FIJI

Protecting Human Health from Climate Change

Working Paper - Climate-Sensitive Infectious Diseases in Fiji

2011 summary report from Fiji's Piloting Climate Change Adaptation to Protect Human Health (PCCAPHH) project

Contents

This report is a result of collaboration among members of the Technical Working Group of the Piloting Climate Change Adaptation to Protect Human Health project in Fiji. This project is funded by the GEF and implemented jointly by the WHO, UNDP and the Fiji Ministry of Health.

List of **Abbreviations**

BoS	Bureau of Statistics
CSD	Climate-Sensitive Disease
ENSO	El Niño-Southern Oscillation
FLIS	Fiji Lands Information Service
FMS	Fiji Meteorological Service
GEF	Global Environment Facility
GIS	Geographic Information Systems
HIU	Health Information Unit
MoH	Ministry of Health
NCCDC	National Centre for Communicable Disease Control
NNDSS	National Notifiable Disease Surveillance System
PCCAPHH	Piloting Climate Change Adaptations to Protect Human Health
PCCSP	Pacific Climate Change Science Program
SPCZ	South Pacific Convergence Zone
UNDP	United Nations Development Programme
WHO	World Health Organization

Message from the Minister of Health

It gives me great pleasure to provide my thoughts on this report given the increasing visibility of climate change impacts on human health globally, but the dearth of required remedial action on the ground.

There is abundant anecdotal information within the Ministry of Health of the climate-sensitivity of various communicable diseases in Fiji. With the analysis in this report, the Ministry of Health is now in a better position to make informed, effective decisions about health interventions in relation to threats posed by climate change. I understand that more work remains to be done, but this is an excellent start.

Information will spur action and long-term policy change towards increased resilience of vulnerable populations to climate-sensitive communicable diseases.

I call upon all stakeholders to take note of this report with the wider view of strengthening human health and national resilience against climate change.

Dr. Neil Sharma
Minister for Health

Foreword

Fiji is no stranger to climate change and it is increasingly becoming clear that climate and weather, in addition to other factors, influence the incidence of communicable and non-communicable diseases in Fiji. Communicable diseases like dengue and typhoid fever, leptospirosis and diarrhoeal illnesses and non-communicable diseases like diabetes are major public health concerns in Fiji.

Therefore I have great pleasure in presenting this report, which is the first to outline and establish the climate-sensitivity of the above-named communicable diseases for various locations around the country.

For the Ministry of Health, this report establishes a baseline of climate-sensitive infectious diseases that provides a comprehensive platform on which to strengthen health information systems and implement health adaptation in vulnerable communities.

For climate change and development stakeholders in Fiji, including donors and adaptation practitioners, this report cements the necessity to engage actively with the health sector to reduce Fiji's overall vulnerability to climate change. It is a useful planning tool.

I congratulate the members of the Piloting Climate Change Adaptation to Protect Human Health (PCCAPHH) project Technical Working Group on the research and production of this report and I look forward to more positive outcomes from the PCCAPHH project.

Dr. Eloni Tora
Permanent Secretary for Health
March 2012

Executive Summary

Human health is susceptible to climate change via multiple, complex pathways. It is estimated that, each year, approximately 150 000 deaths worldwide are attributable to the effects of climate change. These effects are disproportionately borne by vulnerable populations, both in terms of society (the very old and very young, those living in poverty and those with pre-existing medical conditions) and geography (certain countries and regions within countries).

In terms of both geographical and social factors, Pacific island countries are among those most vulnerable to the impacts of climate change, including the detrimental impacts on health. A small but growing body of research seeks to investigate the relationship between climate, climate change and "climate-sensitive diseases" (CSD's), in order that strategies can be put in place to avoid the most serious impacts of climate change on health, but much work remains to be done in this field. The analysis of climate and CSD's in Fiji that is being done as part of this project, as described in this report, will help to fill this knowledge gap.

Fiji is one of seven countries implementing a global project entitled 'Piloting Climate Change Adaptations to Protect Human Health' (PCCAPHH). This project, funded by the Global Environment Facility, aims to enhance the capacity of Fiji's health sector to anticipate and respond effectively to CSD's.

A key outcome of this project is to develop climate-based disease early warning systems to predict outbreaks of climate-sensitive communicable diseases like dengue and typhoid fever, leptospirosis and diarrhoeal illnesses. As such, the analysis presented in this report serves to establish a baseline on the status of, and inform policy development on, CSDs in Fiji.

The report begins by outlining historical incidence trends of the four priority CSD's. The analysis methodologies described in subsequent chapters include space-time analysis, time-series and Poisson regression. To date these analyses have been performed for several medical subdivisions in which the burden of CSD's appears relatively high – Ba, Bua, Lautoka and Suva.

Results from the analysis and modeling processes so far suggest that some significant relationships do exist between one or more of the four priority CSD's in most of the locations studied so far. Examples of these relationships which appear to suggest the possibility of climate-based early warning systems include dengue fever in the Bua, Lautoka and Suva subdivisions; leptospirosis in the Bua subdivision and typhoid fever in the Ba subdivision.

Challenges faced in the analysis include the lack of historical disaggregated population data at the sub-divisional level, weaknesses within the Notifiable Disease Database, gaps in both health and climate data and the scarcity of human resources within the Ministry of Health.

The PCCAPHH Fiji project is implemented jointly by the World Health Organization Division of Pacific Technical Support (Suva, Fiji), the United Nations Development Programme and the Fiji Ministry of Health. Analysis for the purpose of this report was undertaken by PCCAPHH project staff, the Health Information Unit and the National Centre for Communicable Disease Control at the Ministry of Health and the Fiji Meteorological Service, under the guidance of the project's Scientific Consultant, A/Prof. Simon Hales.

1. Introduction

1.1 Background

Fiji is one of seven countries involved in a four-year global project to enhance the capacity of the health sector to respond effectively to climate-sensitive diseases (CSD's). This project, entitled "Piloting Climate Change Adaptation to Protect Human Health" (PCCAPHH hereafter) commenced in 2010 and is a partnership between the Fiji Ministry of Health (MoH), the World Health Organization (WHO) and the United Nations Development Programme, with funding from the Global Environment Facility (GEF). The priority CSD's for the Fiji project are dengue fever, diarrhoeal illnesses, leptospirosis and typhoid fever.

The PCCAPHH project seeks to achieve three key outcomes in Fiji:

Outcome 1: An early warning system provides reliable information on likely incidences of CSD's in pilot sites.

Outcome 2: Improved capacity of health sector institutions to respond to CSD's, based on early warning information provided.

Outcome 3: Health adaptation activities are piloted in areas of heightened health risks due to climate change.

The focus thus far in the project has been on Outcome 1. Specifically, the project has undertaken analysis of the "climate sensitivity" of the four priority CSD's at the national and sub-national levels (divisional, sub-divisional and medical area levels in some cases), with a view to developing early warning systems for pilot sites. The results of the analysis process thus far are presented in detail in this report. This research has been approved by the Fiji National Health Research Council and Fiji National Research Ethics Review Committee.

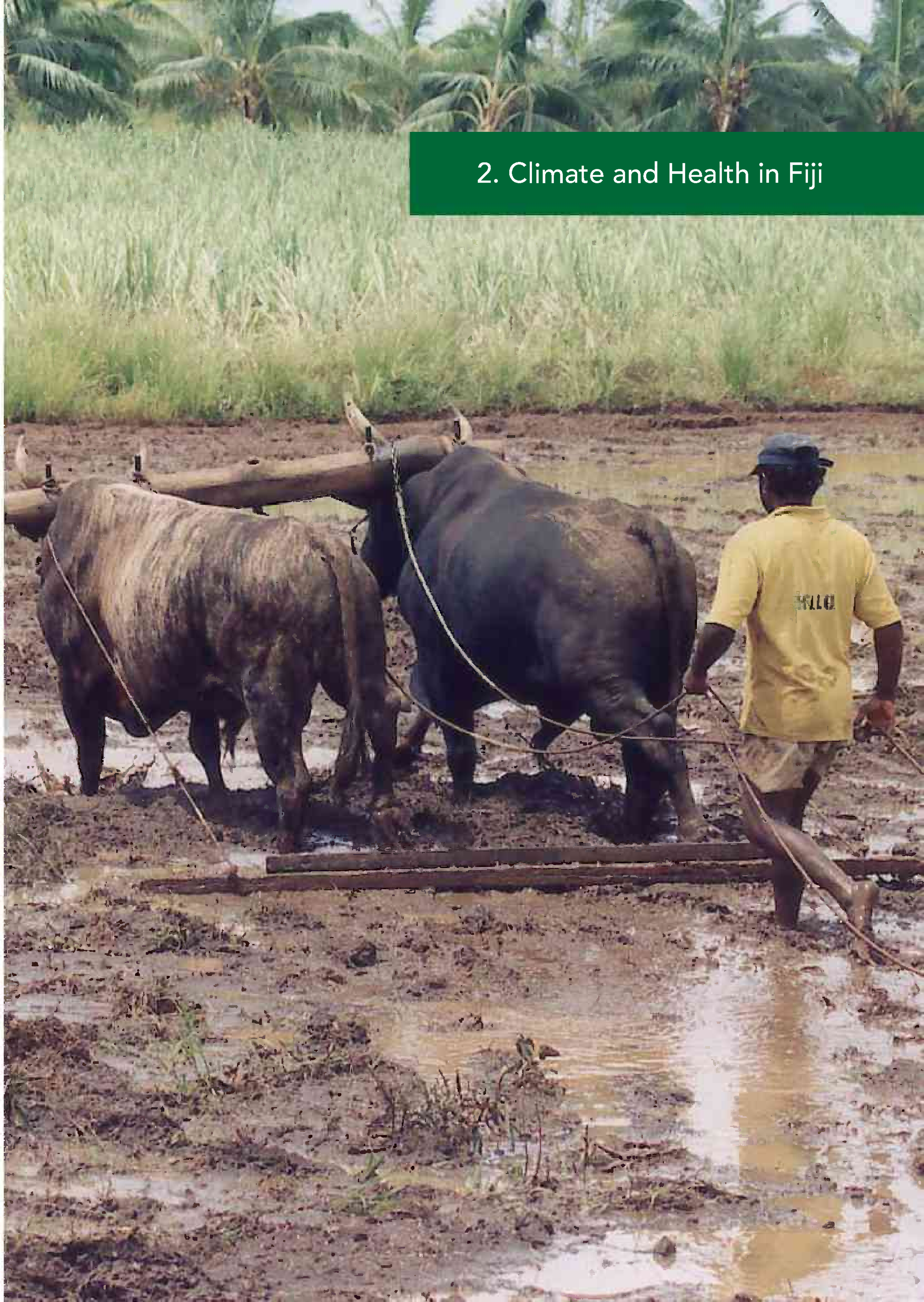
1.2 Scope of Report

This report is a result of collaboration between the Fiji Meteorological Service (FMS) and various units within the Ministry of Health, including the National Centre for Communicable Disease Control (NCCDC) and the Health Information Unit (HIU). It builds on the small amount of research that has previously been done investigating the environmental epidemiology of infectious diseases in Fiji. It also seeks to develop a baseline for the development of climate-based disease early warning systems that may be used in the future in Fiji. Finally, through the spatial analysis undertaken, this report illuminates specific geographical locations requiring priority environmental and climate change-related health adaptation interventions in Fiji.

In summary, upon reading this National Summary Report, readers will have a clear idea of the extent to which these four diseases are influenced by climatic variables like temperature, rainfall and humidity and some of the geographical locations in which this sensitivity is more pronounced. As such, this report is a critical resource to inform national policies to address climate-sensitive communicable diseases in Fiji.

1.3 Outline of Report

Chapter Two gives an overview of climate, climate change and CSD's in Fiji, including a summary of the historical burden of the four priority diseases. Chapter Three presents in detail the climate sensitivity analyses undertaken by members of the project's Technical Working Group. Chapter Four discusses the results of the analysis and presents recommendations on further research and early warning systems, as well as touching upon some potential policy considerations to address CSD's in Fiji.



2. Climate and Health in Fiji

2.1 Climate and Climate Change in Fiji

Fiji's climate is tropical, with two distinct seasons – a warm, wet season from November to April and a cooler, dry season from May to October. The seasonality and variation of Fiji's climate are strongly influenced by the El Niño-Southern Oscillation (ENSO) system and the South Pacific Convergence Zone (SPCZ). Tropical cyclones occur in and around Fiji; seventy cyclones passed within 400km of Suva between 1969 and 2010 (PCCSP, 2011).

Analysis of historical climate data for Fiji by the FMS shows that:

- mean temperatures are increasing at most locations around Fiji (see Figure 2.1); and
- ENSO characteristics are changing.

With respect to rainfall, the observed trends over Fiji suggest that there is no appreciable long term change in average annual rainfall, however, a weak positive linear trend in dry season rainfall and a weak negative trend in wet season rainfall has been observed.

The Pacific Climate Change Science Program (PCCSP), of which FMS is a collaborator, states that the key climate change vulnerabilities for Fiji include (PCCSP, 2011):

- increasing air and sea-surface temperatures;
- increasing intensity and frequency of days with extreme heat (Figure 2.2), extreme winds (Figure 2.3) and extreme rainfall;
- decrease in the frequency (but possibly increased intensity) of tropical cyclones;
- rising sea levels (Figure 2.4) and increasing ocean acidification.

Figure 2.1 Temperature Change in Fiji (source: FMS, 2011)

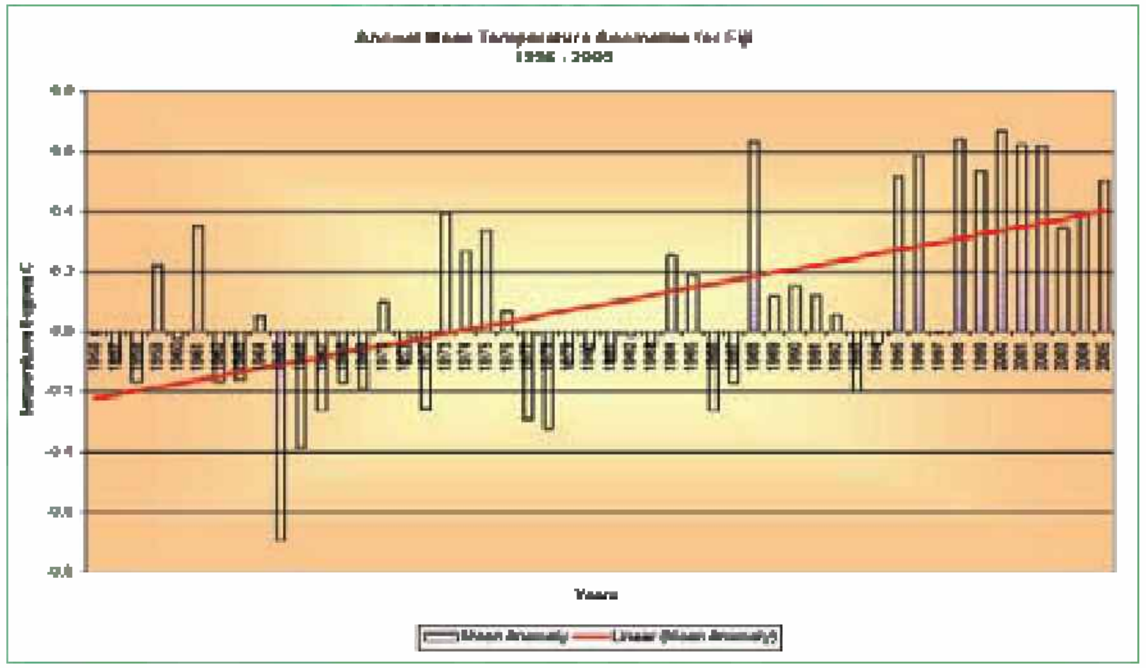


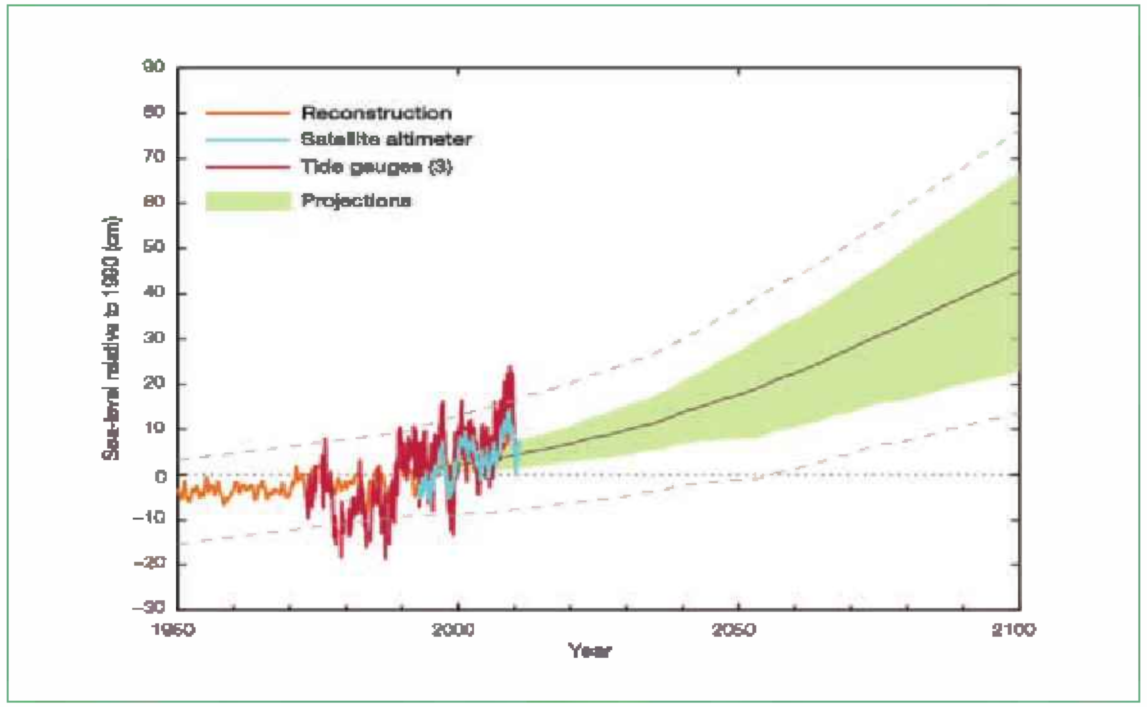
Figure 2.2 Predicted return periods (in years) for extreme high temperatures in Fiji (source: FMS, 2011)

