

DISTRIBUTED HYDROLOGICAL MODEL USING MACHINE LEARNING
ALGORITHM FOR ASSESSING CLIMATE CHANGE IMPACT

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DISTRIBUTED HYDROLOGICAL MODEL USING MACHINE LEARNING
ALGORITHM FOR ASSESSING CLIMATE CHANGE IMPACT

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ABSTRACT

Rapid population growth, economic development, land-use modifications, and climate change are the major driving forces of growing hydrological disasters like floods and water stress. Reliable flood modelling is challenging due to the spatio-temporal changes in precipitation intensity, duration and frequency, heterogeneity in temperature rise and land-use changes. Reliable high-resolution precipitation data and distributed hydrological model can solve the problem. This study aims to develop a distributed hydrological model using Machine Learning (ML) algorithms to simulate streamflow extremes from satellite-based high-resolution climate data. An integrated statistical index coupled with a classification optimisation algorithm was used to select coupled model intercomparison project (CMIP6) global climate model (GCMs). Several bias-correction methods were evaluated to identify the best method for downscaling GCM simulations. The study also evaluated the performance of different Satellite-Based Products (SBPs) in replicating observed rainfall to select the best product. A novel two-stage bias correction method were used to correct the bias of the selected SBP. Besides, four widely used bias correction methods were compared to select the best method for downscaling GCM simulations at SBP grid locations. A novel ML-based distributed hydrological model was developed for modelling runoff from the corrected satellite rainfall data. Finally, the model was used to project future changes in runoff, and streamflow extremes from the downscaled GCM projected climate. The Johor River Basin (JRB) located at the south of Peninsular Malaysia was considered as the case study area. The results showed that three GCMs, namely EC-Earth, EC-Earth-Veg and MRI-ESM-2, were the best in replicating the precipitation climatology in mainland Southeast Asia. IMERG was the best among five SBPs with an R^2 of 0.56 compared to SM2RAIN-ASCAT (0.15), GSMap (0.18), PERSIANN-CDR (0.14), PERSIANN-CSS (0.10) and CHIRPS (0.13). The two-step bias correction approach improved the performance of IMERG, which reduced the mean bias up to 140 % compared to the other conventional bias correction methods. The method also successfully simulates the historical high rainfall events that caused floods in Peninsular Malaysia. The distributed hydrological model developed using ML showed NSE values of 0.96 and 0.78 and RMSE of 4.01 and 5.64 during calibration and validation. The simulated flow analysis using the model showed that the river discharge would increase in the near future (2020 – 2059) and the far future (2060 – 2099) for different SSPs. The largest change in river discharge would be for SSP-585. The extreme rainfall indices, such as R95TOT, R99TOT, Rx1day, Rx5day and RI, were projected to increase from 5% for SSP-119 to 37% for SSP-585 in the future compared to the base period. The ML based distributed hydrological model developed using the novel two-step bias corrected SBP showed sufficient capability to simulate runoff from satellite rainfall. Application of the ML-based distributed model in JRB indicated that climate change and socio-economic development would cause an increase in the frequency streamflow extremes, causing larger flood events. The modelling framework developed in this study can be used for near-real time monitoring of flood through bias correction near-real time satellite rainfall.

