

WATER QUALITY MODELING USING ARTIFICIAL NEURAL NETWORKS
INCORPORATING LAND USE AND SEWAGE TREATMENT PLANT
FACTORS

ARIANI DWI ASTUTI

A thesis submitted in fulfilment of the
requirements for the award of the degree of
Doctor of Philosophy

School of Civil Engineering
Faculty of Engineering
Universiti Teknologi Malaysia

JUNE 2022

DEDICATION

In Loving Memory of My Father and My Little Brother

ACKNOWLEDGEMENT

All praise be to the Almighty God, the Most Gracious and the Most Merciful, for His blessings and gifts, with Whose permission this study has been completed.

I wish to express my sincere appreciation to my main thesis supervisor Prof. Dr. Azmi Aris. for encouragement, guidance, motivation and patience. I have benefited significantly from his wealth of knowledge and meticulous editing, reviewing late at night and early in the morning. His encouraging words and thoughtful, detailed feedback have been very important. I am also very thankful to my co-supervisor, Dr. Mohd Ridza Mohd Haniffah, for his enthusiasm, co-operations, support and suggestions. I want to express my deep and sincere gratitude to Prof. Dr. Razman Salim for guidance, advice, motivation and for trusting me. I am incredibly grateful that you took me on as a student. Thank you very much to Head of Department Water and Environmental Engineering, Dr. Shamila Azman. Without all of them, my PhD experience would be a very difficult. May God bless them.

Many thanks to agencies for providing the data that makes this study feasible: Department of Environment (DOE) Malaysia, Department of Irrigation and Drainage (DID) Malaysia, National Climate Centre, Malaysian Meteorological Department (MMD), Indah Water Konsortium (IWK), Malaysian Centre for Geospatial Data Infrastructure (MaCGDI) and Department of Agriculture (DOA) Malaysia, Syarikat Air Johor (SAJ)

I am also indebted to Universitas Trisakti for funding my Ph.D study, Rector, Vice-Rector, Prof. Ir. Asri Nugrahanti., MS., PhD., IPU., Dean of Faculty of Architecture Landscape and Environmental Technology and Head of Department Environmental Engineering University Trisakti. And many thanks for all my colleagues; unfortunately, it is not possible to list them in this limited space.

I wish to offer my most heartfelt thanks to Dr. Salmiati “K Isal”, Dr. Zaiha, Dr. Iksan and all the IPASA staff for their kind support and friendship. And also thankful to laboratory staffs: Kak Hanna, Faiz, of the IPASA Laboratory, Cik Atikah, Puan Ros, Enc Jimmy, Enc. Razali and Enc. Faizal of the Environmental Engineering Laboratory; Puan Rosmawati of Geotechnical Laboratory.

Also, my thanks are extended to my fellow postgraduate IPASA, my colleagues in PPI UTM, ITB, SMAN 3, Para Navigator, for their immeasurable friendship, motivation and support. My sincere appreciation also extends to all my best friends and others who have assisted. Unfortunately, it is not possible to list all of them in this limited space.

Most importantly, I am grateful for my parents, whose constant love and support have kept me motivated and confident. My accomplishments and success are because they believed in me. I am deeply thankful to my mother for the prayer, encouragement and support during my study, for all of the love and for constantly reminding me of the end goal. I warmly thank my sister, Mbak Lina, Yoyok and other family members for their support, love and prayer. Without them, this thesis would never have been written. Special for Hendy Risdianto Wijaya, I am thankful for the unconditional love for constantly listening to me and supporting me during my study. Thank you so much for providing me with valuable knowledge regarding machine learning, for the encouragement, discussion, and motivation, especially when things were going tough.

ABSTRACT

Skudai River has undergone a general decline in water quality in recent years due to agricultural practices, urbanisation, industrial and other human activities in the river catchment. It is classified as “slightly contaminated” by the Department of Environment (DOE), and as such, immediate actions are needed to prevent further deterioration and improve the water quality. Majority of existing research on water quality modelling focuses on water quality data and the impact of land use on water quality, while those on the effects of sewage treatment plants (STP) discharge on river water quality have also been conducted to a certain extent. However, limited research on water quality prediction is based on land use input, existing STP, and rainfall. This is due to the complicated relationships between these three factors and water quality parameters. River systems are highly complex, hierarchical and patchy. Accurate predictions of the time series concerning the changing water quality could support early warnings on water pollution and help with management decisions. Currently, artificial intelligence (AI) technologies can simulate this behaviour and complement the inherent deficiencies. Among the latest research in integrating AI into water quality modelling, artificial neural networks (ANNs) are the most popular techniques used. This study aimed to identify and determine key water quality parameters using principal component analysis (PCA) based on land use and pollution sources, to correlate and predict water quality index (WQI) based on in-situ parameters using ANNs, and to determine and predict the relationships between land use patterns, precipitation, STP, and WQI, also using ANNs. ANNs were employed in a total of 839 physical and chemical pollution data sets from the Skudai River from 2001 to 2019 as training (70%), test (15%) and validation data (15%) for the analysis in this study. River water sampling was also carried out to evaluate the modelling results (36 data sets). ArcMap 10.4 was used to prepare the map for the changes occurring in land use, observed from 2000 to 2019. The PCA results indicated that the parameters causing water quality variations were mainly related to physical parameters (natural) and organic pollutants (anthropogenic). The study also showed that the cascade-forward net was the optimal ANNs-water quality index-1 (ANNWQI-1) model for WQI prediction with seven parameters: DO, pH, conductivity, temperature, TDS, salinity, and turbidity with an RSME of 7.15, and a coefficient of correlation (R) of 0.92. The analysis with Spearman correlation could explain that in-situ parameters correlated with the parameters used to calculate WQI values. The best ANNWQI-2 model was a feed-forward net with land use, STP service coverage, and precipitation data as input data, resulting in RMSE of 6.98 and R of 0.80. An input data analysis with Spearman correlation could explain that land use data, STP and rainfall data correlated with the parameters used to calculate WQI values. The integrated model of ANNWQI-3 had RMSE and R of 6.01 and 0.92, respectively. ANNWQI-1 demonstrated that accurate WQI predictions could be made, with only seven in-situ water quality parameters, while ANNWQI-3 required more comprehensive input data to get almost the same R . More importantly, the input data was in-situ water quality parameters, and no laboratory analysis was needed. The study determined the effective input parameters using PCA for successful ANN modelling while illustrating the usefulness of ANNs for WQI prediction. Ultimately, the results will give decision-makers valuable information to identify the causes of water pollution and the critical source areas that are useful for protecting the environment in terms of sustainable water resources.

ABSTRAK

Sungai Skudai telah mengalami penurunan kualiti air secara umum dalam beberapa tahun kebelakangan ini kerana amalan pertanian, pembersihan, perindustrian dan kegiatan lain manusia yang berlaku di tadahan sungai. Sungai ini diklasifikasikan sebagai "sedikit tercemar" oleh Jabatan Alam Sekitar (JAS), dan oleh itu, tindakan segera diperlukan untuk mencegah kemerosotan lebih lanjut dan untuk meningkatkan kualiti air. Sebilangan besar kajian sedia ada berkaitan pemodelan kualiti air memfokuskan kepada data kualiti air dan impak penggunaan tanah terhadap kualiti air, sementara kajian mengenai kesan pelepasan dari loji rawatan kumbahan (STP) terhadap kualiti air sungai juga telah dilakukan, pada tahap tertentu. Walau bagaimanapun, kajian mengenai ramalan kualiti air, berdasarkan input penggunaan tanah, STP sedia ada, dan curahan hujan adalah sangat terbatas. Ini disebabkan hubungan yang rumit antara ketiga-tiga faktor dan parameter kualiti air. Sistem sungai sangat kompleks, berhierarki dan tidak sekata. Ramalan yang tepat bagi siri masa, berkaitan dengan perubahan kualiti air, dapat mengukuhkan amaran awal mengenai pencemaran air dan membantu keputusan yang berkaitan dengan pengurusan sumber air. Pada masa ini, teknologi kecerdasan buatan (AI) mampu mensimulasikan tingkah laku ini dan melengkapkan kekurangan yang wujud. Antara kajian mutakhir dalam mengintegrasikan AI ke dalam pemodelan kualiti air, *artificial neural networks* (ANN) ialah teknik yang paling popular digunakan. Kajian ini bertujuan untuk mengenal pasti dan menentukan parameter kualiti air utama, menggunakan analisis komponen utama (PCA), berdasarkan penggunaan tanah dan sumber pencemaran, untuk menghubungkan dan meramalkan indeks kualiti air (IKA) berdasarkan parameter in-situ menggunakan ANN, dan untuk menentu dan meramalkan hubungan antara pola penggunaan tanah, curahan hujan, STP, dan IKA, juga menggunakan ANN. ANN telah digunakan untuk sejumlah 839 kumpulan data pencemaran fizikal dan kimia dari Sungai Skudai, bagi tempoh 2001 hingga 2019, sebagai data latihan (70%), ujian (15%) dan pengesahan (15%) untuk analisis dalam kajian ini. Pengambilan sampel air sungai juga dilakukan untuk menilai hasil pemodelan (36 set data). ArcMap 10.4 diguna untuk menyediakan peta bagi perubahan yang berlaku dalam penggunaan tanah, yang diperhatikan dari tahun 2000 hingga 2019. Hasil PCA menunjukkan bahawa parameter yang menyebabkan kepelbagaian kualiti air adalah terutamanya berkaitan dengan parameter fizikal (semula jadi) dan bahan pencemar organik (antropogenik). Kajian ini juga menunjukkan bahawa, *cascade-forward net* ialah model 1 *artificial neural networks* - Indeks Kualiti Air (ANNWQI-1) yang optimum bagi ramalan IKA dengan tujuh parameter: DO, pH, kekonduksian, suhu, TDS, saliniti, dan kekeruhan dengan nilai RSME 7.15, dan pekali korelasi (R) 0.92. Analisis dengan korelasi Spearman boleh menjelaskan bahawa parameter in-situ berkorelasi dengan parameter yang digunakan untuk mengira nilai IKA. Model ANN-IKA-2 yang terbaik ialah *feed-forward net* dengan penggunaan tanah, liputan perkhidmatan STP, dan data kerpasan, sebagai data input, yang menghasilkan nilai RMSE 6.98 dan koefisien korelasi 0.80. Analisis data input dengan korelasi Spearman boleh menjelaskan bahawa data guna tanah, STP dan data hujan berkorelasi dengan parameter yang digunakan untuk mengira nilai IKA. Hasil model bersepadu ANN-IKA-3 mempunyai nilai RMSE 6.01 dan koefisien korelasi 0.92. ANN-IKA-1 menunjukkan bahawa, ramalan IKA yang tepat dapat dilakukan dengan hanya tujuh parameter kualiti air in situ, sementara ANN-IKA-3 memerlukan data input yang lebih komprehensif untuk mendapatkan R yang hampir sama. Lebih penting lagi, data input adalah dalam bentuk parameter kualiti air in situ, dan analisis makmal tidak diperlukan. Kajian ini dapat menentukan parameter input yang berkesan menggunakan PCA untuk pemodelan ANN yang berjaya, selain menjelaskan kegunaan ANN untuk ramalan IKA. Pada akhirnya, hasil yang didapati akan memberikan maklumat bernilai kepada pembuat keputusan untuk mengenalpasti penyebab pencemaran air dan juga kawasan sumber kritikal yang berguna bagi melindungi alam sekitar daripada sudut sumber air yang lestari.

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	iii
	DEDICATION	iv
	ACKNOWLEDGEMENT	v
	ABSTRACT	vi
	ABSTRAK	vii
	TABLE OF CONTENTS	viii
	LIST OF TABLES	xiv
	LIST OF FIGURES	xviii
	LIST OF ABBREVIATIONS	xxi
	LIST OF MODEL NOTATION	xxiii
	LIST OF APPENDICES	xxiv
CHAPTER 1	INTRODUCTION	1
1.1	Background	1
1.2	Problem Statement	4
1.3	Research Objective	7
1.4	Scope of The Study	7
1.5	Significant of Study	8
1.6	Organisation of Thesis	9
CHAPTER 2	LITERATURE REVIEW	11
2.1	Introduction	11
2.2	Water Resource and Management	11
2.3	Water Quality	13
2.3.1	Parameters	13
2.3.2	Water Quality Index	17
2.4	Factors affecting River Water Quality	22
2.4.1	Land Use	24

2.4.2	Climate Change	25
2.4.3	Sewage Treatment Plant and Wastewater Treatment Plant	29
2.5	Principal Component Analysis	30
2.5.1	Definition and Procedure in Principal Component Analysis	30
2.5.2	Application Principal Component Analysis	34
2.6	River Water Quality Modelling	34
2.6.1	The Benefit of the Water Quality Model	34
2.6.2	Limitation of the Existing Water Quality Model	37
2.7	Artificial Intelligence	40
2.7.1	Why Artificial Intelligence	40
2.7.2	Artificial Intelligence Application in Water Quality Prediction	42
2.8	Artificial Neural Networks	46
2.8.1	Definition of Artificial Neural Networks	46
2.8.2	Artificial Neural Networks Application in Water Quality Prediction	51
2.9	Research Trend and Need	54
CHAPTER 3	RESEARCH METHODOLOGY	57
3.1	Introduction	57
3.2	Study Area	57
3.3	Equipment and Material	59
3.3.1	Laboratory Equipment and Chemicals	59
3.3.2	Software	61
3.4	Analytical Methods	62
3.5	Data Collection	62
3.5.1	Water Quality	62
3.5.2	Secondary Data	65
3.6	Phase 1 Principal Component Analysis	67
3.6.1	Data Preparation	68
3.6.1.1	Land Use	68
3.6.1.2	Rainfall Data	70

	3.6.1.3	Sewage Treatment Plant and Industry Data	71
	3.6.1.4	Water Quality Data	72
	3.6.2	Principal Component Analysis	72
3.7		Phase 2 The Artificial Neural Networks Water Quality Index - 1	73
	3.7.1	Model Development the ANNWQI-1 Model	76
		3.7.1.1 Normalised Data	76
		3.7.1.2 Experimental Set up for the ANNWQI-1 Model	77
	3.7.2	Evaluation and Analysis of the ANNWQI1 - 1 Model	78
		3.7.2.1 Mean Square Error, Root Mean Square Error, and Coefficient of Correlation	78
3.8		Phase 3 - the Artificial Neural Networks Water Quality Index - 2	80
	3.8.1	Model Development of the ANNWQI - 2 Model	83
		3.8.1.1 Normalised Data	83
		3.8.1.2 Experimental Set up of the ANNWQI -2 Model	84
	3.8.2	Evaluation and Analysis of the ANNWQI - 2 Model	85
		3.8.2.1 Mean Square Error, Root Mean Square Error, and Coefficient of Correlation	85
3.9		Phase 4 - The Artificial Neural Networks Water Quality Index - 3	85
	3.9.1	Model Development of the ANNWQI - 3 Model	89
		3.9.1.1 Normalised Data	89
		3.9.1.2 Experiment Set up of the ANNWQI - 3 Model	90
	3.9.2	Evaluation and Analysis of the ANNWQI - 3 Model	91

	3.9.2.1	Mean Square Error, Root Mean Square Error, and Coefficient of Correlation	91
CHAPTER 4		STUDY AREA AND KEY OF WATER QUALITY PARAMETERS	93
4.1		Study Area	93
	4.1.1	Delineation of the Skudai River Watershed	93
	4.1.2	Skudai River as Source of Raw Water	94
	4.1.3	Land Use Each Sub Watershed	96
	4.1.3.1	Sub-Watershed 1	97
	4.1.3.2	Sub Watershed 2	98
	4.1.3.3	Sub Watershed 3	100
	4.1.3.4	Sub Watershed 4	101
	4.1.3.5	Overall Watershed	102
	4.1.4	Rainfall Data	106
	4.1.5	Water Quality Data	110
4.2		Principal Component Analysis	117
	4.2.1	Sampling Station 1 at Skudai River Watershed-Upstream	118
	4.2.1.1	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	118
	4.2.1.2	Anti-image Matrix	119
	4.2.1.3	Communalities	120
	4.2.1.4	Determination of the number of factors	121
	4.2.2	Sampling Station 2 at Skudai River Watershed-Upstream	128
	4.2.2.1	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	128
	4.2.2.2	Anti-image Matrix	129
	4.2.2.3	Communalities	129
	4.2.2.4	Determination of the Number of Factors	130

