LANDSCAPE LOGIC

LINKING LAND AND WATER MANAGEMENT TO RESOURCE CONDITION TARGETS

Technical Report No. 18

Estimating nutrient loads and turbidity for Tasmanian catchments

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LANDSCAPE LOGIC is a research hub under the Commonwealth Environmental Research Facilities scheme, managed by the Department of Environment, Water Heritage and the Arts. It is a partnership between:

- **six regional organisations** – the North Central, North East & Goulburn–Broken Catchment Management Authorities in Victoria and the North, South and Cradle Coast Natural Resource Management organisations in Tasmania;
- **five research institutions** – University of Tasmania, Australian National University, RMIT University, Charles Sturt University and CSIRO; and
- **state land management agencies in Tasmania and Victoria** – the Tasmanian Department of Primary Industries & Water, Forestry Tasmania and the Victorian Department of Sustainability & Environment.

The purpose of Landscape Logic is to work in partnership with regional natural resource managers to develop decision-making approaches that improve the effectiveness of environmental management.

Landscape Logic aims to:

1. Develop better ways to organise existing knowledge and assumptions about links between land and water management and environmental outcomes.
2. Improve our understanding of the links between land management and environmental outcomes through historical studies of private and public investment into water quality and native vegetation condition.

Estimating nutrients and turbidity for Tasmanian catchments

By Shane Broad, Ross Corkrey, Bill Cotching and Jessica Coad
Tasmanian Institute of Agricultural Research

Summary

The Landscape Logic Tasmanian Retrospective project aimed to investigate how water quality and quantity responds to land use and land management practices. Historical datasets of water quantity and quality plus land use information were used to investigate the relationships between land use at catchment and subcatchment scales and water quality data collected at specific points in catchments.

The research was conducted in five distinct phases:

- Phase 1: Estimation of land use nutrient generation rates
- Phase 2: Hydrological modelling across all catchments with available data.
- Phase 3: Modelling of daily total phosphorus concentrations in the Duck catchment.
- Phase 4: Modelling of daily nutrient and turbidity concentrations across all catchments with available data.
- Phase 5: An assessment of the impact of past riparian intervention on water quality.

Consistently collected water quality data used in this research was found to have considerable value in providing greater understanding of catchment functions and behaviour. Catchments in the northwest and northeast of Tasmania have higher annual nutrient loads than other regions in Tasmania. The annual load estimations indicate that there are wide ranges in loads in different catchments. East coast catchments with low rainfall/runoff and less intense land use have the lowest nutrient loads. Flatter land in higher rainfall areas was found to generate greater catchment scale annual nutrient loads. These areas are typically used for agriculture and in particular the most intensive land uses of dairy production and cropping. The more intense the land use in terms of nutrient inputs, the greater the nutrient enrichment in waterways. The nutrient load and catchment metric correlations show that land use has the potential to be used as an integrator. In Tasmania, land use was shown to be a good integrator of soils, climate and slope for use in modelling. Tasmanian dairy land use nutrient generation rates for total phosphorus and total nitrogen are at the higher end of published values with rates of 10–12 kg/ha/yr for total phosphorus and 20 – 30 kg/ha/yr for total nitrogen. WaterCAST modelling indicated that dairy pastures within regions of a catchment can have large variations in total phosphorus losses and these variations were associated with variations in soil test results. There are major drivers of nutrient delivery to surface waters associated with land use that may be little modified by management practices.

A combination of Bayesian and nonlinear modelling proved to be the most consistent method to establish relationships between modelled river flows and land use generation rates for total phosphorus, total nitrogen and turbidity across 34 Tasmanian catchments. The modelled daily nutrient loads were generated for use by the estuary health and river health researchers in the Tasmanian Retrospective project, as well as for use in the Decision Support System developed by the Knowledge Integration project of Landscape Logic. A whole of catchment daily nutrient modelling approach based on Bayesian modelling and the NLMIXED procedure used in modelling the hydrology, was found to be a good predictor of turbidity but was not as reliable for total phosphorus and total nitrogen. The modelled daily nutrient load outputs can be used with confidence in many catchments but in some catchments the outputs should be used with caution and in a small number of cases should not be used at all.

The available data showed little detectable change in water quality (in terms of nutrient loads and turbidity) following investment in rehabilitation of the riparian zone. It is likely that riparian buffers cannot completely compensate for the source of nutrients and sediments generated by intensive land use. However, riparian zones do provide other ecosystem services such as landscape connections and cover for terrestrial wildlife, and livestock and crop shelter. Investing in riparian zone management to minimise direct stock access to streams, channelised flow or runoff from roads and tracks draining to streams is critical to minimizing nutrients and sediment in streams as these can circumvent buffers.

Management interventions to improve water quality should focus on reducing nutrient sources and transport at the landscape scale rather than solely relying on abatement in riparian zones to impact on nutrients and sediment in surface waters. Riparian rehabilitation does play a role, but its effects are not always immediate.

Acknowledgements

This project is part of the Landscape Logic, Commonwealth Environment Research Facilities hub, managed by the Australian Department of the Environment, Water, Heritage and the Arts. We wish to thank David Nash and Tony Weber for providing valuable comments on an early version of this report.

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Background

The focus of Landscape Logic was to better organise knowledge and assumptions about links between management actions and environmental outcomes (**http://www.landscapelogic.org.au**). The research improved our understanding of these links by conducting historical studies that examined relationships between past changes in land use and land management to water quality and vegetation condition. In Tasmania, the research established water quality responses to changes in land use and land management, and provided new knowledge and improved assumptions about the responsiveness of river health and estuarine health to water quality as a result of these historic changes. Landscape Logic attempted to quantify and incorporate assumptions and uncertainties along with known biophysical causal links into a workable decision support system that can be used by catchment managers to help improve decisions about where and when to invest for the best overall environmental outcomes.

The Tasmanian Knowledge Discovery project (Landscape Logic Project 4) investigated how water quality responds to changed land use and land management practices, and how water quality in turn affects the health and productivity of aquatic ecosystems, both riverine and estuarine. The linkages established will assist future environmental management decision making.

The focus on water quality and river and estuarine health as the key resource for investigation and analysis is strongly supported by the three participating Tasmanian NRM Regions because:

- There is uncertainty as to the links between river health & function, estuarine health & function, and water quality parameters.
- There is uncertainty concerning the relative impact of land use, land management & previous landscape interventions on water quality.
- There is a need to know that investment to improve water quality will have environmental outcomes (knowledge verses assumption).

Outputs from historic data sets, i.e. the retrospective basis for this work, and modeled information were tested and confirmed with new data collected in this project. A Landscape Logic workshop in December 2006 identified three core questions as important to the Regional NRM Agencies in Tasmania, and the four integrated activities comprising the Tasmanian Retrospective study are designed to collectively address these. These three core questions are:

NRM Question 1 – *Is the end of catchment a good indicator of the whole system in terms of water quality and quantity? What is the impact of pollutants on estuarine systems?*

NRM Question 2 - *How does land use and land management affect water quality and quantities? How do best management practices for various end uses affect water yield and water quality?*

NRM Question 3 - *Are national water quality standards relevant to Tasmania? Are they relevant at regional and sub-regional scales? What should the trigger values be here? What is the point of monitoring if it is not relevant to our management actions? What are background or natural levels of pollutants versus human induced change?*

In designing specific research activities to address these questions, the project team was mindful first of the need to direct its outcomes to the Regional NRM agencies, and also to the Decision Networks team of Project 6 which developed a decision support system to integrate the research results. The project team was also mindful of feedback from the Advisory Board meeting in January 2007, which reminded us to focus on an achievable set of questions in order to retain the retrospective aspect of the research - "While it will be harder to find data on water (yield and quality) that can be related to documented changes in land use and land management, decisions are being made at the moment with little if any grounded, historical data, so whatever you find should be an improvement on our current knowledge" - and to ensure that work on question 3 remains relevant to the overarching goals of Landscape Logic.

The project addressed these three questions by establishing four activities within the Tasmanian retrospective study. Part of the research focused on one past intervention used by NRM regions to achieve change in resource condition (water, river, and estuary condition) i.e. riparian restoration and management.

Project 4.1: Linkages between land use and land management, and water quality. This addresses NRM Question 2 – focusing on the water quality responses deriving from changes/interventions in land management across a range of land uses, and the effectiveness of catchment and paddock-scale investments in Tasmania.

Project 4.2: Linkages between river ecosystem condition and water quality parameters. This addresses parts of NRM Questions 2 and 3 – focusing on relationships between historic water quality data and symptoms of, and thresholds for, river ecosystem function and health.

Project 4.3: Linkages between estuary ecosystem

condition and changes in land use and management. This addresses NRM Questions 1 and 3 – focusing on the extent to which estuarine ecosystem condition and health depend on changes in water quality resulting from upstream catchment land use and management, compared to the effects of estuary-specific physical process, and on identifying symptoms and thresholds of estuarine ecosystem function and condition.

Project 4.4: Riparian buffering impacts on nitrogen and turbidity water quality parameters. Investigated the impact of intervention and management in the riparian zone in two small catchments, one in southern Tasmania and one in north west Tasmania.

Historical datasets of water quality and land use information from Tasmanian and Australian studies were to be used to investigate the relationships between landscape/land management units and water quality data collected at specific points in catchments. The research focused on catchments that had available data on water quality coincident with documented changes in land use and/or management. These catchments were all a mosaic of land uses rather than a predominance of one land use.

Project 4.1 also linked with Project 2 (Landholder perceptions of the management of riparian zones in Tasmanian agricultural catchments) to consider why landholders uptake NRM strategies and what mix of incentives and motivation is needed in order to increase this adoption.

The principal beneficiaries of Project 4.1 are the partner Regional NRM organisations who are making investment decisions about the management of natural resources and who are responsible for addressing resource condition targets at multiple scales. The model framework linking land use with water quality/quantity responses and aquatic ecosystem health (river and estuary) was developed as a decision support system and is a substantial communication tool and resource.

Catchment selection

The Landscape Logic Project 4 team (projects 4.1, 4.2, 4.3 and 4.4) developed selection criteria for inclusion or exclusion of Tasmanian catchments for studies of water quality, river health and estuarine health studies due to confounding effects. The criteria for exclusion were the presence of hydroelectric developments, major dams and reservoirs at the head of catchments and industrial developments or mining.

To be included in the studies catchments needed to be hydrologically discrete, not prone to extensive flooding, easy to access, had relevant previous research studies, and adequate supporting data be available, in particular water quality and flow data (Cotching and Lefroy 2007). The priority list of catchments for the integrated Tasmanian retrospective study were: George, Black, Little Swanport, Pitt Water/Coal, Pipers, Anson's Bay, Duck, Montagu, Rubicon, Meredith and Carlton (Fig. 2).

The specific research conducted was done and reported in this report in five distinct phases:

- Phase 1: Estimation of land use nutrient generation rates
- Phase 2: Hydrological modelling across all catchments with available data.
- Phase 3: Modelling of daily total phosphorus concentrations in the Duck catchment.
- Phase 4: Modelling of daily nutrient and turbidity concentrations across all catchments with available data.
- Phase 5: An assessment of the impact of past riparian intervention on water quality.

The first 4 phases were written as separate papers for publication in refereed journals and are presented below in this context with separate introduction, methods, and conclusion sections.

The first phase was undertaken to determine from available water monitoring data the annual catchment nutrient loads in 34 Tasmanian catchments and consequently the nutrients generated by each of the main land uses in Tasmania. The river health (project 4.2) and estuary health (project 4.3) research projects required catchment nutrient data on a daily basis as input data for ecological health response models. In order for the daily nutrient outputs to be modeled, a daily time-step rainfall-runoff model across an ensemble of Tasmanian catchments was needed to be developed from the available Tasmanian flow data in phase 2.

A data set of paddock scale soil nutrient levels in the Duck catchment became available from an unrelated project during the course of the landscape Logic research. In phase 3, this soil nutrient dataset was used with the catchment hydrological model to test if the influence of management at the paddock scale could be related to nutrients generated at the subcatchment scale. Turbidity and nutrient concentrations control many ecological functions in rivers and estuaries including light penetration and subsequent phytoplankton productivity. Phase 4 of the research developed daily turbidity, total Phosphorus and total Nitrogen models for an ensemble of 34 Tasmanian catchments. Phase 5 focused on the impact of riparian restoration and management on water quality at the catchment scale because this intervention has been used by NRM regions to achieve change in resource condition.

In the early stages of Phase 1, an understanding of the drivers of nutrient delivery to surface water was developed as an influence diagram (Figure 1). It was acknowledged that all of the identified factors play some role in water quality, whether they be natural or anthropogenic. Rainfall, topography and soil type are natural factors, whereas land use, fertiliser use and drainage are anthropogenic factors. Some of the anthropogenic factors could be influenced by NRM investment (riparian zone extent, tillage practices) whereas others were not (landuse, stream incision). However, determining catchment nutrient loads could be achieved using recorded flow and concentration data in a simpler model that incorporates only a few of the major drivers of nutrient delivery such as rainfall and land use.

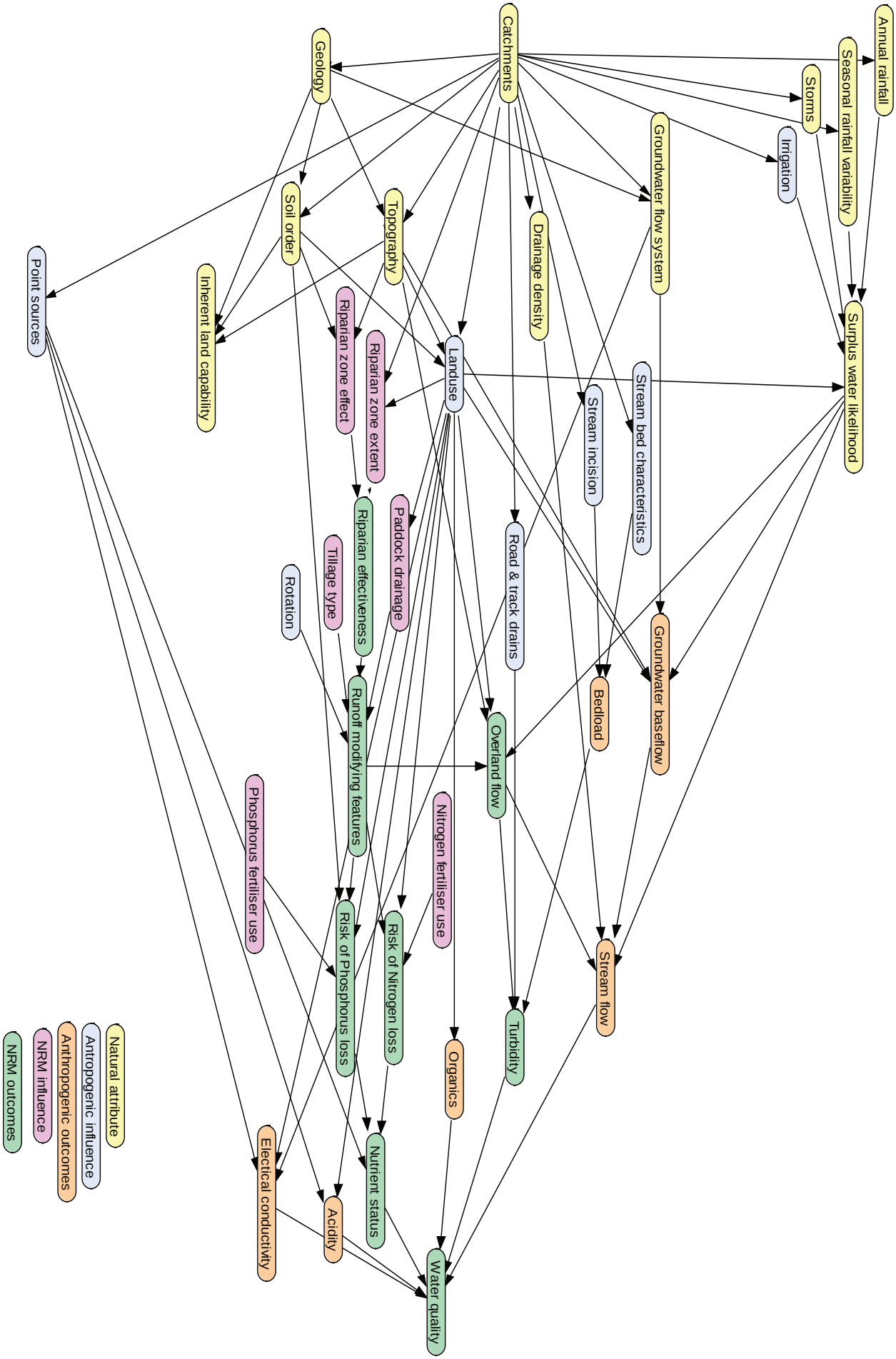


Figure 1. Influence diagram with factors identified that influence delivery of nutrients to surface waters in Tasmania

Phase 1: Estimating annual land use TP and TN generation rates for Tasmania

Introduction

In recent years water quality issues have become increasingly important to Australian catchment stakeholders, such as management groups, land owners and government departments (Letcher *et al.*, 2002). As there is almost always only sparse nutrient sampling in catchments and most of these groups do not have ready access to modelling expertise, simple nutrient balance models can be an attractive option for informing management decisions.

A nutrient balance model predicts total loads produced in the catchment by calculating the nutrient loads generated from different land uses and summing these across all land uses within the catchment (Cuddy *et al.*, 1994). One such model is the Catchment Management Support System (CMSS) (Davis and Farley, 1997), which has been widely adopted for nutrient planning in southern Australia (Davis and Farley, 1997; Davis *et al.*, 1998) Queensland (Joo *et al.*, 2000) and Sydney (Cuddy *et al.*, 1994). The model has proved to be a useful tool for focusing community-based catchment management groups on the problems and potential solutions in catchment scale nutrient management (Young *et al.*, 1995).

Unit area models like CMSS have evolved from the need to be able to use readily available observation data (Baginska *et al.*, 2003) and are based on a concept that the nutrient status of a catchment is a function of geological characteristics, land use and land management practices within the catchment (Baginska *et al.*, 2003). CMSS was developed as a simple decision support system to test various environmental policies and management practices (Young *et al.*, 1995). It requires few parameters and allows land use change scenario testing.

CMSS assumes that nutrient exports are dependent on land use, where each land use has a specific nutrient generation rate (Young *et al.*, 1995), where a generation rate is defined as a mass of a pollutant generated from a given land use area during a specified time interval, usually a year, and expressed in kg/ha/yr (Marston *et al.*, 1995). The model does not explicitly account for the effects of different soil types, rainfalls, slopes and land management factors in its algorithms, therefore it is necessary to define separate land uses (Young *et al.*, 1995).

Nutrient generation rates must be obtained through either local or expert knowledge of the catchment, from previous model applications (Letcher *et al.*, 2002) or from detailed field studies monitoring pollutant concentrations and stream flows for specific catchment conditions and land use composition. An extensive range of Australian and overseas monitoring studies was collated in the Nutrient Data Book (Marston *et al.*, 1995) to provide a set of generation rates for use in CMSS. However, selection of nutrient generation rates can be difficult because nutrients generated can significantly vary with climate, hydrologic conditions, land use distribution population and physiography. Therefore, adjustments of quoted generation rates often have to be made to better reflect the environmental and management conditions within the catchment under study (Baginska *et al.*, 2003). This process is often arbitrary. Therefore the aim of this manuscript is to increase confidence in nutrient generation rates used in CMSS for a region by establishing a more rigorous methodology so that the calculated annual loads can be used in a more informative manner.

Below we begin by outlining the CMSS modeling procedure and describing the catchment and land uses that occur in our study region of Tasmania, Australia. We then describe how we implement the CMSS model, dealing in turn with the stages attenuation, estimation of loads, and estimation of generation rates per land use using a Bayesian model.

Methods

The CMSS model

CMSS is a simple model for assessing annual total phosphorus (TP) and total nitrogen (TN) loads in a catchment. While the model contains a simple attenuation calculation it does not take into account processes or hydrology. Despite these limitations CMSS remains relevant as interest groups and governments want simple explanations to sometimes complex issues. The model itself requires data for total area and land use areas for each catchment (or subcatchment), the length of the main river channel, the mean slope of the river channel, an estimate of the main river channel depth and land use TP and TN generation rates. In this case, the generation rates represent parameters of unknown value and their calculation of these required an estimate of the annual end of catchment loads (kg/year).

Study catchments

Tasmania, the southern island state of Australia, was selected as the source of the test catchments due to data being readily accessible and there being

a wide range of hydrological regimes and land uses in a relatively small area. There have been 131 flow monitoring sites around Tasmania; of which there are 56 that remain operational. Water quality has been previously assessed at 173 sites around Tasmania at least once (from 1992), which includes water quality samples that have been collected monthly, from 2003 until June 2009, at 51 of the flow monitoring sites around the state as part of the Baseline Water Quality Monitoring Program. This data is available on the Water Information Systems Tasmania (WIST) website (**www.water.dpiw.tas.gov.au**).

There were 34 catchments remaining after the removal of those with significant hydroelectric development (Figure 2). Of these catchments Landscape Logic also conducted other studies in 11 estuary catchments Catchment boundaries for the 34 catchments upstream of the flow and nutrient monitoring sites were constructed in CatchmentSIM (Ryan and Boyd, 2003) using data initially processed in ArcGIS 9.0 (Environmental Systems Research Institute, Redlands, California). Catchment areas were then calculated. Evaporation and rainfall data from 1960 to 2009 were obtained from the SILO 0.05 degree climate grid (Jeffrey *et al.*, 2001) and averaged for the whole of each catchment. For descriptive purposes, daily flow data from 1960 (or the start of the record if later) to the end of 2007 were obtained for the 34 Tasmanian catchments from WIST. All the catchment descriptive data is presented in Table 1.

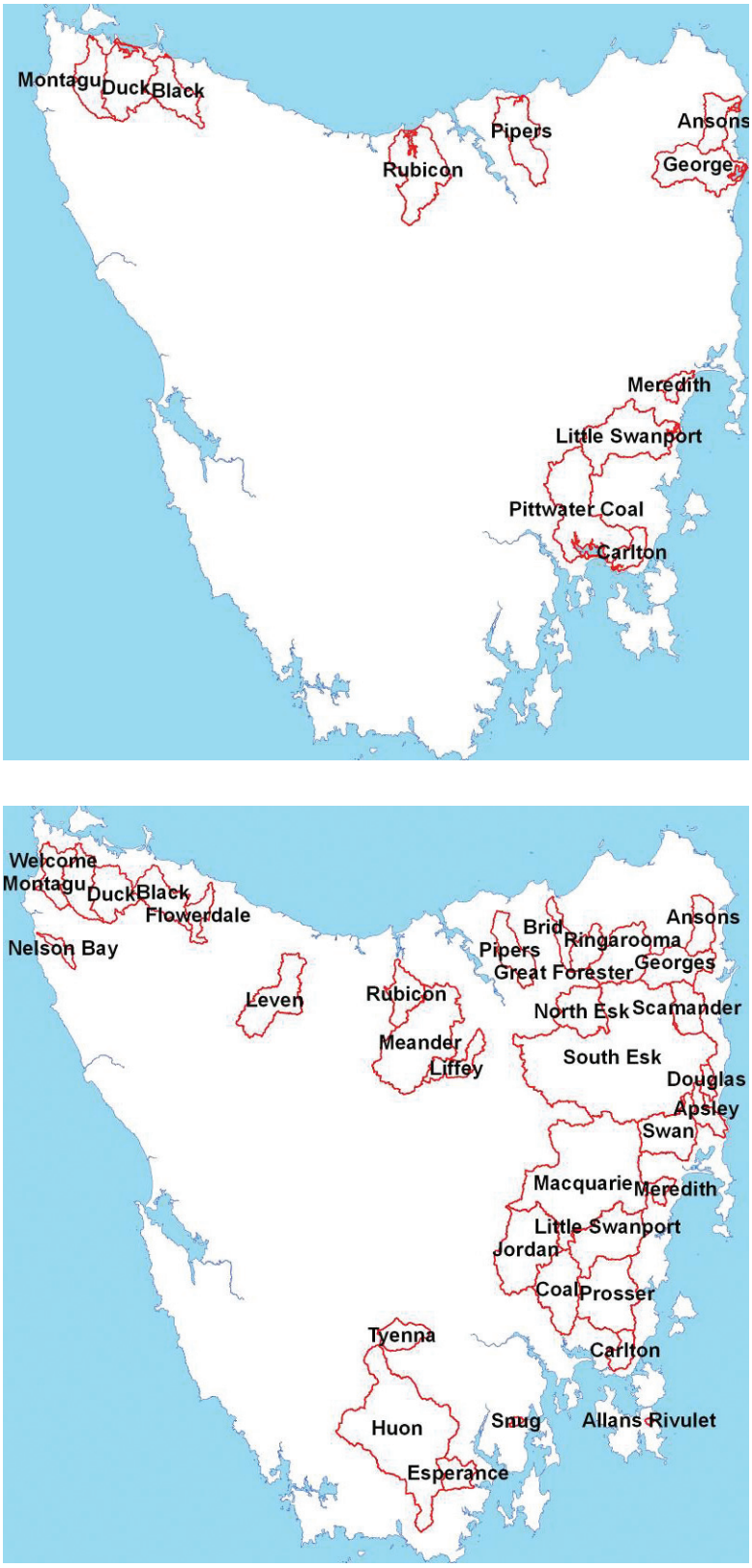


Figure 2. Catchment boundaries of Landscape Logic estuaries under consideration (top); and all 34 catchment boundaries upstream of their monitoring station (bottom).

