

**A PHYSICALLY INFORMED DEEP LEARNING
FRAMEWORK FOR SCALABLE STREAMFLOW
MODELING IN INDIA**

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MODELING IN INDIA**

by

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submitted

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This dissertation is dedicated to my family.

To my parents, Darshan Kumar and Shakti Devi, for their unconditional love, sacrifices, and unwavering belief in me; to my brother, Safal Magotra, for his constant support.

And to my spouse, Vidushi Koul, for her invaluable love, understanding, and encouragement.

CERTIFICATE

This is to certify that the dissertation entitled “**A PHYSICALLY INFORMED DEEP LEARNING FRAMEWORK FOR SCALABLE STREAMFLOW MODELING IN INDIA**”, being submitted by **Mr. Bhanu Magotra**, to the **Indian Institute of Technology Delhi** for the award of the degree of ‘**Doctor of Philosophy**’ in the Department of Civil Engineering is a record of bonafide research work carried out by him under my supervision and guidance. The dissertation work, in my opinion, has reached the requisite standards fulfilling the requirement for the degree of **Doctor of Philosophy**.

The material contained in the dissertation is original and has not been submitted in part or full to any other University or Institute for the award of any other degree or diploma.

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(Bhanu Magotra)

ABSTRACT

Streamflow plays a central role in both providing water for human and economic needs and making a critical contribution to ecological health, making its accurate prediction vital for holistic water management. From ensuring agricultural productivity and industrial development to providing reliable drinking water and preserving ecological balance, the multifaceted demands on this vital resource underscore the need for sophisticated streamflow modeling techniques that balance scalability with local relevance. Addressing this challenge is pivotal for enhancing water resources management strategies and ensuring water security across the nation. This dissertation is oriented towards developing and assessing such models, with a particular emphasis on integrating advanced deep learning techniques with traditional hydrological modeling approaches to predict streamflow more effectively.

The first aim of this research focused on developing an Indian Land Data Assimilation System (ILDAS), motivated by the need for a high-resolution, modular, and open-source hydrological modelling framework over the Indian Subcontinent. ILDAS integrates a coupled land surface model with a hydrodynamic model, enhancing its ability to estimate various hydrological parameters crucial for managing water resources effectively. A detailed reanalysis product spanning 1981 to 2021 is generated by integrating data from four distinct meteorological forcing datasets, selected for their reliability and specificity, to account for various atmospheric and climatic influences. Additionally, all major components of the terrestrial water balance, such as surface runoff, soil moisture, terrestrial water storage anomalies, evapotranspiration, and streamflow, were validated against a diverse array of satellite and in situ observations. This rigorous validation process not only ensures the accuracy of ILDAS outputs but also underscores the system's potential to become a vital tool for water resources management, adapted to the unique challenges faced by India. By having the capabilities of both terrestrial and atmospheric data assimilation, ILDAS represents a

significant advancement in the generation of hydrologically robust and locally relevant information for managing water resources sustainably and mitigating the impacts of extreme weather events.

The streamflow evaluation from ILDAS revealed that at an uncalibrated stage, the predictions are not suitable for operational purposes. Additionally, calibrating a large-scale hydrological model on multiple river basins is computationally prohibitive. Therefore, this research explored an alternative data-driven approach by training state-of-the-art deep learning models: Long Short-Term Memory (LSTM) networks to predict daily streamflow at 220 gauge locations across India. We assessed the efficacy of incorporating meteorological information, catchment-specific geophysical parameters and dynamic land surface states as supplementary inputs to LSTM models. Our results demonstrated that incorporating catchment geophysics into the models led to a substantial improvement in performance over the base LSTM model, However, when it came to the inclusion of dynamic land surface states, the impact on model performance did not align with the expectations, indicating that such information did not contribute significantly to the overall predictive capability of the models.

Building on these findings, the dissertation introduces a hybrid solution aimed at optimizing streamflow prediction by combining ensemble outputs from large-scale hydrological models of ILDAS with advanced deep learning post-processor based on LSTM networks. We proposed a two-stage correction and combination process that involved the residual correction of ensemble members followed by their optimal integration with the moving average of observed streamflow data. Designed to enhance local relevance of streamflow predictions, this approach is validated across the same 220 gauge locations, demonstrating marked improvements in accuracy and reliability. This methodology, sensitive to local

hydrological contexts, presents a significant advancement in the area of generating accurate streamflow estimates relevant to various water resources management practices.

