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Integrated modelling of spatio-temporal variability in stream water quality across Victorian catchments

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ABSTRACT

Degraded water quality in rivers and streams can have large economical, societal and ecological impacts. Stream water quality can be highly variable both over space and time, so understanding and modelling these spatio-temporal variabilities is critical to developing management and mitigation strategies to improve riverine water quality. However, there is currently limited capacity to model stream water quality due to the lack of understanding of the key factors driving spatio-temporal variability in water quality. To address this, a Bayesian hierarchical statistical model has been developed to describe the spatio-temporal variability in stream water quality across multiple catchments in the state of Victoria, Australia. We used monthly water quality monitoring data collected at 102 sites over 20 years. The modelling focused on three key water quality indicators: total suspended solids (TSS), nitrate-nitrite (NOx) and salinity (EC).

It was found that both human-influenced catchment characteristics (land use) and other natural characteristics such as climate or topography are important drivers of spatial variabilities. The key drivers of temporal variability are changes in streamflow, climate and vegetation cover. These key drivers have been integrated into a spatio-temporal modelling framwork. These models can be applied at different spatial and temporal scales, and explain a reasonable proportion of spatio-temporal variation in the different water quality constituents.

The extension and adaption of these models is currently underway to create an operational tool to forecast stream water quality responses to potential land use and climatic changes.

INTRODUCTION

Degraded water quality in rivers and streams can have large economic, societal and ecological impacts (e.g. Kingsford et al., 2011; Qin et al., 2010; Vörösmarty et al., 2010; Whitworth et al., 2012). Stream water quality is often highly variable, both across space and time (Ai et al., 2015; Bengraïne & Marhaba, 2003; Chang, 2008). For example, across different locations, time-averaged water quality conditions can differ significantly (Meybeck & Helmer, 1989). Similarly, at a specific location, water quality conditions can also vary across individual events, as well as at daily, seasonal and inter-annual scales (Arheimer and Lidén, 2000; Kirchner et al., 2004; Larned et al., 2004; Pellerin et al., 2012; Saraceno et al., 2009). These variabilties in stream water quality are driven by three key processes: (1) the source of constituents, which defines the total amount of constituents applied to a catchment; (2) the mobilization of constituents, which removes these constituents from their sources via weathering, erosion or other biogeochemical processes; and (3) the delivery of mobilized constituents from catchments to receiving waters (Granger et al., 2010).

Spatial variability in stream water quality can be driven by human activities within catchments (e.g., land use, vegetation cover and land management) and natural catchment characteristics (e.g., climate, geology, soil type, topography and hydrology), all of which influence the three key processes described above (Lintern et al., 2018). At the same time, temporal shifts in water quality can be influenced by temporal changes in climatic, hydrological and other catchment conditions, such as temperature (Roberts and Mulholland, 2007), rainfall (Fraser et al., 1999), streamflow (Ahearn et al., 2004; Mellander et al., 2015; Sharpley et al., 2002) and vegetation cover (Kaushal et al., 2014; Ouyang et al., 2010).

Understanding and modelling these spatio-temporal variabilities is critical to developing effective strategies to improve and manage stream water quality. Conceptual or physically-based distributed models (Argent et al., 2009; Arnold & Fohrer, 2005) often rely on extensive datasets for implementation. On the other hand, most statistical water quality models focus only on the temporal water quality variation at a single site (Kisi & Parmar, 2016; Kurunç et al., 2005; Parmar & Bhardwaj, 2015), instead of analyzing the spatio-temporal patterns over a wide region. This lack of integrated modelling of spatio-temporal variability can not only limit our understanding of the key factors that can affect water quality dynamics, but also hinder our ability to predict water quality changes for non-monitored locations.

The ARC Linkage project, "*Predicting water quality at the catchment scale: learning from two decades of monitoring"* aims to improve the understanding of spatio-temporal variability in stream water quality and develop a model that can forecast future changes. The analyses and modelling presented in this paper is informed by long-term stream water quality observations across the state of Victoria. The analyses and modelling was approached in the following way. First, spatial variability in water quality was investigated and modelled (Lintern et al. in review), followed by an investigation and development of a model of temporal variability (Guo et al. in review). These two models were then integrated into a spatio-temporal predictive model that is capable of predicting water quality at different spatial and temporal resolutions across Victoria.

In this paper the spatio-temporal water quality modelling framework is introduced first, along with the data collection and detailed modelling approaches. Following that, model performance is evaluated at different spatio-temporal resolutions. The management implications of these models are then discussed and future work to further improve model performance is suggested. Work is being undertaken to extend these model to an operational forecasting tool for stream water quality responses to potential changes in land use and climate.