	Observed	2025	2050	2075	2100
33°C	1.0	1.0	1.0	1.0	1.0
34°C	1.1	1.0	1.0	1.0	1.0
35°C	2.9	1.6	1.1	1.0	1.0
36°C	11.4	5.5	2.7	1.2	1.0
37°C	52.1	24.1	10.6	3.2	1.6
38°C	244.2	11.2	48.2	13.2	5.4

Figure 2.3 Predicted return periods (in years) for extreme winds (source: FMS, 2011)

	Observed	2025	2050	2075	2100
60Knots	2.7	2.4	2.3	2.1	2.0
80Knots	6.8	5.9	5.3	4.6	4.3
90Knots	11.3	9.7	8.4	7.2	6.6
100Knots	19.0	16.0	13.6	11.4	10.2
110knots	32.3	26.7	22.6	18.3	16.2
120Knots	55.2	44.8	36.6	29.5	25.8
140 Knots	94.6	75.3	60.4	47.8	41.5

Figure 2.4 Observed and projected sea-level rise near Fiji (source: PCCSP, 2011)



In the medium term, the PCCSP, drawing on a number of climate prediction models, states that: "The most likely projected change for Fiji centered around the year 2030 is for warmer weather and little change in rainfall, with annual mean temperature increases of 0.7°C and negligible (-1%) change in mean annual rainfall, which is represented by 69% of the models." (PCCSP, 2011)

2.2 Climate-sensitive diseases in Fiji

A rapidly growing body of evidence supports the fundamental premises that:

a) human health is susceptible to changes in climate and weather patterns via multiple, complex pathways (McMichael et al., 2004);

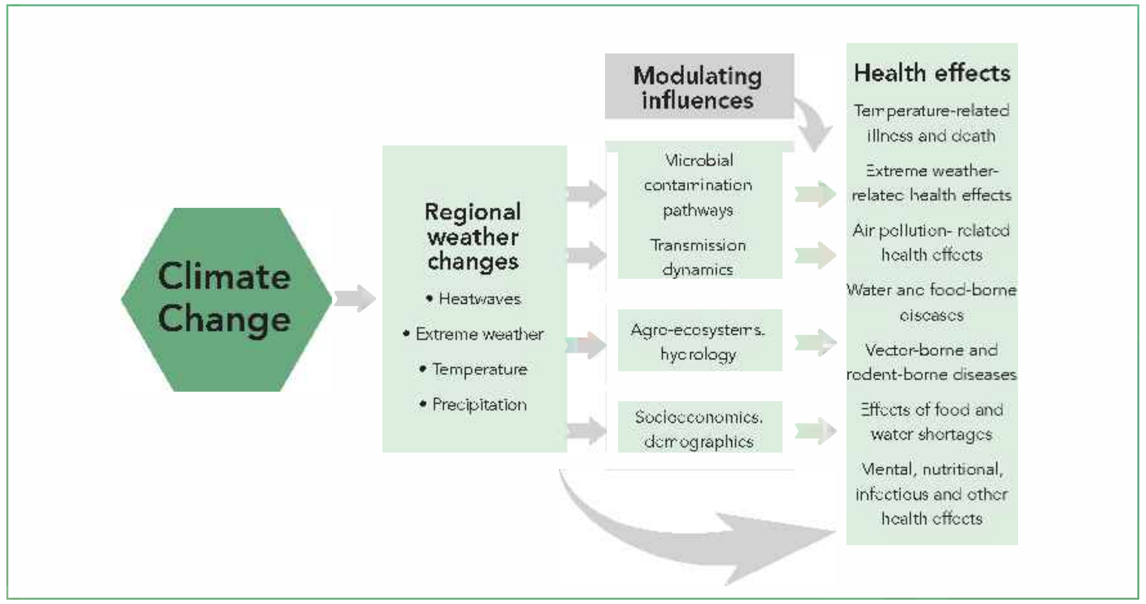
b) the global climate is undergoing unprecedented changes due to the effects of anthropogenic (ie. human-influenced) greenhouse gas emissions (McMichael, 2009, IPCC, 2007);

c) some of the effects of climate change on health are already significant and measurable; in the future, the most severe and widespread effects could be reduced or avoided by implementing effective climate change mitigation and adaptation policies (McMichael et al., 2006); and

d) the net impact of climate change on human health is likely to be detrimental, and the effects will be disproportionately borne by vulnerable populations, both in terms of geography (ie. certain countries and regions within countries) and society (ie. the poor, children, the elderly and those with pre-existing illnesses) (Sheffield et al., 2011; WHO, 2009).

Certain diseases and categories of disease are known to be particularly sensitive to variations in climate. These include food-, water- and vector-borne communicable diseases, cardiovascular and respiratory disease, renal disease, malnutrition, mental health and injuries and deaths due to trauma (Sheffield et al., 2011; McMichael, 2009). The pathways via which these health outcomes can be influenced by climate variability are complex, and include both direct and indirect effects. Some examples of these pathways are the influence of rainfall, humidity and temperature on mosquito abundance, viral replication and epidemics of dengue fever; deaths and injuries from extreme events; and drought causing crop failure, malnutrition, low birthweight, loss of livelihoods and depression. A simplified model of the pathways between climate change and health is presented in Figure 2.5 below.

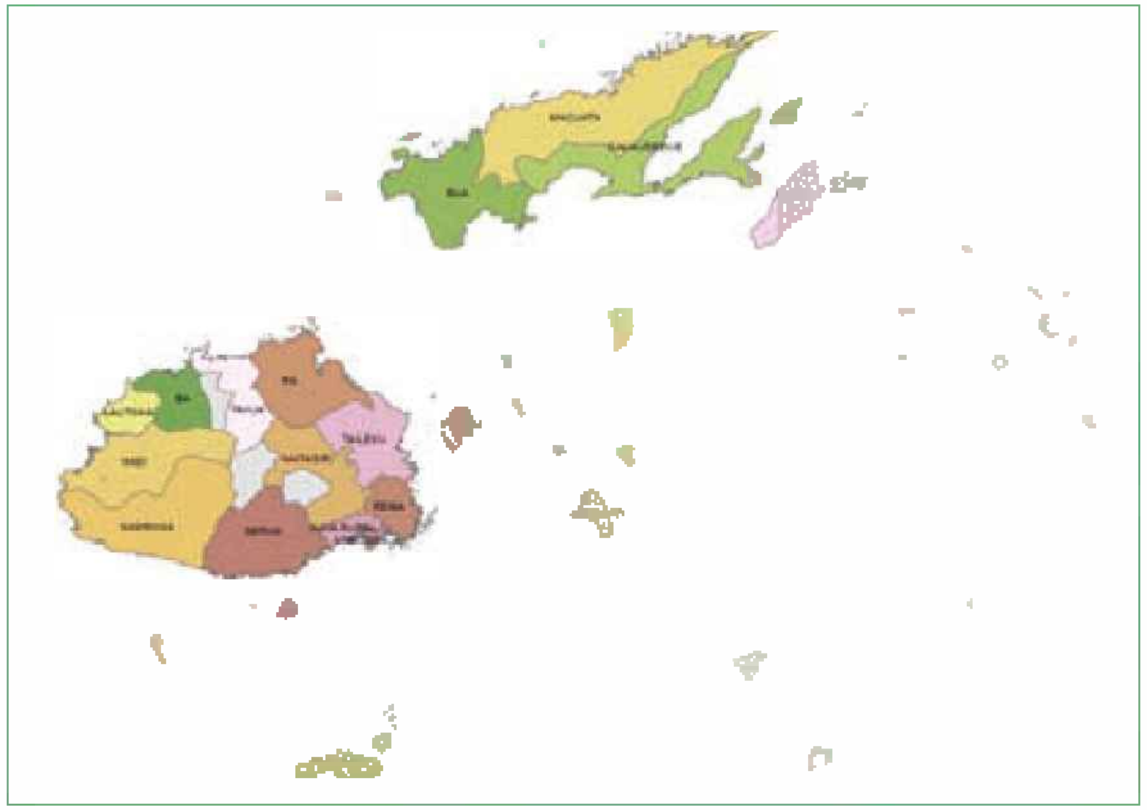
Figure 2.5 Pathways by which climate change may affect human health (adapted from McMichael et al., 2003)



The preliminary baseline analysis which informed the Fiji PCCAPHH proposal identified "water stress" in realtion to hydro-meteorological disasters as the theme for Fiji's project, and highlighted dengue fever, diarrhoeal diseases, leptospirosis and typhoid fever as the priority CSD's for the project. The current burden of these diseases in Fiji and evidence for their susceptibility to climate variability and change is summarised below. In order to familiarise readers with the geographical terminology used in this report, Figures 2.6 and 2.7 show Fiji's administrative Divisions and medical Subdivisions, respectively.

Figure 2.6 Divisions in Fiji

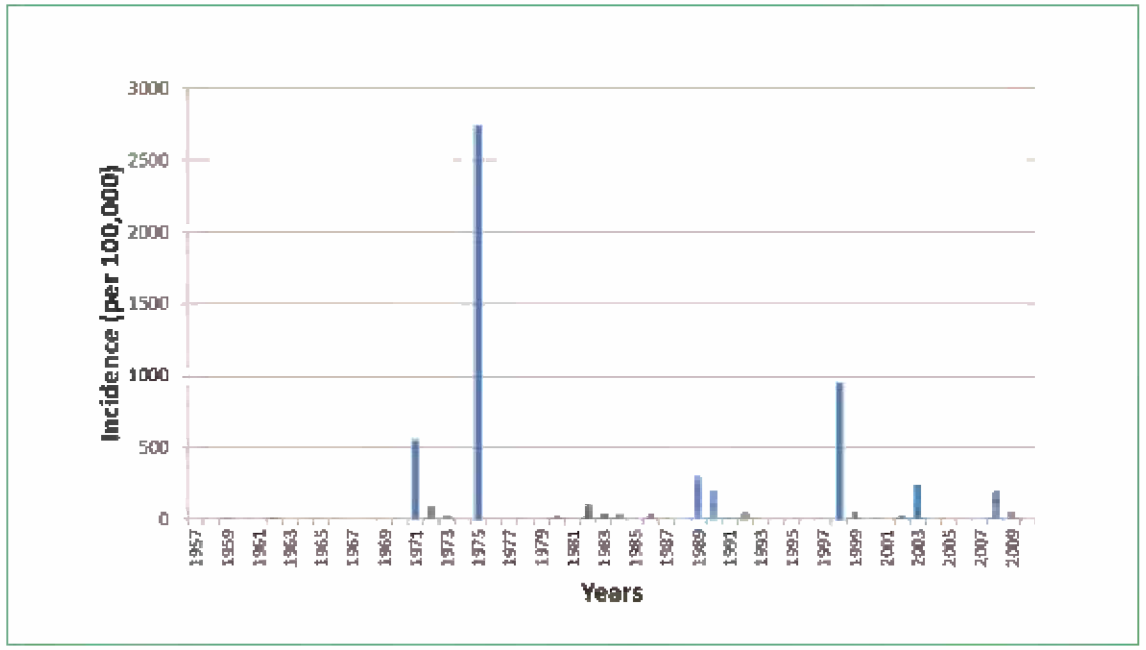
Figure 2.7 Medical subdivisions in Fiji (data source: MoH, FLIS)



2.2.1 Dengue fever

Dengue is the most significant mosquito-borne virus of global public health concern. Over the last 50 years, Fiji has experienced at least six distinct outbreaks of dengue fever, including three in the last 15 years (Figure 2.8). The highest rates of infection occurred in the Central Division in 1998 (see Figures A1.1a-d, Appendix 1). Modeling of dengue fever in the South Pacific showed a positive correlation between La Niña years and dengue fever outbreaks in ten countries, including Fiji (Hales et al., 1999). However, the opposite association was observed in 1998, when a major dengue outbreak occurred in Fiji during a drought associated with El Niño. It is likely that, following the failure of community water supplies, water storage containers near to dwellings provided ideal breeding conditions for Aedes mosquito species and thus increased the risk of transmission of dengue fever (FMS, 2003).

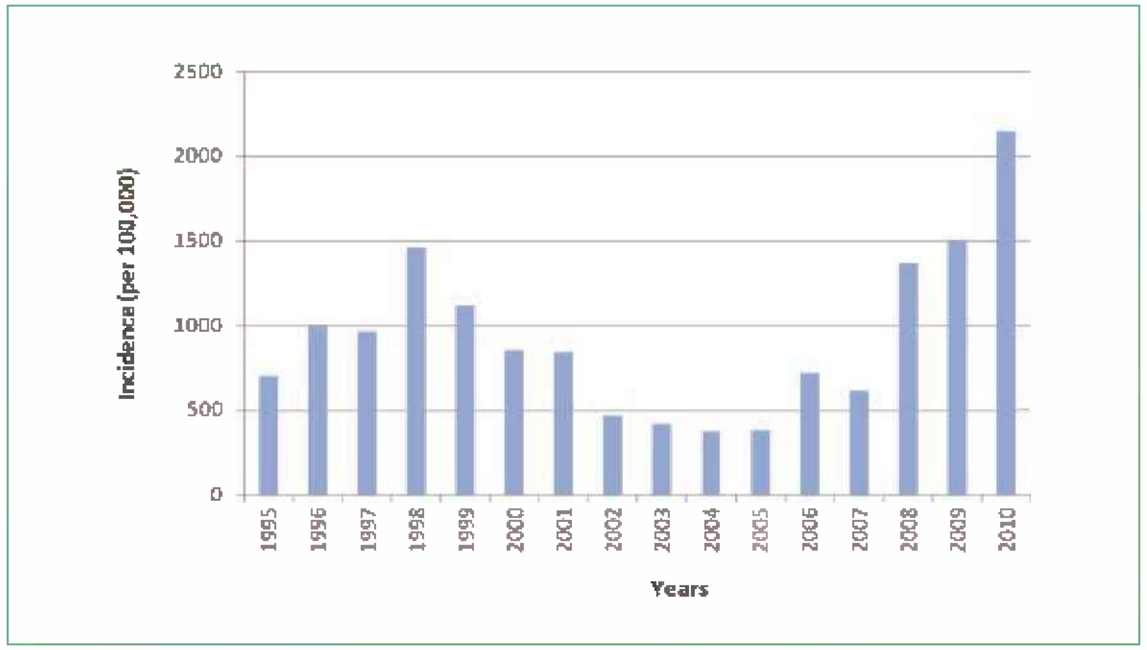
Figure 2.8 Dengue fever in Fiji from 1957 to 2009 (data source: MoH)



2.2.2 Diarrhoeal disease

A well-known study of diarrhoea in infants in Fiji showed a positive association between incidence of diarrhoea, extremes of rainfall and increasing temperature (Singh et al., 2001). Despite the uncertainties associated with future climate projections, a recent study concluded that even the most conservative estimates of the impact of climate change on diarrhoeal disease would be "substantial" (Kolstad et al., 2011). Figure 2.9 shows the burden of disease of diarrhoea in Fiji over the last 15 years; Figures A1.2a-d in Appendix 1 show the incidence of diarrhoea by subdivision, with the highest rates occurring in the Northern and Eastern Divisions.

