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# Verification of probabilistic seasonal rainfall forecasts for Fiji Islands

Arti Pratap[1] · M. G. M Khan[2] · Victor Ongoma[3] · Kenny T.C. Lim Kam Sian[4] · Philip Sagero[1]

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**Abstract**
Accurate and skillful seasonal rainfall forecasting is crucial for various socioeconomic activities, particularly providing essential climate information for agricultural planning and decision-making, prepare and respond to disasters such as droughts, landslides and floods and provide support to water resources management. In Fiji, where the economy is highly reliant on rainfall, reliable forecasts can significantly mitigate the adverse impacts of hydroclimate variability. Although, Fiji Meteorological Services (FMS) issues seasonal rainfall forecast for the country, validation of forecasts has not been done before. This study aims to evaluate the seasonal forecasts for the Fiji Islands using probabilistic verification methods to assess their accuracy and skill. The forecasts, produced by the FMS, are analyzed through probabilistic categories: below-normal (BN), normal (N), and above-normal (AN), across five regions of Fiji (Western, Central, Eastern, and Northern Divisions, and Rotuma). To assess forecast performance, the study compares the regional seasonal forecasts with observations from the FMS. Additionally, the study delineates the climatological zone for Fiji to ensure consistency in the forecast approach. The results show that the percentage correct exceeds 50%, and the Probability of Detection indicates that more than half of the forecasted categories are accurate. However, the False Alarm Ratio shows that 60% of the forecasted events are false alarms. In terms of the Critical Success Index for N category, all Divisions and Rotuma (except Eastern Division) show that more than half of N rainfall events are correctly predicted based on observations. The Heidke skill score ranges from 0.23 (Western Division) to 0.003 (Rotuma), indicating varying degrees of forecast skill across the regions. The study also identifies that some stations belong to different climatological zones than initially assumed. Therefore, there is a need to improve the seasonal forecasts, and the use of consistent and homogeneous climatological zones is recommended to enhance forecast accuracy.

**Keywords** Rainfall · Disaster risk reduction · Climate hazards · Planning · Sustainable development

## 1 Introduction

Weather and climate are key drivers of all ecological and socioeconomic systems (Steiner, 2018). Global warming has led to significant climate changes, including shifts in weather patterns and an increase in the intensity and frequency of extreme weather events (IPCC, 2023a). These extreme events can result in devastating loss of lives and property if not managed well. Small island nations in the South Pacific are particularly vulnerable to climate change due to their heavy reliance on weather- and climate-dependent sectors for socioeconomic sustainability, and their geographic location (IPCC, 2023b). Rainfall is one of the most significant and challenging climate variables to forecast. Seasonal rainfall forecasts are invaluable for sectors such as agriculture, water management, tourism, and disaster preparedness, providing essential information to aid

✉ Arti Pratap
arti.pratap@usp.ac.fj

1 School of Agriculture, Geography, Environment, Ocean and Natural Sciences, University of the South Pacific, Suva, Fiji

2 School of Information Technology, Engineering, Mathematics and Physics, The University of the South Pacific, Suva, Fiji

3 International Water Research Institute, Mohammed VI Polytechnic University, Lot 660, Hay Moulay Rachid, Ben Guerir 43150, Morocco

4 School of Atmospheric Science and Remote Sensing, Wuxi University, Wuxi 214105, China

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decision-making and reduce the risks associated with climate variability (Gold et al. 2019; Shah et al. 2017).

Seasonal rainfall forecasts play a vital role in minimizing the loss of lives, preventing destruction of property, and aiding in the planning of agricultural activities such as timing for planting and harvesting (Ministry of Agriculture 2014; Bruno Soares et al. 2018). Over the years, the accuracy of weather forecasts has significantly improved globally following advancements in computer technology, numerical models, and the availability of quality climate data. Several studies have explored the value of weather forecasts and their applications across various socioeconomic sectors (Hewitt et al. 2013). However, the primary criterion for any forecast is that it must accurately predict the observed weather conditions, perform better than the climatology of the area of interest and provide a measure of uncertainty to assess forecast reliability.

Fiji has experienced extreme rainfall events that have led to floods and droughts. During the 2015–2016 rainfall season, a severe drought affected 50% of the population, prompting the need for humanitarian assistance (Glantz 2022). In 2012, Fiji recorded two of its most devastating floods. The first occurred in January, resulting in eight fatalities, with roads washed away and extensive damage to crops and infrastructure. The estimated loss was around FJ $40 million (Kuleshov et al. 2014). The second event occurred in March, causing widespread destruction on the western side of Viti Levu. Businesses, residential areas, and infrastructure suffered significant damage, including the destruction of major roads and bridges (Kuleshov et al. 2014), with total damages estimated at FJ $70 million (Kuleshov et al. 2014). Floods have severe impacts on Fiji's agriculture and tourism sectors as well. These two sectors are the pillars of the economy, especially for the rural population, with 35.72% of the total employment in agriculture (International Labour and Organisation 2021). The sugar industry, one of Fiji's most significant agricultural sectors, occupies 50% of the country's cultivated land and employs a quarter of the labor force (Meier et al. 2023). Sugar production, like many other agricultural activities, is highly dependent on weather and seasonal climate variations (An-Vo et al. 2019). Given the vital role of weather in these sectors, assessing the contribution and effectiveness of weather and seasonal rainfall forecasts is crucial. However, studies on agriculture in Fiji often fail to give due consideration to the importance of weather forecasts, nor do they assess the accuracy of these forecasts.

Timely and accurate seasonal rainfall forecasts are crucial for the agricultural sector, providing farmers with essential information for planning, especially during planting and harvesting seasons. This information helps farmers make informed decisions about crop management, such as selecting appropriate crops, determining optimal planting times, need-based fertilizer application, and planning for harvests while developing adaptation strategies (Bedane et al. 2022). In rainfed agriculture, the intensity, timing, and duration of seasonal rainfall significantly influence crop yields (Wakjira et al. 2021). Therefore, reliable seasonal rainfall forecasts are vital for guiding farmers' decisions and reducing losses associated with climate-related risks (Guido et al. 2020). Similarly, such forecasts can aid government planning by allowing authorities to anticipate and address food insecurity and drought preparedness in case of poor rainfall and early action to reduce flooding impacts from severe rainfall. The adverse consequences of inaccurate seasonal forecasts on public health and key socioeconomic sectors pose a threat to the realization of several United Nations Sustainable Development Goals (SDGs) (IPCC, 2023b).

The Fiji Meteorological Services (FMS) produces a variety of weather products, including seasonal forecasts. Two key models historically used by the FMS are the Rainfall Prediction Model (RPM) for three-month period forecasts and the Australian Rainman (AusRain) for monthly rainfall forecasts (Pahalad and McGree 2012). The RPM was originally based on successful schemes developed by the Australian Bureau of Meteorology's National Climate Centre (NCC) (Pahalad and McGree 2012). FMS aligns its forecasting regions with Fiji's administrative divisions: Central, Eastern, Northern, and Western, while considering Rotuma as a separate entity due to its geographical isolation. The seasonal rainfall forecasts are produced using statistical models that link the Southern Oscillation Index (SOI) with subsequent three-month rainfall totals. For each Division, two sets of forecasts are generated. The first scheme utilizes the SOI averaged over the most recent three-month period, while the second scheme uses the SOI averaged over two consecutive three-month periods, covering the initial three months of the most recent six-month period (Pahalad and McGree 2012). The RPM became operational in July 1999 and was further refined in March 2000 by the Climate Service Division of FMS to cover twenty-five individual sites across four Divisions. For each site, probabilities were calculated for low, medium, and high rainfall in the coming three months (Shiwangani S, personal communication, October 12, 2023). However, the RPM was phased out in 2005. Since 2006, FMS has relied on the Seasonal Climate Outlook for Pacific Island Countries (SCOPIC; Cottrill and Kuleshov, 2014) as its main tool for producing seasonal climate outlooks on a 3- to 6-month timescale.

SCOPIC is a stand-alone seasonal climate prediction system that employs discriminant analysis, specifically multiple linear regression, to assess the correlations between sea surface temperatures or SOI and monthly rainfall. This scheme is used to forecast rainfall at different lead times based on these relationships (Cottrill et al. 2013). When forecasting seasonal rainfall for a 3-month period, SCOPIC uses observed rainfall data from the current 3-month period to identify similar oceanic patterns from historical records, known as analog years. These historical patterns serve as reference points when compared to current conditions that exhibit similar characteristics. Based on these analogs, SCOPIC computes (in tercile probabilities) the most likely rainfall categories (below-normal, near-normal, and above-normal) for the following three-month period (Fiji Meteorological and Services 2020). In addition to SCOPIC, the FMS also incorporates global models from the National Centers for Environmental Prediction (NCEP) and the European Centre for Medium-Range Weather Forecasts (ECMWF) to compare and develop a consensus for the seasonal forecast for the Fiji Islands.

