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Research Article

Disaggregation of Climate-Projected Rainfall Using an Empirical Approach for Design Rainfall Estimation

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Abstract

The robust regional and seasonal variability exhibited in Australian rainfall patterns, superimposed by the large-scale-continental-climate-volatility, is expected to further intensify under climate change impacts, altering the recurrence and austerity of extreme rainfall intensity event(s) prevalence. This needs to be conscientiously addressed while developing Intensity-Frequency-Duration (IFD) curves for employment in the design of flood-mitigation-infrastructure. Current Australian IFD practices are developed based upon the temporal-stationarity-concept, thereby calling for updated IFD practices based upon non-stationarity approaches for future flood mitigation/planning. However, a major obstacle in the adaptation of this approach is centered around the unavailability of projected future rainfall data records at sub-hourly/sub-daily timescales, crucial for developing IFD curves of any sort. This has led to extensive research on various rainfall disaggregation techniques, using both statistical and empirical methods. This paper proposes the novel application of one such empirical method, a reduction formula used by the Ethiopian Road Authority, dubbed as the ERA Formula, for disaggregating projected daily rainfall data into sub-daily/sub-hourly timescales. The proposed method is attested on an Eastern Melbourne urban catchment, Gardiners Creek, with good-quality observed rainfall data. The original ERA equation, is calibrated to befit Australian climatic and geographical conditions, following which it is applied and evaluated. The results highlight that the application of the ERA approach exhibited supremacy in the accurate replication of the observed temporal variability in the annual maxima rainfall timeseries at the sub-daily/sub-hourly timesteps, with high estimation accuracy (R^2 = 88-92% & NSE = 0.89-0.9) and minimum error magnitude (MAE = 0.85mm & RMSE =1.37 mm), thereby highlighting the efficacy of potentially adopting this approach for disaggregation of the projected rainfall.

Keywords

Intensity-Frequency Duration (IFD) Curves, Disaggregation, Design Rainfall, Climate Change, Empirical Approach, Sub-daily/Sub-hourly

1. Introduction

On a global scale, Australia has been widely acknowledged for the pronounced seasonal, inter/intra-annual and regional variability exhibited in the localized rainfall patterns, on both temporal and spatial scales [1, 2]. Given the escalating climate vulnerability status of Australia and the expansive statewide urban sprawl, this rainfall variability is expected to further intensify, significantly impacting the severity and frequency of extreme rainfall intensity events' prevalence [3,

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4] The downscaled global-regional climate models' projections (GCM-RCM) by the Intergovernmental Panel on Climate Change (IPCC) Coupled Model Intercomparison Project Phase 6 (CMIP6), based upon multiple emissions scenarios, strongly imply with high confidence limit (95%), a significant intensification of 6-7% per °C of warming in short (<24 hours) and long (≥24 hours) duration rainfall extremes and approximately 12-14% per °C of warming in rare, extreme, and localized short duration (sub-daily/sub-hourly) rainfall events in the near future [1, 5, 6]. These projected changes, particularly regarding localized sub-daily and sub-hourly rainfall extremes, are expected to increase the likelihood of more frequent and unprecedented extreme rainfall intensity events, further distorting the variability of temporal and spatial patterns, significantly influencing the magnitude and timing of runoff generation, leading to the imposition of an incessant residual urban flooding risk.

The countless variations in the rainfall extremes is likely to significantly modify the current shape of the Intensity-Frequency-Duration (IFD) curves, where an increase in the rainfall intensity of short duration storm events (both sub-hourly and sub-daily) will stimulate significant variations at both ends of the IFD curve, fluctuating for different return periods (Annual Exceedance Probability (AEP)/Exceedance per Year (EY)) and regions [4, 7] and impacting the fidelity of current design rainfall estimates. Engineers rely on these design rainfall estimates for the assessment and design of hydraulic infrastructure and flood mitigation. The failure to integrate evolving rainfall extremes into design frameworks may result in under-engineered systems, heightening flood risks and structural vulnerabilities, or over-engineered solutions, imposing unwarranted financial constraints.

