

The Australian Centre for Environmetrics

Catchment-wide estimation of nutrient loads and associated uncertainty

FINAL REPORT

CITATION

This report can be cited as:

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.

Acknowledgements

Financial support for this work has been provided under the Victorian Government's Regional Catchment Investment Plan (Project No. WG-0506.10.53). Additional support has been provided by the University of Melbourne (Department of Civil and Environmental Engineering).

Warren Davies and Guillaume Martinez of the Victorian EPA for provided daily water quality data for the Tambo River.

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Executive Summary

The issue of mass load estimation is an important topic in natural resource management. Water quality monitoring in the Gippsland catchments has been undertaken by a number of agencies over many years with a view to quantifying, among other things, annual nutrient loads (principally nitrogen and phosphorous). In 2001 the Victorian DSE established an overall 40% nutrient load reduction target for the Gippsland Lakes. While much of the subsequent focus has been on identifying and implementing on-ground actions and strategies to achieve this reduction, relatively little attention has been given to the issue of *how do we actually measure improvement*? This is a critical question that needs to be answered if we are to assess the cost-effectiveness of any particular course of action or suite of actions. Furthermore, a more comprehensive analysis will require companion estimates of *uncertainty* or *precision* so as to attach levels of confidence that certain targets have been met.

Issues of spatial scale are also important in any assessment of mass loads. The delivery of sediment and nutrient loads is highly variable in both space and time. While periodic (and usually infrequent) monitoring of water quality at a handful of fixed sites provides a 'snapshot' of highly localised conditions it does little to assist in the development of a more holistic assessment.

The use of catchment modelling 'tools' has become ubiquitous and while much good work has and continues to be done with respect to 'tool' development (see for example <u>http://www.toolkit.net.au/cgi-bin/WebObjects/toolkit</u>), we believe there is a pressing need to invest more research effort into the related areas of: (i) (load) prediction accuracy; and (ii) (load) estimation uncertainty. This has already commenced, with a number of eWater CRC research projects tackling issues of 'uncertainty'. The research reported on in this report is thus complimentary to many of those activities and we believe represents the first (albeit limited) statistically-based assessment of the likely errors and uncertainties in catchment-wide load estimates produced by standard catchment modelling 'tools'. Although the scope of this study is very limited, the results suggest that catchment models may seriously underestimate the true sediment / nutrient loads exported from a catchment. If substantiated, this finding has potentially significant (and perhaps serious) implications for governments, NRM agencies, catchment management boards, industry, and individual landowners.

1. Introduction

As noted in Fox (2005b), the accurate estimation of sediment and nutrient loads is an issue that is attracting considerable attention among researchers and NRM agencies in Australia and overseas. To a large extent, this has been driven by the imposition of either compliance-driven or 'aspirational' load reduction targets. 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). Despite the widespread use of load-based targets, load-based licensing, and load reduction agreements, there is little accounting of the uncertainty in the estimates underpinning these instruments. Some would argue that this introduces an unnecessary level of complexity into an assessment process which is more to do with changing behaviours and practice than it is about accurate quantification of loads. Our view is that in the absence of such an assessment, the setting of any numerical target is rendered meaningless. Indeed, it has been shown (Fox 2005b) that nutrient loads are typically underestimated by between 20 to 40% using conventional load sampling and estimation protocols. Thus, one could demonstrate an apparent 40% load reduction by doing nothing more than comparing a current (biased) load estimate with an unbiased estimate of baseline load.

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 computing a load, although the computer software tool GUMLEAF (Tan et al. 2005) was developed in an attempt to streamline the selection process.

The research reported here looks at load estimation at a macro scale ie. whole of catchment and is intended to compliment work undertaken at the micro or point scale such as that reported in Fox (2002, 2003, 2004a, 2004b, 2005a, 2005b, 2007). The present research is unique in that it: (i) attempts to reconcile (or 'groundtruth') catchment-wide estimates of mass load export with empirically-derived estimates of the same quantities; (ii) characterises and exploits spatial continuity in load export to potentially improve predictions of load at unsampled locations; and (iii) provides an analytical framework for 'updating' model-based load estimates using a limited number of empirically-based sub-catchment load estimates. While the numerical results are specific to the Gippsland catchment, we believe the methods have wider applicability.

The motivating context for the present work 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 West Gippsland 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. An assessment of error and uncertainty in load estimates is central to robust, equitable, and statistically-defensible decision-making. As noted by Davies and Marinez (2006) the errors in modelled baseline loads used for setting the 40% nutrient load reduction target for the Gippsland Lakes were thought to be between 20-100%.

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 (2005) 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 EMSS estimated loads. 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. The reporting of mass flux rates either as mass per unit time (eg. t/y) and/or mass per unit area per unit time (eg. t/ha/y) rather than actual loads only serves to mask the magnitude of the error in estimated load. For example, Smith et al (2005) noted that the SedNet estimate of load (more correctly *flux*) for Jugiong creek catchment was 0.374 t/ha/y compared to the empirical estimate of 0.116 t/ha/y. When applied to a catchment area of 2127 km², this discrepancy translates to an overestimation of nearly 55,000 tonnes per year.

This research project builds upon and extends the tools and methodologies developed by researchers at the Australian Centre for Environmetrics. Previous research funded by the WGCMA has resulted in the development of 'optimal' sampling strategies for nutrient load estimation as well as providing computational and software tools for designing monitoring campaigns. To date, the focus of this work has been at the level of an individual river, stream, or drain.

2. Aims and Objectives

In hindsight, the original objectives of this project were overly ambitious given the existing state of knowledge and paucity of published, relevant research upon which to draw. Nevertheless, we believe considerable progress has been made towards identifying critical issues with respect to monitoring design and catchment model parameterisation. For example, this research has provided insights into the number and location of fixed monitoring sites in order to (i) characterise spatial attributes of mass load export; and (ii) act as 'anchors' for refining model-based (sub-catchment) load estimates. With respect to catchment model parameterisation, our results suggest that there is possibly a need to better characterise the overall nutrient/sediment concentration distribution rather than using two statistics (base-flow mean concentration and event mean concentration) as is commonly done at present.

The original conceptual model underpinning the development of the present research project is shown in Figure 1. The idea was relatively straightforward and involved:

- Overlaying a grid onto the region of interest and using a catchment model, predict each grid cell's contribution to the overall catchment load;
- 2. Assemble the predicted loads from 1 into a single $N \times 1$ column vector, \hat{X} in such a way that the first m entries of \hat{X} corresponded to cells for which no empirical load estimate was available. The remaining *N-m* rows of \hat{X} corresponded to cells for which an

empirical load estimate *was* available. Thus $\hat{X} = \left[\frac{\hat{X}^{(1)}}{\hat{X}^{(2)}}\right]$;

- 3. Using all the results from step 1, characterise the spatial correlation structure of predicted loads and denote this as $Cov \begin{bmatrix} \hat{X} \end{bmatrix}$;
- 4. Identify sub-matrices $\Sigma_{11}, \Sigma_{12}, \Sigma_{21}$ and Σ_{22} such that $Cov \begin{bmatrix} \hat{X} \end{bmatrix} = \begin{bmatrix} \Sigma_{11} & \Sigma_{12} \\ \Sigma_{21} & \Sigma_{22} \end{bmatrix}$ where

the partitioning of $Cov \left[\hat{X} \right]$ is done according to the partitioning in 2;

- Use equation 1 to obtain estimates of load at unsampled locations *conditional* upon the loads at sampled locations and;
- 6. Use equation 2 to obtain an estimate of the error in the estimate obtained at step 5.

$$E\left[\hat{X}^{(1)} \middle| \hat{X}^{(2)} = \hat{x}^{(2)} \right] = \mu^{(1)} + \sum_{12} \sum_{22}^{-1} \left\{ \hat{x}^{(2)} - \mu^{(2)} \right\}$$
(1)

$$Cov \left[\hat{X}^{(1)} \middle| \hat{X}^{(2)} = \hat{x}^{(2)} \right] = \Sigma_{11} - \Sigma_{12} \Sigma_{22}^{-1} \Sigma_{21}$$
⁽²⁾

In equation 1, the μ s are vectors of *modelled* loads and $\hat{x}^{(2)}$ is a vector of *empirical* load estimates. It is thus readily apparent from equation 1 that the conditionally estimated loads at *unsampled* locations (ie the elements of $\hat{X}^{(1)}$) are obtained by making an adjustment to the modelled load. The magnitude of this adjustment is a function of both the spatial correlation structure *and* the discrepancy between the empirical and modelled values at a location.

