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ORIGINAL ARTICLE / ÖZGÜN MAKALE

COVID-19 and the city: Statistical analyses indicated COVID-19 epidemiology is influenced by population size, GDP, and conflict rates

COVID-19 ve şehir: İstatistiksel analizler COVID-19 epidemiyolojisinin nüfus büyüklüğü, GSYİH ve çatışma oranlarından etkilendiğini gösterdi

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Abstract

Objective: Numerous host and geographical factors have been discussed in the literature regarding their impact on COVID-19 spread and mortality. This study aims to evaluate which of these factors are more influential from an urban ecological perspective.
Methods: Data on host factors reported to be associated with COVID-19, or potentially related, were collected for 56 countries. These factors were grouped as diet, micronutrient deficiencies, diseases, environmental factors, population structure, and economic parameters. Regression analyses were performed to assess their relationships with the early spread and mortality of COVID-19.
Results: The analyses revealed that population-related parameters were the most influential on COVID-19 spread, while economic factors played the most significant role in mortality. Specifically, population size was correlated with the spread rate, whereas GDP, Gini index, and conflict rates were correlated with death rates.
Conclusion: The findings highlight the critical roles of demographic and economic parameters in shaping the course of COVID-19 and demonstrate that an urban ecological perspective provides a strong framework to interpret these relationships.

Keywords: COVID-19, Urban systems, Economy, Population, Host factors

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Öz

Giriş: COVID-19’un yayılımı ve ölümcüllüğü üzerinde etkili olabilecek birçok konak ve coğrafi faktör literatürde tartışılmıştır. Bu faktörler arasında özellikle kentsel ekolojik ilişkiler dikkat çekmektedir.
Amaç: Bu çalışma, COVID-19’un yayılımı ve ölüm oranları üzerinde hangi konak ve çevresel faktörlerin daha etkili olduğunu kentsel ekoloji bakış açısıyla incelemeyi amaçlamaktadır.
Yöntem: COVID-19 ile ilişkili olduğu bildirilen ya da ilişkili olma potansiyeli bulunan çeşitli konak faktörlerine ait veriler 56 ülke için toplanmış ve diyet, mikro besin eksiklikleri, hastalıklar, çevresel faktörler, nüfus yapısı ve ekonomik faktörler olarak gruplandırılmıştır. Bu gruplar üzerinden regresyon analizleri yapılarak COVID-19’un erken yayılımı ve ölüm oranlarıyla ilişkileri değerlendirilmiştir.
Bulgular: Analizler sonucunda, COVID-19’un yayılımında en etkili grubun nüfusla ilgili parametreler olduğu, ölüm oranlarında ise ekonomik faktörlerin belirleyici olduğu görülmüştür. Ayrıca nüfus büyüklüğü COVID-19’un yayılma hızıyla, ülkenin GSYİH’sı, Gini indeksi ve çatışma oranları ise ölüm oranlarıyla pozitif yönde ilişkilendirilmiştir.
Sonuç: Bulgular, COVID-19’un seyrinde ekonomik ve demografik faktörlerin kritik rol oynadığını ve kentsel ekoloji perspektifinin bu ilişkilerin değerlendirilmesinde güçlü bir araç sunduğunu göstermektedir.
Anahtar Kelimeler: Kovid-19, Kentsel sistemler, Ekonomi, Populasyon, Konak faktörleri

INTRODUCTION

Coronavirus disease 2019 (COVID-19) is the name of a currently well-known pandemic disease that affects hundreds of millions of people all around the world. There are significant variations in COVID-19 susceptibility and severity/fatality from person to person. It is known that COVID-19 vulnerability and fatality are affected by many variables: There are studied relationships between sunlight exposure, dialysis, poverty, race, urbanization and COVID-19. COVID-19 caused many deaths around the world, and at the same time, it caused a social transformation by affecting the human population in different aspects that can be categorized as economic, social, and technological (1-2-7). Significant reductions in income, rising unemployment, technological reshapings in the healthcare area and changes in social decisions are some examples of the different aspects of the impacts of COVID-19 on human life.

Even though COVID-19 emerged as a viral infection, it also has economic, sociological, and technological dimensions. Vaccines illustrate these effects, as their development revealed economic and social challenges alongside scientific advances. Normally requiring around 15 years, vaccine development is costly and resource-intensive (3). In contrast, COVID-19 vaccines were produced within a year and rapidly approved by organizations such as the FDA (9). This accelerated process encouraged the entry of many small companies and acceptance of emerging technologies. For example, RNA-based vaccines, never previously approved, received authorization and were widely produced (4). Due to technological diversity and varying national budgets, multiple vaccine types were developed for global distribution (4; 5). Costs also differed, leading to income-based disparities in vaccine access (5). Acceptance likewise varied, shaped by education, personal preferences, and economic restrictions. Thus, understanding host-related factors of COVID-19 remains crucial for developing novel technologies.

The emergence of SARS-CoV-2 can be associated with both climate change and modern urbanism. Climate change, defined as alterations in climate systems through chemicals, temperature, and biological processes, has occurred throughout history but today mainly results from industrial activities since the 1800s (6). These activities disrupted ecosystems by releasing industrial chemicals, reducing biodiversity, and damaging flora and fauna. Microorganisms such as viruses and bacteria, with their high genomic adaptability, are primary indicators of these ecological changes (7). Alongside this, urbanization significantly shapes microbial composition (8), while urbanism examines the relationship between expanding cities and their environments (9). Together, climate change and urbanization have transformed microbial interactions and accelerated microbial evolution. SARS-CoV-2, which emerged at the interface of rural and urban environments, most notably in Wuhan, is a clear example of this dynamic (10). Thus, both rapid urbanization and climate change are considered key drivers in its emergence (11).