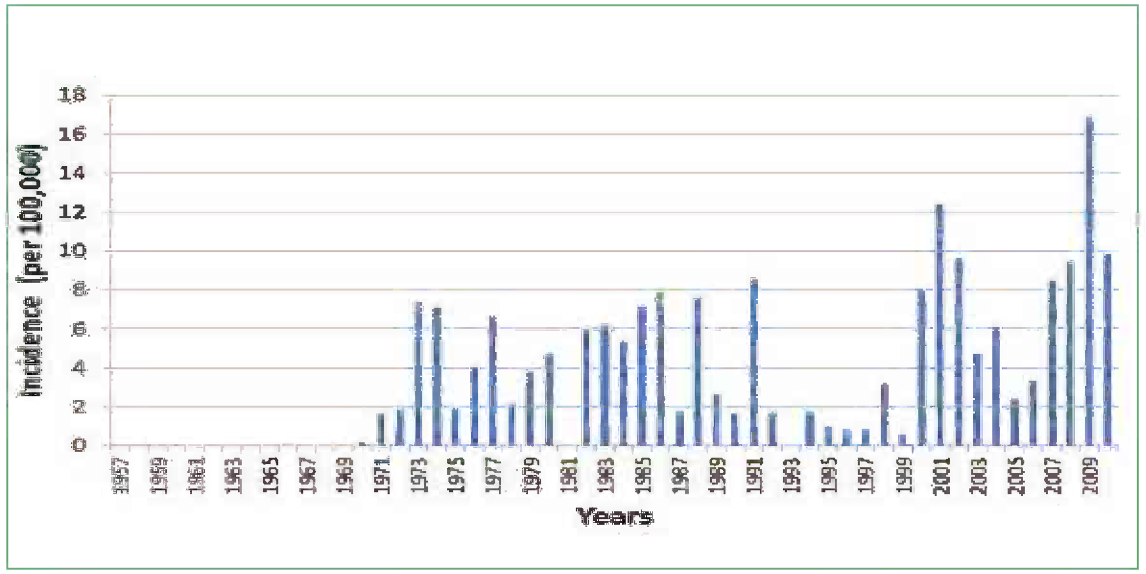
Figure 2.9 Diarrhoeal disease incidence in Fiji from 1995-2010 (data source: MoH)



2.2.3 Leptospirosis

There have been approximately 20-100 reported cases of leptospirosis per year in Fiji over the last 15 years, with the highest incidence rates occurring in the Central and Northern Divisions (see Figures A1.3a-d in Appendix 1). Figure 2.10 displays the increasing incidence (rates in a given population per unit time) of leptospirosis in Fiji over the last several decades (i.e. the number of cases has been increasing faster than that which would be expected due to population increase alone). In addition to this background endemicity, Fiji also experiences outbreaks of leptospirosis, for example after cyclones, and it has been postulated that this correlates with the corresponding risks in agrarian activities that takes place following a natural disaster (Ghosh et al., 2010). Transmission occurs from contact with an infected animal or exposure to soil or water contaminated by a chronic animal carrier (Belioz-Arthaud et al., 2007). In Fiji, young males are the group most commonly affected, and mongooses are an important animal reservoir (Ghosh et al., 2010; Ram et al., 1985). Leptospirosis is also thought to be sensitive to changes in temperature and rainfall patterns, with some published studies reporting higher rates of leptospirosis following rainfall elsewhere in the tropics (Lhomme et al., 1996, Desvars et al., 2011). One of the possible explanations for this phenomenon is that rainfall (particularly heavy rainfall and flooding) may bring humans, domestic animals and rodents into closer proximity.

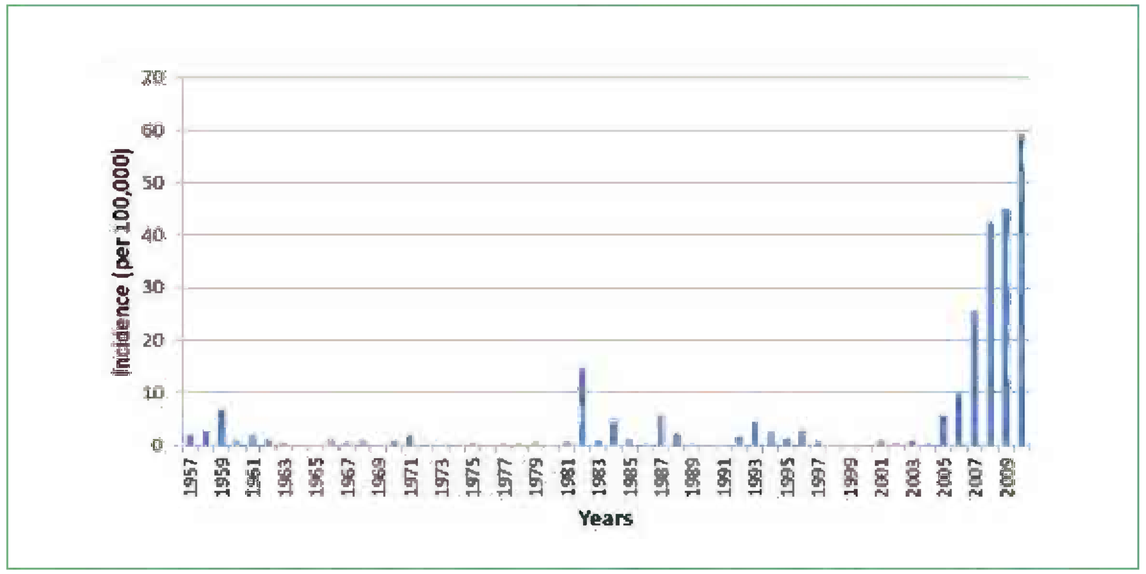
Figure 2.10 Incidence of leptospirosis in Fiji 1957-2009 (data source: MoH)



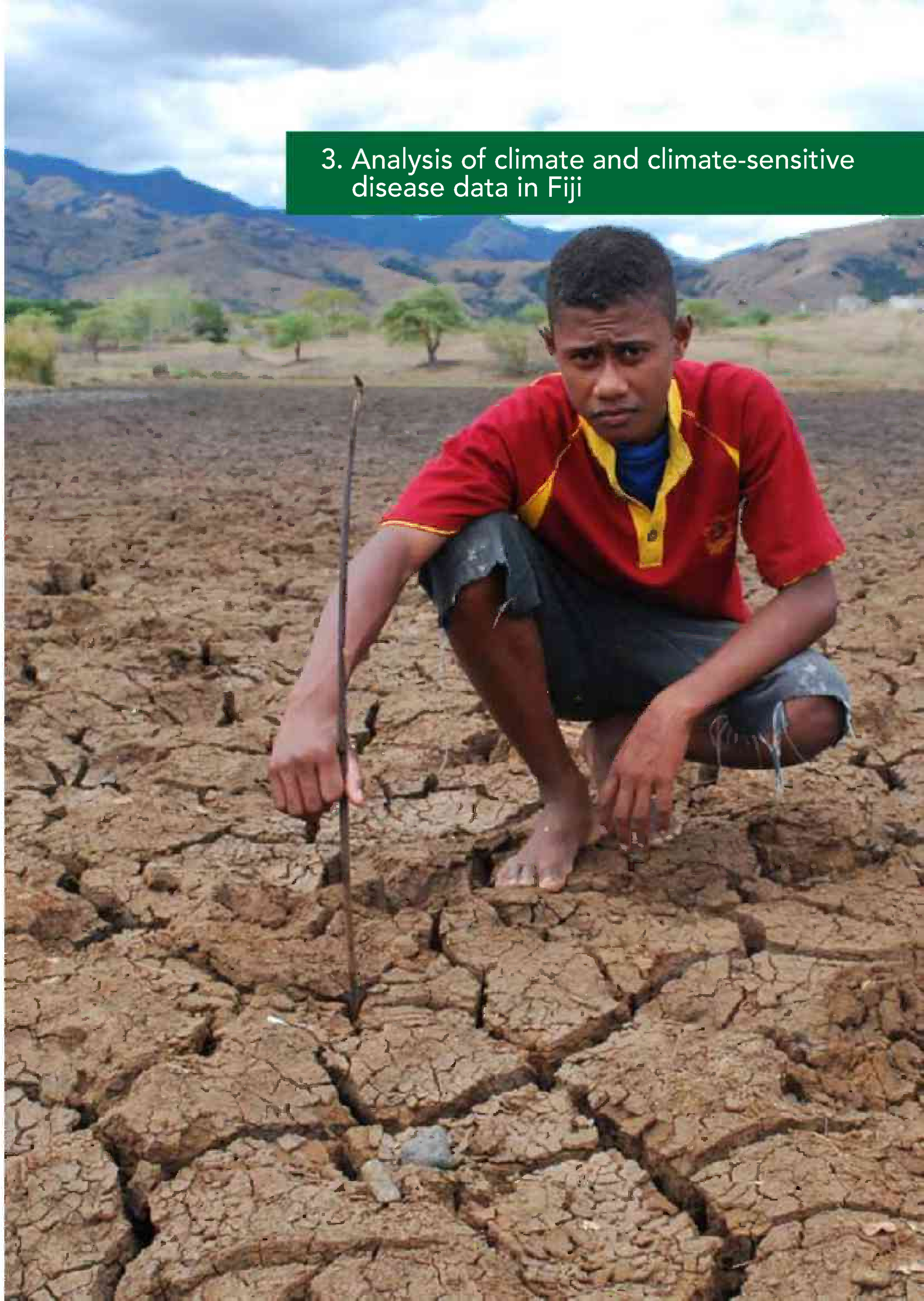
2.2.4 Typhoid fever

Typhoid is endemic in Fiji, where it is considered one of the country's "Three Plagues", along with dengue fever and leptospirosis. Caused by Salmonella typhi but clinically distinct from salmonellosis food poisoning, outbreaks in Fiji have been recognized following mass food distributions (eg. family gatherings and special events) and cyclones (Jenkins, 2010; Ram et al, 1983). The incidence of typhoid in Fiji may be increasing, particularly in the Northern and Western Divisions, although changes in case definitions, reporting and diagnostic capabilities since approximately 2006 may at least partly explain the increase that has been observed (see Figure 2.11 below and Figures A1.4a-d in Appendix 1 for the distribution of typhoid fever in Fiji at the subdivisional level). In December 2011, the village of Nanoko in the Western Division experienced a typhoid outbreak, with at least 16 confirmed and a further 20 suspected cases having occurred so far.

Figure 2.11 Typhoid in Fiji (data source: MoH)



3. Analysis of climate and climate-sensitive disease data in Fiji



Data analysis was undertaken jointly by the MoH Epidemiologist, the NCCDC, FMS and PCCAPHH project staff. Health data was obtained from the National Notifiable Disease Surveillance System (NNDSS) housed at the HIU at the MoH while climate data was obtained from the FMS. Base maps for plotting disease clusters were obtained from the Fiji Lands Information System (FLIS).

3.1 Methodology

The climate and health data were analysed as follows:

1. Calculation of historical disease incidence rates using NNDSS case numbers and MoH population data.
2. Simple correlation (two-way scatterplots with straight lines-of-best-fit and summed residuals) of disease numbers and incidence with climate data, including:
   a. National level: annual aggregate disease numbers and annual averages of climate data from 1957 to 2009; and
   b. Subdivisional level: monthly aggregate disease numbers and monthly averages of climate data from 1995 to 2009.
3. Identification of disease "clusters" (patterns of unusual disease activity in a given area at a given time) at the medical area level between 1995 and 2009, using SaTScan (a space-time analysis software package).
4. Identification of CSD "hotspots"– areas (at the subdivisional and medical area level) where two or more of the four priority diseases occurred at higher-than-average incidence, or in two or more clusters over the study period, or both.
5. Detailed analysis of CSD and climate data in "hotspot" subdivisions, using Stata (a statistical analysis software package) to perform time-series analysis, Poisson regression and lag functions.

These steps are described in more detail below, with a selection of the most relevant results. As a note on terminology, when discussing strengths of correlation and/or association below, in order to avoid confusion or ambiguity given the potential differences in subjective interpretations of statistical results, the following nomenclature has been used in this report:

Table 3.1 Terminology used to describe statistical strengths of association

Correlation coefficient (pseudo r-squared value or similar)	Term used to describe strength of association/ correlation
<0.20	Weak
0.21 – 0.40	Weak – moderate
0.41 – 0.60	Moderate
0.61 – 0.80	Moderate – strong
>0.80	Strong

3.2 Simple correlation of climate and health data

Two-way scatterplots of individual CSD's with individual climate variables (rainfall, maximum temperature, minimum temperature and relative humidity) at the national annual level for aggregate (for diseases) and average (for climate) variables revealed the following correlation coefficients ("r") (Table 3.2):

Table 3.2 Simple correlation of climate and disease data from 1957-2009 at national annual aggregate/average level (data sources: FMS, MoH)

Variable (incidences of disease)	Correlation (r)	Comments
Minimum Temperature/Typhoid	0.00	No Correlation
Average Temperature/Typhoid	0.04	Weak correlation
Maximum Temperature/Typhoid	0.05	Weak correlation
Relative Humidity/Typhoid	0.27	Weak/Moderate correlation
Rainfall/Typhoid	0.16	Weak correlation
Minimum Temperature/Dengue	0.05	Weak correlation
Average Temperature/ Dengue	0.15	Weak correlation
Maximum Temperature/ Dengue	0.20	Weak correlation
Relative Humidity/Dengue	0.09	Weak correlation
Rainfall/Dengue	0.26	Weak/Moderate correlation
Minimum Temperature/Lepto	0.29	Weak/Moderate correlation
Average Temperature/ Lepto	0.41	Moderate correlation
Maximum Temperature/ Lepto	0.41	Moderate correlation
Relative Humidity/Lepto	0.24	Weak/Moderate correlation
Rainfall/Lepto	0.07	Weak correlation
Minimum Temperature/Diarrhoea	0.20	Weak correlation
Average Temperature/ Diarrhoea	0.21	Weak/Moderate correlation
Maximum Temperature/ Diarrhoea	0.17	Weak correlation
Relative Humidity/ Diarrhoea	0.00	No correlation
Rainfall/ Diarrhoea	0.06	Weak correlation

Regional differences and changes over time are hidden in national-level, annual analyses, requiring more focused analysis at the divisional or sub-divisional levels.

3.3 Identification of climate-sensitive disease "clusters"

SaTScan™"…is a free software that analyzes spatial, temporal and space-time data using the spatial, temporal, or space-time scan statistics" (www.satscan.org). For these analyses the "space-time permutation model" (Kulldorff et al., 2005) was used to identify patterns of unusual disease activity in time (the 15 year study period was divided into three five-year periods in order to capture smaller clusters: 1995-1999, 2000-2004 and 2005-2009) and space (medical area levels aggregated within defined geographic boundaries of no more than 100km radii).

The geo-coding process was facilitated by the provision of medical area boundaries from the FLIS and geo-coordinates for health centres from the HIU. For a number of health centres for which no geo-coordinates were available, GoogleMaps (http://maps.google.com) was used to locate approximate coordinates. The approximate locations of all the health centres (excluding Rotuma and Ono-I-Lau) with medical area boundaries are displayed in Figure 3.1. ArcGIS (v.10) software was used for spatial coordination and generation of maps.

The results of this process are presented below for each disease (Figures 3.2-3.5) [NB. In each Figure, the first number represents the five-year period in which the cluster occurred (1=1995-1999; 2=2000-2004; 3=2005-2009) and the second number represents the "number" of the cluster (in order of statistical significance, most likely cluster first); the colours of the dots representing medical areas are intended to help distinguish the clusters visually.

Figure 3.1 Health centres and approximate medical area boundaries in Fiji (NB. Vuna has been incorrectly geo-referenced – this will be rectified in future mapping activities)

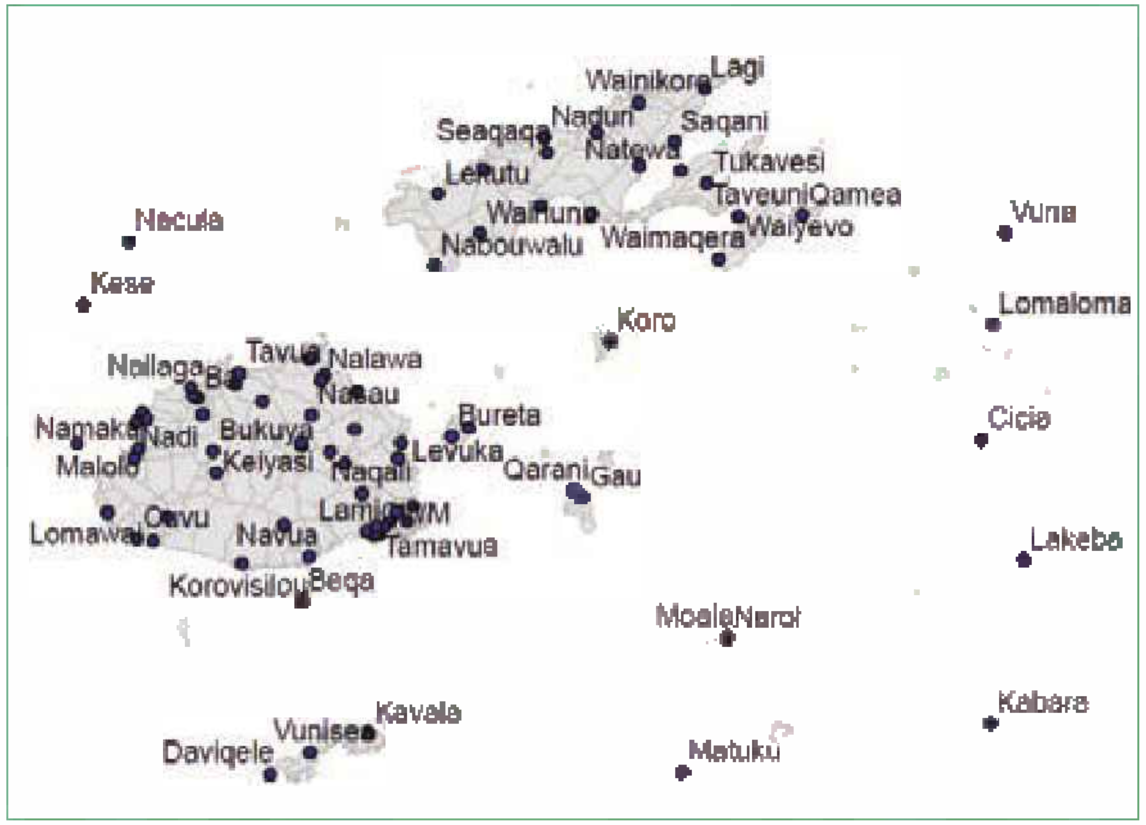


Figure 3.2 Leptospirosis "clusters" in Fiji (1995-2009) (data source: MoH)

