

THESIS

COLORADO ENVIROSCREEN AS A PREDICTOR OF MORTALITY: AN ECOLOGICAL
ANALYSIS OF 2019 COUNTY-LEVEL DATA

Submitted by

Stephanie Pusker

Department of Environmental and Radiological Health Sciences

In partial fulfillment of the requirements

For the Degree of Master of Science

Colorado State University

Fort Collins, Colorado

Spring 2024

Master's Committee:

Advisor: David Rojas-Rueda

Co-Advisor: Maggie Clark

Molly Gutilla

Copyright by Stephanie Pusker 2024

All Rights Reserved

ABSTRACT

COLORADO ENVIROSCREEN AS A PREDICTOR OF MORTALITY: AN ECOLOGICAL ANALYSIS OF 2019 COUNTY-LEVEL DATA

Background

In today's rapidly evolving landscape of environmental awareness in public health, Colorado stands at the forefront of innovation with its Environmental Justice (EJ) mapping and health screening tool, Colorado EnviroScreen (*Colorado EnviroScreen, 2022*). This tool, developed by Colorado Department of Public Health and Environment (CDPHE), empowers governmental agencies, research institutions, and the broader public to quantify and understand the interplay between environmental factors and community health by calculating an "EnviroScreen Score" (*Colorado EnviroScreen, 2022*). The higher the EnviroScreen score, the more likely the area will be affected by environmental health injustices at the census block group, census tract, and/or county levels (*Colorado EnviroScreen, 2022*). The purpose of this study is to bridge a gap in the current research landscape by exploring the association between aggregate county-level data derived from an EJ mapping tool and all-cause mortality rates. Specifically, we aim to investigate the relationship between the CO EnviroScreen score and the component scores – Demographics, Sensitive Populations, Climate Vulnerability, Environmental Effects, and Environmental Exposures – and all-cause mortality rates at the county level in Colorado in 2019. By conducting this ecological analysis, we seek to provide valuable insights into the potential impact of environmental justice factors on public health outcomes, thereby contributing to a more

comprehensive understanding of the interaction between environmental conditions and mortality rates within communities.

Methods

An ecological study was conducted at the county-level spatial scale using a generalized linear model to assess the association between three EnviroScreen component score percentiles (Demographics, Environmental Exposures, and Climate Vulnerability) and age-standardized all-cause mortality at the county level. These three score percentiles were selected due to correlation with other scores, as well as the indicators included in some of the component scores being more comprehensive than others. County-level covariates included in the model were insufficient sleep, alcohol overindulgence, physical inactivity, and smoking. In addition to the full model, secondary models were created, including Demographics, Environmental Exposures, and Climate Vulnerability as independent predictors. Furthermore, the total EnviroScreen score percentile, which includes all component scores, was used in the analysis.

Results

In the fully adjusted model, a 10% increase in the EnviroScreen Environmental Exposures component score was associated with a 3% increase in all-cause mortality rate at the county level in Colorado in 2019 (95% CI: 1.00, 1.05). In the crude model, a 10% increase in EnviroScreen score was associated with a 5% increase in all-cause mortality rate at the county level in Colorado in 2019 (95% CI: 1.03, 1.07). Neither Demographics nor Climate Vulnerability component scores percentile were associated with an increase or decrease in all-cause mortality rates.

Discussion

This study suggests that there is a potential association between a higher EnviroScreen component score and an increase in age-standardized, all-cause mortality at the county level in

Colorado. This is the first study to estimate the association between aggregate environmental and health-related scores from CO EnviroScreen with mortality. This study supports the notion of cumulative impacts as a tool to monitor possible health disparities and environmental injustice.

ACKNOWLEDGEMENTS

The impetus to do this research is my years of work experience in hospitals and emergency medical services that allow me to see the direct impacts of inequity on the health of individuals. In particular, through working on an ambulance for several years, the disparities in health between communities just one block away from each other were obvious and pronounced. People in disproportionately impacted communities tend to use the 911 system for primary care versus emergency care, due to their lack of access to the healthcare system at large, as compared to those living in affluent areas with readily available health services. My professional experiences fueled my desire to return to school to learn about health and social inequities, as well as to find a way to assist in whatever way I could. It just so happens that there was a tool in CO EnviroScreen already developed in Colorado to facilitate my research interests, which are to promote health equity and address the systemic issues that perpetuate disparities in health, social, and environmental outcomes.

I would like to thank my steadfast friend and colleague, Kelly DeBie, for all her support and guidance on this project. I would also like to thank Kellin Slater for being a grounding influence and keeping me focused on the big picture. I would also like to thank my committee members for their help, feedback, and ideas. I could not have done this without them.

TABLE OF CONTENTS

ABSTRACT.....	ii
ACKNOWLEDGMENTS.....	iv
Chapter 1 – Introduction.....	1
Research Aim.....	6
Chapter 2 – Manuscript.....	8
Introduction.....	8
Methods.....	9
Study Design.....	9
Data Sources and Cleaning.....	10
Natural Splines.....	11
Spearman Correlation	12
Statistical Analysis.....	12
Sensitivity Analyses.....	13
Results.....	13
Exploratory Analysis.....	13
Spearman Correlation.....	14
Main Findings.....	15
Sensitivity Analyses.....	16
Discussion.....	16
Strengths and Limitations.....	19
Public Health Implications and Recommendations.....	22
Conclusion.....	24
REFERENCES.....	25
APPENDICES.....	28
Sensitivity Analyses.....	28
Natural Splines.....	35
Glossary.....	38

CHAPTER 1 – INTRODUCTION

“Environmental Justice (EJ) is the fair treatment and meaningful involvement of all people regardless of race, color, national origin, or income with respect to the development, implementation, and enforcement of environmental laws, regulations and policies” (OEJECR US EPA, *Environmental Justice*, 2014). The EJ movement began in the 1980s as a grassroots effort by community members that identified a toxic waste site that was disproportionately impacting people of color (OEJECR US EPA, *Environmental Justice Timeline*, 2015). Many instances of EJ violations have been identified since then, all of which show that “racial, minority, and low-income populations bear a higher environmental risk burden than the general population” (OEJECR US EPA, *Environmental Justice*, 2014). In recent years the definition of epidemiology has expanded from its focus on risk factors at the individual level to a more ecological approach that allows researchers to capture ecologic level exposures related to the environment that are not adequately identified by individual level investigation (*Social Epidemiology*, 2014). This in part reflects the EJ movement, which provides a more holistic and ethical approach to obtaining biological and social data that are consistent with each other in respect to diseases (*Social Epidemiology*, 2014). This approach is more holistic because it can lead to an understanding of social and environmental determinants of health that are more than the sum of individual-level measures (*Social Epidemiology*, 2014). This approach is more ethical than randomized control trials because equipoise is not always possible when an intervention would clearly improve a family’s quality of life, and withholding that intervention would be unethical (*Social Epidemiology*, 2014).

One of the most important ways an agency tasked with the protection of public health and the environment can meet its health equity responsibilities is to use an EJ mapping tool to identify

environmental and social inequities (OEJECR US EPA, *Environmental Justice*, 2014). On July 2nd, 2021, the state of Colorado passed a law called the Environmental Justice Act which defined disproportionately impacted communities in the state and prompted the creation of an interactive EJ mapping tool and health screening tool called Colorado EnviroScreen (Buckner et al., 2021). This tool allows the Colorado Department of Public Health and Environment (CDPHE), as well as public and research institutions to calculate an “EnviroScreen Score” for counties in CO (*Colorado EnviroScreen*, 2022). Launched on June 28, 2022, CO EnviroScreen uses indicator scores combined into component scores that represent health and social factors, and pollution and climate burden to “understand environmental injustice and environmental health risks in Colorado” (*Colorado EnviroScreen*, 2022). Nineteen other states in the US utilize some form of Environmental Justice screening and mapping tools (OEJECR US EPA, *Environmental Justice*, 2014).

The EnviroScreen tool is important to public health because it is a novel way to visualize health disparities at different resolutions and use different filtering criteria that may be of interest to stakeholders. It is easily accessible by the public, open source, and provides up-to-date information on areas with higher environmental injustices. This tool contains a wealth of data that is designed to foster equitable, data-driven decision-making that hopes to improve the environmental health of individuals and communities that are disproportionately impacted (*EnviroScreen v1.0 Technical Documentation*, n.d.). EnviroScreen defines a disproportionately impacted community by the definition used by the Environmental Justice Act: “a community that is in a census block group where more than 40% of households are low income, identify as a minority, or are housing cost-burdened.” It identifies an additional definition that applies to communities that were historically impacted by environmental racism, or where cumulative

impacts have affected health and the environment and contribute to continuing disparities (*EnviroScreen v1.0 Technical Documentation*, n.d.). While the monitoring capabilities EnviroScreen provides do not directly affect health outcomes, its primary use comes in the form of health equity; historically communities of high sociodemographic status already have monitoring capabilities and have better overall environmental and social health than disproportionately impacted communities (*Social Epidemiology*, 2014).

