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Catchment-wide estimation of sediment-nutrient loads

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Abstract: The availability of reliable estimates of sediment and nutrient loads is central to effective catchment management. This requirement becomes even more critical if load-based licensing, regulation, and target-setting are to be at all meaningful. It is not uncommon for numerical targets to be overwhelmed by prediction/estimation uncertainty. Given the reliance on catchment models for target-setting, prediction, and evaluation it is important that their performance characteristics be quantified and their vulnerabilities understood. A number of comparative studies have been undertaken and many have reported significant discrepancies among loads estimated from different models. This paper reports on research that: (i) attempts to reconcile (or 'groundtruth') catchment-wide estimates of mass load export with empirically-derived estimates; (ii) provides an analytical framework for 'updating' model-based load estimates using a limited number of empirically-based sub-catchment load estimates; and (iii) characterises and exploits spatial continuity in load export to potentially improve predictions of load at unsampled locations.

We provide details of a comparison of model-based and empirical nutrient load estimates for the 3,000 km^2 Tambo River catchment in the Gippsland Lakes region of Victoria. The Tambo E2 model was used to estimate flow and constituent loads at various points in the Tambo River and tributaries. The main features of the model included 31 sub-catchments, 8 land-use/land cover based Functional Units (FU) in each sub-catchment, time series rainfall, evaporation and flow data, and constituent dynamics for the major constituents of total nitrogen (TN), total phosphorus (TP), and total suspended sediments (TSS), including FU-based generation.

One of the major sources of error in predicted loads from catchment models is the extremely coarse representation of a concentration distribution – typically this is characterised by only two statistics: a dry weather average and event mean concentration. In contrast, empirical concentration data are generally spatially limited but temporally dense. Thus, we expect an empirical load estimate at a point to be more reliable than its corresponding modelled estimate.

A comparison between catchment model load estimates and empirical load estimates revealed a general lack of agreement. The smallest (absolute) difference is 4.6% while largest is 127%. Overall the average absolute discrepancy is 53.2% with a propensity for the catchment model to yield a smaller load estimate than the corresponding empirical estimate. While our results do not resolve which method is more accurate, they do reinforce previously reported concerns with the bias of model-based estimates (Fox 2007).

We argue that the output from a catchment model which captures and integrates processes and understanding will exhibit spatial dependencies that are representative of the underlying correlation structure. We apply this correlation structure to a sparse configuration of high-quality empirical estimates to refine or update the model estimates over a much wider (unsampled) area.

Keywords: *load estimation; catchment model; watershed; spatial statistics.*

1. INTRODUCTION

An assessment of error and uncertainty in mass load estimates is central to robust, equitable, and statistically-defensible decision-making and management of natural water bodies. Load-based targets have been widely used by governments and NRM agencies for many years now as a means of driving down pollution levels. For example, a 40% reduction in sediment load in rivers in Far North Queensland was deemed necessary to prevent further water quality degradation and impacts on the Great Barrier Reef (Steven et al. 2005). In Gippsland, the Victorian EPA similarly adopted a 40% nutrient (phosphorous) reduction target for the Gippsland Lakes between 2000 and 2005 (EPA Victoria 2001). However, despite widespread use of load-based targets, load-based licensing, and load reduction agreements, there has been little or no quantification of the errors in the estimates that inform these management instruments. While the quantification of uncertainty may be dismissed as introducing an unnecessary level of complexity into the assessment process we believe that in the absence of such an analysis, the setting of numerical targets is rendered meaningless. Indeed, it has been shown by Fox (2005) that nutrient loads are typically underestimated by between 20 to 40% using conventional load sampling and estimation protocols.