Current Australian IFD practices, developed by the Bureau of Meteorology (BoM) in accordance with the Australian Rainfall and Runoff 2016 (ARR2016) guidelines, are based on the concept of temporal stationarity, implying that the probability of rainfall events occurring will not significantly change over time [4, 7, 8]. Given the increasing evidence of a changing climate and rapid urbanization, fluctuations in the recurrence, severity, and timing of hydroclimatic extremes indicate a need to incorporate dynamic behaviour into distribution parameters to avoid underestimation of the expected return levels. In recent times, the hydrological research community has shown moderate interest in the conceptualization and implementation of non-stationary IFD practices, incorporating dynamic behavior and climate change impacts. However, a major impediment hindering the active adaptation of non-stationary IFD practices, especially under climate change scenario, is primarily centered around the CMIP6 climate model projections for all emissions scenarios, being available only at selective timesteps - daily, monthly, seasonally and annually, This is primarily due to the projections being based upon observed rainfall datasets available at only daily temporal resolutions, due to the limited availability of good quality observed rainfall records at sub-daily/sub-hourly timescales, leading towards addressing this impending knowledge gap, proposing various approaches.

Reviewing relevant literature, the most common approaches that have been embraced involve various rainfall disaggregation techniques, both statistical and analytical, for downscaling the daily observed rainfall into the required sub-daily/sub-hourly timesteps. Some of the commonly used statistical rainfall disaggregation techniques over the past decade are Random Cascade Models [9, 10], Method of Fragments (MoF) approach [11, 12], L-Moments and Least Square Regression [13], Multivariate Disaggregation of Rainfall (MuDRain) software [12, 14] and most commonly the Bartlett-Lewis and/or Newman Scott Rectangular Pulse modelling techniques using specialized software known as "HyetosMinutes [13-16]." Despite their wide employment, stochastic approaches have their fair share of limitations, and display high complexity requiring extensive statistical efforts, making them less favorable for routine industrial practice [17, 18].

Apart from statistical approaches, several analytical and empirical approaches have been proposed over the years, although being disregarded primarily due to their subjectivity, formulation complexity and detailed datasets requirements [18, 19]. Despite these drawbacks, these approaches offer favorable benefits, in terms of accuracy, transparency in underlying concepts/relationships and controlled assumption levels. This greatly assists in focusing on specific aspects of climate change modelling, providing an advantage over statistical approaches. Some widely acknowledged and common empirical / analytical approaches include the Bell-Herschfield Method [20] and the Indian Meteorological Department (IMD) Empirical Formula, along with its modified iterations, Modified-IMD and Modified Chowdhury-IMD formulas [17, 20-25].

This research proposes the adaptation of one such analytical approach novel to the Australian environment, an empirical reduction formula, commonly known as the "Ethiopian Road Authority (ERA) empirical reduction formula [25-27], for sub-daily/sub-hourly rainfall disaggregation. The ERA formula has shown to provide favorable outcomes in terms of significant accuracy, simplicity and convenience, significantly assisting towards developing IFD curves covering the rainfall depths of most of Ethiopia's major hydrological regions [25-30]. However, in the case of this research paper, the primary aim is focused towards employing the ERA empirical reduction formula, for assessing the potentiality of its application upon the Australian landscape in disaggregating observed 24-hourly rainfall data into finer temporal resolutions (sub-daily/sub-hourly), potentially based upon which the potentiality of applying this method for disaggregation of projected rainfall data under various greenhouse gas emissions scenarios, RCP4.5 and RCP8.5 will be considered, as part of developing future non-stationary IFD-curves, as part of the simulation-based approach.

2. Materials and Methods

2.1. Materials

2.1.1. Study Area

Gardiners Creek, an urbanized waterway situated in the southeastern suburbs of Melbourne (37°49'S, 145°7'E - 37°50'S, 145°2'E), within the lower-reaches of the Yarra River Basin, proportioning a total impervious fraction of 47%, was selected as the case study catchment. The creek originates at Blackburn Lake, Box Hill, continuously flowing over a total length of 30 km (19 miles), and outlets to the Yarra River, at proximity to the suburb of Heyington, encompassing a total catchment area of 111 km^2. The Gardiners Creek catchment experiences an average annual rainfall depth of 750 mm, while the prevailing mean seasonal maximum and minimum temperatures vary between 25°C and 15.3°C (in summer) and 15°C and 7.6°C (in winter) respectively, procuring a Koppen-Geiger-climate-classification of temperate-oceanic (Cfb). The land-use distribution within the catchment is disparate, with the majority being residential (64%), followed by public-use (11%), roads (9%) and other uses (16%).

