Analysis and synthesis of information for reporting credible estimates of loads for compliance against targets and tracking trends in loads

Final Project Report

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Acronyms and Abbreviations

ACTFR...............Australian Centre for Tropical Freshwater Research

AIMS..................Australian Institute of Marine Science

DERM ....Department of Environment and Resource Management (Queensland)

DPC ....Department of the Premier and Cabinet (Queensland)

GBR...................Great Barrier Reef

LRE....................Loads Regression Estimator

MTSRF..............Marine and Tropical Sciences Research Facility

P2R....................Paddock to Reef

SEQ ....South-east Queensland

TSS....................Total suspended sediment

WfHC ....Water for a Healthy Country

Acknowledgements

We wish to acknowledge the Queensland DERM, AIMS and ACTFR (especially Steven Lewis and Zoe Bainbridge) for kindly providing the GBR data used throughout the project, and helping us to interpret some of the analyses in relation to the Burdekin and Tully sites for TSS that was necessary for testing and applying the LRE methodology. We would also like to acknowledge past collaborators on this three-year project, namely Paul Rustomji, Erin Peterson, Lachlan Stewart and You-Gan Wang. Finally, we thank Rebecca Bartley and Scott Wilkinson for their insights regarding the methodology.

Executive Summary

Quantifying the amount of sediment and nutrients (via a *load*) entering the Great Barrier Reef (GBR) is a primary focus for Water Quality Improvement Plans that aim to halt or reverse the decline in reef health over the next five years. Although substantial work has been undertaken in the literature to define a load under varying conditions and assumptions, the methods currently available do not adequately address all aspects of uncertainty surrounding the load estimate. This reduces the ability to usefully inform future monitoring activities and to report on the status of, or trends in loads.

Loads Methodology

The approach we present in this report is an extension to the regression or rating curve methodology that incorporates three primary aspects of uncertainty specific to the calculation of riverine loads. These represent:

- Measurement Error – the uncertainty in the measured flow and concentration observed at a particular site or at different spatial locations within a site;
- Stochastic Uncertainty – arising from the fact that not all flow and concentration data are sampled; and
- Knowledge Uncertainty – arising from our lack of understanding of the underlying hydrological processes governing the system.

The loads methodology that we propose and refer to as the Loads Regression Estimator (LRE) takes on a four-step process: (1) estimation steps for flow, (2) estimation steps for concentration, (3) estimation of the load, and (4) calculation of the standard error of the load.

The **first step** involves 'regularising' the flow, a process whereby a loess smoother, capturing peak flows, is used to predict flow at regular time intervals (e.g. hourly) and infill any gaps in the flow data. Two datasets are produced as a result of this process. The first is the regularised flow, which will be used for prediction in Step 3, while the second is a modelling dataset, where the concentration samples are matched to the regularised flow values and used in Step 2 to help form the predictive relationships between concentration and flow and its derivatives.

The **second step** in the methodology fits a generalised additive model to concentration (on the log-scale) to model the relationship between concentration and a series of flow terms that attempt to mimic key hydrological processes of the system with the aim of reducing knowledge uncertainty. The terms we consider in any model include:

- Linear and quadratic terms for flow to allow for some non-linearity in the relationship.
- Seasonal terms comprising sines and cosines to capture intra-annual variation.
- A rising or falling limb term represented by a categorical variable that reflects concentration samples captured on the rise (+1), fall (-1) or flat (0) of the event. Here an event or ‘flush’ is determined as flow exceeding the 90th percentile in a water year.
- A discounting term that attempts to mimic exhaustion properties of the hydrological system. This term discounts past flow events according to how influential that event is to the movement of pollutant through the system. The discount factor controls the level of discounting and hence, the weighting of past events. This has been set to 0.95, which equates to 0.5 per fortnight, indicating that in a fortnights time only half the flow is contributing to pollutant runoff now.
- A trend term that attempts to capture inter-annual variability and long-term trends in concentration.

The **third step** involves the estimation of the load, which is the result of multiplying the regularised flow by the concentration predicted at each regularised flow value and then summed over the water year. Steps 1-3 are structured so they correct for the biased sampling regime that targets events.

The **fourth step** involves the construction of the variance around the estimate of the load. The variance is structured so it not only incorporates errors in the concentration but errors in the flow rates (measurement and spatial).

This methodology has been programmed into an R package called LRE that will be freely available to end users.

Application of Methodology

The methodologies are applied to two real long term monitoring datasets: the Burdekin River at Inkerman Bridge and the Tully River at Euramo. We applied the LRE package to these datasets to estimate loads and uncertainties for each water year represented. The results can be summarised as follows:

- **Burdekin**
  - o Annual loads and mean annual concentrations were estimated for the Inkerman Bridge site for 36 water years using the LRE methodology. Summaries of the data indicated considerable bias in the concentration sampling with no bias in flow samples due to the regular sampling intervals (hourly).
  - o A model was fitted to 824 concentration samples where linear and quadratic terms for flow, a seasonal term and smooth terms for the discounted flow and trend were fit. Results showed a reasonable fit with 69.9% of the variance explained. A seasonal term fit in the model showed increases in TSS concentration during the wet months (October to April) and decreases during the drier months of the year (May to September).
  - o Average mean concentrations were higher in some years compared to others. Further investigation revealed cyclones that had passed through the Bowen subcatchment of the Burdekin. Inclusion of terms that reflect these events in the model may help explain increases in concentration for this catchment.
- **Tully**
  - o Data for the Tully River at Euramo Bridge spanned 35 years and was used in an analysis using the LRE package to estimate loads with uncertainties. Unlike the Burdekin River, flow for the Tully was collected at irregular time intervals ranging from 0 hours to 43.91 days with a mean of 1.015 hours and a median of 2.24 days. Summary statistics showed substantial bias in the concentration in addition to the biased sampling of the flow.
  - o A model fit to 489 concentration samples highlighted linear and quadratic terms for flow, a seasonal term, a rising/falling limb term and a discounted flow term that was important for predicting concentration and explained 74.2% of the variation in the data. The seasonal term indicates decreasing concentrations from November through to the end of June and an increase from July through to the end of October. The rising/falling limb term fitted in the model was significant and indicates an increase in concentration (approximately 2.3 times) on the rise of an event, compared to on the flat. A decrease in concentration on the fall is noted, although it is not significant.
  - o Average mean concentrations show a large load (and uncertainty estimate) occurring in 1994/95. Apart from this estimate, the average mean concentrations predicted for all remaining water years exhibit a cyclic behaviour, where approximately every 10 years

the load appears to increase. Further investigation into the behaviour of these estimates and whether like the Burdekin, certain climatic events have contributed to this are required.

Uptake of Methodology

The Department of Premier and Cabinet (DPC) is charged with providing baseline loads for all end of river systems in the GBR to inform the Paddock to Reef (P2R) monitoring program and be a basis for comparison in future years. The method used to estimate loads with uncertainties for rivers with monitoring data was the LRE.

The LRE methodology was extended to calculate 'long-term' loads, where 'long-term' captures the time-frame sampling was conducted for each site and pollutant investigated. These estimates were then adjusted by an area correction to account for additional point sources at the mouth. The number of years and water quality samples contributing to these estimates ranged from 3 to 24 years, and 42 to 869 samples, respectively.

For most rivers and pollutants, the LRE 'long-term' estimates compared well with the modelled estimates, that is, the 80% confidence intervals included the SedNet estimate. This is not surprising for rivers like the Tully and Burdekin, where long term monitoring records provided good temporal coverage. Results for the Fitzroy however, did not compare well.

Of all constituents, DIN, DON, DIP and DOP loads generally match well, which is to be expected given that these components of SedNet are driven by stream concentration monitoring data.

Recommendations

The LRE methodology is a significant advancement on existing loads methods as it captures key sources of uncertainty around flow and concentration, and is able to borrow strength from multiple-year data to estimate loads. Furthermore, it provides interpretation around the relationship between concentration and flow that cannot be easily disentangled using existing methods.

Application to the Burdekin River site at Inkerman Bridge shows variability in the average mean concentrations that may be due to climatic changes and require further investigation.

Estimates for the Tully River at Euramo shows cyclic behaviour in the average mean concentrations.

The involvement in the Department of Premier and Cabinet Project (DPC) has highlighted a need to find a more objective and robust method for estimating loads with uncertainties to assist with baseline reporting and assessment. Current methods are subjective and use a mismatch of methods (deterministic models and estimates from monitoring data) which can lead to inaccurate estimates of loads in the long-term.

Introduction

Nutrients, sediments and pesticides are high priority river contaminants that can result in significant impacts in the freshwater and receiving estuarine and marine environments. Under the 2009 Reef Water Quality Protection Plan (the Reef Plan) and the SEQ Regional Water Quality Monitoring Strategy, there is a requirement to reduce the export of these contaminants to receiving estuaries bays and reefs. Strategies such as the Paddock to Reef Monitoring Program and Water for a Healthy Country (WfHC) programs are aimed at reducing contaminant export from catchments through targeted rehabilitation and the introduction of improved land management practices. These programs represent a significant investment and it is therefore necessary to track their effectiveness.

Estimation of pollutant loads is a challenging but important part of monitoring the effectiveness of land management change faced by many organisations at a range of scales. One of the main challenges of estimating loads is determining an appropriate technique to estimate them with sufficient accuracy. A range of methods currently exist as described by Kuhnert *et al.* (2009) and references therein. Most of these tend to be static and estimate loads on a year-by-year basis. Few attempt to address uncertainty and those that do fail to incorporate all aspects of uncertainty and account for bias in flow and concentration sampling in the derivation of the load. For example, there are many simulation based approaches that tackle uncertainty by examining the variability amongst load methodologies (Guo *et al.* 2002; Etchells *et al.* 2005; Fox 2005; Tan *et al.* 2005) while others develop an approximation for various loads estimation approaches (Baun 1982; Fox 2004, 2005). Tarras-Wahlberg and Lane (2003) use Monte Carlo simulation to generate alternative log concentration values for their regression model and thus enable a family of curves to be generated, while Rustomji and Wilkinson (2008) use bootstrap resampling to place confidence intervals around estimates of load based on a non-linear regression approach.

