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Yvon Carmen Hountondji
University of Parakou

Sabine Henry
University of Namur

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Analysis of high Acute Lower Respiratory Infection levels in children under five linked to specific weather conditions: A case study in Benin (West Africa)

de Longueville Florence[a,*], Hountondji Yvon-Carmen[b], Djivo Vignon Pie[c], Henry Sabine[a]

[a] Department of Geography, University of Namur
Rue de Bruxelles 61, 5000 Namur, Belgium
fdelongu@fundp.ac.be
shenry@fundp.ac.be
Tel: 0032 81724472
Fax: 0032 81724471

[b] Department of Natural Resources Management,
Faculty of Agronomy, University of Parakou BP 123
Parakou, Benin
yvon.hountondji@gmail.com

[c] National Direction of Public Health, Benin Ministry of
Health BP 01–882 Cotonou, Benin
djivopie@yahoo.fr

AQ1 * Corresponding author:

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Abstract

Background: Complex interactions between individuals and their environment influence human health. Local climate plays an important role in these interactions. Acute Respiratory Infections (ARI) are the leading cause of mortality for children under five years of age worldwide and the second cause of children's consultations in West Africa after malaria. This paper aims to answer this question: are there significant relationships between the high monthly Acute Lower Respiratory Infection (ALRI) levels in children under five and weather conditions in four health zones of Benin, West Africa?

Methods: The months recorded particularly high ALRI levels during the study period (1998-2008) were identified using two indicators. Fisher's exact test was used to check the associations between high ALRI levels and extreme weather conditions.

Results: According to the results, high maximum relative humidity during the wet season in the southern zones, low relative humidity and low temperatures during the dry season in the northern zones, and high temperature ranges during the dry season in the north and during the wet season in the south are conditions that appear to coincide with high ALRI levels ($p<0.1$).

Conclusion: In the context of climate change, it is expected that more extreme weather conditions will happen in the future. It is important to evaluate the impacts of extreme weather conditions on ALRI incidences for the planning of public health activities, especially in developing countries, where populations are poorer and more vulnerable.

1.1 Introduction

Local climate plays an important role in determining the relationship between monthly acute lower respiratory infection (ALRI) levels and weather conditions (Lam and Ayres 2011). Approximately 30% of the global burden of disease can be attributed to various environmental risk factors (Smith et al. 1999). The effect of climate variability on human health varies according to region, the vulnerability of individuals or groups, and the ability of the populations to adapt (Lam and Ayres 2011). In tropical areas, relationships between climate variability and malaria have been well established (Craig et al. 1999; Snow et al. 1999; Zhou et al. 2004). An epidemic of meningitis driven by climate in West Africa has been previously described (Molesworth et al. 2003; Sultan et al. 2005). By contrast, only a few researches have established relationships between acute respiratory infections (ARIs) and weather conditions (du Prel et al. 2009).

ARIs are the leading cause of mortality in children under the age of 5 worldwide (over 2 million deaths or 19% of deaths involved children under the age of 5) (Tulloch 1999; Morris et al. 2003; Hart and Cuevas 2007). Based on a detailed study of the literature, Morris et al. (2003) have quantified (by type of causes) the distribution of deaths of children under the age of 5 in sub-Saharan African regions. The study showed that 23% of deaths can be attributed to pneumonia, 24% to malaria, 22% to diarrhea, and finally 31% to neonatal causes and other causes. ARIs are classed as either acute upper respiratory infections or ALRIs. The bronchiolitis and pneumonia are responsible for most deaths and they are ALRIs (Williams et al. 2002). In origin, ALRIs are either viral (respiratory syncytial virus, RSV) or bacterial (mainly *Streptococcus pneumoniae* and *Haemophilus influenzae*) (Enarson et al. 1998; Greenwood 1999; Mulholland 1999; Roca et al. 2006). In industrialized countries, the origin tends to be viral, whereas in developing countries it may be either viral or bacterial (Selwyn 1990; Lafaix and Reinert 1997;

Romieu et al. 2002; Lapeña et al. 2005; Madhi and Klugman 2006). The RSV is the pathogen that is most often cited as the cause of ALRIs worldwide (Stensballe et al. 2003).

Studies on the epidemiology of RSV have been widespread, even in the tropics (Shek and Lee 2003), but there has been some controversy in the literature concerning the environmental conditions that may benefit RSV (Noyola and Mandeville 2008). The main epidemiological characteristic of RSV is its seasonality, with annual epidemics observed at regular time intervals that vary with climate (Checon et al. 2002), latitude, and altitude (Stensballe et al. 2003). In tropical or subtropical regions, RSV often occurs in the wet season (Simoes 1999; Shek and Lee 2003; Hart and Cuevas 2007), with a period of maximum RSV transmission occurring 1 or 2 months after the onset of the wet season (Weber et al. 1998). Other studies have been less definite in their conclusions concerning the existence and importance of the association between RSV transmission and the wet season (Moura et al. 2006). Besides rainfall, it is suggested that a variety of environmental factors including temperature, period of sunshine, and relative humidity might influence the onset and the end of RSV epidemics (Bhatt and Everard 2004). Studies on the epidemiology of ALRIs in developing countries particularly emphasize sociodemographic risk factors, including large family size, lateness in birth order, crowding, low birth weight, lack of breast-feeding, malnutrition, vitamin A deficiency, pollution, and young age (Rudan et al. 2008).

The population structure (50–57% under the age of 20 and only 10% over 50 years) and low average income in most African countries have meant that ALRIs have long been top priorities in African health activities (Chaulet 1989). The impact of weather on respiratory health warrants special attention, as the respiratory system is susceptible to changes in atmospheric parameters (Lam and Ayres 2011). The overall effect of extreme weather conditions on health has been studied conceptually (WHO 2003), but studies of extreme values in series of temporal health data are very rare, possibly nonexistent, in the literature. In Africa, the rarity of such studies may be explained by the difficulty of obtaining health data for sub-Saharan regions (Cooper et al. 1998). This is even more of a challenge for ALRI data (Mulholland 1999; Madhi and Klugman 2006).

