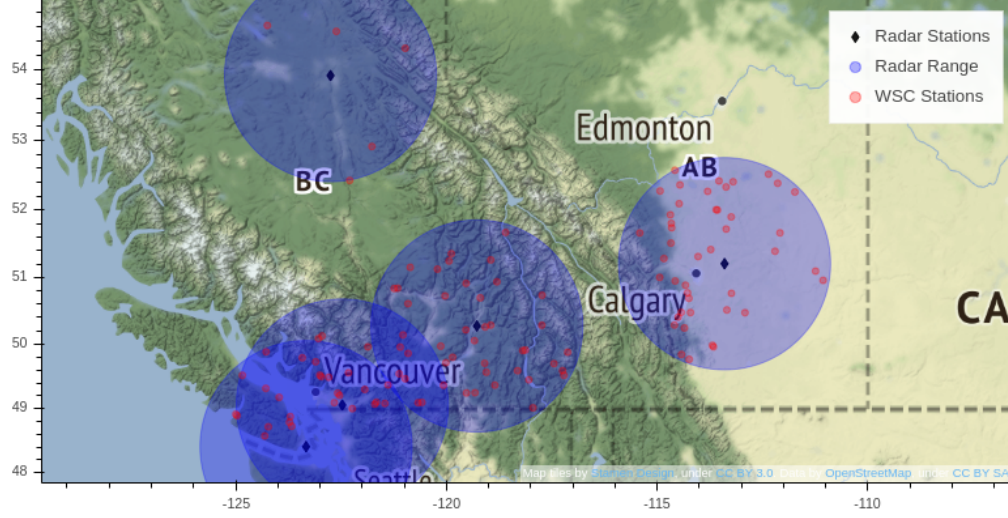


Figure 3: Radar Stations and Range, and WSC Stations within Radar Coverage

3.3 Catchment Boundaries

Geographic polygons corresponding to most of the WSC hydrometric stations are available from the Government of Canada's Open Data Platform. Given the low resolution of the radar images, the shape files are believed to be suitable for the intended purpose of extracting from the radar images the pixels corresponding to each catchment of interest. An example catchment boundary with its corresponding station location is shown in Figure 4

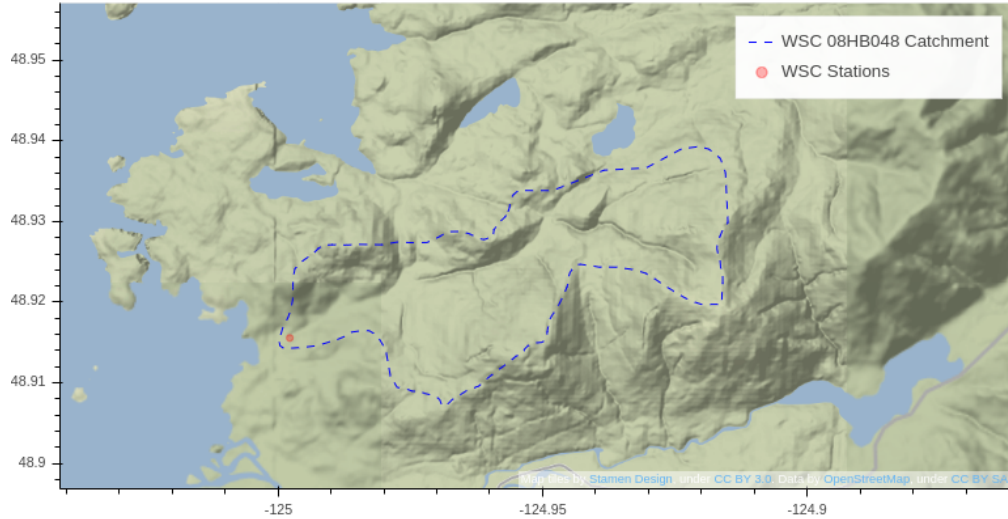


Figure 4: Catchment boundary for WSC 08HB048: Carnation Creek at the Mouth

4 Methodology

The primary research question involves the comparison of weather radar data and streamflow data to ultimately find clustering patterns of watersheds based on spatial distribution of rainfall, physiographic characteristics, and geographic location. The data acquisition process necessitated an additional analytical step which will be addressed first to set the context for the subsequent analysis. The remainder of data pre-processing is then described, including extraction of precipitation data from radar images corresponding to WSC station catchments, and the reconstruction of hydrographs. Finally, the methods used to evaluate the predictive power of radar data are presented.

