Temporal Changes In Urban Stream Macroinvertebrate Assemblages: A Bayesian Hierarchical Approach To Analysing Sparse Monitoring Data

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EXTENDED ABSTRACT

Temporal analysis of ecological monitoring data is of critical importance in order to demonstrate whether management actions are having the desired effects, and whether there are changes in environmental condition. Over recent years in Australia, temporal trend analyses of water quality data by techniques such as Generalised Additive Modelling have become commonplace. In contrast, analyses of temporal trends in biological monitoring data are rare. We believe this is at least partly explained by the fact that biological data time series generally have far fewer points than abiotic time series data, invalidating the use of common trend analysis techniques.

We explore the use of Bayesian hierarchical models for the analysis of biological monitoring data, using stream macroinvertebrate monitoring data from the Dandenong catchment in the eastern Melbourne region. We consider temporal sequences of the SIGNAL score biotic index that have been collected from 1994–2004 at ten sites on two independent streams.

As previous research has indicated that edge-habitat SIGNAL scores appeared to have declined over the period of record, the main parameter of interest was the yearly change in SIGNAL score. We modelled this as a linear function of time and employed a hierarchical model structure, so that the estimate of yearly change for any one sampling site "borrows strength" from the data at the other sites, thereby providing more robust estimates at the site level than would be possible by treating the sites independently. This is particularly relevant for this research, given that no sites have a large number of data points. As initial investigations also found that declines in edge SIGNAL scores appeared greater at sites lower down in the catchment, the hierarchical model treated the yearly change in scores as a linear function of the square root of catchment area.

The arrangement of sites within the catchment, and the fact that samples are taken over time at each site means that both spatial and temporal autocorrelation of the data are possible. We accounted for both effects by applying a first order autocorrelation model to the residuals of the linear models. Due to the short data series available for estimating autocorrelation, we employed a latent data approach, by modelling a latent point to condition the model before the first true data point of each series.

The results provide strong evidence of declines in edge SIGNAL scores across the Dandenong catchment, with a mean of 9.3 out of 10 sites having suffered a decline in stream health. Site-level probabilities of decline ranged between 0.72 and >0.99. There was strong evidence (probability = 0.945) that sites lower in the catchment had experienced greater declines than those higher up.

The pattern of decline in SIGNAL scores may be explained by changes in catchment urbanisation over time: i.e. sites at the top of the catchment are likely to have experienced less development. Alternatively, the long running drought in Melbourne may have led to loss of ecological condition, with the more degraded sites lower in the catchment less being resilient to the effects of drought than those in better condition.

Amongst these results there was very little evidence for autocorrelation, either temporal or spatial. This may be partly data-based: i.e. the small sample sizes do not allow accurate calculation of autocorrelation parameters. However, there are sound biological reasons to explain the lack of autocorrelation, such as the short lifecycle and tolerance to disturbance of many urban macroinvertebrates, as well as their high dispersal capabilities and mobility between sites as both larvae and adults.

Despite the small sample size and limited spatio-temporal resolution of these data, these results highlight the utility of using Bayesian hierarchical models for the analysis of stream monitoring data. Further research is directed at developing posterior predictive model checks and the use of informative priors to better quantify the uncertainty associated with a single sampling value.

1. INTRODUCTION

In order to understand and eventually predict complicated ecological processes, we need to make use of scientific insight, theory and data, and importantly, be explicit in our uncertainty in each (Wikle 2003). The Bayesian statistical framework is being increasingly used in conservation biology and environmental science, as it is able to deal formally with ecosystem uncertainty and offers great flexibility when constructing and fitting complex models. In this approach, uncertainty about parameter values, given the observed data and background information, is expressed in terms of the probabilities of various parameter values being found (Gelman *et al*. 1995). A particular advantage of the Bayesian framework lies in the subjective interpretation of these probabilities.

The model described in this paper attempts to take advantage of these features in the analysis of temporal changes in aquatic macroinvertebrate assemblages. This type of monitoring data is used to characterise in-stream health. Detecting changes in stream condition has important implications for urban stream restoration and management. However, heretofore there have been no attempts to systematically analyse such data over time. We believe this is most likely due to the fact that temporal sequences of data points are short (generally < 10 points), which often precludes a robust analysis on a site-by-site level.

