Regionally Dissected Temperature and Rainfall Models for the South Island of New Zealand

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Abstract

In this study we examine the long term temperature and rainfall trends of the South Island of New Zealand, on a regionally dissected basis. The results are reported on examination of temperature and rainfall data from the South Island of New Zealand, segmented into nine regions, broadly based on NIWA's South Island climate zones (West Coast, Nelson, Marlborough, Canterbury and Southland). The Canterbury climate zone was split into Coastal, Foothills and Mountain regions for both North and South Canterbury. The Southland climate zone was divided into a Northern (Otago) and Southern zone for analysis. ARIMA and regression models have been developed to allow an estimation of longer term temperature and rainfall variability on a regional basis. The study identified regional differences in current and ARIMA simulated rainfall and temperature trends. Broadly, the data indicates decreasing rainfall in the Eastern coastal regions and Southland, especially in the last 35 years of observed data, with a small increase in temperature. Against this a trend of increasing rainfall was identified in the West Coast, Marlborough, Canterbury Foothills and Otago regional data. Temperature trends in these regions showed a very small increase in the West Coast temperature data, but significant increases in the remaining non-coastal regional data. The ARIMA models developed in this study were able to simulate likely temperature and rainfall variability over the next 100 years. There has been much speculation how climate change may affect the New Zealand climate: especially potential effects on agricultural production. The results of this study may be of help in putting the outputs of potential climate change scenarios in context for the New Zealand environment.

Key Words

ARIMA, simulation, model, South Island, rain, temperature, regional, Canterbury, Southland, Marlborough, Canterbury, Otago, Southland, West Coast, Linear Regression, New Zealand

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Chapter 1: Study objectives and background

The South Island of New Zealand has a number of climatically distinct regions. These regions are moderated by the predominantly Westerly wind flow over the country, a maritime temperate climate and steep mountain range: the Southern Alps, that longitudinally traverses along the Western side of the island. This generates a contrasting climate from the West, predominantly wet and mild, to the plains East of the Alps being dry and more variable in temperature.

This study aims to quantify long term temperature and rainfall trends in the selected regions and highlight the effect of the coastal margin (elevations < 120m amsl) in Canterbury on temperature and rainfall compared to inland and mountain regions of Canterbury.

Using the observed data, temperature and rainfall trends, develop ARIMA based models to simulate temperature and rainfall patterns and variability over the next 100 years for the selected regions.

1.1 Background

The study of the interaction and effects of climate drivers is a complex and demanding study area, with a number of complex climate driver interactions, interacting sometimes in unpredictable ways. Climate change is likely to modify these climate driver interactions to effect some dramatic changes to the environment we live in (Jones 2001).

This study uses published temperature and rainfall data to model regionally dissected temperature and rainfall trends and variability. The study regions have been deliberately chosen to reflect the existing broad agricultural regions to bring more relevance to the study output.

The background motivation to the study is the widely publicized issue of climate change and how this is relevant to the New Zealand situation: the rapid intensification of agriculture in the South Island of New Zealand and the realised conflicts and demands for access to scarce resources such as water and land to support this expansion.

Climate change has been an issue of increasing concern in both the scientific community and in the wider NGO Government policy and planning reviews. A key message from the 2007 Stern Review: The economics of Climate change, commissioned by the United Kingdom Treasury was "An overwhelming body of scientific evidence clearly now indicates that climate change is a serious and urgent issue. The Earth's climate is now rapidly changing, mainly as a result of greenhouse gasses caused by human activities"(Stern 2007).

This concern reflected much of the early climate change assessment carried out by Intergovernmental Panel on Climate Change (IPCC): An independent scientific review organisation empanelled by the World Metrological Organisation (WMO) and The United Nations Environment Program (NZEP), specifically to analyse and report on climate change and effects:

”The IPCC is a scientific body. It reviews and assesses the most recent scientific, technical and socio-economic information produced worldwide relevant to the understanding of climate change. It does not conduct any research nor does it monitor climate related data or parameters” (IPCC 2011).

Since the first IPCC Climate Change science review released in 1991, the organisation’s reports have become key resources for Government policy planning: for example providing a key science input to the development and adoption of the 1997 Kyoto Protocol (IPCC 2011).

The 2007 IPCC review confirmed and reinforced many of the earlier climate change predictions claiming major advances in the assessment of climate change over the IPCC 2001 Third Assessment Report, with greater prediction accuracy from a broader range of models when taken together with additional observations (IPCC Working Group I 2007).

The 2007 IPCC Working Group I: The Science Basis, has identified a number of climate predictions based on its 2007 review:

- An average global warming of $0.2^{o}C$ per decade for the next 20 years
- 21st century effects of the current Green House Gas (GHG) emissions may induce larger global climate system changes than seen in the 20th century
- There is now higher confidence in projected patterns of warming and other regional scale features including changes in wind patterns, precipitation and some other [climate] extremes
- Anthropogenic warming and sea level rise would continue for centuries due to the time scales associated with climate processes and their feedback mechanisms, even if GHG concentrations were stabilised (IPCC Working Group I 2007)

While the science appears to present compelling evidence of anthropogenic climate change, there are a number of respected climate scientists that question the climate change assessment methodology and projections, although this number is declining.

However, while some of the scientific community and some governments are not in total agreement as to the causes of climate change, the methodology used or in some cases that climate change exists in any measurable form, it is clear that most governments are now planning how best to protect their economic viability in a world with climate change.

In a 2009 survey of 1372 climate researchers, their publications and citation data, 97-98% of surveyed climate scientists actively publishing in the field supported the tenets of anthropomorphic [induced] climate change (ACC) as outlined by the IPCC. Of those that are unconvinced of ACC, their relative climate expertise and scientific prominence was substantially below the surveyed convinced researchers (Anderegg Willam R L 2009).

While I do not necessarily disagree with the findings, I believe it could be difficult to isolate the climate funding aspect of research publication from the volume of published material.

The report of working group I of the IPCC has observed a variety of climate regional responses attributed to global warming which are in general terms:

- More intense and prolonged droughts, particularly in the tropics and sub tropics
- Frequency of heavy precipitation events has increased over most land areas, but during periods of normally high rainfall
- Mid-latitude Westerly winds have strengthened in both hemispheres

(IPCC Working Group I 2007)

The Stern review takes a more direct view of possible regional climate responses to climate change, predicting an increase in rainfall at higher latitudes, while reductions will be experienced in the lower latitudes. Tropical storms are likely to be more intense and drift further pole-ward (Stern 2007).

The combination of elevated temperatures and increased precipitation may well be a bonus to New Zealand agriculture

There have been a number of research papers published investigating climate variability and the influence of major climatic drivers. Most of this work has been retrospective; looking at the relationship between major climate drivers and climatic event trends.

Mullan (Mullan 1995), found significant linear correlations between the ENSO index, the mean sea-level pressure (MSLP) in the Australian region, and with patterns of rainfall and temperature anomalies in New Zealand.

Madden considered the long range predictability of precipitation over New Zealand (Madden, Shea et al. 1999). In this paper it is assumed that the inter-annual variance of seasonal precipitation is comprised of two components; the first reflecting the daily weather variations which are unpredictable beyond the deterministic predictability limits of about 2 weeks, and the second component is any additional variance that is potentially predictable.

The first component could be considered noise, and as such can be estimated using a statistical model. When the total variance exceeds the estimated noise then there is a potential for long-term prediction. Madden however, found that only 30% or less at the climate station level was predictable.

Kidson did remark in an earlier paper (Kiddson J W 1986), that the “total from all available stations may have greater predictability than individual stations”.

The approach of Madden in his paper and the companion paper on long range temperature predictability (Madden and Kidson 1997), is similar in concept to the ARIMA models developed in this study.

In recent papers the focus has shifted from El Nino Southern Oscillation index (ENSO) to the influence of Southern Annular mode (SAM), being able to explain a greater level of climate variability in mid-latitudes.

ENSO is a measure of the coupled ocean/atmosphere interaction in the tropical Pacific and has a significant importance in explaining tropical climate variability.

The Southern Annular Mode index is a measure of the normalised sea level atmospheric pressure difference between -40^{o} latitude and -60^{o} latitude (Meneghini B 2007).

In its positive phase, light winds and settled weather over New Zealand. In its negative phase, Westerly winds predominate with more unsettled weather (Renwick J 2006).

In an analysis of 1997-2006 data, Ummenhofer noted that the increasing drier periods over New Zealand can be partially explained by SAM and ENSO; especially over the North Island and the South West of the South Island. SAM contributes up to 80% and 20-50% to the overall December, January, February (DJF) rainfall decline in North Island and South West South Island respectively (Ummenhofer, Gupta et al. 2009).

Ummenhofer demonstrated that over a 30 year period (1976-2006), a pronounced drying over the West Coast DJF season of up to $2\%yr^{-1}$, and for the East Coast of the South Island, March-May (MAM) and June –August (JJA) seasons, a $1\text{-}3\%Yr^{-1}$ precipitation reduction (Ummenhofer, Gupta et al. 2009).

Similar trends in rainfall reduction of this period have been observed in South Western Australia and also linked to SAM cycles (Meneghini B 2007).

The New Zealand projection of likely climate change effects has been published by NIWA (NIWA 2008). A projection of an average temperature rise of $1^{o}C$ by 2040, with more warmer years and fewer frosts; overall drier in the East and wetter in the West.

As the intensification of New Zealand agriculture continues, farmers are increasingly being pushed to farm in spite of the environment, rather than working with nature. The key input to intensified agriculture is water, as farmers seek to maintain spring like conditions over the Summer/Autumn period.

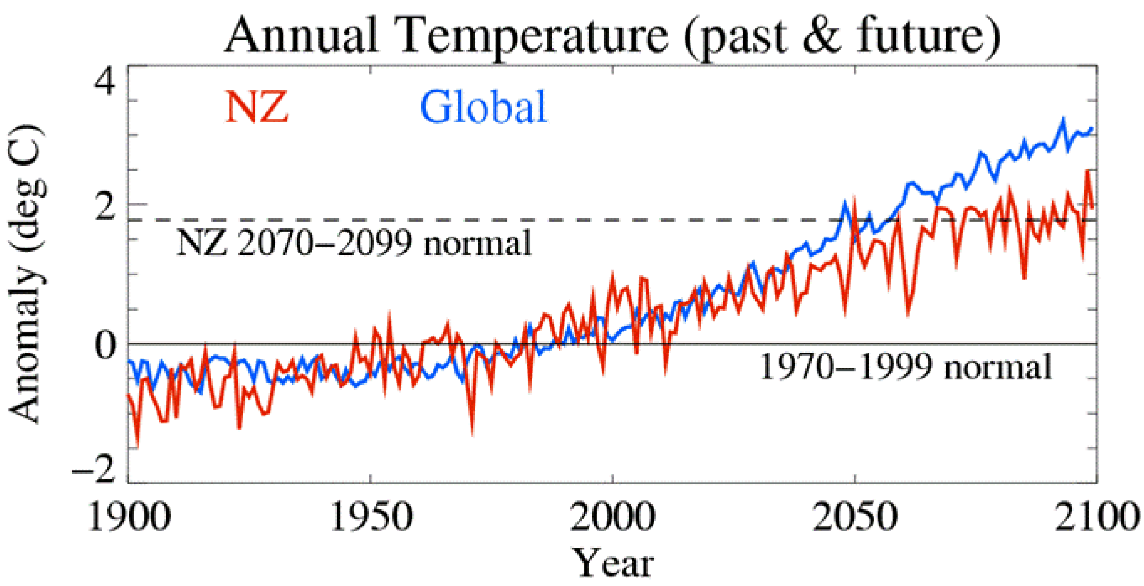


Figure 1: Global and New Zealand temperature anomaly (Source NIWA url-www.niwascience.co.nz/nc)

The examination of temperature variability has been less problematic, in as much as the degree of variability is for seasonal predictions other than winter. 50% of the inter-annual temperature variability is predictable (Mullan and Thompson 2006). Temperature is still affected by the major climate drivers, although the extremes are less significant than for rainfall. Data from this study would indicate that a variability of 20% from the long term trend line is not unusual.

1.2 Potential effects of climate change on New Zealand

For agriculture, a major economic driver for the South Island and New Zealand's economy, a grass fed temperate farming system has some huge advantages in productivity and marketing.

Many critical impacts of climate are driven by infrequent extreme events such as floods, drought, volcanic eruption and tropical storms. Under most of the climate change scenarios published by the IPCC, key effects are increased climate variability and more frequent and more intense tropical storm systems penetrating south into the mid-latitudes (the New Zealand environment) (IPCC Working Group I 2007).

For New Zealand, the initial effects may not be that bad, in that there will be a fertilisation effect through the increased carbon dioxide concentration in the atmosphere and warmer temperatures will result in a longer growing season with increased yield and milder winters (Wratt D.S 2009). The reduction in frost days will be significant for the pastoral agriculture; Blenheim, Christchurch and Invercargill average 60, 70, and 94 ground frost days per year respectively (Moot D 2009).

When the government and local authorities plan for the management of a scarce resource, like water and land, it is the extremes that will have the greatest need for consideration. Industry will easily adapt to a long term gradual change. Short term extreme events however, such as an East Coast drought, although of short duration, can have a long term economic impact.

Critical to the effect on the New Zealand Climate is the effect of climate change on the key atmospheric circulation system. If, as a number of the climate scenarios predict, an increase in summer westerly wind flow over New Zealand eventuates, then the current 1:20 year drought could occur twice as often in Marlborough, Canterbury and Otago (Wratt D.S 2009). This will inevitably result in an increasing demand for irrigation water from an already over allocated resource.

Chapter 2: Methodology

Monthly average rainfall and temperature data was downloaded from the NIWA Cliflo database (NiWA 3/3/2010) for South Island climate stations and loaded into a MS Access database. This allowed for duplicates to be removed and data consistency to be checked.

Climate station physical data such as latitude, longitude, height and station name were collected, along with the data to allow for GIS plotting of station location.

Data was first mined to select only climate stations that had full yearly data. Stations that had incomplete yearly data: i.e. less than 12 months per recording year, were excluded from the analysis.

The remaining climate station data was initially grouped into regional climate groups, based on NIWA's South Island climate regions: West Coast, Marlborough/Nelson, Canterbury, and Otago/Southland.

Each of these regional groupings were again dissected into three interregional groupings, based on climate station altitude: Coastal (<120m amsl), Foothills (between 120 and 500m amsl) and Mountains (>500m amsl).

Canterbury, Otago/Southland and the West Coast were further split into sub-regional groupings, based on regional council boundaries in the case of Canterbury and Otago/Southland. For the West Coast, three sub-regions: South Westland - climate stations south of the township of Ross, Central Westland – climate stations from Ross to the town of Westport and North Westland taking in the climate stations from North of Westport to Farewell Spit.

The climate station records were aggregated within each sub-region based on F test (details are in Appendix 5) of the combined sub-region data. This aggregation of the data resulted in nine broad climate region data sets for analysis. The number of climate stations in each group is summarised in Table 1 below.

The Canterbury region was further split into North and South Canterbury sub regions: Canterbury climate stations below 500m amsl and North of the Rangitata River were assigned to North Canterbury, the remainder to South Canterbury. Similarly in the Southern climate region, climate stations north of the Clutha river to the Waitaki river were assigned to Otago/Northern Southland region, the remainder to Southland.

The aggregated data sets were further examined, and only aggregated records that showed an unbroken and consistent time series set of temperature and rainfall values were included in the analysis.

Table 1: Climate station numbers in each of the aggregated regions

Region	Area Grouping	No Climate Stations Rain	No Climate Stations Temperature	Data Time Span	Years
West Coast	Combined	188	41	1900-2010	110
Marlborough	Combined	153	25	1906-2010	104
North Canterbury	Coastal	101	23	1900-2010	110
North Canterbury	Foothills	140	19	1921-2010	89
South Canterbury	Coastal	100	96	1911-2010	99
South Canterbury	Foothills	94	76	1917-2010	93
Canterbury Mountains	Combined	71	16	1931-2010	79
Otago/Northern Southland	Combined	342	91	1886-2010	124
Southland	Combined	140	24	1911-2010	99

2.1 Data quality

A significant proportion of the data accessed from NIWA had had long periods of missing data, or data of questionable accuracy. This was particularly the case for recorded data before 1900 in many of the regions, and in particular temperature data (arguably the least complicated climate observation to record) was missing. A pragmatic approach was taken as to the inclusion of this data in the study.

The longest period of consistent observations was used for analysis.

If a single data point was missing in an otherwise consistent data series, the missing value was estimated using simple linear regression, using five years data either side of the missing value.

Data points, within an otherwise consistent data series, that were outside three standard deviations of the mean value for that point in the data series were excluded from the analysis. These values were then substituted with an estimated value, using the linear regression technique used for missing values above. This was a rare event, applied only on three occasions.

The data analysis for each regional data set was applied to consistent data sets where both temperature and rainfall data was available. Generally, data sets were around 90-110 years in duration with one regional data (Canterbury Mountain) having only 73 years of consistent temperature and rain data.

2.2 Statistical analysis

Statistical analysis and ARIMA modelling were carried out using the open source software package R (R Statistical Software 2011) and MS Excel. The data was first graphed in MS Excel to visually inspect the data plots for data inconsistencies (see Appendix 1 for temperature and rain data plots for each region).

The raw data, average annual rain and temperature by year, was imported into R (read.csv(file.choose(),h=T)) and individual data sets converted into a time series using the R code: (ts(x,[r:r,c(c:c)],start=Y,frequency =1)).

Statistical analysis was carried out using the following R analysis add in packages: TSA, forecast, tseries and nlme, as well as packages loaded as part of the 2.1.3.1 R package release.

The analysis of each data set followed the following procedure:

- Data is examined to ensure no missing values and a consistent continuous set of rain and temperature data points
- Linear regression for each of the rain and temperature was carried out: The results are available in Appendix 5
- Auto correlation function and partial auto correlation function plots were examined to estimate the level of differencing the data may require in order to generate a stationary difference data set for ARIMA modelling. (See Appendix 3 for regional data set ACF, PACF plots for raw and difference=1 Data)
- Cross Correlation plots for temperature and rainfall for each region data set (c.f Appendix 3)

ARIMA models were initially screened by selecting ARIMA models that minimise the AIC (Akaike Information Criterion) score generated by the R software program.

MAPE (Mean Absolute Percentage Error) and RMSE (Root Mean Square Error) were also considered when selecting between potential valid models. The RMSE, the most commonly referenced goodness of model fit to observed data, is determined by squaring the difference between the model and observed data points, averaging the result. The square root of this figure is presented as RMSE: the larger the number, the poorer the fit. RMSE is particularly sensitive to large errors.

Ultimately when several models are potentially valid, the simplest models (the models with the smallest number of parameters) were plotted, and the model which visually appeared to best visually fit the observed data series best was chosen.

2.3 Time series modelling

ARIMA models are, in theory, the most generalised class of models for forecasting time series (Duke University 2011). These models have a large degree of flexibility, to apply to seasonal as well as non-stationary time series, being especially useful in modelling economic indicators, such as exchange rates and share index time series.

In classical statistics, the independence of the data simplifies analysis, but in the case of many time series, especially economic indices and physical world (such as climate) observations, a series of observations taken at a fixed time interval often show some dependence on previously observed data. For example, rainfall data often exhibits a series of peaks and troughs: a period of high rainfall is often followed by a period of comparatively low rainfall. (see Figure 2 as an example).

ARIMA (p,d,q) models have three components. p, an auto regressive (ar) retrospectively weighted series, d, a difference lag to achieve series stationarity, and q, a retrospectively weighted moving average (ma) random error series, can be represented by the following generalised equation:

$$Y_{(t)} = \phi_{(1)} Y_{(t-1)} + \ldots\ldots + \phi_{(p)} Y_{(t-p)} + \theta\, \varepsilon_{(1)} + \theta_{(1)}\varepsilon_{(t-1)} + \ldots + \theta_{(q)}\varepsilon_{(t-q)} \qquad (1)$$

If the series has a non-zero mean, μ- as many climate series do, then this can be included in the series model as follows:

$$Y(t) - \mu = \phi(1)(\, Y(t-1) - \mu) + \ldots + \phi(p)\,(Y(t-p) - \mu) + \varepsilon(t) + \theta(1)\,\varepsilon(t-1) + \ldots + \theta(q)\,\varepsilon(t-q) \qquad (2)$$

Often a time series will be non-stationary requiring differencing before modelling. If this is the case then it was found that differencing the following generalised equation would apply:

$$\nabla Y_t = Y_t - Y_{t-1} = (1-B)Y_t \qquad (3)$$

Drift can be incorporated into the ARIMA model given a linear trend $Y_t = \beta_0 + \beta_1 t + Z_t$ (4)

$$\text{Hence} \Rightarrow \nabla Y_t = \beta_1 + \nabla Z \qquad (5)$$

Where ϕ_p, θ_q are the model parameters, Z_t is a stationary time series with $E[Z_t]=0$

and ε_t is a normally distributed random noise component, with $\mu_\varepsilon=0$ and standard deviation $=\sigma_\varepsilon$ (Ihaka 2005)

2.3 Non stationary time series and testing for stationarity

Often the observed data will have an underlying trend and/or cyclical nature that will need to be removed before ARIMA modelling can be carried out. Trends in time series can be classified as stochastic or deterministic. A stochastic trend shows random or inexplicable changes in direction and can be attributed to a high serial correlation with random error. This type of trend can be simulated using an autoregressive process. A deterministic trend is one that can be explained by plausible physical influences and generally can be modelled by regression techniques (Cowpertwait S.P. 2009).

For a time series to be stationary its mean and variance must remain constant over time. i.e. $\mu_t =\mu$ and $\sigma_t=\sigma$

ARIMA models are intrinsically stationary, in that they are *mean reverting*: when a value in a stationary time series is greater than the long term mean, then its next value tends to revert towards the mean, similarly if the value is below the long term mean. ARIMA models also have a decaying auto correlation: the influence of today's value in the time series diminishes, influencing future time series values with increasing time. Many time series have a steady Drift (Trend).β_t which must be removed, by differencing if stochastic, or by regression if deterministic in nature before modelling using ARIMA methodology.

In this study, 2nd order stationarity is applied before ARIMA modelling. Second order stationarity is defined as:

$E[Y_t]=\mu$ and $cov[Y_t, Y_{t-\tau}] =\gamma_\tau$ (Chatfield 2004)

Stationarity of a data series in this study was achieved by differencing to an order suggested by inspection of the correlogram plots of the data series.

ARIMA models were generated on first order differencing of the regional data series. The R software package functionality used to generate the ARIMA models confirmed that the models evaluated were stationary.

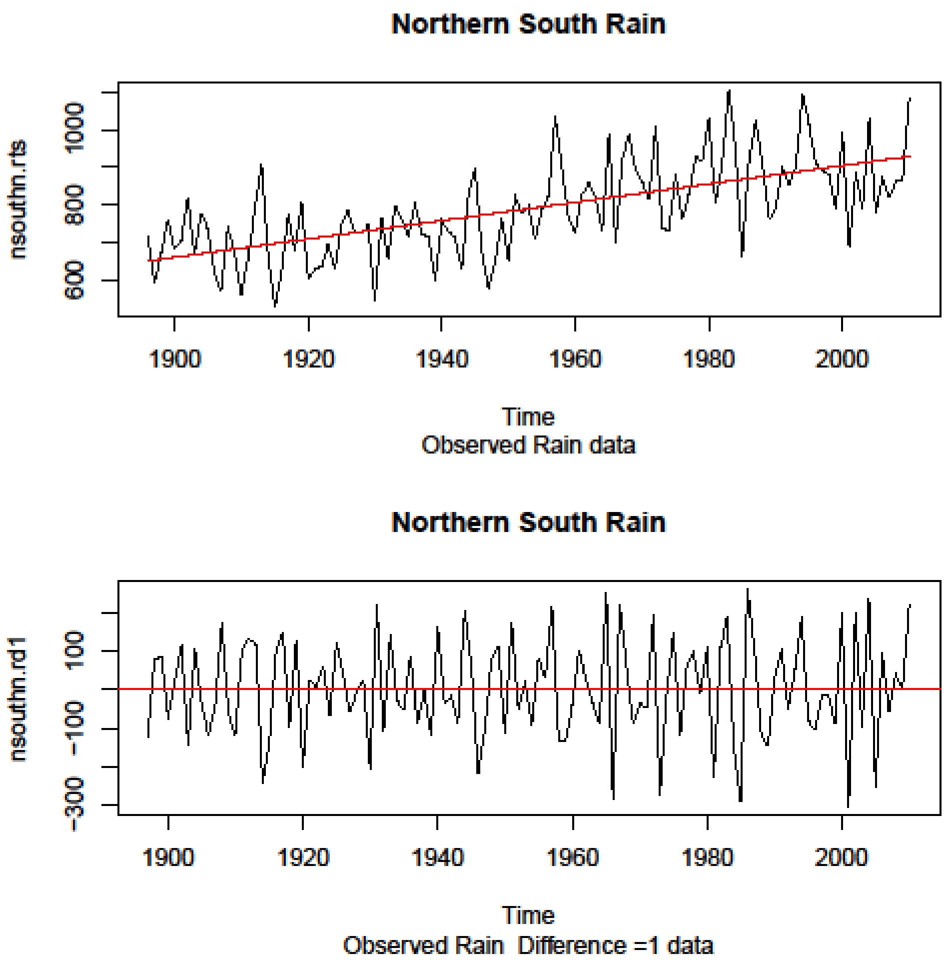


Figure 2: Rainfall time series example

Time series stationarity was assessed using the Phillips-Perron unit root test implemented in the R function *pp.test.* The *auto.ARIMA* function in R can be constrained to only consider differenced stationary time series data, as well as accommodating data series with drift (scholastic trend), as well as minimising the AIC (Akaike Information Criterion) score when selecting potentially valid ARIMA Models.

2.4 Functionality within the R software program

In this study, ARIMA and Linear Regression are used to fit the time series values of each of the data sets and generate an ARIMA model simulation that may allow a degree of prediction of future temperature and rainfall patterns in each of the data set regions. R has a number of ARIMA functions contained in the R packages TSA, forecast, tseries and nlme, all freely available by download from the Cran-R website.

In particular the following R functions were used where x represents the time series:

- *auto.ARIMA(x,stationary=TRUE,ic=c("aic"),test=c("pp"), trace=TRUE, allowdrift=TRUE)*
    - Generates a best fit stationary ARIMA model based on a minimised AIC score allowing for series drift, and testing for model stationarity using the Phillips Perron unit root test
- *acf(x,lag.max=NULL,method=c("correlation"), plot=TRUE)* and *pacf(x,lag.mx=Null,plot=TRUE)*
    - Generates plots of the auto correlation factor and partial autocorrelation factor for time series x
- *ARIMA(x,order=c(p,d,q),xreg=NULL,include.drift=TRUE,include.mean=TRUE)* *[*ARIMA.sim*]*
    - Generates the ARIMA model for time series x and the model parameters ϕ,θ,ε
- *simulate(ARIMA.sim,nsim=y,seed=[mean(x)],xreg=NULL,future=TRUE)* [x.p*]*
    - Generates a simulated time series based on ARIMA (p,d,q) for y periods into the future, from the last data point in x, using the mean of the x time series as a

simulation seed. The time series mean is used a seed to generate a neutral starting value for the ARIMA (p,d,q) simulation. A random seed or a last time series value can lead to distorted simulations if the ARIMA model has an autoregressive component

- *lm(x~time(x)) and Summary(lm(x))*
    - Produces a linear regression of time series x against time
- *Summary* produces a summary of the linear regression coeffients and standard error estimates
- *Fitted(ARIMA.sim)*
    - Generates a time series of the ARIMA (p,d,q) model fitted data from the last data value of the time series
- *Predict(ARIMA.sim, n.ahead=z, newxreg=(length(x)+1): (length(x)+z))*
- Produces a prediction series from the last time series value z periods into the future
- *Tsdiag(ARIMA.sim)*
    - Residuals and ACF(Residuals) plot
- *Summary(ARIMA.sim)*
    - Produces a summary of the ARIMA model coefficients and standard errors

Chapter 3: Results

The results of this study are reported on a regional basis as graphs: the observed data (black points on the graph), ARIMA modelled data fitted to the observed data series (red fitted data on the graphs), and the ARIMA simulated data for the period 2012 to 2112. Also included on the graph are the ARIMA model predicted trend line for 90 years from the last observed data point (ARIMA predicted on the graph) and the two standard deviation ranges around the ARIMA model predicted trend.

A histogram has also been presented, in which the observed data and the ARIMA model simulated data are plotted as deviations from the long term regression trend line for the observed data. This allows a visual comparison of the distribution of more extreme deviations from the long term trend, for both the simulated and observed data. The significance of this variability is examined in the F statistic table associated with each region's data.

Auto correlation and ARIMA Residuals Plots for each of the temperature and rainfall data sets can be found in Appendix 2; a summary of the ARIMA models tested for each data set can be examined in Appendix 3, with the linear regression statistics for the long term trend lines associated with the observed data in each series available in Appendix 4.

In formulating the ARIMA model equations the following transformations have been used:

$$Z_t = Y_t - Y_{t-1} = \nabla Y_t, \qquad X_t = Z_t - \mu \qquad (6)$$

3.1 West Coast rain

ARIMA models (0,0,0), (1,1,1) & (0,1,1) appear to provide a reasonable fit to the data, based on the AIC scores presented in Table 44 in Appendix 3. However when the RMSE value is considered and a visual inspection of the simulated data plots made, the model ARIMA

(0,1,1) was selected: a simple moving average on first differenced data. The following prediction equations have been derived:

ARIMA (0,1,1) Model Equation:

$$Z_t = \beta_1 + \varepsilon_t + \theta\varepsilon_{t-1} \tag{7}$$

where β_1 is the drift component and θ the ma parameter.

Regression Trend Equation:

$$Y_t = 2.6178 * \text{Yar} - 2425.25 \tag{8}$$

The fitted data and regression trend are plotted in Figure 3.

The frequency of the rainfall levels for both the observed and the simulated data was examined. Figure 4 illustrates the annual rainfall frequency distributions for the deviation from the observed data trend line for the observed data and the ARIMA simulated rainfall. The distributions appear to be normally distributed, with the ARIMA simulated rainfall being a reasonable match for the observed data. The F statistic (Table 3), would also suggest no significant difference in rainfall variability between simulated and observed data.

Plots of the correlograms for the West Coast rain data and regression equations are to be found in Appendix 2.

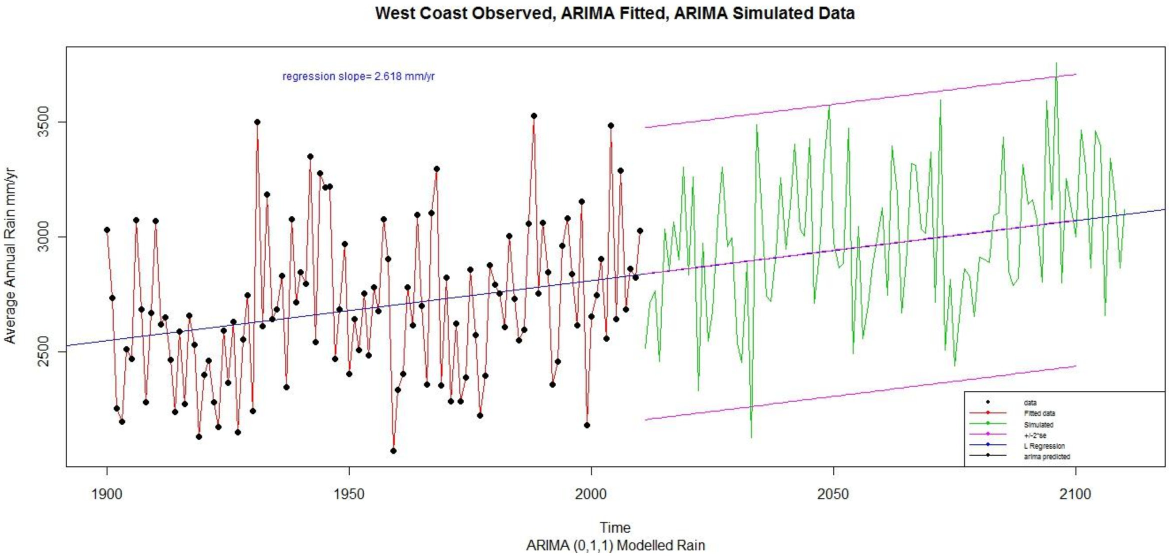


Figure 3: West Coast rain ARIMA simulated data

Table 2: ARIMA model for West Coast rain data

Series: West Coast rain ARIMA (0,1,1) with drift					
Coefficients:	ma1	Drift (Trend).β_t			
	-1	2.6177			
s.e.	0.0343	0.9372			
sigma^2 estimated as		100092:	log likelihood=-791.70		
AIC = 1589.4		AICc =1589.62		BIC = 1597.5	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
10.2672	314.94451	245.505	-1.7187	9.21003	0.68432

Table 3: F Statistic for West Coast rain, observed and ARIMA simulated data

F-Test two sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	2685.433	2993.639
Variance	111832.4	109395.4
Observations	112	112
df	111	111
F		0.978209
P(F<=f) one-tail		0.453905
F Critical one-tail		0.730821

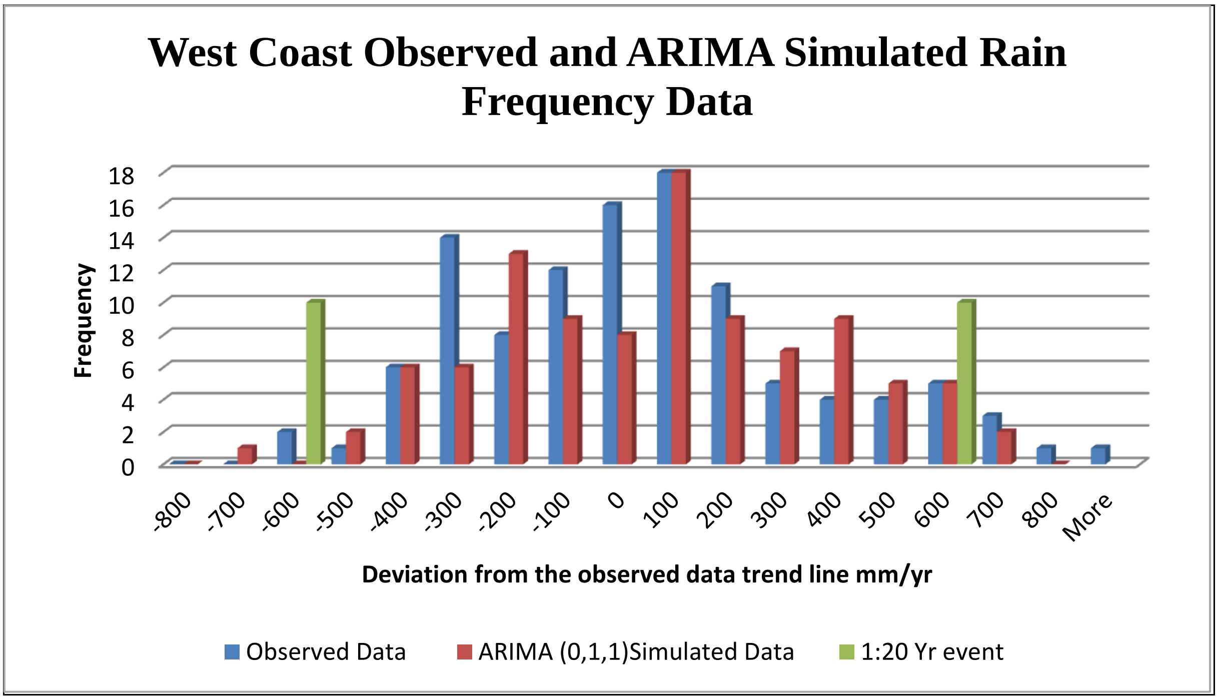


Figure 4: West Coast standardised, simulated and observed rain deviation frequency

3.2 West Coast temperature data

While the linear regression equation and the fitted ARIMA model data suggest no definite long term trend in temperature, it is clear in both the observed data and the simulated data that that there have been some extended periods of wet and dry weather. The period from approximately 1920 to 1940 shows a sustained period of increasing precipitation, but little effect was seen in the temperature plot for the same period. Temperatures showed a similar trend in the period 1980 through to 2005. The ARIMA model suggests a period of cooler temperatures over the next decade that would appear to be, visually, somewhat inconsistent with the observed data, even taking into account the observed data showing prolonged periods of below average temperature. (c.f. Figure 4: period 1915-1930.)

ARIMA (1,0,1) Prediction Equation:

$$Y_t - \mu = \phi Y_{t-1} - \mu + \varepsilon_t + \theta\varepsilon_{t-1} + \beta_t \quad (9)$$

Regression Trend Equation:

$$Y_t = 12.59 - 0.0027*Year \tag{10}$$

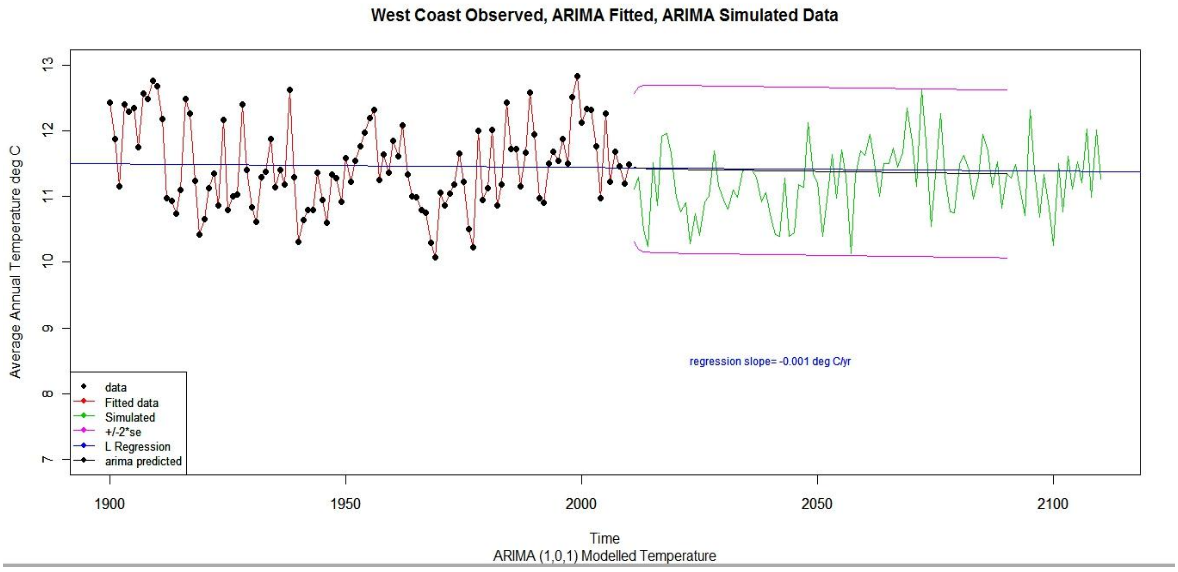


Figure 4: West Coast temperature ARIMA simulated data

Table 4: ARIMA model for West Coast temperature data

Series: West Coast temperature ARIMA (1,0,1) with non-zero mean					
Coefficients:					
	ar1	ma1	E[Mean]	Drift (Trend) β_t	
	0.5628	-0.1206	11.5397	-0.001	
s.e.	0.2279	0.2926	0.212	0.0033	
sigma^2 estimated 0.3176			Log likelihood=-93.97		
AIC=197.94 AICc=198.51 BIC=211.49					
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.00543	0.563539	0.461808	-0.28659	4.01975	0.888092

Table 5: F Statistic for West Coast temperature, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	11.47351	11.7006
Variance	0.412383	0.369188
Observations	111	100
df	110	99
F	1.117001	
P(F<=f) one-tail	0.287985	
F Critical one-tail	1.38449	

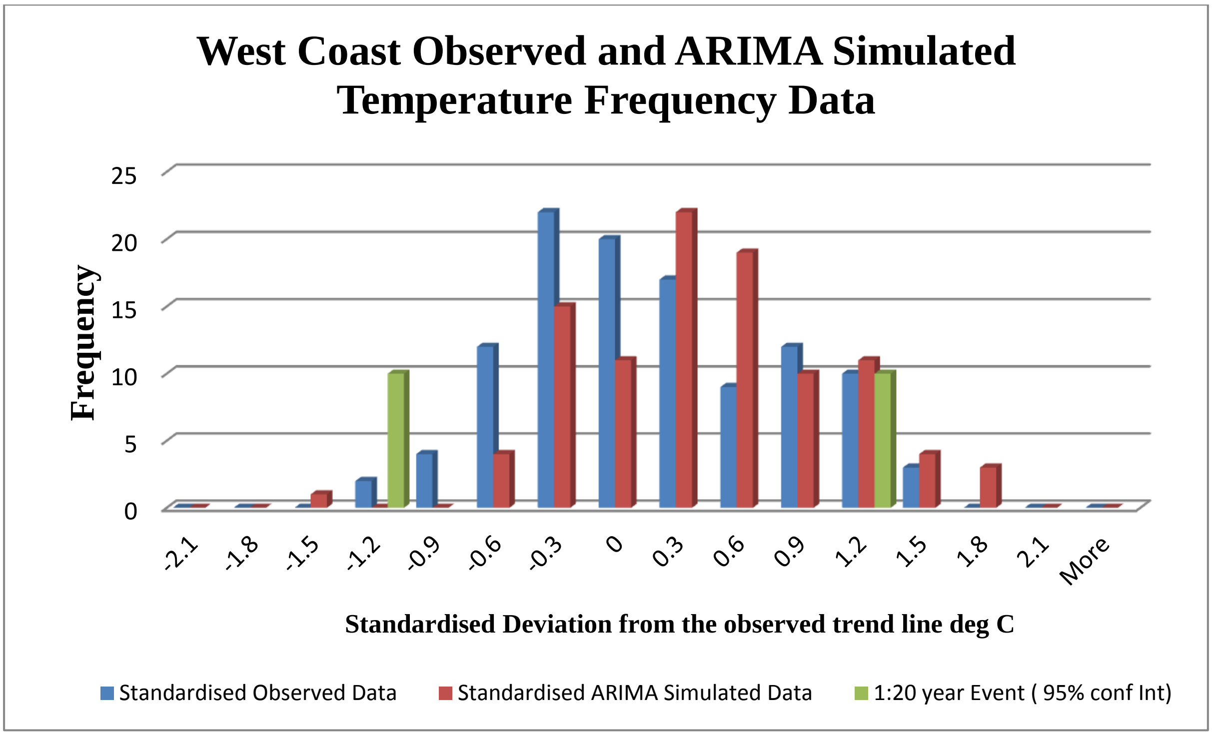


Figure 5: West Coast Observed and ARIMA Simulated Temperature Data

3.4 Marlborough rain

Both the observed and simulated data show a sustained increase in rainfall over time. The fitted data does not appear to match the variability of the observed data particularly well, possibly due to the second order moving average terms in the fitted model. The F statistic also suggests that the simulated data series has a significantly greater variability. Visually however, the ARIMA simulated data series does appear to be reasonably consistent with the observed data series, with the simulated data series showing more rain events 300 and 400mm greater than the observed trend line.

The auto correlation plot for the observed data and residual plots for the fitted data can be found in Appendix 2, Figures 51 & 52.

ARIMA (1,1,2) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \theta_2 \varepsilon_{t-2} + \beta_t \quad (11)$$

Regression Trend Equation:

$$Y(t) = 2.715 \quad * Year - 4115.3 \qquad (12)$$

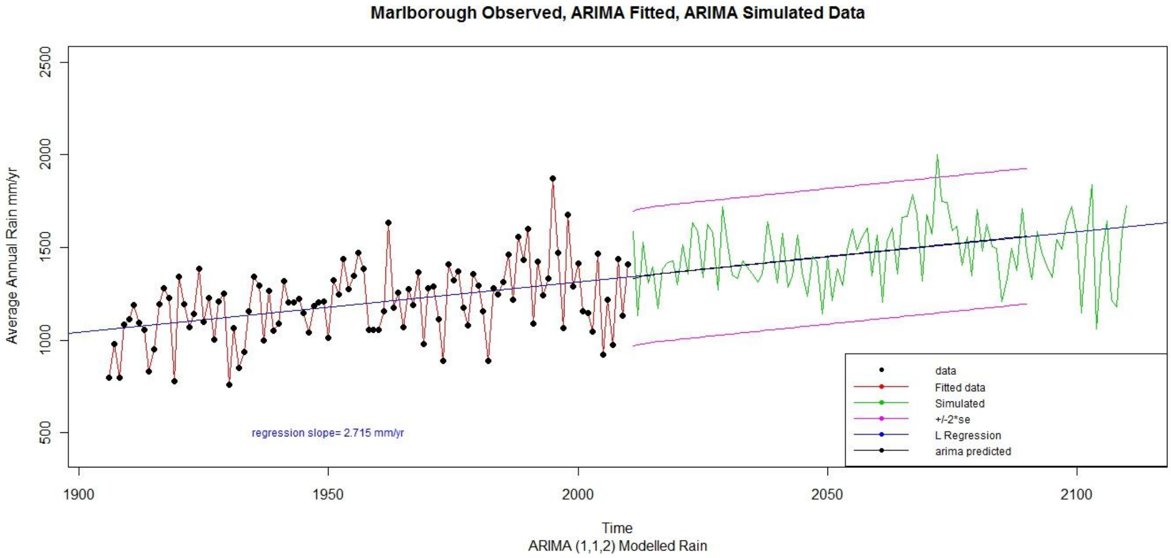


Figure 6: Marlborough rain ARIMA simulated data

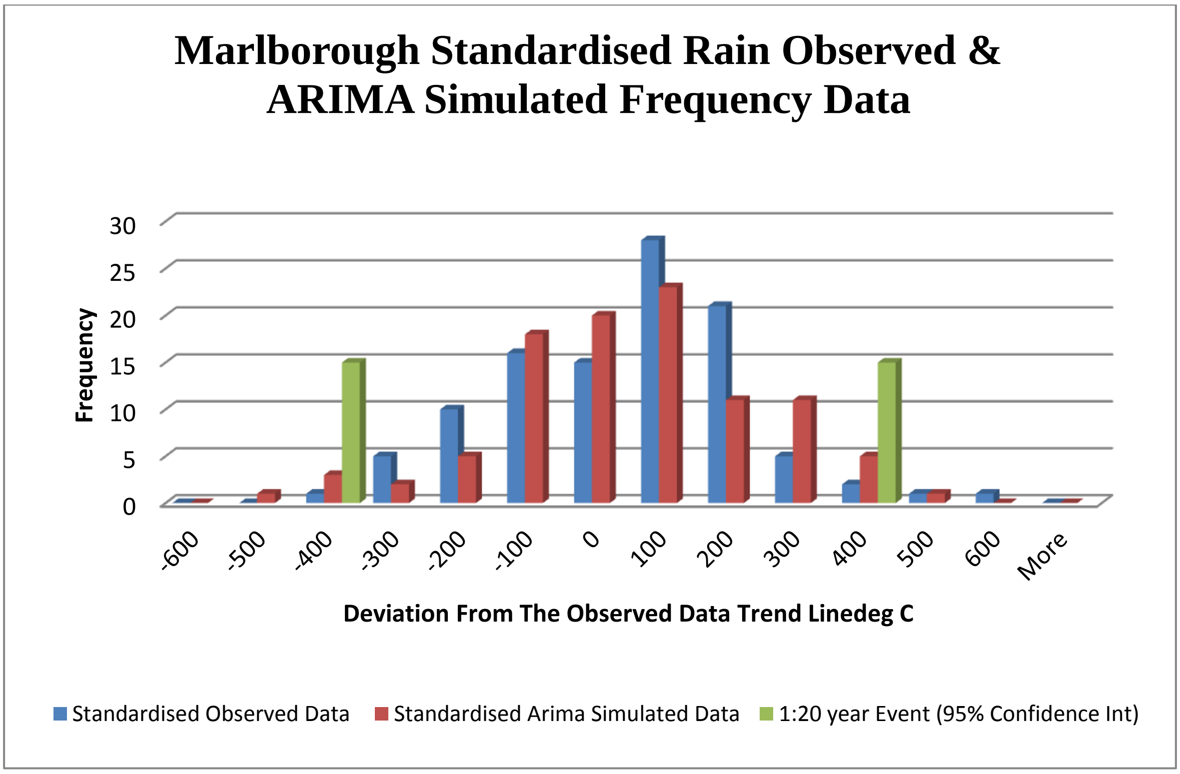


Figure 7: Marlborough standardised, simulated and observed rain deviation frequency

Table 6:ARIMA model for Marlborough rain data

Series: Marlborough rain ARIMA(1,1,2) with drift					
Coefficients	ar1	ma1	ma2	Drift (Trend).β_t	
	0.7104	-1.6559	0.6559	2.7386	
s.e.	0.3703	0.3849	0.3842	0.6837	
sigma^2 estimated as: 32870:			log likelihood=-690.55		
AIC=1391.1	AICc=1391.71	BIC=1404.32			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
15.1447	180.4358	146.2304	-0.7976	12.59222	0.712229

Table 7: F Statistic for Marlborough rain, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	1200.782	1482.226
Variance	39773.76	41227.46
Observations	105	100
df	104	99
F	0.96474	
P(F<=f) one-tail	0.427799	
F Critical one-tail	0.720796	

3.4 Marlborough temperature data

The temperature data for Marlborough shows a slight upward trend of about 0.7°C over the 104 years of data analysed: within this trend however, there have been regular periods of 5-7 years where the average annual temperature has been consistently above or below the long term trend line.