Figure 3.3 Dengue "clusters" in Fiji (1995-2009) (data source: MoH)

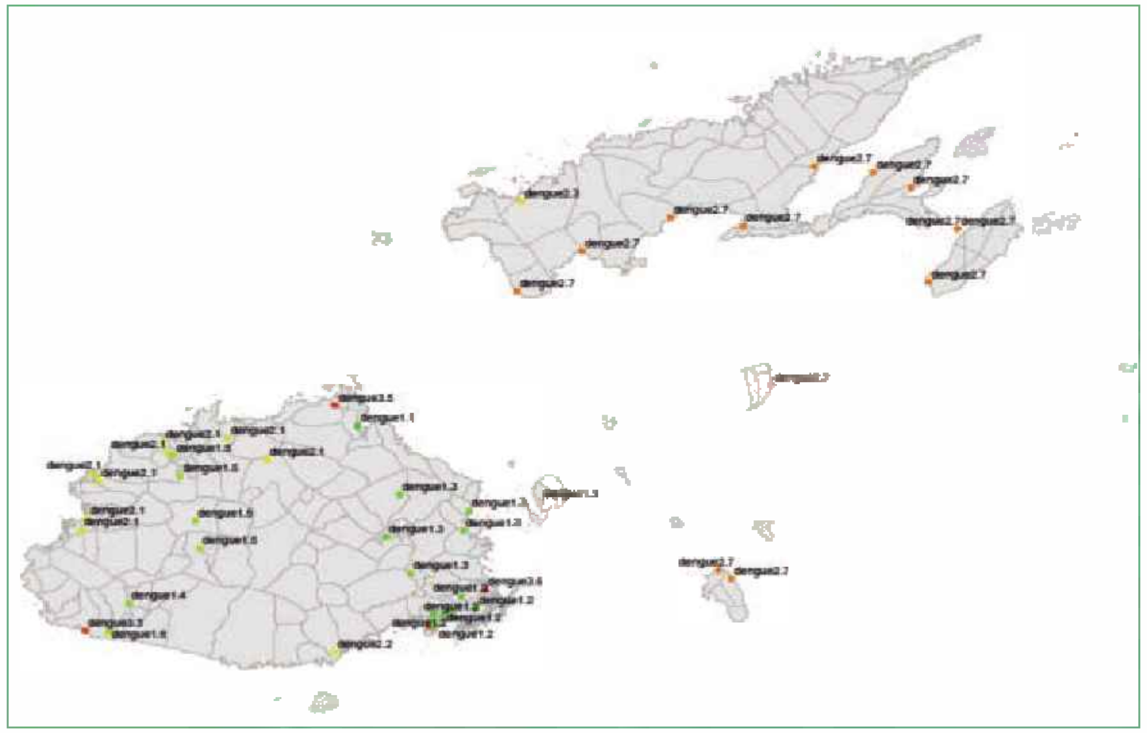


Figure 3.4 Typhoid "clusters" in Fiji (1995-2009) (data source: MoH)

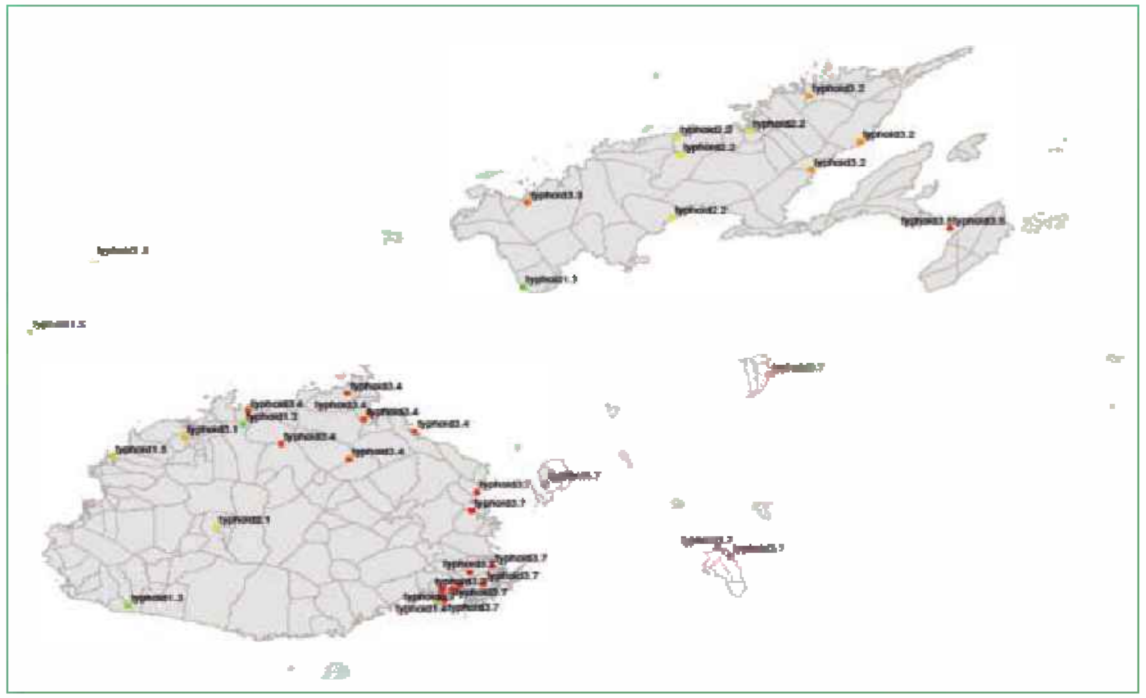


Figure 3.5 Diarrhoea "clusters" in Fiji (1995-2009) (data source: MoH)

3.4 Identification of climate-sensitive disease "hotspots"

Through a process which combined consideration of historical incidence rates and repeated clustering of two or more of the CSD's, the following shortlist was generated of potential CSD "hotspots":

Table 3.3 Potential climate-sensitive disease "hotspots"

Medical area (hospital/health centre)	Subdivision
Labasa	Macuata
Lekutu	Bua
Nabouwalu	Bua
Savusavu	Cakaudrove
Tavua	Tavua
Ba	Ba
Vunidawa	Vunidawa
Korovou	Tailevu
Rakiraki	Ra

In addition to the shortlist above, Suva, Nadi and Lautoka subdivisions were also considered, given the high numbers of cases of diseases that occur in these large population centres. A subsequent process of elimination, based on the consistency (or rather, inconsistency) of disease activity over time, and the completeness and availability of climate data from weather stations sufficiently close to the health centres, excluded several of these locations (Savusavu, Lekutu, Tavua, Korovou and Rakiraki).

For the time being, therefore, the focus (for the purposes of further, more detailed analysis, development of early warning systems and the eventual identification of pilot sites for intervention) will remain on three subdivisions (Bua, Ba and Macuata) along with Nadi, Suva and Lautoka, in order to achieve the dual goals of capturing any significant climate-disease relationships (requiring both sufficient disease activity and proximal climate data) and operating at a scale appropriate for intervention. We note that there is a possible conflict between the geographic scale of analysis at which climate-disease relationships can be demonstrated empirically, and the scale appropriate for a pilot intervention.

3.5 Time series analysis of monthly climate and disease data

Data was analysed graphically, using Lowess smoothed scatterplots, and with Poisson regression, using lagged climate variables and "adjustment" for seasonality using dummy variables for months of the year. Some of the results which appear most promising for application to an early warning system are presented below for Ba, Bua, Suva and Lautoka subdivisions for the study period 1995-2009. A summary of the results for each of the four CSD's in each subdivision analysed thus far is presented at the end of this section in Table 3.5.

3.5.1 Ba subdivision

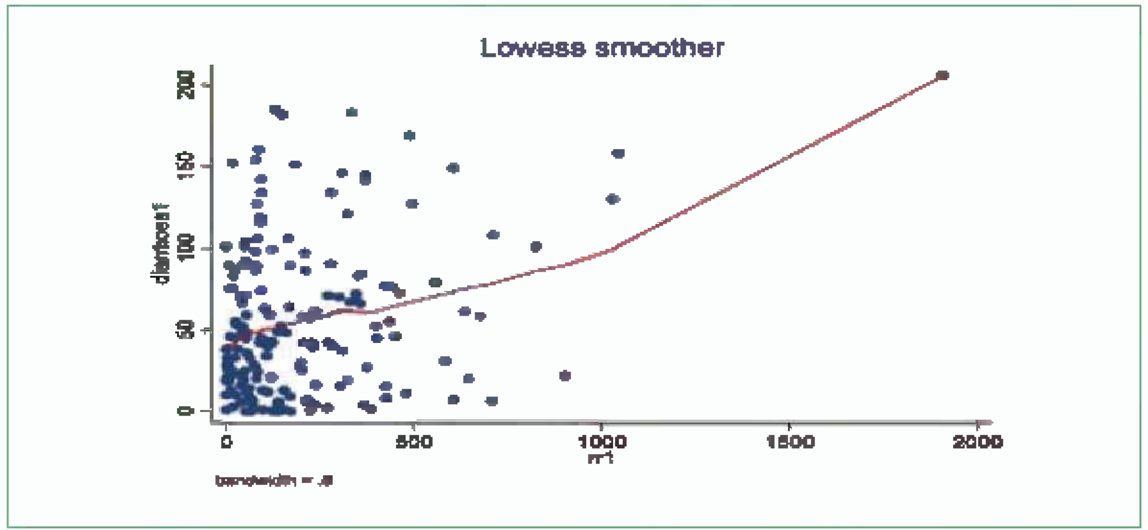
Dengue fever

For dengue fever in Ba, the best model combined rainfall, maximum temperature and humidity, all at a lag of one month.

Diarrhoeal illness

The best model for diarrhoeal illness in the Ba subdivision combined rainfall and humidity at a lag of one month (see Figure 3.9). This scatterplot illustrates that, in general, higher rainfall in the current month is associated with more cases of diarrhoeal illness the following month (NB. it is this principle which may ultimately form the basis of climate-based early warning systems for such diseases).

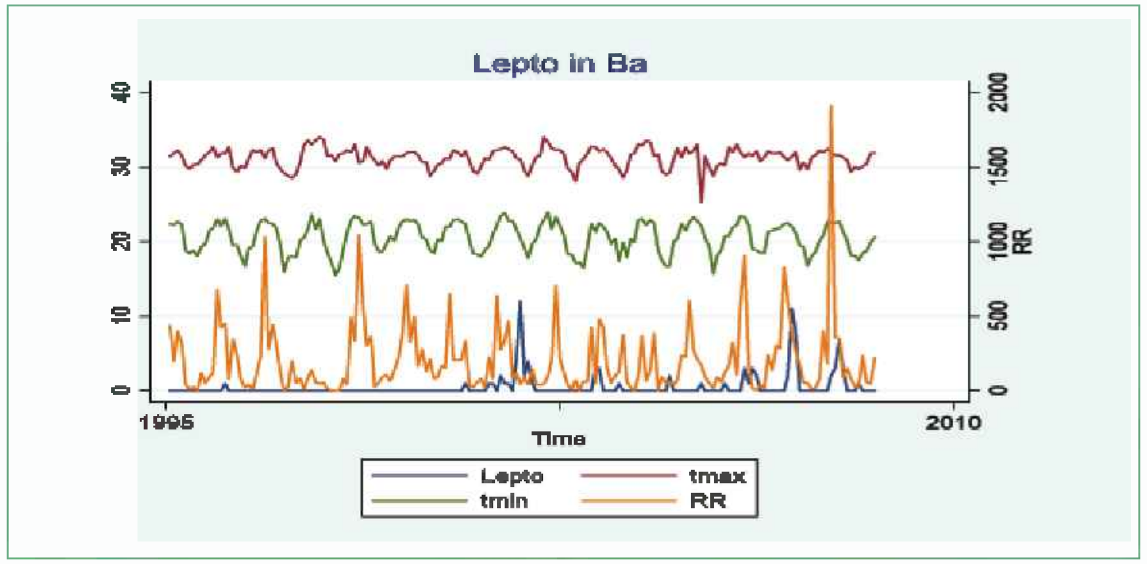
Figure 3.6 Two-way scatterplot with Lowess smooth-line for monthly diarrhoea cases vs. rainfall for the Ba sub-division (lag 1 month)



Leptospirosis

Similarly, for leptospirosis in Ba, there appears to be a lag between rainfall and the number of cases that occur in epidemic months (see Figure 3.8). Further analysis suggests that a seasonally-adjusted model combining rainfall, minimum temperature and possibly humidity, all at a lag of two months, indicates a reasonably strong relationship with leptospirosis.

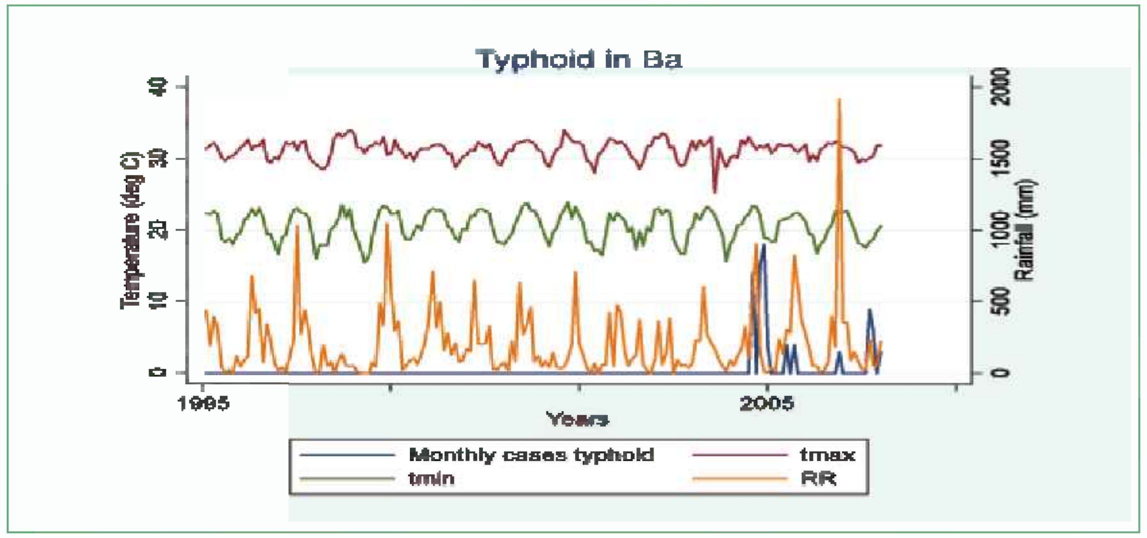
Figure 3.7 Leptospirosis cases and climate in Ba subdivision



Typhoid

A time-series graph of monthly typhoid cases versus aggregate monthly rainfall, average maximum and minimum temperature is shown in Figure 3.6. While the issue of typhoid cases post-1996 has been mentioned previously in Chapter 2 and is discussed again in Chapter 4, what is visible from this graph is that typhoid cases in Ba over the last few years of the study period appear to have occurred in warmer weather, slightly after the start of the rainy season.

Figure 3.8 Typhoid cases and climate in Ba subdivision



This apparent relationship (between temperature, rainfall and typhoid cases in Ba) was explored in more depth via Poisson regression, an example of which is displayed in Figure 3.7 – an excerpt from the Stata output using a model regressing monthly typhoid cases on rainfall and minimum temperature, both at a "lag" of two months (ie. comparing the number of cases in any given month to the rainfall and minimum temperature two months earlier). While caution must be taken not to over-interpret the statistical significance of these results, the pseudo r-squared and p-values (circled) do suggest a reasonably strong relationship between the variables in this combined model.

