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Land Cover Pattern and Case Fatality Rate of COVID-19

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Abstract:

Coronavirus disease 2019 (COVID - 19) has already caused 1,405,029 deaths worldwide, as of November 25th, 2020. Assessing whether land cover in people's living environments affects COVID-19 health outcomes is an urgent and crucial public health problem. Here, we examine land cover data associated with the case fatality rate (CFR) of COVID-19 at the county-level, in the United States. A 1% increase in green space in the county is associated with a statistically significant 0.34% (95% confidence interval 0.13%-0.55%) decrease in the county's COVID-19 CFR, and a 1% increase in emergent herbaceous wetlands are correlated with a 1.65% (0.19%-3.11%) decrease in the CFR. In addition, a 1% increase in high intensity developed area among the total developed area is related to a significant 3.63% (2.14%-5.12%) increase in the CFR, while a 1% increase in medium intensity developed area is associated with a 0.75% (-0.02%-1.51%) decrease. Our research highlights that governments could prevent similar pandemics in the future and even achieve some sustainable development goals by decreasing development intensity and increasing green space in living environments.

Keywords:

COVID-19, Case Fatality Rate, Land Cover, Development Intensity

Introduction

Coronavirus disease 2019 (COVID - 19) has raised serious and urgent concerns globally^{1,2}. As of November 25th, 2020, there were over 59.49 million confirmed cases and 1,405,029 deaths due to COVID-19 worldwide (Data from WHO COVID-19 Dashboard, see <https://covid19.who.int/>). In the United States, the cumulative numbers of confirmed and death cases owing to COVID-19 are 12,502,262 and 257,615, respectively, as of November 25th, 2020 (Data from US Centers for Disease Control and Prevention). However, the COVID-19 case fatality rate (CFR, CFR definition from WHO, see <https://www.who.int/news-room/commentaries/detail/estimating-mortality-from-covid-19>), which is the ratio of the numbers of deaths to confirmed cases, varies significantly among counties, ranging from 0 to 18.18%. A low COVID-19 CFR means that people are likely to recover, after they get infected, and that the local population may have few other chronic diseases^{3,4} and relatively good mental health^{5,6}. Cardiovascular disease is associated with an increased risk of death in COVID-19 patients³; people experience less depression and anxiety, exposed to more green space during COVID-19⁵. Therefore, analyses on the associations between potential environmental factors and the COVID-19 CFR may help identify the high-risk areas and develop optimal land-use policies to deal with other similar public health emergencies in the future⁷.

Investigations regarding the relationships between COVID-19 health outcomes and geographical factors are urgently needed, to locate the high-risk areas, to slow the disease's devastation, and to lower the risk of similar infectious diseases outbreaks ⁸⁻¹⁰. People's living environments have effects on the severity of COVID-19 among individuals, because people with less greenness may have more medical conditions ¹¹, like cardiovascular disease ¹²⁻¹⁴, which would ultimately exacerbate the symptom of COVID-19 ³. Numerous researchers point out that neighborhood greenness may have an effect on health outcomes, by promoting physical exercise and social connections, relieving stress, and removing air pollution, noise, and heat exposure ¹⁵. Moreover, an increasing amount of neighborhood greenness is related to reduced risks of chronic diseases, such as respiratory, cerebrovascular, cardiovascular, among others ¹⁶. It is hypothesized that living with more green land cover reduces the risk of death after infected, by alleviating the severity of COVID-19 symptoms. In other words, increased exposure to green spaces is associated with decreased risks of clinical diseases, which are related to a decreased risk of death after infection.

The positive effects of green land cover on COVID-19 are widely discussed, but urban land impacts remain inconclusive. In fact, an increase in urban land reduces green land cover, suggesting that the impacts of urban land on COVID-19 may be harmful. Exposure to greenery is associated with improved mental health during the pandemic ⁵. Also, urban vegetation is related to a decrease in the prevalence of COVID-19 in the United States ¹⁷. Many studies on this topic are available as preprints. However, due to the suddenness of pandemic, data insufficiency is always a severe problem hindering research. Specifically, individual-level data on COVID-19 health outcomes are still publicly unavailable or inaccessible to academics. Therefore, some models that generally provide more accurate estimation, like proportional hazards models, are

unable to be utilized. In order to analyze the association between the COVID-19 CFR (shown as **Figure 1**) and land cover (illustrated in **Figure 2, 3 and 4**), linear regressions are employed using the county-level data, while controlling for other county-level variables. Here, we explore how multiple land cover factors (percentages of land types in the total area, percentages of development intensity in developed area) affect the COVID-19 CFR across counties in the U.S. Our results highlight the importance of green land cover and vegetation in the developed area to reduce the risk of death after infection.

