STOCHASTIC DYNAMIC PROGRAMMING AND MACHINE LEARNING UNDER CLIMATE CHANGE FOR RESERVOIR AND IRRIGATION OPERATIONS

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

Faculty of Civil Engineering
Universiti Teknologi Malaysia

FEBRUARY 2023

DEDICATION

This thesis is dedicated to:

My beloved parents for their endless love, encouragement, and wish for their son to achieve the higher dream;

My siblings, who are always by my side when needed;

My dear wife, Nurseha, who has always played a significant role during the journey of study;

My daughter, Husna Zahra who, endured hardships all the years without her father quality time; and

My Supervisor, Prof. Dr. Sobri who, has been a source of inspiration to me throughout my study.

ACKNOWLEDGEMENT

All praises and thanks to Allah SWT, the Giver of bountiful blessings and gifts, for granting my prayer to achieve this extraordinary success and giving me the opportunity, strength, and wisdom to accomplish this great work of Doctor of Philosophy (Ph.D.) in Irrigation and Water Resources Engineering. Completion of this research work would not have been possible without the enthusiasm, encouragement, and help I received from various parties and supporters. It has been a challenging three-year journey but enlightening one with abundant beneficial knowledge.

I would like to express my sincere gratitude and regards to my main supervisor, Professor Dr. Sobri Harun, for his guidance, support, ideas, and suggestions throughout my research journey. His patience with me makes my research life more exciting, meaningful, and less painful. I consider myself fortunate to have him as my guide, as he always gives constructive comments on my research work. I am also equally grateful to my co-supervisor, Associate Professor Dr. Zaitul Marlizawati Zainuddin. Without her extraordinary help as an experienced researcher in mathematical sciences background, I would not have been able to accomplish the task.

Heartfelt thanks are extended to the Universiti Putra Malaysia and the Ministry of Higher Education for financial support through Young Academic Schemes. Sincere appreciation is poured to the Department of Irrigation and Drainage (DID), Malaysian Meteorological Department (MMD), and DID Kerian, Bagan Serai, Perak, for providing the necessary data. I am also grateful to Associate Professor Ts. Dr. Rowshon Md. Kamal from Universiti Putra Malaysia for his efforts in giving me training about Global Climate Models (GCMs) and MATLAB Programming. I also would like to thank all the School of Civil Engineering staff, Universiti Teknologi Malaysia (UTM), for their hospitability and cooperation whenever required throughout my Ph.D. study.

It would not have been easy for me to achieve this great work without the support from my wife, Nurseha Ramly, and my daughter, Husna Zahra Muhammad Adib, through their love and sacrifice over numerous days. Sincere gratitude goes to my father, Mohd Nasir A. Wahab, my mother, Norzana Baba, and my mother-in-law Hadijah Janal for their love, affection, encouragement, and prayers for my success. Also not forgotten my siblings, Nuradilah Mohd Nasir and Muhammad Syafiq Mohd Nasir, for always being there to cheer me up when needed. This achievement and success have no meaning without them.

Finally, many thanks to my thesis examiners, Datin Professor Ir. Dr. Lariyah Mohd Sidek from Universiti Tenaga Nasional (UNITEN) and Professor Ir. Ts. Dr. Mohd Fadhil Md. Din from UTM for having examined my thesis thoroughly, chapter by chapter. The constructive comments given based on their extensive experience have helped me improve the quality of this thesis.

ABSTRACT

Anthropogenic climate change potentially causes water shortages over different spatial and temporal scales. Over the coming decades, the impact of climate change would be tangible, with significant increases in the global mean temperature, changes in the frequency and intensity of precipitation, and rising sea levels. These changes will adversely affect the water resource system due to the increased severity of floods, droughts, timing and amount of runoff and evaporation. The reservoir systems require continuous development and revision for optimal operations to deal with the variability of future climate change. Therefore, this study attempted to develop optimal reservoir operation under the new realities of climate change in a tropical agro-hydrological watershed in Perak, Malaysia. Reservoir inflow variability due to climate change affects hydrological processes and irrigation demands at a basin scale. Meta-learning, an ensemble machine learning technique using support vector regression (SVR) and random forest (RF) coupled with the Coupled Model Intercomparison Project Phase 6 (CMIP6) multi-Global Climate Model (multi-GCM), was applied to investigate the impacts of climate change on Kurau River. Five GCMs (CanESM5, MPI-ESM1-2-LR, MRI-ESM2-0, NESM3, and NorESM2-LM) and three shared socioeconomic pathways (SSP1-2.6, SSP2-4.5, and SSP5-8.5) were used. The climate sequences generated by the delta change factor method were applied as input to the meta-learning model to predict the streamflow (reservoir inflow) changes from 2021-2080. The model fitted reasonably well, with Kling–Gupta efficiency (KGE), Nash-Sutcliffe efficiency (NSE), percent bias (PBias), and Root Mean Square Error (RMSE) of 0.79, 0.83, 2.52, and 4.51, respectively, for the training period (1976-1995) and 0.72, 0.72, 5.85, and 6.90, respectively, for the testing period (1995-2005). Future projections of multi-GCM over the 2021-2080 under three SSPs predicted an increase in rainfall for all months except April-June (dry period or off-season), with a higher increase during the wet period (main-season). Temperature projections indicated an increase in maximum and minimum temperatures under all SSPs, with a higher increase of approximately 2.0°C under SSP5-8.5 during 2051-2080 relative to the baseline period of 1976-2005. The model predicted seasonal changes in the inflow by -7.5 to 7.1% and 1.2 to 5.9% during the off-season and the main-season, respectively. A significant inflow decrease was predicted in April and May for all SSPs due to high temperatures during the off-season, with SSP5-8.5 being the worst. The future rice irrigation demand changes for the Kerian Irrigation Scheme compared to the baseline period for two planting periods by -1.0 to 0.1% and -5.3 to -2.6% during the off-season and main-season, respectively. A significant irrigation water demand decrease is predicted in September and October for all SSPs due to increased rainfall during the main-season, with SSP5-8.5 being the most prominent. The stochastic dynamic programming is applied to determine the optimal release policies for Bukit Merah Reservoir considering future climate variability (15 combinations of different GCMs and SSPs for two future periods). The rule curve patterns varied under different scenarios and future periods. The patterns revealed that the reservoir will suffer from tremendous water stress in the far future (2051-2080) than in the near future (2021-2050) and significantly during the off-season.

