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How do low wind speeds and high levels of air pollution support the spread of COVID-19?

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A R T I C L E I N F O

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A B S T R A C T

The pandemic of coronavirus disease 2019 (COVID-19) is generating a high number of infected individuals and deaths. One of the current questions is how climatological factors and environmental pollution can affect the diffusion of COVID-19 in human society. This study endeavours to explain the relation between wind speed, air pollution and the diffusion of COVID-19 to provide insights to constrain and/or prevent future pandemics and epidemics. The statistical analysis here focuses on case study of Italy and reveals two main findings: 1) cities with high wind speed have lower numbers of COVID-19 related infected individuals; 2) cities located in hinterland zones (mostly those bordering large urban conurbations) with little wind speed and frequently high levels of air pollution had higher numbers of COVID-19 related infected individuals. Results here suggest that *high concentrations of air pollutants, associated with low wind speeds, may promote a longer permanence of viral particles in polluted air of cities, thus favouring an indirect means of diffusion of the novel coronavirus (SARS-CoV-2),* in addition to the direct diffusion with human-to-human transmission dynamics.

1. Introduction and goal of the scientific investigation

This study has the main goal to investigate, in environments with frequently high levels of atmospheric pollution, how wind speeds are linked to the spread of severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2), which is the strain of novel coronavirus that causes Coronavirus disease 2019 (COVID-19).

Manifold studies analyse possible relations between air pollution and diffusion of COVID-19 (Bashir et al., 2020; Fattorini and Regoli, 2020; Sciomer et al., 2020; Tung et al., 2021). Coccia (2020) reveals that cities with frequently high levels of air pollution — exceeding safe levels of ozone or particulate matter — had higher numbers of COVID-19 related infected individuals and deaths. Scholars maintain that air pollution can operate as one of the factors determining the spread of COVID-19 in society (cf., Coccia, 2020a). In addition, climatological, environmental, demographic, and geographical factors can influence the spread of COVID-19 in cities (Rosario Denes et al., 2020; Sarmadi et al., 2020; Bashir et al., 2020a; Sahin, 2020). Zhong et al. (2018) argue that static meteorological conditions may explain the increase of bacterial communities in the presence of air pollution. van Doremalen et al. (2020) reveal the stability of SARS-CoV-2 in the air: i.e., this novel coronavirus can remain viable and infectious in aerosols for hours. Overall, then, researchers support that air pollution can create a fruitful habitat for the spread of SARS-CoV-2 (Coccia, 2020; Tung et al., 2021).

The purpose of the present study is to see whether statistical evidence supports the hypothesis that higher numbers of COVID-19 related infected individuals in cities can be explained with an atmosphere having little wind and frequently high levels of air pollution.

This study extends the findings by Coccia, 2020b, Coccia (2020a, 2020b) and presents new experimental results of geo-environmental factors that are supporting the spread of COVID-19 in polluted cities, leading to a higher number of infected individuals and deaths. This study is in line with the Goal 3 (Ensure healthy lives and promote well-being for all at all ages) of the 2030 agenda for sustainable development by the United Nations (2020)–i.e., to substantially reduce the number of deaths and illnesses from hazardous chemicals and air, water and soil pollution and contamination (point 3.9)–. Results here can suggest a long-run environmental policy directed to alleviate air pollution in cities with little wind for reducing the diffusion of future epidemics similar to the COVID-19 and, as a consequence, negative effects on public health.

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2. Methodology

2.1. Working hypothesis (WHP)

WHP here is that high concentrations of air pollutants in the atmosphere, associated with low wind speeds, may promote a longer permanence of the novel coronavirus (SARS-CoV-2) in the air, thus favouring the diffusion of viral infectivity in society.

2.2. Sample and data sources

This study focuses on fifty-five ($N = 55$) polluted cities (randomly selected) that are provincial capitals in Italy (Coccia, 2020). Data of confirmed cases of COVID-19 are from Ministero della Salute (Department of Health) of Italy; data of air pollution are from Regional Agencies for Environmental Protection located in Italian provincial capitals; instead, climatological data are from meteorological stations of Italian provinces (Coccia, 2020); data of the mortality of respiratory and cardiovascular diseases in polluted cities under study are from ISTAT (2020); finally, data of the density of population, index of seniority of people and population aged more than 65 years old in polluted cities are also from the Italian National Institute of Statistics (ISTAT, 2020a, 2020b).