METHOD

Spatio-temporal Modelling Framework

A Bayesian hierarchical approach was used to model the spatio-temporal variability in stream water quality. The Bayesian approach enables the inherent stochasticity in water quality to be incorporated into the model (Clark, 2005), while the hierarchical model structure enables the inclusion of temporal and spatial influences on water quality at multiple scales (Webb & King, 2009).

The transformed concentration of a constituent (see *Data Collection and Processing* for details) at time i and site j (C_{ij}) is assumed to be normally distributed with a mean μ_{ij} and standard deviation σ representing inherent randomness (Eq. 1).

$$\boldsymbol{C_{ij} \sim N(\mu_{ij}, \sigma)} \quad \textbf{(1)}$$

To represent spatio-temporal variability, μ_{ij} is modelled as the sum of the site-level mean constituent concentration ($\bar{C}_j$) and the deviation from that mean at time *i* (Δ_{ij}) (Eq. 2).

$$\boldsymbol{\mu_{ij} = \bar{C}_j + \Delta_{ij}} \quad \textbf{(2)}$$

To describe spatial variability, the site-level mean ($\bar{C}_j$) is modelled as a function of a global intercept (*int*), and the sum of the effects of *m* catchment characteristics ($eff.S_1$ to $eff.S_m$) multiplied by the value of the catchment characteristics $S_{1,j}$ to $S_{m,j}$ (e.g. land use, topography) (Eq. 3).

$$\boldsymbol{\bar{C}_j = int + eff.S_1 \times S_{1,j} + +eff.S_2 \times S_{2,j} + \cdots + eff.S_m \times S_{m,j}} \quad \textbf{(3)}$$

The temporal variability, represented by the deviation from the mean (Δ_{ij}), is a linear combination of *n* temporal variables, $T_{1,ij}$ to $T_{,ijn}$ (e.g. climate condition, streamflow, vegetation cover) (Eq. 4), at time *i* and site *j*.

$$\boldsymbol{\Delta_{ij} = eff.T_{1,j} \times T_{1,ij} + \cdots + eff.T_{n,j} \times T_{n,ij}} \quad \textbf{(4)}$$

To account for differences in these temporal influences across sites, the effects of each temporal variables ($eff.T_{N,j}$ with *N* in 1,2, … *n*) at site *j* is distributed with a mean of $N_{eff.T_{N,j}}$ (Eq. 5), which is then modelled with a linear combination of two additional chatchment characteristics, $S_{TN1,j}$ and $S_{TN2,j}$ (Eq. 6).

$$\boldsymbol{eff.T_{N,j} \sim \left(N_{eff.T_{N,j}}, \sigma_{eff.T_N}\right), for\ N\ in\ 1, 2, \ldots n} \quad \textbf{(5)}$$

$$\boldsymbol{N_{eff.T_{N,j}} = int_{eff.TN} + eff.S_{TN1} \times S_{TN1,j} + eff.S_{TN2} \times S_{TN2,j}} \quad \textbf{(6)}$$

The best spatial predictors (S_1 to S_n in Eq. 3) and the best temporal predictors (T_1 to T_n in Eq. 4) were identified by focusing on only the spatial and temporal variability (Lintern et al. in review; Guo et al. in review). Selections of these predictors were based on an exhaustive search approach (Saft et al., 2016), which considers a large number of potential predictors and all possible combinations of these predictors. This selection approach requires firstly fitting an individual model to each candidate predictor set, and then selecting a single best set of predictors by comparing the performance of all fitted models. Following selection of the best spatial and temporal predictors, S_{TN1} and S_{TN2} (which explain the spatial variability in each temporal effect in Eq. 4) were selected as the two catchment characteristics which had the highest correlations with the fitted parameter values of the temporal effect (Guo et al. in review).

The Bayesian hierarchical model assumes that the value of each temporal parameter, $eff.T_{TN1}$ and $eff.T_{TN2}$ is drawn from a common prior distribution defined by the corresponding hyper-parameters. In this way, this hierarchical structure effectively uses data at multiple sites to strengthen the site-specific models, and reduces unexplained variation in fitted parameters (Webb et al., 2010).

Data Collection and Processing

Stream water quality data were extracted from the Victorian Water Measurement Information System (Department of Environment Land Water and Planning (DELWP), 2016a). This database contains monthly grab samples of water quality at approximately 400 sites across Victoria, with some monitoring sites dating back to 1990. Water quality data sampled between 1994 and 2014 at 102 sites were used (Figure 1), which provide long-term continuous monthly data over a consistent period. The catchments corresponding to these water quality monitoring sites were delineated using the Geofabric tool (Bureau of Meteorology, 2012), with areas ranging from 5 km^2 to 16,000 km^2. The water quality parameters of interest were: total suspended solids (TSS), nitrate-nitrite (NOx) and electrical conductivity (EC), which represented sediments, nutrients and salts, respectively.

