Climate Change and Acute Respiratory Infections in Children Aged 0 to 5 Years in the Poro Region of Côte d'Ivoire

Abstract

This article aims to examine the effect of climate change on the prevalence of acute respiratory infections (ARI) among children aged 0 to 5 years in the Poro region, located in northern Côte d'Ivoire. Specifically, it seeks to contribute to the analysis of the influence of temperature and rainfall variations on child health. The endogenous variable is the prevalence of acute respiratory infection. The exogenous variables are official development assistance, public spending on education, mortality rate, temperature, and precipitation. The climate data used come from the NASA database, while health data are drawn from the Annual Health Situation Reports (RASS) from 2007 to 2020. A MIDAS-PDL/Almon model is applied using the nonlinear least squares method for econometric estimation. The results show that the prevalence of ARI among children aged 0 to 5 years in the Poro region is significantly linked to temperature and precipitation variations. Moreover, development aid and increased public spending on education help mitigate the effects of climate on the health of populations in Poro.

Keywords: climate change, ARI, MIDAS-PDL, Poro region.

1. Introduction

The Poro region, whose capital is Korhogo, is a particularly relevant study setting for analyzing the impact of climate change on the health of children aged 0 to 5 years. Indeed, located in the northeast of Côte d'Ivoire (CI), this region faces harsh climatic conditions. It has recorded temperature increases of 1.2°C over the past four years (Météo Côte d'Ivoire, 2022). This phenomenon is exacerbated by prolonged droughts, making populations vulnerable to worsening living conditions, according to the World Bank Group (2022 and 2023).

Compared to other regions, Poro shows disparities in healthcare provision. For example, Abidjan, the country's economic capital and its surroundings, have a much more developed and relatively accessible healthcare system. Vaccination coverage there exceeds 85% (UNICEF, 2023), and the ratio of doctors per 100,000 inhabitants is significantly higher. In the north of the country, there are only 4 doctors per 100,000 inhabitants (RASS-CI, 2022). Moreover, according to data from the National Institute of Statistics (INS, 2022) and the Harmonized Survey on Household Living Conditions (EHCVM, 2021–2022), the Poro region has a very high poverty rate (64.5%) compared to Abidjan (11.3%).

Regarding climate, the situation is also contrasting. The Lagunes region benefits from a more stable equatorial climate, while southern regions such as Gôh-Djiboua or Bélier have more moderate climates and relatively better-developed healthcare infrastructure, with vaccination coverage close to 80% and better access to healthcare (UNICEF, 2023). These regions also benefit from more regular rainfall and economic diversification, which reduces the impacts of climate change (FAO, 2023). In contrast, a region like Poro is exposed to rainfall deficits, which directly affect living conditions, particularly access to drinking water and food security (Météo Côte d'Ivoire, 2022; Kafoudal, 2022). Demographically, Korhogo and its surroundings account for about 17% of children under 5 years old (RGPH, 2021). Thus, in the Poro region, populations suffer from increased vulnerability and weak adaptive capacity in the face of extreme climate events, unlike regions in the south of the country.

Furthermore, many researchers have already established the relationship between climate variability and the prevalence of malaria (Gouataine, 2018; Diomandé et al., 2018 and 2019). However, very few studies have focused on establishing a link between climate variations and acute respiratory infections (ARI) in children under five years old, specifically in the Poro region.

From the above, it is important to analyze the impact of climate variability on the prevalence of ARI among children under five years old in the Poro region. More specifically: what is the extent of the influence of temperature and rainfall variations on the prevalence of acute respiratory infections among children under five in Poro? Do education and health expenditures contribute to reducing this influence?

At first glance, the hypothesis is that ARI prevalence increases among children under five when temperature and precipitation vary. However, efforts in educating populations and greater funding dedicated to the health sector help mitigate the effect of climate change on ARI in children in the Poro region.

To address this concern, we rely on the Mixed Data Sampling (MIDAS) model, which allows the analysis of data with different frequencies. In fact, we have monthly climate data [temperature and precipitation] to be combined with annual data on acute respiratory infections in children.

This study is part of ongoing research on the link between climate change, public health, and development economics. Moreover, it aims to draw attention to the vulnerability of children aged 0 to 5 years to the effects of climate change. Remaining within a scientific framework, the rest of the paper is structured into literature review, methodology, results, discussion, and conclusion.

2. Literature Review

The literature review is organized into theoretical and empirical approaches. This choice reflects the need to adhere to scientific tradition.

