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Impact of HIV and Covid-19 pandemics on ivorian health system efficiency

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Abstract

The purpose of this study is to estimate the impact of HIV and Covid19 on the efficiency of the public health system in Côte d'Ivoire. To this end, we use non-parametric data envelopment analysis (DEA) and double bootstrap procedures to analyze the data. The analyze reveals that district hospitals are not technically efficient. These estimates show that in 2019, TB-HIV co-infection and geographic accessibility increases technical efficiency, while respiratory diseases reduce it. In contrast, in 2020, the advent of the Covid-19 pandemic blunted the positive impact of TB-HIV co-infection and geographical accessibility on the technical efficiency of the Ivorian health system observed in 2019. This result, due to the reorientation of resources allocated to the health sector to deal with the Covid-19 pandemic, is similar to the crowding out of the HIV pandemic by that of Covid-19.

JEL Classification numbers: C14 - D24 - I12 - I18.
Keywords: Double Bootstrap, Tuberculosis/HIV, Covid-19.

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1 Introduction

The Covid -19 pandemic has plunged the global economy into the worst economic crisis of the early part of this century. The pandemic emerged in the third quarter of 2019 and has spread throughout the world. Contaminations are continuing and deaths are counted in the tens of thousands around the world. For example, according to WHO statistics, by mid-August 2021, the USA will have approximately 36 million cases, including 617 thousand deaths, India will have approximately 32 million cases, including 429 thousand deaths, Brazil will have approximately 20.2 million cases, including 564 thousand deaths, Russia and France will have respectively 6.38 million and 6.32 million cases, including 163 thousand and 112 thousand deaths.

In African countries, which were relatively spared at the beginning of the pandemic, the new *"delta"* variant of Covid -19 has led to an increase in the number of cases and the saturation of hospital facilities. In Tunisia, Morocco, and Senegal, for example, the high number of new cases has led to a massive demand for the vaccine from populations that were initially reluctant to receive it, thus forcing governments to incur additional public expenditure.

In the countries of the West African Economic and Monetary Union (WAEMU), the measures taken, as in all the countries of the world, have had a dampening effect on the economy. The overall growth rate, based on a forecast of 6.6% in 2020, was 0.7% after 5.8% in 20-19 due to the negative impact of the crisis at COVID-19 on all sectors of the economy of WAEMU member states. Indeed, all sectors of economic activity have slowed down in all member states, and in particular the transport, hotel and restaurant sectors have been the most affected, mainly due to the travel restriction and border closure measures taken to limit the spread of the virus.

The corona virus crisis is thus hampering the economic growth efforts of countries struggling to recover from the effects of HIV/AIDS, another pandemic that affected the economies of these countries.

In Côte d'Ivoire, HIV prevalence is 31.5% for the 15-49 age group, yet this age group is the most productive. In addition, women remain the most exposed to HIV/AIDS infection, despite a decrease over the last decade. Indeed, the number of cases of co-infection with tuberculosis and HIV is falling sharply, 14.65% in 2020 compared to 15.92% in 2012. In addition to these worrying HIV statistics, there are also the Covid-19 statistics. Indeed, the Covid-19 pandemic that broke out in this country at the end of the first quarter of 2020 has surely affected the health system. Indeed, the Covid-19 pandemic, as of mid-August 2021, presented a total of 51,399 positive cases for 341 deaths, 50,205 cured cases (i.e., a case-fatality rate of 0.6% for a cure rate of 98.3%) and 853 cases still active. The geographical spread of the pandemic during the same period shows that 89 of the 113 districts and all 33 regions were infected, with 95% of cases located in the Abidjan region.

Although the HIV pandemic knows a relative decline in the recent years the 2020 targets will not be met because of deeply unequal success; Covid-19 risks blowing HIV progress way off course (UNAIDS, 2020). This alert deserves questions about the impact of the covid-19 pandemic on the efficiency of health systems in poor countries that are already dealing with HIV. Also, the objectives of this study are (i) to estimate the technical performance of districts' hospitals and (ii) to identify the effects of HIV and Covid-19 on hospitals in Côte d’Ivoire Coast. To that effect, we made the following assumptions: (i) Ivorian public hospitals are technically inefficient and (ii) the performance of a hospital is negatively impacted by HIV and Covid -19 by factors related to its environment. This study focuses on health districts where cases of Covid-19 have been detected.