This study assumes that specific weather conditions can partially explain increases in ALRI levels in Benin (West Africa). The first objective of this study was therefore to detect high levels of ALRI in children under the age of 5 for monthly intervals between January 1998 and December 2008 in the four study health zones (HZs). The second objective was to assess potential associations between these extreme ALRI levels and specific weather conditions, and, if possible, to determine whether extreme weather conditions may partially explain the increase of ALRI rates. As a result, this study will contribute to a better understanding of the role of weather conditions in the spatiotemporal distribution of ALRIs in rural areas of Benin.

1.2 Study area and health-care system

Benin was chosen as the study area due to its West African location, latitudinal orientation, the presence of synoptic stations in different climatic zones, and the availability of health and weather data. The national health system has a pyramidal structure that is based on the country's administrative geography and comprises of three levels, namely, the central level (the Ministry of Health), the intermediate level (six Departmental Directorates for Health), and the peripheral level (34 HZs) (Benin Ministry of Health 2011). Most of Benin's health data are collected periodically (monthly, quarterly, or annually) by the *Système National d'Information et de Gestion Sanitaires*. Data are collected on paper at health centers, and every month a summary report (epidemiological sheet) is sent to the peripheral level where the data are encoded. Copies of statistical databases are sent to the Departmental Directorates of Health every month, where they are compiled and sent to the Ministry of Health. To guarantee the quality and exhaustiveness of the data, they are passed through two validation processes: first at the departmental level upon receiving the data from the HZs, and second at the central level upon receiving the data from the departmental directorates (Benin Ministry of Health 2009).

1.3 Materials and methods

1.3.1 Health data

In the national database, ALRIs include bronchitis, bronchiolitis, pneumonia, and flu (Benin Ministry of Health 2006). No type-wise information is provided on ALRI. There is also no distinction based on the origin of the disease (viral or bacterial). Each record is a monthly number of children's consultations (0–5 years old) for ALRIs in all the health centers of a municipality. Every HZ includes between one and five municipalities. Daily data and health centre-wise data are not available at this level. To get it, it would be necessary to return to the books of consultations of health centers and even these books are still not archived.

Four HZs in Benin were chosen for the study, based on the presence of synoptic stations in these zones (Figure 1) and on their geographic location, so that the study area could cover as wide a latitudinal range as possible (4°, between 8°N and 12°N). The HZs were located in four different departments, namely, HZ1 in Alibori, HZ2 in Borgou, HZ3 in Collines, and HZ4 in Zou. The monthly numbers of children's consultations for ALRIs between January 1998 and December 2008 were compiled into temporal series. These data were converted to monthly consultation rates (/10,000) based on the size of population under 5 years by HZ. These final used data are qualified as monthly ALRI levels in this study. However, the reliability of data health is not guaranteed.

1.3.2 Weather data

The daily weather data were provided by the National Meteorology Office of Benin. These data were acquired for four synoptic stations located in three climatic zones (Figure 1 and Table 1) and covered the same period as the health data. To meet the needs of this study, the daily values of nine weather parameters were collected every month. These parameters were maximum temperature (T_{max}), minimum temperature (T_{min}), mean temperature (T_{mean}), temperature range (ΔT), maximum relative humidity (RH_{max}), minimum relative humidity (RH_{min}), mean relative humidity (RH_{mean}), relative humidity range (ΔRH), and rainfall (Rain).

1.3.3 Approach by correlation and regression

The first step was the calculation of correlation coefficients between monthly ALRI levels and monthly weather parameters for each month and for each zone separately. Pearson correlation was investigated for each HZ independently, by considering weather condition observed in the same month (SAME) (de Longueville et al. 2013). For this study, a similar operation was reproduced with a time lag period of 1 month, by testing the correlation between ALRI levels and weather conditions of the previous month (LAG). The potential effect of average weather conditions on periods of 2 months, ending with the month for which ALRI values (CUM) were calculated, was also tested.

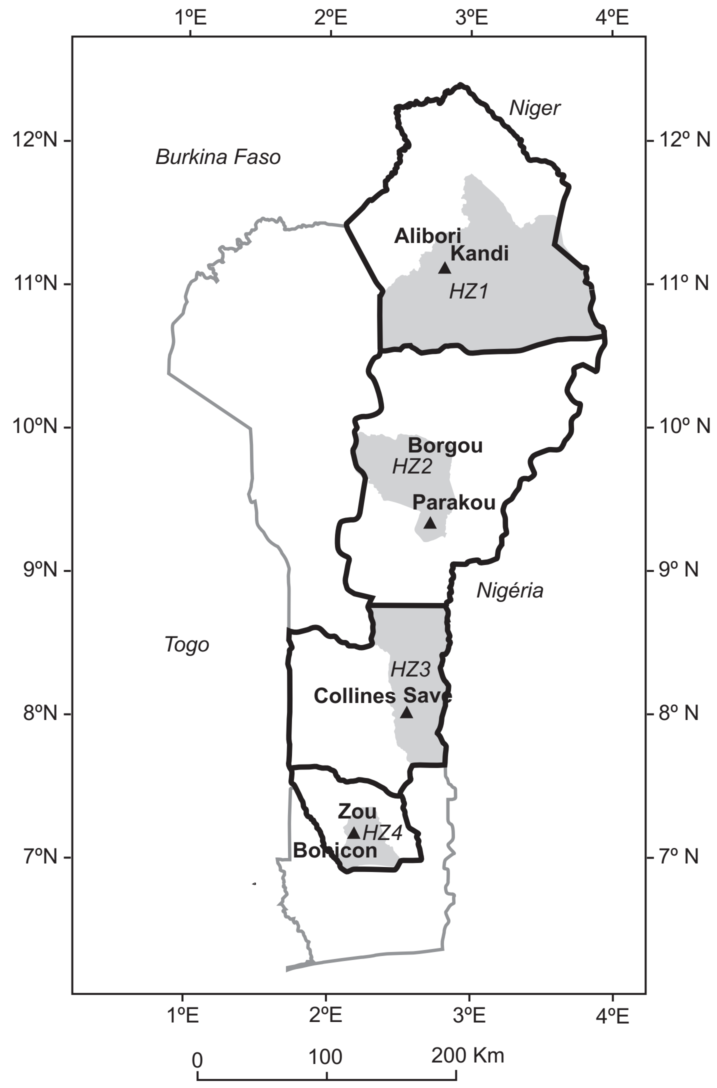

Figure 1. **Map of the study area featuring department borders (bold lines), health zones (in gray), and the locations of weather stations (triangles).**

