Analysis of rainfall variability over temporal and spatial patterns: A case study in Adelaide, South Australia

Hoan To[1,2], Linh Doan[1], and Faisal Ahammed[1]

[1] Sustainable Infrastructure and Resource Management (SIRM), UniSA STEM, University of South Australia, Mawson Lakes, SA 5095, Australia

[2] Southern Institute of Water Resources Research, Ho Chi Minh City, Vietnam

Correspondence: toydy004@mymail.unisa.edu.au; ORCID: 0009-0009-4417-2078

Abstract: Climate change has significantly impacted weather patterns worldwide, including in Australia. Numerous studies have investigated the changing meteorological data across the country, underscoring the need for a deeper understanding of these patterns. This study aims to explore the variability of rainfall over time and terrain in Adelaide, South Australia. The annual daily maximum rainfall (ADMR) data over a 40-year period (1981-2018) in four stations was collected to identify the distribution of rainfall data across the time recorded. Moreover, the ADMR data in 2018 and elevation data across 86 stations were used to investigate the changing rainfall patterns over the terrain. Two non-parametric tests including Kruskal–Wallis, and Mann–Whitney were applied to perform the hypothesis analysis. Correlations, regression, and multivariate tests were performed to identify the relationship between variables. It was found that the ADMR data in four stations did not vary over the 40-year period from 1981 in Adelaide. However, there was a strong correlation between the extreme rainfall data in the year 2018 and elevation data in these stations. Results also suggested that it is relatively possible to use the elevation data to predict ADMR across Adelaide in certain years. Policymakers and researchers can use these tests for climate projections and extreme rainfall forecasts.

Keywords: Rainfall, Kruskal–Wallis, Mann–Whitney, correlation, regression, Adelaide.

1. Introduction

Climate change has been one of the most major concerns in recent years. Many scientists suggest that extreme weather conditions might occur more frequently as the consequences of climate change [1]. Among contributing factors, rising global temperatures were found to be the most significant driver for the increase in the likelihood of climate-related phenomena such as wildfires [2], and severe droughts [3]. Scientists also provide evidence of these disasters related to the fields of meteorology, climatology, and hydrology in which precipitation presents a vital connection with governing moisture content in the hydrological cycle [4]. Many studies have shown that global warming may lead to more droughts due to decreased precipitation and increased evaporation in the 21st century [3,5]. For instance, under the climate change impacts, the precipitation level was predicted to decrease by mid-century in Ireland [6]. Precipitation deficits are also known as an initial condition to triggers droughts to occur; meteorological droughts progress over time to affect soil moisture, runoff, streamflow, and finally socioeconomic aspects [4]. Meanwhile, the extreme rainfall events that are bound to happen more frequently and intensely might partly be due to climate change and global warming [7]. A recent review showed that there was a significant increase in the total volume of rainfall in the rainy season during the last seven decades in Brazil [7]. Apart from that, a similar trend was found in southwest Taiwan where the extreme rainfall intensity and frequency has continuously increased and become unpredictable during the study period 1960-2017 [8]. In Southeastern Australia, a review of climate variability by Murphy & Timbal [9] indicated that a decreasing trend of rainfall was seen due to the effects of the El Nino-Southern Oscillation, highlighting the significant impacts of climate change.

Few recent studies were carried out to investigate the rainfall trends over time in South Australia. Statistics showed that Adelaide experienced prolonged wet periods in the 1850s and 1920s with the wettest year occurring during 1992 due to a very wet austral spring [10]. This study found that the wettest Adelaide day was recorded on 6 February 1925 when 145.5 mm of rainfall was recorded, well-known as a Tropical Downpour in Adelaide. Several previous studies have identified rainfall characteristics, variability, and trends in South Australia. For instance, Chambers [11] found that the coastal regions in the southeast experienced an increase in rainfall over time while a decreasing trend was observed in the inland eastern regions in South Australia in the period of 1900s to 2000s. Chowdhury & Beecham [12] found one station in Adelaide showing an increasing trend of monthly rainfall depth based on its relation to the southern oscillation index (SOI). Having said that, little is known about the recent trends and variability of rainfall in South Australia. Recent studies in Australia showed that they might be likely to stay uncertain. For example, the monthly rainfall in South Australia over the past 100 years was observed not having any consistent tendency or any changes in the seasonal patterns [13]. Recently, a notable trend of decreasing mean rainfall was seen in southwest and southeast Australia while an increase was observed in northwest Australia since the 1950s [14]. In addition, the rainfall variability in South Australia might be affected by seasonal climate factors. It was reported that the most robust decrease in rainfall was found in the winter while it was not particularly true for the other seasons, especially in the summer [15].

Although the question of the relationship between rainfall and spatial patterns remains, several studies in the past have revealed promising results. A study was conducted by Gergis & Ashcroft [16] in eastern New South Wales (NSW) over the 1788-2008 period to identify the relationship between droughts and wet years and El Nino–Southern Oscillation (ENSO). It was found that the relationship between the El Nino phenomenon and the rainfall in the coastal area is much stronger than that in the inland eastern NSW area, indicating that the rainfall can be significantly influenced by the location and climate conditions in Australia [16]. Some scientists suggested that there were upward and downward trends in the rainfall data observed in the regions across South Australia. Chowdhury et al. [17], for example, researched the trends and step changes in different locations in South Australia. Results showed that locations including Adelaide, Arid Lands, Alinytjara Wilinara, and Mount Lofty Ranges regions experienced increasing annual rainfall trends over the period of 100 years whereas decreasing trends were found in the rainfall data in Murray Darling Basin, Eyre Peninsula Southeast regions. Earlier, the study conducted by Chambers [11] discovered that both mean and median rainfall tended to increase from the north to the south in the state of South Australia for the study period in the 20th century. The summer rainfall dominated the winter rainfall in the northern stations while the opposite was true in the southern stations [11]. In addition, a recent study based on a spatial model for daily rainfall in South Australia indicated that there was a strong association between rainfall and climatic indicators related to spatial factors [18]. Although a relationship between rainfall and spatial patterns might exist in several locations across South Australia, a large uncertainty occurs. For instance, Ye & Ahammed [19] found that the factor of distance from the stations to the sea was proved to have an insignificant influence on the temperature and rainfall in South Australia though these data did vary according to station locations.

To identify the relationship between climate data, several statistical hypothesis tests were normally used [19]. The purpose of hypothesis testing is to see whether an assumption or observation is true to describe the sample and population [20]. In other words, hypothesis testing determines how likely it is that the difference would be seen between two (or more) groups by chance alone if the null hypothesis were true [21]. Which, four hypothesis tests are commonly in use, namely t-test, ANOVA, Mann-Whitney, and Kruskal-Wallis [19]. T-test is a type of statistical test used to compare the means of two groups [21]. Researchers suggest that the T-test requires the scale data to be normally distributed [19]; hence, it is a type of parametric test [22]. Likewise, ANOVA is also a parametric method and is used to determine differences among the means of three or more input groups [20]. On the other hand, Mann–Whitney and Kruskal–Wallis tests are well-known as non-parametric statistical tests [19]. Mann-Whitney U test is a test that assesses the differences between two groups on a single with no specific distribution [23]. The Mann-Whitney U test is rather similar to the t-test for identifying whether two sample groups are from a single population; hence, the Mann-Whitney U test is regarded as the non-parametric version of the t-test [24]. Kruskal–Wallis test is known as a test of three or more independently sampled groups on a single and the non-parametric version of ANOVA [24-25]. Although it is claimed to be suitable for non-normally distributed data, there is no specific requirement of the distribution of data for analyzing hypotheses by using this test [24].

There were several applications of these statistical tests in research. Ahammed & Smith [26], for instance, investigated the association between learning online engagement and academic achievement for students at the University of South Australia by using non-parametric Mann–Whitney and Kruskal–Wallis tests. They found that the distribution of student activities on course sites across several categories namely genders, grades, and origin of students showed almost no difference [26]. In terms of applications of statistical tests in the environment and climate field, Ye & Ahammed [19] used Mann-Whiney, Krukal-Wallis, and Correlations tests to determine the relationship between annual daily maximum temperature and annual daily maximum rainfall in South Australia. They suggested that temperatures and rainfall in South Australia varied according to the distance to the sea. The correlation test measures the relation strength of the relationship between variables [20]. The most important fact is that correlation does not determine causation, meaning that each variable does not cause the other [27]. Furthermore, some research used linear regression analysis to predict a phenomenon based on contributing factors. He, Shirowzhan & Pettit [28], for instance, used regression analysis to explore how meteorological factors (temperature, precipitation, wind speed) and natural factors (slope, soil moisture, vegetation, NDVI) influence bushfires in NSW Australia while spatial correlation analysis was applied to support to create a wildfire susceptibility map in Sydney by sixteen wildfire-related factors [29]. In addition, Bayesian Generalized Least Squares Regression (BGLSR), another method, was applied to construct a regression equation to predict rainfall data at ungauged stations in Australia [30]. Since the number of applications of using a statistical test for analyzing rainfall data in the City of Adelaide remains confined, this study might be helpful for further research in the study area in the future.

