Environmental Research 228 (2023) 115796

Contents lists available at ScienceDirect

Environmental Research

journal homepage: www.elsevier.com/locate/envres

The influence of meteorological factors on COVID-19 spread in Italy during the first and second wave

Erica Balboni [a,b], Tommaso Filippini [a,c], Kenneth J. Rothman [d], Sofia Costanzini [e], Stefania Bellino [f], Patrizio Pezzotti [f], Silvio Brusaferro [g,h], Fabrizio Ferrari [i], Nicola Orsini [j], Sergio Teggi [e], Marco Vinceti [a,d,*]

[a] Environmental, Genetic and Nutritional Epidemiology Research Center (CREAGEN), Section of Public Health, Department of Biomedical, Metabolic and Neural Sciences, University of Modena and Reggio Emilia, Modena, Italy
[b] Health Physics Unit, Modena Policlinico University Hospital, Modena, Italy
[c] School of Public Health, University of California Berkeley, Berkeley, CA, USA
[d] Department of Epidemiology, Boston University School of Public Health, Boston, MA, USA
[e] Department of Engineering 'Enzo Ferrari', University of Modena and Reggio Emilia, Modena, Italy
[f] Department of Infectious Diseases, Italian National Institute of Health, Rome, Italy
[g] Presidency, Italian National Institute of Health, Rome, Italy
[h] Department of Medicine, University of Udine, Udine, Italy
[i] TerrAria S.r.l., Milan, Italy
[j] Department of Global Public Health, Karolinska Institutet, Stockholm, Sweden

ARTICLE INFO

Handling Editor: Jose L Domingo

Keywords:
COVID-19
Temperature
Ultraviolet radiation
Humidity
Meteorological factors

ABSTRACT

The relation between meteorological factors and COVID-19 spread remains uncertain, particularly with regard to the role of temperature, relative humidity and solar ultraviolet (UV) radiation. To assess this relation, we investigated disease spread within Italy during 2020. The pandemic had a large and early impact in Italy, and during 2020 the effects of vaccination and viral variants had not yet complicated the dynamics. We used non-linear, spline-based Poisson regression of modeled temperature, UV and relative humidity, adjusting for mobility patterns and additional confounders, to estimate daily rates of COVID-19 new cases, hospital and intensive care unit admissions, and deaths during the two waves of the pandemic in Italy during 2020. We found little association between relative humidity and COVID-19 endpoints in both waves, whereas UV radiation above 40 kJ/m^2 showed a weak inverse association with hospital and ICU admissions in the first wave, and a stronger relation with all COVID-19 endpoints in the second wave. Temperature above 283 K (10 °C/50 °F) showed a strong non-linear negative relation with COVID-19 endpoints, with inconsistent relations below this cutpoint in the two waves. Given the biological plausibility of a relation between temperature and COVID-19, these data add support to the proposition that temperature above 283 K, and possibly high levels of solar UV radiation, reduced COVID-19 spread.

1. Introduction

Many studies have addressed the spread of the COVID-19 pandemic since its origin in 2019. A topic of interest has been the potential influence of meteorological factors in affecting SARS-CoV-2 transmission and virulence, i.e. the capacity of outdoor climate variables and indoor microclimate to modify COVID-19 spread. Though several studies have indicated that meteorological factors could influence the spread of COVID-19, inconsistencies remain regarding effect size and direction for temperature, humidity and ultraviolet (UV) radiation (Byun et al., 2021; Chen et al., 2022; Jerrett et al., 2022; Kaplin et al., 2021; Li et al., 2022; Majumder and Ray, 2021; Romero Starke et al., 2021; Zheng et al., 2021). Explanations for these inconsistencies might include residual confounding due to pharmacological or non-pharmacological interventions (Chen et al., 2022; Nottmeyer et al., 2022), differences in virus lineage and variant in different regions and populations (Neagu

* Corresponding author. Dipartimento di Scienze Biomediche, Metaboliche e Neuroscienze, Facoltà di Medicina e Chirurgia– University of Modena and Reggio Emilia, Via Campi 287, 41125, Modena, Italy.
E-mail address: marco.vinceti@unimore.it (M. Vinceti).

https://doi.org/10.1016/j.envres.2023.115796
Received 12 March 2023; Received in revised form 27 March 2023; Accepted 28 March 2023
Available online 3 April 2023
0013-9351/

et al., 2021; Zhao et al., 2022), changes in season or geospatial scale considered, and other factors (Babin, 2020; Kerr et al., 2021; Li et al., 2022; Tan and Schultz, 2022). Additional uncertainty stems from the unknown lag time between meteorological determinants and COVID-19 endpoints, if they do have an effect (Xiao et al., 2021), or the possibility that weather variables have indirect effects mediated through changes in mobility, social contacts and other behavioral variables (Barceló and Saez, 2021; Paraskevis et al., 2021). In principle, weather-related factors such as temperature, humidity and ultraviolet radiation could affect the spread and virulence of an infectious agent such as SARS-CoV-2 by influencing the viability, pathogenicity, or transmission of the agent, by modulating the mobility and number of social contacts of the host, or by influencing the susceptibility and bodily response to the viral attack (Nottmeyer et al., 2022).

The present study focused on the spread of the virus in Italy in 2020. Two great waves of infection swept across Italy during 2020, before vaccines were available, and before a multitude of viral variants had emerged. Our attempt here has been to assess and disentangle the role of three major meteorological factors, temperature, humidity and ultraviolet radiation, in the spread and clinical severity of COVID-19 in Italy, taking into account the role of public-health measures, allowing for an optimal lag time in the analyses and focusing on a number of health endpoints.

2. Methods

2.1. Outcome data

We analyzed data from all of 2020, comprising the first and second COVID-19 waves in Italy. The first 'internal' case of COVID-19 in Italy was detected on February 20, 2020 in Codogno – Lombardy region, quickly followed by additional cases. On February 23, the national government issued a nationwide 'light' lockdown, slowing the mobility of goods and people and reducing a number of public and private activities that involved social contact. The measures taken in this first lockdown included closure of schools and universities, prohibition of social gatherings (such as in churches and leisure areas), limitations in the use of public transportation, isolation of infected people and their close contacts, and enhanced border control to detect and isolate infected incoming travelers (Vinceti et al., 2020).

A further, tight lockdown was decreed on March 8 in Veneto, Emilia-Romagna and Lombardy Northern Italy regions, and on March 9 across all of Italy, enforcing strict mobility control. This lockdown restricted individuals to their residences apart from health emergencies, a few urgent occupational needs, and weekly grocery shopping. No movement outside the residence was allowed for infected individuals or their contacts. Restriction was further increased on March 22, when people away from their own municipality were forbidden to return, and all non-essential commercial activities were closed. These strict measures ended on May 4, when mobility restrictions were softened, and May 16, when most mobility restrictions were lifted, with reopening of all commercial activities, although social gatherings remained limited and use of personal measures such as face masks were encouraged. Spread of COVID-19 decreased from early April onwards, with a concomitant drop in all COVID-19 related health endpoints into summer.

In the second half of the year SARS-CoV-2 infections increased again, peaking in November. Contrary to the first wave, in this second wave the public-health measures were at least in part geographically uneven. Non-pharmacological interventions (such as use of face masks, mobility restrictions, school closures) were strengthened again by the national government on November 6 specifically for each region, according to a three-level scale of increasing tightness based on severity of COVID-19 spread (Riccardo et al., 2022). Finally, during the last days of December 2020, COVID-19 vaccines became available, and during the first weeks of January 2021, a vaccination program began.