The best fit ARIMA model (1,1,1) produces a very good fit with the observed data: RMSE of 0.48 °C. The simulated data does appear to be centred on the long term trend line, and the F statistic (Table 8) shows no significant variability in the two data series. The simulated temperature data series does show a number of extreme temperature events, two of which fall outside the 2*se of the trend line. The trend deviation histogram (Figure 8) does indicate the simulated data to be positively skewed, in favour of increased temperature over the next 100 years of the simulation.

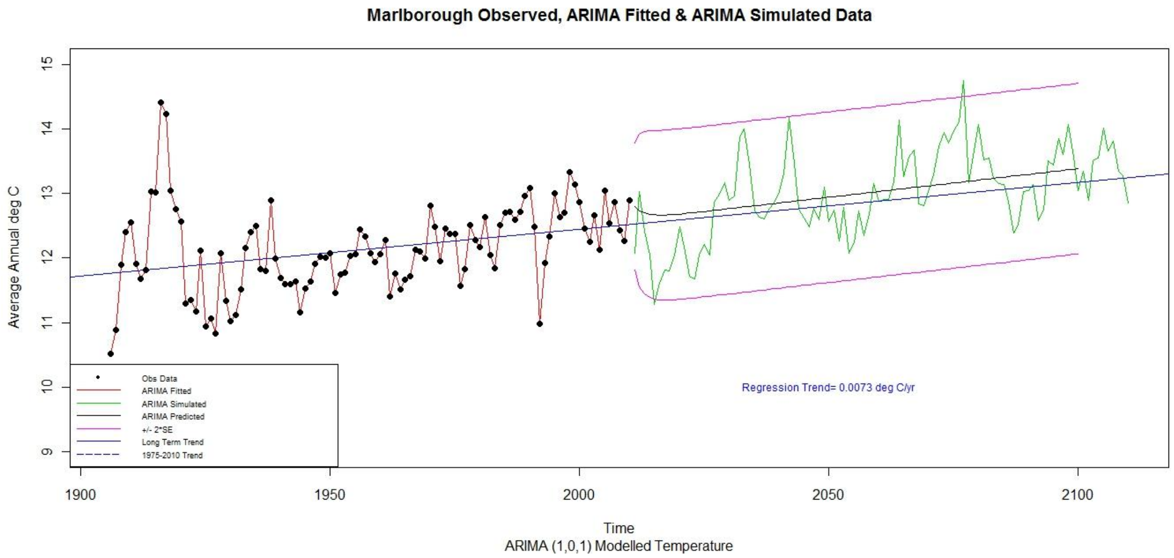


Figure 8: Marlborough temperature ARIMA simulated data

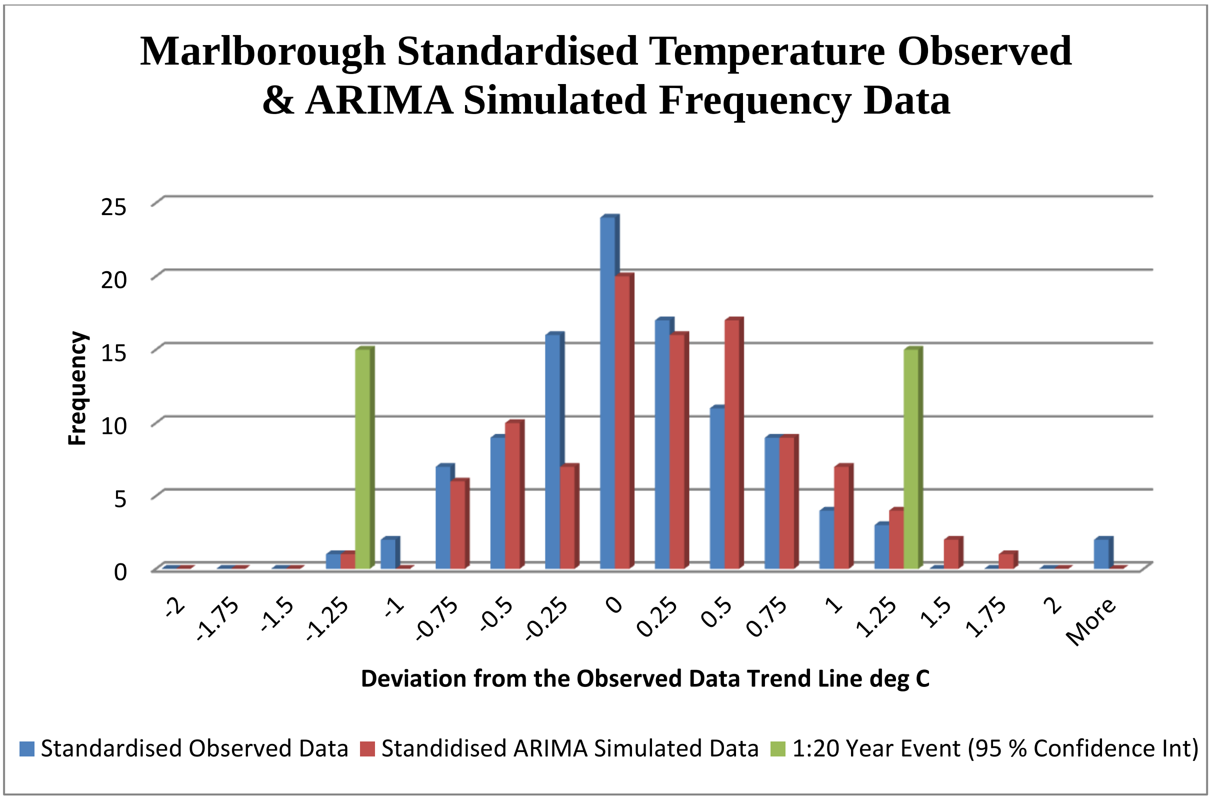


Figure 9: Marlborough standardised, simulated and observed temperature deviation frequency

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \qquad (13)$$

Regression Trend Equation:

$$Y_t = 0.00727 * Year - 2.101 \qquad (14)$$

Table 8: ARIMA model for Marlborough temperature data

Series:	Marlborough temperature				
ARIMA (1,1,1) with drift					
	ar1	ma1	Drift (Trend) β_t		
Coefficients:	0.6567	-1	0.0089		
s.e.	0.0784	0.0279	0.0044		
sigma^2 estimated		0.2377	log likelihood= -74.42		
AIC=156.83	AICc=157.2	BIC=167.41			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
0.011084	0.485219	0.359239	-0.04372	2.958654	0.8961

Table 9: F Statistic for Marlborough temperature, observed and ARIMA simulated data

F-Test two sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	12.14257	13.00106
Variance	0.445362	0.444802
Observations	105	100
df	104	99
F	1.001258	
P(F<=f) one-tail	0.498133	
F Critical one-tail	1.389487	

North Canterbury Coastal rain

The linear regression analysis would tend to support a reduction in average annual rainfall in the observed data series, of approximately 0.9 mm/year over the 110 year data set values. Interesting is the pronounced reduction in annual rainfall over the period 1975 -2010, estimated at -9.6 mm/year over the last 35 years of the data series. Data simulated for ARIMA model (Figure 9), shows the rainfall decline stabilising and a slight increasing rainfall trend establishing for the next 70 years.

ARIMA (0,1,1) Prediction Equation:

$$Z_t = \beta_1 + \varepsilon_t + \theta\varepsilon_{t-1} \quad (15)$$

Regression Trend Equations:

$$Y_t = 2545.953 - 0.8674 * Year \quad (16)$$

$$Y_t = 18947.55 - 9.107 * Year \quad (17)$$

It is of interest to consider the sharp decline in average annual rainfall in the period 1975-2010. This is a significant departure from the long term trend line as shown on Figure 9 below.

The simulated data appears to be still reasonably centred on the long term trend line. It is interesting to note that there is a very wide spread of annual rainfall frequencies, with the standard deviation being close to 20% of the mean (standard deviation=160 mm).

While the ARIMA model simulation data standardised rain fall frequency shows a similar distribution to the observed standardised rainfall distribution (Figure 10), the F statistic would suggest that there is a significant difference in the variability at the 95% confidence interval (Table 10).

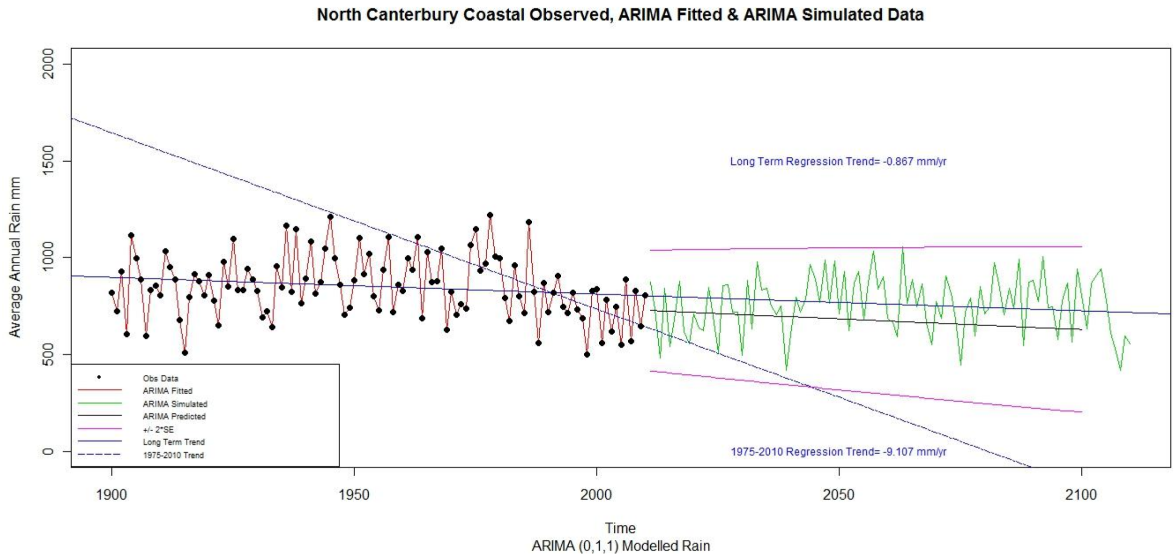


Figure 10: North Canterbury Coastal rain ARIMA simulated data

Table 10: ARIMA model for North Canterbury Coastal rain data

Series:	North Canterbury rain				
ARIMA (0,1,1) with drift					
Coefficients	ma1	Drift (Trend).β_t			
	-0.9006	-1.098			
s.e.	0.0415	1.6155			
sigma^2 estimated as		24238:		log likelihood=-712.18	
AICc=1430.58	AICc=1430.58	BIC=1438.46			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
1.76217	154.9812	123.4931	-3.2293	15.30564	0.698566

Table 11: F Statistic for North Canterbury Coastal rain, observed and ARIMA simulated data

F-Test two sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	850.1991	797.4386
Variance	25701.57	31009.58
Observations	111	100
df	110	99
F	0.828827	
P(F<=f) one-tail	0.168451	
F Critical one-tail	0.724599	

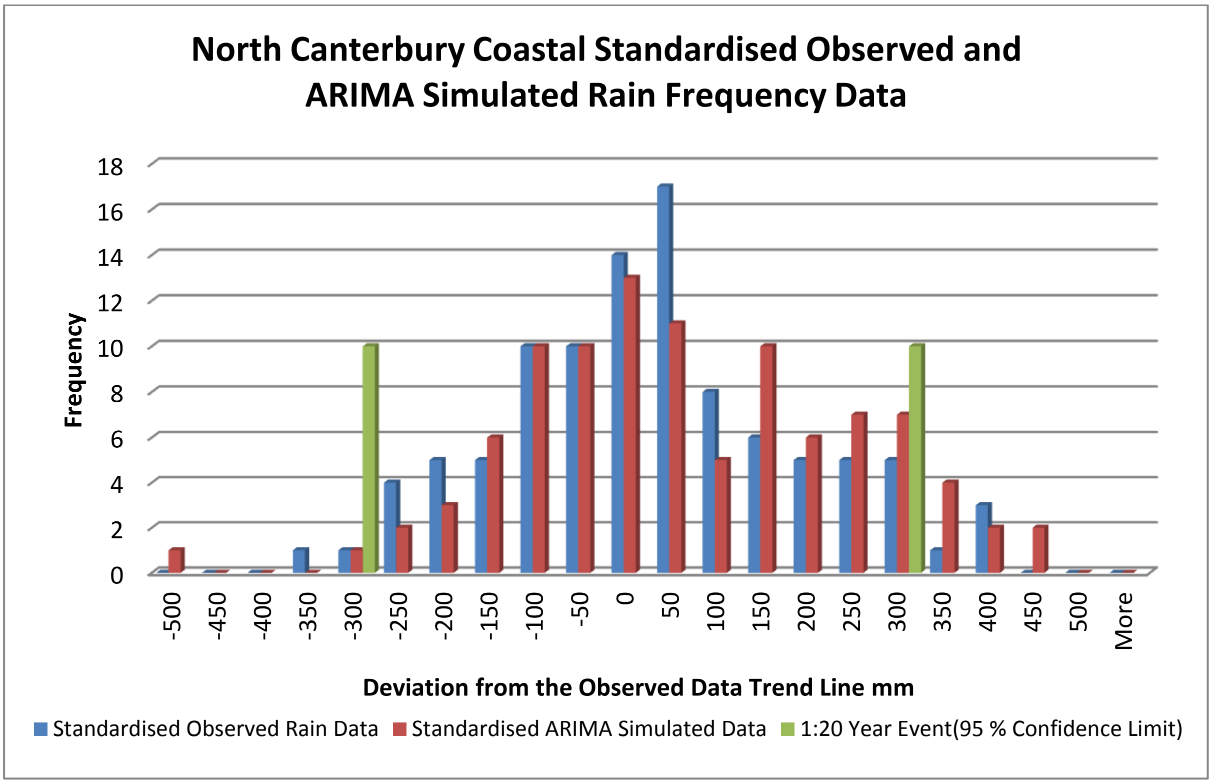


Figure 11: North Canterbury Coastal standardised, simulated and observed rain deviation frequency

3.5 North Canterbury Coastal temperature

An increasing trend in average annual temperature for the North Canterbury Coastal data set is evident from the data plots shown in Figure 13 below and the region graph in Appendix 1.

The ARIMA model (1,1,1) visually is consistent with the observed data, as is the ARIMA model simulated data, although showing an increasing temperature trend over the observed data trend line.

The standardised temperature frequency graph (Figure 14), shows a reasonable match to the standardised observed temperature frequency. It is interesting to note the relatively narrow variation from the series trend line: average annual temperature only varies by approximately +/- 1 degree centigrade.

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \qquad (18)$$

Regression Trend Equation:

$$Y_t = 0.002683 * Year + 6.271 \qquad (19)$$

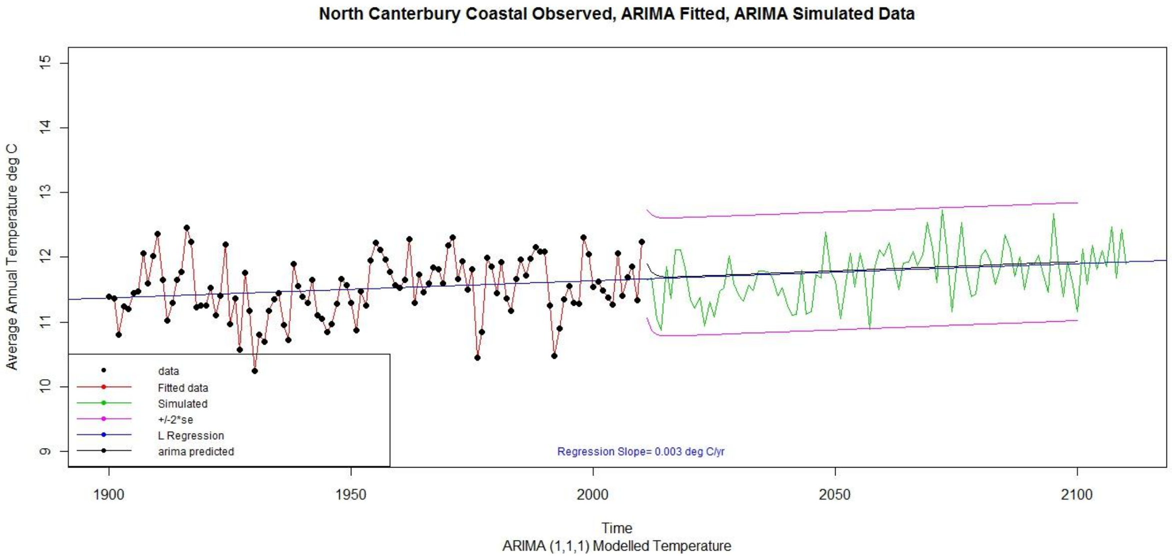


Figure 12: North Canterbury Coastal temperature ARIMA simulated data

Table 12: ARIMA model for North Canterbury Coastal temperature data

Series: North Canterbury Coastal temperature					
ARIMA (1,1,1) with drift					
Coefficient	ar1	ma1	Drift (Trend).β_t		
	0.3896	-1	0.0029		
s.e.	0.0893	0.0292	0.002		
sigma^2 estimated		0.1728:	log likelihood=-61.46		
AICc=131.3		AICc=131	BIC=141.72		
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.0072	0.413758	0.323646	-0.19143	2.826393	0.819735

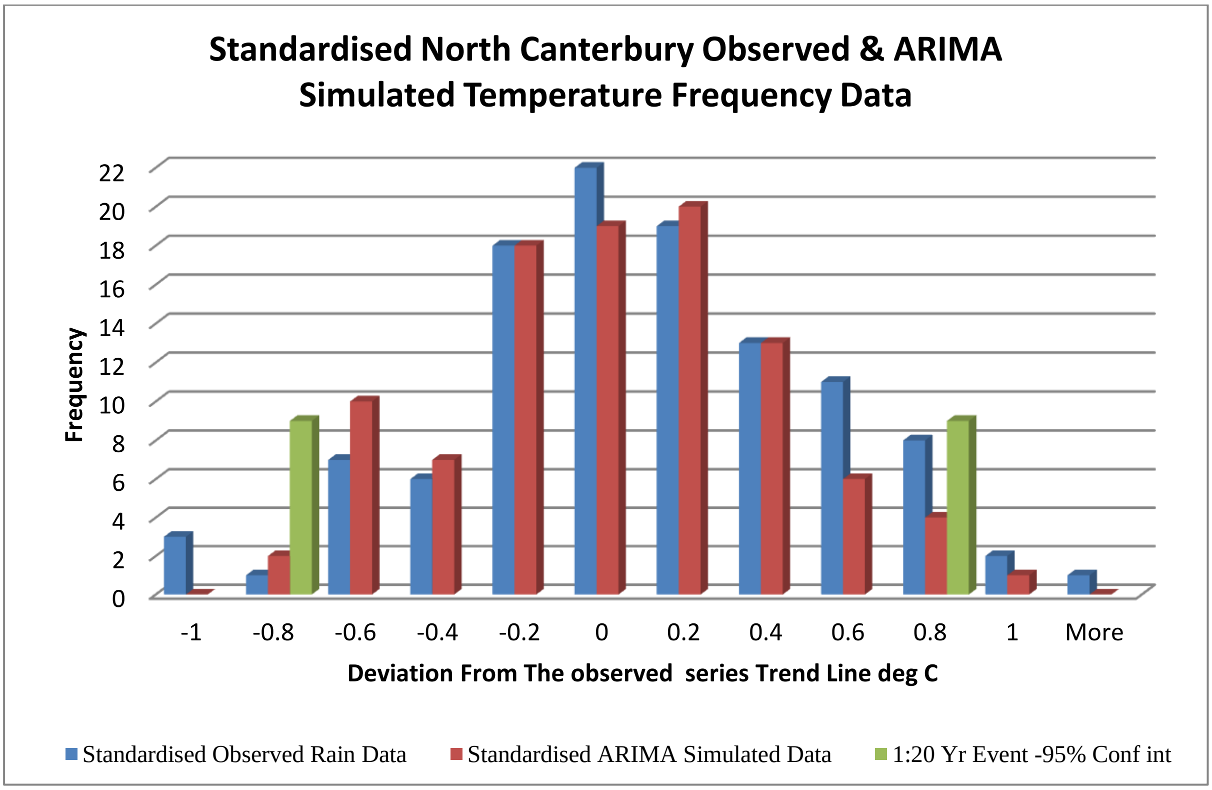


Figure 13: North Canterbury Coastal standardised, simulated and observed temperature deviation frequency

3.5 North Canterbury Foothills rain

The regression trend shows a slight increase in average annual rainfall over the period of the observed data series (1921-2010). The ARIMA model (0,1,1) continues this slight upward trend over the simulation period, with a similar level of variability. The F statistic for the observed and the simulated data indicates no significant difference in the variability in the two data sets.

The standardised frequency distribution does indicate more frequent drier spells, but within the 95% confidence limit of the observed data set.

ARIMA (0,1,1) Prediction Equation:

$$Z_t = \beta_1 + \varepsilon_t + \theta\varepsilon_{t-1} \quad (20)$$

Regression Trend Equation:

$$Y_t = 0.6081*\text{Year} - 10.59 \quad (21)$$

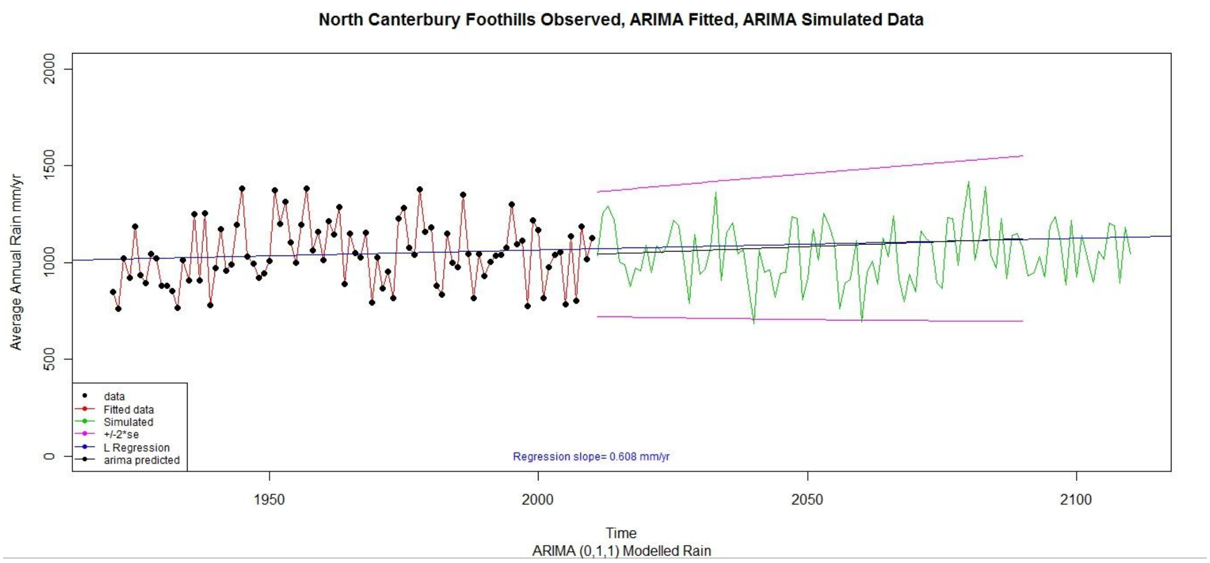


Figure 14: North Canterbury Foothills rain ARIMA simulated data

Table 13: F Statistic for North Canterbury Foothills rain, observed and ARIMA simulated data

F-Test two sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	1044.599	1043.992
Variance	25897.04	24055.08
Observations	90	90
df	89	89
F	1.076573	
P(F<=f) one-tail	0.36429	
F Critical one-tail	1.419888	

Table 14: ARIMA model for North Canterbury Foothills rain data

Series: North Canterbury Foothills rain					
ARIMA(0,1,1) with drift					
Coefficient	ma1	Drift (Trend).β_t			
	-0.902	1.0152			
s.e.	0.0538	1.8901			
sigma^2 estimated as		25835		Log likelihood=-579.22	
AIC=1164.45	AICc=1164.73				
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
5.190757	159.837	123.6218	-1.6342	12.05874	0.68494

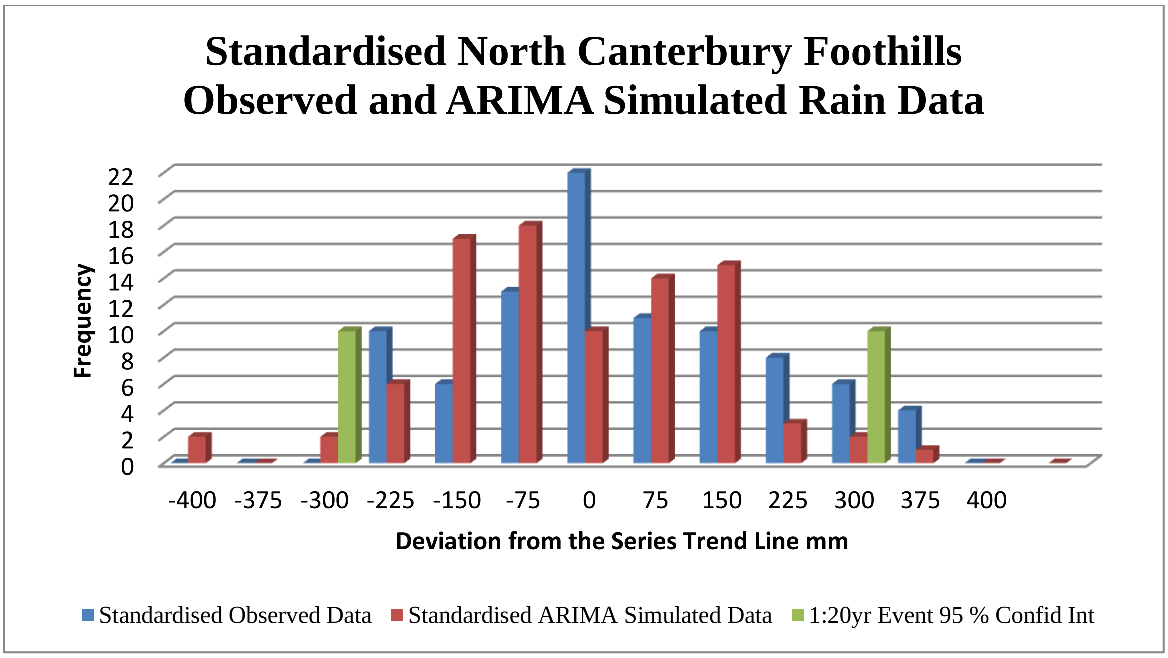


Figure 15: North Canterbury Foothills standardised, simulated and observed rain deviation frequency

3.6 North Canterbury Foothills temperature

The observed temperature data shows a pronounced increasing trend in average annual temperature over the data series (1921-2010). The regression trend line estimates an annual increase of just over one degree centigrade over the 100 year period of the data: A fairly significant annual temperature rise (significant at the 99% confidence interval).

In general, the ARIMA temperature simulation visually is consistent with the observed data variability and does appear to be centred on the long term regression trend line: i.e. maintains an overall annual temperature raise of approximately 1 degree centigrade (Figure 15). The F statistic comparing the two data distributions shows no significant difference in variability between the two data distributions (Table 16).

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \quad (22)$$

Regression Trend Equation:

$$Y_t = 0.01022{*}Year - 8.945 \quad (23)$$

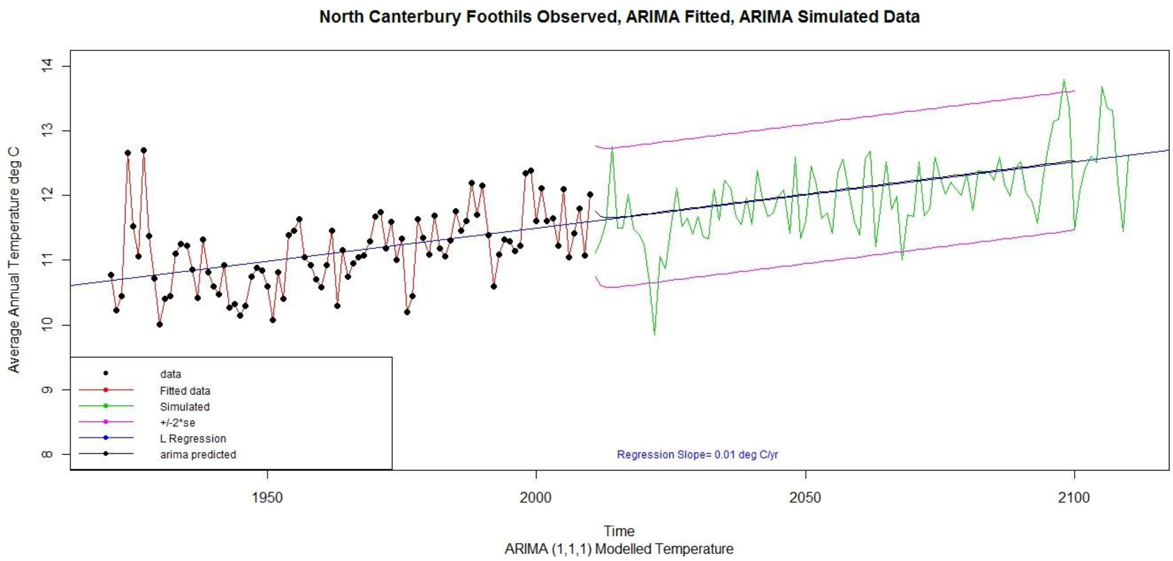


Figure 16: North Canterbury Foothills temperature ARIMA simulated data

Table 15: ARIMA model for North Canterbury temperature data

Series: North Canterbury Foothills temperature					
ARIMA(1,1,1) with drift					
Coefficients	ar1	ma1	Drift (Trend).β_t		
	0.334	-1	0.0103		
s.e.	0.1011	0.047	0.003		
sigma^2 estimated as		0.2516	Log likelihood=-66.79		
AIC=141.58		AICc=142.06		BIC=151.54	
In-sample error					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.03668924	0.4988220	0.376711	-0.52918	3.372275	0.787580

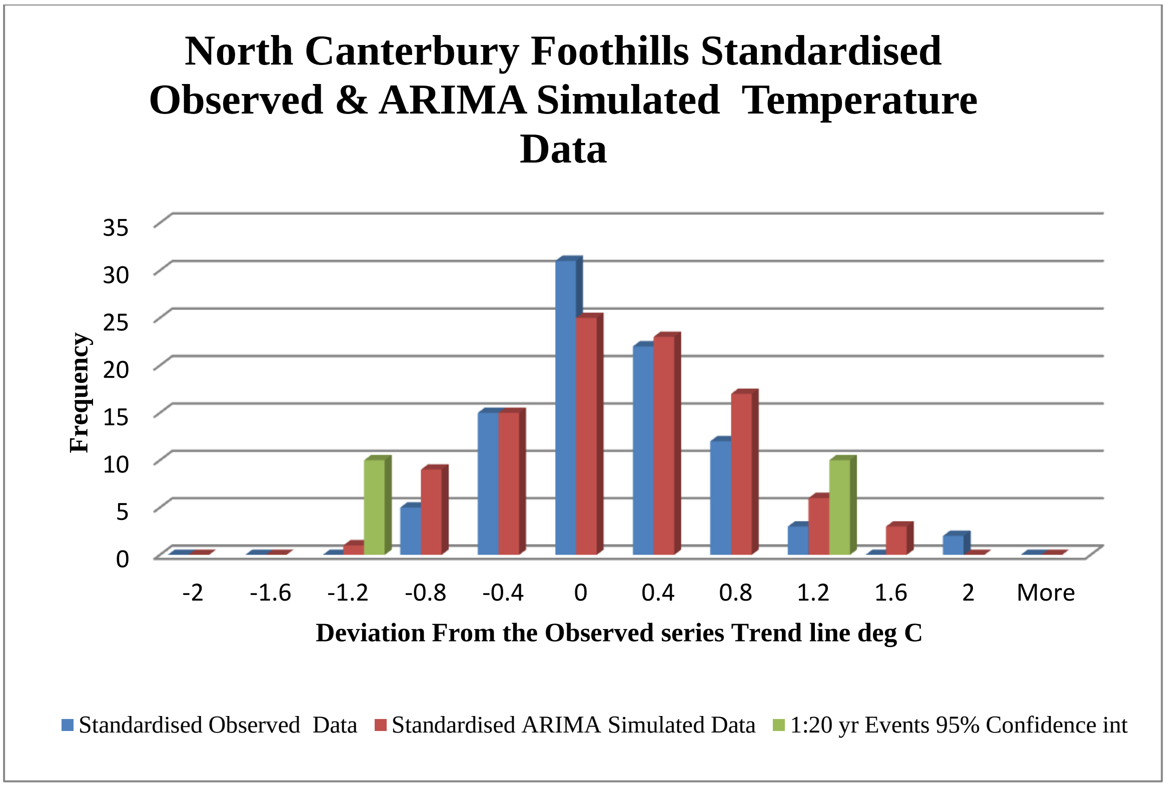


Figure 17: North Canterbury Foothills standardised, simulated and observed temperature deviation frequency

Table 16: F Statistic for North Canterbury Foothills temperature, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	11.146	11.96427
Variance	0.351934	0.32707
Observations	90	90
df	89	89
F	1.076022	
P(F<=f) one-tail	0.365193	
F Critical one-	1.419888	

3.7 Canterbury Mountains

The data for the Canterbury Mountains was of the poorest quality for all the regions. While over 100 years of rainfall data was available, reliable data for temperature could only be used from 1931 to 2010. This still gives over 80 years of consistent data to evaluate.

Rainfall data shows a steady upward trend of approximately 3.5 mm/year increase in annual average rainfall over the period 1931-2010.

The ARIMA simulated data appears visually consistent with the observed data series (Figure 17), with the F statistic indicating there is no significant variability between the data series. The standardised rain frequency distribution (Figure 19), shows a considerable spread in deviations from the observed data trend line.

ARIMA (1,1,2) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \beta_t \qquad (24)$$

Regression Trend Equation:

$$Y_t = 3.491*\text{Year} + 219.44 \qquad (25)$$

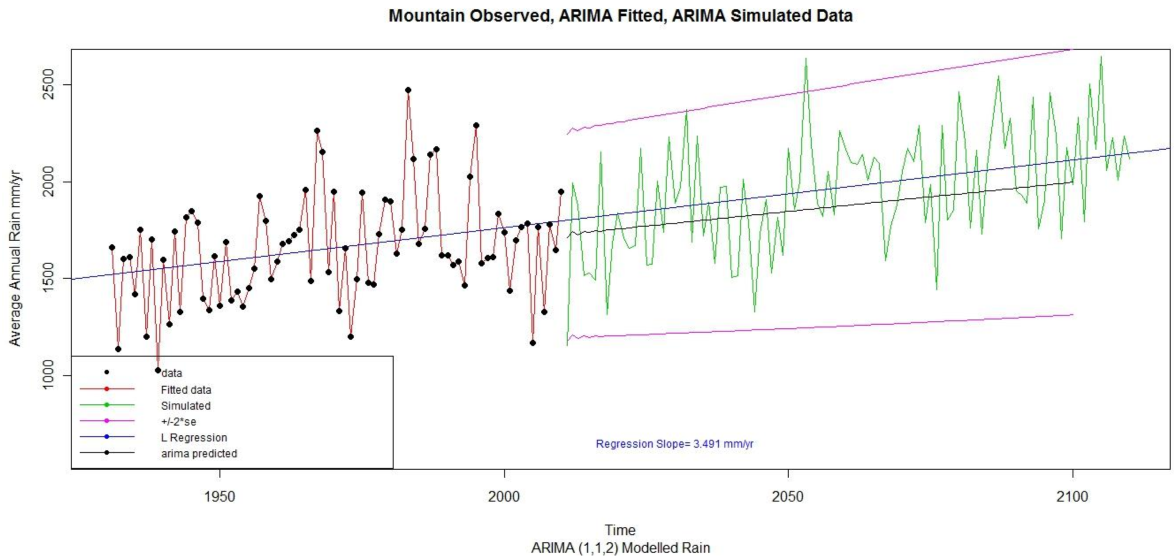


Figure 18: Canterbury Mountains rain ARIMA simulated data

Table 17: ARIMA model for Canterbury Mountains rain data

Series: Canterbury Mountains rain					
ARIMA (1,1,2) with drift					
Coefficients:	ar1	ma1	ma2	Drift (Trend).β_t	
	-0.6987	-0.2488	-0.6059	3.0066	
s.e.	0.4327	0.4433	0.4121	3.0302	
sigma^2 estimated as		70843:	Log likelihood=		-
AIC=1118.32	AICc=1119.1	BIC=1130.1			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.7485004	264.4955	216.8807	-2.4531	13.46035	0.763046

Table 18: F Statistic for Canterbury Mountains rain, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	1659.799	1991.316
Variance	75573.31	58794.47
Observations	80	100
df	79	99
F	1.285381	
P(F<=f) one-tail	0.117928	
F Critical one-tail	1.417375	

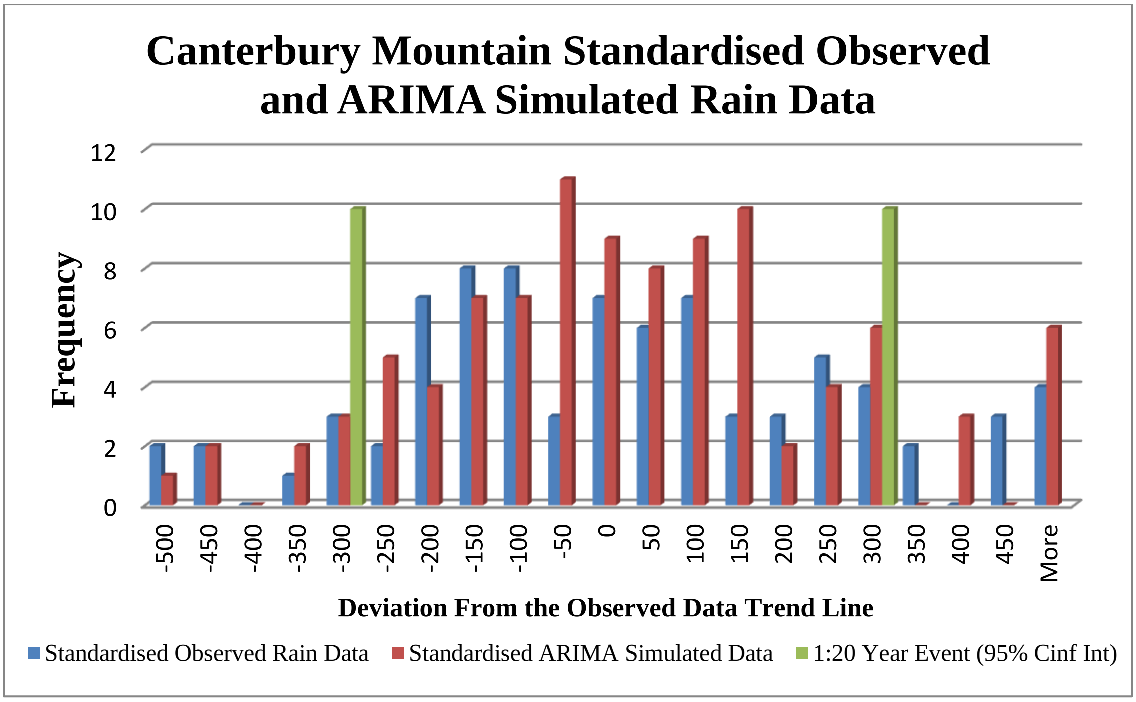


Figure 19: Canterbury Mountains standardised, simulated and observed rain deviation frequency

3.8 Canterbury Mountain temperature

While average annual Canterbury Mountain temperatures have increased by almost 1°C over the last 80 years, the inter-annual variation has been large: over 3°C.

The fitted ARIMA model data appears to provide a good fit for the observed temperature data. Of concern is the low temperature spike that has been generated in the ARIMA model simulation. This is not unusual, as with any random generated process, a small number of data points will be at the extreme limits of the distribution: in this case, the data point at 2020 in the ARIMA model simulated temperature series is within three standard deviations of the observed data trend line (+/- 2.29).

The simulated series appears to get more variable towards the end of the simulation data series: The F statistic (Table 19) indicates that there is no significant difference in the simulated series data variability, compared with the observed data variability.

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \quad (26)$$

Regression Trend Equation:

$$Y_t = 0.010947*\text{Year} - 12.9127 \quad (27)$$

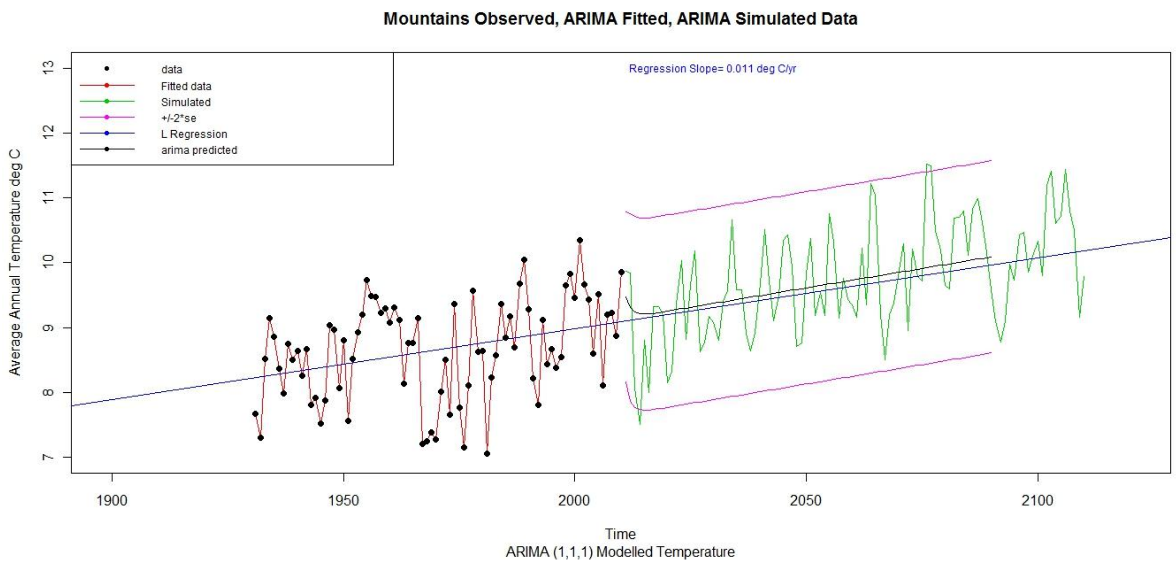


Figure 20: Canterbury Mountains temperature ARIMA simulated data

Table 19: ARIMA model for Canterbury Mountains temperature data

Series: Canterbury Mountains temperature					
ARIMA (1,1,1) with drift					
Coefficients:	ar1	ma1	Drift (Trend).β_t		
	0.4548	-1	0.012		
s.e.	0.1031	0.0429	0.0056		
sigma^2 estimated as		0.4226:	Log likelihood=-79.78		
AIC=167.57		AICc=168.11		BIC=177.04	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
0.007563752	0.645994	0.514138	-0.47019	6.083446	0.834536

Table 20: F Statistic for Canterbury Mountains temperature, observed and ARIMA simulated data

F-Test two sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	8.658625	9.621264
Variance	0.586868	0.582065
Observations	80	100
df	79	99
F	1.008251	
P(F<=f) one-tail	0.48149	
F Critical one-tail	1.417375	

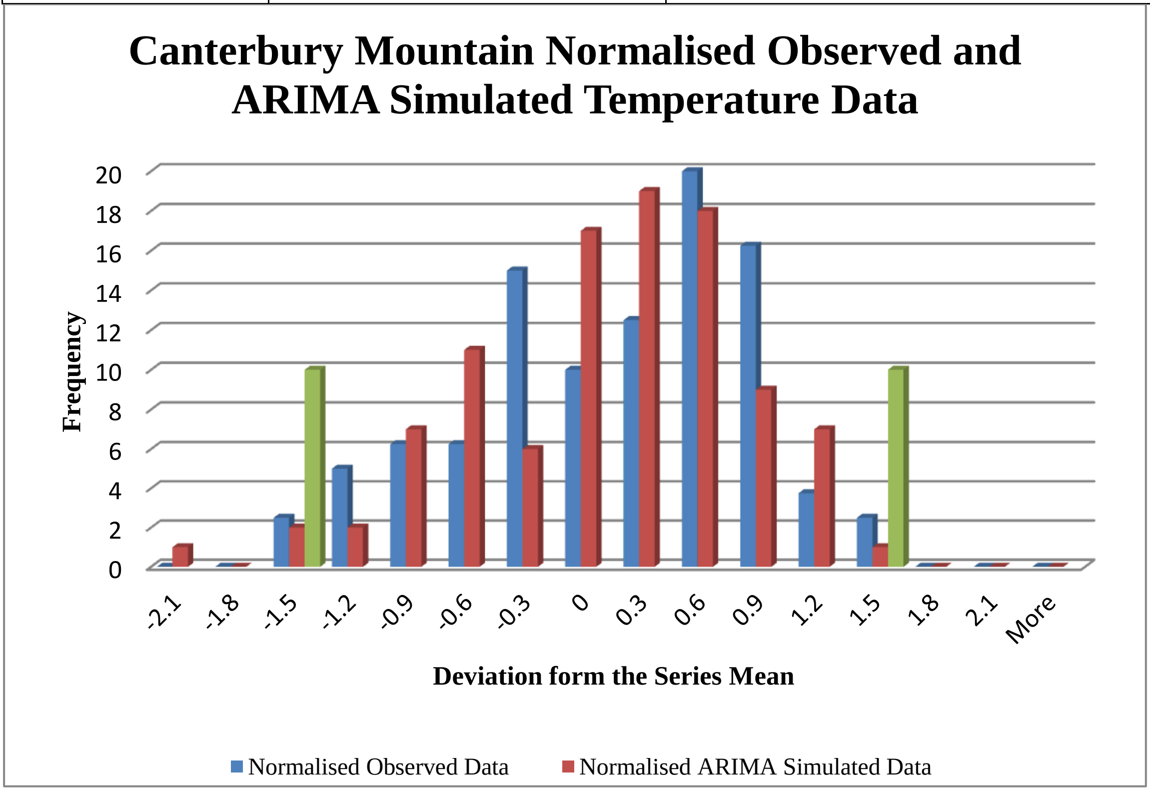


Figure 21: Canterbury Mountains standardised, simulated and observed temperature deviation frequency

3.9 South Canterbury Coastal rain

The observed data does show a long term trend of increasing rainfall, but the time series is punctuated with prolonged periods: both wet and dry periods with quite a wide spread of annual average rainfall: 450mm to 1100mm. These extremes are not rare events over the observed data set. The ARIMA simulated data set reflects the high level of variability in the observed rain data set, with the simulated extreme tending to be short periods of very dry years.

As the best fit ARIMA model (1,1,1) did not appear to be particularly consistent with the observed rain data, an ARIMA model (101) simulation was plotted as a comparison. This model does, visually, appear more consistent with the observed rain data set, in as much as the simulated data is more centred on the long term trend line.

The standardised rain frequency graph (Figure 23), shows a number of drier than expected years in the observed data set, whereas the simulated data set, (using the ARIMA (1,1,1) model data), tends to show a more even distribution of wet and dry years, with the dry years more likely to be extreme events.

The cross correlation plot shows a poor relationship between observed and fitted data, possibly due to the fitted data not fully expressing the extremes present in the observed data.

While the ARIMA model (1,1,1) simulated data is more variable, there is not a significant difference in the variability of the observed and the simulated data (Table 21).

