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Research article

Predicting climate-sensitive water-related disease trends based on health, seasonality and weather data in Fiji

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ABSTRACT

Leptospirosis, typhoid and dengue are three water-related diseases influenced by environmental factors. We examined whether seasonality and rainfall predict reported syndromes associated with leptospirosis, typhoid and dengue in Fiji. Poisson generalised linear models were fitted with s6 early warning, alert and response system (EWARS) syndromic conditions from March 2016 until December 2020, incorporating seasonality, temperature and rainfall. Watery diarrhoea, prolonged fever and suspected dengue displayed seasonal trends with peaks corresponding with the rainy season, while bloody diarrhoea, acute fever with rash and acute jaundice syndrome did not. Seasonality was the most common predictor for watery and bloody diarrhoea, prolonged fever, suspected dengue, and acute fever plus rash in those aged 5 and over, explaining between 0.4% – 37.8% of the variation across all conditions. Higher rainfall was the most common predictor for acute fever plus rash and acute jaundice syndrome in children under 5, explaining between 1.0% – 7.6% variation across all conditions. Each EWARS syndromic condition case peak was associated with a different rainfall lag, varying between 0 and 11 weeks. The relationships between EWARS, rainfall and seasonality show that it is possible to predict when outbreaks will occur by following seasonality and rainfall. Pre-positioning of diagnostic and treatment resources could then be aligned with seasonality and rainfall peaks to plan and address water-related disease outbreaks.

Introduction

Water-related diseases, such as cholera, leptospirosis, typhoid and dengue, are a major public health issue causing 3.4 million deaths annually [1,2]. Diarrhoea alone is the fifth leading cause of death in children under 5 years [3]. In 2019, the World Health Organization (WHO) listed dengue as one of the 10 top public health threats [4]. Drivers of these water-related diseases include climate change, changing weather patterns, and water access and security [5,6].

In Pacific Island Countries (PICs), water-related diseases contribute to a significant disease burden [7]. PICs are at risk and vulnerable to outbreaks because of a variety of factors, including: their tropical climate; location; climate change impacts; poverty; poor sanitation; limited resources (financial and human); location of the population from healthcare facilities; limited outbreak investigation and verification; lack of surveillance infrastructure; laboratory capacity; and wider health systems capacity such as status of preparedness planning that influence the ability to deliver comprehensive health services [7–10]. Because of laboratory capacity and inadequate surveillance, it is thought that conditions such as dengue are likely underdiagnosed and under-reported [7]. Recent outbreaks such as the 2000 Federated States of Micronesia cholera outbreak with 3542 cases, the 2012 New Caledonia dengue outbreak with 10,000 cases, and the Fiji 2013–14 dengue outbreak with 25,000 cases highlight the vulnerability of PICs to water-related disease outbreaks [11–13].

Public health surveillance is a strategy to manage this increased risk of water-related disease. It is an important tool for disease prevention and control, and can help reduce the disease burden [14]. Surveillance is a core function of public health and can inform decisions for prevention, planning, and resource allocation [14,15]. It can provide a timely response to disease outbreaks, mitigating the effects on populations resulting in reductions in morbidity and mortality [16]. There are several types of monitoring systems used to detect disease outbreaks, including sentinel surveillance, clinical-based

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surveillance, event-based surveillance, surveillance by proxy, environmental monitoring, and syndromic surveillance [7,8,15,16].

Syndromic surveillance is a detection method at the individual and population level for disease symptoms prior to clinical or laboratory confirmation [17,18]. There is a growing popularity of syndromic surveillance as it allows real-time outbreak detection, monitoring and investigation that can identify clusters of undiagnosed diseases and help engage a rapid response [17,18]. More timely responses can contribute to a reduction in morbidity and mortality [18].

The early warning, alert, and response system (EWARS) is an example of a public health syndromic surveillance system. It was developed by the WHO to improve disease outbreak detection in emergency settings (e.g., after a natural disaster or in countries in conflict; [19]). EWARS can be rapidly implemented, as it can run off solar chargers in areas without electricity [19–21]. A kit (includes laptops, solar chargers, smartphones preinstalled with open-source EWARS applications) costs approximately US$5000, and can support up to 500,000 people across 50 healthcare facilities [19]. Since EWARS conception in 2012, it has been used in several countries including Brazil, Bangladesh, Indonesia, Malaysia, Mexico and Syria to monitor syndromic conditions and potential outbreaks [20–23]. In February 2016, it was first implemented in Fiji by the Ministry of Health and Medical Services with the help of the WHO after Cyclone Winston hit the country to monitor future outbreaks [24]

Since 2016, only one study has been conducted on EWARS in Fiji; this focused on the performance of EWARS post-Cyclone Winston [24]. Our paper presents findings of a study designed to understand EWARS syndromic conditions over time and the relationship to weather data. Our study aimed to establish: (a) the national and divisional trends for 6 EWARS syndromic conditions that are commonly associated with leptospirosis, typhoid and/or dengue (watery diarrhoea, bloody diarrhoea, prolonged fever, acute fever plus rash, acute jaundice syndrome, and suspected dengue) from 2016 to 2020; (b) any association between the 6 syndromic conditions and meteorological data, including seasonality; and (c) determine the best-fitting models between rainfall time lag and syndromic case numbers. Our findings can help inform the timing of when to pre-position of diagnostic and treatment resources to prevent and address water-related disease outbreaks.