2.3. Measures

- *Diffusion of the COVID-19* in cities under study is measured with the number of infected individuals on April 7, 2020, during the first wave of COVID-19 outbreak in Italy.
- *Atmospheric turbulence/stability* (irregular/regular air motions characterized by winds that vary in speed and direction) is measured with average wind speed (km/h) of cities under study on February-March-April 2020, before and during the diffusion of COVID-19 in Italy.
- *Air pollution* of cities is measured with total days exceeding the limits set for PM_{10} or for ozone in 2018. Experimental results reveal that $PM_{2.5}$ and PM_{10} have a strong correlation (Zhou et al., 2016; Kong et al., 2016). Fig. 1A in Appendix shows the map with the air quality monitoring stations of Italian polluted cities under study (Figure 1A).
- *Demographic data of cities are given by:*
  - Population density of cities (inhabitants/km^2), 2019
  - Elderly people index, 2019
  - People aged >65 years old, 2019
- *Data of public health of cities* are based on mortality of specific diseases:
  - Rate of mortality per malignant tumours of the trachea, bronchi and lungs per 10,000 people in 2017. Lung and bronchi cancer is a: "cancer that forms in tissues of the lung, usually in the cells lining air passages" (National Cancer Institute, 2020).
  - Rate of mortality for diseases of respiratory system per 10,000 people, 2017. Zhu et al., 2019 demonstrate that air pollution can increase respiratory diseases and lung cancer because particulate matter and other air pollutants are genotoxic and contribute to the development of tumour and other diseases (e.g., COPD) via inducing sustained inflammation.
  - Rate of mortality for diseases of cardiovascular system per 10,000 people, 2017 (cf., Hadei and Naddafi, 2020; Çapraz et al., 2016; Pangaribuan et al., 2019).

2.4. Data analysis procedure

Descriptive statistics is performed categorizing Italian provincial capitals in groups, considering:

- *wind speed,* based on arithmetic mean of the sample given by 9.28 km/h
  - cities with *high wind speed* (>9.28 km/h) that in the Beaufort wind scale indicates a wind force from light to moderate breeze (average wind force of *light breeze* means that wind felt on face, leaves rustle, vanes begin to move, whereas a wind force of *moderate breeze* generates the wind effect of dust, leaves and loose paper lifted, small tree branches move)
  - cities with *low wind speed* (≤9.28 km/h) that in the Beaufort wind scale indicates a wind force from *calm* air to *light breeze.*
- *Location of cities*
  - Hinterland
  - Coastal/Near coast (<50 km from coast)
- *Air pollution*
  - Cities with *high air pollution* (>100 days per year exceeding the limits set for PM_{10} or for ozone)
  - Cities with *low air pollution* (≤100 days per year exceeding the limits set for PM_{10} or for ozone)

Correlation (bivariate and partial) and regression analyses verify relationships between variables understudy. Regression analysis considers that the number of infected individuals on April 7, 2020 across Italian cities (dependent variable *y*) is a linear function of the explanatory variable of wind speed (explanatory variable *x*) or Population Density in a model of simple regression.

In order to respect the four assumptions associated with linear regression model (i.e., Linearity, Homoscedasticity, Independence and Normality), the specification is based on a *log-log* model:

$$\log y_t = \alpha + \beta \log x_{t-1} + u \qquad [1]$$

α is a constant; β = coefficient of regression; u = error term/residuals.

The estimation of equation [1], using the explanatory variable of population density, is also performed with a categorization of cities according to wind speed (higher or lower than arithmetic mean of the sample). A multiple regression analysis is also performed with dependent variable given by number of infections (confirmed cases of COVID-19) on April 7, 2020 and explanatory variables given by: Log population density, Log days exceeding limits set for PM_{10} or ozone, Log elderly index of seniority, and wind speed. Visual representation of the effect of wind speed on the spread of COVID-19 is displayed in graphs with regression lines. Of course, factors determining the spread of COVID-19 are complex and variables under study here cannot detect all determinants, and many of them relapse in the residuals of regression models. Ordinary Least Squares (OLS) method is applied for estimating the unknown parameters of linear models [1] just mentioned. Statistical analyses are performed with the Statistics Software SPSS® version 26.

3. Results

Table 1 shows that cities in regions with *low* wind speed have a higher number of days of air pollution than cities with a *high* wind speed (about 88 polluted days *vs.* 65 polluted days exceeding PM_{10} or ozone per year). This preliminary result suggests that high intensity of wind speed improves the dispersion of gaseous and particulate matters, and as a consequence, it can mitigate the diffusion of COVID-19 associated with

Table 1
Descriptive statistics of Italian province capitals according to wind speed (higher or lower than arithmetic mean of 9.28 km/h).

