Federation University

Federation University ResearchOnline

https://researchonline.federation.edu.au

Copyright Notice

This is the author's version of a work that was accepted for publication in 10th International Conference on Water Sensitive Urban Design: Creating water sensitive communities (WSUD 2018 & Hydropolis 2018), 12-15 February 2018, Perth, Western Australia, 2018. Changes resulting from the publishing process, such as peer review, editing, corrections, structural formatting, and other quality control mechanisms may not be reflected in this document.

Copyright @ Engineers Australia

See this record in Federation ResearchOnline at:
http://researchonline.federation.edu.au/vital/access/HandleResolver/1959.17/174282

REGRESSION MODELLING FOR PREDICTION OF CLOGGING IN NON-VEGETATED STORMWATER FILTERS

Ben Meade[1], Hadi A. Khorshidi[2], Harpreet Kandra[3], Andrew Barton[4]

ABSTRACT:

KEYWORDS: Stormwater, Filtration, Clogging, Modelling, Regression

[1] Masters student, Faculty of Engineering, Federation University Australia, Churchill, Australia.
[2] Research Fellow, Faculty of Information Technology, Monash University, Clayton, Australia
[3] Lecturer, School of Engineering & IT, Federation University Australia, Churchill, Australia
[4] Associate Professor, School of Engineering & IT, Federation University Australia, Ballarat, Australia

ISBN: 978-1-925627-03-9

1 INTRODUCTION

Rapid rates of urbanisation and resulting impacts to waterways and aquatic landscapes have led to the development of integrated water management approaches such as- Water Sensitive Urban Design (WSUD) in Australia [1], Low Impact Urban Development and Design (LIUDD) in New Zealand [2], Sustainable Urban Drainage Systems (SUDS) in the UK [3] and Low Impact Development (LID) in the USA [4]. These approaches help restore stormwater flow and quality characteristics to pre-development levels. WSUD can often have several different components to target particular stormwater issues and may include storage tanks, constructed wetlands, rainwater gardens, retention ponds and filtration-based technologies [5]. The main functional issue of filtration systems, of any type, is clogging [6].

Clogging of infiltration systems is the decrease in permeability of a filtration system and occurs due to the accumulation of materials associated with treatment/ sediment removal processes [7, 8]. Clogging has been studied widely for water and wastewater treatment [9-11]. However, limited experimental and fieldwork has been undertaken to understand clogging in non-vegetated filters used for stormwater treatment and harvesting [12-16]. Furthermore, limited research exists in relation to developing models that can predict evolution of hydraulic performance overtime (i.e. development of clogging) [17-19]. Models in this regard can be very helpful in designing of such filters for different catchment conditions and predicting maintenance needs.

This research, therefore, hypothesises that it is possible to develop a model that can predict clogging behaviour of non-vegetated filters used for stormwater treatment using experimental data available for different catchment conditions. This can help in estimating useful life of the filter and planning maintenance.

2 METHODS

2.1 BACKGROUND TO EXPERIMENTAL SETUP

The modelling work undertaken in this study is based on experimental data collected while studying clogging of non-vegetated stormwater filters at Monash University, Australia [16]. Zeolite filter media was placed between a 50 mm layer of coarse gravel at the top and a 50 mm gravel layer at the bottom in 100mm diameter columns (refer Figure 1 [16]). Five different operational regime effects, representing stormwater in different catchment conditions, were tested- concentration of sediment in stormwater; presence of other pollutants; size of sediments in stormwater; stormwater loading rate; and dosing regime. Five replicates of each operational regime were compared with the 'Base case', which represents conditions most likely in Melbourne, as explained in Table 1. Comparisons between designs were made for evolution of hydraulic and treatment performances.

