

A GIS APPROACH TO EXPLORING THE CORRELATION BETWEEN CANCER DEATH RATE AND SOCIOECONOMIC DISPARITIES

Chima Okoli

North Carolina Central University

Tony Esimaje

North Carolina Central University

Timothy Mulrooney

North Carolina Central University

ABSTRACT

Cancer remains a leading cause of death globally, with socioeconomic disparities significantly influencing cancer outcomes. This study examines the relationship between cancer mortality rates and socioeconomic factors in North Carolina, utilizing Geographic Information Systems. Key socioeconomic indicators, including median household income, poverty rate, diabetes prevalence, and access to healthy food, were examined. Data from North Carolina's 2021 vital statistics, covering 747 ZIP codes, were analyzed using spatial mapping and statistical methods, including a two-tailed t-test and Ordinary Least Squares (OLS) regression. The results reveal significant geographic disparities in cancer mortality, with rural areas experiencing higher rates. These areas exhibit lower household incomes, reduced access to healthy food, and higher diabetes rates. The OLS analysis confirms that lower income and greater distance to supermarkets are strong predictors of higher cancer mortality, while the prevalence of diabetes also shows a significant association with elevated mortality. Despite these findings, the study acknowledges the need for more granular data and additional factors such as healthcare quality, environmental exposures, and comorbid conditions to fully explain variability in cancer mortality.

KEYWORDS

Public Health, Mortality, Food Deserts, Spatial Analysis, Healthcare Access

INTRODUCTION

Cancer remains one of the leading causes of mortality worldwide, with its incidence and mortality rates reaching almost 10 million deaths in 2020 (Cancer Fact Sheet 2022). Numerous studies have shown that socioeconomic disparities play a crucial role in influencing cancer outcomes, with individuals from lower socioeconomic backgrounds often experiencing higher cancer incidence and mortality rates compared to their more affluent counterparts (Singh and Jemal 2017). Understanding the spatial distribution of cancer death rates and their relationship with socioeconomic factors is essential for informing targeted public health interventions. Geographic Information Systems offer a powerful tool for analyzing and visualizing spatial data, allowing researchers to explore the relationship

between cancer mortality and socioeconomic determinants at various geographic scales (Cromley and McLafferty 2012).

This study positions cancer mortality within a socio-ecological framework, recognizing that interactions among individual, community, and broader environmental factors shape health outcomes. Social determinants of health—including economic stability, education, healthcare access, neighborhood environment, and community context—affect health behaviors, exposures, and stress levels, which in turn influence cancer outcomes (Alcaraz et al. 2020). By situating our research within this conceptual framework, we acknowledge that spatial disparities in cancer mortality reflect underlying structural inequalities rather than purely biological differences.

In addition to exploring income, poverty, and food access, we explicitly consider diabetes prevalence as a marker of comorbid chronic disease. People with type 2 diabetes have been shown to have more than a 1.5-fold increased risk of colorectal, pancreatic, liver, and endometrial cancer mortality compared with the general population (Giovannucci et al 2010, Ling et al. 2023). Including diabetes prevalence in our model, therefore, provides insight into whether metabolic health acts as an independent predictor of cancer mortality across different geographic regions.

Building on prior GIS research, we aim to answer two key questions: 1) What ZIP-level socioeconomic and health-related variables are statistically associated with higher cancer mortality rates in North Carolina? 2) How do spatial patterns of cancer mortality correspond with indicators such as income, diabetes prevalence, and access to healthy food across ZIP codes?

REVIEW OF RELEVANT LITERATURE

Cancer Mortality and Socioeconomic Disparities

Extensive literature highlights the close relationship between socioeconomic factors, including income, education, and access to healthcare, and cancer outcomes. The CONCORD 3 program reported that five year net survival for many cancers is highest in high income countries such as the United States, Canada, Australia and Northern Europe, whereas survival for the same cancers is often less than half as high in low and middle income countries (e.g., 90 percent five year breast cancer survival in the United States vs. ~40 percent in South Africa) (Allemani et al. 2018). Even within wealthy countries, systematic reviews show that socioeconomic disparities persist after accounting for clinical factors. A meta-analysis of 74 studies found that stage at diagnosis and treatment account for part of the socioeconomic differences in survival, while comorbidities, health-related behaviors, and tumor characteristics contribute substantially. For colorectal and lung cancers, these factors explain the disparities better than stage and treatment (Afshar et al. 2021). These findings emphasize that socioeconomic disadvantage influences cancer outcomes through multiple pathways beyond access to screening.

