Statistical observations of a stormwater monitoring programme; lessons for the estimation of pollutant loads

Observations statistiques d'un programme de surveillance des eaux de ruissellement ; leçons pour l'estimation de la masse de polluants

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RÉSUMÉ

Cet article décrit l'analyse statistique d'un programme de surveillance de la qualité des eaux de ruissellement qui a pour but principal l'estimation de la masse de polluants rejetés dans les fleuves de la région de Melbourne, Australie. La mesure en continue de la turbidité se montre très efficace pour estimer les masses de MES, avec des erreurs dans la prédiction sur le long terme inférieures à 5%. Si l'échantillonnage ponctuel est employé au lieu de la mesure en continue, il faut avoir un écart d'échantillonnage de trois jours maximum afin d'éviter une augmentation des incertitudes. Pour la surveillance pendant le temps de pluie, l'utilisation de préleveurs automatiques pour obtenir des échantillons n'est pas nécessaire si seul l'estimation des masses sur le long terme est recherchée L'importance de l'élimination des erreurs systématiques en effectuant des calibrages fréquents des appareils de mesures ainsi qu'en analysant régulièrement les données, est aussi démontrée.

ABSTRACT

This paper reports on a statistical review of a water quality monitoring programme aimed at estimating long-term pollutant loads discharged from waterways in and around Melbourne, Australia. Use of continuously-measured turbidity was found to be an effective surrogate measure for estimating TSS, with errors in long-term load estimates of less than 5%. Where routine grab sampling is used instead, errors increase with sampling interval; a 3-day interval is required to maintain errors within 10% of the continuously-measured load. For storm event sampling, auto-samplers were found not to be required, if only long-term load estimates are required. The importance of eliminating systematic errors, by ensuring frequent calibration and data verification, were demonstrated.

KEYWORDS

Pollutant load, stormwater monitoring, TSS, turbidity, uncertainty.

1 INTRODUCTION

Estimation of pollutant loads in stormwater is a primary requirement of those charged with the responsibility of managing waterway water quality. Far too often, however, monitoring programmes have not been designed with explicit consideration of the objectives and information requirements of the sampling (e.g. Bertrand-Krajewski et al., 2000a; Bertrand-Krajewski et al., 2000b). As a consequence, the required level of uncertainty is often not specified, and thus the appropriate frequency and timing of sampling is not well understood (Fox et al., 2005; Leecaster et al., 2002).

For example one recent study in rivers by Leecaster *et al.* (2002) found that to sample TSS adequately within a storm event, at least 12 flow-weighted samples were required, and that pollutographs of 7 storm events needed to be sampled within a year to estimate mean annual loads at a reasonable level of accuracy, provided that the sampled storms were classified as ‘medium to large’ storms. Mourad *et al.* (2005) showed that there is no standard number of events which will give a known level of uncertainty in the estimate of Site Mean Concentration (SMC).

It is thus appropriate for agencies responsible for monitoring water quality in waterways or stormwater, to periodically review the quality, representativeness and uncertainty of collected data, in order to refine the frequency, timing and methods of sampling. Melbourne Water (Melbourne, Australia) conduct monitoring of surface water quality, with the primary aim of estimating the loads of pollutants (predominantly TSS, TN, TP, but also heavy metals such as Pb, Zn, Cu, Cd, Ni and Hg) being discharged to receiving waters. Secondary objectives of their water quality monitoring include the (i) ability to assess the effectiveness of management programmes, (ii) development, calibration and verification of water quality models, and to (ii) address knowledge gaps such as longitudinal pollutant transformations through the drainage network.

This paper reports on parts of a review of Melbourne Water’s monitoring programme, with respect to its primary objective: *to **accurately estimate pollutant loads***. We examine the statistical characteristics of the data, and evaluate alternative sampling regimes, in order to estimate loads, with acceptable uncertainty, at the least cost.