We studied four COVID-19 health endpoints, combined with provincial-level data on individual mobility and meteorological factors: 1) new cases of SARS-CoV-2 infections; 2) COVID-19-related hospital admissions; 3) intensive care unit (ICU) admissions; and 4) deaths due to COVID-19. We obtained information separately for the first and the second COVID-19 waves in Italy from the National Public Health Institute (Di Federico et al., 2022; Riccardo et al., 2020). The first wave we took as the period between February 15th-June 2020, and the second wave, the period from September 1st-December 31st. To compute the province-wide occurrence rate of each endpoint during each of the two waves, we used as a denominator the provincial population as of January 1st, 2020 for the 1st wave. For the 2nd wave, we subtracted from the provincial population the number of estimated SARS-CoV-2 infections based on the province-specific seroprevalence case survey at the end of the first wave, so that the denominator represented only the never infected, susceptible population (ISTAT - Italian National Institute of Statistics, 2021; Filippini et al., 2021b; Vinceti et al., 2020).

2.2. Meteorological data

We obtained date- and province-specific meteorological data, including ultraviolet (UV, 200 nm–420 nm) downward ground radiation-outdoor exposure, temperature and relative humidity, from the Copernicus Climate Data Store (European Commission - Copernicus Eyes on Earth, 2023). In particular, data were retrieved from the fifth-generation global climate atmospheric reanalysis (ERA5) of the European Centre for Medium-Range Weather Forecasts, combining model forecasts with observations from across the world (European Centre for Medium-Range Weather Forecasts, 2023). This dataset consists of hourly estimates of a large and comprehensive number of atmospheric, land and oceanic climate variables. For this study, we used 2020 hourly average air temperature, relative humidity at 2 m above the surface and downward UV radiation at the surface, with temperature and relative humidity gridded with a step size of 0.1° and UV radiation gridded with 0.25°. We implemented a Python procedure (van Rossum and Drake, 2011) to process ERA5 gridded network Common Data Form data, especially for spatial resizing and temporal aggregation (daily averaged values). We populated a PostgreSQL database with the PostGIS spatial database extender (Obe and Hsu, 2021) with the aforementioned data and the vector file of the administrative boundaries (municipalities and provinces) with their respective population census data (ISTAT - Italian National Institute of Statistics, 2023). We used several geostatistical interpolation methods - local polynomial, inverse distance weighted (IDW) and area weighted - to obtain daily population-weighted average values for each province, for all the considered variables. Daily population-weighted values of variable V for day j and province i ($V_{w,i,j}$) were obtained using the following formula:

$$V_{w,i,j} = \frac{\sum_{k=1}^{n_i} \left(V_{avg,k,i,j} \bullet P_k\right)}{P_i}$$

where n_i is the number of municipalities in province i, $V_{avg,k,i,j}$ is the average value of V for municipality k, province i and day j, P_k, P_i are the number of inhabitants, from population census data (ISTAT - Italian National Institute of Statistics, 2023) of municipality k and province i respectively.

For UV radiation, we computed daily averages by considering the hours when there was direct or indirect solar irradiation, i.e. UV radiation >0 kJ/m^2. We aggregated the gridded data on a daily basis and using the administrative boundaries to get spatial, population-weighted average values for each province for all the considered variables.

2.3. Confounders

We retrieved hourly particulate matter with aerodynamic diameter <2.5 μm ($PM_{2.5}$) concentrations from the European Centre for Medium-Range Weather Forecast, using data from the Copernicus

Atmosphere Monitoring Service at a spatial resolution of 0.1° degrees. $PM_{2.5}$ concentrations were aggregated by daily average intervals, extracted at municipal level and computed as population-weighted average values for each study province.

We also used individual mobility data as potential confounders, based on a cellphone-based methodology as previously described in a study in Northern Italy (Vinceti et al., 2020) and refined in a more recent investigation extended to the entire country (Vinceti et al., 2022). We estimated individual mobility from total mobile phone movements (identified through the subscriber identification module – SIM), occurring between different cell towers in all of Italy in 2020, based on commercially available data. A cellphone movement was labeled with both the cell of departure and the cell of arrival, and was registered when the mobile signal changed its receiving tower and remained in the same cell for at least 30 min. The dataset consisted of a daily trip counter of movements from one cell of departure to another cell of arrival. Then, we processed the data to obtain the movements on a provincial basis, assigning the daily movements to the province of departure, and we also determined the type of movement, i.e. if occurring by car, plane, train or other means of transportation, and if work-related or unrelated. Daily movements also reflected the lockdown time pattern. In the first wave, we found an overall mobility reduction of 14% on February 24th (light lockdown), 55% on March 9th (tight lockdown) and 82% on March 23rd (additional restrictions), compared with February 10th. Corresponding decreases in the second wave following the mobility restrictions still applied were 36% on November 7th compared to September 5th.

Finally, as additional potential confounders we included percentage of dwellings occupied by only one resident (named single-family homes), and an old age index (ratio of residents aged ≥65/residents aged 0–14 years) on a provincial basis from the National Institute of Statistics (ISTAT - Italian National Institute of Statistics, 2023).

2.4. Data analysis

We estimated a random-effects Poisson regression model to conduct statistical inference (95% confidence interval) on the daily counts of COVID-19 endpoints standardized by the population size (offset), taking into account the correlation across repeated measures in the same province. The main predictors of interest, meteorological variables, were flexibly modeled with restricted cubic splines with 3 knots at fixed percentiles of the distribution, to allow for a non-linear relation between meteorological variables and COVID-19 endpoints. We included a lag time between meteorological variables and health endpoints that was specific for each of the latter. The lag period included the time required on average to show clinical signs and symptoms requiring hospital and ICU admission. With this aim, we assessed the mean time intervals between onset of symptoms and hospitalization (5 days) (Istituto Superiore di Sanità, 2020), onset of symptoms and ICU hospitalization (8 days) (Ciceri et al., 2020), onset of symptoms and death (12 days) (Istituto Superiore di Sanità, 2020). We also included within these intervals a 7-day period for incubation of wild-type SARS-CoV-2 (Wu et al., 2022), and the mean delay between onset of symptoms and swab outcome, estimated to be 5 and 3 days, respectively, in the first and second wave (Task force COVID-19 del Dipartimento Malattie Infettive e Servizio di Informatica, 2020). Thus, the overall lag times used in the model were 12 days (1st wave) and 10 days (2nd wave) for COVID-19 onset, and 12 days, 15 days and 19 days, for time to hospital admission, ICU admission and death, respectively.

We analyzed separately the combinations of meteorological factors and health outcomes for each of the first and the second COVID-19 wave. For each of the two waves, we included in all analyses only the provinces seriously affected by the pandemic, i.e. those experiencing a death toll higher than 50 COVID-19 deaths/10^5 inhabitants. In each model, we adjusted for old age index, population density, daily movements, number of single-family homes and for the remaining meteorological factors, either including or not including $PM_{2.5}$ concentrations. For the latter potential confounder, we assumed that the lag time for its effect on endpoints was 1 day.

To assess if the postulated lag times, which were based on biological and epidemiologic evidence, could have been reliably inferred from the available data, we fitted cubic spline regressions after varying the lag time between 0 and 28 days. For each model, we used Akaike Information Criterion (AIC) as a measurement of relative informativeness of the model, as it provides the goodness of fit of the model, with a penalty for overfitting (Bozdogan, 1987; Xiao et al., 2021). We considered all adjusting factors as explained before, including $PM_{2.5}$ lagged by one day. The resulting local minimum points for the AIC were interpreted as indicating the data-driven most appropriate lag times.

3. Results

There were 70 provinces included in the first wave and 102 provinces in the second wave, based on the requirement of at least 50 cumulative deaths/10^5 inhabitants (Supplementary Table S1).

Fig. 1 shows the daily values of COVID-19 endpoints and meteorological data in all 2020, averaged over the provinces and temporally modeled using restricted cubic splines with 7 knots. While there is a clear-cut end of the first wave, at the end of 2020 the epidemic curves were decreasing but had not reached negligible levels. The number of incident COVID-19 cases was far higher during the second wave than the first one, while other endpoints were of similar magnitude. As expected, UV radiation and temperature peaked during summer, while relative humidity did not show a clear temporal pattern.