Land use areas

Land use information was supplied by the Australian Bureau of Regional Sciences (BRS) (Drenen, 2003) in the form of an ArcGIS shapefile. However, inspection of the data indicated that significant errors and omissions existed, especially for dairy pastures, which are typically significant sources of nutrient and sediment runoff (Barlow *et al.*, 2005). Therefore the BRS data were updated using aerial imagery for the catchments of interest (Figure 3). Dairy pastures in particular were identified by the unique characteristics of dairy production including an extensive system of laneways leading to a central dairy shed and rotational grazing creating a graduated series of light brown to dark green paddocks (Figure 4). This was further enhanced using titles information and dairy shed addresses provided by DPIPWE. The new updated

land use data was then verified using on ground visual assessments. This GIS layer is now the Tasmanian standard and is available at:
http://nrmdatalibrary.dpiw.tas.gov.au/geonetwork/srv/en/metadata.show?id=187&currTab=distribution.
Metadata (Appendix 1)

Attenuation

CMSS has an attenuation (nutrient loss) function necessary to obtain reasonable end of catchment predictions for nutrient export rates (Equation 1).

$L_t = L_o \times \exp(-kt)$ Equation 1

Where:
L_t=the original load at time zero;
L_o=the load at time 't';
t = the time taken for water to exit the catchment; and
k = the rate of loss.

The t component was calculated using the Bransby-Williams formula (Equation 2) as described in (Davis and Farley, 1997) and the slope and main channel length were automatically calculated when establishing the catchment boundaries using CatchmentSIM.

$$t = (0.042 \times L / (S^{.2} \times A^{.1})$$ Equation 2

Where:
L= length of the main river channel (km);
S=slope of the catchment (m/km); and
A=the area of the catchment (ha).

The rate of loss component k was calculated using a relationship described by Davis and Farley (1997) (Equation 3).

$k = \exp(1.4 - 1.2 \times d)$ Equation 3

Where:
d=depth in metres.

In the CMSS manual the user is asked to estimate the depth of the main river channel (Young *et al.*, 1995). If this estimate is greater than four metres then a fixed k value of 0.0302 (or k =exp –3.5) is used (Davis *et al.*, 1996). This is somewhat arbitrary, therefore the method for estimating stream geometry described by Allen et al. (1994) was adapted to calculate the main river channel depth based on the average annual flow of the catchment (Equation 4). The upper limit of four metres was retained as it was assumed that in deep water littoral zone uptake is low (low light penetration) and nutrient loss is dominated by the weaker sedimentation pathway, therefore k is constant (Davis *et al.*, 1996).

$\text{Depth (m)} = 0.3417 \times Q^{0.3785}$ Equation 4

Where:
Q= the annual mean flow in m^3/s ´ 35.31(to convert from $feet^3/s$).

Annual catchment loads

Annual catchment loads were estimated by using a flow weighted mean concentration algorithm (Walling and Webb, 1985) and all nutrient samples with a corresponding flow measurement available on WIST (Equation 6). The equation used was:

$$\text{River Load} = K_r \left(\sum_{i=1}^{n} (C_i \times Q_i) / \sum_{i=1}^{n} Q_i \right) \times Q_r$$ Equation 5

Where:
C_i =the instantaneous nutrient concentration in the river at the time of sampling;
Q_i = the instantaneous river flow at the time of sampling;
Q_r = the average long-term river flow over the period of the record;
K_r = a conversion factor to take into account of the unit and period of record; and
n_i= the number of samples.

The Bayesian model

To estimate the land use generation rates across the 34 catchments we adopted a Bayesian modelling framework. Bayesian modelling was chosen to estimate the "best fit" generation rates as this approach allows all data across the 34 catchments to be simultaneously considered with proper propagation of uncertainty throughout the model. The Bayesian approach also has the advantage that Markov Chain Monte Carlo (MCMC) methods can be used which greatly simplifies the computation compared to the corresponding classical tools.

We based the Bayesian model on Equation 1, which we use to describe the TP and TN generation rates for each catchment. Using j to indicate the the jth catchment, the model for TP was $\delta_j = F_j \exp(-t_j k_j)$ in which π_j was the TP nutrient load, k_j was the catchment loss component, and t was the estimate for the time taken for water to exit the catchment. We also model the load at time zero using $F_j = \sum_{i \in C_j} A_j L_i$ in which A_{ij} is the area (ha) of land use i in catchment j, C_j is the set of land uses present in catchment j, and L_i is the TP generation rate (kg/ha/yr) for land use i. In the computation for F_j the summation is only over land uses that occur in a catchment, which means that catchments that lacked a land use did not contribute to the estimation of the parameter for that land use. This means that that generation rates only depend on land uses and not on specific catchments. For TN the same model structure was used, but with changes in

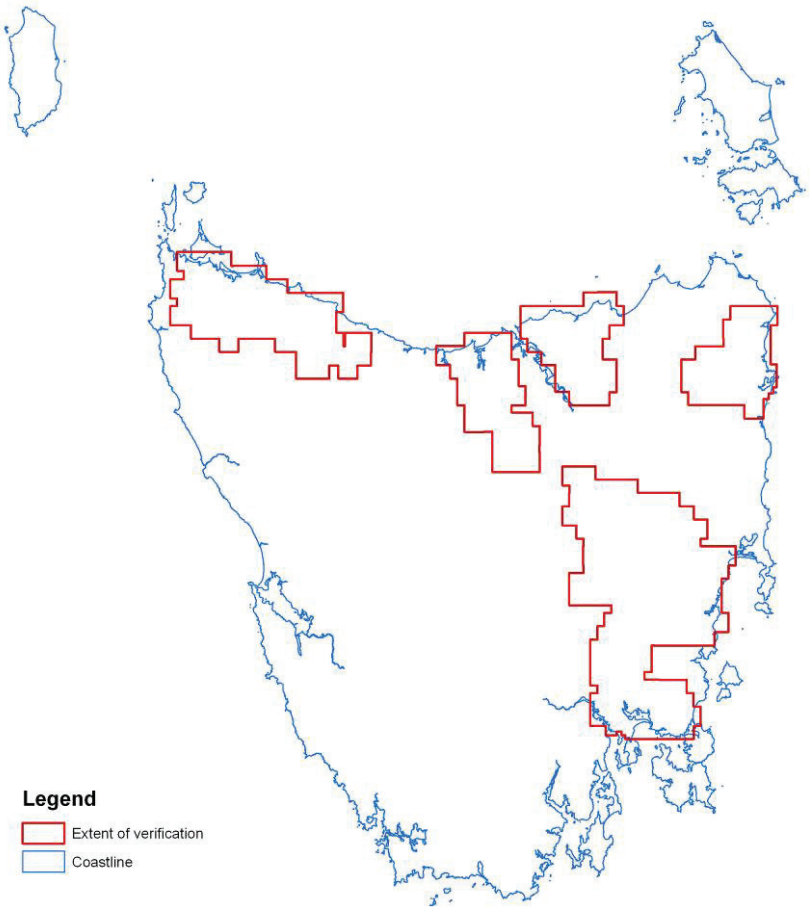


Figure 3. Areas of the updated Tasmanian land use layer verified using aerial photography.

Figure 4. Typical intensive dairy pastures with title boundaries imposed (pink lines)

annotation: $\acute{\imath}_j = G_j \exp(-t_j k_j)$ and $G_j = \sum A_j M_i$. We assumed that the observed nutrient loads were normally distributed, $P_j \sim \mathrm{N}(\eth_j, \acute{o})$ and $N_j \sim \mathrm{N}(\acute{\imath}_j, \hat{o})$, in which s and t are observational precisions (reciprocal variances).

Since this is a Bayesian analysis we assigned prior distributions for each of the model parameters. For the generation rate parameters uniform distributions are used for TP, $M_i \sim \mathrm{Unif}(M_l, M_u)$ and TN, $L_i \sim \mathrm{Unif}(L_l, L_u)$ in which the lower and upper limits were informed by estimates from Letcher et al. (1999), NEXSYS (1997) and the nutrient data book (Marston *et al.*, 1995). These limits are given in Table 2. Uniform priors were used since no information existed on their actual values but the limits were set wide enough to ensure that their values were contained within them. Last, the observation precisions were assigned vague gamma distributions, $\acute{o} \sim \mathrm{G}(0.001, 0.001)$ and $\hat{o} \sim \mathrm{G}(0.001, 0.001)$.

After assigning priors, the full joint distribution consisted of the product of the likelihood with the associated prior distributions. The resulting posterior distribution was complex and high-dimensional and so inference was obtained in the form of posterior means and variances obtained via MCMC simulation. The simulation software was written in JAGS 1.0.3 (Plummer, 2009). The model was run for 10 000 iterations of which 5000 were used to calculate posterior statistics and standard diagnostic methods were used to assess the model fit. The posterior statistics for the L_i and M_i parameters were presented as means and 95% highest posterior density intervals (HPDI) and as density plots. A 95% HPDI is the shortest interval in which the parameter is contained with 95% probability. We also present plots of posterior predicted values versus observed data.

Catchment metrics

A set of catchment metrics for the 34 catchments were generated. These included: Area, perimeter, rainfall (mean & range), elevation (minimum, maximum, mean), slope (mean in degrees & percent), slope class (1 – flat = 0 – 4.1%; 2 – low hills = 4.1 – 18 %; 3 – steep = > 18%), altitude (1 = < 500 m, 2 = > 500 m), and drainage density (summed water course lengths (m)/ catchment area (ha). These catchment metrics were used in 2 ways: to test correlations with annual nutrient loads in the 34 Tasmanian catchments and to test correlations with land use percentages in those same catchments.

Results

The annual total load estimates (Table 1) indicate that the northwest corner of Tasmania tends to have higher TP loads on an annual basis (Figure 5) and per hectare (Figure 6), whereas TN loads are more even across catchments (Figures 5 and 6). The high TP results also correspond to catchments containing dairy pastures as a major land use (Figure 7).

When these TP and TN loads were correlated with various catchment metrics for the 34 catchments there were several significant correlations (Table 3). Total loads of N and P were correlated with different catchment metrics, i.e. Total N load correlated with catchment area, perimeter, rainfall (range and mean), slope and altitude, where as Total P load was correlated only with slope class 1. The Total N and P loads on a per hectare basis were more similar, both being negatively correlated with elevation, slope (%, degrees, class 3) and positively correlated with slope class 1. Total N load per hectare was also positively correlated with mean annual rainfall.

These correlations are not necessarily causative relationships, however, they suggest that larger, higher altitude catchments with greater rainfall and steeper slopes (i.e. generate more runoff) have greater Total N loads than low altitude, flatter catchments with low rainfall. Also, flatter catchments at lower elevations generate greater amounts of N and P per hectare into surface waters than steeper higher catchments. However, these correlations are confounded by land use as more intensive land uses typically occur on flatter, low altitude land under higher rainfall (Table 4).

Dairy pastures were found to occur on flatter land at low altitudes (negatively correlated with elevation, slope %, slope class 3, positively correlated with slope class 1). By comparison, forestry land use occurs on steeper land (positively correlated with slope % and slope class 3, negatively correlated with slope class 1) and more plantations occur under higher rainfall. More grazed modified pastures occur on flatter slopes in drier catchments (negatively correlated with slope %, slope class 3 and mean annual rainfall) and native grassland occurs in drier catchments (negatively correlated with rainfall).

The nutrient load and catchment metric correlations show that land use has the potential to be used as an integrator of soils, climate and slope for the CMSS modelling rather than a combination of other criteria and also that there are major drivers of nutrient delivery to surface waters associated with land use that may be little modified by management practices.

Classical analyses typically only produce statistical summaries such as means and standard deviations for parameters of interest. Bayesian analysis additionally produces probability distributions

that provide more information on the reliability and possible values of parameters. The plots in Figures 8 and 9 show the probability distribution for each nutrient generation parameter. Even though non-informative uniform priors were used for the generation rates of TP and TN the posterior distributions for most land uses were typically peaked and extended over a narrower range than their priors. This indicated that those generation parameters were well informed by the model and data rather than merely following their priors.

For example, the TN posterior distribution for forests had a peak close to 2.6 and most of its probability mass spanned the range 0.5-4 which was well within the prior range of 0.9-13. Its 95% HPDI 1.49-3.8 (Table 3) was also well within its prior range. The only parameters with posteriors that spanned most of their prior ranges were water, marshland, urban, plantations (TN only) and minimal use (TP only). These parameters may have been less well

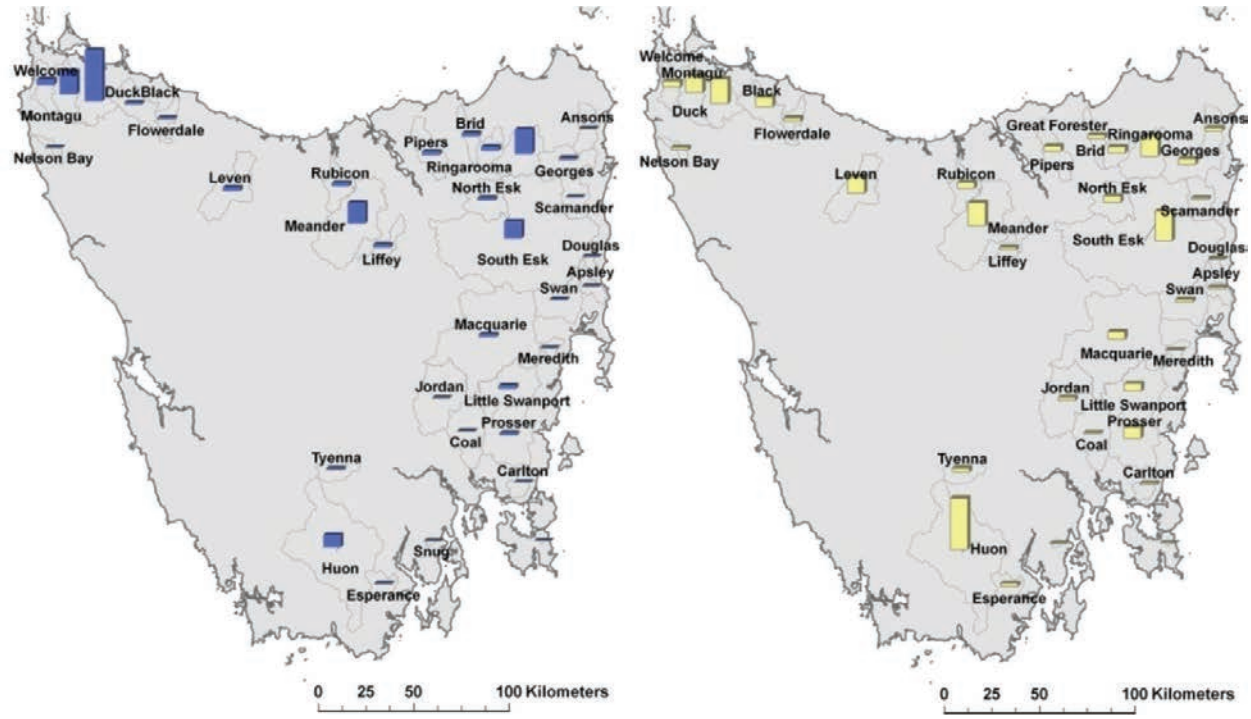


Figure 5. Estimated relative total annual catchment loads for TP (left) and TN (right).

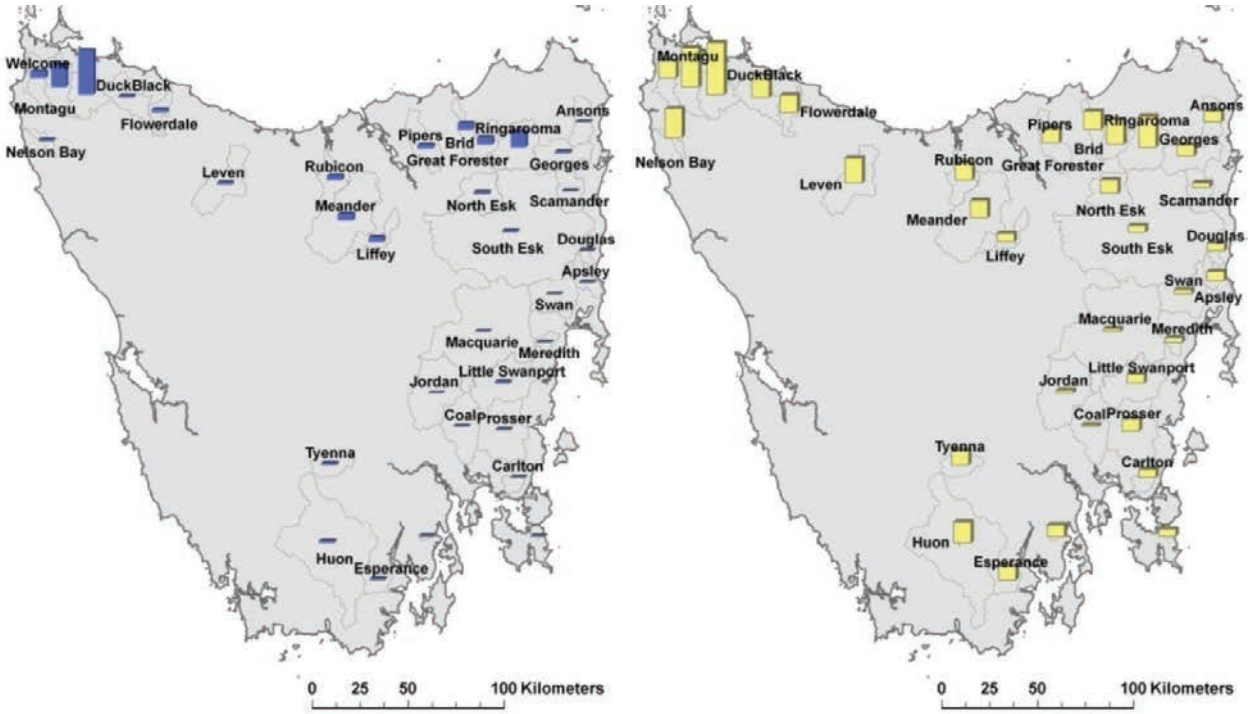


Figure 6. Estimated relative annual per hectare losses for TP (left) and TN (right).

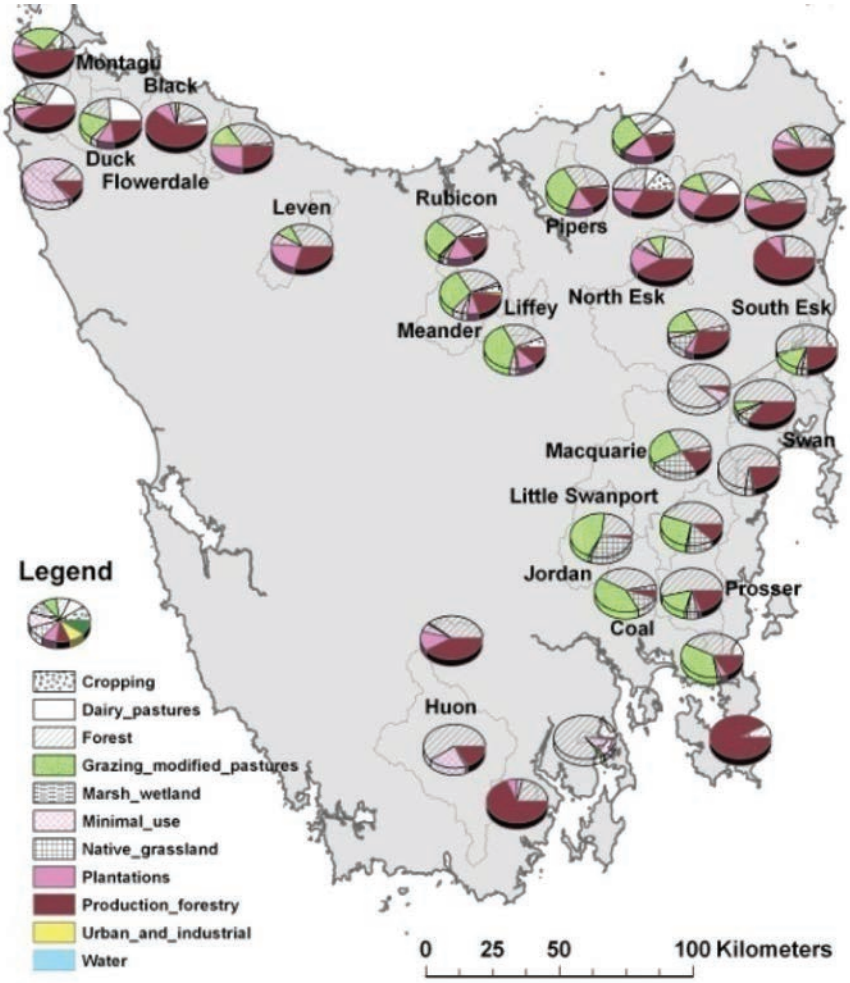


Figure 7.
Land uses in the study catchments.

defined by the model so that a wider range of values were acceptable.

When all the results were expressed as means and 95% HPDIs, dairy pastures and to a lesser extend urban and industrial land uses had the highest annual nutrient generation rates (Table 5). While the means of grazing modified pastures, production forestry, cropping, and forests were smaller than other land uses their narrow ranges compared to their prior ranges indicated that these land uses were quite similar across catchments.

When the model was re-run using updated upper bound of 23kg/ha/year for TP from dairy pastures, based on a study by Barlow et al (2005), the difference in the annual generation rate for any of the land uses, including dairy pastures was negligible (dairy pastures mean=11.23; 95% HPDIs of 10.13-12.32). This indicates that the Bayesian model is indeed informative and not purely an artefact of the elicited priors.

The "observed" catchment loads estimated by using a flow weighted mean concentration algorithm (Walling and Webb, 1985), were similar to the CMSS model outputs based on the mean posterior land use generation rate parameters. The relationship are shown in Figures 10 and 11 with r^2=0.90 (95% HPDI: 0.85-0.93) for TN and r^2=0.96 (95% HPDI: 0.95-0.97) for TP. This means that the model has good predictive capacity across catchments.

Discussion

The main outcome of the estimation of Tasmanian annual TP and TN generation rates is that the land use dairy pastures dominated nutrient losses. This result is not unexpected as dairy pastures are a very high input system, there is often high connectivity with waterways (Wilcock *et al.*, 2009) and the cows themselves can cause erosion and nutrient loss (Trimble and Mendel, 1995). The order and magnitude of the annual land use generation rates are similar to results previously published, with dairy pastures much higher than other land uses like grazing and forests (Drewry *et al.*, 2006). One gap in the available data was that there was no data from predominately cropping catchments in Tasmania, despite a significant vegetable cropping industry and soil erosion is a major management issue (Cotching *et al.*, 2002). This means that cropping can only be analysed as a small component of a catchments dominated by other land uses and is likely to have higher annual generation rates than otherwise indicated by the results. This lack of data

Table 1. Catchment area and average annual rainfall, evaporation, flow and TP and TN nutrient loads.

Catchment	Area (km²)	Rainfall (mm/year)	Evaporation (mm/year)	Flow (ML/ year)	TP (kg/yr)	TN (kg/yr)
Allans Rivulet	8	900	1044	2738	26	1015
Ansons	230	877	1091	48894	1219	45490
Apsley	156	815	989	55778	939	26101
Black	323	1381	1001	179931	3469	128994
Brid	148	984	1086	41859	5258	48384
Carlton	142	738	1037	25363	595	20949
Coal	620	596	1004	17496	1729	16269
Douglas	71	1027	910	34949	386	9766
Duck	360	1270	1039	174337	92901	336306
Esperance	174	1286	759	121828	1567	43079
Flowerdale	152	1394	998	103240	2697	47815
George	48	1069	1018	175701	3484	79389
Great Forester	192	1132	1050	77245	7445	86211
Huon	1837	1756	731	2580276	22140	695123
Jordan	743	537	970	30486	1046	39840
Leven	496	1776	869	480034	6795	220226
Liffey	214	1009	1027	70092	5576	32390
Little Swanport	603	622	987	74100	5914	99656
Macquarie	1976	581	982	108018	5048	105240
Meander	1029	1045	1011	415400	37683	313862
Meredith	87	592	1020	17584	243	7309
Montagu	320	1264	1066	109041	41542	228053
Nelson Bay	66	1426	1001	47276	567	34265
North Esk	374	1092	909	157385	4842	90583
Pipers	299	957	1097	86896	6168	75193
Prosser	681	693	1007	90567	4494	150514
Ringarooma	482	1305	939	251379	44465	272419
Rubicon	262	945	1080	68759	5972	79388
Scamander	270	814	1052	56538	433	23458
Snug	17	1011	919	8793	113	3577
South Esk	3302	815	968	741725	30575	400055
Swan	457	723	947	108472	1492	37855
Tyenna	207	1337	845	165336	2596	54178
Welcome	262	1188	1058	44249	10340	81024

Table 2. Elicited prior nutrient generation rates used in the Bayesian model. Shown are limits used in the uniform priors for TP, $M_i \sim \mathrm{Unif}(M_l, M_u)$ *and TN,* $L_i \sim \mathrm{Unif}(L_l, L_u)$.