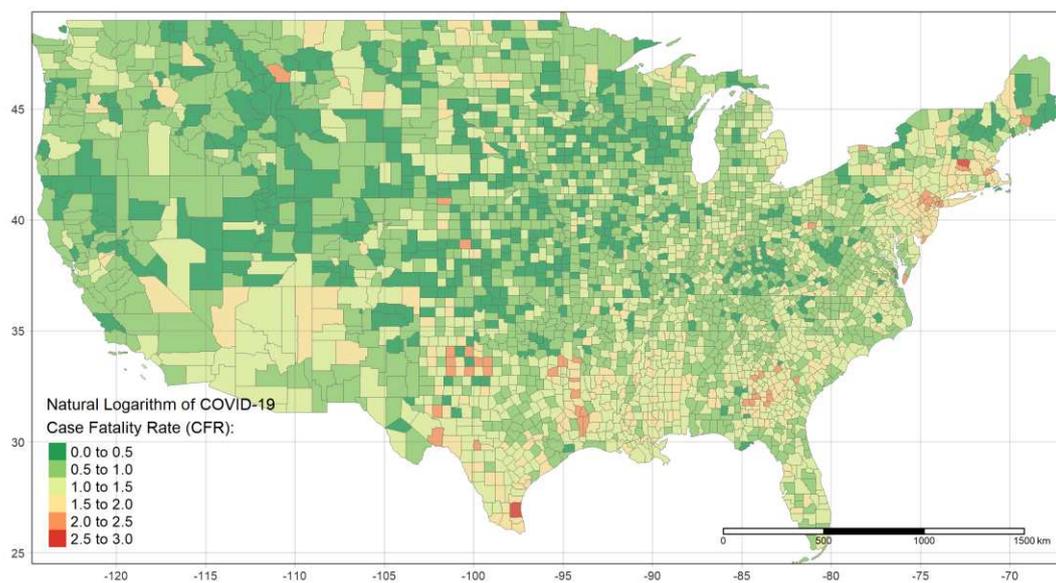


Figure 1: Natural Logarithm of COVID-19 Case Fatality Rate (CFR)