2.1 Theoretical Review

According to WHO (2020), ARIs refer to a set of diseases affecting the respiratory tract, occurring suddenly and manifested by symptoms such as cough, fever, rapid breathing, or suffocation. Climate change, as defined by the United Nations, refers to long-term variations in temperature and weather patterns. These variations, although natural, are increasingly exacerbated by human activities such as deforestation, and the combustion of coal, oil, and gas.

The link between climate and ARI, via health in general, lies at the crossroads of several theoretical formulations, ranging from environmental exposure theory to economic approaches. According to Roux (2006) and François (2024), almost everyone is exposed to varying degrees to air or water pollution and food contaminants found in consumer products. For economist Grossman (2014), climate changes [temperature, humidity, pollution], by increasing exposure to health risks, act as an exogenous shock degrading the production function. Furthermore, when information is imperfect and incomes are low, populations may adopt short-term strategies that do not foster health resilience, such as delaying medical care or choosing housing exposed to extreme climatic conditions (Morgenstern, 1976; Arrow, 1971). According to Becker (1964), child health is an essential component of human capital development; thus, the negative effects of climate not only compromise children's survival but also their long-term educational and productive potential. For Dell et al. (2012), an increase in temperature is associated with lower agricultural productivity, reduced human capital [particularly through health effects], and losses in GDP per capita.

2.2 Empirical Review

Research on the effect of climate on health mostly shows an influence of temperature on mortality. In developed countries, particularly in France, Pascal (2020) conducted a study over 18 urban areas between 2000 and 2010. The results showed that cold and heat accounted for 3.9% and 1.2% of mortality, respectively. Between 1974 and 2013, nearly 32,000 additional deaths were recorded for 921 heat waves in France (Pascal, 2020). In Canada, Charron et al. (2008) blamed the development of disease-transmitting insects due to high temperatures.

In Africa, the situation is no different. Studies such as Koh et al. (2023), conducted in 33 sub-Saharan African countries, and Djibo et al. (2021), conducted in Niger, highlight with concern the negative influence of adverse climatic conditions on population health. More specifically, Uwizeye et al. (2021) emphasized the impact of climate variability on acute respiratory infections (ARI) in children under 5 years old in Rwanda.

In Côte d'Ivoire, respiratory infections in relation to climate have been studied by authors such as Krouba et al. (2024), Mogou et al. (2022), and Ymba (2022). The first conducted their study in the Grand-Bassam department, a particularly humid region. Their results showed a positive but moderate correlation between ARI and temperature, but a negative correlation with rainfall levels. Mogou et al. (2022), whose study was conducted in Soubré, a very rainy region in the southwest of Côte d'Ivoire, found that humidity exposes populations to lower ARIs (bronchitis, pneumonia), while the dry season increases the risk of upper ARIs (angina, acute otitis media, acute sinusitis, laryngitis). In Abidjan, Ymba (2022) found that densely built-up and poorly vegetated areas retain heat, aggravating respiratory diseases in children and the elderly. Informal settlements are the most affected, with an increase in cases of asthma and bronchitis. Despite these studies, the research field linking climate change and health, particularly ARIs in children under 5 years, remains underexplored in Côte d'Ivoire, especially in the north.

In the Poro region, ARIs are among the leading causes of pediatric consultations every year. Several factors contribute to this high prevalence. On one hand, poor socioeconomic conditions make it difficult for a large segment of the population to access healthcare. On the other hand, the local Sudanese-Sahelian climate, characterized by an increasingly long and dusty dry season with the dry Harmattan wind, followed by heavy rains during the farming season, makes living conditions difficult for the population. Changes in rainfall patterns and extreme heat tend to increase the risks of respiratory infections (IPCC, 2021; Hashim et al., 2021). This observation justifies an integrated economic approach that considers interactions between climatic and health variables, in view of better planning of public health policies in the Poro region. It should be noted that the IPCC (2007) report on climate change predicts, in the coming decades, an intensification of heat waves, floods, droughts, and storm winds.

3. Methodology

3.1 Data Sources and Study Variables

- **Data Sources**

The data used to analyze the influence of climate change on the prevalence of ARIs among children aged 0 to 5 years in the Poro region come from two sources. The various Health Situation Reports of Côte d'Ivoire (RASS-CI) provided prevalence rates of ARIs from 2007 to 2020 in the Poro region. For climate-related variables, we relied on secondary data from NASA.

