

Article

Performance Evaluation of a National Seven-Day Ensemble Streamflow Forecast Service for Australia

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Abstract: The Australian Bureau of Meteorology offers a national operational 7-day ensemble streamflow forecast service covering regions of high environmental, economic, and social significance. This semi-automated service generates streamflow forecasts every morning and is seamlessly integrated into the Bureau's Hydrologic Forecasting System (HyFS). Ensemble rainfall forecasts, European Centre for Medium-Range Weather Forecasts (ECMWF), and Poor Man's Ensemble (PME), available in the Numerical Weather Prediction (NWP) suite, are used to generate these streamflow forecasts. The NWP rainfall undergoes pre-processing using the Catchment Hydrologic Pre-Processor (CHyPP) before being fed into the GR4H rainfall-runoff model, which is embedded in the Short-term Water Information Forecasting Tools (SWIFT) hydrological modelling package. The simulated streamflow is then post-processed using Error Representation and Reduction In Stages (ERRIS). We evaluated the performance of the operational rainfall and streamflow forecasts for 96 catchments using four years of operational data between January 2020 and December 2023. Performance evaluation metrics included the following: CRPS, relative CRPS, CRPSS, and PIT-Alpha for ensemble forecasts; NSE, PCC, MAE, KGE, PBias, and RMSE; and three categorical metrics, CSI, FAR, and POD, for deterministic forecasts. The skill scores, CRPS, relative CRPS, CRPSS, and PIT-Alpha, gradually decreased for both rainfall and streamflow as the forecast horizon increased from Day 1 to Day 7. A similar pattern emerged for NSE, KGE, PCC, MAE, and RMSE as well as for the categorical metrics. Forecast performance also progressively decreased with higher streamflow volumes. Most catchments showed positive performance skills, meaning the ensemble forecast outperformed climatology. Both streamflow and rainfall forecast skills varied spatially across the country—they were generally better in the high-runoff-generating catchments, and poorer in the drier catchments situated in the western part of the Great Dividing Range, South Australia, and the mid-west of Western Australia. We did not find any association between the model forecast skill and the catchment area. Our findings demonstrate that the 7-day ensemble streamflow forecasting service is robust and draws great confidence from agencies that use these forecasts to support decisions around water resource management.

Keywords: ensemble streamflow forecast; 7 days; GR4H model; performance evaluation; Australia



Citation: Bari, M.A.; Hasan, M.M.; Amirthanathan, G.E.; Hapuarachchi, H.A.P.; Kabir, A.; Cornish, A.D.; Sunter, P.; Feikema, P.M. Performance Evaluation of a National Seven-Day Ensemble Streamflow Forecast Service for Australia. *Water* **2024**, *16*, 1438. <https://doi.org/10.3390/w16101438>

Academic Editor: Maria Mimikou

Received: 28 March 2024

Revised: 2 May 2024

Accepted: 3 May 2024

Published: 17 May 2024



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1. Introduction

During 1997–2009, south-east Australia experienced its worst drought since 1901 [1]. Known as the 'millennium drought', below-median annual rainfall was frequently observed

with little recovery in intervening years during this period. In particular, observed streamflow in the Murray Darling River Basin, known as Australia's food bowl, was very low, and inflow to major reservoirs was half of the previous recorded minimum [2]. As a result, there was wide societal, economic, and environmental impacts [3,4]. The Federal Government passed the Water Act, 2007 (<https://www.legislation.gov.au/Details/C2017C00151>, accessed on 20 June 2023); this was a water security plan for the future of the nation. The Bureau of Meteorology (the Bureau) was given responsibility to implement the Water Act. Among other services, streamflow forecasting at seasonal and 7-day time scales were developed as part of the water security plan [5].

A 7-day deterministic streamflow forecast service was progressively developed during 2010–2015 and released by the Bureau to the public in September 2015. This was the first nationally operated continuous streamflow forecast system developed in Australia [6]. Subsequent feedback from key customers across state and territory jurisdictions favoured a move to ensemble or probabilistic forecasts. Ensemble forecasting is considered more reliable and skilful, and it can greatly benefit water resource management by providing useful information about uncertainty [7]. In response to customer needs, the Bureau progressively developed the 7-day ensemble streamflow forecasting and released it to the public in 2020 [8]. This is a comprehensive, nation-wide service for Australia, and covers most water resource catchments of high economic value and social significance [9]. The service currently consists of 99 catchments and 208 forecasting locations where observed streamflow records are available (Figure 1), and covers 10 out of the 13 drainage divisions. Catchments vary in area across the country (from 26 to 83,150 km²) and are located in different hydroclimatic regions. The number of forecasting locations distributed across different drainage divisions vary significantly, the selection of which was based heavily on value, with little attention paid to human impact on natural flows or impact for customers—the Murray Darling division has the largest number of stations, while the South-Western Plateau, the Lake Eyre Basin, and the North Western Plateau have no stations at all (Figure 1). Australia has a wide range of climate zones, as defined by Köppen Climate Classification [10]; these include the tropical region in the north, the temperate regions in the south, the grassland, and the desert in the vast interior. The annual rainfall for each of the divisions varies from 410 mm to 2800 mm [8]. The distribution of annual rainfall and potential evapotranspiration (PET) varies significantly across the continent (http://www.bom.gov.au/jsp/ncc/climate_averages/rainfall/index.jsp, accessed on 11 November 2023). Annual average PET is generally higher than annual average rainfall. Therefore, streamflow generation processes in most divisions are different, and are controlled by water-limited environments [11], except for the Tasmania drainage division.

There is a wide range of modelling techniques for streamflow and flood forecasting [12,13]; taking rainfall forecasts from the Numerical Weather Prediction (NWP) system as an input for the hydrological model for prediction is a very popular option. Ensemble streamflow forecasting has also become very popular across the world over the last decade [14,15]. There are various large-scale continental and global hydrological models that are run by communities around the world [15,16]. The Global Ensemble Streamflow Forecasting and Flood Early Warning (GloFAS) service is one of the most popular forecasting systems. The U.S. Hydrologic Ensemble Forecast Service (HEFS) is run by the National Weather Service (NWS), and this service provides ensemble streamflow forecasts that seamlessly span lead times from less than 1 h up to several years; these are spatially and temporally consistent [17]. In Canada, provincial river forecast centres deal with unique challenges in data collection, modelling, and river flow forecasting due to a large diversity in landscape, hydrological features across the country, and distribution of weather and extreme events at different times of the year [18]. Similar results were also found in South America, where a continental-scale hydrological model coupled with ECMWF ensemble rainfall was applied to produce streamflow forecasts up to 15 days in advance [19].

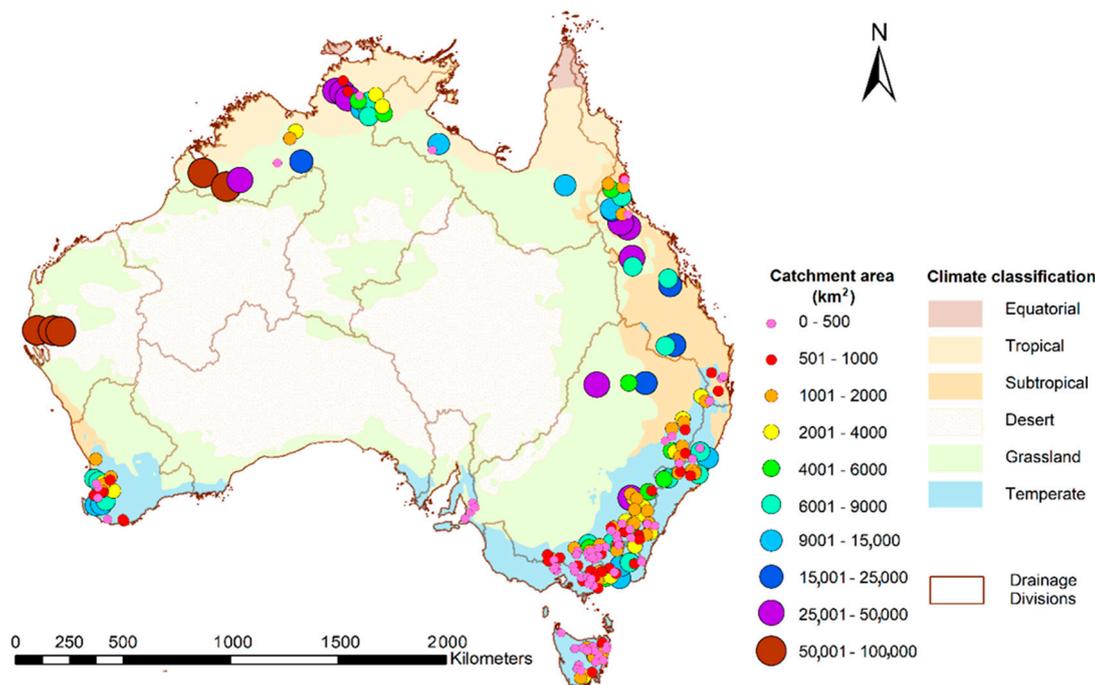


Figure 1. Drainage divisions, hydroclimatic regions, and forecasting locations. Catchment area is shown by size and color of circles.

For users to fully benefit from ensemble streamflow forecasts, they need to comprehend the performance, the model behaviour, and the forcings. Recent studies have focused on the performance evaluation of short–medium-range hydrological streamflow forecasts. The quality of ensemble streamflow forecasts in the U.S. mid-Atlantic region was investigated by Siddique and Mejia [20], and they found that ensemble streamflow forecasts remain skilful for lead times of up to 7 days, and that postprocessing further increased forecast skills across lead times and spatial scales. In Canada, optimal model initial state and input configuration led to reliable short- (days) and long-term (a year) streamflow forecasts [21]. In China, Liu et al. [22] demonstrated that ensemble streamflow forecasting systems are skilful up to a lead time of 7 days ahead; however, accuracy deteriorates as the lead time increases.

The Bureau’s operational ensemble 7-day streamflow forecast service [8] now has 4 years of retrospective (archived) forecast data (January 2020–December 2023). The performance of the overall end-to-end streamflow forecasting has not been analysed yet, and this paper presents the steps in filling this critical operational knowledge gap. The key objectives of this paper are as follows: (i) to discuss the day-to-day operational monitoring and continuity of the service; (ii) to perform a comprehensive evaluation of pre-processed rainfall and streamflow forecasts; (iii) to suggest possible avenues for future improvements.

2. Operational Forecast System and Model

The 7-day ensemble streamflow forecast service for Australia can be accessed through a freely available website (<http://www.bom.gov.au/water/7daystreamflow/>, accessed on 28 February 2024). This service features forecasting locations with forecasting skills and reliability that have passed specified selection criteria. While the primary emphasis is on delivering daily and hourly streamflow forecasts, the service also includes cumulative hourly streamflow and rainfall forecasts.

2.1. Description of the System’s Architecture

The forecasts are generated daily using the Bureau’s Hydrological Forecasting System (HyFS). This national platform for modelling underpins flood forecasting and warning

services for Australia. HyFS is a Delft-FEWS (Flood Early Warning System) based forecasting environment (<https://oss.deltares.nl/web/delft-fews>, accessed on 20 October 2023). The system provides a comprehensive platform for the management of input observations and a Numerical Weather Prediction (NWP) model—Quantitative Precipitation Forecasts (QPFs). It encompasses various tasks such as input data processing, forecasting and maintenance workflows, model internal state management, and forecast visualization. Publication quality plots are generated using a spatial module outside the HyFS (Figure 2) and the products are delivered to the website via the Bureau’s content management system. The publication time of the forecast information to the website varies across states—generally, it is between 10:00 a.m. and 12:00 noon Australian Eastern Standard Time (AEST). An end-to-end forecast generation and publication procedure is presented in Figure 2.

