TITLE:

Commonality of rainfall variables influencing suspended solids concentrations in storm runoff from three different urban impervious surfaces

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Abstract

Finding a common set of rainfall variables to explain the concentration of suspended solids in runoff from typical urban impervious surfaces has many applications in stormwater planning. This paper describes a statistical process to identify key explanatory variables to Non-Coarse Particle (suspended solids<500 μm size) event mean concentrations measured from road, carpark and roof surfaces located in Toowoomba, Australia. The dominant variables for all surfaces were rainfall depth and peak 6-minute rainfall intensity. Storm duration, defined as the time period when rainfall intensity exceeds 0.25 mm/hr and antecedent storm rainfall were also important predictors, but was less dominant. The regression model fitted to non-coarse particle concentration across all surfaces was proportional to rainfall depth raised to a negative power and peak 6-minute rainfall intensity raised to a positive power; the proportionality constant varies by surface type. The form of this common model has a physical basis and is analogous to the Modified Universal Soil Loss equation widely used for soil loss estimation for non-urban areas.

Keywords

Stormwater; urban runoff; suspended solids; regression analysis; low impact development

Abbreviations

Hydrology terms

a, b: proportionality constants

AADT: Average annual daily traffic (vehicles/day)

ADP: Antecedent dry period (hrs, days)

AR: Antecedent rainfall (mm) defined as the rainfall depth of the previous storm event

ED: Event duration (hrs) defined as the time period from start of rainfall to cessation of rainfall

EMC: Event mean concentration (mg/L)

LID: Low-impact development

MI: Mean rainfall intensity (mm/hr)

MUSLE: Modified universal soil loss equation

NCP: Non-coarse particles (size<500 μm)

PI: Peak 6-minute rainfall intensity (mm/hr)

$Q_{p:}$ Peak runoff discharge (m^3/s)

$Q_{v:}$ Runoff volume (m^3)

RD: Rainfall depth (mm)

SD: Storm duration (hrs) defined as the cumulative time within storm event when rainfall intensity exceeded a nominal 0.25 mm/hr

SSC: Suspended sediment concentration

SSGR: Suspended sediment generation rate (fraction)

TSS: Total suspended solids

Statistical terms

AIC: Akaike's An Information Criterion

BIC: Bayesian Information Criterion

BMA: Bayesian Model Averaging

PRESS: Predicted residual sum of squares

r: The correlation coefficient

$\bar{R}^2$: Adjusted R^2, where R^2 is the coefficient of determination

RSS: Residual sums-of-squares

VIF: Variance inflation factor, a measure of the collinearity between predictors in a regression equation

1. Introduction

Unless properly managed, suspended solids in stormwater are a major cause of adverse effects within aquatic ecosystems downstream of urban areas (Borchardt and Sperling, 1997). Low-impact development (LID) has emerged as a management response to address these and other stormwater impacts (Dietz, 2007). Alternative terms for this approach include water sensitive urban design and sustainable urban drainage systems.

LID is transforming the management focus from the reliance on a few large-scale management devices to many controls strategically distributed throughout urban areas. This paradigm shift in stormwater management towards at-source control places greater emphasis on small-scale hydrological processes and, subsequently, more knowledge is needed about stormwater generated from specific types of urban surfaces. This includes techniques to predict suspended solids loads in runoff from impervious urban surfaces such as roads, roofs and carparks.

The estimation of suspended solids in stormwater for the purpose of LID assessment tend to be based on simple methodologies, including buildup-washoff relationships, characteristic concentrations (sometimes with a stochastic component), empirical power rating curves for concentration as a function of discharge and unit area loadings (Elliott and Trowsdale, 2007).

Consistent with the methodologies used in LID modelling, this paper will focus on the use of simple regression-based relationships to estimate the event mean concentration (EMC) of suspended solids in runoff from impervious urban surfaces. Stormwater data collected by the monitoring of three surfaces (road, roof and carpark) located at Toowoomba, Australia (Brodie, 2007) was used in the EMC analysis.

A prerequisite for any regression analysis is the identification of key explanatory variables. An overview by Vaze and Chiew (2003b) found that a wide diversity of variables have been used to estimate the washoff of particles from urban areas including rainfall intensity, rainfall volume, runoff rate, runoff volume, raindrop impact energy and overland flow shear stress. Most of these variables are to some extent correlated with each other, and thus it is difficult to ascertain the dominant drivers of suspended solids washoff. Key variables are discussed in more detail in Section 2 of this paper, based on a review of the literature.