To construct a framework to study COVID-19 with host factors in city systems, urban ecological relations can be applied, as microbial circulations occur across cities and rural areas. Integrated approaches are required to position humans within ecosystems, considering economic and social activities. Thus, relating economic and social aspects to biological-physical systems is essential. Using basic ecological theories such as patch dynamics and spatial heterogeneity is sufficient, since existing frameworks can be adapted for city systems rather than creating new ones (12). Different paradigms explain ecological relations within cities (8), and methods vary across contexts. Urban Ecology, combining human, physical, chemical, and biological elements, provides a growing theoretical basis for such studies (13). Yet, ecological dynamics evolve through evolutionary and geographical processes (14), with climate change and urbanization making city systems hotspots of environmental change. Given that many host factors intersect with urban systems, Urban Ecology offers a foundation to merge and interpret COVID-19 and host factor interactions.

This study introduces a novel contribution by applying an urban ecology framework to the analysis of COVID-19. Unlike earlier research, it collects and evaluates a wide range of urban-related parameters—including diet, diseases, economic indicators, environmental factors, micronutrient deficiencies, and population characteristics—to understand their impact on the spread and mortality of the disease. In a broader perspective, the work is innovative in interpreting a global pandemic explicitly through urban dynamics, emphasizing the role of human–environment interactions in shaping epidemiological outcomes. Based on this approach, the study develops the following hypotheses: the null hypothesis (H0) assumes that none of the urban parameters explain COVID-19 death and reproduction rates, while the alternative hypothesis (HA) suggests that one or more of these parameters can explain COVID-19 death and reproduction rates. The overall aim of this study is to evaluate the influence of urban parameters on COVID-19 epidemiology and to establish an ecological framework linking host factors, urban systems, and disease dynamics.

MATERIAL AND METHODS

Relationships of parameters in the literature: In the literature, many host factors are related -or potentially related- to COVID-19. Diet is one of the main parameters that are related to COVID-19 deaths (15). Some types of diets show a relationship between COVID-19 deaths and COVID-19 cases; people in malnourished countries are more prone to COVID-19 severity compared to people living in countries with no malnutrition problems (16). Moreover, COVID-19 cases show a strong relationship with obesity (17). Among the cases that have a Body-Mass Index (BMI) bigger than 23 kg/

m^2, a linear relationship between increasing COVID-19 severity (18). Since the nutrition status affects the immune system, intake of the necessary macronutrients also has a significant relation with 29 the COVID-19 severity condition (19). Moreover, COVID-19 cases and COVID-19 fatality are related to many diseases: Among cancer patients, COVID-19 death rates are 13.3% higher than other patients and some types of cancer patients are in the highest risk groups for COVID-19, such as lung cancers (20). Chronic obstructive pulmonary disease (COPD) and asthma are related to COVID-19 (21). Many of the non-communicable diseases (NDCs, diseases that cannot pass from person to person) such as diabetes or hypertension are related to COVID-19, and patients who have NDCs are the risk groups for COVID-19 (22). Anemia is also related to COVID-19 severity (23). In addition to these, economic statuses such as conflict, competition, and cooperation are linked with biology, especially with sociobiology, and the philosophical aspect of these connections has been constructed in literature (24). The applications of the economy to biological sciences are also widely studied in many disciplines such as urban ecology and sociobiology. The relationship between economy and biology can also be applied to the COVID-19 problem: The short-term and long-term consequences of COVID-19 are related to household type (25). Moreover, the effects of COVID-19 are socially stratified (26). The relationship between COVID-19 cases and conflict situations is also another aspect of economic status (27). GINI index is a parameter that represents the economic inequality in a society; in other words, it shows the gap between the poor and the rich in a given country and the relationship between the GINI index and COVID-19 deaths are also available in the literature (28). Similar to economic, disease, and dietary factors, there are several factors related to COVID-19. Many environmental factors like temperature sunlight open green areas whether factors such as rainfall air toxicity environmental pollutants are related with COVID-19 cases and COVID-19 deaths (29-64). Also, institutional features affect COVID-19 cases (65). Micronutrients are minerals and vitamins that play important role in homeostasis by providing various functions in the body (66). Micronutrients are also important for the immune system to work properly and micronutrient deficiencies are related to COVID-19 also (66). Zinc deficiency is highly correlated with COVID-19 cases, especially in poor countries and zinc supplementation is offered for COVID-19 patients (68). Vitamin D is another essential micronutrient for the immune system, and COVID-19 cases and severity are strongly related to vitamin D deficiency (69). Also, provide-iodine nasal sprays protect against COVID-19 cross-infection (70). Vitamin A is an important micronutrient for the immune system as playing a role in immune response (71). Vitamin A is important for pneumonia treatments and it can be an anti-SARS-CoV-2 regimen (72). In addition to all these, population size and the median age is related to COVID-19 spread (73). It is also known that air pollution increases the risk of COVID-19 fatality (74). Outdoor air pollution deaths and indoor air pollution deaths are other death rates for air pollution in a population, which may be related to COVID-19 cases. Urbanization is another factor that is related to COVID-19 (65).

To create a research design, the following hypotheses were developed:

Null Hypothesis (H0): None of the following parameters do explain COVID-19 death and reproduction rates: Diet, diseases, economic parameters, environmental factors, micronutrient deficiencies, and population parameters.

Alternative Hypothesis (HA): One (or more) of the following parameters can explain COVID-19 death and reproduction rates: Diet, diseases, economic parameters, environmental factors, micronutrient deficiencies, and population parameters.