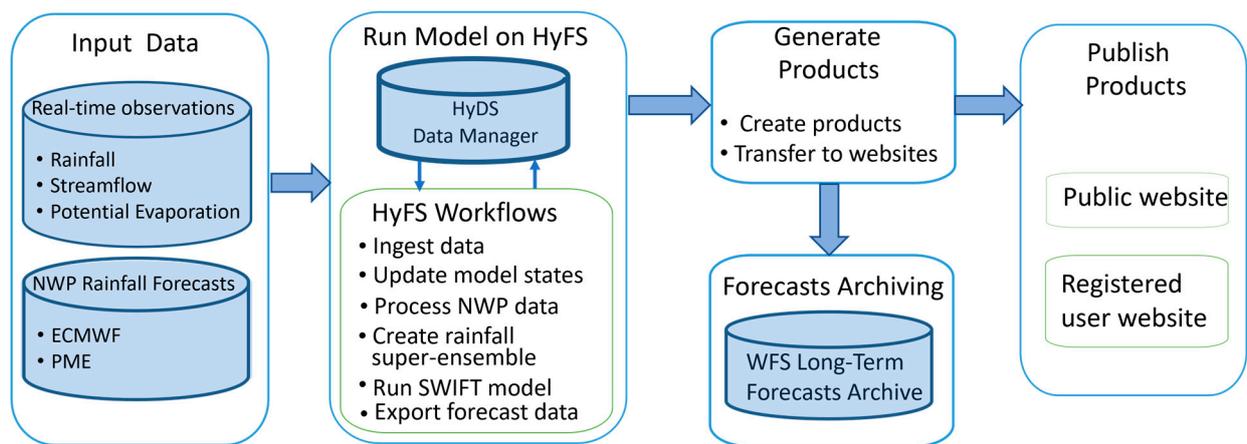


Figure 2. Flow diagram of the forecast generation and publication process for the 7-day streamflow forecast service.

2.2. Input Data

The observed rainfall and water level data are ingested into the HyFS in near-real time through the Bureau’s Australian Water Resources Information System (AWRIS). Potential evapotranspiration (PET) data are extracted from the Australian Water Availability Project, AWAP [23], disaggregated to hourly and sub-catchment scale, and stored in HyFS. Additionally, the Quantitative Precipitation Forecasts (QPFs) from the ECMWF and PME Numerical Weather Prediction (NWP) models’ data are automatically integrated into HyFS. The ECMWF forecast rainfall is processed using the Catchment Hydrology Pre-Processor, CHyPP [24]. CHyPP generates an ensemble comprising 400 members sourced from ECMWF and merges with PME at an hourly time step for each sub-area for a lead time of up to 7 days (Figure 2). Given that PME is a merged, post-processed product of many global NWP products, it shows negligible improvement when CHyPP is used on it [24]. Therefore, the PME forecasts are not post-processed.

2.3. Rainfall–Runoff and Routing Model

The Short-term Water Information Forecasting Tools (SWIFT) constitute a streamflow modelling software package (version 2.1) [25] seamlessly integrated into HyFS (Figure 2). SWIFT encompasses a variety of hydrologic models and provides a semi-distributed modelling approach—conceptual sub-areas and a node–link structure—for channel routing. Its functionality extends to modules for calibration, model initial state (hot start), ensemble forecast runs, and output error correction. Out of the available conceptual rainfall–runoff models in SWIFT GR4H, a four-parameter hourly model developed by Perrin [26] was found to be the most suitable option for Australian applications [27]. The model calibrated the parameter sets, and the initial state conditions were migrated and stored in HyFS for operational application. To enhance the accuracy of the hydrological forecast time series,

an integrated tool within SWIFT known as ERRIS (Error Representation and Reduction In Stages), developed by Li et al. [28], is used for streamflow error correction.

2.4. Operational Platform

The product generator tool produces five graphical outputs: (i) daily flow forecast, (ii) hourly flow forecast, (iii) cumulative flow forecast, (iv) cumulative rainfall forecast, and (v) forecast performance. The first four graphical products (and associated forecast data) are updated and published on the SDF website daily (<http://www.bom.gov.au/water/7daystreamflow/index.shtml>, accessed on 22 March 2024). The generated forecast time series is automatically archived for future analyses and interpretation (Figure 2). Following forecast generation, selected data are packaged for downstream processing by end-users. The ensemble streamflow forecasts also serve as guidance for the Bureau's flood forecasting service (<http://www.bom.gov.au/water/floods/>, accessed on 8 March 2024). Operational day-to-day monitoring involves addressing issues through a systematic approach encompassing data, modelling, and system and customer feedback. A designated monitoring officer logs, escalates, and resolves issues in collaboration with other experts, such as software/system engineers who support the service.

3. Performance Evaluation Methodology

Forecast quality continues to be limited by systematic and random errors from limited knowledge of initial conditions and inherent limits in representing physical processes in model structures [29,30]. Performance evaluation is generally “the process of assessing the quality of a forecast” [31] and serves as a useful tool in identifying the sources of errors [32–34]. Quantitative model performance is generally evaluated by computing metrics based on observed and forecast data. It establishes an appropriate level of confidence in a model's performance before its use can be effective in management and decision making. This confidence level is vital for forecasters to consider and communicate when interacting with users who rely on these forecasts. In hydrological modelling and forecasting, observed values are used as the “point of truth” against which one can assess forecast performance [35,36]. We used streamflow and rainfall (2014–2016) as historical sources of “truth” to verify the model before operational release [8]. While there have been studies that have presented different verification and performance evaluation metrics and diagnostic plots [37,38], we applied some widely used ones for the evaluation of forecasts in ensemble and deterministic forms.

3.1. Performance Evaluation Metrics

The absence of clarity and consensus regarding criteria for defining optimal or sub-optimal forecasts can complicate the formulation, evaluation, and ultimate determination of the utility of operational forecasts. Murphy [34] defined nine forecast quantitative attributes and their relationships with different verification metrics. Additionally, ‘coherence’, a term used to describe whether forecasts are not, at least, worse than climatology (historical data), was also considered [39]. These cross-relationships were recently summarized by Huang and Zhao [38]. We have chosen metrics to provide a comprehensive overview of the operational forecast performance (see Appendix A). This includes all metrics used to evaluate the historical performance of the model before it is used operationally [8]. Additionally, we have incorporated selected supplementary metrics for a more thorough evaluation. These metrics are used for evaluating the quality of rainfall and streamflow forecasts. These are presented in ensemble, deterministic, and categorical forms:

- **Deterministic:** We considered the mean of the ensemble members and assessed the performance using the PBias, NSE, KGE, PCC, RMSE, and MAE metrics.
- **Ensemble:** The metrics included were CRPS, relative CRPS, CRPSS, and PIT-Alpha.
- **Categorical:** Three metrics were included—POD, FAR, and CSI.

These metrics are widely applied for assessing streamflow and rainfall prediction skills across the world [20,40–43].

3.2. Diagnostic Plots

Diagnostic plots allow for the visualisation of verification metrics, and they additionally provide an empirical understanding of ensemble hydroclimatic forecasts [37,44]. There are generally six types of popular diagnostic plots [38,45]. Of these, we chose scatter plots, spatial maps, percentile distribution, and box plots for ensemble forecasts and their deterministic forms.

3.3. Forecast Data and Observations

We have chosen a full four years of data (from January 2020 to December 2023) for use in the performance analysis. The hourly forecast data were accumulated to daily totals for the performance evaluation process. In line with forecast verification analyses conducted by Hapuarachchi et al. [8], we considered the most downstream locations within the catchments for the operational performance evaluation. The continuous hourly forecast data were unavailable for a few catchments, limiting our assessment to 96 out of 99 catchments. During the development of the service, 3 years of retrospective forecast data between 2014 to 2016 were considered for the performance evaluation; hourly observed streamflow data between 1990 and 2016 were used to calculate the climatology as the reference for skill score calculation (CRPSS). Consistently with this historical approach, we maintained the same reference climatology for this research.

4. Results of Predictive Performance

We analysed the performance of the models by computing the metrics, as detailed in Appendix A. Decades of research and investigations consistently reveal that the ensemble mean yields results that are comparable to, or often better than, deterministic forecasts [7,46,47]. To comprehensively assess performance, we conducted analyses in two ways: (i) deterministic—considering only the mean of the ensemble forecasts; (ii) ensemble—accounting for all members of the ensemble. As examples, Figure A1 (rainfall) and Figure A2 (streamflow) show the performances of two randomly selected catchments across all the metrics.

4.1. Evaluation of Rainfall Forecasts

4.1.1. Performance of Ensemble Mean

In our deterministic analysis, we considered several performance metrics, including PBias, MAE, NSE, KGE, RMSE, and PCC (Appendix A), across all forecasting locations. The mean bias for all catchments ($n = 96$) approached zero, and gradually deteriorated with longer forecast horizons (Figure 3a). However, the percentile range of bias remained remarkably consistent across different forecast horizons. Only about 40% and 15% of catchments had positive bias for Day 1 and Day 7, respectively (Figure 3b). These findings closely resemble those obtained for the verification period used in developing the service [8]. The rainfall post-processor, CHyPP, played an important role in reducing bias in NWP rainfall forecasts. As anticipated, based on PBias and MAE, the NSE of the bias-corrected forecast rainfall remained low (despite post-processing) and decreased progressively as the forecast horizon increased. Only about 95% of catchments showed positive KGE for Day 1 forecasts, while this figure dropped to about 10% for the subsequent 6 days (Figure 3c). The percentile range of the forecast also steadily decreased as the forecast horizon increased, with Day 1 having the largest range. Similar trends in steadily declining performance skills have been observed by other researchers—in India [48], Canada [7], China [22,49], and the USA [17]. Furthermore, when assessing rainfall forecast performance using KGE and PCC, we found relative increases, but there was an overall decrease as the forecast horizon extended. These patterns were consistent across both KGE and PCC metrics.

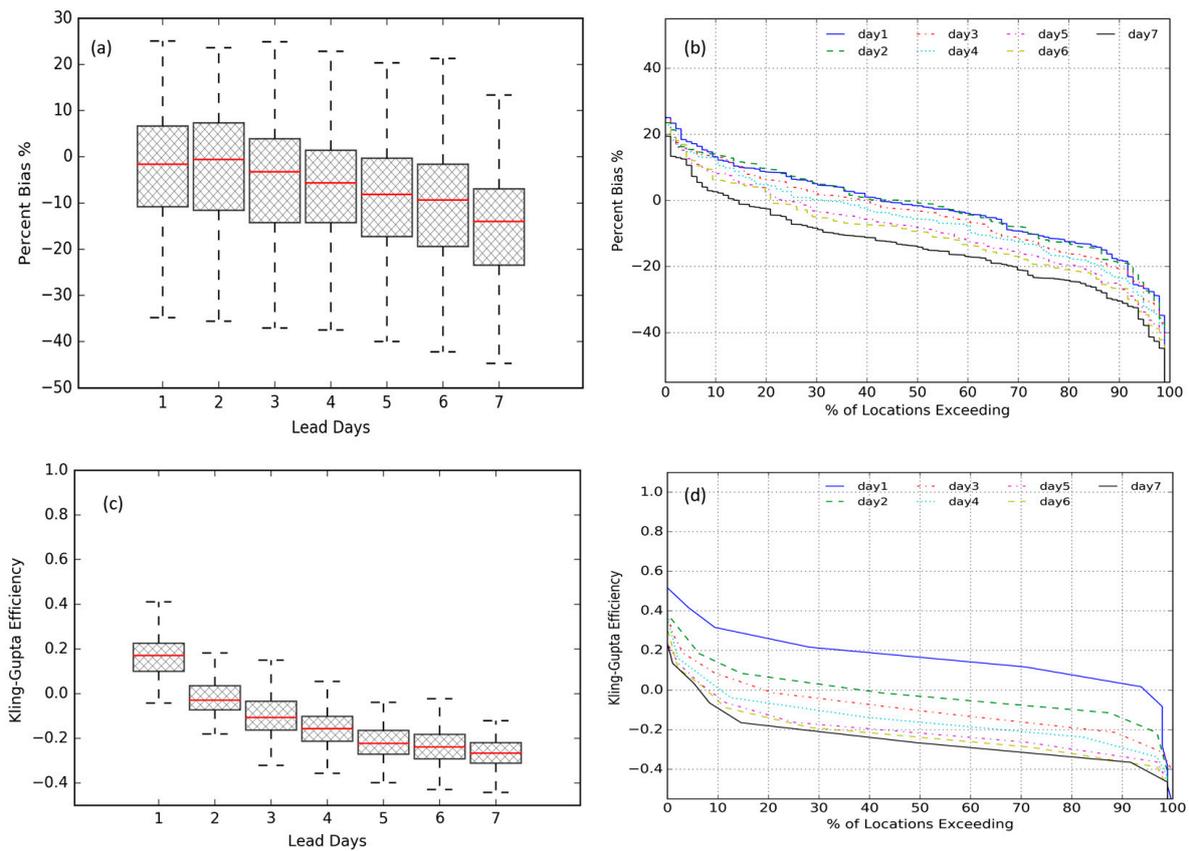


Figure 3. Rainfall forecast skill in deterministic form for all 96 catchments: (a) PBias (%), (b) percentage of forecasting locations exceeding bias, (c) KGE, and (d) percentage of forecasting locations exceeding KGE for different lead times.