2 METHODS

2.1 Sources of data

The existing monitoring programme comprised ten primary sites (Table 1), monitored on a routine (monthly) basis since 2001, with additional opportunistic storm event sampling (Parslow et al., 1999). The catchments varied in size: from a large river basin (Yarra River) to a small urban stream (Gardiners Creek). At five sites, only grab sampling was undertaken, during both dry and wet weather (including in-situ analysis of turbidity, EC, pH, temperature and dissolved oxygen). In addition, in 2004, an autosampler was installed at Gardiners Creek, for monitoring of pollutographs. In the Yarra River a continuous multi-probe was used, whilst at Bunyip, Lang Lang and Cardinia, a similar probe is used alongside grab sampling.

2.2 Data analysis

Analysis of the datasets collected by Melbourne Water was based on asking a number of questions which aimed to determine (i) if the current sampling regimes are adequate and (ii) whether there can be savings made in the cost of the sampling programme, without impacting on the information provided. Three of the specific questions posed to make these determinations, and the methods for assessing these, are presented below.

Catchment	State date (to current)	Parameters Monitored*	Sampling method & frequency
Dandenong Creek Eumemmrring Creek Maribyrnong River Merri Creek Moonee Ponds Creek	Jan 1976 Oct 1975 Jan 1992 Jan 1993 Jan 1993	TSS, TN, N-species, TP, OP, E.coli, metals, BOD Turbidity, EC, pH, Temp, DO	Grab samples (weekly-monthly) In-situ analysis (weekly-monthly)
Gardiners Creek	Feb 1992 (grab) and Jan 2004 (auto)	TSS, TN, N-species, TP, OP, E.coli, BOD, chlorophyll	Weekly-monthly Autosampling:intra-event (up to 24 per event) for 9 events
Yarra River	Jan 1999	Turbidity, EC, pH, Temp, DO	Continuous probe (6 min)
Bunyip River Cardinia Creek Lang Lang River	Aug 2000 Jun 1990	Turbidity, TSS TSS, TN, N-species, TP, OP, E.coli, metals, BOD Temp, DO, EC, pH, Turbidity	Continuous (6 minute) Grab samples (weekly-monthly) In-situ analysis (weekly-monthly)

Table 1. Monitoring site details *Flow is also measured at each site.

2.2.1 Question 1: Can the loads of TSS and other pollutants be estimated (and if so, with what uncertainty) using turbidity as a surrogate?

Melbourne Water installed continuous turbidity probes at three sites where grab sampling and in-situ water quality analyses were also undertaken (Bunyip, Cardinia Creek and Lang Lang: Table 1). The objective was to determine if *TSS could be used as a surrogate measure for estimating the loads of TSS*, and potentially, of other pollutants. Correlations between turbidity and other water quality parameters were calculated, and those with $R^2 > 0.6$ were considered as acceptable for predictions of pollutant loads. Since only TSS was found to consistently satisfy this requirement, a regression relationship between turbidity and TSS was developed (Eqn1), and the uncertainty in estimated TSS concentrations assessed (Eqn 2), based on prediction intervals of the regression (Eqn 3). Based on advice from Melbourne Water, we assumed that turbidity and flow measurements each had an uncertainty of 10%.

$$TSS = K \times Turb \qquad \text{(Eqn 1)}$$

where K = regression coefficient (intercept = 0), Turb = measured turbidity

$$U(TSS_i)^2 = \left[2 \times 1.96 \times SE_i\right]^2 + U(Turb_i)^2 \qquad \text{(Eqn 2)}$$

where $U(TSS_i)$ = uncertainty in concentration of TSS for time step *I*, $u(Turb_i)$ = uncertainty in measurements of turbidity for time step *I*, and SE_i = standard error for each time step *i*,.