Various approaches are used for seasonal forecast verification, each with different resolutions and methodologies. These methods differ in their accuracy and are suitable for specific locations and contexts (Ferranti et al. 2015). Evaluating seasonal forecasts is essential for improving techniques (Guido et al. 2020). Forecasts can be assessed either qualitatively or quantitatively, using different approaches to measure various aspects of forecast quality (Brown 2001). Due to their probabilistic nature, seasonal forecasts describe a range of possible climate outcomes and, therefore, require appropriate ensemble verification tools to effectively assess their quality. Numerous metrics have been developed to evaluate different characteristics of forecast quality (Calì Quaglia et al. 2022). The FMS seasonal forecasts are provided as probabilities of rainfall occurrence, requiring the transformation of probabilistic forecasts into a contingency table to calculate forecasting skills (WWRP/WGNE, 2009). Probabilistic forecasts can be dichotomous (yes/no), multi-categorical, or ensemble-based (Brown 2001). This study uses a multi-categorical verification process to evaluate the FMS seasonal rainfall forecasts.

Classifying a multi-category probabilistic forecast as 'good' or 'bad' based only on correct or incorrect forecasts is challenging. For example, a multi-category probabilistic forecast outcome is never exactly 0%. When the probability is greater than 0%, it suggests that any outcome could potentially be correct. Therefore, it is important to define the attributes that make a probabilistic forecast 'good' (Mason 2015). According to Murphy (1993), a good weather forecast can be classified based on consistency, quality, and value. This study focuses on evaluating the quality of seasonal forecasts. However, forecast quality cannot be measured by a single metric, given that several attributes (such as resolution, discrimination, reliability, and skill) contribute to what constitutes a 'good' probability forecast (Mason 2015). For probabilistic forecasts, reliability and resolution are particularly important in determining forecast quality (Ben Bouallègue and Theis 2014). Reliable forecasts exhibit a consistent relationship between each class of forecasts and the corresponding distribution of observations (Bröcker 2023). Resolution refers to how strongly the outcome is conditioned by the forecast. When the forecast correctly differentiates between different outcomes, it is considered a good or useful forecast (Mason 2015).

In this study, the forecasting divisions used by FMS were examined. Given Fiji's small size and the significant variability in rainfall across the country, the use of homogeneous climate zones is more relevant for seasonal forecasting than divisions based on administrative boundaries. Some divisions have weather stations located close to each other, whereas others have stations separated by ocean bodies, for example, the Eastern division (Fig. 1) which may be affected by different weather systems. Forecasting rainfall for homogenous climatological zones, instead of using administrative boundaries, could improve forecast skill and accuracy. This is because station within the same climate zone are more likely to be influenced by similar weather systems, leading to more consistent and reliable predictions (Shahfahad et al. 2022).

Therefore, this study aims to provide a comprehensive analysis of the reliability and accuracy of the FMS seasonal rainfall forecasts. The findings will serve as a valuable reference for enhancing the skill and accuracy of seasonal rainfall forecasts across Fiji.

## 2 Study area, data and methodology

### 2.1 Study area

Fiji is a group of islands in the South Pacific. Rainfall in the region displays high spatiotemporal variability (Kumar et al. 2014). The country records two main rainfall seasons: the dry season from May to October and the wet season from November to April. The rainfall seasonality is mainly influenced by the movement of the South Pacific Convergence Zone (SPCZ; Mataki et al. 2006). Further, the El Niño-Southern Oscillation (ENSO) is known to influence the rainfall interannual variability, causing above- and below-normal rains during the La Niña and El Niño phases, respectively (Kumar et al. 2014; McAneney et al. 2017). Tropical cyclones commonly occur in the wet season and influence interannual rainfall variability, causing above-normal rainfall (Kuleshov et al. 2013).

Figure 1 shows the Divisions used by FMS for rainfall forecasting, which are based on administrative boundaries in Fiji. The Central Division boundary is relatively small, with ground stations located close to one another, while in other Divisions, stations are more sparsely distributed and

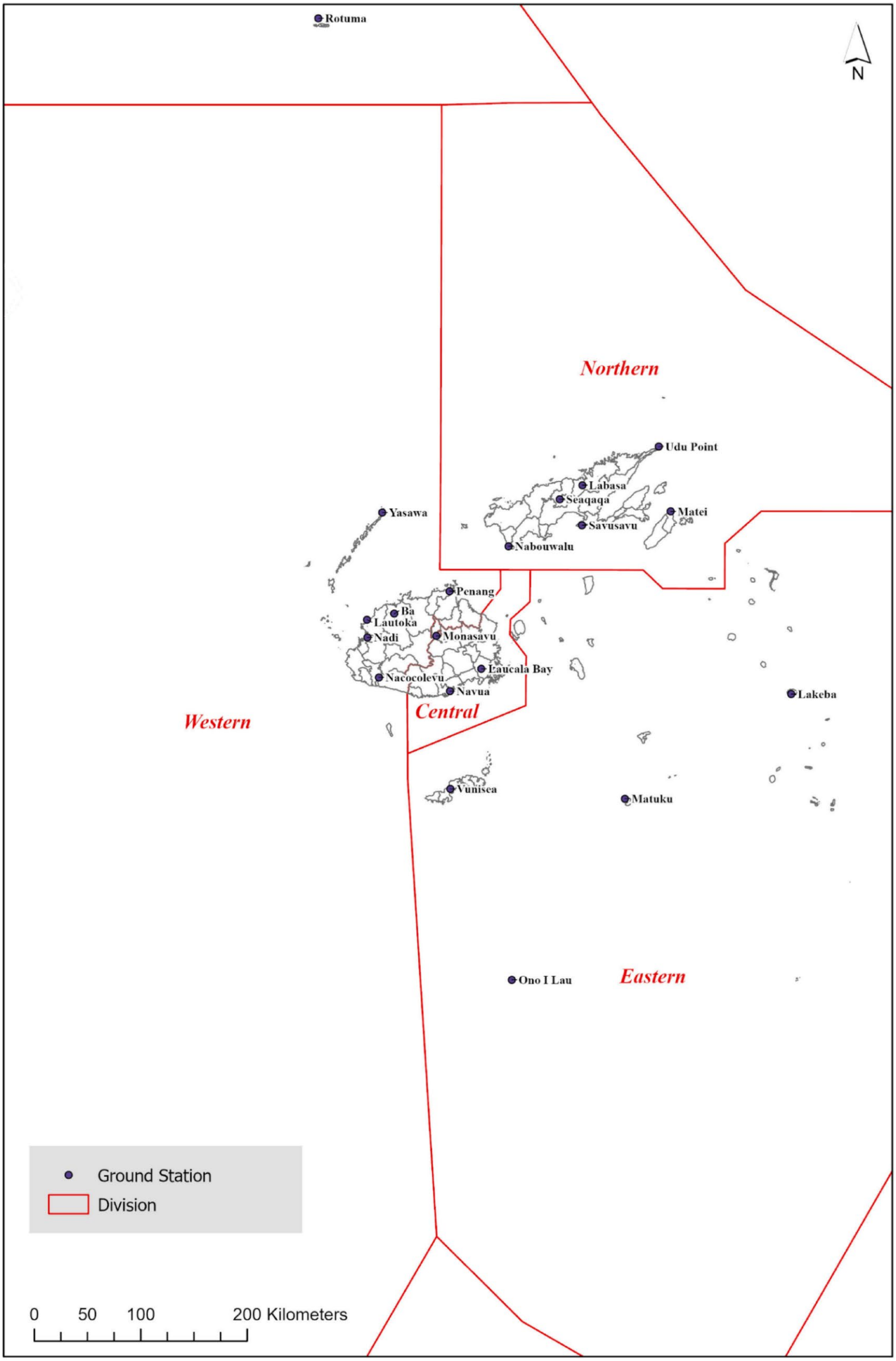



**Fig. 1** Location of the FMS meteorological stations and the delineation of the Western, Central, Eastern and Northern Divisions, and Rotuma

may be influenced by different weather conditions. This study considers Rotuma as a separate division due to its distance from the major divisions.

## 2.2 Data and methodology

*Data:* Daily rainfall data for twenty-one (21) rain gauge stations for 2000–2020 were sourced from the FMS. The data were converted to a seasonal scale by accumulating the daily observed rainfall data from all the stations in each Division for the November– January and February– April period and calculating the mean for each Division. The seasonal data were then used to calculate the total rainfall during the study period for the Western, Central, Eastern and Northern Divisions, and Rotuma (Fig. 2). This calculation was done for the climatological period 1981–2010, since FMS used this period for their forecasting. This approach was adopted due to the availability of the forecast data, which is provided in quarterly intervals: November– January, February– April, May– July, and August– October. December– January and February– April comprise the wet season, and both were computed in the same contingency table for further analysis.

