



## **A Machine Learning Approach to Estimate Riverbank Geotechnical Parameters from Sediment Particle Size Data**

Fabio Iwashita, Andrew Brooks, John Spencer, Daniel Borombovits, Graeme Curwen, and Jon Olley  
Australian Rivers Institute, Griffith University, Brisbane, Australia (f.iwashita@griffith.edu.au)

Assessing bank stability using geotechnical models traditionally involves the laborious collection of data on the bank and floodplain stratigraphy, as well as in-situ geotechnical data for each sedimentary unit within a river bank. The application of geotechnical bank stability models are limited to those sites where extensive field data has been collected, where their ability to provide predictions of bank erosion at the reach scale are limited without a very extensive and expensive field data collection program. Some challenges in the construction and application of riverbank erosion and hydraulic numerical models are their one-dimensionality, steady-state requirements, lack of calibration data, and nonuniqueness. Also, numerical models commonly can be too rigid with respect to detecting unexpected features like the onset of trends, non-linear relations, or patterns restricted to sub-samples of a data set. These shortcomings create the need for an alternate modelling approach capable of using available data. The application of the Self-Organizing Maps (SOM) approach is well-suited to the analysis of noisy, sparse, nonlinear, multidimensional, and scale-dependent data. It is a type of unsupervised artificial neural network with hybrid competitive-cooperative learning. In this work we present a method that uses a database of geotechnical data collected at over 100 sites throughout Queensland State, Australia, to develop a modelling approach that enables geotechnical parameters (soil effective cohesion, friction angle, soil erodibility and critical stress) to be derived from sediment particle size data (PSD). The model framework and predicted values were evaluated using two methods, splitting the dataset into training and validation set, and through a Bootstrap approach. The basis of Bootstrap cross-validation is a leave-one-out strategy. This requires leaving one data value out of the training set while creating a new SOM to estimate that missing value based on the remaining data. As a new SOM is created up to 30 times for each value under scrutiny, it forms the basis for a stochastic framework from which residuals are used to evaluate error statistics and model bias. The proposed method is suitable to estimate soil geotechnical properties, revealing and quantifying relationships between geotechnical variables and particle distribution size, not properly observed by linear multivariate statistical approaches.