Although the full implementation of this algorithm was not able to be implemented, the basic idea of combining an understanding of the spatial correlation structure together with a limited number of empirical load estimates has been exploited. A full description of methods and results is presented in subsequent sections of this report.



Figure 1. Conceptual model for discretising a catchment and conditionally estimating loads within unsampled 'cells'.

3. Catchment characteristics

Catchment loads flowing into Gippsland Lakes are of considerable interest from an ecological and economic perspective, and considerable work has been done in recent years to estimate constituent loads in this region.

A satellite view of the region with a sub-catchment overlay is shown in Figure 2 while Figure 3 shows the locations of water quality monitoring sites and sub-catchment centroids. The Tambo catchment area is approximately 3000 km², flowing generally north to south, with alpine headwaters at elevations of 1000-1500 m. 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 evapotranspiration of approximately 1000mm.

Past studies include the CSIRO/University of Melbourne study of Gippsland Lakes loads, and the work of Grayson and Argent (2002) has been used to inform the current model development.

The current study is investigating a new approach to improve estimates of constituents loads both within waterways and the receiving waters of the Gippsland Lakes system. For this, a model of the Tambo river catchment, Tambo E2, was created using the E2 catchment modelling system, as a tool for estimating catchment loads under a range of current and potential future conditions.



Figure 2. Satellite image of Gippsland catchment with sub-catchment overlay.

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Figure 3. Location of water quality monitoring locations (yellow pin) and sub-catchment centroids (yellow box).

4. Catchment modelling: the Tambo E2 Model

Past studies include the CSIRO/University of Melbourne study of Gippsland Lakes loads, and the work of Grayson and Argent (2002) has been used to inform the current model development.

Tambo E2 has been designed as a tool 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, and to support investigation and comparison of alternative management options.

4.1 The Default Scenario

The default scenario has been developed to represent one set of current conditions, and was based upon time series data from the period 1977-2006, along with various publicly available spatial data. Features of the default scenario include:

- 31 sub-catchments (Figure 4) 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 BRS¹ (Figure 5).
- 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.

¹ "Land Use in the East and West Gippsland Catchment Management Authority Regions of Victoria is mapped for 1996-97 at 1:100,000 scale across the area and at 1:25,000 scale for an intensively used area in West Gippsland. The classification of land uses is based on 4 sources of information: (1) Resource data sets of Victoria held at Corporate Geospatial Data Library (CGDL) of the Department of Natural Resources and Environment, (2) Satellite imagery from Landsat 5 and SPOT 2 satellites for summer of 1996-7, (3) geocoded Australian Bureau of Statistics Agricultural Statistics, and (4) Field information. The land use are mapped according to the Australian Land Use and Management Classification, Version 4. The classification is hierarchical in nature, identifying primary (broadest land use), secondary, and tertiary levels. The five primary levels show a gradation in terms of human intervention in natural environment. This product was produced for the Gippsland Implementation Project, as part of a National Land and Water Resources Audit."



Figure 4 Sub-Catchment map of the Tambo (and Nicholson)



Figure 5 Land use map for the Tambo and Nicholson catchments

4.2 Scenarios in Tambo E2

Tambo E2 has been developed using the E2 catchment modelling software. It is essential that users wishing to explore management scenarios are familiar with the operation of this software tool in order to make the most of the features offered by Tambo E2. The E2 software, along with documentation and example data are available from www.toolkit.net.au/e2. The modelling and scenario comparison capability developed in Tambo E2 was identified from features common to previous catchment models, in addition to the needs of the analysis process that will be applied to the results. Using the default scenario as a basis, it is possible through manipulation of input data and parameters to model scenarios such as:

- Changing forest management
- Changing farm management
- Post bushfire loads and flows
- Bushfire recovery (i.e. regrowth) flows and loads

4.3 Model Development and Calibration

4.3.1 DEVELOPING FUNCTIONAL UNITS

Functional Units (FUs) represent the most fundamental spatial information within E2. In Tambo E2 the FUs are based on land use, with each FU being potentially able to have associated with it:

- a calibrated rainfall-runoff model;
- a calibrated constituent generation model, and
- a filter model that represents the effects of selected management actions.

Together, these models represent the dynamics of behaviour of the FU. In establishing FUs for a model such as Tambo E2 a trade-off is required between the ability to distinguish between behaviour of different land uses (and so to realistically represent this in models), and the requirements for managing different land uses in different ways. The FUs used in Tambo E2 are listed below.

	Functional Units
1	Natural vegetation
2	Grazing
3	Forest Products
4	Irrigation
5	Urban
6	Industrial
7	Roads
8	Water

Table 1 Functional Units used in Tambo E2

4.3.2 SUB-CATCHMENTS

Sub-catchments are the fundamental spatial unit for accumulation of loads generated at the FU level. Selecting sub-catchments involves a trade-off between sub-catchment size, number, the ability to represent relevant behaviour, and the run-time of the software. Sub-catchments in Tambo E2 were selected by consideration of the position of gauging stations and the major confluences and stream reaches in the system. The sub-catchments, along with sub-catchments ID numbers and areas, are given below.

As part of the larger investigation of model-monitoring loads assimilation, it was necessary to identify the centroid of each sub-catchment. Centroid locations (in AMG coordinates) are also given below.

#	ID	Name	Area (km ²)	Zone 55	Zone 55	
				Easting	Northing	
1	SC #1	Tambo Below Battens	93.6	575669	5814579	
2	SC #31	Monkey Creek	86.4	573524	5834000	
3	SC #3	Tambo Dead Horse	161.6	583685	5833612	
4	SC #4	Tambo Above Timbarra	80.1	579691	5843222	
5	SC #5	Tambo Crossing	72.2	575968	5849391	
6	SC #6	Haunted Confluence	0.1	573334	5850988	
7	SC #7	Wattle Circle	46.6	572869	5855694	
8	SC #8	Tambo Below Ensay South	11.8	574276	5860746	
9	SC #28	Tambo Doctors Flat	185.7	566891	5870008	
10	SC #10	Tambo Tongio	204.8	565723	5884129	
11	SC #11	Scrubby Creek	91.4	566209	5898446	
12	SC #12	Tambo Above Scrubby	22.0	574041	5899215	
13	SC #13	Tambo Below Duggan	28.3	576511	5903006	
14	SC #14	Tambo Upper South	125.2	583286	5897473	
15	SC #15	Swifts Creek	206.2	554657	5873857	
16	16 SC #16 Little River		198.7	576850	5872092	
17	17 SC #17 Sandy Creek		90.0	580227	5859197	
18	18 SC #18 Shady Creek		95.5	568448	5844273	
19	19 SC #19 Timbarra Lower		141.6	588354	5851585	
20	SC #20	Timbarra Wilkinson	138.1	588121	5865379	
21	SC #21	Timbarra Mid East	88.0	595063	5863724	
22	SC #22	Tambo Bindi	118.5	572927	5891251	
23	SC #23	Tambo Above Bruthen	16.8	576743	5827801	
24	SC #24	Old Hut Creek	18.7	574502	5895903	
25	SC #26	Timbarra Upper	196.0 587961		5880343	
26	SC #27	Haunted Upper	121.2	557404	5860078	
27	SC #29	Swifts Confluence	2.2	564381	5875524	
28	28 SC #30 Wilkinson Confluence		0.4	594199	5855222	
29	SC #32	Tambo Upper North	91.9	581093	5908558	
30	30 SC #33 Tambo Above Battens		87.3	572181	5825002	
31	SC #34	Haunted Lower	70.3	567297	5855446	

Table 2 Sub-Catchment Information

4.3.3 RAINFALL-RUNOFF

A valuable data source for the calibration of the Tambo E2 runoff models is provided by number of runoff gauging stations positioned within the Tambo and the adjacent Nicholson catchment. The stations considered are listed below.