Then, six groups of parameter sets -diet, environmental factors, micronutrient deficiency, economic parameters, population parameters, and diseases- were created to be used in the analysis

(Figure 1). Each parameter set was tried to be constructed in a holistic structure so that it could represent the main parameter from various angles. The details of the data types in the parameter groups can be seen in Table 1. The Diet parameter set includes the parameters of the selected countries: BMI, undernourishment levels, animal fat consumption, sugar consumption, and vegetable oil consumption; the Diseases parameter set includes the parameters: Anemia, general cancer rates, lung cancer, asthma, COPD, pneumonia, NDCs, diabetes, diarrheal diseases, colorectal cancer levels of the countries; the Economic parameters parameter set includes the parameters: conflict levels, GDP, GINI index, tax rates, and household type of the countries; the Environmental Factors parameter set includes the parameters: sunlight exposure, rainfall, forest area, CO2 emissions, air toxicity levels, general toxicity levels, and the average temperature of the countries; the Micronutrient Deficiency parameter set includes the parameters: vitamin D levels, vitamin A levels, zinc levels, and iodine levels of the countries; the Population Parameters parameter set includes population size, population growth type, urbanization percent, indoor air pollution deaths, outdoor air pollution deaths, and COVID-19 mortality deaths of the selected countries (Figure 2).

The data were compiled from various literature sources and publicly available online databases, covering a wide range of country-level attributes such as sociological, economic, and environmental factors that could influence the survival and spread of SARS-CoV-2. Countries were selected from the covariants.org database, which contained 58 entries at the time of access (10.05.2021; Figure 2). Bonaire and Curacao were excluded due to insufficient information in the selected references, resulting in 56 countries with common SARS-CoV-2 variant data being included in the study (see Appendix: "DATA.xlsx") (Table 1).

The six parameter sets were represented as clusters of independent variables, while the dependent variables of the regression analyses—COVID-19 fatality rate and COVID-19 reproduction rate—were shown as ellipses. The reproduction rate reflects the average number of newly infected individuals generated by one infected person: if the value is greater than 1, the virus spreads, whereas if it is less than 1, the infection gradually declines in the population (Achaiah & Subbarajasetty, 2020) (Figure 1).

