MEASURING PERFORMANCE OF GREEN STORMWATER INFRASTRUCTURE

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ABSTRACT. Heavy rainfall poses a multitude of challenges to infrastructure and communities: runoff from urban areas can pose a flood and pollution risk due to runoff from infrastructure such as highways. In a coastal city such as Vancouver, these risks are worsened by a changing climate. Around Vancouver, several sites have been constructed to allow this excess water to be better controlled, acting as a dampening mechanism and more effectively regulating pollutant levels at large. NOVION provides city workers with a means to monitor these sites remotely using sensors that log and transmit live data to a server, which is then made available via their application. In this report, we investigate techniques to detect important features in the resulting time-series of water levels from these sites. Once these apparent rainfall events are identified, statistics are calculated to quantify the performance of these sites over time.

1. INTRODUCTION AND BACKGROUND

As the climate changes, utilizing rainwater becomes urgent for many cities that are seeking methods to face the water challenges. To meet these challenges, cities are installing green rainwater infrastructure (GRI) systems to absorb and retain rainfall where it lands and reduce sewer overflow. GRI systems have been widely adopted across North America, Europe and Australia. GRI implementation and a more integrated approach to water resource management will lead to holistic integrated water utility services, protect water quality, support resilience and enhance livability and equity.

This project is working with Novion's Climate Intelligence Platform which helps cities monitor their green rainwater infrastructure for performance, optimization, regulatory compliance, and maintenance. Key parameters for understanding performance of green rainwater infrastructure include drawdown time, drawdown rate and well flood duration. Green rainwater infrastructure, such as bioswales (Figure 1), include a monitoring well (Figure 2) which consists of a perforated pipe that extends along the vertical depth of the bioswale. After a rainfall event, as the rainwater soaks into the bioswale, the water level in the monitoring well rises (Figure 3). This water level can be studied to analyze performance of the bioswale.

2. PROBLEM STATEMENT AND THE DATA

In order to evaluate the performance of the specific bioswale, first we need to identify rainfall events using the water level data.

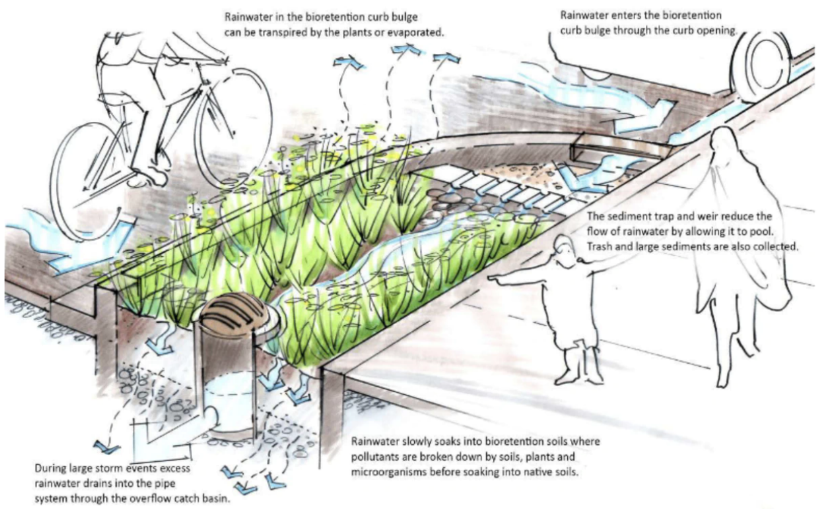

Figure 1. Green Stormwater Infrastructure: A bioretention or bioswale (City of Vancouver, 2019)

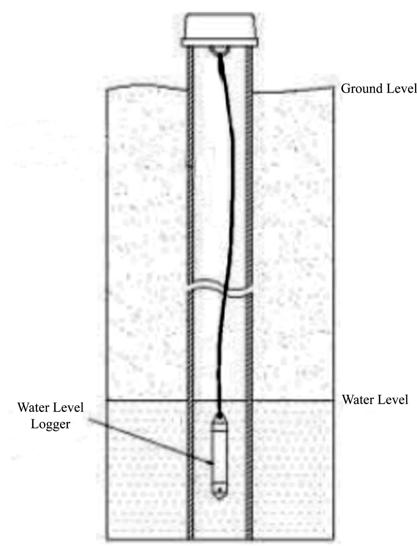

Figure 2. Monitoring Well

Definition 2.1 (Rainfall Event)**.** *A significant rise in the water level preceded by a minimum 6 hours duration of no significant change in water level signals the start of a new rainfall event.*