Socioeconomic disparities also manifest through differential exposure to cancer risk factors such as smoking, poor diet, and environmental pollutants. These disparities contribute to persistent inequalities in cancer mortality across

socioeconomic groups (Henley et al. 2020). Bevel et al. (2023) conducted a county-level ecological study and found that areas classified as food swamps had significantly higher obesity-related cancer mortality rates. Using an age-adjusted, generalized, mixed-effects regression model, the study highlighted how limited access to healthy food contributes to cancer risk at the population level, reinforcing the importance of food environment variables in spatial cancer research (Bevel et al. 2023).

Research suggests that incidence is higher in populations with greater socioeconomic deprivation, reflecting greater exposure to risk factors and delays in detection and treatment (Singh and Jemal 2017; Singh et al. 2011; Lundqvist et al. 2016). Disadvantaged individuals often experience poorer outcomes due to late presentation, comorbidities, and less effective treatment (Singh and Jemal 2017).

These findings justify our inclusion of comorbidity (diabetes prevalence) and food environment variables as potential predictors, underscoring the limited explanatory power of socioeconomic variables alone.

Geographic Information Systems and Spatial Analysis

GIS has become an increasingly critical tool in public health research for geographically mapping cancer incidence and mortality. The spatial analysis capabilities of GIS enable researchers to investigate the intersection of geographic, environmental, and socioeconomic variables, providing insights into how these factors influence health outcomes (Cromley and McLafferty 2012, Bertazzon 2014). Studies like those by Lei et al. (2020) have demonstrated that GIS can be instrumental in identifying high-incidence cancer regions, particularly for lung cancer, enabling more targeted interventions and informed public health planning.

Lei et al. (2020) conducted a study that utilized GIS to analyze the spatial and temporal distribution of lung cancer in Shenzhen, China, from 2008 to 2018. The study revealed distinct patterns of lung cancer incidence, with rural areas experiencing higher rates compared to urban centers. The spatial clustering analysis identified high-incidence "hotspots" where socioeconomic disadvantages, coupled with higher environmental pollution levels, significantly contributed to the elevated cancer risk.

A critical foundation for this study is the research conducted by Burwell et al. (2023), which explores the geospatial associations between female breast cancer mortality rates and environmental socioeconomic indicators in North Carolina. The study examines a similar context of cancer mortality and socioeconomic disparities, making it highly relevant to this work's focus on the broader spectrum of cancer deaths. Using GIS, Burwell et al. (2023) analyzed spatial patterns in breast cancer mortality across North Carolina, identifying significant socioeconomic factors associated with high cancer mortality rates. These included lower household income, higher poverty rates, and a higher percentage of minority population, factors also considered in the present study's analysis of all cancer mortality rates. The study by Burwell et al. (2023) revealed that geographic and environmental factors play a substantial role in cancer health disparities.

Socioeconomic Determinants of Health and Cancer Outcomes

Socioeconomic determinants, including income, education, and access to healthcare, are key factors influencing cancer outcomes (Alcaraz et al. 2020). Lower-income populations, particularly those living in food deserts, are at increased risk of poor cancer survival due to inadequate nutrition, limited healthcare access, and higher prevalence of comorbid conditions (Fong et al. 2021). A review of 75 studies from low- and lower middle-income countries found that lower socioeconomic groups have substantially higher prevalence of tobacco and alcohol use and lower consumption of fruits, vegetables, and fiber (Allen et al. 2017). Such behavioral patterns elevate cancer risk and may worsen survival by contributing to obesity and metabolic disease. Evidence from developed countries similarly shows that living in a “food desert” not only reduces access to healthy foods but is associated with higher prevalence of diabetes and tobacco use; in a large cohort from the California Cancer Registry, five year survival was 78 percent vs. 80 percent for breast cancer and 60 percent vs. 64 percent for colorectal cancer among food desert residents vs. others, and these differences persisted after controlling for treatment (Fong et al. 2021).