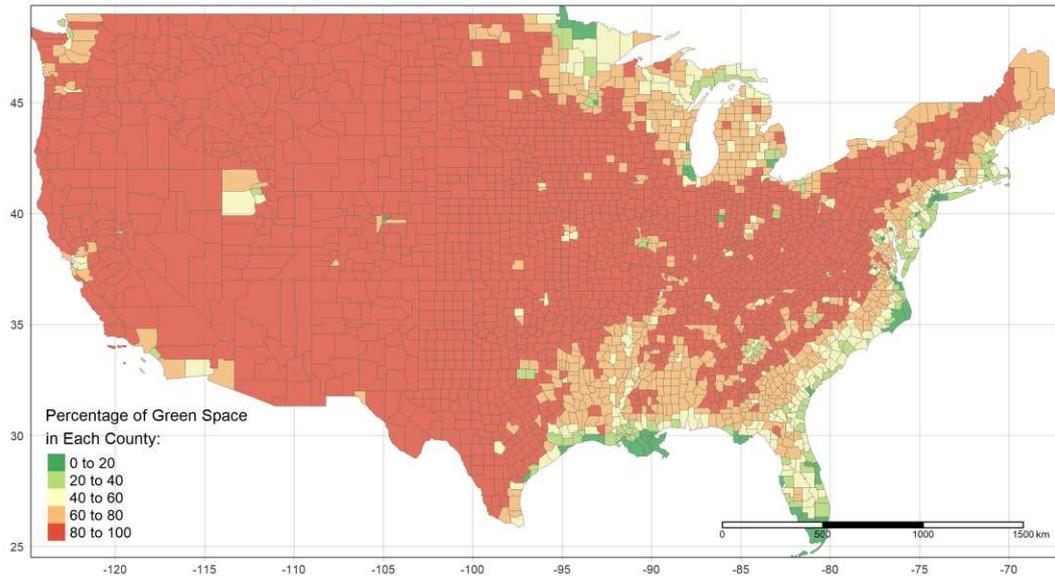


Figure 2: Percentage of Green Space in Each County

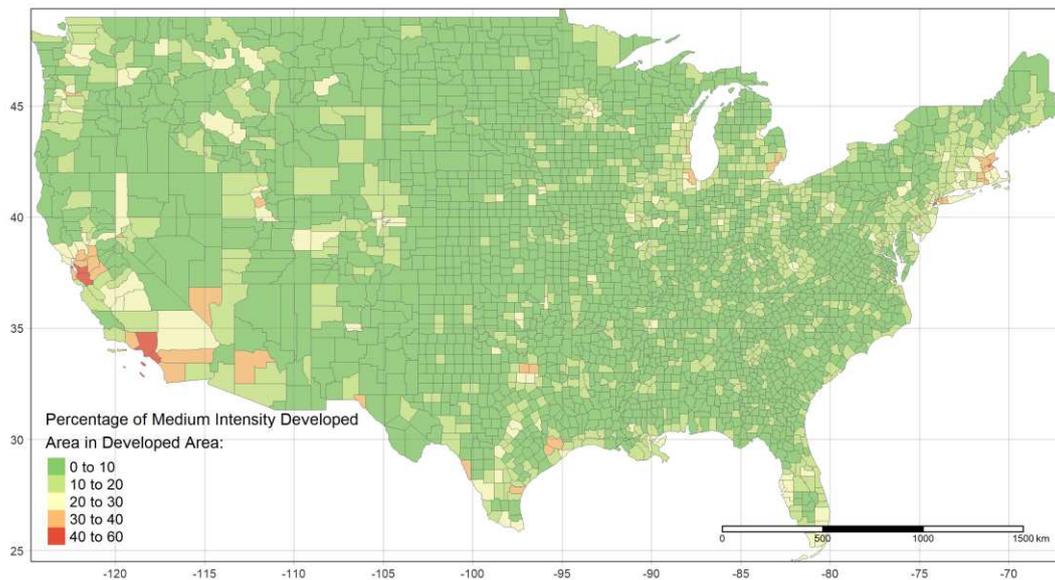


Figure 3: Percentage of Medium Intensity in Developed Area

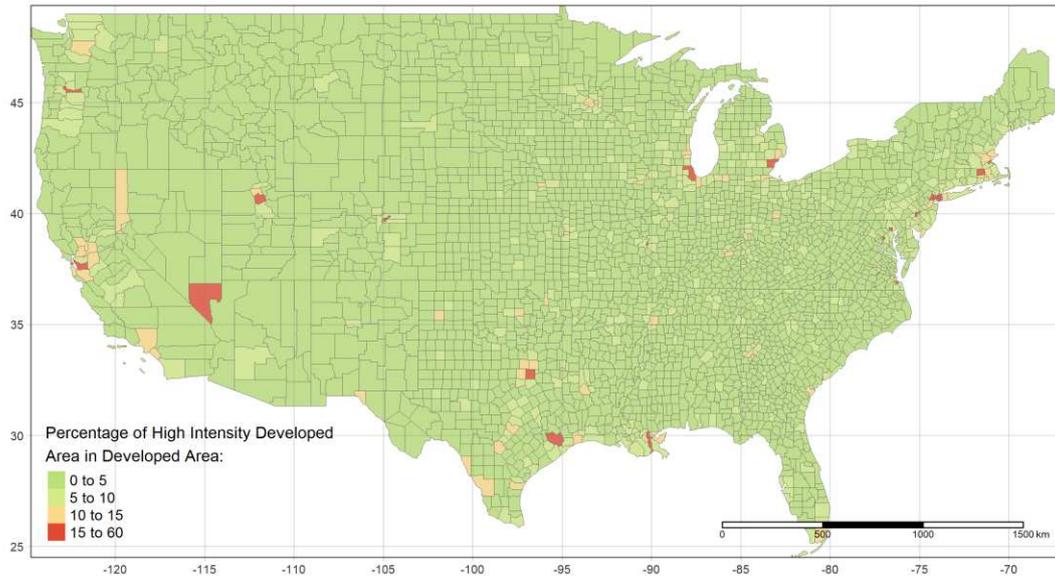


Figure 4: Percentage of High Intensity in Developed Area

Materials and Methods

Materials

CFR of COVID-19

The CFR in each county of the United States is used as the dependent variables in the analyses, which is the ratio between the numbers of death cases and confirmed cases. The CFR is typically considered a measure of disease severity, where a higher CFR means that people are more likely to die after they are infected.

The county-level data regarding COVID-19 confirmed and death cases counts are from the US Centers for Disease Control and Prevention (CDC). Combined with the data from Johns Hopkins University, Center for Systems Science and Engineering Coronavirus Resource Center ¹⁸, these data are official and reliable. We extract the cumulative number of confirmed cases and deaths in each county as of November 25th, 2020.

Land Cover Data

We use the nationwide land cover dataset in 2016 with a 30-meter resolution from the National Land Cover Dataset (NLCD), Multi-Resolution Land Characteristics (MRLC). This dataset includes 20 land types, but there are four land types, namely, dwarf scrub, sedge, lichens, and moss, only in Alaska. In other words, in the Contiguous United States, there are 16 other land types: open water, perennial ice, developed open space, low intensity developed area, medium intensity developed area, high intensity developed area, barren land, deciduous forest, evergreen forest, mixed forest, shrub, grassland, pasture, cultivated crops, woody wetlands, and emergent herbaceous wetlands (Detailed classification description, see <https://www.mrlc.gov/data/legends/national-land-cover-database-2016-nlcd2016-legend>). In this study, high intensity developed areas and medium intensity developed area are considered as urban centers and urban area, respectively. The difference of the four types of developed areas is the proportion of impervious surface in every grid. High intensity developed area has over 80% impervious surface and less than 20% greenery or water. Medium intensity, low intensity, and open space have 50% – 80%, 20% – 50%, less than 20% impervious surface, respectively.

Three sets of county-level land cover variables are employed in the analyses, respectively, the percentages of green-blue-grey land cover in the counties, the percentages of each land type in the counties, and the percentages of the different land types in the developed area. First, the areas of each land type in the counties are obtained by tool in ArcGIS Pro 2.5.0, Tabulate Area, using the boundary shapefile from the U.S. Census Bureau, and then they are transformed into percentages for each land type. Additionally, the percentages of green-blue-grey land cover in the counties are applied. We divide the 16 land types into four categories: green land cover, blue land cover,

grey land cover, and other land cover (**Table 1**). Finally, the percentages of developed land cover with different development intensities in the total developed area of each county are also calculated, which are the ratio of the area with certain development intensity and the total developed area in the county.

Table 1: Green-Blue-Grey Categories of Land Types

Categories	Land Types
Green Space	deciduous forest, evergreen forest, mixed forest, shrub, grassland, pasture, cultivated crops
Blue Space	open water, woody wetlands and emergent herbaceous wetlands
Grey Space	developed open space, low intensity developed area, medium intensity developed area, high intensity developed area
Other Space	perennial ice, barren land

Note: Wetland is considered green space in land use categories, but wetland is easier to confuse with water during remote sensing. Therefore, woody wetland and emergent herbaceous wetlands are classified as blue space, rather than green space, in this study.