This paper is a case study of the City of Adelaide to investigate the association between rainfall data and other factors including time and elevation. The Kruskjal-Wallis and Mann-Whitney tests were performed for hypothesis testing. The first objective of the research is to identify the variability of the extreme rainfall data over the recorded time in the City of Adelaide. In addition, it is aimed to observe how the rainfall data vary over the space by using the terrain data. The annual daily maximum rainfall (ADMR) data in four stations was collected over a 40-year period to identify the relationship between ADMR and time data. Furthermore, the ADMR in the year 2018 and elevation data across 86 stations were collected to determine how the rainfall data vary spatially. By understanding the variability of rainfall data, policymakers and researchers can use the results for climate projections and extreme rainfall predictions in any location across Adelaide.

2. Study area and data

2.1 Study area

The study area is the City of Adelaide with its centroid coordinates of -34.94° South, 138.73° East. Having an area of 3.260 km^2, Adelaide is the capital and largest city in the State of South Australia (SA), Australia. It is the fifth-most populous city in Australia with a population of more than 1.3 million people [31]. Being a coastal city situated in southeast Australia, Adelaide has a Mediterranean climate with hot dry summers and mild winters [32]. The hottest months fall into January and February with the average daily maximum temperature of 29° C compared to about 15° C in the winter months [32].

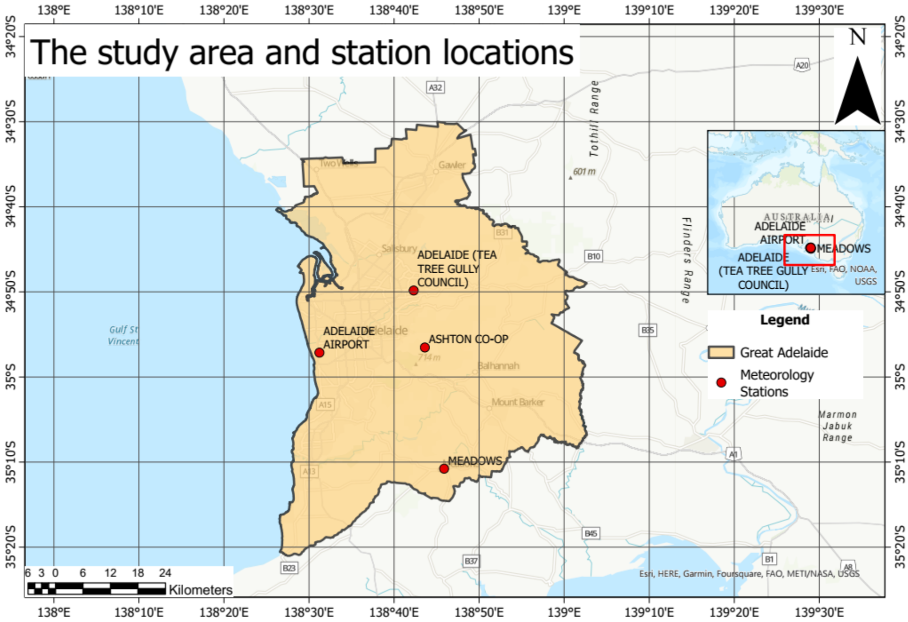


Figure 1. *The study area*

2.2 Data

The Annual Daily Maximum Rainfall (ADMR) data over a 40-year period (1981-2018) in four stations – Adelaide Airport, Tea Tree Gully Council, Ashton Co-op, and Meadows - was collected to use as the SPSS input data to investigate the variability of rainfall data over time. Four random stations from different elevation ranges (from 2m to over 500m) and locations (1 station near the sea, 3 stations on land) were chosen as shown in Figure 1. In this research, the ADMR data was collected from the Australian Bureau of Meteorology (BOM) website. The detail of data collection is shown in Table 1.

Meanwhile, the Annual Daily Maximum Rainfall data in one chosen year and elevation data in 86 stations out of 269 stations across the study area were collected to investigate the changing rainfall patterns over the terrain. In this study, the ADMR_2018 data of the year 2018 was chosen since this year had the most up-to-date data; and it was recorded with many stations. The elevation data was derived from the 3-second SRTM Derived Digital Elevation Model (DEM) Version 1.0. The 3-second DEM was produced for use by the government and the public under Creative Commons attribution. The elevation value in each station was derived by the GIS applications in ArcGIS. The detail of the data is shown in Table 2, and Figure 2. The collected ADMR and elevation data are in the scale measurement.

Table 1. *The details of the ADMR data and stations over the 40-year period*

Weather station name	Adelaide airport	Adelaide (Tea tree gully council)	Meadows	Ashton Co-op
Station number	23034	23748	23730	23803
Data	ADMR	ADMR	ADMR	ADMR
Elevation (m)	2.0	145.0	358.0	553.0
Recorded time	1981-2018	1981-2018	1981-2018	1981-2018
Coordinates	-34.94 S, 138.53 E	-34.83 S, 138.70 E	-35.18 S, 138.76 E	-34.94 S, 138.73 E

Table 2. *The details of ADMR data and elevation data across Adelaide in 2018*

Data	**ADMR_2018 (mm)**	**Elevation (m)**
Year of interest	2018	-
The number of stations	86	86

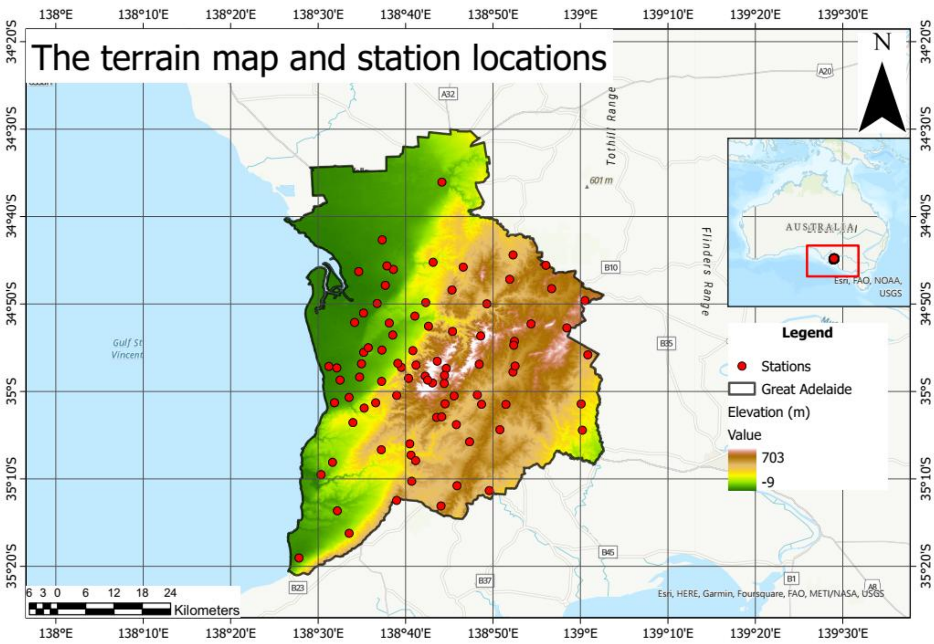


Figure 2. The terrain data and location of 86 stations across the study area.

3. Methodology

In this study, several statistical tests were performed in the software SPSS. A flowchart of the methodology is provided in Figure 3. Before performing the hypothesis tests to identify the variability of the data, the descriptive and normality tests were prepared. In which, descriptive analytics is the first step of data analysis. It gives information about the summary of historical data, and it shows whether additional data is needed for predictive modelling [20]. Afterwards, the normality test was performed. Testing the normality of data is a prerequisite in the hypothesis testing procedure [20]. Its result identifies whether the data is non-parametric or parametric, which provides an indication to choose the suitable type of hypothesis test. For testing the distribution patterns of the data, the number of samples in the population determines which tests can be used. Specifically, the Shapiro-Wilk is used to interpret the result for the population having a small number of samples (<50 samples), while the Kolmogorov–Smirnov test is used for large sample sizes (> 50 samples) [33].

The next step in analysing data is performing statistical hypothesis tests. A hypothesis test is a statistical test that allows researchers to use sample data to evaluate a hypothesis about a population [34]. Depending on the distribution pattern and the number of variables, several hypothesis tests such as t-test, ANOVA, Man-Whitney, and Kruskal-Wallis are valid in use as shown in Table 4. As discussed, while t-test and ANOVA are parametric tests, the Man-Whitney and Kruskal-Wallis tests are used for non-parametric data or the normality unsure [19]. In addition, the t-test and Mann-Whitney can be used for two samples or two variables, whereas ANOVA and Kruskal-Wallis require the data to have a number of comparison groups of 3 or more [20, 22, 33, 34]. In this study, two groups of ADMR data corresponding to two different periods were used to identify the relationship between rainfall data over time. Meanwhile, the ADMR data was also divided into 3 groups or more based on elevation level to investigate the variability of rainfall data over the terrain.