The Gardiners Creek catchment is monitored and managed by Melbourne Water Corporation, the Victorian Government's statutory water authority, through a collection of pluviographic gauging stations, spatially distributed across the entire extent of the catchment, where this paper will be focused upon one of these pluviographic gauging stations, selected based upon the quality and completeness of the rainfall records, being visually represented in Figure 1 below (circled in red). The selected pluviographic station, Gardiners Creek Downstream at Great Valley Road (Station ID 229624A), is positioned at the terminus of the catchment closer to the outlet, thereby capturing the aggregated effects of spatial rainfall distribution, representative of the catchment's downstream hydrological response, thereby validating the selection.

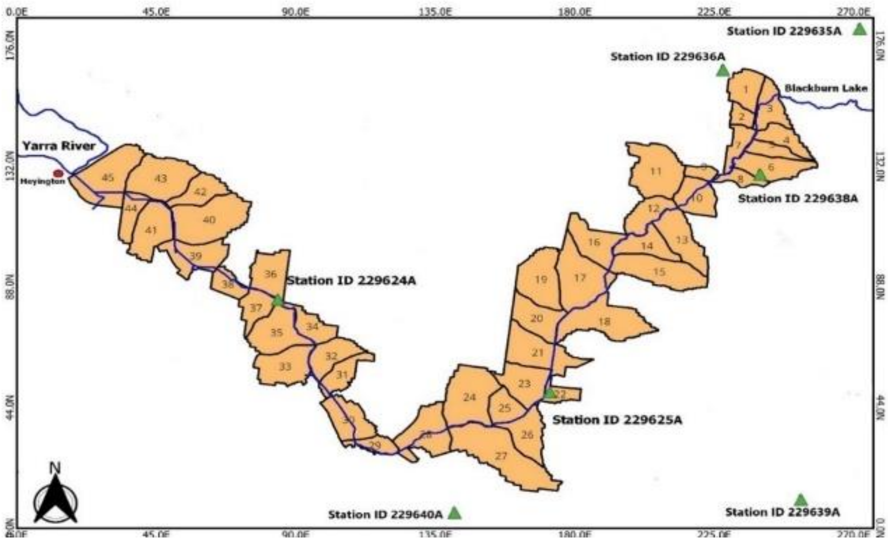


Figure 1. Study catchment and location of selected pluviographic stations.

2.1.2. Datasets Description

(i). Localized Rainfall Datasets

Digital hydrologic timeseries data records of the daily observed localized rainfall depths (in mm), at six-minute time intervals, with varying record lengths ranging from the 8th of April 1977 to the 31st of December 2021, for the selected pluviographic gauging station of the study catchment, was provided by Melbourne Water Corporation. A common timeframe corresponding to the selected station's records availability was established, which in this case was a 33-year time-period ranging from 1st of January 1989 to 31st December 2021. The rainfall data was assessed and pre-processed based upon the hydrologic data quality, completeness, and positioning of the selected station within the catchment boundary (validated based upon Thiessen Polygon method). The six-minute resolution rainfall datasets were then utilized to develop sub-daily/sub-hourly/sub-weekly time intervals for developing a conventional annual maximum rainfall time series for the proposed method appraisal and subsequent comparative performance evaluation against the benchmark data.

(ii). Annual Maximum Series (AMS) Analysis

This six-minute temporal resolution rainfall observations were then pre-processed, transformed, and tabulated into a further nine sub-hourly/sub-daily/sub-weekly time durations - 12 and 30 minutes, 1,3,6 and 12 hours and 1,2 and 3 days, selected based upon the recommendation of current Australian Rainfall and Runoff 2019 (ARR2019) guidelines for developing IFD curves. The annual maxima rainfall depth in each year of record from the 33-year time-period, for all ten selected time durations were then extracted and tabulated accordingly for both stations. The extracted sub-hourly/sub-daily/sub-weekly annual maximum rainfall depths timeseries were used as the benchmark for the analysis of the proposed methodology, while the 24-hourly annual maximum rainfall depths formed the basis for appraisal of the empirical reduction formulae.