Materials and methods

Background

Fiji is composed of 332 islands, and is divided administratively into with four divisions (Central, Western, Eastern and Northern). In Fiji, the average annual temperature is 25 °C, and from May to October it lowers to an average of 22 °C [25,26]. Temperatures range from a high of 30 °C, and as low as 12 °C overnight. December to April is the wet season, especially over the larger islands, Viti Levu and Vanua Levu [26–28]. Rain is variable, and higher in the windward, south-eastern areas (4000–5000 mm/yr), and lower in the leeward, north-western areas (<2000 mm/yr) of larger islands, due to localised island rain shadow effects [29]. Heavy short local showers are common [28].

Fiji is specifically at risk of outbreaks of leptospirosis, typhoid and dengue [13,30,31]. Research findings indicate that leptospirosis incidence rates range between 20 and 100 cases per 100,000, and are highest in *iTaukei* (Indigenous) males 15 to 45 year-olds with peaks occurring between February and June [32–34]. In the Central Division, the typhoid incidence rate is 205.8 cases per 100,000 people, with 90% of cases amongst *iTaukei* people [30,35]. Records indicate that typhoid cases peak 2 months after the rainy season every January to June [36]. Dengue cases peak during the warmer and wetter season every December to July [37]. Incidence rates of dengue vary from 0.34 to 51.15 per 100,000 people during non-outbreak periods to as high as 1057 per 100,000 in outbreaks such as the rate for 20 to 24 year olds in 2014 [38]. Because of the population's susceptibility to water-related diseases, the Fijian Ministry of Health and Medical Services launched a campaign in October 2020 to prevent leptospirosis, typhoid, dengue and diarrhoea outbreaks [39]. This paper provides findings that illustrate that seasonality and weather data can be used as public health tools to guide diagnostic and treatment resources to prevent outbreaks.

Data collection

EWARS data are collected through indicator-based surveillance and events-based surveillance systems, which allows real-time reporting on public health events from 76[1] sites across the four divisions in Fiji (Northern n = 19, Central n = 23, Western n = 24, Eastern = 10) (Fig. 1) [40]. Information is collected on 10 syndromic conditions in people and in this paper is reported in 2 age groups; under 5 years old and 5 years and older. This paper only examines 6 of the syndromic conditions (Table 1). The 2 age divisions were chosen as syndromic conditions influence the age groups differently, for example., diarrhoea is the second leading cause of death in children under the age of 5 [41], and is not a common cause of death in adults. The 6 syndromic conditions chosen are those most closely associated with leptospirosis, typhoid and/or dengue [42–45]. Data are automatically analysed by the EWARS system, and alerts are generated based on predetermined thresholds [40]. More information on the data collection procedure and thresholds is available from the Ministry of Health and Medical Services EWARS standard operating procedure document [40]. The data from the 76 sites from March 6 2016, to December 27 2020, (4.75 years) were collated, cleaned, and checked for duplicates in Microsoft Excel, with duplicates removed.

Meteorological data for 2016 to 2020 were obtained from the Fiji Meteorological Service on daily rainfall and minimum and maximum air temperatures from weather stations across Fiji. Across each weather site, daily data were combined to calculate average weekly rainfalls and average minimum and maximum temperatures. The weekly average data for each site were then combined to provide divisional and national averages. The divisional and national weather data derived were combined with the EWARS data into five datasets on matching dates. Of the five data sets produced, one was at the national level and four for were at the divisional level (one for each division).

Seasonal and meteorological modelling

Microsoft Excel was used to create time series plots with rainfall data to identify seasonal patterns for the 6 syndromic conditions. Poisson generalised linear models (GLMs) were created using the statistical software R (version 4.0.5) (Table 2) [46]. Rainfall time lag periods (the time lag in weeks after the rainfall) were decided based on existing literature for each syndromic condition. Watery and bloody diarrhoea models were run with rainfall time lag of 1 to 12 weeks [47–50]; prolonged fever models time lag was 3 to 12 weeks [51,52]; acute fever plus rash and acute jaundice syndrome models time lag of 4 to 12 weeks [49,50]; and the suspected dengue models used a time lag of 5 to 14 weeks [53–55].