Food deserts—areas with limited access to fresh, healthy foods—are significant contributors to health disparities (Walker et al. 2010). Individuals living in food deserts or food swamps consume more processed, high-fat foods and have higher rates of obesity and diet-related cancers (Larson et al. 2009, Bevel et al. 2023). Studies show that cancer patients residing in food deserts have a 16 percent higher five-year mortality risk for breast cancer and a 12 percent higher risk for colorectal cancer compared with those not in food deserts (Fong et al. 2021).

A comprehensive policy response to cancer disparities must therefore address both socioeconomic deprivation and comorbid health conditions. Interventions targeting economic stability, education, healthcare access, and neighborhood environment—core domains of social determinants of health—can reduce the burden of cancer (Alcaraz et al. 2020).

Conceptual and Theoretical Framework

The study is grounded in the socio-ecological model, which posits that health outcomes result from interactions among individual, interpersonal, community, and societal factors (Falcone et al. 2024). Within this framework, cancer mortality is influenced by personal behaviors (e.g., smoking, diet), neighborhood characteristics (e.g., food access, healthcare infrastructure), and larger structural determinants such as economic policies and systemic inequities (Falcone et al. 2024; Alcaraz et al. 2020). Falcone et al. (2024) propose a conceptual model in which structural racism and racial discrimination promote adverse social determinants of health that increase exposure to environmental hazards and chronic stress, leading to epigenetic and immune dysregulation and ultimately higher breast cancer mortality. The authors emphasize that structural racism shapes economic and housing opportunities (e.g., through redlining) and limits access to high-quality care, producing neighborhood disadvantages that manifest as delayed diagnosis, aggressive tumor subtypes, and higher mortality. Integrating this perspective highlights that spatial patterns of cancer mortality may reflect structural inequities rather than individual behaviors.

Our hypothesis stems from this theoretical perspective: areas with high cancer mortality rates will have higher spatial correlations with economic disparities—such as high poverty rates, low income, limited access to healthy food—and greater health inequalities. We further posit that diabetes prevalence may serve as an independent predictor of cancer mortality, reflecting the burden of chronic disease. This assumption is based on previous literature addressing the association of chronic disease and cancer mortality (Kim and Kim 2022). This theoretical framework informs the selection of variables and highlights the relevance of incorporating comorbidity indicators into spatial analysis to capture the multifaceted determinants of cancer outcomes.

The theoretical framework explicitly integrates GIS as the methodological bridge connecting multilevel socio-ecological determinants to spatial patterns of cancer mortality. By geocoding socio-economic indicators, food environment measures, and comorbidity data at the ZIP code level, GIS enables us to operationalize the socio-ecological model and visualize the spatial interaction of economic stability, healthcare access, neighborhood context, and chronic disease (Skiba et al. 2024). This integration clarifies the rationale for using spatial analysis and informs the choice of variables, including income, poverty, minority composition, age structure, food environment, and diabetes prevalence (Embury et al. 2022).

DATA AND METHODS

Data Management

The data for this study were obtained from the North Carolina vital statistics database, which includes all recorded deaths for the year 2021. The dataset was downloaded in Comma Separated Value (CSV) format and subsequently imported into ArcGIS Pro for spatial analysis. The data included information such as the primary cause of death, ZIP code, and population figures. To focus exclusively on cancer-related deaths, the dataset was filtered using the “Select by Attribute” function in ArcGIS Pro, isolating records where the primary cause of death (COD1) corresponded to an International Classification of Diseases (ICD) code starting with the letter “C,” indicative of cancer-related fatalities.

Once filtered, the cancer-related deaths were aggregated by ZIP (Zone Improvement Plan) code using the “Summarize” tool in ArcGIS Pro. This resulted in cancer-related death counts for each of the 763 ZIP codes in North Carolina. The summarized data were then joined to a pre-existing ZIP code shapefile using the “Join Table” function, which spatially links data to a geographic boundary. A new field, “cancer rate per 10,000 persons,” was calculated for each ZIP code to normalize the mortality rates according to population size. This standardization assumed that the average population per ZIP code contains approximately 10,000 people. Any ZIP codes with population sizes below 50 were removed from the dataset (16 records) to avoid statistical bias or issues resulting from the small number problem, leaving a final dataset of 747 ZIP codes.

