UNIVERSITI PUTRA MALAYSIA

ARTIFICIAL NEURAL NETWORK FOR WATER QUALITY ASSESSMENT AND LAND USE PATTERN RECOGNITION IN KINTA RIVER CATCHMENT

NABEEL MOHAMMAD GAZZAZ

FPAS 2012 23

ARTIFICIAL NEURAL NETWORK FOR WATER QUALITY ASSESSMENT AND LAND USE PATTERN RECOGNITION IN KINTA RIVER CATCHMENT

NABEEL MOHAMMAD GAZZAZ

DOCTOR OF PHILOSOPHY

UNIVERSITI PUTRA MALAYSIA

2012

ARTIFICIAL NEURAL NETWORK FOR WATER QUALITY ASSESSMENT AND LAND USE PATTERN RECOGNITION IN KINTA RIVER CATCHMENT

By

NABEEL MOHAMMAD GAZZAZ

Thesis Submitted to the School of Graduate Studies, Universiti Putra Malaysia, in Fulfillment of the Requirements for the Degree of Doctor of Philosophy

February 2012

Dedication

I dedicate this work to Houreyyah Y. Doudine (my mother); Mohammad S. Gazzaz (my father); Naheel, Fadeyah, Hoda, Ebtesam, Salwa, and Yasmeen (my sisters); and to his Excellency Dr. Waleed, Rami, and Sami (my brothers).

I also dedicate this work to Associate Professor Dr. Mohd Kamil Yusoff, Associate Professor Dr. Wan Nor Azmin Sulaiman, Professor Dr. Mad Nasir Shamsudin, and Associate Professor Dr. Ramdzani Abdullah.

As well, I would like to dedicate this work to my co-supervisors Dr. Hafizan Juahir, Associate Professor Dr. Muhammad Firuz Ramli, and Dr. Ahmad Zaharin Aris.

Abstract of thesis presented to the Senate of Universiti Putra Malaysia in fulfillment of the requirement for the degree of Doctor of Philosophy

ARTIFICIAL NEURAL NETWORK FOR WATER QUALITY ASSESSMENT AND LAND USE PATTERN RECOGNITION IN KINTA RIVER CATCHMENT

By

NABEEL MOHAMMAD GAZZAZ

February 2012

Chairman: Associate Professor Mohd Kamil Yusoff, PhD

Faculty: Environmental Studies

Kinta River (the State of Perak, Malaysia) was classified during the period 1997-2006 with an average class III water quality (WQ) and a water quality index (WQI) in the range of 51.9–76.5. Frequency analysis of the water quality class (WQC) revealed that over this time period Kinta River water assumed the WQCs I, II, III, IV, and V for 5.9%, 31.0%, 54.9%, 7.8%, and 0.4% of the time, respectively. From 2004 until recently, the yearly WQ reports of the Department of Environment (Malaysia) classify Kinta River as a slightly polluted river. Therefore, there is growing interest in identifying the main factors, processes, WQVs, and LU classes responsible for this deteriorated WQ and determining how the desired WQ can be secured on a sustainable basis.

Therefore, the objectives of this study were to (i) assess the water quality of Kinta River

during the period 1997-2006; (ii) recognize patterns and analyze trends in LUs in Kinta River catchment as well as in the river's WQ; (iii) model these patterns and trends; and (iv) model the relative impacts of eight LU categories (agriculture, animal husbandry, forest, logging, mining, oil palm, rubber, and urban areas) on the WQ of Kinta River using data mining techniques including one major chemometric method (principal factor analysis (PFA)) and non-linear, data-driven (artificial neural network (ANN)) methods. The research adopted a comprehensive approach whereby the study scale encompassed eight sub-catchments in Kinta River basin coinciding with one WQ monitoring station, each, and investigations were carried out at six spatial scales: the whole river basin (WRB) and the 0-500 m, 0-1000 m, 0-1500 m, 0-2000 m, and 0-2500 m buffer zones (BZs)). On the other hand, the temporal scale of this study was ten years; 1997-2006.

The PFA highlighted that the latent structure of the WQ data is interpreted in terms of 23 WQVs that sorted in seven factors explaining 74.2% of the total variability in this data. These factors helped in identifying the pollutant origins and the major pollution sources in the basin. A radial basis function (RBF) classification model was created to allow for prediction of the WQC from these 23 WQVs. The optimum classifier obtained had correct classification ratios (CCRs) for the WQCs I-IV ranging from 60.0%-86.7%. The self-organizing feature map (SOFM) illustrated that the spatial patterns in the WQ of Kinta River can be described by two clusters. In terms of the WQI, the first cluster generally had better WQ than the second cluster. The WQVs and LU classes characteristic of each cluster indicate that the first cluster is more influenced by surface runoff, erosion, and organic and microbial sources of pollution than the second cluster which is mainly impacted by agricultural runoff and mineral dissolution. The optimal

RBF model developed for classifying the monitoring stations within these clusters had CCRs of 92.5% and 97.7%, respectively, for the first and second clusters. In addition, the SOFM showed that the temporal trends in the WQ of Kinta River are represented by two groups of similar WQ properties. The first cluster had higher mean values of the majority of the studied WQVs than the second cluster. The RBF classifier backed up this result and generated a classification model with a CCR of 78.0%. Furthermore, the SOFM showed that the spatial patterns in LUs within Kinta River catchment can be described by three clusters. This finding was reinforced by a RBF classifier which additionally provided a classification model with a CCR of 99.3%.

Six ANN models were developed to compute and forecast values of the WQI using LU areas as predictors; one model for each of the six spatial scales of interest. The WQI-LU modeling efforts elucidated that the ANN was capable of rendering non-linear models of appreciably high prediction capacities, ranging from 91.2% (0-1000 m BZ) to 97.8% (0-2500 m BZ). These models were utilized in generating forecasts of the WQ status of Kinta River in the year 2020 based on the land use change designed for the area by the MBI 2020 Development Plan. The WQI and WQC forecasts spotlight that the WRB approach is more representative to the WQ of Kinta River and its degree of pollution than any of the studied buffer strips.

The study results contribute to the LU planning and urban development programs and to river management plans and allow for optimization of the WQ monitoring network. For example, the approaches and results described in this study will help the WQ monitoring authorities in modifying the current monitoring scheme for Kinta River by selecting the most representative monitoring sites; months; and pollution indicators as the study identified the priority WQVs to monitor and the optimum monitoring stations and months for sample collection such that highly reliable and cost-effective WQ data is still secured. As a result, sharp reduction in monitoring time and costs will be achieved. The various modeling approaches established and presented in this study can be applied to river basins in other urban settings provided the necessary data and expertise are available.

Abstrak tesis yang dikemukakan kepada Senat Universiti Putra Malaysia sebagai memenuhi keperluan untuk ijazah Ijazah Doktor Falsafah.

RANGKAIAN NEURAL BUATAN UNTUK PENILAIAN KUALITI AIR DAN PENGESAHAN CORAK GUNA TANAH DI LEMBANGAN SUNGAI KINTA

Oleh

NABEEL MOHAMMAD GAZZAZ

Februari 2012

Pengerusi: Profesor Madya Mohd Kamil Yusoff, PhD

Fakulti: Pengajian Alam Sekitar

Sungai Kinta (dalam Negeri Perak, Malaysia) telah dikelasifikasikan sebagai Kelas III berdasarkan Indeks Kualiti Air (IKA) sepanjang tahun 1997-2006 dengan julat di antara 51.9 hingga 76.5. Berdasarkan analisis kekerapan, kelas kualiti Sungai Kinta di sepanjang tempoh tersebut ialah Kelas I, II, III, IV, dan V masing-masing 5.9%, 31.0%, 54.9%, 7.8%, dan 0.4%. Bermula tahun 2004 hingga terkini, Jabatan Alam Sekitar telah mengkelasifikasikan Sungai Kinta dalam kategori sedikit tercemar. Sehubungan dengan itu keperluan untuk mengenal pasti faktor utama iaitu proses, nilai kualiti air (WQV), dan kelas guna tanah (LU) mempengaruhi perubahan kualiti air (WQ) dan penentuan kaedah untuk memastikan kelestarian Sungai Kinta telah meningkat.

Sehubungan dengan itu, objektif kajian ialah untuk (i) menilai kualiti air Sungai Kinta sepanjang tempoh 1997-2006, (ii) menentukan corak dan analisis guna tanah (LU) di

lembangan Sungai Kinta di samping penilaian kualiti air (WQ) sungai, (iii) pemodelan pola tersebut, dan (iv) pemodelan impak bandingan terhadap lapan kategori LU (pertanian, peternakan haiwan, perhutanan, pembalakan, perlombongan, kelapa sawit, getah dan perbandaran) ke atas WQ Sungai Kinta dengan berpandukan kepada teknik penerokaan data termasuk kaedah kimometrik (analisis faktor utama (PFA)), kaedah tidak linear dan kaedah keberhasilan data (jaringan saraf buatan (ANN)). Kajian ini menggunapakai kaedah menyeluruh di mana kajian merangkumi lapan sub-lembangan dalam lembangan Sungai Kinta yang setiap satunya mempunyai stesen pemantauan kualiti air dengan mengambil kira enam skala reruang; seluruh lembangan (WRB), dan zon penampan (BZ) seperti berikut; 0-500m, 0-1000m, 0-1500m, 0-2000m, dan 0-2500m. Selain itu juga kajian dijalankan berdasarkan skala masa iaitu untuk tempoh kedapatan data selama 10 tahun (1997-2006).

Hasil PFA menggambarkan struktur data WQ yang diwakili oleh 23 WQV dan diasingkan kepada tujuh faktor yang memberi penerangan sebanyak 74.2% daripada jumlah variasi data. Faktor ini sangat berguna dalam penentuan sumber pencemaran utama dalam lembangan sungai. Fungsi asas jejari (RBF) membentukkan model kelasifikasi yang mencorakkan ramalan WQC daripada 23 WQV. Pengkelasan optimum yang membantu dalam proses pembetulan nisbah (CCR) untuk Kelas 1-IV adalah di antara 60.0%-86.7%. Ciri penstrukturan peta kendiri (SOFM) melakarkan bahawa pola reruang WQ Sungai Kinta boleh dikelasifikasikan kepada dua kumpulan. Daripada indeks kualiti air (WQI), kumpulan pertama mempunyai kualiti air yang bagus berbanding dengan kumpulan kedua. Nilai WQV dan LU memperkuatkan lagi ciri-ciri kumpulan pertama dengan menunjukkan kumpulan tersebut dipengaruhi oleh larian permukaan, hakisan, sumber pencemaran organik dan mikrob yang mana merupakan pengaruh daripada air larian pertanian dan pemerlarutan mineral. Model RBF yang optimum menghasilkan pengkelasan untuk stesen pemantauan bagi kedua-dua kumpulan masing-masing mempunyai nilai CCR 92.5% dan 97,7%. Di samping itu SOFM memberi nilai ramalan yang rendah ke atas corak masa kelakuan WQ di Sungai Kinta berdasarkan ciri-ciri WQ yang sama untuk kedua-dua kumpulan tersebut. Sebagai bandingan, kumpulan kedua mempunyai ciri masa kelakuan yang mempunyai nilai purata yang tinggi ke atas WQV. Keputusan ini diperkuatkan lagi dengan nilai pengkelasan RBF yang menghasilkan pengkelasan model yang mempunyai nilai CCR 78.0%. Nilai SOFM menunjukkan corak reruang untuk LU dalam lembangan Sungai Kinta boleh diwakili oleh tiga kumpulan dan keputusan ini diperkuatkan oleh pengkelasan RBF dengan memberi pengkelasan tambahan model dengan nilai CCR sebanyak 99.3%.

Enam model ANN telah dibentuk untuk mengira dan meramal nilai Indeks Kualiti Air dengan menggunakan peramal keluasan LU di mana satu model digunakan untuk setiap skala reruang. Daripada hasil kajian menunjukkan ANN memperkuatkan pemodelan WQI-LU dengan keupayaan di antara 91.2% (0-1000 m BZ) hingga 97.8% (0-2500 m BZ). Model tersebut digunakan untuk meramalkan status kualiti air Sungai Kinta pada tahun 2020 berdasarkan kepada perubahan guna tanah yang telah digubal dalam Pelan Pembangunan Majlis Bandaraya Ipoh 2020. Ramalan WQI dan WQC menggambarkan bahawa pendekatan WRB adalah lebih bermiripkan kepada WQ Sungai Kinta dan tahap pencemaran berbanding dengan semua zon pemampan.

Hasil kajian menunjukkan perancangan LU dan program pembangunan bandar untuk pelan pengurusan sungai membenarkan pengoptimum jaringan stesen pemantauan. Sebagai contoh, kaedah dan keputusan yang dibincangkan dalam kajian ini boleh membantu agensi pemantau mengubahsuai program pemantauan semasa untuk Sungai Kinta dengan memilih stesen pemantauan yang boleh mewakili lokasi, masa dan indikator pencemaran. Kajian ini menitikberatkan kepada keutamaan WQV untuk dipantau dengan mengambilkira stesyen pemantau dan masa yang boleh memberi maklumat yang tepat dan penjimatan kos. Pendakatan pelbagai model yang dibangunkan dan dibenttangkan dalam kajian ini boleh digunakan untuk lembangan dikawasan perbandaran lain dangan syarat adanya data dan kepakaran yang diperlukan.

ACKNOWLEDGEMENTS

I would like to express my deepest, most sincere thanks and debts of gratitude to my supervisor, Associate Professor Dr. Mohd Kamil Yusoff, for providing me with this remarkable opportunity to work with him on this research project. His understanding, trust, patience, keen personal guidance, and steady encouragement and support were ever fueling my spirit, mind, and will with motivation, determination, and hope to finish this research very successfully. The helpful guidance of Associate Professor Dr. Mohd Kamil Yusoff and his directions as well as the invaluable insight into the theory and practice of this research are especially acknowledged. I would like also to acknowledge my supervisory committee members, Dr. Hafizan Juahir, Associate Professor Dr. Mohammad Firuz Ramli, and Dr. Ahmad Zaharin Aris.