ABSTRAK

Perubahan iklim antropogenik berpotensi mengakibatkan kekurangan air pada skala ruang dan masa yang berbeza. Pada masa hadapan, kesan perubahan iklim akan semakin ketara dengan peningkatan ketara purata suhu global, perubahan kekerapan dan keamatan hujan serta peningkatan paras laut. Perubahan ini memberi kesan buruk kepada sistem sumber air disebabkan peningkatan banjir, kemarau, masa dan jumlah air larian, dan kadar sejatan. Sistem takungan memerlukan pembangunan dan semakan berterusan untuk operasi optimum bagi menangani ketidaktentuan perubahan iklim. Oleh itu, kajian ini cuba membangunkan operasi takungan optimum dengan strategi penyesuaian di bawah realiti baharu perubahan iklim di kawasan tadahan air agro-hidrologi tropika di Perak, Malaysia. Kebolehubahan aliran masuk takungan akibat perubahan iklim menjejaskan proses hidrologi dan permintaan pengairan pada skala lembangan. Meta-pembelajaran, satu gabungan teknik pembelajaran mesin di antara sokongan regresi vektor (SVR) dan hutan rawak (RF) digandingkan bersama Projek Perbandingan Model Berganding CMIP6 gabungan-Model Iklim Global (GCM), telah digunakan untuk menyiasat kesan perubahan iklim terhadap Sungai Kurau. Lima GCM (CanESM5, MPI-ESM1-2-LR, MRI-ESM2-0, NESM3, dan NorESM2-LM) dan tiga laluan sosioekonomi bersama (SSP1-2.6, SSP2-4.5, dan SSP5-8.5) telah digunakan. Urutan iklim yang dijana oleh kaedah faktor perubahan delta digunakan sebagai input kepada model meta-pembelajaran bagi meramalkan perubahan aliran masuk takungan dari 2021-2080. Model ini meramal dengan baik, dengan kecekapan Kling-Gupta (KGE), kecekapan Nash-Sutcliffe (NSE), peratusan bias (PBias), dan Ralat Purata Kuasa Dua Akar (RMSE) 0.79, 0.83, 2.52, dan 4.51, masing-masing untuk fasa latihan (1976-1995) dan 0.72, 0.72, 5.85, dan 6.90, masing-masing untuk fasa ujian (1995–2005). Unjuran masa hadapan bagi tempoh 2021-2080 di bawah semua SSP meramalkan peningkatan hujan sepanjang tahun kecuali April-Jun (tempoh kering atau musim-luar), dengan peningkatan yang ketara semasa tempoh basah (musim-utama). Unjuran suhu meramalkan peningkatan terhadap suhu maksimum dan minimum di bawah semua SSP, dengan peningkatan yang tertinggi 2.0°C di bawah SSP5-8.5 semasa tempoh 2051-2080 berbanding tempoh garis dasar 1976-2005. Model tersebut meramalkan perubahan bermusim dalam aliran masuk masing-masing sebanyak -7.5 hingga 7.1% dan antara 1.2 hingga 5.9% semasa musim-luar dan musim-utama. Penurunan aliran masuk yang ketara diramalkan pada bulan April dan Mei untuk semua SSP disebabkan oleh suhu tinggi semasa musim-luar, dengan SSP5-8.5 adalah yang terburuk. Perubahan permintaan pengairan padi masa hadapan bagi Skim Pengairan Kerian berbanding tempoh garis dasar untuk dua tempoh penanaman masing-masing sebanyak -1.0 hingga 0.1% dan -5.3 hingga -2.6% pada musim-luar dan musim-utama. Penurunan permintaan air pengairan yang ketara diramalkan pada bulan September dan Oktober untuk semua SSP disebabkan peningkatan hujan semasa musim-utama, dengan SSP5-8.5 paling menonjol. Pengaturcaraan dinamik stokastik digunakan untuk menentukan dasar pelepasan optimum untuk Takungan Bukit Merah dengan mengambil kira ketidaktentuan iklim masa hadapan (15 kombinasi GCM dan SSP untuk dua tempoh masa hadapan). Corak lengkung operasi berbeza di bawah scenario SSP dan tempoh masa hadapan yang berbeza. Corak tersebut mendedahkan bahawa takungan untuk tempoh 2051-2080 akan mengalami tekanan air yang luar biasa berbanding tempoh 2021-2050 dan lebih ketara semasa di musim-luar.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

