

Reef Rescue Research & Development

Technical Report

Integrating Measurements with Models for Improved Confidence in Pollutant Loads Estimation *RRRD030*



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Acronyms

BHM	Bayesian Hierarchical Model
CSIRO	Commonwealth Scientific Industrial Research Organisation
GBR	Great Barrier Reef
GBRMPA	Great Barrier Reef Marine Park Authority
JCU	James Cook University
LRE	Loads Regression Estimator
MCMC	Markov Chain Monte Carlo
NRM	Natural Resource Management
P2R	Paddock to Reef Integrated Monitoring, Modelling and Reporting
RRRC	Reef and Rainforest Research Centre Limited
RRRD	Reef Rescue Research & Development
SC	Source Catchments
TropWATER	Centre for Tropical Water and Aquatic Ecosystem Research
WfHC	Water for a Healthy Country

Definitions

Credible Interval	A Bayesian “confidence interval.”
Prior Distribution	A probability distribution summarizing the distribution of an uncertain quantity. Typically this represents a subjective assessment or is based on experimental data. Used in Bayesian statistical inference.
Posterior Distribution	The conditional distribution of an uncertainty quantity given data. Represents the output distribution from a Bayesian model.
TN	Truncated Normal distribution.
TC	Two Component model.
SVD	Singular value decomposition.

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Executive Summary

Overview

Complex physical systems can be challenging to observe, model and subsequently comprehend. Considerable time and effort goes into capturing the dominant dynamical concentration and flow processes using numerical and statistical models, while measurements taken at various spatial locations and temporal frequencies are then used to synthesise and validate our understanding of these processes. Typically, the modelling and observational tasks are performed separately, which does not make full use of both sources of information. Alternatively, the “blending” of models and observations can provide an enhanced understanding of the real world processes.

This “blending” methodology is developed in a Bayesian Hierarchical Modelling (BHM) framework that takes the measurements at various spatial and temporal resolutions and “blends” them with process model output to provide maximum efficiency in estimation and computation. The BHM framework requires three components:

- (1) A process model (Source Catchments),
- (2) A parameter model that allows us to prescribe the uncertainty about the parameters, which can be taken from a literature survey; and,
- (3) An observation model that explicitly links the process model to observations of the system.

The framework explicitly blends the model and observations to produce an estimate of the confidence in modelled predictions, and more importantly, it yields the “best estimate” of the state of the system.

In the context of sediment loads in the Great Barrier Reef (GBR) catchments, we developed this “blending” methodology to provide:

- (1) A more realistic estimate of the sediment load, with an estimate of the certainty that takes into account measurement error, as well as error in our process level understanding of the pollutant;
- (2) Different summary measures of loads (e.g. daily, monthly, annual, event based) with estimates of the certainty;
- (3) Scenario analyses based on changes to cover and rainfall (for example) with estimates of certainty;
- (4) An exceedance probability curve or exceedance probability maps, which enable managers to plan for events that lead to high probability of exceeding a load of a given magnitude and could be used to develop more scientifically defensible targets in response to changes in rainfall and cover.

Two case studies are presented in this report to illustrate the power of the BHM approach in quantifying loads and responding to 1-4 above. The first case study focuses on a single, well sampled site, Weany Creek. This basin covers 14 square kilometres and has been sampled over an 11 year period ranging from 2000-2011, providing an extensive record of flow and concentration. The exception being 2007/08, when a tree fell on the turbidity sensor and 2008/09 when a new sensor was introduced and calibrated. During 2007/08 no total suspended sediment (TSS) data was available and limited TSS data was collected during the

second period due to the calibration process. As Source Catchments could not be run at this fine scale, we used SIMHYD to represent the underlying flow process and a mechanistically motivated statistical model (the Loads Regression Estimator or LRE (Kuhnert et al., 2012)) to capture the concentration processes at this site.

The second case study focuses on the Upper Burdekin, covering approximately 40,000 square kilometres, where concentration and flow is available at 5 sites with limited monitoring occurring between 2005 and 2009. Source Catchment model outputs, representing the sediment concentration, erosion and flow processes, were provided at 411 sites (Source Catchment nodes) along the Upper Burdekin stream network.

Results: Weany Creek

Sediment load estimates have been produced at a daily, annual and event based scale with a measure of certainty conveyed through 80% credible intervals (which can be regarded as a confidence interval) for Weany Creek across the 11 year period, including the two years where either TSS concentration was missing or was limited. As expected, the certainty in the model prediction decreased during periods of missing data, and in particular, was largest during the 2008/09 period when the turbidity sensor was calibrated.

Three scenarios were investigated for this site that captured varying rainfall and cover characteristics. The worst case scenario consisted of high rainfall and low cover, while the best case scenario consisted of low rainfall and high cover. Results indicated that the worst case scenario resulted in higher TSS loads than the best case scenario with larger errors noted in the years where data was missing. Exceedance probability curves were produced for the three scenarios and showed higher probabilities of exceedance under the worst case scenario which was to be expected. As an example, if we were to consider the probability of exceeding a load of 1000t in any given year at Weany Creek, we would expect to exceed this load 20% of the time under a high rainfall and low cover scenario (worst case), compared to 9% when both rainfall and cover are high and 0.2% of the time under the low rainfall and high cover scenario.

Results: Upper Burdekin

We fitted a Bayesian hierarchical spatio-temporal model to the Upper Burdekin, employing dimension reduction techniques to assist with the estimation of model parameters. We fitted a model to 21 years worth of data (1986-2007). The model integrates Source Catchments modelled output with measurements at 5 sites in the Upper Burdekin that had limited data. Informative priors for the measured flow and concentration were based on expert opinion. Output from the model consisted of:

- **Daily predictions** of concentration, flow and the load for the 5 sites with data along with 95% credible intervals for the predictions to provide an indication of the confidence of these model predictions.
- **Annual loads** of the load (based on a financial year) for the 5 sites with data along with 95% credible intervals for the predictions to provide an indication of the confidence of these model predictions.
- **Exceedance probability maps** for concentration, flow and the load for each financial year. These can be used to prioritise future investment in the catchment as they can

highlight persistent erosion areas in the catchment. The exceedence probability maps can also be used to inform targeted monitoring in the area, particularly in areas of the catchment that have a high generation of concentration and potentially high flows.

- **A forecast** of the 2008/2009 financial year daily generation of concentration, flow and the load as well as the total load estimated for the year with a measure of confidence.

The daily predictions for each site mimicked the pattern of Source Catchments output and where data was available, provided an estimate that represented a blending of the two. We found the following interesting results from our modeling exercise:

- **Estimates of concentration** for the Sellheim site (end of catchment) were similar to Source Catchments when data was not available. However, for sites such as the Running and Star Rivers, our predictions were quite different from Source Catchments and in fact, we produced estimates that were much lower. Previous work in the Upper Burdekin (Bainbridge et al., 2013) indicates that the Source Catchments outputs for these sites (and potentially others) may be overestimating concentration and further investigation into how Source Catchments generates concentration and the process level understanding of concentration in this model is required.
- **Annual load predictions** for the Sellheim site matched expectations and in fact, mimic the loads that were estimated for the Inkerman Bridge site in the Burdekin (Kuhnert et al., 2012). Higher loads predicted for the 1990/91 financial years in particular are estimated with low precision, indicating a lack of confidence around these predictions.
- **Exceedence probability maps for concentration** show high generation of concentrations along the Clarke River (western arm of the Upper Burdekin) and in the top west part of the Upper Burdekin (near the Dry River). This finding matches recent explorations by Bainbridge et al. (2013), who found the Clarke River and sites in the top western part of the catchment generated large concentrations compared to other sites. Flows for these sites have been found to be much lower than other sites and this has been confirmed by our modeling. Load generations predict lower for these regions as a result, with exceedence probabilities much lower than other sites. High generations of loads also varied temporally, with the 1990/91 financial year exhibiting high and persistent exceedence of loads. This pattern was also noted in Kuhnert et al. (2012) where high loads were estimated for the 1990/91 water year for the Inkerman Bridge site that appeared to be related to high cyclonic activity in the lead up to that year.
- **The forecasted concentration, flow and the load** for the 2008/09 financial year did a reasonable job at predicting each of these measures given there was a large unexpected event in 2008/09. The prediction for concentration from July-January showed considerable error in this 6 month period which may be reflecting lack of data collected for this period and variation in concentration output from the Source Catchments model. The prediction for flow shows confidence in predictions leading up to the wet season. During the wet season, flow is estimated reasonably well over the period but appears to miss a consistent high flow reading (the result of a

persistent high flow). As a result, the load forecasted by this model is lower than expected. As the 2008/09 period is unusual in that it represented a much higher event than expected over the period, the model has a difficult time forecasting it. For the model to do a better job at prediction, we would need to capture this type of variability in the BHM. Incorporating rainfall into the model could also help improve this prediction further.

Benefits and Application

The BHM framework is extremely powerful. It makes use of all of the available information from the measurements as well as the models and as a result, the potential applications of the approach are widespread. The framework can be considered an information product that enables the exploration of a wide range of decision making questions that have been difficult to address in the past using either measurements or models separately. The key questions that can be addressed using this framework are:

- How do we prioritise areas within a catchment to obtain improvements in loads?
- What are the sources of loads? Are they predominantly generated by gullies, or are some due to hillslopes or bank erosion?
- Where is information lacking (i.e. the source of the uncertainty is high)? Where do we need to invest more effort in understanding the load at a site?
- How can we better inform the target setting process to ensure confidence in our decisions?

In this report we demonstrated this methodology using just two case studies but its application is much more widespread. The approach is applicable to other catchments and other constituents, which can also be modelled using the BHM framework. Furthermore, we could also consider incorporating other types of measurements and methods (e.g. tracing techniques) that lead to a better understanding of load generation. Although each catchment and constituent is expected to exhibit unique characteristics and processes, the lessons learned about the implementation of the BHM approach will greatly benefit future applications.

Future Direction and Challenges

In this report we demonstrated the BHM framework for blending measurements with process model outputs using two case studies and focused predominantly on modeling flow and concentration and the subsequent load. One of the biggest advantages of the framework presented here is the ability to predict and forecast concentrations, flows and loads with a level of confidence. We were also able to identify aspects of the Source Catchments model where the underlying process level understanding does not match expert thinking or scientific studies (e.g. Running and Star River concentrations).

We spent considerable effort in this project to ensure the modeling framework could adequately accommodate the size (i.e. number of spatial locations and time points) and highly variable nature of the data, where the computations could be performed feasibly. We

also ensured that the framework is general enough to accommodate other types of concentrations (e.g. nutrients), catchments of different sizes and having different qualities of data. Further work is required to:

1. **Validate both models** (Weany Creek and Upper Burdekin) to ensure they are fit for purpose. This requires omitting periods where we have data, refitting the model and estimating concentrations, flows and loads for the periods that were missing to determine how good the model captures the measurements.
2. **Extend the model to incorporate the erosion processes.** This requires specifying a multivariate process as discussed in Cressie and Wikle (2011) which includes concentration, flow and each of the erosion processes. This will be beneficial to disentangle the sources of the erosion contributing to the load in the catchment.
3. **Translate the methodology across to a faster platform** such as the CSIRO developed LibBi package. This package has been developed specifically for state-space modeling constructed in a BHM framework using particle Markov Chain Monte Carlo methods. The advantage of moving to LibBi is the fast implementation of the methodology and ability to use parallel processing for the computational aspects of the modeling.
4. **Evaluate scenarios** of the Upper Burdekin catchment to examine the changes in loads with changing cover and potentially changing climatic conditions.
5. **Link catchment models with receiving waters.** There is a clear need to link catchment model outputs with marine models to understand how the sources of loads in the catchments are impacting the GBR lagoon and whether certain scenarios of environmental change or management intervention in the catchments can lead to a change in the marine life in the lagoon. One of the models developed within CSIRO and part of eReefs is a Marine biogeochemical model. Using ensemble methods, the linkage of the two is conceptually straightforward where the outputs from the catchment BHM (posterior probability distributions) can feed into the marine biogeochemical model through by sampling the posterior distribution of the catchment BHM. Through this linkage, it is envisaged that scenario investigations occurring in the catchments can feed into the prior distributions for the marine model to examine changes to the marine environment. This approach has the potential to highlight hotspots where load exceedance probabilities are high and lead to more informative and scientifically defensible targets in the marine region.
6. **Inform target setting using exceedance probability maps.** Develop a methodology for using the outputs from this modeling approach to inform target setting practices.

Introduction

As part of the Reef Water Quality Protection Plan (Reef Plan) there is a requirement to reduce the export of nutrients, sediments and pesticides to the Great Barrier Reef (GBR) lagoon (Brodie et al., 2009). Underpinning strategies, such as the Reef Rescue Water Quality Grants, the Paddock to Reef Integrated Monitoring, Modelling and Reporting (P2R) Program and the Reef Rescue Research and Development Program are aimed at measuring contaminant export from catchments, and then reducing those exports through the introduction of improved land management practices.

The current approach for loads estimation feeding into the P2R baseline report card uses a process model to estimate loads from a subset of catchments in the GBR and measurements from monitoring for the remainder (with quantified certainties), providing two different estimates of loads that need to be integrated into the P2R report. See Kroon et al. (2012) for an example and Kuhnert et al. (2012) for details regarding the statistical model developed for monitoring data.

In the context of pollutant loads for the GBR there is a direct need to “blend” the model output from Source Catchments with measurements obtained through monitoring to provide more accurate estimates of pollutant loads, with estimates of certainty, to help address key questions for management, namely:

1. How do we prioritise areas within a catchment to obtain reductions in loads?
2. What and where are the sources of loads?
3. Where is information lacking (i.e. sources of uncertainty are high) and where do we need to invest more effort in collecting more data?

The work outlined in this report develops a methodology for blending measurements with models using a Bayesian Hierarchical Modelling (BHM) approach (Gelman, 2004). We begin with an outline of the proposed methodology, beginning with a single site where extensive measurements and model outputs are available through time. We then extend the methodology to a catchment with information in space and through time. We apply the methodology to two case studies: (1) Weany Creek and (2) the Upper Burdekin, where we showcase the approach and demonstrate how the outputs from the models can lead to more informed decision making. We also identify research gaps where further work is required to ensure this methodology can be operational at larger spatial and temporal scales.

Project Objectives

The objectives of this project are:

1. Provide a robust framework for coupling monitoring data with a physical process-based model (e.g. Source Catchments) to produce a combined estimate of loads with uncertainties that incorporates the errors associated with the model and the measurements collected about the process.
2. Illustrate the methodology using two case studies in the Burdekin catchment: (1) Weany Creek and (2) the Upper Burdekin.

3. Collaborate with NRM catchment modellers on the implementation of the approach within the Source Catchments framework.
4. Develop realistic management scenarios for the trial area within the modelling framework to investigate changes due to management.
5. Engage with Queensland Government P2R monitoring staff (and other P2R project partners) to ensure that the outputs can be used to facilitate reporting.

Methods

Bayesian Hierarchical Modelling Framework

We adopt a Bayesian Hierarchical Modelling (BHM) framework and follow the concepts of Berliner (2003), Cressie and Wikle (2011) and more recently Leeds et al. (2013), to construct a model for quantifying sediment loads with some level of confidence. This type of modeling framework is necessary to ensure we capture the highly complex nature of the data, process understanding and large and small scale variability in space and time.

If we let z represent data on some underlying process y , with process model parameters θ and statistical parameters, s , we can factor the joint distribution of all the parameters in the model as being proportional to the data, process and parameter model as

$$[z, y, \theta, s] \propto [z | y, s] \times [y | \theta] \times [\theta, s]$$

where

$$[z | y, s] = \text{data model} \quad (1)$$

$$[y | \theta] = \text{process model}$$

$$[\theta, s] = \text{prior parameters model}$$

and $[]$ represents some appropriate probability distribution. Figure 1 conceptually illustrates the BHM framework.

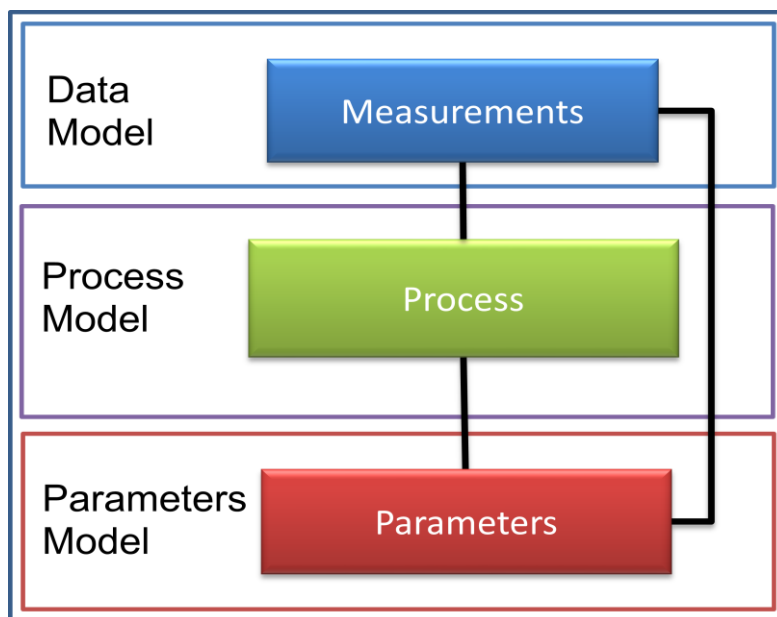


Figure 1: Bayesian Hierarchical Modelling Framework for integrating measurements with models consisting of a data model component, a process model component and a parameters model component.