4.2.3	Sampling Station 3 at Skudai River Watershed- Upstream	138
4.2.3.1	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	138
4.2.3.2	Anti-image Matrix	139
4.2.3.3	Communalities	140
4.2.3.4	Determination of the number of factors	140
4.2.4	Sampling Station 4 at Skudai River Watershed- Upstream	150
4.2.4.1	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	150
4.2.4.2	Anti-image Matrix	151
4.2.4.3	Communalities	152
4.2.4.4	Determination of the number of factors	152
4.2.5	Sampling Station 1-4 at Skudai River Watershed-Upstream	159
4.2.5.1	Kaiser-Meyer-Olkin Measure of Sampling Adequacy	160
4.2.5.2	Anti-image Matrix	160
4.2.5.3	Communalities	161
4.2.5.4	Determination of the number of factors	162
4.3	Chapter Summary	171
CHAPTER 5	ARTIFICIAL NEURAL NETWORK-WATER QUALITY INDEX MODEL	177
5.1	The Artificial Neural Networks Water Quality Index - 1 Model	177
5.1.1	Data Input The ANNWQI-1 Model	177
5.1.2	The Best Analysis of The ANNWQI-1 Model	179
5.1.3	Results of the ANNWQI-1 Model	185
5.2	The Artificial Neural Networks Water Quality Index – 2 Model	187
5.2.1	Data Input The ANNWQI-2 Model	187

5.2.2	The Best Analysis of The ANNWQI-2 Model	189
5.2.3	Results of the ANNWQI-2 Model	196
5.3	The Artificial Neural Networks Water Quality Index – 3 Model	198
5.3.1	Data Input The ANNWQI-3 Model	198
5.3.2	The Best Analysis of The ANNWQI-3 Model	201
5.3.3	Results of the ANNWQI-3 Model	207
5.4	Chapter 5 Summary	208
CHAPTER 6	CONCLUSION AND RECOMMENDATIONS	211
6.1	Conclusions	211
6.2	Recommendations	213
REFERENCES		215
LIST OF PUBLICATIONS		285

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2.1	Other priority pollutants generated by industrial and domestic activities (Metcalf and Eddy, 2014)	15
Table 3.1	List of reagents used in the study	60
Table 3.2	List of equipment used in the study	60
Table 3.3	List of software used in this study	61
Table 3.4	Methods for analysis parameter used in this study	62
Table 3.5	Sampling station at the Skudai River watershed-upstream	64
Table 3.6	List of secondary data used in this study	66
Table 3.7	Features and operating in ArcMap 10.4.1 to delineation watershed	68
Table 3.8	Features and operating in ArcMap 10.4.1 for land use preparation	69
Table 3.9	Data used in the ANNWQI-1 model development and evaluation	74
Table 3.10	Summary parameter setup for the ANNWQI-1 model	77
Table 3.11	Data used in the ANNWQI-2 model development and evaluation	81
Table 3.12	Summary parameter setup for the ANNWQI-2 model	84
Table 3.13	Data used in the ANNWQI-3 model development and evaluation	87
Table 3.14	Summary parameter setup for The ANNWQI-3 Model	90
Table 4.1	Area of the Skudai River sub-watersheds	94
Table 4.2	Rainfall gauging station at the Skudai River watershed-upstream	107
Table 4.3	T-Test of rainfall data 2001-2019	110
Table 4.4	Descriptive statistic water quality data in sampling station 1	112
Table 4.5	Descriptive statistic water quality data in sampling station 2	113

Table 4.6	Descriptive statistic water quality data in sampling station 3	114
Table 4.7	Descriptive statistic water quality data in sampling station 4	115
Table 4.8	KMO and Bartlett's Test on iteration 1 of PCA sampling station 1	118
Table 4.9	Measure of sampling adequacy iteration 1 of PCA sampling station 1	119
Table 4.10	Communalities on iteration 4 of PCA sampling station 1	121
Table 4.11	Total variance explained on iteration 5 of PCA sampling station 1	122
Table 4.12	Component matrix on iteration 5 of PCA sampling station 1	124
Table 4.13	Rotated component matrix on iteration 5 of PCA sampling station 1	126
Table 4.14	Summary VF and parameters on Iteration 5 of PCA sampling station 1	126
Table 4.15	KMO and Bartlett's Test on iteration 4 of PCA sampling station 2	128
Table 4.16	Measure of sampling adequacy on iteration 4 of PCA sampling station 2	129
Table 4.17	Communalities on iteration 4 of PCA sampling station 2	130
Table 4.18	Total variance explained on iteration 4 of PCA sampling station 2	131
Table 4.19	Component matrix on iteration 4 of PCA sampling station 2	133
Table 4.20	Rotated component matrix on iteration 4 of PCA sampling station 2	135
Table 4.21	Summary VF and parameters on Iteration 4 of PCA sampling station 2	136
Table 4.22	KMO and Bartlett's Test on iteration 3 of PCA sampling station 3	139
Table 4.23	Measure of sampling adequacy on iteration 3 of PCA sampling station 3	139
Table 4.24	Communalities on iteration 3 of PCA sampling station 3	140
Table 4.25	Total variance explained on iteration 3 of PCA sampling station 3	141

Table 4.26	Component matrix on iteration 3 of PCA sampling station 3	144
Table 4.27	Rotated component matrix on iteration 5 of PCA sampling station 3	146
Table 4.28	Summary VF and parameters on iteration 3 of PCA sampling station 3	148
Table 4.29	KMO and Bartlett's Test on iteration 4 of PCA sampling station 4	151
Table 4.30	Measure of sampling adequacy on iteration 4 of PCA sampling station 4	151
Table 4.31	Communalities on iteration 4 of PCA sampling station 4	152
Table 4.32	Total variance explained on iteration 4 of PCA sampling station 4	153
Table 4.33	Component matrix on iteration 4 of PCA sampling station 4	155
Table 4.34	Rotated component matrix on iteration 4 of PCA sampling station 4	157
Table 4.35	Summary VF and parameters on iteration 4 of PCA sampling station 4	158
Table 4.36	KMO and Bartlett's Test on iteration 4 of PCA sampling stations 1-4	160
Table 4.37	Measure of sampling adequacy iteration 4 of PCA sampling station 1-4	161
Table 4.38	Communalities on iteration 4 of PCA sampling station 1-4	162
Table 4.39	Total variance explained on iteration 4 of PCA sampling stations 1-4	163
Table 4.40	Component matrix on iteration 4 of PCA sampling station 1-4	165
Table 4.41	Rotated component matrix on iteration 5 of PCA sampling station 1-4	167
Table 4.42	Summary VF and parameters on iteration 4 of PCA sampling station 1-4	169
Table 4.43	Summary of PCA sampling stations 1-4	172
Table 4.44	Summary total variance of the parameters at sampling station 1-4	174
Table 5.1	Brief description of train data for the ANNWQI-1 model	177

Table 5.2 Brief description of evaluation data for the ANNWQI-1 model

178

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 1.1	River water quality trend from 2005 to 2016 (DOE, 2016)	3
Figure 2.1	ANN (MLP) with one hidden layer (adopted from Seo <i>et al.</i> , 2016)	48
Figure 3.1	Framework of research	58
Figure 3.2	The map of the Skudai River watershed-upstream	59
Figure 3.3	The location of the water quality station in the Skudai River watershed-upstream	63
Figure 3.4	Sampling stations 1-4 at the Skudai River watershed-upstream	63
Figure 3.4	Sampling stations 1-4 at the Skudai River watershed-upstream (cont.)	64
Figure 3.5	Flowchart in Phase 1, including PCA Analysis	67
Figure 3.6	The framework of the ANNWQI-1 model	75
Figure 3.7	The running process of the ANNWQI-1 model in Matlab R2018a	76
Figure 3.8	The ANNWQI-1 model's network architecture	78
Figure 3.9	The framework of the ANNWQI-2 model	82
Figure 3.10	The running process of the ANNWQI-2 model in Matlab R2018a	83
Figure 3.11	The ANNWQI-2 Model's Network Architecture	85
Figure 3.12	The Framework of The ANNWQI-3 Model	88
Figure 3.13	The Running Process of The ANNWQI-3 Model in Matlab R2018a	89
Figure 3.14	The ANNWQI-3 Model's Network Architecture	91
Figure 4.1	Sub-watersheds of the Skudai River	93
Figure 4.2	Water total production in Sultan Ismail WTP (2013-2017)	95
Figure 4.3	Study area of the Skudai River watershed-upstream	96
Figure 4.4	Profile of land use at the SW-1 of the Skudai River watershed from 2000 to 2018	97

Figure 4.5	Profile of land use at the SW-2 of the Skudai River watershed from 2000 to 2018	99
Figure 4.6	Profile of land use at the SW-3 of the Skudai River watershed from 2000 to 2018	101
Figure 4.7	Profile of land use at the SW-4 of the Skudai River watershed from 2000 to 2018	102
Figure 4.8	Land use at the Skudai River watershed-upstream 2000-2018	104
Figure 4.15	Scree plot on iteration 5 of PCA sampling station 1	123
Figure 4.16	Scree plot on iteration 4 of PCA sampling station 2	132
Figure 4.17	Scree plot on iteration 3 of PCA sampling station 3	143
Figure 4.18	Scree plot on iteration 4 of PCA sampling station 4	154
Figure 4.19	Scree plot on iteration 4 of PCA sampling station 1-4	165
Figure 5.1	Target distribution (probability) of WQI in: (a) Train data; (b) Evaluation data.	178
Figure 5.2	The average of RMSE for each model/experiment in the ANNWQI-1 model	180
Figure 5.3	The RMSE for each model in the ANNWQI-1 model	180
Figure 5.4	Structure network of the best of the ANNWQI-1 model	181
Figure 5.5	The modelling performance (MSE) of the best of the ANNWQI-1 model	181
Figure 5.6	The modelling performance (R) of the best of the ANNWQI-1 model	182
Figure 5.7	The coefficient of correlation (R) of the best of the ANNWQI-1 Model	183
Figure 5.8	The MSE performance for each model in the ANNWQI-1 model	184
Figure 5.9	The comparison of MSE in modelling and evaluation for the best of the ANNWQI-1 model	184
Figure 5.10	The target vs the predicted output from the best of the ANNWQI-1 model in the evaluation stage	185
Figure 5.11	Target distribution (probability) in: (a) Train data; (b) Evaluation data	189
Figure 5.12	The average of RMSE for each model/experiment in the ANNWQI-2 model	190

Figure 5.13	The RMSE for each model in the ANNWQI-2 model	191
Figure 5.14	Structure network of the best of the ANNWQI-2 model	191
Figure 5.15	The modelling performance (MSE) of the best of the ANNWQI-2 model	192
Figure 5.16	The modelling performance (R) of the best of the ANNWQI-2 model	193
Figure 5.17	The coefficient of correlation (R) of the best of the ANNWQI-2 model	194
Figure 5.18	The MSE performance for each model/experiment in the ANNWQI-2 model	195
Figure 5.19	The comparison of MSE in modelling and evaluation for the best of the ANNWQI-2 model	195
Figure 5.20	The target vs the predicted output from the best of the ANNWQI-2 model in the evaluation stage	196
Figure 5.21	Target distribution (probability) in: (a) Train data; (b) Evaluation data	201
Figure 5.22	The average of RMSE for each model/experiment in the ANNWQI-3 model	202
Figure 5.23	The RMSE for each model/experiment in the ANNWQI-3 model	202
Figure 5.24	Structure network of the best of the ANNWQI-3 model	203
Figure 5.25	The modelling performance (MSE) of the best of the ANNWQI-3 model	203
Figure 5.26	The modelling performance (R) of the best of the ANNWQI-3 model	204
Figure 5.27	The coefficient of correlation (R) of the best of the ANNWQI-3 model	205
Figure 5.28	The MSE performance for each model/experiment in the ANNWQI-3 model	206
Figure 5.29	The comparison of MSE in modelling and evaluation for the best of the ANNWQI-3 model	206
Figure 5.30	The target vs the predicted output from the best of the ANNWQI-3 model in the evaluation stage	207

LIST OF ABBREVIATIONS

AI	- Artificial Intelligence
ANNs	- Artificial Neural Networks
BOD	- Biological Oxygen Demand
COD	- Chemical Oxygen Demand
Cond	- Conductivity
DEM	- Digital Elevation Map
DID	- The Department of Irrigation and Drainage
DOA	- The Department of Agricultural
DO	- Dissolved Oxygen
DOE	- The Department of Environment
GIS	- Geographic Information System
IWK	- the Indah Water Konsortium
KASA	- the Ministry of Environment and Water
KMO	- The Kaiser-Meyer-Olkin
MaCGDI	- Malaysian Centre for Geospatial Data Infrastructure
MatLab	- MATrix Laboratory
MMD	- The Malaysian Meteorological Department
MPlan	- Malaysia Plan
MSA	- Measure of Sampling Adequacy
MSE	- Mean Square Error
PCA	- Principal Component Analysis
PC	- Principal Component
RMSE	- root means square error
Sal	- Salinity
SDG	- Sustainable Development Goals
SPSS	- Statistical Product and Service Solutions-Statistic
STP	- Sewage Treatment Plant
TDS	- Total Dissolved Solids
Temp	- Temperature
TSS	- Total Suspended Solid

- UN - United Nation
- VF - Varimax Factor
- WQI - Water Quality Index

LIST OF MODEL NOTATION

F_1	-	Number of variables, whose objectives are not met.
F_2	-	Number of times by which the objectives are not met
F_3	-	Amount by which the objectives are not met
F_3	-	$[\text{nse}/0.01\text{nse}+0.01]$
n	-	number of water quality parameters
Q_i	-	sub-index for i th water quality parameter
trainlm	-	Training function Lavenberg-Marquadt
trainbr	-	Training function Bayesian Regulation back propagation.
trainbfg	-	Training function BFGS quasi-Newton backpropagation
trainrp	-	Training function Resilient Back propagation
trainscg	-	Training function Scaled Conjugate Gradient
traincgb	-	Training function Conjugate Gradient with Powell/Beale Restarts
traincgf	-	Training function Fletcher-Reeves Conjugate Gradient
traincgp	-	Training function Polak-Ribière Conjugate Gradient
trainoss	-	Training function One Step Secant
traingdx	-	Training function Gradient descent with adaptive learning rate back propagation
$Wifi$	-	the weight associated with the water quality parameter

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Data and PCA Results	249
Appendix B	Analytical Methods	260
Appendix C	Artificial neural networks coding and results	262

CHAPTER 1

INTRODUCTION

1.1 Background

In 2015, the United Nations (UN) promulgated the 2030 Agenda for Sustainable Development which comprises 17 Sustainable Development Goals (SDGs) to promote peace, prosperity, and a sustainable future for all. It recognises water management's importance in tackling global challenges, including climate change and environmental degradation (United Nations, 2020). One of the 17 goals, SDG 6, specifically addresses the clean water resources—*to ensure the availability and sustainable management of water and sanitation for all*. Two other goals, SDG 3 and SDG 11, are also closely related to the clean water resources (including river) management policy. SDG 3 addresses healthy lives and promotes well-being for all ages, while SDG 11 aims to ensure inclusive, safe, resilient, and sustainable human settlements. The quality of river water, particularly that used as a source of water, impacts healthy living for human settlements that are safe, resilient, and sustainable.

The government of Malaysia aligned the SDGs with the national five-year development plan. During the mid-term review of the Eleventh Malaysia Plan in 2019, the government pledged a more profound commitment to implement SDGs by introducing a new framework known as the Prosperity Vision 2030 (Ministry of Environment and Water, 2021). Furthermore, Malaysia also initiated the Sustainable Malaysia 2030 to tackle environmental-related challenges. Led by the Ministry of Environment and Water (KASA), the framework is based on four pillars: empowered governance, green growth, strategic collaboration, and social inclusion. Both frameworks aim to ensure sustainable economic growth, as developments are often the leading cause of environmental degradation due to the lack of a holistic plan to balance economic and environmental gain.

Urban development, usually characterised by rapid land use changes, severely affects the quality of its surrounding. Changes in land use often significantly impact river water quality passing through the developing area. In fact, major river management problems in Malaysia are closely related to water quality issues. This caused problems for the public since the river water is used for various activities such as domestic consumption, tourism activities, fish farming, and recreation. In 2017, river water accounted for 80.5% of Malaysia's raw water supply, making them valuable natural resources (Ahmad Kamal *et al.*, 2020). In order to protect the environment, a balance between land use changes and environmental protection is needed. According to KASA (2020), in the Environmental Sustainability Plan in Malaysia 2020-2030, Malaysia planned to increase the number of clean rivers by 5% in 2023, 10% in 2025, and 25% in 2030. Thus, having a robust method to measure the impact of land use changes on water quality is particularly essential.

The Department of Environment (DOE), Malaysia, monitors 477 rivers throughout the country (DOE, 2016). The trend of the monitored river water quality from 2005 to 2016 is shown in Figure 1.1. It can be shown that there was a declining trend in clean rivers from 2005 to 2016. In 2016, 244 (47%) of the 477 rivers monitored were classified as clean, 207 (43%) as slightly polluted, and 46 (10%) rivers as contaminated. These numbers represent a significant increase compared to 29 rivers classed as polluted in 2013. A study carried out by Ariffin *et al.* (2015) found that most the rivers suffer from high organic matters in terms of Biochemical Oxygen Demand (BOD), ammonia nitrogen (NH₃-N), and suspended solids (SS).