The main objective of this paper is to establish whether a common set of hydrological variables (such as storm rainfall depth, intensity and duration) apply across the three different surfaces under analysis. In keeping with the 'dominant processes concept' used elsewhere in hydrology (Sivakumar, 2004), we aimed to isolate the few dominant variables that capture the essential suspended particle response to storm events. Identification of such dominant predictors avoids overparameterization and leads to more parsimonious regression models. Two different statistical approaches (conventional regression and Bayesian model averaging) were applied to identify dominant predictors and to ascertain whether these predictors are common to all three surface types.

2. Variables influencing suspended solids washoff from urban surfaces

Regression relationships to estimate total suspended solids (TSS) exports from urban catchments as a whole are available (e.g Brezonik and Stadelmann, 2002; Driver and Tasker, 1990; LeBouthillier et al., 2000; McLeod et al., 2006; Vaze and Chiew, 2003a). Pollutant generation from urban surfaces in these studies were aggregated as a single land use category (such as 'residential' or 'commercial'), so do not provide information on the individual contributions made by specific types of surfaces. In this regard, there are other studies that have focussed on runoff from individual urban surfaces, notably roads and highways that are considered herein.

Tasker and Granato (2000) summarised a number of studies that established regression relationships for roads and highways associated with suspended particles (mainly TSS). Further details are compiled in Table 1, and a post-2000 study by Kayhanian et al. (2007) has been added. No clear consensus exists in identifying the explanatory variables important to suspended solids in road runoff. Variables that have been used include various measures of vehicle traffic, storm hydrological characteristics (runoff coefficient, runoff volume and intensity, rainfall depth) and attributes of pre-storm conditions (antecedent dry period, runoff intensity of the previous storm).

Other relevant studies include Gnecco et al. (2005) who monitored a local road surface at the University of Genoa, Italy and reported a simple correlation between TSS (EMC, mg/L) and maximum 5-minute rainfall intensity (n=12, R^2=0.53). No correlation was evident with antecedent dry period (ADP). Desta et al. (2007) conducted a study of the Kildare bypass near Dublin (AADT= 26 000) and found based on visual analysis of scatter plots, no strong relationship existed between TSS concentration with rainfall depth, ADP or event duration. A weak positive correlation with average rainfall intensity was observed. Monitoring of a highway in Japan (AADT=62 000) by Shinya et al. (2003) showed a positive correlation (n=8, R^2=0.877) between TSS load and mean rainfall intensity and a weak correlation with ADP (R^2=0.325).

In contrast to roads, Gilbert and Clausen (2006) stated that little is known about runoff from different types of driveways. In their study, runoff quality was measured from replicated asphalt, permeable paver and crushed-stone driveways in Connecticut, USA. Bannerman et al. (1993) reported TSS concentrations in runoff from asphalt driveways at Wisconsin, USA. An asphalt carpark bay was monitored near Seattle, USA as a control surface in comparing the performance of permeable pavers (Brattebo and Booth, 2003), but suspended solids was not measured. Neary et al. (2002) measured TSS in runoff from a carpark at Cookeville, Tennessee and noted that particle concentration, while generally decreased with cumulative runoff volume, also depended on other factors including ADP and rainfall intensity. Rushton (2001) conducted monitoring of a large parking lot in Tampa, Florida to investigate the performance of LID measures in reducing pollutant generation. A range of surfaces were tested including asphalt, concrete and porous paving with and without grass swales. Samples were collected and analysed for suspended solids, nutrients and metals. Runoff monitoring of a paved parking lot located in Kongju, Korea was conducted for 7 storms by Kim et al. (2005). Values of TSS EMC reduced as the total rainfall of the storm increased.

As is the case for driveways and carparks, a number studies have investigated roof runoff but not with the intention of establishing TSS regressions relationships. For example, Yaziz et al. (1989) sampled runoff from two roof surfaces (galvanised iron and concrete tile) at Serdang, Malaysia. Samples of the initial 5 L of roof water were taken. Data interpretation suggested that total solids concentration tended to increase with ADP and that particle washoff occurred more rapidly in high intensity rainfalls. A literature review by Skarżyńska et al. (2007) also observed that many studies show high concentrations of suspended matter in the first flush runoff from roofs. A major factor influencing the particle load generated during a storm was the type of roof material with ceramic tiles, cement sheets and asbestos cement sheets contributing the highest concentrations. High TSS concentrations were also associated with galvanised iron, and this was attributed to the rapid washoff of dry-deposited solids from its smooth surface.

Key learnings from the review of past studies can be summarised as:

1) Regressions to estimate TSS generation from roads and highways are available, but exhibit a substantial variation in their form (adding variables, multiplying variables or exponential) particularly for load estimation. Also, no consensus exists on the use of concentration (EMC) or load as the dependent variable.
2) Where data from several different road sites were available, the regression variables included site or surface specific variables (typically some form of traffic count) in combination with rainfall event variables (such as rainfall or runoff intensity). Little commonality exists in the explanatory variables adopted across the range of studies.

