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ORIGINAL PAPER

Validation of ERA5 rainfall data over the South Pacific Region: case study of Fiji Islands

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Abstract
Rainfall variability has a significant impact on hydrological cycle. Understanding rainfall variability over Fiji Islands is important for decision-making in the backdrop of global warming. Reanalysis rainfall products are commonly used to overcome observed data quality challenges especially over ungauged highland areas. However, an evaluation of reanalysed datasets is important to ensure accurate and reliable climate information generated using such datasets, especially for small Island with high variable topography like Fiji. This work aims to validate the spatiotemporal performance of European Centre for Medium-Range Weather Forecasts (ECMWF) fifth-generation reanalysis rainfall (ERA5) data against ground-based station data from 19 stations for the period 1971–2020 over Fiji Islands. Correlation coefficient and difference statistics: bias, and root mean square error, are used to assess the performance of the data. Further, common Empirical Orthogonal Function (common EOFs) analysis was used to evaluate spatiotemporal performance of ERA5 datasets. The results of the station-by-station comparison shows that interpolated ERA5 annual rainfall matches the corresponding results from rain gauges remarkably well for many stations. The correlation coefficient values range from 0.5 to 0.85, while the bias spans from a negative 282 to a positive 575, and the root mean square error (RMSE) varies between 285 and 662 mm for the annual rainfall across the study area. However, there is overestimation and underestimation of the observed rainfall by ERA5 datasets. The leading common EOF principal component for annual rainfall suggests that the inter-annual variability in ERA5 dataset is generally consistent with observed station datasets, cross validation results indicated high scores (correlations of 0.82), with limited spatial variation. This work presents a reliable data assessment of the ERA5 data over Fiji Islands, indicating there is good match of the annual observed rain gauged station data and ERA5. The findings give accuracy references for further use of the ERA5 data in understanding rainfall variability and change over the region.

1 Introduction

Global warming is associated with changes in rainfall patterns all over the world, South Pacific region being included (IPCC 2021). In the South Pacific region, the average rainfall is decreasing, while the extreme precipitation and storms are increasing (Thomas et al. 2020). Fiji whose economy and livelihood is mainly dependent on agriculture, rainfall variability has devastating socioeconomic impacts. Thus, there is need for monitoring rainfall variability and change for informed decision-making in effort to build resilience against weather and climate variability impacts, the process requires reliable data (Vystavna et al. 2022; Deo 2011; Egeru et al. 2019; Manton et al. 2001). This calls for a long series of quality historical precipitation data. The data is vital not only to the climate scientist, but for all professions in other socioeconomic sectors (e.g. agriculture, water, health, infrastructure, transport etc.) given that they are affected by

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climate change impacts whether directly or indirectly (Kaspar et al. 2022; Trenberth et al. 2003)

Lack of adequate long-term and high-resolution datasets, inaccessibility of the available station data and missing values in the available data due to technicalities is common in most developing regions including the South Pacific (Barlian Soeryamassoeka et al. 2020). The reliability of observed station datasets is mainly limited by the number and spatial coverage of surface stations, which is not enough to monitor the spatial features of precipitation well over the region (Chen et al. 2018; Sun et al. 2018). Satellite derived and climate reanalysis precipitation data have been widely used to overcome some of these challenges (Bessenbacher et al. 2022). This data is currently being used to understand the long-term trends in rainfall, temperature and their changing patterns globally (Gebrechorkos et al. 2019). With advances in technology, both satellite and reanalysis methods offer precipitation data with fine spatial–temporal resolutions, especially in far-remote areas with sparse in situ precipitation networks such as Fiji. The reanalysis methods offer precipitation estimations by assimilating all available data into a background forecast physical model (Funk et al. 2015; Wong et al. 2017). Over the last decade, satellite and reanalysis gridded precipitation datasets have been released by many forecasting centres which include the European Centre for Medium-Range Weather Forecasts (ECMWF), that is currently providing its fifth generation (ERA5) datasets (Hersbach et al. 2020). There are efforts to continuously upgrade data methodologies to remove some of the biases in the models (Decker et al. 2012). The dataset produced by these centres depends on the quality of the data assimilated as the initial conditions and the parameterization schemes used in the models (Decker et al. 2012; Funk et al. 2015). For the ERA5 data, is produced using 4D-Var data assimilation and model forecasts in Cycle 41r2 of the Integrated Forecasting System (IFS), with 137 hybrid pressure levels. ERA5 benefits from a decade of developments in model physics, core dynamics, and data assimilation. In addition to a significantly enhanced horizontal resolution (31 km grid spacing), it has several innovative features, which include hourly output throughout and an uncertainty estimate. The uncertainty information is obtained from a 10-member ensemble of data assimilations with 3-hourly output at half the horizontal resolution (63 km grid spacing) (Hersbach et al. 2020). Therefore, it is necessary to evaluate the accuracy of these model outputs to understand the biases in the model before the use of the available data. This can only be done by comparing the data with the in-situ data that is strictly quality controlled. The ERA5 reanalysis is developed by the Copernicus Climate Change Service (C3S) and implemented by ECMWF. It combines vast amounts of historical observations into global estimates (Hersbach et al. 2020). Several studies over the South Pacific region have used satellite estimates and reanalysis precipitation data. For example, drought monitoring over the Australia region by Bhardwaj et al. (2022), and studies done to monitor and estimate precipitation over the South Pacific region using both satellite and reanalysis data (Chen et al. 2018; Pfeifroth et al. 2013; Wild et al. 2021). However, few studies have used ERA5 dataset. Yeasmin et al. (2021) studied detection and verification of tropical cyclones and depressions over the South Pacific Ocean basin using the ERA5 reanalysis datasets. Findings showed that ERA5 reanalysis data can capture the climatology distribution of tropical depression over the South Pacific Ocean. These studies provide useful references when using ERA5 datasets. However, there have been few evaluation studies on ERA5 precipitation data over the Southwestern Pacific region, on how well the data represent the observed precipitation. Therefore, evaluating the performance of ERA5 dataset over the region will inform decision making in filling the deficiencies of traditional in situ gauge precipitation data and provide an alternative data source for ungauged areas. This study evaluates ERA5 reanalysis precipitation datasets, to understand the biases in the dataset and to improve future precipitation assessments over the South Pacific region.

2 Data and methods

2.1 Study area

Fiji's Island is unique in term of land mass and diversity in topography. The nation consists of over 300 islands with a total of around 18,300 km of land in the South Pacific region. The country lies between longitudes 175° E and 178° W, and latitudes 15° S and 22° S and is divided into five (5) divisions (S1). Viti Levu, the country's largest island, is characterized by its relatively high topography (Fig. 1). Vanua Levu and Kadavu are located to the northeast and south of Viti Levu, respectively. The larger island is characterized with mountainous topography which is known to influence rainfall over the country with windward side receiving more rainfall than the leeward. This explaining why orographic rainfall is the dominant form of precipitation in Fiji (Chattopadhyay and Katzfey 2015). Further, the Pacific Island countries have been identified as particularly vulnerable to climatic change and variability, because of low adaptive capacity of the communities (IPCC 2022).

