Indigenous Peoples, concentrated disadvantage, and income inequality in New Mexico: a ZIP code-level investigation of spatially varying associations between socioeconomic disadvantages and confirmed COVID-19 cases

Kimberly R Huyser (),¹ Tse-Chuan Yang (),² Aggie J Yellow Horse³

ABSTRACT

Background The coronavirus disease pandemic has disproportionately affected poor and racial/ethnic minority individuals and communities, especially Indigenous Peoples. The object of this study is to understand the spatially varying associations between socioeconomic disadvantages and the number of confirmed COVID-19 cases in New Mexico at the ZIP code level.

Methods We constructed ZIP code-level data (n=372) using the 2014–2018 American Community Survey and COVID-19 data from the New Mexico Department of Health (as of 24 May 2020). The log-linear Poisson and geographically weighted Poisson regression are applied to model the number of confirmed COVID-19 cases (total population as the offset) in a ZIP code.

Results The number of confirmed COVID-19 cases in a ZIP code is positively associated with socioeconomic disadvantages—specifically, the high levels of concentrated disadvantage and income inequality. It is also positively associated with the percentage of American Indian and Alaskan Native populations, net of other potential confounders at the ZIP code level. Importantly, these associations are spatially varying in that some ZIP codes suffer more from concentrated disadvantage than others.

Conclusions Additional attention for COVID-19 mitigation effort should focus on areas with higher levels of concentrated disadvantage, income inequality, and higher percentage of American Indian and Alaska Native populations as these areas have higher incidence of COVID-19. The findings also highlight the importance of plumbing in all households for access to clean and safe water, and the dissemination of educational materials aimed at COVID-19 prevention in non-English language including Indigenous languages.

¹Sociology, The University of British Columbia, Vancouver, British Columbia, Canada ²Sociology, State University of New York, Albany, New York, USA ³School of Social Transformation,

Arizona State University, Tempe, Arizona, USA

Correspondence to

Dr Kimberly R Huyser, Sociology, The University of British Columbia, Vancouver, BC V6T 1Z1, Canada; kimberly.huyser@ubc.ca

Received 7 July 2020 Revised 25 January 2021 Accepted 11 March 2021



© Author(s) (or their employer(s)) 2021. No commercial re-use. See rights and permissions. Published by BMJ.

To cite: Huyser KR, Yang T-C, Yellow Horse AJ. *J Epidemiol Community Health* Epub ahead of print: [*please include* Day Month Year]. doi:10.1136/jech-2020-215055

INTRODUCTION

The COVID-19 pandemic has significantly affected the USA, with more than 22 million confirmed cases and more than 373 000 deaths as of early January 2021.¹ Racial/ethnic minorities have experienced disproportionately negative impacts particularly compared with non-Hispanic whites.² A growing literature on racial/ethnic inequities in COVID-19 infection and deaths has amplified the experiences of black Americans and Latinx individuals.^{3–6} Unfortunately, there has been relatively limited investigation on the experiences of Indigenous Peoples; even though American Indian and Alaska Native Peoples (AIANs) have higher likelihood of contracting COVID-19, experiencing hospitalisation, and dying from COVID-19 than other racial/ ethnic groups in the USA.²⁷

To fully understand the complexity of how COVID-19 has affected Indigenous Peoples in the USA, it is critical to have a careful investigation of the social determinants of health (SDOH) factors. SDOH are the conditions in which people are born, grow, live and work,89 and ecological contexts are good proxy of the social and physical environments individuals are exposed to. The SDOH framework has demonstrated the importance of ecological contexts on health inequities¹⁰ ¹¹ as they serve as critical distal causes of disease and illness including infectious disease.⁸ ¹⁰ The SDOH framework is particularly important for Indigenous Peoples as AIANs have unique ecological contexts (including reservation lands) due to lasting legacies of histor-ical injustices^{12 13}, and may be more vulnerable to poorer health during the pandemic due to greater spatial exposure to COVID-19 in their communities. For example, Tribal lands also have a higher level of poverty compared with non-Tribal lands,¹⁴ which may create living conditions that facilitate the spread of virus. In this ecological study, we use the ZIP code as the unit of analysis to examine the spatially varying associations between socioeconomic disadvantages and the confirmed cases of COVID-19 (COVID-19 cases, hereafter), as well as the presence of AIANs.¹⁵¹⁶ We assess the impacts of socioeconomic disadvantages both in absolute term (ie, concentrated disadvantage) and in relative term (ie, income equality) as the key determinant of health inequities.^{17 18} This is important as socioeconomic disadvantages affect health through multiple interconnected pathways.14 15

