Predicting the effects of secondary salinisation on stream macroinvertebrate communities using artificial neural networks.

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Abstract

This study utilised artificial neural network (ANN) models to predict and analyse changes in the salinity index and percentage of salinity sensitive macroinvertebrate taxa in response to increasing conductivity associated with secondary salinisation. The ANN model was trained using data collected from riffle habitat in Central Queensland over 8 years. Sites located in the moderate and high salinity hazard zones in Burdekin and Fitzroy catchments were used as a simulation set. Two scenarios were tested: scenario 1 considering an increase in conductivity and related variables, and scenario 2 considering an increase in conductivity, related variables and nutrients (total nitrogen and total phosphorus). The scenarios were simulated for 4 conductivity levels with an increment of 1000 $\mu S\ cm^{-1}$. Results indicated that both salinity index and percentage of sensitive taxa were affected by changes in conductivity and associated variables. The results indicated that: (1) on average, about 40% of salinity sensitive macroinvertebrate taxa are threatened to be lost when conductivity increases from 626.9 $\mu S\ cm^{-1}$ to 4422.6 $\mu S\ cm^{-1}$, and (2) combined conductivity and nutrient load may have a synergistic effect resulting in stronger impacts on macroinvertebrate communities.

Introduction

Wide spread secondary salinisation caused by the clearance of deep-rooted native vegetation is one of the major threats facing freshwater ecosystems in Australia. The area estimated to be affected by secondary salinity in Queensland is 48 000 ha, 3.1 million hectares potentially could be affected by salinity by 2050 (Gordon, 2002). A number of streams and wetlands have already been affected by rising salinity leading to significant changes in flora and fauna. Macroinvertebrates seem to be highly salt sensitive. There have been a number of studies on the effect of salinisation on macroinvertebrate taxa using both laboratory experimentations (Kefford et al., 2003; Kefford et al., 2004), field observations (Bunn & Davies, 1992; Kay et al., 2001; Kefford, 1998; Metzeling, 1993; Williams et al., 1991) and mesocosm experiments (Marshall & Bailey, 2004). The majority of these studies were conducted in southern and western states of Australia and there is not much information available for Queensland streams. Horrigan et al. (submitted) investigated the salinity sensitivity of stream macroinvertebrate taxa mainly at family level using ANN based sensitivity analysis and statistical analysis. As a result, 3 groups of macroinvertebrate taxa were identified indicating salinity sensitivity (score 10), general salinity tolerance (score 5) and high salinity tolerance (score 1). The cumulative score per sample divided by total number of taxa per sample was suggested as a salinity index (SI) to be used as an indicator for changes in the community structure in response to salinity. It was demonstrated that the SI decreased along the gradient of increasing conductivity.

Secondary salinisation is a complex process and affects not only conductivity of stream water but other water quality parameters and stream habitats as well. It can be caused by the degradation of riparian vegetation that in turn provides less shade and increases water temperature. Increased nutrient and sediment loads in streams can also be a consequence of deteriorated riparian vegetation. Ground water flow can also contribute to changes in pH, alkalinity and ionic composition as well as to the enrichment of nutrients such as nitrate (NO3) originating from fertilisers (Brodie et al. 1984). There is currently little understanding about additive, synergistic or antagonistic effect of salinity and nutrients. In a study of the biological effects of saline lake water disposal in the Lough Calvert drainage scheme in Southwest Victoria, Kefford (2000) found that the operation of the scheme changed the community structure and abundance of macroinvertebrates. He noted that increased salinity corresponded with increased nutrients and suspended solids having a compounding effect on macroinvertebrates communities.

The current study aims at testing the predictability of the SI and percentage of sensitive taxa (PST) using localised datasets from Central Queensland, and to investigate possible changes in SI and PST in response to two scenarios: scenario 1 considering an increase in conductivity and related variables, and scenario 2 considering an increase in conductivity, related variables and nutrients (total nitrogen and total phosphorus). We used two types of ANN. While modular feedfordward ANN (modified multi-layered perceptron) were used for the prediction, self organising maps (SOM) were applied to analyse the results. ANN have been widely applied to ecological and in particularly stream data (Brosse et al., 2001; Huong et al., 2001; Lek & Guegan, 2000) proving to be efficient for the prediction and pattern analysis in complex heterogeneous datasets.