The performance of rainfall forecasts, calculated using the MAE metric, was similar to the PBias. The median MAE was 3.3 mm/day for the Day 1 forecast and increased for the remaining 6 days, remaining stable at around 3.7 mm/day (Figure 4a). Surprisingly, the percentile range of MAE was the largest for Day 4 and gradually decreased over the remaining three days’ forecasts. The MAE was greater than 5.7 mm/day or greater for only about 4% of the catchments (Figure 4b). Similar results were also evident in the RMSE.

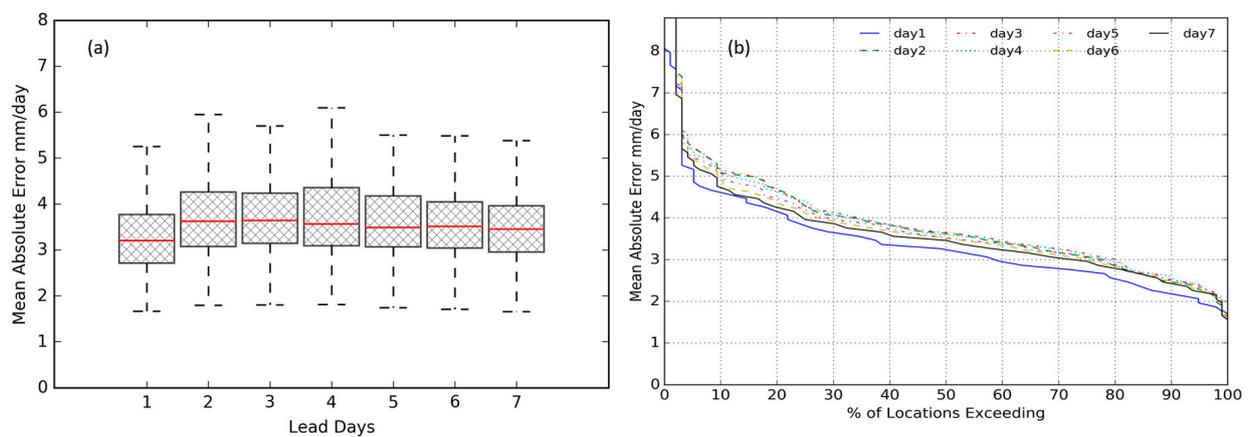


Figure 4. Median MAE (mm/day) of forecast rainfall: (a) 96 catchments; (b) percentage of catchments exceeding median MAE for different lead times.

Three categorical metrics—CSI, POD, and FAR—accurately evaluate the performance of rainfall forecasts across different amounts that fall within specified time frames [50,51]. These metrics have been widely used for the assessment of rainfall forecasts [52,53]. In our deterministic assessment of forecast rainfall performance, we categorised the total daily amounts into five distinct classes—the 5th, 25th, 50th, 75th, and 95th percentiles (an example catchment is shown in Figure A1). The forecast performance of the rainfall varied among these percentiles and across different forecast horizons (Figure 5). The best performance was obtained from the 25th percentile range (from Day 1 to Day 7) and it deteriorated for higher rainfall amounts and forecast horizons. Extreme predicted rainfall events showed minimal or no skill beyond Day 1. These findings aligned with the assessment of POD, which yielded similar results.

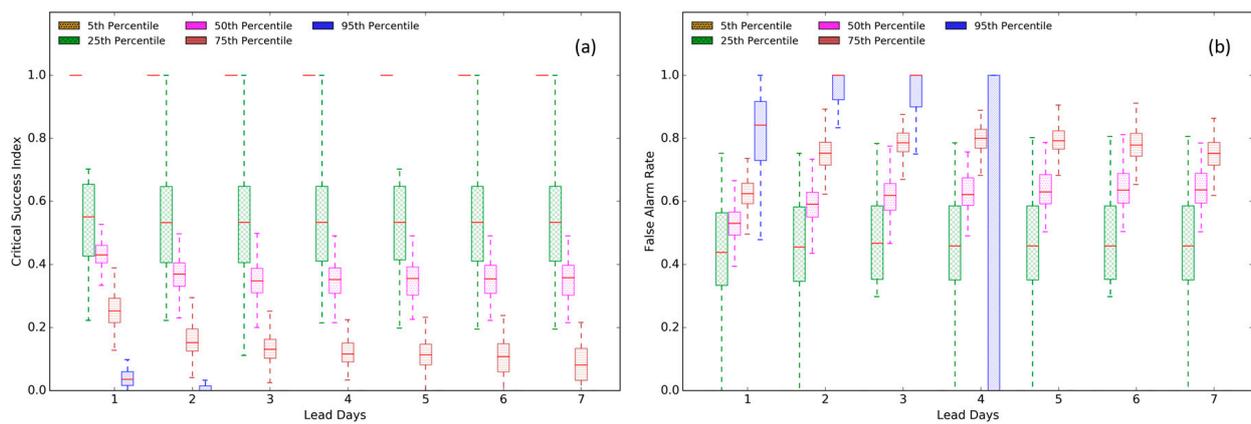


Figure 5. Categorical metrics of all 96 forecasting locations—for different rainfall percentiles: (a) CSI and (b) FAR.

4.1.2. Performance of Ensemble Forecasts

We computed CRPS, relative CRPS, and PIT-Alpha metrics for all 96 catchments (Figure 6). Similarly to the results for the deterministic form, the forecast skills gradually diminished as the forecast horizon increased. The percentile range of CRPS was highest in Days 3 and 4, respectively, and gradually decreased. However, the PIT-Alpha was lowest for Days 2 and 3 and increased successively for the remaining Days 4–7. Our findings are similar to those verification skills from the development phase of the service [5,8].

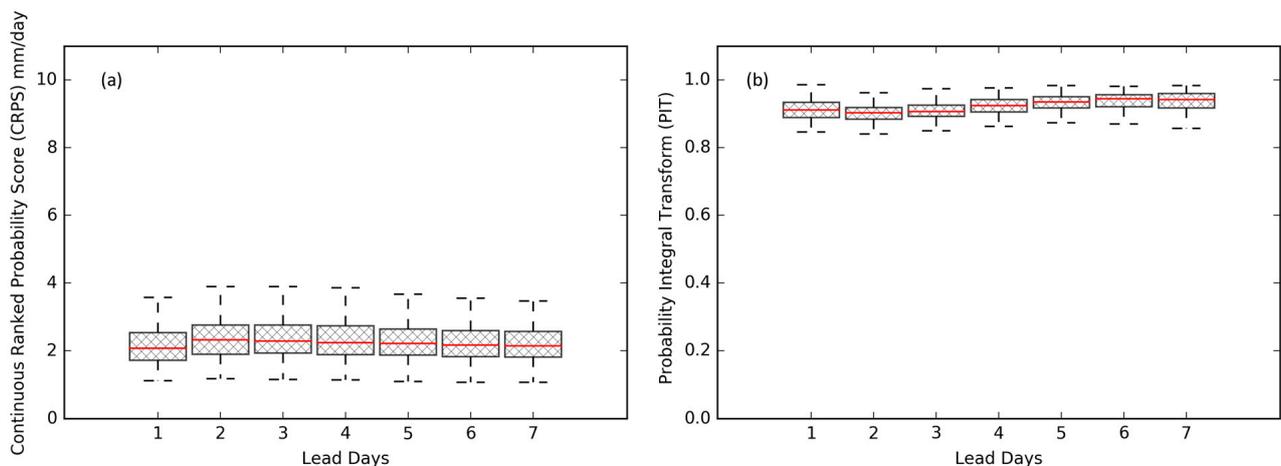


Figure 6. Box plots of rainfall forecasting skills of all 96 forecasting locations: (a) CRPS and (b) PIT-Alpha.

4.1.3. Skills and Catchment Areas

In addition to performance metrics and diagnostic plots, we investigated rainfall forecast skill and its association with catchment area (Figure 7). The catchment area ranges from 26 km² to 86,000 km² (Figure 1). While there was a positive relationship between catchment area and NSE, there appeared to be no relationship with PBias, with PIT-Alpha or with CRPS. This is in contrast to other findings across the world. For example, the national flood warning system in New Zealand has performance skills that increase with the catchment area [54].

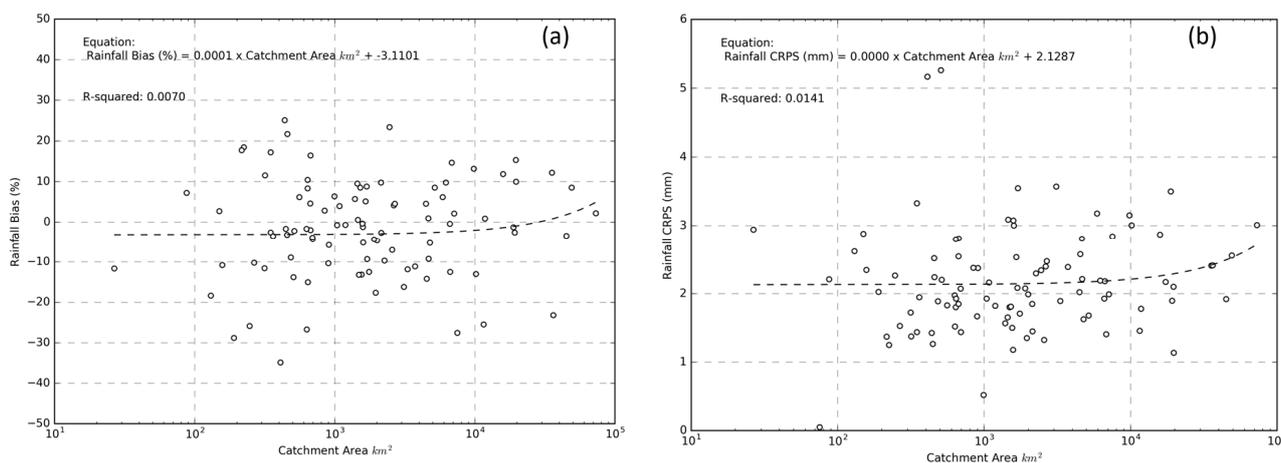


Figure 7. Performance of one-day lead time rainfall forecast and catchment area: (a) PBias and (b) CRPS.

4.2. Evaluation of Streamflow Forecasts

We assessed and evaluated the 7-day ensemble streamflow forecasts using the metric as described in Appendix A and present the results in the following sections. The details of the performance metrics of a randomly selected catchment from New South Wales are shown in Figure A2.