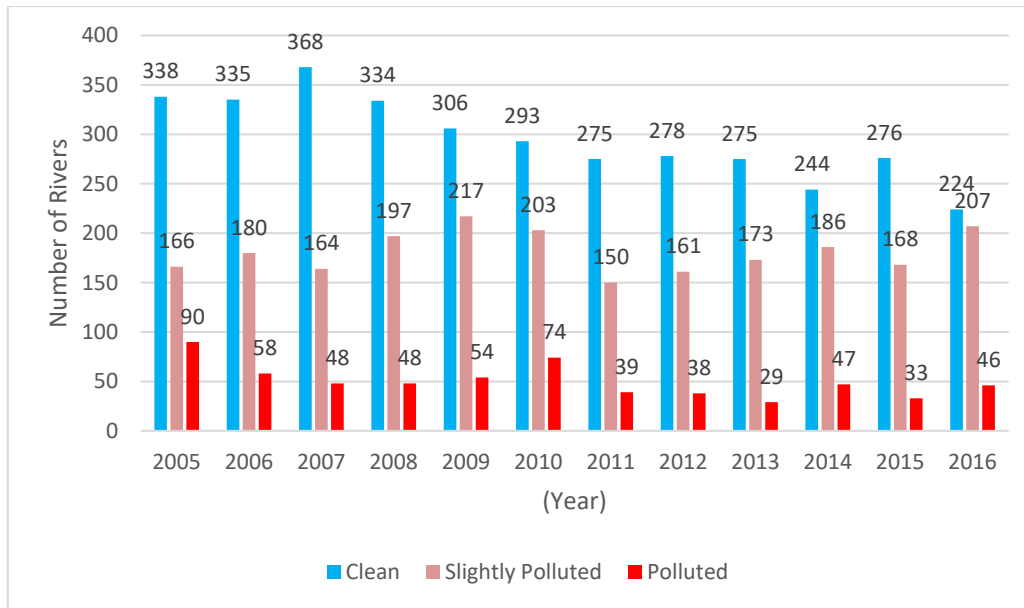


Figure 1.1 River water quality trend from 2005 to 2016 (DOE, 2016)

Biochemical Oxygen Demand, $\text{NH}_3\text{-N}$, and SS are commonly found in domestic wastewater. The operation and maintenance of sewage treatment plants (STP) that treat domestic wastewater in most parts of Malaysia are carried out by the Indah Water Konsortium (IWK). Since IWK became fully operational in 1997, significant improvements have been made as almost all river basins are categorised by the DOE as having better water quality. According to Chan (2012), clean rivers had risen from 28% in 1993 to 64% in 2007. However, according to the DOE report in 2016, 60-70% of river water pollution was from domestic waste, including domestic wastewater (DOE, 2016). In line with the report, several researchers have found that STP negatively impacts river water quality (Vijay et al., 2016, Jerves-Cobo et al., 2018; Theoneste et al., 2020).

Skudai River is one of Johor Bahru city's primary drinking water sources, and the Skudai River watershed is the third largest watershed in Johor Bahru. Several tributaries join the mainstream and travel through housing, industrial, settlements, townships, and commercial centres before finally reaching the coast. Rapid urbanisation has had a significant negative impact on the water quality of the Skudai River and its associated ecosystems with the increasing numbers of residential, industries, commercial areas, and agriculture. Skudai River was included in the "slightly polluted" category, and immediate action is needed to reverse the water

quality and prevent further degradation (Naubi *et al.*, 2016; Ahmad Kamal *et al.*, 2020). Most of the water quality stations in Skudai River were classified as Class III (slightly polluted to polluted). The river contains a high concentration of NH₃-N, particularly during dry weather (Ahmad Kamal *et al.*, 2020). Therefore, understanding the relationship between land use changes, precipitation, and existing sewage treatment facility to water quality is very important to improve the prediction of water contamination in the watershed in guiding watershed land use planning in the future. And also, river management needs an intensive monitoring system program as an early warning.

In analysing the water quality of freshwater ecosystems, a robust method is crucial. The lifeblood of best water resource management lies in accurate, precise, and reliable predictions of future phenomena (Dogan *et al.*, 2009; Ömer Faruk, 2010; Najah *et al.*, 2013; Nourani *et al.*, 2014). More accurate and reliable monitoring may lead to more appropriate policies to keep pollution within the tolerable level. Different techniques, ranging from regression-based methods such as linear and multilinear regression to watershed models, can examine land use's impact on water quality. If there are sufficient data sets of high quality, then Artificial Neural Networks (ANNs) could be used effectively to predict water quality (Kalin *et al.*, 2010).

1.2 Problem Statement

Over the past few decades, researchers have been developing method to assess the general quality of surface water, known as the Water Quality Index (WQI). Water Quality Index is one of the most effective tools for providing feedback on water quality to policymakers and environmentalists. It is helpful to determine river water suitability for various uses, including irrigation, aquaculture, and domestic use. Water quality knowledge and the WQI assessment play an essential role in controlling and managing water quality. The index uses several parameters, including chemical, physical, and biological properties, to measure water quality with a single numerical value (Khalil *et al.*, 2011; Najah *et al.*, 2013; Sahoo *et al.*, 2015). National Standard Malaysia for WQI consists of six parameters; BOD (needed a five-day laboratory analysis), COD,

NH₃-N, TSS, pH, and DO. Monitoring river water quality using WQI is costly and requires some effort. Since 2017, DOE has monitored the Skudai river bimonthly.

Methods of water quality assessment have constantly been improving, along with increasing awareness of the quality of the water environment. Principal component analysis (PCA), a statistical method for multivariate data analysis, is commonly used to discover correlations between original indicator variables and transform them into independent principal components. Principal component analysis has been used to identify the spatial and temporal changes in water quality and possible pollution sources (Jiang *et al.*, 2020; Shi *et al.*, 2020; Yang *et al.*, 2020; Zhao *et al.*, 2020). Many researchers have used this method to determine rivers' most crucial water quality parameters (Varol *et al.*, 2012; Sun *et al.*, 2016; Zeinalzadeh and Rezaei, 2017; Jahin *et al.*, 2020). This method also reduces the number of characters, allowing relationships between individuals and variables. Furthermore, PCA is considered effective in eliminating redundant information (Laghzal *et al.*, 2016; Tripathi and Singal, 2019; Golabi *et al.*, 2020; Venkateswarlu *et al.*, 2020). The general WQI approach is based on the most common factors described in three steps: parameter selection, quality function determination, and sub-index aggregation with mathematical expressions (Tyagi *et al.*, 2020). The selection of parameters is usually carried out using expert judgment (individual interviews, interactive groups, and the Delphi method) and statistical methods (Pearson's correlation coefficient dan PCA/factor analysis) (Sutadian & Muttill, 2016; Banda & Kumarasamy, 2021). Following the success of many researchers in utilising PCA, this approach can be used to select parameters that play an essential role in WQI values.

Water quality modelling plays an essential role in river basin management. It can predict the trend of water quality characteristics following the watershed's current environmental quality and the rules for the transfer and transformation of pollutants in river watersheds. Due to uncertainties of water quality data—including size and heterogeneity, randomness, obscurity, inaccuracy, non-stationary, and the non-linear relation between the parameters of water quality—the prediction accuracy of traditional models has been limited. Artificial intelligence (AI) techniques can simulate this behaviour and complement the weakness. Several researchers have found

that factors having non-linear relationships among many parameters may affect water quality predictions. This substantial constraint cannot be solved by conventional data processing (Zhao *et al.*, 2007; Singh *et al.*, 2009; Barzegar *et al.*, 2016). In recent decades, several studies exploring the use of AI in water quality modelling have shown encouraging results (Diamantopoulou *et al.*, 2005; Palani *et al.*, 2008; Dogan *et al.*, 2009; Singh *et al.*, 2009; Kim & Seo, 2015; Najah *et al.*, 2011; Sarkar & Pandey, 2015; Salami Shahid & Ehteshami, 2016). Artificial neural networks are AI techniques with flexible mathematical structures that can identify complex non-linear relationships between input and output data compared to other classical modelling techniques (Najah *et al.*, 2013a; Barzegar *et al.*, 2016; Elkiran *et al.*, 2018; Zhang *et al.*, 2019). From 2007 to 2019, the most predicted parameters for ANNs were dissolved oxygen (DO), BOD, SS, and temperature (T). There is still a lack of predictive studies using in-situ parameters as input (e.g., DO, pH, conductivity, temperature, salinity, total dissolved solids (TDS), and turbidity). Most ANNs studies used laboratory analysis parameters as input or output (BOD, chemical oxygen demand (COD), SS, etc.).

The majority of existing research about water quality modelling focuses on water quality data and the impact of land use on water quality, while those on the effects of STPs discharges on river water quality have also been conducted to a certain extent (Seanego and Moyo, 2013; Cahoon *et al.*, 2016). However, research on water quality prediction using land use input, existing STP, and rainfall has not yet been carried out. This is due to the complicated relationship between the abovementioned factors and water quality parameters. Moreover, limited water quality modelling studies utilize ANNs that consider these factors (in-situ parameters, land use, precipitation, and existing STP). And also, to date, the limited water quality index model integrates in-situ water quality parameters with land use, rainfall, and STP as input data.

This study aimed to fill the existing research gap by using in-situ parameters, spatial data, precipitation, and the existing STP as input data in the ANNs model. It attempted to demonstrate its applicability to predicting the WQI. The AI approach is an advanced method that allows multiple data inputs from the raw time series. Integrating the three factors above with the ANN model is an interesting research

problem, especially in water resource forecasting problems where the input data are heterogeneous, complex, stochastic, and non-stationary.

1.3 Research Objective

This study involves the development of water quality models using ANNs. The developed model is aimed to assess the influences of land use, precipitation, and sewage treatment plant on a catchment system using the Skudai River catchment as a case study. The followings are the objectives for this study:

- (a) To identify and determine key water quality parameters using PCA based on land use and pollution sources.
- (b) To correlate and predict WQI values based on in-situ parameters using ANNs.
- (c) To determine and predict the relationship between land use patterns, precipitation, sewage treatment plant, and WQI using the ANNs model.
- (d) To develop a WQI Prediction Model using ANNs that integrate the in-situ water quality parameters with land use, precipitation, and existing sewage treatment plant.

1.4 Scope of The Study

The study focused on developing the ANNs model to predict the WQI of the Skudai River upstream watershed. Several inputs are required to create a WQI prediction model, including water quality data, land use data, rainfall data, and existing STP data. The water quality data used in this study were obtained from the DOE (2001 to 2019). The historical land use data for 2000, 2002, 2006, 2008, 2010, 2013, 2015, and 2018 were obtained from the Malaysian Centre for Geospatial Data Infrastructure (MaCGDI), and the Department of Agriculture (DOA) Malaysia processed using ArcMap 10.4. Then rainfall data (2001-2020) used in this study was provided by the

Department of Irrigation and Drainage (DID) and the Malaysian Meteorological Department (MMD). The existing STP development data (1995-2019) were collected from IWK, while the type and amount of industries (2018) were obtained from DOE.

Identification of the key parameters affecting water quality and assessing the correlation between physical and chemical parameters using PCA performed using SPSS 25. The WQI model was developed using Artificial Neural Networks (ANNs) Back Propagation was done using Matlab R2018. The model was trained and tested using time series water data (2001-2019), and the results were validated with the experimental data from the fields. Four water quality stations were selected at upstream of the Skudai River. Data collection was carried out four times between February and March 2020 and six times between July and October 2020. Modelling performance was analysed using Mean Square Error (MSE), root means square error (RMSE), and coefficient of correlation (R).

1.5 Significant of Study

The significances of this study are as follows:

- (a) This study provides information regarding the relationship between physical and chemical water parameters using PCA. Principal Component Analysis is commonly used to identify the spatial and temporal changes in water quality and possible pollution sources and determine the essential water quality parameters in the river. These features can reduce the number of water quality parameters, focusing only on the main parameters and can be used as an alternative approach to determining parameters for calculating the value of the water quality index.
- (b) Water quality monitoring by the DOE is carried out every two months at specific sampling points for river monitoring purposes. The samples are analysed for six parameters to determine the river's WQI value and health status. A newly-developed model, the Artificial Neural Networks Water Quality Index 1 (ANNWQI-1) model, has been proposed to assist river

monitoring. This model will predict the water quality index only by analysing the in-situ parameters. This will significantly reduce the cost of water quality monitoring, enhance the monitoring's frequency and ability, and provide a better tool for managing the river water quality.

- (c) Water quality monitoring is a representative and quantitative collection of information on water quality's physical, biological, and chemical characteristics. Various approaches were made to select the location of the most optimum sampling point for water quality monitoring. The Artificial Neural Networks Water Quality Index-2 (ANNWQI-2) model predicts WQI using input data: land use, rainfall, and existing STPs location. Therefore ANNWQI-2 model enables WQI prediction in an area with similar physiographic characteristics. Especially where the sampling station is unavailable or in an unmonitored watershed.
- (d) The WQI model using the Artificial Neural Networks Water Quality Index-3 (ANNWQI-3) model integrates the ANNWQI-1 and ANNWQI-2 models. Using the ANNWQI-3 model, it is also possible to simulate future WQI values during land use change and STP development. Moreover, the model also helps find effective measures to raise the WQI value. Hence, the model can be used as an input for crucial decision-making.

1.6 Organisation of Thesis

This thesis is structured and designed in six chapters to present the study methods, analysis, results, discussion, and recommendation. The study objectives, problem statements, scope, and contribution to knowledge are described in Chapter 1. Chapter 2 provides a general overview and literature review related to the research methodology and materials used. Chapter 3 presents the framework of research, materials, and methods used to achieve the study objectives. The pre-processing data, to determine key water quality parameters using PCA is shown in Chapter 4. Chapter 5 presents the results and analysis of Model Water Quality 1, 2, and 3. The discussion of the results obtained in this study is included in the same chapter. Finally, in Chapter

6, the conclusion of the findings is presented along with recommendations for future research.

REFERENCES

- Abbasi, T. and Abbasi, S. (2012) *Water Quality Indices, Water Quality Indices*.
- Abbaspour, B. and Haghiabi, A. H. (2015) 'Comparing the Estimation of Suspended Load using Two Methods of Sediments Rating Curve and Artificial Neural Network (A Case Study : Cham Anjir Station , Lorestan Province)', *Journal of Environmental Treatment Techniques*, 3(4), pp. 215–222.
- De Aguiar Netto, A. O., Garcia, C. A. B., Hora Alves, J. D. P., Ferreira, R. A. and Gonzaga Da Silva, M. (2013) 'Physical and chemical characteristics of water from the hydrographic basin of the Poxim River, Sergipe State, Brazil', *Environmental Monitoring and Assessment*, 185(5), pp. 4417–4426.
- Ahmad Kamal, N., Muhammad, N. S. and Abdullah, J. (2020) 'Scenario-based pollution discharge simulations and mapping using integrated QUAL2K-GIS', *Environmental Pollution*. Elsevier Ltd, 259, p. 113909.
- Ahmed, A. A. M. (2017) 'Prediction of dissolved oxygen in Surma River by biochemical oxygen demand and chemical oxygen demand using the artificial neural networks (ANNs)', *Journal of King Saud University - Engineering Sciences*. King Saud University, 29(2), pp. 151–158.
- Ahmed, A. A. M. and Shah, S. M. A. (2017) 'Application of adaptive neuro-fuzzy inference system (ANFIS) to estimate the biochemical oxygen demand (BOD) of Surma River', *Journal of King Saud University - Engineering Sciences*. King Saud University, 29(3), pp. 237–243.
- Akkoyunlu, A. and Akiner, M. E. (2012) 'Pollution evaluation in streams using water quality indices: A case study from Turkey's Sapanca Lake Basin', *Ecological Indicators*. Elsevier Ltd, 18, pp. 501–511.
- Alves, J. do P. H., Fonseca, L. C., Chielle, R. de S. A. and Macedo, L. C. B. (2018) 'Monitoring water quality of the sergipe river basin: An evaluation using multivariate data analysis', *Revista Brasileira de Recursos Hidricos*, 23(0), pp. 1–12.
- Amiri, B. J. and 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), pp.

151–160.