Rainfall in Fiji Island is highly variable in space and time, influenced by the island's topography, and prevailing Southeast trade winds. The mountains in Viti Levu create wet climatic zone on their windward side and dry climatic zones on their leeward side (Mataki et al. 2006). The position and movement of South Pacific Convergence Zone (SPCZ) influence the seasonal rainfall distribution over Fiji which is the

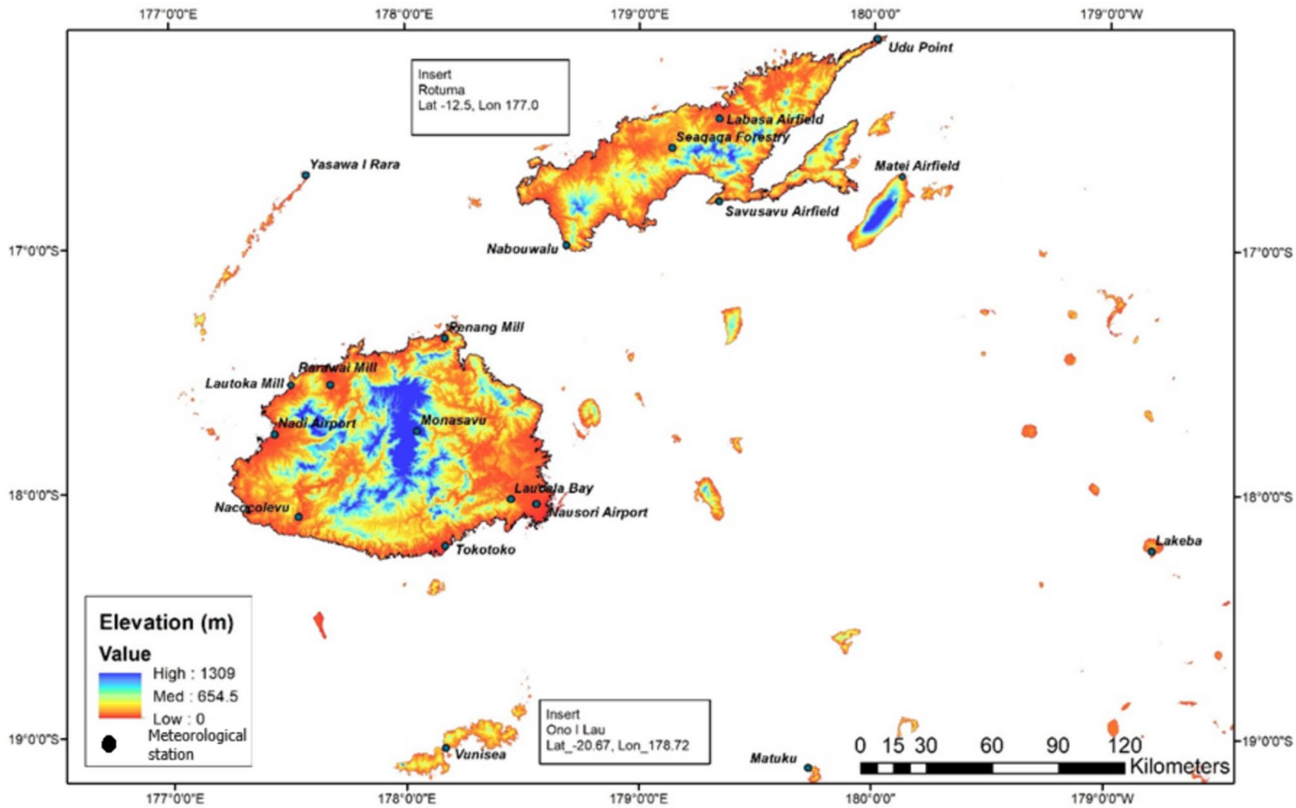

Fig. 1 The elevation map of Fiji showing the location of meteorological stations, Lat and Lon of Rotuma and Ono-i-Lau are shown

main rainfall producing synoptic system over the region (Tigona et al. 2023; Irving et al. 2011). From November to April, the Fiji Islands are also frequented by tropical cyclones originating in the Pacific Ocean, which results in prolonged heavy rainfall and flooding of low-lying coastal areas (Rhee and Yang 2018). The Pacific Ocean also play central roles in the interannual variability of rainfall in Fiji. It is strongly associated with El Niño and La Niña Southern Oscillation (ENSO) (Kumar et al. 2014). The interannual fluctuations in ENSO and longer-term variability from the Interdecadal Pacific Oscillation (IPO), strongly influence moisture availability across the south Pacific region (McGree et al. 2016). La Niña is associated with above normal rainfall while, El Niño is associated with below normal rainfall that adversely affect agriculture and, in turn, causing food shortages (Glantz 2001). On the other hand, ENSO modulate in inter-annual time scale of tropical cyclone activities in the Pacific region, which oscillate between El Niño and La Niña (Chand et al. 2013; Dowdy et al. 2012; Kuleshov et al. 2020; Lin et al. 2020; Zhao and Wang 2019). Therefore, the Pacific region's current and future sustainable socio-economic development will heavily depend on its ability to cope with climate variability and adapt to future climate changes. The country experiences a unimodal rainfall pattern during the austral summer months (November–April). Its mean temperature has low temporal variability, with the difference of 3.61 °C between the warmest month (February) and the coolest month (July) (Ongoma et al. 2021). May–October is considered the cold season, while November–April, during the rainfall season, is considered the hot season.

The cool season is in the months of May–October, while the hot season is the November–April during the rainfall season.

2.2 Data

2.2.1 Weather station data

Daily precipitation data sourced from 21 gauge-based stations in Fiji Islands were used (Fig. 1; Table 1). The data was obtained directly from Fiji Meteorological Service (FMS) for the period of 1970–2020. The stations with high-quality data were selected from a pool of 21 stations. The selected stations had as complete daily records as possible, with most stations having less than 10% of missing data, which is consistent with the findings by Sharma et al. (2021) (Table 1), however, Monasavu and Tokotoko stations had 19.8% and 47.7% missing data respectively and were not used in the evaluation of ERA5 rainfall data. 19 stations were used in this study, their record was as long as possible,

Table 1 List of stations from FMS with their respective location (Fig. 1)

