

LB/TH/22/2026
TH6222

**INTEGRATING REMOTE SENSING AND HYBRID
MACHINE LEARNING FOR DEVELOPING A GRIDDED
GROUNDWATER STORAGE DATASET FOR DIFFERENT
CLIMATE SCENARIOS IN SRI LANKA**

Senanayaka Mudalige Sadeepa Dasan Karunarathna

(248079C)

Degree of Master of Engineering in
Water Resources Engineering and Management

Department of Civil Engineering

University of Moratuwa
Sri Lanka

March 2026

**INTEGRATING REMOTE SENSING AND HYBRID
MACHINE LEARNING FOR DEVELOPING A GRIDDED
GROUNDWATER STORAGE DATASET FOR DIFFERENT
CLIMATE SCENARIOS IN SRI LANKA**

Senanayaka Mudalige Sadeepa Dasan Karunarathna

(248079C)

Supervised by

Dr B. C. Dissanayake

Thesis submitted in partial fulfillment of the requirements for the degree of
Master of Engineering in Water Resources Engineering and Management

UNESCO Madanjeet Singh Centre for South
Asia Water Management (UMCSAWM)

Department of Civil Engineering
University of Moratuwa
Sri Lanka

March 2026

DECLARATION OF CANDIDATE AND SUPERVISOR

“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”.

Also, I hereby grant to University of Moratuwa the non-exclusive right to reproduce and distribute my thesis/dissertation, in whole or in part in print, electronic or other medium. I retain the right to use this content in whole or part in future works (such as articles or books).

Senanayaka Mudalige Sadeepa
Dasan Karunarathna

11/03/2026

Date

The above candidate has carried out research for the Master’s Thesis/Dissertation under my supervision.

Dr B. C. Dissanayake

11/03/2026

Date

ABSTRACT

Integrating Remote Sensing and Hybrid Machine Learning for Developing a Gridded Groundwater Storage Dataset for Different Climate Scenarios in Sri Lanka

Reliable groundwater monitoring is essential to ensure water security. Yet, many regions lack dense observational networks. High-resolution gridded groundwater datasets therefore provide valuable alternatives for characterising groundwater dynamics. The Gravity Recovery and Climate Experiment (GRACE) offers large-scale terrestrial water storage anomaly (TWSA) data, but its coarse spatial resolution limits regional applicability. Recent studies have increasingly utilized machine learning (ML) to improve GRACE-based groundwater estimates; however, most have relied on individual ML models, which enhance prediction accuracy only to a limited extent. Based on these grounds, this study proposes a stacking ensemble machine learning (SEML) framework that integrates Random Forest (RF), eXtreme Gradient Boosting (XGBoost), Light Gradient Boosting Machine (LightGBM), and Categorical Boosting (CatBoost) for more precise statistical downscaling of GRACE-derived groundwater storage anomalies (GWSA) to finer spatial resolutions. The framework was first evaluated in the Kumbukkan Oya Basin, where GWSA was downscaled from 0.25° to 0.05° resolution, achieving strong predictive skill ($R^2 = 0.84$, RMSE = 3.04 cm), with grid-wise validation against GRACE yielding R^2 values exceeding 0.9 and in-situ groundwater level comparisons showing correlations above 0.7 in most wells. To further assess the physical consistency of the downscaled signals, an independent Physics-Informed Neural Network (PINN) framework was developed for the same basin. The groundwater system was idealised as a one-dimensional transient unconfined flow, reflecting the predominantly linear basin geometry. The PINN model embedded the Boussinesq groundwater flow equation directly into the learning process and was trained using rainfall as the primary forcing, with the uppermost and lowermost wells prescribed as transient boundary conditions and two interior wells used for training and testing. The model reproduced historical groundwater dynamics with a correlation coefficient of 0.81 and an RMSE of 0.57 m at the testing interior well, providing physics-based validation of the downscaled GWSA patterns. The methodology was subsequently extended to the entire Sri Lankan domain, generating the first high-resolution national GWSA dataset capable of resolving spatial heterogeneity and groundwater stress patterns. Future groundwater dynamics were assessed using precipitation projections from the CMIP6 CNRM-CM6-1 model under SSP2-4.5 and SSP5-8.5 scenarios for near- (2021–2039) and mid-century (2040–2059) periods. Trend analysis revealed spatially coherent groundwater depletion hotspots, particularly across the dry and intermediate zones, with projected GWSA declines locally exceeding -1.5 cm yr^{-1} under high-emission conditions. By integrating ensemble learning, climate projections, and national-scale analysis, this study delivers a robust, transferable framework for groundwater monitoring, climate impact assessment, and evidence-based groundwater management in data-limited regions.

