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Statistical analysis on variability of Annual Daily Maximum Rainfall of South Australia

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Abstract

Rainfall variability assessment is crucial for effective planning of water resource management in areas with diverse climatic conditions like Australia. The objective of this study is to examine rainfall variability patterns in South Australia (SA) by analyzing Annual Daily Maximum Rainfall (ADMR) and Annual Rainfall (AR) data. Four weather stations were selected: two from the eastern and two from the southern part of SA to consider spatial variation in rainfall distribution. 30 years of rainfall data were acquired from the website of the Australian Government, Bureau of Meteorology. Statistical Package for the Social Sciences (SPSS) software was used to perform Mann-Whitney and Kruskal-Wallis tests because the data were not normal. These tests help to find the spatial variation of rainfall. Kruskal-Wallis tests is suitable for three or more comparison groups whereas Mann-Whitney is suitable for two groups. Besides, the correlation and regression analysis were conducted to establish the relationship between ADMR and AR. It was found that there are similar distributions on ADMR, and variation on AR data of the study area. The annual planning for water resources management may be different in these areas. ADMR can be used to estimate the AR or vice versa as there is a positive and moderate correlation ($AR = 266.236 + 2.716\ ADMR$). The statistical relationship established between daily maximum and total yearly rainfall can be utilized for better planning of water resource management in SA, which considers regional variation.

1. Introduction

In recent years, the sustainable management of water is one of the key issues due to the changing scenario of the availability of water in different stages of the hydrological cycle. One of the major factors for such changes is climate change. It was suggested that the doubts associated with the estimation of climate made the evaluation of climate change impacts more complex, and more uncertainties were reported on the heavy rainfall places, mountains, and coastal areas [1]. Shen et al. [2] also highlighted the importance of a global climate model for the prediction of the impacts of climate change on hydrology. Zhong et al. [3] considered the rainfall variation as an indication of climate change and tried to correlate the changes of rainfall along with other relevant parameters according to the time and places.

Westra et al. [4], evaluated the global ADMR trends and found increasing patterns in nearly 67% of total selected stations with significant relationships between the near-surface temperature and precipitation extremes. Pfleiderer et al. [5] explained that the extremities of temperature and rainfall have triggered devastating events like floods, warms, droughts with more risks associated with summer weather, and these are expected to prolong with the global warming in future. Daneshvar et al. [6] presented the climatic projection of Iran in the coming decades (2.6º increase of average temperature and 35% decline of rainfall) which is the most responsible country for contributing the climate change in the Middle East region. The variability of rainfall can be projected

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in the future in different ways. For example, Sim et al. [7] analyzed the critical daily rainfall, the surface air temperature (SAT) and the dew-point temperature (DPT) for the observed and predicted summer season data of Korea and found the more reliable results on changes of future daily rainfall using variations on SAT and DPT than the direct use of rainfall data.

The reflection of the global impact can be seen in Australia. For instance, it was reported that in the 20th century, the temperature of almost all parts of Australia increased but rainfall had the spatial variation (decreased in the southwest and increased in northeast regions) [8]. Chowdhury et al. [9] also observed the seasonal and spatial variation of the rainfall. They found the increasing patterns of spring and summer rainfalls in most of the area, and the falling trends of winter and autumn rainfall. Their study further showed the increased AR in Mount Lofty Ranges, Arid Lands, Alinytjara Wilinara and Adelaide, decreased AR in Murray Darling Basin, the Eyre Peninsula and Southeast areas, and fluctuating patterns in the Northern and Yorke areas. According to Bureau of Meteorology BOM [10], the low-pressure condition in the Northern Territory (over the top end) created the heavy rainfall, high temperature and extremely high humid condition, and the rainfall of high intensity (short period) affected most of the South Australian part including some parts on northern Western Australia, eastern Western Australia, southern Northern Territory, Victoria, and Melbourne. The prevailing climatic condition may differ with the changing patterns of rainfall. For example, Van Dijk et al. [11] conducted the study to find the causes (man-made and natural) and effects of droughts and highlighted the rainfall depletion scenario in a certain part of Australia. Their study showed the dissemination of meteorological drought which differed from months to a year because of nonlinear responses and cumulative effects over time. They also suggested the handling techniques for the complexity of multi-year droughts in the future using the rainfall based and observation-based remedial methods like remote sensing and models. The climate of Australia is projected to be drier in the future [12][13][14].