Figure 3.9 Poisson regression model of typhoid cases, time-lagged rainfall and minimum temperature in Ba

```
. xi: poisson typhoid rr2 tmin2 year i.month
i.month           _Imonth_1-12         (_Imonth_1 for month==Apr omitted)

Iteration 0:   log likelihood = -204.17328
Iteration 1:   log likelihood = -143.08836
Iteration 2:   log likelihood = -96.382552
Iteration 3:   log likelihood =  -91.65961
Iteration 4:   log likelihood = -90.512217
Iteration 5:   log likelihood = -90.261264
Iteration 6:   log likelihood = -90.209138
Iteration 7:   log likelihood = -90.198421
Iteration 8:   log likelihood = -90.195817
Iteration 9:   log likelihood = -90.195331
Iteration 10:  log likelihood = -90.195209
Iteration 11:  log likelihood = -90.195187
Iteration 12:  log likelihood = -90.195185

Poisson regression                         Number of obs   =        178
                                           LR chi2(14)     =     351.34
                                           Prob > chi2     =     0.0000
Log likelihood = -90.195185                Pseudo R2       =     0.6608

------------------------------------------------------------------------------
     typhoid |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         rr2 |   .0087937   .0015019     5.85   0.000     .0058499    .0117374
       tmin2 |   .8124251   .2118929     3.83   0.000     .3971226    1.227728
        year |   .8918574    .125524     7.10   0.000     .6458349     1.13788
   _Imonth_2 |  -14.70836   14276.19    -0.00   0.999     -27995.4    27965.98
   _Imonth_3 |   4.220528   1.075298     3.92   0.000     2.112984    6.328073
   _Imonth_4 |   2.639795   .5954299     4.43   0.000     1.472774    3.806816
   _Imonth_5 |   1.868106   .6225332     3.00   0.003     .6480629    3.088248
   _Imonth_6 |  -16.31423   13689.84    -0.00   0.999     -26847.9    26815.27
   _Imonth_7 |   2.426789    .821394     2.95   0.003     .8164944    4.037084
   _Imonth_8 |  -29.13002   1602.383    -0.02   0.985    -3169.743    3111.483
   _Imonth_9 |  -1.520941   .5657205    -2.69   0.007    -2.629782   -.4121489
  _Imonth_10 |   3.979459   .9522129     4.18   0.000     2.112961    5.845957
  _Imonth_11 |   6.700777   1.275869     5.25   0.000      4.20012    9.201434
  _Imonth_12 |   7.566785   1.341935     5.64   0.000     4.936561    10.19699
       _cons |  -1811.484   254.4476    -7.12   0.000    -2310.172   -1312.756
------------------------------------------------------------------------------
```

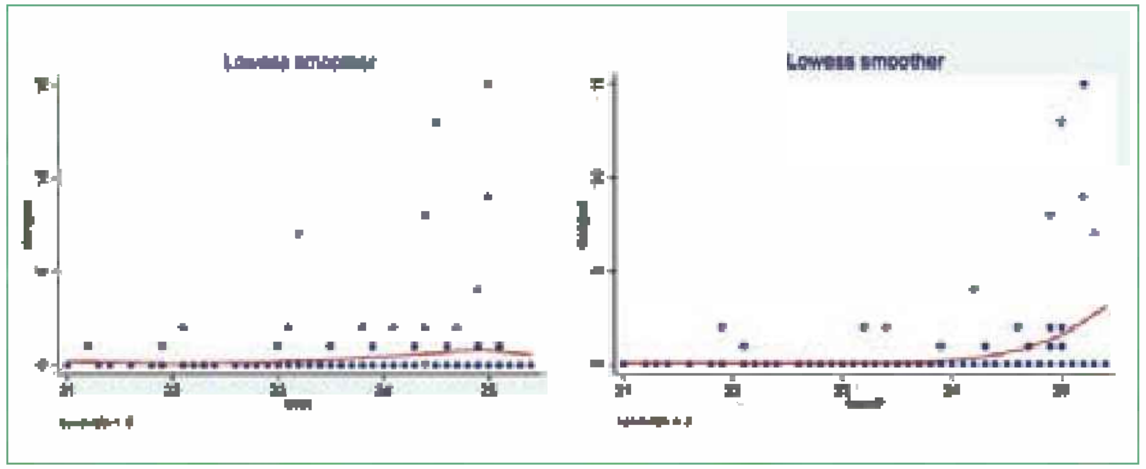
It is worth noting that, in Ba, for both leptospirosis and typhoid fever, the relationship between the number of cases and rainfall and temperature (two months prior) suggests the possibility of a climate-based early warning system for these diseases.

3.5.2 Bua subdivision

Overall, the results for Bua subdivision were less encouraging, in that the relationships between monthly CSD cases and climate variables were not as strong as those shown in Ba. This may be due to a number of reasons, such as: the true relationships between climate and disease do exist, but are not visible due to incomplete or poor-quality data; the true relationships do not exist, or are not as strong as elsewhere; other factors (e.g. resilience factors, including household-, community- or health centre-level planning for, responses to and management of these diseases) which "dampen" the effect of the climate-disease relationship; or some combination of these and other reasons.

Briefly, for leptospirosis in Bua subdivision, the best model combined rainfall, minimum and maximum temperatures, all at a lag of three months (i.e. leptospirosis risk appeared to be higher some months following hot, wet conditions); for typhoid, interestingly, the strongest model included rainfall and minimum temperature in the current month (cf. typhoid in Ba, above); and for diarrhoeal disease, there was the suggestion of a slight negative relationship with rainfall and humidity (i.e. more cases occurred in drier conditions). In the case of dengue fever, analysis of cases in the Bua subdivision demonstrated quite clearly the need to consider the lag effect of climate (particularly temperature) and the "threshold" phenomenon (again for temperature), as shown in Figure 3.10 below.

Figure 3.10 Monthly dengue cases vs minimum temperature in the same month (left) and two months prior (right) in Bua



3.5.3 Suva subdivision

The Suva (urban) area was included for consideration given the high numbers of cases of the "urban diseases" (dengue fever and diarrhoea). Results of analysis of these two diseases for Suva also proved quite encouraging with respect to the prospect of this project producing a climate-based early warning system for at least one disease in at least one location. It is worth noting here that Suva is on the "wet side" of Viti Levu, while Ba and Bua subdivisions are in the "dry side" of Viti Levu and Vanua Levu, respectively.

Dengue

Simple pair-wise correlation of monthly dengue cases versus rainfall, minimum temperature, maximum temperature and relative humidity for Suva suggested that each climate variable was weakly associated with the disease (see boxed results in Table 3.3).

Table 3.3 Simple correlation between monthly cases of dengue fever and climate variables in Suva (NB. correlation coefficient of 1.0 = "perfectly associated")

	dengue	rr	max	min	rh
dengue	1.0000				
rr	0.1594	1.0000			
max	0.1881	0.3127	1.0000		
min	0.2638	0.3900	0.9161	1.0000	
rh	0.1733	0.5117	0.1663	0.2903	1.0000

The "best" model for dengue in Suva combined all four climate variables at a lag of two months; this provided a correlation coefficient of 0.6, indicating a moderate to moderately strong degree of association (Figure 3.11).

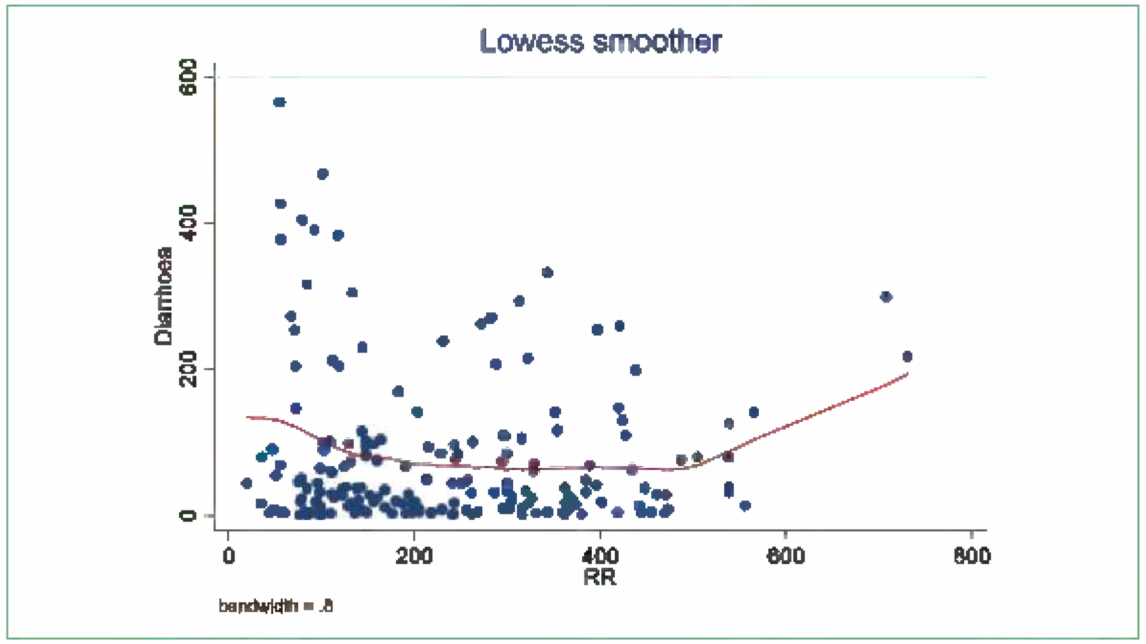
Figure 3.11 Combined model of lagged climate variables (2 months) and monthly dengue cases in Suva

```
. do "C:\Users\user\AppData\Local\Temp\STD00000000.tmp"

. xi: poisson dengue rr2 max2 min2 rh2 year i.month
i.month           _Imonth_1-12        (_Imonth_1 for month==Apr omitted)

Iteration 0:   log likelihood =  -1987.429
Iteration 1:   log likelihood = -1356.6022
Iteration 2:   log likelihood = -1256.7946
Iteration 3:   log likelihood = -1255.8658
Iteration 4:   log likelihood = -1255.8651
Iteration 5:   log likelihood = -1255.8651

Poisson regression                        Number of obs   =        62
                                          LR chi2(16)     =   3761.59
                                          Prob > chi2     =    0.0000
Log likelihood = -1255.8651               Pseudo R2       =    [illegible]

------------------------------------------------------------------------------
      dengue |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
         rr2 |  -.0021411   .0003544    -6.04   0.000    -.0028357   -.0014465
        max2 |  -.7818389    .040083   -19.51   0.000       -.8604   -.7032777
        min2 |   2.118104   .0984043    21.07   0.000     1.929155    2.307053
         rh2 |  -.0845286   .0172848    -4.89   0.000    -.1184062    -.050651
        year |  -.1330424   .0072829   -18.27   0.000    -.1473165   -.1187682
   _Imonth_2 |   3.604332   .2433242    14.81   0.000     3.127425    4.081238
   _Imonth_3 |   1.415364   .2238506     6.32   0.000     .9766055    1.854123
   _Imonth_4 |   1.315082   .1378026     9.54   0.000     1.044818    1.585347
   _Imonth_5 |   3.204787   .1390278    22.90   0.000     2.930534    3.479041
   _Imonth_6 |  -1.234788    .472158    -2.61   0.009    -2.162161   -.3074154
   _Imonth_7 |  -.2071116   .2548014    -0.81   0.416    -.7066894    .2924663
   _Imonth_8 |   .9012355   .1594386     5.65   0.000     .5887415     1.21373
   _Imonth_9 |  -.7119406   .1979157    -3.60   0.000    -1.099848    -.324033
  _Imonth_10 |   2.585241   .2801987     9.23   0.000     2.036061     3.13442
  _Imonth_11 |   3.962312   .2910504    13.61   0.000     3.391864    4.532761
  _Imonth_12 |   5.588093   .2999422    18.60   0.000     5.002176    6.174009
       _cons |   248.9445   14.53504    17.13   0.000     220.4584    277.4337
------------------------------------------------------------------------------
```

Diarrhoeal illness

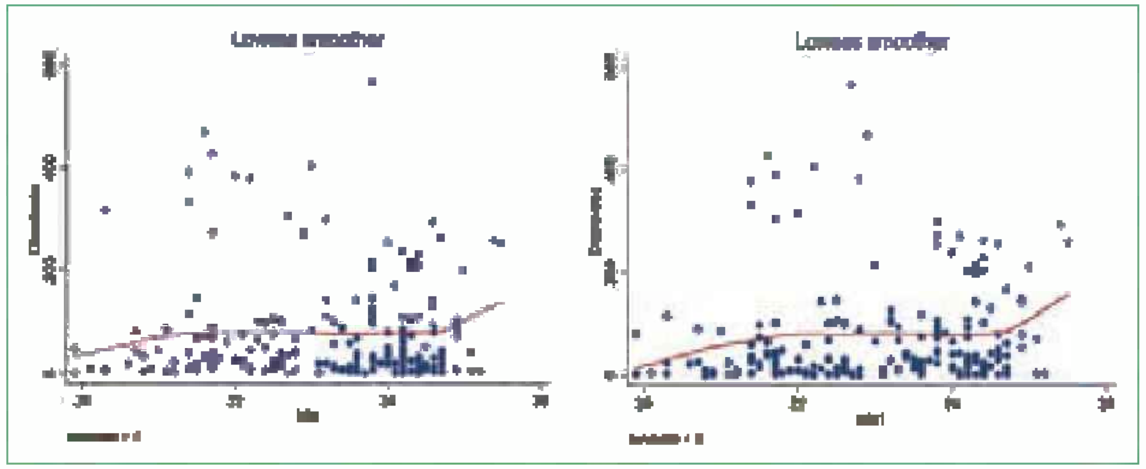
Analysis of rainfall and diarrhoeal illness in Suva revealed the subtle but characteristic U-shape that has been described previously (Singh et al.), where cases of diarrhoea tend to occur with extremes of rainfall (ie. in either very wet or very dry conditions) – see Figure 3.12.

Figure 3.12 Monthly cases of diarrhoea vs rainfall in Suva



There also appears to be a positive association, as well as a possible threshold effect, between temperature (particularly minimum temperature) and cases of diarrhoeal illness in Suva, both in the current month and at lag-1 (see Figure 3.13).

Figure 3.13 Association between monthly diarrhoea cases and minimum temperature (lag 0, left and lag 1, right) in Suva



3.5.4 Lautoka subdivision

Dengue

After "adjusting" for seasonality, a model combining maximum temperature, minimum temperature and rainfall, all at lag-1 month, was quite strongly associated with monthly dengue cases in Lautoka subdivision. Interestingly, from the point of view of a climate-based disease early warning system, this combined model proved only very slightly better (pseudo-r2 = 0.54) than a model with maximum temperature (lag-1) alone (pseudo-r2=0.53).

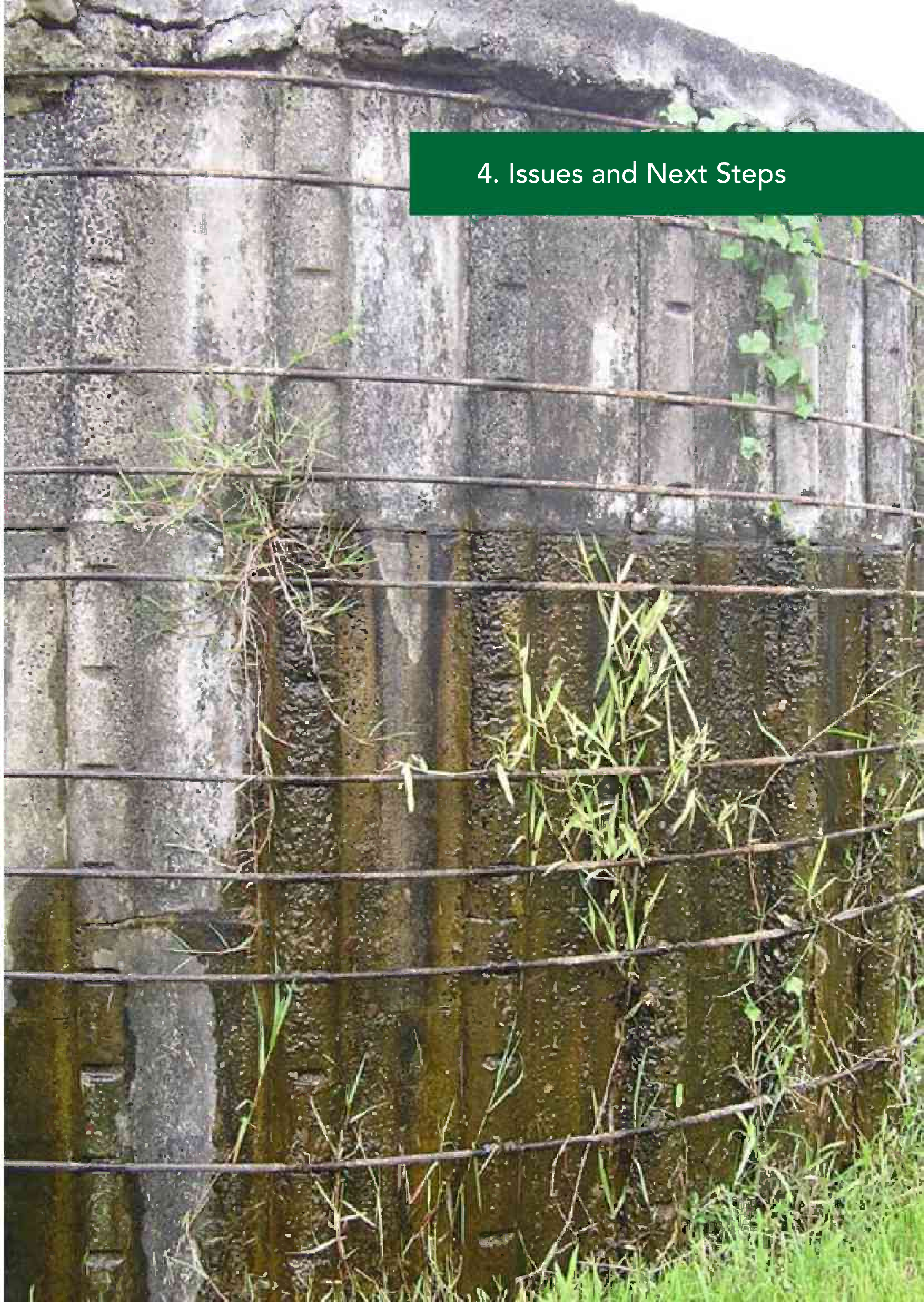
The pseudo-r2 values from the above sub-divisions are summarised below.