ABSTRAK

Pertumbuhan penduduk yang pesat, pembangunan ekonomi, pengubahsuaian guna tanah, dan perubahan iklim adalah pendorong utama bencana hidrologi yang semakin meningkat seperti banjir dan tegasan air. Pemodelan banjir yang andal adalah mencabar kerana perubahan spatio-temporal dalam kelembatan hujan, tempoh masa dan frekuensi, heterogeniti dalam kenaikan suhu dan perubahan guna tanah. Data hujan resolusi tinggi yang andal dan model agihan hidrologi boleh menyelesaikan masalah. Kajian ini bertujuan untuk membangunkan model agihan hidrologi menggunakan algoritma Mesin Pembelajaran (ML) untuk mensimulasikan aliran air yang ekstrem daripada data iklim resolusi tinggi berasaskan satelit. Indeks statistik bersepadu yang digabungkan dengan algoritma pengoptimuman klasifikasi telah digunakan untuk memilih Model Iklim Umum (GCMs) Model Projek Antara-bandingan (CMIP6). Beberapa kaedah pembetulan-bias telah dinilai untuk mengenal pasti kaedah terbaik untuk mengunjurkan simulasi GCM. Kajian ini juga menilai prestasi Produk Berasaskan Satelit (SBP) yang berbeza dalam mereplikasi hujan yang diperhatikan untuk memilih produk yang terbaik. Kaedah nobel pembetulan-bias dua peringkat telah digunakan untuk membetulkan biasan SBP yang dipilih. Selain itu, empat kaedah pembetulan-bias yang digunakan secara meluas telah dibandingkan untuk memilih kaedah terbaik untuk mengunjurkan simulasi GCM di lokasi grid SBP. Model agihan hidrologi berasaskan ML telah dibangunkan untuk pemodelan aliran air daripada data hujan satelit yang diperbetulkan. Akhirnya, model tersebut digunakan untuk mengunjurkan perubahan aliran air pada masa hadapan, dan aliran air ekstrem daripada unjuran iklim GCM. Lembangan Sungai Johor (JRB) yang terletak di selatan Semenanjung Malaysia dipertimbangkan sebagai kawasan kajian kes. Keputusan menunjukkan bahawa tiga GCM, iaitu *EC-Earth*, *EC-Earth-Veg* dan *MRI-ESM-2*, adalah yang terbaik dalam mereplikasikan iklim hujan di tanah besar Asia Tenggara. IMERG adalah yang terbaik antara lima SBP dengan R^2 0.56 berbanding SM2RAIN-ASCAT (0.15), GSMap (0.18), PERSIANN-CDR (0.14), PERSIANN-CSS (0.10) dan CHIRPS (0.13). Pendekatan pembetulan-bias dua peringkat telah meningkatkan prestasi IMERG, dengan pengurangan pembiasan purata sehingga 140 % berbanding kaedah pembetulan-bias konvensional yang lain. Kaedah ini juga berjaya mensimulasikan peristiwa sejarah hujan lebat yang menyebabkan banjir di Semenanjung Malaysia. Model hidrologi teragih yang dibangunkan menggunakan ML menunjukkan nilai NSE 0.96 dan 0.78 dan RMSE 4.01 dan 5.64 semasa penentuan dan pengesahan. Analisis simulasi aliran air menggunakan model tersebut menunjukkan bahawa kadar alir air sungai akan meningkat dalam masa terdekat (2020 - 2059) dan masa depan (2060 - 2099) untuk SSP yang berbeza. Perubahan terbesar dalam kadar alir air sungai adalah untuk SSP-585. Indeks hujan ekstrem, seperti R95TOT, R99TOT, Rx1day, Rx5day dan RI, diunjurkan meningkat daripada 5% untuk SSP-119 kepada 37% untuk SSP-585 pada masa depan berbanding tempoh asas. Model agihan hidrologi berasaskan ML yang dibangunkan menggunakan SBP pembetulan-bias dua peringkat menunjukkan keupayaan yang mencukupi untuk mensimulasikan aliran air daripada hujan satelit. Aplikasi model agihan hidrologi berasaskan ML di JRB menunjukkan bahawa perubahan iklim dan pembangunan sosio-ekonomi akan menyebabkan peningkatan frekuensi aliran air yang ekstrem, menyebabkan kejadian banjir yang lebih besar. Rangka kerja pemodelan yang dibangunkan dalam kajian ini boleh digunakan untuk pemantauan banjir melalui pembetulan-bias hujan satelit hampir masa nyata.

TABLE OF CONTENTS

	TITLE	PAGE
	DECLARATION	iii
	DEDICATION	iv
	ACKNOWLEDGEMENT	v
	ABSTRACT	vi
	ABSTRAK	vii
	TABLE OF CONTENTS	viii
	LIST OF TABLES	xiii
	LIST OF FIGURES	xiv
	LIST OF ABBREVIATIONS	xviii
	LIST OF SYMBOLS	xx
	LIST OF APPENDICES	xxi
CHAPTER 1	INTRODUCTION	1
	1.1 Background of the Study	1
	1.2 Problem Statement	3
	1.3 Objectives of the Study	5
	1.4 Scope of the Study	6
	1.5 Significance of the Study	7
CHAPTER 2	LITERATURE REVIEW	9
	2.1 Introduction	9
	2.2 Climate Modeling	9
	2.2.1 Global Climate Model (GCM) in Climate Projections	10
	2.2.2 Shared Socioeconomic Pathways (SSPs)	10
	2.2.3 Selection of GCMs for Climate Change Projections	12
	2.2.4 GCM Selection based on Past Performance	12
	2.2.5 Envelope Approach	13
	2.2.6 Combine Method of GCM Selection	14

