# DEVELOPMENT AND ASSESSMENT OF AN INTEGRATED LARGE-SCALE HYDROLOGICAL MODELLING TOOL FOR WATER RESOURCES MANAGEMENT IN THE CAUVERY CATCHMENT, INDIA

**ROBYN HORAN**

Submitted in fulfilment of the academic requirements for

the degree of Doctor of Philosophy in Hydrology

Centre for Water Resources Research
School of Agricultural, Earth and Environmental Sciences
University of KwaZulu-Natal
Pietermaritzburg
South Africa
November 2022

# PREFACE

The research contained in this thesis was completed by the candidate while based in the Discipline of Hydrology, School of Agricultural, Earth and Environmental Sciences of the College of Agriculture, Engineering and Science, University of KwaZulu-Natal, Pietermaritzburg, South Africa.

The contents of this work have not been submitted in any form to another university and except where the work of others is acknowledged in the text, the results reported are due to investigations by the candidate.

Signed: Prof JC Smithers (supervisor)

Date: 22 November 2022

# DECLARATION OF PLAGIARISM

I, Robyn Horan, declare that:

(i) the research reported in this thesis, except where otherwise indicated or acknowledged, is my original work;

(ii) this thesis has not been submitted in full or in part for any degree or examination to any other university;

(iii) this thesis does not contain other persons' data, pictures, graphs or other information unless specifically acknowledged as being sourced from other persons;

(iv) this thesis does not contain other persons' writing unless specifically acknowledged as being sourced from other researchers. Where other written sources have been quoted, then:

a) their words have been re-written, but the general information attributed to them has been referenced;

b) where their exact words have been used, their writing has been placed inside quotation marks, and referenced;

(v) where I have used material for which publications followed, I have indicated in detail my role in the work;

(vi) this thesis is primarily a collection of material prepared by myself, published as journal articles or presented as a poster and oral presentations at conferences. In some cases, additional material has been included;

(vii) this thesis does not contain text, graphics or tables copied and pasted from the Internet unless specifically acknowledged, and the source is detailed in the thesis and the References sections.

[redacted]

Signed: Robyn Horan

Date: 22 November 2022

## DECLARATION OF PUBLICATIONS

This work was partially completed under two Natural Environment Research Council (NERC) projects. Extracts of the following published works may be found on project partner websites and within end-of-project reports.

UPSCAPE (Upscaling local water management interventions to inform larger-scale decision-making in the Cauvery Basin, India) was a three-year project funded by the Natural Environmental Research Council (NERC) in the UK and the Ministry of Earth Sciences (MoES) in India through the Newton-Bhabha initiative. The project involved six organisations from India and the United Kingdom; these included the Ashoka Trust for Research in Ecology and the Environment (ATREE), the British Geological Survey (BGS), the UK Centre for Ecology & Hydrology (UKCEH), International Crops Research Institute for the Semi-Arid Tropics (ICRISAT), Indian Institute of Science Bangalore and the University of Dundee. More information regarding this project can be found here: UPSCAPE | UK Centre for Ecology & Hydrology (ceh.ac.uk)

SUNRISE (Sustainable Use of Natural Resources to Improve Human Health and Support Economic Development) was a four-year programme funded by the Natural Environment Research Council (NERC) as part of a National Capability Long-Term Science - Official Development Assistance (LTS-ODA) Award. The Developing Hydro-climate Services for Water Management theme aimed to address the challenge of understanding and predicting water dynamics in incomplete and spatially diverse data, improving decision-making. UK Centre for Ecology & Hydrology (UKCEH) partnered with the National Institute of Hydrology (NIH) in Roorkee, India, to undertake this work. More information regarding this project and specifically this theme can be found here: Developing Hydro-climate Services for Water Management | UK Centre for Ecology & Hydrology (ceh.ac.uk)

It is customary in India to award the project chair, the project administrators and those who contribute to data collection co-authorship.

**DETAILS OF CONTRIBUTION TO PUBLICATIONS** that form part of and/or include research presented in this thesis (including publications submitted and published, giving details of the contributions of each author to the research and writing of each publication):

**Publication 1 – Chapter 2 of this thesis**

Horan, R*, Gowri, R, Wable, PS, Baron, H, Keller, VD, Garg, KK, Mujumdar, PP, Houghton-Carr, H and Rees, G, 2021. A Comparative Assessment of Hydrological Models in The Upper Cauvery Catchment. *Water*, 13(2), p.151.

***Author Contributions:***

This publication used the modelling outputs from three hydrological models in the Upper Cauvery Catchment. This research was undertaken under the UPSCAPE project. R Horan was responsible for applying GWAVA within the region, while R Gowri and P Wable were responsible for the VIC and SWAT applications. R Horan travelled to Bangalore, India, to obtain the VIC and SWAT model outputs. H Baron (GWAVA), K Garg (SWAT) and P Mujumdar (VIC) supervised the various modelling activities. R Horan undertook the literature review, methodological design, results analysis, wrote the entire publication and produced the figures, tables and graphs unless otherwise stated within the text. H Baron and V Keller provided advice regarding the interpretation of the data and structuring of the research presented within the publication. V Keller and H Houghton-Carr undertook project management roles, and G Rees and P Mujumdar were the joint project chairs. All co-authors reviewed the publication.

**Publication 2 – Chapter 3 of this thesis**

Horan, R*, Wable, PS, Srinivasan, V, Baron, HE, Keller, VJ, Garg, KK, Rickards, N, Simpson, M, Houghton-Carr, HA and Rees, HG, 2021. Modelling Small-Scale Storage Interventions in Semi-Arid India at the Basin Scale. *Sustainability*, 13(11), p.6129.

***Author Contributions:***

This publication used the GWAVA model's modelling outputs across the extent of the Cauvery Catchment. This research was undertaken under the UPSCAPE project. R Horan was responsible for the application of GWAVA within the region. P Wable, K Garg and V Srinivasan provided data regarding small-scale runoff harvesting interventions (SSRHIs). These included detailed explanations of how they function within the catchment and provided the field data regarding the dimensions and recharge estimations when the pandemic limited the travel of R Horan to the Catchment in 2020 and 2021. V Srinivasan provided contacts to various regional stakeholders whose indigenous knowledge was utilised without published data.

R Horan and V Keller conceptualised the functioning and critical parameters of each type of SSRHI from field data collected by R Horan and P Wable. H Baron and R Horan undertook the original code review and requirement finalisation. H Baron developed the code for the representation of SSRHIs from the conceptualisation. N Rickards undertook the static code review. H Baron and R Horan determined the final architecture and design within the code base. H Baron compiled the code. R Horan undertook the integration, bug and smoke testing. Issues found through the integration testing were amended by H Baron. V Keller pushed the code into the master branch.

R Horan undertook the literature review, methodological design, results analysis, wrote the entire publication and produced the figures, tables and graphs unless otherwise stated within the text. H Baron, N Rickards and V Keller provided advice regarding the interpretation of the data and structuring of the research presented within the publication. V Keller and H Houghton-Carr undertook project management roles, and G Rees was the project chair. All co-authors reviewed the publication.

**Publication 3 – Chapter 4 of this thesis**

Horan, R*, Rickards, NJ, Kaelin, A, Baron, HE, Thomas, T, Keller, VD, Mishra, PK, Nema, MK, Muddu, S, Garg, KK and Pathak, R, Houghton-Carr, HA, Dixon, H, Jain, S and Rees, G. Extending a Large-Scale Model to Better Represent Water Resources Without Increasing the Model's Complexity. *Water*, 13(21), p.3067.

***Author Contributions:***

This publication used the GWAVA model across the extent of the Cauvery and Narmada Catchments. This research was undertaken under both the UPSCAPE and SUNRISE projects. R Horan was responsible for applying GWAVA within the Cauvery and Narmada Catchments. K Garg provided data regarding SSRHIs dimensions and recharge estimations for the Cauvery Catchment. P Mishra, M Nema and R Pathak provided the land use, groundwater level and observed streamflow data for the Narmada Catchment. S Muddu provided the AMBHAS-1D code base.

Groundwater code: R Horan and H Baron conceptualised the theoretical groundwater functioning with GWAVA. R Horan and H Baron undertook the original code review and requirement finalisation. H Baron adapted the AMBHAS-1D code. R Horan undertook the static code review. H Baron and R Horan determined the final architecture and design within the code base. H Baron compiled the code. R Horan undertook the integration testing, bug testing and smoke testing. Issues found through the integration testing were amended by H Baron. N Rickards pushed the code into the master branch.

Regulated reservoirs code: R Horan and A Kaelin conceptualised the theoretical reservoir functioning. R Horan undertook the original code review and requirement finalisation. R Horan developed the regulated reservoir code. N Rickards undertook the static code review. R Horan and N Rickards determined the final architecture and design within the code base. R Horan compiled the code. R Horan undertook the integration testing, bug testing and smoke testing. Issues found through the integration testing were amended by R Horan. N Rickards pushed the code into the master branch

A Kaelin assisted with the analysis of results from the Narmada modelling exercise. R Horan undertook the literature review, methodological design, results analysis, wrote the entire publication and produced the figures, tables and graphs unless otherwise stated within the text. T Thomas, N Rickards and V Keller provided advice regarding the interpretation of the data and structuring of the research presented within the publication. T Thomas, H Dixon and H Houghton-Carr undertook the roles of project management and S Jain and G Rees took the positions of joint project chairs. N Rickards, H Baron, T Thomas, V Keller and H Houghton-Carr reviewed this publication.

**Publication 4 – Chapter 5 of this thesis**

Horan, R, Smithers JC, Kjeldsen T, Clark D, Rickards NJ and Horan MJC, 2022. An Investigation into The Suitability of Gauge-Corrected Remotely Sensed Rainfall Datasets for Hydrological Modelling in the Western Ghats. In preparation for *Remote Sensing*.

***Author Contributions:***

This publication used a rainfall dataset comparison and the modelling outputs from the GWAVA model across the Upper Cauvery Catchment. R Horan was responsible for the downloading and data manipulation of large-scale rainfall datasets as well as the application of GWAVA. N Rickards supervised the GWAVA modelling activities and code management. M

Horan assisted with scripting to download and manipulate the rainfall data and advised on the presentation of results. R Horan undertook the literature review, methodological design, results analysis, wrote the entire publication and produced the figures, tables and graphs unless otherwise stated within the text. J Smithers, T Kjeldsen, D Clark and N Rickards provided supervision and advice regarding the interpretation of the data and structuring of the research presented within the publication. All co-authors reviewed the publication.

**Data Publications**

Horan, R.; Keller, V.D.J.; Wable P.S.; Baron, H.E.; Houghton-Carr, H.A.; Rees, H.G. (2021). Simulated streamflow, demands and aquifer levels in the Cauvery Basin, India, 1986-2080 using the Global Water Availability Assessment Model (GWAVA). NERC Environmental Information Data Centre. (Dataset). https://doi.org/10.5285/522309f8-59b1-4982-85df-cb3171c2a062

Horan, R.; Rickards, N.; Kaelin, A.; Thomas, T.; Houghton-Carr, H.A. (2021). Simulated streamflow, demands and aquifer levels in the Narmada Basin, India, 1970-2099 using the Global Water Availability Assessment Model (GWAVA). NERC Environmental Information Data Centre. (Dataset). https://doi.org/10.5285/9fc7ab01-c622-46f1-a904-0bcd54073da3

[redacted]

Signed: Robyn Horan

Date: 22 November 2022

# SUMMARY

Economic development and population growth in southern India have resulted in rapid changes to land use, land management and water demand, significantly impacting and degrading water resources. The significant anthropogenic influences across the catchment have contributed to changes in hydrological functioning. Focussing on the highly contentious inter-state Cauvery River Catchment, this study aims to address the key scientific challenges faced within this catchment.

The study was designed to develop an integrated large-scale hydrological model to improve water resource assessments in a highly heterogeneous and data-scarce region whilst considering the primary water resource challenges facing the Cauvery Catchment. The Upper Cauvery region, located in the Western Ghats, acts as the water tower of the catchment. The rainfall in the region is monsoonal, the topography is complex, and the rain gauge network is sparse, resulting in the estimation of rainfall being particularly challenging. The scarce rainfall data available in the Western Ghats region is hindering the understanding of the regional weather system, and the accepted rainfall dataset for India, Indian Meteorological Department rainfall grids, are known to have inaccurate estimations within the Western Ghats. The current knowledge of the meteorology and hydrology of the Upper Cauvery is limited. Additionally, the anthropogenic impact on local hydrological processes, such as streamflow, groundwater recharge and evapotranspiration, is poorly constrained. The current understanding of how these diverse local changes cumulatively impact water availability at the broader catchment scale is minimal. Small-scale rural water management and urban heterogeneity may strongly affect water resource availability across southern India. However, how such fine-scale factors propagate to the river catchment is largely unclear.

The Global Water AVailability Assessment (GWAVA) model was applied initially to the Upper Cauvery region to determine the suitability and compare model results from other modelling tools applied in the region. Two new versions of the GWAVA model were then developed. The first aimed to include small-scale runoff harvesting interventions (SSRHIs) into the model and quantify their impact on catchment water resources to address a renewed scientific interest in assessing their effectiveness in improving local water resources and the effects at a catchment scale. The second aimed to enhance the representation of groundwater and large operational dams whilst maintaining the model’s applicability to regions with low-

data availability. The Indian Meteorological Department (IMD) gridded rainfall was compared to available gauges and selected remotely sensed datasets within the Upper Cauvery region. GWAVA will be utilised to assess the applicability of the remotely sensed data for a catchment rainfall estimation.

GWAVA was determined to be a suitable tool to represent the Cauvery Catchment; however, the importance of an accurate spatial representation of rainfall for input into hydrological models and that comprehensive dam functionality is paramount to obtaining good results in this region was highlighted. Furthermore, the average GWAVA, VIC and SWAT ensemble provided a better predictive ability in catchments with dams than the individual models. The average ensemble offset uncertainty in input data and poor dam operation functionality within individual models.

The inclusion of SSRHIs demonstrated that farm bunds appear to have a negligible effect on the average annual simulated streamflow. In contrast, tanks and check dams have a more significant and time-varying impact. The open water surface of the SSRHIs contributed to an increase in evaporation losses across the sub-catchment. The change in simulated groundwater storage with the inclusion of SSRHIs was not as significant as sub-catchment-scale literature, and field studies suggest. Including groundwater processes into GWAVA improved streamflow simulation in the headwater sub-catchments and the representation of the baseflow component such that low-flow model skill increased approximately 33-67% in the Cauvery and 66-100% in the Narmada. The existing dam routine was extended to account for large, regulated dams with two calibratable parameters. The routine improved streamflow simulation in sub-catchments downstream of major dams, where the streamflow was largely reflective of dam releases. The model performance was improved between 15 and 30% in the Cauvery and 7-30% in the Narmada when the regulated dams were considered. The model provides a more robust representation of the annual outflow volume from major dams, reducing the average bias from -17% to -1% in the Cauvery and from 14% to 3% in the Narmada. The daily dam releases were significantly improved in the Cauvery, approximately 26-164%. The improvement of the groundwater and dam routines in GWAVA proved successful in improving the overall model performance, the low-flow model skill and bias, and the inclusions allowed for improved traceability of simulated water balance components.

It was found that the IMD rainfall within the high-altitude regions of the Western Ghats is underestimated, resulting in the under-simulation of streamflow in the Upper Cauvery. CHIRPS 0.25- and 0.05- degree, MSWEP and PERSIANN remotely sensed rainfall datasets were applied within this region. None of the individual rainfall datasets provided a more accurate representation of the rainfall than the commonly utilised IMD grids. However, using an ensemble of remotely sensed rainfall datasets, primarily the average ensemble, improved the accuracy of rainfall estimation in the catchment. The ‘off-the-shelf’ remotely sensed rainfall products provided a high variation in performance against the in-situ rain gauge data. The IMD grids provided the most accurate representation of rainfall compared to the individual remotely sensed rainfall datasets, despite underestimating the rainfall depths at high altitudes. In the case of the Upper Cauvery, the average ensemble provided a more accurate representation of the rainfall.

An integrated large-scale hydrological model was developed to improve water resources assessments in a highly heterogeneous and data-scarce region whilst considering the major water resource challenges facing the Cauvery Catchment. The effects of runoff harvesting interventions, accounting for hard-rock aquifer groundwater processes and the impact of major dams were represented. The inclusion of these features improved the model performance throughout the Cauvery Catchment.

# ACKNOWLEDGMENTS

I would like to extend my gratitude to the UK Centre for Ecology and Hydrology (UKCEH), the Indian Institute of Science- Bangalore, the Ashoka Trust for Research in Ecology and The Environment (ATREE), the National Institute of Hydrology- Roorkee, International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) and the rest of the UPSCAPE and SUNRISE teams for the funding and support required to complete this research.

My supervisors, Prof Smithers, Dr Kjeldsen and Dr Clark, and Dr Toucher, thank you for your guidance, advice and encouragement. I consider myself fortunate to have had the opportunity to work with and learn from you over these two years. Everyone in the CWRR, thank you; you have always been and will always be my home.

My colleagues at UKCEH, Virginie, Helen and Nathan, and the advice, guidance and tough love you provided me during my three years at UKCEH markedly improved my abilities as a 'baby' researcher. Thank you for the confidence you had in me. It was indeed a pleasure to learn and travel with you.

My colleagues in India, Pawan, Gowri and Thomas, thank you for opening your homes, looking after me in the field, taking me on some 'cultural' excursions and treating me like family during my time in India. Your knowledge of your local catchments was second to none, and it was such a pity that I could not spend more time with you all in India. I sincerely hope that we will work together again in the future.

To Brandon, it has been a long, tough slog for us both, and now we are finally at the end after years of part-time studies. Thank you for putting your life on hold, your endless support, your shoulder to cry on, feeding me and for always believing in me. I love you.

Mikey, you continue to raise the bar. You are everything truly great in this world and I am so proud of you for all you have achieved. Thank you for being my biggest cheerleader.

Mom, there was no doubt that this day would come. Thank you for your encouragement over my entire life and for seeing more potential in me than I ever could. Thank you for standing with me through it all. Thank you for all your love and optimism in the good times and your compassion and care when things weren't going so well. Thank you for always answering my calls and making me tea. Nothing would be possible without you.

Dad, I lack the words to thank you adequately. This one is for you!

# TABLE OF CONTENTS

# LIST OF TABLES

# LIST OF FIGURES

# LIST OF ABBREVIATIONS

| | |
|---|---|
| ANN | Artificial Neural Network |
| ARIMA | Auto-Regressive Moving Average Time Series |
| BF | Baseflow |
| BCM | Billion Cubic Meters |
| CCD | Cold Cloud Duration |
| CGIR | Corporate Governance: An International Review |
| CGWB | Central Groundwater Board |
| CHIRPS | The Climate Hazards Group InfraRed Precipitation with Station data |
| CHPclim | Climate Hazards Rainfall Climatology |
| CN | Curve Number |
| CONUS | Contiguous Unites States |
| CWatM | Community Water Model |
| DEM | Digital Elevation Model |
| DHSVM | Distributed Hydrology Soil Vegetation Model |
| F-SWAT | Forced Soil and Water Assessment Tool |
| F-VIC | Forced Variable Infiltration Capacity Model |
| GAGES-II | Geospatial Attributes of Gages for Evaluating Streamflow, version II |
| GEO | Geosynchronous Equatorial Orbit |
| GCM | Global Climate Model |
| GHCN | Global Historical Climatology Network |

| | |
|---|---|
| GPCP | Global Precipitation Climatology Project |
| GRDC | Global Runoff Data Centre |
| GSOD | Global Summary of the Day |
| GTS | Global Telecommunications System |
| GW | Groundwater |
| GWAVA | Global Water Availability Assessment Tool |
| GWAVA-GW | Global Water Availability Assessment Tool- Groundwater |
| GWAVA-Int | Global Water Availability Assessment Tool- Interventions |
| GWAVA-Res | Global Water Availability Assessment Tool- Reservoirs |
| HiGW-MAT | Human Intervention and Ground Water Coupled MATSIRO |
| HRU | Hydrologic Response Units |
| HYPE | Hydrological Predictions for The Environment |
| IDW | Inverse Distance Weighted |
| IMD | Indian Meteorological Department |
| ISRIC | International Soil Reference and Information Centre |
| JJAS | June, July, August, and September |
| KGE | Kling-Gupta Efficiency |
| KRS | Krishna Raja Sagara |
| KWA | Karnataka Watershed Authority |
| LAI | Leaf Area Index |
| LNE | Log-Nash Efficiency |
| LPJmL | Lund-Potsdam-Jena Managed Land |

| | |
|---|---|
| LULC | Land Use Land Cover |
| MAR | Mean Annual Rainfall |
| MCM | Million Cubic Meters |
| MERRA | Modern-Era Retrospective analysis for Research and Applications |
| MESH | Modélisation Environnementale Communautaire-Surface Hydrology |
| MSWEP | Multi-Source Weighted Ensemble Precipitation |
| NBSS 7 LUP | National Bureau of Soil Survey and Land Use Planning |
| NCEP | National Centres for Environmental Prediction |
| NE | North-Eastern |
| NGO | Non-governmental Organisation |
| NRSC | National Remote Sensing Centre |
| NSE | Nash-Sutcliffe Efficiency |
| OND | October, November, and December |
| OWE | Open Water Evaporation |
| PCR-GLOBWB | PCRaster Global Water Balance |
| PDM | Probability Distribution Model |
| PERSIANN-CDR | Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record |
| PRISM | PRISM High-Resolution Spatial Climate Data for the United States |
| RMSE | Root Mean Squared Error |
| SASSCAL | Southern African Science Service Centre for Climate Change and Adaptive Land Management |

| | |
|---|---|
| SCS-CN | Water Evaluation and Planning System |
| SDG | Sustainable Development Goals |
| SSP | Sardar Sarovar Project |
| SSRHI | Small-scale runoff harvesting interventions |
| SUNRISE | Sustainable Use of Natural Resources to Improve Human Health and Support Economic Development |
| SVR | Support Vector Regression |
| SW | South-Western |
| SWAT | Soil and Water Assessment Tool |
| TMC | Thousand Million Cubic Meters |
| TMPA | TRMM Multi-satellite Precipitation Analysis |
| TRMM | Tropical Rainfall Measuring Mission |
| UKCEH | UK Centre for Ecology & Hydrology |
| UN | United Nations |
| UPSCAPE | The Upscaling Catchment Processes for Sustainable Water Management in Peninsular India |
| USD | US Dollars |
| USGS | United States Geological Survey |
| VSA | Variable Source Area |
| VIC | Variable Infiltration Capacity |
| VIC-mHM | Variable Infiltration Capacity-Macroscale Hydrologic Model |
| VIC-WUR | Variable Infiltration Capacity-Wageningen University and Research |

| | |
|---|---|
| V-SWAT | Virgin Soil and Water Assessment Tool |
| V-VIC | Virgin Variable Infiltration Capacity Model |
| WEAP | Water Evaluation and Planning System |
| WRIS | Water Resources Information System |

# 1. INTRODUCTION

## 1.1. Background

Ground- and surface-water resources have been rapidly declining within India over recent decades, raising concerns about the country's inhabitants' drinking water, food, and livelihood security (Biggs *et al.*, 2007). A changing climate, intensification of agriculture, failing water supply infrastructure, rapid economic development and population growth (Loucks, 2017) have resulted in a reduction in quantity and degradation in the quality of water resources (Cleaver, 2017). The increasing pressure on the available surface and groundwater resources from a changing climate (Christensen *et al*., 2013) and anthropogenic activities (Lannerstad, 2008; Madhusoodhanan *et al*., 2016; Sreelash *et al.*, 2020) pose significant challenges to water managers and local communities (Bookhagen, 2012).

Southern India experiences a monsoonal rainfall pattern (Sen Roy *et al.*, 2009) with recent reports (Joseph & Simon, 2005; Kulkarni, 2012; Dixit *et al.*, 2014; Kumar *et al*., 2020; Swapna *et al*., 2022) of the monsoon significantly weakening. The estimation of rainfall is complicated by the complex topography of the Western Ghats (Malik *et al.*, 2012), the large spatial and temporal variability of the annual monsoons (Daly, 2006) and the conversion of a sparse rain gauge network and proxy measurements into estimates at catchment scale (Ghimire *et al.*, 2018). The seasonal nature of rainfall and resulting streamflow generation within the region has resulted in infrastructural projects being at the forefront of water management planning over the last century (Chowdhury, 2010). More recently, extending existing projects and planning new projects has led to renewed controversy concerning inter-state water-sharing agreements and the displacement of communities (Gupta & Chakrapani, 2005; Jamwal *et al*., 2014). On a local scale, communities have turned to unsustainable groundwater pumping (Bhave *et al*., 2018; Collins *et al*., 2020) and the construction of small-scale runoff harvesting interventions to meet the increasing demand for clean water (Ramaswamy, 2007).

## 1.2. The Cauvery Catchment

The Cauvery Catchment (81,000 km$^2$) in southern India (Figure 1.1) drains nearly 3% of India's landmass (Jain *et al*., 2007). Its tropical setting, diverse terrain, and strong west-to-east rainfall gradient (6000 mm in the upper reaches to 300 mm on the eastern boundary) mean that surface and groundwater availability is regionally variable (Meunier *et al.*, 2015) and, depending on local demand patterns, is a critical and widely limiting factor for agriculture (Madhusoodhanan *et al*., 2016). The catchment is primarily underlain by hard-rock water tables (Collins *et al*., 2020). Although predominantly rural (Sreelash *et al.*, 2020), parts of the catchment have experienced considerable urban and economic growth over recent years, most markedly centred around the cities of Bangalore, in Karnataka, and Coimbatore, in Tamil Nadu (Lannerstad, 2008). Shared between the states of Karnataka and Tamil Nadu (Chidambaram *et al.*, 2018), the Cauvery has long presented water management challenges at the local, regional and catchment scales (Sharma *et al.*, 2020). Competing water demands, which span administrative boundaries, continue to present significant challenges for integrated water management in the catchment.

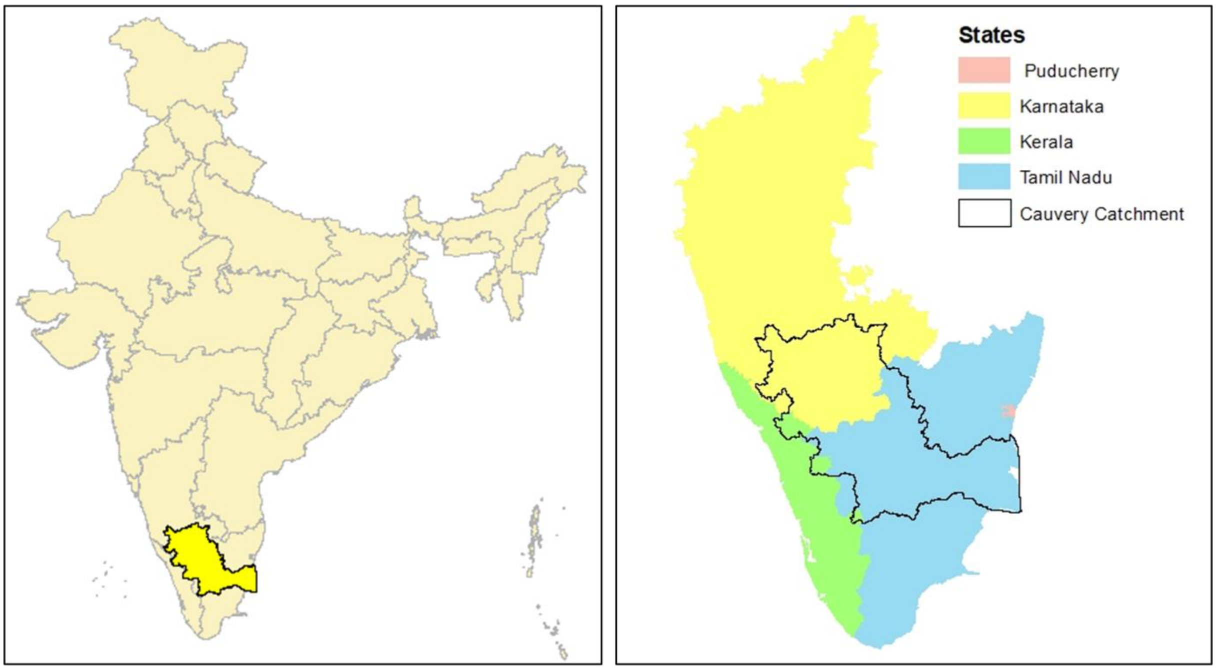



Figure 1.1 The location of the Cauvery Catchment within India (left) and the states within the catchment boundary (right).

The surface water in the catchment has been affected for centuries by human influences. Such artificial influences alter the hydrological functioning of the catchment, but a comprehensive understanding of water transfers and return flow has never been achieved (Gupta & van der Zaag, 2008). This knowledge is especially relevant for improving the estimation of water availability across the catchment. Much irrigated agriculture is dependent on groundwater abstraction from millions of wells. Little is known about the ground- and surface-water interactions, especially in hard-rock areas (Collins *et al*., 2020). Deep water tables appear to respond to monsoonal recharge where the shallow water table is depleted. The drying of streams has been attributed to groundwater depletion, yet the spatial and temporal scale at which this interaction occurs has not been established (Collins *et al.*, 2020). Over recent decades, millions of small-scale runoff harvesting interventions have been built. Such small-scale runoff harvesting interventions effectively convert surface runoff to soil moisture, evapotranspiration and groundwater (Renganayaki & Elango, 2013). Although small and often occurring in an unofficial, decentralized manner, cumulatively, these small-scale runoff harvesting interventions have dramatically altered catchment hydrology and the flow regimes of the region's rivers. Their effects on wider catchment water availability are poorly understood (Xu *et al*., 2013; Van Meter *et al.,* 2015). Addressing concerns around water resources is challenging in southern India as there are significant gaps in the natural and anthropogenic hydrological knowledge (Tessema, 2011).

Water disputes in the Cauvery Catchment differ from other inter-state water disputes, such as in the Krishna, Godavari and Narmada Catchments. In these other catchments, disputes tend to form around the untapped potential of water resources, whereas in the Cauvery, the disputes surround the reallocation of existing water resources (Janakarajan, 2016). The Cauvery Catchment is situated predominantly within the federal states of Karnataka and Tamil Nadu (Sharma *et al.,* 2020). The 'agreements' between Karnataka and Tamil Nadu over the water sharing of the Cauvery have been dysfunctional since they were first drafted in 1872 (Ghosh *et al*., 2018). A Cauvery Water Sharing agreement was signed in 1924, following the first known colonial court proceedings regarding inter-state water sharing (D'Souza, 2005). This agreement allocated a significant share of the Cauvery waters to Tamil Nadu and allowed for the construction of the Krishnarajasagara (KRS) Dam by Karnataka and Mettur Dam by Tamil Nadu (Hussain, 1972; Guhan, 1993). In 1974 the agreement lapsed, after which the conflicts over the sharing and use of water resurfaced (Iyer, 2003), leading to years of unconstrained development and bargaining (Guhan, 1993). In 1990, the Indian Government constituted a Cauvery Water Disputes Tribunal to resolve the dispute without political influence (Swain, 1998; Padhiari & Ballabh, 2008). After 17 years passed, its final recommendations in 2007 of an allocation of 270 thousand million cubic feet (TMC) to Karnataka and 419 TMC to Tamil Nadu (Civil Appeal No: 2453 of 2007 with Civil Appeal No: 2456 of 2007). However, today, there remains no resolution (Ghosh *et al*., 2018) following the adjustment of these allocations in 2013 to 285 TMC and 404 TMC to Karnataka and Tamil Nadu, respectively (Sharma *et al.*, 2020). The conflict has recently resurfaced in the context of drier climatic conditions. Legal battles (Tiwari, 2016) and violent protests have occurred following decisions to alter water distribution between the two states. The conflict over the Cauvery waters peaked in 2016 (Janakarajan, 2016) when protests shut down Bangalore (India's information technology hub) for three days. The violent demonstrations cost the lives of at least three people, damaged 250 busses, trucks and shops and resulted in an economic loss of an estimated USD 3.74 billion (Mehtani, 2017).

The recent reports of significant loss of human life and livelihoods across the Cauvery Catchment (Patil, 2015), as a direct and indirect consequence of high-level water management decisions, draw attention to the water management strategies in the catchment and the lack of holistic understanding of the system (Kaibara, 2021). Farmers in the Cauvery Catchment have reported emotional distress and dire economic situations due to failing crops due to the weakening monsoon (Joseph & Simon, 2005; Kulkarni, 2012; Kannaiyan & Jeyaraman, 2013; Dixit *et al*., 2014; Sabarisakthi, 2019; Sravanth, 2019; Kumar *et al*., 2020; Swapna *et al*., 2022) and agricultural droughts (Lokesh *et al.*, 2020). Large commercial irrigation projects and the competition with urban and industrial centres for the available water resources have left small-scale farmers with a shortfall in water from surface sources. The reallocation of surface water contributes to 83% and 77% of farmers in Tamil Nadu and Karnataka, respectively, being in debt (Manjunatha & Ramappa, 2017). Many farmers have turned to groundwater pumping (Chidambaram *et al.*, 2018) and small-scale runoff harvesting interventions (SSRHIs) (Wable *et al.*, 2021) to provide enough water to yield successful crops. It is believed that SSRHIs have resulted in surface water being retained within the upper reaches of the catchment (Reghunath & Mujumdar, 2020), rapidly depleting groundwater resources and a reduction in baseflow, sustaining the rivers (Collins *et al.*, 2020). The devastating consequence of debt and ongoing water availability concerns has led to farmers cultivating long-growing commercial trees and migrating to urban areas for alternative employment. Additionally, it has been reported that 47 200 farmers have committed suicide in the Cauvery over the last ten years (Rajendran, 2014; Tiwari, 2016; Kumar, 2017; Sabarisakthi, 2019).

### 1.3.Rationale for the Study

Water resources management in India is becoming increasingly challenging with rapid population growth, a changing climate, and increasing competition over limited natural resources. The Cauvery Catchment presents a unique set of additional challenges as there is a great deal of contention over water management decisions and evidence of a significant loss of life and livelihood directly related to these decisions. From available literature as well as several stakeholder engagement meetings (supplementary information in Appendix A), five significant water resource challenges have been highlighted:

a) The understanding of the runoff-generation processes within the headwater sub-catchments is limited.
b) The rainfall estimation in the Western Ghats is challenging due to complex topography and a sparse gauge network.
c) Small-scale runoff harvesting interventions (SSRHI) reduce streamflow in the catchment and promote surface water infiltration to the soil water and groundwater stores.
d) Hard-rock water table stores are being aggressively pumped to meet increasing demand.
e) Major dams have been and continue to be constructed throughout the catchment resulting in river discharge primarily reflecting the dam releases.

Significant gaps in scientific knowledge relating to these major challenges are summarised:

a) Lack of available hydrological and climate data across the region
b) Currently, applied models are not sufficiently capturing the behaviour of the Cauvery headwater sub-catchments. These models can represent natural hydrology well however lack the consideration of anthropogenic influences.
c) The scarce rainfall data in the Western Ghats region has hindered the understanding of the regional weather system.

d) The accepted rainfall dataset for India (IMD rainfall grids) is known to have inaccurate estimations within the Western Ghats.
e) Currently, no studies are quantifying the hydrological effects of small-scale runoff harvesting interventions at a large catchment scale.
f) The functioning of hard-rock water tables is poorly understood at a catchment scale
g) Published modelling studies within the catchment do not address the significant water resource challenges.

There is a need to adapt an existing hydrological modelling tool that can be applied at a daily timescale to capture the high variability of rainfall and consequently streamflow generation in the headwater sub-catchments, incorporate the spatial and temporal functioning of SSRHIs and large dams and explicitly account for the groundwater processes and abstractions. Developing a new reliable hydrological model that can account for general anthropogenic influences and the specific challenges of southern India would not be feasible, financial or otherwise. The most effective solution would be to adapt and improve an existing model that had preferably already been applied and evaluated under Indian or monsoonal conditions. A hydrological model would prove more robust in a data-scarce region as the model can be forced with existing rainfall and temperature data, rather than a land-surface model that estimates atmospheric conditions using complex input data that is unlikely to be available.

The IMD grids are the most popular source of historical rainfall data used in India despite their shortfalls in mountainous regions. The interpolation methodology that has been applied, together with the low density of rain gauges in these regions, has resulted in the spatial variability of rainfall not being captured adequately at a 0.25-degree scale. Satellite rainfall products derived using a different methodology could better reflect the orographic rainfall in the headwaters of the Cauvery Catchment.

## 1.4. Model Review

Water resource models are widely used for the prediction and understanding of hydrological processes (Schaake *et al*., 1996; Martínez-Fernández & Ceballos, 2005). The performance (Bárdossy, 2007) and suitability (Hassan *et al.*, 2015) of a hydrological model can differ between sub-catchments due to sub-catchment size and dominant sub-catchment processes present. Models are often developed for specific purposes (e.g. estimation of water demands, understanding of hydrological processes, drought and flood risk assessments) and for different geographic regions (Devia *et al*., 2015). The most reliable models in regions where data are sparse are models whose results closely represent reality with the use of limited model complexity (Tegegne *et al*., 2017). Table 1.1 provides a list of models that have been applied in India and/or used to represent some of the major water resource challenges identified in India and includes large-scale models that have been applied in India. It is recommended that a catchment of 80 000 km$^2$ such as the Cauvery, be represented using a large-scale model.

Of the models reviewed in this study, and as summarised in Table 1.1, four gridded large-scale hydrological models could be appropriate options for this study; CWatM, GWAVA, HO8 and PCR-GLOBWB. SWAT and VIC are popular model choices in India. However, the VIC code is not available for adaption and SWAT is not feasible at the scale required to model the full extent of the Cauvery. Like most large-scale models, CWatM. HO8 and PCR-GLOBWB, do not have calibration functionality. Although the absence of calibration is largely accepted in large-scale modelling methodology it would be preferable to determine model performance and apply a calibrated model, when sufficiently reliable data is available, across the catchment. Therefore, for this study, GWAVA was selected as the most suitable large-scale modelling tool. The use of GWAVA allows for the representation of the catchment's natural hydrology, dams, water transfer schemes as well as anthropogenic demands on a large scale. The low-data capability of the model ensures it would be suitable in southern India. The modular code allows for a more complex groundwater model to be considered, small-scale runoff harvesting interventions represented, and a regulated dam routine to be included.

Table 1.1 A non-exhaustive list of the characteristics and considerations of available machine learning, statistical, hydrological and land surface models utilised in hydrological studies in India. (Table compiled by the candidate from the sources listed within)

| **Model** | **Model Type** | **Grid/ Catch** | **Rainfall-runoff model** | **Anthropogenic Considerations** | | | | | | **Dam Routine** | **Cal Funct** | **App in data-scarce regions** | **Open-source code** | **App in India** | **App in Cauvery Catchment** | **Reference** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | **Irri** | **Dom** | **Ind** | **Live** | **Tran** | **Res** | | | | | | | |
| Artificial Neural Networks (ANN) | Machine Learning | Catch | | × | × | × | × | × | × | × | × | ✓ | × | ✓ | ✓ | Wasserman, 1989 |
| Auto-Regressive Integrated Moving Average (ARIMA) | Statistic | Catch | Box-Jenkins | × | × | × | × | × | × | × | × | ✓ | × | ✓ | ✓ | Box & Jenkins, 1976 |
| Community Water Model (CWatM) | Hydrological | Grid | Water balance | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | ✓ | ✓ | × | Burek, *et al.*, 2020 |
| The Distributed Hydrology Soil Vegetation Model (DHSVM) | Hydrological | Catch | Saturation excess | × | ✓ | × | × | × | ✓ | ✓ | ✓ | × | ✓ | ✓ | × | Wigmosta et al., 1994 |
| Global Water Availability Assessment Tool (GWAVA) | Hydrological | Grid | PDM | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | Meigh, *et al.*, 1999 |
| Hydrologic Modeling System (HEC-HMS) | Hydrological | Catch | Saturation excess | × | × | × | × | × | ✓ | ✓ | ✓ | × | × | ✓ | × | Peters, 1995 |

Table 1.1 Cont…

| Model | Model Type | Grid/ Catch | Rainfall-runoff model | Anthropogenic Considerations | | | | | | Dam Routine | Cal Funct | App in data-scarce regions | Open-source code | App in India | App in Cauvery Catchment | Reference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Irri | Dom | Ind | Live | Tran | Res | | | | | | | |
| H08 | Hydrological | Grid | Leaky bucket model | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | ✓ | ✓ | × | Hanasaki, *et al.*, 2008 Hanasaki, *et al.*, 2018 |
| Hydrological Predictions for the Environment (HYPE) | Hydrological | Catch | Water balance | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | ✓ | ✓ | × | Lindström *et al.*, 2013 |
| Joint UK Land Environment Simulator (JULES) | Land Surface | Grid | PDM<br>Topmodel | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | × | ✓ | × | Best, *et al.*, 2011<br>Clark, *et al*., 2011 |
| Lund-Potsdam-Jena managed Land (LPJmL) | Land Surface | Grid | Saturation excess | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | ✓ | ✓ | × | Schaphoff, *et al.*, 2018 |
| PCRaster GLOBal Water Balance (PCR-GLOBWB) | Hydrological | Grid | Leaky bucket model | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | ✓ | ✓ | × | Sutanudjaja, *et al*. 2018 |
| MATSIRO | Land Surface | Grid | Water balance | × | × | × | × | × | × | × | × | × | × | ✓ | × | Takata *et al.*, 2003 |
| MIKE BASIN | Hydrological | Catch | NAM | ✓ | ✓ | ✓ | ✓ | × | ✓ | ✓ | | × | × | ✓ | × | Wood, 2006 |

Table 1.1 Cont…

| **Model** | **Model Type** | **Grid/ Catch** | **Rainfall-runoff model** | **Anthropogenic Considerations** | | | | | | **Dam Routine** | **Cal Funct** | **App in data-scarce regions** | **Open-source code** | **App in India** | **App in Cauvery Catchment** | **Reference** |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | **Irri** | **Dom** | **Ind** | **Live** | **Tran** | **Res** | | | | | | | |
| Modélisation Environnementale 10ommunautaire – Surface Hydrology (MESH) | Land Surface | Grid | Water balance | × | × | × | × | × | ✓ | ✓ | × | × | × | ✓ | × | Pietroniro *et al.* 2007 |
| Sacramento Soil Moisture Accounting Model (SAC-SMA) | Hydrological | Catch | Water balance | × | × | × | × | × | × | × | × | × | ✓ | ✓ | × | Burnash *et al*., 1973 |
| SCS-CN | Hydrological | Catch | SCS | × | × | × | × | × | × | × | ✓ | ✓ | × | ✓ | × | |
| Soil and Water Assessment Tool (SWAT) | Hydrological | Catch | Modified SCS | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | ✓ | ✓ | ✓ | Arnold *et al*, 1993 |
| Soil and Water Integrated Model (SWIM) | Hydrological | Catch | Modified SCS | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | ✓ | | Krysanova, *et al.*, 2000 |
| Support Vector Regression (SVR) | Machine Learning | Catch | | × | × | × | × | × | × | × | × | ✓ | × | ✓ | ✓ | Deka, 2014 |

Table 1.1 Cont…

| Model | Model Type | Grid/ Catch | Rainfall-runoff model | Anthropogenic Considerations | | | | | | Dam Routine | Cal Funct | App in data-scarce regions | Open-source code | App in India | App in Cauvery Catchment | Reference |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | | Irri | Dom | Ind | Live | Tran | Res | | | | | | | |
| Variable Infiltration Capacity (VIC) | Land Surface | Grid | Saturation excess | ✓ | × | × | × | ✓ | ✓ | ✓ | ✓ | ✓ | × | ✓ | ✓ | Nijssen, *et al.*, 1997 |
| WaterGAP | Hydrological | Grid | Non-linear function | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | ✓ | × | × | × | ✓ | × | Döll, *et al.*, 2003<br>Alcamo, *et al.*, 2003 |

*Key:
Irri- Irrigation considerations
Dom- Domestic considerations
Ind- Industrial considerations
Live- Livestock considerations
Tran- Inclusion of transfers
Res- Inclusion of dam
Catch- Catchment
Cal Funct- Calibration Functionality
App- Application

## 1.5.Description of the Greater Research Projects

The research described within this thesis was undertaken within two large multi-national, multi-institutional and multi-disciplinary projects (UPSCAPE and SUNRISE). This section contains a summary of the objectives and decision making process within the two projects.

### *1.5.1 The Upscaling Catchment Processes for Sustainable Water Management in Peninsular India (UPSCAPE)*

The Upscaling Catchment Processes for Sustainable Water Management in Peninsular India (UPSCAPE) project was delivered by a consortium of UK and Indian scientists. UPSCAPE was designed to address water resource sustainability issues in Peninsular India using observations from established experimental catchments, and multi-scale hydrological modelling. UPSCAPE had the following objectives:

a) To further understand how SSRHIs affect hydrological change and cumulatively impact on water security at the catchment-scale;
b) To develop novel methods for upscaling improved local-scale process understanding in catchment-wide integrated water resources models;
c) To investigate the key hydrological processes operating in rural Peninsular India catchments, applying coupled surface and groundwater models to assess how local interventions affect water availability.

The work presented in this thesis is fundamental in addressing all the project objectives. Within the effort to better understand SSRHIs, SWAT was selected and implemented by International Crops Research Institute for the Semi-Arid Tropics (ICRISAT) specifically to model the headwater catchments of the Cauvery and to investigate the effect of SSRHIs at a small-scale. GWAVA and VIC are generally not suitable to be used on a scale less than 10 $km^2$ and therefore a significant objective of the greater project was to derive suitable upscaling methodologies and apply knowledge gained at a small-scale to the full extent of the catchment. The knowledge regarding functioning and effect of the SSRHIs from the SWAT modelling exercise was applied to the modelling of the full extent of the catchment using GWAVA. VIC, however, was not suitable to implement SSRHIs as VIC did not account for anthropogenic influences nor was the code adaptable.

GWAVA is the UKCEH in-house large-scale water resources assessment tool. Despite the influence of historical institutional knowledge, project funding, project directive and the framework of the greater project lead by UK Centre for Ecology & Hydrology (UKCEH), the choice to utilise GWAVA for this project was supported by its suitability, to achieving the objectives of the project as well as for the Cauvery Catchment, as described in in Section 1.4. Collaboratively working with project partners at ICRISAT and the Indian Institute of Science (IISc), the SSRHIs conceptualisation and AMBHAS code were integrated into the GWAVA model to account for the millions of SSRHIs in southern Indian and to couple the surface and groundwater processes. Furthermore, once the impact of regulated dams on the streamflow in the Upper Cauvery was identified, there was an opportunity to further develop GWAVA to better account for these. VIC was selected and implemented by IISc. As a land-surface model, VIC was predominantly utilised to investigate climate trends and anomies within the baseline period in a separate piece of work. As part of the initial pilot study for the project, it was deemed suitable to compare the modelling results of SWAT, VIC and the original version of GWAVA to determine their individual performances and provide a comparative assessment. It was understood at this time that there was a need to develop GWAVA and thus comparing its performance to two models that were well established in India and that are fundamentally different, allowed for the shortcomings of the original GWAVA model to be highlighted and addressed.

Although GWAVA needed to be developed further, the original code base enabled the representation of the catchment's natural hydrology, dams, water transfer schemes as well as anthropogenic demands on a large scale. The low-data capability of the model ensured it would be suitable for application in southern India. The modular code allows for a more complex groundwater model to be considered, small-scale runoff harvesting interventions represented, and a regulated dam routine to be included. GWAVA could be considered a suitable model choice due to published applications in southern Africa (Meigh *et al.*, 1999), West Africa (Meigh & Tate, 2002; Meigh *et al*., 2005; Rameshwaran *et al*., 2017; Rickards *et al*., 2019), South America (Ekstrand *et al*., 2008), Europe (Dumont *et al.*, 2012; Johnson *et al.*, 2015; Williams *et al*., 2015), China (Lui *et al*., 2015) and India (Rickards *et al*., 2020).

Significantly, the research undertaken at the catchment scale in this thesis produced the key output of the UPSCAPE project that "the effect of small-scale interventions, such as field bunds, check dams and tanks, on surface flows and groundwater infiltration is localised and they have relatively little impact on surface flows entering the Cauvery delta. Furthermore, the large infrastructures such as major dams and water transfers have a much more significant impact on river flows than small-scale interventions”.

### *1.5.2 Sustainable Use of Natural Resources to Improve Human Health and Support Economic Development (SUNRISE)*

SUNRISE Theme 1 addressed the challenge of understanding and predicting hydro-climatic dynamics in areas of incomplete and spatially diverse data in order to improve water related decision-making. Theme 1 of the SUNRISE programme focused on advancing the application of new scientific knowledge and tools in relation to:

a) soil moisture measurement;
b) drought monitoring;
c) flood risk assessment;
d) sub-seasonal to seasonal hydrological outlooks;
e) the modelling of water resources under future climatic and socio-economic scenarios.

The research in this Theme was conducted in collaboration with leading scientific institutions and water management bodies in China, India and sub-Saharan Africa. All activities included a focus on long-term capacity development, with UKCEH and partners co-developing and delivering new hydro-climatic services as part of the programme as well as advancing the scientific knowledge and skills needed to enable future advances beyond the end of SUNRISE.

The work undertaken in this PhD falls within the work package 1.5 “Improving integrated water resources modelling in South Asia.” This work package aimed to contribute to a reduction in per capita water stress in the Narmada Catchment in India by enhancing stakeholders' (water managers, policy-makers and scientists) understanding of the drivers and impacts of change influencing the water balance. The SUNRISE work with the Indian National Institute of Hydrology was designed to help improve water resource management in the Narmada Catchment, benefiting people, agriculture, industry and the environment. Due to the temporal overlap of the UPSCAPE and SUNRISE projects as well as the common use of GWAVA within both projects, it was decided that both the Cauvery and the Narmada would be used as case studies through the model development. Ultimately, the model results from

GWAVA 5.1 were used in subsequent policy briefs and the GWAVA 5.1 code utilised for the running of future climate and socio-economic scenarios.

## 1.6.Research Aims and Objectives

This study aims to develop an integrated large-scale hydrological model to improve water resources assessments in a highly heterogeneous and data-scarce region whilst considering the major water resource challenges facing the Cauvery Catchment. These significant challenges include the understanding of the hydrology within the Upper Cauvery Catchment, the effects of small-scale runoff harvesting interventions at the full catchment scale, understanding and accounting for hard-rock water table groundwater processes, the representation of the impact of major dams throughout the whole catchment and the estimation of rainfall across the Western Ghats within the Upper Cauvery Catchment.

The following seven objectives guided the study in fulfilling the aim:

a) Evaluate the suitability of the GWAVA model for application in the Cauvery and highlight current shortfalls in its predictive ability (Chapter 2)
b) Contribute evidence-based findings to the ongoing discussion regarding the hydrological effect of SSRHIs at a full catchment scale (Chapter 3).
c) Include new functionality within the GWAVA model to address the significant water resource challenges with the Cauvery Catchment and similar data-scarce catchments (Chapter 4).
d) Develop a better understanding of the functioning of highly abstracted hard-rock water tables and ground- and surface water interactions on a full catchment scale (Chapter 4)
e) Represent major dams without the availability of operational data (Chapter 4)
f) Ascertain whether selected 'off-the-shelf' remotely sensed rainfall products are suitable for hydrological modelling within the Upper Cauvery without regional bias correction (Chapter 5)
g) Determining whether an 'off-the-shelf' remotely sensed product could improve the hydrological simulations within a complex topographical region compared to the IMD gridded dataset (Chapter 5).

### 1.7.Thesis Outline

The thesis consists of six chapters, of which four (Chapters 2 – 5) present the research findings in individual research papers prepared for publication in refereed journals. The structure of the research papers is outlined in Figure 1.2. Chapter 2 provides a pilot study of the application of the GWAVA model in the headwater catchments of the Cauvery Catchment and compares the performance to those of popular models, SWAT and VIC, across the region. Chapter 3 describes the application of the GWAVA model across the extent of the Cauvery Catchment and the in-depth investigation into the effects of SSRHIs. Chapter 4 describes an improvement to the GWAVA model through a more comprehensive account of the groundwater processes and major dams with an application across the Cauvery and Narmada catchments. Chapter 5 analyses the IMD rainfall grids within the Upper Cauvery Catchment and the application of multiple satellite products across the region. Each research paper consists of a literature review related to the aim and methodology of that paper. The original publications are written using the accepted terminology for India. The terminology within this thesis has been adapted from the publications to reflect the accepted terminology used in South Africa.

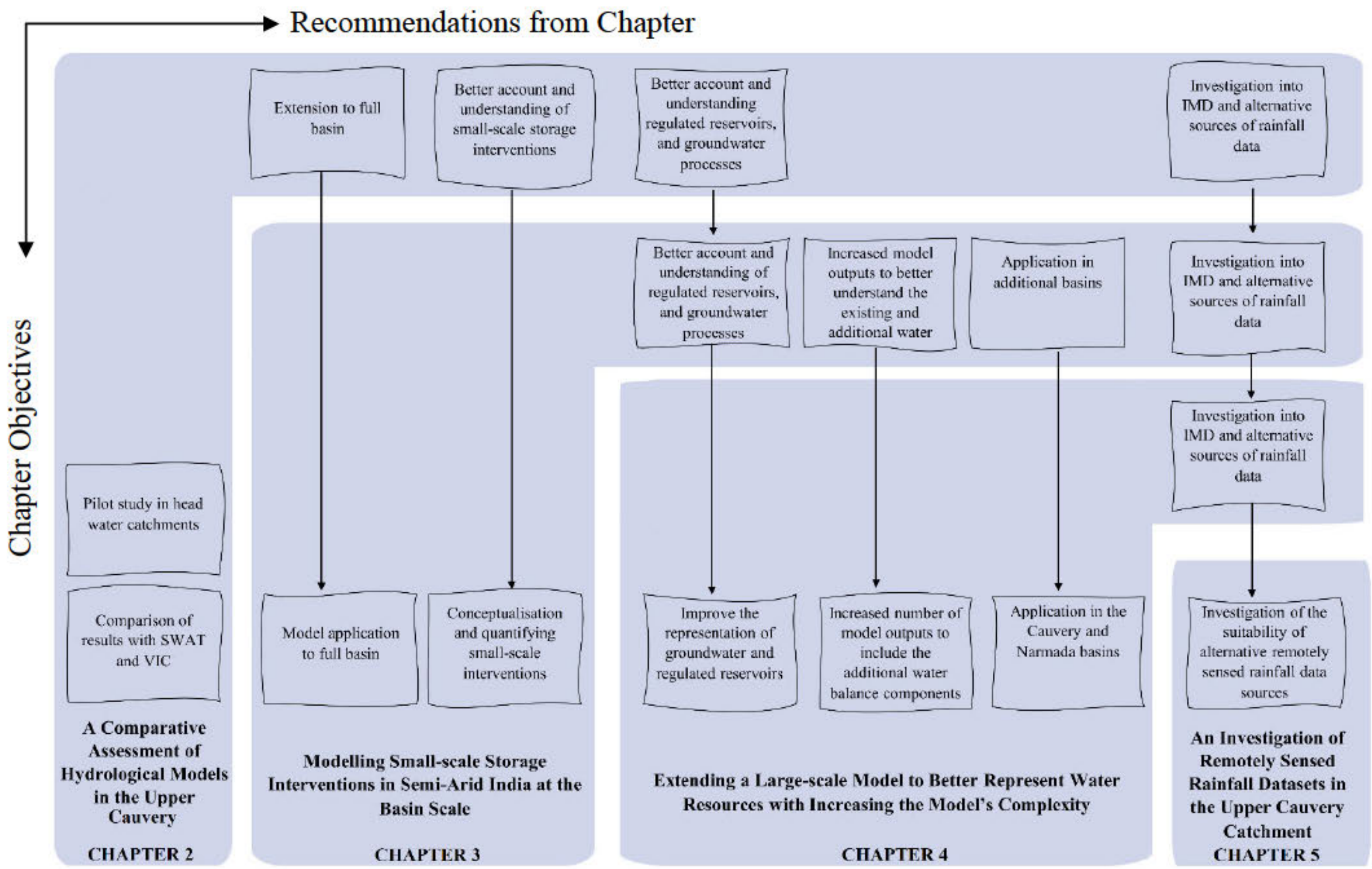



Figure 1.2 Description and workflow of the research project which allowed for the achievement of the overall aim and objectives.

## 1.8. References


Alcamo, J., Döll, P., Henrichs, T., Kaspar, F., Lehner, B., Rösch, T. and Siebert, S., 2003. Development and Testing of the WaterGAP 2 Global Model of Water Use and Availability. *Hydrological Sciences Journal*, 48(3), pp.317-337

Arnold, J.G., Allen, P.M. and Bernhardt, G., 1993. A Comprehensive Surface-Groundwater Flow Model. *Journal of Hydrology*, 142(1-4), pp.47-69.

Bárdossy, A., 2007. Calibration of Hydrological Model Parameters for Ungauged Catchments. *Hydrology and Earth System Sciences*, 11(2), pp.703-710.

Best, M.J., Pryor, M., Clark, D.B., Rooney, G.G., Essery, R., Ménard, C.B., Edwards, J.M., Hendry, M.A., Porson, A., Gedney, N. and Mercado, L.M., 2011. The Joint UK Land Environment Simulator (JULES), Model Description–Part 1: Energy and Water Fluxes. *Geoscientific Model Development*, 4(3), pp.677-699.

Bhave, A.G., Conway, D., Dessai, S. and Stainforth, D.A., 2018. Water Resource Planning Under Future Climate and Socio-Economic Uncertainty in the Cauvery River Basin in Karnataka, India. *Water Resources Research*, 54(2), pp.708-728.

Biggs, T., Gaur, A., Scott, C., Thenkabail, P., Gangadhara Rao, P., Gumma, M.K., Acharya, S. and Turral, H., 2007. *Closing Of The Krishna Catchment: Irrigation, Streamflow Depletion and Macroscale Hydrology (Vol. 111).* International Water Management Institute, Colombo, Sri Lanka.

Bookhagen, B., 2012. Himalayan Groundwater. *Nature Geoscience*, 5(2), pp.97-98.

Box, G.E.P., Jenkins, G.M., Reinsel, G.C. and Ljung, G.M., 1976. *Time Series Analysis: Forecasting and Control.* Holden Bay, San Francisco, United States.

Burek, P., Satoh, Y., Kahil, T., Tang, T., Greve, P., Smilovic, M., Guillaumot, L., Zhao, F. and Wada, Y., 2020. Development of the Community Water Model (CWatM v1. 04)–a High-Resolution Hydrological Model for Global and Regional Assessment of Integrated Water Resources Management. *Geoscientific Model Development*, 13(7), pp.3267-3298.

Burnash, R.J., Ferral, R.L. and McGuire, R.A., 1973. *A Generalized Streamflow Simulation System: Conceptual Modelling For Digital Computers.* US Department of Commerce, National Weather Service, and the State of California, Department of Water Resources, Los Angeles, United States.

Chidambaram, S., Ramanathan, A.L., Thilagavathi, R. and Ganesh, N., 2018. *Cauvery River: The Indian Rivers: Scientific and Socio-economic Aspects*, Springer, Singapore.

Chowdhury, N.T., 2010. Water Management in Bangladesh: an analytical review. *Water Policy*, 12(1), pp.32-51.

Christensen, J.H., Kanikicharla, K.K., Aldrian, E., An, S.I., Cavalcanti, I.F.A., de Castro, M., Dong, W., Goswami, P., Hall, A., Kanyanga, J.K. and Kitoh, A., 2013. Climate Phenomena and their Relevance for Future Regional Climate Change. In *Climate Change 2013 the Physical Science Basis: Working Group I Contributed to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change* (pp. 1217-1308). Cambridge University Press, Cambridge, United Kingdom.

Clark, D.B., Mercado, L.M., Sitch, S., Jones, C.D., Gedney, N., Best, M.J., Pryor, M., Rooney, G.G., Essery, R.L.H., Blyth, E. and Boucher, O., 2011. The Joint UK Land Environment Simulator (JULES), Model Description–Part 2: Carbon Fluxes and Vegetation Dynamics. *Geoscientific Model Development*, 4(3), pp.701-722.

Cleaver, F., 2017. *Development Through Bricolage: Rethinking Institutions for Natural Resource Management*. Routledge, Abingdon-on-Thames, United Kingdom.

Daly, C., 2006. Guidelines for Assessing The Suitability of Spatial Climate Data Sets. International Journal of Climatology: *A Journal of the Royal Meteorological Society*, 26(6), pp.707-721.

Deka, P.C., 2014. Support Vector Machine Applications in The Field of Hydrology: a review. *Applied Soft Computing*, 19, pp.372-386.

Devia, G.K., Ganasri, B.P. and Dwarakish, G.S., 2015. A Review on Hydrological Models. *Aquatic Procedia*, 4, pp.1001-1007.

Dixit, Y., Hodell, D.A., Sinha, R. and Petrie, C.A., 2014. Abrupt Weakening of the Indian Summer Monsoon at 8.2 kyr BP. *Earth and Planetary Science Letters*, 391, pp.16-23.

Döll, P., Douville, H., Güntner, A., Müller Schmied, H. and Wada, Y., 2016. Modelling Freshwater Resources at the Global Scale: Challenges and Prospects. *Surveys in Geophysics*, 37(2), pp.195-221.

D'Souza, R., 2005. Colonial Law and the Tungabhadra Disputes: Lifting the Veil Over the Agreement of 1892. *Natural Resources Journal*, 45, p.311.

Dumont, E., Williams, R., Keller, V., Voß, A. and Tattari, S., 2012. Modelling Indicators of Water Security, Water Pollution and Aquatic Biodiversity In Europe. *Hydrological Sciences Journal*, 57(7), pp.1378-1403

Ekstrand, S., Mancinelli, C., Houghton-Carr, H., Govers, G., Debels, P., Camano, B., Alcoz, S., Filiberto, I., Gámez, S. and Duque, A., 2009. *TWINLATIN: Twinning European and Latin American River Basins for Research Enabling Sustainable Water Resources Management. Final report.* IVL Swedish Environmental Research Institute, Oxford, United Kingdom.

Ghimire, S., Choudhary, A. and Dimri, A.P., 2018. Assessment of the Performance of CORDEX-South Asia Experiments for Monsoonal Rainfall over the Himalayan Region During Present Climate: Part I. *Climate Dynamics*, 50(7), pp.2311-2334.

Ghosh, N., Bandyopadhyay, J. and Thakur, J., 2018. *Conflict over Cauvery Waters: Imperatives for Innovative Policy Options*. Observer Research Foundation, New Delhi, India.

Guhan, S., 1993. *The Cauvery River Dispute*. Madras Frontline Publication, Chennai, India.

Gupta, H. and Chakrapani, G.J., 2005. Temporal and Spatial Variations in Water Flow and Sediment Load in Narmada River Basin, India: Natural And Man-Made Factors. *Environmental Geology*, 48(4), pp.579-589.

Gupta, J. and van der Zaag, P., 2008. Interbasin Water Transfers and Integrated Water Resources Management: Where Engineering, Science and Politics Interlock. *Physics and Chemistry of the Earth*, 33(1-2), pp.28-40

Hanasaki, N., Kanae, S., Oki, T., Masuda, K., Motoya, K., Shirakawa, N., Shen, Y. and Tanaka, K., 2008. An Integrated Model For The Assessment of Global Water Resources–Part 1: Model Description and Input Meteorological Forcing. *Hydrology and Earth System Sciences*, 12(4), pp.1007-1025.

Hanasaki, N., Yoshikawa, S., Pokhrel, Y. and Kanae, S., 2018. A Global Hydrological Simulation to Specify the Sources of Water Used by Humans. *Hydrology and Earth System Sciences*, 22(1), pp.789-817.

Hassan, Z., Shamsudin, S., Harun, S., Malek, M.A. and Hamidon, N., 2015. Suitability of ANN Applied as a Hydrological Model Coupled With Statistical Downscaling Model: A Case Study in the Northern Area of Peninsular Malaysia. *Environmental Earth Sciences*, 74(1), pp.463-477.

Hussain, M.B. and Ḥusain, E.B., 1972. *The Cauvery Water Dispute: An Analysis of Mysore's Case.* Rao and Raghavan, Mysore, India.

Iyer, R.R., 2003. Cauvery dispute: A Dialogue between Farmers. *Economic and Political Weekly*, pp.2350-2352.

Jain, S.K., Agarwal, P.K. and Singh, V.P., 2007. *Hydrology and Water Resources of India*. Springer Science & Business Media, Berlin, Germany.

Jamwal, P., Thomas, B.K., Lele, S. and Srinivasan, V., 2014. *Addressing Water Stress through Wastewater Reuse: Complexities and Challenges in Bangalore, India.* In Proceedings of the Resilient Cities 2014 congress, Bonn, Germany.

Janakarajan, S., 2016. The Cauvery Water Dispute: Need for a Rethink. *Economic and Political Weekly,* pp.10-15.

Johnson, A.C., Keller, V., Dumont, E. and Sumpter, J.P., 2015. Assessing the Concentrations and Risks of Toxicity from the Antibiotics Ciprofloxacin, Sulfamethoxazole, Trimethoprim and Erythromycin in European Rivers. *Science of the Total Environment*, 511, pp.747-755.

Joseph, P.V. and Simon, A., 2005. The Weakening Trend of the Southwest Monsoon Current Through Peninsular India from 1950 to the Present. *Current Science,* pp.687-694.

Kannaiyan, S and Venkatesan, J., 2013. *A Fact Finding Report on Farmer Suicides in the Delta Region of Tamil Nadu*. South Indian coordination committee of farmers movements (SICCFM), Chennai, India.

Krysanova, V., Wechsung, F., Arnold, J., Srinivasan, R. and Williams, J., 2000. *SWIM (Soil and Water Integrated Model).* Potsdam-Institut fuer Klimafolgenforschung (PIK), Potsdam, Germany.

Kulkarni, A., 2012. Weakening of Indian Summer Monsoon Rainfall in a Warming Environment. *Theoretical and Applied Climatology*, 109(3), pp.447-459.

Kumar, V., 2017. Farmers' Distress in Cauvery Delta Region of Tamil Nadu-An Analysis. *Madras Agricultural Journal*, 104, p.1.

Lannerstad, M., 2008. Planned and Unplanned Water Use in a Closed South Indian Basin. *International Journal of Water Resources Development*, 24(2), pp.289-304.

Lindström, G., Pers, C., Rosberg, J., Strömqvist, J. and Arheimer, B., 2010. Development and Testing of the HYPE (Hydrological Predictions for the Environment) Water Quality Model for Different Spatial Scales. *Hydrology Research*, 41(3-4), pp.295-319.

Loucks, D.P. and Beek, E.V., 2017. *Water Resource Systems Modelling: Its Role in Planning and Management.* In Water Resource Systems Planning and Management (pp. 51-72). Springer, Cham, Edinburgh, United Kingdom.

Lui, X, Keller, V D J, Dumont, E L, Shi, J, Johnson, A C, 2015. Risk of Endocrine Disruption to Fish in the Yellow River Catchment in China Assessed using a Spatially Explicit Model. *Environmental Toxicology and Chemistry*, 34 (12), 2870-2877.

Madhusoodhanan, C.G., Sreeja, K.G. and Eldho, T.I., 2016. Climate Change Impact Assessments on the Water Resources of India Under Extensive Human Interventions. *Ambio*, 45(6), pp.725-741.

Malik, N., Bookhagen, B., Marwan, N. and Kurths, J., 2012. Analysis of Spatial and Temporal Extreme Monsoonal Rainfall over South Asia using Complex Networks. *Climate Dynamics*, 39(3), pp.971-987.

Manjunatha, A.V. and Ramappa, K.B., 2017. *Farmer Suicides: An All India Study, Agriculture Development and Rural Transformation Centre Report.* Institute for Social and Economic Change, Bengaluru, Karnataka.

Martínez-Fernández, J. and Ceballos, A., 2005. Mean Soil Moisture Estimation using Temporal Stability Analysis. *Journal of Hydrology*, 312(1-4), pp.28-38.

Mehtani, P.C., 2017. *An Appraisal of Water Sustainability in Bangalore, Karnataka.* Sustainable Smart Cities in India (pp. 493-514). Springer, Cham, Edinburgh, United Kingdom.

Meigh, J.R. and Tate, E.L., 2002. *The GWAVA Model-Development of A Global-scale Methodology to Assess the Combined Impact of Climate and Land Use Changes*. EGS General Assembly Conference Abstracts, Nice, France, p 1276.

Meigh, J.R., Folwell, S. and Sullivan, C., 2005. *Linking Water Resources and Global Change in West Africa: Options for Assessment.* Seventh IAHS scientific assembly, Foz do Iguaçu, Brazil, pp.297-306.

Meigh, J.R., McKenzie, A.A. and Sene, K.J., 1999. A Grid-Based Approach to Water Scarcity Estimates for Eastern And Southern Africa. *Water Resources Management*, 13(2), pp.85-115.

Meunier, J.D., Riotte, J., Braun, J.J., Sekhar, M., Chalié, F., Barboni, D. and Saccone, L., 2015. Controls of DSi in Streams and Reservoirs along The Kaveri River, South India. *Science of the Total Environment*, 502, pp.103-113.

Nijssen, B., Lettenmaier, D.P., Liang, X., Wetzel, S.W. and Wood, E.F., 1997. Streamflow Simulation for Continental-Scale River Catchments. *Water Resources Research*, 33(4), pp.711-724.

Padhiari, H.K. and Ballabh, V., 2008. Inter-state Water Disputes and the Governance Challenge. *Governance of Water: Institutional Alternatives and Political Economy,* SAGE Publications, Thousand Oakes, United States.

Patil, N.N., Selvaraj, K.K., Krishnamoorthy, V., Elaiyaraja, A. and Ramaswamy, B.R., 2015. Organochlorine Pesticide Contamination in the Kaveri (Cauvery) River, India: a Review

On Distribution Profile, Status, and Trends. *Water Challenges and Solutions on a Global Scale*, pp.115-128.

Peters, J.C., 1995. *The HEC Hydrologic Modeling System*. US Army Corps of Engineers, Hydrologic Engineering Center, Davis, United States

Pietroniro, A., Fortin, V., Kouwen, N., Neal, C., Turcotte, R., Davison, B., Verseghy, D., Soulis, E.D., Caldwell, R., Evora, N. and Pellerin, P., 2007. Development of the MESH Modelling System for Hydrological Ensemble Forecasting of the Laurentian Great Lakes at the Regional Scale. *Hydrology and Earth System Sciences*, 11(4), pp.1279-1294.

Rajendran, S., 2014. Drought Mitigation in Tamil Nadu. *Economic and Political Weekly*. p.5

Ramaswamy, S. 2007. *The Groundwater Recharge Movement in India. In The Agricultural Groundwater Revolution.* Opportunities and Threats to Development; CABI: Wallingford, United Kingdom.

Rameshwaran, P., Bell, V., Davies, H., Houghton-Carr, H., Kay, A., Miller, J., Rickards, N., Bologo-Traore, M., Diarra, A., Gnenakantanhan, C., Tazen, F., Traore, K. 2017 Hydrological Research for AMMA-2050. [Poster] In: Future Climate for Africa Mid-Term Conference 2017, Cape Town, South Africa, 4–7 Sept 2017. (Unpublished)

Renganayaki, S.P. and Elango, L., 2013. A Review on Managed Aquifer Recharge by Check Dams: A Case Study near Chennai, India. *International Journal of Research in Engineering and Technology*, 2(4), pp.416-423.

Rickards, N., Thomas, T., Kaelin, A., Houghton-Carr, H., Jain, S.K., Mishra, P.K., Nema, M.K., Dixon, H., Rahman, M.M., Horan, R. and Jenkins, A., 2020. Understanding Future Water Challenges in a Highly Regulated Indian River Catchment—Modelling the Impact of Climate Change on the Hydrology of the Upper Narmada. *Water*, 12(6), p.1762.

Roy, P.S., Meiyappan, P., Joshi, P.K., Kale, M.P., Srivastav, V.K., Srivasatava, S.K., Behera, M.D., Roy, A., Sharma, Y., Ramachandran, R.M. and Bhavani, P., 2016. *Decadal Land Use and Land Cover Classifications across India, 1985, 1995, 2005.* Oak Ridge National Laboratory Distributed Active Archive Center, Oak Ridge, United States.

Sabarisakthi, M., 2019. An Exploration on Farm Crisis and Suicides in the Cauvery Delta Districts of Tamil Nadu. *Shanlax International Journal of Economics*, 7(4), pp.84-90.

Schaake, J.C., Koren, V.I., Duan, Q.Y., Mitchell, K. and Chen, F., 1996. Simple Water Balance Model for Estimating Runoff at Different Spatial and Temporal Scales. *Journal of Geophysical Research: Atmospheres*, 101(D3), pp.7461-7475.

Schaphoff, S., von Bloh, W., Rammig, A., Thonicke, K., Biemans, H., Forkel, M., Gerten, D., Heinke, J., Jägermeyr, J., Knauer, J. and Langerwisch, F., 2018. LPJmL4–a Dynamic Global Vegetation Model with Managed Land–Part 1: Model description. *Geoscientific Model Development,* 11(4), pp.1343-1375.

Sravanth, K.R. and Sundaram, N., 2019. Agricultural Crisis and Farmers Suicides in India. *International Journal of Innovative Technology and Exploring Engineering*, 8(11), pp.1576-1580.

Sutanudjaja, E.H., Van Beek, R., Wanders, N., Wada, Y., Bosmans, J.H., Drost, N., Van Der Ent, R.J., De Graaf, I.E., Hoch, J.M., De Jong, K. and Karssenberg, D., 2018. PCR-GLOBWB 2: a 5 arcmin Global Hydrological and Water Resources Model. *Geoscientific Model Development*, 11(6), pp.2429-2453.

Swain, A., 1998. Fight for the Last Drop: Inter-State River Disputes in India. *Contemporary South Asia*, 7(2), pp.167-180.

Takata, K., Emori, S. and Watanabe, T., 2003. Development of the Minimal Advanced Treatments of Surface Interaction and Runoff. *Global and Planetary Change,* 38(1-2), pp.209-222.

Tegegne, G., Park, D.K. and Kim, Y.O., 2017. Comparison of Hydrological Models for the Assessment of Water Resources in a Data-Scarce Region, the Upper Blue Nile River Basin. *Journal of Hydrology: Regional Studies,* 14, pp.49-66.

Tessema, S.M., 2011. *Hydrological Modelling as a Tool For Sustainable Water Resources Management: a Case Study of the Awash River Basin.* Doctoral dissertation, KTH Royal Institute of Technology, Stockholm, Sweden.