3) Past studies assist in defining representative TSS concentrations in carpark and roof runoff, but do not include regression relationships linking TSS with rainfall or surface characteristics. The type of surface material is a factor in the amount of TSS washoff, especially for roofs.

Evidently, little research has been done in establishing whether different urban impervious surfaces share a common set of underlying hydrological factors that influence their suspended particle response to rainfall. These common factors have the potential to be used as regression variables to estimate suspended solids loads or concentrations in runoff, with the numerical values of the parameters depending on the surface of interest. A similar approach in partitioning hydrological variables from other types of explanatory variables (such as catchment characteristics and activity-related variables) was used by Duke et al. (2007) in their study of Californian urban catchments.

3. Materials and methods

3.1 Measured suspended solids data

Runoff samples were collected from three different urban impervious surfaces located at Toowoomba, Australia (Table 2). Toowoomba is located within a temperate climate region of South East Queensland subject to mild to warm summers and mild, dry winters. A flow splitter device described by Brodie (2005) was used to obtain flow-weighted composite samples in response to 35 storms during the period December 2004 to January 2006. Rainfall was recorded by a 0.25 mm tipping bucket pluviometer installed near the sampling site. Event rainfalls varied from 2.5 mm to 64.25 mm at average intensities ranging from 1 mm/hr to 40 mm/hr. Total rainfall during the monitoring period was substantially below the historical average recorded at Toowoomba. A full description of the monitoring program is provided by Brodie (2007).

Runoff samples were analysed using a modified Suspended Sediment Concentration (SSC) method (ASTM, 2002) to determine the EMC of particles less than 500 μm in size. An additional screening step was used to obtain <500 μm particles, referred to as Non-Coarse Particles (NCP) to distinguish from SSC and the more commonly used Total Suspended Solids (TSS). Further screening and filtration steps were also used to partition NCP into particles < 8 μm, from 8-63 μm and from 63-500 μm. A previous data analysis (Brodie and Dunn, 2009) found that NCP is dominated by clay-silt size particles (<63 μm) representing, on average, 64% (for carpark runoff) up to 79% (for road and carpark runoff) of the particle mass.

3.2 Statistical methods of analysis

Two broad statistical approaches were used to identify a small subset of important predictors of NCP EMC. We explicitly avoided step-wise regression approaches, even though step-wise methods for selecting multiple regression models are prevalent in the literature. Significant and well-documented problems exist with this approach (Whittingham et al., 2006). For example, parameter estimates are biased and the issue of multiple testing increases the probability of false positive results when selecting predictors. In addition, unconstrained use of stepwise methods encourages models without physical basis.

The first methodology uses conventional statistics, incorporating the following steps:

Step 1: Selection of the dependent variable. In this case, NCP EMC or NCP mass load are candidates.

Step 2: Selection of the range of potential hydrological explanatory variables suitable for regression.

Step 3: Selection of the basic form of the regression relationship between NCP and the explanatory variables.

Step 4: Identification of the most significant explanatory variables from the available range of variables. Four different statistical criteria (AIC, BIC, PRESS and Adjusted R^2, described in Table 3) were used to identify variables that are most relevant and to derive regression equations. Each method of analysis provides a different measure of how well the candidate models, and hence candidate explanatory variables, fit the data. The four methods compute the statistic on different scales and measure different quantities, so are not directly comparable.

An alternative approach was also adopted to identify the most significant variables (Step 4), motivated by the expected correlations between the predictors and the importance of identifying the dominant predictors more than the actual model coefficients. This approach is Bayesian model averaging, or BMA (Hoeting et al., 1999), implemented using the statistical analysis software R (R Core Development Team, 2009) and the BMA package for R (Raftery et al., 2006). Conventional approaches to model selection emphasise the identification of a single model as the ‘best’ model not contradicting the data. However, uncertainty exists in the choice of this ‘best’ model, which is rarely acknowledged (Wintle et al., 2003; Whittingham et al., 2006). Not uncommonly, many possible models may perform similarly and the single model finally adopted depends on the randomness of the data under consideration. In contrast, BMA allows multiple models to be considered and the parameter estimates to be averaged across a set of useful models.

The results of the conventional statistical analysis and BMA were then reviewed to determine if the two broad methods produce a similar set of dominant explanatory variables to NCP EMC. As described later in Section 5, this was indeed the case. These variables were incorporated into a single regression model – in this paper, this relationship is referred to as the ‘common’ model as it covers all three surfaces.