The percentage of patients by age group for the 6 syndromic conditions was calculated by dividing the total number of each syndromic condition per year by the total number of patients across all syndromic conditions (Table 3).

[1] *Lodoni Health Center was destroyed by a fire in August 2017

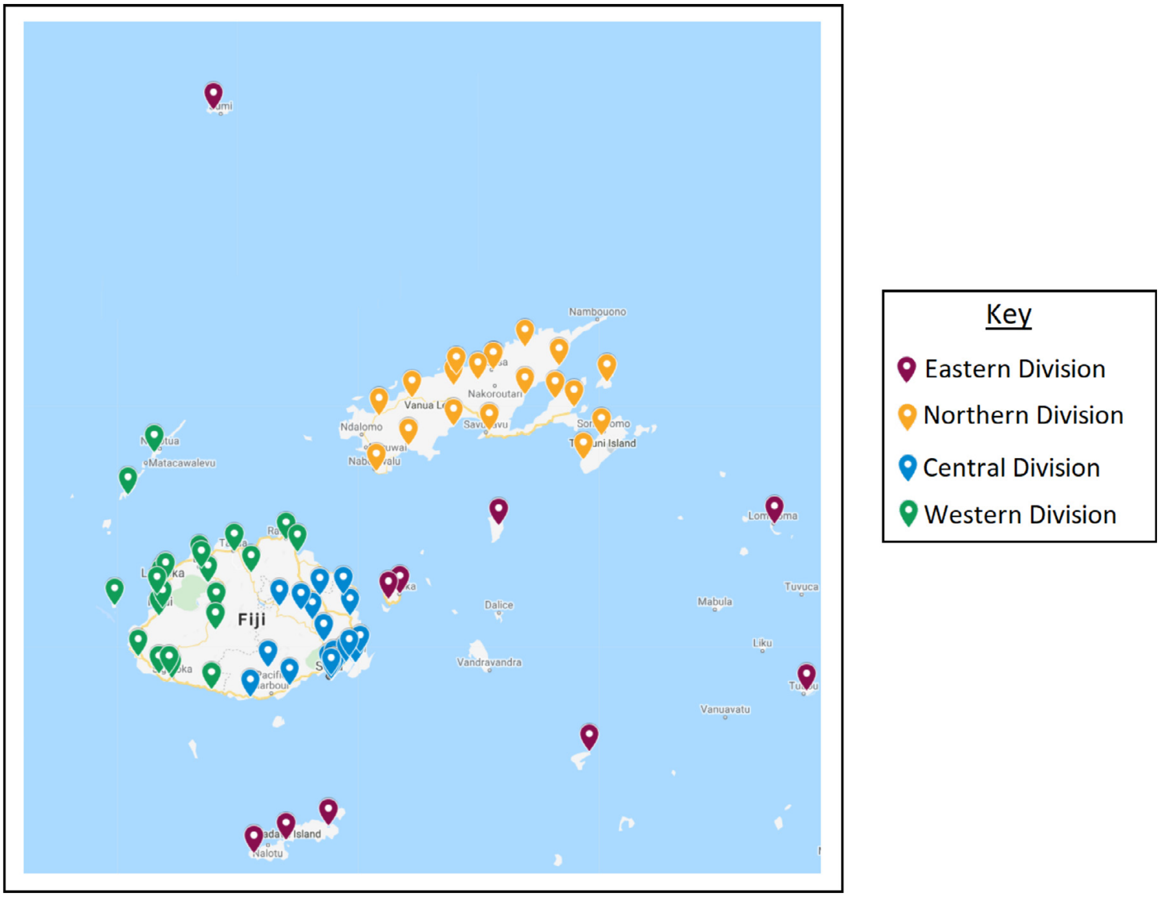

Fig. 1. EWARs locations across the four divisions of Fiji.

Calculating the model fit

The analysis used methods similar to that in Stratton et al. [56] to calculate model fit. The percentage variation explained by each GLM modelled syndromic condition was calculated using the null and residual deviances (Appendix 1 Tables 1 and 2). A comparison between models (Table 2) was conducted to explain the model and rainfall time lag percentage variation, with the aim to identify which rainfall time lag period produced a model of best fit (the model with the highest variation percent). The Pearson's Goodness of Fit test was used to determine the statistical significance of the impact of using time lag in Models 3a and 3b. Once the national models were built, decisions for the divisional level analyses were based on the rainfall time lag model that explained the highest variation at the national level. The divisional level analyses then replicated the earlier steps.

Ethics

The overarching WISH Fiji project received ethical approval from the Fiji National Health Research and Ethics Review Committee

Table 1
EWARs syndrome case definition and trigger threshold.

