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Review article

Conditioning factors in the spreading of Covid-19 – Does geography matter?

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ABSTRACT

There is evidence in literature that the spread of COVID-19 can be influenced by various geographic factors, including territorial features, climate, population density, socioeconomic conditions, and mobility. The objective of the paper is to provide an updated literature review on geographical studies analysing the factors which influenced COVID-19 spreading. This literature review took into account not only the geographical aspects but also the COVID-19-related outcomes (infections and deaths) allowing to discern the potential influencing role of the geographic factors per type of outcome.

A total of 112 scientific articles were selected, reviewed and categorized according to subject area, aim, country/region of study, considered geographic and COVID-19 variables, spatial and temporal units of analysis, methodologies, and main findings.

Our literature review showed that territorial features may have played a role in determining the uneven geography of COVID-19; for instance, a certain agreement was found regarding the direct relationship between urbanization degree and COVID-19 infections. For what concerns climatic factors, temperature was the variable that correlated the best with COVID-19 infections. Together with climatic factors, socio-demographic ones were extensively taken into account. Most of the analysed studies agreed that population density and human mobility had a significant and direct relationship with COVID-19 infections and deaths. The analysis of the different approaches used to investigate the role of geographic factors in the spreading of the COVID-19 pandemic revealed that the significance/representativeness of the outputs is influenced by the scale considered due to the great spatial variability of geographic aspects. In fact, a more robust and significant association between geographic factors and COVID-19 was found by studies conducted at subnational or local scale rather than at country scale.

1. Introduction

Admittedly, COVID-19 outbreak is linked to geographical factors and its diffusion across the globe reflects a geographic control, showing different impacts according to the scale considered (i.e., global, regional, national, sub-national).

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Geographical science through the use of cartographic techniques and analysis has demonstrated to be crucial in the study of the spatial dynamics of COVID-19 spread and transmission [1,2]. In the field of geography, a number of papers focus on the association between COVID-19 diffusion and geographic factors, including physical ones, as well as on the application of spatial tools/techniques for the study of the pandemic.

Already in the first months since the start of the pandemic a few reviews on the topic were published in international journals. One of the earliest was performed by Briz-Redón and Serrano-Aroca [3] who focused on studies investigating the relationships between meteorological variables and the global expansion of COVID-19 analysing both findings and statistical modelling techniques. This review highlighted contradictory results among the analysed literature in the definition of the relationship between climate variables and COVID-19 transmission. Similar conclusions were reached by Paraskevis et al. [4] who reviewed literature on the effects of weather and climate variables (also with reference to urban parameters and air pollution) on the impact of the COVID-19 pandemic. The inconsistency of results among studies investigating the association between weather variables and COVID-19 incidence was also highlighted in the review by McClymont and Hu [5] with the exception of temperature, for which a negative association with incidence was found by the majority of the examined studies. Briz-Redón and Serrano-Aroca [3] emphasized that detailed studies tend to provide more reliable data when climatic and non-climatic factors (e.g., population density, mobility) have to be associated.

One of the most recent reviews is by Wang et al. [6] who focused on the role of natural factors (e.g., climate, geographic location, air pollution) and human activity (e.g., mobility, health factor, economic conditions, demography) on global COVID-19 transmission. The authors found that spatial and temporal heterogeneity varied across countries and during different pandemic stages.

Geographical studies dealing with the COVID-19 pandemic benefitted from the use of mapping and spatial tools, including Geographic Information Systems (GIS). The mapping of territorial variables crossed with that of COVID-19 spread was found to be useful for the interpretation of COVID-19 geography [7]. Reviews on this topic were produced since 2020 [cf. 8,9].

In the early stages of the pandemic Franch-Pardo et al. [10] performed a review on the implementation of geographical and geospatial analyses for understanding distribution patterns of COVID-19. An update of this review [11] showed that the latest research improved in spatial resolution with a consequent decrease in studies conducted at global level. Additionally, the authors found an increase in the number of the studies considering socioeconomic variables which were found to have a greater influence on COVID-19 pandemic at more local level. Fatima et al. [12] produced a similar literature review with a specific focus on methodologies and associated outputs in relation to geospatial analysis applied to the study of COVID-19 showing that GIS was extensively used for analysing, visualizing and identifying COVID-19 patterns.

Another review on the use of GIS and geospatial tools for the study of COVID-19 pandemic was implemented by Ahasan et al. [13] who found an important lack in the literature related to spatial modelling aimed at identifying and predicting the location of potential future outbreak.

Since most of the reviews mentioned above were published during the first phases of the pandemic, we felt the need to provide an updated literature review on geographical studies analysing the factors which influenced COVID-19 spreading. The review presented here covers the period 2020–2022 and also comprises studies carried out after the pandemic peak benefiting from additional knowledge on COVID-19 outbreak and transmission.

The objectives of this review are to: i) understand the role of the geographic determinants in COVID-19 spreading (e.g., geographic location, climatic characteristics, altimetry, morphological features); ii) identify common approaches, materials and methods used in the study of the COVID-19 outbreak from a geographical perspective; iii) recognise possible research gaps to address future in-depth analyses.

2. Materials and methods

2.1. Bibliographic search

A literature search was performed in Scopus and Web of Science (WoS) on 23 January 2023 and updated in November 2023 by applying the following research query to "title", "abstract" and "keywords": (COVID-19 OR CORONAVIRUS OR SARS-Cov-2) AND Geography. The search was limited to peer-reviewed articles published since 2020 considering that the beginning of the COVID-19 outbreak was at the end of 2019.

Scopus and WoS databases were used for the search since they host the widest set of peer reviewed journal articles with reference to Natural Sciences and offer good quality of metadata.

An additional search was also performed in Google Scholar to confirm that no significant papers on the topic of interest were overlooked, having this database a more comprehensive coverage [14]. This literature search was performed by applying the above-mentioned query, looking for the combination of keywords within the entire text.

Articles were considered eligible for our review if they were (i) published in English language, (ii) peer-reviewed, and (iii) if they included statistical analysis, modelling or cartographic representations of one or more geographical factors/variables in relation to the outbreak of the COVID-19 pandemic. On the contrary, articles were excluded from the review if they were (i) not research articles (e.g., commentaries, reviews, editorials): (ii) not considering any geographic variable; (iii) exclusively focusing on COVID-19 medical aspects; (iv) focusing specifically on geography teaching and learning; (v) exclusively focusing on the secondary impacts of COVID-19 outbreak, such as on economy, mobility, and population life/working styles.

The review was performed according to the following steps (Fig. 1): (i) records were identified through Scopus, Web of Science and they were exported in bibtex and plaintext formats respectively; (ii) the retrieved records from both literature databases were merged using the RStudio tool bibliometrix [cf. 15] which also allowed us to remove duplicates; (iii) the identified records were screened and selected according to the above-mentioned inclusion/exclusion criteria by title and abstract reading; (iv) selected records were included in or excluded from the final list after full text reading according to the eligibility criteria; (v) a check of the completeness of the literature search was done by consulting Google Scholar and by the list of references of the literature reviews mentioned above.

Records retrieved from Scopus and WoS were respectively 1730 and 768. The sum of the documents retrieved from both databases totalled 1940 excluding duplicates. Among these, 222 articles fulfilled the eligibility criteria based on their title and abstract. The subsequent analysis of the full texts led to the exclusion of 139 papers which did not satisfy all the eligibility criteria.

The search in Google Scholar returned 16,800 records ranked by pertinence by the default ranking algorithm, being the first 1000 results retrieved and analysed. This check revealed that the literature search carried out in Scopus and Web of Science was highly comprehensive; in fact, only four additional papers were found, making a total of 87 articles.

A further search was performed by checking the list of references of the most relevant papers selected. This allowed us to include 25 additional papers resulting in a total of 112 articles to be finally reviewed. The results from the publications' reference list search brought to our attention that many articles dealing with geographical aspects l.s. did not include "geography" in the papers' key fields (title, abstract, keywords). This was especially true for papers that analysed specific factors, such as air pollution.

2.2. Categorization criteria

The full texts of the articles fulfilling all the eligibility criteria were reviewed, and relevant data were extracted based on the following items.

- Subject macro-area
- Submission and publication date
- Region or country of study
- Aim of the study
- COVID-19 outcome data macro-area (infection, hospitalization, death) and detail (e.g., incidence, reproduction number, lethality, mortality)
- Geographic variables macro-area (e.g., territorial, climatic, socio-demographic) and detail (e.g., latitude, average temperature, population density)
- Data source
- Other variables (e.g., number per-capita of hospital beds, life expectancy)
- Investigated period
- Spatial and temporal resolution
- Statistical methodological approach
- Main findings.