4. Results of statistical analysis

4.1 Step 1 - Selection of the NCP dependant variable

As is the case for all pollutants, NCP can be expressed as a concentration (EMC, mg/L) or as a mass load (L, kg/storm or mg/m^2/storm). In their study of the US National Urban Runoff Program data compiled for total phosphorus, May and Sivakumar (2004) found that regression models using load as the dependent variable had errors 50% higher than the concentration-based models. NCP EMC was selected as the dependent variable in the statistical analysis to limit these potential errors. EMC is based on direct laboratory measurement, whereas load is computed as a product of EMC and runoff volume (which for impervious surfaces is closely related to rainfall depth as losses are generally small). The fact that load is derived from EMC supports the decision to adopt EMC as the dependent variable.

To increase the confidence of the predictive ability of regression models, measured data is often partitioned into two samples: 1) A calibration sample used to derive the model coefficients and 2) a separate independent validation sample used to check the performance of the calibrated model. Such data partitioning for calibration and validation is appropriate in developing NCP predictive models specific to the local South East Queensland region. Given that the main purpose of the statistical analysis is to identify the dominant hydrological variables that are EMC predictors, we decided to use the full set of measured NCP EMC data without partitioning. Mourad et al. (2006) warns against using few data (less than 20) in stormwater quality regressions and this would be the case if the NCP data is partitioned. However, one of the strategies we used for model selection (PRESS) is similar to the idea of partitioning the data without the problems identified by Mourad et al. (2006).

4.2 Step 2 – Selection of the explanatory variables

The storm variables considered as possible variables associated with NCP EMC included rainfall depth (RD, mm), peak 6-minute rainfall intensity (PI, mm/hr) and mean rainfall intensity (MI, mm/hr). Two descriptors of rainfall duration were included: the event duration (ED, defined as the time period from start of rainfall to cessation of rainfall) and the storm duration (SD, or cumulative time within the event when rainfall intensity exceeded a nominal 0.25 mm/hr). SD was introduced as some storms consist of successive rainfall bursts separated by periods of negligible rainfall. Two variables representing pre-storm or antecedent conditions were also included; the antecedent storm rainfall (AR, mm) and the antecedent dry period (ADP, hrs).

Plots of NCP EMC against possible variables were made and suggested taking (natural) logarithms of all variables to stabilize the variances. This is consistent with McLeod et al. (2006) in their study of urban runoff quality in Saskatoon, Canada and who in turn followed statistical practices of the US Geological Survey (e.g. Driver and Tasker, 1990). In addition, NCP EMC was found to be very skewed right and taking logarithms made the distribution more symmetric.

When log-transformed data were used, ED, SD and RD have the highest correlation to NCP EMC (Table 4). This was the outcome across all surfaces, indicating that a commonality of rainfall variables affecting suspended particle washoff may be present. Also, in all cases, a trend of reducing EMC with increasing magnitude of each of these rainfall variables was evident within the measured data.

Ideally, explanatory variables used in a regression relationship should be independent (e.g. Weisberg 1985, Chapter 8; Quinn and Keough, 2002, Section 6.1.11). If explanatory variables are highly correlated, the estimated parameters have small precision so hypothesis testing may lead to incorrect conclusions and confidence intervals become artificially wide (Quinn & Keough, 2002, Section 6.1.11; Weisberg 1985, p 198).

The issue of correlation between explanatory variables also arose in our analysis of the NCP EMC data. Interdependencies between rainfall variables (Table 5) were most evident ($|r| > 0.4$) between ED and SD, ED and RD, RD and SD, SD and MI, and PI and MI. Storm variables RD, PI and ED, in addition to AR and ADP associated with the antecedent storm, are ‘direct’ variables as these rainfall variables were directly determined from the measured data. MI and SD were computed either from other variables or from computational analysis of the measured data and can be considered as ‘derivatives’. For example MI = RD / SD; on the log-scale used in the analysis log(MI) = log(RD) – log(SD), so adding log(MI) to a model already including log(RD) and log(SD) will obviously introduce redundant variables, and hence collinearity. This explains some collinearity between variables (such as log(ED) and log(SD), log(SD) and log(MI)).

Collinearity between the independent variables may be measured using the ‘condition number’; under one definition (Myers 1989), the condition number is the absolute value of the ratio of the largest eigenvalue of the matrix of explanatory variables to the smallest eigenvalue. Various rules-of-thumb exist for declaring collinearity a problem using the condition number, such as values exceeding 1000 (Myers 1989, p 370). NCP data for all surfaces had severe collinearity with the full set of rainfall variables as their respective condition numbers were approx. 2 000 000, and was similar when the explanatory variables were considered within each surface. A second measure of the extent of the collinearity is to compute variance inflation factors (VIF), which give an indication of the amount by which the variance of each regression coefficient is inflated (Myers, 1989, p 127; Weisberg 1985, p 200). VIFs exceeding approximately ten indicate strong collinearity (Quinn and Keough, 2002, p 128). Some of the VIFs using all predictors exceeded10^7; collinearity was thus an extreme concern.