*Methodology:* The 3-month forecasts were obtained from the FMS. The forecast data were in the form of probabilities of rainfall occurrence. Their reliability was assessed by comparing them to the station observation data for 2000–2020. The study period starts from 2000 because the forecast data only dates to 2000. However, the long-term mean used in the study is from 1981 to 2010, which is the climatological period used by FMS in their forecasting.

This study employs a multi-categorical probabilistic verification approach to categorize forecasts into tercile probabilities: below-normal (BN), normal (N), and above-normal (AN). Advanced statistical metrics, including Percent Correct (PC), Post Agreement (PA), False Alarm Ratio (FAR), Probability of Detection (POD), Bias, Heidke Skill Score (HSS), and Threat Score are utilized to provide a comprehensive evaluation. These metrics are chosen for their robustness in capturing the nuanced performance of probabilistic forecasts, which have been underexplored in Fiji's unique climate.

The rainfall forecast is verified qualitatively, relative to the mean, calculated from 1981 to 2010 period. The classification is based on standardized anomalies of data, which is calculated as follows (Eq. 1)

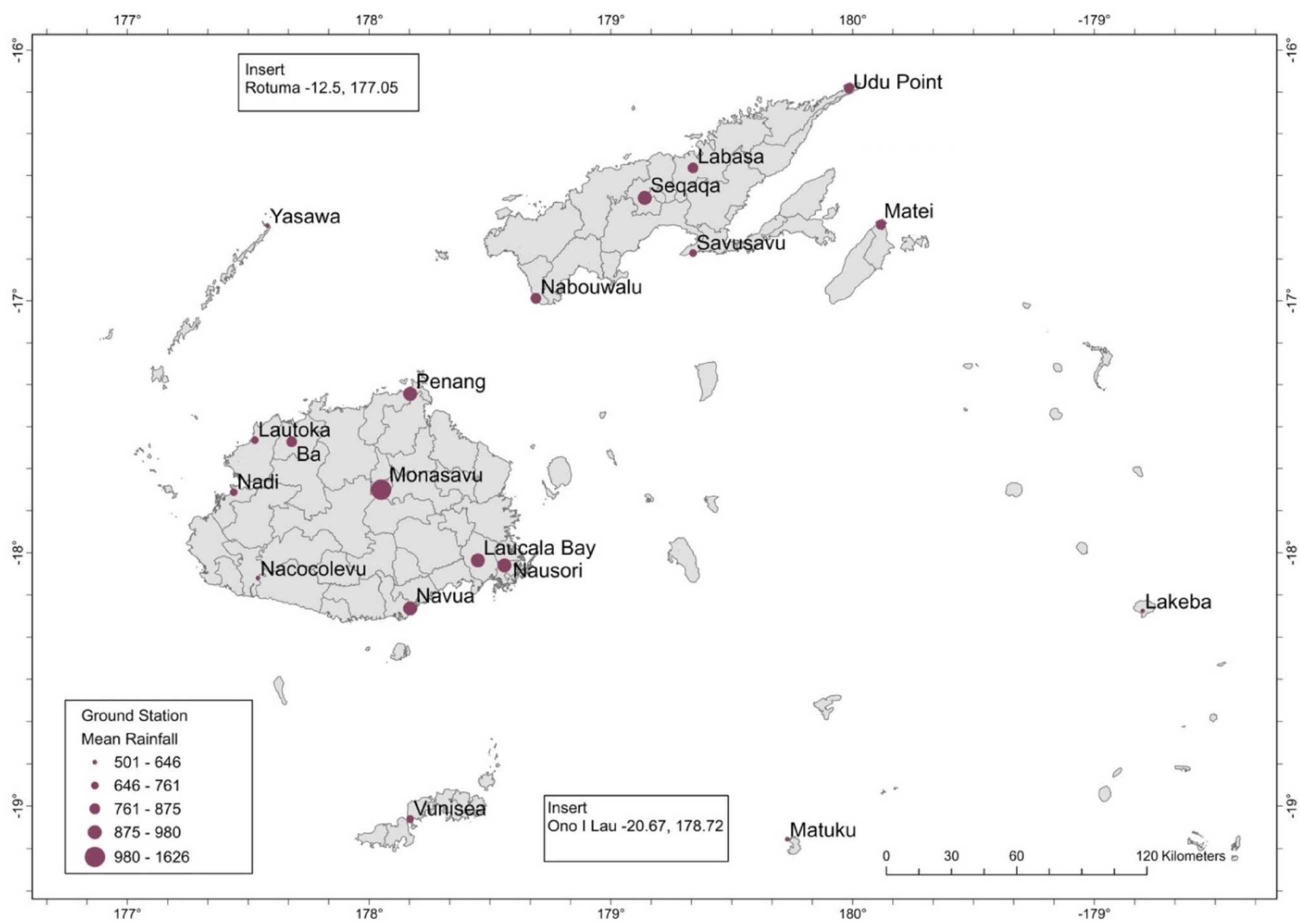



**Fig. 2** Distribution of rainfall amount (mm) during the wet season (November– April) based on rain gauge data from 1970–2020

$$SA = \frac{Mean\ rainfall\ for\ each\ division - climatological\ period\ mean\ for\ the\ division}{standard\ deviation} \quad (1)$$

The rainfall is classified as normal, below normal and above normal, if $-1 < SA < 1$, $SA < -1$ and $SA > 1$, respectively. The standardized (classified) observed rainfall is paired with the respective forecast and then summarized in a 3 × 3 contingency table (Table 1). Contingency tables provide a common method of verifying probability forecasts, commonly applied in operational meteorology (Gold et al. 2019).

### 2.2.1 Performance metrics

This study employs various statistical metrics to assess the accuracy and skill of the forecasts. Based on the contingency table, common performance metrics are used, such as the PC, PA, FAR, and POD.

PC is the ratio of correct forecasts to the total number of forecasts (Eq. 2).

$$PC = \left\{ \frac{BN\,(Hits)\ +\ N\,(Hits)\ +\ AN\,(Hits)}{T} \right\} * 100\% \quad (2)$$

PA is the ratio of correct forecasts to the total number of forecasts for each category. The PA scores for the three classifications are computed by Eq. 3;

Table 1 A 3 × 3 contingency table showing general weather verification classification and general description

| | | Observed | | | |
|---|---|---|---|---|---|
| | | BN | N | AN | Total |
| Forecast | BN | **BN(Hits)** | Under forecast ($UF_1$) | Under forecast ($UF_2$) | BN (Hits) + ($UF_1$) +($UF_2$) = **D** |
| | N | Over forecast ($OV_1$) | **N (Hits)** | Under forecast ($UF_3$) | ($OV_1$) +N (Hits) +($UF_3$) = **E** |
| | AN | Over forecast ($OV_2$) | Over forecast ($OV_3$) | **AN (Hits)** | ($OV_2$) + ($OV_3$) +AN(Hits) = **F** |
| | Total | BN(Hits) + ($OV_1$) + ($OV_2$) = **A** | {($UF_1$) +N (Hits) +($OV_3$)} = **B** | ($UF_3$) + ($UF_2$) +AN (Hits) = **C** | (A + B + C **OR** D + E + F) = **T** |

BN (Hits), N (Hits) and AN (Hits)– are the number of correct forecasts in each category. BN, N and AN are below-normal, normal and above-normal, respectively. T is the total number of forecast/observations. A is the number of BN events observed. B is the number of N events observed. C is the number of AN events observed. D is the number of BN events forecasted. E is the number of N events forecasted. F is the number of AN events forecasted. $UF_1$ and $UF_2$ are the number of under forecasts. $OV_1$ and $OV_2$ are the number of over forecasts

$$PA\ (BN) = \frac{BN\,(Hits)}{D}$$

$$PA\ (N) = \frac{N\,(Hits)}{E}$$

$$PA\ (AN) = \frac{AN\,(Hits)}{F} \quad (3)$$

False alarm serves as a warning for a forecasted event that does not occur. FAR gives the ratio of non-events that are incorrectly forecasted to the total number of forecasts (Barnes et al. 2009). It is given by 1-PA as presented in Eq. (4):

$$FAR\ (BN) = 1 - \frac{BN\,(Hits)}{D}$$

$$FAR\ (N) = 1 - \frac{N\,(Hits)}{E}$$

$$FAR\ (AN) = 1 - \frac{AN\,(Hits)}{F} \quad (4)$$

POD is a measure of the ability to correctly forecast a certain category (Eq. 5):

$$POD\,(BN) = \frac{BN\,(Hit)}{A}$$

$$POD\,(N) = \frac{N\,(Hit)}{B}$$

$$POD\,(AN) = \frac{AN\,(Hit)}{C} \quad (5)$$

Bias (Eq. 6) measures the relative frequencies of forecast and observed events. The bias score ranges from 0 to ∞ and indicates whether the forecast system is under-forecasting (Bias < 1) or over-forecasting (Bias > 1) (WWRP/WGNE, 2009).