Table 3.5 Summary of results of modeling of CSD and climate data to date (NB. Highlights indicate the estimated "explanatory power" of the models: green=weak-moderate; yellow= moderate; red=moderate-strong)

Disease	Subdivision	Climate variables/model*	Strength of association (pseudo-r2 value)**
Dengue	Ba	Rainfall- lag 1,2,3 Maxtemp- lag 0,1,2,3 Mintemp- lag 2 Humidity- lag 1	0.3, 0.27, 0.32 0.29, 0.38, 0.32, 0.29 0.25 0.34
		Model: rainfall, maxtemp, humidity at lag-1	0.39
	Bua	Rainfall - lag 0,1,2, Maxtemp- lag 0,2,3 Mintemp- lag 0,1,2,3 Humidity- lag 0	0.4, 0.3, 0.37 0.37, 0.33, 0.31 0.35, 0.30, 0.32, 0.31 0.33
		Model: rainfall, maxtemp, mintemp at lag-0	0.52
	Lautoka	Rainfall- lag 1 Maxtemp- lag 1 Mintemp- lag 1	0.42 0.53 0.27
		Model: combination of three lagged climate variables above	0.54
	Suva	Rainfall- lag 2 Maxtemp- lag 3 Mintemp- lag 0,2 Humidity- lag 2	0.47 0.50 0.57, 0.52 0.47
		Model: all four climvar's at lag-2	0.6
Diarrhoeal illness	Ba	Rainfall- lag 1 Maxtemp- lag 3 Mintemp- lag 3 Humidity- lag 1	0.1 0.06 0.07 0.14
		Model: model with all four lagged climvar's above	0.17
	Bua	Rainfall- lag 0 Maxtemp- lag 0,1,2, Mintemp- lag 0-3 Humidity- lag 2	0.12 all ~0.10 all ~0.10 0.12
		Model: rainfall, maxtemp, mintemp at lag-0	0.13
	Suva	Rainfall- lag 1,3 Maxtemp- lag 0,3 Mintemp- lag 3	~0.4 " "
		Model: three climvar's above at lag-3	0.41
Leptospirosis	Ba	Rainfall- lag 2 Maxtemp- lag 1,2 Humidity- lag 1,2	0.3 0.32, 0.30 0.3, 0.3
		Model: rainfall lag -2, mintemp lag-1	0.35
	Bua	Rainfall- lag 0,2,3 Maxtemp- lag 0,3 Mintemp- lag 0,1,2,3 Humidity- lag 0,1	0.42, 0.4, 0.48 0.38, 0.45 0.4(all) 0.45, 0.40
		Model: rainfall, maxtemp, mintemp at lag-3	0.59
Typhoid	Ba	Rainfall- lag 1,2,3 Maxtemp- lag 0,3 Mintemp- lag 1,2,3 Humidity- lag 0,1,2,3	0.47, 0.63, 0.49 0.47, 0.49 0.46, 0.52, 0.46 0.48, 0.46, 0.47, 0.5
		Model: rainfall, mintemp at lag-2	0.66
	Bua	Rainfall- lag 0 Mintemp- lag 0,3 Humidity- lag 3	0.35 0.36, 0.36 0.35

*Seasonally-adjusted (i.e. using dummy variable for month), using "best" associations for each lagged climate variable per disease (i.e. weakest associations and those with p-values >0.05 omitted); example models include a combination of lagged climate variables attempting to represent the "ideal" combination

**All results listed are significant to the 5% level (i.e. p-values of ≤0.05)



4. Issues and Next Steps

4.1 Knowledge gaps and needs with respect to CSD's in Fiji

There are a number of challenges with respect to monitoring, preventing and managing these four diseases in Fiji, the detailed discussion of which is outside the purview of this report. Hence, mainly those issues directly relevant to the PCCAPHH project are discussed below.

One of the major issues is the mismatch between the notified (NNDSS) and the laboratory-confirmed case data for these and other diseases (including influenza). This is a well-recognised problem in Fiji, resulting from the gradual strengthening of the laboratory diagnostic capacity in the country (which lies predominantly within NCCDC and the divisional hospitals) and the inconsistencies in reporting of notifiable diseases, due to problems with case definitions, timeliness of report submissions, the attention given to diseases around the time of outbreaks and other factors. Of particular relevance to this project is the fallibility of the NNDSS in accurately and consistently recording cases of dengue fever, leptospirosis and typhoid fever – all of which can be difficult to diagnose clinically without laboratory confirmation, particularly in the context of an outbreak (which can lead to over-diagnosis of the disease in question due to heightened awareness of patients and clinicians alike, as well as potentially under-diagnosis of diseases with similar clinical presentations, as demonstrated in a study of leptospirosis in patients presenting with dengue-like illnesses in Puerto Rico (Bruce et al., 2005). It could also be argued that the lack of routine laboratory confirmation of diagnoses of these three diseases prior to approximately 2006 means that there is a genuine lack of information regarding their true incidence in Fiji.

A critical issue in the study of typhoid fever in Fiji is the apparent sudden rise in cases from around 2005-2006. Possible causes for this include: a true increase in the number of cases of typhoid in Fiji, far in excess of that which may be expected due to population growth; increased awareness on the part of the public and/or health professionals about the risk factors, symptoms and clinical picture of typhoid (NB. this may have the effect of either accurately recognising cases which would have previously gone unrecognised, or incorrectly diagnosing non-typhoid cases as typhoid); a lapse in the typhoid vaccination regimen; antibiotic resistance of the pathogenic organism and myriad other factors. It is likely that, given this discrepancy in the typhoid notifications, for the purposes of subsequent analysis in this project the typhoid data may need to be split (into "before" and "after" the sudden increased incidence) and examined separately.

There are occasional, unexplained gaps in both the health and climate data utilised so far; it is not clear whether, in the case of the disease data, these represent "no cases" and/or "unreported cases" (for the climate data presumably a breakdown in communication and/or technology is to blame). There have also been inconsistencies in the manner in which the health data have been recorded over the study period (most likely due to staff turnover); there is the potential – and intention - for this project to contribute towards the standardisation of disease data record-keeping for improved use in the future.

There is a severe shortage of human resources in the area of public health and epidemiology in Fiji. The MoH employs one full-time epidemiologist, and the NCCDC has only two medical officers. The WHO Epidemiology and Communicable Disease Control unit at the South Pacific office in Suva provides some technical support, but Fiji is only one of over a dozen Pacific island countries and territories supported by this office.

Prior to this Project, the use of spatial analysis and geographic information systems (GIS) technology in Fiji had been on an ad-hoc basis only, and very few MoH staff have in-depth experience using statistical analysis software [although some capacity does exist within the College of Medicine, Nursing and Health Sciences (CMNHS) at the Fiji National University (FNU), formerly the Fiji School of Medicine]. Through the procurement of software for spatial analysis, GIS and statistical analysis and training of key personnel, it is hoped that this project can contribute to building capacity within the health sector in Fiji in analysing health data, anticipating and responding to outbreaks, and performing epidemiological investigations and other health research projects. The use of GIS technology is not without its own challenges, however – early issues with sourcing medical subdivision and medical area boundaries have been adequately but incompletely dealt with to date; and accurate geo-referencing of specific points (e.g. health centres) needs further work. The MoH and FLIS have previously collaborated on making "health-specific" maps for Fiji. However, medical subdivisions and medical area boundaries do not align with other boundaries such as those for census districts or other sector-specific boundaries, nor do they seem to follow any natural or physical features in the landscape. It is expected that this project will be able to make a large contribution towards improving these maps for use in the health and other public service sectors.

Specific to the field of environmental epidemiology, the PCCAPHH project is also supporting Fijian students undertaking Masters degree research projects related to climate change and health (community-level investigations into the epidemiology of scabies and dengue fever, with a focus on adaptation). These Masters projects will be, to the best of our knowledge, among the first environmental epidemiology projects to be led by Fijian students in Fiji; certainly the first in-depth projects specific to climate and health since the Singh et al. study cited above. It is hoped that, with the support of the PCCAPHH team, these projects will be carried out to a level appropriate for publication in the international peer-reviewed literature, thus contributing substantially to the body of knowledge on climate-sensitive diseases in the Pacific region.

4.2 Next steps

As the focus of the PCCAPHH project shifts towards adaptation activities, ongoing data analysis will guide this process. The short-term priorities for the project include:

- extension of the climate-health time-series analyses for other subdivisions and using narrower temporal (i.e. weekly) and spatial (medical area level) windows where possible;
- testing the predictive power of the time series models and development of pilot climate-based early warning systems, if possible;
- identification of specific communities (villages/settlements or groups of villages/settlements within a defined area) with heightened climate-sensitive disease risk/burden as potential "pilot sites" for local-level adaptation activities, which will ideally be linked with a climate-based early warning system
- identification of appropriate pilot adaptation activities, based on the above analyses and experiences from elsewhere in the Pacific, the tropics and the developing world;

In the medium- to long-term, the PCCAPHH project team intend to:

- train key MoH staff in GIS, and statistical analysis techniques;
- improve the geo-coded health information (including subdivision and medical area boundaries and demographic data) in collaboration with FLIS;
- contribute towards harmonising the NNDSS and laboratory-confirmed disease data systems;
- improve the NNDSS data recording, storage and analysis process;
- perform more sophisticated analyses in selected areas and utilise spatial data provided by BoS;
- include water quality data in future analyses;
- encourage integrated approaches to disease epidemiology.

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Appendix 1. Incidence of CSD's by subdivision 1995-2009

Note: all incidence rates were calculated using population data for each subdivision supplied by the MoH for every year included in the analysis

Figure A1.1a Incidence of dengue fever by subdivision 1995-2009 – Central Division

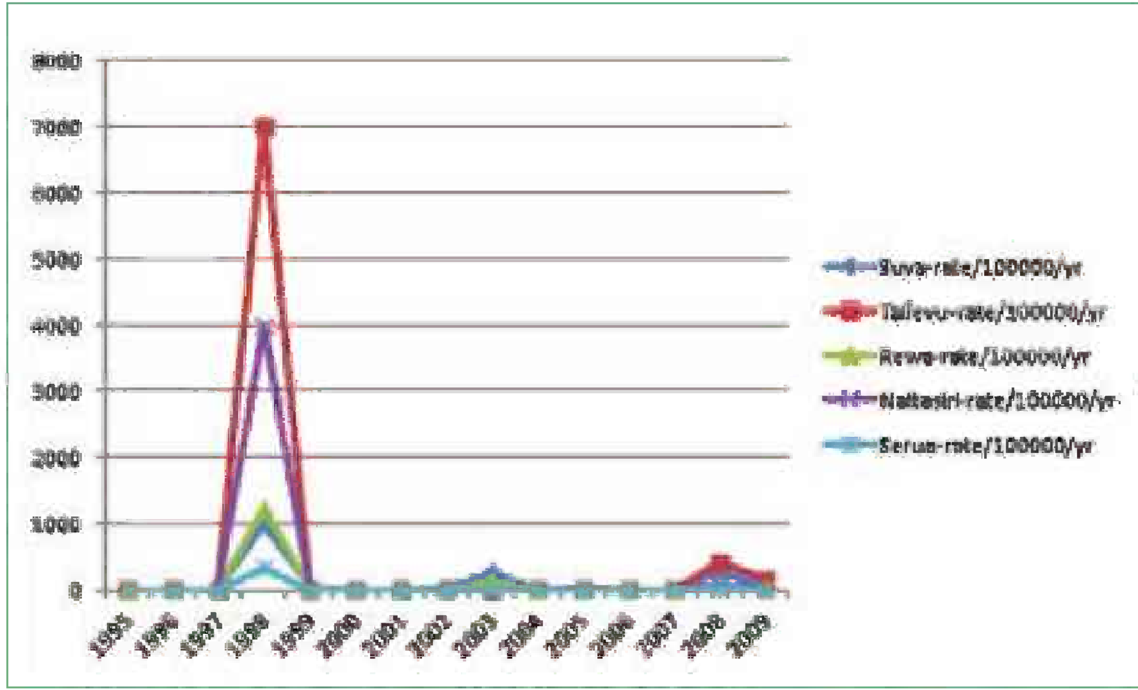


Figure A1.1b Incidence of dengue fever by subdivision 1995-2009 – Western Division

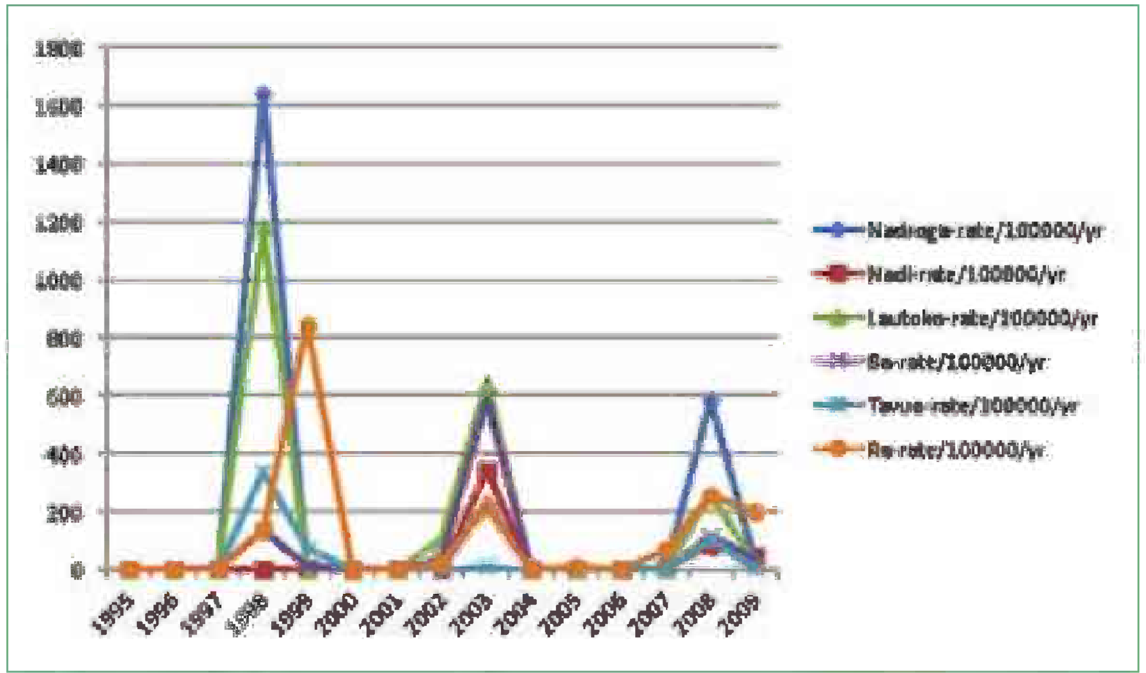


Figure A1.1c Incidence of dengue fever by subdivision 1995-2009 – Northern Division

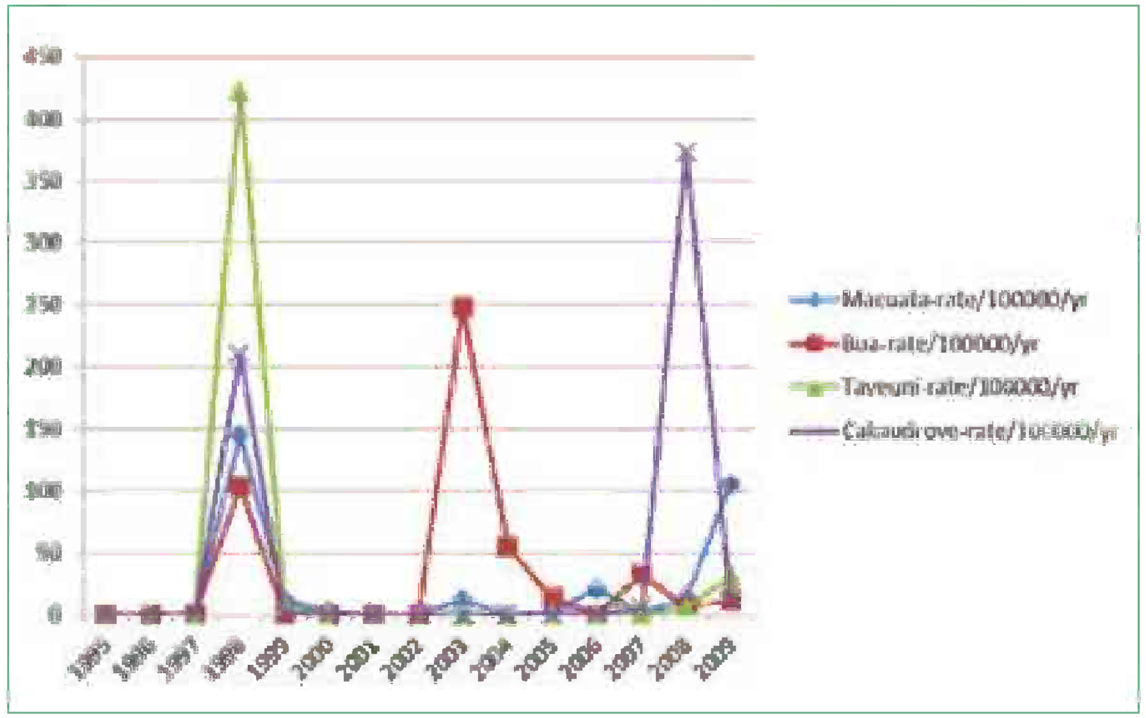


Figure A1.1d Incidence of dengue fever by subdivision 1995-2009 – Eastern Division