Data

Fitzroy and Burdekin are the two largest catchments in Central Queensland and were identified as priority catchments by the National Action Plan for Salinity and Water Quality (NAPSWQ).

The data for this study was collected in Central Queensland in spring and autumn from 1994 to 2001 as a part of several surveys conducted by the Department of Natural Resources and Mines (NR&M). The dataset contains 209 samples collected from riffle habit only. In order to separate data into training and simulation subset we overlayed a GIS map with sample sites and salinity hazard maps for Burdekin and Fitzroy catchments provided by NR&M. Samples collected at the sites located in the areas of moderate to high salinity hazard were selected as the simulation set (36 samples), the rest of the data was used for training (Figure 1). Samples from the same site collected in the different year or season were treated as separate sites.

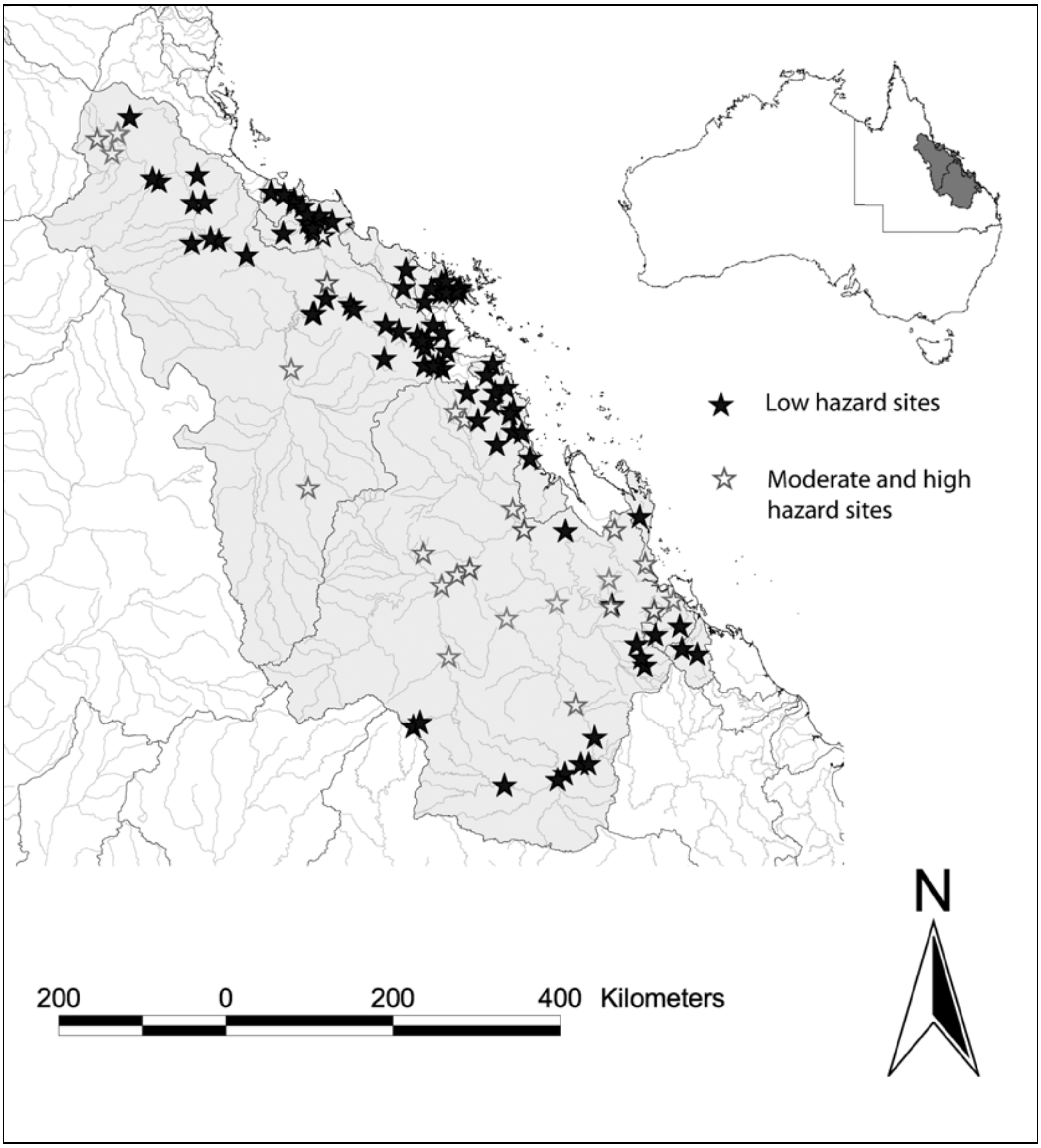


Fig. 1 Map of the Fitzroy and Burdekin catchments with sites marked accordingly to their location in different salinity hazard zones.

