Does Environmental Quality Influence Where People Live?

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Contents

1 Background

The Environmental Quality Index (EQI), developed by the U.S. Environmental Protection Agency (EPA) provides a county level snapshop of environmental conditions throughout the country. EPA first released EQIs for the period 2000-2005 and updated these indexes for 2006-2010. This statistical evaluation focuses on the 2006-2010 EQI. The purpose of the EQI is to use (1) as an indicator of ambient conditions/exposure in environmental health and modeling and (2) as a covariate to adjust for ambient conditions in environmental models (EPA 2020). Previous studies have used the EQI to evaluate relationships between environmental quality and public health outcomes such as cancer incidence, asthma, obesity, and infant mortality.

The EQI is developed from five domains each with identified environmental constructs as shown in Table 1. Each county has an overall environmental index and a domain specific index. Indexes were also stratified by rural-urban continuum codes (RUCCs) for counties classified as metropolitan urbanized, non-metro urbanized, less urbanized, and thinly populated.

Table 1: EQI Environmental Domains and Constructs

Domain	Constructs
air	criteria air pollutants and hazardous air pollutants
water	overall water quality, general water contamination, domestic use, atmospheric deposition, drought, chemical contamination, and drinking water quality
land	agriculture, pesticides, facilities, radon, and mining activity
built	roads, highway/road safety, commuting behavior, housing environment, walkability, and green space
sociodemographic	crime, socioeconomic, political character, and creative class representation

1.1 Limitations

While the EQI can identify counties with higher environmental burdens, it may not identify environmental injustices at the community level. The EQI cannot quantify environmental exposure for individuals and reflects only outside environmental conditions, not indoor conditions. The EQI can be used to identify locations for future research, but is not intended for regulatory purposes or as a diagnostics tool. Due to changes in methodology and datasets, the 2000-2005 and 2006-2010 EQIs should not be directly compared.

2 The Data

2.1 Environmental Quality Index

To develop the Environmental Quality Index (EQI), variables were identified from available data to represent each environmental domain and assessed for collinearity so redundant variables could be excluded. Variables were standardized based on geographic space or on a per capita rate, as appropriate and transformations such as log-transformations were performed as needed based on the normality of each variable. Data gaps were evaluated to distinguish between missing data and meaningful zeros. Where applicable, spatial kriging was used to interpolate values when data was not available for all counties. Principal component analysis was used to aggregate variables into domain specific indexes. The domain indexes were then aggregated into overall indexes for each county. A result of this method is that each domain does not equally influence the overall EQI value for a given county. The EQI is developed to be normally distributed with mean=0 and standard deviation=1. **Higher EQI values correspond with worse environmental quality. Lower (more negative) EQI values correspond with better environmental quality.**

2.2 Census Population Data

County level population data was obtained from the U.S. Census Bureau's county intercensal datasets for 2000-2010. Percent population change was calculated for 2006-2010 then winsorized to remove outliers above the 99.9th percentile (ie. counties with population change above 28.5%).

2.3 Data Cleaning and Tidying

The dataset `fips_codes` is built into the `tidycensus` package and includes FIPS (Federal Information Processing Standard) codes for US states and counties. These codes were used for cleaning and joining the EQI and census data.

```r
fips_codes <- data.frame(fips_codes) %>%
  rename(county_name = county) %>%
  mutate(stfips = paste0(state_code, county_code))
```

2.3.1 Read in and clean Environmental Quality Index data

```r
eqi <- read_csv(here("data", "eqi_data", "Eqi_results_2013JULY22.csv")) %>%
  # select columns of interest
  select(stfips, county_name, state, cat_rucc, EQI_22July2013, air_EQI_22July2013,
         water_EQI_22July2013, land_EQI_22July2013, built_EQI_22July2013,
         sociod_EQI_22July2013) %>%
  # extract county code from full state+county code
  mutate(county_code = str_sub(stfips, -3)) %>%
  # convert rural-urban continuum codes into binary category for future analysis of
  # urban vs. rural conditions
  mutate(rucc_text = case_when(
    cat_rucc %in% c(1, 2) ~ "urban",
    cat_rucc %in% c(3, 4) ~ "rural")) %>%
  mutate(cat_rucc = as.factor(cat_rucc)) %>%
  # join fips_code data to eqi data for use in later merge with census data
  left_join(fips_codes, by = c("state", "county_code")) %>%
  # remove duplicate columns
  select(stfips.y, state_code, county_code, state_name, state, county_name.x,
         county_name.y, cat_rucc, rucc_text, EQI_22July2013, air_EQI_22July2013,
         water_EQI_22July2013, land_EQI_22July2013, built_EQI_22July2013,
         sociod_EQI_22July2013) %>%
  rename(stfips = stfips.y)
```

