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Influence of climate variability on human leptospirosis cases in Jamaica

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ABSTRACT: A retrospective ecological study was conducted using time-series and wavelet analyses to evaluate the impact of weather variables and climatic indicators on the incidence of leptospirosis in Jamaica between 1992 and 2007. Disease incidence was statistically linked to heavier rainfall and declining temperatures, with reported cases of leptospirosis peaking late in the year following a peak in rainfall. There was also some indication that disease spikes may be linked to the El Niño phenomenon. The climatic associations were used as the basis for the creation of statistical models for predicting disease incidence late in the year around the time it peaks. The models showed reasonable skill, explaining up to 72 % of the variability in the disease record. The data also showed 1, 2, and 4 yr periodicities in the wavelet coherency spectrum. The results are significant for surveillance and prediction of the disease.

KEY WORDS: Climate · Disease · Caribbean · Temperature · Rainfall · ENSO

1. INTRODUCTION

Leptospirosis, an infectious disease caused by pathogenic species of *Leptospira*, is considered to be re-emerging, particularly in tropical and subtropical regions (Levett 2001). While much of the recent increase in reported cases is due to increased vigilance, the disease appears to be increasing worldwide in both endemic and epidemic settings (Levett 2001, Meites et al. 2004, Maciel et al. 2008). This is against a background of significant underreporting (Levett 2001).

Leptospires gain entry into the body through cuts and abrasions in the skin, intact mucous membranes (in the nose, mouth, eyes) and perhaps through waterlogged skin (Levett 2001). In its most extreme form, the disease is characterized as a fulminant hemorrhagic fever accompanied by jaundice, renal failure, and multiple organ failure (Bharti et al. 2003). The disease affects people living in urban slums (inner cities) and rural environments in developed and developing countries alike, and transmission is facilitated by overcrowding, scavenging, accumulation of garbage, open sewer drains, blocked drains, stray animals, and livestock in close proximity. Populations at risk include specific industrial occupations, traditional wetland farming communities and adventure tourists (Vinetz et al. 1996, Sejvar et al. 2003).

Linkages with climate arise from the fact that leptospirosis is a waterborne disease. *Leptospira* shed in urine from its animal reservoirs (rodents and a variety of domestic and wild mammals) can survive in the environment for weeks to months under suitable conditions. Smith & Turner (1961) suggest that optimal survival conditions of the spirochete outside the host are a warm, moist climate of 25°C and water and soil pH of 7.0 to 8.0. Not surprisingly, incidence of the disease is highest in humid and warm climates (Levett 2001), and factors that promote these conditions will also likely promote the transmission of the disease.

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For these reasons, outbreaks have been shown to be commonly associated with occurrence of heavy rains and floods in the tropics (Kupek et al. 2000, Johnson et al. 2004, Pappachan et al. 2004, Gaynor et al. 2007, Tassinari et al. 2008, Desvars et al. 2011) including the Caribbean (Lhomme et al. 1996, Herrmann-Storck et al. 2005, Mohan et al. 2009). Fig. 1 is a conceptual model highlighting 3 modes of human transmission that are influenced by heavy rainfall with flooding episodes. Importantly, transmission following heavy rainfall might occur after (1) a short delay, as a result of human contact with the bacteria via wading or swimming in contaminated water; (2) a medium delay, due to increased rodent populations, infected with the disease, and increased transmission to humans as natural habitats become flooded; or (3) an extended lag due to prolonged soil saturation that allows survival of bacteria in the soil. Other studies suggest that disease outbreaks are also associated with temperature changes occurring in tandem with rainfall events (e.g. Smith & Turner 1961, Desvars et al. 2011) or with meteorological events such as El Niño Southern Oscillation (ENSO) (e.g Herrmann-Storck et al. 2005) through its impact on temperature and/or rainfall patterns.

Jamaica is considered to have one of the highest incidence rates of the disease in the Caribbean, which, in turn, is the region with the highest incidence globally (Everard & Everard 1993, Pappas et al. 2008). The disease is endemic in Jamaica with an estimated 153 cases occurring annually, caused mainly by the serovars Portlandvere, Jules, and Icterohaemorrhagiae (Grant et al. 1988, Brown et al. 2011). Rats (mainly *Rattus norvegicus*) and dogs are important urban reservoirs for leptospirosis in Jamaica (Brown et al. 2011). Keenan et al. (2010) also show that risk factors for clinical leptospirosis in western Jamaica include exposure to rodents, exposure to goats and outdoor labor (Keenan et al. 2010). The factors are additive and there is increased risk associated with combinations of exposures. Knowledge of risk factors has, however, been shown to be protective (Keenan et al. 2010). A number of studies have examined leptospirosis in Jamaica (e.g. Grant & Bras 1957, Urquhart et al. 1980, Segree et al. 1982, Brown et al. 2010, Keenan et al. 2010, Brown et al. 2011). There have, however, been none to date that attempt to evaluate the role of climate.

The objective of the present study was to evaluate the impact of climate — specifically precipitation and temperature — on the incidence of leptospirosis in Jamaica between 1992 and 2007. Specifically, this study (1) examined the seasonality of the disease in the light of Jamaica's precipitation and temperature climatology, (2) evaluated whether statistically significant linkages can be found between disease spikes and temperature and rainfall variability, (3) attempted to create and validate prediction models for leptospirosis case incidences using the meteorological parameters, and (4) examined the periodicity of the primary modes of variability in the disease record for possible linkages to meteorological events such ENSO.