BHM for a Single Site

The general BHM framework can be used to develop a model for daily sediment loads captured at a single site as in the case of Weany Creek (case study outlined below). We present a hybrid model for capturing flow and concentration processes that considers a mechanistically motivated statistical model (Kuhnert et al., 2012) for the concentration process and a hydrological model (Chiew et al., 2002, Chiew and Sirwardena, 2005) for the flow process, both of which are described in detail below.

Data Model

The data model for the observed concentration, z_t^c and flow, z_t^q at time t , is characterized using a truncated Normal distribution with a bias correction (Hooten et al., 2011) (where the truncation is at 0). The data model is conditional on the underlying processes, y_t^c and y_t^q respectively, with measurement error represented through the corresponding variances, $\sigma_{z_c}^2$ and $\sigma_{z_q}^2$ as shown in Equation 1.

$$\begin{aligned} z_t^c | y_t^c, \sigma_{z_c}^2 &\sim TN(y_t^c, \sigma_{z_c}^2) \quad \text{observed concentration} \\ z_t^q | y_t^q, \sigma_{z_q}^2 &\sim TN(y_t^q, \sigma_{z_q}^2) \quad \text{observed flow} \end{aligned} \quad (2)$$

Process Model

Zero-inflated truncated Normal models are proposed for the concentration and flow processes (Equation 2). These models were considered to take into account the large proportion of zeros that are expected in an ephemeral creek such as Weany creek. Terms for the first component of the model explain the generation of the concentration or flow, while the terms for the second component attempt to characterize the size of the generation using a bias corrected truncated Normal (TN) distribution (Hooten et al., 2011).

The mechanistically motivated statistical model, LRE (Kuhnert et al., 2012) is used to represent the concentration process of the system. This model is motivated by the hydrology of the system, history of flow (AR1 model), seasonal changes as well as cover, which has been shown to be an important factor in sediment movement (Kuhnert et al., 2012). Terms introduced in Equation 3 are based on a matrix of covariates, $\mathbf{x}_t^c$ identified by Kuhnert et al. (2012) in the LRE model developed for the Burdekin end of catchment site, Inkerman Bridge. In this model specification however, we construct a set of empirical orthogonal basis functions using a singular value decomposition of $\mathbf{x}_t^c$ to assist with the estimation of the model. The zero-inflated model has a probability of generation, p_{c_t} or p_{q_t} at time t that relate to concentration and flow respectively. These probabilities are modelled as a function of rainfall, where rainfall for the current day ($rain.d_t$), past week ($rain.w1_t$), past two weeks ($rain.w2_t$) and past month ($rain.w4_t$) are used as predictors in a logistic model as shown in Equation 3.

$$y_t^c | \mu_t^c, \sigma_{y_c}^2 \sim \begin{cases} TN(\mu_t^c, \sigma_{z_c}^2) & \text{with probability } p_{c_t} \\ 0 & \text{with probability } 1-p_{c_t} \end{cases} \quad \text{statistical model (LRE)}$$

where

$$\mu_t^c = b_1 y_{t-1}^c + b_2 y_{1,t-1}^q + \gamma \mathbf{x}_t^c \quad (3)$$

and

$$\text{logit}(p_{c_t}) = a_{c1} + a_{c2} \text{rain}.d_t + a_{c3} \text{rain}.w1_t + a_{c4} \text{rain}.w2_t + a_{c5} \text{rain}.w4_t$$

The process model defining the hydrology of the system is based on a rainfall-runoff model (SIMHYD) (Chiew et al., 2002, Chiew and Sirwardena, 2005) that consists of a system of deterministic equations with nine input parameters, $\boldsymbol{\theta} = (\theta_1, \dots, \theta_9)$.

$$y_{:,t}^q | \mu_t^q, \sigma_{z_q}^2 \sim \begin{cases} TN(\mu_t^q, \sigma_{z_q}^2) & \text{with probability } p_{q_t} \\ 0 & \text{with probability } 1-p_{q_t} \end{cases} \quad \text{hydrological model}$$

where

$$\mu_{1t}^q = f(\boldsymbol{\theta}, y_{:,t-1}^q) \quad (4)$$

and

$$\text{logit}(p_{q_t}) = a_{q1} + a_{q2} \text{rain}.d_t + a_{q3} \text{rain}.w1_t + a_{q4} \text{rain}.w2_t + a_{q5} \text{rain}.w4_t$$

where $f(\boldsymbol{\theta}, y_{:,t-1}^q)$ represents SIMHYD using information at the previous time point, $t-1$ with forcing variables, rainfall and potential evapotranspiration (PET) and parameters, $\boldsymbol{\theta}$. The flow process, y_{t-1}^q consists of two different types of flow generations, one due to runoff and the second due to groundwater that arise from the SIMHYD model. We are interested in predicting runoff (or flow) in this model. Table 1 outlines the key parameters in the SIMHYD model. As in the process model for concentration, we also model the probability of generating a flow as a function of rainfall.

Table 1: SIMHYD input parameters.

Parameter	Description
θ_1	Impervious threshold (fixed)
θ_2	Rainfall interception store capacity
θ_3	Soil moisture store capacity
θ_4	Infiltration coefficient
θ_5	Infiltration shape
θ_6	Interflow coefficient
θ_7	Recharge coefficient
θ_8	Baseflow coefficient
θ_9	Pervious Fraction (fixed)

Parameters Model

The parameters for this model consist of the measurement error for the observed concentration σ_{zc}^2 and flow σ_{zq}^2 , the process error for concentration σ_{yc}^2 and process error for flow σ_{yq}^2 , coefficients for the rainfall parameters, $\mathbf{a}_q = \{a_{q_1}, \dots, a_{q_5}\}$ and $\mathbf{a}_c = \{a_{c_1}, \dots, a_{c_5}\}$, the SIMHYD parameters, $\boldsymbol{\theta} = \{\theta_1, \dots, \theta_9\}$ and parameters, $\mathbf{b} = \{b_1, b_2\}$ for the concentration model. To ensure the model parameters are identifiable, we assume σ_{zc}^2 and σ_{zq}^2 are known and base their values on experimental data, the details of which are outlined in the case studies section of this report. The priors placed on the remaining parameters are as follows

$$\begin{aligned} \sigma_{yc}^2 &\sim \text{IG}(1,10); \sigma_{yq}^2 \sim \text{IG}(1,10), \\ \theta_1 &= U(0,5), \theta_2 \sim U(0,5), \theta_3 \sim U(1,500), \theta_4 \sim U(0,400), \theta_5 \sim U(0,10), \\ \theta_6 &= U(0,1), \theta_7 \sim U(0,1), \theta_8 = U(0,1), \theta_9 = U(0,1), \\ \mathbf{b} &\sim N(\underline{0}, \underline{\sigma}_b), \underline{\sigma}_b = 1000, \mathbf{a} \sim N(\underline{0}, \underline{\sigma}_a), \underline{\sigma}_a = 1000 \end{aligned}$$

where IG represents the inverse gamma distribution, U represents a uniform distribution and N represents a Normal distribution.

BHM for a Catchment with Multiple Sites

The BHM framework expressed in Equation 1 can be expressed in a spatio-temporal modelling framework where we consider multiple sites in space and time with outputs from the Source Catchments (SC) model which characterizes the system processes at each of those sites. The spatial and temporal dimension to the problem presents a complexity to the estimation and analysis since we have many sites in time to estimate and the dependencies between locations at different time points need to be accommodated. Furthermore the spatial and temporal variability at each of these sites is expected to be large, with some sites carrying most of the load through the system while others having minimal impact. The methodology we considered therefore needs to accommodate all of these complexities in the data and be computationally feasible to cope with larger catchments and longer time series of information.

We consider an approach developed by Oleson & Wikle (2013) that performs two levels of dimension reduction to enable efficient and fast estimation of concentration, flow and the corresponding load in space and time. Dimension reduction through empirical orthogonal functions is not new and has been described extensively in Cressie and Wikle (2011) for the efficient modeling and estimation of spatio-temporal problems. We consider a first layer of dimension reduction which constructs p -seasonal basis functions, $\boldsymbol{\psi}$ that summarise the inter-annual variability across sites in the Upper Burdekin catchment. These are accompanied by a p -dimensional multivariate spatio-temporal process, (or matrix of coefficients), $\boldsymbol{\alpha}$ that weight the seasonal characteristics according to the site and year such that, $\mathbf{Y} \approx \boldsymbol{\psi}\boldsymbol{\alpha}$. The second level of dimension reduction is then performed on the $\boldsymbol{\alpha}$ matrix, which decomposes the coefficients into a q -dimensional spatial basis, $\boldsymbol{\phi}$ with corresponding coefficients, $\boldsymbol{\beta}$ that weight the spatial characteristics across years. Finally, the yearly

dynamic behaviour of the process can be captured through an autoregressive structure placed on the β coefficients. While a number of other models were explored, all of which included at least one form of dimension reduction to cope with the number of spatial and temporal outputs, this model specification was seen as ideal in terms of the ability to perform estimation of parameters in real time and being able to forecast 365 days out with estimates of uncertainty. The latter has enormous benefits to managers who may wish to explore management and climate scenarios and their potential impact on the coming year.

We explore the model for one spatio-temporal measurement (e.g. concentration) in more detail in Equation 1 below using the notation from Oleson & Wikle (2013). The model for flow is analogous to this with the exception to no cover in the model. The load is then calculated as the product of concentration and flow estimates. We could consider a multivariate version of this model (Cressie and Wikle, 2011) that couples flow, concentration and other processes e.g. erosion. However as a first consideration, we outline separate models for concentration and flow in this report and explore moving to a multivariate space-time model in the Discussion.

Data Model

Let $z_{ijk} = z(s_i; t_{jk})$ be a measure of concentration for location $i = 1, \dots, n$, day $j = 1, \dots, T$ of year $k = 1, \dots, K$ where s represents the the location in space and t represents time. Let z_{ijk}^* represent a power transformation of the data (for notational convenience), where the power transform consists of $((y + \lambda_2)^{\lambda_1} - 1) / \lambda_1$ where λ_1 represents the power transform and λ_1 is a small value (typically 0.5 times the minimum non-zero value of the data). We set λ_1 to 0.1 for both concentration and flow. Then

$$z_{ijk}^* = y_{ijk}^* + e_{ijk}^*, \quad e_{ijk}^* \sim N(0, s_{z^*}^2)$$

where $s_{z^*}^2$ represents the error for each measure of concentration.

Process Model

Let y_{ik}^* represent the underlying concentration process (transformed scale) as modelled from Source Catchments (SC) for location $i = 1, \dots, n$, and year $k = 1, \dots, K$ such that

$$y_{ik}^* = \psi \alpha_{ik} + \varepsilon_{ik}, \quad \varepsilon_{ik} \sim N(0, \sigma_e^2)$$

Here, y_{ik}^* represents a log transformation of y_{ik} to make the outputs from Source Catchments Normal. In the above expression, $\psi = [\psi_1, \dots, \psi_p]$, and $\psi_l = (\psi_l(1), \dots, \psi_l(T))$, are $T \times 1$ vectors of orthogonal basis functions that account for inter-annual dependence in the outputs, where $T =$ the number of days (365), $l = 1, \dots, p$ and $\alpha_{ik} = (\alpha_{ik}(1), \dots, \alpha_{ik}(p))'$ are the corresponding expansion coefficients. As highlighted in Oleson & Wikle (2013), we can think of α_{ik} as a p -dimensional multivariate spatio-temporal process and consider a restructure of these coefficients to $\tilde{\alpha}_k(l) = (\alpha_{1k}(l), \dots, \alpha_{nk}(l))'$ for $l = 1, \dots, p$. In other words, $\tilde{\alpha}_k(l)$ represents a spatial field corresponding to the l -th seasonal basis function expansion

coefficient and the k -th year. We can write this np -dimensional vector as

$\tilde{\alpha}_k = (\tilde{\alpha}'_k(1), \dots, \tilde{\alpha}'_k(p))'$, for $k = 1, \dots, K$. This results in a concatenated vector of p separate n -dimensional spatial fields for each year, k .

We propose a second dimension reduction on the expansion coefficients $\tilde{\alpha}_k$ such that

$$\tilde{\alpha}_k = \phi \beta_k + \lambda X_k + \gamma_k, \quad \gamma_k \sim N(0, \Sigma_\gamma)$$

$$\text{where } \phi = [\phi_1, \dots, \phi_q], \text{ and } \phi = (\phi_{11}, \dots, \phi_{n1}, \phi_{12}, \dots, \phi_{n2}, \dots, \phi_{np})'$$

$$\text{and } \beta_k = (\beta_k(1), \dots, \beta_k(q))'.$$

In the above expression, X_k represents a n -dimensional vector of cover values (expressed as a percentage) that reflects changes in cover across K years for each of n sites with corresponding coefficient, λ that will examine the impact of cover through time and in space.

Finally, the variability in yearly dynamics for the q -dimensional vector of coefficients, β_k can be modeled using an autoregressive structure as shown by the following expression.

$$\beta_k = M \beta_{k-1} + \eta_k, \quad \eta_k \sim N(0, \Sigma_b), \quad k = 1, \dots, K.$$

Here, M represents a $q \times q$ dimensional transition matrix with the error being modeled as a Normal distribution with variance, covariance matrix, Σ_b .

Parameters Model

The prior probability distributions for the parameters in both the data and process models are outlined below, where IG represents the inverse gamma distribution, N represents a Normal distribution, W represents a Wishart distribution. All parameters have been assigned a non-informative distribution with the exception to the prior placed on the measurement variance, where we have assigned a value relative to the process error to reflect higher confidence in the measured data with respect to the process. The prior for Σ_b^{-1} was also chosen to be non-informative with scale matrix, $S^{-1} = s^2 \nu I$, ν is the degrees of freedom and I is the identity matrix.

$$\begin{aligned} \sigma_\varepsilon^2 &\sim IG(q_\varepsilon, r_\varepsilon), \text{vec}(M) \sim N(0, \sigma_M) \\ \lambda &\sim N(0, \sigma_\lambda), \sigma_\gamma^2(l) \sim IG(q_\gamma, r_\gamma) \\ \text{vec}(M) &\sim N(\mu_M, \Sigma_M), \Sigma_b^{-1} \sim W((\nu S)^{-1}, \nu) \end{aligned}$$

Case Study I: Weany Creek

This study was carried out in the Weany Creek catchment (S19°5306.79, E146°3206.65), which is dominated by Eucalypt savanna woodland. The catchment is contained within

Virginia Park station which is a privately owned cattle grazing property. The area is representative of the highly erodible goldfields (granodiorite) country between Townsville and Charters Towers in North Queensland, Australia, and has been grazed for more than 100 years. Weany Creek is an ephemeral 14 km² catchment of the larger Burdekin catchment (130,000 km²; Figure 2). The Weany Creek catchment (Figure 2b) was chosen for this study as it had a long term (>10 year), high frequency, flow and sediment concentration measurements (Bartley et al., In Review, Bartley et al., 2010). Figure 3 shows plots of the Weany Creek data over the 11 year period consisting of flow, TSS concentration, rainfall, PET and cover that were used to develop the model. An outline of these datasets is presented below.

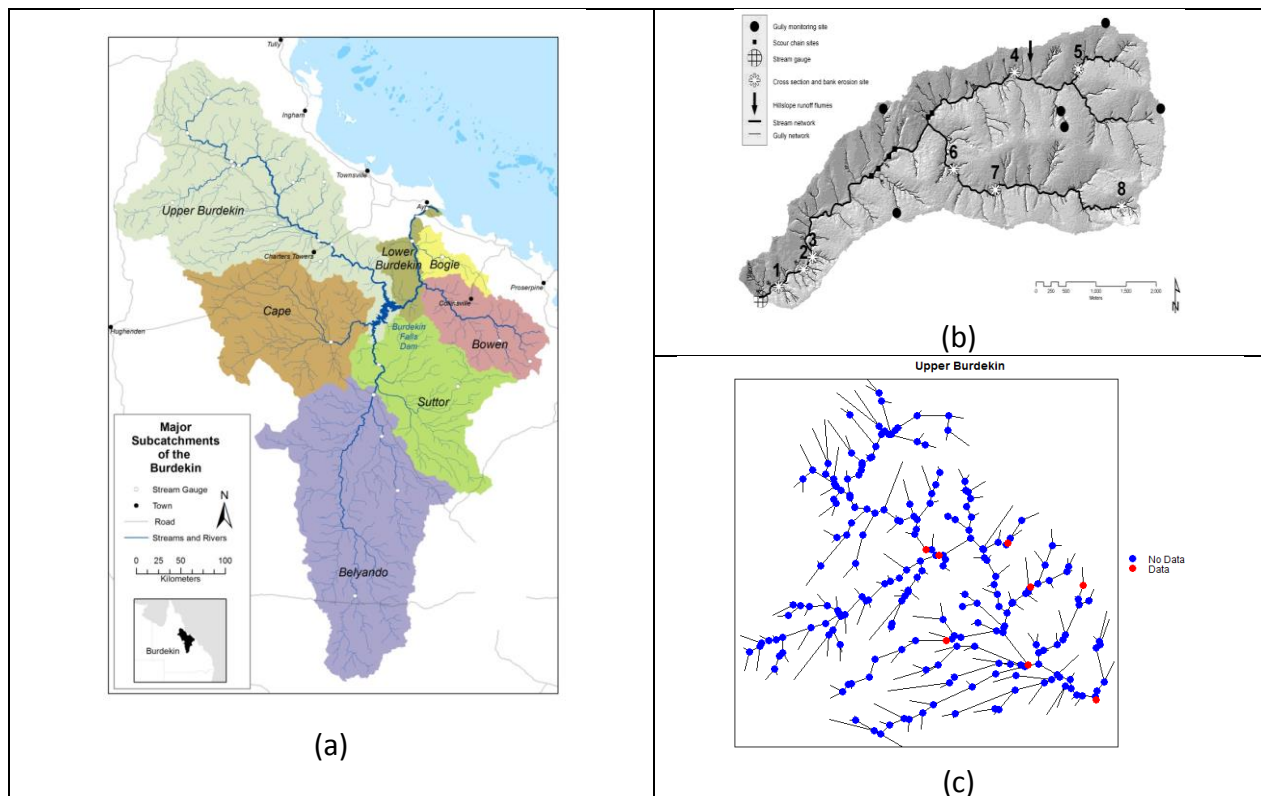


Figure 2: The Burdekin catchment shown in (a) is the focus for this work which contrasts (b) a single, well sampled site, Weany Creek (14 km²) and (c) a larger, multi-site catchment, the Upper Burdekin (40,000 km²) that contains 411 nodes.