1.1 Urban freshwater ecosystems

Urban populations worldwide have increased exponentially and approximately 85% of the Australian population lives in urban areas (Australian State of the Environment Committee 2001). The term urbanisation describes an increase in human habitation linked with increased per capita energy and resource consumption, and extensive landscape modification (McDonnell and Pickett 1990). As ecological theory has previously made limited reference to the massive and pervasive effects of human beings (Grimm and Redman 2004), the study of human-dominated ecosystems is still very much lagging behind non-urban research. A wider appreciation of the role of humans in ecological processes is one of the many research challenges being addressed in the development of urban ecological theory. Given the increasing population pressures and resulting expansion of urbanisation in the landscape, there is an increasing need to ecologically understand cities, and more importantly find solutions to environmental problems where they are most severe.

Previous research on urban freshwater systems has found that urbanisation has a strong degrading influence on the macroinvertebrate communities in stream ecosystems (e.g. Walsh *et al.* 2001). In particular, polluted stormwater runoff is a source of multiple confounded stressors to stream ecosystems (Walsh 2004). The flushing effects of sewage and industrial effluents, as well as storm water running off from impervious surface areas in a catchment, result in an increase in flow-related disturbance, and in the frequency and intensity of floods (Walsh *et al.* 2005). These conditions favour macroinvertebrates that are tolerant to pollutants and have life history characteristics that permit them to re-establish after frequent but irregular disturbance (Walsh *et al.* 2001).

Further research has also found that urban stream sampling sites characterised by high levels of stormwater drainage connection (the proportion of a catchment's impervious surfaces directly connected to stream by pipes) and urban density (Walsh *in press*) have depauperate macroinvertebrate communities.

SIGNAL (Stream Invertebrate Grade Number-Average Level) is a family-level water pollution index based on the known tolerances of aquatic macroinvertebrate families to various pollutants. The index has a gradient from 1 to 10 (ranging from a pollution tolerant to a pollution sensitive community). Different habitats from the same sampling location are considered separately as they contain different microhabitat characteristics, and thus distinct macroinvertebrate communities. The SIGNAL score for each habitat is the average of the scores for each macroinvertebrate family found in that sample (Chessman 2003). Streams in the Melbourne area that are considered to be in excellent condition have a SIGNAL score greater than 6, while a score of less than 4.5 indicates a severely degraded stream (EPA 2003).

This investigation makes use of this index, as previous research has shown SIGNAL to be sensitive to a gradient of urban disturbance in the Melbourne region (Walsh *in press*) and because family level identifications offers numerous practical advantages (see e.g. Hewlett 2000).

Previous graphical investigations of changes in macroinvertebrate stream health in the Melbourne Water management area have identified a general trend of decreasing biological condition across many sites (Walsh *et al.* 2005). It was further noted that sites initially in better ecological condition have tended to show less or no decrease in condition when compared to more degraded sites (Walsh *in press*). We hypothesised that overall declines may have also been attributable to the effects of drought, and that the differences among sites could be due to the degraded sites being more susceptible to further disturbance. Although such hypotheses could only be tested by longer term data sets, these analyses represent an initial step in understanding changes in stream health over time.

In recent years, trend analyses of water quality data have become a common way of determining whether development/management actions are having an impact on water quality. As water quality variables are often taken at monthly or finer time scales, relatively large data sets can be analysed. As a result, trends can be fitted using techniques such as Generalised Additive Modelling, and such analyses have become very common. In contrast, as outlined above, there have been few attempts to subject biological monitoring data to similar trend analyses.

We attempt to overcome or account for the limitations of biological monitoring data by making use of Bayesian hierarchical modelling techniques. The main aim of this research is to determine whether Bayesian techniques can be used to statistically assess the changes in stream condition as measured by the SIGNAL index.

2. METHODS

2.1 Data availability and study area

The model described in this paper was developed using monitoring data from the Dandenong Catchment, Victoria, Australia (Figure 1), which lies in the eastern Melbourne region. Single season SIGNAL scores for edge habitat, catchment area and other site location details were extracted from the CRCFE Urban Macroinvertebrate Database (Walsh, 2005). As we were primarily interested in changes in stream condition over time, we excluded from consideration sites with few data points. We set an arbitrary "cut off" of less than four samples. This criterion resulted in ten sites for consideration, seven of which lie on Dandenong Creek, and three of which are on Eumemmering Creek. The two streams are independent of one another in that there are no sampling sites included that are below the confluence of the two waterways (Figure 1). The total data set contained 84 SIGNAL scores, with between four and ten samples available for each site between 1994 and 2004.