- Antanasijević, D., Pocajt, V., Perić-Grujić, A. and Ristić, M. (2014) ‘Modelling of dissolved oxygen in the danube river using artificial neural networks and Monte carlo simulation uncertainty analysis’, *Journal of Hydrology*, 519(PB), pp. 1895–1907.
- APHA (2012) *Standard Methods For The Examination of Water and Wastewater*. Edited by A. W. W. A. American Public Health Association. Water Environment Federation, Washignton DC, United State of America.
- Artioli, Y., Bendoricchio, G. and Palmeri, L. (2005) ‘Defining and modelling the coastal zone affected by the Po river (Italy)’, *Ecological Modelling*. Elsevier, 184(1), pp. 55–68.
- Astaraie-Imani, M., Kapelan, Z., Fu, G. and Butler, D. (2012) ‘Assessing the combined effects of urbanisation and climate change on the river water quality in an integrated urban wastewater system in the UK’, *Journal of Environmental Management*. Elsevier Ltd, 112, pp. 1–9.
- Ay, M. and Kisi, O. (2014) ‘Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques’, *Journal of Hydrology*. Elsevier B.V., 511, pp. 279–289.
- Ay, M. and Kişi, Ö. (2017) ‘Estimation of dissolved oxygen by using neural networks and neuro fuzzy computing techniques’, *KSCE Journal of Civil Engineering*, 21(5), pp. 1631–1639.
- Banda, T. D. and Kumarasamy, M. V. (2020) ‘Development of water quality indices (WQIs): A review’, *Polish Journal of Environmental Studies*, 29(3), pp. 2011–2021.
- Barakat, A., El Baghdadi, M., Rais, J., Aghezzaf, B. and Slassi, M. (2016) ‘Assessment of spatial and seasonal water quality variation of Oum Er Rbia River (Morocco) using multivariate statistical techniques’, *International Soil and Water Conservation Research*. Elsevier, 4(4), pp. 284–292.
- Barwal, A. and Chaudhary, R. (2014) ‘To study the performance of biocarriers in moving bed biofilm reactor (MBBR) technology and kinetics of biofilm for retrofitting the existing aerobic treatment systems: A review’, *Reviews in Environmental Science and Biotechnology*, 13(3), pp. 285–299.
- Barzegar, R., Adamowski, J. and Moghaddam, A. A. (2016) ‘Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study

- in Aji-Chay River, Iran’, *Stochastic Environmental Research and Risk Assessment*. Springer Berlin Heidelberg, 30(7), pp. 1797–1819.
- Basis, R., Neural, F., Function, B. and Integrated, A. (2014) ‘Water Quality Prediction Based on a Novel Hyb Rid M Odel of Arimaand Rb F Neural’, in *Proceedings of CCIS2014*. IEEE, pp. 33–40.
- Behmel, S., Damour, M., Ludwig, R. and Rodriguez, M. J. (2016) ‘Water quality monitoring strategies — A review and future perspectives’, *Science of the Total Environment*. Elsevier B.V., 571, pp. 1312–1329.
- Brown, R. M., McClelland, N. I., Deininger, R. A. and Tozer, R. G. (1970) ‘A-Water-Quality-Index-Do-we-dare-BROWN-R-M-1970.pdf’, *Data and Instrumentation for Water Quality Management*, 117(10), pp. 339–343.
- Bu, H., Meng, W., Zhang, Y. and Wan, J. (2014) ‘Relationships between land use patterns and water quality in the Taizi River basin, China’, *Ecological Indicators*. Elsevier Ltd, 41, pp. 187–197.
- Cahoon, L. B., Hales, J. C., Carey, E. S., Loucaides, S., Rowland, K. R. and Toothman, B. R. (2016) ‘Multiple modes of water quality impairment by fecal contamination in a rapidly developing coastal area: southwest Brunswick County, North Carolina’, *Environmental Monitoring and Assessment*, 188(2), pp. 1–13.
- Chang, F. J., Tsai, Y. H., Chen, P. A., Coynel, A. and Vachaud, G. (2015) ‘Modeling water quality in an urban river using hydrological factors - Data driven approaches’, *Journal of Environmental Management*. Elsevier Ltd, 151, pp. 87–96.
- Chang, H. (2005) ‘Spatial and temporal variations of water quality in the han river and its tributaries, Seoul, Korea, 1993-2002’, *Water, Air, and Soil Pollution*, 161(1–4), pp. 267–284.
- Chapman, D. V., Bradley, C., Gettel, G. M., Hatvani, I. G., Hein, T., Kovács, J., Liska, I., Oliver, D. M., Tanos, P., Trásy, B. and Várbíró, G. (2016) ‘Developments in water quality monitoring and management in large river catchments using the Danube River as an example’, *Environmental Science and Policy*. Elsevier Ltd, 64, pp. 141–154.
- Chapman, D. V (1996) *Water quality assessments: a guide to the use of biota, sediments and water in environmental monitoring*. CRC Press.
- Chapra, S. C. (2008) *Surface water-quality modeling*. Waveland press.

- Chaturvedi, M. K. and Bassin, J. K. (2010) ‘Assessing the water quality index of water treatment plant and bore wells, in Delhi, India’, *Environmental Monitoring and Assessment*, 163(1–4), pp. 449–453.
- Chau, K. wing (2006) ‘A review on integration of artificial intelligence into water quality modelling’, *Marine Pollution Bulletin*, 52(7), pp. 726–733.
- Chen, J. C., Chang, N. B. and Shieh, W. K. (2003) ‘Assessing wastewater reclamation potential by neural network model’, *Engineering Applications of Artificial Intelligence*.
- Chou, J. S., Ho, C. C. and Hoang, H. S. (2018) ‘Determining quality of water in reservoir using machine learning’, *Ecological Informatics*. Elsevier, 44(February), pp. 57–75.
- Collins, R., Johnson, D., Crilly, D., Rickard, A., Neal, L., Morse, A., Walker, M., Lear, R., Deasy, C., Paling, N., Anderton, S., Ryder, C., Bide, P. and Holt, A. (2020) ‘Collaborative water management across England – An overview of the Catchment Based Approach’, *Environmental Science and Policy*. Elsevier, 112(June), pp. 117–125.
- Dai, X., Zhou, Y., Ma, W. and Zhou, L. (2017) ‘Influence of spatial variation in land-use patterns and topography on water quality of the rivers inflowing to Fuxian Lake, a large deep lake in the plateau of southwestern China’, *Ecological Engineering*. Elsevier B.V., 99, pp. 417–428.
- Deng, W., Wang, G. and Zhang, X. (2015) ‘A novel hybrid water quality time series prediction method based on cloud model and fuzzy forecasting’, *Chemometrics and Intelligent Laboratory Systems*. Elsevier B.V., 149, pp. 39–49.
- Diamantopoulou, M. J., Papamichail, D. M. and Antonopoulos, V. Z. (2005) ‘The use of a Neural Network technique for the prediction of water quality parameters’, *Operational Research*, 5(1), pp. 115–125.
- Ding, J., Jiang, Y., Liu, Q., Hou, Z., Liao, J., Fu, L. and Peng, Q. (2016) ‘Influences of the land use pattern on water quality in low-order streams of the Dongjiang River basin, China: A multi-scale analysis’, *Science of the Total Environment*. Elsevier B.V., 551–552(19), pp. 205–216.
- Dogan, E., Sengorur, B. and Koklu, R. (2009) ‘Modeling biological oxygen demand of the Melen River in Turkey using an artificial neural network technique’, *Journal of Environmental Management*, 90(2), pp. 1229–1235.
- Durán-Sánchez, A., Álvarez-García, J. and del Río-Rama, M. de la C. (2018)

- ‘Sustainable water resources management: A bibliometric overview’, *Water (Switzerland)*, 10(9), pp. 1–19.
- El-Khoury, A., Seidou, O., Lapen, D. R. L., Que, Z., Mohammadian, M., Sunohara, M. and Bahram, D. (2015) ‘Combined impacts of future climate and land use changes on discharge, nitrogen and phosphorus loads for a Canadian river basin’, *Journal of Environmental Management*. Elsevier Ltd, 151, pp. 76–86.
- Elkiran, G., Nourani, V., Abba, S. I. and Abdullahi, J. (2018) ‘Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river’, *Global Journal of Environmental Science and Management*, 4(4), pp. 439–450.
- ENGINEERS, U.-U. A. C. O. F. (2010) ‘HEC-RAS River Analysis System. Hydraulic Reference Manual. Version 4.1’, *US Army Corps of Engineers Hydrologic Engineering Center, Davis, CA*.
- Fahmi, M., Nasir, M., Samsudin, M. S., Mohamad, I., Roshide, M., Awaluddin, A., Mansor, M. A., Juahir, H. and Ramli, N. (2011) ‘River Water Quality Modeling Using Combined Principle Component Analysis (PCA) and Multiple Linear Regressions (MLR): A Case Study at Klang River , Malaysia Department of Environmental Sciences , Faculty of Environmental Studies , Department of Enviro’, *World Applied Sciences Journal*, 14(2002), pp. 73–82.
- Fang, X., Zhang, J., Chen, Y. and Xu, X. (2008) ‘QUAL2K model used in the water quality assessment of Qiantang River, China’, *Water Environment Research*. Wiley Online Library, 80(11), pp. 2125–2133.
- Fijani, E., Barzegar, R., Deo, R., Tziritis, E. and Konstantinos, S. (2019) ‘Design and implementation of a hybrid model based on two-layer decomposition method coupled with extreme learning machines to support real-time environmental monitoring of water quality parameters’, *Science of the Total Environment*. Elsevier B.V., 648, pp. 839–853.
- Fonseca, A., Botelho, C., Boaventura, R. A. R. and Vilar, V. J. P. (2014) ‘Integrated hydrological and water quality model for river management: A case study on Lena River’, *Science of the Total Environment*. Elsevier B.V., 485–486(1), pp. 474–489.
- Gao, L. and Li, D. (2014) ‘A review of hydrological/water-quality models’, *Frontiers of Agricultural Science and Engineering*, pp. 267–276.
- Gazzaz, N. M., Yusoff, M. K., Aris, A. Z., Juahir, H. and Ramli, M. F. (2012) ‘Artificial neural network modeling of the water quality index for Kinta River

- (Malaysia) using water quality variables as predictors’, *Marine Pollution Bulletin*. Elsevier Ltd, 64(11), pp. 2409–2420.
- Gazzaz, N. M., Yusoff, M. K., Juahir, H., Ramli, M. F. and Aris, A. Z. (2013) ‘Water Quality Assessment and Analysis of Spatial Patterns and Temporal Trends’, *Water Environment Research*, 85(8), pp. 751–767.
- Gazzaz, N. M., Yusoff, M. K., Ramli, M. F., Aris, A. Z. and Juahir, H. (2012) ‘Characterization of spatial patterns in river water quality using chemometric pattern recognition techniques’, *Marine Pollution Bulletin*. Elsevier Ltd, 64(4), pp. 688–698.
- Ghose, D. K. and Samantaray, S. (2018) ‘Modelling sediment concentration using back propagation neural network and regression coupled with genetic algorithm’, *Procedia Computer Science*. Elsevier B.V., 125, pp. 85–92.
- Giridharan, L., Venugopal, T. and Jayaprakash, M. (2009) ‘Assessment of water quality using chemometric tools: A case study of river cooum, South India’, *Archives of Environmental Contamination and Toxicology*, 56(4), pp. 654–669.
- Gitau, M. W., Chen, J. and Ma, Z. (2016) ‘Water Quality Indices as Tools for Decision Making and Management’, *Water Resources Management*, 30(8), pp. 2591–2610.
- Golabi, M. R., Farzi, S., Khodabakhshi, F., Sohrabi Geshnigani, F., Nazdane, F. and Radmanesh, F. (2020) ‘Biochemical oxygen demand prediction: development of hybrid wavelet-random forest and M5 model tree approach using feature selection algorithms’, *Environmental Science and Pollution Research*. Environmental Science and Pollution Research, 27(27), pp. 34322–34336.
- Grimsrud, G. P., Finnemore, E. J. and Owen, H. J. (1976) *Evaluation of water quality models: a management guide for planners*. US Environmental Protection Agency, Office of Research and Development.
- Grizzetti, B., Bouraoui, F., Granlund, K., Rekolainen, S. and Bidoglio, G. (2003) ‘Modelling diffuse emission and retention of nutrients in the Vantaanjoki watershed (Finland) using the SWAT model’, *Ecological Modelling*. Elsevier, 169(1), pp. 25–38.
- HACH (2020a) ‘Chemical Oxygen Demand, Method 8000’.
- HACH (2020b) ‘Nitrogen Ammonia Method 8038’.
- He, B., Oki, T., Sun, F., Komori, D., Kanae, S., Wang, Y., Kim, H. and Yamazaki, D.

- (2011) ‘Estimating monthly total nitrogen concentration in streams by using artificial neural network’, *Journal of Environmental Management*. Elsevier Ltd, 92(1), pp. 172–177.
- Hua, A. K. (2017) ‘Identifying the source of pollutants in Malacca river using GIS approach’, *Applied Ecology and Environmental Research*, 15(4), pp. 571–588.
- Huang, L., Bai, J., Xiao, R., Gao, H. and Liu, P. (2012) ‘Spatial distribution of Fe, Cu, Mn in the surface water system and their effects on wetland vegetation in the Pearl River Estuary of China’, *CLEAN–Soil, Air, Water*. Wiley Online Library, 40(10), pp. 1085–1092.
- Hurley, T., Sadiq, R. and Mazumder, A. (2012) ‘Adaptation and evaluation of the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) for use as an effective tool to characterize drinking source water quality’, *Water Research*. Elsevier Ltd, 46(11), pp. 3544–3552.
- Jacobs, K., Lebel, L., Buizer, J., Addams, L., Matson, P., McCullough, E., Garden, P., Saliba, G. and Finan, T. (2016) ‘Linking knowledge with action in the pursuit of sustainable water-resources management’, *Proceedings of the National Academy of Sciences of the United States of America*, 113(17), pp. 4591–4596.
- Jahin, H. S., Abuzaid, A. S. and Abdellatif, A. D. (2020) ‘Using multivariate analysis to develop irrigation water quality index for surface water in Kafr El-Sheikh Governorate, Egypt’, *Environmental Technology and Innovation*. Elsevier B.V., 17, p. 100532.
- Jerves-Cobo, R., Lock, K., Van Butsel, J., Pauta, G., Cisneros, F., Nopens, I. and Goethals, P. L. M. (2018) ‘Biological impact assessment of sewage outfalls in the urbanized area of the Cuenca River basin (Ecuador) in two different seasons’, *Limnologica*. Elsevier, 71(December 2017), pp. 8–28.
- Ji, X., Shang, X., Dahlgren, R. A. and Zhang, M. (2017) ‘Prediction of dissolved oxygen concentration in hypoxic river systems using support vector machine: a case study of Wen-Rui Tang River, China’, *Environmental Science and Pollution Research*. Environmental Science and Pollution Research, 24(19), pp. 16062–16076.
- Jiang, D. yi, Wang, Y. yan, Liao, Q., Long, Z. and Zhou, S. yang (2020) ‘Assessment of water quality and safety based on multi-statistical analyses of nutrients, biochemical indexes and heavy metals’, *Journal of Central South University*, 27(4), pp. 1211–1223.

