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# Spatial and Temporal Correlations of COVID-19 Mortality in Europe with Atmospheric Cloudiness and Solar Radiation

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## Abstract

Previous studies reported the links between the COVID-19 incidence and weather factors, but few investigated their impact and timing on mortality, at a continental scale. We systematically investigated the temporal relationship of COVID-19 mortality in the European countries in the 1st year of pandemic (March–December 2020) with (i) solar insolation ( $W/m^2$ ) at the ground level and (ii) objective sky cloudiness (as decimal cloud fraction), both derived from satellite measurements. We checked the correlations of these factors within a sliding window of two months for the whole period. Linear-mixed effect modeling revealed that overall, for the European countries (adjusted for latitude), COVID-19 mortality was substantially negatively correlated with solar insolation in the previous month (std. beta  $-0.69$ ). Separately, mortality was significantly correlated with the cloudiness in both the previous month (std. beta  $+0.14$ ) and the respective month (std. beta  $+0.32$ ). This time gap of  $\sim 1$  month between the COVID-19 mortality and correlated weather factors was previously unreported. The long-term monitoring of these factors might be important for epidemiological policy decisions especially in the initial period of potential future pandemics when effective medical treatment might not yet be available.

**Keywords:** COVID-19; mortality; solar insolation; cloudiness; latitude; temporal correlation; spatial correlation; satellite data; Europe



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## 1. Introduction

The COVID-19 (coronavirus disease 2019) pandemic, produced by SARS-CoV-2 virus (severe acute respiratory syndrome) has had a significant impact on global health, with millions of people affected by its quick spread. In the initial year of the pandemic (2019–2020) effective countermeasures were not yet available (vaccination, antiviral therapy) and the environmental factors that influenced viral transmission and mortality were intensely debated. If unimpeded by countermeasures, the coronaviruses (and other similar respiratory viruses) spread in the population is influenced by a combination of medical, biological, socio-economic and environmental factors. These environmental factors that might influence the spread and impact of COVID-19 have been then extensively researched (temperature, humidity, season, wind, atmospheric composition, precipitation, dew point and other climate factors) sometimes with mixed results [1–8]. Additionally, it has also been

observed that latitude is a significant factor that modulates the COVID-19 spread dynamics in population [2,9]. This might be due to either UV intensity variation with latitude [10] or the temperature variation with latitude [11,12]. At the same time, other studies argue against the effect of temperature, and focus instead on the effect of vitamin D synthesis variation with latitude [13].

It is known from previous laboratory measurements that SARS-CoV-2 virions are sensitive to light (proportional to the illuminance intensity of the light [14–19]); it seems that SARS-CoV-2 virions aerosolized from infected persons could remain infectious in outdoor settings for prolonged times during low illuminance periods (winter, autumn), posing a risk for re-aerosolization and reinfection [15].

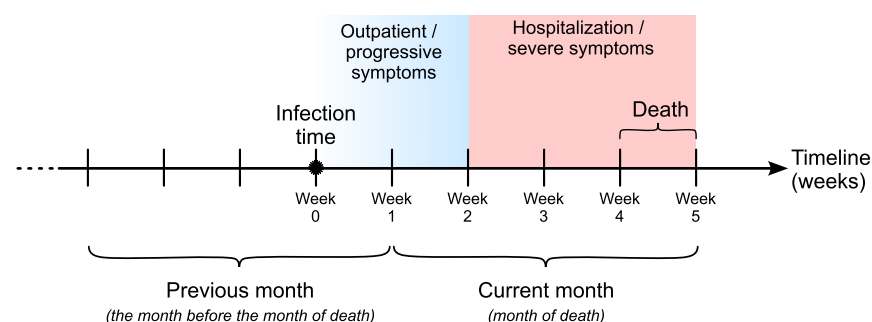
The solar radiation energy reaching earth (UV-B and UV-A at noon time during summers in temperate regions) is highly effective in inactivating SARS-CoV-2 virions [20,21]. The UV component of sunlight could be an additional factor that influences seasonal variations of COVID-19 epidemic (leading to a lower incidence during summertime) [22] among many other investigated meteorological factors (temperature, humidity, wind, precipitation, pollutants) [5,23]. The relationship between meteorological factors and various COVID-19 epidemiological characteristics was extensively investigated [3,5,24,25], but there are still many unknowns about the environmental drivers of transmission and infection [26,27].

These findings indicate a complex relationship between the SARS-CoV-2 virion inactivation by natural sunlight and the factors that modulate the sunlight intensity: latitude, season, and factors that influence optical properties of the atmosphere. Among these, extensive studies were performed, with mixed results, for instance for gases [24,28], natural and artificial pollutants [29], fog, haze and particulate matter [30,31].

There seems to be a mismatch between the laboratory results of sunlight inactivation and theoretical estimates based on photo-chemical reactions (i.e., virions are inactivated several times faster than predicted by theory) [32]. Proposed hypotheses for this finding were: (a) the virions' sensitivity to broader light spectrum (UV-A and natural blue light might additionally impair the virions) [15,32,33], (b) the presence of naturally occurring photo-sensitizer molecules in the medium (water droplets interacting with humic acids from soil or waste dust) [32,34].

As presented, the meteorological influence on COVID-19 *prevalence* or *incidence* (i.e., new cases over a period in a region, or the rate of new cases) was extensively researched; there are comparatively fewer studies and reviews on the meteorological influence on *mortality* [10,35,36].

From a temporal perspective, it is known that in the natural course of the COVID-19 disease, there is a median lag of 2 weeks between the infection time and development of severe symptoms/hospitalization; and in the fatal cases, there is an additional median time of 2–3 weeks between hospitalization and death [37–40]. Therefore, in the majority of the fatal cases, the infection occurred in the month prior to the date of death, see Figure 1.



**Figure 1.** Timeline of the study. By “Current month” we denote the month of death due to COVID-19 in fatal cases; by “Previous month” we denote the month before the month of death.

Therefore we put forth the hypothesis that because of this temporal lag, there should be a correlation between COVID-19 *mortality* in a given month and the meteorological factors in the previous month in the same geographical area; more specifically:

(a) given the light sensitivity of the Sars-CoV-2 virions, we hypothesize that if the solar insolation is higher in a month, this should correlate with a decreased mortality in the following month;

(b) however, given the fact the light–virion interaction is modulated by water droplets and air contaminants [32,34], we hypothesize that there should be a linked dynamics between the mortality and atmospheric cloudiness, as a proxy for both humidity [41] and atmospheric contaminants [42,43]. To the best of our knowledge, this temporal link of cloudiness and mortality was not investigated up to now.

A complication arises because of cross-interactions: solar irradiance at ground level is heavily influenced by the atmospheric composition, primarily by clouds [44] and only secondarily by other factors such as dust, pollutants, and humidity [45]. Clouds exert a complex influence: by reflection of the sunlight (back into space) they reduce the amount of total energy that reaches the earth but by scattering they can counter-intuitively direct some of the energy back to land, especially in the UV portion of the spectrum, thus modulating the biologically effective radiation dose received by living things [46]. Because of this interaction, we took care to model them separately.

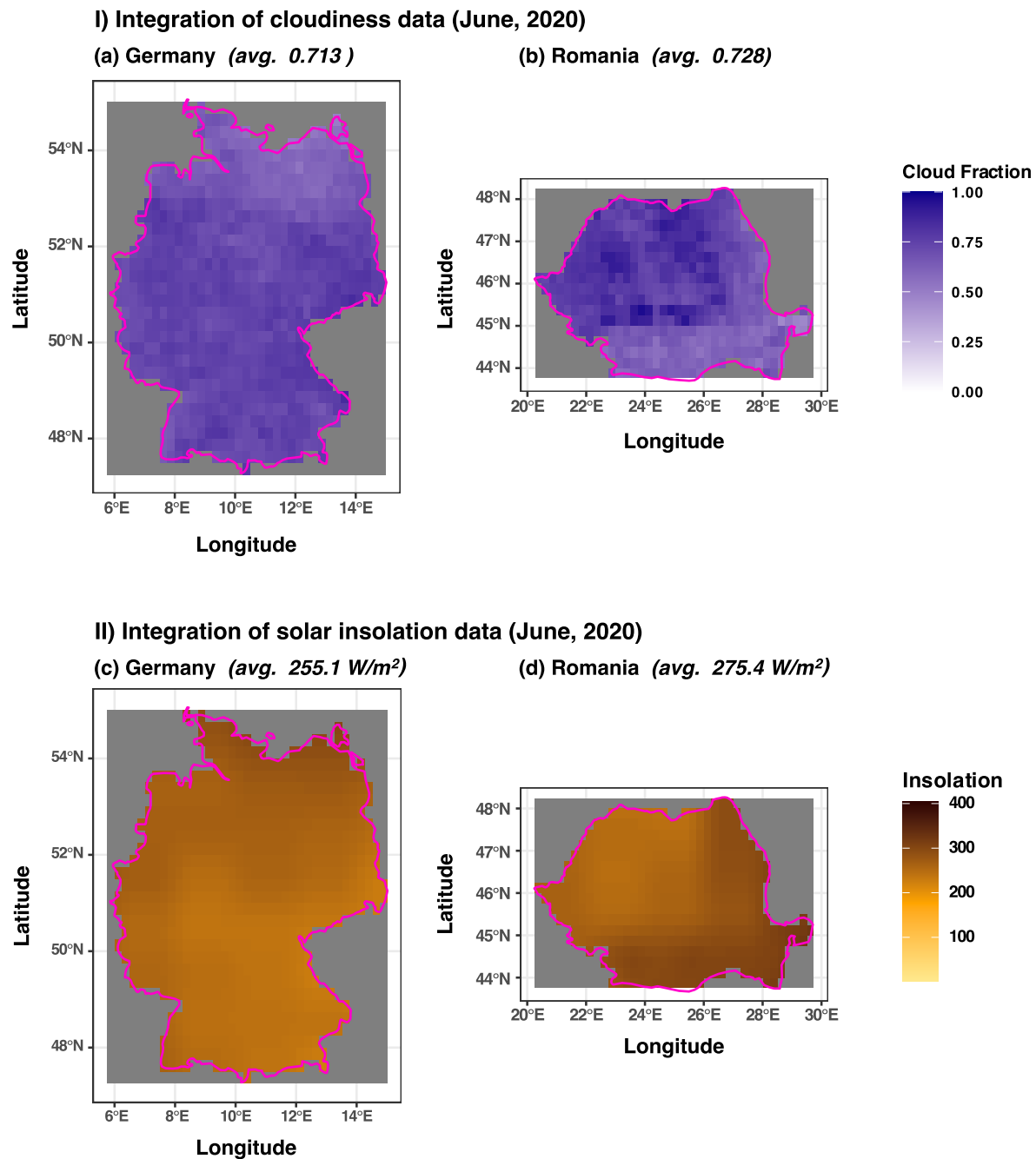
To test these hypotheses, we made a retrospective observational longitudinal study at the continental scale, where the units of observation were the European countries (landmass), the time points were the months of the year 2020, the outcome variable was the COVID-19 mortality in each month and the investigated (possible explanatory) variables were: (a) the satellite–measured solar insolation at the ground level, (b) satellite–measured atmospheric cloudiness (cloud covering), (c) latitude and (d) longitude. We investigated these factors in dynamic (in any given month and with a lag of 1 month relative to the investigated month).

