Analysis of the Excess Deaths in Ecuador caused by the COVID-19 during 2020 and 2021

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ABSTRACT

Ecuador became one of the most affected countries in the world from the COVID-19 pandemic in 2020: the number of deaths during March and April of 2020 suggests that the pandemic in this country was much worse than the studies reported by the Ecuadorian national institutions. A number of studies concerning the number of excess deaths have been conducted, but they used a limited amount of data because of the time they were done. Additionally, these studies do not provide a way of comparing results with those of other countries since they use the raw number of excess deaths, and not a relative measure. This study fills all these gaps by presenting an analysis of the excess deaths (raw and per 100000 inhabitants). For this analysis, Long Short-Term Memory (LSTM) Artificial Neural Network (ANN) and Autoregressive Integrated Moving Average (ARIMA) were used to do a forecasting. These methods were trained using the data of deaths in Ecuador before the pandemic, over a period of 5 years. The methodology used for this work takes steps from recognized guidelines from CDC and the University of Melbourne to compute the excess deaths. In 2020, Ecuador had an excess death of 36399 people, which means an excess death of 207 people per 100,000 inhabitants. The decrease of deaths due to land traffic accidents, congenital malformations, deformities, and chromosomal abnormalities 2314. Additionally, the causes with the highest excess deaths were respiratory insufficiency, influenza and pneumonia, ischemic heart diseases, hypertensive diseases and mellitus diabetes. In order to contrast these numbers, a computation of the excess (decrease) of deaths was computed.

Keywords-excess death rate; artificial neural networks; ARIMA; Ecuador; SARS-CoV-2; COVID-19

I. INTRODUCTION

On December 31, 2019, a new type of coronavirus (COVID-19) was detected in Wuhan, China [1, 2], and by March 11, 2020, the virus had spread to 114 countries, with over 118,000 cases and 4,291 confirmed deaths [4, 5]. This global pandemic has since claimed over 6,524,568 lives [3]. Countries' ability to manage the pandemic depends on their readiness and infrastructure, but local risks must be evaluated to understand the situation more accurately [6]. By July 6, 2021, Ecuador reported 463,951 confirmed cases and 21,708 deaths (16,020 confirmed COVID-19 deaths and 5,688 probable) [8-10]. The mortality rate showed a marked increase during this period. Since the pandemic started, the highest number of deaths was reached on April 5th, 2020, with 7155 deceased, approximately seven times more than the average deceased between 2015 to 2019 [10]. It is important to note that Ecuador has 24 provinces but the most affected were Pichincha, Guayas, and Manabí.

The Ecuadorian Health System has some weaknesses: permanently overloaded public hospitals became COVID-19 hospitals, which forced the patients with other pathologies to stop their treatments or therapies. When the COVID-19 came to Ecuador the health personnel were affected severely since they did not have the appropriate Personal Protective Equipment (PPE) [11]. Ecuador became one of the most affected countries in the world from the COVID-19 pandemic: on October 22nd, 2020, Ecuador's death toll was fourth in the Americas and ninth worldwide according to the World Health Organization (WHO) [12]. The excess deaths of Ecuador were above 50% of the expected annual mortality [13, 14], during March to April 2020. In the case of Guayaquil, the monthly average of the previous two years, tripled. The Ecuadorian Government accepted that 3500 people died from COVID-19 without verification tests, but many people lost their lives from indirect causes such as cerebrovascular, cardiovascular, or oncological diseases. The reported values suggested that the pandemic in Ecuador was much worse than what national institutions' reports showed [11]. The excess deaths refer to the number of deaths above the expected monthly mean of the previous years in the same period [11, 12] which could be computed by statistical or artificial intelligence methods [15, 16].

Authors in [12] used ARIMA, which is a statistical autoregressive method that uses moving average windows to produce time series forecasting [17-19], to predict the excess deaths. The same study mentioned that on April 4th, 2020, the maximum number of excess deaths may have occurred with 909 deaths and a total excess death toll of 36922 with an interval confidence of 32314-42696 (from March 17th to October 22nd, 2020). A (3,0,1) ARIMA model was used, where 3 is the order of the auto-regressive model, 0 is the degree of differencing, and 1 is the order of the moving-average model. This ARIMA model has the lowest amount in the Root Mean Square Error (RMSE) computed from the observed and forecasted values in five testing periods. This study used a limited amount of data because of the timing they were collected. Additionally, the authors did not provide a way of comparing results with other countries: they used the raw number of excess deaths. Other studies used different statistical approaches like Poisson regression, linear Poisson logarithmic model, Chi-square and Fisher test, and negative binomial regression to find the behavior of the data and compare the expected deaths with the real data and throw the excess deaths with a range of error but they did not analyze the death cause [20-28]. These studies made their models utilizing different datasets and starting and ending considered dates. Table I shows some of these studies along with their respective dates.

TABLE I. DATES OF DATA-SETS

Study	Start Date	End Date
[23]	January 01, 2018	December 31, 2021
[24]	March 01, 2020	March 01, 2021
[26]	January 01, 2015	December 31, 2019
[27]	January 01, 2015	November 30, 2020
[28]	January 01, 2015	December 31, 2019

The objective of the current study is to estimate the weekly excess deaths from any cause [29] in Ecuador and analyze the distribution of deaths per 100,000 inhabitants across its provinces and regions (see Table II), between January 1st and December 31st, 2020. Additionally, this study seeks to assess the excess or decrease in deaths and their cause during this period. To achieve this, daily mortality data from Registro Civil (Civil Registration Office) [30], Instituto Nacional de Estadística y Censos (National Institute of Statistics and Censuses) [31], and Secretaría de Gestión de Riesgos (National Secretary for Risk Management) [32] from January 1st, 2015, to December 31st, 2020, were analyzed. The estimation of excess deaths might help in the classification of the direct and indirect deaths caused by COVID-19 and could contribute to a better evaluation of the impact of the COVID-19 pandemic [33] in Ecuador.

TABLE II. REGIONS AND PROVINCES OF ECUADOR

Region	Province(s)
Coast	Guayas, Los Ríos, Manabí, Esmeraldas, El Oro, Santa Elena, Santo Domingo de los Tsachilas
Andes	Azuay, Bolívar, Cañar, Carchi, Cotopaxi, Chimborazo, Imbabura, Loja, Pichincha, Tungurahua
Amazon	Morona Santiago, Napo, Orellana, Pastaza, Sucumbíos, Zamora Chinchipe
Insular	Galápagos

The main contributions of this study are:

- An estimation of the raw number of excess deaths and the death rate per 100,000 inhabitants in Ecuador, from January 1 to December 31, 2020, using time series data disaggregated by region. This study provides a comparative analysis of Recurrent Neural Networks (RNNs), specifically Long Short-Term Memory (LSTM) models, with traditional statistical methods like ARIMA [15] and linear regression [16]. RNNs were selected for their ability to minimize RMSE, offering enhanced predictive accuracy compared to ARIMA and other statistical approaches.
- The computation of the number of excess or decrease of the deaths in 2020 was disaggregated regarding their cause.