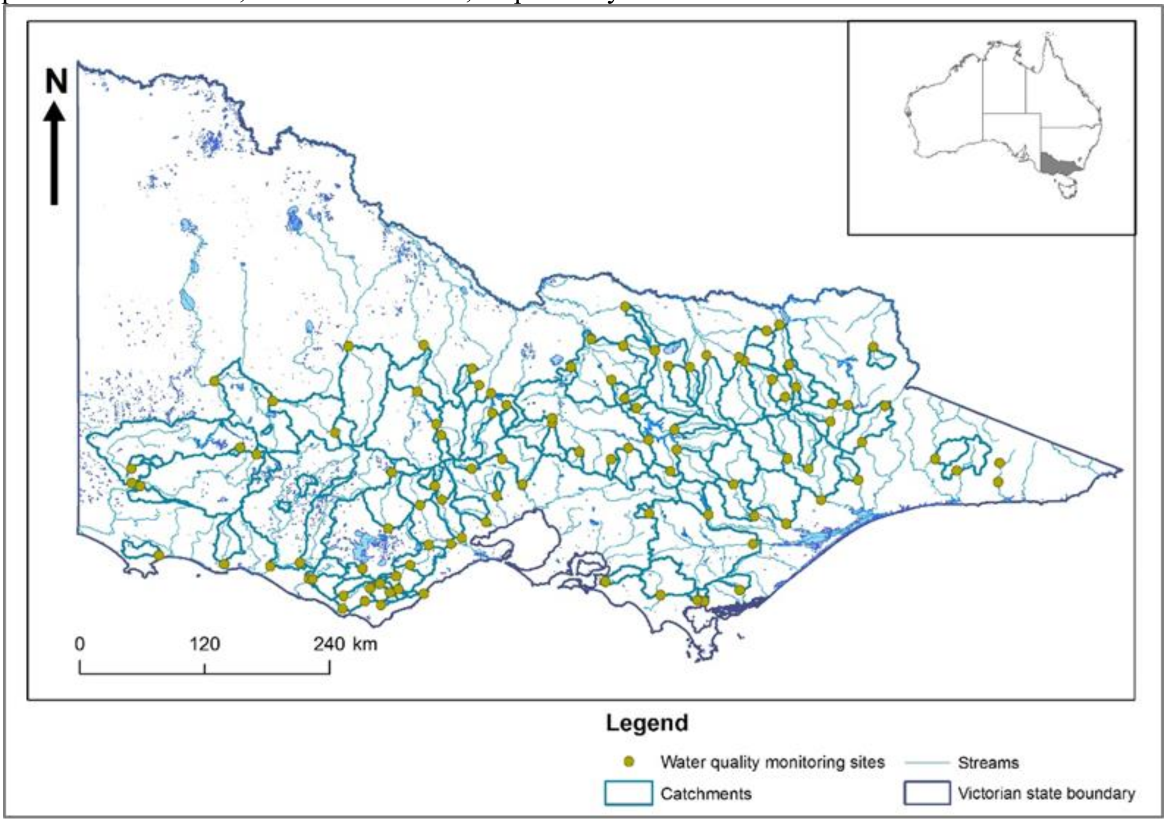

Figure 1. Map of the 102 water quality monitoring sites and their catchment boundaries. Insert shows location of the state of Victoria within Australia

Potential spatial explanatory variables, including catchment average land use, land cover, topographic, climatic, geological, lithological and hydrological catchment characteristics, were derived using datasets obtained from Geoscience Australia (Geoscience Australia, 2004, 2011), the Bureau of Meteorology (BoM) (Bureau of Meteorology, 2012), the Bureau of Rural Sciences (BRS) (Bureau of Rural Sciences, 2010), the Victorian Department of Environment Land Water and Planning (DELWP, 2014, 2016a, 2016b), and the Terrestrial Ecosystem Research Network (Terrestrial Ecosystem Research Network, 2016). Fifty potential explanatory catchment characteristics were selected based on a literature review and conceptual understanding of the key factors affecting spatial variability in water quality (Lintern et al., 2018). A preliminary analysis of the land use data between 1996 and 2011 suggests less than 1% changes in the key land uses in these catchments (i.e. agricultural, grazing, conservation), allowing us to assume constant land use over the study period.