On this basis, MI was excluded from the regression analysis due to its implicit dependence on RD and SD. The condition numbers then became 25, 30 and 24 for the carpark, road and roof data respectively, a substantial improvement on values around 2 000 000 if MI was retained. As further evidence, after excluding MI none of the VIFs exceeded 4.2. The decision to exclude MI was solely based on statistical rigour, as experimental studies using rainfall simulators have demonstrated that mean rainfall intensity is a driving factor in suspended solids loads washed from urban road surfaces (Sartor and Boyd, 1972; Pitt, 1987; Egodawatta et al. 2007). Regression models containing both RD and SD effectively contain at least as much information as models containing MI.

4.3 Step 3 - Selection of the basic form of regression relationship

We sought a simple form of relationship between the rainfall explanatory variables and NCP EMC that allows a common set of these variables across the different surfaces to be identified. Plots of the data (not presented) exhibited linear relationships on the log-log scale, suggesting a suitable model is a regression model of the form

$$\log y_i = \beta_0 + \beta_1 \log X_{1i} + \beta_2 \log X_{2i} + \cdots + \beta_p \log X_{pi} + \varepsilon_i \,, \qquad [1]$$

where the response y_i is the NCP EMC, the p explanatory variables are $X_1, \ldots, X_p$ and ε_i is the error term, where $\log y_i$ has a Normal distribution. Regression models of this form are equivalent in real space to

$$y_i = (\exp\beta_0) X_{1i}^{\beta_1} \cdots X_{pi}^{\beta_p} \exp(\varepsilon_i) \,; \qquad [2]$$

that is, Equation 1 is equivalent to assuming power relationships between the response and the explanatory variables. This approach is consistent with Kayhanian, et al. (2007) and Thomson et al. (1997) listed in Table 1 and also with the use of empirical power based rating curves in LID analysis (Elliot and Trowsdale, 2007).

4.4 Step 4 – Identification of key explanatory variables for NCP EMC

4.4.1 Using conventional statistical criteria

Identification of key explanatory variables for NCP EMC from each of the three surfaces (road, carpark and roof) was based on determining which set of hydrological parameters when incorporated into Equation 1 gave fitted values most consistent with the measured NCP data.

Initially, each surface was treated separately to determine if a small subset of explanatory variables could systematically be identified as suitable for modelling NCP EMC across surfaces. The results of this preliminary statistical analysis for all methods, variable combinations and surfaces (Table 6) produced a short-list of independent variables to consider for the common model.

The four criteria (AIC, BIC, PRESS and Adjusted R^2) identified 'good' models for each surface. Consistently, though not exclusively, RD, PI and SD were identified as important explanatory variables, and are statistically the main drivers affecting NCP EMC. Hydrological parameters relating to antecedent conditions (AR and ADP) which account for buildup or dry-weather accumulation of particles onto the surface made an occasional appearance in the top four models (Table 6) and appear to be secondary to RD, PI and SD.

Assuming a model of the form of Equation [1] involving RD, PI and SD, we then considered the possibility that some (or perhaps all) of the coefficients may change according to the surface. Statistically, this means *interactions* between the surface and each explanatory variable were considered.

Using a series of sequential F-tests (Table 7) with the intercept β_0 differing by surface, log(RD) and log(PI) were found to be statistically significant. However, log(SD) was not necessary in the model with these terms already included, and changing the parameters of log(RD) and log(PI) by surface did not improve the model. Removing the non-significant terms and refitting the model (Table 7, columns 4 and 5) produced the common model.

The common model is of the same form as Equation 1 with just log(RD) and log(PI) as explanatory variables:

$$\log(EMC_{NCP}) = \beta_0 + \beta_1 \log RD + \beta_2 \log PI. \qquad [3]$$

The value of β_0 differs by surface, but the parameter values for log(RD) and log(PI) are the same for all surfaces (Table 8). The R^2 and adjusted R^2 values (Table 9) are similar for each surface, between 0.53 and 0.6 (but higher when the data for all surfaces are pooled).

4. 4.2 Using Bayesian model averaging

As identified earlier in Section 3.2, an alternative model-selection approach is Bayesian model averaging (BMA). For the BMA approach, we considered all variables (including MI omitted from the conventional regression approach), plus many of the interactions with surface that may be possibly important. BMA accounts for model uncertainty present in the variable selection process. Thus, the BMA considers a very large pool of models and finds a smaller subset of models that all represent the data well (and any one may have been chosen depending upon the vagaries of the particular dataset collected). In this application, 41 models were thus found. The most likely model had a posterior probability of less than 13%, suggesting a reasonably large amount of model uncertainty; that is, there is little certainty that the predictors in the most likely model truly form the optimal set of predictors.