	Station	Lat	Lon	% data availability	Annual rainfall (mm)	Summer rainfall (mm)	Winter rainfall (mm)	% contribution of summer rain	% contribution of winter rain
1	Ono-i-Lau	− 20.67	178.72	89.8	1489.7	936.1	559.4	62.8	37.2
2	Yasawa-i-Rara	− 16.7	177.58	91.5	1554.5	1131.1	426.4	72.8	27.2
3	Nacocolevu	− 18.1	177.54	96.1	1738.6	1232.3	503.6	70.9	29.1
4	Matuku	− 19.13	179.73	89.9	1663.7	1048.9	612	63.2	36.8
5	Nadi Airport	− 17.76	177.44	100.0	1937.7	1502.8	437.1	77.6	22.4
6	Lakeba Airfield	− 18.23	− 178.8	97.4	1898.9	1281	623.5	67.2	32.8
7	Lautoka Mill	− 17.55	177.44	99.0	1970.2	1522.7	447.4	77.3	22.7
8	Savusavu Airfield	− 16.81	179.34	97.7	2160.9	1381.7	774.8	63.9	36.1
9	Labasa Airfield	− 16.47	179.34	98.3	2212.2	1732.6	468.7	78.4	21.6
10	Vunisea	− 19.05	178.17	95.4	2174.2	1425.7	762.2	65	35
11	Penang Mill	− 17.37	178.17	98.7	2298.4	1747.2	550.8	76	24
12	Seaqaqa Forestry	− 16.59	179.14	96.8	2326.1	1829	491.1	78.6	21.4
13	Nabouwalu	− 16.99	178.69	96.6	2404.1	1670.2	731.3	69.6	30.4
14	Udu Point	− 16.14	− 179.99	92.5	2419.5	1681.6	733.6	69.5	30.5
15	Nausori Airport	− 18.05	178.56	99.8	2963.1	1912.5	1059.2	64.3	35.7
16	Laucala Bay	− 18.03	178.45	99.9	3043.8	1919.5	1132.8	63.1	36.9
17	Rotuma	− 12.5	177.05	96.7	3369.5	1868	1493.9	55.4	44.6
18	Rarawai Mill	− 17.56	177.68	97.2	2015.8	1553.1	450.8	77.1	22.9
19	Matei Airfield	− 16.69	− 179.58	93.8	2482.8	1612.9	863.1	65.2	34.8
20	TokoToko	− 18.22	178.17	52.3	3232.8	1897.6	1290.4	59.5	40.5
21	Monasavu	− 17.75	178.05	80.2	4942.3	3249.9	1628.2	66.3	33.7

The Percentage of available data, annual, summer and winter rainfall sum totals and % contribution of the seasonal rainfall to the annual total rainfall

and the station remained open at the time of request. The stations selected were of high quality, well maintained and had documented metadata consisting of a history of site location, observing instruments and practices and the station had not been moved from the original site location, for example the Tokotoko station was moved in 1985 because of land use change and further to the current location in 2003, therefore, it was not used in this study (information from station meta data).

2.2.2 ERA 5 datasets

As one of the high-resolution climate reanalysis datasets, ERA5 has a temporal resolution of hourly for large number of climate variables. The ERA5 is a successor of ERA-Interim, provides dataset from 1950 to the present and about 25 km spatial resolution (Hersbach et al. 2020). The data is generated by the ECMWF and is available to the public through https://cds.climate.copernicus.eu/cdsapp#!/search?type=dataset&keywords=((%20%22Product%20type:%20Reanalysis%22%20))&text=ERA5. In this study, daily ERA5 precipitation data from January 1970 to December 2020 was annually aggregated and used in the evaluation.

2.3 Methods

All the station datasets were subjected to quality checks to remove days with negative rainfall values as well as missing values. The performance of ERA5 precipitation estimates in both magnitude and spatiotemporal characteristics were evaluated against observed precipitation from 19 stations for the period of 1971–2020. The evaluation compares the rain gauge data with the corresponding data from ERA5 interpolated to the same coordinate as the observed, this was to ensure the corresponding data from ERA5 is at the exact locations where observations were made and to ensures spatial consistency in the comparison of the two datasets. The comparison was done by computing selected statistical evaluation metrics namely: the Pearson's correlation coefficient (r) and the mean offset (mean bias) and root mean square error (RMSE) computed using the Eqs. (1), (2) and (3) respectively.

The correlation coefficient reflects the degree of linear correlation between the ERA5 precipitation data and observed precipitation data, this can be calculated by Eq. (1);

$$\textit{Correlation coefficient } (r) = \frac{\sum_{i=1}^{n} (X_{ERA5} - \overline{X_{ERA5}})(X_{obs} - \overline{X_{obs}})}{\sqrt{\sum_{i=1}^{n} (X_{ERA5} - \overline{X_{ERA5}})^2 (X_{obs} - \overline{X_{obs}})^2}} \quad (1)$$

The range of r is − 1 to 1, where 1 describes perfect correlation while and − 1 is perfect inverse correlation.

Bias indicates the size of the deviation of ERA5 from the observed precipitation data. The bias can be calculated by Eq. (2);

$$\text{Mean Bias} = \overline{X_{obs}} - \overline{X_{ERA5}} \quad (2)$$

where the range of deviation is $-\infty$ to $+\infty$ (the closer the deviation is to 0, the more accurate the data is) and bias values greater than 0 indicate overestimation, and less than 0 indicate underestimation.

The RMSE reflects the overall level of error between the ERA5 precipitation data and the observed precipitation data.

$$\text{Root mean square error (RMSE)} = \sqrt{\frac{1}{n}\sum_{i=1}^{n} \left(X_{ERA5} - X_{obs}\right)^2} \quad (3)$$

where X_{ERA5} represents the precipitation data of ERA5, X_{obs} represents the observed precipitation,

The range of RMSE is 0 to ∞, the smaller the value the smaller the overall deviation. The metrics are discussed in detail by Wilks (1995).

The station observed data had missing data, therefore when aggregating the annual totals, because of the missing data we used two different methods. First, the mean was multiplied by number of days per year, second, the sum of the daily dataset calculated as shown in the Eq. (4). The reason for using two different methods of estimating annual totals is that there were missing days in the observed data, and if the missing days are random, then we get a better estimate for annual totals with the former, but if the missing days tend to be from dry periods, we get more accurate results with the latter.

$$x_{tot} = n \times x \ \text{and} x_{total} = \sum\nolimits_{n} x_n \quad (4)$$

where n are the days in a given year.

This study used regression-based empirical statistical downscaling (ESD) to compare the rain gauge data with corresponding data from ERA5 interpolated at the same coordinates of the observation station. To do the comparison for the whole group of stations, we applied common empirical orthogonal functions (Common EOFs). The common EOFs emphasize salient features connected to spatiotemporal covariance structures embedded in large climate data volumes (Benestad et al. 2023). It provides the framework enables the extraction of the most pronounced spatial patterns of coherent variability within the joint dataset and provides a set of weights for each model in terms of the principal components (PCs) which refer to the same set of spatiotemporal patterns of covariance. In other words, common EOFs provide a means for extracting information from large volumes of data (Benestad et al. 2023; Hannachi et al. 2023). We used common EOFs to illustrate how well the ERA5 datasets reproduce the mean annual cycle in terms of spatiotemporal covariance compared to the Observed station data.

The common EOF requires complete data series with no missing values, so the missing data was filled with interpolated data based on the assumption of a fixed spatiotemporal covariance structure. In the ESD: $y = f(X)$ where the properties of $f(.)$ is used for the evaluation as explained by (Benestad et al. 2015). We used the open-source package in R esd, designed for climate and weather data analysis, empirical-statistical downscaling, and visualization. The analysis presented here was carried out using the R package esd, version 1.10.15 (Wilks 1995; Benestad et al. 2008; Benestad et al. 2015), within the R environment, version 4.2.2 (R Core Team 2023).