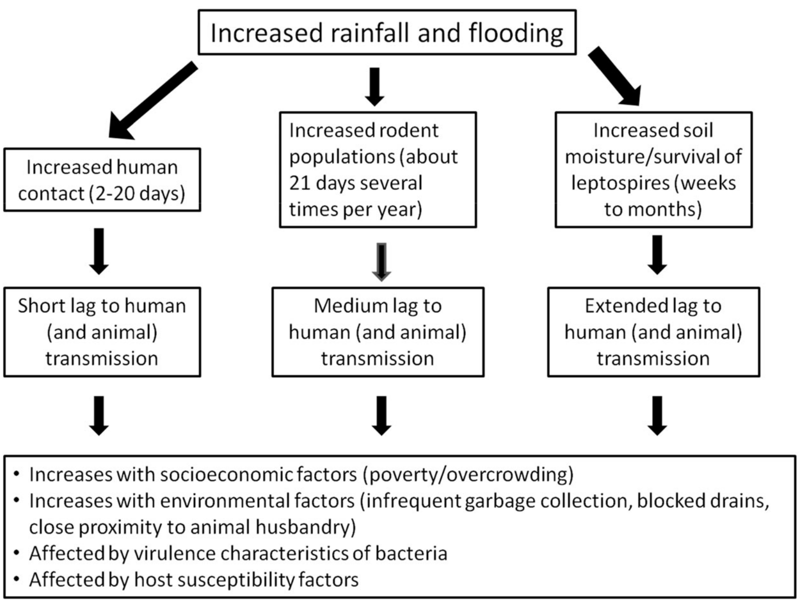

Fig. 1. Conceptual transmission model to illustrate the influence of rainfall and flooding on cases of leptospirosis

2. METHODS

2.1. Data

Data of reported cases of leptospirosis in Jamaica from 1992 to 2007 were obtained from the Veterinary Laboratory at the Ministry of Agriculture and Fisheries, Jamaica. Cases of leptospirosis were confirmed by the microscopic agglutination test (MAT) using a battery of 15 serovars of *Leptospira* (Faine 1999) and/or the IgM ELISA (Brown et al. 1995), and defined as a titre of ≥1:200 in MAT or ≥1:320 in ELISA. To the best of our knowledge, there were no significant changes in the reporting or testing/detection of leptospirosis cases over the duration of this project that might have influenced longer-term trends in the data. The data were aggregated by month for comparison with the available meteorological data.

Monthly temperature and precipitation data for Jamaica from 1992–2000 were obtained from the Climate Studies Group Mona at The University of the West Indies (Taylor & Crosbourne 2007) and were supplemented with additional climate data for 2001–2007 obtained from the KNMI Climate Explorer database (http://climexp.knmi.nl). The data were for the Norman Manley airport station, which represents one of the few reliable stations for which both rainfall and temperature data for the entire period under study was available. The data were available as monthly means.

2.2. Approach

Various statistical techniques were employed to investigate the link between climate and incidence of the disease. Firstly, precipitation and temperature climatologies of Jamaica were plotted and compared with the mean monthly variation of reported cases of leptospirosis. This provided insight into the timing of peak disease case incidence and the prevailing climate conditions at that time. Then time series of annual steps in disease and climate variables were created for each month of the year and for the year divided into 2 mo seasons. For example, time series were created recording yearly variation in October (and October–November) cases of leptospirosis, and yearly variation in October (and October–November) rainfall. Correlations were calculated between the disease and climate time series, with and without lag between disease and climate variables, and the significance of all correlations was assessed at the 95% level.

On the basis of the correlation results, an iterative backward linear regression was performed, using the climate variables as predictors, to create models accounting for the annual variation in disease incidence for the months or seasons (2 mo periods) which exhibited strongest statistical relationships. Regression was used for model creation as it is relatively easy to implement. In the procedure, explained variance was maximized while limiting the number of predictors entering the final model, i.e. terms which did not pass an F-test at the 95% significance level were eliminated. The models created were cross validated to evaluate their skill. Cross validation gives a number of statistics which are representative of the created model's predictive skill and which can be used for comparison between models (see Appendix 1 for additional explanation of the cross validation technique).

Finally, wavelet analysis (Torrence & Compo 1998) was used to analyze the spectral characteristics of the leptospirosis data and to further investigate the relationship with the climate variables. Both the climate and rodent-borne disease data were nonstationary i.e. their mean and variance change over time. For this reason, wavelet analysis was used to visualize the spectral characteristics of the data, as opposed to conventional methods such as Fourier analysis. Wavelet analysis gives a plot of the significant modes and their duration throughout the time series. Specifically, wavelet analysis performs a time frequency decomposition of the data time series and reveals how its periodic components change over time. The wavelet coefficients are used to obtain a wavelet power spectrum which shows the different modes of oscillation, as well as a wavelet coherence pattern which determines the correspondence of a particular frequency at a given time in both the disease and climate variable records. The latter is important for elucidating links between infectious disease and climate.

Examples of the use of wavelet analysis in similar research include Cazelles et al. (2005) who used it to demonstrate the synchrony between dengue in Thailand and an index representative of ENSO occurrences. Chaves & Pascual (2006) also described the oscillating dynamics of cutaneous leishmaniasis incidence in Costa Rica using multiple methods including wavelets.

3. RELATING LEPTOSPIROSIS TO TEMPERATURE AND RAINFALL

Fig. 2a shows the monthly climatology of rainfall and temperature as well as mean monthly incidence of disease in Jamaica. Monthly case numbers for leptospirosis are lowest from March to May and begin to increase from July through October. They reach a maximum in November, which lags behind the late season peak in rainfall by 1 mo. This is in keeping with the idea of a rainfall requirement for disease incidence (Kupek et al. 2000, Herrmann-Storck 2005) and the lag is also consistent with the conceptual model in Fig. 1.