Field measurements

An automatic gauging station that measured catchment runoff and sediment concentration was installed at the outlet of Weany Creek in 1999 (Figure 3). The gauging station recorded rainfall, stage height, flow velocity, turbidity and water temperature at one-minute intervals during events, noting that Weany Creek is ephemeral (no flow) during low rainfall years and flows for approximately 5% of the year. In above average rainfall years, the creek may flow for more than 6 months of the year. Details of the monitoring equipment and water sampling design of the gauging site are given in Bartley et al., (2007, 2010) and Hawdon et al., (2009). To estimate sediment concentration, a 1 L water sample was collected at programmed intervals across the hydrograph. A linear relationship between total suspended

sediment (TSS) and turbidity was developed for each water year (July 1 to June 30), see below for details. Bedload was not sampled at the catchment outlet.

Rainfall and Potential Evapotranspiration (PET) were extracted from the SILO database at the daily time step (Jeffrey et al., 2001), while vegetation cover data, expressed as a percentage, was based on an annual (end of dry season) ground cover index and obtained from the Department of Environment and Resource Management (Queensland Remote Sensing Centre) (Scarth et al., 2006).

Priors for Errors in Flow

We used gauging data to calculate flow and quantify the uncertainty in flow at the Weany Creek site. As highlighted by Tomkins et al. (2012), uncertainty in flow is often ignored in its calculation using stage height data. Using a statistical approach, we quantify the errors in flow calculations using two statistical relationships. The first is the statistical relationship between velocity and depth d (mm). The second is the statistical relationship between flow area A (m²) and depth. The product of the predicted velocity and flow area then provides an estimate of the flow and when constructed in a Bayesian framework we can quantify the error. Of these two relationships, the velocity-depth relationship is the most variable and is the primary source of the variability in the flow calculation presented here. We use a Bayesian model (Equation 5) and the software program, WinBUGS (Spiegelhalter et al., 1999) to quantify the flow and its uncertainty. The model is outlined below, where diffuse priors are assigned to the parameters for each model component. Figure 4 shows the velocity and flow area relationships that were derived using these models.

Flow Area :

$$A_i \sim N(\mu_A, \tau_A)$$

$$\mu_{A_i} = \beta_1 d_i + \beta_2 d_i^2 + \beta_3 d_i^3 + \beta_4 d_i^4 \quad i = 1, \dots, N_F.$$

where β and τ_A represents the parameters to be estimated.

Velocity :

$$\log(V_i) \sim N(\mu_V, \tau_V)$$

$$\mu_{V_i} = \alpha_i + \alpha_2 \log(d_i) + \alpha_3 \log(d_i)^2 + \alpha_4 \log(d_i)^3 + \alpha_5 \log(d_i)^4 + \alpha_6 \log(d_i)^5 \quad (5)$$

where α and τ_V represents the parameters to be estimated.

Flow Calculation :

$$[Q_i | A_i, V_i] \propto [A_i | d_i] \times [V_i | d_i]$$

where $[\]$ represents the probability density function of the enclosed random variable

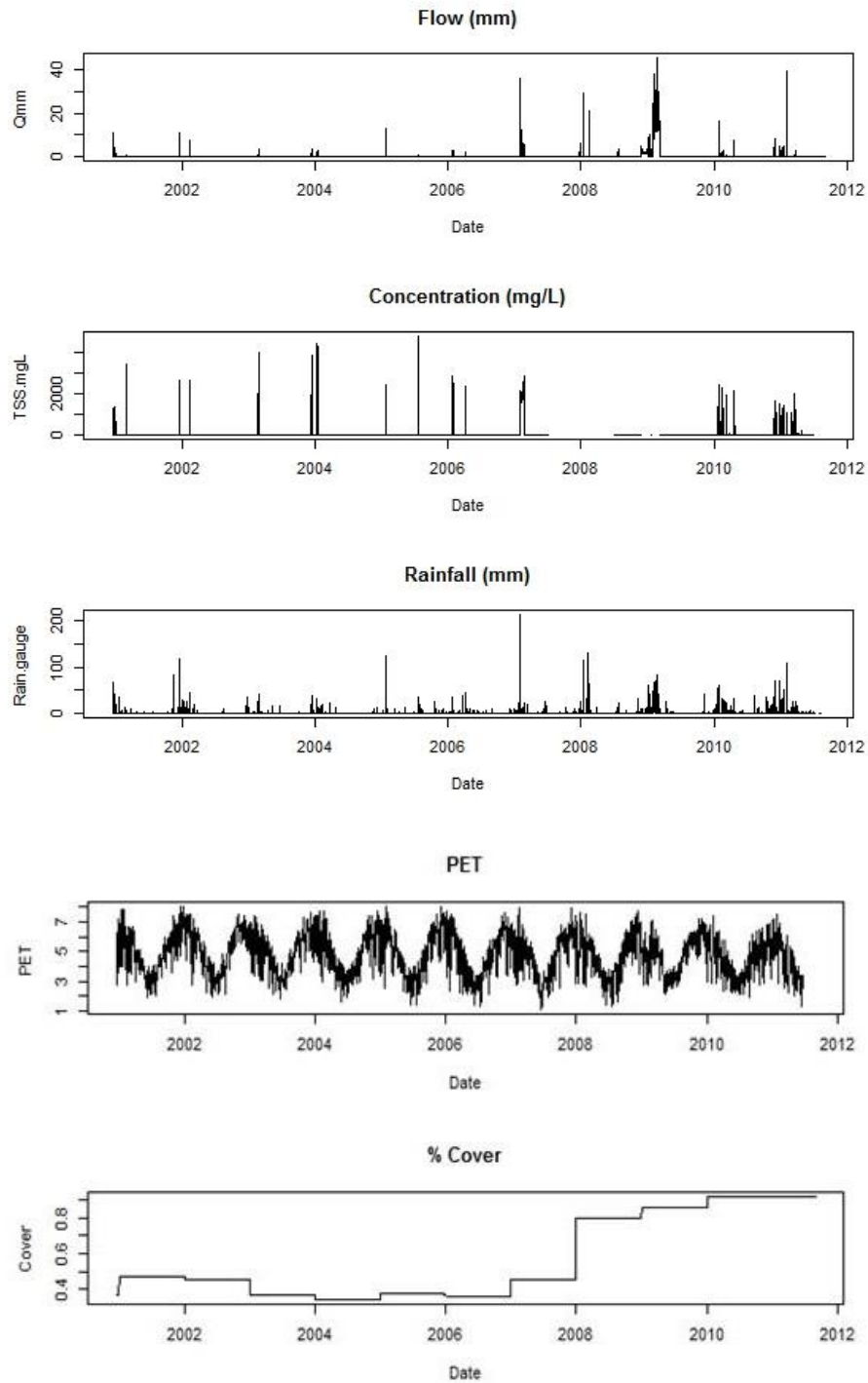


Figure 3: Weany Creek data consisting of a time series of flow (mm), concentration (mg/L), rainfall, PET and percent cover for the period 2000-2011.

The data we use to inform the velocity-depth relationship arises from velocity sensors placed at the Weany Creek site (Bartley et al., 2007, Bartley et al., 2010) for the period 2000-2011. A 5-th degree polynomial was used to construct a realistic relationship for the data that ensured predicted velocity at lower depths decreased and tapered off at larger depths. Data used to construct the flow area and depth relationship is considered deterministic.

Figure 5 shows a plot of the coefficient of variation (CV) of TSS versus the estimated daily flow and shows high variation in estimated TSS for lower values. The CVs range between 0.0001 and 17.6 (not shown on the figure to avoid distorting the plot). The higher CVs area associated with lower flow values, ranging between 0 and 7mm.

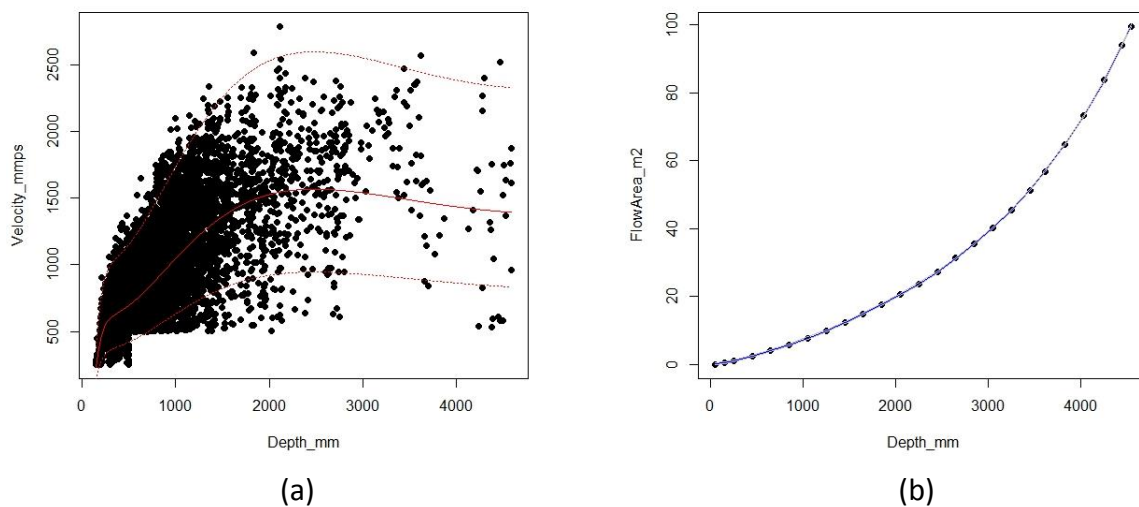


Figure 4: Derived relationships for (a) velocity and (b) flow area data with respect to depth.

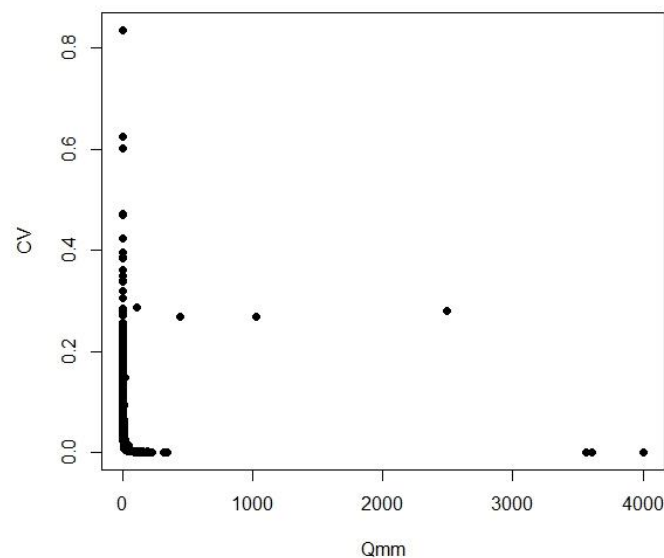


Figure 5: Errors represented as a coefficient of variation of TSS in relation to the size of the flow.

Priors for Errors in Concentration

Priors for TSS were based on a TSS-Turbidity relationship constructed from TSS and Turbidity samples collected at the Weany Creek site (Bartley et al., 2007, Bartley et al., 2010). Data was collected over an 11 year period from December 2000 through to February 2011.

Two relationships were formed from this data (Figure 6) as some of the Turbidity data collected was deemed unreliable (2007-2008) due to a tree falling on the sensor. The first relationship was based on data collected from 2000 to 2006. The second relationship was based on data collected between 2009 and 2011. The models were fit in a Bayesian framework in WinBUGS (Spiegelhalter et al., 1999), where a linear relationship between TSS and Turbidity was assumed. The two relationships are shown below for the Weany Creek site.

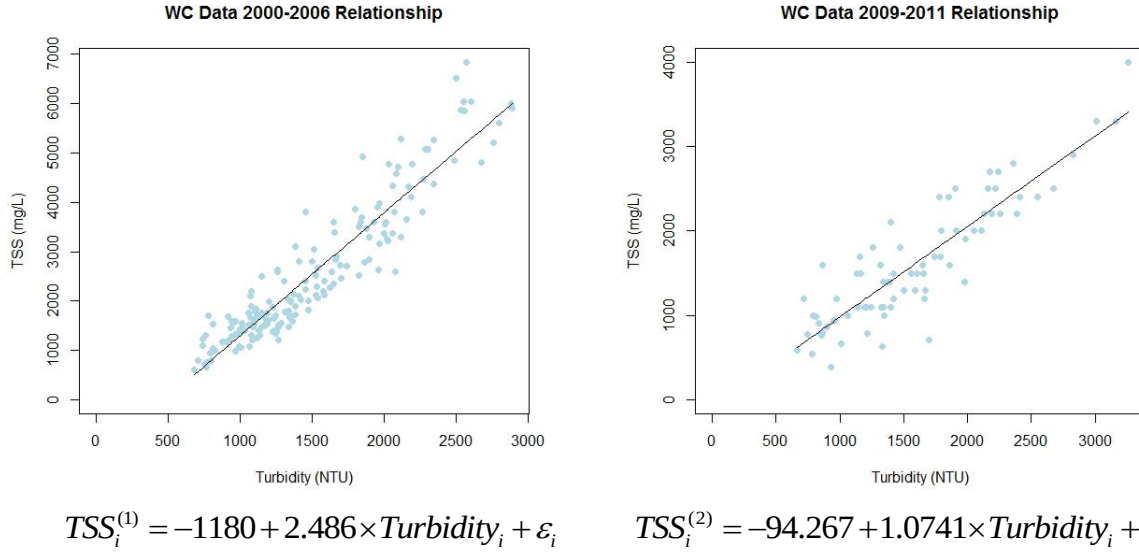


Figure 6: TSS-Turbidity relationships for Weany Creek (2000-2011).

The TSS-Turbidity relationships were applied to the Weany Creek data to provide estimates of TSS, where $z_{c_i}, (i=1, \dots, N)$ and N represents the number of Turbidity samples. Note, for the times where no turbidity data was available or was deemed unreliable (2007-2009), TSS data was assigned a missing value.

From this model a variance for TSS was estimated. A daily estimate of TSS, $z_{c_{d_i}}$, was then derived from the Weany Creek dataset by averaging TSS across the day. The corresponding variance associated with that calculation was computed accordingly as shown in Equation 6. This calculation assumes dependence between sampling times, which is a reasonable assumption since some of the samples were taken at minute intervals.

$$z_{c_d} = \frac{1}{n_d} \sum_{i=1}^{n_d} z_{c_i}, \text{var}(z_{c_d}) = \frac{1}{n_d^2} \underline{z}_c \Sigma_d \underline{z}_c^T$$

where

$\Sigma_d = n_d \times n_d$ covariance matrix

$n_d =$ no. of samples in the day

(6)

Figure 7 shows a plot of the coefficient of variation (CV) versus the estimated daily TSS and shows high variation in estimated TSS for lower values. The CVs range between 0.02 and 364.5. The higher CVs are associated with lower TSS values, ranging between 0 and 120.

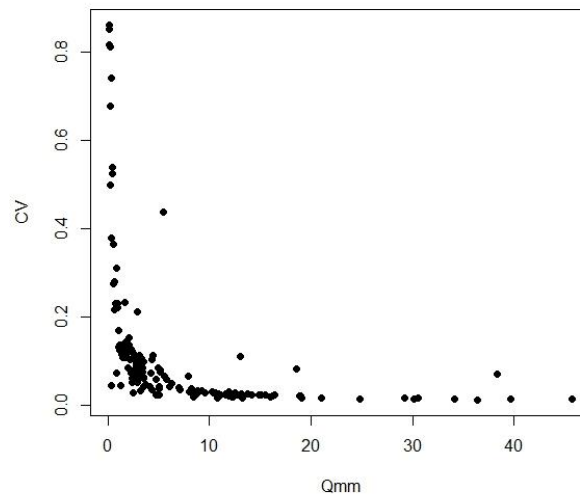


Figure 7: Plot showing the errors in relation to the size of TSS.