The effect of temperature cannot be avoided while taking about the rainfall. Guerreiro et al. [15] conducted the temperature scaling of extreme hourly and daily rainfall data in Australia and found the consistent growing pattern of extreme daily rainfall and the underestimated result of observed variations in case of extreme hourly rainfall. They also suggested the factors affecting the extreme rainfall like alterations on atmospheric circulation and stability, latent heat, movement of moisture, cloud size. Similarly, the variation of rainfall-temperature scaling according to position, temperature and rainfall duration was evaluated, and the negative scaling association was found on Darwin Airport station, while the positive relationship was seen in Adelaide, Canberra, Melbourne, Perth, Brisbane, and Sydney [16]. Barron et al. [17] suggested a considerable impact on water resources (surface and groundwater) in South- Western Australia since 1975 because of drying climate and predicted the effects on the water bodies, indicating the shifting of future dependency more on the groundwater. In this region, the projections of yield and demand for water by 2030 were carried out, and considerable water deficits were expected close to Perth and other regional towns [18]. There will be various socioeconomic effects from such changes. For instance, as a result of high temperature and low rainfall in New South Wales, wheat production decreased [19].

The statistical tests including descriptive analysis, Mann- Whitney, Kruskal- Wallis, correlations and regression have been conducted for numerous analyses for their wide range of acceptability and applicability in the different field of research. [20][21][22][23]. As the climate of Australia is changing [24], and this change has greatly affected rainfall and temperature patterns of the driest state (South Australia-SA) on the driest inhabited continent [25][26], proper assessment of rainfall patterns is essential to develop effective strategies to address climatic variations in regions like SA. However, limited research has explored the relationship between ADMR and annual rainfall (AR) in South Australia, particularly regarding their spatial distribution and mutual predictability, which represents the need of better understanding on regional rainfall patterns.

This study investigates the variability of ADMR of South Australia through SPSS model using the AR and ADMR data. Normality test has been conducted to identify the characteristics of collected data and to select appropriate test method. Descriptive analysis, Mann-Whitney and Kruskal-Wallis tests have been performed as different statistical tests to apprehend the characteristics of variables and to find associations between AR and ADMR across the various rainfall stations of South Australia. The relationship between AR and ADMR was analyzed using correlation and regression methods. This study can help in understanding the variability pattern of rainfall, which is important for planning of climate resilient water resource management and prediction of climate change.

2. Study area

To investigate the variation of rainfall according to the location, weather stations in the eastern and southern parts of SA (two stations from each) were selected in this study. Table 1 and Figure 1 give information about the selected weather stations.

Table 1: Weather stations of the study area

Station name	Station number	Latitude	Longitude	Elevation (m)
Adelaide (Pooraka)	23026	34.83° S	138.61° E	21
Adelaide (Salisbury Bowling Club)	23023	34.77° S	138.64° E	32
Lyrup	24008	34.26° S	140.65° E	22
Berri	24025	34.27° S	140.60° E	50

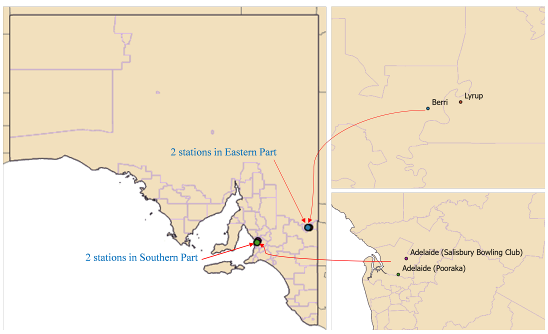

Figure 1: Map of SA showing study area with weather stations, and magnified maps (right side)

3. Methodology

The flowchart shown in Figure 2 summarizes the methodology of this study. With the setting of objective, literature was reviewed and required data of the selected area were collected. For statistical analyses, firstly distribution of data was evaluated and then, appropriate statistical tests were selected based on the distribution patterns of data to observe the variability of AR and ADMR across stations. Brief description of methods adopted have been discussed in the subsections below.