The author thanks the Department of Agriculture (DoA), Malaysia, and Majlis Bandaraya Ipoh (MBI) for their valuable help and support. Very special thanks are due to Mrs. Misnah binti Mohd Ariffin (DoA), Mrs. Jaslina binti Shaidin (MBI), and Mr. haj Mohd Tajuddin bin Mohd Tahir (MBI), for their kindness, help, speedy processing of the LU maps, and for the very high quality maps and relevant material they kindly made available for the researcher.

This research was supported in part by my supervisor, Associate Professor Dr. Mohd Kamil Yusoff; the main library of Universiti Putra Malaysia; Houreyyah Y. Doudine (my mother), Mohammad S. Gazzaz (my father), and his Excellency Dr. Waleed M. Gazzaz (my brother). Their help, encouragement, and support are highly valuated and appreciated.

I certify that a Thesis Examination Committee has met on (**23 February 2012**) to conduct the final examination of Nabeel Mohammad Gazzaz on his Doctor of Philosophy thesis entitled "Artificial Neural Network for Water Quality Assessment and Land Use Pattern Recognition in Kinta River Catchment" in accordance with the Universities and University Colleges Act 1971 and the Constitution of the Universiti Putra Malaysia [P.U.(A) 106] 15 March 1998. The Committee recommends that the student be awarded the degree of Doctor of Philosophy.

Members of the Thesis Examination Committee were as follows:

Ahmad Makmom Abdullah, PhD
Associate Professor
Faculty of Environmental Studies
Universiti Putra Malaysia
(Chairman)

Dato' Nik Muhamad bin Nik Abd Majid, PhD
Professor
Faculty of Forestry
Universiti Putra Malaysia
(Internal Examiner)

Latifah binti Abd Manaf, PhD
Associate Professor
Faculty of Environmental Studies
Universiti Putra Malaysia
(Internal Examiner)

Kyoung-Woong Kim, PhD
Professor
School of Environmental Science and Engineering
Gwangju Institute of Science and Technology
(External Examiner)

SEOW HENG FONG, PhD
Professor and Deputy Dean
School of Graduate Studies
Universiti Putra Malaysia

Date: 21 May 2012

This thesis was submitted to the Senate of Universiti Putra Malaysia and has been accepted as fulfillment of the requirement for the degree of Doctor of Philosophy. The members of the Supervisory Committee were as follows:

Mohd Kamil Yusoff, PhD
Associate Professor
Faculty of Environmental Studies
Universiti Putra Malaysia
(Chairman)

Mohammad Firuz Ramli, PhD
Associate Professor
Faculty of Environmental Studies
Universiti Putra Malaysia
(Member)

Hafizan Juahir, PhD
Lecturer
Faculty of Environmental Studies
Universiti Putra Malaysia
(Member)

Ahmad Zaharin Aris, PhD
Lecturer
Faculty of Environmental Studies
Universiti Putra Malaysia
(Member)

BUJANG KIM HUAT, PhD
Professor and Dean
School of Graduate Studies
Universiti Putra Malaysia

Date:

DECLARATION

I declare that the thesis is my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously, and is not concurrently, submitted for any other degree at Universiti Putra Malaysia or at any other institution.

NABEEL MOHAMMAD GAZZAZ

Date: 23 February 2012

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AA	Appendix A
AAE	Average absolute error
AB	Appendix B
AC	Appendix C
AD	Appendix D
Ag	Silver
AME	Absolute mean error; Absolute average error (AAE)
ANN	Artificial neural network
As	Arsenic
asl	above sea level
B	Boron
Ba	Barium
Be	Beryllium
Bi	Bizmuth
BOD	Biochemical oxygen demand

BP	Back propagation
BZ	Buffer zone
Ca	Calcium
CA	Cluster analysis
CCR	Correct classification ratio
Cd	Cadmium
Cl	Chloride
Cl_2	Chlorine
CN	Cyanide
CO	Carbon monoxide
Co	Cobalt
CO_3^{2-}	Carbonate
COD	Chemical oxygen demand
Cr	Chromium
Cs	Cesium
Cu	Copper

DA	Discriminant analysis
DCA	Distance coverage approach
DEM	Digital elevation model
DF	Discriminant function
DFA	Discriminant function analysis
DM	Data mining
DO	Dissolved oxygen
DoA	The Department of Agriculture, Malaysia
DoE	The Department of Environment, Malaysia
DP	Dissolved phosphorous
EC	Electric conductivity
E. coli	Escherichia coli
EDA	Exploratory data analysis
EHR	Expected hit ratio
F	Fluoride
FA	Factor analysis

Fe	Iron
FF	Feed-forward
GIS	Geographic Information System
HACA	Hierarchical agglomerative cluster analysis
HCO_3^-	Bicarbonate
Hg	Mercury
HP	Highly polluted
INWQSM	Interim National Water Quality Standards for Malaysia
K	Potassium
KMO	Kaiser–Meyer–Olkin
k-NN	K-nearest neighbor algorithm
LC	Land cover
Li	Lithium
LP	Low polluted
LU	Land use
LUC	Land use change

MAE	Mean absolute error
MBI	Majlis Bandaraya Ipoh
Mg	Magnesium
MLP	Multi-layer perceptrons
MLR	Multiple linear regression
Mn	Manganese
Mo	Molybdenum
MP	Medium polluted
MSE	Mean-squared error
RMSE	Root mean-squared error
Na	Sodium
NH_3-N	Ammonia nitrogen
Ni	Nickel
NN	Neural network
NO_2-N	Nitrite nitrogen
NO_3-N	Nitrate nitrogen

NPS	Non-point source
NTU	Nephleometric turbidity unit
OLS	Ordinary least squares
P	Phosphorous
PC	Principal component
PCA	Principal component analysis
PFA	Principal factor analysis
Pb	Lead
PO_4-P	Phosphate phosphorous
PP	Particulate phosphorus
ρ_S	Spearman’s correlation coefficient (Spearman’s rho)
PS	Point source
QP	Quick propagation
R^2	The coefficient of determination
Rb	Rubidium
RBF	Radial basis function

RBFNN	Radial-basis function neural network
RWQ	River water quality
Se	Selenium
SEE	Standard error of estimate
SEM	Standard error of the mean
Sn	Tin
SO_4^{2-}	Sulfate
SOFM	Self-organizing feature map
Sr	Strontium
SS	Suspended solids
SSE	Sum-squared error
T	Temperature
TDN	Total dissolved nitrogen
TDP	Total dissolved phosphorous
TDS	Total dissolved solids
TH	Total hardness

TKN	Total Kjeldhal nitrogen
Tl	Thallium
TN	Total nitrogen
TOC	Total organic carbon
TON	Total organic nitrogen
TP	Total phosphorous
TS	Total solids
TSS	Total suspended solids
U	Uranium
V	Vanadium
VF	Varifactor
WRB	Whole river basin
WQ	Water quality
WQI	Water quality Index
WQV	Water quality variable
Zn	Zinc

CHAPTER ONE

INTRODUCTION

1.1 Background of Study

Anthropogenic perturbations of the landscape, alterations to river systems, and escalating water consumption are adversely impacting the sustainability of freshwater resources throughout the globe. Environmental impacts on the river systems are to a large extent cumulative in nature, brought about by individually minute, yet collectively considerable, actions which accumulate over time and space (Ren et al., 2003; Schindler, 2001; Spaling and Smit, 1995). Within the river system context, cumulative effects originate from changes to catchment processes produced by additive and synergetic interactions of multifold anthropogenic perturbations to the landscape (Seitz et al., 2011; Therivel and Ross, 2007). Nearly all land use (LU) activities directly and/or indirectly affect environmental parameters, e.g., topography, vegetation, soil, surface runoff, and river flow, which in consequence modify the transport of water, organic matter, sediments, and numerous pollutants that ultimately end up in the river systems (Johnson et al., 1997; Schindler, 2001). As such, health of a river system is essentially a function of the types of processes and interactions which occur on the landscape within the watershed boundaries (Seitz et al., 2011).

The quality of surface water in a region depends to a large degree on the anthropogenic activities and on the nature, areas, and distributions of LUs in catchments. Furthermore, the percentages of the individual dominant LUs (e.g., urban, agricultural, forest, industrial, and mining) are quite important since these uses differ in their individual contributions to NPS pollution. Besides these factors, Basnyat et al. (2000a) highlighted that watershed characteristics such as land cover, slope, and soil type affected water quality (WQ) and nutrient concentrations in the Gulf of Mexico by regulating sediment loading in the draining water. Thus, anthropogenic influences and natural characteristics of a watershed should be considered when managing watersheds or examining their WQ (Baker, 2003; Basnyat et al., 2000a; Buck et al., 2004; Griffith, 2002; Moerke and Lamberti, 2006; Sliva and Williams, 2001; Woli et al., 2004).

Urban development in the study area (Kinta River basin, the State of Perak (Malaysia)) has been rapid. For example, the urbanization rate was 32.2% in 1980, grew slightly in ten years to 33.6% in 1990, then marked a sharp jump to 56.2% in 1995, and kept growing afterwards where the urbanization growth rates were 59.5% and 65.3% in 2000 and 2005, respectively (Economic Planning Unit, 2001). On the other hand, the population of Perak was 2,051,236 in the year 2000 and 2,130,397 in 2005. A slight increase was observed in the population between the years 2010 (2,249,029) and 2011 (2,258,428). However, this population is projected to be 2,429,554 in 2015 and 2,676,321 in 2020 (Table A.1, Appendix A). On the other hand, the Ninth Malaysia Plan (2006-2010) highlighted that the average annual growth rate of urban population in Perak was projected to be 2.2% in 2010 (Economic Planning Unit, 2006). Analogous trends are expected for the agricultural and industrial sectors.

These increases had several implications including a growing demand on water. As an example, in the years 1980, 1985, 1990, and 2000, the demand on water for the different uses in the state of Perak amounted to 145, 216, 327, and 596 million cubic meters per year, respectively. Besides the increased demand on water, the population growth and urbanization development are impacting the local water resources through increased loads of sediments, nutrients, organics, and microbes, primarily from human activities. Within this framework, environmental resource management and restoration efforts in this river basin thus necessitate recognition of the patterns, analysis of the trends, and modeling of the discovered patterns and trends in RWQ and LUs besides prediction of river water quality (RWQ) in terms of water quality variables (WQVs) and LU areas, current and projected.

Determining the impacts of urban development and concomitant land use change (LUC) on RWQ has been attempted with some success (e.g., Bolstad and Swank (1997), Coulter et al. (2004), Fisher et al. (2000), Palani et al. (2008), and Tong and Chen (2002)). One approach to measurement of the effects of urban development on the WQ of a river is to compare it with gradients in LU areas at different spatial and temporal scales (Coulter et al., 2004). Within this context, the temporal and spatial scales of cumulative effect assessment of LUC should ideally (i) elucidate how past events, actions, processes, and incremental changes on the landscape impacted the present; and (ii) delineate their ensuing short-, and long-term effects (Therivel and Ross, 2007). In this regard, there are two common methodologies for prediction of RWQ as a function of LU pattern: (i) precise study of the different processes which can affect the WQ and development of statistical (e.g., multivariate, also called chemometrics) or deterministic models accordingly, and (ii) development of data-driven (e.g., artificial neural network (ANN)) models using archived data.

The RWQ is dependent on many factors, including LUs. However, the relative effects of varying LU types on RWQ are yet to be confirmed and quantified. This research attempts to use a comprehensive, integrated approach following two distance coverage approaches (DCAs); the whole river basin (WRB) and buffer zone (BZ) approaches, corresponding to six spatial scales, to examine the relationships between LUs and RWQ at a local scale. The goal of this study was to utilize non-linear, data-driven techniques (the ANN) to analyze and interpret the patterns and trends in LUs and in the RWQ in Kinta River basin, model these patterns and trends, examine the potential relationships of LUs with the WQ of Kinta River, and model the impacts of a number of WQVs and eight LU categories on the WQ of Kinta River. As such, this study was multi-scale, exploratory, inferential, and interpretative in nature.

1.2 Problem Statement

Non-point source pollution and the quality of river water are tightly-related and are vital issues in many parts of the world, including Kinta River basin where LU development is changing formerly forested basins into more of urban and mixed-use basins. Growing population and industries in this river basin resulted in dramatic changes in LUs within the basin exemplified mainly by extended housing and associated residential and commercial development. This growth ultimately lead to deleterious environmental impacts on the local water resources through increased demand on water for the various uses and growing inputs of sediments, nutrients, organics, and microbes from human activities to surface water systems.

In the broad context, although there have been studies on the impacts of LUs on water flows and quality (e.g., Antonopoulos et al. (2001), Astel et al. (2006), Biggs et al. (2002), Fitzpatrick et al. (2007), Sheldon and Fellows (2010), and Su et al. (2011)), the complex inherent relationships between LUs and WQ are yet to be clarified, quantified, and modeled. Establishing links between the ever-changing LUs, LU patterns, and other anthropogenic activities within a river basin and surface WQ over long periods of time is a vital requirement for monitoring and planning the LUC, and, as a result, the WQ of the river(s) of concern, to ultimately secure and sustain the desired quantity and quality of the urban water resources (Ren et al., 2003). However, most of the relevant published research focused on statistical (e.g., Kowalkowski et al. (2006), Perona et al. (1999), and Singh et al. (2004)); or spatial (e.g., Basnyat et al. (2000b), Griffith (2002), Smart et al. (2001), and Wang (1997)); or modeling analyses (e.g., Dawson and Wilby (2001), Smart et al. (2001), and Tong and Chen (2002)). Few studies employed more than one technique like GIS and statistical analysis (e.g., Jarvie et al. (2002)); GIS and modeling (e.g., Xiang (1996)), and GIS and neuro-fuzzy techniques (e.g., Dixon (2004)).

