

**IMPROVING THE POTENTIAL OF SATELLITE-BASED  
PRECIPITATION ESTIMATES FOR HYDROLOGICAL APPLICATIONS**

**SHUSHOBHIT CHAUDHARY**



**DEPARTMENT OF CIVIL ENGINEERING  
INDIAN INSTITUTE OF TECHNOLOGY DELHI  
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PRECIPITATION ESTIMATES FOR HYDROLOGICAL APPLICATIONS**

*by*

**SHUSHOBHIT CHAUDHARY**

Department of Civil Engineering

*Submitted*

*in fulfillment of the requirements for the degree of Doctor of Philosophy*

*to the*



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*Dedicated*

*to*

*My LOVING MOTHER*

*Resting in Eternal Peace*

## CERTIFICATE

This is to certify that the dissertation entitled “**Improving the Potential of Satellite-Based Precipitation Estimates for Hydrological Applications**” which is being submitted by Mr. Shushobhit Chaudhary, for the award of the degree of Doctor of Philosophy in Civil Engineering, to the Indian Institute of Technology (IIT) Delhi is a record of bonafide work carried out by him under my sustained guidance and supervision. The dissertation has reached the standard fulfilling the requirements of the regulations relating to the degree. The results embodied in the dissertation have not been submitted to any other university or institute for the award of any degree or diploma.

**Prof. Dhanya C. T.**

Associate Professor

Department of Civil Engineering

Indian Institute of Technology (IIT) Delhi

New Delhi – 110016

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## ABSTRACT

Satellite-based precipitation estimates (SPEs) provide real-time and fine spatio-temporal precipitation data at the global level. SPEs, however, might differ from ground-based gauge observations since they are indirect estimates of precipitation. When passed through a hydrological model, the error in SPEs may propagate into the streamflow, and thereby limit its utility for hydrological applications. This thesis aims to quantify the sources of error, examine its hydrological utility and explore the dynamics of propagation of error from SPEs to streamflow simulations through the hydrological model. SPEs are evaluated with reference to gauge-based precipitation measurements which often are considered as ground-truth. Given there are multiple gauge-based precipitation datasets (India Meteorological Department (IMD), Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources (APHRODITE), and Climate Prediction Center (CPC)) over India, we first examined the differences in their development algorithms and investigated their variability in representing monsoon spell characteristics. Our analysis revealed that CPC and IMD exhibit similar spell characteristics, while APHRODITE deviates from them. APHRODITE was found to overestimate wet days and underestimate dry days. All the datasets exhibit varying trend patterns. Based on our findings, we chose the IMD dataset as the reference for SPEs verification, since it has a much larger number of rain-gauge stations distributed uniformly throughout India, perhaps leading to a more accurate portrayal of the spatial distribution of precipitation features.

Next, we developed an improved error decomposition approach to detect the sources of error in SPEs introduced at different stages of the satellite precipitation retrieval process. Based on their stage of introduction in the retrieval process, SPE errors may be divided into detection error (false alarms and missed precipitation) and intensity error (hit bias). The standard error decomposition technique under-estimates intensity error or hit bias. We proposed an improved Split-Hit Error Decomposition Scheme (SHEDS) for SPEs that disintegrates total bias into over-hit ( $OH$ ), under-hit ( $-UH$ ), missed ( $-M$ ), and false components ( $F$ ). A multiplicative error model was also adopted to identify systematic and random components. The effectiveness of the improved scheme was demonstrated by comparing six SPEs over India for 16 years. Our analysis confirms that the conventional hit component is often under-valued owing to the cancellation of  $OH$  and  $-UH$  bias components, making it inaccurate. The magnitude of  $OH$  and  $-UH$  was observed to be higher than total bias and hit bias. While total bias and hit bias may

lead to incorrect conclusions, the suggested  $OH$  and  $-UH$  biases may provide better insights to data producers and users.