Tiwari, D., Tiwari, H.L. and Saini, R., 2018. Hydrological Modelling in Narmada Basin using Remote Sensing and GIS with SWAT Model and Runoff Prediction in Patan Watershed. *International Journal of Advanced Research, Ideas and Innovations in Technology*, 4(2), pp.344-352

Van Meter, K.J., Basu, N.B., McLaughlin, D.L. and Steiff, M., 2015. The Socio-ecohydrology of Rainwater Harvesting in India. Understanding Water Storage and Release Dynamics at Tank and Catchment Scales. *Hydrology and Earth System Sciences Discussions*, 12(11), pp.12121-12165.

Wasserman, P. D., 1989. *Neural Computing: Theory and Practice*. Van Nostrand Reinhold, New York, United Kingdom.

Wigmosta, M.S., Vail, L.W. and Lettenmaier, D.P., 1994. A Distributed Hydrology-Vegetation Model for Complex Terrain. *Water Resources Research*, 30(6), pp.1665-1679.

Williams, P. and Drabu, I., 2012. *Environmental and Social Impacts of Dams in India*. Institution of Civil Engineers, London, United Kingdom.

Wood, D., 2006. *MIKE BASIN*. DHI Water and Environment, Copenhagen, Denmark.

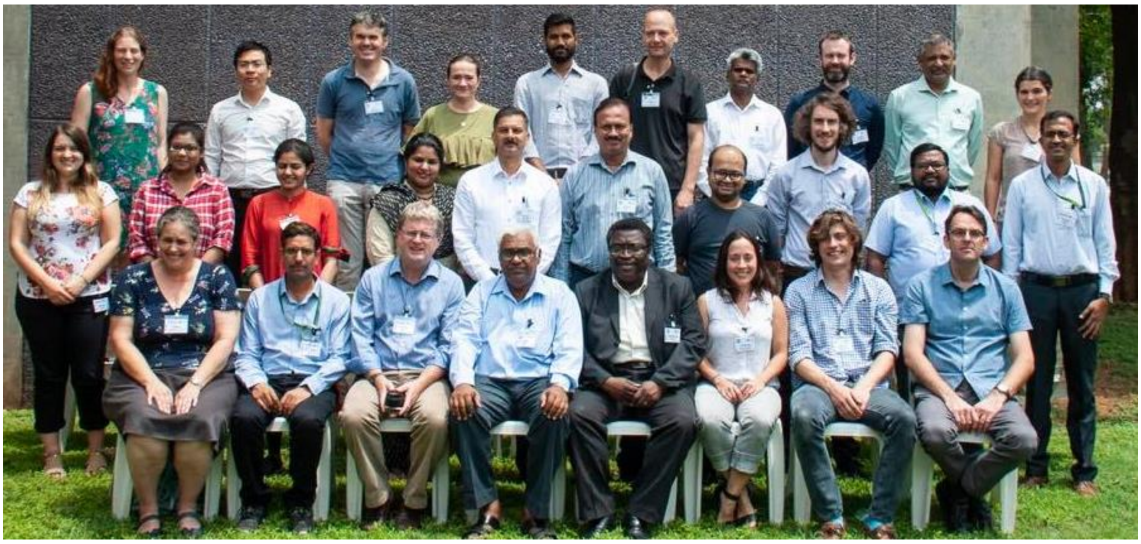
Xu, Y.D., Fu, B.J. and He, C.S., 2013. Assessing the Hydrological Effect of the Check Dams in the Loess Plateau, China, by Model Simulations. *Hydrology and Earth System Sciences*, 17(6), pp.2185-2193.

**Appendix A**

Stakeholder Engagement Events

***Project Meet on Upscaling Catchment Processes for Sustainable Water Management in Peninsular India (UPSCAPE) - 1-3 October 2018***

A project consortium meeting for the collaborative UPSCAPE project with CEH, ATREE, BGS, University of Dundee, and ICRISAT, was conducted on 1st, 2nd and 3rd October 2018 at the International Crops Research Institute for the Semi-Arid Tropics, Hyderabad, India.



***Project Meet on Upscaling Catchment Processes for Sustainable Water Management in Peninsular India (UPSCAPE)- 12-14 March 2019***

A project consortium meeting for the collaborative UPSCAPE project with CEH, ATREE, BGS, University of Dundee, and ICRISAT, was conducted on 12th, 13th and 14th March 2019 at the Indian Institute of Science, Bangalore, India.

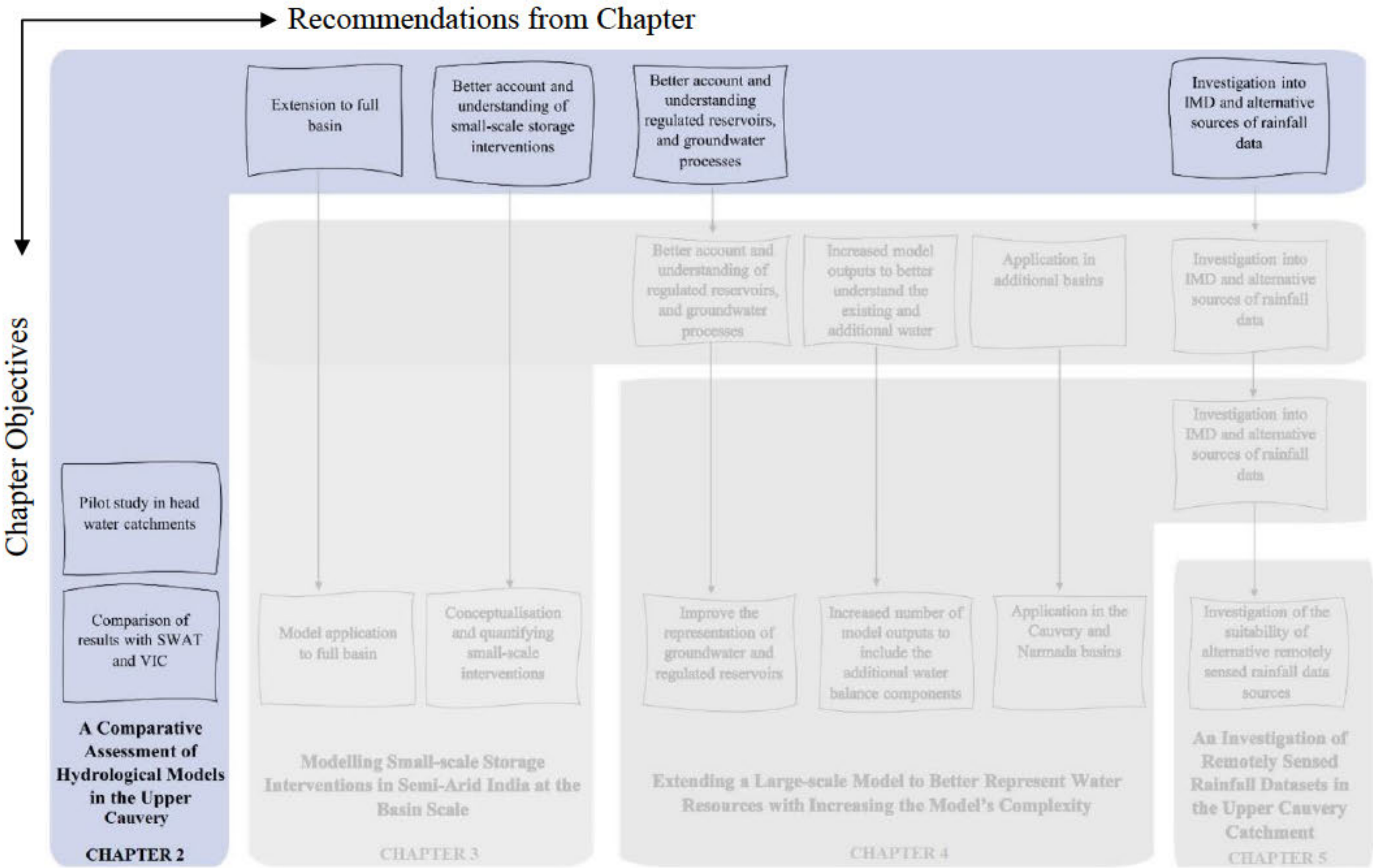
***Final Stakeholder Workshop for Upscaling Catchment Processes for Sustainable Water Management in Peninsular India (UPSCAPE) project- 23 October 2019***

Stakeholder dissemination and training were conducted on the 23rd and 26th of October 2019 in Bangalore and Chennai, India.

*****

**Lead into Chapter 2**

As part of the larger UPSCAPE project, SWAT, VIC and GWAVA had been selected as the modelling tools to be implemented in the Cauvery Catchment. SWAT was only applied to the Upper Cauvery in the UPSCAPE project and thus the three models were only compared within this part of the catchment. The aim of the pilot study was to compare the individual model results to ensure that the choice of models remained suitable as well as to highlight the shortcomings of the GWAVA model to streamline the model development process and thus paving the methodology for the remainder of the study.



# 2. A COMPARATIVE ASSESSMENT OF HYDROLOGICAL MODELS IN THE UPPER CAUVERY CATCHMENT


## Abstract

This paper presents a comparison of the predictive capability of three hydrological models, and an average ensemble of these models in a heavily influenced catchment in Peninsular India: GWAVA model, SWAT and VIC model. The performance of the three models and their ensemble were investigated in five catchments in the upstream reaches of the Cauvery Catchment. Model performances for monthly streamflow simulations from 1983–to 2005 were analysed using Nash-Sutcliffe efficiency, Kling-Gupta efficiency, and percent bias. The predictive capability for each model was compared, and the ability to accurately represent key catchment hydrological processes was discussed. This study highlighted the importance of an accurate spatial representation of rainfall for input into hydrological models and that comprehensive dam functionality is paramount to obtaining good results in this region. The performance of the average ensemble was analysed to determine whether applying a multi-model ensemble approach can help overcome the uncertainties associated with individual models. It was demonstrated that the average ensemble has a better predictive ability in catchments with dams than the individual models, with Nash-Sutcliffe values between 0.49 and 0.92. Therefore, utilising multiple models could be a suitable methodology to offset uncertainty in input data and poor dam operation functionality within individual models



**Keywords:** Cauvery; hydrological modelling; VIC; SWAT; GWAVA; ensemble modelling; water resources


---

Horan, R, Gowri, R, Wable, PS, Baron, H, Keller, VD, Garg, KK, Mujumdar, PP, Houghton-Carr, H and Rees, G, 2021. A Comparative Assessment of Hydrological Models in The Upper Cauvery Catchment. Water, 13(2), p.151.

*Referencing conforms to the format of *Water*

## 2.1 Introduction

Hydrological models are widely used to predict and understand hydrological processes (Schaake *et al*., 1996; Martínez-Fernández & Ceballos, 2005). Models are powerful tools for understanding and quantifying the water balance components and hydrological fluxes within a catchment (Immerzeel *et al*., 2008). Models make use of various parameters and sets of mathematical equations to provide simplified conceptual representations of the complex hydrological cycle (Refsgaard & Storm, 1990; Salvucci & Entekhabi, 1994; Graeff *et al*., 2012). The performance (Bárdossy, 2007) and suitability (Hassan *et al*., 2015) of a hydrological model can differ between catchments due to catchment size and dominant catchment processes present. Hydrological models are often developed for specific purposes (estimation of water demands, understanding of hydrological processes, drought, flood risk assessments, etc.) and different geographic regions (Devia *et al*., 2015). The most reliable models in regions where data is sparse are those whose results closely represent reality with limited model complexity (Tegegne *et al*., 2017). It is important to note that selecting a suitable model should not be solely based on its ability to address specific research aims but also on data availability (Dee *et al*., 2011). The accuracy of simulations generated from the model strongly depends on the model selected and the quality of input data and observations (Dee *et al*., 2011). For example, in instances of poor-quality input data with high uncertainties, a simpler model may be more suitable than a highly complex one (Michaud & Sorooshien, 1994).

Various hydrological models have different strengths when representing hydrological processes (Li *et al*., 2018). Using a single model can lead to simulation uncertainties, especially in catchments of poor input data availability and large-scale modelling exercises. Ensemble modelling combines multiple model predictions to create a single prediction that tends to strongly outperform the individual models (Doblas-Reyes *et al*., 2005; Kumar & Nandagiri, 2015). Ensemble modelling can be widely applied in hydrological modelling to utilise the ensemble for reducing errors with an optimal bias (Baker & Ellison, 2008). It is also important to note that combining the best-performing individual models does not necessarily provide the best ensemble (Viney *et al*., 2009).

The Cauvery has long presented water management challenges at the local, regional and catchment scales. The increasing competition to meet urban and rural water demands, which span administrative boundaries, continues to present significant issues for integrated water management in the catchment. Critical gaps in the scientific knowledge of Peninsular Indian hydrology make it challenging to address these concerns. Many of the catchments of the Cauvery Catchment have been previously modelled using the SWAT model (Gosain *et al*., 2006; Kumar & Nandagiri, 2018), WEAP model (Bhave *et al*., 2018), remote sensing methods (Ramachandra *et al*., 2014), ANN and SVR models (Patel & Ramachandran, 2015), SCS-CN model (Geetha *et al*., 2008; Gupta & Panigraphy, 2008) and VIC-mHM (Jaje *et al*., 2014). Understanding the river flows in headwater catchments is especially relevant for estimating actual water availability. The Western Ghats form the headwaters of the Upper Cauvery Catchment. This region generates the majority of the streamflow with the greater Cauvery Catchment. Representing the catchments using multiple models can provide deeper insight into hydrological processes across the region. Analysing a model ensemble can reduce uncertainty in estimating various water balance components. This study attempts to analyse the capability of the models mentioned above and a model ensemble to capture processes in a catchment.

Five catchments within the Upper Cauvery region were selected for this study to be modelled by SWAT, VIC and GWAVA. The GWAVA model is a gridded large-scale water resources model developed by the UKCEH (Meigh *et al*., 1999). It is a relatively simple model that trades off model complexity for data availability and has a strong anthropogenic influences component. The VIC model has a much more detailed representation of hydrological features and is perhaps more suitable for accurately representing soil water dynamics. SWAT is commonly used in India and has a good representation of agricultural water use with possibly better representation of evaporation.

The VIC model has been widely utilised and performs well for a large number of river catchments across the globe. The model is open-source and has wide acceptance and utility because of its proven capability to capture streamflow processes as well as all the components of the water budget. The model uses complex, widely accepted algorithms to simulate hydrological processes such as evaporation, transpiration and infiltration, which have been validated over many river catchments of the Indian subcontinent. The model was selected for application in the Cauvery Catchment, as it is a grid-based model that considers the sub-grid variability of the land surface vegetation classes and soil moisture storage capacity.

GWAVA is a useful tool in the Cauvery Catchment as it allows for the simulation of most of the components of the hydrological cycle as well as accounting for demands for domestic, agricultural and industrial sectors, dam operations and basic groundwater stores. The model allows for tracking groundwater, dam storage levels and the demands that cannot be met. The model input and output are flexible to the data availability and the output requirements. As Cauvery is a highly heterogenous catchment concerning the climate, soil composition and land use, it is important to incorporate these gridded models to capture the extensive regional variability within the catchment.

SWAT has been widely used across India and around the globe. The model is popular due to the ability to use the model through an ArcGIS interface. The model setup is determined by the availability of LULC, soil, hydrology and biophysical management data. SWAT does not need grid-specific information. In addition, and of high importance within the Cauvery, small-scale runoff harvesting interventions (SSRHI) can be parameterised, dam operations can be included, groundwater usage can be set, and crop management operations can be defined.

Ensemble modelling is a process in which multiple models are utilised to simulate an outcome using many different modelling algorithms. The average ensemble model averages each model's prediction and produces one final simulation of the outcome. Ensemble modelling can be utilised in hydrology to simulate better components of the hydrological cycle, the impacts of land use or other environmental changes, and provide a range of possible outcomes and uncertainty (Viney *et al*., 2005; Muhammad *et al*., 2018; Smith *et al*., 2019). Using a single model can lead to simulation uncertainties in larger catchments with relatively poor input data availability. Ensemble modelling combines multiple model predictions to create a single prediction that tends to strongly outperform the individual models (Doblas-Reyes *et al.*, 2005; Kumar & Nandagiri, 2015). Ensemble modelling can be widely applied to utilise the ensemble for reducing errors with an optimal bias (Baker & Ellison, 2008).

This study investigates the predictive capabilities of GWAVA, SWAT, and VIC when applied to several catchments in the Cauvery and the performance of an average ensemble of these models. Model performance is assessed using a range of efficiency metrics (NSE, KGE, and percent bias). The comparative strengths and weaknesses of each model are evaluated by analysing model performance in the different catchments; this gives insight into the suitability of these models for future studies under similar conditions. The average ensemble is analysed to determine whether an ensemble approach can successfully combine model strengths and compensate for limitations.

## 2.2 Model Descriptions

It is important to evaluate how different hydrological models capture the process dynamics of various catchments. This study used three hydrological models to model the Upper Cauvery Catchment: VIC, SWAT and GWAVA. SWAT (Wagner *et al*., 2011), GWAVA (Rickards *et al*., 2020) and VIC (Jaje *et al*., 2014; Chawla & Mujumdar, 2018) have been applied across large regions of India. The models were selected based on the various theoretical differences and previous applications in India. VIC and SWAT are popular hydrological models across India, and GWAVA has been successfully implemented in the Narmada and Ganges catchments. VIC is a large-scale, physically based gridded hydrological model; GWAVA is a large-scale semi-distributed hydrological model; and SWAT is a semi-distributed, physically-based catchment-scale model. VIC, SWAT and GWAVA are described below, and additional information can be found in Table 2.6 in Appendix B. Each model was calibrated using different techniques; however, the calibration parameters utilised in each case pertained to soil properties and surface-and groundwater routing.

### *2.2.1 Variable Infiltration Capacity (VIC) Model*

The VIC model (Liang *et al*., 1994; Liang *et al*., 1996) is an open-source, grid-based macroscale land-atmosphere transfer model representing surface and subsurface hydrological processes. It solves the energy and water balance equations for spatially distributed grid cells at each time step. The model can be implemented for spatial scales varying from 0.125 to 2 degrees and with temporal resolutions ranging from hourly to daily. The model's key features include the representation of sub-grid vegetation heterogeneity, non-linear baseflow computation and inclusion of multiple soil layers with variable infiltration. Each grid cell can be divided into several tiles based on land use, and each tile generates unique responses to rainfall based on the land surface properties. The VIC model has been extensively implemented in numerous studies across the globe to address challenges related to water resources management, such as flood and drought monitoring (Wu *et al*., 2014; Chawla & Mujumdar, 2018; Shah & Mishra, 2020), assessment of the impact of land use and climate change on the hydrologic response (Jaje *et al*., 2014; Chawla & Mujumdar, 2015) and understanding land-atmosphere interactions (Nijssen *et al*., 2001; Troy *et al*., 2008; Zhang *et al*., 2014).

Meteorological forcings required to run the model include rainfall, maximum temperature, minimum temperature and wind speed at the relevant timescale. This model also requires additional datasets such as elevation and soil characteristics which consist of soil composition and bulk density, along with vegetation properties such as land-use type, LAI, albedo and crop characteristics. For simulating streamflow at the specified gauge locations, the flux files are fed into a routing model (Lohmann *et al*., 1998), which uses linear transfer functions for grid cells and river routing and linearised Saint-Venant equation for channel routing. This version of VIC does not account for any water demands, groundwater pumping or dam storage. The output fluxes from the model are surface runoff, baseflow, evapotranspiration and soil moisture computed for each grid.

### *2.2.2 Soil and Water Assessment Tool (SWAT)*

SWAT is an open-source software widely used around the globe to assess the impact of sediment transport, fertiliser load and different water management practices in an agricultural catchment (Arnold *et al*., 2012). ArcSWAT, a version of SWAT interfaced with ArcGIS, can be used for continuous simulation of a catchment model operating on different time steps and at different spatial scales. In SWAT, a catchment is divided into multiple catchments, further divided into HRUs. HRUs are unique combinations of a specific soil type, land use/land cover type and slope type within a catchment for which the water balance components can be simulated. It is important to note that HRUs vary in size and, as a general rule, should have between one and ten HRUs per catchment. SWAT can predict hourly, daily, monthly and yearly flow volumes. Climatic inputs include daily rainfall, maximum and minimum temperature, solar radiation, relative humidity and wind speed. Various hydrologic processes can be simulated using the SWAT model, including surface runoff, lateral subsurface flow, groundwater flow, evapotranspiration, snowmelt, transmission losses from streams, and water storage and losses from ponds (Neitsch *et al*., 2009).

### *2.2.3 Global Water Availability Assessment (GWAVA) Model*

GWAVA is a large-scale gridded water resources model (Meigh *et al*., 1999; Dumont *et al*., 2012). The model accounts for natural hydrological processes (considering soils, land use and lakes) and anthropogenic influences (crops, domestic and industrial demands, dam operations, and water transfers). The model estimates surface flows and recharge using a conceptual rainfall-runoff model, utilising effective rainfall and evaporation estimates, followed by a demand-driven routine to account for the anthropogenic stresses on the system. The model can be run at a spatial scale ranging from 0.125 to 5 degrees and at a daily or monthly timescale. The GWAVA model is adaptable to the data availability of the region, and the code is flexible to allow for additional processes and features to be represented.

## 2.3 Model Applications and Comparison

### *2.3.1 Site Description*

The Cauvery Catchment is a heterogeneous, transboundary and highly human-influenced catchment in Peninsular India. It is spread across four federal states: Karnataka, Tamil Nadu, Kerala and Puducherry in Southern India (Gosain *et al*., 2006). The four states have varying water policies, water use prioritisation and cultural values associated with the natural environment. The catchment is representative of other large catchments in Peninsular India, with water resources under increasing pressure from urbanisation, population growth and agriculture intensification. Additionally, the Cauvery is a contentious river with concern over water sharing between Karnataka and Tamil Nadu. The catchment is considered highly water-stressed (Hoekstra *et al*., 2012), and the current water abstraction is estimated to exceed the renewable water resources within the catchment (Kumar *et al.*, 2005). The catchment has extensive regional variability in water demand. The agricultural activities within the catchment require approximately 90% of water resources (Folke, 1998; Palanisami *et al*., 2014). Rapid urban and industrial development across the catchment is causing increased inter-sectorial and interstate competition for water (Jamwal *et al*., 2014). Across the catchment, there is an abundance of SSRHIs, medium and large dams, and large-scale transfer schemes. It is essential to understand the catchment hydrology well and develop reliable and robust models to ensure improved water resource management in such highly water-stressed catchments.

The Upper Cauvery Catchment drains an area of 10,619 km$^2$ in the north-western region of the Cauvery Catchment. The upper reaches of the Cauvery River lie within the Nilgiri and Anaimalai mountains and act as critical headwater to the larger catchment (Chidambaram *et al*., 2018). The catchment experiences the SW (JJAS) and NE monsoon (OND). The mean annual rainfall in the Upper Cauvery is 2010 mm; however, the rainfall distribution varies temporally and spatially across the catchment. The Western Ghats form a rain shadow along the western coastline, decreasing the rainfall gradient during the south-western monsoon (Meunier *et al*., 2015). The mean daily temperatures vary between 9 and 25 ℃ throughout the catchment (Sreelash *et al*., 2020). In the area of the Western Ghats, the soils tend to be very deep, valley bottoms are covered in dense forests, and mountain slopes are predominately grassland (Pattabaik *et al*., 2013). Fifty percent of the catchment is under agriculture (Jain *et al*., 2007). The most common crops grown in the catchment are sugarcane, finger millet, sorghum, groundnut and paddy. Paddy and sugarcane are found predominantly in the canal command areas.

Five catchments were chosen for the study, namely the catchments upstream of (Table 2.1; Figure 2.1): Kudige on the Harangi River; KM Vadi on the Lakshmantirtha River; M H Halli, immediately downstream of the Hemavathy Dam; the inflow of the Hemavathy Dam (here forward referred to as Hemavathy); and the inflow to KRS dam (here forward referred to as KRS). More information regarding these catchments can be found in Table 2.1. Hemavathy inflow and M H Halli were chosen to assess the models' ability to simulate the outflow releases from Hemavathy. All five were modelled by VIC and GWAVA on a daily timestep (and aggregated to monthly) and by SWAT on a monthly timestep, as monthly timesteps are generally considered most useful for impact assessments. Kudige, KM Vadi and M H Halli are locations of existing streamflow gauges, whilst Hemavathy and KRS are dams with observed inflows and outflows. These catchments were selected based on their importance within the Cauvery Catchment and observation data availability. The performance of the individual models and the model ensemble was evaluated against the observation data.

Table 2.1 The area (km$^2$), MAP in mm and the predominant land use of each catchment

| Catchment | Area (km$^2$) | MAP (mm) | Predominant Land Use |
|---|---|---|---|
| Kudige | 1934 | 2430 | Forest |
| Hemavathy | 2810 | 1423 | Forest |
| MH Halli | 3050 | 1365 | Forest and agriculture |
| KM Vadi | 1330 | 1448 | Forest and agriculture |
| KRS | 10 619 | 1531 | Forest and agriculture |

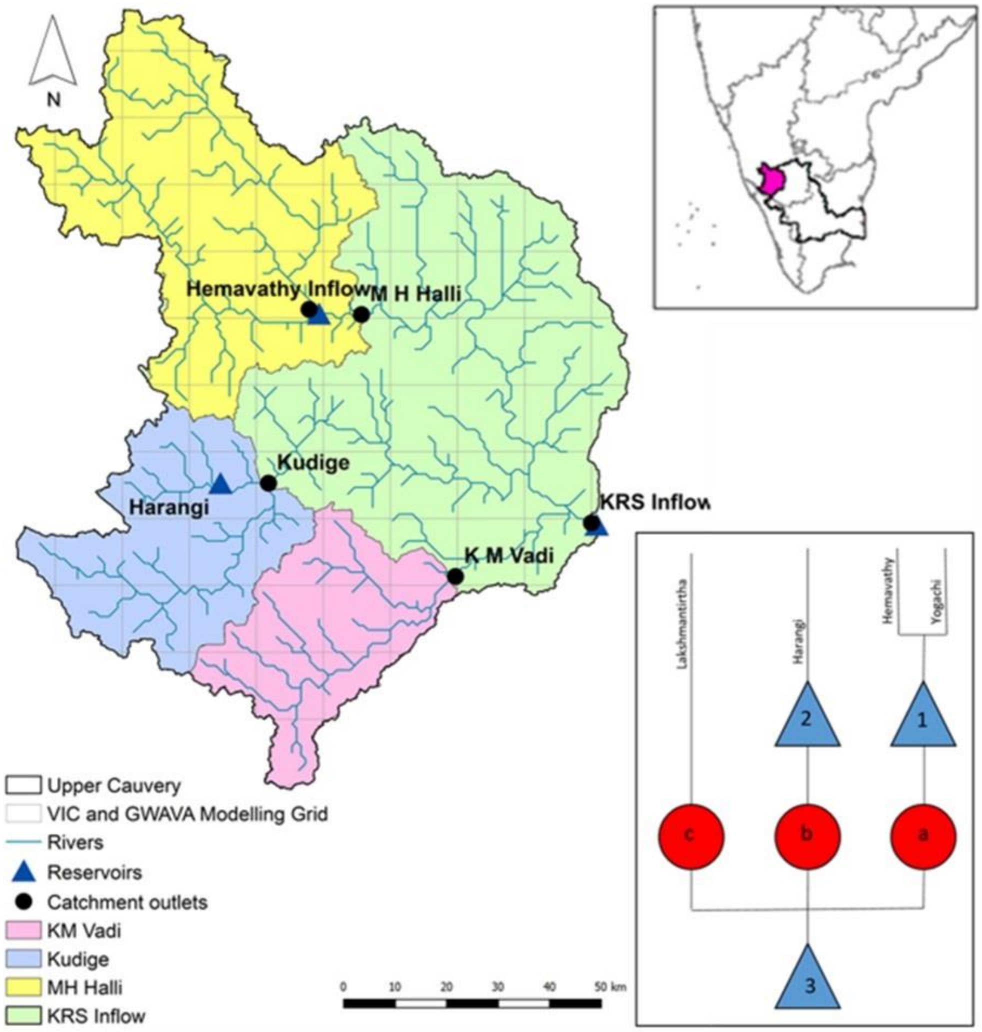



Figure 2.1 The location of the five catchments, outlets of the five catchments analysed in this study and three major dams within the Upper Cauvery Catchment. Inset 1: The location of the greater Cauvery Catchment and the Upper Cauvery Catchment within Peninsula India. Inset 2: A river flow diagram of the Upper Cauvery to demonstrate the flow path through gauging stations and dams.

### *2.3.2 Input Data and Model Application*

All three models utilised rainfall and temperature forcing data (Pai *et al*., 2014) along with soil, land use and altitude data. Additionally, the models used many local datasets, which can be found in Table 2.7 in Appendix B. The performance of the individual models and the model ensemble was evaluated against the observed streamflow data provided by WRIS-India. Hereafter the term virgin simulations refer to simulations that do not include any forcing with the observed dam outflow data.

#### 2.3.2.1 VIC

VIC-3L (VIC-3 layer); version 4.2.d (VIC Model User Guide. 2015) with the Lohmann routing model (Lohmann *et al*., 1998) was run in the water balance mode. The water balance model does not solve the surface energy balance (Hurkmans *et al*., 2008). This model assumes that the land surface soil temperature equals the near-surface air temperature and follows the continuity equation at each time step. A daily time step was adopted for computational efficiency based on data availability. Daily simulations were aggregated into monthly estimates for this study. Two versions of the VIC model were set up for Cauvery Catchment (Figure 2.1) at 0.125-degree grids, and the surface fluxes were computed at a daily time scale for 1951–2014. The first model V-VIC did not incorporate any artificial influences or dams. The second F-VIC utilised the observed dam release data to account for two major dams within the catchment by adding the observation data to the V-VIC simulation streamflow (Harangi and Hemavathy). The V-VIC model was calibrated concerning observed streamflow at four regional stations using model parameters, as Lohmann *et al.* (1998) suggested. The runoff hydrograph was found to be governed by three parameters related to vegetation and soil properties. The overland flow was sensitive to the variable infiltration curve parameter (B). The baseflow had significant sensitivity concerning the fraction of maximum velocity of baseflow where nonlinear baseflow begins (Ds) and the fraction of maximum soil moisture where nonlinear baseflow occurs (Ws) (Liang *et al*., 1996; Chawla & Mujumdar, 2015). Thus, these three parameters were chosen for calibration, and all the other soil and vegetation parameters were obtained from the soil (Cosby *et al*., 1984) and land use land cover datasets (Table 2.7 in Appendix B). To account for the dam operation in VIC, the daily simulated streamflow was aggregated into a monthly flow. The monthly observed dam outflow releases were added to obtain the F-VIC simulations.

#### 2.3.2.2 SWAT

This study utilised SWAT2012 (Arnold *et al*., 2012) on the ArcGIS 10.5 platform. The Upper Cauvery and its catchments (129 in number) were delineated based on the DEM and defining the inflow to the KRS dam as the catchment outlet. Land use, soil and slope (sources described in Table 2.6 in Appendix B) maps were used to create 4432 HRUs based on defining the threshold of 20% for each land use, soil and slope. As far as possible, the soil parameters were either measured or surveyed (Wable *et al*., 2019), failing which, they were estimated based on the literature. Further, the daily meteorological data of rainfall, temperature, wind speed, relative humidity and sunshine hours (sources described in Table 2.6 in Appendix B) were given as input to the model. The Penman-Monteith method was adopted in this study to estimate potential evaporation. The CN method was selected to calculate surface runoff as it was deemed the most suitable for rainfall data at a daily time step.

The intervention density (in-situ and ex-situ) within these catchments was estimated based on expenditure reports for the KWA. As the expenditure on each type of intervention was unknown, the average cost for constructing each intervention based on earlier experience was used. Then, the total estimated cost was converted into storage capacities. Conceptually, the SSRHIs were considered to only exist within areas of agriculture (7272 $km^2$; 70% of the total area). The most common agricultural and water management SSRHIs were considered, including check dams and bunds representing in-situ and ex-situ intervention. The aggregated district-level catchment SSRHIs storages were all lumped into a single-unit dam along the main channel of the catchment. The total storage capacity created due to SSRHIs over the catchment was estimated to be 5 $m^3$/ha in 2006. The depth of the check dam and infiltration rate observed during the survey was 1.5 m and 10 cm/day, and that of bunds was 0.3 m and 30 cm/day, respectively (Wable *et al*., 2019).

Along with the intervention storage, the three major dams (Harangi, Hemvathy and KRS) were incorporated at each catchment as per their actual locations. The monthly outflows were also provided as inputs to the model for these major dams, along with storage capacities and their surface areas. SWAT has the option to bypass the dam outflow simulation and provide the observed outflow time series (F-SWAT). The monthly dam outflow data from Hemavathy and Harangi dams fed these gauging points, allowing the model to better represent the streamflow at the gauges downstream of the dams. Further, the SWAT model was calibrated for the KRS inflows from 1981 through 2003 using surface runoff and baseflow parameters. Table 2.8 in Appendix B shows a list of these parameters.

#### 2.3.2.3 GWAVA

Surface water flows across the Cauvery Catchment (to Musiri) on a daily timestep were estimated utilizing GWAVA (GWAVA: Global Water Availability Assessment Model Technical Guide and User Manual, 2020). Similarly to VIC, GWAVA was set up for the extent of the Cauvery Catchment upstream of Musiri (Figure 2.1) at 0.125◦ grids for the years 1986–2005. A grid cell resolution of 0.125 degrees was chosen based on data availability for the region. The model was calibrated to daily observed streamflow and validated to daily observed streamflow and seasonal groundwater levels at 14 gauging stations across the catchment from 1980– 2005, depending on the period of uninterrupted reliable observed streamflow available from the gauging station. The model included a basic groundwater module, demand (domestic, industrial, agricultural, livestock and the associated conveyance losses and return flows), and major and minor dams. Five parameters were selected in the calibration. These parameters pertain to soil characteristics, surface and groundwater routing and water table level at which baseflow flows.

### *2.3.3 Model Performance Criteria*

The performance measures used in this study are the NSE (Equation 2.1), KGE (Equation 2.2) and percent bias (Equation 2.3). NSE is a popular metric to evaluate hydrological model performance because it aims to normalise model performance into an interpretable scale (Nash & Sutcliffe, 1970; Gupta *et al*., 2009). An NSE of one represents a perfect correspondence between the simulations and the observations. An NSE of zero indicates that the model simulations have the same explanatory power as the mean of the observations. An NSE of less than 0 represents that the model is a worse predictor than the mean of the observations. However, NSE does not provide an equal benchmark for different flow regimes. Utilising the single NSE metric is not sufficient for determining a model's performance; however, it can provide context if utilised in conjunction with additional model performance efficiency.

For this study, an NE score of less than 0.2 is deemed poor, between 0.2 and 0.6 as fair and above 0.6 as good. The NSE is calculated as follows:

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_s^t - Q_o^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q_o}\right)^2} \tag{2.1}$$

where $Q_s^t$ and $Q_o^t$ are, respectively, the simulated streamflow and the observed streamflow at timestep t; $\overline{Q_o}$is the average observed streamflow over all timestep considered.

The KGE is based on correlation, variability, and mean bias (Gupta *et al.*, 2009; Knoben *et al.*, 2009). The metric allows some perceived shortcomings with NSE to be overcome and has become increasingly popular for evaluating hydrological model skill. A KGE of one indicates perfect agreement between simulations and observations. However, there are many opinions about where the differentiation of a ‘good’ and ‘poor’ model performance thresholds lies within the KGE scale. Negative KGE values do not always imply that the model performs worse than the mean flow benchmark. For this study and to compare model performance, a KGE score of less than 0.2 is deemed poor, between 0.2 and 0.6 as fair and above 0.6 as good. The KGE is calculated as follows:

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_s}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_s}{\mu_o} - 1\right)^2} \tag{2.2}$$

where r is the correlation coefficient between simulated and observed data, $\sigma_o$ is the standard deviation of observation data, $\sigma_s$ is the standard deviation of simulated data, $\mu_o$ is the mean of observation data and $\mu_s$ is the mean of simulated data

The bias is the average tendency of the simulated data to over-or underestimate the observed data. The optimal value for the bias is zero. Positive values indicate a model underestimation, and negative values indicate an overestimation.

$$Bias = \frac{\sum_{t=1}^{T}(y_o - y_s)}{\sum_{t=1}^{n}(y_o)} \tag{2.3}$$

where $\gamma_o$ is the observed data value, $\gamma_s$ is the simulated data value, and t is the time-step.

The daily streamflow volume from VIC and GWAVA was summed to generate the monthly streamflow for the VIC and GWAVA simulations to be comparable to the SWAT simulations because monthly timesteps are generally preferred for impact assessments. For the ensemble average evaluation, the mean monthly streamflow was generated by averaging the monthly streamflow from F-VIC, F-SWAT and GWAVA. The model performance efficiencies were calculated from the monthly observed streamflow and the mean monthly ensemble streamflow time series.

Monthly simulations were undertaken using VIC, GWAVA and SWAT. Virgin simulations from SWAT (V-SWAT) and VIC (V-VIC) were included in the analysis of the results. The second set of simulations from SWAT (F-SWAT) and VIC (F-VIC) are improvements on the virgin simulations utilising this observed data. The calibration parameters were kept consistent between V-SWAT, F-SWAT, and V-VIC and F-VIC, respectively.

## 2.4 Results

### *2.4.1 Dam Outflow Evaluation*

To establish confidence within the observed dam outflow data used to force F-SWAT and F-VIC, it was compared to streamflow gauges downstream of the dam. Harangi dam outflow was compared to Kudige, and Hemavathy outflow was compared with M H Halli. The gauging stations (Kudige and M H Halli) are situated a short distance downstream of the dams (Harangi and Hemavathy). The Hemavathy outflow and streamflow observed at M H Halli correspond well, although the dam outflow does not follow a seasonal trend year on year (Figure 2.2a). The Harangi outflow is significantly less than the streamflow observed at Kudige (Figure 2.2b).

This is expected as Kudige drains a larger area than the Harangi dam. However, the coinciding of the peak streamflow indicates that the temporal trend of the dam release is seasonal.

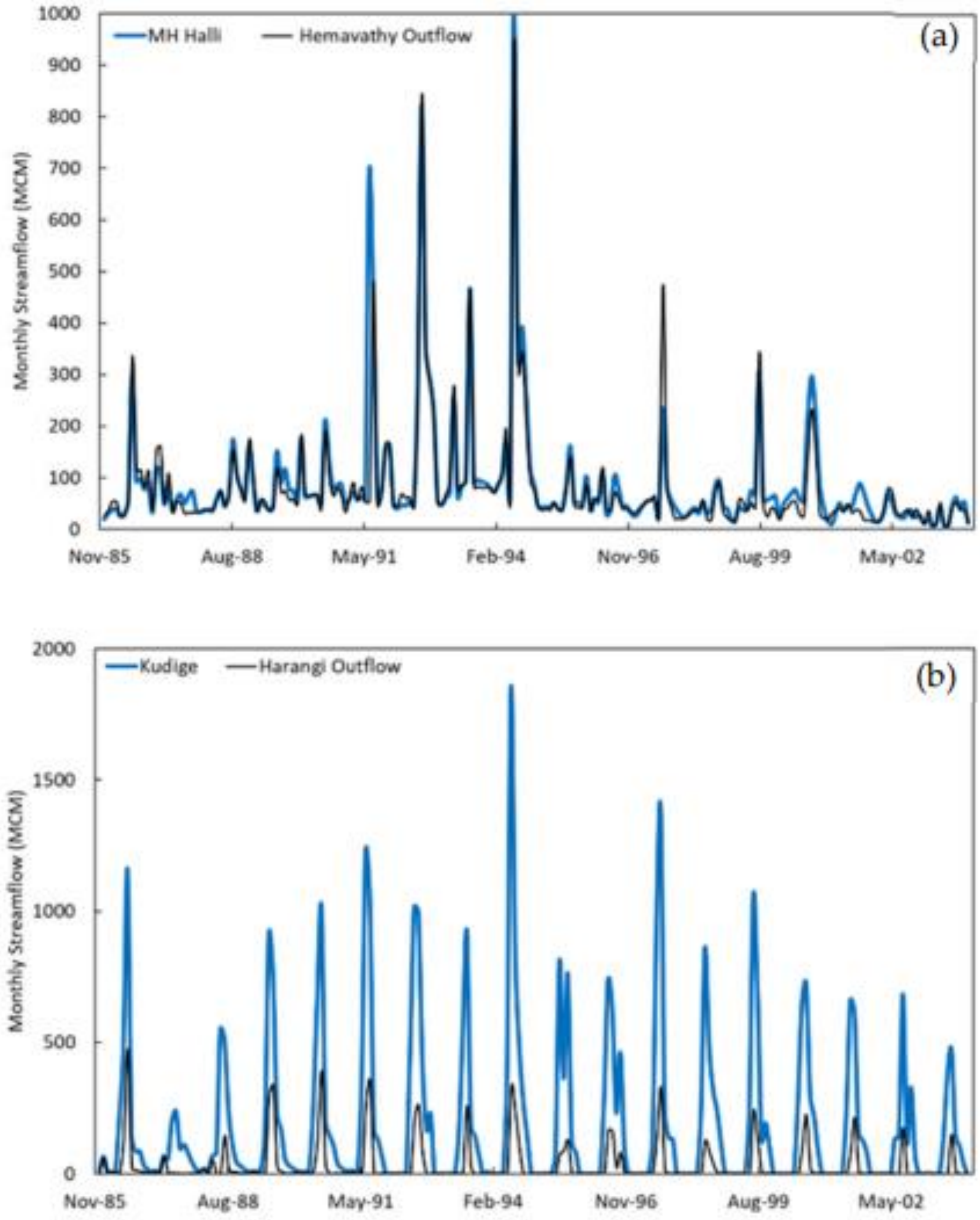



Figure 2.2 The monthly observed streamflow from (a) M H Halli gauging station and Hemavathy dam outflow and (b) Kudige gauging station and Harangi dam outflow.

### *2.4.2 Individual Model Performance*

The calibrated model performance of V-VIC, F-VIC, V-SWAT, F-SWAT and GWAVA was evaluated using the NSE, KGE and the percent bias at five gauging points in the Upper Cauvery from 1986 until 2003 (Table 2.2-Table 2.4). The performance of the models used in this study is compared to existing studies in Table 2.5.

Table 2.2 The NSE values were obtained from monthly streamflow for the five catchments for each model from 1986 to 2003. The values lying in the green shaded area are considered by this study as 'good', the yellow area as 'fair' and the red area as 'poor'.

| | V-VIC | F-VIC | V-SWAT | F-SWAT | GWAVA | Ensemble |
|---|---|---|---|---|---|---|
| Kudige | 0.81 | 0.92 | 0.45 | 0.71 | 0.62 | 0.84 |
| MH Halli | 0.15 | 0.55 | -0.66 | 0.71 | -0.11 | 0.75 |
| KM Vadi | 0.37 | 0.37 | 0.46 | 0.46 | 0.21 | 0.69 |
| Hemavathy | 0.59 | 0.59 | 0.79 | 0.79 | 0.53 | 0.94 |
| KRS | -0.51 | -0.42 | 0.57 | 0.82 | 0.45 | 0.92 |

Table 2.3 The KGE values were obtained from monthly streamflow for the five catchments for each model from 1986 to 2003. The values lying in the green shaded area are considered by this study as 'good', the yellow area as 'fair' and the red area as 'poor'.

| | V-VIC | F-VIC | V-SWAT | F-SWAT | GWAVA | Ensemble |
|---|---|---|---|---|---|---|
| Kudige | 0.78 | 0.85 | 0.42 | 0.56 | 0.52 | 0.71 |
| MH Halli | 0.33 | 0.40 | -0.50 | 0.58 | 0.46 | 0.79 |
| KM Vadi | 0.19 | 0.19 | 0.69 | 0.68 | 0.36 | 0.49 |
| Hemavathy | 0.64 | 0.64 | 0.74 | 0.74 | 0.37 | 0.82 |
| KRS | 0.14 | -0.31 | 0.43 | 0.78 | 0.38 | 0.81 |

Table 2.4 The percent bias was obtained from monthly streamflow for the five catchments for each model from 1986 to 2003. The values lying in the green shaded area are considered by this study as 'good' and the red area as 'poor'.

| | V-VIC | F-VIC | V-SWAT | F-SWAT | GWAVA | Ensemble |
|---|---|---|---|---|---|---|
| Kudige | -13 | 8 | -60 | -42 | -45 | -20 |
| MH Halli | -42 | 55 | -100 | -30 | -5 | -12 |
| KM Vadi | 66 | 66 | -6 | -6 | 1 | 22 |
| Hemavathy | 30 | 30 | -24 | -24 | -60 | -18 |
| KRS | 84 | 130 | -75 | -20 | -61 | 19 |

Table 2.5 A comparison of the NSE values obtained by models (F-VIC, F-SWAT and GWAVA) used in this study and the models (ANN and SVR) used in the Patel and Ramachandran (2015) study. The values lying in the green shaded area are considered by this study as 'good' and the red area as 'poor'.

| Study | Model | Catchment | | | | |
|---|---|---|---|---|---|---|
| | | Kudige | MH Halli | KM Vadi | Hema-vathy | KRS |
| This Study | F-VIC | 0.92 | 0.55 | 0.37 | 0.64 | 0.42 |
| | F-SWAT | 0.71 | 0.71 | 0.46 | 0.74 | 0.82 |
| | GWAVA | 0.62 | -0.11 | 0.21 | 0.37 | 0.45 |
| | Ensemble | 0.84 | 0.75 | 0.69 | 0.82 | 0.92 |
| Geetha *et al.* | SCS-CN | | | | 0.84 | |
| | VSA | | | | 0.74 | |
| | Ensemble | | | | 0.94 | |
| Maheswaran & Khosa | WA-ANN | 0.74 | 0.77 | | | |
| | ANN | 0.65 | 0.66 | | | |
| Patel & Ramachandran | ANN | 0.76 | 0.61 | 0.56 | | 0.63 |
| | SVR | 0.84 | 0.43 | 0.03 | | 0.28 |
| Kumar & Nandagiri | SWAT | | | | 0.85 | |
| | SWAT-VSA | | | | 0.88 | |

The forcing of the streamflow with the observed dam data improves the simulations by F-VIC in the catchments that contain the large dams (Kudige, M H Halli and KRS). However, the inclusion of this observation data causes the model to overestimate the streamflow across these catchments. F-VIC performs well at Kudige, poorly at KRS and fairly across the remaining catchments (Tables 2.2 and 2.3). The performance of both V-VIC and F-VIC is generally weaker in the monsoon season (Figure 2.4 in Appendix B). VIC produces a low bias at Kudige but overestimates at Hemavathy, M H Halli and KM Vadi and severely overestimates at KRS inflow (Table 2.4). F-VIC simulates the monthly average streamflow well at Kudige (Figure 2.4 in Appendix B). The streamflow is overestimated in August, but the rising and falling limbs are simulated well. At KM Vadi, F-VIC captures the rising limb well. However, it overestimates the streamflow in August and subsequently overestimates the falling limb. At M H Halli, Hemavathy and KRS, F-VIC simulates the temporal nature of the observed streamflow well but significantly overestimates across the year (Figure 2.4 in Appendix B). The over-estimation of streamflow by F-VIC downstream of the dams could be a reflection of the inability of the model to account for anthropogenic water abstraction, and the uncertainty in the observed dam outflow data and methodology used to incorporate the observed dam releases could contribute to poor performances at KRS.

The V-SWAT simulations underestimate the streamflow volume at Kudige, M H Halli and KRS and provide fair simulations at Kudige and KRS. However, the performance at M H Halli is very poor (Tables 2.2, 2.4 and 2.5). Following the use of the observed dam outflow data to force the model, the performance at Kudige, M H Halli and KRS are significantly improved. When utilising the observed dam data, SWAT consistently performs well across the five catchments (Tables 2.2, 2.4 and 2.5). SWAT simulates the total streamflow volume well at KM Vadi but underestimates in the remaining catchments (Table 2.4). Despite being fed the Harangi outflow data upstream, SWAT underestimates the streamflow at Kudige. SWAT simulates the streamflow at M H Halli and KM Vadi well in July but does not retain the peak flow through August. The model simulates the second peak in October, which corresponds with VIC and GWAVA but not the observed streamflow data (Figure 2.4 in Appendix B). SWAT simulates the peak streamflow at Hemavathy well; however, it underestimates the  rise and falling limbs. At KRS, SWAT underestimates the peak streamflow in July and August but overestimates the falling limb of the hydrograph.

GWAVA performs fairly across all the catchments across the modelling period (Tables 2.2, 2.4 and 2.5) and during the monsoon season. However, GWAVA performs less well at M H Halli. GWAVA underestimates the total streamflow volume in all the catchments throughout the year (Table 2.4) but overestimates the total streamflow volume at M H Halli in the monsoon season (Figure 2.4 in Appendix B). The peak simulated streamflow followed the trend of the observed streamflow but is underestimated at both Kudige and M H Halli. At KM Vadi, GWAVA significantly underestimates the peak flows through July and August; however, it peaks in October. This second peak does not correspond to the observed streamflow. At KRS, GWAVA is significantly under-estimating the streamflow throughout the year. GWAVA is inaccurately representing the outflows from Hemavathy. This is clearly illustrated by poor simulations and over-estimation of streamflow at M H Halli. The under-estimations of streamflow by GWAVA at Hemavathy, KM Vadi and downstream of Harangi could be a reflection of the inability of the model to capture the outflow characteristics of this dam, an over-estimation of the dam capacity (due to undocumented silting), misrepresentation of the SSRHIs, the poor representation of rainfall in the IMD grids or an over-estimation of the anthropogenic and agricultural water abstraction.

### *2.4.3 Ensemble Model Performance*

The ensemble model mean was calculated using the simulations from F-VIC, F-SWAT and GWAVA. The ensemble model simulations are the most consistent with the observation streamflow. The average streamflow ensemble produced by the three models represented the total volume of observed streamflow across the Upper Cauvery better than the individual models (Table 2.4). The ensemble produced NSE values at Kudige, M H Halli, Hemavathy and KRS close to the optimal NSE of one, which is a significant improvement from the individual model NSE values (Table 2.2). Although the ensemble performs less well at KM Vadi, it outperforms the individual models (Table 2.2). The ensemble closely represents the observed data temporally at KRS (Figure 2.3). Although the ensemble generally overestimated the volume of streamflow, and to a greater extent for the period 1995–1999, it represents the volume of streamflow more accurately than any of the individual models (Figure 2.3)

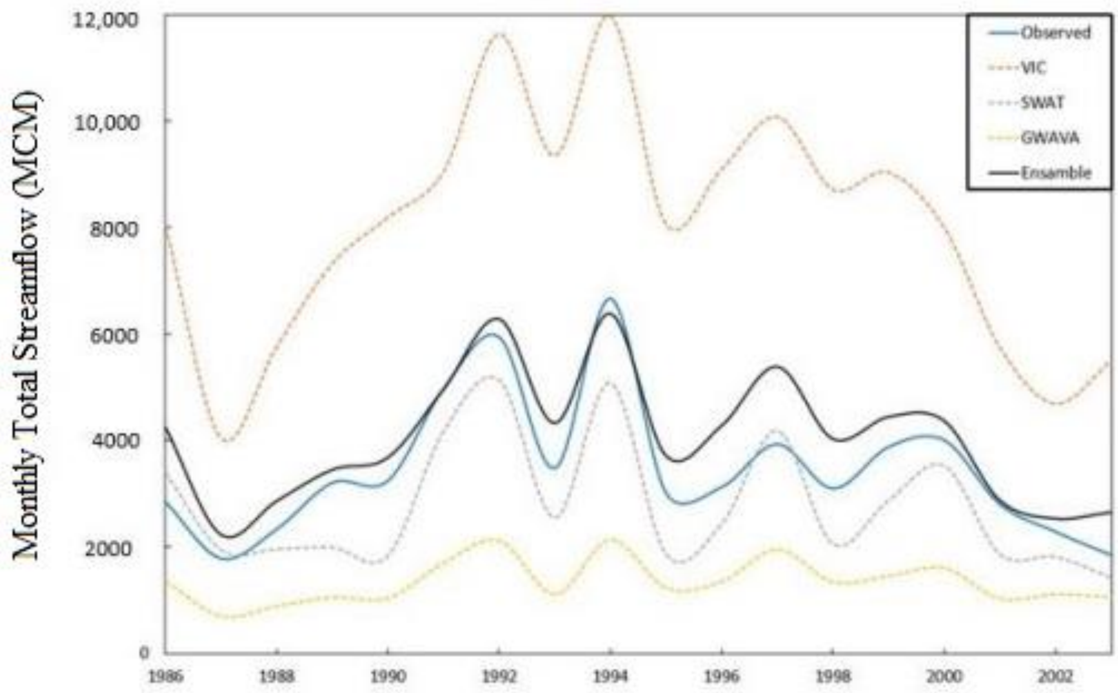



Figure 2.3 The monthly total observed streamflow and streamflow simulated by VIC, SWAT, GWAVA and the ensemble at KRS inflow

**2.5 Discussion**

The models individually had varying results across the five catchments (Tables 2.2–2.5). F-SWAT tended to perform best; however, the observed outflow data from the Hemavathy and Harangi dams cannot be overlooked as a significant reason for the consistent performance. V-SWAT significantly underestimates the streamflow at M H Halli, Kudige and KRS when the rainfall is used as the only source of hydrological forcing data. F-SWAT utilises the observed dam outflow data to offset the underestimation of rainfall within the Western Ghats region. Across the catchments, V-VIC tended to underestimate the streamflow in the catchment with the major dams (Kudige and M H Halli) whilst over-estimating the streamflow in the remaining catchments. F-VIC overestimates the streamflow across all the catchments. GWAVA tended to underestimate the streamflow at Kudige, Hemavathy and KRS. Although F-SWAT, V-SWAT and GWAVA produced a low bias, all five model setups struggled to reproduce the observed streamflow in KM Vadi accurately. Despite the improvement of both V-VIC and V-SWAT utilising the observed streamflow data, this limits their application for modelling future scenarios. The fair simulations in V-VIC, F-VIC and GWAVA and the good performance by V-SWAT and F-SWAT at KM Vadi suggest that the large-scale modelling approach applied in the Upper Cauvery may not be suitable as complex local topography is not sufficiently represented by the gridded models.

The Upper Cauvery region has a low density of rain gauge stations (about 1 for every 460 $km^2$). Thus, the spatial rainfall variability may not be captured adequately, especially in the Western Ghats, where the rainfall varies from 600 to 5000 mm (Sheffield *et al*., 2016) within a 50–100 km radius. The IMD gridded rainfall dataset uses these gauges and a linear interpolation methodology to estimate a spatial representation of rainfall across the region. An average annual runoff coefficient was calculated utilising the IMD gridded rainfall and point gauge rainfall data. An example from this analysis was the average annual runoff coefficient calculated for Harangi inflow was 1.92 using the IMD gridded data; however, the runoff coefficient estimated with rainfall obtained from existing rain gauge stations was only 1.3. This may result from the inability of linear interpolation to capture the high spatial variability of the rainfall pattern in mountainous regions. Therefore, in the Western Ghats region, inaccuracy in the meteorological data is likely to be the most significant driver of erroneous results.

Humans have significantly influenced the hydrological cycle across the Cauvery. These include, but are not limited to, irrigation, dam operation and groundwater pumping. Most hydrological models cannot successfully simulate all these anthropogenic factors, and in those models that consider human intervention, the data about these aspects are often not readily available. Models that calibrate without accounting for water regulation may capture the streamflow, but for the wrong reasons, and will not be robust against future changes in anthropogenic pressures. In catchments with high dependence on streamflow and groundwater to meet demands, it is even more important to capture the catchment processes, including human influences, correctly. To address this, many hydrological models are developing anthropogenic modules. For example, VIC-WUR (Droppers *et al*., 2020) improved data on human interventions (water demands, dams, and groundwater withdrawals being collated).

In the V-SWAT simulations, the model under-simulated the streamflow volume in most of the catchments. The volume of water simulated at KRS is more accurate following the utilisation of the dam outflow data. The temporal trend of the observed and simulated inflow to Hemavathy dam (Figure 2.1) values was well followed; however, the peaks were consistently underestimated using the V-SWAT model setup. Within the V-SWAT and F-SWAT model setup, a limited cropping system has been represented in the command areas. The subsequent irrigation and evaporative demands simulated by the model might not accurately reflect the system that includes multiple cropping systems and land management techniques. The SSRHIs represented in V-SWAT, and F-SWAT is summarised into one dam node for each catchment. In reality, hundreds of small structures are constructed along various streams within the catchment. This is likely a source of uncertainty as the correct response of the small structures to the hydrological regime may not be captured accurately. The SWAT model's surface and lateral runoff depend solely on rainfall. Thus, if the rainfall is under-estimating, the streamflow is likely to be underestimated. Peak flows are challenging to simulate accurately on a monthly scale model because short-term rainstorms are represented as one-day events and thus result in peak flows being under-simulated. This is particularly prominent in mountainous areas with orographic rainfall, such as the Western Ghats. The underestimation of peak flows could result from the erroneous rainfall data used in the simulation. Additionally, linear interpolation generally does not represent the spatial variation in rainfall in high-elevation areas. It is important to understand these limitations in model structure and rainfall data so that suitable model and data combinations can be selected for a given study (for instance, this analysis suggests that the SWAT model would not be well suited for modelling flood risk in mountainous regions)

Although V-SWAT did not perform as well as F-SWAT, V-SWAT would be a more robust model setup to undertake future climate and socio-economic scenario modelling. The impact of any applied changes would be reflected in the dam outflows and streamflow simulations using V-SWAT. As future dam releases are unavailable, F-SWAT would not be suitable for implementing future water resource evaluation scenarios. Any changes applied to Kudige, and the forced dam outflows would mask M H Halli. Subsequently, the simulations at KRS would not necessarily reflect the full extent of the changes applied.

VIC is a useful tool to simulate streamflow on a large scale. Across the catchment, F-VIC tends to over-simulate the total volume of streamflow. This could be attributed to human intervention and dams not being accurately captured, under-estimating evaporation due to high water availability in the Western Ghats, lack of a sufficient irrigation component representing the local/catchment agricultural practice, and poor representation of baseflow in VIC due to the lack of representation of groundwater storage. In the Cauvery, the groundwater level is particularly deep, and the baseflow is limited. The excess baseflow VIC feeding the surface water during low flow conditions is accentuated. The model performs well in naturalised catchments (V-VIC simulations) and provides a good temporal simulation without directly accounting for water resource demand. The VIC model used in this analysis does not include a separate module for the representation of SSRHIs and dams. The simulations of Harangi and Hemavathy catchments could be subjected to model structural uncertainties, uncertainty in the observed dam outflow data (Figure 2.2a,b) and the methodology used to incorporate the effects of the dams to be contributing factors. The model results may also have uncertainties associated with the forcing datasets, which could propagate through the representation of hydrological processes during simulations.

The performance of GWAVA in the selected catchment is inferior to F-VIC and F-SWAT. However, unlike these other models, GWAVA is the only model which can capture high levels of anthropogenic alteration. GWAVA allows the simulated flows to be captured for the right reasons by allowing all the water balance components and the demands to be tracked. Additionally, tracking groundwater levels is critical in catchments such as the Cauvery. The GWAVA set-up utilised in this study provides additional functionality to predict future water availability due to the inclusion of water demands and modelling of dam releases. A significant challenge in large-scale hydrological modelling is quantifying and managing input and validation data uncertainty and the upscaling of processes. There is a high level of uncertainty with the application of the GWAVA model in the Upper Cauvery. The poor representation of dam releases at Harangi and Hemavathy is a reflection of the inability of the model to capture the outflow characteristics of this dam and potentially an over-estimation of the dam capacity (due to undocumented silting). To improve the model performance, an improved dam routine accounting for downstream irrigation demand would be required. The water demands could be overestimated, leading to the unrealistic over-abstraction of groundwater resources. To further improve GWAVA, a more comprehensive dam and groundwater routine could be included and the representation of SSRHIs.

The ensemble model mean is the most consistent with the observation streamflow (Figure 2.3). Prediction uncertainty emanates from data, model structure and parameter uncertainty. Ensemble modelling can reduce prediction uncertainties (Semenova *et al*., 2009). Utilising an ensemble allows for the weaknesses in one model to be shadowed or compensated by the strength of others. The model ensemble accounts for the skill of each model, maximises the available input data and provides an estimate of the range of possible outcomes. Ensembles have higher predictive accuracy and have proven successful in representing non-linear interactions. An ensemble reduces the noise, bias and variance of simulations and can potentially create a more in-depth understanding of the data. However, ensemble modelling results can suffer from a lack of interpretability and are dependent on the prediction accuracy of the ensemble members

In agreement with examples of ensemble modelling literature (Doblas-Reyes *et al*., 2005; Baker & Ellison, 2008; Viney *et al*., 2009; Li *et al*., 2018; Kumar & Nandagriri, 2018), the ensemble predictions outperformed the individual models across all five catchments. The NSE values obtained from this study are compared with those found in the literature (Table 2.5). When the ensemble model performance is compared to that of Patel and Ramachandran (2015) using ANN and SVR models, it would seem that the ensemble of models from the present study performed better across KM Vadi, M H Halli and KRS. The ANN and SVR models utilised the same IMD gridded rainfall and temperature data used in this study. The ANN model and SVR produced maximum NSE values of 0.63 and 0.28 across these catchments. However, both ANN and SVR were able to better capture the dam operations of Harangi. The high level of complexity within these models could be well suited to catchments where the risk of overfitting parameters is limited. Maheswaran and Khosa (2012) improved the simulation of dam releases using the WA-ANN model, which improved streamflow simulation at Kudige and M H Halli.

Kumar and Nandagiri (2018) obtained high NSE values for both Hemavathy inflow and Harangi inflow using the SWAT model by incorporating the VSA mechanism. This mechanism was successful upstream of major dams, but it did not have adequate predictive ability downstream. Geetha *et al*. (2008) modelled Hemavathy using the SCS-CN lumped conceptual model, and VSA lumped conceptual model. Both these studies utilised observed point rainfall within the catchments as opposed to the IMD gridded rainfall. SCS-CN, VSA and the model ensemble from this study showed NSE values of 0.84, 0.78 and 0.94, respectively, at Hemavathy. VIC and GWAVA produced similar or better performances than the more complex SWAT (Kumar & Nandagriri, 2018), ANN and SVR models across the catchments.

These results highlight the strength of large-scale gridded models for modelling the extent of large catchments but can represent the processes of headwater catchments as accurately as in this region as catchment-scale models. Additionally, the importance of accurate climatic forcing in mountainous regions and the ability to simulate dam outflows is emphasised. An accurate spatial representation of rainfall for input into hydrological models, accounting for the SSRHIs and comprehensive dam and groundwater functionality, is paramount to obtaining good results in this region (Li *et al*., 2018).

### 2.6 Conclusion

Literature highlights that many hydrological models fail to simulate the streamflow dominating releases from Hemavathy and Harangi dams accurately. The models utilised in this study had varying results across the five catchments. V-SWAT and GWAVA underestimate the streamflow in catchments with dams when the rainfall is used as the only source of hydrological forcing data. V-VIC tended to underestimate the streamflow in the catchments with the major dams whilst over-estimating the streamflow in the remaining catchments. F-SWAT can offset the under-estimation of rainfall within the Western Ghats region by utilising the observed dam outflow data, whilst F-VIC overestimates the streamflow across all the catchments. Although F-SWAT, V-SWAT and GWAVA produced a low bias, all five model setups struggled to accurately reproduce the observed streamflow at KM Vadi. V-VIC, V-SWAT and GWAVA would be suitable choices to perform future scenario modelling; however, F-SWAT and F-VIC would be unsuitable as future dam release data are not available, nor data on how releases would vary with socio-economic changes.

This study highlights the strength of large-scale gridded models for modelling the extent of large catchments but can also represent the processes of headwater catchments as accurately in this region as catchment-scale models. The ensemble model mean is the most consistent with the observation streamflow. The ensemble predictions outperformed the individual models across all five catchments. The average ensemble has a better predictive ability in catchments with dams than the individual models. Utilising multiple models could be a suitable methodology to offset uncertainty in input data and poor dam operation functionality within individual models. This study has highlighted the importance of an accurate spatial representation of rainfall for input into hydrological models, accounting for SSRHIs and comprehensive dam and groundwater functionality is paramount to obtaining good results in this region.

## 2.7 References


Arnold, J.G.; Kiniry, R.; Srinivasan, R.; Williams, J.R.; Hanely, E.B.; Neitsch, S.L. Soil Water Assessment Tool Input/Output Documentation Version 2012. Available online: https://swat.tamu.edu/media/69296/swat-io-documentation-2012.pdf (accessed on 3 March 2019).

Arnold, J.G.; Moriasi, D.N.; Gassman, P.W.; Abbaspour, K.C.; White, M.J.; Srinivasan Santhi, C.; Harmel, R.D.; Van Grensven, A.; Van Liew, M.W.; Kannan, N. SWAT: Model use, calibration, and validation. *Transactions of the ASABE* 2012, 55, 1491–1508.

Baker, L.; Ellison, D. Optimisation of pedotransfer functions using an artificial neural network ensemble method. *Geoderma* 2008, 144, 212–224.

Bárdossy, A. Calibration of hydrological model parameters for ungauged catchments. *Hydrology and Earth Systems Sciences Discussions*. 2007, 11, 703–719.

Bhave, A.G.; Conway, D.; Dessai, S.; Stainforth, D.A. Water resource planning under future climate and socio-economic uncertainty in the Cauvery River Catchment in Karnataka, India. *Water Resources Research*. 2018, 54, 708–728.

Chawla, I.; Mujumdae, P.P. Partitioning uncertainty in streamflow projections under nonstationary model conditions. *Advances in Water Resources*. 2018, 112, 266–282.

Chawla, I.; Mujumdar, P.P. Isolating the impacts of land use and climate change on streamflow. *Hydrology and Earth Systems Sciences*. 2015, 19,3633–3651.

Chidambaram, S.; Ramanathan, A.L.; Thilagavathi, R.; Ganesh, N. Cauvery River, in The Indian Rivers, 2018, Singapore; Springer: Berlin, Germany, 2018; pp. 353–366.

Cosby, B.J.; Hornberger, G.M.; Cla, R.B.; Ginn, T.R. A statistical exploration of the relationships of soil moisture characteristics to the physical properties of soils. *Water Resources Research*. 1984, 20, 682–690.

Dee, D.P.; Uala, S.M.; Simmons, A.; Berrisford, P.; Poli, P.; Kobayashi, S.; Andrae, U.; Balmaseda, M.A.; Balsamo, G.; Bauer, D.P. The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*. 2011, 137, 553–597.

Dent, D. International Soil Reference and Information Centre (ISRIC). In Encyclopaedia of Soil Science; CRC Press: Boca Raton, FL, USA, 2017; pp. 1232–1236.

Devia, G.K.; Ganasri, B.P.; Dwarakish, G.S. A review on hydrological models. *Aquatic Procedia* 2015, 4, 1001–1007.

Doblas-Reyes, F.J.; Hagedorn, R.; Palmer, T.N. The rationale behind the success of multi-model ensembles in seasonal forecasting—II. Calibration and combination, *Tellus A. Dynamic Meteorology and Oceanography*. 2005, 57, 234–252.

Droppers, B., Franssen, W.H., Van Vliet, M.T., Nijssen, B. and Ludwig, F. Simulating human impacts on global water resources using VIC-5. *Geoscientific Model Development*, 2020.13(10), pp.5029-5052.

Dumont, E.; Williams, R.; Keller, V.; Voß, V.A.; Tattari, S. Modelling indicators of water security, water pollution and aquatic biodiversity in Europe. *Hydrological Sciences Journal*. 2012, 57, 1378–1403.

Farr, T.G.; Rosen, P.A.; Caro, E.; Crippen, R.; Duren, R.; Hensley, S.; Kobrick, M.; Paller, M.; Rodriguez, E.; Roth, L. The shuttle radar topography mission. *Reviews of Geophysics*. 2007, 45, 1–33.

Fischer, G.; Nachtergaele, F.; Prieler, S.; van Velthuizen, H.T.; Verelst, L.; Wiberg, D. Global Agro-ecological Zones Assessment for Agriculture. *IIASA* 2008, 10., 26–31.

Folke, S. Conflicts over water and land in South Indian agriculture: A political economy perspective. *Economic and Political Weekly*. 1998, 33, 341–349.

Geetha, K.; Mishra, S.K.; Eldho, T.I.; Rastogi, A. SCS-CN-based continuous simulation model for hydrologic forecasting. *Water Resources Management*. 2008, 22, 165–190.

Gosain, A.K.; Rao, S.; Basuray, D. Climate change impact assessment on the hydrology of Indian river catchments. *Current Science*. 2006, 90, 346–353.

Graeff, T.; Zehe, E.; Blume, T.; Francke, T.; Schröder, B. Predicting event response in a nested catchment with generalized linear models and a distributed watershed model. *Hydrological Processes*. 2012, 26, 3749–3769.

Gupta, H.V.; Kling, H.; Yilmaz, K.K.; Martinez, G.F. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*. 2009, 377, 80–91.

Gupta, P.K.; Panigraphy, S. Geospatial modelling of runoff of large landmass: Analysis, approach and results for major river catchments of India. The International Archives of the Photogrammetry, *Remote Sensing and Spatial Information Sciences*. 2008, 37, 63–68.

Hassan, Z.; Shamsudin, S.; Harun, S.; Malek, M.A.; Hamidon, N. Suitability of ANN allied as a hydrological model coupled with statistical downscaling model: A case study in the northern area of Peninsular Malaysia. *Environmental Earth Sciences*. 2015, 74, 463–477.

Hoekstra, A.Y.; Mekonnen, M.M.; Chapagain, A.K.; Mathews, R.E.; Ritcher, D.D. Global monthly water scarcity: blue water footprints versus blue water availability. *PLoS ONE* 2012, 7, e32688.

Horan, R.; Wable, P.; Srinivasan, V.; Baron, H.; Keller, V.; Garg, K.; Rickards, N.; Simpson, M.; Houghton-Carr, H.; Rees, G. Modelling Small-scale Storage Interventions at the Catchment Scale. *Earth Space Science Open Archive*. 2020.

Hurkmans, R.W.; De Moel, H.; Aerts, J.; Troch, P.A. Water balance versus land surface model in the simulation of Rhine River discharges. *Water Resources Research*. 2008, 44, 1–14.

Immerzeel, W.W.; Gaur, A.; Zwart, S.J. Integrating remote sensing and a process-based hydrological model to evaluate water use and productivity in a south Indian catchment. *Agricultural Water Management*. 2008, 95, 11–24.

Jain, S.K.; Agarwal, P.K.; Singh, V.P. Hydrology and Water Resources of India, 57th ed.; Springer Science & Business Media: New Delhi, India, 2007.

Jaje, D.; Priya, P.; Krishann, R. Macroscale hydrological modelling approach for the study of large-scale hydrologic impacts under climate change in Indian river catchments. *Hydrological Processes*. 2014, 28, 1874–1889.

Jamwal, P.; Thomas, B.K.; Lele, S.; Srinivasan, A. Addressing Water Stress through Wastewater Reuse: Complexities and Challenges in Bangalore, India; Local Governments for Sustainability: Bonn, Germany, 2014.

Knoben, W.J.M.; Freer, J.E.; Woods, R.A. Technical note: Inherent benchmark or not? Comparing Nash-Sutcliffe and Kling-Gupta efficiency scores. *Hydrology and Earth Systems Sciences*. 2009, 23, 4323–4331.

Kumar, B.K.; Nandagriri, L. Assessment of variable source area hydrological models in humid tropical watersheds. *International Journal of River Basin Management*. 2018, 16, 145–156.

Kumar, R.; Nandagiri, L. Evaluating uncertainty of the soil and water assessment tool (SWAT) model in the upper Cauvery Catchment, Karnataka, India. *International Journal of Earth Sciences and Engineering*. 2015, 8, 1675–1681.

Kumar, R.; Singh, R.D.; Sharma, D. Water Resources of India. *Current Science*. 2005, 89, 794–811.

Li, Z.; Yu, J.; Xu, X.; Sun, W.; Pang, B.; Yue, J. Multi-model ensemble hydrological simulation using a BP Neural Network for the upper Yalongjiang River Catchment, China. *Proceedings of the International Association of Hydrological Sciences*. 2018, 379, 335.

Liang, X.; Lettenmaier, D.P.; Wood, E.F.; Burges, S.J. A simple hydrologically based model of land surface water and energy fluxes for general circulation models. *Journal of Geophysical Research: Atmospheres*. 1994, 99, 14415–14428.

Liang, X.; Wood, E.F.; Lettenmaier, D.P. Surface soil moisture parameterization of the VIC-2L model: Evaluation and modification. *Global and Planetary Change* 1996, 13, 195–206.

Lohmann, D.; Raschke, E.; Nijssen, B.; Lettenmaier, D.P. Regional scale hydrology: I. Formulation of the VIC-2L model coupled to a routing model. *Hydrological Sciences Journal*. 1998, 43, 131–141.

Maheswaran, R.; Khosa, R. Wavelet–Volterra coupled model for monthly stream flow forecasting. *Journal of Hydrology*. 2012, 450, 320–335.

Martínez-Fernández, J.; Ceballos, A. Mean soil moisture estimation using temporal stability analysis. *Journal of Hydrology*. 2005, 312, 28–38.

Meigh, J.R.; McKenzie, A.A.; Sene, K.J. A grid-based approach to water scarcity estimates for eastern and southern Africa, *Water Resources Management* 1999, 13, 85–115.

Meunier, J.D.; Riotte, J.; Braun, J.J.; Sekhar, F.; Chalié, F.; Barboni, D.; Saccone, L. Controls of DSi in streams and reservoirs along the Kaveri River, South India. *Science of the Total Environment*. 2015, 502, 103–113.

Michaud, J.; Sorooshien, S. Comparison of simple versus complex distributed runoff models on a midsized semiarid watershed. *Water Resources Research*. 1994, 30, 593–605.

Muhammad, A.; Stadnyk, T.A.; Unduche, F.; Coulibaly, P. Multi-model approaches for improving seasonal ensemble streamflow prediction scheme with various statistical post-processing techniques in the Canadian Prairie region. *Water* 2018, 10, 1604.

NASA JPL. NASA Shuttle Radar Topography Mission Global 1 arc Second Number, 2013, Archived by National Aeronautics and Space Administration, U.S. Government, NASA EOSDIS Land Processes DAAC; NASA JPL: Pasadena, CA, USA.