Site No.	Name
223202	TAMBO RIVER @ SWIFTS CREEK
223204	NICHOLSON RIVER @ DEPTFORD
223205	TAMBO RIVER @ D/S OF RAMROD CREEK
223207	TIMBARRA RIVER @ TIMBARRA
223208	TAMBO RIVER @ BINDI (NEAR JUNCTION CREEK)
223209	TAMBO RIVER @ BATTENS LANDING
223210	NICHOLSON RIVER @ SARSFIELD
223211	HAUNTED STREAM @ STIRLING
223212	TIMBARRA RIVER @ D/S OF WILKINSON CREEK
223213	TAMBO RIVER @ D/S OF DUGGAN CREEK
223215	HAUNTED STREAM @ HELLS GATE (NOT USED DUE TO
	POSITION OR IRRELEVANT DATA PERIOD)
223200	TAMBO RIVER @ BRUTHEN
223201	TAMBO RIVER @ ENSAY SOUTH
223203	TIMBARRA RIVER @ TIMBARRA @ D/S OF RUNNING CREEK
223206	TAMBO RIVER @ BINDI
223214	TAMBO RIVER @ U/S OF SMITH CREEK
223401	TIMBARRA RIVER @ TIMBARRA
223403	TAMBO RIVER @ NUNNIONG PLAINS

Table 3 Gauging stations used in rainfall-runoff investigation

The stations used generally had good-excellent length of record and few, small gaps. Short gaps in the flow record were filled by linear interpolation of flow in addition to checking for significant rainfall events.

Modelling of flow was done via a regionalised approach, which examines a series of catchments within a region, and endeavours to identify a set of model parameters that represent a reasonable behaviour for most of the sub-catchments under investigation. In the absence of significant urban (impervious) areas, the primary delineator of hydrological behaviour in the Tambo region is the presence or absence of forest cover.

Thus, two regional runoff model parameter sets were developed, for the following:

- Forest
- Non-forest

The general approach taken was to:

- Use the Rainfall-Runoff library (RRL) to investigate the behaviour of the catchments contributing flow to the previously listed gauging stations.
- 2. Identify a small number of catchments containing land uses dominated by the above regionalisation attributes (eg forest) for closer investigation
- 3. Progressively identify and fix the runoff model parameters with least influence (ie sensitivity) on the model result, until obtaining a single parameter set that gave reasonable (based upon mass balance and Nash-Sutcliffe Coefficient of Efficiency (E) criteria, on a monthly basis) simulated flows. Figure 6 shows example model sensitivity to the model parameter "baseflow coefficient".

The SimHyd rainfall runoff model was selected for application to all sub-catchments, and between 20,000 and 30,000 model runs were used during the calibration process. A description of the model can be found in the RRL manual, available from www.toolkit.net.au/rrl (Podger, 2004). Flow routing was not used as the model is built for long term analysis rather than for events or daily analysis.



Figure 6 Rainfall-runoff calibration showing sensitivity to Baseflow Coefficient (K)

4.3.4 FOREST AND NON-FOREST CALIBRATION

Calibration of runoff modelling was done by identifying sub-catchments (or groups of subcatchments) with dominant land uses that were classified as either forest or non-forest, and then identifying which of these coincided with gauging stations having reasonable flow data. Five sites were initially selected for investigation of flows. These were:

- 223202 TAMBO RIVER @ SWIFTS CREEK (909 km²)
- 223204 NICHOLSON RIVER @ DEPTFORD (287 km²)
- 223205 TAMBO RIVER @ D/S OF RAMROD CREEK (2681 km²)
- 223210 NICHOLSON RIVER @ SARSFIELD (471 km²)
- 223211 HAUNTED STREAM @ STIRLING (149 km²)

Calibration runs on these sites were performed iteratively until acceptable values of annual mass balance and Nash-Sutcliffe Coefficient of Efficiency (E) were found.

The model parameters and descriptions are given below, in addition to the final parameters. It should be noted that the non-forest designator and associated parameters were applied to any of the small industrial, urban and water land use areas in various sub-catchments.

Parameter	Description
К	Baseflow linear recession parameter
ImpT	Impervious threshold (threshold for runoff from impervious area) (aka INSC, Interception
	storage capacity)
COEFF	Infiltration coefficient (maximum infiltration loss)
SQ	Infiltration shape (Part of the infiltration exponent)
SUB	Constant of proportionality in interflow equation (interflow coefficient/ constant)
Perv	Pervious fraction
INSC	Interception storage size (aka RISC)
CRAK	Constant of proportionality in groundwater recharge equation (Recharge coefficient)
SMSC	Soil moisture store capacity (maximum storage)

Table 4 SimHyd parameter descriptions

Table 5 Default SimHyd parameters

	K	ImpT	COEFF	SQ	SUB	Perv	INSC	CRAK	SMSC
Non-Forest	0.05	1	230	0.2	0.19	1	5	0.55	320
Forest	0.015	1	230	3.1	0.1	1	5	0.3	260

4.3.5 OTHER HYDROLOGICAL CONSIDERATIONS

E2 has significant capacity to model storages, demands, releases and extractions. There are, however, no significant water storages in the Tambo catchment, so no representation of these had to be made. It is known, however, that the Tambo River has 'losing' reaches where flow decreases in a downstream direction, and improved calibration, if required, could be obtained by estimating these losses and representing them as flow extractions.

Point sources of flow or constituents can be modelled by combined flow and concentration from a Point Source FU identified in those sub-catchments for where point sources occurred. These are, however, no significant point sources in the catchment.

4.3.6 WATER QUALITY MODELLING

A number of water quality monitoring stations with acceptable water quality data sets were selected as the primary data source. These are listed in Table 6.

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

Insufficient land use specific event-based water quality data were available to undertake calibration of EMC and DWC values for each FU type. However, a range of EMC/DWC values can be estimated from the above data and literature sources, as described in the following section.

4.3.7 TN, TP AND TSS CONSTITUENT GENERATION

The values of Duncan (1999; 2006) were used as the base values for constituent generation. When applying these to Tambo E2, scaled values were used that took account of the sub-catchment scale, and no filter models were applied to 'modify' loads between generation and monitoring point. The values used are given in Table 7, along with comparable values taken from a number of monitoring stations.

	TN		ТР		TSS	
	DWC	EMC	DWC	EMC	DWC	EMC
	mg/L	mg/L	mg/L	mg/L	mg/L	mg/L
Natural Vegetation	0.5	1.5	0.05	0.1	6	40
223210	0.09	0.09	.022	0.08	1	4
Grazing	0.5	2.5	0.06	0.18	15	90
223202	0.22	0.22	0.014	0.038	2	10
Forest Products	0.5	2	0.05	0.1	8	60
223210	0.09	0.09	.022	.08	1	4
Irrigation	0.7	3	0.08	0.2	20	100
Urban	1.5	4	0.18	0.6	15	120
Industrial	1.5	4	0.18	0.7	15	120
Roads	1.5	4	0.18	0.7	25	160
Water	0.1	0.1	0.01	0.01	1	1

Table 7 Default constituent concentration/count values for FUs

4.4 Assumptions, Limitations, Errors, and Uncertainty

There are a range of factors that affect the accuracy of the modelling results, and the possible application of Tambo E2 to a range of scenarios, as follow:

- The primary uncertainties associated with the output produced by Tambo E2 arise from the use of regionalised runoff and water quality parameters. In running scenarios these uncertainties can be reduced by ensuring that appropriate management practices are represented, and by using relative, rather than actual, comparisons of scenario results.
- Tambo E2 was constructed using historical flow and water quality data, and it is assumed that these were of reasonable accuracy, with significant errors being identified through institutional quality checking processes. Any errors in these data which were not identified in the data collation process will affect the model accuracy.
- The model outputs are based on calibrations to between daily rainfall, average daily precipitation and monthly flows over the period 1977 to 2006, with the intention of providing output values for comparison and analysis on an *annual* basis. The daily flows produced from these input data should not be considered to be representative of flows occurring on a particular day in history.
- The system representation used in Tambo E2 is essentially a static view, based on a combination of historical (time-varying) catchment runoff and constituent generation processes, and past (late 1990's) land use. When running scenarios, the output will reflect the effects of these static conditions under the range of time-varying factors (eg climate) selected for the model runs.