We applied, in a second step, simple/multiple linear regression to test the possibility of explaining the variability in ALRI levels by weather conditions and to detect weather conditions leading to increased ALRI occurrences. Linear regression takes the form of an equation expressing Y as a linear function of $X_1, X_2, \ldots, X_k$, written in a simple form as follows:

$$Y = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \ldots + \beta_k X_k$$

where Y is the dependent variable (the monthly ALRI levels) and $X_1, X_2, \ldots, X_k$ is the set of explanatory variables (monthly weather variables). In this equation, $\beta_1, \beta_2 \ldots \beta_k$ are the regression coefficients of the model.

In the development of a linear (multiple) regression model, the Student's *t* test was used to determine whether the regression coefficients are different from zero or, to determine whether an explanatory variable is significantly associated with the dependent variable (Deguen 1998).

The preselection of potential explanatory weather variables, "SIM," "LAG," and "CUM" versions all combined, was based on the results of the correlation (coefficient > 0.5 in absolute value). The *best model* function (based on the values of adjusted R^2) of MedCalc software was chosen by specifying that it could include up to three variables. Conservation criteria of a model were as follows:

- R^2 higher than 0.6 and adjusted R^2 higher than 0.5
- Significant model (according to the *F* probability)
- Normality of residuals
- No aberrant value
- Absence of subgroups
- After two validations on two points: predicted values in confidence interval (0.95) and residues below the maximum residue of the calibration sample

1.3.4 Approach by indicators

One binary indicator was calculated based on the monthly ALRI levels, for each HZ separately. Using binary values allows to overcome the weaknesses of the database. The indicator determining the highest monthly values by HZ for the entire study period was called *HIPERC*, because it is a health indicator based on percentile values. The HIPERC was calculated by season, according to the average delimitation of the seasons defined by Sivakumar (1988) (Table 2). HIPERC was said to be 1 if the monthly ALRI value was greater than the value of the 90th percentile, and 0 if the monthly ALRI value was not greater than the value of the 90th percentile.

Table 1. **Geographic and climatic characteristics of the four study health zones.**

Health Zone	HZ1	HZ2	HZ3	HZ4
Department	Alibori	Borgou	Collines	Zou
Synoptic station names	Kandi	Parakou	Save	Bohicon
Coordinates	11.13N; 2.93E	9.35N; 2.61E	8.03N; 2.46E	7.16N; 2.06E
Annual precipitation (mm)	1,074	1,131	1,138	1,193
Number of seasons	2	2	2	4
Mean temperature (°C)	28.4	27.8	28.2	28.3
Climatic zone[a]	North Sudanian	South Sudanian	South Sudanian	Subequatorial

[a] *Source*: Adam and Boko 1993.

Table 2. **Definitions of normal seasons (1998–2008) for the four study health zones.**

Health zone/ Station	Onset of the wet season	End of the wet season	Duration of the wet season (months)
HZ1/Kandi	May	September	5
HZ2/Parakou	April	October	7
HZ3/Save	March	October	8
HZ4/Bohicon	March	November	9

All of the weather indicators used were based on the nine weather parameters and all were binary (Table 3). As many weather indicators as possible were developed, because the hypotheses could not be based on past studies, due to the scarcity of these studies. The 18 weather indicators are compared with HIPERC (Table 3), and the data were divided into two seasonal groups, following the limits shown in Table 2. For each season, each weather station, and each weather parameter, the values from the entire period were arranged in increasing order to determine the values of the 90th percentile (P90). Each monthly value was then compared with P90 values. This was done separately for dry season months and wet season months. If the value was greater than the P90 calculated for this parameter across the entire period, the indicator was said to be 1 and the month was considered to be a month with a particularly high value. In addition, particularly low values for temperature, relative humidity, and rainfall were determined using the 10th percentile (P10). For each season, each weather station, and each weather parameter, the values of the P10 were determined. If the value of the weather parameter during a given month in a particular station is lower than the P10 calculated for this parameter across the entire study period, then indicator was said to be 1, and the value is considered to be particularly low.

Associations between HIPERC (P90) and weather indicators (P90 which reveals particularly high values and P10 which reveals particularly low values) were investigated for each HZ, by considering each observed phenomenon, individually and independently, in the same month (SAME). A similar operation was reproduced with a time lag period of 1 month, by testing for the existence of an extreme value of a weather parameter in the month preceding an extreme value of ALRI (LAG). With all the combinations (SAME, LAG, P10, P90), 144 associations were tested.