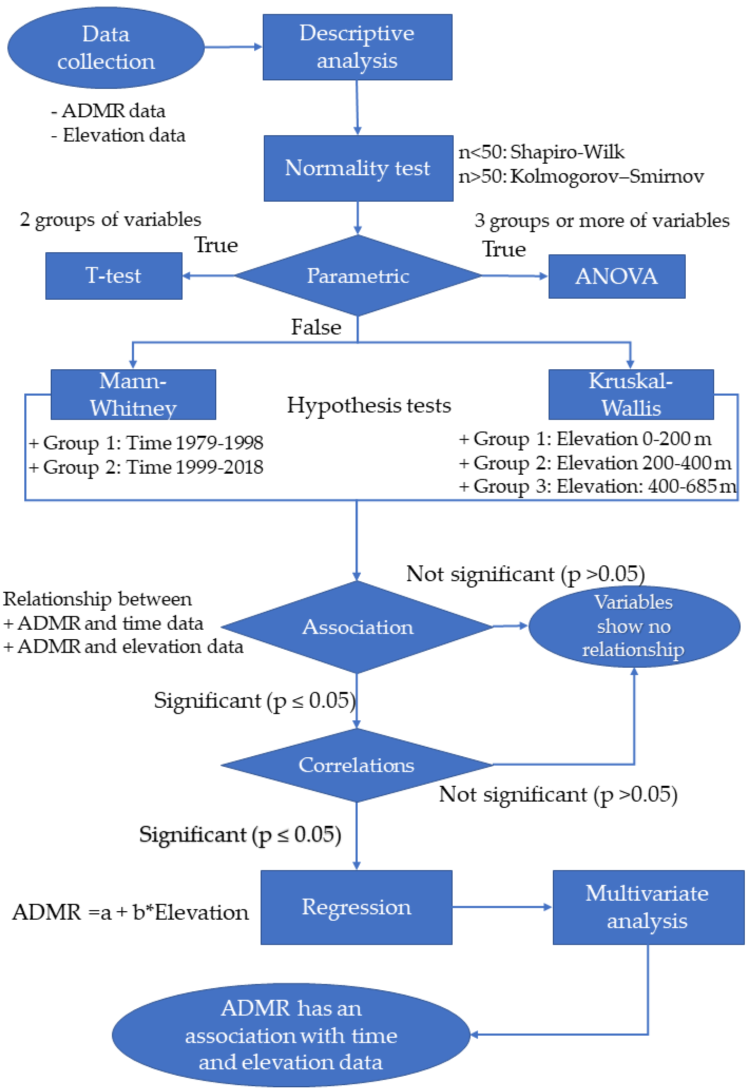


Figure 3. *Flow chart of the methodology*

After the hypothesis tests (Mann-Whitney and Kruskal-Wallis), the relationship or association between dependent and independent variables can be identified. If the association between variables is not statistically significant, it is impossible to identify the significant correlations between them. As such, the testing process can be terminated. Otherwise, the correlation test can be performed to ensure that the assumption is correct. The correlation test was developed to detect the presence of a mathematical relation between two or more variables [35]. If the correlation between them is not statistically significant, the procedure will be stopped; and the decision will be made. On the other hand, if there is a statistically significant correlation between variables, the Regression test will be performed. The result of regression is an equation employing the correlation coefficient to predict one variable from one another [36]. It is clear that the accuracy of the prediction depends on the magnitude of the correlation coefficient [36]; hence, Regression is also a platform to reconfirm the significance level of the test. Finally, the multivariate analysis was performed. It is a technique that investigates the relationship between two or more independent variables and a single dependent variable [20]. The purpose of this test is to confirm the consistency in the results from previous tests. After this test, the final decision will be made.

4. Selection of statistical tests

The Statistical Package for the Social Sciences (SPSS), version 28.0 was used to perform the data analysis. Table 3 and Table 4 show the hypothesis tests and their data requirements. The Chi-square, Cramer's V, and Phi tests need both independent and dependent data in categorical scales [19-20]. The Mann-Whitney, Kruskal-Wallis, t-test, and ANOVA tests require dependent variables in scale measurement and independent variables to be categorical data such as groups [20]. Correlation and regression, on the other hand, use both variables to be in numeric (scale) data [20].

Depending on the nature of the investigation, there is a wide range of statistics. However, the result of any statistical test is a P value [37]. According to Whitley & Ball [37], the 'P' stands for probability, meaning that it measures how likely it is that any observed difference between groups is due to change. As a probability, P can take any value between 0 and 1 [37]. The closer value to 0, the more unlikely the observed differences is due to chance; meanwhile, a P value close to 1 indicates there is no difference between groups [37]. In a hypothesis test, the p-value is the smallest level that is to reject the null hypothesis [20]. While three conventional levels of significance are normally in use such as $P \leq 0.05$; $P \leq 0.01$; and $P \leq 0.001$ [36]. McCarthy et al. [20] claimed that it is usually set to 5% or 0.05. Hence, the value of 0.05 was used in this research. If the p-value is smaller than 0.05, the null hypothesis is rejected [20].

Table 3. *Hypothesis tests for different data types*

Independent variable (data)	Dependent variable (data)	Hypothesis tests
Categorical	Categorical	Chi-square, Cramer's V and Phi
Categorical	Scale	t-test, Mann-Whitney, ANOVA, Kruskal-Wallis
Scale	Scale	Correlation, regression

Table 4. *Dataset requirements for hypothesis tests*

Type of test	No. of comparison groups	Hypothesis test
Parametric	2	t-test
	3 or more	ANOVA
Non-parametric	2	Mann- Whitney
	3 or more	Kruskal-Wallis

It was shown from the normality test results that the ADMR, ADMR_2018, and Elevation data were not normally distributed. Since the t-test and ANOVA require the parametric data, they were both invalid for hypothesis testing. Therefore, the Mann-Whitney and Kruskal-Wallis tests were chosen for checking hypotheses.

Subsequently, the hypothesis dataset was prepared. As mentioned above, the Mann-Whitney was used to identify the relationship between ADMR data over time. The ADMR data from 1979 to 1998 was recoded as Group 1, and data from 1999 to 2018 was recoded as Group 2. Meanwhile, based on the elevation levels of stations, there are two Kruskal-Wallis tests prepared to identify the association between rainfall data and elevation groups. In the first Kruskal-Wallis test, the 40-year ADMR data was categorized as 1= Station 23034/ Elevation: 2m; 2 = Station 23748/ Elevation: 145 m; 3 = Station 23730/Elevation: 358 m; 4= Station 23803/ Elevation: 553 m. For the second Kruskal-Wallis test, the ADMR_2018 data was categorized as 1= Elevation: 0-200 m, 2= Elevation: 200-400 m, 3= Elevation: 400-685 m. Elevation ranges were chosen and based on increasing values which helps determine how the distribution of rainfall data changes in different ranges of elevation. The detailed group information can be found in Table 5.

Table 5. *The groups for hypothesis test*

Test	Dependent variables (Data)	Independent variables (Groups)	Description
Mann–Whitney	40-year ADMR data	Group 1 Group 2	Time: 1979-1998 Time: 1999-2018
Kruskal-Wallis	40-year ADMR data	Group 1 Group 2 Group 3 Group 4	Station 23034/ Elevation: 2 m Station 23748/ Elevation: 145 m Station 23730/ Elevation: 358 m Station 23803/ Elevation: 553 m
Kruskal-Wallis	ADMR_2018 data	Group 1 Group 2 Group 3	Elevation: 0-200 m Elevation: 200-400 m Elevation: 400-685 m

Afterwards, the ADMR_2018 and Elevation data were used to perform the correlation and regression tests. Pearson's correlation and Spearman's correlation are known as two types of correlation tests. Spearman's rank and Pearson's correlations are based on linear relationships between variables [19]. Pearson correlation is used if both variables are parametric data while Spearman's rho is applied if one of two variables is non-parametric data [38]. Since the normality test showed that the ADMR, ADMR_2018, and Elevation data were non-parametric, the Spearman's rho result was employed. In this study, two Correlation tests were performed, including the relationship between ADMR and Year data, and ADMR_2018 and Elevation data.

The final stage in the research is multivariate analysis. In this analysis, the ADMR_2018 data was split into two groups to perform a multivariate hypothesis test using Kruskal-Wallis. Group 1 was defined as a station number less than 23733; Group 2 was defined as a station number more than 23733. The details of the dataset are shown in Table 6.

Table 6. The dataset for multivariate analysis

Test	Dependent variables (Data)	Independent variables (Groups)	Description	Split data	Description
Multivariate analysis for Kruskal-Wallis	ADMR data (2018)	Group 1	Elevation: 0-200 m	Group 1	Station number <23733
		Group 2	Elevation: 200-400 m	Group 2	Station number >23733
		Group 3	Elevation: 400-685 m		

5. Null, alternative hypotheses

The null and alternative hypotheses for the Kruskal–Wallis and Mann–Whitney tests were prepared by the tests themselves in SPSS itself [19]. In the hypothesis test, the significant value determines whether the hypothesis is rejected or retained. The significant level for hypothesis testing in SPSS is 0.05. It means that if the significant value (p-value) is less than 0.05, the null hypothesis is rejected [20].

For the Kruskal–Wallis test, the null hypothesis (H_o) was expressed as the distribution of ADMR is the same across categories of time groups; the alternative hypothesis (H_A) was expressed as the distribution of ADMR is not the same across categories of time groups.

For the Mann–Whitney test, the null hypothesis (H_o) was expressed as the distribution of ADMR is the same across categories of station groups; the alternative hypothesis (H_A) was expressed as the distribution of ADMR is not the same across categories of station groups.