ARIMA (1,0,1) Prediction Equation:

$$Y_t - \mu = \phi Y_{t-1} - \mu + \varepsilon_t + \theta\varepsilon_{t-1} + \beta_t \qquad (28)$$

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \beta_t \qquad (29)$$

Regression Trend Equation:

$$Y_t = 1.012*Year-1201.479 \quad (30)$$

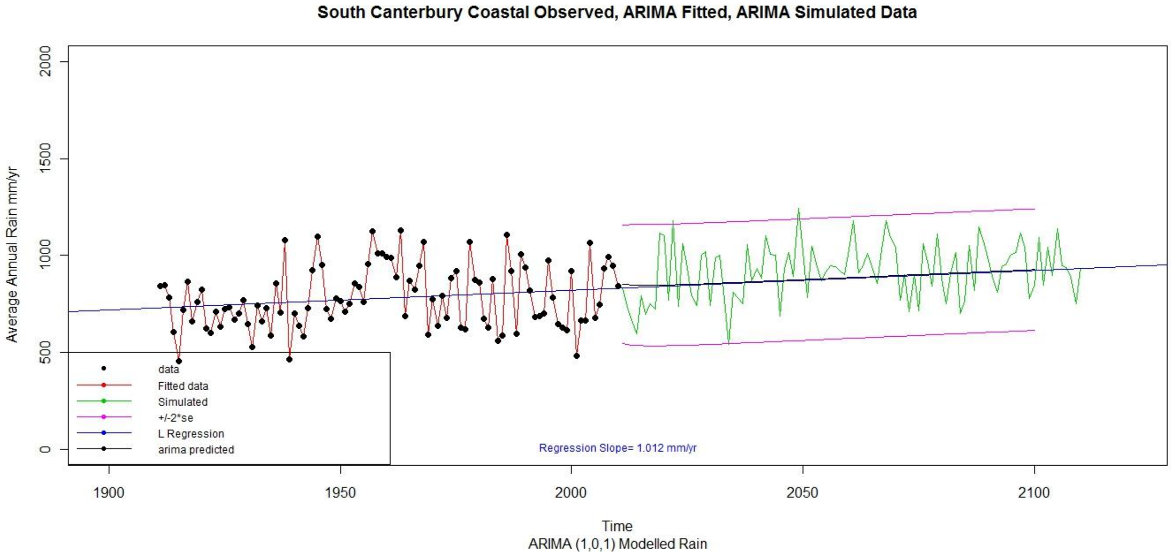


Figure 22: South Canterbury Coastal rain ARIMA simulated data

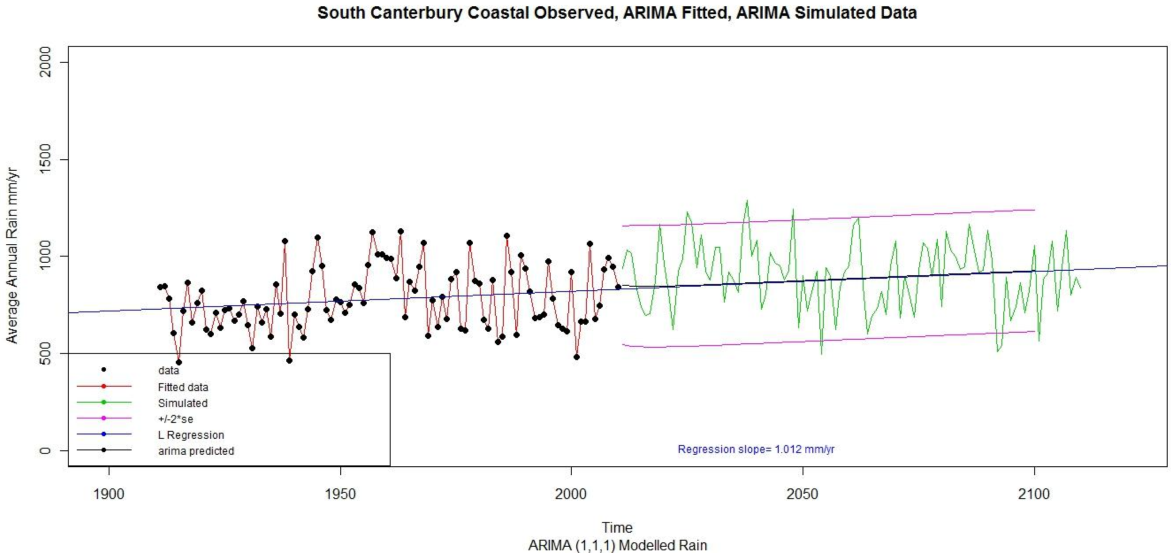


Figure 23: South Canterbury Coastal ARIMA (1,1,1) simulated rain data

Table 21: ARIMA model for South Canterbury Coastal rain data

Series: South Canterbury Coastal rain					
ARIMA (1,0,1) with non-zero mean					
Coefficients:	ar1	ma1	E[mean]	Drift (Trend).β_t	
	0.8297	-0.7108	731.5894	1.0299	
s.e.	0.1863	0.2383	49.5224	0.8415	
sigma^2 estimated as	23489:	log likelihood =, -645.15			
AIC = 1300.3	AICc =1300.94	BIC = 1313.33			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.55716	153.26	124.6382	-4.06736	16.71929	0.813132
Series: ARIMA(1,1,1) with drift					
Coefficients:	ar1	ma1	Drift (Trend).β_t		
	0.1142	-0.9118	1.05		
s.e.	0.1228	0.0702	1.7586		
sigma^2 estimated as 24484			Log likelihood=-641.5		
AIC=1291	AICc=1291.42	BIC=1301.38			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-4.0989591	155.6905	122.989	-4.42387	16.59805	0.802373

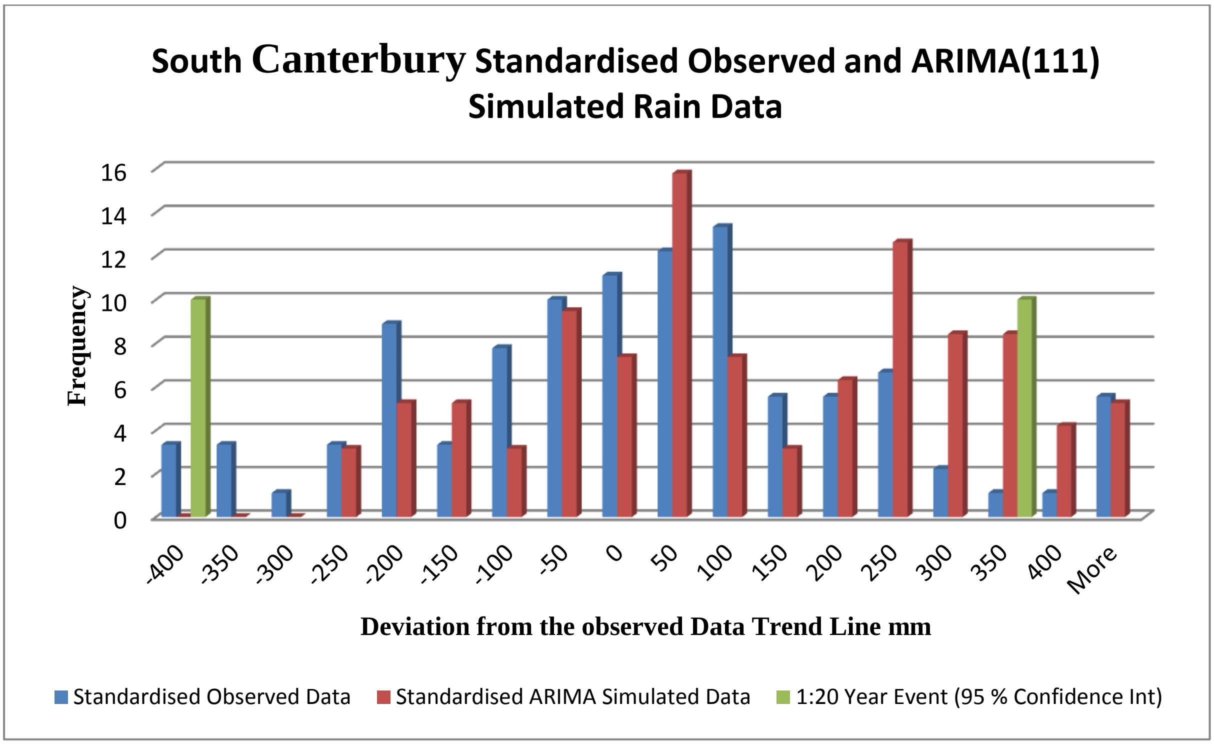


Figure 24: South Canterbury standardised, simulated and observed rain deviation frequency

Table 22: F Statistic for South Canterbury Coastal rain, observed and ARIMA simulated data

F-Test Two-Sample for Variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	781.9816	977.73
Variance	25715.9	44040.03
Observations	100	100
df	99	99
F	0.583921	
P(F<=f) one-tail	0.003978	
F Critical one-tail	0.717329	

3.10 South Canterbury Coastal temperature

The observed temperature data shows a sustained decrease in the average annual temperature of approximately 0.3^{o}C over the last 100 years. Given the variability in the data, this reduction is not significant.

The observed data shows a low degree of temperature variability around the long term trend line, with a number of short duration cold event years. The temperature deviation frequency distribution (Figure 25) however, indicates a reasonably consistent annual average temperature, with the standard deviation of 0.45^{o}C.

The ARIMA model data shows a reasonably good fit to the observed data (Figure 24), but the simulated data set does indicate a number of cool periods, of multiple years in duration. The F statistic indicates that there is no significant difference in the variability of the observed and ARIMA simulated data.

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \quad (31)$$

Regression Trend Equation:

$$Y_t = 17.397 - 0.00348 * Year \quad (32)$$

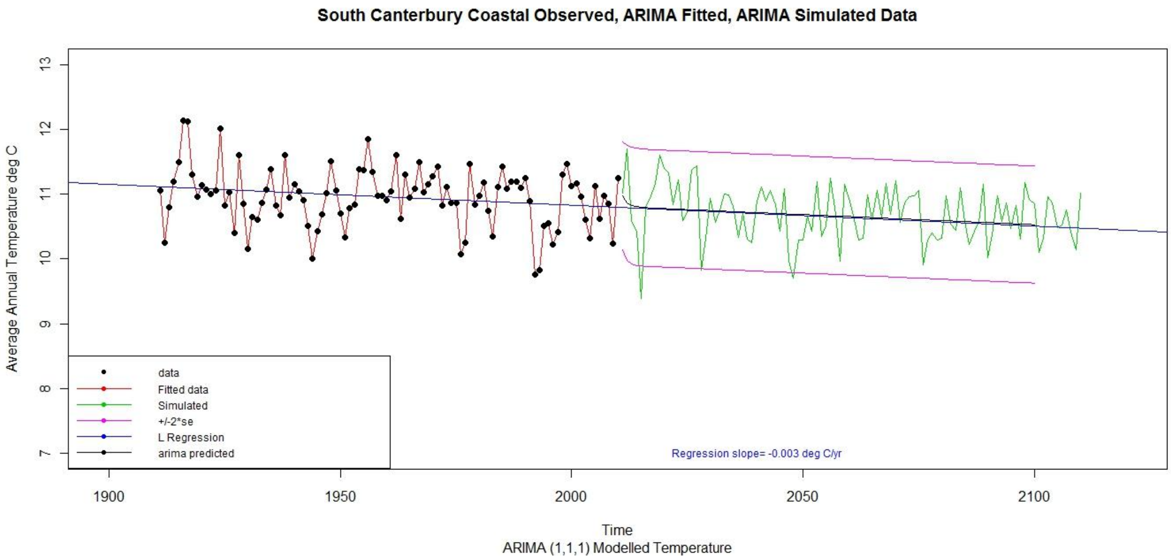


Figure 25: South Canterbury Coastal temperature ARIMA simulated data

Table 23: South Canterbury Coastal temperature F Statistic

F-Test two-sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	10.9596	10.55217
Variance	0.206616	0.187268
Observations	100	99
df	99	98
F	1.103317	
P(F<=f) one-tail	0.31342	
F Critical one-tail	1.395481	

Table 24: ARIMA model for South Canterbury Coastal temperature data

Series: South Canterbury Coastal temperature					
ARIMA(1,1,1) with drift					
Coefficients:	ar1	ma1	Drift (Trend).β_t		
	0.3767	-1	-0.0031		
s.e.	0.0945	0.0278	0.0023		
sigma^2estimated as		0.1714:	log likelihood=-55.07		
AIC=118.14		AICc=118.57		BIC=128.52	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
0.00078692	0.411891	0.323853	-0.13161	2.96700	0.811476

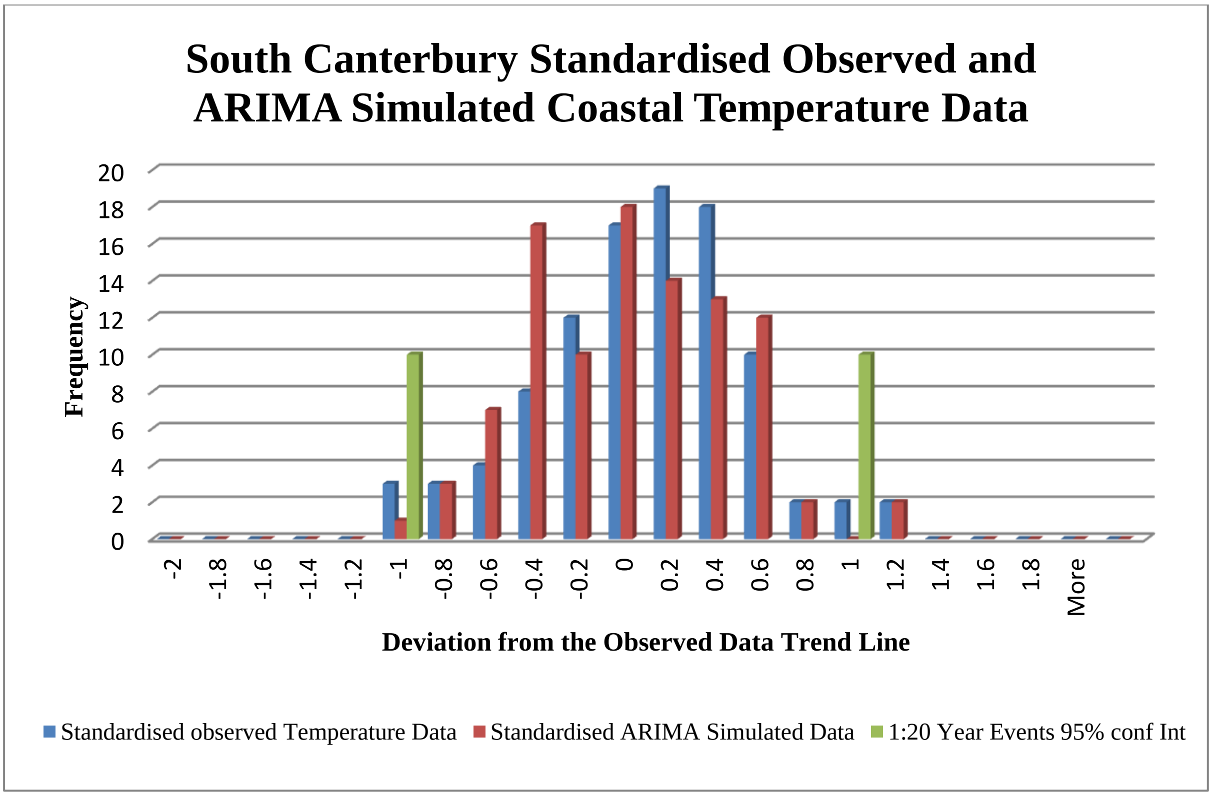


Figure 26: South Canterbury standardised, simulated and observed temperature deviation frequency

3.11 South Canterbury Foothills rain

The linear regression trend line indicates an increase in annual average rainfall for the 90 years of the observed rain data set of 6.2 mm/year, from 800mm in 1920 to 1378mm in 2011, with the greatest rate of increase in the period 1940 to 1970.

The observed rain data series shows extended period of rainfall above the long term trend line and more recently a number of years with very low rainfall.

The ARIMA model data presents a good fit to the observed data: there is no significant difference in the variability in the data sets. The simulated data shows a slight decrease in the rainfall trend, but also indicates extended periods (~5-8 years) of rainfall below or above the trend line for that period.

This is reflected in the rainfall deviation histogram (Figure 27), with the ARIMA simulated data showing greater rainfall frequency below the long term rain trend, with a number of years with rainfall deficits of 400mm or more.

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \qquad (33)$$

Regression Trend Equation

$$Y_t = 6.185 * Year – 11060 \qquad (34)$$

Table 25: F Statistic for South Canterbury Foothills rain, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	1088.308	1554.197
Variance	77016.79	62121.1
Observations	94	100
df	93	99
F	1.239785	
P(F<=f) one-tail	0.146395	
F Critical one-tail	1.400122	

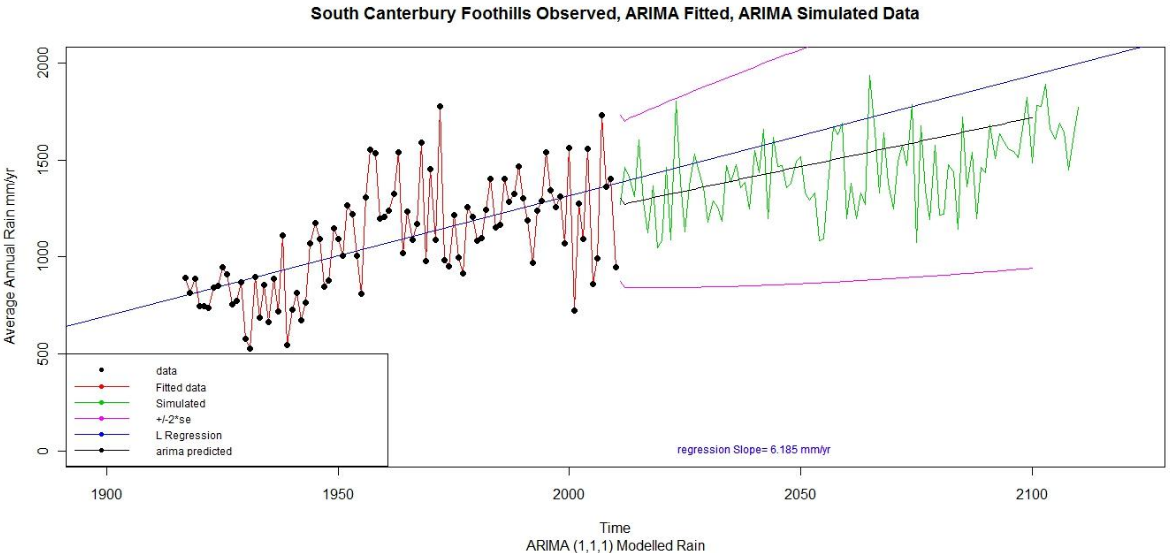


Figure 27: South Canterbury Foothills rain ARIMA simulated data

Table 26: ARIMA model for South Canterbury Foothills rain data

Series: South Canterbury Foothills rain					
ARIMA(1,1,1) with drift					
Coefficients:	ar1	ma1	Drift (Trend) β_t		
	-0.1093	-0.822	5.0275		
s.e.	0.1206	0.0683	3.7721		
sigma^2 estimated as		45867:	Log likelihood=		
AIC=1271.45		AICc=1271.9		BIC=1281.58	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-2.87342	213.0236	165.6087	-3.84632	16.02268	0.754415

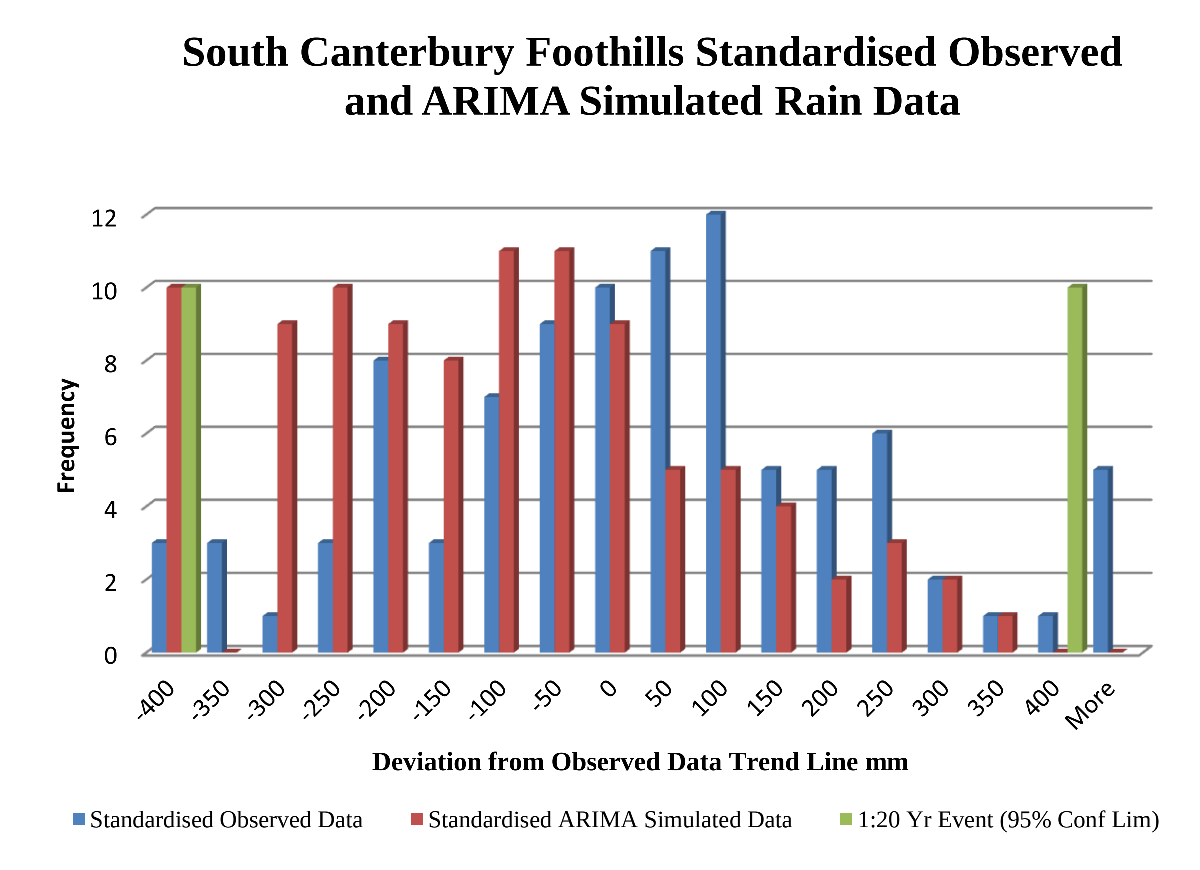


Figure 28: South Canterbury Foothills standardised, simulated and observed rain deviation frequency

3.12 South Canterbury Foothills temperature

The observed temperature data shows a steady trend of increasing average annual temperature at the rate of 1.63^{o}C/100 years. The data series has a number of very warm years, with the cooler years being less extreme. The simulated data shows a similar degree of variability as the observed data, with a number of very warm and cool years. The simulated data appears centred around the long term trend line and appears reasonably consistent with the observed data series.

The temperature deviation histogram (Figure 29) does show the simulated data series to have a greater number of cooler years than the observed temperature series, but there is no significant difference in the variability of the two data sets (Table 27).

ARIMA (1,1,1) Prediction Equation:

$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t$ (35)

Regression Trend Equation:

$Y_t = 0.0163 * Year - 22.119$ (36)

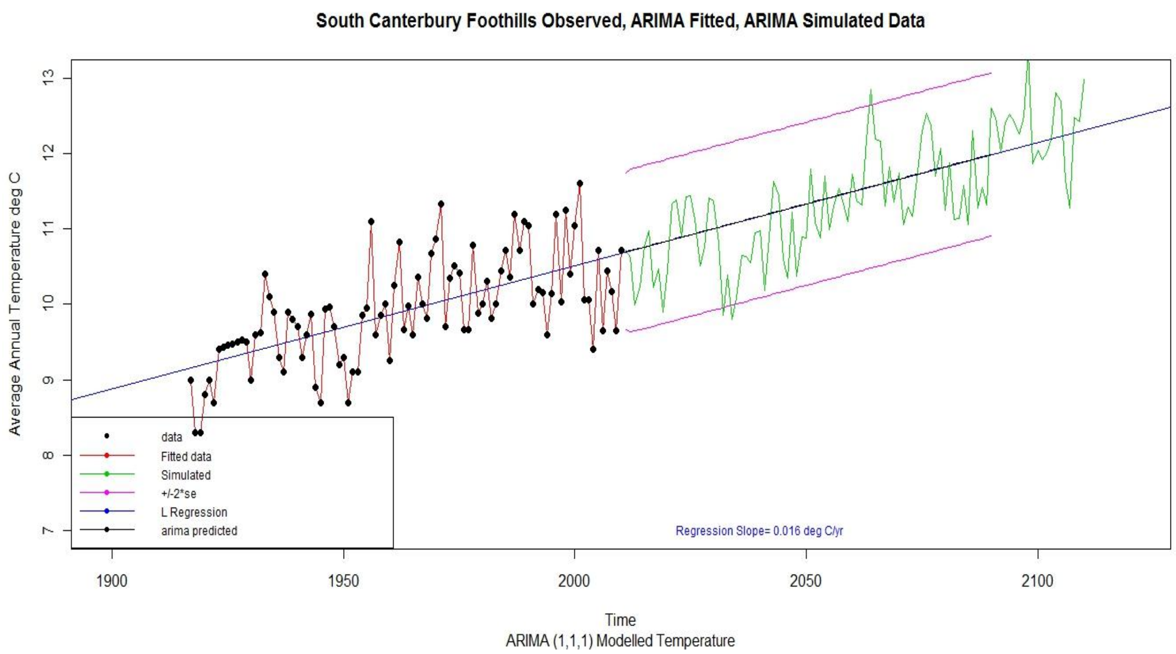


Figure 29: South Canterbury Foothills temperature ARIMA simulated data

Table 27: ARIMA model for South Canterbury Foothills temperature data

Series:	South Canterbury Foothills temperature				
ARIMA (1,1,1) with drift					
Coefficients	ar1	ma1		Drift (Trend).β_t	
	0.2698	-1		0.0164	
s.e.	0.1005	0.0391		0.0027	
sigma^2 estimated as 0.2669		log likelihood=-72.54			
AIC=153.08	AICc=153.54	BIC=163.21			
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
0.039713	0.513883	0.431547	0.181386	4.325243	0.849681

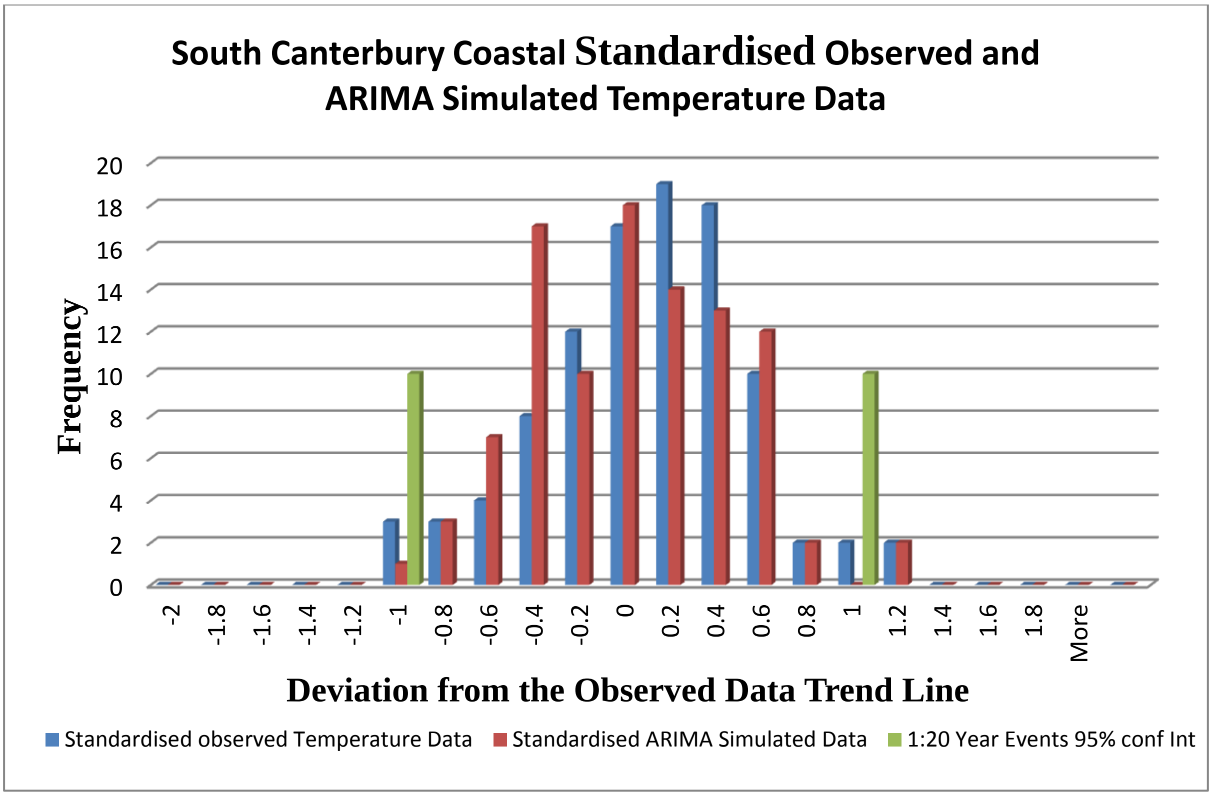


Figure 30: South Canterbury Foothills standardised, simulated and observed temperature deviation frequency

Table 28: F Statistic for South Canterbury Foothills temperature, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	9.911653	11.45798
Variance	0.483067	0.45116
Observations	95	99
df	94	98
F	1.070723	
P(F<=f) one-tail	0.368703	
F Critical one-tail	1.400474	

3.13 Otago/Northern Southland rain

The data shows an increasing average annual rainfall over the time period of the data. The regression trend line indicates a 2.45 mm/year increase in average annual precipitation.

The data plot shows two periods of contrasting rainfall. The period from around 1920 to 1960 was a prolonged period of dry years, while the following period through to 2000 was predominantly wetter.

The ARIMA model simulation appears to be consistent with the observed data, broadly following the long term trend line. The rainfall deviation histogram indicates that the model is generating a rainfall series that has a greater number of rainfall events below the long term trend.

The variability of the observed and simulated data was examined, finding that there is no significant difference in the variability of the two data series (Table 29).

ARIMA (3,0,1) Prediction Equation:

$$Y_t = 792.2038+1.0035*Y_{t-1} -0.1554Y_{t-2}+Y_{t-3} + \varepsilon_t -0.8577\varepsilon_{t-1} \quad (37)$$

Regression Trend Equation:

$$Y_t = 2.449*Year - 3988.889 \quad (38)$$

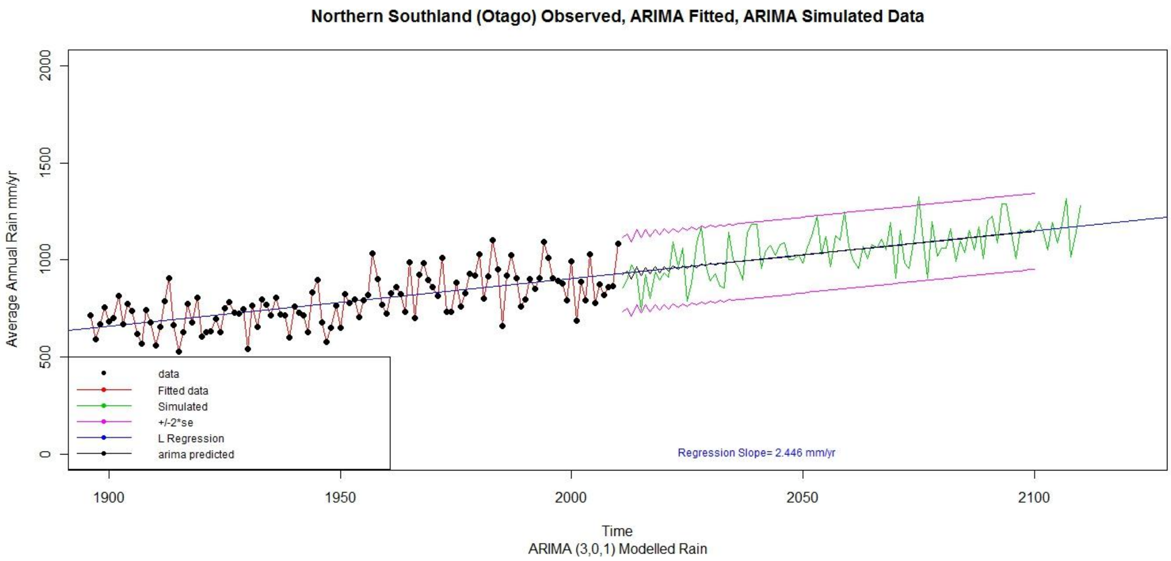


Figure 31: Otago/Northern Southland rain ARIMA simulated data

Table 29: ARIMA model for Otago/Northern Southland rain data

Series:		Otago/Northern Southland rain			
ARIMA (3,0,1) with non-zero mean					
Coefficients:	ar1	Ar2	Ar3	Ma1	E[mean]
	1.0035	-0.1554	0.1411	-0.8577	792.2038
s.e.	0.1038	0.1333	0.0994	0.0493	75.2296
sigma^2 estimated as 10116			Log likelihood =-694.18		
AIC= 1400.36		AICc= 1401.13		BIC=10416.82	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
10.7969	100.5784	80.68331	-0.25081	10.33605	0.729179

Table 30: F Statistic for Otago/Northern Southland rain, observed and ARIMA simulated data

F-Test two sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	789.1084	966.0445
Variance	16268.37	14838.47
Observations	115	100
df	114	99
F	1.096364	
P(F<=f) one-tail	0.320156	
F Critical one-	1.381421	

Figure 32: Northern South (Otago) standardised, simulated and observed rain deviation frequency

3.14 Otago/Northern Southland temperature

The observed temperature data long term trend shows an increase in average annual temperature of 0.12^{o}C/year over the period of the observations. As with the rain data above for the same region, the period to 1960 was marked by long periods of cooler than expected temperature: the period from about 1965 to 2000 shows prolonged periods of warmer than expected temperatures. This corresponds to the rain series, which for the same approximate periods there were drier and wetter than expected periods respectively.

Overall, the warming trend is continued in the ARIMA model simulated series (Figure 32), with a reduced level of temperature variability. The F statistic for the data series (Table 31), indicates a significant difference in the variability of the two series. This is somewhat reflected in the deviation frequency histogram (Figure 33), where the simulated data has generated more frequent, cooler than expected periods.

ARIMA (1,1,2) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} + \beta_t \quad (39)$$

Regression Trend Equation:

$$Y_t = 0.012296*\text{Year} - 14.282 \quad (40)$$

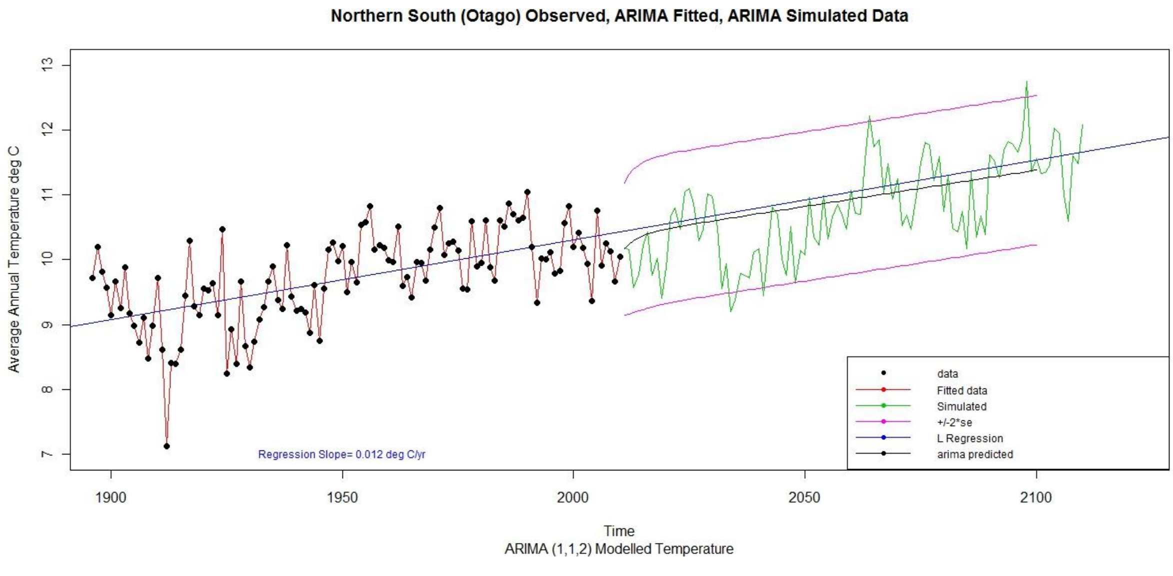


Figure 33: Otago/Northern Southland temperature ARIMA simulated data

Table 31: ARIMA model for Otago/Northern Southland temperature data

Series: Otago/Northern Southland temperature					
ARIMA (1,1,2) with drift					
Coefficients:	ar1	ma1	ma2	Drift (Trend).β_t	
	0.7296	-1.3827	0.3827	0.0112	
s.e.	0.1465	0.1864	0.1845	0.0032	
sigma^2estimatedas	estimated	0.2548:	log likelihood=-85.51		
AIC=181.02		AICc=181.58		BIC=194.71	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.02895437	0.502542	0.393169	-0.59014	4.131212	0.830178

Table 32: F Statistic for Otago/Northern Southland temperature, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	9.730435	10.42875
Variance	0.47692	0.270984
Observations	115	100
df	114	99
F	1.759958	
P(F<=f) one-tail	0.002113	
F Critical one-tail	1.381421	

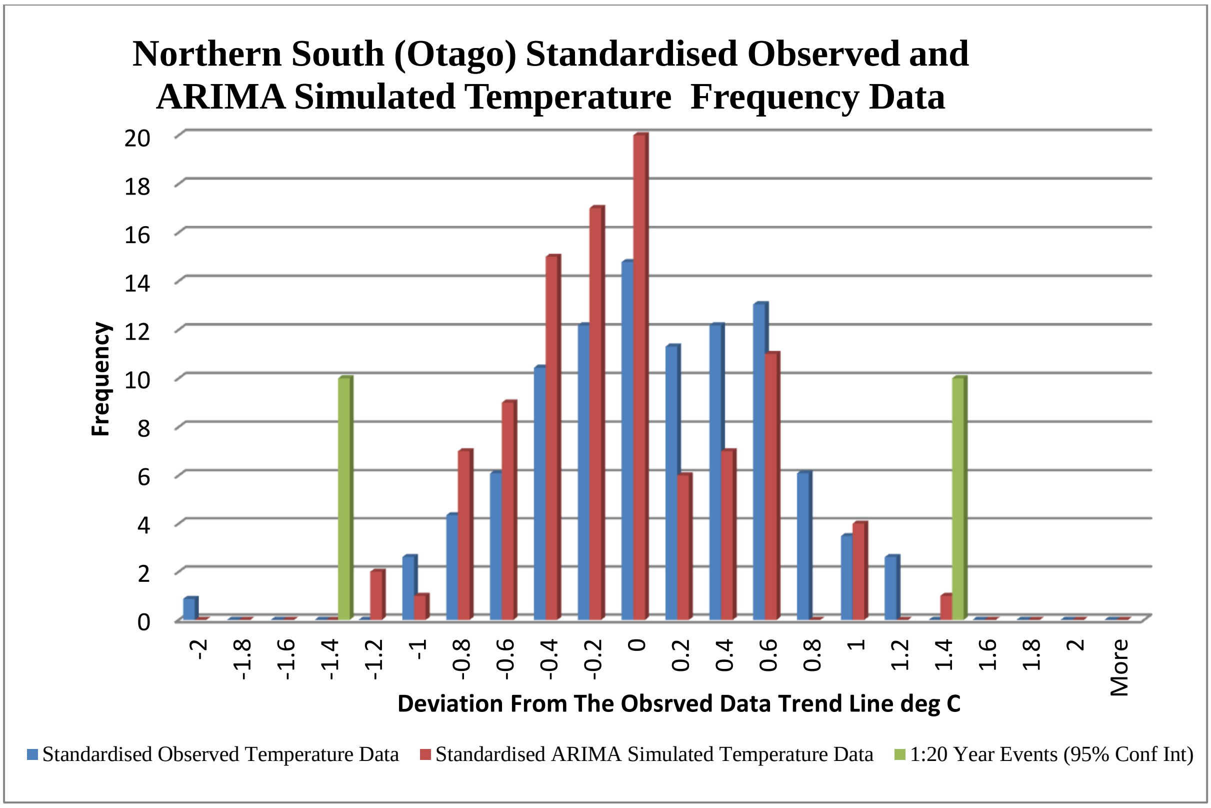


Figure 34: Northern South (Otago) standardised, simulated and observed temperature deviation frequency

3.15 Southland rain

The overall trend of the observed Southland rain data is a decline of 1.2 mm/year over the observed data period. The data however, shows a significant period (~1950-~1970) of drier than expected conditions, followed by a wetter period (1970-2009).

The ARIMA simulated data broadly follows the long term trend line with a reduced level of variability. The F statistic in Table 33 indicates that there is no significant difference in the variability of the two series. The trend deviation histogram (Figure 35) indicates that the simulated rain data is more evenly distributed than the observed data.

ARIMA (0,1,1)Prediction Equation:

$$Y_t = -1.7819t + Y_{t-1} - 0.901 * \varepsilon_{t-1} \quad (41)$$

Regression Trend Equation:

$$Y_t = 3428.122 - 1.212 * Year \quad (42)$$

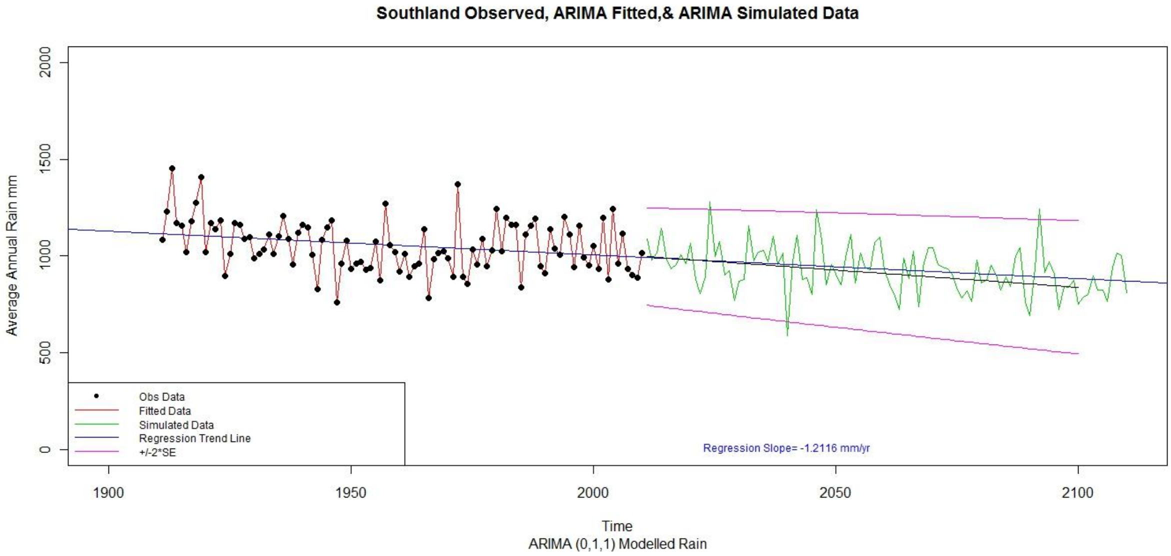


Figure 35: Southland rain ARIMA simulated data

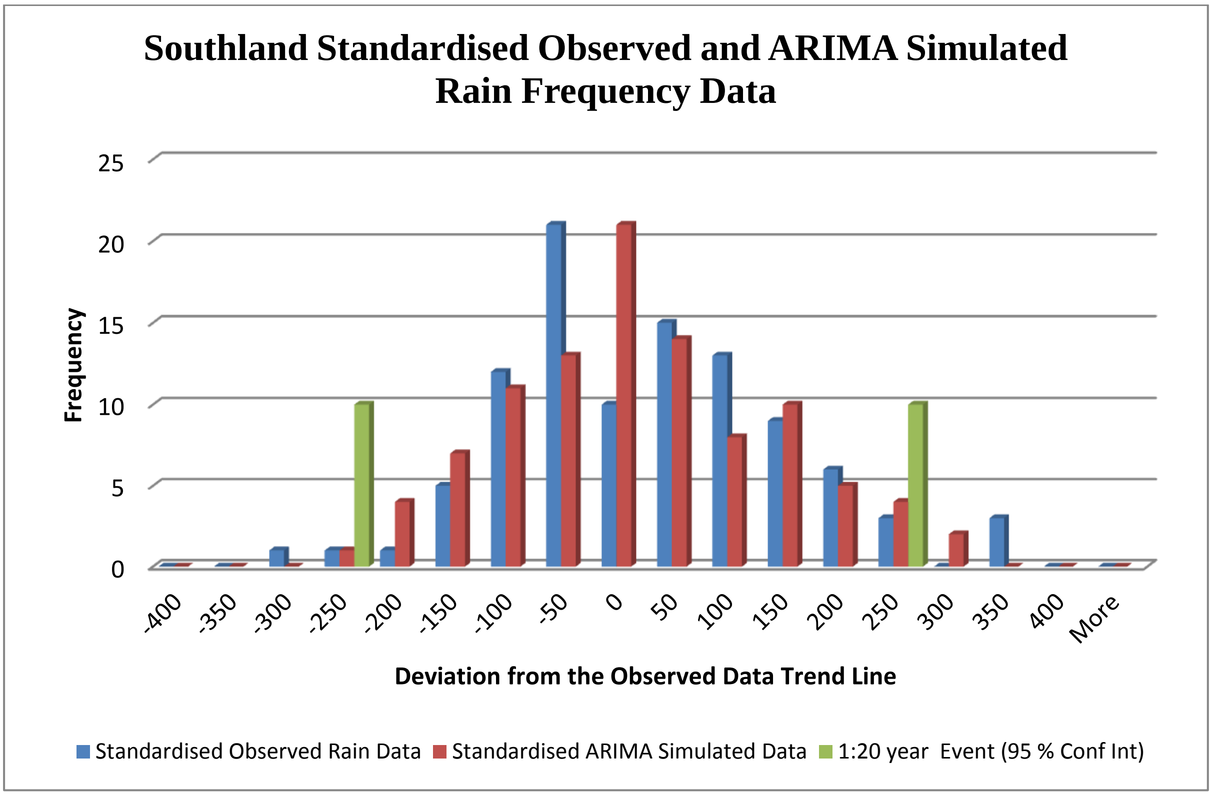


Figure 36: Southland standardised, simulated and observed rain deviation frequency

Table 33: ARIMA model for Southland rain data

Series: Southland rain					
ARIMA (0,1,1) with drift					
Coefficients:	ma1	Drift (Trend).β_t			
	-0.901	-1.7819			
s.e.	0.0428	1.409			
sigma^2 estimated as 15786			Log likelihood =-619.82		
AIC=1245.64		AICc=1245.9		BIC=1253.43	
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
-0.96176	125.0144	98.97694	-1.36406	9.532284	0.710633

Table 34: F Statistic for Southland rain, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed rain data	*ARIMA simulated rain data*
Mean	1052.743	921.3959
Variance	17202.25	15584.51
Observations	100	100
df	99	99
F	1.103805	
P(F<=f) one-tail	0.312066	
F Critical one-tail	1.394061	

3.17 Southland temperature

Although the data plot and ARIMA simulation data, Figure 36, appear to show a positive long term trend, the regression equation for the trend line indicates a comparatively stable average annual temperature, increasing by only 0.3°C over the 100 year observation period. But as can clearly be seen in Figure 36, it is not unusual for the annual average temperature to vary by +/- 1°C from the trend line. These deviations are of short duration, compared to other regions (2-3 years typically).

The ARIMA simulated data is slightly more variable than the observed temperature data, the difference being significant at the 95% confidence interval; (cf Table 35). While not a perfect match to the observed data, the simulated data series does show regular large deviations from the long term trend line. The gross variations are not extreme and only four spikes exceed the two times standard error lines of the ARIMA model prediction. This would not be unusual for a randomly generated sample with the same mean and standard deviation as the model sample.