Nash, J.E.; Sutcliffe, J.V. River flow forecasting through conceptual models. 1: Discussion of principles. *Journal of Hydrology*. 1970, 10, 282–290.

Neitsch, S.L.; Arnold, J.G.; Kiniry, J.R.; Williams, J.R. 1.1 Overview of Soil and Water Assessment Tool (SWAT) Model. Tier B 2009, 8, 3–23.

Nijssen, B.; O'Donnell, G.M.; Lettenmaier, D.P.; Lohmann, D.; Wood, E.F. Predicting the discharge of global rivers. *Journal of Climate*. 2001,14, 3307–3323.

Pai, D.; Latha, S.; Rajeevan, M.; Sreejith, O.P.; Satbhai, N.S.; Mukhopadhyay, B. Development of a new high spatial resolution (0.25◦ × 0.25◦) Long-period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region, 2014. *Mausam*. 2014, 65, 1–18.

Palanisami, K.; Ranganathan, C.R.; Nagothu, U.S.; Kakumanu, K.R. Climate Change and Agriculture in India: Studies from Selected River Catchments; Routledge: Abingdon-on-Thames, UK, 2014.

Patel, S.S.; Ramachandran, P. A comparison of machine learning techniques for modelling river flow time series: The case of Upper Cauvery River catchment. *Water Resources Management*. 2015, 29, 589–602.

Pattabaik, J.K.; Balakrishnan, S.; Bhutani, R.; Singh, P. Estimation of weathering rates and CO2 drawdown based on solute load: Significance of granulites and gneisses dominated weathering in the Kaveri River catchment, Southern India. *Geochimica et Cosmochimica Acta* 2013, 121, 611–636.

Ramachandra, T.V.; Bharath, S.; Bharath, A. Spatio-temporal dynamics along the terrain gradient of diverse landscape. *Journal of Environmental Engineering and Landscape Management*. 2014, 22, 50–63.

Refsgaard, J.C.; Storm, B. Construction, Calibration and Validation of Hydrological Models, in Distributed Hydrological Modelling; Springer: Dordrecht, The Netherlands, 1990; pp. 41–54.

Rickards, N.; Thomas, T.; Kaelin, A.; Houghton-Carr, H.; Jain, S.; Mishra, P.K.; Nema, M.K.; Dixon, H.; Rahman, M.M.; Horan, R. Understanding future water challenges in a highly regulated Indian river catchment—modelling the impact of climate change on the hydrology of the Upper Narmada. *Water* 2020, 12, 1762.

Robinson, T.P.; Wint, G.W.; Conchedda, G.; Van Boeckel, T.P.; Ercoli, V.; Palamara, E.; Cinardi, G.; D’Aietti, L.; Hay, S.I.; Gilbert, M. Mapping the global distribution of livestock. *PLoS ONE* 2014, 9, e96084.

Roy, P.S.; Meiyappan, P.; Joshi, P.K.; Kale, M.P.; Srivastav, V.K.; Srivasatava, S.K.; Behera, M.D.; Roy, A.; Sharma, Y.; Ramachandran, R.M. Decadal Land Use and Land Cover Classifications across India, 1985, 1995, 2005. *ORNL DAAC* 2016.

Salvucci, G.D.; Entekhabi, D. Equivalent steady soil moisture profile and the time compression approximation in water balance modelling. *Water Resources Research*. 1994, 30, 2737–2749.

Schaake, J.C.; Koren, V.I.; Duan, Q.Y.; Mitchell, K.; Chen, F. Simple water balance model for estimating runoff at different spatial and temporal scales. *Journal of Geophysical Research: Atmospheres*. 1996, 100, 7461–7475.

Semenova, O.M.; Vinogradova, T.A. A universal approach to runoff processes modelling: Coping with hydrological predictions in data-scarce regions. *IAHS publication*. 2009, 333, 11–16.

Shah, D.; Mishra, V. Drought onset and termination in India. *Journal of Geophysical Research: Atmospheres*. 2020, 125, 32871.

Sheffield, J.; Goteti, G.; Wood, E.F. Development of a 50-yr high-resolution global dataset of meteorological forcings for land surface modelling. *Journal of Climate*. 2016, 19, 3088–3111.

Smith, K.A.; Barker, L.J.; Tanguy, M.; Parry, S.; Harrigan, S.; Legg, T.P.; Prudhomme, C.; Hannaford, J. A multi-objective ensemble approach to hydrological modelling in the UK: An application to historic drought reconstruction. *Hydrology and Earth Systems Sciences*. 2019, 23, 3247–3268.

Sreelash, K.; Mathew, M.M.; Nisha, N.; Arulbalaji, P.; Bindu, A.G.; Sharma, R.K. Changes in the Hydrological Characteristics of Cauvery River draining the eastern side of southern Western Ghats, India. *International Journal of River Basin Management*. 2020, 18, 153–166.

Subash, Y.; Sekhar, M.; Tomer, S.K.; Sharma, A.K. A framework for the assessment of climate change impacts on. Sustain. *Water Resources ASCE* 2016, 375–397.

Tegegne, G.; Park, D.K.; Kim, Y.O. Comparison of hydrological models for the assessment of water resources in a data-scarce region, the Upper Blue Nile River Catchment. *Journal of Hydrology. Regional Studies*. 2017, 10, 49–66.

Troy, T.J.; Wood, E.F.; Sheffield, J. An efficient calibration method for continental-scale land surface modelling. *Water Resources Research*. 2008, 44.

UK Centre for Ecology and Hydrology (UKCEH). GWAVA: Global Water Availability Assessment Model Technical Guide and User Manual; Technical Report; UK Centre for Ecology and Hydrology: Wallingford, UK, 2020.

University of Washington Computational Hydrology Group, VIC Model User Guide. 2015. Available online: https://vic.readthedocs.io/en/vic.4.2.d/Documentation/UserGuide/ (accessed on 9 September 2019).

Viney, N.R.; Borman, H.; Breuer, L.; Bronstert, A.; Croke, B.F.; Frede, H.; Gräff, T.; Hubrechts, L.; Huisman, J.A.; Jakeman, A.J. Assessing the impact of land-use change on hydrology by ensemble modelling (LUCHEM) II: Ensemble combinations and predictions. *Advances in Water Resources*. 2009, 32, 147–158.

Viney, N.R.; Croke, B.W.; Breuer, L.; Bormann, H.; Bronstert, A.; Frede, H.; Gräff, T.; Hubrechts, L.; Huisman, J.A.; Jakeman, A.J. Ensemble modelling of the hydrological impacts of land-use change. In Proceedings of the MODSIM05 International Congress on Modelling and Simulation: Advances and Applications for Management and Decision Making, Melbourne, Australia, 12–15 December 2005

Wable, P.S.; Garg, K.K.; Nune, R. Impact of Watershed Interventions on Streamflow of Upper Cauvery Sub-Catchment. In Proceedings of the Sustainable Water Futures Conference, Bengaluru, India, 24–27 September 2019.

Wagner, P.D.; Kumar, S.; Fiener, P.; Schneider, K. Hydrological modelling with SWAT in a monsoon-driven environment: Experience from the Western Ghats, India. *Transactions of the ASABE* 2011, 54, 1783–1790.

Wu, H.; Adler, R.F.; Tian, Y.; Huffman, G.J.; Li, H.; Wang, J. Real-time global flood estimation using satellite-based precipitation and a coupled land surface and routing model. *Water Resources Research*. 2014, 50, 2693–2717.

Zhang, B.; Wu, P.; Zhao, X.; Gao, X.; Shi, Y. Assessing the spatial and temporal variation of the rainwater harvesting potential (1971–2010) on the Chinese Loess Plateau using the VIC model. *Hydrological Processes*. 2014, 28, 534–544.

## Appendix B

Table 2.6 Brief Description of functionality/processes summarised from the model user guidance (Arnold *et al*., 2012; VIC Model User Guide, 2015; GWAVA: Global Water Availability Assessment Model Technical Guide and User Manual, 2020)

| Model | Calibration | Surface Runoff Routing | Channel Routing | Interception | Total Evaporation | Baseflow | Infiltration | Channel Characteristics | Groundwater | Anthropogenic Demands | Dam Module | Irrigation Module | SSRHIs |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| GWAVA | Automatic | PDM | | | Hargreaves | | PDM | | | | | | |
| SWAT | Manual | SCS | Muskin-gum | | Penman-Monteith | Steady-State | Green Ampt | | | | | | |
| VIC | Manual | Linear Transfer | Saint-Venant | BATS | Penman-Monteith | Arno | VIC | | | | | | |
| | Included in the model, utilised in the study | | | | | Included in the model, not utilised in the study | | | | Not included in the model | | | |

Table 2.7 Description and source of the model input data

| Input Data | Model | Resolution | Source |
|---|---|---|---|
| Precipitation | VIC<br>GWAVA | 0.25 degrees, daily, 1951-2017 | IMD (Pai *et al*., 2014) |
| | SWAT | 0.25 degrees, daily, 1951-2017 | IMD (Pai *et al*., 2014) |
| | | 0.14 degrees, daily | IMD (Pai *et al*., 2014) |
| | | 34 rain gauges, monthly | IMD (Pai *et al*., 2014) |
| Maximum and Minimum Temperature | VIC<br>GWAVA | 0.25 degrees, daily, 1951-2016 | IMD (Pai *et al*., 2014) |
| | SWAT | 0.25 degrees, daily, 1951-2016 | IMD (Pai *et al*., 2014) |
| Wind speed | VIC | 0.25 degrees, daily, 1971-2016 | Princeton University (Sheffield *et al*., 2016) |
| | SWAT | 0.25 degrees, daily | IMD (Pai *et al*., 2014) |
| Relative Humidity | SWAT | 0.125 degrees, daily | IMD (Pai *et al*., 2014) |
| Sunshine hours | SWAT | 0.125 degrees, daily | IMD (Pai *et al*., 2014) |
| Streamflow gauged data | VIC<br>GWAVA | Cauvery, daily, 1971- 2014 | India-WRIS |
| | SWAT | Upper Cauvery, monthly | India-WRIS |
| Dam inflow and outflow data | VIC<br>GWAVA | Cauvery, monthly 1974-2014 | India- WRIS |
| | SWAT | Upper Cauvery, monthly | India- WRIS |

| Input Data | Model | Resolution | Source |
|---|---|---|---|
| Water transfers | GWAVA | Cauvery Catchment | ATREE |
| SSRHIs | GWAVA<br>SWAT | Karnataka, 2006-2012 | KWA, Karnataka |
| Elevation | VIC<br>GWAVA | 30 m x 30m | NASA Shuttle Radar Mission Global 1 arc second V003 (NASA JPL, 2013) |
| | SWAT | 90m x 90m | Shuttle Radar Topography Mission (Farr *et al*., 2007) |
| Soil type | VIC | 250 m | ISRIC world soil information (Dent, 2017). |
| | GWAVA | 30 arc second | Harmonized World Soil Database v1.2 (Fischer *et al*., 2008) |
| | SWAT | 1: 250 000 | NBSS & LUP |
| Land Cover Land Use | VIC<br>GWAVA | 100m x 100m, 1985, 1995, 2005 | Decadal land use and land cover across India 2005 (Roy *et al*., 2008) |
| | SWAT | 1:250000 | NRSC |
| Crops | GWAVA | Talak, 2000 | NRSC |
| | SWAT | 1:250000 | NRSC |
| LAI | VIC | 1 km resolution | MODIS (USGS Earth Explorer, 2018) |
| Albedo | VIC | 1 km resolution | MODIS (USGS Earth Explorer, 2018) |
| Total Population | GWAVA | Village, 2011 | Indian Decadal Census |

| Input Data | Model | Resolution | Source |
|---|---|---|---|
| Rural Population | GWAVA | Village, 2011 | Indian Decadal Census |
| Livestock | GWAVA | 5km x 5km | CGIR Livestock of the World v2 (Robinson *et al*., 2014) |

Table 2.8 SWAT model inputs and calibration parameters

| Variable (Unit) | Parameter Name | Parameter Value | Source |
|---|---|---|---|
| Sand content (%) | SAND | 20 (10-30) | NBSS&LUP |
| Silt content (%) | SILT | 28 (20-35) | NBSS&LUP |
| Clay content (%) | CLAY | 53 (35-70) | NBSS&LUP |
| Bulk Density (g $cm^{-3}$ ) | SOL_BD | 1.29 (1.24-1.33) | NBSS&LUP |
| Available Water Content (mm H2O/mm soil) | SOL_AWC | 0.14 | NBSS&LUP |
| Soil Depth (mm) | SOL_Z | 750 (300-1200) | NBSS&LUP |
| Saturated Hydraulic Conductivity (mm/hr) | SOL_K | 6.6 (6.03-7.12) | NBSS&LUP |
| Curve number | CN2 | 82 (72-92) | Calibrated |
| Groundwater revapcoeff (-) | GW_REVAP | 0.02 | Default |
| Threshold depth of water for revamp in a shallow aquifer (mm $H_2O$) | REVAP_MN | 750 | Default |
| Threshold depth of water in the shallow aquifer required to return flow (mm $H_2O$) | GWQMN | 1000 | Default |
| Groundwater delay time (days) | GW_DELAY | 31 | Default |

| | | | |
|---|---|---|---|
| Surface runoff lag coefficient | SURLAG | 4 | Default |
| Baseflow alpha factor | ALPHA_BF | 0.048 | Default |
| Hydraulic conductivity of the dam bottom (mm $h^{-1}$)—For ex-situ SSRHIs | RES_K | 4 | Measured |
| Hydraulic conductivity of the dam bottom (mm $h^{-1}$)—For in-situ SSRHIs | RES_K | 12 | Measured |

Groundwater revapcoeff: Water may move from the shallow aquifer into the overlying unsaturated zone. As GW_REVAP approaches 0, the movement of water from the shallow aquifer to the root zone is restricted. As GW_REVAP approaches 1, the rate of transfer from the shallow aquifer to the root zone approaches the rate of potential evapotranspiration. ** REVAP_MN Threshold depth of water in the shallow aquifer for "revap" or percolation to the deep aquifer to occur (mm H2O).

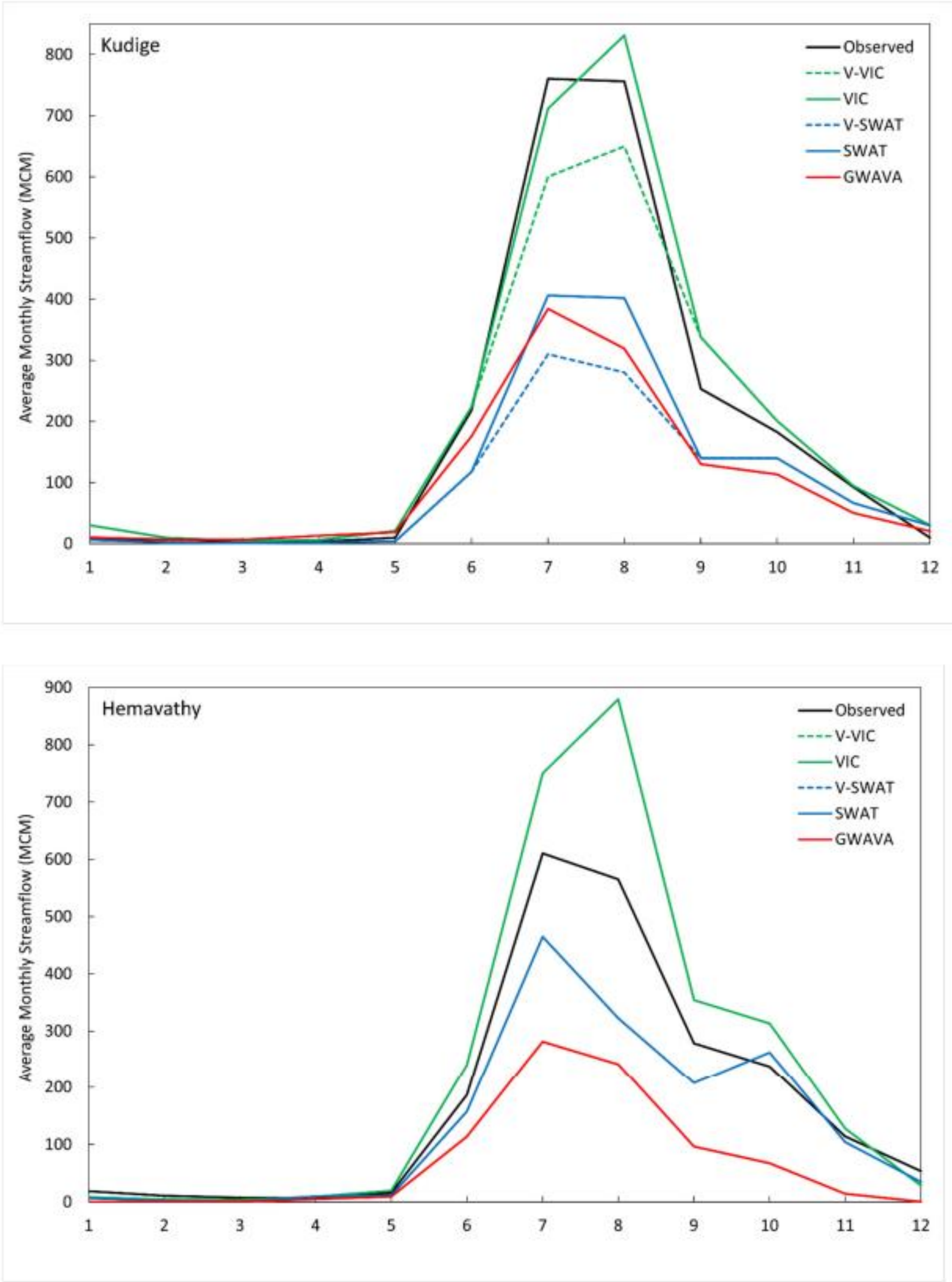
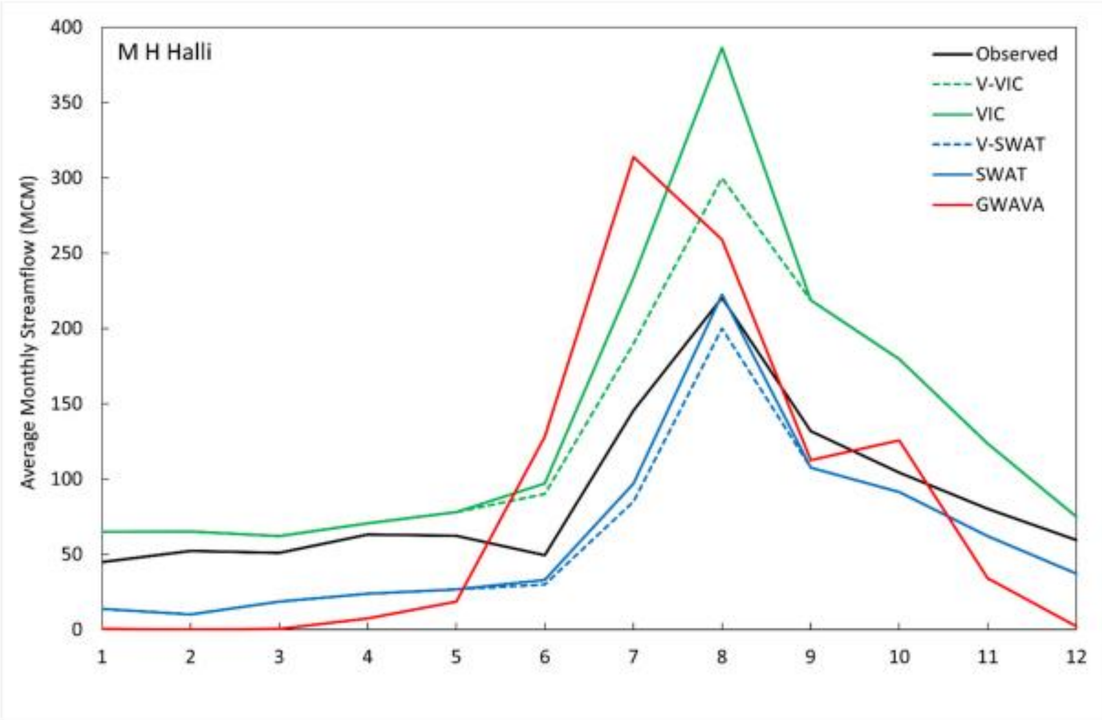



Figure 2.4 The monthly average streamflow in MCM for each catchment simulated by V-VIC, VIC, V-SWAT, SWAT and GWAVA superimposed with the monthly average observed streamflow.



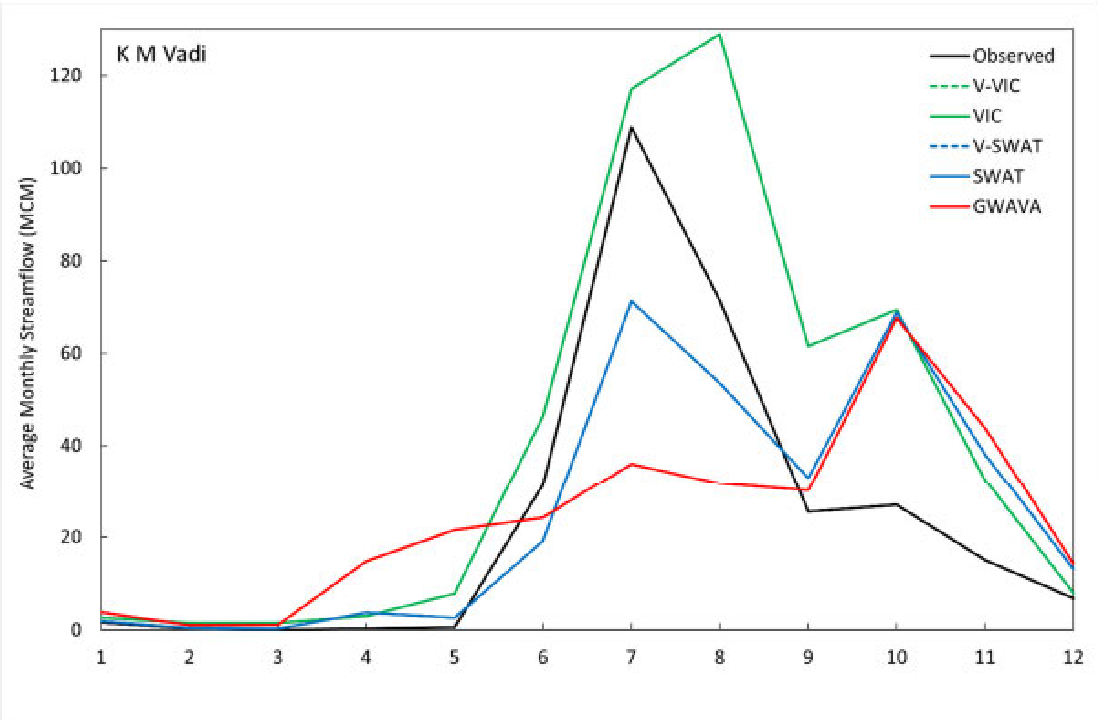




Figure 2.4 *cont.*

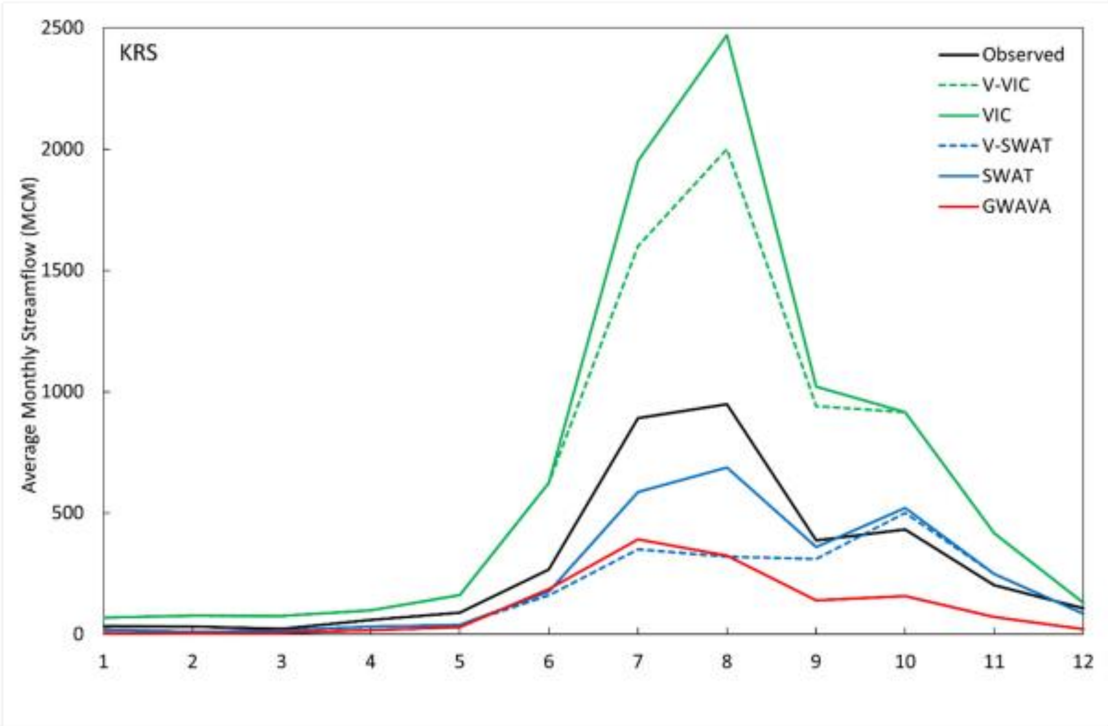
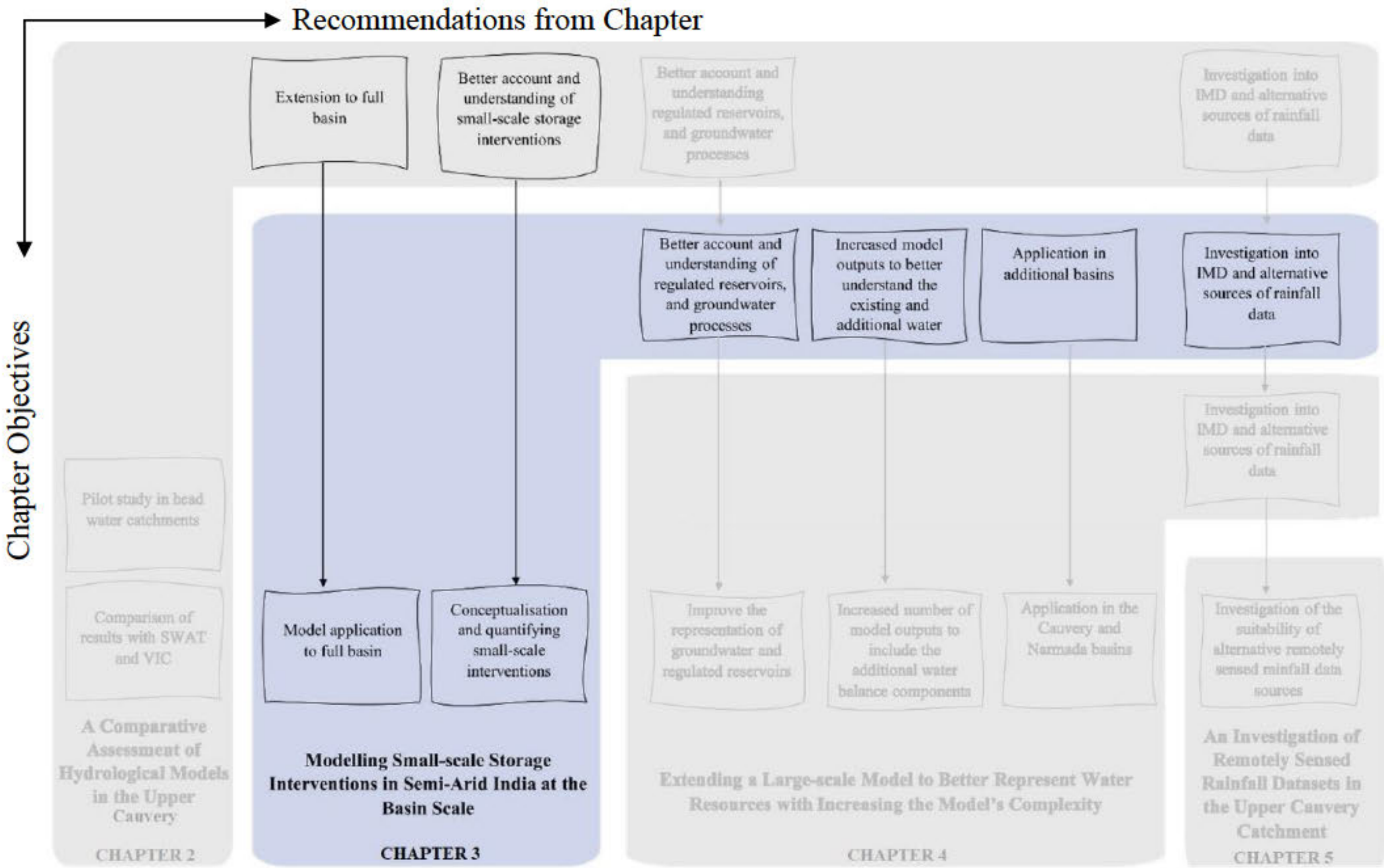



Figure 2.4 *cont.*

*****

**Lead into Chapter 3**

GWAVA has been identified as a suitable choice in Chapter 2 despite recommendations for improving modelling techniques and infrastructural representation to better account for the water resources within the region. In Chapter 3, the model is applied to the Cauvery Catchment. Additionally, this chapter covers the development and testing of a methodology for representing prevalent SSRHIs (check dams, farm bunds and tanks) and their hydrological functioning at a catchment scale. Utilising limited financial records, each SSRHI was derived across the modelling grid and conceptualised based on field data. The effect of the SSRHIs on streamflow, evaporation, groundwater levels and dam inflow was determined.



# 3. MODELLING SMALL-SCALE RUNOFF HARVESTING INTERVENTIONS IN SEMI-ARID INDIA AT THE CATCHMENT SCALE

**Abstract**

There has been renewed interest in the performance, functionality, and sustainability of traditional small-scale storage runoff harvesting interventions (SSRHIs - check dams, farm bunds and tanks) used within semi-arid regions to improve local water security and landscape preservation. The CGWB of India is encouraging the construction of such SSRHIs for the alleviation of water scarcity and to enhance groundwater recharge. It is important for water resource management to understand the hydrological effect of these SSRHIs at the catchment scale. The quantification of SSRHIs in hydrological modelling is often neglected, especially in large-scale modelling activities, as data availability is low, and their hydrological functioning is uncertain. A version of the GWAVA water resources model was developed to assess the impact of SSRHIs on the water balance of the Cauvery Catchment and two smaller sub-catchments. Model results demonstrate that farm bunds appear to have a negligible effect on the average annual simulated streamflow at the outlets of the two sub-catchments and the catchment. In contrast, tanks and check dams have a more significant and time-varying effect. The open water surface of the SSRHIs contributed to an increase in evaporation losses across the sub-catchment. The change in simulated groundwater storage with the inclusion of SSRHIs was not as significant as sub-catchment-scale literature, and field studies suggest. The model adaption used in this study provides a step-change in conceptualising and quantifying the consequences of SSRHIs in large- or catchment-scale hydrological models.

**Keywords:** semi-arid hydrology; small-scale storage; check dams; tanks; farm bunds; Cauvery; GWAVA

---

Horan, R, Wable, PS, Srinivasan, V, Baron, HE, Keller, VJ, Garg, KK, Rickards, N, Simpson, M, Houghton-Carr, HA and Rees, HG, 2021. Modelling Small-Scale Storage Interventions in Semi-Arid India at the Basin Scale. Sustainability, 13(11), p.6129.

*Referencing conforms to the format of *Sustainability*

## 3.1 Introduction

Water resources management is becoming increasingly challenging (Cleaver, 2017) with rapid population growth (Loucks, 2017), a changing climate (Wang *et al.*, 2016), and increasing competition over limited natural resources (Smith, 2018). Local communities and municipalities have altered the landscape for centuries and built informal structures to improve local water security. In semi-arid regions of the world, people have relied on large-scale infrastructures, such as dams and water transfer schemes, and small-scale infrastructures, such as check dams, farm bunds (rainfall harvesting method used in agriculture fields consisting of a raised soil perimeter), and tanks (small informal dams with a sub-catchment area of fewer than 34 hectares), to provide and store water for urban and rural use. Detailed descriptions of these structures can be found in Section 3.2.2.

In India, the shortfall in renewable water resources to meet the increasing demand has resulted in the aggressive abstraction of deep groundwater storage and the construction of small surface-water storage structures (Ramaswamy, 2007). The Government of India and State governments have actively encouraged the construction of SSRHIs, such as check dams, farm bunds, and tanks, as the primary policy response for alleviating water scarcity (Goyal & Sivanappan, 2017). There are now millions of such structures across India (Agoramoorthy & Hsu, 2008), and recently, there has been renewed interest in their effectiveness in improving local water security. Understanding the hydrological effect of these SSRHIs at the local- and catchment scale is critical to inform sustainable water resource management.

In India and other semi-arid regions, SSRHIs are generally constructed to assist in replenishing and maintaining local groundwater resources (Renganayaki & Elango, 2013). The most prolific types of SSRHIs in Southern India are check dams, farm bunds, and tanks (Shah, 2008). In mountainous regions of the world, such SSRHIs are commonly used to reduce streamflow velocity and reduce sediment loss from the sub-catchment. However, these SSRHIs are primarily used in India for artificial groundwater recharge (Ramaswamy, 2007). There is limited knowledge of the hydrological dynamics and performance of SSRHIs (Van Meter *et al.*, 2015). Little research has been undertaken to quantify the hydrological effects of SSRHIs at a catchment-scale (Xu *et al.*, 2013). Some studies have modelled the local impact of SSRHIs on streamflow with different perspectives, including the impact on the water balance (Van Meter *et al.*, 2015), as possible use to treat wastewater (Vidya *et al.*, 2015), and the impact on river flows in headwater sub-catchments (Garg *et al*., 2012; Penny *et al*., 2018). Additionally, many studies have focused on the effects of SSRHIs on sediment transport and local groundwater level (Doolittle, 1985; Armanini *et al*., 1991; Boix-Fayos *et al*., 2007; Mishra *et al*., 2007; Polyakov *et al*., 2014; Dashora *et al*., 2018; Wei *et al*., 2017; Díaz-Gutiérrez *et al*., 2019). The upscaling of SSRHIs is of high interest because it is becoming increasingly popular for water resource management and planning approaches to focus on the catchment as an entity (Krois & Schulte, 2013). A catchment-wide approach is important in semi-arid regions and particularly pertinent in closed and closing catchments, where water is a scarce commodity and upstream SSRHIs directly affect downstream water availability (Krois & Schulte, 2013).

There are concerns regarding the effects and functionality of SSRHIs in Peninsular India. The underlying fissured hard-rock geology of Peninsular India differs from the alluvial deposits in Northern India, where most previous studies have been undertaken. Fissured hard rock has a medium to low permeability and contains water tables with modest water resources compared to porous, karst, and volcanic water tables. These water table systems are well-connected and have transitioned from a laterally to a vertically dominated flow system due to high levels of abstraction. These water tables have decreasing hydraulic conductivity and storage with depth, resulting in the resource depleting quickly when groundwater is withdrawn from increasing depths. The water table systems are now regarded as either depleted or highly variable resources due to the high levels of abstraction and seasonal recharge. It is speculated that the abstraction from these water tables results in decreased base flow into the river system (Ramaswamy, 2007).

The Cauvery Catchment was chosen to be representative of many other catchments in Peninsular India. These catchments are under pressure from urbanisation, population growth, and agriculture intensification (Krois & Schulte, 2013). The Cauvery is also a contentious river with concern over water sharing between Karnataka and Tamil Nadu (Salman, 2002). With water resources in the Cauvery Catchment under severe stress and the abundance of SSRHIs, it is important to understand the effect of SSRHIs on the spatial and temporal hydrological patterns (Xu *et al*., 2013).

There are constraints and uncertainty identified in the current modelling of SSRHIs at the catchment scale:

a) The hydrological functioning of each type of SSRHI is uncertain.
b) Proxy values and parameter adjustments have been utilised to quantify the functioning of SSRHIs.
c) Data on the location and characteristics of SSRHIs are scarce and not well documented when available.

The impacts of such changes and SSRHIs on local hydrological processes, such as streamflow, groundwater recharge, and evapotranspiration, are poorly understood. The knowledge of how these diverse local changes cumulatively affect water availability at the broader catchment scale is very limited.

Over recent decades, the hydrological regime of the Cauvery Catchment has been significantly altered (Sreelash *et al*., 2020) across the four federal states in which it lies (Sharma *et al*., 2020). The catchment is highly water-stressed (Hoekstra *et al*., 2012), and the current water use exceeds the renewable water resources within the catchment. A common technique throughout the four states is using small-scale storage structures to alleviate local water stress in non-monsoon periods (Moore, 1985). All the water resources associated with a “normal” rainfall year are currently allocated by the tribunal (Salman, 2002), and surface water flows only reach the Bay of Bengal in years of strong monsoons (Falkenmark & Molden, 2008). The agricultural activities across the catchment require 90% of the total water resources (Bhave *et al*., 2018). However, rapidly developing urban and industrial centres are creating increased inter-sectorial and inter-state competition for limited renewable resources (Jamwal *et al*., 2014). The four states have different water policies, traditional water harvesting techniques, water use prioritisation, and values associated with the natural environment (Kumar *et al*., 2006).

Several hydrological modelling exercises have already been carried out in the Cauvery Catchment or its sub-catchments. The ARIMA model (Patel & Ramachandran, 2015), ANN model (Patel & Ramachandran, 2015), SVR model (Patel & Ramachandran, 2015), and the SWAT model (Kumar & Nandagiri, 2015) have been utilised in various sub-catchments of the Cauvery Catchment. At the catchment scale, SWAT (Gosain *et al*., 2006; Singh & Gosain, 2011; Bhuvaneswari *et al*., 2013; Mandal *et al*., 2016), SCS-CN (Geetha *et al*., 2008; Parvez & Inayathulla, 2019), and the coupled mesoscale hydrologic model with the VIC-MHM (Raje *et* *al*., 2014) have been used to simulate streamflow. However, none of these previous studies has considered the inclusion of SSRHIs.

Using the GWAVA model in the Cauvery Catchment provides the opportunity to investigate the effect of SSRHIs on catchment-scale hydrology by introducing check dams, farm bunds, and tanks into the model structure. To investigate the impact of the SSRHIs on the hydrology of the Cauvery Catchment, a version of the GWAVA model (GWAVA-Int) made specifically for this use was developed. In GWAVA-Int the SSRHIs were conceptualised within the model structure using local knowledge, observed data, and adaptations of existing dam representations. The effect of SSRHIs on the hydrological regime and water balance of the entire Cauvery Catchment was studied, as well as a more in-depth analysis of two relatively small sub-catchments contained within the catchment.

## 3.2 Materials and Methods

The GWAVA model was used to understand the hydrological functioning and impacts of SSRHIs on the water balance of the Cauvery Catchment.

### *3.2.1 Site Description*

The Cauvery River catchment is the fourth-largest in Peninsular India; it drains an area of 81,155 km$^2$ (Jain *et al*., 2007). The Cauvery originates in the Western Ghats at Talakaveri in the Kodagu district of Karnataka, and the headwaters of the catchment form in the Nilgiri and Anaimalai mountains. The Cauvery Catchment is predominantly situated in the federal states of Karnataka and Tamil Nadu, although it crosses into Kerala and Puducherry (Sharma *et al*., 2020). The main river channel flows south-easterly through Karnataka, and Tamil Nadu states to outflow at the Bay of Bengal (Chidambaram *et al*., 2018).

The Cauvery Catchment is subjected to a large degree of heterogeneity in topography, land use, climate, and economic development (Madhusoodhanan *et al*., 2016). The landscape is semi-arid, with most of the catchment's water coming from the southwestern monsoon in the summer months. The catchment experiences distinct intra-annual seasons, namely the SW monsoon in the spring, the NE monsoon in the autumn, and post-monsoon conditions in the winter. The upper sub-catchment receives rainfall from the SW and NE monsoons, whereas the lower sub-catchment only receives rainfall from the NE monsoon. The mean annual rainfall varies from 6000 mm in the upper reaches to 300 mm on the eastern boundary (Meunier *et al*., 2015). The mean daily temperatures range between 9 and 25 ℃ throughout the sub-catchment (Sreelash, 2020). The Western Ghats form a rain shadow along the western coastline, decreasing the rainfall gradient during the SW monsoon (Gunnell, 1997). In addition to complex water resource management on the ground, high levels of heterogeneity across the catchment pose a challenge when undertaking spatial modelling activities, identifying feedback and upscaling sub-catchment processes.

The catchment is highly anthropogenically influenced. Currently, there are over 100 impounding dams (Figure 3.1a) and approximately 20 major water transfer schemes within the catchment (Figure 3.1c), along with millions of SSRHIs throughout the rural and urban regions of the catchment (Sreelash *et al.,* 2020). The four major dams that are constructed within the sub-catchment are Kabini (440 MCM), Bhavanisagar (791 MCM), Krishna Raja Sagara (1016 MCM), and Mettur (2640 MCM). The releases from these major dams regulate and disrupt the seasonal trend of the streamflow downstream of their release points. The land use of the catchment comprises 48% agriculture, 22% non-arable land, 19% forest, and 9% urban (Figure 3.1b) (Sreelash *et al.*, 2020). Natural forests are under great stress due to increasing demand for forest products and competition over land use. Across the catchment, approximately 60% of the total population relies on agriculture (Sreelash *et al.*, 2020). Crops are grown within irrigated canal command areas or rain-fed areas utilising farm bunding techniques. Paddy and sugarcane, both water-intensive crops, are predominant within the irrigated and rain-fed areas of the catchment and in the delta regions. The urban areas within the catchment have expanded by over 35% over the last decade and are expected to continue to increase with the expansion of industry (Lannerstad, 2008). With the threat of rising surface temperatures, the competition for freshwater resources between the agricultural sector and other water uses are likely to intensify.

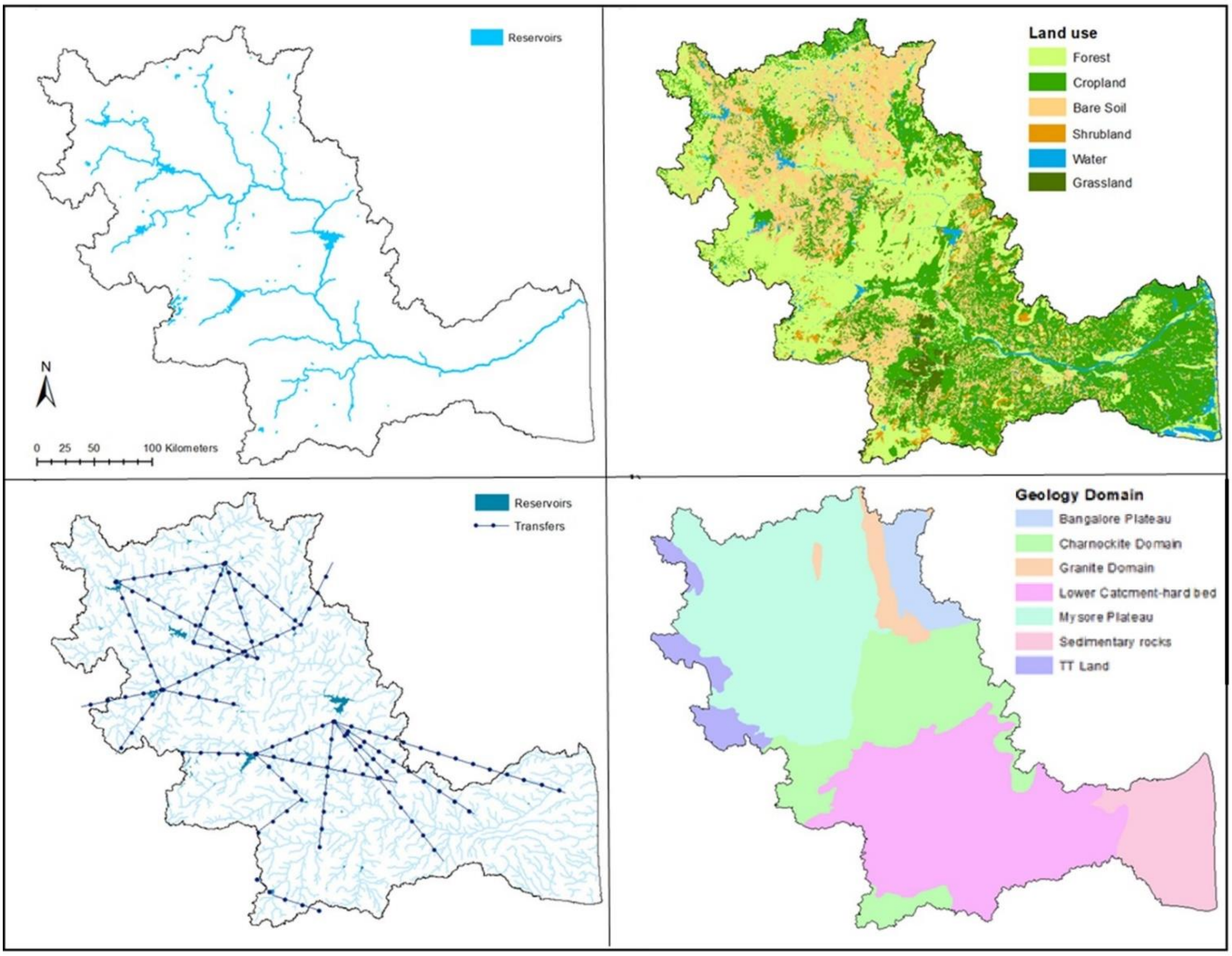



Figure 3.1 Physical characteristics of the Cauvery Catchment. Presented are (top left) the location of dams within the catchment, (top right) the land use of the catchment, (bottom left) the major dams and the water transfer links constructed in the catchment, and (bottom right) the geological domains within the catchment.

Model-simulated streamflow, total evaporation, water table level, and base flow were investigated at two sub-catchment outlets, located in Karnataka and Tamil Nadu, and the furthest downstream gauging point (Musiri) (Figure 3.2) to determine the effects of the SSRHIs on the availability of simulated streamflow and the sub-catchment water balance. The two sub-catchments were selected based on a similar density of SSRHIs but differing underlying geology (Figure 3.1d). The base flow component (groundwater flowing into the river channel from the water table) between the two sub-catchments is different.

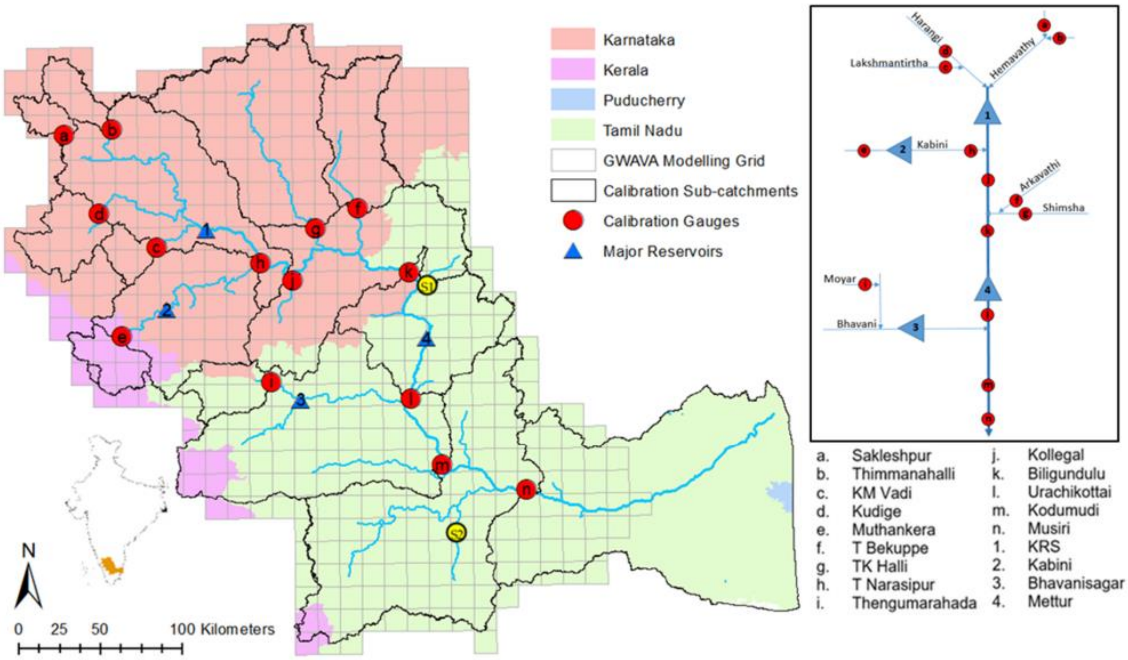



Figure 3.2 Inset: Flow diagram of the Cauvery Catchment; the main map shows the four states falling within the catchment (pastel shading), sub-catchment boundaries, modelling grid, and the locations of the 14 calibration gauges (a–n) and 4 major dams (1–4) within the Cauvery Catchment. S1 and S2 (Table 3.1) represent the points on the stream network where the effect of SSRHIs is investigated.

Table 3.1 The MAP, sub-catchment area (Area), flow characteristics, period of no observed streamflow in the main channel ($T_{noflow}$-days of no streamflow), and underlying geology of two sub-catchments were used in this study.

| **Sub-catchment Number** | **Area (km$^2$)** | **MAP (mm)** | **Rainfall Period** | **Flow Characteristics** | **Period of No Streamflow in Main Channel (Days per year)** |
|---|---|---|---|---|---|
| S1 | 2660 | 864 | Mar-Jan | Non- Perennial | $30 < T_{noflow} < 60$ |
| S2 | 3120 | 867 | Mar-Jan | Perennial | $0 < T_{noflow} < 3$ |

### *3.2.2 Model Development*

The GWAVA model is a large-scale, semi-distributed gridded water resources model developed by the UKCEH (Meigh *et al*., 1999). The model incorporates natural processes (soils, land use, lakes, etc.) and anthropogenic influences (crops, domestic and industrial demands, dam operations, transfers, etc.). GWAVA estimates local runoff from each cell using a lumped conceptual PDM (Moore, 2007). The PDM requires a limited set of parameters, with the model configuration comprising three components: probability-distributed soil moisture storage, surface storage, and groundwater storage. GWAVA utilises a combination of land use and soil types. There are four land use options (trees, shrubs, grass, and bare soil) and seven soil type classifications (ranging from sandy to organic). The soil moisture characteristics for each combination are defined by rooting depths, wilting points, field capacities, and saturation capacities. The evaporation is estimated using the FAO-56 Hargreaves equation from the natural vegetation and crops. At the same time, the effective rainfall is determined using a two-parameter exponential equation, as Calder (1990) described. The soil moisture and direct runoff are calculated separately for each land use type and then summed to obtain a total direct runoff for each grid cell. The total direct runoff is then routed through existing engineering structures within the grid cell using the Muskingum equation and the user-defined dam outflow or transfer parameters. This is followed by a demand-driven routine to account for the anthropogenic stresses on the system. GWAVA accounts for water demands from the domestic (urban and rural), industrial, and agricultural sectors. Domestic, industrial, and livestock demands are user-defined and temporally static but spatially dynamic. Irrigation demand is temporally and spatially dynamic and is estimated via a user-defined crop type and planting month (Meigh *et al*., 1999). For this study, the first major model development was undertaken, including SSRHIs (GWAVA-Int).

The typical characteristics and functioning of each type of SSRHI were determined to aid in the representation of SSRHIs within the GWAVA model. Due to the abundance of these small structures throughout the catchment, the lack of spatially explicit data and the grid resolution of GWAVA, it was deemed impossible to simulate the effect of every single structure. Instead, each type of SSRHI was aggregated for every 0.125 degrees (approximately 12 km × 12 km in India) cell to form a single composite tank, check dam, and farm bund within each cell. For this aggregation to be possible, the surface area of each SSRHI in a cell was required to estimate the total storage capacity for each type of SSRHI in that cell. The check dams utilised trapezoidal scaling, while the tanks and farm bunds used cuboidal scaling to determine the storage capacity.

As a result of the structures, the increased open water surface area increases evaporation losses within a grid cell. A constant OWE factor was applied to all the SSRHIs. The monthly average OWE was estimated from the evaporation-control-in-dams documentation (Central Water Commission, 1987).

#### 3.2.2.1 Urban and Rural Tanks

For this study and referring to terminology used in India (Vidya *et al*., 2015), small, abundant dams with less than 34 hectares of drainage area and built for the decentralised harvesting of runoff, particularly in the monsoon season, are referred to as tanks (Gunnell & Krishnamurthy, 2003). These are typically constructed using a shallow dam across a river channel and are unlined (Penny *et al*., 2018). Tanks provide small-scale storage of rainfall and streamflow, control floodwaters, and increase recharge to groundwater in the immediate area (Bhattacharya, 2010). Rural tank storage is seasonal (Gowda *et al*., 2014), and in many semi-arid regions, tanks provide the only means to store rainwater and streamflow for irrigation (Anbumozhi *et al*., 2001). Urban tanks are fundamental for city drainage systems (Penny *et al*., 2018) and are used for collecting and recycling wastewater.

For their conceptualisation within GWAVA-Int, urban and rural tanks were assumed to have an inflow component comprising daily rainfall, wastewater, and streamflow within the cell, with spills contributing to the outflow (Figure 3.3). Furthermore, these tanks are generally unlined to help groundwater recharge locally. Thus, a leakage rate of 13 mm $d^{-1}$ (Doshora *et al*., 2019) and 6 mm $d^{-1}$ (Lal & Stewart, 2012) were added for the rural and urban tanks, respectively. The recharge from tanks is relatively low as these structures tend to be highly silted, and infiltration is limited through the fine particles lining the bottom. The recharge from rural tanks was higher than from urban tanks under the assumption that tanks in rural areas were constructed more recently and dredged more regularly. Without detailed tank bathymetry data, it was assumed that all tanks are cuboid in shape with a maximum depth of 3.0 m deep at full capacity (Pant & Verma, 2010).

#### 3.2.2.2 Check Dams

Check dams are small water conservation structures (<0.5 ha) built across a stream using concrete, sandbags, or logs (Boix-Fayos *et al*., 2008). These are designed to reduce the streamflow velocity through the sub-catchment and retain the floodwaters (monsoonal rainfall in the case of India) (Xu *et al*., 2013). The process of impounding water at a local scale is thought to increase the groundwater recharge and soil water potential in the adjoining areas (Adhikari *et al.*, 2015).

For the model representation of check dams, it was assumed that daily rainfall, local runoff, and streamflow of the cell contribute to the inflow (Figure 3.3). From a field study in the Upper Cauvery region, the leakage from the bottom of the structure was assumed to be 100 mm $d^{-1}$ across all the check dams in the sub-catchment (Wable *et al*., 2019). The outflows of the check dams comprise spills. For this study and to simplify the data collection of thousands of structures, all check dams in the catchment are assumed to have the same dimensions and, thus, capacity. In the absence of comprehensive dimension data from within the catchment, assumptions have been made based on available literature. The depth is assumed to be 1.5 m (Dashora *et al.*, 2019), the top width of the structure equal to 10 m, and the channel slope to be 1% (Wable *et al*., 2019). In the absence of data quantifying the number and spatial repartition of check dams in the Cauvery Catchment, a surrogate methodology was established to estimate these alongside their storage capacity. Based on discussions with stakeholders and cited literature (Agoramoorthy & Hsu, 2008; Heede, 1966; Djuma *et al*., 2017), it was assumed that an average check dam in the Cauvery Catchment is a 3D trapezoid with a profile that is 10 m in width at a distance of 70 m upstream of the structure. Thus, the surface area of a check dam was assumed to be triangular and fixed at 350 $m^2$ (70 m multiplied by half the wall length) for every check dam included in the model. The assumed average surface area was used solely to determine the total surface area of check dams within a grid cell: The number of check dams (see Section 4.2.5) within a cell was multiplied by 350 $m^2$ to determine the surface area of check dams in each cell. Within the model conceptualisation, the length of the conceptual aggregated check dam was dependent on the surface area. The width and depth remained at 10 m and 1.5 m, but the length was variable.

#### 3.2.2.3 Farm Bunds

Farm bunding is a traditional in-situ method for soil and water conservation (Pathak *et al.*, 2011). Bunds are a raised perimeter at the foot slope of agricultural fields, constructed of soil or stone, to increase the time of concentration of rainfall, allowing rainwater to percolate into the soil (Hudson, 1987). Bunds are constructed to retard the movement of overland flow and encourage infiltration within the field (Alexandrov *et al*., 2007).

Farm bunds are assumed to be filled from daily rainfall and local runoff within the cell. The saturated hydraulic conductivity of the soils (Allen *et al*., 2010) in the catchment and the high diurnal temperatures resulted in the water within the farm bunds infiltrating or evaporating completely within a day. The open water evaporation constant was applied to the surface area of the bunds, while the infiltration rate differed concerning soil type. To simulate groundwater recharge from these structures, a rate relative to the saturated hydraulic conductivity of the soil (Allen *et al*., 2010) of the area was selected. Once the water in the bund was at full capacity, the excess water could flow over the structure and into the stream. Without adequate field measurements, it was assumed from the available literature that all bunds are a maximum of 0.3 m deep (Critchley & Graham, 1991; Verma & Singh, 2017) (Figure 3.3). The surface area of the farm bunds area is derived in Section 3.2.5.

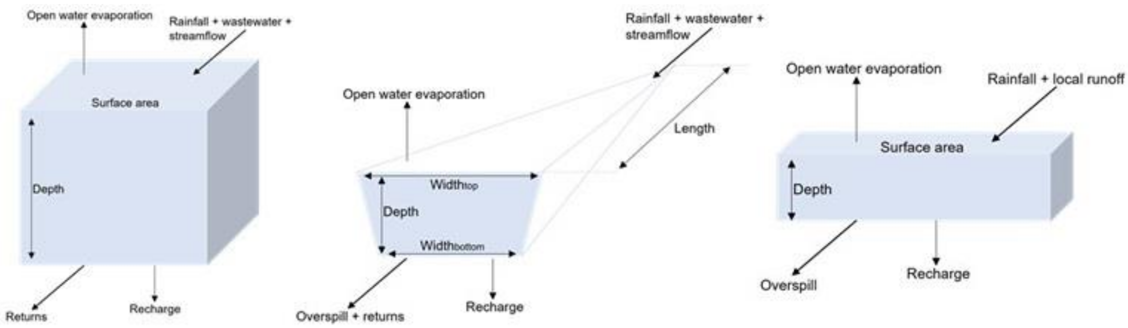



Figure 3.3 Conceptual diagram of the urban and rural tank (left), check dam (middle) and farm bund (right) adopted in the GWAVA-Int model.

Following the inclusion of the SSRHIs within GWAVA, a sensitivity analysis, in line with that of Wable *et al*. (2019), was performed to assess the effect the number and dimensions of the SSRHIs have on the simulated streamflow. A detailed description of the scenarios can be found in Table 3.3 in Appendix C. For this sensitivity analysis, the scenarios presented have been run under natural conditions throughout the sub-catchment to isolate the effects of the dimensions and number of SSRHIs on the streamflow

### *3.2.3 Model Application*

For this application of the GWAVA-Int model in the Cauvery Catchment, a grid cell resolution of 0.125 degrees was chosen based on data availability for the region. The model version, including the improved groundwater module and SSRHIs, was utilised for this study. The model was set up to include the natural vegetation, agricultural areas, urban areas, rural areas, industrial areas, five major dams, 49 minor dams, 27 transfers, and a significant number of SSRHIs. The model was calibrated and validated utilising the available uninterrupted observed streamflow data of adequate quality. A baseline period from 1986 to 2005 was used for the analysis presented in this manuscript. Five scenarios were considered to analyse the effects of the SSRHIs within the Cauvery Catchment:

a) All SSRHIs (tanks, check dams and farm bunds)
b) No SSRHIs
c) Only tanks
d) Only check dams
e) Only farm bunds

### *3.2.4 Model Calibration*

GWAVA and GWAVA-Int are calibrated against observed streamflow data using the SIMPLEX auto-calibration routine. This routine uses five parameters for calibration: a surface and groundwater routing parameter, a PDM parameter that describes spatial variation in soil moisture capacity, and a multiplier to adjust rooting depths and level of groundwater storage below which there is no base flow.

GWAVA and GWAVA-Int were calibrated and validated using observed streamflow gauge data from 14 gauging stations across the catchment (Figure 3.2). The calibration gauges were selected from a set of 28 gauges across the catchment based on the completeness of the data, the time period of the data, and the size of the sub-catchment. Data were deemed sufficient when more than 50% of the data points were identified as 'observed' and not 'calculated' and had at least five consecutive years available. However, this threshold may appear low, considering a higher proportion of observed to calculated data left an insufficient number of gauges to choose from. Additionally, sub-catchments of fewer than four 0.125-degree grid cells were excluded. The name of each gauging station and the years used for calibration and validation are presented in Table 3.4 in Appendix C.

The automatic calibration procedure was run across the 14 delineated sub-catchments: It must be noted that the parameters in the auto-calibration routine only affect the natural components of the system. Due to the observed streamflow being highly influenced by the dam outflows, manual calibration was carried out for gauges downstream of dams by re-running the autocalibration routine with various dam parameters.

### *3.2.5 Data Acquisition*

Input data were collected from several sources and extracted from global and regional datasets (Table 3.5 in Appendix C). Data regarding the number and distribution of SSRHIs in the Cauvery Catchment are sparse. Extrapolation and estimation methods described in this section provided the necessary surface area data for input into GWAVA and GWAVA-Int.

The surface areas of the rural and urban tanks were estimated by isolating the 'tanks' from the Cauvery Water Bodies dataset (Figure 3.4). This dataset consists of a shapefile containing all the medium to large water bodies (rivers, lakes, dams, tanks, wetlands, etc.) in the Cauvery Catchment in 2019, derived using remote sensing techniques. The urban tanks were identified as tanks that fell within urban centre boundaries, and the tanks outside were assumed to be rural. Check dams and field bunds are too small to be detected by this methodology.

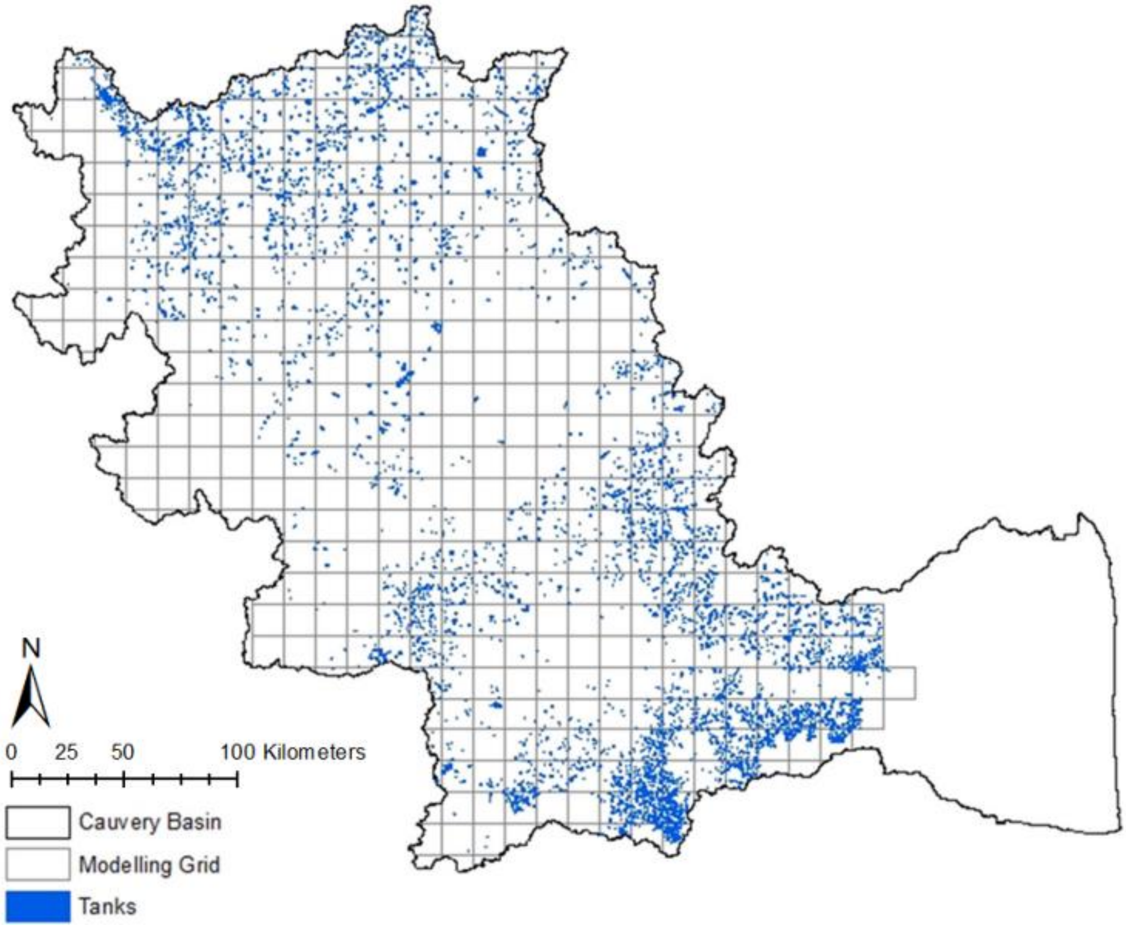



Figure 3.4 The distribution of tanks within the Cauvery Catchment is superimposed with the modelling grid of 0.125 degrees.

Data for the farm bunds and check dams were derived from district-wise Structural Investment Reports available for Karnataka from 2006 to 2012 (Figures 3.5 and 3.6). For each district in Karnataka, the area covered by farm bunds and the number of check dams were calculated from this financial data by dividing the total expenditure for each type of SSRHI by the expenditure per hectare of bunding and a check dam.

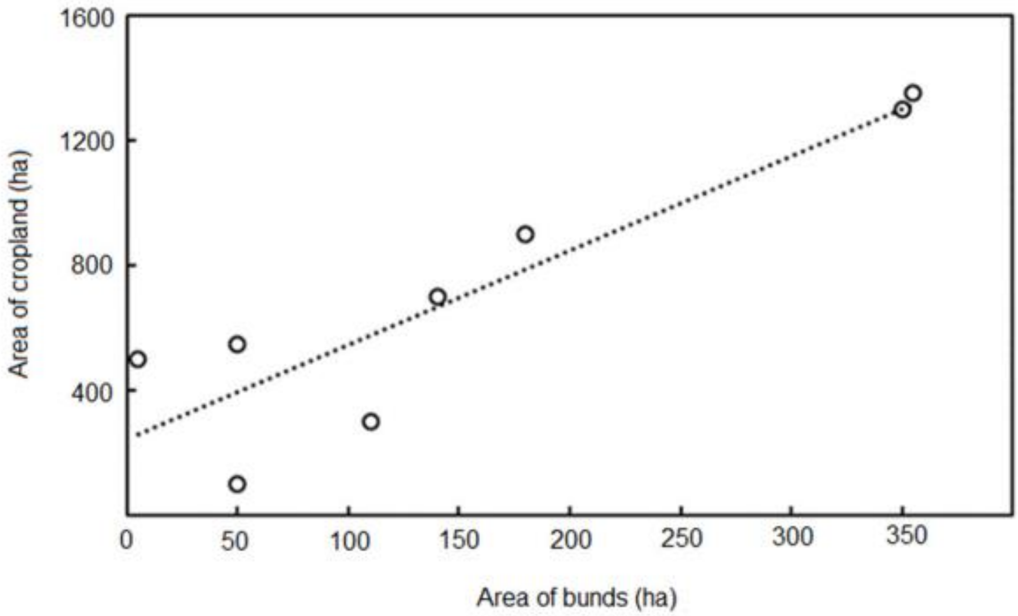



Figure 3.5 Graphical correlation between the area of farm bunds (hectares) and area of cropland (hectares) in each district in Karnataka

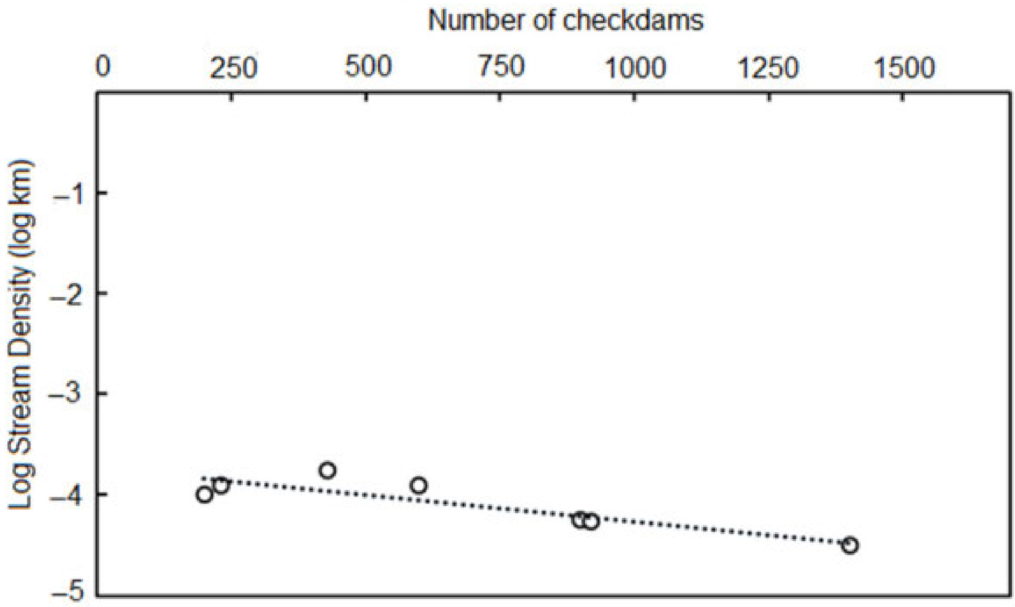



Figure 3.6 Graphical correlation between the number of check dams and stream density in each district in Karnataka.

In the absence of data for the state of Tamil Nadu, the data from Karnataka were extrapolated. Plausible relationships between the number of check dams and the area of bunding with soil type, rainfall, slope, population, land type, irrigation type, and geology in a district were all investigated. None of these yielded any significance. Meaningful relationships, however, were drawn between the number of check dams and the stream density, the area of bunding and the area of rainfed agriculture. These are described below. Within the districts of Karnataka, a relationship was drawn between the area of farm bunds and the area of rainfed cropland within each district ($r^2$ = 0.91, Figure 3.5). Due to a lack of data, it had to be assumed that this relationship was also evident in Tamil Nadu. The regression (Equation 3.1) was utilised to estimate the area of farm bunds within each district of Tamil Nadu:

$$A_c = 2.75A_b + 338 \tag{3.1}$$

where $A_b$ is the area covered by bunding (ha), and $A_c$ is the area of rainfed cropland (ha). Additionally, a relationship was drawn between the log function of the stream density (SD) of each district in Karnataka and the number of check dams ($r^2$ = 0.93, Figure 3.6). The stream density is characterised by Equation 3.2 (Gnanaprakkasam and Ganapathy, 2019).

$$Log\ (SD) = \sum \frac{Length\ of\ streams\ of\ all\ orders}{Area} \tag{3.2}$$

As with the farm bunds, it is assumed that this relationship holds true in the districts of Tamil Nadu. A regression function (Equation 3.3) was used to estimate the number of check dams within each district in Tamil Nadu:

$$Log(SD) = 0.0017N_{cd} - 4.33 \tag{3.3}$$

where $SD$ is the stream density, and $N_{cd}$ is the number of check dams. The district-wise data was applied to the modelling grid using a weighting function of the grid-wise crop area (Figure 3.7a) and stream density (Figure 3.7b), respectively. Across the sub-catchment, the surface area of the SSRHIs within each grid cell ranged between 0.02 and 53 $km^2$

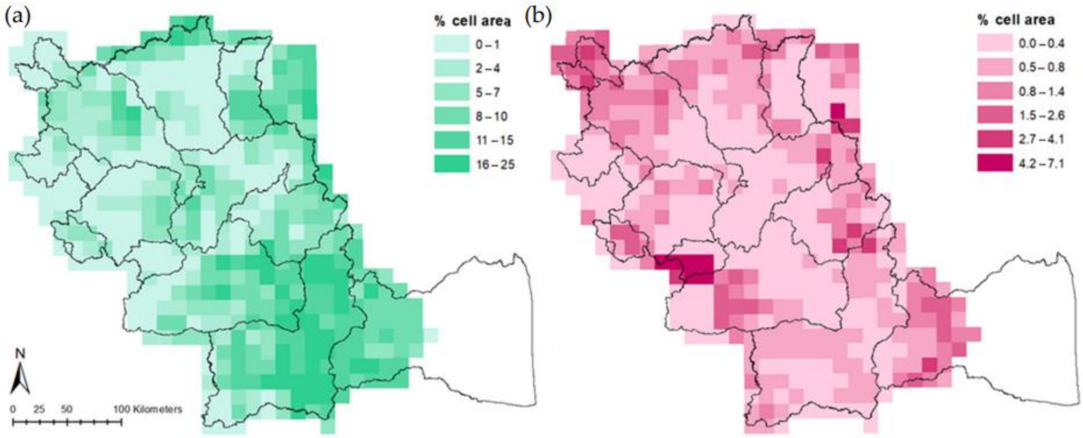



Figure 3.7 The distribution of (a) farm bunds and (b) check dams as a percentage of the GWAVA modelling grid cell area across the Cauvery Catchment.

## 3.3 Results

### *3.3.1 Model Performance*

GWAVA-Int performed well in the sub-catchments of the upper reaches but struggled to reliably simulate the flows downstream of the Mettur Dam (Figure 3.2). Across the calibrated sub-catchments, the model underestimates the total volume of simulated streamflow. The gridded rainfall data (Pai *et al*., 2014) produced by the Indian Meteorological Department (IMD) underestimated the point measured rainfall in the region across the Western Ghats by an excess of 50% (Figure 3.8). This could be the fundamental explanation for the consistent underestimation of simulated streamflow by GWAVA. Inaccurate simulations of the total volume of water within the system and dam releases undermine the value of the model's predictive ability as a water resources management tool.