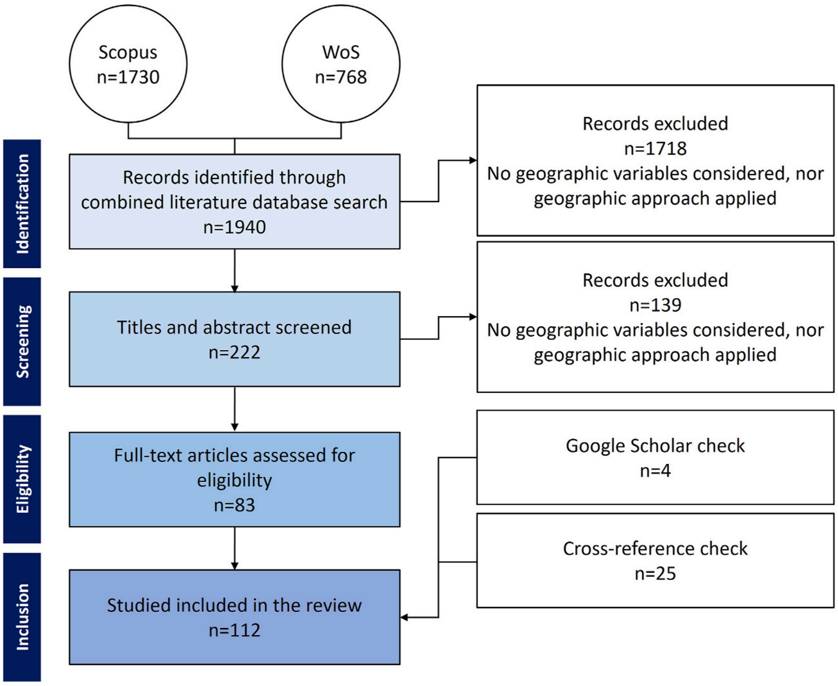

Fig. 1. Workflow of the literature search on the influence of geographic factors on COVID-19 pandemic.

The geographic variables are understood as parameters that provide information about the characteristics of an area (thus not only descriptive of the geographic location) [16].

The selected and analysed papers showed a high heterogeneity of methods, data, and outputs. A narrative description and synthesis of the main results achieved is presented in the following section.

3. Results and discussions

Among the 112 selected articles, 32 studies were conducted at a global scale (Fig. 2), considering single countries as the spatial unit of analysis. Studies conducted at national and subnational level were mainly focused on China, Italy and USA that were among the most affected countries in the earliest phases of the COVID-19 pandemic. With reference to the submission date, the selected literature is mainly clustered around mid-late 2020 on account of the initial/early worldwide interest of academia/science on COVID-19 during the very first period of the pandemic.

The selected papers took into account factors related to both physical and human geography. The factors related to physical geographical aspects comprise: (i) territorial variables, which are descriptive of the geographic location (latitude and longitude), and physical features of the area such as elevation and urbanization degree; and (ii) climatic variables including temperature, humidity, wind speed, precipitation and solar radiation. Air pollution was included among the climatic variables and proved to be an important environmental factor. As a matter of fact, a considerable number of reviewed studies examined the influence of both climatic/weather variables and air pollution on COVID-19 spread and health consequences, since those variables are closely linked one another [cf. 17, 18, 19 and references therein].

The latest studies on the COVID-19 pandemic [cf. 11,20] put a significant emphasis on human geographic aspects since they were found to have had a certain influence on the pandemic trends at a local level from both socio-demographic and socioeconomic aspects.

Based on the outputs of our review, the geographic variables were grouped into three macro-areas: (i) territorial variables, (ii) climatic/weather and environmental variables, (iii) socio-demographic and socioeconomic variables. The variables comprised in each macro-area are listed in Table 1.

Regarding health outcomes, COVID-19 data comprised a wide variety of items from which were grouped into three main categories: infections, hospitalisations and deaths. The infection category includes measures such as number of cases, incidence, prevalence, swab positivity, reproduction number (Rt), spread, transmission and related rates. The hospitalization category comprises measures such as hospitalization rates, hospital and ICU admissions (both COVID-19 positive or total inpatients). The death category relates to measures such as mortality and lethality (and related rates), fatality, absolute number of deaths, excess mortality. For a complete description of COVID-19 related outcomes found in reviewed articles please refer to Appendix A.

In the selected articles, we found that hospitalization variables were never studied independently/alone and had similar behaviour to infection and death in relation to geographic variables. Therefore, for the sake of clarity, we decided to present tabular data only on infections and deaths but detailed information on articles considering hospitalization and geographic variables can be found as supplementary data in Appendix A.

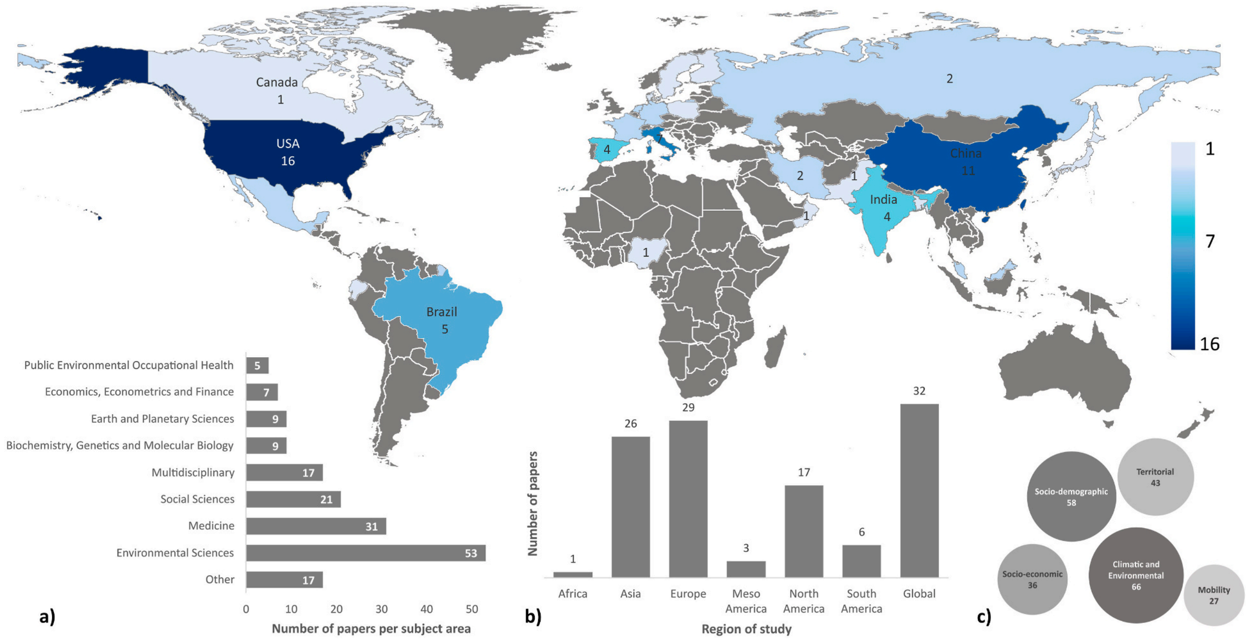

Fig. 2. Geographic distribution of the studied areas: (a) number of papers categorized by Scopus subject areas; (b) number of papers per region and global scale studies; (c) frequency of scientific articles per each group of variables considered.

Table 1
Geographic factors considered in the selected articles.

Geographic variable macro-area	Geographic variables
Territorial	Elevation Geographic location Land use Other territorial variables (e.g., distance from/density of human points of interest such as train stations, airports and other facilities)
Climatic/weather and environmental	Humidity Temperature Precipitation Wind speed Solar radiation Air pollution Other climatic/weather variables (e.g., hours of sunshine, evapotranspiration, permafrost coverage, Köppen classification group)
Socio-demographic and socioeconomic	Age and/or gender and/or ethnic group Total population and/or population density Mobility (e.g., human mobility trends, travel time, tourist flow) Economic stability (e.g., poverty, income, education, GDP, industrial production, trade intensity) Other socio-demographic variables (e.g., proportion of persons living in urban areas) Other socioeconomic variables (e.g., household occupancy/population, number of foreign citizens in residential building, households belonging to the lowest income category)

3.1. *Territorial variables*

Based on the analysis of the results presented in the reviewed articles, the influence of territorial variables on COVID-19 infections and deaths is discussed in the following sections and schematized in Table 2.

3.1.1. *Elevation*

Many studies across the globe agree on the existence of a negative correlation between the severity of COVID-19 pandemic and the elevation, and show that infection rates are lower, and consequences less severe, in regions at high altitudes [52]. A medical review conducted by Millet et al. [53] speculated that this is related to the limited survival of the virus in such environments and to the biological mechanisms (e.g., high concentrations of erythropoietin, optimized cellular oxygenation and antioxidant systems, increased mitochondrial performance at the alveolar level) which may affect people living in those areas [see also 54 and references therein]. However, some authors highlighted that the association among lower case rate and mortality with increasing altitude may be confounded by factors such as population density, socioeconomic features, access to health care services etc. [55 and references therein].