4.2.1. Performance of Ensemble Mean

Box plots of streamflow forecasting performance skills PBias, RMSE, KGE, and PCC for all locations are shown in Figure 8. The skills clearly declined gradually as the forecast horizon increased from Day 1 to Day 7. The median bias for all forecasting locations remained very close to zero, but the percentile range increased steadily. This is different from the rainfall forecast (Figure 4a) where the median of the bias decreased over the forecast horizon and the range bound remained fairly constant. The apparent improvement in skills could be attributed to implementation of streamflow post processing [37] and the streamflow routing scheme in the SWIFT modelling system. Forecast skill using the other three metrics—RMSE, KGE, and PCC—led to a similar conclusion. The performance decayed approximately exponentially as the forecast horizon increased (Figure 8). However, the lower percentile bound of KGE, from Day 3 onwards, was below zero, meaning some forecasting locations had no skill. Similarly, the upper bound of the RMSE was very high for some catchments, indicating poorer performance.

The NSE results for all catchments and forecasting locations are presented in Figure 9. Similarly to the other metrics, the performance decreased as the forecast horizon increased. Only about 25% of catchments had an NSE greater than 0.6 and 0.4, respectively, for lead times of 3–7 days. In an operational context, this performance skill is better than that found in a similar study in India using an ECMWF dataset as the forcing variable [48].

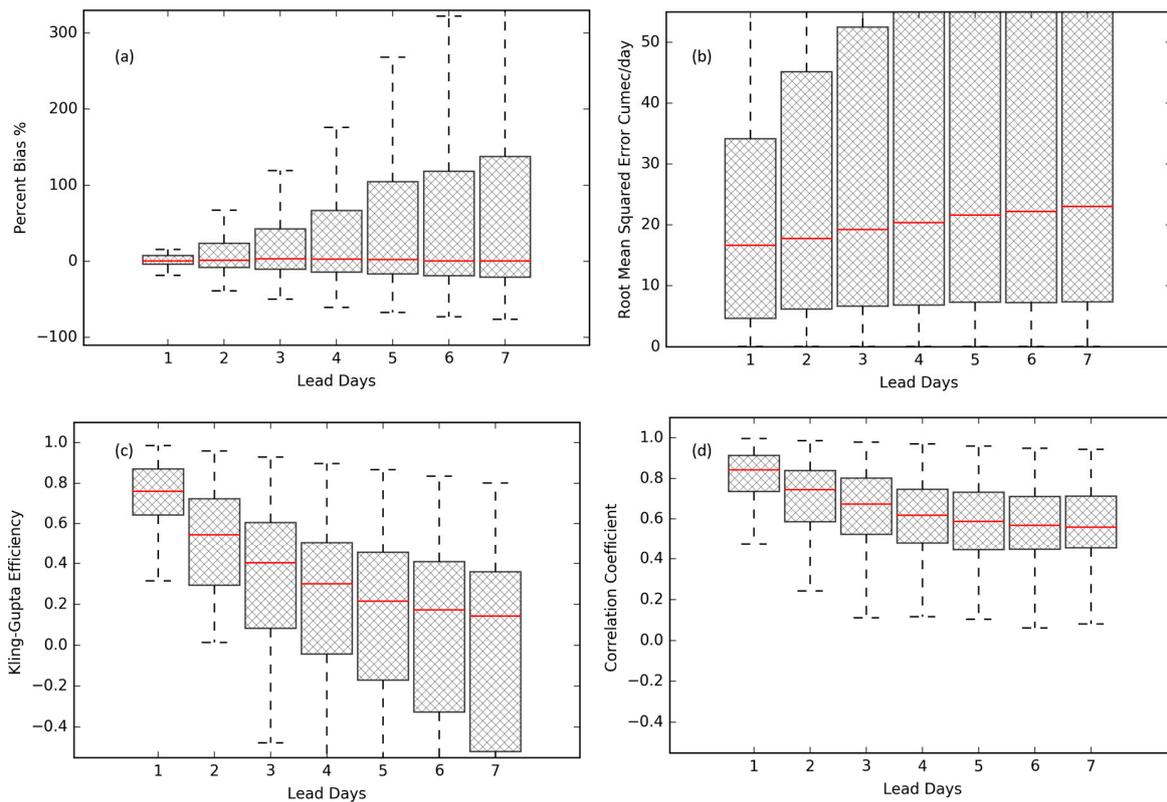


Figure 8. Streamflow forecast skill deterministic form for all 96 forecasting locations: (a) PBias, (b) RMSE, (c) KGE, and (d) PCC.

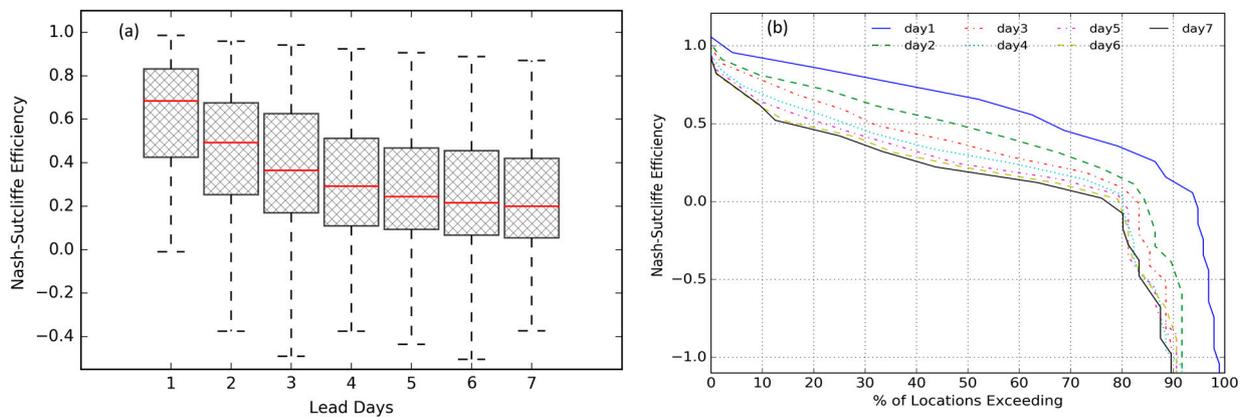


Figure 9. Box plots of streamflow forecasting skills of all 96 forecasting locations: (a) NSE and (b) percentage of catchments exceeding median NSE for different lead times.

Categorical metrics are widely used to assess the performance of the streamflow and flood predictions [52,53,55–57]. Similarly to rainfall, we classified the streamflow of different percentiles and calculated the CSI, POD, and FAR for all catchments (an example is shown in Figure A2) for different flow volumes to further understand the model’s predictive capabilities. The forecast performance progressively decreased with higher discharges and longer lead times (Figure 10). The performance of the rainfall forecast was even poorer (Figure 5), indicating that the streamflow forecast skill was improved by the postprocessing error-correction scheme. Another reason for the poorer performance of extremely high flows could be that there were fewer events used in the analysis and higher measurement uncertainty [58]. Matthews et al. [59] found similar results in Europe when comparing the CRPSS of rainfall and streamflow prediction at different quantile ranges.

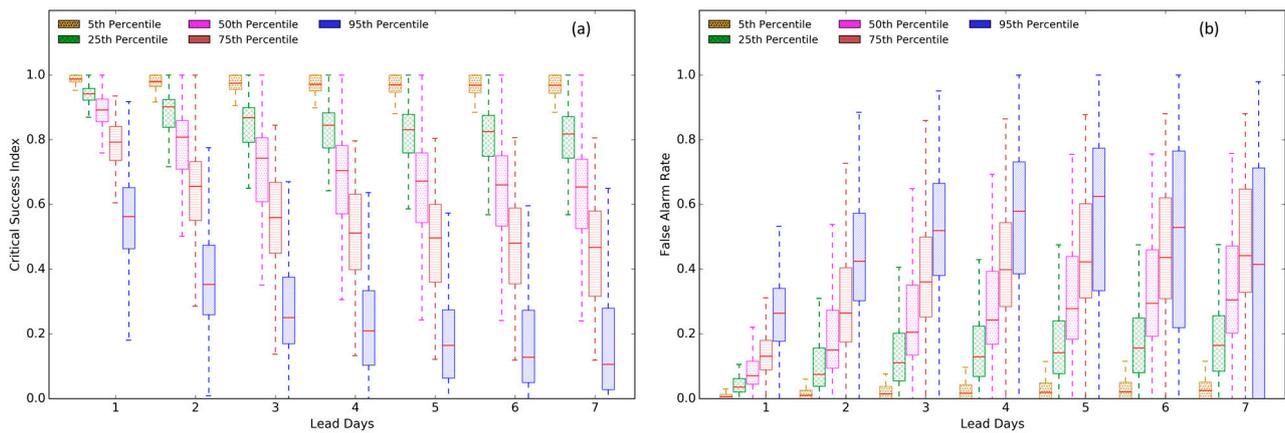


Figure 10. Categorical metrics for all 96 forecasting locations—for streamflow in the 5th, 25th, 50th, 75th, and 95th percentiles: (a) CSI and (b) FAR.

4.2.2. Performance of Ensemble Forecasts

Streamflow forecasting performance skills—CRPSS and PIT-Alpha again reaffirm that skills gradually decline as the forecast horizon increases (Figure 11). The CRPSS skill was somewhat lower than that obtained during the development phase of the service [5,8] for Day 1, but was higher for the subsequent 6 days. Few catchments had negative CRPSS skill, meaning the performance was lower than it might have been if reference climatology had been used. Similar results were also evident for the relative CRPS metric. The median of the PIT-Alpha score was also very similar to that obtained during the development phase of the service. However, the percentile band was much wider (Figure 11b). The streamflow forecasting skills also showed better performance than the skills obtained from a similar studies conducted in USA [20], Canada [60], Europe [59], South America [19], and around the world [38]. Our findings suggest that the operational 7-day ensemble streamflow forecasting service is robust, and this provides greater confidence for end users who use or wish to use these forecasts to support water management decision making.

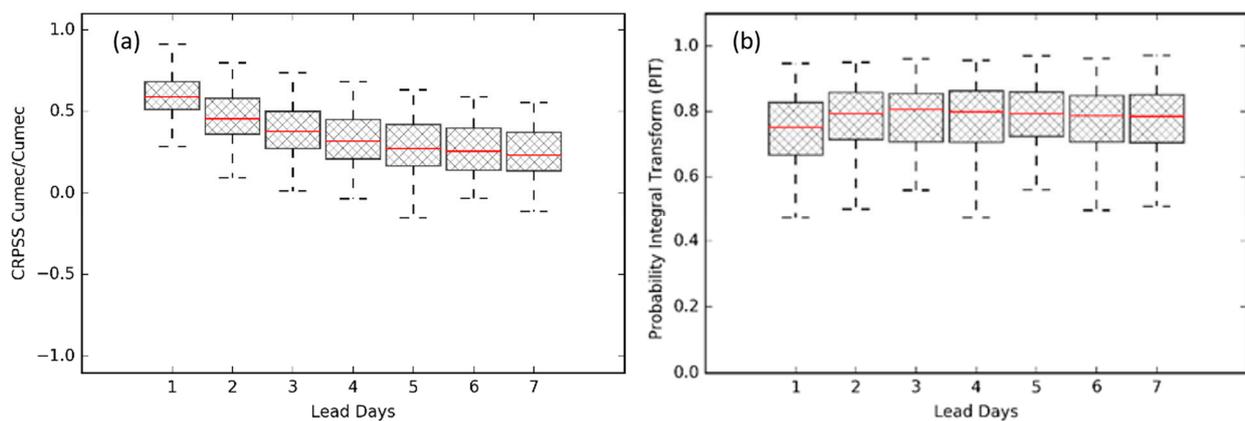


Figure 11. Box plots of streamflow forecasting skill for all 96 forecasting locations: (a) CRPSS (compared to mean observed flow) and (b) PIT-Alpha.

4.2.3. Spatial and Temporal Performance

Here, we present the CRPSS and PIT-Alpha performance statistics for all 96 forecasting locations for the four-year evaluation period (2020–2023). The key idea was to identify any spatial pattern in streamflow forecasting performance skills. It was clear that the model’s performance was poorer for the catchments in the western part of the Great Dividing Range, South Australia, and in the mid-west of Western Australia (Figure 12). The spatial pattern of the two metrics was similar across the continent.