4.5 E2 Catchment Modelling Software

E2 is a modelling software application created specifically for spatio-temporal catchment modelling. The E2 design draws upon developer experiences with previous catchment modelling and software systems (Tarsier, ICMS and the EMSS) to provide a robust and expandable catchment modelling suite.

The basic E2 software system provides essential basic operations, such as flow and water quality modelling and scenario comparison, while the plug-in capability allows addition of custom-built models for specific requirements. Relevant software engineering and modelling expertise are available to meet development requirements imposed by the DSS project.

Developer	Cooperative Research Centre for Catchment Hydrology
Status	Version 1.3.2b is publicly available. Development and
	bug-fixing is on-going.
Availability	Public, free of charge, from www.toolkit.net.au/e2
Architecture	Built using TIME (The Invisible Modelling Environment),
	based on .NET. Object oriented and metadata
	responsive
Supported Domains	1-D, 2-D temporal flow and water quality
Example Models	Rainfall-Runoff models - AWBM, SIMHYD
	Constituent models - EMC/DWC
	Routing – Muskingum, lag
Platforms	Windows™
Users	Research
	Consultancies
References	www.toolkit.net.au/e2

Table 8 Overview information of the E2 catchment modelling software

4.6 TN, TP and TSS Constituent Generation

Following review of the preliminary results (May 2007) the constituent parameters were reviewed, and the decision taken to adopt an Effective Mean Concentration (c.f. Event Mean/Dry Weather Concentration) due to the paucity of supporting data and time for further investigation.

Field data were available to support selection of values for native vegetation / forest products, and for grazing areas. The values of Duncan (1999; 2006) were used as the base values for generation of other constituents. When applying these to Tambo E2, no filter models were applied to 'modify' loads between generation and monitoring point. The values used are given in 9.

	TN	ТР	TSS
	Effective MC mg/L	Effective MC mg/L	Effective MC mg/L
Natural Vegetation	0.35	0.01	4.0
(223215)			
Grazing	0.38	0.02	30
223202			
Forest Products	0.35	0.01	4.0
(223215)			
Irrigation	4.0	0.55	180
Urban	2.8	0.35	160
Industrial	2.5	0.3	160
Roads	2.2	0.26	190
Water	0.4	0.01	4.0

Table 9 Default constituent concentration/count values for FUs

5. Characterising spatial variation in sub-catchment loads

As mentioned in the introduction our initial research design was to generate load estimates on a relatively dense grid and to use these estimates to explore the underlying spatial correlation structure. Even had this been possible, it is recognised that it is an imperfect approach since the *statistical* approach to characterising spatial variation is typically through a variogram analysis which models spatial dependency as a function of separation only (isotropic case) or separation and direction (anisotropic case). While the small-scale contributions to a catchment load are expected to be spatially correlated (eg. a high load in one grid cell probably means a high load in an adjacent grid cell) there are other features that are likely to be important which a variogram analysis does not take into account. These include topography, land-use, micro-climate, and vegetation which could be very different even for cells which are spatially close. Nevertheless, as noted by Blöschl and Grayson (2000) geostatistical methods (such as variogram analysis) "are probably the most widely used interpolation methods in catchment hydrology" although they also allude to problems with a soley geostatistical approach.

5.1 Spatial-temporal analysis of modelled nitrogen loads

Nitrogen loads for each of the 31 sub-catchments in Table 2 were estimated using the E2 model described in section 4.5 for the period 1-Jan-1976 to 18-Dec-2006. An examination of the empirical data (see section 6) indicated that only 8 years of contiguous monitoring was available. A listing of these periods and corresponding dates is given in table 10. A graphical summary of TN loads for each of the eight years, broken down by catchment is shown in Figure 7.

Year	Period
1	21/8/90 – 20/8/91
2	21/8/91 – 20/8/92
3	21/8/92 – 20/8/93
4	21/8/93 – 20/8/94
5	21/8/94 – 20/8/95
6	21/8/95 – 20/8/96
7	21/8/96 – 20/8/97
8	21/8/97 – 20/8/98





Figure 7. TN loads for years 1-8 broken down by sub-catchment.

For the purpose of describing the spatial characteristics in TN-loads, the entire sub-catchment load was assumed to be concentrated at the geographical centroid of the sub-catchment (see Table 2 for coordinates). It is recognised that this is a gross simplification of the system although our primary focus is on developing candidate approaches to catchment-wide load estimation that describe and utilise spatial dependency. Future work will focus on resolving load estimates on a smaller spatial scale. Figure 8 shows yearly 2-D variogram surfaces for the annual sub-catchment nitrogen load. The changing nature of the spatial dependency on a year-to-year basis is clearly evident and this reflects broad-scale meteorological conditions and is therefore to be expected.



Figure 8. Yearly variogram surfaces of modelled TN loads. Figs (a) - (g) correspond to years 1-8 (refer Table 10). *NB:* different scales used for each figure.

This observation nevertheless has implications for more detailed spatial modelling and analysis as it is suggestive of non-stationarity in the underlying response-generating process. The overall spatial characterisation obtained by averaging nitrogen loads over the 8 year period is shown in Figure 9. The highest variogram values tend to orient themselves along a diagonal line from the north-west corner to the south-east corner (approximately Omeo to Orbost) suggesting that differences in TN load are greatest in this direction. Two regions of similarity (in TN loads) are identified off this diagonal band – one in the north-east corner and the other in the south-west corner. This is a consequence of similarities in climate, elevation, and land cover. More detailed variogram modelling shows that for year 1, the direction of anisotropy is 112⁰ (Figure 10a) and the greatest spatial continuity is along the perpendicular axis (Figure 11). The anisotropic variogram in the 112⁰ direction is reasonably well described by a Gaussian model having range of 26,450m and sill of 1.79 (Figure 10b). This suggests that on average, TN loads may be correlated on scales of up to about 26km.



Figure 9. Mean Variogram surface (years 1-8).

An examination of the isotropic variograms for each of the eight year periods (Figure 12) suggests similarity between the following yearly groupings: {1 and 3}; {4, 6, and 8}; {5 and 7}. Year 2 appears to be different to all the rest. The same observations are reflected in the total TN loads for each of the 8 year periods (Figure 7).



Figure 10. (a) Anisotropic variogram of TN load for Year 1. Direction=112⁰; (b) with fitted Gaussian model.



Figure 11. Anisotropic variogram of TN load for Year 1. Direction=22⁰.



Figure 12. Isotropic variograms of modelled SC loads by year.