Given the presence of a low effective value (*Z* value between 0 and 10, inclusive) in the table, Fisher's exact test was used instead of the more common Chi square test (Routledge 2005). Assuming equivalence between the two groups, Fisher's exact test allows for the calculation of the exact probability of obtaining a distance between the two groups in the distribution of two modalities that is greater than or equal to that observed (*p* unilateral) or different from that observed (*p* bilateral) (Routledge 2005). The formula used is as follows:

$$P = \frac{(W+X)!(Y+Z)!(W+Y)!(X+Z)!}{W!X!Y!Z!N!}$$

where *P* is the probability, *W*, *X*, *Y* and *Z* are the four effectives of the contingency table and *N* is the total effective. We focused on associations with alpha value < 0.05. Moreover, we calculated the relative risk (RR) which is, in the present case, the probability that a high ALRI level was observed with an extreme weather condition relative to the probability that an extreme ALRI level was observed without an extreme weather condition.

$$RR = \frac{P(ExtremeALRI = 1 \mid ExtremeWEATHER = 1)}{P(ExtremeALRI = 1 \mid ExtremeWEATHER = 0)} = \frac{(W)/(W+X)}{(Y)/(Y+Z)}$$

Table 3. **List of weather indicators with their logical expression and responses.**

Weather indicators versus HIPERC	
Logical expression	**Response**
If $T_{max} > P90$	=1; else 0
If $T_{min} > P90$	=1; else 0
If $T_{mean} > P90$	=1; else 0
If $\Delta T > P90$	=1; else 0
If $RH_{max} > P90$	=1; else 0
If $RH_{min} > P90$	=1; else 0
If $RH_{mean} > P90$	=1; else 0
If $\Delta RH > P90$	=1; else 0
If Rain > P90	=1; else 0
If $T_{max} < P10$	=1; else 0
If $T_{min} < P10$	=1; else 0
If $T_{mean} < P10$	=1; else 0
If $\Delta T < P10$	=1; else 0
If $RH_{max} < P10$	=1; else 0
If $RH_{min} < P10$	=1; else 0
If $RH_{mean} < P10$	=1; else 0
If $\Delta RH < P10$	=1; else 0
If Rain < P10	=1; else 0

HR_{max} = maximum relative humidity; HR_{mean} = mean relative humidity; P10 = 10th percentile; P90 = 90th percentile; SD = standard deviation; T_{max} = maximum temperature; T_{mean} = mean temperature; T_{min} = minimum temperature; HR_{min} = minimum relative humidity; ΔHR = relative humidity range; ΔT = temperature range.

1.4 Results

1.4.1 ALRIs burden in the study area

ARIs are the second most common cause of children's consultations in Benin after malaria. In 2008, a total of 232,214 consultations (21.1% of all consultations) involving children under the age of 5 took place for ARIs, of which

Table 4. **Cases and incidence (%) of ALRI for the four studied health zones, according to age group in Benin in 2008 (in bold = studied population).**

		[0–1]	[1–5]	[0–5]	[5–15]	15+	Total
HZ1	Cases	3,216	4,493	**7,709**	1,954	4,902	14,565
	Incidence (%)	31.7	9.1	**13**	2.4	3.6	5.3
HZ2	Cases	1,644	2,475	**4,119**	1,665	3,500	9,284
	Incidence (%)	17.5	5.6	**7.6**	2.1	2.7	3.5
HZ3	Cases	1,196	1,711	**2,907**	614	1,550	5,071
	Incidence (%)	15.1	5.6	**7.6**	1.0	1.5	2.5
HZ4	Cases	2,032	2,553	**4,585**	1,339	2,754	8,678
	Incidence (%)	15.7	5.3	**7.5**	1.4	1.6	2.6

Source: Benin Ministry of Health, 2009.

more than 67% were for ALRIs (Benin Ministry of Health 2009). Table 4 shows the number of cases and incidence (%) of ALRIs, based on age group, in the four HZs studied in Benin in 2008. Children less than a year old were the most affected by ALRIs. There were also considerable differences in incidence rates between young (1–5 years old) and older children (5–15 years old). This highlights the relevance of work on children under the age of 5. For this age group, the incidence rates of ALRIs in spatial terms were similar in HZ2, HZ3, and HZ4 (around 7.5%), but higher in HZ1 (13%).

1.4.2 Seasonality of ALRI levels

In terms of seasonality, the study area can be divided into three sections, each of which has a characteristic pattern of ALRI occurrence (Figure 2). The northern HZ (HZ1) characterized by a north Sudanian climate shows clear biannual periodicity with a peak during the dry season (March) and another at the end of the wet season (September/October) [Figure 3(a)]. The central HZs (HZ2 and HZ3) located in the south Sudanian climatic zone show a well-defined annual cycle, with a marked difference in ALRI levels between the dry season (lower ALRI levels) and the wet season (higher ALRI levels), generally with a peak covering several months (July/August to October/November) [Figures 3(b and c)]. Finally, in the southern HZ (HZ4) characterized by a subequatorial climate, the bimodal rainfall regime (two wet seasons alternating with two dry seasons, one large and one small) leads to the profile of ALRI occurrence shown in Figure 3(d) (two peaks of ALRI levels in wet season).

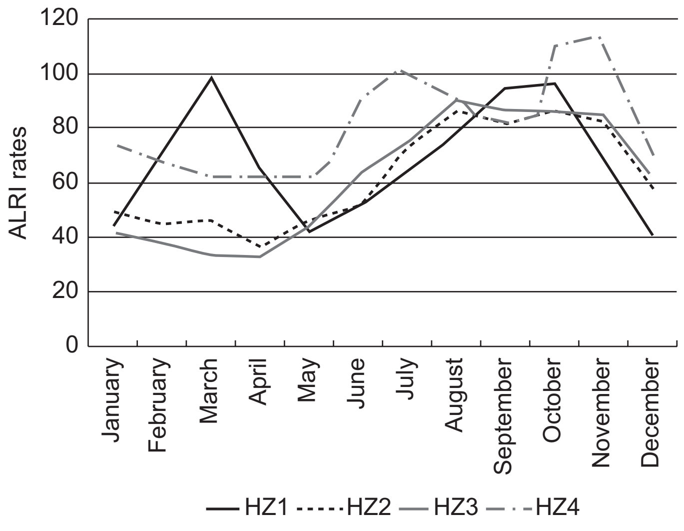

Figure 2. **Intra-annual variability of ALRI levels in the four study health zones (1998–2008).**