Syndrome	Case Definition	Threshold to trigger alert [40]	Associated condition	Citations to supporting associated condition(s)
Watery diarrhoea	3 or more loose or watery stools in 24 h (non-bloody)	Twice the average number of cases seen in the previous 2 weeks	Leptospirosis and typhoid	Haake & Levett [42] Bhandari et al. [44]
Bloody diarrhoea	Any episode of acute bloody diarrhoea	3 cases in one location OR twice the average number of cases seen in the previous 2 weeks	Leptospirosis and typhoid	Najafi et al. [43] Bhandari et al. [44]
Prolonged fever	Any fever either reported or measured (>38 °C) lasting three or more day.	Twice the average number of cases seen in the previous 2 weeks	Typhoid	Bhandari et al. [44]
Acute fever plus rash	Fever either reported or measured (>38 ° C) plus non-blistering rash	1 case	Leptospirosis	Haake & Levett [42]
Acute jaundice syndrome	Jaundice (yellow eyes or dark urine) and severe illness with or without fever	3 cases	Leptospirosis	Haake & Levett [42]
Suspected dengue	Fever for at least 2 days plus at least 2 of the following: 1) nausea or vomiting; 2) muscle or joint pain; 3) severe headache or pain behind the eyes; 4) rash; or 5) bleeding	Twice the average number of cases seen in the previous 3 weeks	Dengue	Gubler [45]

Table 2
Creation of models including seasonality and weather parameters.

Model	Model content
1	Seasonality
2	Model 1 + maximum temperature + minimum temperature
3a	Model 2 + no rainfall time lag
3b	Model 2 + rainfall time lag

Variables: Seasonality: week since EWARS data collection included temperature (maximum + minimum): average weekly temperature in degrees Celsius, rainfall time lag: average weekly rainfall with a time lag.

(FNHRERC No: 2018.231.CEN), Fiji National University's College Health Research Ethics Committee (CHRED ID: 009.19) and the University of Sydney's Human Research Ethics Committee (2019/588). The meteorological and EWARS data are publicly available data sourced from the Fiji Meteorological Service and the Ministry of Health and Medical Services in Fiji.

Results

The percentage of patients experiencing each syndromic condition were different from 2016 to 2020 (Table 3). The peak numbers of total patients seen every year was in March and April. Patient numbers in children under 5 and those aged 5 and over show an annual seasonal trend at the national level and geographical areas. Across the 6 syndromic conditions there is considerable variation, and some syndromic syndromes are rarer than others (e.g., acute jaundice syndrome). More results are available in Appendix 1.

In-depth analysis found there is an annual seasonal trend with higher rates around March/April for watery diarrhoea, prolonged fever and suspected dengue in both age groups at the national level (Appendix 1 Figures 2A, 2B, 3A, 3B, 4C and 4D). Further there is also an annual seasonal trend with higher rates in March/April for watery diarrhoea and suspected dengue at the divisional level (Appendix 1 Figures 2A, 2B, 4C and 4D). However, there is no trend present for bloody diarrhoea, acute fever plus rash, and acute jaundice syndrome in both age groups at the national and divisional levels (Appendix 1 Figures 2C, 2D, 3C, 3D, 4A and 4B).

The models produced show the national-scale variation in the 6 syndromic conditions with seasonality, temperature, and time-lag effects of rainfall (Tables 4 and 5). Variation explained across conditions ranged from 0.4% to 43% amongst the different models. Model 1 showed 0.4% to 37.8% of the variation in the syndromic case numbers could be explained by seasonality. Variation across Model 2 showed minor change from Model 1 with only 1.0% to 38.2% of the syndromic cases numbers being explained by seasonality and temperature. Model 3a showed 2.2% to 38.4% of the variation in syndromic cases numbers could be explained by seasonality, temperature, and rainfall with no lag. Variation in Model 3b showed 1.0% to 42.9% of the syndromic cases numbers could be explained by seasonality, temperature, and different rainfall time lags. Across all the models for the 6 conditions, acute jaundice syndrome in children under 5 had the lowest percent variation and suspected dengue in the 5 and over group had the highest percent variation that could be explained.

Seasonality appeared to contribute significantly to the variability in models, except for acute fever plus rash in children aged under 5, and acute jaundice syndrome for both age groups. Seasonality explained between 0.4% and 37.8% of the variation in syndromic conditions. Rainfall explained the greatest proportion of variability for acute fever plus rash in children aged under 5 and acute jaundice syndrome in both age groups. Rainfall explained between 1.0% and 7.6% of the variation in syndromic conditions. Temperature was not a major contributory factor for any of the conditions; it only explained between 0.4% and 3.7% variation in cases.