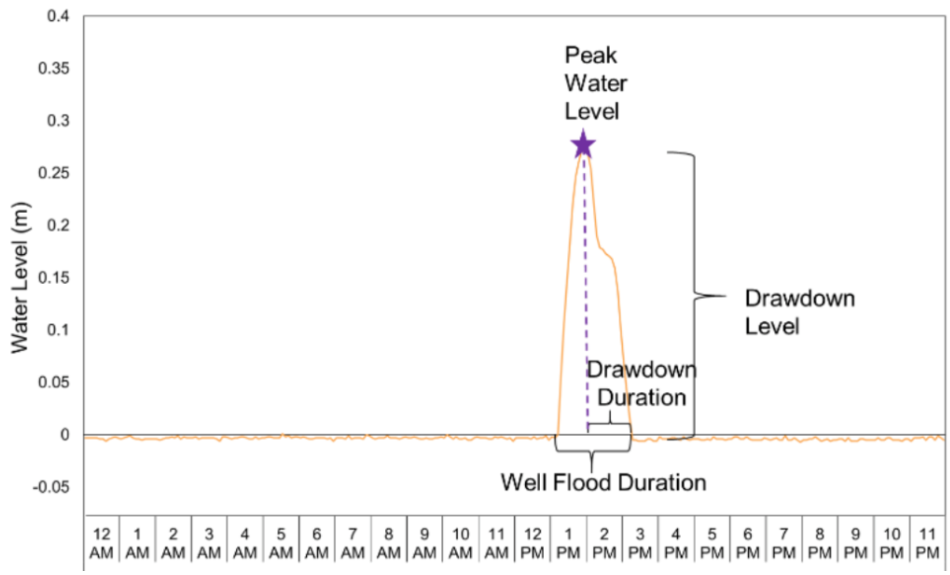

FIGURE 3. Water Level Response after a Rainfall Event (City of Vancouver, 2022)

After that, for each rainfall event the value of the key parameters to figure out are well flood duration, drawdown level, and drawdown duration.

Definition 2.2 (Well Flood Duration)**.** *The duration for the well to fill up to its peak water level and empty out.*

Definition 2.3 (Drawdown Level)**.** *The height from the peak water level to the bottom.*

Definition 2.4 (Drawdown Duration)**.** *The time it takes for the water level to go from its peak water level down to its baseline.*

Definition 2.5 (Drawdown Rate)**.** *It is the drawdown level divided by the drawdown duration.*

Then our problem can be stated as follows:

(1) Identify each rainfall event. What is the average duration of a rainfall event?
(2) What is the well flood duration (hours) for each rainfall event? What is the average well flood duration for each site? List all the rainfall events where the well flood duration exceeds 72 hours.
(3) What are the drawdown levels (mm) and drawdown durations (hours) for each rainfall event? What is the average drawdown level and average drawdown duration? What is the drawdown rate (mm/h) for each rainfall event? Can we list rainfall events where the drawdown rate is less than 40 mm/h?

There are two datasets provided by Novion from the city of Vancouver's two different sites of green rainwater infrastructure, namely Site A and Site B. Both

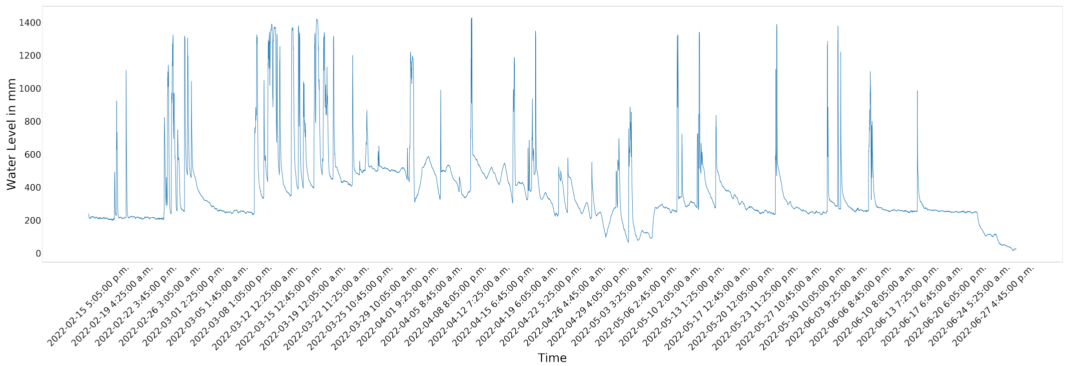

Figure 4. Water level data (Site A)