Wind speed of polluted cities	Air Pollution	COVID-19	Atmosphere	Demographic indicators, 2019			Mortality (per 10000 people in 2017)		
	Days exceeding limits set for PM_{10} or ozone 2018	Infected Individuals 7th April 2020	Wind km/h 2020	People aged >65 years old	Elderly Index of seniority	Population Density inhabitants/km^2	Lung, trachea, bronchi cancer	Respiratory system diseases	Cardio-vascular system diseases
⊕-**Low (< 9.28 km/h), N = 27**									
Arithmetic Mean	89.11	2853.41	7.06	23.81	185.85	1695.11	5.72	9.21	38.78
Std. Error of Mean	8.58	591.55	0.48	0.45	6.92	358.15	0.21	0.41	1.55
⊕-**High (≥ 9.28 km/h), N = 28**									
Arithmetic Mean	64.50	1123.93	11.43	24.40	195.73	1220.18	6.09	9.67	41.81
Std. Error of Mean	6.65	166.81	0.49	0.48	6.72	290.63	0.15	0.30	1.27

Table 2
Descriptive statistics of Italian province capitals according to their location in hinterland/coastal.

Location of cities	Air Pollution	COVID-19	Atmosphere	Demographic indicators, 2019			Mortality (per 10000 people in 2017)		
	Days exceeding limits set for PM_{10} or ozone 2018	Infected Individuals 7th April 2020	Wind km/h 2020	People aged >65 years old	Elderly Index of seniority	Population Density inhabitants/km^2	Lung, trachea, bronchi cancer	Respiratory system diseases	Cardio-vascular system diseases
⊕-**Hinterland, N = 45**									
Arithmetic Mean	80.40	2201.44	8.81	24.02	189.04	1480.11	5.88	9.34	2.72
Std. Error of Mean	6.21	545.05	0.50	0.33	5.01	227.22	0.14	0.27	0.15
⊕-**Coastal, N = 10**									
Arithmetic Mean	59.40	944.70	11.42	24.52	199.14	1332.80	6.04	9.91	2.75
Std. Error of Mean	12.21	227.11	0.74	1.07	14.37	778.88	0.35	0.71	0.39

the interaction between novel coronavirus and air pollution (Coccia, 2020). Table 1 also shows that polluted cities with high wind speed have a lower population density but an older population and a higher incidence of the mortality rate of lung and bronchi cancer, of respiratory and cardiovascular diseases than polluted cities with low wind speed. These demographic and health indicators suggest that cities with a high wind speed have people at increased risk for getting COVID-19 (because of prior higher mortality of respiratory and cardiovascular diseases, and lung cancer, see Table 1; cf., CDC, 2020); however, the number of infected individuals of the SARS-CoV-2 is lower than cities having an atmospheric stability (i.e., low wind speed). In order to confirm this result, Table 2 shows descriptive statistics considering the categorization of polluted cities in hinterland and coastal. Coastal cities in Italy, for their geographical position, are windy and results reveal a lower number of infected people, though having an increased risk factor for COVID-19 because of prior higher incidence of older adults in society and higher mortality of people for diseases of respiratory and cardiovascular system (cf., Coccia, 2020; Nicoll and Coulombier, 2009).

Table 3 focuses on categorization of cities having levels of high or low air pollution: especially, cities with frequently high levels of air

Table 3
Descriptive statistics of Italian provincial capitals according to air pollution.

Level of Air Pollution: Days exceeding limits set for PM_{10}	Air Pollution	COVID-19	Atmosphere	Demographic indicators, 2019			Mortality (per 10000 people in 2017)		
	Days exceeding limits set for PM_{10} or ozone 2018	Infected Individuals 7th April 2020	Wind km/h 2020	People aged >65 years old	Elderly Index of seniority	Population Density inhabitants/km^2	Lung, trachea, bronchi cancer	Respiratory system diseases	Cardio-vascular system diseases
⊕ **> 100 days, N=20**									
Arithmetic Mean	125.25	3650.00	8.24	23.65	183.74	1981.40	5.87	8.65	2.69
Std. Error of Mean	3.00	724.22	0.69	0.49	7.47	444.68	0.15	0.34	0.16
⊕≤ ***100 days*, N=35**									
Arithmetic Mean	48.77	1014.63	9.88	24.37	194.96	1151.57	5.93	9.90	2.75
Std. Error of Mean	3.61	129.97	0.57	0.43	6.24	247.85	0.19	0.33	0.21

Table 4
Bivariate Correlation, categorization of polluted cities with wind speed, one-tailed.