Lower incidence and mortality of COVID-19 in high-altitude places has been outlined in several studies. This is the case of the work by Fernandes et al. [29] that investigated the effect of altitude on the incidence of COVID-19 in 154 Brazilian cities (with a population >200,000 inhabitants). The authors detected a negative correlation between altitude and incidence, being the latter lower in cities located at rather high altitudes (between 795 and 1135 m a.s.l.). Similarly, Gupta et al. [33] found that altitudinal variation had a negative relation with number of infections in India. Based on this finding, the authors suggested that regions located at low lying elevation in India are more prone to experience a higher COVID-19 transmission. The same correlation was found for China by Sun et al. [47] and Han et al. [34]. Han et al. [34] inferred that this negative correlation might be due to the interaction between the meteorological conditions and socioeconomic status which characterize the prefectures located at higher altitudes. Díaz Ramírez et al. [52] excluded elevation from the analysis of the patterns of excess mortality across regions in 36 countries around the globe because they found a multicollinearity between elevation and other variables, namely, share of youth, population density and air pollution (PM2.5).

3.1.2. *Geographic location (latitude and longitude)*

The relationship between geographic location and COVID-19 spreading appears quite controversial, having many authors found different evidence on its possible role.

Li et al. [38] conducted a study at global scale (154 countries) finding that the latitude has a negative correlation with COVID-19 cases and deaths. The authors inferred that this is mainly due to the latitude control on temperatures. On the contrary, they found that longitude has a positive correlation (i.e., direct correlation) with COVID-19 cases, deaths and case fatality rates. The authors did not provide any specific explanation of their finding. However, the fact that their statistical analysis revealed that longitude, as well as latitude, has a correlation with COVID-19 spread can be seen as further proof that there is a geographic signal in the evolution of the pandemic [cf. 56].

Conversely, Sarmadi et al. [43] recognised that latitude had a positive correlation between cases and deaths of COVID-19 at a global scale. The authors found evidence that at latitudes higher than 60° (referring to the northern hemisphere) there was a higher proportion of COVID-19 cases to population per 10^5. According to their findings, this correlation may be due not only to the colder temperatures which favoured the survival of the virus (cf. section 3.2), but also to better socioeconomic conditions which imply, for

Table 2
Territorial variables considered in the selected literature: elevation (Elev), longitude (Long), latitude (Lat), urbanization (Urb) and their association (if any) with respective COVID-19 outcomes. The upturned arrow represents a positive association, the downturned stands for negative association and the horizontal bar is when no or non-statistically significant association was found.

Citation	Elev	Long	Lat	Urb	other	Country/Region of study	Territorial variable detail	COVID-19 outcomes
Amdaoud et al. [21]				X		Europe	Urban regions	Deaths ↑
Armillei et al. [22]				X		Italy	Peripheral areas	Deaths ↑
Ascani et al. [23]					X	Italy	Presence of an airport in the province	Infections ↑
Boterman [24]					X	Netherlands	Distance from train/motorway	Infections –
Chaves et al. [25]					X	Central America and Caribbean	Number of international territories/cities connected through the main airport	Death ↑
Chen et al. [26]					X	Hubei (China)	Distance by road from Wuhan	Infections ↓
Coker et al. [27]					X	Northern Italy	Distance in meters to the closest airport	Death ↑
Dixon et al. [28]				X		Indiana (USA)	Rural regions	Infections ↑
Fernandes et al. [29]	X					Brazil	Altitude	Infections ↓
Florida and Mellander [30]					X	Sweden	Presence of nursing homes	Infections ↑
Fortaleza et al. [31]				X	X	São Paulo State (Brazil)	Urban areas	Infections ↑
							Distance from the State capital	Infections ↓
							Proximity to main roadways/airports	Infections ↑
Grubesic et al. [32]					X	Wisconsin (USA)	Location of federal correctional facilities	Infections ↑
Gupta et al. [33]	X					India	Elevation	Infections ↓
Han et al. [34]	X					China	Elevation	Infections ↓
Hass and Jokar Arsanjani [35]					X	Europe	Number of amenities (e.g., cafes per cap., bars per cap.)	Infections ↑
He et al. [36]					X	Guangzhou (China)	Density of shopping malls, hotels, restaurants etc.	Infections ↑
Karim and Chen [37]				X		USA	Metropolitan areas	Infections ↑
Li et al. [38]		X	X			USA, World	Latitude	Infections and Deaths ↓
							Longitude	Infections and Deaths ↑
Murgante et al. [39]				X		Italy	Soil consumption	Infections and Deaths ↑
Nasiri et al. [40]				X		Tehran (Iran)	Commercial/residential land use	Infections ↑
Niu et al. [41]				X	X	Wuhan (China)	Building density, number of urban facilities	Infections ↑
							Distance from urban open space	Infections ↓
Ramírez and Lee [42]				X		Colorado (USA)	Urban regions	Infections ↑
Sarmadi et al. [43]			X			World	Latitude	Infections and Deaths ↑
Scarpone et al. [44]		X	X		X	Germany	Driving distance to train stations	Infections –
							Latitude	Infections ↓
							Longitude	Infections –
Sigler et al. [45]				X		World	Urbanisation rate	Infections ↑
							Urban density	Infections ↑
Sleszynski [46]				X		Poland	Degree of urbanization	Infections –
Sun et al. [47]	X		X			China	Altitude	Infections ↓
							Latitude	Infections ↓
Topîrceanu and Precup [48]					X	World	Inter- and intra-settlements travel distance	Infections ↑
Vaz [49]					X	Toronto (Canada)	Green spaces	Infections –
Wang et al. [50]				X	X	USA	Metropolitan areas	Infections ↑
							Proximity to nearest core airports	Infections ↑
Wheeler et al. [51]				X		SE Minnesota (USA)	Rural area	Infections ↑

example, a greater accessibility/availability of COVID-19 diagnostic kits.

Scarpone et al. [44] considered longitude and latitude in their models in order to identify spatial patterns for COVID-19 outbreak in the German counties. The results indicated no apparent correlation between longitude and incidence rates and a weak-to-moderate correlation with latitude. Sun et al. [47] found that the cumulative number of infected cases in China shows a linear negative relationship with latitude as well as infective spreading speed but, for the latter, this negative relationship is limited to the first phase of the pandemic (first 21 days). The same authors justified this negative relationship, in contrast with the findings of the other studies, by considering that it reflects a finer scale pattern, at provincial level, with uniform and strict lockdown policies.

3.1.3. Land use

Several studies, carried out at a country scale during the first wave of the pandemic, found a positive correlation with the increase in COVID-19 infections [31,37,42,50] and deaths [21] in urban and/or metropolitan settings with respect to rural ones. Schnake-Mahl and Bilal [57] confirmed this positive correlation after the first wave of the pandemic. Moreover, Sigler et al. [45] found evidence of contagion diffusion from urbanised to non-urbanised areas in a study conducted at a global scale. Furthermore, the authors found a

Table 3
Climatic variables considered in the selected literature: humidity (Hum), precipitation (Prec), solar radiation (SR), temperature (Temp), wind speed (WS) and their association (if any) with respective COVID-19 outcomes. The upturned arrow represents a positive association, the downturned stands for negative association and the horizontal bar is when no or not statistically significant association was found.