3.1. Data collection

30 years of climate data (ADMR and AR) of the selected stations within the study area were collected from the Australian Government, Bureau of Meteorology [27] as shown in Appendix A.

3.2. SPSS process and test selection

Raw data were subjected to the IBM SPSS 26 model with different commands according to the test's requirement. Before performing the hypothesis testing, the central tendency and variability of the data were observed using the descriptive statistics. For assessing the distribution patterns of the data, the skewness and kurtosis values, Q-Q plots, and normality test results were evaluated. The types of data those govern the appropriateness of statistical tests to measures the association between them are shown in Table 2. Likewise, based on

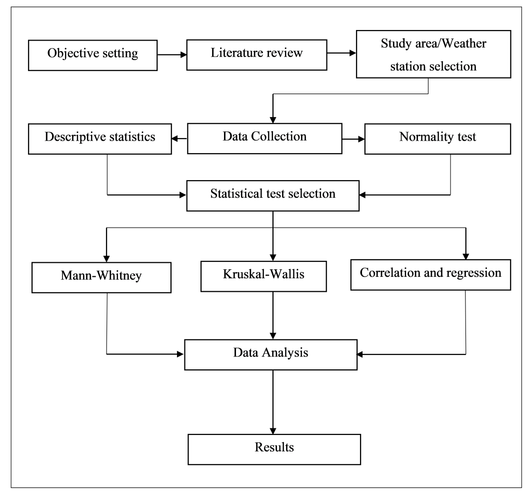

Figure 2: Flow chart of the study

the data type, the suitable hypothesis tests and number of comparison groups are shown in Table 3.

The acquired scale ADMR and AR data were non-parametric. Hence, the non-parametric tests; Mann-Whitney and Kruskal-Wallis were selected for the hypothesis testing in SPSS. To examine spatial variability of AR and ADMR across four distinct stations by Kruskal-Wallis test, data were categorized in four groups according to stations as 1= Adelaide (Pooraka), 2= Adelaide (Salisbury Bowling Club), 3= Lyrup and 4= Berri. In addition, to find the spatial variation across two regions (northern and southern parts) by Mann-Whitney test, stations around Mawson Lakes (Southern part) and Renmark (Eastern part) were re-coded in two categories as 1 and 2 respectively. At the later stage, the relationship between the ADMR and AR was set out by correlation and regression analysis.

3.3. Hypothesis testing

The setting of the hypothesis is the key to any hypothesis test. For Mann-Whitney and Krus-kal-Wallis, the null and alternative hypotheses were set out by tests themselves internally in SPSS along with the decisions

Table 2: Suitability of statistical tests according to data type

Independent variable	Dependent variable	Statistical test
Categorical	Categorical	Chi-square test, Cramer's V and Phi test
Categorical	Scale	t-test, ANOVA, Mann–Whitney, Kruskal–Wallis
Scale	Scale	Correlations, regressions

Table 3: Suitability of statistical tests according to the distribution of scale data

Type of Test	Number of comparison groups	Hypothesis test
Parametric	2	t-test
	3 or more	ANOVA
Non-parametric	2	Mann–Whitney
	3 or more	Kruskal–Wallis

on the null hypothesis with reference to the significance level of 0.05. Following hypotheses were used for this study:

3.3.1. Kruskal-Wallis test

Null hypothesis (H_O): the distribution of ADMR/AR is the same across categories of station.

Alternative hypothesis (H_A): the distribution of ADMR/AR is not the same across categories of station.

3.3.2. Mann-Whitney test

Null hypothesis (H_O): the distribution of ADMR/AR is the same across categories of station location.