Case Study II: Upper Burdekin Catchment

Description of the Upper Burdekin Catchment

The Upper Burdekin catchment at the Selheim gauge (also known as Macrossan Bridge), is approximately 36,260 km², representing approximately 29% of the Burdekin catchment. The Burdekin watershed is dominated by cattle grazing (~91%) which occurs largely on native pastures within open woodland communities (DSITIA, 2012). Vegetation clearing has resulted in 25% less vegetation in 2009 compared with pre-European settlement (Great Barrier Reef Marine Park Authority, 2012). The Upper Burdekin is dominated by igneous derived soils (granodiorites and basalts) (Dight, 2009), and is known to have had periods of severe soil erosion (McCulloch et al., 2003, McKeon et al., 2004). Erosion in the Upper Burdekin has been particularly severe in the first half of the 20th Century with 12.5% or 6,900 km² of this area considered to be impacted by soil erosion resulting in an estimated soil loss of 8.63 million tonnes (Burdekin Project Committee, 1976, p 648).

Data sources

Monitoring data was provided by the Queensland Government (Department of Science, Information Technology Innovation and the Arts; DSITIA), CSIRO and TropWATER JCU for the

sites listed in Table 2. Note, many sites provided by DSITIA were from the SWAN project and collected base flow only and were therefore deemed unsuitable for this analysis. As a result, only 5 sites with monitoring data were included in this analysis. Figure 8 shows the 5 sites in the Upper Burdekin where data was obtained.

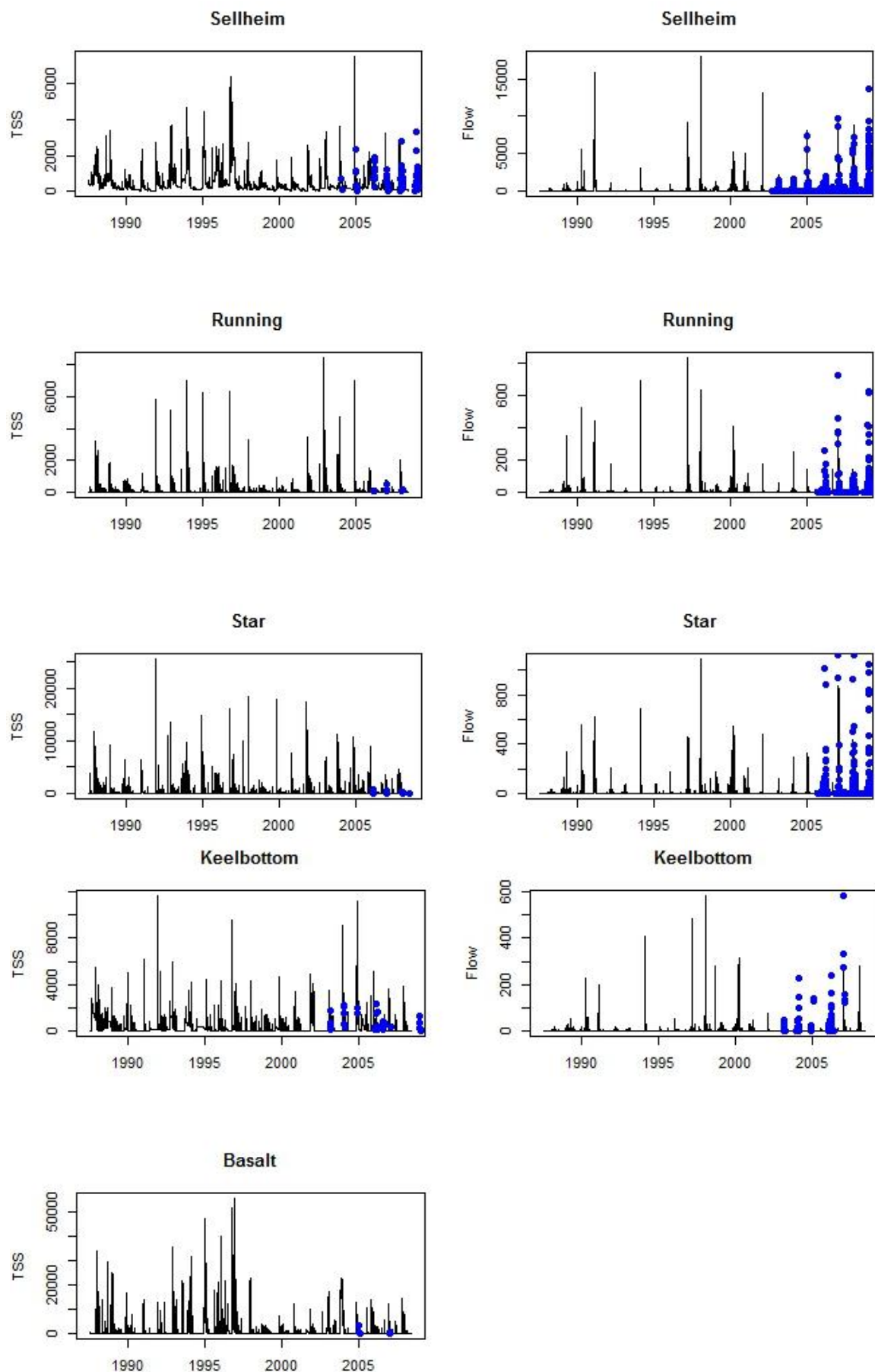


Figure 8: Plots of concentration and flow for sites with data (blue points). Black lines represent the output from the Source Catchments model.

Table 2: Summary of monitoring sites undertaken in the Upper Burdekin catchment.

Station	Stream Name	Location	Latitude	Longitude	Provider	SC node
120002C	Burdekin River	Sellheim	-20.00778	146.43694	DSTIA, TropWATER	501
120102A	Keelbottom Creek	Keelbottom	-19.37188	146.35891	DSTIA, CSIRO	163
120106B	Basalt River	Bluff Downs	-19.68205	145.5403	DSTIA, TropWATER	342
120112A	Star River	Laroon	-19.37777	146.04848	DSTIA, TropWATER	204
120120A	Running River	Mt. Bradley	-19.13201	145.90845	DSTIA, TropWATER	138

Source Catchments Output

Source Catchments output was provided for each of the 411 nodes in the Upper Burdekin and consisted of total suspended sediment concentration, flow, rainfall, PET, gully, hillslope and streambank erosion sources. We focus on using the flow and concentration outputs in a Bayesian Hierarchical Model to quantify loads in the Upper Burdekin catchment in this report. We discuss a multivariate extension to the BHM that incorporates the erosion processes in the discussion, which is left for future investigation.

BHM Implementation

The BHMs were implemented in the R statistical software package (R Development Core Team, 2008) using the Rcpp library (Eddelbuettel and Francois, 2011) that provides C++ classes that can enable faster implementation of code in R. Markov Chain Monte Carlo (MCMC) algorithms and in particular the Metropolis-Hastings algorithm was used to simulate from the conditional distributions for the Weany Creek model presented in the methods section (Metropolis et al., 1953). Typically an adaptive phase of the simulation was conducted to determine appropriate starting values for the Monte Carlo run, followed by a burn-in phase of approximately 10,000 iterations and a monitored run of approximately 10,000 iterations. The Gibbs sampling algorithm was used to generate samples from the target distributions of all parameters for the Upper Burdekin model. For this analysis, diagnostic checks were performed on the output from a model run to ensure convergence and adequate mixing of the Markov Chains as outlined in Cowles & Carlin (1996).

Results

Case Study 1: Weany Creek

Quantifying Load Estimates

The results from fitting the BHM outlined in the Methods Section are shown in Figures 9-12. Figure 9 presents predictions from the model for concentration (top) and flow (middle) with the rainfall time series presented at the bottom. Predictions are shown as a black line, while observations are overlayed as blue points and the credibility interval (80%) is shown in red. The green curve shown for flow represents an emulation of the SIMHYD model that is used to represent the flow process.

The results from the model indicate that events are picked up by the model. Errors in both flow and concentration are evident and are higher where there is little or no data (e.g. 2007/08 where a tree fell on a turbidity sensor and 2008/09 when a new sensor was being calibrated). On closer inspection of these two events (Figure 10), we see that each event was picked up by the model and estimated with a considerable source of uncertainty, particularly for 2008/09 when the sensor was calibrated. We show in Figure 10 that using this method we can estimate a load for each event with a measure of uncertainty around each estimate.

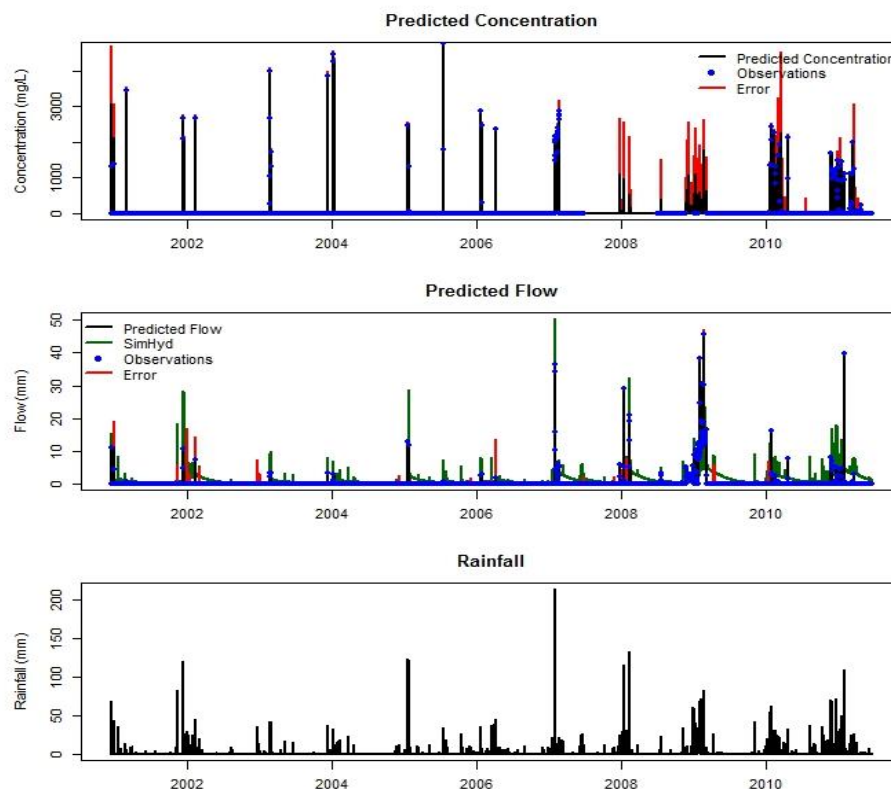


Figure 9: Predicted concentration and flow for the Weany Creek site from 2000-2011. Predictions are highlighted in black, measurements are represented by blue points and 80% credibility intervals are indicated as red lines for the first two plots. A rainfall time series is presented in the last figure.

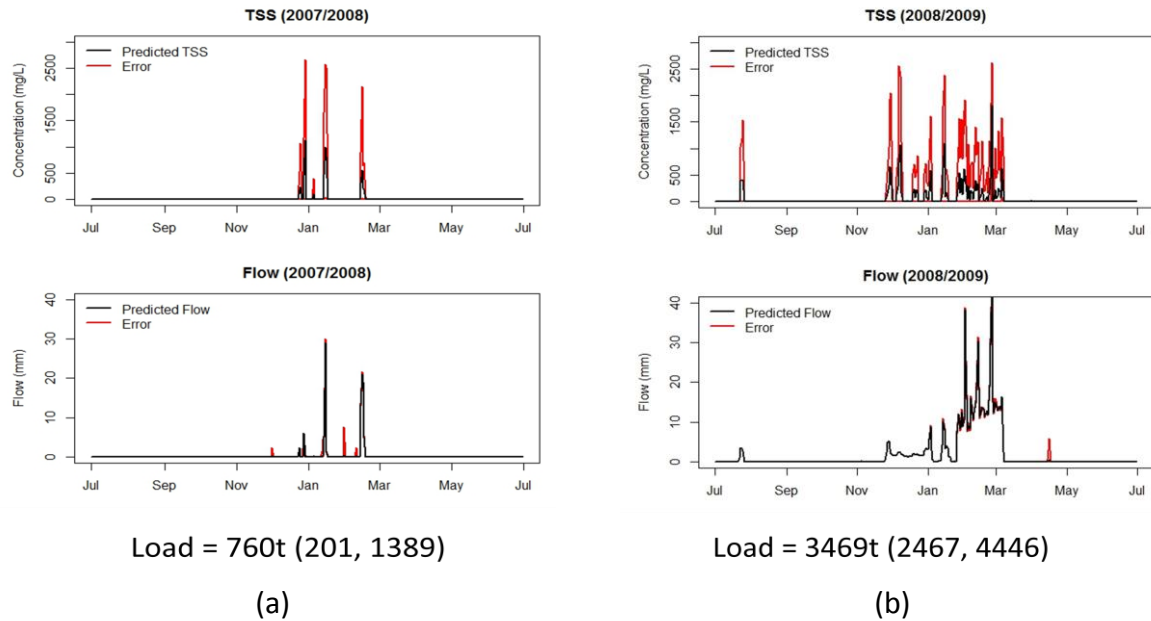


Figure 10: Two events in Weany Creek (a) 2007/2008 and (b) 2008/2009 showing the predicted flow and concentration, the corresponding error (represented as an 80% credible interval).

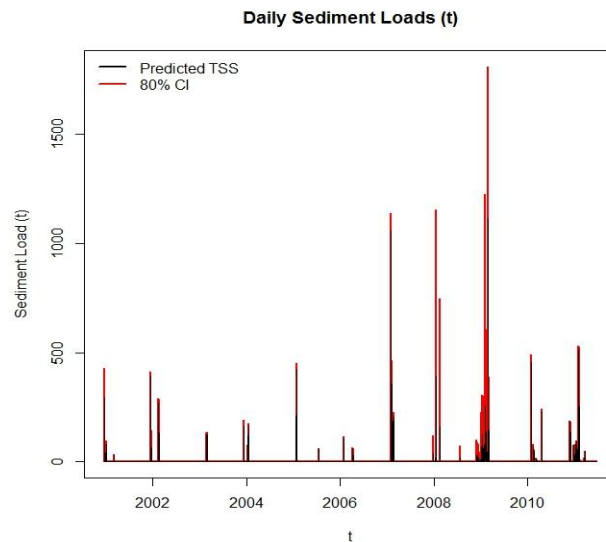


Figure 11: Daily sediment loads in tonnes for the Weany Creek catchment with 80% credible intervals.

The daily sediment load can be estimated as shown in Figure 11, while annual sediment loads with 80% credible intervals can be estimated for the 2000-2011 monitoring and modelling period, demonstrating the flexibility of the model to quantify loads with uncertainties for any time frame of reporting.

Scenario Investigations

Scenario investigations are key to understanding changes to loads in response to environmental pressures or management change. In the context of BHMs we can alter some of the main drivers of these models e.g. rainfall and cover and simulate from the posterior distributions of the model output in response to these changes to understand how the sediment loads change through time. We generated three different rainfall and cover scenarios and examined how these scenarios impacted on the sediment loads estimate

through time. We considered high and low rainfall events, based on years where high (2008/09) and low (2003/04) falls were recorded across the 11 year period. Low cover simply represented the 20th percentile of cover (36.6% cover), while high cover was represented as an 80th percentile (86.1% cover). Each rainfall and cover scenario was imposed on each year in the Weany Creek dataset. The results are presented in Figure 13, which shows the estimated annual sediment loads for each scenario and across the 11 year period. Overall, the loads are higher for the worst case scenario (red line) than the best case scenario (blue line), indicating that loads tend to be high when there is high rainfall and low cover. The uncertainty in each of these annual estimates tend to be high where data was missing (2007-2009) but also appear to be high for 2002/2003 when high rain, low cover (red line) and high rain, high cover (green line) were imposed during that year. This is also evident for the 2010/11 period. This suggests that if we did not use the BHM approach to model the processes at this site, we might be falsely confident in the results for these time periods.

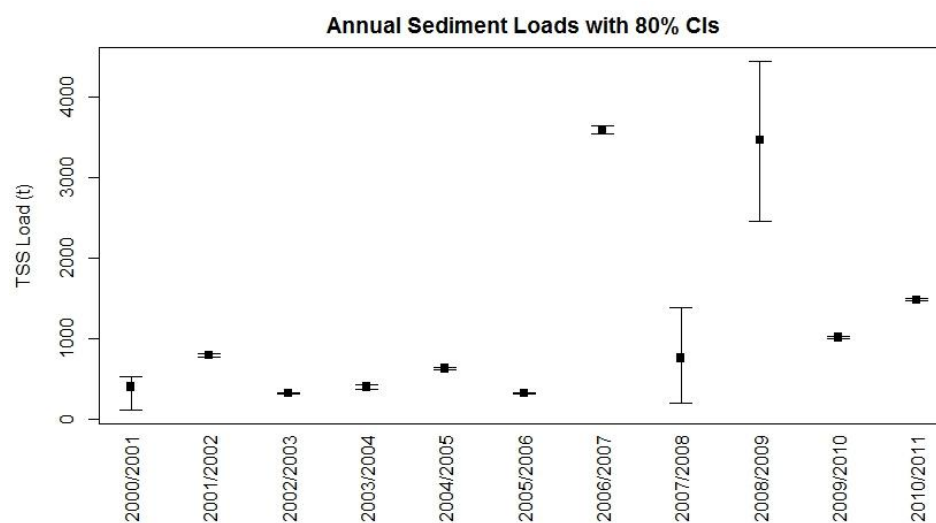


Figure 12: Annual sediment loads for the Weany Creek catchment with 80% credible intervals.