2.2.7	Downscaling of GCM Simulations	17
2.3	Remote Sensing Data	19
2.3.1	Uncertainties in Satellite Precipitation	20
2.3.2	Bias Correction of Satellite Precipitation Data	21
2.4	Hydrological Modelling	23
2.4.1	Empirical and Physically meaningful Models	24
2.4.2	Data-Driven Model	26
2.4.3	Classification of Hydrological Models	27
2.4.3.1	Stochastic Hydrological Models	28
2.4.3.2	Deterministic Hydrological Models	28
2.4.3.3	Process-based Hydrological Models	30
2.5	Climate Change Impacts on Floods	31
2.6	Flood Vulnerability and Risk	32
2.7	Flood in Peninsular Malaysia	33
2.8	Summary	35
CHAPTER 3	RESEARCH METHODOLOGY	37
3.1	Overview of Methodology	37
3.2	Study Area	38
3.2.1	Geography of MSEA	39
3.2.2	Climate of MSEA	39
3.2.3	Geography of Peninsular Malaysia	40
3.2.4	Climate of Peninsular Malaysia	41
3.2.5	Geography of Johor River Basin	42
3.2.6	Climate of Johor River Basin	43
3.3	Data and Sources	44
3.3.1	Observed River Flow and Precipitation Data	44
3.3.2	Remote Sensing Data	46
3.3.2.1	Integrated Multi-Satellite Retrievals for Global Precipitation Measurement (IMERG)	46
3.3.2.2	Global Satellite Mapping of Precipitation (GSMap)	47

3.3.2.3	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks (PERSIANN)	48
3.3.2.4	Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS)	48
3.3.2.5	Soil Moisture to Rainfall (SM2Rain)	48
3.3.2.6	Advanced Land Observing Satellite (ALOS) Phased Array type L-band Synthetic Aperture Radar (PALSAR) DEM	49
3.3.2.7	Soil Type data	50
3.3.3	ERA-5 Land	50
3.3.4	APHRODITE	50
3.3.5	GCM Data	51
3.4	Selection of General Circulation Models and Downscaling	53
3.4.1	Selection of GCMs	53
3.4.1.1	Goodman-Kruskal (GK) Lambda	55
3.4.1.2	Cramer's V	56
3.4.1.3	Map curves	56
3.4.1.4	Theil U	57
3.4.1.5	Compromise Programming (CP)	57
3.4.1.6	Jenks optimized classification (JOC)	58
3.4.2	Downscaling of GCMs	58
3.4.2.1	Gamma Quantile Mapping	59
3.4.2.2	Power Transformation	60
3.4.2.3	Generalized Quantile Mapping	61
3.4.2.4	Linear Scaling Method.	62
3.5	Bias Correction of Satellite Rainfall Data	63
3.5.1	Preparation of Remote Sensing Data	63
3.5.1.1	Bilinear Interpolation with Artificial Neural Network	63
3.5.2	Measuring SBP Data Performance	64

3.5.3	Development of Bias Correction Method	66
3.5.4	Random Forest	67
3.5.5	K-Nearest Neighbour	67
3.5.6	Artificial Neural Network	68
3.6	Hydrological Model Development	69
3.6.1	Concept of the distributed model	71
3.6.1.1	Excess saturation runoff rate	72
3.6.1.2	Subsurface runoff	73
3.6.1.3	Evapotranspiration	73
3.6.2	Flow accumulation and routing	74
3.7	Projections of Climate Change Impacts on Hydrological Extremes	75
3.8	Summary	77
CHAPTER 4	RESULTS	79
4.1	GCM Selection	79
4.1.1	Mean Monthly Rainfall Climatology	79
4.1.2	Spatial Indices	80
4.1.3	Ranking of GCMs	82
4.1.4	Selection of GCM subset	83
4.1.5	Bias in selected GCM Rainfall	84
4.1.6	Downscaling of GCMs	85
4.1.6.1	Downscaling of Precipitation	85
4.1.6.2	Downscaling of Maximum Temperature	91
4.1.6.3	Downscaling of Minimum Temperature	98
4.2	Bias Correction of Satellite Data	105
4.2.1	Evaluation of Satellite Data	105
4.2.2	Bias Correction	108
4.2.3	Performance of Classifiers	109
4.2.4	Performance of Regression Models	111
4.2.5	Comparison of Performance with the Conventional Model	112

4.2.6	Performance in Rainfall Amount Estimation	113
4.2.7	Performance in the Estimation of Spatial Distributions of Rainfall	114
4.2.8	Performance in Constructing Extreme Rainfall Events	116
4.3	Calibration and Validation of Hydrological Model	118
4.4	Hydrological Changes under Future Scenarios	121
4.4.1	Projected Rainfall Extremes	121
4.4.1.1	Total Rainfall above 95 th Percentile (R95pTOT)	122
4.4.1.2	Total Rainfall above 99 th Percentile (R99pTOT)	124
4.4.1.3	Changes in One day Max Rainfall (Rx1day)	126
4.4.1.4	Changes in 5-day max rainfall (Rx5day)	128
4.4.1.5	Changes in Rainfall intensity (RI)	130
4.4.2	Changes in River Flow	132
4.5	Discussion	135
4.5.1	GCM Selection	135
4.5.2	Bias correction of IMERG	137
4.5.3	Calibration and Validation of the Distributed Hydrological Model	140
4.5.4	Changes in Precipitation and Flood Frequency under Future Scenario	141
CHAPTER 5	CONCLUSION	143
5.1	Selection of GCM	143
5.2	Bias Correction of Satellite Data	143
5.3	Distributed Hydrological Model	144
5.4	Changes in River Flow under SSP Scenarios	144
5.5	Future Recommendations	145
	REFERENCES	147
	APPENDICES	171
	LIST OF PUBLICATIONS	186