	Cities with high wind speed (> 9.28 km/h)	**Cities with low wind speed** (≤ 9.28 km/h)
Pearson Coefficient of Correlation	*Log* Days exceeding limits set for PM_{10} or ozone, 2018 **N = 28**	*Log* Days exceeding limits set for PM_{10} or ozone, 2018 **N = 27**
⊗*Log* Infected Individuals 7th April, 2020	.61**	.54**

Note: ** Correlation is significant at the 0.01 (1-tailed).

Table 5
Bivariate Correlation, categorization of cities with days of air pollution, one-tailed.

	Cities with high air pollution: > 100days exceeding limits set for PM_{10} ***N* = 20**	*Cities with low air pollution: ≤ 100days* exceeding limits set for PM_{10} ***N* = 35**
Pearson Coefficient of Correlation	Wind Speed km/h 2020	Wind Speed km/h 2020
⊗Log Infected Individuals 7th April, 2020	.24	−.43**

Note: ** Correlation is significant at the 0.01 (1-tailed).

pollution (>100 days exceeding limits set for PM_{10} or ozone per year) and low wind speed, they have a very high number of infected individuals in April 2020, though an environment with a lower risk of getting infectious diseases because of a low mortality of respiratory and cardiovascular diseases in previous years (cf., CDC, 2020; Coccia, 2020; Nicoll and Coulombier, 2009).

Table 4 shows that cities with high and low wind speed, they have a high positive correlation (*p-value*<.01) between air pollution and infected individuals of COVID-19 in April 2020.

Table 5 shows that cities with low air pollution, they have a high negative correlation ($r = -0.43$, *p-value*<.01) between wind speed and infected individuals of COVID-19, suggesting that wind speed can reduce the numbers of COVID-19 related infected individuals in society because cleaning the air, it decreases the permanence of viral particles (e.g., SARS-CoV-2) commingled with air pollution.

Table 6 shows correlation analysis using all cities of the sample and confirms a negative correlation ($r = -0.27$, *p-value*<.05) between wind speed and infected individuals of COVID-19 in April 2020, but a high positive correlation between infected individuals and air pollution ($r = 0.60$, *p*-value<.001), and population density ($r = 0.53$, *p*-value<.001). The vital role of wind speed in reducing the spread of COVID-19 is confirmed in Table 7 with partial correlation ($r = -0.29$, *p*-value<.01), whereas air pollution has a positive association with infected individuals of COVID-19 ($r = 0.50$, *p*-value<.001), controlling population density; finally, controlling both population density and air pollution, wind speed has also a negative correlation with infected individuals ($r = -0.20$, *p*-value<.07).

Table 8 confirms results with partial correlation, controlling manifold variables. In short, Table 8 revels that wind speed has a negative correlation with infected individuals ($r = -0.23$, *p*-value<.05), whereas air pollution has a positive association with infected individuals ($r = 0.28$, *p*-value<.05), *ceteris paribus*.

Simple regression analysis in Table 9 shows that the increase of wind speed generates, in average, a reduction of infected people given by $\beta = -0.088$ (*p*-value = .05). Fig. 1 shows, *ictu oculi*, the negative relationship between wind speed and numbers of COVID-19 related infected individuals. Table 9 also shows results of multiple regression, which includes three explanatory variables (i.e., Population Density, Air pollution and Wind speed). The partial coefficient of regression of the model indicates that a 1% higher level of the density of population, it increases the expected confirmed cases of infections by 0.32% (*p-value* = .01, controlling other explanatory variables), whereas a 1% higher

Table 6
Bivariate Correlation, one-tailed. (*N*=55 cities)

Pearson Coefficient of Correlation	Wind Speed km/h 2020	*Log* Days exceeding limits set for PM_{10} or ozone 2018	*Log* Population Density 2019
⊗*Log* Infected Individuals 7th April, 2020	−27*	.60**	.53**

Note: * Correlation is significant at the 0.05 (1-tailed); ** Correlation is significant at the 0.01 (1-tailed).

Table 7
Partial Correlation, one-tailed.