These communities often experience cumulative impacts, which are the combined impacts of environmental and social stressors and can be visualized using CO EnviroScreen (Solomon et al., 2016). Environmental stressors can include pollutants in the air, soil, and water that can lead to poor health outcomes in humans and adverse impacts on the environment (ORD US EPA, 2022). Social stressors can include low socioeconomic status, health vulnerabilities, food insecurity, poor housing quality, linguistic isolation, disabilities, and more (Solomon et al., 2016). Both these environmental and social stressors are included in the data that went into the EnviroScreen tool. Cumulative impacts are the combination of exposures to both types of stressors, and their effects on health, well-being, and quality of life (ORD US EPA, 2022). These impacts result in poorer health of communities and lead to a decreased life span (Tulve et al., 2024).

The current version of EnviroScreen includes data from a wide variety of sources, such as the U.S. Environmental Protection Agency (EPA), the Centers for Disease Control and Prevention (CDC), CDPHE, and the Colorado Oil and Gas Conservation Commission (COGCC) (*Colorado EnviroScreen*, 2022). The CO EnviroScreen score is calculated by combining 35 individual indicators into topic-based sub-components and multiplying the combined group component scores, which are broken down into health and social factors, and pollution and climate burden (*Colorado EnviroScreen*, 2022). The higher the EnviroScreen score, the more likely the area is to

be affected by environmental health injustices at the census block group, census tract, and/or county levels (*Colorado EnviroScreen, 2022*). The 35 indicators were aggregated into component scores using a geometric mean of the percentiles (*EnviroScreen v1.0 Technical Documentation, n.d.*). A geometric mean for aggregation was used because individual indicators in the component scores are not independent of each other (*EnviroScreen v1.0 Technical Documentation, n.d.*).

This research focuses on component scores in the EnviroScreen structure, as outlined below and in Table 1. A visual representation of the top 25 counties in terms of EnviroScreen score can be seen in Figure 1. The Sensitive Populations score captures how at risk a community is to environmental exposures and climate impacts as it relates to health (*Colorado EnviroScreen, 2022*). The Demographics score represents a community's social and economic vulnerabilities (*Colorado EnviroScreen, 2022*). The Environmental Exposures score represents a community's exposure to certain environmental risks (*Colorado EnviroScreen, 2022*). The Environmental Effects score represents how many hazardous or toxic sites are in a community (*Colorado EnviroScreen, 2022*). The Climate Vulnerability score represents a community's risk of drought, flood, extreme heat, and wildfire compared to the rest of the state (*Colorado EnviroScreen, 2022*). When calculating the overall EnviroScreen Score, Environmental Effects and Climate Vulnerability component scores were weighted by half based on expert opinion because a population may not be directly exposed to the Environmental Effects and Climate Vulnerability indicators (*Colorado EnviroScreen, 2022*).

Table 1: EnviroScreen data included in component and composite scores				
EnviroScreen Score				
Health and Social Factors		Pollution and Climate Factors		
<i>Sensitive Populations</i>	<i>Demographics</i>	<i>Environmental Exposures</i>	<i>Environmental Effects</i>	<i>Climate Vulnerability</i>
Asthma Cancer Diabetes Heart Disease Life Expectancy Low Birth Weight Mental Health >65 years old <5 years old	Housing Cost Burden Disability Educational Attainment Linguistic Isolation Income Race and ethnicity	Diesel Particulate matter Traffic Proximity PM 2.5 Drinking Water Lead Noise Air toxics Other Air Pollutants	Surface Water Mining Oil and Gas Wastewater Hazardous Chemicals Hazardous Waste Superfund site	Drought Flood Extreme Heat Wildfire

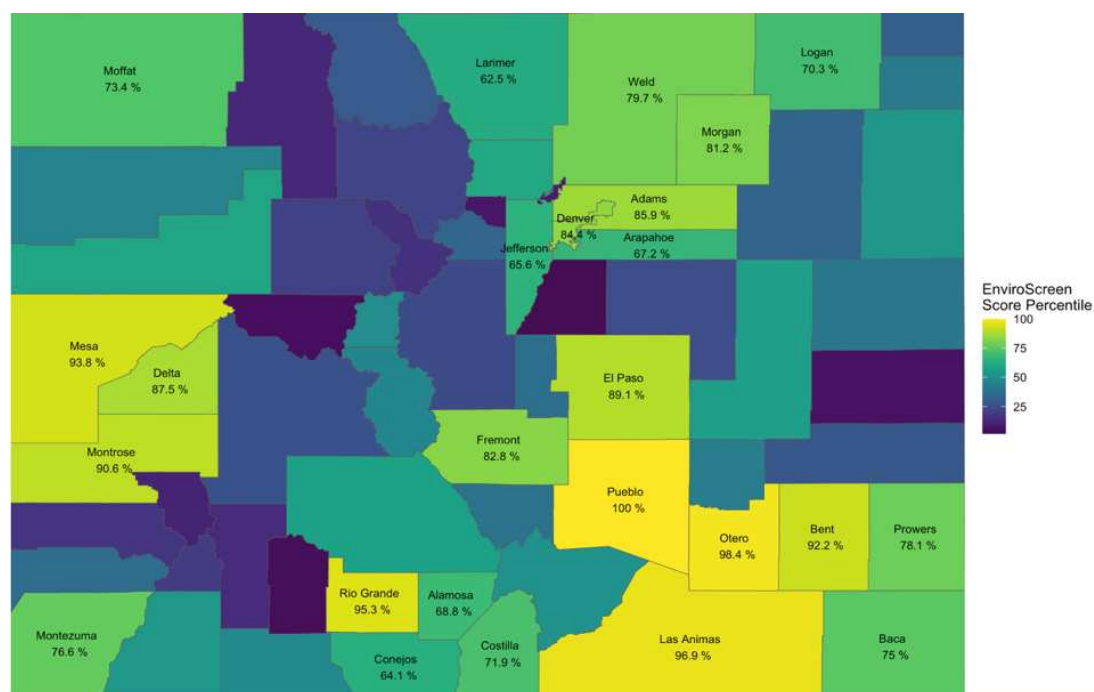


Figure 1: Top 25 most burdened counties by EnviroScreen Score Percentile

All-cause mortality rate was chosen as the outcome variable for this research because it provides a comprehensive measure of the overall health and survival status of a population. It is an objective measure that includes deaths from various causes. All-cause mortality is also often an endpoint for public health planning because monitoring all-cause mortality helps assess the

effectiveness of public health interventions in reducing the overall burden of disease and increasing life expectancy. All-cause mortality allows researchers to compare across different populations and regions, in this case, to compare all the counties in CO (Figure 2).

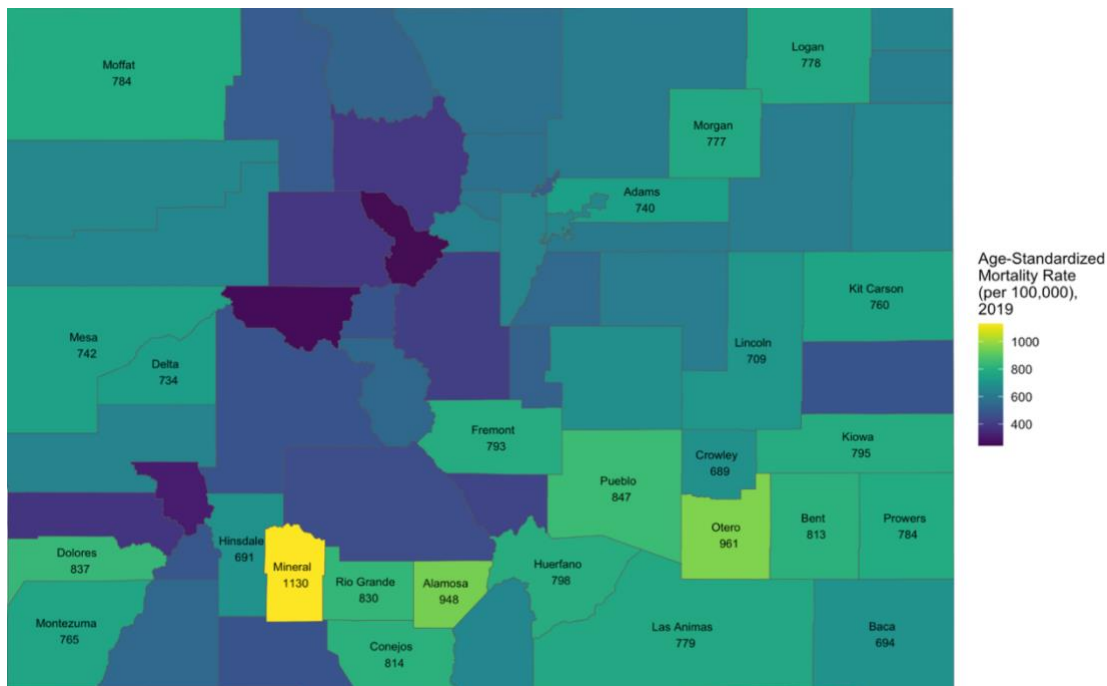


Figure 2: Top 25 counties by mortality rate

The CO EnviroScreen tool was designed with intentional input and feedback from the community to be a user-friendly, public-facing resource for individuals and policymakers to access geographic environmental justice information. There is currently one published study using California EnviroScreen as the exposure variable to examine the association with a health outcome (Alcala, et al., 2019). Little is known about how this data set might be used as a public health tool. One step is to characterize health risks associated with the scores. Filling this knowledge gap may help stakeholders by providing quantitative evidence that may be used to justify policy or other behavior changes.