In these 41 potential models, log(RD) and log(PI) appear in almost all of these models in the subset of adequate models (Table 10), similar to the variables identified using the more conventional statistics. Further, adjusting the constant in the model according to the surface is also recommended; as shown in Table 10, a model is fitted including an intercept term for the constant term (posterior mean value of the intercept is 4.08), and adjustments to this term according to the surface are recommended (for example, the intercept for roads is 4.08 + 1.21 = 5.29). Two other variables commonly identified in the confidence set were log(AR) (posterior probability 55.8%) and log(SD) for the roof surface only (60.1%). Both of these variables have a posterior probability of little more than 50%, suggesting neither of these predictors warrant inclusion in the model, but indicate that log(AR) and log(SD) are secondary factors in model for EMC determination.

In summary, the general results from the BMA concur with those using the more conventional statistics: log(RD), log(PI) and a constant varying by surface are suggested for the model; log(SD) was also initially suggested using the more conventional approach. The fact that two different approaches point to the same models, and similar dilemmas, is encouraging and supports the adopted model.

5. Discussion

5.1 A common NCP regression model

Both statistical approaches adopted suggest the common explanatory variables for determining NCP EMC are log(RD) and log(PI), with the constant term in the model varying by the surface type. In addition, both approaches suggest log(SD) has a more complicated relationship with NCP and perhaps is only useful for the roof surface. BMA also suggests that AR has a role to play, albeit a less important role than the other predictors.

The goal for this paper is to identify the dominating hydrological variables and hence isolate a simple, common model form for NCP. The simplest model is that given in Equation 3, involving log(RD) and log(PI), with the constant term changing according to the surface type. Without doubt, the model can be improved using other predictors by fine-tuning for each surface type separately and effectively generating a separate model for each surface (for example, by including log(SD) for the roof surface); however, that is not the primary goal of the study.

A plot of the fitted log(NCP) against the measured or actual log(NCP) (Figure 1) shows the common model reproduces the log(NCP) reasonably accurately. The separation of the points from each surface also shows how each surface is quite different from the others in overall NCP EMC (and results in the constant in the model changing by surface type). The simple common model performs less well for the roof surface, even though log(RD) and log(PI) were identified as important for the roof before a common model was fitted.

Two possible explanations are suggested for the poorer performance of the common model in Equation 3 when used for the roof when compared to the carpark and road surfaces. Firstly, perhaps the coefficients for log(RD) and log(PI) also depend on the surface, but insufficient statistical power exists to detect this effect and effectively, more samples are needed. A second explanation is suggested by the BMA approach: a model only for the roof would benefit from fine-tuning by adding log(SD) as a predictor. However, plots similar to Figure 1 based on both the above suggestions (including estimates for log(RD) and log(PI) that vary by surface; and including log(SD) as a predictor) do not substantially improve the model, but result in a more complex model. In conclusion, a simple model based on common variables works well for the road and carpark surfaces, but the relationship between NCP and the predictors appears to be more complicated for the roof, and perhaps operates under different physical principles. Nevertheless, the chosen model in Equation [3] works well for the road and carpark surfaces and is a reasonable model for the roof but with identifiable concerns.

In real space, the common model for NCP EMC can be expressed as:

$$EMC_{NCP} = \alpha RD^{-0.736} PI^{0.562} \quad [4]$$

where $\alpha = \exp(\beta_0)$ = 49.2 for the carpark, 213 for the road and 11.7 for the roof.

The structure of the common model confirms the effect of the hydrological explanatory variables RD and PI is very similar for all surfaces, but the responding NCP EMC differs by surface as governed by the different constants in the model β_0 (and α). (As noted above, the relationship is probably more complicated for the roof.) More specifically, road runoff NCP EMC is in excess of four times (213/49.2 = 4.3) and roof runoff is one-quarter (11.7/49.2 = 0.24) of the carpark EMC after accounting for the effects of RD and PI. Examining the correlations between explanatory variables (Table 5), RD and PI are highly correlated with ED, SD and MI. Effectively, AR and ADP are not involved in the equation.

5.2 Physical basis of the common model

While the structure of the model and the identified predictors are the main focus of this study, an examination of the model parameters is nevertheless interesting. The RD exponent of the common model in real space (β_1=-0.736) indicates that NCP EMC in runoff from the three surface types decreases as rainfall depth RD increases, provided all other predictors stay the same. This suggests that a dilution effect applies; the runoff volume generated from the surface in response to rainfall becomes proportionally larger than the suspended solids mass that is washed off. This outcome is consistent with the Kayhanian et al. (2007) regression for Californian highway sites which found a negative exponent applied to total event rainfall (TER in Table 1) and is also consistent with interpretation of measured carpark and parking lot runoff data by Neary et al. (2002) and Kim et al. (2005).