Citation	Hum	Prec	SR	Temp	WS	Country/Region of study	Climatic variable detail	COVID-19 outcomes
Ahmadi et al. [59]	X	X	X	X	X	Iran	Relative humidity	Infections ↓
							Average precipitation	Infections –
							Average solar radiation	Infections ↓
							Average temperature	Infections –
							Wind speed	Infections ↓
Azuma et al. [60]	X	X	X	X	X	Japan	Relative humidity	Infections –
							Mean precipitation	Infections –
							Sunshine hours	Infections ↑
							Mean, maximum, minimum temperature	Infections ↑
							Mean wind speed	Infections –
Baniasad et al. [61]	X			X		Global South (9 countries)	Relative humidity	Infection and Death –
							Daily average temperature	Infection and Death –
Bilal et al. [62]	X	X		X		USA	Humidity	Infections ↑ Deaths ↓
							Rainfall	Infections and Deaths ↓
							Average daily temperature	Infection ↑ Deaths ↓
Cacho et al. [63]	X		X	X		Spain	Monthly average relative humidity	Infections and Deaths –
							Monthly average UVR	Infections and Deaths ↑
							Monthly average temperature	Infections and Deaths ↓
Carleton et al. [64]	X		X	X		World (173 countries)	Daily average specific humidity	Infections –
							Daily average UV radiation	Infections ↓
							Daily average temperature	Infections –
Chakraborti et al. [65]		X		X	X	World	Precipitation	Infections and Deaths –
							Minimum temperature	Infections and Deaths –
							Wind speed	Infections and Deaths ↓
Chen et al. [66]	X			X	X	World (15 countries)	Relative humidity	Infections ↓
							Daily average temperature	Infection ↑
							Daily average wind speed	Infections ↓
Cherrie et al. [67]			X			USA, England, Italy	Mean daily UVA	Deaths ↓
Coker et al. [27]				X		Northern Italy	Average temperature	Infections ↓
da Silva et al. [68]	X	X		X		Brazil	Daily air humidity	Infections ↓↑
							Daily total precipitation	Infections ↓
							Daily minimum, maximum temperature	Infections ↓↑
Díaz Ramírez et al. [52]				X		OECD and European countries	Average temperature	Deaths –
Fernandes et al. [29]	X					Brazil	Relative humidity	Infection ↑
Guo et al. [69]	X			X	X	World	Daily average relative humidity	Infections ↓
							Daily average temperature	Infections ↓
							Daily average wind speed	Infections –
Gupta et al. [33]	X	X	X	X	X	India	Specific humidity	Infections ↓
							Annual rainfall	Infections ↓
							Annual minimum, maximum, mean temperature	Infections ↑
							Annual solar radiation	Infections ↑
							Annual wind speed	Infections ↑
Han et al. [34]	X			X		China	Relative humidity, minimum relative humidity	Infections ↑
							Daily minimum, maximum, mean temperature	Infections ↑
Hass e Jokar Arsanjani [35]				X		Europe	Annual mean temperature	Infections –
Hofmeister et al. [70]			X			World	Global Horizontal Irradiance	Infections ↑
Iqbal et al. [71]	X			X		World	Relative humidity	Infections ↑
							Average maximum, minimum temperature	Infections ↑
Irfan et al. [72]				X		Pakistan	Daily mean temperature	Infections ↓

(continued on next page)

Table 3 (*continued*)

Citation	Hum	Prec	SR	Temp	WS	Country/Region of study	Climatic variable detail	COVID-19 outcomes
Isaia et al. [73]	X		X	X		Italy	Relative humidity	Infections and Deaths –
							UV irradiance	Infections and Deaths ↓
							Monthly mean temperature	Infections and Deaths ↓
Islam et al. [74]	X		X	X	X	World	Relative, absolute humidity	Infections ↑
							UV index	Infections –
							Daily maximum temperature	Infections ↑
							Wind speed	Infections ↓
Jamshidi et al. [75]				X		USA, World	Equivalent temperature (combined effect of temperature and humidity)	Infections ↓
Kubota et al. [76]		X		X		World	Mean precipitation	Infections ↑
							Mean temperature	Infections ↓
Li et al. [77]				X		World	Daily temperature, temperature seasonality	Infections ↓
Li et al. [38]	X			X		USA, World	Relative humidity	Infections and Deaths ↓↑
							Medium, high, low temperature	Infections and Deaths ↓
Liu et al. [78]	X			X		World	Specific humidity	Infections ↓
							Near surface temperature	Infections and Deaths ↓
Ma et al. [79]	X			X		Wuhan (China)	Relative humidity	Deaths ↓
							Daily average temperature, diurnal temperature range	Deaths ↓
Mandal and Panwar [80]				X		World	Monthly average temperature	Infections ↓
Méndez-Arriaga [81]	X	X		X		Mexico	Specific humidity at 1000 hPa	Infections ↑
							Monthly mean precipitation	Infections ↑
							Highest, lowest and mean temperature	Infections ↓
Merow and Urban [82]	X		X	X		Australia, Canada, China, USA	Relative humidity, absolute humidity	Infections ↓
							Total incoming UV radiation	Infections ↓
							14-days average temperature	Infections ↓
Meyer et al. [83]	X			X		World	Daily relative humidity	Infections –
							Daily average temperature	Infections ↓
Moozhipurath et al. [84]	X	X	X	X		World (183 countries)	Daily ultraviolet index (UVI)	Deaths ↓
Paez et al. [85]	X			X		Spain	Relative humidity	Infections ↓
							Mean temperature	Infections ↓
							Daily hours of sunshine	Infections ↑
Pan et al. [86]	X		X	X	X	World (8 countries)	Relative humidity	Infections –
							Daily erythemally weighted daily dose	Infections –
							Daily mean temperature	Infections –
							Wind speed	Infections –
Pramanik et al. [87]	X			X	X	Russia	Relative humidity	Infections ↑
							Average temperature	Infections ↓
							Wind speed	Infections ↑
Prata et al. [88]				X		Brazil	Annual average of temperatures compensation	Infections ↓
Rodríguez-Pose and Burlina [89]		X		X		Europe	Average precipitation 2019	Deaths ↓
							Average temperature 2019	Deaths ↓
Sarkodie and Owusu [90]	X	X		X	X	World (20 countries)	Relative humidity	Infections and Deaths ↓
							Precipitation	Infections and Deaths ↑
							Maximum, minimum temperature	Infections and Deaths ↓
							Wind speed	Infections and Deaths ↑
Sarmadi et al. [43]				X		World	Average temperature	Infections and Deaths ↓
Sergeenko [91]			X				UV-index	Infections ↓
Shao et al. [92]				X	X	World (47 countries)	Mean temperature	Infections ↓
Sobral et al. [93]		X		X		World	Precipitation	Infections and Deaths ↑
							Maximum, minimum, average temperature	Infections ↓
Su et al. [94]	X			X	X	World (277 countries)	Relative humidity	Infections ↑
							Air temperature	Infections ↓

(continued on next page)

Table 3 (*continued*)

Citation	Hum	Prec	SR	Temp	WS	Country/Region of study	Climatic variable detail	COVID-19 outcomes
							Wind speed	Infections ↑
Tang et al. [95]			X			USA	Daily sunlight UV radiation dose	Infections ↓
Tzampoglou and Loukidis [96]	X	X		X		World	Monthly average relative humidity	Infections and Deaths –
							Cumulative precipitation	Infections and Deaths –
							Monthly average atmospheric temperature	Infections and Deaths ↓
Yang et al. [97]	X	X		X	X	China	Relative humidity	Infections ↑
							Total precipitation	Infections –
							Daily maximum, minimum, range, average temperature	Infections ↑
							Average wind speed	Infections ↓↑
Yuan et al. [98]				X	X	World (127 countries)	Daily average temperature	Infections ↓
							Average wind speed	Infections ↓

positive correlation with infections and urbanisation rate/density, showing however that this correlation decreases with time. Dixon et al. [28] studied the spread of the pandemic among rural areas of the Indiana state (USA). They found that by autumn 2020 hospitalization and mortality rates in rural areas exceeded those of urban areas may be because of few ICU beds and lack of healthcare staff in rural regions. On the contrary, the investigation by Sleszynski [46] suggested that there is not a directly proportional correlation between the increase of COVID-19 infections in Poland and the degree of urbanization.

Based on the results of local spatial autocorrelation carried out at provincial scale in Italy, Murgante et al. [39] inferred a positive correlation between urbanization and particularly the lack of green spaces and the high number of positive cases and deaths of the earliest phases of COVID-19 pandemic in Lombardy [cf. 58]. Similarly, Vaz [49] considered the presence of green spaces as a variable which may have limited COVID-19 spreading within the districts of Toronto (Canada); however, the author did not find any significant correlation with COVID-19 density (number of cases per population considering the area of the respective administrative unit) and such variable. A spatial analysis enabled Nasiri et al. [40] to show that in Iran the number of COVID-19 hospitalised cases were higher in commercial and residential areas. By means of a clustering analysis, Niu et al. [41] inferred that floor area ratio and building density in China are positively correlated with COVID-19 middle-aged and elderly patients. The study by Wheeler et al. [51] analysed the spread of the pandemic among Minnesota (USA) rural counties which were found to host a significant number of COVID-19 hotspots. The presence of hotspots was attributed to socioeconomic disparities among Minnesota rural population.

3.2. Climatic variables

Based on the results of the reviewed articles, the influence of climatic/weather variables and air pollution on the spread of COVID-19 is discussed in the following sections and schematized in Tables 3 and 4 respectively.

3.2.1. Humidity

Among the climatic variables, humidity is considered one of the most relevant factors influencing COVID-19 spread and its consequences [cf. 56,59,62,96].