## 2. Materials and Methods

### 2.1. Geographical Data

Geographical data and the administrative boundaries of the countries were retrieved from the public domain repository *Natural Earth* [47] and processed within R version 4.5 [48] with R software packages: *rnaturalearth* [49], *sp* [50,51], *sf* [52], *stars* [53] and *raster* [54]. For this study we set the units of the analysis to be the countries as a whole (i.e., not smaller administrative units). From this dataset, for each country we extracted: (a) the country border (see the magenta lines in Figure 2) and (b) the surface area location and size in a rectangular tiled grid with a fairly detailed resolution of  $0.25^\circ$  latitude  $\times$   $0.25^\circ$  longitude. We ensured that the other geographical datasets that we used in this study matched the same spatial resolution. The marginal tiles (i.e., at the border of the country, peninsulas or small islands) were included only if more than 50% of the area of a tile was inside the country border. This integration algorithm ensures that there are no overlapped nor missed tiles (i.e. each tile can belong to a single country) and results in polygonal surfaces with  $0.25^\circ$  latitude  $\times$   $0.25^\circ$  longitude resolution, that optimally cover the countries at this resolution (Figure 2).

Since latitude is a fixed factor that modulated the COVID-19 pandemic dynamics (see Introduction) we carefully included it in our modeling and adjusted the other factors for it.



**Figure 2.** Two examples of the spatial integration algorithm used at the country level, in the same month. (I) Upper panels: cloudiness maps, with cloudiness values (in decimal cloud fraction) for each  $0.25^\circ$  latitude  $\times$   $0.25^\circ$  longitude grid. (II) Bottom panels, insolation maps of the same countries as above, with insolation values (W/m<sup>2</sup>) for the same grid; magenta lines: border of the respective countries, Germany (a,c) and Romania (b,d). The average value of all tiles within a border represent the average value for the country in that month (in this example, June, 2020).

In order to analyze the latitude and the longitude at the country level (the “latitude of a country” and the “longitude of a country” variables), we chose to use in this study the *country centroid*. A centroid (also known as the center of gravity or center of mass) is the arithmetic mean of the positions of all the points in a geometrical object; for irregular objects, it is closest to the center of the biggest part of the object (i.e., it is less influenced by very thin or heavily scattered boundaries). We chose this measure because several countries have highly irregular geometrical boundaries or long thin peninsulas or numerous islands (i.e., Greece, Norway, etc.); the advantage of the country centroid is that it is located closer

to the widest area of the mainland. We used a standard database of countries' centroids published by *Google Maps* developers [55].

As a verification step, centroids and borders of the countries were laid also on a different digital mapping provider, *OpenStreetMaps* [56] and the overlapping was checked visually; no issues were found. The projection used in this study was the Spherical Pseudo-Mercator Projection (also known as Web Mercator; European Petroleum Survey Group (EPSG) identifier EPSG:3857), which is commonly used by Google Maps Developers [55] and by OpenStreetMaps [56].

## 2.2. Atmospheric Cloudiness Data

Cloudiness (also known as cloud fraction, cloud cover, cloud amount or sky cover) refers to the fraction of the sky obscured by clouds (in a particular location). It can be reported in various units; in this study, we used the decimal cloud fraction (as tenths of the entire sky), where 0.0 indicates a clear sky and 1.0 (or 10/10) indicates a completely covered sky.

We used a publicly available dataset of global cloudiness as measured from space by NASA's Terra and Aqua satellites using the *MODIS* instrument (Moderate Resolution Imaging Spectroradiometer) [57]. This dataset is collected continuously and presented as values averaged daily, weekly and monthly for the entire globe; for this study we chose the monthly averaged values. In this dataset the entire Earth surface is divided into a rectangular grid; each rectangle of the grid contains the average cloud fraction of the sky covering that grid area. The datasets are available at different resolutions, and we used for this study the grid with  $0.25^\circ$  latitude  $\times$   $0.25^\circ$  longitude resolution (as the rest of the datasets used).

For each country and each month of the year 2020 we have extracted the cloudiness values for all tiles within the borders of a given country and averaged them; thus we calculated an "averaged cloudiness for a country" in a given month. For example, see Figure 2 top panel (I) as a visualization of the process for two randomly chosen countries, Germany and Romania. In the month of June 2020 the obtained average cloudiness for Germany was 0.713 (Figure 2a) and for Romania, it was 0.728 (Figure 2b). As a side note, the temporal resolution seems to be detailed enough to observe consistent variations in cloudiness patterns over the surface of the countries—for instance in Figure 2b there is a higher cloudiness that matches the Carpathian mountains arching in the middle of the country.

As a convenience for the reader we included a quick visual overview of these aggregated results in Appendix A.1, for all European countries, for each month of the year, Figure A1.

## 2.3. Solar Insolation Data

The average solar insolation (also known as solar irradiance, solar exposure, incoming sunlight) in  $\text{W}/\text{m}^2$  at the Earth's surface was used in this study. Solar irradiance is one of the main factors that determine the temperature at ground level (with an almost linear dependence [58]), and the climate in general [59]. We used a publicly available dataset inferred from measurements taken by Clouds and Earth's Radiant Energy System (CERES) instrument flying aboard NASA's Terra and Aqua satellites [60]. We used the same temporal and spatial sampling as presented above (Section 2.2), i.e., monthly averaged values over a  $0.25^\circ$  latitude  $\times$   $0.25^\circ$  longitude grid.

We repeated the same algorithm (as used for cloudiness data): for each country and each month of the year 2020 we extracted the solar insolation values for all tiles within the borders of a given country and averaged them; thus we calculated an "averaged insolation

for a country” in a given month. For a visual example of the process see Figure 2, bottom panel (II): for Germany, the average insolation calculated for the month of June 2020 was 255.1 W/m<sup>2</sup> (Figure 2c) and for Romania it was 275 W/m<sup>2</sup> (Figure 2d). The overview of these aggregated results for all countries is presented in Appendix A.2, Figure A2.

#### 2.4. Epidemiological Data (COVID-19 Data Sources)

Different epidemiological variables about COVID-19 epidemics were collected and reported around the world and summarized in various ways (academic institutions, national health bodies, media sites, public data repositories, etc.) in an effort to promote effective research and public understanding of the phenomenon. However, despite the best intentions of the authors, errors and inconsistencies appeared in COVID-19 epidemiological data due to the difficulty of aggregating [61], collecting [62–64], compiling [65] and interpreting conflicting estimates [66,67].

A further complication was the fact that the publicly reported data was sometimes revised retrospectively by the health authorities, as updated epidemiological procedures methods were devised [68] and initial studies (in years 2020–2022) might have inadvertently used out-of-date epidemiological datasets. In order to mitigate these concerns, in this study we used a public data source, *COVID-19 Data Hub* [69] that provides immutable snapshots of the data, taken daily, which are provided to ensure reproducible research. Thus, this database provides the daily time-series of COVID-19 cases, deaths, recovered people, tests, vaccinations, and hospitalizations, for more than 230 countries and their lower-level administrative divisions [69].

From this database we selected the daily confirmed death counts at the country level, within the limits of the entire year 2020 (start date: 1 January 2020, end date: 31 December 2020). The access time was February 13, 2025 (this is the snapshot date); being a late snapshot, it includes the retrospective corrections of the epidemiological data [68]. From the reported daily deaths counts we calculated the *total monthly deaths* for each country, via two different methods (to independently cross-check for possible errors): (a) method 1: total monthly deaths as a sum of the death cases reported in each day of a given month; (b) method 2: total monthly deaths as the difference between the cumulative deaths reported in the last day of each month and the last day of the previous month. The two value sets agreed; (we performed this intermediary check because in a preliminary analysis that we performed with *Worldometer* [70] public data set we have spotted inconsistencies between the results of the two methods).

We then calculated *monthly mortality per million* due to COVID-19 for each country in a month as  $(\text{total monthly deaths} / \text{average country population}) \times 10^6$ . The average country population number was the average for the entire year 2020.

We chose to use the mortality parameter because it seems to be less variable than the incidence. Mortality is usually recorded using a fixed legal procedure and reported by the same personnel (coroners, hospital doctors, etc.). The incidence reports could include self-reports from self-testing, field reports; or the procedures for testing could not always be reliably repeated (especially in the beginning of the pandemic when some countries experienced shortages in supply with testing kits or dealt with sudden changes of testing policies).

There are two issues with this approach that might impact our study. First, there are legal and practical differences among countries regarding death recording and reporting [71]. The COVID-19 database we used records the deaths as reported by local authorities; we could not quantitatively assess the differences between the countries, which could impact comparison of different countries. Second, the time lag between the actual death and the

reported time could be different for each case; we think that the monthly intervals we chose for analysis probably averaged most of the differences.

## 2.5. Inclusion and Exclusion Criteria

The inclusion criteria were as follows: (a) all countries on the European continent; (b) availability of epidemiological and geographical (cloudiness, insolation) data.

The exclusion criteria were as follows: (a) country population < 0.5 million and (b) a geographical bounding box of the countries (or islands or peninsulas) smaller than  $0.25^\circ$  latitude  $\times$   $0.25^\circ$  longitude. We used these criteria because the European micro-states (Monaco, Vatican, San Marino, etc.) were too small to be properly sampled from the available resolution of geospatial data (insolation, cloudiness). Russia was also excluded from analysis because the COVID-19 epidemiological data from the country was publicly available only in an aggregate form (i.e., no data were available detailing the epidemiology in European and Asian parts of Russia; in this study we focused on the Europe landmass).

In this way we obtained a list of 37 European countries (listed alphabetically): *Albania, Austria, Belarus, Belgium, Bosnia and Herzegovina* (abbreviated as *Bosnia\_and\_H* in the graphics), *Bulgaria, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Latvia, Lithuania, Luxembourg, Malta, Moldova, Montenegro, Netherlands, North Macedonia, Norway, Poland, Portugal, Romania, Serbia, Slovakia, Slovenia, Spain, Sweden, Switzerland, United Kingdom* (abbreviated as *UK* in the graphics) and *Ukraine*.

## 2.6. Statistics

### 2.6.1. Variables

For each one of the 37 countries we included in the analysis the following variables:

- (i) calculated *COVID-19 monthly mortality* (deaths per 1 million population) in each month;
- (ii) *time*, as monthly interval (each one of the 10 months in the studied interval (March–December 2020));
- (iii) calculated *monthly insolation value* (averaged solar radiation for each month across the country);
- (iv) calculated *monthly cloud fraction* (averaged decimal cloud fraction);
- (v) the latitude and longitude of the countries (centroid data).

For these variables we thus aggregated a total of 1850 data-points from the datasets; from these, 1110 were independent (latitude and longitude are dependent on the country). In order to ensure reproducible analysis, we have included these data points and the intermediary steps as an open-access dataset (see *Data Availability Statement* at the end).

### 2.6.2. Data Verification and Transformation

For each continuous variable included in the analysis, we calculated the descriptive statistics and visually checked the data distribution with histogram (density) plots and quantile–quantile (QQ) plots and formally with Lilliefors–corrected Kolmogorov–Smirnov test for larger samples ( $n > 30$ ) and for the sub-sets with Shapiro–Wilk normality test for smaller samples (where  $n \leq 30$ ) [72,73].

In the cases of variables where data distribution was found to be non-normal we attempted to linearize the data set, with the formal goal of approximating a normal distribution through reducing the skewness of non-normal data [74,75]. For this dataset we explored several procedures for data transformation: log–transform, log1p–transform, cube–root transform and Box–Cox transform [76,77]). As the mortality data contained a very broad range of values, including very small and zero, we used the standard *log1p* [78] function included in the *R* language to avoid computation singularities or rounding errors;

the function  $\log1p(x)$  computes  $\log(1 + x)$  accurately for  $|x| \ll 1$ . To back transform we used its inverse function,  $\exp1m(x)$  that computes  $\exp(x) - 1$  accurately also for  $|x| \ll 1$ .

Data analysis was performed with R [48] version 4.5, with the additional packages: *lme4* (version 1.1-37) [79], *ggeffects* [80], *ggplot2* [81], *emmeans* [82], *effectsize* [83], *lmttest* [84], *report* [85], *rstatix* [86], *stargazer* [87], *sjPlot* [88], *tidyverse* [89] and *car* [90].