$$Bias\ (BN) = \frac{D}{A}$$

$$Bias\,(N) = \frac{E}{B}$$

$$Bias\,(AN) = \frac{F}{C} \quad (6)$$

#### 2.2.2 Critical success index

Critical Success Index (CSI) is equal to the total number of correct event forecasts (hits) divided by the total number of rainfall forecasts plus the number of misses (hits + false alarms + misses) (Stanski et al. 1989) as given by Eq. (7):

$$CSI\,(BN) = \frac{BN\,(HIT)}{D + A - BN\,(HIT)}$$

$$CSI\,(N) = \frac{N\,(HIT)}{E + B - N\,(HIT)}$$

$$CSI\,(AN) = \frac{AN\,(HIT)}{F + C - AN\,(HIT)} \tag{7}$$

The CSI is more complete than the POD and FAR since it is sensitive to missed events and false alarms (Forecast verification for the African severe weather forecasting demonstration projects, 2014). The value for CSI ranges from 0 to 1, indicating poor to good skill.

#### 2.2.3 Skill score

Although the performance metrics in Eqs. (1–7) give a commonly employed overview of forecast performance, skill scores are necessary to determine the true quality of a forecast.

The HSS (Heidke 1926; Eq. 8) measures the fraction of correct forecasts, which excludes those forecasts that would be correct due to purely random chance (WWRP/WGNE, 2009) and compares the forecast performance to a reference. HSS varies from -∞ to 1, where a negative value indicates that the random forecast is better, 0 indicates no skill compared to the random forecast and 1 indicates a perfect forecast (Sahu et al. 2022).

$$HSS = \frac{\left[BN\,(Hit) + N\ (Hit) + AN\,(Hit) - \frac{DA+EB+CF}{T}\right]}{T - \frac{DA+EB+CF}{T}} \tag{8}$$

#### 2.2.4 Principal component analysis (PCA)

To identify uniform climatological zones, Principal Component Analysis (PCA) is applied to data from all observation stations used in the study. The PCA derives the principal components (PCs) through the Varimax rotation with Kaiser Normalization method (Kaiser 1970), where the explained variance is represented by the eigenvalues. Key parameters from each PC are determined by selecting error indices whose factor loadings or eigenvalues fall within 10% of the highest factor loading. The Varimax rotation is an orthogonal rotation method designed to simplify the interpretation of factors by maximizing the variance of the squared loadings within each factor. This process results in a structure where each variable tends to have a high loading on one factor and near-zero loadings on others, enhancing interpretability (Kaiser 1970). A Pearson correlation coefficient test between stations is done to determine the level of correlation between stations. Kaiser-Meyer-Olkin (KMO) and Bartlett's tests were done to test the suitability of the data for PCA. The KMO test evaluates the adequacy of a correlation matrix for factor analysis by comparing the magnitudes of observed correlation coefficients to partial correlation coefficients. A value closer to 1 indicates that the data are suitable for PCA, while values below 0.5 suggest inadequacy. Bartlett's Test of Sphericityevaluates the null hypothesis that the correlation matrix is an identity matrix (i.e., variables are uncorrelated). A significant result (typically $p<0.05$) indicates that the data have sufficient correlations to justify PCA (Bartlett 1950).

## 3 Results and discussion

### 3.1 Climatology of the study area

On Fiji's two main islands, Viti Levu and Vanua Levu, high mountain peaks strongly influence spatial rainfall variability through orographic effects. The orographic effect favors the mean annual rainfall in the southeastern side of Viti Levu (Central Division) that reaches an average of 1980.87 mm in the wet season, while the lowlands on the western side of Viti Levu (Western Division) are on the leeward side and record an annual average rainfall of 1780.10 mm. The Northern Division which includes all the stations in Vanua Levu experienced a mean annual rainfall of 1,660.4 mm, while the Eastern Division received the lowest average rainfall at 1,281.4 mm. Rotuma in the far North of the Fiji Islands recorded 1,807.7 mm of rainfall. The variations indicate the diverse climatic conditions for Fiji Islands, influenced by the topography and atmospheric factors.

Figure 3 shows the annual cycle of mean daily rainfall over Fiji. The months of January to March receive the most rainfall, while July– August record the least amount of rainfall. The mean daily rainfall for the study period shows that Rotuma (9.54 mm) and the Central Division (8.78 mm) receive more rainfall than the other Divisions. The Eastern Division records the least rainfall (5.32 mm). These results show that the spatial rainfall variability in Fiji is influenced by topography, with the windward side (Central Division) receiving more rainfall than the leeward side (Eastern Division) (Kumar et al. 2014; Mataki et al. 2006). However, Rotuma records higher mean daily rainfall than all the other

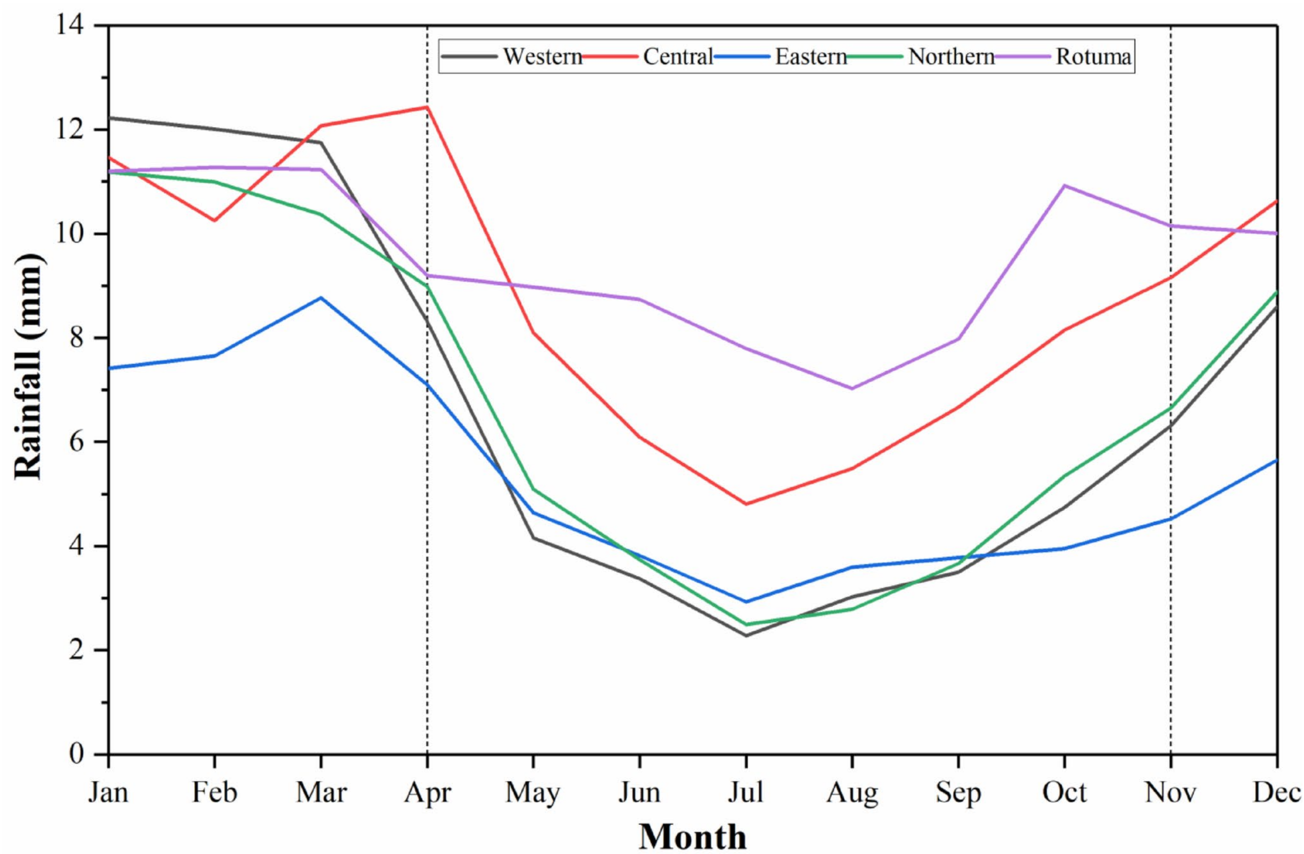



**Fig. 3** Annual rainfall cycle (mean daily rainfall) for the Western, Central, Eastern, Northern and Rotuma from 2000 to 2020

Divisions since it has no mountainous barriers and receives abundant and consistent oceanic rainfall (Deo 2011).