2.2 Bayesian model

As our main aim was to determine whether the data provided evidence for a change in SIGNAL score over time, we considered that at the site level the basic model could be represented by a simple linear regression. Thus we consider the data as:

$$y_{ij} \sim N(\mu_{ij}, \sigma_j)$$
$$\mu_{ij} = \alpha_j + \beta_j t_i \quad (1)$$

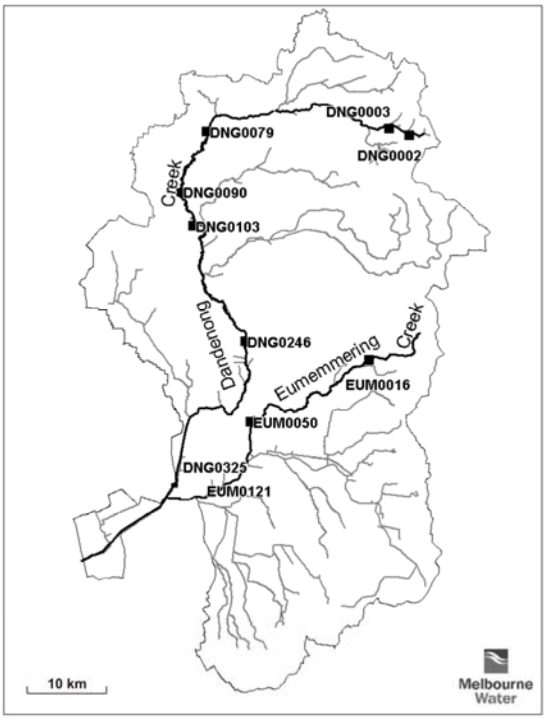

Figure 1. Map of study area. Sampling sites are represented using a three letter abbreviations (DNG=Dandenong Creek, EUM=Eumemmering Creek) and the approximate area of the catchment above the monitoring site in km^2 (4 numerical digits). Thus sites with smaller numbers lie higher in the catchment.

where *ij* represents the *i*th data point at site *j*. α and β are normally distributed with vague priors, $1/\sigma^2$ is gamma distributed with vague prior, and *t* is the time index for point *i*. The parameter of main interest is the slope (β), the yearly change in edge SIGNAL score, and the majority of effort is expended in modelling this parameter appropriately.

Accounting for autocorrelation

The data structure suggests that autocorrelation may be an issue in space and/or time; we cannot assume that each data point is a random sample and that there is independence of errors between readings. Temporally, the data are collected at six monthly intervals, but there were sometimes longer time gaps in the series where some years were not sampled. The macroinvertebrate community present for one sample could be partly dependent on the biota present from the previous sample. Spatially, most of the sites lie downstream of other sites, with varying distances separating the site pairs. The SIGNAL score obtained at one site could be partly dependent on values observed upstream due to shared influences higher in the catchment.

Due to the fact that the minimum temporal and spatial gaps are relatively large, we hypothesise that autocorrelation, if present, is likely to be quite small, and can probably be adequately modelled by a first order regressive (AR1) process applied to the regression residuals.

We deal with both forms of autocorrelation in the same way, employing the latent data approach to AR1 autocorrelation of Congdon (2001), where a latent point is modelled at the start of each data sequence. This avoids the "loss" of the first point from the regression, which would otherwise solely be used to condition the model for the second point. Because we had few data points in each sequence (4 to 10 in the temporal sequences, 7 and 3 in the spatial sequences), avoiding such a loss of data was considered to be of great importance.

Thus for the temporal sequences, we modelled a latent data point immediately preceding the first data point in the sequence as follows (subscript *j* denoting site has been omitted for clarity).

$$\begin{aligned} y_{i_{\min}-1} &\sim N\left(\mu_{i_{\min}-1}, \sigma\right) \\ \mu_{i_{\min}-1} &= \alpha + \beta\left(t_{\min} - 1\right) \end{aligned} \qquad (2)$$

The data in each sequence were then modelled using the AR1 model described by Congdon (2001) with an adjustment to allow for the possibility of different time gaps between readings.

$$\mu_i = \alpha + \beta t_i + \rho\left(y_{i-1} - \alpha - \beta t_{i-1}\right) e^{-\theta\left(t_i - t_{i-1}\right)} \qquad (3)$$

Here, ρ is the standard first order autocorrelation parameter defined with a uniform [-1,1] prior, and θ controls the exponential decay of autocorrelation with increasing temporal separation, and was assigned a uniform [0,1] prior (B. Johnson *pers. comm.*).