However, Jamaica experiences 2 rainfall peaks (May and October) of comparable magnitude, whereas disease incidence does not show a similar bimodality in its signal (Fig. 2a). Other factors besides rainfall may play a role in the disease pat-

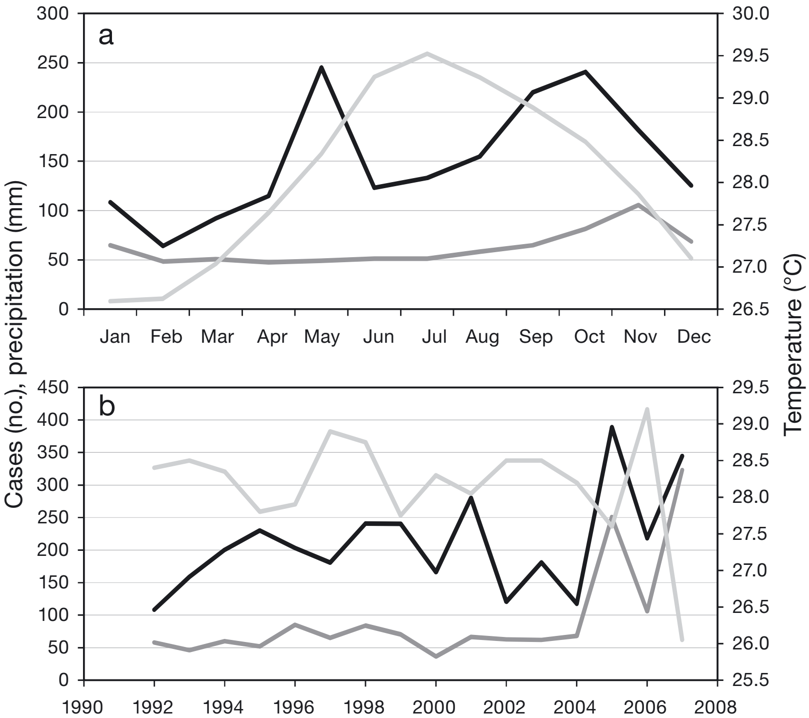

Fig. 2. (a) Climatology of reported cases of leptospirosis, rainfall and temperature in Jamaica, 1992–2007 and (b) yearly variation of leptospirosis with mean temperature and precipitation, October–November 1992–2007. Black: rainfall (mm); dark grey: reported cases of leptospirosis; light grey: temperature (°C)

cept with higher rainfall and disease incidence values. Variability in the October–November 2 mo period largely controls the annual variability of the respective variables (particularly for leptospirosis, but also true for rainfall), and so the focus will be on this period in later analysis. A visual inspection of Fig. 2b suggests that whereas disease incidence generally mirrors rainfall variation (peaks coinciding with peaks), there is an inverse relationship with temperature. This gives credence to the idea of a maximum temperature that inhibits the disease. Fig. 2b also shows that for the years with the highest number of recorded cases in October–November, mean temperatures dip below 27.6°C. The optimum temperature for an outbreak to occur in Jamaica might therefore be ~28°, an idea also supported by Fig. 2a.

Calculated correlations between leptospirosis, temperature and rainfall support the noted relationships. Table 1 shows the correlations be-

tern, with one possibility (as suggested by Fig. 2a) being temperature. It is noted that the peak in disease incidence occurs after maximum temperatures in August and when temperatures are in decline. In contrast, following the early rainfall season peak (May) temperatures increase rapidly and leptospirosis is at a minimum. This suggests there is a maximum temperature above which the bacteria is unlikely to survive (as in the months immediately after the early rainfall peak) and/or the need for prior warming and an optimal (cooler) temperature for disease occurrence (as in the months immediately after the late rainfall season). Since Jamaica's temperatures are higher all year round than Smith & Turner's (1961) optimal temperature of 25°C, the optimal 'cooler' temperature for Jamaica may be slightly higher than this.

Similar relationships between disease incidence, rainfall and temperature can be inferred from Fig. 2b, which shows mean disease incidence, mean rainfall and mean temperature for October–November of each year, i.e. the period when both rainfall and disease incidence peak. A similar plot of annual totals (not shown) shows a similar pattern to Fig. 2b ex-

Table 1. Leptospirosis in Jamaica. Correlations between precipitation and temperature and the number of cases of leptospirosis in the same month or 2 mo season, based on monthly data from 1992–2007. Values in **bold** are significant at the 95% level

Month/season	Precipitation	Temperature
Jan	−0.05	0.15
Feb	−0.20	0.03
Mar	0.45	−0.03
Apr	−0.30	0.23
May	0.04	0.47
Jun	0.13	0.09
Jul	−0.02	0.32
Aug	0.67	−0.15
Sep	−0.26	−0.003
Oct	**0.45**	**−0.56**
Nov	0.38	−0.38
Dec	−0.29	−0.15
Oct–Nov	**0.78**	**−0.74**
Aug–Sep	0.09	−0.13
Jun–Jul	0.16	0.26
Apr–May	−0.03	**0.50**
Annual totals	**0.77**	

tween yearly variation of disease incidence for a given month or 2 mo season and rainfall and temperature for the same month or 2 mo season. For comparison, correlations were also calculated for time series created using annual totals (rainfall and disease) and using the entire 192 months sequentially. From the table, precipitation and temperature are both shown to be significantly correlated with leptospirosis in October. The correlation is positive for rainfall but negative for temperature. The 2 mo seasonal correlations show similar results i.e. during October–November the correlation is significant and positive for rainfall during the same months and significant and negative for temperature. The correlation for annual disease and rainfall totals mirror that of October–November (Table 1). The correlations of the entire time series are, however, very low and not significant (results not shown), suggesting that the disease–climate relationship is strongest at a particular time of year, i.e. October–November, when both rainfall and temperature conditions for disease occurrence are met.