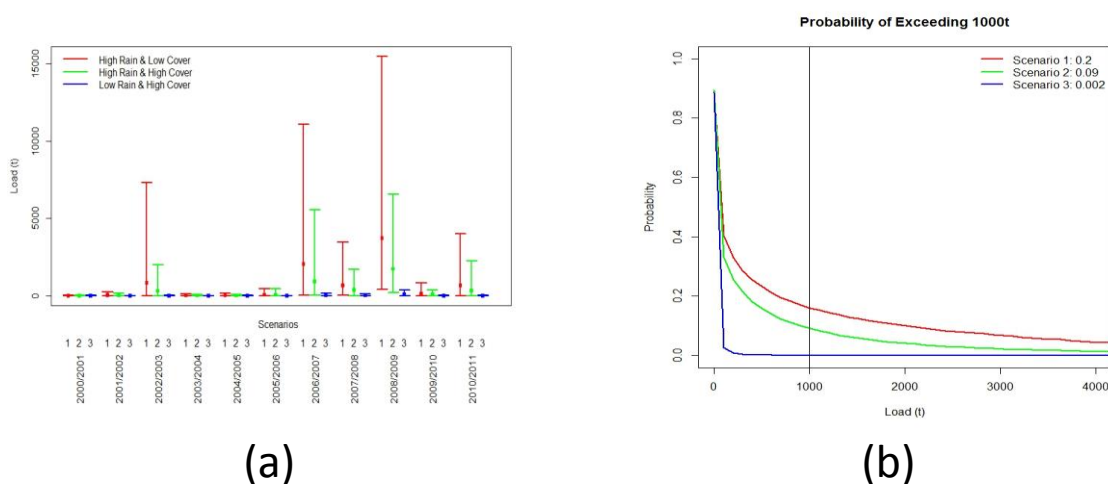


Figure 13: Scenario investigations for the Weany Creek catchment highlighting (a) changes in TSS loads across the 11 year period with changing rainfall and cover and (b) the probability of exceeding loads given each scenario.

The scenario investigations can be used to examine exceedance probability curves and in turn, target setting, where targets can be set according to a desired probability of exceedance. In Figure 13b we show 3 curves depicting probabilities of exceedance based on the three scenarios examined in Figure 13a. A vertical black line drawn at 1000t of sediment allows us to examine the probability of exceeding that load in any given year and under the 3 scenarios investigated. For example under Scenario 1, where we consider high rainfall and low cover, the probability of exceeding a load of 1000t is approximately 0.2. Under Scenario 2 (high rainfall, low cover) the probability is approximately 0.09, while under the best case scenario, the probability of exceeding the load is 0.002.

Case Study II: Upper Burdekin Catchment

Basis function expansion for flow and concentration

We constructed a seasonal basis set for the concentration output from Source Catchments that resulted in 9 basis functions (Figure 14), explaining approximately 99% of the variation in the data. These can be interpreted as the inter-annual variation in concentration common to all sites and all time points in the Upper Burdekin. We can see in this figure that the first basis function highlights differences between the wet and dry seasons. Subsequent basis functions also pick up on this behavior and also exhibit some fine scale variation. The corresponding expansion coefficients, α that weight the seasonal basis set based on site and day of the year are then structured into p separate n -dimension spatial fields which we decompose into 7 basis functions that explain nearly 97% of the variation in the data. We use this reduced rank form to model the spatial structure in the data and include spatial predictors like cover, which only change annually (Figure 15) to determine whether cover has an effect on concentration across all the sites in the Upper Burdekin and through time and therefore impacts on the load.

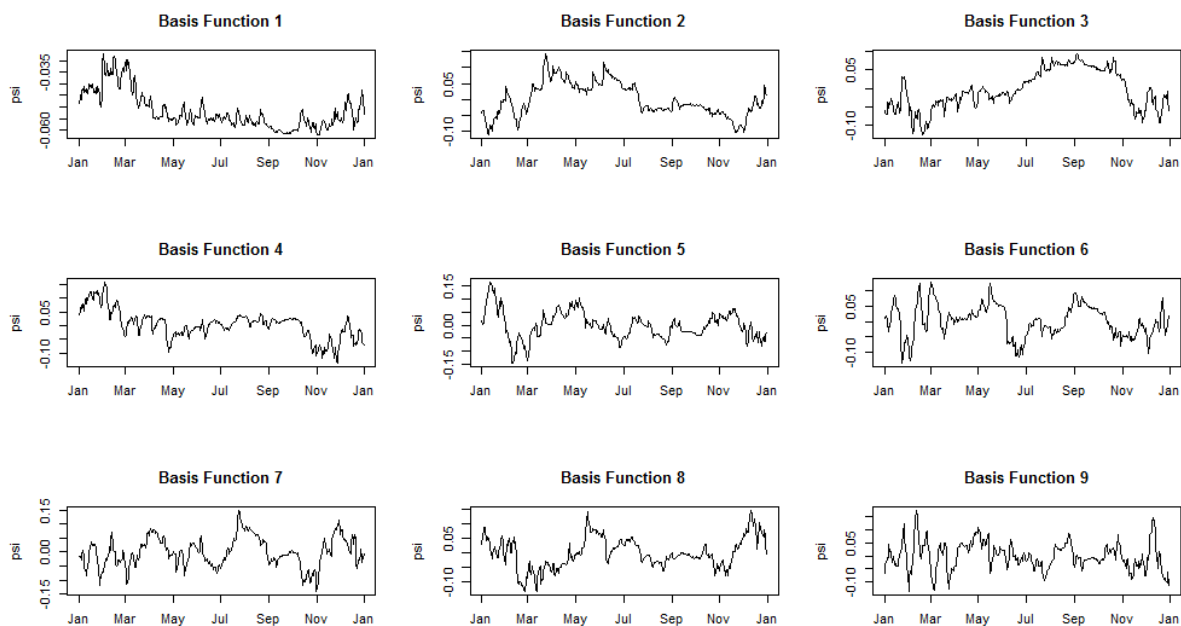


Figure 14: Seasonal basis functions for Source Catchments concentration output.

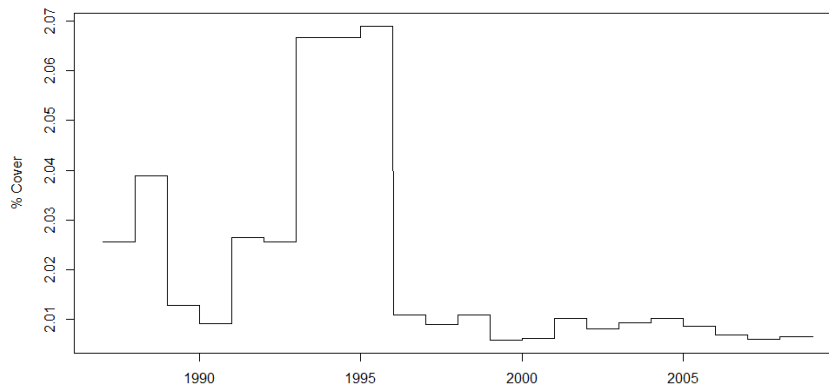


Figure 15: Cover for the Upper Burdekin site.

We also constructed a seasonal basis set for the Source Catchment flow output that resulted in 7 basis functions (Figure 16), which explained approximately 99% of the variation in the data. As for concentration, this basis set describes the seasonal variation that is common across sites and within years for the Upper Burdekin. In Figure 16 we see a much stronger pattern of inter-annual variability compared to the seasonal pattern for concentration. The first basis function distinguishes between the wet and dry season, while the second and third basis functions seem to capture some patterns in flow that occur in Autumn and Spring. Basis function 4 seems to pick up on an increasing or cumulative effect of flow, while the remaining basis functions seem to be identifying some small scale variability. These seasonal patterns almost mimic the types of hydrological processes we tend to observe and may be likened to the discounting terms that Kuhnert et al. (2012) used in the modeling of the Inkerman Bridge site in the Upper Burdekin. Using this seasonal basis set, we then constructed a second decomposition on the seasonal expansion coefficients to create a spatial basis set (as for concentration) and produced 6 basis functions with coefficients that were modelled subsequently using an autoregressive structure. This reduced basis set explained over 97% of the variation in the data.

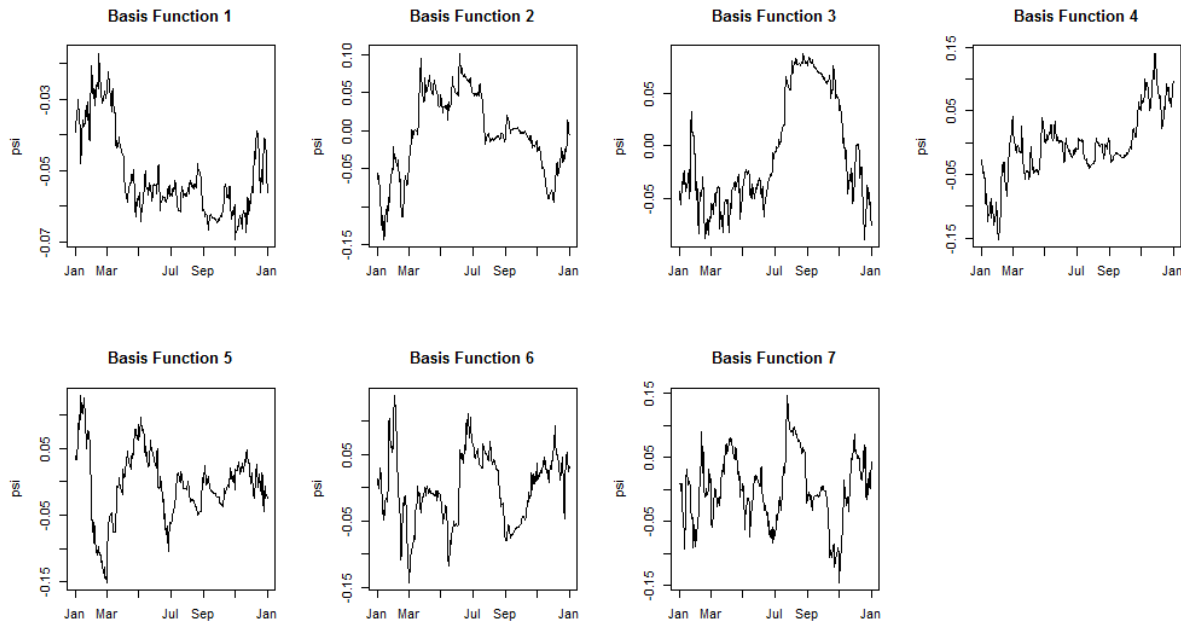


Figure 16: Seasonal basis functions for Source Catchments flow output.

Daily predictions for monitored sites in the Upper Burdekin

Results from the Upper Burdekin catchment highlight the ability of the BHM to blend measurements with modelled output from the Source Catchments model, albeit the small number of measurements available. The model is designed to provide a prediction that represents a weighted sum of the process model output and the measurements, where the weights are based on the variances of the process (and where available), the measurements. As the measurements are sparse and only span the later years, the predictions for earlier years are dominated by the Source catchments model, with model uncertainty estimated. In this particular model, we assigned smaller errors to the measurements, indicating our strong belief in the measurements of concentration and flow compared to the process model. As a result, the predictions for observations where measurements exist are more closely aligned with the measurements than the process model. In the case of the Sellheim site, the measurements actually mimic the process model output well, providing some confidence in the prediction as can be seen by the errors in the predictions and the resulting loads (Figure 17).

Figures 18-20 show similar predictions for the Running River, Keelbottom Creek, Basalt River and Star Rivers, respectively, where we had measurements. In these figures it is interesting to note that the daily predictions from the model for concentration (black line) are much lower when compared to the Source Catchments output (red line). This is particularly true for the Star and Running Rivers. On closer inspection it appears that concentrations predicted from these sites are in line with previous studies conducted in the Upper Burdekin at these sites (Bainbridge et al., 2013).

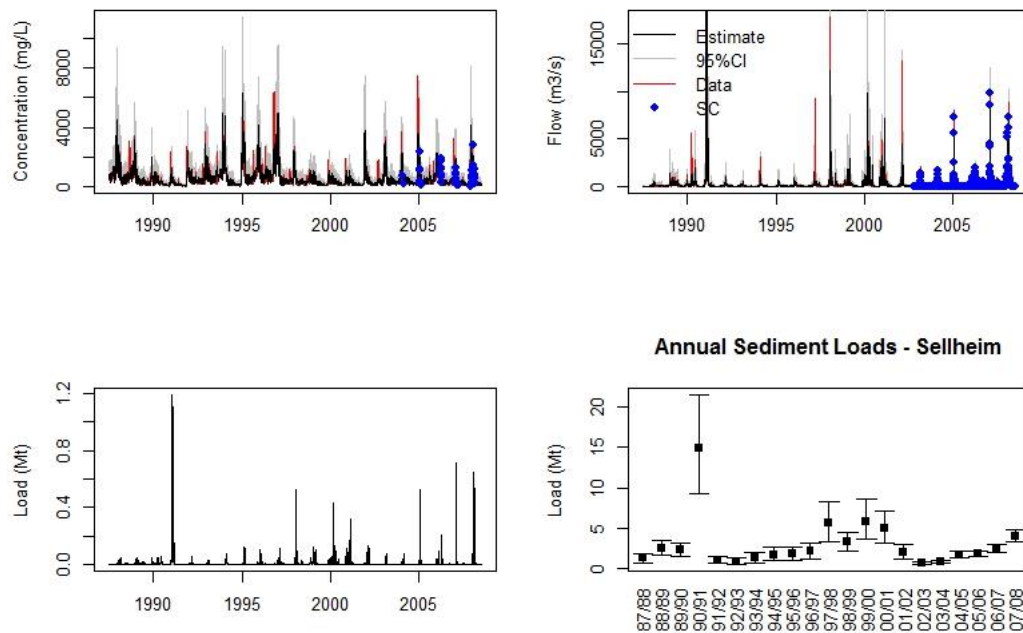
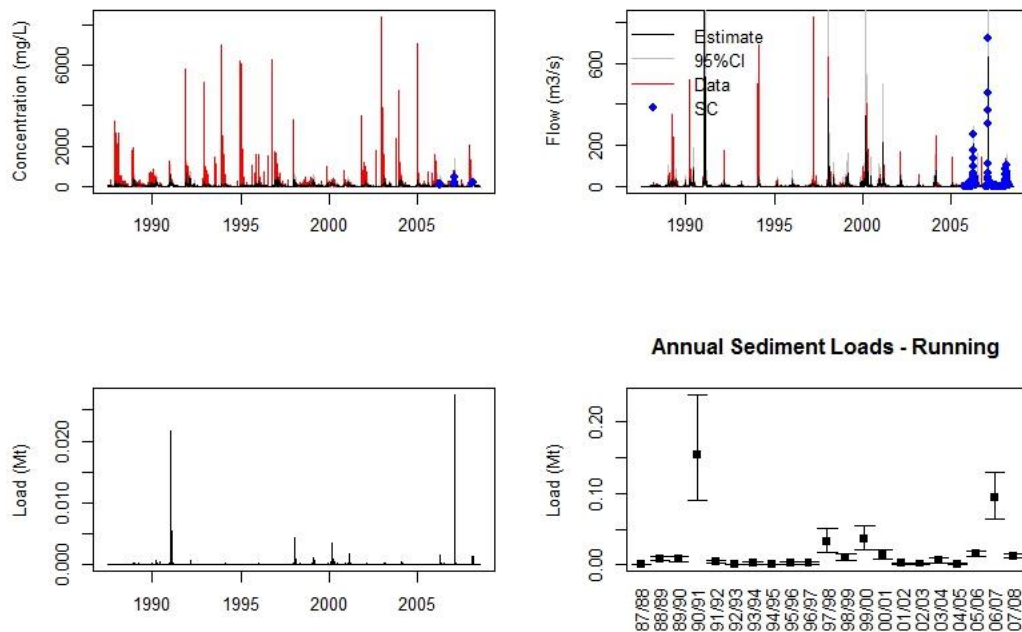


Figure 17: Estimates of the daily Concentration (mg/L), daily flow (m3/s), daily load (Mt) and annual load (Mt) for the Sellheim River site. Black lines are the estimated concentration, grey lines represent the 95% credible intervals and the data are overlayed as blue points.



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Figure 18: Estimates of the daily Concentration (mg/L), daily flow (m3/s), daily load (Mt) and annual load (Mt) for the Running River site. Black lines are the estimated concentration, grey lines represent the 95% credible intervals and the data are overlayed as blue points.