In other respects, the majority of related studies examined the impacts of LUs on either the quantity of surface runoff (e.g., Changnon and Demissie (1996), Ferguson and Deak (1994), and Karunanithi et al. (1994)) or on its quality (e.g., Bolstad and Swank (1997), May and Sivakumar (2009), and Tang et al. (2005)). Few studies examined the effects of

LUs on both water quantity and quality (e.g., Johnston et al. (1990)). Yet, fewer studies have employed an integrated approach involving the use of statistical and spatial analyses, as well as hydrologic modeling, to examine the hydrologic effects of LUs at both local and regional scales (e.g., Tong and Chen (2002)).

Similarly, most early studies focused on the relationships between LUs and WQ in catchments alone (e.g., Jarvie et al. (2002), Liu et al. (2000) and Li et al. (2008)); buffer zones alone (e.g., Jung et al. (2008) and Maillard and Santos (2008)); catchment plus one BZ (e.g., Li et al. (2009), Marryanna et al. (2007), and Moerke and Lamberti (2006)); or catchment plus two or three BZs (e.g., Osborne and Kovacic (1993) and Roth et al. (1996)). Studies where more than three buffer widths were considered besides the catchment are rare (e.g., Bolstad and Swank (1997)). Consequently, the variability and complexity in the spatial patterns and temporal trends of LU and LUC impacts on RWQ have not been fully explored (Guo et al., 2010). Equally important, a bulky volume of the published literature offers only a snapshot of urban WQ for one, mostly short, period of time or a limited number of periods, e.g., one year (e.g., Kotti et al. (2005)); two years (e.g., Perona et al. (1999) and Schoonover et al. (2005)); five years (e.g., Atasoy et al. (2006)); seven years (e.g., Marryanna et al. (2007)), and in very few cases longer time periods, e.g., ten years (e.g., Brett et al. (2005)).

At the local scale, as far as Kinta River and its basin are concerned and to the best knowledge of the researcher, no earlier investigation of the RWQ and LU patterns, trends, and associations over the study period (1997-2006) has been published in the English scientific literature or so far carried out. Thereupon, the main research problem was to (i) determine the reasons why the WQ of Kinta River is generally low; (ii) decide on how this quality is affected by WQVs and eight priority LU classes (agriculture, animal husbandry, forest, logging, mining, oil palm, rubber, and urban areas) within the basin; and (iii) identify the main culprit WQVs and LU classes for the degraded WQ of Kinta River.

Moreover, the spatial and temporal characteristics of LUC and associated effects on the WQ of Kinta River have not been quantified and linked to distinct pollutant sources in Kinta River basin before. Accordingly, there is a need to determine how past LU and WQ records can be utilized to secure a good WQ that can be used on a sustainable basis through recognizing the patterns and analyzing the trends in the priority LU classes and in the WQ of Kinta River as a function of these LUs. So, there is growing interest in finding how ANN approach and models can be best utilized to (a) unveil the spatial patterns and temporal trends in LU patterns and WQ and (b) unravel LU-WQ associations of extremely complex, highly diverse, and naturally-evolving river systems like Kinta River and subsequently predict these associations. All and above, there is pressing need for creating tools that will employ the historic LU and WQ data in inferring the WQ status of Kinta River (expressed in terms of the WQI) through utilizing WQ monitoring data and LU areas as predictors, separately, on the one hand, and in orienting future LU plans in the direction of achieving, and sustaining, an appreciably good WQ, on the other.

1.3 Study Objectives

The main objectives of this study were:

(1) To assess the water quality status of Kinta River in the period 1997-2006;

(2) To analyze patterns and trends in the water quality of Kinta River and in land uses in the river's basin during the study period;

(3) To investigate and model association of the water quality status of Kinta River with water quality variables; and

(4) To quantify and model association of the water quality of Kinta River with priority land use classes by means of the artificial neural network techniques.

1.4 Research Hypotheses

The theoretical framework of this study was developed early 2009. The idea of this project stemmed essentially from speculations that (i) patterns and trends in WQ and LUs can be elucidated and quantified and that (ii) impacts of LUs on RWQ can be disclosed, modeled, and generalized. The theoretical framework of this study consequently leaned heavily on six educated guesses comprising the research hypotheses:

Hypothesis 1: The WQ of Kinta River changes with time, presumably RWQ deteriorates with years.

Hypothesis 2: The WQ of Kinta River varies with space; distance from the headwater and distance from the main stream.

Hypothesis 3: The different studied WQVs vary in their effects on the WQ of the river.

Hypothesis 4: The WQ of the river is affected by the predominant LU types and areas.

Hypothesis 5**:** The different LU classes differ in their effects on the WQ of the river.

Hypothesis 6**:** The LU effects on RWQ vary with spatial scale.

1.5 Significance of the Study

An understanding of the temporal and spatial characteristics of key pollutants and pollutant sources is highly critical for mitigation of environmental contamination. Understanding the effects of contaminants on rivers and determining their sources and relations with LU types helps in formulating the most appropriate strategies for managing urban streams. The research community, environmental managers and planners, and the decision makers seek a deep insight into the cumulative impacts of LUs on RWQ as these uses change along the river course, ultimately for achieving and maintaining a reasonably good WQ and for developing updated WQ regulations for the river basin(s) of concern.

To the researcher's best knowledge, no LU-WQ modeling or even ANN analysis of the patterns and trends in LU and/or WQ have been conducted for Kinta River basin. Lack of such studies hinders assessment of RWQ response to projected and/or planned changes in LU patterns. In line with this and in view of the study objectives, this research assessed the WQ of Kinta River and analyzed the spatial patterns and temporal trends in WQVs and LU classes in connection with Kinta River sub-basins and interpreted them in terms of Kinta River WQ.

Through WQ assessment; the first study objective, this research identified the major WQVs responsible for the deteriorated WQ of the river and revealed links between WQ parameters and between LUs and WQ parameters. Pattern recognition and trend analysis, which are the second objective of this study, identified possible sources and processes of river pollution besides developing numerous clustering and classification models for determining and forecasting the patterns and trends in the WQ and LU data. Non-linear regression modeling using the ANN technique; which is the fourth objective of this study, provided ANN models of the relationships between WQVs and the WQI and between LU classes and the WQI. These models generated forecasts of the WQ of Kinta River in each of its eight sub-basins n the year 2020.

The significance and novelty of this research is embodied in its strength as multidisciplinary, multi-scale, integrated approach using a number of different techniques to solve an environmental problem. By incorporating concepts from chemometrics, LUC, and hydrology within GIS and ANN applications, watershed analysis revealed critical, subtle effects that are not manifested by the raw WQ or LU data. The study outcomes demonstrate that this approach can be used as a screening tool for the basin as a whole and for each sub-basin to further understand problems of deterioration in WQ due to ongoing development. The approach of this study may therefore be used for inter-jurisdictional or currently relevant government LU zoning purposes to focus resources to areas requiring remediation or observation and for economic analysis of needed water control and treatment facilities to ensure compliance with local WQ regulations, and to ensure the ability of Kinta River to meet the supply, demand, and quality requirements of the population while simultaneously considering the interconnectedness of ecosystems and the intrinsic value of human health and environmental safety.

Another manifestation of the significance of this study is that the outcomes of assessment of the WQ of Kinta River and analysis of its trends identified the need for a review of the DoE-WQI formula for Kinta River in terms of the variables to include, the variable weights, and method of calculation. Corollary to this, results of WQ assessment, PFA, pattern recognition, and trend analysis have the additional significance of highlighting the potential for success of a selective chemical monitoring program. Specifically, future monitoring campaigns may lay emphasis particularly on the 23 WQVs identified by PFA to be explaining the latent construct of the WQ data.

In addition to selective chemical monitoring, rapid assessment of WQ using representative sites and months can optimize monitoring cost and time without loosing any significance of the monitoring outcomes. This research prioritized stream sections for careful monitoring and WQ restoration efforts. It identified two zones of priority consideration: (i) the WQ monitoring stations 2PK24, 2PK25, 2PK59, and 2PK34, which are characterized by high levels of microbial pollution; and (ii) the sub-basins 2PK33, 2PK60, and 2PK19, which define the area wherein Kinta River water is expected to experience the deleterious environmental effects of the eight LU classes the most. In consequence, pattern recognition outcomes suggest that future monitoring campaigns may steadily collect water samples from the stations 2PK22, 2PK24, 2PK33, and 2PK19, and occasionally one or two of the rest, especially 2PK25 and 2PK59.

On the other hand, trend analysis results suggest that forthcoming monitoring programs of the WQ of Kinta River may collect samples from four months only in the year; preferably January, April, July, and October. This sampling plan will allow for defining the temporal clusters in future trend analysis studies of Kinta River in view of the two monsoonal and two inter-monsoonal periods and will clarify the role of weather in shaping the current and potential future trends.

The ability to predict changes in WQ as a function of LUC in powerful, reliable manner helps in settling compromise between improving or maintaining or restoring RWQ and sustainable, safe development. The WQI-LU models provided forecasts of the WQ status of Kinta River in the year 2020 using Majlis Bandaraya Ipoh (MBI) 2020 Development Plan. These forecasts have the significance of revealing the sub-basins which will have WQ conditions that are comparable with, or poorer than, the WQ conditions they had in the year 2006. This helps the local urban managers and LU planners in introducing suitable modifications to the MBI 2020 Development Plan such that an appreciably good quality of Kinta River water will be secured in the year 2020 and afterwards. Ultimately, the study findings enable policy and decision makers to establish balance between water use and extended, sound development. And lastly, the various modeling approaches presented in this study can be applied to river basins in other urban settings provided that the necessary data and expertise are available.

1.6 Study Scope and Limitations

This research was longitudinal, historic in nature and local in scale at the level of Kinta River basin. It carried out assessment of the WQ of Kinta River for the period 1997-2006 and conducted spatial and temporal analyses of the RWQ through utilizing 23 WQVs and eight LU classes by means of ANN pattern recognition, trend analysis, and modeling techniques. In addition, this research implemented non-linear regression modeling of the WQI-WQV and WQI-LU relationships using the ANN technique.

The overall spatial scale of the study was Kinta River basin in the State of Perak, Malaysia, which covers an area of about 2,471 km^2. Particular emphasis was paid to the eight sub-basins of this river which were defined such that each sub-basin delineates the area which contributes flow exclusively to one of the eight WQ monitoring stations along the river. Water quality assessment, which is the first study objective, was carried out at the WRB spatial scale over the time period 1997-2006. Analysis of the spatial patterns and temporal trends in the WQ of Kinta River and the LU classes in its basin were too carried out at the WRB spatial scale. However, in the case of ANN non-linear regression modeling of the WQI-WQV and WQI-LU interrelations, which is the fourth objective of this study, the various investigations were carried at both the WRB and BZ approaches, corresponding to six spatial scales (the WRB, and the 0-500 m, 0-1000 m, 0-1500 m, 0-2000 m, and 0-2500 m BZs).

In other respects, the different linear data mining (DM) tools employed in this research included mono-, bi-, and multi-variate analyses covering both exploratory and confirmatory data analysis techniques. The exploratory component of the study consisted of applying multivariate pattern recognition and trend analysis techniques in an attempt to group the variables (using principal factor analysis (PFA)) and samples (using the self-organizing feature map (SOFM)) into initial clusters of similar characteristics. On the other hand, the confirmatory phase involved use of the radial basis function (RBF) neural network (NN) to determine how much distinguishable the clusters are and to determine the combination of variables which best differentiates the identified clusters.

Geographic Information System (GIS) data layers for the basin and sub-basin boundaries, LU maps for five years (1997, 2000, 2002, 2004, and 2006), land use development plan for the year 2020, and locations of the WQ monitoring stations were employed in calculating the areas of eight LU classes, evaluating the impacts of LUs on the WQ of Kinta River, and exploring WQ disturbance indicators at the six spatial extents in the eight sub-basins. The historical WQ data from the eight monitoring stations besides the WQI and WQC were utilized to explore significant relationships between WQ parameters as well as between LU classes and WQ parameters.

Definition of the eight LU classes was essentially based on the Classification Information and Land Use Code Amendment (Version 8, 2008) issued by the Department of Town and Country Planning (Malaysia) with very slight modifications to address the peculiarity of Kinta River basin in connection with LU categories. Furthermore, water quality, LU, and combined LU-WQ working files were prepared. Then, the ANN approach to pattern recognition, trend analysis, and modeling, as well as the MLP NN were utilized for determining the relative impacts of influential WQVs and LU classes on the WQ of Kinta River and to foresee the WQ status of the river in response to future LUC using the LU statistics of the MBI 2020 Development Plan.

However, the researcher would like to highlight the following limitations to this study: (i) lack of WQ data for the monitoring stations 2PK59 and 2PK60 before 2005; (ii) lack of WQ data for the months January, April, July, and October; and (iii) lack of LU statistics for the years 1998, 1999, 2001, 2003, and 2005. Another limitation was related to differences in the numbers of water samples collected from the eight monitoring stations between the various months and between the different years. The number of samples collected from the sampling stations 2PK19, 2PK22, 2PK24, 2PK25, 2PK33, and 2PK34 was 40 each, while the numbers were only 7 and 8 respectively for the stations 2PK59 and 2PK60. Furthermore, the number of samples collected in each year from 1997 through 2004 was 24. As to the years 2005 and 2006, the numbers were 31 and 32, respectively. Besides, the sampling program addresses 8 months only; February, March, May, June, August, September, November, and December. In addition, the sampled months had unequal sample sizes; November (58), August (34), May (33), February and September (32 samples each), March and June (30 samples each), and December (6).

With respect to the LU data, an additional limitation was that the LU maps did not show the industries as separate entities on the maps. So, it was not possible to separate the effects of the industrial from the urban LU areas. The same may apply to the animal husbandry LU as its very small areas in the study period raise the suspicion that this LU was mostly incorporated in the LU maps within the agricultural areas.

1.7 Organization of Thesis

The overall structure of the study takes the form of five chapters, including this introductory chapter, and the rest of this dissertation is organized as follows.

Chapter Two introduces and discusses, in an object-oriented manner, a review of the literature related to RWQ, land use effects on RWQ, and to the theory and practice of ANN pattern recognition, trend analysis, and modeling.