2.3.2 Read in county level census population data

The raw data included a csv file for each state that contained inter-census estimates of the residential population for all counties in that state from April 1, 2000 to July 1, 2010. The function below was used to read all 50 files and bind them into a single dataframe.

```r
# list of fips codes corresponding to each state
codes <- c("01", "02", "04", "05", "06", "08", "09", "10", "11", "12", "13", "15",
           "16", "17", "18", "19", "20", "21", "22", "23", "24", "25", "26", "27",
           "28", "29", "30", "31", "32", "33", "34", "35", "36", "37", "38", "39",
           "40", "41", "42", "44", "45", "46", "47", "48", "49", "50", "51", "53",
           "54", "55", "56")

# column names to use for state_pop_fun.R
header <- c("county_name", "april_1_2000", "2000", "2001", "2002", "2003", "2004",
            "2005", "2006", "2007", "2008", "2009", "april_1_2010", "july_1_2010")
```

```r
# Function to read in data files of census population data for each individual state and
# bind them into a single dataframe
source(here("src", "state_pop_fun.R"))
county_pop = data.frame()
```

```
for (i in seq_along(codes)) {
state <- state_pop_fun(fips = codes[i])
state_df <- data.frame(state)
county_pop <- rbind(county_pop, state_df)
}

county_pop <- county_pop %>%
  # join fips_code data to census data for use in merge with eqi data
  left_join(fips_codes, by = c("county_name", "state_code")) %>%
  # calculate percent population change
  mutate(pop_change_pct = ((july_1_2010 - X2006) / X2006) * 100) %>%
  # create variable to indicate counties with positive and negative population change
  mutate(pop_change_text = case_when(
    pop_change_pct > 0 ~ "positive",
    pop_change_pct <= 0 ~ "negative"))
```

2.3.3 Join EQI and Census Population Data

The environmental quality index data and county population data were joined based on the common `stfips` field.

```
eqi_pop_with_outliers <- left_join(eqi, county_pop, by = c("stfips")) %>%
  select(-april_1_2000, -X2000, -X2001, -X2002, -X2003, -X2004, -X2005, -X2007, -X2008,
         -X2009, -july_1_2010, -april_1_2010, -county_name.y, -county_name,
         -state_code.y, -county_code.y, -state.y, -state_name.y) %>%
  filter(!X2006 == "null") %>%
  # give column names more concise names
  rename(EQI = EQI_22July2013) %>% # overall environmental quality index
  rename(air_EQI = air_EQI_22July2013) %>%
  rename(water_EQI = water_EQI_22July2013) %>%
  rename(land_EQI = land_EQI_22July2013) %>%
  rename(built_EQI = built_EQI_22July2013) %>%
  rename(sociodemographic_EQI = sociod_EQI_22July2013) %>%
  rename(state_code = state_code.x) %>%
  rename(state_name = state_name.x) %>%
  rename(state = state.x) %>%
  rename(county_name = county_name.x) %>%
  rename(county_code = county_code.x) %>%
  select(-X2006)

# remove outlier counties with population change above the 99.9th percentile
quantile_999th <- quantile(eqi_pop_with_outliers$pop_change_pct, 0.999)

eqi_pop <- eqi_pop_with_outliers %>%
  mutate(pop_change_pct = case_when(pop_change_pct < quantile_999th ~ pop_change_pct,
                                    pop_change_pct >= quantile_999th ~ quantile_999th))
```

3 Statistical Analysis

The summary statistics in Table 2 suggest that population growth is correlated with worse environmental characteristics. Kalawao County, Hawaii had the lowest EQI value (highest environmental quality) and