Controlling *Log* Population Density 2019	Wind Speed km/h 2020	*Log* Days exceeding limits set for PM_{10} or ozone 2018
⊗**Log Infected Individuals 7th April, 2020**	−29**	.50***
Controlling - *Log* Population Density 2019 -*Log* Days exceeding limits set for PM_{10} or ozone 2018	Wind Speed km/h 2020	*Log* Days exceeding limits set for PM_{10} or ozone 2018
⊗**Log Infected Individuals 7th April, 2020**	−20*	–

Note: *** Correlation is significant at the 0.001, ** Correlation is significant at the 0.01.
* = *p*-value = .07.

Table 8
Partial Correlation, one-tailed.

Controlling -*Log* Population Density, 2019 -Mortality Lung, trachea, bronchi cancer 10 000 people, 2017 -Mortality Respiratory system diseases 10 000 people, 2017 -Mortality Cardiovascular system diseases 10 000 people, 2017 -Elderly Index of seniority, 2019	Wind Speed km/h 2020	*Log* Days exceeding limits set for PM_{10} or ozone 2018
⊗ **Log Infected Individuals 7th April, 2020**	−23*	.28*

Note: * Correlation is significant at the 0.05.

Table 9
Parametric estimates of the relationship of Log Infected individuals on wind speed (simple regression analysis) and Log Infected individuals on other explanatory variables (multiple regression).

Explanatory variable: Wind speed km/h		**Explanatory variables:** - *Log* Population (density inhabitants/km^2), δ1 - *Log* Days exceeding limits set for PM_{10} or ozone, δ2 - *Wind* speed km/h, δ3	
Constant *α* (St. Err.)	7.86*** (.42)	Constant *α* (St. Err.)	2.24* (.97)
Coefficient *β* (St. Err.)	−.088* (.29)	Coefficient *δ 1* (St. Err.)	.32** (.11)
		Coefficient *δ 2*	.74***
		(St. Err.)	(.21)
		Coefficient *δ 3*	−.05
		(St. Err.)	(.03)
R^2 (St. Err. of Estimate)	.06 (1.04)	R^2 (St. Err. of Estimate)	.47 (.80)
F	4.30*	*F*	15.31***

Note: Dependent variable is Log infected 7th April, 2020.
*** p-value<0.001.
** p-value<0.01.
* p-value<0.05.

Table 10
Estimated relationship of *Log* Infected individuals on *Log* population density (inhabitants/km^2 in 2019), considering wind speed of cities.

	Cities with low wind speed <9.28 km/h		**Cities with high wind speed >9.28 km/h**
	Explanatory variable: *Log* Population Density		Explanatory variable: *Log* Population Density
Constant *α* (St. Err.)	3.49*** (.90)	Constant *α* (St. Err.)	4.45*** (1.20)
Coefficient *β 1* (St. Err.)	.58*** (.13)	Coefficient *β 1* (St. Err.)	.33§ (.18)
Stand. Coefficient Beta	.67	Stand. Coefficient Beta	.35
R^2 (St. Err. of Estimate)	.44(.83)	R^2 (St. Err. of Estimate)	.12 (.89)
F	19.79***	*F*	3.51§

Note: dependent variable: *Log* infected individuals 7th April, 2020.
*** p-value<0.001.
** p-value<0.01.
* p-value<0.05.
§ p-value<0.072.

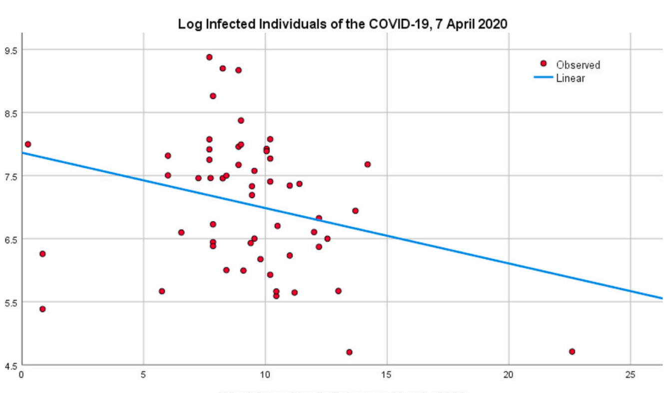

Fig. 1. Regression line of infected individuals on wind speed.

level of days of air pollution, it increases expected infected individuals by 0.74% (*p-value* = .001, controlling other independent variables). The explanatory variable of wind speed is not significant here. The multiple regression model's R^2 value indicates that about 47% of the variation in confirmed cases of the COVID-19 can be attributed (linearly) to these explanatory variables. *F*-test is significant with *p*-value <.001.