In the first wave (Fig. 2), non-linear Poisson regression analysis showed that temperature was inversely associated with all COVID-19 outcomes above 283 K (10 °C, 50 °F). At lower temperatures, there was a weak positive association with daily infections, a weak negative association with ICU admission, and an inverse association with hospital admissions and deaths, with an almost linear pattern for the latter. UV radiation and relative humidity showed little association with all COVID-19 outcomes, with the partial exception of a weak negative and almost linear relation of UV with hospital and ICU admissions.

In the second wave (Fig. 3), all COVID-19 outcomes showed an inverted U-shaped pattern of association with temperature, with an increase from 265 K up to 283 K for all COVID-19 endpoints (less steep for deaths than for the other three outcomes), and conversely a decrease above 283 K up to 300 K. Relative humidity did not appear to be related to COVID-19 outcomes, UV radiation showed a smooth decrease for all endpoints occurring above 40 kJ/m^2. In the lower range of exposure there was an increase, particularly for new infections, though it was slightly shallower than the decrease occurring above 40 kJ/m^2.

The aforementioned results for new SARS-CoV-2 infections changed little in both COVID-19 waves, when we did not include $PM_{2.5}$ as a potential confounder in the multivariable model (Supplementary Figures S1-S2).

The lag time from the combination of meteorological factors and each endpoint showed points of AIC local minima at 5, 12 and 28 days for infection incidence; at 0, 5, 13 and 21 days for hospital admissions; at 0, 5, 8 and 12 days for ICU admissions; at 4, 11, 18 and 28 days for deaths, with reference to the first wave (Fig. 4). Concerning the second wave, points of local minima were located at 14 and 21 days for infection incidence and hospital admissions and at 13 and 18–20 for ICU admissions, while for deaths AIC decreased when increasing the lag time, without local minima. These values were in good agreement with the lag times we used for the first wave, based on biological and epidemiologic evidence, only for hospitalization, while for the second wave the AIC-generated values were close to those a priori-selected, except for new SARS-CoV-2 infections.

4. Discussion

Italy in 2020 presented a nearly unique setting for the investigation

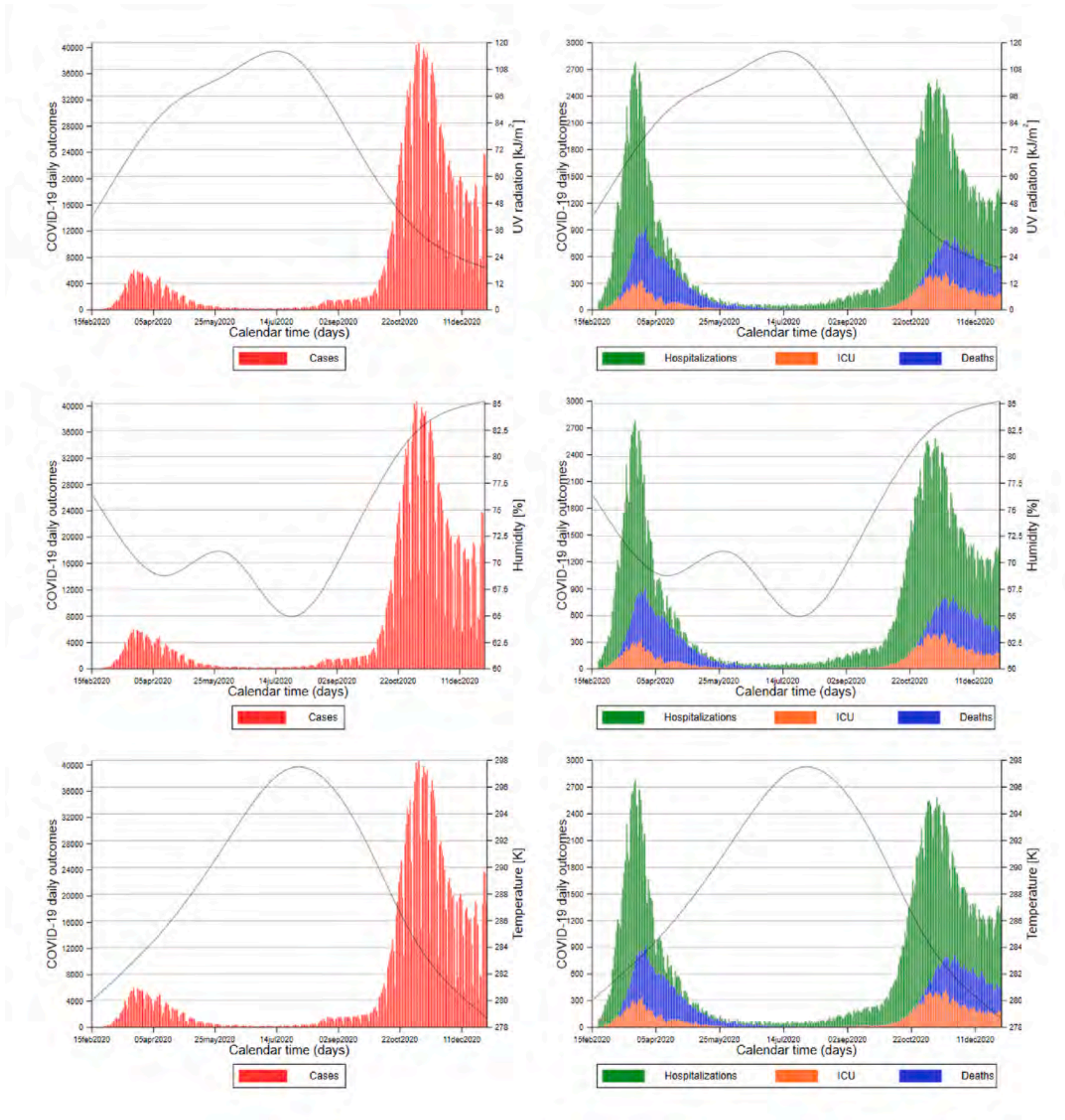

Fig. 1. Daily COVID-19 endpoints and meteorological factors trends in Italy in 2020. The meteorological data were averaged over the provinces and modeled with restricted cubic splines with 7 knots.

of the role of environmental factors on COVID-19 spread, for methodological reasons (Paraskevis et al., 2021). The policy on mobility restriction and use of a face mask was imposed nationally, and there was not yet any vaccine nor new variant of SARS-CoV-2 that might have affected transmission and virulence. This setting presented therefore an unusual opportunity to investigate the effect of meteorological factors on the spread of the pandemic.