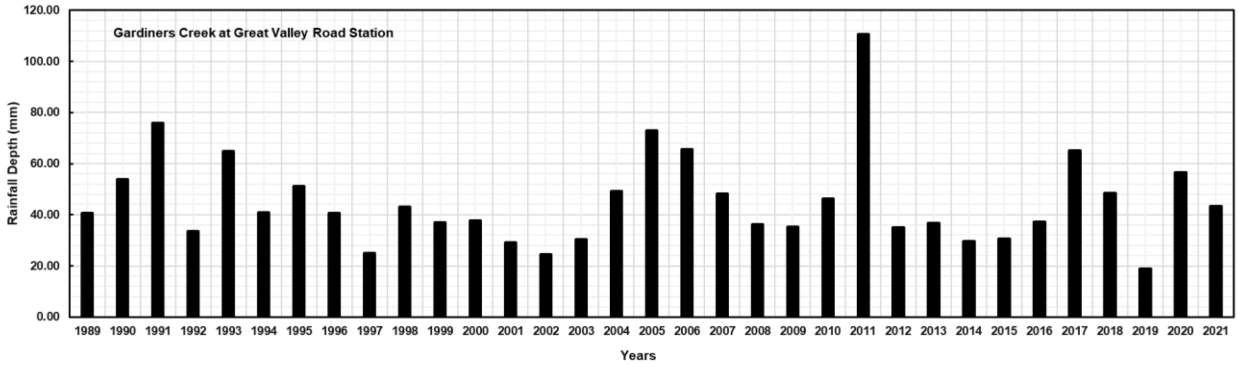


Figure 2. Historical annual maximum daily rainfall time series for selected station.

2.2. Methods

2.2.1. Ethiopian Road Authority (ERA) Approach

The sparse availability and paucity associated with rainfall data at finer temporal resolutions (<24 hours) hindered the development of IFD curves and rainfall frequency distribution plots for Ethiopia's various hydrological regions. This prompted the Ethiopian Road Authority (ERA) towards proposing an empirical reduction formula, based upon scaling relationships between available short-duration rainfall data and 24-hour data, enabling reasonable disaggregated estimates of short-duration rainfall depths [25-27]. This empirical relationship has hence been translated and extensively adopted as part of the Ethiopian Road Authority Drainage Design Manual primarily in the design of hydraulic infrastructure. The empirical formula, dubbed as the ERA Formula, has been represented in Equation 1 below.

$$R_t = R_{24}.\frac{t}{24}.\frac{(b+24)^n}{(b+t)^n} \qquad (1)$$

where t represents the required time duration (in hours), R_t is the required rainfall depth (in mm) for duration t, R_{24} is the daily rainfall depth (in mm), while b and n are fixed calibration coefficients, estimated based upon numerous studies of pluviographic gauges in various climatic conditions, with *b* being fixated at 0.3 and *n* lying within the range of 0.78-1.09 [25-30].

2.2.2. Application of ERA Approach in Rainfall Disaggregation

The 24-hour annual maximum rainfall depths derived from the rainfall time series served as the basis for the appraisal and application of the ERA formula for estimating the rainfall depths for the selected seven sub-hourly/sub-daily/sub-weekly durations, which is closely followed by a comparative evaluation against observed rainfall records using relevant critical statistical indices. Given the significant influence of calibration constants, *b* and *n* upon the ERA formula, namely in terms of restricting the degree of analytical freedom, which in-turn influences the accuracy and efficacy of the estimates, a two-split calibration/validation approach was embraced, to avoid overfitting incidences and enhance generalization capability of the formulae. A 65:35 ratio was embraced, with the first 21 years (1989-2009) being considered for calibration and the remaining twelve years (2010-2021) for validation.

The relevant "n" constant was computed from calibration against observed rainfall records, through non-linear optimization incorporating least squares regression analysis. The iterative process was repeated for all selected time durations until the optimum calibration constants were estimated, following which they were attested using the validation dataset and the most optimum formula is recommended. The statistical indices used in the comparative analysis are coefficient of correlation (R), coefficient of determination (R^2), Mean Absolute Error (MAE), Percentage Bias (PBias), Root Mean Squared Error (RMSE), Index of Agreement (d) and Nash Sutcliffe Efficiency (NSE).

3. Results

The statistical evaluation of the estimated rainfall depths using the ERA formula, based upon the calibration dataset of 21 years (1989 - 2009) has been summarised in Table 1 below, benchmarked against the observed rainfall depths. An overall analytical summary highlights coexistence of a strong correlation in the rainfall depths' estimates across the various time-durations (6 to 720 minutes), in terms of a consistently high correlation (R = 0.93 to 0.96) and a strong explanatory power, pertaining to the variances in observed rainfall depths (R^2 = 86.49% to 92.16%), with the intermediate and longer temporal resolutions (30 mins., 180 - 720 mins.) dominating in terms of superiority. However, the accuracy slightly depreciates, as time duration increases, as reflected in the increasing MAE (0.11 mm to 1.57 mm) and RMSE (0.39 mm to 3.55 mm).