	TP (kg/ha/yr)		TN (kg/ha/yr)	
Landuse	M_L	M_U	L_L	L_U
Cropping	0.2	18.6	4	34.5
Dairy pastures	0.2	11.9	3	30
Forest	0.001	0.8	0.9	13
Grazing modified pastures	0.2	9	0.6	25
Marsh wetland	0.001	0.2	0.5	6
Minimal use	0.001	0.2	0.2	6
Native grassland	0.002	0.4	0.6	5.6
Plantations	0.001	0.8	0.9	13
Production forestry	0.001	0.8	0.5	13
Urban and industrial	0.1	6.2	1	38.5
Waterways	0.001	0.2	0	3

Table 3. Correlation matrix for Tasmanian catchment metrics and annual nutrient loads in surface waters.

Attribute	area (ha)	Perimeter	elev range	elev mean	Drainage density	slope % mean	slope deg mean	Rainfall range	Rainfall mean annual	Slope class 1 %	Slope class 2 %	Slope class 3 %	Slope class 1 ha	Slope class 2 ha	Slope class 3 ha	Altitude class 1 ha	Altitude class 2 ha
Total P	0.262	0.296	-0.09	-0.162	-0.164	-0.285	-0.293	0.029	**0.236**	0.417	-0.337	**-0.277**	0.374	0.199	0.201	0.294	**0.196**
Total P/ha	-0.07	**-0.014**	-0.342	**-0.357**	-0.145	-0.386	**-0.391**	-0.138	**0.256**	0.5	-0.34	**-0.363**	0.103	-0.12	-0.135	-0.028	**-0.131**
Total N	0.659	**0.694**	0.333	0.168	-0.226	0.029	**0.014**	0.51	**0.403**	0.134	-0.252	**-0.017**	0.503	0.56	0.749	0.637	0.649
Total N/ha	-0.147	-0.072	**-0.315**	-0.344	-0.177	-0.408	**-0.417**	0.099	0.645	**0.539**	-0.333	-0.408	-0.035	-0.217	-0.14	-0.137	**-0.151**
bold are significant at P < 0.05																	

Table 4. Correlation matrix for Tasmanian catchment metrics and land use categories.

Land use (%)	elevation mean	drainage density	slope % mean	rainfall mean annual	slope class 1 (%)	slope class 2 (%)	slope class 3 (%)	altitude class 1 (%)	altitude class 2 (%)
Dairy pastures	-0.430	-0.230	-0.390	0.247	0.459	-0.234	-0.372	0.289	-0.289
Forest	0.237	0.220	0.468	-0.233	-0.470	0.120	0.440	-0.237	0.237
Grazing modified pastures	-0.062	-0.221	-0.357	-0.505	0.220	0.259	-0.362	0.142	-0.142
Irrigated cropping	0.084	-0.175	-0.037	-0.078	0.052	0.015	-0.063	-0.052	0.052
Marsh wetland	-0.100	-0.020	-0.347	-0.270	0.317	-0.012	-0.332	0.129	-0.129
Minimal use	-0.116	0.084	-0.227	0.405	0.352	-0.263	-0.244	0.036	-0.036
Native grassland	0.245	0.110	-0.091	-0.654	-0.058	0.304	-0.088	-0.097	0.097
Plantations	0.009	-0.207	-0.114	0.524	0.104	0.075	-0.147	-0.089	0.089
Production forestry	-0.092	0.013	0.135	0.294	-0.085	-0.190	0.184	0.096	-0.096
Urban and industrial	0.111	-0.205	-0.137	-0.054	0.099	0.122	-0.165	-0.002	0.002
Water	0.275	-0.009	-0.082	-0.040	0.073	0.087	-0.121	-0.219	0.219
bold are significant at P < 0.05									

Table 5. Posterior means and 95% HPDIs for the TP and TN land use generation rate parameters.

	TN			TP		
Land Use	**Mean**	**95% HPDI**		**Mean**	**95% HPDI**	
Dairy pastures	27.10	19.80	29.90	11.10	10.10	11.80
Remnant forest	2.68	1.49	3.88	0.06	0.01	0.14
Grazing modified pastures	1.00	0.61	2.09	0.24	0.20	0.34
Irrigated cropping	5.67	4.04	9.99	0.39	0.21	0.87
Marsh wetland	3.03	0.60	5.83	0.10	0.01	0.20
Minimal use	5.21	3.13	5.98	0.14	0.02	0.20
Native grassland	1.02	0.61	2.23	0.04	0.00	0.15
Plantations	5.49	1.21	11.70	0.14	0.01	0.47
Production forestry	0.89	0.51	1.95	0.03	0.00	0.10
Urban and industrial	14.00	1.40	35.70	2.23	0.18	5.54
Dams and waterways	1.46	0.07	2.91	0.10	0.01	0.20

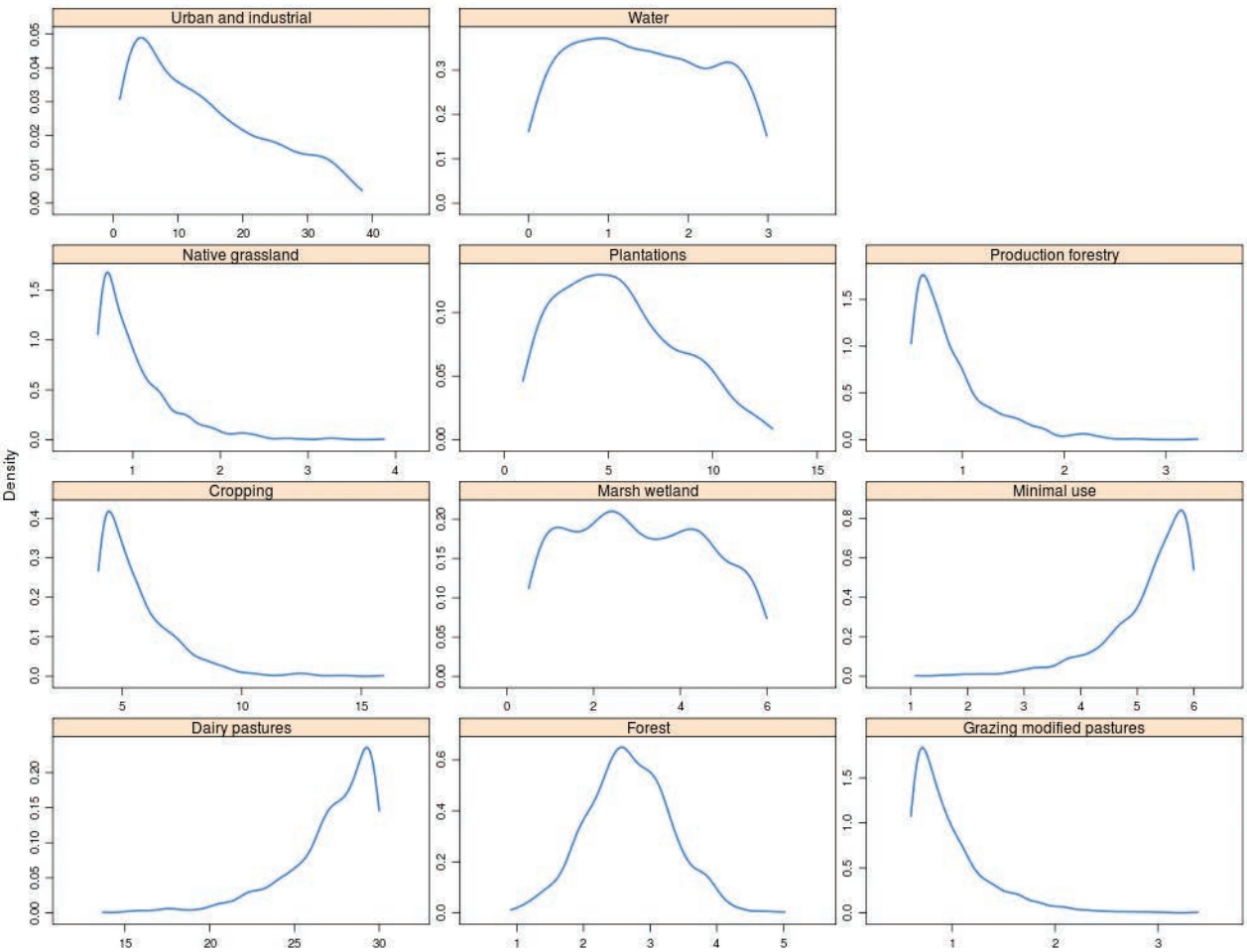


Figure 8. Posterior probability distributions for TN land use generation rate parameters.

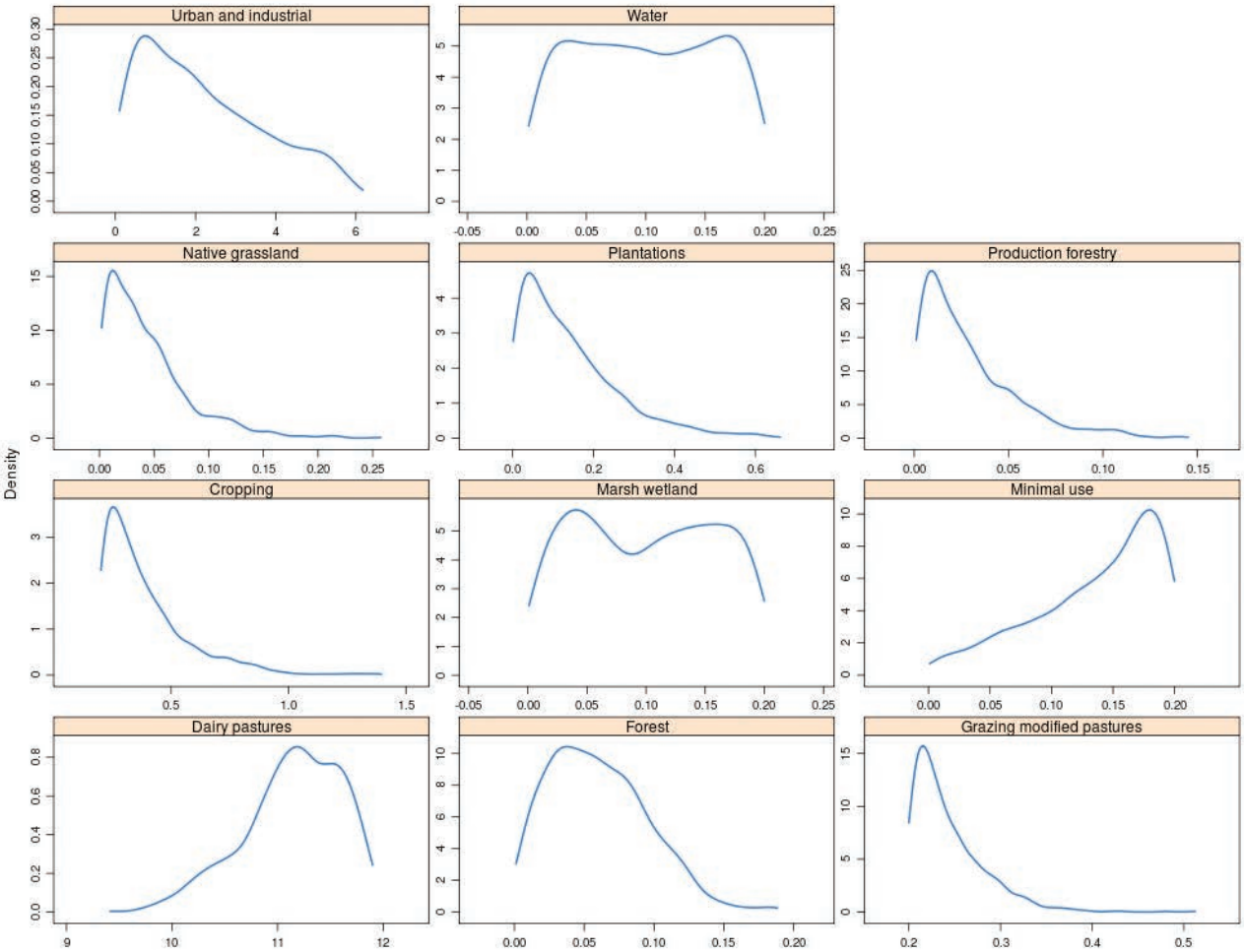


Figure 9. Posterior probability distributions for TP land use generation rate parameters.

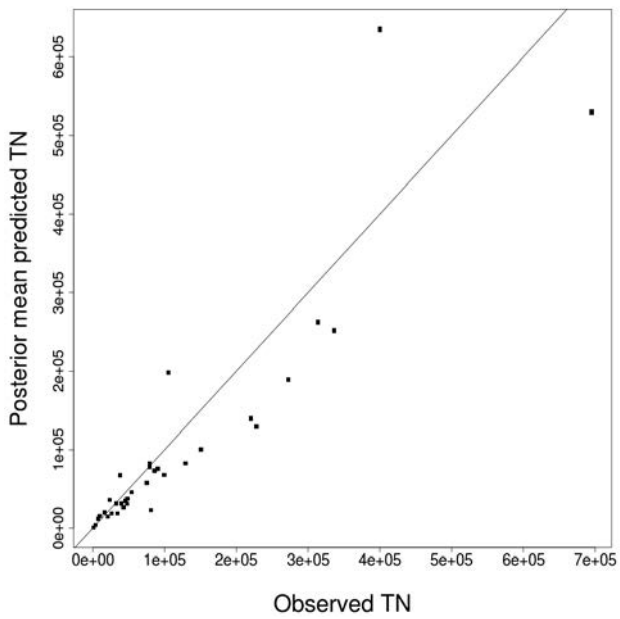


Figure 10. The ''observed'' catchment TN loads compared to the CMSS model TN outputs based on the mean posterior land use generation rate parameters.

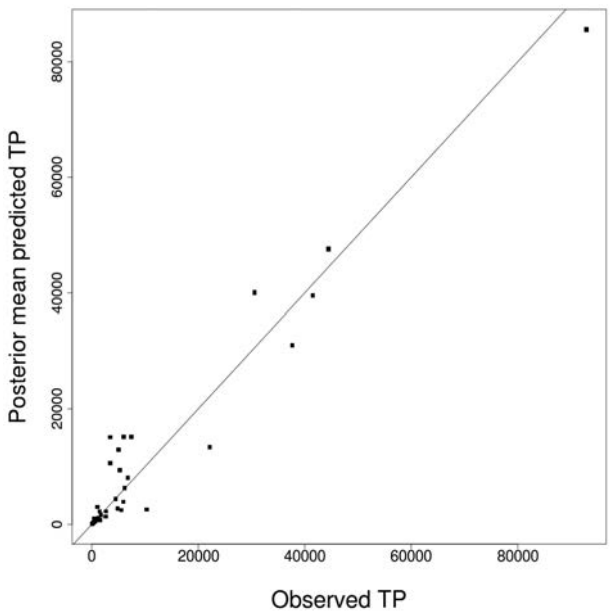


Figure 11. The ''observed'' catchment TP loads compared to the CMSS model TP outputs based on the mean posterior land use generation rate parameters.

could be remedied in future monitoring programs.

The annual load estimations, on which the generation rates were based, indicate that there are wide ranges of different loads in different catchments. The estimates produced the Walling and Webb (1985) algorithm have a relatively small bias and lower variance than other comparable estimators (Jarvie *et al.*, 2003). However, one potential bias of the Walling and Webb method is that monthly grab samples typically miss flood events and as a result can underestimate annual loads, unless by chance some flood events coincide with grab samples (Letcher *et al.*, 1999; McKee *et al.*, 2000). Without establishing a wide ranging monitoring program this is unlikely to change, especially since the Tasmanian State Government has stopped the monitoring program in June 2009. However, this process could be rerun in the future if better data sets become available. It is also necessary to consider that, by their very nature, the results of unit-area load models like CMSS are indicative of long-term average emissions only and may not compare well with the measured annual loads for a particular year due to the high variability in rainfall and runoff generation from year to year (Baginska *et al.*, 2003).

Despite the known limitations of the CMSS model, its advantage lies in minimal input data requirements (Baginska *et al.*, 2003) which means that those interested in catchment land use and water quality issues can use the model as a basis of discussions. The establishment of Tasmanian annual land use generation values and their uncertainty allows more rigor in the creation of a CMSS model rather than relying on a synthesis of published results that may bear no relationship with local Tasmanian conditions.

In the case of the Bayesian model, the inputs included uniform prior limits so that inferences were unaffected by information external to the data (Gelman *et al.*, 1995). While uniform priors are often described as non-informative, their upper and lower limits do provide some information, but these were well informed by literature sources (Marston *et al.*, 1995; Young *et al.*, 1997; Letcher *et al.*, 1999). If alternative independent estimates for the generation rates become available then the model can be easily be modified to utilize them. For example, if the generation rate estimate for cropping was separately estimated to have a particular value within an associated variance then it could be included as an informative prior rather than the non-informative uniform prior used here. However, using an updated upper prior for dairy pastures had a negligible impact on the results. The Bayesian model can also be embedded within a more complex hierarchical model allowing for more elaborate simulation and simultaneous estimation of related parameters (Bernado and Smith, 1994). Lastly, software for Bayesian analysis are now commonly available, making our approach widely accessible.

Conclusion

Bayesian modelling to inform land use generation rates required by the CMSS model removes the arbitrary nature of parameter selection, thus improving the reliability and repeatability of CMSS models and subsequent management decisions.

Flatter land in higher rainfall areas was found to generate greater catchment scale annual nutrient loads. These areas are typically used for agriculture and in particular the most intensive land uses of cropping and dairy production. The more intense the land use in terms of nutrient inputs, the greater the nutrient enrichment in waterways. Consequently, greater intensification of land use in Tasmania is likely to result in greater surface water nutrient loads. In Tasmania, land use is a good integrator of soils, slope and agricultural productivity for use in modeling surface water nutrient loads. Tasmanian dairy land use nutrient generation rates for total Phosphorus and total Nitrogen are at the higher end of published values with rates of 10–12 kg/ha/yr for total Phosphorus and 20–30 kg/ha/yr for total Nitrogen.

Phase 2: Using nonlinear methods for the optimisation of a rainfall-runoff model across an ensemble of Tasmanian catchments

Introduction

There is increasing scientific interest in regional responses to rainfall changes and river flows to, amongst other things, test climate change scenarios (e.g. Chiew *et al.*, 2010). Lumped conceptual models are commonly used for determining these rainfall-runoff relationships in river catchments. These models represent a catchment as a single entity, or a small group of entities, so that river flows are simulated across the whole catchment using basic physical concepts of water balance.

Parameters in many lumped models do not have a physical interpretation and cannot be measured directly in the field (Croke and Jakeman, 2001; Cooper *et al.*, 2007), instead parameters must be derived through calibration against measured historical stream flow data so that the modelled response closely matches to the observed response. As obtaining optimal parameters is crucial to the performance of lumped models there has been a significant effort to determine the "best" automatic optimisation technique or algorithm under varying conditions (e.g. Goswami and O'Connor (Goswami and O'Connor, 2007)), bearing in mind issues such as data limitations, model structural deficiencies and parameter identifiability (Sorooshian and Gupta, 1995).

There are a range of routinely applied parameter optimisation algorithms based on various methods, however, due to the inherent non-linear nature of hydrological systems (Bardossy and Singh, 2008), there have been calls for the exploration of non-linear approaches for parameter optimisation (Sivakumar, 2009) particularly those using Newton-type methods (Kavetski *et al.*, 2006). There are a wide variety of software available for solving nonlinear regression problems, including SAS (SAS Institute, Cary, NC, USA), Genstat (Payne *et al.*, 2009), Minitab (Minitab Inc., 2007) and R (R Development Core Team, 2009).

As more people without a background in hydrology attempt to use conceptual rainfall-runoff models and automatic optimisation algorithms across a large number of catchments, it is important to establish which automatic optimisation method is more or less robust in a wide range of catchments and hydrological regimes for a given model and whether other optimisation options outperform the standard algorithms. The objective of this study was to determine the usefulness of a non-linear regression technique in finding an "optimum" parameter set for a lumped conceptual rainfall runoff model AWBM across multiple catchments (in a batch) by comparing its performance with routinely applied parameter optimisation algorithms available in general purpose statistical software. We examined 30 catchments with a wide range of hydrological characteristics. We chose to use the SAS software package due to its capacity to handle extremely large datasets that can be generated from this approach. If, however, data set size is not a limitation then any of the listed general statistical packages may be used.

Non-linear optimisation

Nonlinear regression procedures are distinguished from linear models, such as those encountered in linear regression, by non-linearity of the parameters. A trivial example is the model $Y=a+x^b$ in which the exponent *b* is a nonlinear coefficient. Unlike linear models, the parameter estimates are not obtainable in closed form but are estimated using iterative procedures.

A good overview to nonlieanr regression is given by (Bates and Watts, 1988). Within the SAS software used in this study, a number of alternative procedures for solving nonlinear problems are available, including NLIN, TRANSREG, MODEL and NLMIXED. We chose NLMIXED procedure here due to its flexibility and the capacity to specify the distribution of the data, such as normal, Poisson, and binomial. Here we assumed a normal distribution with associated unknown variance.

NLMIXED fits nonlinear mixed models by maximizing an approximation to the likelihood using a variety of approximations to the likelihood and optimization techniques to carry out the maximization. On convergence SAS reports the parameter estimates and approximate standard errors. The NLMIXED procedure maximizes an approximation to the likelihood integrated over any random effects that may be present using adaptive Gaussian quadrature, by default, (Pinheiro and Bates, 1995), which is then optimised.

Since no particular technique will necessarily find the global optimum a number of alternative optimisation techniques are available, some of which rely on the second derivative of the likelihood, while others only use the first derivative, or none at all. Such local search methods are

dependent on initial starting values and, as a result, experimentation with choice of iterative procedure and tuning parameters may sometimes be necessary. However, bounds may be set for individual parameters within which SAS will confine its search. Since the standard hydrological objective function of the Nash-Sutcliffe criterion (Nash and Sutcliffe, 1970) assumes a Gaussian likelihood with independent errors model (Iorgulescu and Beven, 2004), we selected the equivalent normal likelihood option for this study.

Parameter optimisation algorithms for comparison

Seven standard rainfall-runoff model parameter estimation algorithms are available in the Rainfall Runoff Library (RRL) (Perraud *et al.*, 2003), a suite of rainfall runoff models and automatic calibration methods commonly used in Australia (available at http://www.toolkit.net.au). Each of these methods was compared to NLMIXED. These were the Genetic Algorithm (Holland, 1975), Pattern Search (Hooke and Jeeves, 1961), a multiple start Pattern Search, multiple and single start derivations of the Rosenbrock method (Rosenbrock, 1960), Shuffled Complex Evolution – University of Arizona (Duan *et al.*, 1994) and Uniform Random Search.

Uniform Random Search

Uniform Random Search (URS) is a very simple optimisation method where the parameter space for each parameter is divided into a specified number of intervals between the minimum and maximum bound. The optimisation then proceeds by randomly sampling from the available options for each parameter, running the model and assessing the objective function. This is repeated for a specified number of times and the option with the best objective function value is taken as the optimum parameter set (Podger, 2004).

Pattern Search

Pattern Search (PS) (Hooke and Jeeves, 1961) is the simplest of all the search methods tested and is quick to perform but can suffer from finding local optimums rather than global optimums, particularly if models are strongly non-linear. The optimisation starts with an initial value and search increment for each of the parameters. The objective function is then evaluated after an incremental increase and decrease in current value. If the objective function improves in one direction the parameter is set to that value. This is repeated until there is no improvement in the objective function.

Pattern Search Multiple Start

The problems of Pattern Search reaching local optimums rather than global optimums can be overcome by using a multi-start search version (PSMS) where multiple initial samplings of the parameter space provide the potential for locating the global optimum without being biased by pre-determined initial starting points. The optimisation starts by dividing the parameter values into a specified number of increments between the specified bounds. For each of these possible starting points a pattern search is carried out and the best optimum of the searches is taken as the global optimum (Podger, 2004).

Rosenbrock Method

The Rosenbrock Method (RM) (Rosenbrock, 1960) is a local search method that returns at each step to a point at least as good as the previous one in the parameter space. It is similar to the Pattern Search method but with two main improvements which are a better use of the local information from the response curve surrounding the point in the parameter space, and an adaptive step size. The optimisation proceeds in a series of searches in parameter space following successive directions along an ortho-normalised set of vectors with the same dimension as the parameter space.

Multi-start Rosenbrock Method

The multiple start version of the Rosenbrock Method (RMMS) divides the parameter values into a specified number of increments between the specified bounds, then for each of these possible starting points a Rosenbrock search is carried out. The best optimum of these searches is taken as the global optimum (Podger, 2004).

Genetic Algorithm

The genetic algorithm (GA) (Holland, 1975) is based on natural selection and genetics, combining an artificial survival of the fittest with genetic operators such as recombination and cross over events. The optimisation process begins by randomly generating m points in the search space. Then an objective function value at each point is calculated, representing the fitness of the point, which is then ranked in descending order from best to worst. Each point is then assigned a probability, giving higher probability to points with a lower objective function value. New points are generated by probabilistically selecting and combining the m points to produce offspring so that better points have a better chance to be chosen to form new points. This is analogous to the survival of the fittest, that is, the

better performing individuals produce more offspring. Occasionally some of the bits of a newly formed point are changed which is analogous to cross over events during genetic recombination. The process is terminated when a specified total number of function evaluations have been reached.