Chapter Three describes the methods and procedures followed in satisfying the goal and objectives of this research and in testing its hypotheses.

Chapter Four presents the research results and discusses them in view of the related, reviewed literature and in view of the study objectives and hypotheses.

Chapter Five draws upon the entire dissertation, tying up the numerous theoretical and empirical strands, so as to give a brief summary and critique of the findings and discuss their implications to future research into this area, and therefore, suggested areas for further research are identified and provided.

REFERENCES

Abowei, J.F.N., 2010. Salinity, Dissolved Oxygen, pH and Surface Water Temperature Conditions in Nkoro River, Niger Delta, Nigeria. Advance Journal of Food Science and Technology 2 (1), 36–40.

Abraham, W., 2011. Megacities as Sources for Pathogenic Bacteria in Rivers and their Fate downstream. International Journal of Microbiology 2011, 1–13.

Abrahart, R.J., See, L., 2000. Comparing neural network and autoregressive moving average techniques for the provision of continuous river flow forecasts in two contrasting catchments. Hydrological Processes 14 (11–12), 2157–2172.

Abrahart, R.J., White, S.M., 2001. Modelling sediment transfer in Malawi, comparing backpropagation neural network solutions against a multiple linear regression benchmark using small data sets. Physics and Chemistry of the Earth Part B, Hydrology, Oceans and Atmosphere 26 (1), 19–24.

Abul, O., Lo, A., Alhajj, R., Polat, F., Barker, K., 2003. Cluster Validity Analysis Using Subsampling. IEEE International Conference on Systems, Man and Cybernetics, 5–8 October, 2003. IEEE, San Diego, CA, USA, 1435–1440.

Aguilera, P.A., Frenich, A.G., Torres, J.A., Castro, H., Vidal, J.L.M., Canton, M., 2001. Application of the Kohonen neural network in coastal water management, methodological development for the assessment and prediction of water quality. Water Research 35 (17), 4053–4062.

Aitchison, J., Kay, J.W., 2003. Possible solutions of some essential zero problems in compositional data analysis. Retrieved 08 August 2009 from http,//ima.udg.edu/Activitats/CoDaWork03/paper_Aitchison_and_Kay.pdf

Alhoniemi, E., Hollmen, J., Simula, O., Vesanto, J., 1999. Process monitoring and modeling using the self–organizing map. Integrated Computer–Aided Engineering 6 (1), 3–14.

Allan, J.D., Erickson, D.L., Fay, J., 1997. The influence of catchment land use on stream integrity across multiple spatial scales. Freshwater Biology 37 (1), 149–161.

Al–Mamun, A., Idris, A., 2008. Revised Water Quality Indices for the Protection of Rivers in Malaysia. In: Proceedings of the 12th International Water Technology Conference, IWTC12. Alexandria, Egypt, pp. 1687–1698.

Alyuda Research Company 2003. Alyuda NeuroIntelligence User Manual. Version 2.1. Alyuda Research Inc., Los Altos, CA, USA.

Amidan, B.G., Ferryman, T.A., Cooley, S.K., 2005. Data Outlier Detection using the Chebyshev Theorem. In: Proceedings of the IEEE Aerospace Conference, 5–12 March 2005. Big Sky, MT, USA, pp. 1–6.

Amiri, B.J., Nakane, K., 2009. Comparative Prediction of Stream Water Total Nitrogen from Land Cover Using Artificial Neural Network and Multiple Linear Regression Approaches. Polish Journal of Environmental Studies, 18 (2), 151–160.

Amusan, A.A., Tongen, S., Speedie, S.M., Mellin, A., 2008. A time–motion study to evaluate the impact of EMR and CPOE implementation on physician efficiency. Journal of Healthcare Information Management 22 (4), 31–37.

Anbumozhi, V., Radhakrishnan, J., Yamaji, E., 2005. Impact of riparian buffer zones on water quality and associated management considerations. Ecological Engineering 24 (5), 517–523.

Antonopoulos, V.Z., Papamichail, D.M., Mitsiou, K.A., 2001. Statistical and trend analysis of water quality and quantity data for the Strymon river in Greece. Hydrology and Earth System Sciences 5 (4), 679–691.

Aruga, R., 1997. Treatment of responses below the detection limit, some current techniques compared by Factor Analysis on environmental data. Analytica Chimica Acta 354 (1–3), 255–262.

Astel, A., Mazerski, J., Polkowska, Z., Namieśnik, J.N. 2004. Application of PCA and time series analysis in studies of precipitation in Tricity (Poland). Advances in Environmental Research 8 (3–4), 337–349.

Astel, A., Biziuk, M., Przyjazny, A., Namiésnik, J., 2006. Chemometrics in monitoring spatial and temporal variation in drinking water quality. Water Research 40 (8), 1706–1716.

Astel, A., Tsakovski, S., Barbieri, P., Simeonov, V., 2007. Comparison of self organizing maps classification approach with cluster and principal components analysis for large environmental data sets. Water Research 41 (19), 4566–4578.

Atasoy, M., Palmquist, R.B., Phaneuf, D.J., 2006. Estimating the effects of urban residential development on water quality using microdata. Journal of Environmental Management 79 (4), 399–408.

Baker, A., 2003. Land use and water quality. Hydrological Processes 17 (12), 2499–2501.

Ballester, M.V.R., D.C. Victoria, A.V. Krusche, R. Coburn, R.L. Victoria, J.E. Richey, M.G. Logsdon, E. Mayorga, E. Matricardi, 2003. A remote sensing/GIS-based physical template to understand the biogeochemistry of the Ji-Paraná river basin (Western Amazon). Remote Sensing of the Environment 87, 429–445.

Banerjee, P., Singh, V.S., Chatttopadhyay, K., Chandra, P.C., Singh, B., 2011. Artificial neural network model as a potential alternative for groundwater salinity forecasting. Journal of Hydrology 398, 212–220.

Basheer, I.A., Hajmeer, M., 2000. Artificial neural networks, fundamentals, computing, design, and application. Journal of Microbiological Methods, 43 (1), 3–31.

Basnyat, P., Teeter, L.D., Lockaby, B.G., Flynn, K.M., 2000a. The use of remote sensing and GIS in watershed level analyses of non–point source pollution problems. Forest Ecology and Management, 128 (1–2), 65–73.

Basnyat, P., Teeter, L., Lockaby, B.G., Flynn, K.M., 2000b. Land Use Characteristics and Water Quality, A Methodology for Valuing of Forested Buffers. Environmental Management 26 (2), 153–161.

Besaw, L.E., Rizzo, D.M., Kline, M., Underwood, K.L., Doris, J.J., Morrissey, L.A., Pelletier, K., 2009. Stream classification using hierarchical artificial neural networks, A fluvial hazard management tool. Journal of Hydrology 373 (1–2), 34–43.

Biggs, T.W., Dunne, T., Domingues, T.F., Martinelli, L.A., 2002. Relative importance of natural watershed properties and human disturbance on stream solute concentrations in the southwestern Brazilian Amazon Basin. Water Resources Research 38 (8), 25.1–25.16.

Bishop, C.M., 1994. Novelty Detection and Neural Network Validation. IEE proceedings on Vision, Image and Signal Processing 141 (4), 217–222.

Bobbin, J., Recknage, F., 2001. Knowledge discovery for prediction and explanation of blue-green algal dynamics in lakes by evolutionary algorithms. Ecological Modelling 146 (1-3), 253–262.

Boniecki, P., 2005. The Kohonen Neural Networks in Classification Problems Solving in Agricultural Engineering. Journal of Research and Applications in Agricultural Engineering, 50 (1), 37–40.

Bolstad, P.V., Swank, W.T., 1997. Cumulative impacts of land use on water quality in a southern Appalachian watershed. Journal of the American Water Resources Association 33 (3), 519–534.

Bouamar, M., Ladjal, M., 2008. A Comparative Study of RBF Neural Network and SVM Classification Techniques Performed on Real Data for Drinking Water Quality. In: Proceedings of the 5th International Multi–Conference on Systems, Signals and Devices, 20-22 July 2008. Amman, Jordan, pp. 1–5.

Boyacioglu, H., Boyacioglu, H., Gunduz, O., 2005. Application of Factor Analysis in the Assessment of Surface Water Quality in Buyuk Menderes River Basin. European Water 9/10, 43–49.

Boyacioglu, H., 2007. Development of a water quality index based on a European classification scheme. Water Research Commission 33 (1), 101–106.

Boyacioglu, H., Boyacioglu, H., 2008. Water pollution sources assessment by multivariate statistical methods in the Tahtali Basin, Turkey. Environmental Geology 54 (2), 275–282.

Boyd, E.C., 1992. Shrimp Pond Bottom Soil and Sediment Management. In Wyban, J. (Editor): Proceedings of the Special Session on Shrimp Farming. World Aquaculture Society, Baton Rouge, LA USA, pp. 166–181.

Brett, M.T., Arhonditsis, G.B., Mueller, S.E., Hartley, D.M., Frodge, J.D., Funke, D.E., 2005. Non–point–source impacts on stream nutrient concentrations along a forest to urban gradient. Environmental Management 35 (3), 330–342.

Bu, H., Tan, X., Li, S., Zhang, Q., 2010. Temporal and spatial variations of water quality in the Jinshui River of the South Qinling Mts., China. Ecotoxicology and Environmental Safety 73 (5), 907–13.

Buchtala, O., Neumann, P., Sick, B., 2003. A Strategy for an Efficient Training of Radial Basis Function Networks for Classification. In: Proceedings of the IEEE–INNS International Joint Conference on Neural Networks (IJCNN 2003), 20-24 July 2003. Portland, USA, pp. 1025–1030.

Buck, O., Niyogi, D.K., Townsend, C.R., 2004. Scale–dependence of land use effects on water quality of streams in agricultural catchments. Environmental Pollution 130 (2), 287–299.

Burke, S., 1999. Missing values, outliers, robust statistics and non–parametric methods. LC*GC Europe Online Supplement, 19–24.

Burman. P., 1989. A Comparative Study of Ordinary Cross–Validation, v–Fold Cross–Validation and the Repeated Learning–Testing Methods. Biornetrika, 76 (3), 503–514.

Carafa, R., Faggiano, L., Real, M., Munné, A., Ginebreda, A., Guasch, H., Flo, M., Tirapu, L., von der Ohe, P.C., 2011. Water toxicity assessment and spatial pollution patterns identification in a Mediterranean River Basin District. Tools for water management and risk analysis. Science of the Total Environment 409, 4269–4279.

Castellanos, A., Blanco, A.M., Palencia, V., 2007. Applications of Radial Basis Neural Networks for Area Forest. International Journal of Information Theories & Applications 14, 218–222.

Céréghino, R., Giraudel, J.L., Compin, A., 2001. Spatial analysis of stream invertebrates distribution in the Adour–Garonne drainage basin (France), using Kohonen self organizing maps. Ecological Modelling 146 (1–3), 167–180.

Chang, F., Chen, Y., 2003. Estuary water–stage forecasting by using radial basis function neural network. Journal of Hydrology 270 (1–2), 158–166.

Chang, H.J., 2008. Spatial analysis of water quality trends in the Han River basin, South Korea. Water Research 42 (13), 3285–3304.

Changnon, S.A., Demissie, M., 1996. Detection of changes in streamflow and floods resulting from climate fluctuations and land use drainage changes. Climatic Change 32 (4), 411–421.

Chapman, D., 1996. Water Quality Assessments – A Guide to Use of Biota, Sediments and Water in Environmental Monitoring. Published on Behalf of the United Nations Educational, Scientific and Cultural Organization, World Health Organization, United Nations Environment Program. The University Press, Cambridge, Great Britain.

Chau, K.W., Muttil, N., 2007. Data mining and multivariate statistical analysis for ecological system in coastal waters. Journal of Hydroinformatics 9 (4), 305–317.

Chau, K.L., 2010. Ecological analysis of health care utilisation for China's rural population, association with a rural county's socioeconomic characteristics. Chau BMC Public Health, 10 (1), 1–9.

Chen, L., Zhang, X., 2009. Application of Artificial Neural Networks to Classify Water Quality of the Yellow River. Fuzzy Information and Engineering, Advances in Intelligent and Soft Computing, 54, 15–23.

Chon, T.–S., Park, Y.S., Moon, K.H., Cha, E.Y., 1996. Patternizing communities by using an artificial neural network. Ecological Modelling 90 (1), 69–78.

Coulter, C.B., Kolka, R.K., James, A., 2004. Water Quality in Agricultural, Urban, and Mixed Land Use Watersheds. Journal of the American Water Resources Association 40 (6), 1593–1601.

Costello, A.B., Osborne, J.W. 2005. Best Practices in Exploratory Factor Analysis: Four Recommendations for Getting the Most from your Analysis. Practical Assessment Research & Evaluation 10 (7), 1–9.

Crampton, W.G.R., 1998. Effects of anoxia on the distribution, respiratory strategies and electric signal diversity of gymnotiform fishes. Journal of Fish Biology 53 (Supplement A), 307–330.

da Costa, A.O.S., Silva, P.F., Sabará, M.G., da Costa, E.F., 2009. Use of neural networks for monitoring surface water quality changes in a neotropical urban stream. Environmental Monitoring and Assessment 155 (4), 527–538.

Dakou, E., D'heygere, T., Dedecker, A.P., Goethals, P.L.M., Lazaridou–Dimitriadou, M., de Pauw, N., 2007. Decision tree models for prediction of macroinvertebrate taxa in the river Axios (Northern Greece). Aquatic Ecology 41 (3), 399–411.

Daniel, E.B., Camp, J.V., LeBoeuf, E.J., Penrod, J.R., Dobbins, J.P., Abkowitz, M.D., 2011. Watershed Modeling and its Applications, A State–of–the–Art Review. The Open Hydrology Journal 5 (1), 26–50.

Das, A.K. 2000. Limno-Chemistry of Some Andhra Pradesh Reservoirs. Journal of the Inland Fisheries Society of India 32 (1), 37–44.

Dawe, P., 2006. A statistical evaluation of water quality trends in selected water bodies of Newfoundland and Labrador. Journal of Environmental Engineering and Science 5 (1), 59–73.