Overall, this dissertation seeks to understand the potential of hybrid models to overcome complex challenges in streamflow modeling and provide the hydrological community with a scalable framework that can integrate physical information with deep learning models. The strategies explored in this dissertation demonstrate that hybrid models, which merge physical hydrological principles with deep learning algorithms, yield superior performance, proving especially beneficial for streamflow modeling in complex environments like India.

सार

जल प्रबंधन में स्ट्रीमफ्लो (नदी प्रवाह) की सटीक भविष्यवाणी महत्वपूर्ण है क्योंकि यह मानवीय और आर्थिक ज़रूरतों के लिए पानी उपलब्ध कराने के साथ-साथ पारिस्थितिक स्वास्थ्य में भी अहम योगदान देता है। कृषि उत्पादकता और औद्योगिक विकास सुनिश्चित करने से लेकर विश्वसनीय पेयजल प्रदान करने और पारिस्थितिक संतुलन बनाए रखने तक, इस महत्वपूर्ण संसाधन की बहुआयामी मांगें परिष्कृत स्ट्रीमफ्लो मॉडलिंग तकनीकों की आवश्यकता को रेखांकित करती हैं। इन तकनीकों में मापनीयता और स्थानीय प्रासंगिकता के बीच संतुलन होना चाहिए। इस चुनौती का समाधान जल संसाधन प्रबंधन रणनीतियों को बढ़ाने और देश भर में जल सुरक्षा सुनिश्चित करने के लिए महत्वपूर्ण है। यह थीसिस ऐसे मॉडल विकसित करने और उनका आकलन करने पर केंद्रित है, जिसमें स्ट्रीमफ्लो की अधिक प्रभावी ढंग से भविष्यवाणी करने के लिए उन्नत डीप लर्निंग तकनीकों को पारंपरिक हाइड्रोलॉजिकल मॉडलिंग दृष्टिकोणों के साथ एकीकृत करने पर विशेष जोर दिया गया है।

इस शोध का पहला उद्देश्य भारतीय उपमहाद्वीप पर उच्च-रिज़ॉल्यूशन, मॉड्यूलर और ओपन-सोर्स हाइड्रोलॉजिकल मॉडलिंग ढांचे की आवश्यकता से प्रेरित होकर भारतीय भूमि डेटा एसिमिलेशन सिस्टम (ILDAS) विकसित करना था। ILDAS एक युग्मित भूमि सतह मॉडल को हाइड्रोडायनामिक मॉडल के साथ एकीकृत करता है, जो जल संसाधनों के प्रभावी ढंग से प्रबंधन के लिए महत्वपूर्ण विभिन्न हाइड्रोलॉजिकल मापदंडों का अनुमान लगाने की इसकी क्षमता को बढ़ाता है। 1981 से 2021 तक का विस्तृत पुनर्विश्लेषण उत्पाद चार अलग-अलग मौसम संबंधी बल डेटासेट से डेटा को एकीकृत करके तैयार किया गया है, जिन्हें विभिन्न वायुमंडलीय और जलवायु प्रभावों को ध्यान में रखते हुए उनकी विश्वसनीयता और विशिष्टता के लिए चुना गया है। इसके अतिरिक्त, स्थलीय जल संतुलन के सभी प्रमुख घटकों, जैसे सतही अपवाह, मिट्टी की नमी, स्थलीय जल भंडारण विसंगतियाँ, वाष्पोत्सर्जन और जलप्रवाह को उपग्रह और इन-सीटू अवलोकनों की एक विविध सरणी के विरुद्ध मान्य किया गया था। यह कठोर