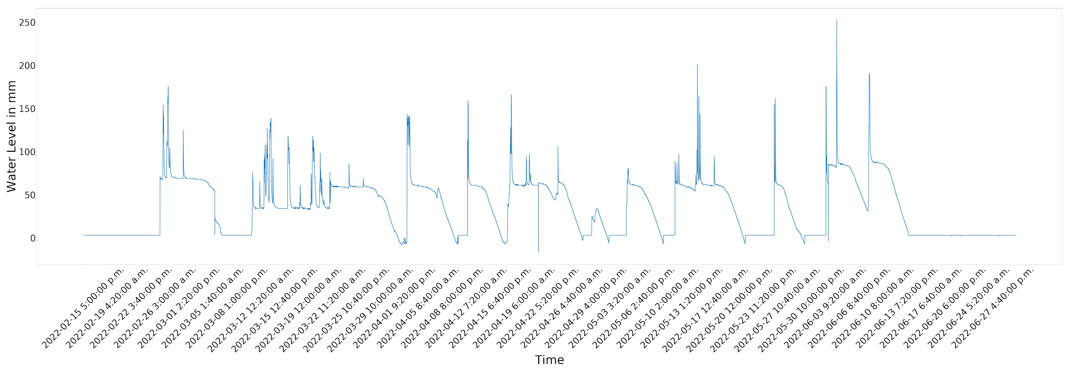

Figure 5. Water level data (Site B)

datasets include time series data of the water level from the monitoring well taken at regular intervals over a period of several months. This time interval Δt was every 5 minutes and the monitoring time period is from 5:00 pm on February 15, 2022 to 11:55 pm on June 30, 2022 for both sites. Figure 4 and Figure 5 shows the water level data for site A and site B respectively for the whole time duration.

3. Methodology

The first task set was to identify rainfall events. These are defined as periods of a significant increase in water levels, preceded by a period of at least 6 hours of no significant changes in water levels. By observing Figure 4 and Figure 5 for the water level from both sides it is clear that after a significant increase water level does not always go back to the same base level, that is, the monitoring well does not empty fully. This could be due to various factors but since we do not have access to the rainfall data of Site A and Site B, it is difficult to conclude.

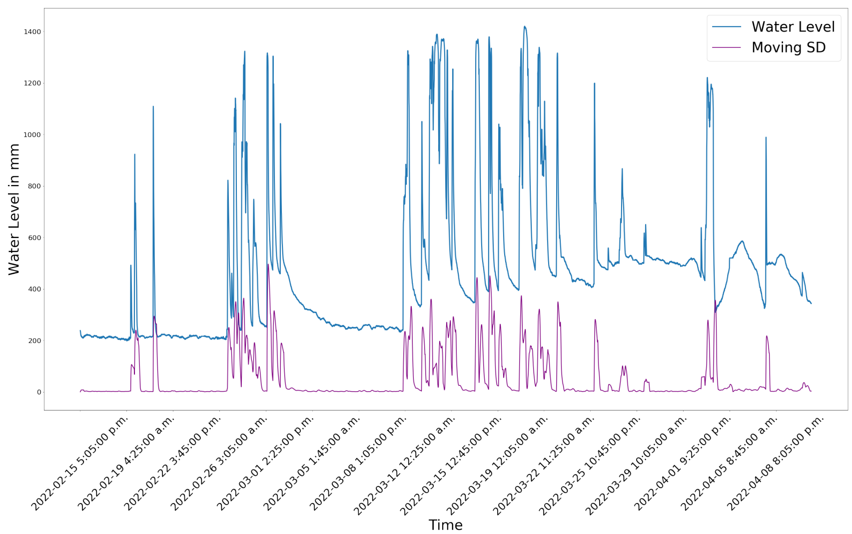

FIGURE 6. Water Level and Moving SD (Site A)

3.1. **Rainfall Event Detection.**

3.1.1. *Start of a Rainfall Event.* Given a series $(X_0, \cdots, X_{N-1})$ representing the water levels, where N is the length of the dataset, there are a few possible ways of detecting significant increases in levels. One initial approach could be to compute the numerical difference, $(Y_0, \cdots, Y_{N-2}) = (X_1 - X_0, X_2 - X_1, \cdots, X_{N-1} - X_{N-2})$, and pick a threshold $S > 0$. Possible event start times would occur whenever $Y_i > S$ for some threshold S. It then remains to filter out the possible start times that occur with at least 6 hours of the continuous dry period prior to that. The main challenge with this approach is what threshold of water level to choose to define a dry period, as from the data it is clear that no fixed threshold would work for this.