TSS loads over time were calculated thus using the TSS concentrations, calculated at 6 minute intervals, from observed turbidity (Eqn 3).

$$Load = \sum_{i=1}^{N} L_i = \sum_{i=1}^{N} Q_i \times TSS_i \times \Delta t \qquad \text{(Eqn 3)}$$

where: Li = Load of TSS for time step *I*, Q_i = flow rate measured at time step *I*, TSS_i = TSS concentration calculated by measuring turbidity at time step *I*, Δt = time step *i* (=1 hour), N = number of time steps for which the load has been calculated

Uncertainty in the TSS load measured over the time-series, was then calculated using the approach of Bertrand-Krajewski & Bardin (2002) (Eqn 4):

$$U(Load)^2 = \sum_{i=1}^{N} U(L_i)^2 + 2 \sum_{i=1}^{N-1} \sum_{k=i+1}^{\min(N,i+m)} R(L_i, L_k) \times U(L_i) \times U(L_k) \qquad \text{(Eqn 4)}$$

where U(Load) = uncertainty of total loads, $U(L_i)$ = uncertainty of load for time step *I*, $U(L_k)$ = uncertainty of load for time step *k*, $R(L_i, L_k)$ = coefficient of correlation between L_i and L_k, m = lag (in time steps) beyond which serial auto-correlation between time steps is non significant (at p=0.05) (see Bertrand-Krajewski & Bardin, 2002).

This approach allowed the long-term load of TSS to be estimated, along with an estimate of its uncertainty. The approach described above assumes that there is no systematic error in measurements, but only random errors, although, these are still likely to be correlated over time (and therefore R(Li,Lk) was estimated using auto-correlation between the measured time series). However, since a likely source of errors includes systematic errors such as incorrect sensor calibration, maximum uncertainties due to systematic errors were also calculated, by multiplying measured turbidity and flow at each timestep by their respective potential errors (errors of 2, 5, 10, 15 and 20% were included in this analysis, after advice from Melbourne Water on sensory accuracy).

2.2.2 Question 2: How frequently do routine samples need to be taken to estimate long-term loads?

At some sites, Melbourne Water operates a storm-event grab sampling routine. However, at most sites, sampling is simply undertaken on a set-frequency ("routine") basis. Samples are taken at the same time each week/fortnight/month, regardless of flow. The frequency of such sampling will affect the probability of capturing the entire distribution of flows and concentrations at a site. Using the continuously-measured turbidity data as a benchmark, we examined the potential errors in long-term load estimates resulting from daily, three-daily, weekly, two-weekly and monthly sampling. This was done by sub-sampling at the appropriate frequency from the 6-minute turbidity time-series, to calculate an equivalent TSS (using Eqn 1), and multiplying it by the integrated flow for the sampling interval (using recorded hourly flow data). The analysis therefore assumed that continuous flow-monitoring would still be undertaken, regardless of the frequency of grab-sampling. For each frequency, 12 replicate tests were applied, starting at randomly located points within the time-series.

2.2.3 Question 3: Are autosamplers needed to estimate long-term loads?

In 2004, Melbourne Water installed an autosampler at Gardiners Creek, in an attempt to better estimate the event pollutant load. Seven storm events were captured during the trial period, with an average 19 samples per event) (Table 2).

Event	Event pollutant loads (kg)						
No.	N (samples)	Flow (m^3)	TN	TP	TSS	Pb	Zn
1	24	84844	160	19.7	4864	2.10	29.14
2	20	87534	387	23.3	24534	3.00	21.71
3	20	89919	269	30.7	24210	3.32	27.38
4	20	26258	102	9.3	1560	0.90	5.90
5	20	146210	394	52.9	44136	7.30	62.10
6	11	36309	74	9.7	4906	0.99	12.00
7	20	166096	426	69.6	7819	9.23	72.69
Total	135	637169	1811	215	112030	27	231

Table 2. Storm event details from autosampled events at Gardiners Creek trial site.

We used this dataset to calculate the 'true' pollutant load for each event. We then compared this true load with that which would be obtained if, instead of using autosamplers, Melbourne Water had:

i. Taken a grab sample, at a random time within the storm event (based on the assumption that the time of sampling will vary randomly, depending on the size of the storm, and the location of the field officer at the time).
ii. Taken a sample at the same time (1 hour) after the start of every event (based on the assumption that when the flow sensor sends a telemetry signal to the field officer, it takes them one hour to get to the site).