LIST OF ABBREVIATIONS

AI	-	Artificial Intelligence
ANN	-	Artificial Neural Network
ANN-ELM	-	Artificial Neural Network-Extreme Machine Learning
ANN-KNN	-	Hybrid of ANN and KNN
AR	-	Autoregressive
AR4	-	Assessment Report Four
AR5	-	Fifth Assessment Report
ARIMA	-	Autoregressive Integrated Moving Average
ARMA	-	Autoregressive Moving Average
BPNN	-	Back-Propagation Neural Network
BSDP	-	Bayesian Stochastic Dynamic Programming
CART	-	Classification Regression Trees
CCLP	-	Chance Constrained Linear Programming
CI	-	Computational Intelligence
CMIP	-	Coupled Model Intercomparison Project
CMIP5	-	Coupled Model Intercomparison Project Phase 5
CMIP6	-	Coupled Model Intercomparison Project Phase 6
CNN	-	Cascade Correlation Neural Network
CO_2	-	Carbon Dioxide
CRCM	-	Canadian Regional Climate Model
CSA	-	Climate-smart Agriculture
DAE	-	Deep Auto-Encoder
DAE-MLR	-	Hybrid Of DAE and MLR
DAE-SVR	-	Hybrid of DAE and SVR
DDDP	-	Discrete Differential Dynamic Programming
DID	-	Drainage and Irrigation Department
DP	-	Dynamic Programming
DPSA	-	Dynamic Programming and Successive Approximation
DSS	-	Decision Support System
DT	-	Decision Tree

EC	-	Evolutionary Computation
ECHAM	-	European Centre-Hamburg
ELM	-	Extreme Learning Machine
ENR	-	Elastic Net Regression
ESP	-	Ensemble Streamflow Prediction
FAO	-	Food and Agriculture Organization
FAR	-	First Assessment Report
FOASVR	-	Hybrid of SVR and Fruit Fly Optimization Algorithm
GA	-	Genetic Algorithm
GBDT	-	Gradient Boosting Decision Tree
GCM	-	General Circulation Model / Global Climate Model
GHG	-	Greenhouse Gases
GMDH	-	Group Method of Data Handling
GPR	-	Gaussian Process Regression
GRNN	-	General Regression Neural Network
HadRM3	-	Hadley Centre's Regional Model Version 3
HIRHAM	-	Combination HIRLAM and ECHAM
HIRLAM	-	High Resolution Limited Area Model
IADA	-	Integrated Agricultural Development Area
IADP	-	Intensive Agricultural Development Programme
IDP	-	Increment Dynamic Programming
IPCC	-	Intergovernmental Panel on Climate Change
IR 4.0	-	Industrial Revolution 4.0
ISA	-	Irrigation Services Area
KADA	-	Kemubu Agriculture Development Authority
KGE	-	Kling-Gupta Efficiency
KNN	-	K-Nearest Neighbor
LAM	-	Limited Area Model
LARS-WG	-	Long Ashton Research Station Weather Generator
LM	-	Linear Model
LP	-	Linear Programming
LR	-	Linear Regression
LSTM	-	Long Short-term Memory

LSTM-PB	-	Hybrid of LSTM and PB
M5Tree	-	M5 Model Tree
MA	-	Moving Average
MADA	-	Muda Agricultural Development Authority
MLP	-	Multilayer Perceptron
MLR	-	Multiple Linear Regression
MMD	-	Malaysian Meteorological Department
MSES	-	Modified Stacking Ensemble Strategy
NHMM	-	Nonhomogeneous Hidden Markov Model
NLP	-	Non-Linear Programming
NN	-	Neural Network
NSE	-	Nash-Sutcliffe Efficiency
NWS	-	National Weather Service’s
PB	-	Process-based
PBias	-	Percent Bias
PCA	-	Principle Component Analysis
PCA-MLR	-	Hybrid of PCA and MLR
PCA-SVR	-	Hybrid of PCA and SVR
RACMO	-	Dutch Regional Atmospheric Climate Model
RBF	-	Radial Basis Function
RCM	-	Regional Climate Model
RCP	-	Representative Concentration Pathway
RegCM3	-	Regional Climate Model Version 3
REMO	-	German Regional Climate Model
RF	-	Random Forest
RF-MLR	-	Hybrid of RF and MLR
RF-SVR	-	Hybrid of RF and SVR
RMSE	-	Root Mean Squared Error
SAR	-	Second Assessment Report
SDP	-	Stochastic Dynamic Programming
SDSM	-	Statistical Downscaling Model
SLP	-	Stochastic Linear Programming
SRES	-	Special Report on Emission Scenarios

SSDP	-	Sampling Stochastic Dynamic Programming
SSP	-	Shared Socioeconomic Pathway
STL	-	Seasonal-Trend Decomposition Procedure Based on Loses
SVC	-	Support Vector Classification
SVM	-	Support Vector Machine
SVR	-	Support Vector Regression
SWAT	-	Soil and Water Assessment Tool
TAR	-	Third Assessment Report
TEM	-	Theoretical Estimation Method
TSBSDP	-	Two-Stage Bayesian Stochastic Dynamic Programming
TTBSDP	-	Two-Stage and Two-Period Bayesian SDP
WEKA	-	Waikato Environment for Knowledge Analysis
XGB	-	Extreme Gradient Boosting

LIST OF SYMBOLS

p	-	Order of Autoregression
d	-	Degree of Differencing
q	-	Order of Moving Average
$V_{d,m}^{scen}$	-	Scenario Daily Variable
$V_{d,m}^{obs}$	-	Observed Daily Climate Variables
$P_{d,m}^{obs}$	-	Observed Daily Rainfall
$V_{m}^{GCMscen}$	-	Mean Monthly GCM Climate Variables
$P_{m}^{GCMscen}$	-	Mean Monthly GCM Rainfall
V_{m}^{GCMcon}	-	Mean Monthly GCM Climate Variables for the Control Period
P_{m}^{GCMcon}	-	Mean Monthly GCM Rainfall for the Control Period
P_{dw}	-	Probability of Wet Day Proceeded by Dry Day
P_{ww}	-	Probability of Wet Day Proceeded by Wet Day
P_{s}	-	Rainfall Occurrence
U_{t}	-	Random Number
P_{c}	-	Critical Transition Probability
P_{dd}	-	Probabilities for Dry Day Following Dry Day
P_{wd}	-	Probabilities for Dry Day Following Wet Day
N_{dd}	-	Number of Dry Days Followed by Dry Days
N_{dw}	-	Number of Rain Days Followed by Dry Days
N_{wd}	-	Number of Dry Days Followed by Rain Days
N_{ww}	-	Number of Rain Days Followed by Rain Days
N_{d}	-	Number of Total Dry Day
N_{w}	-	Number of Total Rain Days
P_{ij}	-	Transition Probabilities
$f(x)$	-	Probability Density Function of the Gamma Distribution
α	-	Shape Parameter
β	-	Scale Parameter
$\Gamma(\alpha)$	-	Gamma Function
R^{FUT}	-	Statistical Property of Observed Rainfall