To avoid issues due to noisy data or short-level spikes that do not lead to unrealistic large events, our approach is to use the moving standard deviation, at a possible cost of a delay in uptick detection. Therefore the choice $Y_i = \mathbf{SD}(X_{i-w}, \cdots, X_{i-1}, X_i)$ where **SD** is the standard deviation and w is a choice of moving window size was made. Figure 6 and Figure 7 shows the water level and moving standard deviation (SD) of the past 6 hours, that is, we choose $w = 6 * \frac{60}{\Delta t}$. Here for sake of the presentation only partial data are shown from both sites. From both figures, it is evident that each uptick in water level also causes an uptick in moving SD but only the latter has a constant base level throughout the whole dataset. We can consider this moving SD as the smooth representation of the noisy water level data.

After Y is computed, possible event start times may be detected by applying a threshold as before, finding indices with $Y_i > S$. When choosing S there are a few possibilities. In this case parameter $0 < \lambda_S < 1$ was fixed, and then $S =$

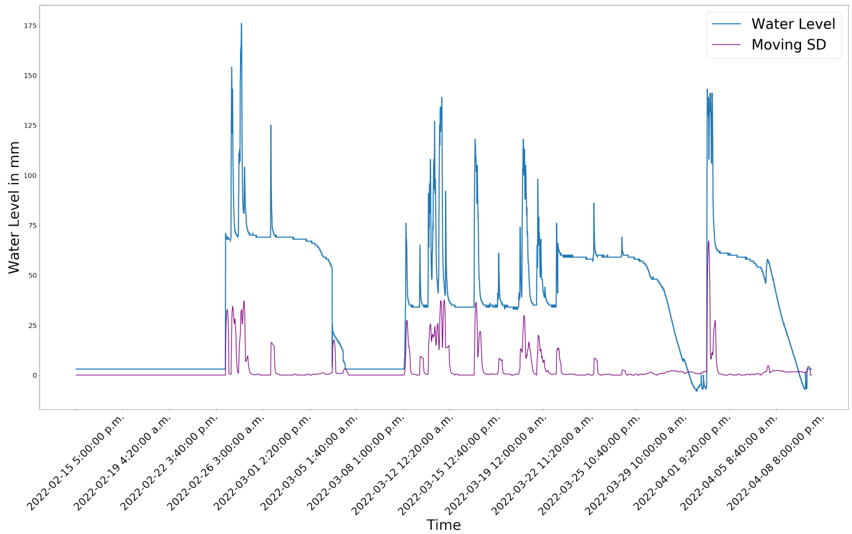

FIGURE 7. Water Level and Moving SD (Site B)

$\lambda_S \max_i\{Y_i\}$, under the notion that $\max_i\{Y_i\}$ gives an indication of the scale of jumps that occur at a fixed site. Theoretically $\max_i\{Y_i\}$ can be taken over any arbitrary time period. For both of our datasets we have taken $\max_i\{Y_i\}$ over the whole time period and $\lambda_S = \frac{3}{40}$ was found to generate a number of start times that seemed to capture important features in the time-series.

3.1.2. *End of Rainfall Event.* After the start of an event has been logged for some index i, so that $Y_i > S$ with no significant activity prior, the routine to find the rainfall event end time again uses a threshold, the end time is the first $j > i$ with $Y_j < E$ for another threshold E chosen to suit the site. Again this parameter was chosen as a proportion of the largest possible value of Y, that is, $E = \lambda_E \max_i\{Y_i\}$ with $0 < \lambda_E < 1$. For our datasets we have chosen $\lambda_E = \frac{3}{100}$.

3.1.3. *Rainfall Event Duration.* Let the pair (i_{k-1}, j_{k-1}) represent the index of start and end of k-th rainfall events and $0 \leq k \leq K-1$ with K being the total number of events found. Then surely $i_0 < j_0 < i_1 < j_1 < \cdots$ and $\frac{(j_k - i_{k-1})\Delta t}{60} \leq 6$ for any k.

The duration for k-th event is then $\frac{(j_{k-1} - i_{k-1})\Delta t}{60}$ hours and average event duration is $\frac{1}{K}\sum_{k=0}^{K-1}(j_k - i_k)\Delta t$.

Figure 8 and 9 shows us the sequence of events being identified from Site A and Site B.