Given the reliance on catchment models for target-setting, prediction, and evaluation it is important that their performance characteristics be quantified and their vulnerabilities understood. A number of comparative studies have been undertaken and many have reported significant discrepancies among loads estimated from different models. Papworth (2004) reported a 2-fold discrepancy in predicted TN loads in the Goulburn catchment using the Adaptive Environmental Assessment and Management process (AEAM) and the Catchment Management Support System (CMSS) and up to 4-fold discrepancies between empirical loads and loads estimated using the Environmental Management Support System (EMSS) model. In Queensland, Fentie et al. (2005) noted that “there has been very little comparison of SedNet outputs with those of other methods”. Fentie et al. also highlighted the wide discrepancy in sediment export estimates among a number of studies in the Fitzroy catchment – ranging from 1,861 kt/y to 11,463 kt/y. Admittedly, the statistical issues associated with load sampling and estimation techniques are numerous and a present difficulty is the lack of clear advice to practitioners on how to collect and analyse data. The situation is further compounded by the plethora of computational formulae available for load computations, although the computer software tool GUMLEAF (Tan et al. 2005) was developed in an attempt to streamline the selection process.
The motivating context for the present study was the increasing need of regional catchment managers and agencies to have better information about sediment and nutrient transport at a catchment and sub-catchment scale and importantly, to understand the uncertainties in load estimates produced from catchment models. Management of nutrient loads has been identified as being particularly critical in the West Gippsland region of Victoria to protect and improve the region’s significant environmental assets. The Regional Catchment Strategy and the Regional Water Quality Plan require a quantitative, rational basis for setting sediment and nutrient load targets on an end-of-valley basis, as well as for entire basins.

In the remainder of this paper we provide details of a comparison of model-based and empirical nutrient load estimates for the Tambo River catchment in the Gippsland Lakes region of Victoria. We also describe a method that exploits the observed spatial correlation structure in load exports to improve model predictions of loads at unsampled locations. While our conclusions are necessarily limited to this particular catchment and model implementation, our results are consistent with the belief that catchment models tend to significantly *underestimate* true mass loads. Our findings also give weight to the suggestion that the error in modelled baseline loads underpinning the 40% nutrient load reduction target for the Gippsland Lakes was between 20-100% (Davies and Martinez, 2006).

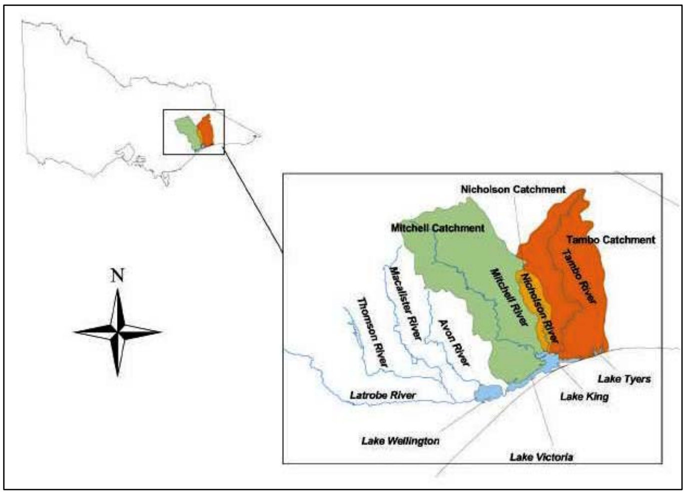

Figure 1. Catchments of the Gippsland Lakes (*Source: EPA Victoria, 2002*)

2. CATCHMENT CHARACTERISTICS

The Tambo catchment area is approximately 3,000 km^2, flowing generally north to south, with alpine headwaters at elevations of 1000-1500 m (Figure 1). The river delivers flow to Lake King, downstream of Swan Reach. The upper sub-catchments are largely forested, with a significant area of farming in the middle-upper region. Downstream of Tambo Crossing the river passes back into forested land before emerging into farmland again near Bruthen, the major town in the lower catchment. The climate has winter dominated precipitation, with average annual rainfall between approximately 600 and 900 mm, and annual average potential evapo-transpiration of approximately 1,000 mm.

2.1. Model development

The Gippsland Lakes catchment has been extensively studied and the results of previous modelling efforts by the CSIRO and University of Melbourne (Webster et al. 2001) as well as Grayson and Argent (2002) were used to inform the development of the model used in this study. The Tambo E2 model (developed using the E2 catchment modelling software available from www.toolkit.net.au/e2) was used to estimate flow and Total Nitrogen (TN), Total Phosphorus (TP) and Total Suspended Solids (TSS) loads at various points in the Tambo River and tributaries. The main features of the model include:

- 31 sub-catchments covering the catchment area of the Tambo River connected in a single node-link network. These sub-catchments align with catchment boundaries defined by confluences and gauging stations. The catchment areas were delineated by analysing the Geoscience Australia GEODATA 9 Second DEM V2.1 for the area;
- 8 land-use/ land cover based Functional Units (FU) in each sub-catchment. Land use areas were calculated from the "Land Use in Gippsland" dataset, obtained from the Bureau of Rural Sciences;
- Time series rainfall, evaporation and flow data for the period 1977-2006;
- Constituent dynamics for the major constituents of TN, TP, and TSS, including FU-based generation.

