Neural Network Based Decision Support Framework for the Assessment and Management of Freshwater Stream Habitats

A thesis submitted for the award of Doctor of Philosophy

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Abstract

Modelling of stream macroinvertebrate communities has been widely accepted as an interesting and powerful tool to support water quality assessment and management. Stream Decision Support Framework (SDSF) offers an alternative approach to the current statistical models as Australian River Assessment Scheme (AusRivAs) for the derivation of scientific basis to support management applications regarding fresh water systems. Implementation of Artificial Neural Networks (ANNs) offers a possibility to overcome constraints of the statistical methods in dealing with high non-linearity of stream data.

This thesis includes several case studies illustrating application of Self Organising Map (SOM) and Multilayer Perceptron (MLP) neural networks to various tasks involving analysis, assessment and prediction of stream macroinvertebrates in three Australian states. The data for this study have been provided by the Queensland Department of Natural Resources (NR&M), EPA Victoria and the Department of Land and Water Conservation, New South Wales (NSW).

SDSF approach utilises predictive models for both 'referential' and 'dirty-water' approaches. Applicability and high accuracy of ANN models for the purpose of prediction both occurrence of individual taxa and taxonomic richness of stream macroinvertebrates have been demonstrated using data from Victoria and NSW. A comprehensive analysis of salinity sensitivity of stream macroinvertebrate has been demonstrated using both types of ANNs plus statistical methods, and pressure specific Salinity Index was suggested as a measurement of changes within macroinvertebrate communities in response to the secondary salinisation. Scenario analysis of the combined effect of increasing salinity and nutrient load demonstrated predictability and ecological meaningfulness of the Salinity Index.

Application of SOM has been demonstrated using the data from Queensland and Victoria in order to analyse natural variability of macroinvertebrate communities between reference sites. SOM component planes provided a valuable insight into the relationships between abiotic variables (as water quality and geoclimatic factors) and distribution of taxa and trophic structure of macroinvertebrate communities. Potential of SOM as data exploration tool has been also demonstrated for the analysis of the output of scenario simulation in order to understand the difference in response to salinisation in different sites.

Flexibility and potential of SDSF have been illustrated by using the combination of SOM and MLP, and combination of ANNs with statistical methods. Application of both SOM and Canonical Correspondence Analysis allowed the extraction of additional information and provided convenient visualisation of the relationships between water quality factors and the structure of macroinvertebrate communities.

In general, SDSF provides convenient, flexible and accurate approach for the analysis, assessment and prediction of stream biota. In addition to the freedom from the limitations inherent to the traditional statistical methods it allows many more options than currently used modelling frameworks, namely: highly accurate predictions using

both 'referential' and 'dirty-water' approaches, sensitivity analysis, scenario analysis and pattern exploration using SOM.

Statement of originality

This work contains no material which has been accepted for the award of any other degree or diploma in any university of other tertiary institution and, to the best of my knowledge and belief, contains no material previously published or written by another person, except where due reference has been made in the text.

I give consent to this copy of my thesis, when deposited in the University Libraries, being available for photocopying and loan.

Nelli Horrigan

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