सत्यापन प्रक्रिया न केवल ILDAS आउटपुट की सटीकता सुनिश्चित करती है, बल्कि भारत के सामने आने वाली अनूठी चुनौतियों के अनुकूल जल संसाधन प्रबंधन के लिए एक महत्वपूर्ण उपकरण बनने की प्रणाली की क्षमता को भी रेखांकित करती है। स्थलीय और वायुमंडलीय दोनों डेटा को आत्मसात करने की क्षमता रखने से, ILDAS जल संसाधनों को स्थायी रूप से प्रबंधित करने और चरम मौसम की घटनाओं के प्रभावों को कम करने के लिए हाइड्रोलॉजिकल रूप से मजबूत और स्थानीय रूप से प्रासंगिक जानकारी के उत्पादन में एक महत्वपूर्ण प्रगति का प्रतिनिधित्व करता है। आईएलडीएस के प्रवाह मूल्यांकन से पता चला है कि बिना कैलिब्रेट किए गए चरण में, पूर्वानुमान परिचालन उद्देश्यों के लिए उपयुक्त नहीं हैं। इसके अतिरिक्त, कई नदी घाटियों पर बड़े पैमाने पर हाइड्रोलॉजिकल मॉडल को कैलिब्रेट करना कम्प्यूटेशनल रूप से निषेधात्मक है। इसलिए, इस शोध ने अत्याधुनिक डीप लर्निंग मॉडल को प्रशिक्षित करके एक वैकल्पिक डेटा-संचालित दृष्टिकोण की खोज की: भारत भर में 220 गेज स्थानों पर दैनिक प्रवाह की भविष्यवाणी करने के लिए लॉन्ग शॉर्ट-टर्म मेमोरी (एलएसटीएम) नेटवर्क। हमने एलएसटीएम मॉडल में पूरक इनपुट के रूप में मौसम संबंधी जानकारी, जलग्रहण-विशिष्ट भूभौतिकीय मापदंडों और गतिशील भूमि सतह की स्थिति को शामिल करने की प्रभावकारिता का आकलन किया। हमारे परिणामों ने प्रदर्शित किया कि मॉडल में जलग्रहण भूभौतिकी को शामिल करने से आधार एलएसटीएम मॉडल की तुलना में प्रदर्शन में पर्याप्त सुधार हुआ, इन निष्कर्षों के आधार पर, थीसिस एक हाइब्रिड समाधान प्रस्तुत करती है जिसका उद्देश्य एलएसटीएम नेटवर्क पर आधारित उन्नत डीप लर्निंग पोस्ट-प्रोसेसर के साथ ILDAS के बड़े पैमाने के हाइड्रोलॉजिकल मॉडल से एनसेंबल आउटपुट को जोड़कर स्ट्रीमफ्लो भविष्यवाणी को अनुकूलित करना है। हमने दो-चरणीय सुधार और संयोजन प्रक्रिया का प्रस्ताव दिया जिसमें एनसेंबल सदस्यों के अवशिष्ट सुधार के बाद उनके देखे गए स्ट्रीमफ्लो डेटा के मूविंग एवरेज के साथ इष्टतम एकीकरण शामिल था। स्ट्रीमफ्लो भविष्यवाणियों की स्थानीय प्रासंगिकता को बढ़ाने के लिए डिज़ाइन किया गया, इस दृष्टिकोण को समान 220 गेज स्थानों पर मान्य किया गया है, जो पूर्वानुमान सटीकता और विश्वसनीयता में उल्लेखनीय सुधार प्रदर्शित करता है। स्थानीय

हाइड्रोलॉजिकल संदर्भों के प्रति संवेदनशील यह पद्धति बाढ़ जोखिम प्रबंधन के क्षेत्र में एक महत्वपूर्ण प्रगति प्रस्तुत करती है, साथ ही व्यापक जल संसाधन प्रबंधन अभ्यास भी। इस थीसिस के दौरान किए गए शोध के संश्लेषण से संकेत मिलता है कि मशीन लर्निंग फ्रेमवर्क में भौतिक अंतर्दृष्टि को शामिल करने से बाढ़ की भविष्यवाणी क्षमताओं में काफी वृद्धि होती है। अध्ययन न केवल बाढ़ जोखिम मूल्यांकन और प्रबंधन में निहित जटिल चुनौतियों पर काबू पाने में हाइब्रिड मॉडल की क्षमता के बारे में हमारी समझ को आगे बढ़ाते हैं बल्कि हाइड्रोलॉजिकल समुदाय को विभिन्न मॉडलिंग दृष्टिकोणों को एकीकृत करने के लिए एक व्यावहारिक और लचीला ढांचा भी प्रदान करते हैं। इस थीसिस में प्रस्तुत मान्य प्रगति अधिक लचीली, अनुकूली और स्थानीय रूप से प्रासंगिक बाढ़ जोखिम प्रबंधन रणनीतियों के विकास के लिए आधार प्रदान करती है। ये रणनीतियाँ जलवायु परिवर्तन और जल विज्ञान चक्र में मानवजनित परिवर्तनों से उत्पन्न होने वाले बढ़ते खतरों से निपटने के लिए अनिवार्य हैं, जो महत्व को रेखांकित करती हैं।