The first SARS-CoV-2 variant in Italy (Variant of Concern, 202012/01, lineage B1.1.1.7) was detected in January 2021 (Messali et al., 2022). Vaccination started on December 27, 2020 in a few locations in the country, and it was only at the beginning of 2021 that the large-scale vaccination program began in Italy. We were also able to control for social distancing, possibly the major determinant in SARS-CoV-2 transmission, by using the proxy of mobility patterns derived from tracking mobile phones throughout the country (Vinceti et al., 2022). The strict rules issued by the national government for face mask wearing were the same throughout the country, and were met with high compliance. In contrast, most epidemiologic studies on the role of meteorological factors in COVID-19 spread studied a variety of communities and countries with limited control of covariates, making it

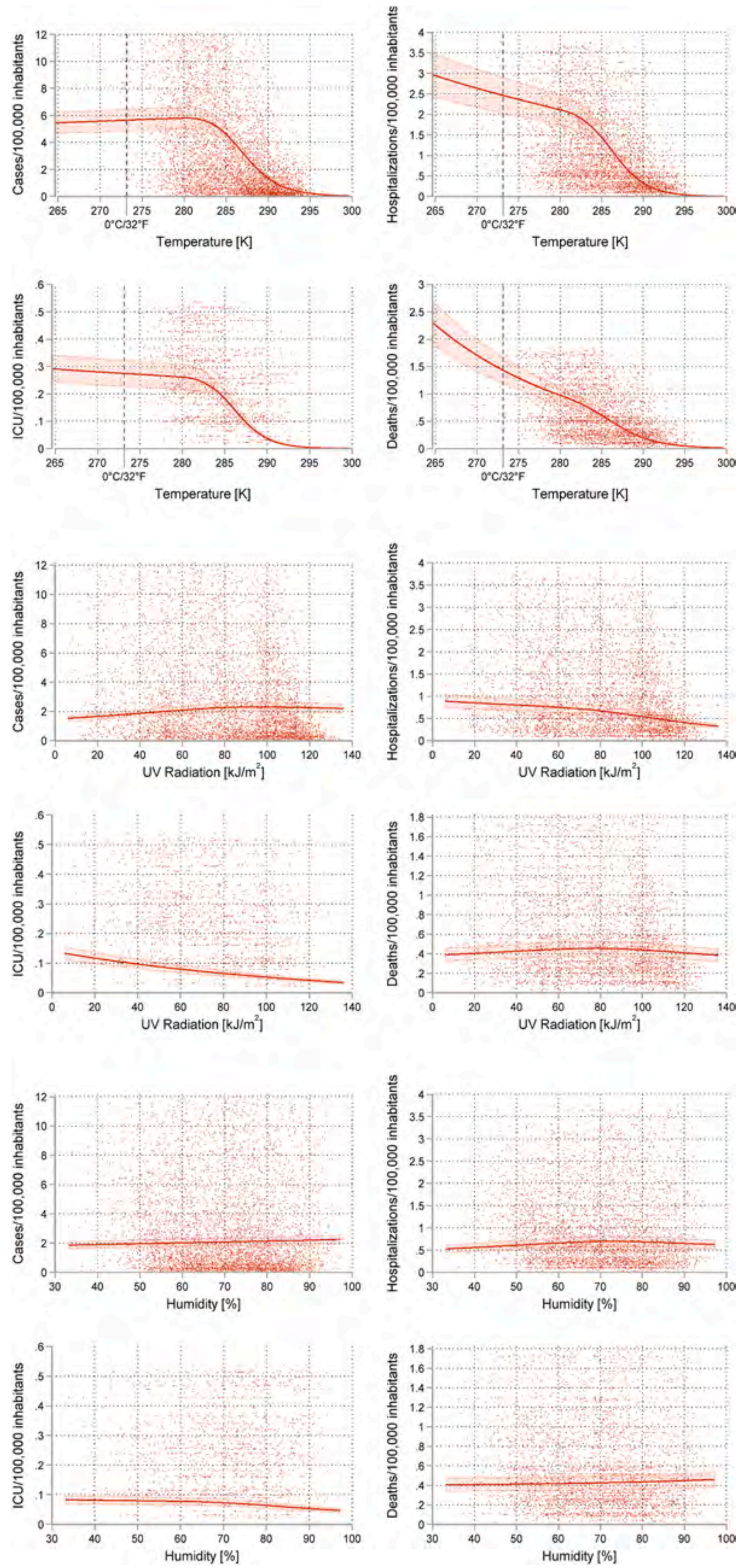

Fig. 2. Average number of cases/hospitalizations/ICU/deaths per 100,000 inhabitants in the first wave, as a function of meteorological factors (temperature/UV radiation/relative humidity) estimated in random-effects restricted cubic spline Poisson regression models adjusting for population density, daily movements, old age index, number of single-family homes, $PM_{2.5}$ with a lag time of 1 day. The shaded area represents pointwise 95% confidence intervals.

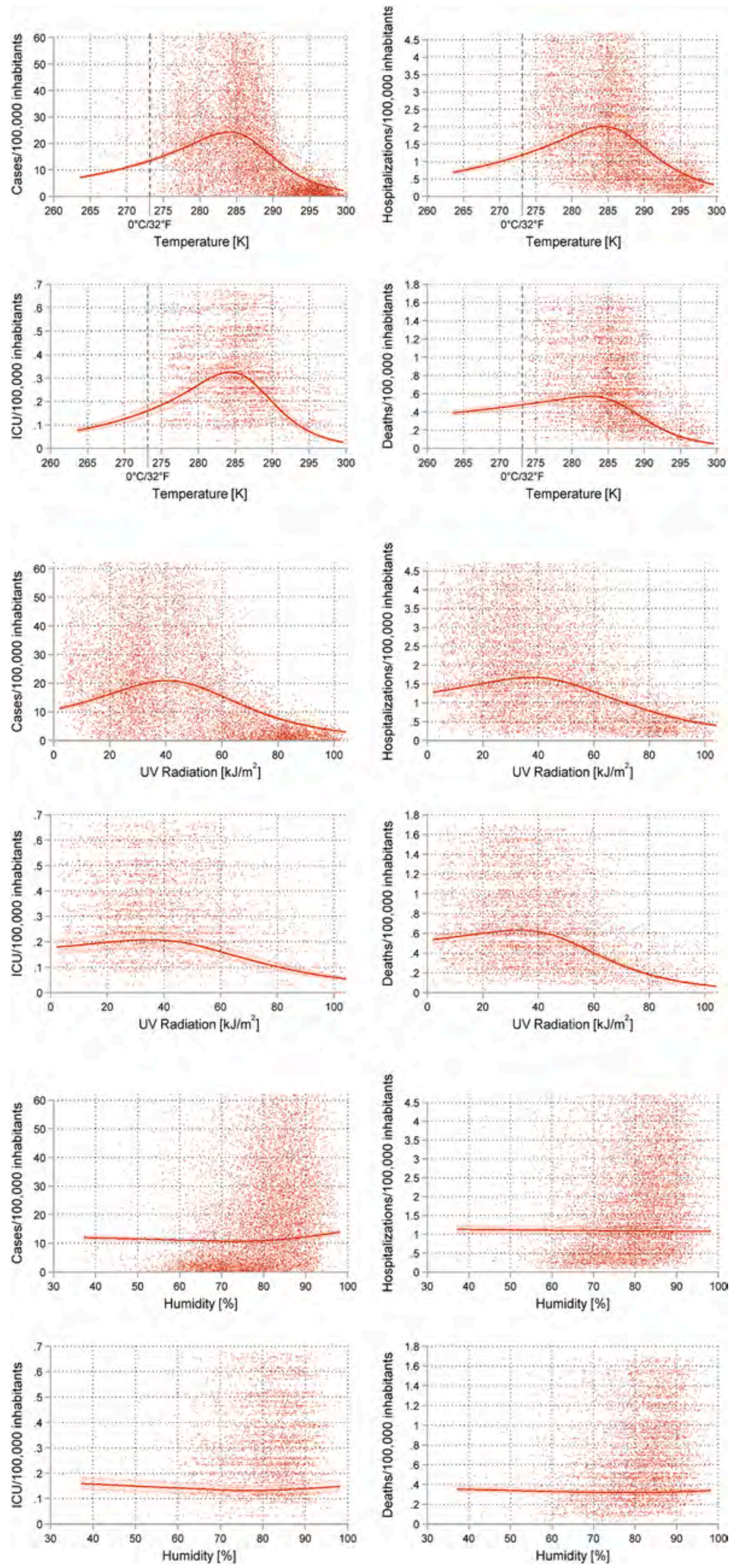

Fig. 3. Average number of cases/hospitalizations/ICU/deaths per 100,000 inhabitants in the second wave, as a function of meteorological factors (temperature/UV radiation/relative humidity) estimated in random-effects restricted cubic spline Poisson regression models adjusting for population density, daily movements, number of single-family homes, old age index, $PM_{2.5}$ with a lag time of 1 day. The shaded area represents pointwise 95% confidence intervals.