The remainder of this document is organized into four sections: Section II describes the method used for this study as well as some considerations regarding the dataset. In Section III, the results are presented. In Section IV some ideas and comparisons with respect to the results are analyzed. Finally, Section V presents conclusions related to the number of deaths, its distribution, and its causes.

II. METHOD

This study considered the daily mortality data of Civil Registration Office, INEC, and National Secretariat for Risk Management SNGRE, but solid steps are needed to follow to estimate the excess deaths. Considering the study presented in [34], some steps were taken, such as the analysis of the Civil Registration and Vital Statistics (CRVS) data set and forecast function creation. Another extra step was the analysis of different disease cases to compare the impact of the COVID-19 outbreak with the death rates of the previous years in Ecuador.

It is important to note that the CRVS system in Ecuador faces limitations [31]. Specifically, there is a lack of regulation uniformly governing the certification of causes of death. Additionally, some records may not arrive on time or are not delivered at all from the Civil Registry. Violent deaths, for instance, documented by the Ministry of the Interior, may not always be formally registered. These gaps, which are further detailed in the INEC's General Deaths Methodological Document [31], do impact the completeness of the data. However, according to the completeness calculation based on the Melbourne Guide [34], Ecuadorian data used in this study reach a high completeness level of 95.71%, which supports the reliability of our estimates. CRVS is the composition of the Civil Registration System, in which a permanent record is created with the vital events as births, deaths, fetal deaths, adoptions, legitimizations, and divorces [35].

A. Completeness Computation

The excess death number associated with COVID-19 is defined as the number of reported deaths during COVID-19 pandemic compared to the expected deaths in the same period calculated for previous trends. It is important to note that the deaths from all causes are included and not only for COVID-19 [34]. In other words, the excess mortality could be expressed by:

$$\text{Excess deaths} = \text{Reported deaths} - \text{Expected deaths} \tag{1}$$

Following the Melbourne guide [34], the completeness of the daily deaths per year is calculated. This was done considering the registered Crude Death Rate (CDR), the mortality of children under 5 years old (5q0), the percentage of the population over 65 years old (p65), and the completeness (measure how well the Civil Registration captures the population events) of the death registry for children under five years old (Under-5 completeness or 5q0R). The completeness calculation per year is performed with:

$$\text{Completeness} = \frac{e^{\text{logit}\left(C_{\text{All}jk}\right)}}{e^{\text{logit}\left(C_{\text{All}jk}\right)}+1} \tag{2}$$

where $\text{logit}\left(C_{\text{All}_{jk}}\right)$ is obtained by:

$$\text{logit}\left(C_{\text{All}jk}\right) = (-0.0177 \cdot \text{CDR}^2) + (0.6375 \cdot \text{CDR}) + (-13.8914 \cdot p65) + (-1.1136 \cdot \ln(5q0)) + (2.2063 \cdot 5q0R) + (-0.0174 \cdot \text{year}) + 29.3677 \tag{3}$$

where the variable year takes the values of 2015, 2016, 2017, 2018, and 2019. The data were obtained from the National Institute of Statistics and Censuses [31], the Ministries of Economic and Social Inclusion [36], and the United Nations Inter-Institutional Group for the estimation of infant mortality [37].

This procedure was conducted for the last 5 years before the pandemic (2015 to 2019). As a result, a completeness percentage is obtained which will indicate how complete the data are. In addition, this percentage suggests whether a treatment should be carried out to complete the data. The percentage of completeness of the data from 2015 to 2019 is shown in Table III.

TABLE III. DATA COMPLETENESS PERCENTAGE

Year	2015	2016	2017	2018	2019
Completeness (%)	97.22	93.78	93.87	96.84	96.83

This was done considering that Ecuadorian data were not considered complete [38-40]. Based on the calculated percentages of completeness, it was determined that although the Ecuadorian data are not taken as complete, the ones we use for the prediction are. For this reason, no procedure was performed on the data since it was not necessary, and it was considered that the data used were adequate and complete to be used in training and predictions.

B. Data Collection

Once the data from the National Institutions were retrieved, some flaws were identified. The data were incomplete, meaning that not all the dates in the time interval of the study (January 1st, 2015 to December 31st, 2020) were represented. To address this, a data cleaning process was implemented as follows: For each dataset archive within the study interval, missing values were filled by performing a linear search over the file and adding a row with the missing date and 0 deaths. A weekly time series using the CDR was created:

$$\text{CDR}_n = \frac{d}{p} \cdot 10^n \tag{4}$$

where *d* represents the number of deaths in a week, *p* is the population forecast for the year of the week being calculated (using information provided by [31]), and $n = 5$, meaning that the CDR_5 number represents the number of deaths per 100,000 inhabitants in a province. After cleaning, the weekly time series of deaths from January 1st, 2015 to December 31st, 2019 (260 weeks total) was obtained. The chosen interval for building the time series follows the recommendations stated in [34], which suggest it due to the underreporting found in daily or monthly intervals.

All data on deaths from various causes were utilized, except for those related to COVID-19. A total of 67 causes of death were considered from 1997 to 2020, sourced from the

Ecuadorian National Institute of Statistics and Census [31]. To prevent errors in calculations, the number of deaths attributed to heart attacks in 2016 was adjusted from 0 to 1. This change was necessary because a value of zero could have led to indeterminate forms, such as division by 0, in the calculations.

C. Forecast Creation

This study analyzed various methods used to forecast deaths using time series. For instance, authors in [12] utilized an ARIMA model. In this study, ARIMA and LSTM neural networks were compared to determine which model could better predict outcomes. An ARIMA (3,0,1) model was used, as in [12], and different configurations of LSTM neural networks were employed. The RMSE was used to evaluate which model performed better. RMSE is calculated by:

$$\text{RMSE} = \sqrt{\frac{1}{n}\sum_{i=1}^{n}(\widehat{y_i} - y_i)^2} \quad (5)$$

where $\widehat{y_i}$ is the predicted number of deaths and y_i is the real number of deaths in each week. To reduce the noisiness of the time series, a data smoothing function with a moving average window of 5 was applied.

The predictions made with ARIMA were more stable than those of LSTM RNNs. The RMSE value computed for ARIMA was almost identical across trials, while the RMSE value for LSTM neural networks varied significantly. This variation was primarily due to the weight randomization during the RNN initialization. Another contributing factor was the dataset itself, as each city in the country had unique disease dynamics. Initial configurations of weights could produce better results than ARIMA, but subsequent executions could yield completely different and sometimes worse results. To achieve more stable results for comparison, 15 ANNs were trained for each province in groups of 5. The mean prediction from each group of ANNs was used to calculate the RMSE for that group. This approach allowed for the comparison of RMSE values across different groups to check for stability.