4.1 Anomaly Detection

A limiting step in the data acquisition process is radar imagery retrieval. The number of server requests required to capture 12 years of radar images at 10-minute intervals at 5 stations in BC and Alberta is in the order of $3E6$, which is excessive for a free service and invites a ban from use. Focusing the study to summer months to simplify the interpretation of radar data (by avoiding precipitation as snow) does not alone reduce the number of requests to a viable level. As a result, an anomaly detection (AD) algorithm is used to identify isolated runoff events in summer and fall to reduce the total number of radar image requests to a reasonable number. However, the execution time of a sufficiently complex AD algorithm could negate the (time) cost savings from a reduced number of image requests, and a sufficiently sensitive AD algorithm could label every oscillation in the input signal, no matter how minute, as a ‘runoff event’, resulting in more image requests and longer AD algorithm execution time. A tradeoff then exists between running the anomaly detection algorithm to reduce the total radar image server calls to a viable number, the time required for the AD algorithm execution, and the number of runoff events identified (true positives).

The AD algorithm is supervised, in the sense that a training period is provided as an input. Initial testing of the AD algorithm demonstrated a high level of sensitivity to the training period selected. The search space of all years and all months is computationally intractable, so Monte Carlo (MC) simulation is used to identify variability in AD performance as a function of training period selection. To quantify the variability of AD performance (using number of events identified as a metric), a sample of 30 random input training periods for each WSC station are used as input into the AD algorithm, and the results for all stations are grouped by training year. Figure 5 shows the variability in number of events identified by the AD algorithm based on 1000 random selections of training year input.

Combining the random selection of a single year (2007-2018) for input training with a random selection of 1-12 months (inclusive) yields a total search space of roughly 50K alternatives. The execution time of the AD algorithm is such that computing the full search space is intractable for practical purposes. Better efficiency in code may be possible, however the main function of the AD algorithm already employs the well-optimized Tensorflow Python library (Abadi et al. 2015). To illustrate the time cost of a random search for input parameters, a random sample of 30 input parameters applied to the AD algorithm took 70 minutes for 144 stations on a six-core gpu-enabled (CUDA) machine. As shown in Figure 6 below, the number of runoff events detected by the AD algorithm using the random sample of 30 training parameter combinations per station are exponentially distributed, highlighting the opportunity for an improved search method.

4.1.1 AD Algorithm

The identification of individual runoff events in highly nonlinear daily streamflow is a difficult problem, and generalizing the problem across catchments of widely variable physiography adds to the challenge. For the specific use case of this study, it is important to identify a sufficient number of samples (true positives) in order to support meaningful analysis in the subsequent steps addressing the primary research question which involves hydrograph reconstruction and calculation of a runoff ratio. False negatives (missing events) are considered less important than false positives in reducing the quality of the dataset, as false positives tend to result in biased outcomes corresponding to either 0 or infinite runoff ratio.

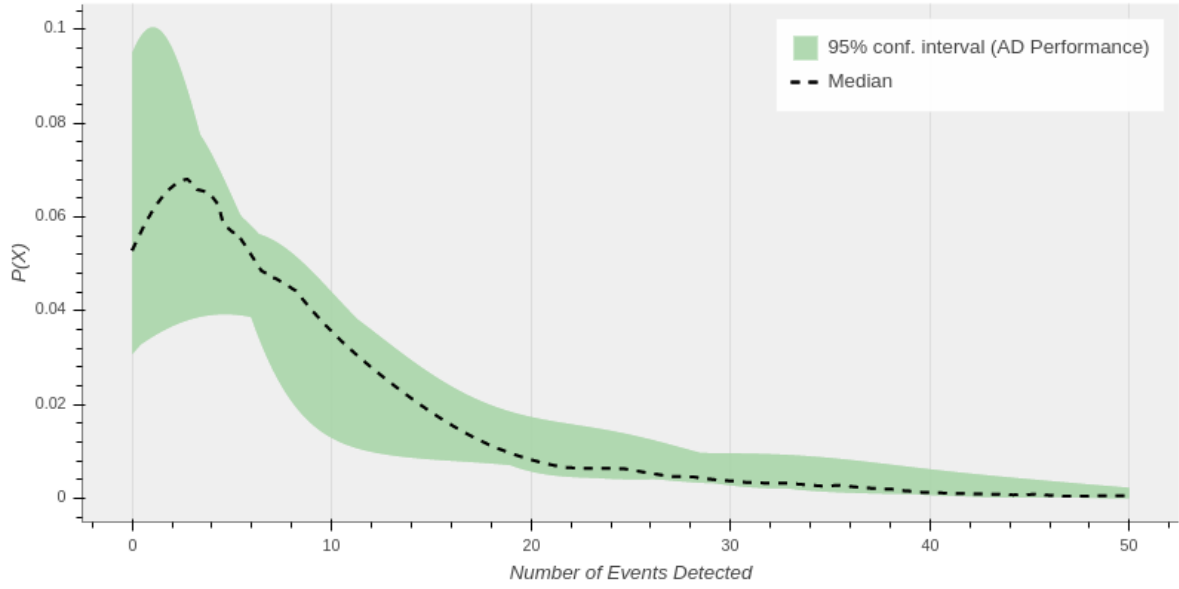


Figure 5: MC simulation: 1000 random selections of training year (KDE probability density function fit)