6. Results and discussions

6.1 The normality test

The result of the frequency analysis is shown in Table 7. As can be seen in the table, there were differences between the mean, median, and mode values. Hence, these three data might be not normally distributed. The normality test result in Table 8 was used to confirm this assumption.

Table 7. *The result of frequency analysis*

		ADMR	ELEVATION	ADMR_2018
	Valid	160	86	86
	Missing	0	0	0
Mean		40.57	257.76	32.42
Median		38	296	32
Mode		26.00a	10.00a	26.00a
Std. Deviation		17.28	179.14	11.46
Skewness		1.16	0.03	0.57
Std. Error of Skewness		0.19	0.26	0.26
Kurtosis		1.92	-1.19	-0.10
Std. Error of Kurtosis		0.38	0.51	0.51
Minimum		13.30	6	13.30
Maximum		107.60	675	65.20

Table 8. *The result of normality test*

Tests of Normality						
	Kolmogorov-Smirnov[a]			Shapiro-Wilk		
	Statistic	df	Sig.	Statistic	df	Sig.
ADMR (4 stations)	.086	160	.006	.925	160	.000
ELEVATION (86 stations)	.133	86	.001	.927	86	.000
ADMR_2018 (86 stations)	.080	86	.200*	.965	86	.021

The ADMR data is comprised of the data in four stations, and each station has 40-year data values. As a result, the number of ADMR samples in the normality test is 160 values (>50). Therefore, the Kolmogorov-Smirnova test was used to interpret the result. Meanwhile, the significant value (p-value) in the normality test was 0.05 as the common value [20]. As such, if the significant value is less than 0.05, the data is non-parametric. As can be seen from Table 8, the significant value is 0.006, which is smaller than 0.05. Therefore, the ADMR data were not normally distributed. Similarly, the values of the Kolmogorov-Smirnova test were also used to determine the normality result for Elevation and ADMR_2018 data since these two types of data have 86 samples. The significance for Elevation and ADMR_2018 data were 0.001 and 0.2, respectively, and both were smaller than 0.05. Therefore, the Elevation and ADMR_2018 data were also not normally distributed.

In addition, the Q-Q plot results showed that the data values in all three graphs shown in Figure 4-6 were not entirely close to diagonal line, claiming that all these data were non-parametric.

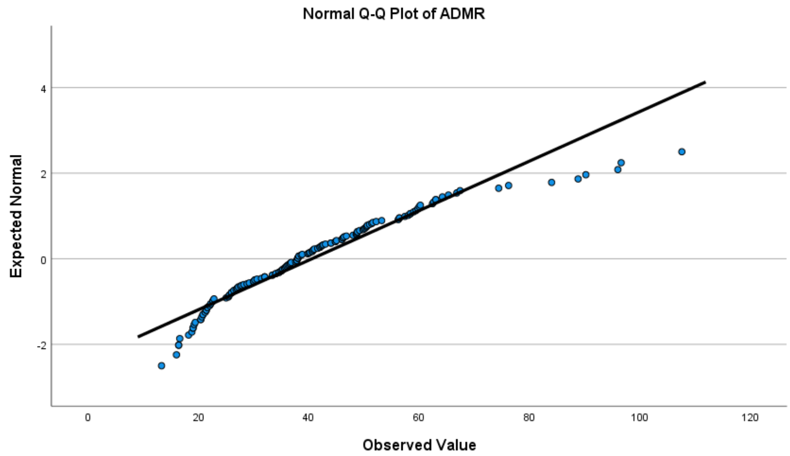


Figure 4. The normal Q-Q Plot of ADMR data in four stations within 40 years

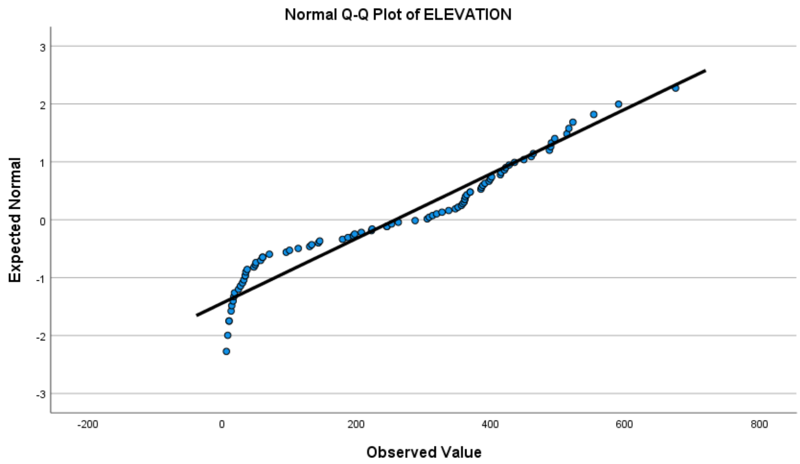


Figure 5. The normal Q-Q plot of Elevation data for 86 stations in 2018

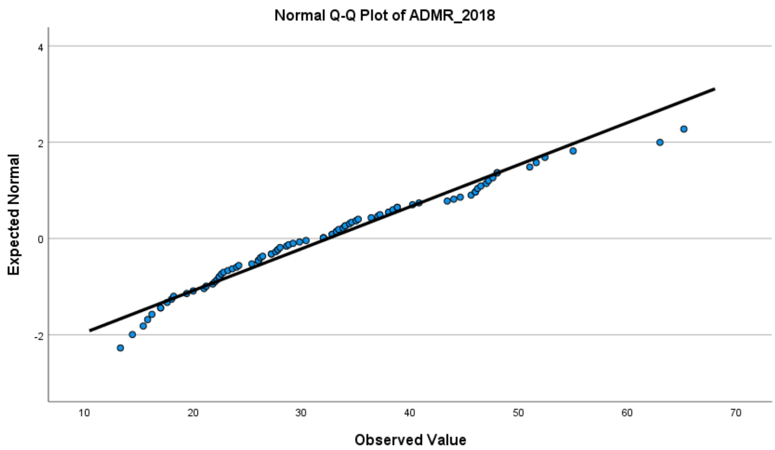


Figure 6. The normal Q-Q plot ADMR data for 86 stations in 2018

6.2 Mann-Whitney U result

The Mann-Whitney test is to check the differences between the ADMR data and year groups. The result of the test is shown in Table 9.

Table 9. The Mann-Whitney U result

	Hypothesis Test Summary			
	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of ADMR is the same across categories of Year groups.	Independent-Samples Mann-Whitney U Test	.309	Retain the null hypothesis.

The null hypothesis is never accepted; the result is either fail to reject or reject it [20]. In other words, if the p-value is bigger than 0.05, the result fails to reject the null hypothesis [20]. In this study, the result of the Mann-Whitney test showed that the significant value is 0.309, which is clearly greater than 0.05. Therefore, the decision for the hypothesis test is to retain the null hypothesis. As such, the distribution of ADMR data is the same across categories of year groups. There is no difference between the ADMR data and Year groups. Therefore, it was claimed that the ADMR data does not vary temporally. In this case, the testing procedure can be terminated. The decision can be made as the ADMR data does not vary over the recorded time.

In this study, to ensure that the result of Mann-Whitney test is accurate, a correlation test was conducted to check the consistency of these two tests. The result can be found in Table 14.

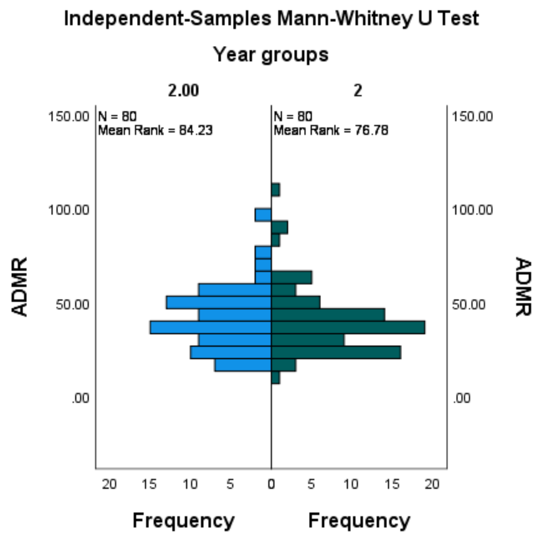


Figure 7. *The Mann-Whitney U result*

6.3 Kruskal-Wallis test

This test is to identify whether there is a difference between the ADMR data and the elevation groups. The result is shown in Table 10.

Table 10. *Hypothesis testing using Kruskal-Wallis for 40-year ADMR data*

	Hypothesis Test Summary			
	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of ADMR is the same across categories of station groups.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

As mentioned above, if the p-value is smaller than 0.05, the null hypothesis is rejected [20]. The result of the Kruskal-Wallis test showed that the significant value is 0.000, which is smaller than 0.05.

Therefore, the decision is rejecting the null hypothesis. Specifically, the distribution of ADMR data is not the same across categories of four station/ elevation groups. Hence, there is a difference between ADMR data over elevation groups.

The pairwise comparisons in Table 11 claimed that there is only one pair of sample groups having a significance value bigger than 0.05. That is the pair group 1-2 where the p-value stands at 1.0, meaning there is no difference between ADMR data in this pair group. However, the other pair groups all have significant values smaller than 0.05. Therefore, there is a relationship between them.