Figure 4 shows the standardized rainfall anomaly over Fiji from 2000 to 2020. The graph shows that rainfall exhibits large interannual variability across all Divisions over the 20 years. Generally, the study area receives higher than average rain during 2008, 2009, 2011, 2012, 2017, and 2018, which coincides with La Niña years, whereas 2003, 2004, 2005, 2006, 2007, 2009, 2010, 2011, 2013, 2014, 2015, 2016, 2019 and 2020 exhibited lower than average rainfall, coinciding with El Niño years. Inter-annual rainfall variability is strongly associated with ENSO activity. During an El Niño event, depressed rainfall is observed in the Fiji Islands, and the opposite occurs during a La Niña event. However, Rotuma presents a nearly inverse pattern compared to all the other Divisions. This is due to the position of the SPCZ. In the La Nina years, Rotuma tends to record significant below-average rainfall, whereas during El Niño years, it receives above-average rainfall while all the other Divisions display contrasting patterns (see Fig. 4). The SPCZ is displaced southwest of its normal position due to La Nina conditions causing rainfall deficits in Rotuma and moves northwards during El Niño years, causing above-average rainfall for Rotuma (Juillet-Leclerc et al. 2006).

## 3.2 Seasonal rainfall forecast evaluation using contingency table matrix

The frequency of each tercile is calculated for the 5 regions (Northern, Eastern, Central, and Western Divisions, and Rotuma) to generate the contingency table for the forecast period (Table 2.). Western Division has 7 stations, Central Division has 3 stations, Eastern Division has 4 stations, Northern Division has 6 stations and Rotuma has 1 station. The Western Division and Rotuma have missing data for 2 seasons. Hence, there are 37 seasons for the Western Division and Rotuma, while the other Divisions have 39 seasons. Missing data accounts for less than 10% of the complete data set.

## 3.3 Assessment of seasonal rainfall forecast using performance metrics

### 3.3.1 Percent correct

The PC results (Fig. 5) indicate that more than 50% of the forecasts match the observed values for all the divisions. The analysis reveals that the Percent Correct (PC) is highest for the Western Division (62.2%), indicating a relatively

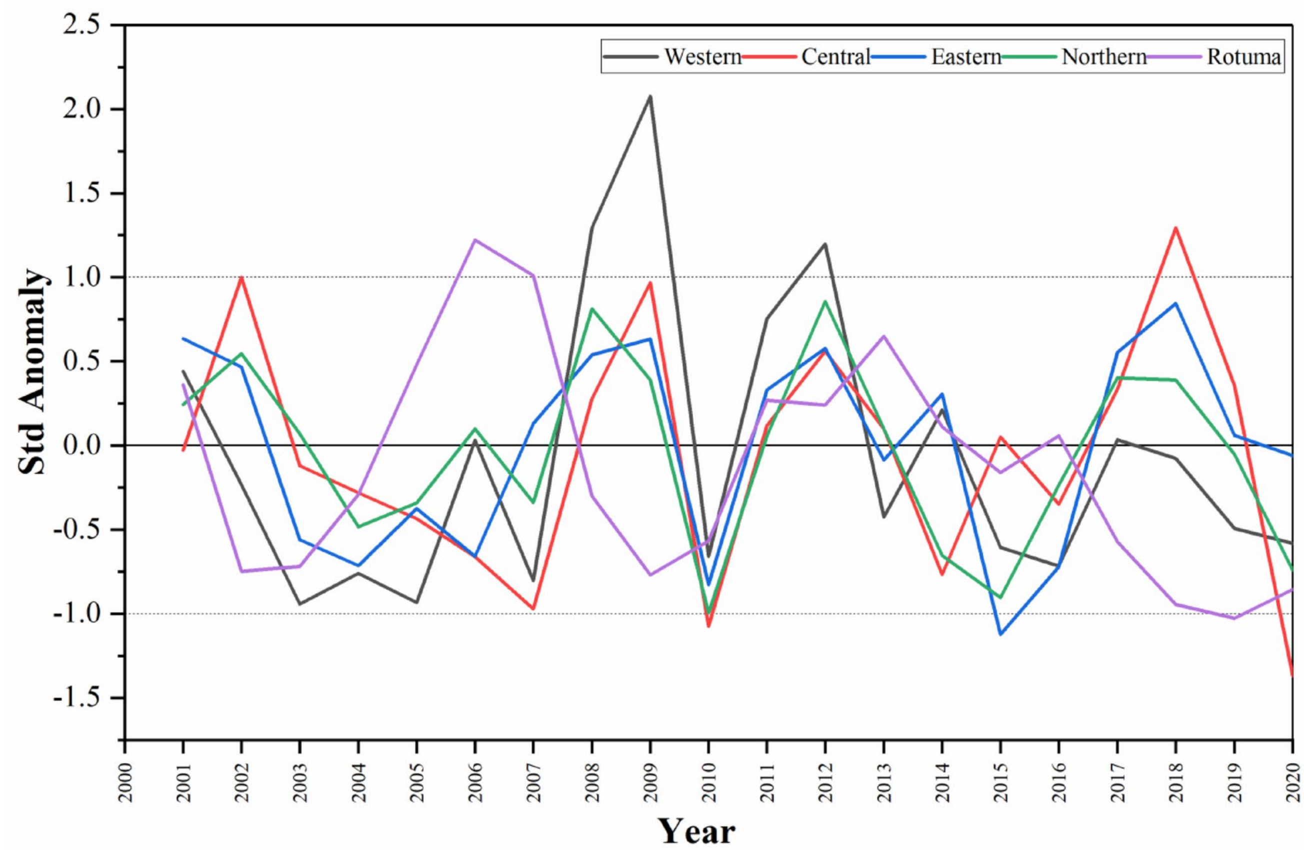



**Fig. 4** Standard anomalies of the wet seasonal rainfall for 2000–2020 average over the Western, Central, Eastern and Northern Divisions, and Rotuma. The dotted lines denote ± 1 indicating dry and wet years

better performance in this region. This could be attributed to the unique topographical and climatic conditions prevalent in the Western Division. Comparatively, the Eastern Division exhibits the lowest PC (53.8%), possibly due to its dispersed geographical setup. Notably, the Post Agreement (PA) values are significantly higher for the normal (N) category across all divisions, reflecting the forecast model's proficiency in predicting average rainfall conditions but highlighting its limitations in accurately forecasting extreme conditions (BN and AN). This discrepancy underscores the need for model improvements to enhance predictive accuracy for extreme weather events.

#### 3.3.2 Post agreement

As shown in Fig. 6, the PA values of N categories for all Divisions are high (Western: 1.00, Northern: 0.84, Rotuma 0.75, Eastern: 0.74, and Central 0.68), which shows that the forecasted rainfall falls within the observation range more than 75% of the time. The PA for all the BN and AN category for all Divisions and Rotuma is notably low, which suggests that the observed rainfall deviates significantly from the forecast range, indicating significant disparity in the forecast accuracy.

#### 3.3.3 Probability of detection

POD is not sensitive to FAR and FAR is not sensitive to missed events. Since they are both incomplete scores, they should be used in connection with each other (Forecast verification for the African severe weather forecasting demonstration projects, 2014). The receiver operating characteristic (ROC) curve is plotted using POD and FAR to assess the overall diagnostic performance of the forecast to determine the presence and absence of events and non-events, hence, discrimination. Figure 7 shows that N for all Divisions and Rotuma, and AN for the Western and Eastern Divisions occur above the diagonal line, indicating POD is always greater than FAR. However, N values for the Western and Northern Divisions appear on the upper left, meaning forecasts can better distinguish between N events than non-events (BN and AN categories). None of the points lie on the diagonal line, showing discrimination between events and non-events based on the forecasts. The diagonal line is where POD equals FAR indicating no discrimination

