A simple forecasting scheme for predicting low rainfalls in Funafuti, Tuvalu

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Abstract

The development of some ability for forecasting low rainfalls would be helpful in Tuvalu as rainwater is the only source of fresh water in the country. The subsurface water is brackish and saline so the entire country depends totally on rainwater for daily domestic supplies, agricultural and farming activities. More importantly, these atolls are often influenced by droughts which consequently make inadequate drinking water an issue.

A simple graph-based forecasting scheme is developed and presented in this thesis for forecasting below average mean rainfall in Funafuti over the next n-month period. The approach uses precursor ocean surface temperature data to make predictions of below average rainfall for n = 1, 2 … 12. The simplicity of the approach makes it a suitable method for the country and thus for the Tuvalu Meteorological Service to use as an operational forecasting tool in the climate forecasting desk.

The graphical method was derived from standardised monthly rainfalls from the Funafuti manual raingauge for the period January 1945 to July 2007. The method uses lag-1 and-lag 2 NINO4 sea surface temperatures to define whether prediction conditions hold. The persistence of predictability tends to be maintained when the observed NINO4 ocean surface temperatures fall below 26.0^{o}C. Although the developed method has a high success probability of up to 80 percent, this can only be achieved when conditions are within the predictable field. A considerable number of below average rainfall periods are not within the predictable field and therefore cannot be forecast by this method. However, the graphical approach has particular value in warning when an existing drought is likely to continue.

Acknowledgements

"ALHAMDOLILLAH"

"ALL PRAISE BELONGS TO ALLAH"

My sincere gratitude to all those who have helped me one way or another and therefore made it possible to come this far. Foremost is my supervisor Earl Bardsley who has been a great motivator until the end.

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To those who provided help with regard to data and information that is used in the study, Cathy Smith from the National Oceanic Atmospheric Administration, Jim Salinger from NIWA, Chris Folland from the Hadley Centre for Climate Prediction and Research, UK and Mrs Pasemeta Talapa at the Tuvalu NZaid office, I would like to thank them for their assistance.

To my Mum and my cousin Paeagi, thank you that I can leave home feeling secure that Mum will be in good health.

Lastly to my son thank you for your great support.

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Chapter 1

Introduction

1.1 Motivation

The scarcity of fresh water resources in the Tuvalu atolls is often a limiting factor for social and economic development. The dependency on rainfall significantly increases vulnerability of the islands to future changes in the distribution of rainfall.

Droughts often change the life of the people on the Tuvalu islands in the Pacific Ocean. The recent dry spell of 1999 was unrecognised as a developing drought until several weeks had elapsed. As a result of the acute and prolonged shortage of water, a state disaster was declared. The drought was so intense that desalination plants were used for the first time on the islands. An assessment report of the disaster was undertaken by Falkland (1999). Dry spells prior to this drought were noted in an earlier study (Thompson, 1987).

Extended periods of dryness are identifiable in the rainfall records held by the Tuvalu Meteorological Service. However efforts to start a scientific based rainfall forecasting scheme only started in 2005. The current capability to respond with an early warning of low rainfall leading up to droughts based on scientific evidence still requires more work, however.

Funafuti is the capital of Tuvalu and about 40 percent of the country's population reside on this atoll. This makes planning and management of rainwater a primary importance. The need for wise decisions by the government and Island leaders on what volumes to ration out ensuring that residents endure through the dry periods become crucial. The family households are the biggest consumers of rainwater and they need to prepare for these dry spells when they happen again. Under such circumstances some knowledge into the likelihood of future rainfall play an essential role in the decisions and preparations required to enable deal with the consequences.

1.2 Objective of study

With time prolonged dry periods will recur, making some ability to forecast future low rainfall periods a useful tool. Rainfall forecasts and their integration into the disaster plans, the water management plans, environmental regulations, agricultural activities and overall in government policies and action plans can have economic and social benefits. The generation of knowledge of the future state of rainfall can be of help to the communities so they can consider appropriate times for alternative means of careful use of the available water. Developing a degree of forecasting low rainfall periods is therefore of value in planning and managing rainwater. The motivation for this thesis is to develop a forecasting scheme for the prediction of low rainfall periods as departures from the mean over coming months. It is desirable that such a scheme can be maintained in a Tuvaluan setting.

Defining “low rainfall” as below average rainfall over future multi-month periods, the aim of the study is to develop a predictive scheme for forecasting low rainfall periods in Funafuti. Such a scheme might be extended to the rest of the islands at a later stage.

1.3 Geographical location

There are nine coral or reef atolls that comprise the Tuvalu islands (Figure 1.1). The atolls are situated in the central southwest Pacific Ocean between 5^oS and 11^oS and from 176^oE to 180^oE. The islands are quite low that none rise above 5 metres. They have a flat topography. Some have lagoons whilst others do not. For islands with lagoons, for example Funafuti, the size of the lagoon is much larger than the island itself. The group of islands are remote as the ocean not only isolates each island from the other but also separates the group from other nations so the atolls can be difficult to reach.

All the islands have raingauges which are manually observed either by Meteorological staff or Telecom operators. The rainfall measurements from the Funafuti raingauge are the only rainfall data used in this study because of it has the longest record.

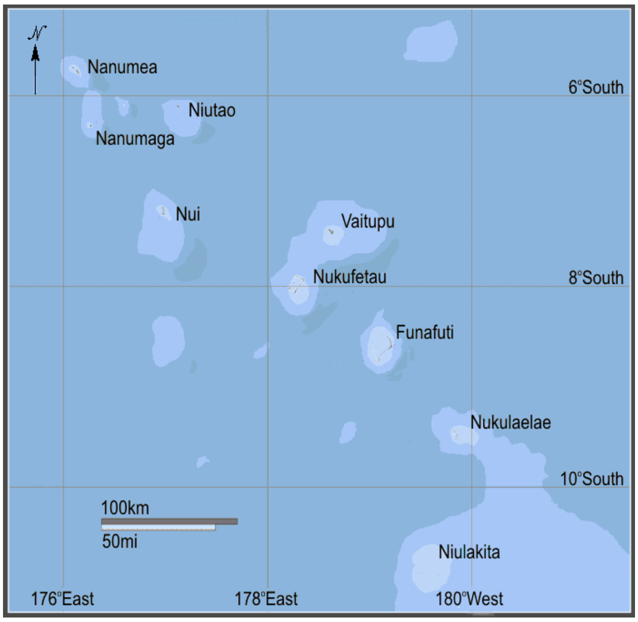


Figure 1.1: The nine islands of Tuvalu.

1.4 Weather and climate

The islands are hot and humid with relatively small temperature differences throughout the year. Convective cumuliform clouds are most common. A large seasonal variability in precipitation form the two seasons dry and wet. The surface winds are seasonal. Easterly trade winds prevail except in the wet season that winds would blow from the west or north. According to Thompson (1987) the monsoon westerly winds come as far as the dateline and at times they reach further east into the Cook Islands.

1.4.1 Influence of the surrounding ocean on Tuvalu climate

The ocean waters around Tuvalu are described as an area favourable for the development of tropical cyclones but these weather phenomena seldom become storms (Thompson, 1987). Conversely observations of the destruction of the atolls from recent cyclones suggest that the islands are prone to tropical cyclones. A recommendation from the post tropical cyclone assessment report of cyclone Keli 1997 is that residents on Niulakita, the southern most island in the group (Figure 1.1) need to consider relocation. This is because in the same year, preceding cyclone Keli were cyclones Gavin and Hina which also brought destructions to the island. The storms were just too many that relief assistance in terms of food and shelter to the island was so costly. In addition the rescue risk during Keli was very high as almost all communications on the island failed. And a boat could only get to the island when the storm has passed.

Given the strong influence of the ocean on the climate on the islands, an increase of SSTs will most likely lead to an increase in rainfall intensity and therefore higher rainfall amounts. These changes can cause changes to the distribution of rainfall.

In the South Pacific mainly eastward from about 160^{o}E surface air temperatures have increased by 0.3 to 0.8^{o}C during the 20th century (Nurse and Sem, 2001). A quantifiable change in the rainfall amounts since the middle of 1970s show western Kiribati, the northern Cook Islands, Tokelau and northern Tahiti are being wetter and New Caledonia, Fiji and Tonga have become drier (Salinger et al., 1995).

Interestingly an outcome of the online climate outlook forum No. 8 from SCOPIC (Seasonal Climate Outlook for Pacific Island Countries) showed that the Equatorial Dry Zone in April 2008 was wetter than the major rainfall maximum in the tropical Pacific which is the region west of 160^{o}East (Dorman 1982). The report on this information can be read on this web http://www.bom.gov.au/climate /pi-cpp/forecast/ocof_summary.pdf. Studies of the Equatorial Dry Zone are further discussed in section 1.7.

1.5 Funafuti rainfall variability

The time series of total monthly rainfall for Funafuti (Figure 1.2), Nanumea (Figure 1.3), Nui (Figure 1.4) and Niulakita (Figure 1.5) show large fluctuations in the rainfall. This seasonal rainfall pattern is a typical characteristic of tropical regions (Pezzoli and Franza, 2003). The rainfall is measured daily at weather monitoring stations on the four islands mentioned above.

The Funafuti rainfall data from January 1945 to July 2007 is the period used in this study for evaluating forecasting methods. The quality of the rainfall data from the Funafuti weather monitoring station is noted in Falkland (1999) as very good. That assessment was based on data up to the middle of 1999. However, given that rainfall measurements from this raingauge has been well maintained until present, the quality of the data is likely to remain good.

Several things to note: rainfall records for the four islands start earlier than 1945 but only for the purposes of this study that the rainfall time series were plotted to cover the period corresponding to the period of the forecasting scheme. A reasonable number of months with missing rainfall readings are obvious in particular Nanumea (Figures 1.3a, 1.3c, 1.3d), Nui (Figures 1.4a, 1.4b, 1.4c, 1.4d) and Niulakita (Figures 1.5a, 1.5b, 1.5c, 1.5d). The gaps in the rainfall data are visible as breaks in the blue solid line. The one break in the Funafuti rainfall data (Figure 1.2b) occurred in October 1972. Tropical cyclone, Bebe that devastated Funafuti during the night of October 21st, 1972 is the cause of the lost record.

1.6 Present operational rainfall forecasting

The Tuvalu Meteorological Service is presently using a statistical climate prediction model in SCOPIC (see Section 1.4.2 for definition of abbreviation) for forecasting rainfall. The computer package uses monthly anomalies of sea surface temperatures (SSTs) and monthly Southern Oscillation Index (SOI) Troup index values as predictors in the model. Definitions of these terms are covered in Chapter 2. The model issues a rainfall forecast of the expected total coming 3 months rainfall. The forecast gives a probability of above normal rainfall, normal rainfall and below normal rainfall based on a lead time of three months. The latest forecast issue can be read from the website http://www.bom.gov.au/climate/pi-cpp/forecast/tuv_bulletin.pdf

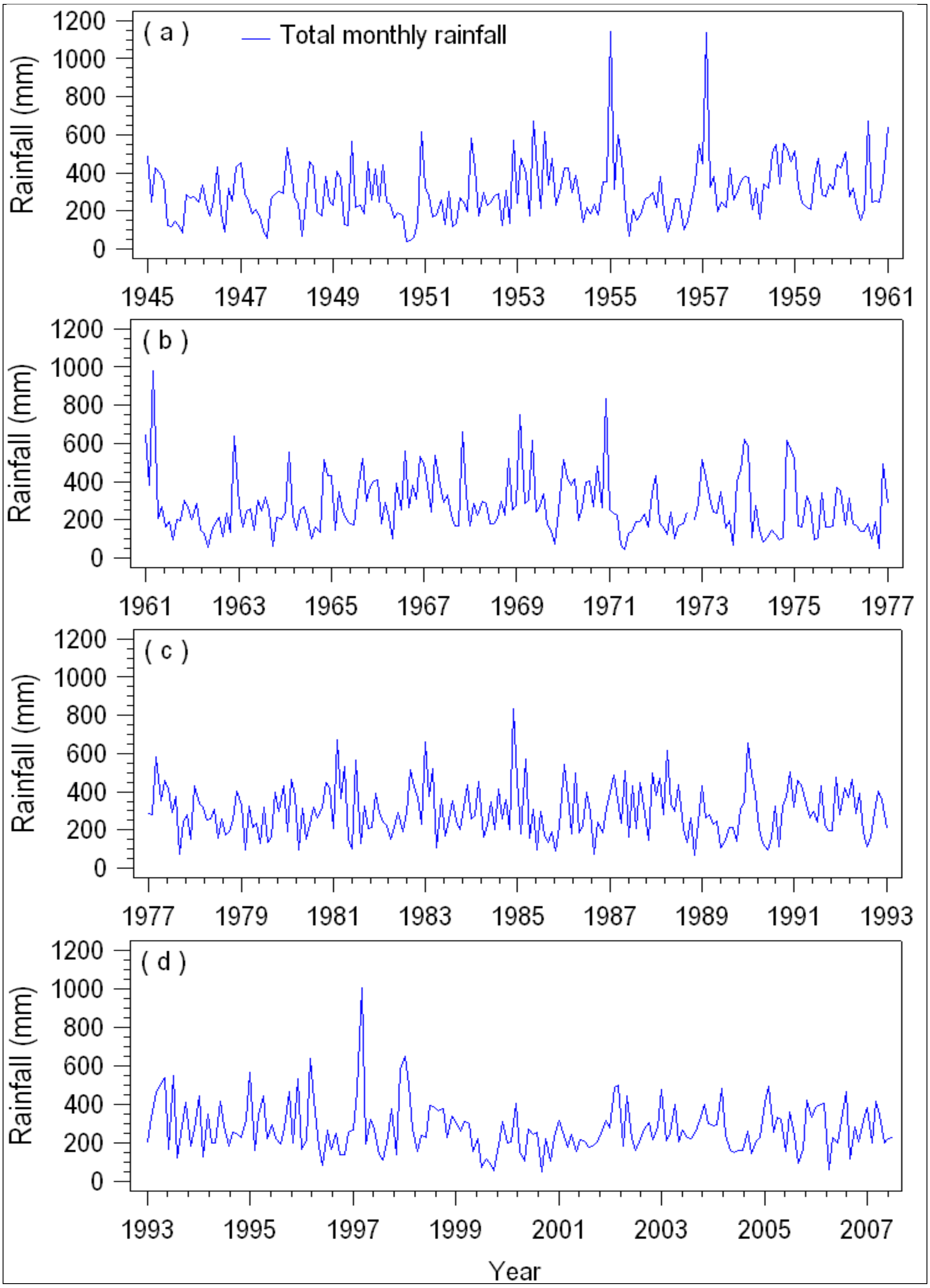


Figure 1.2 (a) – (d): Time series of monthly rainfalls for Funafuti (Jan 1945 to Jul 2007.

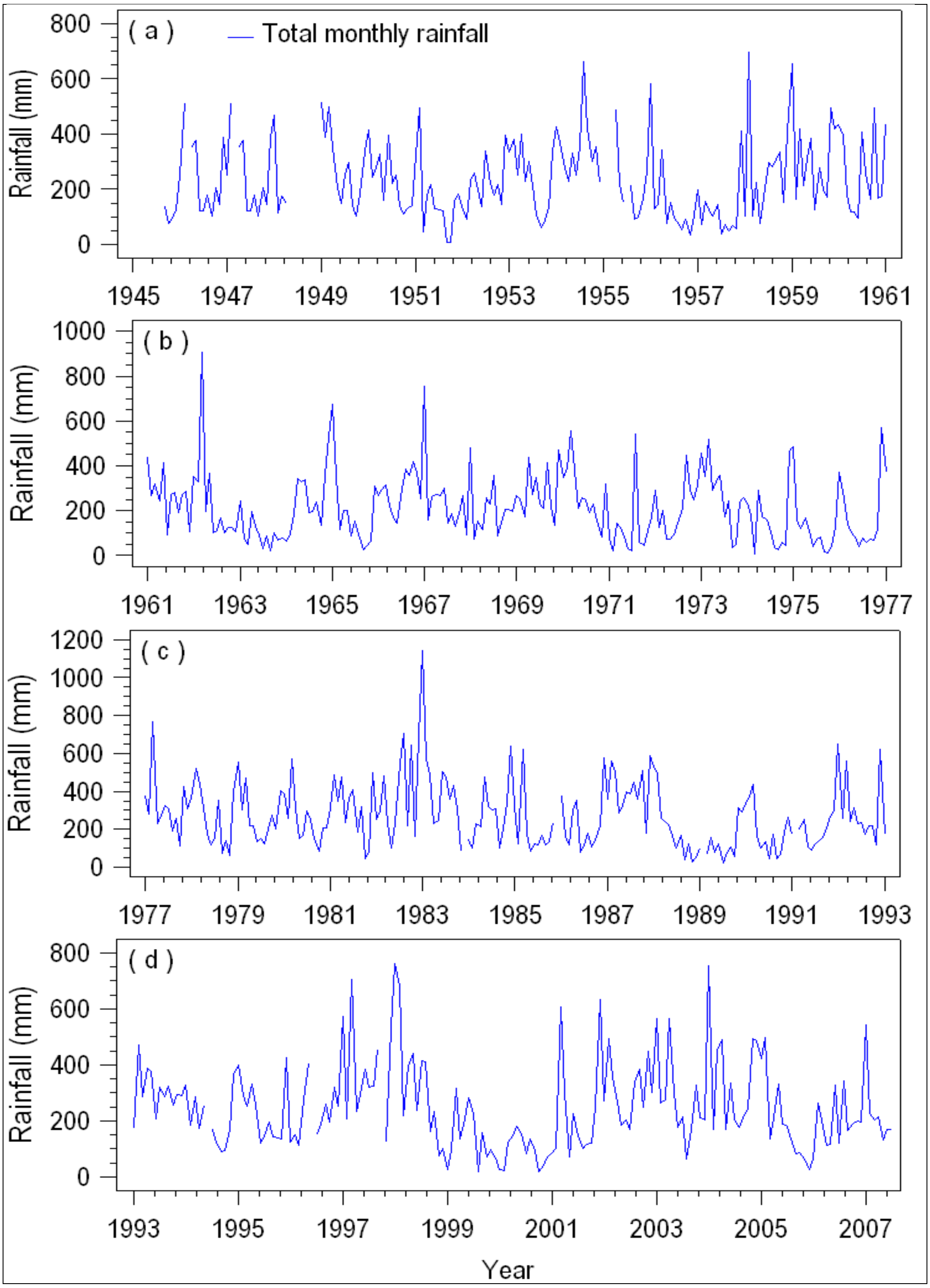


Figure 1.3 (a) – (d): Time series of monthly rainfalls for Nanumea (Jan 1945 to Jul 2007).