Alternative hypothesis (H_A): the distribution of ADMR/AR is not the same across categories of station location.

4. Results and discussion

4.1. Data distribution characteristics

The distribution of data has been evaluated through different tests. Firstly, the outcomes from the descriptive analysis of the ADMR and AR data are presented in Table 4. According to Ahammed et al. [28], the distribution of data could be considered as not normal for the skewness and kurtosis values do not close to 0. Secondly, the normality test results are shown in Table 5. The suitability of the test depends on the size of samples; generally, Shapiro-Wilk is applicable for the sample sizes up to 50. Hence, Kolmogorov-Smirnov test is applicable in this case. In the Kolmogorov-Smirnov (K-S) test, data are considered as not normally distributed, if the significance values are less than 0.05. Finally, on visualizing the Quantile –Quantile (Q-Q) plots in Figures 3 and 4, the AR and ADMR data were found to be apart from the diagonal line. Hence, ADMR and AR data were found to be not normally distributed while assessing the skewness and kurtosis values in Table 4, normality test results in Table 5, and Q-Q plots in Figures 3 and 4. In the next stage, non-parametric tests were performed.

Table 4: Descriptive statistics outcomes

Statistics	AR (mm)	ADMR (mm)
N	120 (Valid)	120 (Valid)
	0 (Missing)	0 (Missing)
Mean	352.30	31.69
Median	350.00	26.90
Mode	274.60[a]	21.20
Std. Deviation	131.27	17.35
Skewness	0.29	1.51
Std. Error of Skewness	0.22	0.22
Kurtosis	−0.45	1.79
Std. Error of Kurtosis	0.44	0.44

[a] Multiple modes exist. The smallest value is shown

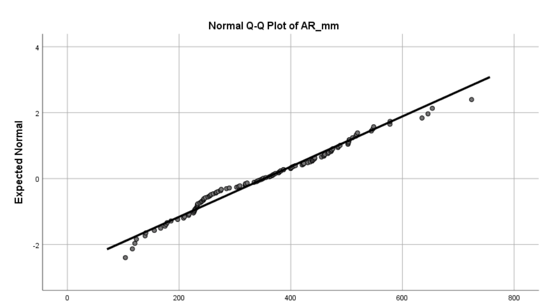

Figure 3: Q-Q plot of AR

Table 5: Normality test outcomes of AR and ADMR

	Tests of Normality					
	Kolmogorov–Smirnov[a]			Shapiro–Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
AR	0.096	120	0.009	0.979	120	0.054
ADMR	0.169	120	0.000	0.839	120	0.000

[a] Lilliefors Significance Correction

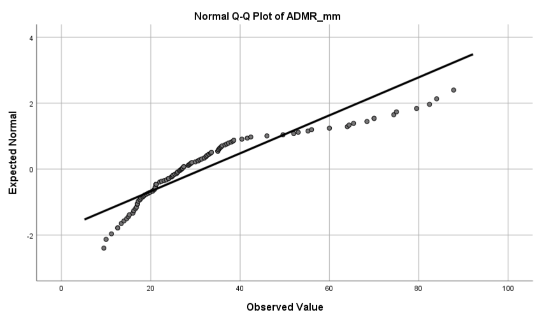

Figure 4: Q-Q plot of ADMR

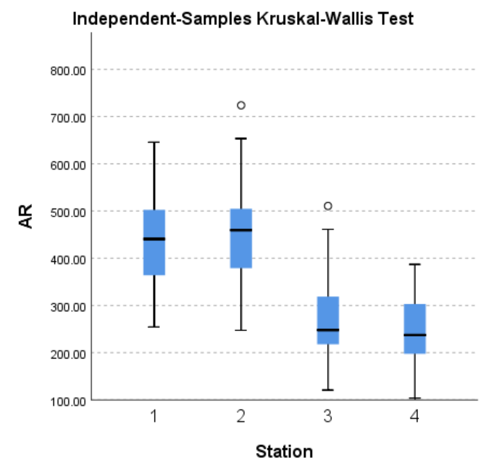

Figure 5: Boxplot of AR

4.2. Kruskal-Wallis H test

Table 6 shows the result of Kruskal-Wallis H test where the null hypothesis along with the decision was given by the test itself. The null hypothesis of AR was rejected and that of ADMR was accepted as per their respective significant values of 0.000 (<0.05) and 0.157 (>0.05). It indicates that ADMR was the same across the four groups (i.e. no statistically significant difference among groups) of weather stations whereas AR was significantly different among these groups.