The RASS data have the advantage of being produced according to national standards and covering all health facilities, thus allowing comprehensive monitoring of ARIs among children aged 0 to 5 years. However, they present limitations such as delays, underreporting, incomplete coverage, and lack of disaggregated data. The secondary climate data come from the NASA POWER database, recognized for the quality of its satellite data, including minimum temperature and precipitation. Finally, the socio-economic variables used are sourced from the World Bank databases.

- **Study Variables**

This study seeks to explain the evolution of ARI prevalence among children aged 0 to 5 years in the Poro region as a function of climate variations. It is therefore appropriate that the endogenous or dependent variable is the prevalence of ARIs in the Poro region (P_ARI). The explanatory or independent variables fall into two categories.

On the one hand, we have variables that capture climatic characteristics: temperature and precipitation. To these climate variables, many authors associate socio-economic variables. In our study, we focus on official development assistance, education, and infant mortality. These different variables are summarized in the following table:

Variable	Description	Source	Expected Sign
ARI	Acute respiratory infections in children aged 0–5	RASS-CI (2007–2020)	–
Temperature	Adjusted temperature at 2 meters (°C)	NASA POWER	(+)
Precipitation	Adjusted precipitation from MERRA-2	NASA POWER	(+)

	(mm/day)		
ODA	Official development assistance (% of central government spending)	World Bank	(–)
IMR	Infant mortality rate	World Bank	(–)
EDU	Education expenditure	World Bank	(+)

Table 1: Presentation of Variables

Source: Authors

3.2 Econometric Model: The MIDAS Model

- **JustificationofModelChoice**

The nature of the data at hand leads us to prefer the MIDAS model to measure the link between climate change and ARIs among children aged 0 to 5 years in the Poro region. Indeed, as in the case of many other authors, we faced the challenge of managing data with different frequencies. The ARI data are available for only 15 years (2007–2020). This period is insufficient for panel data analysis. In addition, information on climate variables such as precipitation, temperature, wind speed, and others is available at quarterly or monthly frequencies (NASA POWER).

The MIDAS model, developed in the early 2000s, makes it possible to model the effects of high-frequency data using a parametric function that smooths the coefficients associated with lags. This approach allows the integration of a large number of past values without inflating the number of parameters to be estimated.

Although the MIDAS model was initially applied mainly in finance, pioneering work by Ghysels et al. (2004) and Santa-Clara et al. (2004) extended its use to complex macroeconomic issues. Others, such as Foroni, Marcellino, and Schumacher (2015), have demonstrated that MIDAS can also be useful in contexts where economic policy shocks or natural disturbances influence the economy irregularly. In this study, the formulation adopted is the MIDAS-PDL (Polynomial Distributed Lags or Almon Lags) model, as the climate effects analyzed are likely to occur over time (Madinier & Mouillart, 1983; Bourbonnais, 2018).

- **GeneralFormulationoftheMIDAS-PDLModel**

The general formulation of the MIDAS-PDL model is written as follows:

$$Y_t = \alpha + \sum_{j=0}^{K} B(\mathrm{j}\,;\theta) X_{t-j/m} + \varepsilon_t$$

(1)

Variable Y_t observed at low frequency is explained by a weighted sum of past values of a variable X observed at high frequency.The weights B(j;θ) are modeled as a polynomial function of the lag rank, such that :

$$B(j;\theta) = \theta_0 + \theta_{1j} + \theta_2$$

$X_{t-j/m}$ represents the high frequency (monthly) observations with j=0,….,K ,m being the number of high frequency observations in a low frequency period,B_j being the coefficients to be estimated for each lag, and $\varepsilon_t$an error term. K Represents the number of high frequency lag.

This formulation allows not only the use of information contained in high-frequency data but also the capture of dynamic and lagged effects in a flexible and rigorous manner.

- **StudyModelSpecification**

Our approach is partly inspired by Omer (2024), who used a MIDAS Poisson model to analyze the effect of climate variables on dengue cases. Although the health context and estimation method differ, his work highlighted the relevance of the MIDAS model in capturing the delayed effects of high-frequency variables on health phenomena.

We adapt this logic by using a MIDAS model estimated by Nonlinear Least Squares, which is more appropriate for the continuous nature of our dependent variable (ARI prevalence), while retaining the central idea of integrating monthly climate data into a public health framework.