The dam outflow parameters within the model were adjusted within the full range of possible values and combinations to provide the best fit to the daily observed outflow data. The temporal signal of the Mettur Dam outflow is noticeable through all the downstream gauges (Urachikottai and Kodumodi) to Musiri. Figure 3.9a illustrates the ability of the model to better capture the temporal trend of the observed streamflow upstream of Mettur. However, the model could not capture the intra- and inter-annual dam operations from the Mettur Dam and thus does not fully represent the timing of the observed streamflow at Urachikottai downstream of the dam (Figure 3.9b). The user-set parameters and the long-term average inflow determine the

GWAVA and GWAVA-Int dam outflow routine. The observed dam outflows appear to be sporadic and have very little correlation to the dam inflow, and thus the dam equation within the model does not represent sporadic outflows well.

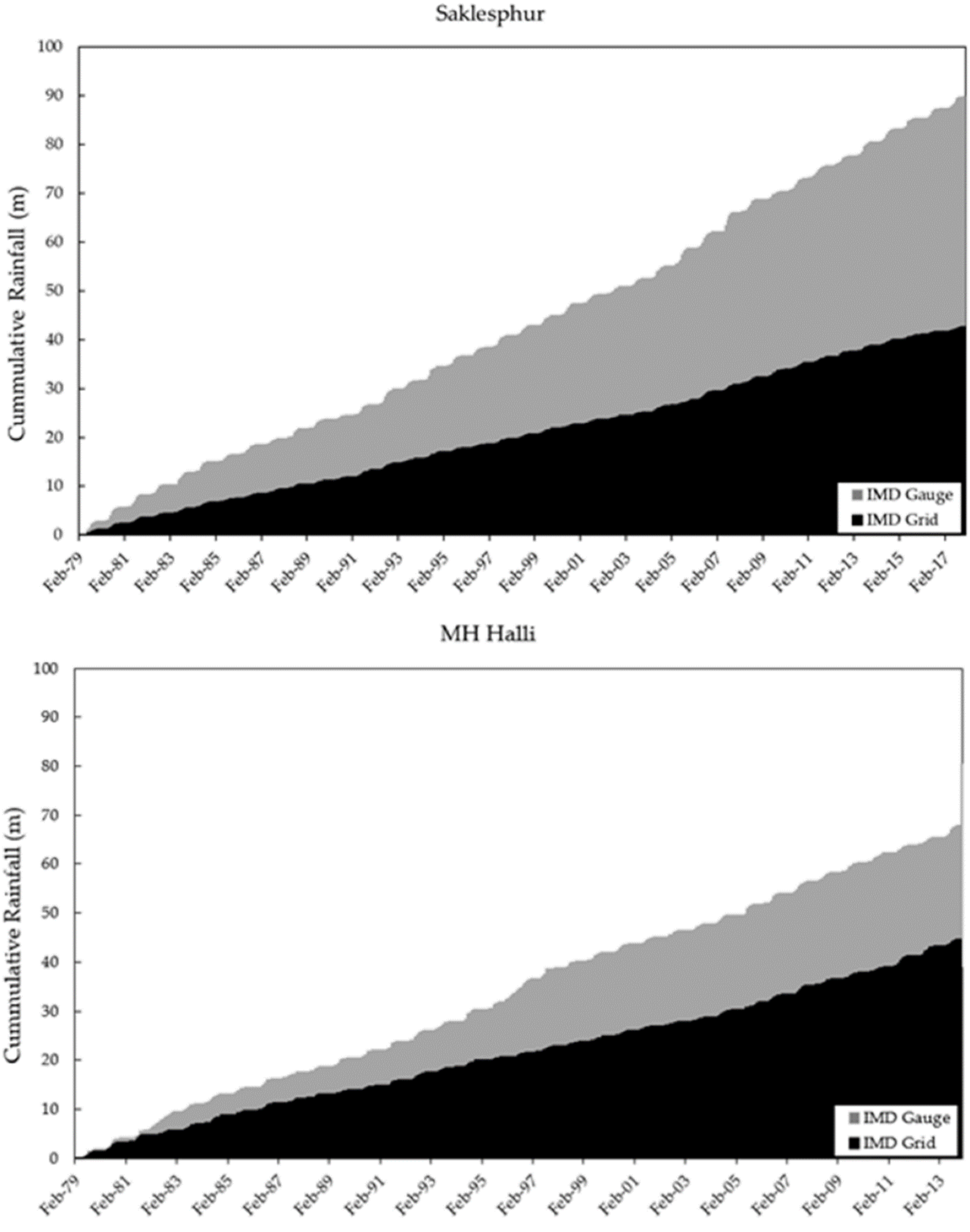



Figure 3.8 The cumulative rainfall (m) from available IMD gauge and gridded sources across Saklesphur and MH Halli sub-catchments (Figure 3.2) in the headwaters of the Cauvery from 1979 until 2017 and 1979 until 2013 respectively.

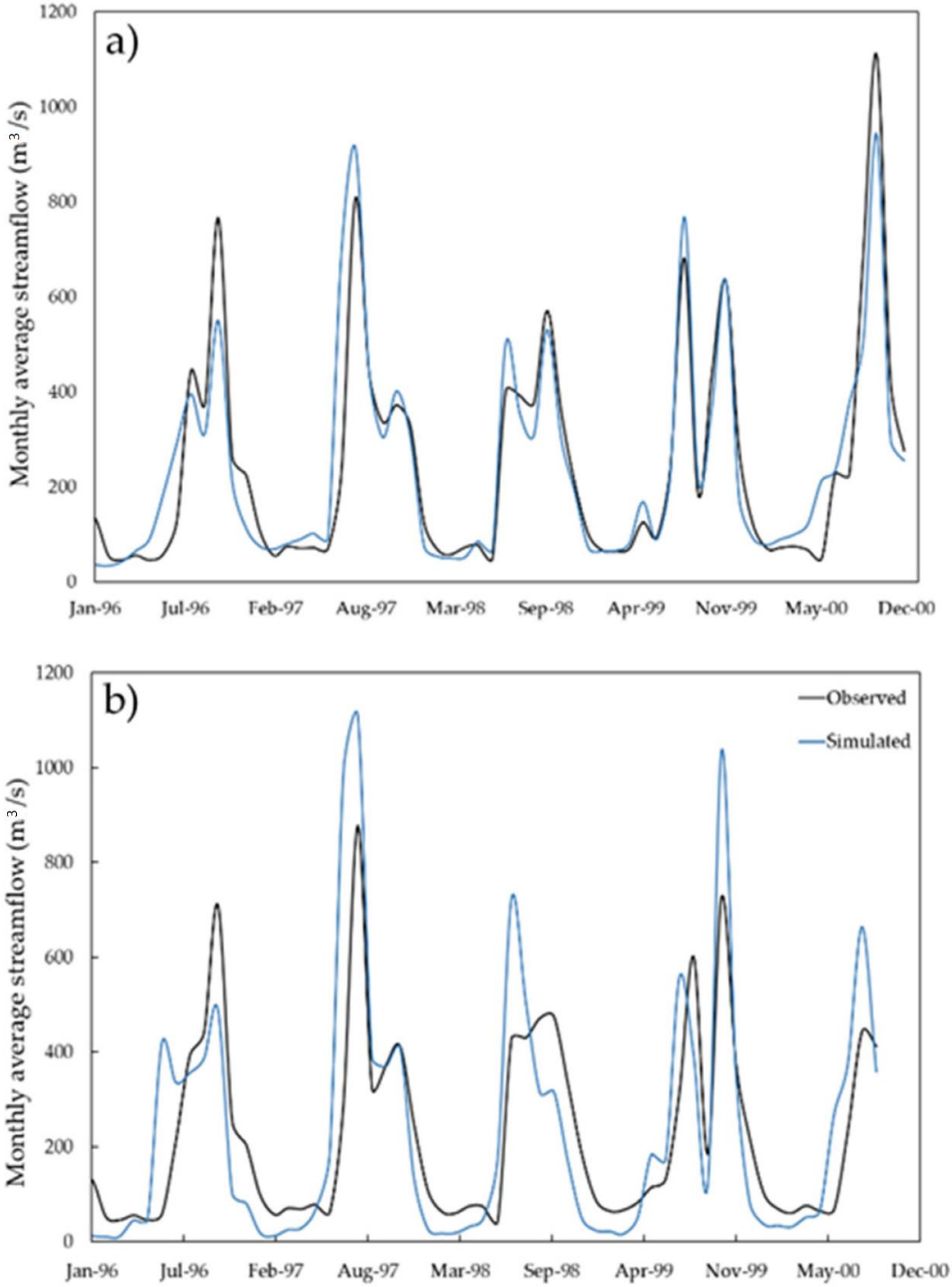



Figure 3.9 The GWAVA-Int simulated and observed monthly average streamflow from 1996 to 2000 at (a) Bilingudulu gauging station (k, Figure 3.2), upstream of the Mettur Dam and (b) Urachikottai gauging station (l- Figure 3.2), downstream of the Mettur Dam.

The inclusion of the SSRHIs improves the model performance (presented here as KGE). During the calibration and validation, the SSRHIs improved the model performance in nine and seven sub-catchments, respectively, but did not affect the calibration or validation in three and five sub-catchments (Table 3.4 in Appendix C). The lower KGE in the validation period indicates that the better fitting calibration results could have been obtained due to overfitting parameters during the calibration process, model equifinality (Beven, 2006), and where the model is not capturing the sub-catchment or dam processes correctly. The lack of reliable data about the Tamil Nadu region and the automatic calibration and conceptual nature of the model could be considered processes that are not included in the model structure through the existing model parameterization. Following calibration and validation of the model, streamflow, quick overland flow, sub-surface flow (water flowing to the stream through the soil profile), base flow (water flowing to the stream from the water table), groundwater levels, dam storage levels at Mettur Dam, and evaporation for five scenarios were simulated.

### *3.3.2 Sensitivity Analysis of SSRHIs within GWAVA*

A sensitivity analysis was conducted by altering the density and dimension of the conceptualised SSRHIs within GWAVA-Int. The scenario list of the varying densities and dimensions utilised in this analysis can be found in Table 3.3 in Appendix C. The results of the conceptual tank, check dam, and farm bund sensitivity analyses are presented in Figure 3.14, Figure 3.15 and Figure 3.16 in Appendix C, respectively.

#### 3.3.2.1 Tanks

The $Q_{10}$ flow is decreased with the increase in the density and depth of the tanks conceptualised in GWAVA-Int. The $Q_{10}$ is affected by both the increase in depth and density. The mean decreases when the density of tanks is 25 $m^3$/ha, while the mean simulated streamflow increases when increasing density of tanks is from 75 to 200 $m^3$/ha. The mean flow is insignificantly affected by the increase in density or depth. The $Q_{90}$ flow is increased by increasing both the depth and density. As the tanks are deeper than the check dams, the evaporative potential from the surface is less, and thus the recharge exceeds the evaporation and can contribute to the base flow. The $Q_{10}$ flows are reduced due to the structural hindrance within the stream channel. When considering the 25 $m^3$/ha density, the $Q_{10}$ is reduced by a greater percentage compared to the increase in $Q_{90}$, thus reducing the mean flow.

#### 3.3.2.2 Check Dams

The $Q_{10}$ flow is decreased with the increase in the density and the dimensions of the check dams conceptualised in GWAVA-Int. The $Q_{10}$ is more sensitive to the increase in dimensions than the increase in density. The mean and $Q_{90}$ simulated streamflow is decreased when the density of tanks is 25 $m^3$/ha, while the mean simulated streamflow is increased when increasing the density of check dams is from 75 to 200 $m^3$/ha. The mean and $Q_{90}$ flow is not highly sensitive to the change in dimensions of the check dams. When the density of conceptualised check dams is less than 25 $m^3$/ha, the rate of evaporation is greater (small volume of stationary water storage) than the rate of recharge and the compounded water is evaporated before it can recharge and contribute to the base flow. Once the density of SSRHIs has exceeded 25 $m^3$/ha, the rate of recharge is greater than the rate of evaporation (the volume-to-surface area ratio is smaller). Thus more water within the check dam can recharge and contribute to the base flow component.

#### 3.3.2.3 Farm Bunds

The farm bunds did not significantly impact the flows, and the changes between the baseline and the four scenarios were less than 1%. Increasing the depth of the farm bunds increased the flows; however, at the spatial scale of GWAVA, this is deemed insignificant, and thus it is concluded that the bunds do not have a significant effect on the flow. Although farm bunds are not constructed on the stream and do not significantly affect the streamflow, they alter other water balance components within the catchment. The open water surface increases the evaporative potential across the field, and the pooling water increases the soil water for the period following a rainfall event.

### *3.3.3 Effect of SSRHIs in the Cauvery*

In this section, all observations are drawn from model simulations (i.e., simulated streamflow, base flow, evaporation, and groundwater level). The effects of SSRHIs on simulated streamflow across the modelling period (1986–2005) were evaluated using the mean flow ($\bar{Q}$), the flow exceeded 90% of the time ($Q_{90}$, quantification of low flows), and the flow exceeded 10% of the time ($Q_{10}$, representation of high flows). Additionally, the effects of the SSRHIs on the simulated streamflow and evaporation in a wet (2005), normal year (1998), and dry (2002) year at the sub-catchment outlet of S1 and S2 and Musiri were investigated. These years were chosen by considering the lowest, highest, and mean total annual rainfall across the sub-catchments (Table 3.2).

Table 3.2 The total annual rainfall and the reduction in flow days with the inclusion of SSRHIs for the selected sub-catchments S1, S2 (Figure 3.2), and Musiri (Figure 3.2) for a wet, dry, and normal year.

| **Sub-catchment** | **Total Annual Rainfall (mm)** | | | **Reduction in Flows Days with the Inclusion of SSRHIs** | | |
|---|---|---|---|---|---|---|
| | **Normal (1998)** | **Dry (2002)** | **Wet (2005)** | **Normal (1998)** | **Dry (2002)** | **Wet (2005)** |
| S1 | 507 | 382 | 668 | 14 | 25 | 3 |
| S2 | 1874 | 656 | 2085 | 2 | 4 | 3 |
| Musiri | 1341 | 685 | 1413 | 0 | 0 | 0 |

In the non-perennial sub-catchment (S1, Table 3.1 and Figure 3.2), the surface flow is the dominant component of the simulated streamflow (Figure 3.10). The simulated streamflow ($Q_{10}$, $\bar{Q}$ and $Q_{90}$) is reduced with the inclusion of SSRHIs. However, the high flows, Q10, are more significantly reduced (Figure 3.11). The SSRHIs have a greater impact on the simulated streamflow in S1 than in S2. The simulated streamflow is reduced to the most considerable extent in the normal year (~10%, Figure 3.11a). The SSRHI intercepts the stormflow and, thus, reduces the simulated streamflow in the wet season ($Q_{10}$, Figure 3.11b).

The dry season flows ($Q_{90}$, Figure 3.11b) are reduced as any subsurface lateral flow (from the soil store) entering the stream is impounded by the SSRHI. The stormflow component is larger than the subsurface lateral flow and baseflow components in this sub-catchment. Thus, the simulated streamflow is affected to a greater extent in the wet season. The non-perennial streams dry out earlier with the inclusion of SSRHIs (Figure 3.12 and Table 3.2). The total evaporation across the sub-catchment is increased with the inclusion of SSRHIs, with the greatest increase occurring in the wet year (Figure 3.11a) as water is present in the SSRHIs for a greater length of time. In this sub-catchment, the water table is increased in the wet season by including SSRHIs (Figure 3.13). Despite the increase in simulated recharge, the water table does not reach a level where the water in the groundwater will contribute significantly to the simulated base flow.

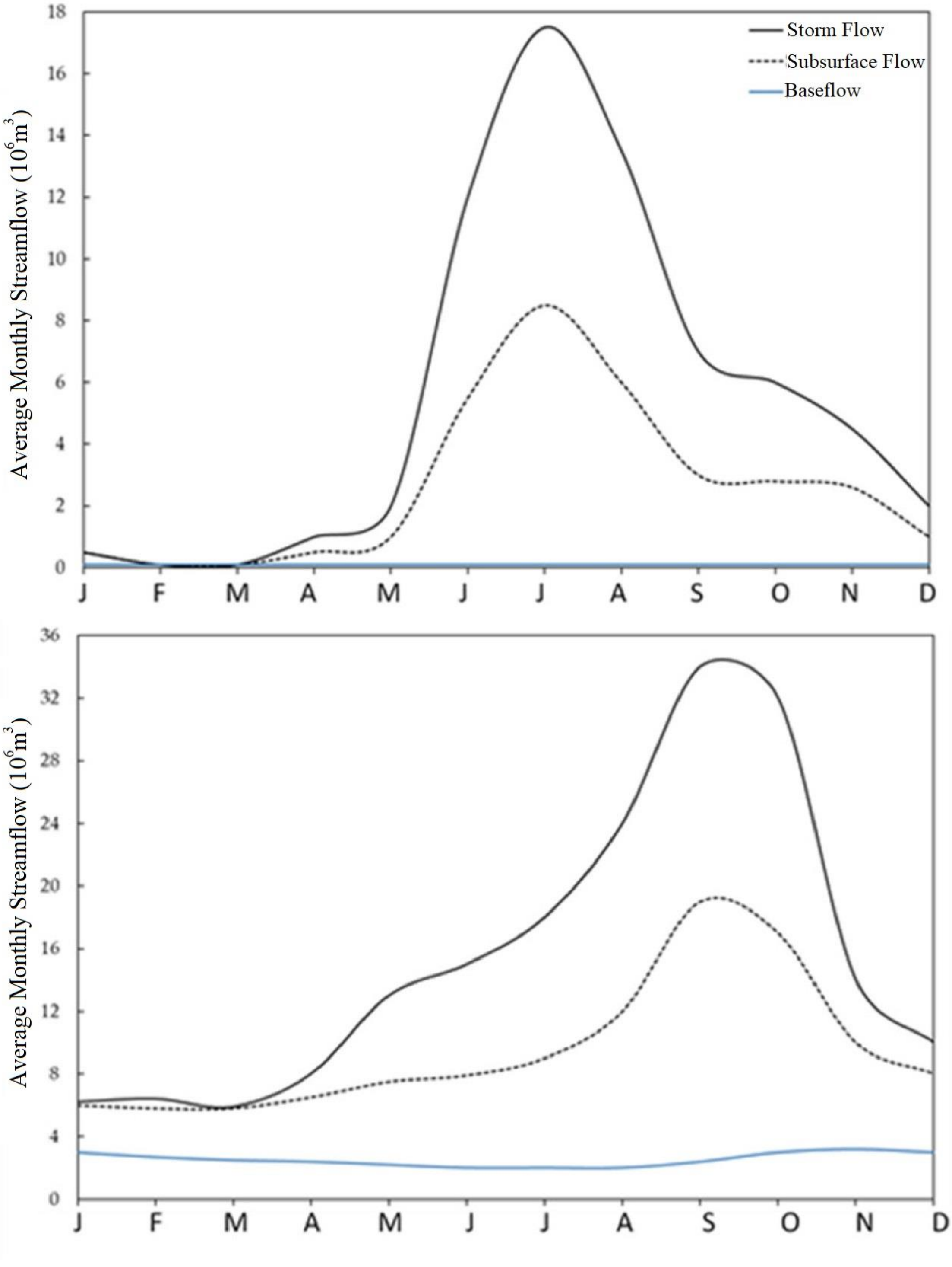



Figure 3.10 The mean monthly simulated separation hydrograph for S1 (top) and S2 (bottom) (Table 3.1 and Figure 3.2) from 1986 until 2005 with all SSRHIs included.

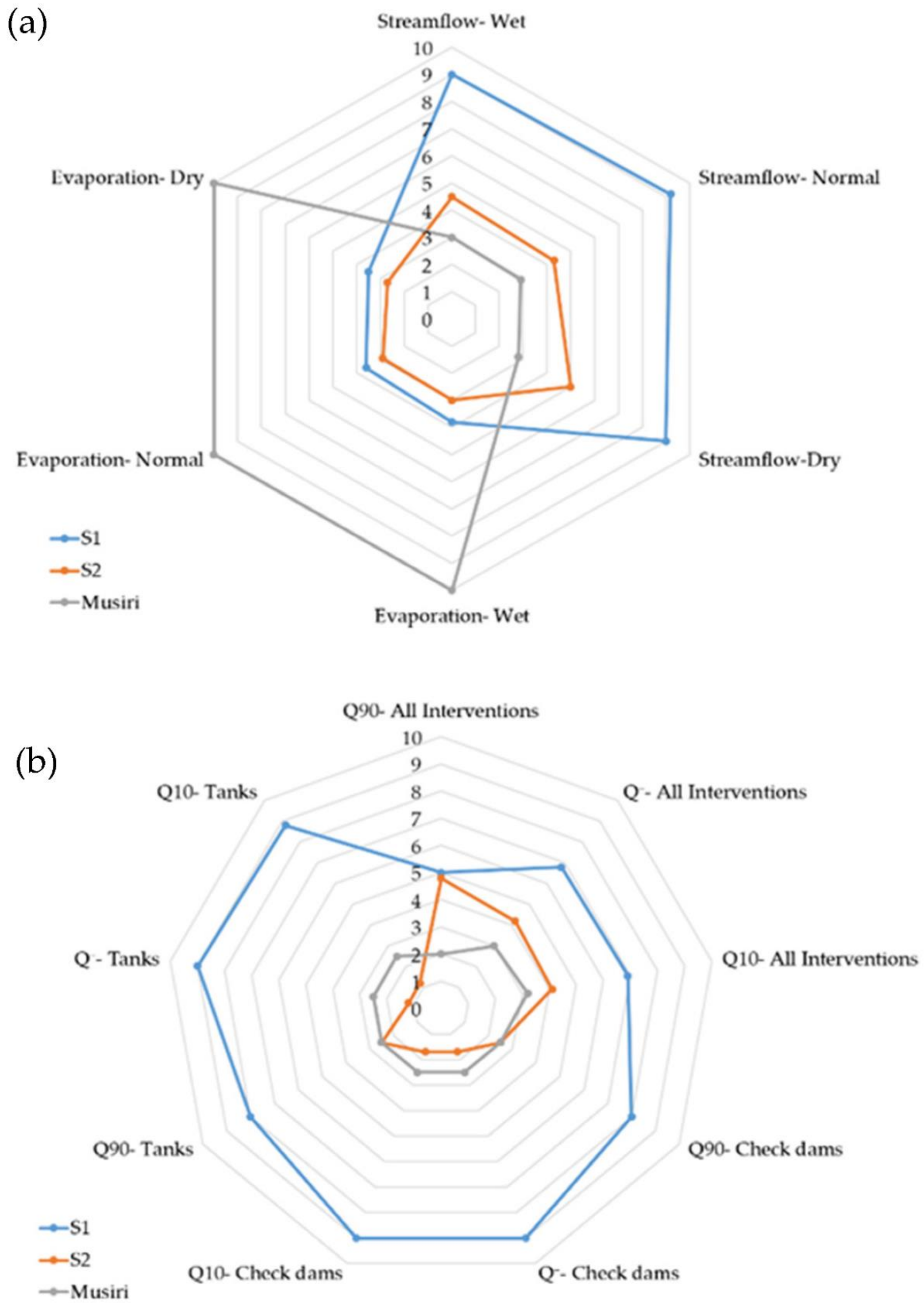



Figure 3.11 (a) The percent reduction in total annual simulated streamflow and increase in total annual simulated evaporation (%) with the inclusion of SSRHIs for S1, S2, and at Musiri in wet (2005), normal (1998), and dry (2002) years. (b) The effect of all the SSRHIs (tanks, check dams and bunds); check dams only and tanks only on high flows ($Q_{10}$); low flows ($Q_{90}$); and mean flows ($\bar{Q}$) flows across S1, S2, and at Musiri (Table 3.1, Figure 3.2).

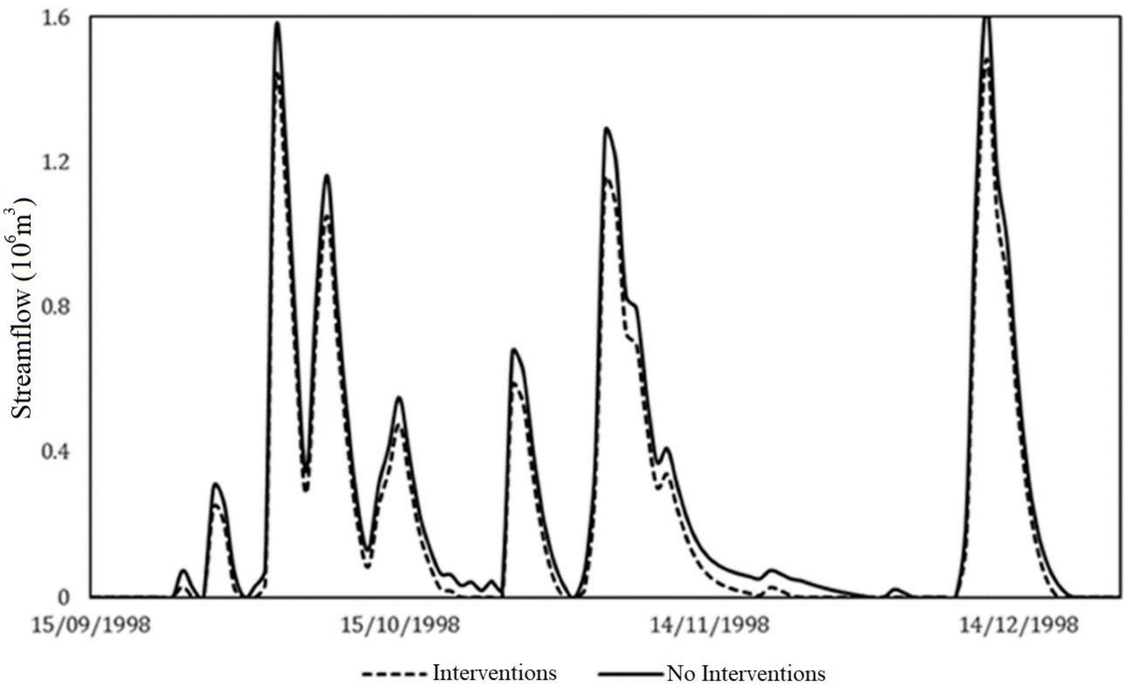



Figure 3.12 An example of the simulated streamflowin sub-catchment S1 (Table 3.1, Figure 3.2) with SSRHIs and without SSRHIs through the period of September 1998 until December 1998 (normal year).

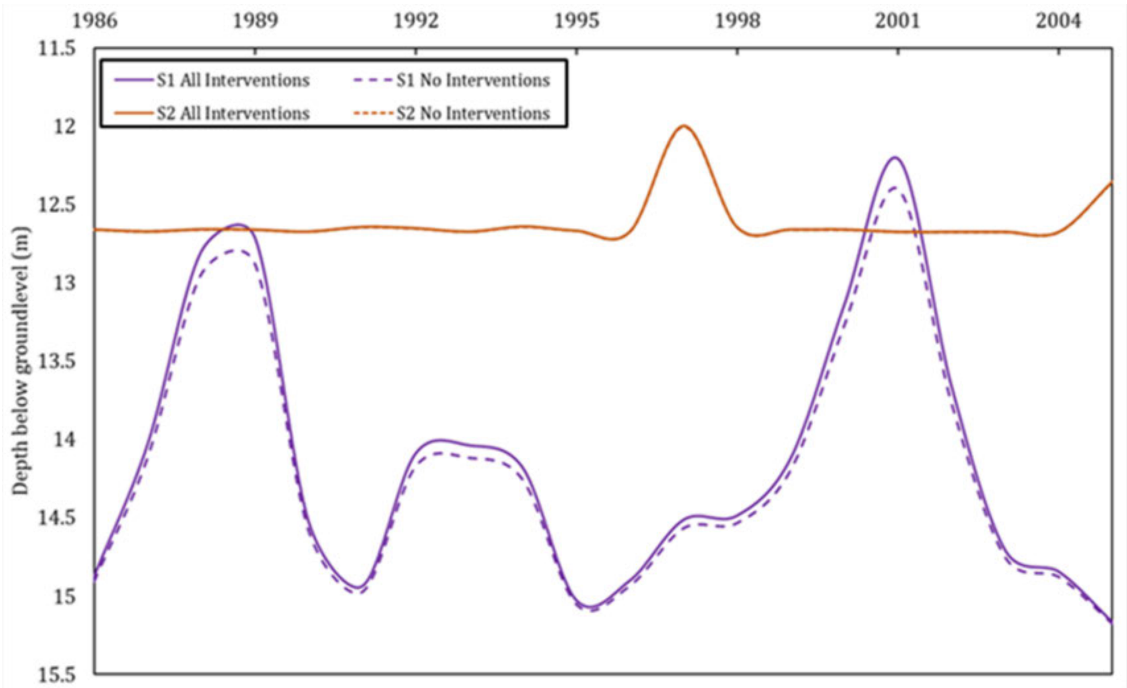



Figure 3.13 Monthly mean groundwater level below ground surface for S1 and S2 (Table 3.1 and Figure 3.2) with and without the inclusion of SSRHIs. There is no change to the water table level in S2—this is illustrated by the S2 no SSRHIs line (orange dash), which falls directly on S2 all SSRHIs line (orange line).

In the perennial sub-catchment (S2, Table 3.1 and Figure 3.2), the stormflow is dominant in the wet season, but the subsurface flow and baseflow are dominant in the dry season (Figure 3.10). The simulated streamflow ($Q_{10}$, $\bar{Q}$ and $Q_{90}$) is reduced, and the $Q_{90}$ is more significantly reduced with the inclusion of all SSRHIs (Figure 3.11b). The SSRHIs have a similar effect on simulated streamflow in the dry and wet years (-5%, Figure 3.11a). In the wet season, the simulated streamflow is reduced due to the in-situ impoundment, and the low flows are maintained but reduced in the dry season. In the dry season, simulated stream/low is reduced because the base flow and any subsurface lateral flows (from the soil store) entering the stream are impounded by the SSRHI. The impounded water is subject to both evaporation and recharge. The total evaporation across the sub-catchment increased with the inclusion of SSRHIs, with the greatest increase occurring in the wet and normal years (Figure 3.11a) as there is water in the SSRHIs for a greater length of time. In this sub-catchment, the groundwater level is minimally affected by the inclusion of the SSRHIs (Figure 3.13). The water table is above the level at which the groundwater will flow as base flow. The baseflow will continue to occur, but simulated streamflow will be reduced in the dry season as any simulated streamflow produced by the base flow above the SSRHI will be impounded.

The responses of the S1 and S2, and Musiri exhibit opposite responses. The change in simulated streamflow in S1 and S2 is greater than the change in evaporation, while at Musiri, the change in evaporation is greater than the change in simulated streamflow. At Musiri, the simulated streamflow is dominated by the Mettur Dam releases (Figure 3.2). The SSRHIs do not significantly affect the simulated Mettur Dam release flows. The minimal reduction in mean simulated streamflow (~3%) seen at Musiri can be considered the consequence of the SSRHIs in the tributaries that join the main Cauvery channel downstream of Mettur Dam. However, on analysis of the effect of SSRHIs on the inflow into Mettur Dam, it was found that the SSRHIs reduced the mean simulated streamflow ($\bar{Q}$) by ~6%, and the simulated streamflow in the wet season ($Q_{10}$) was reduced by ~26%. This demonstrates that the large dam can nullify the impact of the SSRHIs; however, their effect can be seen in the reduced simulated streamflow entering the dam. In this unique case, the effect of the SSRHIs on the Mettur Dam inflow is more representative of the effects of SSRHIs at a catchment scale than those shown at Musiri and corresponds more correctly with the increase in total evaporation across the catchment with the inclusion of SSRHIs of ~10% (Figure 3.11a).

The majority of the flow into the Cauvery Catchment is contributed to by sub-catchments (Arulbalaji *et al*., 2019) along the western boundary (Figure 3.11 in Appendix C). However, most of the SSRHIs are constructed in semi-arid regions. The simulated $Q_{90}$ flow in these humid sub-catchments is affected more by the SSRHIs than in the semi-arid sub-catchments on the eastern boundary (Figure 3.11 in Appendix C). Conversely, there is a greater effect of the SSRHIs on the simulated $Q_{10}$ flow in the semi-arid sub-catchments (Figure 3.11 in Appendix C). The impact on the $Q_{10}$ flows is greater in the semi-arid sub-catchments because the monsoonal streamflow is required to fill these structures before they begin to spill. In the humid sub-catchments, the SSRHIs do not have a great effect on the $Q_{10}$ flow as it is likely to be the presence of water within these structures before the monsoon and the SSRHI immediately spills. Although the percent change in $Q_{10}$ flows in the semi-arid sub-catchments is higher, the volume of water impeded in these structures may be greater in the humid sub-catchments. The $Q_{90}$ flow is impacted more severely in the humid sub-catchments as these streams are fed during the dry season through base flow, whereas in the semi-arid sub-catchments, the streams frequently run dry with or without SSRHIs. The implementation of SSRHIs in these sub-catchments stores water further up in the catchment and essentially impedes the downstream flow. The reallocation of water by these structures limits water, especially the monsoon flows, from entering the ocean unused and provides an inexpensive means of decentralised water management. Although these structures allow available water to be utilised throughout the catchment, there are subsequent implications for users and environmental flows downstream when low flows are reduced. A summary of the total changes in rainfall, simulated streamflow (with and without SSRHIs), simulated evaporation (with and without SSRHIs), and water table levels (with and without SSRHIs) can be found in Table 3.6 in Appendix C.

## 3.4 Discussion

The model calibration was acceptable in the upper reaches of the catchment, but the model fit was weaker downstream of the Mettur Dam (Figure 3.2). The inclusion of SSRHIs improves the model performance. It provides a better account of the surface storage within the catchment and a better estimation of the time of concentration in the sub-catchments without major dams. The farm bunds were found to have little effect on the simulated streamflow, as the high water demands of the rainfed crops cause the infiltrated water from the farm bunds to transpired quickly and there to be little difference in the water converted to base flow or groundwater recharge with or without the bunds. Assuming the relationship between the area of farm bunds and the area of rainfed cropland determined for Karnataka holds into Tamil Nadu, the majority of the bunds were located within the lower regions of the catchment where there is a greater area of rainfed cropland. It is difficult to distinguish the exact effects of the farm bunds in these regions as the Mettur Dam outflows heavily dominate the river system. Farm bunding proves to be an effective method of increasing soil water in areas of rain-fed agriculture and mitigating water allocation challenges and aggressive groundwater pumping associated with intensive irrigation without significantly affecting the catchment hydrology. However, conceptually, the model fills the farm bunds, the tanks, and then the check dams. The simulations with all the SSRHIs included limiting the water available for filling the tanks and check dams. Although individually, the bunds have little effect on the simulated streamflow, when simulated with the tanks and check dams, the reduction in water available to fill tanks and check dams is reflected in the lower impact on the simulated streamflow. Individually, the tanks and check dams have a similar effect on the simulated streamflow (Figure 3.11b).

A significant challenge in large-scale hydrological modelling is quantifying and managing the uncertainty in climate forcing and evaluation data. Uncertainty can arise from observation gauge density, spatial and temporal interpolation methods, and general measurement errors. The Western Ghats region in the NW of the catchment is a known area of uncertainty with the IMD rainfall data (Pai *et al*., 2014). Each 0.5-degree grid cell contains numerous terrain and gradient increments, and the grid cells fall over the catchment boundary. This results in an inaccurate representation of the distribution and total rainfall and the distribution of minimum and maximum temperature in this region of the catchment (Yeggina *et al*., 2020). There is a significant source of uncertainty as this region acts as the headwaters for the larger Cauvery Catchment (Figure 3.8). At some gauging points in the catchment, there is low confidence in the observed streamflow data (Srinivas & Srinivasan, 2005). Eye-witness accounts and some literature (Srinivasan *et al*., 2015) report the drying out of streams in the dry season, which is not reflected in the observed data. Additionally, in reality, rivers downstream of significant urban areas (Arkavathy downstream of Bangalore and Eluthunimangalam downstream of Coimbatore and Tiruppur) are fed by a perennial stream of sewage (Srinivasan *et al.*, 2015). The model represents return flows from domestic demand, but this may be underestimated compared to the volume of effluent released into these rivers. The analysis of the rainfall and the observed streamflow used within this study showed temporal discrepancies.

The temporal difference between rainfall events and the hydrograph peak did not show a systematic error or a consistent lag time.

The scale of this study (0.125 degrees) required the aggregation of the surface area of each type of SSRHI in each cell. The simplification in the conceptualisation of the SSRHIs is a cause of uncertainty in this study (Kim *et al*., 2020). The aggregation of the SSRHIs into one composite tank, check dam, and farm bund within the cell, skews the surface area to capacity ratio. As SSRHI data were limited to the surface area, if one calculates the SSRHI capacity from the combined surface area, the capacity is greater than calculating the capacity of each SSRHI and aggregating the capacity. This causes the holding capacity of the conceptual SSRHIs in each cell to be greater than in reality. Subsequently, the larger conceptual SSRHI will not fill or spill as frequently as many smaller SSRHIs, and thus the estimation of the effect on simulated streamflow of all the SSRHIs is uncertain. Additionally, evaporation could be underestimated as a larger waterbody requires increased energy for evaporation and has a larger lag time (due to heat storage) than a smaller one. This may also lead to the individual smaller SSRHIs being subjected to more evaporative losses than these estimated in the model using the larger conceptual SSRHI. Conversely, the model structure allocates water to the evaporative component first; thus, the evaporative processes are favoured in times of water stress. This could, along with the use of the Hargreaves evaporation estimation method, additionally be one of the fundamental reasons for the systematic underestimation of simulated streamflow across the catchment (Subburayan *et al*., 2011). The aggregation of the cascading tank systems into one large tank, and numerous check dams into one large check dam, results in the true effects of the cascading system not being represented within the model (Van Meter *et al*., 2015). Numerous tanks and check dams on a river network can cause streamflow in the river and the subsurface and base flow emerging into the stream to be obstructed by the downstream check dams.

Due to a lack of data, quantifying the distribution of the SSRHIs across the catchment relies upon many assumptions and, thus, generates significant uncertainty. The accuracy of the Structural Investment Report is unknown, and the assumption of a fixed cost per structure/hectare across Karnataka is unlikely to be accurate. Similarly, assuming that the systems and behavioural patterns (agricultural practices, usage of infrastructure, etc.) in Karnataka and Tamil Nadu are identical is also unlikely. However, due to data scarcity and lack of evidence to validate these assumptions, a pragmatic approach was used to include SSRHIs in a large-scale hydrological model.

In the absence of data to formally validate a new concept introduced into a hydrological model, it is important to measure results against existing literature. Despite the uncertainty and pilot nature of this study, the trends identified within the Cauvery Catchment are in line with the findings from Garg *et al*. (2012). Garg *et al*. (2012) altered several parameters within SWAT (surface runoff, water holding capacity, available soil water, groundwater recharge, and curve number) to reflect the potential influence of the check dams and farm bunds in the catchment. It was found that the SSRHIs have a slightly greater effect on the simulated streamflow in wetter years. The study also found that the largest portion of the water balance is the evaporative component and the evaporative losses increased with the inclusion of the SSRHIs. This is in agreement with this study (Figure 3.11b). Garg *et al*. (2012) found that check dams reduced the annual simulated streamflow at the catchment outlet of the Kothapally sub-catchment by 9%. This corresponds with the GWAVA simulation, which estimated a ~9% reduction in simulated streamflow (Figure 3.11a) in S1 of similar MAP, soil type, and land use. In contrast, the groundwater recharge from the individual SSRHIs was significant in the Garg *et al*. (2012) study.

There is also an agreement between the results of S2 and the work of Xu *et al*. (2013), who concluded that check dams reduce the total runoff in the rainy season (15%, Figure 3.13). Xu *et al*. (2013) did not specifically include the characteristics of the SSRHIs. Instead, they attributed the difference between a period of observed and simulated streamflow to the effect of the SSRHIs. The decrease in mean annual streamflow (14%) estimated by Xu *et al*. (2013) and attributed to the impact of check dams does correlate to the decrease in mean annual streamflow of S2 as a result of check dams (15%, Figure 3.10). Sub-catchment S2 has a similar MAP and type of vegetation as the sub-catchment studied by Xu *et al*. (2013). This is an important correlation, with two different approaches yielding similar results. In the absence of data about pre-and-post-SSRHI construction, conceptualising the structures within a model could provide accurate estimations of their influence.

The decrease in simulated streamflow by GWAVA in S1 and S2 due to tanks was 4% and 5%, respectively. These results differ significantly from Van Meter *et al*. (2015), where the simulated streamflow decreased by 75% from a single cascading tank system in a sub-catchment with a MAP of 850 mm in Tamil Nadu. GWAVA conceptualises the tank systems within a cell into one large hypothetical tank and thus does not capture the cascading characteristics of the tank systems. This could explain the difference in the observed streamflow reduction; alternatively, the tank system Van Meter *et al*. (2015) investigated could be atypical.

GWAVA-Int may not capture the sensitivity of hydrological fluxes at a local scale, as well as some catchment-scale models (Garg *et al*., 2012; Xu *et al*., 2013; Van Meter *et al*., 2015). However, yielding similar results to published small-scale studies provides a good starting point for further refinement of the conceptualisation within large-scale hydrological models.

### 3.5 Conclusions

GWAVA-Int provided a valuable tool to investigate the effects of SSRHIs at a sub-catchment and catchment scale. The main conclusions from this study are:

a) Conceptualised SSRHIs play an important part in allocating and better representing simulated surface water within the catchment.
b) The effect of the conceptualised SSRHIs within GWAVA depends on the hydrogeology of the modelled sub-catchment and the simulated groundwater level.
c) The influence of the SSRHIs is greater on the simulated streamflow in the wet years and on estimated evaporation in the dry years.
d) Farm bunds provide an effective method for reducing the pressure of canal irrigation and groundwater pumping in agricultural areas.

The results of this study corresponded well with existing literature from small-scale studies. However, groundwater levels at the sub-catchment and catchment scale appear less impacted than in the cited literature or indigenous knowledge surrounding the use of SSRHIs for water security at a local scale, suggesting further investigation is required. This study incorporated stakeholder and expert knowledge and published literature information in conceptualising the SSRHIs within the model. New and creative approaches had to be utilised where data gaps existed to model the effects of SSRHIs at the catchment scale. The approach outlined in this study can be applied in different model applications in regions where SSRHIs are prominent if the source code is available for adaptation. This study had to rely on a pragmatic approach, and consequently, many assumptions were made. However, it provides a step forward in the conceptualisation, quantification, and implication of SSRHIs at the catchment scale.

### 3.6 References


Adhikari, R.N.; Singh, A.K.; Math, S.K.N.; Sharma, K.K.; Reddy, K.K. Study on the effect of groundwater recharge through water harvesting structures in semi-arid red soil region of south India. *Indian Journal of Soil Conservation*. 2015, 43, 266–270

Agoramoorthy, G.; Hsu, M.J. Small size, big potential. check dams for sustainable development. *Environment: Science and Policy for Sustainable Development*. 2008, 50, 22–35.

Alexandrov, Y.; Laronne, J.B.; Reid, I. Intra-event, and inter-seasonal behaviour of suspended sediment in flash floods of the semi-arid northern Negev, Israel. *Geomorphology*. 2007, 85, 85–97.

Allen, D.M.; Cannon, A.J.; Toews, M.W.; Scibek, J. Variability in simulated recharge using different GCMs. *Water Resources Research*. 2010, 46, 1–18.

Anbumozhi, V.; Matsumoto, K.; Yamaji, E. Towards improved performance of irrigation tanks in semi-arid regions of India. modernization opportunities and challenges. *Irrigation and Drainage Systems*. 2001, 15, 293–309.

Armanini, A.; Dellagiacoma, F.; Ferrari, L. *From the check dam to the development of functional check dams*. In Fluvial Hydraulics of Mountain Regions; Springer: Berlin/Heidelberg, Germany, 1991.

Arulbalaji, P.; Sreelash, K.; Maya, K.; Padmalal, D. Hydrological assessment of groundwater potential zones of Cauvery River Basin, India: A geospatial approach. *Environmental Earth Science*. 2019, 78, 1–21.

Ashoka Trust for Research in Ecology and the Environment. Waterbodies Dataset; Ashoka Trust for Research in Ecology and the Environment: Bangalore, India, 2019.

Beven, K. A manifesto for the equifinality thesis. Journal of Hydrology. 2006, 320, 18–36.

Bhattacharya, A.K. Artificial ground water recharge with a special reference to India. *Artificial Ground Water Recharge.* 2010, 4, 214–221.

Bhuvaneswari, K.; Geethalakshmi, V.; Lakshmanan, A.; Srinivasan, R.; Sekhar, N.U. The impact of El Nino/Southern oscillation on hydrology and rice productivity in the Cauvery Basin, India. application of the soil and water assessment tool. *Weather and Climate Extremes*. 2013, 2, 39–47.

Boix-Fayos, C.; Barberá, G.G.; López-Bermúdez, F.; Castillo, V.M. Effects of check dams, reforestation and land-use changes on river channel morphology. Case study of the Rogativa catchment (Murcia, Spain). *Geomorphology*. 2007, 91, 103–123.

Boix-Fayos, C.; de Vente, J.; Martínez-Mena, M.; Barberá, G.G.; Castillo, V. The impact of land use change and check-dams on catchment sediment yield. *Hydrological Processes: An International Journal*. 2008, 22, 4922–4935.

Calder, I.R. *Evaporation in the Uplands*; Wiley: Hoboken, NJ, USA, 1990.

Central Water Commission. Evaporation Control in Reservoirs Report 6 No 1087; Central Soil and Materials Research Station: New Delhi, India, 1987.

Chidambaram, S.; Ramanathan, A.L.; Thilagavathi, R.; Ganesh, N. *Cauvery River*. In The Indian Rivers; Springer: Singapore, 2018.

Cleaver, F. *Development through Bricolage*. Rethinking Institutions for Natural Resource Management; Routledge: Abingdon, UK, 2017.

Critchley, W.; Graham, O. Pour Protéger Nos Terres. *Conservation des Eaux et du sol en Afrique Sub-Saharienne*; Oxfam, au nom du Réseau d'information des terres arides et de l'Institut international pour l'Environnement et le Développement: Oxford, UK, 1991.

Dashora, Y.; Dillon, P.; Maheshwari, B.; Soni, P.; Dashora, R.; Davande, S.; Purohit, R.C.; Mittal, H.K. A simple method using farmers' measurements applied to estimate check dam recharge in Rajasthan, India. Sustain. *Water Resources Management*. 2018, 4, 301–316.

Dashora, Y.; Dillon, P.; Maheshwari, B.; Soni, P.; Mittal, H.K.; Dashora, R.; Singh, P.K.; Purohit, R.C.; Katara, P. Hydrologic and cost-benefit analysis at the local scale of streambed recharge structures in Rajasthan (India) and their value for securing irrigation water supplies. *Hydrogeology Journal*. 2019, 27, 1889–1909.

Díaz-Gutiérrez, V.; Mongil-Manso, J.; Navarro-Hevia, J.; Ramos-Díez, I. Check dams and sediment control. final results of a case study in the upper Corneja River (Central Spain). *Journal of Soils and Sediments*. 2019, 19, 451–466.

Djuma, H.; Bruggeman, A.; Camera, C.; Eliades, M.; Kostarelos, K. The impact of a check dam on groundwater recharge and sedimentation in an ephemeral stream. *Water*. 2017, 9, 813.

Doolittle, W.E. The use of check dams for protecting downstream agricultural lands in the prehistoric Southwest. a contextual analysis. *Journal of Anthropological Research*. 1985, 41, 279–305.

Falkenmark, M.; Molden, D. Wake up to realities of river basin closure. Int. J. Water Resour. Dev. 2008, 24, 201–215. 31. Bhave, A.G.; Conway, D.; Dessai, S.; Stainforth, D.A. Water resource planning under future climate and socioeconomic uncertainty in the Cauvery River Basin in Karnataka, India. *Water Resources Research*. 2018, 52, 708–728.

Fischer, G.; Nachtergaele, F.; Prieler, S.; van Velthuizen, H.T.; Verelst, L.; Wiberg, D. *Global Agro-Ecological Zones Assessment for Agriculture*; International Institute for Applied Systems Analysis: Laxenburg, Austria, 2008; Volume 10, pp. 26–31.

Garg, K.K.; Karlberg, L.; Barron, J.; Wani, S.P.; Rockstrom, J. Assessing impacts of agricultural water interventions in the Kothapally watershed, Southern India. *Hydrological Processes*. 2012, 26, 387–404.

Geetha, K.; Mishra, S.K.; Eldho, T.I.; Rastogi, A.K.; Pandey, R.P. SCS-CN-based continuous simulation model for hydrologic forecasting. *Water Resources Management*. 2008, 22, 165–190.

Gnanaprakkasam, S.; Ganapathy, G.P. Evaluation of regional flood quantiles at ungauged sites by employing nonlinearity-based clustering approaches. *Environmental Science and Pollution Research*. 2019, 26, 22856–22877.

Gosain, A.K.; Rao, S.; Basuray, D. Climate change impact assessment on the hydrology of Indian river basins. *Current science*. 2006, 90, 346–353. 3

Singh, A.; Gosain, A.K. Climate-change impact assessment using GIS-based hydrological modelling. *Water International*. 2011, 36, 386–397.

Gowda, K.; Sridhara, M.V.; Chandrashekar, M.N. Planning Strategies for Municipal Solid Waste Management in the City of Hassan, Karnataka. *International Journal of Innovative Technology and Research.* 2014, 2, 948–958.

Goyal, M.R.; Sivanappan, R.K. *Engineering Practices for Agricultural Production and Water Conservation*. An Interdisciplinary Approach. Oakville; Apple Academic Press: Palm Bay, FL, USA, 2017.

Gunnell, Y. Relief and climate in South Asia. the influence of the Western Ghats on the current climate pattern of peninsular India. *International Journal of Climatology*. 1997, 17, 1169–1182.

Gunnell, Y.; Krishnamurthy, A. Past and present status of runoff harvesting systems in dryland peninsular India: A critical review. *Journal of Human Rights and the Environment*. 2003, 32, 320–324.

Heede, B.H. *Design, construction, and cost of rock check dams*. In Forest Service; US Department of Agriculture: Lakewood, CO, USA, 1966.

Hoekstra, A.Y.; Mekonnen, M.M.; Chapagain, A.K.; Mathews, R.E.; Richter, B.D. Global monthly water scarcity. blue water footprints versus blue water availability. *PLoS ONE* 2012, 7, e32688.

Hudson, N. *Soil and Water Conservation in Semi-Arid Areas*; Food & Agriculture Organisation: Rome, Italy, 1987.

Jain, S.K.; Agarwal, P.K.; Singh, V.P. *Hydrology and Water Resources of India*; Springer Science & Business Media: New Delhi, India, 2007.

Jamwal, P.; Thomas, B.K.; Lele, S.; Srinivasan, V. Addressing water stress through wastewater reuse Complexities and challenges in Bangalore, India. In Proceedings of the Resilient Cities 2014 Congress, Bonn, Germany, 29–31 May 2014.

Kim, J.; Read, L.; Johnson, L.E.; Gochis, D.; Cifelli, R.; Han, H. An experiment on reservoir representation schemes to improve hydrologic prediction: Coupling the national water model with the HEC-ResSim. *Hydrological Sciences Journal*. 2020, 65, 1652–1666.

Krois, J.; Schulte, A. Modeling the hydrological response of soil and water conservation measures in the Ronquillo watershed in the Northern Andes of Peru. In Proceedings of the 6th International Conference on Water Resources and Environment Research, Koblenz, Germany, 3–7 June 2013; pp. 147–184.

Kumar, M.D.; Ghosh, S.; Patel, A.; Singh, O.P.; Ravindranath, R. Rainwater harvesting in India. some critical issues for basin planning and research. *Land Use Water Resources Research*. 2006, 6, 1–17.

Kumar, R.; Nandagiri, L. Application and Test of the SWAT Model in the Upper Cauvery River Basin, Karnataka, India. In Proceedings of the 4th International Engineering Symposium Proceedings, Kumamoto, Japan, 23–24 May 2015.

Lal, R.; Stewart, B.A. *Soil Water and Agronomic Productivity*; CRC Press: Boca Raton, FL, USA, 2012.

Lannerstad, M. Planned and unplanned water use in a closed South Indian Basin. International *Journal of Water Resources Development*. 2008, 24, 289–304.

Loucks, D.P. Managing water as a critical component of a changing world. *Water Resources Management*. 2017, 31, 2905–2916.

Madhusoodhanan, C.G.; Sreeja, K.G.; Eldho, T.I. Climate change impact assessments of water resources of India under extensive human interventions. *Ambio* 2016, 45, 725–741.

Mandal, U.; Sahoo, S.; Munusamy, S.B. Delineation of groundwater potential zones of coastal groundwater basin using multi-criteria decision-making technique. *Water Resources Management.* 2016, 30, 4293–4310.

Meigh, J.R.; McKenzie, A.A.; Sene, K.J. A grid-based approach to water scarcity estimates for eastern and southern Africa. *Water Resources Management*. 1999, 13, 85–115.

Meunier, J.D.; Riotte, J.; Braun, J.J.; Sekhar, M.; Chalié, F.; Barboni, D.; Saccone, L. Controls of DSi in streams and reservoirs along the Kaveri River, South India. *Science of the. Total Environment*. 2015, 502, 103–113.

Mishra, A.; Froebrich, J.; Gassman, P.W. Evaluation of the SWAT model for assessing sediment control structures in a small watershed in India. *Transactions of the ASABE*. 2007, 50, 469–477.

Moore, R.J. The Probability- Distributed Principal and Runoff Production at Point and Basin Scales. *Hydrological Sciences Journal*. 1985, 30, 273–297.

NASA Jet Propulsion Laboratory (JPL). NASA Shuttle Radar Topography Mission Global 1 arc Second Number. Archived by National Aeronautics and Space Administration, U.S. Government, NASA. EOSDIS Land Processes DAAC; NASA JPL: Pasadena, CA, USA, 2013.

Pai, D.S.; Sridhar, L.; Rajeevan, M.; Sreejith, O.P.; Satbhai, N.S.; Mukhopadhyay, B. Development of a new high spatial resolution (0.25 × 0.25) long period (1901–2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *MAUSAM*. 2014, 65, 1–18.

Pant, N.; Verma, R.K. *Tanks in Eastern India. A Study in Exploration*; International Water Management Institute: Colombo, Sri Lanka, 2010.

Parvez, M.B.; Inayathulla, M. Estimation of Surface Runoff by Soil Conservation Service Curve Number Model for Upper Cauvery Karnataka. *International Journal of Scientific Research in Multidisciplinary Studies*. 2019, 5, 7–17.

Patel, S.S.; Ramachandran, P. A comparison of machine learning techniques for modelling river flow time series. the case of the upper Cauvery River basin. *Water Resources Management*. 2015, 29, 589–602.

Pathak, P.; Mishra, P.K.; Wani, S.P.; Sudi, R. Soil and water conservation for optimizing productivity and improving livelihoods in rainfed areas. *Integrated Watershed Management: Rainfed Areas* 2011, 19, 205–248.

Penny, G.; Srinivasan, V.; Dronova, I.; Lele, S.; Thompson, S. Spatial characterization of long-term hydrological change in the Arkavathy watershed adjacent to Bangalore, India. *Hydrology and Earth System Sciences*. 2018, 22, 595–610.

Polyakov, V.O.; Nichols, M.H.; McClaran, M.P.; Nearing, M.A. Effect of check dams on runoff, sediment yield, and retention on small semiarid watersheds. *Journal of Soil and Water Conservation.* 2014, 69, 414–421.

Raje, D.; Priya, P.; Krishnan, R. Macroscale hydrological modelling approach for the study of large-scale hydrologic impacts under climate change in Indian river basins. *Hydrological Processes*. 2014, 28, 1874–1889.

Ramaswamy, S. *The groundwater recharge movement in India. In The Agricultural Groundwater Revolution*. Opportunities and Threats to Development; CABI: Wallingford, UK, 2007.

Renganayaki, S.P.; Elango, L. A review on managed aquifer recharge by check dams. A case study near Chennai, India. *International Journal of Engineering and Technology*. 2013, 2, 416–423.

Robinson, T.P.; Wint, G.W.; Conchedda, G.; Van Boeckel, T.P.; Ercoli, V.; Palamara, E.; Cinardi, G.; D'Aietti, L.; Hay, S.I.; Gilbert, M. Mapping the global distribution of livestock. *PLoS ONE* 2014, 9, e96084.

Roy, P.S.; Meiyappan, P.; Joshi, P.K.; Kale, M.P.; Srivastav, V.K.; Srivasatava, S.K.; Behera, M.D.; Roy, A.; Sharma, Y.; Ramachandran, R.M.; et al. *Decadal Land Use and Land Cover Classifications across India, 1985, 1995, 2005*; Oak Ridge National Laboratory Distributed Active Archive Center: Oak Ridge, TN, USA, 2016.

Salman, S.M. Inter-states water disputes in India. an analysis of the settlement process. *Water Policy.* 2002, 4, 223–237.

Shah, T. India's master plan for groundwater recharge. An assessment and some suggestions for revision. *Economic and Political Weekly*. 2008, 20, 41–49.

Sharma, A.; Hipel, K.W.; Schweizer, V. Strategic Insights into the Cauvery River Dispute in India. *Sustainability.* 2020, 12, 1286.

Smith, Z.A. Competition for Water Resources. Issues in Federalism. *Journal of Land Use & Environmental Law*. 2018, 2, 3–10.

Sreelash, K.; Mathew, M.M.; Nisha, N.; Arulbalaji, P.; Bindu, A.G.; Sharma, R.K. Changes in the Hydrological Characteristics of Cauvery River draining the eastern side of southern

Western Ghats, India. *International Journal of River Basin Management*. 2020, 18, 153–166.

Srinivas, V.V.; Srinivasan, K. Hybrid moving block bootstrap for stochastic simulation of multi-site multi-season streamflows. *Journal of Hydrology*. 2005, 302, 307–330.

Srinivasan, V.; Thompson, S.; Madhyastha, K.; Penny, G.; Jeremiah, K.; Lele, S. Why is the Arkavathy River drying? A multiple hypothesis approach in a data-scarce region. *Hydrology and Earth System Sciences*. 2015, 19, 1905–1917.

Subash, Y.; Sekhar, M.; Tomer, S.K.; Sharma, A.K. *A framework for assessment of climate change impacts on*. In Sustainable Water Resources; American Society of Civil Engineers: Reston, VA, USA, 2016.

Subburayan, S.; Murugappan, A.; Mohan, S. Modified Hargreaves equation for estimation of ETo in a hot and humid location in Tamil Nādu State, India. *International Journal of Engineering, Science and Technology*. 2011, 3, 592–600.

Van Meter, K.J.; Basu, N.B.; McLaughlin, D.L.; Steiff, M. The socio-ecohydrology of rainwater harvesting in India. Understanding water storage and release dynamics at tank and catchment scales. *Hydrology and Earth System Sciences Discussions*. 2015, 12, 12121–12165.

Verma, G.P.; Singh, Y. *Rainfed Farming Development in Central India*; Scientific Publishers: Jodhpur, India, 2017.

Vidya, V.K.; Putty, Y.; Mysooru, R.; Manjunath, K.C. Urban Tanks for Facilitating Reuse of Municipal Sewage—A Case Study in Mysuru, Karnataka. *Aquatic Procedia*. 2015, 4, 1508–1513.

Wable, P.S.; Garg, K.K.; Nune, R. Impact of Watershed Interventions on Streamflow of Upper Cauvery Sub-Basin. In Proceedings of the Sustainable Water Resources Special Event at Water Future International Conference, Bengaluru, India, 24–27 September 2019.

Wang, X.J.; Zhang, J.Y.; Shahid, S.; Guan, E.H.; Wu, Y.X.; Gao, J.; He, R.M. Adaptation to climate change impacts on water demand. *Mitigation and Adaptation Strategies for Global Change.* 2016, 21, 81–99.

Wei, Y.; He, Z.; Li, Y.; Jiao, J.; Zhao, G.; Mu, X. Sediment yield deduction from check-dams deposition in the weathered sandstone watershed on the North Loess Plateau, China. *Land Degradation & Development.* 2017, 28, 217–231.

Xu, Y.D.; Fu, B.J.; He, C.S. Assessing the hydrological effect of the check dams in the Loess Plateau, China, by model simulations. *Hydrology and Earth System Sciences.* 2013, 17, 2185.

Yeggina, S.; Teegavarapu, R.S.; Muddu, S. Evaluation and bias corrections of gridded precipitation data for hydrologic modelling support in Kabini River basin, India. *Theoretical And Applied Climatology*. 2020, 140, 1495–1513.

**Appendix C**

Table 3.3 Description of scenarios utilised in the sensitivity

| Scenario | Depth (m) | Width (m) | SSRHI Density ($m^3$/ha) | Scenario | Depth (m) | Width (m) | SSRHI Density ($m^3$/ha) |
|---|---|---|---|---|---|---|---|
| Tanks | | | | | | | |
| T1 | 3 | n/a | 25 | T7 | 5 | n/a | 125 |
| T2 | 3 | n/a | 75 | T8 | 5 | n/a | 200 |
| T3 | 3 | n/a | 125 | T9 | 10 | n/a | 25 |
| T4 | 3 | n/a | 200 | T10 | 10 | n/a | 75 |
| T5 | 5 | n/a | 25 | T11 | 10 | n/a | 125 |
| T6 | 5 | n/a | 75 | T12 | 10 | n/a | 200 |
| Check Dams | | | | | | | |
| C1 | 1 | 7 | 25 | C7 | 1.5 | 10 | 125 |
| C2 | 1 | 7 | 75 | C8 | 1.5 | 10 | 200 |
| C3 | 1 | 7 | 125 | C9 | 2 | 15 | 25 |
| C4 | 1 | 7 | 200 | C10 | 2 | 15 | 75 |
| C5 | 1.5 | 10 | 25 | C11 | 2 | 15 | 125 |
| C6 | 1.5 | 10 | 75 | C12 | 2 | 15 | 200 |
| Farm Bunds | | | | | | | |
| B1 | 0.03 | n/a | 25 | B5 | 0.06 | n/a | 25 |
| B2 | 0.03 | n/a | 75 | B6 | 0.06 | n/a | 75 |
| B3 | 0.03 | n/a | 125 | B7 | 0.06 | n/a | 125 |
| B4 | 0.03 | n/a | 200 | B8 | 0.06 | n/a | 200 |

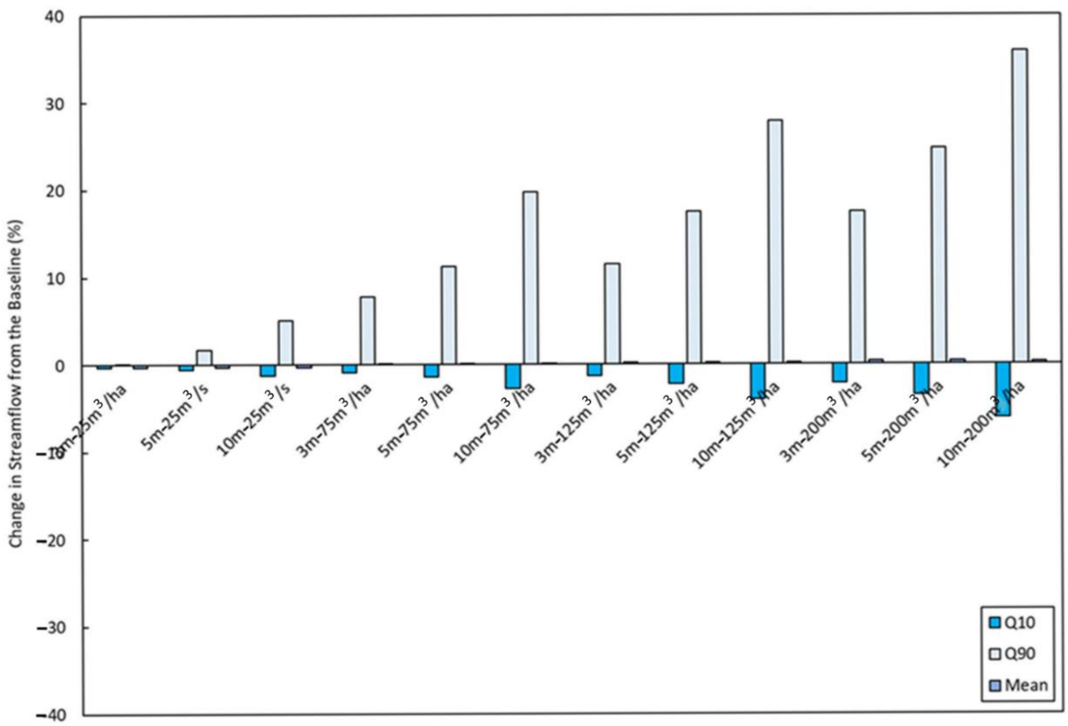



Figure 3.14 The change in the $Q_{10}$, $Q_{90}$ and mean simulated streamflow from the baseline with the inclusion of tanks of various densities and depths (Table 3.3).

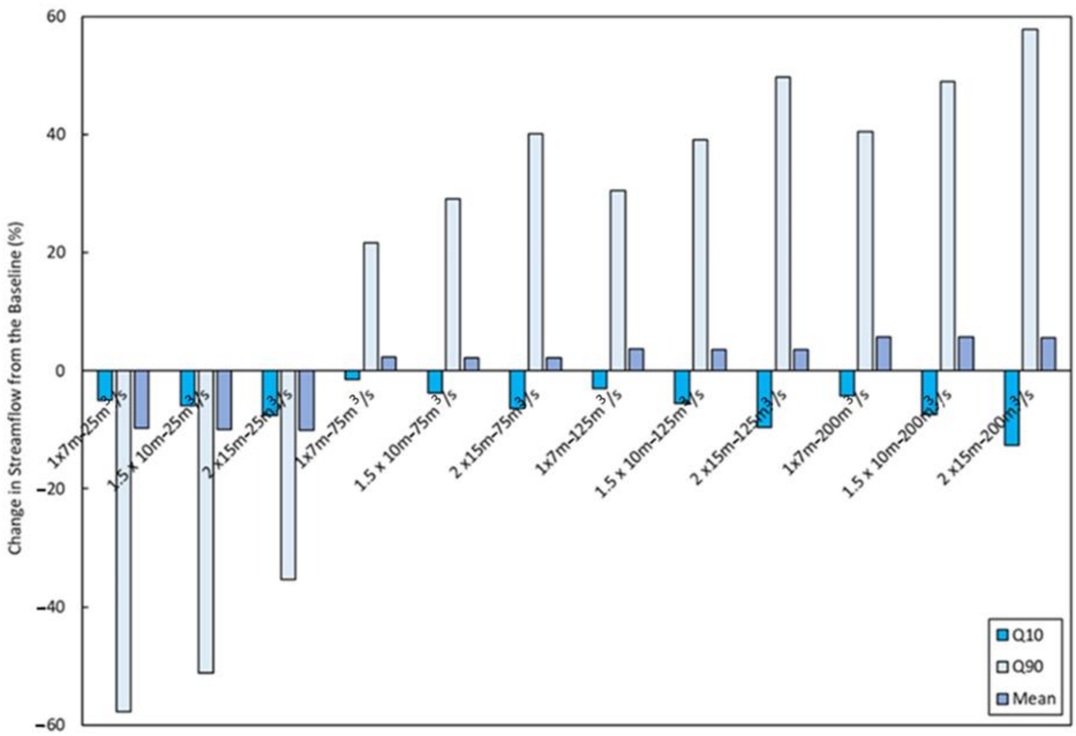



Figure 3.15 The change in the $Q_{10}$, $Q_{90}$ and mean simulated streamflow from the baseline with the inclusion of check dams of various densities and dimensions (Table 3.3).

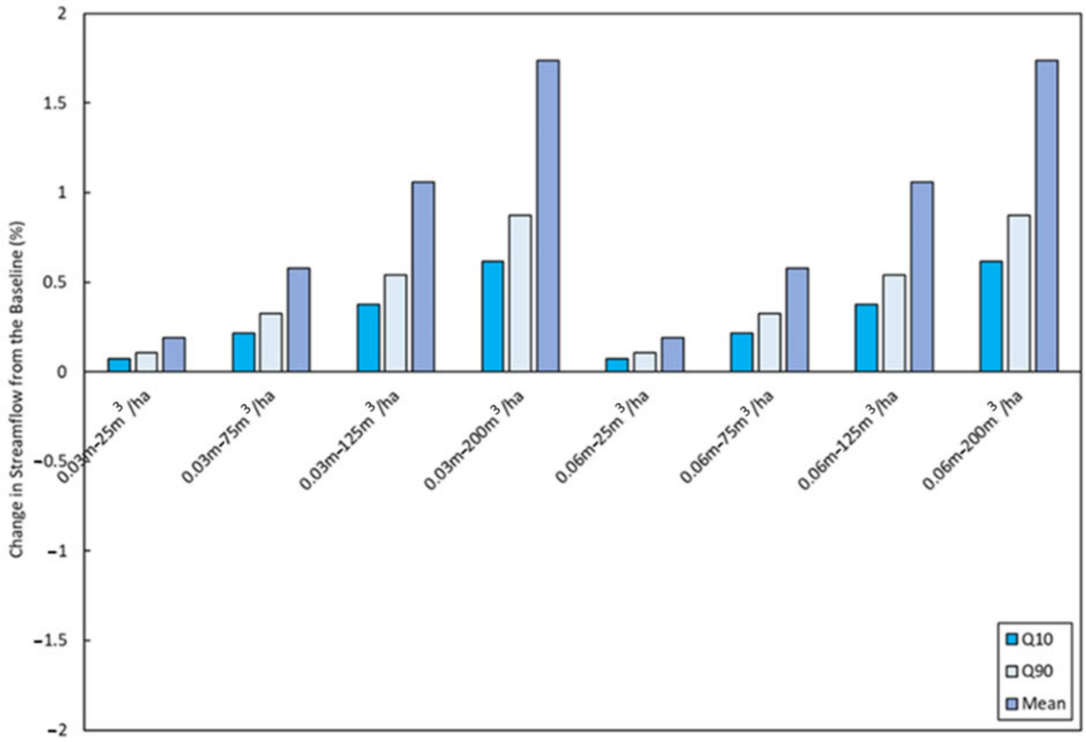



Figure 3.16 The change in the $Q_{10}$, $Q_{90}$ and mean simulated streamflow from the baseline with the inclusion of farm bunds of various densities and dimensions (Table 3.3).

Table 3.4 Calibration and Validation monthly Kling-Gupta Efficiency (KGE) values when GWAVA was calibrated with and without the inclusions of SSRHIs.

| Catchment | | Calibration | | | Validation | | |
|---|---|---|---|---|---|---|---|
| | | **KGE without SSRHIs** | **KGE with SSRHIs** | **Period** | **KGE without SSRHIs** | **KGE with SSRHIs** | **Period** |
| a | Saklesphur | 0.53 | 0.66 | 2006-2010 | 0.37 | 0.38 | 2010-2013 |
| b | Thimmanahali | 0.71 | 0.71 | 2005-2009 | 0.72 | 0.68 | 2010-2013 |
| c | KM Vadi | 0.25 | 0.24 | 1991-2000 | 0.16 | 0.16 | 2001-2011 |
| d | Kudige | 0.48 | 0.59 | 1990-2000 | 0.55 | 0.59 | 2012-2014 |
| e | Muthankera | 0.73 | 0.82 | 1990-2000 | 0.66 | 0.70 | 2001-2011 |
| f | T Bekuppe | 0.41 | 0.32 | 1980-2000 | -1.28 | -1.27 | 2001-2003 |
| g | TK Hali | 0.52 | 0.71 | 1990-2000 | 0.69 | 0.67 | 2001-2008 |
| h | T Narasupuir | 0.60 | 0.68 | 1988-1998 | 0.25 | 0.30 | 1999-2002 |
| i | Kollegal | 0.56 | 0.58 | 2008-2011 | 0.50 | 0.54 | 2012-2013 |
| j | Bilingudulu | 0.74 | 0.74 | 1990-2000 | 0.61 | 0.60 | 2001-2011 |

| Catchment | | Calibration | | | Validation | | |
|---|---|---|---|---|---|---|---|
| | | **KGE without SSRHIs** | **KGE with SSRHIs** | **Period** | **KGE without SSRHIs** | **KGE with SSRHIs** | **Period** |
| k | Urachikottai | 0.34 | 0.74 | 1990-2000 | 0.49 | 0.51 | 2001-2008 |
| l | Kodumodi | 0.25 | 0.62 | 1990-2000 | 0.24 | 0.30 | 2005-2010 |
| m | Thengumarahada | 0.57 | 0.50 | 1990-2000 | 0.39 | 0.44 | 2006-2010 |
| o | Musiri | 0.33 | 0.65 | 1990-2000 | 0.43 | 0.44 | 2001-2008 |

Table 3.5 The spatial and temporal resolutions, periods and sources of the input data used in the setup of GWAVA in the Cauvery catchment

| **Input Data** | **Spatial Resolution** | **Temporal Resolution** | **Time Period** | **Source** |
|---|---|---|---|---|
| Precipitation | 0.25 degree | Daily | 1951-2017 | Indian Meteorological Department (Pai *et al*., 2012) |
| Maximum temperature | 0.25 degree | Daily | 1951-2016 | Indian Meteorological Department (Pai *et al*., 2012) |
| Minimum Temperature | 0.25 degree | Daily | 1951-2016 | Indian Meteorological Department (Pai *et al*., 2012) |
| Streamflow gauged data | Catchment | Daily | 1971-2014 | India-WRIS |
| Dam Characteristics | Catchment | | 2018 | India-WRIS |
| Dam inflow and outflow data | Catchment | Monthly | 1974-2017 | India-WRIS |
| Dam storage | Catchment | Daily | 200-2010 | India-WRIS |
| Water transfers | Catchment | Annual | 2008 | Ashoka Trust for Research in Ecology and the Environment |
| Tanks | Catchment | | 2019 | Waterbodies dataset (ATREE) |
| Check Dams | Karnataka | | 2006-2012 | Structural Investment Report, Watershed Development Department |
| Farm Bunds | Karnataka | | 2006-2012 | Structural Investment Report, Watershed Development Department |
| Groundwater levels | District | Monthly | 1990-2017 | Central Ground Water Board, India |
| Elevation | 0.003 degree | | 2000 | NASA Shuttle Radar Mission Global 1 arc second V003 (NASA Jet Propulsion Laboratory, 2013) |

| Input Data | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|
| Geology | Asia | | | United States Geological Survey |
| Specific yield | India | | | Central Ground Water Board, India |
| Soil type | 0.008 degree | | 1971-1981 | Harmonized World Soil Database v1.2 (Fischer *et al*., 2008) |
| Soil properties | Global | | 2010 | Table 2- Allen *et al*. (2010) |
| Land Cover Land Use | 0.001 degree | | 2005 | Decadal land use and land cover across India 2005 (Roy *et al*., 2016) |
| Crops | Taluk* | | 2000 | National Remote Sensing Centre (NRSC) |
| Total and Rural Population | Village | | 2001 | Census of India 2001 (http://sedac.ciesin.columbia.edu/data/set/india-india-village-level-geospatial-socio-econ-1991-2001) |
| Livestock | 0.05 degree | | 2005 | CGIR Livestock of the World v2 (Robinson *et al*., 2014) |
| Conveyance losses | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx |
| Return flow | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |
| Irrigation efficiency | Continental | | 1986 | Irrigation and Drainage Paper (FAO) No 1 |
| Surface- water fraction | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |

| Input Data | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|
| Industrial demand | Karnataka | | Currently unknown | Industrial Plot Information System- Karnataka Industrial Area Development Board (https://http://164.100.133.168/kiadbgisportal/) |
| Livestock demand | India | | 2006 | CGIR Livestock of the World v2 (Robinson *et al*., 2014) |
| Domestic demand | Village | | 2001 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |

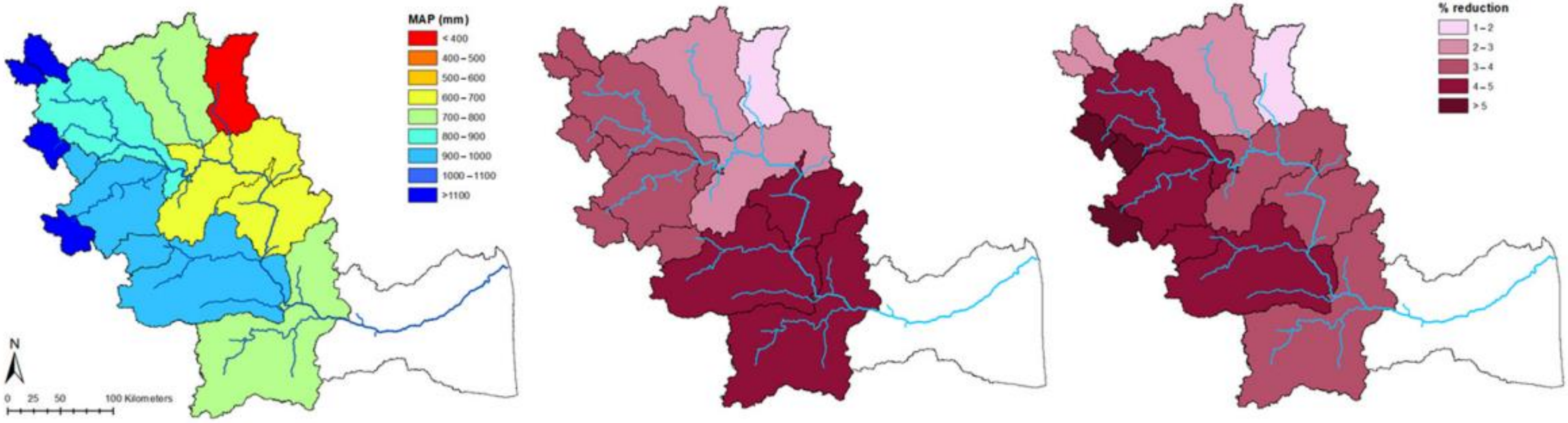



Figure 3.17 (Left): the mean annual precipitation for each calibration catchment over the period 1986–2005; (middle): the percentage reduction in $Q_{10}$ flow for each calibration catchment over the period 1986–2005; (right): percentage reduction in $Q_{90}$ flow for each calibration catchment over the period 1986–2005.