## 2.7. Modeling

The main starting hypothesis of this study is that there might be a temporal correlation between the variation in COVID-19 mortality and the sky cloudiness or insolation (adjusted for latitude), in the first year of the pandemic (before vaccination was available).

For this retrospective longitudinal study we chose two types of models: (1) linear mixed effects (to analyze all longitudinal data series) and (2) classic linear regression (on averaged data set). The former can capture discrete effects but are harder to interpret; the latter are less precise (due to averaging) but were chosen as they are more easily interpreted [91,92]. We also used the two different modeling techniques as a way to independently check the validity of the results.

In both modeling techniques we extensively checked for temporal autocorrelation structures (as there are previous reports of temporal features of other meteorological factors influencing COVID-19 epidemics [31]). As another validity check, in order to avoid possible multicollinearity interactions between insolation and cloudiness, we did not include both variables (solar insolation and cloudiness) in the same model at the same time (i.e., we modeled them separately and compared the results).

### 2.7.1. Linear Mixed-Effects

We used linear mixed-effects modeling (LME) [93] to explore the association between the monthly COVID-19 mortality (outcome variable) and the rest of variables included in the analysis, and in all models we included Country as the random effect variable.

We took a conservative approach in LME modeling [91] and as such: we kept the models as simple as possible (as few parameters and transformations as possible to avoid over-fitting); we compared diverse models using AIC (Akaike information criterion) and BIC (Bayesian information criterion) measures; we report the full model parameters and tests done (in Appendix, in order not to clutter the main text). To aid understanding, we depicted the models graphically and reported  $R^2$ . For mixed-effects models,  $R^2$  can be categorized loosely into two types: marginal  $R^2$  and conditional  $R^2$ . The marginal  $R^2$  is concerned with variance explained by the fixed factors of the model, and conditional  $R^2$  is concerned with variance explained by both fixed and random factors (i.e., by the whole model) [94]. For clarity, in this paper we will note the marginal as  $R_m^2$  and the conditional as  $R_c^2$ . LME models were calculated with *lme4* [79], using the same default settings proposed by its authors—the fitting was done with restricted maximum likelihood (REML) option, using “nloptwrap” (nonlinear optimization) settings. In order to facilitate comparisons of the models and to judge the relative influence of the factors within the same model, we calculated and reported standardized parameters (standardized beta) [91,95]; these were obtained by fitting each model on a standardized version of the dataset. The 95% Confidence Intervals (CIs) and p-values were computed using a Wald t-distribution approximation. The effect sizes were qualitatively judged (as “small”, “moderate”, “substantial”) according to recommendations summarized by [83,96].

### 2.7.2. Linear Regression

Despite its simplicity, the key advantage of the simple linear regression is its easy intuitive understanding of the results.

In order to perform linear regression, we have averaged the data in time (time-averaged models) and separately, in space (space-averaged models). The fitting of the data was performed with the standard *lm* (linear model) included in *R* using default ordinary least squares (OLS) method.

### 2.7.3. Model Selection

Selection of the most likely predictor variable was done with bidirectional (forward and backward) step-wise multivariable regression [97]. Briefly, for each situation, we started with the full model (incorporating all included variables as the possible predictors) and then performed an automated stepwise regression eliminating redundant or low-impact variables from the models, thus selecting the most likely predictor variables. We used AIC and BIC as a quality indicator for each step in model selection; we selected the models with the lowest AIC and BIC scores.

We report here only the significant models that passed the following stringent validity tests: (a) normality of the residuals, (checked with QQ plots, Kolomogorov-Smirnov/Shapiro-Walk tests), (b) presence of outliers, (c) homogeneity of the variance of residuals (we assumed homoscedasticity if the result of the studentized Breusch-Pagan test was bigger than 0.05) and (d) autocorrelation of the residuals with a Durbin-Watson test (we considered that there is no autocorrelation in the residuals of a regression if at this test the *p*-values > 0.05 and the *d*-statistic values were in range 1.5 to 2.5). Additionally, we checked the interrelationships between the predictor variables (statistical collinearity) using the Variance Inflation Factor (VIF) statistic [98]. The temporal correlation between the predictor series was checked with Granger causality test [84,99].

The significance level of all statistics tests used in this paper was set at the typical 5%.

## 3. Results

### 3.1. Aggregated Data

For the described variables (country, time, mortality, insolation, cloudiness, latitude and longitude) we extracted 1850 aggregated data-points from the datasets. From these, 1110 were independent (latitude and longitude are dependent on the country); their statistical summary is shown in Table 1, and a quick visual overview is presented in the Appendix, see Figures A1–A3.

**Table 1.** The statistic summary of the main variables.

| Statistic                                       | N   | Median | Mean    | St.Dev  | Min  | Max    | Skewness |
|-------------------------------------------------|-----|--------|---------|---------|------|--------|----------|
| Monthly insolation<br>(as W/m <sup>2</sup> )    | 370 | 213.34 | 190.77  | 97.46   | 1.31 | 404.12 | −0.27    |
| Monthly cloud fraction<br>(as decimal fraction) | 370 | 0.64   | 0.62    | 0.17    | 0.07 | 0.96   | −0.55    |
| Monthly deaths                                  | 342 | 169    | 1515.23 | 3846.44 | 0    | 33,854 | 4.47     |
| Monthly mortality<br>( as deaths/million )      | 342 | 23.16  | 81.51   | 120.31  | 0    | 600.32 | 2.01     |
| log1p (deaths/million)                          | 342 | 3.18   | 3.29    | 1.64    | 0    | 6.40   | −0.03    |

The *monthly deaths* count and *mortality per million* (the outcome variable) show a severely right-skewed distribution (skewness = 4.47 and 2.01 respectively). Linearization was attempted on the data set, with the goal approaching a normal distribution through reducing the skewness [74,75]; the smallest skewness was achieved with *log1p*-transformation of the data (transformed data skewness = −0.032), see Appendix A.7, Figure A6.

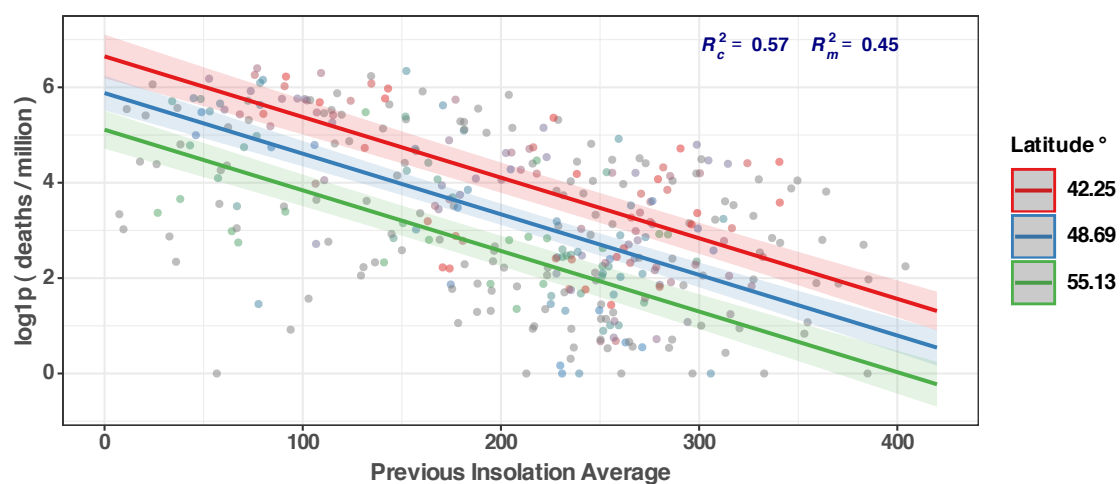
The *monthly insolation* data follows the expected typical annual cycle pattern [100] with a broad maximum during the months of May–July [101], see an overview in Figure A2.

The *monthly cloudiness* data for the year 2020 is more randomly distributed than the insolation data, with the highest variability in months of July–August, see Figure A1.

### 3.2. LME Modeling of Monthly Mortality and Insolation

Within the paradigm: “Atmospheric factors might influence the COVID-19 mortality” we tested the hypothesis “There might be a temporal correlation between the insolation and COVID-19 mortality”.

We investigated the response ( $\log_{10}$ -transformed mortality in a month) to possible explanatory variables: insolation in current month, insolation in previous month and geographical coordinates, using 6 linear mixed models that progressively included the explanatory variables and included Country as a random effect. We selected the final model (Figure 3) based on lowest AIC and BIC score.



**Figure 3.** LME model of monthly mortality and insolation in previous month (in  $\text{W}/\text{m}^2$ ), adjusted for latitude. The dots represent the individual  $\log_{10}$  transformed monthly mortality values from the European countries in the period March–December 2020. The regression model is adjusted for latitude of the countries (for visualization purposes, the figure shows the model at three equally partitioned latitudes). The shaded bands are the 95% CI.

The R formula used for this model:  $\log_{10}(\text{deaths}/\text{million}) \sim \text{Previous\_Insolation\_Average} + \text{Latitude} + (1|\text{Country})$ . The model included the Country as random effect (formula:  $\sim 1|\text{Country}$ ). The *Latitude* is the centroid latitude of the country. The model’s total explanatory power is substantial ( $R_c^2 = 0.57$ ) and the part related to the fixed effects alone is  $R_m^2 = 0.45$ . The model’s intercept, corresponding to  $\text{Previous\_Insolation\_Average} = 0$  and  $\text{Latitude} = 0$ , is at 11.69 (95% CI [9.89, 13.49],  $t(337) = 12.74$ ,  $p < 0.001$ ). Within this model:

- The effect of *Previous\_Insolation\_Average* (i.e., insolation in previous month, averaged for the whole country) is statistically significant and negative ( $\beta = -0.01$ , 95% CI  $[-0.01, -0.01]$ ,  $t(337) = -17.73$ ,  $p < 0.001$ ; Std. beta =  $-0.69$ , 95% CI  $[-0.76, -0.61]$ )
- The effect of *Latitude* is statistically significant and negative ( $\beta = -0.12$ , 95% CI  $[-0.15, -0.08]$ ,  $t(337) = -6.68$ ,  $p < 0.001$ ; Std. beta =  $-0.47$ , 95% CI  $[-0.60, -0.33]$ ). The full statistical details of the model are reported in Appendix A.4.

**Summary:** This statistically significant model ( $p < 0.001$ ) relates the COVID-19 mortality in any given month with the average country insolation in the previous month (adjusted for latitude), showing that the higher the solar radiation in the previous month, the lower the mortality in the following month (Figure 3). The model’s total explanatory power is

substantial ( $R_c^2 = 0.57$ ) and the part related to the fixed effects alone is  $R_m^2 = 0.45$ . Both previous insolation and latitude are significant predictors of the variability of the mortality; the previous month's insolation has the greatest relative influence (standardized beta =  $-0.69$ , see Figure 5a).

### 3.3. LME Modeling of Monthly Mortality and Cloudiness

Within the paradigm: “Atmospheric factors might influence the COVID-19 mortality” we tested the hypothesis “There might be a temporal correlation between the atmospheric cloudiness and COVID-19 mortality”. We investigated the response variable ( $\log_{10}$ -transformed mortality in a month) relationship to possible explanatory variables: sky cloudiness in current month, sky cloudiness in previous month and geographical coordinates, using 6 linear mixed models that progressively included the explanatory variables and included Country as a random effect. We selected the final model (Figure 4) based on the lowest AIC and BIC score.