ARIMA (1,1,1) Prediction Equation:

$$X_t = \phi X_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} + \beta_t \quad (43)$$

Regression Trend Equation:

$$Y_t = 0.003179 * Year + 3.790 \quad (44)$$

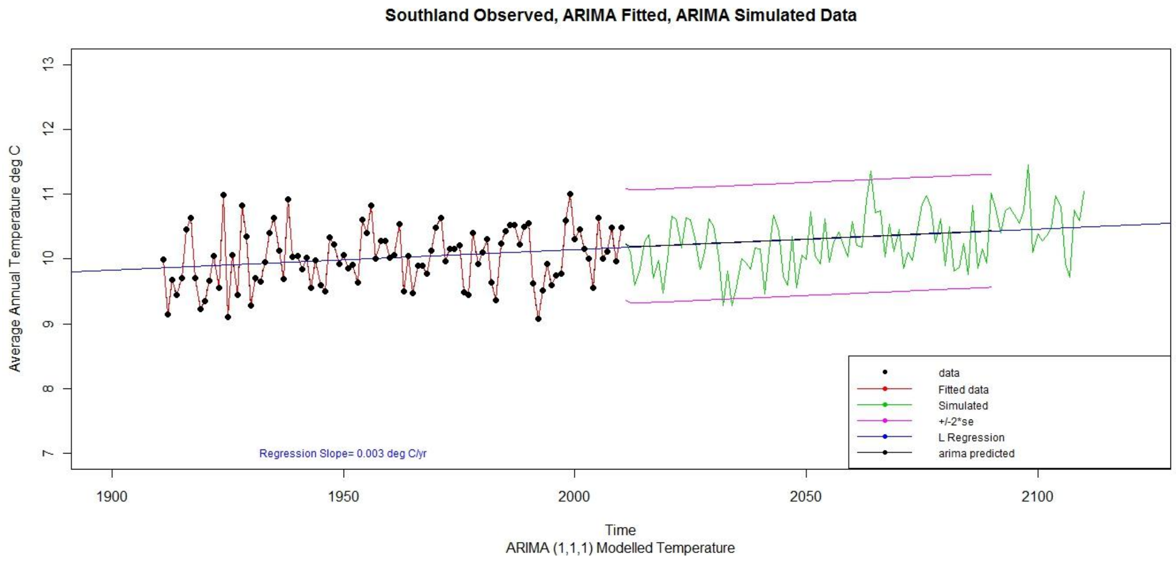


Figure 37: Southland temperature ARIMA simulated data

Table 35: ARIMA model for Southland temperature data

Series: Southland temperature					
ARIMA (1,1,1) with drift					
Coefficients:	ar1	ma1	Drift (Trend).β_t		
	0.1468	-1	0.0032		
s.e.	0.1	0.0282	0.0017		
sigma^2 estimated as 0.1841:				Log likelihood = -58.86	
AIC= 125.71	AICc=126.14		BIC =136.09		
In-sample error measures:					
ME	RMSE	MAE	MPE	MAPE	MASE
0.017023	0.426888	0.338034	-0.00568	3.37191	0.763526

Table 36: F Statistic for Southland temperature, observed and ARIMA simulated data

F-Test two-sample for variances		
	Observed temperature data	*ARIMA simulated temperature data*
Mean	10.022	10.27115
Variance	0.196036	0.197473
Observations	100	100
df	99	99
F	0.992727	
P(F<=f) one-tail	0.485552	
F Critical one-tail	0.717329	

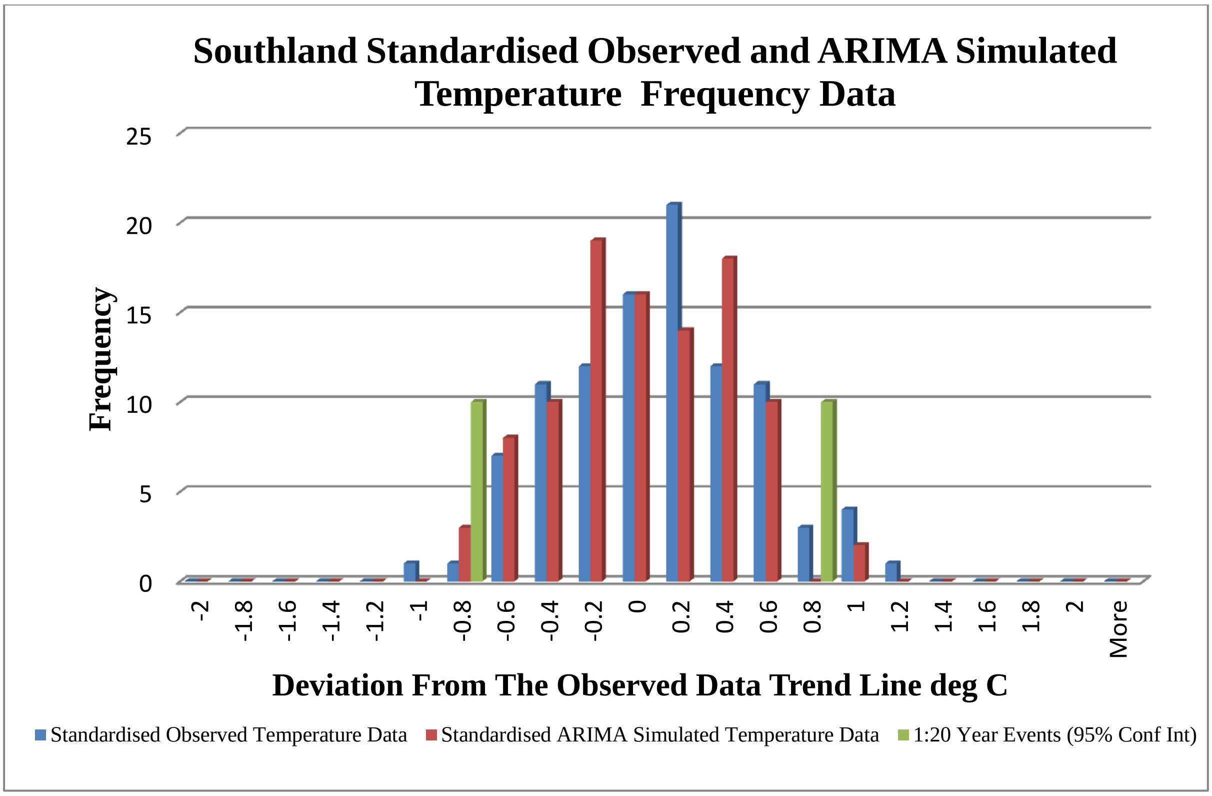


Figure 38: Southland standardised, simulated and observed temperature deviation frequency

Results summary

In summary, the study established the following general temperature and rainfall trends for the selected regions:

- West Coast
    - Both temperature and rain were highly variable
    - Average annual temperature remained reasonably constant with +/ 2 ^{o}C temperature variation round the long term trend line
    - Average annual rainfall showed an increasing trend over time, ~24.6 mm/year on average
- Marlborough
    - The data shows an increasing trend in both rainfall and temperature over time
- North Canterbury Coastal
    - Over the study period, the data shows a slight decrease in average annual rainfall
    - An average annual temperature trend increase of approximately 1^{o}C over the 79 years of the data
- North Canterbury Foothills
    - The data show an increasing trend in both rainfall and temperature
    - The marked decrease in rainfall for the North Canterbury Coastal region was not as evident in the foothills data
- Canterbury Mountain Region
    - The data show an increase in both average annual rain and temperature

- South Canterbury Coastal
    - Slight increase in average annual rain
    - A slight decrease in annual average temperature
- South Canterbury Foothills
    - The data shows a marked increasing trend in average annual rainfall, almost doubling over the 90 year data period
    - Average annual temperature also increasing over the study timeframe by 1.6^{o}C
- Otago/Northern Southland
    - Average annual rainfall trend shows a large increase over the study period, increasing by 2.45mm/year on average
    - The long term temperature trend showed an increasing average annual temperature for the region
- Southland
    - The long term rainfall trends for this region were somewhat mixed, in that a steady decline was seen over the first half of the study period, followed by an increasing trend. Overall, a decreasing rainfall trend was observed for the whole study period
    - The long term temperature trend does show a slight increase in temperature over the study period timeframe

Chapter 4: Discussion

4.1 General climate trends

The nine climate regions for both temperature and rain appear to have their own distinct profiles, following a general trend of high rainfall in the West and drier conditions in the East with the mountain region showing a transition from East to West.

Most regions showed trends which indicated a long term increase in annual average rainfall. A notable exception to this trend is the decrease in the long term rainfall trend for the North Canterbury Coastal region. While the annual rainfall increase was slight in many of the regions, the long term average annual rainfall trends in the South Canterbury Foothills, Otago and West Coast regions did show a large increase over time.

In general, the long term trends in average annual temperature for most regions were a slight increase over time. Notable exceptions were the higher temperature trends for North and South Canterbury Foothills. Both these regions showed a long term temperature increase of over 1^{o}C.

NIWA's climate change analysis (NIWA 2008)indicates an average national temperature rise of 0.9^{o}C over the last 100 years, and project a further 1^{o}C increase by 2045 for New Zealand, with a greater rise likely to be experienced in Eastern areas of both islands (NIWA 2008). This study broadly confirms this trend. However the NIWA prediction of a further increase of 1^{o}C by 2045 is not immediately obvious from the observed data and ARIMA model simulations. It should be noted that the ARIMA models are based only on historical data and do not take into account other climatic drivers that may be having an increasing influence on South Island rainfall and temperature.

In an earlier study, Salinger (Salinger and Mullan 1999), using 21 quality controlled and calibrated climate stations, found that for the decades 1940-1950 and 1981-1990, there was a 0.7^{o}C increase in mean annual temperatures for the South Island.

Salinger also noted that since the mid 1970's, the North West and South of the South Island had become wetter.

The data from this study would broadly support these observations, with South Canterbury, Otago and Westland showing significant increases in rainfall over the study period. But in contrast to this, Coastal Canterbury data shows a decrease in average annual rainfall over the study period.

The data from this study suggests that regional influences may exacerbate or mitigate some of these projected trends, with the South and the West becoming wetter and the East coast becoming drier and warmer.

Against this general agreement, the data from this study does suggest that Otago/Northern Southland and Marlborough have shown an increase in average annual rainfall over the study period, with the regional ARIMA models sustaining this average annual trend over the next 100 years. This would appear to be somewhat at odds with the overall climate predictions by NIWA. The trends detected in this study are at a regional level, and have not incorporated the sophisticated climate models to which NIWA has access to. There are many published papers that include sea surface temperature and major climate drivers to augment observed data in their projections of the effects of climate change.

The South Island has a natural 2 ^{o}C annual average temperature gradient South to North: 9.7^{o}C in South Westland, to 11.5^{o}C in Marlborough. Overall however, average annual temperatures have been relatively constant over the study period data. The largest annual average temperature rises were in North and South Canterbury Foothills, where increases of 1^{o}C and 1.6^{o}C respectively were observed for the data period.

The West Coast region, for example, exhibits a +/- 2^{o}C variation around the long term temperature trend line, while the average annual temperature has remained relatively constant for the last 100 years; this also being the case for Coastal North and South Canterbury data regions: the inland climate stations, on average, showed a 1-1.6^{o}C / 100 year temperature rise.

This may well be due to the narrow coastal strip of the West Coast, and the close proximity of a large thermal mass, the Tasman Sea. Another possible factor is the orientation of the Southern Alps, North East to South West, sheltering the West Coast from the South Easterly weather patterns, which predominantly bring cold weather to the South and East Coast of the South Island.

Overall, there appeared to be no strong correlation between average annual rainfall and average annual temperature within the regions studied. Correlation coefficients for the regional temperature and rainfall relationships are available in Appendix 5 below.

4.2 ARIMA temperature and rainfall simulations

In general, all the regional data sets were non-stationary in nature and required a differenced data series on which the ARIMA models could be developed. Auto correlation coefficient plots for the observed and differenced data used in developing the ARIMA models and the residuals plots for the fitted ARIMA models are available in Appendix 3 below.

The R software selection of the best ARIMA model chose the model with the lowest AIC score. In evaluating these models, often there were a number of alternative ARIMA order models with very similar AIC scores and RMSE figures. The RMSE gives the sum square root of the sum of squared deviances for the ARIMA fitted model from the source data. While it is sensitive to gross deviations, and the square of the deviation amplifies the scale, it still is considered the most relevant comparison for comparing models (Auckland University Statistics Department 2010).

In general, the ARIMA modelled data provided good fits for both the observed temperature and rainfall data for most regions. Most models selected were broadly centred on the long term trend line and showed no significant difference in variability between the observed data and the ARIMA model simulated data.

The Mean Absolute Percentage Error (MAPE) for these regional data sets ranged from 9.5% for Southland, to 16.6% for South Canterbury Coastal rainfall. Models with the higher levels of variability, as would be expected, generated best fit models with high MAPE figures.

Overall, while in some regional data sets the variability of the observed and simulated data sets was significantly different, the modelled data was slightly less variable than the observed data.

In generating the simulated data series for a regional model, selection of the seed value to initiate the simulation was critical to generating a model with a minimum error values and was visually compatible to the observed data set. In this study, it was found that using the trend line value to imitate the simulated data series generated the best results in the simulated data series.

4.3 Canterbury Regional rain and temperature.

As can be seen in the data plots of the Canterbury Coastal data, there is a pronounced difference in the long term rainfall trends: North Canterbury showing a steady reduction in rainfall (Figure 9) against the South Canterbury Coastal region, showing a steady increase over the same period (Figure 21). The inland Foothills annual average rainfall in North Canterbury however, shows a slight increase over this time period. While the Foothills rainfall increase is modest, it contrasts with the Coastal rainfall trend. More interestingly, the marked reduction in annual average rainfall in coastal Canterbury for the period 1975-2005 is not seen in the other Canterbury regional rainfall data: North Canterbury Foothills, Canterbury Mountain and both South Canterbury regional data show increases in rainfall in this period.

In general, a gradient of increasing rainfall can be seen in the regional data from the coastal regions to the mountains.

The question that will be asked is: "How significant is the rainfall decline in the North Canterbury Coastal region and is this an indication of a climatic change, or just a medium term extreme variation (in terms of the time span of the data set)?" As the time span of New Zealand's climate records are comparatively short (~150 years), it would be unsafe to make an assumption of climate change based solely on this observation set. The ARIMA model for this rainfall data series indicates that this decline in rainfall will level out, with a period of ~10 years of below average rainfall, followed by rainfall returning to be centred more on the long term trend line.

Temperature for the coastal regions shows a slight increase for North Canterbury and a slight decline for South Canterbury. Inland (>120 m amsl), all regions show an increase in temperature. This trend is maintained in the ARIMA models for these regions.

From an agricultural perspective, this would provide potential production benefits: an increase in rainfall and an increase in temperature, with the associated reduction in cooler periods increasing pasture, animal and crop growth rates and yields.

Chapter 5: Conclusion

This study has produced a regionally dissected set of temperature and rainfall ARIMA models that best fit the data. The selection of the region boundaries was somewhat arbitrary from a climate perspective, but did reflect the established regional agricultural regions. The boundary selections were validated to some extent by examination of the data variability in average annual rainfall between the regions.

The data does indicate some marked differences in temperature and rainfall patterns between the regions studied. Most notable is the rainfall and temperature trends and simulations between North and South Canterbury.

In general, an overall trend of increasing rainfall and temperature in most regions of the South Island was identified, with the ARIMA models maintaining this trend.

The use of annual data may well have masked some seasonal trends which exist within the data. A useful extension of this study would be the analysis such seasonal trends to clarify seasonal trends and associated data variability.

The ARIMA models developed in this study relied solely on observed average annual rainfall and temperature data and have not taken into account the trends in wider major climate drivers, which will influence the medium to long term climate trends.

The model simulations should be read as an indication of the likely future variability and not as a prediction of actual temperature and rainfall. In planning for the future and managing the best use of land and water, the estimation of the extreme climate events has more value than general trends. It is the extreme events that present the greatest difficulty for people, nature and the environment to adapt to. The result of this study presents an estimation of this future variability and may be useful in managing potential future extreme events..

Appendix 1: Data Graphs, Regression Equations and Correlograms

Regional data set temperature and Rain Plots and Regression Equation

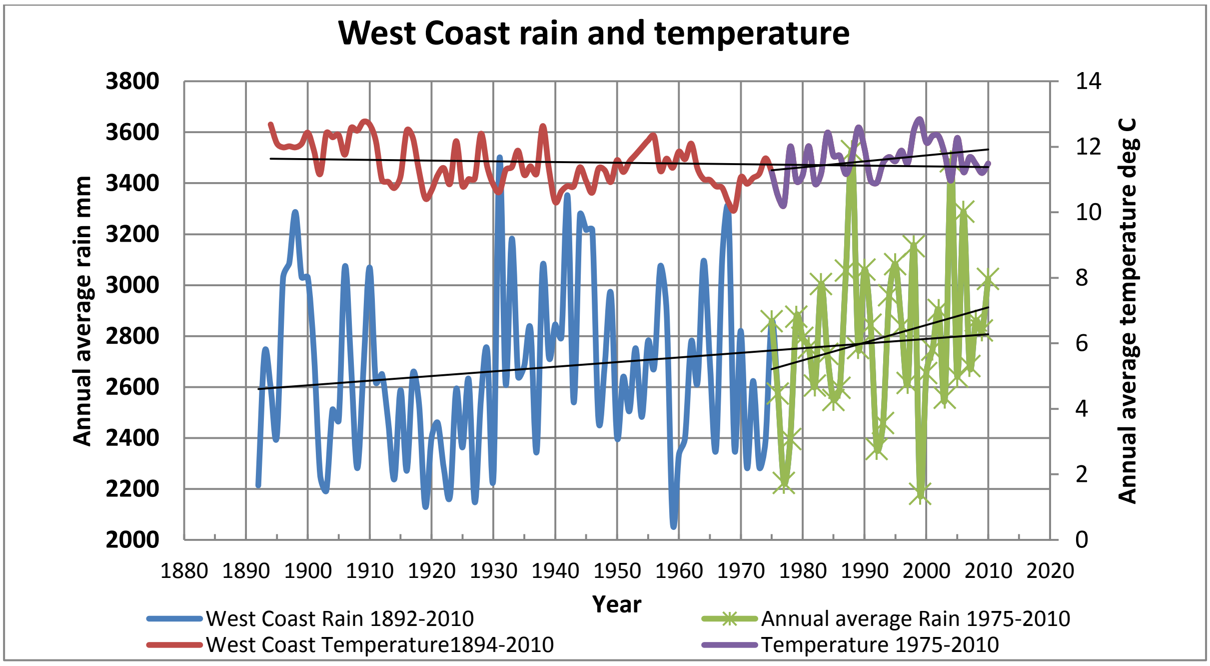


Figure 39: West Coast observed temperature and rain plots

Table 37: Regression Equations, West Coast data

Temperature		Rain	
1894-2010	$y = -0.0022x + 15.736$ $R^2 = 0.013$	1892-2010	$y = 1.829x - 868.71$ $R^2 = 0.0366$
1975-2010	$y = 0.0182x - 24.688$ $R^2 = 0.1006$	1975-2010	$y = 6.9215x – 10999$ $R^2 = 0.0569$

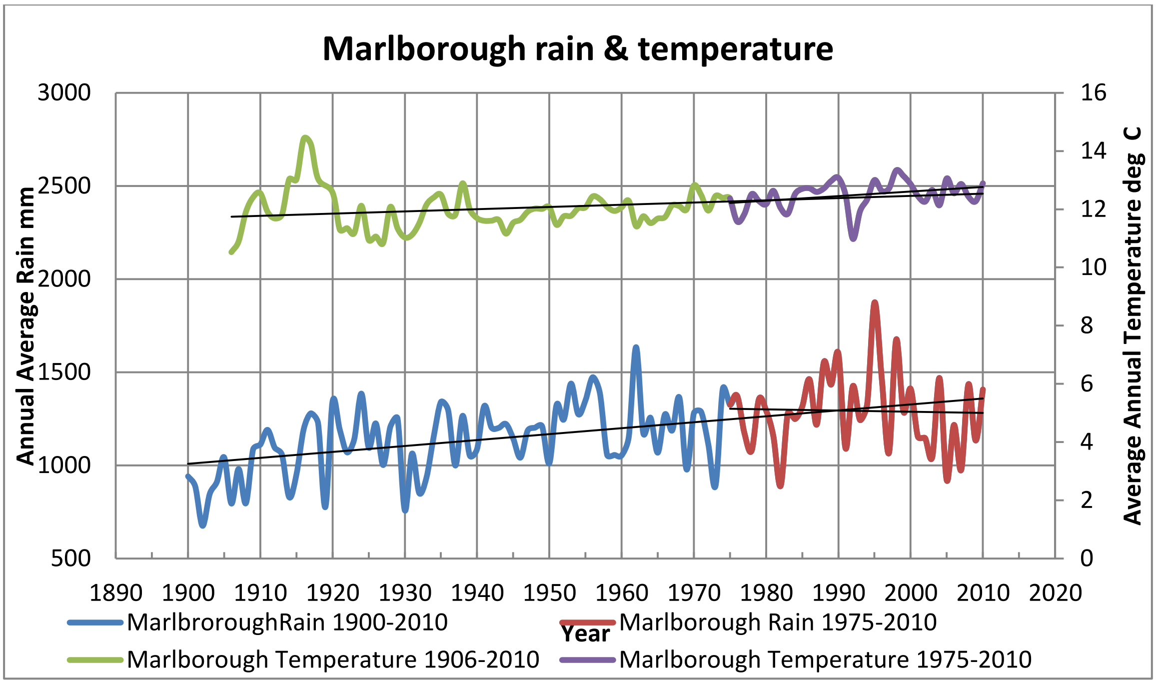


Figure 40: Marlborough temperature and rain graphs

Table 38: Regression Equations, Marlborough data

Temperature		Rain	
1906-2010	y = 3.177x - 5027.4 R^2 = 0.2406	1900-2010	y = 0.0077x - 2.857 R^2 = 0.1211
1975-2010	y = -0.6055x + 2499.2 R^2 =0.001	1975-2010	y = 6.9215x – 10999 R^2 = 0.0569

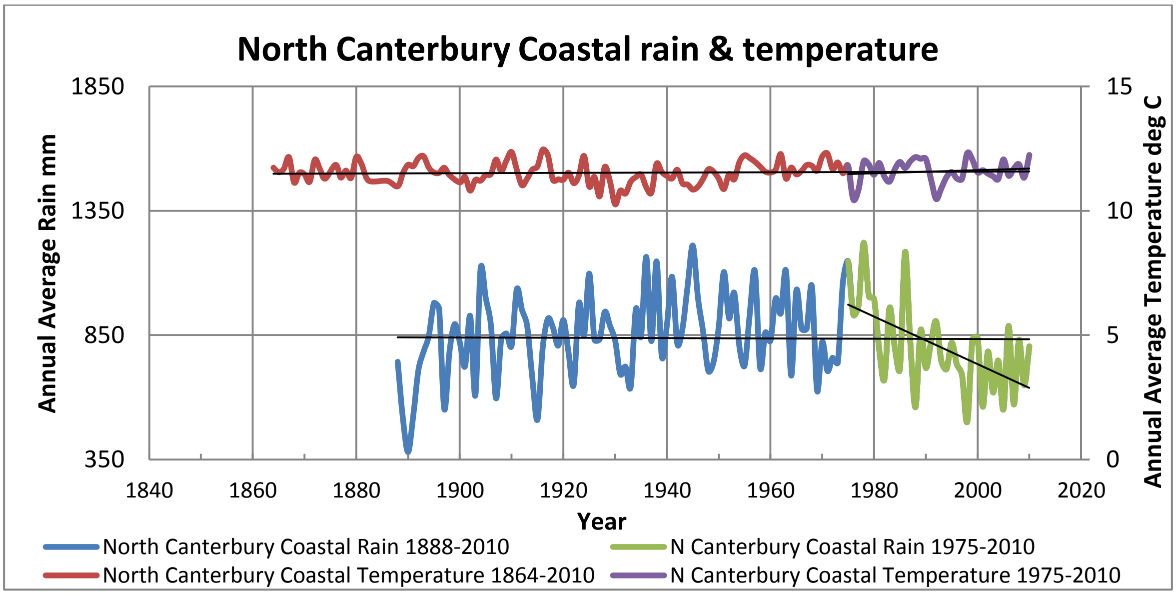


Figure 41: North Canterbury Coastal temperature and rain graphs

Table 39: Regression Equations, North Canterbury Coastal data

Temperature		Rain	
1864-2010	y = -0.0607x + 955.94 R^2 = .00	1888-2010	y = 0.0007x + 10.204 R^2 = 0.0045
1975-2010	y = 0.0061x - 0.5897 R^2 = 0.019	1975-2010	y = -9.5786x + 19890 R^2 = 0.336

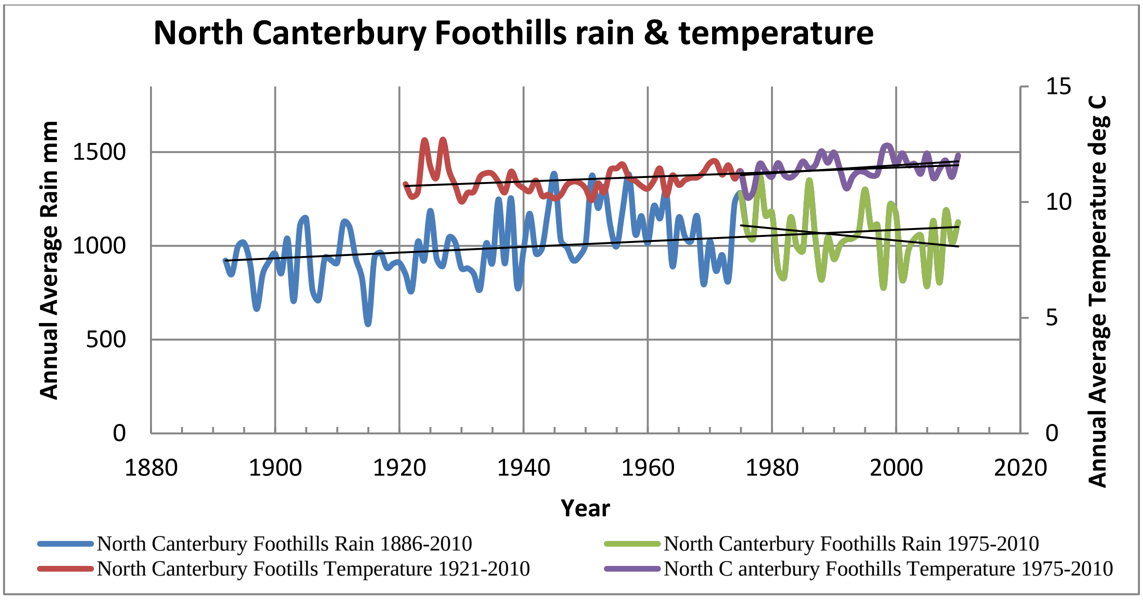


Figure 42: North Canterbury Foothills temperature and rain graphs

Table 40: Regression Equations, North Canterbury Foothills data

Temperature		Rain	
1921-2010	y = 1.5301x – 1974 R^2 = 0.1021	1886-2010	y = 0.0102x – 8.9206 R^2 = 0.2021
1975-2010	y = -3.2106x + 7450.1 R^2 = 0.047	1975-2010	y = 0.0168x – 22.014R^2 = 0.1254

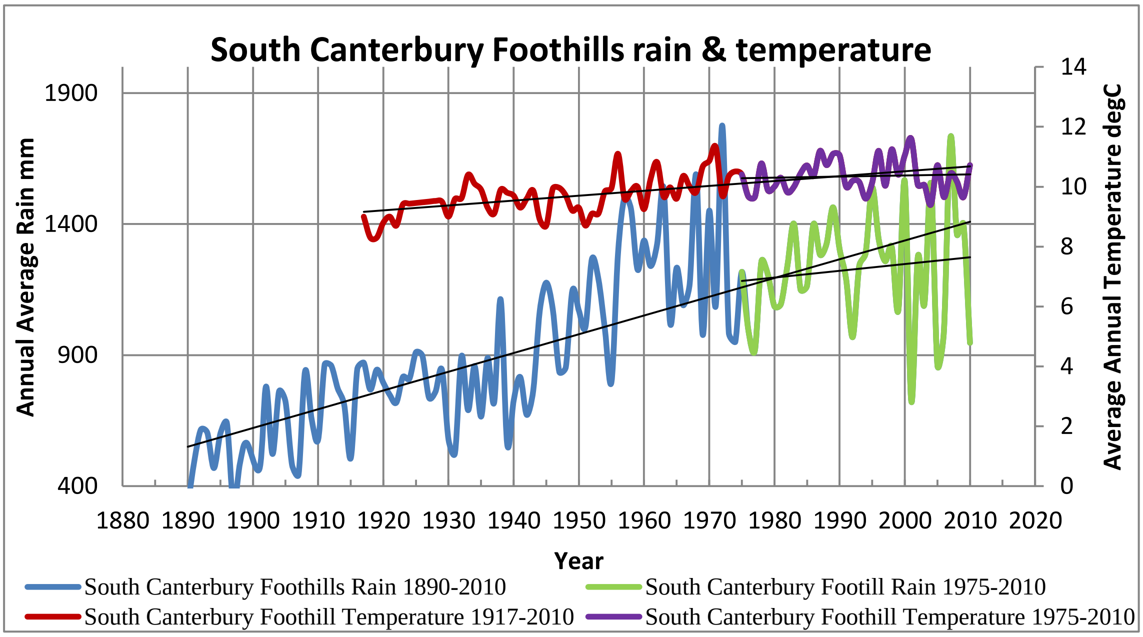


Figure 43: South Canterbury Foothills temperature and rain graphs

Table 41: Regression Equations, South Canterbury Foothills data

Temperature		Rain	
1864-2010	y = 0.0163x - 22.119 R^2 = 0.40	1888-2010	y = 7.1538x - 12971R^2 = 0.5993
1975-2010	y = 0.0036x + 3.1157R^2 = 0.0048	1975-2010	y = 2.566x - 3884.4 R^2 = 0.0159

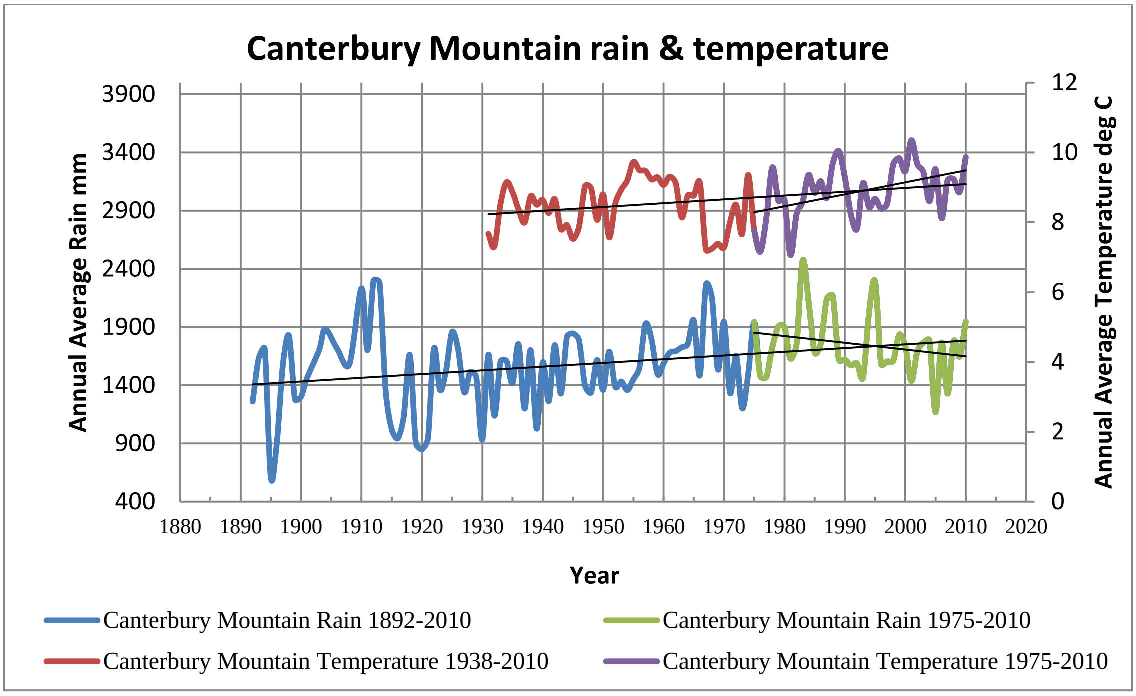


Figure 44: Canterbury Mountain temperature and rain graphs

Table 42: Regression Equations, Canterbury Mountain temperature data

Temperature		Rain	
1938-2010	$y = 3.2031x - 4654.4$ $R^2 = 0.1058$	1892-2010	$y = 0.0109x - 12.91$ $R^2 = 0.1104$
1975-2010	$y = -5.8597x + 13426$ $R^2 = .0529$	1975-2010	$y = 0.0168x - 22.014$ $R^2 = 0.1254$

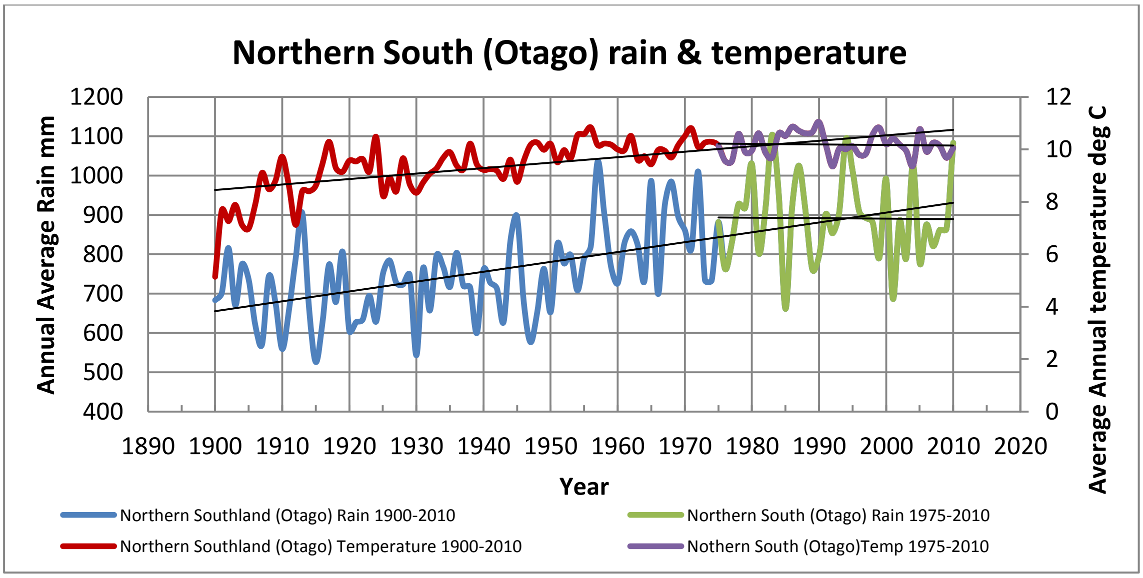


Figure 45: Otago/Northern Southland temperature and rain graphs

Table 43: Regression Equations, Canterbury Mountain data

Temperature		Rain	
1938-2010	$y = 0.0027x + 4.7681$ $R^2 = 0.0335$	1901-2010	$y = 2.5072x - 4108.7$ $R^2 = 0.3994$

1975-2010	y = -0.0019x + 14.02 R^2 = 0.0021	1975-2010	y = -0.108x + 1107 R^2 = 0.0001

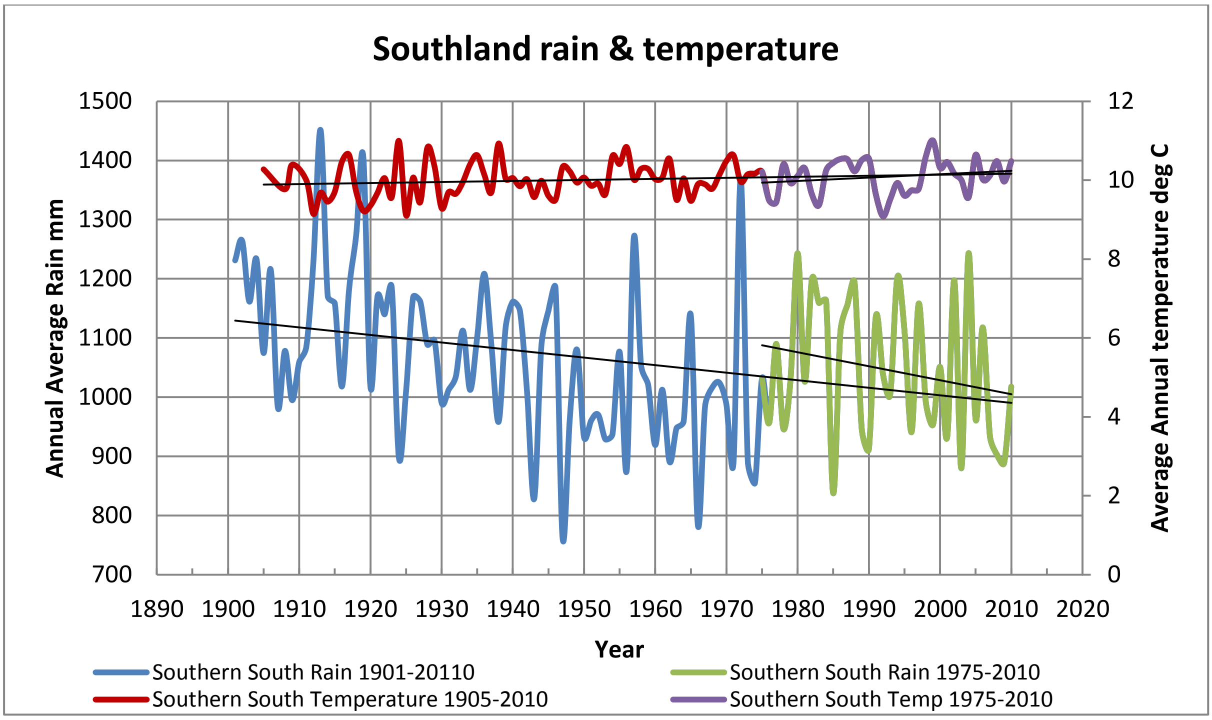


Figure 46: Southland temperature and rain graphs

Table 44: Regression Equations, Southern South data

Temperature		Rain	
1938-2010	y = 0.0027x + 4.7681 R^2 = 0.0335	1901-2010	y = -1.2764x + 3555.8 R^2 = 0.0974
1975-2010	y = 0.0085x - 6.9067 R^2 = 0.0411	1975-2010	y = -2.3496x + 5727.9 R^2 = 0.046