Potential temporal explanatory variables of discharge (ML/d) and water temperature (°C) (both on the same dates as the water quality measurements) were also extracted for each site over the study period (DELWP, 2016a). Discharge was converted to streamflow (mm/d) for each catchment, which allowed the average streamflows over 1, 3, 7, 14 and 30 days preceding the water quality sampling dates to be calculated as well. In addition gridded climate data (Jones et al., 2009) and the normalized difference vegetation index (NDVI) data (NASA DAAC, 2017; Eidenshink, 1992) were used to calculate the catchment average daily rainfall (mm), daily evapotranspiration (ET) (mm), daily average temperature (°C), daily root zone (less than 1-m depth) and deep (more than 1-m depth) soil moisture, as well as monthly NDVI.

The raw input data were filtered and transformed to increase the capacity of the statistical water quality models (Eqs. 1 to 6). First all water quality records with flags of quality issues and values below the limits of reporting (LOR) were removed. Values below the LOR likely have higher proportional uncertainty in the transformed data set, and thus may hinder accurate modelling of water quality variability. In addition, for TSS and NOx ‘categorical’ behaviours in low concentration records (Figure

2) were identified.

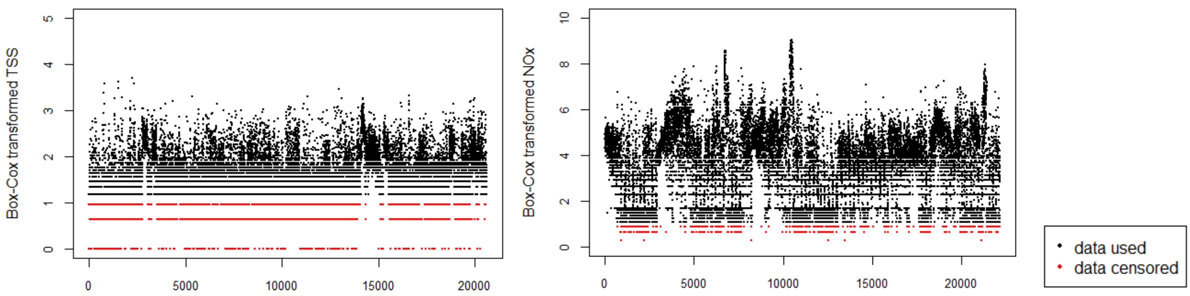

Figure 2. Censoring 'categorical' data from all measured concentrations of TSS and NOx (Box-Cox transformed), with x-axis showing data index

The three lowest levels within these low concentrations for both TSS and NOx (red dots in Figure 2) were censored because: 1) these categorical records can violate assumptions of continuous statistical models; and 2) removal of these values also focuses the analysis more on higher concentrations, which are generally of greater concern in water quality management. All observations of EC are relatively continous with no obvious 'categories' in concentration, so censoring was not performed for the EC data.

All observed constituent concentrations, catchment characteristics, and temporal explanatory variables were Box-Cox transformed to ensure greater normality in their distributions. For each variable, the optimal Box-Cox parameter λ, was identified at each site; and then the average λ across all sites was used for the final transformation. This ensures that all sites were being transformed using consistent transformation parameters.

Evaluation of Model Performance

The fitted models for TSS, NOx and EC were evaluated for their preformance at different spatio-temporal scales. For each constituent, the overall model performance was assessed first by comparing the simulated and observed concentrations at all sites altogether. Note that although the below-LOR data was excluded and the lowest concentrations were further censored during model development, these data were included in model evaluation to better understand the model capacity in simulating the full distribution of constituent concentrations. Following the overall fit, the proportion of spatio-temporal variability explained by each model was also assessed. This was achieve by firstly decomposing the spatial and temporal components of total variability within observations (Fubao et al., 2010), and then estimating the proportion of variaility explained by model for each component, respectively.

The model capacity in simulating statistics at each site was then assessed by comparing the simulated and observed values of:

1) site-level mean concentrations; and
2) site-level distributions of constituent concentrations represented by the 25th, 50th, 75th and 90th quantiles.

RESULTS

Key Factors that explain Spatio-temporal Variabilities

Table 1 and Table 2 summarise the key factors that explain the spatio-temporal variability in TSS, NOx and EC. Theses key influencing factors were identified from two exhaustive searches (see Section *Spatio-temporal Modelling Framework*, and Lintern et al., in review; Guo et al., in review for further details). For each temporal factor, the two key spatial factors that drive the variation of temporal effects across sites are also shown. In general, land-use and long-term climate conditions are key factors controlling the spatial variability in river water quality. Temporal variability is mainly explained by temporal changes in streamflow conditions, water temperature and soil moisture. In addition, catchment characteristics of topography, climate and land-use are also key to explain differences in the impacts of temporal drivers across sites.