Most of the studies analysed in this review identified a negative association between humidity and COVID-19 infections and/or deaths at a global scale [69,71,78,79,82,83,90]. In particular, Iqbal et al. [71] inferred that this indirect association may be due to the fact that low relative humidity may prolong the survival of COVID-19 virus on surfaces, whilst Liu et al. [78] supposed that aerosol transmission, as one of the COVID-19 potential transmission routes, can be enhanced in low humidity environments. In fact, the predominant mode of viral particle transmission involves adherence to droplets. In humid areas, high humidity causes the droplets from an infected person to combine into larger drops that rapidly fall to the ground due to their increased weight [97,102–104]. Conversely, in arid regions, such as deserts, especially in summer, intense evaporation and high temperatures desiccate the virus, diminishing metabolic enzyme activity [105]. Worth mentioning are also the findings of Islam et al. [74] who identified a range among which the absolute humidity is positively associated with higher rates of COVID-19 cases, that is between 5 and 10 g/m^3. Chen et al. [66] showed that the number of daily new cases was correlated with relative humidity with a 7-day lag from the exposure day, and that COVID-19 is easily spread under relative humidity between 70 % and 80 %.

A correlation between humidity and COVID-19 spread was found at a country scale in Brazil [29,68], China [34,97], India [33], Iran [59], Mexico [81], Russia [87], Spain [85] and the USA [62]. Among these studies, there is no agreement on the type of correlation between humidity and COVID-19 spread, e.g., Fernandes et al. [29], Han et al. [34] and Méndez-Arriaga [81] stated this correlation as positive, whilst Ahmadi et al. [59] and Paez et al. [85] as negative. Heterogeneity of results occurred also at a country level; for example, for six Brazilian capital cities humidity correlated negatively with COVID-19 infections whilst the opposite occurred for two others [68]. Similarly, Yang et al. [97] suggested that in China the type of correlation between relative humidity and COVID-19 transmission depends on the season (i.e., warm season or winter) and physiography of the region considered (i.e., coastal or arid inland). Worth mentioning is the study by Gupta et al. [33] from which it was observed that an absolute humidity range of 4–6 g/m^3

Table 4
Air pollutants considered in the selected literature and their association (if any) with respective COVID-19 outcomes. The upturned arrow represents a positive association, the downturned stands for negative association and the horizontal bar is when no or not statistically significant association was found.

Reference	PM10	PM2.5	NO_2	SO_2	CO_2	O_3	Country/region of study	Environmental variable detail	COVID-19 outcome
Azuma et al. [60]		X	X					Five-day mean values	Infections –
Baniasad et al. [61]		X					Global South (9 countries)	Daily value for the period March–December 2020 (short term analysis); Average value for the period 1998–2017 (long-term analysis)	Deaths ↑
Bilal et al. [62]		X					USA	Daily value for the period 2 March - 17 September 2020	Infections, deaths ↑
Chakraborti et al. [65]		X	X		X		World	Mean annual exposure (period not specified) Nitrous oxide emission (metric ton) Total CO_2 emission; CO_2 emission per capita	Infections ↑ Deaths ↑ Deaths ↑
Coker et al. [27]		X					Northern Italy	Average of the annual mean for the period 2015–2019	Deaths ↑
Deguen and Kihal-Talantikite [99]			X				France	Average of the annual mean for the period 2014–2018	Deaths ↑
Díaz Ramírez et al. [52]		X					OECD and European countries	Mean value of 2019	Infections, deaths ↑
Han et al. [34]	X	X	X	X	X		China	PM10, PM2.5, NO_2, SO_2, CO_2 - Daily values to which a lag of 1 and 9 days was applied	Infections ↑
Hass and Jokar Arsanjani [35]	X	X	X				Europe	PM10, PM2.5, NO_2 - Average of the annual mean for the period 2019–2020	Infections ↑
Isaia et al. [73]	X						Italy	Average of the annual mean for the period 2015–2019	Infections, deaths –
Konstantinoudis et al. [100]		X	X				England (UK)	PM2.5, NO_2 - Average of the annual mean for the period 2014–2018	Deaths ↑
Ma et al. [79]	X	X	X	X	X	X	Wuhan (China)	PM10, PM2.5, NO_2, SO_2, CO_2, O_3 - Daily value for the period 20 January –29 February 2020	PM10 – Deaths ↓ PM2.5 – Deaths ↓ NO_2 – Deaths ↑ SO_2 – Deaths ↓ CO_2 – Deaths – O_3 – Deaths –
Middya and Roy [101]		X	X	X			India	PM2.5, NO_2, SO_2 - Daily data averaged across the period 2016–2020	Deaths ↑
Murgante et al. [39]	X	X	X		X	X	Italy	PM10, PM2.5, NO_2, CO_2, O_3 - Annual average values for the period 2019–2020	Infections, deaths ↑
Rodríguez-Pose and Burlina [89]		X			X		Europe	PM2.5 - Value of 2016 CO_2 - Value of 2010	Deaths ↑
Vaz [49]		X	X			X	Toronto (Canada)	PM2.5, NO_2, O_3 - Value of 2011	Deaths –

mainly influenced the spread of COVID-19 in India. This absolute humidity range is partially comparable with the one identified by Islam et al. [74] at a global scale. Furthermore, it has been proven that changes in air humidity can affect respiratory cells and impact mucosal clearance [103]. Therefore, alterations in air humidity can increase the risk of virus exposure for humans, and the severity of infections depends on specific climatic conditions in which changes in air humidity occur [79,97,87,63].

3.2.2. Temperature

The selected literature clearly showed the influence of temperature on COVID-19 spread, most of the authors being convinced that a negative correlation can be inferred. Some authors observed that COVID-19 is less stable at high temperatures [cf. 106]. At the same time, lower temperatures in winter enhance the survival time of viral particles in the atmosphere, facilitating transmission [97,81,63]. However, rising temperatures may be associated with behaviours that increase human exposure to the virus, e.g., increased human mobility and gathering of people for recreational purposes [60,92,107–109]. From a medical point of view, Irfan et al. [72] noted that exposure to colder temperatures adversely affects the immune function of the respiratory tract (see also [63,79,87,97]). In cold weather, the ability of certain lung cells to engulf and remove harmful particles significantly decreases, weakening the body's defence system [110,111].

In the investigated literature, only few authors found a positive association between global COVID-19 spread and deaths and temperature [82,74,65]. Chakraborti et al. [65] collected data on COVID-19 cases and deaths in 180 countries across the globe, finding a positive correlation between minimum temperatures and COVID-19 deaths, whilst Islam et al. [74] found a positive association with 14-day-lagged temperature and COVID-19 confirmed cases. In their study, which considers data from 31 countries all around the world and 428 Chinese cities and districts, Chen et al. [66] found that (i) a temperature range from 5 to 15 °C favours the spread of COVID-19 and (ii) the association between the number of newly confirmed cases correlated best with air temperature with a lag of 3–7 days. Jamshidi et al. [75] found that global highest infections were within the range of −10-0 °C and the lowest in the 20–30 °C range. Li et al. [38] inferred that medium temperatures were a positive predictor of COVID-19 deaths, whilst low temperatures were a negative predictor.

Similarly, several authors found a negative association with the number of COVID-19 cases at a global scale [69,92,76,80,93,98] and deaths [43,96,71,90]. The negative association was generally explained as the warmer temperatures diminish the survival and transmission of the virus [cf. 90], and by the fact that the immune system efficiency decreases at lower temperatures [43]. Li et al. [77] suggested that colder seasons discourage outdoor activities, increasing the probability of being infected indoors. Rodríguez-Pose and Burlina [89] performed a study across European countries with reference to the first wave of COVID-19 discovering a negative correlation with average temperature and excess mortality.

As for single countries, Bilal et al. [62] statistically determined that average daily temperatures in the USA had a positive association with daily new cases and a negative association with daily new COVID-19 deaths. Méndez-Arriaga [81] in Mexico found that temperature negatively associated with the local confirmed COVID-19 cases. Cacho et al. [63] and Paez et al. [85] found a negative association in Spain. In Italy, a negative association between temperatures and COVID-19 deaths was found by Coker et al. [27] and Isaia et al. [73]. An earlier study by Prata et al. [88], focusing on the 27 Brazilian capital cities, showed a negative correlation between temperature and COVID-19 cases below 25.8 °C. More recently da Silva et al. [68], considering the same case studies, found that the statistical significance and the type of correlation between the number of COVID-19 cases and temperature varied depending on the region where the capital cities were located. Gupta et al. [33] discovered a positive relationship with temperature and number of infections in their analysis on all the Indian states. Irfan et al. [72] found that temperature was inversely correlated with COVID-19 cases in Pakistan. As for China, the same type of correlation with COVID-19 deaths was found by Ma et al. [79], while the findings by Han et al. [34] suggested that the number of COVID-19 cases tended to increase with extreme temperatures. Moreover, according to Yang et al. [97], who studied the relationship between meteorological factors and COVID-19 transmission in seven Chinese cities, the influence of temperature (as well as of other meteorological factors) depends on the geographic location. In particular, they stated that, in the arid inland region, the warm season limited COVID-19 transmission and minimum temperatures accelerated COVID-19 transmission. Finally, Pramanik et al. [87] found that temperature had a varied role in influencing the number of COVID-19 cases across Russia. For example, in the humid continental region, the number of cases was mainly linked to temperature seasonality, whilst mean temperature diurnal range was found to be the main influencing factor in the sub-arctic region. In both cases the correlation with temperature is however positive.