Dawson, C.W., Wilby, R.L., 2001. Hydrological modelling using artificial neural networks. Progress in Physical Geography 25 (1), 80–108.

Department of Environment (DoE), 2005. Malaysia Environmental Quality Report 2006. Department of Environment. Ministry of Natural Resources and Environment, Petaling Jaya, Malaysia.

Department of Statistics, Malaysia, 2010. Principal Statistics, Perak 2009. Department of Statistics, Putrajaya, Malaysia.

Diamantopoulou, M.J., Papamichail, D.M., Antonopoulos, V.Z., 2005. The Use of a Neural Network Technique for the Prediction of Water Quality Parameters. Operational Research 5 (1), 115‒125.

Dixon, B., 2004. Prediction of Ground Water Vulnerability Using an Integrated GIS-Based Neuro-Fuzzy Techniques. Journal of Spatial Hydrology 4 (2), 1‒38.

Du, K.L., 2010. Clustering, A neural network approach. Neural Networks 23 (1), 89–107.

Duch, W., Jankowski, N., 1999. Survey of Neural Transfer Functions. Neural Computing Surveys 2 (1), 163–212.

Duda, A.M., Lenat, D.R., Penrose, D.L., 1982. Water quality in urban streams—what we can expect. Journal of the Water Pollution Control Federation 54 (7), 1139–47

Economic Planning Unit, 2001. Eighth Malaysia Plan 2001–2005. National Printing Department, Kuala Lumpur, Malaysia.

Economic Planning Unit, 2006. Ninth Malaysia Plan 2006–2010. National Printing Department, Kuala Lumpur, Malaysia.

Einax, J.W., Truckenbrodt, D., Kampe, O., 1998. River Pollution Data Interpreted by Means of Chemometric Methods. Microchemical Journal 58 (3), 315–324.

Ezekiel, E.N., Hart, A.I., Abowei, J.F.N., 2011. The Physical and Chemical Condition of Sombreiro River, Niger Delta, Nigeria. Research Journal of Environmental and Earth Sciences 3 (4), 327–340.

Fahlman, S.E., 1988. An Empirical Study of Learning Speed in Back–Propagation Networks. School of Computer Science. Carnegie Mellon University, Pittsburgh, USA. 1988.

Farmaki, E.G., Thomadis, N.S., Efstathiou, C.E., 2009. Comparative Use of Artificial Neural Networks for the Discrimination of the Water Reservoirs of Athens According to their Elemental Content. In: Proceedings of the 11th International conference on Environmental Science and Technology, 1–4 September 2009. Chania, Greece, pp. B254–B262.

Farnham, I.M., Singh, A.K., Stetzenbach, K.J., Johannesson, K.H., 2002. Treatment of nondetects in multivariate analysis of groundwater geochemistry data. Chemometrics and Intelligent Laboratory Systems 60 (1–2), 265–281.

Ferguson, B.K., Deak, T., 1994. Role of Urban Storm–Flow Volume in Local Drainage Problems. Journal of Water Resources Planning and Management 120 (4), 523–530.

Fernández, N., Ramírez, A., Solano, F., 2004. Physico–Chemical Water Quality Indices A Comparative Review. Bistua: Revista de la Facultad de Ciencias Básicas, 2(1), 19–30.

Fisher, D.S., Steiner, J.L., Endale, D.M., Stuedemann, J.A., Schomberg, H.H., Franzluebbers, A.J., Wilkinson, S.R., 2000. The relationship of land use practices to surface water quality in the Upper Oconee Watershed of Georgia. Forest Ecology and Management 128 (1–2), 39–48.

Fitzpatrick, M.L., Long, D.T., Pijanowski, B.C., 2007. Exploring the effects of urban and agricultural land use on surface water chemistry, across a regional watershed, using multivariate statistics. Applied Geochemistry 22 (8), 1825–1840.

Fitzpatrick, W.P., 1995. Wisconsin Smart Program: Starkweather Creek. In: Proceedings of the National Conference on Urban Runoff Management: Enhancing Urban Watershed Management at the Local, County, and State Levels. U.S. Environmental Protection Agency, EPA/625/R-95/003, Cincinnati, Ohio, pp. 173–179.

Flavelle, P., 1992. A quantitative measure of model validation and its potential use for regulatory purposes. Advances in Water Resources 15 (1), 5–13.

Foody, G.M., 1995. Estimation of Land Coverage from a Land Cover Classification Derived from Remotely Sensed Data. GeoJournal 36 (4), 361–370.

Foody, G.M., 1996. Relating the Land–Cover Composition of Mixed Pixels to Artificial Neural Network Classification Output. Photogrammetric Engineering and Remote Sensing 62 (5), 491–499.

Foody, G.M. 2004. Supervised image classification by MLP and RBF neural networks with and without an exhaustively defined set of classes. International Journal of Remote Sensing 25 (15), 3091–3104.

Fox, D.G., 1981. Judging air quality model performance, A summary of the AMS Workshop on Dispersion Model Performance. Bulletin of the American Meteorological Society 62 (5), 599–609.

Fry, J., Fry, T.R.L., McLaren, K.R., 2000. Compositional data analysis and zeros in micro data. Applied Economics 32 (8), 953–959.

Garg, R.K., Raom, R.J., Uchchariya, D., Shukla, G., Saksena, D.N., 2010. Seasonal variations in water quality and major threats to Ramsagar reservoir, India. African Journal of Environmental Science and Technology 4 (2), 061–076.

Gatts, C.E.N., Ovalle, A.R.C., Silva, C.F., 2005. Neural pattern recognition and multivariate data, water typology of the Paraíba do Sul River, Brazil. Environmental Modelling and Software 20 (7), 883–889.

Giraudel, J.L., Lek, S., 2001. A comparison of self–organizing map algorithm and some conventional statistical methods for ecological community ordination. Ecological Modelling 146 (1–3), 329–339.

Gove, N.E., Edwards, R.T., Conquest, L.L., 2001. Effects of Scale on Land Use and Water Quality Relationships, A Longitudinal Basin–Wide Perspective. Journal of the American Water Resources Association 37 (6), 1721–1734.

Govindarajan, M., Chandrasekaran, R.M., 2010. Evaluation of k–Nearest Neighbor classifier performance for direct marketing. Expert Systems with Applications 37 (1), 253–258.

Govindaraju, R.S., 2000. Artificial Neural Networks in Hydrology. I, Preliminary Concepts. Journal of Hydrologic Engineering 5 (2), 115–123.

Griffith, J.A., 2002. Geographic techniques and recent applications of remote sensing to landscape–water quality studies. Water, Air, and Soil Pollution 138 (1–4), 181–197.

Guilford, J.P., 1956. Fundamental statistics in psychology and education. McGraw–Hill, New York.

Guo, Q., Ma, K., Yang, L., He, K., 2010. Testing a Dynamic Complex Hypothesis in the Analysis of Land Use Impact on Lake Water Quality. Water Resources Management 24 (7), 1313–1332.

Güler, C., Thyne, G.D., McCray, J.E., Turner, A.K., 2002. Evaluation of graphical and multivariate statistical methods for classification of water chemistry data. Hydrogeology Journal 10 (4), 455–474.

Gutiérrez–Pulido, J.R., Andrade–Aréchiga, M., Herrera–Morales, J.R., Cabello–Espinosa, M.E., Legrand, S., Elliman, D., 2008. Artificial Learning approaches for the next generation web: part II. Ingeniería, investigación y tecnología 9 (2), 161–169.

Ha, H., Stenstrom, M.K., 2003. Identification of land use with water quality data in stormwater using a neural network. Water Research 37 (17), 4222–4230.

Hall, K.J., Anderson, B.C., 1988. The toxicity and chemical composition of urban stormwater runoff. Canadian Journal of Civil Engineering 15 (1), 98–106.

Hani, A., Lallahem, S., Mania, J., Djabri, L., 2006. On the use of finite–difference and neural–network models to evaluate the impact of underground water overexploitation. Hydrological Processes 20 (2), 4381–4390.

Hardy, R.L., 1971. Multiquadric equations of topography and other irregular surfaces. Journal of Geophysical Research, 76 (8), 1905–1915.

Haykin, S., 1999. Neural Networks A Comprehensive Foundation. Prentice Hall International, Inc., New Jersey, USA.

He, H., Zhou, J., Wu, Y., Zhang, W., Xie, X., 2008. Modelling the response of surface water quality to the urbanization in Xi'an, China. Journal of Environmental Management 86 (4), 731–749.

Helsel, D.R., 1987. Advantages of nonparametric procedures for analysis of water quality data. Hydrological Sciences Journal 32 (2), 179–190.

Helsel, D.R., Hirsch, R.M., 2002. Statistical Methods in Water Resources. Chapter A3 in Book 4, Hydrologic Analysis and Interpretation. Techniques of Water–Resources Investigations of the United States Geological Survey, Portland, Oregon, USA.

Hill, T., Marquez, L., O'Connor, M., Remus, W., 1994.Artificial neural network models for forecasting and decision making. International Journal of Forecasting 10 (1), 5–15.

Hinkle, S.R., 1997. Quality of Shallow Ground Water in Alluvial Aquifers of the Willamette Basin, Oregon, 1993–95. U.S. Department of the Interior, U.S. Geological Survey, Earth Science Information Center. Portland, Oregon, USA.

Hirsch, R., Slack, J., 1984. A Nonparametric Trend Test for Seasonal Data with Serial Dependence. Water Resources Research 20 (6), 727–732.

Hong, Y., Rosenm M.R., 2001. Intelligent characterisation and diagnosis of the groundwater quality in an urban fractured–rock aquifer using an artificial neural network. Urban Water 3 (3), 193–204.

Hood, M.A., Ness, G.E., Blake, N.J., 1983. Relationship among Fecal Coliforms, Escherichia coli, and Salmonella spp. in Shellfish. Applied and Environmental Microbiology 45 (1), 122–126.

Hooda, P.S., Edwards, A.C., Anderson, H.A., Miller, A., 2000. A review of water quality concerns in livestock farming areas. The Science of the Total Environment 250 (1–3), 143–167.

Howarth, R., Chan, F., Conley, D.J., Garnier, J., Doney, S.C., Marino1, R., Billen, G. 2011. Coupled biogeochemical cycles: eutrophication and hypoxia in temperate estuaries and coastal marine ecosystems. Frontiers in Ecology and the Environment 9 (1), 18–26.

Hunsaker, C., Levine, D., 1995. Hierarchical approaches to the study of water quality in rivers. Bioscience 45 (3), 193–203.
Hussain, M.F., Barton, R.R., Joshi, S.B., 2002. Metamodeling, Radial basis functions, versus polynomials. European Journal of Operational Research 138 (1), 142–154.

Ibarra–Berastegi, G., Elias, A., Barona, A., Saenz, J., Ezcurra, A., Diaz de Argandoña, J., 2008. From diagnosis to prognosis for forecasting air pollution using neural networks, Air pollution monitoring in Bilbao. Environmental Modelling and Software 23 (5), 622–637.

Ideriah, T.J.K, Amachree, O., Stanley, H.O., 2010. Assessment of Water Quality along Amadi Creek in Port Harcourt, Nigeria. Scientia Africana 9 (1), 150–162.

Iscen, C.F., Emiroglu, Ö., Ilhan, S., Arslan, N., Yilmaz, V., Ahiska, S., 2008. Application of multivariate statistical techniques in the assessment of surface water quality in Uluabat Lake, Turkey. Environmental Monitoring and Assessment 144 (1–3), 269–276.

Ishak, A., Hassan, Z.N.C., Edros, N.H., Zamberi, M.H., Abd Rahman, M.N., 2011. The Effect of Local Climate on Urban Heat Island Trend; A Case Study in Urban Areas of Ipoh and Kuantan. Malaysian Meteorological Department (MMD), Ministry of Science, Technology and Innovation, Kuala Lumpur, Malaysia.

Jackson, B.P., Seaman, J.C., Bertsch, P.M., 2006. Fate of arsenic compounds in poultry litter upon land application. Chemosphere 65 (11), 2028–2034.

Jarvie, H.P., Oguchi, T., Neal, C., 2002. Exploring the linkages between river water chemistry and watershed characteristics using GIS–based catchment and locality analyses. Regional Environmental Change 3 (1–3), 36–50.

Ji, C.Y., 2000, Land–use classification of remotely sensed data using Kohonen self organizing feature map neural networks. Photogrammetric Engineering and Remote Sensing 66 (12), 1451–1460.

Jianwen, M., Bagan, H., 2005. Land–use classification using ASTER data and self–organized neutral networks. International Journal of Applied Earth Observation and Geoinformation 7 (3), 183–188.

Johnston, C.A., Detenbeck, N.E., Niemi, G.J., 1990. The cumulative effect of wetlands on stream water quality and quantity, a landscape approach. Biogeochemistry 10 (2), 105–142.

Johnson, L.B., Gage, S.H. 1997. Landscape approaches to the analysis of aquatic Ecosystems. Freshwater Biology 37 (1), 113–132.

Johnson, L.B., Richards, C., Host, G., Arthur, J., 1997. Landscape influences on water chemistry in Midwestern stream ecosystems. Freshwater Biology 37 (1), 193–208.

Jordan, T.E., Correll, D.L., Weller, D.E., 1997. Nonpoint source discharges of nutrients from Piedmont watersheds of Chesapeake Bay. Journal of the American Water Resources Association 33 (3), 631–646.

Joseph, P.V., Claramma, J., 2010. Physicochemical Characteristics of Pennar River, a Fresh Water Wetland in Kerala, India. E–Journal of Chemistry 7 (4), 1266–1273.

Joseph, S., Ouseph, P.P., 2009. Assessment of nutrients using multivariate statistical techniques in estuarine systems and its management implications, a case study from Cochin Estuary, India. Water and Environment Journal 24 (2), 126–132.

Juahir, H., Zain, S.M., Toriman, M.E., Mokhtar, M., Man, H.C., 2004. Application of Artificial Neural Network Models for Predicting Water Quality Index. Jurnal Kejuruteraan Awam 16 (2), 42–55.