Analyses were also conducted to identify the rainfall time lag of best fit with the highest variation percent for each syndromic condition (Tables 4 and 5). Across the 6 conditions, the rainfall time lag of best fit ranged from a 2-week period to an 11-week period. The lag time of best fit was different for each condition based on the age group. All the best fit time lag models identified were statistically significant based on their p values of less than or equal to 0.5.

Divisional level analysis of the best time fit lag data showed variation across the four divisions for the 6 conditions (Table 6). There was mixed significance in the models, and large differences in the variability across the four divisions for syndromic condition. Watery diarrhoea, prolonged fever and suspected dengue for both age groups were the only statistically significant findings across all four divisions. Central division for prolonged fever and acute fever in both populations had higher variation than present at the national level. Western division had higher variation than the national level for suspected dengue for both age groups and acute jaundice syndrome in those aged five and over. Eastern division also experienced higher variation than at the national level for acute fever in under-fives.

Discussion

Our paper indicates seasonality and meteorological trends from 2016 to 2020 in 6 EWARS syndromic conditions (watery diarrhoea, bloody diarrhoea, prolonged fever, acute fever plus rash, acute jaundice syndrome, and suspected dengue). Rainfall explained the most

Table 3
The percentage of patients diagnosed with the condition aged under 5 and those aged over 5 yearly from 2016 to 2020.

EWARS Condition	2016* (N = 35,581)	2017 (N = 36,551)	2018 (N = 40,875)	2019 (N = 44,033)	2020 (N = 38,250)
Watery diarrhoea in children under 5	22.8%	21.3%	20.4%	20.6%	19.5%
Watery diarrhoea in 5 and over	49.3%	46.2%	42.4%	41.5%	46.6%
Bloody diarrhoea in children under 5	0.5%	0.3%	0.3%	0.3%	0.3%
Bloody diarrhoea in 5 and over	1.1%	0.8%	0.9%	0.7%	1.0%
Acute fever plus rash in children under 5	0.4%	0.1%	0.1%	0.2%	0.1%
Acute fever plus rash in 5 and over	1.9%	0.1%	0.0%	0.2%	0.1%
Prolonged fever in children under 5	1.4%	1.7%	1.0%	3.5%	1.2%
Prolonged fever 5 and over	4.4%	3.7%	3.6%	7.3%	3.8%
Acute jaundice syndrome in children under 5	0.1%	0.2%	0.1%	0.2%	0.2%
Acute jaundice syndrome in 5 and over	0.4%	0.2%	0.2%	0.3%	0.6%
Suspected dengue in children under 5	0.5%	1.3%	1.2%	0.8%	1.0%
Suspected dengue in 5 and over	17.2%	23.9%	29.7%	24.3%	25.6%

*2016 data starts from the week of March 13th, 2016 N = the total number of syndromic cases per year.
% = number cases of each syndromic condition divided by the total number of syndromic cases per year (N).

Table 4
Variation explained by GLM models of watery diarrhoea, bloody diarrhoea and prolonged fever by age group with seasonality, temperature, and time-lag effects of rainfall.

Models#	Watery diarrhoea <5	Watery diarrhoea >5	Bloody diarrhoea <5	Bloody diarrhoea >5	Prolonged fever >5	Prolonged fever >5
Model 1	12.4%	10.8%	3.1%	6.1%	24.6%	24.5%
Model 2	13.8%	13.8%	4.8%	7.1%	24.7%	25.1%
Model 3a	14.0%*	13.8%*	4.9%*	7.1%*	31.6%*+	31.8%*+
Model 3b with 1 week rainfall time lag	14.7%*	15.1%*	5.8%*	7.3%*	–	–
Model 3b with 2-week rainfall time lag	14.0%*	14.4%*	8.9%*+	7.6%*	–	–
Model 3b with 3-week rainfall time lag	13.8%*	14.5%*	6.3%*	7.6%*+	26.7%*	26.2%*
Model 3b with 4-week rainfall time lag	15.6%*+	15.5%*	4.5%*	7.2%*	25.5%*	25.1%*
Model 3b with 5-week rainfall time lag	15.5%*	18.3%*+	4.8%*	7.0%*	25.3%*	25.1%*
Model 3b with 6-week rainfall time lag	14.9%*	16.4%*	4.5%*	6.8%*	24.6%*	26.2%*
Model 3b with 7-week rainfall time lag	15.2%*	15.5%*	3.4%*	6.5%*	26.2%*	28.5%*
Model 3b with 8-week rainfall time lag	14.8%*	15.9%*	4.2%*	6.3%*	26.2%*	27.0%*
Model 3b with 9-week rainfall time lag	14.3%*	15.6%*	3.2%*	6.4%*	25.3%*	25.9%*
Model 3b with 10-week rainfall time lag	14.3%*	15.5%*	3.2%*	6.1%*	26.7%*	28.2%*
Model 3b with 11-week rainfall time lag	14.1%*	15.5%*	3.6%*	6.1%*	27.7%*	26.3%*
Model 3b with 12-week rainfall time lag	13.3%*	15.0%*	3.2%*	5.7%*	26.8%*	26.8%*