The box plot of AR (Figure 5) depicts an almost similar distribution of data for stations 1 and 2. However, median values of AR of stations 3 and 4 were similar but significantly less than that of stations 1and 2. Figure 6 shows the boxplot of ADMR for different stations with outliers on each. In the case of ADMR, stations 2 and 3 had higher spreading of data but stations 1, 2 and 3 had almost the same median values which were slightly higher than that of station 4. SPSS showed the pairwise comparison for AR as shown in Figure 7 but did not produce the pairwise comparison to ADMR as the test did not show the considerable differences among the stations for ADMR.

4.3. Mann-Whitney U test

This test also provided the decision on the null hypothesis itself as in Table 7. The null hypothesis of AR was rejected and that of ADMR was accepted as per their respective significant values of 0.000 (<0.05) and 0.076 (>0.05). It reveals that the AR was significantly different across the groups of the station location (one group in eastern and another in the southern part of the SA) whereas the ADMR was the same in these groups (i.e. no statistically significant difference among groups). These differences and similarities of AR and ADMR can be visualised in Figures 8 and 9, respectively. For AR, the mean rank value for group 1 was considerably higher than group 2 which confirmed the significant difference among the groups. However, the mean rank values of ADMR for both groups were at a closer level so that, there was no significant difference among the groups.

4.4. Correlation and regression

As ADMR and AR data were non-parametric scale data, Spearman's rho test was applicable for correlation. The SPSS outcome of correlation is shown in Table 8. The correlation was statistically significant at 0.01 significant level as the significant value was 0.000. The correlation between AR and ADMR was 0.458 in Spearman's rho which indicates the positive and moderate correlation. It is to be noted that for non-normally distributed data, linear regression considers the residuals are normally distributed and exhibit homoscedasticity [29]. As a non-parametric measure, Spearman's rho test provides

Table 6: Testing of hypothesis by Kruskal–Wallis test

Hypothesis Test Summary				
	Null Hypothesis	**Test**	**Sig.**	**Decision**
1	The distribution of AR is the same across categories of Station.	Independent-Samples Kruskal–Wallis Test	.000	Reject the null hypothesis.
2	The distribution of ADMR is the same across categories of Station.	Independent-Samples Kruskal–Wallis Test	.157	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .050.

Table 7: Testing of hypothesis by Mann-Whitney U test

Hypothesis Test Summary				
	Null Hypothesis	**Test**	**Sig.**	**Decision**
1	The distribution of AR is the same across categories of Station.	Independent-Samples Mann-Whitney U Test	.000	Reject the null hypothesis.
2	The distribution of ADMR is the same across categories of Station.	Independent-Samples Mann-Whitney U Test	.076	Retain the null hypothesis.

Asymptotic significances are displayed. The significance level is .050.