शोध का शीर्षक: भारत में स्केलेबल स्ट्रीमफ्लो मॉडलिंग के लिए भौतिक रूप से सूचित गहन शिक्षण ढाँचा

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TABLE OF CONTENTS

CERTIFICATE	i
ACKNOWLEDGEMENTS	ii
ABSTRACT	iii
TABLE OF CONTENTS	x
LIST OF FIGURES	xiii
LIST OF TABLES.....	xix
LIST OF ABBREVIATIONS	xxi
Chapter 1.....	1
1.1 Problem Statement.....	2
1.2 Science Questions.....	5
1.3 Objectives	6
1.4 Structure of the dissertation.....	6
Chapter 2.....	7
2.1 Introduction	7
2.2 Data and Methods.....	9
2.2.1 Study Area.....	9
2.2.2 Modelling Framework.....	10
2.2.3 MERRA-2	19
2.2.3 CHIRPS.....	19
2.2.3 ERA-5	19
2.2.4 Indian Meteorological Department (IMD) Precipitation	20
2.2.5 GRUN (Runoff)	20
2.2.6 Observed Soil Moisture (COSMOS)	21
2.2.7 ESA-CCI (Satellite Soil Moisture)	21
2.2.8 MODIS Evapotranspiration	21
2.2.9 GRACE Terrestrial Water Storage Anomalies (TWSA).....	21
2.2.10 Observed streamflow	22
2.2.11 Mann-Kendall Trend Analysis	22
2.2.12 Evaluation criteria	23

2.3 Results and Discussion	24
2.3.1 Precipitation analysis	24
2.3.2 Evaluation of simulated soil moisture.....	27
2.3.3 Evaluation of simulated evapotranspiration.....	30
2.3.4 Evaluation of simulated runoff	30
2.3.5 Evaluation of simulated streamflow	33
2.3.6 Evaluation of simulated Terrestrial Water Storage Anomaly (TWSA)	38
2.3.7 Long-term seasonal water balance cycle	42
2.3.8 Hydroclimatic Extreme Event Analysis.....	44
2.4 Conclusions	45
Chapter 3.....	48
3.1 Introduction	48
3.2 Data and Methods.....	52
3.2.1 Dataset.....	52
3.2.2 Modeling Framework.....	55
3.2.3 Evaluation Criteria	58
3.3 Results and Discussion	60
3.3.1 Performance of physically informed LSTM models	60
3.3.2 Evaluation of Hydrological Signatures	65
3.3.3 Discussion	69
3.4 Conclusions	72
Chapter 4.....	74
4.1 Introduction	74
4.2 Data and Methods.....	78
4.2.1 Hydrological Simulations from Indian Land Data Assimilation System (ILDAS)	78
4.2.2 Observed Streamflow.....	78
4.2.3 Meteorological and Geophysical Datasets.....	79
4.2.4 Experimental Setup	81
4.2.5 Evaluation Criteria	85

4.3 Results and Discussion	89
4.3.1 Performance of hybrid LSTM models	89
4.3.2 Peak Flow Analysis	93
4.4 Discussion.....	97
4.5 Conclusions	99
Chapter 5.....	101
5.1 Summary.....	101
5.2 Limitations and Future Work.....	103
REFERENCES.....	106
APPENDICES	120
JOURNAL PUBLICATIONS	122
CURRICULUM VITAE	123