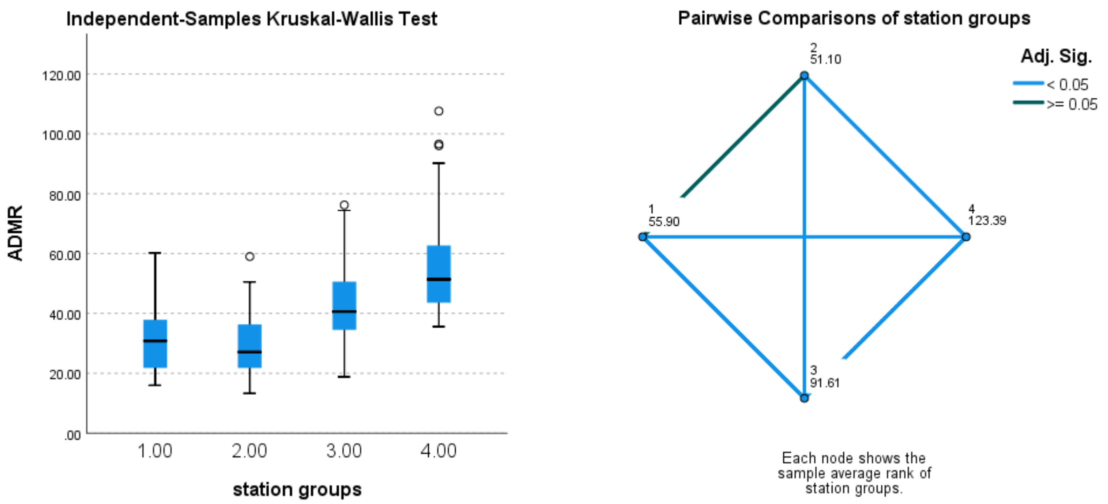


Figure 8. *Kruskal-Wallis test results for 40-year ADMR data*

Table 11. *The pairwise comparisons of station groups for 40-year ADMR data*

Pairwise Comparisons of station groups

Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
2.00-1.00	4.800	10.360	.463	.643	1.000
2.00-3.00	-40.513	10.360	-3.911	.000	.001
2.00-4.00	-72.288	10.360	-6.978	.000	.000
1.00-3.00	-35.713	10.360	-3.447	.001	.003
1.00-4.00	-67.488	10.360	-6.514	.000	.000
3.00-4.00	-31.775	10.360	-3.067	.002	.013

The results of hypothesis testing using ADMR data in the four stations above indicated that there is a relationship between the ADMR and elevation data, which means that the ADMR data might spatially vary with the elevation data. To check this assumption, another Kruskal-Wallis test was performed by using the ADMR data in one year (ADMR_2018) and the elevation data in stations across the study area.

In this research, the year 2018 for the one-year ADMR data was chosen since this year satisfies the availability and quality of data. Regarding the year 2018 data, the latest data can be obtained. In terms of the elevation data, 86 stations out of 269 stations across the City of Adelaide were used, each station provided one data of elevation.

Table 12. *Hypothesis testing using Kruskal-Wallis for ADMR_2018 data*

Hypothesis Test Summary

	Null Hypothesis	Test	Sig.[a,b]	Decision
1	The distribution of ADMR_2018 is the same across categories of Elevation groups.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.

The result for this Kruskal-Wallis test in Table 12 showed that the significant value is 0.000, which is clearly smaller than 0.05. The decision is to reject the null hypothesis. It means that the distribution of ADMR_2018 data is not the same across categories of three elevation groups. Therefore, there is an association between the ADMR_2018 data and elevation groups. The difference between groups and pairwise comparisons are shown in Table 10 and Table 13.

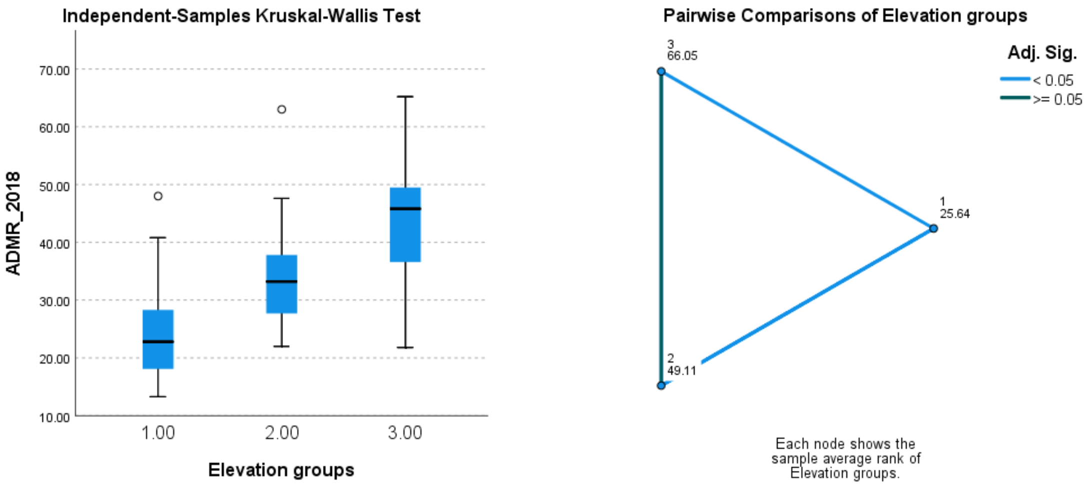


Figure 9. Kruskal-Wallis test results for ADMR_2018 data

Table 13. The pairwise comparisons of elevation groups for the ADMR_2018 data

Pairwise Comparisons of Elevation groups					
Sample 1-Sample 2	Test Statistic	Std. Error	Std. Test Statistic	Sig.	Adj. Sig.[a]
1.00-2.00	-23.470	6.158	-3.811	.000	.000
1.00-3.00	-40.407	6.999	-5.774	.000	.000
2.00-3.00	-16.937	7.161	-2.365	.018	.054

6.4 Correlations

As mentioned above, the first correlation test was performed to examine the consistency of Mann-Whitney U and correlations tests. Since the ADMR data is non-parametric, Spearman's rho table was used to interpret the result. One common way to determine the strength of relationships between two variables is using the scatter plot [20]. The more points are close to the fitting line, the more strength association has. Additionally, the value of the correlation coefficient (r) also represents the strength of the association; it ranges from -1 to 1 [20]. The closer the correlation coefficient (r) to zero suggests no or weak correlation, whereas the closer the correlation coefficient (r) to either -1 or 1, the greater the association strength [20]. If the significant value (p-value) in the Correlations test is smaller than 0.01, it indicates the test is statistically significant.

As can be seen from Table 14, the Correlation coefficient value is -0.046, which is very close to 0. Therefore, it indicates no linear relationship exists between ADMR and Year data. In addition, the significant value is 0.559 which is significantly bigger than 0.01. Hence, the relationship between the two data is realatively weak. In short, it can be observed that the Mann-Whitney U and Correlations tests showed consistency in their results. The decision was made as the ADMR data does not vary according to the time of the data.

Table 14. *The result of Correlations test for ADMR and Year data*

Correlations				
			ADMR	YEAR
Spearman's rho	ADMR	Correlation Coefficient	1.000	-0.046
		Sig. (2-tailed)	.	.559
		N	160	160
	YEAR	Correlation Coefficient	-0.046	1.000
		Sig. (2-tailed)	.559	.
		N	160	160

Following the result from the Kruskal-Wallis test above, this second Correlations test is to determine the size and direction of association between the ADMR_2018 and Elevation data. Since the ADMR_2018 and Elevation data are not normally distributed, Spearman's rho table was used to interpret the results. The result is shown in Table 15.

Table 15. *The result of Correlations test for ADMR_2018 and Elevation data*

Correlations				
			ELEVATION	ADMR_2018
Spearman's rho	ELEVATION	Correlation Coefficient	1.000	.679**
		Sig. (2-tailed)	.	.000
		N	86	86
	ADMR_2018	Correlation Coefficient	.679**	1.000
		Sig. (2-tailed)	.000	.
		N	86	86

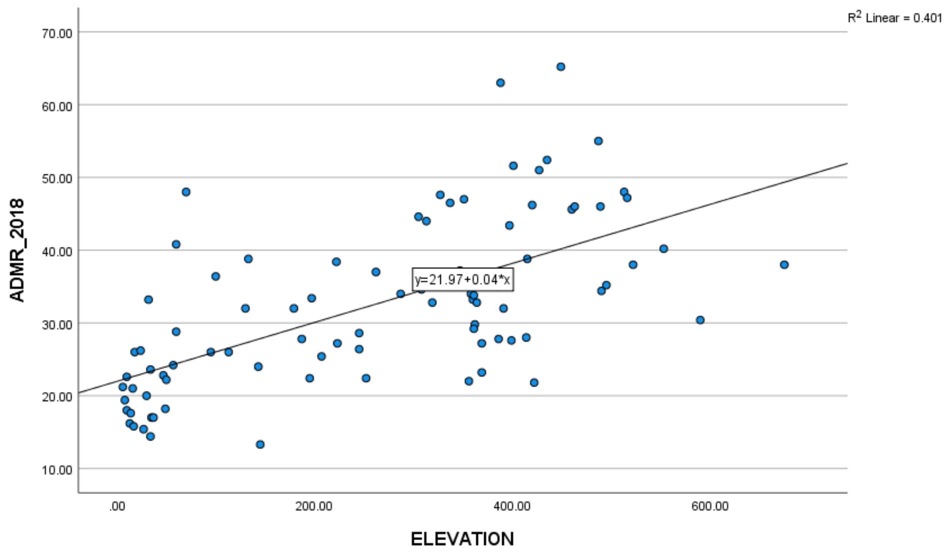


Figure 10. The scatter graph for ADMR_2018 and elevation data

The Spearman's is based on linear relationships between variables and its value is measured between -1 and +1 [20]. As shown in Table 15, the correlation coefficient value is 0.679, which is not too close to 0. Therefore, the correlation between the ADMR_2018 and elevation data is significantly strong. In addition, the significant value (p-value) is 0.000, which is clearly smaller than 0.01. As a result, the test is statistically significant. It is clear to see that these two criteria showed consistency in their result. Therefore, it is reasonable to claim that there is a strong relationship between the ADMR_2018 and Elevation data.