R^{OBS}	-	Statistical Property of Future Rainfall Scenarios
$R^{GCM.FUT}$	-	Statistical Property of GCM Generated for Future Scenarios
$R^{GCM.CTS}$	-	Statistical Property of GCM Generated for Baseline
ε	-	Insensitive Loss Function
w, b	-	Coefficient of the Weight Vector
x	-	Input Vector
$\emptyset(x)$	-	Feature Space Vector
C	-	Penalty Parameter
ξ_i, ξ_i^*	-	Slack Variables
$K(x, x_i)$	-	Kernel Function
$\alpha_i,\ \alpha_i^*$	-	Lagrange Multipliers
B	-	Bias
μ	-	Bandwidth of Kernel Function
θ	-	Distributed Random Variables
$h(x, \theta)$	-	Decision Tree
N	-	Number of Regression Trees
y	-	Average Probabilities Voting
P	-	Probability
r	-	Correlation Coefficient
σ^{obs}	-	Standard Deviation of Observed Flow
σ^{ML}	-	Standard Deviation of Generated Flow
Q_i^{obs}	-	Observed Flow
Q_i^{ML}	-	Generated Flow
$\overline{Q^{obs}}$	-	Mean of Observed Flow
$\overline{Q^{ML}}$	-	Mean of Generated Flow
n	-	Total Number of Flow Observations
WD	-	Water Depth
WD_{max}	-	Maximum Water Depth
WD_{min}	-	Minimum Water Depth
IR	-	Irrigation Supply
ER	-	Effective Rainfall
ET	-	Evapotranspiration
DR	-	Drainage

RF	-	Rainfall
ET_o	-	Reference Evapotranspiration
R_n	-	Net Radiation
G	-	Soil Heat Flux Density
T	-	Air Temperature
u_2	-	Wind Speed
$e_s\text{-}e_a$	-	Saturation Vapor Pressure Deficit
Δ	-	Slope Vapor Pressure Curve
γ	-	Psychrometric Constant
R_s	-	Solar Radiation
k_{Rs}	-	Adjustment Coefficient for Solar Radiation
$\mathrm{T_{max}}$	-	Mean Monthly Maximum Air Temperature
T_{min}	-	Mean Monthly Minimum Air Temperature
R_a	-	Extraterrestrial Radiation
ET_c	-	Crop Evapotranspiration
K_c	-	Crop Coefficient
P_{SAT}	-	Water Requirement during Pre-saturation
IR_{LS}	-	Water Requirement to Saturate the Soil
EP_S	-	Evaporation Loss from Saturated Soil Surface
SP	-	Seepage and Percolation Loss
IE	-	Irrigation Efficiency
k	-	Irrigation Service Area (ISA) Number
RP	-	Ponding Water Depth
K	-	Evaporation Coefficient
Q	-	Inflow
R_{kilt}	-	Reservoir Release
E	-	Evaporation
S_{kt}	-	Initial Reservoir Storage Capacity
$S_{l\ t+1}$	-	Final Reservoir Storage Capacity
B_{kilt}	-	Reservoir System Performance Measure
D_T	-	Target Demand
Rl_v	-	Volumetric reliability
R_{opt}	-	Optimum Release Volume from the Reservoir

D_{irr}	-	Rice Irrigation Water Demand Volume
Rl_p	-	Periodic Reliability
n_f	-	Total Number of Time Periods Meeting Irrigation Demand
N	-	Total Number of Time Periods
Rs	-	Resilience
N_m	-	Total Number of Times Reservoir Release Meets Irrigation Demand follows Water Shortage
N_s	-	Total Number of Time Periods Suffered from Water Shortage
V	-	Vulnerability
m	-	Deficit Events for Reservoir Release
M	-	Total Number of Deficit Events for Reservoir Release

LIST OF APPENDICES

CHAPTER 1

INTRODUCTION

1.1 Background

Water is an essential natural resource and a fundamental need for the survival of every living thing on earth. All economic sectors need water, where productions are impossible without it, especially agriculture, industry, and energy (cooling in power plants). In recent years, struggling for water to satisfy the daily requirements of the endless burgeoning population, increasing demands of agriculture and industry, and the worsening impacts of climate change have reached extreme threats to the point of the physical scarcity of resources (Dolan et al., 2021; Kummu et al., 2016). According to global-scale water scarcity projection studies by United Nations World Water Development Report, over 4 billion of the population worldwide is likely to face tremendous water stress and scarcity by 2050 (Boretti & Rosa, 2019). Climate change is expected to alter weather patterns, disrupting water availability, rising sea levels, worsening soil conditions and crop diseases, and significantly increasing greenhouse gas emissions (Mikhaylov et al., 2020).