With funding from the Australian Government's Marine and Tropical Sciences Research Facility (MTSRF) Project 3.7.7, we developed methodology to estimate credible estimates of loads from monitoring data that incorporates key measures of uncertainty (measurement, knowledge and stochastic) that have been described in detail elsewhere (Kuhnert *et al.* 2009). This work has been implemented in the Loads Regression Estimator (LRE), a package in the R statistical language (www.r-project.org), details of which are outlined elsewhere (Kuhnert & Henderson 2010).

We outline the loads methodology in the next section of this report and apply it to two long-term total suspended sediment (TSS) monitoring datasets using the LRE package. The first case study we examine is the Burdekin site at Inkerman Bridge that has monitoring data spanning 36 years. The second is the Tully site at Euramo Bridge, which captures 35 years of monitoring. Following on from this we discuss the uptake of the LRE methodology by the Department of Premier and Cabinet baseline loads reporting project, where this methodology was used to estimate baseline loads with uncertainties for end of GBR river systems with adequate monitoring data. Finally, we outline recommendations for the implementation of this work more generally and highlight the necessary work required to develop a methodology for loads that assimilates monitoring data with models to provide a single unified approach for estimating loads with uncertainties anywhere in the Great Barrier Reef (GBR) catchments.

Methodology

The loads methodology represents a four-step process as shown in Figure 1 and outlined below.

The **first** step involves 'regularising' the flow, a process whereby a loess smoother (Cleveland *et al.* 1992), capturing peak flows, is used to predict flow at regular time intervals (e.g. hourly) and infill any gaps in the flow data. Two datasets are produced because of this process. The first is the regularised flow, which is used for prediction in Step 3, while the second is a modelling dataset, where the concentration samples are matched to the regularised flow values and used in Step 2 to help form the predictive relationships between concentration and attributes of flow.

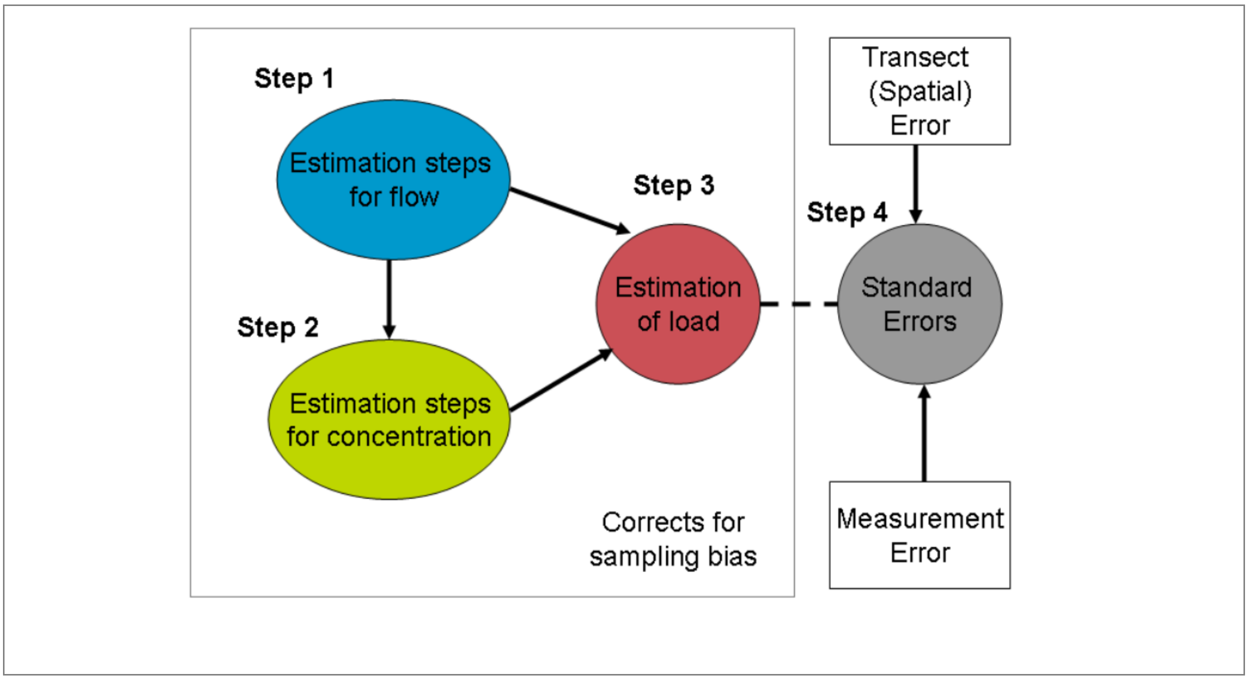


Figure 1: Conceptual diagram outlining the statistical methodology used to quantify pollutant loads with uncertainties from flow and concentration data.

The **second** step in the methodology fits a generalised additive model (GAM) (Wood 2006) to concentration (on the log-scale) to model the relationship between concentration and a series of flow terms that attempt to mimic key hydrological processes of the system with the aim of reducing knowledge uncertainty. This an extension of the popular regression or rating curve approaches that rely on a simple regression relationship between concentration and flow. The incorporation of additional hydrologically meaningful terms can lead to improved predictions of concentrations, and drive more accurate load estimation. This generalized additve model is comprised of two components. The first includes terms that enter into the model linearly, while the second incorporates flexible (smooth) terms driven by the data. The model is considered semi-parametric and represented mathematically as

$$\log(c_i) = \beta_0 + \sum_{k=1}^{p} \beta_k x_{ki} + \sum_{k=1}^{m} s_k(z_{ki}) + \varepsilon_i \qquad (1.1)$$

where x_{ki} and z_{ki} are covariates measured at the i-th sample and $s_k(\cdot)$ represents a spline (flexible) function. The terms we consider in any model include:

- Linear and quadratic terms for flow to capture nonlinearity in the relationship
- Seasonal terms comprising sines and cosines to capture intra-annual variation
- A rising or falling limb term represented by a categorical variable that reflects concentration samples captured on the rise (+1), fall (-1) or flat (0) of the event. Here an event or "flush" is determined as flow exceeding the 90th percentile in a water year. Other percentiles can be selected.
- A discounting term that attempts to mimic exhaustion properties of the hydrological system. This term discounts the effect of the current event if there have been significant events in the recent past. The discount factor controls the level of discounting and hence, the weighting of past events. This has been set to 0.95, which equates to 0.5 per fortnight, indicating that in a fortnights time only half the flow is contributing to pollutant runoff now.
- A trend term that attempts to capture inter-annual variability and long-term trends in concentration.

These terms can be represented in the model as follows for each sampling time point, i:

$$\begin{aligned}
&x_{1i} = \log(\hat{q}_i), x_{2i} = \log(\hat{q}_i)^2 \ \text{(flow)} \\
&x_{31} = \sin(2\pi t/365.25), x_{4i} = \cos(2\pi t/365.25) \ \text{(seasonal terms)} \\
&x_{5i} = \begin{cases} 1 & \text{if } \hat{q}_i > \hat{q}_{i-1} \text{ and } q_i > q^{[90th\ \%\text{ile}]} \\ -1 & \text{if } \hat{q}_i < \hat{q}_{i-1} \text{and } q_i > q^{[90th\ \%\text{ile}]} \\ 0 & \text{otherwise} \end{cases} \ \text{(rising/falling limb)} \\
&z_{1i} = s(t) \ \text{(trend)} \\
&z_{2i} = s(\log(D_i)), \text{ where } D_i = \frac{1-d}{1-d^i} \sum_{m=1}^{i} d^{i-m} \hat{q}_m \ \text{(discounted flow)} \\
&\text{for discount factor } d.
\end{aligned} \qquad (1.2)$$

Note that other terms can be incorporated in this model. These may represent additional derivatives of the hydrograph such as the rate of change (possibly a surrogate for intensity), or possibly other phenomena such as pollutant sources, structures (e.g. a dam) or terms that capture management intervention if available and relevant.

The **third** step is the estimation of the annual load. This involves multiplying the regularised flow by the concentration predicted at each regularised flow value and then summed over the water year, and is represented as

$$\hat{L} = K\sum_{m=1}^{M} \hat{c}_m \hat{q}_m \exp(\varepsilon_m) \qquad (1.3)$$

where *K* is a unit conversion constant to produce a load in tonnes, $\hat{Q}$ and $\hat{C}$ represent predicted regularized vectors of flow and concentration such that $\hat{Q} = \left(\hat{q}_1, \hat{q}_2, \ldots, \hat{q}_M\right)$ and $\hat{C} = \left(\hat{c}_1, \hat{c}_{2,} \ldots, \hat{c}_M\right)$ respectively, and $\exp\left(\varepsilon_m\right)$ represents the bias correction term at each regularised time point m, and is necessary because we model on the log scale and then transform back to the natural scale. Steps 1-3 are structured so they correct sampling regimes that targets events, ad will result in biased estimates of load unless they are taken into account.

The **fourth** and final step involves the construction of the standard errors around the estimate of each annual load. The expression is shown below in Equation 1.4 and incorporates errors in the flow rates that the user can provide in the form of a coefficient of variation, α_1 and α_2

$$\begin{aligned} \mathrm{var}(\hat{L}) &= \mathrm{trace}\{\mathrm{var}(\hat{\beta}) X^T P P^T X\} \\ &\quad + \alpha_1^2 \sum_m \hat{L}_m^2 \left\{1 + \partial / \partial \log \hat{Q}_m\right\}^2 + \alpha_2^2 \left\{1 + \partial / \partial \log \hat{Q}_m\right\}^2 \end{aligned} \qquad (1.4)$$

Here, $P = \left(\hat{l}_1, \hat{l}_2, \ldots, \hat{l}_M\right)$, a vector of loads estimated for each regular time interval, m and $\hat{l}_m = K\hat{c}_m \hat{q}_m \exp(\varepsilon_m)$. The second term in Equation 1.4 represents a transect or spatial error representing error in the spatial positioning of the gauge, while the third term represents measurement error in the flow rate. For the complete mathematical derivation of Equation 1.4, contact the lead author.

Comparing loads over time

The LRE package and loads methodology described above produces a total load in tonnes for each water year where concentration and flow data were collected. The amount of flow occurring in a water year will influence the size of the load as outlined in Equation 1.3. A method of standardising the load to provide an average mean concentration is required if we are to compare years.