**Table 2.** Contingency tables for (a) Western Division; (b) Central Division; (c) Eastern Division; (d) Northern Division; and (e) Rotuma for the wet season (November– April) from 2000–2020. BN, N and AN are below-normal, normal and above-normal, respectively

| | Observed | | | |
|---|---|---|---|---|
| | BN | N | AN | Total |
| (a) Forecast | | | | |
| BN | 0 | 11 | 0 | 11 |
| N | 0 | 20 | 0 | 20 |
| AN | 0 | 3 | 3 | 6 |
| Total | 0 | 34 | 3 | 37 |
| (b) Forecast | | | | |
| BN | 0 | 4 | 1 | 5 |
| N | 5 | 21 | 5 | 31 |
| AN | 0 | 3 | 0 | 3 |
| Total | 5 | 28 | 6 | 39 |
| (c) Forecast | | | | |
| BN | 1 | 6 | 1 | 8 |
| N | 4 | 17 | 2 | 23 |
| AN | 1 | 4 | 3 | 8 |
| Total | 6 | 27 | 6 | 39 |
| (d) Forecast | | | | |
| BN | 2 | 7 | 0 | 9 |
| N | 1 | 21 | 3 | 25 |
| AN | 0 | 5 | 0 | 5 |
| Total | 3 | 33 | 3 | 39 |
| (e) Forecast | | | | |
| BN | 2 | 8 | 1 | 11 |
| N | 3 | 18 | 3 | 24 |
| AN | 1 | 1 | 0 | 2 |
| Total | 6 | 27 | 4 | 37 |

between different categories. However, points lie above and below the diagonal line, and except for the N category for Western and Eastern Divisions, there is hardly any point close to the upper left, which shows that overall discrimination is poor. AN for Eastern Division falls almost on the diagonal line, indicating no discrimination between events and non-events. FAR for BN and AN for all Divisions and Rotuma are higher than 0.6, which indicates that over 60% of the BN and AN forecasts of the event are false alarms.

### 3.3.4 Heidke skill score

The HSS results presented in Table 3 show that forecasts for all categories are closer to 0, indicating very low skill. HSS for the Central Division is −0.15, indicating that the forecast is worse than the reference forecast. In this case, the reference forecast is a simple random guess as to which of the three categories will occur (Forecast verification for the African severe weather forecasting demonstration projects, 2014). The Western Division indicates moderate positive skill, with a slightly better performance than the other Divisions.

### 3.3.5 Bias

Bias is computed to assess the accuracy of the forecast. The results are presented in Table 4. Bias does not measure how well the forecasts correspond to the observation, but it shows whether the forecasts are underestimating or overestimating rainfall (Gold et al. 2019). The results show that the forecast is either underestimated or overestimated, with generally low skill and accuracy. The Bias analysis results (Table 4) indicate a significant deviation from 1 for all categories. This indicates that the forecasts overestimate and underestimate the observed values. However, the BN for the

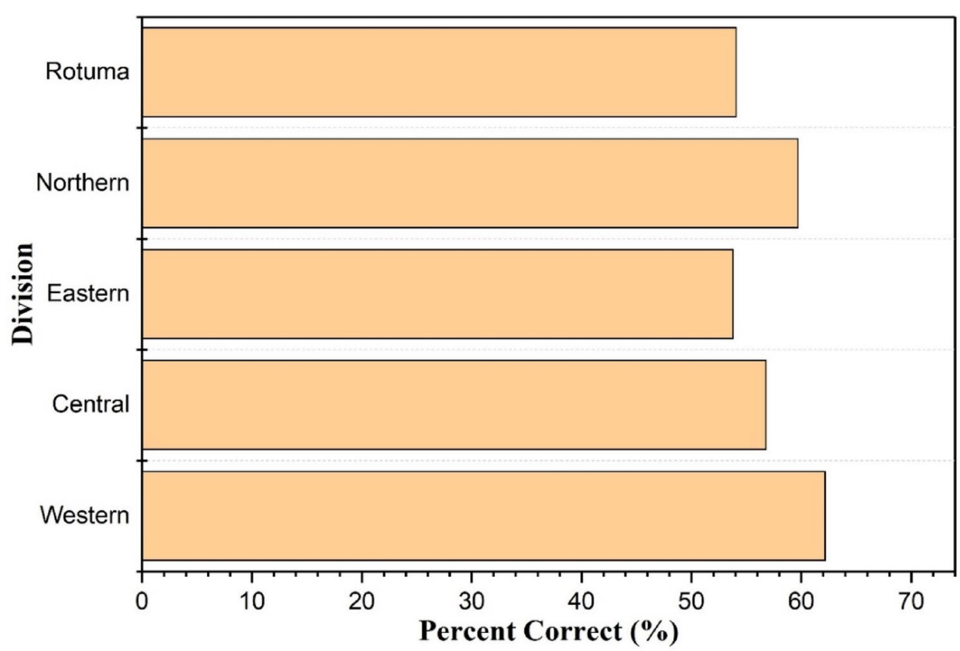
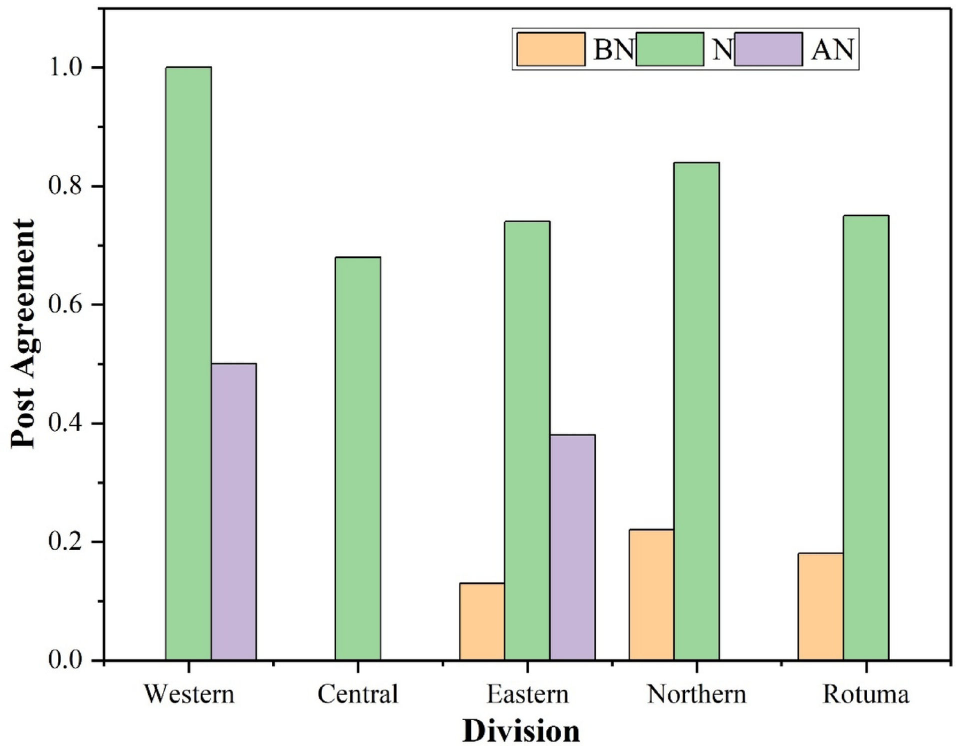



**Fig. 5** Percent correct for Western, Central, Eastern, and Northern Divisions, and Rotuma during the wet season (November– April) from 2000–2020

**Fig. 6** Post Agreement results for Western, Central, Eastern, and Northern Divisions, and Rotuma. BN, N and AN are below-normal, normal, and above-normal, respectively




Central Division has a score of 1, which means that all forecasted BN events perfectly match the observed.

### 3.3.6 Critical success index

Finally, the critical success index was computed to assess the relative accuracy of correct forecast events corresponding to observed events (Table 5). N for Western, Central, Eastern, Northern Division, and Rotuma have a critical success index of 0.59, 0.55, 0.52, 0.57 and 0.55, respectively, showing that slightly more than half of the predicted normal rainfall is correctly forecasted. However, BN and AN for these Divisions and Rotuma have less than half of the predicted BN and AN rainfall, therefore, are not accurate.

## 3.4 Verification and bias correction of seasonal rainfall forecasting

FMS uses the percent of normal rainfall for the verification process, comparing the BN, N, and AN category with seasonal predictions. They categorize the comparison based on consistent, near-consistent, and inconsistent forecasts. For example, if the rainfall outlook (forecast) for a particular Division is above-average and the observed rainfall is in the above-average category, then FMS categorizes that as a consistent forecast, and if it is near to the above-average value, then they categorize it as near-consistent. When rainfall falls under the below-average value, it is categorized as an inconsistent forecast (S. Shiwangani, personal communication, November 29, 2022).

Moreover, verification results for different Divisions do not show any significant differences in the accuracy or skill for the Divisions, which indicates that forecast model performance is similar for all the Divisions. Usually, climate models perform better for some regions than others, but the study area has a very small landmass surrounded by a vast expanse of ocean. The ocean is the key part of the climate system that influences weather on land (Sun et al. 2018). The rain gauge stations in the Eastern Division are located on very small land masses separated by ocean compared to all the other Divisions, where all gauge stations are on the same land mass and close together. This may be why the Eastern Division has the lowest accuracy and skill compared to all the other Divisions and Rotuma. In contrast, there is a significant difference in the results among different categories. The accuracy and skill seem to improve when N is forecasted, with none of the scores for N falling below 50%. This highlights how extreme events, such as tropical cyclones, which are difficult to predict on a seasonal time scale, can reduce the accuracy of seasonal forecasts.