Keywords: climate scenarios, GRACE/GWSA, groundwater monitoring, Kumbukkan oya, PINN, remote sensing in hydrology, statistical downscaling

DEDICATION

This thesis is dedicated to all those who provided unwavering support and encouragement throughout my academic journey. It stands not only as a scholarly contribution but also as a testament to perseverance during one of the most challenging periods of my life, reflecting the guidance and compassion of those who stood by me throughout this endeavour.

I express my sincere gratitude to my supervisor, Dr. Chatura Dissanayake, whose insightful guidance, constant encouragement, and generous mentorship were instrumental in shaping this research. I also respectfully dedicate this work to Dr. Luminda Gunawardhana and Prof. Lalith Rajapakse, whose exceptional subject knowledge, thoughtful guidance, and humanistic approach greatly enriched both this study and my academic growth.

This thesis is lovingly dedicated to my family for their continuous encouragement and unconditional support. In particular, I dedicate this work to my parents, whose patience, sacrifices, and belief in my abilities enabled me to pursue and fulfil an important academic aspiration that has long been close to their hearts.

I further dedicate this thesis to my friends and research colleagues for their motivation, support, and positivity throughout this journey. Finally, this work is dedicated to all those who are passionate about research, to those who courageously pursue academic advancement despite challenges, and to everyone who supported me in becoming independent in both my academic pursuits and personal life.

ACKNOWLEDGEMENT

First and foremost, I extend my sincere and heartfelt gratitude to my supervisor, Dr. Chatura Dissanayake, Department of Civil Engineering, University of Moratuwa, for his steadfast guidance, insightful mentorship, and continuous encouragement throughout the course of this research. His expertise, patience, and unwavering support were pivotal in shaping both the direction and the academic quality of this thesis.

I also wish to express my sincere appreciation to Prof. Lalith Rajapakse and Dr. Luminda Gunawardhana for their thoughtful guidance, consistent support, and valuable academic guidance. I am equally grateful to the Progress Review Committee member, Dr. Nimal Wijayaratna, for his critical feedback and constructive suggestions, which significantly enhanced the depth, clarity, and rigour of this work.

Special thanks are due to the Water Resources Board (WRB) and the Department of Meteorology of Sri Lanka for providing the essential datasets required for this study. In particular, I am grateful to Ms. Aruni Egodawithana, Hydrogeologist at the Water Resources Board, and all associated staff members for their kind cooperation and timely provision of data, which were instrumental in the successful execution of this research.

I gratefully acknowledge the financial support received from the Climate Action for Advanced Inclusive Education (CAFIED) initiative under the Participation Programme (PP) for the acquisition of rainfall data. I also extend my sincere thanks to the UNESCO Madanjeet Singh Centre for South Asia Water Management (UMCSAWM), University of Moratuwa, for their continued institutional and academic support throughout the study.

I further acknowledge with deep gratitude the Late Shri Madanjeet Singh, Founder of the SAF–Madanjeet Singh Scholarship Scheme, the South Asia Foundation (SAF), and the University of Moratuwa for providing me with the opportunity to pursue a Master's degree in Civil Engineering. My sincere thanks are also extended to Mr. Wajira Kumarasinghe, Mr. Samantha Ranaweera, Mrs. K. A. V. Kalanika, Ms. L. J. N. Silva, and all staff members of UMCSAWM for their guidance, encouragement, and support during my academic tenure at the University of Moratuwa.

I would also like to thank my fellow researchers and colleagues for their collaboration, knowledge sharing, and encouragement, which enriched this research journey and fostered a supportive academic environment. Finally, I express my deepest gratitude to my family and friends for their constant motivation, patience, and unwavering belief in me. Their love, understanding, and emotional support provided the strength needed to overcome every challenge encountered along this path.

