

Modelling the impact of land use and catchment characteristics on stream water quality using a Bayesian hierarchical modelling approach in the Great Barrier Reef catchments

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Abstract: The near-shore ocean ecosystem is influenced by catchment runoff. The Great Barrier Reef has been experiencing significant water quality deterioration over the past 150 years, due in part to agricultural intensification and urban settlement in adjacent catchments (Thorburn et al., 2013). There is a need for us to understand the influences of catchment characteristics on stream water quality, with an aim to mitigate and manage the water quality issue in the terrestrial stream runoff derived from the adjacent Great Barrier Reef catchments. The event-based water quality monitoring data set from the Paddock to Reef Integrated Monitoring Program across six Natural Management Regions provides a potential opportunity to develop a data-driven understanding of catchment characteristics affecting water quality at the catchment scale. This requires a robust and reliable modelling tool to relate the monitoring data to anthropogenic and natural processes.

In this study, monitoring data of Total Suspended Solids (TSS) and dissolved Oxidised Nitrogen (NO_x) from 32 sites across the Great Barrier Reef catchments are selected as case study constituents due to the high risk they pose to reef health when exported from catchments to the receiving marine environment. Also, these two constituents have distinct biogeochemical processes in catchments. Specifically, TSS is typically conserved (although mobilized and deposited) while travelling through river systems; while NO_x can be potentially processed and removed from the system altogether. A Bayesian hierarchical linear modelling framework is adopted, due to its ability to borrow strength among sites, allowing information to be transferred across space, and due to its ability to provide uncertainty of the predictions. The Bayesian hierarchical linear regression model in this study is developed to evaluate the significance of various catchment characteristics (e.g., land uses, catchment topography and geology) on spatial variation in water quality.

The main findings of this study are listed as follows,

- Sites located in the Burdekin and Fitzroy Natural Management Regions tend to have greater TSS concentrations, illustrated by the modelled site-specific spatial random effects (deviation from the overall average concentration). Additionally, grazing and dry land agriculture land uses are positively correlated with the spatial random effect on TSS. The complexity of interaction between different catchment characteristics (e.g., land use and topography) can potentially result in a negative spatial random effect on TSS, which is reduced in the relatively steeper Great Barrier Reef catchments with a denser stream network.
- Sugar cane is one of the most significant NO_x contributors according to the modelling results, likely partially due to the excessive application of fertilizers; however, conservation land use has limited effect on NO_x removal, indicating denitrification process alone may not be sufficient to remove NO_x.

The modelling results demonstrate different land management strategies are required for the purpose of reducing different constituents. This work will provide scientific insights for water quality management at the catchment scale.

Keywords: *Water quality, land use, Suspended Solids, Oxidised Nitrogen, Bayesian hierarchical modelling*

1. INTRODUCTION

In coastal areas around the world, coral reefs are being degraded. In an Australian context, the coral cover in the Great Barrier Reef has declined significantly, due to a range of threats. Water quality degradation is one of these threats. The Great Barrier Reef marine ecosystem has been experiencing significant water quality deterioration due in part to agricultural intensification and urban settlement in adjacent catchments. The degradation of water quality in rivers draining into the Great Barrier Reef is primarily caused by agricultural land-derived, non-point source pollutants including fine sediments, nutrients and pesticides (Brodie *et al.*, 2013). There is an evident link between elevated terrestrial runoff carrying pollutants, and the degradation of coral reefs in the Great Barrier Reef lagoon (Thorburn *et al.*, 2013). However, water quality in streams is highly variable across space and time, and many factors influence water quality dynamics and pollutant generation and transport, so managing it is a challenge.

Differences in land use and catchment characteristics are likely to be responsible, in part, for spatial variability in water quality, therefore it is important to understand the link between land use and catchment characteristics, and water quality behavior. In this study, we use a Bayesian hierarchical modelling (BHM) framework to investigate the effects of land use and catchment characteristics on spatial variability in water quality. Bayesian Hierarchical Modelling has been implemented in complex ecological and environmental studies, to understand the complex interrelated nature of multivariate systems (Wan *et al.*, 2014). Bayesian hierarchical modelling can provide estimates of the uncertainty in model predictions. This is because it can consider uncertainties in the model parameters, observed data, and discrepancies between model structures and true natural processes. Therefore, estimates are more reliable and can provide insights into decision-making (e.g., water quality management policy) under scenarios with high uncertainty.