D. Analysis of Death Causes

The LSTM ANN was not used to predict deaths by specific causes, because the data were insufficient for adequate training. Instead, ARIMA with the (3,0,1) configuration was used to predict deaths from 2015 to 2019. The error was calculated by comparing the predicted value with the actual value for each cause. This error was later used to establish the confidence interval for the 2020 prediction. For example, to predict deaths from a specific cause in 2015, data from 1997 to 2014 were used. To predict deaths in 2016, data from 1997 to 2015 were used, etc. The error for this test dataset (2015 to 2019) for each cause was calculated by:

$$\text{error} = \frac{1}{5} \cdot \sum_{i=1}^{n} \frac{\left(y_{\text{predicted}_i} - y_{\text{real}_i}\right)}{y_{\text{predicted}_i}} \quad (6)$$

III. RESULTS

In this section, a thorough comparison between ARIMA and LSTM models is presented as well as the national forecast of deaths (relative to the population using (4)) with the chosen model. Additionally, the excess death number computed using deaths from different causes is also shown, to compare results procured using different data sets. The comparison between ARIMA and LSTM models was conducted at a provincial level (Table IV). The architecture chosen for the LSTM model consisted of 3 LSTM layers with 365, 168, and 100 hidden units respectively. Between each LSTM layer, a fully connected layer was placed, using a 20% and 10% dropout for the first two fully connected layers. The only hyperparameter considered was the number of epochs, which was set to 2000. Both the ANN and the ARIMA models were trained using data from 2015 to the second semester of 2019.

TABLE IV. RMSE OF LSTM AND ARIMA MODELS

Province	RMSE ANN 1	RMSE ANN 2	RMSE ANN 3	ANN Average	RMSE ARIMA
Azuay (1)	74.384	67.105	76.110	72.533	56.815
Bolivar (2)	14.569	16.692	16.804	16.022	21.694
Cañar (3)	39.743	41.999	44.875	42.206	29.245
Carchi (4)	24.024	25.491	25.671	25.062	20.817
Cotopaxi (5)	72.797	70.736	70.135	71.223	67.775
Chimborazo (6)	44.560	45.471	44.937	44.989	35.170
El Oro (7)	58.542	73.407	62.484	64.811	37.670
Esmeraldas (8)	45.017	40.694	38.069	41.260	29.492
Guayas (9)	301.369	334.261	328.012	321.214	100.812
Imbabura (10)	35.710	37.219	37.412	36.781	41.528
Loja (11)	50.239	51.289	61.600	54.376	37.832
Los Ríos (12)	48.887	48.209	48.740	48.612	59.642
Manabí (13)	68.801	69.064	69.305	69.057	81.235
Morona Santiago (14)	18.565	18.709	18.772	18.682	17.157
Napo (15)	19.138	19.524	18.855	19.172	21.476
Pastaza (16)	15.468	15.395	15.556	15.473	16.897
Pichincha (17)	158.797	148.40	127.181	144.792	73.725
Tungurahua (18)	66.739	66.229	67.306	66.758	29.905
Zamora (19)	16.210	18.489	17.278	17.326	24.051
Galápagos (20)	0.4810	0.4713	0.4784	0.4769	0.5637
Sucumbíos (21)	24.735	24.765	24.785	24.762	19.289
Orellana (22)	17.002	16.933	17.159	17.032	15.872
Santo Domingo (23)	61.787	56.564	55.941	58.098	34.524
Santa Elena (24)	46.624	45.283	47.728	46.545	41.555
Average				**5.5898± 6.2486**	**3.8326 ± 2.3141**

The results shown in Table IV demonstrate that on average ARIMA does a better forecast than LSTM networks. It is clear that the prediction made by ARIMA is much closer to the real data than the that of the LSTMs. In fact, the standard deviation from ARIMA's average shows that RMSE is closer to the mean among all provinces. The results also show that the trained ANNs had similar RMSE values. This means that training five ANNs (and using the mean predicted values) is enough to obtain stability. Then, a model was trained using ARIMA and the number of deaths from 2015 to 2019 (relative to the population) in order to forecast the number of deaths in 2020 and 2021. Figure 1 shows the forecast of the number of deaths and the reported number of deaths. The Figure uses relative numbers of deaths calculated with (4). In particular, the national CDR was computed using the national population forecast for 2020 and 2021. Furthermore, Figure 1 has timestamps of important milestones that occurred in the country during the pandemic, such as the first detected case, holidays that might have increased the number of deaths, etc.

(a)

(b)

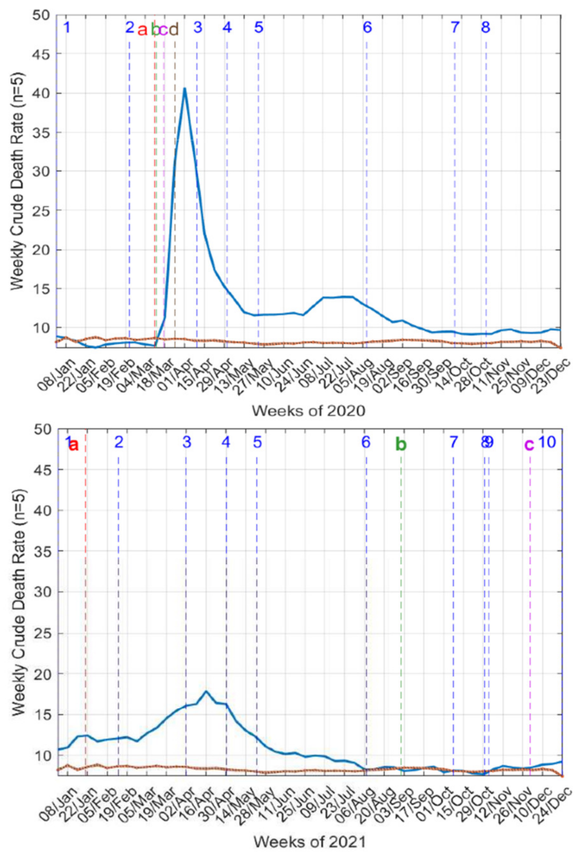
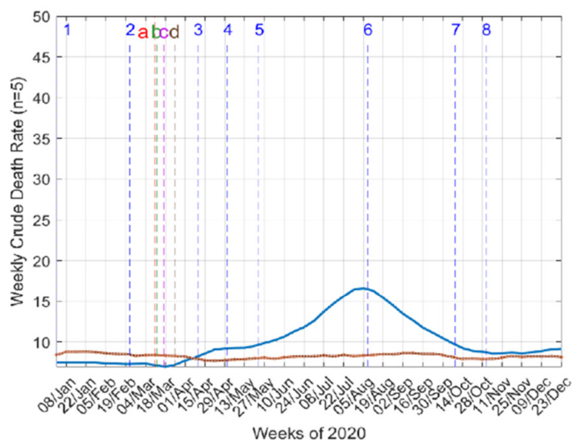


Fig. 1. National forecast using ARIMA(3,0,1): (a) 2020, (b) 2021.

Analogously, forecasted time series for each region were computed as the sum of the results for each province in a region, with a regional CDR calculated using the sum of the population for each province in the region. Figure 2 shows the forecasts in each region for 2020, and Figure 3 for 2021.