The R formula used for this model:  $\log_{10}(\text{deaths}/\text{million}) \sim \text{Previous\_Cloud\_Fraction} + \text{Cloud\_Fraction} + \text{Latitude} + (1|\text{Country})$ . The model included the Country as random effect (formula:  $\sim 1|\text{Country}$ ). The *Latitude* is the centroid latitude of the country.

The model's total explanatory power is moderate ( $R_c^2 = 0.24$ ) and the part related to the fixed effects alone is  $R_m^2 = 0.16$ . The model's intercept, corresponding to *Previous\_Cloud\_Fraction* = 0, *Cloud\_Fraction* = 0 and *Latitude* = 0, is at 6.21 (95% CI [4.57, 7.85],  $t(336) = 7.45$ ,  $p < 0.001$ ). Within this model:

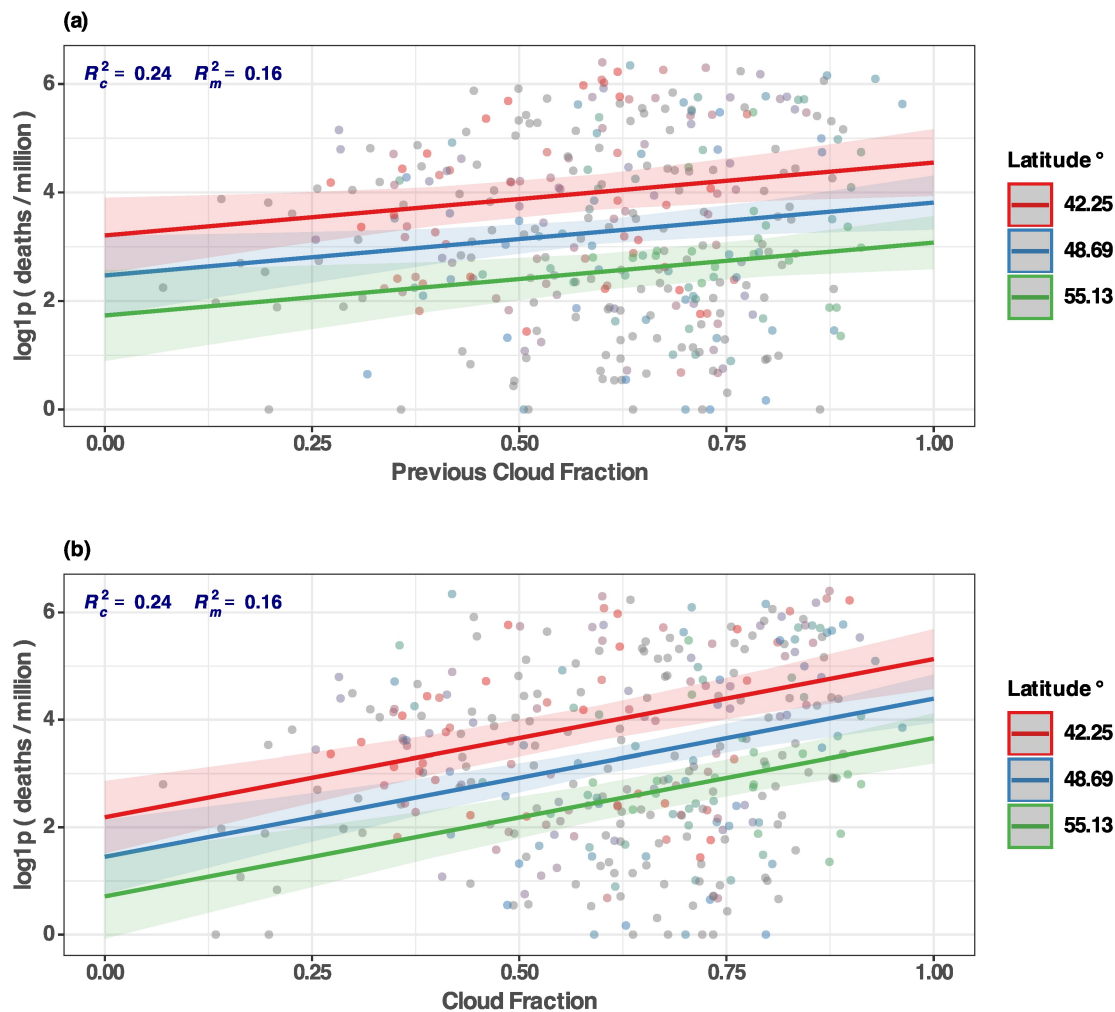
- The effect of *Previous Cloud Fraction* is statistically significant and positive (beta = 1.34, 95% CI [0.20, 2.49],  $t(336) = 2.31$ ,  $p = 0.022$ ; Std. beta = 0.14, 95% CI [0.02, 0.26])
- The effect of *Cloud Fraction* is statistically significant and positive (beta = 2.94, 95% CI [1.89, 3.99],  $t(336) = 5.52$ ,  $p < 0.001$ ; Std. beta = 0.32, 95% CI [0.21, 0.44])
- The effect of *Latitude* is statistically significant and negative (beta =  $-0.11$ , 95% CI [ $-0.15$ ,  $-0.08$ ],  $t(336) = -5.93$ ,  $p < 0.001$ ; Std. beta =  $-0.45$ , 95% CI [ $-0.60$ ,  $-0.30$ ]). The full statistical details of the model are in Appendix A.5.

*Summary:* The model found a relationship of the variability of the COVID-19 mortality in a given month with the average atmospheric cloudiness in that month, and with the cloudiness in the previous month (adjusted for latitude). The statistically significant model ( $p < 0.001$ ) has a moderate total explanatory power (conditional  $R^2 = 0.24$ ) and the part related to the fixed effects alone (marginal  $R^2$ ) is 0.16. A greater cloudiness in the previous month and in the current month correlates with a greater COVID-19 mortality (when adjusted for latitude); the relative influence of the cloudiness in previous month is about half of the influence for current month (standardized beta = 0.14 for previous month and 0.32 for the current month), see Figure 5b.

### 3.4. Time-Averaged Modeling

For each one of the 37 countries, for all year 2020, we averaged the values:

- of the insolation in all months, thus obtaining an *average insolation* in 2020 for each country;
- of the cloud fraction in all months, thus obtaining an *average cloud fraction* in 2020 for each country;
- of the mortality/million values, thus obtaining an average mortality for the year 2020 for each country; for consistency purposes with the rest of models, we  $\log_{10}$  transformed this averaged mortality.



**Figure 4.** LME model of monthly mortality and monthly cloudiness, adjusted for latitude. The dots represent the individual  $\log_{1p}$ -transformed monthly mortality values from the European countries in the period March–December 2020. The regression model is adjusted for latitude of the countries (for visualization purposes, the figure shows the model at three equally partitioned latitudes). The shaded bands are the 95% CI. (a) Modeled influence of the cloudiness in the previous month (b) Modeled influence of the cloudiness in the current month.

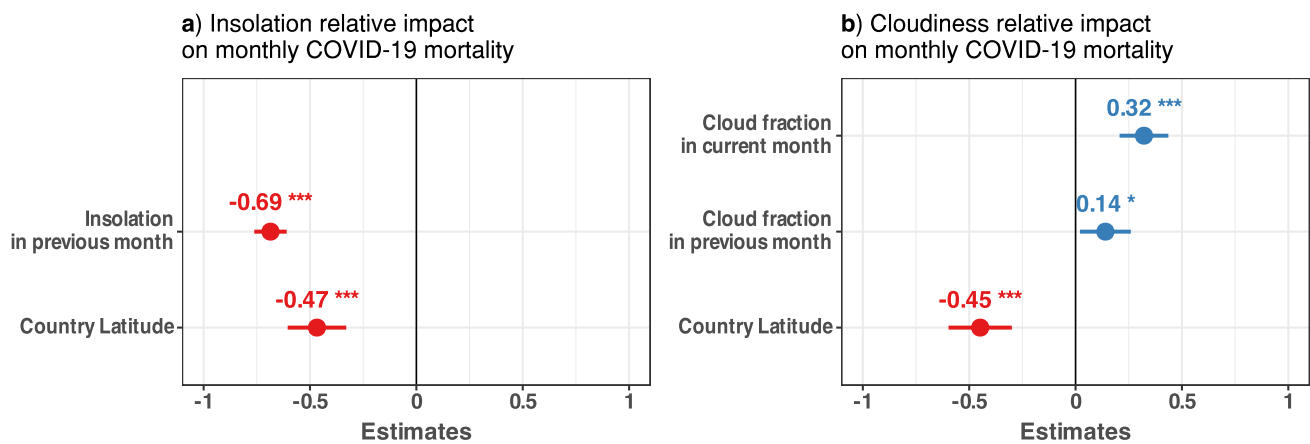
We therefore transformed the longitudinal data in a reduced data (retaining spatial information—i.e., countries, latitude, and longitude) but averaging temporal variations in the data, as a prerequisite of linear modeling (to avoid including repeated measurement data in a linear model). We then ran a step-wise regression to find the most significant predictors (if any) of averaged mortality (as described in Section 2.7). The most significant model (listed below) found in time-averaged data correlates yearly averaged mortality in a country with the yearly cloudiness values (adjusted for latitude), see Figure 6. The other factors were not significant in time-averaged data.

The linear model had the R formula:  $\text{Avg. log1p(deaths/million)} \sim \text{Avg. cloud fraction} + \text{Latitude}$ . The model explains a statistically significant and substantial proportion of variance ( $R^2 = 0.38$ ,  $F(2, 34) = 10.30$ ,  $p < 0.001$ , adj.  $R^2 = 0.34$ ). The model's intercept, corresponding to  $\text{Avg. cloud fraction} = 0$  and  $\text{Latitude} = 0$ , is at 6.97 (95% CI [5.50, 8.43],  $t(34) = 9.63$ ,  $p < 0.001$ ). Within this model:

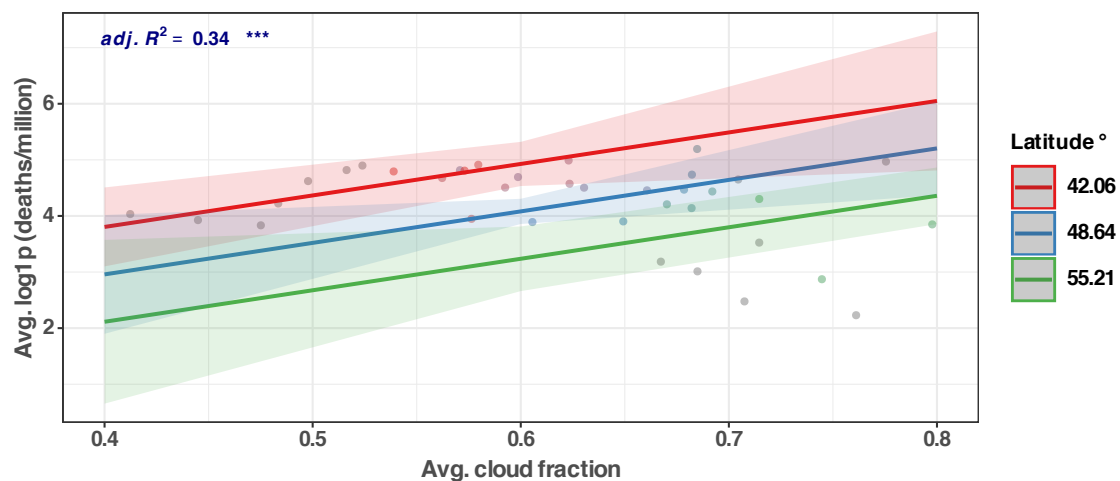
- The effect of *Avg. cloud fraction* is statistically significant and positive (beta = 5.62, 95% CI [0.98, 10.25],  $t(34) = 2.46$ ,  $p = 0.019$ ; Std. beta = 0.74, 95% CI [0.13, 1.36])

- The effect of *Latitude* is statistically significant and negative (beta =  $-0.13$ , 95% CI  $[-0.20, -0.06]$ ,  $t(34) = -3.91$ ,  $p < 0.001$ ; Std. beta =  $-1.18$ , 95% CI  $[-1.79, -0.57]$ ). The full statistical details of the model and its validation are presented in Appendix A.6.