Scenario (i) was analysed using bootstrapping (a non-parametric resampling technique: see Chernick, 1999), such that the concentration of a single randomly-chosen sample bottle was multiplied by the event volume, to calculate the event load. This was repeated 20 times for each event, and appropriate statistics (μ, 95%ile) calculated. Scenario (ii) was simply calculated by multiplying the concentration in the sample bottle taken at one hour after storm commencement, by the storm event volume. The analysis was undertaken for TSS, TP, TN, Pb and Zn.

3 RESULTS

3.1.1 Question 1: Can the loads of TSS and other pollutants be estimated (and if so, with what uncertainty) using turbidity as a surrogate?

Turbidity proved to be a useful predictor for TSS (Table 3), but not for other pollutants, as shown by the low R^2 values obtained. There is some suggestion that Chromium (Cr) could be reliably predicted by TSS (since it has a high affinity to fine particles), but given that heavy metal laboratory analysis is done as a "suite" (such that there is typically little or no extra cost to do one extra metal in the analysis).

Interestingly, the regression coefficient between turbidity and TSS, for the three sites chosen as 'trials' for this question, were quite statistically different, reflecting differences in geology, land-use and channel form within the three catchments (Wallbrink et al., 2003):

Bunyip River: TSS = 0.705 x Turbidity
Lang Lang River: TSS = 1.376 x Turbidity
Cardinia Creek : TSS = 0.301 x Turbidity

Parameter	Dandenong	Eumemmerring	Gardiners	Maribyrnong	Merri	Moonee Ponds	Yarra	Cardinia	Bunyip	Lang Lang
Temp	0.10	0.11	0.01	0.04	0.14	0.05	0.04	0.00	0.00	0.00
DO	0.04	0.01	0.01	0.01	0.00	0.00	0.01	0.00	0.00	0.00
%sat DO	0.01	0.00	0.03	0.03	0.03	0.00	0.00	0.00	0.00	0.00
Cond	0.34	0.18	0.04	0.29	0.22	0.04	0.00	0.00	0.11	0.01
pH	0.01	0.07	0.00	0.06	0.00	0.05	0.02	0.00	0.00	0.00
SS	**0.78**	**0.65**	**0.63**	**0.62**	**0.68**	**0.63**	**0.63**	0.51	**0.69**	0.45
NO3-N	0.00	0.02	0.05	0.03	0.06	0.00	0.08	0.53	0.24	0.00
NO2-N	0.03	0.00	0.01	0.11	0.00	0.06	0.29	0.33	0.22	0.04
NH3-N	0.04	0.01	0.00	0.00	0.00	0.00	0.05	0.48	0.42	0.16
TKN	0.03	0.04	0.15	0.01	**0.53**	0.25	0.47	0.60	0.42	0.19
T-N	0.02	0.02	0.13	0.02	**0.53**	0.12	0.48	**0.74**	0.33	0.08
O-P	0.09	0.04	0.01	0.00	0.01	0.10	0.08	0.05	0.50	0.05
TP	0.07	0.02	0.16	0.08	**0.52**	0.45	0.49	0.56	0.42	0.20
E.coli	0.12	0.00	0.02	0.00	0.25	0.01	0.01	0.17	0.19	0.03
BOD5	0.00	0.00	0.04	0.02	0.10	0.24	0.21	-	-	-
Chl a	0.03	0.00	0.00	0.00	0.00	0.00	0.00	-	-	-
Org-N	0.02	0.23	0.23	**0.63**	**0.81**	0.29	0.45	0.45	0.15	0.38
Rainfall	0.02	0.00	0.00	0.00	0.00	0.00	0.00	-	-	-
As	0.00	0.00	0.03	0.03	0.17	0.01	0.41	0.16	0.00	0.21
Cd	0.00	0.00	0.00	0.03	0.06	0.00	0.14	0.01	0.00	0.00
Cr	0.36	**0.69**	0.38	0.42	**0.74**	**0.62**	0.25	**0.71**	**0.62**	0.43
Cu	0.10	0.08	0.05	0.00	0.24	0.10	0.03	0.26	0.01	0.06
Pb	0.42	0.20	0.18	0.05	0.24	0.19	0.00	0.10	0.14	0.18
Ni	0.04	0.00	0.00	0.08	0.22	0.19	**0.51**	**0.61**	0.36	0.20
Zn	0.13	0.04	0.29	0.09	0.44	0.19	0.07	0.13	0.19	0.32

Table 3. Correlations (R^2 values) between turbidity and other water quality parameters. R^2>0.6 shown n bold.