New Mexico is ideal for investigating the associations between socioeconomic disadvantages and the COVID-19 cases, particularly for Indigenous Peoples. AIANs make up about 11% of New Mexico's total population, but make up more than half (52.7%) of the COVID-19 cases (as of mid-May 2020).^{19 20} Although only 9.4% of the state population are foreign born,²¹ nearly 35% of New Mexico's residents speak a language other than English in the home, compared with 20% in the US population.²¹ Compared with the national average (9.5%), New Mexico has a substantially higher poverty rate of 14.5%, which is the second highest state-level poverty rate (after Mississippi with 15.5%).²¹ New Mexico also has the widest income gap between richest and poorest households in the USA: the average income of the first quintile (top 20%) is about 10 times that of the last quintile (bottom 20%).²² In addition to the large presence of AIANs and stark socioeconomic disadvantages overall, there are likely to have inequalities across space due to presence of multiple Tribal sovereign Nations and their Tribal lands. Together, New Mexico provides an excellent opportunity to understand the *spatially varying* associations between socioeconomic disadvantages and the COVID-19 cases.

METHODS

We used data from the 2014–2018 American Community Survey (ACS) and COVID-19 data from the New Mexico Department of Health (as of 24 May 2020) to construct a ZIP code–level data set (N=372).¹⁹ The dependent variable was the number of confirmed COVID-19 cases. We created variables to gauge socioeconomic, demographic and housing characteristics.

Measures

Concentrated disadvantage was created using principal component analysis (PCA) to the following five variables (with factor loading in parentheses): percentage of female-headed households (0.60), percentage of households with public assistance income (0.55), percentage of the population aged 25 and older without high school or equivalent (0.51), the unemployment rate (0.59) and the poverty rate (0.79). Only one factor has an eigenvalue greater than 1, suggesting a single composite factor score sufficiently captured the variation among these variables. We used linear regression to calculate the factor score (with a mean of 0 and SD of 1), with higher scores indicating higher levels of concentrated disadvantage.²³ Median family income did not have a factor loading greater than 0.5 in PCA, we included logged median family income separately. Income inequality was assessed with the Gini coefficient ranging from 0 (completely equal) to 1 (completely unequal).

To assess racial/ethnic composition, we included the percentage of AIANs. Population density was calculated by dividing total population by land area (ie, per square mile) as it is closely related to the transmission of infectious disease.²⁴ We log-transformed population density to avoid numeric singularity. Drawing from other important ecological studies assessing the determinants of differential COVID-19 cases, we included the variables to capture the characteristics that may be associated with COVID-19 both directly (eg, population characteristics) and indirectly (eg, structural conditions).^{14 25-28} We included two variables to capture vulnerable populations: the percentage of population aged 65 and older, and the percentage of working population with no health insurance.²⁹ Three housing conditions were the percentage of housing units with more than one person per room (ie, overcrowding), the percentage of housing units without complete kitchen facilities, and the percentage of housing units without complete plumbing facilities.14 25 28 To assess the potential exposure to infection while commuting, we included the percentage of workers who commute more than 30 min to work. The final variable was the percentage of households with limited English speaking.^{25 28}

Outcome variable

In light of the count nature of our dependent variable, we used both log-linear Poisson regression and geographically weighted Poisson regression (GWPR) to understand how the covariates are associated with COVID-19 cases. A log-linear Poisson regression model was expressed as:

$$\log(Y_i) = \log(E_i) + \beta_0 + \sum_j \beta_j * x_{j,i}$$
(1)

where Y_i represented the observed number of COVID-19 cases in ZIP code *i*, and E_i was the total population at risk (ie, exposure variable), which was forced to have a regression coefficient of 1 in a log-linear Poisson model. β_0 was the intercept, and β_j was estimated relationship between the independent variables *j* ($x_{j,i}$) and COVID-19 cases.