Hierarchical structure

We attempted to model the sites hierarchically because we had few data points at any given site. A feature of Bayesian hierarchical models is that the result at one site "borrows strength" from the data at the other sites (Gelman *et al.* 1995), thereby providing more robust estimates at the site level, when few data are available.

As noted above, previous investigations noted that in the Dandenong catchment the more downstream sites appeared to show a greater decline in SIGNAL scores (Walsh *in press*). We hypothesise that such a difference may be due to higher levels of effective catchment imperviousness (ECI) occurring in downstream areas. However, as obtaining these values requires detailed GIS calculations, only selected sampling sites and time periods in the database currently have estimates of ECI. For this initial investigation, we chose to use catchment area (km^2) as a surrogate for measuring urbanisation in the Dandenong catchment. The streams at the top of this catchment occur in forested areas (e.g. DNG0002 & 0003) and have relatively little impervious area, whilst waterways closer to the base are highly urbanised (e.g. DNG0246) and/or industrial (e.g. EUM0050).

We modelled the site-level β values as a linear function of the square root of catchment size. Thus the β estimates are initially envisaged as:

$$\begin{aligned} \beta_j &: N\left(\mathrm{B}_j, \sigma_{\mathrm{B}}\right) \\ \mathrm{B}_j &= \delta + \varphi\sqrt{a_j} \end{aligned} \qquad (4)$$

where δ and φ are normally distributed hyperparameters with vague priors, and a_j is the area of catchment *j*.

Conceptually, the approach taken to deal with spatial autocorrelation among the sites is identical to that for temporal autocorrelation within sites. Thus, for each of the two independent river systems we modelled a latent data point "upstream" of the uppermost site, conceptually identical to a site with zero catchment area. The values of β for each site were then modelled using the variant on the Congdon (2001) AR1 model.

$$\begin{aligned} \beta_j &\sim N\left(\mathrm{B}_j, \sigma_{\mathrm{B}}\right) \\ \mathrm{B}_0 &= \delta \\ \mathrm{B}_j &= \delta + \varphi\sqrt{a_j} + \gamma\left(\beta_{j-1} - \delta - \varphi\sqrt{a_{j-1}}\right) e^{-\phi d_j} \end{aligned} \qquad (5)$$

where d_j is the approximate river distance (km) between sites *j* and *j*-1, and γ and ϕ are hyperparameters describing first order autocorrelation and autocorrelation decay, as described for temporal autocorrelation above and with the same prior distributions.

In addition to β, we also modelled the temporal autocorrelation parameters ρ and θ hierarchically, so as to gain better overall estimates of these parameters than were possible with the relatively few data points available at each site. We considered that these parameters could be modelled without the need for any model structure. Thus we have

$$\begin{aligned} \rho_j &\sim \left(\mathrm{P}, \sigma_{\mathrm{P}}\right) \\ \theta_j &\sim \left(\Theta, \sigma_{\Theta}\right) \end{aligned} \qquad (6)$$

The hyperparameters had vague normal prior distributions for the means and vague gamma distributions for the precisions.

Implementation

The model was coded in WinBUGS 1.4 (Bayesian inference Using Gibbs Sampling; Spiegelhalter *et* *al.* 2003). In addition to the model itself, we used the step function in WinBUGS to calculate the probability for each of the ten sites that SIGNAL scores were declining. The step results were also used to calculate an interval on the number of sites showing a decline in SIGNAL score. We also calculated the probability that the parameter φ was negative – i.e. the probability that rate of decline in SIGNAL score was inversely related to sqrt (catchment area). We ran the model with a single Markov Chain with a burn in of 10,000 iterations followed by a further 100,000 iterations for parameter estimation. In addition to the parameters described immediately above, we monitored the values of the yearly slope for each catchment and those of the catchment scale estimates of temporal autocorrelation parameters and the spatial autocorrelation parameters.