The AD algorithm itself takes a daily average runoff time series, and builds a matrix of some number of lag periods proportional to the size of the catchment. Using up to 7 lag periods of one day is expected to be suitable for the time of concentration of catchments in the range of 30 to 1000 km^2 . Principal Component Analysis (PCA) then reduces the number of lag series to those describing a minimum of 90% of the variance in the data. Figure 7 shows that just 2 components are required to meet the 90% variance target most of the time, however the expected AD performance is a maximum for between 4 and 5 components, and the confidence interval highlights the large amount of variance in the data for between 2 and 6 PCA components. Much of this variance is expected to result from the runoff signals themselves. A large number of runoff events will not be identified from June to September in the semi-arid climate of the BC interior.

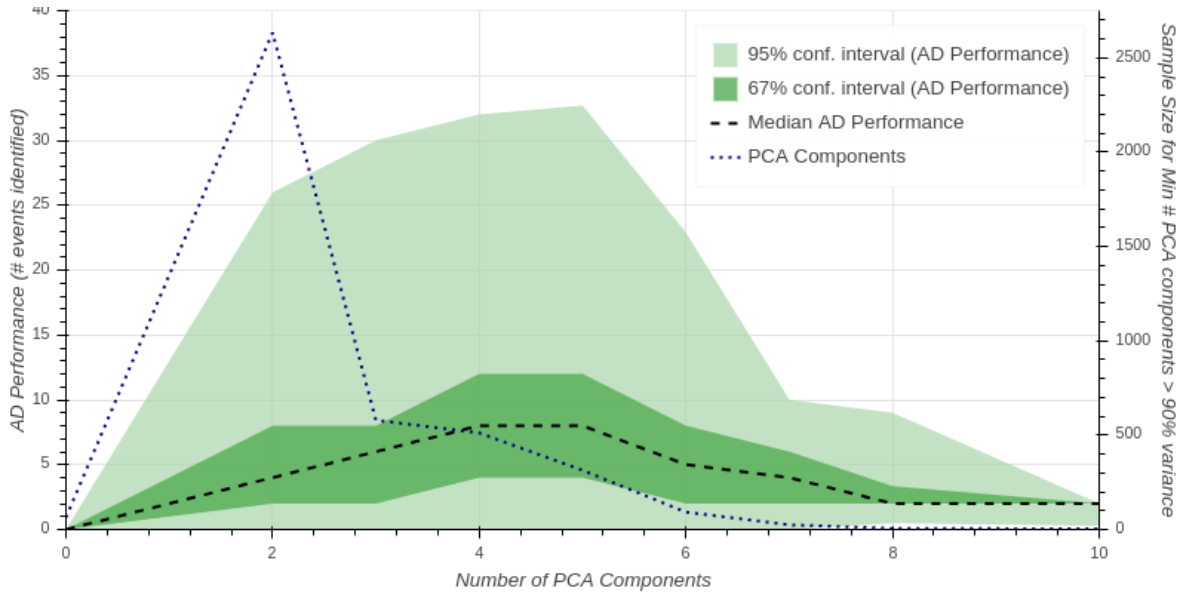


Figure 6: PCA Components and AD Performance

The principal components (PCs) comprising a minimum 90% of the variance in lagged data are then

used to create a single variable time series corresponding to the Mahalanobis distance (MD) – the Euclidean distance from each row of data points (each detrended observation and its n lags) to the corresponding PCs. A threshold Mahalanobis distance then represents some magnitude of deviation from the PC within a timeframe correspondent with the number of lags (components). The full MD time series is reduced to just the runoff events by finding the timestamps where the MD crosses the threshold (in both directions). The results are plotted in a small multiples format to facilitate verification, an example of which is presented in Figure 8 below.