Let $\hat{L}_w$ represent the load in millions of tonnes calculated for a water year, w and $\hat{F}_w$ represent the total volume of flow in megalitres occurring in a water year. A water year represents the period between the 1st October through to the 30th of September. We constructed an average mean concentration, A_w by dividing the total load by the total volume of flow and multiplying by the necessary constant λ to obtain a result in mg/L:

$$A_w = \lambda \hat{L}_w / \hat{F}_w \tag{1.5}$$

with corresponding variance of

$$\mathrm{Var}(A_w) = \frac{\lambda^2}{\hat{F}_w^2} \mathrm{Var}(\hat{L}_w) \tag{1.6}$$

Case Studies

The Burdekin Catchment

Catchment characteristics

The Burdekin catchment is the second largest catchment draining to the GBR lagoon and it represents the largest in terms of mean gauged annual discharge (Furnas 2003). The Burdekin River itself drains an area of 130,126 km^2. The distribution of land use within the catchment is dominated by cattle grazing (95%) with small percentages of cropping (5%) (Rayment & Neil 1996; Furnas 2003). The geology of the catchment is quite varied containing igneous, sedimentary and metamorphic rock provinces (Fielding & Alexander 1996; Furnas 2003) and a wide variety of soil covers. Precipitation within the catchment occurs within a well-defined, summer wet season with higher falls near the coast and declining westwards of the Great Dividing Range (Furnas 2003; Amos *et al.* 2004). Area weighted annual rainfall within the catchment is 727 mm (Furnas 2003). The recorded annual discharge of the Burdekin River is highly variable ranging from 247,110 Ml (1930/31, Home Hill) to 54,066,311 Ml (1973/74, Clare), representing the end of catchment over the 84 years of the record.

Several attempts have been made to estimate recent annual-average, and event based, sediment loads from the Burdekin River to the GBR lagoon. Belperio (1979) estimated annual average load to be 3.45×10^6 tonnes, but Amos *et al.* (2004) consider this early estimate to be unreliable due to the highly variable seasonal and intra annual discharge patterns. Amos *et al.* (2004) estimated a load of 3.7×10^6 tonnes of suspended sediment, but noted that 3×10^5 tonnes of bedload were transported past a monitoring site in the Burdekin River during a 29 day discharge event in February and March 2000. Mitchell & Furnas (1997) monitored suspended sediment transport in the river between 20 December 1995 and 12 February 1996 and obtained a load of $2.6\text{-}4.8\times10^6$ tonnes over that period. That the two event-based estimates were of similar size but the corresponding peak discharges were of different magnitude (3166 m^3s^{-1} versus 11155 m^3s^{-1}) is believed to indicate influence of antecedent weather conditions upon the availability of sediment for transport (Amos *et al.* 2004).

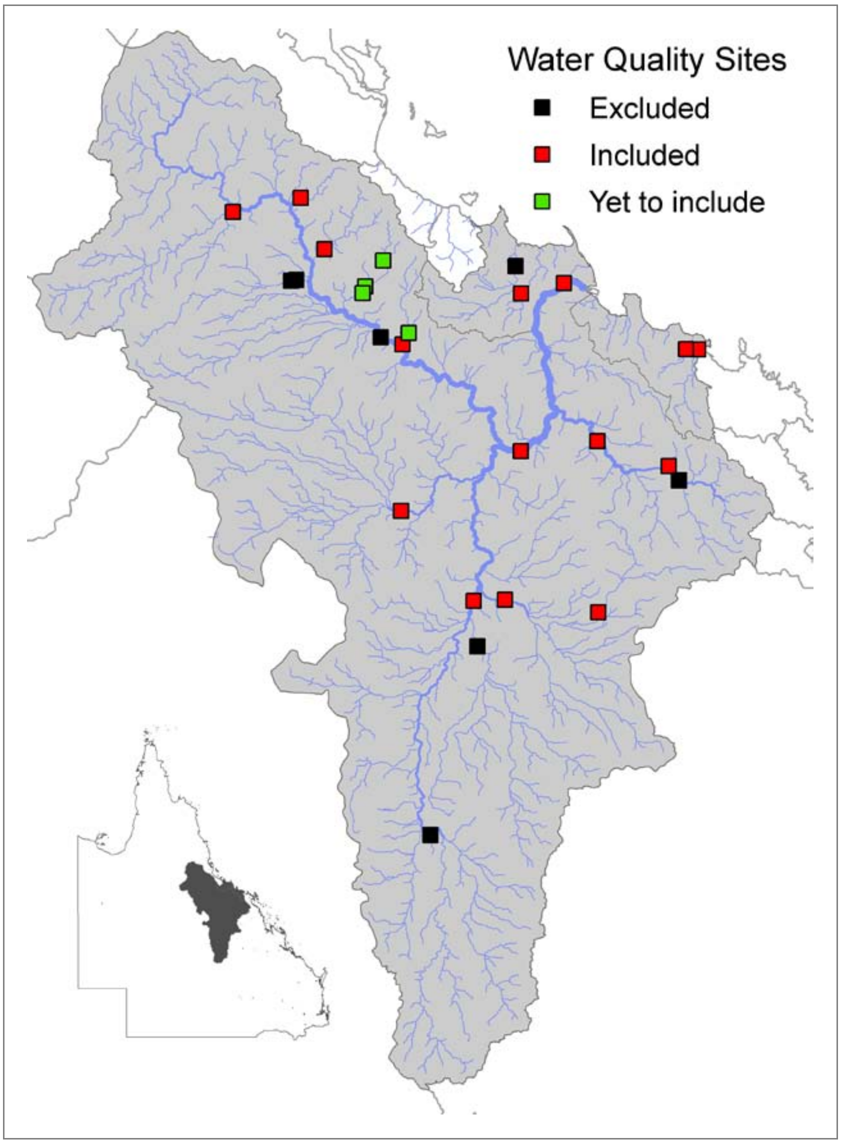


Figure 2: Sites in the Burdekin where TSS sampling of TSS has been undertaken. Black squares indicate exclusion, red squares indicate inclusion and green squares are sites yet to be included.

TSS loads

We obtained flow data from Queensland Department of Environment and Research Management (DERM) and total suspended sediment (TSS) data from a collection of organisations and agencies, namely, DERM, Australian Institute of Marine Science (AIMS) and the Australian Centre for Tropical Freshwater Research (ACTFR), who regularly monitor sites in the Burdekin. Figure 2 shows the Burdekin catchment with 19 sampling locations with varying temporal resolutions of TSS sampling undertaken. We focus on the Inkerman Bridge site, located approximately 23km downstream from the mouth of the river. Figure 3 shows flow (log-scale) for the period between December 1973 through to December 2009 with TSS samples (also on the log-scale) overlayed. Flow was measured every hour with no notable gaps. However, gaps were apparent in concentration sampling between 1978-1983 and 1991-1995 where very few samples were taken. Changes in the sampling regime were noted on events occurring from 1996 onwards. These sampling inconsistencies were due to changes in sampling regimes that arose from the different sampling protocols used by the agencies that provided data. Summaries of the data indicated considerable bias in the concentration sampling with no bias in flow samples due to the regular sampling intervals taken. Figure 4a shows a barchart of the percentage of samples captured by flow, which indicates the sampling captured considerable flow ranges, concentrating on the high flow periods. The relationship between concentration and flow on the raw and log scale is shown in Figure 4b, which indicates a quadratic relationship between concentration and flow on the log scale.

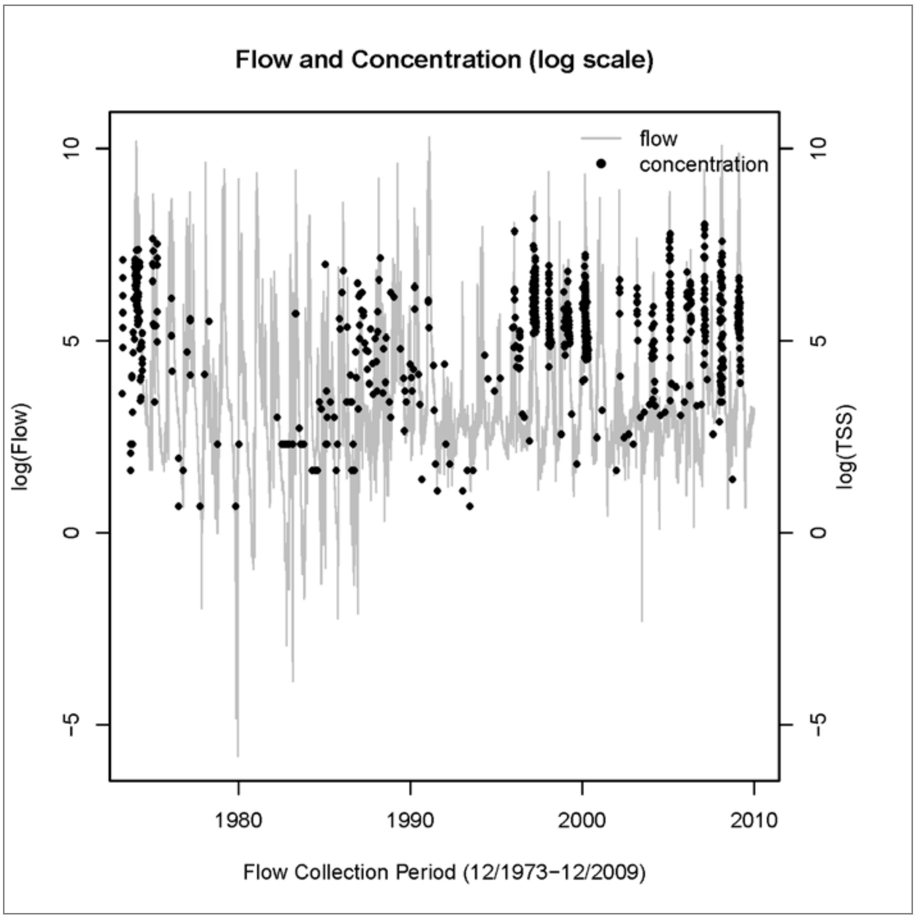


Figure 3: Flow (solid line) and TSS concentration (points) shown on the log-scale and sampled from the Burdekin River site at Inkerman Bridge etween December 1973 and December 2009.

Following the methodology described above, we used the LRE package to create a modeling dataset consisting of 824 observations and a regularised flow dataset that was used for prediction and the calculation of the load. The modeling results are displayed in Table 1 and show the estimates, standard errors and corresponding p-values for each term included into the model. Diagnostics from the model fit are shown in Figure 5 and indicate a reasonable fit to the data.