Despite this depreciation, the prediction efficiency is retained, as validated by the NSE values ranging between 0.89 to 0.95, suggesting reliable predictions of rainfall dynamics, particularly for shorter durations. The negativity in the Percentage Bias ranging between -0.72% to -5.25% indicates slight underestimation as the time durations increases, but the high index of agreement (d = 0.82 to 0.85) confirms the capability of the ERA formula in effectively capturing and replicating overall rainfall patterns. The outcomes from the calibration provide robust "n" constants that are adopted for the subsequent validation of the ERA formula's rainfall depth estimates, further reinforcing the suitability for application in hydrological and atmospheric sciences, namely finer temporal resolutions, and evaluate the predictive ability on unseen data.

The validation dataset which comprises of observed rainfall depths for the twelve-year period from 2010-2021, was used to assess the robustness of the model and the derived constants. Suitable averaging techniques were embraced to the calibrated constants, following which the efficacy was attested upon the validation dataset. The calibration constants (post-averaging) for the two formulae have been summarized in Table 2 below.

Table 1. *Statistical evaluation summary of ERA formula estimates (Calibration Dataset).*

	Time Duration (in minutes)						
Statistics	**6**	**12**	**30**	**60**	**180**	**360**	**720**
R	0.93	0.94	0.96	0.95	0.96	0.96	0.96
R^2 (%)	86.5	88.4	92.2	90.3	92.2	92.2	92.2
MAE (mm)	0.27	0.11	0.52	0.28	0.91	1.61	1.57
RMSE (mm)	0.75	0.39	0.81	0.44	1.67	3.55	2.96
NSE	0.91	0.93	0.93	0.89	0.94	0.93	0.95
PBias (%)	-0.72	-4.26	-5.25	-5.25	-4.79	-5.20	-4.89
d	0.84	0.83	0.83	0.84	0.82	0.84	0.85

Table 2. *Summary of Calibration Constants for ERA Formula.*

	Formula	**ERA**	
	Calibration Constants	**n**	**b**
Time Duration	6 mins	0.910	0.30
	12 mins	0.864	0.30
	30 mins	0.825	0.30
	60 mins	0.816	0.30
	180 mins	0.840	0.30
	360 mins	0.885	0.30
	720 mins	0.917	0.30

Following the application of the calibration constants to the validation dataset, the performance was assessed using the same statistical indices, which have been summarized in Table 3 below. A high positive correlation (R = 0.94 to 0.96) and high explanatory power (R^2 = 88.36% to 92.16%) representing the variance in the observed rainfall depths is observed, providing high confidence in the reliability of the ERA formula-based rainfall depth estimates. The MAE and RMSE, like the calibration dataset, is highly varied, initially increasing with longer durations (upto 3.71 mm and 5.40 mm at 180 minutes), and then declining (2.29 mm and 2,9 mm at 720 minutes), which is however offset by the high NSE values (0.89 to 0.96) indicating excellent predictive skill and the ability to closely match observed rainfall patterns.

The slightly negative percentage bias (ranging between -9.11% to -0.08%) suggests minor underestimation, which however diminishes at longer durations almost reaching neutralization point (negligible bias) (contradicting calibration outcomes), while the index of agreement remains above 0.8 across all durations, indicating a good level of agreement between the observed and estimated rainfall depths, reliably capturing the key dynamics of the rainfall incidences.

On an overall basis, comparatively assessing the evaluation outcomes for both datasets with relevance to Tables 1 above and 3 below, the consistent high R values (0.93-0.96) and R^2 values (>86%) demonstrates strong generalization capability and high predictive strength, suggesting robustness in the application of the ERA formula in capturing the temporal patterns across different time scales, from short-duration intense convective storm events to longer duration, low-intensity stratiform rainfall events. The NSE and the *d* values remain robust across both datasets, ranging between 0.89 to 0.96 and 0.82 to 0.88, showcasing high predictivity skill, efficiency and high level of agreement across both datasets in replicating rainfall dynamics and capturing the general patterns of rainfall depth, inclusive of the domineering impact exhibited by convective and stratiform events in short and medium-duration rainfall incidences.