- Kaiser, H. F. (1974) *An index of factorial simplicity*, *Psychometrika*.
- Kalin, L., Isik, S., Schoonover, J. E. and Lockaby, B. G. (2010) 'Predicting Water Quality in Unmonitored Watersheds Using Artificial Neural Networks', *Journal of Environmental Quality*, 39(4), pp. 1429–1440.
- Kazi, T. G., Arain, M. B., Jamali, M. K., Jalbani, N., Afridi, H. I., Sarfraz, R. A., Baig, J. A. and Shah, A. Q. (2009) 'Assessment of water quality of polluted lake using multivariate statistical techniques: A case study', *Ecotoxicology and Environmental Safety*, 72(2), pp. 301–309.
- Keshtegar, B. and Heddami, S. (2018) 'Modeling daily dissolved oxygen concentration using modified response surface method and artificial neural network: a comparative study', *Neural Computing and Applications*. Springer London, 30(10), pp. 2995–3006.
- Khaled, B., Abdellah, A., Noureddine, D., Heddami, S. and Sabeha, A. (2018) 'Modelling of biochemical oxygen demand from limited water quality variable by anfis using two partition methods', *Water Quality Research Journal*, 53(1), pp. 24–40.
- Khalil, B., Ouarda, T. B. M. J. and St-Hilaire, A. (2011) 'Estimation of water quality characteristics at ungauged sites using artificial neural networks and canonical correlation analysis', *Journal of Hydrology*. Elsevier B.V., 405(3–4), pp. 277–287.
- Kim, S. E. and Seo, I. W. (2015) 'Artificial Neural Network ensemble modeling with conjunctive data clustering for water quality prediction in rivers', *Journal of Hydro-Environment Research*. Elsevier B.V., 9(3), pp. 325–339.
- Kisi, O. and Parmar, K. S. (2016) 'Application of least square support vector machine and multivariate adaptive regression spline models in long term prediction of river water pollution', *Journal of Hydrology*. Elsevier B.V., 534, pp. 104–112.
- Kornienko, A. A., Kornienko, A. V., Fofanov, O. B. and Chubik, M. P. (2015) 'Knowledge in Artificial Intelligence Systems: Searching the Strategies for Application', *Procedia - Social and Behavioral Sciences*. Elsevier B.V., 166, pp. 589–594.
- Kumar, D., Pandey, A., Sharma, N. and Flügel, W. A. (2016) 'Daily suspended sediment simulation using machine learning approach', *Catena*. Elsevier B.V., 138, pp. 77–90.
- Laghzal, A., Salmoun, F., Boudinar, B., Khaddor, M., Cherroud, S., Fihri, M. and

- Mammad, C. (2016) 'Evaluation of physico-chemical and bacteriological quality of water springs by using a principal component analysis (PCA): A case study of Tingitane Peninsula (Morocco)', *Journal of Materials and Environmental Science*, 7(2), pp. 456–462.
- Li, C., Li, Z., Wu, J., Zhu, L. and Yue, J. (2018) 'A hybrid model for dissolved oxygen prediction in aquaculture based on multi-scale features', *Information Processing in Agriculture*. China Agricultural University, 5(1), pp. 11–20.
- Liu, L. (2018) 'Application of a hydrodynamic and water quality model for inland surface water systems', *Applications in water systems management and modeling*, pp. 87–109.
- Liu, M. and Lu, J. (2014) 'Support vector machine—an alternative to artificial neuron network for water quality forecasting in an agricultural nonpoint source polluted river?', *Environmental Science and Pollution Research*, 21(18), pp. 11036–11053.
- Liu, Q. J., Shi, Z. H., Fang, N. F., Zhu, H. De and Ai, L. (2013) 'Modeling the daily suspended sediment concentration in a hyperconcentrated river on the Loess Plateau, China, using the Wavelet-ANN approach', *Geomorphology*. Elsevier B.V., 186, pp. 181–190.
- Loucks, D. P. and Beek, E. van (1981) *Water resource systems planning and analysis*, *Advances in Water Resources*.
- Lumb, A., Sharma, T. C. and Bibault, J.-F. (2011) 'A Review of Genesis and Evolution of Water Quality Index (WQI) and Some Future Directions', *Water Quality, Exposure and Health*, 3(1), pp. 11–24.
- Manewan, C. and Van Roon, M. (2017) 'Challenges in implementing integrated catchment management and sustainable stormwater solutions in Bangkok, Thailand', *Water Practice and Technology*, 12(4), pp. 780–789.
- Metcalf and Eddy (2014) 'Metcalf and Eddy, AECOM - Wastewater Engineering_ Treatment and Resource Recovery (2014, McGraw-Hill).pdf'.
- Miller, J. D. and Hutchins, M. (2017) 'The impacts of urbanisation and climate change on urban flooding and urban water quality: A review of the evidence concerning the United Kingdom', *Journal of Hydrology: Regional Studies*, 12(July), pp. 345–362.
- Ministry of Environment and Water (2021) 'Environmental Sustainability in Malaysia 2020-2030', *Ministry of Environment and Water*, pp. 83–101.

- Mohd, N. and Bee, Y. (2011) 'Power comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests', *Journal of Statistical Modeling and Analytics*, 2(1), pp. 13–14.
- Najah, A., El-Shafie, A., Karim, O. A. and El-Shafie, A. H. (2013a) 'Application of artificial neural networks for water quality prediction', *Neural Computing and Applications*, 22(SUPPL.1), pp. 187–201.
- Najah, A., El-Shafie, A., Karim, O. A. and El-Shafie, A. H. (2013b) 'Application of artificial neural networks for water quality prediction', *Neural Computing and Applications*, 22(SUPPL.1), pp. 187–201.
- Najah, A., El-Shafie, A., Karim, O. A., Jaafar, O. and El-Shafie, A. H. (2011) 'An application of different artificial intelligences techniques for water quality prediction', *International Journal of Physical Sciences*, 6(22), pp. 5298–5308.
- Najar, I. A. and Khan, A. B. (2012) 'Assessment of water quality and identification of pollution sources of three lakes in Kashmir, India, using multivariate analysis', *Environmental Earth Sciences*, 66(8), pp. 2367–2378.
- Naubi, I., Zardari, N. H., Shirazi, S. M., Ibrahim, N. F. B. and Baloo, L. (2016) 'Effectiveness of water quality index for monitoring Malaysian river water quality', *Polish Journal of Environmental Studies*, 25(1), pp. 231–239.
- Noori, R., Berndtsson, R., Hosseinzadeh, M., Adamowski, J. F. and Abyaneh, M. R. (2019) 'A critical review on the application of the National Sanitation Foundation Water Quality Index', *Environmental Pollution*. Elsevier Ltd, 244, pp. 575–587.
- Noori, R., Karbassi, A., Ashrafi, K., Ardestani, M., Mehrdadi, N. and Bidhendi, G. R. N. (2012) 'Active and online prediction of BOD 5 in river systems using reduced-order support vector machine', *Environmental Earth Sciences*, 67(1), pp. 141–149.
- Noori, R., Sabahi, M. S., Karbassi, A. R., Baghvand, A. and Zadeh, H. T. (2010) 'Multivariate statistical analysis of surface water quality based on correlations and variations in the data set', *Desalination*. Elsevier B.V., 260(1–3), pp. 129–136.
- Nourani, V., Hosseini Baghanam, A., Adamowski, J. and Kisi, O. (2014a) 'Applications of hybrid wavelet-Artificial Intelligence models in hydrology: A review', *Journal of Hydrology*. Elsevier B.V., 514, pp. 358–377.
- Nourani, V., Hosseini Baghanam, A., Adamowski, J. and Kisi, O. (2014b)

- ‘Applications of hybrid wavelet-Artificial Intelligence models in hydrology: A review’, *Journal of Hydrology*, 514, pp. 358–377.
- Oehler, F., Rutherford, J. C. and Coco, G. (2010) ‘The use of machine learning algorithms to design a generalized simplified denitrification model’, *Biogeosciences*, 7(10), pp. 3311–3332.
- Oliveira, M. D. de, Rezende, O. L. T. de, Fonseca, J. F. R. de and Libânio, M. (2019) ‘Evaluating the surface Water quality index fuzzy and its influence on water treatment’, *Journal of Water Process Engineering*. Elsevier, 32(December 2018), p. 100890.
- Olowe, K. O. and Kumarasamy, M. vellaisamy (2018) ‘Assessment of some existing water quality models’, *Nature Environment and Pollution Technology*, 17(3), pp. 939–948.
- Olyaie, E., Zare Abyaneh, H. and Danandeh Mehr, A. (2017) ‘A comparative analysis among computational intelligence techniques for dissolved oxygen prediction in Delaware River’, *Geoscience Frontiers*. Elsevier Ltd, 8(3), pp. 517–527.
- Ömer Faruk, D. (2010a) ‘A hybrid neural network and ARIMA model for water quality time series prediction’, *Engineering Applications of Artificial Intelligence*, 23(4), pp. 586–594.
- Ömer Faruk, D. (2010b) ‘A hybrid neural network and ARIMA model for water quality time series prediction’, *Engineering Applications of Artificial Intelligence*, 23(4), pp. 586–594.
- Palácio, S. M., Espinoza-Quñones, F. R., de Pauli, A. R., Piana, P. A., Queiroz, C. B., Fabris, S. C., Fagundes-Klen, M. R. and Veit, M. T. (2016) ‘Assessment of Anthropogenic Impacts on the Water Quality of Marreco River, Brazil, Based on Principal Component Analysis and Toxicological Assays’, *Water, Air, and Soil Pollution*. Water, Air, & Soil Pollution, 227(9).
- Palani, S., Liong, S. Y. and Tkalich, P. (2008) ‘An ANN application for water quality forecasting’, *Marine Pollution Bulletin*, 56(9), pp. 1586–1597.
- Pullanikkatil, D., Palamuleni, L. and Ruhiiga, T. (2015) ‘Impact of land use on water quality in the Likangala catchment, southern Malawi’, *African Journal of Aquatic Science*, 40(3), pp. 277–286.
- Raheli, B., Aalami, M. T., El-Shafie, A., Ghorbani, M. A. and Deo, R. C. (2017) ‘Uncertainty assessment of the multilayer perceptron (MLP) neural network model with implementation of the novel hybrid MLP-FFA method for

- prediction of biochemical oxygen demand and dissolved oxygen: a case study of Langat River’, *Environmental Earth Sciences*. Springer Berlin Heidelberg, 76(14).
- Ranjith, S., Shivapur, A. V., Kumar, P. S. K., Hiremath, C. G. and Dhungana, S. (2019) ‘Water Quality Model for Streams: A Review’, *Journal of Environmental Protection*, 10(12), pp. 1612–1648.
- Ranković, V., Radulović, J., Radojević, I., Ostojić, A. and Čomić, L. (2010) ‘Neural network modeling of dissolved oxygen in the Gruža reservoir, Serbia’, *Ecological Modelling*, 221(8), pp. 1239–1244.
- Rode, M., Arhonditsis, G., Balin, D., Kebede, T., Krysanova, V., Van Griensven, A. and Van Der Zee, S. E. A. T. M. (2010) ‘New challenges in integrated water quality modelling’, *Hydrological Processes*. Wiley Online Library, 24(24), pp. 3447–3461.
- Ruggieri, N., Castellano, M., Capello, M., Maggi, S. and Povero, P. (2011) ‘Seasonal and spatial variability of water quality parameters in the Port of Genoa, Italy, from 2000 to 2007’, *Marine Pollution Bulletin*. Elsevier Ltd, 62(2), pp. 340–349.
- Sahoo, M. M., Patra, K. C. and Khatua, K. K. (2015) ‘Inference of Water Quality Index Using ANFIA and PCA’, *Aquatic Procedia*. Elsevier B.V., 4(Icwrcoe), pp. 1099–1106.
- Salami Shahid, E. and Ehteshami, M. (2016) ‘Application of artificial neural networks to estimating DO and salinity in San Joaquin River basin’, *Desalination and Water Treatment*, 57(11), pp. 4888–4897.
- Sarkar, A. and Pandey, P. (2015) ‘River Water Quality Modelling Using Artificial Neural Network Technique’, *Aquatic Procedia*. Elsevier B.V., 4(Icwrcoe), pp. 1070–1077.
- Sattari, M. T., Joudi, A. R. and Kusiak, A. (2016) ‘Estimation of water quality parameters with data-driven model’, *Journal - American Water Works Association*, 108(4), pp. E232–E239.
- Seanego, K. G. and Moyo, N. A. G. (2013) ‘The effect of sewage effluent on the physico-chemical and biological characteristics of the Sand River, Limpopo, South Africa’, *Physics and Chemistry of the Earth*. Elsevier Ltd, 66, pp. 75–82.
- Sengorur, B., Koklu, R. and Ates, A. (2015) ‘Water Quality Assessment Using

- Artificial Intelligence Techniques: SOM and ANN—A Case Study of Melen River Turkey’, *Water Quality, Exposure and Health*. Springer Netherlands, 7(4), pp. 469–490.
- Seo, I. W., Yun, S. H. and Choi, S. Y. (2016) ‘Forecasting Water Quality Parameters by ANN Model Using Pre-processing Technique at the Downstream of Cheongpyeong Dam’, *Procedia Engineering*. The Author(s), 154, pp. 1110–1115.
- Shen, Z., Hou, X., Li, W., Aini, G., Chen, L. and Gong, Y. (2015) ‘Impact of landscape pattern at multiple spatial scales on water quality: A case study in a typical urbanised watershed in China’, *Ecological Indicators*. Elsevier Ltd, 48, pp. 417–427.
- Shi, P., Zhang, Y., Li, Z., Li, P. and Xu, G. (2017) ‘Influence of land use and land cover patterns on seasonal water quality at multi-spatial scales’, *Catena*. Elsevier B.V., 151, pp. 182–190.
- Shi, R., Zhao, J., Shi, W., Song, S. and Wang, C. (2020) ‘Comprehensive assessment of water quality and pollution source apportionment in wuliangshuai lake, inner mongolia, china’, *International Journal of Environmental Research and Public Health*, 17(14), pp. 1–12.
- Sincock, A. M. and Lees, M. J. (2002) ‘Extension of the QUASAR River-Water Quality Model to Unsteady Flow Conditions’, *Water and Environment Journal*. Wiley Online Library, 16(1), pp. 12–17.
- Singh, K. P., Basant, A., Malik, A. and Jain, G. (2009) ‘Artificial neural network modeling of the river water quality-A case study’, *Ecological Modelling*, 220(6), pp. 888–895.
- de Souza Pereira, M. A., Cavalheri, P. S., de Oliveira, M. Â. C. and Magalhães Filho, F. J. C. (2019) ‘A multivariate statistical approach to the integration of different land-uses, seasons, and water quality as water resources management tool’, *Environmental Monitoring and Assessment*. Environmental Monitoring and Assessment, 191(9), pp. 538–356.
- Sugiyono (2012) *Metode Penelitian Kualitatif, Kuantitatif dan R & D*. Bandung, Indonesia: Alfabeta pp. 184.
- Sun, W., Xia, C., Xu, M., Guo, J. and Sun, G. (2016) ‘Application of modified water quality indices as indicators to assess the spatial and temporal trends of water quality in the Dongjiang River’, *Ecological Indicators*. Elsevier Ltd, 66, pp.

306–312.

- Sutadian, A. D., Muttill, N., Yilmaz, A. G. and Perera, B. J. C. (2016) ‘Development of river water quality indices—a review’, *Environmental Monitoring and Assessment*, 188(1), pp. 1–29.
- Tariq, S. R., Shah, M. H., Shaheen, N., Jaffar, M. and Khalique, A. (2008) ‘Statistical source identification of metals in groundwater exposed to industrial contamination’, *Environmental Monitoring and Assessment*, 138(1–3), pp. 159–165.
- Telci, I. T., Nam, K., Guan, J. and Aral, M. M. (2009) ‘Optimal water quality monitoring network design for river systems’, *Journal of Environmental Management*. Elsevier Ltd, 90(10), pp. 2987–2998.
- Theoneste, S., Vincent, N. and Xavier, N. (2020) ‘The Effluent Quality Discharged and Its Impacts on the Receiving Environment Case of Kacyiru Sewerage Treatment Plant, Kigali, Rwanda’, *International Journal of Environmental & Agriculture Research*, 6(2), pp. 20–29.
- Tian, Y., Jiang, Y., Liu, Q., Dong, M., Xu, D., Liu, Y. and Xu, X. (2019) ‘Using a water quality index to assess the water quality of the upper and middle streams of the Luanhe River, northern China’, *Science of the Total Environment*. Elsevier B.V., 667, pp. 142–151.
- Tikhamarine, Y., Souag-Gamane, D., Ahmed, A. N., Sammen, S. S., Kisi, O., Huang, Y. F. and El-Shafie, A. (2020) ‘Rainfall-runoff modelling using improved machine learning methods: Harris hawks optimizer vs. particle swarm optimization’, *Journal of Hydrology*. Elsevier, 589(June), p. 125133.
- Tiyasha, Tung, T. M. and Yaseen, Z. M. (2020) ‘A survey on river water quality modelling using artificial intelligence models: 2000–2020’, *Journal of Hydrology*. Elsevier B.V., 585, p. 124670.
- Tripathi, M. and Singal, S. K. (2019) ‘Use of Principal Component Analysis for parameter selection for development of a novel Water Quality Index: A case study of river Ganga India’, *Ecological Indicators*. Elsevier, 96(September 2018), pp. 430–436.
- Tyagi, S., Sharma, B., Singh, P. and Dobhal, R. (2020) ‘Water Quality Assessment in Terms of Water Quality Index’, *American Journal of Water Resources*, 1(3), pp. 34–38.
- Varol, M., Gökot, B., Bekleyen, A. and Şen, B. (2012) ‘Spatial and temporal variations

- in surface water quality of the dam reservoirs in the Tigris River basin, Turkey’, *Catena*, 92, pp. 11–21.
- Vega, M., Pardo, R., Barrado, E. and Debán, L. (1998) ‘Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis’, *Water Research*, 32(12), pp. 3581–3592.
- Venkateswarlu, T., Anmala, J. and Dharwa, M. (2020) ‘PCA, CCA, and ANN Modeling of Climate and Land-Use Effects on Stream Water Quality of Karst Watershed in Upper Green River, Kentucky’, *Journal of Hydrologic Engineering*, 25(6), p. 05020008.
- Vijay, R., Mardikar, T. and Kumar, R. (2016) ‘Impact of sewage discharges on coastal water quality of Mumbai, India: present and future scenarios’, *Environmental Monitoring and Assessment*. Environmental Monitoring and Assessment, 188(7).
- Wada, Y. and Bierkens, M. F. P. (2014) ‘Sustainability of global water use: Past reconstruction and future projections’, *Environmental Research Letters*. IOP Publishing, 9(10).
- Walsh, P. and Wheeler, W. (2012) *Water Quality Index Aggregation and Cost Benefit Analysis National Center for Environmental Economics Water Quality Index Aggregation and Cost Benefit Analysis*.
- Wang, L., Li, X. and Cui, W. (2012) ‘Fuzzy Neural Networks enhanced evaluation of wetland surface water quality’, *International Journal of Computer Applications in Technology*, 44(3), pp. 235–240.
- Wang, Q., Li, S., Jia, P., Qi, C. and Ding, F. (2013) ‘A review of surface water quality models’, *The Scientific World Journal*. Hindawi, 2013.
- Wang, Q., Zhao, X., Ding, F., Li, S. and Zhao, Y. (2009) ‘Numerical model of thermal discharge from Laibin power plant based on Mike21FM.’, *Research of Environmental Sciences*. China Environmental Science, 22(3), pp. 332–336.
- Wang, X., Cai, Q., Ye, L. and Qu, X. (2012) ‘Evaluation of spatial and temporal variation in stream water quality by multivariate statistical techniques: A case study of the Xiangxi River basin, China’, *Quaternary International*. Elsevier Ltd and INQUA, 282, pp. 137–144.
- Wang, X., Fu, L. and He, C. (2011) ‘Applying support vector regression to water quality modelling by remote sensing data’, *International Journal of Remote Sensing*, 32(23), pp. 8615–8627.