Theoretical models have been fitted to each of the sample variograms in Figure 12. Because of strict mathematical requirements, only certain functional forms qualify as legitimate variogram models. The most common of these are: (i) Gaussian; (ii) spherical; (iii) exponential; (iv) linear; and (v) power. We have used combinations of Gaussian and spherical models to describe the yearly sample variograms in Figure 12. The forms for each of these are given by equations 1 and 2 respectively where the parameters r_1 and r_2 are the *ranges* for each model.

$$\gamma(h) = \begin{cases} 0 & \|h\| = 0 \\ \left[1 - e^{-3\left(\frac{h}{r_1}\right)^2} \right] & \|h\| \neq 0 \end{cases}$$
(1)
$$\gamma(h) = \begin{cases} 0 & h = 0 \\ \left[\frac{3}{2} \frac{\|h\|}{r_2} - \frac{1}{2} \left(\frac{\|h\|}{r_2}\right)^3 \right] & 0 \le \|h\| \le r_2 \\ 1 & \|h\| > r_2 \end{cases}$$
(2)

Table below summarises the model parameters for each of the yearly variograms. In Table G(h) refers to equation 1 and Sp(h) refers to equation 2. *Nested* models (ie. linear combinations) take the form $a + \sigma_1^2 G(h) + \sigma_2^2 Sp(h)$ where the parameter *a* is referred to as the *nugget*.

Year	а	σ_1^2		σ^2_2	r_2
1	0.666	0.548	30565.7	0.879	8909.5
2	0.0	0.179	30565.7	0.317	9117.514
3	0.742	0.497	30565.7	0.9	10001.169
4	0.0	0.309	2381.324	0.876	31630.233
5	0.0	0.458	172431.761	0.206	14183.655
6	0.0	0.483	30565.699	0.629	7493.414
7	0.0	0.125	102817.857	0.138	7744.703
8	0.0	0.276	30565.7	0.683	7973.037

Table 11 Parameters for isotropic, yearly variogram models.

Individual isotropic variograms for each year and the fitted models are shown in Figure 13. Table 11 shows that except for years 5 and 7, the maximum range is about 31km. For years 5 and 7 the range is considerably larger (over 100km). From Figure 7 it is seen that nitrogen loads in years 5 and 7 were the lowest over the 8 year period – reflecting lower than average rainfall/runoff for 1994/5 and 1996/7. That the variogram model range is larger for these two years simply reflects the more homogenous, drought conditions. Furthermore, table 11 shows that only years 1 and 3 had non-zero nugget parameter values. Years 1 and 3 are seen to have the highest nitrogen loads (Figure 7) and the non-zero nugget suggests that during these two periods, localised (small-scale) variability was important.

In the next section we turn attention to an examination of the fixed-site monitoring data and the computation of empirical nitrogen loads.



Figure 13. Yearly isotropic variagrams for modelled TN loads. Figs (a) - (g) correspond to years 1-8 (refer Table 10). *NB:* different vertical scale used for each figure.

6. Empirical nitrogen load estimates

The location of fixed water-quality monitoring sites within the Tambo catchment was shown in Figure 3 and is reproduced without topographic features in Figure 14 below. A description of the sites together with information on water quality sampling dates is given in Table 12. From Table 12 we see that only sites 223202, 223204, 223205, 223212, 223213, 223214, and 223215 are still listed as 'active' sites. Of those, only 223202, 223205, 223212, 223213, and 223214 have sufficient, contemporaneous TN data.



Figure 14. Water Quality monitoring locations in Tambo catchment

6.1 Data Imputation

Numerous methods exist for the computation of an empirical mass load (Fox 2004a, 2004b). The simplest approach is by direct summation of fluxes according to equation 3.

$$\hat{L} = k \sum_{i=1}^{N} c_i q_i$$
(3)

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).

Table 12 Tambo catchment water quality site information (Source: http://www.vicwaterdata.net/vicwaterdata/home.aspx)

Site	Description	Status	Longitude	Latitude	Elevation	Quantity	Data	Quality D	ata	Catchment	TN date	s	N	Period
Code						From	То	From	То	Area (km ²)	From	То		
223202	TAMBO RIVER @ SWIFTS CREEK	Active	147.72860	-37.26772	286.019	12-Feb-1965	19-Jun-07	06-Aug-1975	23-Oct-07	943	10-Jan-1979	18-Sep-07	246	43
223204	NICHOLSON RIVER @ DEPTFORD	Active	147.69725	-37.59380	0	13-May-1961	26-Jun-07	07-Aug-1975	25-Oct-07	287	18-Nov-1993	27-Sep-07	162	31
223205	TAMBO RIVER @ D/S OF RAMROD CREEK	Active	147.87038	-37.67304	24.615	10-Jun-1965	22-Jun-07	07-Aug-1975	22-Oct-98	2681	10-Jan-1979	22-Oct-98	143	51
223212	TIMBARRA RIVER @ D/S OF WILKINSON CREEK	Active	148.06338	-37.44644		06-May-1982	22-Mar-07	21-Jun-1982	21-Oct-98	438	21-Aug-1990	09-Sep-98	98	30
223213	TAMBO RIVER @ D/S OF DUGGAN CREEK	Active	147.88359	-37.00283	747.267	16-Sep-1987	20-Jun-07	27-Jul-1988	24-Oct-07	96	21-Aug-1990	19-Sep-07	200	31
223214	TAMBO RIVER @ U/S OF SMITH CREEK	Active	147.92747	-36.95499	0	02-Mar-1989	14-Mar-07	02-Mar-1989	24-Oct-07	32	21-Aug-1990	19-Sep-07	200	31
223215	HAUNTED STREAM @ HELLS GATE	Active	147.82657	-37.48181	156.385	08-Feb-1990	19-Apr-07	30-Jan-1991	27-Jun-07	180	07-Jan-94	20-Apr-94	3	34
223200	TAMBO RIVER @ BRUTHEN	Inactive	147.84000	-37.71000	0	Unknown	Unknown			2727	#N/A	#N/A	#N/A	#N/A
223201	TAMBO RIVER @ ENSAY SOUTH	Inactive	147.83000	-37.38000	0	Unknown	Unknown			1326	#N/A	#N/A	#N/A	#N/A
223203	TIMBARRA RIVER @ TIMBARRA @ D/S OF RUNNING CREEK	Inactive	147.68000	-37.59000	0	Unknown	Unknown			222	#N/A	#N/A	#N/A	#N/A
223206	TAMBO RIVER @ BINDI	Inactive	147.80000	-37.08000	0	08-Aug-1957	19-Dec-74	Unknown		401	#N/A	#N/A	#N/A	#N/A
223207	TIMBARRA RIVER @ TIMBARRA	Inactive	148.05000	-37.31000	0	26-Jan-1971	5-Jan-84	25-Aug-1975	12-Dec-83	205	#N/A	#N/A	#N/A	#N/A
223208	TAMBO RIVER @ BINDI (NEAR JUNCTION CREEK)	Inactive	147.77000	-37.16000	0	04-Nov-1974	21-Jun-01	06-Aug-1975	27-Apr-88	523	10-Jan-1979	27-May-87	31	99
223210	NICHOLSON RIVER @ SARSFIELD	Inactive	147.71099	-37.73758	9.468	21-Sep-197	26-Jun-07	03-Aug-197	30-Oct-07	471	04-Oct-2004	23-Oct-07	226	5
223211	HAUNTED STREAM @ STIRLING	Inactive	147.74000	-37.44000	0	26-Jun-1980	20-Sep-93	Unknown		149	#N/A	#N/A	#N/A	#N/A
223209	TAMBO RIVER @ BATTENS LANDING	Inactive	147.8502	-37.7557	0	26-Jan-1977	26-Jun-07	07-Jan-1977	23-Oct-07	2781	23-Apr-2004	23-Oct-07	411	3

* Period is approximate number of days between consecutive samples

Daily flow records are generally complete for each of the 5 sites to be analysed. However, water quality monitoring for TN is variable but generally monthly. Daily flow and concentration records have been imputed using interpolatory splines. The method is illustrated with reference to site 223202.

6.1.1 ILLUSTRATIVE EXAMPLE AND RESULTS

The daily flow record for site 223202 is shown in Figure 15 and re-expressed on a logarithmic scale (Figure 16). The (approximate) monthly TN concentration data are shown in Figure 17 and on a logarithmic scale (Figure 18).