In this study, spatial variability in Total Suspended Solid (TSS) and Oxidised Nitrogen (NO_x , a major form of Dissolved Inorganic Nitrogen) across 32 water quality monitoring sites is evaluated using a Bayesian Hierarchical Modelling framework. The two constituents are selected for different reasons. Fine sediments (often derived from soil erosion) results in a reduction in the light that is essential for organisms in marine ecosystems, including seagrass and coral. Fine particulate sediments and organic rich flocculent masses can also smother marine organisms (Brodie *et al.*, 2013). NO_x is closely linked to the decline in coral cover, since excessive NO_x facilitates outbreaks of the crown-of-thorns starfish, a major coral predator, and also the occurrence of coral bleaching (Hoegh-Guldberg, 1999). They are also controlled by different processes within the catchment so should exhibit contrasting behaviors.

This paper aims to investigate the complex influences of land use and catchment characteristics on water quality under uncertainties. This can inform the design of land management practices that aims to reduce pollutant loads and protect the marine ecosystem.

2. METHODOLOGY

2.1. Study area and materials

In GBR catchments, there are six Natural Resource Management (NRM) regions (Figure 1). Climate within the GBR catchment ranges from tropical to subtropical, with highly variable rainfall across the area. Coastal areas (Cape York, Wet Tropics and Mackay-Whitsunday) receive significantly higher rainfall than the inland areas (Burdekin, Fitzroy and Burnett-Mary). Therefore, there is more dense settlement and intensive agricultural landscape in the coastal catchments.

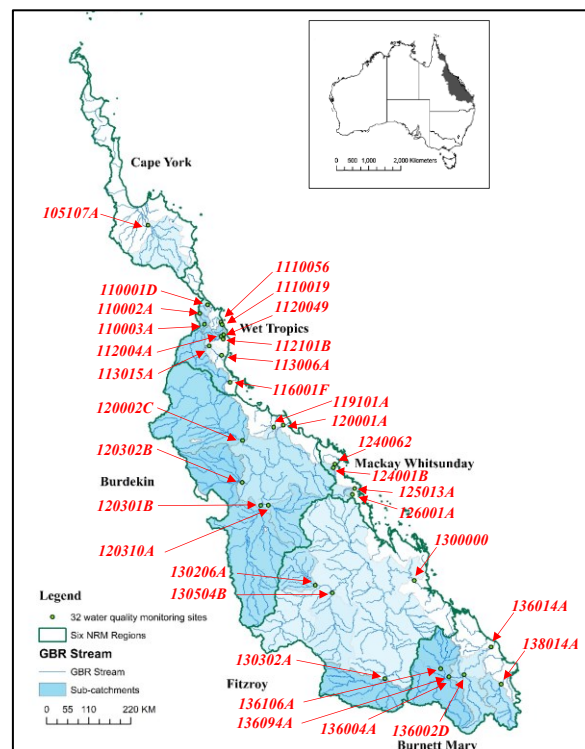


Figure 1. Location of 32 water quality monitoring sites in the Great Barrier Reef catchments

Thirty-two water quality monitoring sites in the Paddock to Reef Integrated Monitoring Program (Waters *et al.*, 2014) across six Natural Resource Management regions are selected in this study. Event-based water quality monitoring data is obtained from the Paddock to Reef Integrated Monitoring Program, sampled between 2006 and 2016. The selected sites and their corresponding contributing area can be delineated based on stream network database provided by the Geofabric from the Bureau of Meteorology (Bureau of Meteorology, 2011). The locations and corresponding delineated sub-catchment areas for 32 sites are shown in Figure 1. The natural catchment topographic and geological characteristics data were retrieved from the National Environmental Stream Attributes dataset (version 1.1.5) and Queensland government (Bureau of Meteorology, 2011; Queensland Government, 2017). The land use information is derived from a product of the Queensland Land Use Mapping Program (QLUMP), which represents the most recent mapping of land use features according to the Australian Land Use and Management (ALUM) Classification. The detailed information for each catchment characteristic evaluated in this study is listed in Table 1.