TABLE OF CONTENT

1	Introduction	1
1.1	Background of the Study	1
1.2	Research Gap Identification.....	3
1.3	Aims and Objectives.....	4
1.4	Scope and Limitations.....	4
1.5	Significance of this Study	5
1.6	Methodology.....	5
1.7	Structure of the Thesis/ Dissertation.....	7
2	Literature Review.....	9
2.1	Chapter Introduction	9
2.2	General.....	9
2.3	GRACE Data and Terrestrial Water Storage Anomalies (TWSA).....	11
2.4	GRACE Data Usage for Hydrological Applications and Groundwater Monitoring	12
2.5	Deriving Groundwater Storage Anomalies (GWSA) from TWSA	13
2.6	Downscaling Techniques.....	14
2.6.1	Dynamic Downscaling (DD).....	14
2.6.2	Statistical Downscaling (SD)	15
2.6.3	Review of Downscaling Techniques and Rationale for Statistical Approach	16
2.7	Machine Learning Models in GRACE Downscaling	18
2.7.1	Ensemble and Hybrid Machine Learning Approaches.....	25
2.8	Hydrological Variables Influencing Groundwater Storage.....	26
2.9	Machine Learning in Groundwater Modelling	27
2.9.1	Groundwater Modelling Paradigms: Process-based and Data-driven Approaches	28
2.9.2	Limitations of Conventional Groundwater Modelling Approaches	30

2.9.3	Physics-Informed Neural Networks (PINNs).....	30
2.9.4	Application of PINN in Groundwater Modelling.....	31
2.10	Climate Change Impacts Assessment.....	34
2.10.1	Climate Change and Hydrological Processes Governing Groundwater Recharge 35	
2.10.2	Observed and Projected Impacts of Climate Change on Groundwater Storage ..	36
2.10.3	Climate Change Projections for Groundwater Impact Assessment.....	36
2.10.4	Methods of Bias Correction	41
2.11	Objective Functions.....	42
2.12	Literature Summary.....	43
3	Methodology.....	45
3.1	General	45
3.2	Study Area.....	45
3.3	Data Sources.....	47
3.3.1	GRACE and GRACE-FO	48
3.3.2	GLDAS Products	49
3.3.3	CHIRPS Precipitation Data.....	50
3.3.4	Evapotranspiration data.....	50
3.3.5	Normalised Difference Vegetation Index (NDVI) Data	51
3.3.6	Land Surface Temperature (LST) Data.....	51
3.3.7	Digital Elevation Model (DEM) Data.....	51
3.3.8	In-situ Groundwater Level Data.....	52
3.3.9	Observed Rainfall Data	52
3.4	Methodology	55
3.5	Statistical Downscaling of GRACE-Derived Groundwater Storage Anomaly (GWSA).....	56
3.5.1	Estimating the Groundwater Storage Anomalies using GRACE Data.....	57
3.5.2	Temporal Lags and Feature Selection.....	58

3.5.3	Machine Learning Models	59
3.5.4	Statistical Downscaling Methodology Framework	63
3.5.5	Residual Correction.....	64
3.5.6	Model Training and Evaluation.....	65
3.5.7	Validation of Downscaled GWSA	66
3.6	Physics-Informed Neural Network (PINN) Modelling of Basin-Scale Groundwater Variability	67
3.6.1	Methodology Flowchart	68
3.6.2	PINN Model Development.....	68
3.7	Assessment of Future Groundwater Availability under Climate Change Scenarios	73
3.8	Trend and Change-Point Analysis of Groundwater Storage Time Series.....	75
3.8.1	Mann–Kendall Trend Test	75
3.8.2	Sen’s Slope Estimator	76
3.8.3	Pettitt’s Change-Point Detection Test	77
4	Data Checking and Analysis.....	79
4.1	CHIRPS Precipitation Data Bias Correction	79
4.2	Groundwater Monitoring Well Selection for the PINN Model	83
5	Results and Discussion	85
5.1	Chapter Introduction	85
5.2	PINN model	85
5.2.1	Model Convergence Behaviour, Loss Evolution, and Optimised Parameters	86
5.2.2	Training and Testing Performance of the PINN Model	87
5.2.3	Seasonal Groundwater Profiles and Validation of Spatial Downscaling.....	90
5.3	Statistical Downscaling Framework Development for Basin Scale	91
5.3.1	Input Combination	91
5.3.2	Model Accuracy	93
5.3.3	Lagged Correlation Analysis Between GWSA and Environmental Predictors..	97