In our study, Y_t represents the annual rate of acute ARI in children aged 0 to 5 years in the Poro region, and $X_{t-j/12}$represents a monthly climatic variable, either temperature or precipitation.
So we have :

$$ARI_t = \alpha + \sum_{j=0}^{K} B_j \, Temp_{t-j/12} + \varepsilon_t$$
(2)

Or

$$ARI_t = \alpha + \sum_{j=0}^{K} B_j \, Prec_{t-j/12} + \varepsilon_t \qquad (3)$$

However, this form suffers from the over-parameterization problem as soon as K becomes large. To correct this, we introduce a polynomial constraint on the B_j through the Almon polynomial. We therefore specify that the weights associated with each month are a polynomial function of j , such that:

$$B_j = \theta_0 + \theta_{1j} + \theta_{2j^2}$$

By injecting this form into our equation, we obtain the MIDAS-PDL version with Almon polynomial of degree 2. We obtain the following form:

$$ARI_t = \alpha + \sum_{j=0}^{K} (\theta_0 + \theta_{1j} + \theta_{2j^2}).Temp_{t-j/12} + \varepsilon_t$$
(4)

This equation means that the effect of each month j on the incidence of ARIs is not estimated independently but is modeled according to a polynomial structure, which ensures the parsimony of the model while capturing temporal dynamics.

With precipitation and control variables, the specified model retained in this study is:

$$ARI_t = \alpha + \sum_{j=0}^{K}(\theta_0 + \theta_{1j} + \theta_{2j^2}).Temp_{t-j/12} + \sum_{j=0}^{K}(\theta_0 + \theta_{1j} + \theta_{2j^2}).Prec_{t-j/12} + \gamma_1 Educ_t + \gamma_2 IMR_t + ODA_t + \varepsilon_t \quad (5)$$

With

α: Model constant

$\mathrm{Temp}_{t-j/12}$ and $\mathrm{Prec}_{t-j/12}$: Lagged monthly temperature and precipitation data

$\theta_{i,k}$: Coefficients of the Almon polynomial (order 2) for each climate variable

$Educ_t$: Public education expenditure in year t

IMR_t : Annual infant mortality rate

ODA_t : Official development assistance

γ_1 and γ_2:Coefficients of the annual variables

ε_t: Error term

This model allows capturing the non-linear delayed effects of climate variables while taking into account the structural socio-economic impact through $Educ_t$ (education expenditure) and IMR_t (Annual infant mortality rate).

3.3 Estimation Procedure

3.3.1Pre-estimationTests:StationarityTests(Bourbonnais,2018)

Several tests exist to determine whether variables are stationary or not. In this study, we use the Augmented Dickey-Fuller (ADF) and Phillips-Perron (PP) unit root tests.

- **ADF Test**: The ADF test is conducted under the null hypothesis of a unit root. If the ADF statistic is greater (in absolute value) than the critical value, we reject the null hypothesis, and the series is stationary.
- **Phillips-Perron Test**: The PP test is based on a non-parametric correction of the Dickey-Fuller statistic, accounting for heteroskedasticity. Unlike ADF, it can handle unknown autocorrelation structures. The null hypothesis assumes non-stationarity; rejection occurs if the probability value is ≤ 5%.

3.3.2EstimationoftheMIDAS-PDLModel

The MIDAS-PDL model is estimated using the nonlinear least squares (NLS) method, automatically integrated in the MIDAS tool of EViews. This approach models the relationship between variables of different frequencies—monthly climate data and annual health data—while imposing a polynomial structure (Almon-type) on lag coefficients.

To evaluate model fit and compare different specifications, we use the Akaike Information Criterion (AIC) and the Bayesian Information Criterion (BIC). Lower values of AIC and BIC indicate a better balance between fit and parsimony.

In this study, we use EViews 12 software for preliminary tests and estimations

4. Results and Discussion

Section 4 presents the results and their discussion.

4.1 Results

The results presented are, on the one hand, descriptive statistics and, on the other hand, outputs from econometric estimations.

4.1.1 Descriptive Statistics

Table 2 presents the descriptive statistics of the study variables.