Shuffled Complex Evolution Algorithm – University of Arizona

The Shuffled Complex Evolution Algorithm, developed at the University of Arizona (SCE-UA), is based on a synthesis of deterministic and probabilistic approaches, systematic evolution of points spanning the parameter space in the direction of global improvement, competitive evolution, and complex shuffling (Duan *et al.*, 1994).

The optimisation begins by generating *s* sample points randomly in the feasible parameter space and computing the objective function value at each point. Each objective function of the *s* points is ranked and partitioned into *p* complexes, each containing *m* points. Each complex then evolves according to the competitive complex evolution algorithm. This is followed by a shuffling of the points in the evolved complexes into a single sample population; sorting of the sample population in order of increasing objective function value; and reshuffling of the sample population into *p* complexes containing *m* points etc. Before recommencing the evolution loop, there is a check for convergence by using pre-specified convergence criteria.

Methodology

Test catchments

Tasmania, the southern island state of Australia, was selected as the source of the test catchments due to data being readily accessible and there being a wide range of hydrological regimes in a relatively small area. Thirty catchments were identified, out of a possible 75, based on continuity of flow records, flow monitoring being close to the outlet of the river system and absence of hydroelectric development (Figure 1). Pan evaporation and rainfall data from 1960 to 2007 were obtained from the SILO 0.05 degree climate grid (Jeffrey *et al.*, 2001) and averaged for the whole of each catchment. Daily flow data from 1960 (or the start of the record if later) to the end of 2007 were obtained for the 30 Tasmanian catchments from Water Information Systems Tasmania (www.water.dpiw.tas.gov.au).

Rainfall-runoff model

Australian Water Balance Model (AWBM) is the most widely used rainfall-runoff model in Australia (Boughton, 2005) and as such was chosen as a reliable model. AWBM is a six parameter lumped conceptual rainfall-runoff model that consists of three surface stores which are routed through a surface flow store and a baseflow store (Figure 12) (A1 and A2 are fixed at 0.134 and 0.433 respectively). The version of AWBM used to estimate the rainfall-runoff relationships of the 30 catchments was contained in the RRL (Perraud *et al.*, 2003).

The objective function

There are many methods for determining how closely the model represents the observed data, and there are many papers dedicated to this issue (for example: (Legates and McCabe, 1999; Moriasi *et al.*, 2007; Jain and Sudheer, 2008). The most widely used statistical measure, or objective function, in hydrology is the Nash Sutcliffe criterion (NS) (Nash and Sutcliffe, 1970). However, for descriptive purposes it is recommended that *post hoc* calculations of the square root of the mean square error (RMSE) and a measure of bias such as the mean absolute error (MAE) be presented in summary tables, along with observed and modelled means and standard deviations (Legates and McCabe, 1999). As stated above the nonlinear method used the Nash Sutcliffe Criterion equivalent normal likelihood surface.

Rainfall-Runoff Library automatic optimisation methods

Due to the number of catchments and methods, for pragmatic purposes the seven standard rainfall-runoff model parameter estimation algorithms available in the RRL (Perraud *et al.*, 2003) were implemented once for each catchment using default settings.

Nonlinear regression procedure

We coded the AWBM model into SAS programming language (Appendix), tested and found to be consistent with the RRL version of AWBM. We used AWBM defaults from RRL as the initial parameter values and the parameter bounds were the RRL defined limits for the AWBM model (from Podger, 2004). Using this method no models failed to converge.

Hydrological model calibration and verification

In every case first three quarters of the flow data from each catchment were used for calibration and the remaining quarter (the most recent) for verification as per Goswami and O'Connor (Goswami and O'Connor, 2007). The verification of the 30 catchment parameter sets for each of the eight parameter estimation methods was undertaken

using the AWBM model implemented in SAS code. Each catchment was calibrated individually as there is a limited ability to transfer parameters to other catchments (Croke and Jakeman, 2001).

Results

The catchments selected represented a very wide range of catchment sizes and climatic conditions, with areas of 8km^2 to 3300km^2, annual rainfall of 580mm to 1800mm, annual evaporation of 730mm to 1100mm and annual flows of 2700 ML to 2.5 million ML (Table 1).

A wide range of parameter values were estimated for each catchment as illustrated by results from Allans Rivulet (Table 6), which was typical of other catchments (data not shown). As the BFI parameter in AWBM controls whether excess rainfall was routed predominately to the baseflow storage (BFI>0.5) or the surface flow storage (BFI<0.5) and these stores are in effect exchangeable, different parameter estimation algorithms could find similar almost mirror image parameters, with high BFI values in one and low BFI in another, balanced by opposite KS and BS parameters (for example, the comparison of the parameters of the Genetic Algorithm and Pattern Search multi-start the Allans Rivulet catchment data contained in Table 2). There were also large differences in the combinations of the C1, C2 and C3 parameters using different calibration algorithms across for Allans Rivulet and typical across all catchment (data not shown).

For almost every catchment the nonlinear method had the highest NS, the lowest RMSE and lowest average MAE, which is reflected in the mean and standard errors (Table 7). The nonlinear method also had the lowest bias for both the calibration and verification datasets, slightly over estimating the flow for the calibration and slightly underestimating flow for the verification (Table 8). All other methods (except URS) tended to underestimate average flow in both the calibration and verification datasets (Table 8).

A multivariate analysis of variance of NS, RMSE and MAE statistics was conducted but resulted in residuals that were not multivariate normally distributed. Therefore we replaced the three statistics by their ranks within each catchment and calculated the mean ranks by method (with the ranking for NS being reversed for comparability). Their residuals were then satisfactorily multivariate normally as determined by a chi-square quantile plot (Everitt, 2005). The mean rankings vector differed significantly between groups using Wilks' test ($F_{7,232} = 6.5$, P<0.05). Since all separate analyses of variance were significant we calculated Tukey honest significant differences on each statistic to identify which mean ranks differed at a significance level of 0.05. In Table 9 we show the mean rankings and indicate with letters those pairs of means that differed significantly from each other. Using this method we found that the nonlinear method had the lowest mean rank for NS, RMSE and MAE statistics.

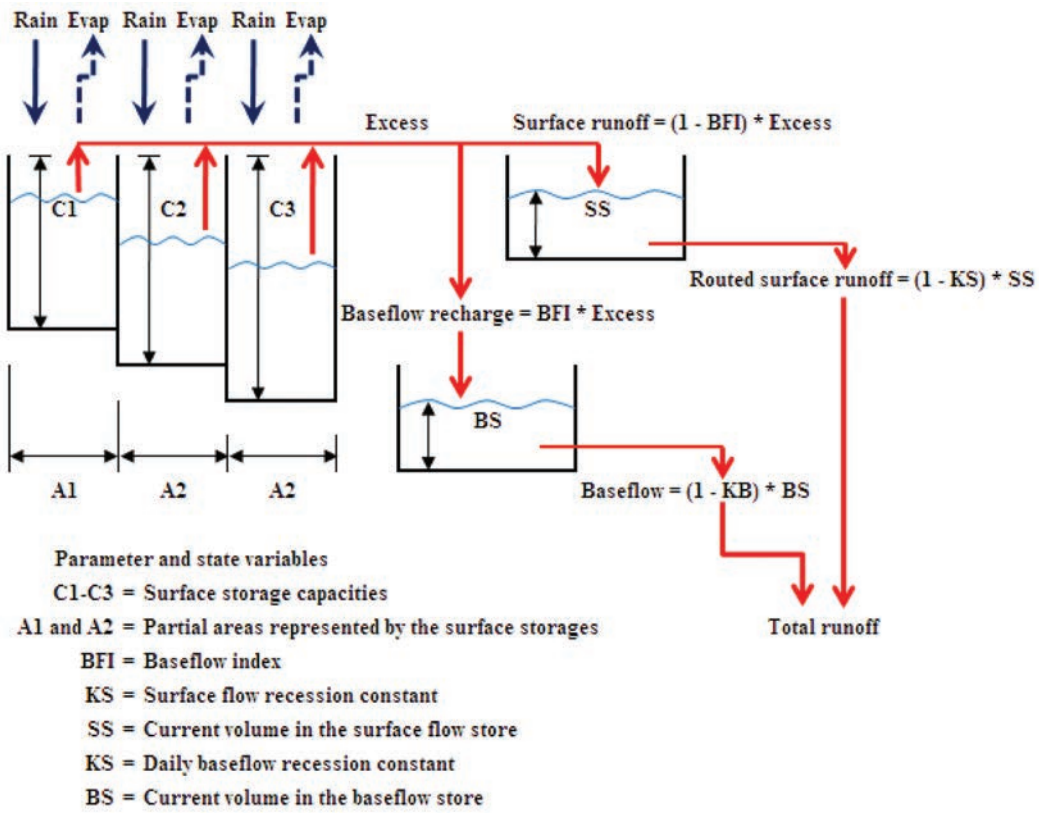


Figure 12. Structure of the AWBM rainfall-runoff model

Table 6. AWBM parameters and Nash Sutcliffe Criterion (NS) for the Allans Rivulet Catchment

	Parameters						NS
Method	**BFI**	**C1**	**C2**	**C3**	**KB**	**KS**	
Genetic algorithm	0.396	4.10	67.5	11.8	0.263	0.894	0.696
Nonlinear method	0.665	2.14	28.9	130.3	0.830	0.132	0.721
Pattern search multi-start	0.619	0.10	68.2	14.8	0.899	0.211	0.694
Pattern search	0.628	37.10	4.8	68.2	0.896	0.202	0.702
Rosenbrock multi-start	0.420	31.20	138.5	10.0	0.218	0.854	0.706
Rosenbrock single start	0.364	35.40	139.9	3.4	0.168	0.841	0.706
Shuffled complex evolution – UA	0.442	27.70	1.7	174.4	0.891	0.385	0.690
Uniform random sampling	0.236	0.36	52.7	6.6	0.106	0.947	0.651

Table 7. Average Nash Sutcliffe criterion (NS), root mean square error (RMSE) and mean absolute error (MAE) ± standard error (SE) for the calibration and verification of eight different parameter estimation methods across 30 catchments.

Method	**Average NS ± SE**			**Average RMSE ± SE**			**Average MAE ± SE**		
Calibration									
Nonlinear method	0.768	±	0.020	5.769	±	1.800	2.858	±	1.065
Pattern search multi-start	0.747	±	0.022	5.980	±	1.804	2.994	±	1.060
Rosenbrock single start	0.742	±	0.022	6.187	±	1.863	3.083	±	1.075
Shuffled complex evolution - UA	0.742	±	0.022	6.084	±	1.789	3.029	±	1.058
Pattern search	0.740	±	0.023	6.099	±	1.798	3.079	±	1.063
Rosenbrock multi-start	0.730	±	0.022	6.255	±	1.860	3.141	±	1.094
Genetic algorithm	0.724	±	0.021	6.233	±	1.881	3.250	±	1.154
Uniform random sampling	0.670	±	0.028	6.343	±	1.862	3.379	±	1.170
Verification									
Nonlinear method	0.719	±	0.021	4.909	±	1.553	2.554	±	1.033
Pattern search multi-start	0.678	±	0.025	5.163	±	1.558	2.785	±	1.037
Shuffled complex evolution - UA	0.671	±	0.032	5.259	±	1.551	2.770	±	1.030
Rosenbrock single start	0.665	±	0.028	5.338	±	1.599	2.861	±	1.044
Pattern search	0.661	±	0.031	5.304	±	1.562	2.872	±	1.039
Rosenbrock multi-start	0.648	±	0.029	5.361	±	1.592	2.918	±	1.077
Genetic algorithm	0.634	±	0.033	5.457	±	1.667	2.991	±	1.126
Uniform random sampling	0.580	±	0.048	5.416	±	1.609	3.019	±	1.173

Table 8. The mean bias for the calibration and verification of eight different parameter estimation methods across 30 catchments. A negative value means flow was under prediction on average, whereas a positive value means flow was over predicted on average.

Method	**Calibration**	**Verification**
Genetic algorithm	-0.3971	-0.5387
Nonlinear method	0.1660	-0.0227
Pattern search multi-start	-0.5603	-0.7054
Pattern search	-0.5356	-0.7015
Rosenbrock multi-start	-0.3901	-0.5010
Rosenbrock single start	-0.5347	-0.6807
Shuffled complex evolution - UA	-0.3284	-0.4718
Uniform random sampling	0.4644	0.3598

Table 9. Mean verification rankings for parameter estimation methods Nash Sutcliffe criterion (NS), root mean square error (RMSE) and mean absolute error (MAE). Letters indicate means that are not significantly different at a significance level of 0.05.

Row Labels	NS	RMSE	MAE
Nonlinear method	1.7 a	2.3 a	1.9 a
Pattern search multi-start	3.6 b	3.7 ab	3.6 b
Shuffled complex evolution - UA	4.0 b	4.7 bc	4.5 bc
Pattern search	4.4 bc	4.6 bc	4.7 bc
Rosenbrock single start	4.5 bc	4.7 bc	4.7 bc
Rosenbrock multi-start	5.6 cd	4.6 bc	5.3 cd
Genetic algorithm	5.6 cd	5.5 c	5.1 bcd
Uniform random sampling	6.6 d	5.9 c	6.2 d

Discussion and conclusions

Across a wide range of hydrological regimes the nonlinear method typically resulted in the highest NS and the lowest RMSE and MAE values. This would indicate that the nonlinear method was the best performing optimiser of the eight tested, followed by PSMS and SCE-UA. The worst performer was URS. However, Uniform Random Search is rarely used in practice but may be used as a reference to compare the performance of optimisation methods for a given problem (Podger, 2004) so it is not surprising that this was the poorest performing method.

It has often been noted that different sets of parameter values using the same model structure can produce very similar values of the objective function, due to multiple local optima (Bates and Campbell, 2001) which has been termed "equifinality" (Beven, 2006). The wide range of parameter realisations for AWBM and the ability of the model to produce mirror BFI to KS and KB parameter sets means that the baseflow and surface flow stores work in name only.

In the nonlinear method we used the default software settings and did not include more complicated options such as allowing for serial correlations. However, the flexible nature of SAS's NLMIXED procedure does allow for additive and nested random effects. Other procedures in SAS such as the NLINMIX further allow for serial correlations using a generalised estimating equation approach (Zeger and Liang, 1986). While the method worked admirably in our study, it may not necessarily work as well where hydrological data are not identically and independently distributed. The availability of these other options and methods within SAS and other statistical software opens the possibility of coping with more general data. This conclusion, while important, is secondary to the ease with which data from large number of catchments may be handled within readily available programs such as SAS.

The main conclusion from previous studies that have investigated automatic optimisation routines is that the global population/evolutionary optimisation tends to outperform multi-start local searches, which in turn tend to outperform purely local search methods (Madsen *et al.*, 2002). The results from this study indicate that the local search Pattern Search Multi-start and the Rosenbrock Single-start were at least as good as the evolutionary Genetic Algorithm and Shuffled Complex Evolution – UA. However, the nonlinear method outperformed all optimisation algorithms tested. As programs like as SAS are commonly available at Universities and research institutions, this method could be utilised in the optimisation of hydrological models without the need for standalone specialist software packages.

Phase 3: WaterCAST modelling of the Duck catchment

The next step in the project was to model daily nutrient concentrations using the data collected and created so far. For this catchment modelling the WaterCAST model (previously E2) was assessed as it is a flexible catchment modelling framework that allows modellers to construct models by selecting and linking component models from a range of available options (Argent *et al.*, 2004). The available component options model rainfall/runoff, nutrient generation, attenuation, catchment structures (links and nodes) and routing. Numerous plug-in applications have also been developed and are continuing to be developed.

Construction of the Duck E2 Model

The Duck River catchment is a highly developed 540 km^2 drainage basin in the northwest corner of Tasmania, dominated by dairy production (19% of the total area) (Figure 13). The Duck has a gentle gradient with an elevation of approximately 200m above sea level in the far south and east, then trending from low hills to undulating plains and river terraces. Extensive low lying areas comprised of drained swamps are prone to water logging in winter, resulting in the extensive use of "hump and hollow" drainage (Pinto *et al.*, 2003).

Land management practices in the catchment appear to have significantly impacted water quality, particularly total phosphorus (TP), resulting in much higher nutrient loads than other Tasmanian catchments (Pinto *et al.*, 2003). As there is growing awareness of water quality issues by catchment stakeholders in Australia (Letcher *et al.*, 2002), this is potentially a divisive issue because, as well as the dairy industry, the Duck also supports recreational activities and a significant shellfish industry (Pinto *et al.*, 2003). This catchment also forms part of the Robbins Passage wetlands, the largest and most diverse community of migratory and resident shorebirds in Tasmania (Spruzen *et al.*, 2008). Therefore it is important to understand the sources of nutrients in the catchment to facilitate changes in management or undertake interventions to improve water quality. This is of particular interest to the dairy industry as previous work in the neighbouring Montagu catchment identified dairy as the major source of nutrient pollution (Holz, 2007).

Due to low phosphorus parent materials and *in situ* weathering, Australian soils are typically low in TP (Handreck, 1997), meaning high rates of TP in water quality samples indicate anthropogenic influences and to some extent intensity of management. Therefore, to understand differences in dairy farm management throughout the Duck catchment TP was chosen for this initial investigation. As there is currently a lack of high frequency (daily to sub daily) data to accurately predict end-of-catchment nutrient fluxes for the Duck catchment (although equipment has been installed and is currently being tested), catchment and sub-catchment scale modeling was required.

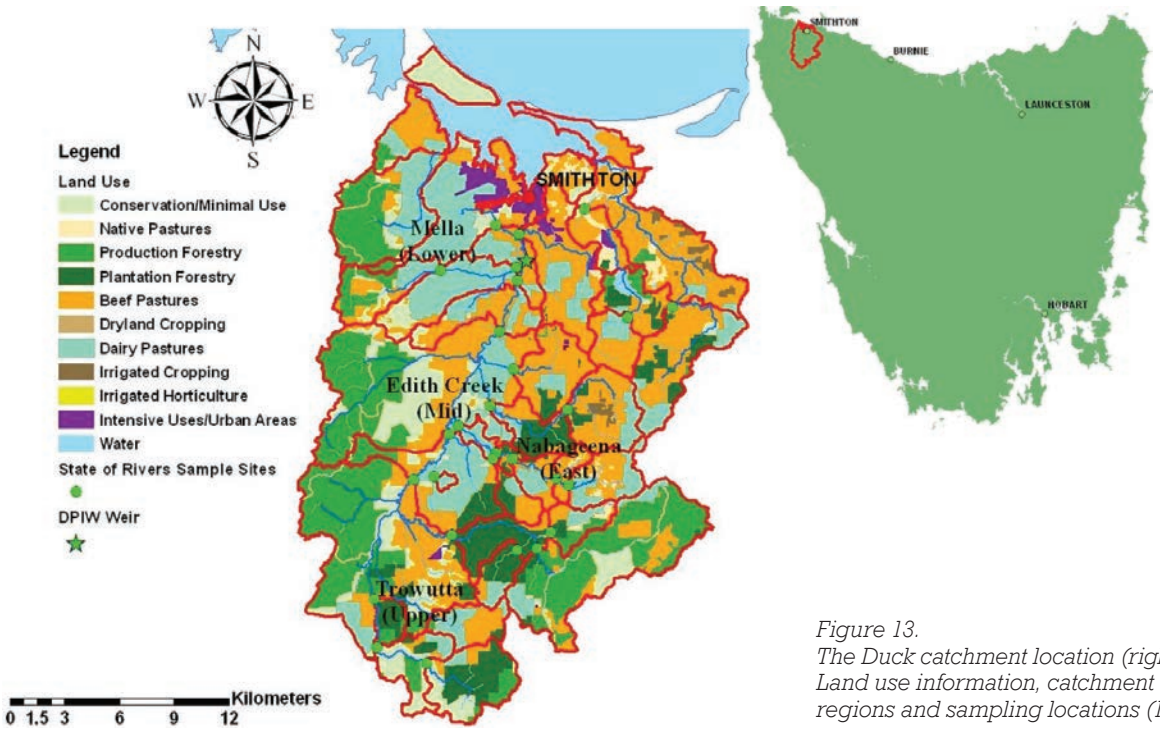


Figure 13.
The Duck catchment location (right), Land use information, catchment regions and sampling locations (left).

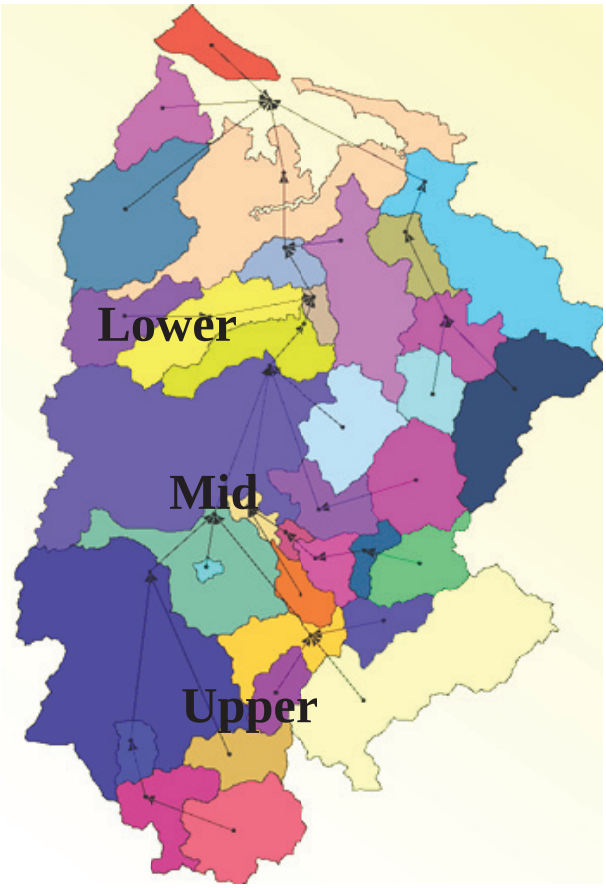


Figure 14. Link and node arrangements and regionalisation of the Duck WaterCAST model.

Model Structure

WaterCAST, an evolution of E2 (Argent *et al.*, 2004), was chosen to model the spatial variation in TP concentrations in the Duck. WaterCAST is a lumped, semi-distributed, conceptual catchment modelling framework that allows modellers to construct models by selecting and linking component models from a range of options (Argent *et al.*, 2008). Multiple component models are available for rainfall/runoff, nutrient generation, attenuation, catchment structures (links and nodes) and routing. Numerous plugin applications have also been created and are continuing to be developed. Important stages in the development of a WaterCAST model include land use assessment, subcatchment delineation, rainfall runoff model calibration and nutrient generation model calibration.

Input data included the catchment boundaries and link node arrangements delineated by CatchmentSIM (Figure 14), land use information from the updated land use layer, the previously derived AWBM hydrology parameters and rainfall and evaporation data from SILO data drills on an approximately 5km grid (Jeffrey *et al.*, 2001) resulting in a good relationships between modelled and observed flows (Figure 15).

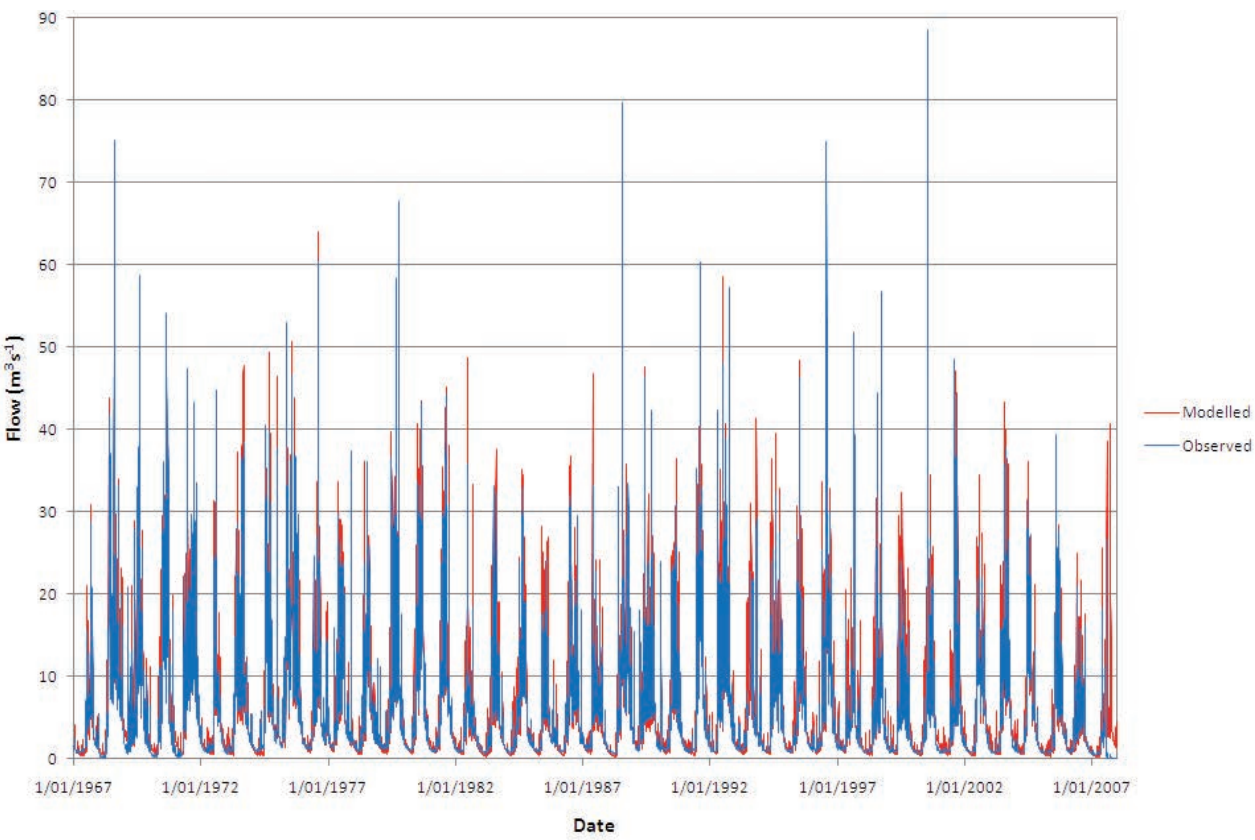


Figure 15. Modelled and observed flows for the Duck AWBM rainfall/runoff model.