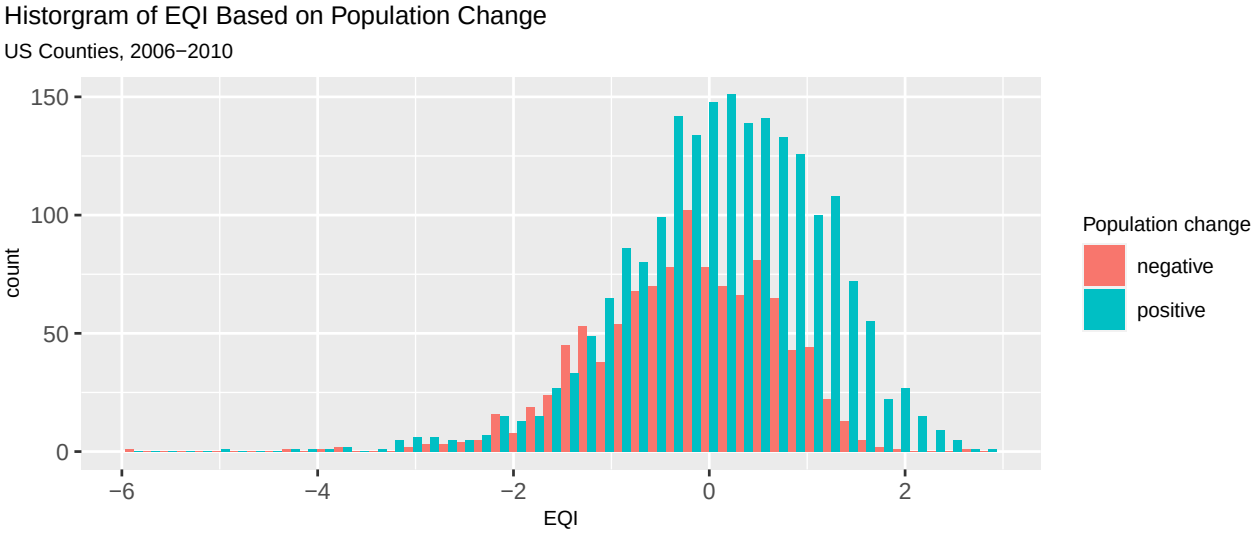
greatest decrease in population (-17.4%). Falls Church, Virginia had the highest EQI (lowest environmental quality) and a population change of 15.4% which falls is the 99th percentile.

Table 2: EQI summary statistics for counties based on population change between 2006 and 2010

Population Change	Min	Max	Mean	Standard Deviation	Variance	Number of Counties
negative	-5.88	2.59	-0.24	0.93	0.87	1088
positive	-5.05	2.85	0.13	1.01	1.02	2052
all counties	**-5.88**	**2.85**	**0.00**	**1.00**	**1.00**	**3140**

3.1 Hypothesis Testing

A different means test was completed to determine if mean environmental quality was statistically different for counties that experienced positive vs. negative population change between 2006-2010. The figure below shows a histogram of EQI values for counties with negative and positive population change.



null hypothesis: There is no difference in mean EQI for counties with positive and negative population change.

$$H_0 : \mu_{posPopChange} - \mu_{negPopChange} = 0$$

alternative hypothesis: There is a difference in mean EQI for counties with positive and negative population change.

$$H_A : \mu_{posPopChange} - \mu_{negPopChange} \neq 0$$

$$\text{point estimate} = \mu_{posPopChange} - \mu_{negPopChange} = 0.131 - -0.245 = 0.376$$

The standard error for the difference in means is:

$$SE = \sqrt{\frac{s_1^2}{n_1} + \frac{s_2^2}{n_2}} = \sqrt{\frac{1.009^2}{2052} + \frac{0.933^2}{1088}} = 0.036$$

The z-score for hypothesis testing is:

$$z = \frac{\text{point estimate - null}}{SE} = \frac{0.376 - 0}{0.036} = 10.443$$

The p-value, the probability of getting a point estimate at least as extreme as calculated if the null hypothesis were true, is:

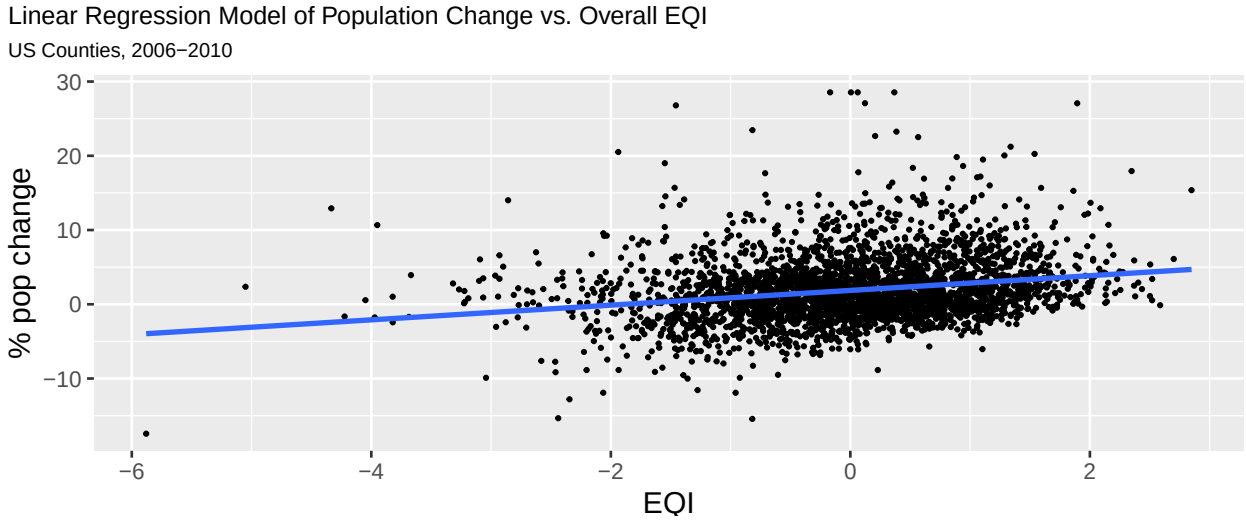
$$p\text{-value } = \Pr(Z < -|z| \text{ or } Z > |z|) = 2 * \Pr(Z > |z|) = 1.5809578 \times 10^{-25}$$

Since the p-value is < 0.001 we reject the null that there is no difference in EQI for counties with positive population change versus negative population change. There is a statistically significant difference (at the 0.1% significance level) in EQI across the two population change groups. The 95% confidence interval ranges from 0.31 to 0.45. This means that there is a 95% chance that this interval includes the true difference in mean EQI between counties with positive and negative percent population change.

3.2 Linear Regression

Linear regression was used to model the relationship between population change and environmental quality using the overall EQI value and each domain specific EQI to determine if a particular domain was a stronger predictor of population change.

$$\text{percent population change}_i = \beta_0 + \beta_1 \cdot EQI_i + \varepsilon_i$$



First, hypothesis testing was used to test whether the slope coefficient for the percent population change rate is equal to zero or not.

null hypothesis: The slope coefficient is equal to zero

$$H_0 : \beta_1 = 0$$

alternative hypothesis: The slope coefficient is **NOT** equal to zero

$$H_A : \beta_1 \neq 0$$

The point estimate, $\beta_1 = 0.991$ and the standard error, SE $= 0.077$.