3.2. **Well Flood Duration.** Let us first look into a single rainfall event closely before we start to identify the well flood duration for each event. Figure 10 is for a single rainfall event taken from Site A. We can see that the water level reaches its peak and then comes down to the baseline several times and there are several

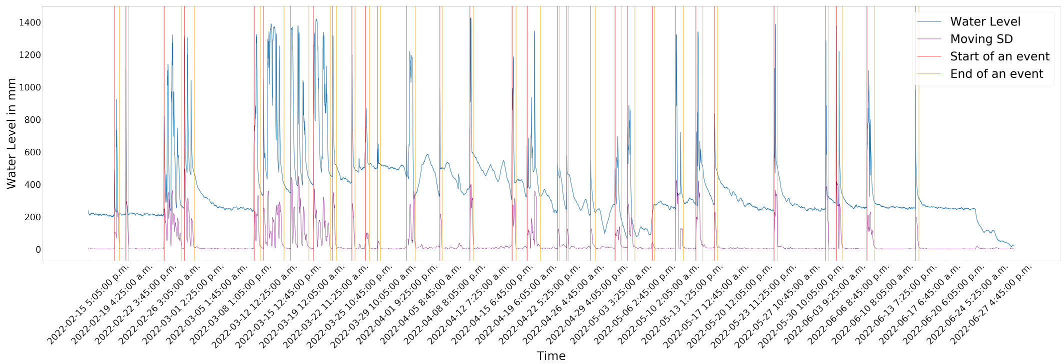

FIGURE 8. Rainfall events identified (Site A)

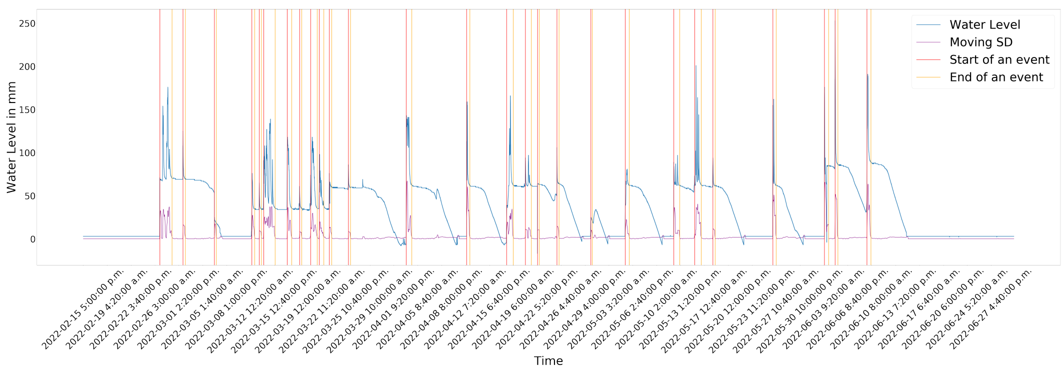

FIGURE 9. Rainfall events identified (Site B)

smaller (less than 6 hours) dry periods. But since the baseline of water level for each event are different and it does not necessarily mean that the monitoring well is emptied out entirely, for k-th event we need to set some threshold W_k for the water level and whenever for k-th event water level is staying below the threshold we would consider that as a dry period. And thus the well flood duration D_k^W for the k-th event will be the time the water level stays above or equal to W_k. We define

$$W_k = X_{min}^k + \lambda_k (X_{max}^k - X_{min}^k),$$

where $0 < \lambda_k < 1$, and X_{min}^k, X_{max}^k are minimum and maximum water level for k-th event. The green horizontal line in Figure 10 represent W_k with $\lambda_k = \frac{5}{100}$.

3.3. **Drawdown Level, Duration and Rate.** To identify the drawdown level, duration, and rate we just need to identify the peaks and bottoms of each event. First, we use the moving maximum to identify all local maximum and minimum points. Figure 11 shows the water level and a moving maximum for the last 30 minutes for a single event and we can see that at a local maximum point, the moving maximum surpasses the water level, and next they get equal at a local minimum point. We will address these local maximum points as peaks and local minimum