3.2.3. Wind speed

The role of wind speed in influencing the geography of COVID-19 is twofold. Chakraborti et al. [65] performed a study at global scale (180 countries) during the first half of 2020 and found that for Europe wind speed was one of the variables which showed the highest relative negative influence on COVID-19 cases. Guo et al. [69] performed a study considering COVID-19 confirmed cases and deaths from 190 countries during the earlier pandemic phases (January–April 2020) investigating the role of meteorological factors on COVID-19 incidence, and they found a weak negative correlation with wind speed.

A 7-day-lagged and 14-day-lagged global analysis revealed that for the latter there is a significant negative correlation between wind speed and COVID-19 cases [74]. A negative association between wind speed and daily new cases was also discovered by Yuan et al. [98]. In 20 countries across the globe, the association with daily recoveries was found as negative whilst the one with confirmed cases and deaths was found as positive [90]. Su et al. [94] also suggested a positive relationship between wind speed and number of confirmed cases.

At a country scale, Chen et al. [66] found that the number of confirmed new cases in the city of Wuhan (China) correlated well with wind speed on the exposure day (no temporal lag) and that a peak of cases was recorded when wind speed was 1.88 m/s. Moreover, the authors suggested that COVID-19 spread easier under wind speed ranging between 1.5 and 4.5 m/s. In China, Yang et al. [97] found that the influence of wind speed on infections varied according to geographic locations. For example, a significant positive influence was found in Beijing, but not in other cities. The authors tried to explain the nature of this relation by stating that wind speed turbulence increases the spread distance and the virus diffusion rate in the atmosphere. As wind speed is positively related with the speed and distance of virus transmission in the atmosphere, and the virus is also adsorbed on suspended particles that accumulate near the ground, an increase in wind speed is likely to accelerate the spread of COVID-19 [90,97,63]. As for other countries, wind speed showed a significant and inverse relationship with COVID-19 infections in Iran [59], whilst the same correlation was found to be positive in India [33].

3.2.4. Precipitation

In the analysed literature, precipitation is rarely taken into account and this is accompanied by the lack of a common agreement on its role in influencing COVID-19 spread and deaths. Kubota et al. [76] suggested that precipitation is relevant to habitat suitability for the virus.

Globally, the conclusion of studies which investigated the impact of precipitation on COVID-19 pandemic are varied depending on the outcome variable and the study period considered. Kubota et al. [76] and Sobral et al. [93] identified a positive correlation of the number of COVID-19 cases with precipitation, in the earlier phases of the pandemic; on the contrary, Sarkodie and Owusu [90] discovered a negative association with both infections and deaths. Instead, neither significant nor weak correlation has been identified with COVID-19 deaths [96,93].

At a national level, precipitation showed varied relationships with COVID-19 depending on the region considered as well as on the considered health outcomes. Gupta et al. [33] found a negative association with COVID-19 number of infections in India. The analysis conducted by Bilal et al. [62] suggested that precipitation was among the most significant factors influencing COVID-19 pandemic in the 10 greatly affected states of the USA. The study also showed that daily new cases and deaths had a negative association with this weather variable. A negative correlation was found also for some capital cities in Brazil [68] and Europe [89]. On the contrary, a study focused on 31 states and the capital of Mexico outlined that daily local COVID-19 confirmed cases and local transmission ratio had a positive association with precipitation [81]. No significant correlation was found by Ahmadi et al. [59] in Iran and by Yang et al. [97] in China.

3.2.5. Solar radiation

Studies carried out at both global and national levels suggested that Solar UV radiation may have an impact on the development of COVID-19 through the positive effect of vitamin D on the immune system. In fact, UV rays play a crucial role in converting provitamin D3 into the active form vital for immune defence mechanisms [63,112–114]. Moreover, increased solar radiation, particularly in the UV-B region, may serve as a disinfectant for non-porous materials, potentially reducing the spread of the virus.

In this context, at a global level, a negative association of COVID-19 cases [82,64] and deaths [84] was found. This negative correlation was confirmed also at a national level [33,59,73,91]. In contrast, Hofmeister et al. [70] suggested that the increases in COVID-19 cases in spring and summer may be linked to high solar irradiance, causing ultraviolet immune suppression as one means of amplification. Only a few studies discovered no correlation between solar radiation and COVID-19 at global [74,86] and country scales [63].

3.2.6. Air pollution

Literature on the topic suggests that air pollution could act as a carrier of the viral particles and a factor which aggravates COVID-19 severity [115–121]. In particular, it has been considered as a potential explanatory variable for COVID-19 geography in 15 studies. The main air pollutants considered were PM10, PM2.5 (fine particle matter with a diameter smaller than 10 and 2.5 μm respectively), nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon dioxide (CO_2) and ozone (O_3). The possible correlations between air pollutants and COVID-19 outcomes are reported in Table 4. According to the literature review by Copat et al. [116] regarding the influence of air pollution on COVID-19 infectivity and lethality, PM2.5 and NO_2 are the most influent pollutants, and to a lesser extent PM10. Worth mentioning is that Deguen and Kihal-Talantikite [99] found NO_2 to be a good indicator for traffic-related air pollution since it correlates well with other traffic-related air pollutants, (i.e. particulate matter), and chose it for their analysis due to its higher spatial variability.

At a global scale, Chakraborti et al. [65] found that environmental pollution had a strong causal impact on COVID-19 cases in Asian countries. In particular, NO_2 and PM2.5 concentration was significantly correlated with total cases and deaths. The same study showed that CO_2 emissions had a certain influence in American countries whilst in African countries, considering COVID-19 deaths as the response factor in the modelling, only PM2.5 and CO_2 emission proved to be statistically significant. It was also discovered that NO_2 was positively correlated with deaths in Oceania.

Baniasad et al. [61] investigated the long-term effect of air pollution on COVID-19 health outcomes for eight countries of the Global South considering PM2.5 data over the period 1998–2017. The authors did not find any significant correlation between the air quality and a possibly higher risk of COVID-19. They suggested that it is necessary to consider a greater scale, e.g., at a subnational level, in order to better investigate this association.

At a country scale, the statistical analysis of Bilal et al. [62] highlighted a negative association of PM2.5 with daily new cases as well as COVID-19 daily fatalities in the USA. On the contrary, the analysis by Coker et al. [27] suggested a positive association of ambient PM2.5 concentration and excess mortality in northern Italy. In France, the analysis carried out by Deguen and Kihal-Talantikite [99] revealed a significant correlation between long-term exposure to NO_2 and COVID-19 incidence and hospitalised cases. As for China, the analysis by Han et al. [34] revealed a positive correlation of PM2.5 with infected cases. Hass and Jokar Arsanjani [35] found that PM10 is one of the variables with higher significance in the northern European countries. In England (UK), COVID-19 mortality risk positively correlated with long-term exposure to NO_2 and PM2.5 [100]. A strong positive correlation was found mainly in the western part of India between PM2.5 and COVID-19 deaths, whereas in the other parts of the country such a relationship was not observed [101]. Finally, Rodríguez-Pose and Burlina [89] found a positive correlation of COVID-19 deaths with PM2.5 in their study at a European level.

3.3. Socio-demographic and socioeconomic variables

As far as human geography factors are concerned, the reviewed articles showed a significant influence of demographic and socioeconomic features on COVID-19 infections and deaths, which is discussed in the following sections.

3.3.1. Age

The age structure of a population may help in explaining differences in the severity of COVID-19 consequences, e.g., in terms of hospitalization and fatality rates throughout regions and on how transmission took place [21]. It is clear that age is an important parameter to be considered in studying a pandemic. In fact, it has been estimated that 95 % of COVID-19 deaths in Europe were among people aged over 60 years old being more than 50 % $\geq$ 80 years old [21,30].

Only a few studies considered age structure in their analysis at a global scale. Chakraborti et al. [65] found that for 180 countries COVID-19 infection risk was high with age >80. Li et al. [38] found that a high percentage of the population less than 10 years old was a negative predictor of the number of COVID-19 cases in 154 countries. Su et al. [94] reported that the percentage of people aged over 65 can explain approximately 50 % of variation in transmission rate across the 277 regions. Finally, Tzampoglou and Loukidis [96] found a strong correlation between both the total cases and the total deaths per million of inhabitants with the increasing median age of the population.