(a)



(b)

(c)

(d)

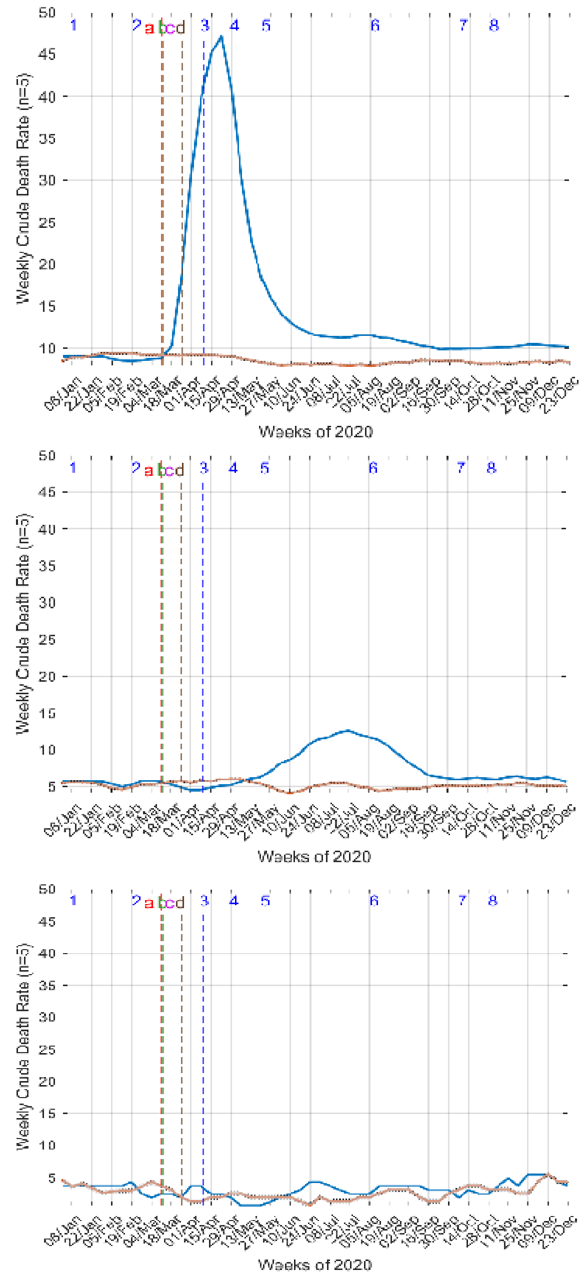


Fig. 2. Accumulated forecast of 2020 on Ecuadorean regions: (a) Andes, (b) Coast, (c) Amazon, (d) Insular.

Figure 4 presents a heat map that illustrates the official, excess, and predicted deaths for each province during 2020 and 2021. The provinces are listed vertically, while the columns represent Official Deaths 2020, Excess Deaths 2020, Predicted Deaths 2020, Official Deaths 2021, Excess Deaths 2021, and Predicted Deaths 2021. The heat map uses color gradients to represent the magnitude of deaths in relation to the population of each province. This visual representation helps identify regions with significant differences between the predicted and the actual number of deaths.

(a)
(b)
(c)
(d)

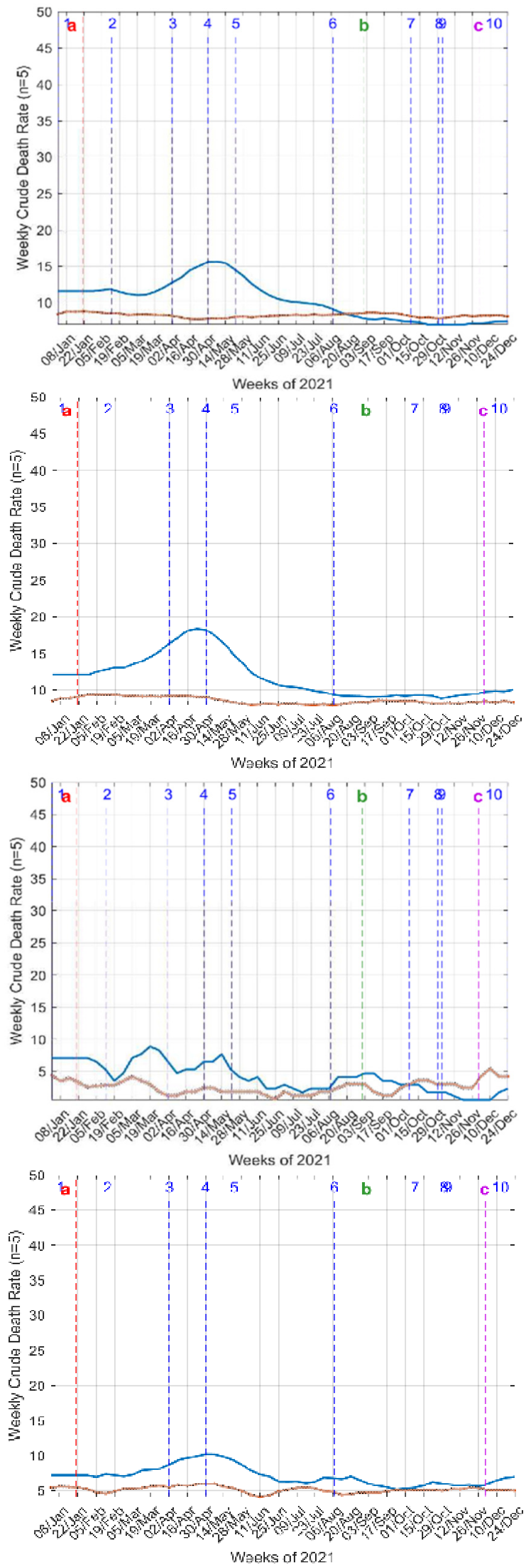


Fig. 3. Accumulated forecast of 2021 on Ecuadorean regions: (a) Andes, (b) Coast, (c) Amazon, (d) Insular.

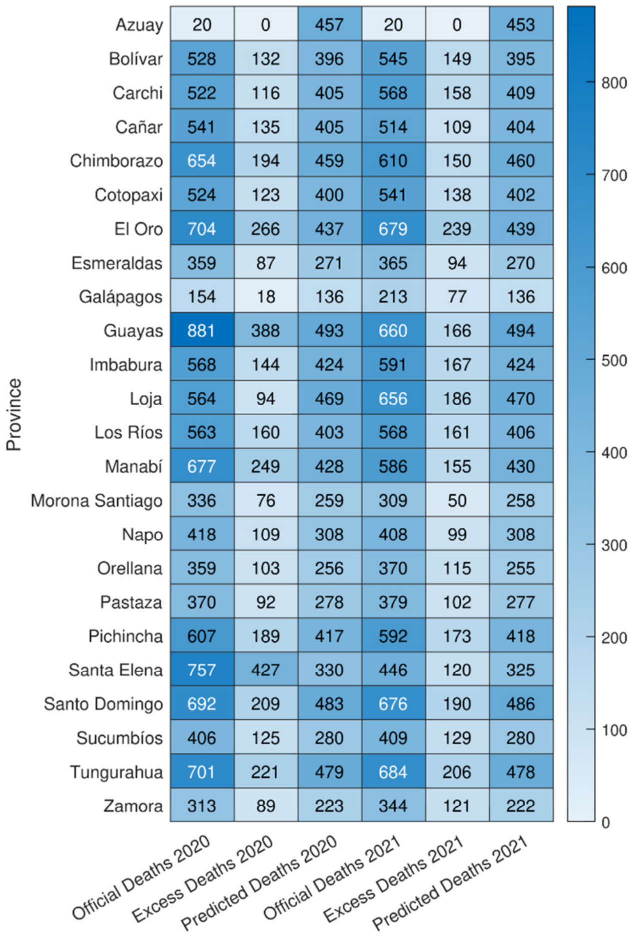


Fig. 4. Real, excess, and estimated forecasted deaths, per 100000 inhabitants (relative to province population).