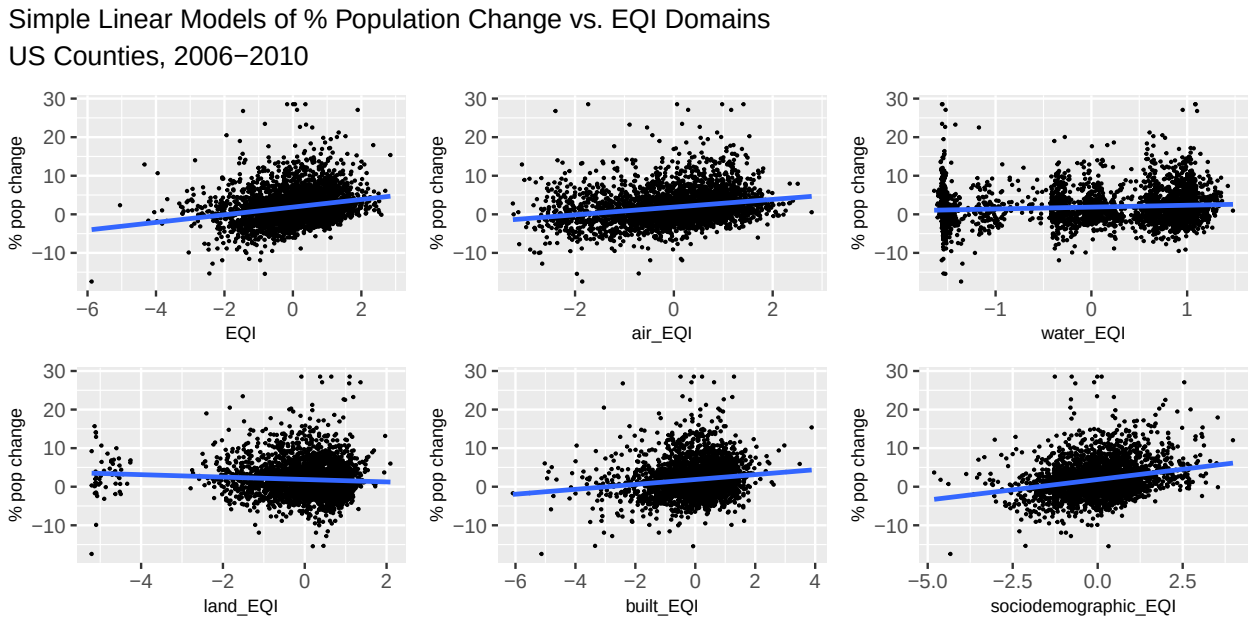
$$z = \frac{\text{point estimate - null}}{SE} = \frac{0.991 - 0}{0.077} = 12.817$$

$$p\text{-value } = \Pr(Z < -|z| \text{ or } Z > |z|) = 2 * \Pr(Z > |z|) = 1.0849376 \times 10^{-36}$$

Since the p-value for the slope coefficient was < 0.001, we reject the null hypothesis that EQI has no influence on population change at the 0.1% level. There is a statistically significant relationship between EQI and percent population change and the coefficient is significantly different from zero. Based on value of β_1, for each one unit increase in EQI, the percent population change increases by 0.991. The 95% confidence interval for the slope coefficient ranges from 0.84 to 1.143. This means that there is a 95% chance that this interval includes the true county level rate of change for percent population change for each one unit change in EQI.

3.2.1 Domain Specific Linear Models

$$\text{percent population change}_i = \beta_{0,domain} + \beta_{1,domain} \cdot EQI_{i,domain} + \varepsilon_i$$