Figure 15. Daily flow record for site 223202.







Figure 17. Measured TN concentration at site 223202 - approximate monthly sampling.





Cubic splines have been used to 'reconstruct' the daily TN concentration series (Figure 19). It is acknowledged that this is an approximation to the actual series and that there is no physical justification for assuming concentration varies in a smooth fashion. However, experience has shown that the error in the final annual load resulting from this form of interpolation is likely to be relatively small.



Figure 19. Measured TN concentration (red crosses) and interpolated series on daily time-step (blue line).

Applying equation 3 with k = 1 to the daily concentration and discharge series provides estimates of the annual TN load which can also be broken down on monthly basis. This has been done for each of the 8 year periods for each of the 5 sites identified in the previous section (Tables 13 -17).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	All
Year													
1	0.573	0.163	0.15	0.266	0.253	1.271	13.972	2.695	19.622	16.744	2.316	0.348	58.374
2	0.486	0.293	0.153	0.097	0.116	0.231	0.147	1.197	2.162	0.828	0.121	0.142	5.972
3	0.984	0.999	0.492	0.445	0.217	0.399	0.989	1.445	8.919	9.45	4.477	7.291	36.106
4	0.369	3.081	2.007	0.789	0.759	0.686	0.537	0.64	5.275	10.27	1.271	1.227	26.91
5	1.543	0.557	0.092	0.185	0.845	0.794	0.817	0.294	0.262	0.561	2.312	0.484	8.747
6	0.712	0.411	0.384	3.212	2.641	0.932	0.755	0.968	1.663	7.288	2.986	1.105	23.058
7	0.279	0.16	0.407	0.307	0.243	0.354	0.369	0.799	3.653	5.082	1.23	1.6	14.482
8	0.056	0.031	0.004	0.021	0.07	10.197	8.186	10.419	0.276	0.155	0.214	0.097	29.727
All	5.002	5.696	3.69	5.322	5.142	14.863	25.771	18.456	41.833	50.378	14.928	12.294	203.375

Table 13. Site 223202 TN load (tonnes).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	All
Year													
1	2.281	0.759	0.696	0.508	0.709	12.586	60.669	9.336	30.115	50.696	4.322	2.383	175.061
2	2.4	1.211	0.427	0.487	0.572	1.333	2.304	2.835	5.082	0.436	0.266	1.403	18.758
3	4.274	3.113	2.317	1.066	0.969	1.349	2.258	2.967	21.885	44.236	16.069	44.724	145.23
4	1.429	8.633	10.519	1.046	1.973	3.074	2.203	2.242	29.696	32.315	3.125	3.513	99.767
5	3.027	1.525	0.645	0.446	1.246	1.064	0.759	1.058	1.385	1.32	2.253	1.147	15.875
6	4.766	2.837	1.444	3.269	7.767	1.303	1.512	1.621	1.519	10.531	5.472	5.652	47.693
7	1.266	0.22	1.369	0.639	0.624	3.651	6.639	2.22	7.897	3.956	2.6	2.046	33.126
8	0.587	0.508	0.107	0.072	0.18	272.756	45.995	40.85	0.64	1.295	1.547	0.514	365.05
All	20.03	18.806	17.525	7.532	14.041	297.116	122.341	63.13	98.22	144.784	35.654	61.381	900.559

Table 14. Site 223205 TN load (tonnes).

Table 15. Site 223212 TN load (tonnes).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	All
Year													
1	1.369	0.195	0.367	0.297	0.159	2.578	9.774	1.844	8.109	9.33	0.824	0.752	35.597
2	1.436	0.629	0.226	0.22	0.239	0.715	0.9	0.56	0.753	0.443	0.134	0.498	6.754
3	1.328	0.556	1.798	0.56	0.278	0.347	0.795	0.715	6.665	15.501	8.198	8.453	45.193
4	0.83	1.632	1.143	1.046	0.384	0.981	0.338	0.309	3.426	5.114	1.26	1.027	17.49
5	0.721	0.318	0.307	0.316	0.729	0.614	0.266	0.248	0.461	0.631	0.811	1.54	6.96
6	2.813	0.931	1.453	1.85	3.424	0.566	0.449	0.442	0.593	2.549	2.015	3.557	20.642
7	0.688	0.408	0.468	0.236	0.718	1.088	1.115	0.601	1.183	0.925	1.143	0.557	9.13
8	0.249	0.161	0.102	0.065	0.121	19.709	3.634	5.695	0.355	0.477	0.641	0.374	31.583
All	9.434	4.83	5.863	4.59	6.052	26.598	17.27	10.415	21.545	34.97	15.026	16.757	173.35

Table 16. Site 223213 TN load (tonnes).

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	All
Year													
1	0.089	0.002	0.003	0.005	0.005	0.063	0.386	0.315	1.000	1.114	0.076	0.022	3.081
2	0.037	0.026	0.004	0.003	0.007	0.019	0.045	0.138	0.143	0.033	0.004	0.012	0.470
3	0.048	0.024	0.158	0.028	0.014	0.023	0.141	0.118	0.736	1.526	0.564	0.552	3.932
4	0.114	0.307	0.165	0.085	0.035	0.080	0.028	0.032	0.532	1.127	0.146	0.246	2.898
5	0.125	0.030	0.007	0.014	0.074	0.075	0.049	0.026	0.037	0.041	0.064	0.061	0.603
6	0.111	0.052	0.092	0.243	0.524	0.060	0.089	0.174	0.052	0.548	0.242	0.180	2.367
7	0.039	0.030	0.026	0.008	0.041	0.063	0.046	0.083	0.413	0.391	0.205	0.037	1.383
8	0.001	0.003	0.000	0.000	0.005	0.740	0.748	0.529	0.035	0.039	0.048	0.007	2.156
All	0.566	0.474	0.455	0.388	0.705	1.123	1.530	1.416	2.949	4.818	1.350	1.116	16.889

	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec	All
Year													
1	0.009	0.000	0.000	0.001	0.001	0.010	0.121	0.139	0.258	0.402	0.051	0.004	0.994
2	0.003	0.007	0.002	0.000	0.000	0.005	0.020	0.144	0.140	0.018	0.001	0.002	0.344
3	0.017	0.005	0.028	0.004	0.006	0.012	0.043	0.144	0.395	0.493	0.151	0.154	1.450
4	0.058	0.067	0.064	0.019	0.015	0.036	0.021	0.041	0.280	0.469	0.088	0.357	1.516
5	0.202	0.023	0.001	0.004	0.027	0.073	0.134	0.035	0.011	0.019	0.047	0.004	0.581
6	0.014	0.011	0.011	0.050	0.141	0.034	0.154	0.340	0.149	0.611	0.189	0.040	1.743
7	0.016	0.007	0.005	0.002	0.016	0.022	0.010	0.096	0.428	0.401	0.124	0.011	1.136
8	0.001	0.001	0.000	0.001	0.001	0.141	0.322	0.150	0.018	0.009	0.007	0.001	0.654
All	0.319	0.122	0.112	0.080	0.207	0.332	0.824	1.088	1.680	2.422	0.659	0.573	8.419

Table 17. Site 223214 TN load (tonnes).

7. 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. An analysis of the modelled outputs for the Tambo catchment allowed us to quantify the relative sub-catchment TN load contributions at each of the 5 monitoring locations under consideration (Table 18). Thus, for example the TN load at site 223213 is derived entirely from sub-catchment 32 (Tambo Upper North) while the TN load at site 223202 is comprised of contributions in varying proportions from 10 sub-catchments. By applying these relative contributions (weightings) to the modelled sub-catchment loads, we can obtain an estimate of the TN load at each monitoring location. The yearly comparison between these catchment model estimates and the empirical estimates is shown in Table 19. The lack of agreement between the two sets of load estimates is clearly evident. The smallest (absolute) error in Table 19 is 4.6% while largest is 127%. Overall the average absolute error is 53.2%. Of the 32 estimates, 26 (81%) are negative and 6 (19%) positive thus indicating the propensity of the catchment model to underestimate true load. Site specific average errors are: -20.6% (223202); -41.1% (223205); -76.2% (223213); and +13.2% (223213).