3. RESULTS

Examination of residual plots revealed a normally distributed error structure, supporting the choice of model structure. The predictions (i.e. the modelled individual SIGNAL scores) showed variable precision, with 95% credible intervals ranging from 0.35 to 2.1 (median = 0.68).

At the site level, the model found fair to overwhelming evidence of declines in SIGNAL scores (Table 1). The probability of SIGNAL decline was generally higher with increasing catchment size. The histogram for the estimate of the number of sites with a negative slope is shown in Figure 2. The 95% credible interval states that between 7 and 10 out of the 10 sites show a decline in edge SIGNAL score, with a mean value of 9.3. These results, together with the site-level results provide very strong evidence for a catchment-wide decline in edge SIGNAL scores

Table 1. Site level estimates of yearly change in SIGNAL score. Table shows site code as indicated in Figure 1, the sample size for each site (n), the 95% credible interval for the parameter β (the yearly change in score) and the probability that β is negative (i.e. that SIGNAL score has declined).

Site		β (yearly change)			
	n	2.5%	Median	97.5%	P(β< 0)
DNG0002	4	-0.20	-0.03	0.10	0.720
DNG0003	6	-0.13	-0.03	0.07	0.738
DNG0079	10	-0.17	-0.10	-0.04	0.998
DNG0090	10	-0.17	-0.10	-0.02	0.990
DNG0103	4	-0.17	-0.11	-0.03	0.994
DNG0246	10	-0.24	-0.15	-0.05	0.996
DNG0325	10	-0.27	-0.17	-0.08	0.999
EUM0016	6	-0.12	-0.05	-0.03	0.915
EUM0050	4	-0.15	-0.07	-0.02	0.954
EUM0121	10	-0.17	-0.10	-0.02	0.989

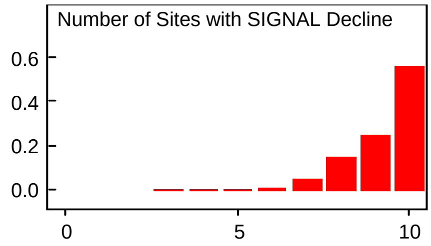

Figure 2. Probability distribution of estimates of the number of sites in Dandenong catchment with declining edge SIGNAL scores.

over the period of record. The uncertainty of these yearly changes was greater in sites towards the top of the catchment. Overall, the hierarchical model chosen did a reasonable job of explaining and modelling the changes in SIGNAL score. There was strong evidence that SIGNAL scores declined faster for areas with larger catchments (Pr (φ < 0) = 0.945. However, there was little evidence of autocorrelation, either spatially or temporally, and thus little need for the four autocorrelation-related parameters (Table 2).

Table 2. 95% credible intervals for the autocorrelation and autocorrelation decay parameters.

Parameter		2.5%	Median	97.5%
Temporal	P	-0.87	-0.12	0.69
	Θ	0.08	0.71	0.99
Spatial	γ	-0.93	0.01	0.94
	ϕ	0.02	0.49	0.97

4. DISCUSSION

The importance of long term monitoring data is widely recognised for assessing the variation in natural systems and the extent of anthropogenic disturbance. Unfortunately, for most biotic systems, including this one, there is a direct lack of observational data of sufficient accuracy for the actual state to be defined. Bayesian hierarchical treatment of the data has provided considerable improvement in helping determine and characterise changes in urban stream systems using a sparse data set. The characteristic of borrowing strength has led to more robust site-level estimates than would be possible if sites were analysed individually. The flexibility of model structure afforded by the Bayesian approach allowed us to account for the spatial and temporal limitations of the data. The Bayesian framework has also allowed us to establish strong inference from the site-level, to patterns at the catchment scale, and to quantify the uncertainty of these relationships.

This initial investigation of changes in edge SIGNAL score over time has showed strong overall evidence of declines across the Dandenong catchment. Moreover, sampling sites lower in the catchment (which we take as being a surrogate of increasing urbanisation) declined at a faster rate over the period of record. Two immediate hypotheses consistent with these observations suggest themselves. Firstly, it is probable that sites lower in the catchment have undergone greater development over the period of record, leading to greater declines in stream condition. Temporal records of ECI would be needed to confirm this hypothesis. Second, it is possible that the drought that Melbourne has experienced since approximately 1997 has led to degradation of stream assemblages, with the already degraded assemblages lower in the catchment less resilient to the effects of drought, and suffering greater degradation accordingly. Such relationships between low flows and depauperate macroinvertebrate communities have previously been found in the Melbourne region (e.g. Papas *et al.* 2000 and reference therein). We would only be able to attribute drought as the sole explanatory factor if we were able to show that urbanisation has not changed. Clearly, this is difficult to justify without data that that show changes in ECI. However, the two sites in the forested headwaters showed less evidence of declines than the more downstream sites. Whether these patterns can also be found across other catchments, and for riffle SIGNAL scores in the Melbourne, region warrants further investigation. Future efforts in trying to quantify catchment influences on macroinvertebrate assemblages in urban streams should be based on ECI, rather than catchment size.