Model 1 syndromic case number and seasonality.
Model 2 syndromic case number, seasonality, maximum and minimum temperature.
Model 3a syndromic case number, seasonality, maximum and minimum temperature, and no rainfall time lag.
Model 3b syndromic case number, seasonality, maximum and minimum temperature and with varying rainfall time lag.
Significance: * < 0.05.
+ The rainfall lag time of best fit per condition.

variance in watery and bloody diarrhoea syndromic conditions, and the peak number of cases for both conditions were similar to other rainfall time lag periods reported in other studies. Carlton et al. [47] reported peak cases of diarrhoea in Ecuador 2 weeks after heavy rainfall, whereas Bhavnani [48] reported peak cases in Ecuador five weeks after rainfall. The differences in peaks may indicate that different pathogens are responsible for cases. Heavy rainfall can damage or overwhelm WASH systems, cause faecal material to enter waterways leading to water source contamination, which in turn leads to increased rates of diarrhoea [57]. Further, rainfall can create a muddy environment contaminated with human or animal faeces, which is common in rural agricultural areas with poor sanitation and

Table 5
Variation explained by GLM models of acute fever plus rash, acute jaundice syndrome and suspected dengue by age group with seasonality, temperature, and time-lag effects of rainfall.

Models#	Acute fever plus rash <5	Acute fever plus rash >5	Acute jaundice syndrome <5	Acute jaundice syndrome >5	Suspected dengue <5	Suspected dengue >5
Model 1	0.4%	7.0%	0.7%	2.8%	23.0%	37.8%
Model 2	1.7%	7.8%	1.0%	6.5%	23.8%	38.2%
Model 3a	3.5%*	8.4%*	2.2%*	7.0%*	24.0%*	38.4%*
Model 3b with 4-week rainfall time lag	1.1%	4.7%*	1.9%*	7.2%*	–	–
Model 3b with 5-week rainfall time lag	1.0%	4.1%*	1.4%	5.8%*	30.0%*+	41.1%*
Model 3b with 6-week rainfall time lag	1.7%*	5.0%*	2.0%*	7.9%*+	28.8%*	42.4%*
Model 3b with 7-week rainfall time lag	2.5%*	10.2%*	2.5%*+	6.1%*	29.2%*	42.9%*+
Model 3b with 8-week rainfall time lag	4.3%*	7.7%*	2.1%*	4.6%*	26.0%*	42.2%*
Model 3b with 9-week rainfall time lag	3.8%*	9.2%*	1.8%*	4.6%*	27.0%*	41.1%*
Model 3b with 10-week rainfall time lag	4.0%*	11.4%*+	1.3%	5.0%*	26.1%*	40.4%*
Model 3b with 11-week rainfall time lag	8.0%*+	11.2%*	1.5%	4.6%*	24.7%*	39.8%*
Model 3b with 12-week rainfall time lag	4.0%*	4.9%*	1.3%	5.3%*	24.0%*	39.2%*
Model 3b with 13-week rainfall time lag	–	–	–	–	24.3%*	38.1%*
Model 3b with 14-week rainfall time lag	–	–	–	–	24.1%*	37.3%*

Model 1 syndromic case number and seasonality.
Model 2 syndromic case number, seasonality, maximum and minimum temperature.
Model 3a syndromic case number, seasonality, maximum and minimum temperature, and no rainfall time lag.
Model 3b syndromic case number, seasonality, maximum and minimum temperature and with varying rainfall time lag.
Significance: * < 0.05.
+ The rainfall lag time of best fit per condition.

Table 6
GLM models variation by age for the best time fit lag on a divisional level.

Model	Central division	Western division	Eastern division	Northern division
Watery diarrhoea <5 (4-week lag)	9.9%*	8.3%*	4.3%*	11.4%*
Watery diarrhoea >5 (5-week lag)	7.8%*	12.3%*	8.1%*	6.1%*
Bloody diarrhoea <5 (2-week lag)	6.2%*	3.1%*	5.8%	1.2%
Bloody diarrhoea >5 (3-week lag)	7.4%*	5.5%*	1.8%	1.9%*
Prolonged fever <5 (No time lag)	22.9%*	27.8%*	4.8%*	11.8%*
Prolonged fever >5 (No time lag)	32.3%*	24.6%*	3.9%*	12.0%*
Acute fever plus rash <5 (11-week lag)	11.5%*	5.4%*	8.4%	5.3%*
Acute fever plus rash >5 (10-week lag)	3.5%*	7.0%*	29.4%	0.9%
Acute jaundice syndrome <5 (7-week lag)	3.1%	2.2%	5.0%	2.4%*
Acute jaundice syndrome >5 (6-week lag)	12.4%*	12.4%	2.2%	3.1%*
Suspected dengue <5 (5-week lag)	19.4%*	33.0%*	4.7%*	14.0%*
Suspected dengue >5 (7-week lag)	21.6%*	47.0%*	19.7%*	24.0%*

Significance: * < < 0.05.

may lead to the ingestion of diarrhoea pathogens [58]. Research in the PICs by Singh et al. [9] found that climate change and the increased extremes in rainfall will exacerbate diarrhoeal illness.