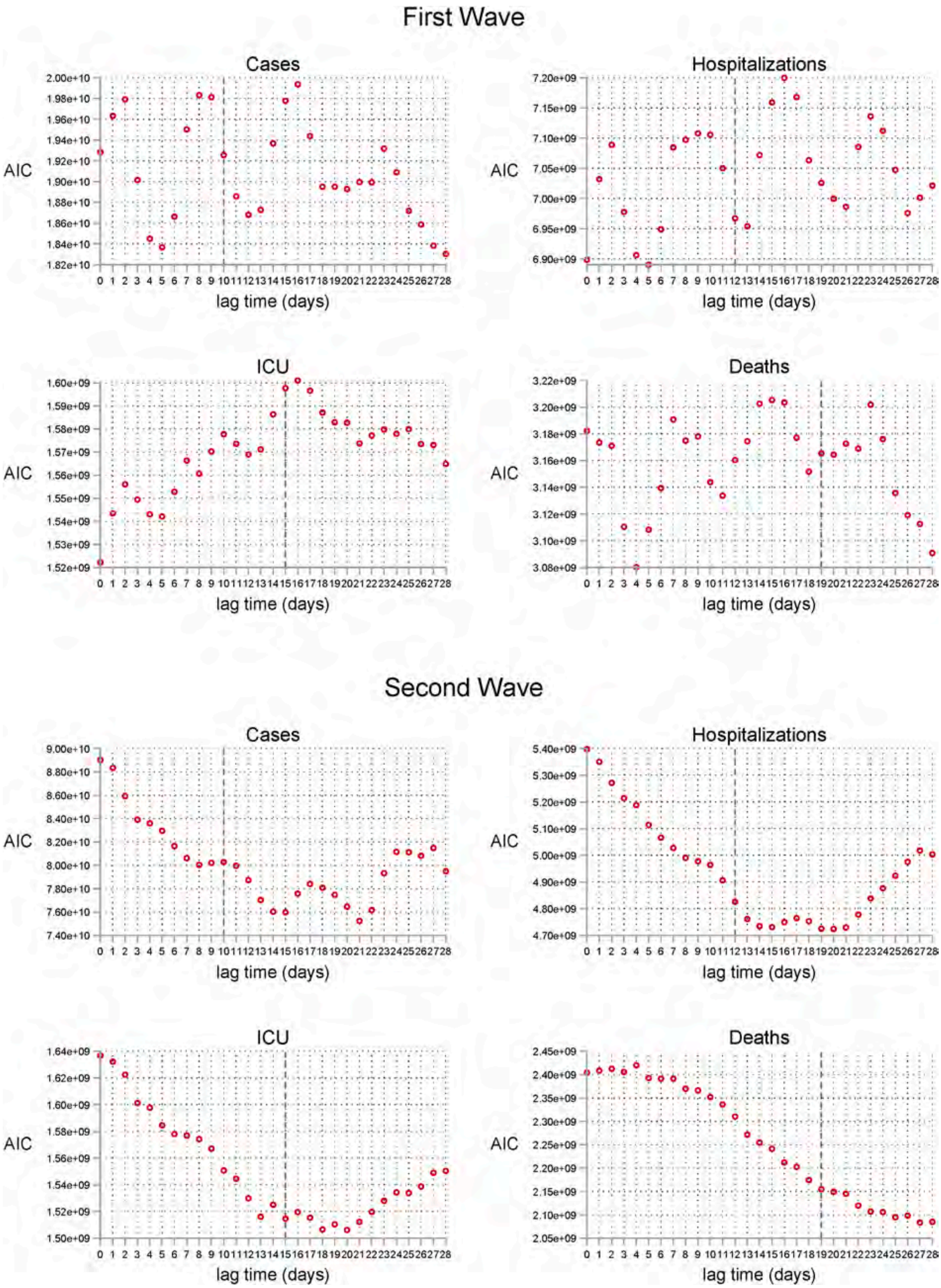

Fig. 4. Akaike Information Criterion (AIC), when varying the lag time between health endpoints and meteorological variables, estimated in random-effects restricted cubic spline Poisson regression models. Lower values of AIC mean that the selected model is better. We adjusted for old age index, density, daily movements, old age index, number of single-family homes and $PM_{2.5}$, the latter with a lag time of 1 day. The dashed lines represent the lag times emerging from *a priori* interpretation based on nationwide epidemiologic data.

difficult to separate the effect of meteorological factors from the effect of confounders and modifying factors, especially mobility and social interaction (Damette et al., 2021; Nottmeyer et al., 2022; Sciannameo et al., 2022; Wang et al., 2022; Zhai et al., 2023).

To compute more accurate estimates of the population at risk in the second wave, we subtracted from the provincial population the estimated percentage of residents who contracted COVID-19 during the first wave, given that such individuals were much less susceptible to reinfection, as also shown by the inverse relation of COVID-19 incidence in the Italian provinces between the first and the second wave (Vinceti et al., 2021). Air pollution has been suggested to be linked to increased COVID-19 incidence and severity (Copat et al., 2020; Filippini et al., 2020; Jerrett et al., 2022), and therefore could either confound or mediate the effect of meteorological factors on COVID-19. We analyzed our data controlling for population-weighted mean levels of ambient air $PM_{2.5}$ and also without controlling for it, with no appreciable differences in the results.

The associations that emerged from our analyses, specifically the inverted U-shaped association for temperature and to some extent for UV, confirmed the value of fitting non-linear models. In contrast, reliance on linear models, in addition to lack of control for confounding factors, could explain the null or otherwise inconsistent findings reported by others (Chen et al., 2022; Jerrett et al., 2022; Kerr et al., 2021; Nottmeyer et al., 2022).

We studied the four most commonly used and most relevant COVID-19 endpoints, i.e. incidence of SARS-CoV-2 infections, admissions to hospitals or to their intensive care units for COVID-19, and COVID-19 deaths. Only the last three outcomes may be considered complete, because, especially in the first wave, the number of available tests to detect SARS-CoV-2 infection was limited, and its use was largely restricted to symptomatic individuals. Therefore, there was undoubtedly substantial underascertainment of the incidence and the prevalence of the infection during the first wave, when number of new cases more closely reflected incident COVID-19 cases than new SARS-CoV-2 infections (Filippini et al., 2021b). We included the better ascertained outcomes of hospital referrals and deaths not only because they were more reliably measured, but also because meteorological factors might affect not just viral transmission, but also virulence, pathogenicity, and the host response, thus potentially affecting COVID-19 severity and lethality (Filippini et al., 2021a; Sciannameo et al., 2022). However, the lack of sex-specific data on most confounders precluded the implementation of sex-stratified analysis. Consequently, we were unable to address the possibility of different susceptibility for males and females, as was suggested in a previous study (Pivonello et al., 2021).

We made *a priori* estimates of likely lag times in our regression models, basing these on reports of COVID-19 incubation time, and the time needed in Italy to receive a diagnosis, to be referred to a hospital, time to death in fatal cases. We compared these lag times to those that corresponded to local minima of the AIC in our regression models. We had a good agreement between these two approaches only for hospitalization in the first wave, and for all the endpoints apart from new SARS-CoV-2 infections in the second wave. This phenomenon could have been related to the high temperatures that occurred during summer, which were better associated with the successive COVID-19 epidemic trend. The AIC model also generated other potentially optimal lag times, which could reflect specific impacts on individual susceptibility to infection and to subsequent disease progression or could be computational artifacts. However, and in comparison with AIC-based *a posteriori* modeling of lag times (Xiao et al., 2021), we consider more reliable their *a priori* interpretation based on nationwide epidemiologic data processed and released by the Italian National Institute of Health, and on biological and epidemiologic evidence about the latent period from infection onset to disease detection and hard endpoint occurrence.