Table 1. Key factors affecting the spatial variability, based on the best model structures selected for TSS, NOx and EC.

Constituent	Key factors that affect spatial variability
TSS	Hottest month maximum temperature Percentage area covered by grass Percentage area covered by shrub Percentage cropping area Maximum elevation Dam storage Percentage clay area
NOx	Annual radiation Warm quarter rainfall Hottest month maximum temperature Average soil TP content Mean channel slope
EC	Annual radiation Annual rainfall Wettest quarter rain Hottest month maximum temperature Percentage agriculture area Percentage cropping area Percentage area covered by shrub Average soil TN content

Table 2. Key factors affecting the temporal variability, and factors that affect the spatial variability in these temporal effects, based on the best model structures selected for TSS, NOx and EC.

Constituent	Key factors that affect temporal variability	Key factors that affect spatial variability in temporal effects
TSS	Same-day streamflow	Annual rainfall, Hottest month maximum temperature
	7-day antecedent streamflow	Annual runoff, Mean elevation
	Water temperature	Daily flow standard deviation, Total catchment length
	Soil moisture root	Percentage area with saline aquifers, Hottest month maximum temperature
	Soil moisture deep	Maximum distance upstream to dam wall or reservoir, Percentage area covered by grassland
NOx	Same-day streamflow	Total storage capacity of dams in catchment, Mean soil TN content
	30-day antecedent streamflow	Coldest quarter rainfall, Hottest month maximum temperature
	Water temperature	Percentage area covered by woodland, Maximum elevation
	NDVI	Percentage area underlain by mixed igneous bedrock, Percentage urbanized area
	Soil moisture root	Annual rainfall,

		Warmest quarter average temperature
	Soil moisture deep	Percentage horticulture area, Wettest quarter rainfall
EC	Same-day streamflow	Percentage area covered by grassland, Percentage area covered by woodland
	14-day antecedent streamflow	Mean 7-day low flow, Percentage area covered by forest
	Water temperature	Coldest month minimum temperature, Mean catchment slope
	Soil moisture root	Mean 7-day low flow, Average soil TN content
	Soil moisture deep	Maximum elevation, Percentage area covered by woodland

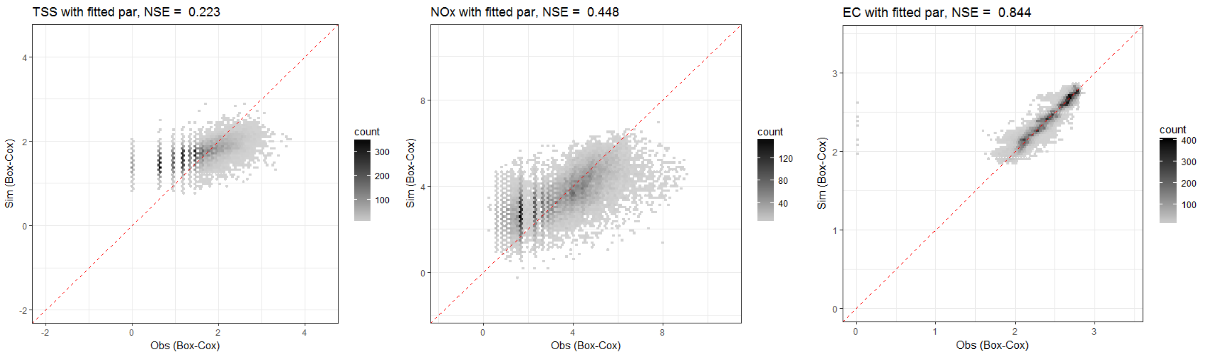

Figure 3. Performance of the spatio-temporal models for TSS, NOx and EC, represented by the simulated and observed concentrations across all sites. Darker regions represent denser distribution of values of simulations and observations. The Nash-Sutcliffe Efficiency (NSE) for each constituent is also shown.

Overall Performance

The spatio-temporal water quality models show varying performances among constituents, as shown by the comparison of simulated and observed concentrations (Figure 3). The models also show varying capacities to explain the spatial and temporal components of the observed variability for each constituent (Table 3).