Further details of the model development and parameterisation can be found in Fox and Argent (2007).

2.2. Water Quality Monitoring

A number of water quality monitoring stations with acceptable water quality data sets were selected as the primary data source for model parameterisation (Table 1). Of these, five had sufficient contemporaneous data for the estimation of empirical loads. These are: 223202, 223205, 223212, 223213, and 223214. Examination of the associated data between 1-Jan-1976 to 18-Dec-2006 for these sites indicated that 8 years of contiguous monitoring data were available, extending from 21/8/1990 (Year 1) to 20/08/1998 (Year 8).

Table 1. Locations of water quality monitoring stations and period of data collection.

Number	Name	Start	End
223202	TAMBO RIVER @ SWIFTS CREEK	Aug-75	Jul-06
223204	NICHOLSON RIVER @ DEPTFORD	Aug-75	Jul-06
223205	TAMBO RIVER @ D/S OF RAMROD CREEK	Aug-75	Oct-88
223208	TAMBO RIVER @ BINDI (NEAR JUNCTION CREEK)	Aug-75	Apr-88
223209	TAMBO RIVER @ BATTENS LANDING	Jan-77	Jul-06
223210	NICHOLSON RIVER @ SARSFIELD	Aug-77	Jul-06
223212	TIMBARRA RIVER @ D/S OF WILKINSON CREEK	Jun-82	Oct-98
223213	TAMBO RIVER @ D/S OF DUGGAN CREEK	Jul-88	Jul-06
223214	TAMBO RIVER @ U/S OF SMITH CREEK	Mar-89	Jul-06
223215	HAUNTED STREAM @ HELLS GATE	Jan-91	Oct-98

3. COMPARISON OF MODELLED AND EMPIRICAL LOAD ESTIMATES

Conceptually, the mass load passing through a cross-section of river at a particular location is a measure of the cumulative contributions of all sub-catchments that are hydrologically connected to the monitoring location. In some cases, the load at a monitoring site is generated within a single sub-catchment. In other cases, the total load is comprised of contributions from a number of sub-catchments. By applying the relative contributions (weightings) to the modelled sub-catchment loads, we obtain an estimate of the TN load at each monitoring location. The method is summarised by equation 1.

$$W^T L_{sc} = \hat{L}_{gs} \tag{1}$$

where W is a matrix of weights whose $\{i, j\}^{th}$ element is the relative contribution of subcatchment *j* to the load at gauging station *i* ; L_{sc} is a column vector of sub-catchment loads; and $\hat{L}_{gs}$ is the vector estimated loads at each gauging station.

Both empirical and (E2) modelled nitrogen loads were estimated for the 31 sub-catchments for each of the 8 12-month periods from 08/1990 to 08/1998. Empirical loads were calculated using equation 2.

$$\hat{L} = k\sum_{i=1}^{N} c_i q_i \tag{2}$$

where c_i and q_i are, respectively, the measured concentration and discharge (flow) on the i^{th} sampling occasion and k is a scaling constant equal to the reciprocal of the sampling fraction (eg. $k = 365/30$ if an annual load estimate is required based on $N = 30$ observations).

The yearly comparison between catchment model load estimates and empirical load estimates is shown in Table 2. The lack of agreement is clearly evident. The smallest (absolute) difference in Table 2 is 4.6% while largest is 127%. Overall the average absolute discrepancy is 53.2% which accords with the Davies and Martinez (2006) observation that the errors in modelled baseline loads used for setting nutrient load reduction target for the Gippsland Lakes were thought to be between 20-100%.

Of the 32 estimates in Table 2, 27 (84%) are negative and 5 (16%) positive thus indicating the propensity of the catchment model to yield a smaller load estimate than corresponding empirical estimate. While this result cannot resolve which method is more accurate, it does reinforce previously reported concerns with the bias of model-based estimates (Fox 2002, 2007).