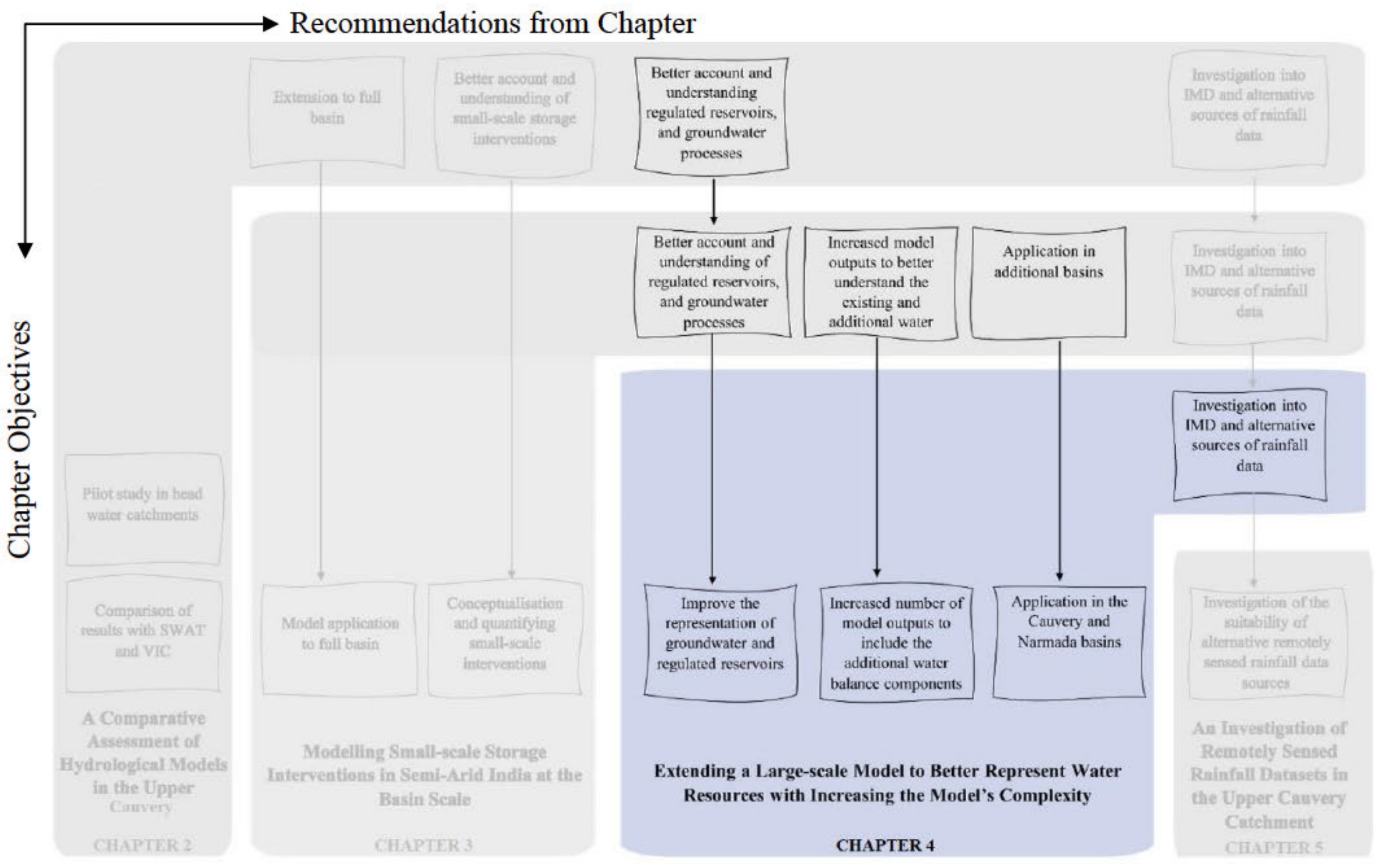
Table 3.6 The total annual (for 1998, 2002 and 2005) precipitation (P), simulated streamflow (Q), simulated total evaporation (ET) and average annual aquifer level (Aq) below ground level with and without SSRHIs (int). The change (Δ) with the inclusion of SSRHIs is presented as a percentage change.

| | **Year** | **P (mm)** | **Q-int (mm)** | **Q- no int (mm)** | **ΔQ (%)** | **ET-int (mm)** | **ET- no int (mm)** | **ΔET (%)** | **Aq-int (m)** | **Aq- no int (m)** | **ΔAq (m)** |
|---|---|---|---|---|---|---|---|---|---|---|---|
| S1 | 1998 | 507 | 118 | 130 | -9.4 | 624 | 602 | 3.4 | 14.02 | 14.42 | 2.7 |
| | 2002 | 382 | 44 | 48 | -8.8 | 436 | 421 | 3.4 | 12.46 | 12.86 | 3.1 |
| | 2005 | 668 | 68 | 75 | -8.6 | 735 | 708 | 3.6 | 14.52 | 14.92 | 2.6 |
| S2 | 1998 | 1874 | 977 | 1020 | -4.2 | 1527 | 1485 | 2.7 | 12.61 | 12.61 | 0.0 |
| | 2002 | 656 | 669 | 704 | -5.0 | 489 | 477 | 2.5 | 12.64 | 12.64 | 0.0 |
| | 2005 | 2085 | 802 | 840 | -4.5 | 1301 | 1262 | 3.0 | 12.32 | 12.32 | 0.0 |
| Outlet | 1998 | 1341 | 325 | 334 | -2.6 | 1030 | 928 | 9.9 | 8.97 | 9.00 | 0.2 |
| | 2002 | 685 | 130 | 134 | -2.6 | 521 | 469 | 9.9 | 8.97 | 8.99 | 0.3 |
| | 2005 | 1413 | 432 | 446 | -3.1 | 1067 | 962 | 9.8 | 8.95 | 8.96 | 0.1 |

*****

**Lead into Chapter 4**

This chapter addresses the recommendations of Chapter 2 and Chapter 3 regarding improving key components of GWAVA to better represent water management while maintaining low input data requirements and model complexity. The regulated dam and groundwater routines are updated, introducing only five new parameters. The model improvements were tested in two catchments, the Cauvery and Narmada, to determine the success of the incorporated functionality. The additional model outputs are included (dam storage levels, groundwater levels, groundwater abstraction and recharge) to gain insight into various components of the catchment water balance.



# 4. EXTENDING A LARGE-SCALE MODEL TO BETTER REPRESENT WATER RESOURCES WITHOUT INCREASING THE MODEL'S COMPLEXITY

## 4.1 Abstract

The increasing impact of anthropogenic interference on river catchments has motivated hydrologists to develop and improve the representation of human influences in large-scale models. Surface-groundwater interactions and the representation of large dams have seen significant developments recently. These changes must be balanced against the idea of keeping models parsimonious and applicable to regions with low data availability. The surface-groundwater interactions and dam representation in the Global Water Availability Assessment (GWAVA) model have been improved critically, with a minimal increase in model complexity and data input requirements. This increased functionality was assessed in two highly anthropogenically influenced catchments, the Cauvery and Narmada. A revised groundwater routine was incorporated into GWAVA, which can be varied in complexity when sufficient input data is available but fundamentally is driven by three input parameters. This inclusion improved streamflow simulation in the headwater sub-catchments and the representation of the baseflow component such that low-flow model skill increased by approximately 33-67% in the Cauvery and 66-100% in the Narmada. The existing dam routine was extended to account for large, regulated dams with two calibratable parameters. The routine improved streamflow simulation in sub-catchments downstream of major dams, where the streamflow was largely reflective of dam releases. The model performance was improved between 15 and 30% in the Cauvery and 7-30% in the Narmada when the regulated dams were considered. The model provides a more robust representation of the annual outflow volume from major dams, reducing the average bias from -17% to -1% in the Cauvery and from 14% to 3% in the Narmada.

---

Horan, R, Rickards, NJ, Kaelin, A, Baron, HE, Thomas, T, Keller, VD, Mishra, PK, Nema, MK, Muddu, S, Garg, KK and Pathak, R, 2021. Extending a Large-Scale Model to Better Represent Water Resources Without Increasing the Model's Complexity. Water, 13(21), p.3067.

*Referencing conforms to the format of *Water*

The daily dam releases were significantly improved in the Cauvery, approximately 26-164%. The improvement of the groundwater and dam routines in GWAVA proved successful in improving the overall model performance, the low-flow model skill and bias, and the inclusions allowed for improved traceability of simulated water balance components. This study illustrates that the improvement in the representation of human–water interactions in large-scale models is possible without excessively increasing the model complexity and input data requirements

## 4.2 Introduction

Humans are increasingly altering the hydrological cycle through the construction of dams, changes in land use, water abstractions and urbanisation (Döll *et al*., 2016). Accurate quantification of freshwater flows and storage is therefore important to support water management and governance in the near and far future (Vorosmarty *et al.,* 2015). Large-scale hydrological modelling estimates water fluxes, such as evapotranspiration, river discharge and groundwater recharge, and water storage, including soil water, groundwater and dams (Liu *et al*., 2008; Döll *et al*., 2016; Kingston *et al*., 2020) at a catchment or continental scale.
Groundwater accounts for approximately one-third of total water withdrawals globally, and an estimated two billion people rely on groundwater as their primary source of water. Additionally, more than half of the irrigation water globally is abstracted from groundwater sources (Famiglietti, 2014). It is, therefore, important to select a model that can accurately simulate the generation of groundwater, particularly in catchments where the primary source of baseflow depends upon groundwater storage (Mackellar *et al.,* 2013).

A better representation of groundwater processes needs to be included in large-scale hydrological models to improve simulations and the understanding of feedback between the human and natural systems (Clark *et al*., 2015; Pokhrel *et al*., 2016; Scheidegger *et al*., 2021). Simple one-dimensional groundwater routines currently exist within HiGW-MAT (Pokhrel *et al.,* 2016), H08 (Hanasaki *et al.*, 2018), PCR-GLOBWB (Sutanudjaja *et al*., 2018), CWatM (Burek *et al*., 2020), WaterGAP (Müller Schmied *et al*., 2020) and VIC (Droppers *et al*., 2020), with the focus on quantity and change in groundwater storage. Most models allow groundwater to be recharged through rainfall, wetlands and dams, and groundwater abstractions are often incorporated to meet demand. As far as the author is aware, none of these models, except VIC (Scheidegger *et al*., 2021), consider lateral flow within the groundwater store without being fully coupled to MOD-FLOW (Harbaugh, 2005). Using MOD-FLOW significantly increases the data and computational requirements.

Approximately one-sixth of the annual global river discharge is stored because of the construction of an estimated 70 300 dams (Downing *et al*., 2006). Dam operations have a considerable impact on the natural discharge regime of a river. Simulating the available storage, volume and timing of dam releases pose a significant challenge to hydrological modelling at a catchment and continental scale (Zhao *et al.,* 2016). Dam operational data are rarely freely available, if at all. Therefore, hydrological models include various schemes to estimate dam storage and releases.

A module that optimises dam outflow based on the operational purpose of the dam is included in VIC (Haddeland *et al*., 2006), WaterGAP (Döll *et al.*, 2003) and H08 using the Hanasaki dam routine (Hanasaki *et al*., 2006; Hanasaki *et al*., 2008), and H08 has been updated to represent water transfers and local dams (Hanasaki *et al*., 2018). The dam scheme used in LPJmL (Biemans *et al*., 2011) combines aspects used in H08 (Hanasaki *et al*., 2008) and VIC (Haddeland *et al*., 2006). Monthly target releases are calculated for each month of each operational year according to the primary purpose of the dam. The dam scheme in PCR-GLOBWB (Sutanudjaja *et al.,* 2018) is based on that included with VIC (Haddeland *et al*., 2006) but uses estimates of future inflows and demands via a weighted average of antecedent conditions. CWatM utilises a function of three storage limits and three outflow functions to determine dam releases. The storage limits are user-specified and depend on the physical characteristics of the dam. Other examples of recent dam routine implementations include, but are not limited to, SWAT (Chen & Wu, 2012), DHSVM (Zhao *et al.*, 2016), VIC (Scheidegger *et al*., 2021), MESH (Yassin *et al*., 2019) and HYPE (Tefs *et al*., 2021).

Although the above-mentioned models are valuable tools, in this study, GWAVA is used because it is a water resource model specifically designed to work in low-data environments. GWAVA is a large-scale gridded water resource model (Meigh *et al*., 1999) which accounts for natural hydrological processes (soils, land use and lakes) using a conceptual rainfall-runoff model and anthropogenic stresses (groundwater abstraction, irrigation, domestic and industrial demands, dam storage and water transfers) using a demand-driven routine. The model can be run at a daily or monthly time scale and is adaptable to the data availability of the region. GWAVA was developed primarily for use in large, data-scarce regions. The model comprises only eleven mandatory parameters- four parameters about the physical parameters of the catchment, three-time series about the climate variables (rainfall, potential evaporation, temperature) and four calibratable factors. The model further incorporates five dam parameters, nineteen water demand constraints and six characteristics of mountains and glaciers that are optional input when the relevant data are available. GWAVA does not comprehensively account for groundwater processes or regulated dam releases. GWAVA has a simplistic representation of groundwater. The groundwater store for each grid cell receives groundwater recharge from the soil moisture storage and produces the baseflow component of streamflow. As a basic representation of deeper groundwater processes, water can drain from the groundwater store, and this water is lost from the system. Water abstractions from the groundwater store are decoupled and are not abstracted in each time step but summed after the run. GWAVA simulates regulated dam release using a non-linear equation utilising mean inflow, dam capacity and two outflow parameters.

GWAVA has proven to be a useful tool for assessing water resource management; however, fundamental functionality for improving water resource estimations in highly anthropogenically influenced catchments needs revision. With the increasing reliance on groundwater in semi-arid and arid regions and the continuous construction of major dams globally, there is a critical need for water resource assessment tools to accurately consider these impacts not only on the hydrological system but on water resource management. In line with existing large-scale models and the requirements to accurately represent highly anthropogenically influenced regions, this study aims to:

a) Improve key components of GWAVA to better represent water management while maintaining low input data requirements and model complexity
b) Test the improvements in suitable catchments to determine the success of the incorporated functionality
c) Use the additional model output to gain insight into components of the catchment water balance.

The GWAVA model is updated to better represent groundwater abstraction, artificial recharge, and regulated dam releases. These updates are based largely on the principles of the AMBHAS-1D model and dam operations incorporating a routine derived from the Hanasaki dam routine.

A groundwater routine based on AMBHAS-1D is included, introducing one calibratable parameter regarding the groundwater depth below ground level and two input parameters regarding the specific yield and depth of underlying geology. The Hanasaki equations are modified to allow two calibratable outflow parameters to replace physical dam engineering parameters. The addition of these two routines introduces only two input parameters and three calibratable parameters into the model.

The original and revised models are applied in two highly anthropogenically influenced catchments, the Cauvery and Narmada Catchments, India. The choice of the catchment was based on the Cauvery being subjected to a high degree of groundwater pumping while the Narmada houses three of the largest dams in India. The overall model performance is evaluated using the KGE, while the model's ability to represent the low flow periods is evaluated using the Log-Nash Efficiency at a sub-catchment scale. The change in dam outflows using the original GWAVA equation and the newly modified Hanasaki equations is evaluated using the NSE and the bias at the outlets of major dams. Observed and simulated average sub-catchment groundwater and major dam storage levels are directly compared

## 4.3 Methodology

### *4.3.1 Catchment Descriptions*

The Cauvery and the Narmada Catchments (Figure 4.1) are situated in Peninsula India and are the fifth and sixth largest river catchments in India, respectively. Both catchments are snow-free, highly anthropogenically influenced and dam-regulated to sustain the livelihoods of a collective of 45 million people. The catchments experience a large degree of heterogeneity in topography, land use, climate, and economic development (Madhusoodhanan *et al*., 2016).

Both catchments are highly regulated by dam releases, with a visible impact on the downstream flows. The base flow sustains the Narmada through the dry periods, and the domestic and agricultural activities in the Cauvery depend highly on groundwater sources. Both catchments suffer from water scarcity; therefore, modelling and understanding water resources are important for water management. Thus, it is critically important that both dam releases and groundwater are accurately represented to undertake effective water resources modelling exercises.

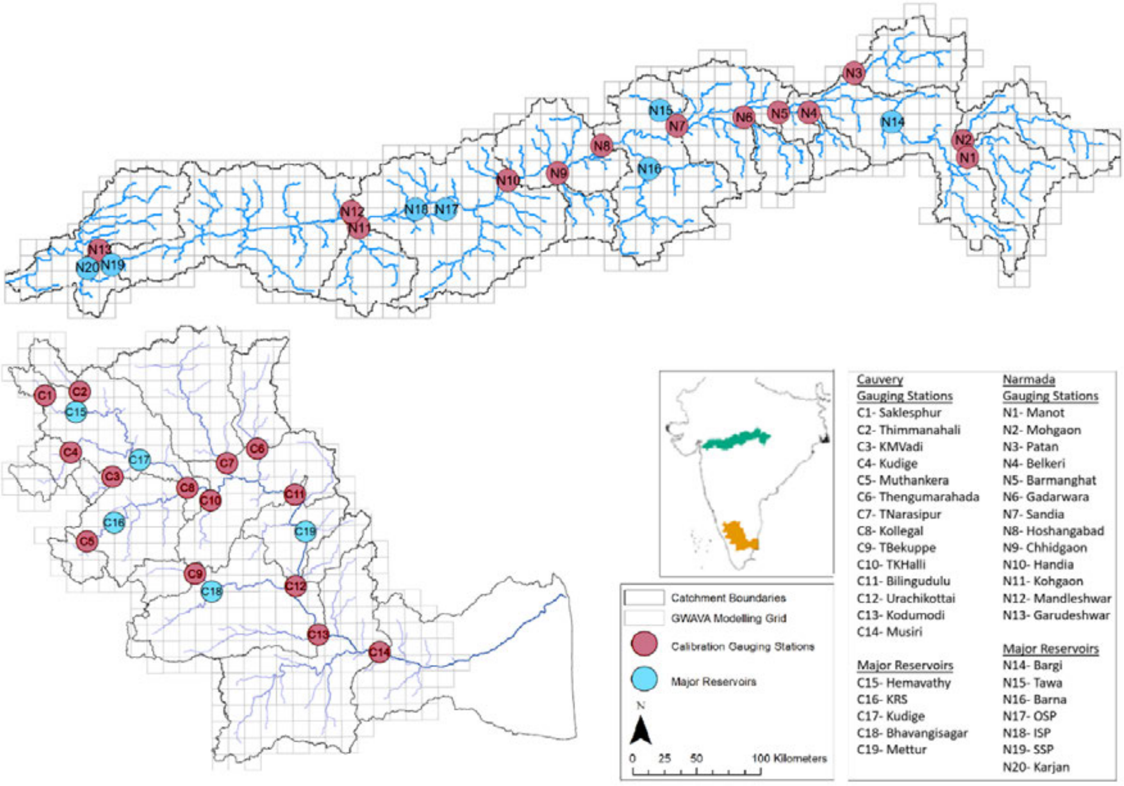



Figure 4.1 Inset: the location of the Cauvery (orange) and Narmada (green) Catchments within India; main maps: sub-catchment boundaries, modelling grid and the locations flow gauges used for calibration and major dams within the Cauvery Catchment and the Narmada Catchment.

The Cauvery is considered semi-arid, with the SW monsoon supplying most of the water in the catchment. The catchment experiences distinct intra-annual seasons, namely the SW monsoon between June and August, the NE monsoon in September and October, and post-monsoon conditions in the winter. The upper catchment receives rainfall from both the SW and NE monsoons, whereas the lower catchment only receives rainfall from the NE monsoon. The mean annual rainfall varies from 6000 mm in the upper reaches to 300 mm on the eastern boundary. The mean daily temperatures range between 9 and 25 °C throughout the catchment (Sharma *et al*., 2021). The Western Ghats form a rain shadow along the western boundary, decreasing the rainfall gradient during the SW monsoon.

The current hydrological functioning of the Cauvery Catchment has been significantly altered over the last century by water supply infrastructure, urbanisation, land-use change and increased groundwater use. The Cauvery Catchment is predominantly within the federal states of Karnataka and Tamil Nadu (Sharma *et al*., 2021) and has been identified as highly water-stressed (Hoekstra *et al*., 2012). Despite rapidly developing urban and industrial centres, irrigation throughout the catchment requires approximately 90% of the total water resources (Bhave *et al*., 2018). The catchment is highly regulated by aggressive groundwater pumping and dam release along the tributaries and main channel, with surface water and streamflow only reaching the Bay of Bengal in years of strong monsoons (Falkenmark & Molden, 2008). Several hydrological modelling exercises have been conducted in the Cauvery Catchment or sub-catchments. Remote sensing methods (Patel & Ramachandran, 2015), ANN model (Patel & Ramachandran, 2015), GWAVA model (Horan *et al.*, 2021a; Horan *et al.*, 2021b), VIC model (Horan *et al*., 2021a) and the SWAT model (Raju & Nandagiri, 2018; Horan *et al*., 2021a) have been applied in various sub-catchments of the Cauvery. At a catchment scale, SWAT (Gosain *et al*., 2006; Singh & Gosain, 2011; Bhuvaneswari *et al*., 2013; Mandal *et al*., 2016), SCS-CN (Geetha *et al*., 2008; Parvez *et al.*, 2019), and VIC- MHM (Raje *et al*., 2014) have been used to simulate various components of the hydrological cycle.

The Narmada Catchment is subject to a tropical monsoon climate, with the SW monsoon between July and September. The monsoon supplies over 75% of the catchment's annual rainfall, with a rainfall gradient of 650 mm per annum to more than 1400 mm per annum in the upper regions. The mean daily temperatures vary between 18 and 32 °C throughout the catchment. The Narmada Catchment is facing numerous resource management challenges, including state and sectoral competition for water. This highly regulated river flows through the states of Chhattisgarh, Madhya Pradesh, Maharashtra and Gujarat, housing more than 250 dams of various sizes and purposes (Gupta & Chakrapani, 2005). More than half of the catchment is used for agriculture, with most of this land within designated irrigation command areas. Agriculture within the command areas is highly intensified, with an average cropping intensity of 135% (Thomas *et al*., 2015). The low flows in the catchment are sustained by base flow and dam releases. The Narmada has been modelled at the catchment scale using the SCS-CN method (Nayak *et al*., 2012), VIC-MHM (Raje *et al*., 2014) and geoinformatics (Rai *et al.*, 2017). Sub-catchments of the Narmada have been represented using SHE (Jain *et al*., 1992), SCS-CN (Gajbhiye *et al*., 2013; Khare *et al*., 2017; Pathan & Joshi, 2019), and SWAT (Tiwari *et al*., 2018). The above-mentioned studies focussing on the Cauvery and the Narmada Catchments highlight the minimal representation of anthropogenic influences, groundwater abstraction and dam operations within existing modelling exercises. GWAVA has been applied in both the Cauvery Catchment (Horan *et al*., 2021a; Horan *et al.*, 2021b) and the Upper

Narmada Catchment (Rickards *et al*., 2020). These publications highlight the need for a more comprehensive dam routine when modelling highly regulated catchments and for the inclusion of a coupled groundwater module to account for the limitations of natural groundwater resources and groundwater abstraction to meet anthropogenic demand.

### *4.3.2 Model Improvement*

GWAVA has proven to be a useful tool for assessing water resource management; however, it extends the representation of processes and stores in the GWAVA model to better represent groundwater and major dams due to the increasing reliance on groundwater in semi-arid and arid regions and the continuous construction of major dams globally.

#### 4.3.2.1 Representing Groundwater Processes

AMBHAS-1D (Tomer *et al*., 2012) is a spatial groundwater model that determines a daily groundwater level based on equations from McDonald and Harbaugh (1988). AMBHAS-1D implements distributed transient groundwater modelling. The model is based on the groundwater flow equation numerically solved using the finite-difference scheme (Subash *et al.,* 2016). The implementation of various AMBHAS versions in India was shown to be highly successful in simulating groundwater levels across areas of Karnataka (Mondal *et al*., 2016), in the Barembadi sub-catchment (Shekar *et al*., 2016; Robert *et al*., 2018) and an idealised system based on the Ganges River (Hanasaki *et al.*, 2018). Additionally, de Bruin *et al.* (2012) utilised the results generated from AMBHAS-1D to guide the set of SWAT groundwater parameters for use in the Jaldhaka Catchment. The successful application of AMBHAS-1D highlighted its suitability in India and other regions with low data availability.

In line with the AMBHAS-1D conceptualisation, additional groundwater processes have been incorporated into GWAVA through the full coupling of the recharge, streamflow, water abstractions and base flow (Figure 4.2). The groundwater store was conceptualised as a vertically layered water table. Each layer was allocated a specific yield and depth and can vary from cell to cell based on data available about local hydrogeology. The water table can be recharged from soil moisture, the bottom of lakes, dams, and SSRHIs and leaking via the water supply infrastructure.

Water can be directly abstracted from the water table to its maximum depth. The groundwater contribution to baseflow (BF) was calculated as follows:

$$BF = \begin{cases} \gamma \times (GW_{store} - GW_{BF}), & GW_{store} > GW_{BF} \\ 0, & GW_{store} \leq GW_{BF} \end{cases} \quad (4.1)$$

where $\gamma$ is a routing coefficient, $GW_{store}$ is the groundwater store, and $GW_{BF}$ is the level of groundwater storage below which there is no baseflow. $GW_{BF}$ can be converted to a water table depth below ground level by dividing by the specific yield.

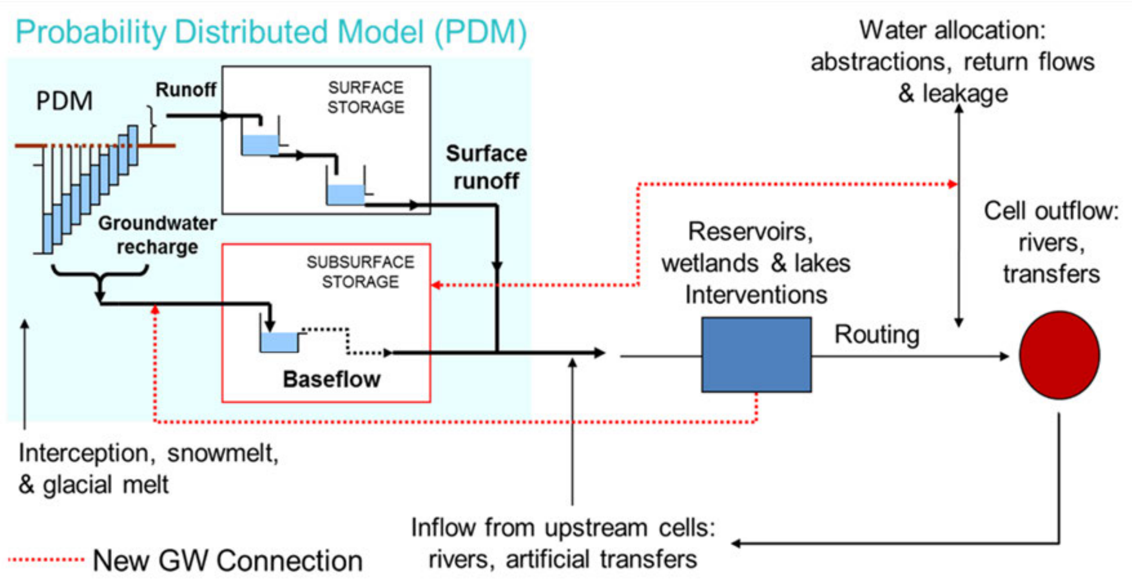



Figure 4.2 Schematic of the new groundwater (GW) connections and feedbacks included in the GWAVA model (Baron *et al.*, 2019)

The implementation of the fully coupled groundwater functionality with GWAVA is flexible. The necessary input is limited to the specific yield and water table depth. In areas where data is limited, the water table characteristics can be agglomerated into a single layer, whereas in regions with more comprehensive data, the water table can be divided into more layers (with no upper limit).

#### 4.3.2.2 Regulated Dams

In practice, dam operating rules are normally based on the specifications of each dam, the hydrometeorological conditions of the catchment, and the water demand downstream. Hanasaki *et al*. (2006) developed an algorithm to approximate dam-operating rules within global hydrological and land-surface models. The algorithm reflects these parameters and can be implemented with currently available global datasets (dam dimensions and purpose, simulated inflow, river discharge, water use, etc.). A dam operation scheme is a valuable tool in regions where specific data about the dam characteristics of the outflow volumes is not available. The algorithm consists of two equations. The first is used when a consistent dam release is expected (i.e. when used for hydropower or to meet domestic demand), and the second is for a seasonal release (i.e. when used for irrigation).

For consistent release dams, the operating rules are set to minimize inter-annual and seasonal dam releases. Hanasaki *et al*. (2006) present the equations as follows.

When the dam capacity divided by the mean annual inflow (c) is greater than 0.5:

$$r = \frac{S_{ini}}{0.85C} \times i_{mean} \qquad (4.2)$$

When the dam capacity divided by the mean annual inflow($c$) is less than or equal to 0.5:

$$r = \left(\frac{C}{0.5}\right)^2 \times \frac{S_{ini}}{0.85C} \times i_{mean} + \left[1 - \left(\frac{C}{0.5}\right)^2\right] \times i \qquad (4.3)$$

Where $r$ is the simulated dam release ($m^3/s$), $S_{ini}$ is the simulated storage at the beginning of the operational year ($m^3$), $C$ is the user input dam capacity ($m^3$), $i_{mean}$ is the simulated mean annual inflow ($m^3/s$) and, $i$ is the simulated daily inflow ($m^3/s$).

This algorithm has been successfully incorporated into H08 (Hanasaki *et al*., 2010) and influenced the dam routines of WATERGAP (Döll *et al*., 2016) and LPJmL (Chen & Wu, 2012) The scheme is simple and designed primarily to represent inter-annual and monthly fluctuations in dam release. This approach has been demonstrated to be largely valid, but because dam operations are highly complex and tend to be based on human decisions, there is inevitably a level of uncertainty associated with its application. The two new dam equations added to the GWAVA model are a simplified version of the Hanasaki equations (Hanasaki *et al*., 2006), while the existing dam routine is maintained as an option (Meigh *et al*., 1999). Since GWAVA can account for irrigation water demand within the transfers' routine, the equations for consistent dam release have been implemented. In the original Hanasaki equation, $i_{mean}$ was calculated as the mean inflow overall simulated years, as $S_{ini}$ accounted for inter-annual variability. In Equation 4.5, $i_{mean}$ has been changed to reflect the yearly mean inflow to introduce inter-annual variability.

When the dam capacity divided by the mean annual inflow ($c$) is greater than 0.5:

$$r = \alpha \times i_{am} \tag{4.4}$$

When the dam capacity divided by the mean annual inflow ($c$) is less than or equal to 0.5:

$$r = \alpha \times \beta \times i_{am} + [1 - \beta] \times i \tag{4.5}$$

Where $i_{am}$ are the mean yearly inflow (m$^3$/s), and $\alpha$ and $\beta$ are user-set parameters between 0-1, replacing $\frac{S_{ini}}{0.85C}$ and $(\frac{C}{0.5})^2$ from the original Hanasaki equations, respectively.

The user-set parameters can be manually calibrated to best fit either the observed streamflow at the next downstream gauging point of the dam or the reported dam outflow data. The addition of the regulated dam routine includes an additional two calibratable parameters ($\alpha$ and $\beta$) and thus does not increase the input data required to incorporate this routine.

### *4.3.3 Data Acquisition*

Input data were collected from several sources and global and regional datasets. The sources and details of the data used in this modelling exercise can be found in Table 4.3 and Table 4.4 in Appendix D.

### *4.3.4 Model Setup*

The Cauvery and Narmada Catchments were modelled at a spatial scale of 0.125 degrees using four different versions of the GWAVA model.

a) GWAVA- the original version of GWAVA (Meigh *et al*., 1999)
b) GWAVA-GW- the original version of GWAVA with groundwater coupling
c) GWAVA-Res- the original version of GWAVA with the regulated dams
d) GWAVA 5.1- the original version of GWAVA with both the groundwater coupling and regulated dams

A thirty-year simulation period from 1981 to 2010 was chosen. The Cauvery and Narmada Catchments were disaggregated into 444 and 653 modelling cells. Both catchments included domestic, irrigation and livestock demand (with the inclusion of industrial demand limited to the Cauvery due to data limitations in the Narmada), large-scale water transfers, hydropower dams, irrigation dams and agriculture within the command and rural areas.

### *4.3.5 Model Calibration*

Several calibration gauges were included within each catchment: 14 in the Cauvery and 13 in the Narmada (Figure 4.1). The simulated streamflow was calibrated against the observed streamflow using the SIMPLEX auto-calibration routine. This routine utilises four parameters (a surface and groundwater routing parameter, a PDM parameter that describes spatial variation in soil moisture capacity, and a multiplier to adjust rooting depths).

Available observed streamflow records were provided by India-WRIS for the period 1971 to 2014; however, the most complete streamflow records provided were between 1981 and 2010. Between 1971 and 1981, rainfall records from the monsoon season were missing at 87% of gauging sites. Data was provided for 7% of gauging sites between 2010 and 2014. It was thus decided that the calibration period would be from 1981 until 2010 to allow the greatest number of gauging stations to be included and to insure that the monsoon season rainfall was sufficiently represented.

The calibration gauges were selected based on the completeness of the data, the time period of the data, and the size of the sub-catchment. The observed data was deemed sufficient when more than 50% of the values were identified as ‘observed’ and not ‘computed’ and had at least five consecutive years available from 1981 until 2010. Additionally, sub-catchments smaller than 800 $km^2$ (six GWAVA grid cells) were nested into the larger sub-catchment in which they are located. The dam outflow parameters were manually calibrated. Table 4.1 presents the parameters for each dam that provided the best fit to either observed outflow data, where available, or downstream observed streamflow.

Table 4.1 Dam outflow parameters determined by a manual calibration for each major dam in the Cauvery and Narmada Catchments.

| **Dam** | **Catchment** | **Capacity ($10^9$ m$^3$)** | **Simulated average annual inflow ($10^{10}$ m$^3$/year)** | **c** | **Equation** | **α** | **β** |
|---|---|---|---|---|---|---|---|
| Hemavathy | Cauvery | 0.99 | 0.22 | 0.45 | 5 | 0.7 | 0.8 |
| KRS | Cauvery | 1.016 | 0.35 | 0.29 | 5 | 0.7 | 1 |
| Kabini | Cauvery | 0.44 | 0.15 | 0.29 | 5 | 0.1 | 1 |
| Bhavanisagar | Cauvery | 0.791 | 0.09 | 0.86 | 4 | 1 | |
| Mettur | Cauvery | 2.64 | 0.70 | 0.38 | 5 | 1 | 0.1 |
| Bargi | Narmada | 3.18 | 0.32 | 1.01 | 4 | 0.3 | |
| Barna | Narmada | 0.539 | 0.21 | 0.26 | 5 | 0.3 | 0.3 |
| Tawa | Narmada | 2.313 | 0.27 | 0.86 | 4 | 0.3 | |
| ISP | Narmada | 10 | 3.03 | 0.33 | 5 | 0.1 | 1 |
| OSP | Narmada | 0.987 | 1.40 | 0.07 | 5 | 0.1 | 1 |
| SSP | Narmada | 9.5 | 3.69 | 0.26 | 5 | 0.5 | 0.3 |
| Karjan | Narmada | 0.63 | 3.89 | 0.02 | 5 | 0.1 | 0.3 |

## 4.4 Model Evaluation

Due to the high streamflow variability in both the Cauvery and Narmada Catchments, several different metrics are used to quantify the model performance under various flow regimes. In this study, the KGE was used to determine the model's ability to represent the entirety of the hydrograph, the NSE to determine the model's performance in representing the high flow periods, the LNE was used to determine the model’s performance in representing the low flow periods, and the bias was used to evaluate the model ability to estimate the total volume of streamflow across the modelling period. The change in model skill was utilised to compare the performance of two model configurations (GWAVA and GWAVA-GW, GWAVA and GWAVA-Res, and GWAVA and GWAVA 5.1).

### *4.4.1 Kling-Gupta Efficiency (KGE)*

The KGE is based on correlation, variability bias and mean bias and is calculated as follows:

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_s}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_s}{\mu_o} - 1\right)^2} \quad (4.6)$$

where $r$ is the correlation coefficient between the simulated and observed data, $\sigma_o$ is the standard deviation of observation data, $\sigma_s$ is the standard deviation of the simulated data, $\mu_o$ is the mean of observation data, and $\mu_s$ is the mean of simulated data.

The KGE indicates the overall performance of the model. The metric allows some perceived shortcomings with NSE to be overcome and has become increasingly popular for evaluating hydrological model skill. A KGE of one indicates perfect agreement between simulations and observations. However, there are many opinions about where the differentiation of 'good' and '-poor' model performance thresholds lie within the KGE scale. Negative KGE values do not always imply that the model performs worse than the mean flow benchmark. For this study, and to compare model performance, a KGE score of less than 0.2 was deemed poor, between 0.2 and 0.6 as fair and above 0.6 as good.

### *4.4.2 Nash-Sutcliffe Efficiency (NSE)*

NSE is a popular metric to evaluate hydrological model performance because it normalises model performance into an interpretable scale and was calculated as the following:

$$NSE = 1 - \frac{\sum_{t=1}^{T}\left(Q_s^t - Q_o^t\right)^2}{\sum_{t=1}^{T}\left(Q_o^t - \overline{Q_o}\right)^2} \quad (4.7)$$

where $Q_s^t$ and $Q_o^t$ are, respectively, the simulated streamflow and the observed streamflow at time-step $t$; $\overline{Q_o}$ is the average observed streamflow over all timesteps considered.

An NSE of one represents a perfect correspondence between the simulations and observations. An NSE of zero indicates that the model simulations have the same explanatory power as the mean of the observations. An NSE of less than zero represents that the model is a worse predictor than the mean of the observations. However, NSE does not provide an equal benchmark for different flow regimes. Utilising the single NSE metric is not sufficient for determining the performance of a model; however, it can provide context if utilised in conjunction with additional model performance efficiencies. For this study, an NSE score of less than 0.2 was deemed poor, between 0.2 and 0.6 as fair and above 0.6 as good.

### *4.4.3 Log-Nash Efficiency (LNE)*

LNE is used for model evaluation when low-flow performance is of importance and was calculated as the following:

$$\mathrm{LNE} = 1 - \frac{\sum_{t=1}^{T}\left(Q_{s\_log}^{t} - Q_{o\_log}^{t}\right)^2}{\sum_{t=1}^{T}\left(Q_{o\_log}^{t} - \overline{Q_{o\_log}}\right)^2} \tag{4.8}$$

with

$$Q_{s\_log}^{t} = log_{10}(Q_s^t + c) \tag{4.9}$$

$$Q_{o\_log}^{t} = log_{10}(Q_o^t + c) \tag{4.10}$$

Where $Q_{s\_log}^{t}$ and $Q_{o\_log}^{t}$ are, respectively, the log of simulated streamflow and the log of observed streamflow at time-step *t*; $\overline{Q_{o\_log}}$ is the average of log-observed streamflow over all timesteps considered. *c* is a positive constant equal to the 10th percentile of the observed flow. The use of the constant *c* reduced emphasis on negligible flows, which tend to be unreliable, and avoids numerical problems with calculating the logarithm of zero flows. The LNE was interpreted in the same way as the NSE.

### *4.4.4 Bias*

The bias is the average tendency of the simulated data to over-or underestimate the observed data (Equation 4.11). The optimal value for the bias is zero. Positive values indicate a model underestimation, and negative values indicate an overestimation. When assessing a model's ability to simulate streamflow, the bias indicates the ability of the model to predict the overall streamflow volume across the modelling period.

$$Bias = \frac{\sum_{t=1}^{T}(y_o - y_s)}{\sum_{t=1}^{n} y_o} \times 100 \tag{4.11}$$

where $y_o$ is the observed data value, $y_s$ is the simulated data value, and t is the time-step.

### *4.4.5 Model Skill*

The change in model skill, Δskill, between the different model configurations for streamflow prediction was calculated as follows:

$$\Delta skill = \frac{R_2 - R_1}{R_{optimal} - R_1} \tag{4.12}$$

where $R_1$ and $R_2$ are the efficiency values (KGE, NSE or bias) for the two model configurations being compared, and $R_{optimal}$ is the best possible efficiency value for a given metric. A positive value of Δskill indicates that model configuration two performs better than model configuration one, a zero value suggests similar performance, and a negative value shows that model configuration two performs less well than model configuration one.

## 4.3 Results

### *4.3.1 Streamflow*

The ability of the four model versions to predict the observed streamflow was presented through the monthly KGE at each gauging station (Figure 4.3) to demonstrate the model's overall performance and an indication of the model's skill in representing the low flows (Figures 4.3 and 4.4). The monthly bias, NSE, KGE and LNE values for each sub-catchment for each model version can be found in Table 4.5 in Appendix D. The model performance was higher in the Narmada compared to the Cauvery. In the sub-catchments of the Cauvery and Narmada, GWAVA 5.1 outperforms GWAVA. However, the performance of GWAVA-GW and GWAVA-Res varies between the sub-catchments. As expected, in sub-catchments without major dams, GWAVA produced the same results as GWAVA-Res, and GWAVA-GW produced the same results as GWAVA 5.1. All the simulated flows for the sub-catchments in the Narmada are classified as 'good' in performance, except for the simulation of Belkeri without the groundwater routine, which was classified as 'fair' (Figure 4.3). In the Cauvery, the results are more varied, with eight sub-catchments classified as good and six sub-catchments as fair when using GWAVA 5.1. The performance of the downstream sub-catchments without the combination of groundwater and the regulated dam routine falls within the fair range (Figure 4.4).

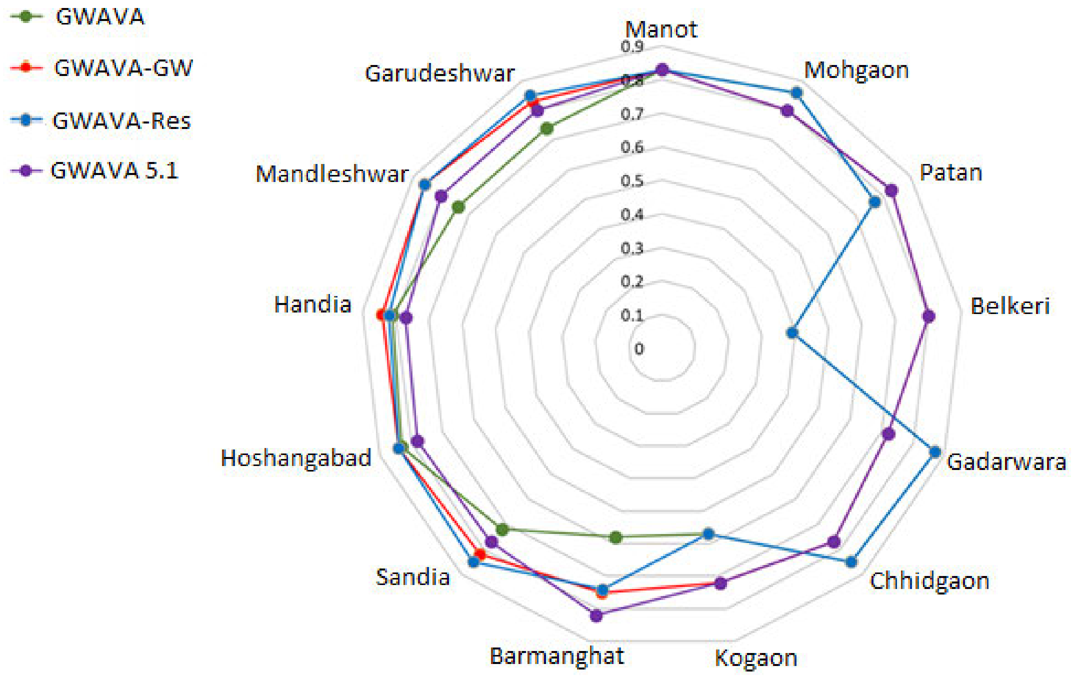



Figure 4.3 A representation of the monthly KGE values obtained for each model at each gauging station within the Narmada Catchment. The values on the y-axis represent the KGE value.

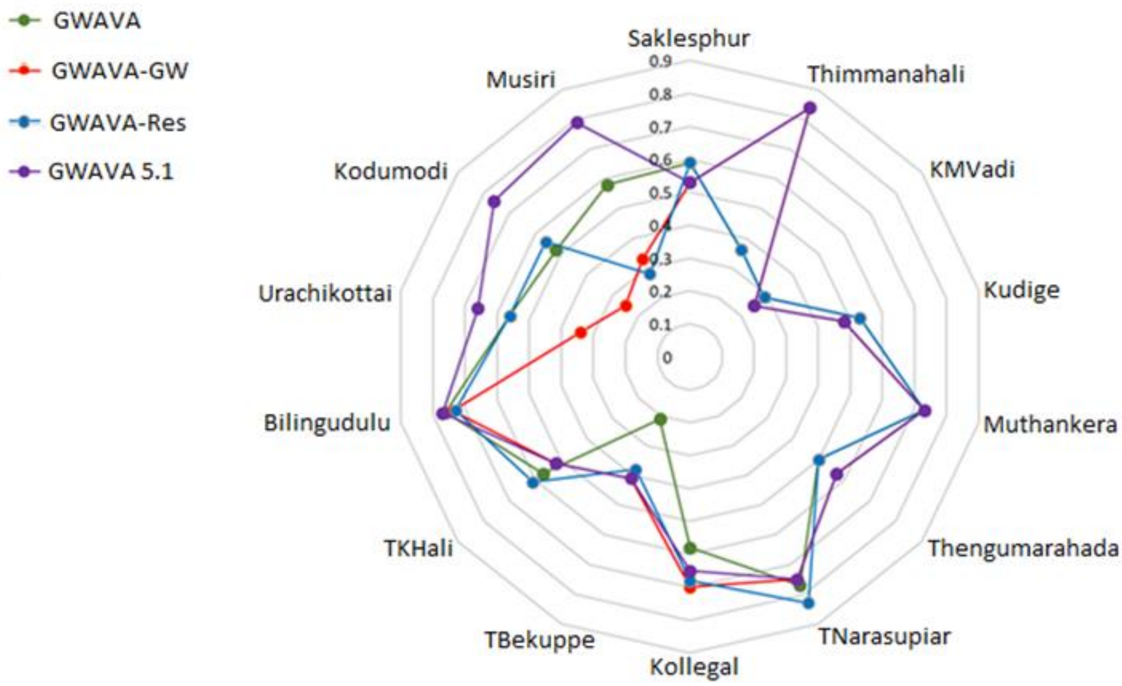



Figure 4.4 A representation of the monthly KGE values obtained for each model at each gauging station within the Cauvery Catchment. The values on the y-axis represent the KGE value

The ability of the model to represent the low flow periods well is critical in catchments that suffer from water scarcity. In the Cauvery Catchment, the aggressive pumping of groundwater limits the baseflow released from the groundwater store to sustain the streamflow in the dry season, and the large dams store and release water in contrast to the seasonal patterns. Including groundwater feedback in GWAVA improves the simulation of the low flows within the headwater sub-catchments, which is critical for assessing water resources and surface water-groundwater interactions (Figure 4.5iii). The incorporation of the regulated dam module allows for the release of water in the dry season. The dam module markedly improves the simulation downstream of these major dams in the Cauvery (Figure 4.5ii). The combination of the groundwater processes and inclusion of the regulated dams improves the ability of GWAVA to represent the low flows throughout the catchment (Figure 4.5i).

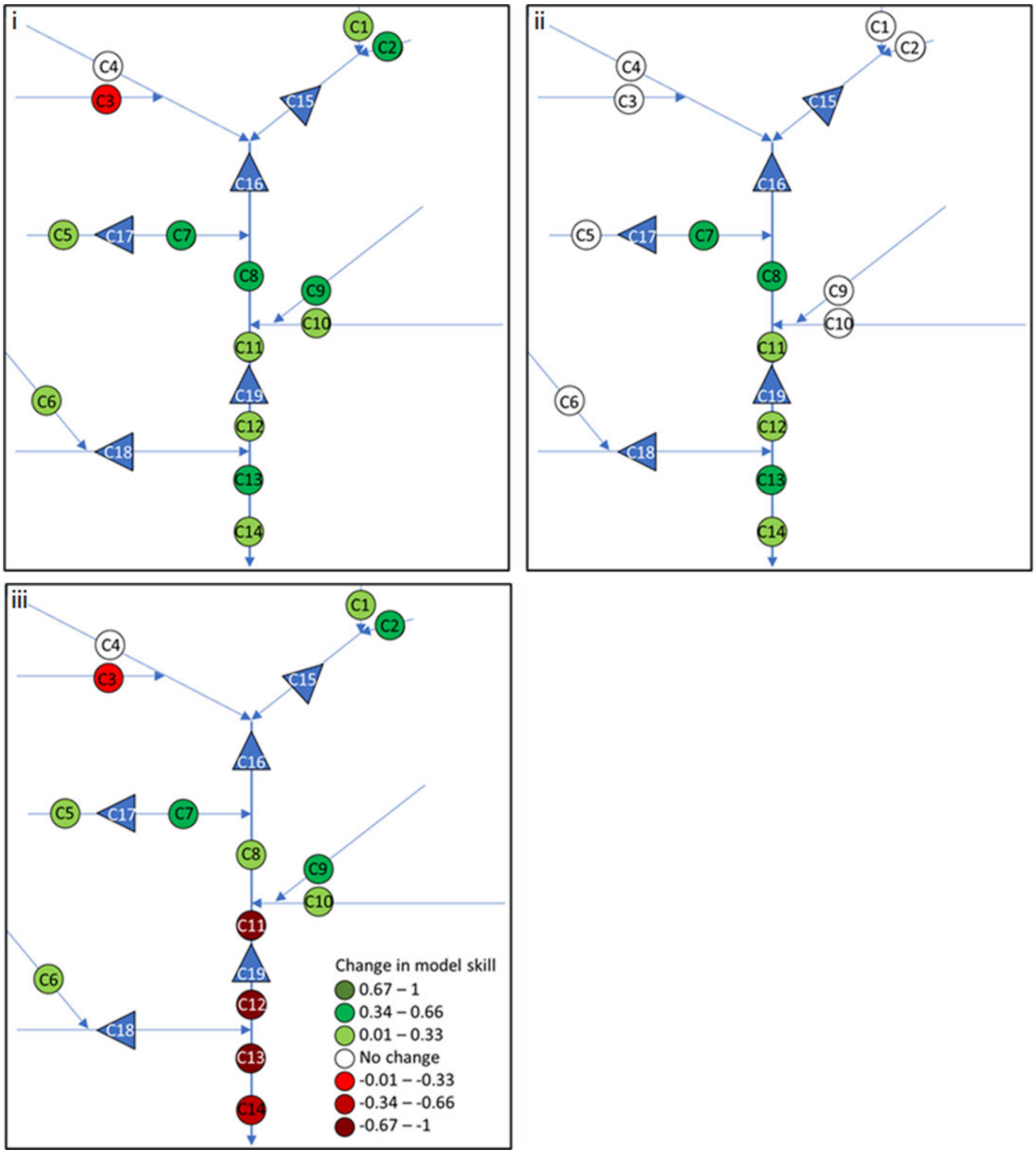



Figure 4.5 A representation of the low-flow model skill for each sub-catchment in the Cauvery Catchment for the i) GWAVA 5.1, ii) GWAVA-Res and iii) GWAVA- GW versions, compared to GWAVA.

The Narmada River is primarily groundwater-fed following the monsoon. Understanding the baseflow contribution to streamflow and the impact that the large dams have on the dry season flow poses a challenge for water managers. The inclusion of the groundwater module improves the model's representation of the low flows within the headwater sub-catchments (Figure 4.6iii). The inclusion of the groundwater processes allows the model to retain water within the groundwater store better and release baseflow throughout the year. The large dams within the Narmada consistently release water through the hydropower plants. Thus the incorporation of the regulated dam routine allows the model to release water from the dams throughout the year. The regulated dam routine better matches the observed low flow data periods compared to results using the original GWAVA dam routine (Figure 4.6ii). The dual incorporation of the groundwater processes and the regulated dam routine better represent the low flow periods across the catchment (Figure 4.6i).

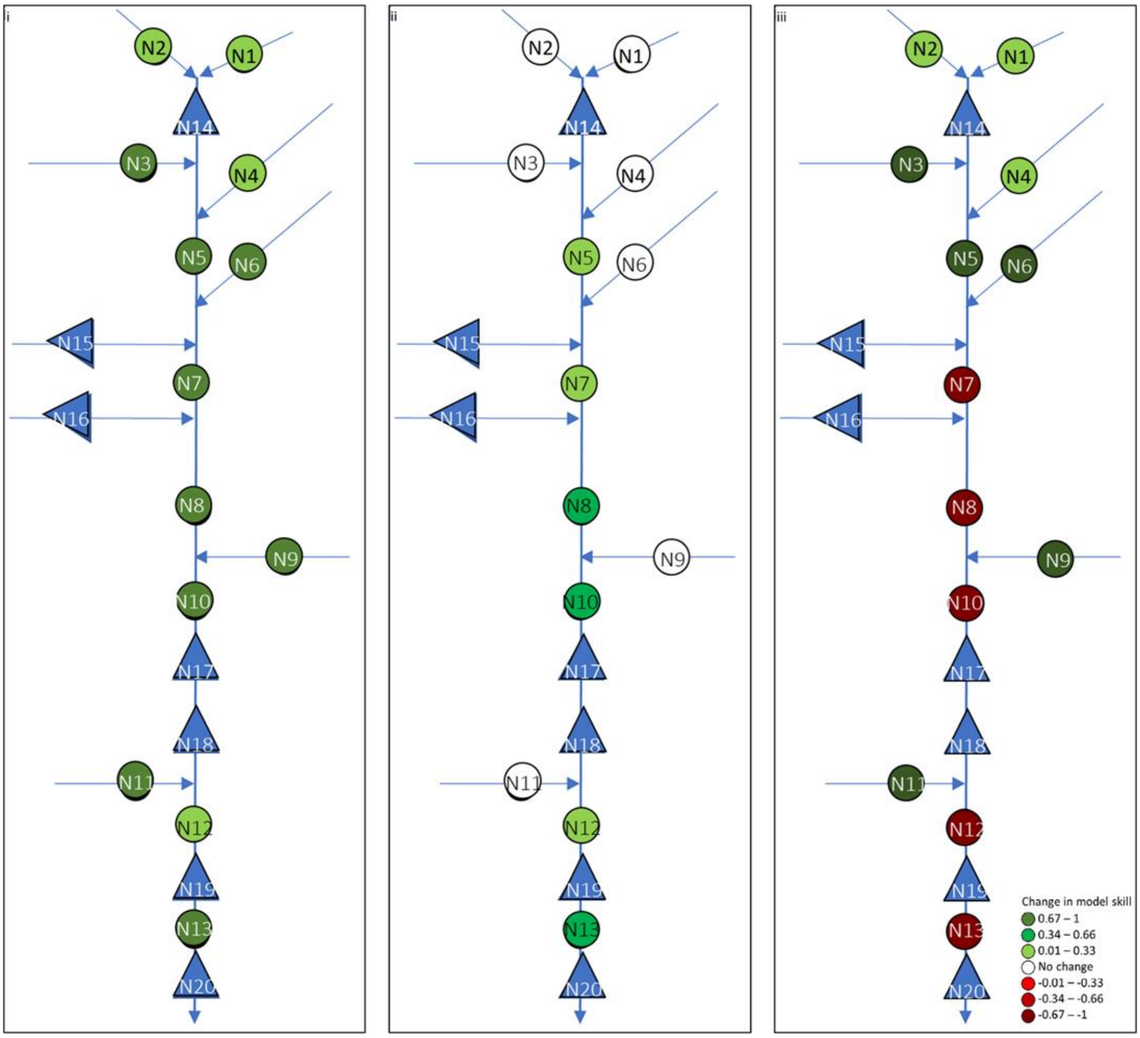


Figure 4.6 A representation of the low-flow model skill for each sub-catchment in the Narmada Catchment for the i) GWAVA 5.1, ii) GWAVA-Res and iii) GWAVA-GW versions compared to GWAVA.

### *4.3.2 Groundwater*

The average observed depth to groundwater (measured from ground level) is deeper in the Cauvery than in the Narmada (Figure 4.7). In the Cauvery, the wetter, more pristine sub-catchments along the western boundary (Western Ghats) have a shallower observed groundwater level (5 to 10 meters below ground level). In comparison, the groundwater level deepens (11 to 35 meters below ground level) throughout the remainder of the catchment. In the Cauvery, GWAVA 5.1 can represent shallower groundwater levels with higher accuracy than the deeper levels; however, it systematically overestimates the depth of groundwater throughout the catchment. The average observed groundwater depth within the Narmada Catchment is no deeper than 10 meters below the ground level. GWAVA 5.1 can represent the average groundwater levels well throughout the sub-catchments, with the observed average differing a maximum of two meters from the simulated average in the most downstream sub-catchment. The representation was more accurate in the upstream sub-catchments where the water table is shallower, and the landscape is less degraded.

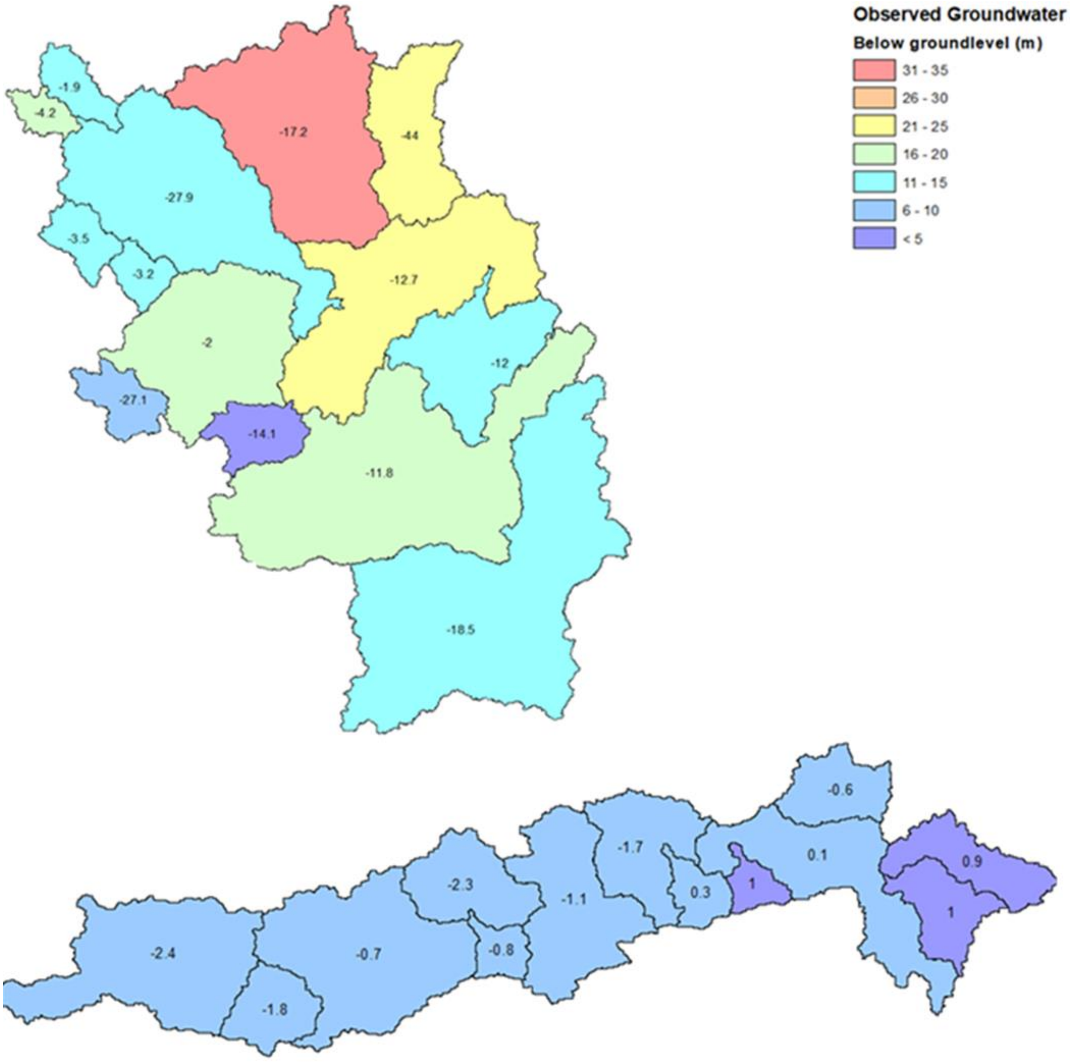



Figure 4.7 Average observed groundwater levels below ground level (legend), and the difference between the observed and GWAVA 5.1 simulated groundwater levels in meters (numerical values on maps) from 1981 to 2010 for the Narmada and Cauvery Catchments.

### *4.3.3 Dams*

In the Narmada, GWAVA represents the daily dam releases well but overestimates the total volume of water released at Bargi, Tawa and SSP (Table 4.2). The inclusion of the regulated dam routine in the Narmada did not significantly improve the daily release representation but did improve the total volume of water being released over the simulation period. In the Cauvery, GWAVA represents the daily release well at Kabini and KRS but poorly at Mettur. The total volume of water released from the major dams in the Cauvery is underestimated. When applying the regulated dam routine, the daily releases and total volume of water released are significantly improved (Table 4.2).

Table 4.2 The percent bias and daily NSE at the outlets of the major dams for GWAVA and GWAVA-Res

| **Dam Outlet** | **Bias (%)** | | **Daily NSE** | |
|---|---|---|---|---|
| | **GWAVA** | **GWAVA-Res** | **GWAVA** | **GWAVA-Res** |
| Bargi | 17.8 | 3.2 | 0.53 | 0.62 |
| Tawa | 7.57 | 0.4 | 0.74 | 0.7 |
| SSP | 16.09 | 4.35 | 0.62 | 0.65 |
| Kabini | -13.45 | 3.64 | 0.37 | 0.59 |
| KRS | -33.69 | -15.43 | 0.38 | 0.52 |
| Mettur | -4.69 | 9.35 | -0.25 | 0.39 |

The application of the regulated dam routine better represents the annual dam releases throughout the observational time period at Kabini, Tawa, KRS and SSP (Figure 4.8). At Bargi, GWAVA-Res simulates the normal and dry years better than GWAVA but underestimates the annual releases in wet years (Figure 4.8). The annual releases were improved until 1995 at Mettur dam, but following 1995, GWAVA-Res had a better temporal pattern and GWAVA a better representative release volume (Figure 4.8). Although the annual volume at Mettur was better represented by GWAVA, at the daily scale, GWAVA-Res can capture the regulated dam pattern significantly better than GWAVA (Figure 4.9).

GWAVA 5.1 represents the daily dam capacity during the monsoon period well at Tawa and SSP. The model was depleting the dam storage through irrigation demand during the dry seasons, which was not reflected in the observed data. The filling and release temporal patterns were good at Tawa, accurately reflecting the observational data (Figure 4.10). At SSP, the model tends to reach full capacity and begin releasing water earlier in the monsoon than suggested by the observed data (Figure 4.10). At KRS, the observed data show a depletion or near-depletion of dam storage during the dry season. The model, however, overestimated the volume of water remaining in the dam during these times. GWAVA 5.1 does not capture the 2002-2003 drought period particularly well in the upper regions of the catchment (Figure 4.10). At the Mettur Dam, the model produces a satisfactory temporal pattern; however, it overestimates the volume in the dry season and underestimates in the monsoon. The model in this dam better captured the 2002-2003 drought compared to the upper regions of the catchment (Figure 4.10).

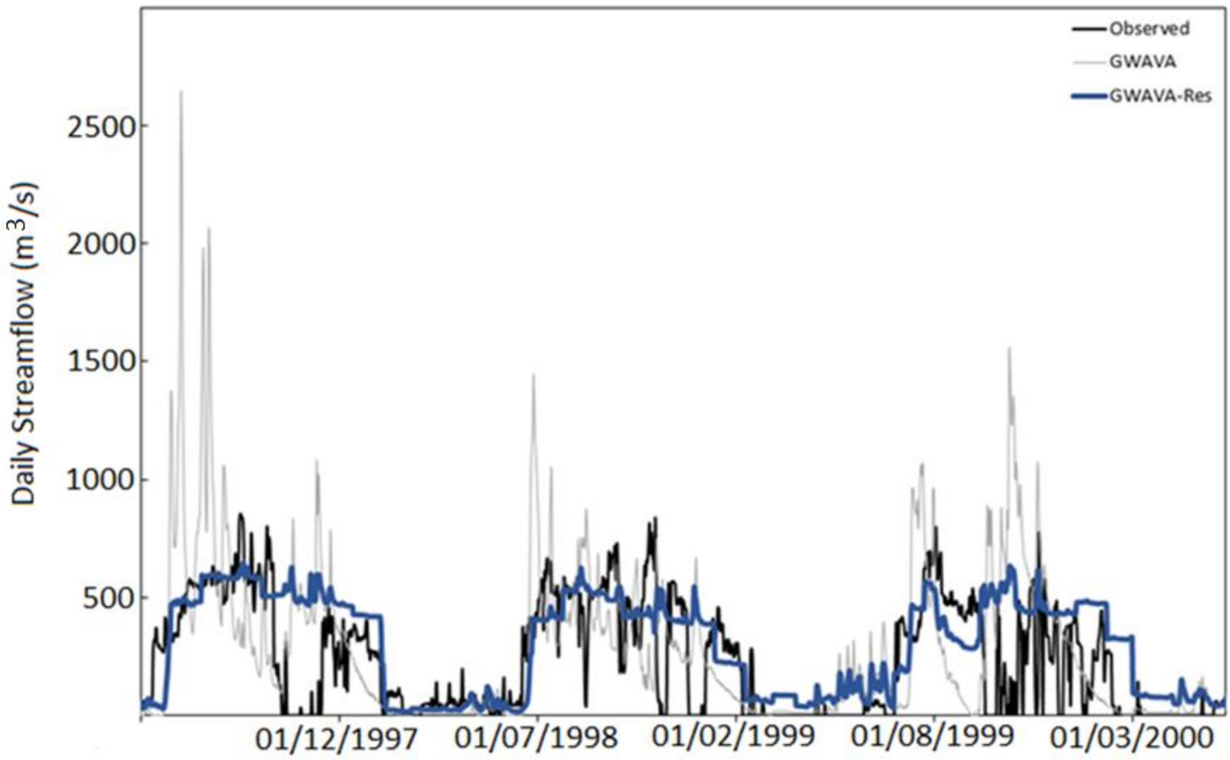



Figure 4.8 Daily observed and GWAVA and GWAVA-Res simulated dam outflows at the outflow of Mettur Dam.

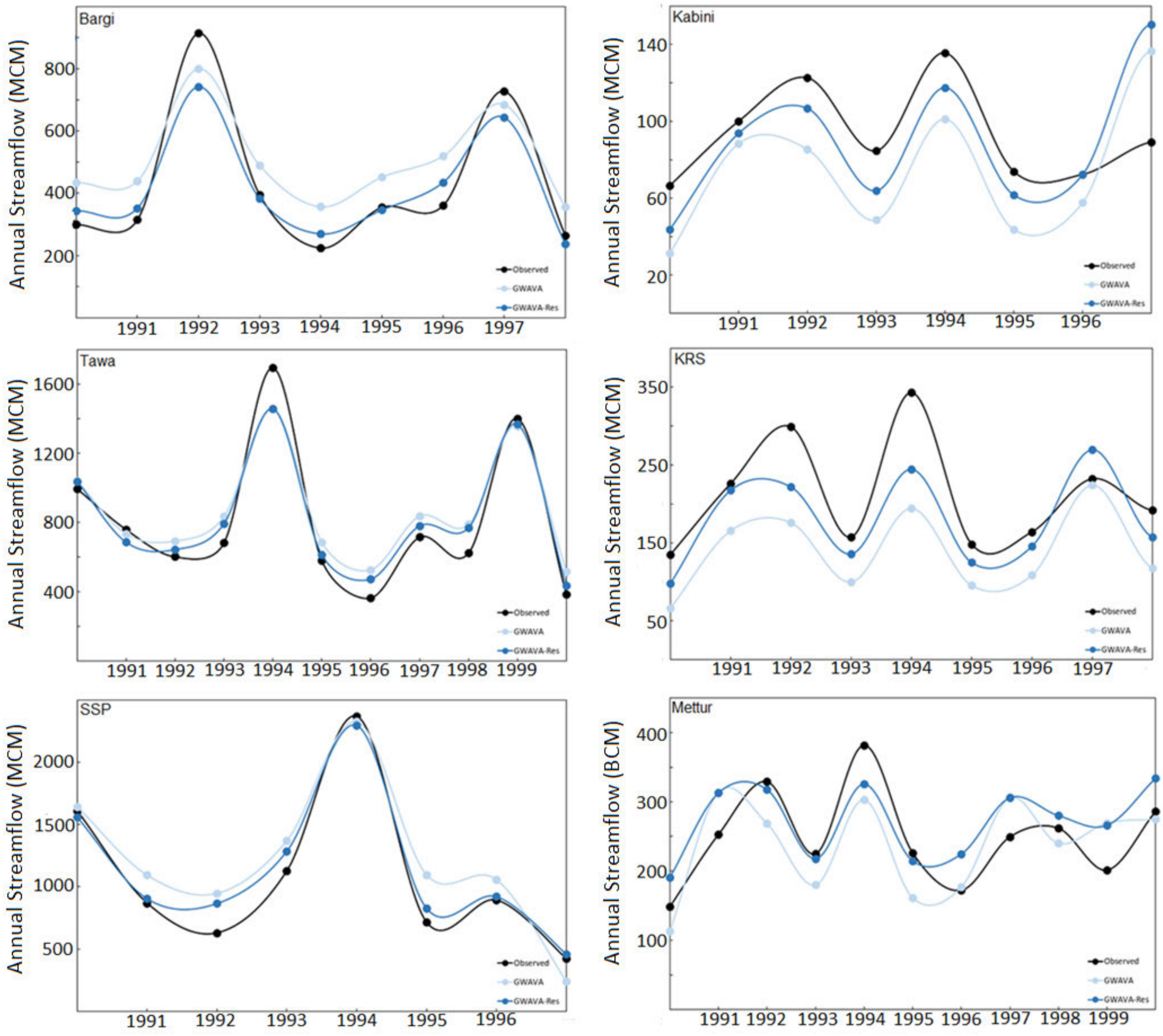



Figure 4.9 Annual observed and GWAVA and GWAVA-Res simulated dam releases at the outflow of Bargi, Tawa, SSP, Kabini, KRS and Mettur dams in million (MCM) and billon (BCM) cubic meters.