Our study is structured around four sections: after the introduction in the first section, section 2 will lead us to the methodology which will present the econometric modelling and the data to be analyzed, then the results of the analysis will be discussed in section 3 and finally, section 4 will close the study by presenting the conclusion.

2 Methodology and Data

2.1 Econometrical model

2.1.1 The DEA Approach

According to Leleu and Dervaux (1997), the enthusiasm for the use of non-parametric estimation in the hospital field is due to their ability to consider the specificities of this sector, namely: (i) the complexity of the multi-product/multi-factor technology, (ii) the absence of real prices for both outputs and inputs, and (iii) the uncertainty linked to the behavior in the hospital sector. So, the DEA method easily incorporates several outputs, so it is particularly more practical for measuring the efficiency of hospitals which, by their activities, necessarily use several inputs and produce several outputs.

Among other relevant applications, Steinmann and Zweifel (2003) measure the technical efficiency of Swiss hospitals and Ventura et al. (2004) estimate the productive performance of Spanish public hospitals. Thus Valdmanis et al. (2004) use the DEA to estimate the performance of sixty-eight (68) Thai public hospitals with respect to the care provided to patients according to their social situation (rich or poor) and find that all patients are treated equally without discrimination. In 2011, using data envelopment analysis (DEA) and free disposal hull (FDH) models, Hakos and Tzeremes (2011) evaluate performance of public health delivery services of the Greek prefectures. The efficiency levels of the Greek prefectures are compared and analyzed in a regional context. Moreover, by using convex and non-convex models alongside with bootstrap techniques and conditional full frontier applications the paper develops models for regional public health delivery policy evaluation. From the major results of this study, we can retain (i) higher levels of GDP per capita (GDPc) have a negative influence on the efficiency of regional healthcare delivery, indicating that regional economic growth does not ensure better healthcare delivery service; and (ii) population density increases the prefectures' efficiency of public health provision, indicating the over-supply of health services by urban hospitals.

Although it is regularly used to evaluate the performance of hospitals, DEA's nonparametric approach is also used in other sectors. For example, recently, in the agricultural sector, Aldieri et al (2021) used the non-parametric DEA approach and Tobit regression on panel data set over the period of 2002–2017. They found a negative effect of land use spillovers on efficiency indicator for American firms and a positive effect for European ones.

In this study, the estimation of the efficiency by the DEA approach goes through the resolution of the K linear programs of each hospital under the assumption of *variable returns to scale (vrs)*. We consider an input-oriented method in the sense that according to the following publications (Coelli et al, -1998), hospital has a better control on the input than the output. Moreover, the allocation of capital and labor factors is under the prerogative of the public authority. On the other hand, the output is nearly out of control of the hospital. Thus, given a level of input and a level of output for each hospital, the measure of the technical efficiency is obtained by resolving the DEA linear program defined by Farell (1957):

$$
\begin{aligned}
&TE_I(x, y) = \theta(x, y) = \min\{\theta / \theta \succ 0;\} \\
&y_i \le \sum_{i=1}^{n} \lambda_i y_i \\
&x_i \ge \sum_{i=1}^{n} \lambda_i x_i \\
&\sum_{i=1}^{n} \lambda_i = 1 \\
&\lambda_i \ge 0; i = 1,...n
\end{aligned} \quad (1)
$$

In the DEA linear program, x is the inputs vector, y the outputs vector for each hospital i and λ_i an optimization parameter. By assumption, the technical efficiency TE cannot be negative nor grader than 1; in other words, $0 \prec \theta(x, y) \le 1$. The studies admit that TE is influenced by environmental variables whose impact needs to be captured. Commonly, the regression of a Tobit model is used to estimate the impact of environmental variables in this second stage (Scheraga, 2004; Kirjavaïnen and Loikkanen -1998; Chilingerian, -1995) but according to Simar and Wilson (2007) this approach is not appropriate because the estimators are not censored but truncated, they are biased and unpredictable (Battese and Corra, -1977). Moreover, $\hat{\theta}_i$ et ε_i are correlated in series, what make impossible the inference by standard methods.