Table 2: Descriptive Statistics of Variables

	Temperature	Precipitation	ODA	Infections	EDU	Infant Mortality
Mean	35.54714	3.597202	23.94804	143.3500	3.370441	62.37857
Median	36.12000	3.5150000	14.86369	110.9000	3.363620	61.80000
Maximum	41.36000	9.950000	70.76251	365.5400	3.935930	75.60000
Minimum	29.80000	0.000000	6.094133	50.10000	2.865760	50.90000
Std. Dev.	3.283478	2.700816	19.70911	92.02251	0.292741	7.644200
Skewness	–0.112559	0.311535	1.364970	1.147234	0.282014	0.153878
Kurtosis	1.720925	2.002037	3.528841	3.309942	2.352861	1.815428
Jarque-Bera	11.80698	9.689012	54.12575	37.52584	5.158418	10.48546
Probability	0.002730	0.007872	0.000000	0.000000	0.075834	0.005286
Observations	168	168	14	14	14	14

Source: Authors, from EViews 12, RASS-CI (2007-2020) and NAZA POWER Data

Table 2 shows that the climate is particularly hot, with temperatures ranging between 29.8°C and 41.36°C, with an average of 35.547°C—higher than the national average (27.38°C). Precipitation averages 3.59 mm/day, much lower than the national average. Official development assistance averages 23.945% of GDP, and education spending averages 3.37% of GDP. ARIs among children range from 50.1 to 365.5 per thousand, while infant mortality in Poro ranges between 50.9 and 75.6 ‰.

The econometric model results measure the degree of significance between ARIs in children aged 0 to 5 in Poro and explanatory variables.

4.1.2 Econometric Test Results

The results of the econometric model are presented through the correlation matrix of the variables and the results of the stationarity tests.

- **Correlation matrix of the study variables**

Table 3 presents the correlation between the explanatory variables.

Tableau 3 : **Pearson Correlation Matrix**

Correlation	ODA	Healthcare expenditures	Infecions	Infant mortality	Precipitation
ODA	1.000				
Healthcare expenditures	-0.23434 -3.10576	1.000			
Infection	-0.29380 -3.96023	0.03279 0.42274	1.000		
Infant mortality	0.31026 4.20493	-0.69432 -12.4305	-0.51770 -7.79620	1.000	
Precipitation	0.00833 -0.10736	0.07958 1.02869	0.06559 0.84697	-0.11702 -1.51815	1.000
Temperature	-0.07681 -0.99259	0.05599 0.72260	-0.08343 -1.07872	0.04762 0.61434	-0.57726 -9.10831

Source: Authors, from EViews 12, RASS-CI (2007-2020) and NAZA POWER Data

The results show no strong linear correlation between variables, reducing risks of multicollinearity in further estimations. Most coefficients are below 0.7 in absolute value.For instance, a negative correlation (–0.6943) exists between education spending and infant mortality, suggesting that higher educational investment reduces child mortality.There is also a moderate negative correlation (–0.5177) between temperature and precipitation, reflecting a common climatic dynamic where heavy rains coincide with lower temperatures. ODA is weakly correlated with infant mortality (0.3102).

- **Unit Root Tests**

Table 4 presents the results of the unit root test

Variables	Level		1st Defference		2nd Différence		Decision
	ADF	PP	ADF	PP	ADF	PP	
ARI	-1.86 (0.3470)	-1.90 (0.3314)	-12.80 (0.0000)***	-12.80 (0.0000)***	-	-	I (1)
Temperature	-1.95 (0.3.59)	-5.20 (0.0000)***	-10.79 (0.0000)***	-8.21 (0.0000)***	-	-	I (1)
Precipitation	-2.86 (0.0516)	-4.00 (0.0018)	-12.31 (0.0000)***	-13.41 (0.0000)***	-	-	I (1)
ODA	-1.83 (0.3618)	-1.87 (0.3455)	-12.84 (0.0000)***	-12.84 (0.0000)***	-	-	I (1)
IMR	-1.98 (0.2932)	-1.87 (0.7059)	-12.84 (0.3315)	-12.84 (0.000)***	-	-	I (1)

EDU	-1.83 (0.3618)	-1.87 (0.3455)	-12.84 (0.000)***	-12.84 (0.000)***	-	-	I (1)

ADF and PP tests indicate that most series are stationary at the first difference (I(1)). Infant mortality rate results diverged: ADF suggested I(2), while PP suggested I(1). Given PP's robustness and graphical consistency, IMR was considered I(1).

4.1.3 Estimation Results of the MIDAS-PDL/Almon Model

The MIDAS-PDL model quantified the effects of monthly climate variables on annual ARIs among children under 5 in Korhogo. Using a second-order Almon polynomial with 49–51 monthly lags, the model captured the dynamic effects of climate shocks. Estimation employed nonlinear least squares.