1.4.3 Correlation between monthly ALRI levels and monthly weather variables

In another study, we focused on the interannual variability of ALRI levels in the same study area. To do this, we examined correlations between monthly ALRI levels and weather variables, month by month, for the four HZs (de Longueville et al. 2013). We combined the previous results with the new one on LAG and CUM versions. It was found that February alone showed similar results in all the studied HZs. Conditions that are particularly dry and cold are associated with increases in ALRI cases. This was most marked in HZ2 (R close to 0.75 in absolute value) and less pronounced in HZ3 (R not significant at alpha value < 0.05). During the other months, significant relations vary across regions, but generally coincide with the results published in the literature, although these studies often have a different objective (seasonality of RSV, which is one of the most important causes of ALRI). In HZ1, rainfall was rather negatively correlated with the monthly ALRI levels during the dry season ($R = -0.53$ in March) and positively correlated during the wet season ($R = 0.65$ in July and $R = 0.51$ in September). Warm conditions ($R = 0.71$ with T_{max}), high temperature ranges ($R = 0.58$), and low relative humidity rates ($R = -0.60$ with RH_{mean}) were associated with high ALRI levels in August. In HZ2, the strongest correlations were observed in April. Low temperatures and wet conditions in March were observed together with high ALRI rates in April. In June, temperatures are positively correlated with ALRI levels ($R = 0.51$ with T_{max} and $R = 0.58$ with T_{min}). The persistence of cold conditions is associated with increasing ALRI levels in the dry season, which was also observed in HZ4. High relative humidity rates at the end of the wet season were concomitant with higher ALRI levels (e.g., $R = 0.89$ with RH_{min} in November). In HZ3, low relative humidity rates and high relative humidity ranges were associated with an increase of ALRI levels in June and July. Rainfall was negatively correlated to ALRI levels in June ($R = -0.57$) and October ($R = -0.53$). In HZ4, the months of April and May with less rainfall recorded more ALRI cases. In June to September, heavy rainfall, high maximum relative humidity, and high relative humidity ranges seemed to be associated with higher ALRI levels.

As important associations were detected using this approach, the relative importance of different weather variables was explored using linear regression. In all, 12 regression models emerged from the analysis to meet all the criteria. For each HZ, we get at least two significant and satisfactory explanatory models with one or, more often, two independent variables (Table 5).

The majority of significant models are applicable for several months of the wet season. Few redundancies appear in the results, but trends can be seen. In the dry season, cold and dry conditions seem to explain the increase in ALRI rate in February in HZ2 and HZ4. The relationship between the ALRI rate and the minimum temperature for February in the HZ4 is illustrated in Figure 4. Minimum temperatures fall over a range of variation from 22.9° up to 25.2°, whereas the ALRI levels vary from 26 to 84. The slope of the regression line is negative, meaning that the lower T_{min} is the higher ALRI rate. The model explains 83.6% (adjusted R^2 of 0.82) of the variability of the ALRI rate. Significant models for the other months of the dry season and two other HZs (HZ1 and HZ2) explain 60.3% and 79.3% of the variability of the ALRI rate, respectively.