Table 1. Description and data source for catchment characteristics

Catchment characteristics	Unit	Description	Data source
Conservation	%	Land used primarily for conservation purposes, based on maintaining the essentially natural ecosystems present, such as national park.	Queensland Government, 2017
Dryland agriculture	%	Land used mainly for primary production based on dryland farming systems (excluding grazing and sugar cane).	Queensland Government, 2017
Irrigated agriculture	%	Land used mostly for primary production based on irrigated farming (excluding grazing and sugar cane).	Queensland Government, 2017
Intensive uses	%	Land subject to extensive modification, generally in association with closer residential settlement, commercial or industrial uses (e.g. urban, utilities, roads).	Queensland Government, 2017
Water	%	Lake, reservoir/dam, river, channel, marsh/wetland.	Queensland Government, 2017
Grazing	%	Grazing native vegetation, Grazing modified pastures (Native/exotic pasture mosaic, Woody fodder plants), Grazing irrigated modified pastures.	Queensland Government, 2017
Sugar cane	%	Dryland Cropping (sugar), Irrigated cropping (sugar).	Queensland Government, 2017
Slope	°	Catchment average slope.	Bureau of Meteorology, 2011
Stream density	km/km ²	Ratio of total stream segment length of all upstream to the contributing area.	Bureau of Meteorology, 2011
Soil Erodibility	/	Degrees of erosion vulnerability using a limited set of locally relevant soil properties. Considering both surface soil stability and subsoil erodibility.	Queensland Government, 2017

2.2. Data treatment

The raw water quality measurements are highly right-skewed with positive skewness 35.2 for TSS and 15.2 for NO_x. Therefore, data transformation is required before the Bayesian statistical modelling. The Box-Cox transformation (Box *et al.*, 1964) is one widely used parametric transformation technique to improve normality. The power parameters used for TSS and NO_x are 0.0058 and 0.1358, respectively. After application of Box-Cox transformation, the kurtosis and skewness decrease significantly to close to 0 for these two constituents.

2.3. Bayesian Hierarchical Modelling Structure and Implementation

Bayesian Hierarchical Modelling decomposes the complex and poorly-understood interactions in the observed data into a series of conditional models, which are linked together by probability relationships, following Bayes' theorem (Webb *et al.*, 2010; Wikle, 2003).

The individual Box-Cox transformed TSS and NO_x measurements for each water quality site are predictands, and spatial variability of individual pollutants between sites is incorporated within the modelling structure using a linear regression against land use and other catchment characteristics (i.e., catchment slope, stream density and soil erodibility, etc.) as predictors. The detailed model structure is as follows.

Data model: This part of the Bayesian Hierarchical Model specifies the water quality constituent concentration (TSS or NO_x) data:

$$P(y_{i,j} | \mu_j, \sigma^2) \sim N(\mu_j, \sigma^2) \quad (1)$$

The data-level model assumes that the i^{th} constituent concentration (TSS or NO_x) in the j^{th} sub-catchment, $y_{i,j}$, follows a normal distribution, with mean μ_j (defined in the process model) and variance σ^2 (a constant estimated by the observations). In that case, σ^2 represents within-site variation, which includes the measurements error and natural variability in concentration levels within site.

Process model: The mean concentration at a site, μ_j is defined by a constant α combined with a spatial random term $\beta_{i,j}$ (i.e., the deviation from the mean resulting from differences in land use/other natural catchment characteristics).

$$\mu_j = \alpha + \beta_{i,j} \quad (2)$$

The spatial random effect $\beta_{i,j}$ is assumed to follow a normal distribution with mean $\mu_{\beta,j}$, and variance σ_{β}^2 .

$$P(\beta_{i,j} | \mu_{\beta,j}, \sigma_{\beta}^2) \sim N(\mu_{\beta,j}, \sigma_{\beta}^2) \quad (3)$$

The mean spatial effect is modelled as a linear additive function of land use and natural catchment characteristics. Land use categories and catchment characteristics are explanatory covariates:

$$\mu_{\beta,j} = \gamma_0 + \sum_{n=1}^k \gamma_n \times \text{Catchment characteristics}_n(j) \quad (4)$$

where, k is total number of covariates (i.e., 7 land use and 3 other catchment characteristics) evaluated in this Bayesian Hierarchical Modelling framework. γ_0 is regression intercept parameter, and γ_n is regression slope parameter for the n^{th} covariate. The variance term σ_{β}^2 accounts for variations in concentration levels and spatial random effects between sites not captured by the site-level covariate predictor. All covariates are z -scale standardized (mean=0, standard deviation=1). As such, the magnitude of a coefficient indicates the effect of each covariate relative to other covariates (Wan *et al.*, 2014).