Table 3. Partition of spatial and temporal components within observed variability, and proportion of variability explained within each component, for TSS, NOx and EC. For each constituent, all variability components are presented as percentage of total observed variability

	Observed variability		Variability explained by model		
	Spatial variability	Temporal variability	Spatial variability	Temporal variability	Total
TSS	36.1	63.9	14.8	9.5	22.3
NOx	39.3	60.7	22.3	23.0	44.8
EC	86.1	13.9	83.1	1.3	84.4

It is clear that model performance for individual constituent is not only related to the proportion of observed spatial and temporal variability that can be explained by model, but also influenced by the partition of spatial and temporal variability within observed total variabilty. Specifically, the models for TSS and NOx show poorer performance (with NSE values of 0.223 and 0.448, respectively). These can be explained as the total variabilities in both constituents are dominated by temporal variability (63.9% and 60.7%, respectively), within which only small portions can be explained by the models (9.5% out of 63.9% for TSS, and 23% out of 60.7% for NOx). In contrast, the EC model shows a very good fit with 84.4% total variability explained. This is because 86.1% of the total variability within data is spatial, of which 83.1% can be explained by the model. Therefore, although the model is only able to explain a small portion of temporal variaility in EC (1.3% out of 13.9%), the overall model performance remains largely unaffected.

Site-specific Statistics

The models for TSS and NOx show reasonable performance in simulating the site-level mean concentrations (with NSE values of 0.41 and 0.57, respectively), while the EC model has very high performance (NSE = 0.97) (Figure 4). It is interesting that for both TSS and NOx, the spatial variability within simulated mean concentrations across sites are greater than that of the observations. This may be due to the model structure, which simulates spatial and temporal variability collectively (i.e. model is fitted to observed total variability, see Eq. 2). Therefore, for each constituent, the spatial and temporal components represented in the model may compensate each other to improve fitting to the total variability. Consequently, for both TSS and NOx, the modelled spatial variability can be overestimated due to the influences of temporal variability, which contributes to the major part of total variability (Table 2).

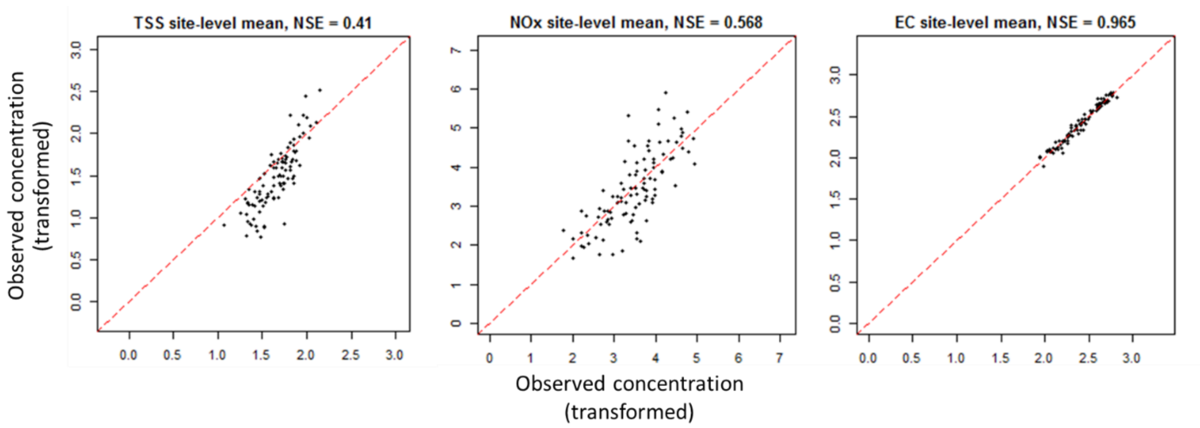

Figure 4. Model fit for site-level mean concentration, for TSS, NOx and EC. The Nash-Sutcliffe Efficiency (NSE) for simulating the site-level means of each constituent is also shown.

When simulating the site-level distributions of constituent concentrations, the spatio-temporal models again show contrasting performance among constituents (Figure 5). For TSS and NOx, models are particularly weak in simulating the lower quantiles (i.e. 25^{th} and 50^{th} percentiles). In particular, sites with relatively low concentrations (which often display ‘categorical’ behaviour) are largely overestimated. These poor performances are somewhat expected, because much of these low concentrations were excluded in model fitting, as explained in *Data Collection and Processing*. In contrast, the models have greater performance in simulating high concentrations at each site (i.e. 75^{th} and 90^{th} percentiles), which are often more of interest for catchment management.