Research Aim

Estimate the association between environmental exposures, as measured by the Colorado EnviroScreen component scores, and all-cause mortality rates at the county level in Colorado in 2019.

CHAPTER 2 – MANUSCRIPT

Introduction

The Environmental Justice (EJ) movement is founded on the principle that no person, regardless of race, socioeconomic status, or any other aspect of their identity, should be disproportionately burdened by environmental hazards (OEJECR US EPA, *Environmental Justice, 2014*). On July 2nd, 2021, the state of Colorado passed a law called the Environmental Justice Act which defined disproportionately impacted communities in the state and prompted the creation of an interactive EJ mapping tool and health screening tool called Colorado EnviroScreen (Buckner et al., 2021). This tool allows the Colorado Department of Public Health and Environment (CDPHE), as well as public and research institutions to calculate an “EnviroScreen Score” for counties in CO (*Colorado EnviroScreen, 2022*). Launched on June 28, 2022, CO EnviroScreen uses indicator scores combined into component scores that represent health and social factors, and pollution and climate burden to “understand environmental injustice and environmental health risks in Colorado” (*Colorado EnviroScreen, 2022*).

The EnviroScreen tool is important to public health because it is a novel way to visualize health disparities at many different levels and use different filters that may be of interest to stakeholders. The CO EnviroScreen score is calculated by combining 35 individual indicators into topic-based sub-components and multiplying the combined group component scores, which are broken down into health and social factors, and pollution and climate burden (*Colorado EnviroScreen, 2022*). The higher the EnviroScreen score, the more likely the area is to be affected by environmental health injustices at the census block group, census tract, and/or county levels

(*Colorado EnviroScreen, 2022*). The 35 indicators were aggregated into component scores using a geometric mean of the percentiles (*EnviroScreen v1.0 Technical Documentation, n.d.*).

This research focuses on component scores in the EnviroScreen structure, as outlined below. The sensitive populations score captures how at risk a community is to environmental exposures and climate impacts as it relates to health (*Colorado EnviroScreen, 2022*). The demographics score represents a community's social and economic vulnerabilities (*Colorado EnviroScreen, 2022*). The Environmental exposures score represents a community's exposure to certain environmental risks (*Colorado EnviroScreen, 2022*). The Environmental effects score represents how many hazardous or toxic sites are in a community (*Colorado EnviroScreen, 2022*). The Climate vulnerability score represents a community's risk of drought, flood, extreme heat, and wildfire compared to the rest of the state (*Colorado EnviroScreen, 2022*).

The CO EnviroScreen tool was designed with intentional input and feedback from the community to be a user-friendly, public-facing resource for individuals and policymakers to access geographic environmental justice information. Little is known about how the cumulative impacts concepts represented by CO EnviroScreen scores are associated with health outcomes. Filling this knowledge gap may help stakeholders by providing quantitative evidence that may be used to support the use of CO EnviroScreen, and related policy or behavior changes. The aim of this study is to estimate the association between environmental exposures, as measured by the CO EnviroScreen component scores, and all-cause mortality rates at the county level in Colorado.

Methods

Study Design

This is an ecological, cross-sectional study of CO counties that estimates the association between all-cause mortality at the county level in Colorado in 2019 and the CO EnviroScreen

component scores. This study is ecological because the primary data analysis and interpretation are conducted at the group level, rather than the individual level. This study is cross-sectional because it looks at the exposure at a specific moment in time, the outcome at a single point in time, and there is no follow-up over time.

Data Sources and Cleaning

EnviroScreen data at the county level was obtained from the CO EnviroScreen webpage (*Colorado EnviroScreen, 2022*). Data was downloaded for the different available geographies: census block group (most granular), census tract, and county level (least granular). Exploratory analyses were performed using R software at each geo-scale to inform which level had the least missingness at the indicator level (*R: The R Project for Statistical Computing, n.d.*). It was found that county-level data had the least missingness, and was chosen as the level for analysis due to a lack of data availability at more granular levels for outcome and covariate data. Data cleaning included limiting the data set to county name and the percentile scores for each of the five components. Missingness was further explored in the cleaned data, revealing no apparent systematic missingness, therefore the missing values were removed from the data.

Mortality data at the county level for 2019 was obtained from a CDPHE data request on 8 November 2023. 2019 data was chosen to mitigate the effects of increased mortality rates due to the COVID-19 pandemic. The data included the age-standardized, all-cause mortality rate for each Colorado county in 2019, the crude rate, the number of deaths, and the population of the county. There were no missing values in the data set. This data was merged by county name to the EnviroScreen component score percentile data.

Covariate data was collected from the CDC PLACES website at the county level (*PLACES: Local Data for Better Health: Compare Counties | CDC, n.d.*). CDC PLACES obtained data from

the Behavioral Risk Factor Surveillance System (BRFSS), which is a self-reported sample survey. These covariates were chosen for inclusion in the analysis because the EnviroScreen data does not provide any information on them, and they are known to affect all-cause mortality. The included covariates are: percentage of adults aged ≥ 18 years sleeping less than 7 hours (age-adjusted prevalence); percentage of adults aged ≥ 18 years binge drinking (age-adjusted prevalence); percentage of adults aged ≥ 18 years with no leisure time physical activity (age-adjusted prevalence); and percentage of adults aged ≥ 18 years current smoking (age-adjusted prevalence). We manually entered data from this page into an R data frame. Data was manually entered twice and summary analysis was performed on both sets to mitigate errors during the entry process. The data was obtained from 2021 for all covariates except insufficient sleep, which was obtained from 2020. This was due to data availability. This data was merged by county with the mortality and EnviroScreen data.

Natural Splines

Splines were plotted by regressing the natural spline of each component score with three degrees of freedom against mortality and a Quasi-Poisson method. Three degrees of freedom were chosen to adequately capture the flexibility of the underlying trend, and minimize the complexity and the risk for overfitting. Each spline was then plotted against a scatterplot with points that represented individual Colorado counties. The independent variable was each of the EnviroScreen component scores and the dependent variable was all-cause mortality rate per 100,000 people. In total, six plots were created to explore the data, five for each component score, and one for the overall EnviroScreen score against mortality.

Spearman Correlation

To determine if there was a strong correlation between the EnviroScreen component scores, a Spearman correlation analysis was performed. Spearman correlation measures the trend between variables using their rank and does not assume any data structure (*Spearman Correlation Coefficient*, n.d.). The correlation matrix was generated from a dataset that included the five component score percentiles and was visualized as a heatmap with colors representing the numerical values of the correlation.

Statistical Analysis

A generalized linear model was selected to allow for flexibility of the assumption of normality in the data, and a Quasi-Poisson method was used due to the overdispersion of the outcome variable. The full model used is shown below:

$$\log(E(Y)) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \beta_3 X_3 + \beta_4 C_1 + \beta_5 C_2 + \beta_6 C_3 + \beta_7 C_4$$

In the full model, Y is the age-standardized all-cause mortality rate, X₁ is the demographics score percentile; X₂ is the environmental exposures score percentile; X₃ is the climate vulnerability score percentile. These three score percentiles were selected due to correlation with other scores, as well as the indicators included in some of the component scores being more comprehensive than others. C₁₋₄ are the covariates: binge drinking, insufficient sleep, physical inactivity, and smoking (Table 3). Estimates were multiplied by 10 to represent a 10% increase in EnviroScreen score percentile, then exponentiated to make a rate ratio.

In addition to the full model, the total EnviroScreen score percentile, which includes all the component scores, was individually regressed on mortality, and each of the five component scores was regressed independently on mortality (Table 2). A secondary modeling approach included the component scores included in the full model individually regressed on mortality, with the four covariates included in each model (Table S1).