Irrigation systems are vital for economic advancement, food security enhancement, and poverty alleviation. Nevertheless, existing irrigation management systems are criticized for low efficiency and poor performance, causing massive water losses that lead to severe water shortages. Food and Agriculture Organization (FAO) of the United Nations stressed that the agricultural sector remains the leading consumer of water in the world for irrigation supply, contributing to approximately three-quarters of total water withdrawals (FAO, 2010). Crop cultivation acutely relies on plant roots absorbing water from the soil and conveying it to the leaves to restore water losses caused by the transpiration of the photosynthesis process. Unfortunately, agriculture is often hampered due to randomness, uncertainty, and insufficient rainfall, consequently requiring proper irrigation systems to secure food security. The agricultural sectors will encounter the great challenge of increasing future food demands with limited water resources. The situation is exacerbated when a massive amount of water is also decisively desired for environmental concerns, including aquatic life, wildlife refuges, forestry, riparian habitats, recreation, and inland navigation. Furthermore, Tripathi et al., 2018 reported that agricultural yield production needs to be enhanced by 70% in conjunction with the global population boost by 2025.

Rice is the daily staple food and a rich source of carbohydrates and protein for over half the population globally, with more than 90% of the rice in the world being produced and consumed in Asia (Fukagawa & Ziska, 2019). In Malaysia, the scenario shows that rice production is not possible to accommodate the rapid increase in the population (Munusam et al., 2017). In order to meet the demand, approximately half a billion Ringgit Malaysia has been allocated annually to import rice from abroad (Sarwar & Khanif, 2005). According to Alam et al. (2010), Malaysia has approximately 300,000 rice farmers covering more than 322,000 hectares of rice granaries under the irrigation scheme. Rice cultivation in Malaysia is implemented twice a year under irrigation schemes during the off-season (first season) and main-season (second season), also known as double cropping practice. Water is the main driving factor for rice production, with irrigation and drainage facilities being the keys for rice-growing areas (Akinbile et al., 2011). Rice cultivation systems in Malaysia consume a massive volume of freshwater, and the irrigation requirement water depth is around 100 to 150 cm (Amin et al., 2011).

Despite the fact that Malaysia is bestowed with an average annual rainfall of 2500 mm to 3000 mm with copious water resources that potentially cause floods, climate change coupled with rising population, industrialization and urbanization acceleration, and pollution would cause the opposite impacts (Hamidon et al., 2015; Rashid et al., 2021). The concept of drought resilience and water security has gained attention due to ever-increasing water demand. Zhang et al. (2021) reported that the world is experiencing a global water crisis due to the worsening water scarcity aggravated by increased population and economic activities, and inefficient water resource management. Cook & Bakker (2012) stated that water security is an integrative approach to highlight good governance issues by promising realistic approaches to water management suitable for the current scenario. Heat and drought are prominent for impacting the growth and productivity of crops by declining and varying crop yields and quality (Fahad et al., 2017). Due to climate change, changes in rainfall and evaporation are thought to augment irrigation requirements globally (Konapala et al., 2020). Many studies related to agricultural water demand emphasized that climate change would alter global and regional water allocation for irrigation (Calzadilla et al., 2013; Chaturvedi et al., 2015; Guo & Shen, 2016; Iglesias & Garrote, 2015; Malhi et al., 2021; Rowshon et al., 2019). Sufficient irrigation water availability can be guaranteed by using appropriate techniques and models to estimate future irrigation requirements based on future climate trends. The future irrigation water requirements under appropriate irrigation management systems potentially maximize production and minimize the adverse impact on the environment (Hamidon et al., 2015; Taghvaeian et al., 2020). Good irrigation management practices will apply water at the right time with the right quantity to ensure sustainable water availability.

Climate change has crept into every continent of the world by disrupting national economies and lives, costing people, communities, and countries (IPCC, 2013). Many studies have revealed that the phenomena would alter future climate conditions, in which extreme drought and severe flood events would turn erratic and more frequent. Agriculture is sensitive to climatic conditions such as variations in rainfall, average temperature, solar radiation, and atmospheric carbon dioxide concentration (Mulla et al., 2020; Raza et al., 2019). Large-scale rice cultivation, which requires massive amounts of water, would be very vulnerable to water stress caused by heat waves under global warming. Hydrologic processes are highly at-risk due to the impact of climate forcing in the Southeast Asia regions, of which Malaysia is a branch of the continent (Tan et al., 2019). Global warming would increase by at least more than 50%, which exceeds 1.5 °C although under the lowest greenhouse gas emission scenario, impacting the evapotranspiration rates and causing high demand for irrigation supplies, exacerbated by the changes in rainfall pattern, intensity, and frequency of extreme events during the northeast monsoon and rainfall intensity during the southwest monsoon. (IPCC, 2022). Therefore, adaptation strategies for water resource systems at the basin scale against climate risks have become essential. Integrated hydrological assessment with water availability, resilience, and risk under current and future climate scenarios, potentially enhancing water resource availability and delivery and inspiring in modeling water resource scenarios.

In Malaysia, rice cultivation has the highest volume of annual irrigation water releases to fulfill the demand for eight granary schemes (210500 ha), mini-granary (29500 ha), and non-granary schemes (100633 ha) (Toriman & Mokhtar, 2012); unfortunately, due to low efficiency, and poor management and performance, it has been criticized for causing too much water wastage (Akinbile et al., 2011). These issues are strongly linked with uncertainty in water resource management, exacerbated by the impacts of climate change. Moreover, continuous measurement of river flow discharge is problematic to execute, expensive, and time-consuming. Therefore, improving the water allocation and delivery through predictions and simulations of river water flow changes within a catchment by incorporating the uncertainty in available water resources and crop irrigation requirements is urged, as has been done by Adnan et al. (2021), Bayesteh & Azari (2021), Khosravi et al. (2021) and Jia et al. (2022). Notwithstanding, the imbalance often occurs between the irrigation demand in the irrigation scheme and the water supply from the basin, resulting in either water wastage during low demand or water shortage during high demand (Ismail et al., 2020). Therefore the role of the reservoir or dam has become crucial to meet the water demand as it is the pillar in the management of water resources of a river basin.