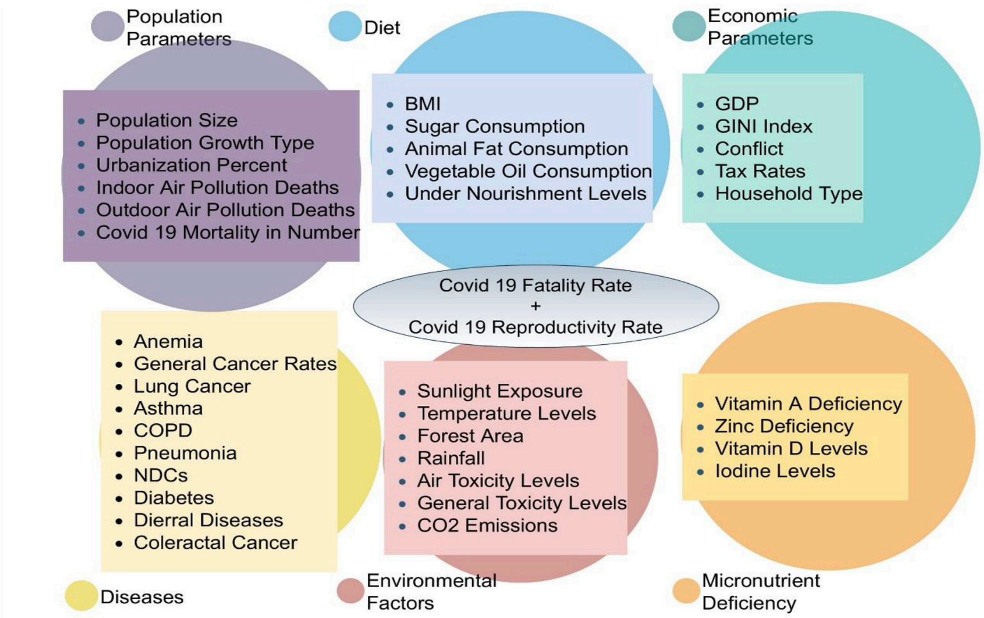

Figure 1. Representation of the selected parameter sets and dependent variables

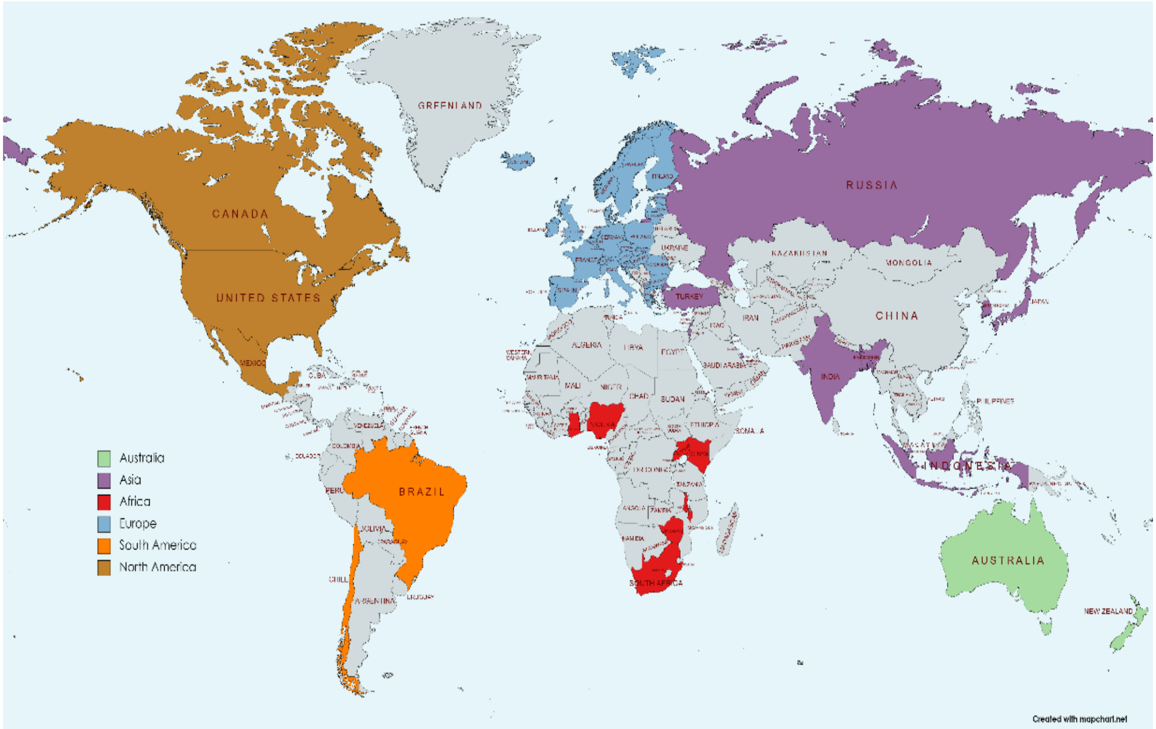

Figure 2. The geographical distribution of the selected countries for the analysis

As a math model, regression models were used. There are numerous regression analysis models, and the model should be selected based on the distribution of the type of response variable. Linear regression models are based on linear equations to produce the results whereas logistic regression uses odds ratios of the independent variables to produce output. Confidence intervals (in this study, p-values) are used to represent the statistical errors in the statistical analyses, in other words, they show how reliable the results are; 0.05 p-value represents the repeatability of the study is 95 %. In the multilinear regression method, a linear equation is created about how more than one variable can explain a dependent variable. In this study, classical multi-linear regression analysis was performed with the enter method in SPSS, and the most reasonable equation was tried to be reached with the Stepwise method. The stepwise method is a method used to reach the highest value of the regression equation. It looks at the biggest partial correlation to construct the regression equation, not the biggest correlation between the independent variable and dependent variable, and tries to reach the highest regression result step by step by creating a separate equation for adding each independent variable to the previous equation.

IBM SPSS Statistics version 26 was used with analyses for multiple linear regression analysis and bivariate correlation analysis. The missing value analysis was performed for parameters with missing data. The mean of the series was used for those whose significant value was greater than 0.05 in missing value analysis, and thus new parameter sets were created by transferring missing values. Analyzes were made with these new parameter sets. Missing values for countries were detected in parameter values. It was checked whether the blank answers were randomly distributed. According to the results of the analysis, it was assumed that the values with significance values of the EM mean values greater than 0.05 were randomly distributed, and the null values resulting in this way were assigned with the replace missing value assignment in SPSS via the series mean method. The resulting values were used as SMEAN values for the analyses. Later, all variables were standardized. For this, new standardized variables (Zvariable) whose Z-scores (to represent the deviations) were obtained using the standardization method in the Descriptive option in SPSS. These standardized values were used in further analyses. For each subgroup parameter, both step-wise and multi-linear regression analyzes were performed. In addition, stepwise regression analysis including all independent parameters was performed. While independent variables in these analyzes were variables in parameter sets, COVID-19 fatality, and COVID-19 reproduction rate values were used as dependent variables.

Table 1. Data sources and attributes used for the analysis

Variable name	Variable type:	Used in the equation of:	Data source:
Population Parameters			
Population size (in number)	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.populationpyramid.net/
Urbanization percentage of the population	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldbank.org/indicator/SP.URB.TOTL.IN.ZS
Deaths by indoor air pollution rates	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/indoor-air-pollution?country=
Deaths by outdoor air pollution rates	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/outdoor-air-pollution
Deaths by Covid-19 (in number)	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.worldometers.info/coronavirus/?utm_campaign=homeAdvegas1?

Economic Parameters			
GDP per capita	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldbank.org/indicator/NY.GDP.PCAP.CD The fractional numbers rounded to whole numbers, The last entry (current) data was used.
Gini index (income inequality)	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldbank.org/indicator/SI.POV.GINI?name_desc=false&view=map&year=2019 The fractional numbers rounded to whole numbers
Conflict cases	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://acleddata.com/dashboard/#/dashboard Total events (reported) were used
Corporate Tax Rates	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://taxfounhttps://data.worldbank.org/indicator/SI.POV.GINI?name_desc=false&view=map&year=2019dation.org/publications/corporate-tax-rates-around-the-world/ The fractional numbers are rounded to whole numbers.
Average Household Size: Number of members	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://population.un.org/Household/index.html#/countries/533
Diet Parameters			
Prevalence of Total Overweight Adults	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://apps.who.int/gho/data/view.main.CTRY2430A?lang=en The last entry (current) data was used (2016), The fractional numbers are rounded to whole numbers.