While disintegrating hit bias, we also proposed a true-hit ( $TH$ ) component, which represents the events wherein neither intensity nor detection error was observed. In our subsequent work, we proposed an expanded contingency table comprising ' $TH$ ' as a measure to assess the accuracy of SPEs. We expanded the conventional contingency table by categorising hit events as over-hit, true-hit, and under-hit based on observed and satellite rainfall event detection and magnitude. True-hit represents the frequency of those rainy events which have similar magnitude of precipitation intensity in SPEs as well as observed datasets. Over-hit (under-hit) indicates the frequency of rainy occurrences detected in both SPEs and observed datasets when the SPEs overestimate (underestimate) the observed rainfall. The usefulness of the expanded contingency table was shown by evaluating synthetic precipitation time series and SPEs over India.

Further, we proposed to reduce the bias in SPEs by merging information from gauge-based precipitation datasets. Although numerous time-domain bias correction techniques exist in the literature, their efficiency in correcting daily precipitation is limited. Moreover, most of the high-performance techniques are cumbersome and time exhaustive. We presented two bias correction methods, one correcting the SPEs conjointly in frequency and time domains, and the other an extremely fast machine learning approach. A hybrid approach comprising Variational Mode Decomposition (VMD) and Empirical Cumulative Distribution Function (ECDF) is proposed to bias correct SPEs time series in the time and frequency domains. An optimized version of incremental Extreme learning machine (ELM) is also proposed to bias correct the SPEs. The proposed methods are applied to bias correct real-time SPEs across India. The results show that the proposed techniques remove a major fraction of bias from SPEs in all seasons. Post-bias correction, decrease in root mean square error (RMSE) and improvement in correlation was also observed. Both the bias correction schemes could reduce the magnitudes of  $OH$ ,  $-UH$ ,  $-M$ , and  $F$  components. Improved representation of extreme precipitation characteristics in SPEs is also observed after bias correction. VMD-ECDF and ELM methods outperform the traditional bias correction techniques to provide more accurate precipitation forcing.

Further, we evaluated the hydrological utility of SPEs by feeding them (raw as well as bias corrected) into a hydrological model and thereafter, compared the simulated streamflow

with the observed streamflow. This thesis evaluated the streamflow response from SPEs simulated using Hydrological Predictions for the Environment (HYPE) model over six-gauge stations in India's Mahanadi River basin. Model parameter uncertainty was accounted while calibrating the HYPE model. The calibrated HYPE model was effective in simulating observed discharge. The results highlighted large biases in raw SPEs' simulated streamflow response at upstream sites. Bias correction of SPEs improved the streamflow simulations; however, the extent of improvement varied with varying algorithm. Streamflow simulations from VMD-ECDF bias corrected approach closely resembled observed flows. Recalibration of the HYPE model using SPEs increased parameter uncertainty and lowered generalisation. This study cautions against utilising raw SPEs for hydrological modelling. SPEs must be bias corrected prior to their application in hydrological modelling.

Lastly, we focused on understanding the dynamics of error propagation of SPEs when processed through a hydrological model. We proposed a novel CONceptual DUal-STaged (CONDUST) framework to isolate the impact of SPEs error and hydrological model errors propagating into the streamflow. SPE-to-model and model-to-streamflow error propagation factors were defined using a conceptual framework. The impact of regional catchment characteristics on the error propagation factors was also examined. CONDUST framework is deployed over the Mahanadi River basin in India. Error-corrupted ensembles of SPEs are created using the satellite rainfall error model (SREM) accounting spatial heterogeneity. The results of this thesis cross-verifies our consideration of heterogeneity in SREM rainfall parameters owing to the significant variability of SREM parameters over the basin. The SPE-to-model and model-to-streamflow bias propagation factors were observed to be greater than one, indicating that SPE bias is magnified when conveyed to the model, whereafter model also contributes to bias leading to significant error amplification in the streamflow. Model-to-streamflow error propagation factor was found to be higher than SPE-to-model factor. Dependency of error propagation factors was also explored on catchment area, elevation, rainfall and stream order of the subbasins.