Table 2. TN load estimates (tonnes) at four water quality monitoring sites for eight 12 month periods in the Tambo catchment. First cell entry is empirical load estimate; second entry is estimate from E2 model; third entry is relative discrepancy of catchment estimate compared to the empirical estimate.

Site	Year							
	1	2	3	4	5	6	7	8
223202	58.38 17.56 -70%	5.97 9.10 +52%	36.11 22.54 -38%	26.91 16.36 -40%	8.75 8.16 -7%	23.06 15.72 -32%	14.48 7.16 -51%	29.73 12.59 -58%
223205	175.06 51.67 -70%	18.76 23.69 +26%	145.23 56.34 -61%	99.77 35.68 -64%	15.88 16.58 +4%	47.69 36.81 -23%	33.13 16.18 -51%	365.05 36.38 -90%
223212	35.60 5.44 -85%	6.75 2.85 -58%	45.19 6.72 -85%	17.49 4.78 -73%	6.96 2.33 -66%	20.64 4.55 -78%	9.13 2.04 -78%	31.58 4.00 -87%
223213	3.08 1.98 -36%	0.47 1.07 +127%	3.93 3.16 -20%	2.90 2.36 -19%	0.60 1.23 +105%	2.37 2.26 -5%	1.38 1.16 -16%	2.16 1.52 -30%

4. ESTIMATING LOADS AT UNSAMPLED WQ MONITORING SITES

Modelling tools are critical for broad scale assessments of catchment condition, trends, and response to natural and anthropogenic forcings. The advantages of catchment models are that they identify and encapsulate our understanding of the critical components and their interactions. As such, they are particularly well-suited to examining 'what-if' scenarios over long time-periods and/or large spatial extents. When it comes to providing quantitative estimates of mass load, we believe that the *relative* rather than absolute values from catchment models are more credible. One of the major sources of error in predicted loads from catchment models is the extremely coarse representation of a concentration distribution – typically this is characterised by only two statistics: a dry weather average and event mean concentration. In contrast, empirical concentration data are generally spatially limited but temporally dense. Thus, we expect an empirical load estimate *at a point* to be more reliable than its corresponding modelled estimate.

In this section we outline a hybrid strategy which combines the features of both empirical and modelled estimates. Although untested, our premise is that the output from a catchment model which captures and integrates processes and understanding will exhibit spatial dependencies that are representative of the underlying correlation structure. We apply this correlation structure to a sparse configuration of high-quality empirical estimates to refine or update the model estimates over a much wider (unsampled) area.

Spatial interpolation techniques are widely used in catchment hydrology (Blöschl and Grayson 2000). In the following section we briefly describe how the characterisation of spatial dependency in mass load over a region can be used to infer mass load at an unsampled location within the catchment. The idea is to use model estimates of sub-catchment loads to characterise the spatial covariance structure and to then use this as the kernel of a spatial interpolation technique such as kriging to provide point estimates at unsampled locations. This coupling of model and empirical load estimates in a spatially explicit manner is potentially very powerful, although more work is required to: determine suitable scales for generating model outputs; determine appropriate numbers and locations of sampled sites for empirical load estimates; assess the impact of non-stationarity and identify methods for handling ‘discontinuities’ as a result of localised features (topography, land-use/cover, micro-meteorology etc.). Additional research is required to gain a better appreciation of both model calibration and water quality network design in order to use the technique to infer mass loads on a catchment-wide scale.

4.1. Spatial-temporal analysis of modelled nitrogen loads

For the purpose of describing the spatial characteristics in TN-loads, the sub-catchment load was assumed to be concentrated at the geographical centroid of the sub-catchment. Detailed variogram analyses (not reported here) showed that, when averaged over all years, differences in TN load are greatest along a line extending from the north-west corner to the south-east corner (approximately Omeo to Orbost) of the catchment. Two regions of similarity (in TN loads) were identified off this diagonal band – one in the north-east corner and the other in the south-west corner. This is explained by similarities in climate, elevation, and land cover. Individual yearly variograms were also examined to more fully explore the nature of the space-time dependencies in modelled TN loads.