Methods

The aim of the modelling process was to predict the effects of likely increases in conductivity by ANN, which were trained with existing data. The measured conductivity ranged from 40 to 4700 μS cm^{-1}. It was shown by Hart et al. (1991) that freshwater ecosystems can be affected when conductivity reaches 1500 μS cm^{-1}. Horrigan *et al* (submitted) demonstrated significant changes in the SI by conductivity values between 800-1000 μS cm^{-1}. Therefore, we assume that conductivities up to 4700 μS cm^{-1} are reasonable for the ANN modelling in order to reveal possible deleterious effects.

By aiming to define a scenario for likely stream salinisation we have taken into consideration possible interactions between conductivity and other factors, such as temperature, nutrient load, turbidity, pH and dissolved oxygen. These interactions have been analysed by using scatter plots and product moment correlation. In cases where such interactions were detected, linear or logarithmic trends have been fitted and related variables have been calculated in accordance to the conductivity level used for the simulation.

A variety of ANN models with different architecture was built, trained and tested, including Multilayered Perceptron (MLP), Generalized Feed Forward network (a generalization of MLP were connections can jump over one or more layers) and Modular Feedforward neural network. We found that for a given dataset Modular Feedforward neural network showed the best performance when tested on simulation subset, which was not used for training. We used 29 input variables, including both physico-geomorphological features and water quality variables (Table 1), 2 hidden layers with 6 neurons in each and tahn-sigmoid transfer function and 2 neurons in the output layer for the SI and the PST. Modular feedforward networks are a modification of commonly used Multi-Laeyered Perceptron neural networks (MLPs). These networks process their input using several parallel MLPs, and then recombine the results. This tends to create some structure within the topology, which will foster specialization of functions in each sub-module. In contrast to the MLPs, modular networks do not have full interconnectivity between their layers. Therefore, a smaller number of weights are required for the same size. This tends to speed up training times and reduce the number of required training exemplars (Principe *et al*. 2000). The model was trained for 1500 iterations using only the training sub-set and validated using a simulation set from the moderate and high hazard salinity areas. To use as much data as possible we did not use cross-validation, instead the model was trained for a various number of iterations and simulated on both training and simulation sets. The models showing big discrepancies between the accuracy of prediction for training and validation sets were discarded as overtrained.

Table 1. Input variables used for training of the predictive neural network.

Variable (units)	
Season (categorical)	Slope (m/m)
Habitat depth (m)	Distance from source (km)
Maximal current velocity (m/s)	Mean wet season monthly rainfall (mm)
Bedrock (%)	Mean dry season monthly rainfall (mm)
Boulder (%)	Mean annual rainfall (mm)
Cobble (%)	Conductivity (µs/cm)
Pebble (%)	Water temp (°c)
Gravel (%)	Dissolved oxygen (mg/L)
Sand (%)	pH
Silt/clay (%)	Alkalinity (mg/L CaCO3)
Mean phi	Turbidity (NTU)
Latitude (s) decimal	Total nitrogen (mg/l as n)
Longitude (e) decimal	Total phosphorus (mg/l as p)
Altitude (m)	0-8 substrate categories (categorical)
Stream order (categorical)	

The accepted model was simulated five times. First the model was simulated (Simulation 1) using actual data, then four more times with conductivity values increased in increments of 1000 $\mu S\ cm^{-1}$ and related variables calculated in relation to the new conductivity values. In other words, conductivity was increased by 1000 $\mu S\ cm^{-1}$ for simulation 2, by 2000 $\mu S\ cm^{-1}$ for simulation 3 and so on. At the sites where conductivity was initially high, increases of conductivity by 3000 and 4000 $\mu S\ cm^{-1}$ resulted in the exceedance of maximal conductivity value in the model's expertise (4700 $\mu S\ cm^{-1}$) so these values were capped at the 4700 $\mu S\ cm^{-1}$. The same capping by the maximal values in the dataset was performed for some sites with the high concentration of nutrients in case of Scenario 2.