This thesis advances the era of satellite-based precipitation measurement by enhancing its accuracy and dependability for hydrologic applications. This thesis adds to the continued validation effort of satellite-based precipitation databases across the globe. The methods proposed in this thesis are generic and can be applied over any region or any simulated/observed precipitation datasets.

## सार

उपग्रह-आधारित वर्षा अनुमान (एसपीई) वैश्विक स्तर पर वास्तविक समय और ठीक स्थानिक-सामयिक वर्षा डेटा प्रदान करते हैं। हालांकि, एसपीई जमीन-आधारित गेज डेटा से भिन्न हो सकते हैं क्योंकि वे वर्षा के अप्रत्यक्ष अनुमान हैं। जब एक हाइड्रोलॉजिकल मॉडल के माध्यम से एसपीई को पारित किया जाता है, तो एसपीई में त्रुटि धारा-प्रवाह में फैल सकती है, और इस तरह हाइड्रोलॉजिकल अनुप्रयोगों के लिए इसकी उपयोगिता को सीमित कर सकती है। इस शोध-प्रबन्ध का उद्देश्य त्रुटि के स्रोतों को मापना, इसकी हाइड्रोलॉजिकल उपयोगिता की जांच करना और हाइड्रोलॉजिकल मॉडल के माध्यम से धारा-प्रवाह सिमुलेशन के लिए एसपीई से त्रुटि के प्रचार की गतिशीलता का पता लगाना है। एसपीई का मूल्यांकन गेज-आधारित वर्षा माप के संदर्भ में किया जाता है जिसे अक्सर जमीन-सत्य के रूप में माना जाता है। यह देखते हुए कि भारत में कई गेज-आधारित वर्षा डेटासेट (भारत मौसम विज्ञान विभाग (आईएमडी), एशियाई वर्षा हाइली रेसोल्व्ड ऑब्ज़र्वेशनल डाटा इंटीग्रेशन टुवर्ड्स इवैल्यूएशन ऑफ़ वाटर रिसोर्सिज (एफ्रोडाइट), और जलवायु भविष्यवाणी केंद्र (सीपीसी)) हैं, हमने पहले उनके विकास एल्गोरिदम में अंतर की जांच की और मानसून वर्तनी विशेषताओं का प्रतिनिधित्व करने में उनकी परिवर्तनशीलता की जांच की। हमारे विश्लेषण से पता चला है कि सीपीसी और आईएमडी समान वर्तनी विशेषताओं को प्रदर्शित करते हैं, जबकि एफ्रोडाइट उनसे विचलित होता है। एफ्रोडाइट गीले दिनों को अत्यधिक करने और सूखे दिनों को कम करने के लिए पाया गया है सभी डेटासेट अलग-अलग प्रवृत्ति पैटर्न प्रदर्शित करते हैं। हमारे निष्कर्षों के आधार पर, हमने आईएमडी डेटासेट को एसपीई सत्यापन के संदर्भ के रूप में चुना, क्योंकि इसमें बहुत बड़ी संख्या में वर्षा-गेज स्टेशन पूरे भारत में समान रूप से वितरित हैं, जो शायद वर्षण सुविधाओं के स्थानिक वितरण का अधिक सटीक चित्रण करते हैं।