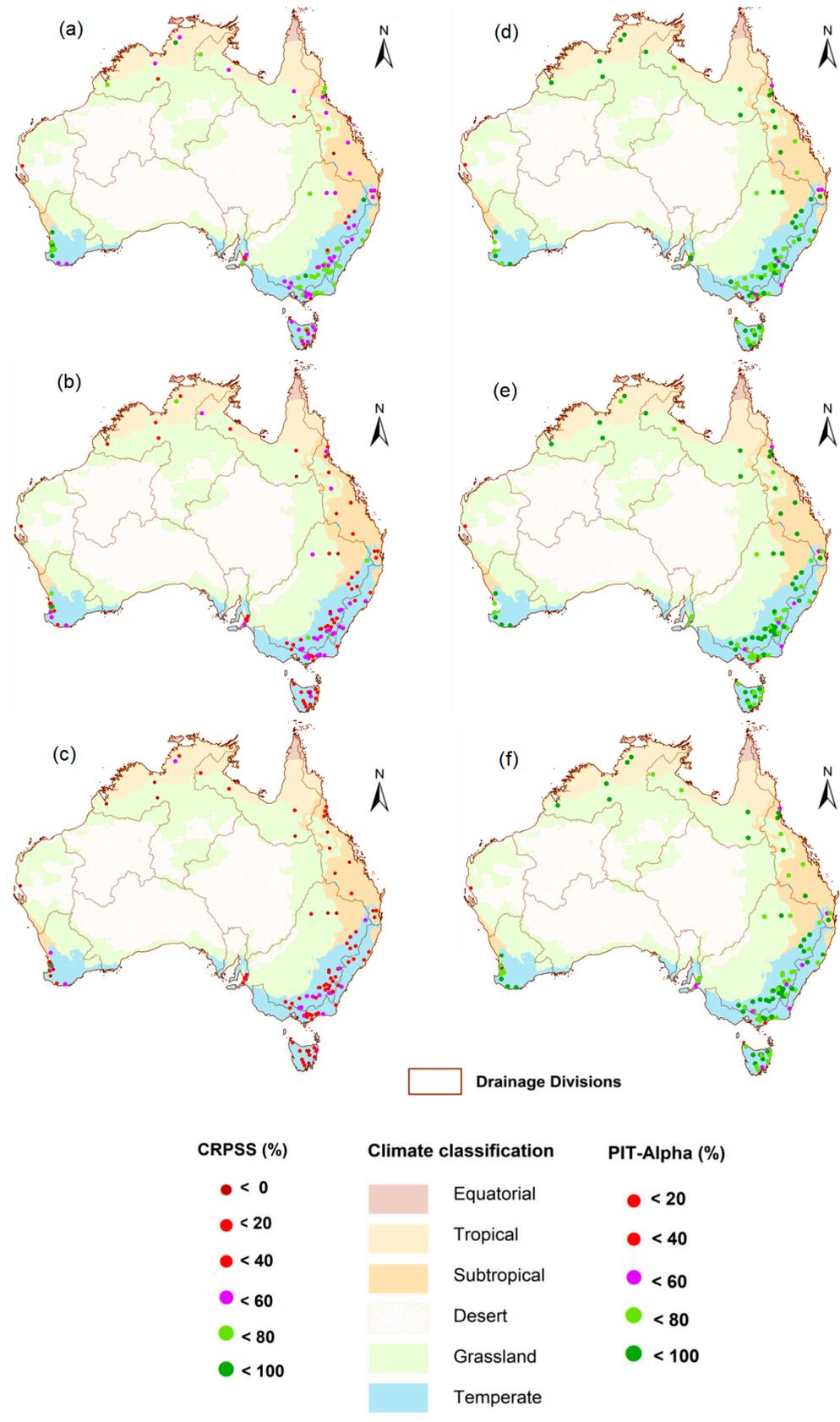


Figure 12. Spatial plots of ensemble streamflow forecast skills: (a) CRPSS Day 1; (b) CRPSS Day 3; (c) CRPSS Day 7; (d) PIT-Alpha Day 2; (e) PIT-Alpha Day 4; (f) PIT-Alpha Day 6.

In addition to the spatial mapping of the results, we investigated the regional patterns of the forecast performance skills for different states and territories (jurisdictions); we present only the results for Day 3's skills (NSE, CRPSS, and PIT-Alpha) in Table 1. Except for the Northern Territory, performance of only a small number of catchments at all other jurisdictions were poorer, as evidenced by the deterministic, ensemble median NSE (Figure 9a). This may not represent the reality, as the sample number is only 4 in the Northern Territory. The maximum NSE among different jurisdictions ranged from 71% (Tasmania) to 94% (Western Australia). There were also a small number of catchments in New South Wales, Queensland and Tasmania where the CRPSS scores were negative. Most of these forecasting locations had poorer NSE scores as well. The CRPSS score were greater than 20% for half of the forecasting locations in Queensland, which seemed to be poorest performer among all jurisdictions. The performance skills of all forecasting locations, as computed by PIT-Alpha, seemed to be better than those of the other two metrics (Table 1). Overall, it appeared that the forecast performance of the operational service was better in Western Australia and poorer in South Australia and Queensland. Most of the underperforming locations across the continent are situated in the interior part of Australia (Figure 12). The principal reason for this spatial variation in performance across the continent could be attributed to the following: (i) the ranges of the mean annual rainfall with higher inter-annual variability [61]; (ii) the catchments' physical attributes, including slope, soil properties, Köppen climate classes [10], and the intermittent nature of streamflow; (iii) the sparse monitoring network; (iv) the poor performance of the rainfall forecasts. Overall, the performance of the system in the operational setting seems to be very similar to the one obtained during development phase [8] and gives greater confidence in end-user decision making.

Table 1. Streamflow performance skills (NSE, CRPSS, and PIT-Alpha) for different jurisdictions—forecast horizon Day 3.

Jurisdiction	Number of Locations	NSE (%)				CRPSS (%)				PIT-Alpha (%)			
		5 th	50 th	95 th	Max	5 th	50 th	95 th	Max	5 th	50 th	95 th	Max
New South Wales	28	<0	29	63	68	13	39	57	63	57	81	91	92
Northern Territory	4	43	59	88	91	29	41	65	67	70	81	85	85
Queensland	15	<0	13	82	83	<0	20	60	70	50	81	93	94
South Australia	4	<0	22	62	68	6	24	50	54	51	71	78	78
Tasmania	14	<0	43	71	71	<0	33	57	63	63	78	91	91
Victoria	19	<0	38	72	82	21	47	60	63	55	79	91	93
Western Australia	12	<0	75	88	94	12	44	84	92	45	83	91	96

4.2.4. Performance and Catchment Area

In addition to the performance metrics and diagnostic plots, we investigated the streamflow forecast skill and its relationship with the catchment area (Figure 13). We found no relationships between the catchment area, the NSE, the PBias, the PIT-Alpha, the CRPS, or the other performance metrics. This finding is different from those of other studies around the world. For a national flood warning system in New Zealand, it was found that forecast performance skills increase with the catchment area [40,54]. Similarly, in the USA, the predictive flood forecasting skill of a real-time operational hydrological forecasting model showed positive relationships between the catchment areas [20,62]. In South America, performance skills of medium range (up to 15 days) ensemble streamflow forecasts were investigated and found a positive relationship between the forecast skills and the catchment area [19]. Similar results were also found in China [49], but with varying relationships between geographical location and differences in climate.

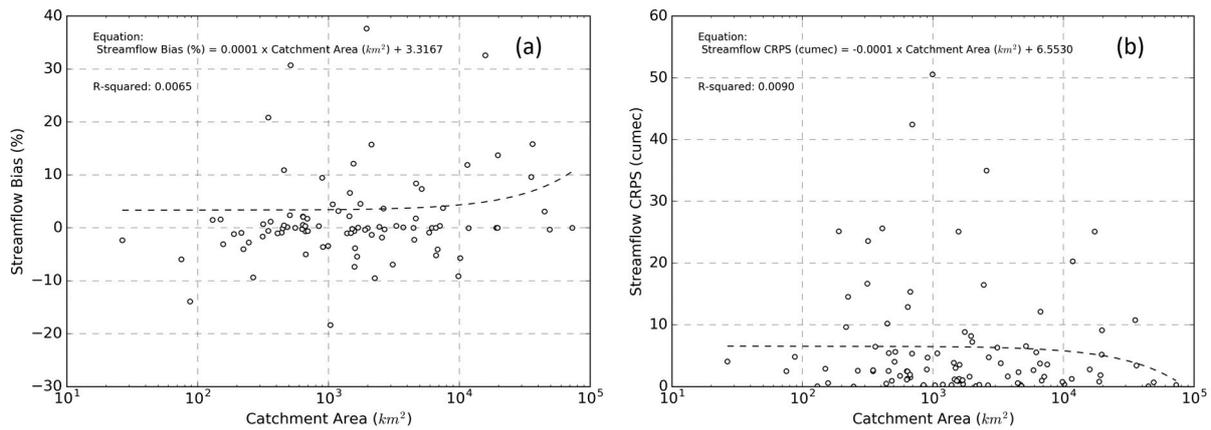


Figure 13. Performance of one-day lead time streamflow forecast and catchment area for all 96 forecasting locations: (a) PBias and (b) CRPS.

A fundamental property of spatial scale in hydrology [63] is that streamflow varies less with increasing catchment area; this is due to the averaging and smoothing effects of the complex river network. Additionally, as the catchment time of concentration (time for water to flow from the most remote point in a catchment to the outlet) increases and approaches the forecast time horizon, a larger portion of the forecast streamflow volume at the catchment outlet is already in the river network; therefore, it is in the forecast model. In this case, the skill of rainfall prediction plays a relatively reduced role as the catchment area increases. Across Australia, 50% of catchments in the 7-day streamflow forecasting service have an area greater than 1500 km². There is an indication that CRPS skill score deteriorates for the catchments smaller than 1500 km² (Figure 13b). Operationally, we implemented ERRIS to post-process the hydrological model’s generated streamflow; it has been proven that implementing ERRIS significantly increases forecast skill [8]. Further investigation and research in this area may reveal more about the complex relationships between forecast rainfall, flow generation processes, and the relationships with the catchment area.

4.2.5. Comparison of Forecast Rainfall and Streamflow Forecast Metrics

We found no clear relationships between the different performance evaluation metrics for either the rainfall forecast or the streamflow forecast (Figure 14). This finding is in contrast to those of other studies around the world [7,17,22,49]. Further investigation is necessary to better understand these different findings.

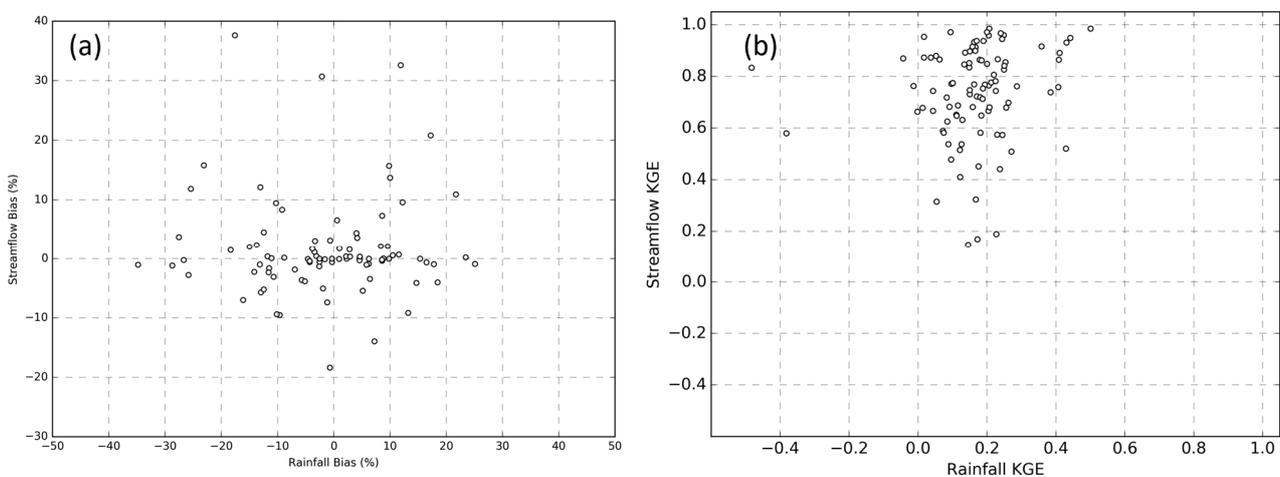


Figure 14. Cont.