Nutrient model calibration

Nutrient generation rates for each land use was determined using the event mean concentration (EMC), dry weather concentration (DWC) approach (Chiew *et al.*, 2002). Initial values for EMC and DWC for the Duck catchment were obtained from a previous E2 model developed in the neighbouring Montagu catchment (Holz and Weber, 2007). These values were then adjusted to fit observed concentrations from samples taken throughout the catchment between 1999 and 2001 (Pinto *et al.*, 2003). The adjustment process started in furthest upstream catchments with the fewest land uses. These EMC and DWC parameters were then checked the next sampling site, with the process ending at the subcatchment of the DPIW monitoring station at Scotchtown Road. The fit of the model was then tested using data collected from 2003 the Scotchtown Road station as part of the Baseline Water Quality Monitoring Program (BWQMP), obtained from the WIST database. No attenuation was used as previous work indicated that using the attenuation capabilities of WaterCAST would result in excessively reduced phosphorus concentrations in this catchment (Holz and Weber, 2007).

Soil testing

Extensive soil nutrient testing is been undertaken in the Duck catchment as part of the an Australian Government funded project by the Tasmanian Institute of Agricultural Research (TIAR), in conjunction with DairyTas, called '*Adoption of nutrient budgeting for sustainable dairy farms and healthy rivers*'. All suitable paddocks on each participating property were sampled. Suitable paddocks were generally larger than 1ha and did not have fertiliser applied within the 5-6 weeks prior to sampling. Paddocks were sampled with a corer to 7.5 cm depth. 30 cores were collected from each paddock, making up one composite sample, collected in a plastic sample bag and labelled.

Cores were not collected from urine or dung patches, in gateways, on fence lines, areas of high traffic or in the bottom ¼ of the hollows of 'hump and hollow' drains. Cores were taken in a straight line transect across each paddock (e.g. to diagonally opposite corners in rectangular paddocks). Transects were marked onto a farm map supplied by the farmer for later input into ArcMap. Samples were stored in eskies out of direct sunlight while out in the field. Samples were transferred to aluminium trays for drying in ovens at 40°C for at least 48 hours before grinding and sieving to pass through a 2 mm sieve (Figure 12). Samples were sent to CSBP Soil and Plant Analysis Laboratory in Western Australia for analysis of pH (water), Olsen phoshorus (P), Colwell potassium (K) and KCL sulphur (S). If time constraints and demands on ovens did not allow for immediate drying, samples were stored in a cool room at 4°C. Preliminary paddock results were divided into regions (Figure 12) and analysed using a Kruskal-Wallis test (Proc NPAR1WAY) in SAS version 9.2 (SAS Institute, Cary, NC).

Results

Land use areas

The land use assessment indicated that dairy pastures constitute approximately 19% of the total catchment area and 18% of the area upstream of the Scotchtown Road weir (Table 10). This land use assessment did not discriminate between beef production and runoff pastures for dairy heifers and silage production, which were both deemed to be "Grazing modified pastures". Therefore some extra area could be attributed to dairy production, albeit not as intensively managed as areas containing milking herds.

Table 10. Duck catchment land use areas

Land use	Whole catchment Area (ha)	Above Scotchtown Road Area (ha)
Grazing modified pastures	18662	10141
Grazing natural vegetation	976	220
Irrigated cropping	349	116
Dairy pastures	10530	6266
Manufacturing and industrial	85	
Marsh/wetland	406	
Mining	138	33
Nature conservation/ minimal use	6562	4843
Plantation forestry	5019	4343
Production forestry	10673	8555
Reservoir/dam	175	
Residential	451	4
Services	184	
Transport and communication	75	10
Total	**54210**	**34533**

Total phosphorus concentrations

The verification of the Duck model using data from the BWQMP resulted in an NS=0.60 and an R^2=0.66 (Figure 16). However, this required regional parameterisation of EMC and DWC values which

indicated that the land uses "dairy pastures" and "grazing modified pastures" in the lower areas of the catchment had much greater TP losses than the mid-catchment; and the mid catchment had much greater losses than the upper catchment (Table 11). Altering all other land use EMC and DWC parameters at the subcatchment level was not justified by the subcatchment data fitting process meaning the EMC and DWC values for these land uses were kept consistent throughout the catchment. The biggest change required to the EMC values was for a tributary, Geales Creek at Mella (in the lower section), just upstream of the Scotchtown Road weir. This subcatchment required an EMC of 5 mg/L to fit observed data.

Soil test results

Soil test results indicate the Olsen P levels on soils in the lower catchment were significantly higher than the mid catchment, which was in turn significantly higher than the upper and eastern catchment (Table 12).

Discussion of the WaterCAST modelling

Work from Tasmania by Holz (2007) indicated that the contribution of dairy pastures to nutrient losses in northwest Tasmanian was significantly higher than previously published studies. The results from this WaterCAST modelling indicate that dairy pastures

Table 11. Event mean concentrations (EMC) and dry weather concentrations (DWC) for the Duck Catchment and regionally specific changes for the mid and lower regions (mg/L).

	Upper		Mid		Lower	
	DWC	EMC	DWC	EMC	DWC	EMC
Grazing modified pastures	0.012	0.12	0.05	0.9	0.06	0.09
Grazing natural vegetation	0.007	0.015				
Irrigated cropping	0.6	3.00				
Dairy pastures	0.02	0.18	0.08	1.5	0.08	5.00
Mining	0.11	0.28				
Nature conservation	0.005	0.01				
Plantation forestry	0.008	0.06				
Production forestry	0.008	0.05				
Residential	0.07	0.28				
Roads and Powerlines	0.007	0.015				

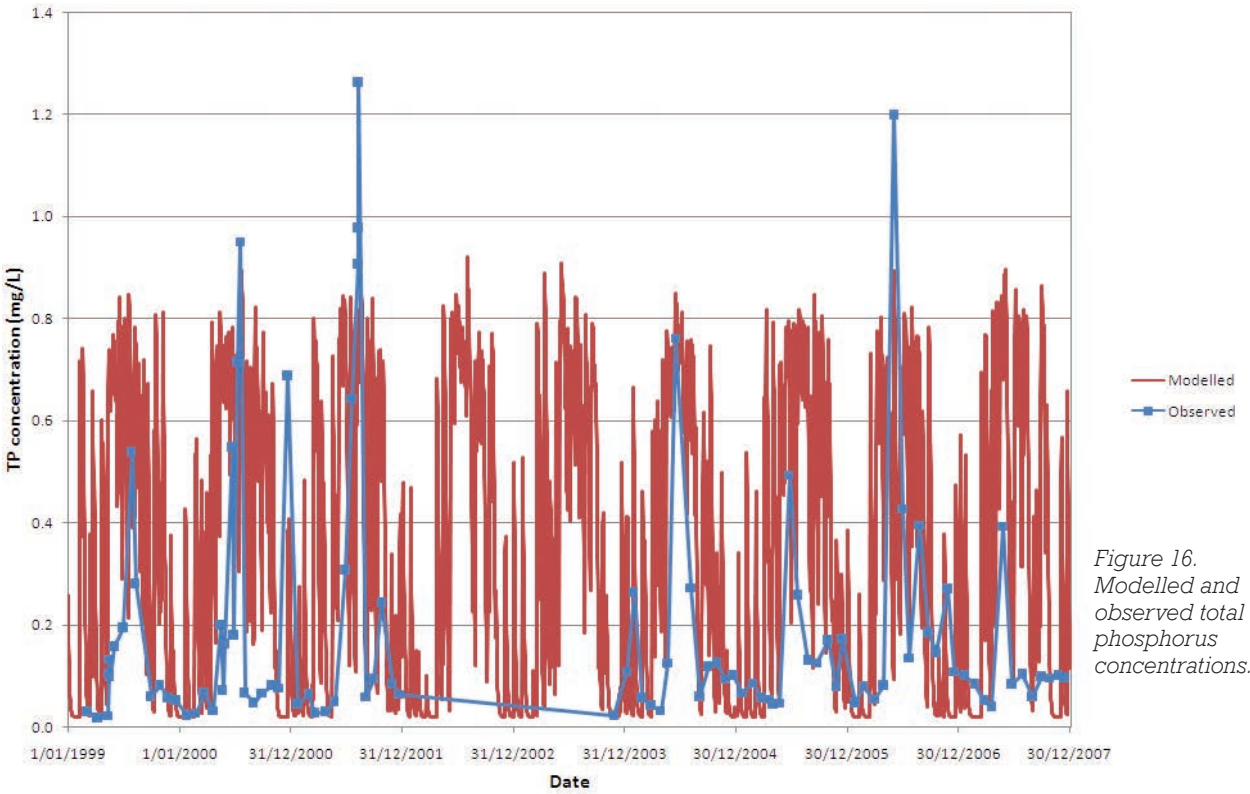


Figure 16. Modelled and observed total phosphorus concentrations.

within regions of a catchment can have large variations in TP losses. These findings are backed up by the soil test results. These regional differences appear to be driven by the extent of hump and hollow drainage, soil characteristics including acid sulphate soils, etc. Therefore, it was concluded that for further modelling work, soils information should also be taken into account as well as land use information.

While this WaterCAST modelling exercise proved successful for modelling daily TP concentrations in the Duck it required a degree of parameterisation based on the judgement rather than science making the results less objective. The EMC/DWC method also tends to be too restrictive in terms of predicting peak nutrient movements during floods. Furthermore, as parameterisation was time consuming continuing to use WaterCAST would limit the number of catchments that could be modelled in the Landscape Logic project's time frame. Therefore another modelling approach based on Bayesian modelling and the NLMIXED procedure used in modelling the hydrology was used.

Table 12. Soil test Olsen phosphorus results.

Catchment Region	Modelled Dairy TP EMC (mg/L)	n	Mean Olsen P ± SE (mg/kg)	Kruskal-Wallis test probability (P)		
				Trowutta (Upper West)	Edith Creek (Mid)	Mella (Lower)
Nabageena (Upper East)	0.2	191	29.48 ± 1.16	0.6016	<0.0001	<0.0001
Trowutta (Upper West)	0.2	174	27.91 ± 0.70		<0.0001	<0.0001
Edith (Mid)	1.5	108	37.75 ± 1.09			<0.0001
Mella (Lower)	5.0	133	53.58 ± 1.65			

Phase 4: Calibration and verification of turbidity models

Introduction

In recent years water quality issues have become increasingly important to Australian catchment stakeholders, such as management groups, land owners and government departments (Letcher *et al.*, 2002). As a reflection of this growing concern the Landscape Logic (LL) project was conceived with the aim of finding links between land and water management to resource condition in Australia and to investigate how water quality and quantity responds to land use and land management practices, and how water quality in turn affects the health and productivity estuarine aquatic ecosystems (http://www.landscapelogic.org.au). As turbidity in estuaries controls many factors including light penetration and subsequent phytoplankton productivity (Cloern, 1987), there was a need to develop daily turbidity models for a ensemble of 34 catchments.

Turbidity is an indirect measurement of suspended sediment (Gao, 2008) which can be readily measured using various probes and is often be part of routine water sampling programs enabling models to be constructed. Turbidity models are typically designed to model water supply reservoirs and are mostly process based (e.g. (Gelda and Effler, 2007). Suspended sediment models can be constructed using a rating curve approach (Gao, 2008) of which power functions are the most commonly used in sediment studies (Asselman, 2000). These can be readily represented by:

$$S = \theta \times Q^{\delta} \qquad (1)$$

Where S is suspended sediment (mg L^{-1}), Q is flow (m^3 s^{-1}) and θ and δ are curve parameters that need to be estimated by regression. Power functions have been used to describe the relationship between the load emission ratio and the specific runoff with high accuracy (Behrendt, 1996) and could potentially be applied to modelling turbidity at a daily time step.

LL was an integrated project with teams investigating the impacts of turbidity and nutrients on estuarine and riverine health. To fit in with the sampling regimes at these scales the modelling results had to have a foundation for extrapolating results to the increased scale of the whole of estuary level or a reduction in scale to river subcatchment level. To facilitate this extrapolation a power function relationship was established at the land use level as land use is a primary driver of constituent losses (Baginska *et al.*, 2003).

Estimating the curve parameters for each land use in each catchment could potentially be undertaken using a number of methods. We adopt a Bayesian approach, which allows for uncertainty in measurement and parameters used. In general, the Bayesian approach allows all data and models to be simultaneously considered which allows for the proper propagation of uncertainty throughout the model. Identifiability is also less of a concern in a Bayesian analysis in which prior information is supplied (Gelfand and Sahu, 1999). Finally, the Bayesian approach has the advantage that Markov chain Monte Carlo (MCMC) methods can be used which greatly simplifies the computation compared to the corresponding classical tools.

As LL required an ensemble of catchment to be optimised we required an "automatic" method to determine the best fit rather than a method that required significant manual manipulation of the parameters to further improve performance. As there were data from 34 catchments the Bayesian method had the potential to find both a "global" solution (i.e. a set of land use parameters for each catchment) or "local" parameters (i.e. a set of parameters for each land use in each catchment that share a common distribution). We describe a model in which estimate the local parameters simultaneously across all catchments, and a simpler model in which we estimate the global parameters.

This paper describes the ensemble calibration and verification process of turbidity models for 34 Tasmanian catchments.

Methods

Test catchments

Tasmania, the southern island state of Australia, was selected as the source of the test catchments due to data being readily accessible and there being a wide range of hydrological regimes in a relatively small area. Water quality has been previously assessed at 173 sites around Tasmania at least once (from 1992), which includes water quality samples that have been collected monthly, from 2003 until June 2009, at 51 of the flow monitoring sites around the state as part of the Baseline Water Quality Monitoring Program. These data are all freely available from Water Information Systems Tasmania (www.water.dpiw.tas.gov.au). Thirty four catchments were identified for this study based on the availability of hydrological modelling (from Broad and Corkrey in review), the number of turbidity samples (in nephelometric turbidity units, or NTUs) and the absence of hydroelectric development (Figure 1).

Land uses

Land use information based on improved mapping of work by was supplied by the Australian Bureau of Regional Sciences (Drenen, 2003) as described in (Broad and Corkrey2, in review). The land uses mapped were dairy pastures (specifically), remnant forest (remnants of forests in agricultural and riparian areas); grazing modified pastures (other improved pastures); cropping; marsh and wetlands; minimal use (conservation areas); forestry plantations; production forestry (native forests managed for wood production); and urban and industrial areas.

The hydrological component model

Australian Water Balance Model (AWBM) is the most widely used rainfall-runoff model in Australia (Boughton, 2005) and as such was chosen for the hydrological component of the turbidity model. AWBM is a six parameter lumped conceptual rainfall-runoff model that consists of three surface stores which are routed through a surface flow store and a baseflow store, which operate on a daily time step (Figure). The 34 catchments were optimised using a nonlinear method previously described (Broad and Corkrey in review).

Turbidity generation assumptions

The model assumes that land use is the primary driver of nutrient concentrations and that in Tasmania it is the best available integrator of soils, aspect and innate productivity, as per simple unit area-load models (Baginska *et al.*, 2003). This assumption also allows for the extrapolation of results from above a river flow monitoring site to an entire catchment. The second assumption is that turbidity generation follows a power relationship with flow based on model fitting a power NTU and previously modelled river flows. Modelled river flows were used instead of measured flows due to the presence of missing values and to aid the extrapolation to estuaries.

The Bayesian model

Since land use is assumed to be primary consideration to turbidity generation we adopt a model in which we sum contributions from the land uses found within a catchment.

$$T_{ci} = \sum_{j \in J_c} \theta_{cj} (p_{cj} Q_{ci})^{\delta_{cj}}$$

In the model, T_{ci}, is the modelled turbidity (mg L^{-1}) and Q_{ci} is the observed flow (m^3 s^{-1}) on day *i* in catchment *c*. The p_{cj} is the proportion of the area in catchment *c* that consists of land use *j*. The θ_{cj} and δ_{cj} are parameters associated with catchment *c* and land use *j* and are to be estimated. The J_c is the set of land uses found in catchment *c*, which means that catchment *c* has a set of parameters, $\theta_{c1} \cdots \theta_{d_c}$ and $\delta_{c1} \cdots \delta_{d_c}$, corresponding to its land uses. To ensure that the modelled values remain reasonable we adopt the constraint $0 \le \theta_{cj} \le 6$ for all land uses; $0 \le \theta_{cj} \le 2$ for land uses dairy pastures, grazing modified pastures, irrigated cropping, plantations, production forestry, and urban and industrial; and $1 \le \delta_{cj} \le 2$ for land uses forest, marsh wetland, minimal use, and native grassland. The modelled turbidity was assumed to be normally distributed, $S_{ci} \sim (T_{ci}, 10^6)$.

Since this is a Bayesian model we assign priors to the parameters. We use the truncated normal distributions, $\theta_{cj} \sim N(\mu_j, \tau_j)$ and $\delta_{cj} \sim N(\lambda_j, \sigma_j)$, in which μ_j and λ_j are mean parameters, and τ_j and σ_j are precision (reciprocal variance) parameters for land use j. The normal distributions are truncated on the left and right using the land use limits listed above. The precisions are assigned uniform priors, $\tau_j \sim U(10^{-1}, 10^4)$ and $\sigma_j \sim U(10^{-1}, 10^4)$, and the mean parameters are assigned truncated normal distributions $\mu_j \sim N(0,10)$ and $\lambda_j \sim N(0.01,10)$ with the same limits as above.

Inference is obtained in the form of posterior means and variances obtained via MCMC simulation. Throughout we use adaptive Metropolis-Hastings updates in which we update parameters using the Haario Adaptive Metropolis (AM) algorithm (Haario et al, (2001) as modified by Roberts et al (2009)). This uses a multivariate Gaussian distribution to simultaneously propose a set of parameters. This approach is used to update each set of catchment parameters ($\theta_{c1} \cdots \theta_{d_c}$, $\delta_{c1} \cdots \delta_{d_c}$) in turn. The same approach is used to update the global parameters, means μ_j and λ_j, and also the precisions, τ_j and σ_j. A total of 10^6 iterations are used and the last 50% are retained for further analysis. All simulation software is written in FORTRAN 95.

The posterior means are obtained using calibration data sets and used to calculate goodness of fit statistics using validation datasets, described below.

The θ_{cj} and δ_{cj} can be considered as local parameters since they apply at the catchment level, while their prior means μ_j and λ_j are global parameters since they are common to all catchments. The model was fitted as above and we refer to this as the local model. We then refitted the model just using the global parameters and refer to this as the global model. In the global model the global parameters are used in place of the local parameters. That is, the global model is given by:

$$T_{ci} = \sum_{j \in J_c} \mu_j (p_{cj} Q_{ci})^{\lambda_j}$$

Model calibration and verification

For each catchment the turbidity dataset was numbered and divided into odd and even so that every second datapoint was allocated to the calibration set, with the remainder to remain independent for validation of the model. Model fit was assessed *post hoc* by the calculation of the Nash Sutcliffe criterion (NS) (Nash and Sutcliffe, 1970) and the square root of the mean square error (RMSE) and the mean absolute error (MAE) as a measure of bias as recommended by Legates and McCabe (1999), for hydrological and hydroclimatic model evaluation. Duration curves were also created by dividing the modelled and observed data into percentile bins from the 1st percentile to the 100th.

Results

The application of one set of parameters for each land use to all the catchments did not result in consistently good fits (Figure 17). Catchments such as the Leven, Huon, Meredith, South Esk and Ringarooma were especially poor as the observed and modelled duration curves were separated. Furthermore many NS statistics were negative indicating that the model performed worse than simply constructing and linear regression through all data points.

The use of the parameters from the local model for each catchment resulted in good fits across the majority of the catchments tested with similar observed and modelled duration curves (Figure 18). However, some catchments still performed poorly. Duration curves from the Ringarooma were separated and there was a negative NS. The Carlton also had a negative NS, while duration curves from catchments like the Jordan, Little Swanport and South Esk showed some separation in the lower range percentiles. The number of observations did not appear to be related to the goodness of fit as catchments like the Huon and Ansons, with 34 and 35 observations respectively, appear to outperform catchment like South Esk and Jordan with 92 and 71 observations.

Plotting the global land use parameters across a range of flows from 0.01 m^3/s to $10m^3/s$ indicated that the land uses were in a realistic order, with the exception of remnant forest, with land uses with typically higher constituent generation rates (Broad and Corkrey2) indicating higher rates of turbidity generation (Figure 19). Similar trends were also evident in the locally fitted parameters (data not shown).

Discussion

Most of the catchments fitted locally had similar observed and modelled duration curves and acceptable NS statistics (i.e. greater than 0.20) considering all the potential sources of error and the daily time step. However, one set of global land use parameters could not be readily applied to all catchments.

The relative performance of the global and local models indicates that the differences between catchments are sufficiently distinctive that we cannot generalise across them. Instead we need parameters that are tuned to each catchment. A further point is that the local model has a hierarchical structure in which the local parameters depend on the values of their prior means. This means that parameter estimates in one catchment can benefit from estimates in other catchments. This is likely to be particularly important in catchments with very few data for which reasonable parameter estimation might otherwise be difficult or unobtainable.

In analysing some of the catchments with poor fits, there is the potential to make manual manipulations to improve the results. The calibration of the Ringarooma catchment was almost perfect (NS=0.98), indicating over-parameterisation stemming from the fitting of some extreme flood sampling not present in the verification dataset (due to chance). Therefore, manual stratification of the calibration and verification datasets based on flow might overcome this problem. Some catchments, like the Carlton, Coal and Jordan, have periods of low or zero flows and yet samples collected during these periods remain turbid. As the model assumes that turbidity is generated by flow, points with zero flows and turbidity inhibit the calibration resulting in poorer fits at lower percentiles. This could again be potentially improved with model refinement.

When analysing land use contributions, one would expect remnant forest to be lower than land uses like grazing modified pastures, however on review of the mapping small remnants were often immediately adjacent to intensive land uses and the riparian/river interface meaning that these were potentially areas of significant turbidity generation due to activities like cropping and stock access to rivers.

Conclusion

Local fitting of turbidity land use power function parameters using Bayesian modelling shows promise as an automatic calibration procedure, as reasonable calibrations were obtained for the majority of catchments studied. Potential improvements to individual catchment fits could also be made using manual methods. One set of land use parameters could not be applied to all catchments.