अगला, हमने उपग्रह वर्षा पुनर्प्राप्ति प्रक्रिया के विभिन्न चरणों में पेश किए गए एसपीई में त्रुटि के स्रोतों का पता लगाने के लिए एक बेहतर त्रुटि अपघटन दृष्टिकोण विकसित किया। पुनर्प्राप्ति प्रक्रिया में परिचय के उनके चरण के आधार पर, एसपीई त्रुटियों को पहचान त्रुटि (गलत अलार्म और चूक वर्षा) और तीव्रता त्रुटि (हिट त्रुटि) में विभाजित किया जा सकता है। मानक त्रुटि अपघटन तकनीक तीव्रता त्रुटि या हिट त्रुटि का कम-अनुमान लगाता है। हमने एसपीई के लिए एक बेहतर स्प्लिट-हिट त्रुटि अपघटन योजना (एसएचईडीएस) का प्रस्ताव दिया है जो कुल त्रुटि को ओवर-हिट (ओएच), अंडर-हिट (-यूएच), चूक वर्षा (-एम), और गलत अलार्म (एफ) में विभाजित करता है। गुणक त्रुटि मॉडल को व्यवस्थित और यादृच्छिक घटकों की पहचान करने के लिए भी अपनाया गया था। भारत में 16 वर्षों के दौरान छह एसपीई की तुलना करके बेहतर योजना की प्रभावशीलता का प्रदर्शन किया गया। हमारा विश्लेषण पुष्टि करता है कि पारंपरिक हिट त्रुटि अक्सर ओएच और -यूएच त्रुटि के रद्द होने के कारण कम-मूल्यांकित होता है, जिससे यह गलत हो जाता है। ओएच और -यूएच की तीव्रता कुल त्रुटि और हिट त्रुटि से अधिक देखी गई। जबकि

कुल त्रुटि और हिट त्रुटि गलत निष्कर्ष का कारण बन सकते हैं, सुझाए गए ओएच और -यूएच त्रुटि डेटा उत्पादकों और उपयोगकर्ताओं को बेहतर अंतर्दृष्टि प्रदान कर सकते हैं।

हिट त्रुटि को विघटित करते हुए, हमने एक टू-हिट (टीएच) घटक भी प्रस्तावित किया, जो उन घटनाओं का प्रतिनिधित्व करता है जिनमें न तो तीव्रता और न ही पहचान त्रुटि देखी गई थी। अपने बाद के काम में, हमने एसपीई की सटीकता तक पहुंचने के उपाय के रूप में 'टीएच' को शामिल करते हुए एक विस्तारित कंटिजेंसी तालिका का प्रस्ताव किया। हमने हिट घटनाओं को ओवर-हिट, टू-हिट और अंडर-हिट के रूप में वर्गीकृत करके पारंपरिक कंटिजेंसी तालिका का विस्तार किया, जो अवलोकन और उपग्रह वर्षा घटना का पता लगाने और परिमाण पर आधारित है। टू-हिट उन वर्षा की घटनाओं की आवृत्ति का प्रतिनिधित्व करता है जिनके पास एसपीई में वर्षा की तीव्रता के साथ-साथ मनाया डेटासेट भी है। ओवर-हिट (अंडर-हिट) एसपीई और अवलोकन किए गए डेटासेट दोनों में बारिश की घटनाओं की आवृत्ति को संकेत करता है जब एसपीई प्रेक्षित वर्षा को अधिक (कम) आंकते हैं। विस्तारित कंटिजेंसी तालिका की उपयोगिता को भारत में सिंथेटिक वर्षा समय श्रृंखला और एसपीई का मूल्यांकन करके दिखाया गया था।