			https://data.worldobesity.org/maps-obesity-day/?mapid=62
Consumption of the Vegetable Oil	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	This database uses the data of the FAO (Food and Agriculture of the United Nations: http://www.fao.org/faostat/en/#data/FBS) and visualizes the data. The fractional numbers are rounded to whole numbers.
Consumption of the Animal Fat	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldobesity.org/maps-obesity-day/?mapid=62 This database uses the data of the FAO (Food and Agriculture of the United Nations: http://www.fao.org/faostat/en/#data/FBS) and visualizes the data. The fractional numbers are rounded to whole numbers.
Consumption of Sugars	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldobesity.org/maps-obesity-day/?mapid=62 This database uses the data of the FAO (Food and Agriculture of the United Nations: http://www.fao.org/faostat/en/#data/FBS) and visualizes the data. The fractional numbers are rounded to whole numbers.
Prevalence of undernourishment by percentage	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldbank.org/indicator/SN.ITK.DEFC.ZS
Micronutrient Deficiency Parameters			
Prevalence of Vitamin A deficiency	Independent variable	Multi-Linear Regression Analysis, Bi-variate Correlation Analysis	https://ourworldindata.org/grapher/prevalence-of-vitamin-a-deficiency-in-children?tab=table The fractional numbers are rounded to whole numbers.

Vitamin D status Around the World	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.osteoporosis.foundation/educational-hub/topic/vitamin-d The fractional numbers are rounded to whole numbers.
The global prevalence of Zinc Deficiency	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/global-prevalence-of-zinc-deficiency Most recent data was used, The fractional numbers are rounded to whole numbers.
Iodine Levels	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.who.int/vmnis/iodine/status/summary/IDD_estimates_table_2007.pdf?ua=1
Environmental Parameters			
Exposure to Solar UV Radiation	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://apps.who.int/gho/data/view.main.35300 For the countries that do have not any information about sunlight exposure in this application, the information of the nearest country was used (for Aruba, Venezuela used.)
Average temperature	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://worldpopulationreview.com/country-rankings/hottest-countries-in-the-world
Forest Area	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldbank.org/indicator/AG.LND.FRST.ZS
Average Precipitation	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://data.worldbank.org/indicator/AG.LND.PRCP.MM

Air Toxicity Levels	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.iqair.com/world-air-quality-ranking For countries that have more than one entry, the most toxic city data was used.
General Toxicity Levels	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.iqair.com/world-most-polluted-countries
CO2 Emissions per capita	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/co2-emissions
Diseases Parameters			
Anemia in pregnant women	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/anemia-pregnant-women-vs-children?tab=table The fractional numbers are rounded to whole numbers.
CANCER (For All Types of Cancer)	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://gco.iarc.fr/today/online-analysis-map?v=2020&mode=population&mode_population=continents&population=900&populations=900&key=asr&sex=0&cancer=39&type=0&statistic=5&prevalence=0&population_group=0&ages_group%5B%5D=0&ages_group%5B%5D=17&nb_items=10&group_cancer=1&include_nmsc=1&include_nmsc_other=1&projection=natural-earth&color_palette=default&map_scale=quantile&map_nb_colors=5&continent=0&show_ranking=0&rotate=%255B10%252C0%255D

Lung Cancer	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/lung-cancer-deaths-per-100000-by-sex-1950-2002?tab=table
Asthma	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/asthma-prevalence
COPD	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	Data is used from the Number of Deaths by COPD per million sections in this database.
Pneumonia	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/pneumonia-death-rates-age-standardized
NDCs (Non-communicable Diseases)	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/burden-of-disease-rates-from-ncds?tab=table To get more information about NDCs: https://ourworldindata.org/burden-of-disease
Diabetes	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/diabetes-prevalence
Diarrheal Diseases	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://ourworldindata.org/grapher/diarrheal-disease-death-rates
Colorectal Cancer	Independent variable	Multi-Linear Regression Analysis, Bivariate Correlation Analysis	https://www.worldgastroenterology.org/UserFiles/file/wdhd-2008-map-of-digestive-disorders.pdf The data from the “Global Colorectal Cancer Incidence” section was used, and The sum of female and male incidence rates was used.

RESULTS

Multiple linear regression was calculated to predict fatality based on the economy. A regression equation was found (F(5,49)=6,980.,p<.000), with an adjusted R2 of .356 (Table 2). Multiple linear regression was calculated to predict reproduction based on population. A regression equation was found (F(5,49)=6,162.,p<.000), with an adjusted R2 of .323 (Table 2). Therefore H(A) cannot be rejected. Apart from these, no meaningful regression relationship was found. In addition to these, correlations between economic variables and fatality; and correlations between population parameters and reproduction were investigated. Some correlations were found between the dependent and independent variables (Table 2, Figure 3, and Figure 4).

After regression analysis, correlation analyses were performed between each variable in the parameter sets and the related dependent variables, and only significant correlations are reported. NSR indicates non-significant results; * and ** represent significance at the 0.01 and 0.05 levels, respectively. Missing values were handled through SPSS missing value analysis: when the significance of EM means was greater than 0.05, SMEAN variables were created by replacing missing values with the series mean. These SMEAN variables, along with standardized values (Z-scores), were then used in the multi-linear regression analysis (Table 2).

The correlation analysis showed associations between COVID-19 fatality rate (cov19fatality) and several economic parameters. These included GDP (SMEAN[gdp]), income inequality measured by the Gini Index (MEAN[gini index]), conflict rates (SMEAN[conflict]), and corporate tax rates (SMEAN[tax]). The results were obtained by generating a correlation matrix using IBM SPSS version 26 (Figure 3).