Other Demographic, Socioeconomic and Environmental Variables

27 other county-level variables are controlled for in the analyses: population density ¹⁹, percentage of male ²⁰, percentage of population from 15 to 44 years old, percentage of population from 45 to 64 years old, percentage of population over 65 years old ²¹, percentage of black people ²², percentage of Hispanic people ¹¹, natural logarithm of median household income in 2018, natural logarithm of the median house value, percentage of owner-occupied housing, unemployment rate in 2019, poverty rate in 2018, percentage of adults with less than high school diploma in 2018, percentage of the population with poor or fair health in 2019, poor physical health days in 2019, poor mental health days in 2019, adult smoking rate in 2019, obesity rate in 2019, physical inactivity rate in 2019, percentage of the population with access to exercise opportunities in 2019, numbers of hospital beds per unit population, the mean of PM_{2.5} value during 2000-2016, and means of daily temperature and relative humidity in

summer (June to September) and winter (December to February) during 2000-2016 ²³. All these variables are proven that they are associated with COVID-19 health outcome in previous studies. Due to missing values of the variables, Alaska and Hawaii are not included in analyses. (Supplementary Materials **Table S1**: Data Statistic Summary, **Table S2**: Data Source, **Figure S1.1 – S1.4**: Linear Trends between Dependent Variable and Independent Variables)

Methods

Linear Regression Model

The following equations are built to analyze the effects of land cover variables on the COVID-19 CFR in each county, while controlling for other county-level demographic, socioeconomic, and environmental characteristics:

$$CFR_i = \beta_0 + \beta_1 LC'_i + \beta_2 DEE'_i + \varepsilon_i \quad (I)$$

where CFR_i represents the COVID-19 CFR of county i , LC_i represents a vector of land cover data of county i , DEE_i represents a vector of demographic, socioeconomic and environmental variables of county i as control variables, and ε_i represents the error term. In this model β_0 , β_1 and β_2 are parameters to be estimated.

Spatial Autoregressive Model (SAR)

The SAR model assumes that one observation's dependent variable is associated with its neighborhoods' dependent variable. In our study, the COVID-19 CFR of a specific county is related to the CFR of the counties surrounding it ²⁴. The SAR model is as follows:

$$CFR_i = \beta_0 + \rho \mathbf{W}_i \mathbf{NECFR}'_i + \beta_1 \mathbf{LC}'_i + \beta_2 \mathbf{DEE}'_i + \varepsilon_i \quad (\text{II})$$

where \mathbf{W}_i represents a vector of spatial weights of neighboring regions of county i , \mathbf{NECFR}_i represents a vector of the CFR of neighboring county i , and ρ represents the spatial lag parameter to be estimated. To obtain the spatial weight vectors of each observation, we use the queen method ²⁵. In the queen method, two polygons are considered contiguous, if they share one point.

Quantitative Effects of Land Cover Factors on the COVID-19 CFR

To estimate the quantitative effects of land cover factors on the COVID-19 CFR, we build an equation to calculate the case fatality rate ratio (CFRR), which is the ratio of the change in the CFR after adjusting for land cover and the current CFR in the U.S.:

$$CFRR_j = \frac{\beta_{1j} \Delta LC_j}{CFR} \quad (\text{III})$$

where $CFRR_j$ represents the ratio of the CFR after adjusting land cover j and the current CFR, β_{1j} represents estimated the parameter of land cover j , ΔLC_j represents the percentage of adjustment of land cover j , and CFR represents the COVID-19 CFR in the U.S. Assuming that ΔLC_j is 1%, the equation is as follows:

$$CFRR_j = \frac{\beta_{1j}}{CFR} \quad (\text{IV})$$

The CFRR for certain land types can be interpreted as a relative increase or decrease in the COVID-19 CFR associated with a 1% increase in this land type in a county.

Results

Regression Results

Table 2 demonstrates the linear regression results. **Model I** is the estimating results of **Equation (I)** using the percentages of green-blue-grey land cover in counties; **Model II** takes the percentages of each land type in counties as the land cover data; and **Model III** employs the percentages of different land types in developed area. It must be noted that the COVID-19 CFR is a negative factor. In other words, the negative coefficients of some factors mean that with these factors, people are more likely to recover after infection. According to the result of **Model I**, the higher green space is associated with the lower CFR. In addition, open water, emergent herbaceous wetlands, deciduous forest, evergreen forest, shrub, grassland, pasture, cultivated crops, and low intensity developed land cover are negatively related to the CFR. However, their effects on the CFR are different, based on **Model II**. Moreover, the association between the ratio of high intensity developed area in the total developed area and the CFR is strongly positive. In contrast, the relationship between the ratio of medium intensity developed area in developed area and the CFR is positive, as shown in **Model III**.

For other demographic, socioeconomic, and environmental variables, the results are various. Several variables are positively associated with the COVID-19 CFR, which means these factors may aggravate the symptoms of COVID-19. Population density ¹⁹, including the percentage of the population over 65 years old ²¹, percentage of black people ²², percentage of Hispanic people ¹¹, the natural logarithm of the median house value, percentage of owner-occupied housing, unemployment rate, poverty rate, percentage of the adults with less than high school diploma, poor mental health days, physical inactivity rate and mean of relative humidity in summer ⁸, whereas the percentage of male ²⁰, the natural logarithm of the median household income ⁸,

percentage of the population with poor or fair health, population with obesity, access to exercise opportunities and mean of relative humidity in winter⁸ are negatively related to the COVID-19 CFR (full regression results shown in **Table S3**).

The spatial independence among residuals and the dependent variable is tested, because a previous study shows county-level COVID-19 incidence rate is spatially dependent⁸. Lagrange Multiplier diagnostics are applied to examine spatial dependence in all three linear models. Robust tests for the spatially lagged dependent variable are significantly positive in all three models, while robust tests for error dependence are insignificant. According to the spatial tests, one county's COVID-19 CFR is correlated with the CFR of its surrounding counties. The impacts of variables in the SAR model are summarized in **Table S4-S6**. As the SAR model results show, only high intensity developed area in developed area has impacts on county-level CFR of COVID-19, which is similar to the estimation of linear regression analysis.