- Wen, X., Fang, J., Diao, M. and Zhang, C. (2013) ‘Artificial neural network modeling of dissolved oxygen in the Heihe River, Northwestern China’, *Environmental Monitoring and Assessment*, 185(5), pp. 4361–4371.
- Weng, T. K. and Mokhtar, M. Bin (2009) ‘An appropriate institutional framework towards integrated water resources management in Pahang River Basin, Malaysia’, *European Journal of Scientific Research*, 27(4), pp. 536–547.
- Wu, Z., Wang, X., Chen, Y., Cai, Y. and Deng, J. (2018) ‘Assessing river water quality using water quality index in Lake Taihu Basin, China’, *Science of the Total Environment*. Elsevier B.V., 612, pp. 914–922.
- Xiao, S., Hu, S., Zhang, Y., Zhao, X. and Pan, W. (2018) ‘Influence of sewage treatment plant effluent discharge into multipurpose river on its water quality: A quantitative health risk assessment of *Cryptosporidium* and *Giardia*’, *Environmental Pollution*. Elsevier Ltd, 233, pp. 797–805.
- Xu, F., Dong, G., Wang, Q., Liu, L., Yu, W., Men, C. and Liu, R. (2016) ‘Impacts of DEM uncertainties on critical source areas identification for non-point source pollution control based on SWAT model’, *Journal of Hydrology*. Elsevier B.V., 540, pp. 355–367.
- Xu, L. and Liu, S. (2013) ‘Study of short-term water quality prediction model based on wavelet neural network’, *Mathematical and Computer Modelling*. Elsevier Ltd, 58(3–4), pp. 807–813.
- Yang, W., Zhao, Y., Wang, D., Wu, H., Lin, A. and He, L. (2020) ‘Using principal components analysis and idw interpolation to determine spatial and temporal changes of Surfacewater quality of Xin’Anjiang river in huangshan, china’, *International Journal of Environmental Research and Public Health*, 17(8), pp. 1–14.
- Zeinalzadeh, K. and Rezaei, E. (2017) ‘Determining spatial and temporal changes of surface water quality using principal component analysis’, *Journal of Hydrology: Regional Studies*. Elsevier, 13(July), pp. 1–10.
- Zhang, Y., Fitch, P., Vilas, M. P. and Thorburn, P. J. (2019) ‘Applying multi-layer artificial neural network and mutual information to the prediction of trends in dissolved Oxygen’, *Frontiers in Environmental Science*, 7(MAR), pp. 1–11.
- Zhao, J., Lin, L., Yang, K., Liu, Q. and Qian, G. (2015) ‘Influences of land use on water quality in a reticular river network area: A case study in Shanghai, China’, *Landscape and Urban Planning*. Elsevier B.V., 137, pp. 20–29.

- Zhao, Y., Nan, J., Cui, F. Y. and Guo, L. (2007) 'Water quality forecast through application of BP neural network at Yuqiao reservoir', *Journal of Zhejiang University: Science A*, 8(9), pp. 1482–1487.
- Zhao, Y. ping, Wu, R., Cui, J. li, Gan, S. chai, Pan, J. chuan and Guo, P. ran (2020) 'Improvement of water quality in the Pearl River Estuary, China: a long-term (2008–2017) case study of temporal-spatial variation, source identification and ecological risk of heavy metals in surface water of Guangzhou', *Environmental Science and Pollution Research*. *Environmental Science and Pollution Research*, 27(17), pp. 21084–21097.
- Zhao, Y., Song, Y., Cui, J., Gan, S., Yang, X. and Wu, R. (2019) 'Assessment of Water Quality Evolution in the Pearl', pp. 1–16.
- Zhao, Y., Xia, X. H., Yang, Z. F. and Wang, F. (2012) 'Assessment of water quality in Baiyangdian Lake using multivariate statistical techniques', *Procedia Environmental Sciences*, 13(2011), pp. 1213–1226.
- Zhou, F., Guo, H. cheng, Liu, Y. and Hao, Z. jia (2007) 'Identification and spatial patterns of coastal water pollution sources based on GIS and chemometric approach', *Journal of Environmental Sciences*, 19(7), pp. 805–810.
- Zhou, T., Wu, J. and Peng, S. (2012) 'Assessing the effects of landscape pattern on river water quality at multiple scales: A case study of the Dongjiang River watershed, China', *Ecological Indicators*. Elsevier Ltd, 23, pp. 166–175.
- Zhu, W., Niu, Q., Zhang, R., Ye, R., Qian, X. and Qian, Y. (2015) 'Application of QUAL2K model to assess ecological purification technology for a polluted river', *International Journal of Environmental Research and Public Health*, 12(2), pp. 2215–2229.
- Ziemińska-Stolarska, A. and Skrzypski, J. (2012) 'Review of Mathematical Models of Water Quality', *Ecological Chemistry and Engineering S*, 19(2), pp. 197–211.
- Abbasi, T. and Abbasi, S. (2012) *Water Quality Indices, Water Quality Indices*.
- Abbaspour, B. and Haghiabi, A. H. (2015) 'Comparing the Estimation of Suspended Load using Two Methods of Sediments Rating Curve and Artificial Neural Network (A Case Study : Cham Anjir Station , Lorestan Province)', *Journal of Environmental Treatment Techniques*, 3(4), pp. 215–222.
- De Aguiar Netto, A. O., Garcia, C. A. B., Hora Alves, J. D. P., Ferreira, R. A. and Gonzaga Da Silva, M. (2013) 'Physical and chemical characteristics of water from the hydrographic basin of the Poxim River, Sergipe State, Brazil',

- Environmental Monitoring and Assessment*, 185(5), pp. 4417–4426.
- Ahmad Kamal, N., Muhammad, N. S. and Abdullah, J. (2020) ‘Scenario-based pollution discharge simulations and mapping using integrated QUAL2K-GIS’, *Environmental Pollution*. Elsevier Ltd, 259, p. 113909.
- Ahmed, A. A. M. (2017) ‘Prediction of dissolved oxygen in Surma River by biochemical oxygen demand and chemical oxygen demand using the artificial neural networks (ANNs)’, *Journal of King Saud University - Engineering Sciences*. King Saud University, 29(2), pp. 151–158.
- Ahmed, A. A. M. and Shah, S. M. A. (2017) ‘Application of adaptive neuro-fuzzy inference system (ANFIS) to estimate the biochemical oxygen demand (BOD) of Surma River’, *Journal of King Saud University - Engineering Sciences*. King Saud University, 29(3), pp. 237–243.
- Akkoyunlu, A. and Akiner, M. E. (2012) ‘Pollution evaluation in streams using water quality indices: A case study from Turkey’s Sapanca Lake Basin’, *Ecological Indicators*. Elsevier Ltd, 18, pp. 501–511.
- Alves, J. do P. H., Fonseca, L. C., Chielle, R. de S. A. and Macedo, L. C. B. (2018) ‘Monitoring water quality of the sergipe river basin: An evaluation using multivariate data analysis’, *Revista Brasileira de Recursos Hidricos*, 23(0), pp. 1–12.
- Amiri, B. J. and 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), pp. 151–160.
- Antanasijević, D., Pocajt, V., Perić-Grujić, A. and Ristić, M. (2014) ‘Modelling of dissolved oxygen in the danube river using artificial neural networks and Monte carlo simulation uncertainty analysis’, *Journal of Hydrology*, 519(PB), pp. 1895–1907.
- APHA (2012) *Standard Methods For The Examination of Water and Wastewater*. Edited by A. W. W. A. American Public Health Association. Water Environment Federation, Washington DC, United State of America.
- Artioli, Y., Bendoricchio, G. and Palmeri, L. (2005) ‘Defining and modelling the coastal zone affected by the Po river (Italy)’, *Ecological Modelling*. Elsevier, 184(1), pp. 55–68.
- Astaraie-Imani, M., Kapelan, Z., Fu, G. and Butler, D. (2012) ‘Assessing the combined

- effects of urbanisation and climate change on the river water quality in an integrated urban wastewater system in the UK’, *Journal of Environmental Management*. Elsevier Ltd, 112, pp. 1–9.
- Ay, M. and Kisi, O. (2014) ‘Modelling of chemical oxygen demand by using ANNs, ANFIS and k-means clustering techniques’, *Journal of Hydrology*. Elsevier B.V., 511, pp. 279–289.
- Ay, M. and Kişi, Ö. (2017) ‘Estimation of dissolved oxygen by using neural networks and neuro fuzzy computing techniques’, *KSCE Journal of Civil Engineering*, 21(5), pp. 1631–1639.
- Banda, T. D. and Kumarasamy, M. V. (2020) ‘Development of water quality indices (WQIs): A review’, *Polish Journal of Environmental Studies*, 29(3), pp. 2011–2021.
- Barakat, A., El Baghdadi, M., Rais, J., Aghezzaf, B. and Slassi, M. (2016) ‘Assessment of spatial and seasonal water quality variation of Oum Er Rbia River (Morocco) using multivariate statistical techniques’, *International Soil and Water Conservation Research*. Elsevier, 4(4), pp. 284–292.
- Barwal, A. and Chaudhary, R. (2014) ‘To study the performance of biocarriers in moving bed biofilm reactor (MBBR) technology and kinetics of biofilm for retrofitting the existing aerobic treatment systems: A review’, *Reviews in Environmental Science and Biotechnology*, 13(3), pp. 285–299.
- Barzegar, R., Adamowski, J. and Moghaddam, A. A. (2016) ‘Application of wavelet-artificial intelligence hybrid models for water quality prediction: a case study in Aji-Chay River, Iran’, *Stochastic Environmental Research and Risk Assessment*. Springer Berlin Heidelberg, 30(7), pp. 1797–1819.
- Basis, R., Neural, F., Function, B. and Integrated, A. (2014) ‘Water Quality Prediction Based on a Novel Hyb Rid M Odel of Arimaand Rb F Neural’, in *Proceedings of CCIS2014*. IEEE, pp. 33–40.
- Behmel, S., Damour, M., Ludwig, R. and Rodriguez, M. J. (2016) ‘Water quality monitoring strategies — A review and future perspectives’, *Science of the Total Environment*. Elsevier B.V., 571, pp. 1312–1329.
- Brown, R. M., McClelland, N. I., Deininger, R. A. and Tozer, R. G. (1970) ‘A-Water-Quality-Index-Do-we-dare-BROWN-R-M-1970.pdf’, *Data and Instrumentation for Water Quality Management*, 117(10), pp. 339–343.
- Bu, H., Meng, W., Zhang, Y. and Wan, J. (2014) ‘Relationships between land use

- patterns and water quality in the Taizi River basin, China', *Ecological Indicators*. Elsevier Ltd, 41, pp. 187–197.
- Cahoon, L. B., Hales, J. C., Carey, E. S., Loucaides, S., Rowland, K. R. and Toothman, B. R. (2016) 'Multiple modes of water quality impairment by fecal contamination in a rapidly developing coastal area: southwest Brunswick County, North Carolina', *Environmental Monitoring and Assessment*, 188(2), pp. 1–13.
- Chang, F. J., Tsai, Y. H., Chen, P. A., Coynel, A. and Vachaud, G. (2015) 'Modeling water quality in an urban river using hydrological factors - Data driven approaches', *Journal of Environmental Management*. Elsevier Ltd, 151, pp. 87–96.
- Chang, H. (2005) 'Spatial and temporal variations of water quality in the han river and its tributaries, Seoul, Korea, 1993-2002', *Water, Air, and Soil Pollution*, 161(1–4), pp. 267–284.
- Chapman, D. V., Bradley, C., Gettel, G. M., Hatvani, I. G., Hein, T., Kovács, J., Liska, I., Oliver, D. M., Tanos, P., Trásy, B. and Várbíró, G. (2016) 'Developments in water quality monitoring and management in large river catchments using the Danube River as an example', *Environmental Science and Policy*. Elsevier Ltd, 64, pp. 141–154.
- Chapman, D. V (1996) *Water quality assessments: a guide to the use of biota, sediments and water in environmental monitoring*. CRC Press.
- Chapra, S. C. (2008) *Surface water-quality modeling*. Waveland press.
- Chaturvedi, M. K. and Bassin, J. K. (2010) 'Assessing the water quality index of water treatment plant and bore wells, in Delhi, India', *Environmental Monitoring and Assessment*, 163(1–4), pp. 449–453.
- Chau, K. wing (2006) 'A review on integration of artificial intelligence into water quality modelling', *Marine Pollution Bulletin*, 52(7), pp. 726–733.
- Chen, J. C., Chang, N. B. and Shieh, W. K. (2003) 'Assessing wastewater reclamation potential by neural network model', *Engineering Applications of Artificial Intelligence*.
- Chou, J. S., Ho, C. C. and Hoang, H. S. (2018) 'Determining quality of water in reservoir using machine learning', *Ecological Informatics*. Elsevier, 44(February), pp. 57–75.
- Collins, R., Johnson, D., Crilly, D., Rickard, A., Neal, L., Morse, A., Walker, M., Lear,

- R., Deasy, C., Paling, N., Anderton, S., Ryder, C., Bide, P. and Holt, A. (2020) ‘Collaborative water management across England – An overview of the Catchment Based Approach’, *Environmental Science and Policy*. Elsevier, 112(June), pp. 117–125.
- Dai, X., Zhou, Y., Ma, W. and Zhou, L. (2017) ‘Influence of spatial variation in land-use patterns and topography on water quality of the rivers inflowing to Fuxian Lake, a large deep lake in the plateau of southwestern China’, *Ecological Engineering*. Elsevier B.V., 99, pp. 417–428.
- Deng, W., Wang, G. and Zhang, X. (2015) ‘A novel hybrid water quality time series prediction method based on cloud model and fuzzy forecasting’, *Chemometrics and Intelligent Laboratory Systems*. Elsevier B.V., 149, pp. 39–49.
- Diamantopoulou, M. J., Papamichail, D. M. and Antonopoulos, V. Z. (2005) ‘The use of a Neural Network technique for the prediction of water quality parameters’, *Operational Research*, 5(1), pp. 115–125.
- Ding, J., Jiang, Y., Liu, Q., Hou, Z., Liao, J., Fu, L. and Peng, Q. (2016) ‘Influences of the land use pattern on water quality in low-order streams of the Dongjiang River basin, China: A multi-scale analysis’, *Science of the Total Environment*. Elsevier B.V., 551–552(19), pp. 205–216.
- Dogan, E., Sengorur, B. and Koklu, R. (2009) ‘Modeling biological oxygen demand of the Melen River in Turkey using an artificial neural network technique’, *Journal of Environmental Management*, 90(2), pp. 1229–1235.
- Durán-Sánchez, A., Álvarez-García, J. and del Río-Rama, M. de la C. (2018) ‘Sustainable water resources management: A bibliometric overview’, *Water (Switzerland)*, 10(9), pp. 1–19.
- El-Khoury, A., Seidou, O., Lapen, D. R. L., Que, Z., Mohammadian, M., Sunohara, M. and Bahram, D. (2015) ‘Combined impacts of future climate and land use changes on discharge, nitrogen and phosphorus loads for a Canadian river basin’, *Journal of Environmental Management*. Elsevier Ltd, 151, pp. 76–86.
- Elkiran, G., Nourani, V., Abba, S. I. and Abdullahi, J. (2018) ‘Artificial intelligence-based approaches for multi-station modelling of dissolve oxygen in river’, *Global Journal of Environmental Science and Management*, 4(4), pp. 439–450.
- ENGINEERS, U.-U. A. C. O. F. (2010) ‘HEC-RAS River Analysis System. Hydraulic Reference Manual. Version 4.1’, *US Army Corps of Engineers Hydrologic Engineering Center, Davis, CA*.