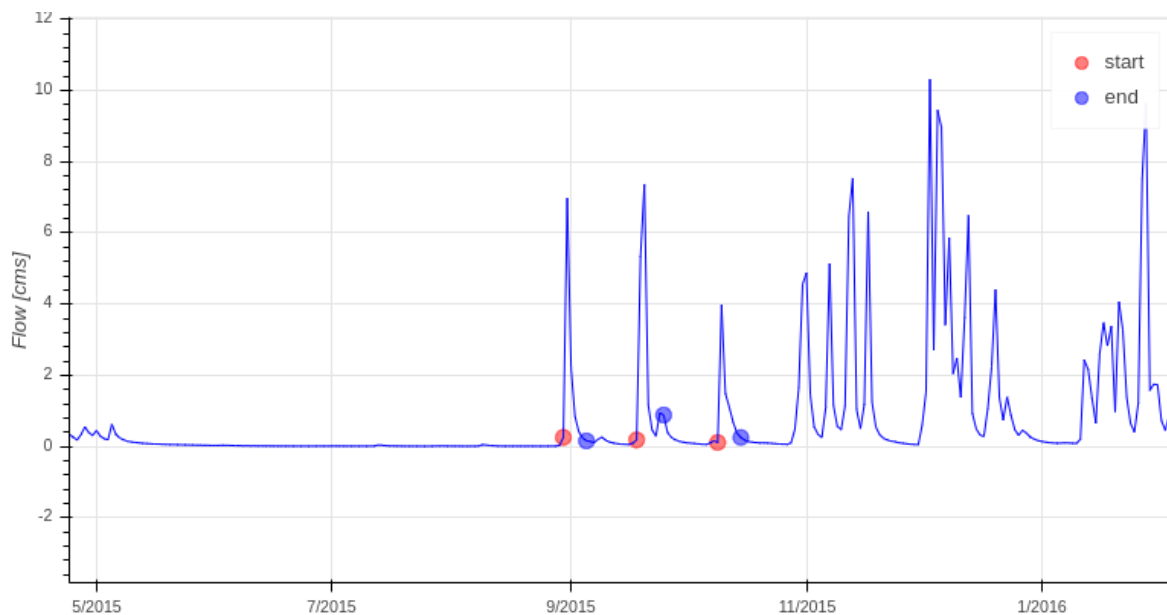


Figure 7: Example AD Results (Timeseries) for WSC 08HB048: Carnation Creek at the Mouth

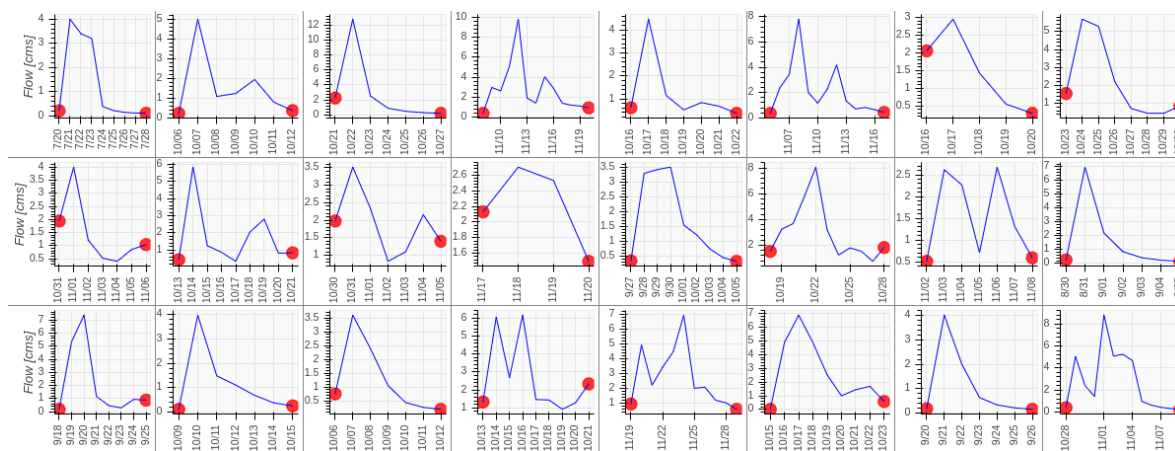


Figure 8: Example AD Results (Event Hydrographs) for WSC 08HB048: Carnation Creek at the Mouth

4.1.2 Hydrograph Reconstruction

5 Results and Discussion

6 Conclusions

References

Abadi, Martín, Ashish Agarwal, Paul Barham, Eugene Brevdo, Zhifeng Chen, Craig Citro, Greg S. Corrado, et al. 2015. “TensorFlow: Large-Scale Machine Learning on Heterogeneous Systems.” <http://tensorflow.org/>.

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