Figure 1: *Column configuration*

ISBN: 978-1-925627-03-9

Table 1: *Comparison of operational conditions [16]*

Tested effects	Operational Conditions
Base Case	Inflow TSS of about 150mg/L; Stormwater made of sediments only; Sediment particle size in stormwater <100 um; Stormwater hydraulic loading of 15 L/day; Daily dosing
1. Effect of inflow sediment concentration (Low TSS and High TSS)	*Inflow TSS: Low (about 25mg/L) and High (about 400mg/L);* Stormwater made of sediments only; Sediment particle size in stormwater <1000 um; Stormwater hydraulic loading of 15 L/day; Daily dosing
2. Effect of other (than TSS) pollutant concentrations	Inflow TSS of about 150mg/l; *Complete stormwater made of sediments, nutrients and heavy metals (using typical stormwater composition);* Sediment particle size in stormwater <1000um; Stormwater hydraulic loading of 15 L/day; Daily Dosing
3. Effect of stormwater sediment particle size (Fine sediment)	Inflow TSS of about 150mg/L; Stormwater made of sediments only; *Sediment particle size in stormwater <75 um;* Stormwater hydraulic loading of 15 L/day; Daily dosing
4. Effect of hydraulic loading rate (High and Low loading rate)	Inflow TSS of about 150mg/L; Stormwater made of sediments only; Sediment particle size in stormwater <75 um; *Low loading rate of 5 L/day and High loading rate of 45 L/day* Daily dosing
5. Effect of loading regime (Alternate day and Weekly)	Inflow TSS of about 150mg/L; Stormwater made of sediments only; Sediment particle size in stormwater <75 um; Stormwater hydraulic loading of 15 L/day; *Alternate day dosing and Once a week dosing*

2.2 MODELLING

2.2.1 SIMPLE UNIVARIATE REGRESSION

A simple univariate regression model was derived for each operational regime in the first stage of this modelling exercise. Nine combinations of simple univariate models (both linear and exponential) have been created using Infiltration Rate (mm/hr) and Normalized Volume (Equivalent metres). Each model has been created using the regression analysis tool on MS-Excel. The "Normalized Volume" has been calculated by dividing the total mass of sediment applied by 150 mg/l (the target inflow TSS concentration) and then expressing all results in Equivalent Meters of treated water for same inflow sediment conditions, as reported in Kandra et al (2015) [16]. When creating the Simple univariate models data from each of the replicate columns was used to determine what type of model (linear or exponential) best predicts clogging.

2.2.2 MULTIVARIATE REGRESSION

Multivariate regression models have been developed using the information gained from the Simple Regression analysis aiming to develop more comprehensive predictive models representing mix of catchment conditions. The Multivariate models have been created using median values for the different column replicates again using the regression analysis tool on excel. Kandra et al (2015) [16] observed that Sediment Concentration, Sediment Size, and Loading Rate have significant effects on infiltration rate. Therefore, following four Multivariate models have been developed for practical use using a mix of operational regimes to predict the volume of stormwater treated in relation to hydraulic performance:

1. Normalized Volume, Loading rate and Sediment Concentration
2. Normalized Volume, Loading Rate and Particle Sediment Size
3. Normalized Volume, Sediment Concentration and Sediment Size, and
4. Normalized Volume, Loading Rate, Sediment Concentration, and Sediment size all together.

The multivariate regression models created are compared using Adjusted R^2 instead of R^2. The issue with using R^2 is that it always increases as more variables are added, while the Adjusted R^2 will decrease for the inclusion of unnecessary variables [20].

Bi-linear models have also been derived to better model the data for different rates of decline in hydraulic performance. Best practices have been followed by using a training data set (Median

ISBN: 978-1-925627-03-9

Values) and a test data set (all replicate data excluding 75 µm replicates) [20]. From this, Root Mean Square Error (RMSE) has been calculated for each equation to determine which model works best.