CFRR of Each Land Cover Variable

The CFRR of each land cover variable is estimated, based on the parameters of the regressions and the COVID-19 CFR in the U.S., using **Equation (IV)**. The CFRRs of land cover variables, their 95% confidence intervals (CIs), and the p-value are listed in **Table 2**. In **Model I**, we find that a 1% increase in green space is associated with a statistically significant 0.34% decrease in the county's COVID-19 CFR. In **Model II**, the result indicates that a 1% increase in low intensity developed areas is related to a statistically significant 2.91% decrease in the county's COVID-19 CFR. Additionally, open water, emergent herbaceous wetlands, deciduous forest, evergreen forest, shrub, grassland, pasture, and cultivated crops are also negatively associated with the COVID-

19 CFR. Furthermore, emergent herbaceous wetlands have the most substantial effect on decreasing the COVID-19 CFR among those land types (CFRR = -1.65%). In **Model III**, the result shows that a 1% increase in high intensity developed area in the total developed area is related to a statistically significant 3.63% increase in the county's COVID-19 CFR. In comparison, a 1% increase in medium intensity developed area is associated with a statistically significant 0.75% decrease.

To conclude, the percentage of green space is negatively associated with the COVID-19 CFR, and the type of green space also influences the degree of its impact on the COVID-19 CFR. In addition, low intensity development is associated with a low CFR. In other words, high intensity development aggravates the severity of infectious diseases, such as COVID-19, which might increase both their morbidity rate and their CFRs. More greenness in the county is associated with a decreased risk of death from COVID-19 after infected among Americans. In contrast, more high intensity development is related to an increased risk of death, because of lack of green space.

Table 2: Coefficients, CFRR, 95% confidence intervals (CI), and P values for land cover data in the main analyses

	Variable	Coefficient	CFRR(%)	95% CI	P value
Model I	Green Space (%)	-0.007***	-0.34	(-0.55--0.13)	0.002
	Grey Space (%)	0.001	0.03	(-0.33-0.39)	0.867
	Other Space (%)	-0.003	-0.16	(-1.94-1.62)	0.86
Model II	Low Intensity Developed Area (%)	-0.06**	-2.91	(-5.43--0.38)	0.024
	Medium Intensity Developed Area (%)	-0.009	-0.44	(-3.02-2.14)	0.738
	High Intensity Developed Area (%)	0.037	1.8	(-1.41-5.01)	0.271
	Open Water (%)	-0.024*	-1.15	(-2.51-0.22)	0.099
	Woody Wetlands (%)	-0.017	-0.83	(-2.19-0.52)	0.228
	Emergent Herbaceous Wetlands (%)	-0.034**	-1.65	(-3.11--0.19)	0.027
	Deciduous Forest (%)	-0.032**	-1.54	(-2.92--0.17)	0.028
	Evergreen Forest (%)	-0.029**	-1.39	(-2.74--0.05)	0.043
	Mixed Forest (%)	-0.019	-0.92	(-2.33-0.49)	0.200

	Shrub (%)	-0.025*	-1.23	(-2.56-0.1)	0.070
	Grassland (%)	-0.033**	-1.58	(-2.92--0.24)	0.021
	Pasture (%)	-0.033**	-1.6	(-2.94--0.27)	0.019
	Cultivated Crops (%)	-0.031**	-1.53	(-2.86--0.19)	0.025
	Barren Land (%)	-0.03	-1.44	(-3.63-0.74)	0.196
	Low Intensity Developed Area In Developed Area (%)	0.003	0.17	(-0.12-0.46)	0.261
Model III	Medium Intensity Developed Area In Developed Area (%)	-0.015*	-0.75	(-1.51-0.02)	0.055
	High Intensity Developed Area In Developed Area (%)	0.075***	3.63	(2.14-5.12)	0.000

Note: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Discussion

The reasons for the large variation among county-level COVID-19 CFR in the U.S. remain unclear. Here, we examine the roles of three sets of land cover variables (see the section: Land Cover Data) in the variation in the CFR, by applying linear regression analyses. Our results show a significantly negative linear correlation between the amount of green space and the CFR. Especially, among the amount of green spaces, a 1% increase in emergent herbaceous wetlands in the county leads to a statistically significant 1.65% increase in the county's COVID-19 CFR. Furthermore, the high intensity developed area among the total developed area is positively associated with the COVID-19 CFR, while the medium intensity developed area among the total developed area is negatively. In a nutshell, high intensity developed area is correlated with a high risk of death after infected COVID-19.

Several recent studies argue that green space may be a critical factor in the COVID-19 pandemic, on the one hand. An increase in urban vegetation is associated with a decrease in cumulative COVID-19 infected cases in the U.S.¹⁷. The presence of parks and green space encourages physical activity, which has positive effects on human health²⁶. Agricultural land-uses are negatively associated with infectious disease risks in Southeast Asia²⁷. COVID-19 infection is related to the ecological environment in

South Korea ²⁸. On the other hand, built-up areas are oppositely related to COVID-19 health outcomes, because of high population density.

The importance of green space and the negative impact of high intensity development in the COVID-19 pandemic are illustrated in our research. In fact, our analyses show that green space plays a critical part in cutting down the COVID-19 CFR, while high intensity developed area is strongly positively correlated with it. In a way, our finding provides evidence for the previous perspectives and studies ^{26,29-31}. Green space has effects on physical activity, obesity, mental health, cardiovascular outcomes ¹⁵, air pollution ³², and even human well-being ³³, especially in people living or working in high intensity developed area. These factors are associated with the possibility of several medical conditions, like cardiovascular and respiratory diseases, which may ultimately aggravate the severity of symptoms after infected COVID-19. Notably, our research discusses the long-term effects of green space and urban land on health, rather than their impacts during COVID-19. Based on these findings, policymakers could make the prevention and control measures more flexible to reduce the negative impacts of those strategies ¹⁰. Therefore, decreasing development intensity and adding more green spaces to living environments should be considered in future urban planning, leading to achieving several Sustainable Development Goals (SDGs).