Sensitivity Analyses

Sensitivity analyses were performed, which involved obtaining 2019 county-level suicide data from the same data request to CDPHE on 8 November 2023 to explore an alternative, specific outcome that contributes to all-cause mortality. Information on rural and urban classification of counties was obtained for sensitivity analysis from the Colorado Rural Health Center. Another data set was created with all the county data on all-cause mortality, covariates, and EnviroScreen component scores, excluding Mineral County. A fourth sensitivity analysis was performed using the environmental effects component score percentile instead of the climate vulnerability score percentile.

All sensitivity analyses included the same sets of models: component scores included in the full model separately regressed on mortality, with the four covariates included in each model (Table S1); the data set that excluded Mineral County (Tables S2-S4); rural versus urban data sets (Tables S5-S10); substituting environmental exposures for climate vulnerability included the full model and the component scores included in the full model separately regressed on mortality, with the four covariates included in each model (Tables S11 and S12); and using suicide data (Tables S13-15). All analysis and mapping were performed in R Version 4.2.1 (*R: The R Project for Statistical Computing*, n.d.).

Results

There were a total of 64 observations in the final data set, correlating to the 64 counties in Colorado.

Exploratory Analysis

The analysis showed an approximately linear relationship between all component scores and mortality. Mortality data is non-normally distributed and overdispersed; covariate data is

normally distributed. Mineral County, with only 745 residents, had an age-adjusted mortality rate of 1,130 per 100,000 due to 14 deaths reported in 2019.

Spearman Correlation

This study found moderate correlation between demographics and sensitive populations (0.56) and environmental exposures and environmental effects (0.53) (Figure 3). However, sensitive populations and environmental effects were both removed due to correlation issues and because sensitive populations included life expectancy. Other component correlations ranged between -0.5 and 0.5.

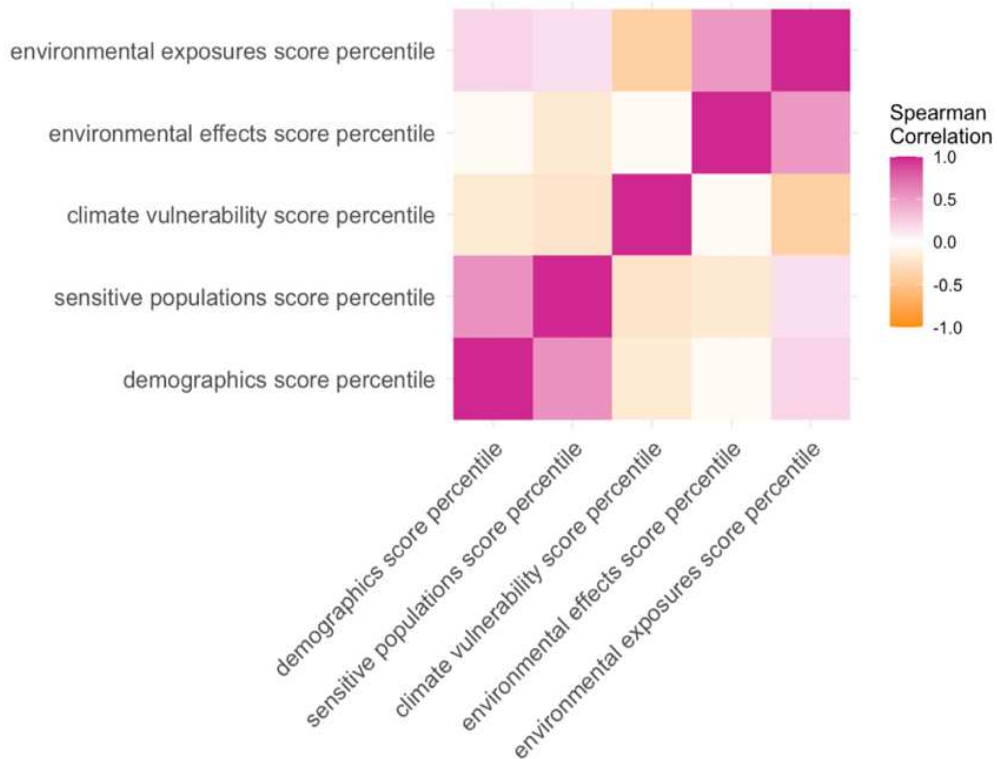


Figure 3: Spearman Correlation Matrix of CO EnviroScreen component scores

Main Findings

In the crude model CO EnviroScreen score was found to be associated with an increase in all-cause mortality rate (RR: 1.05, 95% CI: 1.03, 1.07) (Table 2). Demographics score percentile, environmental exposures score percentile, and sensitive populations were also associated with an increase in all-cause mortality rate (Table 2). Environmental effects and climate vulnerability score percentiles are non-significantly associated with a decrease in all-cause mortality rate (Table 2).

Table 2: Crude Association: Mortality and EnviroScreen Component Scores, County Level, per 10 percentile increase in component score (n = 64)			
Component Scores	Rate Ratio	95% CI	P-value
<i>EnviroScreen Total</i>	1.05	1.03, 1.07	<0.01
Demographics	1.04	1.02, 1.07	<0.01
Environmental Effects	0.99	0.97, 1.01	0.31
Environmental Exposures	1.03	1.01, 1.05	0.02
Climate Vulnerability	0.98	0.96, 1.00	0.11
Sensitive Populations	1.06	1.04, 1.08	<0.01

All-cause mortality regressed on each component score individually, as well as the EnviroScreen total score. No covariates were included in any of the six models.

In the fully adjusted model, demographics score percentile was not associated with all-cause mortality rate (Table 3). The addition of behavioral risk factors in this case made the estimate of demographics score less important. Environmental exposures score percentile was associated with an increase in mortality (RR: 1.03, 95% CI: 1.01, 1.05) per each 10-percentile increase (Table 3). Climate Vulnerability score percentile was not associated with all-cause mortality rate (Table 3).

Table 3: Adjusted Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 64)			
Component Scores	Rate Ratio	95% CI	P-value
Demographics	0.99	0.95, 1.03	0.49
Environmental Exposures	1.03	1.00, 1.05	0.02
Climate Vulnerability	1.01	0.99, 1.04	0.23

All-cause mortality regressed on three component scores. Covariates were included in the model. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Sensitivity Analyses

There was little difference in the individual association of each component score and mortality with covariates included in the model (Table S1). Excluding Mineral County from the analysis did not meaningfully change any of the effect estimates (Tables S2-S4). Splitting the data set into rural and urban counties reduced the strength of association between the Environmental Exposures component score and mortality in the full model for urban counties, however, it did not notably change any other effect estimates, for either rural or urban counties (Tables S5-S10). Replacing Climate Vulnerability with Environmental Effects also did not have any notable effect on the rate ratios (Tables S11-S12). In the full model that used suicide as the outcome, Climate Vulnerability was harmful (RR: 1.12, 95% CI: 1.02, 1.22) (Table S13).

Discussion

This ecological, cross-sectional study found that an increase in EnviroScreen total score and Environmental Exposures score were associated with an increase in all-cause mortality rate at the county level in 2019. As far as we know, this is the first study of its kind to associate CO EnviroScreen component scores with all-cause mortality. These findings add to the growing body of evidence that suggest the potential association between disproportionately impacted communities indicators and health outcomes.

Few studies have used the Environmental Justice mapping tools that are available in other states and countries. When they are utilized, most studies do not use the mapping tool as the sole exposure variable, but as a covariate. Previous studies have associated pollution data from the EPA's environmental justice mapping tool, EJScreen, with COVID-19 prevalence and mortality rates (Hendryx and Luo, 2020). Niu, et al. used the CalEnviroScreen tool for its cumulative impact score, which they used to represent neighborhood-level cumulative impacts from environmental pollution and population vulnerability (Niu, et al., 2022). One paper recently used the CO EnviroScreen health and social factors score to account for modification in their estimation of the association between maternal exposure to fine particulate matter to assess how maternal neighborhoods influence vulnerability to air pollution (Demateis et al., 2023)

In California, one study directly examined the association between CalEnviroScreen composite scores and a health outcome (Alcala, et al., 2019). Alcala, et al. used a retrospective design to assess cumulative impacts, as measured by CalEnviroScreen composite scores, on pediatric asthma hospitalization (Alcala, et al., 2019). The composite scores for CalEnviroScreen are similar to CO EnviroScreen's component scores and represent population characteristics and pollution burden scores (*CalEnviroScreen 4.0*, 2021). This study used several years of outcome data, as well as Poisson multilevel modeling (Alcala, et al., 2019). The main finding was that every unit increase in the CalEnviroScreen Score was associated with an increase of 1.6% above the mean rate of pediatric asthma hospitalizations (95% CI: 1.014, 1.018) (Alcala, et al., 2019). One of the goals of their analysis was to identify how well CalEnviroScreen's composite scores identify disproportionately impacted communities in association with a health outcome (Alcala, et al., 2019). This reflects the goal of the current study.