2.1.2 The Truncated Regression

Considering this critic, we use the double Bootstrap method (Algorithm 2) to estimate a truncated regression by the maximum likelihood method.

$$\hat{\theta}_i = z_i \beta + \varepsilon_i; \qquad i = 1,...n \quad (2)$$

With $\hat{\theta}_i$ being the technical efficiency score in each hospital i, z_i the factors' vectors likely to affect the technical efficiency of the hospital i, β the vectors of parameters and ε_i is the error term identically and independently distributed.

2.1.3 Double Bootstrap Procedure

The applied procedure in this study follows strictly the Algorithm 2 of Simar and Wilson (2007) which main stages are the following:

i. Using the initial sample, we will estimate technical efficiency scores under the DEA input oriented: $\hat{\theta}_i^{'}(i = 1...n)$
ii. The estimators $\hat{\beta}$ are obtained from a truncated regression $0 \prec \hat{\theta}_i - \hat{\beta} z_i + \varepsilon_i \le 1$, by using $m \le n$ observations with $\hat{\theta}_i \prec 1$, where $\hat{\theta}_i$ is the hospital technical efficiency i estimated by DEA, ε_i is normally distributed with a truncation to the left at $-z_i \hat{\beta}$ and a truncation to the right at $1 - z_i \hat{\beta}$, z_i is the vector of environmental variables that affect the hospital efficiency and $\hat{\beta}$ is the vector of parameters to be estimated.

iii. By successive iterations (in four stages) $L_1 = 500$ times, we obtain a sample of Bootstrap estimators, $B - \left\{\hat{\theta}^*_{ib}\right\}_{b-1}^{L_1}; i = 1,...n$. We will therefore proceed as follow:

a. For each $i = 1...n$, we extract ε_i from the formula $\mathrm{N}(0;\sigma^2)$ truncated to the left at $-z_i\hat{\beta}$ and truncated to the right at $1 - z_i\hat{\beta}$

b. Then we calculate the following estimator θ_i^* so that $\theta_i^* = z_i\hat{\beta} + \varepsilon_i; i = 1,...n$.

c. Then we build a bogus sample $(x_i^*; y_i^*)$, with $x_i^* = x_i$ et $y_i^* = y_i\hat{\theta}_i / \theta_i^*$.

d. The new DEA estimator or Bootstrap estimator is calculated from the created bogus sample $(x_i^*; y_i^*)$; in other words, the variables X et Y are respectively replaced by $Y^* = \{y_i^*\ i = 1............n\}$ et $X^* = \{x_i^*\ i = 1............n\}$ in the initial program.

iv. For each hospital $i = 1,....,n$ the unbiased estimator $\hat{\hat{\theta}}_i\ (i = 1...n)$ is calculated by using the Bootstrap estimator obtained from B and the initial estimators $\hat{\theta}_i$.

v. We then estimate a truncated regression of $\hat{\hat{\theta}}_i\ (i = 1...n)$ sur $z_i\ (i = 1...n)$ to obtain the estimators $\hat{B}$.

vi. By successive iterations (in three stages) $L_2 = 3500$ times, we obtain a sample Bootstrap estimator, $\Delta - \left\{\hat{\hat{B}}^*_{ib}\right\}_{b-1}^{L_2}; i = 1,...n$. To this effect we proceed as follow:

a. For each $i = 1...n$, we extract ε_i from the formula $\mathrm{N}(0;\hat{\hat{\sigma}}^2)$ truncated to the left at $-z_i\hat{\beta}$ and truncated to the right at $1 - z_i\hat{\beta}$,

b. Next, we calculate the following estimator θ_i^{**} so that $\theta_i^{**} = z_i\hat{\beta} + \varepsilon_i; i = 1,...n$.

c. We then estimate a truncated regression of θ_i^{**} sur z_i to obtain the estimators $\hat{\hat{B}}^*$

vii. Finally, we use the Bootstrap estimators of Δ and the initial estimators $\hat{\hat{B}}^*$ to build the confidence intervals for each B. The confidence interval for a random B_j is built by finding the values $a_{\alpha/2}$ and $b_{\alpha/2}$ so that: $P_{rob}(-b^*_{\alpha/2} \le \hat{\hat{\beta}}_j - \hat{\beta}_j \le -a_{\alpha/2}) \cong 1 - \alpha$ this allows to obtain an estimated confidence interval $\left[\hat{\hat{\beta}}_j + a^*_{\alpha/2}, \hat{\hat{\beta}}_j + b^*_{\alpha/2}\right]$

The bias in the double Bootstrap model from Simar and Wilson (2007) is non positive and is obtained as follow: $\hat{\hat{\theta}}_i = \hat{\theta}_i - bias(\hat{\theta}_i)$ with $bias(\hat{\theta}_i) = \left(\frac{1}{L_1}\sum_{b=1}^{L_1}\hat{\theta}_{ib^*}\right) - \hat{\theta}_i$.