The connection with rainfall is important because the impact of climate change in Fiji is predicted to cause increased intensity and frequency of days that have extreme rainfall [59]. In contrast, in other PICs such as Papua New Guinea and Tonga, changes in rainfall from climate change will lead to increased experiences of droughts [60]. In Fiji increased rainfall will exacerbate already existing problems in capacity, funds, and resources to address water supply problems, and increase water-related diseases [9]. Changes in rainfall can lead to flash flooding, erosions, and landslides, which in turn can impact food security, infrastructure and human health [61]. Evidence shows the link between climate change and health in the Pacific through changes in water-related disease levels. For example, extensive flooding in Honiara and the province of Guadalcanal in the Solomon Islands in April 2014 from heavy rainfall was linked to increased rotavirus cases [62]. After the 2018 Cyclone Gita in Tonga, there was a significant focus to ensure safe drinking water by the WHO and partners to prevent disease outbreaks [63].

While seasonality, temperature and rainfall accounted for a limited amount of the variation in both watery and bloody diarrhoea syndromic cases, other factors may also be contributing. Other factors that could explain the variation in diarrhoea cases include food contamination, close human-animal contact, levels of tank water, hand washing levels, and poor hygiene [9,64,65]. These other factors could also contribute to other syndromic factors.

In Fiji, typhoid case numbers peak in January to June annually, 2 months after the rainy season [36]. This supports the peaks found in the prolonged fever data reported in this paper. Dewan et al. [51] found typhoid cases from 2005 to 2009 had a 3 to 5 week rainfall time lag in Bangladesh, and Thindwa [52] found a 2-month time lag in Malawi. These timeframes of peak typhoid cases were different to those found in this paper. Rainfall can cause increased contamination of rivers (e.g. with human faecal waste) that is used for bathing, cooking and cleaning, and in turn lead to increased typhoid cases [36,51,66]. The variation in peak cases after rainfall could reflect the presence of 2 different transmissions patterns, short and long cycle typhoid [52]. Short cycle transmission can be linked with households, while long cycle transmission can be linked with environmental factors including contaminated water [67].

While the relationship between rainfall and typhoid is important to consider in prevention, the residential setting (the environment people live in which includes infrastructure, microbiological and physicochemical characteristics (such as the concentration of phosphate of drinking water)) is also key. Jenkins et al. [36] found 42.5% of the variance in typhoid risk could be explained by the residential setting. The factors they examined included the external condition (e.g., garden, drainage), drinking water condition (e.g., water storage), sanitation (e.g., toilet smell), and microbial loads (e.g., ammonia concentration). Cases of typhoid are more likely to have occurred in areas that have experienced flooding of a stream or river in the last 2 months [68]. This is important to consider as some PICs such as the Marshall Islands and Kiribati are predicted to face increased flooding, and rising sea levels from climate change [69,70], and in turn greater risk from water-related diseases.

Acute fever with rash and acute jaundice syndrome are both symptoms of leptospirosis, with different rainfall time peaks. Other studies have also found an impact of rainfall time lags. Matsushita et al. [50] found a 2-week time lag in the Philippines and Desvars et al. [71] found a 2-month rainfall time lag in Reunion Island. The variation of peak leptospirosis cases could be due to the level of rainfall [50]. Heavy rainfall has been linked to leptospirosis outbreaks in India, Brazil and Sri Lanka [72–74]. One route of transmission for leptospirosis is the ingestion of contaminated water [75]. Rainfall increases the risk of leptospirosis as it brings the bacteria and animal hosts in closer contact with humans and increases the risk of contaminated water sources [75].

Climate change predictions in Fiji indicate there will be an increased intensity and frequency of extreme rainfall, and increased numbers of severe cyclones [59], which means Fiji is at risk of an increase in leptospirosis in Fiji unless more is known about the patterns of infection such as this paper contributes so that strategies can be implemented to minimise risk. While this paper focuses on Fiji, other countries in the PICs such as French Polynesia, and Futuna and Wallis face issues with leptospirosis [76,77]. Strategies that Fiji and other PICs could implement to help address leptospirosis include increased monitoring and surveillance, increasing community and health professionals' knowledge about leptospirosis as it not well recognised as a cause of fever, changing agriculture practices, and requiring safe rubbish dump practices that involve creating clear boundaries between humans and animals to prevent contamination of water sources and rodent control [75–78].

