The role of tropospheric Ozone in flagging COVID-19 pandemic transmission.

Simone Lolli (simone.lolli@imaa.cnr.it)
CNR-IMAA

Gemine Vivone
CNR-IMAA

Short Report

Keywords: COVID-19, tropospheric ozone, air-quality, infectious diseases

Posted Date: October 8th, 2020

DOI: https://doi.org/10.21203/rs.3.rs-89804/v1

Version of Record: A version of this preprint was published on December 15th, 2020. See the published version at https://doi.org/10.1007/s42865-020-00026-1.

Abstract

COVID-19 pandemic outbreak, caused by the SARS-CoV-2 virus, affected millions of people worldwide causing hundreds of thousands of related fatalities. It is crucial to understand why the virus transmission seems to spread more easily in some regions with respect to others. The residuals, with respect to the modeled COVID-19 per-day hospitalized patients in Intensive Care Unit, were linked to meteorological and air-pollutant variables in four major metropolitan areas in Italy. COVID-19 pandemic related infections are slow down by higher tropospheric Ozone concentrations ($p < 0.01$). We quantitatively assessed that higher levels of tropospheric Ozone, already proven effective against viruses and microbial contaminants, play a role in flagging COVID-19 pandemic transmission. Because the tropospheric ozone production is depending, among others, by air-quality and sunlight, this can explain why the virus is spreading differential.

Background

In March 2020, the World Health Organization declared pandemic the new SarS-CoV-2 virus outbreak that infected millions of people worldwide with consequent hundreds of thousands of fatalities. Understanding why the SARS CoV-2 is selectively spreading, i.e. to understand why some large metropolitan areas are devastated by the virus in term of infected people and fatalities, while in others the virus transmission is limited with consequent much lesser fatalities, is of fundamental importance to implement strategies at government level to contrast and contain any possible outbreak. A recent study (Liu et al., 2020) has already highlighted how the meteorological variables, e.g. temperature and humidity, can affect COVID-19 pandemic transmission. In this study we assessed how the ozone tropospheric concentration affected COVID-19 pandemic transmission in four major metropolitan areas in Italy. We collected the main meteorological and air-pollution related variables from 1 February 2020 to 31 May 2020 in Milan, Trento, Florence and Rome. We tested the non-linear Kendall and Spearman correlations among those parameters and the residual number of the hospitalized patients in the Intensive Care Unit (ICU) as shown in Lolli et al., 2020. The number of hospitalized patients in ICU unit is a much stronger indicator of COVID-19 pandemic transmission because it is independent of the number nasopharyngeal swabs performed. Accordingly, we considered the latency and the incubation period of the patients admitted into the ICU unit in critical conditions. ICU patients are, on average, admitted two-weeks after getting infected. For this reason, both the meteorological and air-pollution data are two weeks back time-shifted. This means that the daily number of ICU patients from 24 February 2020 to 14 June 2020 are the result of infections that happened from 10 February 2020 to 31 May 2020. The ICU per-day cases are modeled following the Gaussian Mixture Model (GMM) (Singhal et al., 2020, Lolli et al., 2020). The observational data show different trends with respect to time. In the early phase, the ICU patient number grows exponentially, followed by plateau and an exponential drop in the late phase. The curve symmetry is strictly dependent, among other variables, on lock-down policies implemented by the government. For this reason, the correlation analysis would give very different results if applied on diff, i.e. the results from

Spearman and Kendall rank tests during the growing phase will be completely different with respect to the drop phase. To make the analysis independent on those issues, we consider instead the per-day residual number of ICU patients with respect to the GMM model, extrapolated from the data trend. The model should account for the natural trend of viral epidemic and the effect of the lock-down on it. Thus, the residual analysis (i.e., the differences between the GMM model and the observed cases) should preserve from spurious correlations between the above-mentioned effects and the parameters under analysis. Indeed, the considered atmospheric parameters quickly change (sometimes day-to-day), thus representing a divergence factor (residue) with respect to the model and characterizing the existing anomaly about the classical behavior described by the model.

Results

In Figure 1 we show the model and the per-day number of ICU hospitalized patients for Milan, Trento, Florence and Rome and the corresponding residuals.

The correlations between COVID-19 pandemic, meteorological and air pollution variables were investigated using non-linear Spearman and Kendall rank correlation tests. The Spearman rank correlation non-parametric test is described as follows (Lolli et al., 2020):

$$r_s = 1 - \frac{6 \times \sum_i d_i^2}{n(n^2 - 1)}, \qquad (1)$$

where represents the difference between the ranks of two parameters, and the number of alternatives. Equation (2) shows the Kendall rank correlation non-parametric test :

$$\tau = \frac{\boldsymbol{concor - discor}}{\boldsymbol{0.5 \times n \times (n-1)}}, \qquad (2)$$