Assuming that uncertainties in turbidity and flow measurement are largely randomly distributed (correlation of measurement errors have been taken into account), the overall uncertainty in estimated TSS loads are extremely low over the five year sampled period (less than 5% at all sites) (Table 4). Even over a single year, the potential error in the estimated TSS load is less than 10%. However, the potential errors are much greater if systematic errors in measurement are allowed to occur (e.g. due to infrequent or incorrect calibration) (Table 5). Systematic errors of 20% in both turbidity and flow (which are quite conceivable) result in errors in the long-term TSS load of up to 44%.

Catchment	Monitoring period		No. years	TSS Load		U(Load)		Error (%)
	Start	End		Total (t)	Per year (t/yr)	(t)	(t/yr)	
Bunyip	17/08/2000	13/12/2005	5.3	11506	2160	140	14	1
	17/08/2000	17/08/2001	1.0	3684		58		2
Lang Lang	17/08/2000	24/11/2005	5.3	18350	3478	696	66	4
	17/08/2000	17/08/2001	1.0	3937		257		7
Cardinia	17/08/2000	24/11/2005	5.3	1073	203	32	3	3
	17/08/2000	17/08/2001	1.0	225		13		6

Table 4. Estimated loads of TSS, based on continuous (6-minute) turbidity measurements. Uncertainties in the loads are provided, and expressed as a percentage of the estimated load.

Assumed error (%)		Error in Loads, E_L (%)			
E_{Qmeas}	E_{Tmeas}	Maximum Range		Minimum Range	
2	2	-4	4	0	0
5	5	-10	10	0	0
10	10	-19	21	-1	-1
15	15	-28	32	-2	-2
20	20	-36	44	-4	-4

Table 5. Errors in TSS load due to systematic errors in turbidity (E_{Tmeas}) and flow (E_{Qmeas}).

3.1.2 Question 2: How frequently do routine samples need to be taken to estimate long-term loads?

As expected, errors in the estimated load of TSS increase with decreases in the frequency of sampling. There is no absolute determinant of the appropriate frequency, but clearly, at a sampling interval of greater than three days, the absolute error in load increases to above 10% of the total load (Figure 1).

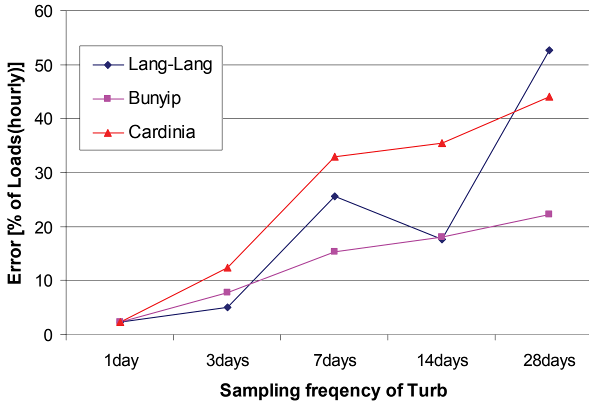

Figure 1. Absolute errors in TSS load estimates, relative to sampling frequency.

3.1.3 Question 3: Are autosamplers needed to estimate long-term loads?

At the Gardiners Creek trial site, the random and fixed (1 hour after commencement of storm) grab-sampling strategies produced overall load estimates that varied by generally around 10% from the 'true' load obtained by autosampling (Table 6). The 'fixed time' sampling strategy (ie. taking samples one hour after the commencement of the storm) has slightly lower errors than the random grab sampling strategy, but both are relatively low, compared to likely uncertainties in flow measurement, and even laboratory analysis of water quality samples (Greenberg et al., 1999).

Grab sample	Parameter (%)	TSS	TP	TN	Pb	Zn
Random time within storm (20 replicates)	Mean difference	8	12	11	12	10
	95%ile difference	10	16	12	14	17
1 hour after storm commencement	Difference	9	8	5	13	7

Table 6. Differences (%) between 'true' load and load estimated from grab samples taken (i) randomly and (ii) one hour after commencement of storm.