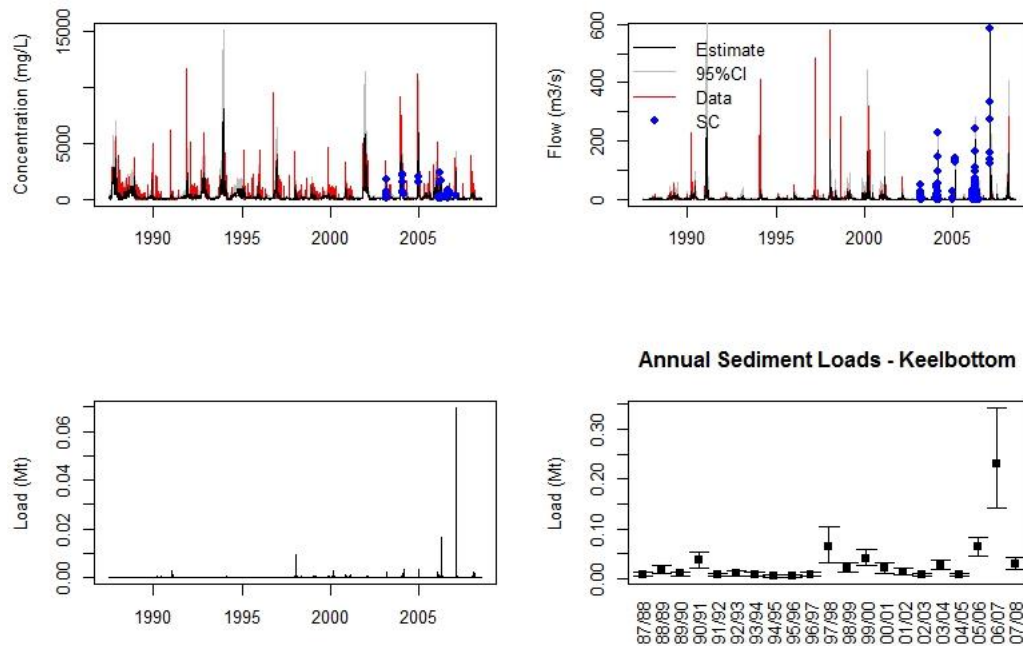


Figure 19: Estimates of the daily Concentration (mg/L), daily flow (m3/s), daily load (Mt) and annual load (Mt) for the Keelbottom Creek site. Black lines are the estimated concentration, grey lines represent the 95% credible intervals and the data are overlayed as blue points.

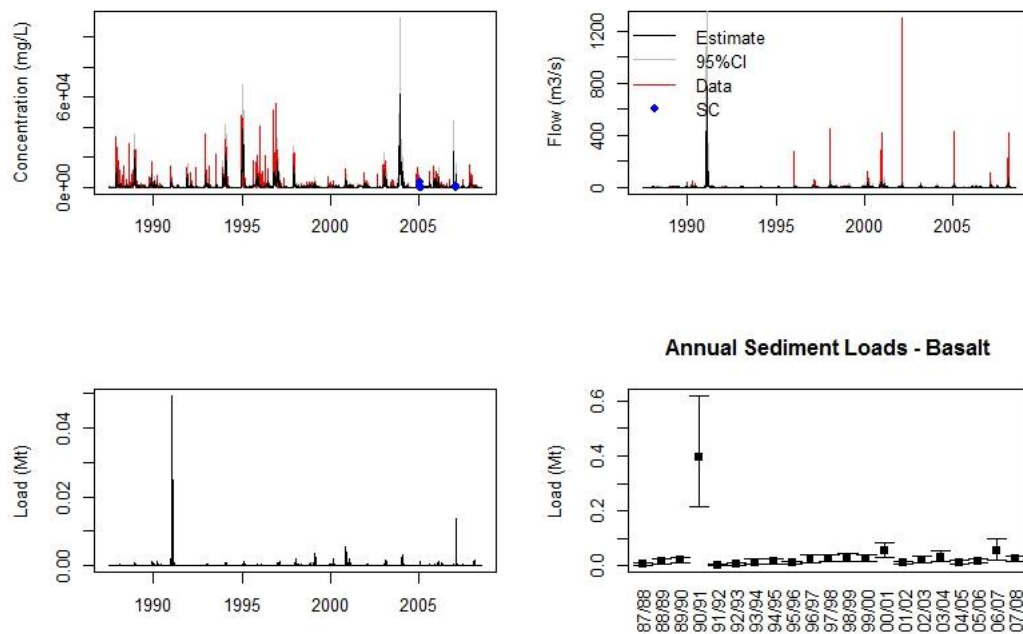


Figure 20: Estimates of the daily Concentration (mg/L), daily flow (m3/s), daily load (Mt) and annual load (Mt) for the Basalt River site. Black lines are the estimated concentration, grey lines represent the 95% credible intervals and the data are overlayed as blue points.

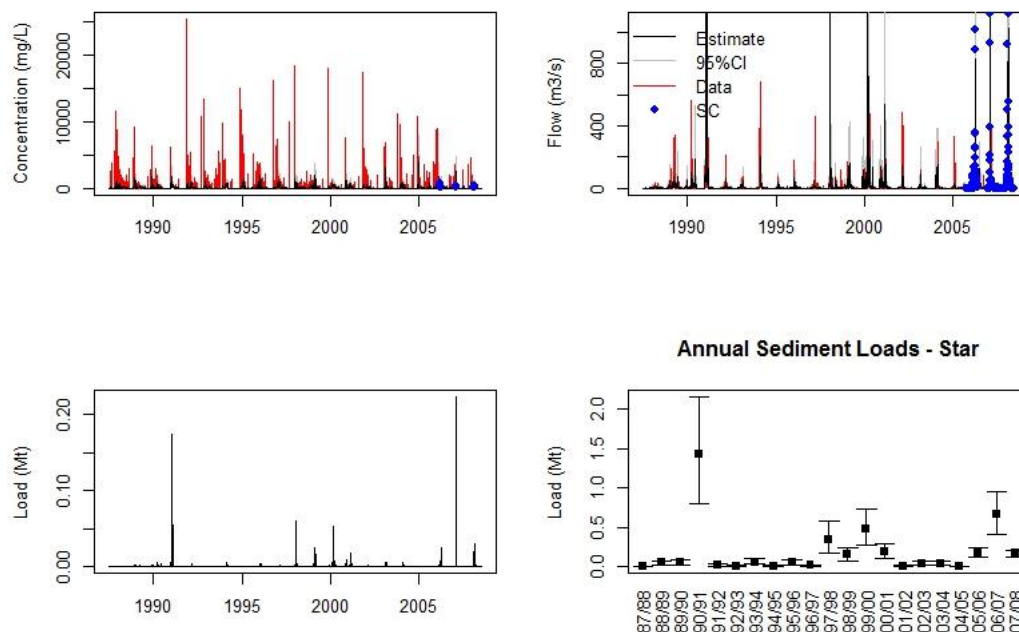


Figure 21: Estimates of the daily Concentration (mg/L), daily flow (m³/s), daily load (Mt) and annual load (Mt) for the Star River site. Black lines are the estimated concentration, grey lines represent the 95% credible intervals and the data are overlaid as blue points.

Annual Loads

Annual load predictions presented in Figures 17-21 for the key sites with measurements show some variability in the financial year loads estimate, particularly when the estimate is high. The 1990/91 financial year is consistently promoting larger loads, attributed to a large event that occurred during this year. The 2006/07 financial year is also indicative of higher loads and due to some big events occurring in parts of the catchment. It is interesting to see that for some sites (Running, Keelbottom and Star) the 2006/07 event is quite prominent, while for the Basalt and Sellheim sites, this event is somewhat diminished.

Although we only present annual predictions for 5 sites in the catchment, maps of loads can be easily estimated and presented for the remaining sites in the catchment. However, for brevity we restrict our attention to the sites where we had measurements to explore the confidence in predictions that resulted from our model.

Relevance of Ground Cover

We included cover as a predictor of concentration in the model to determine whether ground cover played a role in the generation of TSS concentrations. The regression coefficient for cover was estimated as -36.126 with 95% credible intervals ranging -38.53 and -33.74, indicating a significant impact of cover on concentration measurements through time and across the Upper Burdekin catchment. In fact, we can conclude that as the percent ground cover increases, we see a significant decrease in TSS concentrations, indicating that cover is a major influence on TSS concentrations in the catchment.

Exceedence Probability Maps

One of the exciting outputs from this modeling approach is the ability to use the uncertainties from the model to help inform management activities. Exceedence probability maps are a useful visual way of understanding the movement of concentration, flow and the load throughout a catchment and through time. They represent a probability of a concentration, flow or load that exceeds a certain size and when mapped, they provide a visual assessment of the region in terms of the chance of exceeding a load. Appendix A presents exceedence probability maps for concentration, flow and the subsequent load for different size concentrations, flows and loads, respectively. In each map, the colours span blue through to red indicating a low probability of exceeding the value (blue) through to a very high probability (red) and almost certain to exceed the value. Colours in between (e.g. yellow) indicate a 50% chance of exceeding the value investigated.

The exceedence probability maps for concentration (Figures 1A-1D) show an interesting spatio-temporal pattern of concentration. Concentration generations greater than 100 mg/L and even greater than 200 mg/L are noted in the western arm of the catchment (Clarke River) and the top west part of the catchment (Dry River). This is also event once we reach concentrations of 500 mg/L for some years (87/88, 88/89, 93/94-96/97, 02/03-05/06) and 1000 mg/L for 93/94 to 96/97, where the Clarke River is highlighted. These patterns have been noted in a recent paper by Bainbridge et al. (2013) (see Figure 5) where they show high generations of concentration occurring in these parts of the Upper Burdekin catchment.

The exceedence probability maps for flow (Figures 1E-1H) highlight some large events across the Upper Burdekin catchment and across years. This is evident for the 1990/91 financial year and periods between 1997-2000 and 2006-2008 where some large events occurred and appeared to persist through time. It is not until we investigate exceedences greater than 100,000,000 ML that we see only the central river, the Burdekin River showing the only areas where the flow is exceedence. This is with exception to the 1990/91 exceedence probability map which highlights the high generation of flows in the catchment.

Finally, the exceedence probability maps for the load (Figures 1I-1L) show high generation of loads for the 1990/91 financial year where we noted high generations of flow. The bulk of the load generation appears to occur along the Burdekin River and in some instances is negligible for some years and particularly at larger loads (greater than 500,000 t). Figure 1L that shows the probability of exceeding 1Mt really highlights some of the persistent high generations of loads that occur on sites along the main river and in the years where high flows were generated.

Forecasting

Forecasting of the concentration, flow and loads can be achieved after fitting and training the model on measurements and Source Catchments output from the previous years. Forecasting involves obtaining a spatio-temporal prediction of all sites in the Upper Burdekin catchment for the following financial year. Examples of the types of forecasts we can achieve by this model in Figures 22-24, representing the forecast for the 2008/09 financial year. Our forecasted prediction is shown in black along with 95% credible intervals showing the

uncertainty around the forecast. Measurements of concentration and flow are overlayed in the concentration and flow forecasts and where available, we overlayed the Source Catchments generated output (red line). Our forecasts show some variability through the year expressed by the wide credible interval in parts, particularly for concentration during the first 6 months of the financial year. This variability might be reflecting the lack of data collected during these periods and variability in the Source Catchments output across the years. The prediction for flow shows confidence in predictions leading up to the wet season. During the wet season, flow is estimated reasonably well over the period but appears to miss a consistent high flow reading (the result of a persistent high flow). As a result, the load forecasted by this model is lower than expected. As the 2008/09 period is unusual in that it represented a much higher event than expected over the period, the model has a difficult time forecasting it. For the model to do a better job at prediction, we would need to capture this type of variability in the BHM. Incorporating rainfall into the model could also help improve this prediction further. We are yet to conduct some extensive validation on this model and examine its true power in forecasting the loads across the catchment but early results look promising, particularly since our first attempt is predicting flow, concentration and the load for a year where a large event was experienced.

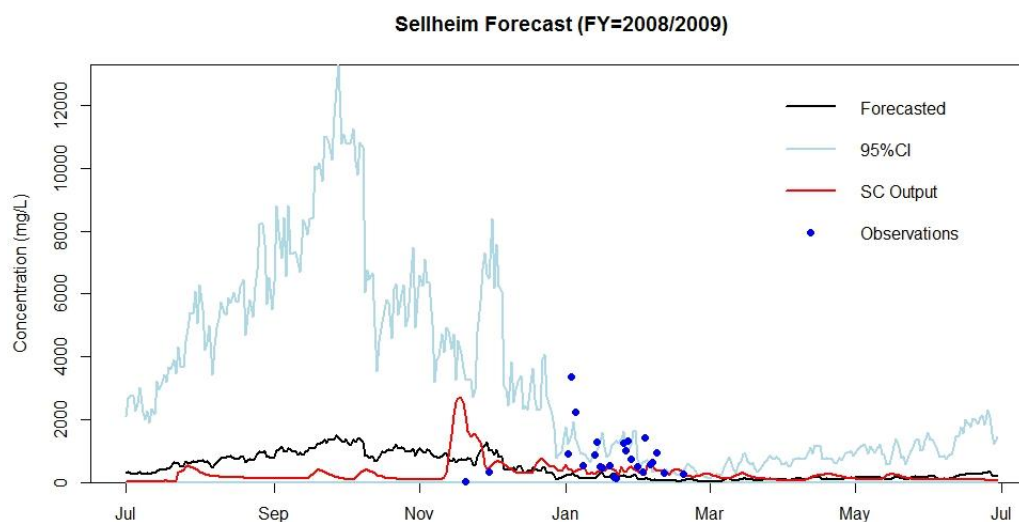


Figure 22: Forecasted concentration in mg/L (black line) for the 2008/09 financial year with 95% credible intervals (light blue lines). The Source catchment modelled outputs (red line) and measurements (blue points) are overlayed on this plot.

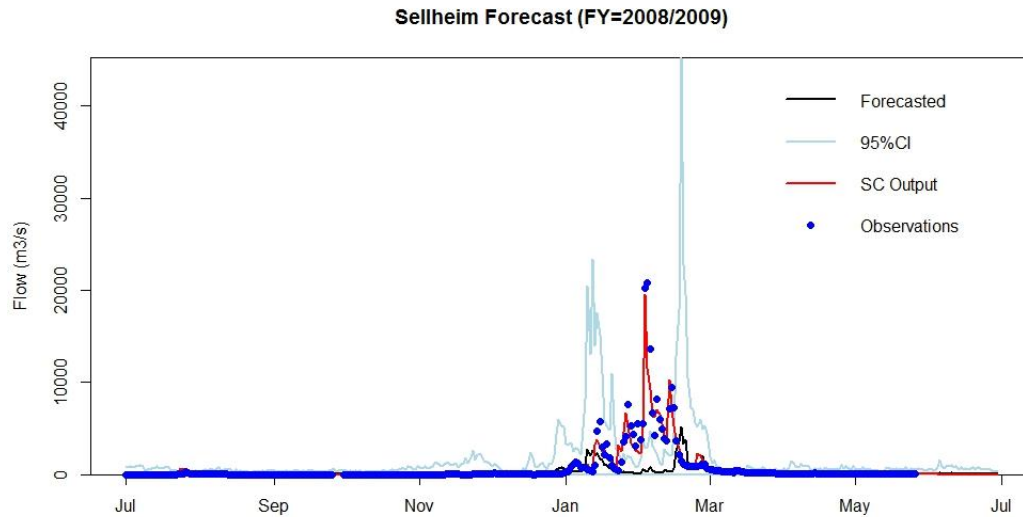


Figure 23: Forecasted flow in m³/s (black line) for the 2008/09 financial year with 95% credible intervals (light blue lines). The Source catchment modelled outputs (red line) and measurements (blue points) are overlayed on this plot.

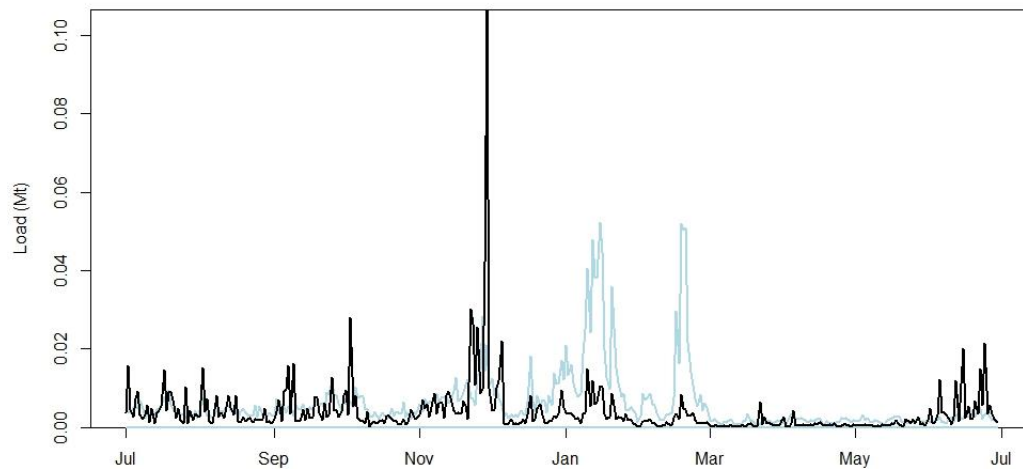


Figure 24: Forecasted load in Mt (black line) for the 2008/09 financial year with 95% credible intervals (light blue lines). The Source Catchment modelled outputs (red line) and measurements (blue points) are overlayed on this plot.

Discussion and Conclusions

The methodology presented in this report is the first attempt at providing estimates of sediment loads with a measure of certainty around the prediction. Provided we have informative prior information about the measurement error, we can use the BHM to quantify the uncertainty in the process model and inform predictions on loads that take into account the error in measurements as well as errors in the process. However, this approach offers much more than load predictions with a measure of confidence. The uncertainty

aspect of this approach and the ability to report loads at different spatial and temporal scales is extremely powerful as it facilitates a framework for addressing important management questions with a better understanding about the level of confidence. For example, various scenarios can be implemented to examine changes to loads under different environmental changes or management interventions. Unlike current scenario evaluations, BHM scenarios provide a level of confidence in load estimates. Furthermore, they also allow the estimation of exceedance probability curves or maps to determine probabilities of exceeding a load of a certain magnitude under different scenarios or conditions. This in turn can be used to inform target setting and in particular, help managers to identify desired loads targets under different climate and management scenarios, which lead to an acceptable probability of exceedance. The BHM methodology can also be used to identify hotspots (i.e. nodes within the catchment where sediment loads are high and measured with certainty) where managers may want to focus restoration activities. The method also has the ability to identify regions where further measurements are required to understand the nature of the erosion because the estimate of load is uncertain. Finally, the ability of this approach to identify sources of erosion processes, for example, whether the source is due to hillslope, gully or stream bank erosion with some level of confidence is paramount to determining where to target future investment.