where represents the number of concordant pairs, while represents the discordant pairs, and is the number of pairs. Values of and τ equal to +1 and −1 imply a perfect positive and negative correlation, respectively. We analyzed the non-linear correlation among the daily max temperature (T_{max}), the daily average temperature (T_{avg}), the minimum daily temperature (T_{min}). For humidity, the correlation was tested for the maximum, average and minimum Dew Point (DP) temperature, denoted as DP_{max}, DP_{avg} and DP_{min}, respectively. Moreover, the Water Vapor (WV in g kg^{-1}) concentration and the Absolute Humidity (AH) in g m^{-3}) through Clausius-Clapeyron equation (Qi et al., 2020) are considered. These can be described through the following equations:

$$\boldsymbol{WV = 6.22 \times RH \times \frac{6.112 \times \exp\left(\frac{17.67 \times T}{243.5 + T}\right)}{P}}, \quad (3)$$

$$AH = 2.1674 \times RH \times \frac{6.112 \times \exp\left(\frac{17.67 \times T}{243.5 + T}\right)}{273.15 + T}, \quad (4)$$

where *RH* is the daily averaged relative humidity, *T* is the daily averaged temperature and *P* is the daily averaged atmospheric pressure. Regarding to the air-pollution parameters, we tested the correlations for the Nitrogen Dioxide (NO_2), the fine particulate matter ($PM_{2.5}$) and the Ozone (O_3) concentrations. The meteorological data are publicly available on https://wunderground.com, while the air-pollution data, i.e. NO_2, $PM_{2.5}$ and O_3 daily averaged concentrations, are freely available (or upon request for Milan and Lombardy region) from the regional environmental protection agency websites.

Table 1 Analysis on meteorological and air-pollution parameters. Temperature and Ozone correlate significantly with ICU residual patient number for all the metropolitan areas (confidence interval > 99%); ns stands for correlation not statistically significative.

	Kendall				**Spearman**			
	Milan	Trento	Florence	Rome	Milan	Trento	Florence	Rome
T_{max}	-0.21	-0.23	-0.29	-0.21	-0.3	-0.37	-0.4	-0.42
T_{avg}	-0.19	-0.28	-0.28	-0.17	-0.31	-0.45	-0.4	-0.39
T_{min}	-0.19	-0.34	-0.24	-0.12	-0.27	-0.52	-0.34	-0.31
DP_{max}	-0.19	-0.41	ns	-0.13	-0.27	-0.61	ns	-0.19
DP_{avg}	-0.21	-0.38	ns	-0.13	-0.31	-0.56	ns	-0.2
DP_{min}	-0.22	-0.33	ns	-0.15	-0.32	0.51	ns	-0.19
AH	-0.25	-0.42	ns	ns	-0.37	-0.61	ns	ns
WV	-0.23	-0.41	ns	ns	-0.33	-0.62	ns	ns
NO_2	ns	0.26	ns	-0.18	ns	0.39	ns	-0.26
$PM_{2.5}$	ns	ns	0.27	ns	ns	ns	0.41	ns
O_3	-0.22	-0.18	-0.2	-0.37	-0.29	-0.27	-0.31	-0.54

The results, reported in Table 1, put in evidence that the Ozone concentration, the temperature and the humidity (except for Florence) strongly negatively correlates with COVID-19 pandemic transmission for all the analyzed metropolitan areas. Regarding to Nitrogen Dioxide, results are not significant or in contrast (positive correlation for Trento, negative correlation for Rome). For $PM_{2.5}$ concentrations instead, only Florence shows a strong positive correlation. With respect to the meteorological parameters, the analysis corroborates the results found in a preliminary work performed only on Milan data (Lolli et al., 2020).

Discussion

To the best of our knowledge, no previous studies demonstrated a strong and clear negative correlation between ozone concentration and COVID-19 pandemic transmission. This result can explain in part the different virus transmission in different part of the world. This speculation is corroborated by Dubuis et al., 2020. Their findings suggest that low concentration ozone is a powerful disinfectant for airborne viruses in combination with higher humidity of the air. Ozone production in the troposphere is strongly linked to sunlight and pollutants, i.e. precursors as NO_2. On other hand, ozone production is inhibited by the presence of black carbon in the boundary layer (Li et al., 2005). All those factors should be then taken into consideration to explain the differential transmission. The results highlight that the ozone concentration should be considered as a co-factor in COVID-19 pandemic transmission, while all the epidemiological aspects should not be neglected and have obviously the primary role.

Declarations

Conflict of Interest

The Authors declare that there is no conflict of interest.

References

Dubuis ME, Dumont-Leblond N, Laliberté C, et al. Ozone efficacy for the control of airborne viruses: Bacteriophage and norovirus models. *PLoS One*. 2020;15(4):e0231164. Published 2020 Apr 10. doi:10.1371/journal.pone.0231164

Li, G., Zhang, R., Fan, J., and Tie, X. (2005), Impacts of black carbon aerosol on photolysis and ozone, *J. Geophys. Res.*, 110, D23206, doi:10.1029/2005JD005898.

Liu, Y., Ning, Z., Chen, Y., Guo, M., Liu, Y., Gali, N. K., Sun, L., Duan, Y., Cai, J., Westerdahl, D., Liu, X., Xu, K., Ho, K., Kan, H., Fu, Q., Lan, K., 2020. Aerodynamic analysis of SARS-CoV-2 in two Wuhan hospitals.