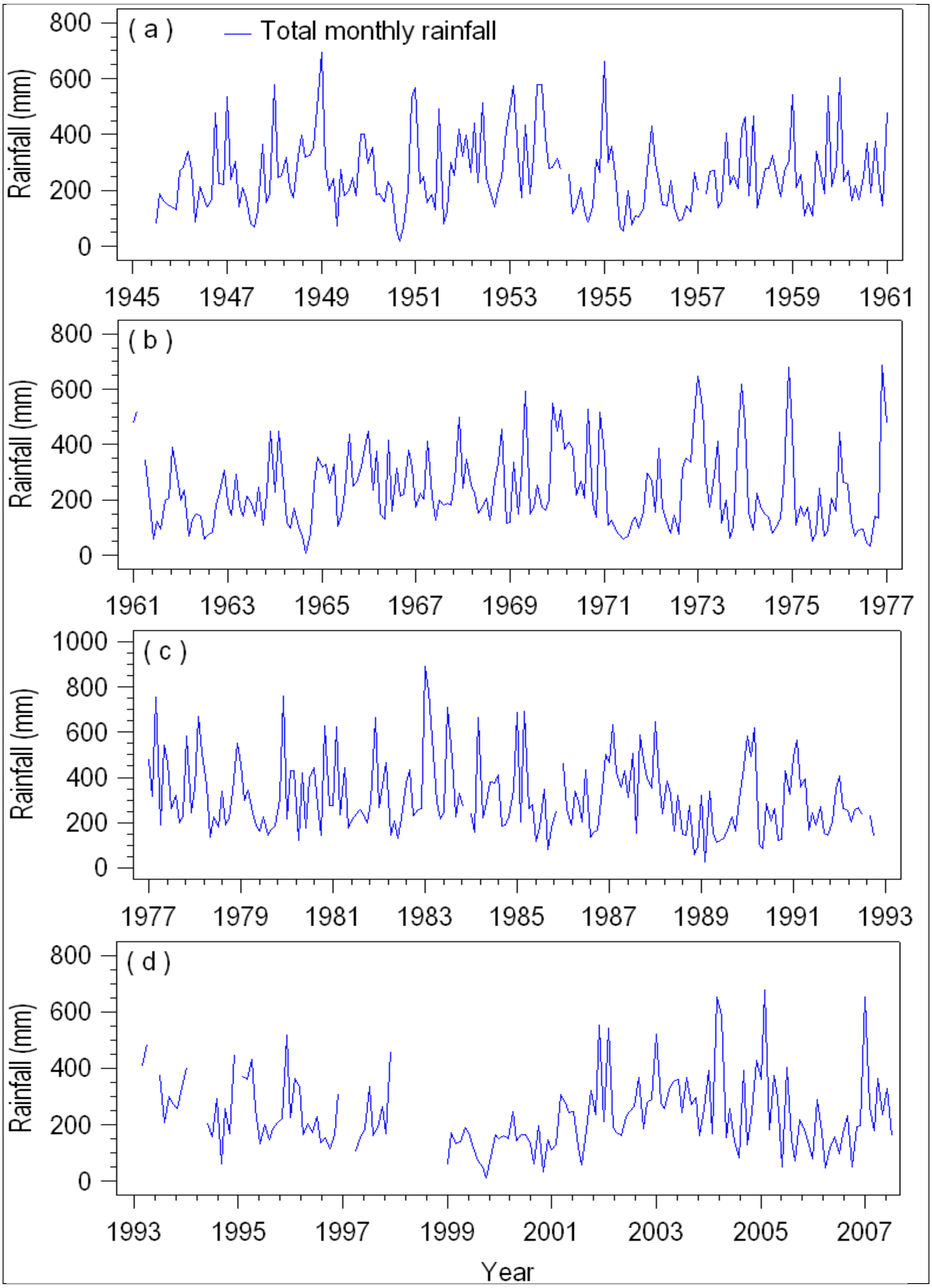


Figure 1.4 (a) – (d): Time series of monthly rainfalls for Nui (Jan 1945 to Jul 2007).

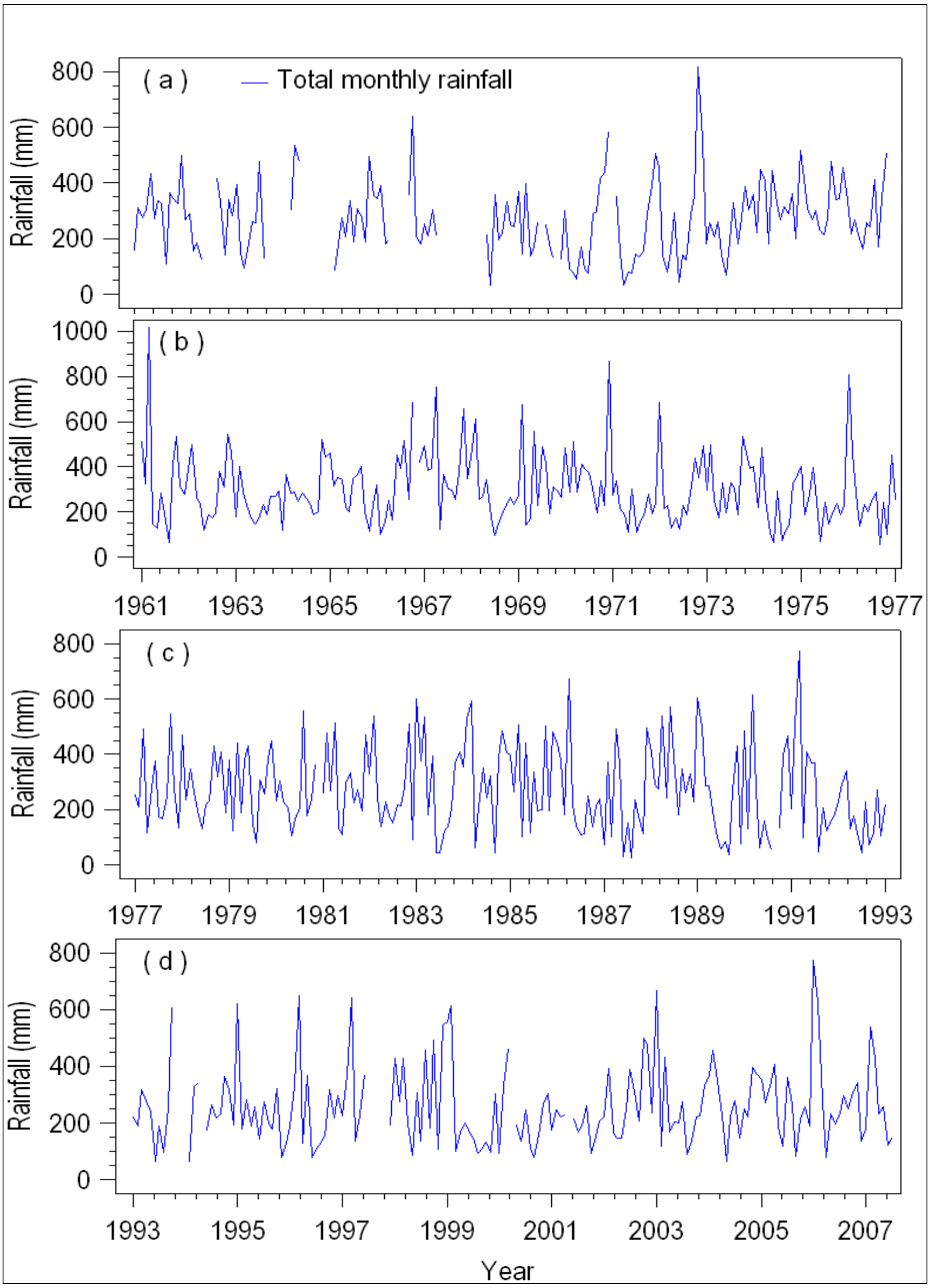


Figure 1.5 (a) – (d): Time series of monthly rainfalls for Niulakita (Jan 1945 to Jul 2007).

1.7 Previous studies of Tuvalu rainfall

Doberitz, Flohn and Schütte (1967) studied the monthly rainfall observations of Funafuti from 1932-1963 amongst other rainfall data from other tropical Pacific Islands to search for linkages between rainfall observed on the tropical coast of South America and rainfall on the remote islands of the tropical Pacific Ocean. Within the Pacific Equatorial Ocean is a region known as the Equatorial Dry Zone (refer to Doberitz (1968) for description of the zone and to Flohn (1967) for wherefores of the zone). Islands within this zone are frequently hit by droughts. Funafuti is located just south of the western end of the Equatorial Dry Zone, see map in Doberitz (1968) and gets its turn with the dry spells. Results from the study showed rainfall over the equatorial Pacific Islands is influenced from the Equatorial Dry Zone and not from South America. In addition, a zonal distribution between 3^{o}South and 10^{o}South and from the coast of South America to about 165^{o}East is strongly linked to the Equatorial Dry Zone (Schütte 1967), indicative of the influence of the Equatorial Dry Zone exerts on precipitation experienced by the neighbourhood islands.

Schütte (1967) demonstrated southward rainfall propagation displaying time lags that gradually increase from 6 to 11 months. The strong persistence of the lag correlations with time make seasonal climate forecasting possible in the Tuvalu Islands. Contrarily to the rainfall pattern of the equatorial Pacific Islands and the tropical west coast of South America are the rainfall patterns at Aitutaki in the Cook Islands (data: 1932-1965), Rarotonga in the Cook islands (data: 1899-1963), Niue (data: 1921-1965), Samoa (data: 1890-1957) and Suva in Fiji (data: 1921-1961) which behaved differently (Schütte 1967).

Statistical analysis in Doberitz (1967) of the Funafuti rainfall data showed the annual cycle was weak in the 32 years. Thus it does not contribute much to the variability in the rainfall of the island but there is a notable influence of the low frequency bands (i.e. periods over one year). Conversely in the period 1971-1990 Morrissey and Greene (1993) found the annual cycle strong and is dominating over the interannual signal. The length of data records used in the studies may possibly be the cause of the disagreement between the findings from the studies. Doberitz (1967) illustrated a strong indication in the Funafuti rainfall record of the dominance of low frequency signals; 18 to 28 months and above 7 years in the variability of the rainfall spectrum. Thus a quasibiennial pulse is significant at Funafuti. The 7 years frequency signal, probably is in the range of the Interdecadal Pacific Oscillation (IPO) and Pacific Decadal Oscillation (PDO).

Thompson (1987) showed that ENSO (El-Niño Southern Oscillation) is highly correlated with the rainfall in the Tuvalu islands. Thus low rainfall periods are associated mostly with the La Niña events than the El Niño events. Two rainfall indexes were calculated. One was a combined rainfall index for rainfalls from these three islands: Nanumea, Niutao and Nui. The other rainfall index used the monthly rainfalls for Vaitupu, Funafuti and Niulakita. The method in Wright (1984) was used in the formation of these rainfall indexes. Based on the two rainfall indexes, the rainfall was shown to lag behind the SOI. The highest correlations for the northern islands occurred at 2 to 3 months when the rainfall lags the SOI. In the southern islands the highest correlation occurred at 5 to 6 months when the rainfall is behind the SOI.

The report by Falkland (1999) in response to the drought at the time, mentioned similar severe droughts which occurred in 1950 and 1970. There are other rainfall studies of Funafuti mentioned in this report however the periods mentioned as covered in the studies may likely be insignificant as they are quite short.

1.8 Thesis structure

Chapter 2 describes the data used in the study and the sources of the data are identified. Initial examination of the data is shown of linkages between rainfall and some of the predictor variables. Some of these correlations were cited by previous authors in Section 1.7.

Chapter 3 covers the methods explored to investigate the predictability of the Funafuti rainfall data. The methods are tested using independent data sets for calibration and validation. Results show the methods are incapable of producing answers to the purpose of the study.

Chapter 4 describes the prediction method derived from study. It shows how a simple graphical method was derived to forecast below average rainfall, averaged over periods of up to one year. This chapter is presented in a form of a paper for publication.

Chapter 5 summarises the study and comments on future study topics relevant to build on the findings from this study.

Chapter 2

Data and predictor variables

2.1 Introduction

The potential predictor variables selected in this thesis to investigate predictability of low rainfall periods in Funafuti are limited only to those that are available on the internet or free of cost. Previous research on forecasting rainfall in Tuvalu specifically were not found anywhere in the literature when the search was made for this study. Despite this factor, a national study of the climate of the atolls and some regional studies that included the Tuvalu islands, these studies are discussed in Section 1.7, have given some support of the selected predictor variables for predicting low rainfall periods in Funafuti. This chapter discusses the rainfall data and how the independent variables are selected and where they are sourced from. Graphical illustrations of discriminating between the predictor variables are shown. Visual illustration of individual independent variable showing potential lag relationships to low rainfalls is shown.

2.2 Standardisation of the Funafuti rainfall data

The total monthly rainfall is used as the dependent variable as residuals from monthly averages. The climatological monthly mean rainfall is defined as the mean monthly rainfall based on the period used in the forecasting scheme, January 1945 to July 2007. A “dry” month is defined for the purposes of this study as the month when the monthly total rainfall is below the climatological monthly mean rainfall. Henceforth, unless otherwise specified, “rainfall” will refer to residuals from the monthly means.

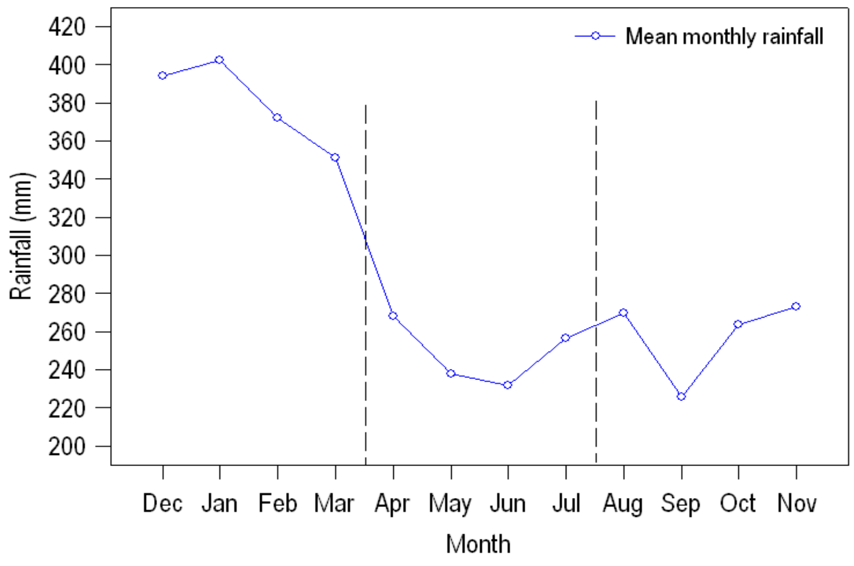


Figure 2.1: Mean monthly rainfall with seasonal effects showing the 4 month divisions are identified by dashed lines.

Investigation of the seasonal trend in the monthly rainfalls as depicted by the rainfall graph (Figure 2.1) seems to suggest that the changes in the amounts of rainfall are more representative if a 4 months period is chosen as the time interval to subdivide the annual rainfall and that this 4 month period should start from December. Therefore December of the preceding year is pooled together with January, February and March of the current year. Then April, May, June and July of the same year form the second division and August, September, October and November of the same year the third division. This 4 month period are marked by the dashed lines (Figure 2.1).

2.3 Identification of potential predictors

Previous studies on the rainfall of Tuvalu discussed in Section 1.7 have linked rainfall to the SOI (Thompson, 1987). Thus the NINO regions (see definition in Section 2.4.1) sea surface temperatures have been a focus when identifying the predictors because the specified region of the tropical Pacific Ocean have been highlighted as being important for monitoring and identifying El Niño and La Niña episodes. The SOI is one index that measures the strength of these climate episodes. The low frequency decadal and interdecadal climate indexes, Interdecadal Pacific Oscillation (IPO) and Pacific Decadal Oscillation (PDO) may have an effect on the rainfall of Tuvalu (Doberitz, 1967).

2.4 Ocean-climatic indices as independent variables

The complete monthly rainfall residual and predictor variables initially investigated and their available data record are shown in Table 2.1. The Madden Julian Oscillation (MJO) which is marked with an asterisk did not seem to show usefulness to the predictability of low rainfalls. Preliminary analysis of the data showed the index is less correlated to low rainfalls. Therefore this index will not be discussed further from this point.

Table 2.1: Initial ocean-climatic variables and available data record

Ocean-Climate Variables	**Length of record**
NINO4	Jan 1945 – Jul 2007
NINO3	Jan 1945 – Jul 2007
NINO3.4	Jan 1945 – Jul 2007
NINO1+2	Jan 1945 – Jul 2007
Pacific Decadal Oscillation (PDO)	Jan 1945 – Jul 2007
Interdecadal Pacific Oscillation (IPO)	Jan 1945 – Jul 2007
Madden Julian Oscillation (MJO)*	Apr 1979 – Nov 2005
Sunspot number	Jan 1945 – Apr 2006
SOI	Jan 1945 – Jul 2007
Previous 1-month rainfall	Jan 1945 – Jul 2007
Previous 2-month rainfall	Jan 1945 – Jul 2007
Previous 3-month rainfall	Jan 1945 – Jul 2007
Total Monthly Rainfall	Jan 1945 – Jul 2007

2.4.1 NINO region SST Indices

The NINO region refers to the equatorial Pacific regions; NINO1+2, NINO3, NINO3.4 and NINO4 (Figure 2.2). NINO1+2 are the areas between 0-10^{o}S and 80^{o}W-90^{o}W. NINO3 is from 5^{o}N-5^{o}S and from 150^{o}W-90^{o}W, NINO3.4 is from 5^{o}N-5^{o}S and from 170^{o}W-120^{o}W and NINO4 is from 5^{o}N-5^{o}S to 160^{o}E-150^{o}W (Brassington 1997).

The NINO indices used in the study are the average values of the SST anomalies in the specified region of the Pacific Ocean. The index SST values for each NINO region are available from the NOAA (National Oceanic Atmospheric Administration) website http://www.cdc.noaa.gov/Pressure/Timeseries/. The SSTs of the NINO region provide a measure of the ENSO index. More importantly the NINO regions SSTs exert control not only on the local climate but also on the climate over certain areas many thousands of kilometres away. This connection between ENSO and climate has been known as 'teleconnection' (Bjerknes, 1969). In regions where these teleconnections may persist for a number of months or seasons, they may serve as a basis for forecasting rainfall.

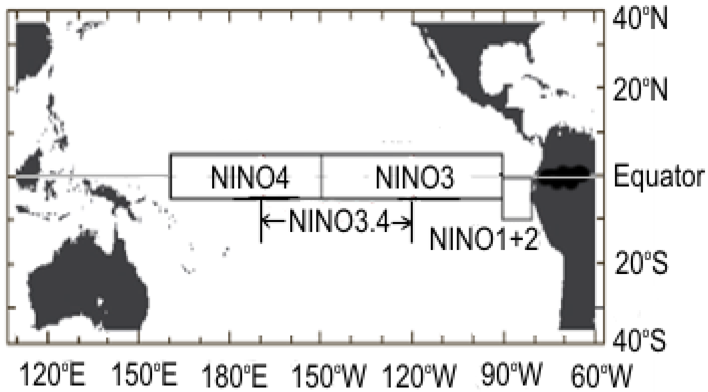


Figure 2.2: The NINO regions (modified from Zubair et al., 2008)

2.4.2 Interdecadal Pacific Oscillation (IPO) and Pacific Decadal Oscillation (PDO)

The IPO and PDO are modes of variability with decadal time-scale. They both describe variations in SSTs of the Pacific Ocean (Folland et al., 2002). However IPO is defined in Power et al., (1999) as fluctuation in SST and circulation across the whole Pacific basin whereas PDO is confined to the North Pacific (Mantua et al., 1997). Since IPO change the SST in the equatorial Pacific then it may affect ENSO and thus the two together influence the SPCZ (South Pacific Convergence Zone) (Folland 2002). The IPO data for the present study was sourced from Chris Folland (Hadley Centre for Climate Prediction and Research, UK). The monthly IPO data is characterised by 10 Empirical Orthogonal Functions (i.e. EOF1 to EOF10). Only EOF2 is chosen and is used in the analysis. The decision is based on preliminary analysis of the data which showed that EOF2 is more highly correlated to the rainfall than the rest. The PDO indexes were downloaded from the same website in which the SSTs of the NINO regions were sourced from see Section 2.4.1.