LIST OF FIGURES

Figure 2.1: A map depicting the ILDAS spatial domain, Indian Central Water Commission River basins and streamflow gauge stations considered in the study.	11
Figure 2.2: Schematic diagram of energy budget and processes represented in Noah-MP (He et al., 2023).	13
Figure 2.3: Schematic diagram of water budget and processes represented in Noah-MP (He et al., 2023).	14
Figure 2.4 Schematic diagram of carbon budget and processes represented in Noah-MP (He et al., 2023).	15
Figure 2.5: Comparison of correlation coefficient (a-c), Pbias (d-f), and RRMSE (g-i) of Annual precipitation for different precipitation datasets (i.e., MERRA-2, CHIRPS, and ERA-5) with respect to the India Meteorological Department (IMD) precipitation dataset for 1981-2021.	26
Figure 2.6: Nationwide mean annual precipitation plot for different precipitation datasets (IMD, MERRA-2, CHIRPS, ERA-5) for 1981-2021(a) and basin wise precipitation Mann Kendall (M.K.) trend analysis, colored boxes show a significant trend (b).	27
Figure 2.7: Basin-wise comparison of correlation, and unbiased RMSE of simulated monthly soil moisture anomalies for different meteorological forcings (IMD, MERRA-2, CHIRPS, and ERA-5) with ESA-CCI soil moisture anomalies for 2007-2021.	28
Figure 2.8: Comparison of simulated monthly mean soil moisture for different meteorological forcings (IMD, MERRA-2, CHIRPS, and ERA-5) with COSMOS (in-situ) soil moisture at two-gauge stations (a) SGR and (b) MDH from June 2015 to December 2019.....	29

Figure 2.9: Comparison of simulated daily mean soil moisture for different meteorological forcings (IMD, MERRA-2, CHIRPS, and ERA-5) with COSMOS (in-situ) soil moisture at two-gauge stations (a) SGR and (b) MDH from June 2015 to December 2019.....	30
Figure 2.10: Basin-wise comparison of KGE, correlation, α , and β of simulated monthly mean evapotranspiration for different meteorological forcing (IMD, MERRA-2, CHIRPS, and ERA-5) with MODIS Aqua (MYD16A2GF) Evapotranspiration product for 2002-2021.....	31
Figure 2.11: Basin-wise comparison of KGE, correlation, α , and β of simulated monthly mean Runoff for different meteorological forcings (IMD, MERRA-2, CHIRPS, and ERA-5) with monthly mean GRUN Runoff for 1981-2014.....	32
Figure 2.12: Comparison of KGE (a-d), r (e-h), α (i-l), and β (m-p) of simulated monthly mean streamflow annually for different meteorological forcings at 162 gauge stations.....	35
Figure 2.13: Comparison of KGE (a-d), r (e-h), α (i-l), and β (m-p) of simulated monthly mean streamflow in JJAS season for different meteorological forcings at 162 gauge stations.	36
Figure 2.14: Anomaly correlation coefficient (a-d) and unbiased RMSE (e-h) for monthly mean streamflow in annual season for different meteorological forcings at 162 gauge stations.	37
Figure 2.15: Anomaly correlation coefficient (a-d) and unbiased RMSE (e-h) for monthly mean streamflow in JJAS season for different meteorological forcings at 162 gauge stations.	37

Figure 2.16: Anomaly correlation coefficient (a-d) and unbiased RMSE (e-h) for daily streamflow in JJAS season for different meteorological forcings at 162 gauge stations.	39
Figure 2.17 Scatter plots of various hydrological signatures for 162 catchments across Indian subcontinent on log-scale. The values in-set denote coefficient of determination (R^2) corresponding to each hydrological signature.	39
Figure 2.18: A plot of time series plot for nationwide monthly mean terrestrial water storage anomaly for GRACE, IMD, MERRA-2, CHIRPS, and ERA-5 for 2003-2017 (a) and basin-wise R^2 (b).	41
Figure 2.19: A time-series plot showing long-term variation of various components of simulated water balance at Kudige, Cauvery River basin.	42
Figure 2.20: Seasonal variations of different water balance components as monthly anomalies simulated using ILDAS forced by CHIRPS at Kudige, Cauvery River basin.....	43
Figure 2.21. Reconstructed daily soil moisture anomaly in Haflong, Assam for the extreme hydroclimatic event that occurred from 11-18 May 2022.	44
Figure 3.1: Methodology adopted in for development and validation of deep learning streamflow prediction model.	53
Figure 3.2: A map of India showing the location of streamflow gauge points, major river basins and Köppen-Geiger climate classes considered in the study.	54
Figure 3.3: Representative hydrograph plot showing daily streamflow time series of testing period (2013-2016) for a catchment to highlight the agreement between observed and simulated flows by various LSTM models.	61