Nature. https://doi.org/10.1038/s41586-020-2271-3..

Lolli, S., Chen, Y., Wang, S. and Vivone, G.:. Impact of meteorological conditions and air pollution on COVID-19 pandemic transmission in Italy., *Sci Rep* **10,** 16213 (2020). https://doi.org/10.1038/s41598-020-73197-8

Qi H., Xiao S., Shi R., Ward M.P., Chen Y., Tu W., Su Q., Wang W., Wang X., Zhang Z. COVID-19 transmission in mainland China is associated with temperature and humidity: a time-series analysis. Sci. Total Environ. 2020;728 doi: 10.1016/j.scitotenv.2020.138778.

Singhal A., P. Singh, B. Lall, S. D. Joshi, Modeling and prediction of COVID-19 pandemic using Gaussian mixture model, Chaos, Solitons & Fractals, Volume 138,2020.

Figures

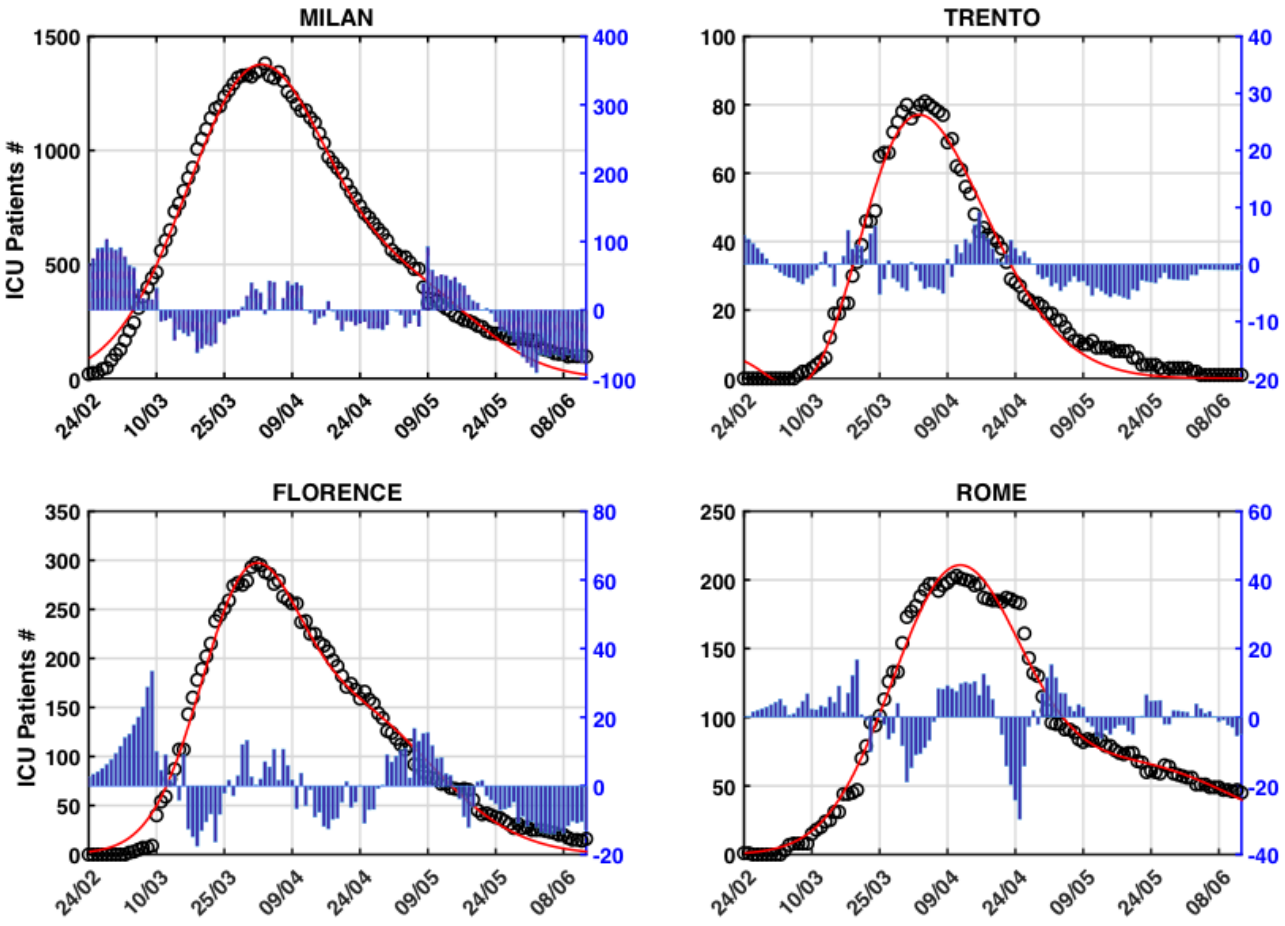

Figure 1

ICU Admitted patients fitted by a Bi-Gaussian function (red line) extrapolated from the observed data (black circle dots). The residuals are used to investigate the correlation with the meteorological and air-pollution variables. In blue are shown the residuals (Bi-Gaussian Model – ICU patients)