2.4.3 Sunspot number

The sunspot number is a measure for the variation in the solar energy (Lakshmi et al., 2003). The sunspot activity is in cycles of 11, 22 and 80 years. A possible connection between solar activity and the climate has been suggested in several studies (e.g. Doberitz, 1967; Labitzke and Van Loon, 1992). So was included here as a potential variable for the sake of completeness as the data is readily available.

2.4.4 Southern oscillation index

The SOI is commonly used as the index that measures the strength of the ENSO conditions. There are different methods used to calculate the SOI. The index used in the study is the TROUP SOI (Troup, 1965), defined as the "standardised anomaly of the mean sea level pressure difference between Tahiti and Darwin" http://www.bom.gov.au/climate/glossary/soi.shtml The monthly SOI values used for the study were downloaded from the Australian Bureau of Meteorology website http://www.bom.gov.au/climate/current/soihtm1.shtml

Taking the 1999 drought (Figure 2.3) as an example; monthly SOI values from -5 and greater than -5 which are indicated as the lighter black bars and the dry months are represented by negative residual rainfall or the dark black bars.

The SOI value of -5 is an arbitrary cut-off point chosen for identifying the shift of the SOI phase to positive and the ensuing change in the rainfall to dry months. Basically the cut-off point is based on subjective judgment at the exploration stage of the data.

In May 1998 the SOI shifted to positive and remained positive at significant amplitude almost every month after and into the start of 2001. The swing of the SOI to the positive phase is marked in Figure 2.3 with the thick black curved line labelled May 1998. The dry months subsequently started 6 months after the change of the SOI phase. This is illustrated in Figure 2.3 by the thick black line with November 1998 as the start of the dry months.

Although the SOI index may be a useful indicator for the onset of some major dry periods, a preliminary evaluation showed that it is not helpful for forecasting low rainfalls in Funafuti. Being an index, SOI only gives an indication of the pressure differences across the Pacific Ocean. It does not consider the direction or the rate of change in pressure values over time which means that correlation with stationary values of SOI may only explain part of the relationship between SOI and rainfall (Stone and Auliciems 1992).

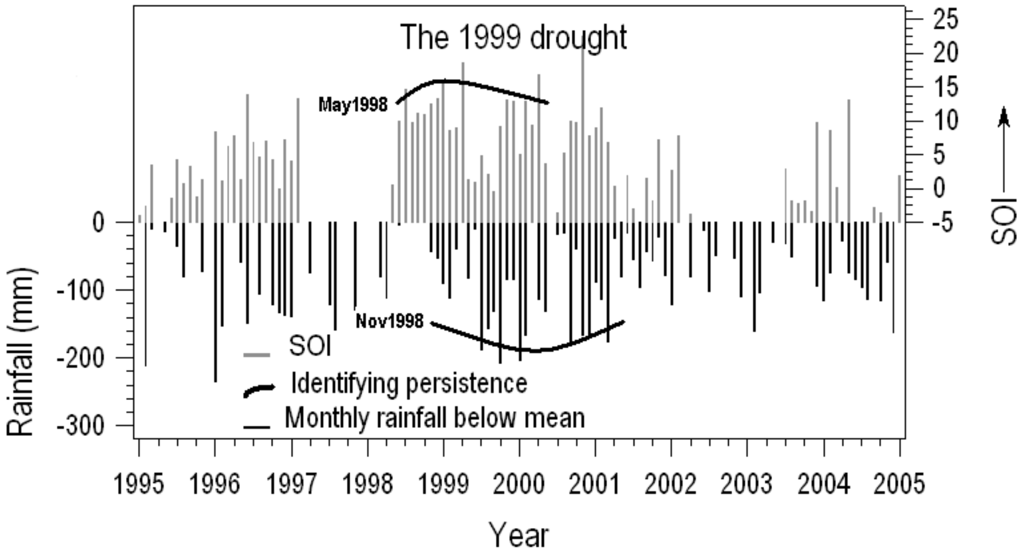


Figure 2.3: Time series of SOI and standardised monthly rainfall for period Jan1995-Dec2005, for below-average rainfalls. Refer to text for details.

2.5 Rainfall serial correlation as a potential predictor

If persistence of monthly rainfall deviations is useful to forecast future rainfalls then the consecutive rainfall residuals must be correlated to each other. Serial correlation therefore is tested by examining if the autocorrelation between lag-1 rainfall residuals and lag-0 rainfall residuals is significant. To do this, time averaging periods of 1-month (Figure 2.4a), 2-months (Figure 2.4c), and 3-months (Figure 2.4e) for lag-1 and lag-0 of monthly rainfalls January 1945 to July 2007 are plotted on scatter diagrams. Then the coefficient of determination, R^2 is calculated to quantify the degree of correlation.

The results in Figures 2.4a, c, e, all show values of R^2 are close to 0.0. To confirm that these results are coherent, R^2 values of lag-2 rainfall residuals and lag 0 rainfall residuals are calculated for the same averaging periods as used with lag 1 rainfall residuals and lag 0 rainfall residuals. It is obvious from Figures 2.4b, d, f, that the R^2 are close to 0.0 and are consistently insignificant.

Therefore since all the R^2 values are low we conclude that previous standardised rainfalls are of no value in forecasting future rainfall residuals. However, the scatter diagram in Figure 2.5a suggests that current residual rainfalls are correlated to the previous 1-month raw rainfalls. However this was not investigated further here.

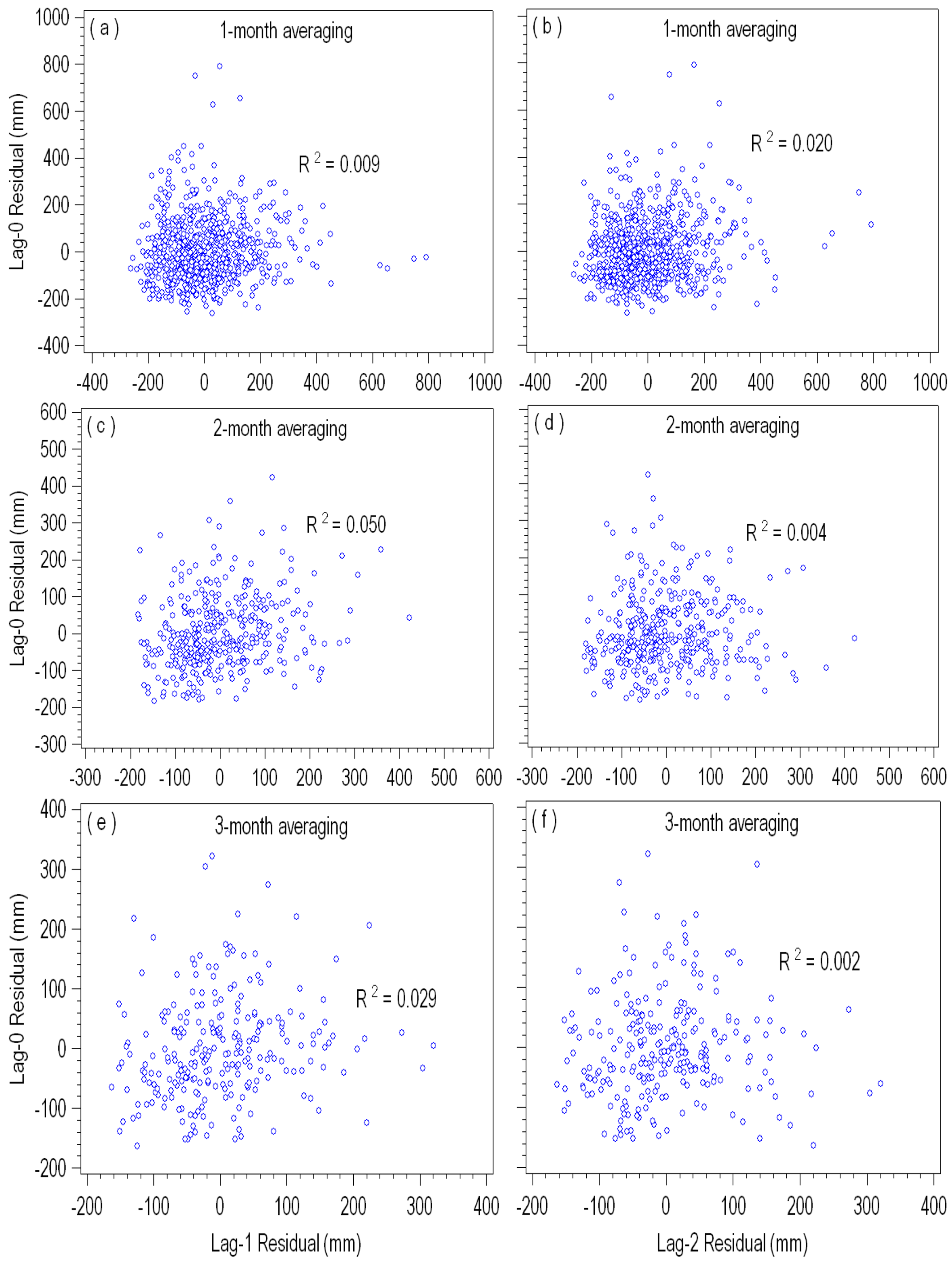


Figure 2.4 (a) – (f): Scatter diagram showing the lack of serial correlation between current and lag-1 standardised rainfall (left) and current and lag-2 standardised rainfall (right), 1945 – 2007 for different time averaging periods.

2.6 Cross correlations between rainfall and ocean-climatic indices

The findings in Section 2.2 are adopted in this section to investigate the relationships between rainfall and the ocean-climatic indices. Therefore we assign the predictand as the 4-month residual mean rainfall. An arbitrary choice of the 6-month mean is assigned on the predictors. The following predictor variables are investigated; SOI, PDO, NINO1+2, NINO3, NINO3.4, NINO4, sunspot number, previous 1-month raw rainfall (R_1), previous 2-month raw rainfall (R_2), previous 3-month raw rainfall (R_3) and IPO-EOF2. Therefore the 6-month mean of the previous values of the predictor variables are calculated for the data record 1945 to 2007. Similarly the current 4-month residual mean rainfalls are calculated for the same time period. Then lag-0 of the 4-month residual mean rainfall is plotted as a linear regression function of lag-1 of the 6-month mean of previous predictor values for each of the 11 independent variables. These results are shown in the scatter diagrams (Figures 2.5a-f and Figures 2.6a-e) together with the R^2 values indicating the degree of the association of rainfall to each of the independent predictor variables. A summary of the R^2 values is tabled in Table 2.2.

The results shown in the scatter diagrams Figures 2.5a-f and Figures 2.6a-e suggest that there is some possibility of forecasting fields for low rainfall and NINO4 looked to be the most promising for further investigations.

Some of the scatter diagrams, however suggest a degree of predictability of low rainfalls. This is identified by the ‘two rectangles’ containing relatively high or low number of data points (Figures 2.5a-f). The predictability of low rainfalls stands out more clearly in Figure 2.5d. At temperatures less than 26.0^{o}C most of the rainfalls are below the average rainfall with rainfall residuals therefore being negative. This is clearly illustrated in the lower red box by many points and the upper red box

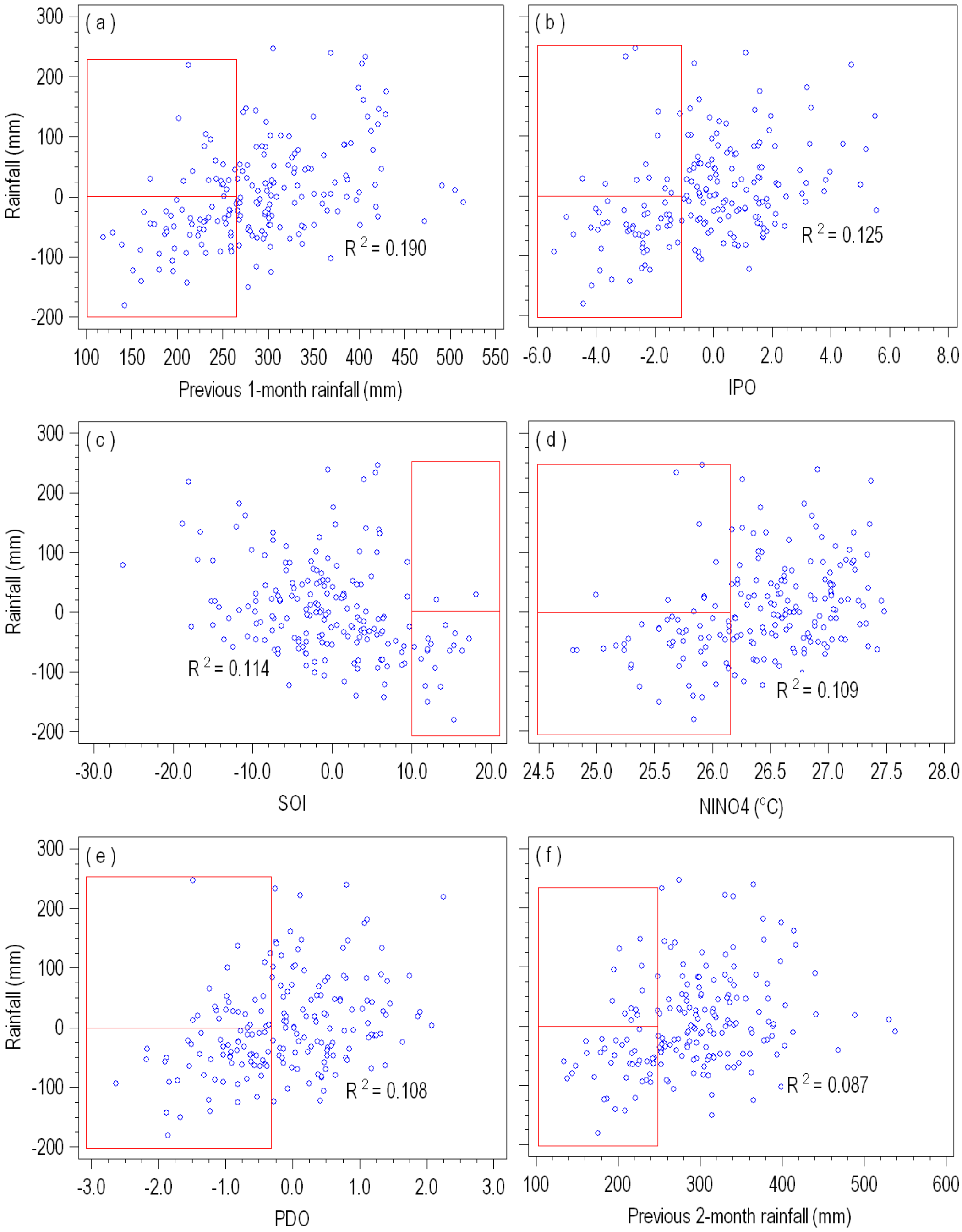


Figure 2.5 (a) – (f): Scatter diagrams showing some degree of predictability of low rainfalls, despite overall low R^2. The plots show the current 4-month residual rainfall versus lag-1 of the mean previous 6-month values of the predictor variables (1945-2007).

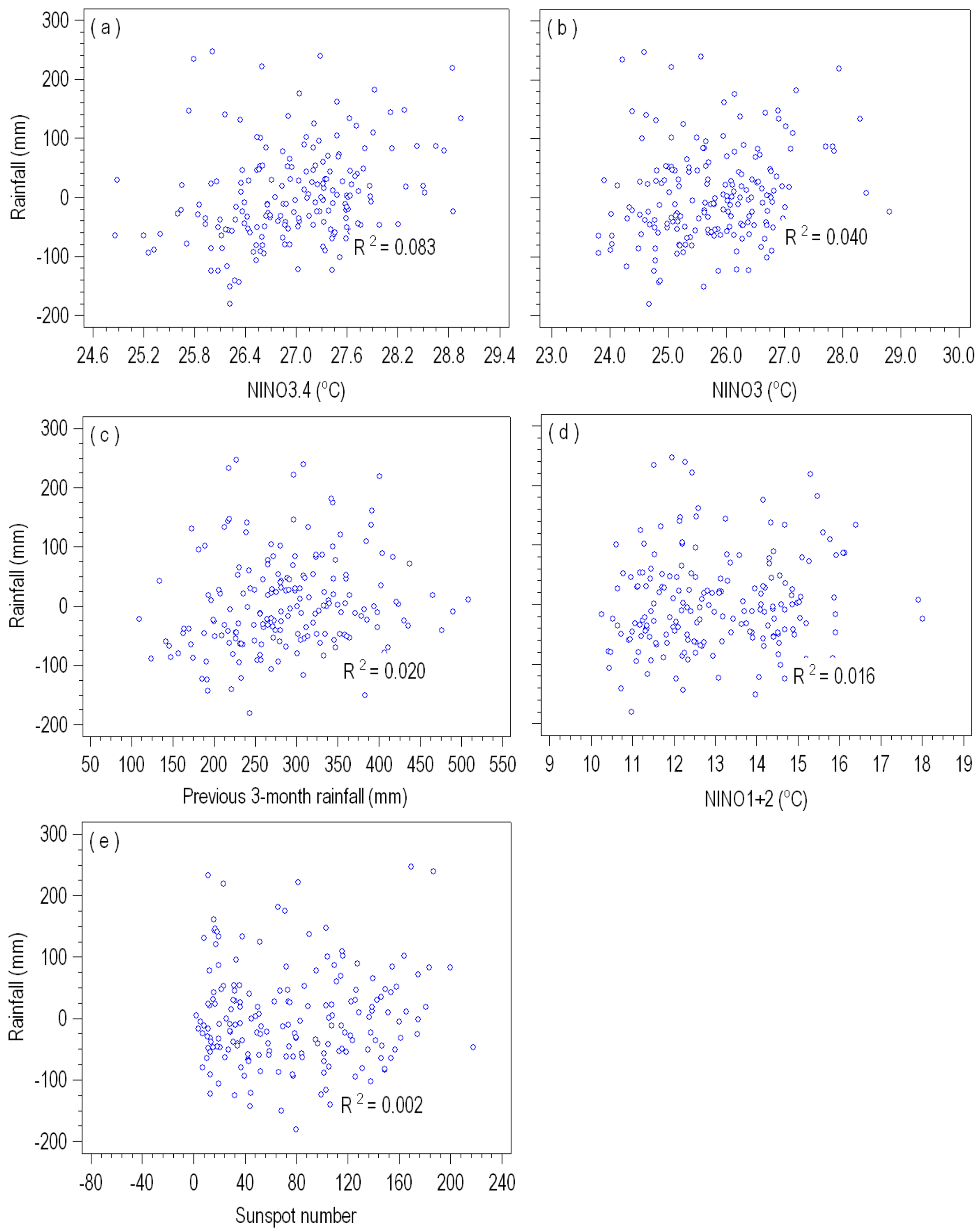


Figure 2.6 (a) – (e): Scatter diagrams showing lack of predictability of low rainfalls by these particular predictor variables. The plots show the current 4-month residual rainfall versus lag-1 of the mean previous 6-month values of the predictor variables (1945-2007).

with almost no points. This indicates that NINO4 reveals the pattern of an 'almost-empty rectangle' better than the other predictor variables. For the purpose of the study, NINO4 SSTs seems the best predictor of low rainfalls. This is developed further in Chapter 4.

Table 2.2 shows that the following predictors: previous 3-month raw rainfalls (R_3), NINO1+2 and sunspot number are not significant. The low correlation shown in this study between the SSTs in the NINO1+2 regions and the rainfall in Funafuti is consistent with findings by Shütte (1967). The only difference lie in the data, where this study uses SSTs of the coastal waters of Ecuador and Peru, the 1967 study was using rainfalls recorded at land climate stations along the coasts of Ecuador and Peru which showed that rainfall in Funafuti is not influenced from the tropical coast of South America.