We found that relative humidity had little association with COVID-19 spread or severity, whereas increasing solar UV radiation above a threshold of 40 kJ/m^2 had a small beneficial influence. UV light has been shown in a number of laboratory studies to decrease SARS-CoV2-viability (Park et al., 2022; Schuit et al., 2022; Su et al., 2022), and there is some epidemiologic evidence suggesting an effect in reducing coronavirus transmission among animals and humans (Carleton et al., 2021; Isaia et al., 2021; Perez-Gilaberte et al., 2023; Sehra et al., 2020; Thornton et al., 2022), with evidence of a possible threshold (Nottmeyer et al., 2022). The lack of association between outdoor relative humidity and COVID-19 endpoints does not preclude a role for indoor humidity, which could affect airborne infectious disease susceptibility (Aganovic et al., 2022; Wolkoff et al., 2021). Nevertheless, indoor relative humidity is kept more stable than outdoor humidity, increasing relative humidity while heating and decreasing it while cooling (Verheyen and Bourouiba, 2022).

The main finding of the current study was the substantial effect of temperature above a threshold of 10 °C/50 °F. Above this value, increasing temperatures were associated with decreased rates of SARS-CoV-2 infections and COVID-19 hospitalizations, ICU and deaths, during both the first and the second wave in Italy. This effect could reflect inhibition of viral spread from one individual to another, reduced virulence, or other factors (Chan et al., 2011; Chen et al., 2022; Lin et al., 2006). Laboratory studies have also provided evidence supporting deleterious effects of higher temperature on coronavirus viability and transmission (Biryukov et al., 2021; Casanova et al., 2010; Chan et al., 2011). Conversely, at low temperatures we did not find a clear pattern of association with COVID-19 endpoints.

Credit author statement

Marco Vinceti and Tommaso Filippini designed the original study, and with KJR and EB analyzed and interpreted the data, and drafted the manuscript. Nicola Orsini designed the code with Tommaso Filippini. Erica Balboni and Tommaso Filippini carried out data analysis. Stefania Bellino, Patrizio Pezzotti and Silvio Brusaferro provided processed health data for analysis, Sofia Costanzini, Fabrizio Ferrari and Sergio Teggi downloaded and processed the environmental data. All authors contributed to, read and approved the final manuscript.

Funding

This study was supported by grant FISR-EPICELLULARCOVID19 2021 from the Italian Ministry of the University and Research (Dr. Vinceti).

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Data availability

The authors confirm that the data supporting the findings of this study are available within the article and its supplementary materials.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.envres.2023.115796.

References

Aganovic, A., Bi, Y., Cao, G., Kurnitski, J., Wargocki, P., 2022. Modeling the impact of indoor relative humidity on the infection risk of five respiratory airborne viruses. Sci. Rep. 12, 11481 https://doi.org/10.1038/s41598-022-15703-8.
Babin, S., 2020. Use of weather variables in SARS-CoV-2 transmission studies. Int. J. Infect. Dis. 100, 333–336. https://doi.org/10.1016/j.ijid.2020.09.032.

Barceló, M.A., Saez, M., 2021. Methodological limitations in studies assessing the effects of environmental and socioeconomic variables on the spread of COVID-19: a systematic review. Environ. Sci. Eur. 33, 108. https://doi.org/10.1186/s12302-021-00550-7.

Biryukov, J., Boydston, J.A., Dunning, R.A., Yeager, J.J., Wood, S., Ferris, A., Miller, D., Weaver, W., Zeitouni, N.E., Freeburger, D., Dabisch, P., Wahl, V., Hevey, M.C., Altamura, L.A., 2021. SARS-CoV-2 is rapidly inactivated at high temperature. Environ. Chem. Lett. 19, 1773–1777. https://doi.org/10.1007/s10311-021-01187-x.

Bozdogan, H., 1987. Model selection and Akaike's Information Criterion (AIC): the general theory and its analytical extensions. Psychometrika 52, 345–370. https://doi.org/10.1007/BF02294361.

Byun, W.S., Heo, S.W., Jo, G., Kim, J.W., Kim, S., Lee, S., Park, H.E., Baek, J.H., 2021. Is coronavirus disease (COVID-19) seasonal? A critical analysis of empirical and epidemiological studies at global and local scales. Environ. Res. 196, 110972 https://doi.org/10.1016/j.envres.2021.110972.

Carleton, T., Cornetet, J., Huybers, P., Meng, K.C., Proctor, J., 2021. Global evidence for ultraviolet radiation decreasing COVID-19 growth rates. Proc. Natl. Acad. Sci. U. S. A. 118, e2012370118 https://doi.org/10.1073/pnas.2012370118.

Casanova, L.M., Jeon, S., Rutala, W.A., Weber, D.J., Sobsey, M.D., 2010. Effects of air temperature and relative humidity on coronavirus survival on surfaces. Appl. Environ. Microbiol. 76, 2712–2717. https://doi.org/10.1128/AEM.02291-09.

Chan, K.H., Peiris, J.S., Lam, S.Y., Poon, L.L., Yuen, K.Y., Seto, W.H., 2011. The effects of temperature and relative humidity on the viability of the SARS coronavirus. Adv Virol, 734690. https://doi.org/10.1155/2011/734690, 2011.

Chen, S., Huang, L., Cai, D., Li, B., Yang, J., 2022. Association between meteorological factors and COVID-19: a systematic review. Int. J. Environ. Health Res. 1–15 https://doi.org/10.1080/09603123.2022.2083090.

Ciceri, F., Castagna, A., Rovere-Querini, P., De Cobelli, F., Ruggeri, A., Galli, L., Conte, C., De Lorenzo, R., Poli, A., Ambrosio, A., Signorelli, C., Bossi, E., Fazio, M., Tresoldi, C., Colombo, S., Monti, G., Fominskiy, E., Franchini, S., Spessot, M., Martinenghi, C., Carlucci, M., Beretta, L., Scandroglio, A.M., Clementi, M., Locatelli, M., Tresoldi, M., Scarpellini, P., Martino, G., Bosi, E., Dagna, L., Lazzarin, A., Landoni, G., Zangrillo, A., 2020. Early predictors of clinical outcomes of COVID-19 outbreak in Milan, Italy. Clin. Immunol. 217, 108509 https://doi.org/10.1016/j.clim.2020.108509.

Copat, C., Cristaldi, A., Fiore, M., Grasso, A., Zuccarello, P., Signorelli, S.S., Conti, G.O., Ferrante, M., 2020. The role of air pollution (PM and NO2) in COVID-19 spread and lethality: a systematic review. Environ. Res. 191, 110129 https://doi.org/10.1016/j.envres.2020.110129.

Damette, O., Mathonnat, C., Goutte, S., 2021. Meteorological factors against COVID-19 and the role of human mobility. PLoS One 16, e0252405. https://doi.org/10.1371/journal.pone.0252405.

Di Federico, S., Filippini, T., Marchesi, C., Vinceti, M., 2022. Availability of open data related to COVID-19 epidemic in Italy. Ann Ig. https://doi.org/10.7416/ai.2022.2514.

European Centre for Medium-Range Weather Forecasts, 2023. ECMWF. https://www.ecmwf.int/. (Accessed 10 March 2023).

European Commission - Copernicus Eyes on Earth, 2023. Climate Data Store. https://cds.climate.copernicus.eu/#!/home. (Accessed 10 March 2023).

Filippini, T., Rothman, K.J., Goffi, A., Ferrari, F., Maffeis, G., Orsini, N., Vinceti, M., 2020. Satellite-detected tropospheric nitrogen dioxide and spread of SARS-CoV-2 infection in Northern Italy. Sci. Total Environ. 739, 140278 https://doi.org/10.1016/j.scitotenv.2020.140278.