At a national level, Middya and Roy [101] observed that the total number of persons aged 50 years or more positively correlated with COVID-19 mortality in India. On the contrary, Paez et al. [85] stated that the percentage of older people was negatively associated with incidence in Spain. The authors inferred that this finding might have been due to the fact that older adults may tend to have a lower level of social contacts/higher level of social distancing than younger people. This evidence is also confirmed by Rahman et al. [122] who found that the infection rate was the highest among those aged 21–50 years. The authors also underlined that this did not contradict the evidence that older adults are more vulnerable, since older people mortality rates are the highest among all age groups. This finding actually indicates that older people's presence within a community tends to lower virus transmission.

As for studies conducted at a more local scale, Lopez-Gay et al. [123] found that in Barcelona higher rates of infection characterized geographical units that had more residents aged 70 years, and that the percentage of people older than 70 years was positively correlated with COVID-19 infection rates. Similarly, Coker et al. [27] showed that COVID-19 infection risk was high with age >80 in northern Italy. In New York (USA), percentages of people aged 18–44 and 45–64 were negatively associated with COVID-19 death rate [124].

3.3.2. Population size and density

Since the earlier phases of the pandemic, population size and density were considered to play a central role in explaining the geography of COVID-19. The pandemic has in fact hit harder the highly connected global cities [cf. 30] which are characterized by high frequency of social interaction that can surely be a driver of rapid contagion [23,125]. A total of 50 studies examined data relative to population size or population density to analyse possible relationships with COVID-19 infections and deaths. Twenty-three of these studies considered population density whilst the other 27 took into account the total population of the spatial unit of analysis (e.g., state, county, region). Actually, the above-mentioned positive correlation was confirmed by many of the studies analysed in our literature review, both at global and national/subnational levels.

At a global level, it was found that population size was directly associated with case-fatality rate [126] and number of infections [45,75,76]. The factors that may have determined this direct correlation are: i) the higher strain on the healthcare system, ii) the higher risk of transmission, and/or iii) scant population health conditions in highly populated countries. On the contrary, the correlation of population density with COVID-19 infections and deaths is not univocal. For example, some authors found no significant correlation between population density and transmission and fatalities [38,126], whilst Díaz Ramírez et al. [52] found a strong association with mortality excess in their study focused on OECD and European countries. The discordant results are perhaps due to the fact that the population density was calculated by dividing population size by the country extent, being in many countries the population not homogeneously distributed (see also [96]).

At a country scale, it was confirmed the positive correlation between population size and/or density. For example, in Iran Ahmadi et al. [59] and, specifically for the city of Tehran, Nasiri et al. [40] found a significant and direct relationship between the number of infected people and population density. In São Paulo State (Brazil), Fortaleza et al. [31] discovered a higher influence of demographic density on COVID-19 spread during the earlier phases. Similarly, population density showed a positive correlation with COVID-19 spread in Malaysia [127,128]. The same correlation was found for China [34], Nigeria [129] and India [33,101,130]. Holmager et al. [131] reported that high population density in Denmark as well as large households, seemed to increase the risk of COVID-19 spread. A positive association between COVID-19 deaths and population density [42,50] and county population [37] were found in the USA.

On the contrary, no or unclear correlation between population and the geographic variation of COVID-19 was found in Italy [23, 27], The Netherlands [24] and Sweden [30].

It is worth mentioning that not in all the studies analysed population was used as a conditioning factor for COVID-19 geography; in fact, in some of them, population data were used to normalize infections and deaths [cf. 75] or to assign weights to the investigated spatial unit of analysis [22,132]. In some other studies, population was also considered as a confounding factor [83,133].

3.3.3. Economic stability (e.g., poverty, income, education, GDP, industrial production, trade intensity)

Admittedly, welfare and income dimensions had a major role in driving the pattern of COVID-19 cases and deaths around the world.

The Gross Domestic Product (GDP) well represents the country wealth and GDP per capita was taken into account as an explanatory variable in many of the analysed studies. In fact, at least during the first phase of the pandemic, the importance of GDP for the geography of COVID-19 could be inferred by observing that the regions hardest affected by the pandemic were characterized by relatively higher GDP. This was the case of northern Italy, where the provinces most affected by the pandemic were those characterised by a GDP above the national average [23]. Statistical analysis conducted at the national level for Chinese prefectures confirmed the positive correlation between the GDP [34] and, more broadly, economic development [134], with the number of confirmed COVID-19 cases. Paez et al. [85] estimated that higher incidence was associated with higher GDP per capita in Spain. At a global level, almost all the investigated studies agree on the existence of a positive correlation between country GDP per capita and COVID-19 infections [76, 126] and deaths [43,65]. This is probably due to the fact that high GDP implies more intense international economic exchanges and consequently higher levels of global interconnection among individuals increasing the possibilities of virus transmission [135]. This is supported also by some studies which conclude that trade intensity showed a positive correlation with COVID-19 infections and deaths [25,136].

The role of income in affecting the distribution of COVID-19 was investigated mainly at sub-national level. Studies conducted in Sweden and in Finland [cf. 30,137] found that COVID-19 cases were more concentrated in the less advantaged areas. The impact of unemployment rate on COVID-19 at country level is twofold. A negative correlation was found in Italy and the USA regarding the number of infections and deaths, respectively [37,23] whilst a positive correlation was found with infections in Germany. The unemployment status implies no human interactions within the working environment as well as reduced necessity to commute e.g., by using crowded public transport, thus less chance for virus transmission; on the contrary, a lower unemployment rate implies poor economic conditions which are often accompanied by scant access to medicine and health assistance.

3.3.4. Human mobility

Owing to the high transmissibility of COVID-19, many studies in literature analysed the effects of human mobility on infections and/or death rates. Topîrceanu and Precup [48] modelled epidemic diffusion integrating population characteristics with human mobility, finding that the number of infections was more sensitive to the increase in travel distance between settlements (positive

Table 5
Main methods and tools applied in the 112 reviewed studies. Classification of methodology macro-area and area is based on the work by Franch-Pardo et al. [11]. In the second column, the figures in the brackets represent the numbers of papers which have applied a methodology included in the respective area.

Methodology macro-area	Methodology area (number of articles)	Specific methods and/or tools
Mapping	Choropleth mapping (56)	Mapping spatial distribution of COVID-19 data (e.g., number of infections/deaths per administrative unit) and geographic factors (e.g., temperature, rainfalls, population density)
	Hotspot and cluster mapping (19)	Mapping spatial autocorrelation based on hotspots and cluster analysis (e.g., LISA maps)
	Dot distribution mapping (11)	Mapping locations of COVID-19 cases or points of interest
	Spatial heat mapping (11)	Mapping geographic factors (e.g., temperature, precipitation) and COVID-19 spread (e.g., density of infections, COVID-19 risk) through interpolated surfaces
	Flow mapping (4)	Mapping mobility and urban networks
Statistical analysis/ modelling	Aspatial models (49)	Pearson Correlation; Poisson regression; Kendall and Spearman test; Negative binomial model; Analysis of variance (ANOVA); Exponential regression; Zero-inflated negative binomial (ZINB) regression; Quantile regression model; Generalized additive model (GAM)
	Machine learning (10)	Random Forest algorithm; LASSO regression; Gradient Boosting Decision Tree
Spatial statistics	Hotspots and clustering (22)	Spatial autocorrelation (Global Moran Index, Local Indicator of Spatial Association, LISA); Getis-Ord Gi; Kernel density estimation; Spatial and Space-Time Scan Statistics
	Spatial regression (13)	Geographical weighted regression (GWR); Ordinary Least Square (OLS) model; Spatial error model (SEM); Spatial lag model (SLM); Conditional autoregressive (CAR) model; Spatial Seemingly Unrelated Regressions (SPSUR); Autoregressive Integrated Moving Average (ARIMA)
	Interpolation and geostatistics (3)	Inverse Distance Weighting
	Other spatial models (5)	Global geographical gravity models
Multicriteria analysis	Multicriteria analysis (12)	Analytical hierarchical process; Hierarchical cluster analysis; Bayesian hierarchical Poisson log-linear models; Bayesian hierarchical space–time SEIR model; Geo-hierarchical population mobility model; Time-geography model based on space-time discs and control points; Grey relational analysis model (GRA)

association), rather than to the travel frequency.

Generally speaking, it was observed that government-imposed mobility restrictions were successful in mitigating COVID-19 transmission [61,138]. At a global level, a positive correlation was found between human mobility and COVID-19 infections [45, 92,75,76,139]. At a national scale, several studies found that mobility reduction generally implies a restrain on infections [59,140, 141]. A positive correlation between mobility and excess mortality was also found in Italy [23] and Ecuador [142].