Table 18. Relative load weightings. Tabulated value is the fraction of TN load at a given site (column) which is derived from the relevant sub-catchment (row).

Sub-	223202	223205	223212	223213
1	0.000	0.000	0.000	0.000
3	0.000	0.054	0.000	0.000
4	0.000	0.041	0.000	0.000
5	0.000	0.044	0.000	0.000
6	0.000	0.000	0.000	0.000
7	0.000	0.027	0.000	0.000
8	0.000	0.008	0.000	0.000
10	0.238	0.071	0.000	0.000
11	0.053	0.016	0.000	0.000
12	0.029	0.009	0.000	0.000
13	0.064	0.019	0.000	0.000
14	0.119	0.036	0.000	0.000
15	0.258	0.077	0.000	0.000
16	0.000	0.066	0.000	0.000
17	0.000	0.053	0.000	0.000
18	0.000	0.046	0.000	0.000
19	0.000	0.069	0.000	0.000
20	0.000	0.037	0.339	0.000
21	0.000	0.029	0.264	0.000
22	0.100	0.030	0.000	0.000
23	0.000	0.000	0.000	0.000
24	0.021	0.006	0.000	0.000
26	0.000	0.044	0.396	0.000
27	0.000	0.058	0.000	0.000
28	0.000	0.060	0.000	0.000
29	0.003	0.001	0.000	0.000
30	0.000	0.000	0.000	0.000
31	0.000	0.031	0.000	0.000
32	0.114	0.034	0.000	1.000
33	0.000	0.000	0.000	0.000
34	0.000	0.034	0.000	0.000

The preceding analysis raises the prospect of an interesting 'inverse' problem: what adjustments to the modelled sub-catchment loads are necessary so as to minimize a measure of total discrepancy between the empirical and modelled load estimates over a set of monitoring locations? We are unaware of any published approaches to this problem or its solution. The approach outlined in the next section is thus claimed to represent a new contribution to catchment modelling practice. Table 19. TN load estimates (tonnes) at four water quality monitoring sites for eight 1-year periods in the Tambo catchment. First cell entry is empirical load estimate; second entry is estimate from E2 model. Numbers in parentheses are relative error of catchment estimate.

Year	223202	223205	223212	223213
1	58.374	175.061	35.597	3.08059
	17.565 (-70%)	51.672 (-70%)	5.437 (-85%)	1.984 (-36%)
2	5.972	18.758	6.754	0.47042
	9.099 (+52%)	23.689 (+26%)	2.854 (-58%)	1.068 (+127%)
3	36.106	145.23	45.193	3.93209
	22.538 (-38%)	56.343 (-61%)	6.715 (-85%)	3.163 (-20%)
4	26.91	99.767	17.49	2.89779
	16.364 (+39%)	35.682 (-64%)	4.779 (-73%)	2.359 (-19%)
5	8.747	15.875	6.96	0.60273
	8.16 (-7%)	16.577 (+4%)	2.329 (-66%)	1.233 (+105%)
6	23.058	47.693	20.642	2.36668
	15.721 (-32%)	36.81 (-23%)	4.546 (-78%)	2.258 (-5%)
7	14.482	33.126	9.13	1.38297
	7.155 (-51%)	16.179 (-51%)	2.041 (-78%)	1.164 (-16%)
8	29.727	365.05	31.583	2.1555
	12.594 (-58%)	36.381 (-90%)	4.003 (-87%)	1.516 (-30%)

8. Imputing sub-catchment load from Gauging station load

The modelled load estimates in Table 19 were obtained by applying the weightings in Table 18 to the modelled sub-catchment load estimates. Mathematically we can write this as the linear combination:

$$W^T L_{sc} = \hat{L}_{gs} \tag{4}$$

where W is (in this case) a 31 x 4 matrix of weights (ie. the entries in Table 18); L_{sc} is a 31 x 1 column vector of sub-catchment loads; and \hat{L}_{gs} is the 4 x 1 vector estimated loads at each gauging station.

By replacing \hat{L}_{gs} in equation 4 with the empirical estimates, \hat{L}_{e} we can find a least-squares solution for the vector L_{sc} using equation 5:

$$\hat{L}_{sc} = \left(W W^{T}\right)^{-} W \hat{L}_{e}$$
(5)

where $(WW^T)^-$ is a *pseudo-inverse*. The use of the pseudo-inverse is necessary due to the rankdeficiency of the term WW^T . In practice this means that the resulting solution is still a leastsquares solution (in that it minimizes $\begin{bmatrix} \hat{L}_{sc} - \hat{L}_{s} \end{bmatrix}^T \begin{bmatrix} \hat{L}_{sc} - \hat{L}_{s} \end{bmatrix}$) but that it is not unique. This has been done for each of the eight, one-year time periods. The results are shown in Table 20.

Sub- catchment	Year 1	Year 2	Year 3	Year 4	Year 5	Year 6	Year 7	Year 8
3	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
4	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
5	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
6	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
7	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
8	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
10	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
11	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
12	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
13	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
14	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
15	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
16	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
17	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
18	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
19	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
20	11.866	2.251	15.064	5.83	2.32	6.881	3.043	10.528
21	11.866	2.251	15.064	5.83	2.32	6.881	3.043	10.528
22	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
24	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
26	11.866	2.251	15.064	5.83	2.32	6.881	3.043	10.528
27	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
28	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
29	6.144	0.611	3.575	2.668	0.905	2.299	1.455	3.064
30	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
31	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
32	3.081	0.47	3.932	2.898	0.603	2.367	1.383	2.155
34	5.406	0.402	4.262	3.691	0.011	0.266	0.634	20.249
Re- calibrated total	175.1	18.8	145.2	99.8	15.9	47.7	33.1	365.1
Original E2 total	58.0	26.7	63.0	40.2	18.3	42.0	18.5	41.1

Table 20. Re-calibrated sub-catchment TN loads (tonnes). Last row (highlighted in blue) are original summed model loads over all sub-catchments. NB: Sub-catchments 1, 23, and 33 do not appear since they make zero contributions to the TN loads at the four gauging stations used in the calibration.

Overall, the re-calibrated loads are 2.65 times greater than those produced from the E2 model (or equivalently, the E2 loads underestimate the re-calibrated loads by approximately 62%. This figure accords with the Davies and Marinez (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%.

9. Estimating loads at unsampled WQ monitoring sites

Spatial interpolation techniques are widely used in catchment hydrology (Blöschl and Grayson 2000). We demonstrate here 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, landuse/cover, micro-meteorology etc.). In the illustrative application that follows, we have been restricted to using the (limited) available data and it should be kept in mind that neither the E2 catchment model nor the water quality monitoring network has been 'optimized' for the current task. 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 catchmentwide scale.

9.1 Illustrative example

An immediate by-product of the variogram analysis (see section 5) is that spatial correlations (in TN load) between any given two locations can be readily determined. Table 21 shows the matrix of pairwise correlations between water quality monitoring sites estimated from the anisotropic variogram model depicted in Figure 10.

Table 21. TN mass load correlations between pairs of water quality monitoring sites.