Table 5 : MIDAS-PDL Estimation

Variable	Coefficient	Std-Error	t-statisique	Prob
EDU	-1.75441	23.06837	-7.605290	0.0000
ODA	-1.7700	0.583310	-3.034476	0.0031
IMR	-2.016277	3.143891	-0.641332	0.5228
Précipitationlags : 51				
PDL 01	-4.814033	1.308252	-3.679745	0.0004
PDL 02	0.315647	0.055755	5.661349	0.0000
Températurelags : 49				
PDL 01	-0.061151	0.635235	-0.096264	0.9235
PDL 02	0.160416	0.029299	5.475184	0.0000

Source: Authors, from EViews 12, RASS-CI (2007-2020) and NAZA POWER Data

- Education (EDU): coefficient –1.75441 (significant, p=0.0000)
- ODA: coefficient –1.7700 (significant, p=0.0031)
- IMR: not significant
- Precipitation (PDL 1: –4.814033; PDL 2: 0.315647) both significant
- Temperature (PDL 1: not significant; PDL 2: 0.160416 significant, p=0.0000)

Table 6 : Model Validation

	AIC	BIC	Log likelihood
MIDAS PDL/ALMON Lags (49,51)	11.01486	10.81733	-581.5442

$R^2 = 0.77$

- $R^2 = 0.77 \rightarrow$ model explains 77% of ARI prevalence variability
- AIC = 11.01486, BIC = 11.61 → moderate values, good model fit

4.2 Discussion

- **EducationSpending**

The negative sign associated with education spending suggests that improved parental education reduces ARI incidence. In Poro, this is explained by better adoption of health practices, awareness of environmental risks, and improved child hygiene.

- **OfficialDevelopmentAssistance(ODA)**

ODA also shows a significant negative impact on ARIs, implying that when properly allocated to social sectors such as health and environment, aid strengthens local capacities, improves healthcare access, and supports prevention. This aligns with Burnside & Dollar (2000), who argued that aid is effective only in the presence of sound policies.

- **Temperature**

Results reveal that immediate effects of temperature are insignificant (p=0.9235), but the second-order lag (0.160416) is significant and positive. This suggests that extreme temperature effects accumulate over time. This finding is consistent with Pascal (2020) in France and Koh et al. (2023) in Sub-Saharan Africa, who showed links between prolonged heat exposure and respiratory illnesses.

- **Precipitation**

Both lagged components of precipitation are significant: the first negative (–4.814033), the second positive (0.315647). This indicates that rainfall initially reduces risks (through air cleaning and domestic confinement), but delayed effects increase risks due to excess humidity, stagnant water, and mold growth. These findings are consistent with Currie & Neidell (2005) and Hashizume et al. (2007), who showed that heavy rainfall is followed by increased respiratory illnesses in vulnerable populations.

Hypotheses Testing

- Hypothesis 1: Higher temperature and rainfall increase ARIs → confirmed.
- Hypothesis 2: Reduced ODA lowers ARIs → not confirmed, though expected sign was consistent.
- Hypothesis 3: Higher education spending reduces ARIs → confirmed.

Conclusion

The main objective of this study was to analyze the lagged effects of climate change on the prevalence of acute respiratory infections (ARI) among children under five years old in the Poro region. Specifically, it sought first to analyze the effect of climatic variables such as temperature and precipitation on ARIs in children aged 0 to 5 in Poro. Second, it aimed to highlight the contribution of official development assistance (ODA) to ARI cases among children in this age group. Finally, it sought to demonstrate whether public education expenditures influence ARIs among children in Poro.

We used a MIDAS-PDL approach combined with Nonlinear Least Squares due to the weighting properties of the model, which allow us to capture the effect of different variables over time. This method made it possible to identify both short- and long-term effects, from the first month up to the last (168 months in our case). The results revealed delayed and cumulative effects of climatic variables. Rising temperatures are associated with a progressive increase in ARI cases, reaching a significant long-term cumulative impact. Similarly, precipitation showed a non-linear effect—negative in the short term, but strongly positive in the long term, suggesting favorable conditions for pathogen development.

Moreover, socio-economic variables such as education spending and ODA showed significant influence in reducing ARIs, highlighting the importance of social and health investments in mitigating child vulnerabilities. Based on model performance comparisons, results were assessed using the log-likelihood function, AIC, and BIC, all of which confirmed that the model was well-suited to our variables.