Two scenarios were defined: Scenario 1 with only increases in conductivity and directly related variables. Scenario 2 – with increases in conductivity, related variables and nutrients (total nitrogen and total phosphorus). The simulation dataset prepared for scenario 1 was used for scenario 2 plus total nitrogen was increased by 1 mg L^{-1} for each conductivity increment (1000 $\mu S\ cm^{-1}$), total phosphorus was calculated from an equation describing the relationship between total nitrogen and total phosphorus for the given area. In order to compare the combined effect of conductivity and nutrients and nutrients only we simulated the model once using only increase in nutrients (+ 4mg L^{-1} of total nitrogen and the calculated total phosphorus) keeping conductivity and related variables as actual values.

In order to investigate how the differences in the rate of loss of sensitive taxa can be explained by conditions in each particular site we calculated the difference between the first simulation (actual data as predictor variables) and each subsequent simulation using Scenario 1 output. A new data matrix with four variables for the differences between simulated outputs was prepared. For each site we calculated the difference (d) as:

$d_{i-1} = s_1 - s_i$,

Where, i – simulation number, s – simulation output.

In order to group sites by similar pattern in PST change we partitioned this new matrix unto 4 clusters using a Self Organising Map (SOM) neural network. The optimum number of clusters was chosen using the Silhouette index (Rousseuw, 1987). Resulting clusters were further analysed using univariate analysis of variance.

The Artificial Neural Net used for the prediction purpose was built, trained and simulated using NeuroSolutions 4.0 software package and the SOM was built using MOPED 1.11 (Modelling Patterns in Environmental Data, by NIWA).

Results

Defining relationships between water quality variables

Product moment correlations between all water quality variables are shown in Table 2. The highest correlation was between conductivity and alkalinity (0.53) and total N and total P (0.46).

Table 2. Product moment correlations between water quality variables in Central Queensland.

	Conductivity ($\mu S\ cm^{-1}$)	Water temp (°c)	DO (mg/L)	pH	Alkalinity (mg/L CaCO3)	Turbidity (ntu)	Total n (mg/l as n)	Total p (mg/l as p)
Conductivity ($\mu S\ cm^{-1}$)	1.00	-.01	-.03	.17*	.53*	-.15*	.09	-.02
Water temp (°c)		1.00	-.11	.14*	.03	-.05	.17*	.03
DO (mg/L)			1.00	.24*	-.05	-.04	.05	-.01
pH				1.00	.36*	-.02	.02	-.06
Alkalinity (mg/L CaCO3)					1.00	-.14*	-.00	-.06
Turbidity (ntu)						1.00	.19*	.13
Total n (mg/l as n)							1.00	.46*

*significant ($p < 0.05$)

Given that conductivity is the sum of all the ions present in the solution, higher concentration of Ca and CO_3 ions associated with increase in alkalinity will result in increased conductivity as well. Similarly for pH, increase in either Hydroxyl or Hydrogen ions will contribute to increase in conductivity.
A scatter plot for conductivity and alkalinity with fitted logarithmic trendline
(y = 88.602Ln(x) - 386.17, $R^2 = 0.57$) is shown at Figure 2.

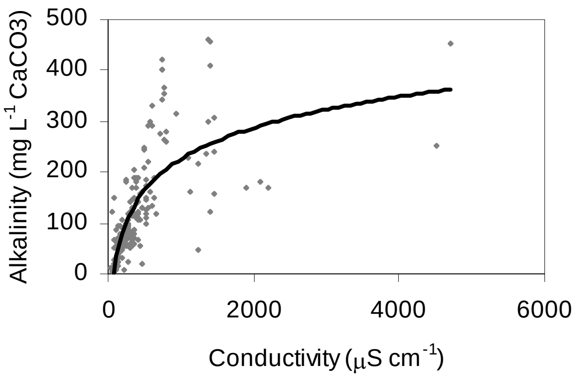


Fig. 2 Scatterplot of alkalinity versus conductivity with fitted trendline.

We used the above mentioned trend to calculate changes in alkalinity with simulated increases in conductivity. A similar relationship was observed between pH and conductivity, r = 0.17, and a scatter plot with fitted logarithmic trend (y = 0.2964Ln(x) + 6.0412, $R^2 = 0.15$), is shown at Figure 3.