Parameter model: Model parameters ($\alpha, \gamma_0, \gamma_n, \sigma, \sigma_{\beta}$) were assumed to be independent from each other. Non-informative uniform priors were assigned to standard deviations (σ, σ_{β}) and non-informative normal distribution were assigned as the prior distribution for regression coefficients ($\alpha, \gamma_0, \gamma_n$) that describe the data model and the process model (Gelman, 2006):

$$p(\alpha, \gamma_0, \gamma_n, \sigma, \sigma_{\beta}) = p(\alpha) \cdot p(\gamma_0) \cdot \prod_{n=1}^k p(\gamma_n) \cdot p(\sigma) \cdot p(\sigma_{\beta}) \quad (5)$$

$$\alpha \sim N(0, 0.0001); \gamma_0 \sim N(0, 0.0001); \gamma_n \sim N(0, 0.0001), \text{ for } k = 1, 2, \dots, 10; \quad (6)$$

$$\sigma \sim \text{Uniform}(0, 100); \sigma_{\beta} \sim \text{Uniform}(0, 100)$$

Model Implementation

Markov Chain Monte Carlo (MCMC) with Gibbs sampling is used to obtain samples from the posterior probability distribution. The MCMC simulation was implemented in OpenBUGS from R by using *R2OpenBUGS* package (Sturtz *et al.*, 2010). The model was run with 3 chains, and 10,000 iterations for each chain. The first 5,000 iterations were discarded as 'burn-in' period to allow convergence of the Markov chains, and the remaining iterations were thinned by every 3 iterations (i.e., discard all but every 3rd observation) to reduce the effect of auto-correlation within the Markov chains when estimating the posterior distributions. The convergence of each chain was evaluated using the potential scale reduction factor, Rhat (at convergence, Rhat \approx 1), along with trace plots of model parameters.

3. RESULT AND DISCUSSION

The model converged rapidly after approximately 500 iterations and the Rhat values are close to 1 for all monitored parameters, indicating convergence. The detailed model results and discussions for each of the two constituents are presented as follows.

3.1. TSS Modelling

Figure 2 A and Figure 2 B depict the distribution of the modelled site-specific spatial random effect β_j for TSS and the posterior distributions of regression parameters for each catchment characteristics, respectively. The site-specific spatial random effect is the difference between event-based constituent (TSS or NO_x) concentrations and overall average concentration, which can be attributed, in part, to the differences in land uses and other catchment characteristics.

As can be seen in Figure 2 A, sites in the large Burdekin and Fitzroy basins (e.g., posterior median of β_j 2.14 for 130504B Comet River at Comet Weir, 1.86 for 130206A Theresa Creek at Gregory Highway, 1.04 for 120002C Burdekin River at Sellheim and 0.92 for 120302B Cape River at Taemas) have a large positive deviation from the average TSS concentration, indicating a higher risk of TSS for these catchments during flow

events. The land use for the majority of sites in the Burdekin and Fitzroy regions is dominated by grazing and dry land agriculture, indicating the significant source of suspended sediment from such land uses. This result is also supported by the findings from a recent modelling study, that grazing land was the largest source of TSS load (45 % of total exported load), and 81% of sediment generated from grazing land comes from Fitzroy (30%) and Burdekin (51%) catchments (Waters *et al.*, 2014).