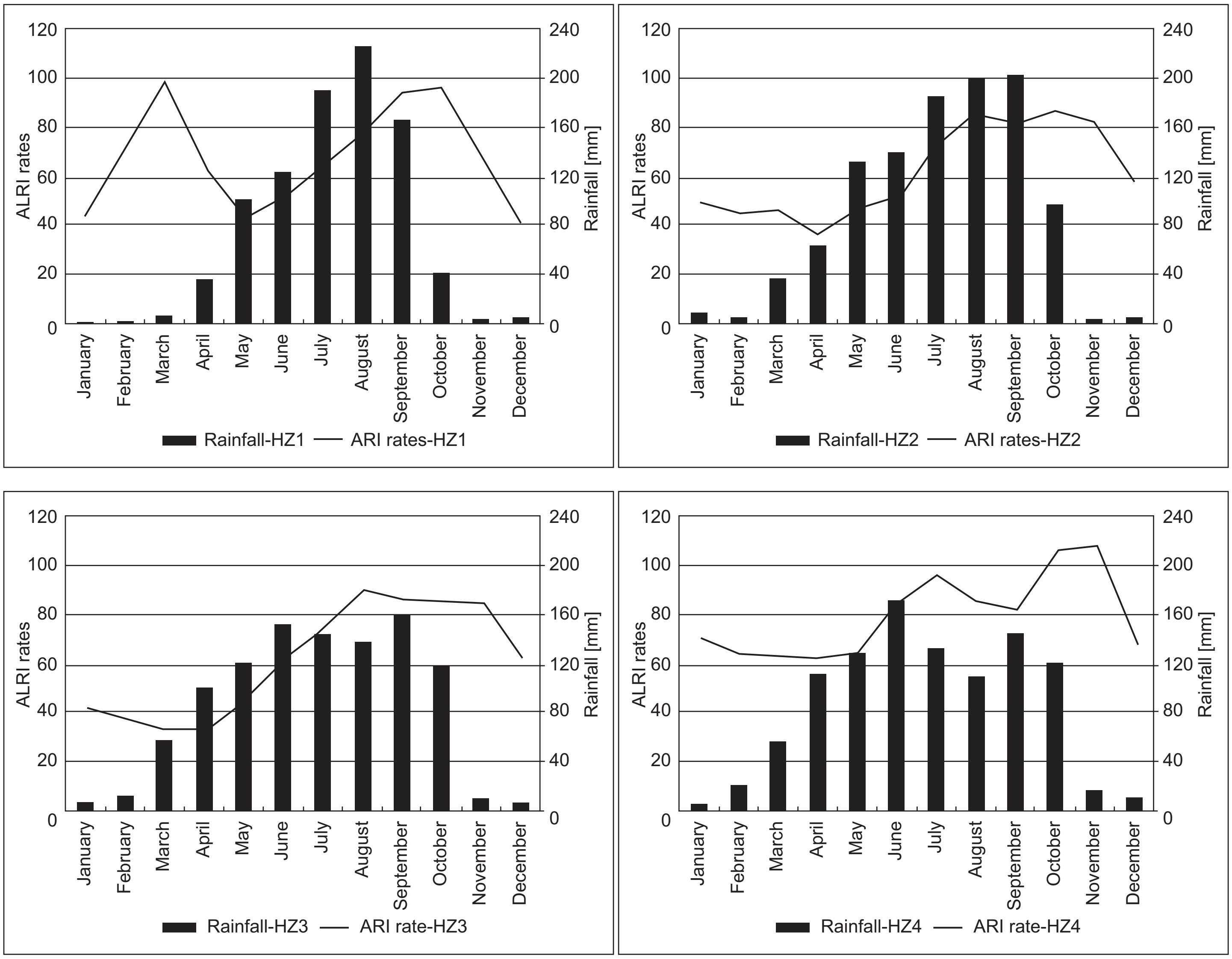

Figure 3. **Associations between ALRI seasonality and rainfall profiles in HZ1, HZ2, HZ3, and HZ4.**

For the months of the wet season, significant models generally include two variables that are mostly related to the combination of two different meteorological factors (Rain and *T*, Rain and RH or RH and *T*). One model includes a single independent variable where the minimum relative humidity explained 77.1% of the variability in the ALRI rate in June: the more the RH_{min} decreases, the more the ALRI rate increases. The RH_{min} values range from 56.2% to 67.3%, and the field variations of ALRI rate range from 17 to 116.

In the wet season, the T_{min} comes in four models as explanatory variables. Signs of coefficient for this variable are always negative. The variable temperature range appears in two models. The higher the temperature differences between minima and maxima, the more the ALRI rate increases. Variable rainfall comes in six models in the wet season. Unlike the dry season and leaving aside the month of July in the HZ3 where the coefficient is negative, higher rainfall in the wet season tends to increase the ALRI rate. The coefficients of the variables linked to relative humidity are negative in the models of the three northernmost HZs and positive in the models established for HZ4.

Among all models, with the two seasons combined, the highest determination coefficient reached 93.8% (adjusted R^2 of 0.91) and is valid for the HZ3 in July. The variability of the ALRI rate recorded in July in this zone is explained by the combination of the average relative humidity in July and rainfall in June.

1.4.4 Detection of high ALRI levels using HIPERC and associations with weather conditions

There were more extreme ALRI values during the wet season in the central and southern zones (HZ3 and HZ4) than during the dry season (Figure 5). This can be explained by the duration of the seasons. The results for both seasons were combined and the sum of ALRI values for three consecutive months (maximum period of accumulation observed) was calculated for each HZ. Periods of three consecutive months with extreme ALRI levels occurred once each in HZ1, HZ2, and HZ3 over the entire study period (1998–2008), and twice in HZ4. Most of these periods included the change from one season to the next. This

Table 5. **Results of regression analyses with monthly ALRI rates as dependent variable.**

	FEBRUARY	MARCH	APRIL	JUNE	JULY	AUGUST	SEPTEMBER
HZ1							
Variable(s)		Rain_lag (–)		$T_{min_}$cum (–)	Rain_sim (+)	$RH_{mean_}$sim (–)	Rain_sim (+)
		$RH_{min_}$lag (–)		ΔT_sim (+)	$T_{min_}$lag (–)	ΔT_cum (+)	$RH_{mean_}$lag (–)
R^2		0.603		0.685	0.630	0.619	0.638
Adjusted R^2		0.503		0.606	0.537	0.524	0.548
Prob *F*		0.025		0.010	0.019	0.021	0.017
HZ2							
Variable(s)	$T_{max_}$cum (–)		$T_{min_}$cum (–)				
	$RH_{min_}$sim (–)		Rain_cum (+)				
R^2	0.793		0.691				
Adjusted R^2	0.724		0.614				
Prob *F*	0.009		0.009				
HZ3							
Variable(s)				$RH_{min_}$sim (–)	$RH_{mean_}$sim (–)		
					Rain_lag (–)		
R^2				0.771	0.938		
Adjusted R^2				0.732	0.913		
Prob *F*				0.004	0.001		
HZ4					Rain_sim (+)		$T_{min_}$sim (–)
Variable(s)	$T_{min_}$sim (–)				$RH_{max_}$lag (+)		Rain_lag (+)
					0.802		0.635
R^2	0.836				0.753		0.544
Adjusted R^2	0.818				0.002		0.018
Prob *F*	<0.0001						

HZ = health zone; RH_{max} = maximum relative humidity; RH_{mean} = mean relative humidity; RH_{min} = minimum relative humidity; T_{max} = maximum temperature; T_{min} = minimum temperature; T_{range} = range of temperature; +/– = the sign of coefficient..

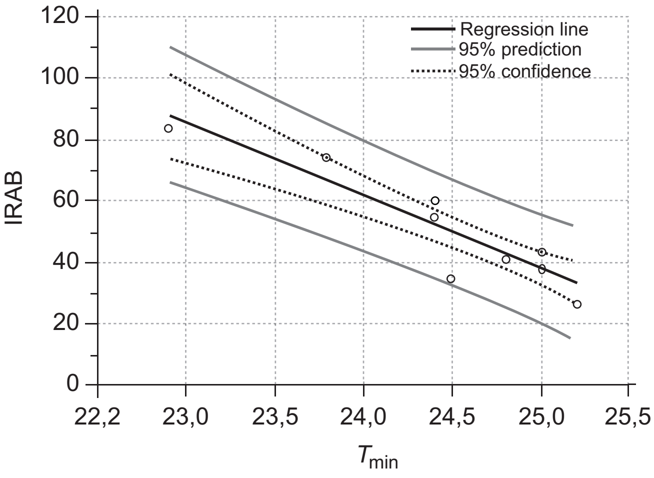

Figure 4. **Scatter diagram between ALRI and T_{min} for the month of February (1998–2008) in HZ4.**

mainly occurred during the last quarter of the year, particularly in the northern study zones (from August to October 2006 in HZ1 and from September to November 2007 in HZ2). An intense period was observed between May and July 2000 in HZ3, and two more were observed between October and December 1998 and between July and September 1999 in HZ4. In terms of spatial recurrence, intense 3-month periods occurred simultaneously in at least three HZs only once during the entire study period (1998–2008). In October 2007, HIPERC was equal to 1 in three of the four study HZs.