Given the lag relationship suggested by the climatology plot (Fig. 2a), correlations with a 1 time step lag were also calculated. Table 2 shows the correlations between monthly rainfall and temperature and disease incidence in the following month. The highest correlations occur between October climate and November disease incidence, for both rainfall (+0.9) and temperature (–0.7). The signs indicate the relationships noted earlier i.e. disease incidence increases 1 mo after increased rainfall and after the onset of cooler temperatures.

It is to be noted that leptospirosis cases increase sharply at the end of the record in 2005 and 2007 (Fig. 2b). The high disease incidence in these 2 years makes a strong case for the 'late season' rainfall-disease link as both years were notable for enhanced tropical hurricane activity in the Caribbean basin (Shein 2006, CMO 2007) and significant October rainfall in Jamaica (CMO 2006, Spence & Taylor 2008). Rainfall was 3 times higher in October 2005, and twice as high in October 2007, compared to the October average in the preceding 13 years. 2007 was also notable for heavy rains which began in August and persisted through November. Total leptospirosis cases for both years are dominated by large numbers recorded in November. In 2005 and 2007, November cases of leptopspirosis were 4 and 3 times higher, respectively, in comparison to the mean number of November cases calculated using the entire dataset, i.e. in 1992–2007.

The climate in the Caribbean is also modulated by ENSO occurrences (Giannini et al. 2000, Taylor et al. 2002). During an El Niño (La Niña) event, rainfall totals tend to be lower (higher) during the late season due to an alteration of the regional climate dynamics (Chen & Taylor 2002, Taylor et al. 2002). Given the rainfall–leptospirosis relationship noted above, El Niño and La Niña occurrences should be reflected in the disease record. This is suggested by Fig. 3, which depicts annual reported cases and years in which El Niño and La Niña events occurred. El Niño (La Niña) years coincide with years with a decrease (increase) in total reported cases of leptospirosis, with the exception of the El Niño year 1994. The effect of the La Niña years 2005 (when it developed in the late season) and 2007 can be clearly seen. The calculation of similar correlation coefficients as in Tables 1 & 2, but in this case of the relation between incidence of

Table 2. Correlations between precipitation and temperature in the month shown and the number of cases of leptospirosis in the following month, based on data from 1992–2007. Values in **bold** are significant at the 95% level

Month	Precipitation	Temperature
Jan	–0.02	0.40
Feb	–0.02	0.00
Mar	0.17	0.29
Apr	0.30	**0.53**
May	0.27	0.17
Jun	0.21	0.13
Jul	0.17	0.41
Aug	**0.74**	0.40
Sep	–0.20	0.15
Oct	**0.87**	–0.66
Nov	**0.49**	–0.30
Dec	–0.26	0.12

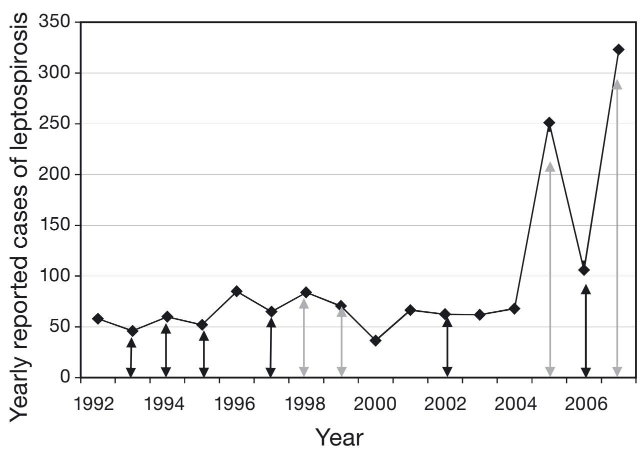

Fig. 3. Annual variability of reported cases of leptospirosis in Jamaica during October–November in 1992–2007. Black (grey) arrows denote El Niño (La Niña) years

leptospirosis and the Niño 3 index (results not shown) revealed negative correlations in the range −0.3 to −0.5, with the highest significant correlation (−0.5) occurring for concurrent values in September.

4. PREDICTION MODEL ANALYSIS

Given the climate associations noted, models of disease incidence premised on climatic variables were created. Using the previously created time series, models were first developed to account for the annual variations in disease incidence in a given month or 2 mo period using concurrent climate conditions. Caribbean sea surface temperature was also included as a predictor since it is a primary modulator of Caribbean climate (Enfield & Alfaro 1999, Taylor et al. 2002) and can facilitate prediction a few months in advance (see Ashby et al. 2005). Leptospirosis cases for the previous month or 2 mo season were also used as a predictor for comparison with the climate-driven models. Table 3 shows a selection of the >40 models created from the regression technique using various combinations of the 4 predictors (concurrent rainfall, temperature, sea surface temperature and prior disease incidence) as input. The primary interest was in models capturing variations during the months of peak disease incidence (October–November), though other models representing periods when there is reasonably high explained variability are shown in the table for comparison. The model for the October–November season using both concurrent temperature and precipitation explains a high percentage of variability (72%). This reinforces the link between leptospirosis and these climate variables at this time of year. Interestingly, the number of leptospirosis cases in the previous 2 mo period (August–September) is a comparably good predictor (73%) of October–November disease occurrence. It is, however, the combination of concurrent climate variables and leptospirosis cases in the previous period which yields the highest explained variability (82% for concurrent rainfall and prior disease and 85% for concurrent temperature and rainfall and prior disease). Other models created which explained variability fairly well included those for August using precipitation as the predictor (45%) and for January using sea surface temperature as the predictor (40%). Models using temperature alone captured 31% of the annual variability of October cases and 25% of April–May cases. No model could be created that explained variation of May cases; i.e. the procedure for identifying predictors described in Section 2.2 did not retain any of the variables irrespective of the combination inputted.