The main weakness of the model lies in its sensitivity to the choice of lag length. If too few lags are chosen, long-term effects are underestimated; if too many, the risk of overfitting and statistical inefficiency increases. It is therefore recommended to analyze residual plots, as we did, to determine the appropriate lag structure.

Policy Recommendations for Côte d'Ivoire (especially the Poro region):

- Invest more in education and health infrastructure.
- Mobilize ODA more effectively, targeting climate-sensitive disease prevention.
- Adopt local environmental policies to limit population exposure to extreme climate effects.

For households and parents of young children in Poro:

- Adopt preventive measures during hot or humid periods.
- Protect young children against sudden temperature changes.
- Strengthen domestic hygiene.
- Seek medical attention promptly in case of cough or fever in children.

In summary, this study makes an original contribution to understanding the link between climate change and child health in Côte d'Ivoire by using an econometric approach suited to complex data. It highlights the importance of climatic factors in the dynamics of ARIs and underscores the critical role of public policy in prevention. This work provides a useful empirical basis for guiding health and environmental decision-making in northern Côte d'Ivoire. It also calls for further research integrating additional social and environmental determinants and testing alternative dynamic methods capable of better capturing the complex interactions between climate and health.

Bibliography

Arrow, K. (1971). *Essays in the Theory of Risk-Bearing*. North-Holland.

Becker, G. (1964). *Human Capital: A Theoretical and Empirical Analysis*. Chicago: University Press.

Bell, M. L., McDermott, A., Zeger, S. L., Samet, J. M., & Domini, F. (1987–2000). Ozone and short-term mortality in 95 US urban communities. *Journal of Epidemiology*, pp. 2372–2379.

Bloom, D. E., & Canning, D. (n.d.). *The Health and Wealth of Nations*. *Science*, 302(5648), 1142–1145.

Bourbonnais, R. (2018). Chapter 7. *Time-lagged models*. Éco Sup, 10, 191–233.

Burnside, C., & Dollar, D. (2000). Aid, Policies, and Growth. *American Economic Review*, 90(4), 847–868.

Charron, D., Fleury, M., Lindsay, L. R., Ogden, N., & Schuster, C. J. (2008). Impacts of Climate Change on Water-, Food-, Vector-, and Rodent-Borne Diseases. In J. Séguin (Ed.), *Health and Climate Change*. Ottawa: Health Canada, 195–224.

Currie, J., & Neidell, M. (2005). Air pollution and infant health: What can we learn from California's recent experience? *Quarterly Journal of Economics*, 120(3), 1003–1030.

Dell, M., Jones, B. F., & Olken, B. A. (2012). Temperature Shocks and Economic Growth: Evidence from the Last Half Century. *American Economic Journal: Macroeconomics*, 3(12), 66–95.

Djibo, I., Sissoko, D., Boukari, S., & Coulibaly, Y. (2021). Colonization of pasture areas by invasive species: The case of *Pergularia tomentosa L.* in the rural commune of Azagor, Niger. *Afrique Science*, 18(5), 118–130.

Diomandé, B. E., Kouadjo, N. Y., & Logbo, M. B. (2019). Climate and Acute Respiratory Infections in the Soubré Region. *Ivorian Journal of Health Sciences*, 12(2), 100–110.

Diomandé, B. I., Doumbia, Y., & Kouassi, D. Y. (2018). Environmental impacts of climate change on the San-Pédro coast (southwest Côte d'Ivoire). *Climate and Development*, LACEEDE, University of Abomey-Calavi, (24).

EHCVM-CI (2021–2022). *Harmonized Household Living Conditions Survey, Côte d'Ivoire, 2nd Edition.* https://phmecv.uemoa.int/nada/index.php/catalog/61

FAO (2020–2023). *Reports on Climate and Agriculture in Côte d'Ivoire.* United Nations Food and Agriculture Organization.

Foroni, C., Marcellino, M., & Schumacher, C. (2015). Unrestricted Mixed Data Sampling (MIDAS): Regressions with Unrestricted Lag Polynomials. *Journal of the Royal Statistical Society, Series A: Statistics in Society*, 178(1), 57–82.

Ghysels, E., Santa-Clara, P., & Valkanov, R. (2004). The MIDAS Touch: Mixed Data Sampling Regression Models.

IPCC (2007, 2021, 2022, 2023). *Climate Change Assessment Reports*. Intergovernmental Panel on Climate Change.