Because the log-linear Poisson regression model did not take any locational information into account, it can yield only the overall (ie, global) relationships between covariates and COVID-19 cases. To assess how these associations vary across space, GWPR generated estimates specific to each ZIP code, which allowing us to identify whether some SDOH characteristics are more important in some ZIP codes than others. GWPR extended the log-linear model by incorporating the coordinates of an area into estimation,¹⁸ and a GWPR model was expressed as:

$$\log(O_i) = \log(E_i) + \beta_{0,i} + \sum_{i} \beta_{j,i} * x_{j,i}$$
(2)

In contrast to equation (1), the regression coefficients in equation (2) were specific to each ZIP code *i* (). To obtain local $\beta_{j,i}$ coefficients, GWPR first determined the bandwidth (*h*) that minimised the Akaike Information Criterion corrected (AICc). Using the golden-section search method, GWPR implemented several models with different *h* and chose the one with the smallest AICc as the final bandwidth. GWPR then placed a kernel-based geographical weighting function (kernel radius=*h*) on each ZIP code to create spatial weights and computed the local coefficients ($\beta_{i,i}$) with all the ZIP codes covered by the kernel window.

We used the following bisquare kernel function to obtain the results 18 :

Table 1 Descriptive statistics (N=372)								
	Mean	SD	Min	Max				
COVID-19 cases	15.60	47.58	0.00	509.00				
Total population	5664.70	12 093.04	0.00	78900.00				
Concentrated disadvantage	0.00	1.00	-1.54	4.97				
American Indian and Alaska Native population	13.18	28.79	0.00	100.00				
Logged population density	2.13	2.90	-7.60	8.77				
% Population over 65	23.16	18.00	0.00	100.00				
% of Adults without insurance	17.67	17.21	0.00	100.00				
Logged median income	10.83	0.36	7.82	11.97				
% Overcrowded household	4.39	8.25	0.00	76.92				
% Households without kitchen	11.20	13.00	0.00	100.00				
% Households without plumbing	2.77	6.62	0.00	54.29				
% Workers commuting more than 30 min.	38.58	24.84	24.84 0.00					
% Households with limited English speaking	6.51	11.85	0.00	100.00				
Gini coefficient	0.41	0.10	0.01	0.87				

$$w_{ik} = \left[1 - \left(\frac{d_{ik}}{h}\right)^2\right]^2$$

where d_{ik} was the distance between ZIP code *i* and nearby ZIP code *k*. ZIP codes close to *i* had stronger impacts on parameter estimation. When the distance between two ZIP codes was greater than *h*, they were not considered in estimation. Our results did not change when different kernel functions (eg, Gaussian) were used.

Both global and local coefficients can be interpreted the same way: after being exponentiated, the coefficients referred to the sensitivity of the number of COVID-19 cases to the change in independent variables. The only difference between the log-linear and GWPR results was the local coefficients can be generalised only to ZIP codes *within* the kernel window rather than to all ZIP codes.

RESULTS

Table 1 presents the descriptive statistics. There were, on average, almost 16 confirmed COVID-19 cases, and 5665 residents in a ZIP code. Approximately 13% of the population was AIANs. Almost one-quarter of the population (23.16) was 65 years or older. The logged median family income was 10.83 (roughly \$50,504), and almost 18% of working-age adults did not have health insurance. With respect to housing conditions, 4.39% of housing units were overcrowded (ie, more than one person per room). About 11.20% and 2.76% of households

did not have complete kitchen facilities and complete plumbing facilities, respectively, 38.58% of workers commuted more than 30 min to work, and 6.51% of households had limited English speaking ability. The minimum Gini coefficient was 0.01 and the maximum income inequality was 0.87, suggesting a great variation among ZIP codes in New Mexico.