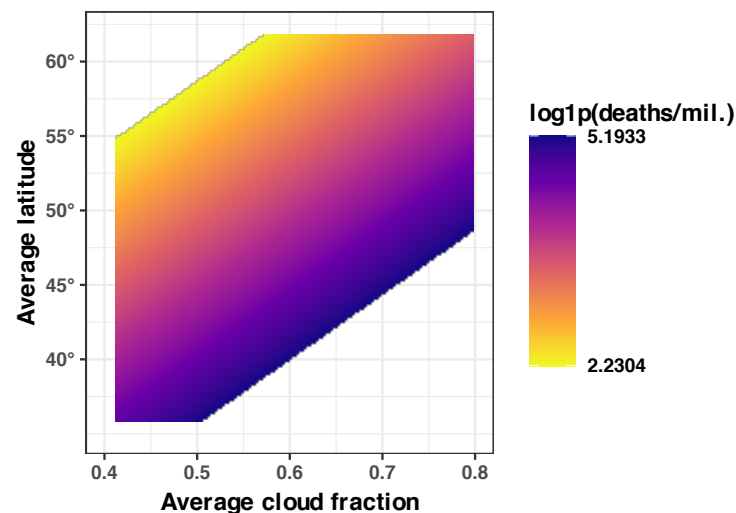
*Summary:* even with a time-averaged data, our data suggest that there is a consistent correlation between the COVID-19 mortality and the cloudiness; about 34% of the variance in COVID-19 mortality appears to be influenced by the cloudiness fraction of the sky, adjusted for latitude (Figures 6 and 7 for a model visualization across the range of collected variables).



**Figure 5.** Comparative view of the standardized beta estimates of the LME models presented above in Sections 3.2 and 3.3. Relative impact on COVID-19 mortality in a given month (a) of the insolation in previous month and (b) of the cloudiness in the same month and in the previous month. Notes: \*  $p < 0.05$ ; \*\*\*  $p < 0.001$ .



**Figure 6.** Yearly-averaged cloud fraction relationship with yearly-averaged mortality, adjusted for latitude. Dots: mortality, averaged for the entire year 2020, for each country (i.e., each country is a dot); the shaded areas: the CI limits of the fitted model. The regression model is adjusted for latitude of the countries (for visualization purposes, the figure shows the model at three equally partitioned latitudes). Note: \*\*\*  $p < 0.001$ .



**Figure 7.** Visualization of estimated European COVID-19 mortality from the time-averaged model, for the entire year 2020, in the form of a heat-map. To avoid extrapolation, the range of the plotted variables is clipped to the range of collected values.

### 3.5. Space-Averaged Modeling

An alternative approach to reduce the longitudinal data dimensions is to average it over the spatial dimensions, retaining chronological information (i.e., losing spatial details, like distribution over latitude and longitude).

For each month (March–December) of 2020, we have averaged the values:

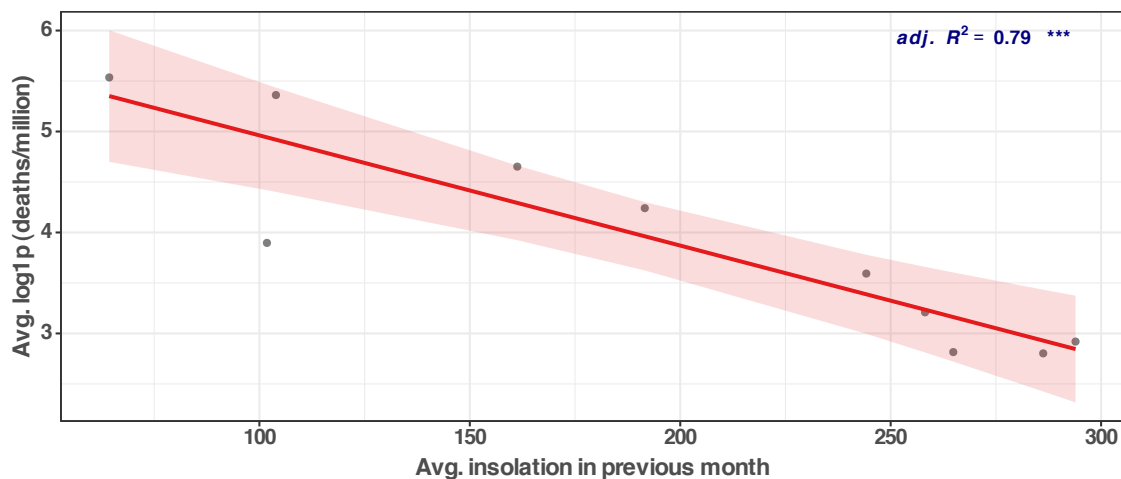
- of the insolation values in all countries, obtaining an European *average insolation* for each month;
- of the cloud fraction in all countries, obtaining an European *average cloud fraction* for each month;
- of the mortality/million values, in all countries, obtaining an European *average mortality* for each month; for consistency purposes with the rest of models, we again  $\log_{1p}$  transformed this average value before modeling.

We ran the same algorithm as in the previous section (a step-wise regression) with these variables; the major difference is that we could include in the model the insolation and cloudiness in the previous months (as the space-averaging preserves time information). In the space-averaged data, the most significant predictor that correlates with the European average mortality in a month was the European average insolation in the previous month (see Figure 8). The other factors were not significant in space-averaged data.

The linear model had the R formula:  $\text{Avg. } \log_{1p}(\text{deaths/million}) \sim \text{Average\_Previous\_Insolation}$ . The model explains a statistically significant and substantial proportion of variance ( $R^2 = 0.82$ ,  $F(1, 8) = 35.90$ ,  $p < 0.001$ , adj.  $R^2 = 0.79$ ). The model's intercept, corresponding to  $\text{Average\_Previous\_Insolation} = 0$ , is at 6.05 (95% CI [5.16, 6.95],  $t(8) = 15.62$ ,  $p < 0.001$ ). Within this model:

- The effect of *Average\\_Previous\\_Insolation* is statistically significant and negative (beta =  $-0.01$ , 95% CI [ $-0.02$ ,  $-6.71 \times 10^{-3}$ ],  $t(8) = -5.99$ ,  $p < 0.001$ ; Std. beta =  $-0.90$ , 95% CI [ $-1.25$ ,  $-0.56$ ]). The full statistical details of the model and its validation are presented in Appendix A.7.

**Summary:** This linear model implies that in spatially-averaged data over the entire European landmass, in 2020, there is a strong temporal influence of the insolation in the previous month. About 79% of the COVID-19 mortality in a month appears to be correlated with the geographical insolation in the previous month.



**Figure 8.** European averaged COVID-19 mortality in a month (in the period March–December 2020) relationship with averaged insolation over all Europe in the previous month. The shaded areas: the CI limits of the fitted model. Note: \*\*\*  $p < 0.001$ .

To check for this we performed a Granger causality test [84,99]. On this averaged dataset, between the monthly averaged mortality (outcome) and monthly insolation (predictor), with a lag of 1 (i.e., 1 month lag) there is a strong Granger causality correlation ( $F = 92.73$ ,  $p < 0.001$ ). If the dependence is true, the reverse Granger causality test should fail (i.e. testing for spurious correlation by reversing outcome and the predictor). Our results suggest that is the case, the reverse test is not significant ( $F = 1.406$ ,  $p = 0.28$ ) so these tests indicate that indeed there is a consistent temporal correlation between the values of insolation in one month and the values of the COVID-19 mortality in the following month.

## 4. Discussion

The results of our data sampling suggest that there is a statistically significant temporal correlation between COVID-19 mortality and meteorological factors investigated (insolation, cloudiness) with a lag of one month. The significant factors and their impact are summarized in Figure 5, that compares the relative factors in both models, for the European continent, during the first year of COVID-19 epidemic, when no targeted treatments were available; in both models, the latitude appears to have roughly the same modulating effect, with notable differences for insolation and for cloudiness. We discuss these in detail in the following subsections.

### 4.1. Insolation

We have found that the insolation in the *previous month* negatively correlates with COVID-19 mortality in the following month (the higher the solar energy at the ground level in a month; Figure 3 and 5a). To the best of our knowledge, this time lag was not reported up to now in previous studies. We propose three possible explanations for the observed correlation:

First, in previous studies of the interactions between sunlight—COVID-19 epidemics, increased solar exposure was linked to increased vitamin D synthesis in the skin and its beneficial immunological roles [10–13], so this might be a possible explanation, population-wide.

Second, it is known that coronaviruses in general survive better in environments with low temperature and low radiation/sunlight [102]. As the Sars-CoV-2 virions' ability to survive in environment is impeded by light [14–19], presumably in a month with a

higher insolation, the average number of viable virions in the environment decreases, thus the incidence decreases [5,22] and therefore the fatalities in the next month decrease (as it takes ~1 month from infection to death in fatal cases). Consequently, a consistent effect of decreased mortality should be associated with increased sunlight, regardless of geographical position. We checked for this by averaging data over all surfaces (i.e., all countries), in Section 3.5, Figure 8. Within this explanation, we think we can regard our results as a different confirmation, applied to a large geographical area, of the laboratory studies of [14–16].

Finally, it was observed that longer exposure to natural sunlight appears to be beneficial to patients, increasing recovery rates [103] and thus reducing patient mortality purportedly via different mechanisms than vitamin D (other physiological parameters [104] or immuno-modulation [18]).

#### 4.2. Cloudiness

We have found that the cloudiness *in the previous month* and cloudiness *in the current month* both correlate with a higher COVID-19 mortality in the current month, albeit with a smaller relative impact than insolation (Figure 4, Figure 5b). This has been, to the best of our knowledge, unreported up to now.

Based on our results of insolation effects presented above, we expected that: (i) the relative amount of influence of cloudiness to be in a comparable range with the effect of insolation—but it is smaller; (ii) only the cloudiness in the previous month to be correlated to mortality (as cloudiness heavily influences the amount of insolation at ground level [46])—but we found that both months are significant. We discuss these novel points below.

(i) The cloud fraction does not linearly reduce solar insolation [105,106]; in particular, the shading created by the clouds changes the light spectral distribution at the ground level. The clouds exert a complex influence on UV-B radiation and hence impact vitamin D formation. A limitation in our study is that we could not account for different cloud types and thus their particular influence. In past studies, the overcast cumulus-type clouds were found to attenuate almost all (99%) UV-B radiation, but surprisingly a partly cloudy sky with the same clouds can actually increase UV-B radiation at ground level up to 27% [107]. Also, in some particular conditions, multiple scattering due to cirriform clouds can actually increase the effect of UV radiation on horizontal surfaces [108]. As a limitation, in our analysis we could not distinguish between cloud types; this would be an interesting point for future research.

(ii) It is surprising that higher cloudiness in *both* months (current and previous) correlates with higher mortality. This is different from insolation data; we think therefore that cloudiness correlation might have an additional underlying mechanism. We suggest that the cloudiness data may actually be a proxy for persistent pollution data.

Even moderate pollution in the atmosphere helps clouds form [109], and it was also previously found that airborne pollution was linked to worse outcomes for the COVID-19 patients [26,29,30,110]. The airborne pollution particles have complex interactions with Sars-CoV-2 virions [27]; by reducing the UV radiation, air pollutants might promote viral persistence in air [29], thus prolonging the exposure time. Higher pollution levels, especially with smaller particulate matter, impair human health (via increased oxidative stress and altered immune response [111,112]). Therefore, a persistent particulate pollution, for a long period, could theoretically be both a favoring factor for persistent cloudiness and at the same time increases mortality via direct immunological effects of the pollutants.