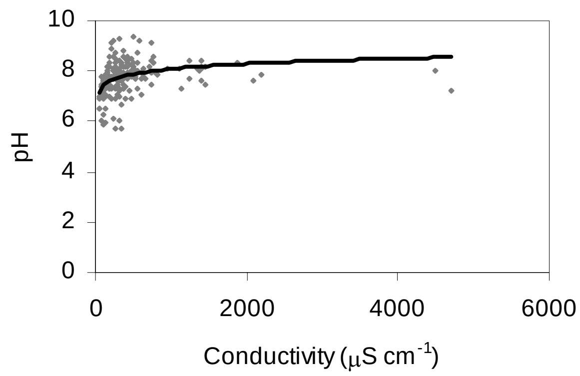


Fig. 3. Scatter plot of pH versus conductivity with fitted trendline.

Turbidity was negatively correlated with conductivity, however, we could not fit any statistically sound trend to the scatter plot (Figure 4) nor predict turbidity using ANN model. Generally, turbidity is the highest at conductivities between 100 $\mu S\ cm^{-1}$ and 500 $\mu S\ cm^{-1}$, but it is almost never high when conductivity is higher than 1000 $\mu S\ cm^{-1}$. This might be explained by the effect of coagulation and settling of suspended particles with a consequent clarification of the water column. Oliver *et al*. (1999) examined the effect of saline groundwater intrusion on water quality in Darling river (NSW, Australia) showing that increases in water column conductivity under low flow conditions caused major decreases in the turbidity of surface water. A statistically significant inverse correlation between conductivity and turbidity was also observed in the Klein Modder and Modder Rivers (South Africa), where forty-six per cent of the variation in conductivity was associated with the variation in turbidity (Koning and Roos, 1999).

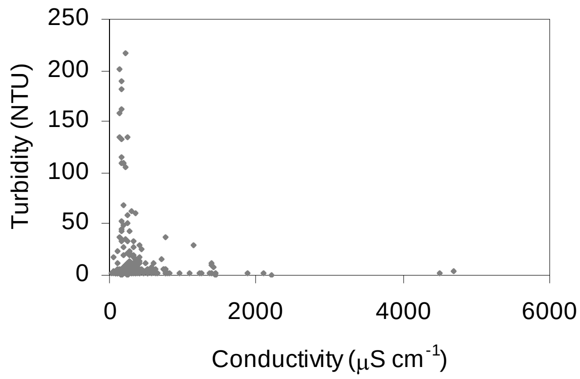


Fig. 4. Scatter plot of turbidity versus conductivity..

The possible effects of an interaction between turbidity and conductivity are highly dependent on local conditions (such as particle size and current velocity and may be very complex. Despite the complexities associated with this phenomenon, it was necessary to simplify it for the purpose of this study. As turbidity was observed to be below 30 NTU for all samples having a conductivity less than 1000 μS cm^{-1} (the value accepted as in increment for the simulation of increase in conductivity) 30 NTU was used as a maximum turbidity value for all samples having conductivity > 1000 μS cm^{-1}, with all the values below that being kept at their actual level.

It is possible that a rise of groundwater can cause deterioration of riparian vegetation with subsequent effect of more light coming into the stream. This could cause an increase in water temperature, algal growth and other water quality parameters. However, in the content of this study we do not attempt to model interactions of conductivity and water temperature and keep water temperature at the observed values in all simulations.

No correlation between nutrients and conductivity were found to be significant (Table 2), however, there is a significant correlation between nutrients themselves. As we later attempt to model the combined effect of increased conductivity and nutrients values this relationship needs to be taken in consideration for the simulation process. Figure 5 shows a scatter plot with fitted linear trend ($y = 0.1251x - 0.01$, $R^2 = 0.22$) for total nitrogen and total phosphorus. For the subsequent simulations (Scenario 2) we used increases in total nitrogen up to 5.3 mg L^{-1} (maximum occurrence in the dataset for Central Queensland) with an increment of 1 mg L^{-1} , and phosphorus values calculated using abovementioned equation.