The primary analysis in the current study utilized data from 2019 for the outcome, data from 2020 and 2021 for covariates, and data from 2010-2021 for the exposure. Data for mortality was chosen to mitigate the effects of the COVID-19 pandemic; however, the covariate data from pandemic years and the aggregation of data over several years from EnviroScreen both serve to potentially obscure the true association. We believe the trends in behavioral risk factors from 2019 to 2020 and 2021 did not change meaningfully to impact the findings. The only covariates we were concerned about during these years were alcohol overconsumption and physical inactivity, as these were seen to increase during the pandemic (Akwa et al., 2023).

Interestingly, the addition of health behavior covariates had different impacts on the various models. Demographics score was associated with an increase in mortality in the crude model but not in the adjusted model. This was most likely because the Demographics score and the health behavior covariates were at least partially explaining the same variability in mortality. Therefore the addition of health behavior covariates (likely to be more causally associated with mortality) to the model ameliorated the significance of the Demographics association.. Little impact on the models was observed when the health behavior covariates were included in models evaluating the other component scores.

Several sensitivity analyses were performed in hopes of better understanding the association between mortality and the component scores. It was hypothesized that removing Mineral County from the data set would increase the effect estimates, due to Mineral having a very high mortality rate as well as a low EnviroScreen score. However, it had very little effect. The impact of Environmental Exposures with Mineral removed was slightly larger than in the primary analysis. This is potentially due to the small sample size, and the fact that smaller counties in Colorado already have an outsized effect on the association.

It was posited that suicide as an outcome would have an association with EnviroScreen component scores, and was explored as an alternative, specific outcome that contributes to all-cause mortality. Climate Vulnerability was significantly associated with an increase in suicide rate, but neither Environmental Exposures nor Demographics were. This association was seen as likely because climate change is a known contributor to increased rates of suicide (Belova et al., 2022). However, it is difficult to draw even associational conclusions, due to the small sample size of counties that reported suicides in 2019 (n = 51), with many of them reporting zero suicides (n = 7).

An unexpected finding was that there was no notable difference between rural and urban counties. It was theorized that Climate Vulnerability would have more of an effect in rural counties and that Environmental Exposures would have a larger impact in urban counties. Climate Vulnerability did have a slightly larger effect in rural than urban counties, however these results were not significant. The effect of Environmental Exposures was also slightly higher in rural counties than in urban counties, but again, not significantly. This has several potential causes, including the small sample size of 17 for urban and 47 for rural counties. Another reason is that this sample size is potentially not adequately powered to elucidate the true association.

Strengths and Limitations

The biggest limitation of this study is in the design. The ecological design was appropriate for this study because of the novelty of the research question, and because the CO EnviroScreen component and indicator scores are at the group, not the individual level. In addition, the goal of this study was to examine association, rather than causation. However, this design potentially leads to the ecological fallacy, which, in this context means that drawing conclusions about individual-level relationships based solely on county-level data may lead to inaccurate assumptions about the

outcomes for individuals within those counties. This leads to issues with generalizability, as well as interpretation on the individual level. We attempted to overcome these limitations by adjusting for appropriate covariates and performing robust sensitivity analyses.

In the statistical model, a linear relationship between all component scores and outcome was not found, however, observations were independent, they demonstrated homogeneity of variance, normality of residuals, and little multicollinearity. A limitation was that while demographics and sensitive populations scores demonstrated a linear relationship with mortality, environmental exposures, climate vulnerability, and environmental effects scores did not. Mortality data was non-normally distributed and the modeled data demonstrated heteroskedasticity, which was why a quasi-Poisson distribution of the outcome was selected. There was moderate correlation between the component scores, which makes it challenging to assess the individual effects of exposures on the outcome. This effect was somewhat mitigated by the removal of the most highly correlated scores from the full model.

Further limitations include unmeasured confounding and potential information bias of the exposure. Unmeasured confounding could be due to other variables that were not in the health risk behaviors covariate data set that were important and associated with both the exposure and outcome. There could be residual confounding due to measurement error in the EnviroScreen indicator scores or in measurement of the covariates. It is possible there could be bias introduced when controlling for health risk behavior covariates with demographics score as the exposure variable, as these covariates are most likely in the causal pathway between demographics and mortality.

An additional limitation is that some environmental exposures, climate impacts, health outcomes, and demographic factors were not included in EnviroScreen because of the lack of

reliable data sources (*Colorado EnviroScreen, 2022*). In the future, merging a data set with these missing factors to the CO EnviroScreen data set would be a way to overcome this limitation. The indicators used in CO EnviroScreen were often secondary data that was compiled from different years, which makes comparing data sets difficult (*EnviroScreen v1.0 Technical Documentation, n.d.*). A way to address this limitation in the future is to aggregate mortality and other outcome data over several years, to give a more accurate picture of the true association.

Not all data was available at the same geographical scale, with some reported at the county level, and others at the census tract or census block group level (*EnviroScreen v1.0 Technical Documentation, n.d.*). To account for this spatial variability, we used data at the county level to coincide with outcome and covariate data due to data availability. Spatial autocorrelation is a potential issue for this study, in that we would be concerned that exposure is occurring in a county other than the county of residence. However, we would be more worried about spatial autocorrelation at a smaller scale than county-level, as census block groups and census tracts tend to be more similar to each other than individual Colorado counties. In this case, we are unable to change the county boundaries and sources of pollution, therefore spatial autocorrelation is less concerning. The Modifiable Area Unit Problem (MAUP) can affect statistical relationships and lead to different results depending on how the data are aggregated into geographic units (Keeler & Emch, 2017). In this study there was a choice of scales for the exposure variables, however, due to data availability only at the county level for the outcome and covariates, MAUP is not an issue.

Strengths of this study include the readily obtainable data, easily interpretable findings, and the utilization of publicly available data sources. Additionally, robust sensitivity analyses contribute to the findings by showing similar results. Mortality as the outcome is a strength because, unlike other disease outcomes, mortality is a specific health endpoint that precludes

further disease risk. CO EnviroScreen has several strengths, in that it was generated with community input to be accessible to users, and is already in revision for the next version (*Colorado EnviroScreen, 2022*).

Public Health Implications and Recommendations

Knowing where disparities exist is the first step to creating public health programs that are targeted at the right population. The public health importance of this data set is that CO EnviroScreen demonstrates geographic disparities, which allows us to know where resources can be allocated to apply meaningful and focused interventions. This is important for health equity because disproportionately impacted communities also often experience cumulative impacts, and do not have access to healthcare and health information that more privileged areas do. CO EnviroScreen allows us to visualize these cumulative impacts, and therefore create more tailored and specific population-level solutions. It is important to associate the CO EnviroScreen index with health outcomes because, in this case, it shows that communities experiencing cumulative impacts based on this measure may have higher rates of mortality. This study has validated the use of CO EnviroScreen as a predictor of mortality at the county level and shows that this tool has potential for use in other health outcomes such as heart disease, diabetes, asthma, and other diseases that are more prevalent in areas that experience health inequities.

The findings from this ecological study should be taken as exploratory and require additional confirmatory research. While assumptions about causation cannot be drawn, this study is useful in showing a novel association between CO EnviroScreen component scores and mortality. In the future, it would be helpful to increase the quality of data collected to create the EnviroScreen score, as well as create versions of the tool associated with individual years of CO data, to align the data set more with other potential data, and track changes in health over time.

Recommendations for next steps include further observational studies, such as a cross-sectional study at the individual level linking people in disproportionately impacted communities identified by CO EnviroScreen score with the outcome of mortality. This will give more information on the individual level that an ecological analysis is unable to.

Environmental exposures can have profound and enduring impacts on health disparities, and exacerbate existing inequities and perpetuate adverse health outcomes over the long term. Future research could use the cumulative impacts capabilities of CO EnviroScreen to examine how social determinants intersect with environmental exposures to shape health outcomes. Moreover, as climate change continues to worsen the effects environmental hazards and disproportionately impact vulnerable communities, research should also focus on anticipating and addressing the evolving health risks associated with changing environmental conditions. This includes using CO EnviroScreen to study the potential health impacts of extreme weather events, air and water pollution, as well as developing adaptive strategies and resilience-building interventions to mitigate these risks.

To effectively translate research findings into actionable policy and practice, it is imperative to foster partnerships between researchers, government agencies, non-profit organizations, and community-based groups to co-create solutions that address the root cause of environmental injustices and promote health equity. Strategies for engagement may include convening stakeholder meetings and workshops to facilitate knowledge exchange and collaboration, conducting community-based participatory research to ensure that research priorities and methodologies are aligned with community needs and priorities. Efforts to implement findings should be guided by principles of equity, transparency, and accountability, and ensure that interventions are targeted toward the most affected communities.