For example, the directional variogram for Year 1 (Figure 3) suggests that on average, TN loads may be correlated on scales of up to about 26km in the 112^0 direction. Combinations of Gaussian and spherical models were used to describe the yearly sample variograms. The forms for each of these are given by equations 4 and 5 respectively where the parameters r_1 and r_2 are the ranges for each model.

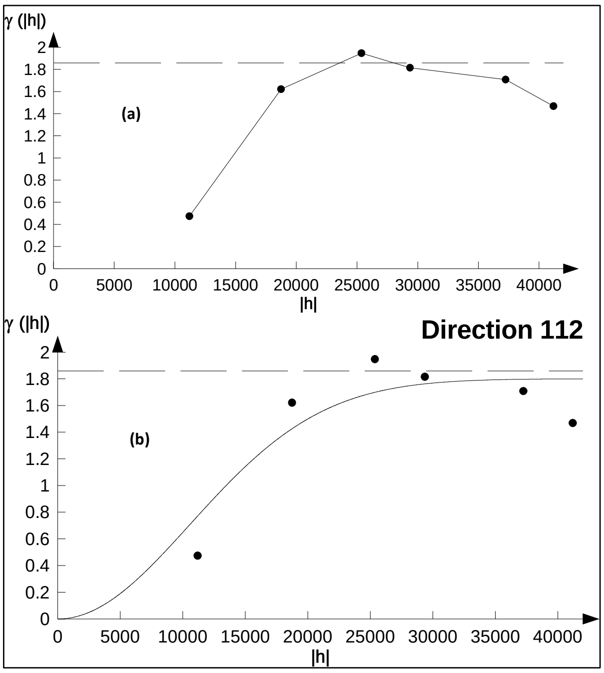

Figure 3. (a) Anisotropic variogram of TN load for Year 1. Direction=112^0; (b) with fitted Gaussian model.

$$\gamma(h)=\begin{cases}0 & \|h\|=0\\ \left[1-e^{-3\left(\frac{h}{r_1}\right)^2}\right] & \|h\|\neq 0\end{cases} \qquad (4)$$

$$\gamma(h)=\begin{cases}0 & h=0\\ \left[\frac{3}{2}\frac{\|h\|}{r_2}-\frac{1}{2}\left(\frac{\|h\|}{r_2}\right)^3\right] & 0\le\|h\|\le r_2\\ 1 & \|h\|>r_2\end{cases} \qquad (5)$$

Having characterised spatial dependency via the variogram, it is possible to obtain kriged estimates of TN loads at unsampled sites. The basic (ordinary) Kriging equation is given by equation 6.

$$C\,w = D \tag{6}$$

where:

$$C = \begin{bmatrix} \hat{C}_{11} & \cdots & \hat{C}_{1n} & 1 \\ \vdots & \ddots & \vdots & \vdots \\ \hat{C}_{n1} & \cdots & \hat{C}_{nn} & 1 \\ 1 & \cdots & 1 & 0 \end{bmatrix} \;;\; w = \begin{bmatrix} w_1 \\ \vdots \\ w_n \\ \lambda \end{bmatrix};\; \text{and } D = \begin{bmatrix} \hat{C}_{10} \\ \vdots \\ \hat{C}_{n0} \\ 1 \end{bmatrix}$$

and $\hat{C}_{ij}$ is the estimated covariance between *sampled* locations *i* and *j*, w_i is the Kriging weight to apply to the *measured* load at location *i*, $\hat{C}_{i0}$ is the estimated covariance between sampled location *i* and *unsampled* location 0; and λ is the Langrange multiplier. Given *C* is a full-rank, square matrix the Kriging weights are obtained using equation 7:

$$w = C^{-1} D \tag{7}$$

The predicted load $\left(\hat{L}_0\right)$ at the *unsampled* site is obtained using equation 8:

$$\hat{L}_0 = \sum_{i=1}^{n} w_i\, l_i \tag{8}$$

where l_i is the measured load at site *i*. Further details and an illustrative example can be found in the report by Fox and Argent (2007).

5. DISCUSSION AND CONCLUSIONS

Catchment models are extremely valuable tools for informing and guiding large-scale monitoring and management programs. However, care needs to be exercised when using model predictions of mass load export due to the unquantified biases and uncertainties associated with these estimates. Although not definitive, the results of this preliminary analysis provide another line of evidence to support our contention that there is a propensity for catchment models to *underestimate* true sediment-nutrient loads.