4 DISCUSSION

The use of turbidity as a surrogate measure for estimating long-term TSS loads has been shown to be effective, although not without caveats and limitations. Firstly, it will often be necessary to know not just sediment loads, but also loads of other pollutants such as nitrogen or heavy metals, for which turbidity does not provide such a good surrogate. On the other hand, there is an argument for the use of turbidity as a surrogate even for pollutants for which the regression has a low R^2. For TSS, the error in long-term loads, assuming that errors are randomly distributed, was always less than 5% (5 years of data), and less than 10% (one year). This very small error is a simple expression of the *Central Limit Theorem*. Whilst individual estimates of TSS concentration may have substantial errors, the *long-term* estimate is mitigated by the counter-balancing of individual *over-* and *under-estimates.* Therefore, even when the regression R^2 between turbidity and another parameter (e.g. TN) is low, the long-term load estimates predicted by turbidity could be quite accurate.

The indisputable advantage of a continuously-measured variable such as turbidity is the ability to capture variations at high frequency. The analysis showed that should a grab-sampling campaign be used instead, substantial errors will accrue where the sampling interval exceeds three days. This is a very demanding requirement, and difficult to meet, due to logistic and financial constraints.

On the other hand, one cannot overlook the critical importance of calibration, quality control and verification of data obtained from a continuous monitoring sensor. Uncertainty will grow rapidly if systematic errors are allowed to occur (due to sensor drift, improper calibration, or, for example, inaccurate flow rating curves). Bertrand-Krajewski et al. (2000b) offers a rigorous approach for addressing such problems, and a very useful practical example is given by the OTHU (Field Observatory for Urban Water Management) project in Lyon, France (see http://www.graie.org/othu/).

We did not expect to find such good representation of storm loads by grab sampling, relative to the 'true' load estimated from autosamplers. One might argue that the 'random timing' of grab samples works, because it again expresses the Central Limit Theorem (ie. some storms are under-estimated because they are sampled when the concentration has receded, but others are over-estimated, because the sample is taken at the peak of the pollutograph). However, the 'fixed-time' grab sample gave similar results, because it too expresses the Central Limit Theorem. Taking a sample one hour from storm commencement will, for some storms be before the peak, for others after the peak, and for others, right at the peak; *the timing of the sample relative to the storm peak* is again a random distribution.

Our finding that long-term pollutant loads (or site mean concentrations) can be adequately captured without the use of autosamplers has significant benefits in terms of cost reduction, and reducing the need for complex installation and problem-solving which are inevitably associated with automatic-sampling equipment. However, there are situations where autosamplers may still be the best solution. In catchments with very 'flashy' hydrologic response, or which are located far from field staff, it is likely that many storms will simply be missed. Thus, the statistical behaviour of grab sampling is only one consideration. Lastly, understanding the intra-event variation is often important; for example, understanding the frequency of exceeding certain pollutant concentration thresholds is often necessary to understand the ecological response of receiving waters (Taylor et al., 2005).

5 CONCLUSION

Frequently, water quality monitoring programmes are established, for the purposes of meeting a given objective, such as determining mean annual pollutant loads. Rarely, however, are such programmes reviewed, to see if these objectives are being met. This paper presents a subset of the key questions which were used, in a review of Melbourne Water's loads monitoring programme, to determine the uncertainties in the data being collected, and to identify ways of collecting better quality data, at a lower cost. The results showed the value of continuously measured variables (such as turbidity) as surrogate measures, given their ability to capture variability (provided that calibration and quality control are given appropriate attention). The study also showed that grab sampling can provide reliable estimates of storm event loads. On the other hand, a routine-sampling campaign (which does not specifically respond to storm events) will have increasingly large uncertainty, as the sample interval grows. An interval of 3 days will generally deliver errors of less than 10%. As a result of this study, Melbourne Water has designed and implemented a revised monitoring programme, and will review it again after one year of operation.

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