In the graph, several scatter points tended to distribute close to each other and close to the fitting line. The R^2 value is relatively significant (0.401), indicating that the correlation between the two variables is relatively strong. The line had the slope>0; therefore, the relationship is positive. In short, the results from the Correlations and Kruskal-Wallis tests were the same.

6.5 Regression

The result from the correlations test showed a strong relationship between the ADMR_2018 and elevation. Based on this validation, the regression was considered to identify how the ADMR data changes corresponding to the Elevation. The equation between two variables can be determined by: Y= a +bX.

Where, Y is dependent (target) variable; X is independent (input) variable; b is a slope of the best-fit line (Beta coefficient); and a is the point at which the line crosses the Y-axis (intercept). In this research, the ADMR (mm) is considered as the dependent variable, while the Elevation (m) is considered as independent the variable. The value of a and b can be determined as the result from coefficient below.

Table 16. The result of coefficients test

Coefficients[a]

Model		Unstandardized Coefficients		Standardized Coefficients	t	Sig.
		B	Std. Error	Beta		
1	(Constant)	21.973	1.693		12.979	.000
	ELEVATION	.041	.005	.633	7.503	.000

a. Dependent Variable: ADMR_2018

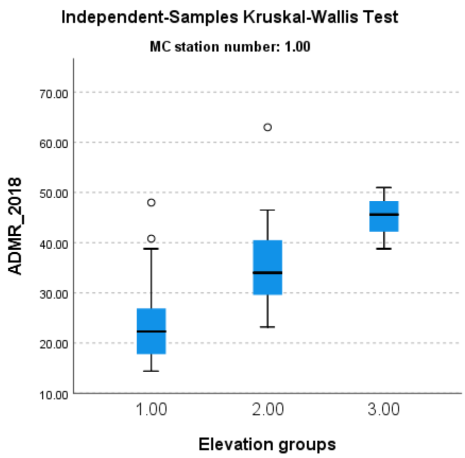
Firstly, the significance value is 0.000 which is smaller than 0.05, indicating that the test is statistically significant. Furthermore, the result illustrates that the coefficient Beta (that is Pearson's) is equal to 0.633, which is not close to 0. Hence, it showed the strong positive associations between the ADMR_2018 and Elevation variables. After the test, the a and b values can be obtained as 21.97 and 0.04, respectively. Therefore, the regression equation is formed as ADMR_2018=21.97 +0.04*Elevation.

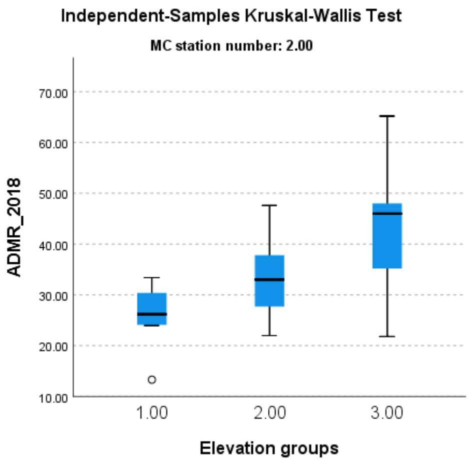
6.6 Multivariate analysis

The result of Multivariate analysis using Kruskal-Wallis is shown in Table 17. The significant values in the two split groups were 0.000 and 0.001, which are both smaller than 0.05. As a result, the hypothesis is rejected. The result was expressed as the distribution of ADMR_2018 is not the same across categories of Elevation groups. These differences can be observed in Figure 11. This result is the same as the Kruskal-Wallis test above. Thus, the Multivariate analysis reconfirmed the validation of the Kruskal-Wallis test. It is reasonable to conclude that the results from the Kruskal-Wallis, Correlations, and Regression tests are credible.

Table 17. Multivariate analysis for hypothesis testing using Kruskal-Wallis Test

Hypothesis Test Summary					
MC station number		Null Hypothesis	Test	Sig.[a,b]	Decision
1.00	1	The distribution of ADMR_2018 is the same across categories of Elevation groups.	Independent-Samples Kruskal-Wallis Test	.000	Reject the null hypothesis.
2.00	1	The distribution of ADMR_2018 is the same across categories of Elevation groups.	Independent-Samples Kruskal-Wallis Test	.001	Reject the null hypothesis.





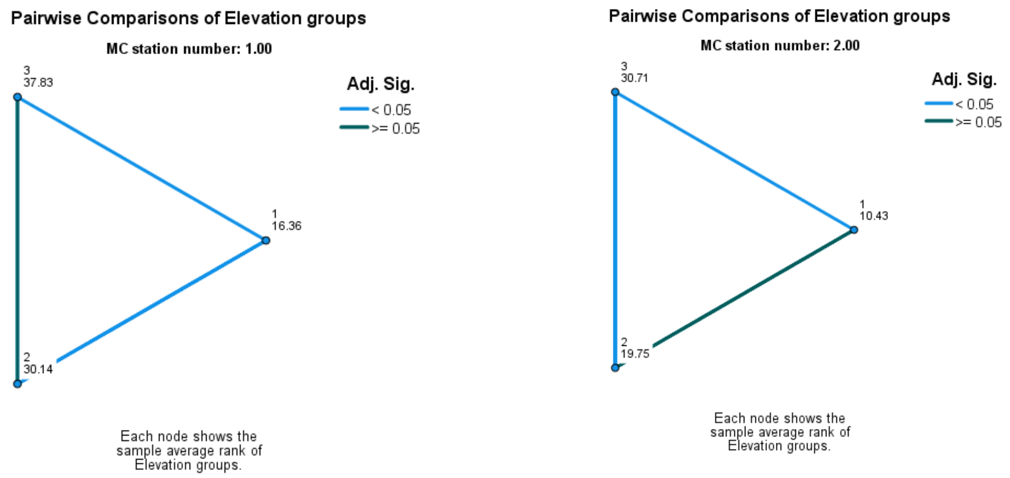


Figure 11. *Multivariate analysis results for ADMR_2018 data*

7. Summary and discussion

This study is to investigate the variability of rainfall over time and terrain in the City of Adelaide. Several statistical tests were performed, namely Kruskal–Wallis, Mann–Whitney, correlation, and regression tests. It was found that the Annual Daily Maximum Rainfall (ADMR) data showed no significant difference over the recorded time. Meanwhile, the elevation has a significant influence on the ADMR data. The research has shown that the distributions of ADMR across categories of elevation groups were different by using Mann–Whitney and Kruskal-Wallis tests. Plus, there was a strong correlation between ADMR and elevation data. Although there was a relationship, there is no evidence to claim that the elevation causes the variability of rainfall data. However, it is relatively possible to use elevation data to predict ADMR data in Adelaide.

It is important to note that the application of the Kruskal–Wallis, Mann–Whitney tests in rainfall data is not common. Hence, more research needs to be done to fully understand the extreme rainfall patterns in the study area. In further research, it is necessary to collect more data in the long time series and different locations to obtain comprehensive results.

This study investigated the variability of rainfall over time and terrain in the City of Adelaide using several statistical tests, including Kruskal–Wallis, Mann–Whitney, correlation, and regression tests. The analysis revealed that the Annual Daily Maximum Rainfall (ADMR) data did not show significant variation over the recorded time period. However, elevation was found to have a significant influence on ADMR data. The distributions of ADMR across different elevation groups differed significantly, as demonstrated by the Mann–Whitney and Kruskal-Wallis tests. Additionally, there was a strong correlation between ADMR and elevation data, suggesting that while elevation may not directly cause variability in rainfall, it can be used as a predictive factor for ADMR in Adelaide. Policymakers and researchers can use the results for climate projections and extreme rainfall predictions in any location across Adelaide.

The application of Kruskal–Wallis and Mann–Whitney tests in rainfall data analysis is relatively uncommon. Therefore, more research is required to fully understand extreme rainfall patterns in the study area. Future research should focus on collecting more extensive long-term data from various locations to obtain comprehensive results. Policymakers and researchers can use the results for climate projections and extreme rainfall predictions in any location across Adelaide.

Declarations

Author Contributions: Conceptualization and methodology, H.T and F.A; Writing original draft preparation, H.T; Feedback and advice, F.A. All authors have read and agreed to the published version of the manuscript.