Table 2 presents the log-linear Poisson regression results. Model 1 considered only concentrated disadvantage, percentage of AIAN residents, and logged population density. The results suggest that every one-unit (ie, SD) increase in concentrated disadvantage was associated with a 33% increase in the number of COVID-19 cases ((exp(0.2881)–1)×100%). Similarly, a one percentage increase in AIANs was related to a 3.23% increase in the number of COVID-19 cases ((exp(0.0318)–1)×100%).

The percentages of older adults and the working population without health insurance, and logged median income were added to model 2. The association between concentrated disadvantage and the number of COVID-19 cases increased: every one-unit increase in concentrated disadvantage was associated with a 35% increase in COVID-19 cases ((exp(0.03501)-1)×100%). The effect of the percentage of AIANs was almost unaltered in Model 2.

Model 3 further considered housing conditions and commuting pattern. The effect of concentrated disadvantage increased: a one-unit increase in concentrated disadvantage increased the number of COVID-19 cases by 47%. Housing

Table 2 Poisson regression model predicting the logged odds of COVID-19 confirmed cases in New Mexico (global regression model) N=372							
	Model 1	Model 2	Model 3	Model 4			
Concentrated disadvantage	0.2881***	0.3501***	0.3901***	0.2067***			
	(0.0211)	(0.0318)	(0.0326)	(0.0408)			
American Indian and Alaska Native population	0.0318***	0.0309***	0.0266***	0.0303***			
	(0.0005)	(0.0006)	(0.0008)	(0.0009)			
Population density	0.1506***	0.1317***	0.1382***	0.0970***			
	(0.0084)	(0.0088)	(0.0094)	(0.0099)			
% Population over 65		-0.0305***	-0.0295***	-0.0635***			
		(0.0033)	(0.0034)	(0.0038)			
% of Adults without insurance		0.0007	0.002	-0.0119***			
		(0.002)	(0.0021)	(0.0023)			
Logged median income		0.4409***	0.7920***	1.0868***			
		(0.0785)	(0.0879)	(0.092)			
% Overcrowded household			0.0179***	0.0033			
			(0.0041)	(0.0046)			
% Households without kitchen			-0.0109***	-0.0203***			
			(0.0031)	(0.0034)			
% Households without plumbing			0.0363***	0.0411***			
			(0.0032)	(0.0034)			
% Workers commuting more than 30 min.			0.002	0.0068***			
			(0.0011)	(0.0011)			
% Households with limited English speaking				0.0232***			
				(0.0031)			
Gini coefficient				7.6082***			
				(0.3576)			
Intercept	-7.4867***	-11.7494***	-15.7662***	-21.6959***			
Pseudo-R ²	0.5952	0.6042	0.623	0.6534			
AIC	5742.6687	5620.2369	5362.9684	4936.4552			
* p<0.05; ** p<0.01; *** p<0.001.							

AIC, Akaike Information Criterion.

Table 3 Geographically weighted regression summary results

Table 5 Geographically weighted regression summary results									
	Min.	Q1	Q2	Q3	Max.	Diff-criterion ⁺			
Intercept	-51.1452	-25.3470	-14.9626	-5.6791	19.5692	-110.2911			
Concentrated disadvantage	-1.0194	0.1835	0.6205	1.0611	4.8453	-89.1893			
American Indian and Alaska Native population	-0.8980	-0.0090	0.0150	0.0308	0.2600	-61.4442			
Logged population density	-0.6008	-0.0435	0.0578	0.1787	0.4183	-64.8459			
% Population over 65	-0.1099	-0.0360	-0.0216	-0.0070	0.0436	-19.2598			
% of Adults without insurance	-0.2019	-0.0208	0.0007	0.0148	0.0545	-170.0925			
Logged median income	-2.6788	-0.1945	0.5840	1.4915	4.1357	-159.8876			
% overcrowded household	-0.6340	-0.0627	-0.0217	0.0064	0.1206	-60.1454			
% Households without kitchen	-0.2488	-0.0736	-0.0287	-0.0127	0.0472	-114.3319			
% Households without plumbing	-0.1186	-0.0365	0.0384	0.0940	0.2278	-66.1428			
% Workers commuting more than 30 min.	-0.0452	-0.0108	-0.0007	0.0148	0.0493	-120.1968			
% Households with limited English speaking	-0.1752	-0.0028	0.0199	0.0497	0.0845	-2.9078			
Gini coefficient	-6.0546	1.5256	3.2049	5.8544	14.4680	-64.5240			