While this study focuses on environmental justice issues within Colorado, the findings and methodologies can offer valuable insights for addressing similar challenges in other regions. By comparing and contrasting the CO EnviroScreen tool with similar EJ tools used in other states, researchers can identify common patterns and trends, as well as unique contextual factors that may influence the effectiveness and applicability of these tools in different settings. Furthermore, multi-state collaborations and knowledge-sharing initiatives can facilitate the transferability of best practices and lessons learned. This would enable policymakers and practitioners to adapt and customize strategies to suit local contexts and priorities. This may involve conducting comparative analysis of EJ policies and interventions across different regions, synthesizing evidence from multiple studies to identify effective approaches, as well as developing toolkits and guidelines for implementing EJ initiatives in diverse settings.

Conclusion

This study found that CO EnviroScreen score may be associated with an increase in all-cause mortality rate at the county level in Colorado in 2019. Environmental exposures score was the only component score that represented this association when adjusted for health and behavioral covariates. This study offers a first look at how aggregate environmental and health-related scores from CO EnviroScreen are associated with health outcomes such as mortality.

REFERENCES

- Akwa, L. G., Smith, L., Twiddy, M., Abt, G., Garnett, C., Oldham, M., Shahab, L., & Herbec, A. (2023). Associations between physical activity, sedentary behaviour, and alcohol consumption among UK adults: Findings from the Health Behaviours during the COVID-19 pandemic (HEBECO) study. *PLOS ONE*, *18*(10), e0287199. <https://doi.org/10.1371/journal.pone.0287199>
- Alcala, E., Brown, P., Capitman, J. A., Gonzalez, M., & Cisneros, R. (2019). Cumulative Impact of Environmental Pollution and Population Vulnerability on Pediatric Asthma Hospitalizations: A Multilevel Analysis of CalEnviroScreen. *International Journal of Environmental Research and Public Health*, *16*(15), 2683. <https://doi.org/10.3390/ijerph16152683>
- August, L. (2021, September 20). *CalEnviroScreen 4.0* [Text]. OEHHA. <https://oehha.ca.gov/calenviroscreen/report/calenviroscreen-40>
- Belova, A., Gould, C. A., Munson, K., Howell, M., Trevisan, C., Obradovich, N., & Martinich, J. (2022). Projecting the Suicide Burden of Climate Change in the United States. *GeoHealth*, *6*(5), e2021GH000580. <https://doi.org/10.1029/2021GH000580>
- Colorado EnviroScreen*. (2022). Retrieved February 1, 2024, from https://teeo-cdphe.shinyapps.io/COEnviroScreen_English/
- Demateis, D., Keller, K. P., Rojas-Rueda, D., Kioumourtoglou, M.-A., & Wilson, A. (2023). Penalized distributed lag interaction model: Air pollution, birth weight, and neighborhood vulnerability. *Environmetrics*, *n/a*(*n/a*), e2843. <https://doi.org/10.1002/env.2843>

Environmental Justice Disproportionate Impacted Community, HB21-1266, Colorado General Assembly 2021 Regular Session.

EnviroScreen v1.0 Technical Documentation. (n.d.). Google Docs. Retrieved February 1, 2024, from https://drive.google.com/file/d/1aZfZnLeEPxvpFBILOFGpYGKlQbDxhMMF/view?usp=sharing&usp=embed_facebook

Hendryx, M., & Luo, J. (2020). COVID-19 prevalence and fatality rates in association with air pollution emission concentrations and emission sources. *Environmental Pollution (Barking, Essex : 1987)*, 265, 115126. <https://doi.org/10.1016/j.envpol.2020.115126>

Keeler, C., & Emch, M. (2017). Geographic Information Systems (GIS) in Public Health. In S. R. Quah (Ed.), *International Encyclopedia of Public Health (Second Edition)* (pp. 253–255). Academic Press. <https://doi.org/10.1016/B978-0-12-803678-5.00174-0>

Niu, Z., Habre, R., Chavez, T. A., Yang, T., Grubbs, B. H., Eckel, S. P., Berhane, K., Toledo-Corral, C. M., Johnston, J., Dunton, G. F., Lerner, D., Al-Marayati, L., Lurmann, F., Pavlovic, N., Farzan, S. F., Bastain, T. M., & Breton, C. V. (2022). Association Between Ambient Air Pollution and Birth Weight by Maternal Individual- and Neighborhood-Level Stressors. *JAMA Network Open*, 5(10), e2238174. <https://doi.org/10.1001/jamanetworkopen.2022.38174>

PLACES: Local Data for Better Health: Compare Counties | CDC. (n.d.). Retrieved February 1, 2024, from <https://places.cdc.gov/?view=county>

R: The R Project for Statistical Computing. (n.d.). Retrieved March 21, 2024, from <https://www.r-project.org/>

Social Epidemiology. (2014). Oxford University Press.

<https://doi.org/10.1093/med/9780195377903.001.0001>

Solomon, G. M., Morello-Frosch, R., Zeise, L., & Faust, J. B. (2016). Cumulative Environmental Impacts: Science and Policy to Protect Communities. *Annual Review of Public Health*, 37(1), 83–96. <https://doi.org/10.1146/annurev-publhealth-032315-021807>

Spearman correlation coefficient—OpenTURNS 1.22 documentation. (n.d.). Retrieved February 1, 2024, from

https://openturns.github.io/openturns/latest/theory/data_analysis/spearman_coefficient.html

Tulve, N. S., Geller, A. M., Hagerthey, S., Julius, S. H., Lavoie, E. T., Mazur, S. L., Paul, S. J., & Frey, H. C. (2024). Challenges and opportunities for research supporting cumulative impact assessments at the United States environmental protection agency’s office of research and development. *The Lancet Regional Health - Americas*, 30, 100666.

<https://doi.org/10.1016/j.lana.2023.100666>

US EPA, O. (2014, November 3). *Environmental Justice* [Collections and Lists].

<https://www.epa.gov/environmentaljustice>

US EPA, O. (2015, April 15). *Environmental Justice Timeline* [Collections and Lists].

<https://www.epa.gov/environmentaljustice/environmental-justice-timeline>

US EPA, O. (2022, October 11). *EPA Researchers Release Cumulative Impacts Report*,

Prioritizing Environmental Justice in New Research Cycle [Overviews and Factsheets].

<https://www.epa.gov/sciencematters/epa-researchers-release-cumulative-impacts-report-prioritizing-environmental-justice>

APPENDICES

Sensitivity Analyses

Sensitivity analyses were performed, which involved obtaining 2019, county-level suicide data from the same data request to CDPHE on 8 November 2023. 13 counties had missing values for the suicide data, and eight counties reported zero suicides for 2019. Suicide data was explored due to interest in the association between climate, environmental, and social exposures and suicide at a population level.

Information on rural and urban classification of counties was obtained for sensitivity analysis from the Colorado Rural Health Center. This source identified 17 urban counties, and 24 and 23 rural and frontier counties, respectively. Rural and frontier counties were merged into the same dataset as rural counties, which is defined as a population of less than 2,500 people. Rural versus urban analysis was performed because it was suspected that climate vulnerability would play more of a role in rural counties and that environmental exposures would be more important in urban counties.

Another data set was created with all the county data on all-cause mortality, covariates, and EnviroScreen component scores, but without Mineral County. Mineral County by far had the highest mortality rate in 2019, and we wanted to ascertain how large the magnitude of change in the results was without Mineral included. A fourth sensitivity analysis was performed using the environmental effects component score percentile instead of the climate vulnerability score percentile, due to the theory that climate vulnerability was more important to mortality than environmental effects. People are more likely to be directly exposed to drought, flood, heat, and

wildfires (included in Climate Vulnerability score) than factors included in environmental effects (mining, oil and gas, superfund sites, etc.).

Table S1: Individual Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10% increase in component score (n = 64)			
Component Scores	Rate Ratio	95% CI	P-value
Demographics	1.00	0.96, 1.04	0.91
Environmental Exposures	1.02	1.00, 1.04	0.05
Climate Vulnerability	1.00	0.98, 1.02	0.85
<i>All-cause mortality regressed on each of the three component scores in three different models. Covariates were included in each of the three models. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.</i>			

Table S2: Crude Association: Mortality and EnviroScreen Component Scores, County Level, per 10% increase in component score, excluding Mineral County (n = 63)

Component Scores	Rate Ratio	95% CI	P-value
<i>EnviroScreen Total</i>	1.06	1.05, 1.08	<0.01
Demographics	1.05	1.03, 1.07	<0.01
Environmental Effects	0.99	0.97, 1.02	0.64
Environmental Exposures	1.04	1.02, 1.06	<0.01
Climate Vulnerability	0.98	0.95, 1.00	0.03
Sensitive Populations	1.07	1.05, 1.08	<0.01

All-cause mortality regressed on each component score individually, as well as the EnviroScreen total score. No covariates were included in any of the six models.