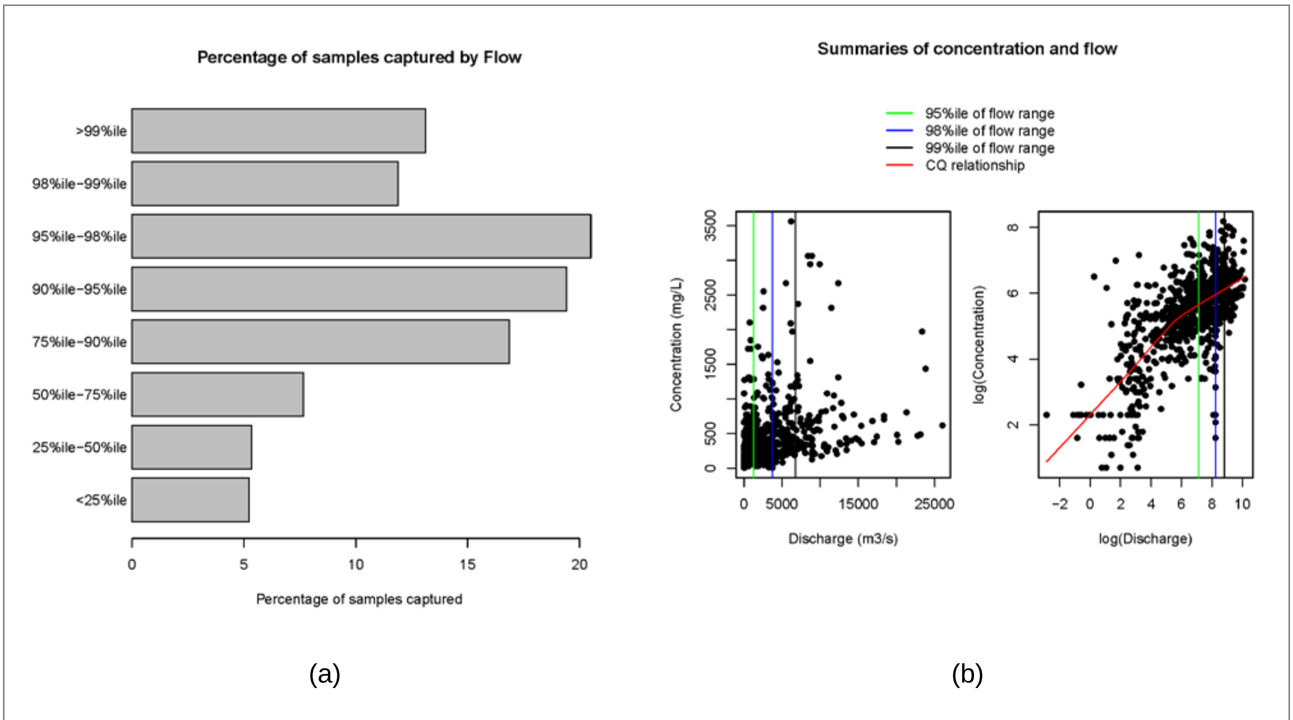


Figure 4: Data summaries for the Burdekin site showing (a) the percentage of samples captured by flow and (b) the relationship between concentration and flow overlayed with percentiles of flow range (95% green; 98% blue; 99% black) and a loess smoother (red) summarising the relationship between flow and concentration.

Table 1: Summaries from the fit of LRE model to the Burdekin data showing the estimate, standard error and p-value for each non-smooth term in the model. Summaries for smoothed terms consist of the effective degress of freedom and p-value. This model explained 69% of the variation in the data and was based on 824 observations, spanning 36 years.

Parameter	Estimate	Standard Error	p-value
Intercept	2.608	0.28	<0.001
Linear + Quadratic terms for flow			
- linear	0.134	0.09	0.132
- quadratic	0.025	0.01	<0.001
Seasonal terms			
- c1	0.389	0.07	<0.001
- s1	1.039	0.09	<0.001
- c2	0.219	0.06	<0.001
- s2	-0.130	0.06	0.019
Smooth Terms	**Effective Degrees of Freedom**		**p-value**
Discounted Flow	6.064		<0.001
Trend	8.926		<0.001

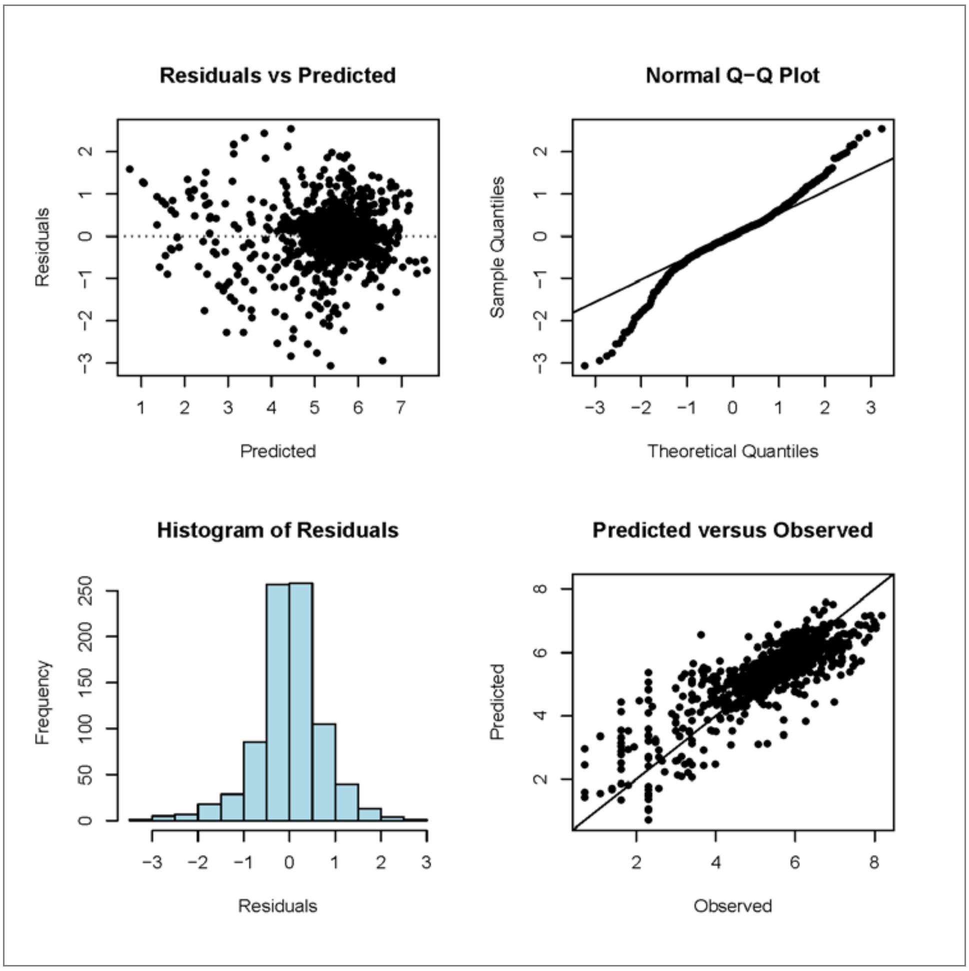
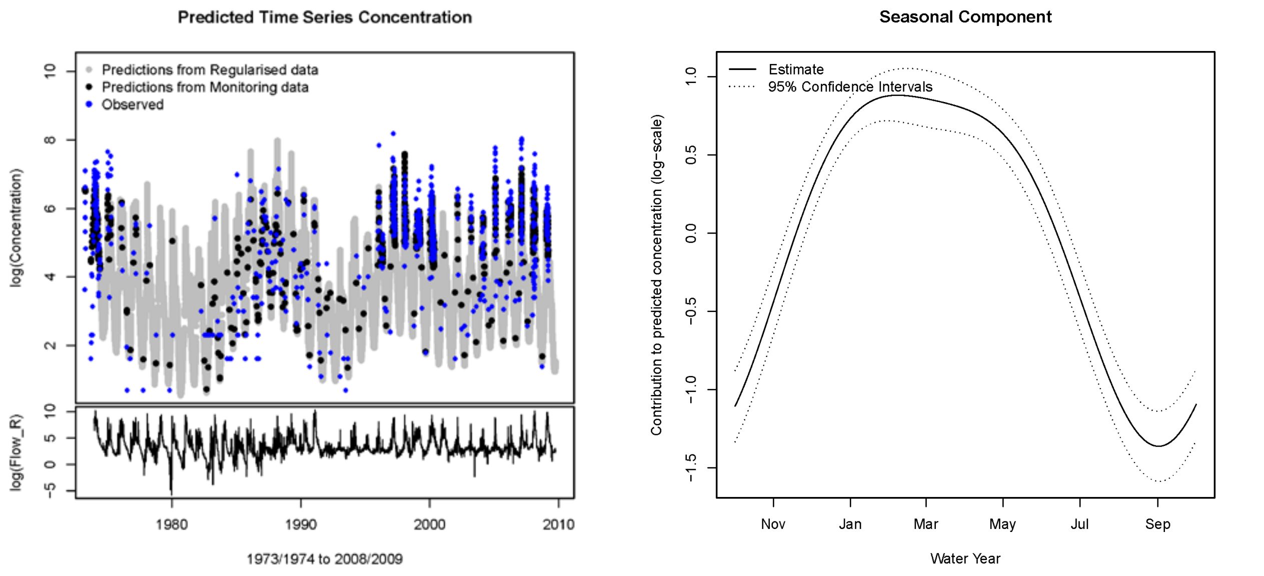


Figure 5: Diagnostic plots from the fitted model showing plots of the residuals versus predicted values (top left), quantile-quantile plot (top right), histogram of residuals (bottom left) and predicted versus observed (bottom right).