The International Commission on Large Dams (ICOLD) recorded that a single reservoir (dam) built in the world acts to store and supply water for agricultural irrigation (48%), hydropower generation (20%), industrial and domestic consumption (13%), flood mitigation (9%), recreation (5%), and navigation (5%) (Lee et al., 2018). Additionally, about 17% of the remaining dams are built to execute multi-objectives to fulfill the demand for more than two of these purposes. Water supply from reservoirs is the primary key contributing to the sustainability of life through satisfying water demand in each sector, especially agriculture (rice). Reservoirs play an essential role in storing available water surplus obtained during the wet period for use during low water availability during the dry period to ensure sustainable and uniform crop production. Due to the increasing demand for future food, the expansion of irrigated agricultural land is essential, urging further reservoir construction (Nüsser & Baghel, 2017); however, mismanagement and climate change would potentially harm the environment and its utility for human purposes (Guo et al., 2021). Downstream hydrologic infrastructure and its operation are vulnerable to an increase in the frequency of extreme weather and changes in reservoir inflow patterns triggered by climate change (Ehsani et al., 2017). The performance of reservoir systems usually relies upon the operational decisions related to storage, release, and demand volumes (Chadwick et al., 2021). Water resource management which covers the water availability from the basin and reservoir, irrigation demand, and climatic parameters, needs to be thoroughly studied to project best practices to balance future irrigation supply and demand for the scheme. Accordingly, a quantitative assessment of various water management elements needs to be integrated under temporal and spatial variations of the climate change scenarios. The optimization solution for reservoir operation can be achieved by establishing a set of optimal release decisions for consecutive periods to maximize water management objectives (Dobson et al., 2019).

1.2 Problem Statement

Rice cultivation is a crop that requires a sufficient volume of water to ensure healthy and uniform growth. Despite that, rainfall is characterized by inconsistent distribution and volatile intensity, consequently leading to significant problems affecting crop productivity and yields under unideal water depth on the field (Firdaus et al., 2020). Supplemental and full irrigation is needed during the off-season and main-season to ensure growth and maximize rice yields. Many tropical regions depend on the reservoir as a reliable source of water supply to fulfill rice water demand and for a sustainable environment through irrigation structures (Nam et al., 2015). Bukit Merah Reservoir is the primary water source for the large-scale rice granary of the Kerian Irrigation Scheme. The rice scheme is one of the eight main granaries in Malaysia, contributing to approximately 24000 hectares of net rice area (Karim et al., 2004; Vaghefi et al., 2016). Water coming from Kurau River Basin is stored and released from the reservoir according to the decision of the operator. Reservoir inflows mainly depend on the fluctuations of stream discharges from river basins, the driving factor for sustainable rice production, which varies significantly during the dry and wet periods compounded by the influence of global climate change. The impact of climate change significantly alters the hydrological processes, directly threatening rice production, which is related to food security in Malaysia (Firdaus et al., 2020). The rising global temperature and change in rainfall patterns likewise affect crop evapotranspiration, irrigation demand, and shrinking rice yield (Houma et al., 2021; Rowshon et al., 2019). In recent literature, impact assessment studies related to climate change have highlighted the sensitivity of water resources to climatic variations. Global climate change would alter the streamflow fluctuations, reservoir levels, groundwater recharge, soil moisture, and crop irrigation demands disturbing the existing ecosystem and hydrological balance (Chan et al., 2021).

One of the major challenges in adapting to the impact of climate change on managing water resources is the lack of climate scenarios at a local scale. To develop adaptation strategies to climate risk, the projection of climate variables for assessing the risk at the local scale or basin scale has become a necessary approach. However, the drawback arises from the following reasons; (1) projected climate information from the Global Climate Models (GCMs) cannot be directly used due to the large resolution for local application, and (2) GCMs do not simulate the ultimate variable of interest to decision-makers such as streamflow, reference evapotranspiration (ET_o), and irrigation requirement directly (Rummukainen, 2010). Obtaining climate projections at fine spatial (local) scales involves a downscaling procedure. Downscaling can be achieved using different techniques based on spatial and temporal considerations for the hydro-meteorological variables. Weather generators are stochastic models under statistical methods used for generating hydro-meteorological parameters for a local scale by referring to historical data series as a baseline (Kilsby et al., 2007). The stochastic nature of the model is receiving attention in water resources-related applications such as agriculture to generate long daily synthetic data such as rainfall as input parameters since it is always related to the randomness of nature (Verdin et al., 2018). Most researchers suggested that the stochastic projection of more than one climate model (GCMs) and ensemble modeling is necessary to provide insights into model uncertainties and develop risk management strategies (Adib et al., 2020; Hamed et al., 2022; Houma et al., 2021; Kumar et al., 2014; Rowshon et al., 2019). These valuable remarks are well established for the climate projection based on historical and GCM-based extracted climate data, and it is now a well-established technique for assessing climate change impacts. Therefore, applying the stochastic downscaling model is appropriate for assessing the impact of climate change under different new shared socioeconomic pathways (SSPs) scenarios of Coupled Model Intercomparison Project Phase 6 (CMIP6).

