Diet, nutrition, obesity and the prevention of COVID-19

Naser Mohammad Gholi Mezerji, Ali Reza Soltanian, Hossein Mahjub, Abbas Moghimbeigi

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Table of Contents

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Naser Mohammad Gholi Mezerji[1] MSc; Ali Reza Soltanian[2] PhD; Hossein Mahjub[3] PhD; Abbas Moghimbeigi[4] PhD

[1]Department of Biostatistics School of Public Health Hamadan University of Medical Sciences Hamadan IR
[2]Modeling of Noncommunicable Diseases Research Center Hamadan University of Medical Sciences Hamadan IR
[3]Research Center for Health Sciences School of Public Health Hamadan University of Medical Sciences Hamadan IR
[4]Department of Biostatistics and Epidemiology School of Health & Determinants of Health Research Center Alborz University of Medical Sciences Karaj IR

Corresponding Author:
Ali Reza Soltanian PhD
Modeling of Noncommunicable Diseases Research Center
Hamadan University of Medical Sciences
Street of Mahdieh, Department of Biostatistics, School of Public Health.
Hamadan
IR

Abstract

This study aims to assess the effect of diet, nutrition, and obesity in preventing COVID-19 among 188 countries by using new statistical marginalized two-part (mTP) models. For this, we globally evaluate the distribution of diet and nutrition in national level with considering the varieties between different who regions. The effects of food supply categories and obesities, as well as associations, on/with the number of deaths and the number of recovers, reported globally by estimating coefficients and conducting the color maps. Findings show that more consume of Eggs, Cereals Excluding Beer, Spices, and Stimulants had the greatest impact on the recovery of patients with COVID-19. Also, more consume of Meat, Vegetal products, Sugar & Sweeteners, Sugar crops, Animal fats, and Animal products were associated with more death and less recovery in patients. The effect of consuming sugar products on mortality is very considerable, while Obesity has affected in more deaths and fewer recovery rates.

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1. **Naser Mohammad Gholi Mezerji, MSc.**
   Department of Biostatistics, School of Public Health, Hamadan University of Medical Sciences, Hamadan, Iran. mezerji@gmail.com, **ORCID:** 0000-0001-6245-5447
2. **Ali Reza Soltanian, PhD.**
   Modeling of Noncommunicable Diseases Research Center, Hamadan University of Medical Sciences, Hamadan, Iran. soltanian@umsha.ac.ir, **ORCID:** 0000-0002-7483-3502
3. **Hosein Mahjub, PhD.**
   Research Center for Health Sciences, School of Public Health, Hamadan University of Medical Sciences, Hamadan, Iran. mahjub@umsha.ac.ir, **ORCID:** 0000-0002-9375-3807
4. **Abbas Moghimbeigi, PhD.**
   Department of Biostatistics and Epidemiology, School of Health & Determinants of Health Research Center, Alborz University of Medical Sciences, Karaj, Iran. moghimb@yahoo.com, **ORCID:** 0000-0002-3803-3663

Corresponding Author:

Professor Ali Reza Soltanian

Street of Mahdieh, Department of Biostatistics, School of Public Health. Tel +98(81)38380025, soltanian@umsha.ac.ir, **ORCID:** 0000-0002-7483-3502.

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Abstract

This study aims to assess the effect of diet, nutrition, and obesity in preventing COVID-19 among 188 countries by using new statistical marginalized two-part (mTP) models. For this,

we globally evaluate the distribution of diet and nutrition in national level with considering the varieties between different who regions. The effects of food supply categories and obesities, as well as associations, on/with the number of deaths and the number of recovers, reported globally by estimating coefficients and conducting the color maps. Findings show that more consume of Eggs, Cereals Excluding Beer, Spices, and Stimulants had the greatest impact on the recovery of patients with COVID-19. Also, more consume of Meat, Vegetal products, Sugar & Sweeteners, Sugar crops, Animal fats, and Animal products were associated with more death and less recovery in patients. The effect of consuming sugar products on mortality is very considerable, while Obesity has affected in more deaths and fewer recovery rates.
Keywords: COVID-19; Diet; Nutrition; Obesity; Marginalized two-part model.

Introduction

Transmission of coronavirus-associated pneumonia 2019 (COVID-19) began in Wuhan, China on December 31, 2019 [1]. According to the latest World Health Organization (WHO) report on July 3, 2020, there were 11 188 120 confirmed cases and 528 431 deaths worldwide, with 1 505 total cases and 69.3 deaths in 1 million population (1/M pop) [2]. The WHO named it a global pandemic because of the rapid outbreak of the disease worldwide [3].

The COVID-19 epidemic started at wintertime in areas of the world where consumption of wildlife is not uncommon. Coronavirus is one of the viruses causing the common cold, a disease that has never had a cure nor any effective prevention or vaccine. However, there are relatively consistent data suggesting that the risk of contracting the common cold is high under inadequate sleep, psychosocial or physical stress including exposure to cold temperatures, inadequate nutrition, and any condition that compromises the body's immune system [4].

A high percentage of COVID-19 deaths worldwide are associated with one or more chronic conditions. It is also evident that older people are at a higher risk for severe illness with this pandemic [5]. Nutrition is not a treatment for COVID-19, but it is a modifiable contributor to the development of chronic disease, which is highly associated with COVID-19 severe illness and deaths [6]. A well-balanced diet and healthy patterns of eating strengthens the immune system, improve immunometabolism, and reduces the risk of chronic disease and infectious diseases [7, 8]. Furthermore, nutrition may have a positive or negative impact on COVID-19 as it may be a way to support people at higher risk for the disease i.e. older people and people with pre-existing conditions (non-communicable diseases) [9].

It is clear in these challenging times that optimizing nutrition is important, not only for ourselves but also for every patient that goes through its own period of treatment. Every

healthy system should be aware of the benefits of healthy eating and be able to provide sound nutritional guidance to their patients, especially those with chronic disease. Having knowledge about nutritional interventions that may help prevent chronic conditions and their associated risks is now more important than ever [10].
On the other hand, overweight and obesity are interpreted as excessive fat [11] accumulation, so they represent a risk to health [12]. Most of the world's populations live in countries where overweight and obesity kill more people than underweight. However, does it cause to decrease immune system or severity of COVID-19? Is it dangerous to get an infection and the mortality of COVID-19?
This study aims to assess the effect of diet, nutrition, and obesity in preventing COVID-19 among 188 countries by using new statistical marginalized two-part (mTP) models. Hence, we globally evaluate the distribution of diet and nutrition in national level with considering the varieties between different regions. The effects of food supply categories and obesities, as well as associations, on/with the number of deaths and the number of recovers, reported globally by estimating coefficients and conducting the color maps.

Materials and Methods

This section starts with a short description of the dataset and relevant sources information. In the following Section, we will introduce the conventional two-part (TP) regression model and the proposed marginalized two-part regression (mTP) model for semi-continuous data. We will also describe their properties to assess the overall impact of covariates on the marginal mean, and demonstrate that the proposed model outperforms the conventional model. Finally, the proposed marginalized two-part model are applied to Healthy diet dataset on fat quantity and protein to investigate the effects of nutrition categories and obesity on the number of deaths and recovered in 100 cases of COVID-19.

Dietary, Obesity and COVID-19 data

Food supply data is some of the most important data in both FAO/WHO STAT [13]. In fact, this data is for the basis for estimations of global and national undernourishment assessment, when it is combined with parameters and other datasets. Also, both business and governments for economic analysis and policy setting, as well as being used by the academic community access the data.
In this dataset, we combined data of different types of food, world population obesity and undernourished rate, and global COVID-19 cases count from around the world, 188 countries, in order to learn more about how a healthy eating style could help combat the Coronavirus. In addition, from the dataset, we can gather information regarding diet patterns from countries with lower COVID-19 infection rate, and adjust our own diet accordingly. However, the spread of the disease deaths and its different distribution are well shown in Figure 1, which can be evaluated according to the WHO regions.
From datasets, source link at: https://github.com/CSSEGISandData/COVID-19, we have used fat quantity and protein for different categories of food (all calculated as percentage of total intake amount). We have also added on the obesity rate (in percentage) for comparison. The end of the datasets also included the most up to date confirmed/deaths/recovered/active cases (also in percentage of current population for each country). In this study, response variables were the deaths in 100 cases and the recovers in 100 cases that continuously, ranged 0 to 100, measured for 188 countries (Latest data publicly available at

https://www.worldometers.info/).

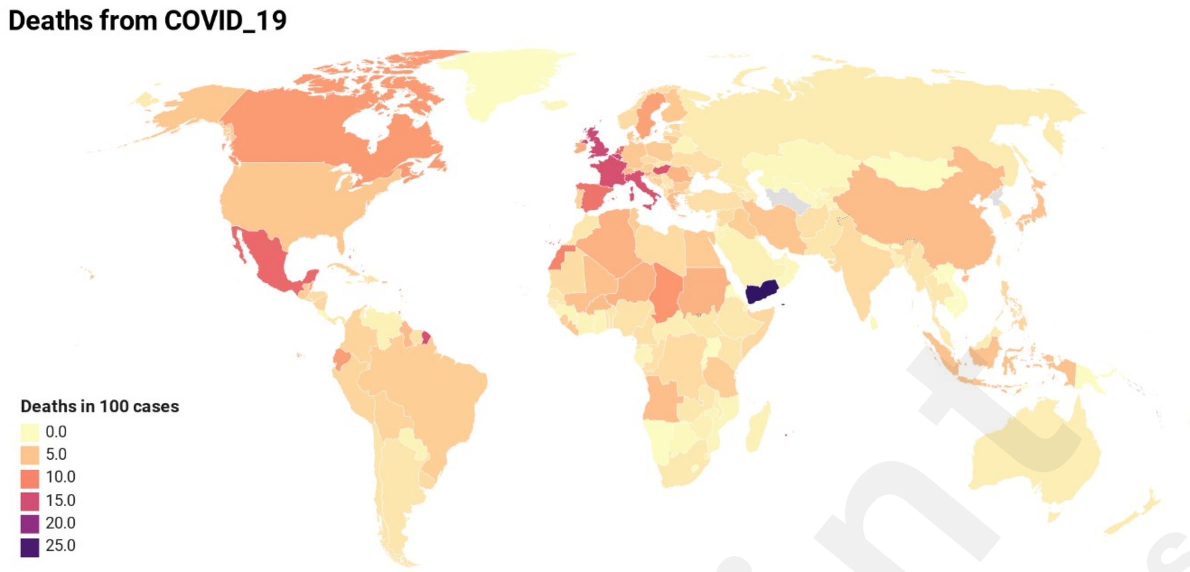

Figure 1. World map related to the number of deaths in 100 cases of COVID_19 by July 3, 2020.

In order to synchronize results relative to interregional variations, datasets grouped according to WHO regions (www.who.org) (Supplementary Figure 1) and Marginalized two-part analysis of deaths and recovered was conducted using a random-effect (regions cluster) model. Supply food data description prepared in Supplementary Table 1. Both fat quantity and protein datasets, include 23 categories, are obtained from FAO.org, and is used to show the specific types of food that belong to each category for assessing influential effects of the fat quantity and protein supply.