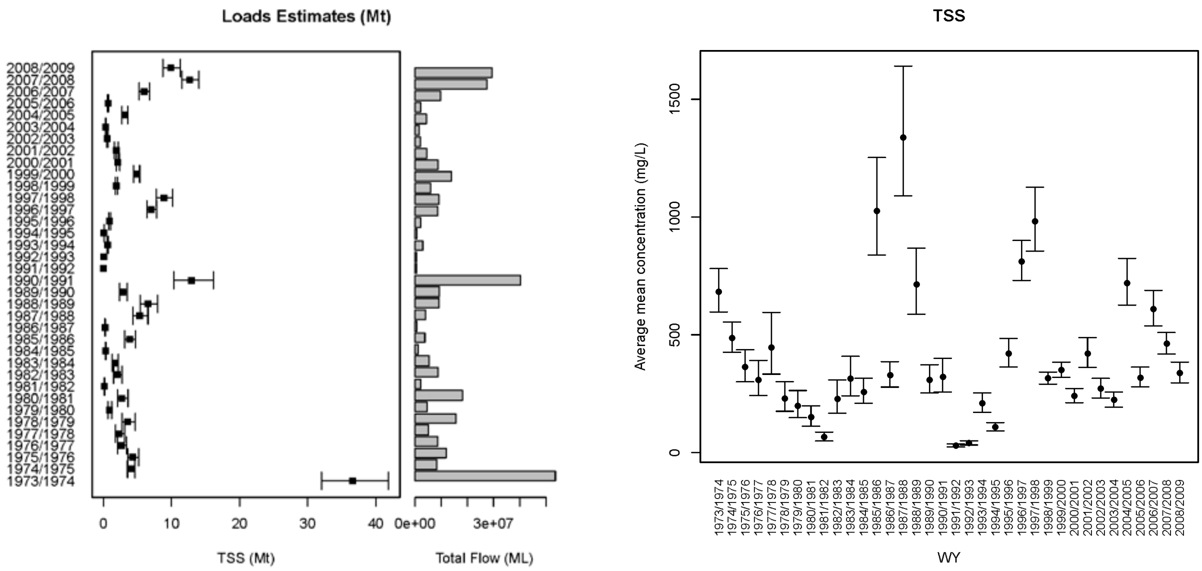
Predictions made using the regularised dataset are shown in Figure 6a along side a plot of the seasonal component from the model in Figure 6b. In Figure 6a, the grey points in the top plot show the predictions from the entire regularised data, the black points show the predictions from monitoring data only, while the blue points represent observed data. Predictions from monitoring data match closely with observed. The plot at the bottom shows the regularised flow for the period that sampling was undertaken. Figure 6b shows the seasonal component estimated from the model (black line) along with 95% confidence intervals (dotted line). This plot shows an increase in the predicted concentration between October through to April and decreases from May through to September, distinguishing between the drier and wetter months of the year.

Figure 7a displays load estimates and corresponding 80% confidence intervals for each water year in millions of tonnes, accompanyied by the total volume of flow in megalitres. In this figure, the TSS loads are higher when the flow is large. To obtain a more accurate picture of loads through time, we standardise by flow and produce Figure 7b. This shows the average mean concentration in TSS across water years. Significant features of this plot are the large concentrations in 1985/86, 1987/88-1988/89 and later in 1996/97-1997/98. A closer inspection of the data and climatic events during these periods revealed cyclones that passed through the Bowen subcatchment of the Burdekin. Inclusion of terms that reflect these events in the model may help explain increases in concentration for this catchment. Furthermore, inclusion of a term that captured the Burdekin dam construction may also explain changes in concentration from 1987 onwards.



(a) (b)

Figure 6: Plots from the Burdekin analysis showing (a) the predicted time series concentration where grey points represent the predictions from regularised data, black points represent predictions from monitoring data and blue points represent observed concentrations. A plot of the regularised flow (log-scale) isdisplayed beneath it; and (b) a plot of the seasonal component from the model showing the estimate (solid line) and 95% confidence interval (dotted line).



(a) (b)

Figure 7: Plots for the Burdekin site showing (a) the estimated TSS load (Mt) and 80% confidence intervals for each water year accompanyied by the total volume of flow (ML) and (b) the average mean concentration (mg/L) for each water year.

The Tully Catchment

Catchment characteristics

The Tully River in North Queensland, Australia is a small, faster flowing tropical river that extends approximately 130km before discharging into Rockingham Bay. The Tully catchment itself is located in the southern part of the Wet Tropics region in Queensland covering an area of 2790 km^2 when combined with the Murray catchment (Furnas 2003). Topography of the catchment varies from steep mountainous areas in the west to the low relief floodplain in the east (Karim *et al.* 2008). Flow discharge within each year is highly variable, peaking between February through to April. As the topography is flat and the location of the Tully and Murray rivers is close, floodwaters have the tendency to merge during floods causing the export of sediment and nutrients to be much higher when compared to the annual average riverine load (Wallace *et al.* 2009).

TSS loads

Flow records for the Tully River site at Euramo were provided by the DERM for the period January 1974 through to January 2009, spanning 35 years. Unlike the Burdekin River, flow for the Tully was collected at irregular time intervals ranging from 0 hours to 43.91 days with a mean of 1.015 hours and a median of 2.24 days. Summary statistics from the LRE package showed substantial bias in the concentration in addition to the biased sampling of the flow. Figure 8 shows a plot of flow and concentration records for the 35 years of data collected in the Tully River. Note changes in the sampling regime and an increase in concentration sampling during events during the later years.

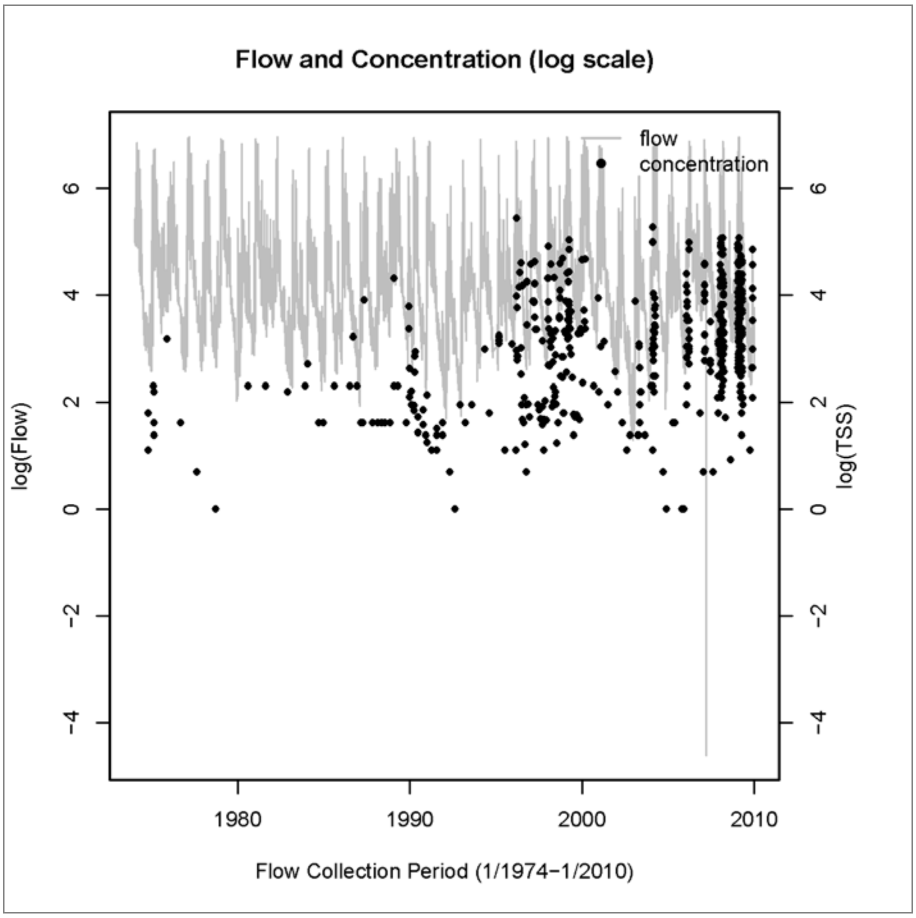


Figure 8: Flow (solid line) and TSS concentration (points) shown on the log-scale and sampled from the Tully River at Euramo between January 1974 and January 2010. Note, the large negative flow value corresponds to a zero observed flow.

Data summaries showing the distribution of flow captured by the sampling at the Euramo site are shown in Figure 9. Figure 9a shows the percentage of samples captured by flow and highlights a broad cross-section of flows being sampled with the highest proportion residing in the 75-90 percentile range. A possible quadratic relationship between flow and concentration (log-scale) is indicated by Figure 9b with percentile cut-offs overlayed on the plot indicating high flows.

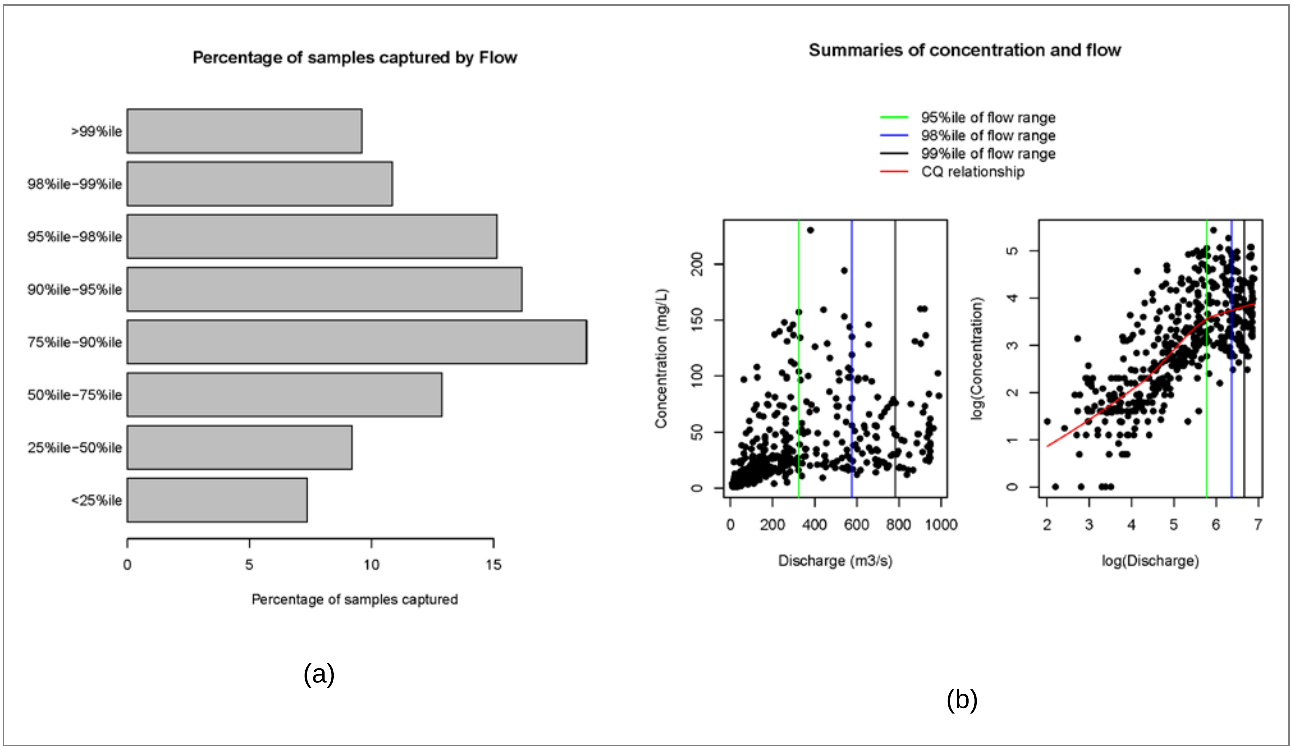


Figure 9: Data summaries for the Tully site showing (a) the percentage of samples captured by flow and (b) the relationship between concentration and flow overlayed with percentiles of flow range (95% green; 98% blue; 99% black) and a loess smoother (red) indicating the relationship between flow and concentration.