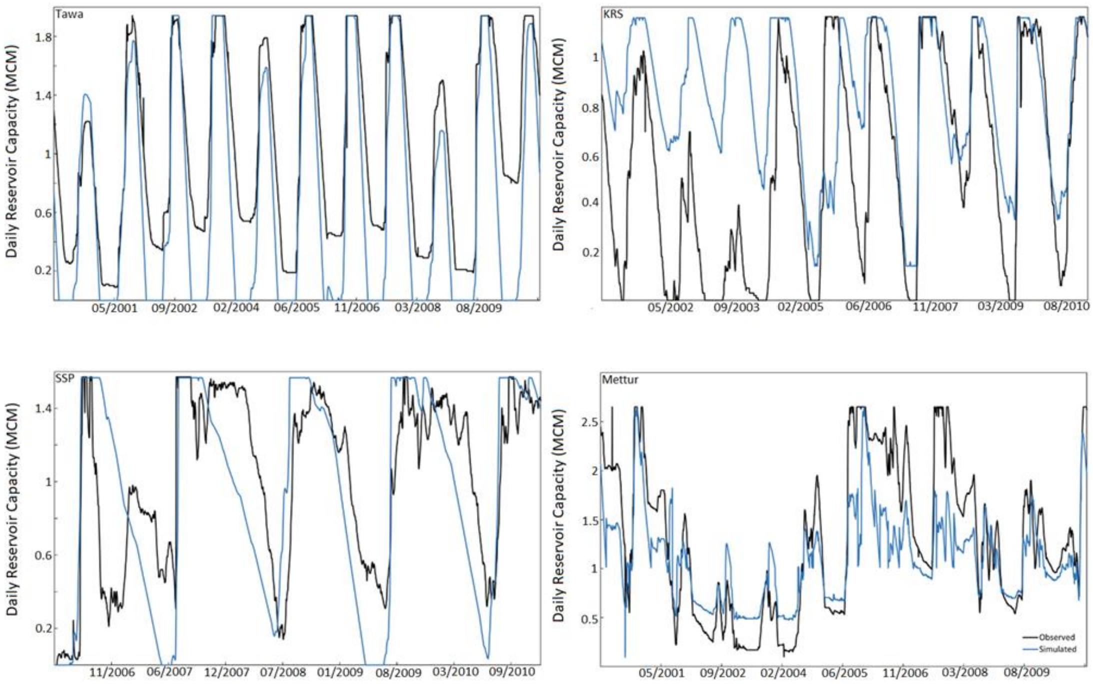



Figure 4.10 Observed and GWAVA 5.1 simulated daily dam storage in million cubic meters for Tawa, KRS and Mettur, and billion cubic meters for SSP across varying periods for which observed data were available.

### 4.4 Discussion

Revising the groundwater routine allows for the traceability of recharge, baseflow, groundwater levels and volume of abstraction from groundwater resources. The regulated dam routine provides for a release from the major dams throughout the year and the output of dam storage capacity throughout the simulation period. The improved groundwater and dam routines were included in the GWAVA model, with the addition of three and two input parameters, respectively.

The inclusion of the revised groundwater routine improved streamflow simulation in the headwater sub-catchments, while the new dam routine improved the simulation of streamflow in sub-catchments downstream of major dams in both the Cauvery and Narmada. The regulated dam routine improves the timing and volume of releases from major dams. In line with GWAVA 5.1, revisions to the dam routines in SWAT (Wu & Chen, 2012), DHSVM (Zhao *et al*., 2016), VIC (Wang *et al*., 2019), MESH (Tefs *et al.*, 2021) and HYPE (Meigh *et al*., 1999) improved representation and parameterization of major operational dam outflows, illustrating that such revisions in large-scale models can be of benefit to both the temporal and volumetric simulation of streamflow downstream of dams. GWAVA 5.1 can track the dam capacity throughout the simulation period. In the Narmada, the seasonality and filling of Tawa and SSP are well represented; however, the model was drying out the dams each year, which was not reflected in reality. It is, therefore, necessary to introduce a user-defined limit into the dam routine to restrict extraction and release below a realistic dam level. In the Cauvery, at KRS, the opposite was occurring. The observed dam levels are reducing to empty each year, but the model simulated water in the dams during this time. At the Mettur Dam, the daily dam capacity was highly sensitive to the volume of inflow. Although the temporal pattern was adequate, the model overestimated the volume of water in the dam during the dry season but underestimated the volume during the monsoon.

The streamflow in the Narmada is primarily base flow fed (Thomas *et al.*, 2021), and groundwater pumping is limited to periods of drought. The groundwater tends to fluctuate within ten meters of the ground level. The model accurately represented the average groundwater depth within two meters of the observed average over the simulation period. The inclusion of more comprehensive groundwater processes within the model structures allows for a more accurate simulation of the hydrograph within the Narmada, especially during the dry season.

Thomas *et al.* (2021) applied SWAT in the Upper Narmada. This study allowed irrigation demands to be met from shallow and deep water table stores. The dam simulation required the engineering particulars of the dam and inflows into the dam to estimate the probable flow at 50%, 75% and 90% dependability for different months. In the headwater sub-catchments, GWAVA and GWAVA 5.1 outperform SWAT in the prediction of streamflow. The original and revised groundwater routines with the original dam equation perform well within these sub-catchments where the dams are small and the steep topography results in the overland flow being the dominant streamflow generation process. At Barmanghat, downstream of Bargi Dam (regulated dam) and with a more considerable base flow contribution, SWAT performs better than GWAVA, but with the inclusion of the more comprehensive groundwater and regulated dams, GWAVA 5.1 performs better than SWAT.

Goswami and Kar (2018) represented the full extent of the Narmada catchment using a version of SWAT where groundwater flow contribution to streamflow was simulated by routing through a shallow water table store but with no considerations for dams within the catchment.

GWAVA-GW and GWAVA 5.1 significantly outperform SWAT in streamflow prediction at Garudeshwar. Pechlivanidis and Arheimer (2015) applied India-HYPE in the Narmada catchment using a 15-parameter dam routine and a comprehensive, multi-parameter groundwater routine. All the versions of GWAVA presented in this study out-performers India-HYPE at Garudeshwar. The average groundwater depth estimations by GWAVA 5.1 in the Hoshangabad district of Madhya Pradesh are consistent with those simulated using a conceptual groundwater model by Nema *et al*. (2019).

The satisfactory performance of GWAVA 5.1 to represent streamflow, groundwater levels and dam fluxes throughout the catchment, compared with observed data and existing literature, demonstrates the value of the simple, low-input routines incorporated into GWAVA. Therefore, the inclusion of groundwater processes and regulation dams was justified when modelling catchments with natural and anthropogenic characteristics similar to that of the Narmada.

In the upper regions of the Cauvery, ANN (Maheswaran & Khosa, 2012; Patal & Ramachandran, 2015), SWAT (Horan *et al*., 2021a) and VIC (Horan *et al*., 2021a) outperform both GWAVA and GWAVA 5.1. However, the performance of GWAVA was improved when the groundwater routine was applied to this region. GWAVA 5.1 underestimated the water table level across the catchment. Collins *et al*. (2020) showed largely under-simulated groundwater levels compared to the observed data in the Berambadi sub-sub-catchment of the Cauvery using a one-dimensional numerical transect model. It was suggested that a poor representation of the IMD rainfall in this region is a critical part of the poor simulations of both recharge to groundwater and streamflow in this region (Horan *et al*., 2021b).

Quantifying and managing uncertainty is a significant challenge in large-scale modelling. The model structure allocates water to the evaporative component first; thus, the evaporative processes are favoured in times of water stress. This could also be one of the fundamental reasons for the underestimation of streamflow during the dry season. Additionally the use of the Hargreaves evaporation estimation method, which is known to overestimate the evaporation in regions of high temperatures (Shahidian *et al*., 2012), humid conditions (Bertie *et al.*, 2014) and significant commercial forestry (Bourletsikas *et al*., 2018), could have contributed to the underestimation of streamflow in models that consider the water balance.

The one-dimensional groundwater representation may not represent the groundwater processes in regions with highly depleted water tables and gneiss geomorphology or underlying shale. The non-uniformity of the groundwater observation network in the Narmada and Cauvery is a source of uncertainty for the accurate calibration of the model. The conversion of point well data to a spatial average could be a significant source of uncertainty as groundwater levels tend to be highly dynamic across small areas.

The simplified approach to representing the outflows of the regulated dams has proven largely valid but inevitably carries uncertainty as actual dam operations are more complex and highly individual. Although a more complex module could have been incorporated, data availability and the fundamental low data principle of GWAVA were carefully considered. The performance of the modified Hanasaki routine is largely dependent on the quality of the observed dam outflow or downstream streamflow used in the calibration. In regions of poor data quality, the performance of the routine could be compromised. Although the routine utilises daily inflows and consistently updates the dam storage, determining two parameters that influence the dam outflow over some time could cause stationarity issues when modelling future periods.

Uncertainty arises from observation station mechanical errors, spatial distribution, and various spatial and temporal interpolation methods. At some gauging points in the catchment, there is low confidence in the observed streamflow and dam outflow data. On occasion, the dam outflow data does not resemble streamflow records in close proximity downstream. Eye-witness accounts and some literature report drying out of streams in the dry season, which is not reflected in the observed data. Additionally, in reality, rivers downstream of significant urban and agricultural areas are often fed by a perennial stream of human or livestock sewage (Horan *et al*., 2021b). Although the model represents return flows from domestic demand, this may be underestimated compared to the volume of effluent being released into these rivers in reality. The IMD gridded rainfall and temperature data are provided in a 0.5-degree grid. Each 0.5-degree grid cell contains numerous terrain and gradient increments, and the grid cells may fall over the catchment boundary. This results in an inaccurate representation of the distribution and total rainfall and the distribution of minimum and maximum temperature in this region of the catchment (Horan *et al*., 2021a; Horan *et al*., 2021b). A known source of uncertainty within the Western Ghats region acts as the headwaters for the larger Cauvery Catchment.

GWAVA 5.1 potentially overestimates water withdrawals in catchments, particularly in the Cauvery, where the exact anthropogenic water use was uncertain and poorly documented. The depth of groundwater depends on the estimated water withdrawal of the region. The potential overestimation of demand could cause the early or complete depletion of wells not reflected in reality. The cost and availability of electricity are not considered within GWAVA and thus do not form realistic constraints when modelling the processes of groundwater abstraction. The underestimation of the groundwater levels and subsequent base flow component hinders the ability of the model to accurately represent the streamflow. There was low confidence in the data concerning the pumping depth and observed groundwater level data in this region (Bhave *et al*., 2018; Hora *et al*., 2019).

When improving a low-data input hydrological model, such as GWAVA, caution must be taken to not complicate the model beyond its underlying capability. The improvements to GWAVA utilising simple modified routines demonstrate that adapting existing hydrological models can be suitable for the improvement in the reliability of streamflow, dam, and groundwater prediction.

## 4.5 Conclusions

Robust simulations of groundwater availability and dam storage and releases are important for water resource management in semi-arid catchments where the groundwater was an important water source during the dry season, and the streamflow in the main channel of the lower reaches was largely dam-regulated.

The main conclusions from this study are:

a) Key components of GWAVA were improved to better represent water management while maintaining low input data requirements and model complexity
b) The model improvements successfully improved model performance in both the Narmada and Cauvery catchments.
c) Simulated groundwater and dam storage levels were output to gain further insight into components of the catchment water balance.

Although these simplified routines improve the model performance throughout the catchment, it is recommended that further application in a wider geographic area is necessary to ensure the routines' suitability represents a range of catchment characteristics. Investigation into multiple parameter configurations would assist in quantifying uncertainty and potentially improve abstractions and release parameters.

## 4.6 References

Allen DM.; Cannon AJ.; Toews MW, Scibek J. Variability in Simulated Recharge Using Different GCMS. *Water Resources Research*. 2010, *46.*

Baron, H.; Keller, V.; Simpson, M.; Collins, S.; Jackson, C and Muddu, D.; Extending the GWAVA Model to Better Represent Water Resources in the Cauvery Basin, in Sustainable Water Futures, Bangalore, 2019.

Berti, A., Tardivo, G., Chiaudani, A., Rech, F. and Borin, M.; Assessing reference evapotranspiration by the Hargreaves method in north-eastern Italy. *Agricultural Water Management*, 2014, *140*, 20-25.

Beven, K. A Manifesto for the Equifinality thesis. J. Hydrol. 2006, *320*, 18–36.

Bhave, A.G.; Conway, D.; Dessai, S.; Stainforth, D.A. Water Resource Planning Under Future Climate and Socioeconomic Uncertainty in the Cauvery River Basin in Karnataka, India. *Water Resources Research*. 2018, *54*, 708-728.

Bhuvaneswari, K.; Geethalakshmi, V.; Lakshmanan, A.; Srinivasan, R.; Sekhar, N.U. the Impact of El Nino/Southern Oscillation on Hydrology and Rice Productivity in the Cauvery Basin, India, Application of the Soil and Water Assessment Tool. *Weather and Climate Extremes*. 2013, *2*, 39-47.

Biemans, H.; Haddeland, I.; Kabat, P.; Ludwig, F.; Hutjes, R.W., Heinke, J.; Von Bloh, W., Gerten, D. Impact of Reservoirs on River Discharge and Irrigation Water Supply During the 20th Century. *Water Resources Research*. 2011, *47*.

Bourletsikas, A., Argyrokastritis, I. and Proutsos, N.; Comparative evaluation of 24 reference evapotranspiration equations applied on an evergreen-broadleaved forest. *Hydrology Research*, 2018, *49*, 1028-1041.

Burek, P.; Satoh, Y.; Kahil, T.; Tang T.; Greve P.; Smilovic M.; Guillaumot L.; Zhao F.; Wada Y. Development of the Community Water Model (Cwatm V1. 04)–A High-Resolution Hydrological Model for Global and Regional Assessment of integrated Water Resources Management. *Geoscientific Model Development*. 2020, *13*, 3267-3298.

Chen, J.; Wu, Y. Advancing Representation of Hydrologic Processes in the Soil and Water Assessment Tool (SWAT) Through the integration of the topographic MODEL (TOPMODEL) Features. *Journal of Hydrology*. 2012, *420*, 319-328.

Clark, M.P.; Fan, Y.; Lawrence, D.M.; Adam, J.C.; Bolster, D.; Gochis, D.J.; Hooper, R.P.; Kumar, M.; Leung, L.R.; Mackay, D.S.; Maxwell, R.M. Improving the Representation of

Hydrologic Processes in Earth System Models. *Water Resources Research.* 2015, *51*, 5929-5956.

Collins SL.; Loveless SE.; Muddu S.; Buvaneshwari S.; Palamakumbura RN.; Krabbendam M.; Lapworth DJ.; Jackson CR.; Gooddy DC.; Nara SN.; Chattopadhyay S. Groundwater Connectivity of a Sheared Gneiss Aquifer in the Cauvery River Basin, India. *Hydrogeology Journal*. 2020, *28*, 1371-1388.

De Bruin, A.; De Condappa, D.; Mikhail, M.; Tomer, S.K.; Sekhar, M.; Barron, J. Simulated Water Resource Impacts and Livelihood Implications of Stakeholder-Developed Scenarios in the Jaldhaka Basin, India. *Water international*. 2012, *37*, 492-508.

Döll, P.; Douville, H.; Güntner, A.; Schmied, H.M.; Wada, Y. Modelling Freshwater Resources at the Global Scale, Challenges and Prospects. *Surveys in Geophysics*. 2016, *37*, 195-221.

Döll, P.; Kaspar, F.; Lehner, B. A Global Hydrological Model for Deriving Water Availability indicators, Model Tuning and Validation. *Journal of Hydrology*. 2003, *270*, 105-134.

Downing, J.A.; Prairie, Y.T.; Cole, J.J.; Duarte, C.M.; Tranvik, L.J.; Striegl, R.G.; Mcdowell, W.H.; Kortelainen, P.; Caraco, N.F.; Melack, J.M.; Middelburg, J.J. the Global Abundance and Size Distribution of Lakes, Ponds, and Impoundments. *Limnology and Oceanography*. 2006, *51*, 2388-2397.

Droppers, B.; Franssen, W.H.; Van Vliet, M.T.; Nijssen, B.; Ludwig, F. Simulating Human Impacts on Global Water Resources Using VIC-5. *Geoscientific Model Development.* 2020, *13*, 5029-5052.

Falkenmark, M.; Molden, D. Wake Up to Realities of River Basin Closure. *International Journal of Water Resources Development*. 2008, *24*, 201-215.

Famiglietti, J.S. the Global Groundwater Crisis. *Nature Climate Change*. 2014, *4*, 945-948.

Fischer G.; Nachtergaele F.; Prieler S.; Van Velthuizen H.; Verelst L and Wiberg D.; Global Agro-Ecological Zones Assessment for Agriculture, Laxenburg, Austria, 2008, P. 26–31.

Gajbhiye, S.; Mishra, SK.; Pandey, A. Effects of Seasonal/Monthly Variation on Runoff Curve Number for Selected Watersheds of Narmada Basin. *International Journal of Environmental Sciences*. 2013, *3*, 2019-2030.

Geetha, K.; Mishra, S.K.; Eldho, T.I.; Rastogi, A.K.; Pandey, R.P. SCS-CN-Based Continuous Simulation Model for Hydrologic forecasting. *Water Resources Management*. 2008, *22*, 165-190.

Gosain, A.K.; Rao, S.; Basuray, D. Climate Change Impact Assessment on Hydrology of Indian River Basins. *Current Science*. 2006, *90*, 346-353.

Goswami SB.; Kar SC. Simulation of Water Cycle Components in the Narmada River Basin by forcing SWAT Model with CFSR Data. Meteorology Hydrology and Water Management. *Research and Operational Applications*. 2018, *6*, 13-25.

Gupta, H.; Chakrapani, G.J. Temporal and Spatial Variations in Water Flow and Sediment Load in Narmada River Basin, India, Natural and Man-Made Factors. *Environmental Geology*. 2005, *48*, 579-589.

Haddeland, I.; Skaugen, T.; Lettenmaier, D.P. Anthropogenic Impacts on Continental Surface Water Fluxes. *Geophysical Research Letters*. 2006, *33*.

Hanasaki, N.; Inuzuka, T.; Kanae, S.; Oki, T. An Estimation of Global Virtual Water Flow and Sources of Water withdrawal for Major Crops and Livestock Products Using a Global Hydrological Model. *Journal of Hydrology*. 2010, *384*, 232-244.

Hanasaki, N.; Kanae, S.; Oki, T. A Reservoir Operation Scheme for Global River Routing Models. *Journal of Hydrology*. 2006, *327*, 22-41.

Hanasaki, N.; Kanae, S.; Oki, T.; Masuda, K.; Motoya, K.; Shirakawa, N.; Shen, Y.; Tanaka, K. An integrated Model for the Assessment of Global Water Resources–Part 1, Model Description and input Meteorological forcing. *Hydrology and. Earth Systems Science*. 2008, *12*, 1007-1025.

Hanasaki, N.; Yoshikawa, S.; Pokhrel, Y.; Kanae, S. A Global Hydrological Simulation to Specify the Sources of Water Used by Humans. *Hydrology and. Earth Systems Science.* 2018, *22*, 789-817.

Harbaugh, A.W. MODFLOW-2005, the US Geological Survey Modular Ground-Water Model, the Ground-Water Flow Process. Reston, VA.; US Department of the interior, US Geological Survey, 2005.

Hoekstra, A,Y.; Mekonnen, M.M.; Chapagain, A.K.; Mathews, R.E.; Richter, B.D. Global Monthly Water Scarcity, Blue Water Footprints versus Blue Water Availability. *PloS one*. 2012, *7*, E32688.

Hora T.; Srinivasan V.; Basu NB. the Groundwater Recovery Paradox in South India. *Geophysical Research Letters*. 2019, *46*, 9602-9611.

Horan, R.; Gowri, R.; Wable, P.S.; Baron, H.; Keller, V.D.; Garg, K.K.; Mujumdar, P.P.; Houghton-Carr, H.; Rees, G. A Comparative Assessment of Hydrological Models in the Upper Cauvery Catchment. *Water*. 2021, *13*, 151.

Horan, R.; Wable, P.S.; Srinivasan, V.; Baron, H.E.; Keller, V.J.; Garg, K.K.; Rickards, N.; Simpson, M.; Houghton-Carr, H.A.; Rees, H.G. Modelling Small-Scale Storage Interventions in Semi-Arid India at the Basin Scale. *Sustainability*. 2021,*13*, 6129.

Jain, S.K.; Storm, B.; Bathurst, J.C.; Refsgaard, J.C.; Singh, R.D. Application of the SHE to Catchments in India Part 2. Field Experiments and Simulation Studies with the SHE on the Kolar Subcatchment of the Narmada River. *Journal of Hydrology*. 1992, *140*, 25-47.

Khare, D.; Patra, D.; Mondal, A.; Kundu, S. Impact of Landuse/Land Cover Change on Run-off in the Catchment of a Hydro Power Project. *Applied Water Science*. 2017, *7*, 787-800.

Kingston, D.; Massei, N.; Dieppois, B.; Hannah, D.; Hartmann, A.; Lavers, D.; Vidal, J.P. Moving Beyond the Catchment Scale, Value and Opportunities in Large-Scale Hydrology to Understand Our Changing World. *Hydrological Processes*. 2020, *34*, 2292-2298.

Liu, Y.; Gupta, H.; Springer, E.; Wagener, T. Linking Science with Environmental Decision Making, Experiences from An Integrated Modeling Approach to Supporting Sustainable Water Resources Management, *Environmental Modelling & Software*. 2008, *23*, 846-858.

Mackellar, N.C.; Dadson, S.J.; New, M.; Wolski, P. Evaluation of the JULES Land Surface Model in Simulating Catchment Hydrology in Southern Africa. *Hydrology and Earth System Sciences Discussions.* 2013, *10*, 11093-11128.

Madhusoodhanan, C.G.; Sreeja, K.G.; Eldho, T.I. Climate Change Impact Assessments on the Water Resources of India Under Extensive Human Interventions. *Ambio*. 2016, *45*, 725-741.

Maheswaran R.; Khosa R. Wavelet–Volterra Coupled Model for Monthly Stream Flow forecasting. *Journal of Hydrology*. 2012, *450*, 320-335.

Mandal, U.; Sahoo, S.; Munusamy, S.B.; Dhar, A.; Panda, S.N.; Kar, A.; Mishra, P.K. Delineation of Groundwater Potential Zones of Coastal Groundwater Basin Using Multi-Criteria Decision Making Technique. *Water Resources Management*. 2016, *30*, 4293-4310.

Mcdonald, M.G.; Harbaugh, A.W. A Modular Three-Dimensional Finite-Difference Ground-Water Flow Model. US Geological Survey, 1988.

Meigh, J.R.; Mckenzie, A.A.; Sene, K.J. A Grid-Based Approach to Water Scarcity Estimates for Eastern and Southern Africa. *Water Resources Management*. 1999, *13*, 85-115.

Mondal, A.; Narasimhan, B.; Sekhar, M.; Mujumdar, PP. Hydrologic Modelling. Proceedings of the Indian National Science Academy-Part A.; *Physical Sciences*. 2016, *82*, 817-832.

Müller Schmied, H.; Cáceres, D.; Eisner, S.; Flörke, M.; Herbert, C.; Niemann, C.; Peiris, T.A.; Popat, E.; Portmann, F.T.; Reinecke, R.; Schumacher, M. the Global Water Resources and Use Model Watergap V2. 2d, Model Description and Evaluation. *Geoscientific Model Development.* 2021, *14*, 1037-1079.

NASA Jet Propulsion Laboratory (JPL), NASA Shuttle Radar Topography Mission Global 1 Arc Second Number, National Aeronautics and Space Administration, U.S. Government, NASA. EOSDIS Land Processes DAAC.; NASA JPL.; Pasadena, CA.; USA.; 2013.

Nayak, T.; Verma, M.K.; Bindu, S.H. SCS Curve Number Method in Narmada Basin. *International Journal of Geomatics and Geosciences*. 2012, 3, 219-228.

Nema S.; Awasthi MK.; Nema RK. Conceptual Groundwater Modelling in An Alluvial Aquifer of Upper Narmada Basin. *Journal of Soil and Water Conservation*. 2019*, 18*, 179-187.

Pai DS.; Rajeevan M.; Sreejith OP.; Mukhopadhyay B.; Satbha NS. Development of A New High Spatial Resolution (0.25× 0.25) Long Period (1901-2010) Daily Gridded Rainfall Data Set Over India and Its Comparison with Existing Data Sets Over the Region. *Mausam*. 2014, *65*, 1-8.

Parvez, M.B.; Inayathulla, M. Estimation of Surface Runoff by Soil Conservation Service Curve Number Model for Upper Cauvery Karnataka. I*nternational Journal of Scientific Research. in Multidisciplinary Studies*, 2019, *5*, 11.

Patel, S.S.; Ramachandran, P. A Comparison of Machine Learning Techniques for Modeling River Flow Time Series, The Case of Upper Cauvery River Basin. *Water Resources Management*. 2015, *29*, 589-602.

Pathan, H.; Joshi, G.S. Estimation of Runoff Using SCS-CN Method and Arcgis for Karjan Reservoir Basin. *International Journal of Applied Engineering Research*. 2019, *14*, 2945-2951.

Pechlivanidis IG.; Arheimer B. Large-Scale Hydrological Modelling by Using Modified PUB Recommendations, the India-HYPE Case. *Hydrology and Earth System Sciences*. 2015, *19*, 4559-4579.

Pokhrel, Y.N.; Hanasaki, N.; Wada, Y.; Kim, H. Recent Progresses in incorporating Human Land–Water Management into Global Land Surface Models toward their integration into Earth System Models. *Wiley interdisciplinary Reviews, Water.* 2016, *3*, 548-574.

Portmann FT.; Siebert S.; Döll P. MIRCA2000—Global Monthly Irrigated and Rainfed Crop Areas Around the Year 2000, A New High-Resolution Data Set for Agricultural and Hydrological Modeling. *Global Biogeochemical Cycles*. 2010, *24*.

Rai, P.K.; Chaubey, P.K.; Mohan, K.; Singh, P. Geoinformatics for Assessing the inferences of Quantitative Drainage Morphometry of the Narmada Basin in India. *Applied Geomatics.* 2017, *9*, 167-189.

Raje, D.; Priya, P.; Krishnan, R. Macroscale Hydrological Modelling Approach for Study of Large Scale Hydrologic Impacts Under Climate Change in Indian River Basins. *Hydrological Processes*. 2014, *28*, 1874-1889.

Raju, B.K.; Nandagiri, L. Assessment of Variable Source Area Hydrological Models in Humid Tropical Watersheds. International Journal of River Basin Management. 2018, 16, 145-156.

Rickards, N.; Thomas, T.; Kaelin, A.; Houghton-Carr, H.; Jain, S.K.; Mishra, P.K.; Nema, M.K.; Dixon, H.; Rahman, M.M.; Horan, R.; Jenkins, A. Understanding Future Water Challenges in A Highly Regulated Indian River Basin—Modelling the Impact of Climate Change on the Hydrology of the Upper Narmada. *Water*. 2020, *12*, 1762.

Robert, M.; Thomas, A.; Sekhar, M.; Raynal, H.; Casellas, É, Casel, P.; Chabrier, P.; Joannon, A.; Bergez, J.É. A Dynamic Model for Water Management at the Farm Level integrating Strategic, Tactical and Operational Decisions. *Environmental Modelling & Software*. 2018, *100*, 123-135.

Robinson TP.; Wint GW, Conchedda G.; Van Boeckel TP.; Ercoli V.; Palamara E.; Cinardi G.; D'Aietti L.; Hay SI.; Gilbert M. Mapping the Global Distribution of Livestock. *Plos one*. 2014, *9*, E96084.

Roy PS.; Meiyappan P.; Joshi PK.; Kale MP.; Srivastav VK.; Srivasatava SK.; Behera MD.; Roy A.; Sharma Y.; Ramachandran RM.; Bhavani P. Decadal Land Use and Land Cover Classifications Across India, 1985, 1995, 2005. *ORNL DAAC*. 2016.

Scheidegger, J.M.; Jackson, C.R.; Muddu, S.; Tomar, S.K.; Filgueira, R. integration of 2D Lateral Groundwater Flow into the Variable infiltration Capacity (VIC) Model and Effects on Simulated Fluxes for Different Grid Resolutions and Aquifer Diffusivities. *Water*. 2021, *13*, 663.

Sekhar, M.; Riotte, J.; Ruiz, L.; Jouquet, P.; Braun, J.J. Influences of Climate and Agriculture on Water and Biogeochemical Cycles, Kabini Critical Zone Observatory. *Proceedings of the Indian National Science Academy*. 2016, *82*, 833-846.

Shahidian, S., Serralheiro, R., Serrano, J., Teixeira, J., Haie, N. and Santos, F.; Hargreaves and other reduced-set methods for calculating evapotranspiration, *IntechOpen*, 2012, *1*, 59-80.

Sharma, A.; Hipel, K.W., Schweizer, V. Strategic insights into the Cauvery River Dispute in India. *Sustainability*. 2020, *12*, 1286.

Singh, A.; Gosain, A.K. Climate-Change Impact Assessment Using GIS-Based Hydrological Modelling. *Water international*. 2011, *36*, 386-397.

Subash, Y.; Sekhar, M.; Tomer, S. and Sharma, A.; A Framework for Assessment of Climate Change Impacts on the Groundwater System, in Sustainable Water Resources Management, ASCE Book Chapter, 2016.

Sutanudjaja, E.H.; Van Beek, R.; Wanders, N.; Wada, Y.; Bosmans, J.H.; Drost, N.; Van Der Ent, R.J.; De Graaf, I.E.; Hoch, J.M.; De Jong, K.; Karssenberg, D. PCR-GLOBWB 2, A 5 Arcmin Global Hydrological and Water Resources Model. *Geoscientific Model Development.* 2018, *11*, 2429-2453.

Tefs, A.A.; Stadnyk, T.A.; Koenig, K.A.; Dery, S.J.; Macdonald, M.K.; Slota, P.; Crawford, J.; Hamilton, M. Simulating River Regulation and Reservoir Performance in A Continental-Scale Hydrologic Model. *Environmental Modelling & Software*. 2021, *141*,105025.

Thomas T.; Ghosh NC.; Sudheer KP. Optimal Reservoir Operation–A Climate Change Adaptation Strategy for Narmada Basin in Central India. *Journal of Hydrology*. 2021, *598*, 126238.

Thomas, T.; Gunthe, S.S.; Ghosh, N.C.; Sudheer, K.P. Analysis of Monsoon Rainfall Variability Over Narmada Basin in Central India, Implication of Climate Change. *Journal of Water and Climate Change*. 2015, *6*, 615-627.

Tiwari, D.; Tiwari, H.L.; Saini, R. Hydrological Modelling in Narmada Basin Using Remote Sensing and GIS with SWAT Model and Runoff Prediction in Patan Watershed. *International Journal of Advanced Research, Ideas and Innovations in Technology*. 2018, *4*, 344-352.

Tomer, S.K.; Al Bitar, A.; Sekhar, M.; Merlin, O.; Bandyopadhyay, S.; Kerr, Y.H. An intercomparison of RADARSAT-2, SMOS and Field Measured Soil Moisture in the Berambadi Watershed, South India. in AGU Fall Meeting Abstracts 2012, H13F-1425.

Vorosmarty, C.J.; Hoekstra, A.Y.; Bunn, S.E.; Conway, D.; Gupta, J. Fresh Water Goes Global. *Science*. 2015, *349*, 478-479.

Wang K.; Shi H.; Chen J.; Li T. An Improved Operation-Based Reservoir Scheme integrated with Variable infiltration Capacity Model for Multiyear and Multipurpose Reservoirs. *Journal of Hydrology*. 2019, *57*, 365-375.

Wu, Y.; Chen, J. An Operation-Based Scheme for A Multiyear and Multipurpose Reservoir to Enhance Macroscale Hydrologic Models. *Journal of Hydrometeorology*. 2012, *13*, 270-283.

Yassin, F.; Razavi, S.; Elshamy, M.; Davison, B.; Sapriza-Azuri, G.; Wheater, H. Representation and Improved Parameterization of Reservoir Operation in Hydrological and Land-Surface Models. *Hydrology and Earth System Sciences*. 2019, *23*, 3735-3764.

Zhao G.; Gao H.; Naz BS.; Kao SC.; Voisin N. integrating A Reservoir Regulation Scheme into A Spatially Distributed Hydrological Model. *Advances in Water Resources*. 2016, *98*, 16-31.

Zhao, G.; Gao, H.; Naz, B.S.; Kao, S.C.; Voisin, N. integrating A Reservoir Regulation Scheme into A Spatially Distributed Hydrological Model. *Advances in Water Resources*. 2016, *98*,16-31.

**Appendix D**

Table 4.3 The spatial and temporal resolutions, periods and sources of the input data used in the setup of GWAVA in the Cauvery (C) and Narmada (N) catchments

| | Catchment | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|---|
| Precipitation | C, N | 0.25 degree | Daily | 1951-2017 | Indian Meteorological Department (Pai *et al.*, 2012) |
| Maximum temperature | C, N | 0.25 degree | Daily | 1951-2016 | Indian Meteorological Department (Pai *et al.*, 2012) |
| Minimum temperature | C, N | 0.25 degree | Daily | 1951-2016 | Indian Meteorological Department (Pai *et al.*, 2012) |
| Streamflow gauged data | C, N | Catchment | Daily | 1971-2014 | India-WRIS |
| Dam characteristics | C | Catchment | | 2018 | India-WRIS |
| | N | Catchment | | 2020 | Narmada Control Authority, India- WRIS |
| Dam inflow and outflow data | C | Catchment | Monthly | 1974-2017 | India-WRIS |
| | N | Catchment | Monthly | 2007-2017 | Narmada Control Authority |
| Dam storage | C, N | Catchment | Daily | 200-2010 | India-WRIS |
| Water transfers | C | Catchment | Annual | 2008 | Ashoka Trust for Research in Ecology and the Environment |
| | N | Catchment | Annual | 2009 | Narmada Control Authority |
| Groundwater levels | C, N | District | Monthly | 1990-2017 | Central Ground Water Board, India |

| Input data | Catchment | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|---|
| Elevation | C, N | 0.003 degree | | 2000 | NASA Shuttle Radar Mission Global 1 arc second V003 (NASA Jet Propulsion Laboratory, 2013) |
| Geology | C, N | Asia | | | United States Geological Survey |
| Specific yield | C, N | India | | | Central Ground Water Board, India |
| Soil type | C | 0.008 degree | | 1971-1981 | Harmonized World Soil Database v1.2 (Fischer *et al*., 2008) |
| | N | 1:10 000 | | 1958- 2020 | Soil and Land-use Survey of India |
| Soil properties | C, N | Global | | 2010 | Table 2- Allen *et al*. (2010) |
| Land Cover Land Use | C, N | 0.001 degree | | 2005 | Decadal land use and land cover across India 2005 (Roy *et al*., 2016) |
| Crops | C | Taluk* | | 2000 | National Remote Sensing Centre (NRSC) |
| | N | 5 arcmin | | 2010 | Portmann (2010) |
| Total and Rural Population | C, N | Village | | 2001 | Census of India 2001 (http://sedac.ciesin.columbia.edu/data/set/india-india-village-level-geospatial-socio-econ-1991-2001) |
| Livestock | C | 0.05 degree | | 2005 | CGIR Livestock of the World v2 (Robinson *et al.*, 2014) |
| | N | Rural villages, India | | 2012 | 19th Livestock Census- 2012. Government of India |
| Conveyance losses | C, N | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx |

| Input data | Catchment | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|---|
| Return flow | C, N | Village | | 2011 | Household Return & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |
| Irrigation efficiency | C, N | Continental | | 1986 | Irrigation and Drainage Paper (FAO) No 1 |
| Surface-water fraction | C | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |
| | N | 5 arcmin | | 2013 | Global Map of Irrigation Areas- version 5.0 http://www.fao.org/aquastat/en/geospatial-information/global-maps-irrigated-areas/map-quality |
| Industrial Demand | C | Karnataka | | Currently unknown | Industrial Plot Information System- Karnataka Industrial Area Development Board (https://http://164.100.133.168/kiadbgisportal/) |
| Livestock demand | C, N | India | | 2006 | CGIR Livestock of the World v2 (Robinson *et al.*, 2014) |
| Domestic demand | C | Village | | 2001 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |
| | N | India | | | AQUASTAT |

Table 4.4 Input Demand Constraints for the Cauvery and Narmada Catchments

| Demand Constraints | Cauvery | Narmada |
|---|---|---|
| Conveyance loss (%)- Urban | 23 | 15 |
| Conveyance loss (%)- Rural | 25 | 15 |
| Irrigation Efficiency (%) | 44 | 70 |
| Return flow (%)- Urban | 62 | 45 |
| Return flow (%)- Rural | 0 | 45 |
| Demand per head (L/d)- Cattle | 77 | 40 |
| Demand per head (L/d)- Sheep and goat | 5 | 4 |
| Surface water abstraction (%)- Urban | 44 | 57 |
| Surface water abstraction (%)- Rural | 62 | 57 |
| Surface water abstraction (%)- Industrial | 80 | 80 |
| Surface water abstraction (%)- Irrigation | 31 | 47 |

Table 4.5 The percent bias, monthly Nash-Sutcliffe Efficiency (NSE), monthly log-Nash Efficiency (LNE) and the monthly Kling-Gupta Efficiency (KGE) for each sub-catchment in the Narmada and Cauvery Catchments. The metrics are provided for GWAVA (G), GWAVA-GW (G-GW), GWAVA-Res (G-Res) and GWAVA 5.1 (G 5.1).

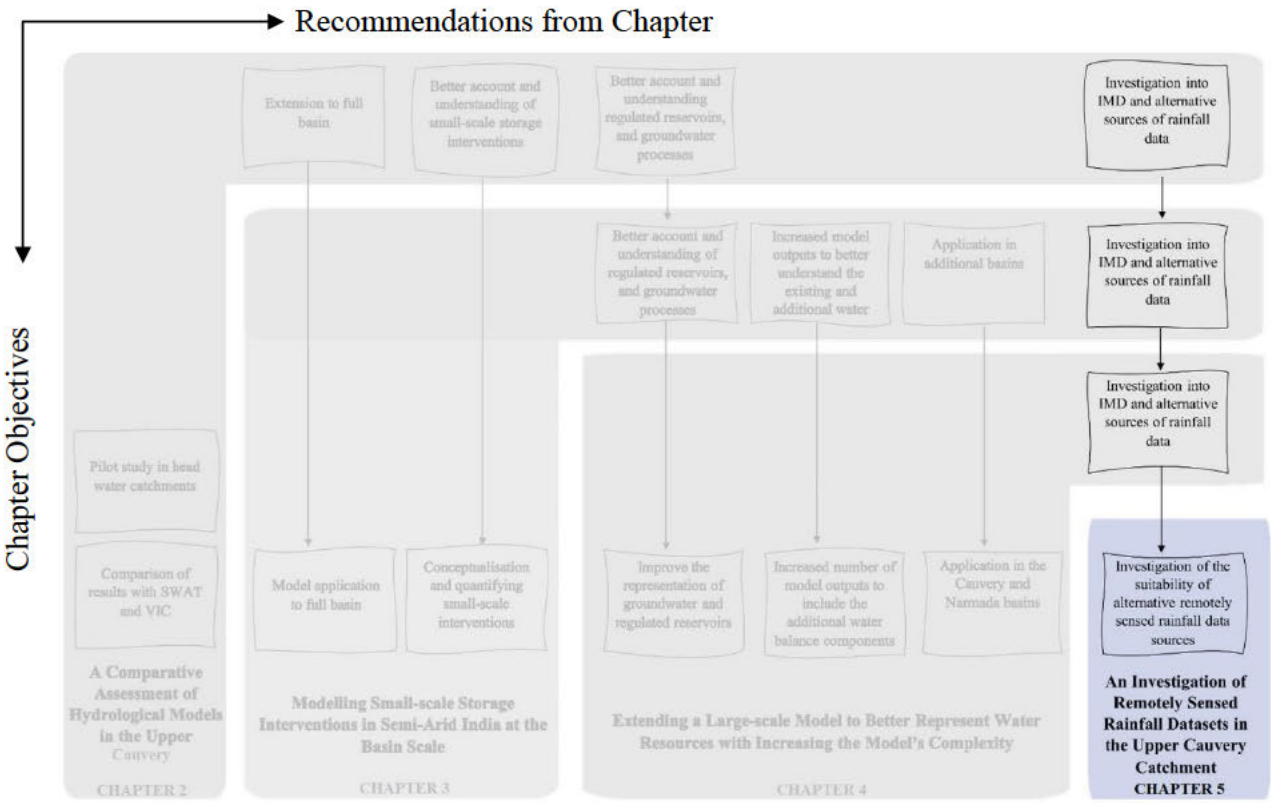
| **Sub-catchment** | **Bias (%)** | | | | **Monthly NSE** | | | | **Monthly LNE** | | | | **Monthly KGE** | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | **G** | **G-GW** | **G-Res** | **G 5.1** | **G** | **G-GW** | **G-Res** | **G 5.1** | **G** | **G-GW** | **G-Res** | **G 5.1** | **G** | **G-GW** | **G-Res** | **G 5.1** |
| Narmada | | | | | | | | | | | | | | | | |
| Manot | 11.37 | 4.24 | 11.37 | 4.24 | 0.95 | 0.92 | 0.92 | 0.93 | 0.78 | 0.86 | 0.78 | 0.86 | 0.83 | 0.84 | 0.83 | 0.83 |
| Mohgaon | 2.77 | 8.26 | 2.77 | 3.4 | 0.87 | 0.83 | 0.83 | 0.83 | 0.73 | 0.85 | 0.73 | 0.85 | 0.86 | 0.8 | 0.86 | 0.8 |
| Patan | 17.17 | -0.77 | 17.17 | 12.3 | 0.9 | 0.83 | 0.83 | 0.91 | 0.59 | 0.83 | 0.59 | 0.91 | 0.77 | 0.75 | 0.77 | 0.83 |
| Belkeri | 33.9 | 2.94 | 33.9 | 2.46 | 0.84 | 0.85 | 0.85 | 0.84 | 0.6 | 0.62 | 0.6 | 0.71 | 0.39 | 0.81 | 0.39 | 0.8 |
| Gadarwara | 7.03 | -1.8 | 7.03 | 1 | 0.92 | 0.82 | 0.82 | 0.83 | -0.45 | 0.71 | -0.45 | 0.83 | 0.87 | 0.7 | 0.87 | 0.72 |
| Chhidgaon | -12.36 | -45 | -12.36 | -13.29 | 0.89 | 0.62 | 0.62 | 0.86 | -0.33 | 0.66 | -0.33 | 0.88 | 0.85 | 0.6 | 0.85 | 0.77 |
| Kogaon | 30.39 | -19.5 | 30.39 | 2.03 | 0.79 | 0.74 | 0.74 | 0.79 | -0.32 | 0.68 | -0.32 | 0.76 | 0.57 | 0.66 | 0.57 | 0.72 |
| Barmanghat | 17.8 | 3.9 | -2.88 | 3.2 | 0.74 | 0.7 | 0.82 | 0.81 | 0.51 | 0.78 | 0.8 | 0.81 | 0.58 | 0.75 | 0.74 | 0.82 |
| Sandia | 6.73 | 7.55 | 3.24 | 9.11 | 0.84 | 0.77 | 0.93 | 0.84 | 0.51 | -0.04 | 0.84 | 0.88 | 0.72 | 0.82 | 0.85 | 0.77 |
| Hoshangabad | 7.57 | -0.68 | 2.92 | 0.4 | 0.89 | 0.82 | 0.94 | 0.9 | 0.08 | -0.94 | 0.85 | 0.90 | 0.83 | 0.84 | 0.84 | 0.78 |
| Handia | 14 | 4.75 | 11.17 | 9.92 | 0.89 | 0.82 | 0.95 | 0.91 | -0.33 | -1.94 | 0.84 | 0.90 | 0.81 | 0.84 | 0.82 | 0.77 |
| Mandleshwar | 10.6 | 4.25 | 4.73 | 4.35 | 0.9 | 0.84 | 0.95 | 0.92 | 0.71 | -1.25 | 0.85 | 0.88 | 0.74 | 0.86 | 0.86 | 0.80 |
| Garudeshwar | 16.09 | 12.74 | 4.43 | 13.4 | 0.9 | 0.78 | 0.94 | 0.9 | 0.18 | -1.8 | 0.84 | 0.89 | 0.74 | 0.83 | 0.85 | 0.80 |
| Cauvery | | | | | | | | | | | | | | | | |
| Saklesphur | -37 | -46.4 | -37 | -46.4 | 0.77 | 0.57 | 0.77 | 0.57 | 0.31 | 0.81 | 0.31 | 0.81 | 0.59 | 0.53 | 0.59 | 0.53 |
| Thimmanahali | -58.1 | -3.6 | -58.1 | -3.6 | 0.21 | 0.71 | 0.21 | 0.71 | 0.34 | 0.58 | 0.34 | 0.58 | 0.36 | 0.84 | 0.36 | 0.84 |
| KMVadi | -21 | -50.3 | -21 | -50.3 | 0.21 | 0.14 | 0.21 | 0.14 | 0.14 | -0.07 | 0.14 | -0.07 | 0.29 | 0.25 | 0.29 | 0.25 |
| Kudige | -43 | -50.7 | -43 | -50.7 | 0.67 | 0.55 | 0.67 | 0.55 | 0.70 | 0.70 | 0.70 | 0.70 | 0.53 | 0.48 | 0.53 | 0.48 |
| Munthankera | -21.6 | -25.4 | -21.6 | -25.4 | 0.8 | 0.78 | 0.8 | 0.78 | 0.74 | 0.89 | 0.74 | 0.89 | 0.73 | 0.73 | 0.73 | 0.73 |

| | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Thengumara hada | 1.2 | -22.3 | 1.2 | -22.3 | 0.07 | 0.43 | 0.07 | 0.43 | 0.22 | 0.59 | 0.22 | 0.59 | 0.50 | 0.57 | 0.50 | 0.57 |
| T narasupiar | -13.4 | -12.0 | 3.6 | -11.6 | 0.66 | 0.6 | 0.75 | 0.6 | -9.83 | -1.6 | -0.4 | -1.2 | 0.77 | 0.75 | 0.83 | 0.75 |
| Kollegal | -33.6 | -16.9 | -15.4 | -24.9 | 0.54 | 0.56 | 0.70 | 0.56 | -7.46 | -2.18 | 0.69 | 0.56 | 0.58 | 0.7 | 0.68 | 0.65 |
| Tbekuppe | 2.6 | -5.4 | -12 | -5.4 | -0.81 | -0.09 | 0.62 | 0.49 | -23.97 | -0.72 | 0.53 | -0.72 | 0.21 | 0.41 | 0.38 | 0.41 |
| TKHali | 4.1 | 7.3 | 3.4 | 7.3 | 0.36 | 0.43 | 0.4 | 0.43 | -1.68 | -0.29 | -0.91 | -0.29 | 0.57 | 0.52 | 0.61 | 0.52 |
| Bilingudulu | -14.7 | -2.2 | 12.1 | -10.5 | 0.63 | 0.5 | 0.79 | 0.64 | 0.07 | -0.77 | 0.69 | 0.65 | 0.76 | 0.74 | 0.73 | 0.77 |
| Urachikottai | -4.6 | -11.5 | 21.0 | 9.3 | 0.09 | -0.35 | 0.13 | 0.57 | 0.07 | -0.77 | 0.69 | 0.71 | 0.56 | 0.34 | 0.56 | 0.66 |
| Kodumodi | -14.5 | -22.7 | 20.0 | -5.9 | 0.14 | -0.3 | 0.52 | 0.64 | -1.56 | -3.80 | 0.41 | 0.51 | 0.52 | 0.25 | 0.56 | 0.76 |
| Musiri | -5.8 | -6.8 | 18.2 | -2.1 | 0.15 | -0.45 | 0.14 | 0.66 | -0.81 | -1.69 | -0.12 | 0.37 | 0.58 | 0.33 | 0.28 | 0.79 |

*****

**Lead into Chapter 5**

This chapter addresses the recommendations of Chapter 2, Chapter 3 and Chapter 4 regarding the uncertainty in rainfall input. The IMD rainfall grids are compared with CHIRPS 0.05 and 0.25 degree, MSWEP and PERSIANN datasets and against the IMD in-situ rainfall gauges. Each rainfall input is applied within the GWAVA model to determine the effect on broader water resources of the Upper Cauvery.



# 5. AN INVESTIGATION INTO THE SUITABILITY OF GAUGE-CORRECTED REMOTELY SENSED RAINFALL DATASETS FOR HYDROLOGICAL MODELLING IN THE WESTERN GHATS

***Horan, R[1], Smithers JC[1], Kjeldsen TR[2], Clark D[1], Rickards NJ[3] and Horan MJC[1]***

*[1]Centre for Water Resources Research, University of KwaZulu-Natal, Pietermaritzburg 3201, South Africa*

*[2]Department of Architecture and Civil Engineering, University of Bath, Bath BA2 7AY, United Kingdom*

*[3]UK Centre for Ecology & Hydrology, Wallingford OX10 8BB, United Kingdom*

*Corresponding Author: Robyn Horan, robynhoran8@gmail.com*

**Abstract**

An accurate spatial and temporal representation of rainfall is essential for hydrological assessments and water resources management. Rainfall is monitored in India's mountainous Western Ghats region via in-situ rainfall gauging stations maintained by the Indian Meteorological Department (IMD). However, the network is sparse, and significant periods of data are missing. Furthermore, the IMD gridded rainfall dataset is known to underestimate the depth of rainfall at the high altitudes within this region. In this study, rainfall estimated by the IMD grids and from remote sensing using the CHIRPS (0.25- and 0.05- degree), MSWEP and PERSIANN datasets are compared to the IMD in-situ gauged rainfall within the Western Ghats using a point-to-pixel analysis. The GWAVA model is utilised to determine the effect of the selected rainfall input datasets on representing wider water resources. It was found that the average ensemble provided the best representation of the in-situ gauged and catchment rainfall and a better representation than the IMD grids. It remains critical for water resources management to ensure that in-situ rainfall gauging networks are maintained. In-situ data sources of high confidence remain important for the continuous development and ground-truthing of different rainfall datasets.

**Keywords:** Rainfall, Western Ghats, Cauvery, GWAVA, Remote Sensing

## 5.1 Introduction

Knowledge of the spatial and temporal distribution of rainfall is essential for hydro-climatic studies. However, many regions are subject to highly variable rainfall, and those vulnerable to climate extremes are among the most data sparse (Wambura, 2020). Many catchments, particularly in the developing world, lack sufficient rainfall records due to sparsely distributed and/or poorly maintained meteorological stations (Wilby & Yu, 2013). The development of remotely sensed technologies and methodologies to combine satellite estimates with in-situ observation data has facilitated the production of more reliable large-scale climate datasets (Hong *et al.*, 2019). These datasets are often spatially gridded and temporally complete on a regional or global scale. However, these datasets contain large uncertainties and regional bias, thus posing concern and hesitation in utilising them (Nashwan, 2020).

Hydrological models are driven by available rainfall data, and their performance is thus directly linked with the quality of these data (Wagener *et al.*, 2001). Rain gauge networks are the most trusted means for accurate point rainfall measurement. However, sparse rain gauge networks in remote areas and mountainous terrain lead to erroneous rainfall estimates when averaged over a region (Liang *et al.*, 2020). Additionally, monsoonal rainfall is specifically challenging to represent as the timing of the monsoon is not consistent year-on-year, and the rainfall tends to be intense for long periods. An expanding selection of large-scale gridded rainfall datasets, both from remote sensing, reanalysis or interpolation of in-situ observations, are becoming available (Le Coz & van de Giesen, 2020). These datasets are proposed to be of value to overcome the absence of in-situ observations and provide an alternative for estimating catchment rainfall.

Southern India experiences a monsoonal rainfall pattern (Sen Roy *et al.*, 2009) with reports of significant weakening of the monsoon in recent years (Joseph & Simon, 2005; Kulkarni, 2012; Dixit *et al.*, 2014; Kumar *et al.*, 2020; Swapna *et al.*, 2022). The southwest monsoon generally brings rainfall between June and October, and the northeast monsoon in November and December. In addition to the monsoon strength, timing and duration, topographic factors considerably influence the distribution and concentration of rainfall across the region (Bauer & Morrison, 2008). The estimation of catchment rainfall is complicated by the complex topography of the Western Ghats (Malik *et al.*, 2012), the large spatial and temporal variability of the annual monsoons (Daly, 2006) and the conversion of a sparse rain gauge network and proxy measurements (cloud top temperature, raindrop reflectivity, solar energy, brightness temperature, microwave emission, etc.) into quantitative rainfall estimates (Ghimire *et al*., 2018; Hong *et al.*, 2019). The seasonal nature of rainfall and the resulting streamflow generation within the region has resulted in infrastructural projects being at the forefront of water management planning over the last century (Chowdhury, 2010). The Upper Cauvery Catchment region, located in the Western Ghats, acts as the water tower of the greater catchment.

The Western Ghats act as a barrier to the southwest monsoon clouds and influence the distribution of rainfall in the region. The undulating landscape, slope and aspect of these mountains to the monsoonal winds pose many challenges to the scientific community in understanding the spatial and temporal distribution of rainfall (Venkatesh *et al*., 2021). Along the southwestern and western coasts, the Mean Annual Rainfall (MAR) can be as high as 6000 mm due to the orographic effects of the Western Ghats. In contrast, in the rain shadow on the eastern side of the Western Ghats, the rainfall is markedly reduced to a low of 300 mm (Chidambaram *et al.*, 2018). A delayed or weakened monsoon significantly influences the rainfall in the higher latitudes of the country. Both the steepness and aspect of the mountains in this region directly affect the occurrence and location of rainfall. The steep slopes of the Western Ghats in Maharashtra and Kerala result in a strong orographic effect and drier conditions on the leeward side of the range (Meunier *et al.*, 2015).

The scarce rain gauge data in the Western Ghats region has been a major impediment to scientific studies, limiting the understanding of the regional weather system (Venkatesh *et al*., 2021). The major rivers of southern India originate in this mountain range, and the livelihoods of people in this region depend on the water available (Reddy *et al.*, 2021). Many major dams and water transfers are constructed within this region to provide water for domestic, industrial, and agricultural needs (Rajesh *et al.*, 2016). Any changes in the rainfall pattern result in variations in water availability and directly impacts the livelihoods of the people and economy of the region. Rain gauge data are the primary source of historical rainfall data (Sun *et al*., 2018). Consequently, due to the sparse gauge network over the Western Ghats (and the Indian mainland), the IMD has made a significant effort to convert the available station data to a regular space-time grid (Pai *et al*., 2014). These 0.25-degree daily rainfall grids created by the IMD are the accepted rainfall dataset for India within the scientific community and are considered the rainfall standard across environmental, industrial, and operational companies within India (Singh *et al*., 2021; Buri *et al.*, 2022).

An accurate rainfall representation in India is essential for understanding the hydrological responses during the monsoon rainfall season. Satellite-derived rainfall datasets have succeeded in depicting region-specific rainfall patterns across climatologically different parts of India. Most of the published studies utilising remotely sensed data have taken place across India or in small sub-catchments near the Himalayas. The remotely sensed data are generally compared to the IMD rainfall grids and, in some cases, to the IMD gauge data. These studies have concluded that the remotely sensed data sets struggle to estimate orographic rainfall, particularly in the Western Ghats and the Himalayan foothills (Palazzi *et al*., 2013; Prakash *et al*., 2015; Shah & Mishra, 2016). Therefore, the performance of new remotely sensed datasets which have not been applied in the region needs to be assessed.

In instances where 'off-the-shelf' remotely sensed datasets do not represent the point rainfall nor the simulated catchment streamflow to an acceptable standard, it is common practice to utilise available in-situ rain gauge data to perform a bias-correction (Guo & Liu, 2016). This technique has proven effective globally (Luo *et al.*, 2020); however, it falls short in regions where in-situ rain gauge data are not available or accessible, or there is high uncertainty in the gauged measurements (Kimani *et al.*, 2018). A probable solution is utilising an average ensemble of the selected remotely sensed rainfall datasets in a similar capacity to that which is common practice in the application of global climate model (GCM) data (Noor *et al.*, 2019; Rickards *et al.*, 2020).

This study aims to provide insight into the suitability of selected remotely sensed rainfall datasets and improve the estimation of catchment rainfall by improving the fundamental understanding of rainfall in the Upper Cauvery Catchment.

a) Evaluating remotely sensed rainfall datasets not previously applied at a catchment scale in the Upper Cauvery Catchment and assessing the performance of various ‘off-the-shelf’ remotely sensed datasets against in-situ rain gauge data.
b) Identifying the best-performing rainfall dataset, including the IMD and remotely sensed datasets.
c) Determine whether the spatial resolution of a rainfall dataset improves the performance in the Upper Cauvery Catchment.
d) Ascertain whether an ‘off-the-shelf’ remotely sensed rainfall dataset is suitable for hydrological modelling within the Upper Cauvery Catchment without regional bias correction.
e) Determining whether an ‘off-the-shelf’ remotely sensed dataset could improve the hydrological simulations within a complex topographical region compared to the IMD gridded dataset.
f) Establish whether an ensemble could more accurately represent the catchment rainfall and the simulated streamflow than the IMD gridded rainfall data.

## 1.2 Materials and Methods

The performance of the widely used IMD (Pai *et al*., 2014) gridded rainfall and selected remote sensing (RS) datasets not previously used in the region will be compared to the available in-situ observations. Hydrological simulations will be utilised to determine the effects of various rainfall data on water resource representation.

### *5.2.1 Catchment Description*

The Cauvery Catchment (81,000 km$^2$) is situated in southern India (Figure 5.1). The diverse terrain and strong west-to-east rainfall gradient (6000 mm in the upper reaches to 300 mm on the eastern boundary) result in regionally variable surface and groundwater availability (Meunier *et al.*, 2015) and, depending on local demand patterns, is a critical and widely limiting factor for agriculture (Madhusoodhanan *et al*., 2016), with much of the irrigated agriculture dependent on groundwater abstraction from millions of wells. The catchment is primarily underlain by hard-rock aquifers (Collins *et al*., 2020). Although predominantly rural (Sreelash *et al.*, 2020), parts of the catchment have experienced considerable urban and economic growth over recent years (Gupta & Horan, 2022).

The surface water in the catchment has been affected for centuries by human influences, which have impacted the hydrological functioning of the catchment (Gupta & van der Zaag, 2008). In addition to the significant anthropogenic influence within the catchment, there are ongoing inter-state water-sharing disputes. Water disputes in the Cauvery Catchment differ from other inter-state water disputes, such as in the Krishna, Godavari and Narmada Catchments. These tend to form around the untapped potential of water resources, whereas in the Cauvery Catchment, the disputes surround the reallocation of existing water resources (Janakarajan, 2016) between the federal states of Karnataka and Tamil Nadu (Sharma *et al*., 2020). As the water-sharing agreement in the Cauvery is legally founded, the estimation and distribution of water resources throughout the catchment must be accurately understood.

The Upper Cauvery Catchment drains an area of 10 619 $km^2$ in the north-western region of the Cauvery Catchment (Figure 5.1) and constitutes 21% of the total catchment area but generates 82% of the total streamflow (Horan *et al*., 2021a). The upper reaches of the Cauvery River lie within the Western Ghats (Figure 5.1: Inset 1). The Upper Cauvery Catchment drains into the Krisharaja Sagar (KRS) dam, where it is stored for domestic and agricultural use. The Western Ghats act as a critical headwater to the larger catchment and a barrier to the southwest monsoon (Chidambaram *et al*., 2018). In the area of the Western Ghats, the soils tend to be very deep, valley bottoms are covered in dense forests, and mountain slopes are predominately grassland (Pattabaik *et al*., 2013). As shown in Figure 5.1, the Upper Cauvery Catchment consists of four gauged sub-catchments (Saklesphur, Thimmanahali, Kudige and KM Vadi). The Upper Cauvery will be modelled at a 0.125-degree resolution for the period 1985-2013 due to data availability and to correspond with the pilot study (Horan *et al.*, 2021a).

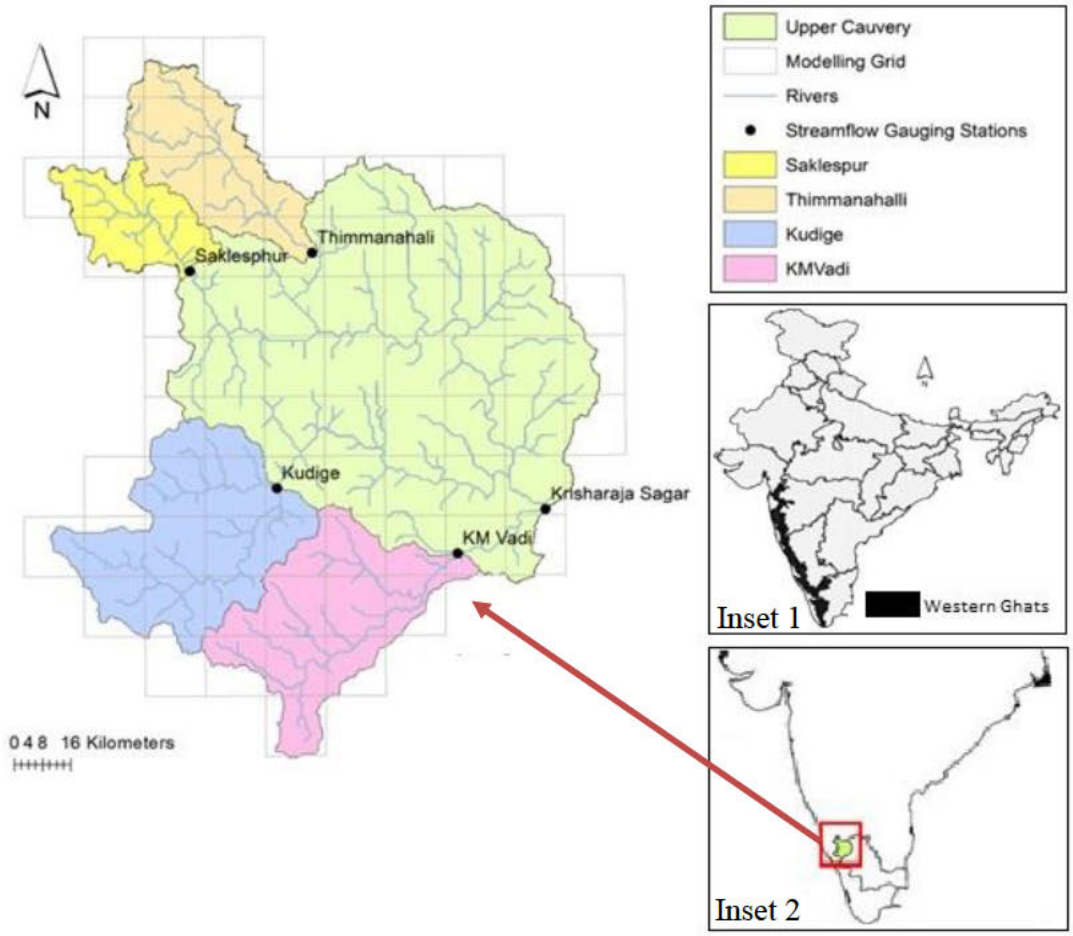



Figure 5.1 Inset 1: the location of the Western Ghats within India; Inset 2: the location of the Cauvery Catchment within India; Main map: Cauvery Catchment sub-catchment boundaries, modelling grid and the location of streamflow gauges used for hydrological model calibration.

### *5.2.2 Rainfall Data*

#### 1.2.1.1 In-situ Rain Gauge Data

The IMD provided daily in-situ rain gauge data for 21 gauges in the Upper Cauvery Catchment (Figure 5.2; Table 5.5 in Appendix E). The data records were inconsistent between gauging stations, and thus a period of 1985 to 2013 was selected as the majority of the gauges had data available for this period. There were, however, significant gaps within the remaining data. In this study, no effort was made to infill these gaps as the gauges were not deemed close enough to each other, and due to the complex topography, no meaningful relationships could be drawn. The available data was compared to the gridded datasets using a point-to-pixel analysis.

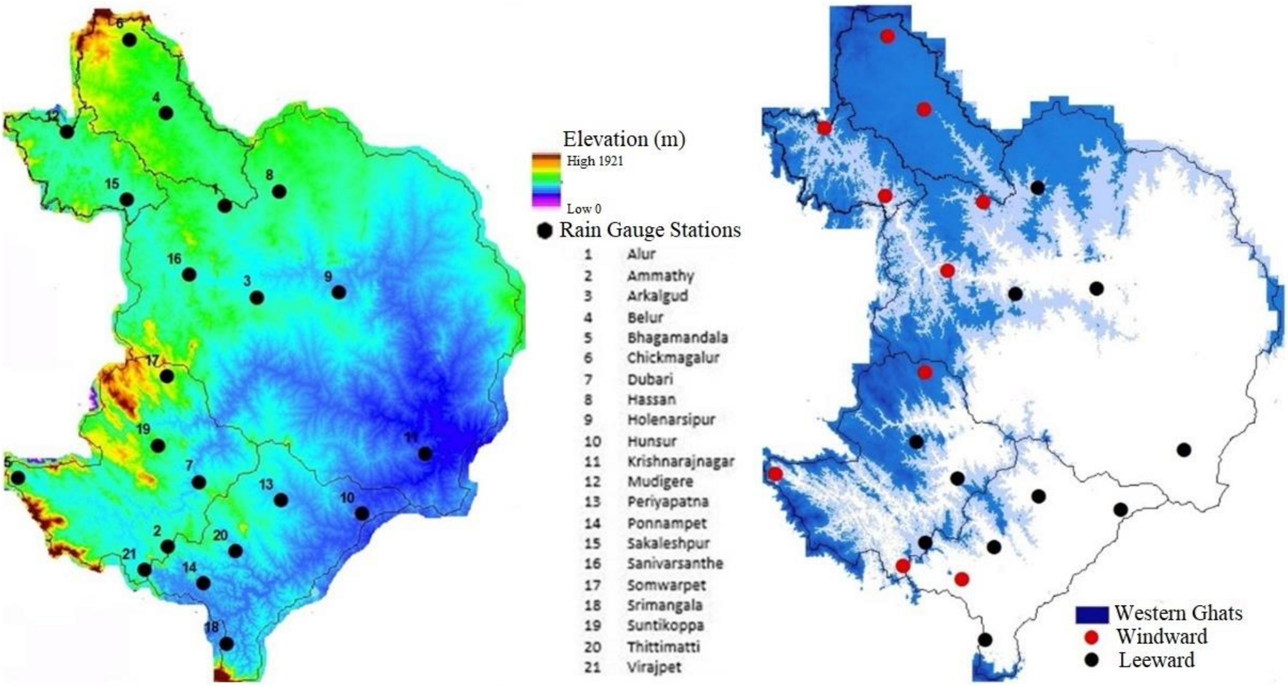



Figure 5.2 The location of rain gauges and elevation (left) and the demarcation of the Western Ghats within the Upper Cauvery Catchment and windward and leeward positioned gauges (right) within the Upper Cauvery Catchment.

### 1.2.1.2 Gridded Rainfall Data

Several remotely sensed rainfall datasets were considered for this study (Table 5.6 in Appendix E). As summarised in Table 5.1, only four remotely sensed rainfall datasets met all five of the following criteria, at the time of publication, and thus were selected for this study.

1. Not been explicitly applied within the Upper Cauvery Catchment
2. A spatial resolution of not more than 0.25 degree (IMD grid size)
3. Temporal coverage between 1985 and 2013 (period of available observed rainfall and streamflow data)
4. If a reanalysis dataset, it did not make use of the IMD gridded rainfall data within the compilation
5. The datasets must have undergone a degree of bias correction with gauged rainfall within the dataset production methodology

Table 5.1 The rainfall datasets utilised in this study, including the methodology, spatial and temporal coverage and resolution, their application in India and reference source.

| Dataset | Methodology | Spatial coverage | Temporal coverage | Spatial resolution | Temporal resolution | Application in India | Application in Western Ghats | Reference |
|---|---|---|---|---|---|---|---|---|
| Indian Meteorological Department (IMD) | Gauges | India | 1901-2014 | 0.25 | Daily | ✓ | ✓ | Pai *et al.*, 2014 |
| Climate Hazards Group InfraRed Rainfall with Station data (CHIRPS) | Infrared Gauge | 50°N - 50°S | 1981- NRT | 0.25° | Daily | ✓ | ✓ | Funk *et al.*, 2015 |
| CHIRPS v2.0 | Infrared Gauge | Global | 1981 -NRT | 0.05° | Daily | × | × | Funk *et al.*, 2015 |
| Multi-Source Weighted-Ensemble Rainfall (MSWEP) v2.0 | Infrared Microwave Gauges | Global | 1979- NRT | 0.1° | 3 hour | ✓ | ✓ | Beck *et al.*, 2017 |
| PERSIANN-Climate Data Record (CDR) | Infrared Gauge | 60°N - 60°S | 1983-2016 | 0.25° | 6 hour | ✓ | ✓ | Ashouri *et al.*, 2015 |

*i) IMD*

The IMD has developed a daily rainfall dataset at a 0.25-degree grid size over the Indian mainland for the period from 1901- to 2013 based on a network of 6 955 rain gauge stations (Rajeevan & Bhate, 2009; Pai *et al.*, 2014). The IMD gridded rainfall dataset uses these gauges and the simplest form of inverse distance weighted (IDW) interpolation (Shepard, 1968) to estimate a spatial representation of rainfall. Spatial interpolation uses gauging stations with known values to estimate rainfall at points without available data (Li & Heap, 2008). In the IDW method, the rain gauging points are weighted such that the influence of one gauge relative to another declines with distance from the point of unknown rainfall. Weighting is assigned to gauging points using a weighting coefficient that controls the weighting influence—the greater the weighting coefficient, the less effect the gauge will have. The quality of the interpolation can decrease if the distribution of gauging stations is uneven. The maximum and minimum values in the interpolated surface can only occur at sample gauging points. To speed up the computation, only rainfall data from a few of the nearest neighbour stations (minimum of 1 station and a maximum of 4 stations) within a radial distance of 1.5-degrees (166 $km^2$) around the grid point was used in the IDW interpolation. In the mountainous regions of India, there is a low density of rain gauge stations (approximately 1 station for every 460 $km^2$) and highly variable rainfall. Thus, the spatial variability of rainfall may not be captured adequately using the IDW methodology. In addition, the maximum rainfall can occur only at gauging points; the rainfall in ungauged areas may be systematically underestimated, especially in the Western Ghats, where the rainfall varies from 600 mm to 5000 mm within 50–100 km.

The IMD gridded daily rainfall data were obtained from the IMD in New Delhi. The data was provided at a 0.25-degree scale in comma-separated values format for the peninsula region of India. Using the coordinates of the in-situ rain gauges, the relevant grids were identified, and the data were extracted using an R statistical software script. The 0.25-degree data were resampled to the 0.125- degree modelling grids, whereby the finer grids retained the value of the 0.25-degree grid cell they overlay.

*ii) CHIRPS 0.25- and 0.05-degree*

The Climate Hazards Group Infrared Rainfall with Stations (CHIRPS) dataset is available at a spatial resolution of 0.25- and 0.05- degrees across a latitude band of 50ºS–50ºN from 1981 to the present (Funk *et al.*, 2015). CHIRPS utilises high-resolution infrared Cold Cloud Duration (CCD) observations interpolated with a global 0.05° monthly rainfall archive, Climate Hazards Rainfall Climatology (CHPclim), and historical station data from several public data streams and private archives. Monthly rainfall estimates are produced at a 0.25° scale using the CCD observations and TRMM 3B42 rainfall data. These are downscaled to 0.05º. The 0.25° and 0.05° datasets are corrected using the long-term means and CHPClim data. The corrected datasets are blended with available station data to produce the published datasets. Station data is obtained from Global Historical Climatology Network (GHCN), Global Summary of the Day (GSOD), Global Telecommunications System (GTS), Southern African Science Service Centre for Climate Change and Adaptive Land Management (SASSCAL) and national meteorological agencies in Central and South America and sub-Saharan Africa (Funk *et al.*, 2015).

The 0.05- and 0.025-degree daily rainfall data were downloaded using the in-built chirps R package (https://cran.r-project.org/web/packages/chirps/index.html). The data was provided at a 0.05-and 0.025- degree scale in NetCDF format. Using the coordinates of the in-situ rain gauges, the relevant data were identified and extracted using an R statistical software script. Furthermore, the 0.05- degree data was clipped and aggregated to the 0.125-degree modelling grid using R statistical software. Each 0.125-degree grid was assigned the daily mean of the CHIRPS grids that it fell within. The 0.25-degree data was disaggregated to the 0.125- degree modelling grids, whereby the finer grids retained the value of the 0.25-degree grid cell they overlay. The 0.125-degree datasets were output as a comma-separated values file.

*iii) MSWEP*

Multi-Source Weighted Ensemble Rainfall (MSWEP) is a global rainfall dataset available from 1979–2015 at a temporal resolution of three hours and a spatial resolution of 0.25°. The dataset is derived from several data sources, including 13 762 rain gauges, satellites, and atmospheric reanalysis models. The long-term mean is derived from the CHPclim dataset, corrected for orographic effects, and then downscaled to a monthly timestep using multiple satellite rainfall datasets. The monthly rainfall is then downscaled to a daily resolution using the CPC Unified rainfall gauged dataset and the area weighting technique. Available three-hourly satellite rainfall estimates are utilised to further downscale the daily resolution rainfall to three-hour MSWEP data. MSWEP undergoes a long-term bias correction using both rainfall (CHPclim and PRISM) and streamflow data (GAGES-II and GRDC) (Beck *et al*., 2017).

MSWEP daily rainfall data were obtained from the GloH2O (http://www.gloh2o.org/mswep/). The data was provided at a 0.1-degree scale in NetCDF format. Using the coordinates of the in-situ rain gauges, the relevant data were identified and extracted using an R script. Furthermore, using R statistical software, the data was clipped and aggregated to the 0.125-degree modelling grid. Each 0.125-degree grid was assigned the daily mean of the MSWEP grids that it fell within. The 0.125-degree dataset was output as a comma-separated values file.

*iv) PERSIANN-CDR*

The Rainfall Estimation from Remotely Sensed Information using Artificial Neural Networks-Climate Data Record (PERSIANN-CDR) is available from 1983 to the present at a daily 0.25° resolution. The dataset covers between 60°N and 60°S. PERSIANN-CDR uses a modified PERSIANN algorithm that inputs infrared imagery from GEO satellites into an ANN model and includes gauge measurements from the contiguous United States (CONUS) to estimate global surface rainfall rates from satellite-based infrared measurements (Ashouri *et al.*, 2015). PERSIANN-CDR uses the National Centres for Environmental Prediction (NCEP) Stage IV hourly rainfall to train the ANN model. Bias correction is undertaken on a monthly scale using the Global Rainfall Climatology Project (GPCP) monthly 2.5º rainfall data (Nguyen *et al.*, 2018).