Models

1. Marginalized two-part models for semi-continuous data

1.1. Conventional two-part model

We begin with a review of the conventional two-part model presented in Cragg [14], Manning and Duan [15, 16], and elsewhere. Let Y_{ij} be a semi-continuous variable for the i-*th* ($i=1,2,\ldots,n$) subject at cluster j ($j=1,2,\ldots,n_i$). For non-negative data ($Y_{ij}\geq 0$) consisting of independent observations that clustered in j-*th* level, the generic form of the conventional two-part model can be written as:

$$f\left(y_{ij}\right)=\left(1-\pi_{ij}\right)^{1_{\left(y_{ij}=0\right)}}\times\left[\pi_{ij}\,g\left(y_{ij}\vee y_{ij}>0\right)\right]^{1_{\left(y_{ij}>0\right)}},\ y_{ij}\geq 0 \quad (1)$$

where $\pi_{ij}=Pr\left(Y_{ij}>0\right)$, $1_{(.)}$ is the indicator function, and $g\left(y_{ij}\vee y_{ij}>0\right)$ is any density function applicable to the positive values of Y_{ij}, although the log-normal density is often chosen. This model is parameterized as following (2) and (3) equations relevant to zero and non-zero components respectively:

$$logit\left(\pi_i\right)=Z_{ij}^{'}\times\alpha+b_{1i} \quad (2)$$

where Z_{ij} is a $1\times q$ covariate (used as explanatory variable) vector, α is a $q\times 1$ regression coefficient vector, and b_{1i} is the cluster-level random effect in zero-component. The location parameter μ_{ij} is modeled in the second part of the TP model assuming a log link:

$$E\left(\ln Y_{ij}\vee Y_{ij}>0\right)=\mu_{ij}=X_{ij}^{'}\times\beta+b_{2i}+\varepsilon_{ij} \quad (3)$$

where X_{ij} is a $1\times p$ covariate vector, β is a $p\times 1$ regression coefficient vector, and b_{2i} is again the

cluster-level random effect in non-zero component. The error term ε_{ij} is assumed to be normally distributed as $N(0,\sigma_e^2)$. Note that this two-part mixed model can be extended to include additional random effects. For illustration purposes and simplicity, we restrict attention here to two-part mixed models with two level; extensions to multilevel models are straightforward.
When fitting this model to independent responses, the binary and conditionally continuous components of the likelihood are separable, and therefore, these two parts are fit separately. The binary component is often modeled using logistic regression, and the continuous component can be fit using standard regression models, such as the Beta Prime (BP) [17], log-normal (LN) [18], Gamma (G) [19, 20], and long-skew normal (LSN) [21].
The marginal mean and variance of Y_{ij} from a TP model can be derived as follow:
$E(Y_{ij})=\pi_{ij}E(Y_{ij}\vee Y_{ij}>0), Var(Y_{ij})=\pi_{ij}\left[E(Y_{ij}^2\vee Y_{ij}>0)-\pi_{ij}E(Y_{ij}\vee Y_{ij}>0)^2\right]$
When log-normal is assumed in the continuous part, the marginal mean is
$E(Y_{ij})=v_{ij}=\pi_{ij}\exp\left(\mu_{ij}+\sigma^2/2\right)$

1.2. Marginalized two-part model
To obtain interpretable covariate effects on the marginal (unconditional) mean, we propose the following mTP model that parameterizes the covariate effects directly in terms of the marginal mean, $v_i=E(Y_i)$, on the original (i.e., untransformed) data scale. The mTP model specifies the linear predictors:
$logit(\pi_i)=logit(Pr(Y_{ij}=0\vee b_{1i}))=Z_{ij}'\times\alpha+b_{1i}$ (4)
where b_{1i} represents the random effect that accounts for the within subject correlation pertaining to the clustered measures in the zero part, $b_{1i}\ N(0,\sigma_{b_1}^2)$.
$E(Y_i)=v_i=\log(Pr(Y_{ij}>0\vee b_{2i}))=\exp(X_{ij}'\times\beta+b_{2i}+\varepsilon_{ij})$ (5)
where b_{2i} represents the random effect that accounts for the within subject correlation pertaining to the clustered measures in the continuous part, $b_{2i}\ N(0,\sigma_{b_2}^2)$.
The two random effect intercepts b_{1i} and b_{2i} in the two process of zero and non-zero are assumed to be independent and uncorrelated. Z_{ij}' is the vector of covariates for the i-*th* subject measured at the j-*th* cluster for the binary part and X_{ij}' is the vector of covariates for the i-*th* subject measured at the j-*th* cluster used for the continuous part. The two parts might have common covariates or completely different ones. α is the vector of model coefficients corresponding to the binary part and β is the vector of coefficients corresponding to the continuous part conditional on the values being non-zero. The model can be easily extended to include higher-order random effects.

1.2.1 Marginalized two-part log-normal model
When modeling semi-continuous data, the continuous component is most frequently modeled using a log-normal (LN) distribution. The generic form of the marginalized two-part log-normal (mTP.LN) model for independent responses can be written as in (1) with $g(y_{ij}\vee y_{ij}>0)$ taking the log-normal density function $\ln(.;\mu,\sigma^2)$ with mean μ and variance σ^2 on the log scale. The marginal mean and variance of Y_{ij} are:
$E(Y_{ij})=v_{ij}=\pi_{ij}\exp\left(\mu_{ij}+\sigma^2/2\right)$ (6)
$Var(Y_{ij})=\pi_{ij}\exp\left(2\mu_{ij}+\sigma^2\right)\left[\exp(\sigma^2)-\pi_{ij}\right]$ (7)
The likelihood (L), parameterized in terms of π_{ij} and μ_{ij}, is

$$L=\prod_{i=1}^{n}\left(1-\pi_{ij}\right)^{1_{(y_{ij}=0)}}\left\{\frac{\pi_{ij}}{y_{ij}\sqrt{2\pi\sigma}}\exp\left[\frac{-1}{2\sigma^2}\left(\ln y_{ij}-\mu_{ij}\right)^2\right]\right\}^{1_{(y_{ij}>0)}}\prod_{j=1}^{n_i}\phi\left(b_{1i},b_{2i}\vee\sigma^2_{b_1},\sigma^2_{b_2}\right)$$

where $\phi\left(b_{1ij},b_{2ij}\right)$ represents the bivariate normal distribution for the random effects with mean vector of zeros and variance–covariance matrix $\sigma^2_{b_1}$ and $\sigma^2_{b_2}$ for zero and non-zero part respectively.

In order to utilize this log-normal likelihood framework, the marginal mean in Equation (6) can be rearranged to solve for μ_{ij}, yielding

$$\mu_{ij}=\ln v_{ij}-\ln\pi_{ij}-\sigma^2/2=X'_{ij}\beta+b_{2i}-\ln\pi_{ij}-\sigma^2/2$$

Noting that:

$$\pi_i=\frac{\exp\left(Z'_{ij}\alpha+b_{1i}\right)}{1+\exp\left(Z'_{ij}\alpha+b_{1i}\right)}\Longrightarrow\ln\pi_{ij}=Z'_{ij}\alpha+b_{1i}-\ln\left(1+\exp\left(Z'_{ij}\alpha+b_{1i}\right)\right)\text{, and}$$

$$\ln\left(1-\pi_{ij}\right)=-\ln\left(1+\exp\left(Z'_{ij}\alpha+b_{1i}\right)\right)$$

we can express the log-likelihood in terms of α, β, and σ:

$$l\left(\alpha,\beta,\sigma\right)=l_1+l_2$$

$$l_1=\sum_{y_{ij}=0}-\ln\left(1+\exp\left(Z'_{ij}\alpha\right)\right)+\sum_{y_{ij}>0}\left\{Z'_{ij}\alpha-\ln y_{ij}-\frac{1}{2}\ln 2\pi-ln\sigma-\frac{1}{2\sigma^2}\left[\ln y_{ij}+Z'_{ij}\alpha-\ln\left(1+\exp\left(Z'_{ij}\alpha\right)\right)+\sigma^2/2-X'_{ij}\beta\right]\right\}$$

$$l_2=\frac{-1}{2}n_i\log\left(2\pi\sigma^2_{b_1}\right)+\sigma^{-2}_{b_1}b'_{1i}b_{1i}-\frac{1}{2}n_i\log\left(2\pi\sigma^2_{b_2}\right)+\sigma^{-2}_{b_2}b'_{2i}b_{2i}$$

with score equations

$$U_i=\left[\frac{\partial l_i\left(\alpha,\beta,\sigma\right)}{\partial\alpha}\quad\frac{\partial l_i\left(\alpha,\beta,\sigma\right)}{\partial\beta}\quad\frac{\partial l_i\left(\alpha,\beta,\sigma\right)}{\partial\sigma}\right]'$$

Where

$$\frac{\partial l_i\left(\alpha,\beta,\sigma\right)}{\partial\alpha}=\left\{\frac{-\exp\left(Z'_{ij}\alpha\right)}{1+\exp\left(Z'_{ij}\alpha\right)}+\left[1-\frac{1}{\sigma^2}\left[\ln y_{ij}+Z'_{ij}\alpha-\ln\left(1+\exp\left(Z'_{ij}\alpha\right)\right)+\frac{1}{\sigma^2}-X'_{ij}\beta\right]\times\left(\frac{1}{1+\exp\left(Z'_{ij}\alpha\right)}\right)\right]1_{(y_i>0)}\right\}Z'_{ij}$$

$$\frac{\partial l_i\left(\alpha,\beta,\sigma\right)}{\partial\beta}=\left\{\frac{1}{\sigma^2}\left[\ln y_{ij}+Z'_{ij}\alpha-\ln\left(1+\exp\left(Z'_{ij}\alpha\right)\right)-X'_{ij}\beta\right]+\frac{1}{2}\right\}X'_{ij}$$

$$\frac{\partial l_i\left(\alpha,\beta,\sigma\right)}{\partial\sigma}=\frac{-1}{\sigma}\left\{1-\frac{1}{\sigma^2}\left[\ln y_{ij}+Z'_{ij}\alpha-\ln\left(1+\exp\left(Z'_{ij}\alpha\right)\right)+\frac{\sigma^2}{2}-X'_{ij}\beta\right]^2+\ln y_i+Z'_{ij}\alpha-\ln\left(1+\exp\left(Z'_{ij}\alpha\right)\right)+\frac{\sigma^2}{2}-X'_i\beta\right\}$$

which can be implemented in the SAS NLMIXED procedure by quasi-Newton optimization with adaptive Gaussian quadrature techniques [22]. With the conventional model, the likelihood and score equations can be separated into two independent components: one for the binary part and one for the continuous part. In contrast, note that the score equations for the mTP model are not separable, and thus, the binary and continuous parts are fit simultaneously. Model-based asymptotic standard errors are computed using Fisher's information matrix, $I\left(\alpha,\beta,\sigma\right)$ as

$$s.e.\left(\widehat{\alpha},\widehat{\beta},\widehat{\sigma}\right)=\sqrt{diag\left[I^{-1}\left(\alpha,\beta,\sigma\right)\right]}$$

with the maximum likelihood estimates substituted for α, β, and σ.

Results

In this section, the proposed marginalized two-part model are applied to Healthy diet dataset on fat and protein to investigate the effects of supplementation categories on the number of deaths/100 cases and recovered/100 cases of COVID-19. The estimations with 95% confidence interval (CI) related to deaths and recovers prepared in Tables 2 and 3 respectively. In these tables, variances ($\sigma_{b_1}^2$ and $\sigma_{b_2}^2$) show the variety of responses among level 2 (i.e., the WHO regions) related to each part of zero and non-zero (i.e., positive) components. Tables 2 and 3 show that almost all categories have the same effect on the number of deaths and recovers in 100 cases. Besides, the number of deaths/100 cases, number of recovered/100 cases, and the obesity rats until July 3, 2020, by all countries and split by the WHO regions prepared in Supplementary Table 2. Deaths are more common in Western and Southwest Europe (e.g., Belgium, United Kingdom, France, Italy, Hungary, Netherlands, and Spain), North America (e.g., Mexico, Bahamas, Canada, Barbados, Belize, and United States) and North Africa (e.g., Western Sahara, Chad, Algeria, and Niger). The highest number of deaths occurred in Yemen (26.62 death/100 cases), which could be due to the crises caused by the war and the poor health conditions in this country in the last years. Frequently, it seems that the northern regions of the world appear to have had more deaths, which one reason may be due to temperature differences between the two hemispheres.