LIST OF TABLES

TABLE NO.	TITLE	PAGE
Table 2.1	Description of shared Socioeconomic Pathways (SSPs) (O'Neill et al., 2016b)	11
Table 2.2	Review of GCM selection methods.	15
Table 3.1	Description of river flow data	45
Table 3.2	CMIP6 GCMs evaluated in the study	51
Table 3.3	Description of the spatial indices used for the assessment of GCM performance	54
Table 3.4	The contingency table for calculation of categorical matrices	65
Table 3.5	The joint distribution of the categorical matrices output	65
Table 3.6	WMO hydrological extreme indices used in this study.	77
Table 4.1	The ranking of GCMs based on different spatial indices and Compromise Programming	82
Table 4.2	Classification of GCMs based on compromise programming index using Jenks optimization algorithm	84
Table 4.3	Performances of the model during the calibration and validation periods	120

LIST OF FIGURES

FIGURE NO.	TITLE	PAGE
Figure 2.1	Classification of hydrological models	27
Figure 3.1	The overview of the research methodology	38
Figure 3.2	The mainland Southeast Asia (MSEA) in the southern Asia map is used to select GCMs.	40
Figure 3.3	Location of study area showing the rainfall stations. Red circles show the observed stations used for calibration while the purple triangle shows the stations used for validation	42
Figure 3.4	The Johor River Basin used to develop the hydrological model.	43
Figure 3.5	Peninsular Malaysia shows the rainfall stations. red circles show the observed stations used for calibration, while the purple triangle shows the stations used for validation.	45
Figure 3.6	Geographical location of river and rainfall gauges in JRB	46
Figure 3.7	Distribution of the study area into grids and bucket hydrological cycle, modified from Pagano and Sorooshian (2002).	70
Figure 3.8	Bucket model for a single grid. Modified figure from Kumar et al. (2017).	72
Figure 3.9	Flow routing model used to determine flow path	75
Figure 3.10	Framework to analyse the impact of climate change on hydrological extremes	76
Figure 4.1	Mean monthly rainfall (1975–2014) of APHRODITE and GCMs	80
Figure 4.2	Spatial indices values of GCMs	81
Figure 4.3	Pbias in annual mean rainfall of the selected GCMs: (a) MRI-ESM2-0; (b) EC-Earth3: and (c) EC-Earth-Veg	85
Figure 4.4	Index of agreement for the downscaled models as compared to the GCM	86
Figure 4.5	NRMSE % plot for the downscaling models	87
Figure 4.6	Pbias in downscaled GCM data	88

Figure 4.7	Boxplot shows bias correction methods' performance to improve the Skill Scores.	89
Figure 4.8	Taylor diagram showing the performance of bias correction methods to correct EC-Earth for(a) calibration period and (b) validation period	90
Figure 4.9	Taylor diagram showing the performance of bias correction methods to correct EC-Earth-Veg for (a) calibration period and (b) validation period	90
Figure 4.10	Taylor diagram showing the performance of bias correction methods to correct MRI-ESM2 for (a) calibration Period and (b) validation Period	91
Figure 4.11	Index of Agreement in downscaled maximum temperature data.	93
Figure 4.12	Performance of downscaling models in terms of NRMSE %.	94
Figure 4.13	Performance of downscaling models in terms of Pbias	95
Figure 4.14	Performance of downscaling models in terms of skill score	96
Figure 4.15	Taylor diagram showing the performance of bias correction methods to correct EC-Earth during (a) calibration period (b) validation period	97
Figure 4.16	Taylor diagram showing the performance of bias correction methods to correct EC-Earth-Veg during (a) calibration period and (b) validation period	97
Figure 4.17	Taylor diagram showing the performance of bias correction methods to correct MRI-ESM2 during (a) calibration period and (b) validation period	98
Figure 4.18	Index of Agreement in downscaled minimum temperature.	100
Figure 4.19	Performance of downscaling models in terms of NRMSE % for minimum temperature.	101
Figure 4.20	Pbias in downscaled GCM minimum temperature.	102
Figure 4.21	Performance of downscaling models in terms of skill score in downscaling minimum temperature.	103
Figure 4.22	Taylor diagram showing the performance of bias correction methods to downscale EC-Earth minimum temperature during (a) calibration period and (b) validation period	104
Figure 4.23	Taylor diagram showing the performance of bias correction methods to downscale EC-Earth-Veg minimum	