Table S4: Adjusted Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10% increase in component score, excluding Mineral (n = 63)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	0.99	0.96, 1.02	0.68
Environmental Exposures	1.04	1.02, 1.06	<0.01
Climate Vulnerability	1.01	0.99, 1.03	0.19

All-cause mortality regressed on three component scores. Covariates were included in the model. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S3: Individual Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10% increase in component score, excluding Mineral (n = 63)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	1.01	0.97, 1.04	0.71
Environmental Exposures	1.03	1.02, 1.05	<0.01
Climate Vulnerability	1.00	0.98, 1.02	0.73

All-cause mortality regressed on each of the three component scores in three different models. Covariates were included in each of the three models. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S5: Crude Urban Association: Mortality and EnviroScreen Component Scores, County Level, per 10 percentile increase in component score (n = 17)

Component Scores	Rate Ratio	95% CI	P-value
<i>EnviroScreen Total</i>	1.04	1.02, 1.06	<0.01
Demographics	1.04	1.02, 1.06	<0.01
Environmental Effects	1.06	1.03, 1.10	<0.01
Environmental Exposures	1.04	1.01, 1.06	0.02
Climate Vulnerability	0.99	0.95, 1.03	0.56
Sensitive Populations	1.03	1.00, 1.06	0.06

All-cause mortality regressed on each component score individually, as well as the EnviroScreen total score. No covariates were included in any of the six models.

Table S6: Individual Urban Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 17)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	1.03	0.99, 1.07	0.13
Environmental Exposures	1.02	1.00, 1.05	0.07
Climate Vulnerability	1.01	0.97, 1.05	0.58

All-cause mortality regressed on each the three component scores in three different models. Covariates were included in each of the three models. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S7: Adjusted Urban Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 17)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	1.01	0.95, 1.07	0.82
Environmental Exposures	1.02	0.98, 1.06	0.37
Climate Vulnerability	1.01	0.97, 1.05	0.67

All-cause mortality regressed on three component scores. Covariates were included in the model. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S8: Crude Rural Association: Mortality and EnviroScreen Component Scores, County Level, per 10 percentile increase in component score (n = 47)

Component Scores	Rate Ratio	95% CI	P-value
<i>EnviroScreen Total</i>	1.06	1.03, 1.09	<0.01
Demographics	1.04	1.01, 1.07	0.01
Environmental Effects	0.98	0.94, 1.01	0.15
Environmental Exposures	1.04	1.01, 1.08	0.02
Climate Vulnerability	0.98	0.95, 1.01	0.15
Sensitive Populations	1.07	1.04, 1.09	<0.01

All-cause mortality regressed on each component score individually, as well as the EnviroScreen total score. No covariates were included in any of the six models.

Table S9: Individual Rural Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 47)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	0.99	0.94, 1.04	0.66
Environmental Exposures	1.02	0.99, 1.06	0.17
Climate Vulnerability	1.01	0.98, 1.04	0.61

All-cause mortality regressed on each of the three component scores in three different models. Covariates were included in each of the three models. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S10: Adjusted Rural Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 47)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	0.98	0.93, 1.04	0.57
Environmental Exposures	1.03	0.99, 1.07	0.11
Climate Vulnerability	1.02	0.99, 1.05	0.28

All-cause mortality regressed on three component scores. Covariates were included in the model. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S11: Crude Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 64)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	1.04	1.02, 1.07	<0.01
Environmental Effects	0.99	0.97, 1.01	0.31
Environmental Exposures	1.03	1.01, 1.05	0.02

All-cause mortality regressed on each of the three component scores in three different models. Covariates were included in each of the three models. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S12: Adjusted Association: Mortality and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 64)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	1.00	0.96, 1.04	0.85
Environmental Effects	0.99	0.96, 1.01	0.26
Environmental Exposures	1.03	1.01, 1.06	0.02

All-cause mortality regressed on three component scores. Covariates were included in the model. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S13: Crude Association: Suicide and EnviroScreen Component Scores, County Level, per 10 percentile increase in component score (n = 51)

Component Scores	Rate Ratio	95% CI	P-value
<i>EnviroScreen Total</i>	1.06	0.98, 1.14	0.17
Demographics	1.05	0.98, 1.14	0.19
Environmental Effects	0.98	0.91, 1.06	0.65
Environmental Exposures	0.95	0.89, 1.02	0.19
Climate Vulnerability	1.08	1.01, 1.18	0.04
Sensitive Populations	1.06	0.99, 1.14	0.10

All-cause mortality regressed on each component score individually, as well as the EnviroScreen total score. No covariates were included in any of the six models.

Table S14: Individual Association: Suicide and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 51)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	0.92	0.79, 1.08	0.32
Environmental Exposures	0.93	0.87, 1.00	0.07
Climate Vulnerability	1.12	1.03, 1.21	0.01

All-cause mortality regressed on each of the three component scores in three different models. Covariates were included in each of the three models. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Table S15: Adjusted Association: Suicide and EnviroScreen Component Scores and covariates, County Level, per 10 percentile increase in component score (n = 51)

Component Scores	Rate Ratio	95% CI	P-value
Demographics	0.91	0.79, 1.06	0.25
Environmental Exposures	0.99	0.91, 1.08	0.83
Climate Vulnerability	1.12	1.02, 1.22	0.02

All-cause mortality regressed on three component scores. Covariates were included in the model. Covariates are insufficient sleep, alcohol overconsumption, physical inactivity, and smoking.