Juahir, H., Zain, S.M., Kamil, M.Y., Hanidza, T.I.T, Mohd, A.S.A, Toriman, M. E., Mokhtar, M., 2011. Spatial water quality assessment of Langat River Basin (Malaysia) using environmetric techniques. Environmental Monitoring and Assessment 173 (1–4), 625–641.

Jung, K., Lee, S., Hwang, H., Jang, J., 2008. The effects of spatial variability of land use on stream water quality in a costal watershed. Paddy Water Environment 6 (3), 275–284.

Junninen, H., Niska, H., Tuppurainen, K., Ruuskanen, J., Kolehmainen, M., 2004**.** Methods for imputation of missing values in air quality data sets. Atmospheric Environment 38 (18), 2895–2907.

Kaiser, H.F., 1974. An index of factorial simplicity. Psychometrika 39 (1), 31–36.

Kalteh, A.M., Hjorth, P., Berndtsson, R., 2008. Review of the self–organizing map (SOM) approach in water resources, Analysis, modelling and application. Environmental Modelling and Software 23 (7), 835–845.

Kalyan, B., Balasuriya, A., 2004. Multiple Sensors based Navigation Scheme for AUV Position Estimation. In: Proceedings of the International Symposium on Underwater Technology, 20–23 April 2004. pp. 201–207.

Kangur, K., Park, Y.–S., Kangur, A., Kangur, P., Lek, S., 2007. Patterning long–term changes of fish community in large shallow Lake Peipsi. Ecological Modelling 203 (1–2), 34–44.

Kannel, P.R., Lee, S., Kanel, S.R., Khanc, S.P., 2007. Chemometric application in classification and assessment of monitoring locations of an urban river system. Analytica Chimica Acta 582 (2), 390–399.

Kannel, P.R., Kanel, S.R, Lee, S., Lee, Y.S., 2011. Chemometrics in assessment of seasonal variation of water quality in fresh water systems. Environmental Monitoring and Assessment 174 (1–4), 529–545.

Keramitsoglou, I., Sarimveis, H., Kiranoudis, C.T., Sifakis, N., 2005. Radial basis function neural networks classification using very high spatial resolution satellite imagery: an application to the habitat area of Lake Kerkini (Greece). International Journal of Remote Sensing 26, 1861–1880.

Karunanithi, N., Grenney, W.J., Whitley, D., Bovee, K., 1994. Neural networks for river flow prediction. Journal of Computing in Civil Engineering 8 (2), 201–220.

Kaune, A., Kettrup, A., 1994. Treatment of Values below the Detection Limits in Correlation Analysis of Chlorinated Dioxins and Related Compounds. Chemosphere 29 (9–11), 1811–1818.

Kaurish, F.W., Younos, T., 2007. Developing a Standardized Water Quality Index for Evaluating Surface Water Quality. Journal of the American Water Resources Association 43 (2), 533–545.

Khalid, M.N., 2011. An Overview of Statistical Approaches for Assessing Model Fit. The International Journal of Educational and Psychological Assessment 8 (2), 69–87.

Khalil, B., Ouarda, T.B.M.J., St–Hilaire, A., 2011. Estimation of water quality characteristics at ungauged sites using artificial neural networks and canonical correlation analysis. Journal of Hydrology 405 (3–4), 277–287.

Khuan, L.Y., Hamzah, N., Jailani, R., 2002. Prediction of Water Quality Index (WQI) Based on Artificial Neural Network (ANN). In: Proceedings of the Student Conference on Research and Development, 07 November 2002. Shah Alam, Malaysia, pp. 157–161.

Klein, R.D., 1979. Urbanization and stream quality impairment. Water Resources Bulletin 15 (4), 948–963.

Kohonen, T., 1982a. Self–organized formation of topologically correct feature maps. Biological Cybernetics 43 (1), 59–69.

Kohonen, T., 1982b. Analysis of a simple self–organizing process. Biological Cybernetics 44 (2), 135–140.

Kohonen, T., 1990. The self–organizing map. Proceedings of the IEEE 78 (9), 1464–1480.

Koklu, R., Sengorur, B, Topal, B., 2010. Water Quality Assessment Using Multivariate Statistical Methods—A Case Study: Melen River System (Turkey). Water Resources Management 24, 959–978.

Kotti, M.E., Vlessidis, A.G., Thanasoulias, N.C., Evmiridis, N.P., 2005. Assessment of river water quality in Northwestern Greece. Water Resources Management 19 (1), 77–94.

Kowalkowski, T., Zbytniewski, R., Szpejna, J., Buszewski, B., 2006. Application of chemometrics in river water classification. Water Research 40 (4), 744–752.

Kowalkowski, T., 2009. Classification of nutrient emission sources in the Vistula River system. Environmental Pollution 157 (6), 1867–1872.

Kroll, S.A., Llacer, C.N., Cano, M., Heras, J., 2008. The influence of land use on water quality and macroinvertebrate biotic indices in rivers within Castilla–La Mancha (Spain). Limnetica 28 (2), 203–214.

Kubota, T., Ahmad, S., 2006. Wind Environment Evaluation of Neighborhood Areas in Major Towns of Malaysia. Journal of Asian Architecture and Building Engineering 5 (1), 199–206.

Kuo, Y., Liu, C., Lin, K., 2004. Evaluation of the ability of an artificial neural network model to assess the variation of groundwater quality in an area of blackfoot disease in Taiwan. Water Research 38 (1), 148–158.

Kuppusamy, M.R., Giridhar, V.V., 2006. Factor analysis of water quality characteristics including trace metal speciation in the coastal environmental system of Chennai Ennore. Environment International 32 (2), 174–179.

Kurosawa, K., Egashira, K., Tani, M., Jahiruddin, M., Moslehuddin, A.Z.M., Zulfikar, R.M., 2008. Variation in Arsenic Concentration Relative to Ammonium Nitrogen and Oxidation Reduction Potential in Surface and Groundwater. Communications in Soil Science and Plant Analysis 39 (9–10), 1467–1475.

Lai, F.S., Norajiki, A.J., 1988. Some stream quality characteristics of two small logged over watersheds in Selangor. Pertanika 11 (3), 461–468.

Lambrakis, N., Antonakos, A., Panagopoulos, G., 2004. The use of multicomponent statistical analysis in hydrogeological environmental research. Water Research 38 (7), 1862–1872.

LeBlanc, R.T., Brown, R.D., FitzGibbon, J.E., 1997. Modeling the Effects of Land Use Change on the Water Temperature in Unregulated Urban Streams. Journal of Environmental Management 49 (4), 445–469.

Leclerc, H., Mossel, D.A.A., Edberg, S.C., 2001. Advances in the Bacteriology of the Coliform Group, Their Suitability as Markers of Microbial Water Safety. Annual Reviews of Microbiology 55, 201–34.

Lee, S., Lathrop, R.G., 2006. Subpixel Analysis of Landsat ETM+ Using Self Organizing Map (SOM) Neural Networks for Urban Land Cover Characterization. IEEE Transactions on Geoscience and Remote Sensing 44 (6), 1642–1654.

Lee, Y.H., Shahril, M.H., Md, F.H.Y., Lim, C.Y., Lim, A.G., 2002. The Water Quality of Streams at the Watershed of the Putrajaya Wetlands. In: Proceedings of the Regional Symposium on Environment and Natural Resources, 10–11 April 2002. Hotel Renaissance Kuala Lumpur, Malaysia.

Lek, S., Guiresse, M., Giraudel, J.L., 1999. Predicting stream nitrogen concentration from watershed features using neural networks. Water Research 33 (16), 3469–3478.

Lenat, D.R., Crawford, J.K., 1994. Effects of land use on water quality and aquatic biota of three North Carolina piedmont streams. Hydrobiologia 294 (3), 185–199.

Li, S., Gu, S., Liu, W., Han, H., Zhnag, Q., 2008. Water quality in relation to land use and land cover in the upper Han River Basin, China. Catena 75 (2), 216–222.

Li, S., Gu, S., Tan, X., Zhang, Q., 2009. Water quality in the upper Han River basin, China, The impacts of land use/land cover in riparian buffer zone. Journal of Hazardous Materials 165 (1–3), 317–324.

Liao, K., Fildes, R., 2005. The accuracy of a procedural approach to specifying feedforward neural networks for forecasting. Computers and Operations Research 32 (8), 2151–2169.

Lin, G., Chen, L., 2006. Identification of homogenous regions for regional frequency analysis using the self–organizingmap. Journal of Hydrology 324 (1–4), 1–9.

Liou, S.M., Lo, S.L., Wang, S.H., 2004. A generalized water quality index for Taiwan. Environmental Monitoring and Assessment 96 (1–3), 35–32

Lischeid, G., 2001. Investigating short–term dynamics and long–term trends of SO_4 in the runoff of a forested catchment using artificial neural networks. Journal of Hydrology 243 (1–2), 31–42.

Liu, Z., Weller, D.E., Correll, D.L., Jordan, T.E., 2000. Effects of Land Cover and Geology on Stream Chemistry in Watersheds of Chesapeake Bay. Journal of the American Water Resources Association 36 (6), 1349–1365.

López-Granados, F., Gómez-Casero, M.T., Peña-Barragán, J.M., Jurado-Expósito, M., García-Torres, L., 2010. Classifying Irrigated Crops as Affected by Phenological Stage Using Discriminant Analysis and Neural Networks. Journal of the American Society for Horticultural Science 135, 465–473.

Loukas, Y.L., 2000. Radial basis function networks in host–guest interactions, instant and accurate formation constant calculations. Analytica Chimica Acta 417 (2), 221–229.

Lucio, P.S., Conde, F.C., Cavalcanti, I.F.A., Serrano, A.I., Ramos, A.M., Cardoso A.O., 2007. Spatiotemporal monthly rainfall reconstruction via artificial neural network – case study, south of Brazil. Advances in Geosciences 10, 67–76.

Lyautey, E., Lu, Z., Lapen, D.R., Wilkes, G., Scott, A., Berkers, T., Edge, T.A., Topp, E., 2010. Distribution and Diversity of *Escherichia coli* Populations in the South Nation River Drainage Basin, Eastern Ontario, Canada. Applied and Environmental Microbiology 76 (5), 1486–1496.

Ma, L., Xin, K., Liu, S., 2008. Using Radial Basis Function Neural Networks to Calibrate Water Quality Model. World Academy of Science, Engineering and Technology 38, 385–393.

Maier, H.R., Dandy, G.C., 2000. Neural networks for the prediction and forecasting of water resources variables, a review of modelling issues and applications. Environmental Modelling and Software 15 (1), 101–124.

Maillard, P., Santos, N.A.P., 2008. A spatial–statistical approach for modeling the effect of non–point source pollution on different water quality parameters in the Velhas river watershed – Brazil. Journal of Environmental Management 86 (1), 158–170.

Mainville, N., Webb, J., Lucotte, M., Davidson, R., Betancourt, O., Cueva, E., Mergler, D., 2006. Decrease of Soil Fertility and Release of Mercury following Deforestation in the Andean Amazon, Napo River Valley, Ecuador. Science of The Total Environment 368 (1), 88-98.

Mak, K.L., Li, W., 2008. Objective Evaluation of Seam Pucker on Textiles by Using Self–Organizing Map. IAENG International Journal of Computer Science 35 (1), 47–54.

Mander, Ü., Kull, A., Tamm, V., Kuusemets, V., Karjus, R., 1998. Impact of climatic fluctuations and land use change on runoff and nutrient losses in a rural landscape. Landscape and Urban Planning 41 (3–4), 229–238.

Marryanna, L., Aisah, S.S., Iskandar, K.S., 2007. Water Quality Response to Clear Felling Trees for Forest Plantation Establishment at Bukit Tarek F.R., Selangor. Journal of Physical Science 18 (1), 33–45.

Martín–Fernández, J.A., Barceló–Vidal, C.B., Pawlowsky–Glahn, V., 2003. Dealing with zeros and missing values in compositional data sets using nonparametric imputation. Mathematical Geology 35 (3), 253–278.

Mas, D.M.L., Ahlfeld, D.P., 2007. Comparing artificial neural networks and regression models for predicting faecal coliform concentrations. Hydrological Sciences 52 (4), 713–731.

Mas, J.F., 2004. Mapping land use/cover in a tropical coastal area using satellite sensor data, GIS and artificial neural networks. Estuarine, Coastal and Shelf Science 59 (2), 219–230.

Mas, J.F., Flores, J.J., 2008. The application of artificial neural networks to the analysis of remotely sensed data. International Journal of Remote Sensing 29 (3), 617–663.

Masala, G.L., 2005. Pattern Recognition Techniques Applied to Biomedical Patterns. International Journal of Biological and Life Sciences 1 (1), 47–55.

May, D.B., Sivakumar, M., 2009. Prediction of urban stormwater quality using artificial neural networks. Environmental Modelling and Software 24 (2), 296–302.

McNeil, V.H., Cox, M.E., Preda, M., 2005. Assessment of chemical water types and their spatial variation using multi–stage cluster analysis, Queensland, Australia. Journal of Hydrology 310 (1–4), 181–200.

Mendiguchía, C., Moreno, C., Galindo–Riaño, M.D., García–Vargas, M., 2004. Using chemometric tools to assess anthropogenic effects in river water. A case study, Guadalquivir River (Spain). Analytica Chimica Acta 515 (1), 143–149.

Meyer, J.L., Mcdowell, W.H., Bott, T.L., Elwood, J.W., Ishizaki, C., Melack, J.M., Peckarsky, B.L., Peterson, B.J., Rublee, P.A., 1988. Elemental dynamics in streams. Journal of the North American Benthological Society 7 (4), 410–432.

Miao, Y., Mulla, D.J., Robert, P.C., 2006. Identifying important factors influencing corn yield and grain quality variability using artificial neural networks. Precision Agriculture 7 (2), 117–135.

Mingoti, S.A., Lima, J.O., 2006. Comparing SOM neural network with fuzzy c–means, K–means and traditional hierarchical clustering algorithms. European Journal of Operational Research 174 (3), 1742–1759.