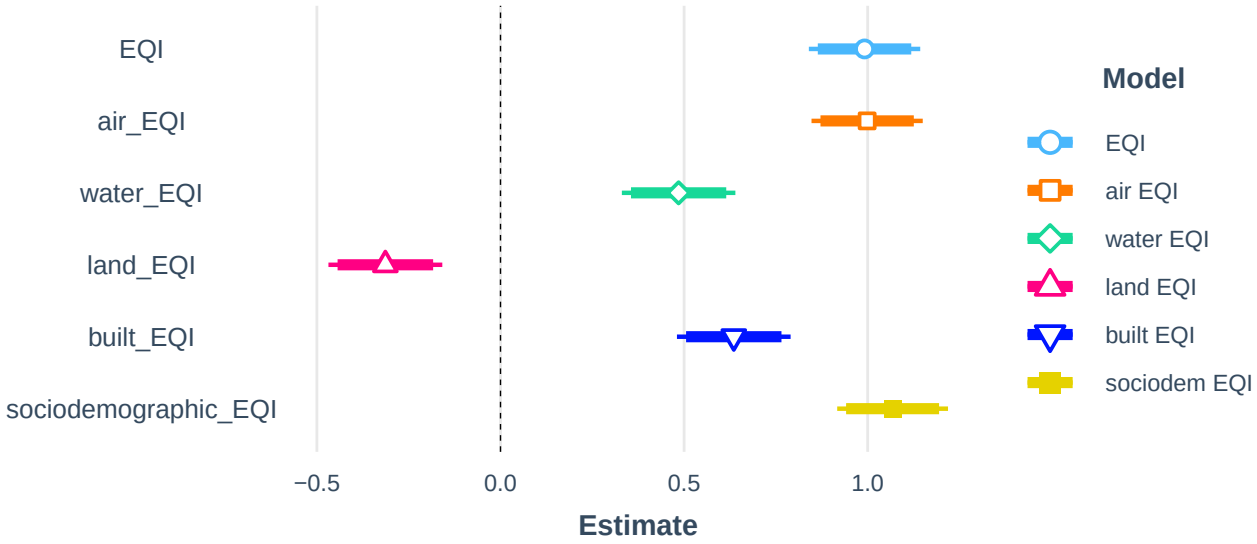


While a partly manual method was used above, statistical functions in R were used to test for the significance of domain models. Table 3 presents coefficients for each domain specific model. The numbers in [brackets] are the 95% confidence intervals for each estimated coefficient.

Table 3: Summary of EQI Domain Slope Coefficients

coefficient	overall EQI	air model	water model	land model	built model	sociodem model
Intercept	**1.868 *****	**1.869 *****	**1.868 *****	**1.868 *****	**1.867 *****	**1.868 *****
	[1.716, 2.019]	[1.717, 2.020]	[1.714, 2.023]	[1.713, 2.024]	[1.713, 2.021]	[1.718, 2.019]
EQI	**0.991 *****					
	[0.840, 1.143]					
air EQI		**0.998 *****				
		[0.847, 1.150]				
water EQI			**0.485 *****			
			[0.331, 0.640]			
land EQI				**-0.314 *****		
				[-0.469, -0.158]		
built EQI					**0.635 *****	
					[0.481, 0.790]	
sociodem EQI						**1.068 *****
						[0.917, 1.219]
n	3140	3140	3140	3140	3140	3140
R2	0.050	0.051	0.012	0.005	0.020	0.058

The figure below provides a visual comparison of each model result. The bold portion of the line represents the 90% confidence interval and the full line represents the 95% confidence interval for each estimate.



The p-value on the slope coefficient was < 0.001 for all domain specific linear models which indicates a statistically significant relationship at the 0.01% level. Based on the R^2 values and slope coefficients, the air and sociodemographic domains account for most of the overall relationship between population change and EQI. All domains except land are positively correlated with population change. Since higher EQI values indicate poorer environmental quality, these models show that population increased more in counties with worse environmental conditions. For a one unit increase in sociodemogrpahic EQI, the percent population change increases by 1.068. For a one unit increase in air EQI, the percent population change increases by 0.998. The R^2 terms represent the variance in percent population change that can be explained by EQI. For the overall EQI value, 5% of the variance in percent population change is explained by environmental conditions. The sociodemographic EQI explains 5.8% of the variance in population change while the air EQI explains 5.1%.

4 Conclusions

The identified relationships between population change and environmental quality are noteworthy for their public health and environmental justice implications. Positive population trends in areas with worse environmental conditions could result in increased incidences of cancer, asthma, obesity, and infant mortality. While this project did not evaluate economic variables, locations with higher environmental quality could also have higher living costs which drive people to move to more affordable places. If economic factors contribute to population growth in counties with poor environmental quality, then this could negatively affect the health of vulnerable populations and perpetuate social inequalities. Further analysis could evaluate trends in mean household income to determine if there is growing income inequality between counties with better and worse environmental quality. Economic variables and other factors influencing demographic shifts from rural areas to cities may be stronger predictors of population change than environmental quality.

Data availability:

EPA Datasets and files from the EQI county data from 2006-2010:
https://edg.epa.gov/data/public/ORD/CPHEA/

U.S. Census Bureau County Intercensal Tables: 2000-2010:
https://www.census.gov/data/tables/time-series/demo/popest/intercensal-2000-2010-counties.html

5 References

1. U.S. EPA. Environmental Quality Index - Technical Report (2006-2010) (Final, 2020). U.S. Environmental Protection Agency, Washington, DC, EPA/600/R-20/367, 2020.
2. U.S. Census Bureau. County Intercensal Datasets: 2000-2010. https://www.census.gov/data/datasets/time-series/demo/popest/intercensal-2000-2010-counties.html