Table 10 shows that:

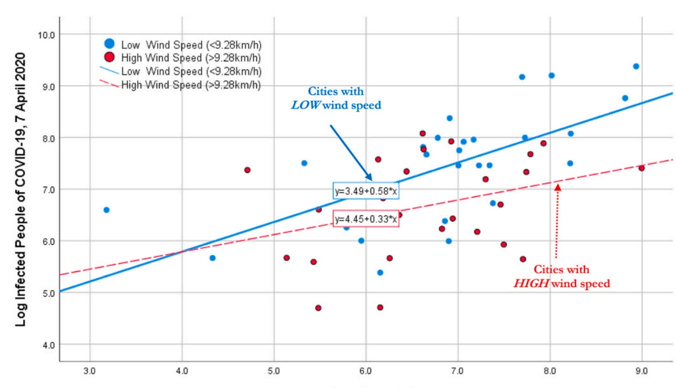

Fig. 2. Regression lines of *Log* Infected Individuals on *Log* Density of population according to high/low wind speed of polluted cities. *Note*: This result suggests that the diffusion of COVID-19 is higher in polluted cities with low wind speed and moderate density of population.

- *in polluted cities with low wind speed,* an increase of 1% of the density of population, it increases the expected number of infected individuals by about 0.58% (*p*-value = .001)
- *in polluted cities with high wind speed,* an increase of 1% of the density of population, it increases the expected number of infected individuals by about 0.33% (*p*-value = .07), a lower magnitude!

Finding in Table 10 reveals that in polluted cities with high wind

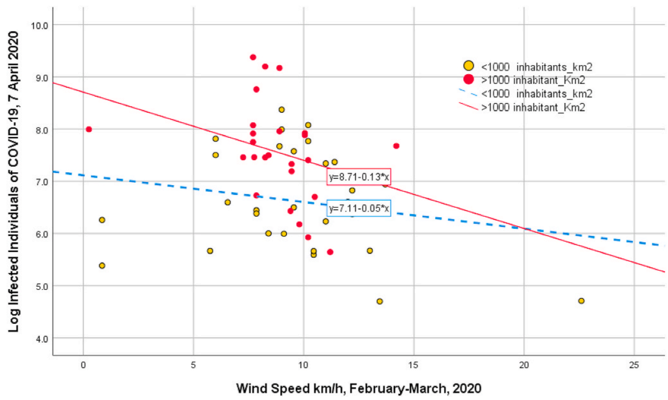

Fig. 3. Relationships of *Log* Infected Individuals on *Log* wind speed according to cities with high/low density of population. This visual representation suggests that diffusion of COVID-19 is lower in cities with high wind speed, though estimated relationships are not significant.

speed, the increase of infected individuals is lower, suggesting that a high intensity of wind speed improves the dispersion of air pollution including viral agents, and as a consequence, this environment can mitigate the diffusion of COVID-19 in society (cf., Coccia, 2020; Coccia, 2020); whereas cities with lower wind speeds and frequently high levels of air pollution — exceeding safe levels of ozone or particulate matter —may promote a longer permanence of the SARS-CoV-2 in polluted air, thus favouring an indirect means of viral diffusion, in addition to direct mechanism of human-to-human transmission of the COVID-19. These results are displayed in Fig. 2.

Fig. 3 provides a visual representation of the relationships of infected individuals on wind speed of cities with high or low density of population. In particular, Fig. 3 reveals that infected individuals of COVID-19 decrease with wind speed, both in cities with a high density of population (>1000 inhabitants per km^2) and with low population density (<1000 inhabitants per km^2), though estimated relationships are not significant. Of course, results of these relationships are tentative because a lot of factors determining the spread of COVID-19 are not considered here.

4. Discussion

This study extends the results by Coccia (2020); Coccia, 2020; Coccia, 2020 and endeavours to explain how COVID-19 transmitted so rapidly in polluted cities of Northern Italy, analysing the relationships between infected people and environmental, demographic, and atmospheric (wind speed) factors that influenced its spread. Results here suggest that, among Italian cities, number of infected people are higher in polluted cities with >100 days per year exceeding limits set for PM_{10} or ozone, cities located in hinterland zones (i.e. away from the coast), and cities having a low average intensity of wind speed. Coşkun et al. (2021) argue that COVID-19 spreads more in windy weather because wind speed increases air circulation. However, this study here analyses the interaction between wind speed and air pollution and reveals that in Italy, cities with little wind and frequently high levels of air pollution in the atmosphere had higher numbers of COVID-19 related infected individuals and deaths. The explanation is that little wind can increase the stagnation of polluted air embodying viral agents (SARS-CoV-2) and support diffusion of viral infectivity, creating problems for public health.