The value of decreasing development intensity and increasing green space in living environments does not directly prevent the impacts of COVID-19, but it improves public health status. In other words, with more green space and lower development intensity, people have fewer clinical factors associated with a high risk of death infected by COVID-19 ¹¹. Therefore, these strategies would also prevent outbreaks of other diseases in the future. In this way, an increase in green space and reducing development

intensity, at least, help achieve SDG 3 (good health and well-being) and 11 (sustainable cities and communities).

There are some limitations worth noting in this study. Firstly, some potential factors may be overlooked or unable to be obtained, although we have already controlled 27 county-level variables. Secondly, the resolution of land cover and the lag of these data increase the uncertainty of the results, because the land cover data are from 2016 with a resolution of 30 meters^{34,35}. Thirdly, the COVID-19 data are county-level data possibly resulting in ecological fallacy. Future studies are better to use finer-scale data, or even individual-level data, to detect the casual interpretation of associations discussed in this article. Additionally, the specific benefits and costs of increasing green space and reducing development intensity to achieve SDGs need further estimation.

Conclusion

Our results indicate that a 1% increase in green space is associated with a 0.34% decrease in the county's COVID-19 CFR, and this relationship is influenced by the type of green space. In addition, a 1% increase in high intensity developed area among the total developed areas is related to a 3.63% increase in the CFR, while a 1% increase in medium intensity developed areas is associated with a 0.75% decrease. Our research highlights that governments could prevent other pandemics in the future and even achieve some SDGs by decreasing development intensity and increasing green space in living environments.

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Figures

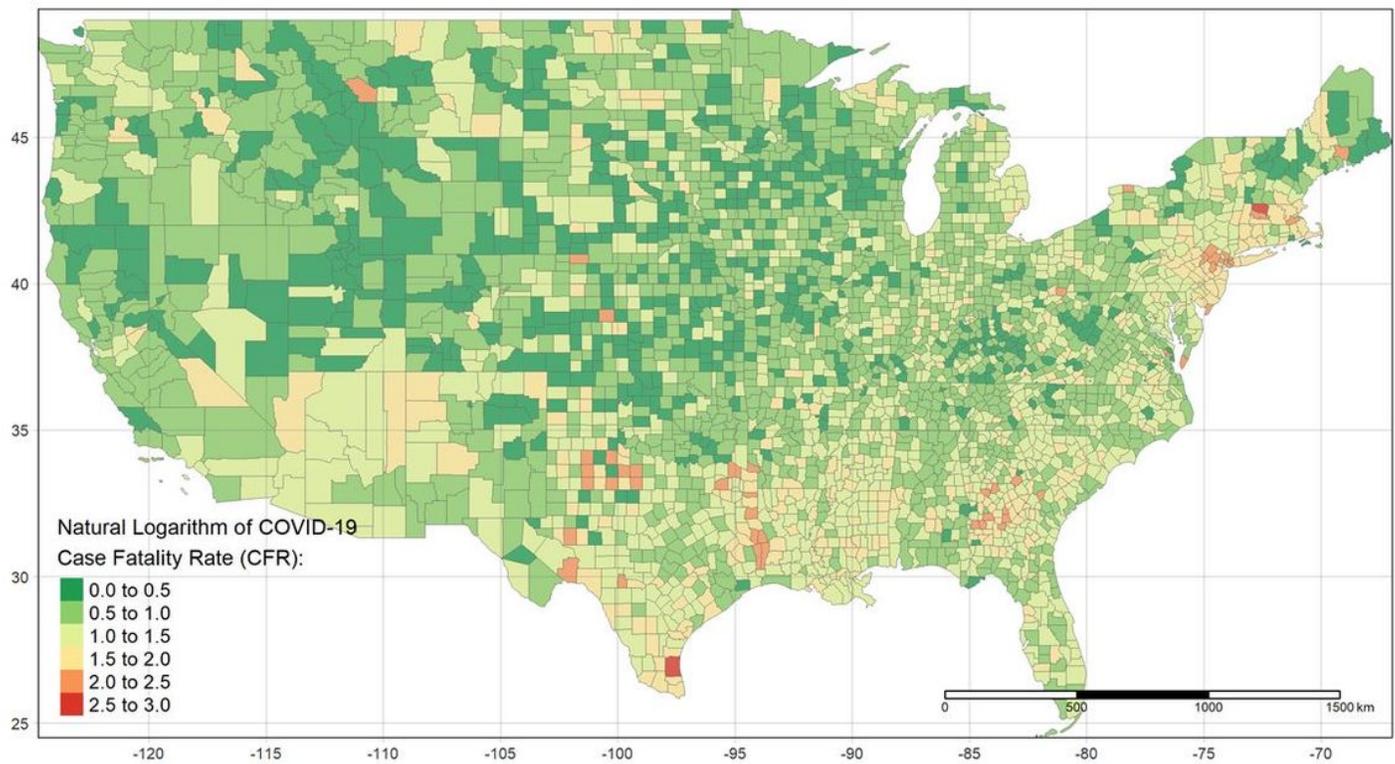


Figure 1

Natural Logarithm of COVID-19 Case Fatality Rate (CFR) Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