According to the results of Table 2, expect Pulses in fat quantity and Animal Products, Meat, Treenuts, and vegetables in protein dataset, all other categories have not significant effect on the number of deaths. One percent increase in supplementation of Pulses, reduced the odds of having a zero death by 4-fold ($1/\exp(-1.417)=4.125\,1$). Also, One percent increase in supplementation of Animal Products and Meat, increase the odds of having a zero death by 1.076-fold ($\exp(0.0736)=1.076$) and 1.133-fold ($\exp(0.0736)=1.133$) respectively. Treenuts, reduced the odds of having a zero death and Vegetables increase the number of deaths.

Continuously, and according to the results in Table 3, expect Animal fats, Sugar Sweeteners, and Treenuts in fat quantity and Animal fats and Sugar Crops, in protein data, all other categories have not significant effect on the number of recovers. The effect of consuming sugar products on mortality is very considerable. Every one percent increment in Sugar Sweeteners decreases the number of recovers by 98.17 percent [-9.68, 95% CI (-12.6440 to -6.7098)]. Treenuts in fat quantity also reduced the number of recovers by 16.9 percent [-0.1732, 95% CI (-0.3157 to -0.3070)]. In protein data, Sugar Crops reduced the number of recovers by 99.11 percent ($1-\exp(-4.7273)=0.9911$). World map related to sugar & sweeteners supply shows in Figure 4. Based on the results of the proposed model and estimates of the effects of sugar, our prediction for the coming days is that the countries of the Americas, with more intake sugar products, probably will face more deaths.

Figure 2. Bivariate Pearson correlation between nutrition categories (plus obesity) and the number of deaths and number of recovers in 100 cases with COVID_19.

For more evaluation, we have calculated correlations between categories (plus obesity rate) with the number of deaths and the number of recovers by using bivariate Pearson correlation (Figures 2). Results of correlations show that, in the protein data, countries that consumed more Spices, Treenuts, Cereals, Aquatic products, Stimulants, Vegetable oils, Oil crops, Pulses, Fruit (wine), and Alcoholic beverage, in order, had fewer deaths by COVID-19, and conversely, countries that consumed more Meat, Vegetables, Vegetal products, Sugar & Sweeteners, Animal products, Animal fats, Sugar crops, Milk, Fish, Offals, Miscellaneous, Eggs, and starchy roots, in order, had more deaths by COVID-19. In fat quantity data, countries that consumed more Sugar & Sweeteners, Miscellaneous, Treenuts, Meat, Animal products, Animal fats, Offals, and Fish had more deaths by COVID-19. Finally, same as the results of marginalized two-part model, Obesity has affected in more deaths and fewer recovery rates in all correlation analysis (Figures 2 & 3).

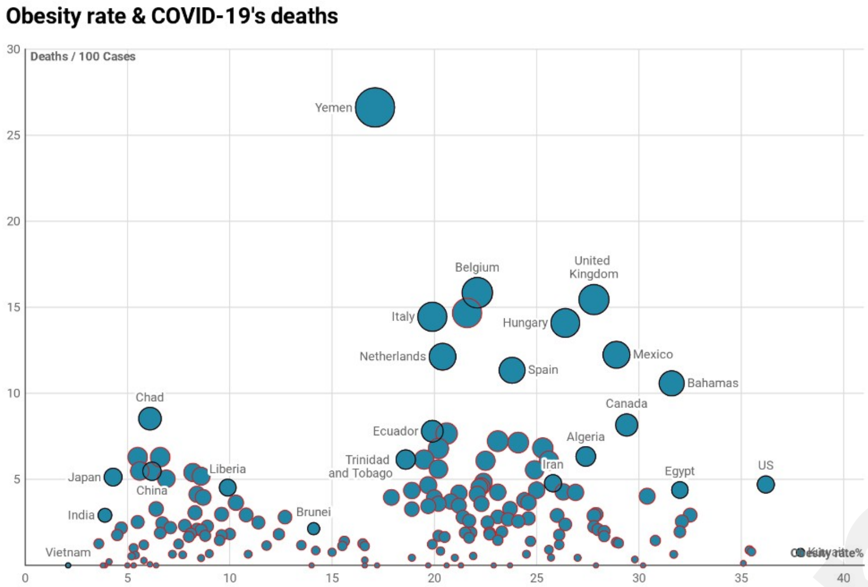

Figure 3. Scatter plot of Obesity rate and Deaths / 100 cases of COVID_19 by countries. Circle's size related to the number of deaths/ 100 cases.

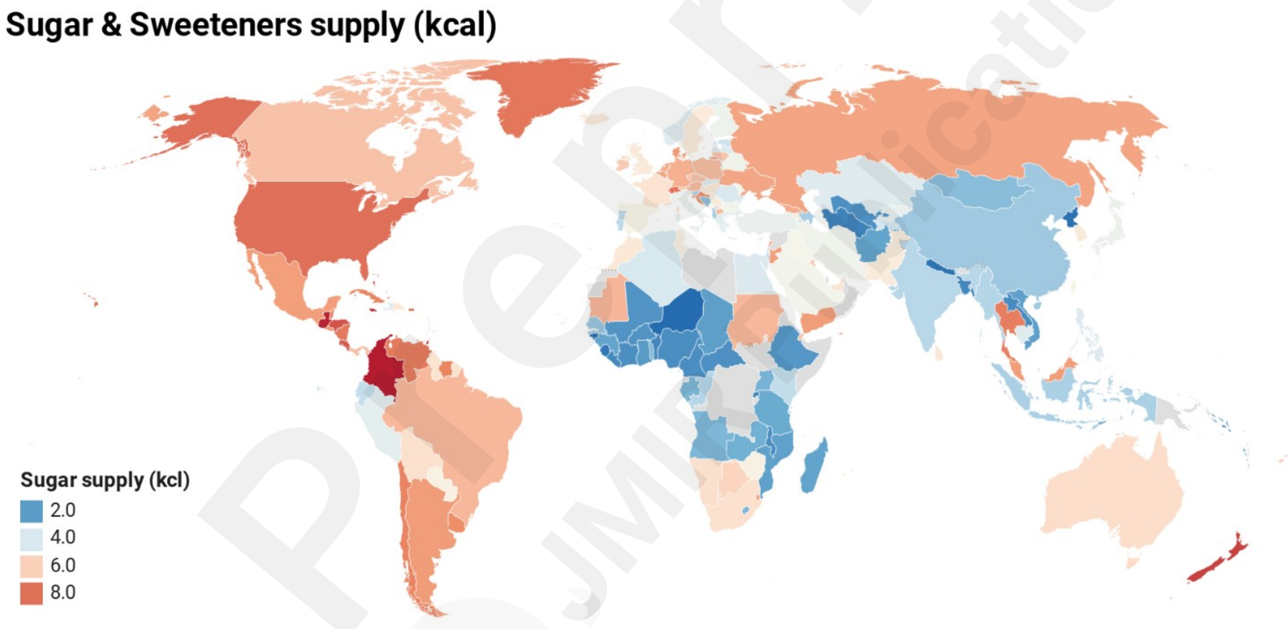

Figure 4. World map related to Sugar & Sweeteners supply (kcal).

Table 2. Results of marginalized two-part Log-Normal model in predicting number of Deaths/100 cases and considering the cluster effect of who regions in fat dataset.

	Fat quantity				Protein			
	Zero component		Non-zero component		Zero component		Non-zero component	
Fat (categories)	Coefficient (**α**)	$\sigma^2_{b_1}$	Coefficient (**β**)	σ^2_2	Coefficient (**α**)	$\sigma^2_{b_1}$	Coefficient (**β**)	$\sigma^2_{b_2}$
Alcoholic Beverages	- (-)	-	-7.0449 (-26.8066 – 12.7167)	0.1145	1.3670 (-1.3215 – 4.0555)	0.4907	0.04707 (-0.6272 – 0.7214)	01286
Animal Products	0.0401 (-0.0236 – 0.1038)	0.7457	-0.0028 (-0.0241 – 0.0184)	0.1539	***0.0736*** (0.0070 – 0.1401)	0.6212	0.0105 (-0.0113 – 0.0323)	0.1236
Animal fats	0.1505 (-0.0526 – 0.3537)	0.6458	0.0009 (-0.0495 – 0.0513)	0.1223	7.6487 (-1.0158 – 16.3131)	0.3055	0.3259 (-0.8172 – 1.4690)	0.1212
Aquatic Products Other	4.3474 (-130.52 – 139.21)	0.7746	-13.9857 (-52.2468 – 24.2754)	0.1123	30.9618 (-69.7172 – 131.64)	0.4060	-0.7270 (-2.5100 – 1.0561)	0.1201
Cereals Excluding Beer	-0.0839 (-0.2226 – 0.0549)	0.6195	-0.02183 (-0.0771 – 0.0334)	0.1485	-0.05487 (-0.1347 – 0.0250)	0.4994	-0.0171 (-0.0439 – 0.00978)	0.1163
Eggs	0.3217 (-0.5091 – 1.1526)	0.6155	-0.1291 (-0.3841 – 0.1260)	0.1391	0.3993 (-0.3079 – 1.1066)	0.4487	-0.0466 (-0.2632 – 0.1701)	0.1297
Fish Seafood	-0.0556 (-0.5394 – 0.4283)	0.6000	0.0383 (-0.1491 – 0.2258)	0.1903	0.0542 (-0.1415 – 0.2500)	0.4220	0.0305 (-0.0293 – 0.0902)	01318
Fruits Excluding Wine	-0.4420 (-0.9779 – 0.0940)	0.6323	0.0933 (-0.2595 – 0.4462)	0.1633	-0.4744 (-1.0143 – 0.0655)	0.5036	0.0783 (-0.2107 – 0.3673)	0.1176