इसके अलावा, हमने गेज-आधारित वर्षा डेटासेट से जानकारी का विलय करके एसपीई में त्रुटि को कम करने का प्रस्ताव किया। हालांकि कई समय-डोमेन त्रुटि सुधार तकनीक साहित्य में मौजूद हैं, दैनिक वर्षा को सही करने में उनकी दक्षता सीमित है। इसके अलावा, उच्च प्रदर्शन तकनीकों के अधिकांश बोझिल और समय संपूर्ण हैं। हमने दो त्रुटि सुधार विधियों को प्रस्तुत किया, एक आवृत्ति और समय डोमेन में संयुक्त रूप से एसपीई को सही करना, और दूसरा एक बेहद तेज़ एक्सट्रीम लर्निंग मशीन का दृष्टिकोण। समय और आवृत्ति डोमेन में एसपीई की समय श्रृंखला को सही करने के लिए एक हाइब्रिड दृष्टिकोण प्रस्तावित किया गया है, जिसमें वैरिएशनल मोड डिफरेंशियल (वीएमडी) और एक्सपीरिमेंटल क्विमुलेटिव डेंसिटी फंक्शन (ईसीडीएफ) शामिल हैं। एसपीई को सही करने के लिए वृद्धिशील एक्सट्रीम लर्निंग मशीन (ईएलएम) का एक अनुकूलित संस्करण भी प्रस्तावित है। प्रस्तावित तरीकों को पूरे भारत में एसपीई की त्रुटि सही करने के लिए लगाया जाता है। परिणामों से पता चलता है कि प्रस्तावित तकनीकें सभी मौसमों में एसपीई से त्रुटि का एक बड़ा अंश हटा देती हैं। त्रुटि के बाद सुधार, रूट मीन स्क्वायर एरर (आरएमएसई) में कमी और कोरेलेशन में सुधार भी देखा गया। दोनों त्रुटि सुधार योजनाएं ओएच, -यूएच, -एम, और एफ घटकों के परिमाण को कम कर सकती हैं। त्रुटि सुधार के बाद एसपीई में अत्यधिक वर्षा विशेषताओं का बेहतर प्रतिनिधित्व भी देखा जाता है। वीएमडी-ईसीडीएफ और ईएलएम विधियां अधिक सटीक वर्षा को मजबूर करने के लिए पारंपरिक त्रुटि सुधार तकनीकों को बेहतर बनाती हैं।

इसके अलावा, हमने एसपीई की हाइड्रोलॉजिकल उपयोगिता का मूल्यांकन उन्हें एक हाइड्रोलॉजिकल मॉडल में डालकर (असुधारित के साथ-साथ त्रुटि को ठीक किया) और उसके बाद, वास्तविक धारा-प्रवाह के साथ सिमुलेटेड धारा-प्रवाह की तुलना की। इस शोध-प्रबन्ध ने भारत के महानदी बेसिन में छह गेज स्टेशनों पर हाइड्रोलॉजिकल प्रेडिक्शन फॉर द एनवायरनमेंट (एचवाईपीई) मॉडल का उपयोग करके नकली एसपीई से धारा-प्रवाह प्रतिक्रिया का मूल्यांकन किया। एचवाईपीई मॉडल को कैलिब्रेट करते समय मॉडल पैरामीटर अनिश्चितता को ध्यान में रखा गया था। कैलिब्रेटेड एचवाईपीई मॉडल मनाया निर्वहन अनुकरण में प्रभावी था। परिणामों ने अपस्ट्रीम साइटों पर असुधारित एसपीई के नकली धारा-प्रवाह प्रतिक्रिया में बड़े त्रुटि को उजागर किया। एसपीई के त्रुटि सुधार ने धारा-प्रवाह सिमुलेशन में सुधार किया; हालांकि, सुधार की सीमा अलग-अलग एल्गोरिदम के साथ भिन्न थी। वीएमडी-ईसीडीएफ त्रुटि से धारा-प्रवाह सिमुलेशन बारीकी से मनाया प्रवाह के समान दृष्टिकोण को ठीक किया। एसपीई का उपयोग करके एचवाईपीई मॉडल का पुनर्मूल्यांकन पैरामीटर अनिश्चितता में वृद्धि और सामान्यीकरण को कम किया। यह अध्ययन हाइड्रोलॉजिकल मॉडलिंग के लिए असुधारित एसपीई के उपयोग के खिलाफ चेतावनी देता है। एसपीई को हाइड्रोलॉजिकल मॉडलिंग में अपने आवेदन से पहले त्रुटि को सही किया जाना चाहिए।