	temperature during (a) calibration period and (b) validation period	104
Figure 4.24	Taylor diagram showing the performance of bias correction methods to downscale MRI-ESM2 minimum temperature for (a) calibration period and (b) validation period	105
Figure 4.25	Annual average rainfall estimated using (a) observed (b) IMERG (c) SM2RAIN-ASCAT (d) GMap (e) PERSIANN-CDR (f) PERSIANN-CSS and (g) CHIRPS.	106
Figure 4.26	Boxplot showing the relative performance of IMERG and SM2RAIN-ASCAT in term of (1) Mean Square Error; (2) percentage of bias; (3) coefficient of determination; and (4) Kling–Gupta efficiency.	107
Figure 4.27	Probability density function for observed, IMERG, SM2RAIN-ASCAT, CHIRPS, PERSIANN-CDS, PERSIANN-CSS and GMap.	108
Figure 4.28	Comparison of IMERG rainfall with KNN and RF corrected data in estimation of rainfall events (a) Hit Rate (b) Heidke Skill Score (c) Gerrity Skill Score (d) Bias and (e) Pierce Skill Score.	110
Figure 4.29	Performance of regression algorithms in the correction of IMERG rainfall amount on rainy	111
Figure 4.30	Comparison of newly developed bias-correction method with conventional methods in correcting bias in IMERG rainfall	112
Figure 4.31	Spatial comparison of the raw and corrected IMERG	114
Figure 4.32	Spatial distribution of annual, Northeast monsoon and Southwest monsoon (a) observed, and (b) bias-corrected IMERG rainfall	115
Figure 4.33	Performance of IMERG and bias-corrected IMERG in reconstructing heavy rainfall event on December 09, 2007.	117
Figure 4.34	Performance of IMERG and bias-corrected IMERG in reconstructing heavy rainfall event on December 18, 2014.	118
Figure 4.35	Observed and modelled river flow during calibration and validation period of 2007 – 2017.	119
Figure 4.36	Seasonal variation in mean monthly rainfall	121
Figure 4.37	Change in annual total rainfall above 95 percentile in near future	123
Figure 4.38	Change in annual total rainfall above 95 percentile in far future	124

Figure 4.39	Change in annual total rainfall above 99 percentile in near future	125
Figure 4.40	Change in annual total rainfall above 99 percentile in far future	126
Figure 4.41	Change in one-day max rainfall in near future	127
Figure 4.42	Change in one-day max rainfall in far future	128
Figure 4.43	Change in five-day max rainfall in near future	129
Figure 4.44	Change in five-day max rainfall in far future	130
Figure 4.45	Change in rainfall intensity in near future	131
Figure 4.46	Change in rainfall intensity in far future	132
Figure 4.47	Changes in simulated flow for GCM EC-Earth	133
Figure 4.48	Changes in simulated flow for GCM EC-Earth-Veg	134
Figure 4.49	Changes in simulated flow for GCM MRI-ESM2	134

LIST OF ABBREVIATIONS

GHG	-	Green House Gases
UTM	-	Universiti Teknologi Malaysia
XML	-	Extensible Markup Language
ANN	-	Artificial Neural Network
GA	-	Genetic Algorithm
ML		Machine Learning
SVR		Support Vector Regression
GCM		Global Climate Model
CMIP		Coupled Model Intercomparison Project
RCP		Radiative Concentration Pathways.
SSP		Shared Socioeconomic Pathway
MSEA		Mainland South-East Asia
SBP		Satellite-Based Precipitation
DEM		Digital Elevation Model
RF		Random Forest
JRB		Johor River Basin
IPCC		Intergovernmental Panel on Climate Change
PCMDI		Program for Climate Model Diagnosis & Intercomparison
RMSE		Root Mean Square Error
SU		Symmetrical Uncertainty
MCDM		Multi-Criteria Decision Making
NSE		Nash-Sutcliffe efficiency
PCA		Principle Component Analysis
MEP		Maximum Entropy Production
SD		Statistical Downscaling
MOS		Model Output Statistics
SVM		Support Vector Machine
SS		Skill Score
RS		Remote Sensing
PMW		Passive Micro Waves

VIR	Visible Infrared
AMW	Active Micro Waves
TRMM	Tropical Rainfall Measuring Mission
GPM	Global Precipitation Measurement
IMERG	Integrated Multi-Satellite Retrievals for Global Precipitation Measurement
SWM	Southwest Monsoon
NEM	Northeast Monsoon
WMO	World Meteorological Organization
CHIRPS	Climate Hazards Group InfraRed Precipitation with Station
PERSIANN	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks
SMOS	Soil Moisture and Ocean Salinity,
ESM	Earth System Model (ESM)
AOGCM	Atmosphere-Ocean General Circulation Model
GammaQM	Gamma Quantile Mapping
PowerTr	Power Transformation
GenQM	Generalized Quantile Mapping
LS	Linear Scaling
HR	Hit Rate
HSS	Heidke Skill Score
GSS	Gerrity Skill Score
HB	Hit Bias
PSS	Pierce Skill Score
RI	Rainfall Intensity
R95pTOT	Total Rainfall above 95 th Percentile
R99pTOT	Total Rainfall above 99 th Percentile
Rx1day	One day Max Rainfall
Rx5day	Five day Max Rainfall