Table of Content

5.3.4	Spatial Downscaling of GWSA.....	99
5.3.5	Validation of GRACE Downscaling	100
5.3.6	Spatiotemporal Variability and Long-Term Trends of Downscaled GWSA	110
5.3.7	Long-Term Groundwater Storage Anomaly (GWSA) Variations	113
5.3.8	Summary of the Basin-Scale Statistical Downscaling Framework Development 117	
5.4	Extension of Basin-Scale GWSA Downscaling to Sri Lanka	117
5.5	Long-Term Monthly Mean GWSA Variability over Sri Lanka	122
5.6	Climate Change Effect on GWSA.....	124
6	Conclusions.....	127
7	Recommendations and Future Work.....	131
	Bibliography	133
	Annexure 1	157
	Annexure 2	158

LIST OF FIGURES

Figure 2-1: Conceptual illustration of the terrestrial water storage (TWS) system and its major components within the hydrological cycle, including groundwater, soil moisture, surface water (rivers, lakes, and reservoirs), and cryospheric storage (ice and snow).....	12
Figure 2-2: Projected changes in global average mean surface air temperature from 1950 to 2100 under different Shared Socioeconomic Pathway (SSP) scenarios	40
Figure 3-1: Kumbukkan Oya Basin and associated groundwater monitoring network within the study area. (a) The topography of the basin (m MSL) and groundwater monitoring wells within the basin (b) Climatic zone distribution across Sri Lanka	46
Figure 3-2: Spatial distribution of the 46 meteorological stations across Sri Lanka used in this study, obtained from the Department of Meteorology. The stations provide broad spatial coverage across the country's major hydroclimatic zones	53
Figure 3-3: Overall methodological framework of the study, including statistical downscaling of GRACE-derived groundwater storage anomalies, PINN-based groundwater modelling, and future groundwater availability assessment under climate change scenarios	56
Figure 3-4: Conceptual architecture of the proposed Stacking Ensemble Machine Learning (SEML) model. Multiple base learners are trained using k-fold cross-validation to generate intermediate predictions, which are subsequently used as inputs to a meta-learner that produces the final groundwater storage anomaly (GWSA) prediction	62
Figure 3-5: Methodological framework for downscaling GWSA, showing the input data sources, anomaly estimation, downscaling algorithms, and performance evaluation. Flowchart of the study design, divided into three parts: data preprocessing, model building, and downscaling and validation	64
Figure 3-6: Methodological flowchart of the Physics-Informed Neural Network (PINN)-based groundwater simulation model	68
Figure 4-1: Spatial bias correction framework for CHIRPS precipitation data using Thiessen polygons derived from 46 rain-gauge stations across Sri Lanka. Each polygon represents the area of influence of a station used to compute polygon-specific monthly correction factors.....	80
Figure 4-2: Spatial distribution of the 23 rain-gauge stations used for validating the bias-corrected CHIRPS precipitation dataset across the wet, intermediate, and dry climatic zones of Sri Lanka	81
Figure 4-3: Correlation heatmap of observed groundwater level time series among monitoring wells used to guide boundary, interior, and testing well selection for the PINN model	84
Figure 4-4: Idealized one-dimensional groundwater flow profile with inter-well distances and elevations	84
Figure 5-1: Evolution of total loss and individual loss components, highlighting progressive reduction of the PDE loss during PINN training	87
Figure 5-2: Comparison of observed and PINN-simulated groundwater levels at training wells (a) KUB-004, (b) KUB-007, and (c) KUB-038	88
Figure 5-3: Observed and predicted groundwater levels at the testing well (KUB-011)	89