PERSIANN daily rainfall data were obtained from the National Centers for Environmental Information (https://www.ncei.noaa.gov/datasets/climate-data-records/ rainfall-persiann). The data was provided at a 0.25-degree scale in NetCDF format. Using the coordinates of the in-situ rain gauges, the relevant data were identified and extracted using an R script. Furthermore, using R statistical software, the data was clipped, and the 0.25-degree data were resampled to the 0.125- degree modelling grids, whereby the finer grids retained the value of the 0.25-degree grid cell they overlay. The 0.125-degree dataset was output as a comma-separated values file.

*v) Ensemble*

An ensemble uses the variation of input data, analysis, and methodologies of its component members and tends to be less prone to systematic biases and errors. An ensemble rainfall combines multiple rainfall datasets to create a single dataset. In regions where in-situ rainfall gauge measurements may not be available, an ensemble of selected remotely sensed rainfall datasets may provide a better and more consistent representation of the rainfall than the individual datasets. An ensemble can be applied in rainfall studies to reduce errors with an optimal bias (Baker & Ellison, 2008). Although most published studies utilise an ensemble when applying future GCM predictions, an example of a published study (Cornes *et al*., 2018) has used the concept to improve estimates of historical rainfall. Cornes *et al*. (2018) found that utilising an ensemble of gridded rainfall datasets improved uncertainty estimates compared to individual datasets across Europe.

An average ensemble was determined utilising the 0.125-degree re-gridded CHIRPS 0.05- and 0.25- degree datasets, MSWEP dataset and PERSIANN dataset from 1985-2013. The daily rainfall for each 0.125-degree grid was averaged with equal weighting to produce a single daily time series for each grid (Equation 5.1).

$$\bar{x} = \frac{\sum x}{n} \tag{5.1}$$

where $\bar{x}$ is the mean, *x* is the values, and *n* is the number of x values in the dataset.

A median ensemble was determined utilising the median of the 0.125-degree re-gridded CHIRPS 0.05- and 0.25- degree datasets, MSWEP dataset and PERSIANN dataset from 1985-2013.

Four weighted ensembles were determined using the 0.125-degree resampled CHIRPS 0.25- and 0.05- degree, MSWEP and PERSIANN datasets from 1985-2013.

$$C_{25}\,Weighted\ average = \frac{2x_{C25} + x_{C05} + x_M + x_P}{5} \tag{5.2}$$

$$C_{05}\,Weighted\ average = \frac{x_{C25} + 2x_{C05} + x_M + x_P}{5} \tag{5.3}$$

$$M\ Weighted\ average = \frac{x_{C25} + x_{C05} + 2x_M + x_P}{5} \tag{5.4}$$

$$P\ Weighted\ average = \frac{x_{C25} + x_{C05} + x_M + 2x_P}{5} \tag{5.5}$$

Where $x$ is the value in the CHIRPS 0.25-degree ($C25$), CHIRPS 0.05-degree ($C05$), MSWEP ($M$) and PERSIANN ($P$) datasets.

For each of the ensembles, using R statistical software and the coordinates of the in-situ rain gauges, the relevant data were identified and extracted for a point-to-pixel evaluation. The average ensemble was consolidated into a comma-separated values file for input to GWAVA.

### *5.2.3 Model Selection*

Several hydrological modelling studies have been carried out in the headwater sub-catchments of the Cauvery. These include using the auto-regressive moving average time series (ARIMA) model (Maheswaran & Khosa, 2012), an artificial neural network (ANN) model (Maheswaran & Khosa, 2012; Patel & Ramachandran, 2015), a support vector regression (SVR) model (Patel & Ramachandran, 2015), the Water Evaluation And Planning (WEAP) model (Bhave *et al.*, 2018), GWAVA (Horan *et al.*, 2021a), the Soil and Water Assessment Tool (SWAT) (Kumar

& Nandagiri, 2018; Horan *et al.*, 2021a; Wable *et al.*, 2021) and the Variable Infiltration Capacity (VIC) model (Gowri *et al*., 2021; Horan *et al*., 2021a).

The above-listed model applications within this region have not been highly successful in representing the sub-catchments; however, they provide useful scientific lessons and the identification of various shortfalls. The applications by Maheswaran and Khosa (2012), Patel and Ramachandran (2015), Bhave *et al*. (2018), Horan *et al.* (2021a, b, c), and Gowri *et al.* (2021) utilised the IMD 0.25-degree daily rainfall grids (Pai *et al.*, 2014) as the source of rainfall data. Bhave *et al*. (2018) and Horan *et al.* (2021a) noted that a limitation of their work was the restricted availability of some specific input data, particularly observed rainfall. Kumar and Nandagiri (2018) and Wable *et al.* (2021) utilised the data from ten and sixteen rain gauges for simulations in the headwater sub-catchments using the SWAT model, respectively produced significantly better results than the studies carried out using the IMD gridded rainfall data. The ability of the SWAT model to simulate daily streamflow was reasonably good, with better low-flow than high-flow simulations. Both Kumar and Nandagiri (2018) and Wable *et al.* (2021) point to rainfall estimation in complex topography as a large source of uncertainty within the modelling exercise.

This study used an improved version of the GWAVA model (Meigh *et al.,* 1999; Horan *et al.,* 2021c). GWAVA is a large-scale gridded water resource model that accounts for natural hydrological processes (soils, land-use, and lakes), using a conceptual rainfall-runoff model and anthropogenic stresses (groundwater abstraction, irrigation, domestic and industrial demands, dam storage, and water transfers) via a demand-driven routine (Meigh *et al*., 1999). The model can be run at a daily or monthly time scale across modelled areas greater than 1000 $km^2$ and is adaptable to the data availability of the region. GWAVA was developed primarily for use in large, data-scarce regions.

The low-data requirement of the GWAVA model, with published applications in southern Africa (Meigh *et al.*, 1999), West Africa (Meigh & Tate, 2002; Meigh *et al*., 2005; Rameshwaran *et al*., 2017; Rickards *et al*., 2019), South America (Ekstrand *et al*., 2008), Europe (Dumont *et al.,* 2012; Johnson *et al.*, 2015; Williams *et al*., 2015), China (Lui *et al*., 2015) and India (Rickards *et al*., 2020) and a successful pilot study within the Upper Cauvery Catchment (Horan *et al*., 2021a), makes it suitable for application in southern India. The GWAVA model has been updated to better represent small-scale runoff harvesting interventions (Horan *et al*., 2021b), groundwater abstraction, artificial recharge, and regulated dam releases (Horan *et al*., 2021c). These updates are based largely on field data, the principles of the AMBHAS-1D (Tomer *et al*., 2012) groundwater model and the Hanasaki dam routine (Hanasaki *et al*., 2006).

GWAVA simulates the local runoff from each grid cell using a lumped conceptual, Probability Distributed rainfall-runoff Model (PDM) (Moore, 1985). The PDM is used to simulate the spatial variations in soil moisture by means of a probability distribution (Moore, 2007). The PDM utilises a 'bucket' approach, allocating the rainfall amongst various 'buckets' to determine the partitioning of water into the components of the water balance (UKCEH, 2020). Figure 5.3 illustrates the model configuration.

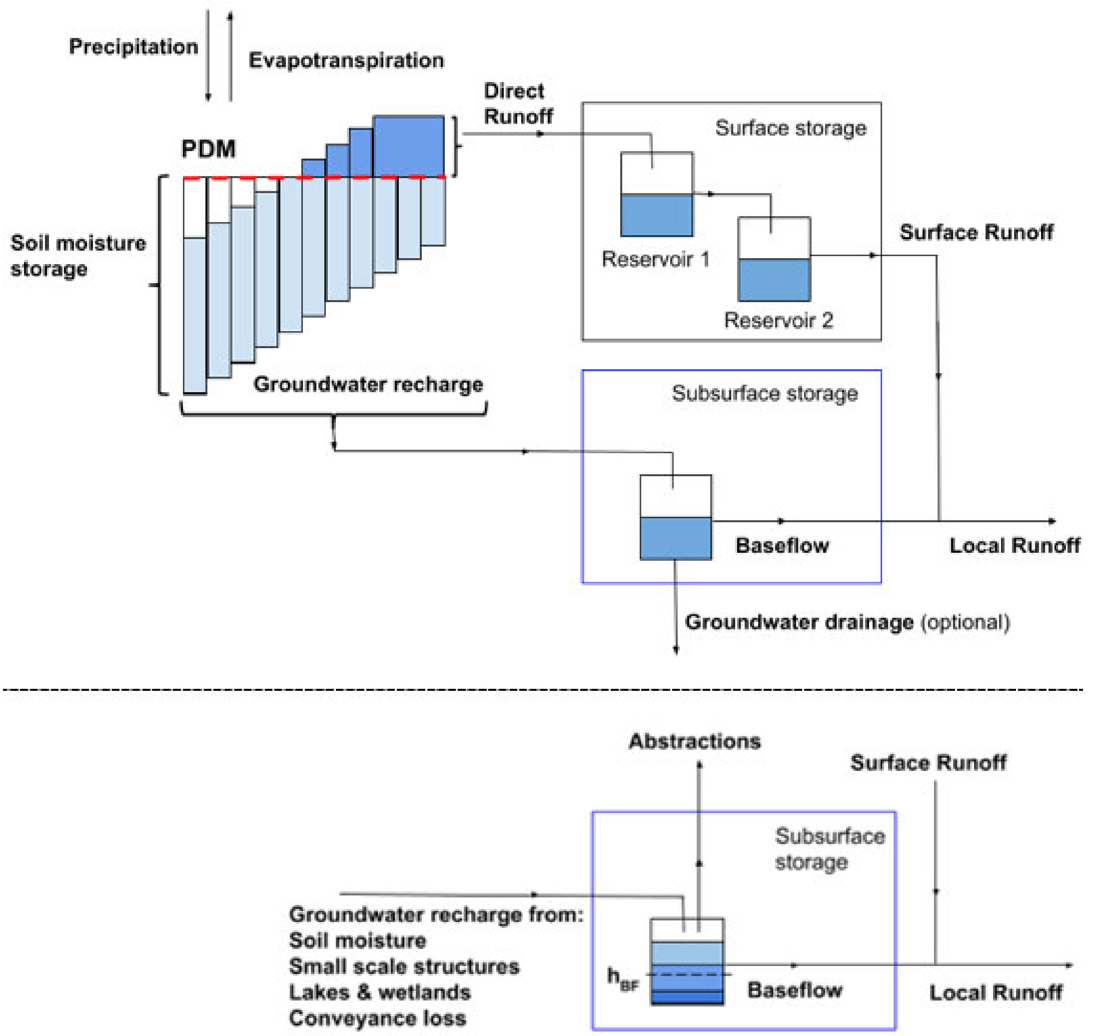



Figure 5.3 Schematic of the rainfall-runoff model, including the configuration of the probability distributed model (PDM) (UKCEH, 2020).

### *5.2.4 Model Application*

#### 5.2.4.1 Input Data

Input data were collected from several sources and extracted from global and regional datasets. The sources and details of the data used in this modelling exercise are summarised in Table 5.7 in Appendix E.

#### 5.2.4.2 Model Setup

The Upper Cauvery Catchment was modelled using a gridded configuration with a spatial resolution of 0.125 degrees (Figure 5.1) using the GWAVA 5.1 model (Horan *et al*., 2021c) forced by various rainfall input datasets:

a) IMD daily rainfall gridded data
b) 0.25- degree CHIRPS daily rainfall data
c) 0.05- degree CHIRPS daily rainfall data
d) 0.1- degree MWESP daily rainfall data
e) 0.25- degree PERSIANN daily rainfall data
f) 0.125-degree ensemble rainfall data

The domestic, irrigation, industrial and livestock demand, large-scale water transfers, hydropower dams, irrigation dams, and agriculture within the irrigation and rural areas were included.

#### 5.2.4.3 Model Calibration

Five streamflow gauges were used to calibrate the GWAVA model in the Upper Cauvery Catchment using the IMD gridded rainfall dataset (Figure 5.1). It was then assumed that these calibration parameters would be reasonable for the remotely sensed rainfall datasets. The simulated streamflow was calibrated against the observed streamflow using the SIMPLEX auto-calibration routine. This calibration routine utilises five parameters; (i) a surface routing parameter, (ii) a groundwater routing parameter, (iii) a Probability Distributed Model (PDM) parameter that describes spatial variation in soil moisture capacity, (iv) groundwater initializing depth parameter, and (v) a multiplier to adjust rooting depths. The calibration gauges were selected based on the completeness and temporal coverage of the data and the size of the sub-catchment. The observed streamflow data were deemed sufficient when it had at least five consecutive years of data available from 1981 until 2010.

#### 5.2.4.4 Evaluation

Due to the high variability of rainfall and streamflow in the Upper Cauvery Catchment, the Kling-Gupta Efficiency (KGE) was used to determine the ability of the rainfall dataset and GWAVA to represent the temporal characteristics of the rainfall and streamflow against the observed data. The Root Mean Squared Error (RMSE) was used to determine the accuracy of the rainfall datasets compared to the observed values. The bias was used to evaluate the ability of the rainfall datasets and GWAVA to estimate the total volume of streamflow across the modelling period.

*i) Kling-Gupta Efficiency (KGE)*

The KGE (Gupta *et al.*, 2009) is based on correlation, variability bias and mean bias and is calculated (Equation 5.3) as:

$$KGE = 1 - \sqrt{(r-1)^2 + \left(\frac{\sigma_s}{\sigma_o} - 1\right)^2 + \left(\frac{\mu_s}{\mu_o} - 1\right)^2} \qquad (5.3)$$

where $r$ is the correlation coefficient between the monthly simulated and observed data, $\sigma_o$ is the standard deviation of monthly observation data, $\sigma_s$ is the standard deviation of the monthly simulated data, $\mu_o$ is the mean of monthly observation data, and $\mu_s$ is the mean of monthly simulated data.

The KGE indicates the overall performance of the model. The metric allows some perceived shortcomings with the Nash-Sutcliffe Efficiency (NSE) metric to be overcome and has become increasingly popular for evaluating hydrological model skill. A KGE of one indicates perfect agreement between simulations and observations. However, there are many opinions about where the differentiation of ‘good’ and ‘poor’ model performance thresholds lie within the KGE scale. Negative KGE values do not always imply that the model performs worse than the mean flow benchmark. For this study, and to compare model performance, a KGE score of less than 0.2 was deemed poor, between 0.2 and 0.6 as fair and above 0.6 as good.

*ii) Root Mean Squared Error*

The root-mean-square error (RMSE) is a measure of accuracy and a frequently used measure of the differences between the simulated and observed values (Equation 5.4). The RMSE represents the square root of the second sample moment of the differences between predicted and observed values or the quadratic mean of these differences.

$$RMSE = \sqrt{\frac{\sum(y_s - y_o)^2}{n}} \tag{5.4}$$

where $y_o$ is the monthly observed data value, $y_s$ is the monthly simulated data value, and $n$ is the number of samples.

*iii) Bias*

The bias is the average tendency of the simulated data to over-or underestimate the observed data (Equation 5.5). The optimal value for the bias is zero. Positive values indicate a model underestimation, and negative values indicate an overestimation. When assessing a model's ability to simulate streamflow, the bias indicates the ability of the model to predict the overall streamflow volume across the modelling period. A bias of between -10 and 10% is considered acceptable.

$$Bias = \frac{\sum y_o - y_s}{\sum y_o} \times 100 \tag{5.5}$$

where $y_o$ is the monthly observation data, and $y_s$ is the monthly simulated data.

The performance of each rainfall dataset and the streamflow generated by each rainfall dataset are ranked from best to worst performing and given a score from one to five. The best performing was assigned a one and the worst a five. The performance was evaluated across the KGE, RMSE and bias statistics within each sub-catchment. Each rainfall dataset was ranked across the individual sub-catchments and the whole Upper Cauvery Catchment to determine the spatial performance across the region and whether a dataset performs better than the IMD grids in the Upper Cauvery Catchment.

## 5.3 Results

### *5.3.1 Performance of the Rainfall Estimated by the Selected Datasets*

Compared to the monthly observed rainfall values in Figure 5.4, the graphs pertaining to the IMD grids, CHIRPS and MSWEP illustrate a notable scatter above and below the 1:1 line, provide a good fit at lower magnitude events and underestimate at higher magnitude events. PERSIANN overestimates the rainfall depth during lower magnitude events but significantly underestimates the rainfall depth at mid-to-high magnitude rainfall events. The IMD grids present the highest $R^2$ value of the individual rainfall datasets.

Six ensemble techniques were investigated for use in the Upper Cauvery Catchment. The various methodologies provide similar results regarding the depth of rainfall across events of varying magnitude. As expected, the ensembles produce similar results that fit well to the 1:1 line at lower magnitude events. The clustering around the 1:1 line is more pronounced in the ensembles than in the individual datasets. At high-magnitude events, like individual datasets, the ensembles underestimate the rainfall depth. The degree to which PERSIANN underestimates the high-magnitude events affects the ensembles at these magnitudes. The average ensemble presents a higher $R^2$ value than the IMD grids.

Using the KGE, RMSE and bias statistics, all the ensembles performed more accurately than the individual rainfall datasets, as shown in Table 5.2. Although the median, CHIRPS, MSWEP and PERSIANN weighted ensembles produced good KGE scores, the bias was higher than the average ensemble.

As evident from Table 5.2, the various ensemble methodologies produced the most accurate overall representation (KGE) of the observed rainfall with the lowest margin of error (RMSE), followed by IMD and CHIRPS 0.25-degree, CHIRPS 0.05-degree, PERSIANN and MSWEP. PERSIANN and MSWEP, however, provide the best representation of the overall depth of rainfall across the Upper Cauvery Catchment, followed by the average ensemble, CHIRPS 0.05- degree, CHIRPS 0.25-degree and IMD. The average ensemble provided the best performance of the ensemble methodologies and all the rainfall datasets utilised (Table 5.2).

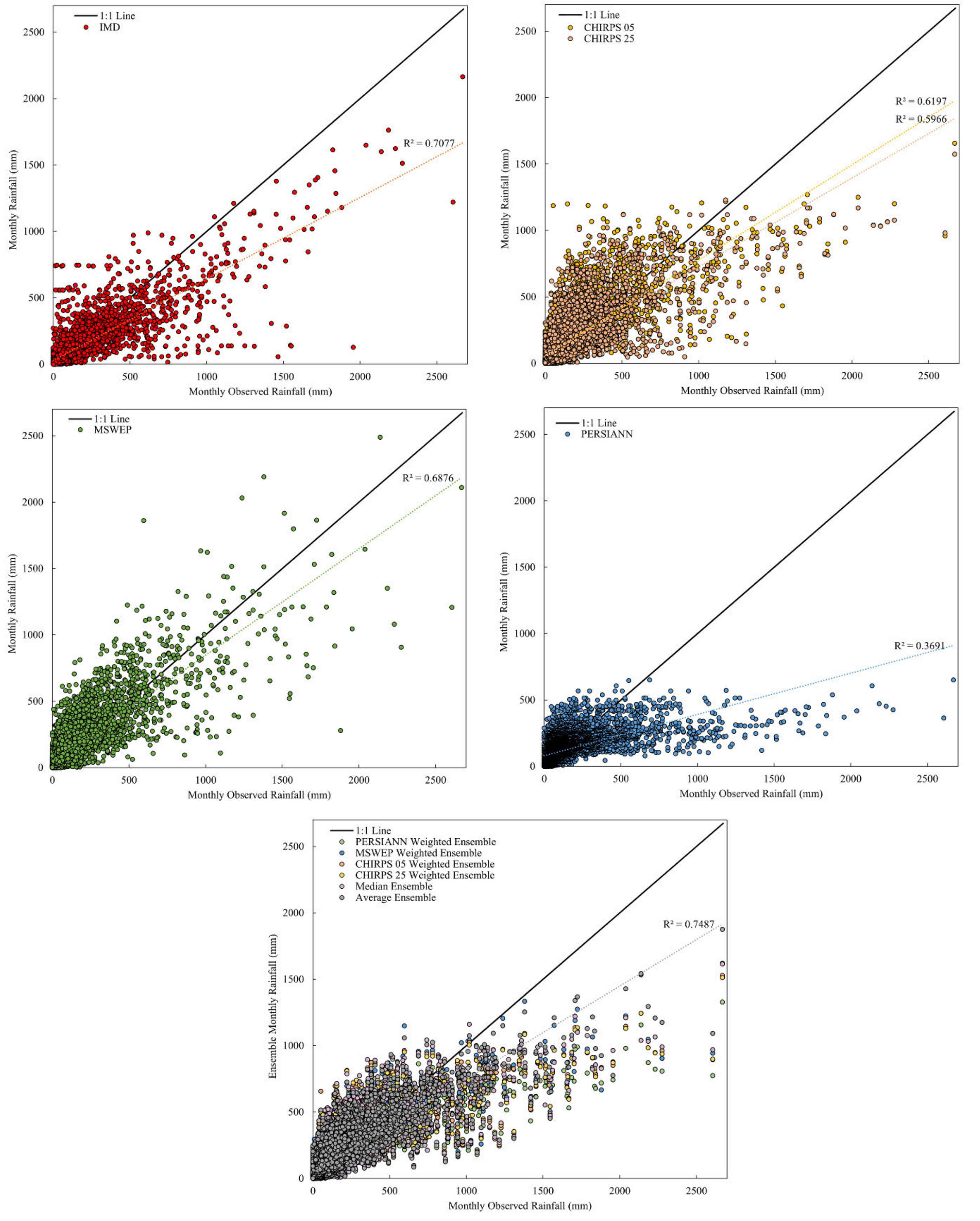



Figure 5.4 The monthly in-situ observed rainfall against the monthly rainfall from the gridded rainfall datasets (left) and the various ensembles (right)

Table 5.2 The average KGE, RMSE and bias value (V) when utilising the various rainfall datasets and ensemble techniques across the Upper Cauvery Catchment compared to the monthly observed values. A score (S) is assigned from the best-performing dataset from 1(best) to 11 and these are summed to indicate the overall best-performing dataset.

| **Metric** | **IMD** | | **CHIRPS 25** | | **CHIRPS 05** | | **MSWEP** | | **PERSIANN** | | **Average ensemble** | | **Median ensemble** | | **CHIRPS 0.25-degree weighted ensemble** | | **CHIRPS 0.05-degree weighted ensemble** | | **MSWEP weighted ensemble** | | **PERSIANN weighted ensemble** | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | V | S | V | S | V | S | V | S | V | S | V | S | V | S | V | S | V | S | V | S | V | S |
| KGE | 0.54 | 7 | 0.45 | 8 | 0.4 | 9 | 0.13 | 10 | 0.21 | 11 | 0.74 | 1 | 0.72 | 2 | 0.69 | 5 | 0.7 | 4 | 0.71 | 3 | 0.64 | 6 |
| Bias | -20.4 | 11 | 12.5 | 10 | 9.6 | 9 | 1.9 | 2 | 0.4 | 1 | 3.5 | 3 | 7.6 | 5 | 8.5 | 6 | 9.3 | 8 | 9.1 | 7 | 4.9 | 4 |
| RMSE | 129.3 | 5 | 148.9 | 8 | 152.4 | 9 | 161.7 | 10 | 204.1 | 11 | 120.4 | 1 | 127.3 | 3 | 129.4 | 6 | 129.3 | 4 | 124.1 | 2 | 134.6 | 7 |
| Score | **23** | | **26** | | **27** | | **22** | | **23** | | **5** | | **10** | | **17** | | **16** | | **12** | | **17** | |

As shown in Figure 5.5, the central tendency of the data from across the year is similar between datasets. The rainfall distribution presents a negative skewness, with the median shifted towards the lower quartile. Considering the nature of rainfall in this region, this is expected as there are a high proportion of days without rainfall. The overall ability of the remotely sensed datasets to represent the distribution of rainfall is fairly accurate when considering the $10^{th}$ and $90^{th}$ percentiles, the medians and the interquartile ranges (Table 5.8 in Appendix E).

During the monsoon (June-September), the data demonstrate a wider variability of data from the median and a relatively large interquartile range (Figure 5.5; Table 5.8 in Appendix E) is presumably associated with the variable timing of the onset and the strength of the monsoon. Although the data still demonstrates a positive skewness, it is not as prominent as when considering the rainfall across the year. The 'drizzle day' nature of remotely sensed datasets is evident in the representation of the $10^{th}$ percentile. 'Drizzle day' nature is caused by the remotely sensed data consisting of spatial means rather than point estimates, which can result in a smaller number of no-rain days when spatial estimates are compared to observed gauge data. The observed and IMD datasets present the $10^{th}$ percentile of zero, whilst the remotely sensed datasets vary between 10-45mm. The ability of the remotely sensed datasets to represent the distribution of rainfall for the monsoon season is more varied. The median and interquartile range values of the remotely sensed datasets are greater than that of the observed and IMD (Table 5.8 in Appendix E). The IMD data represents the lower distribution but not, the higher distribution well. PERSIANN presents a small interquartile range suggesting that the rainfall values are clustered around the median and do not represent the high or low quartiles well. The average and median ensembles provide the closest representation of the $10^{th}$ and $90^{th}$ percentiles and the interquartile range of observed rainfall, especially in the monsoon season. (Figure 5.5; Table 5.8 in Appendix E). Considering the $10^{th}$ and $90^{th}$ percentiles, the interquartile range and the $R^2$ value, the average ensemble was selected as the most accurate and will be used.

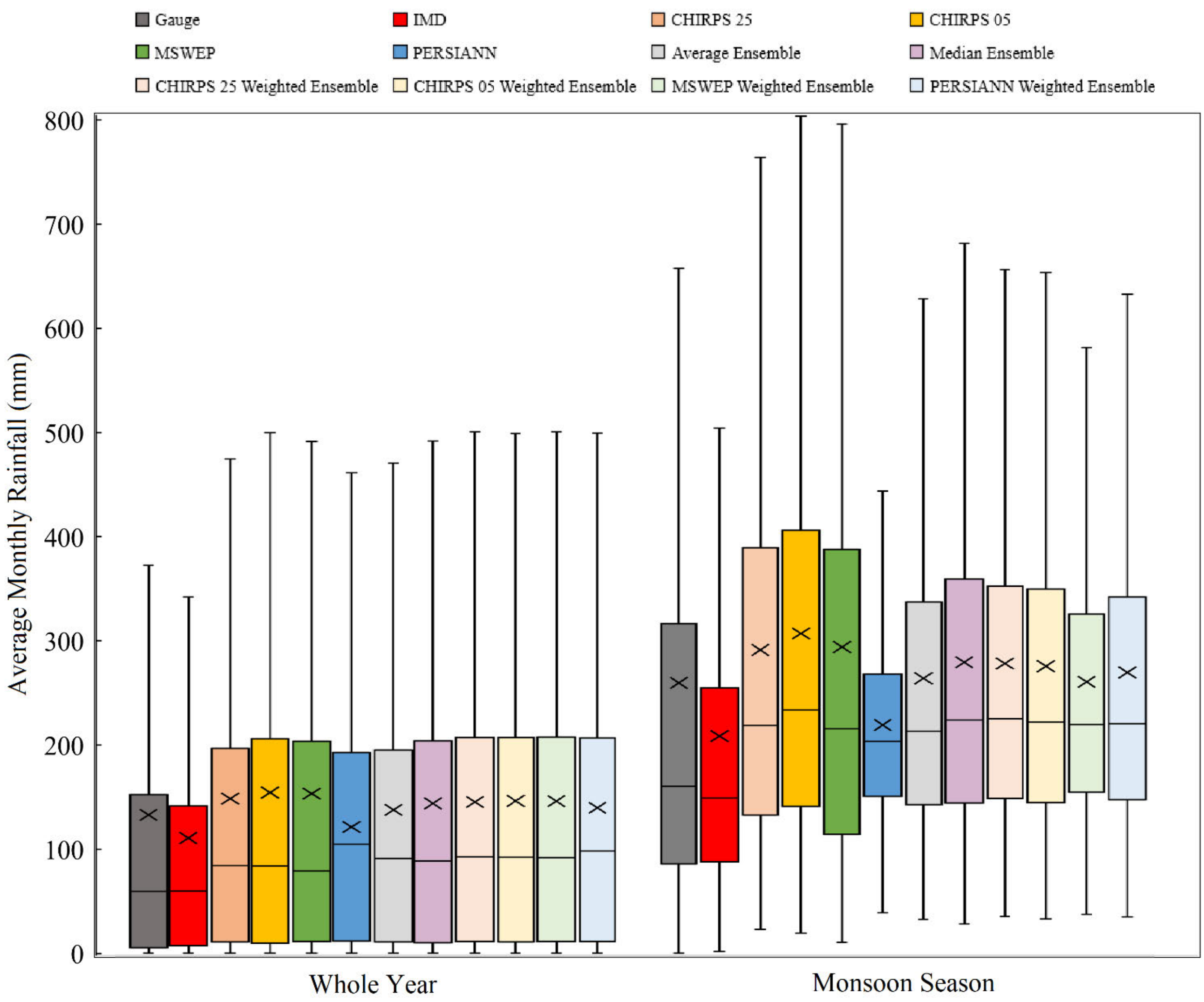



Figure 5.5 The range of average monthly rainfall produced by each rainfall dataset across the period of 1985 until 2013 and within the monsoon season. The whiskers represent the $10^{th}$ and $90^{th}$ percentiles, the line within the box represents the median and the 'X' represents the average.

Figure 5.6 illustrates that the estimation of rainfall by large-scale remotely sensed datasets within the Upper Cauvery Catchment is variable. The IMD grids underestimate the rainfall systematically across the Upper Cauvery Catchment, and the underestimation is particularly prevalent within the rain shadow.

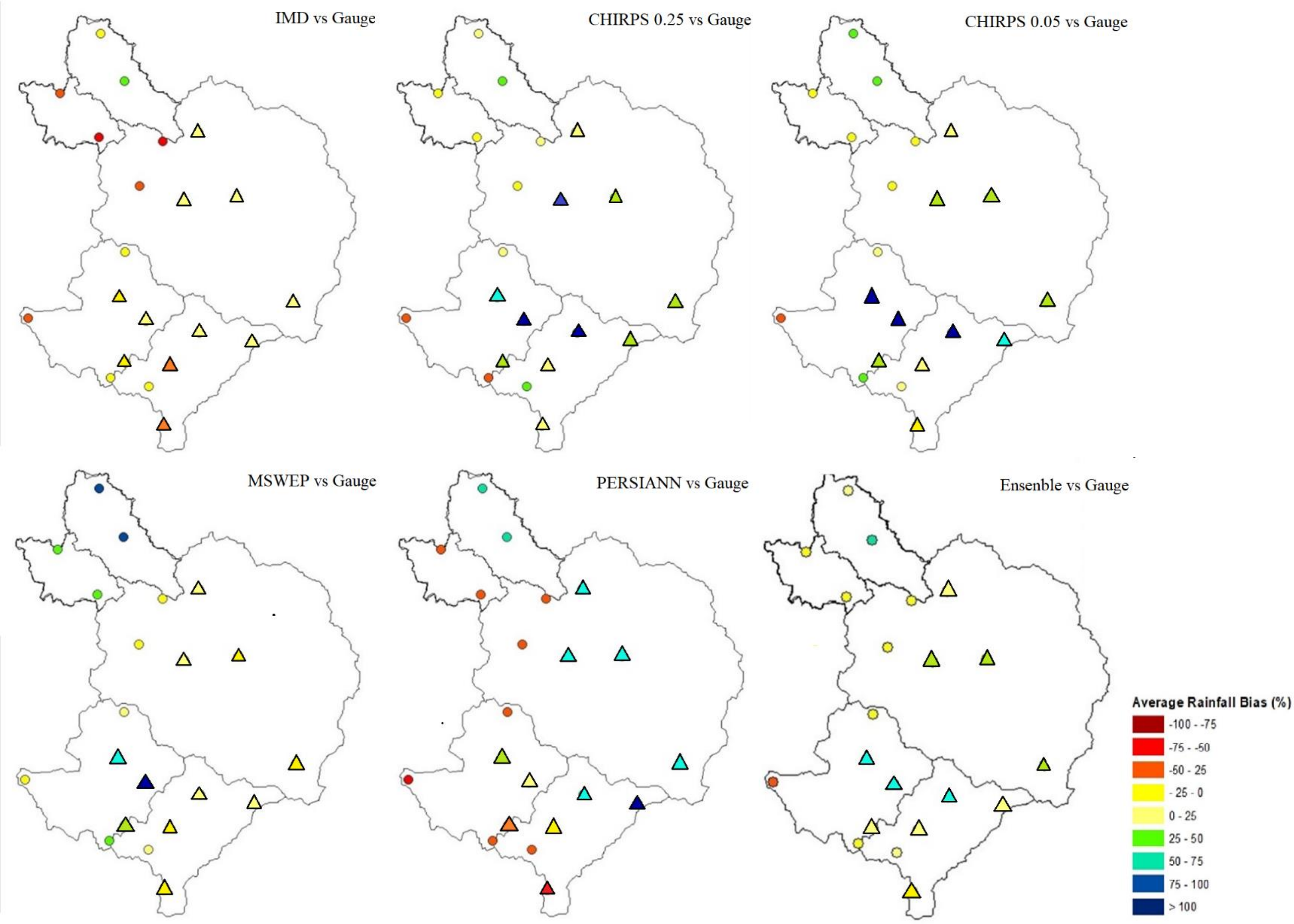
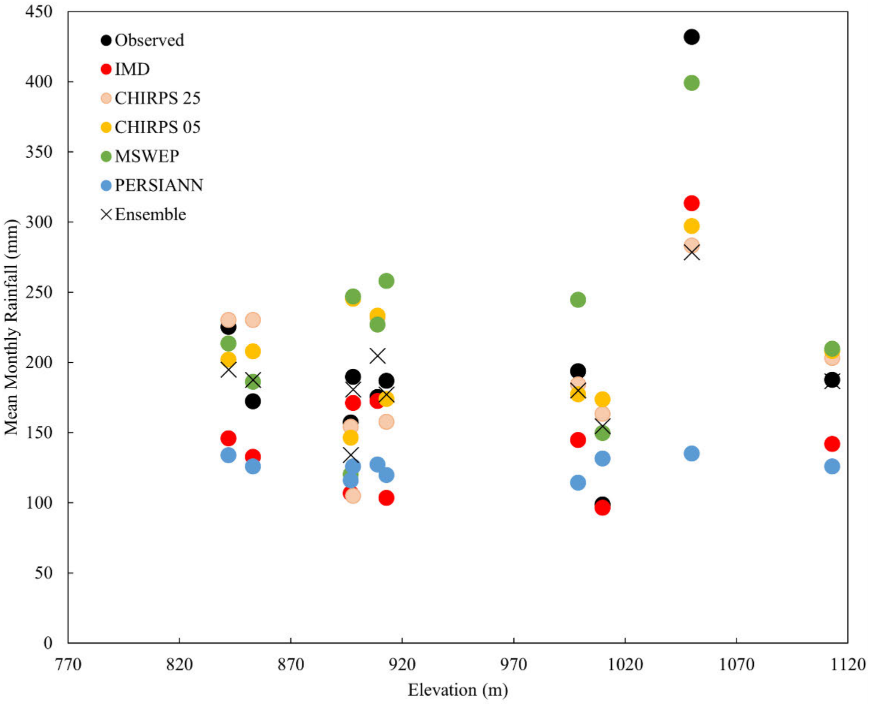



Figure 5.6 Average monthly rainfall bias (%) from 1985- 2013 between the rainfall datasets (IMD grids, CHIRPS 0.25-and 0.05- degree, MSWEP, PERSIANN and the average ensemble) and the station gauge data. The windward gauges are denoted as a circle and the leeward gauges as a triangle.

At lower altitudes, the CHIRPS datasets overestimate the rainfall but underestimate it at higher altitudes (Figure 5.6; Figure 5.7). In the rainshadow, CHIRPS demonstrates a decrease in rainfall with altitude (Figure 5.7). The performance of the CHIRPS datasets is not dependent on the spatial scale (Figure 5.2; Figure 5.5 and Figure 5.6). The results at both 0.05- and 0.25-degree datasets are similar and, therefore, reflect the methodology rather than the scale at which they are published. Although CHIRPS is published daily, regression slopes and rainfall anomalies are produced at a pentadal (five-year) resolution (Funk *et al.*, 2015). Within the Upper Cauvery Catchment, inter- and intra- annual rainfall and monsoonal conditions vary year on year; therefore, a pentadal methodology is unlikely to fully capture the extreme rainfall.

Furthermore, the gauge correction is undertaken at a 1.5-degree scale (Funk *et al*., 2015). Due to the high rainfall variability and topography in this mountainous region and a sparse rain gauge network (Venkatesh *et al*., 2021), it is probable that although gauge correction has occurred, it is not at a resolution fine enough to be effective.



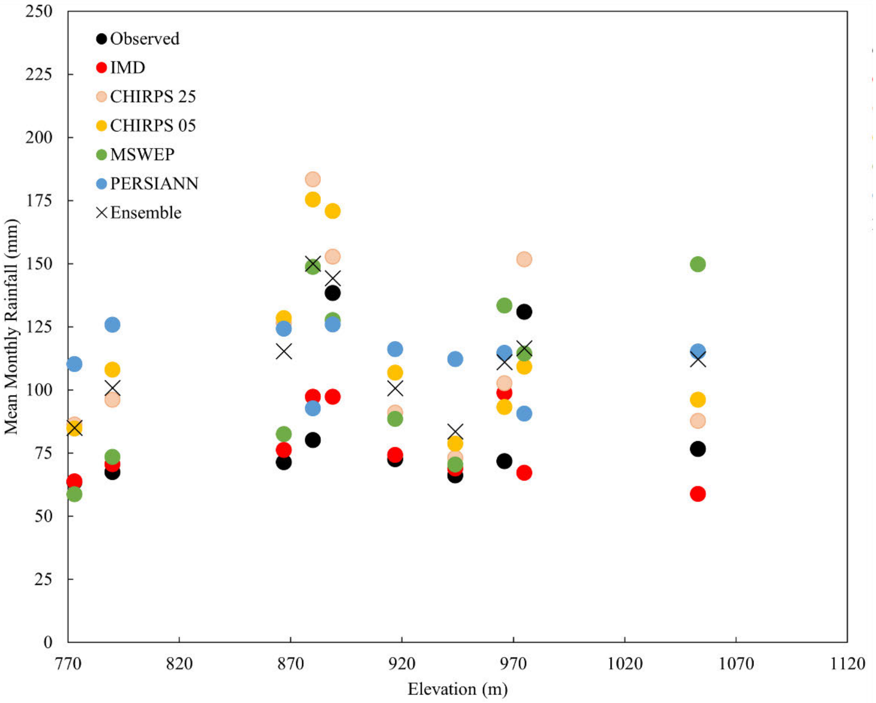




Figure 5.7 The mean monthly rainfall from 1985 – 2013 provided by each rainfall dataset (IMD grids, CHIRPS 0.25-and 0.05- degree, MSWEP, PERSIANN and the average ensemble) compared with the observed values across the elevation of the windward slope (top) and in the rain shadow (bottom) across the Upper Cauvery Catchment.

MSWEP overestimates the mean rainfall, particularly in the rainshadow (Figure 5.7). In agreement with the results reported by Prakash *et al*. (2019) and Bhattacharyya *et al*. (2022) across the Western Ghats, in the Upper Cauvery Catchment, MSWEP overestimates the rainfall in the rain shadow and underestimates the rainfall on the windward slopes compared to the in-situ gauge data (Figure 5.6; Figure 5.7). Furthermore, similar to Prakash *et al*. (2019) but in contradiction to the results of Liu *et al*. (2019) in Tibet, MSWEP overestimates the rainfall compared with the in-situ gauge data (Figure 5.6). Considering MSWEP is derived from multiple satellite sources and published at a 0.1-degree resolution, it is surprising that the performance of this dataset was not better in this region. MSWEP is generated through a complex multi-step process, and the long-term mean is corrected for orographic influence but not gauge under-catch. The underestimation of the rainfall on the windward slope could be explained by the lack of consideration for gauge under-catch, specifically in this high altitude and intense rainfall region. However, inverse-distance weighting is utilised via gauges to correct the monthly merged dataset. Inverse-distance weighting is not the most suitable methodology for gauge correction in this region as the gauging network is sparse (Section 5.2.2.2.).

On the leeward slope, PERSIANN demonstrates a decrease in rainfall with altitude (Figure 5.7). Similar to the results reported by Prakash *et al.* (2019), the PERSIANN rainfall was underestimated on the windward slopes and overestimated on the leeward slopes compared to the IMD grids (Figure 5.6; Figure 5.7). As in Sharannya *et al.* (2020), the rainfall was underestimated in the windward slope compared to the IMD grids. Sharannya *et al.* (2020) estimated a 10% underestimation on the windward slopes throughout the Western Ghats, whereas this study has shown an underestimation of between 25% and 50% compared to the IMD grids. In agreement with the work of Bhardwaj *et al*. (2017) in the Himalayas and Faridzad *et al*. (2018) in the high-elevation regions of the United States of America, PERSIANN consistently underestimated station rainfall depths within the Upper Cauvery Catchment (Figure 5.6). The coarse-scale gauge correction performed in the generation of this dataset may not capture the complex topography and subsequent variation in rainfall

When applied to the Upper Cauvery Catchment, the average ensemble provides a better point-to-pixel representation of the rainfall in the high-altitude windward regions but not in the rain shadow compared to the IMD grids (Figure 5.6; Figure 5.7). The IMD grids would be expected to perform better at the gauging points as they are generated from the IMD in-situ gauged data (Section 5.2.2.2.). However, in high-altitude areas, the IDW technique is known not to capture the variation in intense rainfall well (Lynch, 2003; Naoumi & Tsanis, 2004; Mair & Fares, 2011; Pingale *et al*.,2014). In the rain shadow, where the rainfall is less intense and variable, the IMD grids represent the rainfall more accurately.

In the Upper Cauvery Catchment, using CHIRPS 0.25- and 0.05- degree, MSWEP and PERSIANN datasets, the average ensemble improved the representation of monthly rainfall (Table 5.2; Figure 5.6). The ability of the average ensemble to improve the representation of catchment rainfall and simulated streamflow provides a strong case for this technique, specifically in high-altitude regions with no or low in-situ rainfall availability.

It is evident in Figure 5.8 that the largest root mean squared error occurs within the monsoon season, June to August, across all the rainfall datasets. PERSIANN has the greatest RMSE, followed by CHIRPS, MSWEP, IMD grids, and the ensemble. The monthly bias of the IMD data is least throughout the year, whereas MSWEP overestimates whilst CHIRPS and PERSIANN underestimates in the dry months of January and February. All the satellite-derived datasets overestimate the rainfall during the pre-monsoon season (April and May). During the monsoon season (June to September), CHIRPS and MSWEP overestimate the rainfall, while IMD and PERSIANN provide a good representation of the volume of rainfall. The ensemble provides the most accurate representation of the rainfall depth across the year (Figure 5.8). During the dry season, the performance of CHIRPS and MSWEP reduces. IMD has a consistently good KGE score across the year. Despite the good bias of the PERSIANN and the ensemble estimates, the KGE score between December and March is poor (Figure 5.8)

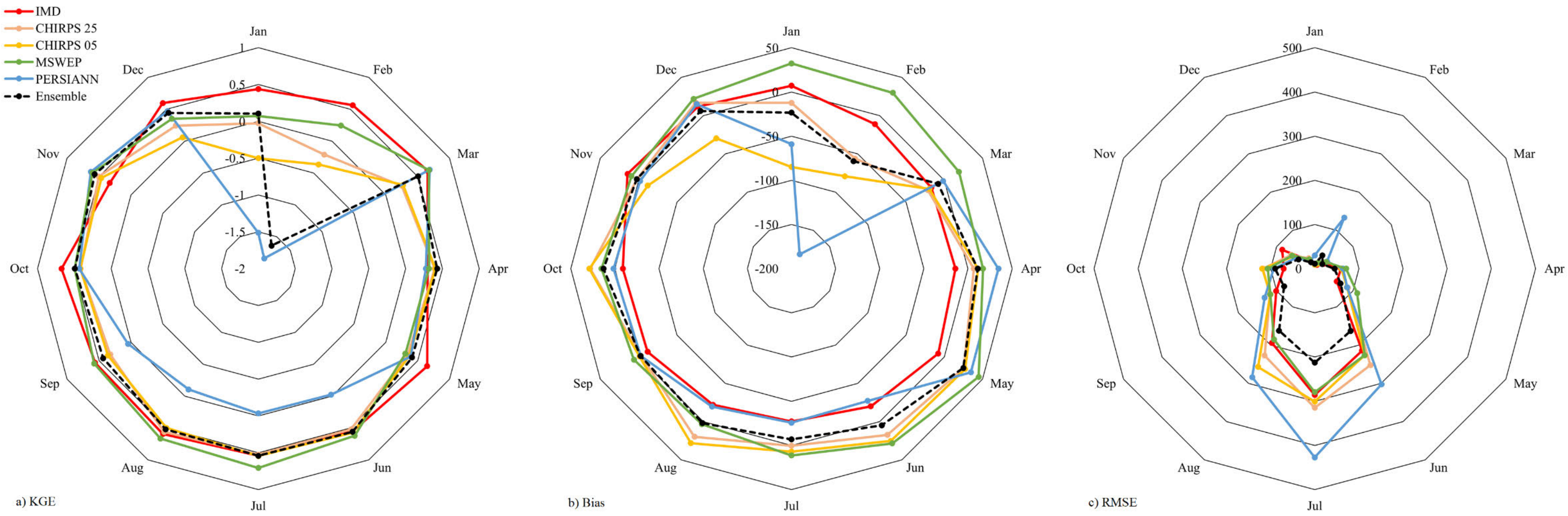



Figure 5.8 a) Kling-Gupta Efficiency (KGE), b) Bias in percentage and c) Root mean squared error (RMSE) of the rainfall datasets compared with the observed monthly rainfall from 1985 until 2013.

### *5.3.2 Performance of Streamflow Simulated Using the Selected Rainfall Datasets*

The GWAVA model was calibrated using the observed streamflow at five gauging points using the IMD gridded rainfall. The results of the calibration are provided in Table 5.3. The results provided compare the GWAVA streamflow simulations using the IMD rainfall grids compared to the observed streamflow.

The monthly streamflow KGE statistics illustrate that the model was calibrated to an acceptable standard (Table 5.3). However, the streamflow is substantially underestimated at the Saklesphur, KM Vadi, Kudige and KRS Catchments (Figure 5.9). The sub-catchments with the largest rainfall RMSE produce the highest streamflow RMSE except in the case of Kudige. Thimmanahali Catchment, where the rainfall depth estimation is the most accurate, produces the most accurate simulation of the observed streamflow.

Table 5.3 The monthly streamflow statistics (KGE, RMSE and bias) of each calibration sub-catchment in the Upper Cauvery Catchment.

| Sub- catchment | Monthly KGE | Monthly RMSE | Bias (%) |
|---|---|---|---|
| Saklesphur | 0.55 | 40.7 | -46.4 |
| Thimmanahali | 0.84 | 9.2 | 1.6 |
| KMVadi | 0.25 | 19.5 | -33.6 |
| Kudige | 0.48 | 15.8 | -32.3 |
| KRS | 0.47 | 25.6 | -54.9 |

As shown in Table 5.4, the ensemble produces the most accurate representation of streamflow across the Upper Cauvery Catchment, followed by IMD, PERSIANN, CHIRPS 0.25-degree, MSWEP and then CHIRPS 0.05-degree. At the Saklesphur catchment CHIRPS 0.25-degree provides the most accurate simulation of streamflow, IMD at Thimmanahali and Kudige, MSWEP at KM Vadi and PERSIANN at KRS.

The accuracy of the simulated streamflow using the selected rainfall input is highly variable (Table 5.4; Figure 5.9) between the different datasets. As for the rainfall (Table 5.2), the ensemble provided the best KGE and RMSE scores across the Upper Cauvery Catchment, followed by the IMD grids. Regarding streamflow, PERSIANN outperforms CHIRPS and MSWEP. PERSIANN provides the lowest bias, followed by CHIRPS 0.25-degree, the ensemble, IMD, MSWEP and CHIRPS 0.05-degree (Table 5.4).

Table 5.4 Average KGE, RMSE and bias of simulated streamflow across the Upper Cauvery Catchment generated by the selected datasets

| **Metric** | **IMD** | **CHIRPS 25** | **CHIRPS 05** | **MSWEP** | **PERSIANN** | **Ensemble** |
|---|---|---|---|---|---|---|
| KGE | 0.46 | 0.13 | -0.37 | -0.18 | 0.23 | 0.50 |
| Bias | -35.06 | 26.12 | 83.21 | 61.15 | 5.52 | 28.21 |
| RMSE | 103.98 | 123.82 | 128.06 | 138.30 | 131.93 | 62.37 |

In the monsoon season, the simulated streamflow produced using CHIRPS and MSWEP rainfall inputs was significantly overestimated compared to the observed streamflow, whereas PERSIANN and IMD underestimated the streamflow (Figure 5.10). The ensemble tends to overestimate the simulated streamflow during the monsoon season but provides a better representation than the individual remotely sensed dataset and the IMD grids. In the dry season, all the datasets tend to produce streamflow that underestimate compared to the observed. Of the remotely sensed datasets, PERSIANN produces simulated streamflow that best represents the observed data at KRS (Figure 5.9; Figure 5.10).

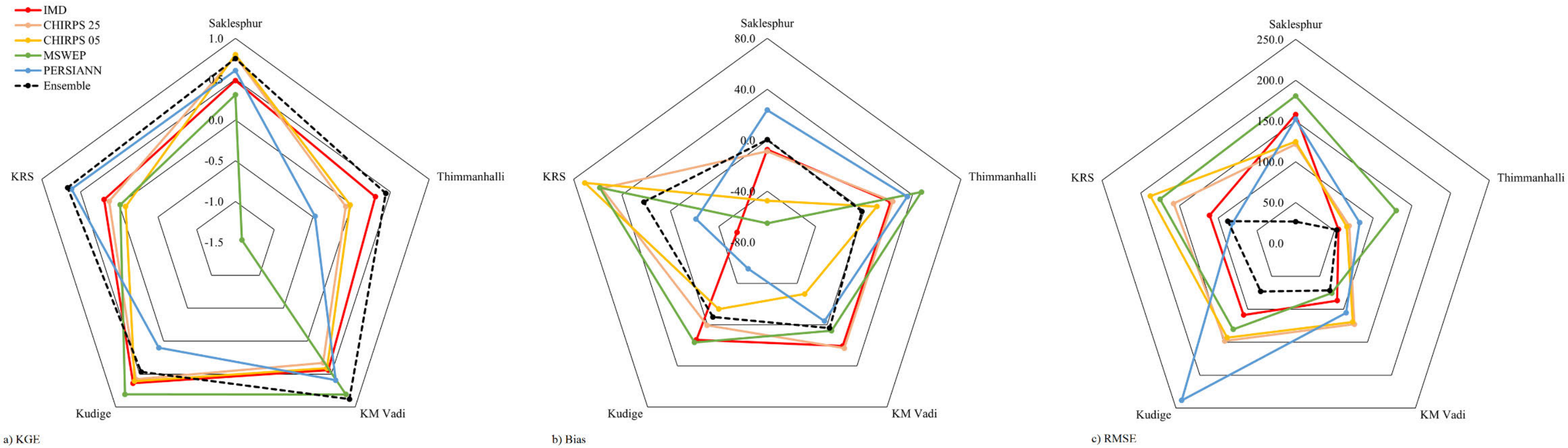



Figure 5.9 The monthly a) Kling-Gupta Efficiency (KGE) b) Bias in percentage and c) Root mean squared error (RMSE) of the simulated streamflow produced using the selected rainfall datasets (IMD, CHIRPS 0.25- and 0.05- degree, MSWEP, PERSIANN and the ensemble) compared with the observed streamflow.

The monthly average streamflow at the entrance to KRS is of significance as approximately 82% of the total catchment streamflow is recorded at this point. Successfully simulating the temporal trend and the volume of streamflow at KRS is critical aspect to understanding and accurately representing the water resources of the greater catchment. The streamflow during the monsoon season reflects the rainfall performance across June to October, with CHIRPS, MSWEP and the ensemble overestimating, and PERSIANN and the IMD grids underestimating the volume of both streamflow and rainfall (Figure 5.10). However, the bias in streamflow during the monsoon season exceeds the rainfall bias of each rainfall input. The overestimation of rainfall likely causes this during the pre-monsoon period, which overestimates the filling of engineered water storage structures and groundwater stores. This results in an overestimation of the lagged baseflow contribution during the monsoon season, further increasing the over estimation of total streamflow during this period.

During the dry season, the variation in bias and KGE of the rainfall is not reflected in the streamflow (Figure 5.10). This could be caused by the high number of engineered water storage structures in the catchment and the intensive groundwater pumping that limits baseflow into the main channels that tend to nullify any variation of rainfall bias in the dry months between the rainfall sources. The significant underestimation of rainfall by PERSIANN from December to March will affect the volume of water for groundwater recharge during this period. This results in an underestimated peak flow during the monsoon season, despite the overestimated rainfall in March to May, as the lagged baseflow component will be significantly underestimated.

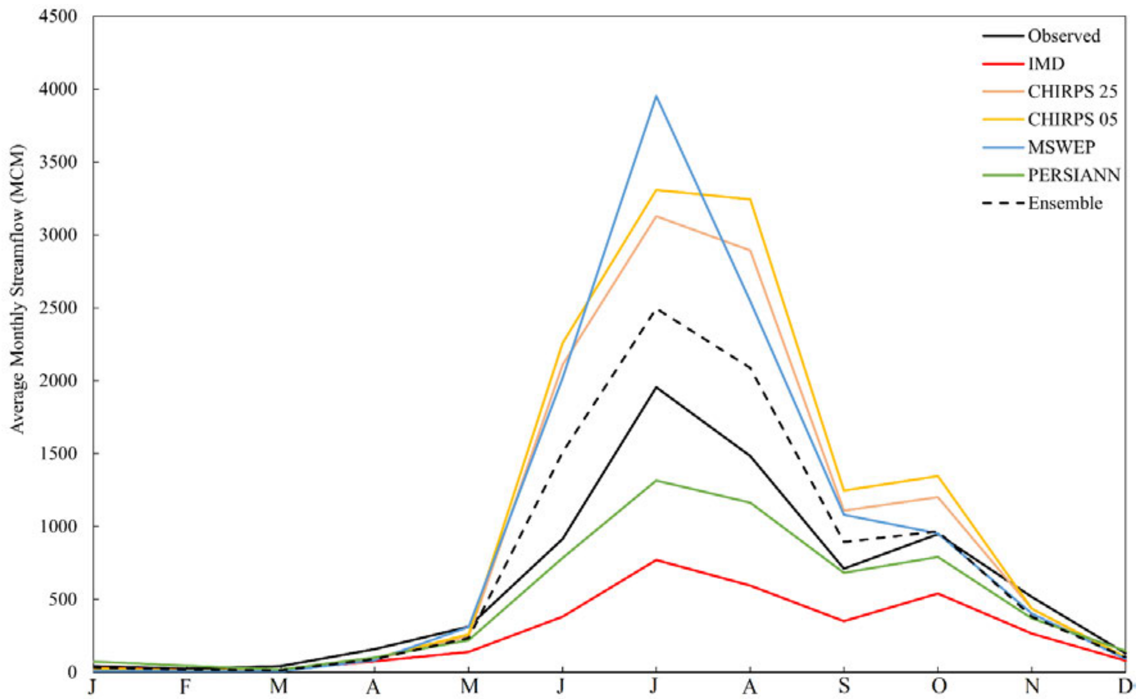



Figure 5.10 The monthly average streamflow in MCM at KRS simulated using the IMD, CHIRPS 0.25- and 0.05-- degree, MSWEP, PERSIANN and an ensemble rainfall dataset superimposed with the monthly average observed streamflow.

## 5.3 Discussion

The Western Ghats region northwest of the catchment is a known area of uncertainty for the IMD rainfall data (Pai *et al*., 2014). Each 0.25-degree grid cell contains numerous terrain and gradient increments, and the grid cells span the catchment boundary. This results in an inaccurate representation of the total rainfall and distribution and the distribution of minimum and maximum temperature in this region of the catchment (Yeggina *et al*., 2020). Several studies have reported that conventional spatial interpolation techniques, such as the inverse distance weighting utilised to derive the IMD grid, do not fully account for both climatological and spatial-statistical properties of rainfall fields at high altitudes (Prudhomme & Reed, 1999; Guan *et al*., 2005; Vogel *et al*., 2015). Despite the well-reported underestimation of rainfall in high-altitude regions (Raman *et al*., 2013; Tawde & Singh, 2015; Bharti *et al*., 2016; Dahri *et al*., 2016; Bhardwaj *et al*., 2017; Li *et al*., 2018; Horan *et al.*, 2021a,b,c), the IMD grids have proven to provide one of the most accurate representations of rainfall across the Upper Cauvery Catchment (Table 5.2). Along with the findings of this study, where the IMD grids outperformed CHIRPS, MSWEP and PERSIANN-CDR, Bhardwaj *et al*. (2017), Yeggina *et al.*

(2020) and Reddy *et al*. (2022) found that the IMD grids provided better performance than PERSIANN-CDR, TMPA-3B42 and TRMM 3B43 and MERRA within the Western Ghats.

Rainfall across the study region was found to be highly variable (Figure 5.7; Table 5.5 in Appendix E), supporting the findings of Sharannya *et al*. (2018), Wagener *et al*. (2015) and Varikoden *et al*. (2019). Despite all the remotely sensed datasets integrating in-situ gauged data into their methodologies, there were disparities between the rainfall provided by these remotely sensed datasets and the in-situ gauged data provided by the IMD for the Upper Cauvery Catchment. In the Upper Cauvery Catchment, all the datasets tend to underestimate the average rainfall at higher altitudes and overestimate the rainfall in the rain shadow (Figure 5.7; Figure 5.8). Previous studies by Prakash *et al.* (2014) and Shah and Mishra (2016) indicated that the CHIRPS datasets underestimate the rainfall on the windward slope compared to the IMD grids. This study found that the CHIRPS datasets tend to underestimate the total volume of rainfall in the high-altitude regions and on the windward slopes, supporting previous studies. Similar results were presented by Saeidizand *et al*. (2018) in Iran and Divya and Shetty (2020) across the Western Ghats. In these studies, and similar to this study, CHIRPS did not accurately represent the rainfall in the high-altitude regions and produced an overestimation of rainfall in the lower-lying regions of the Zagros (Iran) and Western Ghats mountains. Contrary to the conclusions of Huffman *et al*. (2007), Huffman *et al*. (2010), Terzago *et al.* (2018) and Lengfeld *et al*. (2020), the finer scale rainfall datasets, i.e. CHIRPS 0.05-degree and MSWEP did not perform better than the coarser scale datasets in this region of complex topography. This might be because both datasets are produced at a coarser scale, downscaled through various methods, and are gauge-corrected using the same limited number of available rainfall gauges as the coarse-scale datasets.

It was found that the rainfall in the region does not simply increase with altitude as occurs in other mountainous regions of the world (Fowler *et al*., 1988; Al-Ahmadi & Al-Ahmadi, 2013; Morris *et al*., 2016) or decrease in the high altitudes as Singh and Mal (2014) reported in the Himalayas. In the Upper Cauvery Catchment, there does not seem to be a straightforward correlation between altitude and rainfall (Figure 5.7). The orographic effect on the rainfall was more evident in the Upper Cauvery Catchment (Figure 5.6; Figure 5.7), with the Western Ghats forcing the upward movements of moisture-filled air resulting in increased rainfall on the windward slope and less rainfall on the leeward (rains shadow) slope (Arora *et al*., 2006; Chang *et al*., 2014; Morris *et al*., 2016).

Several methodologies of building an ensemble of remotely sensed datasets were tested. All the ensembles tested outperformed the individual rainfall datasets. The ensemble representing the average of the remotely sensed datasets was the best-performing ensemble. Average ensembles can be effectively utilised to reduce uncertainties (Hughes, 2016). Utilising an ensemble allows for the weaknesses in one technique and/or dataset to be shadowed or compensated by the strength of others. The average ensemble accounts for the skill of each technique, maximises the available input data and provides an estimate of the range of possible outcomes. Ensembles can have higher predictive accuracy and successfully represent non-linear interactions. An ensemble can reduce the noise, bias and variance of simulations and potentially create a more in-depth understanding of the data. However, ensemble modelling results can suffer from a lack of interpretability and depend on the ensemble members' prediction accuracy. In areas with perhaps more availability of in-situ rainfall data, more complex techniques such as machine learning (Zhang *et al*., 2021), Google Earth Engine (Banerjee *et al*., 2020) and big data merging (Hu *et al*., 2019) could be utilised to improve the representation of rainfall. In the case of the Upper Cauvery Catchment, these techniques would not have been feasible, nor would a regional bias correction, due to the sparse and missing in-situ rainfall data. The average ensemble of the chosen datasets provided a more accurate representation of the rainfall than the IMD gridded and the individually remotely sensed datasets. However, it remains critical to ensure that in-situ rainfall gauging networks are maintained and expanded as in-situ data sources of high confidence remain important for the continuous development and ground-truthing of different rainfall datasets.

In agreement with the findings of Sylla *et al.* (2013), Beck *et al.* (2017) and Dembélé *et al.* (2020), it was illustrated that there is no single rainfall dataset which provides the best representation of rainfall and streamflow across the five sub-catchments. Also, the large-scale performance for rainfall datasets is not always valid for sub-catchments in the same catchment. The average ensemble rainfall dataset also provided the most accurate simulation streamflow and, therefore, can be assumed to have accounted for the catchment rainfall most appropriately. A significant challenge in large-scale hydrological modelling is quantifying and managing the uncertainty in climate forcing and evaluation data (e.g. streamflow). Although the model was calibrated to a satisfactory standard using the observed streamflow, at some gauging points in the catchment, there is low confidence in the observed streamflow data (Srinivas & Srinivasan, 2005). Eye-witness accounts and some literature (Srinivasan *et al*., 2015) report the drying out of streams in the Upper Cauvery Catchment in the dry season, which is not reflected in the observed data. Furthermore, the model structure can exaggerate the over-and underestimation of streamflow in both dry and wet periods. The model structure allocates water to the evaporative component first, and thus, the evaporative processes are favoured in times of water stress, and streamflow is favoured in the wet season. This can result in a further underestimation of streamflow when the rainfall is underestimated and an overestimation of streamflow when the rainfall is overestimated.

## 5.4 Conclusion

CHIRPS 0.25- and 0.05- degree MWSEP and PERSIANN-CDR rainfall data were applied at a catchment scale in the Upper Cauvery Catchment for the first time alongside the IMD 0.25-degree gridded and an ensemble rainfall. The ‘off-the-shelf’ remotely sensed rainfall datasets provided a high variation in performance against the in-situ rain gauge data. The IMD grids provided the most accurate representation of rainfall of the individual datasets, despite underestimating the rainfall depths at high altitudes; however, the ensembles, notably the average ensemble, provided the overall best estimates. The following conclusions were drawn from this study:

a) The ensemble rainfall, notably the average ensemble, produced the most accurate representation of the rainfall, followed by IMD, CHIRPS 0.05-and 0.25-degree, MSWEP and then PERSIANN.
b) The spatial scale of the rainfall dataset does not necessarily affect the performance in the high-altitude regions of the Upper Cauvery Catchment.
c) The rainfall in the Upper Cauvery Catchment does not have a distinct correlation to the altitude but correlates strongly to the aspect of the mountains.
d) None of the individual remotely sensed datasets tested could be utilised with confidence in the Upper Cauvery Catchment.
e) The average ensemble and IMD rainfall data produced the most accurate simulation of the observed streamflow across the sub-catchments of the Upper Cauvery, followed by PERSIANN, CHIRPS 0.25-degree, MSWEP and then CHIRPS 0.05-degree.
f) PERSIANN and the average ensemble provided the most accurate simulation of observed streamflow at KRS.

This study evaluated the performance of remotely sensed rainfall datasets not applied in the Upper Cauvery Catchment previously, proposed an ensemble approach to improve rainfall estimations and applied multiple rainfall estimations within the GWAVA water resources model.

## 5.6 References


Al-Ahmadi, K. and Al-Ahmadi, S., 2013. Rainfall-altitude relationship in Saudi Arabia. *Advances in Meteorology*, 2013.

Allen, D.M., Cannon, A.J., Toews, M.W. and Scibek, J., 2010. Variability in simulated recharge using different GCMs. *Water Resources Research*, 46(10).

Arora, M., Singh, P., Goel, N.K. and Singh, R.D., 2006. Spatial distribution and seasonal variability of rainfall in a mountainous basin in the Himalayan region. *Water Resources Management*, 20(4), pp.489-508.

Ashouri, H., Hsu, K.L., Sorooshian, S., Braithwaite, D.K., Knapp, K.R., Cecil, L.D., Nelson, B.R. and Prat, O.P., 2015. PERSIANN-CDR: Daily precipitation climate data record from multi-satellite observations for hydrological and climate studies. *Bulletin of the American Meteorological Society*, 96(1), pp.69-83.

Baker, L. and Ellison, D., 2008. Optimisation of pedotransfer functions using an artificial neural network ensemble method. *Geoderma*, 144(1-2), pp.212-224.

Banerjee, A., Chen, R., E. Meadows, M., Singh, R.B., Mal, S. and Sengupta, D., 2020. An analysis of long-term rainfall trends and variability in the Uttarakhand Himalaya using the google earth engine. *Remote Sensing*, 12(4), p.709.

Bauer, A.M. and Morrison, K.D., 2008. Water management and reservoirs in India and Sri Lanka. *Encyclopaedia of the History of Science, Technology, and Medicine in Non-Western Cultures*, pp.4376-4385.

Beck, H.E., Van Dijk, A.I., Levizzani, V., Schellekens, J., Miralles, D.G., Martens, B. and De Roo, A., 2017. MSWEP: 3-hourly 0.25 global gridded precipitation (1979–2015) by merging gauge, satellite, and reanalysis data. *Hydrology and Earth System Sciences*, 21(1), pp.589-615.

Bhardwaj, A., Ziegler, A.D., Wasson, R.J. and Chow, W.T., 2017. Accuracy of rainfall estimates at high altitude in the Garhwal Himalaya (India): A comparison of secondary precipitation products and station rainfall measurements. *Atmospheric Research*, 188, pp.30-38.



Bhardwaj, A., Ziegler, A.D., Wasson, R.J. and Chow, W.T., 2017. Accuracy of rainfall estimates at high altitude in the Garhwal Himalaya (India): A comparison of secondary precipitation products and station rainfall measurements. *Atmospheric Research*, 188, pp.30-38.

Bharti, V., Singh, C., Ettema, J. and Turkington, T.A.R., 2016. Spatiotemporal characteristics of extreme rainfall events over the Northwest Himalayas using satellite data. *International Journal of Climatology*, 36(12), pp.3949-3962.

Bhattacharyya, S., Sreekesh, S. and King, A., 2022. Characteristics of extreme rainfall in different gridded datasets over India during 1983–2015. *Atmospheric Research*, 267, p.105930.

Bhave, A.G., Conway, D., Dessai, S. and Stainforth, D.A., 2018. Water resource planning under future climate and socioeconomic uncertainty in the Cauvery River Basin in Karnataka, India. *Water Resources Research*, 54(2), pp.708-728.

Burek, P., Satoh, Y., Kahil, T., Tang, T., Greve, P., Smilovic, M., Guillaumot, L., Zhao, F. and Wada, Y., 2020. Development of the Community Water Model (CWatM v1. 04)–a high-resolution hydrological model for global and regional assessment of integrated water resources management. *Geoscientific Model Development*, 13(7), pp.3267-3298.

Buri, E.S., Keesara, V.R. and Loukika, K.N., 2022. Long-term trend analysis of observed gridded precipitation and temperature data over Munneru River basin, India. *Journal of Earth System Science*, 131(2), pp.1-18.

Chang, F.J., Chiang, Y.M., Tsai, M.J., Shieh, M.C., Hsu, K.L. and Sorooshian, S., 2014. Watershed rainfall forecasting using neuro-fuzzy networks with the assimilation of multi-sensor information. *Journal of Hydrology*, 508, pp.374-384.

Chidambaram, S., Ramanathan, A.L., Thilagavathi, R. and Ganesh, N., 2018. Cauvery River. In The Indian Rivers (pp. 353-366). Springer, Singapore.



Chidambaram, S., Ramanathan, A.L., Thilagavathi, R. and Ganesh, N., 2018. Cauvery River. In The Indian Rivers (pp. 353-366). Springer, Singapore.



Ciabatta, L., Massari, C., Brocca, L., Gruber, A., Reimer, C., Hahn, S., Paulik, C., Dorigo, W., Kidd, R. and Wagner, W., 2018. SM2RAIN-CCI: A new global long-term rainfall data set derived from ESA CCI soil moisture. *Earth System Science Data*, 10(1), pp.267-280.

Chowdhury, N.T., 2010. Water management in Bangladesh: an analytical review. *Water Policy*, 12(1), pp.32-51.

Collins, S., Loveless, S.E., Muddu, S., Buvaneshwari, S., Palamakumbura, R.N., Krabbendam, M., Lapworth, D.J., Jackson, C.R., Gooddy, D.C., Nara, S.N.V. and Chattopadhyay, S., 2020. Groundwater connectivity of a sheared gneiss aquifer in the Cauvery River basin, India. *Hydrogeology Journal*, 28(4), pp.1371-1388.

Contractor, S., Donat, M.G., Alexander, L.V., Ziese, M., Meyer-Christoffer, A., Schneider, U., Rustemeier, E., Becker, A., Durre, I. and Vose, R.S., 2020. Rainfall Estimates on a Gridded Network (REGEN)–a global land-based gridded dataset of daily rainfall from 1950 to 2016. *Hydrology and Earth System Sciences*, 24(2), pp.919-943.

Cornes, R.C., van der Schrier, G., van den Besselaar, E.J. and Jones, P.D., 2018. An ensemble version of the E-OBS temperature and precipitation data sets. *Journal of Geophysical Research: Atmospheres*, 123(17), pp.9391-9409.

Dahri, Z.H., Ludwig, F., Moors, E., Ahmad, B., Khan, A. and Kabat, P., 2016. An appraisal of precipitation distribution in the high-altitude catchments of the Indus basin. *Science of the Total Environment*, 548, pp.289-306.

Daly, C., 2006. Guidelines for assessing the suitability of spatial climate data sets. International Journal of Climatology: *A Journal of the Royal Meteorological Society*, 26(6), pp.707-721.

Dee, D.P., Uppala, S.M., Simmons, A.J., Berrisford, P., Poli, P., Kobayashi, S., Andrae, U., Balmaseda, M.A., Balsamo, G., Bauer, D.P. and Bechtold, P., 2011. The ERA-Interim reanalysis: Configuration and performance of the data assimilation system. *Quarterly Journal of the Royal Meteorological Society*, 137(656), pp.553-597.

Dembélé, M., Hrachowitz, M., Savenije, H.H., Mariéthoz, G. and Schaefli, B., 2020. Improving the predictive skill of a distributed hydrological model by calibration on spatial patterns with multiple satellite data sets. *Water Resources Research*, 56(1), p.e2019WR026085.

Demirel, M.C., Mai, J., Mendiguren, G., Koch, J., Samaniego, L. and Stisen, S., 2018. Combining satellite data and appropriate objective functions for improved spatial pattern performance of a distributed hydrologic model. *Hydrology and Earth System Sciences*, 22(2), pp.1299-1315.

Divya, P. and Shetty, A., 2021. Evaluation of CHIRPS satellite rainfall datasets over Kerala, India. Trends in Civil Engineering and Challenges for Sustainability, pp.655-664.

Dixit, Y., Hodell, D.A. and Petrie, C.A., 2014. Abrupt weakening of the summer monsoon in northwest India~ 4100 yr ago. *Geology*, 42(4), pp.339-342.

Döll, P., Douville, H., Güntner, A., Müller Schmied, H. and Wada, Y., 2016. Modelling freshwater resources at the global scale: challenges and prospects. *Surveys in Geophysics*, 37(2), pp.195-221.

Dumont, E., Williams, R., Keller, V., Voß, A. and Tattari, S., 2012. Modelling indicators of water security, water pollution and aquatic biodiversity in Europe. *Hydrological Sciences Journal*, 57(7), pp.1378-1403

Ekstrand, S., Mancinelli, C., Houghton-Carr, H., Govers, G., Debels, P., Camano, B., Alcoz, S., Filiberto, I., Gámez, S. and Duque, A., 2009. TWINLATIN: Twinning European and Latin American river basins for research enabling sustainable water resources management. Final report.

Faridzad, M., Yang, T., Hsu, K., Sorooshian, S. and Xiao, C., 2018. Rainfall frequency analysis for ungauged regions using remotely sensed precipitation information. *Journal of Hydrology*, 563, pp.123-142.

Fischer, G., Nachtergaele, F., Prieler, S., Van Velthuizen, H.T., Verelst, L. and Wiberg, D., 2008. Global agro-ecological zones assessment for agriculture (GAEZ 2008). IIASA, Laxenburg, Austria and FAO, Rome, Italy, 10.

Food and Agriculture Organization of the United Nations, AQUASTAT. Food and Agriculture Organization of the United Nations. Available online: http//www.Fao.Org/Aquastat/Statistics/Query/index.Html?Lang=En (accessed on 19 January 2019).

Fowler, D., Cape, J.N., Leith, I.D., Choularton, T.W., Gay, M.J. and Jones, A., 1988. The influence of altitude on rainfall composition at Great Dun Fell. *Atmospheric Environment* (1967), 22(7), pp.1355-1362.

Funk, C., Peterson, P., Landsfeld, M., Pedreros, D., Verdin, J., Shukla, S., Husak, G., Rowland, J., Harrison, L., Hoell, A. and Michaelsen, J., 2015. The climate hazards infrared precipitation with stations—a new environmental record for monitoring extremes. *Scientific Data*, 2(1), pp.1-21.

Ghimire, G.R., Krajewski, W.F. and Mantilla, R., 2018. A power law model for river flow velocity in Iowa basins. *JAWRA Journal of the American Water Resources Association*, 54(5), pp.1055-1067.

Gowri, R., Dey, P. and Mujumdar, P.P., 2021. A hydro-climatological outlook on the long-term availability of water resources in the Cauvery river basin. Water Security, 14, p.100102.

Guan, H., Wilson, J.L. and Makhnin, O., 2005. Geostatistical mapping of mountain precipitation incorporating auto-searched effects of terrain and climatic characteristics. *Journal of Hydrometeorology*, 6(6), pp.1018-1031.

Guo, R. and Liu, Y., 2016. Evaluation of satellite precipitation products with rain gauge data at different scales: Implications for hydrological applications. *Water*, 8(7), p.281.