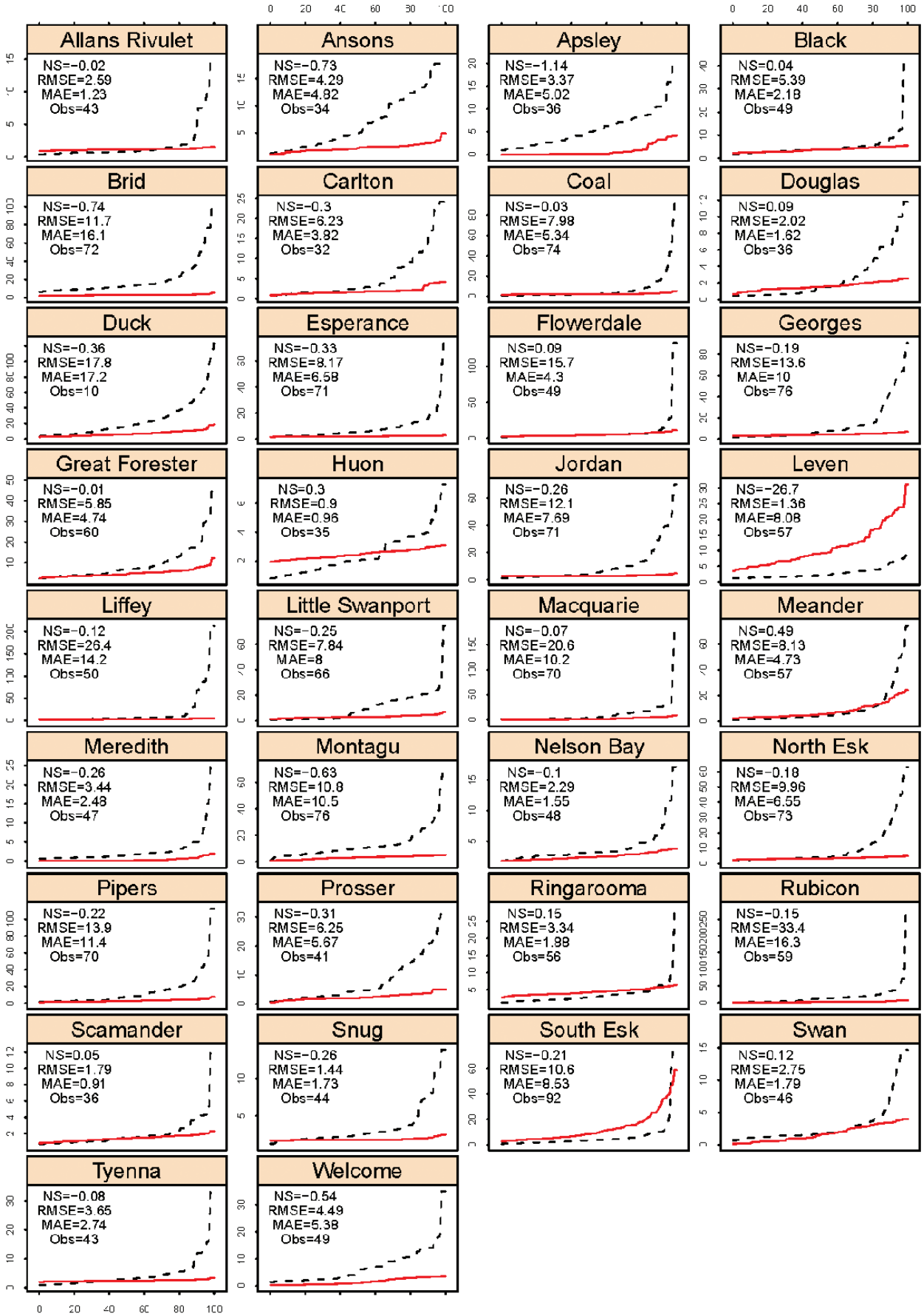


Figure 17. Catchment turbidity duration curves for the verification of global parameter fitting with observed (dashed line) and modelled (solid line) data, Nash Suttclife criterions (NS), root mean square error (RMSE), the mean absolute error (MAE) and the number of observations in the verification (Obs).

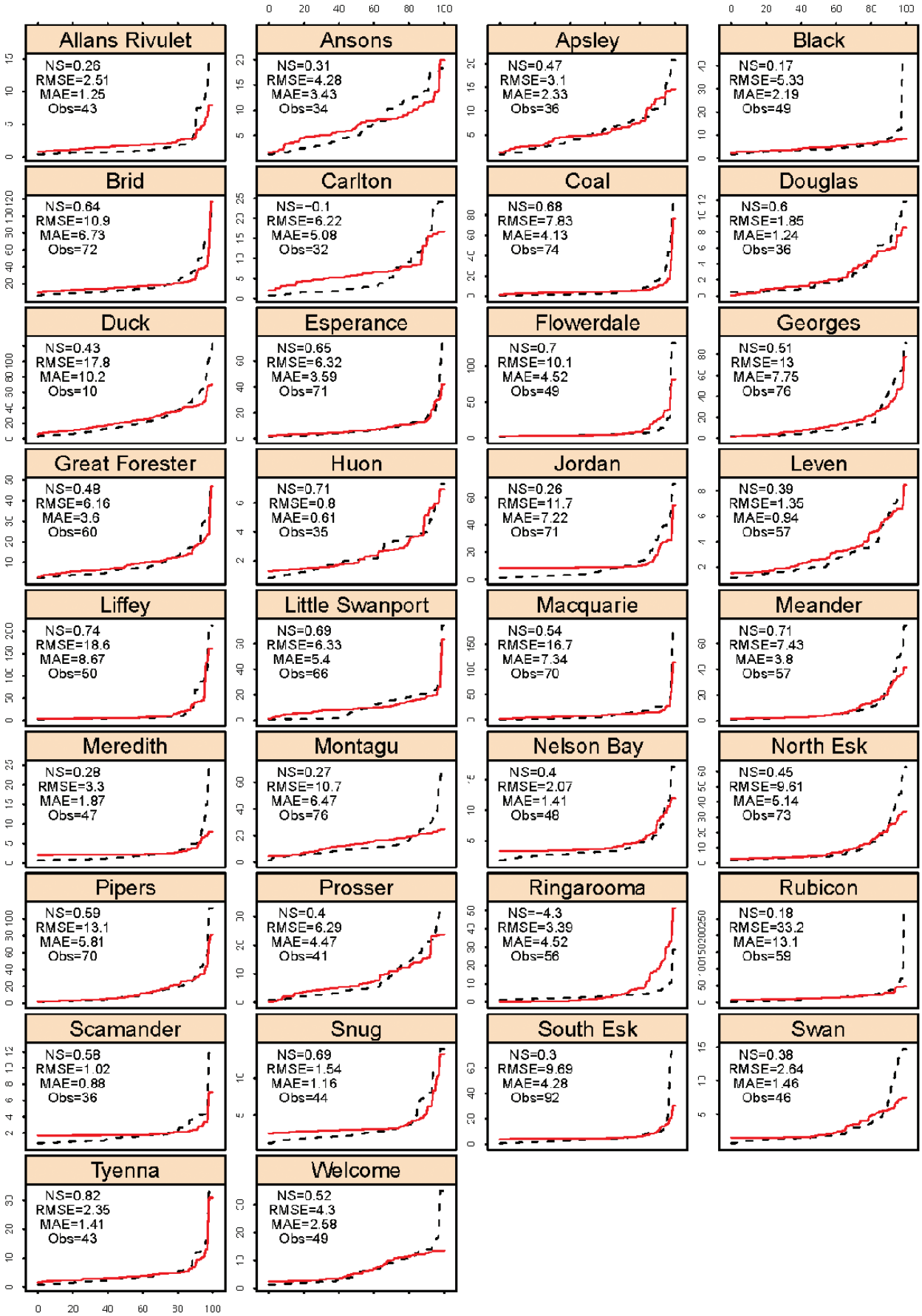


Figure 18. Catchment turbidity duration curves for the verification of local parameter fitting with observed (dashed line) and modelled (solid line) data, Nash Suttclife criterions (NS), root mean square error (RMSE), the mean absolute error (MAE) and the number of observations in the verification (Obs).

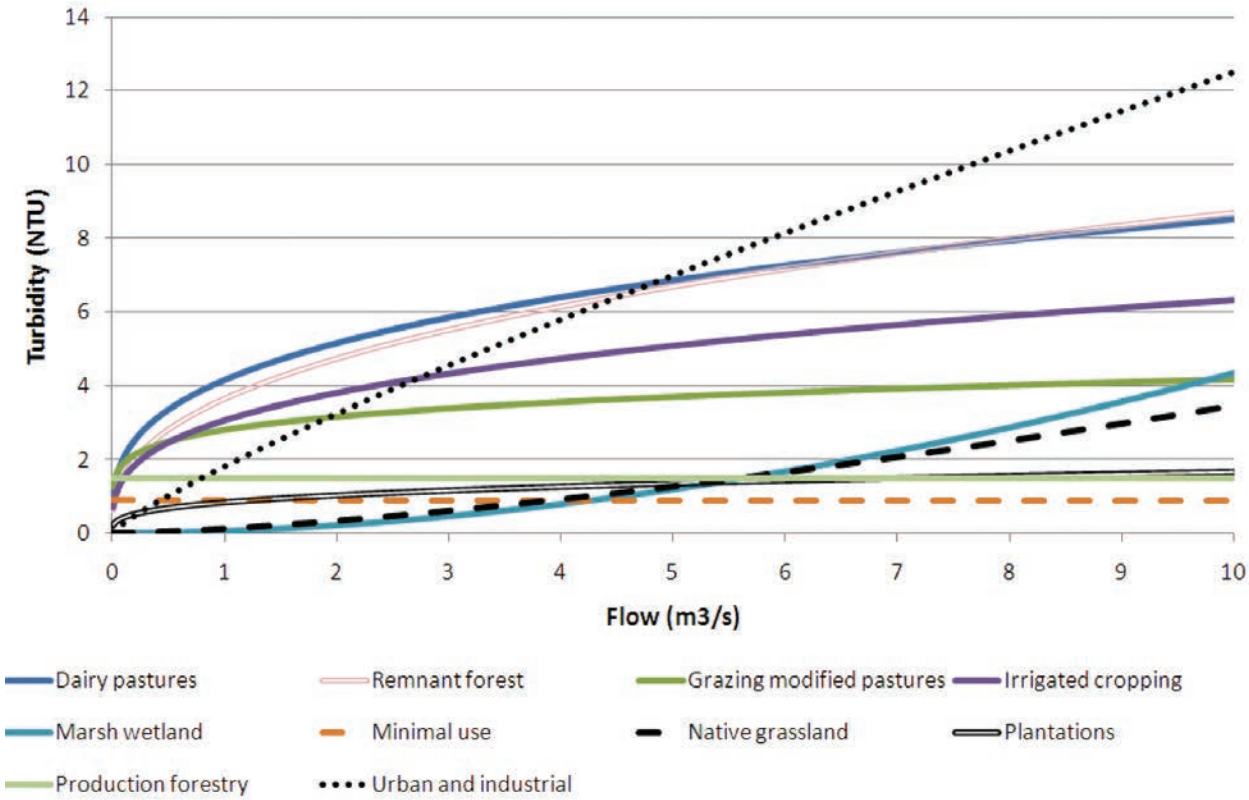


Figure 19. Potential land use contributions to turbidity from set flows from the global parameter set.

Calibration and verification of total phosphorus and total nitrogen models

Introduction

The calibration and verification process for total phosphorus and total nitrogen models used the same power function relationship as the turbidity models and the same Bayesian statistical model. However, due to there being fewer observations and the different behaviours of these nutrients, a slightly modified method was used which involved a secondary calibration process.

Method

This calibration and verification process for the total phosphorus and total nitrogen models involved two modifications to the method used in the turbidity model. Firstly the Bayesian statistical model was constrained so that there was also an ordering enforced on the land use parameters so that when the model randomly assigned parameter values for the next update, urban and industrial land uses had to be higher than intensive agriculture, which was then higher than extensive agriculture and then all other land uses. This process was implemented to ensure that the final parameters were in a realistic order (which was not an issue for turbidity). Secondly, due to there being generally fewer observations compared to the turbidity data set, the Bayesian statistical model would become fixed on local optimums and not converge in a reliable manner. Therefore, we opted for a hybrid approach using the Bayesian statistical model parameter results to define the starting point (parameter mean) and bounds (minimum and maximum parameter values + or - 10%) for each land use in the NLMIXED procedure, as previously discussed for the hydrological calibration. This process in effect formed a secondary calibration and resulted in a much better optimisation.

Results

Despite the modified methods the results for both the total phosphorus and total nitrogen were not as reliable as the turbidity results, as evidenced by the divergence of the observed and modelled duration curves in some instances and generally lower Nash Sutcliffe criterions (NS) (Figures 20 and 21). The total nitrogen results were generally more reliable than the total phosphorus results.

Discussion

The process of nutrient enrichment of waterways is a much more complicated process than the creation of turbidity. In effect there are more processes at play than a simple power relationship with flow. As a result the TP and TN results were far more variable and inconsistent, both in terms of lower Nash Sutcliffe criterions and significant divergences in the observed and modelled duration curves. These divergences in the duration curves could occur only at higher concentrations, e.g. the Swan TP; only at lower concentrations, e.g. Liffey TN; while some catchments had good relationships across all concentrations, e.g. Meander TN; and some were unresponsive flat lines, e.g. Swan TN, which indicates that the model is not predictive. Therefore when using these modelled data the duration curves should be taken into account when determining which catchments can be used with confidence and which concentrations are more reliable.

Conclusion

Calibration of the total phosphorus and total nitrogen models was not as reliable as the turbidity models. However, some individual catchments performed very well. Therefore these results should be used with caution and the duration curves should be taken into account. The modelled daily nutrient load outputs can be used with confidence in many catchments but in some catchments the outputs should be used with caution and in a small number of cases should not be used at all.

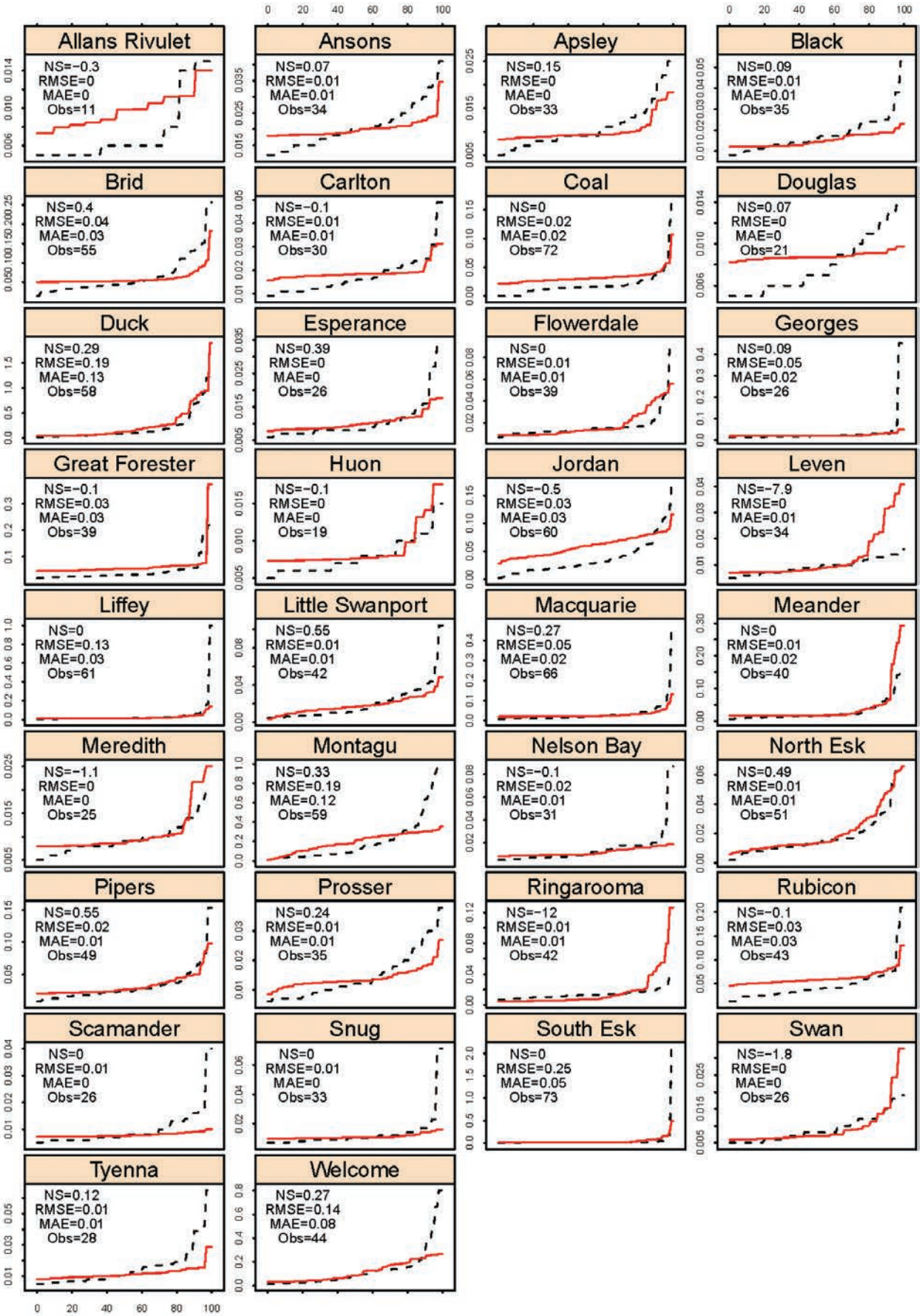


Figure 20. Catchment total phosphorus duration curves for the verification of local parameter fitting with observed (dashed line) and modelled (solid line) data, Nash Suttclife criterions (NS), root mean square error (RMSE), the mean absolute error (MAE) and the number of observations in the verification (Obs).

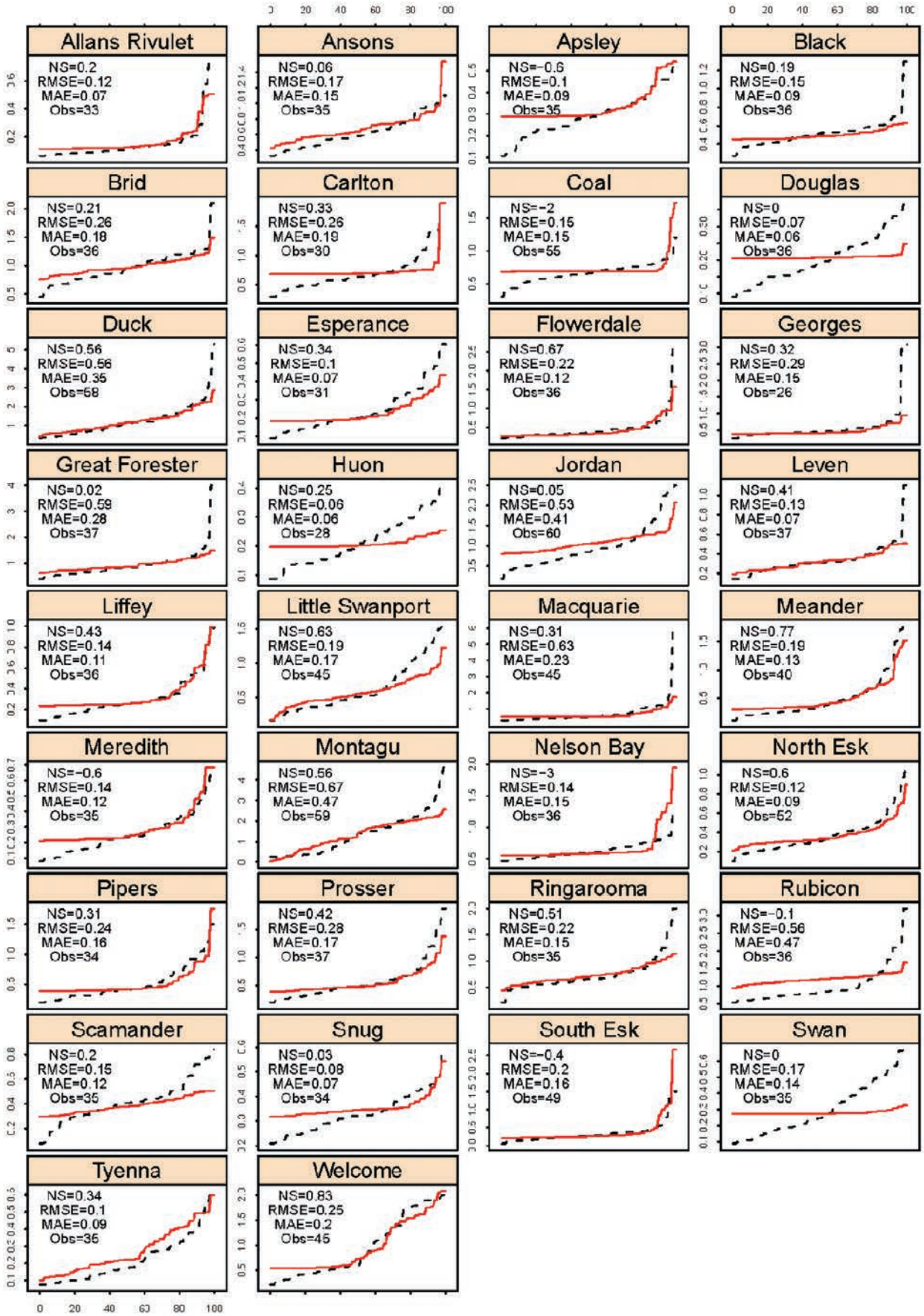


Figure 21. Catchment total nitrogen duration curves for the verification of local parameter fitting with observed (dashed line) and modelled (solid line) data, Nash Suttclife criterions (NS), root mean square error (RMSE), the mean absolute error (MAE) and the number of observations in the verification (Obs).

Phase 5: Effectiveness of Riparian interventions

Riparian zones have been used as buffers to mitigate the potential adverse effects of agricultural and forestry practices on adjacent surface water quality (Cooper et al. 1987; Comerford et al. 1992; Correll 2005). The concept is quite old, dating back to the 1700s (Lee et al. 2004). Riparian zones came into common use in the 1960s to improve water quality by functioning as barriers or treatment zones to protect adjoining water resources from disturbances associated with agriculture and forestry. They have been identified as one of the most effective tools for reducing nonpoint source pollution from managed landscapes (Phillips 1989). The main water quality functions provided by riparian zones are maintenance of low temperatures, filtration of nutrients and sediments, detention of contaminants, uptake of nutrients in plants, transformations of nitrogen compounds and pesticides, reduction of macrophyte growth, and delivery of organic matter as a source of energy and nutrients for stream biota (Neary et al. 2010). Riparian zone vegetation can reduce channel erosion by stabilizing banks. However, there are some conditions where vegetation along the edge of channels can contribute to bank scouring and erosion (Ffolliott et al. 2003).

The final component of the project was to determine if there were any detectable differences in the nutrient loads of catchments where significant riparian interventions, in the form of fencing and revegetation programs, were carried out. After consulting with local stakeholders and undertaking an extensive search of available data, the Macquarie, Quamby, Flowerdale and Pet catchments were selected for this part of the study.

Methods

Data was collected from various groups including Landcare organisations, Tasmanian Alkaloids (Quamby), the Burnie City Council (BCC) (Pet and Guide), SoR reports and the BWQMP. Hydrological models were then constructed and flow was calculated for the day each sample was taken. The samples from the Macquarie, Quamby and Flowerdale catchments were then divided into two groups (before and after intervention) and regression relationships between nutrients and flows were compared. For the Pet and Guide catchments, each subcatchment was used as a pseudo replicate allowing a comparison to be made between the percentage of the subcatchment revegetated and the change in the nutrient before and after the intervention.

The Macquarie catchment

The Macquarie catchment covers approximately 3860 km2 and drains north through the Macquarie River and the major tributaries of the Blackman, Isis, Elizabeth and Lake rivers (DPIF, 1996) (Figure 22). The water storages of Tooms Lake, Lake Leake and Woods Lake in the upper catchment are used to supplement flows in the Macquarie River during summer for irrigation purposes (DPIF, 1996). From 2002 to 2003 approximately 691 hectares of riparian enhancement, covering 71.35 km of waterways, where fenced with 3.22 km revegetated as part of the Bushweb, a Natural Heritage Trust (NHT) funded project operating devolved grants in the Northern Midlands. Bushweb also assisted in the control of 1022 ha of woody weeds (Freudenberger and Harvey, 2003). It was predicted by Freudenberger and Harvey (2003) that riparian protection would improve habitat for a wide range of aquatic and terrestrial species, and improve water quality, although they commented that there was little scientific evidence to support these predictions.

Results from the Macquarie catchment

The water quality results from the Macquarie catchment are difficult to interpret due the low explanatory power of the post intervention data points (low R2 values) and the presence of outliers biasing the R2 statistic (Figure 23). It is not surprising that it is difficult to detect any changes as the interventions were mostly completed in the upper catchment a long way from the monitoring station which would buffer all but changes of a large magnitude. However, we can say that turbidity has not changed.