The process of model creation was repeated with an additional lag for the climate variables to investigate predictability. Table 4 shows a selection of these models. For annual variation of monthly cases, the highest explained variability of 76% was achieved for November (again during the period when the dis-

Table 3. Results of selected monthly and seasonal (2 mo) disease models, showing month(s) modeled, variables retained as model predictor(s) (for details of the method see Section 2.2) and the percentage variability in the number of leptospirosis cases explained by the model. Climate variables are for the same month as the disease models. In the bottom 3 rows, the leptospirosis predictor is the number of cases recorded in the previous 2 months, i.e. August–September (AS)

Month/season	Model variables	%variability explained
Jan	Sea surface temperature	40
Apr–May	Temperature	25
May[a]	None	None
Aug	Precipitation	45
Oct	Temperature	31
Oct–Nov	Temperature and precipitation	72
Oct–Nov	Precipitation and AS leptospirosis	82
Oct–Nov	Temperature, precipitation and AS leptospirosis	85
Oct–Nov	AS leptospirosis	73

[a]The procedure for identifying predictors did not retain any of the variables irrespective of the combination inputted

Table 4. Percentage variability in the number of leptospirosis cases explained by selected monthly and seasonal (2 mo) disease models, where the climate variables retained as predictors lead the month modeled by 1 or 2 mo

Month/season	Model variables	%variability explained
May	Temperature (Apr)	28
Sep	Precipitation (Aug)	54
Nov	Precipitation (Oct)	76
Dec[a]	None	None
Oct–Nov	Temperature, rainfall, leptospirosis (all Aug–Sep)	74

[a]The procedure for identifying predictors did not retain any of the variables irrespective of the combination inputted

ease peaks) with October precipitation as the retained predictor. For the 2 mo time series, highest explained variability (74%) was for October–November with temperature, rainfall and leptospirosis cases, all from August–September, as predictors. Other models of note were created for the annual variation of September cases with August precipitation as the predictor (54% explained variability) and May cases using April temperatures as the predictor (28% explained variability).

Table 5 gives the model statistics after cross-validation for 5 of the best models (i.e. those with highest explained variability). The model predicting October–November leptospirosis from concurrent rainfall and temperature does fairly well, having a positive skill score (SS) and positive linear error in probability space (LEPS), low false alarm rates (FAR), and high probability of detection (POD) of above-normal events (67%). Its primary deficiency is a low POD for below-normal events. Fig. 4a shows that this model captures variations in the reported cases of leptospirosis fairly well, particularly toward the end of the data period. This model's performance is improved by the inclusion of August–September leptospirosis cases as an additional predictor. An October–November model using the same 3 variables measured in August–September also does fairly well, as does a November model using October precipitation as a predictor (see also Fig. 4b). In general, Table 5 shows a fairly high skill level in all the models created for months near or coinciding with peak disease incidence. For comparison, the January model statistics are also shown (see also Fig. 4c).

5. WAVELET ANALYSIS

Finally, wavelet analysis was carried out to better characterize periodicities in the disease data (Fig. 5) and in the relations between leptospirosis and precipitation (Fig. 6) and temperature (Fig. 7). The

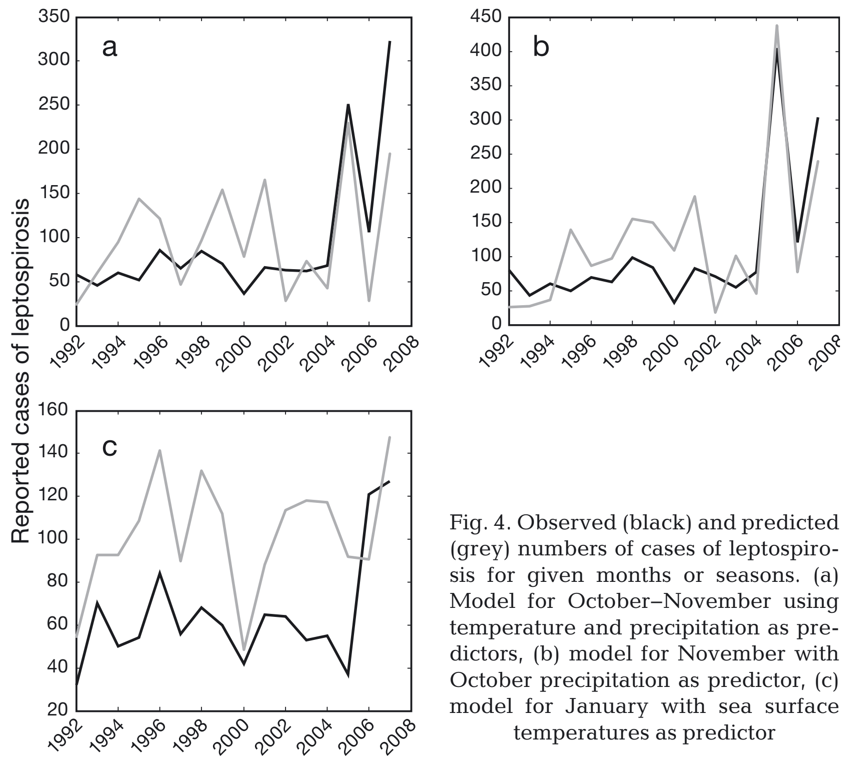

Fig. 4. Observed (black) and predicted (grey) numbers of cases of leptospirosis for given months or seasons. (a) Model for October–November using temperature and precipitation as predictors, (b) model for November with October precipitation as predictor, (c) model for January with sea surface temperatures as predictor

Table 5. Model statistics after cross-validation of 5 of the best models, i.e. those that explained the greatest percentage of variability in the number of leptospirosis cases in Jamaica from 1992–2007. The month(s) and variables used as model predictors are shown. AS: August–September; ON: October–November. See Appendix 1 for explanation of other abbreviations