Map Visualization

To visualize spatial disparities, we created a choropleth map using the calculated cancer mortality rates per 10,000 persons. To focus on areas with the greatest burden, we classified ZIP codes into high- and low-mortality groups. ZIP codes

with cancer mortality rates exceeding 28 % (approximately the top quartile of the distribution) were categorized as 'high-mortality' regions, while those below this threshold were categorized as 'low-mortality' regions. This cutoff was chosen based on distribution percentiles and previous literature identifying high-risk thresholds (Burwell et al. 2023) and was tested for robustness by evaluating alternative percentiles (25th and 33rd). The 28 percent threshold used to delineate high-mortality ZIP codes corresponds approximately to the top quartile of cancer mortality rates. Nevertheless, the epidemiological justification for such thresholds remains limited, and future research may explore data-driven clustering or risk classification methods.

Statistical Analysis

We conducted two principal statistical analyses: a two-tailed t-test to compare cancer mortality rates between high- and low-mortality regions, and an Ordinary Least Squares (OLS) regression to evaluate the relationship between cancer mortality and multiple socioeconomic variables. The two-tailed t-test was performed in Microsoft Excel, while the OLS was performed in ArcGIS Pro version 4.0.

The two-tailed t-test assesses whether the means of two independent samples differ significantly. The test statistic is calculated as:

$$t = \frac{(\bar{x}_1 - \bar{x}_2)}{s_p \sqrt{\frac{1}{n_1} + \frac{1}{n_2}}}$$

where \bar{x}_1 and \bar{x}_2 are the mean cancer mortality rates in the high- and low-mortality groups, n_1 and n_2 are their respective sample sizes, and s_p is the pooled standard deviation. A significance level of 0.05 was used to evaluate the null hypothesis that the group means are equal.

The OLS regression model estimates the linear relationship between cancer mortality (dependent variable) and several independent socioeconomic variables: median household income, poverty rate, percent minority, median age, diabetes rate, distance to the nearest supermarket, spending on fruits and vegetables, and the modified retail food environment index (mRFEI). The basic OLS equation is:

$$\begin{aligned} \text{CancerMortality} = & \beta_0 + \beta_1(\text{MedianIncome}) + \beta_2(\text{PovertyRate}) \\ & + \beta_3(\text{PercentMinority}) + \beta_4(\text{MedianAge}) \\ & + \beta_5(\text{DiabetesRate}) + \beta_6(\text{DistanceToSupermarket}) \\ & + \beta_7(\text{FruitVegetableSpending}) + \beta_8(\text{mRFEI}) + \varepsilon \end{aligned}$$

Coefficients (β) were estimated using least squares, and p-values were calculated to test whether each predictor significantly differs from zero. We assessed model fit using the adjusted R^2 statistic. Multicollinearity was evaluated with variance inflation factors (VIFs).

While OLS provides a straightforward approach for assessing linear associations, it assumes that observations are independent and spatially homogeneous. To address potential spatial autocorrelation, future studies could incorporate spatial lag or spatial error models, as well as geographically weighted regression (GWR),

to explore local variations in predictor effects (Matthews and Yang 2012; Anselin and Rey 2014). Additionally, non-parametric tests or analysis of variance (ANOVA) may be appropriate when normality assumptions are violated.

RESULTS AND DISCUSSION

The choropleth map shown in Figure 1 revealed marked geographic disparities in cancer mortality across North Carolina. High-mortality clusters were concentrated in rural western and eastern counties, while urban and suburban areas generally exhibited lower mortality. These clusters correspond closely with regions characterized by lower median household incomes, higher poverty rates, and limited access to healthcare services and healthy foods.

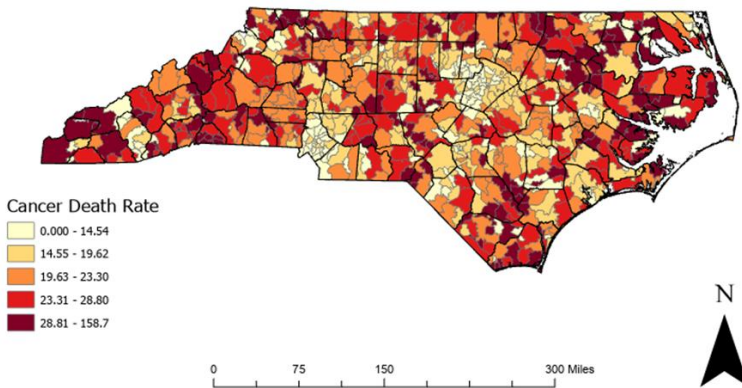


Figure 1. Map showing cancer mortality rate based on 2021 death data for North Carolina.