The Quamby catchment

The Quamby Brook is a sub catchment of the Meander River Catchment, encompassing state and privately owned forests, agricultural areas (dairying, cropping and grazing), hobby farms, and urbanised areas (Westbury township) (Figure 24). Over time there has been a deterioration of water quality due to factors that have included land clearing, levee bank construction, weed infestations, willow (Salix fragile) growth, livestock, sewage treatment plant construction, agricultural runoff, Westbury stormwater, and historical industry/forestry practices (Lester, 2005). From 1998 until 2005 there were a series of River Care plans developed and funded by Landcare, NHT and local Government and private industry. Actions included revegetation, weed

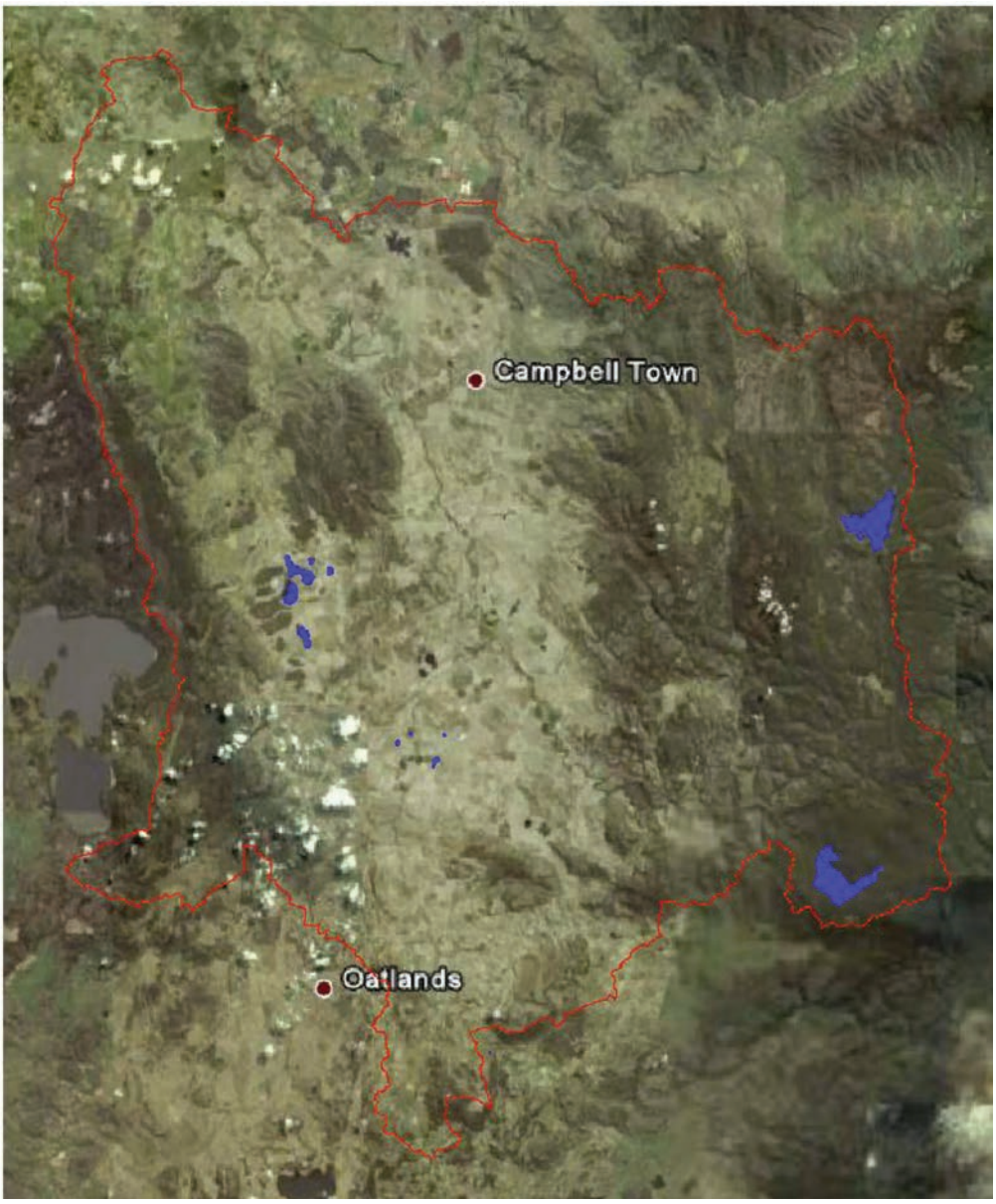


Figure 22. The Macquarie catchment with the catchment boundary (red line) (Photo source: Google Earth)

removal and riparian fencing (Lester, 2005). The water quality data from before the interventions was sourced from the Meander SoR report, while the data from after the interventions was collected by Tasmanian Alkaloids.

Results from the Quamby Catchment

The water quality results indicate that there has been a reduction in the turbidity response (and perhaps TSS) of the catchment to flows, but there is little evidence of trend changes in the nutrients TP, ammonia and nitrate (Figure 25).

While the interventions were funded from approximately 1998 until 2005, there appear to have been rapid changes in vegetation at the Westbury end of the catchment, near the catchment outlet and sampling sites, between 1994 and 1997 before the implementation of these plans, followed by little apparent change between 1997 and 2007 (Figure 26). Therefore, the reduction in the turbidity response might be an artefact of higher initial turbidity levels due to clearing between 1994 and 1997, rather than a reduction after the subsequent interventions. A further complication to any interpretation was the addition of a four lane highway and the expansion of the Tasmanian Alkaloids factory between 1997 and 2005.

Where we can detect an increase in the tree cover in riparian vegetation from aerial imagery, we also found a reduction in TSS and turbidity. However, in the case of the lower reaches of the Quamby River, the changes in vegetation occurred very rapidly between 1994 and 1997 and were not a product of intervention funding. There was little additional change in vegetation from 1997 to 2005 but other changes included the construction of a four lane highway and the expansion of the Tasmanian Alkaloids factory.

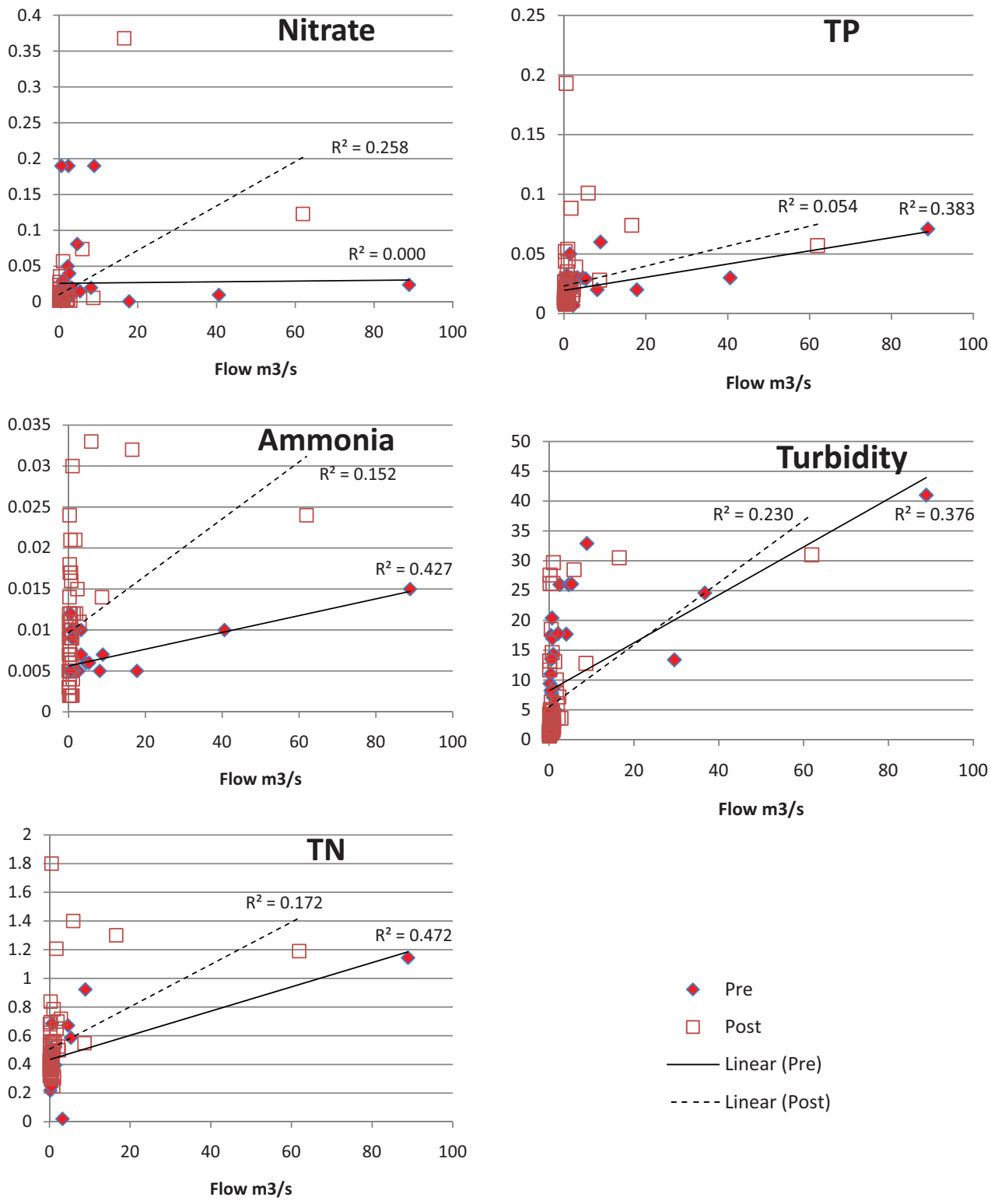


Figure 23. Water Quality results for the Macquarie catchment

Figure 24. The Quamby catchment with the catchment boundary (red line) (Photo source: Google Earth)

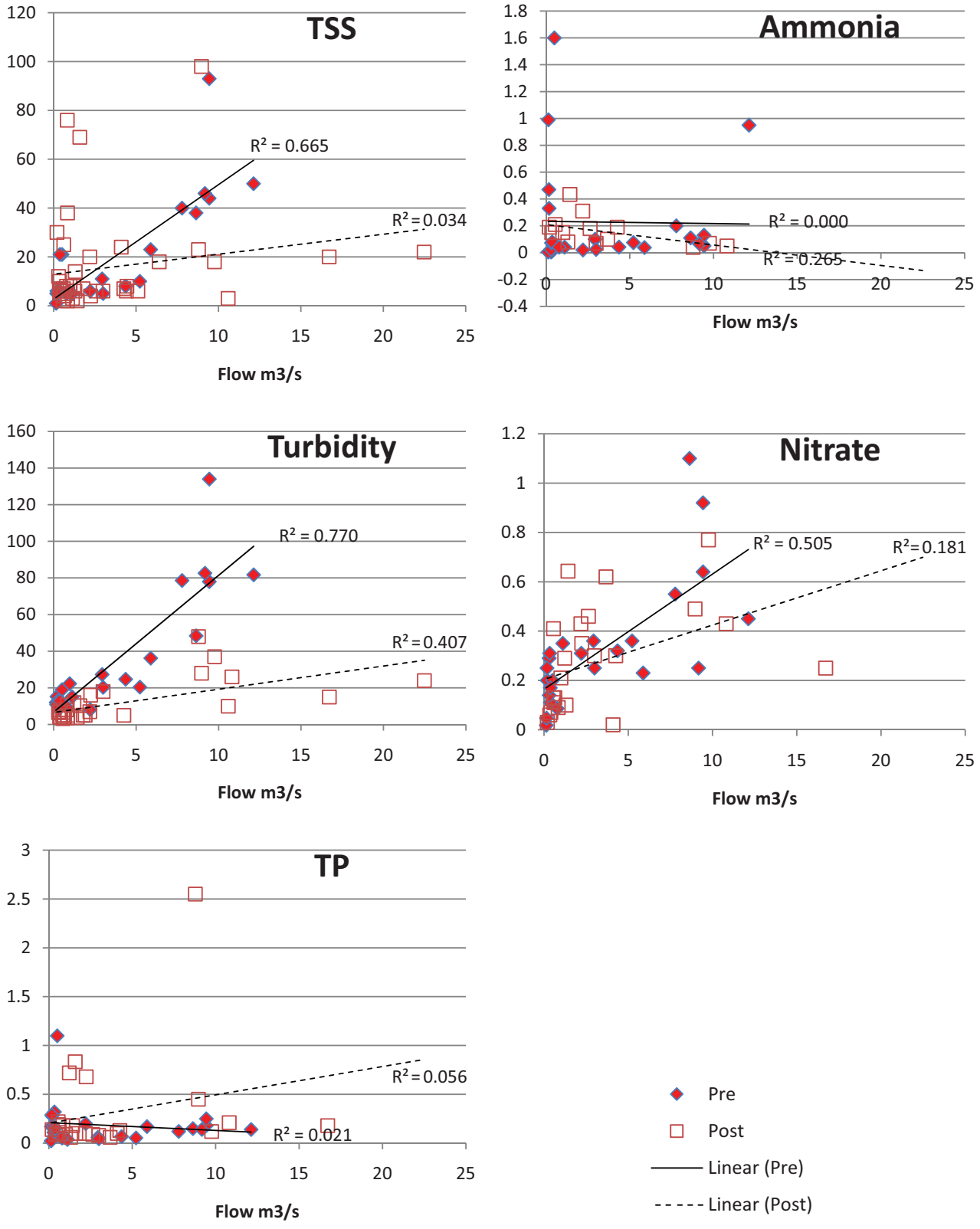


Figure 25. Water quality results from the Quamby catchment

Figure 26. Aerial photography of the lower end of the Quamby catchment near the water quality monitoring sites between 1994 (top left), 1997 (top right) and 2005 (bottom) with the catchment boundary (red line)

The Flowerdale catchment

The Flowerdale catchment is located on the north–west coast of Tasmania between Smithton and Burnie. Originating in the Campbell Range at 350 m above sea level, the Flowerdale River drains approximately 150 km2 (Figure 27). Forestry (native and pine plantation) dominates the middle and upper catchment, while grazing, cropping and dairy agriculture dominates the lower catchment (DPIWE, 2003).

The Rivercare report (Armstrong, 1999) reported members of the Wynyard Landcare group had expressed concerns about the water quality, stream bank erosion and adverse effects of willow. Land owners had consistently reported concerns about willow infestations and the adverse consequence of river blocks, flooding, and bank erosion (Armstrong, 1999). Between 1999 and 2002, NHT funded priorities were the removal of willows, the erection of fences and the revegetation of some areas (Armstrong, 1999). The water quality information from before the intervention was collected as part of a SoR report, while the post intervention data comes from the BWQMP.

Figure 27. The Flowerdale Catchment with the catchment boundary (red line) (Photo source: Google Earth).

Flowerdale catchment results

Examination to the trend responses in the relationship between flow and water quality samples indicates that there is no evidence of an improvement in water quality (Figure 28). Indeed, there is limited evidence that there may have been a decrease in water quality with more TN, TP and turbidity for each cumec of water flowing in the river. However, significant changes in land use occurred between 1994 and 2006, with significant expansion of plantation forestry (green) in grazing areas (grey) (Figure 29). This means that any water quality results are likely to be confounded by land use changes and associated changes in hydrology.

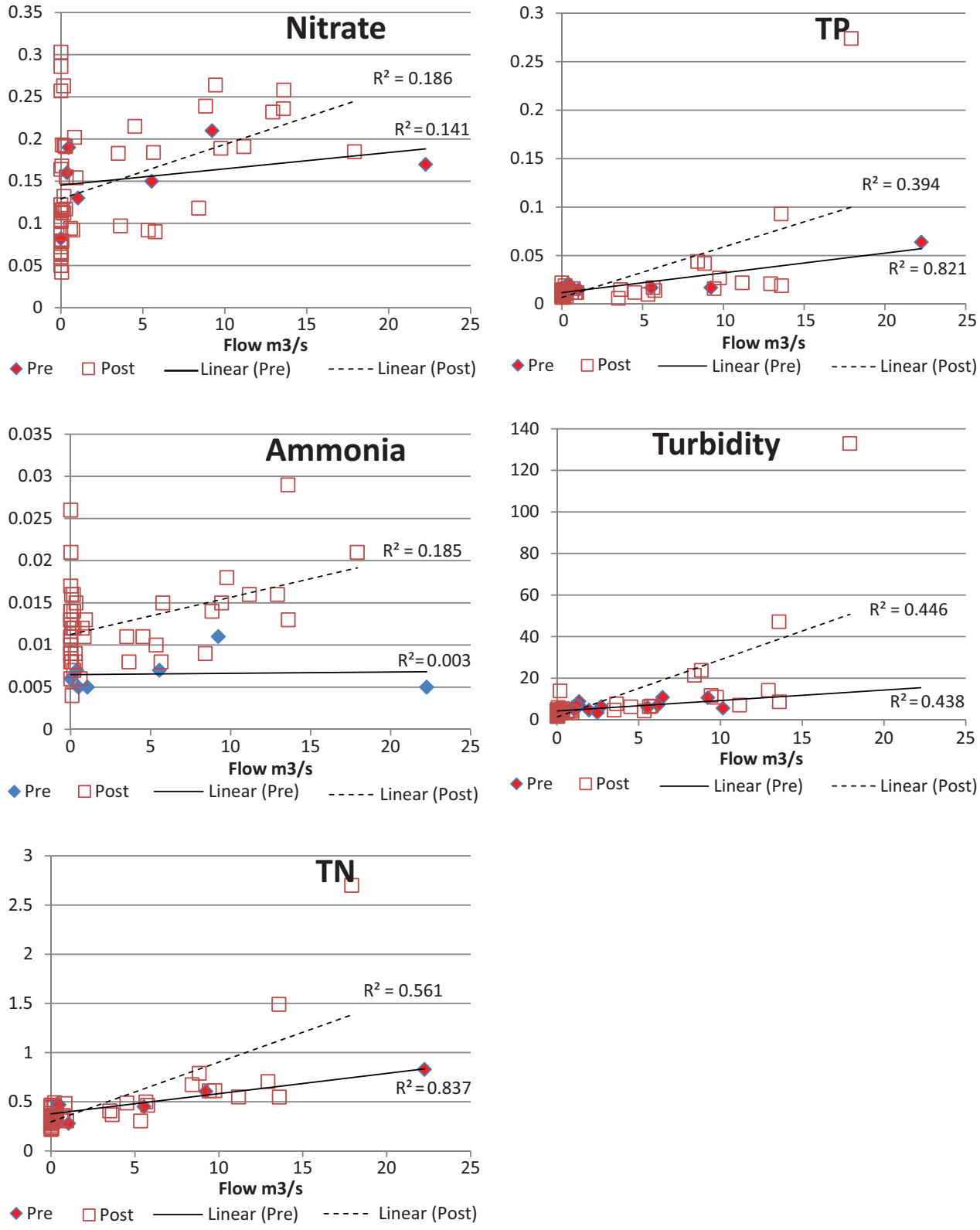


Figure 28. Flowerdale catchment water quality results

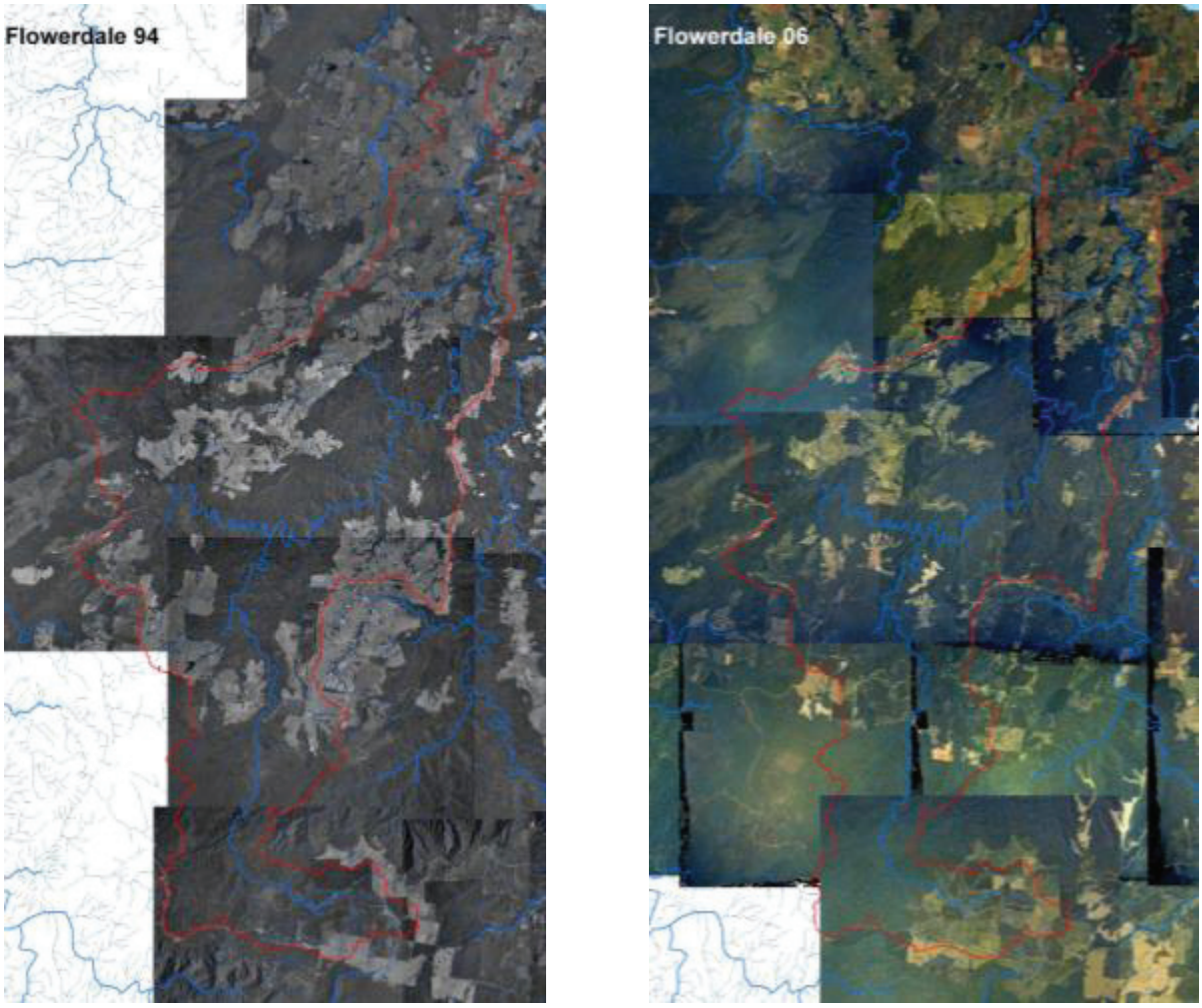


Figure 29. Aerial photography of the Flowerdale catchment in 1994 (left) and 2006 (right) with the catchment boundary (red line).

The Pet and Guide Catchments

The Pet and Guide river catchments have an area of 31 km^2 and supply potable water for 19,000 residents in the Burnie Municipality (Figure 30). The catchment is primarily used for cattle grazing, both beef and dairy, with a significant portion used for plantation forestry. Mean annual rainfall is approximately 1500 mm. Over a hundred years of conventional agricultural practices, and more recently forestry operations, have reduced biodiversity values and degraded the water quality through soil erosion, nutrient loads, effluent run-off, and clearing of riparian vegetation.

In 1997 and 1999 the Burnie City Council (BCC) received grants from the NHT to fence and revegetate almost the entire length of the riparian zones in the Pet and Guide catchments (Figure 31). BCC also instigated an ongoing nutrient sampling program which constitutes the data assessed. Unfortunately this sampling does not include turbidity or total suspended sediment.

Pet and Guide catchments results

The Pet and Guide catchment results indicate that the percentage area of revegetation of the sub-catchments sampled had no influence on the nutrient loads, due to the scattered appearance of the points rather than a consistent trend (Figures 32 and 33). However, the results do indicate that there was potentially an increase in TN loads and a decrease in TP loads (Figure 32). The increase in TN may be due to the use of nitrogen fixing tree species in the riparian revegetation like blackwoods (Acacia melanoxylon), although aerial photos from before and after the interventions do not indicate that there were significant increases in vegetation around the rivers (Figure 34). The decrease in TP is most likely due to a land use change in the period of sampling that saw high fertiliser nutrient input dairy farms shift to lower input beef grazing systems and forestry plantations.