Another possible explanation could be that heavy cloudiness is linked with colder outdoor surfaces. A higher cloud cover quickly cools down the outdoor surfaces, especially at lower latitudes [113]. Colder surfaces facilitate the survival of SARS-CoV-2 for longer

periods [114]; thus cloud fraction over a geographical area could also be regarded as a proxy variable for the temperature of the surfaces (not only of the air temperature) and be therefore a confounding factor for an increased incidence.

#### 4.3. Latitude (and Geographical Distribution)

Our results confirm previous studies that, for the European continent, latitude appears to be an important modulator of the epidemiological waves of COVID-19. Many previous studies linked the COVID-19 *incidence* to latitude (see for instance [9,11–13,115] and somewhat fewer with mortality [10,35,36]. A meta-analysis by Li et al. [2] concluded that the influence of the factors, while important, is uneven and difficult to generalize.

Latitude is a main driver of the average local climate and therefore is a confounding factor for variations in temperature, average sunlight, cloudiness (and other proposed climatological factors that influence COVID-19 epidemic). It is also (somewhat loosely) linked to socioeconomic status [116–118] and this in turn correlates with the quality of the healthcare. For these reasons, we think it is perhaps useful to consider the influence of any of these climatological factors not as independent or absolute but always adjusted for latitude.

In this regard, our numerical results on latitude influence on mortality are an independent confirmation of the results of spatio-temporal analysis done by Martínez-Portillo et al. [9]. However, as a difference, in our study we did not find a correlation of COVID-19 mortality with longitude, and this may be due to a methodological difference (they examined the surge dates in space and time). Another possible explanation could be that we examined a time-frame lag of 1 month, which might be too narrow to catch the West–East longitudinal gradient of the spreading pandemic on European countries, but wide enough to capture the latitudinal gradient.

#### 4.4. Results of Granger Causality Tests

Separately from LME modeling, we checked the temporal lag of one month in our data sample with a Granger causality test in the averaged data (Section 3.5). We again have found a significant temporal correlation of mortality in a month with the average insolation in the previous month (a temporal lag of one month). We are fully aware that the Granger causality is not necessarily true causality, and that the test itself might fail to reject the alternative hypothesis if both tested processes are driven by a common unknown third process with a different time lag. As a limitation of this paper, we did not attempt to test for other time lags or for varying time lags, as this would require more granular data.

#### 4.5. Limitations

We stress that our study is a retrospective longitudinal one and we developed the models to answer the starting hypothesis; the aim of the study was not to build predictive models. Our study only modeled a specific year and a specific population and while the sample was large it is unknown if a predictive extrapolation can be done to other populations/geographical regions—this is for future research.

We are aware that this study has limitations: we did not investigate the precipitation rate, relative humidity, temperature, wind velocity, air pressure, air pollution and density. The solar radiation measure was the net amount of energy and did not analyze spectral distribution: we were unable to differentiate between visible, infrared and ultraviolet radiation components from the measured data. Due to orbital dynamics, MODIS data is unavailable for some regions on certain days, and different effective imputation methods were developed [119–122]; we used a monthly aggregated MODIS data set that has no missing data (due to averaging method), but we cannot exclude variations in its temporal quality.

Of a particular concern is the inter-dependence between cloudiness and the rest of the factors. We carefully modeled to isolate it; but in one verification model (Section 3.4) a standardized beta for latitude was greater than 1—this is conceivable in multiple regression models, but raises the possibility of collinearity between predictor variables [123]. We checked this, and VIF statistics found in this case was 4.97. VIF values over the range 5 . . . 10 indicate a strong collinearity. For an extra caution in interpreting, we consider that values greater than 2.5 could be a point of concern [124]. Although the model formally passed the the quality criteria we set (Appendix A.6), we cannot therefore exclude a multiple collinearity issue here: (i) latitude influences cloudiness; (ii) cloudiness influence mortality, but at the same time, (iii) latitude influences mortality via a different, unknown dynamic. Also, this issue does not appear in the corresponding more precise LME model (Section 3.3), so it might be a result of averaging.

As cloudiness is both influenced by and influences the temperature and humidity which are also influencing mortality [1], we could not differentiate the confounding factors. These influences seem to be different at different scales (national scale vs. urban scale, see [2] for an in-depth meta-analysis). We acknowledge that our analysis is limited to the national scale only. We acknowledge that using centroid data and the averaged insolation/cloud fraction at the country level cannot capture details of spatial variation in population density [125].

From the epidemiological perspective, the authors acknowledge that this study did not include in the modeling done the major clinical confounding factors, like age, comorbidities, sex, lifestyle patterns, etc. We also note that especially during the initial phase of pandemic, mortality data was likely influenced by other factors as well: technical (limited testing capabilities [126]), socio-economic (delayed diagnosis [127]) or governmental (testing at scale [128], introduction and extent of social distancing measures). These were different for each country; in this regard, the sampling time chosen could have biases that we were unable to address.

In spatial analysis in geographical epidemiology, latency and mobility are two factors known to alter statistical analysis of the temporal data [129]. Latency is the time lag between the exposure to a hazardous factor and the emergence of an outcome (disease, death). In this study we chose an interval of one month as this seems to cover the reported pathological findings between the time of viral exposure and death (see Introduction, Figure 1). One month is also broad enough to average out the weekend-weekdays systematic variations of mortality observed during the initial year of the pandemic [130,131], and the variations in mobility caused by different national policies on social distancing.

The level of population mobility across the borders of the spatial unit changes with the area of the unit and this implies that reliability of inference will be lower for areas of high mobility (such as highly urbanized counties) vs. less urbanized ones. In our study, we chose the highest administrative area (country) [129] to minimize this effect, but we acknowledge that we could not account for it.

Therefore, for a future study it might be interesting to investigate the relationship between COVID-19 mortality, cloudiness and solar radiation at a finer temporal and spatial scale, perhaps also taking in account the mobility patterns.

## 5. Conclusions

The data from the European continent in the spring–winter of 2020, when targeted countermeasures (vaccination, effective treatments) were not available yet for COVID-19, suggest that there might be a longer term (1 month) correlation between weather and mortality. Due to the generally long period between infection and death (in fatal cases), our results suggest that COVID-19 mortality in any given month was negatively correlated

with insolation and positively correlated with prolonged cloudiness. This knowledge might help advise public health policies related to COVID-19 mitigation and control; we propose increased vigilance and increased frequency of sanitation of outdoor high-risk surfaces during prolonged overcast weather.

**Author Contributions:** Conceptualization, Adrian Iftime and Secil Omer; methodology, Adrian Iftime, Secil Omer; formal analysis and data visualization, Adrian Iftime; data curation and storage, Victor-Andrei Burcea; writing—original draft preparation, Adrian Iftime, Secil Omer; writing—review and editing, Adrian Iftime, Secil Omer, Victor-Andrei Burcea, Octavian Călinescu, Ramona-Madalina Babes; validation, Octavian Călinescu, Ramona-Madalina Babes; clinical virology expertise: Victor-Andrei Burcea; biology expertise, Ramona-Madalina Babes; clinical care expertise, Secil Omer. All authors have read and agreed to the published version of the manuscript.

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**Institutional Review Board Statement:** Not applicable; this study used only previously published, anonymous, aggregated human mortality data.

**Informed Consent Statement:** Not applicable.

**Data Availability Statement:** We made available the full data-set that we aggregated, curated, computed and analyzed in this study at the Zenodo open-access repository: [132]. The raw data that support the findings of this study are openly available at: [57,60,69].

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**Conflicts of Interest:** The authors declare no conflicts of interest.

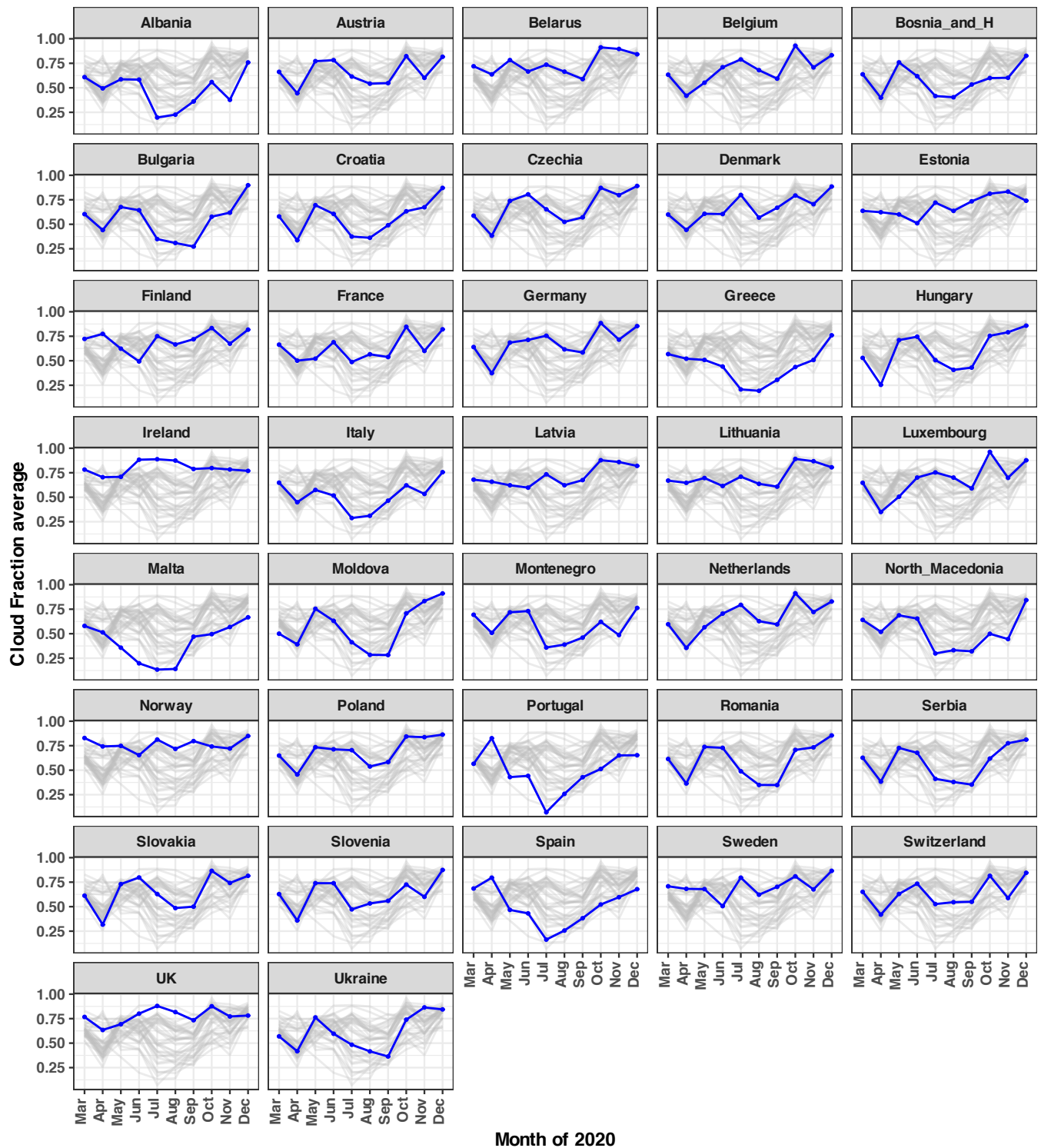
## Abbreviations

The following abbreviations are used in this manuscript:

|              |                                                          |
|--------------|----------------------------------------------------------|
| avg.         | average                                                  |
| Bosnia_and_H | Bosnia and Herzegovina                                   |
| CI           | confidence interval                                      |
| COVID-19     | Coronavirus disease 2019                                 |
| LME          | linear mixed effect                                      |
| mil.         | million                                                  |
| NASA         | National Aeronautics and Space Administration            |
| OLS          | ordinary least squares                                   |
| QQ           | quantile–quantile plot                                   |
| REML         | restricted maximum likelihood                            |
| SARS-CoV-2   | Severe acute respiratory syndrome coronavirus 2          |
| Std. beta    | standardized beta coefficient                            |
| UK           | The United Kingdom of Great Britain and Northern Ireland |
| UV           | Ultraviolet radiation                                    |
| UV-A         | Ultraviolet radiation, type A                            |
| UV-B         | Ultraviolet radiation, type B                            |
| VIF          | Variable inflation factor                                |