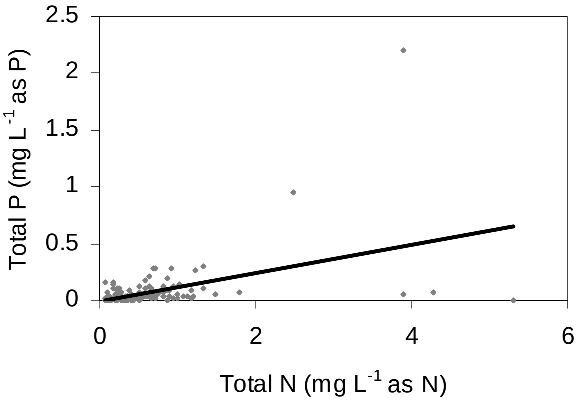
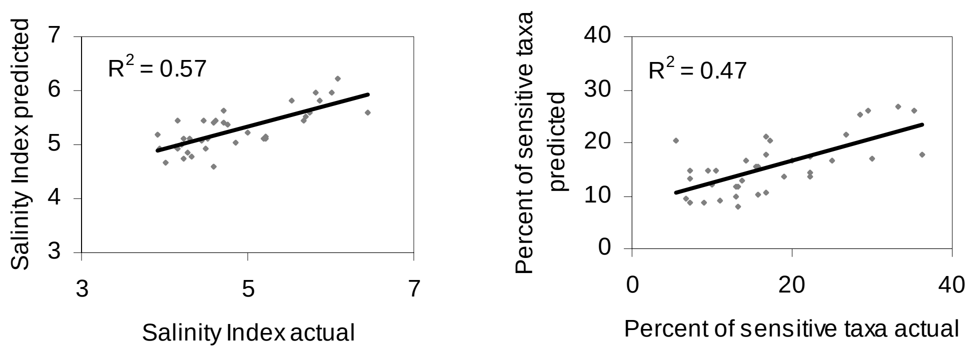


Fig. 5 Scatter plot of total phosphorus versus total nitrogen with fitted trendline.

Simulation Results

The correlation coefficient between the actual and predicted output for the simulation set was 0.75 for the Salinity Index and 0.68 for the Percent of Sensitive taxa (0.79 and 0.77 respectively for the training set). Figure 6 shows scatter plots with fitted linear trends and R^2 values for both variables.

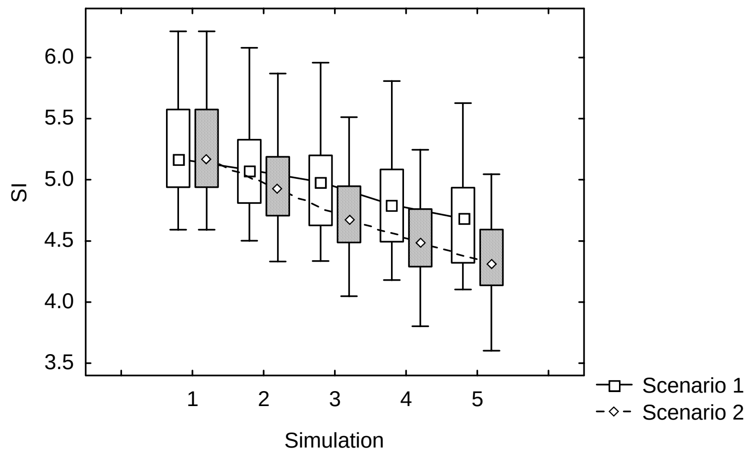


(a) (b)

Fig. 6 Actual versus predicted Salinity Index (a) and Percent of sensitive taxa (b), simulation dataset.

Figure 7 shows the range and the median of predicted outputs for SI and PST for both Scenario 1 and Scenario 2. It is obvious that the combined increases in conductivity and nutrient concentrations has more effect on the macroinvertebrate communities than an increase in conductivity only. For Scenario 1 the mean SI and PST decreased from 5.27 and 15.53 respectively in Simulation 1 (actual values for conductivity and related variables) to 4.68 and 9.94 in Simulation 5 (actual conductivity + 4000 μS cm^{-1}). When effect of nutrients has been added the Simulation 5 output for SI and PST was 4.32 and 7.14 respectively. Figure 8 shows comparisons of the PST outputs for the Simulation 5 (+4000 μS cm^{-1}), under Scenario 1 (Conductivity), Scenario 2

(Combined) and only increase in nutrients (+ 4mg L^{-1} of total nitrogen, total phosphorus = 0.1251x (total nitrogen)- 0.01).