The significant results ($p < 0.05$) obtained using Fisher's exact test are summarized in Table 6. Weather parameters related to relative humidity were barely significant when considering indicators based on the 90th percentile, whereas for indicators based on the 10th percentile, the weather parameters that showed significant relationships with particularly high ALRI values were largely those based on temperature data. Particularly high ALRI values coincided with extreme values of maximum relative humidity in HZ4. This trend was also observed in HZ2 with RH_{mean}. There were associations of extreme ALRI levels with cold conditions

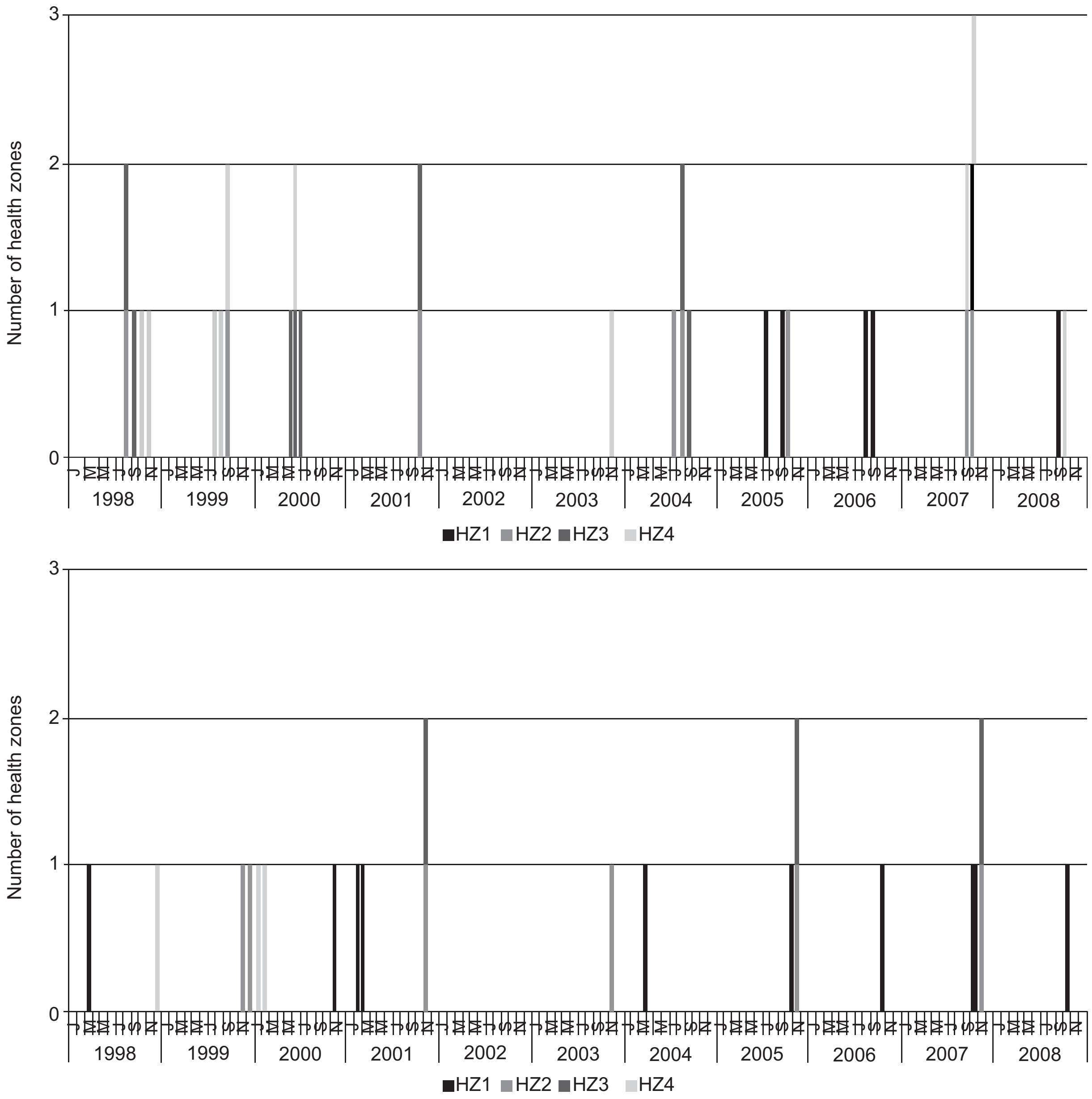

Figure 5. **Temporal distribution of the extreme ALRI values (based on HIPERC) by health zone in the wet season (top) and the dry season (bottom).**

Table 6. **Results of significant relationships between HIPERC and weather indicators.**

Health zone	Weather parameter	High/low value of weather parameter	Type	Alpha value	RR	95% CI
HZ1	Rain	P90	SAME	0.03	3.7	1.3–10.6
HZ2	RH_{mean}	P90	SAME	0.01	5.3	1.8–16.2
HZ4	RH_{max}	P90	SAME	0.03	3.7	1.3–10.6
HZ2	T_{max}	P10	SAME	0.0012	6.7	2.8–16.3
HZ3	T_{min}	P10	SAME	0.05	3.7	1.2–11.2
HZ4	T_{max}	P10	SAME	0.02	4.1	1.5–11.4
HZ3	T_{min}	P10	LAG	0.05	3.7	1.1–12.2

CI = confidence interval; HZ = health zone; P10 = 10th percentile; P90 = 90th percentile; RH_{mean} = mean relative humidity; RR = relative risk; T_{max} = maximum temperature; T_{min} = minimum temperature.