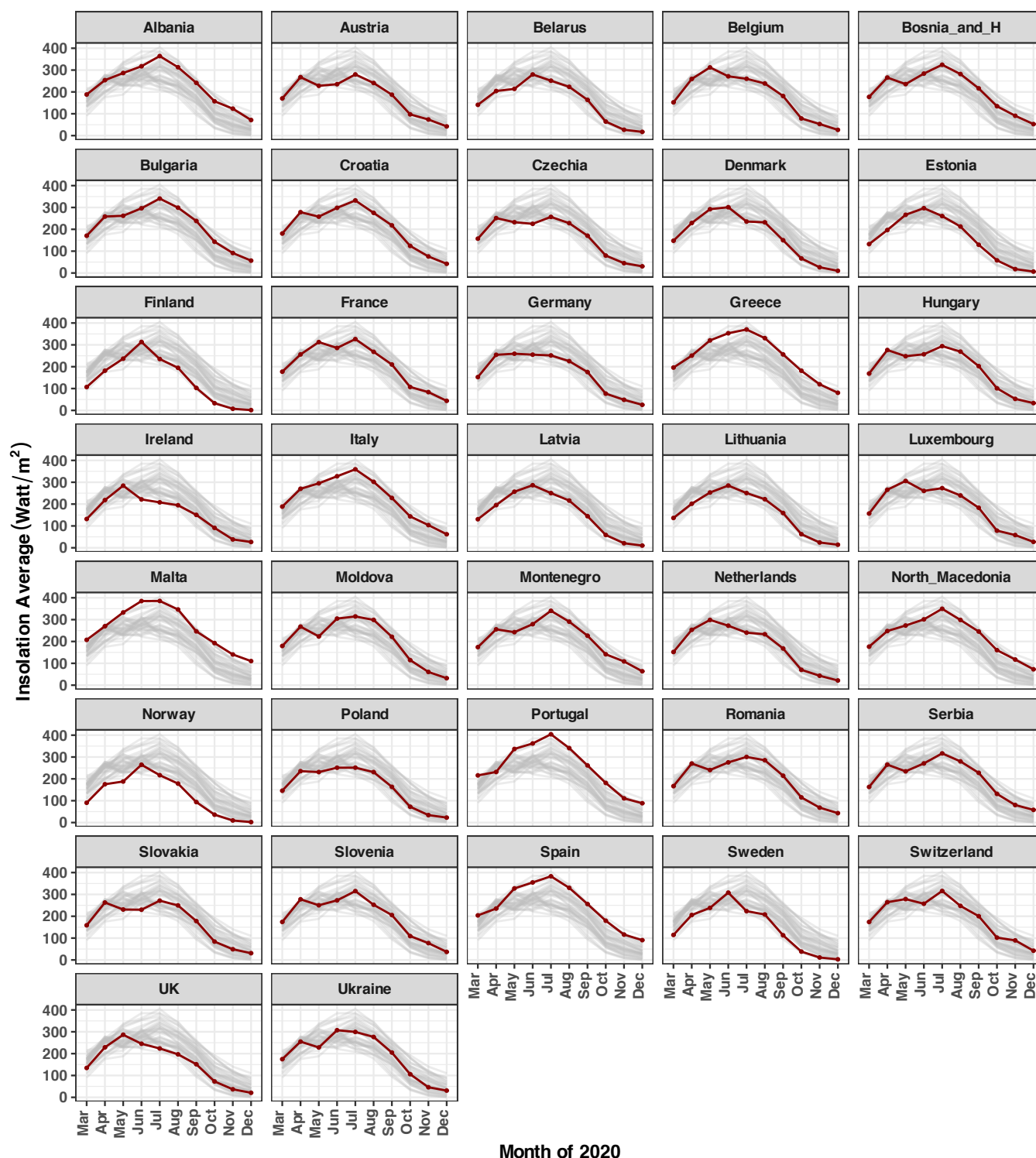
## Appendix A. Statistical Details

### Appendix A.1. Monthly Cloudiness Data Points Used in This Study



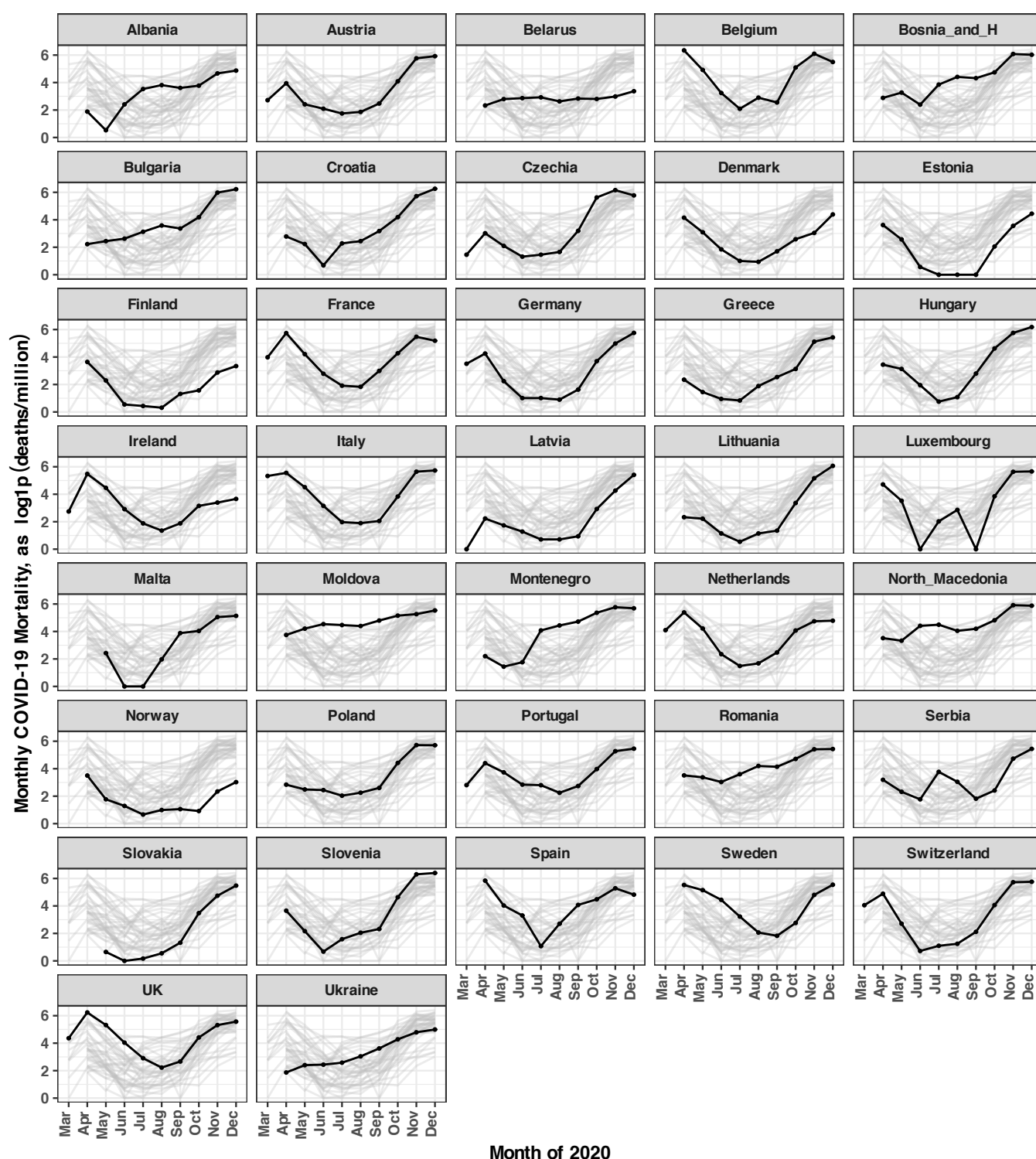
**Figure A1.** The average monthly cloudiness calculated for each European country. Each blue dot on the foreground blue line represents the average of the cloud fraction values over the area of the respective country in the respective month. A cloud fraction of 0.0 means a completely sunny sky; 1.0 means a completely overcast sky. To visually compare the values in each country with the rest of the countries, the cloudiness values for all the countries are drawn as background gray lines in each panel. The procedure used for the calculation of these data points is presented in Section 2.2.

## Appendix A.2. Monthly Insolation Data Points Used in This Study



**Figure A2.** The average insolation in each European country. Each red dot on the foreground red line represents the averaged measured energy flux from the sun over the area of the country in each month, expressed in W/m<sup>2</sup>. To visually compare the values in each country with the rest of the countries, the insolation values for all the countries are drawn as background gray lines in each panel. The procedure used for the calculation of these data points is presented in Section 2.3.

## Appendix A.3. Monthly Mortality Data Points Used in This Study



**Figure A3.** The average monthly mortality in each European country in the year 2020. Each black dot on the foreground black line represents the  $\log_{1p}$  transformed total deaths in a month in the country. The cloudiness values of all countries are drawn as a background gray lines in each panel to aid the visual comparison. The procedure used for the calculation of these data points is presented in Section 2.4.

## Appendix A.4. LME Modeling of Monthly Mortality and Insolation

**Table A1.** Characteristics of the Linear Mixed-Effects (LME) modeling of mortality vs. insolation (Section 3.2, Figures 3 and 5a).

|                             | Dependent Variable:                                        |
|-----------------------------|------------------------------------------------------------|
|                             | Monthly Mortality<br>as $\log_{10}(\text{Deaths/Million})$ |
| Previous Insolation Average | −0.01 ***<br>(0.001)                                       |
| Latitude                    | −0.12 ***<br>(0.02)                                        |
| Constant                    | 11.69 ***<br>(0.92)                                        |
| Observations                | 342                                                        |
| Conditional $R^2$           | 0.57                                                       |
| Marginal $R^2$              | 0.45                                                       |
| Log Likelihood              | −546.46                                                    |
| AIC                         | 1102.93                                                    |
| BIC                         | 1122.10                                                    |

Notes: \*\*\*  $p < 0.001$ ; the numbers in parentheses are the standard errors.