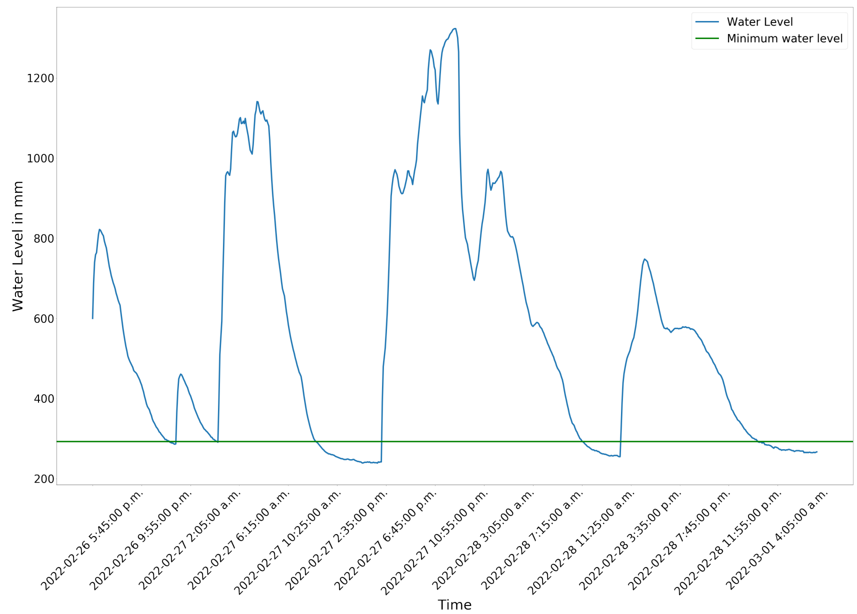

FIGURE 10. Single rainfall event

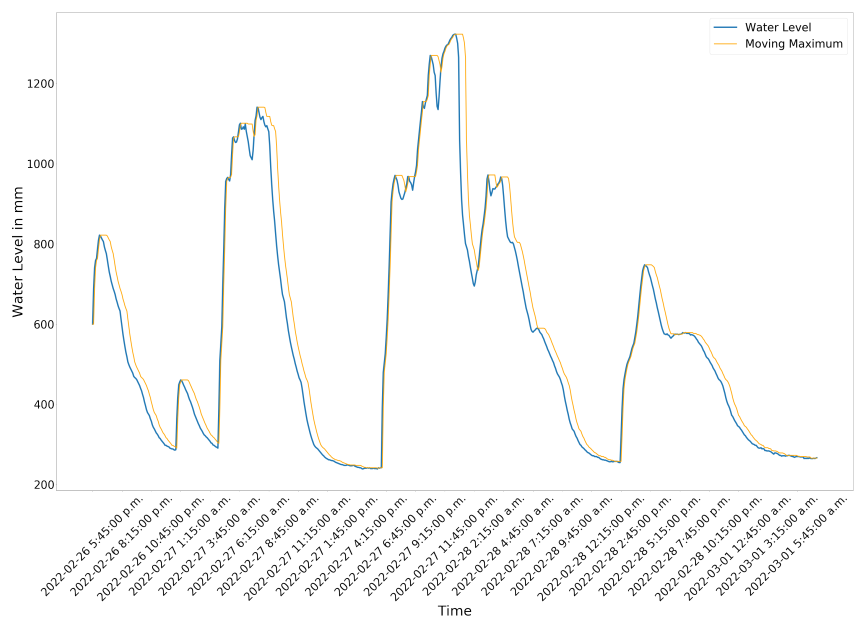

FIGURE 11. Moving maximum of last 30 minutes

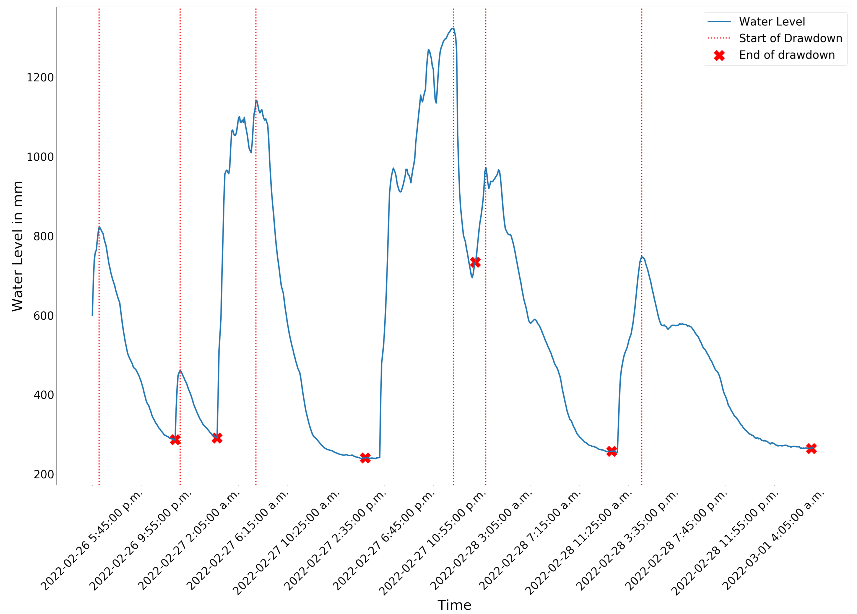

FIGURE 12. Start and end of drawdown

points as bottoms. A peak followed by a bottom will represent the time when the drawdown of water starts and ends. Next, we discard insignificant peaks, that is, discard peaks that are very close to the next one or have a very small drawdown. Figure 12 shows the start and end of several drawdowns from a single event.

Finally, Figure 13-14 and Figure 15-16 shows the histogram for drawdown rates and well flood durations from Site A and B respectively. We can see that for Site B drawdown rates were faster (small values) and well flood duration was shorter compared to Site A. This makes sense as from the water level data it was clear that the rainfall amount in Site B was significantly less compared to Site A.