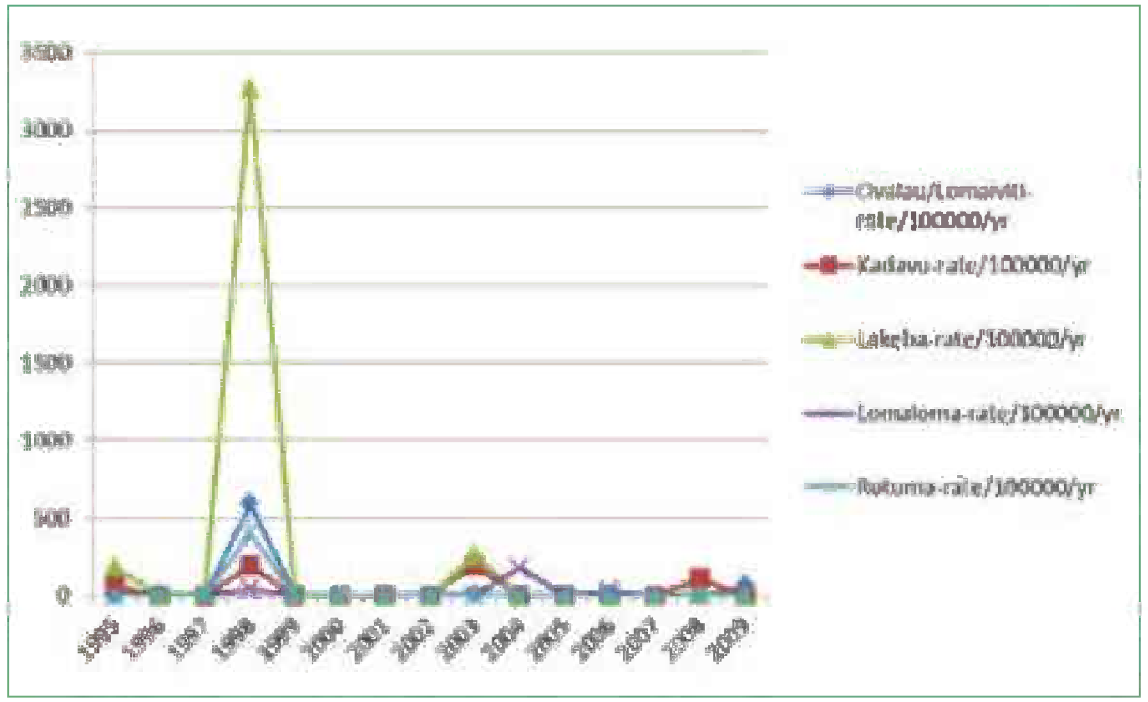


Figure A2.1a Incidence of diarrhoeal disease by subdivision 1995-2009 – Central Division

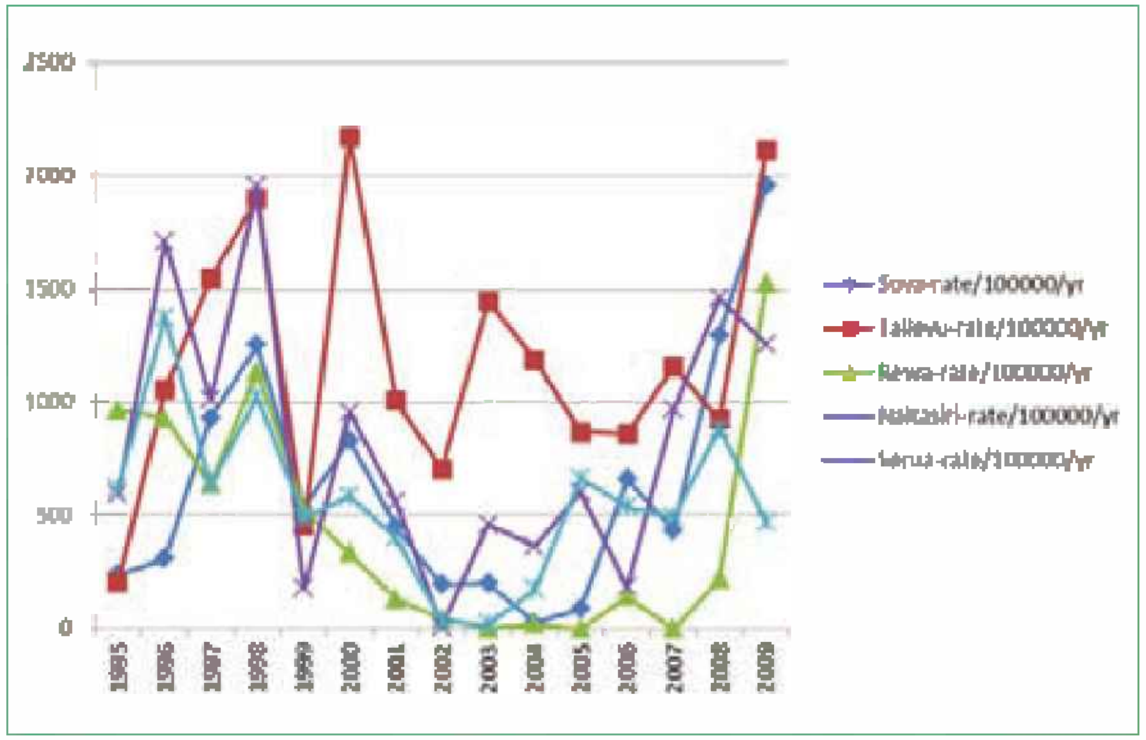


Figure A2.1b Incidence of diarrhoeal disease by subdivision 1995-2009 – Western Division

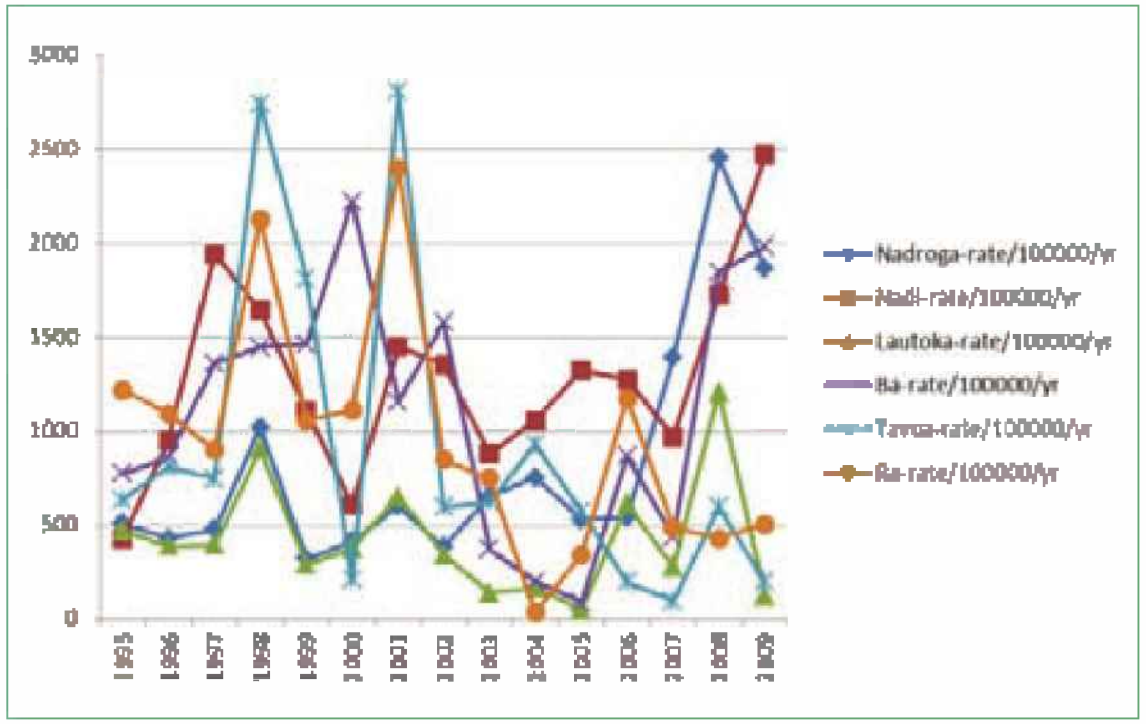


Figure A2.1c Incidence of diarrhoeal disease by subdivision 1995-2009 – Northern Division

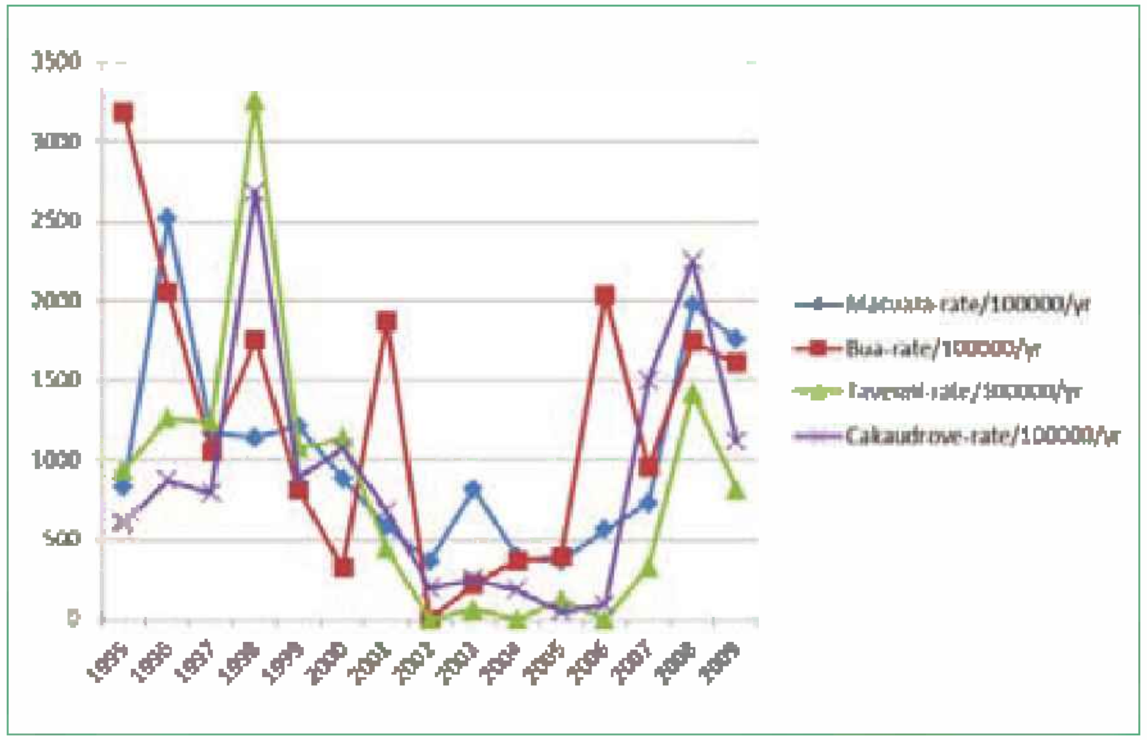


Figure A2.1d Incidence of diarrhoeal disease by subdivision 1995-2009 – Eastern Division

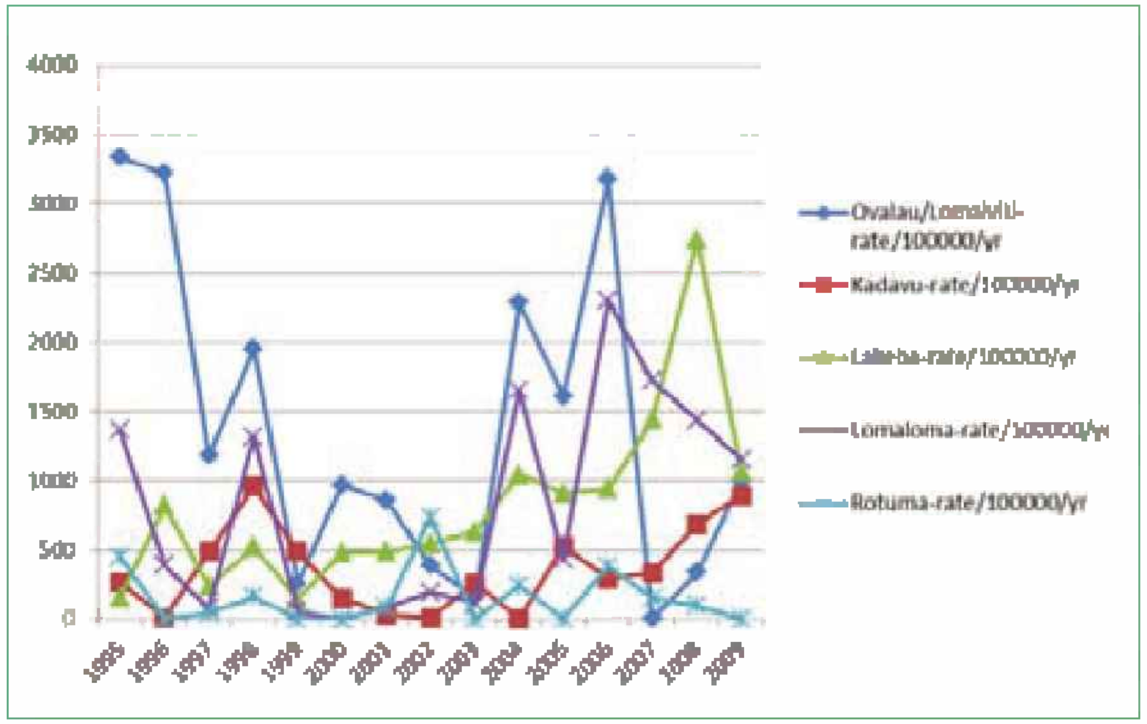


Figure A3.1a Incidence of leptospirosis by subdivision 1995-2009 – Central Division

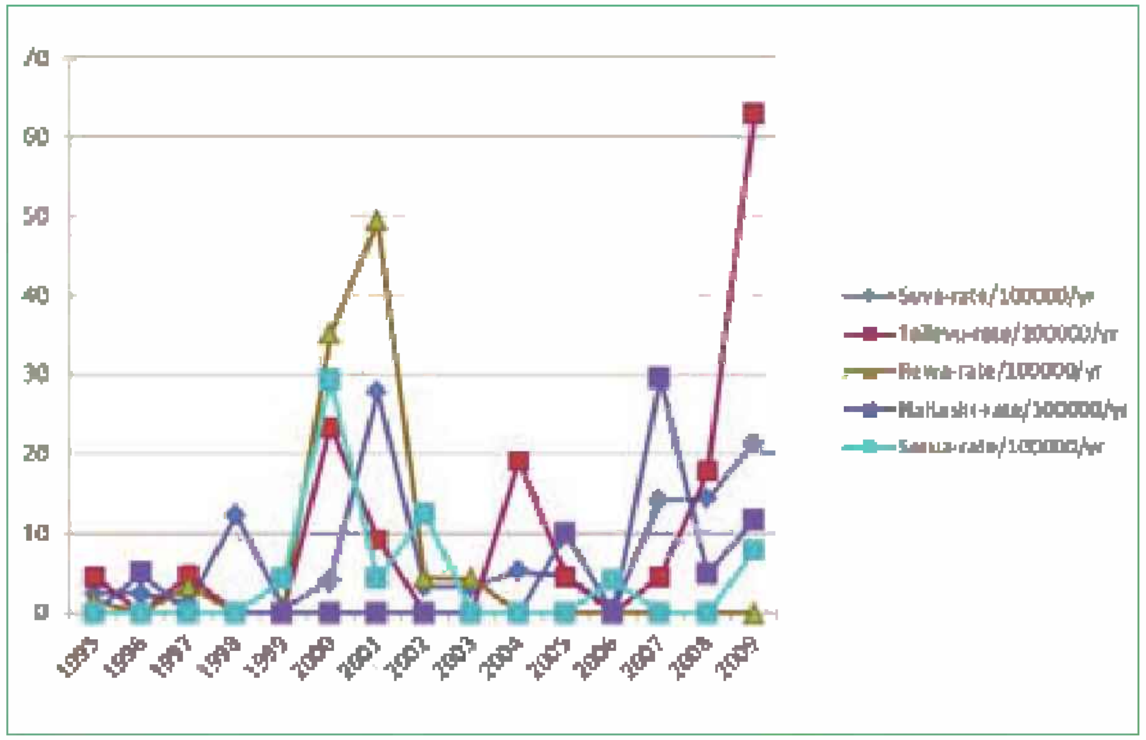


Figure A3.1b Incidence of leptospirosis by subdivision 1995-2009 – Western Division

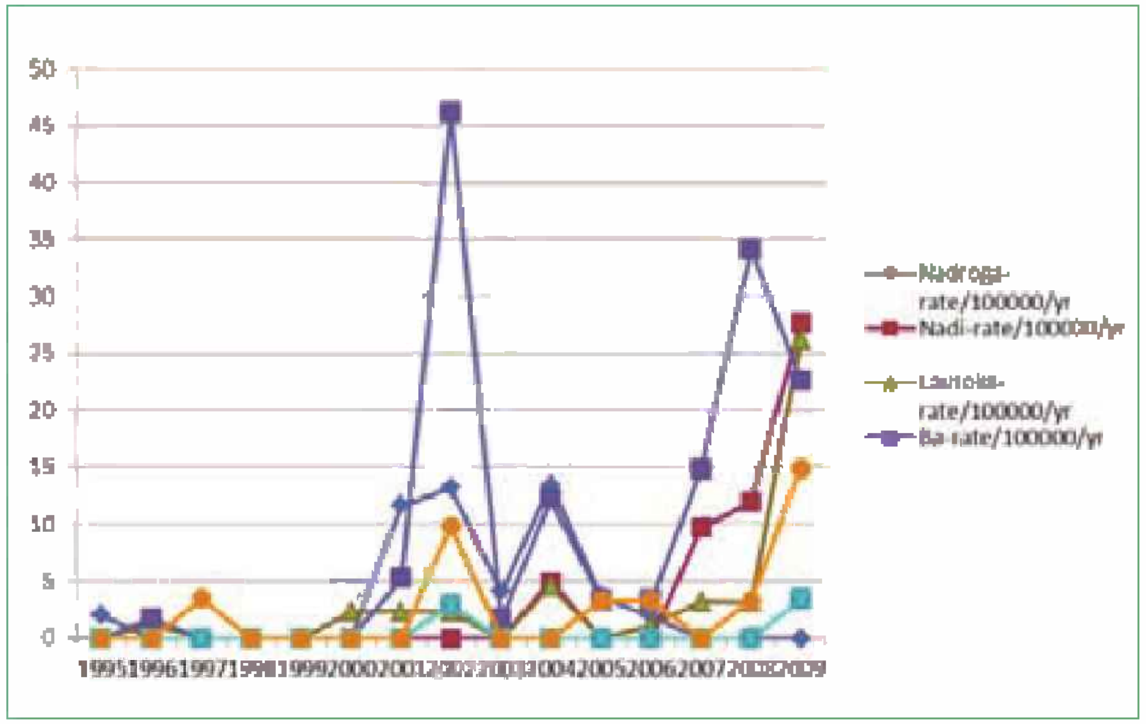


Figure A3.1c Incidence of leptospirosis by subdivision 1995-2009 – Northern Division