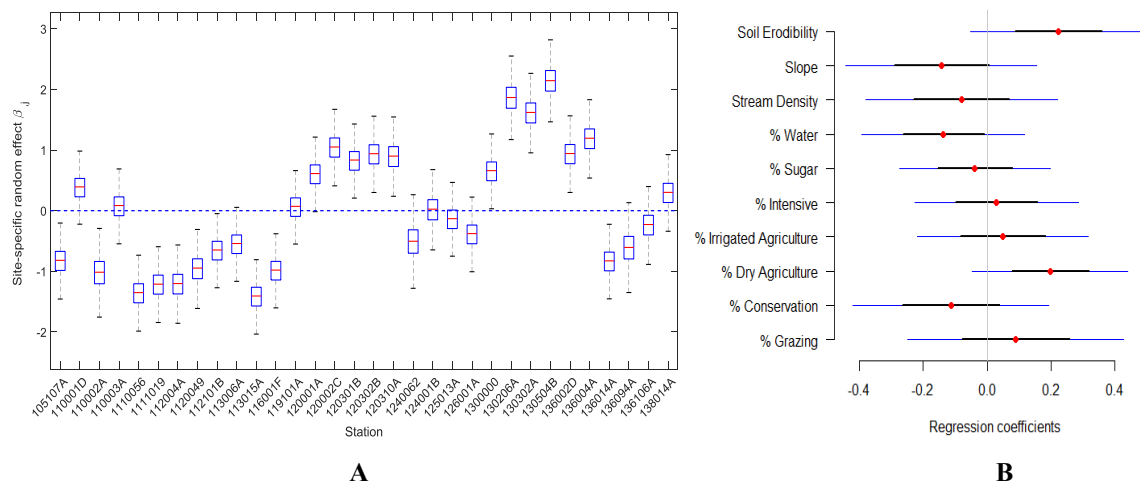


Figure 2. Modelling results of TSS modelling. (A) Modelled site-specific random effect β_j , and red horizontal bar indicating posterior median; (B) Posterior distributions of regression coefficients (γ_n) for catchment characteristics in TSS model, and red circles are estimated posterior means, short black lines are 50% posterior credible intervals and blue lines indicate 95% credible intervals.

To further quantify the effect of land use and catchment characteristics on spatial variability in TSS, the posterior distribution of the regression coefficients of the catchment characteristics in the site-level model are presented in Figure 2 B. The regression parameters illustrate that catchments with high erodibility and intensive cropping and grazing activities, experienced higher TSS concentrations in streams. The average catchment soil erodibility (mean \pm standard deviation of coefficient 0.22 ± 0.14) and proportion of dry land agriculture (0.20 ± 0.12) provide the most significant positive contribution to spatial variability, followed by the proportion of the catchment used for cattle grazing. Higher soil erodibility is more likely to result in higher rates of soil erosion, leading to an increase in hillslope erosion. This is the major source of fine sediment, supported by the utility of soil erodibility dataset in Universal Soil Loss Equation (USLE) (Renard *et al.*, 1997). Percentage of conservation land, catchment slope and stream density have negative effect on deviation of TSS from the mean concentration, but these effects are smaller and the 50% credible intervals of all these parameters cross the 0 line of ‘no effect’. Sub-catchments with steeper slopes and denser stream network tend to have lower TSS concentration during the sampled events. This contrasts with previous studies which state that there is a positive correlation between catchment slope and suspended solids concentrations in streams, due to higher runoff velocity and greater erosion processes (Yu *et al.*, 2016). The effect of slope and stream density on TSS illustrated by the modelling results could be explained by complexity in the interactions between different catchment characteristics. For example, most of the flat catchments in this study are located in inland catchments (e.g., the Fitzroy and Burdekin), where large areas with a high percentage of grazing might act as a source of sediment. Therefore, higher TSS concentrations were observed compared with coastal steeper catchments in Wet Tropics, Burnett Mary and Cape York regions, consistent with the findings from Varanka *et al.* (2015) and Ye *et al.* (2009).

3.2. NO_x Modelling

The site-specific spatial variability in NO_x is demonstrated by Figure 3 A. For several sites, the modelled median NO_x concentration is completely above zero. These sites are located in coastal downstream regions, such as the Wet Tropics (e.g., median β_j of 0.57 for 110003A Barron River at Picnic Crossing, 0.52 for 1111019 (Brodie, 2006) Russell River at East Russell, 0.59 for 113006A Tully River at Euramo), Mackay Whitsunday (e.g., 0.89 for 126001A Sandy Creek at Homebush and 0.51 for 125013A Pioneer River at Dumbleton Pump Station). In these regions, there is a high percentage of sugar cane cropping (> 8 %) in the catchments.