Meat	0.0394 (-0.0805 – 0.1593)	0.7340	0.0008 (-0.0354 – 0.0370)	0.1699	**0.1246** (0.0018 – 0.2473)	0.4690	0.0256 (-0.0103 – 0.0614)	0.1174
Miscellaneous	2.9863 (-5.5797 – 11.5524)	0.6822	2.0655 (-0.0920 – 4.2230)	0.0994	0.0900 (-0.5087 – 0.2309)	0.6768	-0.0090 (-0.0519 – 0.0339)	0.1336
Milk Excluding Butter	0.0589 (-0.1038 – 0.2217)	0.6160	-0.0139 (-0.0641 – 0.0364)	0.1667	0.5456 (-0.6494 – 1.7406)	0.4718	0.0561 (-0.2342 – 0.3464)	0.1259
Offals	0.0196 (-4.9871 – 5.0263)	0.6429	-0.1844 (-1.6248 – 1.2561)	0.1022	-0.0526 (-0.3739 – 0.2687)	0.4808	0.0704 (-0.0524 – 0.1932)	0.1227
Oilcrops	-0.2833 (-0.1215 – 0.0648)	0.5580	0.0179 (-0.0229 – 0.0586)	0.1876	-0.1453 (-0.2710 – -0.0196)	0.5600	0.0090 (-0.0580 – 0.0760)	0.1245
Pulses	***-1.4170*** (-2.4828 – -0.3513)	0.1944	0.1150 (-0.5176 – 0.7475)	0.1434	-0.1583 (-1.5638 – 1.2472)	0.4308	0.1496 (-0.3397 – 0.6388)	0.1290
Spices	-0.5889 (-1.4091 – 0.2313)	0.4622	0.0476 (-0.3547 – 0.4500)	0.1907	-0.0916 (-0.3597 – 0.1765)	0.4309	-0.0561 (-0.1498 – 0.0376)	0.1161
Starchy Roots	-0.9187 (-2.0219 – 0.1845)	0.5559	-0.3262 (-0.8582 – 0.2058)	0.1637	0.3208 (-1.1999 – 1.8414)	0.4513	-0.0469 (-0.4783 – 0.3846)	0.1246
Stimulants	0.6042 (-0.3940 – 1.6024)	0.6715	-0.0287 (-0.2590 – 0.2016)	0.1704	0.3476 (-34.4185 – 35.1136)	0.4530	-2.4158 (-13.1577 – 8.3260)	0.1227
Sugar Crops	-13.0537 (-26.8920 – 0.7847)	0.5727	-6.2283 (-17.0084 – 4.5518)	0.1063	5.7548 (-28.4441 – 39.9538)	0.4394	1.4861 (-2.1023 – 5.0746)	0.1217
Sugar Sweeteners	-0.8040 (-75.3168 – 73.7088)	0.6104	10.2992 (-9.2969 – 29.8953)	0.2136	1.7184 (-1.1295 – 4.5662)	0.4899	0.5042 (-0.0606 – 1.0690)	0.1328
Treenuts	0.3739 (-0.5196 – 1.2674)	0.6207	0.1138 (-0.0816 – 0.3092)	0.2178	***-0.0736*** (-0.1401 – -0.0071)	0.6211	-0.0105 (-0.0323 – 0.0113)	0.1236
Vegetal Products	-0.0401 (-0.1037 – 0.0237)	0.8313	0.0028 (-0.0184 – 0.0241)	0.1485	39.1538 (-2.4289 – 80.7364)	0.5764	2.8053 (-4.0774 – 9.6879)	0.1327
Vegetable Oils	-0.0008 (-0.0794 – 0.0778)	0.6667	0.0025 (-0.0227 – 0.0277)	0.1663	0.0228 (-0.4939 – 0.5396)	0.4442	-0.0376 (-0.2045 – 0.1292)	0.1228
Vegetables	-0.5748 (-2.7770 – 1.6274)	0.6205	-0.4784 (-1.2890 – 0.3322)	0.1099	1.363 (-1.5981 – 4.3237)	0.3991	***0.7713*** (0.0799 – 1.4628)	0.1050
Obesity	0.0228 (-0.0268 – 0.0724)	0.5954	0.0054 (-0.0117 – 0.0225)	0.1716	0.0228 (-0.0268 – 0.0724)	0.4798	0.0054 (-0.01168 – 0.0225)	0.1261

Note: Empty cells related to un-estimated/ no converged values.
Parentheses indicate (lower - upper) 95% confidence interval for each fit-derived value.
Italic values indicate statistical significance at the 0.05 significance level.

Table 3. Results of marginalized two-part Log-Normal model in predicting number of Deaths in 100 cases and considering the cluster effect of who regions in protein dataset.

	Fat quantity				Protein			
	Zero component		Non-zero component		Zero component		Non-zero component	
Protein (categories)	**Coefficient (α)**	$\sigma^2_{b_1}$	**Coefficient (β)**	σ^2_2	**Coefficient (α)**	$\sigma^2_{b_1}$	**Coefficient (β)**	$\sigma^2_{b_2}$
Alcoholic Beverages	0.3934 (-)	-	-3.3321 (-18.9871 – 12.3229)	0.0053	-0.5040 (-3.6581 – 2.6501)	-	0.3291 (-0.1644 – 0.8227)	0.0241
Animal Products	-0.0518 (-0.1806 – 0.0771)	-	-0.0030 (-0.01874 – 0.0127)	5.0390	-0.0377 (-0.1705 – 0.0951)	-	-0.0036 (-0.0194 – 0.0122)	-
Animal fats	-0.1417 (-0.3828 – 0.0994)	0.6458	0.0037 (-0.0355 – 0.0429)	0.1223	***-4.3929*** (-7.9510 – -0.8348)	0.6854	-0.1882 (-1.2078 – 0.8314)	0.0291
Aquatic Products Other	0.1026 (-177.24 – 177.45)	0.7746	0.0998 (-28.7115 – 28.9112)	0.1123	13.6501 (-162.63 – 189.93)	0.6543	-0.1588 (-1.5364 – 1.2188)	0.0102
Cereals Excluding Beer	0.2108 (-0.2520 – 0.6737)	0.6195	0.0201 (-0.0186 – 0.0587)	0.1485	0.0935 (-0.0866 – 0.2736)	0.5987	0.0070 (-0.0122 – 0.02614)	-
Eggs	1.0198 (-0.9042 – 2.9439)	0.6155	0.0585 (-0.1279 – 0.2449)	0.1391	0.3015 (-1.0934 – 1.6965)	0.7154	0.0971 (-0.0601 – 0.2544)	1.0199
Fish Seafood	2.1882 (-0.8220 – 5.1984)	0.6000	-0.0587 (-0.1866 – 0.0693)	0.1903	0.3784 (-0.2179 – 0.9747)	0.6542	-0.0109 (-0.0544 – 0.0327)	2.0553
Fruits Excluding Wine	3.5529 (-1.5969 – 8.7027)	0.6323	0.0049 (-0.1322 – 0.1419)	0.1633	0.5023 (0.6500 – -1.6800)	0.6980	-0.0284 (-0.2127 – 0.1560)	0.3869
Meat	-0.0020 (-0.1961 – 0.1922)	0.7340	-0.0081 (-0.0350 – 0.0189)	0.1699	-0.0720 (-0.2753 – 0.1313)	0.7012	-0.0050 (-0.0317 – 0.0218)	2.8965
Miscellaneous	8.988 (-13.9276 – 31.9035)	0.6822	-0.1517 (-1.7701 – 1.4666)	0.0994	-0.1208 (-0.3424 – 0.1007)	0.6503	-0.0057 (-0.0375 – 0.0262)	1.8106
Milk Excluding Butter	-0.1359 (-0.3700 – 0.0981)	0.6160	-0.0020 (-0.0396 – 0.0356)	0.1667	-0.3806 (-1.8083 – 1.0470)	0.4562	0.0398 (-0.2029 – 0.2824)	0.4047
Offals	-3.0231 (-9.5088 – 3.4627)	0.6429	-0.1611 (-1.3609 – 1.0388)	0.1022	-0.1169 (-0.7218 – 0.4879)	0.6985	0.0301 (-0.0579 – 0.1180)	-
Oilcrops	0.0091 (-0.2361 – 0.2543)	0.5580	0.0070 (-0.0213 – 0.0353)	0.1876	-0.1958 (-0.4096 – 0.0180)	0.5913	-0.0269 (-0.0763 – 0.0224)	1.2942
Pulses	***-1.6086*** (-2.9469 – -0.2704)	0.1944	-0.3639 (-0.8713 – 0.1434)	0.1434	4.1312 (-2.8302 – 11.0926)	0.2456	-0.2215 (-0.5719 – 0.1289)	0.0303
Spices	3.1903 (-2.6678 – 9.0484)	0.4622	-0.2388 (-0.4933 – 0.0158)	0.1907	0.0560 (-0.4308 – 0.5427)	0.5441	0.0208 (-0.0418 – 0.0834)	0.6601
Starchy Roots	0.4714 (-2.6068 – 3.5496)	0.5559	0.0997 (-0.2235 – 0.4229)	0.1637	-0.2431 (-2.2868 – 1.8007)	0.6003	0.1089 (-0.2039 – 0.4217)	0.0603
Stimulants	0.5780 (-0.0993 – 2.2554)	0.6715	0.1503 (-0.0215 – 0.3221)	0.1704	-0.0752 (-57.0402 – 56.889)	0.6439	2.1776 (-5.6550 – 10.0096)	0.0100
Sugar Crops	0.3393 (-36.6976 – 37.3762)	0.5727	0.9821 (-4.2187 – 6.1829)	0.1063	0.3819 (-81.2066 – 81.97)	0.5589	***-4.7273*** (-8.1560 – -1.2986)	0.1670

Sugar Sweeteners	1.3970 (-72.8962 – 75.6902)	0.6104	***-9.6769*** (-12.6440 – -6.7098)	0.2136	0.5242 (-3.1195 – 4.1679)	0.6987	-0.4085 (-0.8273 – 0.0104)	0.2326
Treenuts	0.2521 (-0.9646 – 1.4688)	0.6207	***-0.1732*** (-0.3157 – -0.3070)	0.2178	0.0378 (-0.0950 – 0.1705)	0.7432	0.0036 (-0.0122 – 0.0194)	2.8525
Vegetal Products	0.05177 (-0.0771 – 0.1806)	0.8313	0.0030 (-0.0127 – 0.0187)	0.1485	-18.9397 (-42.1004 – 4.2211)	0.7823	0.7848 (-4.9151 – 6.4847)	0.0053
Vegetable Oils	0.0081 (-0.1303 – 0.1465)	0.6667	-0.0007 (-0.0189 – 0.0175)	0.1663	0.4467 (-0.7511 – 1.6446)	0.5968	-0.0039 (-0.1235 – 0.1158)	2.4944
Vegetables	2.7153 (-3.8863 – 9.3169)	0.6205	-0.1959 (-0.7611 – 0.3693)	0.1099	1.6107 (-4.2909 – 7.5123)	0.5935	0.1003 (-0.4256 – 0.6263)	0.0184
Obesity	0.0042 (-0.4208 – 0.6467)	0.5954	-0.0009 (-0.0125 – 0.0107)	0.1716	0.0042 (-0.0882 – 0.0966)	0.4986	-0.0009 (-0.0125 – 0.1069)	4.1135

Note: Empty cells related to un-estimated/ no converged values.
Parentheses indicate (lower - upper) 95% confidence interval for each fit-derived value.
Italic values indicate statistical significance at the 0.05 significance level.

Discussion

In this study, we propose a marginalized two-part Log-Normal regression model for clustered semi-continuous Diet/Nutrition data. This model allows investigators to obtain covariate effects on the marginal mean of the outcome (e.g., deaths and recovers). It also has an unconditional interpretation of the covariate effect on the marginal mean. Our proposed marginalized two-part model has satisfactory performance in Diet/Nutrition data analysis.

Healthy diets and physical activity are key to good nutrition and necessary for a long and healthy life and prevention of chronic disease [23]. Eating nutrition dense foods and balancing energy intake with the necessary physical activity to maintain a healthy weight is essential at all stage of life. Unbalanced consumption of foods high in energy (sugar, starch, and/or fat) and low in essential nutrition contributes to energy excess, overweight, and obesity. The amount of energy consumed in relation to physical activity and the quality of food are key determinants of nutrition related chronic disease [8]. In January 2020, and in a review study, Lei. Z and Yunhui. L reviewed the importance of some nutrition interventions (vitamins, minerals, Immunoenhancers) in infectious/respiratory diseases. Authors suggest that the nutritional status of each infected patient should be evaluated before the administration of general treatments and the current children's RNA-virus vaccines including influenza vaccine should be immunized for uninfected people and health care workers. Moreover, The results of review showed that all the potential interventions (nutritional and/or immunoenhancers) be implemented to control the emerging COVID-19 if the infection is uncontrollable [10]. Our results also confirm these associations by introducing influential diets category include Sugar & Sweeteners, Animal products, Animal fats, Sugar crops, Miscellaneous, and Treenuts as more important risk factors for death and/or slowdown of recovery in coronavirus patients.

Recent studies point to obesity as a critical risk factor for being hospitalized/deaths with COVID-19 [24-26]. Indeed, a high prevalence of obesity has been observed in COVID-19 patients requiring invasive mechanical ventilation [27], a robust proxy of SARS-CoV2 severity. In patients under the age of 60, those with obesity were at almost double risk of being admitted to critical care when compared with normal-weight patients [28]. Results from this study confirm previous findings on the risk of obesity and add that obesity slows down patients' recovery and treatment of coronavirus patients.