In order to represent these results, Fig. 4 shows a comparison of three maps of Italy. The *Map 1* (at left) shows the areas into which the Italian territory is divided considering the actions of wind speed on buildings, from Northern regions of Italy having a low wind speed and low wind effect on buildings (in white colour) to South Italy and Italian islands having a high wind force that in the Beaufort wind scale is indicated as

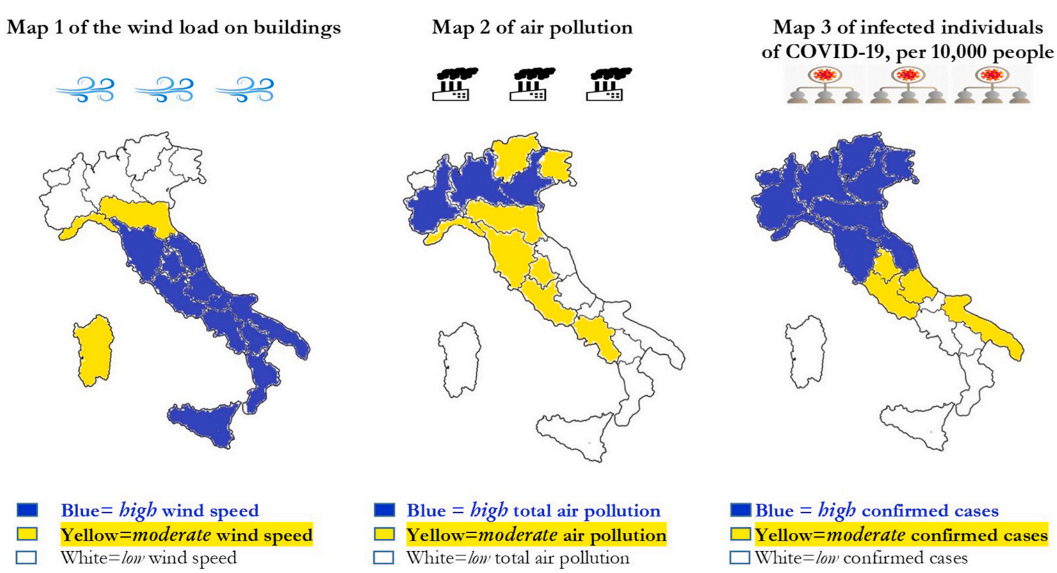

Fig. 4. Maps of the wind load on buildings (1), of air pollution (2) and of total infected individuals of SARS-CoV-2 per 10 000 people (3). *Notes*: Colour of regions in Map 1 is created combining wind speed with altitude, wind pressure, wind tangent action, soil roughness and other parameters. (For interpretation of the references to colour in this figure legend, the reader is referred to the Web version of this article.)

fresh and strong breeze (i.e., small trees in leaf begin to sway and larger tree branches moving, whistling in wires; cf., Furcolo, 2016). The *Map 2* (in the centre of Fig. 4) shows Italian regions according to air pollution (the number of days exceeding ozone and particulate matter 10 μm or less in diameter $-PM_{10}-$limits). Finally, the *Map 3* (at right) shows Italian regions according to the average number of infected individuals of the severe acute respiratory syndrome coronavirus 2 (SARS-CoV-2) that causes COVID-19 per 10,000 people from February to July 2020.

Map 1, Map 2 and Map 3 are based on three colours given by values lower than 25th percentile (white/low intensity), from 25th to 75th percentiles (yellow/moderate intensity), and finally values higher than 75th percentile (Blue/high intensity).