Following the methodology described above we used the LRE package to create a modelling dataset consisting of 489 observations and a regularised flow dataset that was used for prediction and the calculation of the load. The modelling results are displayed in Table 2 and show the estimates, standard errors and corresponding p-values for each term included into the model. Terms seen to be important in predicting concentration are linear and quadratic terms for flow, a seasonal term, rising/falling limb and a smoothed discounting term. The trend term was not fitted because it did not explain a considerable portion of the deviation in the model after the inclusion of all the other terms. This final model explained 74.2% of the variation in the data and therefore produced a very good fit. Diagnostics from the model fit are shown in Figure 10 and indicate a reasonable fit to the data apart from two outlying points. We kept these points in the analyses as we had no reason to exclude those values.

Predictions from the regularised dataset are shown in Figure 11a along side a plot of the seasonal component from the model in Figure 11b. In Figure 11a, the grey points in the top plot show the predictions from the entire regularised data, the black points show the predictions from monitoring data only, while the blue points represent observed data. Note, the large negative values correspond to zero flow. (In instances where a zero flow was observed, we added on a small value before taking logs of the data.) Predictions from monitoring data match closely with observed. The plot appearing below the predictions displays the regularised flow for the period on the log scale. Figure 11b shows the seasonal component estimated from the model (black line) along with 95% confidence intervals (dotted line). This plot shows decreasing predicted concentrations from November through to the end of June and an increase from July through to the end of October. The rising/falling limb term fitted in the model was significant and indicates an increase in concentration (approximately 2.3 times) on the rise of an event compared to on the flat. A decrease in concentration on the fall is noted, although it is not significant.

Table 2: Summaries from the fit of LRE model to the Tully data showing the estimate, standard error and p-value for each non-smooth term in the model. Summaries for smoothed terms consist of the effective degress of freedom and p-value. This model explained 74.2% of the variation in the data and was based on 489 observations, spanning 35 years.

Parameter	**Estimate**	**Standard Error**	**p-value**
Intercept	-8.759	0.76	<0.001
Linear + Quadratic terms for flow			
- linear	3.813	0.29	<0.001
- quadratic	-0.288	0.03	<0.001
Seasonal terms			
- c1	0.211	0.07	0.002
- s1	0.171	0.05	0.002
- c2	0.081	0.05	0.083
- s2	0.016	0.05	0.744
Rising/Falling Limb			
- fall versus flat	-0.094	0.09	0.303
- rise versus flat	0.823	0.10	<0.001
Smooth Terms	**Effective Degrees of Freedom**		**p-value**
Discounted Flow	8.415		<0.001

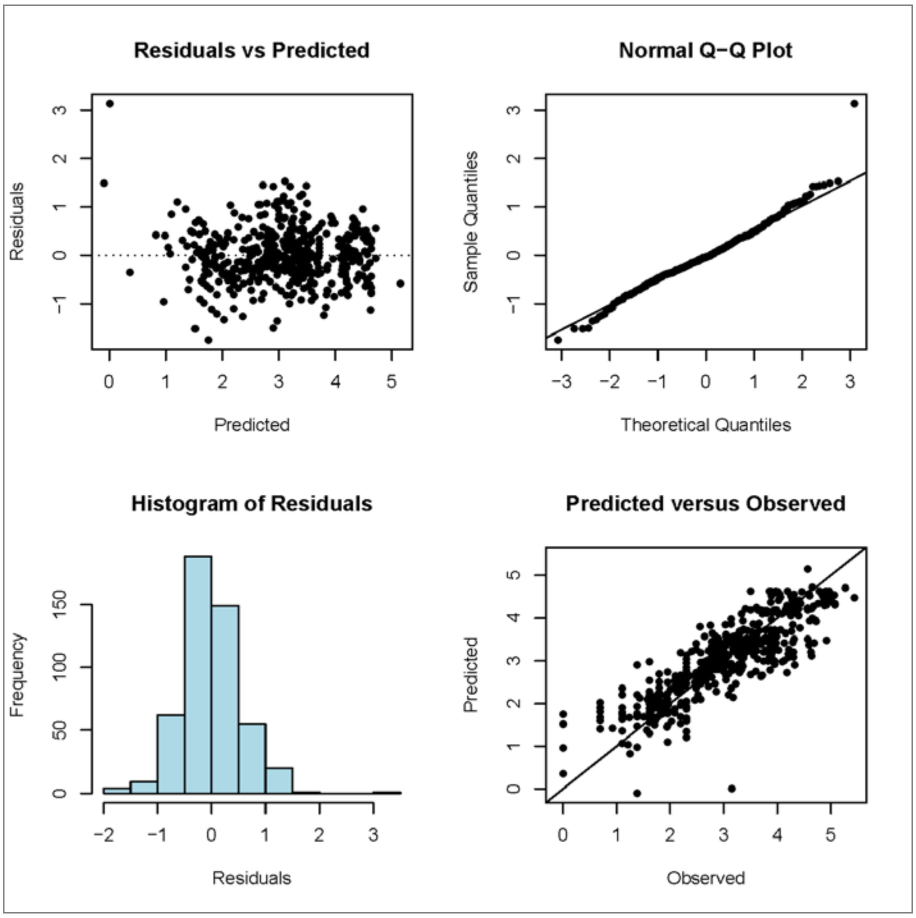
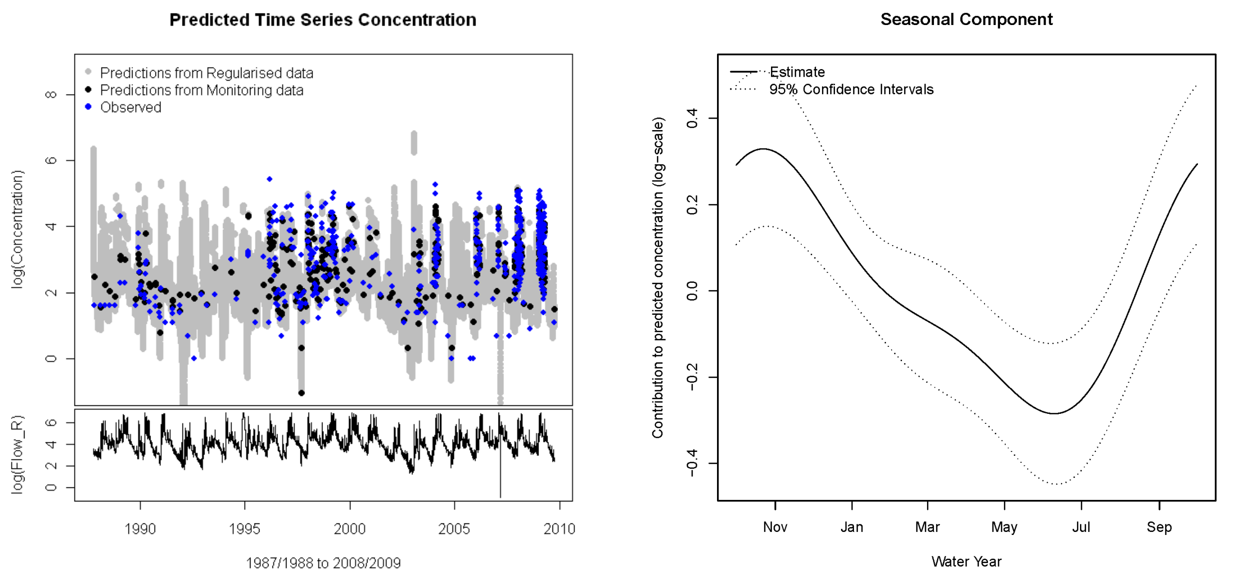


Figure 10: Diagnostic plots from the fitted model showing plots of the residuals versus predicted values (top left), quantile-quantile plot (top right), histogram of residuals (bottom left) and predicted versus observed (bottom right).



(a) (b)

Figure 11: Plots from the Tully analysis showing (a) the predicted time series concentration where grey points represent the predictions from regularised data, black points represent predictions from monitoring data and blue points represent observed concentrations. A plot of the regularised flow (log-scale) is displayed beneath it; and (b) a plot of the seasonal component from the model showing the estimate (solid line) and 95% confidence interval (dotted line). Note the large negative value and corresponding predicted large negative values in Figure a represent a zero observed flow.

