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**ASSESSING THE EFFICACY OF PHYSICS-INFORMED
NEURAL NETWORKS FOR ENHANCED FLOOD
ROUTING SIMULATION**

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Master of Science (Major Component of Research)

Department of Civil Engineering

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DECLARATION

I declare that this is my own work and this thesis/dissertation does not incorporate without acknowledgement any material previously submitted for a degree or diploma in any other University or Institute of higher learning and to the best of my knowledge and belief it does not contain any material previously published or written by another person except where the acknowledgement is made in the text. I retain the right to use this content in whole or part in future works (such as articles or books).

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Name of Supervisor: Prof. R. L. H. L. Rajapakse

Signature of the Supervisor:

Date: 2025/10/30

DEDICATION

This thesis is dedicated to all those who offered unwavering support and encouragement throughout my academic journey. This achievement is not mine alone; it is also a reflection of the compassion, guidance, and solidarity of the remarkable individuals who stood by me during this transformative period.

To my supervisor, Prof. Lalith Rajapakse, I express my heartfelt gratitude. Your insightful guidance, generous mentorship, and encouragement have been instrumental in shaping this research.

I lovingly dedicate this work to my family, whose constant encouragement and patience have been my greatest strength. To my parents and brother, thank you for your unconditional support and belief in me. A special tribute goes to my late mother, whose dream for my academic success continues to inspire and guide me every day.

I also dedicate this thesis to my friends and research colleagues for their motivation, support, and positivity throughout this endeavor. Finally, this work is for anyone passionate about learning and committed to the pursuit of knowledge through research.

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ABSTRACT

Assessing the Efficacy of Physics-Informed Neural Networks or Enhanced Flood Routing Simulation

Flooding has emerged as one of the most destructive natural hazards, causing extensive damage to infrastructure, livelihoods, and ecosystems. The intensifying impacts of climate change, particularly altered rainfall patterns and increased frequency of extreme precipitation events, have further amplified the severity and recurrence of both riverine and localized urban flooding. These conditions often overwhelm existing channel capacities, highlighting the need for accurate flood modeling to support critical decisions related to urban resilience and disaster preparedness. While traditional hydrodynamic models such as HEC-RAS remain widely used for flood simulation, the recent advancement of data-driven methods, particularly Machine Learning (ML), offers promising alternatives. This study explores the application of Physics-Informed Neural Networks (PINNs) as a novel approach for 1D flood routing and peak flow prediction within urban canal networks, especially in data-scarce environments. The PINN framework integrates physical laws, as partial differential equations (PDEs), directly into the model, enhancing the ability to address data scarcities. The 1D Saint-Venant equations were used as the guiding PDE within this particular model. Observed water level data, canal cross sections and rainfall data from the Urban Water Management Division of the Sri Lanka Land Development Corporation (SLLDC) were used as model inputs. The methodology was implemented on three major canal systems in Colombo, Sri Lanka: Madiwela East Diversion, Dehiwala-Wellawatta-Kirulapone Canal System, and Parliament Lake-Kiththampahuwa-Kinda-Dematagoda Canal System. The performance of the PINN model was evaluated by comparing its predicted water levels against observed data at multiple water level monitoring stations along the mentioned canals, using Nash-Sutcliffe-Efficiency (NSE) and Root Mean Square Error (RMSE) as evaluation metrics. In parallel, HEC-RAS 1D hydraulic models were developed for each canal system using the same boundary and terrain data. These models served as a benchmark for comparison with the PINN approach. The results revealed that the PINN model consistently achieved higher accuracy, outperforming HEC-RAS at intermediate water level validation locations. PINN model predictions exhibited NSE values exceeding 0.98 at training locations and above 0.95 at validation points, with corresponding RMSE values below 0.10 m (10 cm). In comparison, while HEC-RAS also demonstrated acceptable performance with NSE values above 0.90 in most cases, its RMSE values were comparatively higher, ranging from 0.10-0.17 m in some locations. These findings highlight higher accuracy of the PINN model, particularly in predicting flood peaks and spatial water level profiles. The integration of physics-based constraints with machine learning allows PINNs to outperform traditional models like HEC-RAS, especially in urban flood scenarios with sparse data availability.