We have presented a novel technique that characterises the spatial correlation structure exhibited in catchment model outputs and coupled this with sparsely distributed empirical load estimates to refine modelled loads at *unsampled* locations.

Further work is required to determine suitable scales for generating model outputs; determine minimum numbers and locations of sampled sites for empirical load estimates; assess the impact of non-stationarity and identify methods for handling ‘discontinuities’ as a result of localised features (topography, land-use/cover, micro-meteorology etc.). Additionally, research is required to gain a better appreciation of both model calibration and water quality network design in order to use the technique to infer mass loads on a catchment-wide scale.

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REFERENCES

Blöschl, G. and Grayson, R. (2000) Spatial observations and interpolation. In *Spatial Patterns in Catchment Hydrology*: *Observations and Modelling*, pp 17-50, Cambridge University Press, Grayson and Blöschl, Eds.

Davies, W. and Martinez, G. (2006) Estimation of riverine nutrient input into the Gippsland Lakes During 2004-2005. EPA Victoria, Marine Science 05-06.

EPA Victoria (2001) Protocol for Calculating Phosphorus Loads for the Macalister Irrigation District. February 2001.

EPA Victoria (2002) Environmental Condition of the Rivers and Streams in the Mitchell, Tambo and Nicholson Catchments, Publication 858, 2002.

Fentie, B., Joo, M., Yu, B., Hunter, H., Marsh, N., Carroll, C., and Dougall, C. (2005) Comparison of Mean Annual Suspended Loads Estimated By The Sednet Model And Rating Curves In The Fitzroy Catchment, Australia. Proc. MODSIM 2005 International Congress on Modelling and Simulation, 1133-1139.

Fox, D.R. (2002) Quantifying errors and uncertainties associated with Nutrient Reduction Targets. Technical Note, Centre for Environmental Applied Hydrology, University of Melbourne. November 2002.

Fox, D.R. (2005) Protocols for the Optimal Measurement and Estimation of Nutrient Loads: Error Approximations. Technical Report 03/05, Australian Centre for Environmetrics, University of Melbourne.

Fox, D.R. (2007) Water Quality Monitoring in the Gippsland Catchments – Efficient Sampling Strategies and Load Estimation Techniques. The Australian Centre for Environmetrics, Occasional Report, May 2007, University of Melbourne, Parkville Australia.

Fox, D.R. and Argent, R.M. (2007) Catchment-wide estimates of nutrient loads and associated uncertainty. The Australian Centre for Environmetrics, December 2007, University of Melbourne, Parkville Australia.

Grayson, R. B., Argent, R. M., (2002). A tool for investigating broad-scale nutrient and sediment sources from the catchments of the Gippsland Lakes: Melbourne, Centre for Environmental Applied Hydrology, p. 44.

Grayson, R. B., Argent, R. M., (2002). A tool for investigating broad-scale nutrient and sediment sources from the catchments of the Gippsland Lakes. Centre for Environmental Applied Hydrology. CEAH Report 1/02. 44 pp.

Papworth, S. (2004) Major storages water quality study: Upper-Mid Goulburn EMSS, A Preliminary Report on Catchment Surface Water Quality Investigations. Cooperative Research centre for Catchment Hydrology.

Steven, A., Fox, D., Tan, KS., Farthing, B., Grayson, R., Marsh, N., Peterson, P., Tenakoon, S., and Williams, R.(2005) Protocols for defining, measuring and auditing load-based targets in Queensland Catchments - A Report to the Department of the Environment and Heritage.

Tan, K.S., Fox, D.R., Etchells, T. (2005) GUMLEAF: Generator for Uncertainty Measures and Load Estimates using Alternative Formulae. User Guide and Reference Manual. The Australian Centre for Environmetrics, University of Melbourne.

Webster, I.T., Parslow, J.S., Grayson, R.B., Molloy, R.P., Andrewartha, J., and Pavel, (2001) Gippsland Lakes Environmental Study: Assessing Options for Improving Water Quality and Ecological Function, CSIRO and the University of Melbourne.