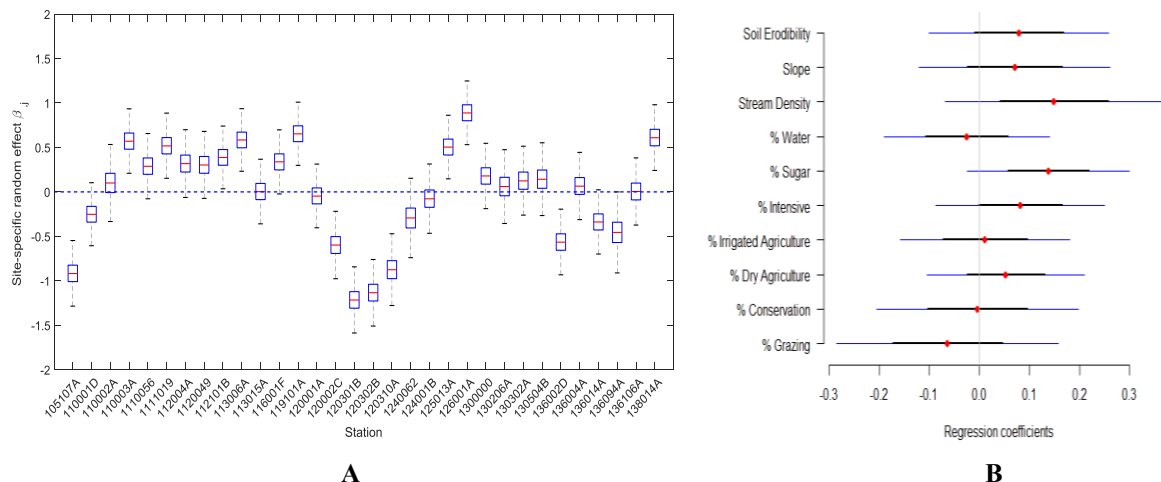


Figure 3. Modelling results of NO_x modelling. (A) Modelled site-specific random effect β_j , and red horizontal bar indicating posterior median; (B) Posterior distributions of regression coefficients (γ_n) for catchment characteristics in NO_x model, and red circles are estimated posterior means, short black lines are 50% posterior credible intervals and blue lines indicate 95% credible intervals.

Indeed, the posterior distributions of the regression coefficients in Figure 3 B indicate that, sugar cane is one of the most significant factors leading to increased NO_x . The 50% credible interval for sugar cane land use regression coefficient of 0.057 to 0.219 indicate a positive correlation between sugar cane and in-stream NO_x concentrations. Brodie (2006) shows that typically high percentage of the N source for sugar cane is nitrogenous fertilizer. The strong effect of sugar cane cropping together with this suggests that nitrogenous fertilizer is likely to be the main source of NO_x in stream. The mean regression coefficient of conservation land is close to 0, indicating its limited effect of this land use on NO_x removal. A regional study conducted by Connor *et al.* (2013) revealed that high dissolved inorganic nitrogen in humid tropics areas in Queensland, occurs because denitrification may not be sufficient to remove NO_x . The positive effects of stream density and slope in Figure 3 B (posterior mean of 0.15 and 0.06, respectively) indicates that NO_x can be transported through drainage networks. These effects might reduce the residence time and retention effect in the soil for plant uptake, leaching to subsurface flow and denitrification.

3.3. Management Implications

The models indicate that the catchment characteristics influencing in-stream TSS and NO_x concentrations are different. Therefore, different management strategies are needed for the two constituents. Specifically, to reduce in-stream TSS concentrations, grazing and dry land agriculture land uses should be targeted. Management strategies, such as fencing by land type and riparian re-vegetation in order to manage the land types of different vulnerability and improve the riparian vegetation restoration. In addition, management of vulnerable streambank and floodplain, such as installation of off stream watering points, enables grazing pressure to be distributed more evenly, and reduces the risk of streambank erosion. To reduce NO_x concentration in streams, management of fertilizer application on cropping lands (e.g., sugar cane) should be addressed. In particular, strategies such as applying only the necessary amount of fertilizer, applying this fertilizer at the appropriate time and control traffic, should be adopted. These results are consistent with expectations that the current BMPs can reduce the water quality impacts from agriculture.

4. CONCLUSION

This paper reveals the ability of Bayesian hierarchical regression models to evaluate the relationship between land use and other catchment characteristics and two water quality indicators (TSS and NO_x concentrations) in the Great Barrier Reef catchments. The effects of land use and catchment characteristics are estimated with uncertainties, which is essential for informing the practice management strategies aiming at pollutant reduction. The modelling results illustrate grazing and dry land agriculture land uses are the most relevant to spatial variation in in-stream TSS concentration; while, sugar cane land use is by far the most significant NO_x contributor. A data-driven understanding of controls on site-level spatial variation in pollutants concentration facilitates the prioritization of best management practices to address the deterioration of terrestrial runoff. We found that the current adopted BMPs in the Great Barrier Reef catchment are in line with results of the Bayesian

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hierarchical modelling, suggesting that the current mitigation strategies are appropriate for reducing TSS and NO_x concentrations in the Great Barrier Reef catchment streams. Future study opportunities involve incorporation of temporal covariate in data-level of the Bayesian hierarchical model to better capture the temporal variability in water quality; meanwhile, developing event mean concentration for individual event would be a potential way to better relate catchment antecedent conditions and catchment characteristics.

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