Keywords: Climate variability, data-scarce regions, flood peaks, flood modelling, HEC-RAS, PINN

TABLE OF CONTENTS

Declaration	i
Dedication	ii
Acknowledgement.....	iii
Abstract	iv
Table of Contents	v
List of Figures	viii
List of Tables.....	xiii
List of Abbreviations.....	xiv
Chapter 1	16
INTRODUCTION	16
1.1 Background of the Study	16
1.2 Research Gap Identification	17
1.3 Aims and Objectives	17
1.4 Methodology	18
1.5 Main Findings.....	19
1.6 Dissertation Structure	19
Chapter 2	21
LITERATURE REVIEW.....	21
2.1 Chapter Introduction.....	21
2.2 General	21
2.3 Hydrological Models	22
2.4 Types of Hydrologic Models.....	22
2.4.1 Empirical Models	22
2.4.2 Conceptual Models	23
2.4.3 Physically-based Models	23
2.5 Need for Artificial Intelligence Techniques in Hydrology.....	23
2.6 Applications of AI Techniques in Hydrology	24
2.7 Physical-based Models for Flood-Modelling	24
2.8 Application of AI models in Flood Routing.....	27
2.9 Application of PINN in Hydrology	28

2.9.1	Application of PINN in Streamflow Modelling	30
2.9.2	Application of PINN in Groundwater Modelling	30
2.9.3	Application of PINN in Flood Modelling	31
2.9	Objective Functions.....	31
2.10	Summary	32
Chapter 3.....		33
METHODOLOGY.....		33
3.1	General	33
3.2	Case Study Area	34
3.3	Physics-Informed Neural Network Code Development.....	36
3.3.1	Physical Law - Partial Differential Equation (PDE)	36
3.4	HEC-RAS Model Development	41
3.5	Data Collection	41
3.5	Data Processing	44
3.6	Summary	49
Chapter 4.....		50
RESULTS AND DISCUSSION		50
4.1	Chapter Introduction.....	50
4.3	Hyperparameter Optimization	50
4.3.1	Hyperparameter Tuning for Canal System 01	51
4.3.2	Hyperparameter Tuning for Canal System 02	54
4.3.2	Hyperparameter Tuning for Canal System 03.....	58
4.4	Model Outputs.....	61
4.4.1	Madiwela East Diversion.....	62
4.4.1.1	PINN Approach.....	62
4.4.1.2	HEC-RAS Approach.....	66
4.4.1.2	Comparison of PINN and HEC-RAS Results.....	69
4.4.2	Dehiwala-Wellawatta-Kirillapone Canal System.....	71
4.4.2.1	PINN Approach	72
4.4.2.2	HEC-RAS Approach	75
4.4.3	Parliament Lake - Kiththampahuwa - Kinda - Dematagoda Canal System	80

4.4.3.1	PINN Approach.....	81
4.4.3.2	HEC-RAS Approach.....	85
4.5	Sensitivity Analysis-PINN code.....	90
4.6	Summary	92
Chapter 5		94
CONCLUSIONS, RECOMMENDATIONS AND FUTURE WORK.....		95
5.1	Conclusions	94
5.2	Limitations.....	95
5.3	Recommendations	96
5.4	Future Work	97
References		98