(based on low T_{min} or low T_{max}). Finally, a significant relationship between high ALRI values and high rainfall values during the dry season in HZ1 was also observed.

1.5 Discussion

A distinctive feature of the approach adopted in this paper is that we focused on particularly high ALRI levels in temporal series (month by month and across the entire series), going beyond classic seasonality studies that focus exclusively on annual peaks. It complements a study on the interannual variability of ALRI levels in connection with the weather conditions to better understand the effect of weather conditions on ALRI in West Africa (de Longueville et al. 2013).

First, in terms of seasonality, a close relationship between ALRI levels and rainfall profile was revealed. In a detailed review of the literature, Stensballe et al. (2003) offered a geographical subdivision of the tropics based on factors associated with seasonality. According to this subdivision, in the tropical north, seasonality is associated with lower temperatures and higher levels of rainfall (Weber et al. 1998). In the equatorial zone, ALRIs are observed throughout the year, with a peak during the wet season (Chew et al. 1998). Finally, seasonality in areas south of the equator is linked to lower temperatures and rainfall levels. In another literature review about the seasonality of RSV infection in tropical countries, Shek and Lee (2003) listed 20 studies. Three of these studies looked specifically at the seasonality of lower respiratory tract infections. They showed that annual peaks coincided with the wet season in South India (Cherian et al. 1990), Colombia (Bedoya et al. 1996), and Malaysia (Chan et al. 2002). In Africa, Vaahtera et al. (2000) showed that respiratory infections affect children in the cold, dry season in rural Malawi. A study conducted in Lomé (Togo) between 1989 and 1992 on Togolese nursing infants and children showed peaks in ARI occurrence in January. Second, while the analysis initially appeared to show no systematic relationships between high ALRI levels and extreme weather conditions, it did reveal some significant results. We cautiously suggest that it is likely that certain weather conditions, working in combination with other factors, may have caused a substantial increase in cases of ALRI for some months of the study period. Our results are in agreement with previous findings on RSV or ALRI (e.g., Chew et al. 1998; Dosseh et al. 2000; Lapeña et al. 2005), even though these studies focused on annual peaks rather than extreme values. Lower temperature was the most recurrent factor, whatever the season. This is in agreement with the previous study that analyzed the relationship between the most commonly known ARI pathogens in children and different meteorological parameters (e.g., Chan et al. 2002; Shek and Lee 2003; Stensballe et al. 2003). Rainy months during the wet season were also associated with increases of ALRI prevalence. Low RH_{min}, high RH_{max}, and high RH range were factors that could result in more ALRI occurrences. Low temperatures and other meteorological factors may influence interactions between host, pathogen, and environment, increasing the probability of exposure, susceptibility, and infection (du Prel et al. 2009).

These results, however, are not conclusive, because these weather conditions were not always recorded during months with particularly high ALRI levels, and similar weather conditions were recorded at the other times over the study period or in the other HZs that did not coincide with particularly high ALRI levels. These conditions therefore probably only partly contributed to the increase in ALRI levels, alongside the socioeconomic factors whose importance has been clearly demonstrated in literature. A possible partial explanation of the results is the likely existence of multiple pathogens that cause ALRIs as in Mali (Findley et al. 2005), but the used health database did not provide this kind of information. The study process itself may also have been a factor that influenced results. The study period, although relatively exceptional for health data—particularly for a developing country—remained short. An 11-year period seems not long enough to establish any real significant trend or to advance any definite potential series breaks, for either ALRI occurrence or weather conditions. Furthermore, the use of monthly time intervals was not ideal, but daily data were not available at this spatial scale. According to Tissot-Dupont (2009), wind is one of the main weather phenomena that can influence the transmission of infectious diseases, especially respiratory diseases. Atmospheric dust may also be a factor influencing ALRI levels (Ozer et al. 2006; de Longueville et al. 2010). These two parameters were not studied here due to the lack of data. Finally, the multiplicity of factors—even if only meteorological factors are being considered—should not be ignored.

In the context of climate change, more extreme weather conditions would be expected in the future. Therefore, it is important to evaluate the effects of extreme weather conditions on ALRI incidences for the planning of public health activities, especially in developing countries in which populations are poorer and more vulnerable. Focus on the children is particularly relevant to be in agreement with the millennium development goals. This study could help for better understanding of the impacts of environmental factors on health in West Africa, where such studies are very scarce. Further research on all of these various elements is needed to be able to deepen the interpretation of these results. Replicate studies of this kind in other areas would also be useful to confirm or refute the results obtained here.

1.6 Conclusion

The aims of this study were to detect extreme values of monthly ALRI levels in four rural Beninese HZs between January 1998 and December 2008 to speculate on potential relationships between these and weather conditions, and to check whether extreme weather conditions could explain the increases of ALRI prevalence. The results showed that weather conditions that are likely to be factors influencing increased levels of ALRIs in children under the age of 5 are particularly low minimum or maximal temperatures, abnormally high temperature ranges, high values of maximum relative humidity in the south of the study area, low values of relative humidity in the northern part, and high rainfall during the wet season. In the north of the study area, most of the particularly high ALRI levels were observed during the dry season. In the south of the study area, most abnormally high ALRI levels were recorded during the wet season. However, none of the results were definitive or recurring. Moreover, the variety of the results obtained suggests that weather conditions are neither the sole nor the main cause of particularly high ALRI levels, at least when using monthly weather data and at this spatial scale. The duration of the study period, the use of daily data, a more precise spatial scale, the inclusion of additional parameters such as wind and dust, and the interaction between the parameters should be explored to improve our findings. The results presented here clearly underline that further research is still needed to better understand the effect of weather conditions on ALRI levels in West Africa, where ALRIs are particularly frequent and deadly.

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Declaration of Competing Interests

No competing interest

1.8 References

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