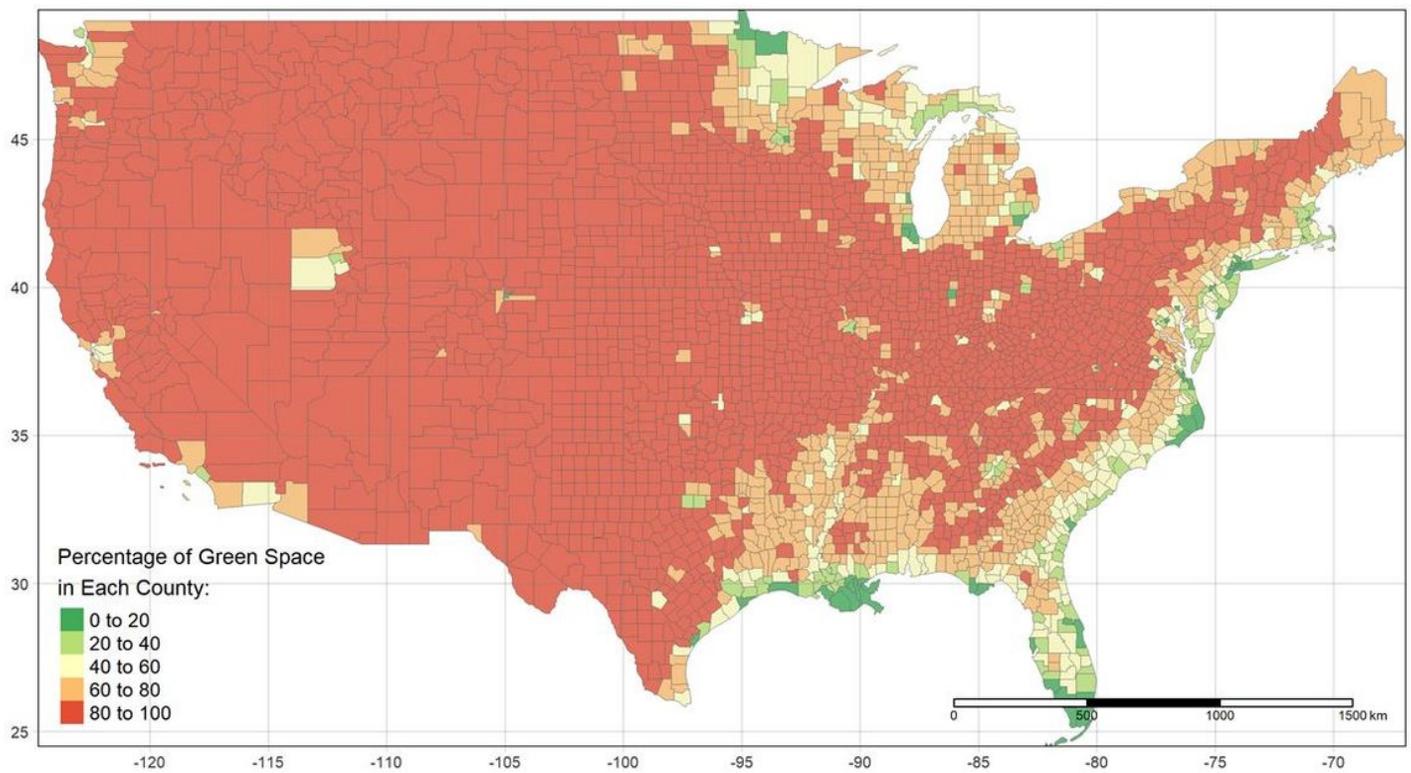


Figure 2

Percentage of Green Space in Each County Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