LIST OF FIGURES

Figure No.	Description	Page No.
Figure 1	Network visualization and overlay visualization using VOSviewer	30
Figure 2	Methodology Flow Chart	34
Figure 3	Colombo Metropolitan Area, Sri Lanka	35
Figure 4	Schematic Diagram for Canals and Water Level Monitoring Locations (Wagenaar et al., 2019)	36
Figure 5	Canal System and Water Level Monitoring stations proposed by SLLDC in Colombo Metropolitan Area, Sri Lanka (Source: https://pub.curwsl.org/)	36
Figure 6	Canal Cross-section points along the canals and data available from rainfall Stations	43
Figure 7	A schematic diagram showing the selected canal systems covering the total canal network in the Colombo Metropolitan Area	45
Figure 8	A Google satellite image with marked canal paths in red is used as three distinct canal systems	45
Figure 9	Time series plot of water levels vs time and rainfall vs time at the Chandrika Kumarathunga MW water level monitoring location representing the Madiwela East Diversion (Canal System 01)	46
Figure 10	Time series plot of water levels vs time and rainfall vs time near Lanka Hospital water level monitoring location representing the Dehiwala-Wellawatta-Kirillapone Canal System (Canal System 02)	46
Figure 11	Time series plot of water levels vs time and rainfall vs time at Kimbulawala Bridge monitoring location representing the Parliament Lake-Dematagoda canal system (Canal System 03)	46
Figure 12	Thiessen Polygons for rainfall stations	48
Figure 13	Selected flood event with elevated water levels at Chandrika Kumarathunga MW, representing Madiwela East Diversion (Canal System 01)	49
Figure 14	Selected flood event with elevated water levels near Lanka Hospital, representing Dehiwala-Wellawatta-Kirillapone Canal System (Canal System 02)	49

Figure 15	Selected flood event with elevated water levels at Kimbulawa Bridge, representing Parliament Lake - Kiththampahuwa – Kinda – Dematagoda Canal System (Canal System 03)	49
Figure 16	Tests conducted to identify the most preferable layer count in the PINN code	53
Figure 17	Tests conducted to identify the most preferable neurons per layer PINN code	53
Figure 18	Tests conducted to identify the most preferable activation function for the PINN code	54
Figure 19	Tests conducted to identify the most preferable loss weights for the PINN code	54
Figure 20	Tests conducted to identify the most preferable loss weights for the PINN code	55
Figure 21	Tests conducted to identify the most preferable activation function for the PINN code	55
Figure 22	Tests conducted to identify the most preferable layer count in the PINN code	56
Figure 23	Tests conducted to identify the most preferable neurons per layer PINN code	57
Figure 24	Tests conducted to identify the most preferable activation function for the PINN code	57
Figure 25	Tests conducted to identify the most preferable loss weights for the PINN code	58
Figure 26	Tests conducted to identify the most preferable loss weights for the PINN code	58
Figure 27	Tests conducted to identify the most preferable activation function for the PINN code	59
Figure 28	Tests conducted to identify the most preferable layer count in the PINN code	60
Figure 29	Tests conducted to identify the most preferable neurons per layer PINN code	60
Figure 30	Tests conducted to identify the most preferable activation function for the PINN code	61
Figure 31	Tests conducted to identify the most preferable activation function for the PINN code	61
Figure 32	Tests conducted to identify the most preferable loss weights for the PINN code	62
Figure 33	Tests conducted to identify the most preferable loss weights for the PINN code	62