The FMS use Linear Error in Probability Space (LEPS) metric to assess forecast skill, categorize the confidence of the outlook as very low, low, moderate, good, high, very high, and exceptional. The LEPS score is used to assess forecasts of both continuous and categorical variables and is independently sensitive to bias and forecast variance, particularly in cases where the forecast underestimates the

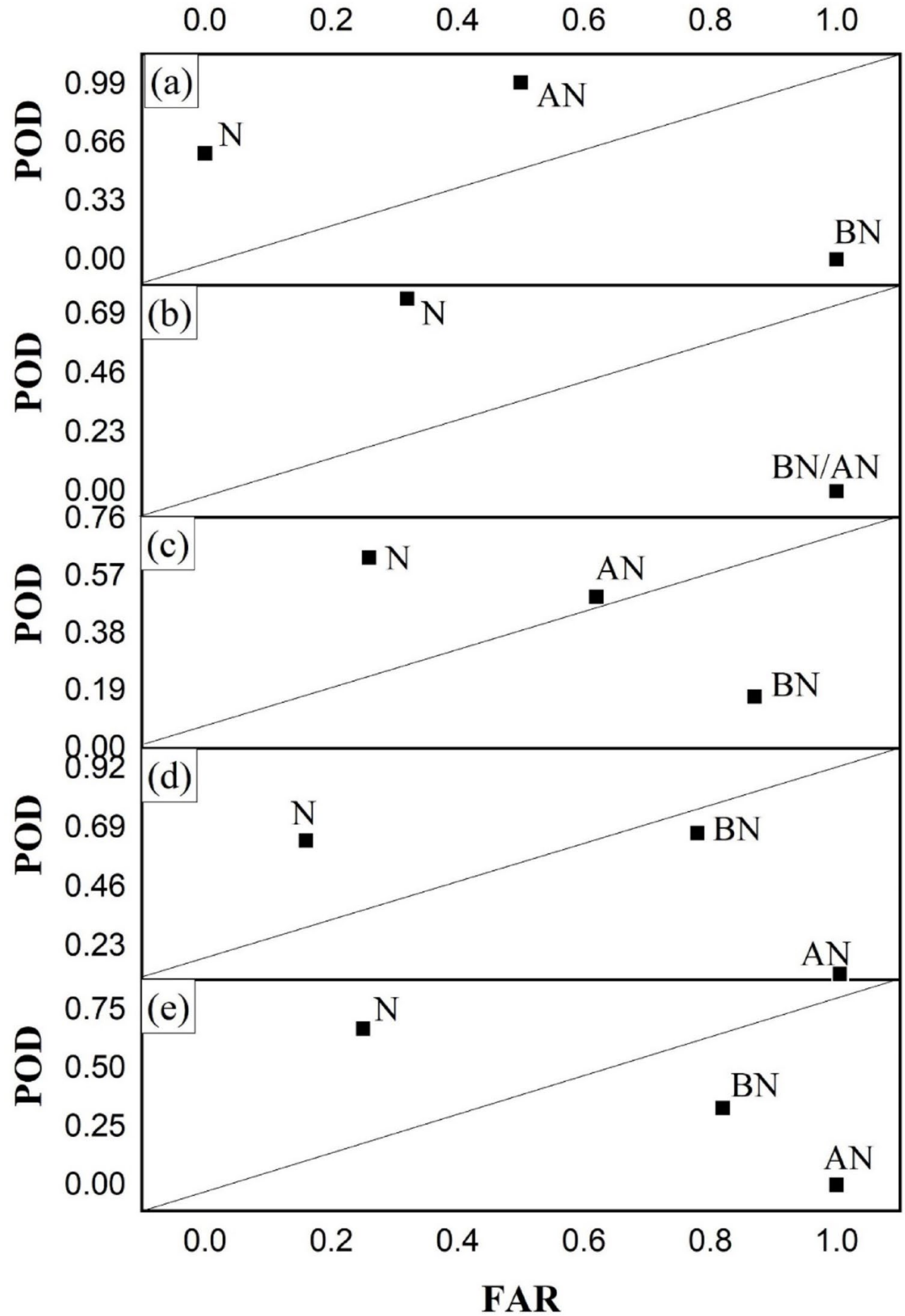



**Fig. 7** A receiver operating characteristic (ROC) curve showing discrimination between probability of detection and false alarm rate for Western (a), Central (b), Eastern (c), Northern (d) and Rotuma (e) for the wet season (November–April) from 2000–2020. BN, N and AN are below-normal, normal and above-normal, respectively

**Table 3** Heidke skill score (HSS) for the Western, central, Eastern and Northern divisions, and Rotuma during the wet season of 2000–2020

| | Western | Central | Eastern | Northern | Rotuma |
|---|---|---|---|---|---|
| HSS | 0.23 | −0.15 | 0.13 | 0.046 | 0.003 |

observed values, while being less sensitive to outliers (Potts et al. 1995). Table S1 summarizes the results of the verification process by FMS for the study period. The results from this study and Table S1 show that the forecast model works

**Table 4** Bias for the Western, central, Eastern and Northern divisions, and rotuma. BN, N, AN are below-normal, normal, and above-normal, respectively, during the wet season of 2000–2020

| Divisions | BN | *N* | AN |
|---|---|---|---|
| Western | 0 | 0.6 | 2 |
| Central | 1 | 1.11 | 0.5 |
| Eastern | 1.33 | 0.85 | 1.33 |
| Northern | 3 | 0.76 | 1.67 |
| Rotuma | 1.83 | 0.89 | 0.5 |

**Table 5** Critical success index for the Western, central, Eastern and Northern divisions, and rotuma. BN, N and AN are below-normal, normal, and above-normal, respectively, during the wet season of 2000–2020

| Divisions | BN | *N* | AN |
|---|---|---|---|
| Western | 0 | 0.59 | 0.33 |
| Central | 0 | 0.55 | 0 |
| Eastern | 0.077 | 0.52 | 0.27 |
| Northern | 0.2 | 0.57 | 0 |
| Rotuma | 0.13 | 0.55 | 0 |

**Table 6** Detailed variability accentuated by the respective PCs for station variance

| Principal Component | Eigen Value | % of Variance | Cumulative variance % |
|---|---|---|---|
| PC1 | 9.874 | 47.021 | 47.021 |
| PC2 | 2.215 | 10.550 | 57.571 |
| PC3 | 1.370 | 6.524 | 64.094 |
| PC4 | 1.302 | 6.200 | 70.295 |
| PC5 | 1.176 | 5.601 | 75.895 |

better for the Western Division when compared to the other Divisions and Rotuma.

To address these biases, FMS could enhance seasonal forecasts using station observations for bias correction, a process involving historical comparison of model outputs with observed data and applying techniques like quantile mapping or ensemble recalibration (Manzanas et al. 2019). For example, quantile mapping adjusts the model's rainfall distribution to match observed distributions, reducing systematic errors, as demonstrated in (Hemri et al. 2020). This improves forecast accuracy and reliability, critical for Fiji's agriculture and disaster preparedness given its oceanic exposure.

Rainfall has a high spatio-temporal variability and is one of the most complex elements of the hydrological cycle to model owing to the complexity of the atmospheric processes and since it is highly variable over a wide range of spatial and temporal scales (French et al. 1992). Weather forecast models provide forecasts for a grid cell, posing a challenge to compare and evaluate forecast accuracy with point-based observed values (Hogan and Mason 2011). As a result, rainfall forecasts directly provided by weather models may contain a large bias or variance that limits the accuracy of quantitative rainfall forecasts (Lima et al. 2021). However, station observation can be used for bias correction in seasonal forecasting models. It involves identifying systematic errors by comparing historical model outputs with observed data and applying techniques like quantile mapping or ensemble recalibration to adjust forecasts, thereby improving their overall performance and consistency (Hemri et al. 2020; Manzanas et al. 2020).