Benefits and Application

The BHM framework is extremely powerful. It makes use of all of the available information from the measurements as well as the models and as a result, the potential applications of the approach are widespread. The framework can be considered an information product that enables the exploration of a wide range of decision making questions that have been difficult to address in the past using either measurements or models separately. The key questions that can be addressed using this framework are:

- How do we prioritise areas within a catchment to obtain improvements in loads?
- What are the sources of loads? Are they predominantly generated by gullies, or are some due to hillslopes or bank erosion?
- Where is information lacking (i.e. the source of the uncertainty is high)? Where do we need to invest more effort in understanding the load at a site?
- How can we better inform the target setting process to ensure confidence in our decisions?

Future Direction and Challenges

In this report we demonstrated the BHM framework for blending measurements with process model outputs using two case studies and focused predominantly on modeling flow and concentration and the subsequent load. One of the biggest advantages of the framework presented here is the ability to predict and forecast concentrations, flows and loads with a level of confidence. We were also able to identify aspects of the Source Catchments model where the underlying process level understanding does not match expert thinking or scientific studies (e.g. Running and Star River concentrations).

We spent considerable effort in this project to ensure the modeling framework could adequately accommodate the size (i.e. number of spatial locations and time points) and highly variable nature of the data, where the computations could be performed feasibly. Further work is required to:

1. Validate both models (Weany Creek and Upper Burdekin) to ensure they are fit for purpose. This requires omitting periods where we have data, refitting the model and estimating concentrations, flows and loads for the periods that were missing to determine how good the model captures the measurements.
2. Extend the model to incorporate the erosion processes. This requires specifying a multivariate process as discussed in Cressie and Wikle (2011) which includes concentration, flow and each of the erosion processes. This will be beneficial to disentangle the sources of the erosion contributing to the load in the catchment.
3. Translate the methodology across to a faster platform such as the CSIRO developed LibBi package. This package has been developed specifically for state-space modeling constructed in a BHM framework using particle Markov Chain Monte Carlo methods. The advantage of moving to LibBi is the fast implementation of the methodology and ability to use parallel processing for the computational aspects of the modeling.
4. Scenario evaluation of the Upper Burdekin catchment to examine the changes in loads with changing cover.
5. The approach is applicable to other catchments and other constituents, which can also be modelled using the BHM framework. Furthermore, we could also consider incorporating other types of measurements and methods (e.g. tracer techniques) that lead to a better understanding of load generation. Although each catchment and constituent is expected to exhibit unique characteristics and processes, the lessons learned about the implementation of the BHM approach will greatly benefit future applications.
6. Linking catchment models with receiving waters. There is a clear need to link catchment model outputs with marine models to understand how the sources of loads in the catchments are impacting the GBR lagoon and whether certain scenarios of environmental change or management intervention in the catchments can lead to a change in the marine life in the lagoon. One of the models developed within CSIRO and part of eReefs is a Marine biogeochemical model. Using ensemble methods, the linkage of the two is conceptually straightforward where the outputs from the catchment BHM (posterior probability distributions) can feed into the marine biogeochemical model through by sampling the posterior distribution of the catchment BHM. Through this linkage, it is envisaged that scenario investigations occurring in the catchments can feed into the prior distributions for the marine model to examine changes to the marine environment. This approach has the potential to highlight hotspots where load exceedance probabilities are high and lead to more informative and scientifically defensible targets in the marine region.

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Appendix A: Exceedence Probability Maps for the Upper Burdekin

Concentration

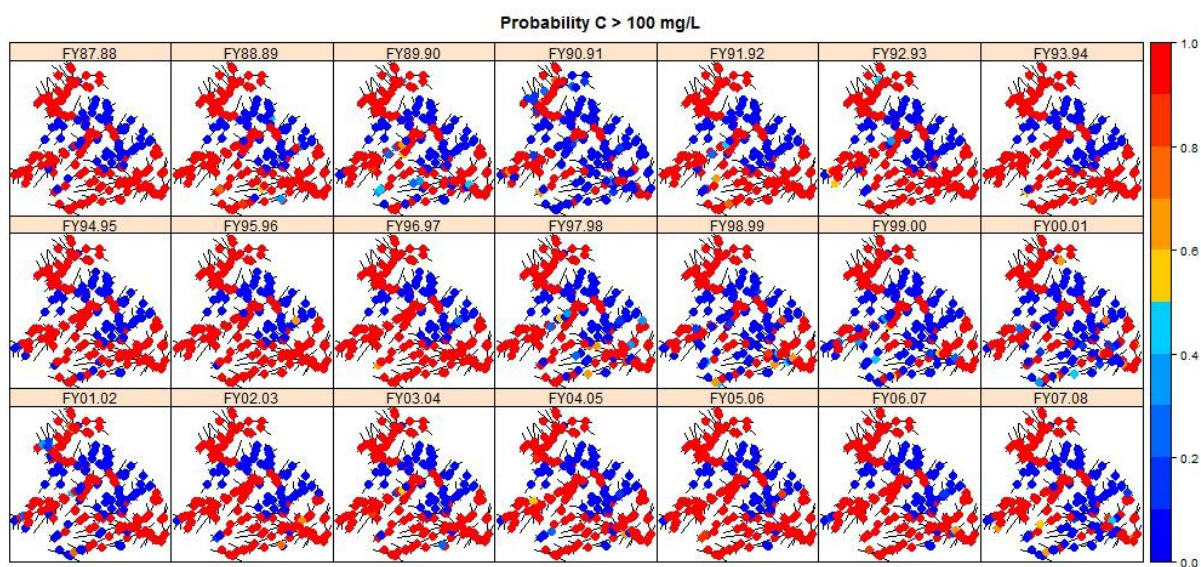


Figure A 1: Probabilities of concentration exceeding 100 mg/L for financial years spanning 1987-2008.

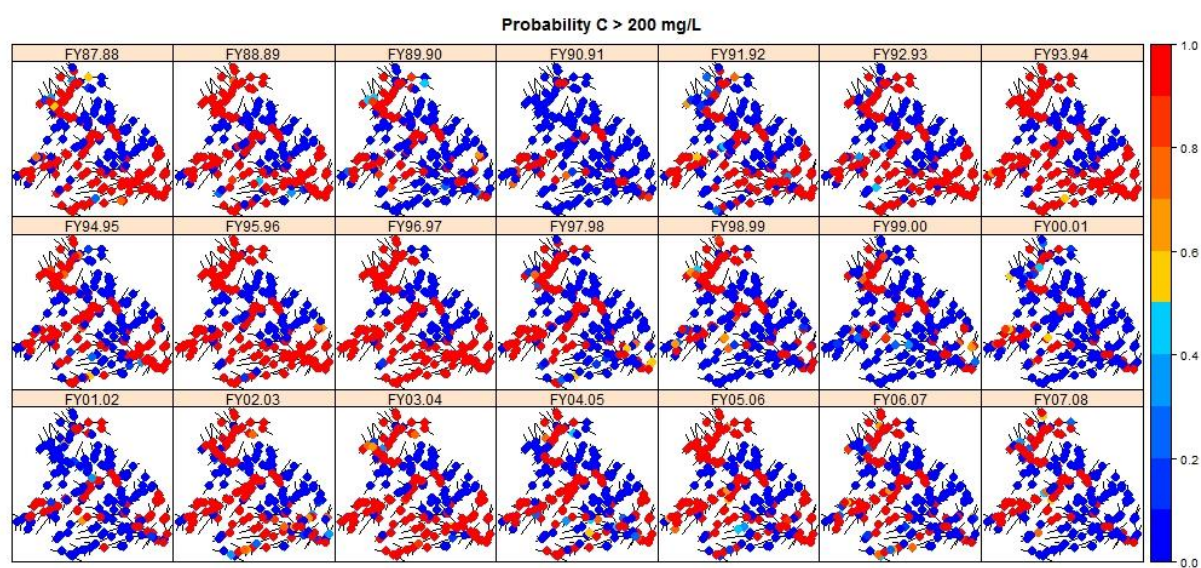


Figure A 2: Probabilities of concentration exceeding 200 mg/L for financial years spanning 1987-2008.

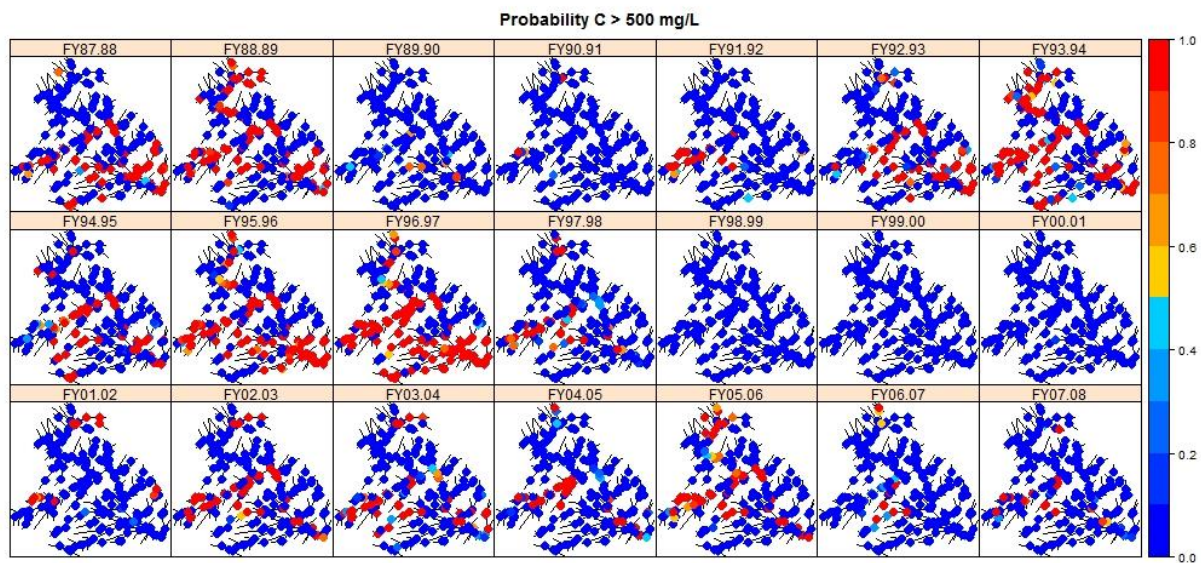


Figure A 3: Probabilities of concentration exceeding 500 mg/L for financial years spanning 1987-2008.

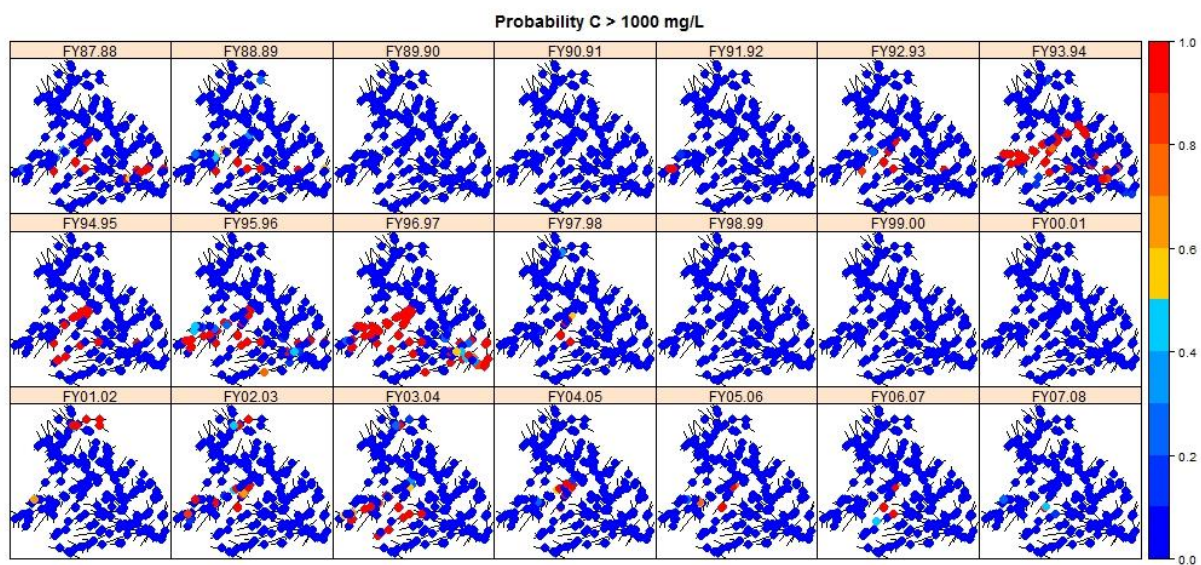


Figure A 4: Probabilities of concentration exceeding 1000 mg/L for financial years spanning 1987-2008.

Flow

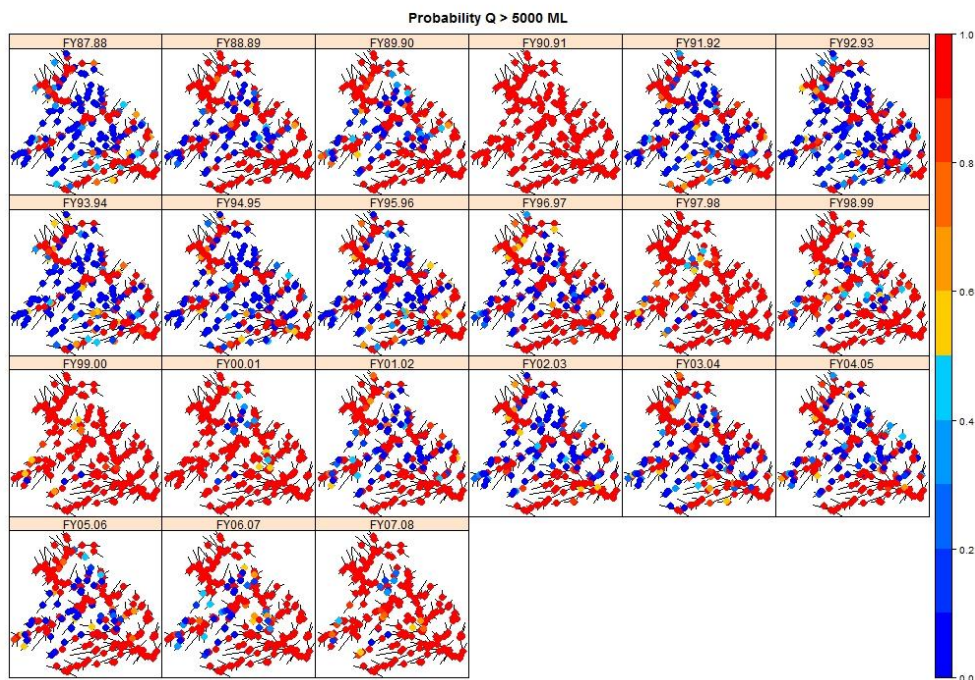


Figure A 5: Probabilities of flow exceeding 5000 ML for financial years spanning 1987-2008.

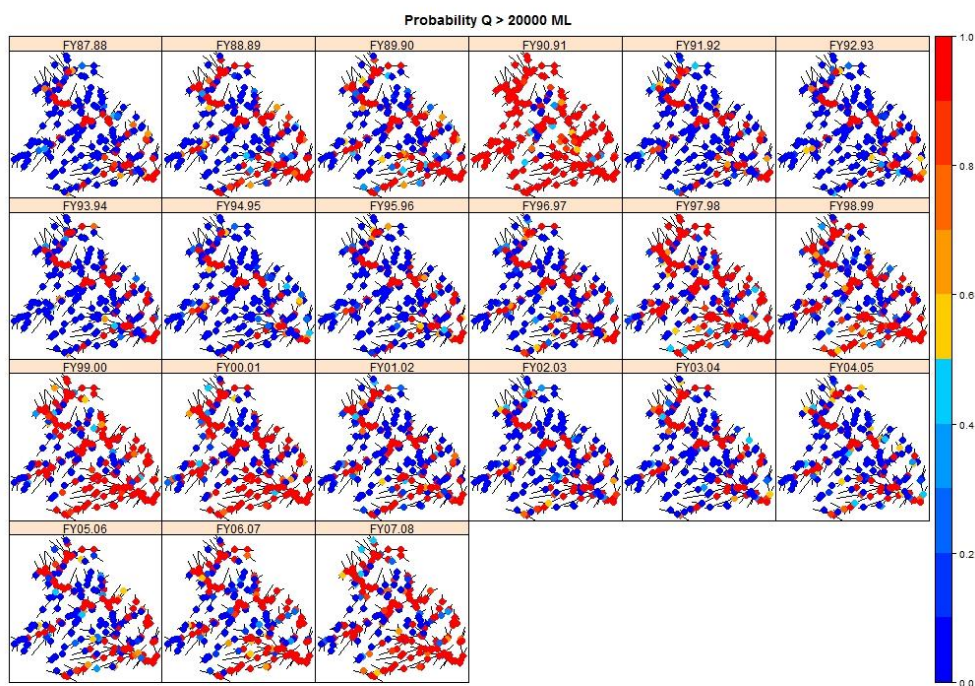


Figure A 6: Probabilities of flow exceeding 20,000 ML for financial years spanning 1987-2008.