Figure 34	Input water level station and collocation points used in spatial validation and intermediate points in canal networks	63
Figure 35	Madiwela East Diversion and $x=0$, $x=L$, and collocation points including three water level monitoring locations, Chandrika Kumarathunga MW, Rajasinghe MW, and Ambathale Downstream	64
Figure 36	Training for Chandrika Kumarathunga MW (Station 01) and Rajasinghe MW (Station 02) along the Madiwela East Diversion	65
Figure 37	PDE loss reduction and total loss reduction, along with 1000 epochs in the PINN code	65
Figure 38	Validation for flood peaks to check the ability of modelling flood peaks (for Stations 01 and 02)	66
Figure 39	Spatiotemporal validation for water levels in the given time domain in the flood period at the Rajasinghe water level monitoring location ($x = 5.60$ km)	67
Figure 40	Predicted water levels at Intermediate locations, $x=3,500$ m; $4,000$ m; and $4,500$ m	67
Figure 41	Channel geometry, including the canal center line, bank lines, flow lines, and cross sections, was drawn manually with the support of Google satellite imagery	68
Figure 42	Stage Hydrograph at Chandrika Kumarathunga MW water level station used as the upstream boundary condition for Madiwela East Diversion	69
Figure 43	Stage Hydrograph at Ambathale Downstream water level station used as the downstream boundary condition for Madiwela East Diversion	69
Figure 44	Maximum flood condition along the Madiwela East Diversion on 10/14/2025	70
Figure 45	HEC-RAS predicted water level and observational data for the Rajasinghe MW water level monitoring location	70
Figure 46	Comparison of predicted water levels from PINN and HEC-RAS at $x = 3,500$ m from the origin ($x = 0$)	71
Figure 47	Comparison of predicted water levels from PINN and HEC-RAS at $x = 4,000$ m from origin ($x = 0$)	71
Figure 48	Comparison of predicted water levels from PINN and HEC-RAS at $x = 4,500$ m from origin ($x = 0$)	72
Figure 49	Dehiwala-Wellawatta-Kirillapone Canal System, showing four water level monitoring stations, Nawala Road Bridge (0.63 km), Near Lanka Hospital (2.00 km), Wellawatta Canal Outlet (4.08 km) from the canal origin ($x = 0$ m) in	73

	the Kirullapone Canal, and Dehiwala Canal Outlet (3.68 km) from the connection junction	
Figure 50	Training for Nawala Road Bridge (Station 01) and Wellawatta Canal Outlet (Station 02) along the Canal System 02	74
Figure 51	PDE loss reduction and total loss reduction, along with 1,200 epochs in the PINN code	74
Figure 52	Validation for flood peaks to check the ability of modelling flood peaks (for Stations 01 and 02)	75
Figure 53	Spatiotemporal validation for water levels in the given time domain in the flood period near Lanka Hospital water level monitoring location ($x = 2$ km)	76
Figure 54	Predicted water levels at Intermediate locations, $x=1,000$ m; 3,000 m and 4,000 m	76
Figure 55	Channel geometry, including the canal center line, bank lines, flow lines, and cross sections, was drawn manually with the support of Google satellite imagery	77
Figure 56	Stage Hydrograph at Nawala Road Bridge water level station used as the upstream boundary condition for Dehiwala-Wellawatta-Kirillapone Canal System	78
Figure 57	Stage Hydrograph at Dehiwala Canal Outlet water level station used as the downstream boundary condition for Dehiwala-Wellawatta-Kirillapone Canal System	78
Figure 58	Stage Hydrograph at Wellawatta Canal Outlet water level station used as the downstream boundary condition for Dehiwala-Wellawatta-Kirillapone Canal System	78
Figure 59	Maximum flood condition along the Dehiwala-Wellawatta-Kirulapone canal system on 10/14/2025	79
Figure 60	Stage hydrograph at the water level monitoring station near Lanka hospital for the considered time domain	80
Figure 61	Spatiotemporal validation for water levels in the given time domain in the flood period near Lanka Hospital water level monitoring location ($x = 2$ km)	80
Figure 62	Comparison of predicted water levels from PINN and HEC-RAS at $x = 1,000$ m from the origin ($x = 0$)	80
Figure 63	Comparison of predicted water levels from PINN and HEC-RAS at $x = 3,000$ m from the origin ($x = 0$)	81
Figure 64	Comparison of predicted water levels from PINN and HEC-RAS at $x = 4,000$ m from the origin ($x = 0$)	81
Figure 66	Parliament Lake-Kiththampahuwa-Kinda-Dematagoda Canal System, showing four water level monitoring	83