Table 2.2: Showing R^2 values from Figures 2.5a-f and Figures 2.6a-e.

Predictor variable	**R^2**	**p**
R_1	0.190	< 0.000
IPO	0.125	< 0.000
SOI	0.114	< 0.000
NINO4	0.109	< 0.000
PDO	0.108	< 0.000
R_2	0.087	< 0.000
NINO3.4	0.083	< 0.000
NINO3	0.040	0.006
R_3	0.020	0.051
NINO1+2	0.016	0.089
Sunspot number	0.002	0.533

2.7 Summary

This chapter has shown the extent to which low rainfall can be estimated by the oceanic-climate variables chosen in this study. Some variables have shown some predictability of rainfall. These independent variables are the previous 1-month raw rainfalls, IPO, SOI, NINO4, PDO, previous 2-months raw rainfalls and NINO3.4 which were assigned an averaging time period of 6-months in the analysis. NINO4 sea surface temperatures showed some ability to forecast low rainfalls and this will be further looked at in Chapter 4.

However the answer to forecasting low rainfalls depends on whether the predictive method can show a realistic enough forecast. The next chapter will evaluate the following predictive methods: artificial neural networks, all-possible-subset regression and logistic regression to the extent they can forecast low rainfalls.

Chapter 3

Initial Prediction Evaluations

3.1 Introduction

This chapter discusses the methods used to make a preliminary investigation of rainfall forecasts in Funafuti. The specific techniques considered are artificial neural network (ANN), all-possible-subset regression (ASR) and logistic regression (LR).

All analyses use standardised monthly rainfall as the dependent variable, being residuals from long-term monthly means. The same set of independent variables are used in the ANN, ASR and LR methods. These independent variables include SOI, PDO, IPO, NINO4, NINO3.4, NINO3, NINO1+2, R_1, R_2 and R_3 and sunspot number. Calibration and validation of each method using two independent data sets are examined. The validation results will be illustrated and presented in graphical form.

The fit measure utilised is the Nash-Sutcliffe efficiency, E (Legates and McCabe, 1999). This will be referred to in the analysis simply as 'goodness of fit' or 'fit'. The highest fit value is +1.0 which indicates a perfect match between the predictions and the observations. A fit value of 0.0 means the climatological mean is just as good as the model in forecasting rainfall. A zero or negative value of E indicates the model has failed because the climatological mean is at least as good a predictor as the model.

3.2 Artificial neural network (ANN)

Artificial neural networks use artificial intelligence to model complex physical relationships with arbitrary non-linearity, such as between hydroclimate variables and the underlying physical processes that involve these variables (Hornik et al., 1990). Since rainfall sometimes shows non-stationary and nonlinear physical properties, neural networks have been used by researchers to forecast droughts (e.g Mishra and Desai, 2006; Morid et al., 2007).

In the neural network structure, the “neurons” are arranged in interconnected groups called layers. Every ANN include: an input layer(s), a hidden layer(s) and an output layer(s). The input layer is where the data are entered. The hidden layer is where the entered data is processed. The output layer produces the results of the problem investigated. Further information on the method is given by Morid et al., (2007). One of the advantages of the ANN technique is there is no need to explicitly define the physical relationships between the independent variables and the dependent variables.

3.2.1 Method

The ANN method is used to capture linkages between input (independent) and output (dependent) variables. It does this by learning from past experience the possibly complex relationships between the predictands and the predictors and then estimate these functional relationships. This process is known as training the data by adjusting the weights or constraints such that a predetermined objective function is minimised and the best fit of the model predictions to the observed data is obtained. See Kingston et al., (2004) for a full discussion.

The trained model is then presented to an independent validation data for testing. As with any model, the model performance can only be validated on an independent data set which has not been used in the training process.

3.2.2 Calibration and Validation

In terms of the ANN terminology, one example of a specific model investigated in this study is the MLP 2:2-7-4:1 network with two input variables, one output variable, and three hidden layers of 2, 7 and 4 units (Morid et al., 2007).

Independent calibration and validation datasets were used being the periods 1945-1976 and 1977-2007, respectively. The results from the calibration and validations are plotted in Figures 3.1a-d, together with the E goodness of fit index.

3.2.3 ANN results

The calibration prediction time series (Figures 3.1a, b) does not fit the data well and fails, not unexpectedly, in the validation process (Figures 3.1c, d).

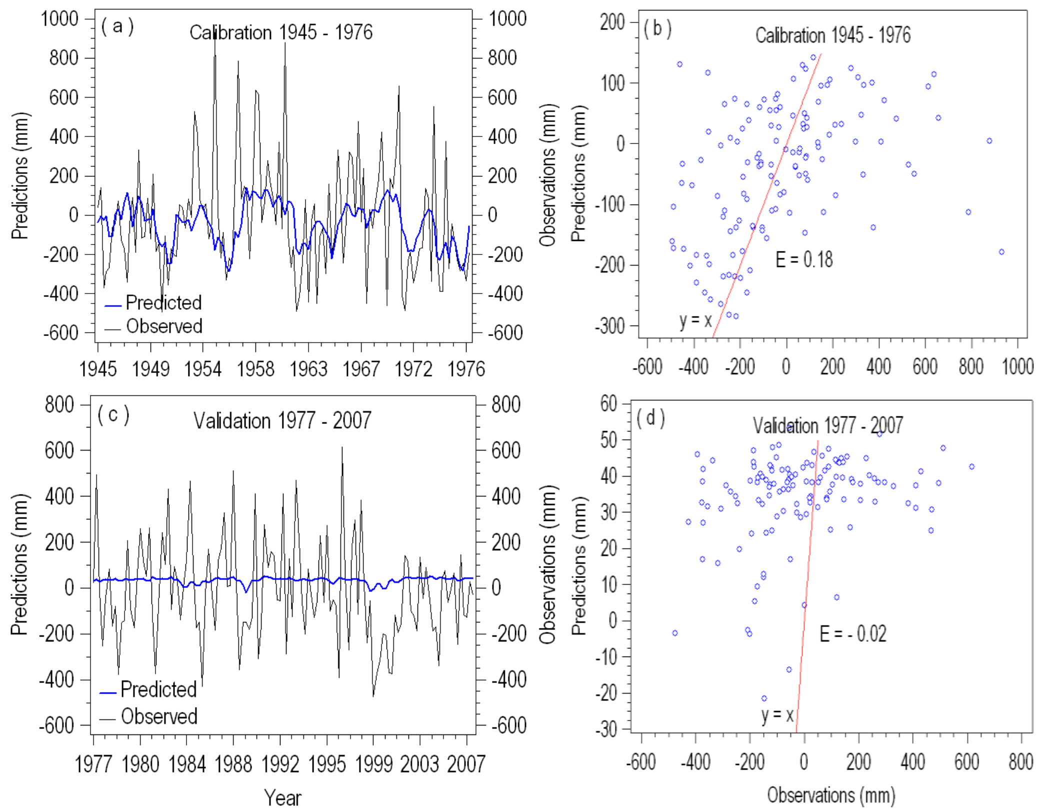


Figure 3.1 (a) – (d): Lack of forecasting ability for forecasting rainfall using neural network; calibration time series (a) and scatter diagram (b) (1945-1976), validation time series (c) and scatter diagram (d) (1977-2007).

3.3 All-possible-subset regression (ASR)

All-possible-subset regression is a linear regression statistical method of searching for the best subsets of independent variables to give maximum explanation of the dependent variable. The ASR is a possible alternative method that can be used to learn the empirical linkages directly from the measured data given a linear relation between observed and independent variables. The main advantage of ASR is that unhelpful variables can be eliminated easily. The next sections will use the method to examine the rainfall data.

3.3.1 Method

From a given number of independent variables the ASR method finds the best subsets of predictor variables for a specified number of subset variables less than the original number of independent variables. The ASR algorithm does this by explicitly or implicitly evaluating all the possible combinations of the predictors which explain the variability of the dependent variable for any given number of subset of independent variables (Hofmann et al., 2007). The method tables these combinations in descending values of R^2.

ASR is particularly useful when there are a large number of independent variables as long as this does not exceed the ASR algorithm capacity.

A number of different numbers of variables in the optimal subset were investigated. These will be discussed in the subsequent sections.

3.3.2 Hindcast from previous 6 months averages

An arbitrary choice of 6-month time average is explored for independent variables. Forecasting residual rainfall for the next 6 months, by hindcasting over a calibration time period. The subsequent sections discuss these time periods.

3.3.2.1 Calibration – with ASR

The data used in the analysis is from 1945 to 1976, and the remaining independent data 1977-2007 set aside for validation. The 6-month mean of the previous values for the following predictor variables; SOI, PDO, NINO1+2, NINO3, NINO3.4, NINO4, sunspot number, previous 3-month raw rainfalls (R_3), previous 2-month raw rainfalls (R_2) and previous 1-month raw rainfalls (R_1) are assigned as the predictors and the mean residual 4-month rainfall as the predictand. It is noted here that the IPO data is not yet available at this time so this analysis was carried without IPO. However the subsequent analyses were undertaken with IPO included as shown in calibration and validation results Figures 3.4a - 3.8f.

Table 3.1: The Best subsets retained from the ASR execution run

R^2	No. of variables	SOI	PDO	NINO3.4	NINO4	R_2	R_1
0.1759	6	-0.12	0.25	-0.46	0.30	0.13	0.20
0.1632	5	-0.09	0.26	-0.39	0.27		0.23
0.1479	4	-0.18	0.26	-0.22			0.23
0.1231	3	-0.06	0.22				0.21
0.0857	2	-0.17					0.22

The best subsets from the regression combinations of the predictors are executed in MLR to get the coefficients of the linear regression equation for each subset. Predictions for each best subset are calculated using the respective regression equations. Each subset is tested for goodness of fit.

3.3.2.2 Validation

The validation results are plotted in Figures 3.2a-d of the best subsets for 2 independent variables to 5 independent variables respectively and Figures 3.3a-d of the best subsets for 6 independent variables to 9 independent variables respectively. All the validation plots show negative fit values. So all ASR failed in this case as a method for predicting rainfall. Similar lacks of results hold for the other time periods, as can be seen in the validation plots Figures 3.4a, b, 3.7b, d, f, 3.8b, d, f. However these same scatter diagrams although they show failures in the overall prediction of rainfall but for the predictions of low rainfalls there is some degree of predictability evident.

This can happen because, the E value measures a fit that considers the whole data set and thus can be misleading when only a subset e.g. the dry periods is considered.

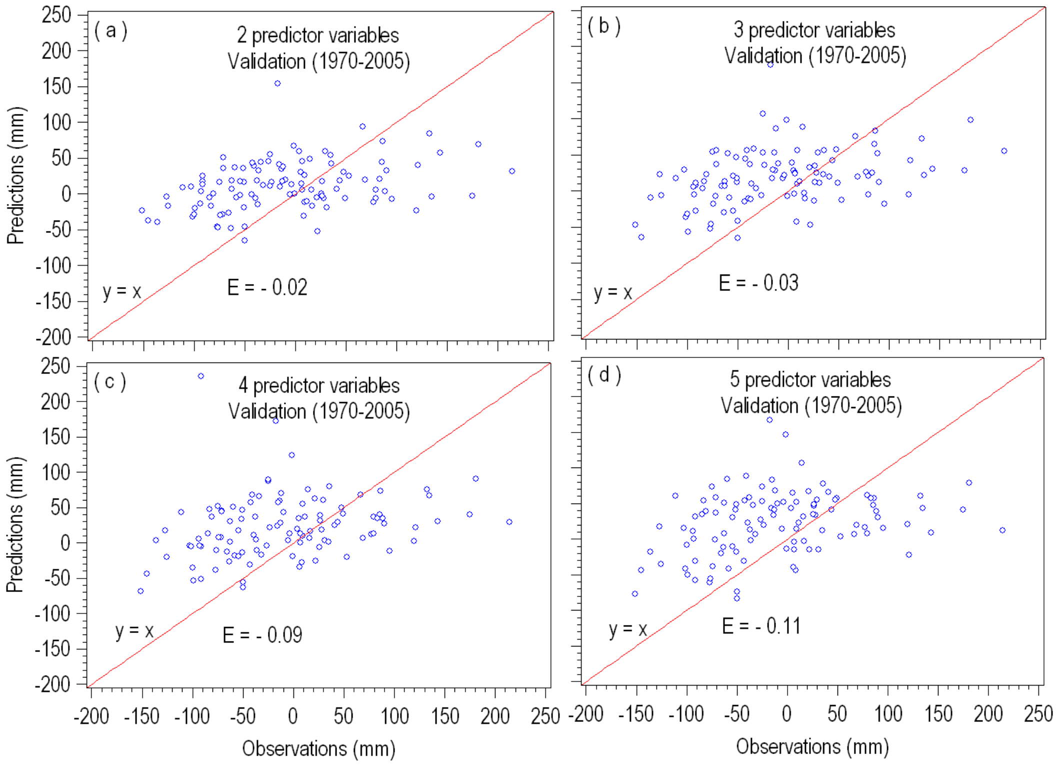


Figure 3.2 (a) – (d): Failed validation for forecasting rainfall using best subset of combinations of predictor variables 2-5 optimal predictor variables. See Table 3.2 for details.

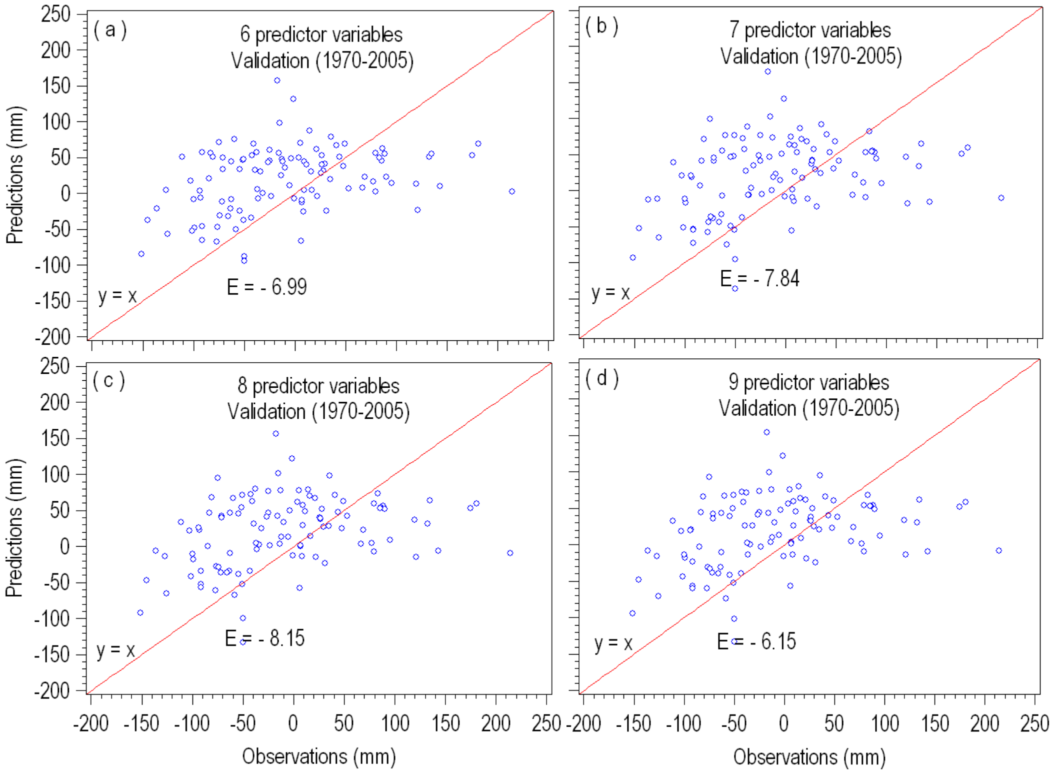


Figure 3.3 (a) – (d): Failed validation results for forecasting rainfall using best subset of combinations of predictor variables 6-9 optimal predictor variables. Refer to Table 3.2 for details.

Table 3.2: The optimal number of predictors described in Figures 3.2a-d, 3.3a-d

Optimal no. of predictors	Predictor variables
2	SOI, R_1
3	SOI, $R_{1,}$ PDO,
4	SOI, $R_{1,}$ PDO, NINO3.4
5	SOI, $R_{1,}$ PDO, NINO3.4, NINO4
6	SOI, R_1 PDO,NINO3.4, NINO4, R_2
7	SOI, R_1 PDO, NINO3.4, NINO4, $R_{2,}$ NINO1+2
8	SOI, R_1 PDO, NINO3.4, NINO4, $R_{2,}$ NINO1+2,Sunspot
9	SOI, R_1 PDO, NINO3.4, NINO4, $R_{2,}$ NINO1+2, Sunspot, NINO3