The observation of these maps reveals, *ictu oculi,* that regions of North Italy with little wind (Map 1) and frequently high levels of air pollution (Map 2) have higher numbers of COVID-19 related infected individuals (Map 3). To put it differently, regions with high speed winds and low air pollution (mainly in the South of Italy) are associated with lower numbers of COVID-19 related infected individuals (see, Fig. 4). Hence, Northern regions of Italy with little wind (white colour in the Map 1) and frequently high levels of air pollution (blue/yellow colour in the Map 2) had higher numbers of COVID-19 related infected individuals (Blue colour in Map 3 of Fig. 4). Statistical evidence, with correlation and regression analyses, substantiates these results. This study is consistent with results by Ahmadi et al. (2020) that wind speed has a significant and inverse relationship with the rate of COVID-19 related infected individuals, such that: "in the lower speed of the wind, the infection rate is higher". Other studies maintain that "the prevalence of the COVID-19 …. in most cases, with increasing humidity and wind speed, …has decreased" (Eslami and Jalili, 2020, p. 3). Rosario Denes et al. (2020) also reveal that wind speed presented a negative correlation with confirmed cases of the COVID-19. These results are in the context described by Cohen (2020) that transmission dynamics of the novel coronavirus is affected by different environmental factors, such as climate conditions.

In addition, the effect of wind speed on diffusion of COVID-19 can be distinguished in the presence of indoor and outdoor environments.

- *Indoor environment* can transmit COVID-19 by droplets created when infected humans cough, sneeze, talking, shouting, yawning, etc. Feng et al., 2020 argue that ambient wind and relative humidity can cause SARS-CoV-2 laden droplets to transport farther in the air. By contrast, Jiang et al. (2003) found that higher wind speeds decrease the viral load of indoor environments, preventing SARS outbreaks.
- *In outdoor environment*, studies suggest that the concentration of atmospheric pollutants is a main factor affecting the spread of SARS-CoV-2 (Coccia, 2020; Martelletti and Martelletti, 2020), but a high intensity of wind speed sustains clean days from air pollution including viral agents, reducing whenever possible the ambient concentration of the SARS-CoV-2 and as a consequence the spread of COVID-19 in society (cf., Coccia, 2020; Rosario Denes et al., 2020). In fact, researchers maintain that in external environments, higher wind speed supports the dilution and removal of droplets, decreasing the concentration of viral agents in polluted air and reducing the transmission dynamics of viral infectivity among people, such as in the case of the SARS (cf., Cai et al., 2007). Rosario et al. (2020, p. 4) suggest that wind improves the circulation of air and also increases the exposure of the novel coronavirus to solar radiation effects, a factor having a negative correlation in the diffusion of COVID-19. However, Fattorini and Regoli (2020, p. 4) argue that: "Although the capability of this coronavirus to bind particulate matters remains to be established, chronic exposure to atmospheric contamination and related diseases may represent a risk factor in determining the severity of Covid-19 syndrome and the high incidence of fatal events".

In order to generalize these results here, cities with low wind speed and frequently high levels of air pollution can sustain, mainly in fall and winter season, the stagnation of air pollution with viral agents that may support the spread of COVID-19 and other infectious diseases (cf., Coccia, 2020; Caliskan et al., 2020). Overall, then, Northern regions of Italy and in particular hinterland cities, covered by the study here, and other similar cities worldwide having an atmosphere with low wind speed and frequently high levels of air pollution should apply an environmental policy and sustainable technologies to reduce air pollution (Coccia, 2009, 2017; Coccia and Watts, 2020, Coccia, 2017). In fact, health and economic benefits associated with national and local reduction of air pollution have more and more a strong evidence (Coccia, 2020).

5. Conclusions and limitations

This study finds that atmospheric factors (eind speeds) and air pollution may have supported the spread of COVID-19 in Northern Italian cities, leading to a higher number of infected individuals and deaths. The statistical evidence here seems in general to support the hypothesis stated in previous section, that transmission dynamics of the SARS-CoV-2, in addition to human-to-human diffusion, can be also explained by a stagnation of atmospheric pollutants and viral agents because low wind speeds may promote a longer permanence of viral particles (e.g., the SARS-CoV-2) in polluted air, thus favouring the spread of COVID-19 in society.

However, these conclusions are of course tentative because the diffusion of infectious diseases is due to manifold factors. These findings suggest that current pandemic of the novel Coronavirus and future epidemics similar to the COVID-19 cannot be solved only with research and practicein medicine, but with interdisciplinary scientific research also based on environmental and sustainable science. To conclude, there are several challenges to such studies of factors determining the diffusion of viral infectivity and there is need for much more detailed investigations into the complex relations between the spread of COVID-19, environmental and atmospheric factors to design appropriate sustainable policies for reducing air pollution and consequential interactions with viral agents that negatively affect public health of countries.

Declaration of competing interest

The author declares that he is the sole author of this manuscript and he has no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper. This study has none funders.

APPENDIX A

Fig. 1A. Maps of the air quality monitoring stations in Italian cities under study

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