Figure 5 presents the calculation of excess deaths by cause, showing an excess of 13,737 deaths, which, when added to the 23,793 deaths from COVID-19, gives a total of 37,560 deaths. An overview of deaths from other causes (excluding COVID-19) can also be found in Figure 5, and more detailed data is available in Table VII.

IV. DISCUSSION

The obtained results gave a weekly national forecast of CDR, as well as the distribution of these deaths for each region and province in the country. Using this information, the number of excess deaths can be computed using (1), which is the main goal of this study. Since the relative number of excess deaths is also needed, (4) was used to compute its value.

Figure 1(a) shows 36,399 net excess deaths during 2020, while Figure 1(b) shows 22,763 net excess deaths in 2021. One of the key points for these results is that the computed number of excess deaths uses the upper bound of a 95% confidence interval on the forecasted time series as in (1).

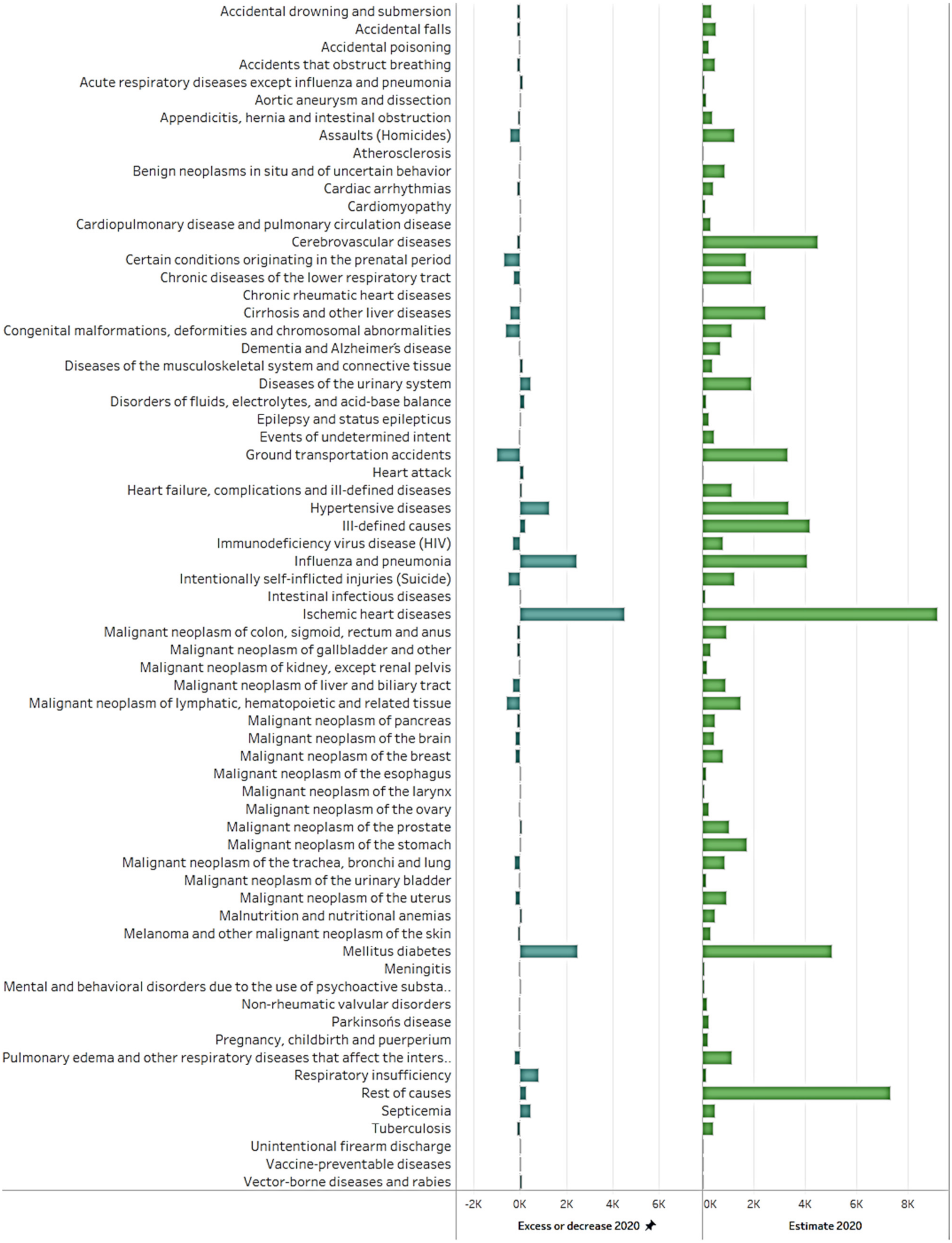


Fig. 5. Death rate increase and decrease in 2020 from various causes.

The regional results show the following 2020 crude excess death rate values: 108, 302, 105, and 41 for the Andes, Coast, Amazon, and Insular regions, respectively. This information is consistent with the events of the pandemic in Ecuador. The explosive increase of deaths during March 2020 in Guayas was followed by an increase of deaths in the Andes. For 2021, the crude excess death rates were the following: 120, 166, 101, and 104 for the Andes, Coast, Amazon, and Insular regions, respectively. As presented in Figure 3, the number of deaths relative to the population began to normalize to its historical tendency in the second semester of 2021 once the national mass vaccination plan started. Thus, the excess deaths of 2021 still reflect the outcome of an uncontrolled disease. The national forecast supports the results presented in [12]. The forecast shown in Figure 1(a) clearly demonstrates that the peak of deaths occurred in the second week of April, with a crude excess death rate of 32. Moreover, the national crude excess death rate allows comparison between countries. Figure 6 shows the comparison of the number of excess deaths per 100,000 people in Ecuador with this number from other countries. This comparison was done using excess deaths and population data from the Covid-19 Dataset by Our World in Data [13], considering countries from both North and South America that report the number of excess deaths weekly. Tables V and VI show these numbers in detail.