Table 3. *Statistical evaluation summary of ERA formula estimates (Validation Dataset).*

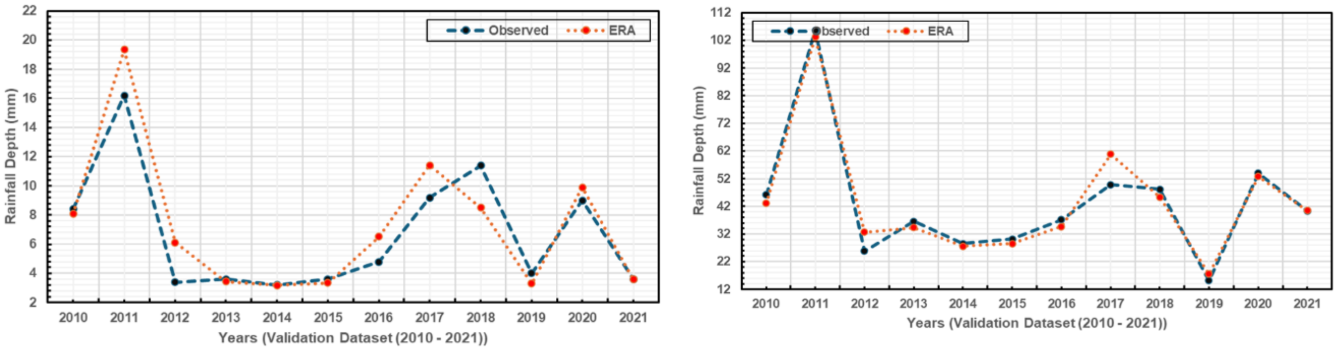
	Time Duration (in minutes)						
Statistics	**6**	**12**	**30**	**60**	**180**	**360**	**720**
R	0.96	0.94	0.96	0.96	0.95	0.96	0.96
R^2 (%)	92.2	88.4	92.2	92.2	90.1	92.2	92.1
MAE (mm)	0.85	1.59	1.04	1.41	3.71	3.47	2.29
RMSE (mm)	1.37	2.33	1.87	2.29	5.40	4.48	2.90
NSE	0.91	0.89	0.95	0.95	0.93	0.96	0.96
PBias (%)	-9.11	-8.86	-5.22	-7.67	-4.35	0.24	0.08
d	0.84	0.86	0.86	0.88	0.83	0.83	0.84

Comparatively evaluating the error metrics, MAE and RMSE, across both datasets reveals a similar trend, with better estimation capability for shorter time intervals (0.11-0.39 mm (12 mins.) for calibration and 0.85-3.71 mm (6 mins.) for validation) and an increase in the level of generalization error as the time duration increases (0.39-3.55 mm (12 mins) for calibration and 1.37-5.40 mm (180 mins) for validation), further indicating growing uncertainty in the rainfall depth estimates. Regarding the percentage bias, a similar trend is observed in the calibration dataset, with an increasing bias as the time duration increases, suggesting consistent underestimation in the rainfall depths.

In contrast, the percentage bias in the validation dataset exhibits more variability, commencing with higher bias and slight underestimation at shorter time intervals (6 and 12 mins), which gradually diminishes as the time duration increases, nearly becoming neutral at 360- and 720-minute time duration with values of 0.24% and 0.08%. The increasing error for longer time duration can be associated with the cumulative nature of rainfall temporal variability, reflecting the compounded aggregation of cumulative errors from smaller, shorter durations being prolonged over time and potentially hydrological lag.

In terms of the contrasting varied performances showcased by the percentage bias in both datasets, this can be ascribed to the challenges associated with replicating the inherent variability associated with intense, short-duration convective rainfall and long-duration, widespread and uniform stratiform rainfall systems. The higher bias in shorter duration events is associated with modelling challenges of convective storms events (common in shorter durations such as 6 - 30 mins.), namely the drastic spatial/temporal variability and erratic rainfall patterns, influenced by rapid atmospheric changes. The following gradual depreciation in the bias can be ascribed to the more uniform, continuous and steady stratiform rainfall, driven by broader atmospheric dynamics, which is common in longer duration events.