4. Conclusion

In this report, we propose a general workflow to monitor fluctuation in the water level within bioswales. We have three suggestions for further development of the approach that we feel will yield significant improvements in performance. These are: Expanding the current dataset, incorporating additional rainfall data, and increasing model complexity.

Firstly, we suggest increasing the amount of data available to the model. The current algorithm is built on only 120 days of data, taken at 5-minute intervals, from two sites in the Vancouver, Canada area. The current time-series data does not account for seasonal changes which we suspect would be useful directly as rain and snowfall are seasonal. In addition, there are indirect changes in water level measurements due to physical properties of the Green Infrastructure such as porosity

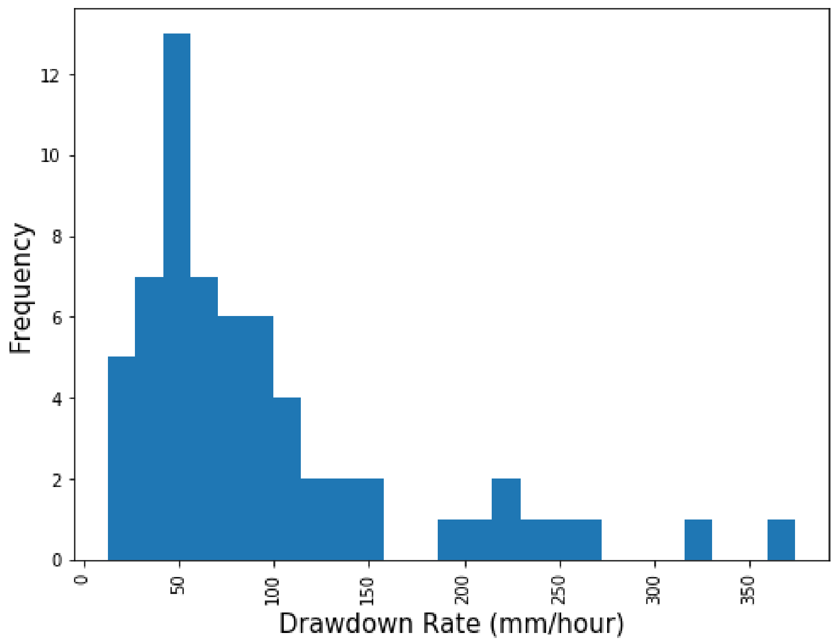

FIGURE 13. Histogram of drawdown rate (Site A)

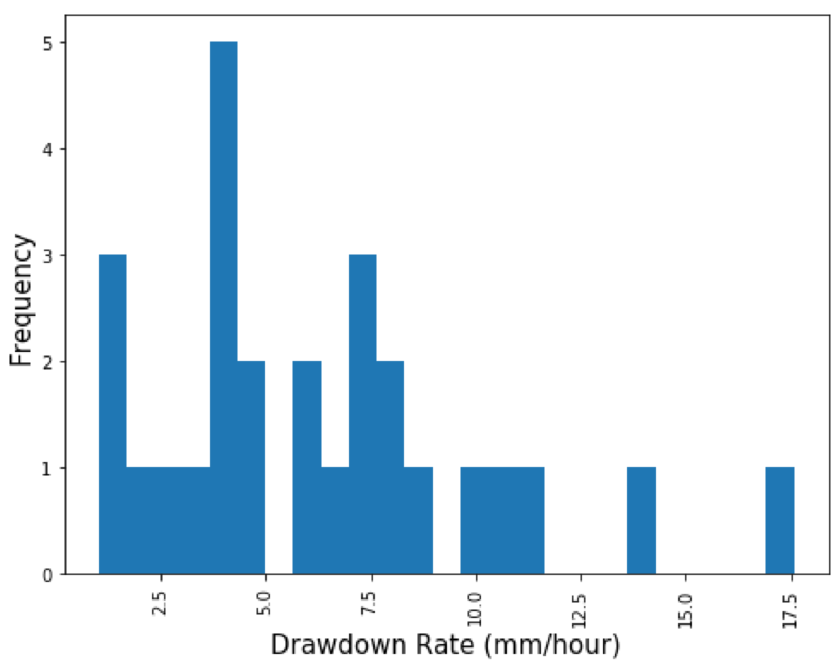

FIGURE 14. Histogram of drawdown rate (Site B)