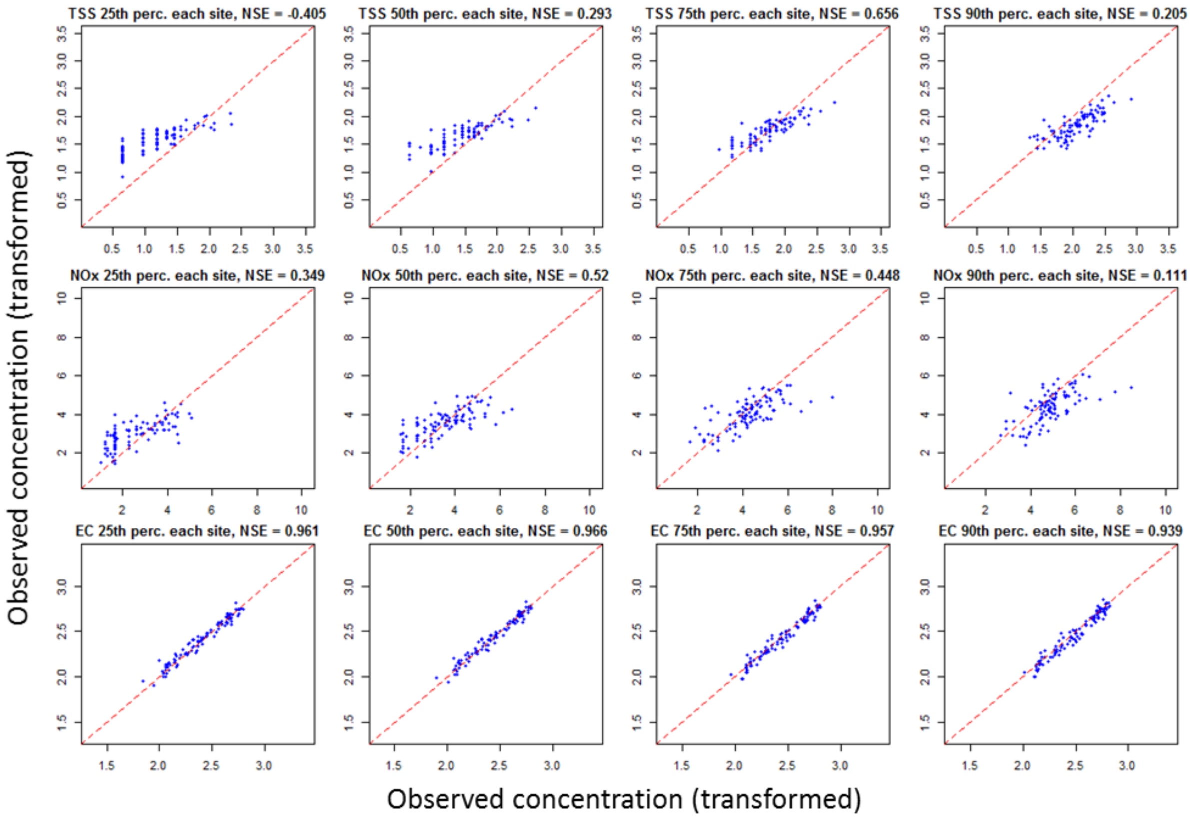

Figure 5. Model fit for the 25th, 50th, 75th and 90th percentile of constituent concentration at each site, for TSS (top row), NOx (middle row) and EC (bottom row). The Nash-Sutcliffe Efficiency (NSE) for simulating each quantile of each constituent is also shown.

The EC model shows consistently good performance across all four quantiles (Figure 5). This can be related to the relatively small variation across different quantiles in the transformed EC data, consistent with the low contribution of temporal variability in EC observations, compared with spatial variability (Table 2). Therefore, model performance is likely largely advantaged by its high capacity to simulate spatial variability (Figure 4), even when simulating for both the spatio-temporal variabilities. Furthermore, the use of full, uncensored EC data enabled model to better fit to the full distribution of observations.

DISCUSSION

Further Improvements

In this study statistical models were developed to explain the spatio-temporal variabilities within long-term river water quality data across Victoria. The models highlight the role of specific land use types in affecting wate quality variability across sites, and the importance of temporal variability in streamflow and climatic conditions in affecting within-site water quality variability. These understandings are useful to identify potential 'hot-spot' locations and periods that have higher risks of water quality issues.

Generally, the spatio-temporal models perform well in explaining the observed variability, although modelling capacity varies with constituent. This depends on the relative contribution of spatial and temporal variability within observed constituent concentrations, as well as how well the model can explain each component of variability. Additional model evaluations are being undertaken through cross-validation with diffenrent sites and time periods, to assess the model capacity as a management tool for predicting water quality.

For TSS and NOx, model performances are clearly limited by the capacity to explain temporal variability, particularly for lower concentrations. Potential improvement in model performance could be achieved by further improvements such as:

- alternative statistical model structure, including non-linear relationships between spatio-temporal variability and their driving variables; the use of threshold-type models could also be explored to address issues with simulating low concentrations (Taranu et al., 2017).
- identify optimal level of censoring which retains the maximum number of data points used in model fitting while having minimum impact on the overall model performance.