On an overall scale, despite the presence of an increasing error with longer time intervals, slight degradation in the ERA formula estimates over time and slight underestimation of rainfall, specifically at the short-durations, the level of error can be considered to be generally low, and within the acceptable ranges for hydrological forecasting applications, falling below ±10%, and further evidenced by the high NSE and Index of Agreement (d) values demonstrating the reliability of the ERA formula's estimates in effectively disaggregating rainfall depths across various durations, amking it suitable for use in future hydrological applications such as climate vulnerability assessments and flood mitigation studies.



(a) (b)

Figure 3. ERA Formula-based rainfall depth estimation capacity for 6- and 720-minutes time duration for validation data (a) - (b).

4. Conclusion

In the wake of climate change's intensification of Australian rainfall patterns, particularly the increasing severity and frequency of short-duration extreme storm events, a revision of the current Australian IFD practice is being recommended, possibly through non-stationary approaches. However, the lack of high-quality sub-daily/sub-hourly/ sub-weekly rainfall data necessitates the use of rainfall disaggregation methods. This research applies the analytical approach, ERA formula, tailored to local Australian climatic conditions.

The validation results demonstrate that ERA formula delivers superior accuracy based upon the outcomes of the validation dataset, replicating observed rainfall variability with high precision (R^2 88-92%, NSE: 0.89-0.96), minimal bias (0.08%) and minimal errors (MAE: 0.85 mm, RMSE: 1.37 mm). In conclusion, it can be inferred from the results that the ERA formula has exhibited supremacy in accurately replicating and representing the observed temporal variability exhibited in the annual maxima rainfall patterns at the sub-hourly/sub-daily/sub-weekly durations, with minimal error magnitude, highlighting its potential for application in future rainfall disaggregation practices.

The applicability of the ERA formula across various Australian catchments is contingent upon the availability of high-quality datasets from a minimum of one gauging station for calibration and the accuracy varies from station to station. Also, a few limitations of this approach would involve the replication of short-duration, convective rainfall events and the degradation exhibited in the performance metrics as a results of rapid atmospheric variability influencing erratic rainfall patterns, which needs to further be researched upon and offset prior to full scale adaptation/application of ERA Formula.

Future research work will focus upon further validation of the proposed method using rainfall data from additional pluviographic stations and other urban catchments located in the Yarra River basin. This will be followed by applying the proposed method to disaggregate downscaled CMIP6 climate model projections under the currently recommended RCP-SSP ensemble scenarios for both medium and high emissions. This will be followed by fitting a Generalised-Extreme Value (GEV) distribution to the downscaled rainfall projections from the climate models for the study catchment(s) to obtain the respective return levels for specified time durations (6,12,30,60,180,360, 720 mins and 1,2,3 days) and return periods (50,20,10,5,2,1% AEP), which can then be utilised to developed future climate-refined IFD curves, which will be comparatively assessed against current ARR2016-based Australian IFD practices, to assess the level of variability in the results, and accordingly recommendations will be provided for devising suitable mitigation practices and developing climate-resilient infrastructure.

Abbreviations

IPCC	Intergovernmental Panel on Climate Change
CMIP6	Coupled Model Intercomparison Project Phase 6

GCM	Global Climate Model
RCM	Regional Climate Model
BOM	Bureau of Meteorology
ARR2016	Australian Rainfall and Runoff 2016
AEP	Annual Exceedance Probability
EY	Exceedance per Year
IFD	Intensity Frequency Duration
MoF	Method of Fragments
MuDRain	Multivariate Disaggregation of Rainfall
IMD	Indian Meteorological Department
ERA	Ethiopian Road Authority
RCP	Representative Concentration Pathway
R	Pearson's Coefficient of Correlation
R^2	Coefficient of Determination
MAE	Mean Absolute Error
PBias	Percentage Bias
RMSE	Root Mean Squared Error
D	Index of Agreement
NSE	Nash Sutcliffe Efficiency

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Author Contributions

Harshanth Balacumaresan: Conceptualisation, Resources, Data Curation, Formal Analysis, Validation, Investigation, Visualisation, Methodology, Writing - original draft, Writing - editing

Iqbal Hossain: Conceptualisation, Data Curation, Supervision, Project Administration, Formal Analysis, Investigation, Visualisation, Methodology, Writing - review & editing

Monzur Imteaz: Supervision, Project Administration, Methodology, Writing - review & editing

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Data Availability Statement

The data supporting the outcome of this research work has been reported in this manuscript and will be made available upon reasonable request.

Conflicts of Interest

The authors declare no conflicts of interest.

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