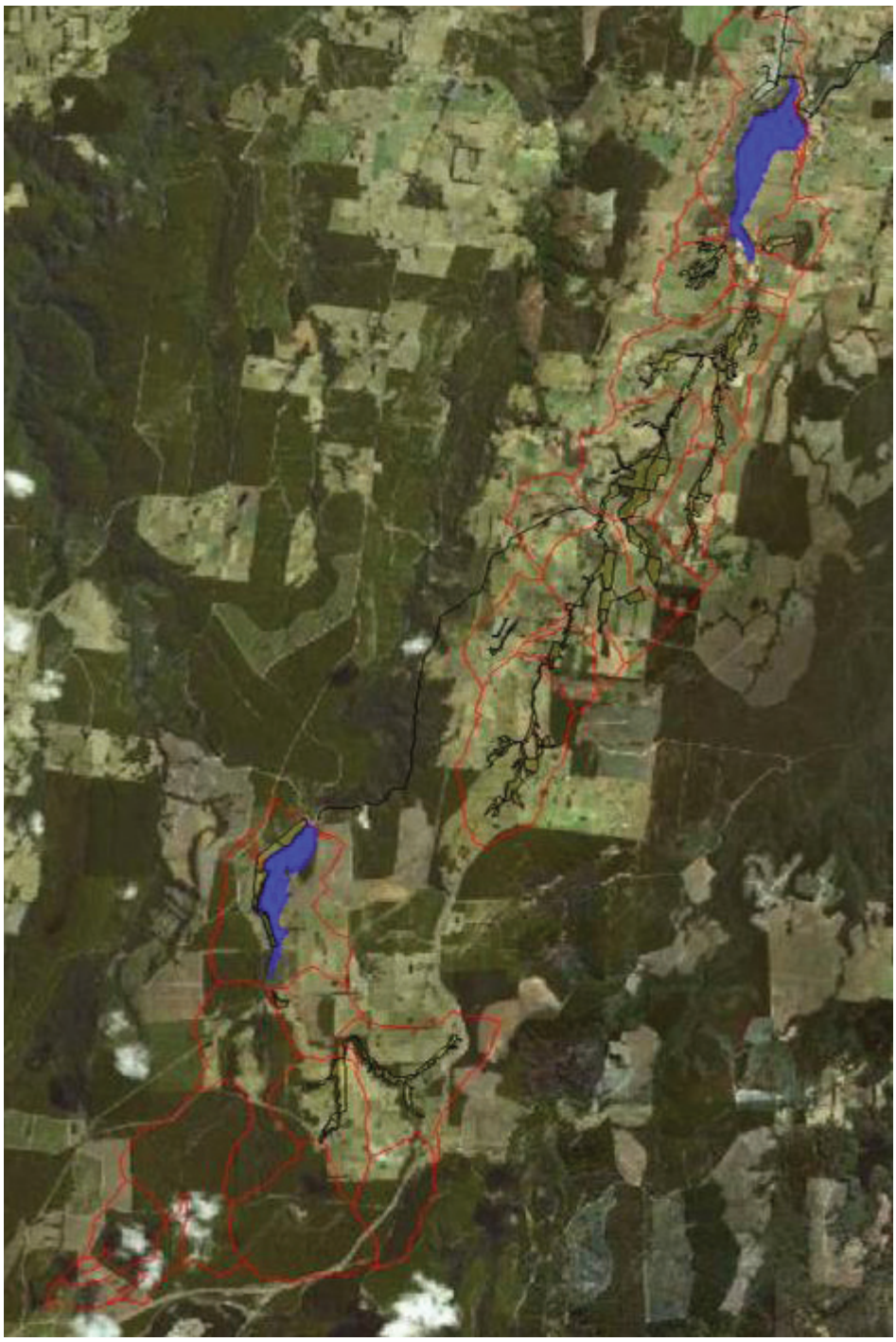


Figure 30. The Pet and Guide catchments, with their storage dams (blue areas), sampling catchment boundaries (red lines) and revegetation areas (yellow areas). (Photo source: Google Earth)

Figure 31. A riparian intervention site on the Pet River

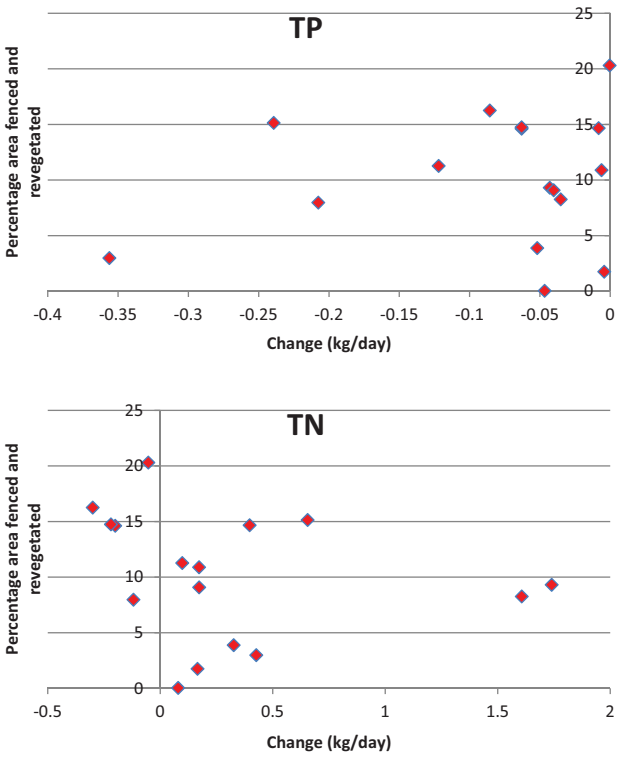


Figure 32. Combined Pet and Guide subcatchment changes in TP and TN loads (x-axis) compared to the percentage of the subcatchment revegetated (y-axis).

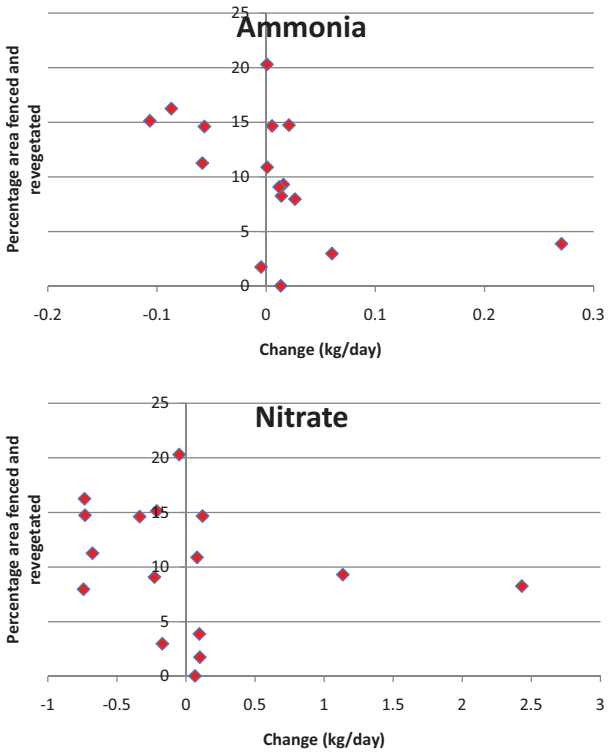


Figure 33. Combined Pet and Guide subcatchment changes in Ammonia and Nitrate loads (x-axis) compared to the percentage of the subcatchment revegetated (y-axis).

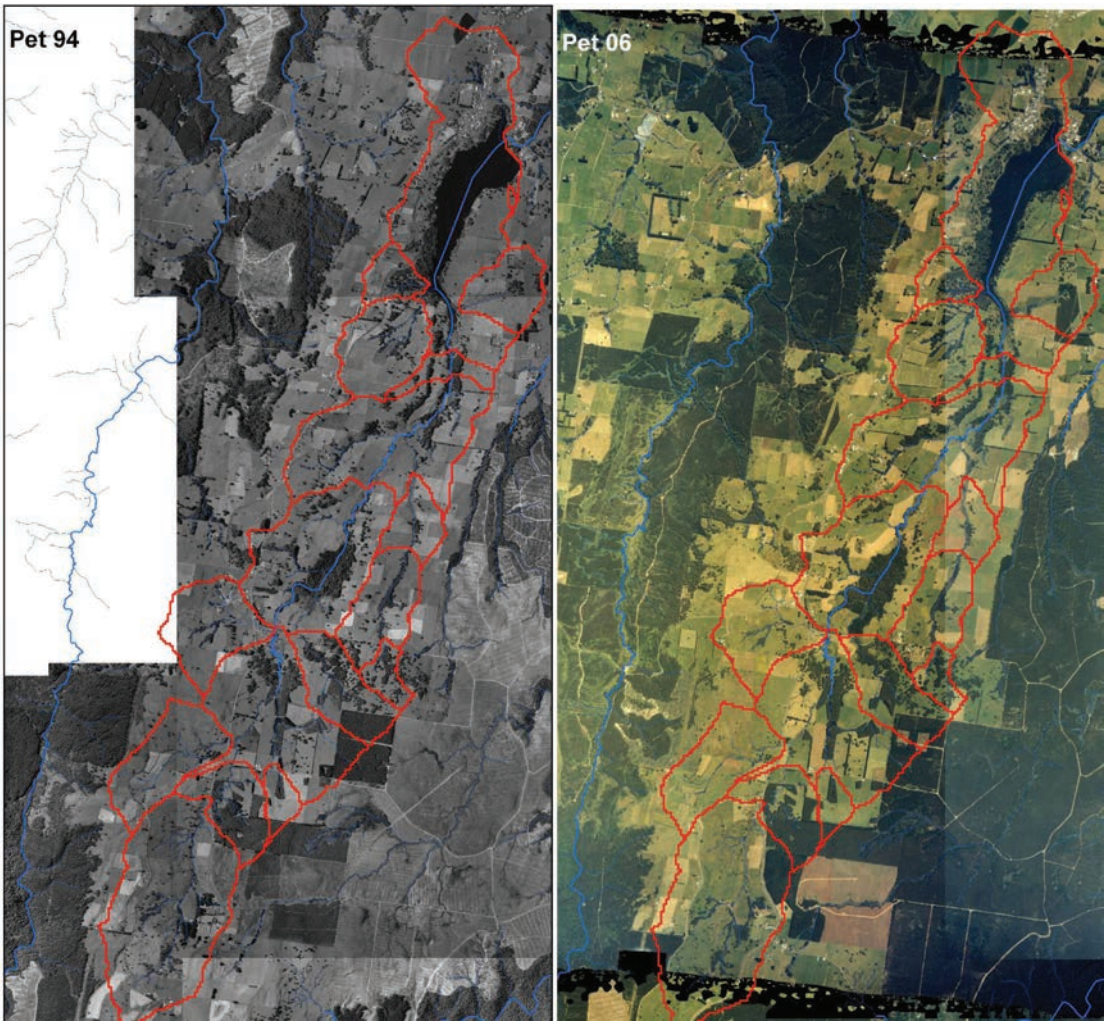
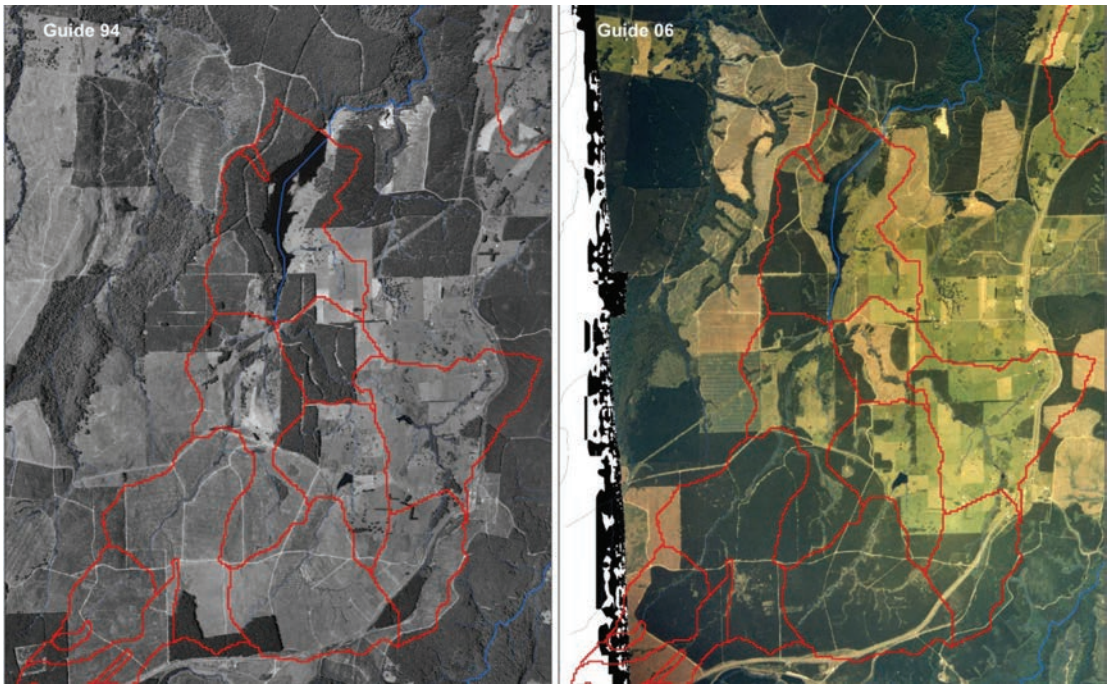


Figure 34. Aerial photography of the Pet catchment in 1994 (top left) and 2006 (top right) and the guide catchment in 1994 (bottom left) and 2006 (bottom right).



Conclusions from the investigation of riparian interventions

The data interrogated for this phase of the project showed no consistent response in physico-chemical water quality parameters following significant intervention in the riparian zone including willow removal, revegetation and streamside fencing. Across the four catchments studied, turbidity decreased in one catchment, increased in another and did not change in a third.

Nutrient levels did not change in two catchments, increased in one catchment and had a variable response in the fourth catchment. The data did not allow for a response in water quality resulting from riparian rehabilitation to be distinguished from other human intervention or natural variation. The data included the Pet and Guide catchments where almost the entire stream length was fenced for stock exclusion, but there appeared to be little if any measurable change in riparian vegetation extent or nutrient loads over seven years since intervention.

The absence of good quality, long term data meant that there was little chance of detecting water quality improvements due to riparian investments, and there were confounding factors in each of the four catchments studied. Therefore, unless a well designed long term study is put in place that has the ability to prove a difference, strategies for improving water quality need to focus on the paddock and landscape scale as well as the riparian zone.

Explanations for the lack of evidence linking riparian zone rehabilitation to changes in water quality include:

- Water quality monitoring was not established to test the relationship, either temporally or spatially;
- Key water quality parameters were not always monitored e.g. turbidity;
- Too little time has elapsed to measure a change in water quality resulting from rehabilitation by intervention (Parkyn et al., 2003);
- It's a whole of catchment phenomenon requiring broad scale change in land use or land management to reduce sediment and nutrient loads;
- Riparian vegetation does not reduce nutrient inputs to streams;
- There wasn't enough riparian zone change over the whole catchment;
- The riparian zone changes were not located in places that impact on nutrient and sediment delivery processes;
- There remain major stream inputs through road crossings & culverts;
- The residual effects of sediment and nutrients in the stream bed could take many years to pass through the catchment.

The lack of evidence linking riparian zone rehabilitation to changes in water quality in this study does not imply that investment in rehabilitating riparian zones has been futile or should stop. There are reasons other than water quality improvement that justify the investment. An important function of riparian zones is providing terrestrial and aquatic habitat for both flora and fauna. This function contributes greatly to landscape biodiversity, especially in semi-arid environments (Baker et al. 2003).

Riparian zones also provide important landscape connections and cover for terrestrial wildlife and aquatic species. River health parameters (e.g. light, temperature) may have changed in the catchnets studied, but these were not monitored. Some other key functions provided by riparian zone vegetation include livestock and crop shelter, forage sources, livestock safety, aiding farm certification, providing a source of wood and additional farm income, and potential carbon sequestration (Specht and West 2003). The potential for Riparian zones to provide a future wood supply and source of income for farmers could develop as one of several major incentives for farmers to establish tree plantations along streams (Neary et al. 2010). Investing in riparian zone management to minimise direct stock access to streams, channelized flow or runoff from roads and tracks draining to streams is critical to minimizing nutrients and sediment in streams as these can circumvent buffers.

Project conclusions

Catchments in the northwest and northeast of Tasmania have higher annual nutrient loads than other regions in Tasmania. The annual load estimations indicate that there are wide ranges in loads in different catchments. East coast catchments with low rainfall/runoff and less intense land use have the lowest nutrient loads. Flatter land in higher rainfall areas was found to generate greater catchment scale annual nutrient loads. These areas are typically used for agriculture and in particular the most intensive land uses of cropping and dairy production. The more intense the land use in terms of nutrient inputs, the greater the nutrient enrichment in waterways. In Tasmania, land use is a good integrator for use in modeling surface water nutrient loads.

Tasmanian dairy land use nutrient generation rates for total Phosphorus and total Nitrogen are at the higher end of published values with rates of 10–12 kg/ha/yr for total Phosphorus and 20–30 kg/ha/yr for total Nitrogen. WaterCAST modelling indicated that dairy pastures within regions of a catchment can have large variations in TP losses and these variations were associated with variations in soil test results. One gap in the available data was that there were no predominately cropping catchments sampled in Tasmania.

Bayesian modelling to inform land use generation rates required by the CMSS model removes the arbitrary nature of parameter selection, thus improving the reliability and repeatability of CMSS models and subsequent management **decisions.The** Non linear mixed procedure (NLMIXED) was the best method of calibrating the AWBM rainfall runoff model. This method could be utilised in the optimisation of hydrological models using SAS, which is commonly available at Universities and research institutions, without the need for standalone specialist software packages. A whole of catchment daily nutrient modelling approach based on Bayesian modelling and the NLMIXED procedure used in modelling the hydrology, was found to be a good predictor of turbidity but was not as reliable for total phosphorus and total nitrogen. The modelled daily nutrient load outputs can be used with confidence in many catchments but in some catchments the outputs should be used with caution and in a small number of cases should not be used at all.

There are many factors that play a role in determining water quality including natural factors such as rainfall, runoff and slope, and anthropogenic factors such as land use, fertiliser practices and erosion control. However the modelling and analysis undertaken in this project has resulted in the development of a simple conceptual model of the major drivers of nutrient loads and turbidity in Tasmanian rivers (Figure 35). Catchment nutrient loads are driven largely by rainfall and topography that results in flow to the rivers via various land uses. There is some modification of nutrient delivery to waterways by land management practices such as timing of fertiliser application.

The data interrogated showed no consistent response in physico-chemical water quality parameters following significant intervention in the riparian zone including willow removal, revegetation and

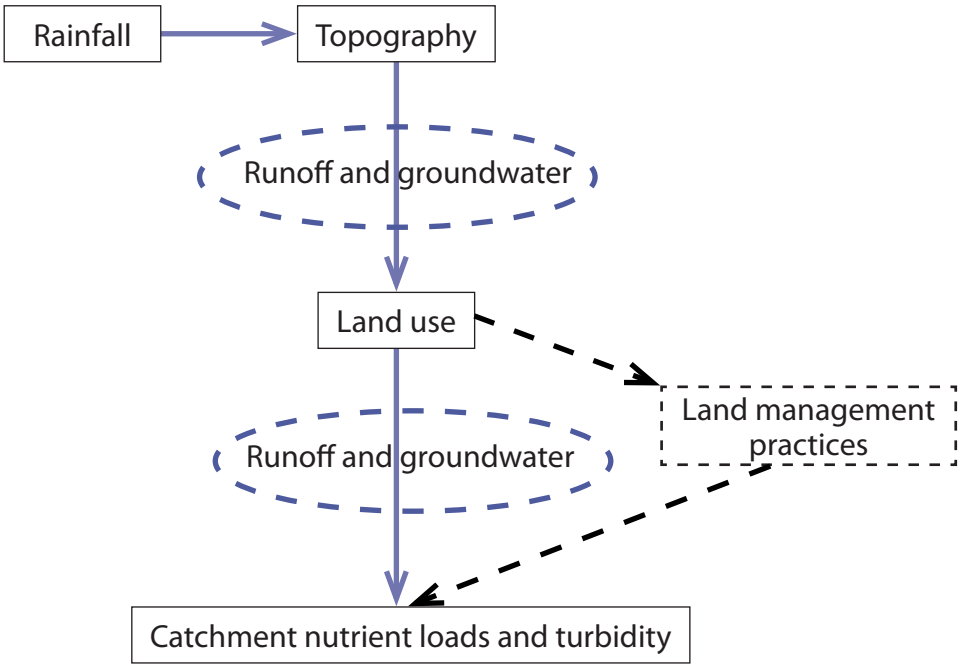


Figure 35. Simple conceptual model of the major drivers of river nutrient loads.

streamside fencing. The lack of evidence linking riparian zone rehabilitation to changes in nutrient loads or turbidity in this study does not imply that investment in rehabilitating riparian zones has been futile or should stop. Reasons to continue rehabilitating riparian zones include providing landscape connections and cover for terrestrial wildlife and aquatic species, livestock and crop shelter, forage sources, aiding farm certification and providing a source of wood and additional farm income.

Pre-existing data sets provided essential information for designing models and conceptual understanding of catchment level functions and behaviour. However, there were issues with data quality, quantity and functional availability either because data collection was not designed to test appropriate hypotheses or because of poor data management (e.g. Storage, versioning and metadata to appropriate standards).

Key messages

1. The major driver of sediment and nutrient delivery to surface waters at the catchment scale is intensive land use, in particular the most intensive land uses of cropping and dairy production. Management interventions should focus on reducing nutrient sources and transport at the landscape scale rather than solely relying on abatement in riparian zones to impact on nutrients and sediment in surface waters. Riparian rehabilitation does play a role, but its effects are not always immediate.
2. Land management practices are important to reduce the total nutrient and sediment delivery to rivers and estuaries, but even where best management practices are adopted, nutrients and sediments resulting from intensification of land use will still be delivered at higher than natural rates. One of the consequences of this finding is that greater intensification of land use in Tasmania is likely to result in greater surface water nutrient and sediment loads.
3. The available data showed little detectable change in water quality (in terms of nutrient loads and turbidity) following investment in rehabilitation of the riparian zone. It is likely that riparian buffers cannot completely compensate for the source of nutrients and sediments generated by intensive land use. However, riparian zones do provide landscape connections and cover for terrestrial wildlife and aquatic species, livestock and crop shelter, forage sources, aid in farm certification and provide a source of wood and additional farm income. Investing in riparian zone management to minimise direct stock access to streams, channelized flow or runoff from roads and tracks draining to streams is critical to minimizing nutrients and sediment in streams as these can circumvent buffers.
4. Consistently collected water quality data has considerable value in providing greater understanding of landscape functions and behaviour. The value of these data could be further enhanced by improved monitoring design (e.g. collection of event-based data, within catchment sampling, covering a variety of catchment types). Both the SoR and the BWQMP were essential to the success of this project. Catchments with a longer period of collected data had much better performing models, as did catchments with a least one flood sampling data set.

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Appendix 1. Tasmanian Land Use Layer metadata

Title Tasmanian Land Use Layer

Custodian DPIPWE

Jurisdiction Tasmania

Description

Abstract	Landscape Logic, A CERF (Commonwealth Environmental Research Facility) funded project, used DPIPWE nutrient samples to primarily model historical nutrient concentrations 11 Tasmanian estuaries. As part of this project an updated land use layer for Tasmania was required. This layer was constructed by intersecting TasVeg 1.3 VEGCODE "FAG", or "Agricultural land", with the BRS land use layer 2003. The Landscape Logic catchments of interest were then verified using aerial imagery and on ground visual assessments.
Search word	Land use, vegetation, Tasmania
Geographic Extent	N -39.2 E 149.0 S -44.0 W 143.5
Beginning date	5/1/2009
Ending date	22/6/2009

Dataset Status

Progress	Complete
Maintenance and update	Not planned

Dataset Status

Stored Data Format(s)	Digital – ESRI ArcGIS shapefile
Available Format Type(s)	Digital – ESRI ArcGIS shapefile
Access Constraints	All graphical and digital data produced by DPIW are subject to Crown Copyright. Accordingly, it is a requirement that all digital data be distributed with a Digital Data License Agreement or a Memorandum of Understanding in the case of Government clients. These agreements define the terms and conditions under which the client can use the data.

Data Quality

Lineage Positional	TasVeg 1.3 (1:25,000) and BRS 2003 (1:25,000).
Accuracy Attribute	1:25,000
Accuracy	Validation using the most up to date aerial imagery available was conducted for each Landscape Logic Catchment. Field validation was conducted for each catchment.
Logical Consistency	All polygons, lines and point data labelled. All vertices are snapped and all polygons closed. All data is topologically related. There are no duplicates.
Completeness	The data set covers all of mainland Tasmania and Flinders and King Islands. However, the dataset has only been validated for Landscape Logic catchments.

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Appendix 2: Sample SAS code for non-linear hydrology model optimisation

```
****************************************;
* Hydrology calculation;
****************************************;

/* Initiate AWBM hydrology model macro*/
%macro hydro(y);

/* Calculate cumulative sum of rainfall minus evaporation */
        cs1 + (rain/3) - (evap/3);
        cs2 + (rain/3) - (evap/3);
        cs3 + (rain/3) - (evap/3);

/* Reset 'excess buckets' to zero to prevent carryover from previous days calculation*/
        excess1=0;
        excess2=0;
        excess3=0;

/* Storage capacities need to be reset to zero if negative (evaporation losses cannot exceed water stores)*/
        if cs1<0 then cs1=0;
        if cs2<0 then cs2=0;
        if cs3<0 then cs3=0;

/*If a 'cs' store exceeds capacity then extra water gets added to an 'excess bucket' */
        if cs1>(a1*c1) then excess1=cs1-(a1*c1);
        if cs2>(a2*c2) then excess2=cs2-(a2*c2);
        if cs3>(a2*c3) then excess3=cs3-(a2*c3);

/*Remove excess from cs so that the storage doesn't keep getting bigger than capacity*/
        cs1=cs1-excess1;
        cs2=cs2-excess2;
        cs3=cs3-excess3;

/*Calculate total excess to water storage capacity */
        excesst=excess1+excess2+excess3;

/*Accumulate surface runoff into surface flow store */
        surstore + ((1-bfi)*excesst);

/*Accumulate base flow runoff into baseflow store */
        basestore + (bfi*excesst);

/*Calculate runoff from surface store using surface flow recession constant 'ks'*/
        surflow=(1-ks) * surstore;

/*Calculate runoff from baseflow store using baseflow recession constant 'kb'*/
        baseflow=(1-kb) * basestore;

/*Reduce storages volumes by the flow losses*/
        surstore=surstore-surflow;
        basestore=basestore-baseflow;

/*Add baseflow and surface flows to get total flows for the day*/
        totalflow=surflow+baseflow;

/*Convert totalflow into an catchment area based flow in cumecs (cubic metres per second)*/
        &y=totalflow*area/86.4;

/*End hydrology macro*/
%mend;

*********************************************************************;
* fit nonlinear model of observed flow (obsflow) vs modelled flow (modflow) assuming a normal distribution;
```

```
*******************************************************************;
proc nlmixed data=nlindata
/*Establish initial values, i.e. the model starting point*/
  parms BFI=0.35 C1=7  C2=70  C3=150  KB=0.95 KS=0.35 s2=1;

/*Establish parameter bounds*/
          bounds 0<=bfi<=1;
          bounds 0<=c1<=50;
          bounds 0<=c2<=200;
          bounds 0<=c3<=500;
          bounds 0<=kb<=1;
          bounds 0<=ks<=1;
          bounds s2>0;

/*Implement the nonlinear model*/
  %Hydro(modflow);
          model obsflow ~ normal(modflow,s2) ;
          predict modflow out=preds;
          id c1 c2 c3 bfi kb ks;
run;
```