Water stored and released from the Bukit Merah Reservoir, mainly used to irrigate Kerian Irrigation Scheme, is regulated by the decision of the operators. However, reservoir inflow influences the reservoir function, which primarily depends on the entering streamflow of the Kurau River fluctuation. The streamflow prediction and simulation processes are not easy tasks due to the limitations and benefits of each existing model. Machine learning algorithms are arguably the most relevant current development for hydrology in line with Industrial Revolution 4.0 (IR 4.0). The ability to self-learn from previous events and respond to nonlinear physical processes to make accurate predictions based on minimum data and mathematical equations has received significant attention among researchers in the last few years (Hussain & Khan, 2020). Support Vector Regression (SVR) and Random Forest (RF) are two machine learning models the most applied in dealing with hydrological processes, which have proven to perform well as a prediction model (Hussain & Khan, 2020; Pham et al., 2021; Tongal & Booij, 2018). However, based on the literature review, SVR and RF models still need to be improved to reduce errors in predicting peak flows (Wu et al., 2014) and low flows (Li et al., 2019), respectively. Therefore, it will be a good opportunity to fill this gap to handle the imbalance of predicted output of these individual machine learning models to reduce the error by applying the ensembling method to form meta-learning.

The release from the Bukit Merah Reservoir system requires an optimal operation to supply sustainable irrigation water over a long-term period while at the same time considering future climate change impacts. The future impact of climate change potentially increases the risk in the reservoir operation and management (Yasarer & Sturm, 2016). Hence, the reservoir systems in Malaysia require more attention to integrate the operation and management of the reservoir system with the climate change issues. Release decisions from the reservoir for irrigation management are typically performed at specific time intervals such as daily, weekly, every ten days, or monthly (Bras et al., 1983). Operationally, optimal operation scheduling is crucial in water resource management, especially for rice field irrigation, where an effective method is needed to achieve the goal. The appropriate approach to allocation policies of irrigation water requires a dynamic sequential decision (Singh et al., 2016). Furthermore, in order to increase the reality and reliability of the model, the uncertainty of the water resource system must be addressed in the management. As deterministic models ignore uncertainties, applying them to problems in the real world is often difficult. Stochastic models are more related to principles of probability theory to consider uncertainty. Markov process models can deal with the characteristics of random variables such as rainfall and streamflow based on transition probabilities relating past information to a future occurrence of phenomena (Hossain & El-shafie, 2013). For this purpose, the Stochastic Dynamic Programming (SDP) is the best selection, with the capability of representing the reality of the parameters included in the reservoir system, making it qualify to determine the optimal release policy for the reservoir and fully represent the risks associated with release decision under randomized environments.

In summary, this research presumes that future climate forcings may contribute additional constraints on rice production due to the uncertainty in rainfall and irrigation water supplies, which is likely exacerbated by future population rises. Climate change eventually impacts the streamflow discharge or reservoir storage level, which would lead to water stress and scarcity during the dry season. Therefore, adaptive solutions for satisfying irrigation requirements for rice production are mandatory under the likely evolving future climate condition. Feedback release policies based on SDP combined with machine learning techniques are yet to be explored for Bukit Merah Reservoir, particularly to be adaptive for the future hydrological environment and irrigation water demand predicted based on GCMs and SSP scenarios of CMIP6. This idea highlights the novelty of this research; it will establish a new form of adaptive reservoir operation.

1.3 Research Objectives

This study aims to develop an optimal operating policy for reservoir operation with adaptation strategies under new realities of future climate variability using a combination of statistical downscaling model (SDSM), machine learning, and stochastic dynamic programming (SDP) on the hydrological regimes of Bukit Merah Reservoir. The goal can be achieved with the following objectives:

1. To generate future hydro-meteorological variables of multi-GCM and SSP scenarios under CMIP6 using a statistical downscaling approach.
2. To predict and project the monthly streamflow of Kurau River using an ensemble of machine learning algorithms coupled with CMIP6 multi-GCM.
3. To assess the rice water requirement for the Kerian Irrigation Scheme considering future climate change scenarios of CMIP6.
4. To develop an optimal operating model for the Bukit Merah Reservoir using SDP for best management practices of water resources under future uncertainties.

1.4 Research Scope

The scope of the research is focused on developing an appropriate reservoir operation system that derives a monthly optimal reservoir operating policy to fulfill water requirements for a large-scale rice irrigation scheme considering future climate change impacts and the uncertainties of input arising from the random nature of the reservoir inflows. The optimal irrigation and reservoir operations model are developed solely based on empirical models, making the model entirely dependent on mathematical equations and algorithms without the involvement of watershed physiographic features. The development under the climate change limit for 60 years, from 2021 to 2080, requires a new model generation for operations beyond this year. Despite that, in the case climate change is neglected, the rule curve pattern developed based on historical data could be considered for continued use as the optimal operation developed based on the stochastic model as it considers the streamflow or reservoir inflow uncertainties. However, it is always recommended to keep revising the reservoir operation rule curve for better water security for irrigation. The list of works that led to the model development and analysis are as follows:

- Collection of relevant information on the historical, operation, and maintenance of the reservoir and rice schemes.
- Collection of observed hydro-meteorological data from multiple stations within the study area and watershed.
- Downloading and extraction of multiple GCMs and SSP scenarios under CMIP6 data from .nc file format to .mat file using MATLAB Programme.
- Detailed study and selection of GCMs downscaling techniques and predictor variables suitable for the study purpose.
- Downscaling the climate variables through a specified downscaling domain with coordinates.
- Evaluation of the performance of machine learning techniques (SVR and RF) for predicting monthly streamflow for Kurau River.
- Selection of best ensemble technique for the machine learning algorithms to improve their prediction performance for monthly streamflow.
- Projection of future streamflow of Kurau River using meta-learning considering the effects of climate change on hydrology using multiple GCMs.
- Evaluation of the projected streamflow of Kurau River under each different future SSP scenario (SSP1-2.6, SSP2-4.5, and SSP5-8.5) of ensemble GCM.
- Projection of future rice irrigation demand of Kerian Irrigation Scheme using multiple GCMs and SSP scenarios under CMIP6.
- Evaluation of the projected rice irrigation demand of the Kerian Irrigation Scheme under each different future SSP scenario (SSP1-2.6, SSP2-4.5, and SSP5-8.5) of ensemble GCM.
- Development of a stochastic optimization model based on dynamic programming (DP) in order to produce an optimal reservoir operating policy for the Bukit Merah Reservoir system with the objective of minimizing the sum of square deviations between reservoir releases and rice irrigation water demand.
- Derivation of an optimal reservoir operation policy using the SDP model that takes into account future climate change impacts.