(a)

(b)

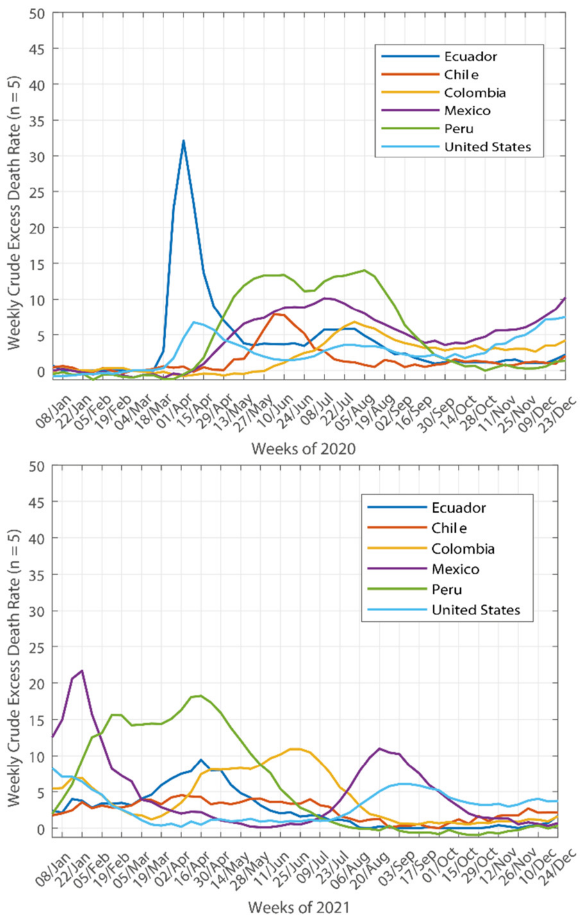


Fig. 6. Comparison of the crude excess death rate between countries: (a) 2020, (b) 2021.

For excess deaths from different causes, the results indicate that diseases of the urinary system, respiratory insufficiency, influenza and pneumonia, ischemic heart diseases, hypertensive diseases, diabetes mellitus, and septicemia showed a high excess. This suggests that due to COVID-19, many people with previous illnesses lost their lives, either due to the saturation of the Ecuadorian hospital care service or for other reasons. As a result, there were 13,737 excess deaths without considering COVID-19 deaths, and when considering COVID-19-related cases, the final result was 37,530 deaths. This shows that there were more excess deaths from COVID-19 than from other causes, but at the same time, the excess from other causes accounted for 36.60%, which is also alarming.

While there was an excess of deaths in some cases, in others such as land transport accidents, congenital malformations, deformities and chromosomal abnormalities, and certain conditions originating in the prenatal period, there was a considerable decrease. There was a total decrease of 2,314 deaths in these causes, and it is worth mentioning that the decrease in deaths due to traffic accidents could be attributed to local and national regulations on free movement.

Similarly to the calculation of excess national and provincial deaths, to calculate the excess and decrease in deaths due to causes, the lower and upper limits of the prediction were considered to obtain more reliable results. These values were subtracted from the real values in order to obtain more reliable data on the excess and decrease for each of the causes.

V. CONCLUSIONS

This study computed the number of deaths from official datasets in two different ways: (a) using weekly time series data from January 1st, 2015 to December 31st, 2019 to generate a forecast for 2020 and 2021 and (b) using the number of deaths disaggregated by various causes from 1997 to 2020.

From the first perspective, the following results were obtained: The number of excess deaths for every cause in 2020 ranged between 36,399 and 36,922, or 207 to 210 deaths per 100,000 inhabitants in Ecuador. In other words, there were 46.81% to 48.01% more deaths than the expected in 2020. For 2021, the number of excess deaths ranged between 22,763 and 23,323 deaths, or 128 to 131 deaths per 100,000 inhabitants, representing a 29.12% to 30.31% increase in deaths in 2021.

Additionally, this study considered the distribution of deaths across the country. The results show that the most affected region by the pandemic in 2020 was the Coast, with 302 deaths per 100,000 inhabitants, followed by the Andes (108 deaths per 100,000 inhabitants), the Amazon (105 deaths per 100,000 inhabitants), and the Insular Region (41 deaths per 100,000 inhabitants). The Coast region experienced a peak in deaths during April and May, while the Andes and the Amazon had their peaks later in the year.

The most affected province by the pandemic during 2020 was Santa Elena with 427 deaths per 100,000 people, also being the most affected province on the coast. In other regions, the most affected provinces were Tungurahua (221 deaths per 100,000 people) in the Andes, Sucumbíos (125 deaths per 100,000 people) in the Amazon, and Galápagos (18 deaths per

100,000 people) in the Insular region. The Insular region, specifically Galápagos province, is a special case as it consists of only one province. Moreover, this region was not as affected as the rest of the country during 2020, possibly due to the restrictions imposed by the Ecuadorian government and the geographical constraints.

The second perspective provides complementary information about causes of deaths. In 2020, the excess deaths from different causes, including those caused by COVID-19, totaled 37,530. The causes with the highest excess deaths were respiratory insufficiency (773), influenza and pneumonia (2,427), ischemic heart diseases (4,486), hypertensive diseases (1,252), and diabetes mellitus (2,457). Additionally, reductions in deaths were observed in land transport accidents (993), congenital malformations, deformities, and chromosomal abnormalities (623), and certain conditions originating in the prenatal period (698).