People need to eat fewer prepared foods and more complex plant-based foods [8]. Although there are differences in pattern diets across the world, overall, unbalanced diets are a health threat across the globe and not just affecting death rates but also the quality of life. To achieve best results in preventing nutrition-related pandemic diseases, strategies and policies should fully recognize the essential role of both diet and obesity in determining good nutrition and optimal health. Policies and programs must address the need for change at the individual level as well as the modifications in society and the environment to make healthier choices accessible and preferable.

We have some limitation in performing nutrition datasets. The study is based on observational data and, inevitably with 188 countries included there were variations in how the data were collected. Twenty three dietary attributes were selected for inclusion in the study – some that are of interest to health such as saturated and monounsaturated fatty acids and free sugars across the diet (not just those in drinks) were not included in the analysis. The study also did not take into account lifestyle factors, such as smoking and physical activity, that can have a significant impact on the risk of the disease outcomes used in the study.
Finally, we wish all of our readers and the patients to be well during this pandemic and to remember to take care to protect yourself by following the guidelines of the Centers for Disease Control and Prevention [29], and eat healthy foods with sufficient amounts of fruits and vegetables as discussed previously.

Conclusions

Good nutrition is very important before during and after an infection. Findings of this study resulted that more consume of Eggs, Cereals Excluding Beer, Spices, and Stimulants had the greatest impact on the recovery of patients with COVID-19. Also, more consume of Meat, Vegetal products, Sugar & Sweeteners, Sugar crops, Animal fats, and Animal products were associated with more death and less recovery in patients. The effect of consuming sugar products on mortality is very considerable. Also, Obesity has affected in more deaths and fewer recovery rates.

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Abbreviations

COVID-19: coronavirus disease
WHO: World Health Organization
FAO: Food and agriculture Organization
mTP: Marginalized two-part model
TP: two part model
LN: Log-normal

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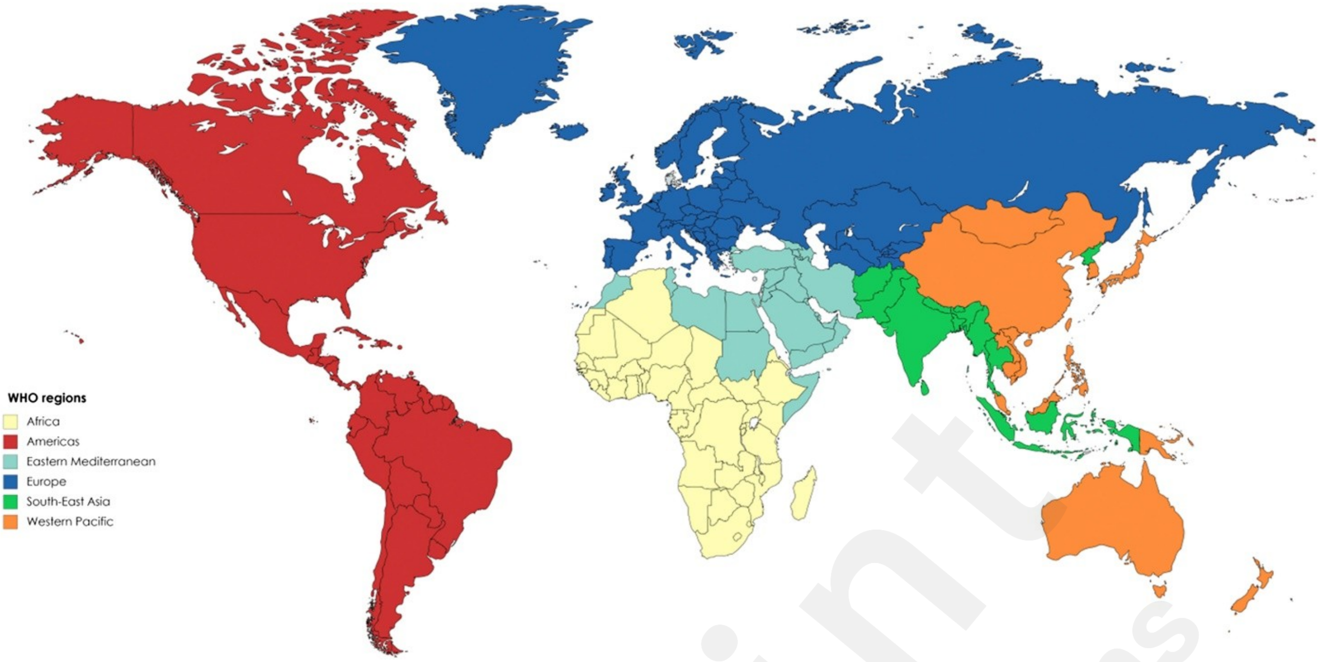
Supplementary Table 1. The specific types of food that belongs to each category for the fat quantity and protein datasets.

Categories	**Items**
Alcoholic Beverages	Alcohol, Non-Food; Beer; Beverages, Alcoholic; Beverages, Fermented; Wine
Animal fats	Butter, Ghee; Cream; Fats, Animals, Raw; Fish, Body Oil; Fish, Liver Oil
Animal Products	Aquatic Animals, Others; Aquatic Plants; Bovine Meat; Butter, Ghee; Cephalopods; Cream; Crustaceans; Demersal Fish; Eggs; Animals, Raw; Fish, Body Oil; Fish, Liver Oil; Freshwater Fish; Marine Fish, Other; Meat, Aquatic Mammals; Meat, Other; M Excluding Butter; Molluscs, Other; Mutton & Goat Meat; Offals, Edible; Pelagic Fish; Pigmeat; Poultry Meat
Aquatic Products, Other	Aquatic Animals, Others; Aquatic Plants; Meat, Aquatic Mammals
Cereals - Excluding Beer	Barley and products; Cereals, Other; Maize and products; Millet and products; Oats; Rice (Milled Equivalent); Rye and proc Sorghum and products; Wheat and products
Eggs	Eggs
Fish, Seafood	Cephalopods; Crustaceans; Demersal Fish; Freshwater Fish; Marine Fish, Other; Molluscs, Other; Pelagic Fish
Fruits - Excluding Wine	Apples and products; Bananas; Citrus, Other; Dates; Fruits, Other; Grapefruit and products; Grapes and products (excl w Lemons, Limes and products; Oranges, Mandarines; Pineapples and products; Plantains
Meat	Bovine Meat; Meat, Other; Mutton & Goat Meat; Pigmeat; Poultry Meat
Milk - Excluding Butter	Milk - Excluding Butter
Miscellaneous	Infant food; Miscellaneous
Offals	Offals, Edible
Oilcrops	Coconuts - Incl Copra; Cottonseed; Groundnuts (Shelled Eq); Oilcrops, Other; Olives (including preserved); Palm kernels; Rap Mustardseed; Sesame seed; Soyabeans; Sunflower seed
Pulses	Beans; Peas; Pulses, Other and products
Spices	Cloves; Pepper; Pimento; Spices, Other

Starchy Roots	Cassava and products; Potatoes and products; Roots, Other; Sweet potatoes; Yams
Stimulants	Cocoa Beans and products; Coffee and products; Tea (including mate)
Sugar & Sweeteners	Honey; Sugar (Raw Equivalent); Sugar non-centrifugal; Sweeteners, Other
Sugar Crops	Sugar beet; Sugar cane
Treenuts	Nuts and products
Vegetable Oils	Coconut Oil; Cottonseed Oil; Groundnut Oil; Maize Germ Oil; Oilcrops Oil, Other; Olive Oil; Palm Oil; Palmkernel Oil; Rape Mustard Oil; Ricebran Oil; Sesameseed Oil; Soyabean Oil; Sunflowerseed Oil
Vegetables	Onions; Tomatoes and products; Vegetables, Other
Vegetal Products	Alcohol, Non-Food; Apples and products; Bananas; Barley and products; Beans; Beer; Beverages, Alcoholic; Beverages, Ferme Cassava and products; Cereals, Other; Citrus, Other; Cloves; Cocoa Beans and products; Coconut Oil; Coconuts - Incl Copra; C and products; Cottonseed; Cottonseed Oil; Dates; Fruits, Other; Grapefruit and products; Grapes and products (excl w Groundnut Oil; Groundnuts (Shelled Eq); Honey; Infant food; Lemons, Limes and products; Maize and products; Maize Gern Millet and products; Miscellaneous; Nuts and products; Oats; Oilcrops Oil, Other; Oilcrops, Other; Olive Oil; Olives (inclu preserved); Onions; Oranges, Mandarines; Palm kernels; Palm Oil; Palmkernel Oil; Peas; Pepper; Pimento; Pineapples products; Plantains; Potatoes and products; Pulses, Other and products; Rape and Mustard Oil; Rape and Mustardseed; (Milled Equivalent); Ricebran Oil; Roots, Other; Rye and products; Sesame seed; Sesameseed Oil; Sorghum and products; Soya Oil; Soyabeans; Spices, Other; Sugar (Raw Equivalent); Sugar beet; Sugar cane; Sugar non-centrifugal; Sunflower Sunflowerseed Oil; Sweet potatoes; Sweeteners, Other; Tea (including mate); Tomatoes and products; Vegetables, Other; W and products; Wine; Yams



Supplementary Figure 1. Geographical distribution of the six WHO regions and member states for each region (alphabetical order).

Africa Region (AFR), 47 countries:
Algeria, Angola, Benin, Botswana, Burkina Faso, Burundi, Cameroon, Cabo Verde, Central African Republic, Chad, Comoros, Congo, Côte d'Ivoire, Democratic Republic of the Congo, Equatorial Guinea, Eritrea, Ethiopia, Gabon, Gambia, Ghana, Guinea, Guinea-Bissau, Kenya, Lesotho, Liberia, Madagascar, Malawi, Mali, Mauritania, Mauritius, Mozambique, Namibia, Niger, Nigeria, Rwanda, Sao Tome and Principe, Senegal, Seychelles, Sierra Leone, South Africa, South Sudan, Swaziland, Togo, Uganda, United Republic of Tanzania, Zambia, Zimbabwe.

Americas Region (AMR), 35 countries:
Antigua and Barbuda, Argentina, Bahamas, Barbados, Belize, Bolivia, Brazil, Canada, Chile, Colombia, Costa Rica, Cuba, Dominica, Dominican Republic, Ecuador, El Salvador, Grenada, Guatemala, Guyana, Haiti, Honduras, Jamaica, Mexico, Nicaragua, Panama, Paraguay, Peru, Saint Kitts and Nevis, Saint Lucia, Saint Vincent and the Grenadines, Suriname, Trinidad and Tobago, United States of America, Uruguay, Venezuela.

Eastern Mediterranean Region (EMR), 21 countries:
Afghanistan, Bahrain, Djibouti, Egypt, Iran (Islamic Republic of), Iran, Jordan, Kuwait, Lebanon, Libya, Morocco, Oman, Pakistan, Qatar, Saudi Arabia, Somalia, Sudan, Syrian Arab Republic, Tunisia, United Arab Emirates, Yemen.