The correlation matrix indicated that the COVID-19 reproduction rate (cov19reproduction) was associated with several population-related factors. Among these, population size (popsize, in numbers) and indoor death rates (indeath) showed stronger correlations, whereas urbanization percentage (urban), COVID-19 mortality in numbers (cov19mort), and outdoor death rates (outdeath) were less influential. These results were obtained using a correlation matrix created in IBM SPSS version 26 (Figure 4).

The calculations were two-tailed, and adjusted R^2 values were used for multiple linear regression. All results presented in this study are accessible through the corresponding SPSS reports and WebPPL data, codes, and outputs, which are available at the following link: https://drive.google.com/drive/folders/1paPEhtOng3zS3Azu_TlhxzsyjnXqaasP?usp=sharing .

Table 2. Multi-linear regression analysis results of the dependent and independent variables

Predictor values	Predicted value	Multi-lineer regression	Correlated variables
Population parameters	Covid-19 reproduction rate	Adjusted R Square = 0.323	**Population size vs Covid-19 reproduction rate:** Pearson = 0.307**, & Spearman = NSR; **Deaths by indoor air pollution rates vs Covid-19 reproduction rate:** Pearson = NSR & Spearman = - 0.295**
Economy parameters	Covid-19 fatality rate	Adjusted R Square = 0.356	**SMEAN(GDP) vs Covid-19 fatality rate:** Pearson = - 0.360* & Spearman = - 0.369*; **SMEAN(Gini index) vs Covid-19 fatality rate:** Pearson = 0.350* & Spearman = NSR; **SMEAN(Conflict cases) vs Covid-19 fatality rate:** Pearson = 0.483* & Spearman = NSR

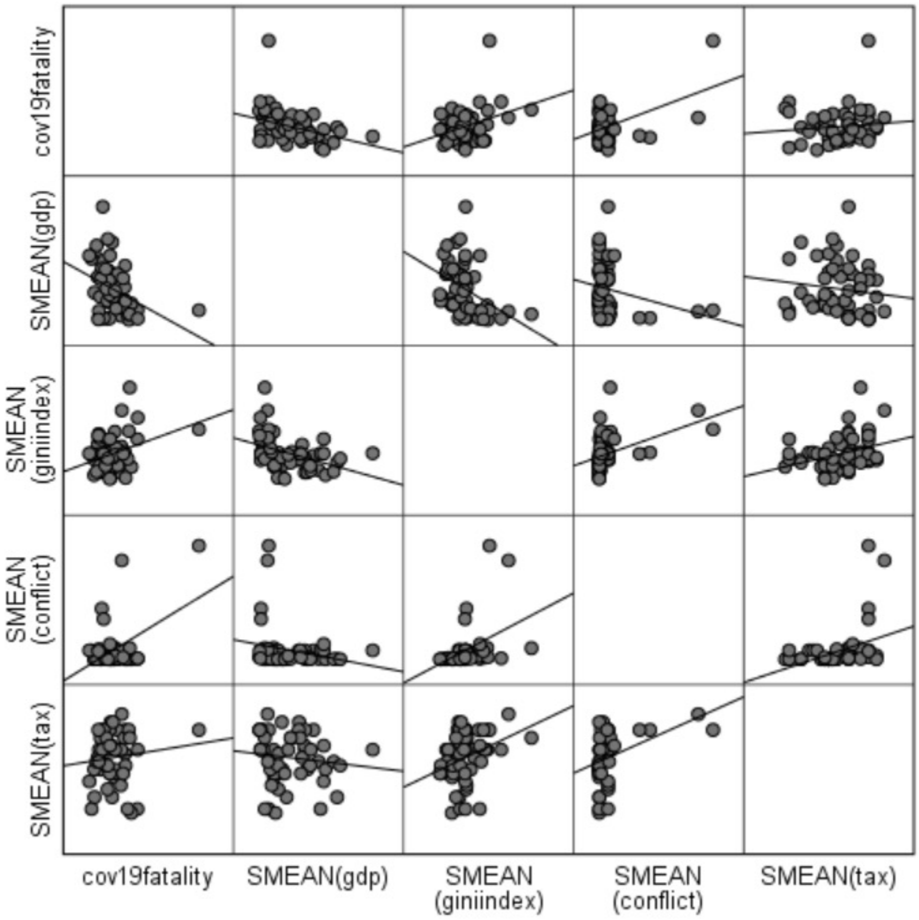

Figure 3. Correlation matrix for variables in the economy parameter set and COVID-19 fatality rate