Filippini, T., Rothman, K.J., Cocchio, S., Narne, E., Mantoan, D., Saia, M., Goffi, A., Ferrari, F., Maffeis, G., Orsini, N., Baldo, V., Vinceti, M., 2021a. Associations between mortality from COVID-19 in two Italian regions and outdoor air pollution as assessed through tropospheric nitrogen dioxide. Sci. Total Environ. 760, 143355 https://doi.org/10.1016/j.scitotenv.2020.143355.

Filippini, T., Zagnoli, F., Bosi, M., Giannone, M.E., Marchesi, C., Vinceti, M., 2021b. An assessment of case-fatality and infection-fatality rates of first and second COVID-19 waves in Italy. Acta Biomed. 92, e2021420 https://doi.org/10.23750/abm.v92iS6.12241.

Isaia, G., Diemoz, H., Maluta, F., Fountoulakis, I., Ceccon, D., di Sarra, A., Facta, S., Fedele, F., Lorenzetto, G., Siani, A.M., Isaia, G., 2021. Does solar ultraviolet radiation play a role in COVID-19 infection and deaths? An environmental ecological study in Italy. Sci. Total Environ. 757, 143757 https://doi.org/10.1016/j.scitotenv.2020.143757.

ISTAT - Italian National Institute of Statistics, 2021. SARS-CoV-2 Seroprevalence Survey; Data Tables. https://www.istat.it/it/archivio/256536. (Accessed 10 March 2023).

Istituto Superiore di Sanità, 2020. Report sulle caratteristiche dei pazienti deceduti positivi a SARS-CoV-2 in Italia sui dati aggiornati al 2 dicembre 2020. https://www.salute.gov.it/portale/nuovocoronavirus/dettaglioNotizieNuovoCoronavirus.jsp?id=5242. (Accessed 10 March 2023).

ISTAT - Italian National Institute of Statistics, 2023. Populations and Families. https://www.istat.it/it/files//2020/08/ReportPrimiRisultatiIndagineSiero.pdf. (Accessed 10 March 2023).

Jerrett, M., Nau, C.L., Young, D.R., Butler, R.K., Batteate, C.M., Su, J., Burnett, R.T., Kleeman, M.J., 2022. Air pollution and meteorology as risk factors for COVID-19 death in a cohort from Southern California. Environ. Int. 171, 107675 https://doi.org/10.1016/j.envint.2022.107675.

Kaplin, A., Junker, C., Kumar, A., Ribeiro, M.A., Yu, E., Wang, M., Smith, T., Rai, S.N., Bhatnagar, A., 2021. Evidence and magnitude of the effects of meteorological changes on SARS-CoV-2 transmission. PLoS One 16, e0246167. https://doi.org/10.1371/journal.pone.0246167.

Kerr, G.H., Badr, H.S., Gardner, L.M., Perez-Saez, J., Zaitchik, B.F., 2021. Associations between meteorology and COVID-19 in early studies: inconsistencies, uncertainties, and recommendations. One Health 12, 100225. https://doi.org/10.1016/j.onehlt.2021.100225.

Li, H.L., Yang, B.Y., Wang, L.J., Liao, K., Sun, N., Liu, Y.C., Ma, R.F., Yang, X.D., 2022. A meta-analysis result: uneven influences of season, geo-spatial scale and latitude on relationship between meteorological factors and the COVID-19 transmission. Environ. Res. 212, 113297 https://doi.org/10.1016/j.envres.2022.113297.

Lin, K., Yee-Tak Fong, D., Zhu, B., Karlberg, J., 2006. Environmental factors on the SARS epidemic: air temperature, passage of time and multiplicative effect of hospital infection. Epidemiol. Infect. 134, 223–230. https://doi.org/10.1017/S0950268805005054.

Majumder, P., Ray, P.P., 2021. A systematic review and meta-analysis on correlation of weather with COVID-19. Sci. Rep. 11, 10746 https://doi.org/10.1038/s41598-021-90300-9.

Messali, S., Campisi, G., Giovanetti, M., Ciccozzi, M., Caruso, A., Caccuri, F., 2022. The first Italian outbreak of SARS-CoV-2 B.1.1.7 lineage in Corzano, Lombardy. J. Med. Virol. 94, 413–416. https://doi.org/10.1002/jmv.27333.

Neagu, M., Calina, D., Docea, A.O., Constantin, C., Filippini, T., Vinceti, M., Drakoulis, N., Poulas, K., Nikolouzakis, T.K., Spandidos, D.A., Tsatsakis, A., 2021. Back to basics in COVID-19: antigens and antibodies-Completing the puzzle. J. Cell Mol. Med. 25, 4523–4533. https://doi.org/10.1111/jcmm.16462.

Nottmeyer, L., Armstrong, B., Lowe, R., Abbott, S., Meakin, S., O'Reilly, K., von Borries, R., Schneider, R., Royé, D., Hashizume, M., Pascal, M., Tobias, A., Vicedo-Cabrera, A.M., Lavigne, E., Correa, P.M., Ortega, N.V., Kynčl, J., Urban, A., Orru, H., Ryti, N., Jaakkola, J., Dallavalle, M., Schneider, A., Honda, Y., Ng, C.F.S., Alahmad, B., Carrasco, G., Holobâc, I.H., Kim, H., Lee, W., Íñiguez, C., Bell, M.L., Zanobetti, A., Schwartz, J., Scovronick, N., Coélho, M., Saldiva, P.H.N., Diaz, M.H., Gasparrini, A., Sera, F., 2022. The association of COVID-19 incidence with temperature, humidity, and UV radiation - a global multi-city analysis. Sci. Total Environ. 854, 158636 https://doi.org/10.1016/j.scitotenv.2022.158636.

Obe, R.O., Hsu, L.S., 2021. PostGIS in Action, Third ed. Manning Publications.

Paraskevis, D., Kostaki, E.G., Alygizakis, N., Thomaidis, N.S., Cartalis, C., Tsiodras, S., Dimopoulos, M.A., 2021. A review of the impact of weather and climate variables to COVID-19: in the absence of public health measures high temperatures cannot probably mitigate outbreaks. Sci. Total Environ. 768, 144578 https://doi.org/10.1016/j.scitotenv.2020.144578.

Park, S., Perlin, D.S., Fitzgerald, S., Petraitis, V., Walsh, T.J., 2022. Focused multivector ultraviolet (FMUV) technology rapidly eradicates SARS-CoV-2 in-vitro: implications for hospital disinfection of COVID-19 environments. Am. J. Infect. Control 50, 828–830. https://doi.org/10.1016/j.ajic.2022.02.001.

Perez-Gilaberte, J.B., Martin-Iranzo, N., Aguilera, J., Almenara-Blasco, M., de Galvez, M.V., Gilaberte, Y., 2023. Correlation between UV index, temperature and humidity with respect to incidence and severity of COVID 19 in Spain. Int. J. Environ. Res. Publ. Health 20 (1973). https://doi.org/10.3390/ijerph20031973.

Pivonello, R., Auriemma, R.S., Pivonello, C., Isidori, A.M., Corona, G., Colao, A., Millar, R.P., 2021. Sex disparities in COVID-19 severity and outcome: are men weaker or women stronger? Neuroendocrinology 111, 1066–1085. https://doi.org/10.1159/000513346.

Riccardo, F., Ajelli, M., Andrianou, X.D., Bella, A., Del Manso, M., Fabiani, M., Bellino, S., Boros, S., Urdiales, A.M., Marziano, V., Rota, M.C., Filia, A., D'Ancona, F., Siddu, A., Punzo, O., Trentini, F., Guzzetta, G., Poletti, P., Stefanelli, P., Castrucci, M.R., Ciervo, A., Di Benedetto, C., Tallon, M., Piccioli, A., Brusaferro, S., Rezza, G., Merler, S., Pezzotti, P., group, C.-w., 2020. Epidemiological characteristics of COVID-19 cases and estimates of the reproductive numbers 1 month into the epidemic, Italy, 28 January to 31 March 2020. Euro Surveill. 25, 2000790 https://doi.org/10.2807/1560-7917.ES.2020.25.49.2000790.