Minsky, M.L., Papert, S.A., 1969. Perceptrons. MIT Press, Cambridge, UK.

Moerke, A.H., Lamberti, G.A., 2006. Scale–dependent influences on water quality, habitat, and fish communities in streams of the Kalamazoo River Basin, Michigan (USA). Aquatic Science 68 (2), 193–205.

Morgan, M.D., Good, R.E., 1988. Stream Chemistry in the New Jersey Pinelands: The Influence of Precipitation and Watershed Disturbance. Water Resources Research 24 (7), 1091–1100.

Moreno–Jiménez, B., Rodríguez–Muñoz, A., Pastor, J.C., Sanz–Vergel, A.I., Garrosa, E., 2009. The moderating effects of psychological detachment and thoughts of revenge in workplace bullying. Personality and Individual Differences 46 (3), 359–364.

Moriasi, D.N., Arnold, J.G., Van Liew, M.W., Bingner, R.L., Harmel, R.D., Veith, T.L., 2007. Model Evaluation Guidelines for Systematic Quantification of Accuracy in Watershed Simulations. Transactions of the American Society of Agricultural and Biological Engineers 50 (3), 885–900.

Murtojärvi, M., Suominen, T., Uusipaikka, E., Nevalainen, O.S., 2011. Optimising an observational water monitoring network for Archipelago Sea, South West Finland. Computers and Geosciences. Computers and Geosciences 37 (7), 844–854.

Mutihac, L., Mutihac, R., 2008. Mining in chemometrics. Analytica Chimica Acta 61 (2), 1–18.

Muttiah, R.S., Srinivasan, R., Allen, P.M., 1997. Prediction of two–year peak stream discharges using neural networks. Journal of the American Water Resources Association 33 (3), 625–630.

Nagorski, S.A., Moore, J.N., McKinnon, T.E., 2003. Geochemical response to variable streamflow conditions in contaminated and uncontaminated streams. Water Resources Research 39 (2), 1–14.

Negm, K.E.A., 2005. Validation Testing for Temporal Neural Networks for RBF Recognition. In: Proceedings of the Third World Enformatika Conference (WEC 05), 27–29 April 2005. Istanbul, Turkey, pp. 88–93.

Nowlan, S.J., Hinton, G.E., 1992. Simplifying Neural Networks by Soft Weight–Sharing. Neural Computation 4 (4), 473–493.

Oha, H., Ahna, C., Leea, J., Chonb, T., Choib, K.H., Parkc, Y., 2007. Community patterning and identification of predominant factors in algal bloom in Daechung Reservoir (Korea) using artificial neural networks. Ecological Modeling 203 (1–2), 109–118.

Olszewski, T., Ryniecki, A., Boniecki, P., 2008. Neural Network Development for Automatic Identification of the Endpoint of Drying Barley in Bulk. Journal of Research and Applications in Agricultural Engineering 53 (1), 26–31.

Orr, J.M., 1994. Outlier Detection and Treatment in I/O Psychology, A Survey of Researcher Beliefs and an Empirical Illustration. Personnel Psychology 44 (3), 473–486.

Osborne, L.L., Wiley, M.J., 1988. Empirical Relationships between Land Use/Cover and Stream Water Quality in an Agricultural Watershed. Journal of Environmental Management 26 (1), 9–27.

Osborne, L.L., Kovacic, D.A., 1993. Riparian vegetated buffer strips in water–quality restoration and stream management. Freshwater Biology 29 (2), 243–258.

Özesmi, S.L., Tan, C.O., Özesmi, U., 2006. Methodological issues in building, training, and testing artificial neural networks in Ecological Applications. Ecological Modelling 195 (1–2), 83–93.

Palani, S., Liong, S., Tkalich, P., 2008. An ANN application for water quality forecasting. Marine Pollution Bulletin 56 (9), 1586–1597.

Paliwal, M., Kumar, U.A., 2009. Neural networks and statistical techniques, A review of applications. Expert Systems with Applications 36 (1), 2–17.

Panda, U.C., Sundaray, S.K., Rath, P., Nayak, B.B., Bhatta, D., 2006. Application of factor and cluster analysis for characterization of river and estuarine water systems – A case study, Mahanadi River (India). Journal of Hydrology 331 (3–4), 434–445.

Perona, E., Bonilla, I., Mateo, P., 1999. Spatial and temporal changes in water quality in a Spanish river. Science of the Total Environment 241 (1–3), 75–90.

Pesce, S.F., Wunderlin, D.A., 2000. Use of Water Quality Indices to Verify the Impact of Cordóba City (Argentina) on Suquía River. Water Research 34 (11), 2915–2926.

Pijanowski, B.C., Brown, D.G., Shellito, B.A., Manik, G.A., 2002. Using neural networks and GIS to forecast land use changes, a Land Transformation Model. Computers, Environment and Urban Systems 26 (6), 553–575.

Plaia, A., Bondi, A.L., 2006. Single imputation method of missing values in environmental pollution data sets. Atmospheric Environment 40 (38), 7316–7330.

Plaia, A., Bondi, A.L., 2010. Regression Imputation for Space–Time Datasets with Missing Values. In: Proceedings of the 6th Conference of the Classification and Data Analysis Group of the Società Italiana di Statistica. Società Italiana di Statistica, Rome, Italy, pp. 465-472.

Pond, G.J., Passmore, M.E., Borsuk F.A., Reynolds, L., Rose, C.J., 2008. Downstream effects of mountaintop coal mining, comparing biological conditions using family– and genus–level macroinvertebrate bioassessment tools. Journal of the North American Benthological Society 27 (3), 717–737.

Presti, R.L., Barca, E., Passarella, G., 2010. A methodology for treating missing data applied to daily rainfall data in the Candelaro River Basin (Italy). Environmental Monitoring and Assessment 160 (1–4), 1–22.

Qi, M., Zhang, G.P., 2001. An investigation of model selection criteria for neural network time series forecasting. European Journal of Operational Research 132 (3), 666–680.

Rao, C.R., Wu, Y., Konishi, S., Mukerjee, R., 2001. On Model Selection. Lecture Notes-Monograph Series, 38, 1–64.

Real, C., Fernández, J.A., Jesús R. Aboal, J.R., Carballeira, A., 2011. Substituting missing data in compositional analysis. Environmental Pollution 159 (10), 2797–2800.

Reimann, C., Filzmoser, P., Garrett, R.G., 2002. Factor analysis applied to regional geochemical data, problems and possibilities. Applied Geochemistry 17 (3), 185–206.

Ren, W., Zhong, Y., Meligrana, J., Anderson, B., Watt, W.E., Chen, J., Leung, H., 2003. Urbanization, land use, and water quality in Shanghai 1947–1996. Environment International, 29 (5), 649– 659.

Ren, W., Zhong, Y., Meligrana, J., Anderson, B., Watt, W.E., Chen, J., Leung, H., 2003. Urbanization, land use, and water quality in Shanghai 1947–1996. Environment International 29 (5), 649–659.

Riad, S., Mania, J., Bouchaou, L., Najjar, Y., 2004. Rainfall-runoff model using an artificial neural network approach. Mathematical and Computer Modelling 40 (7–8), 839–846.

Rieser, A., 1987. Managing the Cumulative Effects of Coastal Land Development: Can Maine Law Meet the Challenge? Maine Law Review 39 (2), 321–389.

Rösner, U., 1998. Effects of historical mining activities on surface water and groundwater - an example from northwest Arizona. Environmental Geology 33 (4), 224–230.

Roth, N.E., Allan, J.D., Ericson, D.E., 1996. Landscape influences on stream biotic integrity assessed at multiple spatial scales. Landscape Ecology 11(3), 141–156.

Royston, J.P., 1982. An Extension of Shapiro and Wilk's W Tests for Normality to Large Samples. Applied Statistics 31 (2), 115–124.

Sabuti, A.Z., Mohamed, C.A.R., 2011. Natural Radioisotopes of Pb, Bi and Po in the Atmosphere of Coal Burning Area. EnvironmentAsia 4 (2), 49–62

Sahu, M., Mahapatra, S.S., Sahu, H.B., Patel, R.K., 2011. Prediction of Water Quality Index Using Neuro Fuzzy Inference System. Water Quality, Exposure and Health 3 (3-4), 175–191.

Sajikumar, N., Thandaveswar, B.S., 1999. A non-linear rainfall–runoff model using an artificial neural Network. Journal of Hydrology 216 (1-2), 32–55.

Salvarredy–Aranguren, M.M., Probst, A., Roulet, M., Isaure, M., 2008. Contamination of surface waters by mining wastes in the Milluni Valley (Cordillera Real, Bolivia), Mineralogical and hydrological influences. Applied Geochemistry 23 (5), 1299–1324.

Sánchez–Martos, F., Aguilera, P.A., Garrido–Frenich, A., Torres, J.A., Pulido–Bosch, A., 2002. Assessment of groundwater quality by means of self–organizing maps, application in a semiarid area. Environmental Management 30 (5), 716–726.

Sanford, R.F., Pierson, C.T., Crovelli, R.A., 1993. An objective replacement method for censored geochemical data. Mathematical Geology 25 (1), 59–80.

Santos–Román, D.M., Warner, G.S., SCatena, F., 2003. Multivariate analysis of water quality and physical characteristics of selected watersheds in Puerto Rico. Journal of the American Water Resources Association 39 (4), 829–839.

Sapkota, A.R., Lefferts, L.Y., McKenzie, S., Walker, P., 2007. What Do We Feed to Food–Production Animals? A Review of Animal Feed Ingredients and Their Potential Impacts on Human Health. Environmental Health Perspectives 115 (5), 663–670.

Sarle, W.S., 1994. Neural networks and statistical models. In: Proceedings of the Nineteenth Annual SAS Users Group International Conference. SAS Institute, Dallas, USA, pp. 1538–1550.

Schafer, J.L., Schenker, J.W., 2000. Inference with Imputed Conditional Means. Journal of the American Statistical Association 95 (449), 144–154.

Schafer, J.L., Graham, J.W., 2002. Missing Data, Our View of the State of the Art. Psychological Methods 7 (2), 147–177.

Schenker, B., Agarwal, M., 1996. Cross–Validated Structure Selection for Neural Networks. Computers and Chemical Engineering 20 (2), 175–186.

Schindler, D.W., 2001. The cumulative effects of climate warming and other human stresses on Canadian freshwaters in the new millennium. Canadian Journal of Fisheries and Aquatic Sciences 58 (1), 18–29.

Schmidt, A. Hanson, C., Kathilankal, J., Law, B.E., 2011. Classification and assessment of turbulent fluxes above ecosystems in North–America with self–organizing feature map networks. Agricultural and Forest Meteorology 151 (4), 508–520.

Schoonover, J.E., Lockaby, B.G., Pan, S., 2005. Changes in chemical and physical properties of stream water across an urban–rural gradient in western Georgia. Urban Ecosystems 8 (1), 107–124.

Seitz, N.E., Westbrook, C.J., Noble, B.F., 2011. Bringing science into river systems cumulative effects assessment practice. Environmental Impact Assessment Review 31 (3), 172–179.

Shamseldin, A.Y., 1997. Application of a neural network technique to rainfall–runoff modelling. Journal of Hydrology 199 (3–4), 272–94.

Shamseldin, A.Y., Nasr, A.E., O'Connor, K.M., 2002. Comparison of different forms of the multi-layer feed-forward neural network method used for river flow forecast combination. Hydrology and Earth System Sciences 6 (4), 671–684.

Shanthi, D., Sahoo, G., Saravanan, N., 2009. Comparison of Neural Network Training Algorithms for the prediction of the patient's post–operative recovery area. Journal of Convergence Information Technology 4 (1), 24–32.

Sharpley, A.N., Withers, P.J.A., 1994. The environmentally-sound management of agricultural phosphorus. Fertilizer Research 39 (2), 133–146.

Sheldon, F., Fellows, C.S., 2010. Water quality in two Australian dryland rivers, spatial and temporal variability and the role of flow. Marine and Fresh Water Research 61 (8), 864–874.

Shin, M., Park, C., 2000. A Radial Basis Function Approach to Pattern Recognition and its Applications. ETRI Journal 22 (2), 1–10.

Shrestha, S., Kazama, F., Sakamoto, Y., Bastola, S., 2005. Statistical Modeling of Pollutant Load in Subbasins of the Fuji River Basin, Japan. Agricultural Engineering International, The CIGR e–Journal VII, 1–20.

Shrestha, S., Kazama, F., 2007. Assessment of surface water quality using multivariate statistical techniques, A case study of the Fuji river basin, Japan. Environmental Modelling & Software 22 (4), 464–475.

Simeonov, V., Einax J.W., Stanimirova, I., Kraft, J., 2002. Environmetric modeling and interpretation of river water monitoring data. Analytical and Bioanalytical Chemistry 374 (5), 898–905.

Simeonov, V., Stratis, J.A., Samara, C., Zachariadis, G., Voutsa, D., Anthemidis, A., Sofoniou, M., Kouimtzis, T., 2003. Assessment of the surface water quality in Northern Greece. Water Research 37 (7), 4119–4124.

Simeonova, P., Lovchinov, V., Dimitrov, D., Radulov, I., 2010. Environmetric approaches for lake pollution assessment. Environmental Monitoring and Assessment 164 (1–4), 233–248.

Singh, K.P., Malik, A., Mohan, D., Sinha, S., 2004. Multivariate statistical techniques for the evaluation of spatial and temporal variations in water quality of Gomti River (India)—a case study. Water Research 38 (18), 3980–3992.

Singh, K.P., Malik, A., Sinha, S., 2005. Water quality assessment and apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques–a case study. Analytica Chimica Acta 538 (1–2), 355–374.

Singh, K.P., Basant, A., Malik, A., Jain, G., 2009. Artificial neural network modeling of the river water quality—A case study. Ecological Modelling 220 (6), 888–895.

Sliva, L., Williams, D.D., 2001. Buffer Zone versus whole Catchment Approaches to Studying Land Use Impact on River Water Quality. Water Research 35 (14), 3462–3472.