Figure 3.4: A histogram plot showing the distribution of various error metrics calculated by comparing observed and simulated daily streamflow for in-sample (IS) and out-of-sample (OS) catchments for four models. The numbers on y-axis indicate median values for each metric, and the hatching pattern distinguishes between in-sample and out-of-sample catchments.	61
Figure 3.5: Spatial distribution of KGESS by comparing the KGE for the base model (LSTM-B) with the other three models. The inset value denotes median KGESS for in-sample (IS) and out-of-sample (OS) catchments. The dots represent in-sample catchments while triangles are used to show out-of-sample catchments. The color scale ranges from -0.5 to 1.0 for KGESS value at each point.....	62
Figure 3.6: Spatial distribution of error metrics of the base model (LSTM-B) and the best-performing model (LSTM-CA). The inset value denotes the nationwide median of each error metric for in-sample (IS) and out-of-sample (OS) catchments. The dots represent in-sample catchments while triangles are used to show out-of-sample catchments. The color scale range varies as per the error metric displayed.	63
Figure 3.7: Histogram showing the relative difference in KGE metric for 170 in-sample catchments with (w Reservoir) and without reservoir (w/o Reservoir). All LSTM model variants perform better in catchments without an upstream reservoir.	66
Figure 3.8: Scatter plot of observed vs simulated hydrological signatures calculated for in-sample catchments for all LSTM variants on a log scale.	66
Figure 4.1: A map of India showing the location of 220 streamflow gauge stations, their data length and major river basins	80
Figure 4.2: An illustration of the methodology adopted in this study	85

Figure 4.3 A hydrograph showing the agreement between ILDAS ensemble, LSTM post-processed, and observed daily streamflow at Ramamangalam gauge station, West Flowing Rivers from Tadri to Kanyakumari.....	88
Figure 4.4 Comparison of daily streamflow residual for different seasons in each model. The box plots correspond to each of the four models. The seasons correspond to the Indian subcontinent climate as per following: Monsoon (Jun, Jul, Aug, Sep), Post-Monsoon (Oct, Nov), Winter (Dec, Jan, Feb), Pre-Monsoon (Mar, Apr, May).....	91
Figure 4.5 Comparison of nationwide error metrics across 220 gauge stations for all model configurations. The evaluation is performed using daily streamflow observations considering all seasons (annual). The evaluation period varied for each individual gauge station due to non-uniform observation records. Each column corresponds to KGE and its three components while colors represent the four models. The top row shows cumulative distribution of error metrics, and bottom row represents box plots for each metric.	92
Figure 4.6: Distribution of KGESS by comparing KGE for various models (ILDAS, LSTM and ILDAS-rLSTM) with ILDAS-mLSTM. ILDAS-mLSTM is the best performing model, and hence, the KGESS calculated to understand the scale of improvement it made over the other models. The inset value denotes the number of gauges where KGESS is positive (improved KGE) or negative (degraded KGE).	94
Figure 4.7: Comparison of peak timing and peak magnitude errors in ILDAS vs ILDAS-mLSTM. The improvement at each location is highlighted by an upward triangle and is color coded by the magnitude of improvement.	96
Figure 4.8. Correlations between KGE of various models and static catchment attributes. We calculated Pearson correlation to understand the role of various catchment properties in	

the model's overall performance. The positive (blue) value of Pearson-r signifies an increase in the model performance with a higher value of the catchment property and vice versa.96

LIST OF TABLES

Table 2.1: List of ILDAS components and their specifications.....	18
Table 2.2: Detailed analysis of monthly simulated streamflow against observed streamflow for annual and JJAS (monsoon season) from 1981-2019 for the four forcings. The digits represent the number of gauge stations (out of 162) falling under the specified criteria.	40
Table 3.1: Hyperparameters and their values used for hyperparameter tuning. The bold values represent the final selection for training the models.....	57
Table 3.2: Details of four model configurations that were evaluated in the study. Each model is trained using a distinct set of input variables including meteorological data, land surface model outputs, and catchment geophysical attributes.....	57
Table 3.3: A summary of various hydrograph evaluation metrics with nationwide median values. %FHV, % FMS, and %FLV represent bias in high flow volume, mid-section slope and low flow volume of flow duration curve. Peak timing and Peak MAPE represent mean timing and magnitude error in simulating the streamflow peaks. The values are provided separately for in-sample (IS) and out-of-sample (OS) catchments.	68
Table 4.1: Hyperparameters and their values used for hyperparameter tuning. The bold values represent the final selection for training the models.....	81
Table 4.2: Details of various model configurations used in the experimental setup.	84
Table 4.3: A brief overview of performance for all models. The highest scores are highlighted in bold. Uncalibrated ILDAS is the worst performing model in terms of nationwide KGE and residual error IQR (inter quartile range) for all seasons. The LSTM-based	

post-processing model (ILDAS-mLSTM) outperforms other models by improving KGE in 94.54% locations and reducing the residual error IQR in monsoon and post-monsoon season. The base LSTM model slightly outperforms ILDAS-mLSTM in residual error IQR in two out of the four seasons.....89