Appendix 2: Auto Correlation and ARIMA model Residuals Plots

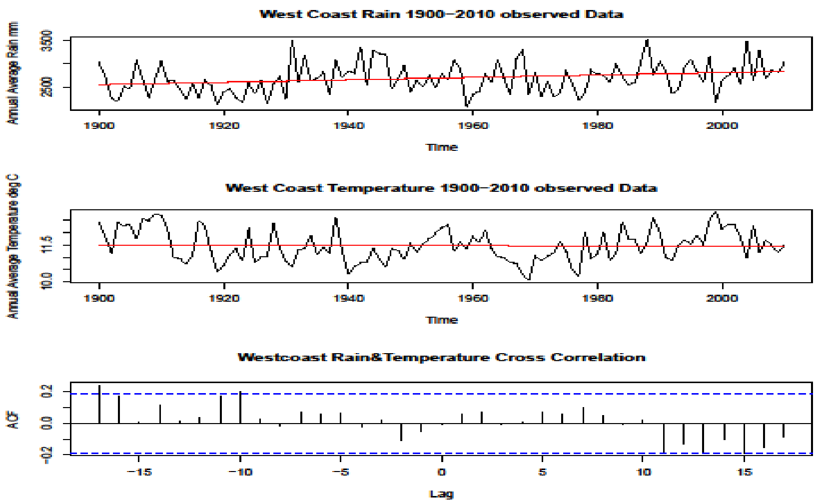


Figure 47: West Coast rain ARIMA Residuals Plots

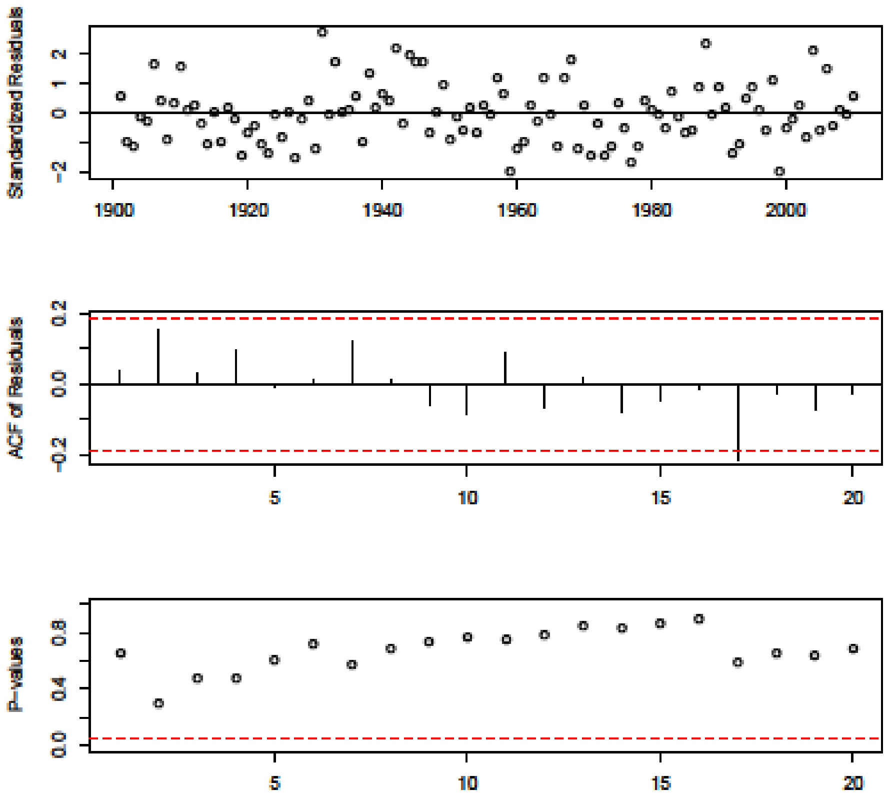


Figure 48: West Coast rain ARIMA simulation Residuals Plots

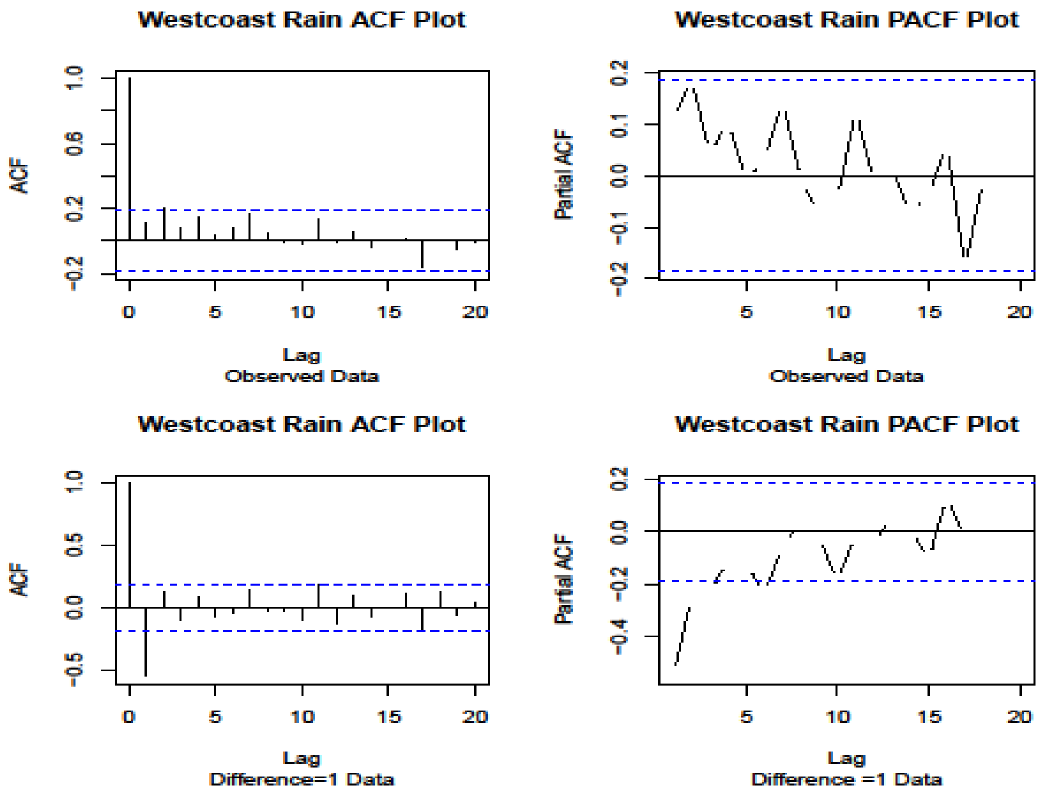


Figure 49: West Coast rain Correlograms

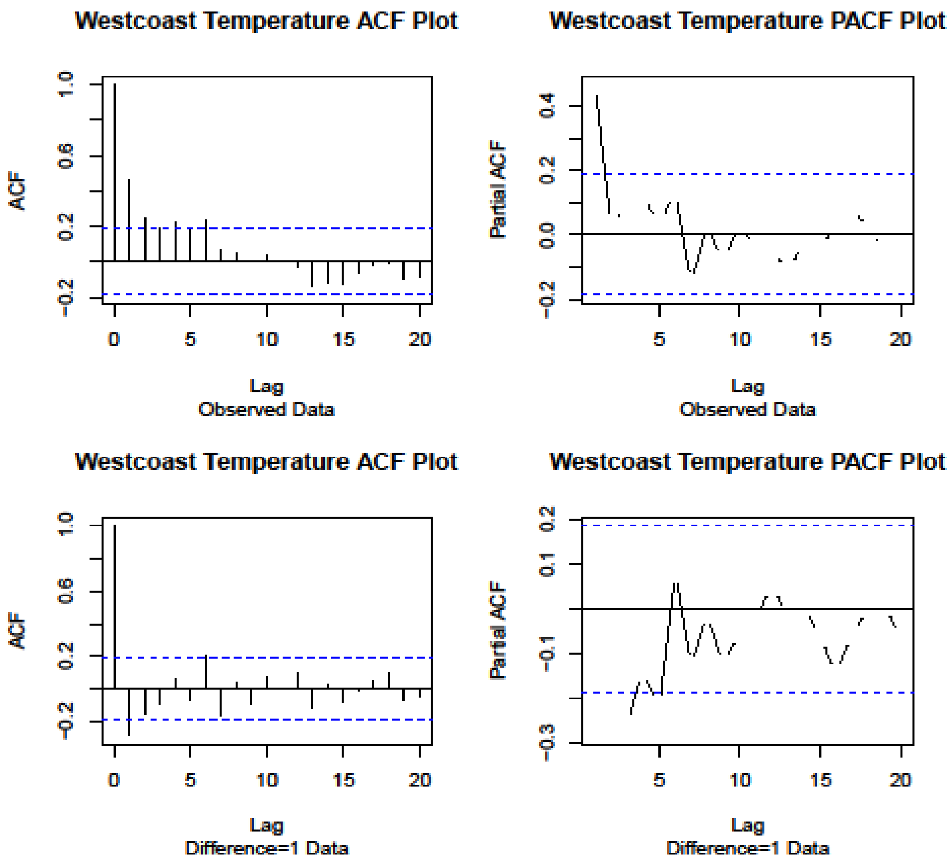


Figure 50: West Coast temperature ACF Plots

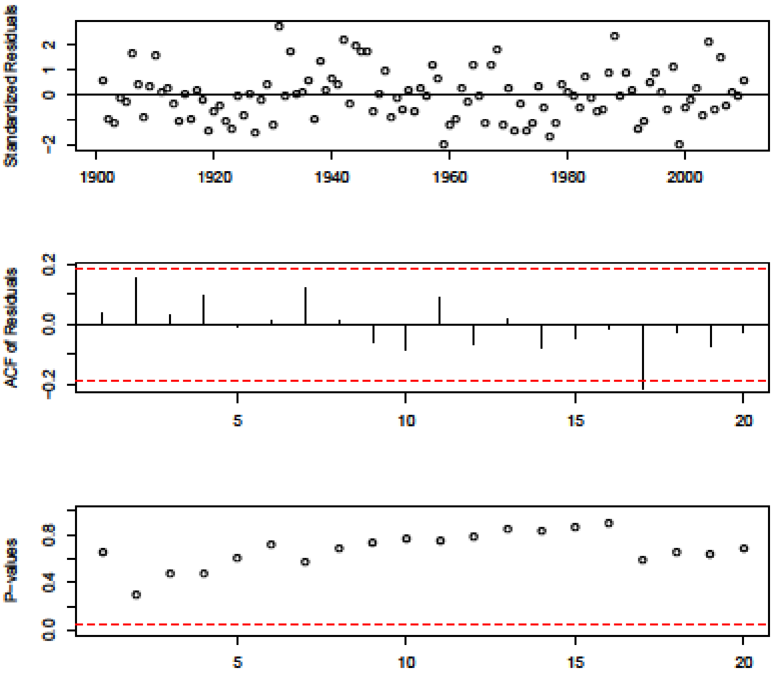


Figure 51: West Coast temperature ARIMA Residuals Plots

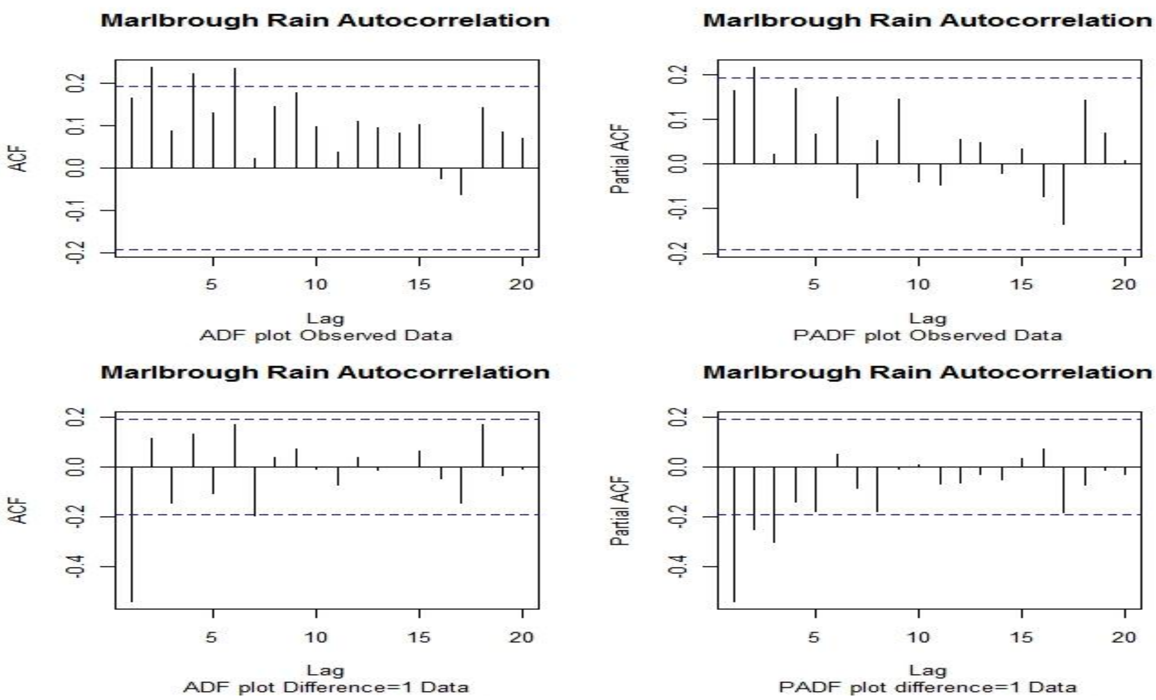


Figure 52: Marlborough rain ACF Plots

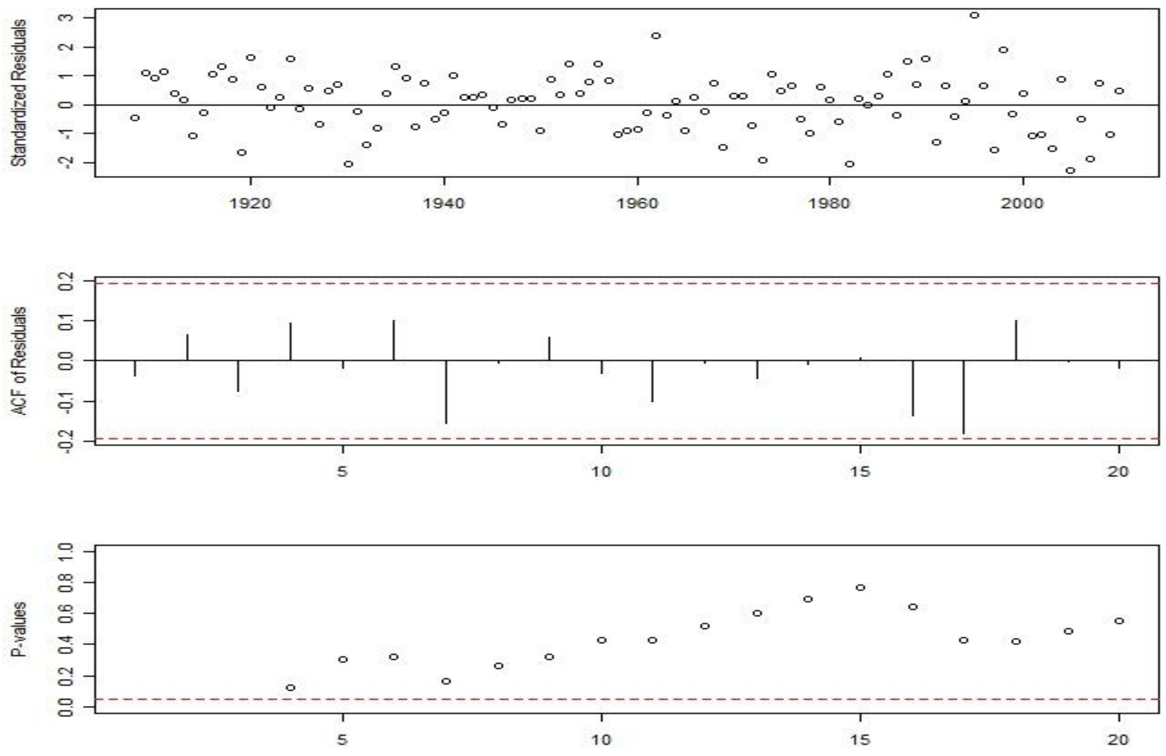


Figure 53: Marlborough rain ARIMA model Residuals Plots

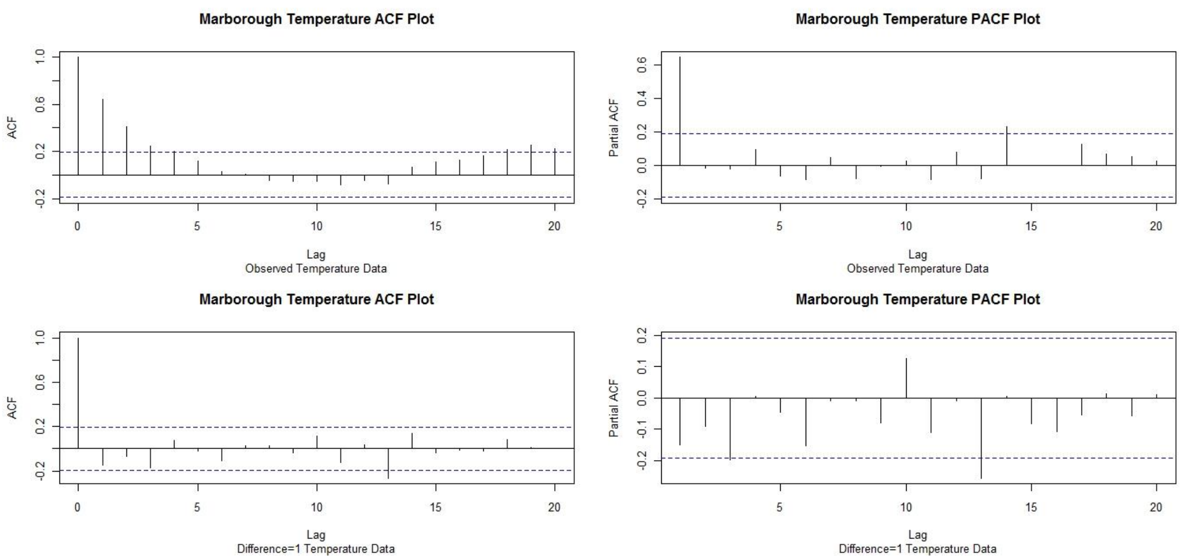


Figure 54: Marlborough temperature ACF Plots

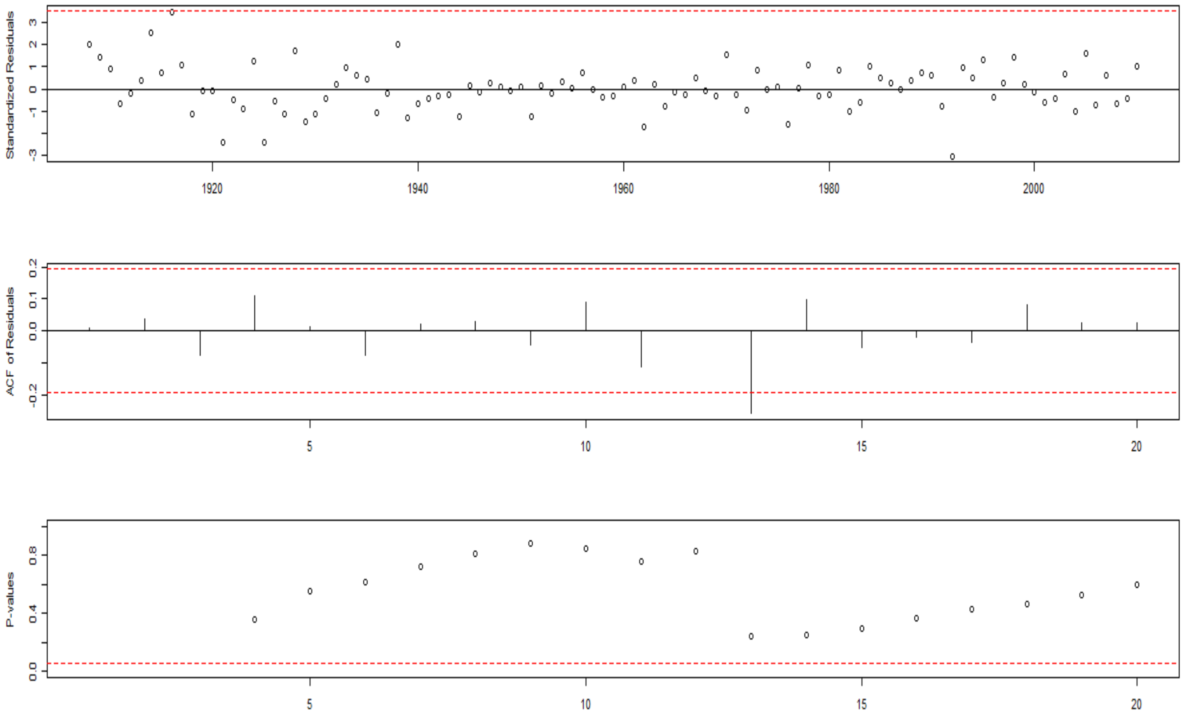


Figure 55: Marlborough temperature ARIMA model Residuals Plots

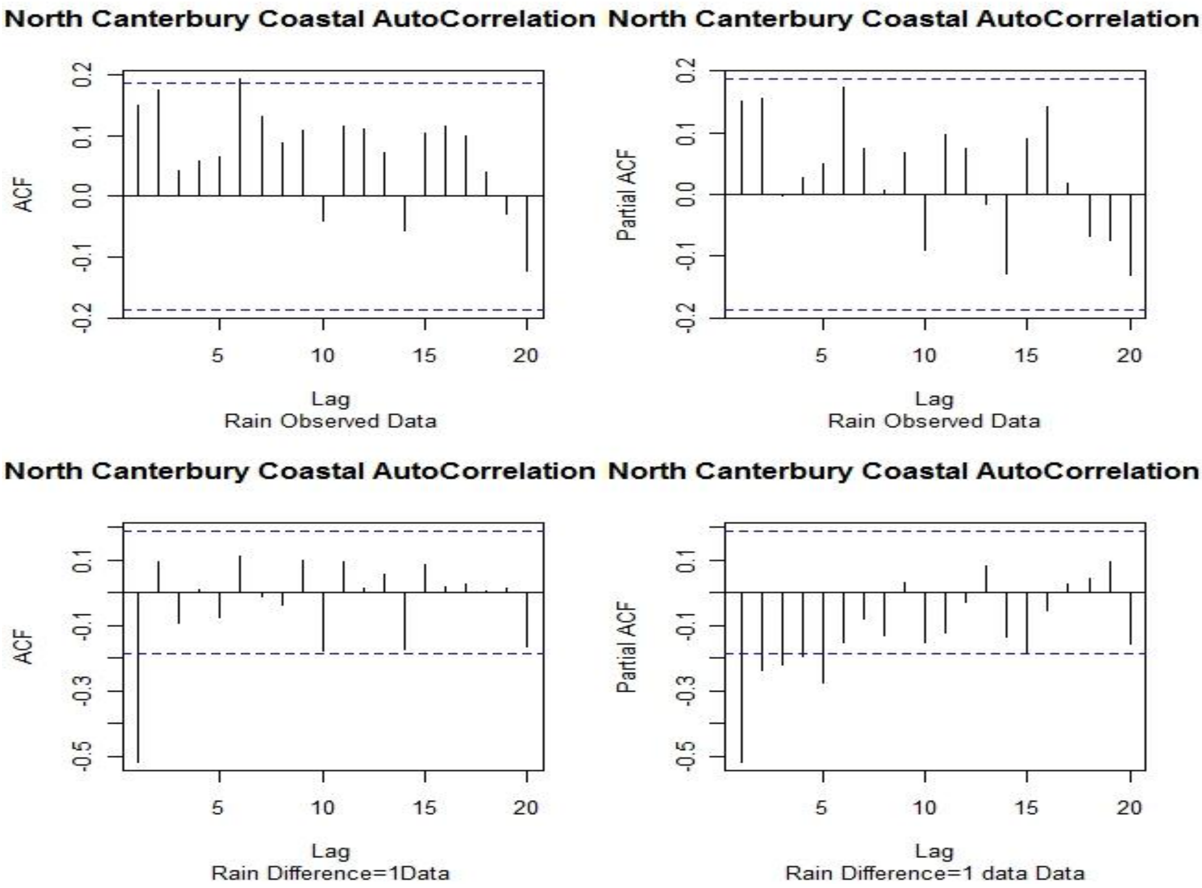


Figure 56: North Canterbury Coastal rain ARIMA model Residuals Plots

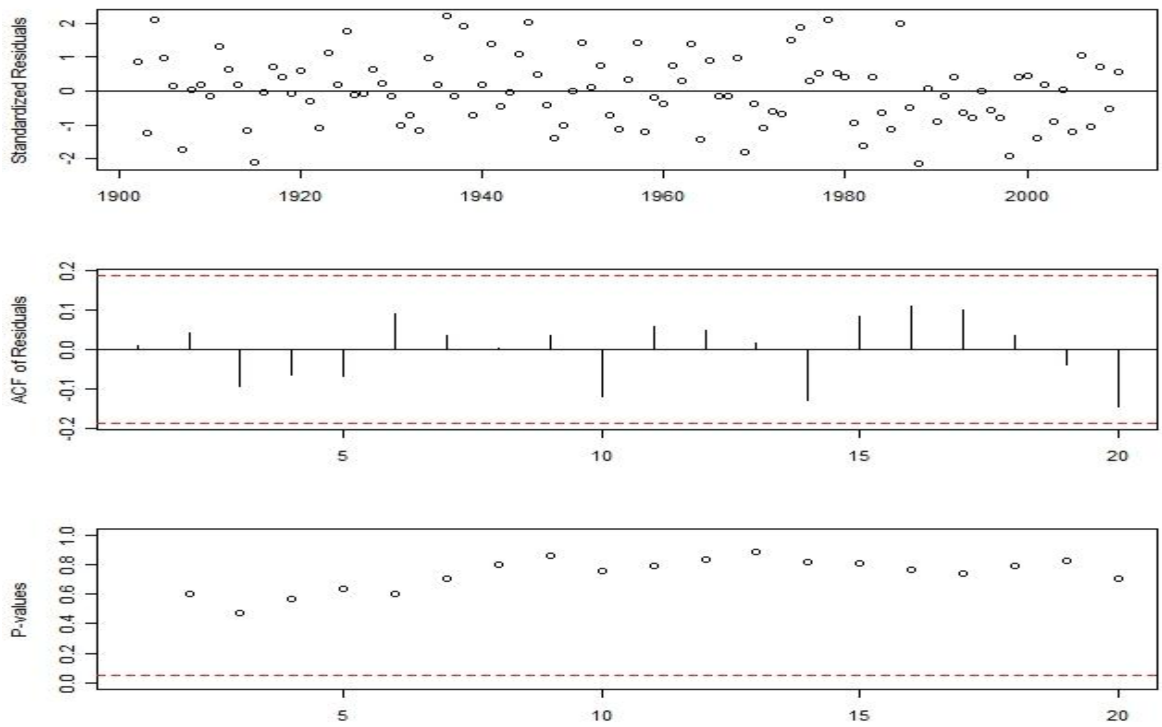


Figure 57: North Canterbury Coastal temperature ACF Plots

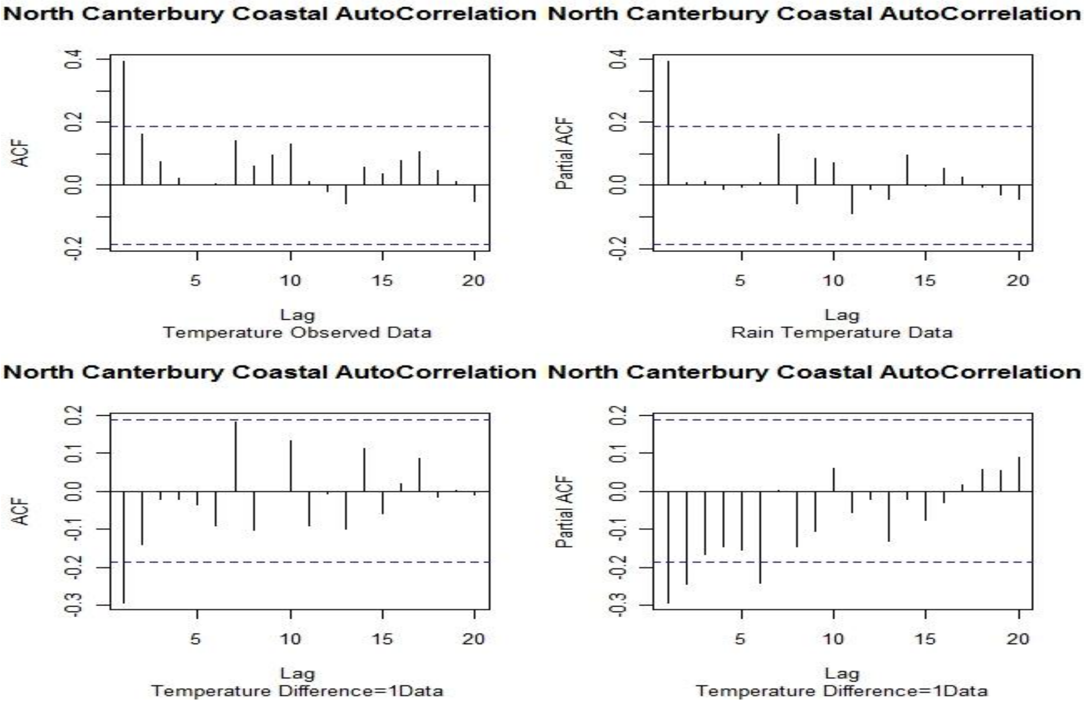


Figure 58: North Canterbury Coastal temperature ARIMA model Residuals Plots

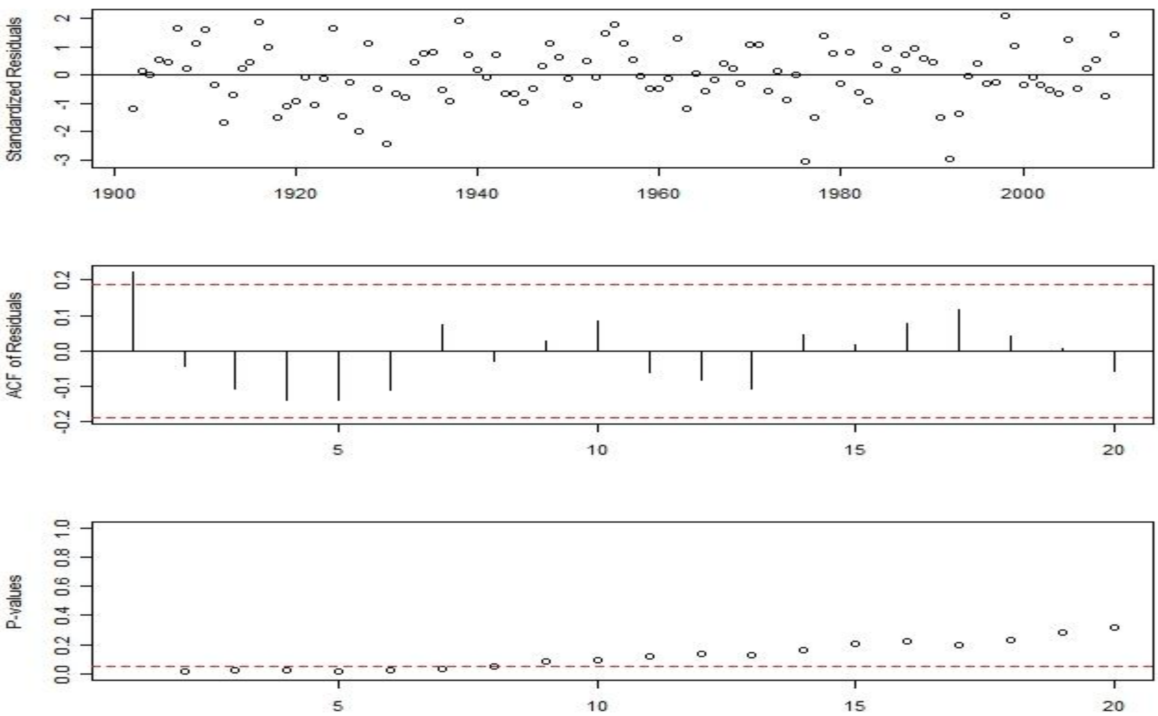


Figure 59: North Canterbury Foothills rain ACF Plots

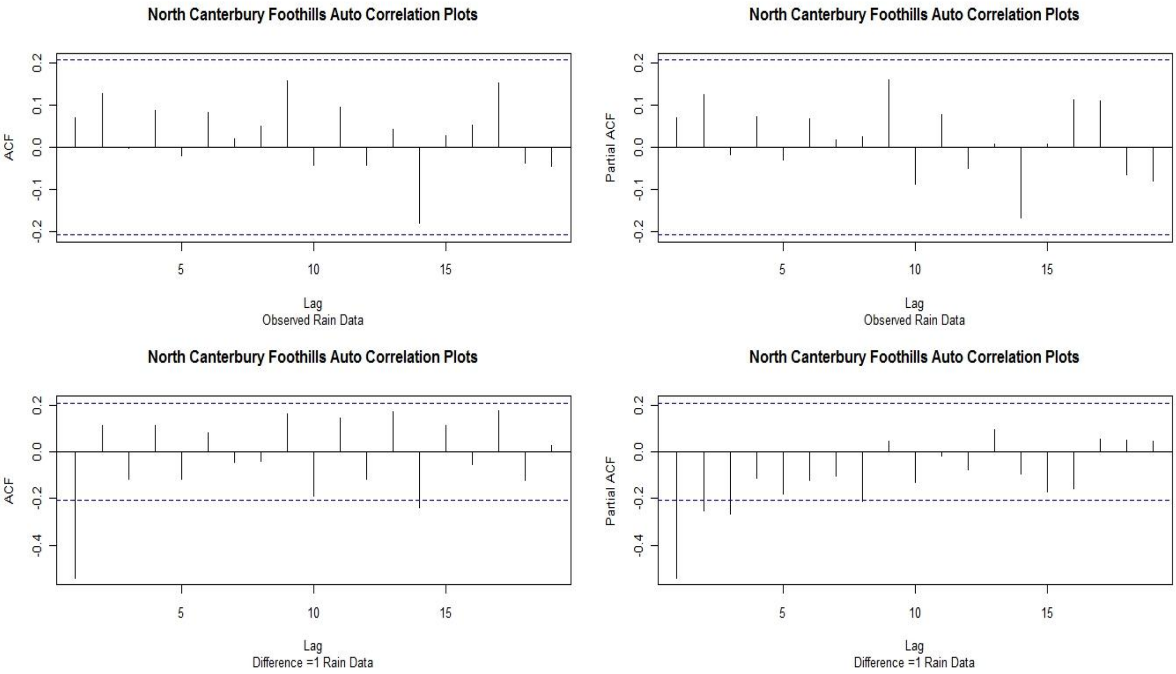


Figure 60: North Canterbury Foothills rain ARIMA model Residuals Plots

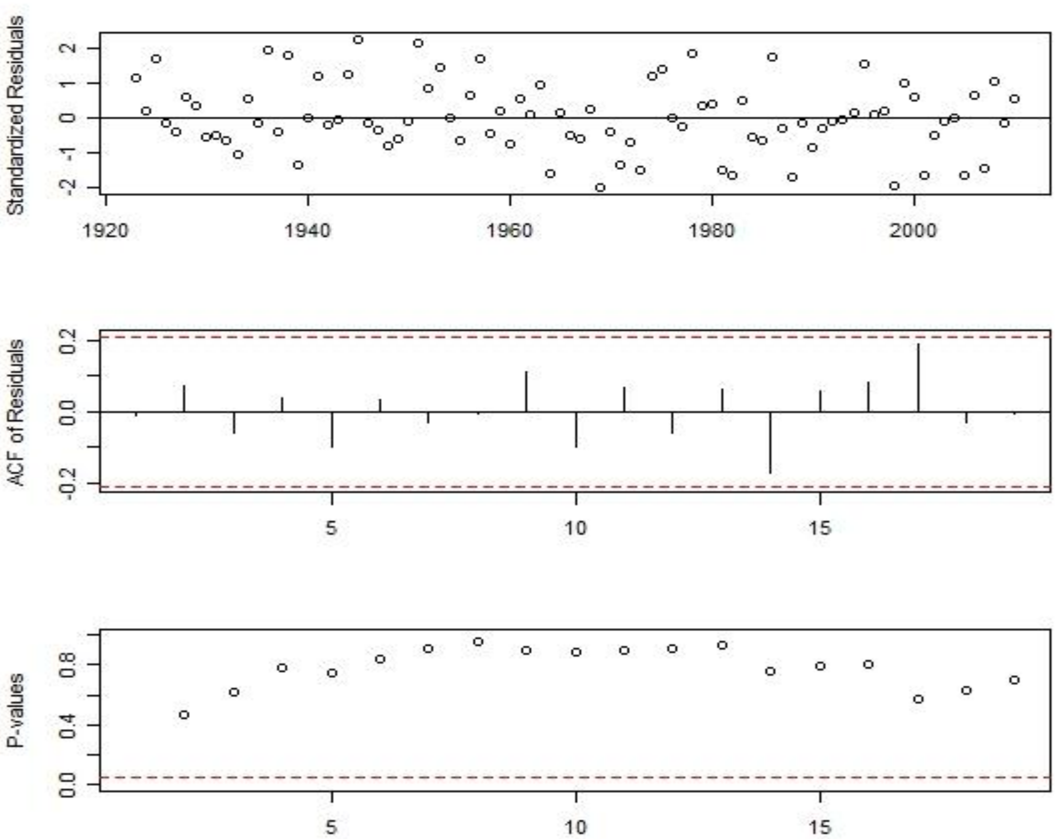


Figure 61: North Canterbury Foothills temperature ACF Plots

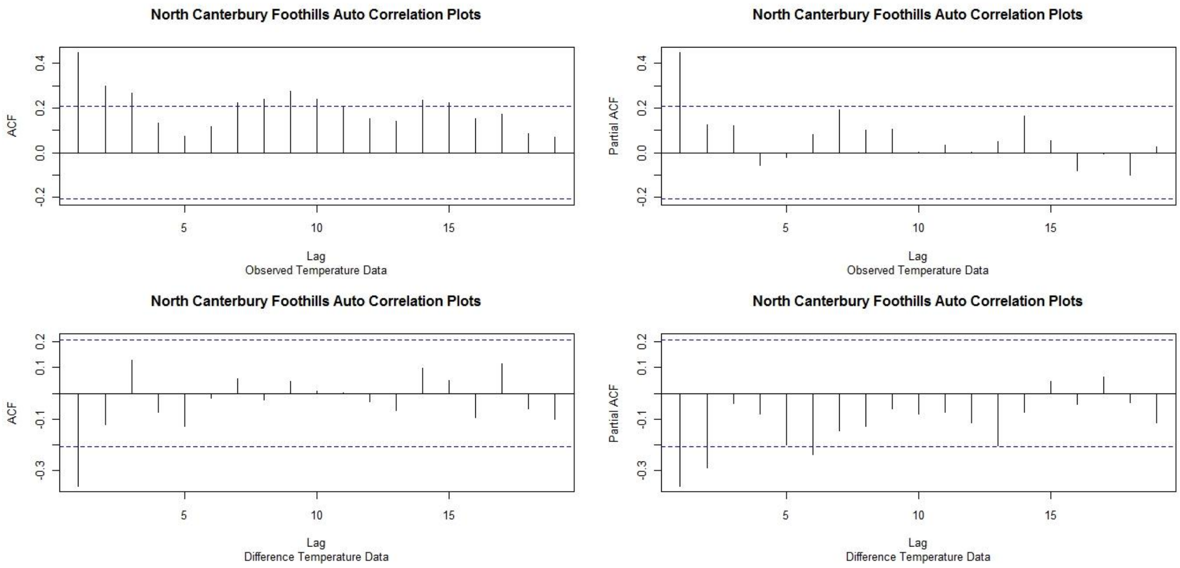


Figure 62: North Canterbury Foothills temperature ARIMA model Residuals Plots

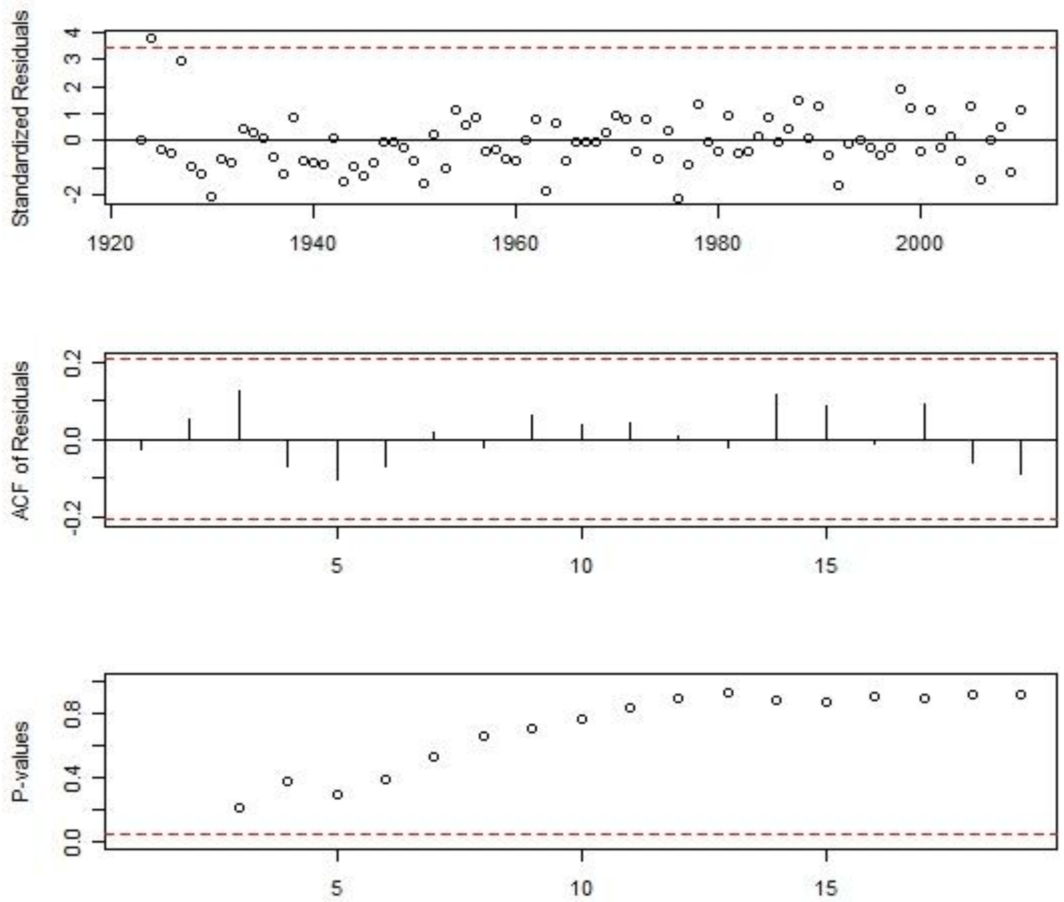


Figure 63: Canterbury Mountains ACF Plots

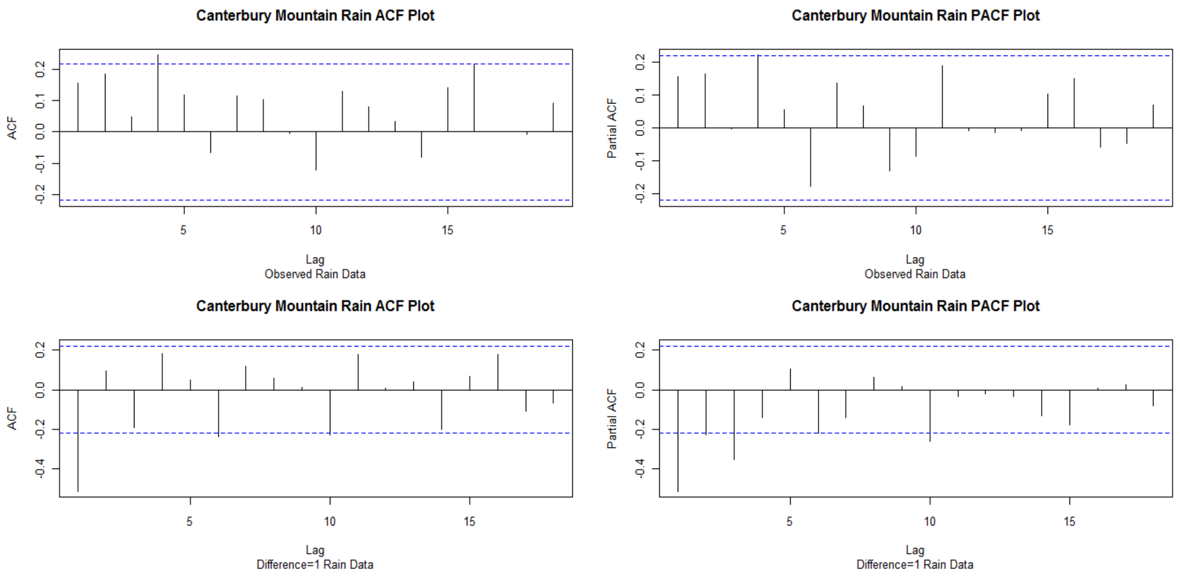


Figure 64: Canterbury Mountains rain ARIMA model Residuals Plots

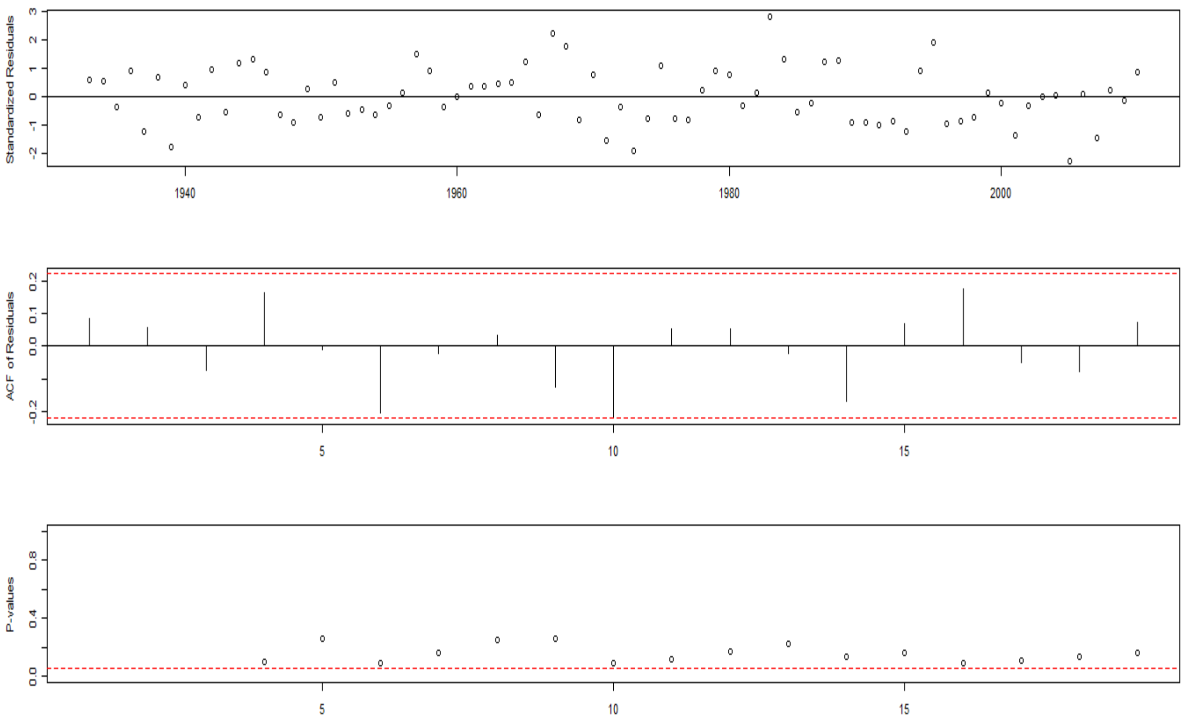


Figure 65: Canterbury Mountain temperature

ACF Plots

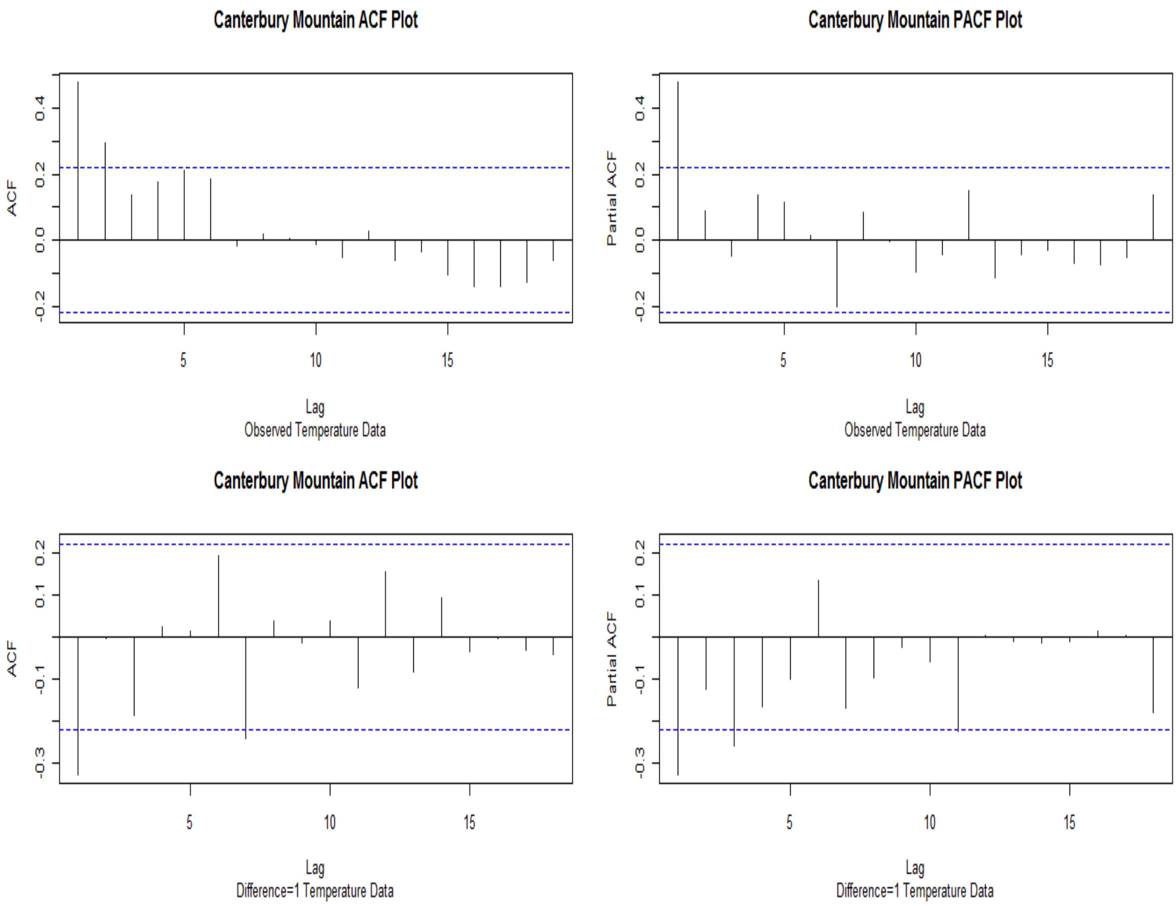


Figure 66: Canterbury Mountain temperature ARIMA model Residuals Plots

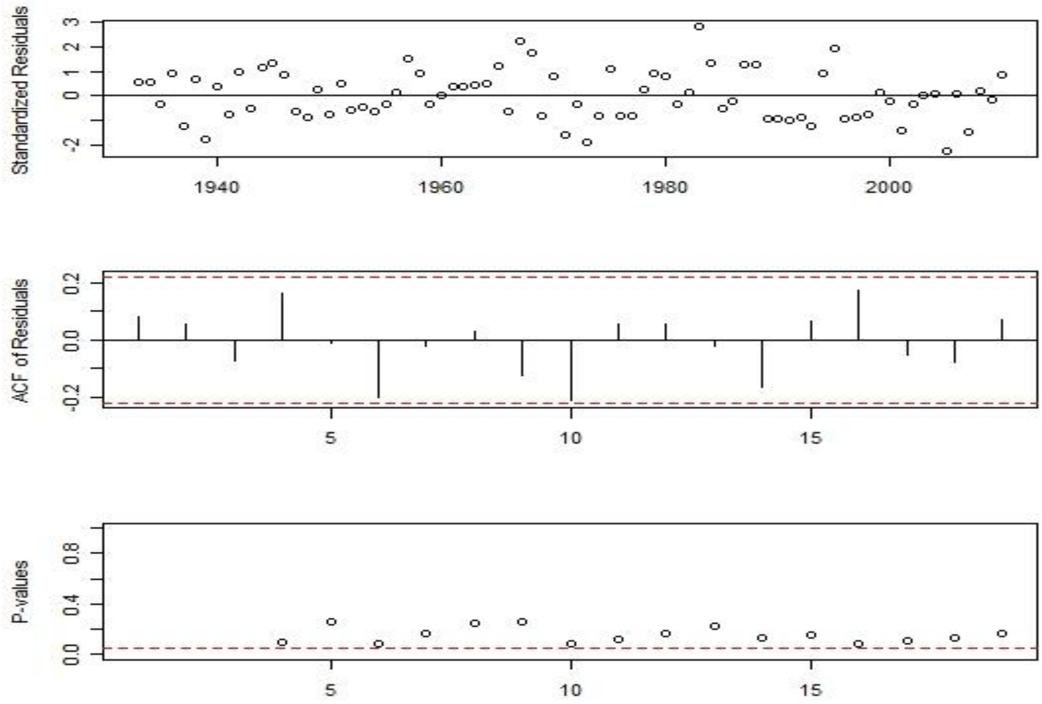


Figure 67: South Canterbury Coastal rain ACF Plots

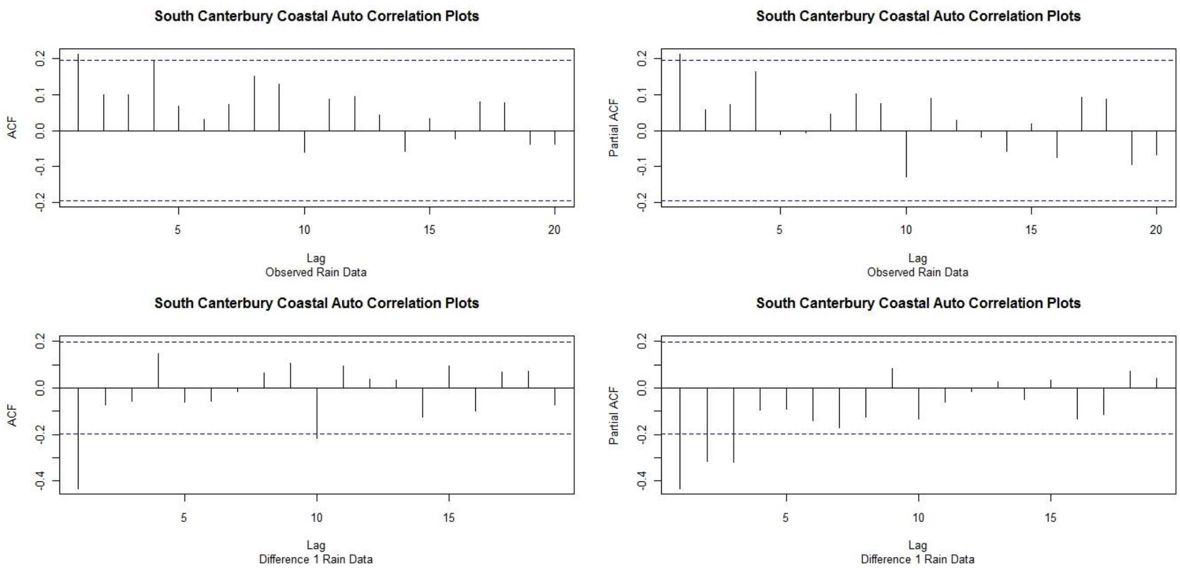


Figure 68: South Canterbury Coastal rain ARIMA model Residuals Plots

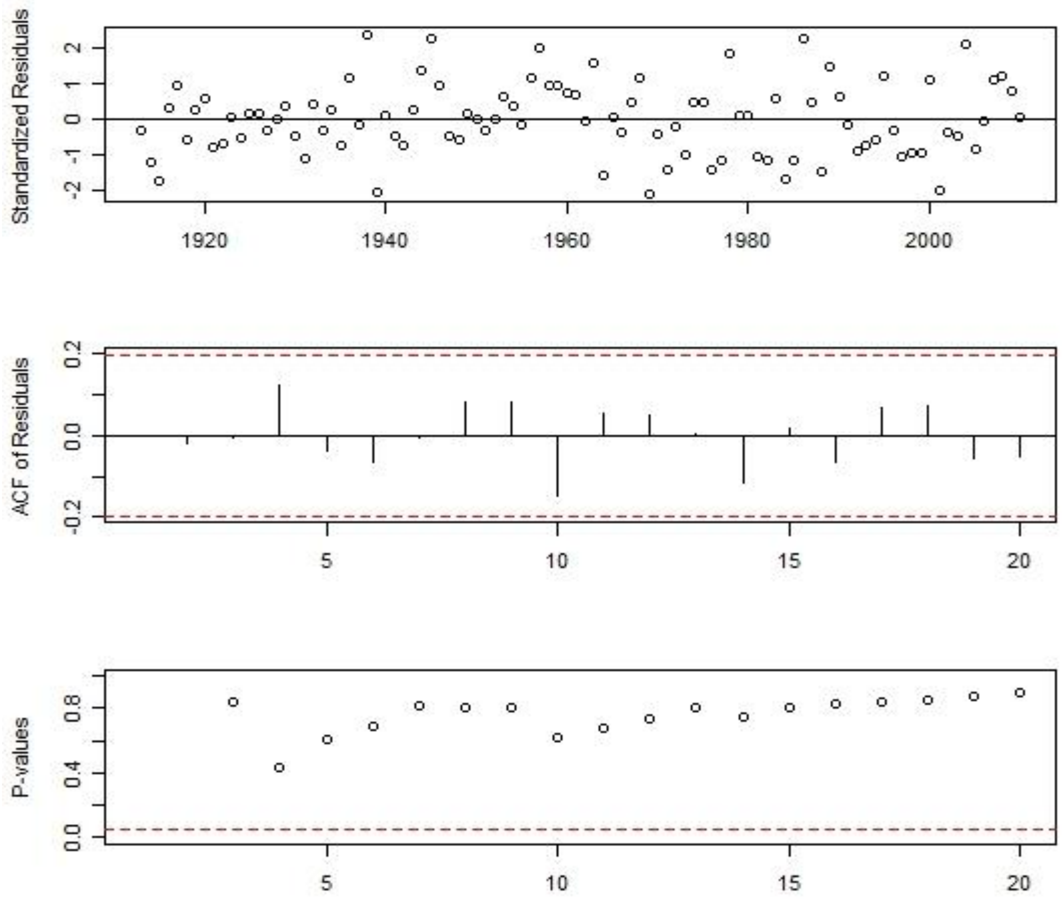


Figure 69: South Canterbury Coastal temperature ACF Plots

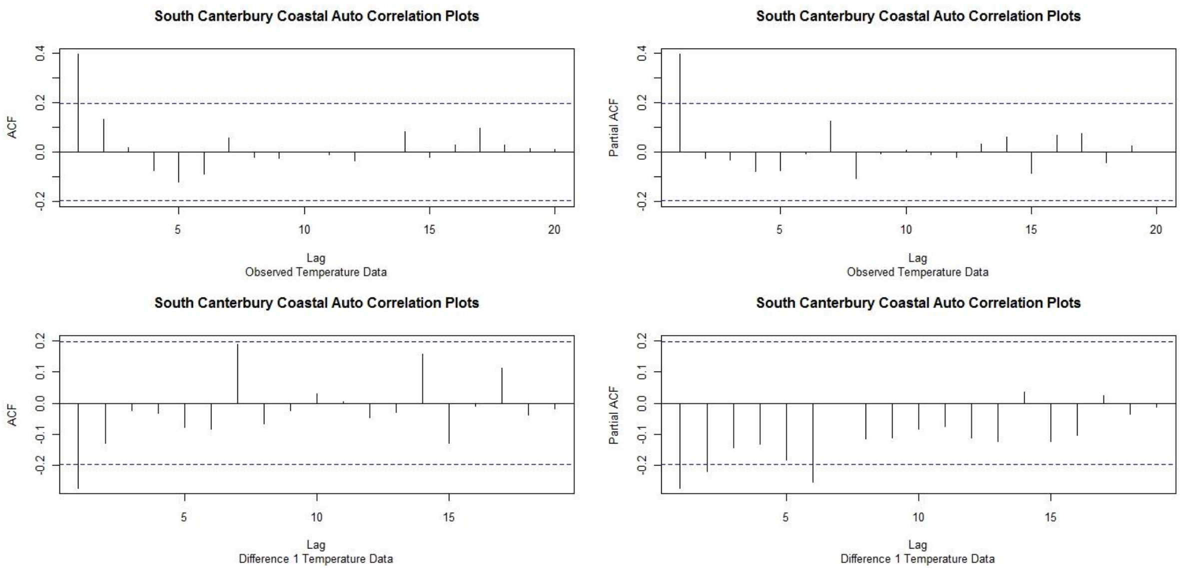


Figure 70: South Canterbury Coastal Temperature ARIMA model Residuals Plots

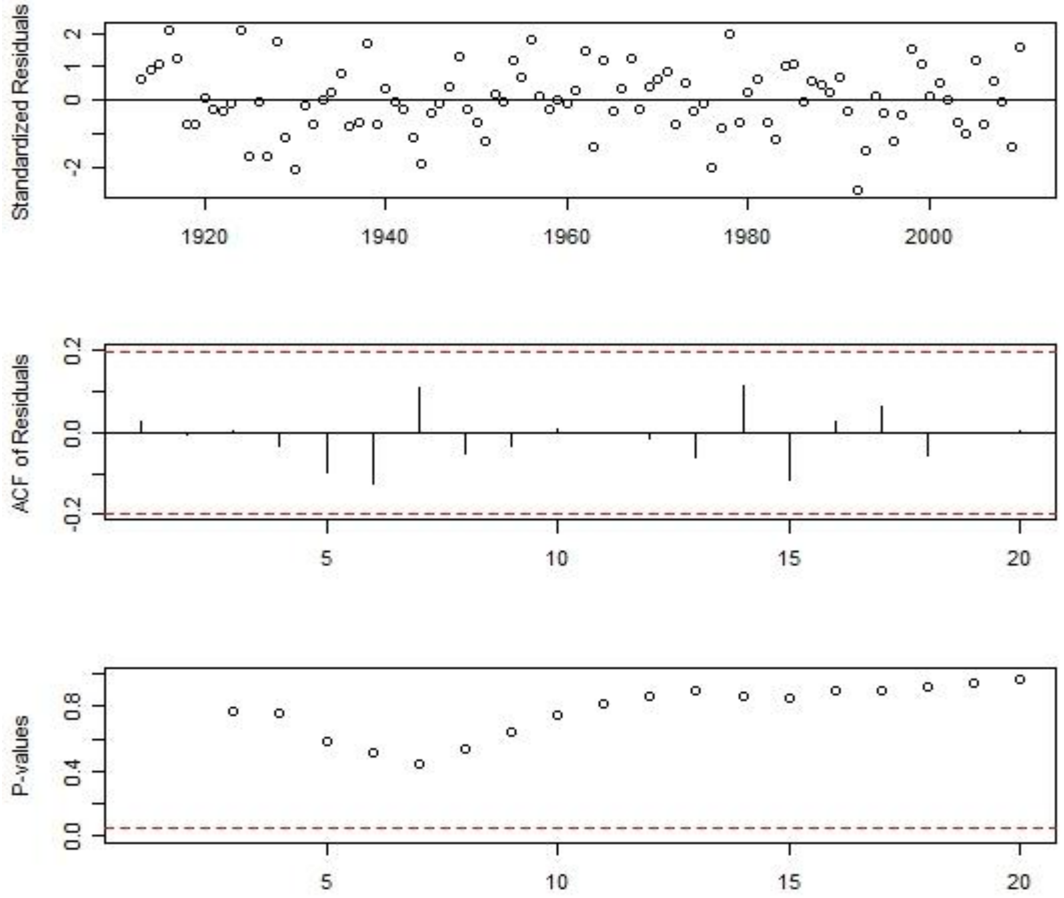


Figure 71: Northern Southland (Otago) rain ACF Plots

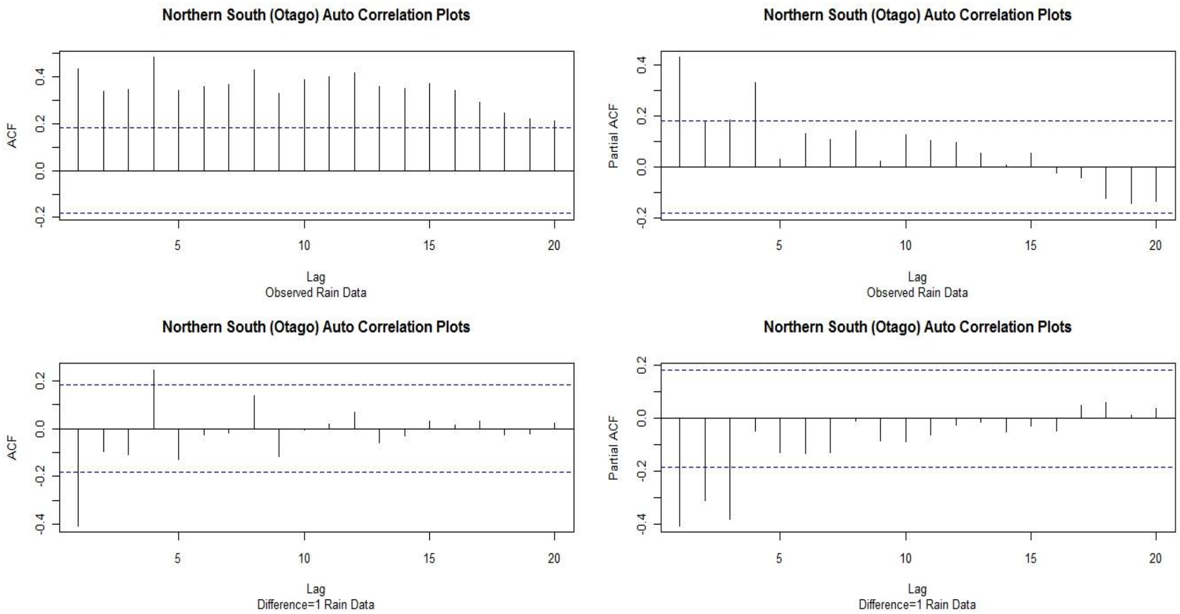


Figure 72: Northern Southland (Otago) rain ARIMA model Residuals Plots

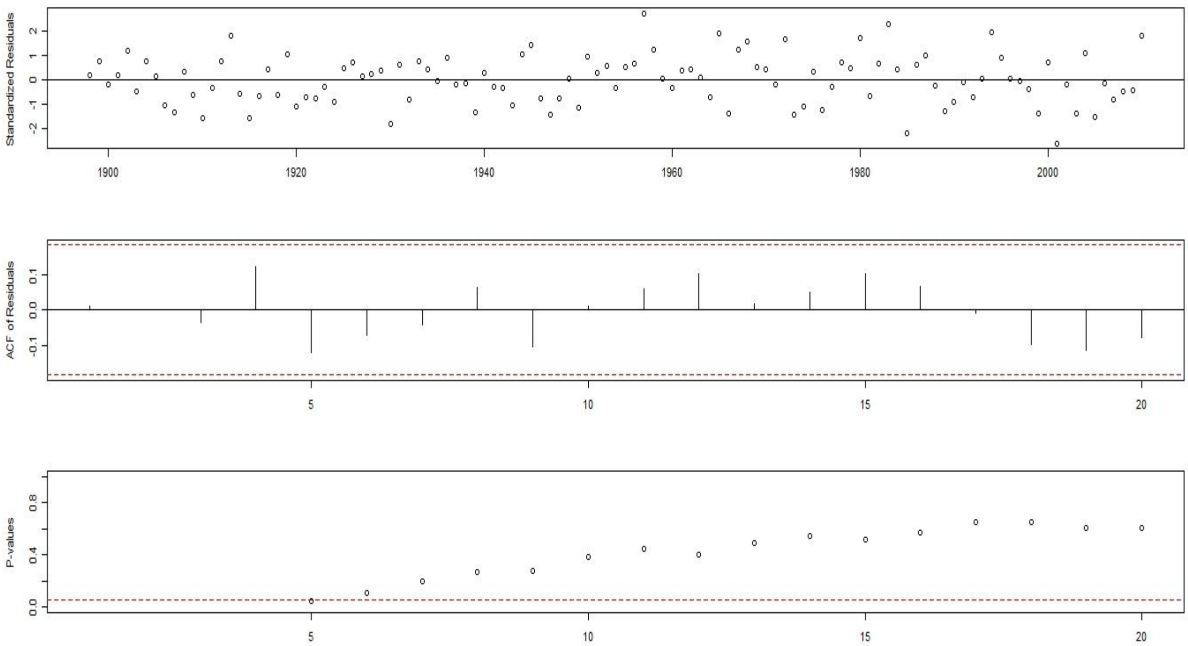


Figure 73: Northern Southland (Otago) temperature ACF Plots

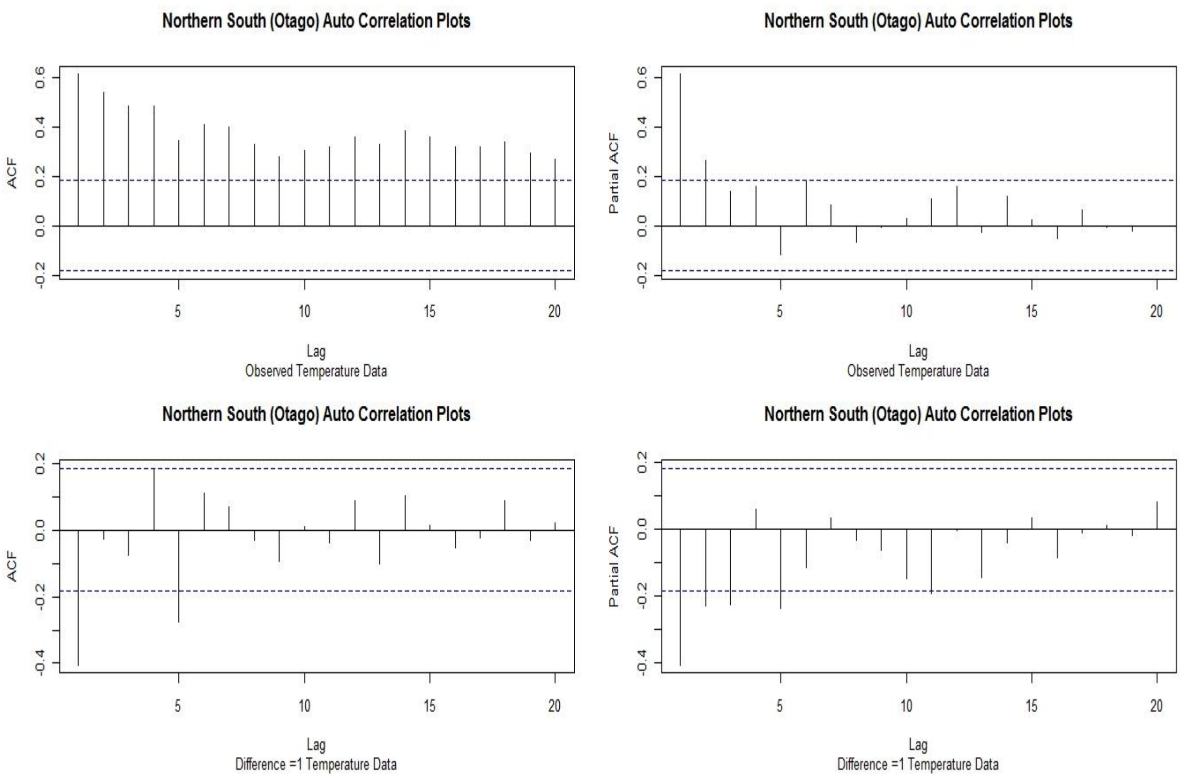


Figure 74: Northern Southland (Otago) temperature ARIMA model Residuals Plots

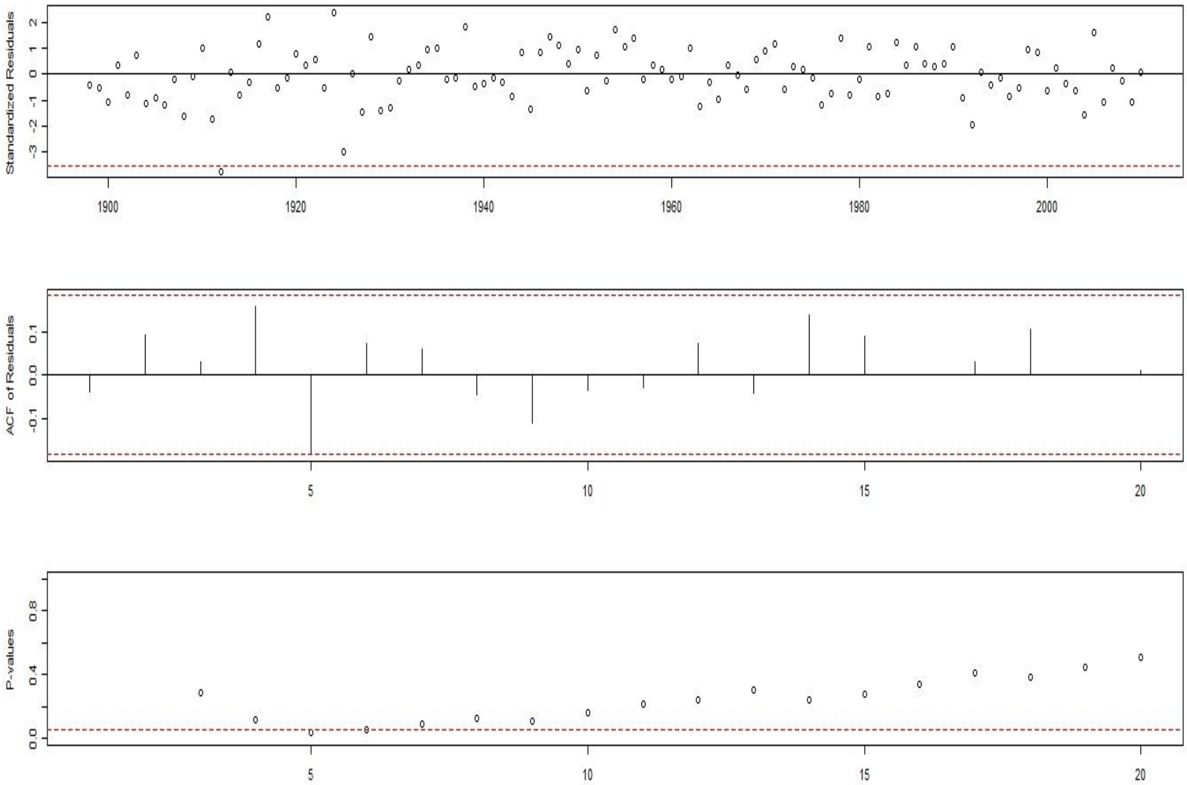


Figure 75: Southland Rain ACF Plots

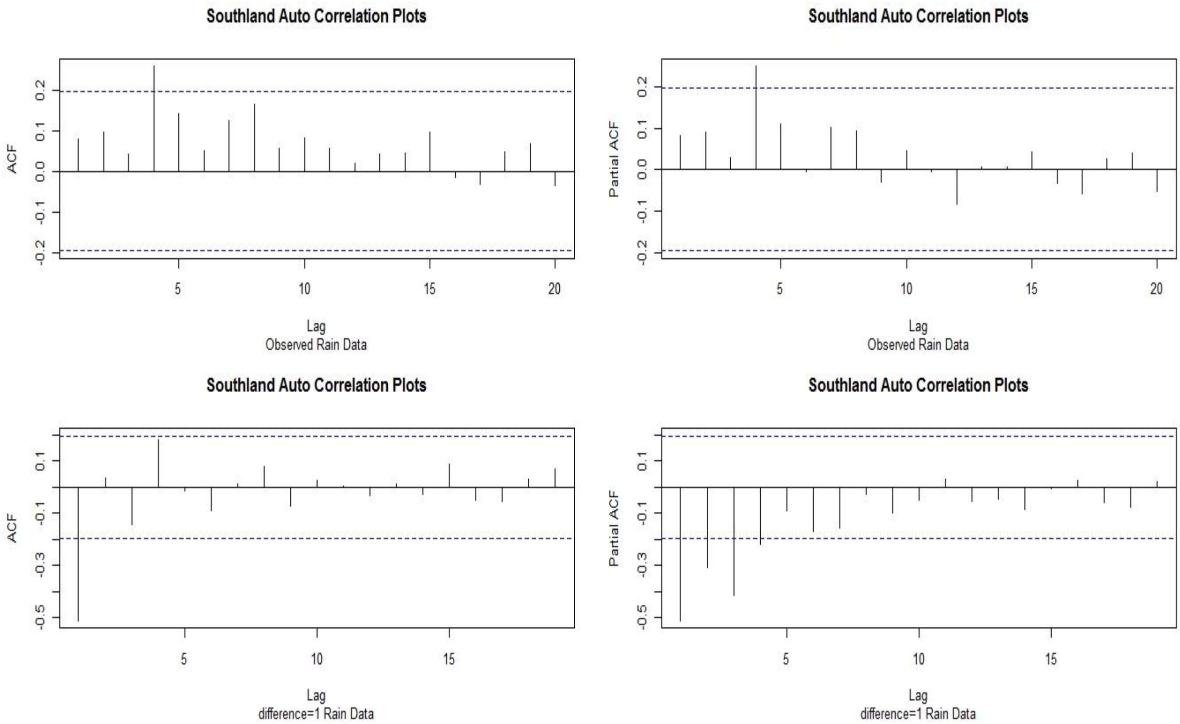


Figure 76: Southland Rain ARIMA model Residuals Plots

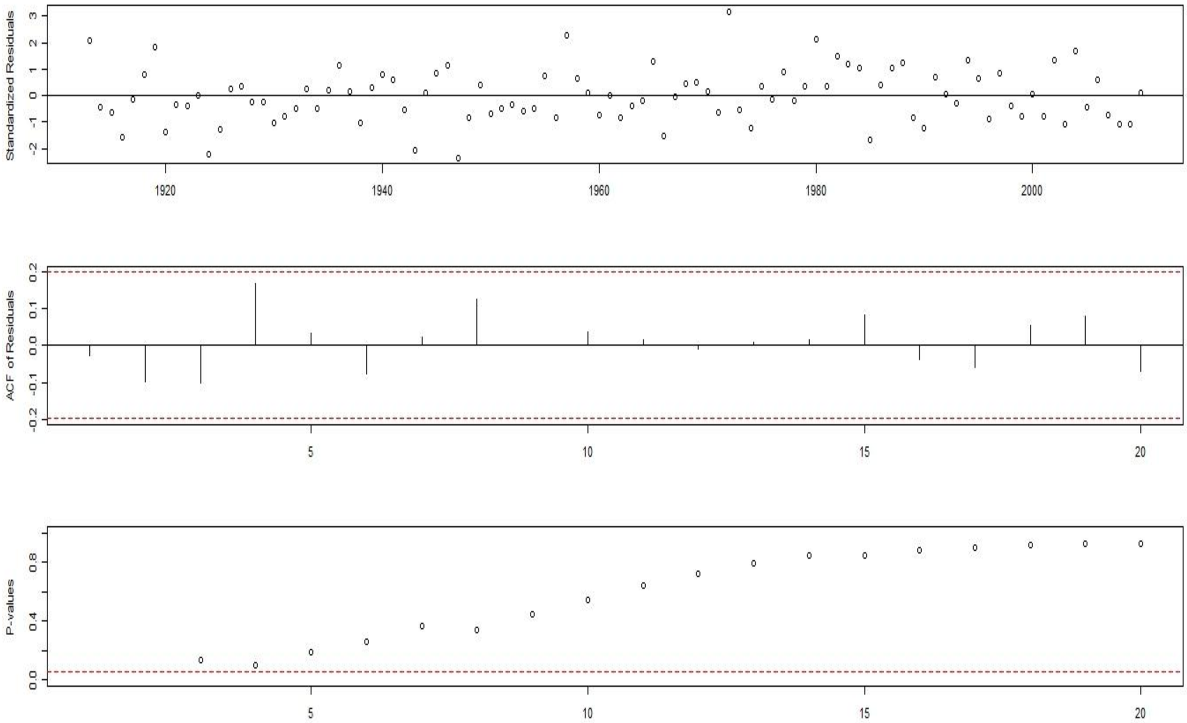
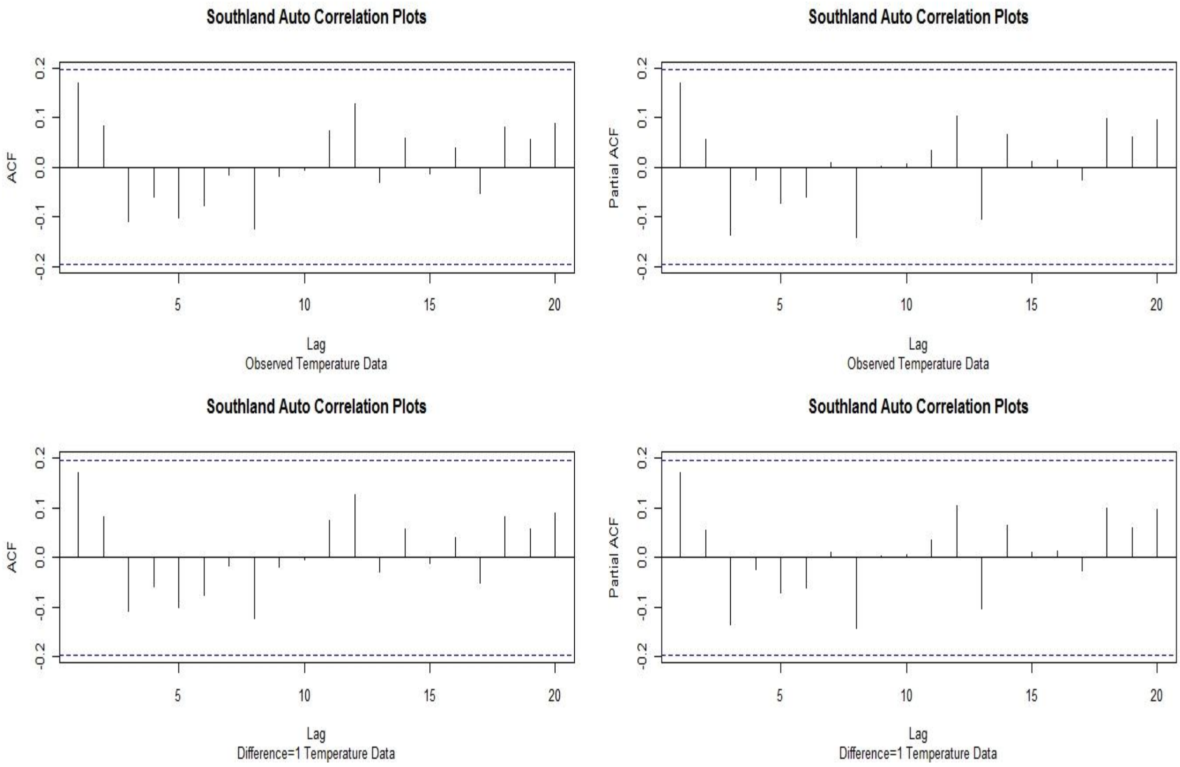


Figure 77: Southland temperature ACF Plots



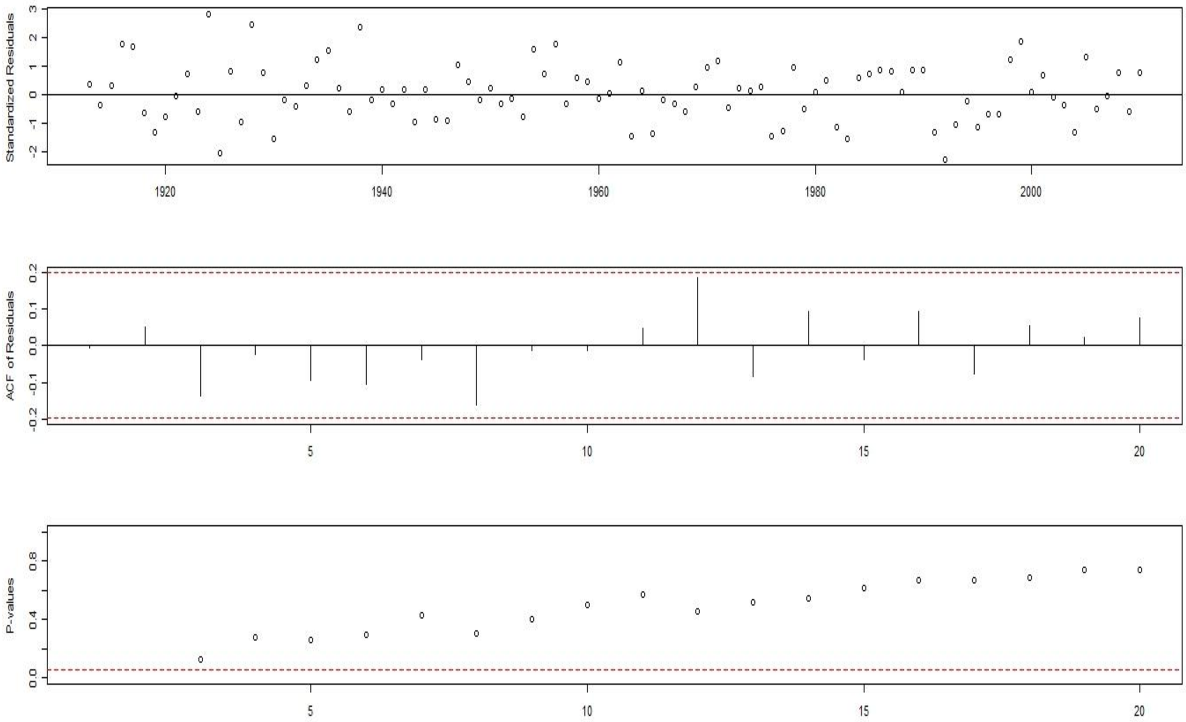


Figure 78: Southland temperature ARIMA model Residuals Plots

Appendix 3: ARIMA models tested on difference =1 data

Table 45: West Coast rain ARIMA models

West Coast rain tested ARIMA models		
ARIMA(2,0,2) with non-zero mean : 1604.190	ARIMA(0,0,1) with non-zero mean : 1604.704	
ARIMA(0,0,0) with non-zero mean : 1603.654	ARIMA(1,0,1) with non-zero mean : 1604.672	
ARIMA(1,0,0) with non-zero mean : 1604.24	ARIMA(0,0,0) with zero mean : 2072.038	
Best model: West Coast rain: ARIMA(0,0,0) with non-zero mean		
Coefficients: 2692.5095		
s.e. 30.9351		
sigma^2 estimated as 106225: log likelihood = -799.82		
AIC = 1603.64	AICc = 1603.75	BIC = 1609.06

Table 46: West Coast temperature ARIMA models

West Coast temperature tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 197.4101	ARIMA(2,0,0) with non-zero mean : 195.8411		
ARIMA(0,0,0) with non-zero mean : 219.926	ARIMA(1,0,1) with non-zero mean : 194.8064		
ARIMA(1,0,0) with non-zero mean : 192.9401	ARIMA(2,0,1) with non-zero mean : 196.2369		
ARIMA(0,0,1) with non-zero mean : 199.9623	ARIMA(1,0,0) with zero mean : 226.0882		
Best Model: West Coast Temperature ARIMA(1,0,0) with non-zero mean			
Coefficients:	ar1	E[mean]	
	0.4705	11.4812	
s.e.	0.084	0.1004	
sigma^2 estimated as 0.3184: log likelihood = -94.11			
AIC = 194.22	AICc = 194.44,	BIC = 202.35	

Table 47: Marlborough rain ARIMA models

Marlborough rain tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 1e+20	ARIMA(2,0,1) with non-zero mean : 1e+20		
ARIMA(0,0,0) with non-zero mean : 1413.053	ARIMA(3,0,1) with non-zero mean : 1405.802		
ARIMA(1,0,0) with non-zero mean : 1408.720	ARIMA(2,0,0) with zero mean : 1430.116		
ARIMA(0,0,1) with non-zero mean : 1413.056	ARIMA(3,0,0) with non-zero mean : 1405.712		
ARIMA(2,0,0) with non-zero mean : 1405.551			
Best model Marlborough rain: ARIMA (2,0,0) with non-zero mean			
Coefficients:	ar1	ar2	E[Mean]
	0.1358	0.2274	1198.745
s.e.	0.0965	0.0969	28.9788
sigma^2 estimated as 36338: log likelihood = -700.34			
AIC = 1408.68,	AICc = 1409.08,	BIC = 1419.3	

Table 48: Marlborough temperature ARIMA models

Marlborough temperature tested ARIMA models				
ARIMA(2,0,2) with non-zero mean : 156.4769			ARIMA(1,0,1) with non-zero mean : 153.4058	
ARIMA(0,0,0) with non-zero mean : 216.6742			ARIMA(2,0,1) with non-zero mean : 151.0287	
ARIMA(1,0,0) with non-zero mean : 151.4058			ARIMA(2,0,1) with zero mean : 1e+20	
ARIMA(0,0,1) with non-zero mean : 178.9270			ARIMA(3,0,1) with non-zero mean : 157.2973	
ARIMA(2,0,0) with non-zero mean : 154.1924			ARIMA(3,0,2) with non-zero mean : 1e+20	
Best model Marlborough temperature: ARIMA(2,0,1) with non-zero mean				
Coefficients:	ar1	ar2	ma1	E[mean]
	-0.2649	0.6811	0.9361	12.1232
s.e.	0.0895	0.0807	0.0624	0.1555
sigma^2 estimated as 0.2409: log likelihood = -74.64				
AIC = 159.29		AICc = 159. 89		AIC = 159.29

Table 49: North Canterbury Coastal rain tested ARIMA models

North Canterbury Coastal rain tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 1e+20		ARIMA(2,0,1) with zero mean : 1e+20	
ARIMA(0,0,0) with non-zero mean : 1445.150		ARIMA(1,0,0) with zero mean : 1503.311	
ARIMA(1,0,0) with non-zero mean : 1445.584		ARIMA(1,0,2) with zero mean : 1443.744	
ARIMA(0,0,1) with non-zero mean : 1445.240		ARIMA(0,0,0) with zero mean : 1818.365	
ARIMA(1,0,1) with non-zero mean : 1442.969		ARIMA(2,0,2) with zero mean : 1e+20	
ARIMA(1,0,1) with zero mean : 1441.755		ARIMA(0,0,1) with zero mean : 1719.088	
Best fit North Canterbury Coastal rain: ARIMA(1,0,1) with zero mean			
Coefficients:	ar1	ma1	
	0.9988	-0.9039	
s.e.	0.0018	0.0389	
sigma^2 estimated as 24262: log likelihood = -717.87			
AIC = 1441.76, ,		AICc = 1441.98	BIC = 1449.88

Table 50: North Canterbury Coastal temperature tested ARIMA models

North Canterbury temperature tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 134.5438		ARIMA(2,0,0) with non-zero mean : 131.1842	
ARIMA(0,0,0) with non-zero mean : 144.3504		ARIMA(1,0,1) with non-zero mean : 130.238	
ARIMA(1,0,0) with non-zero mean : 128.2398		ARIMA(2,0,1) with non-zero mean : 132.6102	
ARIMA(0,0,1) with non-zero mean : 129.6873		ARIMA(1,0,0) with zero mean : 1e+20	
Best fit: North Canterbury Coastal temperature ARIMA(1,0,0) with non-zero mean			
Coefficients:	ar1	E[Mean]	
	0.3981	11.5191	
s.e.	0.0876	0.0655	
sigma^2 estimated as 0.1744:			log likelihood = -60.66

AIC = 127.32,	, AICc = 127.54	BIC = 135.45

Table 51: North Canterbury Foothills rain tested ARIMA models

North Canterbury Foothills rain tested ARIMA models				
ARIMA(2,0,2) with non-zero mean : 1178.395		ARIMA(0,0,1) with non-zero mean : 1174.624		
ARIMA(0,0,0) with non-zero mean : 1172.973		ARIMA(1,0,1) with non-zero mean : 1175.082		
ARIMA(1,0,0) with non-zero mean : 1174.533		ARIMA(0,0,0) with zero mean : 1510.747		
Best fit: North Canterbury Foothills rain ARIMA(0,0,0) with non-zero mean				
Coefficients:	E[Mean]			
	1044.5994			
s.e.	16.8686			
sigma^2 estimated as 25609: log likelihood = -584.49				
AIC = 1172.97,	AICc = 1173.1,1	BIC = 1177.97		

Table 52: North Canterbury Foothills temperature tested ARIMA models

North Canterbury Foothills temperature tested ARIMA models				
ARIMA(2,0,2) with non-zero mean : 147.4505		ARIMA(1,0,1) with zero mean : 1e+20 *		
ARIMA(0,0,0) with non-zero mean : 164.4154		ARIMA(2,0,1) with non-zero mean : 145.4807		
ARIMA(1,0,0) with non-zero mean : 145.9665		ARIMA(3,0,2) with non-zero mean : 148.9686		
ARIMA(0,0,1) with non-zero mean : 150.7999		ARIMA(2,0,1) with zero mean : 1e+20 *		
ARIMA(2,0,0) with non-zero mean : 146.5053		ARIMA(3,0,1) with non-zero mean : 148.488		
ARIMA(1,0,1) with non-zero mean : 145.7858				
Best fit: North Canterbury Foothills temperature: ARIMA(2,0,1) with non-zero mean				
Coefficients:	ar1	ar2	ma1	E[Mean]
	1.2451	-0.2697	-0.8846	11.1938
s.e.	0.1294	0.1169	0.0719	0.213
sigma^2 estimated as 0.2623: log likelihood = -67.74				