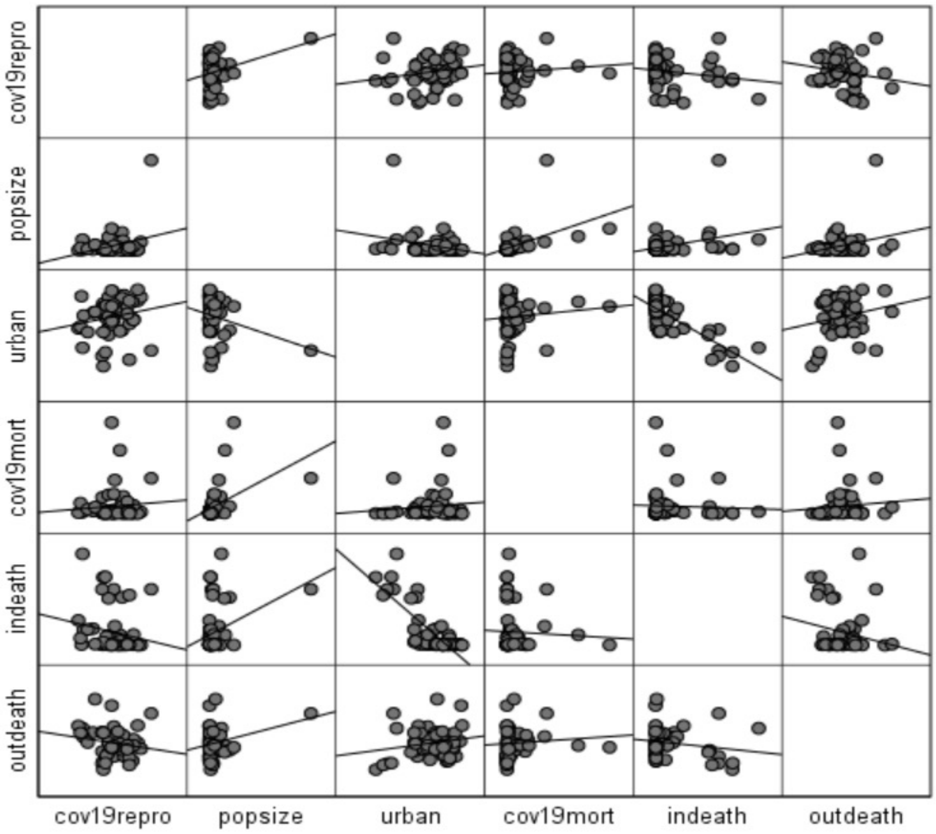

Figure 4. Correlation matrix for variables in the population parameter set and COVID-19 reproduction rate

DISCUSSION

The COVID-19 fatality rate was related to economic parameters (Table 2). The effort for constructing a linkage between the biological processes with the socioeconomic process is common in many disciplines such as socio-biology and urban ecology . The results of the analysis of the COVID-19 fatality support these efforts by giving a piece of evidence showing that the economic parameters can be related to the COVID-19 death rate (Table 2). The economic parameters set include the independent variables of conflict levels, GDP, GINI index, tax rates, and household types of the countries (Figure 1). The relatedness of COVID-19 cases and COVID-19 fatality rates with conflict cases income inequality and socio-economic stratifications were already investigated in the literature. In addition to the COVID-19 fatality rate, the COVID-19 reproduction rate was related to population structure (Table 2 and Figure 3). It is known that the spread of SARS-CoV-2 is dependent on population structure such as population size and the median age of the population and the results of the analyses of COVID-19 reproduction rate are relevant to these results, (Table 1 and Figure 4). The population parameters parameter set includes the independent variables of population size, population growth type, urbanization percent, indoor and outdoor air pollution deaths, and COVID-19 mortality deaths of the countries (Figure 2). In this parameters set, the COVID-19 reproduction rate was correlated with the single parameters of population size and indoor deaths (Table 2 and Figure 4). The correlation between population size and COVID-19 reproduction rate is consistent with previous results in the literature.

The reason why COVID-19-related deaths are related to the economic parameter group (Table 2) may be related to the fact that economic parameters are an indicator that can represent other parameters of the host (Figure 5). There are many linkages between biological facts and the economy. The relationship of economic factors with host factors in a wide spectrum from determining the gut microbiota to diseases has been shown in the literature (86). The relationship between economic factors, dietary habits, urban structure, population structure, micronutrient deficiency, environmental factors, etc. is also found in the literature (86). Other parameter groups, depending on the context, may have a decisive influence in specific countries or geographical regions, but the distribution of countries used in this analysis is spread across the world (Figure 2), which