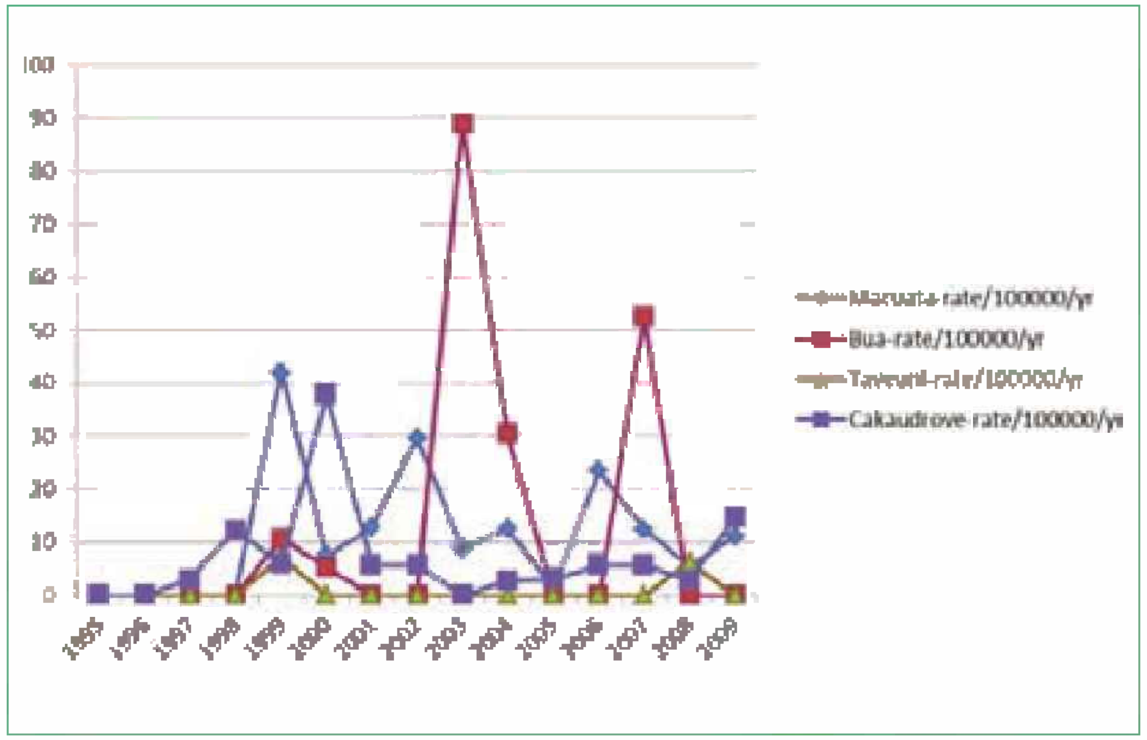


Figure A3.1d Incidence of leptospirosis by subdivision 1995-2009 – Eastern Division

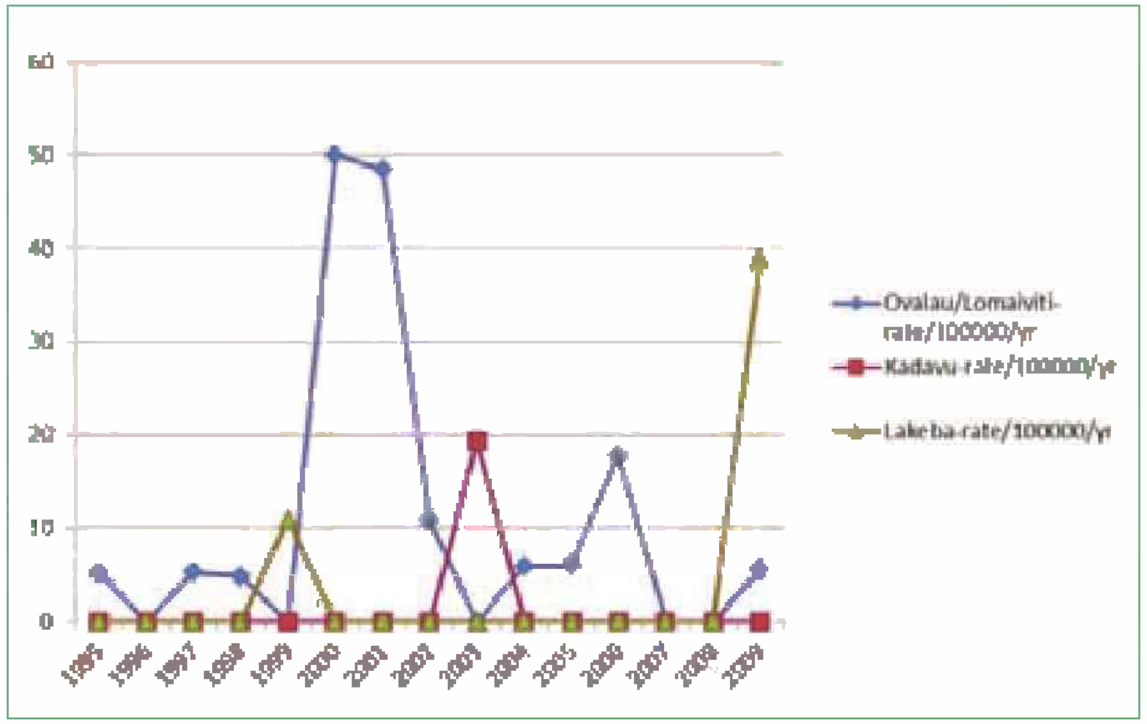


Figure A4.1a Incidence of typhoid by subdivision 1995-2009 – Central Division

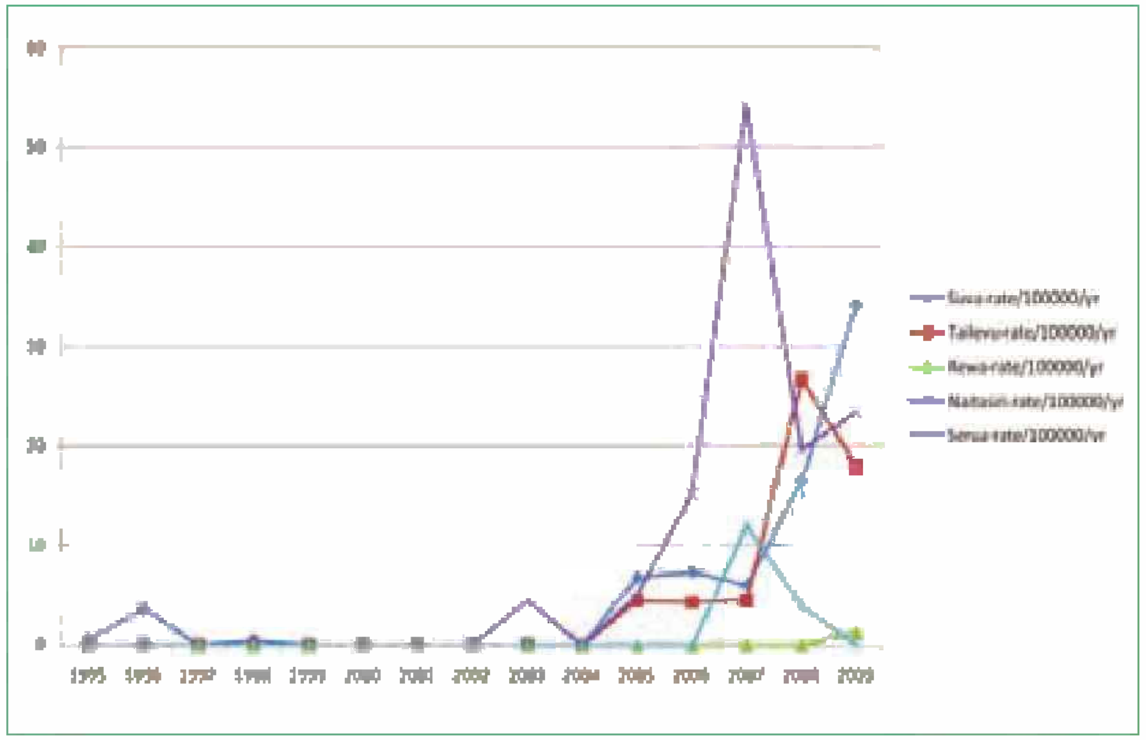


Figure A4.1b Incidence of typhoid by subdivision 1995-2009 – Western Division

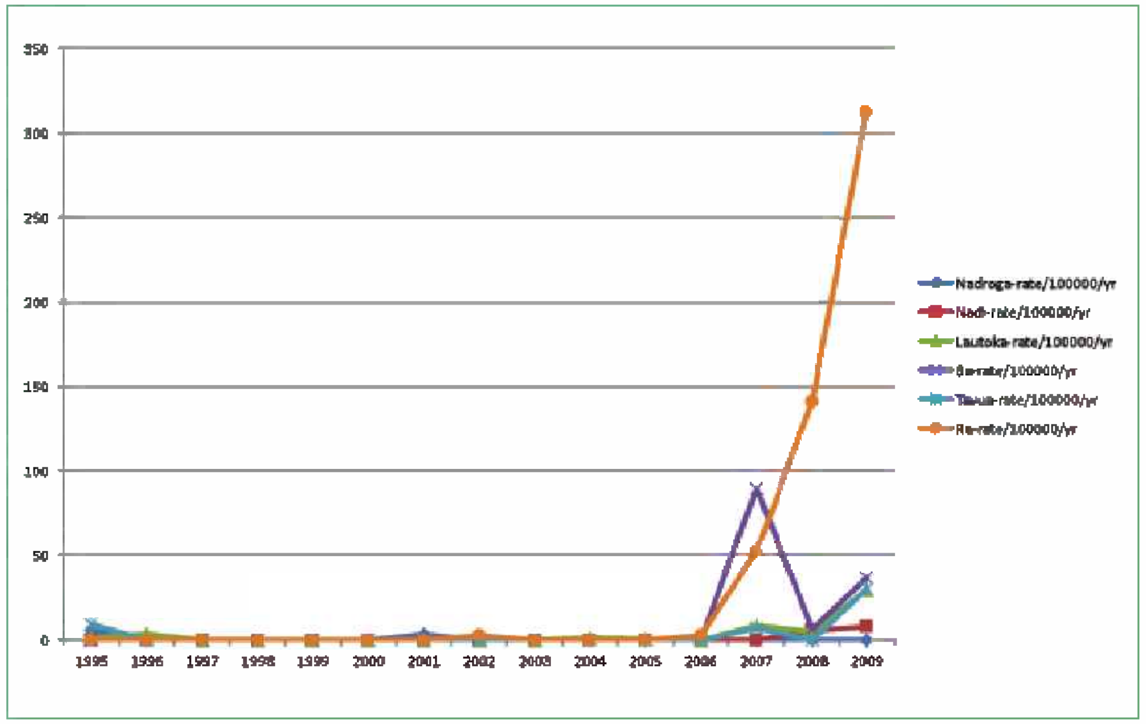


Figure A4.1c Incidence of typhoid by subdivision 1995-2009 – Northern Division

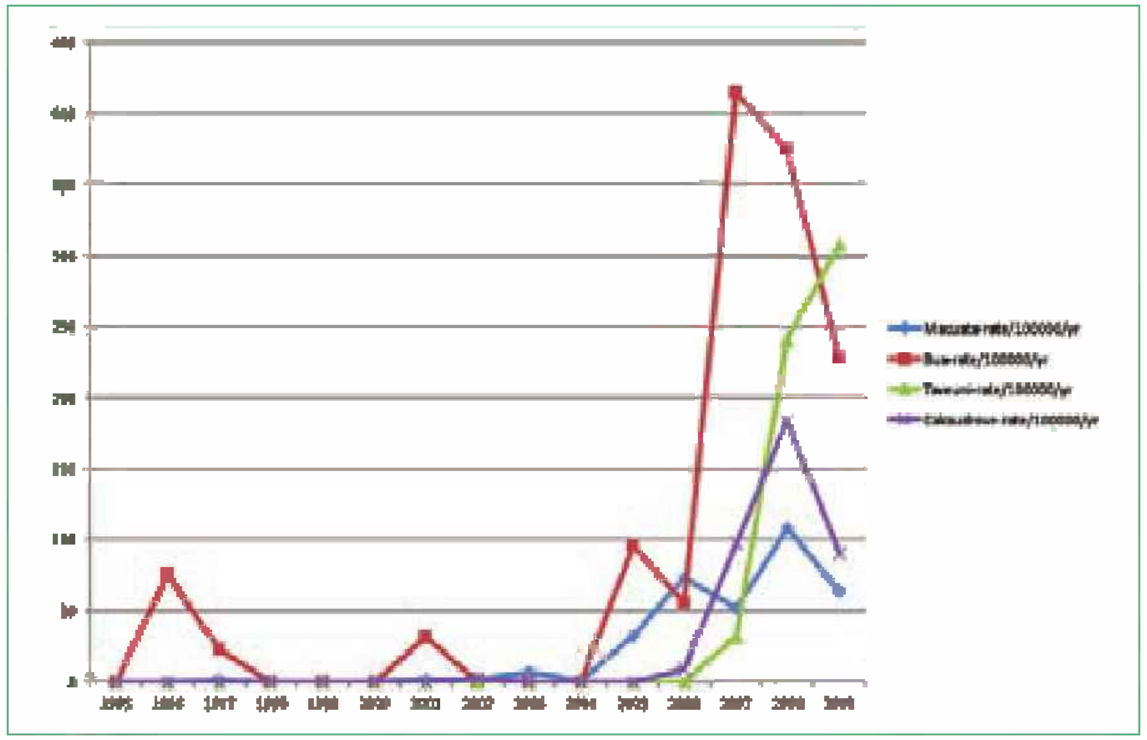
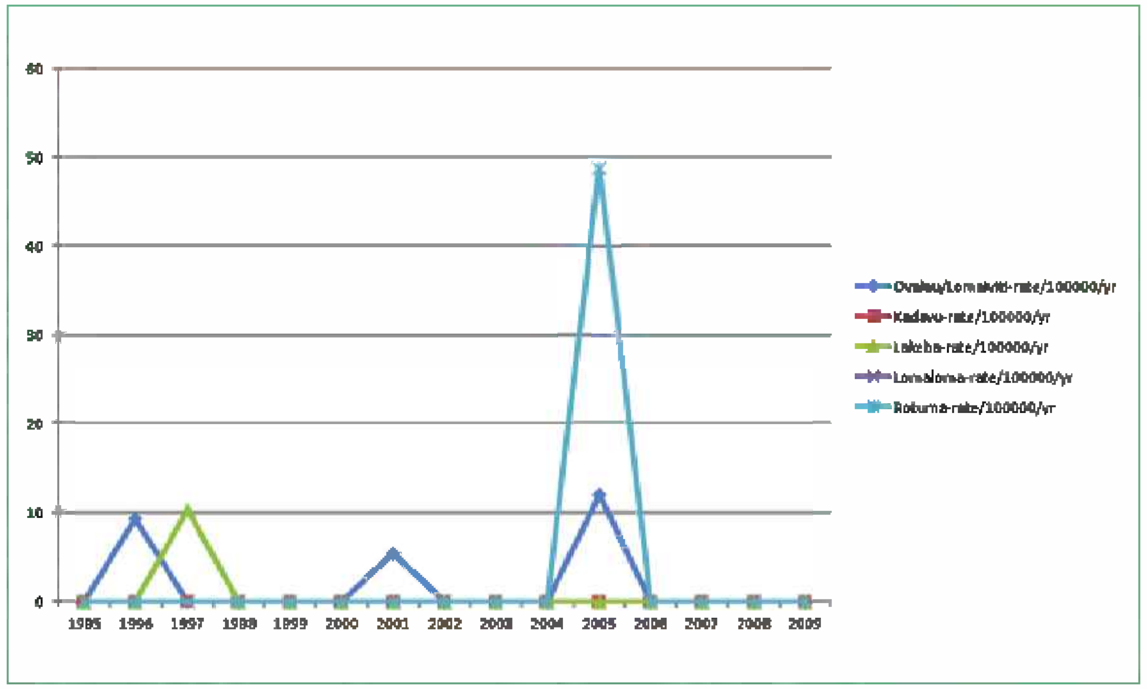


Figure A4.1d Incidence of typhoid by subdivision 1995-2009 – Eastern Division



NB. Rotuma had only one case, but small population (~2000) gives high rate.