AIC = 145.48,	AICc = 146.2		BIC = 157.98	

Table 53: South Canterbury Coastal rain tested ARIMA models

South Canterbury Coastal rain tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 1303.226		ARIMA(1,0,1) with non-zero mean : 1299.649	
ARIMA(0,0,0) with non-zero mean : 1302.269		ARIMA(1,0,1) with zero mean : 1e+20 *	
ARIMA(1,0,0) with non-zero mean : 1299.702		ARIMA(2,0,1) with non-zero mean : 1301.316	
ARIMA(0,0,1) with non-zero mean : 1300.259		ARIMA(1,0,2) with non-zero mean : 1301.267	
ARIMA(2,0,0) with non-zero mean : 1301.362			
Best fit: South Canterbury Coastal rain ARIMA(1,0,1) with non-zero mean			
Coefficients:	ar1	ma1	E[Mean]
	0.8642	-0.7336	783.989
s.e.	0.1426	0.1952	29.2725
sigma^2 estimated as 23795: log likelihood = -645.82			
AIC = 1299.65,	AICc = 1300.07,	BIC = 1310.07	

Table 54: South Canterbury Coastal temperature tested ARIMA models

South Canterbury Coastal temperature tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 119.5998			ARIMA(2,0,0) with non-zero mean : 116.2717
ARIMA(0,0,0) with non-zero mean : 129.0933			ARIMA(1,0,1) with non-zero mean : 116.2849
ARIMA(1,0,0) with non-zero mean : 114.3841			ARIMA(2,0,1) with non-zero mean : 117.733
ARIMA(0,0,1) with non-zero mean : 115.7839			ARIMA(1,0,0) with zero mean : 155.2438
Best fit: South Canterbury Coastal temperature ARIMA(1,0,0) with non-zero mean			
Coefficients:	ar1	E[Mean]	
	0.3911	10.9621	
s.e.	0.0915	0.0678	
sigma^2 estimated as 0.1728: log likelihood = -54.19			
AIC = 114.38, ,	AICc = 114.63		BIC = 122.2

Table 55: South Canterbury Foothills rain tested ARIMA models

South Canterbury Foothills rain tested ARIMA models				
ARIMA(2,0,2) with non-zero mean : 1289.003				ARIMA(1,0,2) with non-zero mean : 1287.396
ARIMA(0,0,0) with non-zero mean : 1327.422				ARIMA(1,0,1) with non-zero mean : 1286.495
ARIMA(1,0,0) with non-zero mean : 1309.136				ARIMA(1,0,1) with zero mean : 1e+20 *
ARIMA(0,0,1) with non-zero mean : 1318.066				ARIMA(2,0,1) with non-zero mean : 1287.471
Best fit: South Canterbury Foothills rain ARIMA(1,0,1) with non-zero mean				
Coefficients:	ar1	ma1	E[mean]	
	0.9779	-0.8066	1061.375	
s.e.	0.0231	0.0592	144.3128	
sigma^2 estimated as 46711: log likelihood = -639.25				
AIC = 1286.5,	, AICc = 1286.94			BIC = 1296.67

Table 56: South Canterbury Foothills temperature tested ARIMA models

South Canterbury Foothills temperature tested ARIMA models				
ARIMA(2,0,2) with non-zero mean : 162.6210				ARIMA(1,0,2) with non-zero mean : 161.2468
ARIMA(0,0,0) with non-zero mean : 201.5800				ARIMA(1,0,1) with non-zero mean : 160.0969
ARIMA(1,0,0) with non-zero mean : 169.3726				ARIMA(1,0,1) with zero mean : 1e+20 *
ARIMA(0,0,1) with non-zero mean : 182.6233				ARIMA(2,0,1) with non-zero mean : 160.9960
Best fit: South Canterbury Foothills temperature ARIMA(1,0,1) with non-zero mean				
Coefficients:	ar1	ma1	E[Mean]	
	0.9588	-0.6905	9.79	
s.e.	0.0511	0.1435	0.3657	
sigma^2 estimated as 0.2922: log likelihood = -76.05				
AIC = 160.1,	AICc = 160.5,5			BIC = 170.27

Table 57: Canterbury Mountain rain tested ARIMA models

Canterbury Mountains rain tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 1130.974		ARIMA(1,0,1) with non-zero mean : 1127.565	
ARIMA(0,0,0) with non-zero mean : 1128.653		ARIMA(1,0,1) with zero mean : 1e+20 *	
ARIMA(1,0,0) with non-zero mean : 1128.663		ARIMA(2,0,1) with non-zero mean : 1130.053	
ARIMA(0,0,1) with non-zero mean : 1129.181		ARIMA(1,0,2) with non-zero mean : 1129.556	
Best fit: Canterbury Mountain rain ARIMA(1,0,1) with non-zero mean			
Coefficients:	ar1	ma1	E[Mean]
	0.8858	-0.7662	1653.2548
s.e.	0.1730	0.2429	59.3122
sigma^2 estimated as 69900: log likelihood = -559.78			
AIC = 1127.56	AICc = 1128.1		BIC = 1137.09

Table 58: Canterbury Mountains temperature tested ARIMA models

Canterbury Mountains temperature tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 171.8831		ARIMA(2,0,0) with non-zero mean : 168.8730	
ARIMA(0,0,0) with non-zero mean : 187.3874		ARIMA(1,0,1) with non-zero mean : 168.9549	
ARIMA(1,0,0) with non-zero mean : 167.6548		ARIMA(2,0,1) with non-zero mean : 169.4283	
ARIMA(0,0,1) with non-zero mean : 174.3274		ARIMA(1,0,0) with zero mean : 192.5504	
Best fit: Canterbury Mountains temperature ARIMA(1,0,0) with non-zero mean			
Coefficients:	ar1	E[Mean]	
	0.4973	8.6612	
s.e.	0.0989	0.1457	
sigma^2 estimated as 0.4401: log likelihood = -80.83			
AIC = 167.65,	AICc = 167.97,		BIC = 174.8

Table 59: Northern South (Otago) rain tested ARIMA models

Northern South (Otago) rain tested ARIMA models					
ARIMA(2,0,2) with non-zero mean : 1e+20			ARIMA(3,0,1) with non-zero mean : 1395.885		
ARIMA(0,0,0) with non-zero mean : 1444.73			ARIMA(3,0,1) with zero mean : 1e+20		
ARIMA(1,0,0) with non-zero mean : 1422.317			ARIMA(4,0,1) with non-zero mean : 1399.345		
ARIMA(0,0,1) with non-zero mean : 1429.709			ARIMA(3,0,0) with non-zero mean : 1417.175		
ARIMA(2,0,0) with non-zero mean : 1418.923			ARIMA(3,0,2) with non-zero mean : 1397.915		
ARIMA(2,0,1) with non-zero mean : 1e+20			ARIMA(4,0,2) with non-zero mean : 1397.336		
Best fit: Northern South (Otago) rain ARIMA(3,0,1) with non-zero mean					
Coefficients:	ar1	ar2	ar3	ma1	E[Mean]
	1.0035	-0.1554	0.1411	-0.8577	792.2038
s.e.	0.1038	0.1333	0.0994	0.0493	75.2296
sigma^2 estimated as 10116: log likelihood = -694.18					
AIC = 1400.36		AICc = 1401.13		BIC = 1416.82	

Table 60: Northern South (Otago) temperature tested ARIMA models

Northern South (Otago) temperature tested ARIMA models				
ARIMA(2,0,2) with non-zero mean : 185.8712			ARIMA(1,0,2) with non-zero mean : 184.8456	
ARIMA(0,0,0) with non-zero mean : 244.6651			ARIMA(1,0,1) with non-zero mean : 183.2756	
ARIMA(1,0,0) with non-zero mean : 193.6822			ARIMA(1,0,1) with zero mean : 1e+20	
ARIMA(0,0,1) with non-zero mean : 215.5905			ARIMA(2,0,1) with non-zero mean : 186.5638	
Best fit: Northern South (Otago) temperature ARIMA(1,0,1) with non-zero mean				
Coefficients	ar1	ma1	E[Mean]	
	0.9054	-0.545	9.7518	
s.e.	0.0563	0.1245	0.2162	
sigma^2 estimated as 0.2654: log likelihood = -87.25				
AIC = 182.5,1	AICc = 182.87,		BIC = 193.49	

Table 61: Northern Southern (Otago) rain tested ARIMA models

Northern Southern (Otago) rain tested ARIMA models					
ARIMA(2,0,2) with non-zero mean : 1e+20			ARIMA(3,0,1) with non-zero mean : 1395.885		
ARIMA(0,0,0) with non-zero mean : 1444.73			ARIMA(3,0,1) with zero mean : 1e+20		
ARIMA(1,0,0) with non-zero mean : 1422.317			ARIMA(4,0,1) with non-zero mean : 1399.345		
ARIMA(0,0,1) with non-zero mean : 1429.709			ARIMA(3,0,0) with non-zero mean : 1417.175		
ARIMA(2,0,0) with non-zero mean : 1418.923			ARIMA(3,0,2) with non-zero mean : 1397.915		
ARIMA(2,0,1) with non-zero mean : 1e+20			ARIMA(4,0,2) with non-zero mean : 1397.336		
Best fit: Northern Southern (Otago) rain ARIMA (3,0,1) with non-zero mean					
	ar1	ar2	ar3	ma1	E[mean]
Coefficients:	1.0035	-0.1554	0.1411	-0.8577	792.2038
s.e.	0.1038	0.1333	0.0994	0.0493	75.2296
sigma^2 estimated as 10116: log likelihood = -694.18					
AIC = 1400.36	AICc = 1401.13		BIC = 1416.82		

Table 62: Southern South rain tested ARIMA models

Southern South rain tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 1262.418			ARIMA(1,0,1) with non-zero mean : 1259.274
ARIMA(0,0,0) with non-zero mean : 1262.062			ARIMA(1,0,1) with zero mean : 1e+20
ARIMA(1,0,0) with non-zero mean : 1263.415			ARIMA(2,0,1) with non-zero mean : 1260.293
ARIMA(0,0,1) with non-zero mean : 1263.516			ARIMA(1,0,2) with non-zero mean : 1259.940
Best fit : Southern South rain ARIMA (1,0,1) with non-zero mean			
Coefficients:	ar1	ma1	E[mean]
	0.9619	-0.8688	1062.732
s.e.	0.0457	0.0645	38.5241
sigma^2 estimated as 15851: log likelihood = -625.64			
AIC = 1259.27,	AICc = 1259.69,		BIC = 1269.69

Table 63: Southland temperature tested ARIMA models

Southern South temperature tested ARIMA models			
ARIMA(2,0,2) with non-zero mean : 126.2788		ARIMA(2,0,0) with non-zero mean : 124.5730	
ARIMA(0,0,0) with non-zero mean : 123.8372		ARIMA(1,0,1) with non-zero mean : 124.7670	
ARIMA(1,0,0) with non-zero mean : 122.8827		ARIMA(2,0,1) with non-zero mean : 125.9102	
ARIMA(0,0,1) with non-zero mean : 123.3141		ARIMA(1,0,0) with zero mean : 180.506	
Best fit: Southern South temperature ARIMA(1,0,0) with non-zero mean			
Coefficients:	ar1	E [Mean]	
	0.1707	10.0229	
s.e.	0.0985	0.0522	
sigma^2 estimated as 0.1884: log likelihood = -58.44			
AIC = 122.88,	AICc = 123.13,		BIC = 130.7

Correlation tables and graphs

Table 64: Pearson's product-moment correlation: West Coast rain & temperature

West Coast observed rain and temperature data		
t = -0.0935,	df = 109	p-value = 0.9257
alternative hypothesis: true correlation is not equal to 0		
95 percent confidence interval:	-0.19502	0.177738
Sample estimates: cor	-0.00895	

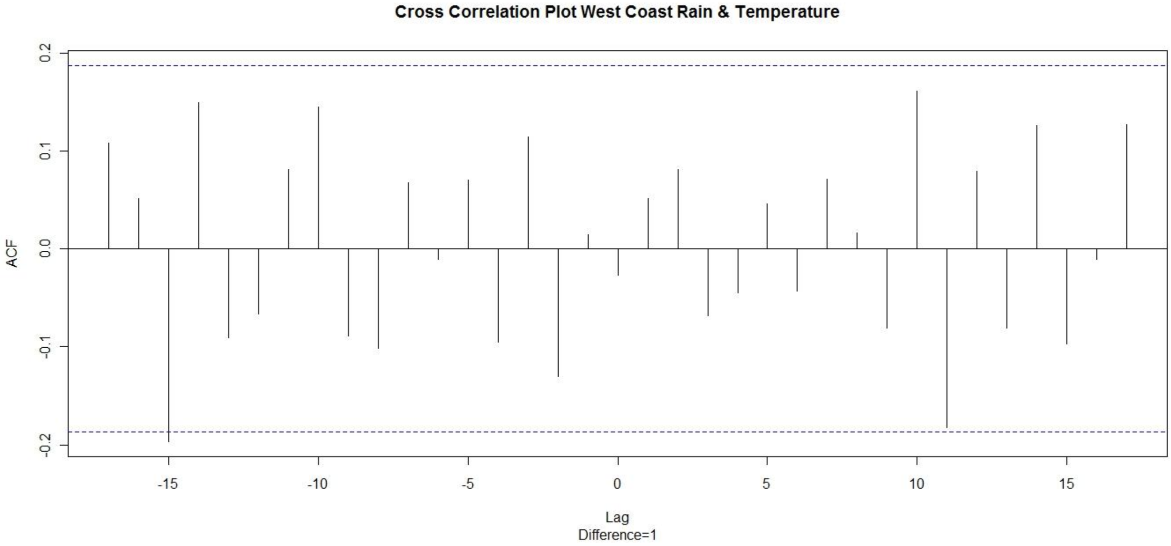


Figure 79: West Coast temperature and rain Cross Correlation Plot

Table 65: Pearson's product-moment correlation: Marlborough rain & temperature

Marlborough observed rain and temperature data		
t = 2.705,	df = 103	, p-value = 0.007993
alternative hypothesis: true correlation is not equal to 0		
95 per cent confidence interval:	0.0693	0.428078
sample estimates: correlation	0.257544	