Table 4.4: An overview of peak event analysis showing various metrics such as Peak MAPE, Peak timing error, Critical Success Index (CSI), False Alarm Ratio (FAR), and Probability of Detection (POD). The ILDAS-mLSTM exhibits lowest Peak MAPE and FAR while LSTM has slightly better peak timing and CSI.95

LIST OF ABBREVIATIONS

ADAM	Adaptive Moment Estimation
ANN	Artificial Neural Networks
BMA	Bayesian Model Averaging
CaLDAS	Canadian Land Data Assimilation System
CAMELS	Catchment Attributes and Meteorology for Large-sample Studies
CCD	Cold Cloud Duration
CHIRPS	Climate Hazards Center Infrared Precipitation with Station data
CLSM	Catchment Land Surface Model
CONUS	Conterminous United States
CPU	Central Processing Unit
CRNP	Cosmic Ray Neutron Probe
CWC	Central Water Commission
DEM	Digital Elevation Model
DL	Deep Learning
ECMWF	European Centre for Medium-Range Weather Forecasts
ELDAS	European Land Data Assimilation System
ERA	ECMWF Reanalysis
ESA-CCI	European Space Agency - Climate Change Initiative
ET	Evapotranspiration
FDC	Flow Duration Curve
FHV	High Flow Volume
FLV	Low Flow Volume
FMS	Mid-Section Slope
GEOS	Goddard Earth Observing System

GLDAS	Global Land Data Assimilation System
GLMPP	General Linear Model Post-Processor
GMAO	Global Modeling and Assimilation Office
GPCC	Global Precipitation Climatology Centre
GPU	Graphics Processing Unit
GRACE	Gravity Recovery and Climate Experiment
GRUN	Global Runoff Reconstruction
GSIM	Global Streamflow Indices and Metadata
GSWP	Global Soil Wetness Project
HPC	High Performance Computing
HyMAP	Hydrological Modeling and Analysis Platform
ICON	Indian Cosmic Ray Network
ILDAS	Indian Land Data Assimilation System
IMD	Indian Meteorological Department
IMDAA	Indian Monsoon Data Assimilation and Analysis
IQR	Inter Quartile Range
IS	In-Sample
IWRIS	India Water Resources Information
JJAS	June July August September
KGE	Kling-Gupta Efficiency
KGESS	Kling-Gupta Efficiency Skill Score
LAI	Leaf Area Index
LDAS	Land Data Assimilation System
LDT	Land Data Toolkit
LISF	Land Information System Framework

LPRM	Land Parameter Retrieval Model
LSM	Land Surface Model
LSTM	Long Short-Term Memory
LSTM-CA	Long Short-Term Memory with Catchment Attributes
LSTM-PBM	Long Short-Term Memory with Physically Based Model
LU/LC	Land Use/ Land Cover
MAE	Mean Absolute Error
MAPE	Mean Absolute Percentage Error
MDH	Madahalli
MERIT	Multi-Error-Removed Improved-Terrain
MERRA	Modern-Era Retrospective analysis for Research and Applications
MODIS	Moderate Resolution Imaging Spectroradiometer
MP	Multi Parameterization
NASA	National Aeronautics and Space Administration
NLDAS	North American Land Data Assimilation System
NMAE	Normalized Mean Absolute Error
NRSC	National Remote Sensing Centre
NSE	Nash Sutcliffe Efficiency
OS	Out-of-Sample
RMSE	Root Mean Squared Error
RNN	Recurrent Neural Networks
RRMSE	Relative Root Mean Squared Error
RTX	Ray Tracing Texel eXtreme
SALDAS	South American Land Data Assimilation System
SGR	Singanallur

SIMG	Simple Groundwater Model
TOPMODEL	Topography-based Hydrological Model
TWSA	Terrestrial Water Storage Anomalies
RMSE	Root Mean Squared Error
USD	United States Dollars
VRAM	Video Random Access Memory