LIST OF SYMBOLS

%	-	Percentage
>	-	Greater than
<	-	Less than
mm	-	Millimetre
km	-	Kilo Meter

LIST OF APPENDICES

APPENDIX	TITLE	PAGE
Appendix A	Rainfall Extremes	171

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Hydrological disasters like floods and water stress have become a common phenomenon in many countries globally. Flood in a catchment is triggered when precipitation becomes more than the storage and drainage capacity of the catchment (Konrad, 2003). On the other hand, the water stress of a catchment depends on water balance, measured as the difference between water supply and water demand (European Commission and Environment, 2015). Due to rapid population growth, economic development, land-use modifications and climate change, many catchments globally become highly prone to hydrological disasters like floods and water stress (Dai et al., 2017). Consequently, a moderate dry spell often forces water rationing and moderate or extreme rainfall causing floods, especially in rapidly developing urban catchments (Pereira et al., 2009). The changing pattern of hydrological disasters due to environmental changes is a major concern for scientists and policy-makers all over the globe.

The increase in atmospheric greenhouse gases (GHG) caused a significant rise in global temperature (Shahid et al., 2017). The changes in precipitation patterns, including intensity, duration, and frequency, have been recorded with the rise in temperature over the last few decades, resulting in frequent hydrological extremes (Ziarh et al., 2021). Water is the most important resource for the survival of living beings (UNIDO, 2003). Almost 80% of the world's population lives under different forms of water scarcity (UNEP, 2005). Increasing hydrological disasters may cause a quick depletion of the available water resources (Iqbal et al., 2019). The water management system needs to be advanced with better management policy to attain sustainable development and management of water resources to adapt to climate

change (Ahmad and Simonovic, 2000). This needs reliable information on climate change projections and implications in catchment hydrological processes.

However, the projection of water-related hazards in a catchment is very intricate due to the complex relationship of climate and land use with various ecological and socio-economic factors, including population growth, economic development, urbanization as well as policy-related factors, like water management strategies and legislation (Guo et al., 2001). Therefore, it is always challenging to reciprocate the actual hydrological conditions using hydrological models (Sood, 2009). A hydrological model requires a lot of observed data and optimising different parameters (Minville et al., 2014). The data availability or mismatch of any data leads to errors in simulation (Bárdossy and Singh, 2008). Therefore, the major challenge is finding the relationship among the water cycle components that affect a system in various dimensions. Successful simulation of a hydrological cycle using a dynamic approach can address hydrological modelling challenges.

Rainfall-runoff models simulate the relationships between rainfall and the runoff generated in a catchment (Sitterson et al., 2018). Various methods and techniques have been developed to simplify this complex relationship, ranging from a simple mathematical model to a complex “black box” and physical models (Young, 2002). According to the methods used to develop the relationship between rainfall and runoff, the models are categorised as empirical, conceptual, and physical (Devia et al., 2015). They are also categorized as lumped, semi-distributed and distributed models based on their ability to consider the spatial variability of catchment properties. Devia et al. (2015) conducted a comparative study to compare various rainfall-runoff models. The study revealed that the empirical models require fewer input data but are limited to a certain region or a boundary, whereas the conceptual models are parametric. The parameters are catchment dependent, thus, needs large hydrological and meteorological data (Perrin et al., 2001). The physical-based model establishes the rainfall-runoff relationship based on the governing physical laws (Agrawal and Desmukh, 2016). These models are most accurate but suffer from scale-related issues and require extensive data (Devia et al., 2015). Therefore, they are considered the most complex rainfall-runoff models. The uncertainties associated with extensive data and

the parameters used to develop models are specific to the region, making these models more time consuming and site-specific.

In recent years, soft computing or machine learning (ML) methods, such as Artificial Neural Network (ANN), Support Vector Regression (SVR), and Fuzzy Logic and Genetic Algorithm (GA), have been employed to develop rainfall-runoff models (Dawson and Wilby, 2001, Johari et al., 2011, Özger, 2011). However, these approaches cannot completely manage the dynamics of hydrological processes because of the inherent limitations in the approaches (Wang et al., 2011). Potential challenges also arise as these methods require long-term, continuous historical records of hydrological and other variables (Qin et al., 2011, Tidwell et al., 2004). Furthermore, many of these approaches simplify the multi-factors and often make the nonlinear systems linear, reducing the simulation accuracy (Ropero et al., 2016a). The hybridization of ML and conventional physical or conceptual model can improve the capability to model complex interactions. Such an approach also can replicate the functional relationship between input and output by enhancing the original methodologies by data processing, parameter estimation and routing using machine learning algorithms (Chandwani et al., 2015). The application of such complex problem-solving methodologies in hydrology and water resources can help to provide a technique for reliable simulation of hydrological disasters, particularly water scarcity and floods, due to the changes in land use driven by physical and socio-economic factors and climate. Incorporating quantitative information on complex interactions of runoff with land use and climate can enhance the model's accuracy in simulating hydrological disasters (Koch et al., 2018).