Month/season	Model predictors	R	SS	LEPS	FAR (below normal)	FAR (above normal)	POD (below normal)	POD (above normal)
Oct–Nov	ON Temperature and ON precipitation	85	44	22	20	17	20	67
Oct–Nov	ON temperature, ON precipitation and AS leptospirosis	92	53	38	20	0	40	67
Oct–Nov	AS temperature, AS precipitation and AS leptospirosis	86	63	50	0	17	40	83
Nov	Oct precipitation	87	63	50	20	0	40	83
Jan	Jan sea surface temperature	63	44	18	20	33	40	50

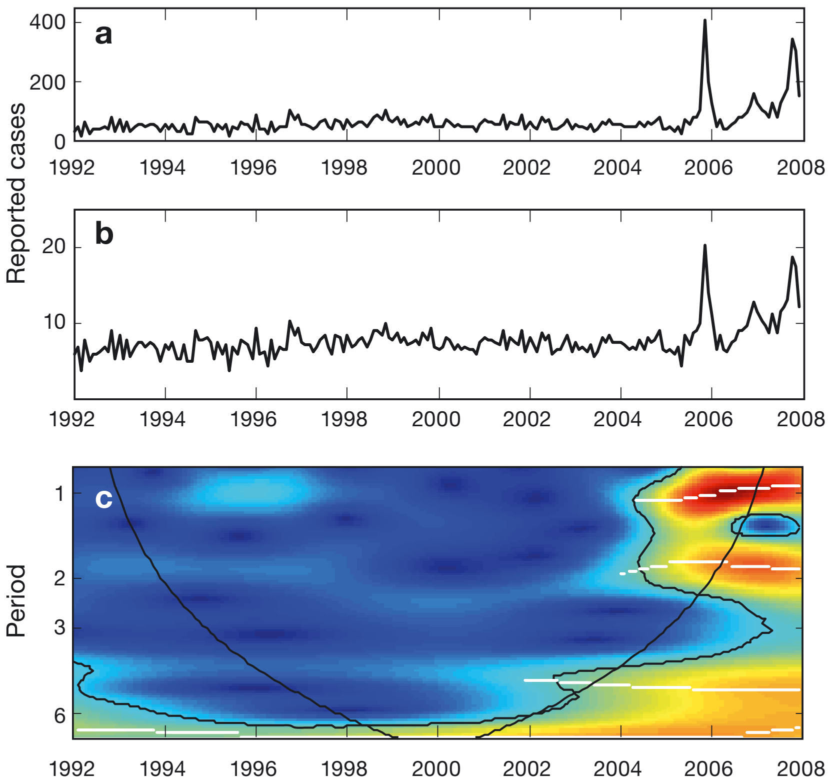

Fig. 5. Leptospirosis in Jamaica, 1992–2007: (a) original time series; (b) normalized time series, where normalization is done using a square root transform to manage the variability in the amplitude of the time series; (c) wavelet power spectrum. The color code for the power values ranges from dark blue for low values to dark red for high values. Statistically significant areas (where a threshold of 5% confidence interval is used) are highlighted by a solid line. The cone of influence is also shown indicating regions not influenced by edge effects

wavelet power spectrum of the time series of reported cases shows significant periodicities of oscillation of 1 and 2 yr only in the latter part of the record, i.e. from 2004–2006. If, however, the last 3 years of data are removed (i.e. eliminating the strong influence of the 2005 and 2007 peaks), the power spectrum (not shown) reveals significant periodicities of 1 yr from 1994–2001, 2 yr from 1996–1998, and 2.5 yr from 1998–2001.

The coherency spectrum plots show some weak coherency between leptospirosis and rainfall (Fig. 6b) and temperature (Fig. 7b) for limited periods of the record. For the 1 yr cycle there is transient coherency between disease cases and rainfall from 1994–1997 and again from 2005–2007. The phase analysis for disease and rainfall (Fig. 6c) indicates that during these periods rainfall is in advance of leptospirosis, which is consistent with previously noted observations about the relationship between these 2 variables. For temperature and disease incidence the periods of coherency likewise occur between 1995–1997 and 2005–2007 (Fig. 7b) for the 1 yr cycle, with temperature also leading disease cases but with a greater lead time than that seen for rainfall (Fig. 7c versus Fig. 6c).

Figs. 6b & 7b also suggest that there are other periodicities for which coherency between disease cases and the climate variables exists. There is a 4 yr periodicity (3.9 to 4.1 yr) in coherence between temperature and leptospirosis from 1997–2002 (Fig. 6b), and between rainfall and leptospirosis from 1998–2002 (Fig. 7b). It is possible that this is a manifestation of the ENSO phenomenon which has a known periodicity of 3 to 5 yr. There is also significant disease-temperature coherency for 2 yr periodicity from 1994–1999 and 2004–2006 (Fig. 7b), and significant disease-rainfall coherency for 2 yr periodicity from 2004–2006 (Fig, 6b).

6. SUMMARY AND DISCUSSION

Several factors, including environmental and climatic ones, influence the transmission of infectious diseases associated with water. Within this context, the effect of weather variables and climatic indicators associated with the incidence of leptospirosis in Jamaica between 1992–2007 was evaluated. Data analysis suggests that increasing rainfall coupled with decreasing temperatures is conducive for leptospirosis outbreaks in Jamaica. Climatological plots show that both conditions are met in the late rainfall season, causing reported cases to peak late in the year, 1 mo after the October rainfall maximum. The 1 mo lag in rainfall is consistent with the effect of water-soaked soils on organism survival and an average incubation period for leptospirosis of 1 to 3 wk (see Fig. 1).