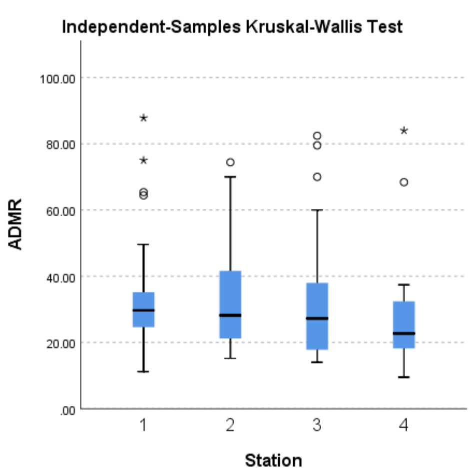

Figure 6: Boxplot of ADMR

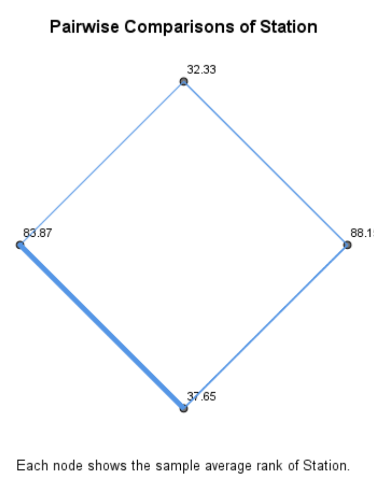

Figure 7: Kruskal-Wallis test result (Pairwise comparison of AR)

the monotonic relationship among variables [30] and hence, this method was followed here. Figure 10 shows the scatter plot of AR and ADMR, where data points were scattered leading to a moderate correlation. The value of Spearman's rho was 0.458 in the range of 0.4 to 0.6 suggested by Dancey et al. [31] to be moderate relationship. The relationship between AR and ADMR can be found either through the regression equation 1 obtained from Table 9 or through the scatter plot in Figure 10.

$$AR = 266.236 + 2.716\,ADMR \tag{1}$$

Table 8: Correlation between AR and ADMR

Correlations				
			AR	**ADMR**
Spearman's rho	AR	Correlation Coefficient	1.000	.458**
		Sig. (2-tailed)		.000
		N	120	120
	ADMR	Correlation Coefficient	.458**	1.000
		Sig. (2-tailed)	.000	
		N	120	120

Correlation is significant at the 0.01 level (2-tailed).

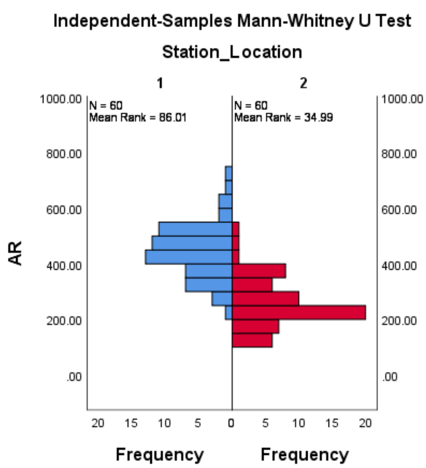

Figure 8: Bar chart of AR for groups of station according to location

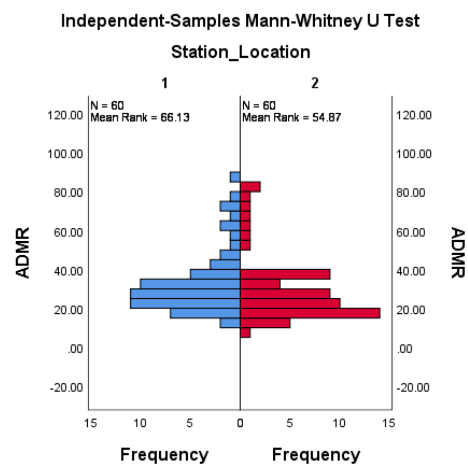

Figure 9: Bar chart of ADMR for groups of station according to location

5. Conclusion

The variability of ADMR data along with AR data was observed by Mann-Whitney and Kruskal-Wallis tests, and their association was performed by correlation and regression analysis. It is found that the location of the weather station has an influence on the distribution of AR and showing the variation in the eastern part and southern part of SA. However, a similar distribution of ADMR was observed around these areas. One of the limitations of this study is that it considers of only four stations (two in each part). Hence, further study has been recommended using more data points from other weather stations. Likewise, future study on variations in other climate parameter such as temperature, relative

Table 9: Outcome of the regression

Coefficients[a]						
		Unstandardized Coefficients		Standardized		
Model		**B**	**Std. Error**	**Beta**	**t**	**Sig.**
1	(Constant)	**266.236**	23.464		11.347	.000
	ADMR	**2.716**	.650	.359	4.178	.000