1.2 Problem Statement

Climate is the major driver of the water balance and hydrological extremes. Global climate models (GCM) are generally used for generating knowledge of possible changes in water resources due to climate change. Coupled model intercomparison project (CMIP) phase 5 GCMs have been used globally to generate projection for different radiative concentration pathways (RCPs). The major drawback of RCPs is

not considering the land use and socio-economic changes in the climate projection. Recently released CMIP6 GCMs projections are driven by land use and emission scenarios, leading to new social and economic development pathways, the Shared Socioeconomic Pathway (SSP) (Riahi et al., 2017). Several studies showed higher consistency, lower uncertainty and better reliability in CMIP6 model projections than CMIP5 models. This urges the update of the existing RCP-based knowledge to SSPs. However, all CMIP6 GCMs are not equally capable of reliable climate projection in all regions. Therefore, selecting an appropriate set of GCM remained a major challenge for studying impact assessment and changes in climate variables at local and regional scales. However, the major problem in GCM selection is the uncertainties associated with the selection procedure. This emphasizes the need for a new robust selection method for GCM selection to reduce uncertainties in climate change projections (Iqbal et al., 2021).

Reliable modelling of hydrology and water resources needs accurate high-resolution rainfall data (Tegegne et al., 2017). However, high-resolution dependable quality data is absent in most regions of the world (Valeriano et al., 2009, Nikolopoulos et al., 2013, Harris et al., 2007). Satellite rainfall data can be an alternative for such data-scarce regions. However, large and complex biases are the major obstacle for using satellite rainfall data in hydrological studies. Several attempts have been made to remove or reduce biases in satellite rainfall data before using them for hydrological studies (Soo et al., 2019, Semire et al., 2012, Tan et al., 2015b). However, the biases are often highly nonlinear in space and time and cannot be removed using the existing bias-correction methods. This indicates the need for improvement of the existing bias-correction techniques.

Spatial heterogeneity of climate variables has a significant impact on the hydrological behaviour of the catchment. The distributed hydrological model can simulate runoff considering catchment spatial heterogeneity. However, calibration and validation of the distributed hydrological model are time-consuming and complex (Vojinovic and Seyoum, 2008). They also need a large amount of data for several hydrological variables (Mitchell and Diaper, 2005, Hardy, 2005). The performance of the distributed model is often very poor, even if all the data requirements and

complexities are considered. ML-based models have shown their efficiency in complex non-linear processes and reliable rainfall-runoff simulations. However, ML-based hydrological models are not developed to cater for the spatial variability in the catchment characteristics and atmospheric variables, so they use the whole catchment as a single unit (Jiang et al., 2018). The ML-based distributed hydrological model is a recently evolved research topic, where catchment spatial heterogeneity is integrated into the ML modelling process. Thus, it uses ML and distributed hydrological models to provide reliable runoff estimates from rainfall. Several attempts have been made to implement distributed ML model but have not been successfully implemented (Konapala et al., 2020, Schmidt et al., 2020). There is a need to advance the effort in this regard.

The influence of land use and climate changes in the hydrology of an area is important to quantify for devising adaptation planning (Zhang et al., 2016, Shahid et al., 2017). Deficiencies in data are the major obstacle to such analysis in many regions. The reliable flood forecasting in real-time and projections due to climate change need high-resolution satellite rainfall and downscaled high-resolution GCM rainfall as input in a hydrological model developed through the integration of ML with the physical-based model. However, the complexity of incorporating distributed hydrology concept in ML algorithms is a major challenge. A framework is still lacking in this regard.

1.3 Objectives of the Study

The main objective of this study is to develop a machine learning-based distributed hydrological model for runoff simulation using remote sensing data and future flood projections using global climate model data. The specific objectives of the study are;

- (a) To evaluate the performance of CMIP6 GCMs, to select suitable subset and downscale rainfall for different shared socioeconomic pathways scenarios.

- (b) To develop a novel two-step model for correcting bias in satellite rainfall to generate high-resolution near-real-time rainfall data.
- (c) To develop a machine learning-based distributed hydrological model to simulate the impacts of land use and rainfall changes on surface runoff
- (d) To project the changes in surface runoff in different future periods for different shared socioeconomic pathways.

1.4 Scope of the Study

The GCMs of CMIP6 that have projections for four SSPs (SSP-119, SSP-245, SSP-375 and SSP-585) were considered in the study. For the selection of GCM, Mainland South-East Asia (MSEA) was considered. The best gauge-based gridded data set suggested in existing literature was used for GCM downscaling. The four SSPs were used to study the effect of upcoming economic and demographic changes on water resources for informing stakeholders and aid climate change mitigation.