Established that mobility is a very important variable in explaining the geography of COVID-19, retrieving mobility data is often challenging [143]. Considering this, it is worthy to mention that for the studies conducted at a global scale, mobility data were mainly retrieved from Google's or Apple's COVID-19 Community Mobility Reports [52,92,65,138]. At a national level, where a granular scale was required, human mobility data were often provided by mobile phone datasets [e.g., 124,142]. Additionally, Ascani et al. [23] studying the effect of mobility on the spread of COVID-19 pandemic between Labour Market Areas (LMAs) used Facebook Disease Prevention Maps data based on tracking Facebook users' movements.

In other studies, conducted at both global and country scales, mobility was measured by passenger traffic in airports [30,65,89, 144], finding a positive correlation with COVID-19 outcomes.

3.4. Spatial and temporal resolution, and statistical methodological approach

Among the revised studies, 71 were conducted at sub-national level considering varied spatial units of analysis (e.g., counties, provinces, districts, municipalities, cities) almost exclusively based on administrative boundaries. This was due to the fact that COVID-19 data, climatic/weather and environmental data, as well as the socio-demographic and socioeconomic ones, were mostly provided for administrative units (e.g., regions, provinces, municipalities). In this context, the variations that can significantly affect such data within a certain administrative unit are often disregarded [145]. This may prevent the understanding of the significant uneven patterns of COVID-19 pandemic which in fact overcame administrative boundaries.

Only a few studies considered spatial units not based on administrative boundaries. For example, Ascani et al. [23] studied the geography of COVID-19 at a local level in Italy by considering labour market areas based on commuting data as spatial units of analysis. Similarly, Carballada and Balsa-Barreiro [2] based their analysis on mobility areas in Spain. Only a few studies were performed at a neighbour level [cf. 44,123,140] counting on granular data on COVID-19 and socio-demographic/socioeconomic features.

With reference to the temporal resolution, most of the studies were relevant to the first phases of the pandemic, during the year 2020, and mainly focused on a relatively short time frame, varying from 30 to 180 days, whilst only few studies exceeded one year of data collection and analysis [50,65,133]. If, on the one hand, the level of spatial granularity of the studies was modest, on the other hand, we encounter that the analyses were based on a high temporal resolution mainly including daily or weekly data. This reflects the wide availability of daily or weekly open data concerning both COVID-19-related outcomes (e.g., available at Our World in Data or John Hopkins University Coronavirus Research Centre websites), and geographic factors (e.g., available at Copernicus Climate Change Service and NASA Climate Data Service repositories).

The literature review carried out showed that integrating both space and time in the analysis of COVID-19 spread is a challenging issue. In most of the studies, the time dimension is considered by comparing the results of the analysis at discrete individual time points. Only few studies integrated both temporal and spatial dimensions in their analysis and/or models [e.g., 66,68,76,146].

Different approaches in trying to decipher the role of geographical and environmental factors in the spreading of the COVID-19 pandemic were applied including both spatial and aspatial techniques. The spatial distribution of COVID-19 data (e.g., infection and excess mortality rates) and geographic factors (e.g., temperatures, precipitation, population density) have been represented primarily through choropleth maps. Regression models were used to analyse the correlation with many kinds of variables. Among others, the Pearson correlation was used to investigate the correlation of COVID-19 related outcomes with climate/weather variables [33,59,97], elevation and geographic location [29,47]. The Poisson regression was instead applied to study the correlation between the independent socioeconomic and demographic variables with COVID-19 related outcomes [e.g., 123,142,147] but this method is also suitable for investigating the relation with meteorological factors [e.g., 148].

The geography of COVID-19 was also investigated by applying the hotspots and clustering analysis through the Global Moran Index, which measures the spatial correlation based on spatial distribution of the values of a variable. This tool evaluates if the variable values are spatially clustered, dispersed or random [149]. Since the Moran index is a global statistical index and provides only one value for the entire spatial pattern (and no information on the location of the clusters), the Local Indicators of Spatial Association (LISA) tool was frequently applied to achieve more significant outputs. The hotspot and clustering analysis were generally accompanied by the related maps (e.g., LISA maps).

The limit of the spatial techniques used in the analysed studies is that they are generally based on the Tobler's law according to which "everything is related to everything else, but near things are more related than distant things" [150] but many studies revealed that this cannot always be applied in describing COVID-19 spatial dynamics. This was particularly true in the first phases of the pandemic during which transmission could occur over a long distance through train and highway networks and airplane routes. On the contrary, aspatial techniques did not consider the potential spatial correlation of both COVID-19-related outcomes (e.g., infections, hospitalization and deaths) and geographic variables.

Other methods and tools, which are not mentioned above, were applied in the analysed investigations (see Table 5).

4. Conclusions and perspectives

The literature review confirmed that there is a geographic signal in COVID-19 spreading since both physical and human geographical factors have proved to be significant in explaining the spatial distribution of the contagion and its consequences. The novelty of our review with respect to the previous ones resides in: (i) the use of an interdisciplinary approach to analyse the selected papers, including expertise in epidemiology and physical geography; (ii) the emphasis on the spatial and temporal resolution of the analysed papers; (iii) the wider range of variables influencing COVID-19 outbreak and transmission considered; and (iv) the overview of the varied health outcomes considered by the reviewed studies, which are aspects often neglected by existing literature reviews in the field.

Among the territorial variables, latitude and elevation, due to their control on temperatures and environmental features, showed a negative association with COVID-19 related outcomes. For what concerns elevation, its negative association with infections and deaths must be taken with caution since other factors, such as population density, socioeconomic characteristics, availability of health care services, may act as confounders. Urbanization was one of the most investigated variables in the analysed literature which in general showed a certain agreement in stating that there is a positive correlation between urbanization degree and COVID-19 infections. However, some studies highlighted that often COVID-19 had more severe consequences in rural settings due to the lower availability/accessibility of health care services.

For what concerns climatic variables, temperature is the one that best correlates with COVID-19 infections and this correlation was found to be negative in most of the analysed studies. From the analysis of the literature under investigation, it has also been revealed that correlations between humidity and COVID-19 must be considered. However, the role played by humidity can vary depending on factors such as scale and seasonality.

The influence of wind speed on the geographical spread of COVID-19 is twofold. According to literature, wind speed is positively correlated with the speed and distance of virus transmission in the atmosphere, and an increase in wind speed will expedite the spread of COVID-19. Solar UV radiation was identified as impacting the development of COVID-19 through the positive influence of vitamin D on the immune system or virus inactivation.

Admittedly, owing to the high transmissibility of COVID-19, human interactions must have played a major role in virus diffusion, in fact, the pandemic hit the highly populated and connected cities harder. This is in accordance with most of the analysed studies which showed that population density and human mobility have a significant and direct relationship with COVID-19 infections and deaths.

The analysis of the different approaches used to decipher the role of geographic and environmental factors in the spreading of the COVID-19 pandemic revealed that it is advisable to look at the geographic aspects, considering their great variability, at a high level of granularity (e.g., subnational or local scales) in order to ensure the representativeness of the data with respect to the spatial unit of analysis. This is particularly true for the climatic/weather and environmental variables.

From a public health perspective, the significant heterogeneity of the epidemiological outcomes measured in the analysed works makes it challenging to compare and interpret the actual contribution of each geographic parameter on COVID-19 outcomes.

Given the transdisciplinary character of investigations linking geographical factors and COVID-19 spread, it would be desirable to involve public health experts in such kind of research, in addition to the necessary expert knowledge in physical geography, economy, sociology etc. This would avoid inappropriate usage of epidemiological terms (i.e., using the term “mortality” when considering the absolute number of COVID-19 related deaths), or not accounting for outcome indicators limits. In fact, the number of COVID-19 hospitalised patients can be overestimated during periods of intense virus circulation, when all the patients are tested for SARS-CoV-2 infection independently from the reason of hospitalization (“incidental COVID-19 hospitalizations”). In this context, it would be advisable to align with the indications provided by the World Health Organization (WHO) in the specific interim guidance published in March 2023 [151]. The latter proposes a series of COVID-19 indicators capable of providing epidemiological assessment methods which consider, as key areas, COVID-19 transmissibility, impact on comorbidity and mortality, and impact on the health system.

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Data availability statement

Data regarding the detailed information on the 112 papers analysed and commented in this review are included in the supplementary material (cf. Appendix A).

CRediT authorship contribution statement

Vittoria Vandelli: Writing – original draft, Investigation, Data curation. **Lucia Palandri:** Writing – original draft, Methodology, Data curation. **Paola Coratza:** Writing – review & editing. **Cristiana Rizzi:** Investigation, Data curation. **Alessandro Ghinoi:** Investigation. **Elena Righi:** Writing – review & editing, Funding acquisition, Conceptualization. **Mauro Soldati:** Writing – review & editing, Funding acquisition, Conceptualization.

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.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.heliyon.2024.e25810.

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