The EWARS data shows a seasonal trend for suspected dengue from March to April. This is similar to data from Suva, Fiji with dengue being most common during December to July [37]. The variation for dengue found in this paper is lower than that seen in Australia [56]. The rainfall time lags found were in line with Chang et al. [55] who found a 4 to 8-week peak rainfall time lag in Taiwan, but different from Kakarla [53] findings of an 8 to 12-week peak rainfall time lag in India. One explanation for the increased presence of dengue after rainfall is rain creates abundant stagnant water pools that enable mosquito breeding and dengue transmission rates [79,80]. Dengue is likely to become a growing public health concern within PICs as changes in rainfall and temperatures occur due to climate change and these factors can contribute to ideal breeding grounds for mosquitoes [38,81]. It is estimated by 2080, 60% of the world's population will be at risk of dengue [82]. This finding provides further support to Hii et al. [80] findings from their Singaporean-based study on the relationship between temperature and rainfall and levels of dengue, and indicates the usefulness of monitoring weather and temperature data as a public health tool to predict water-related diseases such as dengue.

The rainfall and temperature differences across divisions can be used to explain the variation in syndromic case numbers across the four divisions. Wider literature shows risk factors for leptospirosis, typhoid, and dengue are geographically different [51,75,83–85]. Our results highlight the growing importance of weather and seasonality data for public health planning in Fiji and other PICs, as these data can help guide and inform where resources should go and ensure that the most appropriate areas are prioritised. This is specifically important for Fiji as geographical inequalities of healthcare provision exist, with the Eastern division having reduced numbers of nurses and doctors [86].

It is apparent from the findings that the use of EWARs is another tool to help understand water-related disease outbreaks. To date, syndromic surveillance such as EWARS is underutilised for infectious disease outbreak, with only 15% of infectious disease outbreaks being detected using this form of surveillance [8]. Since its introduction in Fiji, EWARS is credited with saving human resources, reducing human error and helping ensure data surveillance teams focus on data collection, management, and alert response [24]. Other countries have not had the same success as Fiji has had with EWARS. For example in Brazil and Mexico following dengue outbreaks and evaluations of EWARS systems in Nepal there was a lack of intersectoral work and engagement from sectors other than health [23,87]. Many countries could learn from Fiji and implement EWARS as part of their regular disease monitoring system rather than only implementing it in emergency and humanitarian situations.

Unreliable or lack of Wi-Fi or internet services, poor mobile ne2rks, and lack of mobile credit can all make it difficult to edit and update the case records, causing issues to review surveillance information that EWAR relies on [20,21,24]. Limited funding and lack of resources can also make it difficult to investigate outbreaks because of issues in the verification of the system alerts [21,23,87]. Variations in data can be linked to the size of the healthcare facility, and staff training, motivation and supervision [24]. In Nepal, for example not every disease in the EWARS systems was found to be prone to outbreaks [87]. Fiji can learn from this and ensure that only relevant data are recorded. This finding of country differences indicates that to improve EWARS usefulness and effectiveness as a surveillance system it should be tailored to a country's specific syndrome data so that relevant and useful trends can be captured [23,24].

Strengths and limitations

The strength of our study is we used weekly and longitudinal syndromic data at a national level, that could also be analysed at a regional level. By combining weather and syndrome data over time we were able to track the impact of specific events such as natural disasters on the volume of cases of specific conditions. The limitation of the data is that there is no information about gender and the only data about age was under 5 and 5 and over. Different age groups may generate different patterns. Some of the data collected can be more easily linked back to a specific disease e.g., there is a specific variable for dengue, whereas something like diarrhoea can be a condition or a symptom of something else such as typhoid or leptospirosis.

Conclusion

The findings indicate the connection between water-related diseases, rainfall and seasonality in Fiji. Further research needs include exploring the connection between EWARS data, seasonality, and rainfall in the PICs. Rainfall and seasonality data can be used as a tool to help guide decision-making to pre-position of diagnostic and treatment resources to prevent and reduce water-related disease outbreaks. The priority is to create resilient adaptable systems that mitigate the negative impacts of climate change on human health, and prevent disease outbreaks in Fiji, and the wider Pacific Island Region.

Authorship agreement

SN, AJ and JN generated the study idea. SN, AR, and AJ designed the methods. SN conducted data analysis. SN, AJ and JN wrote the first draft of the manuscript. All authors contributed and reviewed the final manuscript. AJ, JN, SJ, SM, PH and SA secured funding.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Supplementary materials

Supplementary material associated with this article can be found, in the online version, at doi:10.1016/j.joclim.2022.100112.

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