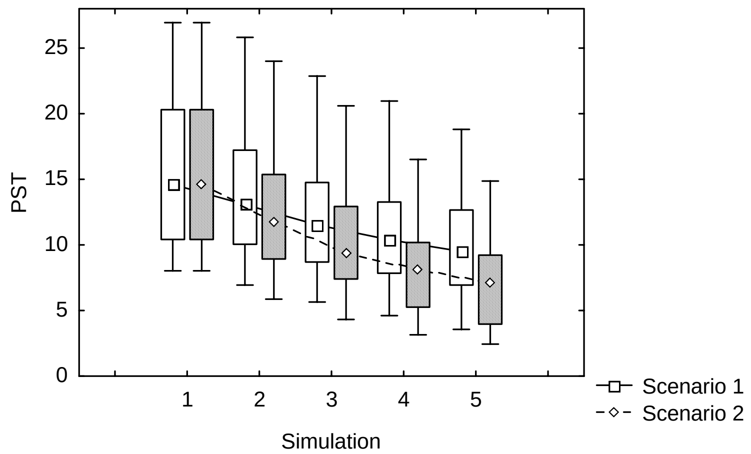


Fig. 7 Box plots for simulation results for Scenario 1 and Scenario 2, median values, box 20-80%, whiskers minimum and maximum.

The lowest PST resulted from the combined impact of conductivity and nutrients. Nutrients only had the lowest impact on the percent of sensitive taxa.

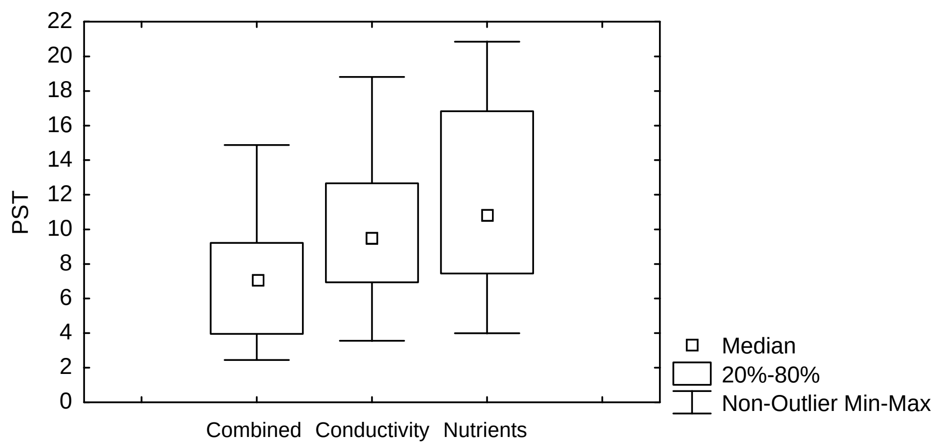


Fig. 8 Box plot for the PST outputs for the Simulation 5 (+ 4000 $\mu S\ cm^{-1}$), for Scenario 1(Conductivity), Scenario 2 (Combined) and only increase in nutrients (+ 4mg L^{-1} of total nitrogen, total phosphorus = 0.1251x (total nitrogen)- 0.01).

Resulted SOM (size 6x5, average SOM quantisation error = 2.307) was partitioned into 4 clusters with k-means algorithms using the Silhouette index (Rousseeuw, 1987) as an indicator of clustering quality. The Silhouette index for the resulting clustering was 0.79 indicating a strong structure. Mean values of the water quality variables in each cluster are shown at Table 3. Only 1 and 3 sites were in Clusters 3 and 4 respectively, and these clusters are not considered in any further analysis. Table 4 shows the results of individual univariate analysis of variance

Table 3. Mean values of the water quality variables and actual PST in four SOM defined clusters.

Number of the cluster	1	2	3	4
Number of sites in cluster	14	18	1	3
Water temp (°C)	21.87	21.58	23.10	23.33
Dissolved oxygen (mg L^{-1})	8.40	7.61	7.60	6.06
Total N (mg L^{-1}as N)	0.46	0.73	0.83	0.41
Total P (mg L^{-1} as P)	0.04	0.06	0.03	0.01
Conductivity ($\mu S\ cm^{-1}$)	438.14	713.4	1391.00	734.66
pH	8.18	7.46	8.10	7.75
Alkalinity (mg L^{-1} CaCO3)	172.98	141.23	408.00	189.16
Turbidity (NTU)	29.21	62.15	11.90	4.66
Actual PST	21.63	15.54	6.66	13.22

between remaining clusters 1 and 2. Only three variables were significant in discriminating between clusters: pH, total N and actual PST. Although the statistical difference in conductivity between clusters is not significant, the mean values of conductivity for cluster 1 and 2 are quite different, 438.14 $\mu S\ cm^{-1}$ and 713.4 $\mu S\ cm^{-1}$ respectively.