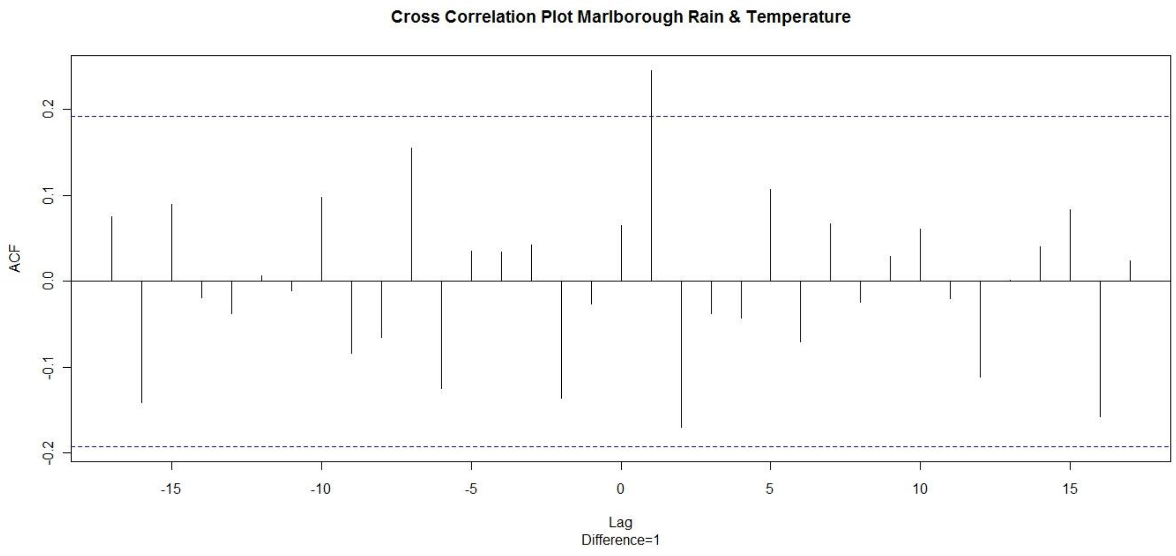


Figure 80: Marlborough rain and temperature Cross Correlation Plot

Table 66: Pearson's product-moment correlation: North Canterbury Coastal rain & temperature

North Canterbury Coastal observed rain and temperature data			
t=-2.0934, df=109 ,p-value=0.03863			
alternative hypothesis: true correlation is not equal to 0			
95 percent confidence	-0.36945	0.01059	
sample estimates: cor	-0.1966		

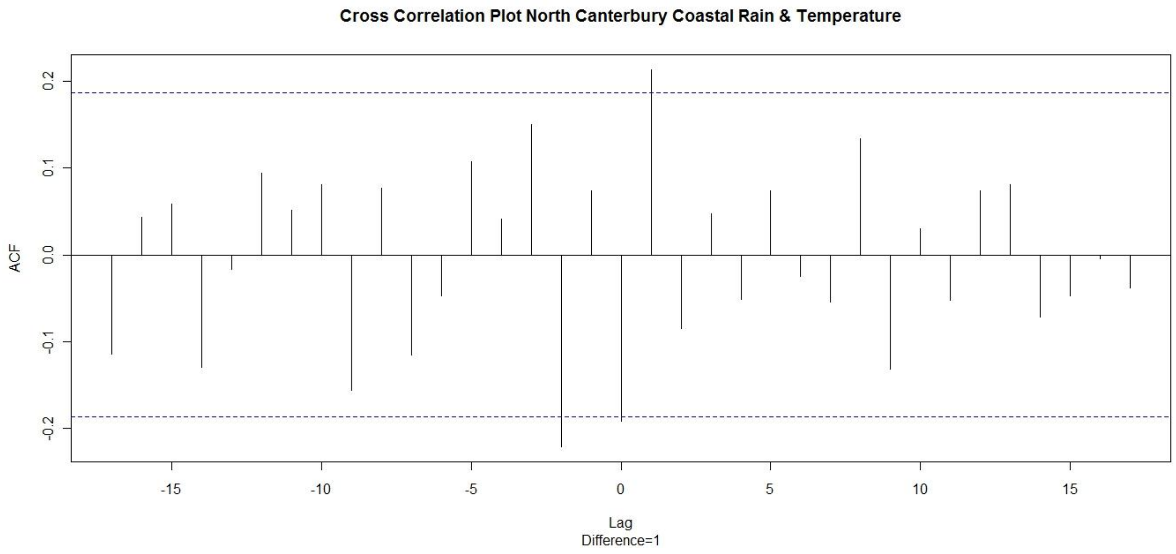


Figure 81: North Canterbury Coastal rain and temperature Cross Correlation Plot

Table 67: Pearson's product-moment correlation: North Canterbury Foothills observed data

North Canterbury Foothills observed rain and temperature data		
t = -1.6857	df=88	p-value=0.0954
alternative hypothesis: true correlation is not equal to 0		
95 per cent confidence interval:	-0.37039	0.03138

sample estimates: Correlation	-0.17686

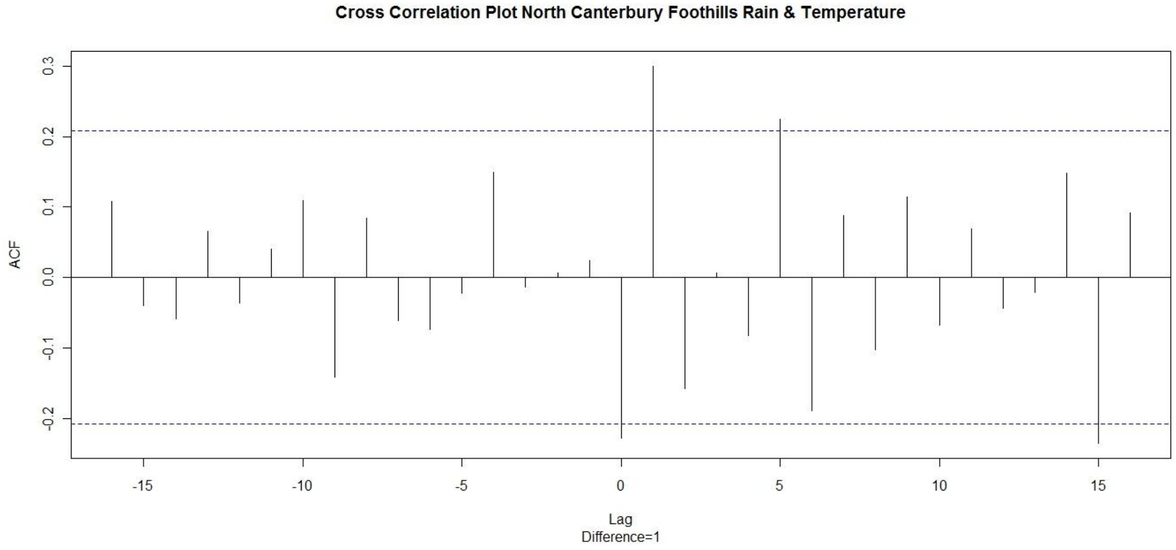


Figure 82: North Canterbury Foothill rain and temperature Cross Correlation Plot

Table 68: Pearson's product-moment correlation: South Canterbury Coastal observed data

South Canterbury Coastal observed rain and temperature data				
t = -0.1958, df df=98,	p-value=0.8452			
Alternative hypothesis: TRUE correlation<>0				
95 per cent confidence interval:			-0.21535	0.17733
sample estimates: Correlation				-0.01977

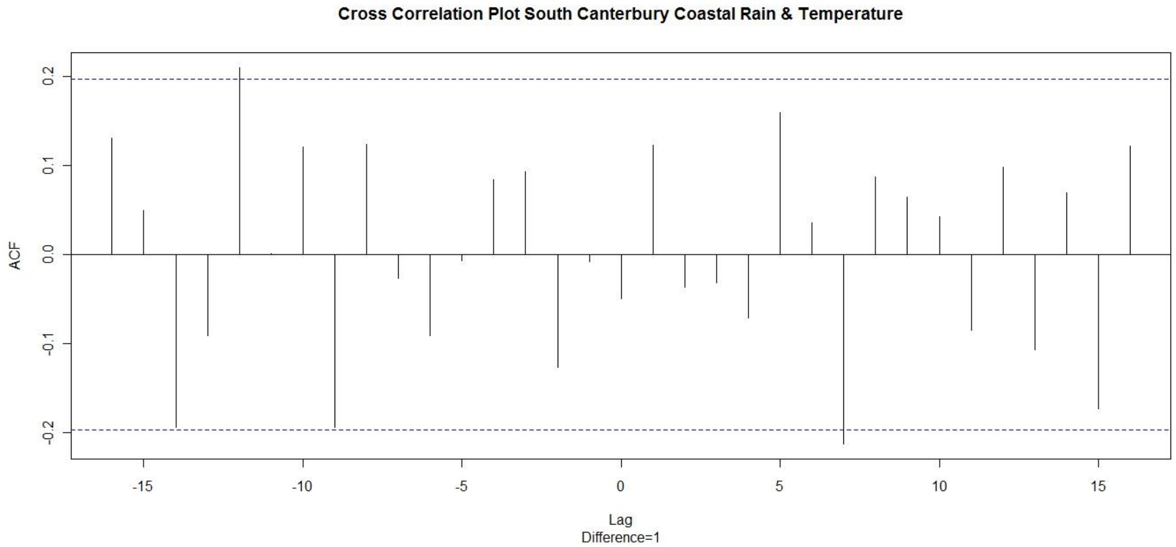


Figure 83: South Canterbury rain and temperature Cross Correlation Plot

Table 69: Pearson's product-moment correlation: South Canterbury Foothills observed data

South Canterbury Foothills observed rain and temperature data		
t = 3.4347	df=92	p-value=0.0008916
Alternative hypothesis :TRUE correlation<>0		

95 per cent confidence interval:	0.14437	0.50523
sample estimates: Correlation		0.337127

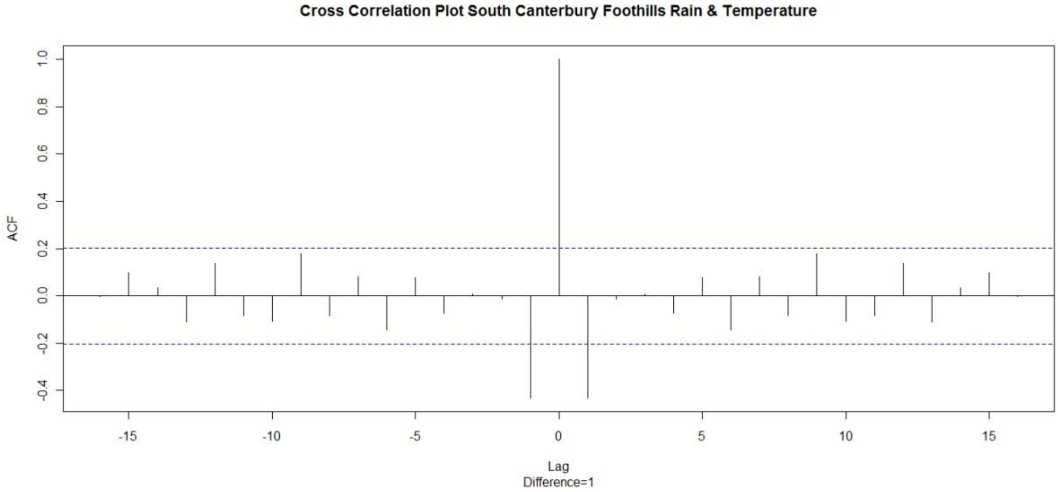


Figure 84: South Canterbury Coastal observed rain and temperature Cross Correlation Plot

Table 70: Pearson's product-moment correlation: Canterbury Mountain observed data

Canterbury Mountains observed rain and temperature data			
t = -0.1289,	df=78,	p-value=0.900	
Alternative hypothesis :TRUE correlation<>0			
95 per cent confidence interval:		-0.2337	0.2058
sample estimates: Correlation			-0.0146

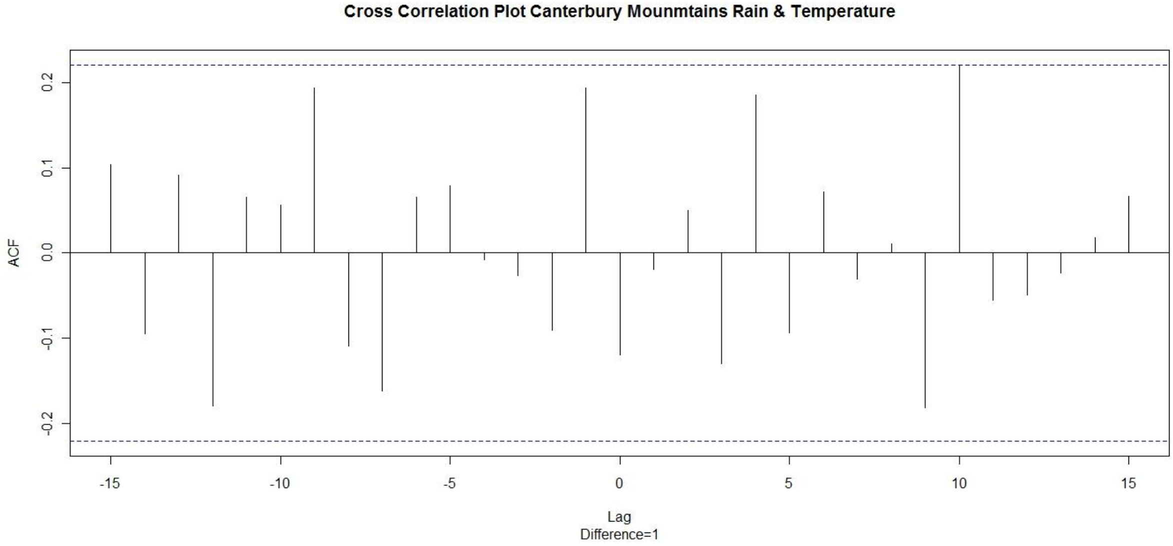


Figure 85: Canterbury Mountain observed rain and temperature Cross Correlation Plot

Table 71: Pearson's product-moment correlation: Northern South (Otago) observed rain and temperature data

Northern South (Otago) observed rain and temperature data		
t = 3.345	df=113,	p-value=0.001117
Alternative hypothesis : TRUE correlation<>0		

95 per cent confidence interval:	0.123857	0.45809
sample estimates: Correlation		0.652733

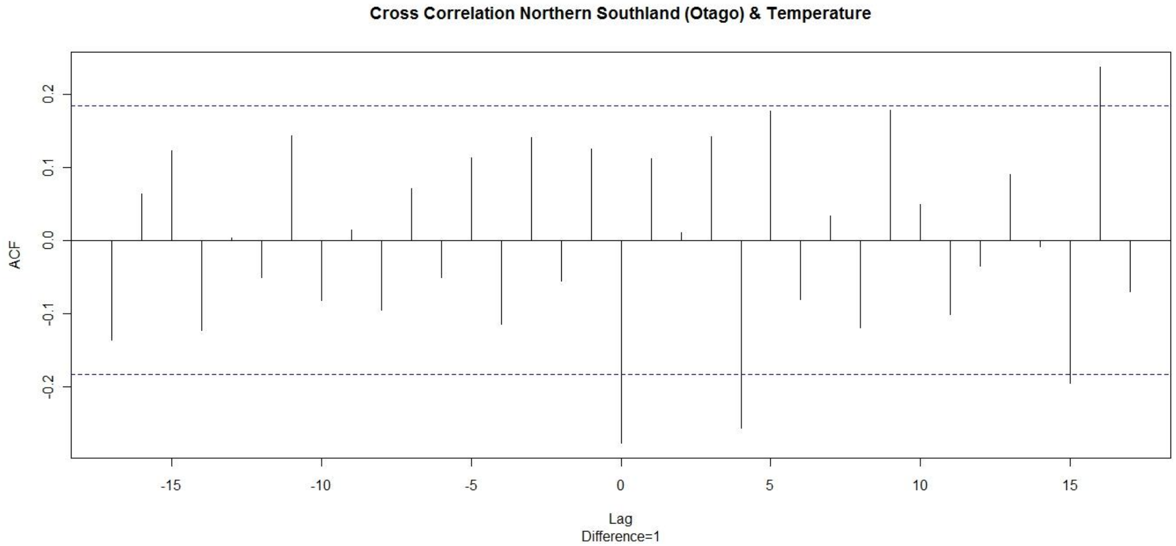


Figure 86: Northern South (Otago) observed rain and temperature Cross Correlation Plot

Southern South observed rain and temperature data		
t = -3.7148	df=98,	p-value=0.00034
Alternative hypothesis: TRUE correlation <> 0		
95 per cent confidence interval:	-0.51239	-0.1664
sample estimates: Correlation		-0.35133

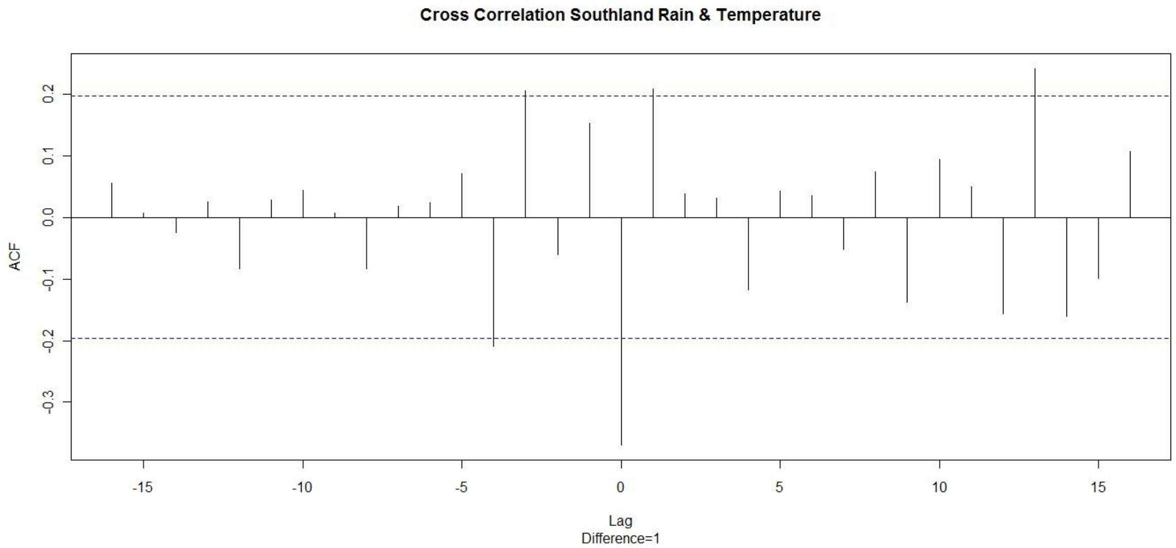


Figure 87: Southland observed rain and temperature Cross Correlation Plot

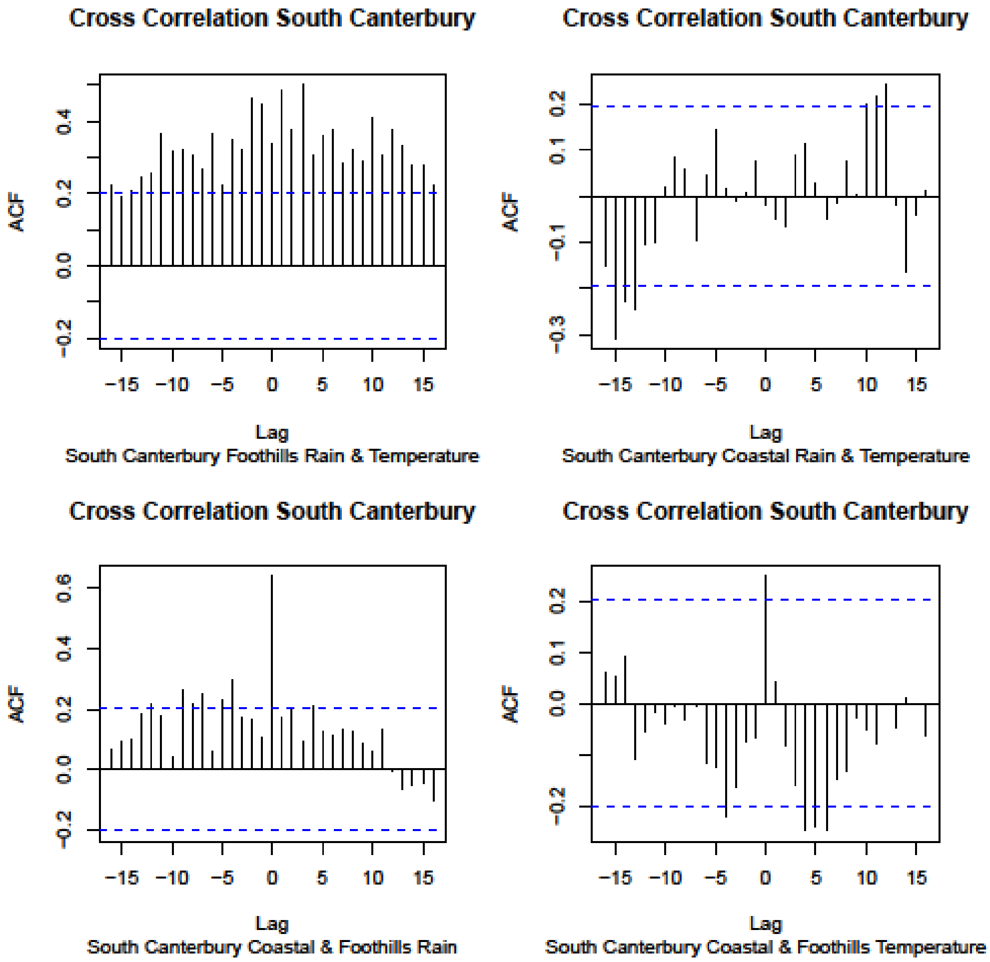
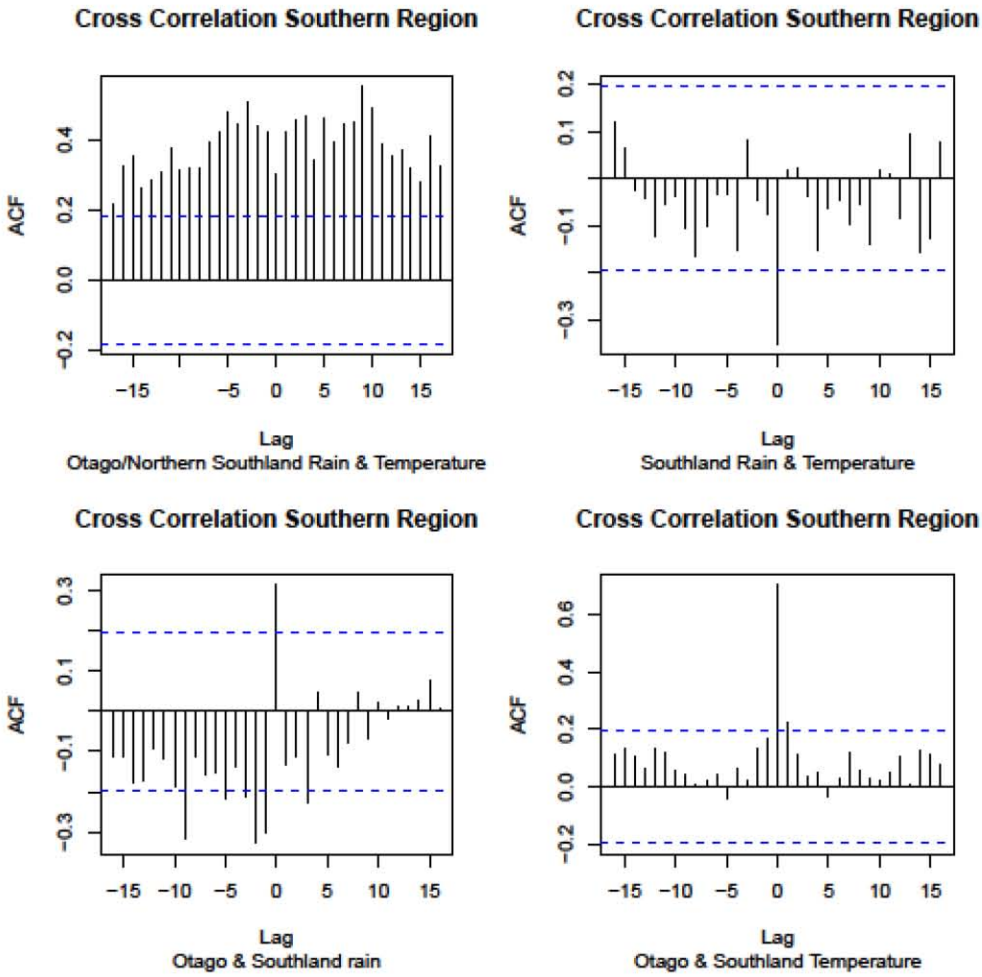


Figure 88: South Canterbury inter-regional observed rain and temperature Cross Correlation Pots


Cross Correlation Southern Region
ACF
Lag
Otago/Northern Southland Rain & Temperature
Cross Correlation Southern Region
ACF
Lag
Southland Rain & Temperature
Cross Correlation Southern Region
ACF
Lag
Otago & Southland rain
Cross Correlation Southern Region
ACF
Lag
Otago & Southland Temperature

Correlogram plots for each of the study regions

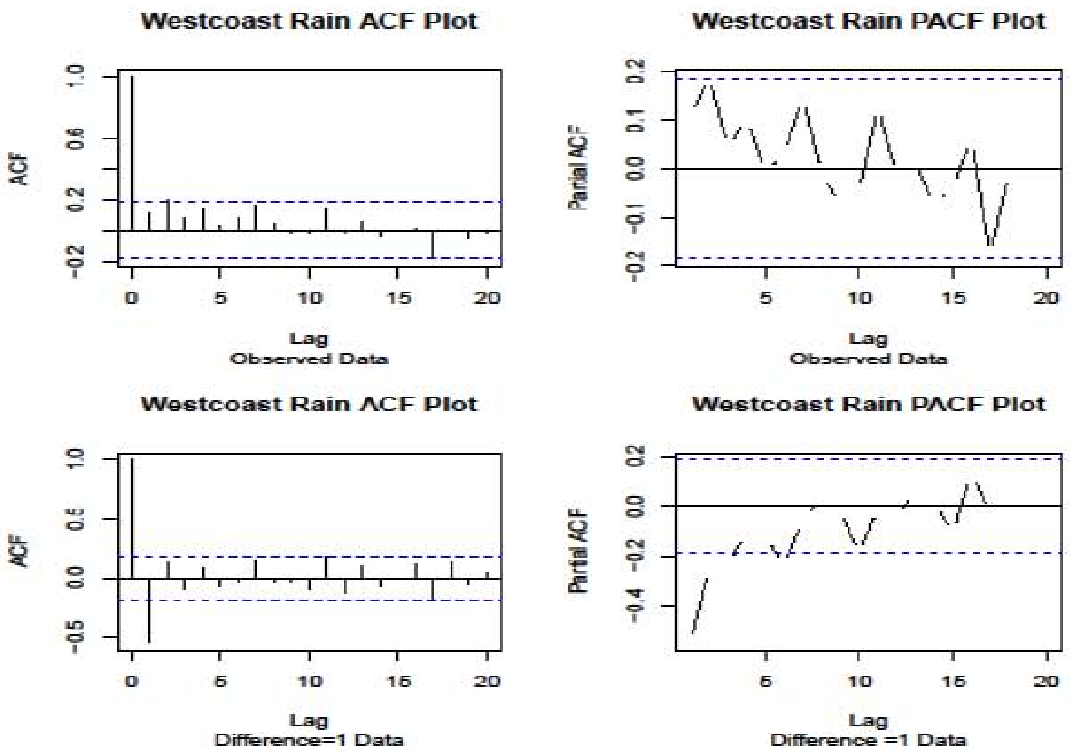


Figure 89: West Coast rain Auto Correlation observed and difference =1 Plots

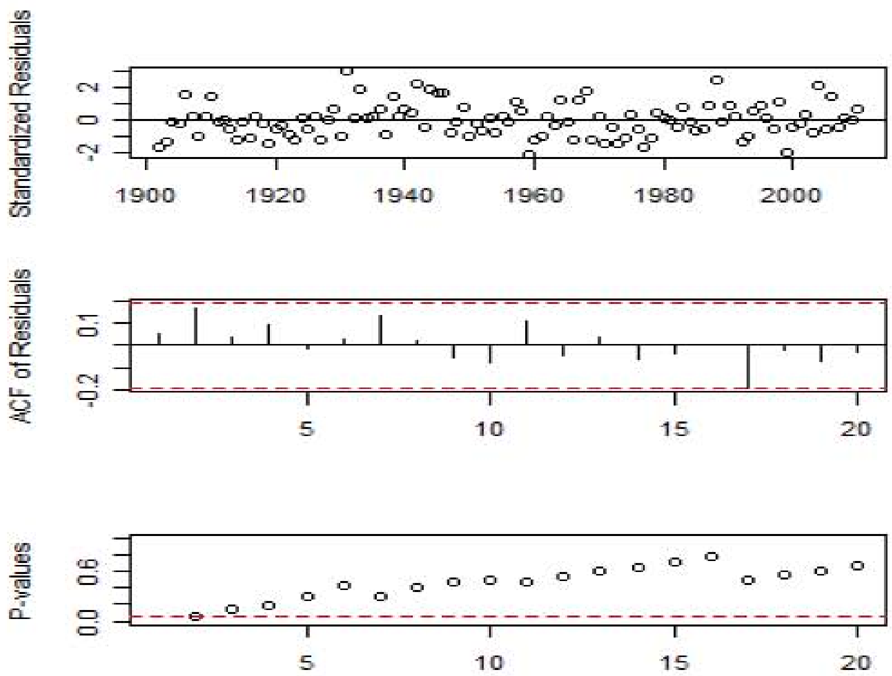


Figure 90: West Coast rain ARIMA model Residuals ACF Plot:

West Coast temperature Auto Correlation graphs

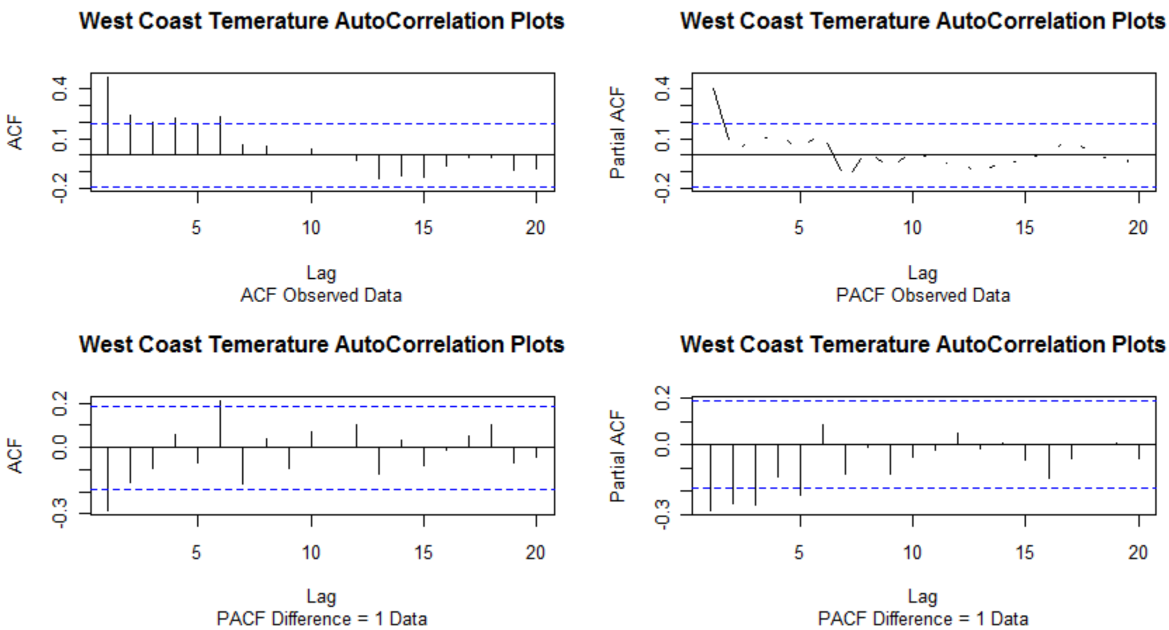


Figure 91: West Coast temperature Auto Correlation Plots

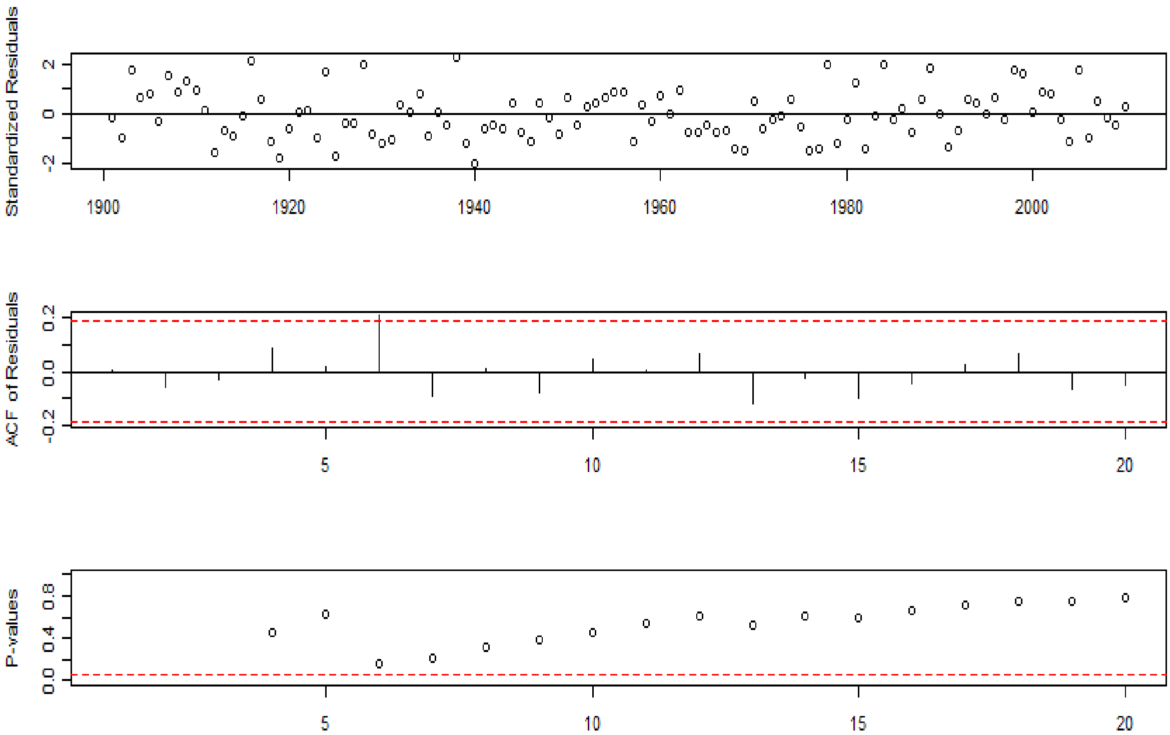


Figure 92: West Coast temperature ARIMA model Residuals ACF Plot

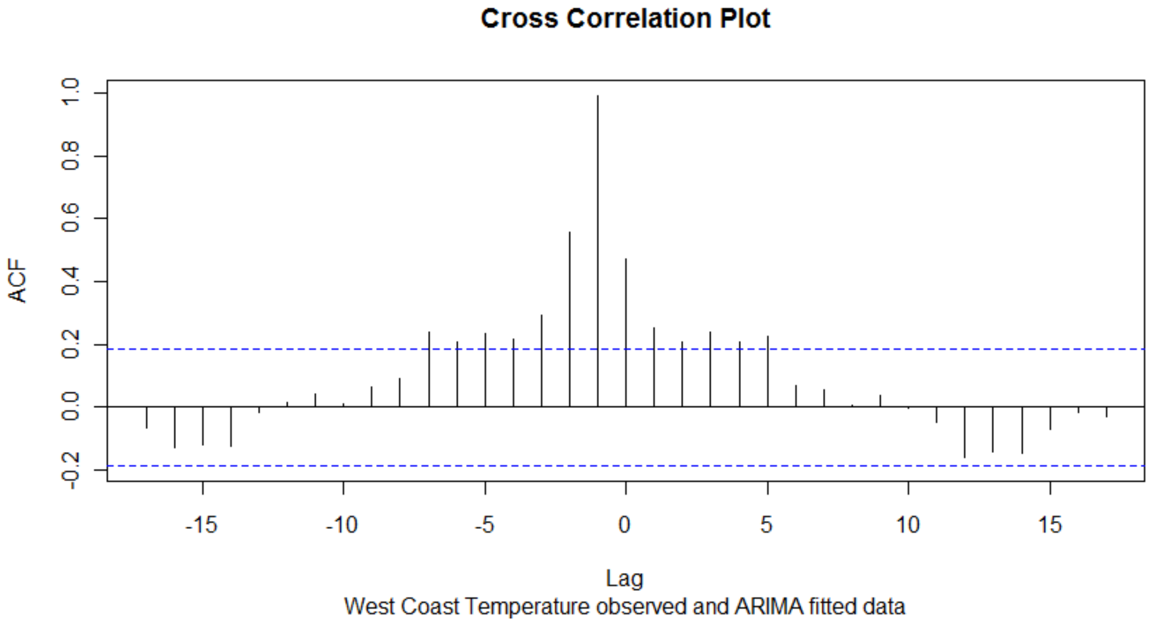


Figure 93: West Coast rain Cross Correlation Plot observed and ARIMA fitted data

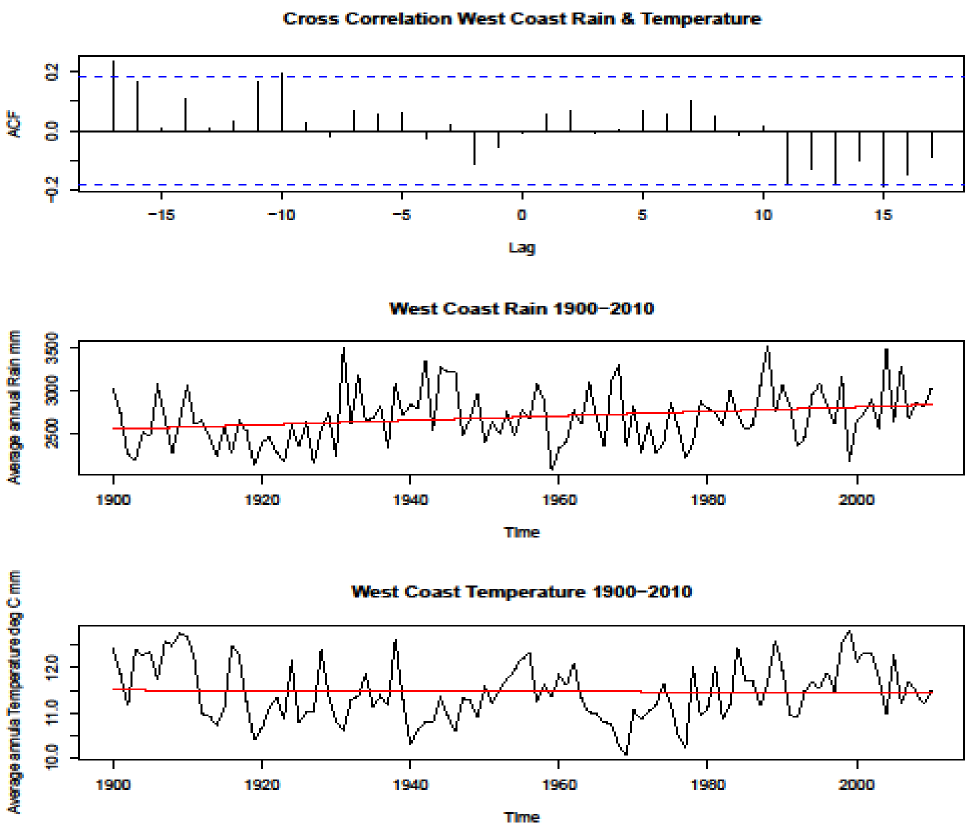


Figure 94: Cross Correlation West Coast rain and temperature observed data plot

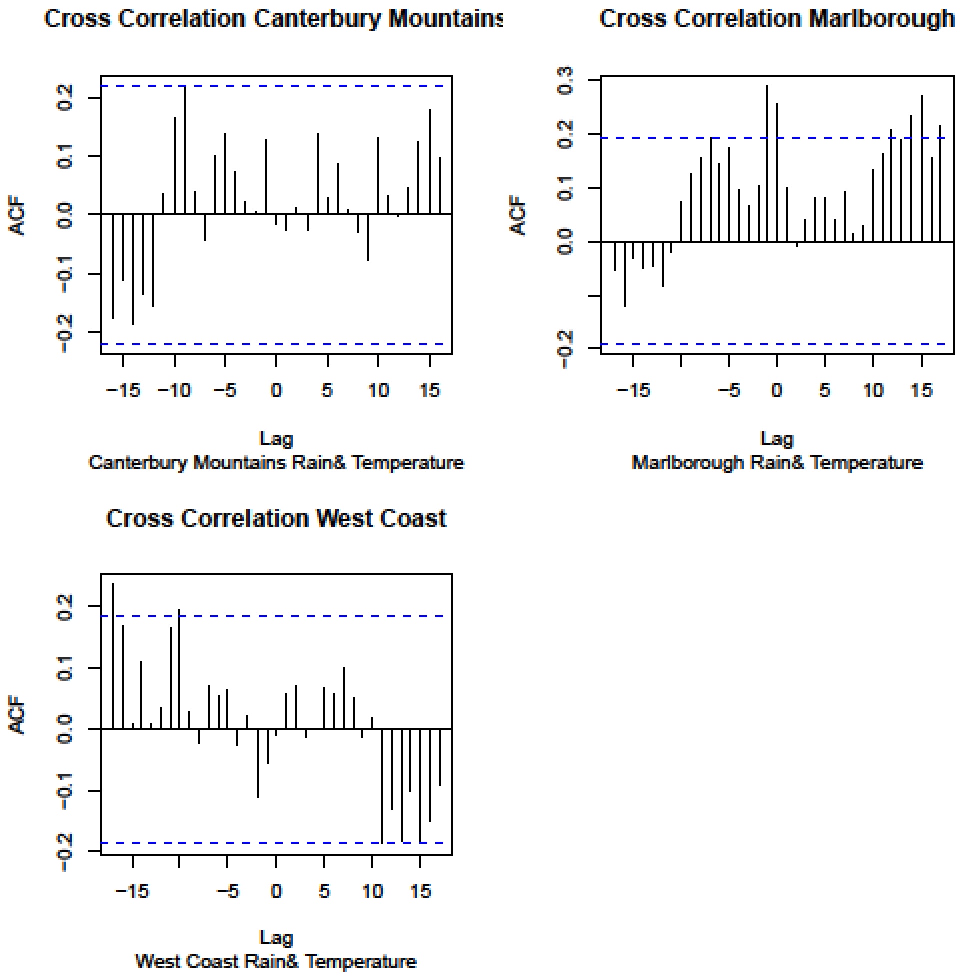
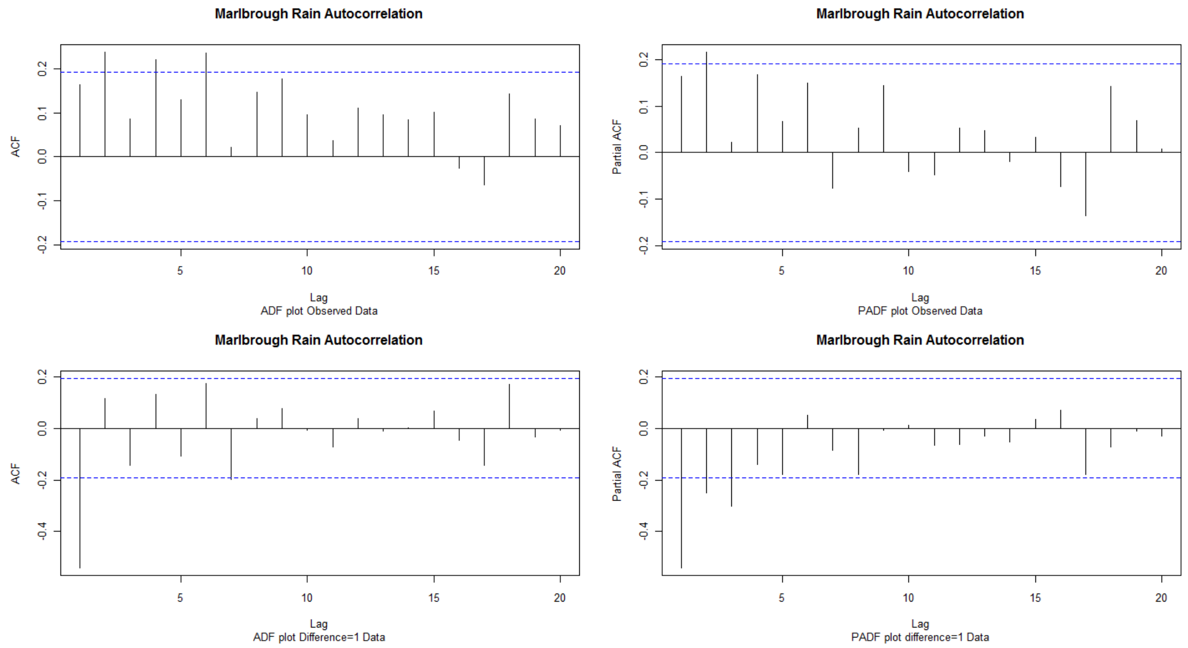


Figure 95: Marlborough rain Auto Correlation Plots



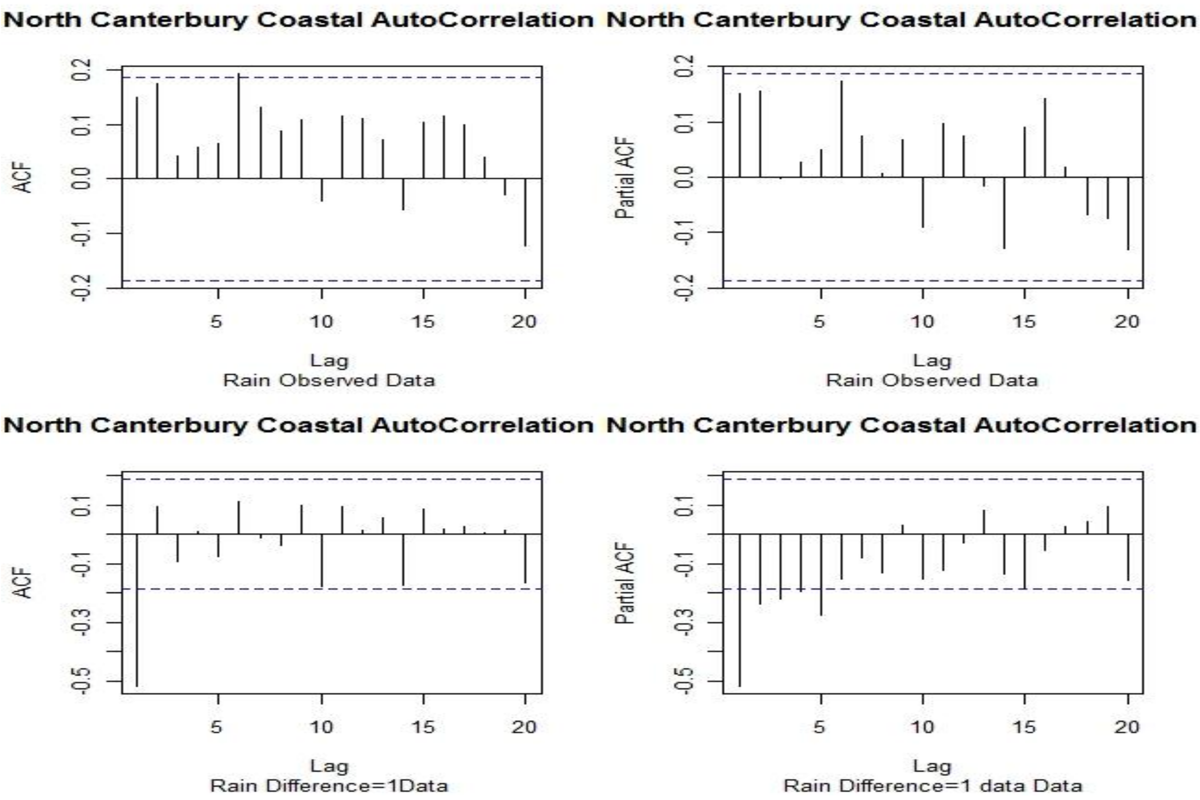


Figure 96: Marlborough rain ARIMA fitted model Residuals, and Auto Correlation Plots

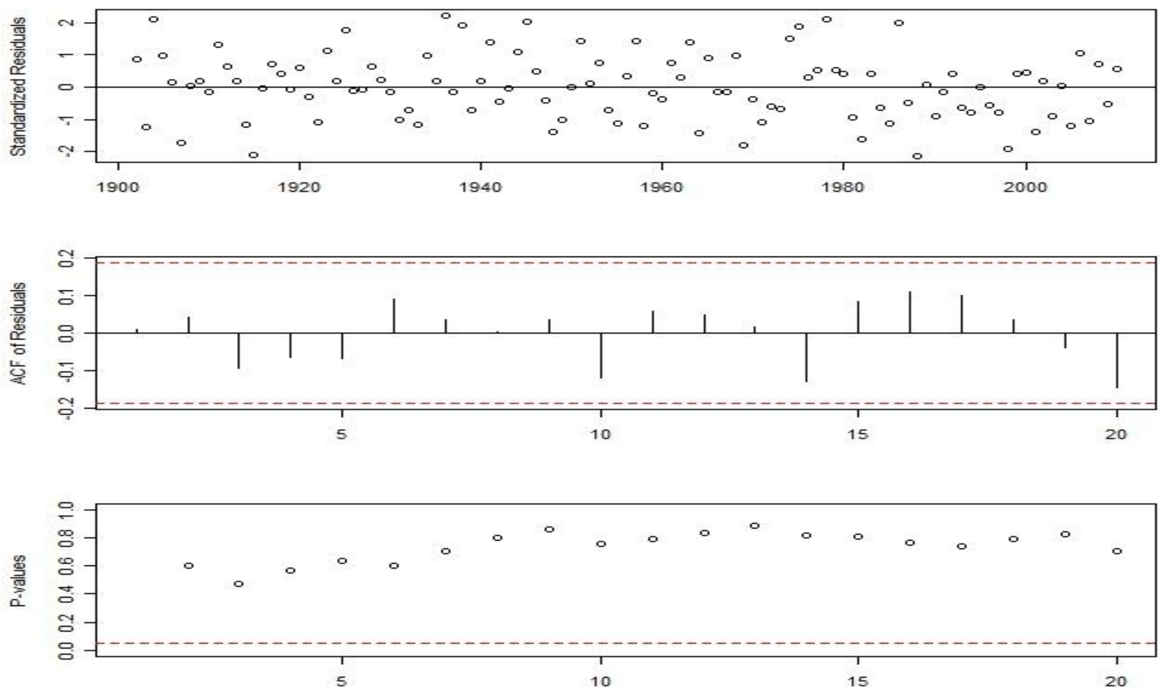


Figure 97: North Canterbury Coastal rain model Residual Plots.