3 RESULTS AND DISCUSSIONS

3.1 SIMPLE UNIVARIATE REGRESSION

In general, simple univariate models are not practical for estimating the evolution of hydraulic performance and/or the design life of a filter. However, they help us identify which operational regimes significantly affect hydraulic performance and nature of relationship, such as linear or exponential. From the outputs shown in Table 2, the following observations can be made:

- Each univariate model has a different Initial Infiltration Rates (IIR) because hydraulic performance at the start varied across all replicates but in practice, the design IIR can be assumed to be around 90,000 mm/hr.
- In all of the regimes, bar the 75 µm sediment size regime, the linear model produces a coefficient of determination

Table 2: Results from Univariate Regression Modelling

Where 'm' is the Normalized Volume of stormwater applied

Regime	Equation	R^2	T-Stat	P-Values	F	Number of Observations
Base case: Linear model	IR = 90984.459 – 6264.552 x m	0.814	-23.762	<0.001	564.6	131
Base case: Exponential model	Log_{10} (IR) = 5.411 – 0.159 x m	0.377	-8.834	<0.001	78	131
Heavy Metals & Nutrients: Linear model	IR = 96298.408 – 7439.584 x m	0.859	-26.371	<0.001	695.4	116
Heavy Metals & Nutrients: Exponential model	Log_{10} (IR) = 5.354 – 0.156 x m	0.333	-7.54	<0.001	56.9	116
75 µm Size: Linear model	IR = 86796.679 – 265.027 x m	0.779	-61.643	<0.001	3799.9	1080
75 µm Size : Exponential model	Log_{10} (IR) = 4.944 – 0.002 x m	0.761	-58.586	<0.001	3432.4	1080
Inflow sediment concentration - 5L/day: Linear model	IR = 104754.413 – 6384.190 x m	0.87	-31.962	<0.001	1021.6	154
Inflow sediment concentration - 5L/day: Exponential model	Log_{10} (IR) = 5.442 – 0.128 x m	0.389	-9.842	<0.001	96.86	154
Inflow sediment concentration - 45L/day: Linear model	IR = 90026.842 – 7420.498 x m	0.762	-15.921	<0.001	253.5	81
Inflow sediment concentration - 45L/day: Exponential Model	Log_{10} (IR) = 5.289 – 0.178 x m	0.319	-6.087	<0.001	37.1	81
TSS concentration 25mg/L: Linear model	IR = 91228.812 – 3865.798 x m	0.865	-35.301	<0.001	1246.2	196
TSS concentration 25mg/L: Exponential Model	Log_{10} (IR) = 5.309 – 0.081 x m	0.308	-9.282	<0.001	86.1	196
TSS concentration 400 mg/L: Linear model	IR = 102632.312 – 9236.023 x m	0.924	-36.84	<0.001	1357.2	114
TSS concentration 400 mg/L: Exponential model	Log_{10} (IR) = 5.569 – 0.222 x m	0.459	-9.74	<0.001	94.9	114
Alternate Day dosing: Linear model	IR = 89939.841 – 6619.844 x m	0.816	-22.574	<0.001	509.6	117
Alternate Day dosing: Exponential model	Log_{10} (IR) = 5.331 – 0.153 x m	0.293	-6.905	<0.001	47.7	117
Weekly dosing: Linear model	IR = 95500.953 – 6984.458 x m	0.845	-25.292	<0.001	639.7	119
Weekly dosing: Exponential model	Log_{10} (IR) = 5.433 – 0.168 x m	0.328	-7.56	<0.001	57.2	119

(R^2) which is significantly larger than the corresponding exponential model. The linear models have a goodness of fit ranging from 76.2%, for the 45L/day regime, to 92.4%, for the 400mg/l regime. Whereas the corresponding R^2 values for exponential models range between 29.3% to 76.1%.

- A comparison of the rates of change between the base case and other operational regimes indicates which regimes are more significant than others. For instance, particle sediment size was most different with an infiltration decline rate of 265 per m (normalize volume) applied as compared to the Base case that had an infiltration decline rate of 6265 per m.