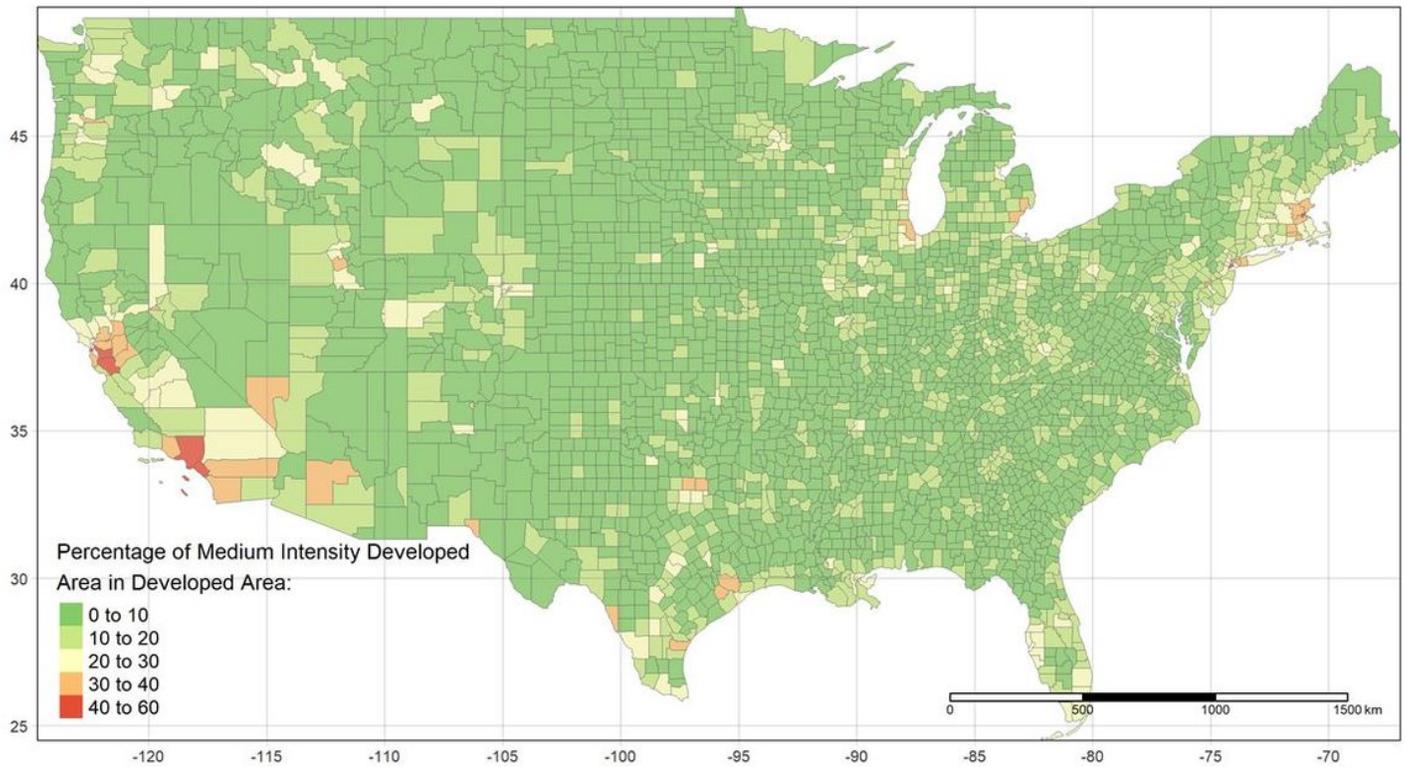


Figure 3

Percentage of Medium Intensity in Developed Area Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

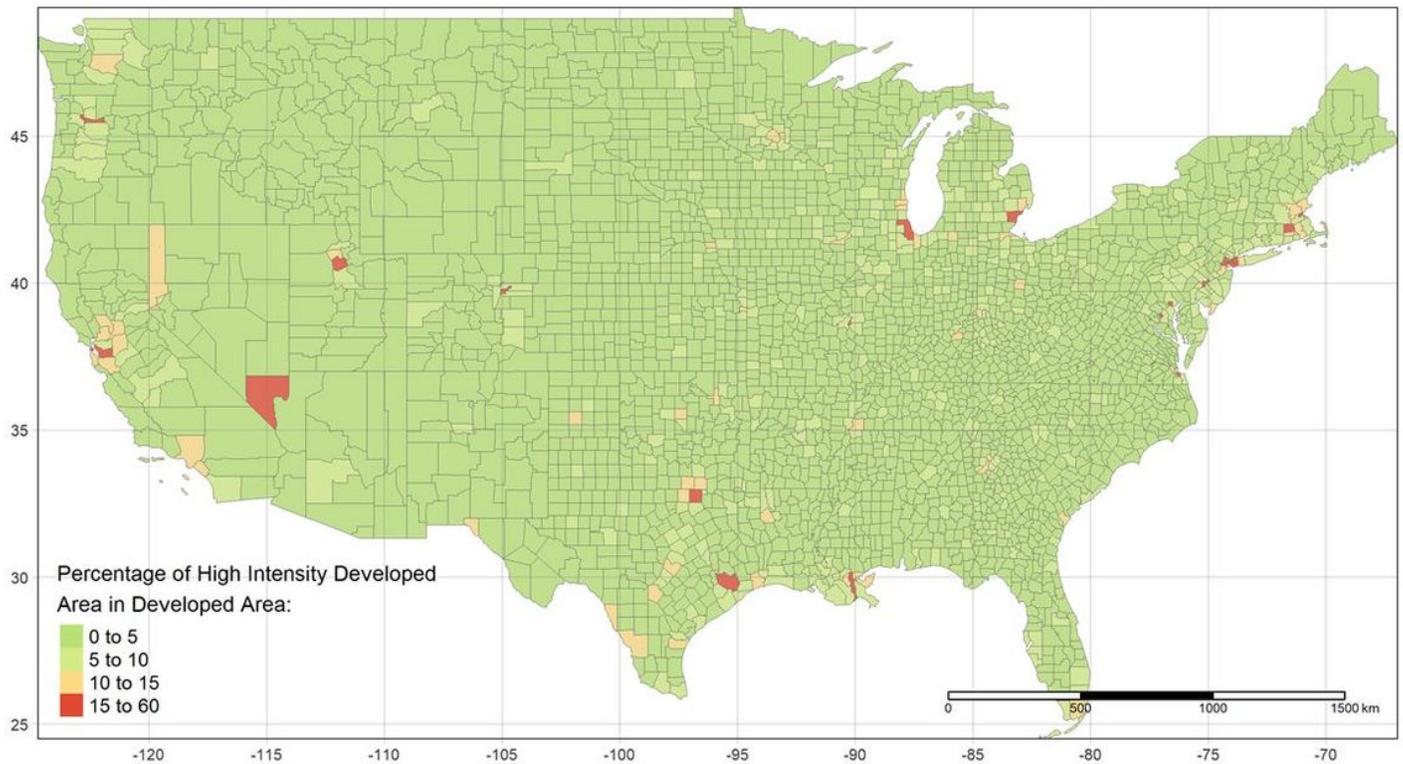


Figure 4

Percentage of High Intensity in Developed Area Note: The designations employed and the presentation of the material on this map do not imply the expression of any opinion whatsoever on the part of Research Square concerning the legal status of any country, territory, city or area or of its authorities, or concerning the delimitation of its frontiers or boundaries. This map has been provided by the authors.

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