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## ABBREVIATIONS

AIMSR	All-India Summer Monsoon Rainfall
ANN	Artificial Neural Networks
APHRODITE	Asian Precipitation Highly Resolved Observational Data Integration Towards Evaluation of Water Resources
CWC	Central Water Commission
CFSR	Climate Forecast System Reanalysis
CHPclim	Climate Hazard group Precipitation climatology
CHIRPS	Climate Hazards group Infrared Precipitation with Stations
CPC	Climate Prediction Center
CMORPH	CPC Morphing method
CRU	Climate Research Unit
CCS	Cloud Cluster System
CONDUST	CONceptual DUal-Staged
CDD	Consecutive Dry Days
CWD	Consecutive Wet Days
CT	Contingency Table
CC	Correlation Coefficient
CSI	Critical Series Index
CDF	Cumulative Distribution Function
DJF	December-February
DE	Differential Evolution
DE-MCMC	Differential Evolution - Markov Chain Monte Carlo
DEM	Digital Elevation Model
ECDF	Empirical Cumulative Distribution
EMD	Empirical Mode Decomposition
ERA-Interim	European Centre for Medium-Range Weather Forecasts - Interim
ELM	Extreme Learning Machine
FAR	False Alarm Ratio
FBI	Frequency Bias Index
GH	Games–Howell
GA	Genetic Algorithm
GIS	Geographic Information System

GHCN	Global Historical Climatology Network
GLWD	Global Lakes and Wetlands Database
GLCC	Global Land Cover Characterization
GPCP	Global Precipitation Climatology Project
GPM	Global Precipitation Mission
GRanD	Global Reservoir and Dam
GSMaP	Global Satellite Mapping of Precipitation
GMI	GPM Microwave Imager
HWSD	Harmonized World Soil Database
HYPE	Hydrological Predictions for the Environment
HRU	Hydrological Response Unit
IMERGE	IMERG Early
IMERGF	IMERG Final
IMERGL	IMERG Late
IMD	India Meteorological Department
ISMR	Indian Summer Monsoon Rainfall
IR	InfraRed
IMERG	Integrated Multi-satellite Retrievals for GPM
IMF	Intrinsic Mode Functions
IDW	Inverse Distance Weighted
JF	January-February
JJAS	June, July, August and September
KS	Kolmogorov–Smirnov
LULC	Land Use and Land Cover
LS	Linear Scaling
LOCI	Local Intensity Scaling
LSTM	Long Short-Term Memory
ML	Machine Learning
MK	Mann-Kendall
MAM	March-May
MCMC	Markov Chain Monte Carlo
MSE	Mean Square Error
MW	MicroWave

MERRA	Modern-Era Retrospective Analysis for Research and Applications
NSE	Nash-Sutcliffe Efficiency
NOAA	National Oceanic and Atmospheric Administration
NN	Neural Network
OND	October-December
OI	Optimal Interpolation
PMW	Passive MicroWave
PSS	Peirce Skill Score
PERSIANN-CDR	Precipitation Estimation from Remotely Sensed Information using Artificial Neural Networks- Climate Data Record
PDF	Probability Density Function
POD	Probability Of Detection
POOD	Probability Of Over-Detection
POTD	Probability Of True-Detection
POUD	Probability Of Under-Detection
PF	Propagation Factor
QQ	Quantile-Quantile
RT	Regression Trees
RMSD	Root Mean Square Difference
RMSE	Root Mean Square Error
SREM	Satellite Rainfall Error Model
SPEs	Satellite-based Precipitation Estimates
HydroSHEDS	SHuttle Elevation Derivatives at multiple Scales
SRTM	Shuttle Radar Topography Mission
SDII	Simple Daily Intensity Index
SLCs	Soil and Landuse Classes
SHEDS	Split-Hit Error Decomposition Scheme
SVM	Support Vector Machine
SMHI	Swedish Meteorological and Hydrological Institute
TMI	TRMM Microwave Imager
TMPA	TRMM Multi-Satellite Precipitation Analysis
TRMM	Tropical Rainfall Measurement Mission
VMD	Variational Mode Decomposition

VCSI	Volumetric Critical Success Index
VFAR	Volumetric False Alarm Ratio
VHI	Volumetric Hit Index
VMI	Volumetric Miss Index
VOHI	Volumetric Over-Hit Index
VTHI	Volumetric True-Hit Index
VUHI	Volumetric Under-Hit Index
WHIST	World Hydrological Input Setup Tool
WRIS	Water Resources Information System