Natural Splines

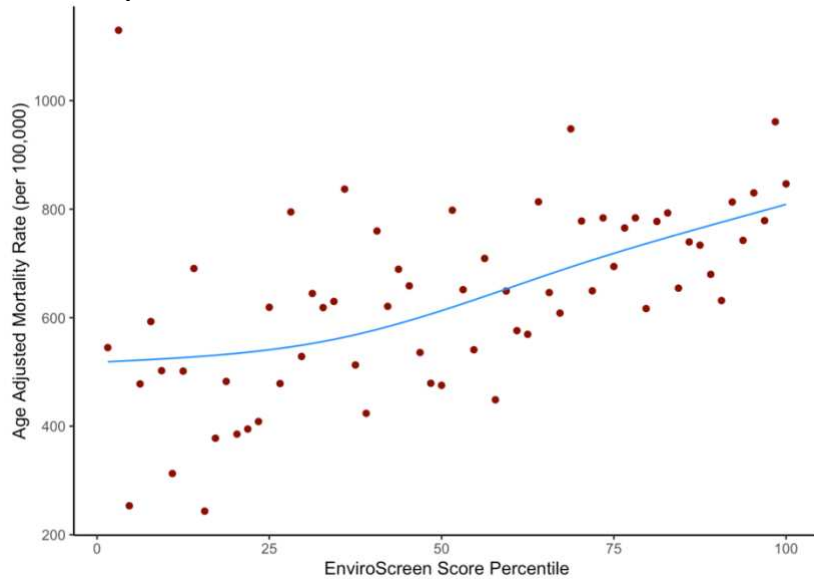


Figure S1

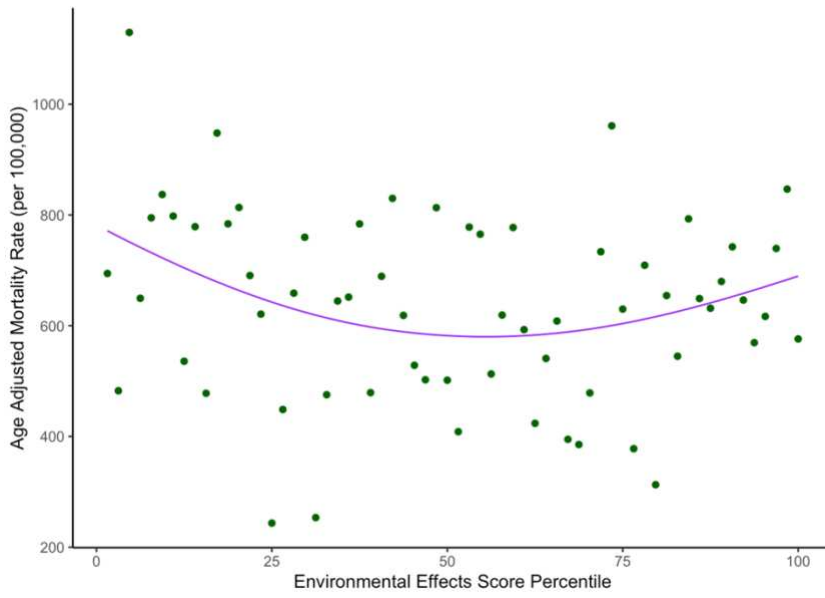


Figure S2

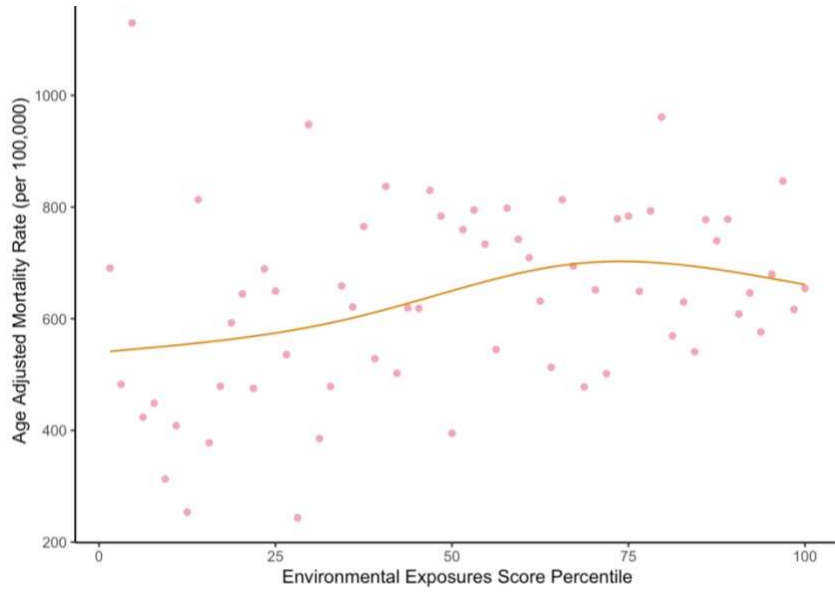


Figure S3

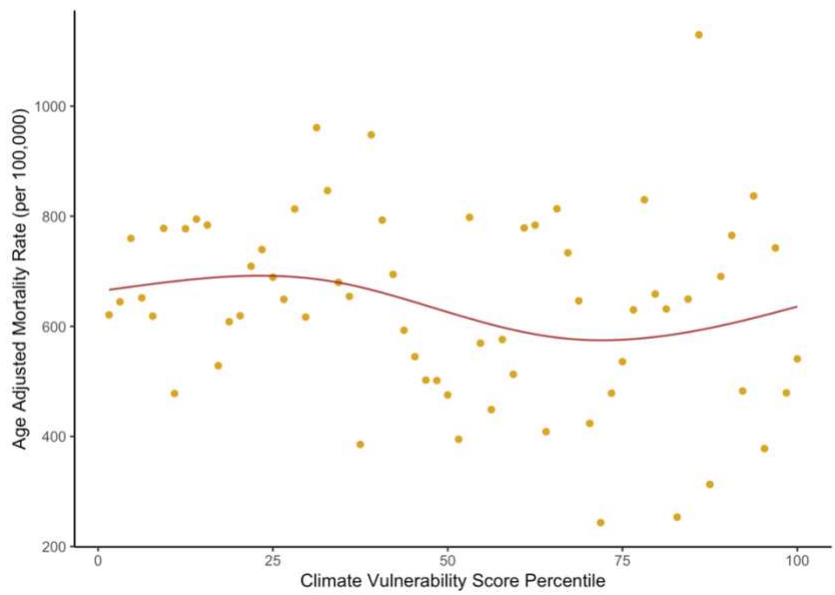


Figure S4

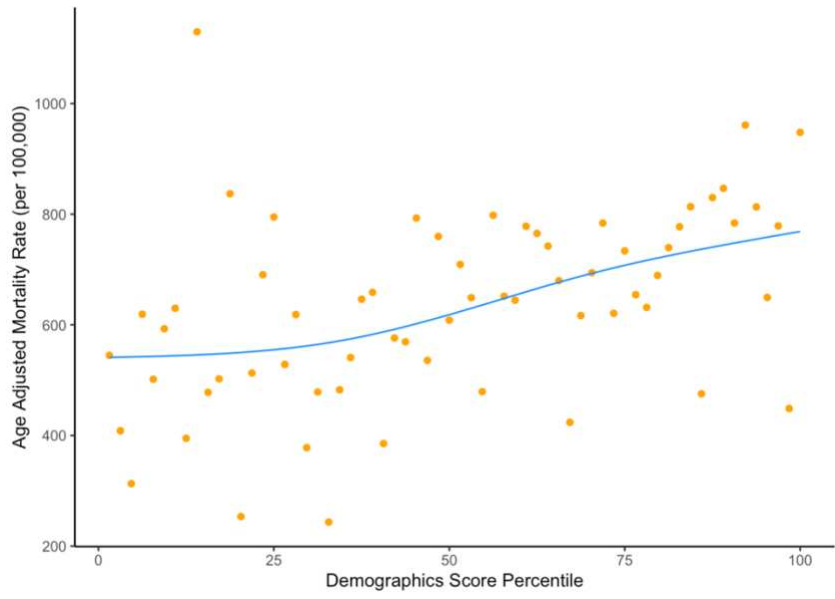


Figure S5

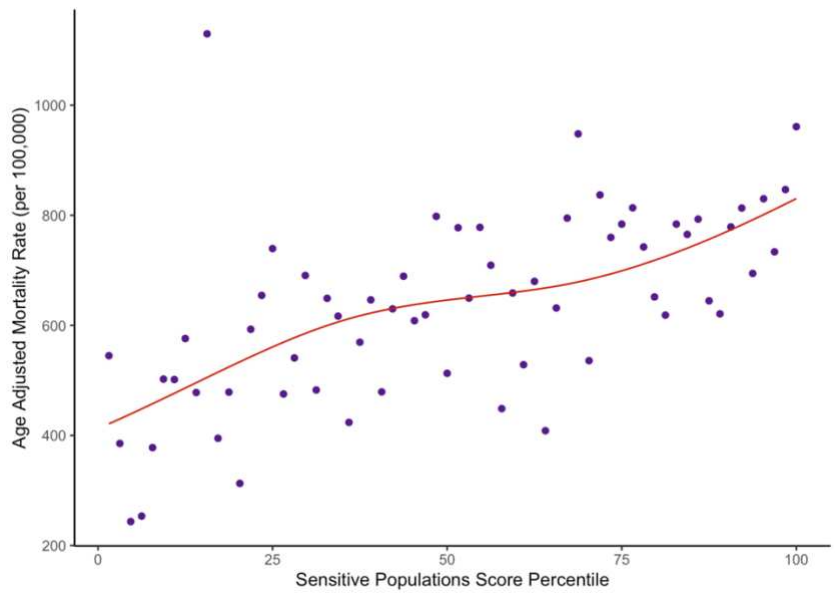


Figure S6

Glossary

Age-Standardized All-Cause Mortality: Refers to the number of deaths from all causes in a population, adjusted for differences in age between population. This allows for a comparison of mortality rates between different groups of people

Census Block Group/Tract: Small geographic areas used by the United States Census Bureau for reporting data. Smaller than county level and provide more granular information

CO EnviroScreen: A tool used by CO to assess EJ developed by CSU and CDPHE

Correlation: Statistical measure of the strength and direction of association between variables

Component Scores: Individual scores representing different aspects of EJ within a community. Includes sensitive populations, demographics, environmental exposures, environmental effects, and climate vulnerability

Covariates: Factors other than the main exposure of interest that may influence the outcome being studied, such as demographic characteristics or health behaviors

Cross-sectional Study: Study design that examines a population at a single point in time, and provides a snapshot of associations between variables without follow-up over time

Ecological Fallacy: Logical error that occurs when conclusions about individuals are drawn from group-level data, potentially leading to incorrect assumptions about individual-level relationships

Ecological Study: Study design that looks at groups of people rather than individuals. In this context, it means looking at data from entire counties rather than individual people in those counties

Generalized Linear Model: Statistical method used to understand the relationship between different variables. It is a tool that helps understand if one thing (EnviroScreen score) is connected to another thing (all-cause mortality rates)

Modifiable Area Unit Problem (MAUP): Challenge in spatial analysis where results may vary depending on how geographic data is aggregated into units, potentially influencing the interpretation of relationships between variables

Natural Splines: Statistical method used to model complex relationships between variables by fitting smooth curves, often used to analyze non-linear associations in data. Degrees of freedom selection for a spline involves finding the balance between flexibility and stability to accurately fit data

Percentile: Where a particular score falls compared to others

Quasi-Poisson Method: Statistical approach used to analyze count data with overdispersion, allows for variability in the data that exceeds what would be expected from a Poisson distribution

Rate Ratio: Measure of association in epidemiology that compares the rate of an event between two groups, used to assess the impact of exposures or interventions on outcomes

Sensitivity Analyses: Additional analyses conducted to assess the robustness of study findings by testing the influence of different assumptions or methods on the results

Spatial Autocorrelation: Tendency for values of a variable to be correlated with values of the same variable in nearby geographic locations, which can affect statistical analyses in spatial data

Spearman Correlation: Statistical measure used to assess the strength and direction of association between two ranked variables, without assuming a specific data distribution