Gouataine, R. (2018). Climate and Malaria: Case of Northern Cameroon. *Annales Universitaires de Ngaoundéré*, 17, 149–163.

Grossman, M. (2014). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy*, 80(12).

Hashim, B. M., Al-Naseri, S. K., Al-Maliki, A., & Al-Ansari, N. (2021). Impact of COVID-19 lockdown on NO_2, O_3, PM2.5 and PM10 concentrations and air quality evolution in Baghdad, Iraq. *Science of the Total Environment*, 754, 141978.

Hashizume, M., Armstrong, B., Hajat, S., Wagatsuma, Y., Faruque, A. S., Hayashi, T., & Sack, D. A. (2007). Association between climate variability and hospital visits for non-cholera diarrhea in Bangladesh: Effects and vulnerable groups. *International Journal of Epidemiology*, 36(5), 1030–1037.

INS (2022). *Demographic and Health Survey of Côte d'Ivoire, 2021.* Rockville, Maryland, USA: INS/Côte d'Ivoire and ICF.

Kafoudal (2022). *Journal of Social Sciences, University of Péléforo Gbon Coulibaly of Korhogo (Côte d'Ivoire).*

Koh, H. B., et al. (2023). Impact of Climatic Conditions on Respiratory Diseases in Sub-Saharan Africa: A Multinational Analysis. *Journal of Global Health*.

Krouba, G. D. I., Kouassi, Y. D., & Coulibaly, B. (2024). Climate evolution and dynamics of ARIs in children aged 0–5 in the Grand-Bassam Department (southeast Côte d'Ivoire). *Journal of Geography, University of Ouagadougou*, No. 13, Vol. 1.

Madinier, H., & Mouillart, M. (1983). Methods of Estimating Distributed Lag Models in Economics. *Applied Statistics Review*, 31(4), 53–73.

Météo Côte d'Ivoire (2022). https://meteofrance.com/meteo-cote-d-ivoire

Mogou, B. É. L., Kouadio, N. Y. C., & Diomandé, B. I. (2022). Climate evolution and ARI dynamics in Soubré, southwestern Côte d'Ivoire. *Journal of Social Sciences: African Spatial and Societal Mutations*, 1, 38–59.

Morgenstern, O. (1976). Collaboration between Oskar Morgenstern and John von Neumann on Game Theory. *Journal of Economic Literature*, 14(3), 805–816.

NAZA. (s.d.). https://power.larc.nasa.gov/data-access-viewer/.

Santa-Clara, P., Ghysels, E., & Valkanov, R. I. (2004). There is a risk-return trade-off after all. *NBER Working Paper* No. 10913.

Omer, T. (2024). Advances in MIDAS Poisson Regression for Dengue Forecasting Using Google Trends and Environmental Data.

WHO (2020). ARI in Children: Case Management in Small Hospitals in Developing Countries. https://iris.who.int/bitstream/handle/10665/62086/WHO

Pascal, M. (2020). *Epidemiology in the Service of Climate Change Adaptation.* Doctoral Dissertation, University of Paris-Sud.

RASS-CI (2007–2020). *Health Situation Reports.https://www.snisdiis.com/rass*

RASS-CI (2022). https://www.snisdiis.com/rass

RGPH-CI (2021). *General Population and Housing Census, Global Results.*https://plan.gouv.ci

Roux, J. (2006). *Being Vigilant: The Discreet Operativity of the Risk Society.* University of Saint-Etienne.

François, M. (2024). *Waste Management and Environmental Protection in Haiti: The Difficult Balance.* Doctoral Dissertation, University of the Antilles.

UNICEF (2023). *Growing Up in a Changing Climate: Children's Climate Risk Index Supplement.* UNICEF, New York, November 2023.

Uwizeye, S., et al. (2021). Climate Variability and Respiratory Infections in Rwanda. *Rwanda Journal of Medicine and Health Sciences*, 4(1), 30–40.

World Bank Group (2022). *World Development Report: Finance for an Equitable Recovery.https://openknowledge.worldbank.org*

World Bank Group (2023). *Country Climate and Development Report: West and Central Africa – Côte d'Iv*oire.https://environnement.gouv.ci ; https://openknowledge.worldbank.org

Ymba, M. (2022). Urban Heat Islands and Respiratory Diseases in Abidjan. *African Journal of Sustainable Cities*, 6(3), 98–112.