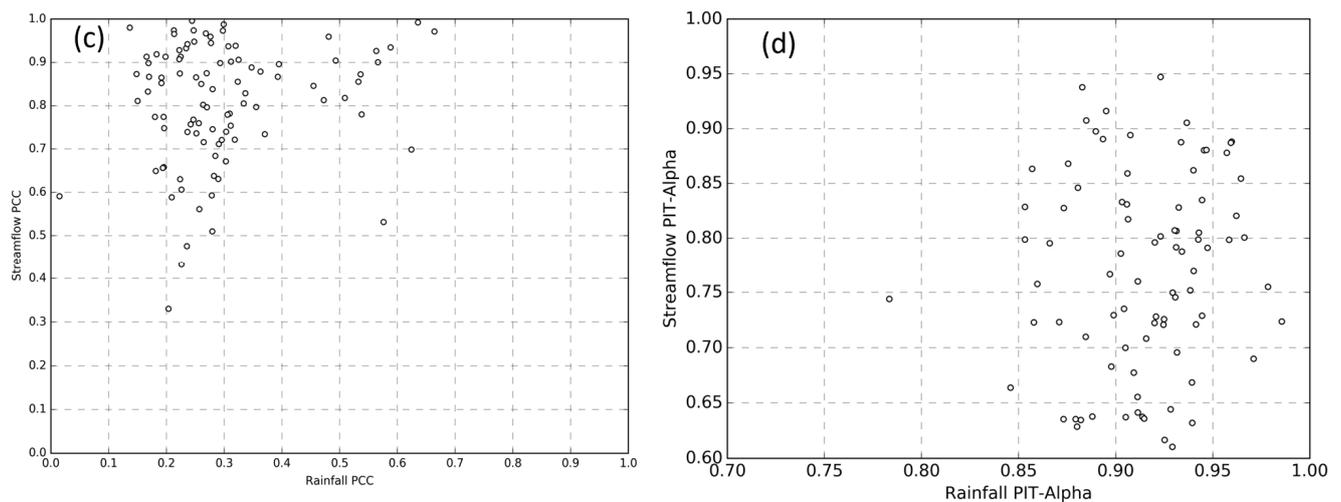


Figure 14. Scatter plots of one-day lead time forecast streamflow against rainfall metrics for all 96 forecasting locations: (a) PBias, (b) KGE, (c) PCC, and (d) PIT-Alpha.

5. Discussion and Future Directions

5.1. Service Expansion

Extensive customer consultation was undertaken during the development of the 7-day streamflow forecasting service. More than 50 important customers across the country were consulted to identify high-value catchments and forecasting locations, and to help understand how the service is likely to bring the most benefits for them. Due to resource constraints, some selected catchments were not included in the service. Initiatives should be undertaken to revisit these catchments and to see whether the forecasting service could be developed there. At present, the service is available only for catchments located upstream of significant infrastructure developments, where there is no return flow to rivers, or diversion from the rivers. Research is needed to understand how infrastructure, river operations, and management influence the landscape's water balance and how the forecasting service could be expanded to manage systems including reservoir inflows, water balance, and forecasting locations downstream of reservoirs.

5.2. Benefits and Adoption of Forecasting

Is there any benefit to using ensemble 7-day streamflow forecasts over simple climatology? The answer is yes—in terms of overall accuracy, performance, and reliability. However, forecast skill varied across different regions within the country (Figure 12), and varied with lead times (Figure 11). Generally, improvements in NWP rainfall forecasts lead to more accurate and reliable streamflow forecasts. However, our analysis of operational data shows that the primary source of streamflow forecast skill lies in the post-processing error-correction scheme—ERRIS—and hydrological persistence, rather than in the rainfall forecasts. This finding is different from those of studies in other parts of the world [19,20,38,59,60]. Additionally, factors such as model initial states, catchment aridity, seasonality, and geographical location may also significantly influence forecast performance. It has been demonstrated that combining state updating and the error-correction model leads to lower streamflow forecast errors [64]. Further investigation is essential in comprehensively understanding the variability of forecast skill across different flow regimes, including peak flow magnitude, timing, and recession.

How can the ensemble SDF service benefit the community? This can be carried out by encouraging the adoption of ensemble forecasts among users and implementing them in decision-making tools. However, replacing traditional deterministic hydrological forecasts with ensemble forecasts presents challenges. A valuable scientific finding does not automatically align with end-users' decision-making processes [65]. Several studies have explored the usability of streamflow forecasts in supporting decisions for reservoir operations [66,67],

flood forecasting [22], water resource management [68], and hydropower generation [69,70]. One key challenge lies in the operational capacity to ingest and incorporate ensemble forecasts into water management decision-support tools. Many existing tools are designed for deterministic inflow scenarios and would require significant upgrades to accommodate automated ensemble streamflow forecasts. The Bureau has been closely working with key stakeholders to increase and improve adoption of the ensemble SDF service in end-user decision-making tools. For example, forecast streamflow time series are delivered to the Murray Darling Basin Authority through the file transfer protocol (FTP) and are ingested into their ROWS system for optimal release from the Hume Dam and the operation of the River Murray system [71].

5.3. Understanding Forecast Skills and Uncertainties

Rainfall forecasting is very challenging due to the chaotic nature of the atmosphere [72]. Small changes in initial conditions can lead to an entirely different outcome. Modelling deficiencies further add to forecast inaccuracies, especially for longer lead times. However, due to ongoing improvements in NWP models, the skills of rainfall forecasting have increased significantly [73,74]. Skilful rainfall forecasts are now being generated by NWP models worldwide, enabling the production of relatively skilful streamflow forecasts for water resource management and planning. Ensemble rainfall forecasts, extending up to at least 30 days ahead, are available from over five NWP models globally. Analysing rainfall data revealed that a multi-model ensemble approach enhances the predictability and reliability of these rainfall forecasts [75]. Exploring the potential applications of extended rainfall forecast data for streamflow forecasting remains an avenue for future research.

The inherent uncertainties in NWP rainfall forecasts are one of four key sources of uncertainty, alongside input data, model structure, and the parameters and their combinations [76]. These uncertainties vary across catchments, due to the catchments' characteristics, streamflow magnitude, and lead time. Within the hydrological modelling community, it is widely acknowledged that the greatest uncertainty in forecasting beyond 2–3 days originates with rainfall input [16]. However, when considering streamflow forecasts up to 2–3 days ahead, skill primarily originates from rainfall forecasts and catchment persistence. Surprisingly, our study revealed limited skill in rainfall forecasts beyond Day 2 (Figures 3, 4 and 6). Notably, improvements in streamflow forecast skill were due to post-processing error corrections (Figures 8, 9 and 11). The role of persistence in forecast skill shows strong dependence on catchment area, network characteristics, and geometric properties [77]. Although catchment area sizes vary significantly across Australia, we observed no clear relationship with forecast skill (Figures 7 and 13). Consequently, it became clear that the primary source of skill was in the streamflow post-processing error-correction scheme, ERRIS, with minimal contribution from rainfall forecasts and possibly persistence, or a combination of all three.

Variation in runoff and catchment area across the continent is significant, and some catchments flow only during a few months of the year [8]. There are challenges in accurately measuring low flows due to the rating curve, the gauging structure, or the sensor issues [58]. Conversely, the accuracy of high flow measurements might be limited to a specific occurrence. Our analysis revealed that streamflow forecast performance skills were notably lower for high-flow components (Figure 10). As we develop an ensemble flood forecasting service, it becomes crucial to evaluate high-extreme-flow events using longer periods of data.

In this study, we investigated the streamflow forecast skill and its geographical patterns (Figure 12, Table 1). However, research from the United Kingdom [78] demonstrates that forecast skills depend on the initial state and the catchment characteristics, declining exponentially beyond three days. This decline was found to be consistent with our findings, and the skills were not uniformly distributed across different hydroclimatic regions. Further investigations are necessary in building an understanding of this relationship.

5.4. Adoption for Flood Forecasting Guidance

The ensemble 7-day streamflow forecasting approach provides additional guidance for the Bureau's current deterministic and event-based flood forecasting and warning service. However, there is a growing trend toward using ensemble hydrologic forecasting to produce probabilistic flood forecasts [79]. While many aspects of ensemble forecasts for flood preparedness are still being explored, two critical points must be addressed before the end-to-end adoption and operation of the ensemble forecasts are possible:

- Accuracy and timing: We must improve flood forecast accuracy and skills in terms of the magnitude and timing peaks. Achieving precise predictions for flood peaks is crucial for effective preparedness and response.
- Enhanced communication and support: Effective communication with end-users is essential. Providing timely and actionable information to decision makers, emergency services, and the flood preparedness community is vital. The focus typically lies on time scales ranging between hours and a couple of days.

Our forecast horizon is 7 days, and this is considered to be adequate for covering a wide range of flood events, depending on factors such as the catchment area, the flow-generation mechanism, and the within-year flow distribution across Australia. It is vital for the development of the service that the Bureau explores the use of ensemble forecasting data in its operational flood forecasting and warning service. This will be possible through leveraging the technology stack used here for operational 7-day ensemble streamflow forecasting.

6. Summary and Conclusions

The Australian Bureau of Meteorology launched its semi-automated operational 7-day ensemble forecasting service in July 2020. The service covers most of the high-value water resources across Australia and fulfils government and stakeholder requirements.

We evaluated the performance of the Bureau's operational forecasts using four years of operational output data from between 2020 and 2023. Ensemble rainfall forecasts—the European Centre for Medium-Range Weather Forecasts (ECMWF) and the Poor Man's Ensemble (PME), available in the Numerical Weather Prediction (NWP) suite—were taken as the input to generate streamflow forecasts. The GR4H lumped rainfall–runoff model, embedded in the Short-term Water Information Forecasting Tools (SWIFT) was used to generate the streamflow forecasts. We evaluated the ensemble rainfall and streamflow forecast through CRPS, CRPSS, and PIT-Alpha metrics and its deterministic form, using NSE, KGE, PCC, MAE, RMSE, and categorical metrics CSI, POD, and FAR. Diagnostic plots were also considered for visual inspection and empirical judgements.

We found that the performance skills of the current operational ensemble streamflow forecasts remain consistent with those obtained during the development phase of the service. As we extended the forecast horizon from Day 1 to Day 7, the ensemble forecasting performance scores gradually decreased. This pattern was consistent across various metrics, including CRPS, CRPSS, PIT-Alpha, NSE, KGE, PCC, MAE, RMSE, and categorical metrics like CSI, POD, and FAR. Across the catchments, most results showed positive skills, indicating that the ensemble forecast outperformed climatology. Notably, there was no significant association between the performance skill scores and the catchment area. Spatially, streamflow and rainfall forecast skills were generally higher in the high-value water resource catchments, and lower in the western part of the Great Dividing Range, South Australia, and the mid-west of Western Australia. Our findings demonstrate that the 7-day streamflow forecasting service is robust; this ensures confidence among stakeholders in using them to support water resource management decision-making processes. The streamflow forecasts are already used by stakeholders and embedded into their decision-making models. The Bureau is applying a similar forecasting approach in developing an integrated ensemble flood and streamflow forecasting service.