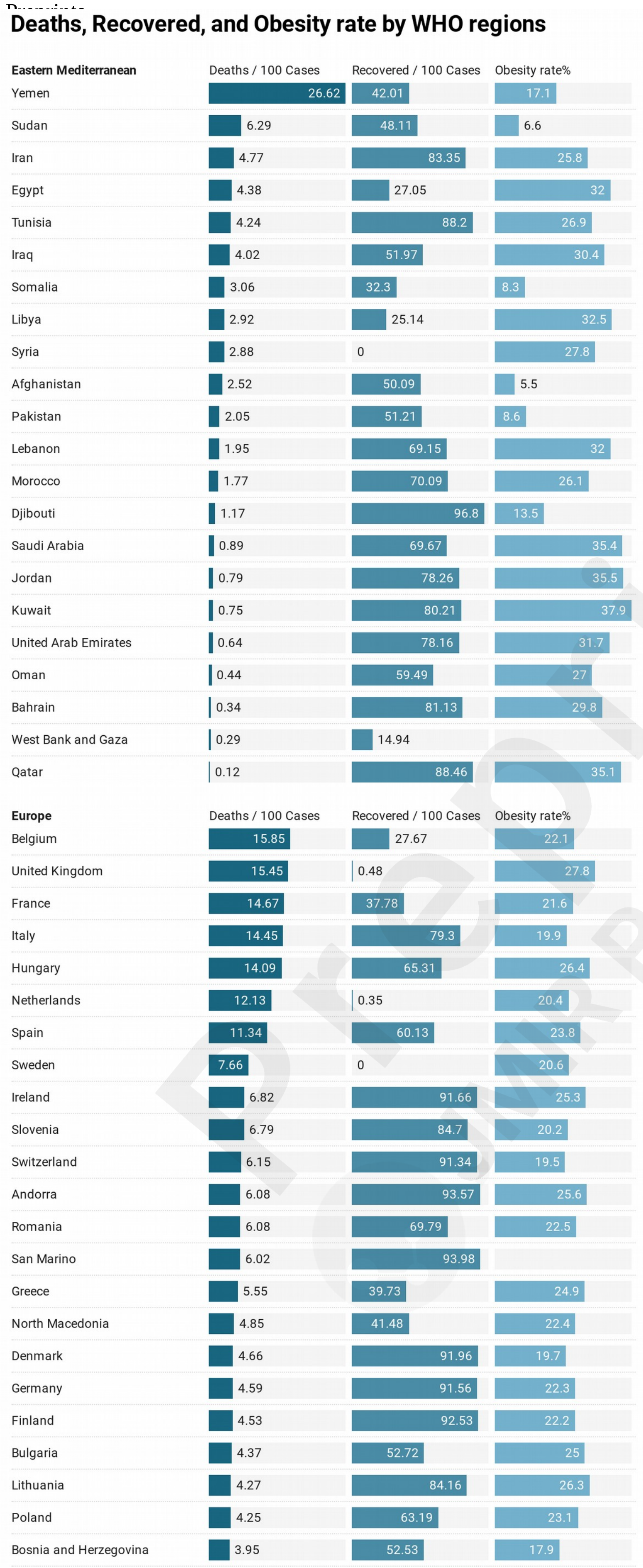
Europe Region (EUR), 48 countries
Albania; Andorra; Armenia; Austria; Azerbaijan; Belarus; Belgium; Bosnia and Herzegovina; Bulgaria; Croatia; Cyprus; Czech Republic; Denmark; Estonia; Finland; France; Georgia; Germany; Greece; Hungary; Iceland; Ireland; Israel; Italy; Kazakhstan; Kyrgyzstan; Latvia; Lithuania, Luxembourg, Malta, Monaco, Montenegro, Netherlands, Norway, Poland, Portugal, Republic of Moldova, Romania, Russian Federation, San Marino, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, Tajikistan, The former Yugoslav Republic of Macedonia, Turkey, Turkmenistan, Ukraine, United Kingdom, Uzbekistan.

South-East Asia Region (SEAR), 10 countries:

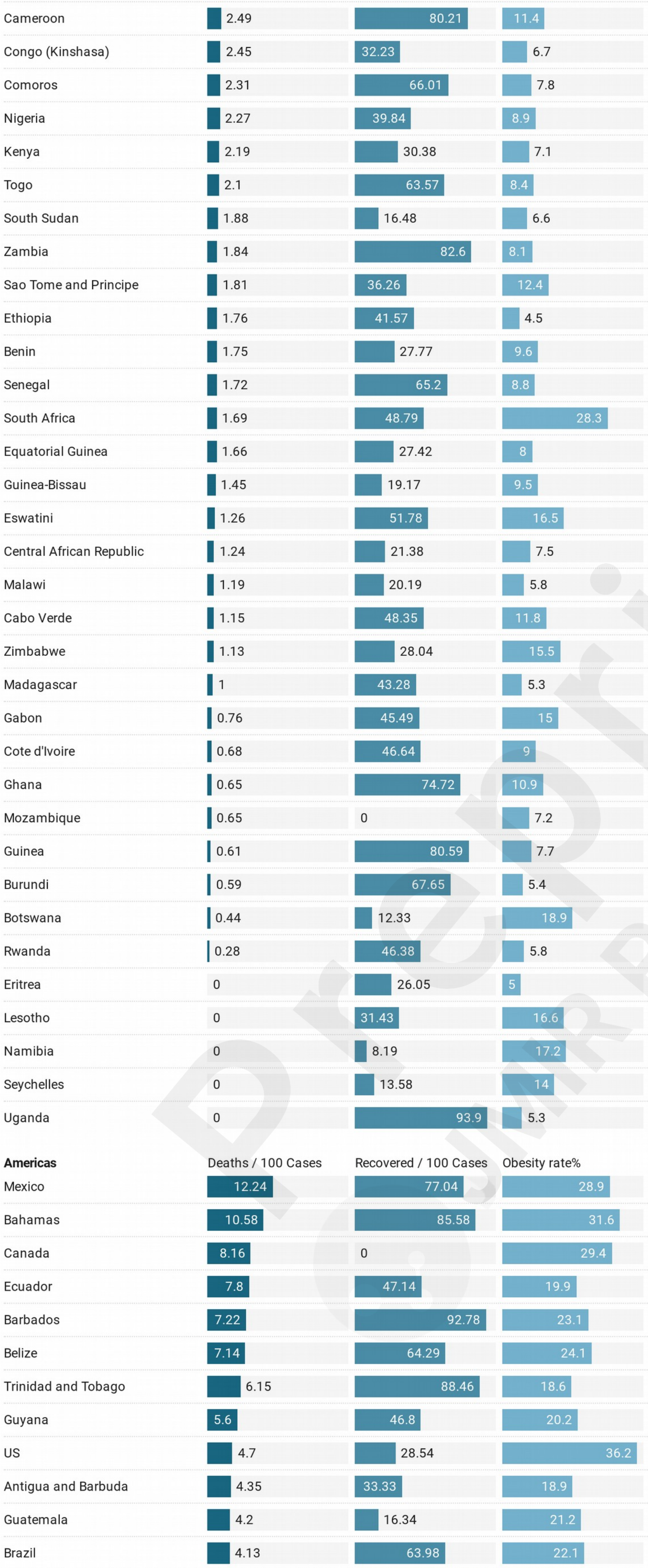
Bangladesh, Bhutan, Democratic People's Republic of Korea, India, Indonesia, Maldives, Myanmar, Nepal, Sri Lanka, Thailand, Timor-Leste.

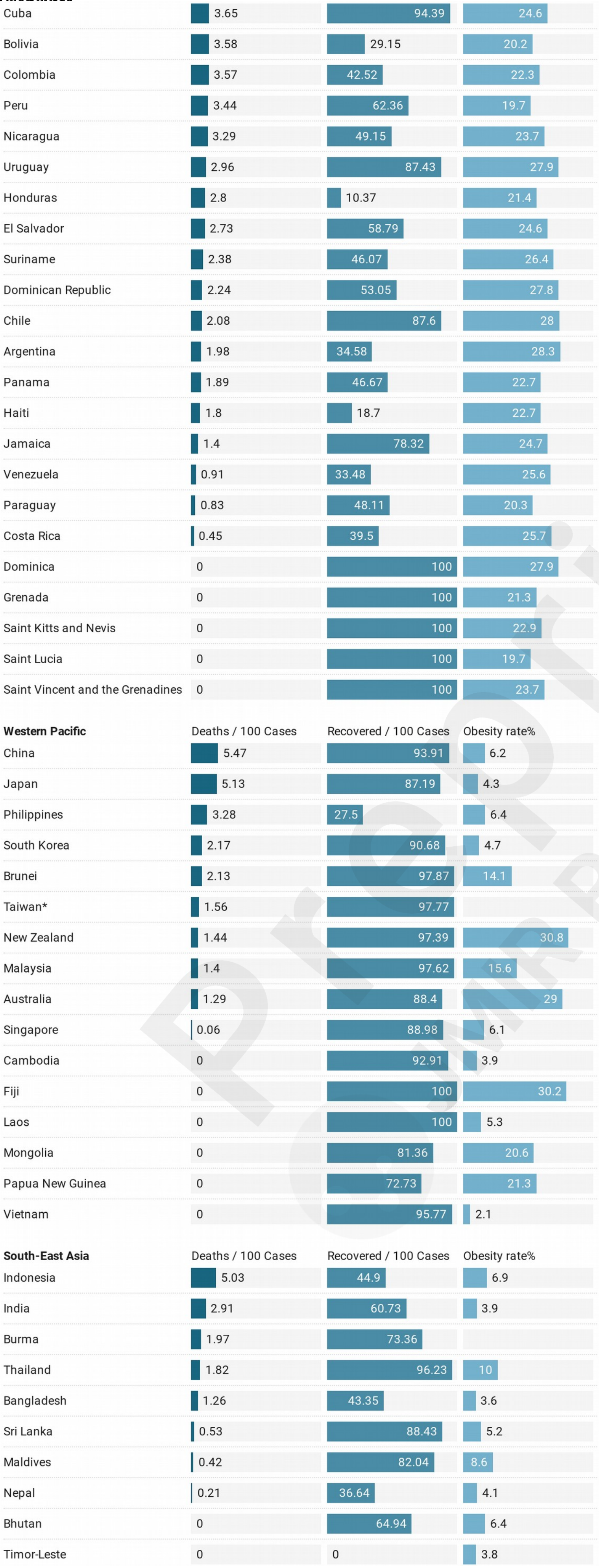
Western Pacific Region (WPR), 27 countries:
Australia, Brunei Darussalam, Cambodia, China, Cook Islands, Fiji, Japan, Kiribati, Lao People's Democratic Republic, Malaysia, Marshall Islands, Micronesia (Federated States of), Mongolia, Nauru, New Zealand, Niue, Palau, Papua New Guinea, Philippines, Republic of Korea, Samoa, Singapore, Solomon Islands, Tonga, Tuvalu, Vanuatu, Viet Nam.

Supplementary Table 2. Number of deaths/100 cases, number of recovered/100 cases, and Obesity rats until July 3, 2020, by countries and split by WHO regions.