- Fahmi, M., Nasir, M., Samsudin, M. S., Mohamad, I., Roshide, M., Awaluddin, A., Mansor, M. A., Juahir, H. and Ramli, N. (2011) 'River Water Quality Modeling Using Combined Principle Component Analysis (PCA) and Multiple Linear Regressions (MLR): A Case Study at Klang River , Malaysia Department of Environmental Sciences , Faculty of Environmental Studies , Department of Enviro', *World Applied Sciences Journal*, 14(2002), pp. 73–82.
- Fang, X., Zhang, J., Chen, Y. and Xu, X. (2008) 'QUAL2K model used in the water quality assessment of Qiantang River, China', *Water Environment Research*. Wiley Online Library, 80(11), pp. 2125–2133.
- Fijani, E., Barzegar, R., Deo, R., Tziritis, E. and Konstantinos, S. (2019) 'Design and implementation of a hybrid model based on two-layer decomposition method coupled with extreme learning machines to support real-time environmental monitoring of water quality parameters', *Science of the Total Environment*. Elsevier B.V., 648, pp. 839–853.
- Fonseca, A., Botelho, C., Boaventura, R. A. R. and Vilar, V. J. P. (2014) 'Integrated hydrological and water quality model for river management: A case study on Lena River', *Science of the Total Environment*. Elsevier B.V., 485–486(1), pp. 474–489.
- Gao, L. and Li, D. (2014) 'A review of hydrological/water-quality models', *Frontiers of Agricultural Science and Engineering*, pp. 267–276.
- Gazzaz, N. M., Yusoff, M. K., Aris, A. Z., Juahir, H. and Ramli, M. F. (2012) 'Artificial neural network modeling of the water quality index for Kinta River (Malaysia) using water quality variables as predictors', *Marine Pollution Bulletin*. Elsevier Ltd, 64(11), pp. 2409–2420.
- Gazzaz, N. M., Yusoff, M. K., Juahir, H., Ramli, M. F. and Aris, A. Z. (2013) 'Water Quality Assessment and Analysis of Spatial Patterns and Temporal Trends', *Water Environment Research*, 85(8), pp. 751–767.
- Gazzaz, N. M., Yusoff, M. K., Ramli, M. F., Aris, A. Z. and Juahir, H. (2012) 'Characterization of spatial patterns in river water quality using chemometric pattern recognition techniques', *Marine Pollution Bulletin*. Elsevier Ltd, 64(4), pp. 688–698.
- Ghose, D. K. and Samantaray, S. (2018) 'Modelling sediment concentration using back propagation neural network and regression coupled with genetic algorithm', *Procedia Computer Science*. Elsevier B.V., 125, pp. 85–92.

- Giridharan, L., Venugopal, T. and Jayaprakash, M. (2009) 'Assessment of water quality using chemometric tools: A case study of river coom, South India', *Archives of Environmental Contamination and Toxicology*, 56(4), pp. 654–669.
- Gitau, M. W., Chen, J. and Ma, Z. (2016) 'Water Quality Indices as Tools for Decision Making and Management', *Water Resources Management*, 30(8), pp. 2591–2610.
- Golabi, M. R., Farzi, S., Khodabakhshi, F., Sohrabi Geshnigani, F., Nazdane, F. and Radmanesh, F. (2020) 'Biochemical oxygen demand prediction: development of hybrid wavelet-random forest and M5 model tree approach using feature selection algorithms', *Environmental Science and Pollution Research*. *Environmental Science and Pollution Research*, 27(27), pp. 34322–34336.
- Grimsrud, G. P., Finnemore, E. J. and Owen, H. J. (1976) *Evaluation of water quality models: a management guide for planners*. US Environmental Protection Agency, Office of Research and Development.
- Grizzetti, B., Bouraoui, F., Granlund, K., Rekolainen, S. and Bidoglio, G. (2003) 'Modelling diffuse emission and retention of nutrients in the Vantaanjoki watershed (Finland) using the SWAT model', *Ecological Modelling*. Elsevier, 169(1), pp. 25–38.
- HACH (2020a) 'Chemical Oxygen Demand, Method 8000'.
- HACH (2020b) 'Nitrogen Ammonia Method 8038'.
- He, B., Oki, T., Sun, F., Komori, D., Kanae, S., Wang, Y., Kim, H. and Yamazaki, D. (2011) 'Estimating monthly total nitrogen concentration in streams by using artificial neural network', *Journal of Environmental Management*. Elsevier Ltd, 92(1), pp. 172–177.
- Hua, A. K. (2017) 'Identifying the source of pollutants in Malacca river using GIS approach', *Applied Ecology and Environmental Research*, 15(4), pp. 571–588.
- Huang, L., Bai, J., Xiao, R., Gao, H. and Liu, P. (2012) 'Spatial distribution of Fe, Cu, Mn in the surface water system and their effects on wetland vegetation in the Pearl River Estuary of China', *CLEAN–Soil, Air, Water*. Wiley Online Library, 40(10), pp. 1085–1092.
- Hurley, T., Sadiq, R. and Mazumder, A. (2012) 'Adaptation and evaluation of the Canadian Council of Ministers of the Environment Water Quality Index (CCME WQI) for use as an effective tool to characterize drinking source water

- quality', *Water Research*. Elsevier Ltd, 46(11), pp. 3544–3552.
- Jacobs, K., Lebel, L., Buizer, J., Addams, L., Matson, P., McCullough, E., Garden, P., Saliba, G. and Finan, T. (2016) 'Linking knowledge with action in the pursuit of sustainable water-resources management', *Proceedings of the National Academy of Sciences of the United States of America*, 113(17), pp. 4591–4596.
- Jahin, H. S., Abuzaid, A. S. and Abdellatif, A. D. (2020) 'Using multivariate analysis to develop irrigation water quality index for surface water in Kafr El-Sheikh Governorate, Egypt', *Environmental Technology and Innovation*. Elsevier B.V., 17, p. 100532.
- Jerves-Cobo, R., Lock, K., Van Butsel, J., Pauta, G., Cisneros, F., Nopens, I. and Goethals, P. L. M. (2018) 'Biological impact assessment of sewage outfalls in the urbanized area of the Cuenca River basin (Ecuador) in two different seasons', *Limnologica*. Elsevier, 71(December 2017), pp. 8–28.
- Ji, X., Shang, X., Dahlgren, R. A. and Zhang, M. (2017) 'Prediction of dissolved oxygen concentration in hypoxic river systems using support vector machine: a case study of Wen-Rui Tang River, China', *Environmental Science and Pollution Research*. Environmental Science and Pollution Research, 24(19), pp. 16062–16076.
- Jiang, D. yi, Wang, Y. yan, Liao, Q., Long, Z. and Zhou, S. yang (2020) 'Assessment of water quality and safety based on multi-statistical analyses of nutrients, biochemical indexes and heavy metals', *Journal of Central South University*, 27(4), pp. 1211–1223.
- Kaiser, H. F. (1974) *An index of factorial simplicity*, *Psychometrika*.
- Kalin, L., Isik, S., Schoonover, J. E. and Lockaby, B. G. (2010) 'Predicting Water Quality in Unmonitored Watersheds Using Artificial Neural Networks', *Journal of Environmental Quality*, 39(4), pp. 1429–1440.
- Kazi, T. G., Arain, M. B., Jamali, M. K., Jalbani, N., Afridi, H. I., Sarfraz, R. A., Baig, J. A. and Shah, A. Q. (2009) 'Assessment of water quality of polluted lake using multivariate statistical techniques: A case study', *Ecotoxicology and Environmental Safety*, 72(2), pp. 301–309.
- Keshtegar, B. and Heddami, S. (2018) 'Modeling daily dissolved oxygen concentration using modified response surface method and artificial neural network: a comparative study', *Neural Computing and Applications*. Springer London, 30(10), pp. 2995–3006.

- Khaled, B., Abdellah, A., Nouredine, D., Heddami, S. and Sabeha, A. (2018) 'Modelling of biochemical oxygen demand from limited water quality variable by anfis using two partition methods', *Water Quality Research Journal*, 53(1), pp. 24–40.
- Khalil, B., Ouarda, T. B. M. J. and St-Hilaire, A. (2011) 'Estimation of water quality characteristics at ungauged sites using artificial neural networks and canonical correlation analysis', *Journal of Hydrology*. Elsevier B.V., 405(3–4), pp. 277–287.
- Kim, S. E. and Seo, I. W. (2015) 'Artificial Neural Network ensemble modeling with conjunctive data clustering for water quality prediction in rivers', *Journal of Hydro-Environment Research*. Elsevier B.V., 9(3), pp. 325–339.
- Kisi, O. and Parmar, K. S. (2016) 'Application of least square support vector machine and multivariate adaptive regression spline models in long term prediction of river water pollution', *Journal of Hydrology*. Elsevier B.V., 534, pp. 104–112.
- Kornienko, A. A., Kornienko, A. V., Fofanov, O. B. and Chubik, M. P. (2015) 'Knowledge in Artificial Intelligence Systems: Searching the Strategies for Application', *Procedia - Social and Behavioral Sciences*. Elsevier B.V., 166, pp. 589–594.
- Kumar, D., Pandey, A., Sharma, N. and Flügel, W. A. (2016) 'Daily suspended sediment simulation using machine learning approach', *Catena*. Elsevier B.V., 138, pp. 77–90.
- Laghzal, A., Salmoun, F., Boudinar, B., Khaddor, M., Cherroud, S., Fihri, M. and Mammad, C. (2016) 'Evaluation of physico-chemical and bacteriological quality of water springs by using a principal component analysis (PCA): A case study of Tingitane Peninsula (Morocco)', *Journal of Materials and Environmental Science*, 7(2), pp. 456–462.
- Li, C., Li, Z., Wu, J., Zhu, L. and Yue, J. (2018) 'A hybrid model for dissolved oxygen prediction in aquaculture based on multi-scale features', *Information Processing in Agriculture*. China Agricultural University, 5(1), pp. 11–20.
- Liu, L. (2018) 'Application of a hydrodynamic and water quality model for inland surface water systems', *Applications in water systems management and modeling*, pp. 87–109.
- Liu, M. and Lu, J. (2014) 'Support vector machine—an alternative to artificial neuron network for water quality forecasting in an agricultural nonpoint source

- polluted river?', *Environmental Science and Pollution Research*, 21(18), pp. 11036–11053.
- Liu, Q. J., Shi, Z. H., Fang, N. F., Zhu, H. De and Ai, L. (2013) 'Modeling the daily suspended sediment concentration in a hyperconcentrated river on the Loess Plateau, China, using the Wavelet-ANN approach', *Geomorphology*. Elsevier B.V., 186, pp. 181–190.
- Loucks, D. P. and Beek, E. van (1981) *Water resource systems planning and analysis, Advances in Water Resources*.
- Lumb, A., Sharma, T. C. and Bibault, J.-F. (2011) 'A Review of Genesis and Evolution of Water Quality Index (WQI) and Some Future Directions', *Water Quality, Exposure and Health*, 3(1), pp. 11–24.
- Maneewan, C. and Van Roon, M. (2017) 'Challenges in implementing integrated catchment management and sustainable stormwater solutions in Bangkok, Thailand', *Water Practice and Technology*, 12(4), pp. 780–789.
- Metcalf and Eddy (2014) 'Metcalf and Eddy, AECOM - Wastewater Engineering_ Treatment and Resource Recovery (2014, McGraw-Hill).pdf'.
- Miller, J. D. and Hutchins, M. (2017) 'The impacts of urbanisation and climate change on urban flooding and urban water quality: A review of the evidence concerning the United Kingdom', *Journal of Hydrology: Regional Studies*, 12(July), pp. 345–362.
- Ministry of Environment and Water (2021) 'Environmental Sustainability in Malaysia 2020-2030', *Ministry of Environment and Water*, pp. 83–101.
- Mohd, N. and Bee, Y. (2011) 'Power comparisons of Shapiro-Wilk, Kolmogorov-Smirnov, Lilliefors and Anderson-Darling tests', *Journal of Statistical Modeling and Analytics*, 2(1), pp. 13–14.
- Najah, A., El-Shafie, A., Karim, O. A. and El-Shafie, A. H. (2013a) 'Application of artificial neural networks for water quality prediction', *Neural Computing and Applications*, 22(SUPPL.1), pp. 187–201.
- Najah, A., El-Shafie, A., Karim, O. A. and El-Shafie, A. H. (2013b) 'Application of artificial neural networks for water quality prediction', *Neural Computing and Applications*, 22(SUPPL.1), pp. 187–201.
- Najah, A., El-Shafie, A., Karim, O. A., Jaafar, O. and El-Shafie, A. H. (2011) 'An application of different artificial intelligences techniques for water quality prediction', *International Journal of Physical Sciences*, 6(22), pp. 5298–5308.

- Najar, I. A. and Khan, A. B. (2012) ‘Assessment of water quality and identification of pollution sources of three lakes in Kashmir, India, using multivariate analysis’, *Environmental Earth Sciences*, 66(8), pp. 2367–2378.
- Naubi, I., Zardari, N. H., Shirazi, S. M., Ibrahim, N. F. B. and Baloo, L. (2016) ‘Effectiveness of water quality index for monitoring Malaysian river water quality’, *Polish Journal of Environmental Studies*, 25(1), pp. 231–239.
- Noori, R., Berndtsson, R., Hosseinzadeh, M., Adamowski, J. F. and Abyaneh, M. R. (2019) ‘A critical review on the application of the National Sanitation Foundation Water Quality Index’, *Environmental Pollution*. Elsevier Ltd, 244, pp. 575–587.
- Noori, R., Karbassi, A., Ashrafi, K., Ardestani, M., Mehrdadi, N. and Bidhendi, G. R. N. (2012) ‘Active and online prediction of BOD 5 in river systems using reduced-order support vector machine’, *Environmental Earth Sciences*, 67(1), pp. 141–149.
- Noori, R., Sabahi, M. S., Karbassi, A. R., Baghvand, A. and Zadeh, H. T. (2010) ‘Multivariate statistical analysis of surface water quality based on correlations and variations in the data set’, *Desalination*. Elsevier B.V., 260(1–3), pp. 129–136.
- Nourani, V., Hosseini Baghanam, A., Adamowski, J. and Kisi, O. (2014a) ‘Applications of hybrid wavelet-Artificial Intelligence models in hydrology: A review’, *Journal of Hydrology*. Elsevier B.V., 514, pp. 358–377.
- Nourani, V., Hosseini Baghanam, A., Adamowski, J. and Kisi, O. (2014b) ‘Applications of hybrid wavelet-Artificial Intelligence models in hydrology: A review’, *Journal of Hydrology*, 514, pp. 358–377.
- Oehler, F., Rutherford, J. C. and Coco, G. (2010) ‘The use of machine learning algorithms to design a generalized simplified denitrification model’, *Biogeosciences*, 7(10), pp. 3311–3332.
- Oliveira, M. D. de, Rezende, O. L. T. de, Fonseca, J. F. R. de and Libânio, M. (2019) ‘Evaluating the surface Water quality index fuzzy and its influence on water treatment’, *Journal of Water Process Engineering*. Elsevier, 32(December 2018), p. 100890.
- Olowe, K. O. and Kumarasamy, M. vellaisamy (2018) ‘Assessment of some existing water quality models’, *Nature Environment and Pollution Technology*, 17(3), pp. 939–948.

- Olyaie, E., Zare Abyaneh, H. and Danandeh Mehr, A. (2017) 'A comparative analysis among computational intelligence techniques for dissolved oxygen prediction in Delaware River', *Geoscience Frontiers*. Elsevier Ltd, 8(3), pp. 517–527.
- Ömer Faruk, D. (2010a) 'A hybrid neural network and ARIMA model for water quality time series prediction', *Engineering Applications of Artificial Intelligence*, 23(4), pp. 586–594.
- Ömer Faruk, D. (2010b) 'A hybrid neural network and ARIMA model for water quality time series prediction', *Engineering Applications of Artificial Intelligence*, 23(4), pp. 586–594.
- Palácio, S. M., Espinoza-Quñones, F. R., de Pauli, A. R., Piana, P. A., Queiroz, C. B., Fabris, S. C., Fagundes-Klen, M. R. and Veit, M. T. (2016) 'Assessment of Anthropogenic Impacts on the Water Quality of Marreco River, Brazil, Based on Principal Component Analysis and Toxicological Assays', *Water, Air, and Soil Pollution*. *Water, Air, & Soil Pollution*, 227(9).
- Palani, S., Liong, S. Y. and Tkalich, P. (2008) 'An ANN application for water quality forecasting', *Marine Pollution Bulletin*, 56(9), pp. 1586–1597.
- Pullanikkatil, D., Palamuleni, L. and Ruhiiga, T. (2015) 'Impact of land use on water quality in the Likangala catchment, southern Malawi', *African Journal of Aquatic Science*, 40(3), pp. 277–286.
- Raheli, B., Aalami, M. T., El-Shafie, A., Ghorbani, M. A. and Deo, R. C. (2017) 'Uncertainty assessment of the multilayer perceptron (MLP) neural network model with implementation of the novel hybrid MLP-FFA method for prediction of biochemical oxygen demand and dissolved oxygen: a case study of Langat River', *Environmental Earth Sciences*. Springer Berlin Heidelberg, 76(14).
- Ranjith, S., Shivapur, A. V., Kumar, P. S. K., Hiremath, C. G. and Dhungana, S. (2019) 'Water Quality Model for Streams: A Review', *Journal of Environmental Protection*, 10(12), pp. 1612–1648.
- Ranković, V., Radulović, J., Radojević, I., Ostojić, A. and Čomić, L. (2010) 'Neural network modeling of dissolved oxygen in the Gruža reservoir, Serbia', *Ecological Modelling*, 221(8), pp. 1239–1244.
- Rode, M., Arhonditsis, G., Balin, D., Kebede, T., Krysanova, V., Van Griensven, A. and Van Der Zee, S. E. A. T. M. (2010) 'New challenges in integrated water quality modelling', *Hydrological Processes*. Wiley Online Library, 24(24), pp.