Dependent Variable: AR

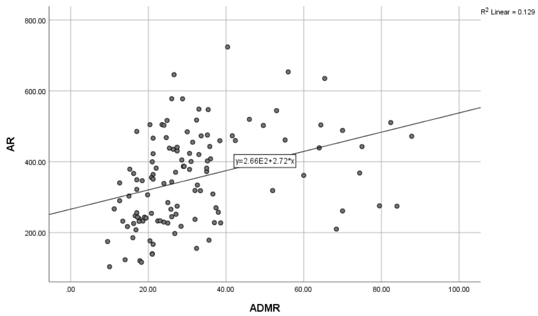

Figure 10: Scatter plot of AR and ADMR

humidity etc. would be recommended for better water resources planning. The positive and moderate correlation was revealed between ADMR and AR. Hence, water resources planning can be performed differently in these areas, and it is possible to predict AR approximately from the known value of ADMR or vice versa using the correlation, $AR = 266.236 + 2.716\ ADMR$. Caution should be applied as the correlation strength was moderate which could affect the prediction accuracy. These statistical concepts explained in this article could be used for assessing the variability of any kind of atmospheric data in any location.

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Appendix A.

Table: Rainfall stations with rainfall data from BOM [27]

Year	Adelaide (Pooraka)		Adelaide		Lyrup		Berri	
	ADMR (mm)	AR (mm)	ADMR (mm)	AR (mm)	ADMR (mm)	AR (mm)	ADMR (mm)	AR (mm)
2019	20.8	254.4	32.0	318.8	17.8	120.8	18.2	116.4
2018	17.0	321.9	17.0	349.0	35.6	178.6	32.4	155.6
2017	26.4	435.0	38.4	459.3	38.0	257.4	37.0	228.2
2016	65.4	635.0	56.0	653.5	30.6	378.4	29.2	387.0
2015	32.6	334.2	26.0	343.0	28.4	217.8	26.8	197.4
2014	87.8	471.9	64.0	439.2	79.5	275.5	84.0	274.6
2013	21.0	399.8	70.0	488.3	18.6	232.6	24.0	229.6
2012	30.6	423.6	27.4	430.5	70.0	261.2	68.4	209.8
2011	31.4	455.0	46.0	519.6	55.2	461.2	33.4	318.2
2010	49.6	502.4	53.0	544.2	82.4	510.6	15.0	303.0
2009	24.8	516.5	23.5	504.7	32.0	237.4	16.0	185.5
2008	12.6	340.3	36.0	408.2	25.0	226.9	9.5	174.8
2007	28.6	405.0	21.2	422.6	27.4	274.6	25.8	265.9
2006	11.2	266.9			20.4	176.8	21.2	167.0
2005	35.4	547.0			21.2	351.0	19.8	306.6
2004	24.6	468.1	20.4	504.7	16.8	208.0	22.4	232.8
2003	33.6	473.1	30.0	484.5	17.0	256.1	23.0	233.5
2002	18.4	346.6	20.8	355.4	14.0	123.5	10.0	103.8
2001	28.8	577.6	26.0	577.9	17.6	239.7	17.6	231.6
2000	32.4	517.6	33.0	548.5	60.0	361.4	35.0	372.6
1999	35.2	475.4	24	503.0	16.2	225.7	19	243.5
1998	33	420.4	41.6	473.2	27.1	251.8	19.4	241.2
1997	75	442.7	74.4	368.1	36.6	308.9	37.4	270.0
1996	64.4	503.8	17	458.5	17.2	243.8	12.6	289.9
1995	31	400.6	15.2	379.0	52	318.6	24	338.6
1994	25	284.8	16.6	247.4	21	140.4	21	139.1
1993	35.8	443	42.4	459.7	27	370.2	22	358.0
1992	26.6	645.7	40.4	723.8	35.2	402.2	35	381.8
1991	21.2	364	16.2	367	38.6	227.4	26	244.8
1990	25.4	438.4	29	387	14.6	217.1	13.4	232.4
1989			27.4	440.9				
1988			21.2	466.5				