The spatiotemporal patterns of Common EOFs from different data sources can be compared effectively when the data is standardized onto a common grid and consolidated into a single matrix. Both conventional EOF and common EOFs can be used in diagnostic analyses as well as providing a basis for comparison of the two datasets. The conventional EOFs and the associated principal components (PCs) are model dependent while the common EOF method is a generalized PC analysis that involves combining multiple datasets onto a common grid or spatial domain before performing the EOF analysis. This enables the identification of shared spatial patterns of variability across the datasets, which can be useful for understanding different datasets (Jolliffe 2002; Hannachi et al. 2007; Hannachi 2021). It is possible to combine a number of different data sets through concatenation along the time dimension, and then estimate EOFs for the combined data matrix. Such EOFs are known as common EOFs (Barnett 1999), and were used here to represent the ERA5 data, where the PCs contained information about the different stations and the EOFs described spatial structures common to all. Hence, the assessment of skill involved a comparison between the PCs from the common EOFs.

3 Results and discussion

The observed rainfall data was analysed to establish the completeness of the station dataset or the percentage of the missing data in each station (Table 1). Two stations had more than 10% of the data missing, therefore, they were excluded from further analysis. Figure 2 shows the percentage of valid points for the 19 observing stations used. Fourteen (14) stations had nearly 100% of the valid points.

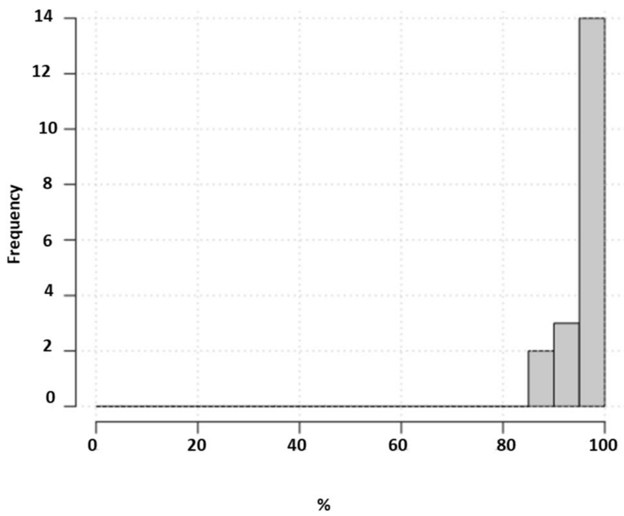

Fig. 2 Percentage of valid data points in the observed stations

Nadi airport station and Laucala bay had less than 0.2% of the data missing (Table 1). The evaluation was important because it enabled us to decide which aggregation method to use for the annual totals in the analysis. The gaps were filled with interpolated data based on the assumption of a fixed spatiotemporal covariance structure; this is provided in the esd r package. This was done to enable the use of common EOFs on the two datasets.

Figure 3 shows the standardized annual rainfall time series for some of the rainfall stations in Fiji. It is evident that rainfall over Fiji Islands is highly variable in time and space. The variability of the annual rainfall, both wet and dry seasons have considerable year-to-year variation, as indicated in Fig. 3. The annual variability is evident in all meteorological stations used. The variability of dry and wet years is clearly seen, with 1987, 1998 and 2015 amongst the driest years, while 1975, 1999, 2012 being the wet years. The driest and wettest year's conditions are strongly associated with El Niño and La Niña phenomenon (Kumar et al. 2006, 2014; Kuleshov et al. 2014). During El Niño event, the SPCZ moves towards northeast resulting in dry season in most part of Fiji Islands. Conversely, during the La Niña the SPCZ tend to move southward, resulting to wet conditions in most part of Fiji (Mataki et al. 2006). In addition, tropical cyclone plays a major role in the inter-annual rainfall variability over Fiji Island, by contributing to the extreme rainfall, especially in the months of January–February–March this is because the peak tropical cyclone activities occurs during these months (Deo et al. 2021; Hannachi et al. 2007).

The annual rainfall cycle indicates that the summer rainfall season starts in the month of November and ends in the month of April, and it's called the wet season (Fig. 4). While May–October is the winter rainfall season, which is known as the dry season in Fiji. The peak rainfall month is between January and April, whereas, July is the driest month for most of the stations (Fig. 4). The wet season accounts for more than 60% of the total annual rainfall in all stations, and less than 40% during the dry season. This implies that most of the stations received their rainfall during the summer season, but Rotuma station receive nearly equal amount of rainfall in both seasons.

Figure 5 shows the spatial variability of rainfall over Fiji Island, with the mean annual rainfall ranging from 1600 to