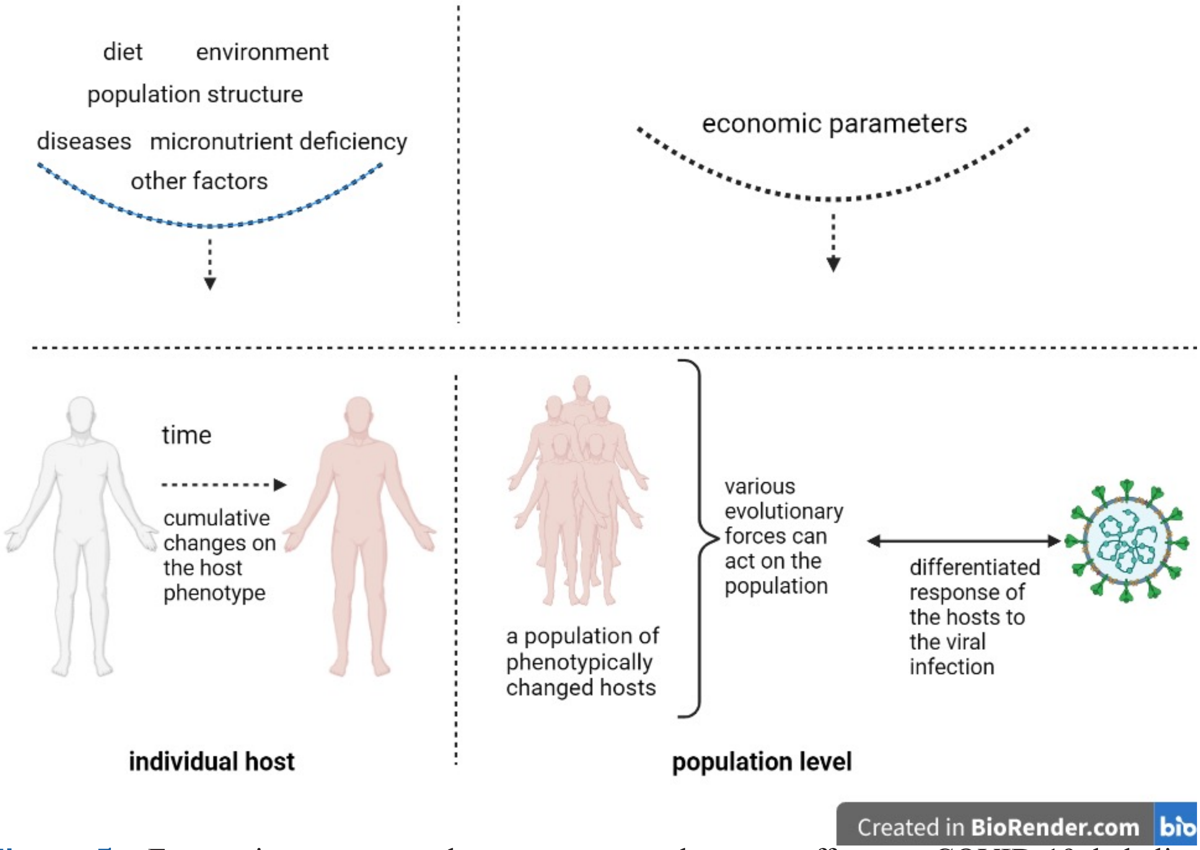

Figure 5. Economic parameters have a more explanatory effect on COVID-19 lethality compared to other factors

may indicate that a global result which is including all the components of the human population that cause death from the virus may be related to economic parameters (Figure 5). Biological modeling of the impact of economic parameters on human populations as a biological system is a problem. There are some efforts where biology is used to link economical human factors to biological human life. In terms of how economic differentiation leads to biological differences in the host's response to a viral infection, the accumulation of the differences that are caused by different parameters over time and their influence on the host's phenotype may lead to the treatment of these phenotypes by evolutionary forces (Figure 5). These results suggest that economic parameters may encompass other host-related variables that influence phenotypic changes in the human population. Over time, evolutionary processes can amplify the cumulative effects of diet, micronutrient deficiencies, and other factors, positioning economic conditions as a key determinant of population-level responses to viral infections such as SARS-CoV-2 (Figure 5).

In particular, the fact that modern world problems such as climate change and urbanization are closely related to ecosystem services suggests that the solution to these problems is mainly biological. Considering biological factors in the context of ecosystem services provides a reference point for understanding a multifactorial microbial circulation such as COVID-19. Increased research on the evolutionary mechanisms by which economic factors act on biological factors and the host factors that drive phenotypic differentiation will contribute to the understanding of urban systems as biological structures. The fact that the effects of the economy, especially the GINI index, conflict rates, and GDP on the host, lead to phenotypic variation in the population, and that the population's response to a microbial circulation change as a result of this variation - survival or death - may provide a starting point for a quantitative assessment of human factors from a biological perspective.

This study has several limitations that should be acknowledged. The dataset was restricted to 56 countries, which limits the generalizability of the findings and leaves the representation of low-income countries uncertain. Data were compiled from multiple heterogeneous sources with varying completeness, leading to missing values—particularly in disease and micronutrient parameters—and requiring imputation methods that may have reduced robustness. Moreover, COVID-19 data were drawn from a single time period, without accounting for temporal variability such as different waves, variants, or vaccination rates. While many independent variables were included, the risk of multicollinearity was not systematically evaluated, and the use of stepwise regression increased the likelihood of overfitting. In addition, the integration of diverse datasets meant that some parameters may have overshadowed others or been lost during successive analysis steps. Theoretical frameworks such as urban ecology and microbial metacommunity provided useful perspectives, but these fields are still developing, and the connection between theory and empirical analysis remained relatively weak. Finally, although economic parameters appeared to be the most decisive group in explaining COVID-19 fatality, this conclusion is correlational rather than causal, and the biological mechanisms linking economic factors to host-level responses were not fully explored.

CONCLUSION

The findings of this study demonstrate that COVID-19 outcomes cannot be explained solely through biological or clinical determinants but are strongly shaped by economic and demographic structures. Specifically, the results show that fatality rates are most closely associated with economic parameters such as GDP, income inequality, and conflict levels, while the spread of the virus is strongly linked to population-related factors, particularly population size and indoor pollution deaths. These outcomes highlight the importance of viewing the pandemic not only as a medical crisis but also as a socio-ecological event shaped by interactions between host biology, economic conditions, and urban structures.

By integrating concepts from urban ecology and socio-biology, this study underscores the necessity of considering multiple layers of human-environment interactions when evaluating pandemic dynamics. Although limitations such as missing data and overfitting should be acknowledged, the global distribution of the dataset strengthens the generalizability of the conclusions. Future work should expand on these findings by incorporating more detailed ecological and evolutionary mechanisms, examining how economic disparities and urbanization processes influence population-level vulnerabilities. Ultimately, recognizing the central role of socio-economic parameters in shaping phenotypic responses to viral infections may guide more effective and equitable public health interventions in the face of future pandemics.

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Conflict of interest statement:

The authors declare that there is no conflict of interest.

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This study does not involve any human or animal subjects; therefore, ethical approval was not required.

Authors› contributions

L.N.N. and S.E. contributed to the design and implementation of the research, to the analysis of the results and to the writing and reviewing of the manuscript.

Availability of data and materials

Data set of this study can be reached as a Supplementary Material: «DATA.xlsx».

Thesis

This study has been revised from the master's thesis entitled "A Probabilistic Assessment of SARS-CoV-2 Host Interactions in the Context of Meta-Community and Urban Ecology" prepared by Leman Nur Nehri.

Author Contributions:

LNN: Writing, analysis, data collection, experimental design, interpretation, literature review.

SEK: Writing, editing, interpretation, critical review.

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