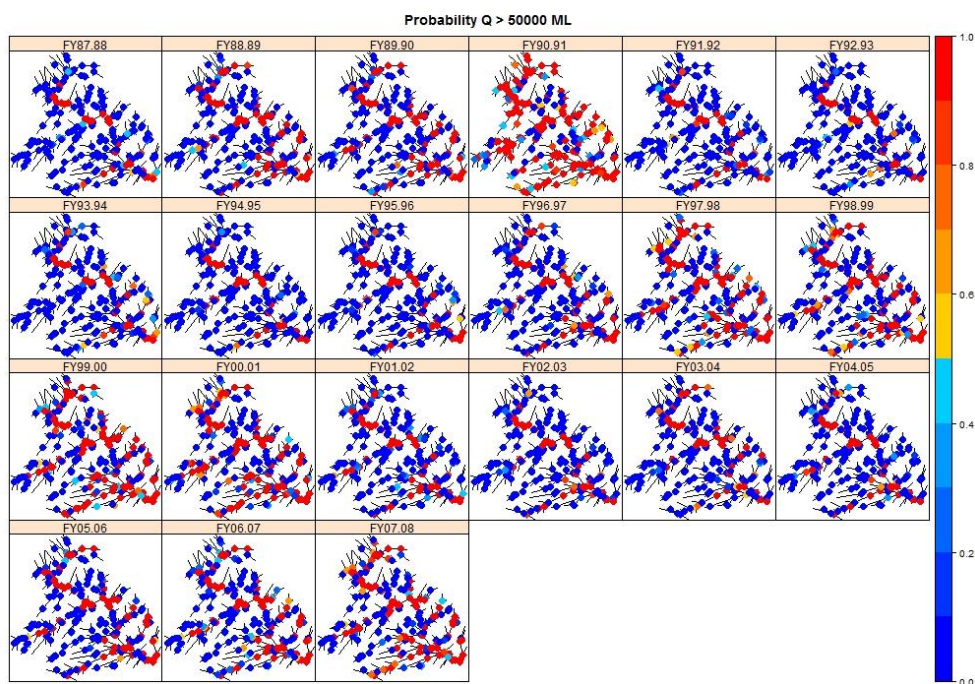


Figure A 7: Probabilities of flow exceeding 50,000 ML for financial years spanning 1987-2008.

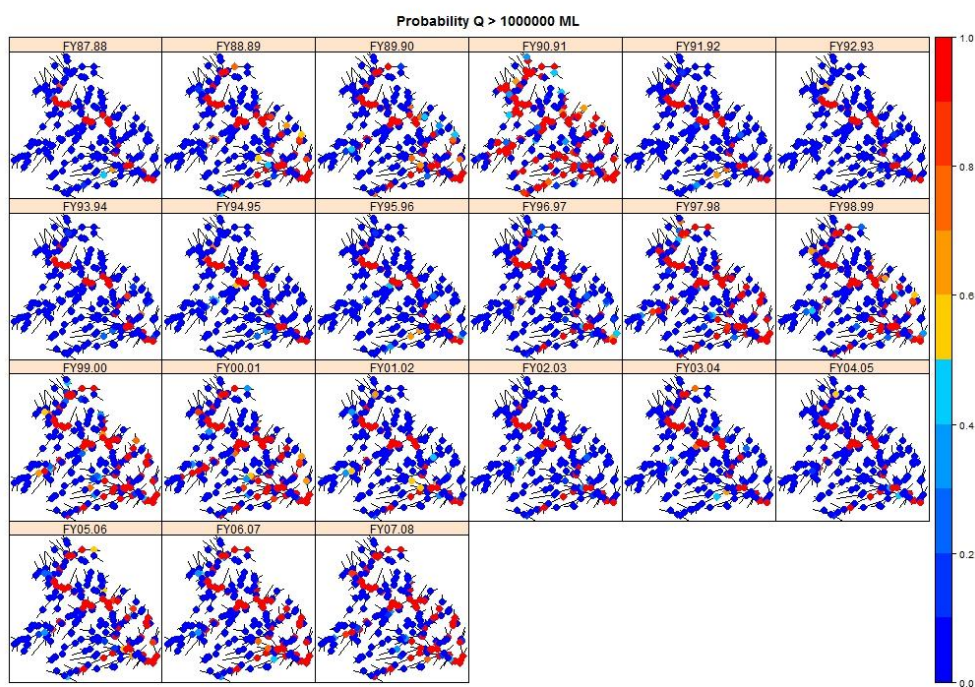


Figure A 8: Probabilities of flow exceeding 100,000 ML for financial years spanning 1987-2008.

Loads

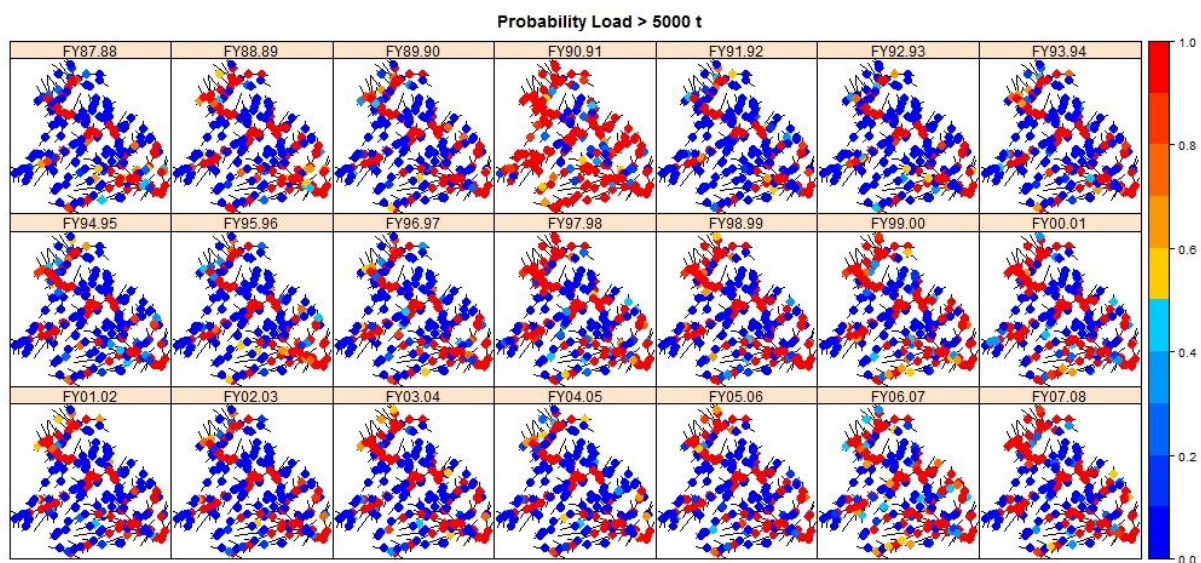


Figure A 9: Probabilities of the load exceeding 5,000t for financial years spanning 1987-2008.

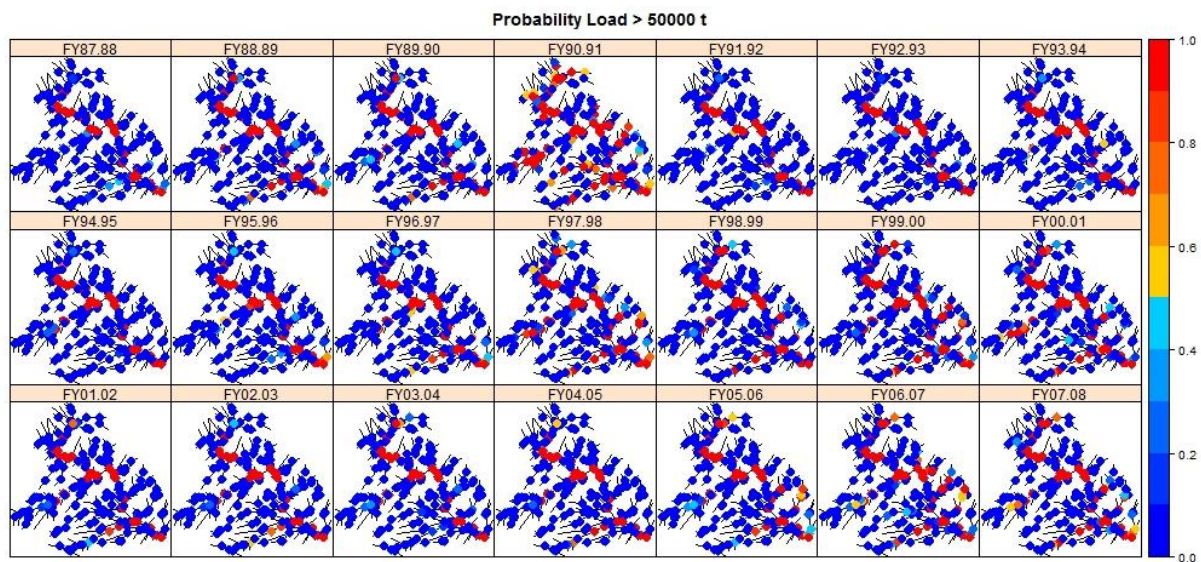


Figure A 10: Probabilities of the load exceeding 50,000t for financial years spanning 1987-2008.

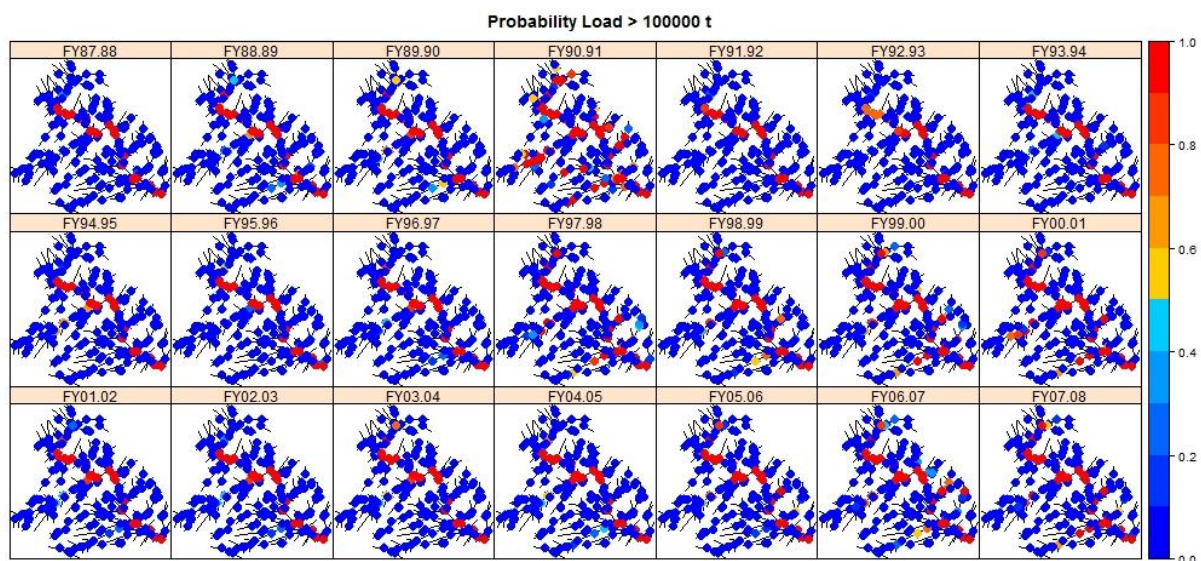


Figure A 11: Probabilities of the load exceeding 100,000t for financial years spanning 1987-2008.

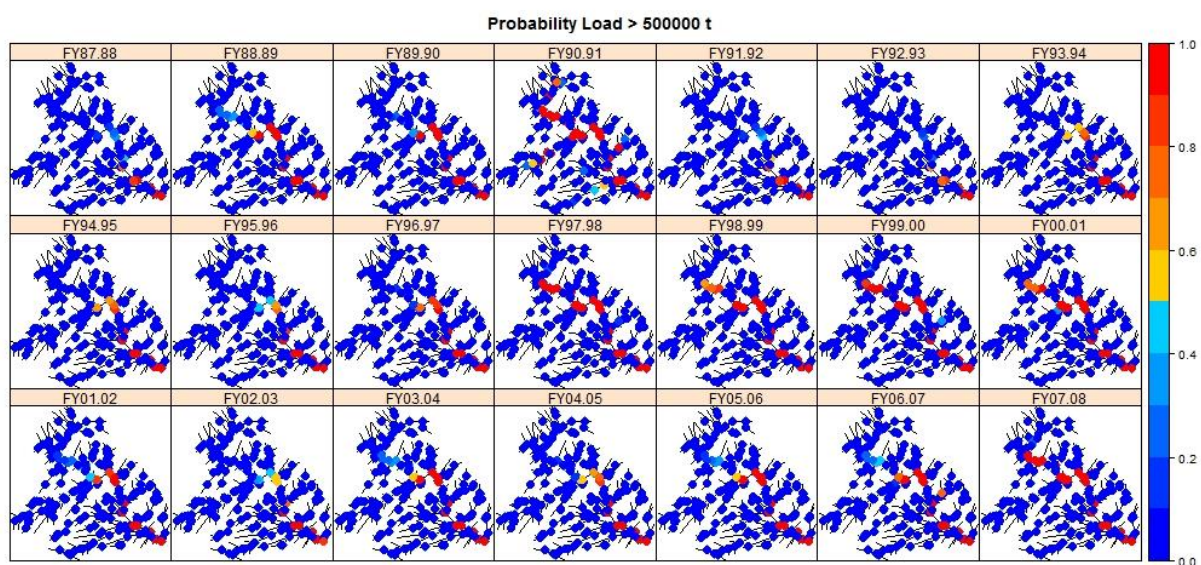


Figure A 12: Probabilities of the load exceeding 500,000t for financial years spanning 1987-2008.

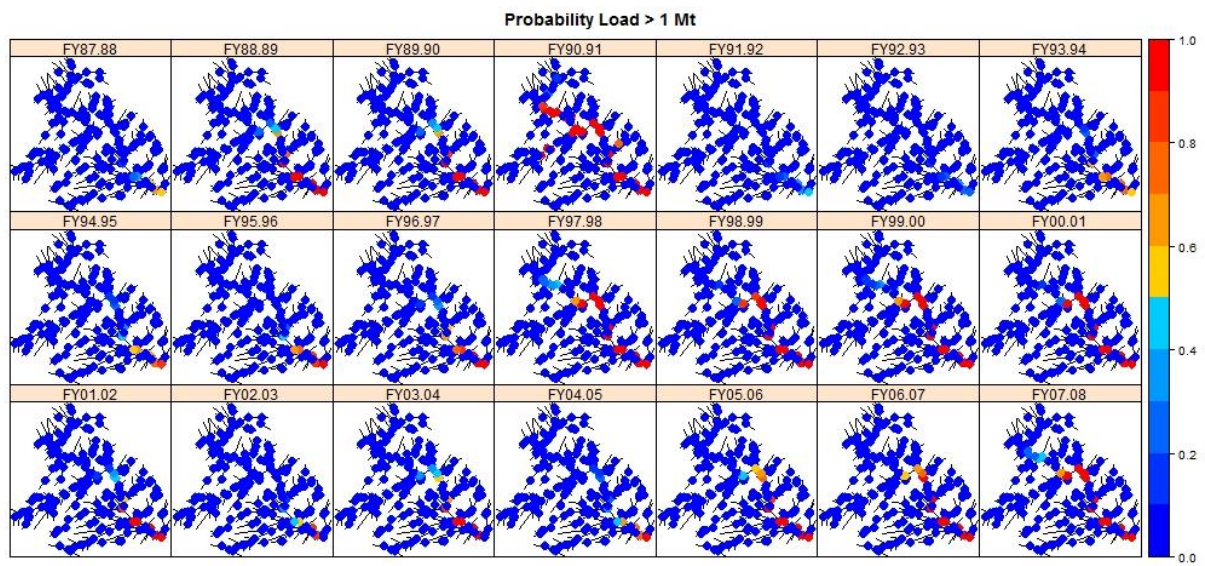


Figure A 13: Probabilities of the load exceeding 1Mt for financial years spanning 1987-2008.

Appendix B: Publications

Kuhnert et al. (2013) A Bayesian Hierarchical modelling approach for integrating a pollutant loads model with measurements in the Great Barrier Reef catchments, *Environmetrics*, Special Issue on Physical-Statistical modelling, In prep.

Bainbridge, Z., Lewis, S., Smithers, S., Kuhnert, P., Henderson, B., Brodie, J. In review (July 2013). Suspended sediment sources, transport and export from a large, seasonally-dry tropical catchment: Burdekin River catchment, Queensland, Australia. Water Resources Research.

Lewis, S., Bainbridge, Z., Kuhnert, P.M., Sherman, B.S., Henderson, B., Dougall, C., Cooper, M. and Brodie, J.E. (2013) Calculating sediment trapping efficiencies for reservoirs in tropical settings: A case study from the Burdekin Falls Dam, NE Australia, Water Resources Research, VOL. 49, 1017–1029, doi:10.1002/wrcr.20117, 2013