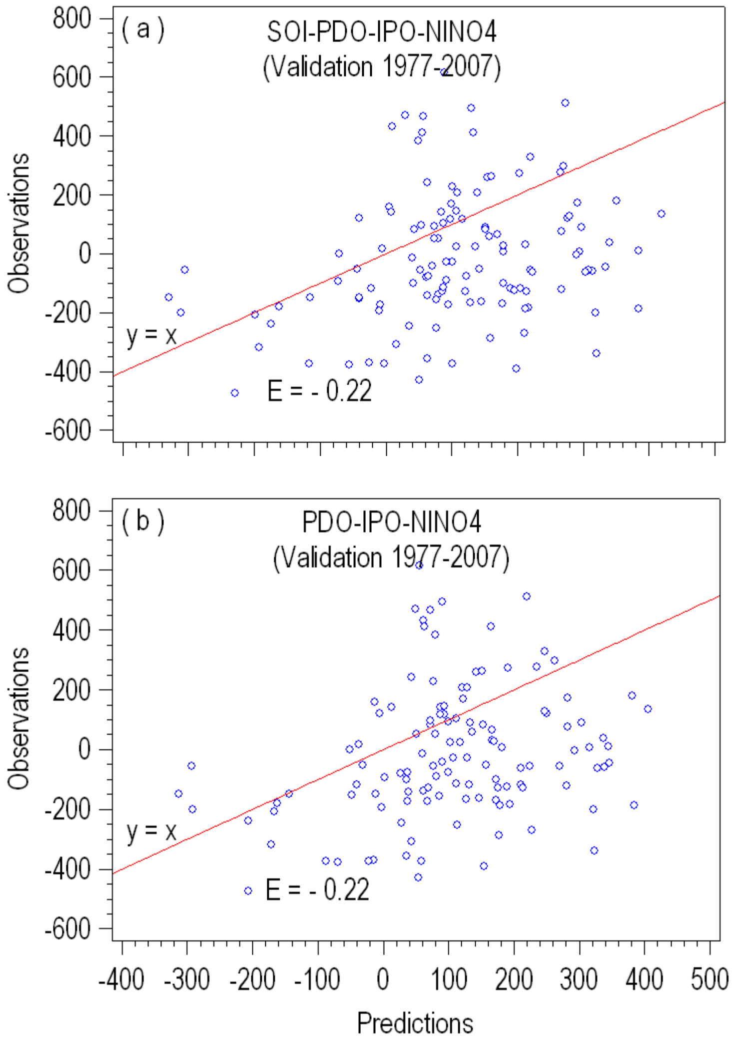
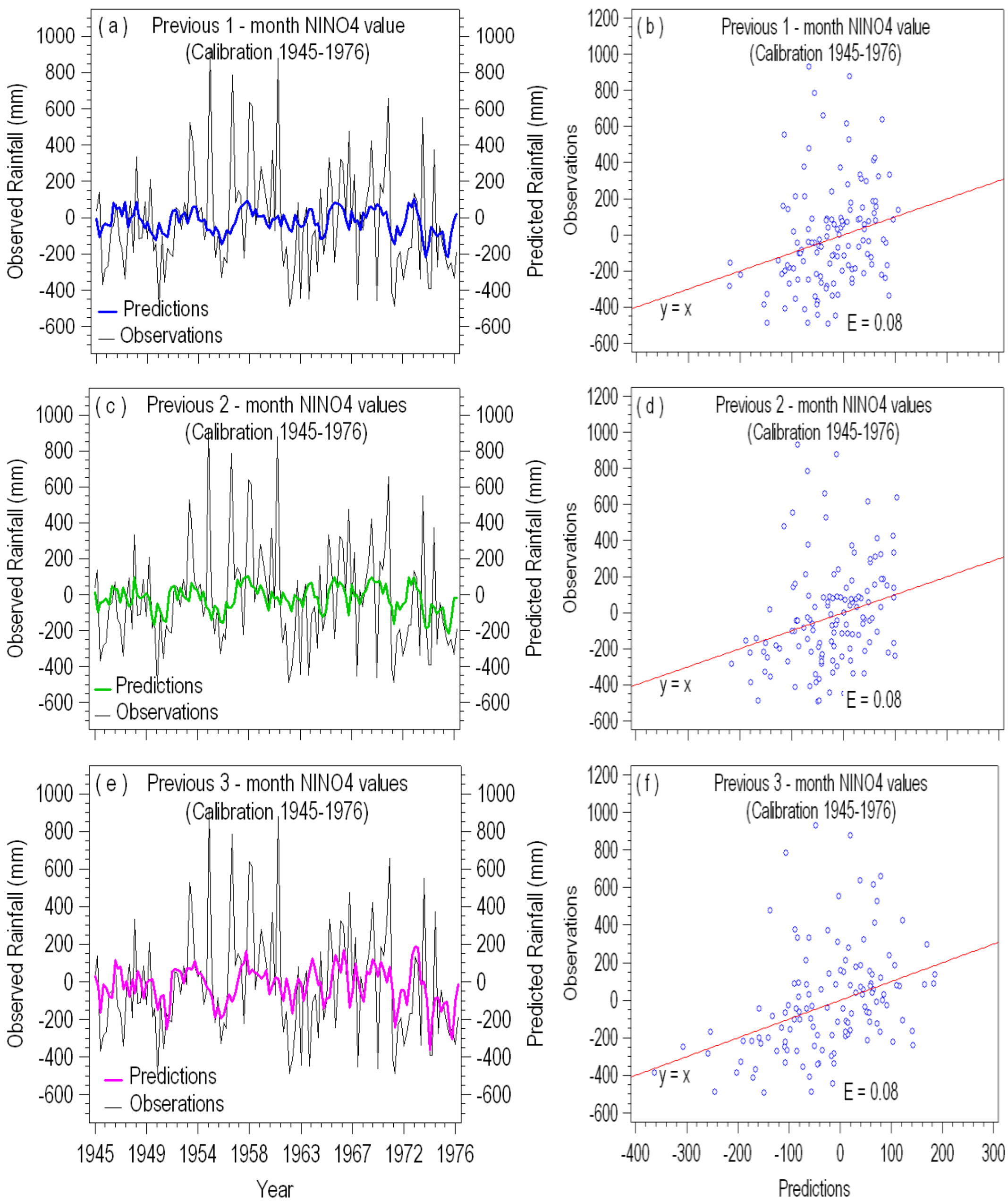
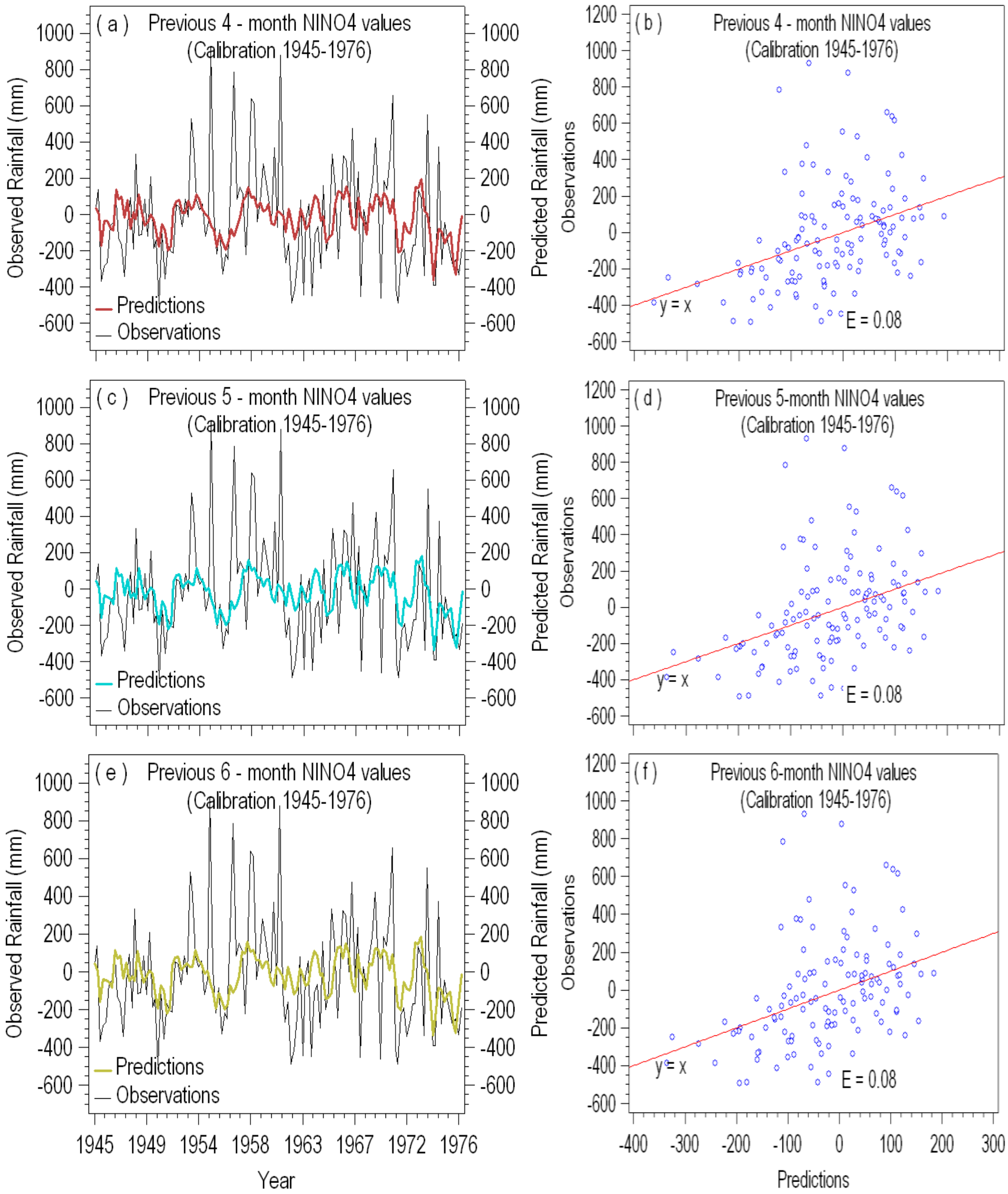


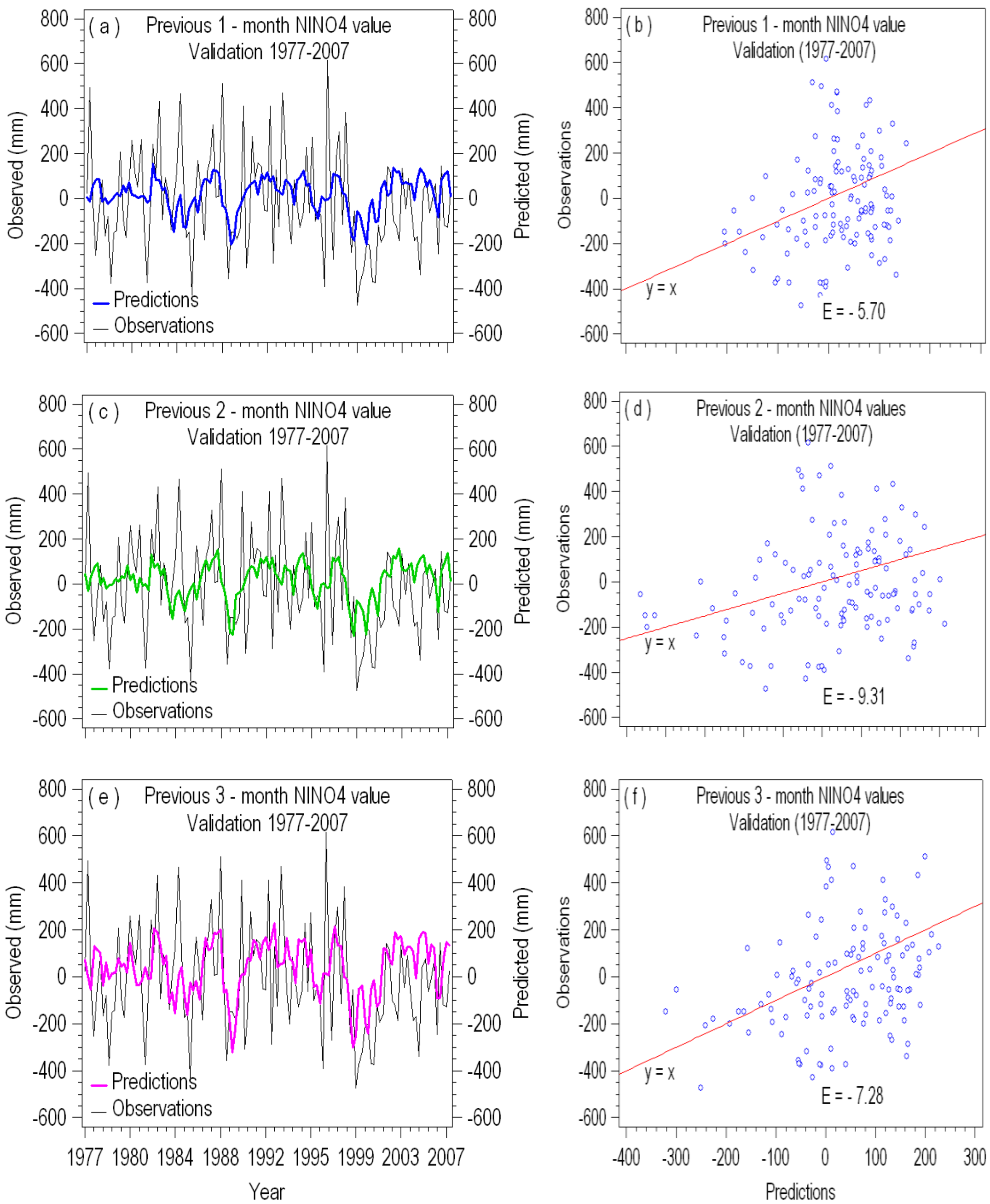
Figure 3.4 (a), (b): Failed validation results of forecasting current 3-month residual rainfall for the next 6 months by hindcasting over the calibration time period 1945-1976.



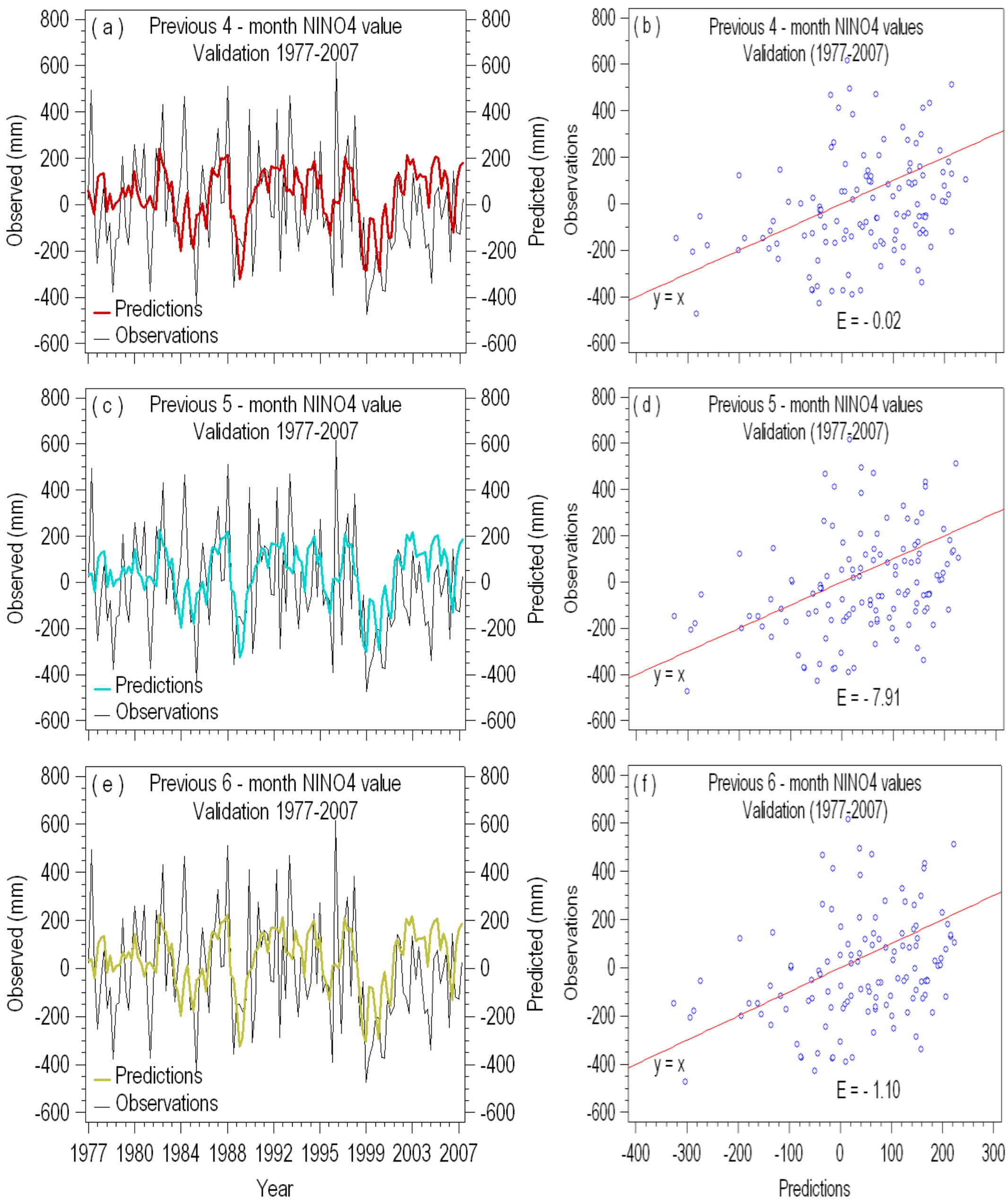
Figures 3.5 (a) – (f): Time series and scatter diagrams of calibration results of NINO4 previous 1-3 month values (1945-1976).



Figures 3.6 (a) – (f): Time series and scatter diagrams of calibration results of NINO4 previous 4- 6 month values (1945-1976).



Figures 3.7 (a) – (f): Time series and scatter diagrams of failed validation results of NINO4 previous 1- 3 month values (1977-2007).



Figures 3.8 (a) – (f): Time series and scatter diagrams of failed validation results of NINO4 previous 4- 6 month values (1977-2007).

3.4 Logistic Regression

This nonlinear modelling method also confines the dependent variable to only two values (0 or 1)and gives the outcome as a probability of a ‘0’ or ‘1’, defined for the present purposes as below or above average rainfall, respectively. Therefore the predictands can only be assigned one of these two values. A previous study using logistic regression probability models have been shown useful to the management of water resources in the southern and central United States (Kurtzman and Scanlon 2007) where the method was used to predict above average and below average winter precipitation to calculate probabilities. The logistic regression method is chosen for the more robust situation of forecasting simply above or below average rainfall.

3.4.1 Method

The predictand being the 3-months residual rainfalls are now recoded as a 1.0 (above average) or 0.0 (below average). These become the new dependent variables. The previous NINO4 monthly values are averaged over time periods 1-month to 6-months. The data is divided into two subsets, a calibration data set Jan1945-Dec1976 and a validation data set Jan1977-July2007. Then a single logistic run to calibrate on the individual time periods, one at a time is undertaken.

This procedure was carried out on those predictor variables that had been shown in Section 2.6 to have significant p values (refer to Table 2.2 in Chapter 2). However, only NINO4 is shown here, as it seems to show a greater ability to forecast periods of low rainfalls than the other significant independent variables.

3.4.2 Calibration and validation results

The logistic regression makes predictions of the probability of above mean rainfall or below mean rainfall, it does not make predictions of rainfall magnitudes. The calibration values are plotted in Figures 3.9a–f, as probability of above average rainfall, however, for simplicity of viewing Figures 3.10a –f, only results from the averaging periods 1 to 3 months are shown.

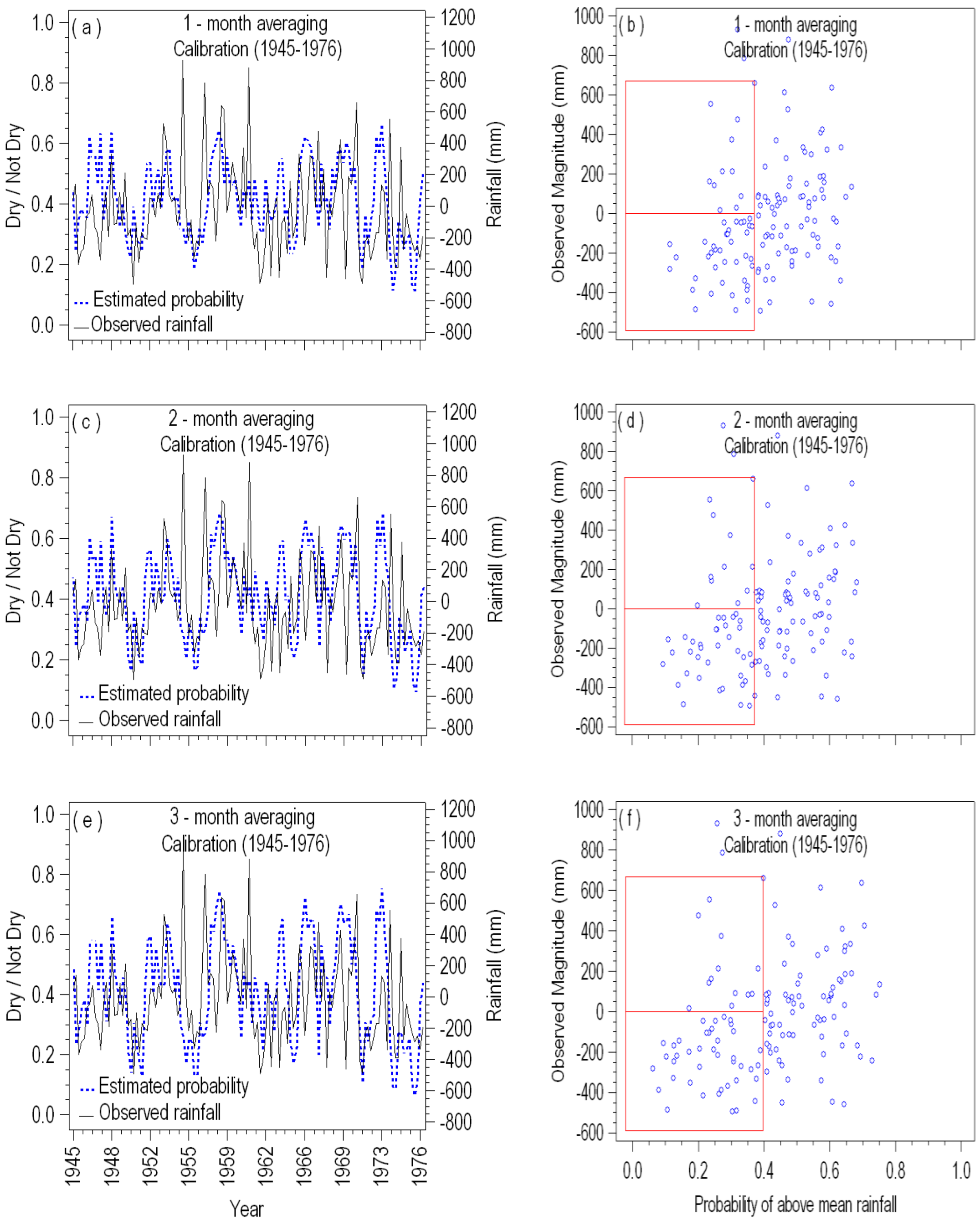
3.4.3 Logistic- forecast analysis

Since the main test of the prediction method is the validation stage we will focus only on the validation results. The time series plots of the 3-months residual sum as the predictand and previous NINO4 values averaged at 1 to 3 months (Figures 3.10a, c, e) show the logistic regression method to some extend tries to follow the trend of the rainfall however the method is tasked only to predict above mean rainfall or below mean rainfall. An obvious example from the validation time series is the 1999 drought, where the model made a correct prediction of some parts of the event.