2.2 Data

The efficiency being linked to some socio-economical *(External environment)* and institutional *(Internal environment)* constraints in the management of the production unit (Leleu and Derveaux -1997), we have therefore collected data on the different constraints. Thus, we set as inputs the number of beds, used as proxy to the capital factor (Blank and Valdmanis 2010). The use of the number of beds as proxy to the capital factor helps evade possible biases linked to prices that are

regulated by the public health services. The workforce characterizes the labor factor namely the physicians, the nurses, the mid-wives to which we added the other hospital agents.
About the outputs, following the path of Romley and Goldman, (2011), we measure the number of admissions and the number of hospitalization days which are the indicators of the level of activity for the hospitals, under the assumption that hospitals are paid according to their level of activity.
The institutional constraints facing the hospital is the average length of stay in the hospital that is frequently used as an indicator of the efficiency. However, the socio-economic constraints are translated by four variables indicative of the living conditions of the population and the geographical accessibility (approximated by the distance to access to the hospital), the malaria prevalence, and the co-infection tuberculosis-HIV, the respiratory diseases, and the Covid-19 infection.

Table 1: Variables specification

Variables			**Explanation**
Input	Numbers of beds	*Bed*	Proxy to the capital factor in the hospital
	Numbers of physicians	*Phy*	Indicator's hospital workforce or labor factor in the hospital
	Numbers of midwives	*Midw*	
	Numbers of nurses	*Nurs*	
Output	Admission	*Admi*	Indicators of hospital activity
	Hospitalization	*Hosp*	
Environmental	Average length of stay	*Als*	Proxys of the institutional constraints
	Coinfection Tuberculosis-HIV	*T-hiv*	Proxys of the socio-economic constraints
	Respiratory diseases	*Resp-d*	
	Malaria	*Mria*	
	Geographical accessibility	*Dist*	
	Covid19 infection	*Covid*	

Source: Author

3 Results and Interpretation

3.1 Descriptive Analysis of variables

The level of inputs (hospital resources) has increased except for the number of beds, which has decreased between the period 2019 and 2020. Similarly, hospital activity has increased significantly between these two periods. This increase in the level of inputs is the result of the measures taken by the authorities to combat Covid-19. In terms of environmental variables, there is a slight decrease in the tuberculosis/HIV co-infection rate, which has fallen from 95% to 94% between 20-19 and 2020. Regarding respiratory diseases and malaria prevalence, there was a drop between 20-19 and 2020. This drop may be the result of patients not attending health centers for fear of being identified as covid-19 patients. Finally, there is an increase in the number of Covid-19 patients in relation to the different variants, because of poor compliance with the measures to combat the pandemic.

Table 2: Descriptive Statistics

		2019				*2020*			
Variables		Mean	Std, Dev	Min	Max	Mean	Std, Dev	Min	Max
Input	*Bed*	87.771	71.684	12	330	78.1041	58.7016	16	309
	Phys	41.125	47.008	6	254	41.9166	48.9597	8	267
	Midw	133.771	74.416	36	358	136.0417	72.404	40	327
	Nurs	72.208	61.074	18	316	78.0208	66.7693	21	354
Output	*Admi*	4947.85	3674.897	62	15714	5217.89	3975.421	480	16554
	Hosp	14103.63	11018.31	257	42655	14405.69	11128.79	1	43677
Environmental	*Als*	2.777	0.6206	1.2	4.1	2.8264	0.7917	1	6.67
	T-hiv	95.687	152.273	1	734	94.8729	16.5955	10	100
	Resp-d	5.891	7.70031	0	33.5	1.8614	2.3196	0	11.12
	Mria	269.482	101.073	60.31	447.84	205.14	83.0264	47.94	380.05
	Dist	19.625	60.9508	0	428	9.0062	8.0078	0	39.8
	Covid	-	-	-	-	15.3425	9.6101	4.76	50