Two-tailed t-test results (Table 1) showed statistically significant differences between high- and low-mortality cohorts for several variables. High-mortality ZIP codes had significantly lower median household incomes, reduced spending on fruits and vegetables, longer distances to the nearest supermarket, older median age, and higher diabetes rates. The difference in poverty rate and mRFEI was not statistically significant, although trends pointed in the expected directions.

In the OLS regression model (Table 2), median household income ($\beta \approx -0.000094$; robust $t \approx -2.79$; $p \approx 0.0055$) and distance to the nearest supermarket ($\beta \approx 0.666$; robust $t \approx 2.19$; $p \approx 0.029$) emerged as statistically significant predictors of cancer mortality—higher income is associated with lower mortality, and greater distance to healthy food access is associated with higher mortality. Diabetes rate also showed a significant positive association ($\beta \approx 0.205$; robust $t \approx 2.71$; $p \approx 0.0069$), showing how chronic disease comorbidity relates to spatial patterns of mortality. While median age had the strongest effect in the model (robust $t \approx 11.10$; $p < 0.001$), fruit and vegetable spending were marginally non-significant ($\beta \approx -0.10$; $p \approx 0.06$), suggesting a possible but not definitive protective effect. The model explained approximately 20 % of the variance in cancer mortality (adjusted $R^2 \approx 0.20$), indicating that unmeasured factors—such as environmental

Table 1. Two-tail t-test results comparing socioeconomic factors in high vs. low cancer mortality cohorts. Statistical significance is indicated by *** (p < 0.01).

	High Cancer Mortality Cohort	Low Cancer Mortality Cohort
Description	Highest Quintile of Cancer Mortality in the state (n = 149)	All other Quintile of Cancer Mortality in the state (n = 598)
Median Household Income	\$44,684.24***	\$48,835.11***
Poverty Rate	17.01%	17.72%
Spending on Fruits and Vegetables	\$773.04***	\$826.95***
MRPEI	14.27	14.78
Median Age	72.26 years***	68.71 years***
Distance to nearest supermarket	4.90 miles***	3.30 miles***
Diabetes Rate	26.77%***	16.88%***

Table 2. Ordinary Least Squares regression analysis for Cancer mortality rate

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_S E	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-0.74741	2.736741	-0.2731	0.784858	2.319189	-0.32227	0.74735	-----
MED_HH_INC	-9.40E-05	0.000032	-2.91162	0.00371*	0.000034	-2.7867	0.005462*	1.147468
DIST_TO_NEAR	0.665921	0.148042	4.498187	0.00001*	0.304391	2.187712	0.028987*	1.053965
DIABETES_RAT	0.204946	0.024379	8.406631	0.0000*	0.075635	2.709671	0.006888*	1.095553
MEDIAN_AGEYR	0.312893	0.033453	9.353123	0.0000*	0.028193	11.09823	0.0000*	1.071972

exposures, health care access quality, stage at diagnosis, screening rates, or genetic predispositions—likely contribute substantially to mortality differences across ZIP codes. The observed association between diabetes prevalence and cancer mortality highlights metabolic health as a key independent predictor of cancer outcomes. Individuals with type 2 diabetes face significantly higher mortality risks from cancers such as colorectal, pancreatic, and liver, potentially due to chronic inflammation and hormonal dysregulation (Ling et al. 2023). The inclusion of the diabetes rate variable supports the argument that chronic disease burdens must be considered alongside socioeconomic indicators when addressing cancer disparities.

The poverty rate and percentage of minority individuals were not significant in the multivariate model, suggesting that income or health variables, such as diabetes, may mediate their effects. This supports the case for localized modeling approaches such as Geographically Weighted Regression (GWR), which can uncover spatially variable associations (Matthews and Yang 2012; Anselin and Rey 2014). Additionally, while median age had a measurable effect, it alone does not explain spatial differences, reinforcing the need for age-standardized rates and interaction analysis between age and socioeconomic status.