3.2 MULTIVARIATE REGRESSION ANALYSIS (MVRA)

3.2.1 MULTIVARIATE REGRESSION ANALYSIS TO PREDICT INFILTRATION RATE

As univariate regression analysis showed that linear modelling is more suitable than exponential one, the multivariate regression models were developed in linear ways. The following four equations were derived to predict the infiltration rate:

$$IR = 112672 - 5473.2 \times m - 491.6 \times LR - 68.1 \times TSS \quad (1)$$

$$IR = 92294.4 - 290.4 \times m - 87.3 \times LR - 34.7 \times SS \quad (2)$$

$$IR = 93027.2 - 296.7 \times m - 10.6 \times TSS - 36.2 \times SS \quad (3)$$

$$IR = 95868.9 - 322.5 \times m - 89.4 \times LR - 11.3 \times TSS - 36.34 \times SS \quad (4)$$

where, IR = Infiltration Rate,
m = Normalized Volume in Equivalent metres,
LR = Loading Rate in L/day,
TSS = Sediment Concentration in mg/L,
SS = Sediment Size in microns (µm)

The linear equation for ‘Normalized Volume, Loading Rate & Sediment Concentration’, Equation (1), gives a significantly better-adjusted coefficient of determination (Adjusted R^2) of 78.3% as compared to Equation (2)- 36.6%, Equation (3)- 41.0%, and Equation (4)- 33.0%.

The possible reason for the observed changes in the accuracy of these linear models, as in Equations 2,3,4, is due to the inclusion of data for the design with 75 µm sized particles. While it is obvious that sediment size is a significant factor, the data collected from the experiment was too broad and these columns did not clog. Therefore, for the remainder of the study the 75 µm sediment size case data was no longer used. It is also recommended that in future experiments more sediment sizes should be tested for much longer periods.

Further testing of Equation (1) to predict the infiltration rate of a hypothetical stormwater filter, we found that it would give an appropriate result for Infiltration Rate at high levels only (those greater than 45000 mm/hr), but would over predict for low infiltration rates and hence a single linear model cannot accurately predict when the subject stormwater filter will clog. Analysis of evolution of hydraulic performance suggests that filters have different decline behaviours during different stages of their operational life. It was observed that the decline behaviour changes approximately around 6 m of stormwater application. Therefore, it was decided to create a bi-linear regression model.

The bi-linear model includes a linear multivariate mode for normalized volume values from 0 m to 6 m; and another linear model for normalized volume values from 6 m onwards. Important to note here is that data for operational regime using sediment size less than 75 µm has not been used for reasons discussed earlier. These bi-linear models were created using the median values and were then tested against data from all other cases, including the heavy metals and Nutrients regime and the dosing regimes. The following bi linear equation was derived:

$$\begin{cases} IR = 93108.1 - 3582.1 \times m - 268.7 \times LR - 1.6 \times TSS, & m < 6 \ (5a) \\ IR = 132623.4 - 6166.1 \times m - 800.2 \times LR - 131.3 \times TSS, & m \geq 6 \ (5b) \end{cases} \quad (5)$$

Equation 5a has an Adjusted R^2 value of 70.4% (for Normalized Volume less than 6 m) and Equation 5b has an Adjusted R^2 value of 71.7% (for Normalized Volume equal to or greater than 6 m).

Comparison of the linear and bi-linear multivariate equations (Equation 1 and 5) suggests that:

- Equation 1 has a slightly higher adjusted R^2 of 78.3%;

- Equation 1 has a Root Mean Square Error (RMSE) of 11101 mm/hr for normalized volume less than 6m, which is higher than RMSE, of 8516, for Equation 5a;
- Equation 1 has a RMSE of 17018 mm/hr for normalized volume equal or greater than 6m, which is slightly higher than RMSE, of 16101, for Equation 5b.

When testing Equation (5) to predict the infiltration rate of a hypothetical stormwater filter, we found that it would still over predict for low infiltration rates. While initially theorised that by splitting the model, by 0 m to 6 m of Normalized Volume and from 6m onwards of Normalized volume, would produce significantly better results for filtration rates under 45,000 mm/hr the results show otherwise. Further investigation could produce a more appropriate Normalized Volume change point.