The analysis also suggest (1) prior warming as well as (2) a threshold temperature above which the bacteria is unlikely to survive and/or (3) an optimal temperature of ~28°C, as conditions which need to be met for the outbreak to occur. Correlation analysis supports the conclusions as there are significant positive (negative) correlations between precipitation (temperature) and disease occurrence in the later months of the year. The correlations are stronger

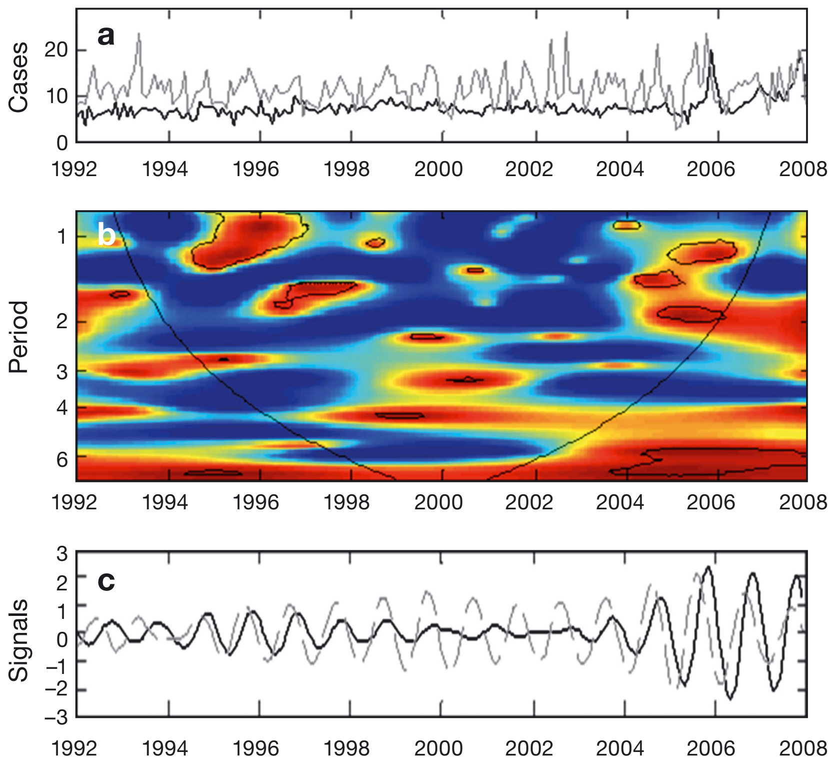

Fig. 6. Leptospirosis and precipitation in Jamaica, 1992–2007. (a) Original time series: precipitation (grey) and reported cases of leptospirosis (black). (b) Wavelet coherency between leptospirosis and precipitation. The color code for the power values ranges from dark blue for low values to dark red for high values. Statistically significant areas (where a threshold of 5% confidence interval is used) are highlighted by a solid line. The cone of influence is also shown indicating regions not influenced by edge effects. (c) Oscillating components computed with the wavelet transform in the 0.8–1.2 yr periodic band: precipitation (broken grey line) and leptospirosis (solid black line)

when the climate variables lead disease occurrence by 1 mo. Wavelet analysis suggests the same kind of phase relationships between leptospirosis and the climatic variables i.e. with leptospirosis cases lagging rainfall and temperature changes.

Backward regression was utilized to show that models can be created for leptospirosis outbreaks using precipitation and/or temperature as predictors. The most significant models predict disease incidence in October–November and explain upwards of 72% of the variability exhibited during the 17 yr period under analysis. The high explained variability is retained if the climate variables lead by 1 or 2 mo, and/or if the number of leptospirosis cases in the previous (1 or 2 mo period) is factored in. The implication is that the period October–November is a significant season for outbreaks of leptospirosis and that temperature and precipitation play an important role in the spread of the virus. As considerable effort is being made to predict Caribbean climate a few months in advance (e.g. the Caribbean Institute for Meteorology & Hydrology's seasonal outlooks, www.cimh.edu.bb/?p=precipoutlook), there is good potential for predicting conditions under which disease outbreaks are likely to be severe during this time of the year. Tracking disease cases throughout the year will also enhance the likelihood of effective prediction.

The data analysis also suggests other points worthy of note. The wavelet coherency plot shows periods in the record when there is coherency between disease cases and rainfall and temperature for 2 and 4 yr periodicities. The latter periodicity may indicate that the ENSO phenomenon plays a role in the outbreak of the disease. In an El Niño (La Niña) year, the Caribbean tends to be drier (wetter) during the latter half of the year. On the premise of the associations made earlier, an El Niño (La Niña) event would reduce (increase) the magnitude of an outbreak of leptospirosis. It is likely that the anomalously heavy rainfall attributable to La Niña events in 2005 and 2007 contributed to the large increase in disease incidence observed at the end of the record analyzed in this study.

One can extend the analysis to hypothesize the effect of global warming on the disease if climate parameters are the only factors considered. Climate models indicate that the Caribbean will likely experience both an increase in temperature of 1 to 5°C and a decrease in mean annual rainfall (up to 30% drier) by the end of the century (Taylor et al. 2007, Campbell et al. 2010). The results of this study suggest that these warmer temperatures and drier conditions in themselves would not favor increased disease occurrence, i.e. when other non-climatic factors are not considered. However future climate scenarios suggest that rainfall, when it does occur, may be more intense, leading to flooding (Campbell et al. 2010), which would favor the spread of the disease.