Table 4. Results of the univariate analysis of variance between clusters 1 and 2.

Variable	F	P
pH	9.4	0.00
Total N (mg L^{-1}as N)	5.6	0.02
Actual PST	4.0	0.05
Total P (mg L^{-1} as P)	2.0	0.17
Conductivity ($\mu S\ cm^{-1}$)	1.9	0.18
Dissolved oxygen (mg L^{-1})	1.3	0.26
Turbidity (NTU)	0.9	0.62
Alkalinity (mg L^{-1} CaCO3)	0.6	0.53
Water temp (°C)	0.1	0.77

Figure 9 shows a box plot with median values (wiskers for maximum and minimum) of differences (d) between simulation outputs in clusters 1 and 2. All the differences between simulations are noticeably larger in the first cluster than in the second, in other words, macroinvertebrate communities from the sites in cluster 1 show more pronounced response in all simulations than the communities from cluster 2 sites.

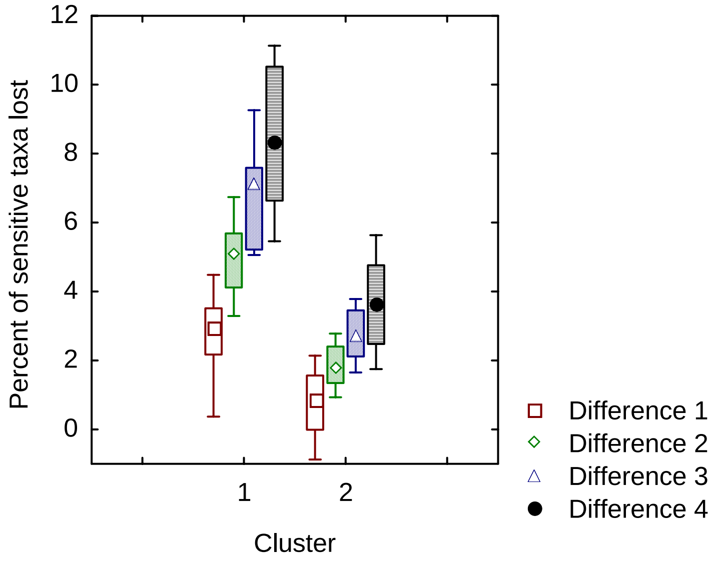


Fig. 9 Box plot for median values (box 80-20%, wiskers for maximum and minimum) of differences between simulation outputs in two SOM defined clusters.

Discussion

It was possible to predict the SI and PST as outlined by Horrigan *et al*. (submitted) with reasonable accuracy. Although the SI was defined using state-wide data it was still predictable on a smaller geographical scale. The model responded well to the increases in conductivity and changes in alkalinity, pH and nutrient concentration. It has been shown that combined conductivity and nutrient concentrations may have a synergistic effect resulting in stronger impact on macroinvertebrate communities than single impacts of conductivity or nutrients only. This may also indicate that when the immediate effect of increased salinity appears as insignificant the indirect cumulative effects can still make the ecosystem vulnerable. The response of the macroinvertebrate communities to increased salinity appeared to be site specific. When the PST was analysed with SOM all streams were clustered into two broad groups, one that responded rapidly and the other that responded much slower and experienced less significant loss. The first group was characterised by initially larger PST, higher pH, lower nutrients and lower conductivities, even though the differences in conductivity between the groups was not statistically significant. This implies that the macroinvertebrate communities with a high number of sensitive taxa that usually occur at low conductivity and good water quality are likely to experience stronger changes when conductivity rises compared to communities which are already under some kind of stress and dominated by opportunistic taxa. This may have some implications for sustainable environmental management to decide about acceptable conductivity levels for specific ecosystems. Further research is needed to understand the response of geographically specific stream ecosystems to simulated impacts.

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