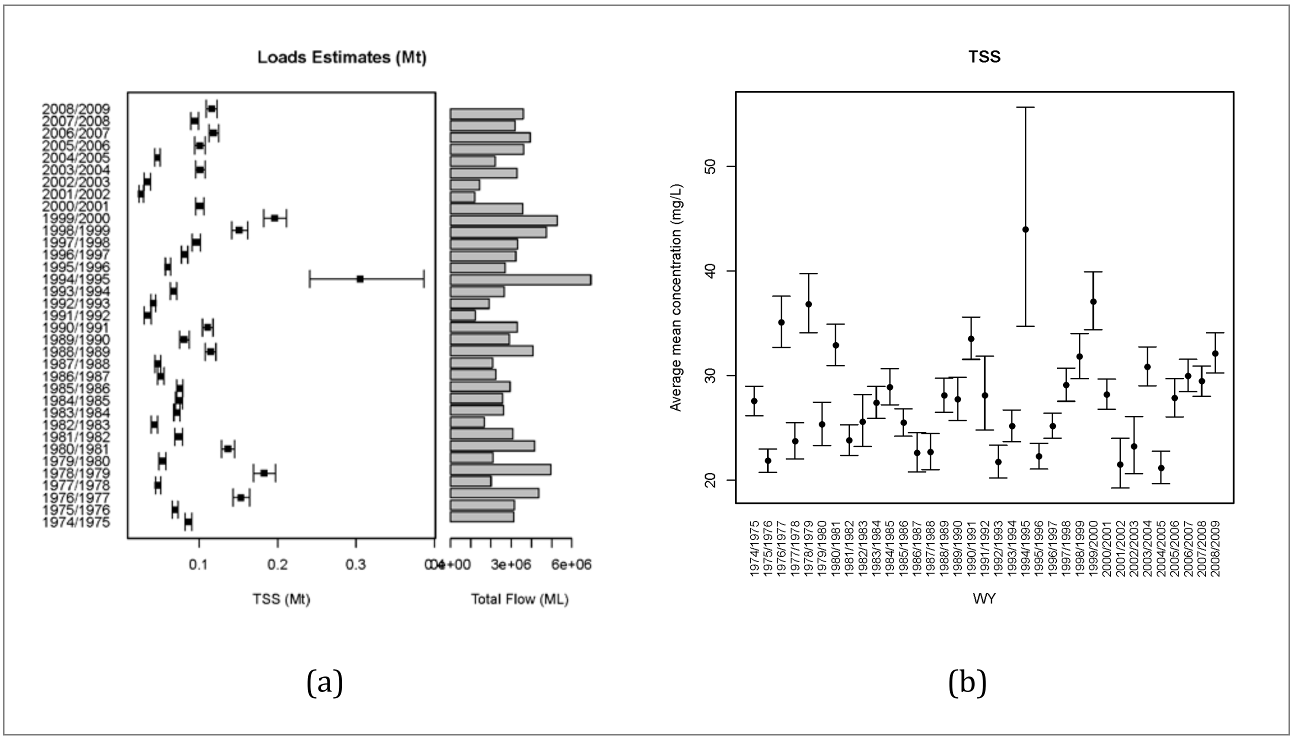


Figure 12: Plots for the Tully site showing (a) the estimated TSS load (Mt) and 80% confidence intervals for each water year accompanyied by the total volume of flow (ML) and (b) the average mean concentration (mg/L) for each water year.

Loads estimates for the Tully site are displayed in Figure 12 with corresponding 80% confidence intervals as illustrated by the solid lines in each plot. Figure 12a shows the loads estimates in millions of tones along side the total volume of flow (mega litres) for each water year as summarised by a bar plot. As expected, the load increases as the total volume of flow increases. To enable comparisons across year, we divided the annual load with the total volume of flow to produce an average mean concentration (mg/L) which is shown in Figure 12b. Apart from a large load (and uncertainty estimate) occurring in 1994/95, the estimates in this plot exhibit a cyclic behaviour, where approximately every ten years the load appears to increase.

Uptake of Methodology

The DPC Project

Overview

The DPC is charged with providing baseline loads for all end of river systems in the GBR to inform the Paddock to Reef (P2R) monitoring program and be a basis for comparison in future years. The method used to estimate loads with uncertainties for rivers with monitoring data was the LRE. After a quality assessment of all the rivers, where reporting is required, the LRE methodology was applied to 12 rivers and 9 pollutants (TSS, DIN, DON, PN, TN, DIP, DOP, PP, TP) to estimate annual loads with uncertainties. These were then used to calculate long-term loads. SedNet, a deterministic (process based) model that does not incorporate uncertainties into estimates of load was used for the remainder of the basins being assessed.

Application of LRE Methodology

Using catchment monitoring data, we developed a “long term” loads estimate that incorporated area corrections to include additional point sources occurring at the mouth of each river system as described in Kroon et al. (2010) through the following process. First, we estimated annual loads (Mt) and average mean concentrations (mg/L) with uncertainties for each water year where monitoring data was collected using the Load Regression Estimator (LRE) methodology and the four step process outlined in previous sections. Second, we constructed long-term loads by calculating the mean of the average mean concentration estimates across water years for a site and multiplied by the average flow that spanned the monitoring data. Finally, we adjusted the long-term loads estimates by the area corrections. Confidence intervals assuming log-normality were constructed accordingly for each stage of this estimation process. Where sites were combined because they were regarded as independent river systems, but resided in the same basin, we applied the same methodology. In these instances we (i) summed the average mean concentrations for each matched water year at the sites of interest, (ii) calculated a combined flow, weighted by the volume of flow in each river, and (iii) calculated a long-term load. We describe the calculation of the long-term loads at single and multiple sites in more detail below.

Long Term Loads

Obtaining a 'long term' loads estimate requires calculating a mean of the average mean concentration estimates across water years for a site and multiplying by the average flow that spanned the monitoring data. Ideally, we would use an average obtained from long term flow records. However, these were not available to us at the time of analysis., and we based the average on the range of flow records provided by DERM. Mathematically this calculation can be expressed as

$$\hat{S} = \delta \bar{F} \frac{1}{W} \sum_{w=1}^{W} A_w \tag{1.7}$$

where W represents the number of water years, $\bar{F}$ represents the average flow spanning the water years where monitoring data was collected and δ represents a constant to convert the estimate to tonnes per year. A corresponding variance estimate can be expressed in terms of the variance estimates of the load and assuming independence between water years. Note, we assume no error in the flow in this calculation as this was not available at the time of the analysis. The variance estimate can be formulated as

$$\mathrm{Var}(\hat{S}) = \frac{\delta^2 \bar{F}^2}{W^2} \sum_{i=1}^{W} \mathrm{Var}(A_w) \tag{1.8}$$

and confidence intervals can be constructed accordingly. We assumed log-normality in the construction of the confidence intervals.

Combining Loads at Sites

For basins that have multiple rivers we need to combine loads from each site to obtain a total load for that basin. We approached this problem using the following process:

1. Sum the average mean concentration for each matched water year at the sites of interest.
2. Calculate a combined flow that is weighted according to the amount of flow occurring in each of the sites for each water year.
3. Calculate the long-term load as expressed prior by averaging across years and multiplying by the average combined flow.

Assuming once again no errors in flow, we can construct the following expression for the combined long-term load and corresponding variance.

$$\hat{S}^c = \delta \bar{F}^* \frac{1}{W} \sum_{w=1}^{W} \sum_{i=1}^{n\_rivers} A_{w,i} \text{ and } \mathrm{Var}(\hat{S}^c) = \frac{\delta^2 \bar{F}^{*2}}{W^2} \sum_{w=1}^{W} \sum_{i=1}^{n\_rivers} \mathrm{Var}(A_{w,i})$$
$$\text{where } \bar{F}^* = \frac{1}{W} \sum_{w=1}^{W} \sum_{i=1}^{n\_rivers} p_{wi} F_{wi} \text{ and } p_{wi} = F_{wi} / \sum_{i=1}^{n\_rivers} F_{wi} \tag{1.9}$$

Results

Using the LRE methodology, we estimated annual loads for each water year where monitoring data was collected. The number of years and water quality samples contributing to these estimates ranged from 3 to 24 years, and 42 to 869 samples, respectively. See Kroon *et al.* (2010) for details regarding datasets used. Models fitted to the concentration data that led to the annual estimates varied in terms of their predictive ability, depending on the temporal frequency of the concentration and sampling regime undertaken. As a result, some of the analyses produced poor fits, resulting in large variances and wide confidence intervals. From these annual estimates, we computed long term loads and applied the area corrections, where required (See Appendix 5, Table A5.3 in Kroon *et al.* (2010) for a summary of the long-term area corrected loads for each of the 9 basins analysed).

The final long term average (corrected) load estimates were subsequently compared with pollutant load estimates derived from the latest, most reliable SedNet run (Figure 13). For most rivers and pollutants, the LRE estimates compared well with the modelled estimates, that is, the 80% confidence intervals included the SedNet estimate. This is not surprising for rivers like the Tully and Burdekin, where long term monitoring records provided good temporal coverage. At these sites, good agreement may indicate that SedNet models have been adjusted to produce similar TSS loads to those previously estimated from monitoring data. As an exception, results for the Fitzroy did not compare well, though the model was not that predictive, possibly due to some irregularities in the flow record. Overall, the mean-annual LRE loads, valid for the monitoring periods, differed from the long-term mean-annual load estimated by SedNet if the monitoring period was on average wetter or drier than the long-term average.

Of all constituents, DIN, DON, DIP and DOP loads generally match well, which is to be expected given that these components of SedNet are driven by stream concentration monitoring data. However, in several rivers the SedNet PP and PN loads, and consequently TP and TN loads, were larger than the 80% confidence intervals of the LRE load estimates. This mismatch may be attributed to large gaps in the flow record. Alternatively, over-estimation of particulate nutrient loads in SedNet modelling has been previously identified. See Kroon *et al.* (2010) for more details.

Loads Recommendations

Comparison to Previous Loads Methodologies

The LRE methodology is a significant advancement on previous approaches to loads estimation using monitoring data for several reasons, which we outline below:

- The methodology presented here is a regression-based methodology that incorporates terms to mimic key hydrological processes operating in a river system. It is also general enough to incorporate a suite of additional variables (e.g. sources, management interventions, structures such as a dam) into the model depending on the type of river being analysed.
- The nature of the additive model allows the inclusion of smooth, flexible terms, which can help to explain large sources of variability in the data.
- Unlike previous static approaches such as the average, ratio and interpolation estimators, LRE can make use of the existing data and borrowing strength across years when characterising the relationship between flow and concentration, which is used for prediction and loads estimation. This may mean that reduced monitoring is required for future years once the relationships are well characterised.
- Provided that the data is representative of the river system, this method has the ability to predict where there are gaps in concentration sampling and provide load estimates where no concentration data was collected. We do however caution about predicting outside the range of the data because it is possible that relationships between characteristics of flow and concentration may change over time, and that applying it may deliver poor load estimates for years outside the range.
- Adjusting for bias and accounting for uncertainty in flow and concentration is explicitly captured in the LRE methodology.
    - Bias is taken into account by predicting concentration at regular flow values and calculating a load.
    - Uncertainty relating to concentration is captured through the generalized additive model used to characterise the hydrological system, while errors in flow rates are captured through two coefficient of variation estimates that can be set in the model. The first captures measurement errors in sampled flow, while the second coefficient of variation expresses the error in the spatial positioning of the gauge in the river.