Management Implications of Spatio-temporal Modelling

As a limitation of this study, temporal changes in land use management (e.g. tillage, fertiliser application, irrigation) are currently not considered as predictors of water quality temporal variability. A key reason for this is the inconsistency of the temporal resolution of available data for land use management with that of water quality observations. However, changes in these land use management practices can occur in short time spans and can lead to increases in pollutant sources and changes to runoff generation processes (e.g. DeFries & Eshleman, 2004; Tang et al., 2005). Therefore, the model performance can potentially be further improved by increasing capacities in the monitoring of temporal patterns in land management.

In the current models, water quality temporal variability is represented by monthly monitoring data. The model capacity to explain temporal variability can be potentially strengthened by utilizing data with higher temporal resolution. Alternatively, high frequency sampling of proxy data could also be utilized to enhance the learning from existing monthly samples. For examples, continuous monitoring data of EC and turbidity can be good proxies for salts and sediments, and are readily available from state agencies, such as the Victorian Water Quality Monitoring Network database (DEWLP, 2016) and the NSW Water Information database (State of New South Wales, 2018).

CONCLUSIONS

Stream water quality can be highly variable both over space and time, so understanding and modelling these spatio-temporal variabilities is critical to developing management and mitigation strategies to improve riverine water quality. Using monthly water quality monitoring data collected at 102 sites over 20 years, a Bayesian hierarchical statistical model was developed to describe the spatio-temporal variability in concentrations of three water quality constituents: total suspended solids (TSS), nitrate-nitrite (NOx) and salinity (EC). Apart from limitations in simulating low concentrations for TSS and NOx, these models can explaine a reasonable proportion of spatio-temporal variation in the constituent concentrations. Thus, these models are capable to simulate stream water quality at different spatial and temporal resolutions. The extension and adaption of these models is currently underway to create an operational tool, to explore the impacts of potential changes in climate, land use and land management practices in these catchments on stream water quality. Such a modelling tool will be highly valuable to inform future decision-making in catchment water quality management.

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BIOGRAPHY

Dr Danlu Guo is a Research Associate in the Infrastructure Engineering at the University of Melbourne. She has completed her PhD in hydro-climatology at the University of Adelaide in 2017, and since then she has been working on understanding the impacts of climate variability on various water resources systems, which include drinking water supplies in developing countries and catchment water quality in Australia. She is also interested in estimating potential changes in water resources systems due to anthropogenic climate change.

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Dr Angus Webb is a quantitative ecologist in the Environmental Hydrology and Water Resources group within the Department of Infrastructure Engineering, University of Melbourne. Quantitative ecology is the use of maths and statistics to try to make sense of our natural environment, or to try to make predictions about individuals, populations or ecosystems. Currently, we spend a lot of money collecting data, but not getting maximal value from this investment. Through more advanced analytical approaches, we can often gain additional insight into these complex environments. His research focuses on the study of landscape-scale impacts of human-induced disturbances on freshwater systems, and what can be done to restore these systems.

Associate Professor Dongryeol Ryu is a Senior Lecturer in the Environmental Hydrology and Water Resources group in the Department of Infrastructure Engineering at The University of Melbourne. He leads the Hydrology and Remote Sensing group in the Department with a special interest in surface water hydrology and microwave remote sensing. Dr Ryu is currently working on developing microwave soil moisture retrieval algorithms and on investigating an innovative method of flood forecasting by using various satellite observations, which are funded by ARC. He is also a past recipient of a NASA Earth System Science Fellowship and the University of California, Irvine Medal.

Shuci Liu is a current PhD candidate in the Environmental Hydrology and Water Resources group in the Department of Infrastructure Engineering at The University of Melbourne. He has completed a bachelor in environmental engineering in 2009, and then a masters degree in mining engineering in the University of Science and Technology Beijing (China) in 2012. He also holds masters environmental engineering at the University of Melbourne in 2015. His PhD work focus on catchment water quality in the Great Barrier Reef regions, which is part of the ARC Linkage project '*Predicting water quality at catchment scale-learning from two decades monitoring data*'.

Professor Andrew Western has more than twenty-five years of experience in catchment and waterway research, teaching and consulting. He is now the deputy Head of Department of Infrastructure Engineering at the University of Melbourne. He completed his PhD over the period 1991-1994 on hydraulic and hydrologic modelling. He has then worked as a researcher for the Centre for Environmental Applied Hydrology, Technical University of Vienna, The CRC for Catchment Hydrology and eWater CRC. Prof Western has expertise in field experimentation, physically-based and conceptual catchment and river modelling, catchment analysis and remote sensing and has concentrated on integrating these areas to support catchment system understanding and management.

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