Site	223202	223204	223205	223206	223207	223208	223209	223210	223211	223212	223213	223214	223215	223800	223801	223203	223401
223202	1	0	0	0	0	0.079	0	0	0.03	0	0	(0 0	0	0	0	0
223204	0	1	0	0	0	0	0	0.054	0.032	0	0	(0.017	0	0	0.899	0
223205	0	0	1	0	0	0	0.307	0.018	0	0	0	(0.013	0.012	0.012	0	0
223206	0	0	0	1	0	0.226	0	0	0	0	0.069	0.013	0	0	0	0	0
223207	0	0	0	0	1	0	0	0	0	0.063	0	(0 0	0	0	0	1
223208	0.079	0	0	0.226	0	1	0	0	0	0	0	(0 0	0	0	0	0
223209	0	0	0.307	0	0	0	1	0.051	0	0	0	(0 0	0	0	0	0
223210	0	0.054	0.018	0	0	0	0.051	1	0	0	0	C	0 0	0	0	0.043	0
223211	0.03	0.032	0	0	0	0	0	0	1	0	0	(0.103	0	0	0.028	0
223212	0	0	0	0	0.063	0	0	0	0	1	0	(0 0	0.043	0.042	0	0.063
223213	0	0	0	0.069	0	0	0	0	0	0	1	0.305	0	0	0	0	0
223214	0	0	0	0.013	0	0	0	0	0	0	0.305	1	. 0	0	0	0	0
223215	0	0.017	0.013	0	0	0	0	0	0.103	0	0	() 1	0.1	0.108	0.012	0
223800	0	0	0.012	0	0	0	0	0	0	0.043	0	0	0.1	1	0.991	0	0
223801	0	0	0.012	0	0	0	0	0	0	0.042	0	0	0.108	0.991	1	0	0
223203	0	0.899	0	0	0	0	0	0.043	0.028	0	0	0	0.012	0	0	1	0
223401	0	0	0	0	1	0	0	0	0	0.063	0	(0 0	0	0	0	1

9.1.1 SPATIAL INTERPOLATION

Having characterised spatial dependency via the variogram, it is possible to obtain kriged estimates of TN loads at unsampled sites. There are however some significant assumptions that underpin this technique and these would require careful evaluation in a more detailed analysis of a designed R&D program. Specifically:

- It is assumed that the spatial correlation structure of loads obtained from an analysis of the *modelled* (sub) catchment loads provides a reasonable representation of the spatial dependency between loads at water quality monitoring sites;
- The spatial *correlation* structure referred to in the first dot point is reasonably accurate even if the modelled loads underestimate the true loads. The assumption here is that the E2 model (say) can reasonably delineate topography, land-use, regolith, etc. that is, spatially-distributed attributes that are likely to be responsible for imparting spatial dependency in loads;
- The spatial covariance structure need not be stationary.

The basic (ordinary) Kriging equation is given by equation 6:

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

where

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

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.

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 $\left(\hat{L}_{_{0}}
ight)$ at the *unsampled* site is obtained using equation 8:

$$\hat{L}_{0} = \sum_{i=1}^{n} w_{i} l_{i}$$
(8)

where l_i is the measured load at site *i*.

We have applied this method to the Tambo data. The results are presented in Table 22.

Table 22. Predicted (kriged) loads at each *unsampled* water quality monitoring site for each of 8 one-year periods based on single, overall variogram model.

	Water Quality Monitoring Site													
Period		223204	223206	223207	223208	223209	223210	223211	223214	223215	223800	223801	223203	223201
	1	68.028	63.572	65.995	67.268	100.931	69.965	67.737	48.206	69.439	67.945	67.915	68.028	65.995
	2	7.989	7.473	7.911	7.83	11.299	8.183	7.928	5.694	8.131	8.068	8.063	7.989	7.911
	3	57.615	53.932	56.837	55.922	84.549	59.201	56.967	41.231	58.77	58.161	58.118	57.615	56.837
	4	36.766	34.442	35.558	35.99	56.133	37.906	36.469	26.43	37.596	36.709	36.692	36.766	35.558
	5	8.046	7.535	7.978	8.101	10.453	8.188	8.067	5.774	8.149	8.096	8.092	8.046	7.978
	6	23.44	21.994	23.265	23.41	30.896	23.879	23.428	17.008	23.76	23.619	23.606	23.44	23.265
	7	14.53	13.628	14.192	14.526	20.247	14.867	14.529	10.518	14.775	14.526	14.521	14.53	14.192
	8	107.129	99.926	102.394	101.036	186.416	111.796	104.796	75.091	110.528	107.041	106.967	107.129	102.394

Again, we re-iterate our cautionary note about the credibility of the results given in Table 22 they are based on weighted combinations of loads measured at only 4 locations and are thus subject to potentially large errors. Ideally, we would require 2-3 times as many sites for which empirical load estimates were available.

Slight differences in predicted loads are obtained if separate variogram models are used for each year rather than one overall variogram model (Table 23). Parameters of the individual yearly variogram models are given in Table 11.

Table 23. Predicted (kriged) loads at each unsampled water quality monitoring site for each of 8 one-year periods based on individual, yearly variogram models.

	Water Quality Monitoring Site (yearly variograms)													
Period		223204	223206	223207	223208	223209	223210	223211	223214	223215	223800	223801	223203	223201
	1	78.18	56.223	63.408	61.846	89.809	80.47	68.537	49.834	71.747	69.289	68.99	76.456	63.408
	2	9.387	6.035	7.656	6.806	11.012	9.705	7.987	4.978	8.615	8.562	8.514	9.148	7.656
	3	64.931	48.232	55.582	51.14	74.14	66.591	57.205	42.511	60.631	60.286	60.031	63.681	55.582
	4	48.43	23.896	31.868	29.403	64.441	51.388	35.827	19.15	40.626	37.639	37.239	46.187	31.868
	5	11.029	5.115	7.292	6.183	12.888	12.12	9.393	2.637	9.708	9.565	9.532	11.011	7.292
	6	27.236	17.376	22.644	20.865	31.608	28.098	23.995	14.925	25.364	25.067	24.947	26.587	22.644
	7	20.111	9.644	12.498	10.876	21.556	21.587	17.021	8.168	17.628	17.258	17.186	20.049	12.498
	8	134.025	82.111	94.13	85.218	164.81	140.095	103.719	75.736	115.137	110.07	109.185	129.456	94.13

10. Conclusions

This report provides details of investigations into the catchment-wide estimation of nutrient loads, their spatial attributes and associated uncertainty. We believe the description of an analytical framework for using predicted loads from a catchment model to parameterise spatial models which in turn are coupled with empirical load estimates to refine the predictions is a new development. Given that neither the catchment model nor the water quality monitoring network has been tuned or 'optimised' to provide data on scales most suited to the present research means that our results should be treated as indicative only rather than definitive. Further work is required to provide better spatial-temporal alignment of modelled and measured data.

From these limited investigations we have another line of evidence that nutrient loads are being substantially underestimated by catchment models – we believe this is in the order of about a 60% underestimation.

Finally, the use of spatial statistical modelling approaches to load estimation has provided a potentially new way of characterising catchments and catchment condition in terms of key spatial attributes such as the variogram *range* and *sill*.

11. AWBM	Glossary A rainfall-runoff model
D/S	Downstream
DWC	Dry Weather Concentration
E	Nash-Sutcliffe Coefficient of Efficiency
E2	Catchment Modelling Software
EMC	Event Mean Concentration
FU	Functional Unit
mg/L	milligram per Litre
RRL	Rainfall-Runoff Library (computer software)
SC	Sub-Catchment
SILO	Spatio-temporal climate data
SIMHYD	A rainfall-runoff component model
TN	Total Nitrogen
ТР	Total Phosphorus
TSS	Total Suspended Solids

U/S Upstream

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Appendix A - Output from Default Scenario

The following maps show output from the Default Scenario.



Figure A 1 Mean sub-catchment TN load



Figure A 2 Mean sub-catchment TP load



Figure A 3 Mean sub-catchment TSS load

Appendix B – Input Time Series Files

Development of the Tambo E2 tool required the following daily time series files:

- 4 rainfall series obtained from SILO, for positions (Lat., Long.) 147.75, 37.15; 147.75, 37.35; 147.75, 37.55, and 147.75, 37.75. These were applied to sub-catchments nearby to each SILO point, using a grouping by longitude.
- 1 potential evapotranspiration (FAO56), also obtained from SILO for a position close to the centre of the Tambo catchment.