Conversely, the PI exponent of the common model in real space (β_2=0.562) demonstrates a trend of increasing EMC with increasing peak 6-minute rainfall intensity PI, provided all other predictors stay the same. Mobilisation of particles from street surfaces have been conceptualised by others (Price and Mance, 1978; Deletic et al., 1997) as a two-step process; particle detachment and washoff by rainfall from the surface followed by a transport phase by the runoff generated as overland flow. Particle detachment at the surface is driven by the kinetic energy of raindrops which increases with rainfall intensity (Van Dijk et al., 2002), as does the peak overland flow from the surface (discussed further below). Thus, the interrelationship between PI and NCP EMC also appears to have a physical basis.

These interpretations are somewhat simplistic, since a correlation of 0.32 exists between RD and PI (on the log scale). (Alternatively, variation in log(RD) explains about 0.32^2 = 10.2% of the variation in the values of log(PI).) While this correlation isn't very large, it does suggest that the physical interpretation is more involved that described here.

The introduction of PI is expected to account for the potential capabilities of a storm event to washoff and transport particles, which are not accounted for if rainfall depth RD is used in isolation. Although the rainfall depths may be identical, a short-duration, high-intensity storm is expected to have a greater particle washoff capacity compared to a long-duration, low-intensity storm. This observation has its precedence in soil erosion research, specifically in the development of the Modified Universal Soil Loss Equation (MUSLE) by Williams (1975), to estimate soil loss from agricultural lands for individual storms:

$$E = 11.8(Q_v \times Q_p)^{0.56} \times K \times LS \times C \times P \qquad [5]$$

where E is the soil loss (t/event), Q_v is the runoff volume (m^3), Q_p is the peak runoff discharge (m^3/s), K is the soil erodibility factor (measure of the resistance of the soil to erosion), LS is the slope length and steepness factor, C is the crop and cover management factor and P is the support practice factor (accounts for soil conservation measures).

Brodie and Rosewell (2008) used the soil loss E as the basis to estimate the suspended solids EMC (in this case, TSS) in stormwater runoff from undeveloped, pre-urban land:

$$EMC_{TSS} = 10^6 \times SSGR \times E / Q_v \qquad [6]$$

where SSGR is the suspended sediment generation rate (proportion of soil loss suspended in runoff).

For a given set of soil and surface conditions, the non-discharge factors (K, LS, C, P and SSGR) are constant and can be condensed to a single scaling factor, so Equation 6 combined with Equation 5 can be reduced to:

$$EMC_{TSS} = a(Q_v)^{-0.44}(Q_p)^{0.56} \qquad [7]$$

where a is a proportionality constant

For the case of stormwater runoff from small, urban impervious surfaces, the discharge parameters (Q_v and Q_p) can be related back to more fundamental storm rainfall explanatory variables. Being impervious, infiltration losses of rainfall prior to runoff initiation are generally small (typically 0.5-1mm from Goyen and O'Loughlin, 1999) for the urban surfaces under consideration. Providing depression storage effects are also minor, the runoff volume is approximately in proportion to rainfall depth (i.e. $Q_v \propto RD$). By use of the Rational Method (Mulvaney, 1851), peak runoff discharge is proportional to the peak rainfall intensity of the storm period corresponding to the time of concentration of the catchment. In the case of the small urban surfaces considered here, the time of concentration is of the order of 5 minutes, comparable with the 6-minute rainfall intensity (PI) adopted as a key rainfall parameter. As a result, runoff peak discharge is approximately in proportion to peak rainfall intensity (i.e. $Q_p \propto PI$). Equation 7 can be then restated for small impervious surfaces as:

$$EMC_{TSS} \approx b(RD)^{-0.44}(PI)^{0.56} \qquad [8]$$

where b is a proportionality constant

Equation 8 shows a close resemblance in form to the common regression equations relating NCP EMC to RD and PI given as Equation 4. The exponent to PI is positive in both relationships suggesting that EMC increases with higher PI. Conversely, the RD exponent in both cases is negative indicating EMC reduces with increasing RD. Overall, the common regression equations are analogous in form to the MUSLE that is in widespread use to estimate soil erosion from predominately non-urban landscapes during individual storms.

The magnitude of the PI exponent is also of interest; in both Equations 4 and 8 the exponent is less than 1 indicating that the rate of EMC increase becomes less as PI reaches higher intensities. This trend is consistent with rainfall simulator studies of particle washoff from roads which suggest that the suspended solids mass load washed from the surface tended to plateau at high intensities (Egodawatta, et al. 2007) or the rate of load increase becomes less (Sartor and Boyd, 1972; Pitt, 1987).