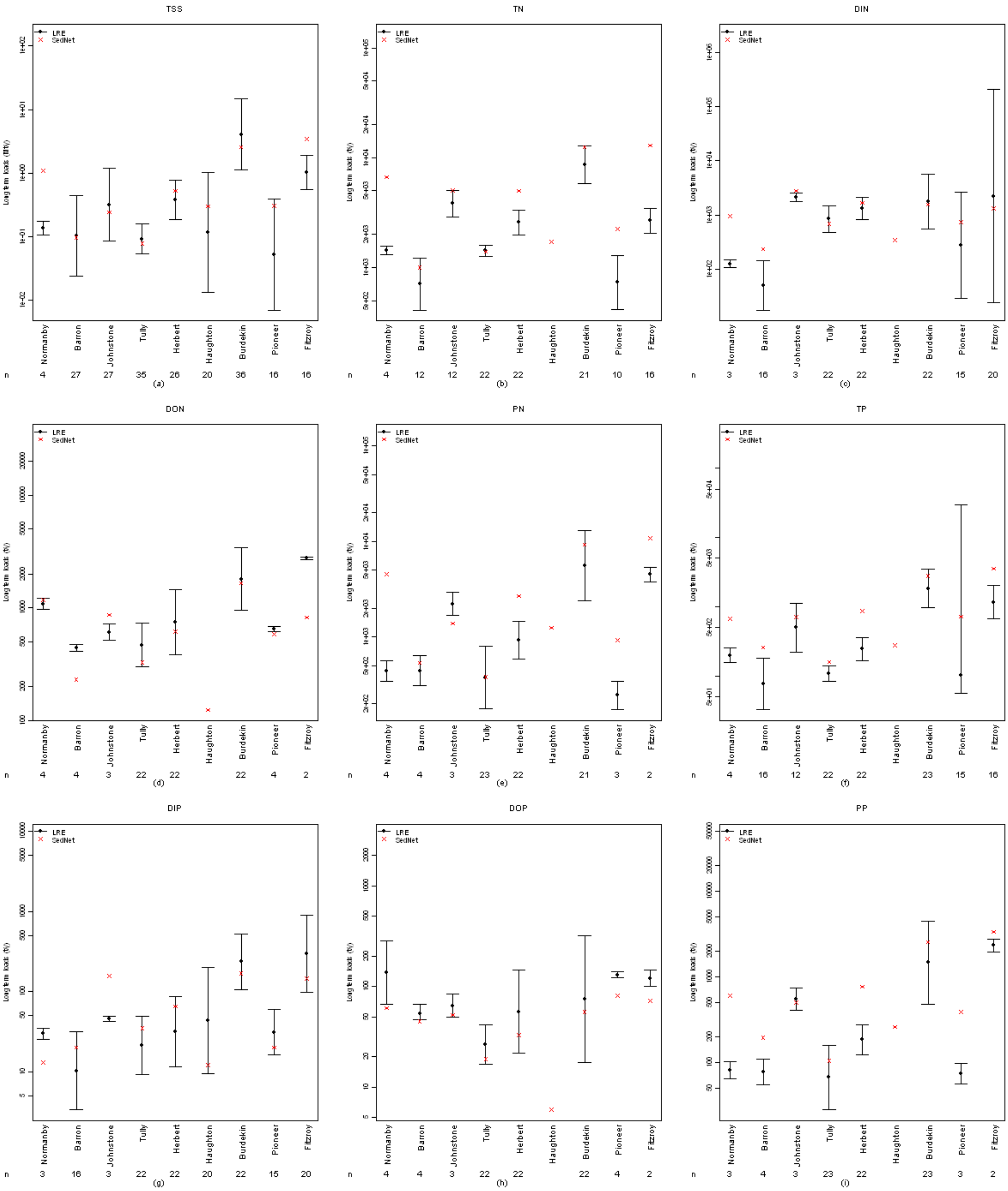


Figure 13: Long term (area corrected) loads estimates for (a) TSS, (b) TN, (c) DIN, (d) DON, (e) PN, (f) TP, (g) DIP, (h) DOP and (i) PP. Sednet estimates are overlayed as red crosses. Note the y-axis is logarithmic.

Future Recommendations

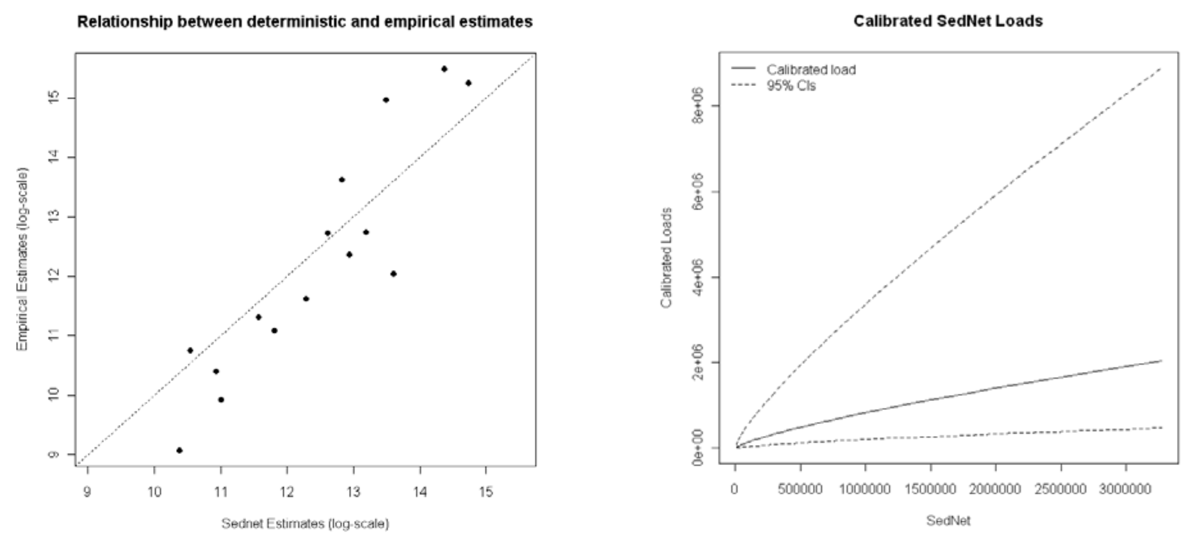
Our involvement in the DPC project has highlighted an issue relating to the calculation of baseline loads estimates for the GBR. At present, there are two primary approaches for estimating a pollutant load:

1. A (deterministic) process-based model (e.g. SedNet and the soon to be released WaterCAST) that incorporates mapped information about different sources of erosion and takes into account the hydrology and contaminant transport characteristics of the system. This information is used to route the pollutants through a river network and to estimate a load; and
2. A statistical modelling framework, LRE that makes use of monitoring data collected at a site within a catchment over a specified period.

The decision as to which model to use is largely subjective and depends on the resolution and representativeness of the data captured and how well the process model is believed to mimic the underlying hydrological processes and variability of the system. Where the monitoring data is representative of the river system, statistical approaches tend to be applied as in the DPC project; when monitoring data is sparse or unavailable, process-based models are typically used. As a result, we currently have a mixture of the two types of models applied throughout the GBR catchments to estimate pollutant loads and inform a baseline in the P2R program (*subjective analysis)*. In addition, process based models are calibrated using monitoring data that is used as a means for calculating loads, ignoring uncertainty in the model structure as well as on the data that is used for calibration purposes. This mismatch of methods results in load estimates developed for *different catchments,* at *different spatial scales*, with *different sources of error*, making it difficult to monitor and track change (if any) through time and in space – an outcome which is considered a high priority for Reef Rescue R&D investment. To ensure that the resultant load estimates are beyond reproach, it is essential that all sources of uncertainty (parameter, model and data) associated with load estimates are propagated through the catchment models, resulting in transparent, *objective* and repeatable estimates of end-of-catchment loads.

The use of process-based models to estimate loads for paddock, catchment and marine components of the GBR has been advocated by Waterhouse *et al.* (2009). The difficulty in relying *solely* on models (with parameters calibrated using monitoring data) is that monitoring data is unavailable in some parts of the GBR. This may result in an unrealistic and biased load estimate for these areas since the model is not calibrated to actual values.

A preliminary calibration analysis of 15 sites in the Burdekin (red squares in Figure 2) based on some simple assumptions has highlighted large errors on the raw scale for SedNet estimates at sites where loads are high (Figure 14). See Kroon et al. (2010) for a complete summary of the analyses investigated for this data. Further development of a model that assimilates both modeled and monitoring data is required to provide an objective and repeatable analysis for loads estimation that accounts for the uncertainty in both the monitoring data and in the modeled estimates.



(a) (b)

Figure 14: Results from calibrating monitoring estimates of loads with modeled estimates where (a) represents the relationship (log-scale) between the deterministic and empirical estimates and (b) shows the calibrated estimated with 95% confidence intervals.

A another key aspect of pollutant load estimation from a management perspective is detecting changes over time, particularly in response to catchment initiatives designed to reduce loads. This is difficult because GBR pollutants loads can exhibit substantial inter-annual variability, driven by large variations in rainfall. In making the comparison between years we typically consider loads under ‘average’ conditions. This is what SedNet does as it is a long term average. In the DPC project loads were averaged in some way over the different years that we had monitoring data available. The LRE method currently provides load estimates for each year, drawing upon all available monitoring data to characterise relationships between flow and concentration. When data for a new year comes in the model is updated and used to predict that year. This means it may take some time for new data to update the relationship enough to show up in different load estimates. Modifications are however possible to improve our ability to detect changes over time (e.g. allowing time-varying relationships, comparing estimates derived from data over different time ranges). This may require us to update how ‘average loads’ are calculated if the focus is on detecting change rather than one off baseline estimates.

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