⁺Diff-criterion refers to the χ^2 test result for the difference between the original GWPR model and the constant model. A negative value suggests spatial variability.

conditions and the number of COVID-19 cases were also statistically related. Housing units with more than one person per room and without complete plumbing each had a positive association with increased the number of COVID-19 cases—nearly 2% and 4%, respectively (((exp(0.0179)-1)×100%)) and ((exp(0.0363)-1)×100%))). Housing units with a full kitchen had a slight negative association with the number of COVID-19 cases.

In model 4, the Gini coefficient and language limitation seemed to modify the association between concentrated disadvantage and the number of COVID-19 cases. Specifically, a one-unit increase in concentrated disadvantage was associated with only a 23% increase in the number of COVID-19 cases ($(\exp(0.2067)-1)\times100\%$). Every one percentage point increase in households with limited English use was associated with a 2.35% increase in the number of COVID-19 cases ($(\exp(0.0232)-1)\times100\%$). Income inequality, measured by the Gini coefficient, had a strong positive association with the number of COVID-19 cases. A 0.1-unit (approximately 1 SD) increase in the Gini coefficient was associated with a 114% increase in the number of COVID-19 cases ($(\exp(7.6082\times0.1)-1)\times100\%$), net of other factors.

We summarised the local estimates in table 3. The first five columns show how the local estimates vary. The last column shows the difference in criterion ('Diff-criterion'): χ^2 test results for spatially varying associations. A negative number in in this column suggests that the variation in local estimates of a certain variable was large enough to conclude that the relationship between this variable and the number of COVID-19 cases varied by location.³⁰ All our covariates demonstrated spatially varying relationships with the number of COVID-19 cases. For example, concentrated disadvantage had a minimum relationship with the number of COVID-19 cases of -1.02 but a maximum relationship of 4.85. The IQR is 0.88. The negative diff-criterion (-89.19) indicates that the variation in these estimates was large enough to reject the null hypothesis that there is no spatial variability.

The local coefficients of concentrated disadvantage were visualised in figure 1. ZIP codes not covered by colour report a null relationship between concentrated disadvantage and the number of COVID-19 cases. The area with the strongest detrimental impact was represented in red. This area of

northern New Mexico includes four of the major cities as well as Tribal and Pueblo lands. Areas shown in yellow are those in which highly concentrated disadvantage was positively associated with the number of COVID-19 cases, net of other covariates. These yellow areas included Tribal lands. Some ZIP codes in the southwestern area showed a negative relationship between concentrated disadvantage and the number of COVID-19 cases (shown in blue). Figure 1 shows significant variation for concentrated disadvantage and confirms the spatially varying association between



Figure 1 Impacts of concentrated disadvantage on COVID-19 cases in New Mexico.

concentrated disadvantage and the number of COVID-19 cases.

DISCUSSION

The COVID-19 pandemic has disproportionately affected racial/ ethnic minorities,^{1 2 31} especially for AIAN persons and communities.^{14 25 28 32} Our study sought to understand the roles of AIAN presence, socioeconomic disadvantages and other key SDOH indicators in the number of COVID-19 cases in New Mexico. We found the positive associations among socioeconomic disadvantages (concentrated disadvantage and income inequality), SDOH characteristics (percentage of households without complete plumbing), and the number of COVID-19 cases.