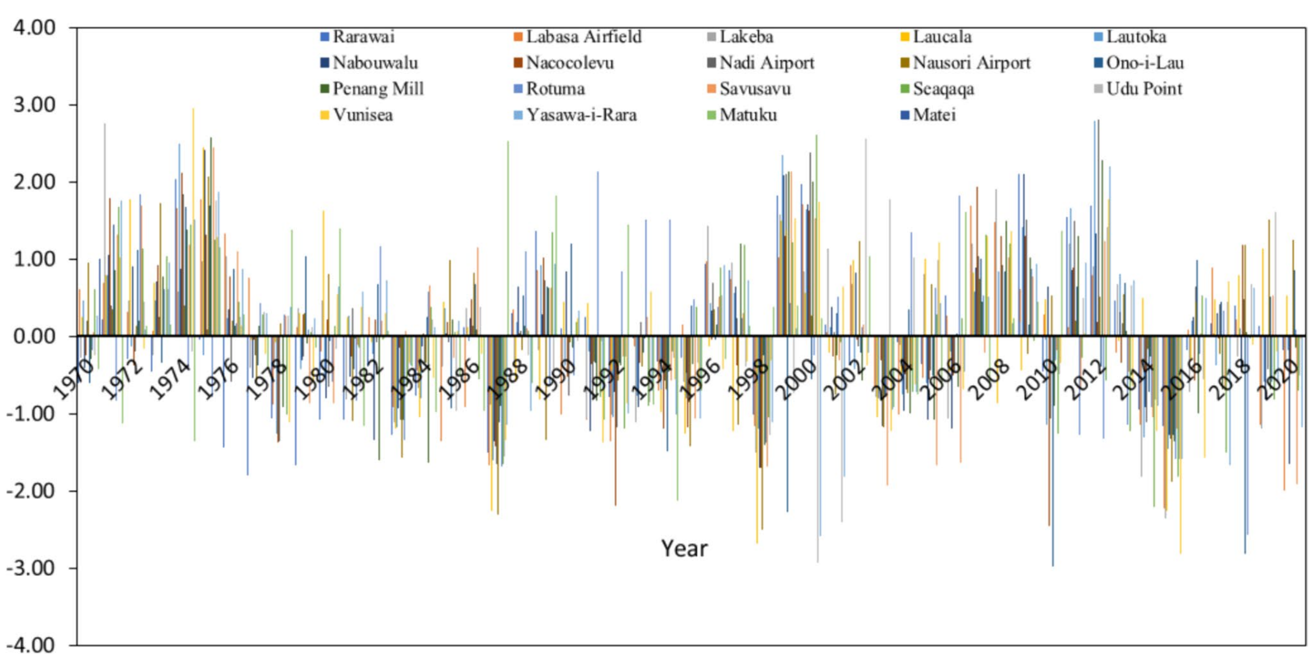

Fig. 3 Standardized annual rainfall over Fiji Island for the period 1971–2020

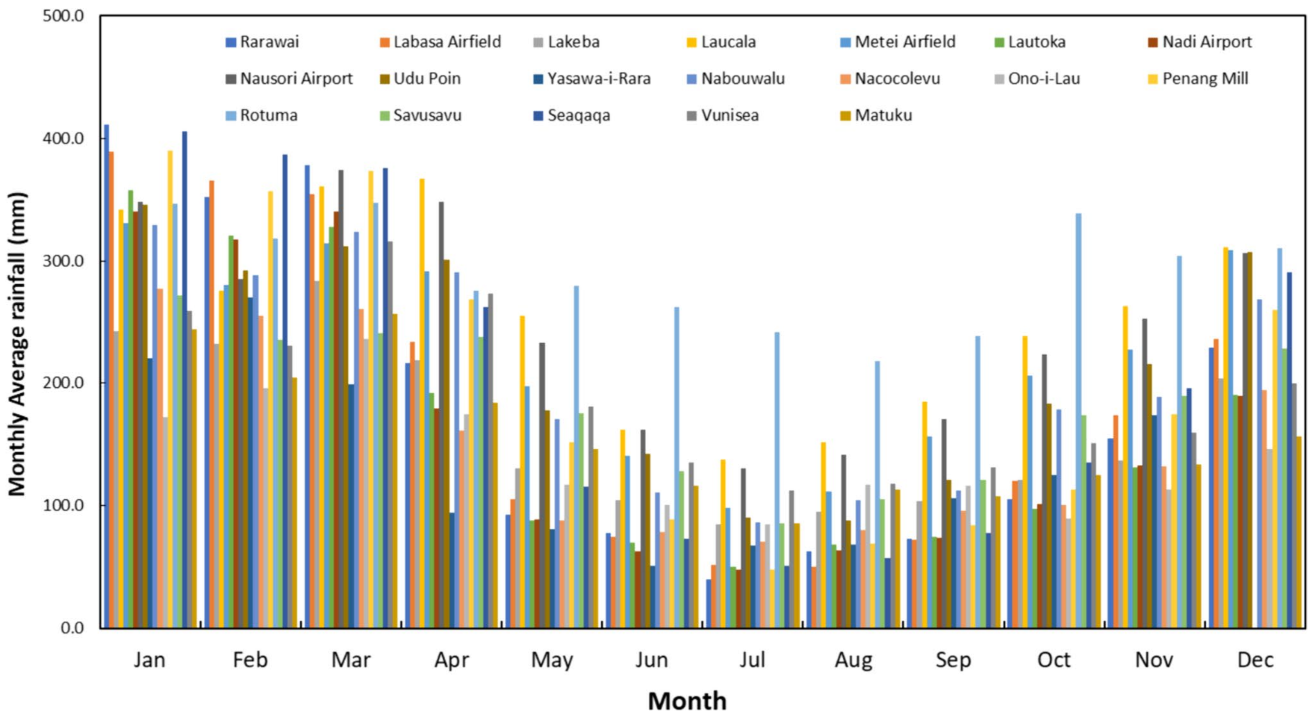

Fig. 4 Mean monthly rainfall over Fiji Island for the period 1971–2020

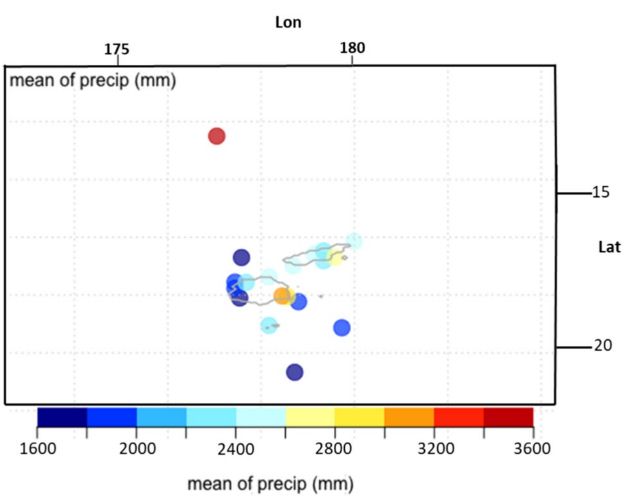

Fig. 5 Special map of Fiji showing the annual mean rainfall for the meteorological stations

3600 mm. Rotuma station records the highest rainfall over Fiji Island. In the two main Island of Fiji (Vanua Levu and Viti Levu), the spatial variability is mainly influenced by the topography, mountainous elevation of up to 1300 m above sea level. This is indicated by high rainfall spatial variability rainfall on the two main Island. For instance, Laucala bay and Nausori station which are located on the wind ward side receive more rainfall than Nadi Airport, Nacocolevu, Lautoka and Rawawai mill stations which are on the leeward side (Fig. 5; Table 1). The topography has a strong influence on rainfall generation during tropical storms and passing trade winds, blowing from the east or south-east directions associated with the Hadley Circulation, bringing moisture onshore (Kuleshov et al. 2014). Resulting in more rainfall in eastern side of Fiji which is the wind side and less rainfall in the leeward on the western side (Terry et al. 2004; Kumar et al. 2014). It is evident from the fact that the yearly rainfall at Nadi (on the leeward side) is only approximately 60% of what is observed at Laucala (on the windward side), that orography has a significant effect in the spatial distribution of rainfall over Viti Levu as compared to the Vanua Levu where low spatial variability between stations (Fig. 5).

Figure 6 shows a time series of annual rainfall for both observed station data and ERA5. The ERA5 captured the interannual variability of rainfall relatively well. The station-by- station comparison shows that interpolated ERA5 annual rainfall matches the corresponding results from rain gauges for many of the stations, however, there are few instances of underestimation and over estimation from the ERA5 datasets. For instance, between 1990 and 1998, ERA5 underestimated rainfall in Nausori Airport, Vunisea and Rotuma stations and overestimated for Yasawa-I-Rara station. The results also suggest that both the annual summed values and that of the product between mean and number of days have very similar estimates, reducing the concern about missing data. This is important because we were able to use any of the aggregated annual totals in the common EOFs analysis