3.2.2 MULTIVARIATE REGRESSION ANALYSIS TO PREDICT EQUIVALENT METERS OF STORMWATER TREATED

Above results of the bi-linear model suggest further analysis of the data to create a better model to predict the clogging rate of a stormwater filter. It was therefore theorized that creating a multivariate model that predicts equivalent meters of stormwater passed will better predict when a stormwater filter will clog and therefore the following multivariate Equation 6 was derived to predict the meters of stormwater passed:

$$m = 18.397 - 0.00014 \times IR - 0.0873 \times LR - 0.0121 \times TSS \qquad (6)$$

where, IR = Infiltration Rate,
m = Normalized Volume,
LR = Loading Rate in L/day,
TSS = Sediment Concentration in mg/L,

Equation (6) produced a good Adjusted R^2 value of 80.7%. When tested to predict the equivalent meters of stormwater passed of a hypothetical stormwater filter, we found that it would give an appropriate result of equivalent meters of stormwater passed for all levels, but would still slightly over predict for low infiltration rates. Given that, as discussed earlier, filters have different decline behaviours during different stages of their operational life, a bi-linear regression model was attempted.

This bi-linear model again includes a linear multivariate mode for Infiltration Rate values larger than 45,000 mm/hr; and another linear model for Infiltration Rate values from below 45,000 mm/hr, using same approach as in the earlier section but developed for volume of stormwater passed (equivalent metres). The following bi- linear equation was created:

$$\begin{cases} m = 25.406 - 2.6 \times 10^{-4} \times IR - 0.0867 \times LR - 0.0044 \times TSS, & IR > 45000 \ (7a) \\ m = 18.974 - 8 \times 10^{-5} \times IR - 0.1224 \times LR - 0.0203 \times TSS, & IR < 45000 \ (7b) \end{cases} \qquad (7)$$

Using Equation 7, it is possible to predict the equivalent meters of stormwater passed before the filter clogs at an infiltration rate of approximately 100 mm/hr for given catchment conditions (loading rate and sediment concentration). Alternatively, if the treated stormwater has been measured, Equation 7 can be re written as below to predict filter's infiltration rate using Equation 8, as below:

$$\begin{cases} IR = \dfrac{m - 25.406 + 0.0867 \times LR + 0.0044 \times TSS}{-2.6 \times 10^{-4}}, & IR > 45000 \ (8a) \\ IR = \dfrac{m - 18.974 + 0.1224 \times LR + 0.0203 \times TSS}{-8 \times 10^{-5}}, & IR < 45000 \ (8b) \end{cases} \qquad (8)$$

Equation 7a has an Adjusted R^2 value of 85.7% (for Infiltration Rates larger than 45,000 mm/hr) and Equation 7b has an Adjusted R^2 value of 78.2% (for Infiltration Rates below 45,000 mm/hr).

Comparison of statistical values is as below:
The bi-linear multivariate equation has slightly better adjusted R^2 of 85.7%;
RMSE for Equation 7a is 1.849 m, which is better than linear Equation 6- 2.1711 m (for infiltration rates larger than 45,000 mm/hr)
RMSE for Equation 7b is 2.447 m, which is again better than linear Equation 6- 2.7362 m (for Infiltration Rates less than 45,000 mm/hr)
As shown above the RMSE for infiltration rates under 45,000 mm/hr is significantly higher than for infiltration rates larger than 45,000 mm/hr therefore more investigation could produce a more accurate model. When testing Equation 7 to predict the infiltration rate of a hypothetical stormwater filter, we found that it would produce appropriate results for all infiltration rates.

4 CONCLUSIONS

The univariate models, while not practically useful, gave good insight into predicting the final model to be of a linear relationship. It was found that even though sediment size is a significant factor affecting hydraulic performance, it could not be used in developing the models using available data

set and it would be impractical in field to estimate size of sediment in stormwater. Several multi-variate regression analysis models were developed, tested and compared using adjusted R^2 values and Root mean square error (RMSE) between Normalized volume (equivalent metres of stormwater treated), Stormwater loading rate (L/day), Sediment Concentration (mg/L), and Infiltration rate (mm/hr).

Eventually, the bi-linear model created for calculating Normalized volume (equivalent metres of stormwater treated), which is a combination of two separate equations, corresponding to different decline rates produced the best results with acceptable Adjusted R^2 and RMSE values. The model produced gives good estimates for stormwater with sediment size close to 1000 µm as observed for urban catchments. Further investigation needs to be completed for sediment size and polynomial models could be applied to create better results.