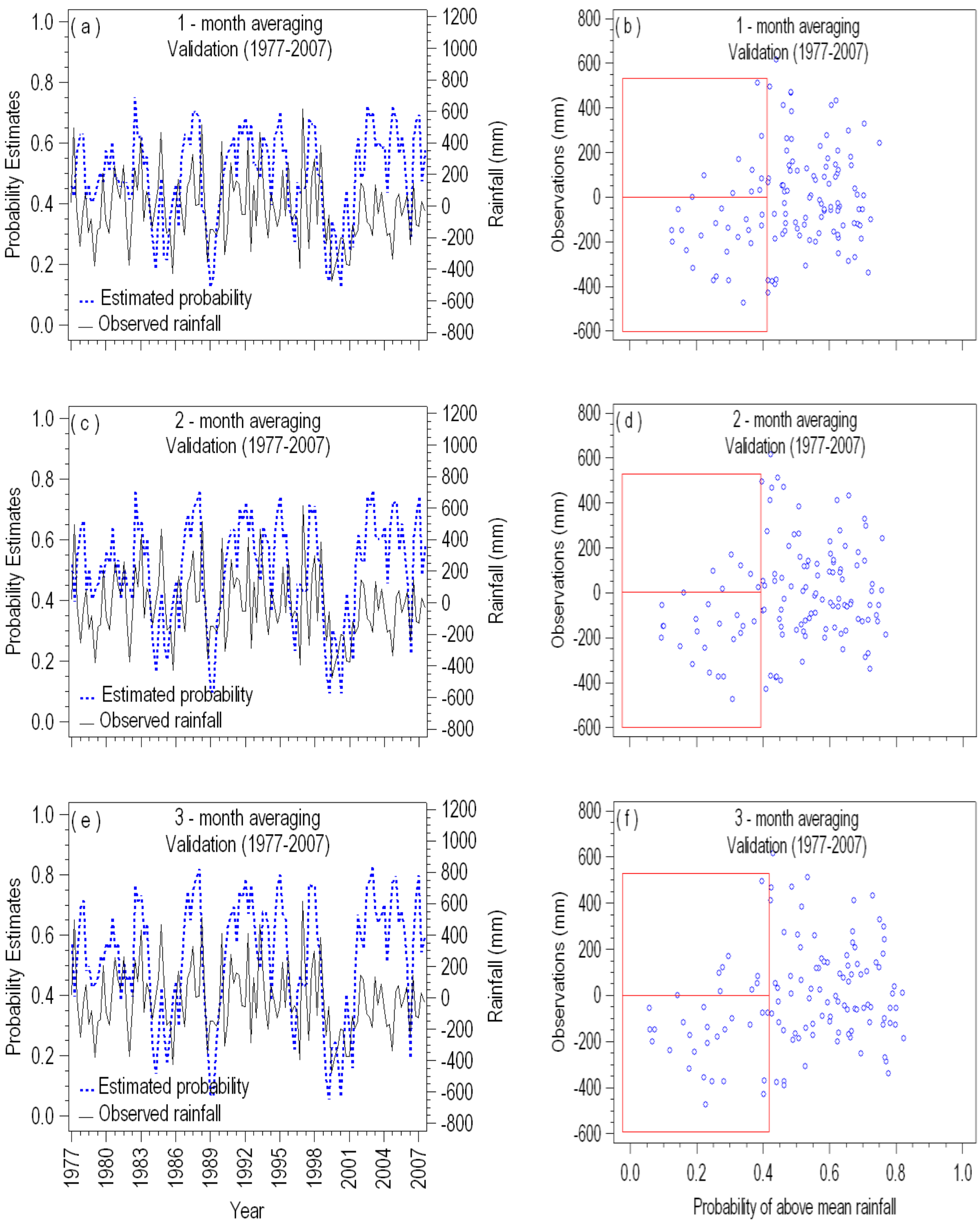
One obvious observation of the time series predictions plots is that all the plots are almost identical. Thus it is hard to distinguish between the different averaging periods, even up to the 6-months averaging period, not shown.

There are some obvious periods where logistic regression forecasting is definitely issuing the wrong forecast for the sign of the rainfall. For example the periods 1978 to about 1981 and 2002 to 2005 in Figures 3.10a,c,e. During these time periods, Funafuti is actually in a wet period as the rainfall residuals are above the mean but the method is forecasting dry. So overall the method is of little use for forecasting above average rainfall and encouraging for below average rainfall.

The scatter diagrams of the validation results (Figures 3.10b,d,f) show that predictability of below mean rainfall may seem possible. This is because from less than 0.4 of the probability of above mean rainfall, a dry forecast is for most of the time will be correct since very few of the actual observed rainfalls are above the mean rainfall. The few observations of above the mean rainfall have been marked with the two rectangles.



Figures 3.9 (a) – (f): Time series and scatter diagrams of calibration results of logistic regression 1-3 month averaging periods of NINO4 (1945-1976).



Figures 3.10 (a) – (f): Time series and scatter diagrams of validation results of logistic regression 1-3 month averaging period of NINO4 (1977-2007).

3.5 Summary

The purpose of the chapter is to attempt find a formal predictive scheme to forecast months of low rainfall in Funafuti. The methods investigated in this chapter are artificial neural network, all-possible-subset regression and logistic regression. All these three methods were shown from the analysis results that they cannot forecast the magnitude of the rainfall in Funafuti.

Artificial neural network failed to capture the relationships between the variables during the training period and hence the failure of the model to forecast rainfall is clearly shown from the validation results having negative fit values and prediction outputs were almost constant throughout the whole time. Hence the prediction outputs are very different from the observations and therefore the long term mean would be a better forecaster of rainfall than ANN.

The all subset regression method failed all the validation predictions as given from the negative fit values. This means that the long term mean does better to forecast rainfall than the ASR. However for the subset of dry periods there is some degree of predictability as shown in the scatter diagrams Figures 3.4a, b, 3.5b, d, f, 3.6b, d, f, 3.7b, d, f, 3.8b, d, f.

Similarly the logistic regression often gives frequent incorrect predictions of the sign of the rainfall when the probability of above average rainfall is greater than 0.4. However, for lower probability values there is some degree of predictability of below mean rainfalls, which indicates the overall weak association (Figures 10b, d, f) may be a little misleading. Of the various independent variables identified, NINO4 values appear most useful for detecting future below average rainfalls. This is expanded in the next chapter, in the format of a scientific paper with focus on a simple graphical means of using just lag-1 and lag-2 NINO4 values to identify conditional predictable fields of rainfall.

Chapter 4

NINO4 indices in a simple graphical technique for conditional long range forecasting of low rainfall periods in Tuvalu

4.1 Introduction

The scattered atolls of the small island nation of Tuvalu are located in the region 5^{o}S to 11^{o}S and 176^{o}E to 180^{o}E in the central southwest Pacific Ocean. Climatically, the islands lie between the Intertropical Convergence Zone and the South Pacific Convergence Zone, and are at the edge of the Equatorial Doldrums Belt (Thompson, 1987). These large-scale features induce different characteristics on the local wind field throughout the year (Wyrtki and Meyers, 1975).

The islands are hot and humid and convective cumuliform clouds are common. Temperature are near-constant throughout the year but there is a significant seasonal variability in precipitation, with a May to October dry season and a November to April wet season (Figure 4.1). There is also an associated seasonality of surface winds. Easterly trade winds prevail except in the wet season when winds blow from the west or north. Tuvalu often experiences droughts because of its location near the Pacific equatorial dry zone. The development of some ability to forecast future low rainfall periods would therefore be advantageous because rain is the only source of fresh water to the local population.

The Southern Oscillation Index (SOI) provides some basis for rainfall forecasting in Tuvalu (Thompson, 1987), but we report here a better alternative for future below-average rainfall forecasting based on precursor NINO4 temperatures. On the basis of the long rainfall record from the Funafuti Atoll gauge, the method uses a simple empirical approach to assign high probabilities for below-average rainfalls in coming months. The probability assignment is conditional upon precursor NINO4 sea surface temperatures being within a predictable field defined by a subjective linear partition. Keeping in mind the need for understanding of any forecasting procedure, this simple approach seems well suited for local conditions because forecasting requires only reference to diagrams and no external information is required other than NINO4 temperature values.

While the forecasting approach adopted is empirical, it is recognised that the causes of Tuvalu dry periods are related to such factors as the association of precipitation with migration of atmospheric convergence zones, the strength of the Southern Oscillation, and ocean heat content (Flohn, 1967; Wyrtki and Meyers, 1975; Alory and Delcroix, 1999; Thompson, 1987; Ueyama and Deser, 2008; Wyrtki and Meyers, 1975; Amador et al., 2006; Folland et al., 2002; Basher and Zheng 1998; Ruiz et al., 2006).

Similarly, we recognise that formal forecasting techniques have produced useful results in the past. For example, a neural network model was used to forecast droughts in the Kansabati River Basin in West Bengal in India (Mishra and Desai, 2006) and logistic regression models were used to forecast above or below average winter precipitation in the southern and central United States (Kurtzman and Scanlon, 2007). However, we found that a preliminary application of both multiple linear regression and neural networks to be not very helpful for anticipating Tuvalu dry periods, although the neural networks fared slightly better. The empirical approach adopted here therefore seems justified, but this does not preclude more sophisticated methods being utilised at some later date.

4.2 Forecasting Approach

The method was developed with respect to the 1945-2007 record of the rain gauge on Funafuti Atoll, which is the main population centre (Figure 4.2). The rainfall data was first converted to monthly values with seasonal effects removed by subtracting the respective monthly means. A corresponding NINO4 time series was constructed as monthly averages of daily values. The lag-1 and lag-2 NINO4 monthly values were used to construct simple data plots to serve as the basis of forecasts when conditions permitted. A similar approach was applied for time scales comprised of 2, 3, 4 ...12 months time scales. The time intervals here are non-overlapping. For example, 12 month rainfall values are always with reference to a January start time.

The graphical method is illustrated with reference to Figure 4.3(a). The lag-2 and lag-1 NINO4 monthly values are plotted on the x- and y axes respectively and whether the current month's (lag-0) rainfall is above or below it's long term average is indicated by colour coding. The high r^2 value of 0.85 in this case simply reflects the high degree of serial correlation of NINO4 values at this time scale. The interesting feature of this plot is that it is possible to bifurcate the scatter of points using a subjective linear boundary such that the left field contains a high 68% of points representing below-average monthly rainfall. However, the proportion of all the data points falling in the left field is only 0.38.

Summarising, *s* gives the percentage of points in the left field less than mean rainfall, and *q* gives the proportion of all the data points in the left field, and the linear function is the equation of the subjective partitioning line The value of *p* indicates the significance level as obtained by randomisation testing through a large number of random swapping of the data points and finding the proportion of *s* values equal to or exceeding the original percentage. In fact this test is somewhat compromised by the serial correlation of the NINO4 values, but it is encouraging that low p values are still maintained for low serial correlation at larger time units (Figure 4.4), with only the 10-month time units indicating non-significance at the 0.05 level.

The partitioning to create a predictable field for low rainfalls appears to require both lag-2 and lag-1 NINO4 values up to time intervals of four months. Only the lag-1 values have value for prediction for greater time intervals (Figure 4.4).

With reference to a given time interval, the prediction method is simply obtaining the lag-1 NINO4 value (and also lag-2 for shorter time intervals), and then checking whether that defines a location within the predictability field. If so, then a forecast is made for below-average rainfall with the s value being interpreted as probability of below-average rainfall actually occurring.

Conditional on falling within the predictability field, some of the s values involved are surprisingly high. The best is for 6-month time intervals with a success probability of 0.89 based on the past record. The negative aspect is that many periods of below-average rainfall occur in the unpredictable field and therefore cannot be forecast by this approach. For example, for 12-month time intervals (Figure 4.4f) it is only likely to be possible 30% of the time to actually make forecast at all of a coming below-average rainfall year. The method cannot therefore be described as a general forecasting method for below-average rainfalls. However, forecasts can be given with some confidence when the predictability field applies.

A below-average rainfall forecast for an given n-month future period need not imply that all the component months are also below their respective averages. However, there appears to be a bias toward individual months in multi-month forecasts having less than average rainfall. This is illustrated in Figure 4.5 where the frequency histogram of monthly rainfalls is skewed toward below average rainfalls for 2-month and 3-month hindcasts.

The conditional prediction approach should be applicable in future years in Tuvalu because the approach appears to have a degree of robustness against climatic variation. For example, there appears to be a change in the rainfall regime from 1976 as seen in a decline in the standard deviations on the monthly rainfalls, even though the monthly means remain unchanged (Figure 4.6 a, b). Applying the hindcast approach independently to these two time series shows very little difference in predictability between the earlier and later periods (Figure 4.7).

The success of the conditional forecasting method derives from persistence of cooler NINO4 temperatures which tend to be associated with lower rainfalls at Funafuti. The persistence is evident in Figure 4.8, where 70% of the NINO4 runs below 26ºC are of 3 months or longer duration. For this reason there tends to be a strong clustering of successful hindcasts of below-average rainfalls over shorter time intervals, illustrated in Figure 4.9 for the particular case of forecasting two-month time periods. A likely practical application of the method is therefore likely to be within drought periods, as an indication of whether the drought is likely to persist.

We applied the graphical approach to other combinations of variables also, but did not find predictability fields as well defined as for NINO4. This is presumably due to the dominating effect of the proximity of the NINO4 region to Tuvalu. One of the combinations investigated is shown in Figure 4.10 which plots current rainfall (above or below average) as a function of current SOI and NINO4 value for selected time intervals. There is some suggestion of lower rainfalls for lower NINO4 temperatures and higher SOI values but the effect is not so well developed as for lagged NINO4 axes.

The lack of success of standard statistical approaches mentioned earlier appears to be a consequence of the inconsistent degree of causality in the independent variables. That is, there is a breakdown in the correlation of rainfall and the various independent variables over the range of the variables. Even within the prediction subset we were unable to establish a quantitative linkage between the magitude of the NINO4 lower temperatures and rainfall as deviations below the respective long-term means. More sophisticated statistical methods might be applied in future to make allowances for the inconsistent nature of the causal linkages with rainfall, but the simple graphical approach utilised here gives a working method in the meantime.

4.3 Conclusion

NINO4 lower temperatures appear to be associated with lower than average rainfalls in Tuvalu, and persistence of lower NINO4 temperatures allow forecasting of lower rainfall periods to a high degree of accuracy as multi-month averages, after prior correction for seasonal variation of monthly means. However, the forecasting is conditional on low precursor NINO4 temperatures which means a significant number of dry periods cannot be predicted. Further work should focus on these dry periods so the conditionality of the forecasts is not so restrictive.

4.4 Figures

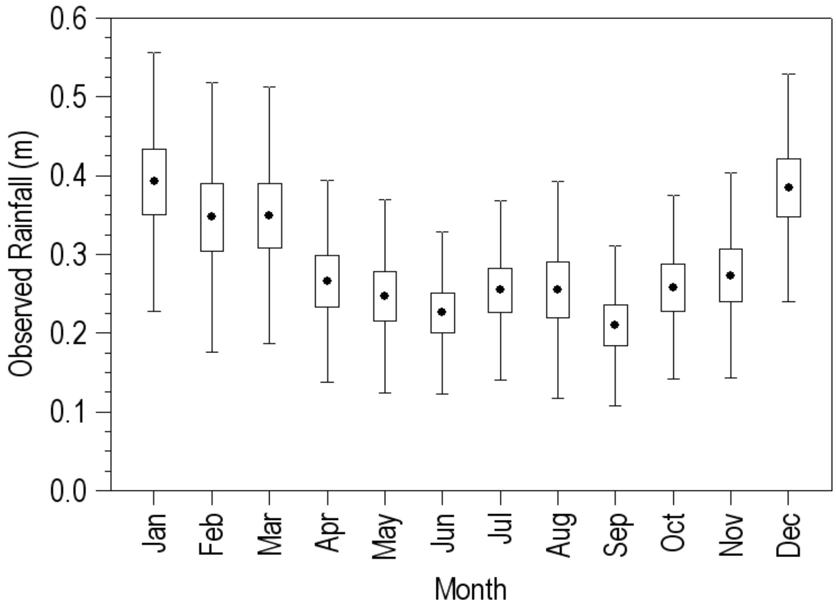


Figure 4.1 – Monthly rainfall at Funafuti 1945-2007. Solid points denote mean, boxes indicate ±2 standard errors (box), and line range is ±1 standard deviation.