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APPENDIX

TABLE V. WEEKLY CRUDE EXCESS DEATH RATE FROM AMERICAN COUNTRIES IN 2020

Week	Chile	Colombia	Ecuador	Mexico	Peru	United States
Week 1	0.459819204	-0.166853727	0.690634644	-0.005196507	-0.46736832	-0.794691722
Week 2	0.633493806	0.320146904	0	0.23865154	-0.214728599	-0.728497583
Week 3	0.395475902	0.062692979	0.027990647	-0.031411724	-0.586560889	-0.684810657
Week 4	-0.178382649	0.042253888	0	-0.269054986	-0.438252577	-0.481099248
Week 5	-0.172105254	-0.021028679	0	-0.5260882	-1.261.075.583	-0.480013109
Week 6	0.363042693	0.30206617	0	-0.17257058	-0.558355014	-0.329401831
Week 7	-0.064866418	0.349626361	0	-0.585654136	-0.577158931	-0.429205939
Week 8	-0.364088926	0.344516588	0	-0.679036148	-0.87498871	-0.187841711
Week 9	0.070097581	-0.050901196	0	-0.951581325	-0.961122781	0.018222999
Week 10	0.039756837	-0.126761665	0	-0.585499016	-0.612947031	0.081581109
Week 11	0.233309858	-0.371637689	0	-0.507939205	-0.627504902	0.083512023
Week 12	0.595829435	-0.168032905	2.725.045.282	-1.030.071.855	-1.188.286.227	0.355469168
Week 13	0.399660832	-0.534364292	2.256.847.357	-0.39873499	-1.175.244.801	1.728.590.264
Week 14	0.556595714	-0.752119214	3.212.327.081	-0.602717294	-0.506189309	4.555.267.085
Week 15	-0.154842417	-0.601577454	2.335.420.965	0.07794761	0.237475272	6.725.855.592
Week 16	0.470281529	-0.407799156	1.367.530.827	0.936534722	1.798.806.946	6.377.023.941
Week 17	0.117178045	-0.451428752	9.006.137.667	2.419.943.674	4.892.354.552	5.690.282.369
Week 18	0.081606139	-0.685299112	6.971.153.873	3.827.188.891	7.607.397.509	4.291.999.052
Week 19	1.560.978.958	-0.398758789	5.480.221.156	5.265.768.272	1.031.940.758	3.789.177.023
Week 20	1.635.261.468	-0.443567564	3.801.526.811	6.535.112.145	118.737.636	3.252.322.638
Week 21	3.496.509.167	-0.138160389	3.535.147.858	7.097.110.538	1.285.399.359	2.423.176.172
Week 22	5.743.293.558	-0.066623573	3.759.020.851	736.779.428	1.330.710.733	1.954.869.228
Week 23	7.847.267.207	0.643241753	3.686.763.753	819.814.962	132.886.067	1.581.780.472
Week 24	7.740.028.371	1.093.687.857	3.654.971.909	8.797.842.081	1.337.443.748	146.067.597
Week 25	6.373.648.666	1.877.448.355	3.808.410.638	8.894.171.367	1.252.401.518	1.488.372.515
Week 26	5.179.374.216	245.721.101	3.440.466.013	8.846.704.762	1.112.221.351	167.814.514
Week 27	3.096.325.218	2.775.196.087	4.544.087.555	937.814.459	1.116.406.739	201.436.551
Week 28	2.710.265.409	3.799.508.955	5.724.274.463	1.012.101.246	1.247.366.921	275.239.698
Week 29	1.575.103.097	5.140.234.662	5.678.504.802	9.982.955.999	1.313.938.852	3.229.634.401
Week 30	1.256.002.171	6.144.108.439	5.807.584.537	9.388.692.724	1.327.313.896	3.585.405.274
Week 31	1.155.563.846	6.784.795.306	5.831.486.538	8.561.594.896	1.364.527.454	3.564.346.245
Week 32	0.785197525	6.225.078.681	4.872.617.322	7.978.500.234	1.401.710.683	3.357.859.147
Week 33	0.512130831	584.813.469	4.072.844.284	705.522.824	1.317.062.729	3.403.959.715
Week 34	1.490.358.261	4.994.409.614	3.174.936.258	6.449.020.754	1.111.736.089	3.120.899.816
Week 35	1.234.031.287	4.270.787.208	230.335.383	5.783.557.573	9.060.151.728	2.566.003.454
Week 36	0.489636831	3.828.988.412	2.391.151.397	5.179.366.642	6.352.084.417	2.241.730.613
Week 37	0.850587059	3.531.835.485	1.780.590.651	4.483.189.776	487.203.419	1.990.711.816
Week 38	0.518408226	314.388.583	1.366.938.858	3.858.057.696	3.504.807.464	1.983.470.889
Week 39	0.802460362	3.195.376.615	0.981520156	4.161.937.037	2.157.597.811	2.221.154.313
Week 40	0.955210314	280.742.696	1.170.722.322	3.568.294.241	1.606.521.732	1.656.120.654
Week 41	1.581.903.609	3.082.568.559	1.387.773.716	3.865.348.318	1.147.948.793	2.301.528.601
Week 42	1.242.924.264	3.113.227.195	1.128.223.428	3.810.280.852	0.599905604	1.764.432.851
Week 43	1.349.116.867	3.510.217.216	1.136.853.416	4.342.341.158	0.646308818	218.561.343
Week 44	1.244.493.613	2.844.374.546	113.791.029	4.719.592.081	-0.005459202	2.455.700.002
Week 45	1.069.249.661	315.724.985	1.096.671.801	5.569.802.733	0.424301284	3.626.618.216

Week 46	0.705683852	2.881.322.132	1.430.476.313	5.634.952.974	0.828888785	3.765.040.601
Week 47	0.803506595	3.041.690.379	1.532.067.077	5.711.271.829	0.41975195	4.617.478.715
Week 48	1.146.147.753	3.027.540.239	1.075.650.211	6.026.319.782	0.289337688	4.974.999.478
Week 49	1.232.461.938	2.638.411.406	1.102.889.296	6.724.358.085	0.310871205	5.870.340.084
Week 50	1.092.789.894	3.485.454.472	1.022.337.582	7.629.325.963	0.555322124	7.133.218.068
Week 51	0.957825895	3.519.257.583	1.574.918.548	8.543.135.661	1.252.280.202	7.187.223.315
Week 52	2.047.477.091	4.209.076.878	2.232.597.335	1.024.557.352	1.358.734.635	7.471.852.081