The model's adjusted R^2 of 0.20 indicates that other critical factors are not captured. Prior studies emphasize that while socioeconomic and comorbidity variables account for part of the disparity, much remains unexplained—such as stage at diagnosis, tumor biology, access to treatment, and health behaviors (Alcaraz et al. 2020). Consistent with the socio-ecological framework, multilevel and structural influences must be integrated into future research, with mediation analysis and longitudinal data needed to clarify causal pathways (Williams and Mohammed 2013; Tervonen et al. 2017; Quaglia et al. 2013).

CONCLUSION

The spatial distribution of cancer mortality rates across North Carolina reveals significant geographic disparities, with higher mortality rates concentrated in rural and socioeconomically disadvantaged regions, particularly in the western and eastern portions of the state. These areas are characterized by lower median incomes, higher poverty rates, and limited access to healthcare and nutritious food, all of which are likely to contribute to elevated cancer mortality. Conversely, urban and suburban ZIP codes generally exhibit lower cancer mortality rates, reflecting improved access to healthcare, increased preventive screenings, and socioeconomic advantages that mitigate cancer risk.

Descriptive statistical analysis of the dataset further underscores these disparities. Among the 747 ZIP codes analyzed, cancer mortality rates ranged from 0 to 158.7 deaths per 10,000 persons, with a mean of 22.8, a median of 21.6, and a standard deviation of 14.2. The positive skewness (4.0) and high kurtosis (33.1) suggest that while most ZIP codes experience moderate cancer mortality rates, a subset of regions faces disproportionately high mortality, contributing to a long-tailed distribution. Findings from Table 1 (t-test results) and Table 2 (OLS regression analysis) reinforce these patterns, indicating that median household income, poverty rate, distance to supermarkets, and diabetes prevalence are significant predictors of cancer mortality. The OLS regression results confirm that lower-income communities and those with greater distances to grocery stores exhibit

significantly higher cancer mortality rates, emphasizing the role of socioeconomic determinants in shaping cancer outcomes.

LIMITATIONS

Several limitations should be noted. First, the adjusted R^2 of 0.20 indicates that the socioeconomic variables considered explain only a portion of the variability in cancer mortality. Important factors, such as environmental exposures, health behaviors, genetic predispositions, and the quality of medical care, were not included in the analysis and may account for a substantial share of the unexplained variance.

Second, the study relies on cross-sectional data aggregated at the ZIP code level, which may obscure within-area heterogeneity and limit causal inference. An ecological fallacy may arise when drawing individual-level conclusions from aggregated data (Kwan 2012). Future research should incorporate finer spatial units (e.g., census tracts) and longitudinal data to capture temporal dynamics.

Third, we did not formally test for spatial autocorrelation or heteroskedasticity in the residuals, which may bias OLS estimates. While initial diagnostics suggested mild clustering, spatial regression techniques such as spatial lag, spatial error, or GWR models are recommended for future analyses to account for spatial dependence and non-stationarity.

Finally, median age was included as a crude demographic control, but it does not fully adjust for age structure. Stratifying analyses by age groups or using age-standardized mortality rates would provide a more accurate assessment of socioeconomic effects. Additionally, the 28 percent threshold used to define high-mortality areas, although informed by distribution percentiles, is somewhat arbitrary; sensitivity analyses using alternative cutoffs indicated similar spatial patterns, yet further justification from epidemiological thresholds would strengthen the classification.

IMPLICATIONS FOR PUBLIC HEALTH POLICY

The findings from this study have immediate implications for public health policymakers seeking to reduce cancer disparities. First, targeted investments in rural and low-income areas should focus on improving access to healthy foods by expanding supermarkets, farmers' markets, and SNAP programs. Reducing food deserts and food swamps can lower obesity-related cancer risks and improve diet quality (Fong et al. 2021).

Second, public health strategies must prioritize diabetes prevention and management through screening, education, and the expansion of primary care services. Integrating chronic disease management with cancer prevention efforts can address the intertwined burden of diabetes and cancer mortality.

Finally, policies that address broader social determinants—such as poverty, education, and housing—and structural inequities are essential for long-term reductions in cancer disparities (Babatunde et al. 2021). Multisector collaboration among health, transportation, economic development, and community

organizations is critical for implementing comprehensive interventions (Montez and Zajacova 2019; Alcaraz et al. 2020).

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