Author Contributions: M.A.B.—project administration, conceptualisation, methodology, investigation, analysis, supervision, and writing. M.M.H.—data curation, analyses, investigation, validation, and visualisation. G.E.A.—spatial analyses, investigation, and visualisation. A.K.—analysis, review, and validation. H.A.P.H.—analyses, review, and validation. P.M.F.—project administration, resource allocation, and technical editing. A.D.C.—project administration, resource allocation, and technical editing. P.S.—systems integrity, review, and editing. All authors have read and agreed to the published version of the manuscript.

Funding: The research was conducted under the Bureau’s day-to-day operational and research business activities. No additional research funds were received from any external sources.

Data Availability Statement: The codes, scripts, and workflows developed in analysing the operational streamflow forecast data are not available to the public. The day-to-day forecast data are available to the user community upon request via the “Feedback” page of the 7-day ensemble streamflow forecast website (<http://www.bom.gov.au/water/7daystreamflow/>, accessed on 10 March 2024).

Acknowledgments: The SWIFT modelling system was developed through the funding from the Water Information Research and Development Alliance (WIRADA) between the Bureau and CSIRO. We sincerely thank our technical reviewers Christopher Pickett-Heaps, Urooj Khan, and Biju George for their time, careful review, and valuable comments and suggestions. We also sincerely thank three anonymous reviewers whose contribution enriched the article. The large computations for this research were undertaken through the use of the National Computational Infrastructure (NCI), supported by the Australian Government.

Conflicts of Interest: We declare that the present research was conducted in the absence of any commercial or financial relationships that could be interpreted as potential conflicts of interest.

Appendix A. Forecast Performance Evaluation Metrics

Streamflow data from 1990 to 2016 are used for climatological streamflow calculations. Climatological streamflow values are calculated on a daily basis using data from a 29-day window. For a given day, the climatology value is the distribution of data within the period from 2 weeks before to 2 weeks after the target day over the climatology period. Metrics were computed for each lead time—Day 1–Day 7.

DETERMINISTIC FORECAST

PBias: This metric estimates whether the model is consistently underestimating or overestimating streamflow. It can be positive (underestimation) or negative (overestimation) and was calculated for each lead time (in days) as follows:

$$PBias = \frac{\sum_{i=1}^n (Q_{i,obs} - Q_{i,sim})}{\sum_{i=1}^n (Q_{i,obs})} \times 100 \quad (A1)$$

In the above equation, $Q_{i,obs}$ was the observed streamflow, $Q_{i,sim}$ was the modelled streamflow, and n was the total number of observations.

Pearson’s Correlation Coefficient (PCC): PCC measures the linear correlation between observed and simulated time series; in our case, this is the rainfall and the streamflow, respectively, for each day. It is calculated as follows:

$$PCC = \frac{\sum_{i=1}^n (Q_{i,sim} - \overline{Q_{i,sim}}) (Q_{i,obs} - \overline{Q_{i,obs}})}{\sqrt{\sum_{i=1}^n (Q_{i,sim} - \overline{Q_{i,sim}})^2} \sqrt{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_{i,obs}})^2}} \quad (A2)$$

The value of PCC is bounded between -1 and 1 and measures the strength and direction of a relationship. When one variable changes, the other variable changes in the same direction.

Mean Absolute Error (MAE): Mean absolute error (MAE) is the average of the magnitude of the errors. The perfect score is zero, as calculated by:

$$MAE = \frac{\sum_{i=1}^n |Q_{i,obs} - Q_{i,sim}|}{n} \quad (A3)$$

Nash–Sutcliffe Efficiency (NSE): The Nash–Sutcliffe efficiency [80] quantifies the relative magnitude of residual variance compared to the observed streamflow variance:

$$NSE = 1 - \frac{\sum_{i=1}^n (Q_{i,obs} - Q_{i,sim})^2}{\sum_{i=1}^n (Q_{i,obs} - \overline{Q_{obs}})^2} \quad (A4)$$

In the above equation, $\overline{Q_{obs}}$ was the mean observed streamflow. In this study, *NSE* is used to assess the performance of the model forecast for each of the lead time.

Kling–Gupta Efficiency (KGE): The KGE [81] performance metric is widely applied in environmental and hydrologic forecasting and is defined as follows:

$$KGE = 1 - \sqrt{(r - 1)^2 + (\alpha - 1)^2 + (\beta - 1)^2} \quad (A5)$$

In the above equation, *r* is Pearson's Correlation Coefficient (Equation (A2)), α is a term that represents the variability of the forecast errors and is defined by the ratio of the standard deviation of the observed and predicted data $\left(\frac{\sigma_{sim}}{\sigma_{obs}}\right)$, and β is the ratio of the mean of the observed and simulated data, $\left(\frac{\mu_{sim}}{\mu_{obs}}\right)$, respectively.

Root Mean Square Error (RMSE): The RMSE measures the average difference between the predicted values and observed ones. It provides an estimate of how accurately the model can predict the target time series.

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (Q_{i,sim} - Q_{i,obs})^2} \quad (A6)$$

ENSEMBLE FORECAST

CRPS: This metrics allows for a quantitative comparison between the deterministic and the ensemble forecasts. It is calculated as the difference between the cumulative distribution of forecast and the corresponding observation [82]. The *CRPS* reduces to the mean absolute error for (MAE, Equation (A3)) deterministic forecasts and is given by:

$$CRPS = \frac{1}{T} \sum_{t=1}^T \int_{x=-\infty}^{x=\infty} (F_t^f(x) - F_t^o(x))^2 dx \quad (A7)$$

In the above equation, $F_t^f(x)$ is the forecast cumulative distribution (CDF) probability for the *t*th forecast; $F_t^o(x)$ is the observed CDF probability (heaviside function). For ensemble rainfall, the relative *CRPS*, as a function of catchment mean rainfall (\overline{R}) is calculated as follows:

$$CRPS(\%) = \frac{CRPS}{\overline{R}} \times 100 \quad (A8)$$

CRPSS: This metric measures the relative performance of the streamflow forecast and is calculated with respect to the reference forecast. It is calculated as follows:

$$CRPSS = 1 - \frac{CRPS_{forecast}}{CRPS_{clim}} \quad (A9)$$

In the above equation, $CRPS_{clim}$ is the reference forecast, calculated from the streamflow climatology period.

PIT: The Probability Integral Transform diagram (PIT) is applied to assess the reliability of ensemble forecasts [83]. It is the cumulative distribution function (CDF) of the forecasts, $F_t(f_t)$, evaluated with the observations, Q_t (rainfall or streamflow), and is given by the following:

$$PIT_t = F_t(Q_t) \quad (A10)$$

PIT is uniformly distributed for reliable forecasts and falls on the 1:1 line for a perfect forecast. To avoid visual disparity, we have used a quantitative score of the Kolmogorov–Smirnov goodness (KS-D) statistic to measure the deviation of the PIT values from the perfect forecast. The KS-D statistic is used to compare the maximum deviation of the cumulative PIT distribution from the uniform distribution of the forecasts. We used PIT-Alpha [84] to compare the PIT values of the forecast ensemble streamflow and the rainfall from all the catchments:

$$\alpha = 1 - \frac{2}{T} \sum_{t=1}^T \left| PIT_t^* - \frac{t}{T+1} \right| \quad (A11)$$

In the above equation, PIT_t^* is the sorted PIT_t .

CATEGORICAL METRICS

The categorical metrics for the assessment of the streamflow and rainfall forecasts included [85] the following: probability of detection (POD), false alarm ratio (FAR), and critical success index (CSI). These metrics are extensively used in operational forecast assessments [52,53,55].

Probability of Detection (POD): The *POD* is based on the correctly identified (X) and missed (Y) number of forecast class. The value ranges from 0 to 1 and a perfect score is 1.

$$POD = \frac{X}{X+Y} \quad (A12)$$

False Alarm Ratio (FAR): The *FAR* depends upon the classes which are detected by the forecasts, but which are not observed (Z), and the correctly identified (X) ones. The value of the metric ranges from a perfect score of 0 to 1.

$$FAR = \frac{Z}{X+Z} \quad (A13)$$

Critical Success Index (CSI): The *CSI* represents the overall number for forecasts correctly produced by the model. Its value ranges from 0 to a perfect score of 1.