Early evidence from the initial phase of the COVID-19 pandemic indicates that the number of COVID-related deaths has been higher in areas with higher poverty in the USA.³¹ Our results support this general finding in that ZIP codes with higher concentrated disadvantage had greater number of COVID-19 cases. The concentrated disadvantage measure could be considered an important proxy measure of household access to resources, economic stability, healthcare, and remote-access jobs to reduce exposure to the COVID-19 virus.^{8 9 18 33-35} Furthermore, as presented in figure 1, the impact of concentrated disadvantage on COVID-19 cases vary spatially. The areas impacted by concentrated disadvantage share several characteristics that increase the risk of contracting COVID-19 including poor housing conditions.³⁶ Four of the nine major cities in New Mexico (ie, Albuquerque, Rio Rancho, Santa Fe, and Farmington) are represented in the hardest-hit areas, which might be explained by higher population density (ie, more face-to-face contacts) and more AIANs.³⁷ For areas with higher concentrated disadvantage, federal, state and local agencies should consider place-based mitigating strategies to allocate additional resources to ameliorate the effects of concentrated disadvantage. Income inequality is a key factor in racial health inequities.^{35 38} Our result also suggests that differential COVID-19 cases are also associated with income inequality. Our results also hint that sociospatial sorting of income groups may occur at a larger geographical scale than a ZIP code level, and future study should investigate how the association between income inequality and COVID-19 cases may differ across geographical scales.

We found that areas with higher percentage of AIANs are associated with higher COVID-19 cases, consistent with other ecological studies.^{14 25 28} Although our results show the independent association of AIANs with COVID-19, it is important to note that these areas impacted by concentrated disadvantage closely overlap with multiple Tribal lands with high concentration of AIANs. The majority of residents on Tribal lands consist of AIANs, thereby suggesting the exacerbating effects of existing social inequalities during the pandemic and disproportionately affecting Indigenous Peoples. Unfortunately, it was beyond the scope of our analysis to examine this type of interaction effect; yet future research should consider innovative ways to measure multifaceted and multiple experiences of disadvantage and inequality.

Lastly, we found that areas with increased population density and a higher percentage of households without complete plumbing had a higher number of COVID-19 cases, which is consistent with other previous findings using the ecological level analyses with emphasis on AIANs.^{14 25 28}

Strengths and limitations

The strengths of our study are that we used COVID-19 data from the New Mexico Department of Health (as of 24 May 2020) and 2014–2018 ACS to construct an innovative ZIP code-level data set (n=372), which permitted more nuanced analyses than county-level or state-level data would allow. In addition, this study is among the first to provide evidence for the relationship between AIANs and COVID-19 cases after controlling for potential confounders. Furthermore, using a spatial perspective that highlights the local spatial variations, this study offers further insight into how the effects of SDOH characteristics vary within New Mexico. This has implications for designing the effective place-based policies to mitigate the spatially differing impacts of COVID-19.

We note three limitations of our study. First, the study is an ecological assessment at the ZIP code level, and the findings cannot be inferenced to AIAN persons or to other units of analysis (eg, ecological fallacy). It is also a cross-sectional study that captures the associations between social inequalities and the number of confirmed COVID-19 cases based on data collected through 24 May. Given that the pandemic is ongoing and ever shifting, future research should explicitly consider the temporal component. Second, the current study focuses only on New Mexico, and the experiences of Indigenous Peoples from other states likely differ qualitatively and substantively. Finally, the results should be interpreted cautiously because the number of confirmed COVID-19 cases does not reflect the current risk of transmission but rather the accumulated total over a few months.

Indigenous communities in the USA have experienced a higher incidence of COVID-19.⁵ ⁷ Our study suggests the importance of addressing multiple pathways of socioeconomic disadvantages (ie, concentrated disadvantage and income inequality) in the COVID-19 pandemic. To address inequities, public health policy interventions should advocate the building of infrastructure, such as plumbing in all households to allow access to clean and safe water as well as

What is already known on this subject

The coronavirus disease has disproportionally affected population health across poor and racial/ethnic minority individuals and communities. The social determinants of health framework and the infection trends in the USA have documented that individuals of lower income and individuals who belong to racial and ethnic groups are unequally infected.

What this study adds

This study showed that geographical areas with socioeconomic disadvantages—measured by concentrated disadvantage, income inequality—and a higher percent of American Indian and Alaska Native persons are associated with a higher number of confirmed COVID-19 cases. Public health policy interventions should also advocate the access to clean and safe water for all households as well as educational materials in non-English including Indigenous languages. the dissemination of educational materials aimed at prevention—especially in multiple Indigenous languages.

Twitter Kimberly R Huyser @NavajoProf and Aggie J Yellow Horse @DrYellowHorse

Contributors All authors participated in the formulation of the research questions and writing. TCY is responsible for the data analysis. All authors contributed to the article and approved the submitted version.