Source: Author

3.2 The Efficiency Scores

The estimates of the DEA and double bootstrap DEA models in Table 3 show that Ivorian hospitals are technically inefficient in 2019 and 2020, but even less so in 2020. Furthermore, it appears from these results that DEA scores are indeed subject to bias as shown by various studies comparing DEA scores to double Bootstrap DEA scores (Anang et al., 2020; Tiehi, 2020). Indeed, the average bias-corrected technical efficiency scores are respectively 0.62 in 2019 and 0.59 in 2020. This shows that, on average, the Covid-19 pandemic has affected hospitals in Côte d'Ivoire.

Table 3: Descriptive of technical efficiency scores

	2019		**2020**	
	$\hat{\theta}$ (VRS)	$\hat{\hat{\theta}}$ (corrected)	$\hat{\theta}$ (VRS)	$\hat{\hat{\theta}}$ (corrected)
Obs.	48	48	48	48
Mean	0.7751	0.6186	0.7758	0.5880
Std. Dev.	0.2090	0.1602	0.1985	0.1665
Min	0.1635	0.3204	0.3861	0.1328
Max	1	0.9368	1	0.8840

Source: Author

However, the impact of covid-19 on the efficiency of health districts varies from one district to another, reflecting regional inequalities in the effects of the pandemic on the health system. Table 4 shows that the Cocody-Bingerville health district was the most negatively impacted in terms of performance in 2020 with a bias-corrected score of 0.133, while the Tingrela district recorded the lowest negative impact on its functioning with a bias-corrected score of 0.884.

Table 4: Technical Efficiency Score by hospitals

Years	***2019***		***2020***	
Hospital	$\hat{\theta}$	$\hat{\hat{\theta}}$	$\hat{\theta}$	$\hat{\hat{\theta}}$
Touleupleu	0.913	0.840	0.911	0.757
Zuenoula	0.624	0.549	0.620	0.502
Kouibly	0.988	0.851	0.999	0.821
Niakaramadougou	0.914	0.815	1.000	0.837
Zouan-hounien	0.690	0.641	0.680	0.569
Blolequin	1.000	0.776	1.000	0.604
Gueyo	1.000	0.937	1.000	0.591
Abengourou	0.446	0.365	0.537	0.462
Korhogo	1.000	0.623	1.000	0.765
Aboisso	0.422	0.336	0.440	0.350
Tengrela	0.885	0.816	1.000	0.884
Bouaflé	0.666	0.519	0.602	0.501
Agnibilekrou	0.584	0.503	0.669	0.587
Koumassi-Portbouet-Vridi	0.646	0.512	0.476	0.378
Buyo	1.000	0.857	0.995	0.852
San-Pedro	1.000	0.702	1.000	0.468
Dimbokro	0.780	0.639	0.881	0.710
Dabou	0.461	0.349	0.449	0.340
Danané	0.839	0.694	1.000	0.795
Gagnoa	1.000	0.738	1.000	0.345
Daloa	1.000	0.566	1.000	0.390
Katiola	1.000	0.544	1.000	0.515
Sakassou	0.939	0.856	0.844	0.721
Soubré	0.888	0.658	0.940	0.784
Marcoru-Treichville	0.560	0.446	0.637	0.529
Vavoua	0.858	0.712	1.000	0.764
Akoupé	0.737	0.665	0.684	0.568
Bouna	0.886	0.815	0.848	0.721
Tiassalé	0.514	0.363	0.799	0.651
Man	1.000	0.799	0.788	0.592
Agboville	0.542	0.458	0.594	0.501
Adjamé-Plateau-Attécoubé	0.637	0.520	0.742	0.618
Bondoukou	1.000	0.731	0.767	0.561
Cocody-Bingerville	0.500	0.368	0.164	0.133
Abobo Est	0.386	0.320	0.706	0.478
Guiglo	1.000	0.575	0.965	0.763
Grand-Bassam	0.851	0.672	1.000	0.746
Adzopé	0.688	0.557	0.526	0.420
Alépé	0.685	0.547	0.776	0.638
Issia	0.829	0.656	0.708	0.569
Anyama	0.572	0.455	0.707	0.593
Odienné	0.584	0.493	0.671	0.546
Yamoussoukro	1.000	0.694	0.489	0.358
Adiaké	0.580	0.538	0.498	0.425
Jacqueville	0.616	0.550	0.548	0.432
Bongouanou	0.957	0.699	0.880	0.703
Abobo Ouest	0.938	0.803	1.000	0.819
Sinfra	0.637	0.572	0.667	0.571