Ethical Approval: Not applicable.

Funding: Not applicable.

Availability of data and materials: This paper used the Climate data online from the Australian Government Bureau of Meteorology (BOM) website.

Acknowledgments: The authors would like to acknowledge the generous provision of data by the Australian Government Bureau of Meteorology (BOM).

Conflicts of Interest: The authors declare no conflict of interest.

References

1. Akompab, D, Bi, P, Williams, S, Grant, J, Walker, I & Augoustinos, M 2012, 'Awareness of and Attitudes towards Heat Waves within the Context of Climate Change among a Cohort of Residents in Adelaide, Australia', *International Journal of Environmental Research and Public Health*, vol. 10, no. 1, pp. 1–17. https://doi.org/10.3390/ijerph10010001

2. Liu, Z, Eden, JM, Dieppois, B & Blackett, M 2022, 'A global view of observed changes in fire weather extremes: uncertainties and attribution to climate change', *Climatic Change*, vol. 173, no. 1–2, p. 14. https://doi.org/10.1007/s10584-022-03409-9

3. Cook, BI, Smerdon, JE, Seager, R & Coats, S 2014, 'Global warming and 21st century drying', *Climate Dynamics*, vol. 43, no. 9–10, pp. 2607–2627. https://doi.org/10.1007/s00382-014-2075-y

4. Cook, BI, Mankin, JS & Anchukaitis, KJ 2018, 'Climate Change and Drought: From Past to Future', *Current Climate Change Reports*, vol. 4, no. 2, pp. 164–179. https://doi.org/10.1007/s40641-018-0093-2

5. Dai, A, Zhao, T & Chen, J 2018, 'Climate Change and Drought: A Precipitation and Evaporation Perspective', *Current Climate Change Reports*, vol. 4, no. 3, pp. 301–312. https://doi.org/10.1007/s40641-018-0101-6

6. Nolan, P, Sullivan, J & McGrath, R 2017, 'Impacts of climate change on mid-twenty-first-century rainfall in Ireland: a high-resolution regional climate model ensemble approach', *International Journal of Climatology*, vol. 37, pp. 4347–4363. https://doi.org/10.1002/joc.5091

7. Marengo, JA, Alves, LM, Ambrizzi, T, Young, A, Barreto, NJC & Ramos, AM 2020, 'Trends in extreme rainfall and hydrogeometeorological disasters in the Metropolitan Area of São Paulo: a review', *Annals of the New York Academy of Sciences*, vol. 1472, no. 1, pp. 5–20. https://doi.org/10.1111/nyas.14307

8. Tung, Y-S, Wang, C-Y, Weng, S-P & Yang, C-D 2022, 'Extreme index trends of daily gridded rainfall dataset (1960–2017) in Taiwan', *Terrestrial, Atmospheric and Oceanic Sciences*, vol. 33, no. 1, p. 8. https://doi.org/10.1007/s44195-022-00009-z

9. Murphy, BF & Timbal, B 2008, 'A review of recent climate variability and climate change in southeastern Australia', *International Journal of Climatology*, vol. 28, no. 7, pp. 859–879. https://doi.org/10.1002/joc.1627

10. Ashcroft, L, Karoly, DJ & Dowdy, AJ 2019, 'Historical extreme rainfall events in southeastern Australia', *Weather and Climate Extremes*, vol. 25, p. 100210. https://doi.org/10.1016/j.wace.2019.100210

11. Chambers, LE 2003, *South Australian rainfall variability and trends*, BMRC Research Report, 92, Bureau of Meteorology Research Center, Australia.

12. Chowdhury, RK & Beecham, S 2010, 'Australian rainfall trends and their relation to the southern oscillation index', *Hydrological Processes*, vol. 24, no. 4, pp. 504–514. https://doi.org/10.1002/hyp.7504

13. Kamruzzaman, M, Beecham, S & Metcalfe, AV 2017, 'Changing patterns in rainfall extremes in South Australia', *Theoretical and Applied Climatology*, vol. 127, no. 3–4, pp. 793–813. https://doi.org/10.1007/s00704-015-1667-8

14. Dey, R, Lewis, SC, Arblaster, JM & Abram, NJ 2019, 'A review of past and projected changes in Australia's rainfall', *WIREs Climate Change*, vol. 10, no. 3, p. e577. https://doi.org/10.1002/wcc.577

15. McKay, RC, Boschat, G, Rudeva, I, Pepler, A, Purich, A, Dowdy, A, Hope, P, Gillet, ZE, Rauniyar, S 2023, 'Can southern Australian rainfall decline be explained? A review of possible drivers', *WIREs Climate Change*, vol. 14, no. 2, p. 820. https://doi.org/10.1002/wcc.820

16. Gergis, J & Ashcroft, L 2013, 'Rainfall variations in south-eastern Australia part 2: a comparison of documentary, early instrumental and palaeoclimate records, 1788-2008: Rainfall variations in South-eastern Australia part 2', *International Journal of Climatology*, vol. 33, no. 14, pp. 2973–2987. https://doi.org/10.1002/joc.3639

17. Chowdhury, RK, Beecham, S, Boland, J & Piantadosi, J 2015, 'Understanding South Australian rainfall trends and step changes: South Australian rainfall trends and step changes', *International Journal of Climatology*, vol. 35, no. 3, pp. 348–360. https://doi.org/10.1002/joc.3982

18. Kamruzzaman, M, Metcalfe, A & Beecham, S 2020, 'Modelling spatial and temporal rainfall and their relationship to climatic indicators in South Australia', *Theoretical and Applied Climatology*, vol. 142, no. 1–2, pp. 543–553. https://doi.org/10.1007/s00704-020-03314-0

19. Ye, Q & Ahammed, F 2020, 'Quantification of relationship between annual daily maximum temperature and annual daily maximum rainfall in South Australia', *Atmospheric and Oceanic Science Letters*, vol. 13, no. 4, pp. 286–293. https://doi.org/10.1080/16742834.2020.1755599

20. McCarthy, RV, McCarthy, MM, Ceccucci, W & Halawi, L 2019, *Applying Predictive Analytics: Finding Value in Data*, Springer International Publishing, Cham.

21. Mishra, P, Pandey, C, Singh, U, Gupta, A, Sahu, C & Keshri, A 2019a, 'Descriptive statistics and normality tests for statistical data', *Annals of Cardiac Anaesthesia*, vol. 22, no. 1, p. 67. https://doi.org/10.4103/aca.ACA_157_18

22. Kim, TK 2015, 'T test as a parametric statistic', *Korean Journal of Anesthesiology*, vol. 68, no. 6, p. 540. https://doi.org/10.4097/kjae.2015.68.6.540

23. Mann, HB & Whitney, DR 1947, 'On a Test of Whether one of Two Random Variables is Stochastically Larger than the Other', *The Annals of Mathematical Statistics*, vol. 18, no. 1, pp. 50–60.

24. Weiner, IB & Craighead, WE (eds) 2010, *The Corsini encyclopedia of psychology*, 4th ed, Wiley, Hoboken, NJ.

25. Kruskal, WH & Wallis, WA 1952, 'Use of Ranks in One-Criterion Variance Analysis', *Journal of the American Statistical Association*, vol. 47, no. 260, pp. 583–621.

26. Ahammed, F & Smith, E 2019, 'Prediction of Students' Performances Using Course Analytics Data: A Case of Water Engineering Course at the University of South Australia', *Education Sciences*, vol. 9, no. 3, p. 245. https://doi.org/10.3390/educsci9030245

27. Akoglu, H 2018, 'User's guide to correlation coefficients', *Turkish Journal of Emergency Medicine*, vol. 18, no. 3, pp. 91–93. https://doi.org/10.1016/j.tjem.2018.08.001

28. He, W, Shirowzhan, S & Pettit, CJ 2022, 'GIS and Machine Learning for Analysing Influencing Factors of Bushfires Using 40-Year Spatio-Temporal Bushfire Data', *ISPRS International Journal of Geo-Information*, vol. 11, no. 6, p. 336. https://doi.org/10.3390/ijgi11060336

29. Nur, A, Kim, Y, Lee, J & Lee, C-W 2023, 'Spatial Prediction of Wildfire Susceptibility Using Hybrid Machine Learning Models Based on Support Vector Regression in Sydney, Australia', *Remote Sensing*, vol. 15, no. 3, p. 760. https://doi.org/10.3390/rs15030760

30. Haddad, K, Johnson, F, Rahman, A, Green, J & Kuczera, G 2015, 'Comparing three methods to form regions for design rainfall statistics: Two case studies in Australia', *Journal of Hydrology*, vol. 527, pp. 62–76. https://doi.org/10.1016/j.jhydrol.2015.04.043

31. Australian Bureau of Statistics 2018, *Annual report 2017-18*, ABS Website, accessed 11 December 2023.

32. Varghese, BM, Barnett, AG, Hansen, AL, Bi, P, Hanson-Easey, S, Heyworth, JS, … Pisaniello, DL 2019, 'The effects of ambient temperatures on the risk of work-related injuries and illnesses: Evidence from Adelaide, Australia 2003–2013', *Environmental Research*, vol. 170, pp. 101–109. https://doi.org/10.1016/j.envres.2018.12.024

33. Mishra, Prabhaker, Singh, U, Pandey, C, Mishra, Priyadarshni & Pandey, G 2019b, 'Application of student's t-test, analysis of variance, and covariance', *Annals of Cardiac Anaesthesia*, vol. 22, no. 4, p. 407. https://doi.org/10.4103/aca.ACA_94_19

34. Frederick, G & Larry, W 2017, *Statistics for the behavioral sciences*, 10th edition, Cengage Learning, 20 Channel Center Street, Boston, MA 02210, USA.