Smart, R.P., Soulsby, C., Cresser, M.S., Wade, A.J., Townende, J., Billett, M.F., Langan, S., 2001. Riparian zone influence on streamwater chemistry at different spatial scales, a GIS–based modeling approach, an example for the Dee, NE Scotland. The Science of the Total Environment 280 (1–3), 173–193.

Solomatine, D.P., Ostfeld, A., 2008. Data–driven modelling, some past experiences and new approaches. Journal of Hydroinformatics 10 (1), 3–22.

Spaling, H., Smit, B., 1995. A conceptual model of cumulative environmental effects of agricultural land drainage. Agriculture, Ecosystems and Environment 53 (2), 99–108.

StatSoft Inc., 2004. StatSoft Statistica Electronic Manual. STATISTICA Data Analysis Software System version 7.0. StatSoft Inc., OK, USA.

Stewart, C., Field, C., 2010. Managing the Essential Zeros in Quantitative Fatty Acid Signature Analysis. Journal of Agricultural, Biological, and Environmental Statistics 16 (1), 45–69.

Su, S., Zhi, J., Lou, L., Huang, F., Chen, X., Wua, J., 2011. Spatio–temporal patterns and source apportionment of pollution in Qiantang River (China) using neural–based modeling and multivariate statistical techniques. Physics and Chemistry of the Earth 36 (9–11), 379–386.

Suhaila, J., Jemain, A.A., 2007. Fitting daily rainfall amount in Malaysia using the normal transform distribution. Journal of Applied Sciences, 7 (14), 1880–1886.

Suhaila, J., Jemain, A.A., 2009. Investigating the impacts of adjoining wet days on the distribution 30 of daily rainfall amounts in Peninsular Malaysia. Journal of Hydrology 368 (1–4), 17–25.

Suhaila, J., Deni, S.M., Zin, W.Z.W., Jemain, A.Z., 2010. Trends in Peninsular Malaysia Rainfall Data during the Southwest Monsoon and Northeast Monsoon Seasons: 1975–2004. Sains Malaysiana 39 (4), 533–542.

Suk, H., Lee, K., 1999. Characterization of a Ground Water Hydrochemical System Through Multivariate Analysis, Clustering into Ground Water Zones. Ground Water 37 (3), 358–366.

Tallon, P., Magajna, B., Lofranco, C., Leung, K.T., 2005. Microbial indicators of faecal contamination in water: a current perspective. Water, Air, and Soil Pollution 166 (1–4), 139–66.

Tang, Z., Engel, B.A., Pijanowski, B.C., Lim, K.J., 2005. Forecasting land use change and its environmental impact at a watershed scale. Journal of Environmental Management 76 (1), 35–45.

Tangang, F.T., 2001. Low frequency and quasi–biennial oscillations in the Malaysian precipitation anomaly. International Journal of Climatology 21 (10), 1199–1210.

Tecle, A., Neary, D.G., Ffolliott, P., Baker, M.B. 2003. Water quality in forested watersheds of the southwestern United States. Journal of the Arizona–Nevada Academy of Science 35 (1), 48–57.

Templ, M., Filzmoser, P., Reimann, C., 2008. Cluster analysis applied to regional geochemical data, Problems and possibilities. Applied Geochemistry 23 (8), 2198‒2213.

Teschl, R., Randeu, W.L., 2006. A neural network model for short term river flow prediction. Natural Hazards and Earth System Sciences 6 (4), 629–635.

Thangavel, K., Kumar, A.D., 2005. Simple Multi Pass Pattern Clustering Neural Networks. International Journal on Artificial Intelligence and Machine Learning 5 (3), 69‒78.

The Economic and Social Research Institute (ESRI), 2010. Arc Hydro Tools – Tutorial. Version 1.4. ESRI, CA, USA.

Therivel, R., Ross, W., 2007. Cumulative effects assessment, does scale matter? Environmental Impact Assessment Review 27 (5), 365–85.

Thilagamani, S., Shanthi, N., 2010. Literature Survey on Enhancing Cluster Quality. International Journal on Computer Science and Engineering 2 (6), 1999‒2002.

Thomas, S.M., Neill, C., Deegan, L.A., Krusche, A.V., Ballester, V.M., Victoria, R.L., 2004. Influences of land use and stream size on particulate and dissolved materials in a small Amazonian stream network. Biogeochemistry 68, 2, 135‒151.

Tian, Y., Jia, L., Wang, B., 2010. Application of artificial neural network in urban landscape water quality evaluation. In: Proceedings of the 4th International Conference on Bioinformatics and Biomedical Engineering (iCBBE), 18–20 June 2010. Tianjin University, Tianjin, China, pp. 1–4.

Tong, S.T.Y., 1990. The hydrologic effects of urban land use, A case study of the Little Miami River Basin. Landscape and Urban Planning 19 (1), 99−105.

Tong, S.T.Y., Chen, W., 2002. Modeling the relationship between land use and surface water quality. Journal of Environmental Management 66 (4), 377−393.

Topouzelis, K., Karathanassi, V., Pavlakis, P., Rokos, D., 2009. Potentiality of feed–forward neural networks for classifying dark formations to oil spills and look–alikes. Geocarto International 24 (3), 179−191.

Tourbier, J.T., 1994. Open Space through Stormwater Management, Helping to Structure Growth on the Urban Fringe. Journal of Soil and Water Conservation 49 (1), 14–22.

Tsirkunov, V.V., Nikanorov, A.M., Laznik, I.M.M., Dongwei, Z., 1992. Analysis of Long–Term and Seasonal River Water Quality Changes in Latvia. Water Research 26 (9), 1203–1216.

Varol, M., Şen, B., 2008. Assessment of surface water quality using multivariate statistical techniques, a case study of Behrimaz Stream, Turkey. Environmental Monitoring and Assessment 159 (1−4), 543−553.

Vega, M., Pardo, R., Barrado, E., Debán, L., 1998. Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis. Water Research 32 (12), 3581–3592.

Velicer, W.F., Fava, J.L., 1998. Effects of variable and subject sampling on factor pattern recovery. Psychological Methods 3 (2), 231–251.

Venkatesh, E.T., Thangaraj, P., 2008. Self–Organizing Map and Multi–Layer Perceptron Neural Network Based Data Mining to Envisage Agriculture Cultivation. Journal of Computer Science 4 (6), 494−502.

Vesanto, J., Alhoniemi, E., 2000. Clustering of the Self–Organizing Map. IEEE Transactions on Neural Networks 11 (3), 586−600.

Vidal, M., López, A., Santoalla, M.C., Valles, V., 2000. Factor analysis for the study of water resources contamination due to the use of livestock slurries as fertilizer. Agricultural Water Management 45 (1), 1‒15.

Walker, W.W., 2003. Consideration of Variability and Uncertainty in Phosphorus Total Maximum Daily Loads for Lakes. Journal of Water Resources Planning and Management 129 (4), 337‒344.

Walker, P., Rhubart–Berg, P., McKenzie, S., Kelling, K., Lawrence, R.S., 2005. Public health implications of meat production and consumption. Public Health Nutrition 8 (4), 348–356.

Wang, H., Wang, S., 2010. Mining incomplete survey data through classification. Knowledge and Information Systems 24 (2), 221–233.

Wang, L., Lyons, J., Kanehl, P., Bannerman, R., 2001. Impacts of urbanization on stream habitat and fish across multiple spatial scales. Environmental Management 28 (2), 255–266.

Wang, X., 1997. Using GIS to assess the relationship between land use and water quality at a watershed level. Environment International 23 (1), 103–114.

Wear, D.N., Turner, M.G., Naiman, R.J., 1998. Land cover along an urban– rural gradient, implication for water quality. Ecological Applications 8 (3), 619–630.

Wen, C., Lee, C., 1998. A neural network approach to multiobjective optimization for water quality management in a river basin. Water Resources Research 34 (3), 427–436.

Whitlock, J.E., Jonesb, D.T., Harwood, V.J., 2002. Identification of the sources of fecal coliforms in an urban watershed using antibiotic resistance analysis. Water Research 36 (17), 4273–4282.

Willmott, C.J., 1982. Some Comments on the Evaluation of Model Performance. Bulletin American Meteorological Society 63 (11), 1309–1313.

Willmott, C.J., Matsuura, K., 2005. Advantages of the mean absolute error (MAE) over the root mean square error (RMSE) in assessing average model performance. Climate Research 30 (1), 79–82.

Woli, K.P., Nagumo, T., Kuramochi, K., Hatano, R., 2004. Evaluating river water quality through land use analysis and N budget approaches in livestock farming areas. Science of the Total Environment 329 (1–3), 61–74.

Wong, C.L., Venneker, R., Uhlenbrook, S., Jamil, A.B.M., Zhou, Y., 2009. Variability of rainfall in Peninsular Malaysia. Hydrology and Earth System Sciences Discussions 6 (4), 5471–5503.

Wu, R.S., Haith, D.A., 1993. Land use, climate, and water supply. Journal of Water Resources Planning Management 119 (6), 685–704.

Wu, S., Chow, T.W.S., 2004. Clustering of the self–organizing map using a clustering validity index based on inter–cluster and intra–cluster density. Pattern Recognition 37 (2), 175–188.

Wunderlin, D.A., Díaz, M.D.P, Amé, M.V., Pesce, S.F., Hued, A.C., Bistoni, M.D.L.A., 2001. Pattern Recognition Techniques for the Evaluation of Spatial and Temporal Variations in Water Quality. A Case Study, Suquía River Basin (Córdoba Argentina). Water Research 35 (12), 2881–2894.

Wurbs, R.A., 1998. Dissemination of generalized water resources models in the United States. Water International 23 (3), 190–198.

Ye, L., Cai, Q., Liu, R. and Cao, M., 2009. The influence of topography and land use on water quality of Xiangxi River in Three Gorges Reservoir region. Environmental Geology 58 (5), 937–942.

Yeung, I.M.H., 1999. Multivariate analysis of the Hong Kong Victoria harbour water quality data. Environmental Monitoring and Assessment 59 (3), 331–342.

Yeung, K.Y., Haynor, D.R., Ruzzo, W.L., 2001. Validating Clustering for Gene Expression Data. Bioinformatics 17 (4), 309–318.

Young, K.D., Thackston, E.L., 1999. Housing Density and Bacterial Loading in Urban Streams. Journal of Environmental Engineering 125 (12), 1177–1180.

Yu, Y.S., Zou, S., Whittemore, D., 1993. Non–parametric trend analysis of water quality data of rivers in Kansas. Journal of Hydrology 150 (1), 61–80.

Yung, Y.K, Wong, C.K., Yau, K., Qian, P.Y., 2001. Long–term changes in water quality and phytoplankton characteristics in Port Shelter, Hong Kong, from 1988–1998. Marine Pollution Bulletin 42 (10), 981–992.

Yusop, Z., Suki, A., 1994. Effects of Selective Logging Methods on Suspended Solids Concentration and Turbidity Level in Streamwater. Journal of Tropical Forest Science 7 (2), 199–219.

Zampella, R.A., Procopio, N.A, Lathrop, R.G., Dow, C.L., 2007. Relationship of Land-Use⁄Land-Cover Patterns and Surface-Water Quality in the Mullica River Basin. Journal of the American Water Resources Association 43 (3), 594–604.

Zandbergen, P.A., Hall, K.J., 1998. Analysis of the British Columbia Water Quality Index for Watershed Managers: A Case Study of Two Small Watersheds. Water Quality Research Journal of Canada 33 (4), 519–549.

Zeghal, M., Khogali, W.E.I., 2007. On the use of artificial neural networks as quality control tool. In: Proceedings of the CANCAM 2007. NRC Institute for Research in Construction; National Research Council Canada, Ontario, Canada, pp. 594–595.

Zeghnoun, A., Pascal, M., Fréry, N., Sarter, H., Falq, G., Focant, J.F., Eppe, G., 2007. Dealing with the Non–Detected and Non–Quantified Data. The Example of The Serum Dioxin Data in the French Dioxin and Incinerators Study. Organohalogen Compounds 69, 2288–2291.

Zhang, C., Zhu, X., Zhang, J., Qin, Y., Zhang, S., 2007. GBKII, An Imputation Method for Missing Values. Advances in Knowledge Discovery and Data Mining, Lecture Notes in Computer Science 4426/2007, 1080–1087.

Zhang, G., Hu, M.Y., Patuwo, B.E., Indro, D.C., 1999. Artificial neural networks in bankruptcy prediction: General framework and cross–validation analysis. European Journal of Operational Research 116 (1), 16–32.

Zhang, Y., Luo, A., Zhao, Y., 2004. Outlier detection in astronomical data. In: Proceedings of the International Society for Optics and Photonics (SPIE), Optimizing Scientific Return for Astronomy through Information Technologies 5493, 16 September 2004. Glasgow, Scotland, UK, pp. 521–529.

Zhang, Y., Guo, F. Meng, W., Wang, X., 2009. Water quality assessment and source identification of Daliao river basin using multivariate statistical methods. Environmental Monitoring and Assessment 152 (1–4), 105–121.

Zhao, Y., Nan, J., Cui, F., Guo, L., 2007. Water quality forecast through application of BP neural network at Yuqiao reservoir. Journal of Zhejiang University – Science A 8 (9), 1482–1487.

Zhen–Wu, B.Y., 2010. Water Quality of the Victoria River Basin in the Pailas Geothermal Field, Guanacaste, Costa Rica (2007–2008). In: Proceedings of the World Geothermal Congress 2010, 25–29 April 2010. Bali, Indonesia, pp. 1–7.

Zhou, F., Guo, H.C., Liu, Y., Jiang, Y., 2007a. Chemometrics data analysis of marine water quality and source identification in Southern Hong Kong. Marine Pollution Bulletin 54 (6), 745–756.

Zhou, F., Liu, Y., Guo, H., 2007b. Application of Multivariate Statistical Methods to Water Quality Assessment of the Watercourses in Northwestern New Territories, Hong Kong. Environmental Monitoring and Assessment 132 (1–3), 1–13.