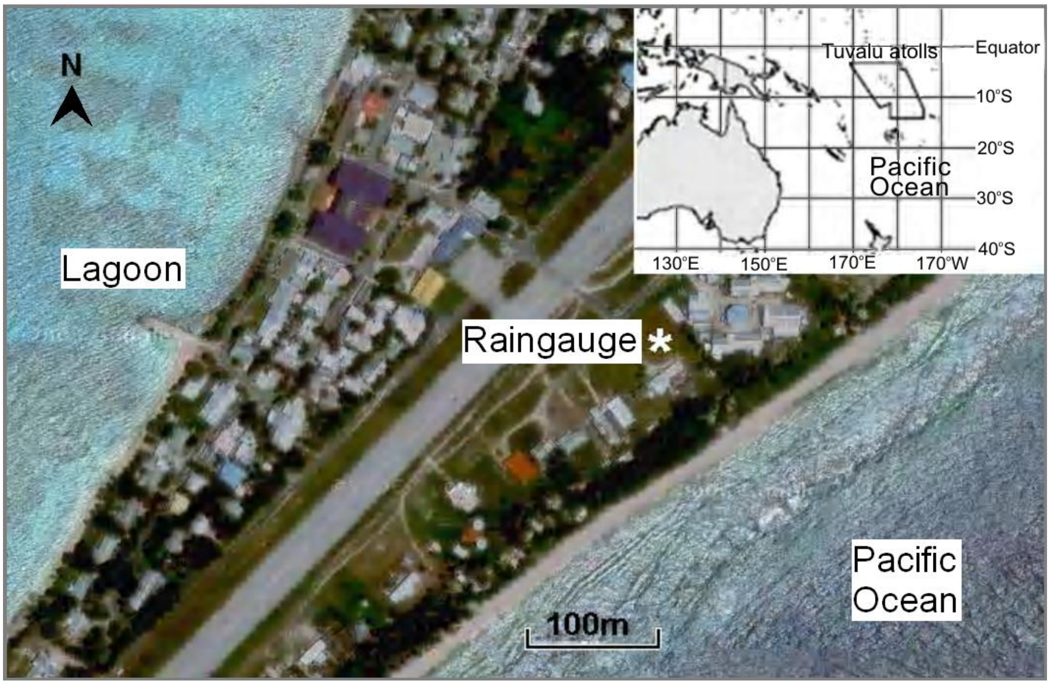


Figure 4.2 – Raingauge site on Funafuti Atoll, Tuvalu

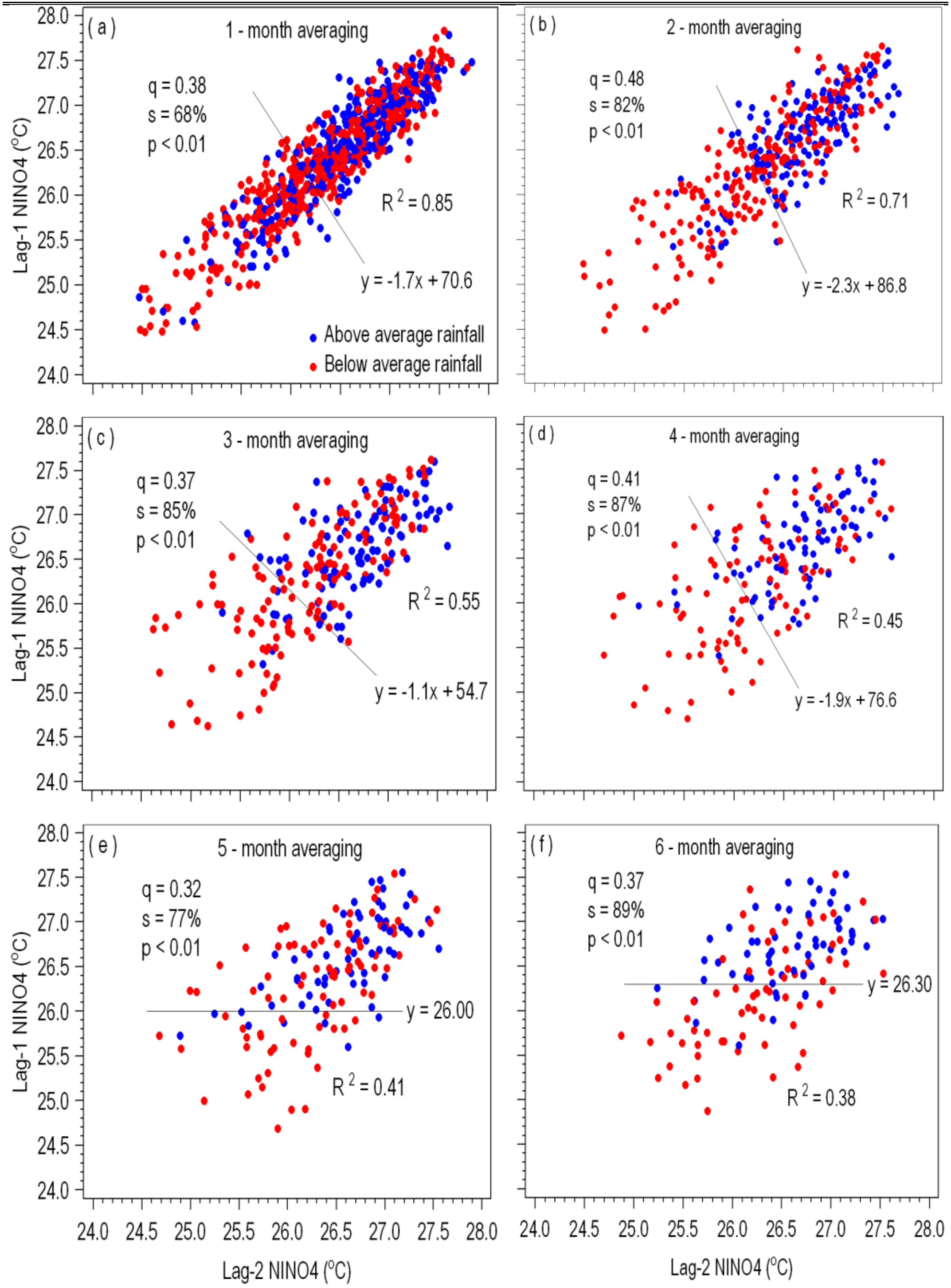


Figure 4.3 – Scatter plots showing above- or below-average rainfall for current monthly time intervals (various n-month periods shown), illustrating predictability fields (to left or below line) based on lag-1 and lag-2 NINO4 values, 1945-2007. See text for further description.

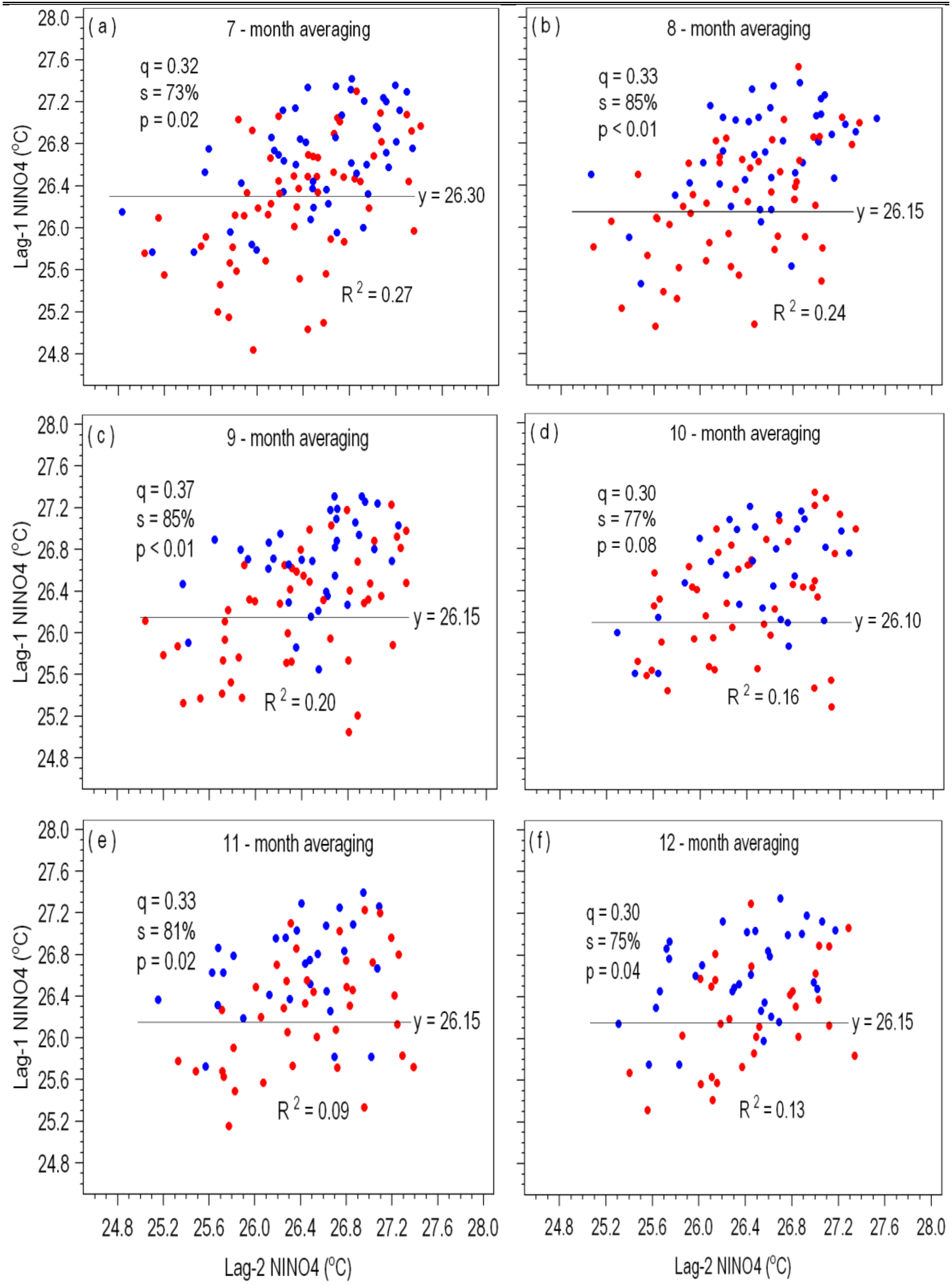


Figure 4.4 – Scatter plots as for Fig. 3, illustrating the lack of predictability contribution for lag-2 NINO4 values for longer multi-month intervals.

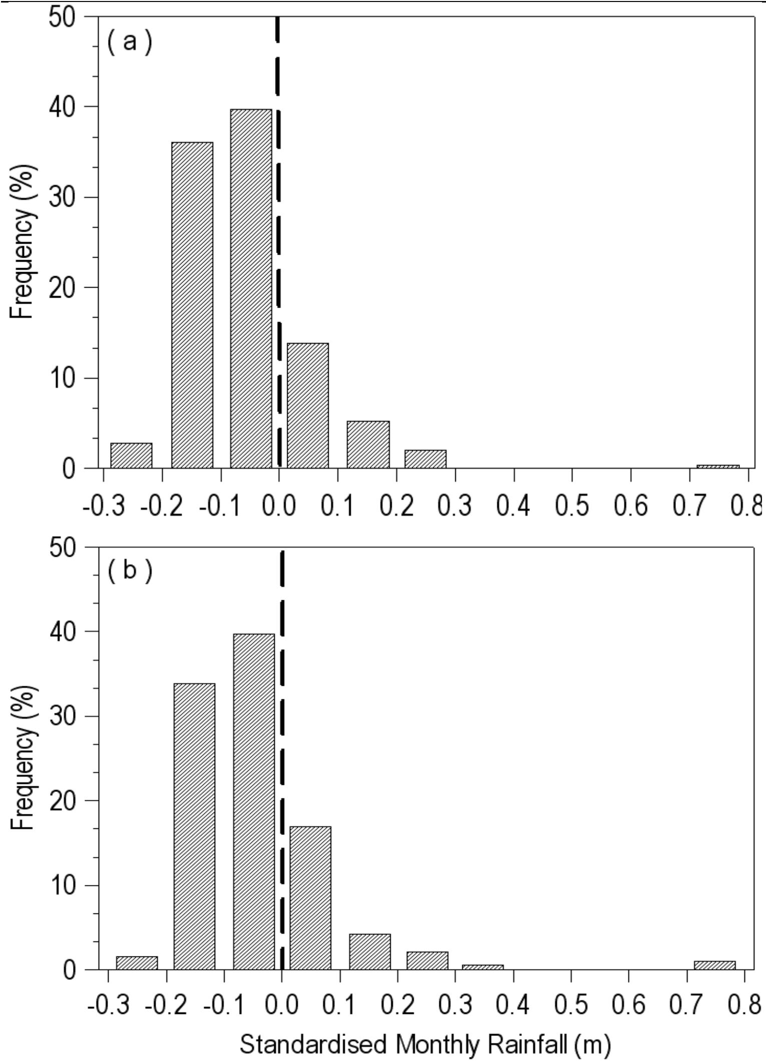


Figure 4.5 – Histogram illustrating percent frequency distribution of hindcast results for each month’s actual rainfall within the (a) 2-month hindcast and (b) 3-month hindcast periods.

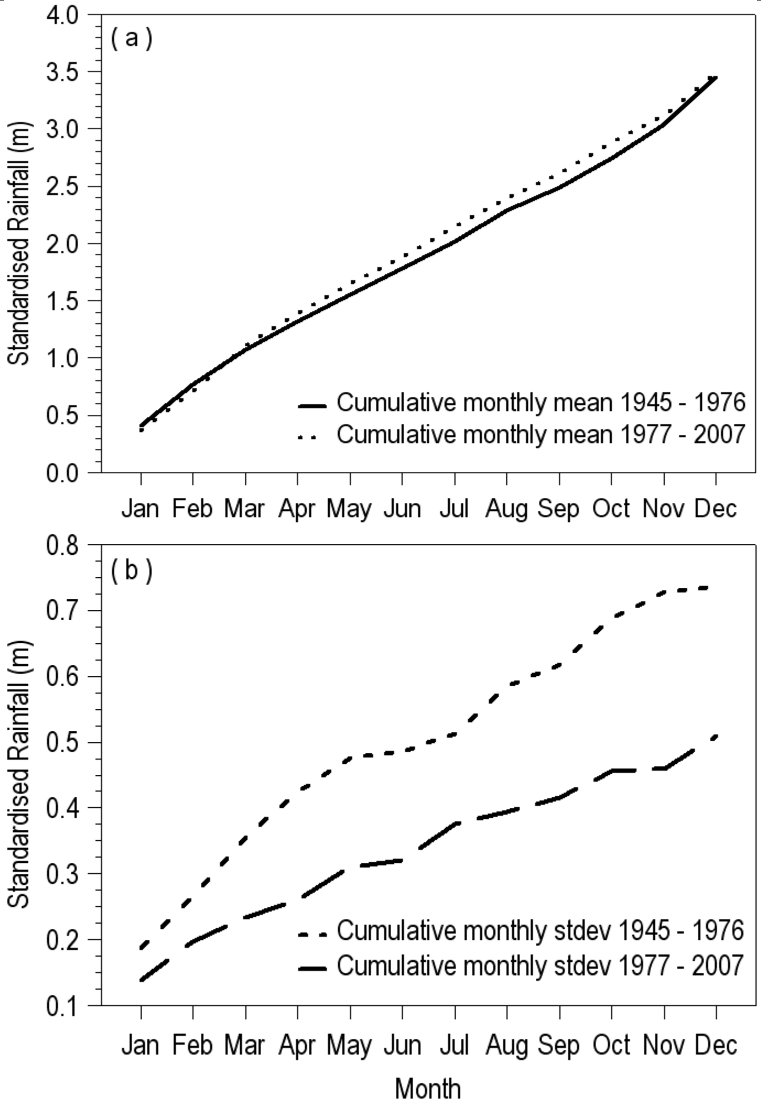


Figure 4.6 – Cumulative rainfall by month for years 1945-1976 and 1977-2007 by mean (a) and standard deviation (b).

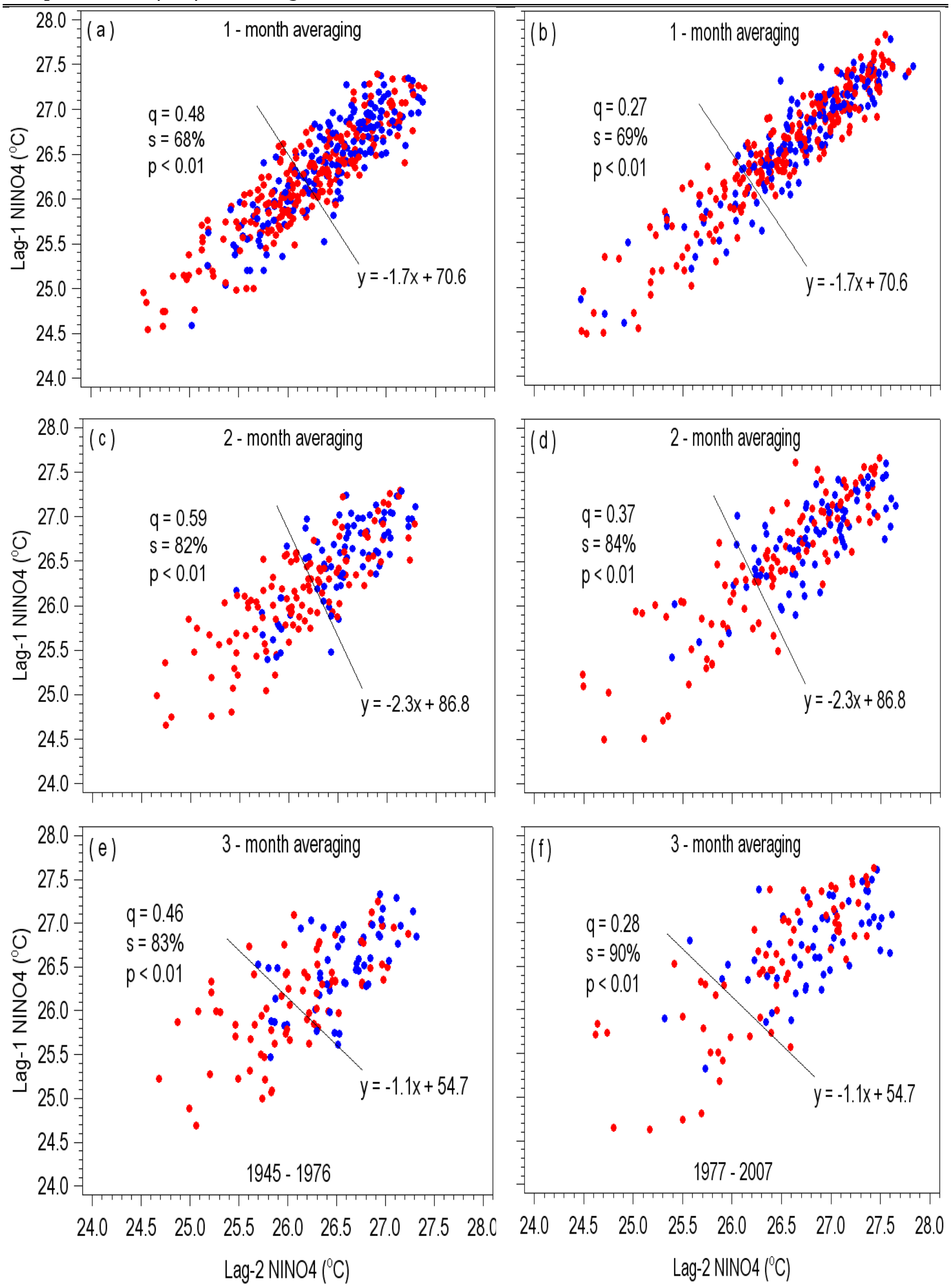


Figure 4.7 – Scatter plots showing current month status of above- or below-average rainfall with predictability fields (left of indicated line) as a function of lag-1 and lag-2 NINO4 values for various n-month periods, for 1945-1976 (left) and 1977-2007 right

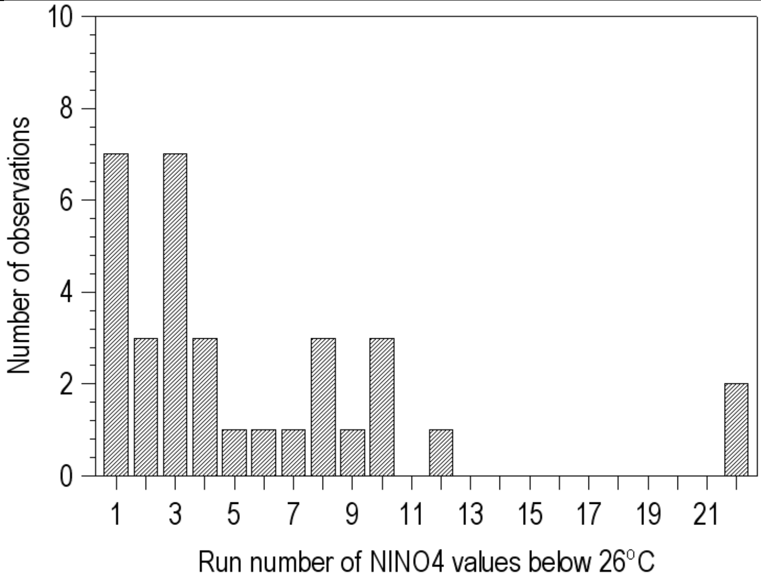


Figure 4.8 – Histogram showing observed frequency distribution of run number of monthly NINO4 sea surface temperatures below 26^{o}C, 1945-2007.