Gupta, B. and Horan, R., 2022. Hydrological modelling to assess the impacts of socio-economic development and climate change on water resources in Cauvery Basin, India. Preprint: DOI: https://doi.org/10.21203/rs.3.rs-1393124/v1

Gupta, H.V., Kling, H., Yilmaz, K.K. and Martinez, G.F., 2009. Decomposition of the mean squared error and NSE performance criteria: Implications for improving hydrological modelling. *Journal of Hydrology*, 377(1-2), pp.80-91.

Gupta, J. and van der Zaag, P., 2008. Interbasin water transfers and integrated water resources management: Where engineering, science and politics interlock. *Physics and Chemistry of the Earth*, Parts A/B/C, 33(1-2), pp.28-40.

Haiden, T., Janousek, M., Vitart, F., Ben-Bouallegue, Z., Ferranti, L., Prates, F. 2021. Evaluation of ECMWF forecasts, including the 2021 upgrade. Technical memorandum. ECMWF Technical Memoranda. https://www.ecmwf.int/node/20142

Hanasaki, N., Kanae, S. and Oki, T., 2006. A reservoir operation scheme for global river routing models. *Journal of Hydrology*, 327(1-2), pp.22-41.

Hanasaki, N., Kanae, S., Oki, T., Masuda, K., Motoya, K., Shirakawa, N., Shen, Y. and Tanaka, K., 2008. An integrated model for the assessment of global water resources–Part 1: Model description and input meteorological forcing. *Hydrology and Earth System Sciences*, 12(4), pp.1007-1025.

Hanasaki, N., Yoshikawa, S., Pokhrel, Y. and Kanae, S., 2018. A global hydrological simulation to specify the sources of water used by humans. *Hydrology and Earth System Sciences*, 22(1), pp.789-817.

Hong, Y., Gochis, D., Cheng, J.T., Hsu, K.L. and Sorooshian, S., 2007. Evaluation of PERSIANN-CCS rainfall measurement using the NAME event rain gauge network. *Journal of Hydrometeorology*, 8(3), pp.469-482.

Hong, K.Y., Pinheiro, P.O., Minet, L., Hatzopoulou, M. and Weichenthal, S., 2019. Extending the spatial scale of land use regression models for ambient ultrafine particles using satellite images and deep convolutional neural networks. *Environmental Research*, 176, p.108513.

Horan, R., Gowri, R., Wable, P.S., Baron, H., Keller, V.D., Garg, K.K., Mujumdar, P.P., Houghton-Carr, H. and Rees, G., 2021a. A comparative assessment of hydrological models in the Upper Cauvery catchment. *Water*, 13(2), p.151.

Horan, R., Wable, P.S., Srinivasan, V., Baron, H.E., Keller, V.J., Garg, K.K., Rickards, N., Simpson, M., Houghton-Carr, H.A. and Rees, H.G., 2021b. Modelling small-scale storage interventions in semi-arid India at the basin scale. *Sustainability*, 13(11), p.6129.

Horan, R., Rickards, N.J., Kaelin, A., Baron, H.E., Thomas, T., Keller, V.D., Mishra, P.K., Nema, M.K., Muddu, S., Garg, K.K. and Pathak, R., 2021c. Extending a large-scale model to better represent water resources without increasing the model's complexity. *Water*, 13(21), p.3067.

Hu, Q., Li, Z., Wang, L., Huang, Y., Wang, Y. and Li, L., 2019. Rainfall spatial estimations: A review from spatial interpolation to multi-source data merging. *Water*, 11(3), p.579

Huffman, G.J., Bolvin, D.T., Nelkin, E.J., Wolff, D.B., Adler, R.F., Gu, G., Hong, Y., Bowman, K.P. and Stocker, E.F., 2007. The TRMM multi-satellite precipitation analysis (TMPA): Quasi-global, multiyear, combined-sensor precipitation estimates at fine scales. *Journal of Hydrometeorology*, 8(1), pp.38-55.

Huffman, G.J., Adler, R.F., Bolvin, D.T. and Gu, G., 2009. Improving the global rainfall record: GPCP version 2.1. *Geophysical Research Letters*, 36(17).

Huffman, G.J., Adler, R.F., Bolvin, D.T. and Nelkin, E.J., 2010. The TRMM multi-satellite precipitation analysis (TMPA). In Satellite rainfall applications for surface hydrology (pp. 3-22). Springer, Dordrecht.

Huffman, G.J., Bolvin, D.T., Braithwaite, D., Hsu, K.L., Joyce, R.J., Kidd, C., Nelkin, E.J., Sorooshian, S., Stocker, E.F., Tan, J. and Wolff, D.B., 2020. Integrated multi-satellite retrievals for the global rainfall measurement (GPM) mission (IMERG). In Satellite rainfall measurement (pp. 343-353). Springer, Cham.

Hughes, D.A., 2016. Hydrological modelling, process understanding and uncertainty in a southern African context: lessons from the northern hemisphere. *Hydrological Processes*, 30(14), pp.2419-2431.

Janakarajan, S., 2016. The Cauvery Water Dispute: Need for a Rethink. *Economic and Political Weekly*, pp.10-15.

Johnson, A.C., Keller, V., Dumont, E. and Sumpter, J.P., 2015. Assessing the concentrations and risks of toxicity from the antibiotics ciprofloxacin, sulfamethoxazole, trimethoprim and erythromycin in European rivers. *Science of the Total Environment*, 511, pp.747-755.

Joseph, P.V. and Simon, A., 2005. The weakening trend of the southwest monsoon current through peninsular India from 1950 to the present. *Current Science*, pp.687-694.

Joseph, R., Smith, T.M., Sapiano, M.R. and Ferraro, R.R., 2009. A new high-resolution satellite-derived rainfall dataset for climate studies. *Journal of Hydrometeorology*, 10(4), pp.935-952.

Kimani, M.W., Hoedjes, J.C. and Su, Z., 2018. Bayesian bias correction of satellite rainfall estimates for climate studies. *Remote Sensing*, 10(7), p.1074.

Knapp, K.R. and Wilkins, S.L., 2018. Gridded satellite (GridSat) GOES and CONUS data. *Earth System Science Data*, 10(3), pp.1417-1425.

Kobayashi, S., Ota, Y., Harada, Y., Ebita, A., Moriya, M., Onoda, H., Onogi, K., Kamahori, H., Kobayashi, C., Endo, H. and Miyaoka, K., 2015. The JRA-55 reanalysis: general specifications and basic characteristics. *Journal of the Meteorological Society of Japan*. Ser. II, 93(1), pp.5-48.

Kulkarni, A., 2012. Weakening of Indian summer monsoon rainfall in a warming environment. *Theoretical and Applied Climatology*, 109(3), pp.447-459.

Kumar, P.V., Naidu, C.V. and Prasanna, K., 2020. Recent unprecedented weakening of Indian summer monsoon in a warming environment. *Theoretical and Applied Climatology*, 140(1), pp.467-486.

Le Coz, C. and van de Giesen, N., 2020. Comparison of rainfall products over sub-Saharan Africa. *Journal of Hydrometeorology*, 21(4), pp.553-596.

Lengfeld, K., Kirstetter, P.E., Fowler, H.J., Yu, J., Becker, A., Flamig, Z. and Gourley, J., 2020. Use of radar data for characterizing extreme precipitation at fine scales and short durations. *Environmental Research Letters*, 15(8), p.085003.

Li, H., Haugen, J.E. and Xu, C.Y., 2018. Precipitation pattern in the Western Himalayas revealed by four datasets. *Hydrology and Earth System Sciences*, 22(10), pp.5097-5110.

Li, J. and Heap, A.D., 2008. Spatial interpolation methods: a review for environmental scientists. *Geoscience Australia, Record*. Geoscience Australia, Canberra.

Liang, Z., Liu, H., Zhao, Y., Wang, Q., Wu, Z., Deng, L. and Gao, H., 2020. Effects of rainfall intensity, slope angle, and vegetation coverage on the erosion characteristics of Pisha sandstone slopes under simulated rainfall conditions. *Environmental Science and Pollution Research*, 27(15), pp.17458-17467.

Lindström, G., Pers, C., Rosberg, J., Strömqvist, J. and Arheimer, B., 2010. Development and testing of the HYPE (Hydrological Predictions for the Environment) water quality model for different spatial scales. *Hydrology Research*, 41(3-4), pp.295-319.

Liu, X., Keller, V., Dumont, E.L., Shi, J. and Johnson, A.C., 2015. The risk of endocrine disruption to fish in the Yellow River catchment in China was assessed using a spatially explicit model. *Environmental Toxicology and Chemistry*, 34(12), pp.2870-2877.

Liu, J., Shangguan, D., Liu, S., Ding, Y., Wang, S. and Wang, X., 2019. Evaluation and comparison of CHIRPS and MSWEP daily-precipitation products in the Qinghai-Tibet Plateau during the period of 1981–2015. *Atmospheric Research*, 230, p.104634.

Luo, X., Fan, X., Ji, X. and Li, Y., 2020. Evaluation of corrected APHRODITE estimates for hydrological simulation in the Yarlung Tsangpo–Brahmaputra River Basin. *International Journal of Climatology*, 40(9), pp.4158-4170.

Lynch, S.D., 2004. Development of a raster database of annual, monthly and daily rainfall for southern Africa: WRC Report No. 1156/1/04.

Madhusoodhanan, C.G., Sreeja, K.G. and Eldho, T.I., 2016. Climate change impact assessments on the water resources of India under extensive human interventions. *Ambio*, 45(6), pp.725-741.

Maheswaran, R. and Khosa, R., 2012. Comparative study of different wavelets for hydrologic forecasting. *Computers & Geosciences*, 46, pp.284-295.

Mair, A. and Fares, A., 2011. Comparison of rainfall interpolation methods in a mountainous region of a tropical island. *Journal of Hydrologic Engineering*, 16(3), pp.371-383.

Malik, N., Bookhagen, B., Marwan, N. and Kurths, J., 2012. Analysis of spatial and temporal extreme monsoonal rainfall over South Asia using complex networks. *Climate dynamics*, 39(3), pp.971-987.

Meigh, J.R. and Tate, E.L., 2002. The Gwava Model-Development of A Global-scale Methodology To Assess The Combined Impact of Climate and Land Use Changes. In EGS General Assembly Conference Abstracts (p. 1276).

Meigh, J.R., Folwell, S. and Sullivan, C., 2005. Linking water resources and global change in West Africa: options for assessment. Seventh IAHS scientific assembly, Foz do Iguaçu, Brazil, pp.297-306.

Meigh, J.R., McKenzie, A.A. and Sene, K.J., 1999. A grid-based approach to water scarcity estimates for eastern and southern Africa. *Water Resources Management*, 13(2), pp.85-115.

Meunier, J.D., Riotte, J., Braun, J.J., Sekhar, M., Chalié, F., Barboni, D. and Saccone, L., 2015. Controls of DSi in streams and reservoirs along the Kaveri River, South India. *Science of the Total Environment*, 502, pp.103-113.

Moore, R. J., 1985. The probability-distributed principle and runoff production at point and basin scales. *Hydrological Sciences Journal*, 30(2), pp.263-297.

Moore, R.J., 2007. The PDM rainfall-runoff model. *Hydrology and Earth System Sciences*, 11(1), pp.483-499.

Morris, F., Toucher, M.W., Clulow, A., Kusangaya, S., Morris, C. and Bulcock, H., 2016. Improving the understanding of rainfall distribution and characterisation in the Cathedral Peak catchments using a geo-statistical technique. *Water SA*, 42(4), pp.684-693.

Naoum, S. and Tsanis, I.K., 2004. Ranking spatial interpolation techniques using a GIS-based DSS. *Global Nest*, 6(1), pp.1-20.

NASA Jet Propulsion Laboratory (JPL), NASA Shuttle Radar Topography Mission Global 1 Arc Second Number, National Aeronautics and Space Administration, U.S. Government, NASA. Pasadena, CA, USA. 2013. Available online: https://www2.jpl.nasa.gov/srtm/ (accessed on 20 October 2018).

Nashwan, M.S. and Shahid, S., 2020. A novel framework for selecting general circulation models based on the spatial patterns of climate. *International Journal of Climatology*, 40(10), pp.4422-4443.

Nguyen, P., Ombadi, M., Sorooshian, S., Hsu, K., AghaKouchak, A., Braithwaite, D., Ashouri, H. and Thorstensen, A.R., 2018. The PERSIANN family of global satellite precipitation data: A review and evaluation of products. *Hydrology and Earth System Sciences*, 22(11), pp.5801-5816.

Nijssen, B., Lettenmaier, D.P., Liang, X., Wetzel, S.W. and Wood, E.F., 1997. Streamflow simulation for continental-scale river catchments. *Water Resources Research*, 33(4), pp.711-724.

Noor, M., Ismail, T., Shahid, S., Nashwan, M.S. and Ullah, S., 2019. Development of multi-model ensemble for projection of extreme rainfall events in Peninsular Malaysia. *Hydrology Research*, 50(6), pp.1772-1788.

Pai, D.S., Rajeevan, M., Sreejith, O.P., Mukhopadhyay, B. and Satbha, N.S., 2014. Development of a new high spatial resolution (0.25× 0.25) long period (1901-2010) daily gridded rainfall data set over India and its comparison with existing data sets over the region. *Mausam*, 65(1), pp.1-18.

Palazzi, E., Von Hardenberg, J. and Provenzale, A., 2013. Precipitation in the Hindu-Kush Karakoram Himalaya: observations and future scenarios. *Journal of Geophysical Research: Atmospheres*, 118(1), pp.85-100.

Patel, S.S. and Ramachandran, P., 2015. A comparison of machine learning techniques for modelling river flow time series: the case of upper Cauvery River basin. *Water Resources Management*, 29(2), pp.589-602.

Pattanaik, J.K., Balakrishnan, S., Bhutani, R. and Singh, P., 2013. Estimation of weathering rates and CO2 drawdown based on solute load: Significance of granulites and gneisses dominated weathering in the Kaveri River basin, Southern India. *Geochimica et Cosmochimica Acta*, 121, pp.611-636.

Pingale, S.M., Khare, D., Jat, M.K. and Adamowski, J., 2014. Spatial and temporal trends of mean and extreme rainfall and temperature for the 33 urban centres of the arid and semi-arid state of Rajasthan, India. *Atmospheric Research*, 138, pp.73-90.

Portmann, F.T., Siebert, S. and Döll, P., 2010. MIRCA2000—Global monthly irrigated and rainfed crop areas around the year 2000: A new high-resolution data set for agricultural and hydrological modelling. *Global Biogeochemical Cycles*, 24(1).

Prakash, S., 2019. Performance assessment of CHIRPS, MSWEP, SM2RAIN-CCI, and TMPA precipitation products across India. *Journal of Hydrology*, 571, pp.50-59.

Prudhomme, C. and Reed, D.W., 1999. Mapping extreme rainfall in a mountainous region using geostatistical techniques: a case study in Scotland. *International Journal of Climatology: A Journal of the Royal Meteorological Society*, 19(12), pp.1337-1356.

Rajeevan, M. and Bhate, J., 2009. A high-resolution daily gridded rainfall dataset (1971–2005) for mesoscale meteorological studies. *Current Science*, pp.558-562.

Rajesh, S.V.J.S.S., Rao, B.P. and Niranjan, K., 2016. Inter-Basin Water Transfer Impact Assessment on the Environment of Pennar to Cauvery Link Canal. *IRA-International Journal of Technology & Engineering* Vol. 03 no. 03, 3, pp.175-194.

Raju, B.K. and Nandagiri, L., 2018. Assessment of variable source area hydrological models in humid tropical watersheds. *International Journal of River Basin Management*, 16(2), pp.145-156.

Raman, A.T.V.R., Gurugnanam, B. and Arunkumar, M., 2013. One decade hydro-meteorological data assessment through statistics, Dindigul district, Tamil Nadu, South India. *International Journal of Geomatics and Geosciences*, 3(3), pp.659-667.

Rameshwaran, Ponnambalam; Bell, Vicky; Davies, Helen; Houghton-Carr, Helen; Kay, Alison; Miller, James; Rickards, Nathan; Bologo-Traore, Maimouna; Diarra, Abdoulaye; Gnenakantanhan, Coulibaly; Tazen, Fowe; Traore, Karim. 2017 Hydrological research for AMMA-2050. [Poster] In: Future Climate for Africa Mid-Term Conference 2017, Cape Town, South Africa, 4–7 Sept 2017. (Unpublished)

Reddy, B.S.N. and Pramada, S.K., 2022. Suitability of different precipitation data sources for hydrological analysis: a study from Western Ghats, India. *Environmental Monitoring and Assessment*, 194(2), pp.1-20.

Reddy, S., Gupta, H., Reddy, D.V. and Kumar, D., 2021. The suitability of surface waters from small west-flowing rivers for drinking, irrigation, and aquatic life from a global biodiversity hotspot (Western Ghats, India). *Environmental Science and Pollution Research*, 28(29), pp.38613-38628.

Rickards, Nathan; Kaelin, Alexandra; Houghton-Carr, Helen. 2019 Implications of climate change and anthropogenic activity for the water security of West African river basins. [Poster] In African Climate Risks Conference 2019, Addis Ababa, Ethiopia, 7-9 Oct 2019. (Unpublished)

Rickards, N., Thomas, T., Kaelin, A., Houghton-Carr, H., Jain, S.K., Mishra, P.K., Nema, M.K., Dixon, H., Rahman, M.M., Horan, R. and Jenkins, A., 2020. Understanding future water challenges in a highly regulated Indian river basin—modelling the impact of climate change on the hydrology of the Upper Narmada. *Water*, 12(6), p.1762.

Robinson, T.P., Wint, G.W., Conchedda, G., Van Boeckel, T.P., Ercoli, V., Palamara, E., Cinardi, G., D'Aietti, L., Hay, S.I. and Gilbert, M., 2014. Mapping the global distribution of livestock. *PloS one*, 9(5), p.e96084.

Roy, P.S., Meiyappan, P., Joshi, P.K., Kale, M.P., Srivastav, V.K., Srivasatava, S.K., Behera, M.D., Roy, A., Sharma, Y., Ramachandran, R.M. and Bhavani, P., 2016. Decadal land use and land cover classifications across India, 1985, 1995, 2005. ORNL DAAC.

Saeidizand, R., Sabetghadam, S., Tarnavsky, E. and Pierleoni, A., 2018. Evaluation of CHIRPS rainfall estimates over Iran. *Quarterly Journal of the Royal Meteorological Society*, 144, pp.282-291.

Saha, S., Moorthi, S., Wu, X., Wang, J., Nadiga, S., Tripp, P., Behringer, D., Hou, Y.T., Chuang, H.Y., Iredell, M. and Ek, M., 2014. The NCEP climate forecast system version 2. *Journal of Climate*, 27(6), pp.2185-2208.

Sheffield, J., Goteti, G., and Wood, E. F.: Development of a 50-Year high-resolution global dataset of meteorological forcings for land surface modelling, J. *Climate*, 19, 3088–3111, https://doi.org/10.1175/JCLI3790.1, 2006.

Sen Roy, S., 2009. A spatial analysis of extreme hourly precipitation patterns in India. International Journal of Climatology: *A Journal of the Royal Meteorological Society*, 29(3), pp.345-355.

Shah, H.L. and Mishra, V., 2016. Uncertainty and bias in satellite-based precipitation estimates over Indian subcontinental basins: Implications for real-time streamflow simulation and flood prediction. *Journal of Hydrometeorology*, 17(2), pp.615-636.

Sharannya, T.M., Al-Ansari, N., Deb Barma, S. and Mahesha, A., 2020. Evaluation of satellite precipitation products in simulating streamflow in a humid tropical catchment of India using a semi-distributed hydrological model. *Water*, 12(9), p.2400.

Sharannya, T.M., Mudbhatkal, A. and Mahesha, A., 2018. Assessing climate change impacts on river hydrology–A case study in the Western Ghats of India. *Journal of Earth System Science*, 127(6), pp.1-11.

Sharma, A., Schweizer, V. and Hipel, K.W., 2020, October. Analyzing the Cauvery river dispute using a system of systems approach. In 2020 IEEE International Conference on Systems, Man, and Cybernetics (SMC) (pp. 3969-3975). IEEE.

Shepard, D., 1968, January. A two-dimensional interpolation function for irregularly-spaced data. In Proceedings of the 1968 23rd ACM national conference (pp. 517-524).

Singh, R.B. and Mal, S., 2014. Trends and variability of monsoon and other rainfall seasons in Western Himalaya, India. *Atmospheric Science Letters*, 15(3), pp.218-226.

Singh, S., Mall, R.K. and Singh, N., 2021. Changing Spatio-temporal trends of heat wave and severe heat wave events over India: An emerging health hazard. *International Journal of Climatology*, 41, pp.E1831-E1845.

Sorooshian, S., Hsu, K.L., Gao, X., Gupta, H.V., Imam, B. and Braithwaite, D., 2000. Evaluation of PERSIANN system satellite-based estimates of tropical rainfall. *Bulletin of the American Meteorological Society*, 81(9), pp.2035-2046.

Sreelash, K., Mathew, M.M., Nisha, N., Arulbalaji, P., Bindu, A.G. and Sharma, R.K., 2020. Changes in the Hydrological Characteristics of Cauvery River draining the eastern side of southern Western Ghats, India. *International Journal of River Basin Management*, 18(2), pp.153-166.

Srinivas, V.V. and Srinivasan, K., 2005. Hybrid moving block bootstrap for stochastic simulation of multi-site multi-season streamflows. *Journal of Hydrology*, 302(1-4), pp.307-330.

Srinivasan, V., Thompson, S., Madhyastha, K., Penny, G., Jeremiah, K. and Lele, S., 2015. Why is the Arkavathy River drying? A multiple-hypothesis approach in a data-scarce region. *Hydrology and Earth System Sciences*, 19(4), pp.1905-1917.

Sun, Q., Miao, C., Duan, Q., Ashouri, H., Sorooshian, S. and Hsu, K.L., 2018. A review of global precipitation data sets: Data sources, estimation, and intercomparisons. *Reviews of Geophysics*, 56(1), pp.79-107.

Sutanudjaja, E.H., Van Beek, R., Wanders, N., Wada, Y., Bosmans, J.H., Drost, N., Van Der Ent, R.J., De Graaf, I.E., Hoch, J.M., De Jong, K. and Karssenberg, D., 2018. PCR-GLOBWB 2: a 5 arcmin global hydrological and water resources model. *Geoscientific Model Development*, 11(6), pp.2429-2453.

Swapna, P., Sreeraj, P., Sandeep, N., Jyoti, J., Krishnan, R., Prajeesh, A.G., Ayantika, D.C. and Manmeet, S., 2022. Increasing frequency of extremely severe cyclonic storms in the north Indian Ocean by anthropogenic warming and southwest monsoon weakening. *Geophysical Research Letters*, 49(3), p.e2021GL094650.

Sylla, M.B., Giorgi, F., Coppola, E. and Mariotti, L., 2013. Uncertainties in daily rainfall over Africa: assessment of gridded observation products and evaluation of a regional climate model simulation. *International Journal of Climatology*, 33(7), pp.1805-1817.

Tawde, S.A. and Singh, C., 2015. Investigation of orographic features influencing spatial distribution of rainfall over the Western Ghats of India using satellite data. *International Journal of Climatology*, 35(9), pp.2280-2293.

Terzago, S., Palazzi, E. and von Hardenberg, J., 2018. Stochastic downscaling of precipitation in complex orography: A simple method to reproduce a realistic fine-scale climatology. *Natural Hazards and Earth System Sciences*, 18(11), pp.2825-2840.

Tomer, S.K., Al Bitar, A., Sekhar, M., Zribi, M., Bandyopadhyay, S. and Kerr, Y., 2016. MAPSM: A Spatio-temporal algorithm for merging soil moisture from active and passive microwave remote sensing. *Remote Sensing*, 8(12), p.990.

UK Centre for Ecology and Hydrology (UKCEH). GWAVA: Global Water Availability Assessment Model Technical Guide and User Manual; Technical Report; UK Centre for Ecology and Hydrology: Wallingford, UK, 2020.

Ushio, T., Sasashige, K., Kubota, T., Shige, S., Okamoto, K.I., Aonashi, K., Inoue, T., Takahashi, N., Iguchi, T., Kachi, M. and Oki, R., 2009. A Kalman filter approach to the Global Satellite Mapping of Precipitation (GSMaP) from combined passive microwave and infrared radiometric data. *Journal of the Meteorological Society of Japan*. Ser. II, 87, pp.137-151.

Varikoden, H., Revadekar, J.V., Kuttippurath, J. and Babu, C.A., 2019. Contrasting trends in southwest monsoon rainfall over the Western Ghats region of India. *Climate Dynamics*, 52(7), pp.4557-4566.

Venkatesh, B., Nayak, P.C., Thomas, T., Jain, S.K. and Tyagi, J.V., 2021. Spatio-temporal analysis of rainfall pattern in the Western Ghats region of India. *Meteorology and Atmospheric Physics*, 133(4), pp.1089-1109.

Venkatesh, B., Nayak, P.C., Thomas, T., Jain, S.K. and Tyagi, J.V., 2021. Spatio-temporal analysis of rainfall pattern in the Western Ghats region of India. *Meteorology and Atmospheric Physics*, 133(4), pp.1089-1109.

Vogel, B. and Henstra, D., 2015. Studying local climate adaptation: A heuristic research framework for comparative policy analysis. *Global Environmental Change*, 31, pp.110-120.

Wable, P.S., Garg, K.K., Nune, R., Venkataradha, A., Srinivasan, V., Ragab, R., Rowan, J., Keller, V., Majumdar, P., Rees, G. and Singh, R., 2022. Impact of agricultural water management interventions on upstream-downstream trade-offs in the upper Cauvery catchment, southern India: a modelling study. *Irrigation and Drainage*, 71(2), pp.472-494.

Wagener, T., Boyle, D.P., Lees, M.J., Wheater, H.S., Gupta, H.V. and Sorooshian, S., 2001. A framework for the development and application of hydrological models. *Hydrology and Earth System Sciences*, 5(1), pp.13-26.

Wagner, P.D., Reichenau, T.G., Kumar, S. and Schneider, K., 2015. Development of a new downscaling method for hydrologic assessment of climate change impacts in data-scarce regions and its application in the Western Ghats, India. *Regional Environmental Change*, 15(3), pp.435-447.

Wambura, F.J., 2020. Potential of rainfall data hybridization in a data-scarce region. *Scientific African*, 8, p.e00449.

Weedon, G.P., Balsamo, G., Bellouin, N., Gomes, S., Best, M.J. and Viterbo, P., 2014. The WFDEI meteorological forcing data set: WATCH Forcing Data methodology applied to ERA-Interim reanalysis data. *Water Resources Research*, 50(9), pp.7505-7514.

Wilby, R.L. and Yu, D., 2013. Rainfall and temperature estimation for a data-sparse region. *Hydrology and Earth System Sciences*, 17(10), pp.3937-3955.

Williams, R., Neal, C., Jarvie, H., Johnson, A., Whitehead, P., Bowes, M., Jenkins, A., 2015. Water Quality, in Progress in Modern Hydrology: Past, Present and Future, First Edition, Rodda, J C, Robinson, M (eds), Wiley and Sons Ltd.

Yeggina, S., Teegavarapu, R.S. and Muddu, S., 2020. Evaluation and bias corrections of gridded precipitation data for hydrologic modelling support in Kabini River basin, India. *Theoretical and Applied Climatology*, 140(3), pp.1495-1513.

Zhang, L., Li, X., Zheng, D., Zhang, K., Ma, Q., Zhao, Y. and Ge, Y., 2021. Merging multiple satellite-based precipitation products and gauge observations using a novel double machine learning approach. *Journal of Hydrology*, 594, p.125969.

## Appendix E

Table 5.5 Analysis of the available in-situ rainfall data within the Upper Cauvery

| Gauging station | X co-ord | Y co-ord | Start Date | End Date | Missing days | Total Days | Missing % | Mean | Standard Dev | Total |
|---|---|---|---|---|---|---|---|---|---|---|
| Alur | 12.97 | 75.98 | 01/1979 | 12/2013 | 315 | 12784 | 2.00 | 4.33 | 12.69 | 44082.7 |
| Ammathy | 12.23 | 75.85 | 01/1979 | 11/2013 | 615 | 12753 | 5.00 | 5.84 | 16.46 | 60267.0 |
| Arkalgud | 12.77 | 76.05 | 01/1979 | 12/2013 | 92 | 12784 | 1.00 | 2.38 | 7.70 | 25212.9 |
| Belur | 13.17 | 75.85 | 01/1979 | 12/2013 | 158 | 12784 | 1.00 | 2.36 | 8.12 | 24952.7 |
| Bhagamandala | 12.38 | 75.52 | 01/1979 | 12/2013 | 2103 | 12784 | 16.00 | 15.27 | 33.89 | 131053 |
| Chickmagalur | 13.33 | 75.77 | 01/1981 | 12/2009 | 1826 | 10592 | 17.00 | 2.45 | 8.10 | 18361.4 |
| Dubari | 12.37 | 75.92 | 01/1979 | 12/2009 | 614 | 11323 | 5.00 | 2.73 | 8.17 | 24915.0 |
| Hassan | 13 | 76.1 | 01/1979 | 12/2013 | 370 | 12784 | 3.00 | 2.01 | 7.84 | 22621.2 |
| Holenarsipur | 12.78 | 76.23 | 01/1979 | 12/2013 | 1166 | 12784 | 9.00 | 2.20 | 7.55 | 21042.9 |
| Hunsur | 12.3 | 76.28 | /01/1981 | 12/2013 | 2203 | 12022 | 18.00 | 2.12 | 7.90 | 18547.4 |
| Krishnarajnagar | 12.67 | 76.48 | 01/1979 | 12/2013 | 731 | 12784 | 6.00 | 2.16 | 7.77 | 21320.6 |
| Mudigere | 13.13 | 75.63 | 01/1979 | 12/2013 | 909 | 12784 | 7.00 | 6.11 | 17.02 | 62511.9 |
| Periyapatna | 12.33 | 76.1 | 01/1979 | 12/2013 | 975 | 12784 | 8.00 | 2.31 | 7.24 | 23449.4 |
| Ponnampet | 12.15 | 75.93 | 01/1979 | 12/2013 | 785 | 12784 | 6.00 | 5.52 | 16.57 | 57831.4 |
| Sakaleshpur | 12.95 | 75.78 | 01/1989 | 12/2013 | 3537 | 9131 | 39.00 | 5.90 | 15.21 | 34359.2 |
| Sanivarsanthe | 12.82 | 75.9 | 01/1979 | 12/2013 | 1281 | 12753 | 10.00 | 4.78 | 12.90 | 49779.3 |
| Somwarpet | 12.6 | 75.85 | 01/1981 | 12/2013 | 6493 | 12053 | 54.00 | 5.69 | 15.55 | 25319.6 |
| Srimangala | 12.02 | 75.98 | 01/1979 | 12/2013 | 827 | 12753 | 6.00 | 6.96 | 21.41 | 74981.2 |
| Suntikoppa | 12.45 | 75.83 | 01/1979 | 12/2013 | 859 | 12753 | 7.00 | 3.96 | 10.43 | 41480.8 |
| Thittimatti | 12.22 | 76 | 01/1979 | 12/2013 | 1678 | 12753 | 13.00 | 4.11 | 12.26 | 42207.0 |
| Virajpet | 12.18 | 75.8 | 01/1979 | 12/2013 | 402 | 12784 | 3.00 | 6.09 | 16.29 | 66006.8 |

Table 5.6 Non-exhaustive list of spatial and temporal considerations of available satellite rainfall products

| **Dataset** | **Methodology** | **Spatial coverage** | **Temporal coverage** | **Spatial resolution** | **Temporal resolution** | **Application in India** | **Application in WGs** | **Reference** |
|---|---|---|---|---|---|---|---|---|
| Climate Hazards Group InfraRed Precipitation with Station data (CHIRPS) | Infrared Gauge | 50°N - 50°S | 1981- NRT | 0.25° | Daily | ✓ | ✓ | Funk *et al.*, 2015 |
| CHIRPS v2.0 | Infrared Gauge | Global | 1981 -NRT | 0.05° | Daily | × | × | Funk *et al.*, 2015 |
| CICS High-Resolution Optimally Interpolated Microwave Precipitation from Satellites (CHOMPS) | Microwave | Global | 1998-2007 | 0.25° | Daily | × | × | Joseph *et al*., 2009 |
| CPC MORPHing technique (CMORPH) v1.0 | Microwave | 60°N - 60°S | 1998- NRT | 0.25° | 3 hour | ✓ | ✓ | Joyce *et al.*, 2004 |
| European Re-analysis (ERA)-Interim | Reanalysis | Global | 1979- 2017 | 0.75° | 3 hour | ✓ | ✓ | Dee *et al.*, 2011 |
| European Re-analysis (ERA) 5 | Reanalysis | Global | 1979-NRT | 0.14° | Hourly | ✓ | ✓ | Haiden *et al*., 2021 |
| Global Precipitation Climatology Project (GPCP)-1DD v2.1 | Microwave Infrared Gauge | Global | 1996-2015 | 1° | Daily | ✓ | ✓ | Huffman *et al*., 2009 |
| Gridded Satellite (GridSat) v1.0 | Microwave Infrared | 50°N - 50°S | 1983-2016 | 0.01° | 3 hour | × | × | Knapp & Wilkins, 2018 |

Table 5.6 Cont…

| Dataset | Methodology | Spatial coverage | Temporal coverage | Spatial resolution | Temporal resolution | Application in India | Application in WGs | Reference |
|---|---|---|---|---|---|---|---|---|
| Global Satellite Mapping of Precipitation (GSMaP) v6 | Microwave Infrared | 60°N - 60°S | 2000- NRT | 0.01° | Hourly | ✓ | ✓ | Ushio *et al.*, 2009 |
| Integrated Multi-satellitE Retrievals for GPM (IMERG) | Microwave | 60°N - 60°S | 2014-NRT | 0.1° | ½ hour | ✓ | ✓ | Huffman *et al*., 2020 |
| JRA-55 | Reanalysis | Global | 1959 - NRT | 0.56° | 3 hour | × | × | Kobayashi *et al.*, 2015 |
| Multi-Source Weighted-Ensemble Precipitation (MSWEP) v2.0 | Infrared Microwave Gauges | Global | 1979- NRT | 0.1° | 3 hour | ✓ | ✓ | Beck *et al.*, 2017 |
| National Centers for Environmental Prediction- Climate Forecast System Reanalysis (NCEP-CFSR) | Reanalysis | Global | 1979-2010 | 0.31° | Hourly | ✓ | ✓ | Saha *et al*., 2010 |
| Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) | Infrared | 60°N - 60°S | 2000-NRT | 0.25° | Hourly | ✓ | ✓ | Sorooshian *et a*l., 2000 |
| PERSIANN- Cloud Classification System (CCS) | Infrared | 60°N - 60°S | 2003-NRT | 0.04° | Hourly | ✓ | ✓ | Hong *et al.*, 2004 |
| PERSIANN- Climate Data Record (CDR) | Infrared Gauge | 60°N - 60°S | 1983-2016 | 0.25° | 6 hour | ✓ | ✓ | Ashouri *et al.*, 2015 |

Table 5.6 Cont…

| Dataset | Methodology | Spatial coverage | Temporal coverage | Spatial resolution | Temporal resolution | Application in India | Application in WGs | Reference |
|---|---|---|---|---|---|---|---|---|
| Precipitation Estimation from Remotely Sensed Information Using Artificial Neural Networks (PERSIANN) | Infrared | 60°N - 60°S | 2000-NRT | 0.25° | Hourly | ✓ | ✓ | Sorooshian *et a*l., 2000 |
| Global Meteorological Forcing Dataset for land surface modelling (PGF) | Gauge, Reanalysis | Global | 1948-2012 | 0.25° | 3 hour | ✓ | ✓ | Sheffield *et al*., 2006 |
| Rainfall Estimates on a Gridded Network (REGEN) | Gauge | Global | 1950 - 2016 | 1° | Daily | ✓ | ✓ | Contractor *et al*., 2020 |
| Soil Moisture to Rain -Advanced SCATterometer (SM2RAIN- ASCAT) | Microwave Infrared | Global | 2007-2021 | 0.5° | Daily | ✓ | ✓ | Ciabatta *et al*., 2018 |
| Multi-satellite Precipitation Analysis (TMPA) 3B42RT v7 | Microwave | 50°N - 50°S | 2000-NRT | 0.25° | 3 hour | ✓ | ✓ | Huffman *et al.*, 2007 |
| Tropical Rainfall Measuring Mission (TRMM)-3B42 v7 | Microwave Gauge | 50°N - 50°S | 1997- 2019 | 0.25° | 3 hour | ✓ | ✓ | Huffman *et al.*, 2010 |
| WFDEI-CRU | Reanalysis | Global | 1979-2015 | 0.5° | 3 hour | ✓ | ✓ | Weedon *et al*., 2014 |

Table 5.7 The spatial and temporal resolutions, periods and sources of the input data used in the setup of GWAVA in the Cauvery Catchment

| Input Data | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|
| Maximum temperature | 0.25 degree | Daily | 1951-2016 | Indian Meteorological Department (Pai *et al*., 2012) |
| Minimum Temperature | 0.25 degree | Daily | 1951-2016 | Indian Meteorological Department (Pai *et al*., 2012) |
| Streamflow gauged data | Catchment | Daily | 1971-2014 | India-WRIS |
| Dam Characteristics | Catchment | | 2018 | India-WRIS |
| Dam inflow and outflow data | Catchment | Monthly | 1974-2017 | India-WRIS |
| Dam storage | Catchment | Daily | 200-2010 | India-WRIS |
| Water transfers | Catchment | Annual | 2008 | Ashoka Trust for Research in Ecology and the Environment |
| Tanks | Catchment | | 2019 | Waterbodies dataset (ATREE) |
| Check Dams | Karnataka | | 2006-2012 | Structural Investment Report, Watershed Development Department |
| Farm Bunds | Karnataka | | 2006-2012 | Structural Investment Report, Watershed Development Department |
| Groundwater levels | District | Monthly | 1990-2017 | Central Ground Water Board, India |
| Elevation | 0.003 degree | | 2000 | NASA Shuttle Radar Mission Global 1 arc second V003 (NASA Jet Propulsion Laboratory, 2013) |
| Geology | Asia | | | United States Geological Survey |
| Specific yield | India | | | Central Ground Water Board, India |
| Soil type | 0.008 degree | | 1971-1981 | Harmonized World Soil Database v1.2 (Fischer *et al*., 2008) |
| Soil properties | Global | | 2010 | Table 2- Allen *et al*. (2010) |

| Input Data | Spatial Resolution | Temporal Resolution | Time Period | Source |
|---|---|---|---|---|
| Land Cover Land Use | 0.001 degree | | 2005 | Decadal land use and land cover across India 2005 (Roy *et al.*, 2016) |
| Crops | Taluk* | | 2000 | National Remote Sensing Centre (NRSC) |
| Total and Rural Population | Village | | 2001 | Census of India 2001 (http://sedac.ciesin.columbia.edu/data/set/india-india-village-level-geospatial-socio-econ-1991-2001) |
| Livestock | 0.05 degree | | 2005 | CGIR Livestock of the World v2 (Robinson *et al.*, 2014) |
| Conveyance losses | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx |
| Return flow | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |
| Irrigation efficiency | Continental | | 1986 | Irrigation and Drainage Paper (FAO) No 1 |
| Surface-water fraction | Village | | 2011 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |
| Industrial demand | Karnataka | | Currently unknown | Industrial Plot Information System- Karnataka Industrial Area Development Board (https://http://164.100.133.168/kiadbgisportal/) |
| Livestock demand | India | | 2006 | CGIR Livestock of the World v2 (Robinson *et al.*, 2014) |
| Domestic demand | Village | | 2001 | Household & Irrigation Census 2011- Town and Village directory (https://censusindia.gov.in/DigitalLibrary/TablesSeries2001.aspx) |

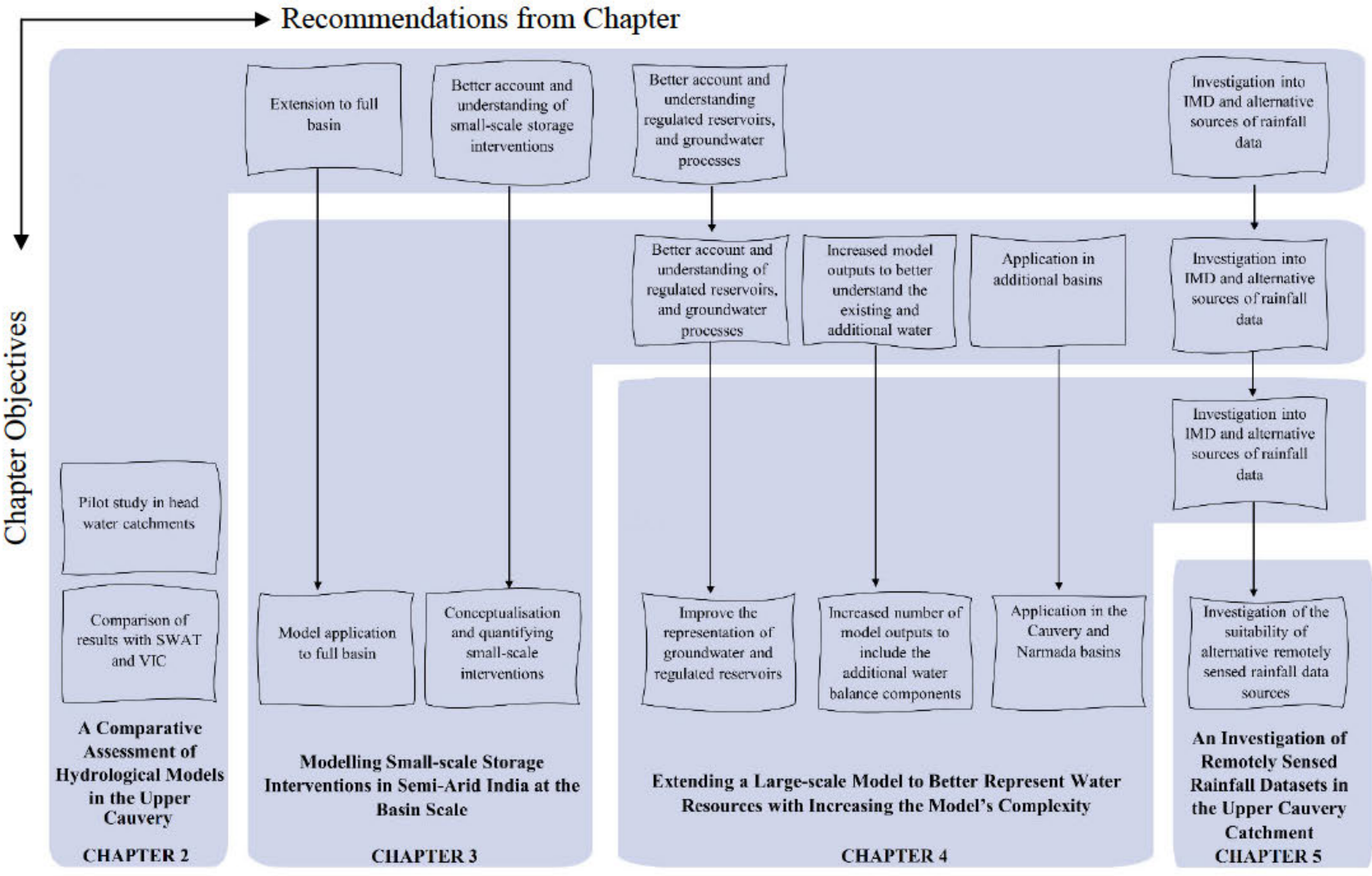
Table 5.8 Statistical analysis of the distribution of rainfall values produced by each rainfall dataset during the whole year as well as the monsoon season.

| Dataset | Whole year | | | Monsoon Season | | |
|---|---|---|---|---|---|---|
| | **10th Percentile** | **90th Percentile** | **Interquartile Range** | **10th Percentile** | **90th Percentile** | **Interquartile Range** |
| **Gauge** | **0.0** | **346.1** | **146.8** | **40.0** | **589.7** | **230.5** |
| IMD | **0.0** | 272.1 | **134** | **45.5** | 436.2 | 167.1 |
| CHIRPS 25 | 1.1 | **404.0** | 185.9 | 86.8 | 624.0 | **256.4** |
| CHIRPS 05 | 0.0 | 420.8 | 196.2 | 88.1 | 652.1 | 265.4 |
| MSWEP | 0.9 | 409.9 | 192.2 | 65.6 | 627.8 | 273.5 |
| PERSIANN | 0.5 | 275.4 | 180.7 | 108.6 | 347.3 | 117.4 |
| Average Ensemble | **1.0** | **349.6** | **184.2** | **92.3** | **544.2** | **215.1** |
| Median Ensemble | 1.6 | 370.8 | 193.8 | 94.8 | 552.7 | 194.6 |
| CHIRPS 25 Weighted Ensemble | 1.9 | 370.0 | 195.9 | 98.5 | 534.2 | 203.5 |
| CHIRPS 05 Weighted Ensemble | 1.5 | 377.9 | 196.2 | 94.4 | 528.8 | 205.3 |
| MSWEP Weighted Ensemble | 1.8 | 373.8 | 196.1 | 104.5 | 468.5 | 170.9 |

*****

**Lead into Chapter 6**

The overall objective of this thesis is to develop an integrated large-scale hydrological model to improve water resource assessments in a highly heterogeneous and data-scarce region whilst taking into account the major water resource challenges facing the Cauvery Catchment. Having presented the pilot study in Chapter 2, the quantification and effect of small-scale runoff harvesting SSRHIs in Chapter 3, the integration of regulated dams and groundwater processes in Chapter 4 and the investigation into several rainfall input datasets in Chapter 5, the key conclusions, contributions, challenges and future research recommendations are drawn out in Chapter 6.



# 6. DISCUSSION, CONCLUSIONS AND RECOMMENDATIONS FOR FURTHER RESEARCH

## 6.1 Discussion

The Cauvery Catchment is of significance because of its dynamic economy, growing population and apparent shifts in monsoon-driven rainfall and temperature patterns. Additional impetus for selecting this catchment is the contested nature of water resources occurring across state borders in the transboundary Cauvery Catchment and to provide better evidence to inform sustainable and equitable water futures consistent with the ambitions of the UN's Sustainable Development Goals (SDGs), especially Goal 6.1 Water and Sanitation (General Assembly of the United Nations, 2015). This thesis aimed to develop an integrated large-scale hydrological model to improve water resource assessments in a highly heterogeneous and data-scarce region whilst taking into account the major water resource challenges facing the Cauvery Catchment.

### *6.1.1 Summary*

#### 6.1.1.1 Chapter 2

The pilot study utilised the original version of GWAVA (GWAVA 5.0) developed by Meigh *et al*. (1999) (Figure 6.1) and highlighted the strength of large-scale gridded models for modelling the extent of large catchments but can also represent the processes of headwater catchments as accurately in this region as catchment-scale models. This study has highlighted the importance of an accurate spatial representation of rainfall for input into hydrological models, accounting for SSRHIs and comprehensive dam and groundwater functionality is paramount to obtaining good results in this region.

#### 6.1.1.2 Chapter 3

GWAVA 5.0 was updated to allow for the representation of SSRHIs (GWAVA-Int, Figure 6.1). The quantity, spatial distribution and dimensions of the check dams, tanks and farm bunds across the catchment were determined using financial records and field data. The inclusion of SSRHIs in the modelling of the catchment reduced the simulated bias across the catchment; however, the simulated streamflow remained underestimated, and the groundwater and dam routines required updating (Chapter 3). The effect of the representation of SSRHIs corresponded well with existing literature from small-scale studies. However, groundwater levels at the sub-catchment and catchment scale appear to be less impacted than in the cited literature or indigenous knowledge surrounding the use of SSRHIs for water security at a local scale, suggesting further investigation is required. Stakeholder and expert knowledge were incorporated, as well as published information from literature in the conceptualisation of the SSRHIs within the model. New and creative approaches had to be utilised where data gaps existed to model the effects of SSRHIs at the catchment scale. This study had to rely on a pragmatic approach, and consequently, many assumptions were made, and runoff harvesting in the region below Mettur Dam was disregarded. However, this study provides a step forward in the conceptualisation, quantification, and implication of SSRHIs at the catchment scale.

#### 6.1.1.3 Chapter 4

GWAVA 5.0 was updated to better represent groundwater dynamics (GWAVA-GW) and regulated dams (GWAVA-Res). These improvements were included along with those of GWAVA-Int in GWAVA 5.1 (Figure 6.1). Robust simulations of groundwater availability and dam storage and releases are important for water resource management in semi-arid catchments where the groundwater is an important water source during the dry season, and the streamflow in the main channel of the lower reaches was largely dam-regulated. Key components of GWAVA were improved to better represent water management while maintaining low input data requirements and model complexity. Using the principles of AMBHAS-1D (Tomer *et al.*, 2012) and Hanaski (Hanasaki *et al.*, 2006), a more comprehensive groundwater and regulated dam routine were added in GWAVA 5.1. Although both these routines significantly improved the model performance, the simulated streamflow was underestimated in the upper reaches of the catchment (Chapter 4). Although these simplified routines improve the model performance throughout the catchment, it is recommended that further investigation is undertaken regarding the representation of rainfall in the Western Ghats, and an application in a wider geographic area is necessary to ensure the routines' suitability represents a range of catchment characteristics.

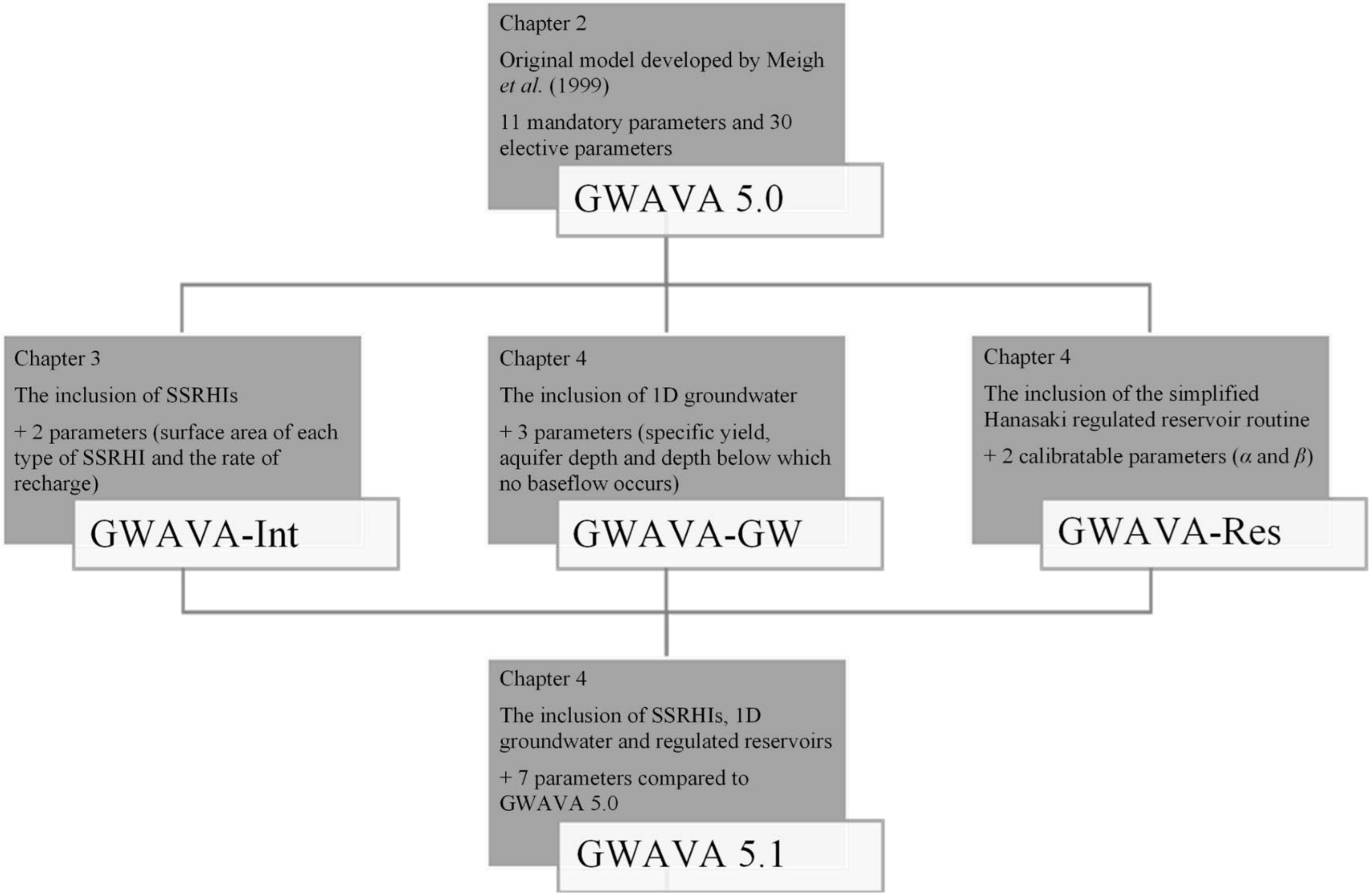



**Figure 6.1 The iterative development of GWAVA from GWAVA 5.0 to GWAVA 5.1 including the development of SSRHI, groundwater and regulated dam processes within the model**

6.1.1.4 Chapter 5

It was found that the IMD rainfall within the high-altitude regions of the Western Ghats is underestimated, resulting in the under-simulation of streamflow in the Upper Cauvery. CHIRPS 0.25- and 0.05- degree, MSWEP and PERSIANN remotely sensed rainfall datasets were applied within this region. None of the individual rainfall datasets provided a more accurate representation of the rainfall than the commonly utilised IMD grids. However, using an ensemble of remotely sensed rainfall datasets, primarily the average ensemble, improved the accuracy of rainfall estimation in the catchment (Chapter 5). The ‘off-the-shelf’ remotely sensed rainfall products provided a high variation in performance against the in-situ rain gauge data. The IMD grids provided the most accurate representation of rainfall compared to the individual remotely sensed rainfall datasets, despite underestimating the rainfall depths at high altitudes. In the case of the Upper Cauvery, the average ensemble provided a more accurate representation of the rainfall.

### *6.1.2 Achievement of the Aims and Objectives*

The overall aim of this study was to develop an integrated large-scale hydrological model to improve water resource assessments in a highly heterogeneous and data-scarce region whilst taking into account the major water resource challenges facing the Cauvery Catchment. These major challenges included the understanding of the hydrology within the Upper Cauvery Catchment, the effects of runoff harvesting SSRHIs at the full catchment scale, understanding and accounting for hard-rock aquifer groundwater processes, the representation of the impact of major dams throughout the full catchment and the estimation of rainfall across the Western Ghats within the Upper Cauvery Catchment. With each iteration of the model (GWAVA > GWAVA-Int > GWAVA-GW > GWAVA-Res > GWAVA5.1 and GWAVA5.1 + ensemble rainfall) the model performance improved. The study's aim was achieved as demonstrated by the following discussion of the objectives stated in Section 1.3 of the Introduction.

**Objective a: Determine whether the GWAVA model is suitable for application in the Cauvery and highlight current shortfalls in its predictive ability.** In *Chapter 2,* it was concluded that GWAVA was an appropriate model to represent the Cauvery Catchment and emphasised the ability to represent the processes of headwater catchments as accurately as more complex (VIC) and smaller-scale (SWAT) models. Three aspects of the model were highlighted as areas where development was necessary: the representation of SSRHIs, groundwater processes and regulated dams. Additionally, there was uncertainty around using the IMD gridded rainfall data in the Upper Cauvery region.

**<u>Objective b</u>: Contribute evidence-based findings to the ongoing discussion regarding the hydrological effect of small-scale runoff harvesting interventions at a full catchment scale.** In *Chapter 3,* it was concluded that conceptualised SSRHIs play an important part in the allocation and better representation of simulated surface water within the Catchment. The representation of SSRHIs within GWAVA proved successful compared to existing literature and indigenous knowledge. For the first time, the effects of millions of SSRHIs on water balance were quantified at a full catchment scale. The effect SSRHIs is dependent on the hydrogeology of the sub-catchment, as well as the groundwater level. The influence of the SSRHIs is greater on the simulated streamflow in the wet years and on estimated evaporation in the dry years.

**<u>Objective c</u>: Include new functionality within the GWAVA model to address the major water resource challenges with the Cauvery Catchment without increasing model complexity.** In ***Chapter 3*** and ***Chapter 4,*** the incorporation of the representation of SSRHIs and the improvement to the groundwater and regulated dam processes within GWAVA to improve water management while maintaining the low input data and model complexity philosophy was described and demonstrated. The satisfactory performance of GWAVA 5.1 to represent streamflow, groundwater levels, and dam fluxes throughout the catchment demonstrates the value of the simple, low-input routines incorporated. Therefore the inclusion of groundwater processes and regulation dams was justified when modelling catchments with natural and anthropogenic characteristics.

**<u>Objective d</u>: Develop a better understanding of the functioning of highly abstracted hard-rock aquifers and ground- and surface-water interactions on a full catchment scale.** In ***Chapter 4,*** the inclusion of the revised groundwater routine improved the simulation of streamflow in the headwater catchments of both the Cauvery and Narmada catchments was described and evaluated. The revision of the groundwater routine allows for the traceability of recharge, baseflow, groundwater levels, and volume of abstraction from groundwater resources with the addition of three input parameters. The model accurately represented the average groundwater depth over the simulation period. The inclusion of more comprehensive groundwater processes produced a more accurate hydrograph simulation, especially during the dry season.

**<u>Objective e:</u> Represent major dams without the availability of operational data**. A regulated dam routine was incorporated into GWAVA in ***Chapter 4***. The regulated dam routine allows for a release from the major dams throughout the year and the output of dam storage capacity throughout the simulation period with the addition of two input parameters. The new input parameters are calibratable using observed streamflow data from downstream of the dam. The new dam routine improved the simulation of streamflow in catchments downstream of major dams in both the Cauvery and Narmada. The regulated dam routine improves the timing and volume of releases from major dams.

**<u>Objective f:</u> Ascertain whether an 'off-the-shelf' remotely sensed rainfall product would be suitable for hydrological modelling within the Upper Cauvery without regional bias correction.** ***Chapter 5*** concluded that despite all the remotely sensed products integrating in-situ gauged data into their methodologies, there were disparities between the rainfall provided by these remotely sensed products and the in-situ gauged data provided by the IMD. Therefore, the 'off-the-shelf' data was not suitable to represent the rainfall in the Upper Cauvery. For cases where regional bias correction would not be possible, the use of an ensemble was investigated. The average ensemble provided the best representation of rainfall within the Upper Cauvery.

**<u>Objective g:</u> Determining whether an 'off-the-shelf' remotely sensed product could improve the hydrological simulations within a complex topographical region compared to the IMD gridded dataset.** None of the individual 'off-the-shelf' rainfall products could improve the hydrological simulations within the Upper Cauvery compared to the IMD gridded dataset. However, using the average ensemble provided a better representation of the simulated streamflow at KRS. ***Chapter 5*** illustrates that within this complex topographical and monsoonal region, the rainfall and subsequent water balance components are challenging to represent and require the utilisation of multiple datasets to match the observed values closely.

### *6.1.3 Key Conclusions*

- Large-scale gridded models can represent the processes of headwater catchments as accurately in complex and data-scarce regions as semi-distributed catchment models.

- New and creative approaches enhanced with indigenous knowledge can be utilised to bridge the data gaps for catchment scale hydrological modelling.
- Improvement to groundwater and regulated dam functionality in the GWAVA model provides a better representation of the simulated streamflow, baseflow, groundwater levels, dam storage and dam capacity while maintaining low input data requirements and model complexity.
- An ensemble of remotely sensed rainfall datasets can provide a better estimate of catchment rainfall than individual remotely sensed datasets, and in this instance, also the IMD gridded rainfall dataset.
- It remains critical to ensure that in-situ rainfall gauging networks are maintained an expanded to better understand the spatial and temporal nature of rainfall in complex topographical regions, improve the accuracy of large-scale gauge-corrected remotely sensed data and allow for increased ground-truthing.

## 6.2 Contributions to New Knowledge

The contributions of this research to new knowledge are listed below:

- A large-scale, data-light water resources model can provide more accurate simulations than a small-scale catchment model (SWAT) and a highly complex large-scale land-surface model (VIC) in a region of complex topography and high heterogeneity. (Objective a)
- A new approach to determine both the quantity and spatial distribution of SSRHIs was developed using financial records, stream density and proportions of rain-fed agriculture in the absence of specific data (Objective b)
- For the first time, the effects of millions of SSRHIs on water balance were quantified at a full catchment scale. In sub-catchments of the Cauvery, the results correlated well with existing small-scale studies despite the data limitations. As not understood before from small-scale studies, the effect SSRHIs is dependent on the underlying hydro-geology and the average annual rainfall (Objective b).
- The development of the groundwater and regulated dams processes without increasing the model's fundamental complexity and low input data philosophy improved the understanding of the simulated surface and groundwater interactions, the groundwater fluxes under the significant anthropogenic influence and the impact of dam releases on the streamflow in a large, data-scarce catchment. In contrast to the current philosophy

that increased complexity and input parameters improve hydrological simulations, this study demonstrated that the hydrological simulations could be improved by incorporating simplified routines and minimal additional input parameters (Objective c, d and e)

- Application of CHIRPS 0.25- and 0.05- degree, MWSEP and PERSIANN-CDR were applied at a catchment scale in the Upper Cauvery for the first time. None of these individual 'off-the-shelf' products proved suitable to represent the catchment rainfall in the Upper Cauvery Catchment (Objective f and Objective g)
- It was demonstrated that an ensemble of remotely sensed rainfall datasets can provide a successful alternative means of estimating catchment rainfall when in-situ rainfall gauges are not available for regional bias correction (Objective f)
- The regional rainfall dataset (IMD grids) produced the most accurate representation of observed rainfall when considering the individual datasets. However, an average ensemble (of the remotely sensed datasets) was demonstrated to outperform the IMD dataset regarding rainfall accuracy. It generated the best-performing streamflow simulation across the Upper Cauvery Catchment (Objective g).

### 6.3 Lessons Learnt, Limitations and Future Research Recommendations

Water in India, especially in the Cauvery Catchment, is ***highly political***. Water management decisions have the potential to have significant impacts on political power, financial gains and legal obligation. As a politicised commodity, data relating to water is rarely freely available, key information is often withheld, and stakeholders are hesitant to engage. Throughout this study, data availability and access were limiting factors. Data that could be accessed were predominantly obtained through Indian project partners or from large global datasets. Very rarely were catchment-specific data publically available. For scientific projects about water in these regions to be successful, partnerships must be built with trusted regional scientific organisations and NGOs. These organisations are critical for access to local knowledge, data resources and understanding the political landscape.

**Recommendation 1: Develop and foster effective partnerships and trust for data sharing and collaboration.**

***Scientific tools*** are essential integrated for water resources management and law-making. Due to the sensitivity of water-related issues in this region, there is a definitive need for an integrated tool to be used when undertaking impartial water management decisions. Adopting a tool for both near-time and future water management scenarios will strengthen data-driven decision-making and allow a more resilient water resources landscape to be developed. Once the improvements were made to GWAVA and the model was suitably calibrated, stakeholder dissemination and training were undertaken. The enthusiasm for utilising the tool was variable. The more established practitioners were more resistant to learning and using the tool than the students and graduates. This poses a future challenge. Both land use and climate change are evident in the catchment. Using a scientific tool to navigate the understanding and mitigate the anticipated effects of these changes on both the natural environment and domestic, agricultural and industrial use would be beneficial. Therefore, the scientific tool must be utilised for water resources management; however, getting the required individuals to buy into a universal tool and methodology will be challenging.

**Recommendation 2: Continue to develop, improve and implement scientific tools in highly vulnerable and data scarce regions.**

**Recommendation 3: Engage, listen and collaborate with key stakeholders and academic institutions.**

***The Cauvery Catchment has undergone and continues to undergo significant change.*** To represent this catchment as accurately as possible requires a dynamic modelling tool that cannot only represent the temporal climate change but additionally account for the rapid land use change, increase in water supply demand from all sectors and the consistent change in cropping variations within the catchment. A challenge within this study was determining which time period best represented the catchment conditions and when the most relevant data were available. Although from small field studies and stakeholder knowledge, the catchment had undergone the highest degree of change in the last decade, there is a very limited amount of hydrological, land use and demand data available for this period. Although GWAVA can run dynamically, the lack of accessibility of data from all historical epochs was a limitation to the complete understanding of how extensive change within the catchment has affected the water resources. With the improved modelling tool available and calibrated, future work could include the acquisition of the required historical data to represent the change within the catchment from the onset of extensive development (+- the 1950s, Gupta & Horan, 2022) and the application of future climate and socio-economic scenarios such as in Rickards *et al*. (2020).

**Recommendation 4: Focus and understand the continually changing hydrological landscape and consider the assumption of stationarity of climate and land cover/use within the current scientific methodologies used in highly anthropogenically influenced catchments.**

In ***data-scarce areas,*** it is challenging to represent all the relevant processes to a suitable accuracy. GWAVA is considered a low-date input model, and there were instances in this study when the necessary data was not available or accessible to meet the minimum data requirements. In these situations, new and creative approaches have to be utilised where data gaps are present. Indigenous knowledge can lay the foundation for further scientific research and be used as an informal data verification technique. Although some techniques to extrapolate data from small-scale examples or proxy data brings uncertainty, work must be undertaken to understand whether the uncertainty of this input data outweighs the benefit of including relevant processes.

**Recommendation 5: Innovate to fill data gaps while assessing uncertainty.**

***Monsoonal rainfall*** in high-altitude regions does not necessarily have a straightforward correlation to altitude or aspect. The rainfall in these regions is highly complex and requires significant future focus. The monsoonal conditions superimposed onto the undulating landscape result in a high rainfall variation over a short distance, and this variation does not always correlate to traditional rainfall influencing factors. Shortcomings in the IMD gridded rainfall were highlighted throughout this study; however, there were not a sufficient number of in-situ rain gauges within the Upper Cauvery to solely utilise the gauge data for hydrological modelling, nor were there any in-situ gauge observations available for the larger catchment. Due to this lack of data, the rainfall study had to be limited to the Upper Cauvery. There is a fundamental need for increased monitoring within these regions to better understand the hydrological cycle and catchment processes. These regions will remain a challenge when developing and publishing remotely sensed or large-scale rainfall datasets, as a specific focus will have to be applied to represent the rainfall accurately at any scale.

**Recommendation 6: Increase the hydrological monitoring within highly heterogeneous and socio-economically vulnerable catchments.**

**Recommendation 7: The application of GCM derived future climate data could provide valuable insight to how the catchment responds to changes in the monsoonal rainfall.**

It is critical to maintain and expand current ***observation networks***. This study has highlighted the requirement and importance of observation networks. The challenges with observed data (sparse nature of in-situ gauged rainfall, inaccurate groundwater levels and uncertainty in streamflow data) and engineered structures and operational data (limited SSRHIs and dam operational data) were a limitation to the methodologies, spatial and temporal scales and application of this study. The spatial distribution of these networks and the availability of data is critical for understanding hydrological processes now and through future change. Understanding of these complex environments is gained through observational data. To comprehensively understand the functioning of catchments, such as the Cauvery, the currently available datasets need to continue to be updated while opportunities for developing new critical datasets must be sought.

**Recommendation 8: Maintain and expand current observation networks.**

The chosen remotely sensed rainfall datasets were not appropriate for this area of the Western Ghats. Although these datasets were specifically selected because of the incorporation of in-situ gauge data within their development, along with other applied datasets (TMPA-3B42, TRMM 3B43 and MERRA), in their ***'off-the-shelf' form, they did not provide an appropriate level of accuracy***. Additionally, in this study, the remotely sensed rainfall data and generated simulated streamflow were aggregated to a monthly timescale. The product development methodologies incorporate rain gauge data at a monthly scale before disaggregating to a daily or sub-daily scale. It is anticipated that the performance would have been more variable on a daily scale. There is a need for the refinement of existing products over areas of complex topography and rainfall patterns but also the need to make use of emerging techniques, such as machine learning (Zhang *et al*., 2021), Google Earth Engine (Banerjee *et al*., 2020) and big data merging (Hu *et al*., 2019), to improve the representation of rainfall.

**Recommendation 9: Refine existing products and methodologies over areas of complex topography and rainfall patterns and make use of emerging techniques.**

The ***headwater catchments*** of these large Indian catchments generate a disproportional volume of water compared to the proportion of land they cover. Additionally, these catchments are subject to the most complex rainfall patterns. Previous studies within the headwater catchments of the Cauvery were unsuccessful in representing both the streamflow and groundwater. Within these catchments, understanding both the natural hydrological processes and the anthropogenic effects was challenging. Despite a high proportion of the catchment area being under natural vegetation, large dams, water transfers and SSRHIs within the regions provide complexity to the hydrological understanding. Therefore, a starting point in understanding the catchment dynamics would be to focus on monitoring these areas. The existing rainfall stations, groundwater wells and streamflow gauging sites need to be continuously maintained, and this data becomes available to improve scientific understanding of these critical catchments. In developing countries, a significant challenge in maintaining these observation networks is the financial and personnel overheads.

**Recommendation 10: Improve the understanding and representation of highly contributing head water catchments.**

From the limited consideration of evaporation within this study, it can be understood that ***the evaporative component is the most significant 'loss' from the water balance*** in this region. In this study, no observed evaporation data were utilised. The Hargreaves equation determined the daily evaporation from the IMD 0.5- degree temperature datasets. This provided a coarse representation of the daily evaporation that potentially misrepresented a major 'loss' from the water balance, especially over the highly heterogeneous vegetation in the region. To better understand the significance of this component, there is scope to undertake a detailed spatial and temporal evaporation study in this region. No known long-term evaporation observations are available, and the use of any earth observation techniques has been limited. The effect of the choice of evaporation estimation techniques in hydrological modelling and the extent to which any technique can be applied in this region is not well understood.

**Recommendation 11: Deployment of evaporation estimation equipment to gain better understanding of the evaporative trends of the region and provide valuable ground truthing data as the current reliance is on mathematical estimation equations and large-scale satellite products.**

**<u>Recommendation 12: Further investigation into the most accurate evaporation estimation methodologies (both technical and mathematical) could improve water resources modelling and reduce uncertainty in the outcomes.</u>**

To accurately represent catchments similar to the Cauvery, the natural and ***anthropogenic hydrological cycles*** must be considered. Humans have significantly modified the natural system; thus, hydrological models must incorporate anthropogenic influences. This study demonstrated that in a historically challenging catchment to model, the results improved as more anthropogenic influences were incorporated into the model structure. However, the data necessary to accurately represent the human impact on a catchment are not freely available. Therefore broad assumptions and indigenous knowledge are necessary to supplement the available data. Although several modelling tools provide a more detailed natural hydrological representation than GWAVA, the application of these will remain limited without considering anthropogenic influences.

**<u>Recommendation 13: The anthropogenic hydrological cycles need to be considered in water resources assessments of highly influenced catchments as the anthropogenic effects on hydrological processes can be more prominent than that of climate and other natural phenomena.</u>**

**<u>Recommendation 14: The consideration of water quality in anthropogenically influenced and degraded catchments would contribute to the scientific body of knowledge.</u>**

***Uncertainty*** should always be considered during hydrological modelling studies; however, in cases of substantial upscaling and data scarcity, understanding the level of uncertainty is critical when informing management and legal decisions. The most significant area of uncertainty in this study is the quality of data and the impact of the assumptions made in the absence of appropriate data. Uncertainty in observational data arises from observation station mechanical errors, lack of maintenance of existing observation stations, the non-uniformity of observation networks, and various spatial and temporal interpolation methods. In addition to input and observational data uncertainties, this study is subjected to several sources of uncertainties, such as the model structure, the representation of hydrological processes, the upscaling of processes, the process of quantifying the distribution of the SSRHIs, the representation and simplification of the conceptualisation of the SSRHIs, the conversion of point data to spatial averages and the simplification of groundwater processes and dam operations. Although this tool has been designed for application in large, data-sparse catchments, it has not been tested outside the Cauvery and the Narmada in its current form. Additional application and development would be necessary to reduce the level of uncertainty.

**Recommendation 15: Understand, quantify, and reduce uncertainty involved in hydrologic modelling in a cohesive, systematic manner to provide more robust modelling techniques and improve the confidence in model output.**

## 6.4 References


Banerjee, A., Chen, R., E. Meadows, M., Singh, R.B., Mal, S. and Sengupta, D., 2020. An analysis of long-term rainfall trends and variability in the Uttarakhand Himalaya using the google earth engine. Remote Sensing, 12(4), p.709.

General Assembly of the United Nations. (2015). Resolution was adopted by the General Assembly on 25 September 2015. New York: United Nations.

Gupta, B. and Horan, R., 2022. Hydrological modelling to assess the impacts of socio-economic development and climate change on water resources in Cauvery Basin, India. Preprint: DOI: https://doi.org/10.21203/rs.3.rs-1393124/v1

Hanasaki, N.; Kanae, S.; Oki, T. A Reservoir Operation Scheme for Global River Routing Models. Journal of Hydrology. 2006, 327, 22-41.

Hu, Q., Li, Z., Wang, L., Huang, Y., Wang, Y. and Li, L., 2019. Rainfall spatial estimations: A review from spatial interpolation to multi-source data merging. Water, 11(3), p.579.

Meigh, J.R., McKenzie, A.A. and Sene, K.J., 1999. A grid-based approach to water scarcity estimates for eastern and southern Africa. *Water Resources Management*, 13(2), pp.85-115.

Rickards, N., Thomas, T., Kaelin, A., Houghton-Carr, H., Jain, S.K., Mishra, P.K., Nema, M.K., Dixon, H., Rahman, M.M., Horan, R. and Jenkins, A., 2020. Understanding future water challenges in a highly regulated Indian river basin—modelling the impact of climate change on the hydrology of the Upper Narmada. Water, 12(6), p.1762.

Tomer, S.K.; Al Bitar, A.; Sekhar, M.; Merlin, O.; Bandyopadhyay, S.; Kerr, Y.H. An intercomparison of RADARSAT-2, SMOS and Field Measured Soil Moisture in the Berambadi Watershed, South India. in AGU Fall Meeting Abstracts 2012, H13F-1425.

Zhang, L., Li, X., Zheng, D., Zhang, K., Ma, Q., Zhao, Y. and Ge, Y., 2021. Merging multiple satellite-based precipitation products and gauge observations using a novel double machine learning approach. Journal of Hydrology, 594, p.125969.


****