Deaths, Recovered, and Obesity rate by WHO regions
Eastern Mediterranean
Deaths / 100 Cases
Recovered / 100 Cases
Obesity rate%
Yemen 26.62 42.01 17.1
Sudan 6.29 48.11 6.6
Iran 4.77 83.35 25.8
Egypt 4.38 27.05 32
Tunisia 4.24 88.2 26.9
Iraq 4.02 51.97 30.4
Somalia 3.06 32.3 8.3
Libya 2.92 25.14 32.5
Syria 2.88 0 27.8
Afghanistan 2.52 50.09 5.5
Pakistan 2.05 51.21 8.6
Lebanon 1.95 69.15 32
Morocco 1.77 70.09 26.1
Djibouti 1.17 96.8 13.5
Saudi Arabia 0.89 69.67 35.4
Jordan 0.79 78.26 35.5
Kuwait 0.75 80.21 37.9
United Arab Emirates 0.64 78.16 31.7
Oman 0.44 59.49 27
Bahrain 0.34 81.13 29.8
West Bank and Gaza 0.29 14.94
Qatar 0.12 88.46 35.1
Europe
Deaths / 100 Cases
Recovered / 100 Cases
Obesity rate%
Belgium 15.85 27.67 22.1
United Kingdom 15.45 0.48 27.8
France 14.67 37.78 21.6
Italy 14.45 79.3 19.9
Hungary 14.09 65.31 26.4
Netherlands 12.13 0.35 20.4
Spain 11.34 60.13 23.8
Sweden 7.66 0 20.6
Ireland 6.82 91.66 25.3
Slovenia 6.79 84.7 20.2
Switzerland 6.15 91.34 19.5
Andorra 6.08 93.57 25.6
Romania 6.08 69.79 22.5
San Marino 6.02 93.98
Greece 5.55 39.73 24.9
North Macedonia 4.85 41.48 22.4
Denmark 4.66 91.96 19.7
Germany 4.59 91.56 22.3
Finland 4.53 92.53 22.2
Bulgaria 4.37 52.72 25
Lithuania 4.27 84.16 26.3
Poland 4.25 63.19 23.1
Bosnia and Herzegovina 3.95 52.53 17.9

	Deaths / 100 Cases	Recovered / 100 Cases	Obesity rate%
Austria	3.93	92.05	20
Croatia	3.78	74	24.4
Monaco	3.77	89.62	
Portugal	3.71	65.67	20.8
Estonia	3.47	92.56	21.2
Moldova	3.27	57.41	18.9
Czechia	2.9	64.23	26
Norway	2.82	91.42	23.1
Latvia	2.67	88.06	23.6
Albania	2.59	58.56	21.7
Ukraine	2.56	44.33	24.1
Turkey	2.55	87.48	32.1
Luxembourg	2.5	91.29	22.6
Montenegro	1.95	51.14	23.3
Cyprus	1.9	83.38	21.8
Serbia	1.89	84.98	21.5
Kosovo	1.8	55.71	
Armenia	1.72	56.4	20.2
Slovakia	1.65	86.24	20.5
Georgia	1.6	87.01	21.7
Russia	1.46	64.87	23.1
Malta	1.34	96.72	28.9
Azerbaijan	1.22	55.8	19.9
Israel	1.2	64.88	26.1
Liechtenstein	1.2	97.59	
Kyrgyzstan	1.12	39.23	16.6
Tajikistan	0.86	77.42	14.2
Belarus	0.65	77.73	24.5
Iceland	0.54	98.81	21.9
Kazakhstan	0.44	34.71	21
Uzbekistan	0.3	66.47	16.6
Greenland	0	100	
Holy See	0	100	
Africa	Deaths / 100 Cases	Recovered / 100 Cases	Obesity rate%
Western Sahara	10	80	
Chad	8.53	90.44	6.1
Algeria	6.33	70.56	27.4
Niger	6.29	88.71	5.5
Burkina Faso	5.48	87.49	5.6
Angola	5.4	30.79	8.2
Mali	5.18	66.46	8.6
Liberia	4.52	41.27	9.9
Tanzania	4.13	35.95	8.4
Sierra Leone	3.95	66.34	8.7
Gambia	3.64	49.09	10.3
Congo (Brazzaville)	2.97	35.17	9.6
Mauritius	2.93	96.77	10.8
Mauritania	2.8	37.49	12.7

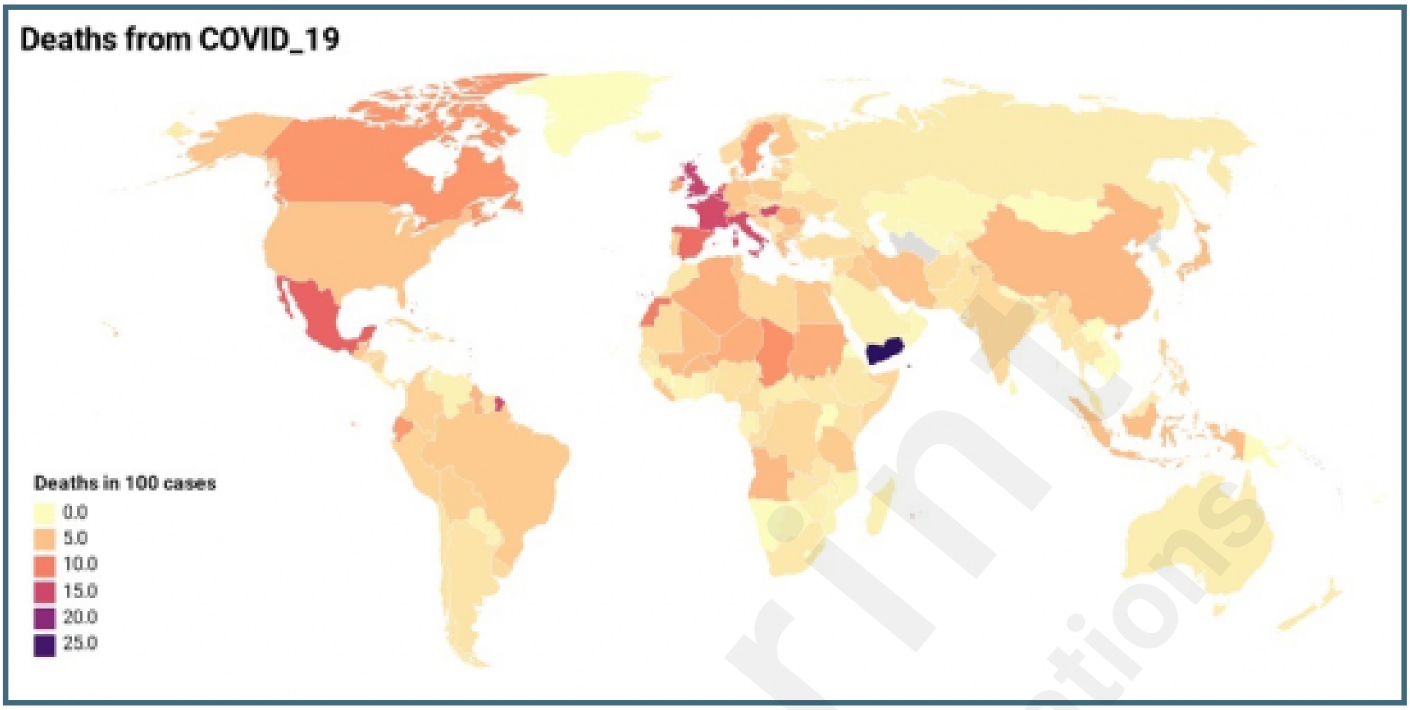

Cameroon 2.49 80.21 11.4
Congo (Kinshasa) 2.45 32.23 6.7
Comoros 2.31 66.01 7.8
Nigeria 2.27 39.84 8.9
Kenya 2.19 30.38 7.1
Togo 2.1 63.57 8.4
South Sudan 1.88 16.48 6.6
Zambia 1.84 82.6 8.1
Sao Tome and Principe 1.81 36.26 12.4
Ethiopia 1.76 41.57 4.5
Benin 1.75 27.77 9.6
Senegal 1.72 65.2 8.8
South Africa 1.69 48.79 28.3
Equatorial Guinea 1.66 27.42 8
Guinea-Bissau 1.45 19.17 9.5
Eswatini 1.26 51.78 16.5
Central African Republic 1.24 21.38 7.5
Malawi 1.19 20.19 5.8
Cabo Verde 1.15 48.35 11.8
Zimbabwe 1.13 28.04 15.5
Madagascar 1 43.28 5.3
Gabon 0.76 45.49 15
Cote d'Ivoire 0.68 46.64 9
Ghana 0.65 74.72 10.9
Mozambique 0.65 0 7.2
Guinea 0.61 80.59 7.7
Burundi 0.59 67.65 5.4
Botswana 0.44 12.33 18.9
Rwanda 0.28 46.38 5.8
Eritrea 0 26.05 5
Lesotho 0 31.43 16.6
Namibia 0 8.19 17.2
Seychelles 0 13.58 14
Uganda 0 93.9 5.3
Americas
Deaths / 100 Cases
Recovered / 100 Cases
Obesity rate%
Mexico 12.24 77.04 28.9
Bahamas 10.58 85.58 31.6
Canada 8.16 0 29.4
Ecuador 7.8 47.14 19.9
Barbados 7.22 92.78 23.1
Belize 7.14 64.29 24.1
Trinidad and Tobago 6.15 88.46 18.6
Guyana 5.6 46.8 20.2
US 4.7 28.54 36.2
Antigua and Barbuda 4.35 33.33 18.9
Guatemala 4.2 16.34 21.2
Brazil 4.13 63.98 22.1


Cuba 3.65 94.39 24.6
Bolivia 3.58 29.15 20.2
Colombia 3.57 42.52 22.3
Peru 3.44 62.36 19.7
Nicaragua 3.29 49.15 23.7
Uruguay 2.96 87.43 27.9
Honduras 2.8 10.37 21.4
El Salvador 2.73 58.79 24.6
Suriname 2.38 46.07 26.4
Dominican Republic 2.24 53.05 27.8
Chile 2.08 87.6 28
Argentina 1.98 34.58 28.3
Panama 1.89 46.67 22.7
Haiti 1.8 18.7 22.7
Jamaica 1.4 78.32 24.7
Venezuela 0.91 33.48 25.6
Paraguay 0.83 48.11 20.3
Costa Rica 0.45 39.5 25.7
Dominica 0 100 27.9
Grenada 0 100 21.3
Saint Kitts and Nevis 0 100 22.9
Saint Lucia 0 100 19.7
Saint Vincent and the Grenadines 0 100 23.7
Western Pacific
Deaths / 100 Cases
Recovered / 100 Cases
Obesity rate%
China 5.47 93.91 6.2
Japan 5.13 87.19 4.3
Philippines 3.28 27.5 6.4
South Korea 2.17 90.68 4.7
Brunei 2.13 97.87 14.1
Taiwan* 1.56 97.77
New Zealand 1.44 97.39 30.8
Malaysia 1.4 97.62 15.6
Australia 1.29 88.4 29
Singapore 0.06 88.98 6.1
Cambodia 0 92.91 3.9
Fiji 0 100 30.2
Laos 0 100 5.3
Mongolia 0 81.36 20.6
Papua New Guinea 0 72.73 21.3
Vietnam 0 95.77 2.1
South-East Asia
Deaths / 100 Cases
Recovered / 100 Cases
Obesity rate%
Indonesia 5.03 44.9 6.9
India 2.91 60.73 3.9
Burma 1.97 73.36
Thailand 1.82 96.23 10
Bangladesh 1.26 43.35 3.6
Sri Lanka 0.53 88.43 5.2
Maldives 0.42 82.04 8.6
Nepal 0.21 36.64 4.1
Bhutan 0 64.94 6.4
Timor-Leste 0 0 3.8

Supplementary Files

Figures

World map related to the number of deaths in 100 cases of COVID_19 by July 3, 2020.



Bivariate Pearson correlation between nutrition categories (plus obesity) and the number of deaths and number of recovers in 100 cases with COVID_19.