Funding The authors have not declared a specific grant for this research from any funding agency in the public, commercial or not-for-profit sectors.

Map disclaimer The depiction of boundaries on this map does not imply the expression of any opinion whatsoever on the part of BMJ (or any member of its group) concerning the legal status of any country, territory, jurisdiction or area or of its authorities. This map is provided without any warranty of any kind, either express or implied.

Competing interests None declared.

Patient consent for publication Not required.

Ethics approval This study included only public secondary data without any individual identifiers and did not require ethics committee approval.

Provenance and peer review Not commissioned; internally peer reviewed.

Data availability statement Data are available in a public, open access repository. We use publicly available data. The data are from the 2014–2018 American Community Survey five-year estimates and COVID-19 data from the New Mexico Department of Health website accessed on 24 May 2020. The data can be found at these two websites: https://www.census.gov/programs-surveys/acs/ technical-documentation/table-and-geography-changes/2018/5-year.html; https:// cvprovider.nmhealth.org/public-dashboard.html.

This article is made freely available for use in accordance with BMJ's website terms and conditions for the duration of the covid-19 pandemic or until otherwise determined by BMJ. You may use, download and print the article for any lawful, non-commercial purpose (including text and data mining) provided that all copyright notices and trade marks are retained.

ORCID iDs

Kimberly R Huyser http://orcid.org/0000-0003-3700-0621 Tse-Chuan Yang http://orcid.org/0000-0002-4271-4584

REFERENCES

- 1 CDC. Coronavirus Disease 2019 (COVID-19) Cases, Data & Surveillance: Cases in the U.S. Centers for Disease Control and Prevention, 2020.
- 2 CDC. COVID-19 in racial and ethnic minority groups. Centers for Disease Control and Prevention, 2020.
- 3 Laurencin CT, McClinton A. The COVID-19 pandemic: a call to action to identify and address racial and ethnic disparities. J Racial Ethn Health Disparities 2020;7:398–402.
- 4 Braithwaite R, Warren R. The African American Petri dish. J Health Care Poor Underserved 2020;31:491–502.
- 5 Webb Hooper M, Nápoles AM, Pérez-Stable EJ. COVID-19 and racial/ethnic disparities. JAMA 2020;323:2466–7.
- 6 Garcia MA, Homan PA, García C. The color of COVID-19: structural racism and the disproportionate impact of the pandemic on older black and Latinx adults 2021;76:e75–80.
- 7 Arrazola J, Masiello MM, Joshi S, et al. COVID-19 Mortality Among American Indian and Alaska Native Persons - 14 States, January-June 2020. MMWR Morb Mortal Wkly Rep 2020;69:1853–6.
- 8 Link BG, Phelan J. Social conditions as fundamental causes of disease. J Health Soc Behav 1995;Spec No:80–94.
- 9 Healthy People. Office of disease prevention and health promotion. Washington DC: US Department of Health and Human Services, 2020. https://www.cdc.gov/nchs/ healthy_people/hp2020.htm
- 10 Solar O, Irwin A. A conceptual framework for action on the social determinants of health. social determinants of health discussion paper 2 (policy and practice. World Health Organization, 2010.