35. Oosterbaan, RJ 1994, *Drainage Principles and Applications*, Second revised edition, Wageningen, The Netherlands.

36. Ho, R 2017, *Understanding Statistics for the Social Sciences with IBM SPSS*, 1st edn, Chapman and Hall/CRC.

37. Whitley, E & Ball, J 2002, 'Statistics review 3: Hypothesis testing and P values', *Critical Care*, vol. 6, no. 3, pp. 222–225. https://doi.org/10.1186/cc1493

38. Hauke, J & Kossowski, T 2011, 'Comparison of Values of Pearson's and Spearman's Correlation Coefficients on the Same Sets of Data', *QUAGEO*, vol. 30, no. 2, pp. 87–93. https://doi.org/10.2478/v10117-011-0021-1

39. Australian Government Bureau of Meteorology (BOM), Climate data online, http://www.bom.gov.au/climate/data/, accessed 13 June 2023.

Appendix A: The details of ADMR data in 4 stations

Table 18. *Details of ADMR data in four stations (mm)*

Number	Year	ADMR_23034 (mm)	ADMR_23748 (mm)	ADMR_23730 (mm)	ADMR_23803 (mm)
1	2018	21.2	13.3	34	40.2
2	2017	22.2	35.8	36.8	36.4
3	2016	38	41	62.6	84
4	2015	31.4	25.6	35.2	40
5	2014	60.2	25	25.5	88.8
6	2013	35.6	22.6	42.2	52.2
7	2012	46.2	27	27.8	38.6
8	2011	34.6	50.5	38	63
9	2010	44.8	59	46	59.8
10	2009	20.4	26	34	40.8
11	2008	20.4	18.2	45	37.8
12	2007	30.2	41.6	32	64.2
13	2006	16.6	22	30	35.6
14	2005	22.6	42.6	46	107.6
15	2004	27.6	21.6	30.6	50.4
16	2003	40.8	35.3	46.4	49.8
17	2002	22.2	28.8	36	48.6
18	2001	36.6	20.6	38	50.6
19	2000	37.8	25.4	63	59.4
20	1999	22.6	*19.4*	42	90.2
21	1998	37.6	42	43	62.4
22	1997	57.4	50	76.2	44.8
23	1996	22.8	19	48.6	46.2
24	1995	16.4	21.4	38	38.8
25	1994	30	27.2	51.6	48.8
26	1993	58.4	32	59.8	42.4
27	1992	48	36	66.8	96.6
28	1991	26.4	21.6	38.2	46.8
29	1990	16	35	74.4	49.2
30	1989	34.6	19.2	51.4	48.7
31	1988	21.4	26	51	58.4
32	1987	28.2	36.6	50.2	65.3
33	1986	20.8	29.2	56.2	58
34	1985	38.2	26	35	67.4
35	1984	20.8	19	36.2	39.8

36	1983	48.8	32	26.8	60
37	1982	16.4	30	18.8	96
38	1981	33.4	44	40.6	56.4
39	1980	37.8	26	27	53.2
40	1981	33.4	44	40.6	56.4

Appendix B: The detail of ADMR_2018 and Elevation data for 86 stations in the study area

Table 19: The detail of ADMR_2018 and Elevation data for 86 stations

No.	STN_NO	STATION NAME	Elevation (m)	ADMR_2018 (mm)
1	23000	ADELAIDE WEST TERRACE	47	22.8
2	23001	ADELAIDE (BRIGHTON)	18	26
3	23005	ADELAIDE (GLEN OSMOND)	133	38.8
4	23011	NORTH ADELAIDE	30	20
5	23013	PARAFIELD AIRPORT	13	16.2
6	23023	ADELAIDE (SALISBURY BOWLING CLUB)	35	17
7	23026	ADELAIDE (POORAKA)	27	15.4
8	23034	ADELAIDE AIRPORT	6	21.2
9	23043	HALBURY ROAD SALISBURY (HALBURY ROAD)	34	14.4
10	23055	ADELAIDE AIRPORT ALERT	10	22.6
11	23081	BOLIVAR TREATMENT WORKS	10	18
12	23083	EDINBURGH RAAF	17	15.8
13	23085	ROSSLYN PARK (SEAVIEW)	187	27.8
14	23090	ADELAIDE (KENT TOWN)	50	22.2
15	23093	ADELAIDE (CLARENCE GARDENS BOWLING CLUB)	37	17
16	23096	ADELAIDE (HOPE VALLEY RESERVOIR)	113	26
17	23101	FELIXSTOW (PAYNEHAM)	60	40.8
18	23105	BROWNHILL CREEK (SCOTCH COLLEGE)	100	36.4
19	23107	GAWLER	49	18.2
20	23108	LONGWOOD	460	45.6
21	23114	BEAUMONT	223	27.2
22	23115	ADELAIDE (KESWICK)	34	23.6
23	23133	GREENACRES	70	48
24	23134	KILBURN	8	19.4
25	23137	REGENCY PARK	14	17.6
26	23140	MITCHELL PARK (MARION)	32	33.2
27	23143	MORPHETTVILLE	16	21
28	23704	BELAIR (STATE FLORA NURSERY)	313	44
29	23705	BIRDWOOD	391	32
30	23707	BRIDGEWATER	388	63
31	23710	CLARENDON	262	37
32	23713	ECHUNGA GOLF COURSE	369	27.2
33	23720	HAHNDORF	337	46.5

34	23721	HAPPY VALLEY RESERVOIR	179	32
35	23722	HARROGATE	369	23.2
36	23724	KANMANTOO	195	22.4
37	23726	LOBETHAL	415	38.8
38	23727	LONGWOOD	427	51
39	23728	MACCLESFIELD	308	34.6
40	23730	MEADOWS	358	34
41	23731	CUDLEE CREEK (MILLBROOK RESERVOIR)	319	32.8
42	23732	ADELAIDE (MORPHETT VALE)	95	26
43	23733	MOUNT BARKER	360	33.2
44	23734	MOUNT BOLD RESERVOIR	245	28.6
45	23748	ADELAIDE (TEA TREE GULLY COUNCIL)	145	13.3
46	23750	URAIDLA	487	55
47	23753	WILLUNGA	130	32
48	23758	KERSBROOK (MABENJO)	287	34
49	23786	BIRDWOOD (MCVITTIE'S HILL)	490	34.4
50	23787	BALHANNAH (KILLARA PARK)	420	46.2
51	23788	PICCADILLY (MOUNT LOFTY BOTANIC GARDEN)	513	48
52	23799	PROSPECT HILL	364	32.8
53	23801	LENSWOOD RESEARCH CENTRE	449	65.2
54	23803	ASHTON CO-OP	553	40.2
55	23806	UPPER HERMITAGE	399	27.6
56	23810	MOUNT LOFTY (CLELAND CONSERVATION PARK)	590	30.4
57	23817	ALDGATE	397	43.4
58	23829	WOODSIDE	362	29.8
59	23839	BLACKWOOD (WITTUNGA)	245	26.4
60	23842	MOUNT LOFTY	675	38
61	23858	GOULD CREEK (HERMITAGE)	356	22
62	23860	LONG RIDGE (GREENHILL)	422	21.8
63	23862	LOBETHAL	401	51.6
64	23863	KANMANTOO (MILLBRAE)	252	22.4
65	23865	LENSWOOD (STRINGYBARK)	522	38
66	23866	VERDUN	327	47.6
67	23871	SELLICKS BEACH	24	26.2
68	23874	LEAWOOD GARDENS (EAGLE ON THE HILL)	414	28
69	23876	MCLAREN VALE (PIRRAMIMMA WINERY)	60	28.8
70	23877	KERSBROOK	361	33.8
71	23880	IRONSTONE ROAD	463	46
72	23882	LOBETHAL (MAIDMENT ROAD)	489	46
73	23885	NOARLUNGA	57	24.2
74	23887	KUITPO FOREST RESERVE	361	29.2
75	23891	PICCADILLY (WOODHOUSE)	435	52.4
76	23892	MONTACUTE	347	37.2
77	23896	ATHELSTONE (BLACK HILL)	197	33.4

78	23905	URAIDLA (SUTTON CREEK)	495	35.2
79	23906	MOUNT WILSON	386	27.8
80	23910	KANGARILLA (SADDLEBAGS)	385	35
81	23911	MYLOR (BIGGS FLAT)	305	44.6
82	23915	GOULD CREEK (LITTLE PARA RESERVOIR)	143	24
83	23916	BELLEVUE HEIGHTS	207	25.4
84	23920	WOODSIDE (WICKS ESTATE)	351	47
85	23921	MT BOLD (SCOTT CREEK)	222	38.4
86	24579	MT TORRENS	516	47.2