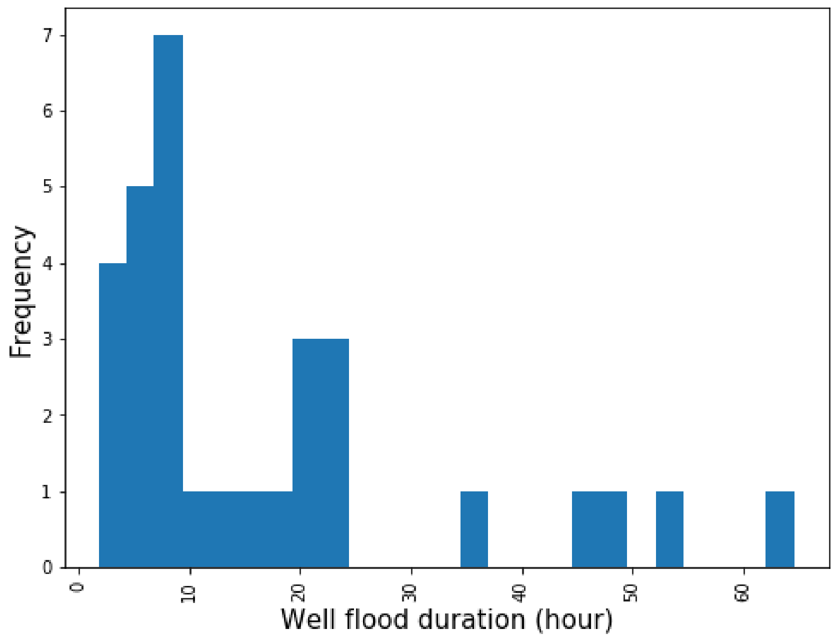

Figure 15. Histogram of well flood duration (Site A)

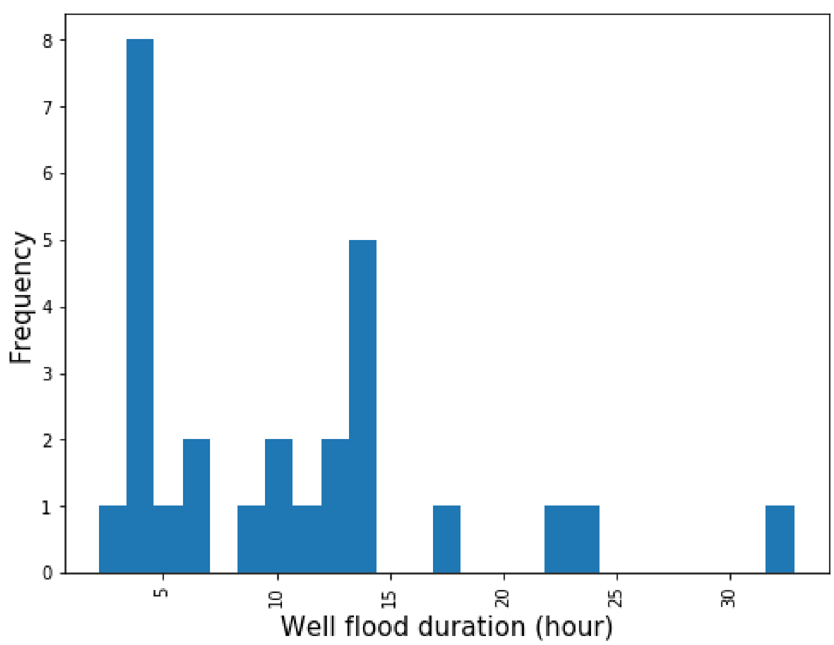

Figure 16. Histogram of well flood duration (Site B)

and physical obstruction (eg. snowfall lockages). From a Geographical perspective, these two site analyses could be expanded to more sites to make the approach more robust with respect to changes in elevation and surrounding infrastructure. This can be implemented as a single, more complex model applied to every site's data. We feel that given that the number of features used for prediction is currently low, that individual, per-site models may be preferable as this allows for better fine-tuning of each model's parameters.

Secondly, we suggest incorporating historical rainfall data, which is not included in the current model due to access restrictions. Acquiring rainfall data helps with the previously mentioned data scarcity problem as well as provides a method to detect anomalies in the data. In the latter case, having a historical or current reading for rainfall would allow Novion to detect cases where the measured water level in the GI differed significantly from the actual rainfall quantity. This disparity could be driven by censor malfunction or human actions such as illegal dumping of liquids which could lead to environmental damage.

Thirdly, we suggest increasing the model complexity by adding additional features or using an alternative model architecture. Using data that spans a further time period, features can be built and stored across time to help fine-tune the model's parameters. Alternatively, we may want to move to more complex model architectures such as SARIMA or even more current Deep Learning approaches such as LSTM / RNN models.

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