The analysis also suggests topics for further investigation. One is the absence of a peak in disease incidence immediately following the first rainfall peak in May–June. In addition to the increasing temperatures, we suggest that the Caribbean Low Level Jet

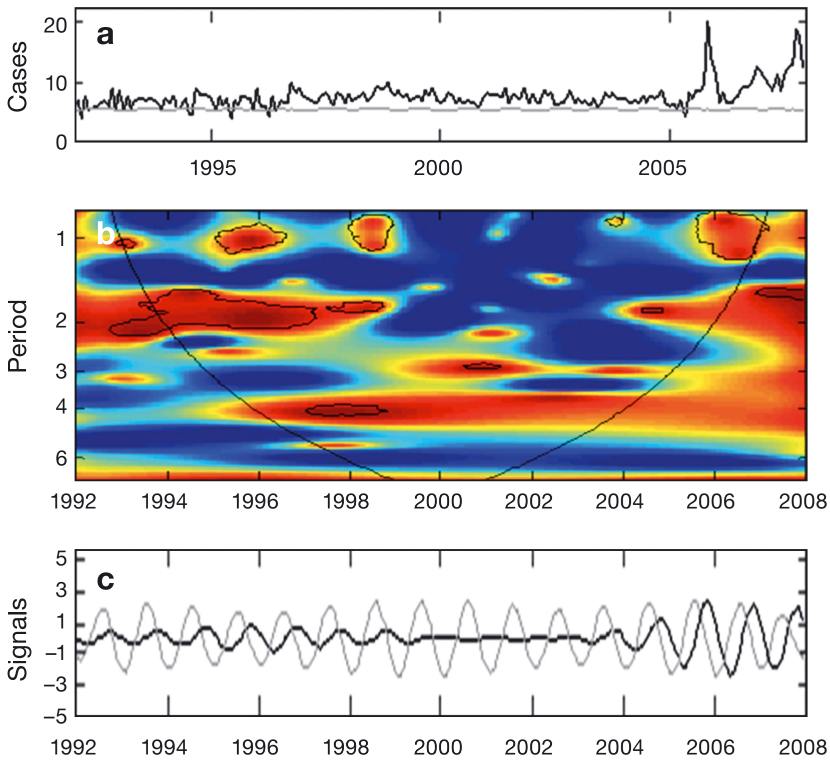

Fig. 7. Leptospirosis and temperature in Jamaica, 1992–2007. (a) Original time series: temperature (grey) and reported cases of leptospirosis (black). (b) Wavelet coherency between leptospirosis and temperature. The color code for the power values ranges from dark blue for low values to dark red for high values. Statistically significant areas (where a threshold of 5% confidence interval is used) are highlighted by a solid line. The cone of influence is also shown indicating regions not influenced by edge effects. (c) Oscillating components computed with the wavelet transform in the 0.8–1.2 yr periodic band: temperature (grey) and leptospirosis (black)

(CLLJ) — a region of strong winds in the lower part of the atmosphere of the western Caribbean basin — may also play a role. The CLLJ increases in strength in May and reaches a maximum in July, decreasing thereafter (Whyte et al. 2007). Strong winds coupled with increasing temperatures will likely affect the intensity of evaporation during June–July, thereby minimizing the water content in the soil in spite of the rainfall maximum. Hence, we theorize that the likelihood of an outbreak in the early rainy season is low as the climatological conditions are not conducive for it. The role of evaporation and/or humidity and their potential as predictors of the disease will be the subject of future investigations.

Another point of interest is the seeming lack of a strong disease–climate relationship during the period 2000–2004 (Figs. 6 & 7) i.e. the seemingly transient nature of the annual signal. This is a reminder that, although the link between climate and leptospirosis is important, other non-climatic risk factors favoring the spread of the virus likely dominate when the climate signal is not very strong or extreme. It is, then, the integrated climate and non-climatic effect which is important. We try to capture some of the complexity of the system in the bottom panel of Fig. 1. The factor(s) that might have offset the climate effects during 2000–2004 are worthy of investigation, particularly for the development of early warning systems for the disease.

Notwithstanding the above, given the fairly robust climate links presented for the period of peak case incidences (i.e. October–November), the possibility exists to use information on impending climatic conditions (e.g. El Niño occurrences) as an initial basis for an early warning system that, depending on the severity of the perceived threat, could issue alerts or initiate action on the part of relevant stakeholders. The statistical models developed in this paper therefore have potential to contribute to the implementation of preventative/mitigative measures with significant socioeconomic benefit for those most at risk from the disease.

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APPENDIX 1. Cross validation

To estimate the forecast skill of the models, trial forecasts (or hindcasts) are made using a Jackknife method. Forecasts are made for a given year in the data period (for each month or season) using the regression equation calculated using every other remaining year (the predictor is fixed). The process is repeated for every year of the data period. The result is a time series of forecasted values which can be compared with the original time series of observed values. The Jackknife method is a reasonable option for validation when analyzing a relatively small data period as in this case.

The models were first evaluated by calculating the correlation coefficient (R) between the forecast and observed values. They were also evaluated via categorical scores for High Incidence (upper tercile), Average Incidence (middle tercile), Low Incidence (lower tercile). Categorical scores were assigned for:

(1) The skill score (SS): a variation of the hit rate (HR), where SS has a chance value of zero, a score of +100 % for a set of perfect hits and of −100 % for a set of forecasts with no hits.

(2) The linear error in probability space (LEPS) score. LEPS measures how close the forecast and observed values are in terms of the probability density function of the observations. It penalizes a forecast that is 2 categories in error more than one which is only 1 category in error. (For further explanation, see Potts et al. 1996).

(3) The probability of detection (POD), above or below normal: the percentage of correct above or below normal events predicted.

(4) The false alarm rate (FAR), above or below normal: the percentage of above or below normal forecasts which failed to materialize.

A perfect model would have SS, LEPS, and POD scores of 100 % and a FAR score of zero. A good model would have positive SS and LEPS, POD scores >50 % and a FAR score <33.3 %.

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