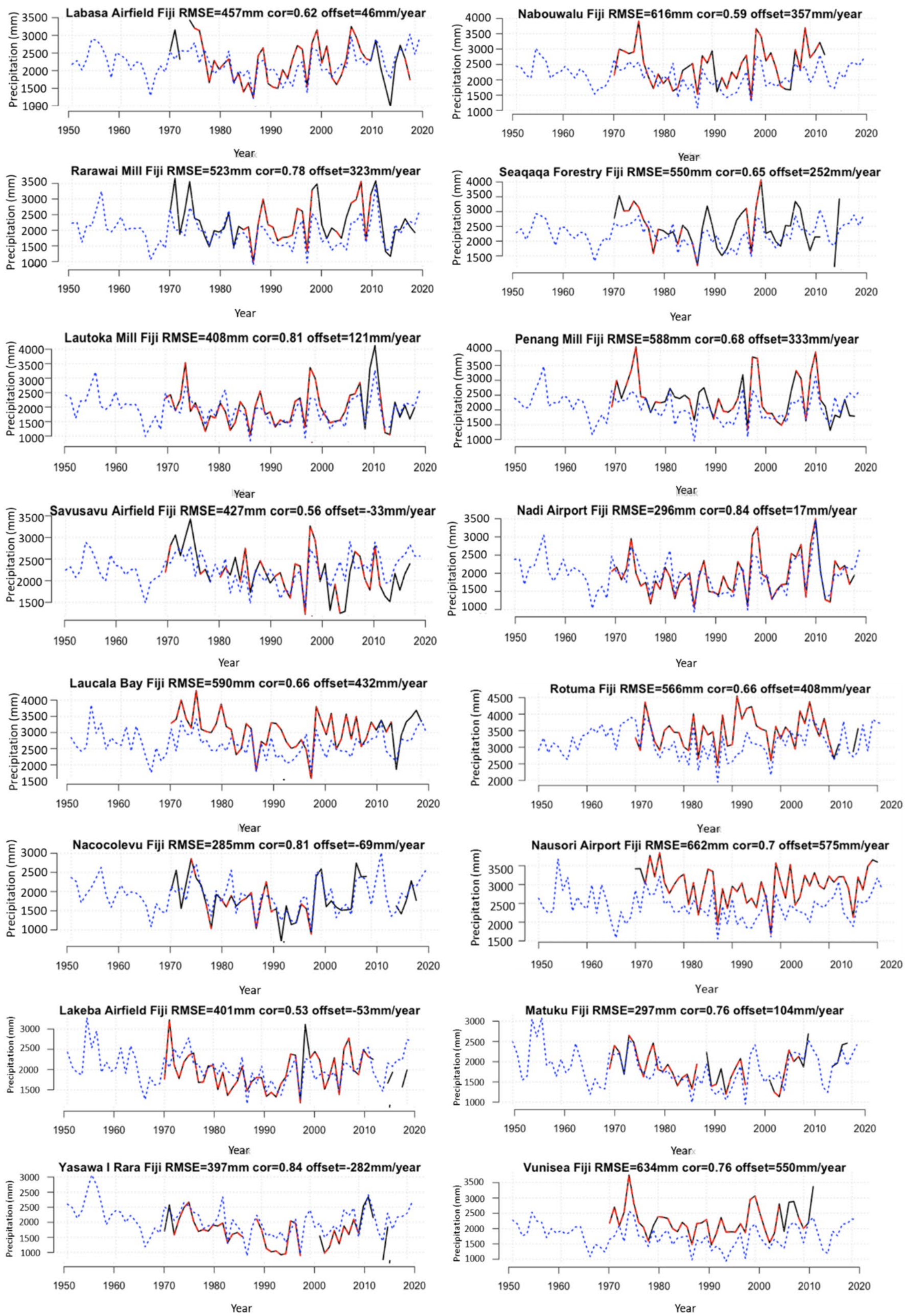

Fig. 6 Comparison of annual rainfall time series derived from station gauge observations and ERA5, where black curves represent annual rainfall based on the product between the mean and the number of days, red dashed are estimates based on the summed values and dashed blue curves represent ERA5 datasets

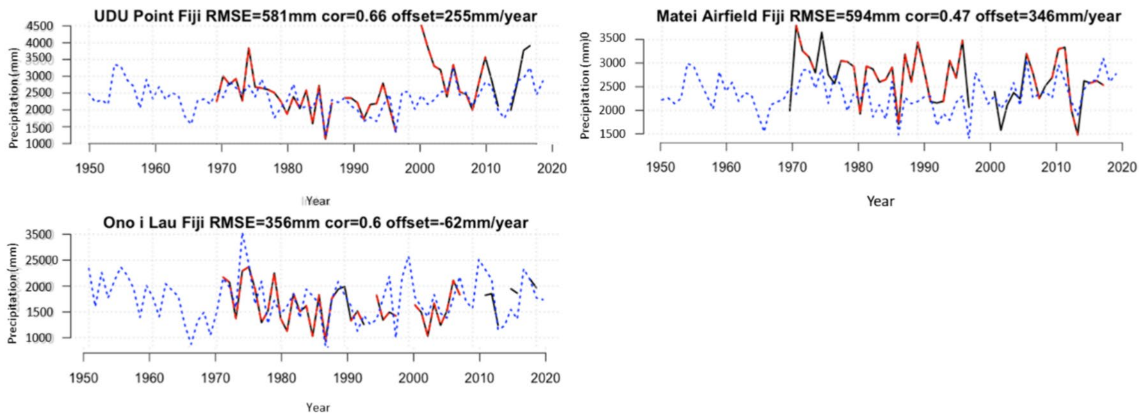

Fig. 6 (continued)

Table 2 Root mean square error (RMSE), correlation coefficient (r) and bias

Station	RMSE (mm)	r	Bias (mm/year)
Ono-i-Lau	356	0.6	− 62
Yasawa-i-Rara	397	0.84	− 282
Nacocolevu	285	0.81	− 69
Matuku	297	0.76	104
Nadi airport	296	0.84	17
Lakeba airfield	401	0.53	− 53
Lautoka mill	408	0.81	121
Savusavu airfield	427	0.56	− 33
Labasa airfield	457	0.62	46
Vunisea	634	0.76	550
Penang mill	588	0.68	333
Seaqaqa forestry	550	0.65	252
Nabouwalu	616	0.59	357
Udu point	581	0.66	255
Nausori airport	662	0.7	575
Laucala bay	590	0.66	432
Rotuma	566	0.66	408
Rarawai mill	523	0.78	323
Matei airfield	594	0.47	346

and got similar results. Despite high temporal rainfall variability in Fiji, ERA5 was able to capture the temporal variability in all the stations analyzed.

Table 2 presents the annual bias, RMSE and r, and the spatial pattern of the RMSE is shown in Fig. 7. The annual rainfall totals for observed and ERA5 are moderately to highly correlated with corresponding r, RSME and bias ranging from; 0.47 to 0.84, 285 to 662, and − 282 to 575 respectively. Most of the stations had high values of r. Nadi, Yasaw-I-Rara, Lautoka and Nacocolevu have high r values and low RMSE. In addition, the RMSE values were lower in stations located in the western division as compared to the stations in the central division. This indicates that ERA5 can adequately determine precipitation in areas that receive low rainfall. For instance, Laucala, and Nausori Airport have higher RMSE than Nadi station which had the lowest RMSE (Table 2). The bias also show the same pattern as RMSE, whereby the wet areas have higher bias as compared to the dry areas of the study area. The low values of RMSE, high r values and the low bias indicate that ERA5 performed well in the study area. Therefore, there is high reliability of the ERA5 rainfall data over the study area. The result of bias analysis also gives an indication of overestimation and underestimation of ERA5 datasets. The High correlation coefficient values indicate that good correlation of ERA5 dataset to station observed data.

The ability of the ERA5 data to accurately represent the spatiotemporal variability of rainfall over Fiji was assessed by applying common EOF analysis to the annual rainfall totals. A large spread would indicate less similarity between the two data sets compared to smaller spread, the results are shown in Figs. 8 and 9. The results indicated that there was a moderate spread, suggesting that the ERA5 dataset was moderately constrained in reproducing the observed data.