Figure 5-4: 2D Line Plot GWL profile over domain at four dates in 4 different monsoonal seasons ...	91
Figure 5-5: Comparison of RMSE (cm) for different machine-learning models under multiple predictor combinations used in GWSA downscaling	92
Figure 5-6: Comparison of R^2 for different machine-learning models under multiple predictor combinations used in GWSA downscaling	92
Figure 5-7: Scatter plots of comparison between model-predicted GWSA and GRACE derived GWSA anomalies for training (70%) data. (a) RF, (b) XgBoost, (c) CatBoost, (d) LightGBM and (e) SEML models.....	95
Figure 5-8: Scatter plots of comparison between model-predicted GWSA and GRACE derived GWSA anomalies for testing (30%) data. (a) RF, (b) XgBoost, (c) CatBoost, (d) LightGBM and (e) SEML models	96
Figure 5-9: Distribution of prediction uncertainty from 100 bootstrap runs	97
Figure 5-10: Pearson correlation between GWSA and predictor variables at different lag times (0 to 6 months).....	98
Figure 5-11: Workflow of the downscaling process for GWSA in January 2023: (a) Original GRACE-derived GWSA at 0.25° resolution, (b) Predicted GWSA from the SEML model, (c) Residuals between GRACE and predicted GWSA at 0.25°, (d) Residuals resampled to 0.05° resolution, (e) Predicted high-resolution GWSA (0.05°) from the SEML model, and (f) Final corrected high-resolution GWSA after residual adjustment	100
Figure 5-12: Timeseries of GRACE-derived GWSA and GWSA after downscaling in Kumbukkan Oya Basin.....	101
Figure 5-12: Timeseries of GRACE-derived GWSA and GWSA after downscaling in Kumbukkan Oya Basin.....	102
Figure 5-13: SEML model simulated (orange line), GRACE-derived (blue line) monthly time series GWSA data for the entire study area, highlighting the GRACE–GRACE-FO 11-month data gap (gray hatched area)	103
Figure 5-14: Scatter plot comparing basin-mean predicted GWSA with GRACE-derived GWSA ...	103
Figure 5-15: STL decomposition of basin-mean GRACE-derived and downscaled GWSA into (a) trend component, (b) seasonal component, and (c) residual components.....	104
Figure 5-16: Climatological seasonal cycles derived from the STL seasonal component. Shaded bands represent 95% bootstrap confidence intervals, reflecting uncertainty in the monthly mean seasonal variations	105
Figure 5-17: Study area map showing the locations of GW monitoring wells. Time series plots compare in situ groundwater level anomalies (GWLA; blue line, primary axis) with downscaled groundwater storage anomalies (GWSA; orange line, secondary axis) at each well location across the basin. Correlation coefficients (CC) between the two datasets are also calculated	107
Figure 5-18: Time series plots compare long term monthly average in situ groundwater level anomalies (GWLA; blue line, primary axis) with downscaled groundwater storage anomalies (GWSA; orange line, secondary axis) at each well location across the basin	108

Figure 5-19: Comparison between PINN-simulated groundwater level profile and downscaled GWSA profile along the selected one-dimensional transect for January 2023	109
Figure 5-20: Spatial distribution of downscaled GWSA across the Kumbukkan Oya Basin for January 2023, showing the location of the extracted one-dimensional profile	110
Figure 5-21: Long-term average cumulative monthly spatial variation of GWSA across the Kumbukkan Oya Basin (2002–2023). The Maha season extends from September to March, while the Yala season spans April to June	112
Figure 5-22: Spatial and temporal variability of annual average groundwater storage anomalies (GWSA) in the Kumbukkan Oya Basin from 2002 to 2023 derived from the SEML-based downscaling framework.....	114
Figure 5-23: Long-term trends in GWSA for the Kumbukkan Oya Basin from 2002–2023. (a–b) Time series of GRACE-derived and downscaled GWSA showing pre-2020 stability and post-2020 decline	116
Figure 5-24: Spatial distribution of post-2020 GWSA trends (cm/month)	116
Figure 5-25: Scatter plot comparing observed GRACE-derived GWSA and SEML-predicted GWSA at 0.25° resolution for the training dataset across Sri Lanka	118
Figure 5-26: Scatter plot comparing observed GRACE-derived GWSA and SEML-predicted GWSA at 0.25° resolution for the testing dataset across Sri Lanka	118
Figure 5-27: Spatial comparison of (a) CC, (b) R ² , and (c) RMSE between aggregated 0.05° downscaled GWSA and original 0.25° GRACE-derived GWSA across Sri Lanka, illustrating mass-consistency preservation of the downscaling framework	119
Figure 5-28: Spatial distribution of selected groundwater observation wells within the Maduru Oya Basin used for validating the downscaled GWSA dataset	120
Figure 5-29: Comparison between observed groundwater level anomalies (GWLA) and downscaled groundwater storage anomalies (GWSA) at selected observation wells in Sri Lanka, illustrating the temporal consistency and agreement between in situ observations and satellite-derived estimates	121
Figure 5-30: Spatial distribution of long-term monthly mean groundwater storage anomalies (GWSA) across Sri Lanka, illustrating the seasonal recharge–depletion cycle driven by the island’s monsoonal climate.....	123
Figure 5-31: Spatial distribution of projected precipitation trends across Sri Lanka under SSP2-4.5 and SSP5-8.5 scenarios for short-term and medium-term periods	124
Figure 5-32: Spatial distribution of projected groundwater storage anomaly (GWSA) trends across Sri Lanka under SSP2-4.5 and SSP5-8.5 scenarios for short-term (2021–2039) and medium-term (2040–2059) periods.....	126