TABLE VI. WEEKLY CRUDE EXCESS DEATH RATE FROM AMERICAN COUNTRIES IN 2021

Week	Chile	Colombia	Ecuador	México	Perú	United States
Week 1	1.766.570.919	5.433.832.319	2.421.916.557	1.255.383.219	1.980.250.375	8.251.851.462
Week 2	2.043.475.966	5.512.247.102	2.132.495.037	1.496.504.558	3.916.734.998	7.071.356.623
Week 3	2.456.231.045	6.881.189.745	3.998.475.956	2.059.630.246	6.027.683.097	7.071.476.959
Week 4	356.749.472	6.914.350.225	377.572.913	2.167.090.417	9.398.245.497	6.403.853.578
Week 5	2.740.943.565	5.575.447.075	2.807.250.432	1.571.031.158	1.253.079.415	5.319.687.599
Week 6	3.106.853.806	4.517.822.822	3.404.018.946	1.203.971.534	1.313.602.054	4.611.992.375
Week 7	2.842.440.716	3.262.406.057	3.344.572.849	8.198.847.162	1.559.619.535	3.063.630.796
Week 8	2.838.797.229	2.517.660.687	3.475.872.754	7.218.823.914	1.556.142.256	2.563.093.764
Week 9	3.139.124.695	1.853.280.715	3.153.198.392	6.438.551.606	1.419.958.825	1.939.453.142
Week 10	3.930.281.972	1.772.915.316	4.051.864.555	3.925.620.304	1.429.311.507	1.102.216.359
Week 11	3.869.383.681	1.200.214.318	459.965.565	3.615.476.648	1.442.711.021	0.503846268
Week 12	3.286.425.688	1.676.944.985	5.928.228.315	2.877.733.939	1.438.064.657	0.366482878
Week 13	4.224.363.459	2.479.818.727	6.804.536.507	2.395.475.907	1.507.550.282	0.606372425
Week 14	4.518.444.947	3.512.865.213	7.487.179.221	2.007.796.336	1.628.655.512	0.194282255
Week 15	4.367.500.467	4.976.217.694	7.852.703.885	2.258.060.772	1.806.985.961	0.915394928
Week 16	4.289.425.735	7.439.066.057	9.453.898.922	2.209.389.713	1.823.443.083	0.477793553
Week 17	3.287.466.684	8.111.248.495	7.962.552.407	1.575.284.118	1.732.044.606	1.151.313.392
Week 18	3.534.703.333	8.071.846.042	7.985.316.332	1.069.074.397	1.589.086.476	1.209.916.958
Week 19	329.163.067	8.175.228.716	5.975.174.587	0.84752128	1.386.085.333	0.956730297
Week 20	3.581.548.172	8.289.924.964	4.821.079.407	0.625507553	1.212.730.989	1.038.378.182
Week 21	4.035.943.108	8.153.771.934	4.182.370.604	0.209116664	1.029.814.129	1.291.865.682
Week 22	4.065.611.506	8.710.477.877	3.137.644.376	0.141253547	8.733.365.792	0.897404716
Week 23	3.573.740.699	9.643.652.799	241.175.966	0.147395005	7.584.964.462	1.051.073.616
Week 24	3.632.556.996	1.017.070.937	2.029.844.667	0.320584136	5.412.264.686	0.82075077
Week 25	3.348.885.473	1.093.379.054	21.872.131	0.604780131	4.126.570.793	0.991206523
Week 26	3.368.143.907	1.092.559.795	1.603.050.419	0.503599601	2.823.490.506	0.9330843
Week 27	3.970.880.832	1.046.915.369	1.739.299.057	0.886519541	2.253.936.205	1.149.087.178
Week 28	3.157.342.132	9.163.801.146	1.715.897.658	1.467.040.911	1.399.904.519	0.996080125
Week 29	2.909.064.487	761.930.302	1.112.731.751	2.322.085.477	0.957450756	1.092.108.146
Week 30	1.665.073.769	5.612.508.789	1.172.662.098	3.764.560.554	0.461938515	1.564.967.929
Week 31	1.331.954.915	4.638.761.043	0.949081492	5.629.107.369	0.106116959	2.163.999.866
Week 32	0.898379908	306.851.478	0.075446035	7.880.412.537	-0.064449566	3.193.232.523
Week 33	1.181.010.435	1.955.102.895	0	9.732.983.508	-0.104917898	4.120.600.869
Week 34	1.273.138.618	1.614.135.134	0.229366101	1.098.169.557	-0.285076916	5.064.876.404
Week 35	0.081197721	1.174.466.181	0.100653948	1.044.616.038	0.305161199	5.777.204.559
Week 36	0.315421914	0.666915773	0	102.327.447	-0.360917568	606.444.627
Week 37	0.314380918	0.602935553	0	8.631.359.381	-0.586940695	6.064.807.277
Week 38	0.579835004	0.538175086	0	7.531.577.691	-0.621713484	5.862.643.024
Week 39	0.124399072	0.863147791	0.177040225	5.941.707.609	-0.58993835	5.492.309.398
Week 40	0.021340427	0.670426883	0	5.024.173.702	-0.815661712	52.151.759
Week 41	0.699549592	0.845202119	0	3.906.121.173	-0.238613276	4.229.083.652
Week 42	1.213.281.324	0.62868369	0	2.977.225.568	-0.685263754	3.801.951.498
Week 43	0.611064897	0.526471387	0	2.021.461.081	-0.927474214	3.462.544.189
Week 44	1.684.332.202	0.748841665	0	1.535.518.174	-0.94546014	3.242.329.556
Week 45	0.950429729	0.690713294	0.12551236	140.455.157	-0.569254536	3.181.018.432
Week 46	1.692.139.675	0.97784404	0.407979061	1.327.169.192	-0.721835135	3.349.187.804
Week 47	1.772.816.898	0.951705779	0.226583911	1.321.027.734	-0.401385899	2.965.256.226
Week 48	1.766.570.919	0.87485149	0.029011558	0.533692748	-0.261095682	3.261.101.951
Week 49	2.706.070.185	1.217.769.866	0.282283272	0.809444237	0.158276143	3.793.287.315
Week 50	2.130.919.665	1.172.905.687	0.471592745	0.576068812	0.355222025	4.037.147.946
Week 51	2.147.575.608	0.93883171	0.714396355	0.314135605	-0.044065517	3.673.372.625

TABLE VII. EXCESS DEATHS IN 2020 AND CAUSES

Cause	Excess	Decrease
Ill-defined causes	255	-
Rest of causes	250	-
Events of undetermined intent	-	38
Assaults (Homicides)	-	450
Intentionally self-inflicted injury (Suicide)	-	518
Accidental poisoning	-	60
Breathing-obstructing accidents	-	117
Accidental drowning and submersion	-	114
Unintentional firearm discharge	45	-
Accidental falls	-	135
Land transport accidents	-	993
Congenital malformations, deformities and chromosomal abnormalities	-	623
Certain affections originating in the prenatal period	-	698
Pregnancy, childbirth and the puerperium	-	33
Diseases of the urinary system	464	-
Diseases of the musculoskeletal system and connective tissue	94	-
Cirrhosis and other liver diseases	-	428
Appendicitis, hernia and intestinal obstruction	-	86
Respiratory insufficiency	773	-
Pulmonary edema and other respiratory diseases affecting the interstitium	-	223
Chronic lower respiratory diseases	-	271
Influenza and pneumonia	2427	-
Acute respiratory diseases except influenza and pneumonia	107	-
Aneurysm and aortic dissection	-	12
Atherosclerosis	9	-
Cerebrovascular diseases	-	119
Heart failure, complications and ill-defined diseases	66	-
Cardiac arrhythmias	-	145
Heart attack	135	-
Cardiomyopathy	10	-
Non-rheumatic valve disorders	-	56
Cardiopulmonary disease and pulmonary circulation disease	20	-
Ischemic heart disease	4486	-
Hypertensive diseases	1252	-
Chronic rheumatic heart diseases	7	-
Epilepsy and status epilepticus	-	21
Parkinson’s disease	-	52
Mental and behavioral disorders due to use of psychoactive substances	12	-
Dementia and Alzheimer’s disease	-	47
Fluid, electrolyte, and acid-base balance disorders	167	-
Malnutrition and nutritional anemia	81	-
Diabetes mellitus	2457	-
Benign neoplasms in situ and of uncertain behavior	-	50
Malignant neoplasm of lymphatic, hematopoietic and related tissue	-	585
Malignant neoplasm of the encephalon	-	214
Malignant neoplasm of the urinary bladder	-	48
Malignant neoplasm of kidney, except renal pelvis	-	33
Malignant neoplasm of the prostate	75	-
Malignant neoplasm of the ovary	-	36
Malignant neoplasm of the uterus	-	208
Malignant neoplasm of the breast	-	219
Melanoma and other malignant neoplasm of the skin	-	83
Malignant neoplasm of the trachea, bronchi and lung	-	248
Malignant neoplasm of larynx	-	11
Malignant neoplasm of pancreas	-	116
Malignant neoplasm of the gallbladder and others	-	145
Malignant neoplasm of the liver and bile ducts	-	319
Malignant neoplasm of the colon, sigmoid, rectum and anus	-	137
Malignant neoplasm of the stomach	33	-
Malignant neoplasm of the esophagus	-	26
Immunodeficiency virus (HIV) disease	-	304
Septicemia	446	-
Meningitis	-	39
Immunopreventable diseases	-	17
Vector-borne diseases and rabies	60	-
Tuberculosis	-	120
Infectious intestinal diseases	36	-
TOTAL	13737	8197