Although there was no evidence of autocorrelation in our study, it was important to establish if there was any effect on the non-independent spatial and temporal sampling regimes, and avoid making the equivalent of Type 1 errors, before alternative hypotheses could be proposed. There are a number of possible explanations for the lack of autocorrelation found. Firstly, the small data series mean that it is difficult to calculate reliable estimates of autocorrelation; a larger sample size may be better able answer whether autocorrelation is a necessary consideration for the model. Biologically, the relatively large temporal and spatial distances between samples may lead to statistical independence for the stream macroinvertebrate communities. Many urban aquatic macroinvertebrates are common, hardy taxa well adapted to harsh, frequent hydraulic scour and pollutants (Walsh *et al.* 2001). Even the most frequent six-monthly sampling interval found in this data set may be sufficient for new communities, with short lifecycles to re-establish following disturbance.

The lack of spatial autocorrelation between sampling sites on the same stream may indicate that there is limited interaction between up and down stream communities. Recent studies examining distance measures of spatial autocorrelation of urban macroinvertebrates found spatial effects occurred over short distances (<200m) (Sanderson *et al.* 2005). Other spatial hierarchical analyses of stream macroinvertebrates have found that there is more variation within sample units than at larger reach, segment or river scales (e.g. Downes *et al.* 1993). The greater level of variation present at these smaller spatial scales can be attributed to the highly mobile nature of many stream macroinvertebrates. They are able to easily move within the stream if they are faced with changes in habitat and fluctuating resources, through drifting and crawling (e.g. Miyake *et al.* 2005). Furthermore, the aerial adult stage of many taxa and their high dispersal capabilities combined with the shifting stream habitat mosaic means that there is perhaps little consistency in spatial and temporal community dynamics.

Given that there is possibly high variation among sample units (each score is based on a single monitoring event), an important consideration for future analyses includes the incorporation of prior error estimates of an individual SIGNAL score. The measurement error of a SIGNAL score is believed to be approximately 0.5 for a site in good condition (C. Walsh *pers. comm.*), which is more precise than the posterior estimate generated here with the vague prior (median=0.68). Considering this uncertainty, it is difficult to determine whether a substantial result is actually biologically relevant. The variation will be quantified by making use of a rare data set with multiple replicates (L. Metzeling *pers. comm.*) to generate informative prior distributions on the sample precision of the data ($1/\sigma^2_j$). Being able to factor out the sampling technique and small-scale variation may improve the explanatory power of our model and better answer the question as to whether the changes seen over time are biologically relevant.

Current modelling efforts are also focused on the development of posterior predictive error checks to establish how well our model represents the data. This may be particularly important if the use of informative priors may call into the question the linear models currently employed.

|In order to be able to better answer questions about changes in stream ecological condition, further data collation efforts should be focused on increasing the temporal extent of the existing series of monitoring data, and quantifying changes

in temporal ECI. Future designs of monitoring programs in the Melbourne region should include sampling sites located in areas yet to undergo urbanisation. Monitoring stream health as well as ECI in such growth corridors areas could allow us to better quantify this relationship within a short space of time. Importantly, larger and more complete data sets will give us greater confidence to make wider generalistions about changes in urban stream condition, and assist in the implementation of urban conservation and restoration efforts, such as water sensitive urban design.

5. CONCLUSIONS

Bayesian hierarchical modelling is an effective method for examining temporal changes in stream macroinvertebrate communities. The ability to "borrow strength" reduces the effect of small sample sizes and helps overcome such data limitations. The Bayesian hierarchical framework offers considerable potential for the future analyses of monitoring data that have previously been deemed to be too sparse, or too poorly 'designed' to yield robust results.

6. ACKNOWLEDGMENTS

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