The high bias and variance in rainfall forecasts has led to the emergence of empirical models, statistical techniques, and machine learning-based models as an alternative to weather forecasting models for daily rainfall forecasts. Including rainfall predictors from weather models in empirical models can help improve forecasting at seasonal scales (Lima et al. 2021). There has been significant progress from the conventional approach of linear mathematical relationships supported by the operator's experience, mathematical curves, and guidelines to machine learning tools for rainfall forecasting (Tokar and Markus, 2000). These methods require many physical parameters and involve complex computations of mathematical and physics equations hence reducing bias into the predictions which may be due to the subjective reasoning in conventional methods based on operator's experience. (Hung et al. 2009) used an Artificial Neural Network (ANN) technique to improve rainfall forecast performance. The study indicated that the wet bulb temperature is the most important input parameter besides rainfall in forecasting rainfall. Another study by (Badr et al. 2014) on the Sahel region of Africa revealed that nearly all statistical models in forecasting use linear models. In contrast, ANN, which can capture nonlinear influences on rainfall, demonstrated a higher level of predictive accuracy than the other eight statistical models examined (Badr et al. 2014). Climate models provide a platform for continuous monitoring of the land-atmosphere system processes and parameters, which are more reliable. However, their performance must be understood across space-time scales and factors relating to their errors (Kimani et al. 2017). Climate models are used to predict seasonal rainfall forecasts that cover a wider area, including the ocean. Fiji has a sparse distribution of land-based rain gauges. Therefore, the drawbacks associated with these measurements are the incomplete areal coverage and deficiencies in most oceanic and sparsely populated areas (Sun et al. 2018).

### 3.5 Homogenous climatological zones in seasonal forecasting

Seasonal rainfall forecast for Fiji Islands is done in divisions where ground stations are grouped into divisions based on administrative boundaries rather than homogenous climatological zones. Dimension reduction techniques (PCA) identified five principal components for our station rainfall datasets accounting 75.89% cumulative variance (Tables 6 and 7). The five components are the most essentials distinct indices for the rainfall stations for Fiji. The use of the Division boundaries rather than the climatological zone may reduce the accuracy of the forecast for a small country with many small islands which has high rainfall variability like Fiji. The correlation matrix for annual and all three months rainfall period showed very high correlations

**Table 7** Factor loading of rainfall stations for respective PCs in rotated component matrix

| Stations | Component | | | | |
|---|---|---|---|---|---|
| | PC1 | PC2 | PC3 | PC4 | PC5 |
| Nadi | 0.844 | | | | |
| Ba | 0.830 | | | | |
| Lautoka | 0.829 | | | | |
| Matuku | 0.792 | | | | |
| Nacocolevu | 0.747 | | | | |
| Ono-i-Lau | 0.669 | | | | |
| Penang | 0.646 | | | | |
| Matei | | 0.885 | | | |
| Udu Point | | 0.807 | | | |
| Labasa | | 0.782 | | | |
| Seaqaqa | | 0.550 | | | |
| Laucala Bay | | | 0.809 | | |
| Nausori | | | 0.748 | | |
| Yasawa | | | 0.731 | | |
| Lakeba | | | 0.617 | | |
| Navua | | | | 0.765 | |
| Nabouwalu | | | | 0.617 | |
| Monsasavu | | 0.535 | | 0.579 | |
| Vunisea | 0.546 | | | 0.548 | |
| Savusavu | | | | 0.520 | |
| Rotuma | | | | | 0.871 |

between stations within the Western Division, such as Nadi and Lautoka, Nadi and Ba, Lautoka and Ba and Nacocolevu and Nadi, Penang showed strong correlation with Nadi, Ba and Lautoka for the wet season (S2). However, Monasavu does not show strong correlation with any of the stations in the western division and neither with any other station in the other Divisions and Rotuma, while Yasawa shows moderate to low positive correlation with the stations in the western division. The PCs further confirm that Monasavu is not loaded with stations from the western division and Yasawa does not show high loading in the component with all the stations from the western division. It is grouped with Ono-i-Lau in PC5 but has a negative value, which indicates opposite weather pattern in Yasawa, which may be due to its remoteness. Monasavu is grouped with PC 3 and 4 for November– January and February– April period, respectively (Table 7). Monasavu station is located at a high elevation of 808 m above sea level and therefore, may be influenced by local microclimate conditions such as stronger winds and wind- driven rain and cooler temperatures reducing evaporation rates.

The stations in the Eastern Division are dispersed between different islands and separated by ocean and have the lowest accuracy skill in terms PC, POD, FAR and CSI compared to all the other Divisions and Rotuma. The correlation among the stations is weak (S2) and they are not grouped together in the PCs as well (S3). The variance between the stations is considerably different and therefore, may not share the same weather patterns affecting rainfall for the four locations and grouping them into same forecasting zone may be the reason for low accuracy skill.

Some stations in the Central and Northern Divisions display considerably different behavior compared to the rest of the stations. For Central Division, Laucala Bay and Nausori are highly correlated and PC analysis also confirms this; however, Navua behaves differently. Navua shares characteristics with Western and Central Division due to its location. It is not strongly aligned with either Divisions (Table 6). The stations in the Northern Division show variability in their grouping for both annual and seasonal periods (November– January and February - April) (S3). Matei, Nabouwalu and Udu Point do not show correlation with other stations in the Northern Division for the wet season and Nabouwalu only shows moderate correlation with Labasa, Seaqaqa and Savusavu for the annual period. Matei is a separate island from Vanua Levu and Udu Point and Nabouwalu are located at the opposite tips of Vanua Levu and their weather patterns maybe influenced more by ocean conditions than inland influence and differ from the stations inland.

The PCA analysis indicates that the Division are not appropriate for the seasonal forecast, due to high variability of rainfall within each division and hence low skill and accuracy in the seasonal forecast.

## 4 Conclusions and recommendations

According to Scher and Messori (2019), the ability to make accurate weather forecasts in the Northern Hemisphere is affected by the current changes in the global climate, especially rainfall forecasts. Global warming and climate change are not unique to the Northern Hemisphere, meaning similar challenges can also be expected in the Southern Hemisphere. Rainfall prediction might become more challenging in the future as climate variability increases. Seasonal forecasts are influenced by the large-scale climate drivers, such as ENSO and Madden-Julian Oscillation (MJO) which are difficult to predict with precision then there are uncertainties associated with initial climatic conditions and model bias adding to the issue of forecast accuracy. These factors contribute to the challenging nature of probabilistic forecasts given that the probabilistic forecasts produce probabilities of different outcomes unlike deterministic forecasts which provide a single expected outcome. The probabilistic nature of forecast outcomes introduces added complexity to seasonal forecasting (Pirret et al. 2020).

This study uses a probabilistic 3 × 3 contingency table to verify multi-category seasonal rainfall events. Tercile forecasts of BN, N, and AN seasonal rainfall for the wet season

(Nov– Apr) for the Fiji Islands were evaluated. Verification measures computed from the contingency table include PC, PA, FAR, POD, Bias, Critical Success Index, and HSS. All the verification metrics used in this study show that the rainfall forecasts for the Fiji Islands generally have low accuracy and skill. ROC plots and Bias results indicate that discrimination and resolution for the forecasting model are poor.

This study was carried out based on available data from FMS for a period of 2000 to 2020. FMS uses the RPM forecast model from 2000 to 2005 and the SCOPIC climate model thereafter. The study period includes data from both models that may have affected the verification process. The forecast evaluation shows low accuracy and skill for the FMS seasonal predictions. This is the first verification study done on the seasonal rainfall forecasts. Therefore, further studies are required to understand the cause of the low skill and accuracy of the model being used.

A study by Lee et al. (2022) introduced the Pacific Island Countries Advanced Seasonal Outlook (PICASO). This hybrid seasonal prediction system combines statistical and dynamic systems to generate station-level rainfall forecasts for 49 stations in 13 countries in the Pacific. The study found that the PICASO system performed well for approximately half of the stations compared to the existing models. However, it performed poorly for the stations in the southern central Pacific, where rainfall is strongly affected by the SPCZ, including the study area of the current research. Further research into hybrid systems for seasonal forecasts may enhance the forecast quality.

The findings suggest substantial room for improvement in the accuracy and reliability of seasonal forecasts by the FMS, particularly in predicting extreme weather conditions. A study by (De Zoysa et al. 2023) which utilizes gauge rainfall and the satellite-based precipitation product (SPP)-TRMM3B42 to develop IDF curves for the Nadi and Nausori ground stations in Fiji, found that TRMM3B42 tends to both overestimate and underestimate extreme weather events. Future research should focus on integrating higher-resolution datasets and employing advanced statistical models, such as machine learning techniques, to enhance forecast precision. This study predicts that the possible reason for low forecast accuracy and skill may be due to the grouping of stations based on administrative boundaries rather than climatological zones. It highly recommends using homogeneous climatological zones for seasonal rainfall forecasts instead of boundary divisions. Additionally, expanding the scope of verification studies to include the onset and cessation of seasonal rainfall could provide valuable insights for local stakeholders, thereby increasing the practical utility and adoption of seasonal forecasts

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## Declarations

**Competing interests** The authors declare no competing interests.

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