ACF plots

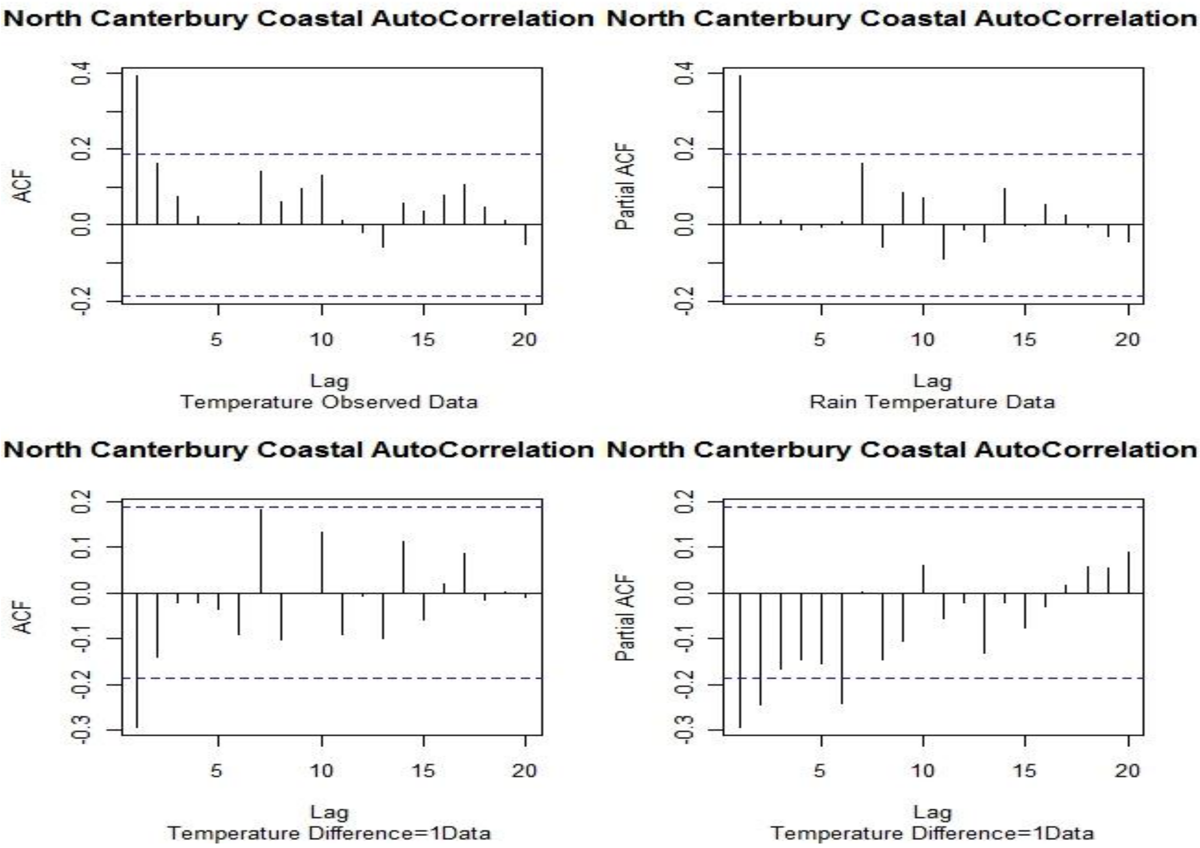


Figure 98: North Canterbury Coastal temperature Auto Correlation Plots

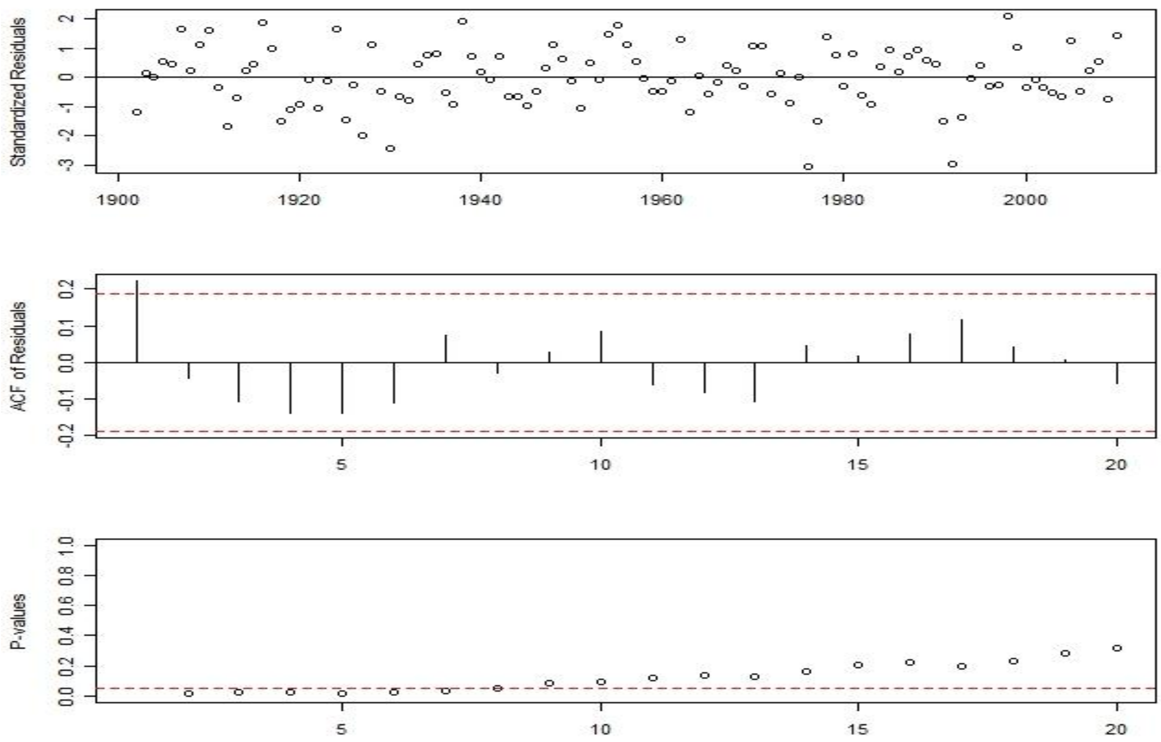


Figure 99: North Canterbury Coastal temperature ARIMA model Residuals Plots

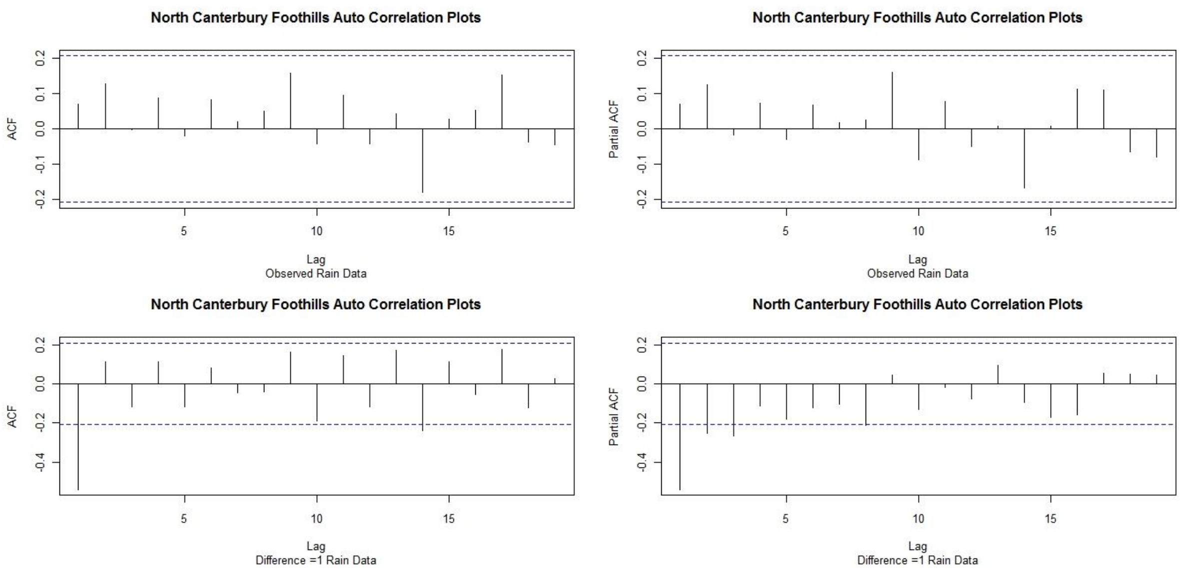


Figure 100: North Canterbury Foothills rain ACF Plots

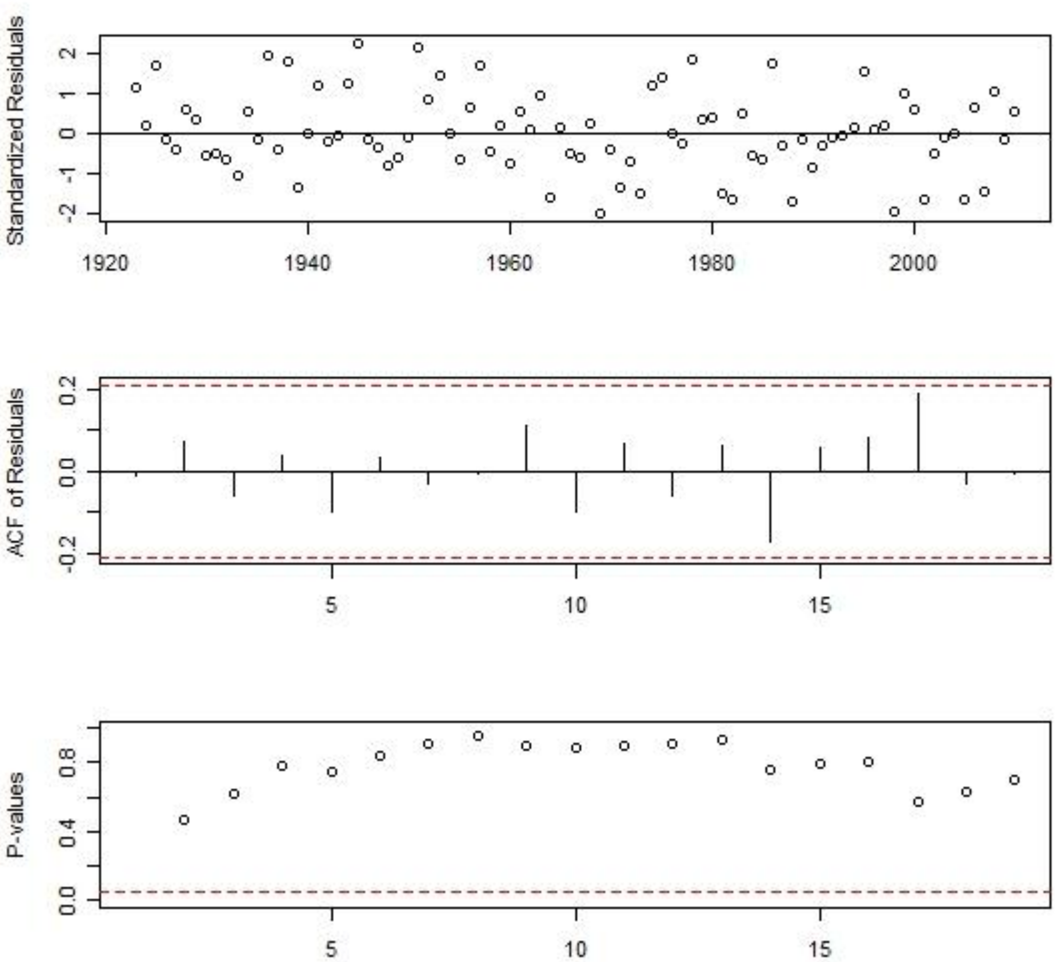


Figure 101: North Canterbury Foothills rain ARIMA model Residuals Plot

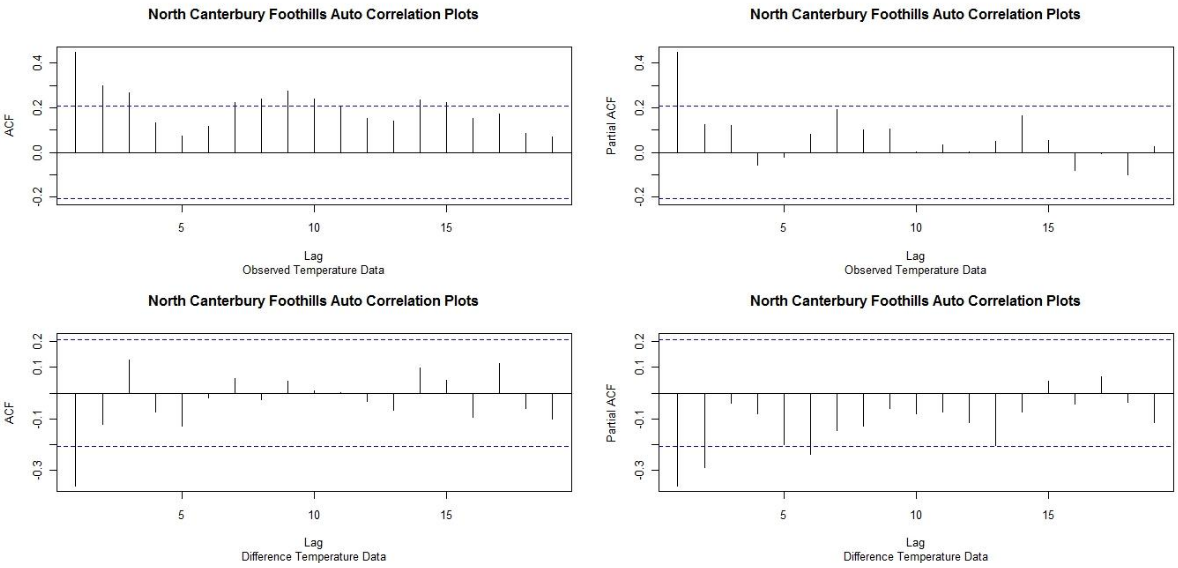


Figure 102: North Canterbury Foothills temperature ACF Plots

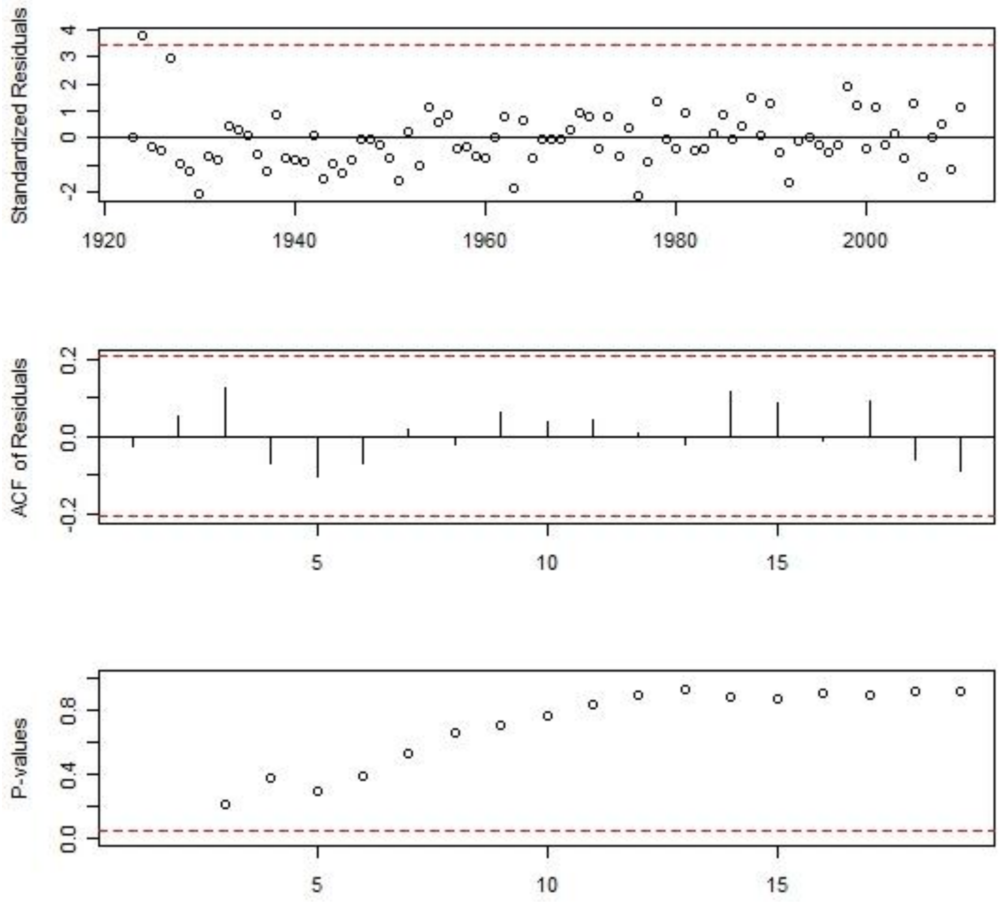


Figure 103: North Canterbury Foothills temperature ARIMA model Residuals Plots

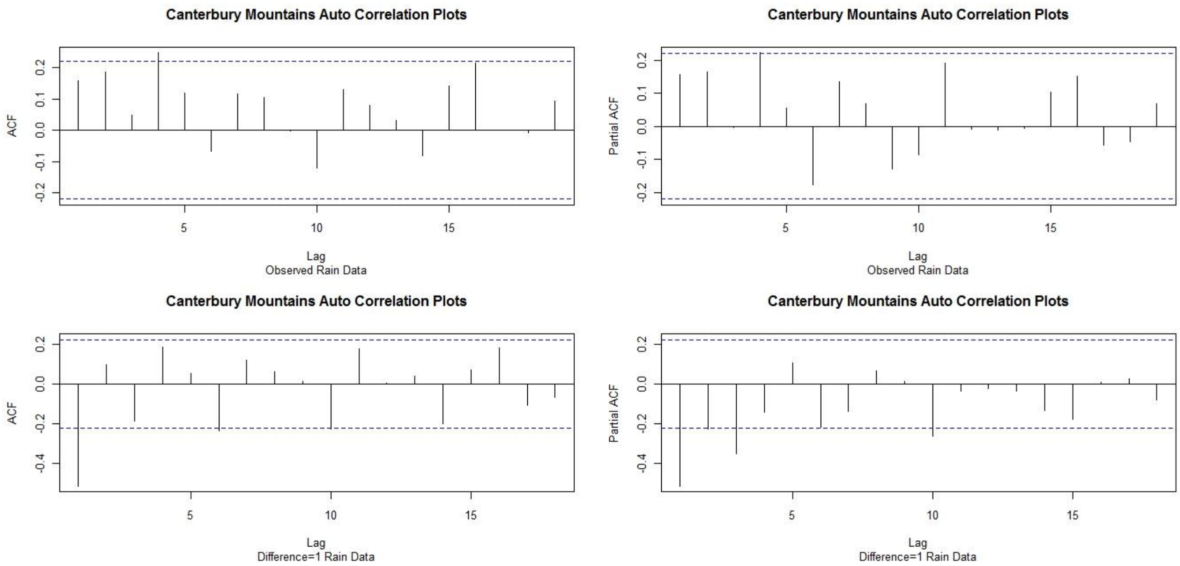


Figure 104: Canterbury Mountain rain ACF Plots

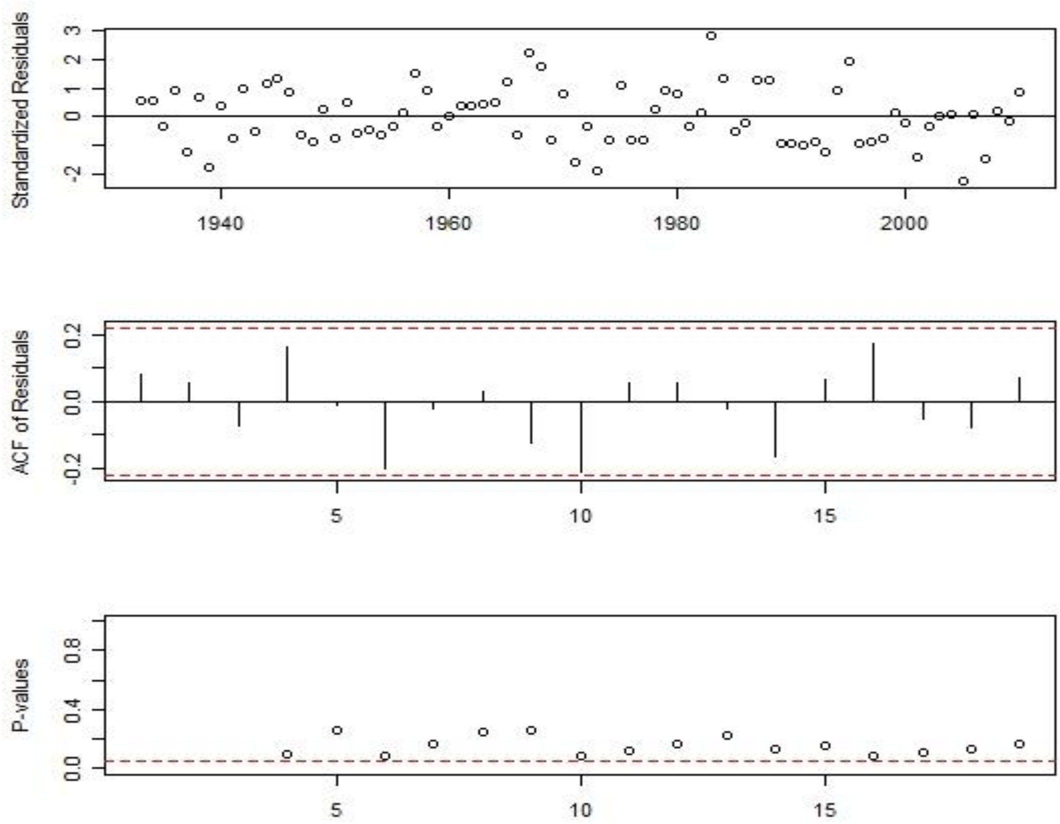


Figure 105: Canterbury Mountain rain ARIMA model Residuals Plots

Appendix 4: Linear regression statistics.

Table 72: West Coast rain Linear Regression Coefficients

Series: West Coast rain				
Residuals				
Min	1Q	Median	3Q	Max
-634.7	-214.77	-18.42	173.3	869.32
Coefficients	Estimate	Std Error	t Value	Pr(>|t|)
(E[mean])	-2425.25	1840.81	-1.317	0.19044
time(west.rts)	2.6178	0.9415	2.781	0.00639
signif codes	0‘***’	0.001 ‘**’	0.01 ‘*’	0.05 ‘.’
Residual standard error:	317.8	Degress of Freedom	109	
Mutiple R=-sq	0.06623,	Adj R-Sq	0.05767	
F-statistic:	7.731	DF 1 ,109	p-value:	0.006395

Table 73: West Coast temperature Linear Regression Coefficients

Series: West Coast temperature				
Residuals				
Min	1Q	Median	3Q	Max
-1.3955	-0.4789	-0.1112	0.4962	1.3816
Coefficients	Estimate	Std Error	t Value	Pr(>|t|)
(E[mean])	12.591	3.734943	3.371	0.0010
time(West Coast	-0.00057	0.00191	-0.299	0.7653
Residual standard	0.6448	Degrees of Freedom	109	
	Adj R-Sq	-0.00835		
F-statistic:	0.08954	DF 1 ,109	P-value	0.7653

Table 74: Marlborough rain Linear Regression Coefficients

Series: Marlborough rain					
Residuals:					
Min	1Q	Median	3Q	Max	
-408.83	-126.89	28.35	119.8	573.34	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-4115.3	1149.818	-3.579	0.000528	***
time(marlb.rTS)	2.7151	0.5872	4.624	0.000011	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**	‘**’0.0
Residual standard error:		182.4	DF=182.4on103		
MultipleR-squared:0.1719,		Adjusted	R-squared:	0.1639	
F-statistic:	21.38	DF=1 ,103	p-value:	1.1E-05	

Table 75: Marlborough temperature Linear Regression Coefficients

Series: Marlborough temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-1.4099	-0.41894	-0.06075	0.31198	2.57295	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-2.10053	3.988334	-0.527	0.599556	0
time(marlb.tts)	0.007274	0.002037	3.572	0.000541	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		0.6326	DF=1,103		
MultipleR-squared:0.1102,		Adjusted R-squared:		0.1016	
F-statistic:	12.76	DF=1 ,103	p-value: 0.000541		

Table 76: North Canterbury Coastal rain Linear Regression Coefficients

Series: North Canterbury Coastal rain					
Residuals:					
Min	1Q	Median	3Q	Max	
-374.94	-101.49	-2.54	90.44	391.19	
Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)	
(E[mean])	2545.953	918.5534	2.772	0.00656	**
time(ncant.crts)	-0.8674	0.4698	-1.846	0.06755	.
Signif. codes:	0‘***’	0.001‘**’	0.01‘*’	0.05‘.’	0.1‘
Residual standard error:		158.6	On 109 degrees of freedom		
Multiple R-squared:		0.03033,	Adjusted R-squared:		0.02143
F-statistic:	3.409	On 1 and109 DF,		p-value:	0.06755

Table 77: North Canterbury Coastal temperature Linear Regression Coefficients

Series: North Canterbury Coastal temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-1.19852	-0.26728	-0.01072	0.30453	1.03904	
Coefficients:	Estimate	Std.Errorr	t value	Pr(>|t|)	Sig
(E[mean])	6.270916	2.611409	2.401	0.018	*
time(ncant.ctts)	0.002683	0.001336	2.009	0.047	*
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**	‘**’0.0
Residual standard error:		0.4509	DF=0.4509on109	of	freedom
Multiple R-squared: 0.03569,		Adjusted R-squared:		0.02685	
F-statistic:	4.035	DF=1 ,109	p-value:	0.04705	

Table 78: North Canterbury Foothills rain Linear Regression Coefficients

Series: North Canterbury Foothills rain				
Residuals:				
Min	1Q	Median	3Q	Max
-288.36	-108.04	-13.97	108.86	350.48
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)
(E[mean])	-150.594	1284.449	-0.117	0.907
time(ncant.frts)	0.6081	0.6534	0.931	0.355
Residual standard error:	161	DF= 88		
Multiple R-squared:			R-squared:0.009745,	
F-statistic: 0.866		DF=1 and 88	p-value:	0.3546

Table 79: North Canterbury Foothills temperature Linear Regression Coefficients

Series: North Canterbury Foothills temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-1.05333	-0.33227	-0.05401	0.35611	1.94755	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-8.94535	4.248914	-2.105	0.0381	*
time(ncant.ftts	0.01022	0.002162	4.729	8.53E-06	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.0
Residual standard error:		0.5327	DF=0.5327on8	of	freedom
MultipleR-squared: 0.2026,			Adjusted R-squared:		0.1936
F-statistic:	22.36	DF=1 ,88	p-value:	8.53E-06	

Table 80: Canterbury Mountains rain Linear Regression Coefficients

Series: Canterbury Mountains rain					
Residuals:					
Min	1Q	Median	3Q	Max	
-612.32	-166.22	-14.49	161.82	767.28	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-	2522.093	-2.069	0.04181	*
time(cant.mrts)	3.491	1.28	2.728	0.00787	**
Signif.codes:0		0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		264.3	On 78 DF		
MultipleR-squared:0.08709,			Adjusted:	R-squared	0.07538
F-statistic:	7.441	DF=1	p-value:	0.007874	

Table 81: Canterbury Mountain temperature Linear Regression Coefficients

Series: Canterbury Mountain temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-1.7136	-0.5289	0.1513	0.5552	1.3575	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-12.9127	6.938434	-1.861	0.06651	.
time(cant.mtts)	0.010947	0.003521	3.109	0.00262	**
Signif.codes:0	codes: 0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		0.7272	On 78	of	freedom
MultipleR-squared:0.1103,			Adjusted:	R-squared	0.09886
F-statistic:	9.667	DF=1 ,78	p-value:	0.002619	

Table 82: South Canterbury Coastal rain Linear Regression Coefficients

Series: South Canterbury Coastal rain					
Residuals:	Min	1Q	Median	3Q	Max
	-339.76	-125.82	-15.22	109.27	345.64
Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)	
(E[mean])	-1201.48	1076.298	-1.116	0.267	
time(scant.crts)	1.0117	0.5489	1.843	0.0683	.
Signif. codes:	0‘***’	0.001‘**’	0.01‘*’	0.05‘.’	0.1‘
Residual standard error:		158.5	On 98 degrees of freedom		
Multiple R- squared:		0.0335,	Adjusted R-squared:		0.02364
F-statistic:	3.397	On 1 and 98 DF,		p-value	0.06834

Table 83 : South Canterbury Coastal temperature Linear Regression Coefficients

Series: South Canterbury Coastal temperature					
Residuals:	Min	1Q	Median	3Q	Max
	-1.09654	-0.2578	0.01423	0.31792	1.03481
Coefficients:	Estimate	Std. Error	t value	Pr(>|t|)	Signif
(E[mean])	17.3739	3.034809	5.725	1.13E-07	***
time(scant.ctts)	-0.00327	0.001548	-2.114	0.0371	*
Signif. codes:	0‘***’	0.001‘**’	0.01‘*’	0.05‘.’	0.1‘
Residual standard error:		0.4468	On 98 DF		

Multiple R-squared:		0.04361,	Adjusted R-squared:	0.03385
F-statistic:	4.468	On 1 and 98 DF,	p-value:	0.03707

Table 84: South Canterbury Coastal temperature Linear Regression Coefficients

Series: South Canterbury Coastal temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-1.09654	-0.2578	0.01423	0.31792	1.03481	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	17.3739	3.034809	5.725	1.13E-07	***
time(scant.ctts)	-0.00327	0.001548	-2.114	0.0371	*
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		0.4468	98	of	freedom
Multiple R-squared:0.04361,		Adjusted	R-squared:	0.03385	
F-statistic:	4.468	DF=1,98	p-value:	0.03707	

Table 85: South Canterbury Foothills rain Linear Regression Coefficients

Series: South Canterbury Foothills rain					
Residuals:					
Min	1Q	Median	3Q	Max	
-597.13	-127.95	-0.25	129.5	635.4	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-11060	1654	-6.686	1.74E-09	***
time(scant.frts)	6.185	0.8421	7.345	8.1E-11	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		221.5	On 92	of	freedom
MultipleR-squared:0.3696,			Adjusted R-squared:		0.3628
F-statistic:	53.95	DF=1, 92	p-value:	8.11E-11	

Table 86: South Canterbury Foothills temperature Linear Regression Coefficients

Series: South Canterbury Foothills temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-1.17897	-0.38222	0.03894	0.30583	1.30421	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-22.1189	4.014103	-5.51	3.24E-07	***
time(scant.ftts)	0.016316	0.002044	7.982	3.93E-12	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		0.5378	DF=0.5378on92	of	freedom
MultipleR-squared:0.4092,		Adjusted	R-squared:	0.4027	

F-statistic:	63.71	DF=1 ,92	p-value:	3.93E-12	

Table 87: Otago/Northern Southland rain Linear Regression Coefficients

Series: Otago/Northern Southland rain					
Residuals:					
Min	1Q	Median	3Q	Max	
-219.3	-79.616	-3.701	64.152	241.337	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	-3988.89	540.3883	-7.382	2.85E-11	***
time(nsouthn.rts)	2.4465	0.2767	8.843	1.44E-14	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		98.49	DF=98.49on113	of	freedom
MultipleR-squared:0.409,		0	0	0	
F-statistic:	78.2	DF=1 ,113	p-value:	1.44E-14	

Table 88: Otago/Northern Southland temperature Linear Regression Coefficients

Series: Otago/Northern Southland temperature					
Residuals:					
Min	1Q	Median	3Q	Max	
-2.10633	-0.37093	-0.00978	0.40915	1.1481	
Coefficients:	Estimate	Std .Error	t value	Pr(>|t|)	Sig
(E[mean])	-14.2824	3.06282	-4.663	8.59E-06	***
time(nsouthn.tts)	0.012295	0.001568	7.841	2.72E-12	***
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘**’	‘**’0.01
Residual standard error:		0.5582	DF=0.5582on113	of	freedom
Multiple R-squared :0.3524,					
F-statistic:	61.48	DF=1 ,113	p-value:	2.72E-12	

Table 89: Southland rain Linear Regression Coefficients

Series: Southland rain					
Residuals:					
Min	1Q	Median	3Q	Max	
-308.37	-88.841	-3.323	77.625	341.145	
Coefficients:	Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])	3428.122	862.657	3.974	0.00013	***
time(ssouthn.rts)	-1.212	0.44	-2.754	0.00702	**
Signif.codes:0	codes:0	0‘***’	‘***’0.001	0.001‘*	‘**’0.0
Residual standard error: 127		DF=127 on 98 of freedom			
MultipleR-squared:0.07183,		Adjusted	R-squared:	0.06236	

F-statistic:	7.584	DF=1 ,98	p-value:	0.00702	

Table 90: Southland temperature Linear Regression Coefficients

Series: Southland temperature						
Residuals:						
Min		1Q	Median	3Q	Max	
-1.042135		-0.29675	0.008663	0.307566	1.08402	
Coefficients:		Estimate	Std.Error	t value	Pr(>|t|)	Sig
(E[mean])		3.78981	2.956429	1.282	0.2029	
time(ssouthn.tts)		0.003179	0.001508	2.108	0.0376	*
Signif. codes		0	0‘***’	‘***’0.001	0.001‘**	‘**’0.0
Residual standard error: 0.4353			DF=0.4353 on 98 of freedom			
MultipleR-squared:0.04339,			Adjusted	R-squared:	0.03362	
F-statistic:	4.445		DF=1 ,98	p-value:	0.03756	

Appendix 5: Regional data F Statistics

Table 91:Intra-Regional F Statistics for combined regional data

F-Test Two-Sample for Variances West Coast average Rainfall						
	Coast	Foothills	Coast	Mountains	Foothills	Mountains
Mean	2792.31	2616.25	2792.31	2467.75	2573.19	2467.75
Variance	1399089	1587083	1399089	2832908	1522103	2832908
Observations	2411	1170	2411	298	1084	298
df	2410	1169	2410	297	1083	297
F	0.88155		0.49387		0.53729	
P(F<=f) one-tail	0.0058		0		6.4E-13	
F Critical one-tail	0.92105		0.87057		0.86181	

F-Test Two-Sample for Variances Marlborough Rainfall						
	Coast	Foothills	Mountains	Foothills	Coast	Mountains
Mean	1207.47	1150.24	1496.14	1150.24	1207.47	124.678
Variance	*180618*	*123940*	*276702*	*123940*	*180618*	*1921.54*
Observations	2236	810	76	810	2236	76
df	*2235*	*809*	*75*	*809*	*2235*	*75*
F	1.4573		2.23254		93.9965	
P(F<=f) one-tail	*1.7E-10*		*5.7E-08*		*1.6E-59*	
F Critical one-tail	1.10156		1.30109		1.34303	

F-Test Two-Sample for Variances Southland		
	Coast	Foothills
Mean	1029.15	1061.78
Variance	*74547.7*	*52961*
Observations	2730	616
df	*2729*	*615*
F	1.4076	
P(F<=f) one-tail	*9.6E-08*	
F Critical one-tail	1.11168	

F-Test Two-Sample for Variances Otago/Northern Southland						
	Coast	Foothills	Coast	Mountains	Foothills	Mountains
Mean	726.032	863.017	726.032	766.609	863.017	766.609
Variance	*40668.1*	*282911*	*40668.1*	*161609*	*282911*	*161609*
Observations	2153	5228	2153	881	5228	881
df	*2152*	*5227*	*2152*	*880*	*5227*	*880*
F	0.14375		0.25165		1.75059	
P(F<=f) one-tail	*0*		*0*		*1.7E-24*	
F Critical one-tail	0.94175		0.91205		1.09011	

Table 92: Inter-Regional rain data variability F statistic data

Inter regional F Test statistic									
F Test against Westland Data	*Westland*	*Marlborough*	*N.Cant Coastal*	*N Cant Foothills*	*Cant Mountains*	*S Cant Coastal*	*S Cant Foothills*	*N Southland*	*Southland*
Mean	2714.2733	1199.6521	860.36086	1048.0775	1663.183	1079.6257	1079.6257	817.0394	1035.1608
Variance	1576203	170937.91	75872.679	148165.81	1200430.9	333863.29	333863.29	210583.74	70716.511
Observations	3879	3122	3033	5041	1846	828	828	8262	3346
df	3878	3121	3032	5040	1845	827	827	8261	3345
F	9.2209097		20.774316	10.638102	1.3130309	4.7211031	4.7211031	7.4849226	22.289038
P(F<=f) one-tail	0		0	0	1.139E-11	1.03E-128	1.03E-128	0	0
F Critical one-tail	1.0576444		1.0581396	1.0508515	1.0684921	1.0948661	1.0948661	1.0461017	1.056501
F Test against Marlborough Data	*Marlborough*	*N.Cant Coastal*	*N Cant Foothills*	*Cant Mountains*	*S Cant Coastal*	*S Cant Foothills*	*N Southland*	*Southland*	
Mean	1199.6521	860.36086	1048.0775	1663.183	1079.6257	1079.6257	817.0394	1035.1608	
Variance	170937.91	75872.679	148165.81	1200430.9	333863.29	333863.29	210583.74	70716.511	
Observations	3122	3033	5041	1846	828	828	8262	3346	
df	3121	3032	5040	1845	827	827	8261	3345	
F	2.2529573		1.1536933	0.1423971	0.5119997	0.5119997	0.8117336	2.4172276	
P(F<=f) one-tail	2.6E-109		4.027E-06	0	0	0	2.571E-12	3.72E-136	
F Critical one-tail	1.0611362		1.0542191	0.9342795	0.9142749	0.9142749	0.9519965	1.0595734	
F Test against North Canterbury Coastal Data	*N.Cant Coastal*	*N Cant Foothills*	*Cant Mountains*	*S Cant Coastal*	*S Cant Foothills*	*N Southland*	*Southland*		
Mean	860.36086	1048.0775	1663.183	1079.6257	1079.6257	817.0394	1035.1608		
Variance	75872.679	148165.81	1200430.9	333863.29	333863.29	210583.74	70716.511		
Observations	3033	5041	1846	828	828	8262	3346		
df	3032	5040	1845	827	827	8261	3345		
F	0.5120795		0.0632045	0.2272567	0.2272567	0.360297	1.0729132		
P(F<=f) one-tail	0		0	0	0	0	0.0235185		
F Critical one-tail	0.947739		0.9339186	0.914006	0.914006	0.9514894	1.0600221		

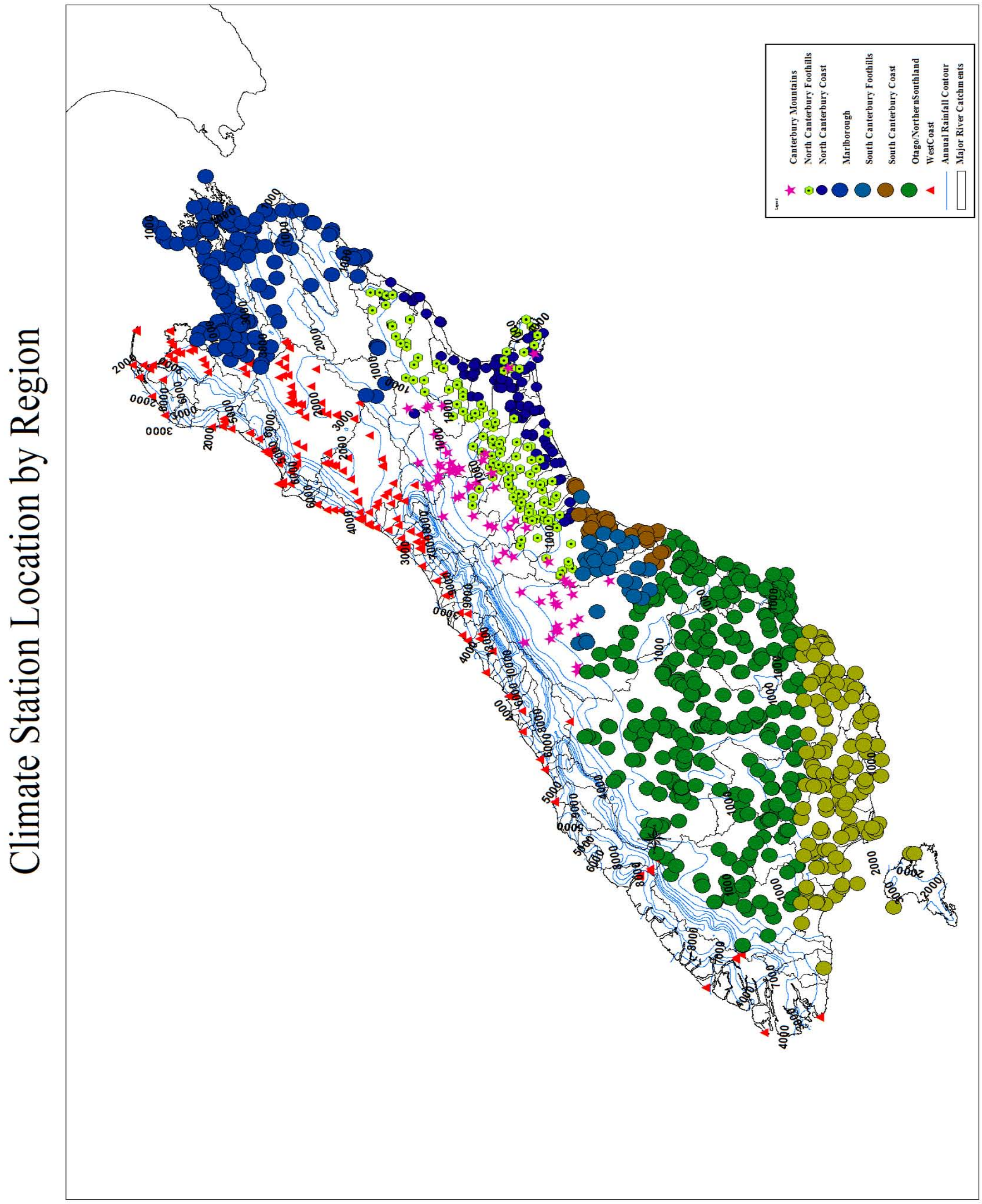
F Test against North Canterbury Foothills data		*N Cant Foothills*	*Cant Mountains*	*S Cant Coastal*	*S Cant Foothills*	*N Southland*	*Southland*
	Mean	1048.0775	1663.183	1079.6257	1079.6257	817.0394	1035.1608
	Variance	148165.81	1200430.9	333863.29	333863.29	210583.74	70716.511
	Observations	5041	1846	828	828	8262	3346
	df	5040	1845	827	827	8261	3345
	F	0.1234272		0.4437919	0.4437919	0.7035957	2.0952082
	P(F<=f) one-tail	0		0	0	0	6.82E-114
	F Critical one-tail	0.9391589		0.9178435	0.9178435	0.9591559	1.0534197
		F-Test Two-Sample for Variances					

F Test against Canterbury Mountains		*Cant Mountains*	*S Cant Coastal*	*S Cant Foothills*	*N Southland*	*Southland*
	Mean	1663.183	1079.6257	1079.6257	817.0394	1035.1608
	Variance	1200430.9	333863.29	333863.29	210583.74	70716.511
	Observations	1846	828	828	8262	3346
	df	1845	827	827	8261	3345
	F	3.5955764		3.5955764	5.7004921	16.975257
	P(F<=f) one-tail	2.04E-85		2.04E-85	0	0
	F Critical one-tail	1.1034444		1.1034444	1.0610412	1.0693922

F Test against South Canterbury Coastal Data		*S Cant Coastal*	*S Cant Foothills*	*N Southland*	*Southland*
	Mean	1079.6257	1079.6257	817.0394	1035.1608
	Variance	333863.29	333863.29	210583.74	70716.511
	Observations	828	828	8262	3346
	df	827	827	8261	3345
	F	1		1.5854182	4.7211504
	P(F<=f) one-tail	0.5		7.896E-22	1.5E-224
	F Critical one-tail	0.8918475		1.0867318	1.0930258

F Test against South Canterbury Data		*S Cant Foothills*	*N Southland*	*Southland*
	Mean	1079.6257	817.0394	1035.1608
	Variance	333863.29	210583.74	70716.511
	Observations	828	8262	3346
	df	827	8261	3345
	F	1.5854182		4.7211504
	P(F<=f) one-tail	7.896E-22		1.5E-224
	F Critical one-tail	1.0867318		1.0930258
F Test against Northern Southland data		*N Southland*	*Southland*	
	Mean	817.0394	1035.1608	
	Variance	210583.74	70716.511	
	Observations	8262	3346	
	df	8261	3345	
	F	2.9778582		
	P(F<=f) one-tail	1.12E-259		
	F Critical one-tail	1.0491257		

Appendix 6: Climate station map



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