- Comparison of optimal operational rule curve results obtained among different future scenarios as well as the baseline period for evaluation of the effectiveness of optimal operation policies based on performance criteria.

1.5 Significance of the Study

The optimal operation and management of the reservoir have been an active area of water research for years. Numerous techniques and algorithms have been explored for reservoir operation by incorporating uncertainties due to the climate variability and stochastic nature of hydrological processes. This study focused on uncertainty in reservoir operation, considering the impact of future climate change to achieve optimal use of reservoir storage to meet irrigation demand for rice fields. Most rice farming systems in Malaysia depend primarily on river water, which is often inadequate. Hence, reservoirs become a promising tool to store river water and mitigate water scarcity, provided that rational operating techniques ensure adequate water provision for irrigation purposes. In reservoir systems, reservoir inflow possesses random behavior called stochastic processes, making it difficult to mimic the flow patterns perfectly.

Most researchers involved in hydrological modeling will choose physical-based models over empirical ones. However, the physical-based models were found to consume a lot of input data, costly, and time-consuming. Therefore, the empirical approach will be adopted to overcome the drawback. Machine learning with self-learn from previous events and responding to nonlinear physical processes to make accurate predictions based on minimum data and mathematical equations have received significant attention among hydrologists in the last few years. Although machine learning techniques are not input data demanding, it is able to perform well by using unique mathematical algorithms. In order to enhance the prediction output by machine learning techniques, several machine learning algorithms are recommended to be evaluated and ensembled. The selection of a good inflow prediction model enables it to project the future reservoir inflow considering climate change impact with minimum error while reducing uncertainties. These inflow uncertainties will be further considered in the reservoir operation model using the stochastic dynamic operation to reduce the decision risks. This model, coupled with multiple GCMs with three levels of SSP scenarios of CMIP6, will be beneficial for future planning to conserve water and ensure the resilience of the reservoir to cope with the water demands of large rice irrigation schemes.

The outcome of the study will support the Government's food security measures and rural development programs [National Key Economic Area (NKEA) on agriculture] with Adaptation and Mitigation Strategies and Policy Options in Paddy Production for future planning in Malaysia. The study will also provide valuable guidelines for developing conjunctive water use practices and water-saving technologies under uncertainty associated with hydrological phenomena and become important input for Malaysia Dam Safety Management Guidelines (MyDAMS) on the reservoir operation for irrigation. Moreover, this study will also contribute to United Nations Sustainable Development Goals (SDG)s, such as (1) SDG goal 12, to achieve the target of the sustainable management and efficient use of natural resources, and (2) SDG goal 13, to strengthen resilience and adaptive capacity to climate-related hazards and natural disasters in all countries.

1.6 Thesis Outline

The thesis is organized into five chapters. Chapter 1 is the introduction, Chapter 2 is the literature review, Chapter 3 is the research methodology, Chapter 4 is the results and discussions, and Chapter 5 is the conclusion.

Chapter 1 clarifies an overview of the significance of water in rice production, climate change impacts, streamflow prediction, and reservoir operation. This section also highlights the problem faced by the agriculture sector and water resources management, and the necessity for the sector to establish an optimal solution for irrigation release policy. The aim and direction of the study and its contribution are also stated in this chapter.

Chapter 2 presents a relevant literature review of the overview of rice cultivation and climate scenarios, techniques, and approaches related to the study. It includes a detailed discussion of irrigation and water resources management, downscaling methods for GCMs, hydrological modeling, rice water demand, and reservoir operation and management systems. This chapter also further reviews various optimization models suitable for developing irrigation release policies for agricultural purposes.

Chapter 3 explains the methodology with background information on the study area, data collection, and a detailed explanation of the methods used to downscale GCMs data, determination of future hydro-meteorological data projection, models applied to predict and project the reservoir inflow, estimation of rice irrigation demands, and development of optimal reservoir operating policy together with the option in adaptation strategies.

Chapter 4 reveals the study results and discussions involving downscaled hydro-meteorological parameters, the reservoir inflow forecasting models, rice water demand, and the rule curves of the optimal operating policy of the reservoir. The outcomes will help farmers and water authorities implement irrigation water release from Bukit Merah Reservoir, considering the uncertainties in reservoir inflow and future climate change impact under three levels of SSP scenarios of CMIP6.

Chapter 5 concludes the study by summarizing the entire research work, emphasizing the conclusion of each research objective, its novelty and contribution, and methodological limitation with recommendations for future research improvement.

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LIST OF PUBLICATIONS

Journal with Impact Factor

1. **Adib, M. N. M.**, & Harun, S. (2022). Metalearning approach coupled with CMIP6 multi-GCM for future monthly streamflow forecasting. *Journal of Hydrologic Engineering*, 27(6), 05022004. https://doi.org/10.1061/(ASCE)HE.1943-5584.0002176. **(Q2, IF: 2.064)**

Indexed Journal

1. **Adib, M. N. M**., Harun, S., & Rowshon, M. K. (2022). Long-term rainfall projection based on CMIP6 scenarios for Kurau River Basin of rice-growing irrigation scheme, Malaysia. *SN Applied Sciences*, 4, 70. https://doi.org/10.1007/s42452-022-04952-x. **(Indexed by SCOPUS)**