Riccardo, F., Guzzetta, G., Urdiales, A.M., Del Manso, M., Andrianou, X.D., Bella, A., Pezzotti, P., Carbone, S., De Vito, T., Maraglino, F., Demicheli, V., Dario, C., Coscioni, E., Rezza, G., Urbani, A., Merler, S., Brusaferro, S., Italian, C.-m.g., 2022. COVID-19 response: effectiveness of weekly rapid risk assessments, Italy. Bull. World Health Organ. 100, 161–167. https://doi.org/10.2471/BLT.21.286317.

Romero Starke, K., Mauer, R., Karskens, E., Pretzsch, A., Reissig, D., Nienhaus, A., Seidler, A.L., Seidler, A., 2021. The effect of ambient environmental conditions on COVID-19 mortality: a systematic review. Int. J. Environ. Res. Publ. Health 18, 6665. https://doi.org/10.3390/ijerph18126665.

Schuit, M.A., Larason, T.C., Krause, M.L., Green, B.M., Holland, B.P., Wood, S.P., Grantham, S., Zong, Y., Zarobila, C.J., Freeburger, D.L., Miller, D.M., Bohannon, J.K., Ratnesar-Shumate, S.A., Blatchley 3rd, E.R., Li, X., Dabisch, P.A., Miller, C.C., 2022. SARS-CoV-2 inactivation by ultraviolet radiation and visible light is dependent on wavelength and sample matrix. J. Photochem. Photobiol., B 233, 112503. https://doi.org/10.1016/j.jphotobiol.2022.112503.

Sciannameo, V., Goffi, A., Maffeis, G., Gianfreda, R., Jahier Pagliari, D., Filippini, T., Mancuso, P., Giorgi-Rossi, P., Dal Zovo, A.L., Corbari, A., Vinceti, M., Berchialla, P., 2022. A deep learning approach for Spatio-Temporal forecasting of new cases and new hospital admissions of COVID-19 spread in Reggio Emilia, Northern Italy. J. Biomed. Inf. 132, 104132 https://doi.org/10.1016/j.jbi.2022.104132.

Sehra, S.T., Salciccioli, J.D., Wiebe, D.J., Fundin, S., Baker, J.F., 2020. Maximum daily temperature, precipitation, ultraviolet light, and rates of transmission of severe acute respiratory syndrome coronavirus 2 in the United States. Clin. Infect. Dis. 71, 2482–2487. https://doi.org/10.1093/cid/ciaa681.

Su, W.L., Lin, C.P., Huang, H.C., Wu, Y.K., Yang, M.C., Chiu, S.K., Peng, M.Y., Chan, M.C., Chao, Y.C., 2022. Clinical application of 222 nm wavelength ultraviolet C irradiation on SARS CoV-2 contaminated environments. J. Microbiol. Immunol. Infect. 55, 166–169. https://doi.org/10.1016/j.jmii.2021.12.005.

Tan, L., Schultz, D.M., 2022. How is COVID-19 affected by weather? Metaregression of 158 studies and recommendations for best practices in future Research. Weather, Climate, and Society 14, 237–255. https://doi.org/10.1175/WCAS-D-21-0132.1.

Task force COVID-19 del Dipartimento Malattie Infettive e Servizio di Informatica, 2020. Epidemia COVID-19, Aggiornamento Nazionale: 29 Dicembre 2020. https://www.epicentro.iss.it/coronavirus/bollettino/Bollettino-sorveglianza-integrata-COVID-19_29-dicembre-2020.pdf. (Accessed 10 March 2023).

Thornton, G.M., Fleck, B.A., Fleck, N., Kroeker, E., Dandnayak, D., Zhong, L., Hartling, L., 2022. The impact of heating, ventilation, and air conditioning design features on the transmission of viruses, including the 2019 novel coronavirus: a systematic review of ultraviolet radiation. PLoS One 17, e0266487. https://doi.org/10.1371/journal.pone.0266487.

van Rossum, G., Drake, F.J.J., 2011. The Python Language Reference Manual (Python Manual). Network Theory.

Verheyen, C.A., Bourouiba, L., 2022. Associations between indoor relative humidity and global COVID-19 outcomes. J R Soc Interface 19, 20210865. https://doi.org/10.1098/rsif.2021.0865.

Vinceti, M., Filippini, T., Rothman, K.J., Ferrari, F., Goffi, A., Maffeis, G., Orsini, N., 2020. Lockdown timing and efficacy in controlling COVID-19 using mobile phone tracking. EClinicalMedicine 25, 100457. https://doi.org/10.1016/j.eclinm.2020.100457.

Vinceti, M., Filippini, T., Rothman, K.J., Di Federico, S., Orsini, N., 2021. SARS-CoV-2 infection incidence during the first and second COVID-19 waves in Italy. Environ. Res. 197, 111097 https://doi.org/10.1016/j.envres.2021.111097.

Vinceti, M., Balboni, E., Rothman, K.J., Teggi, S., Bellino, S., Pezzotti, P., Ferrari, F., Orsini, N., Filippini, T., 2022. Substantial impact of mobility restrictions on reducing COVID-19 incidence in Italy in 2020. J. Trav. Med. 29 https://doi.org/10.1093/jtm/taac081 taac081.

Wang, W., Ji, S., Wang, J., Liao, F., 2022. Using a novel two-stage strategy to characterize the spatial distribution of associations between temperature and COVID-19: a case study in the continental United States. Sci. Total Environ. 850, 158003 https://doi.org/10.1016/j.scitotenv.2022.158003.

Wolkoff, P., Azuma, K., Carrer, P., 2021. Health, work performance, and risk of infection in office-like environments: the role of indoor temperature, air humidity, and ventilation. Int. J. Hyg Environ. Health 233, 113709. https://doi.org/10.1016/j.ijheh.2021.113709.

Wu, Y., Kang, L., Guo, Z., Liu, J., Liu, M., Liang, W., 2022. Incubation Period of COVID-19 caused by unique SARS-CoV-2 strains: a systematic review and meta-analysis. JAMA Netw. Open 5, e2228008. https://doi.org/10.1001/jamanetworkopen.2022.28008.

Xiao, S., Qi, H., Ward, M.P., Wang, W., Zhang, J., Chen, Y., Bergquist, R., Tu, W., Shi, R., Hong, J., Su, Q., Zhao, Z., Ba, J., Qin, Y., Zhang, Z., 2021. Meteorological conditions are heterogeneous factors for COVID-19 risk in China. Environ. Res. 198, 111182 https://doi.org/10.1016/j.envres.2021.111182.

Zhai, G., Qi, J., Zhou, W., Wang, J., 2023. The non-linear and interactive effects of meteorological factors on the transmission of COVID-19: a panel smooth transition regression model for cities across the globe. Int. J. Disaster Risk Reduc. 84, 103478 https://doi.org/10.1016/j.ijdrr.2022.103478.

Zhao, Y., Huang, J., Zhang, L., Chen, S., Gao, J., Jiao, H., 2022. The global transmission of new coronavirus variants. Environ. Res. 206, 112240 https://doi.org/10.1016/j.envres.2021.112240.

Zheng, H.L., Guo, Z.L., Wang, M.L., Yang, C., An, S.Y., Wu, W., 2021. Effects of climate variables on the transmission of COVID-19: a systematic review of 62 ecological studies. Environ. Sci. Pollut. Res. Int. 28, 54299–54316. https://doi.org/10.1007/s11356-021-15929-5.