ACKNOWLEDGEMENT

Enter acknowledgements directly before the references. Use the format of primary section headers, but do not number the acknowledgement and references sections.

REFERENCES

[1] Morison, P.J. et al. Understanding the nature of publics and local policy commitment to Water Sensitive Urban Design. Landscape and Urban Planning 99, 83-92, 2011

[2] van Roon, M. et al. Low Impact Urban Design and Development: the big picture. Auckland: Manaaki Whenua Press. 2009

[3] Martin, P. Sustainable Urban Drainage Systems: Best Practice Manual for England, Scotland, Wales and Northern Ireland. Construction Industry Research and Information Association, 2000

[4] Martin-Mikle, C.J. et al. Identifying Priority sites for low impact development (LID) in a mixed-use watershed. Landscape and Urban Planning 140, 29-41, 2015.

[5] Massoudieh, A. et al. A flexible modeling framework for hydraulic and water quality performance assessment of stormwater green infrastructure. Environmental Modelling & Software 92, 57-73, 2017

[6] Siriwardene, N., Deletic, A. and Fletcher, T.D., 2007. Clogging of stormwater gravel infiltration systems and filters: Insights from a laboratory study. Water Research, 41, pp. 1433 – 1440.

[7] Perez-Paricio, A., 2001. Integrated modelling of clogging processes in artificial groundwater recharge, Technical University of Catalonia, Barcelona, Spain.

[8] Bouwer, H., 2002. Artificial recharge of groundwater: Hydrogeology and engineering. Journal of Hydrogeology, 10(1), pp. 121-142.

[9] Spychala, M. and Blazejewski, R., 2003. Sand filter clogging by septic tank effluent. Water Science and Technology, 48(11-12), 153-159.

[10] Winter, K.J. and Goetz, D. (2003) The impact of sewage composition on the soil clogging phenomena of vertical flow constructed wetlands.Water Science and Technology, 48(5), pp. 9-14.

[11] Yaman, C., Martin, J.P. and Korkut, E., 2006. Effects of wastewater filtration on geotextile permeability. Geosynthetics International, 13(3), pp. 87-97.

[12] Abbott, C.L. and Comino-Mateos, L., 2001. In situ performance of an infiltration drainage system and field testing of current design procedures. Journal of Charted Institution of Water and Environmental Management, 15(3), pp. 198-202.

[13] Birch, G. F., Fazeli M. S. and Niatthai C., 2005. Efficiency of an infiltration basin in removing contaminants from urban stormwater. Environmental Monitoring and Assessment, 101(1-3), 23-38.

[14] Bratieres, K., Schang, C., Deletic, A. and McCarthy, D.T., 2012. Performance of enviss™ stormwater filters: results of a laboratory trial. Water Science and Technology. 66(4), pp 719-727.

[15] Dechesne, M., Barraud, S. and Bardin, J.P., 2005. Experimental assessment of stormwater infiltration basin evolution. Journal of Environmental Engineering. 131(7), pp. 1090-1098.

[16] Kandra H, McCarthy D, Deletic A: Assessment of the Impact of Stormwater Characteristics on Clogging in Stormwater Filters. Water Resources Management, 1031-1048, 2015.

[17] Yong, C.F., McCarthy D.T. and Deletic A., 2013. Predicting physical clogging of porous and permeable pavements. Journal of Hydrology 481, pp. 48–55.

[18] Siriwardene, N., Deletic, A. and Fletcher, T.D., 2007. Modeling of sediment transport through stormwater gravel filters over their lifespan. Environment Science Technology, 41, pp. 8099-8103.

[19] Siriwardene, N.R., 2008. Development of an experimentally-derived clogging prediction method for stormwater infiltration and filtration systems. PhD thesis, Institute for Sustainable Water Resources, Department of Civil Engineering, Monash University, Melbourne.

[20] James G, Witten D, Hastie T, Tibshirani R: An Introduction to Statistical Learning. Springer New York Heidelberg Dordrecht London, 2013