$$CSI = \frac{X}{X+Y+Z} \quad (A14)$$

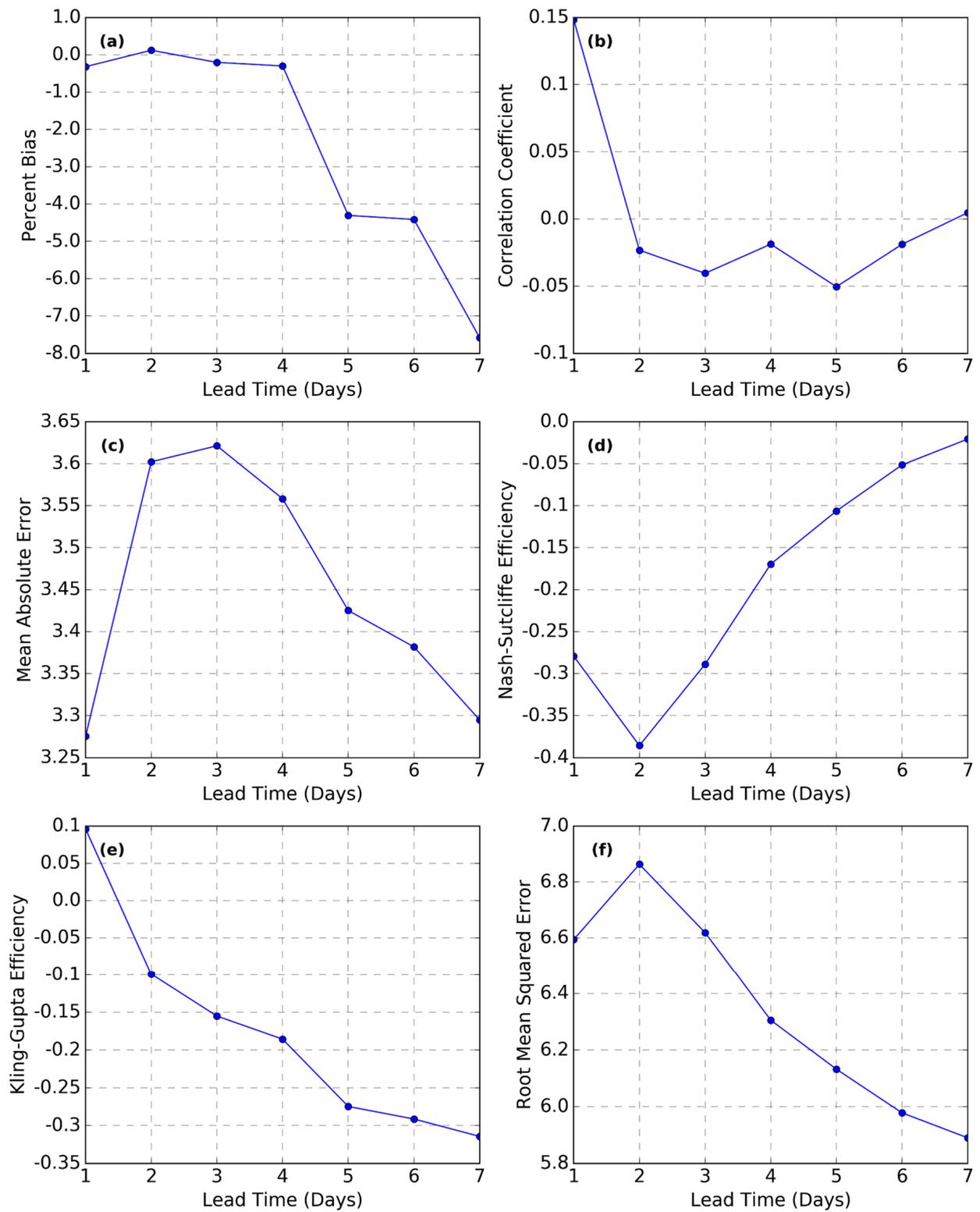


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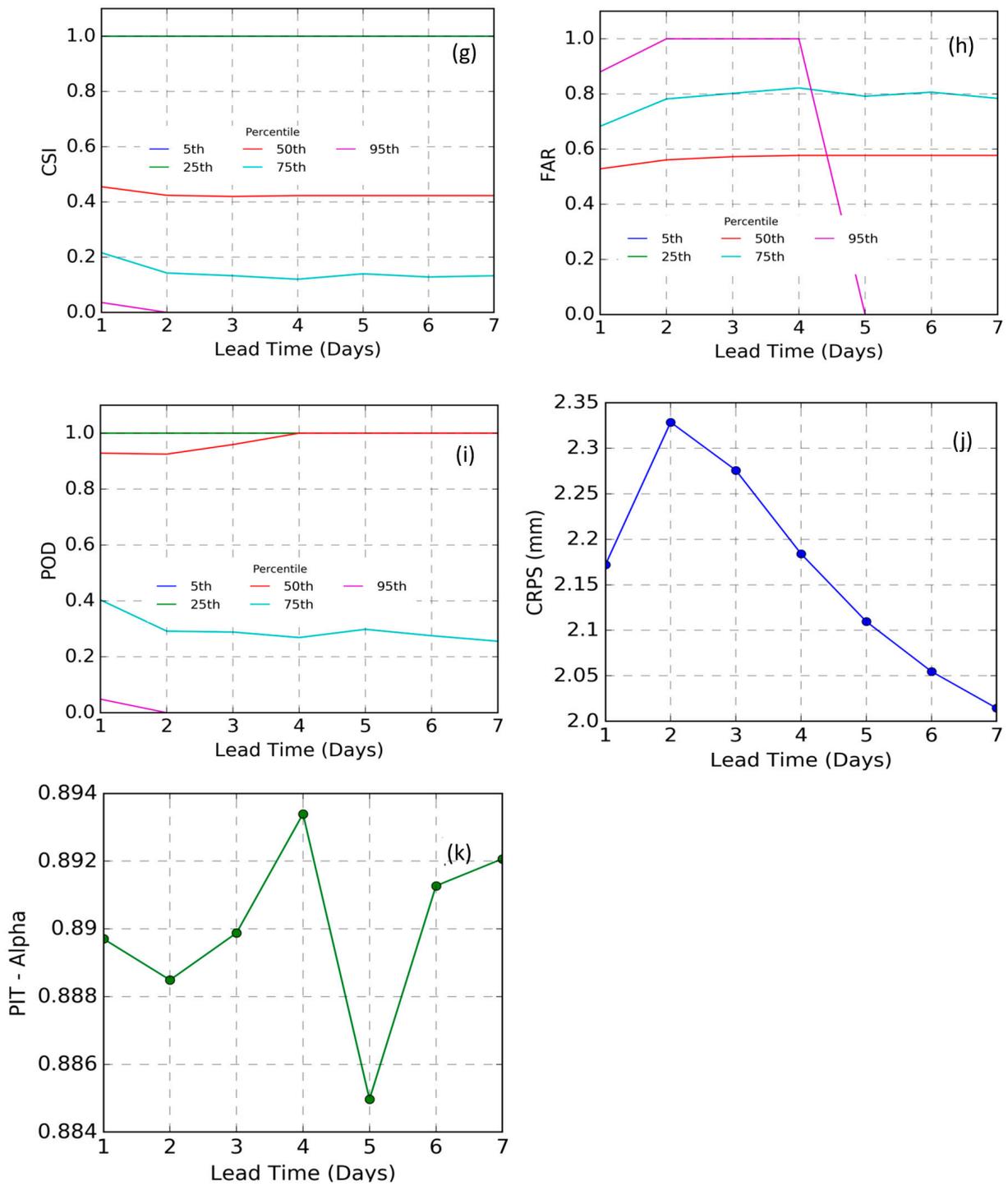


Figure A1. Graphical representation of forecast rainfall performance metrics of a randomly selected catchment from Tasmania: (a) PBias, (b) PCC, (c) MAE, (d) NSE, (e) KGE, (f) RMSE, (g) CSI, (h) FAR, (i) POD, (j) CRPS, and (k) PIT-Alpha.

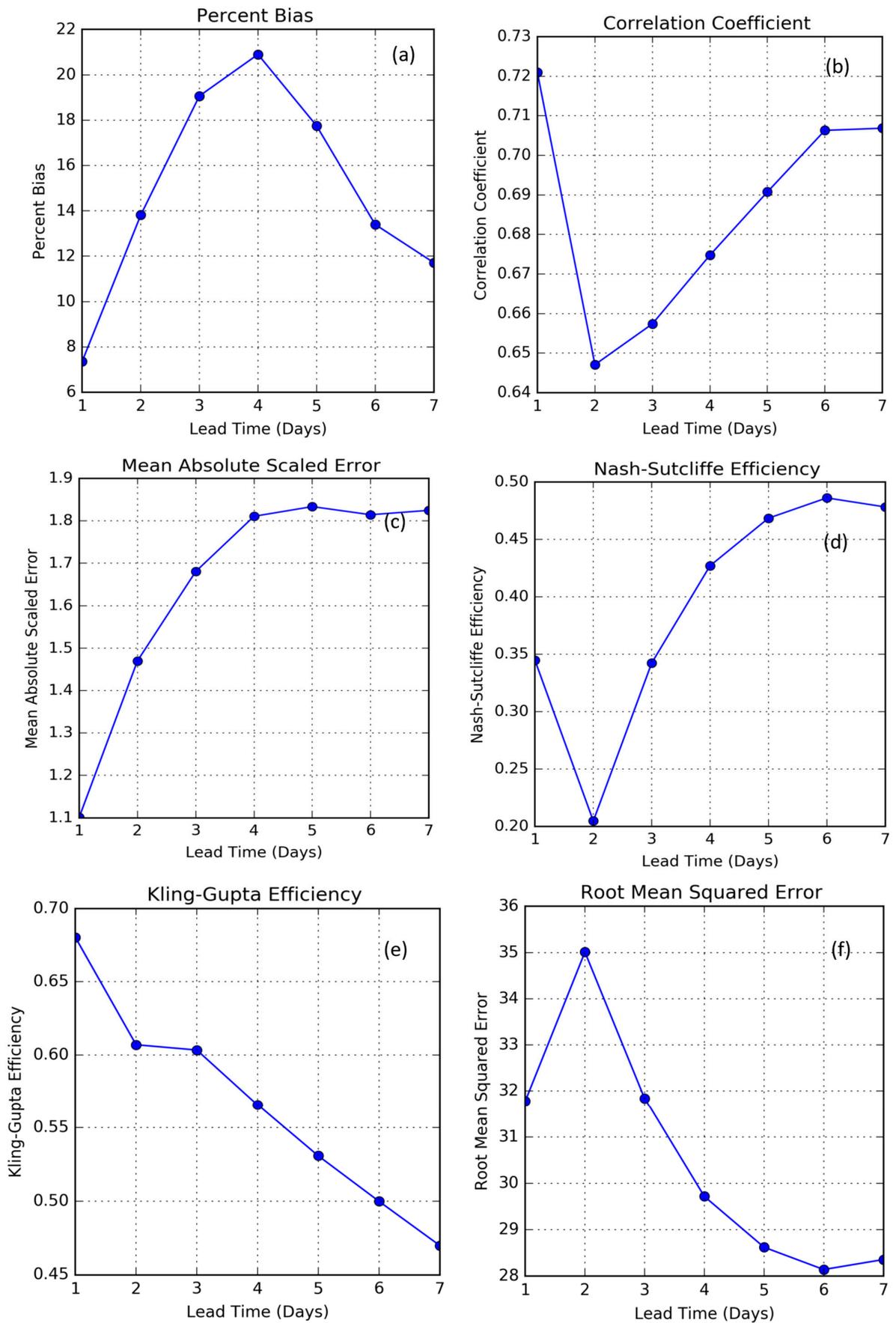


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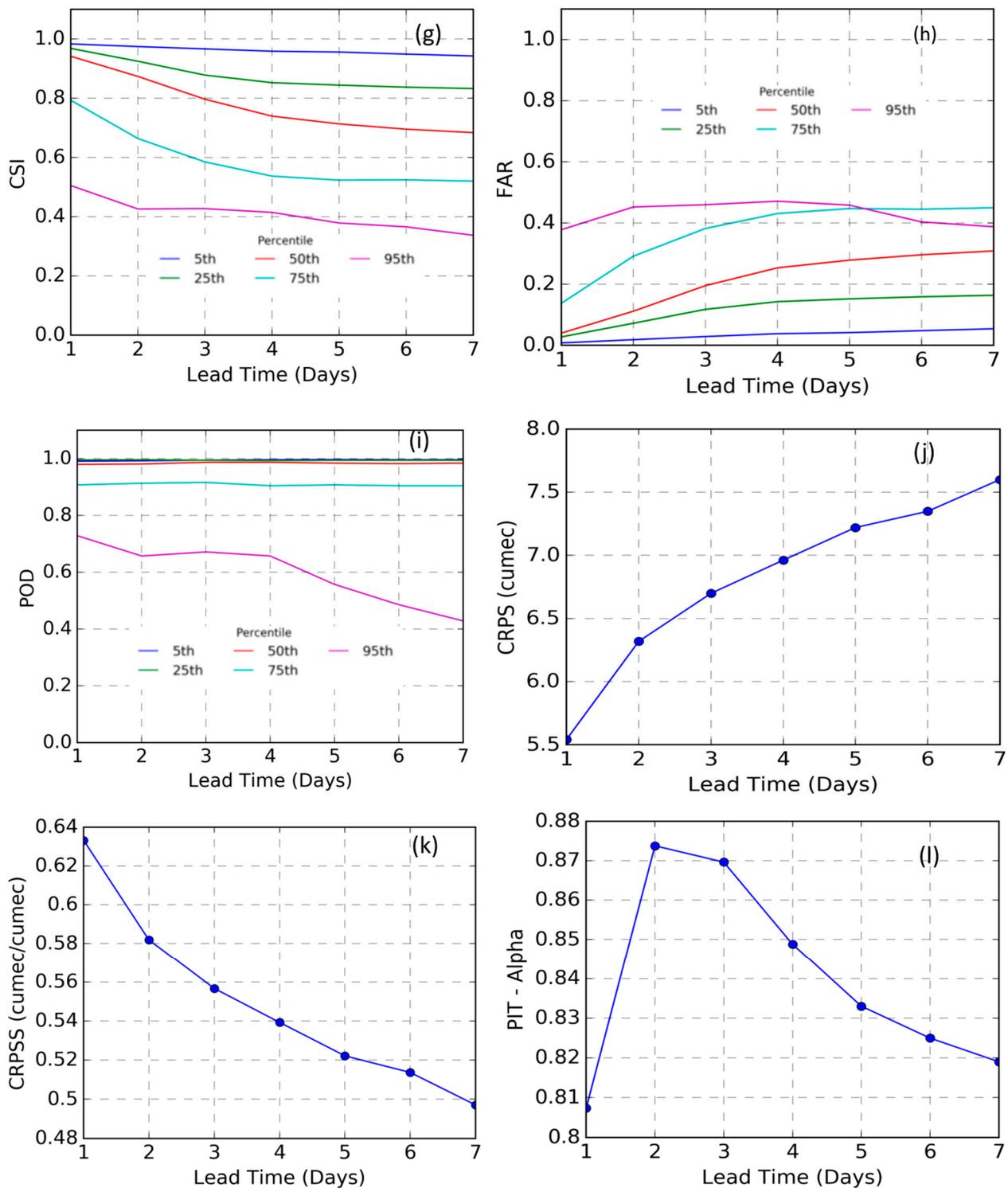


Figure A2. Graphical representation of forecast streamflow performance metrics of a randomly selected catchment from New South Wales: (a) PBias, (b) PCC, (c) MAE, (d) NSE, (e) KGE, (f) RMSE, (g) CSI, (h) FAR, (i) POD, (j) CRPS, and (k) CRPSS and (l) PIT-Alpha.

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