Figure 8 presents the leading EOF mode of the annual rainfall for the observed and ERA5 data over Fiji. The spatial map (Fig. 8a) shows the structure of the most dominant covariance pattern of the annual rainfall and the eigenvalues (Fig. 8b) suggest that this mode dominates the annual rainfall behaviour. Both the spatial pattern and eigenvalues were estimated from both ERA5 and observed datasets. In Fig. 8c, show the Principal Component (PC) time series of the annual rainfall totals of the first model (Fig. 8c). Based on the PC time series, it is found that the annual rainfall in Fiji show a strong inter-annual variability. Moreover, it is observed ERA5 data capture the largest positive and negative peaks, corresponding to ENSO years.

The first mode explains 79.5% of the total variance in the annual rainfall (Fig. 8a). The results from the leading

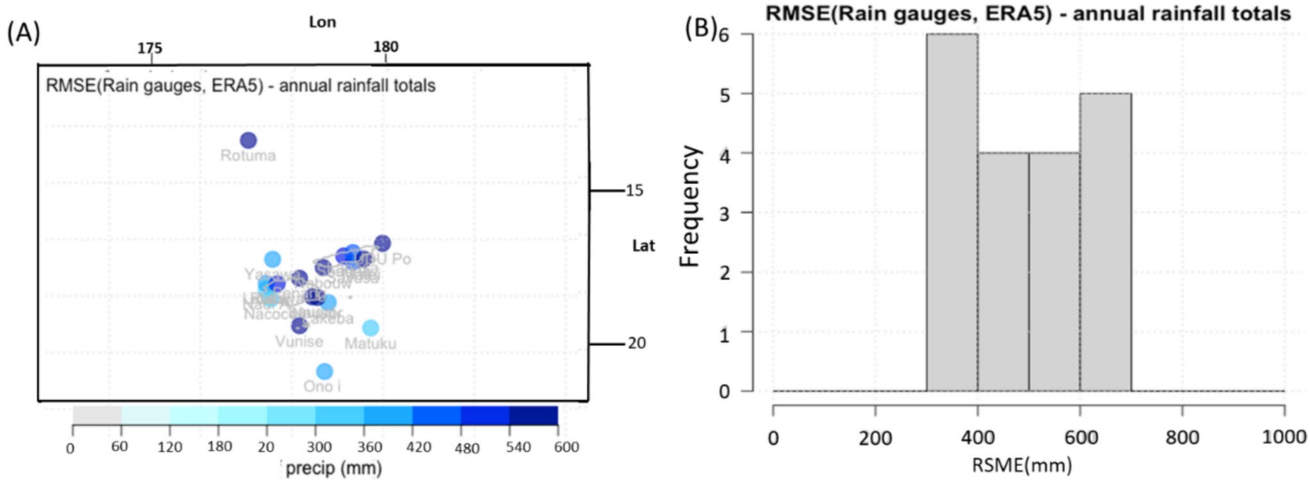

Fig. 7 Distribution of RMSE for annual rainfall for each station, **a** Spatial RMSE. **b** Bar graph of RMSE between Observed and ERA5

EOF, suggest that rainfall in Fiji is variable from one station to the other, suggesting that different mechanism maybe responsible for the spatial variability in the study area (Park et al. 2020). The singular values suggested that this leading mode could account for almost 80% of the variance, which also indicated that the ERA5 spatial covariance structure was like that of the observed. The two leading EOFs could explain 94% of the total variance as explained by the scree plot (Fig. 8b), suggesting that the ERA5 was able to produce spatiotemporal pattern with similar characteristics as those in the observed data (Fig. 8b). The spatial structure associated with the common EOFs indicated that the strongest rainfall variability was in the stations in the western division and there was least rainfall variability at the Rotuma station (Fig. 8a), which is in northwest of Fiji. This explains the high skill of the ERA5 data in representing the observed rainfall pattern in Fiji with all the stations having positive EOF loadings.

The cross validation of the PCA mode 1 (Fig. 9a), Indicate a high score of 0.82 with similar pattern with that of EOF (Fig. 8a). The combination of spatial weights from the multiple regression in the ESD cross-validation exercise reproduced a similar spatial pattern as the leading EOF (Fig. 8a), and a correlation coefficient of 0.82 in the cross-validation indicated a strong link between the two datasets as shown by the time series on Fig. 9d. The observed and reconstructed (ERA5) trends matched well (de-trended data were used for calibration but the trends in ERA5 were included in the reconstruction). Here, only the results for the leading EOF and PCA mode are shown as the higher order patterns were associated with lower proportion of the total covariance. The principal of retention of the EOF modes for further analysis followed the elbow rule in the scree plot as in Fig. 8b. These results are encouraging for using the ERA5 to represent the observed datasets where there are data inadequacies. Generally, based on the evaluation of ERA5 and ground observation, we found out that ERA5 performs well in reproducing the spatiotemporal variability of annual rainfall over Fiji. However, bias exists in reproducing the annual rainfall. The results from the evaluation show a high correlation, low bias and low RMSE between the two datasets. Jiang et al. (2021) in their comparison of ERA5 with gauge-based precipitation datasets found out that ERA5 has relatively high biases in precipitation estimates over areas of high topography variation. However, they also note that the performance of ERA5 in precipitation estimates varies significantly across different sub-regions of mainland China. The study also confirms that the performance of reanalysis datasets could be different in different regions. Hou et al. (2023) evaluated the performance of ERA5 over the desert area in the northern China, found out that the ERA5 has some biases in both annual and seasonal precipitations, similar results were obtained by Ren et al. (2022), who compared the performance of reanalysis datasets in Central Asia, and their results show that ERA5, had higher correlation and high deviation with gauge-based precipitation datasets.

The biases in the ERA5 rainfall data are likely attributed to the significant variation in topography across Fiji, which affects the spatial distribution of rainfall. Additionally, the representation of small islands in the models may have resulted in high biases for stations such as Vunisea, located on low-lying small islands. As shown in the previous work by Gomis-Cebolla et al. (2023), the performance of ERA5 is dependent on the climatic region, precipitation intensity and orography. This also confirms the findings of Smith et al. (2001), which highlighted the uncertainty in model simulations compared to observed data. Other studies have also found the overestimation and underestimation of ERA5 datasets (Hou et al. 2023; Jiang et al. 2021; Nogueira 2020). The spatial and temporal variability of rainfall in Fiji,