LIST OF TABLES

Table 2-1: Comparison of dynamic and statistical downscaling methods for GRACE applications ...	17
Table 2-2: Summary of key studies on statistical downscaling of GRACE TWSA/GWSA to finer spatial resolutions.....	20
Table 3-1: Datasets used in this research with detailed spatial and temporal resolutions	48
Table 3-2: Metadata of groundwater observation wells used for validation in the Kumbukkan Oya Basin	52
Table 3-3: Metadata of the meteorological stations used in this study, including station location, geographic coordinates, and period of record.....	54
Table 3-4: Different combinations of input predictors used to train and evaluate machine learning models for groundwater storage anomaly (GWSA) prediction	58
Table 4-1: Validation statistics (CC: correlation coefficient) comparing observed rainfall with bias-corrected CHIRPS datasets for the selected rain-gauge stations	82
Table 5-1: Evaluation metrics of the PINN model for groundwater level prediction at the withheld validation well (KUB-011), including R^2 , correlation coefficient (CC), and RMSE.....	90
Table 5-2: Comparison of training and testing performance metrics of the machine learning models evaluated for groundwater storage anomaly (GWSA) prediction.....	94
Table 5-3: Model performance (R^2 , RMSE, CC) with and without lag features for training, testing, and overall datasets	99
Table 5-4: Statistical comparison between downscaled GWSA and GRACE-derived GWSA at GRACE grid points, showing R^2 , RMSE, and CC.....	101

LIST OF ABBREVIATIONS

ANN	Artificial Neural Network
CC	Pearson Correlation Coefficient
CHIRPS	Climate Hazards Center Infrared Precipitation with Stations
CLM	Common Land Model
CMIP	Coupled Model Intercomparison Project
CNRM	Centre National de Recherches Météorologiques
CSR	Center for Space Research
CRI	Climate Risk Index
CWSA	Canopy Water Storage Anomaly
DA	Data Assimilation
DD	Dynamic Downscaling
ERA5	ECMWF Reanalysis, 5th Generation
ET	Evapotranspiration
FDM	Finite Difference Method
FEFLOW	Finite Element subsurface FLOW
FIM	First Inter-Monsoon
GCM	General Circulation Model
GFZ	German Research Centre for Geosciences (GeoForschungsZentrum)
GIA	Glacial Isostatic Adjustment
GLDAS	Global Land Data Assimilation System
GNN	Graph-based Neural Networks
GRACE	Gravity Recovery and Climate Experiment
GRACE-FO	Gravity Recovery and Climate Experiment Follow On
GWL	Groundwater Level
GWLA	Groundwater Level Anomaly
GWS	Ground Water Storage
GWSA	Ground Water Storage Anomaly
IPCC	Intergovernmental Panel on Climate Change
JPL	Jet Propulsion Laboratory
LightGBM	Light Gradient Boosting Machine

LSMs	Land Surface Models
LST	Land Surface Temperature
LSTM	Long Short-Term Memory
ML	Machine Learning
MLR	Multiple Linear Regression
MODFLOW	Modular finite-difference groundFLOW
MODIS	Moderate Resolution Imaging Spectroradiometer
NASA	National Aeronautics and Space Administration
NDVI	Normalized Difference Vegetation Index
NEM	Northeast Monsoon
PDE	Partial Differential Equation
PINN	Physics-Informed Neural Network
Pr	Precipitation
R ²	Coefficient of Determination
RF	Random Forest
RRE	Richards Equation
RMSE	Root Mean Square Error
SEML	Stacking Ensemble Machine Learning
SD	Statistical Downscaling
SIM	Second Inter-Monsoon
SMSA	Soil Moisture Storage Anomaly
SSP	Shared Socioeconomic Pathways
SRTM	Shuttle Radar Topography Mission
SUTRA	Saturated-Unsaturated TRANsport
SWEA	Snow Water Equivalent Anomaly
SWM	Southwest Monsoon
SWSA	Surface Water Storage Anomaly
TWS	Total Water Storage
TWSA	Total Water Storage Anomalies
VIC	Variable Infiltration Capacity
WGHM	WaterGAP Global Hydrology Model
WRB	Water Resources Board
XGBoost	eXtreme Gradient Boosting