- 11 World Health Organization Commission on Social Determinants of Health. Closing the gap in a generation: health equity through action on the social determinants of health, 2008. Available: http://www.who.int/social_determinants/en
- 12 Snipp CM. *American Indians: the first of this land*. Russell Sage Foundation, 1989.
- 13 Thornton R. American Indian holocaust and survival: a population history since 1492. University of Oklahoma Press, 1987.
- 14 Yellow Horse AJ, Deschine Parkhurst NA, Huyser KR. COVID-19 in New Mexico tribal Lands: understanding the role of social vulnerabilities and historical Racisms. *Frontiers* in Sociology 2020;5:610355.
- 15 Yang T-C, Emily Choi S-W, Sun F. COVID-19 cases in US counties: roles of racial/ethnic density and residential segregation. *Ethn Health* 2021;26:11–21.
- 16 Andersen LM, Harden SR, Sugg MM, et al. Analyzing the spatial determinants of local Covid-19 transmission in the United States. Sci Total Environ 2021;754:142396.
- 17 Pickett KE, Wilkinson RG. Income inequality and health: a causal review. Soc Sci Med 2015;128:316–26.
- 18 Kawachi I, Kennedy BP. Income inequality and health: pathways and mechanisms. *Health Serv Res* 1999;34:215–27.
- 19 New Mexico Department of Health. COVID-19 in New Mexico data Dashboard, 2020. Available: https://cvprovider.nmhealth.org/public-dashboard.html
- 20 U.S. Census Bureau. Quick facts: new Mexico, 2020. Available: https://www.census. gov/quickfacts/NM
- 21 American Community Survey. American community survey 2018 (5-year estimates). Washington DC: U.S. Census Bureau, 2018.
- 22 McNichol EC, Hall D, Cooper D. Pulling apart: a state-by-state analysis of income trends. Washington, DC: Center on Budget and Policy Priorities, 2012.
- 23 Thomson GH. *The factorial analysis of human ability*. London: University of London Press, 1951.
- 24 Hu H, Nigmatulina K, Eckhoff P. The scaling of contact rates with population density for the infectious disease models. *Math Biosci* 2013;244:125–34.
- 25 Yellow Horse AJ, Yang T-C, Huyser KR. Structural inequalities established the architecture for COVID-19 pandemic among native Americans in Arizona: a geographically weighted regression perspective. *J Racial Ethn Health Disparities* 2021. doi:10.1007/s40615-020-00940-2. [Epub ahead of print: 19 Jan 2021].
- 26 Sun F, Matthews SA, Yang T-C, *et al*. A spatial analysis of the COVID-19 period prevalence in U.S. counties through June 28, 2020: where geography matters? *Ann Epidemiol* 2020;52:54–9.
- 27 Liao TF, De Maio F. Association of social and economic inequality with coronavirus disease 2019 incidence and mortality across us counties. *JAMA Netw Open* 2021;4:e2034578.
- 28 Rodriguez-Lonebear D, Barceló NE, Akee R, et al. American Indian Reservations and COVID-19: correlates of early infection rates in the pandemic. J Public Health Manag Pract 2020;26:371–7.
- 29 S-wE C, Yang T-C. Are older populations at a disadvantage? County-level analysis of confirmed COVID-19 cases in urban and rural America. *The Journals of Gerontology: Series B* 2020;76:e93–8.
- 30 Nakaya T. Semiparametric geographically weighted generalised linear modelling: the concept and implementation using GWR4. Sage Publication, 2015.
- 31 Finch WH, Hernández Finch ME, Poverty HFME. Poverty and Covid-19: rates of incidence and deaths in the United States during the first 10 weeks of the pandemic. *Frontiers in Sociology* 2020;5:47.
- 32 Hatcher SM, Agnew-Brune C, Anderson M, et al. COVID-19 Among American Indian and Alaska Native Persons - 23 States, January 31-July 3, 2020. MMWR Morb Mortal Wkly Rep 2020;69:1166–9.
- 33 Shi L, Stevens GD. Vulnerability and unmet health care needs. The influence of multiple risk factors. J Gen Intern Med 2005;20:148–54.
- 34 U.S. Bureau of Labor Statistics. *Percent of employed people who worked at home and at their workplace on days worked*, 2018.
- 35 Kawachi I, Subramanian SV. Income Inequality. In: Berkman LF, Kawachi I, Maria G, eds. Social epidemiology. New York, NY: Oxford University Press, 2014: 126–52.
- 36 CDC COVID-19 Response Team. Geographic Differences in COVID-19 Cases, Deaths, and Incidence - United States, February 12-April 7, 2020. MMWR Morb Mortal Wkly Rep 2020;69:465–71.
- 37 Carpio MV. Indigenous Albuquerque. Texas: Tech University Press Lubbock, 2011.
- 38 Harling G, Subramanian SV, Bärnighausen T, et al. Income inequality and sexually transmitted in the United States: who bears the burden? Soc Sci Med 2014;102:174–82.