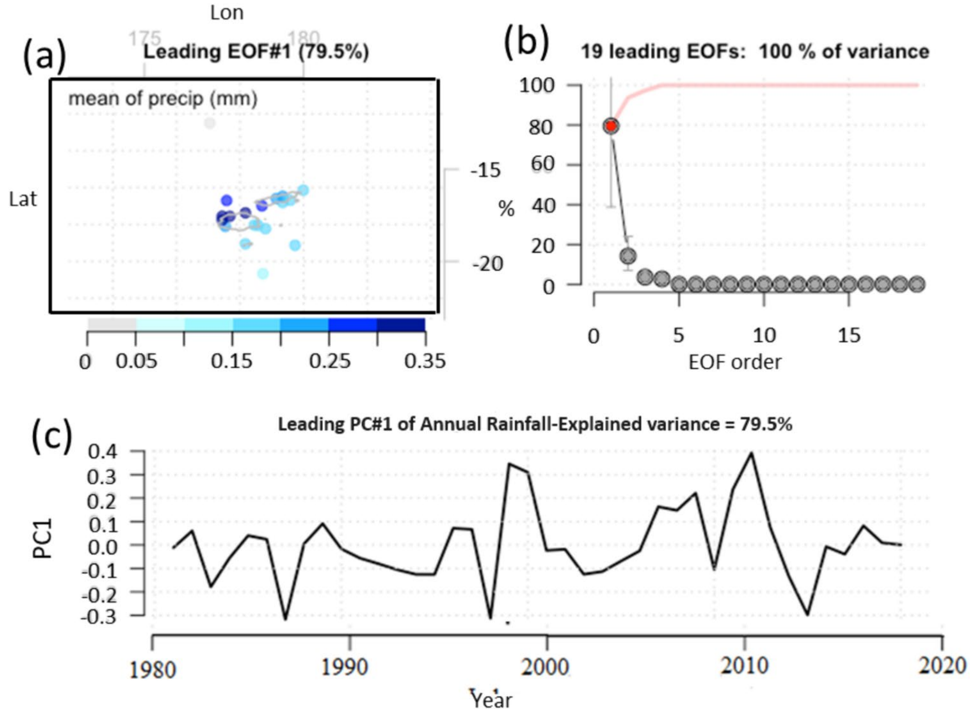

Fig. 8 Common EOFs which represent the Covariance structure of the inter-annual variability in the annual mean rainfall for ERA5 and Observed data. **a** Present the spatial covariance structure of the leading mode, **b** indicate the variance associated with 19 leading modes, and **c** the leading PC

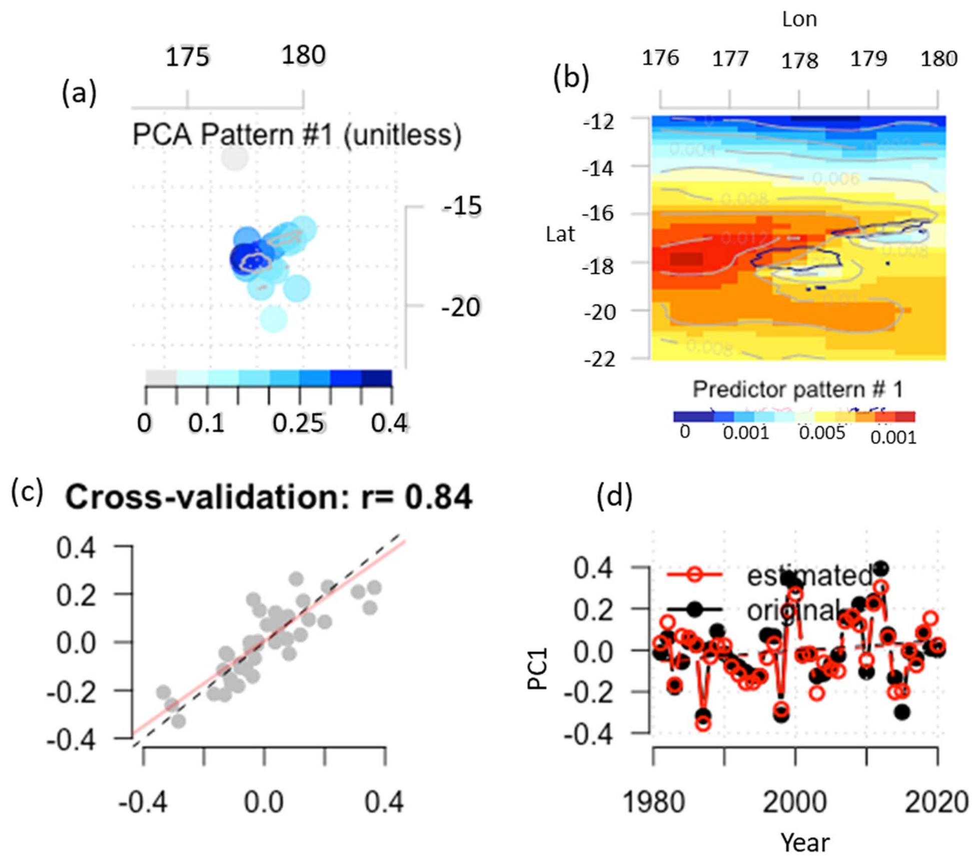

Fig. 9 Results from the ESD downscaling indicated; **a** shows the pattern of the leading EOF estimated for the annual rainfall, **b** shows the anomalies from the ERA5 associated with variations in the leading PC, **c** shows a scatter plot between the Observed data and ERA5 cross-validation, and the **d** shows the observed (original) time series (black) and the ERA5 (estimated) data (red)

is controlled by different factors which include the terrains which has significantly dynamical and thermal impacts on local climate (Ma et al. 2009). Fiji has over 300 small Island, therefore, simulation of the mesoscale convective system in ERA5 data is needed, to reduce the biases. The poor representation of complex topography in the models may lead to uncertainty in precipitation simulation (Zhang et al. 2013). Several studies have indicated that assimilation of more observations in the model may help to reduce the uncertainty of precipitation estimates in the reanalysis products (Zhang et al. 2012).

4 Conclusion

The present study utilized common EOFs method to give a spatiotemporal evaluation of ERA5 rainfall dataset over Fiji. The study finds ERA5 perform well in reproducing the spatiotemporal variability of annual rainfall over Fiji Island, with correlation coefficient of greater than 0.5 and low RMSE for the annual rainfall for most stations and the leading mode of Common EOFs analysis was able to explain more than 75% of the spatial and temporal variance. However, the biases exist with high biases in areas receiving high amount of rainfall, while low biases were observed in areas that receives less than 70% of the annual total rainfall in one season. While this study has provided some initial assessment of ERA5 rainfall data over small island countries with high topography, more work is needed to explore the causes of the biases in the ERA5 data. In addition, this study provided reference for the ERA5 rainfall data for climate simulation and other analysis. It also gives feedback to the global community in fine turning the model parameters to enhance the performance of the ERA5 data for small Island countries with high topography variation. The study identifies a margin of variance between the observed and the ERA5 data to be 20%. The analysis of the merged ERA5 and the gauged stations (Multi-Source Weighted-Ensemble Precipitation) is required to assess whether there are variance in the two datasets.

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Authors contribution Philip Obaigwa Sagero: conceptualization, methodology, software, formal analysis, writing original draft. Arti Pratap collected the data used, developed the study area map, and reviewed the manuscript. Royford Magiri: review and edit the manuscript. Victor Ongoma: review and editing. Philip Okello: reviewed the manuscript.

Data availability The datasets used in this study is available on request to the corresponding author.

Declarations

Conflict of interest The authors declare no competing interests.

Ethics approval Not applicable.

Consent to participate Not applicable.

Consent for publication Consents for publication from all the co-authors are received.

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