	stations, Kimbulawala Bridge at the canal origin ($x = 0$ m), Diyatha Bridge (3.780 km), Yakbedda Bridge (7.530 km), Orugodawatta (10.900 km), and Ingurukade Junction (12.100 km)	
Figure 67	Training for Kimbulawala Bridge (Station 01) and Ingurukade Junction (Station 02) along the Parliament Lake-Kiththampahuwa-Kinda-Dematagoda Canal System	83
Figure 68	PDE loss reduction and total loss reduction along with 1,200 epochs in the PINN code	84
Figure 69	Validation for flood peaks to check the ability of modelling flood peaks (for Stations 01 and 02)	85
Figure 70	Predicted water levels at Intermediate locations, at Diyatha Bridge (3.780 km), Yakbedda Bridge (7.530 km), Orugodawatta (10.900 km)	85
Figure 71	Spatio Temporal validation using Intermediate stations for Diyatha Bridge (3.780 km), Yakbedda Bridge (7.530 km), Orugodawatta (10.900 km) along the Canal System 3	86
Figure 72	Channel geometry, including the canal center line, bank lines, flow lines, and cross sections, was drawn manually with the support of Google satellite imagery	88
Figure 73	Stage Hydrograph at Kimbulawala Bridge water level station used as the upstream boundary condition for Canal System 3	88
Figure 74	Stage Hydrograph at Wellampitiya Bridge water level station used as the upstream boundary condition for Canal System 3	89
Figure 75	Stage Hydrograph at Orugodawatta Bridge used as the downstream boundary condition for Canal System 3	89
Figure 76	Stage Hydrograph at SLLDC Bridge used as the downstream boundary condition for Canal System 3	89
Figure 77	Maximum flood condition along the Parliament Lake-Kiththampahuwa-Kinda-Dematagoda canal system on 10/14/2025	90
Figure 78	Spatio Temporal validation using Intermediate stations at Diyatha Bridge along the Canal System 3	91
Figure 79	Spatio-Temporal validation using Intermediate stations at Yakkbedda Bridge along the Canal System 3	91
Figure 80	Variation of model performances with changing learning rates for intermediate stations at Canal System 2	94

LIST OF TABLES

Table No.	Description	Page No.
Table 1	Hydrological Models used in flood simulations	26
Table 2	Number of canal cross sections and water level monitoring points along the canals	44
Table 3	Rainfall Stations where data was collected by the Urban Water Management Center, SLLDC, and data available time domains	44
Table 4	Missing Data percentages for water levels on important locations along the canals	48
Table 5	Used rainfall gauging station for each Canal System	48
Table 6	The training NSE and RMSE values for accuracy	65
Table 7	The Validation NSE and RMSE values for accuracy	66
Table 8	Comparison of agreements of predicted water levels with observation data at Rajasinghe MW	72
Table 9	The training NSE and RMSE values for accuracy	74
Table 10	The testing NSE and RMSE values for accuracy	75
Table 11	Comparison of agreements of predicted water levels with observation data near Lanka Hospital	82
Table 12	The training NSE and RMSE values for accuracy	84
Table 13	The training NSE and RMSE values for accuracy	85
Table 14	NSE and RMSE values for the intermediate stations along the canal for the PINN model	87
Table 15	NSE and RMSE values for the intermediate stations along the canal for the HEC-RAS model	91
Table 16	Sensitivity Analysis for Canal Systems 01,02, and 03 for No. of Layers, Neurons per layer, and the activation function were found to be the most sensitive parameters	93
Table 17	Summary of Training, Testing NSE and RMSE values of PINN code and HEC-RAS results	95
Table 18	NSE and RMSE values for collocation points within the canals	95

LIST OF ABBREVIATIONS

Abbreviation	Description
ANN	Artificial Neural Network
BC	Boundary Condition
CNN	Convolutional Neural Network
DP	Deep Learning
GNN	Graph Neural Network
HEC-RAS	Hydrologic Engineering Center - River Analysis System
IC	Initial Condition
LSTM	Long Short-Term Memory
ML	Machine Learning
NSE	Nash–Sutcliffe Efficiency
PDE	Partial Differential Equation
PINN	Physics-Informed Neural Network
RMSE	Root Mean Square Error
R-R	Rainfall–Runoff
SLLDC	Sri Lanka Land Development Corporation
SRM	Short-Term Runoff Modelling
CRM	Continuous Runoff Modelling
GS	Gaussian Software