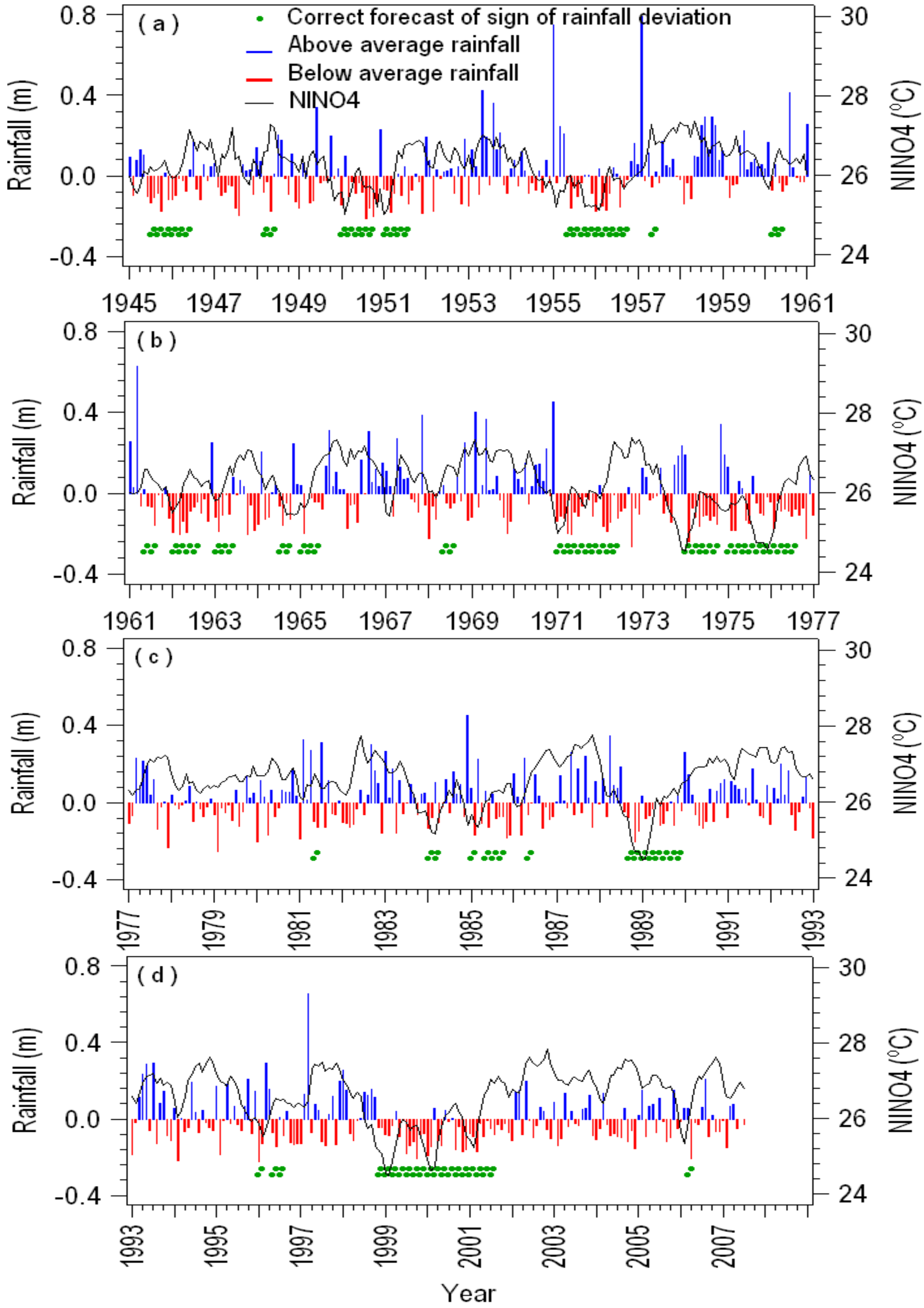


Figure 4.9 – Time series showing time locations of the correct 2-month hindcasts (green dots). NINO4 and plotted rainfalls are monthly values of below-average rainfall, 1945-2007.

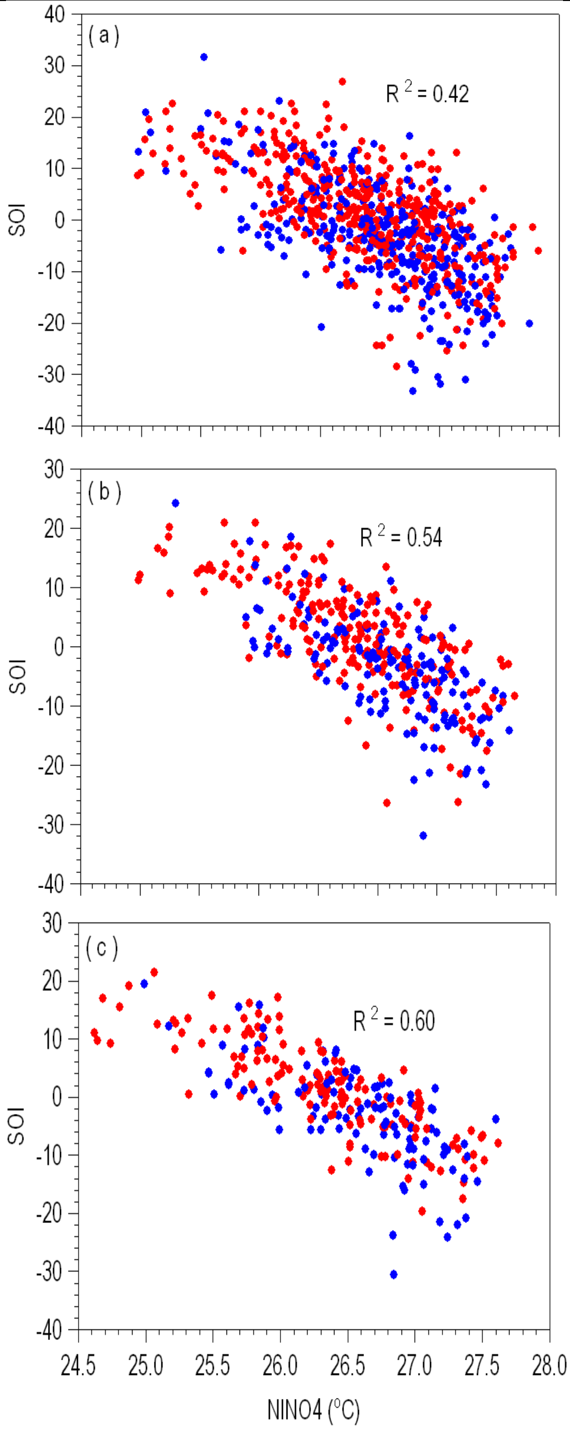


Figure 4.10 – Scatter diagrams of SOI, NINO4 and above- or below-average rainfall 1945-2007 with respect to (a) 1-month, (b) 2-month and (c) 3-month time units. All variables are with respect to the current (lag-0) time interval. The current SOI and NINO4 values have a strong negative correlation for all three time periods.

4.5 References

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4.6 Serial correlation of NINO4 sea surface temperature as a predictor of low rainfalls

The previous sections in this chapter were in the form of a paper format for publication. The remainder of this chapter presents some further material on the same theme.

Persistence is described in this thesis as serial correlation. That is, the sea surface temperature (SST) e.g. NINO4 SST are likely to be maintained over several seasons into the future. This is because the ocean surface temperature varies slowly relative to the air. This means that the current observed NINO4 SSTs are likely to persist as above or below average for some time.

Using the data record 1945 to 2007 the predictand, residual rainfalls and the predictors, previous values of NINO4 for 1 month to 12 months are used on scatter graphs represented as lag-1 NINO4 and lag-0 rainfalls for each time average.

We have learnt from Section 2.6 that the existence of the two squares with the upper square having very few points and the lower square with more points indicates that low rainfalls to a certain degree can be forecast.

Therefore if there is persistence in the cooler NINO4 SSTs then the two squares pattern should remain throughout the entire averaging periods. Evidently the scatter diagrams (Figures 4.1a-f and Figures 4.2a-f) confirm that from a short lag of 1 month to a long lag of 1 year the empty square is preserved. Therefore we conclude that lag autocorrelation of NINO4 SSTs is a practical predictor of low rainfalls in Funafuti, conditional on the NINO4 precursor conditions allowing a low-rainfall forecast to be made.

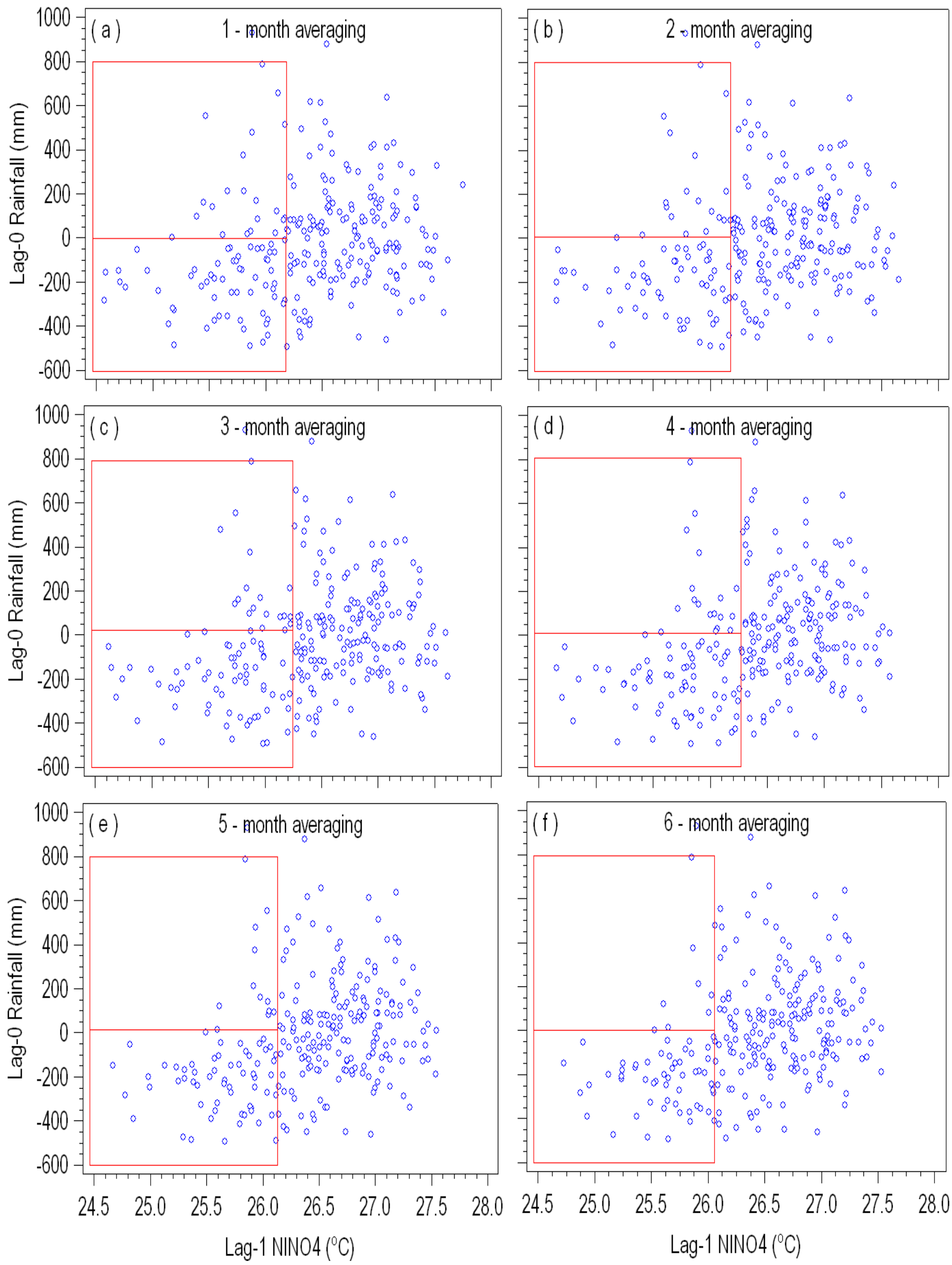

Figure 4.11 (a) – (f): Scatter diagrams showing the relationship between current 3-month residual rainfall and previous NINO4 for 1-month to 6-month averaging periods (1945-2007).

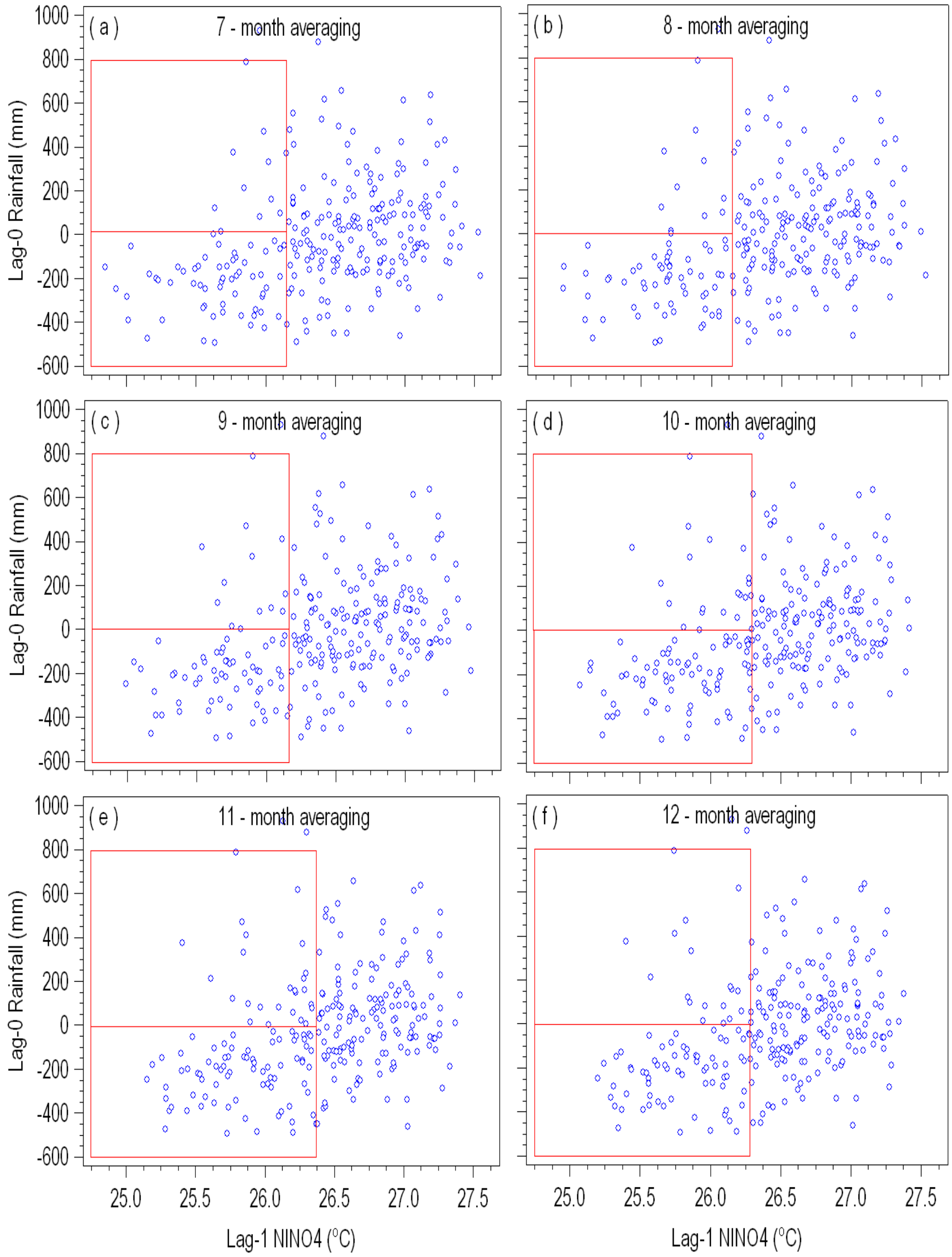

Figure 4.12 (a) – (f): Scatter diagrams showing the relationship between current 3-month residual rainfall and previous NINO4 for 7-month to 12-month averaging periods (1945-2007).

Chapter 5

Conclusions and future work

5.1 Summary of results

A simple forecasting scheme has been developed to predict multi-months of below average rainfall in Funafuti with a high probability of a correct dry forecast conditional on the precursor NINO4 cooler temperatures. Based on monthly rainfall for the period 1945-2007 from the Funafuti raingauge, the graphical approach uses lag-1 and lag-2 NINO4 temperatures and standardised monthly rainfalls to enable identification of a predictable subset of low rainfalls from time periods of 1-month to 1-year.

However, as has been stated, the method will most likely fail if it was applied to conditions outside of this predictable field. But when conditions are within the predictable subset then a low rainfall forecast has a probability of as high as 80 percent that the dry forecast being issued is true. This dry forecast is possible over a whole range of time periods.

The persistence of the predictable conditions seems to hold when the observed values of the NINO4 sea surface temperatures are below 26.0^{o}C.

A previous study on the rainfall (refer to section 1.7) of the Tuvalu islands (Thompson, 1987) have shown that there is a stronger correlation of the SOI with the northern islands rainfall than the southern islands rainfall. Since the forecasting scheme has shown promising results for the rainfall of Funafuti, this could mean that the scheme will work even better when applied to the northern group.

The other predictive methods investigated in this study were artificial neural networks, all-subset regression and logistic regression. Only logistic regression showed for some subsets some ability of forecasting a dry period.

Overall the adopted graphical method seems to at least have done no worse than these three methods. The simplicity of the adopted scheme and the ready availability of the NINO4 sea surface temperatures at no cost make the forecasting scheme a suitable and intuitive method for the Tuvalu islands.

One thing is common in these methods and including the adopted scheme is none have the ability to forecast the magnitude of rainfall.

However, as stated in the first paragraph the sign of the rainfall can be reliably forecast using the adopted forecasting approach. More importantly is that the approach has capability of issuing an advance warning that an existing drought would likely to continue.

5.2 Suggestions for further work

The conditional aspect of the forecasting scheme is a barrier to forecasting low rainfalls in Funafuti, therefore more research is needed to minimise this predictability barrier and try to widen the predictability conditions.

This could include investigation of other potential predictors not included in this study e.g.

1. Data on the heat content of the ocean area bounded by the NINO4 region. since Ocean heat has been shown to be successful in some studies dealing with the prediction of rainfall (e.g Ruiz et al., 2006) then it may worth exploring this data.

2. Data on wind measurements and the sea surface temperatures at proximity to Tuvalu e.g the sea temperatures of coastal area. These are available from tide gauge recordings.
3. Upper air data from the Funafuti monitoring site. These data include wind, temperature, humidity and pressure. The data may assist, in setting up a more realistic coupled climate system over the Tuvalu islands.
4. Satellite data of convective cloud cover if can be sourced may help as convection is probably the main process of rain formation in the Tuvalu atolls.

Although these other methods; logistic regression and neural networks may have not worked that well, it may be possible that further refinement may make these more sophisticated methods more applicable.

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