The Satellite-Based Precipitation (SBP) products, having data availability for 2007-2017, were used to assess their performance. Only the available gauge data in Peninsular Malaysia was used for bias correction. The highest resolution Digital Elevation Model (DEM) and soil type data that are freely available were used.

ML algorithms, Random Forest (RF), was only considered to develop ML-based distributed hydrological model owing to its ability to handle the large, noisy dataset. The physically-based bucket model concept was considered to develop the ML-based distributed model. The model was used to estimate the runoff at only one gauge station located on Johor River Basin (JRB).

The future projection of the best GCM was used to study the effect of climate change on the hydrological extremes of the region. The four SSPs were considered to analyse the different possible changes in the future hydrology of the region catchment.

The considered hydrological extremes were limited to quantiles of river flow and few precipitation extremes only.

1.5 Significance of the Study

The novelty of this research is the development of a spatially distributed hydrological model based on an ML algorithm. The model is developed with the latest data set along with the most suitable empirical relationship between the hydrological variables.

Selecting a suitable set of GCMs from CMIP6 using spatial indices is another significant contribution of this study. The model selected in this study can be employed in hydrometeorological studies in the whole MSEA region.

Data availability is the major constraint of the modelling process. Recent satellite-based data sets have been used to predict hydrology in this study. A novel two-step bias correction method is proposed for correcting satellite rainfall data. The concept can be used in any other region for correcting bias in satellite rainfall.

The integrated modelling framework developed in this study can be used to assess the climate change effects on runoff and, therefore, water resource planning in the region. The maps and information generated in this study can be used to educate the people about the effect of the action of human beings and its consequences on long term climatic conditions affecting their economy and living.

1.6 Thesis Outline

The thesis is divided into five chapters. Descriptions of the chapters are given below in brief.

Chapter 1 gives a general introduction comprising the background of the study, problem statement, objectives of the study, scope of the work, and significance of the study.

Chapter 2 reviews relevant literature from previous studies on GCM selection, climate downscaling and projection, hydrological modelling, satellite rainfall bias correction, and climate change projections.

Chapter 3 presents the methods used in the study. The chapter describes the data and sources, methods employed for selecting GCM, Statistical Downscaling (SD) and climate projection, the procedure developed for the bias correction of satellite data and the steps used to develop the hydrological model.

Chapter 4 presents the results of the studies. Various statistical and spatial maps are presented in this chapter to show the results. Besides, a discussion section is also provided to analyse the results critically.

Chapter 5 provides the conclusions drawn from the results presented in Chapter 4. It also provides recommendations for future works to advance the knowledge generated in this study.

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LIST OF PUBLICATIONS

Journal with Impact factor

1. **Iqbal, Z.**, Shahid, S., Ismail, T., Sa'adi, Z., Farooque, A. & Yaseen, Z. M. 2022. Distributed Hydrological Model Based on Machine Learning Algorithm: Assessment of Climate Change Impact on Floods. *Sustainability*, 14, 6620. **(Q2)**
2. **Iqbal, Z.**, Shahid, S., Ahmed, K., Ismail, T., Ziarh, G. F., Chung, E.-S. & Wang, X. 2021. Evaluation of CMIP6 GCM rainfall in mainland Southeast Asia. *Atmospheric Research*, 254, 105525. **(Q1, I.F 4.14)**
3. **Iqbal, Z.**, Shahid, S., Ahmed, K., Ismail, T., Khan, N., Virk, Z. T. & Johar, W. 2020. Evaluation of global climate models for precipitation projection in sub-Himalaya region of Pakistan. *Atmospheric Research*, 245, 105061. **(Q1, I.F 4.14)**
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5. Noor, M., Ismail, T. B., Ullah, S., **Iqbal, Z.**, Nawaz, N. & Ahmed, K. 2019. A non-local model output statistics approach for the downscaling of CMIP5 GCMs for the projection of rainfall in Peninsular Malaysia. *Journal of Water and Climate Change*. **(Q2, I.F.0.96)**
6. Ahmed, K., **Iqbal, Z.**, Khan, N., Rasheed, B., Nawaz, N., Malik, I. & Noor, M. 2019. Quantitative assessment of precipitation changes under CMIP5 RCP scenarios over the northern sub-Himalayan region of Pakistan. *Environment, Development and Sustainability*, 1-15. **(Q2, I.F 1.676)**

7. Ahmed, K., Sachindra, D. A., Shahid, S., **Iqbal, Z.**, Nawaz, N. & Khan, N. 2020. Multi-model ensemble predictions of precipitation and temperature using machine learning algorithms. Atmospheric Research, 236, 104806. (**Q1, I.F 4.14**)