The common regression model (Equation 4) also exhibits a similarity to regressions by others to estimate TSS EMC in runoff from urban catchments. The French stormwater quality model Canoe (INSA/SOGREAH, 1999) uses a power function that includes the peak five-minute rainfall intensity (close to our six-minute PI) and RD, but ADP is also incorporated. Other options in Canoe include a variant to the three-variable power function that uses runoff volume instead of RD (attributed to Servat, 1984).

6. Conclusions

Two statistical approaches (conventional regression and Bayesian model averaging) were applied to identify key hydrological factors of suspended solids runoff from representative urban impervious surfaces. Non-Coarse Particle (NCP, <500 μm) event mean concentration (EMC) data in runoff collected from a road, a carpark and a roof located in Toowoomba, Australia were used in the analyses.

Both statistical approaches isolated rainfall depth and peak 6-minute rainfall intensity as the dominant explanatory variables of NCP EMC. This outcome was applicable to all three surface types. Storm duration, defined as the cumulative time within the event when rainfall intensity exceeded 0.25 mm/hr, was an important although less dominant variable, particularly for the roof surface. Antecedent rainfall depth was also identified, but its influence on NCP EMC is considered to be much weaker than the other hydrological variables.

Further statistical analysis found that a power relationship including rainfall depth and peak 6-minute rainfall intensity provided a fit to the measured NCP EMC data (R^2 =0.53-0.59 for individual surfaces) that was not significantly different to a similar expression containing more explanatory variables. This led to a parsimonious ‘common’ model applicable to all analysed urban surfaces (Equation 4). The model fits well for road and carpark surfaces, and is a reasonable model for the roof but with identifiable concerns.

The inclusion of rainfall depth and peak 6-minute rainfall intensity is considered to have a physical basis. As demonstrated, the common model exhibits a consistent form to the Modified Universal Soil Loss Equation widely used in non-urban soil erosion investigations.

The common model is based on a specific measure of suspended solids (NCP) and data collected at a temperate-climate Australian location for three examples of urban surface type. More work is required to test the generality of the model form to other suspended solids measures (TSS and SSC), climatic zones and urban surfaces. However, the identification of dominant hydrological variables and a basic regression form provides a useful starting point to formulate similar parsimonious relationships for impervious surface runoff elsewhere. Consistency with the Modified Universal Soil Loss Equation and a similarity with the Canoe TSS EMC relationship suggest that the common model could be generally adaptable, but this aspect needs to be confirmed with further research.

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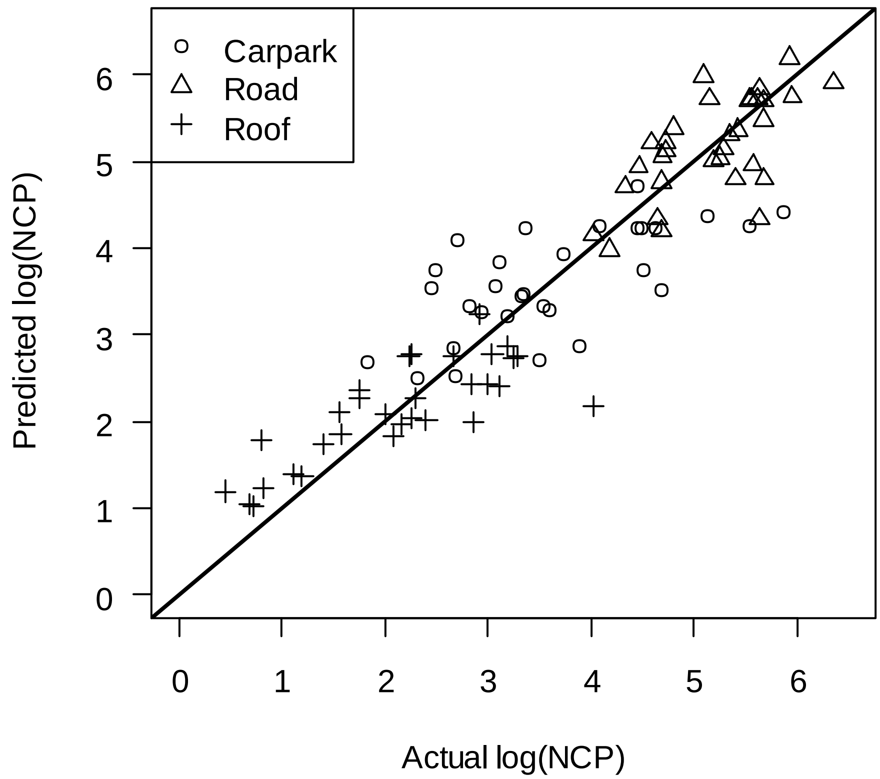

Figure 1: Explanatory variable ln(NCP) against actual ln(NCP) for the three surfaces, using the common regression model