3447–3461.

- Ruggieri, N., Castellano, M., Capello, M., Maggi, S. and Povero, P. (2011) ‘Seasonal and spatial variability of water quality parameters in the Port of Genoa, Italy, from 2000 to 2007’, *Marine Pollution Bulletin*. Elsevier Ltd, 62(2), pp. 340–349.
- Sahoo, M. M., Patra, K. C. and Khatua, K. K. (2015) ‘Inference of Water Quality Index Using ANFIA and PCA’, *Aquatic Procedia*. Elsevier B.V., 4(Icwrcoe), pp. 1099–1106.
- Salami Shahid, E. and Ehteshami, M. (2016) ‘Application of artificial neural networks to estimating DO and salinity in San Joaquin River basin’, *Desalination and Water Treatment*, 57(11), pp. 4888–4897.
- Sarkar, A. and Pandey, P. (2015) ‘River Water Quality Modelling Using Artificial Neural Network Technique’, *Aquatic Procedia*. Elsevier B.V., 4(Icwrcoe), pp. 1070–1077.
- Sattari, M. T., Joudi, A. R. and Kusiak, A. (2016) ‘Estimation of water quality parameters with data-driven model’, *Journal - American Water Works Association*, 108(4), pp. E232–E239.
- Seanego, K. G. and Moyo, N. A. G. (2013) ‘The effect of sewage effluent on the physico-chemical and biological characteristics of the Sand River, Limpopo, South Africa’, *Physics and Chemistry of the Earth*. Elsevier Ltd, 66, pp. 75–82.
- Sengorur, B., Koklu, R. and Ates, A. (2015) ‘Water Quality Assessment Using Artificial Intelligence Techniques: SOM and ANN—A Case Study of Melen River Turkey’, *Water Quality, Exposure and Health*. Springer Netherlands, 7(4), pp. 469–490.
- Seo, I. W., Yun, S. H. and Choi, S. Y. (2016) ‘Forecasting Water Quality Parameters by ANN Model Using Pre-processing Technique at the Downstream of Cheongpyeong Dam’, *Procedia Engineering*. The Author(s), 154, pp. 1110–1115.
- Shen, Z., Hou, X., Li, W., Aini, G., Chen, L. and Gong, Y. (2015) ‘Impact of landscape pattern at multiple spatial scales on water quality: A case study in a typical urbanised watershed in China’, *Ecological Indicators*. Elsevier Ltd, 48, pp. 417–427.
- Shi, P., Zhang, Y., Li, Z., Li, P. and Xu, G. (2017) ‘Influence of land use and land

- cover patterns on seasonal water quality at multi-spatial scales', *Catena*. Elsevier B.V., 151, pp. 182–190.
- Shi, R., Zhao, J., Shi, W., Song, S. and Wang, C. (2020) 'Comprehensive assessment of water quality and pollution source apportionment in wuliangsu hai lake, inner mongolia, china', *International Journal of Environmental Research and Public Health*, 17(14), pp. 1–12.
- Sincock, A. M. and Lees, M. J. (2002) 'Extension of the QUASAR River-Water Quality Model to Unsteady Flow Conditions', *Water and Environment Journal*. Wiley Online Library, 16(1), pp. 12–17.
- Singh, K. P., Basant, A., Malik, A. and Jain, G. (2009) 'Artificial neural network modeling of the river water quality-A case study', *Ecological Modelling*, 220(6), pp. 888–895.
- de Souza Pereira, M. A., Cavalheri, P. S., de Oliveira, M. Â. C. and Magalhães Filho, F. J. C. (2019) 'A multivariate statistical approach to the integration of different land-uses, seasons, and water quality as water resources management tool', *Environmental Monitoring and Assessment*. Environmental Monitoring and Assessment, 191(9), pp. 538–356.
- Sugiyono (2012) *Metode Penelitian Kualitatif, Kuantitatif dan R & D*. Bandung, Indonesia: Alfabeta.
- Sun, W., Xia, C., Xu, M., Guo, J. and Sun, G. (2016) 'Application of modified water quality indices as indicators to assess the spatial and temporal trends of water quality in the Dongjiang River', *Ecological Indicators*. Elsevier Ltd, 66, pp. 306–312.
- Sutadian, A. D., Muttill, N., Yilmaz, A. G. and Perera, B. J. C. (2016) 'Development of river water quality indices—a review', *Environmental Monitoring and Assessment*, 188(1), pp. 1–29.
- Tariq, S. R., Shah, M. H., Shaheen, N., Jaffar, M. and Khalique, A. (2008) 'Statistical source identification of metals in groundwater exposed to industrial contamination', *Environmental Monitoring and Assessment*, 138(1–3), pp. 159–165.
- Telci, I. T., Nam, K., Guan, J. and Aral, M. M. (2009) 'Optimal water quality monitoring network design for river systems', *Journal of Environmental Management*. Elsevier Ltd, 90(10), pp. 2987–2998.
- Theoneste, S., Vincent, N. and Xavier, N. (2020) 'The Effluent Quality Discharged

- and Its Impacts on the Receiving Environment Case of Kacyiru Sewerage Treatment Plant, Kigali, Rwanda’, *International Journal of Environmental & Agriculture Research*, 6(2), pp. 20–29.
- Tian, Y., Jiang, Y., Liu, Q., Dong, M., Xu, D., Liu, Y. and Xu, X. (2019) ‘Using a water quality index to assess the water quality of the upper and middle streams of the Luanhe River, northern China’, *Science of the Total Environment*. Elsevier B.V., 667, pp. 142–151.
- Tikhmarine, Y., Souag-Gamane, D., Ahmed, A. N., Sammen, S. S., Kisi, O., Huang, Y. F. and El-Shafie, A. (2020) ‘Rainfall-runoff modelling using improved machine learning methods: Harris hawks optimizer vs. particle swarm optimization’, *Journal of Hydrology*. Elsevier, 589(June), p. 125133.
- Tiyasha, Tung, T. M. and Yaseen, Z. M. (2020) ‘A survey on river water quality modelling using artificial intelligence models: 2000–2020’, *Journal of Hydrology*. Elsevier B.V., 585, p. 124670.
- Tripathi, M. and Singal, S. K. (2019) ‘Use of Principal Component Analysis for parameter selection for development of a novel Water Quality Index: A case study of river Ganga India’, *Ecological Indicators*. Elsevier, 96(September 2018), pp. 430–436.
- Tyagi, S., Sharma, B., Singh, P. and Dobhal, R. (2020) ‘Water Quality Assessment in Terms of Water Quality Index’, *American Journal of Water Resources*, 1(3), pp. 34–38.
- Varol, M., Gökot, B., Bekleyen, A. and Şen, B. (2012) ‘Spatial and temporal variations in surface water quality of the dam reservoirs in the Tigris River basin, Turkey’, *Catena*, 92, pp. 11–21.
- Vega, M., Pardo, R., Barrado, E. and Debán, L. (1998) ‘Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis’, *Water Research*, 32(12), pp. 3581–3592.
- Venkateswarlu, T., Anmala, J. and Dharwa, M. (2020) ‘PCA, CCA, and ANN Modeling of Climate and Land-Use Effects on Stream Water Quality of Karst Watershed in Upper Green River, Kentucky’, *Journal of Hydrologic Engineering*, 25(6), p. 05020008.
- Vijay, R., Mardikar, T. and Kumar, R. (2016) ‘Impact of sewage discharges on coastal water quality of Mumbai, India: present and future scenarios’, *Environmental Monitoring and Assessment*. Environmental Monitoring and Assessment,

188(7).

- Wada, Y. and Bierkens, M. F. P. (2014) ‘Sustainability of global water use: Past reconstruction and future projections’, *Environmental Research Letters*. IOP Publishing, 9(10).
- Walsh, P. and Wheeler, W. (2012) *Water Quality Index Aggregation and Cost Benefit Analysis National Center for Environmental Economics Water Quality Index Aggregation and Cost Benefit Analysis*.
- Wang, L., Li, X. and Cui, W. (2012) ‘Fuzzy Neural Networks enhanced evaluation of wetland surface water quality’, *International Journal of Computer Applications in Technology*, 44(3), pp. 235–240.
- Wang, Q., Li, S., Jia, P., Qi, C. and Ding, F. (2013) ‘A review of surface water quality models’, *The Scientific World Journal*. Hindawi, 2013.
- Wang, Q., Zhao, X., Ding, F., Li, S. and Zhao, Y. (2009) ‘Numerical model of thermal discharge from Laibin power plant based on Mike21FM.’, *Research of Environmental Sciences*. China Environmental Science, 22(3), pp. 332–336.
- Wang, X., Cai, Q., Ye, L. and Qu, X. (2012) ‘Evaluation of spatial and temporal variation in stream water quality by multivariate statistical techniques: A case study of the Xiangxi River basin, China’, *Quaternary International*. Elsevier Ltd and INQUA, 282, pp. 137–144.
- Wang, X., Fu, L. and He, C. (2011) ‘Applying support vector regression to water quality modelling by remote sensing data’, *International Journal of Remote Sensing*, 32(23), pp. 8615–8627.
- Wen, X., Fang, J., Diao, M. and Zhang, C. (2013) ‘Artificial neural network modeling of dissolved oxygen in the Heihe River, Northwestern China’, *Environmental Monitoring and Assessment*, 185(5), pp. 4361–4371.
- Weng, T. K. and Mokhtar, M. Bin (2009) ‘An appropriate institutional framework towards integrated water resources management in Pahang River Basin, Malaysia’, *European Journal of Scientific Research*, 27(4), pp. 536–547.
- Wu, Z., Wang, X., Chen, Y., Cai, Y. and Deng, J. (2018) ‘Assessing river water quality using water quality index in Lake Taihu Basin, China’, *Science of the Total Environment*. Elsevier B.V., 612, pp. 914–922.
- Xiao, S., Hu, S., Zhang, Y., Zhao, X. and Pan, W. (2018) ‘Influence of sewage treatment plant effluent discharge into multipurpose river on its water quality: A quantitative health risk assessment of *Cryptosporidium* and *Giardia*’,

- Environmental Pollution*. Elsevier Ltd, 233, pp. 797–805.
- Xu, F., Dong, G., Wang, Q., Liu, L., Yu, W., Men, C. and Liu, R. (2016) ‘Impacts of DEM uncertainties on critical source areas identification for non-point source pollution control based on SWAT model’, *Journal of Hydrology*. Elsevier B.V., 540, pp. 355–367.
- Xu, L. and Liu, S. (2013) ‘Study of short-term water quality prediction model based on wavelet neural network’, *Mathematical and Computer Modelling*. Elsevier Ltd, 58(3–4), pp. 807–813.
- Yang, W., Zhao, Y., Wang, D., Wu, H., Lin, A. and He, L. (2020) ‘Using principal components analysis and idw interpolation to determine spatial and temporal changes of Surfacewater quality of Xin’Anjiang river in huangshan, china’, *International Journal of Environmental Research and Public Health*, 17(8), pp. 1–14.
- Zeinalzadeh, K. and Rezaei, E. (2017) ‘Determining spatial and temporal changes of surface water quality using principal component analysis’, *Journal of Hydrology: Regional Studies*. Elsevier, 13(July), pp. 1–10.
- Zhang, Y., Fitch, P., Vilas, M. P. and Thorburn, P. J. (2019) ‘Applying multi-layer artificial neural network and mutual information to the prediction of trends in dissolved Oxygen’, *Frontiers in Environmental Science*, 7(MAR), pp. 1–11.
- Zhao, J., Lin, L., Yang, K., Liu, Q. and Qian, G. (2015) ‘Influences of land use on water quality in a reticular river network area: A case study in Shanghai, China’, *Landscape and Urban Planning*. Elsevier B.V., 137, pp. 20–29.
- Zhao, Y., Nan, J., Cui, F. Y. and Guo, L. (2007) ‘Water quality forecast through application of BP neural network at Yuqiao reservoir’, *Journal of Zhejiang University: Science A*, 8(9), pp. 1482–1487.
- Zhao, Y. ping, Wu, R., Cui, J. li, Gan, S. chai, Pan, J. chuan and Guo, P. ran (2020) ‘Improvement of water quality in the Pearl River Estuary, China: a long-term (2008–2017) case study of temporal-spatial variation, source identification and ecological risk of heavy metals in surface water of Guangzhou’, *Environmental Science and Pollution Research*. Environmental Science and Pollution Research, 27(17), pp. 21084–21097.
- Zhao, Y., Song, Y., Cui, J., Gan, S., Yang, X. and Wu, R. (2019) ‘Assessment of Water Quality Evolution in the Pearl’, pp. 1–16.
- Zhao, Y., Xia, X. H., Yang, Z. F. and Wang, F. (2012) ‘Assessment of water quality

- in Baiyangdian Lake using multivariate statistical techniques’, *Procedia Environmental Sciences*, 13(2011), pp. 1213–1226.
- Zhou, F., Guo, H. cheng, Liu, Y. and Hao, Z. jia (2007) ‘Identification and spatial patterns of coastal water pollution sources based on GIS and chemometric approach’, *Journal of Environmental Sciences*, 19(7), pp. 805–810.
- Zhou, T., Wu, J. and Peng, S. (2012) ‘Assessing the effects of landscape pattern on river water quality at multiple scales: A case study of the Dongjiang River watershed, China’, *Ecological Indicators*. Elsevier Ltd, 23, pp. 166–175.
- Zhu, W., Niu, Q., Zhang, R., Ye, R., Qian, X. and Qian, Y. (2015) ‘Application of QUAL2K model to assess ecological purification technology for a polluted river’, *International Journal of Environmental Research and Public Health*, 12(2), pp. 2215–2229.
- Ziemińska-Stolarska, A. and Skrzypski, J. (2012) ‘Review of Mathematical Models of Water Quality’, *Ecological Chemistry and Engineering S*, 19(2), pp. 197–211.

LIST OF PUBLICATIONS

1. **Ariani Dwi Astuti**, Azmi Bin Aris, Mohd Razman Bin Salim, Shamila Binti Azman, Mohd Ismid Bin Md Said and Salmiati (2020). Artificial Intelligence Approach to Predicting River Water Quality: A Review. *Journal of Environmental Treatment Techniques*. 8, 1023-1100. **SCOPUS**.
2. **Ariani Dwi Astuti**, Azmi Bin Aris, Mohd Razman Bin Salim, Shamila Binti Azman, Mohd Ismid Bin Md Said and Salmiati (2019). A Mini Review: Artificial Intelligence Based Models for River Water Quality Prediction For River In Tropical Climate. *International Conference on Environmental Sustainability and Resource Security 2019*. 5th-6th November 2019, Kuala Lumpur. ISBN 978-967-17605-0-5, 21-27. **International Conference Proceeding**.
3. **Ariani Dwi Astuti**, Azmi Bin Aris, Mohd Ridza Mohd Haniffah, Mohd Razman Bin Salim, Shamila Binti Azman, and Salmiati (2022). The Power of Artificial Neural Network Approach: Water Quality Index Prediction Using In-situ Parameter in Skudai River, Malaysia. *Environmental Science: Water Research & Technology*. **(WOS Q1 Submitted)**.
4. **Ariani Dwi Astuti**, The Miracle of Artificial Intelligence: Water Quality Index Prediction Model in Skudai River using In-situ Parameters. in Graduate Research Exhibition (GREx 2021) Category Engineering, Research Carnival Week 2021. 16 June 2021, PGSS and SPS UTM. **(Poster Presentation Competition, Silver Medal Award)**
5. **Ariani Dwi Astuti**, The Power of Artificial Intelligence: Water Quality Index Prediction Model in Skudai River using In-situ Parameters. in 4th Research Canvas Competition 2021, 30 September 2021, UTM Library, UTM Alumni and Springer Nature Asia Pacific. **(Poster Presentation Competition, Third Prize)**