Source: Author

3.3 Determinants of the Technical Efficiency

The explanatory factors of the technical efficiency of the health districts are presented and discussed (Table 5) with regard to the overall significance and the variation of these factors according to the two periods. Thus covid-19 contributed significantly to reduce the technical efficiency of health districts in 2020. Indeed, the coefficient associated with the covid-19 infection variable (-0.0042) is negative and statistically significant. The advent of covid-19 in 2020 has therefore contributed to a deterioration in the technical efficiency of Ivorian health districts.

In parallel with this negative impact of covid-19 on the technical efficiency of health districts, a positive impact of the average length of stay in hospitals and a negative impact of geographical accessibility are observed in the same year. Indeed, while the average length of stay in hospitals increases technical efficiency, geographical accessibility reduces it. In other words, geographical accessibility would be an obstacle and the average length of stay a lever for improving the efficiency of these districts. In view of the very limited resources in sub-Saharan African countries in general and in Côte d'Ivoire, coupled with a reorientation of resources towards the fight against the covid-19 pandemic, better access to health centers could replace the acquisition of technical equipment. Incidentally, technical efficiency could be negatively affected. On the other hand, the increase in the average length of stay in hospitals, due to a certain extent to the increase in cases of covid-19 infection, requires an improvement in the technical facilities. This is reflected, for example, in the increase in hospital beds and other necessary medical equipment.

In addition, covid-19 seems to have contributed to blurring the positive impact of TB-HIV co-infection and geographical accessibility on the technical efficiency of the Ivorian health system in 2019. While these two variables contributed to improving the technical efficiency of the health system in 2019, their impact in 2020, the year of the advent of the co-infection pandemic in the country, is quite different. The impact of TB-HIV co-infection is now insignificant in 2020, and geographic accessibility contributes to the deterioration of technical efficiency in 2020. The reorientation of efforts towards the health emergency imposed by covid-19 could justify these changes in the contribution of TB-HIV co-infection and geographical accessibility to the technical efficiency of the health system in Côte d'Ivoire between 2019 and 2020.

Table 5: Technical efficiency determinants of hospitals

	2019		**2020**	
	Coef	P.values	Coef	P.values
Const	-0.882***	0.000	-0.8538***	0.000
Als	0.051	0.163	0.0562**	0.019
T-hiv	0.0005***	0.008	0.0026	0.151
Resp-d	-0.005*	0.092	-0.009	0.279
Dist	0.0007*	0.074	-0.0104*	0.000
Mria	0.0004	0.145	-0.00003	0.889
Covid-19	-	-	-0.0042**	0.032

Source: Author *** = Significant at 1% ** = Significant at 5% * = Significant at 10%

4 Conclusion

Our study aimed to analyze the productive activity of the health system in Côte d'Ivoire and to understand the impact of the Covid-19 and HIV pandemics on the technical efficiency of hospitals. To this end, we estimated the technical efficiency of hospitals that admitted HIV patients and Covid-19 patients, and then analyzed the effect of these two pandemics on technical efficiency.

From these estimates, in 2019 the average length of stay in hospitals and TB-HIV co-infection increases technical efficiency, while geographical accessibility reduces it. In contrast, in 2020, the advent of the Covid-19 pandemic blunted the positive impact of TB-HIV co-infection and geographical accessibility on the technical efficiency of the Ivorian health system in 2019. This result, which is explained by the reorientation of resources allocated to the health sector to deal with the Covid-19 pandemic, is like the eviction of the HIV pandemic by that of Covid-19. This result is consistent with the observation of UNAIDS (2021) on the fact that COVID-19 pandemic has seriously impacted the AIDS response and could disrupt it more.

Thus, if this situation persists, there is a risk of a resurgence of diseases such as malaria, diarrheal diseases, and other respiratory infections, most of which affect vulnerable populations (women, children, and the elderly). In these conditions, awareness-raising and care actions for vulnerable people are necessary.

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