R formula:  $\log_{10}(\text{deaths}/\text{million}) \sim \text{Previous\_Insolation\_Average} + \text{Latitude} + (1 | \text{Country})$ . The model included the Country as random effect (formula:  $\sim 1 | \text{Country}$ ). The Latitude is the centroid latitude of the country. The model's total explanatory power is substantial ( $R_c^2 = 0.57$ ) and the part related to the fixed effects alone is  $R_m^2 = 0.45$ . The model's intercept, corresponding to Previous\_Insolation\_Average = 0 and Latitude = 0, is at 11.69 (95% CI [9.89, 13.49],  $t(337) = 12.74$ ,  $p < 0.001$ ). Within this model:

- The effect of Previous\_Insolation\_Average (i.e., insolation in previous month) is statistically significant and negative ( $\beta = -0.01$ , 95% CI [−0.01, −0.01],  $t(337) = -17.73$ ,  $p < 0.001$ ; Std. beta = −0.69, 95% CI [−0.76, −0.61])

- The effect of Latitude is statistically significant and negative ( $\beta = -0.12$ , 95% CI [−0.15, −0.08],  $t(337) = -6.68$ ,  $p < 0.001$ ; Std. beta = −0.47, 95% CI [−0.60, −0.33])

## Appendix A.5. LME Modeling of Monthly Mortality and Cloudiness

**Table A2.** Characteristics of the Linear Mixed-Effects (LME) modeling of monthly COVID-19 mortality vs. cloudiness (Section 3.3, Figures 4 and 5b).

|                                                      | Dependent Variable:                                        |
|------------------------------------------------------|------------------------------------------------------------|
|                                                      | Monthly Mortality<br>as $\log_{10}(\text{Deaths/Million})$ |
| Previous_Cloud_Fraction<br>(i.e., in previous month) | 1.34 *<br>(0.58)                                           |
| Cloud_Fraction<br>(i.e in current month)             | 2.94 ***<br>(0.53)                                         |
| Latitude                                             | −0.11 ***<br>(0.02)                                        |
| Constant                                             | 6.21 ***<br>(0.83)                                         |

Table A2. Cont.

|                   | Dependent Variable:<br>Monthly Mortality<br>as $\log_{1p}(\text{Deaths/Million})$ |
|-------------------|-----------------------------------------------------------------------------------|
| Observations      | 342                                                                               |
| Conditional $R^2$ | 0.24                                                                              |
| Marginal $R^2$    | 0.16                                                                              |
| Log Likelihood    | −625.49                                                                           |
| AIC               |                                                                                   |
| BIC               | 1286.00                                                                           |

Notes: \*  $p < 0.05$ ; \*\*\*  $p < 0.001$ ; the numbers in parentheses are the standard errors.

R formula used:  $\log_{1p}(\text{deaths/million}) \sim \text{Previous\_Cloud\_Fraction} + \text{Cloud\_Fraction} + \text{Latitude} + (1 \mid \text{Country})$ . The model included the Country as random effect (formula:  $\sim 1 \mid \text{Country}$ ). The *Latitude* is the centroid latitude of the country.

The model's total explanatory power is moderate ( $R_c^2 = 0.24$ ) and the part related to the fixed effects alone is  $R_m^2 = 0.16$ . The model's intercept, corresponding to *Previous\_Cloud\_Fraction* = 0, *Cloud\_Fraction* = 0 and *Latitude* = 0, is at 6.21 (95% CI [4.57, 7.85],  $t(336) = 7.45$ ,  $p < 0.001$ ). Within this model:

- The effect of *Previous Cloud Fraction* is statistically significant and positive (beta = 1.34, 95% CI [0.20, 2.49],  $t(336) = 2.31$ ,  $p = 0.022$ ; Std. beta = 0.14, 95% CI [0.02, 0.26])

- The effect of *Cloud Fraction* is statistically significant and positive (beta = 2.94, 95% CI [1.89, 3.99],  $t(336) = 5.52$ ,  $p < 0.001$ ; Std. beta = 0.32, 95% CI [0.21, 0.44])

- The effect of *Latitude* is statistically significant and negative (beta = −0.11, 95% CI [−0.15, −0.08],  $t(336) = -5.93$ ,  $p < 0.001$ ; Std. beta = −0.45, 95% CI [−0.60, −0.30])

#### Appendix A.6. Time-Averaged Model Details

The model formula:  $\text{Avg.log}_{1p}(\text{deaths/million}) = \alpha + \beta_1(\text{Avg.CloudFraction}) + \beta_2(\text{Latitude}) + \epsilon$  (on time-averaged dataset)

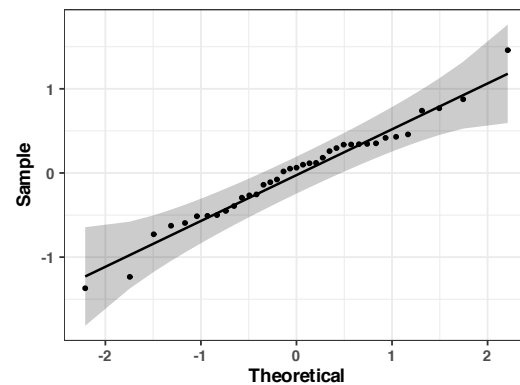
Table A3. Characteristics of the time—averaged model.

|                     | Dependent Variable:<br>Avg. $\log_{1p}$ (Deaths/Million) |
|---------------------|----------------------------------------------------------|
| Avg. Cloud Fraction | 5.62 *<br>(2.28)                                         |
| Latitude            | −0.13 ***<br>(0.03)                                      |
| Constant            | 6.97 ***<br>(0.72)                                       |
| Observations:       | 37                                                       |
| $R^2$               | 0.38                                                     |
| Adjusted $R^2$      | 0.34                                                     |
| Residual Std. Error | 0.58 (df = 34)                                           |
| F Statistic         | 10.30 *** (df = 2; 34)                                   |
| AIC                 | 69.74                                                    |
| BIC                 | 76.19                                                    |

Notes: \*  $p < 0.05$ ; \*\*\*  $p < 0.001$ ; the numbers in parentheses are the standard errors.

The residuals of this linear model appear to fall on the expected diagonal line on a QQ-plot (see Figure A4) and to be normally distributed (formal Lilliefors corrected Kolmogorov-

Smirnov test  $D = 0.10$ ,  $p = 0.45$ ). The residuals appear to be independent (no autocorrelation between them, Durbin-Watson test  $DW = 2.39$ ,  $p = 0.88$ ). There seems to be a little heteroscedasticity of the residuals (Breusch-Pagan test,  $BP = 6.39$ ,  $df = 2$ ,  $p = 0.04$ )—at further investigation we think this to be an artifact induced by the  $\log_{1p}$  transform at the extremely low values of the interval: in the non-transformed model (i.e., just mortality/million), the homoscedasticity is present (Breusch-Pagan test  $BP = 2.33$ ,  $df = 2$ ,  $p$ -value = 0.31).



**Figure A4.** Quantile–Quantile plot of the residuals of the time–averaged model.

#### Appendix A.7. Space–Averaged Model Details

The model formula:  $\text{Avg.log1p}(\text{deaths/million}) = \alpha + \beta(\text{Avg.PreviousInsolation}) + \epsilon$  (on space–averaged dataset)

**Table A4.** Characteristics of the space—averaged model.

|                          | Dependent Variable:         |
|--------------------------|-----------------------------|
|                          | Avg. log1p (Deaths/Million) |
| Avg. previous insolation | −0.01 ***<br>(0.002)        |
| Constant                 | 6.05 ***<br>(0.39)          |
| Observations             | 10                          |
| $R^2$                    | 0.82                        |
| Adjusted $R^2$           | 0.79                        |
| Residual Std. Error      | 0.46 (df = 8)               |
| F Statistic              | 35.90 *** (df = 1; 8)       |
| AIC                      | 16.74                       |
| BIC                      | 17.65                       |

Notes: \*\*\*  $p < 0.001$ ; the numbers in parentheses are the standard errors.

The residuals of this linear model appear to be normally distributed (Shapiro-Wilk test:  $W = 0.85$ ,  $p = 0.055$  and Figure A5). The residuals appear to be independent (no autocorrelation of the residuals, Durbin-Watson test:  $DW = 1.51$ ,  $p = 0.12$ ) and without heteroscedasticity (studentized Breusch-Pagan test:  $BP = 2.27$ ,  $df = 1$ ,  $p$ -value = 0.13).

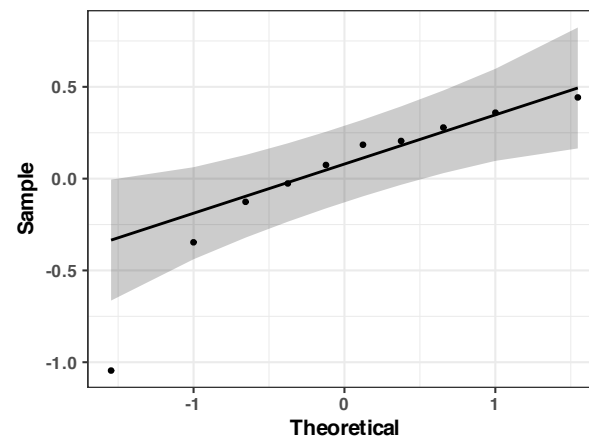


Figure A5. Quantile–Quantile plot of the residuals of the space-averaged model.

#### Appendix A.8. Diagnostic Plots for Data Transformation

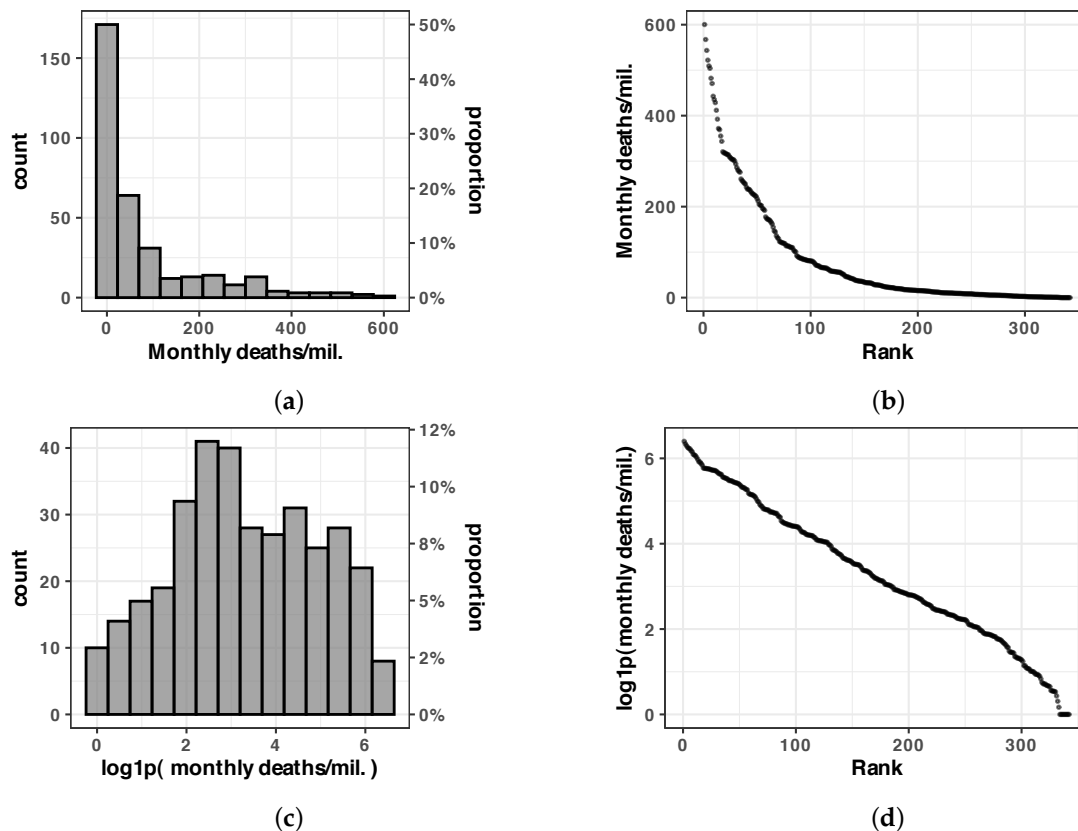


Figure A6. Top panels: the raw values of COVID-19 calculated mortality data (as monthly deaths/1 million): (a) histogram (highly skewed) and (b) rank-value plot; Bottom panels: the same data,  $\log_{1p}$  transformed: (c) histogram (reduced skewness) and (d) rank-value plot (more linear)

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