Categories (Protein)	Deaths / 100 Cases	Recovered / 100 Cases
Alcoholic Beverages	-0.008	0.029
Animal fats	0.082	-0.094
Animal Products	0.119	-0.058
Aquatic Products, Other	-0.060	-0.049
Cereals - Excluding Beer	-0.107	0.068
Eggs	0.009	0.090
Fish, Seafood	0.045	0.022
Fruits - Excluding Wine	-0.013	-0.080
Meat	0.151	-0.037
Milk - Excluding Butter	0.057	-0.001
Miscellaneous	0.015	-0.096
Offals	0.032	0.075
Oilcrops	-0.020	-0.005
Pulses	-0.018	-0.063
Spices	-0.135	0.008
Starchy Roots	0.004	0.014
Stimulants	-0.055	0.010
Sugar & Sweeteners	0.136	-0.114
Sugar Crops	0.080	-0.125
Treenuts	-0.119	0.055
Vegetable Oils	-0.039	-0.009
Vegetables	0.143	0.037
Vegetal Products	0.140	-0.061
Obesity	0.067	-0.011

Categories (Fat)	Deaths / 100 Cases	Recovered / 100 Cases
Alcoholic Beverages	-0.052	-0.063
Animal fats	0.040	-0.015
Animal Products	0.056	-0.040
Aquatic Products, Other	-0.046	-0.028
Cereals - Excluding Beer	-0.078	0.106
Eggs	-0.043	0.052
Fish, Seafood	0.004	-0.025
Fruits - Excluding Wine	-0.031	0.019
Meat	0.095	0.006
Milk - Excluding Butter	-0.029	-0.091
Miscellaneous	0.119	-0.003
Offals	0.010	-0.017
Oilcrops	-0.008	0.078
Pulses	-0.040	0.041
Spices	-0.043	-0.087
Starchy Roots	-0.130	0.028
Stimulants	-0.050	0.109
Sugar & Sweeteners	0.151	-0.061
Sugar Crops	-0.101	0.036
Treenuts	0.101	-0.112
Vegetable Oils	-0.014	-0.045
Vegetables	-0.106	-0.063
Vegetal Products	-0.056	0.040
Obesity	0.067	-0.011

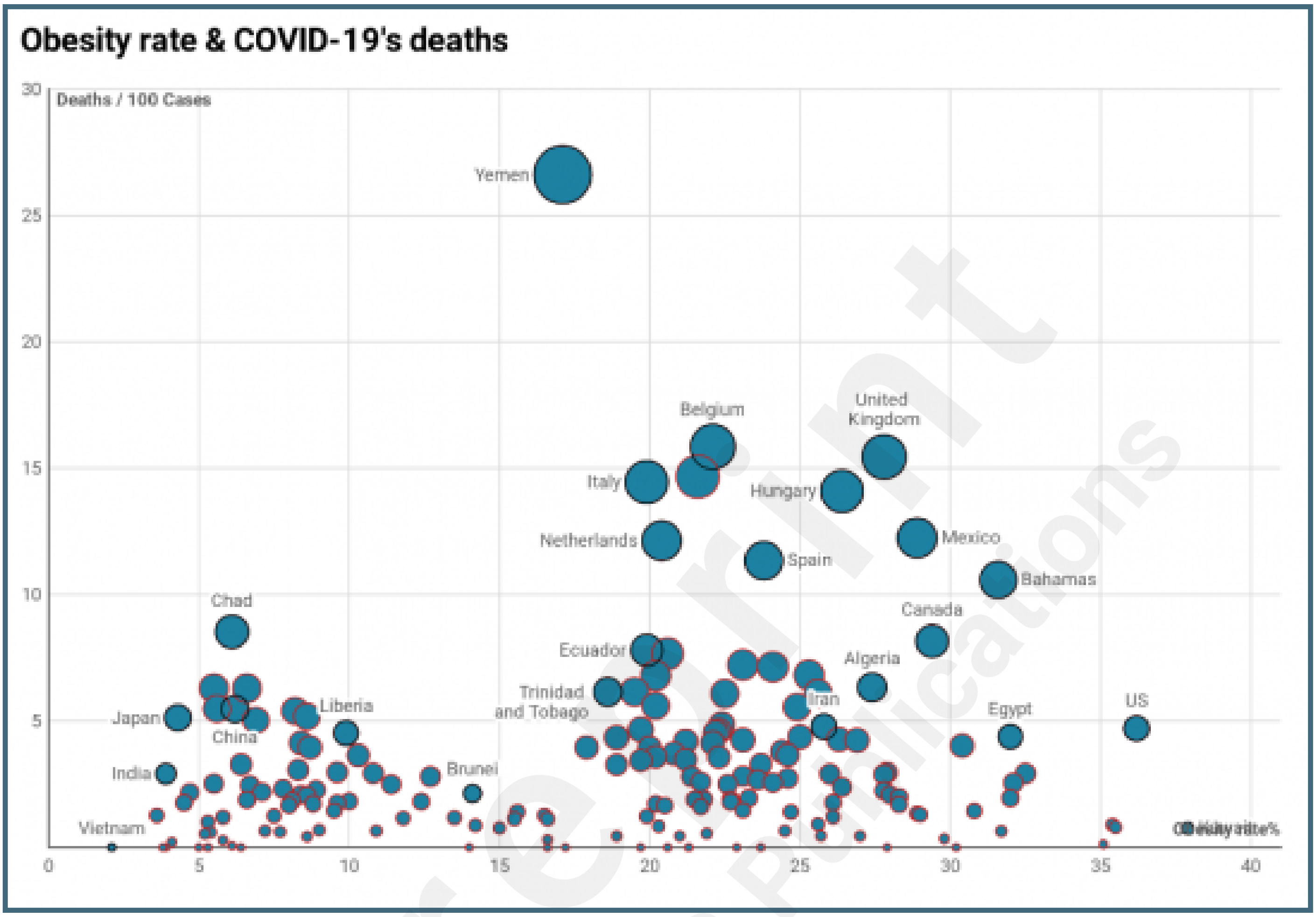
Categories (Protein)	Deaths / 100 Cases
Spices	-0.135
Treenuts	-0.119
Cereals - Excluding Beer	-0.107
Aquatic Products, Other	-0.060
Stimulants	-0.055
Vegetable Oils	-0.039
Oilcrops	-0.020
Pulses	-0.018
Fruits - Excluding Wine	-0.013
Alcoholic Beverages	-0.008
Starchy Roots	0.004
Eggs	0.009
Miscellaneous	0.015
Offals	0.032
Fish, Seafood	0.045
Milk - Excluding Butter	0.057
Obesity	0.067
Sugar Crops	0.080
Animal fats	0.082
Animal Products	0.119
Sugar & Sweeteners	0.136
Vegetal Products	0.140
Vegetables	0.143
Meat	0.151

Categories (Protein)	Recovered / 100 Cases
Sugar Crops	-0.125
Sugar & Sweeteners	-0.114
Miscellaneous	-0.096
Animal fats	-0.094
Fruits - Excluding Wine	-0.080
Pulses	-0.063
Vegetal Products	-0.061
Animal Products	-0.058
Aquatic Products, Other	-0.049
Meat	-0.037
Obesity	-0.011
Vegetable Oils	-0.009
Oilcrops	-0.005
Milk - Excluding Butter	-0.001
Spices	0.008
Stimulants	0.010
Starchy Roots	0.014
Fish, Seafood	0.022
Alcoholic Beverages	0.029
Vegetables	0.037
Treenuts	0.055
Cereals - Excluding Beer	0.068
Offals	0.075
Eggs	0.090

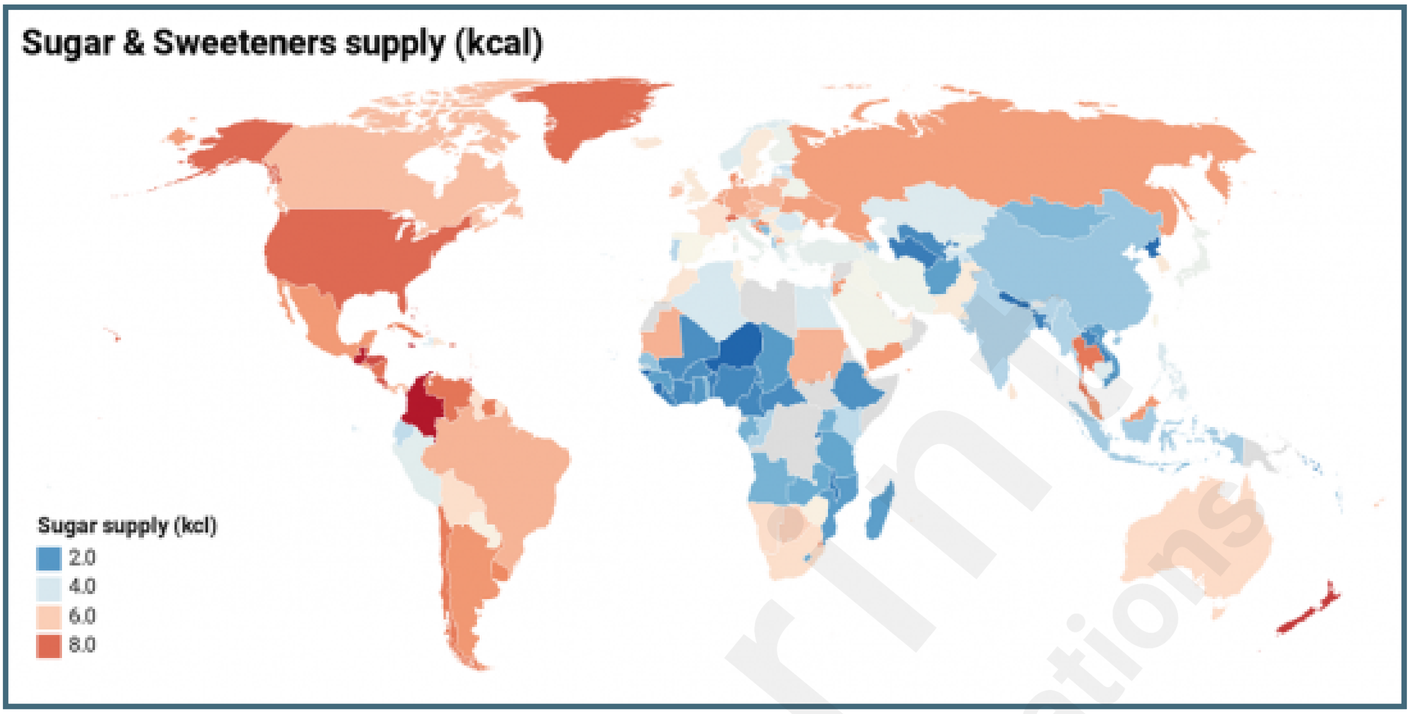
Categories (Fat)	Deaths / 100 Cases
Starchy Roots	-0.130
Vegetables	-0.106
Sugar Crops	-0.101
Cereals - Excluding Beer	-0.078
Vegetal Products	-0.056
Alcoholic Beverages	-0.052
Stimulants	-0.050
Aquatic Products, Other	-0.046
Eggs	-0.043
Spices	-0.043
Pulses	-0.040
Fruits - Excluding Wine	-0.031
Milk - Excluding Butter	-0.029
Vegetable Oils	-0.014
Oilcrops	-0.008
Fish, Seafood	0.004
Offals	0.010
Animal fats	0.040
Animal Products	0.056
Obesity	0.067
Meat	0.095
Treenuts	0.101
Miscellaneous	0.119
Sugar & Sweeteners	0.151

Categories (Fat)	Recovered / 100 Cases
Treenuts	-0.112
Milk - Excluding Butter	-0.091
Spices	-0.087
Alcoholic Beverages	-0.063
Vegetables	-0.063
Sugar & Sweeteners	-0.061
Vegetable Oils	-0.045
Animal Products	-0.040
Aquatic Products, Other	-0.028
Fish, Seafood	-0.025
Offals	-0.017
Animal fats	-0.015
Obesity	-0.011
Miscellaneous	-0.003
Meat	0.006
Fruits - Excluding Wine	0.019
Starchy Roots	0.028
Sugar Crops	0.036
Vegetal Products	0.040
Pulses	0.041
Eggs	0.052
Oilcrops	0.078
Cereals - Excluding Beer	0.106
Stimulants	0.109

Scatter plot of Obesity rate and Deaths / 100 cases of COVID_19 by countries. Circle's size related to the number of deaths/ 100 cases.



World map related to Sugar & Sweeteners supply (kcal).



Multimedia Appendixes

Geographical distribution of the six WHO regions and member states for each region (alphabetical order).
URL: https://asset.jmir.pub/assets/d4ab494c6e0bcacfb8117b7e111552bf.png

The specific types of food that belongs to each category for the fat quantity and protein datasets.
URL: https://asset.jmir.pub/assets/d5fe2b56875111413021fdbcf28cf01e.docx

Number of deaths/100 cases, number of recovered/100 cases, and Obesity rats until July 3, 2020, by countries and split by WHO regions.
URL: https://asset.jmir.pub/assets/18b124b2d095bbe36df7b29da51b11f5.docx