HiLL PUBLISHING

OAJRC Environmental Science, 2022, 3(1), 30-35
https://www.hillpublisher.com/journals/oajrces/
ISSN Online: 2632-2331

Climate Change Impact on Health—Modelling Climate Change Impacts use R

Ronald Wang[1,*], Carly Wang[2]

[1]Indiana Area Senior High School, PA, 15701, USA.
[2]John Hopkins University, MD, 21218, USA.

How to cite this paper: Ronald Wang, Carly Wang. (2022) Climate Change Impact on Health—Modelling Climate Change Impacts use R. *OAJRC Environmental Science*, 3(1), 30-35.
DOI: 10.26855/oajrces.2022.12.004

Received: October 28, 2022
Accepted: November 25, 2022
Published: December 30, 2022

[*]**Corresponding author:** Ronald Wang, Indiana Area Senior High School, PA, 15701, USA.

Abstract

This research is to explore how the change in temperature, average temperature, and days of air pollution in several types affect the occurrences of Youth Asthma, Adult Asthma, and Lung Cancer. This study tried to figure out whether there was interaction among these variables and if any statistical models of climate change variables can explain occurrences of these diseases. Through the data analysis, the research result shown that high level of ozone, PM 2.5, and PM 10 did affect the occurrences of Adult and Youth Asthma in a statistically significant way. No variables in the model significantly affected the occurrences of Lung Cancer. The change in temperature and the average temperature is significantly affected on Youth and Adult Asthma, but the change in temperature does not affect Lung Cancer. The results of this study indicate there is strong correlation between O_3, PM 2.5, and PM 10 and Pediatric and Adult Asthma.

Keywords

Pediatric Asthma, Adult Asthma, Climate Change, Lung Cancer

1. Introduction

Climate change is an ongoing problem. The Greenhouse effect is one of its most known factors affecting our planet health. The Greenhouse gases stay in the atmosphere for a long time. The plants and oceans cannot absorb the enormous amounts of carbon dioxide, so it continually increases [1, 2]. This causes the average temperature to go up, which is harmful for many reasons. Heat waves have wreaked havoc in Europe [3-5]. With climate change causing the rise in average temperature, these may become more apparent.

The emissions of the gases from the U.S. commonly come from the uses of transportation, electricity, and industry: 29% came from transportation, 28% from electricity, and 22% from industry [6-8]. The emissions of transportation primarily come from burning fossil fuel for cars, trucks, trains, ships, and planes [9, 10]. These emissions may consist of ozone, carbon monoxide, nitrogen dioxide, sulfur dioxide, and lead [11-13].

These chemicals can cause damage to the human respiratory system. More than 4 in 10 Americans live in places with unhealthy air quality/pollution [14, 15]. Ozone pollution is a type of pollution that happens in warmer areas and is known to cause the “sunburn of the lung” [1, 16, 17]. This can cause more Americans to obtain asthma and shorten lives. Particle pollution is commonly found in places where wildfires, burning wood, or coal fired plants are frequent [18] [15]. Once these harmful particles enter the bloodstream and lungs, they can lead to cancer, heart attacks, strokes, asthma, and other complicated health problems [12] [19] [20]. For this research, this study was decided to focus on Asthma and Lung Cancer to see how they are affected by climate change related variables.

2. Methods

2.1 Study design

The U.S. Air quality Index (Airnow.gov) is a tool to check air quality. Data about 43 metropolitan areas of the United States was collected from the American Lung Association, Climate Central, and NOAA (NCEI) [21] [16]. State and national data was collected from NCEI "Climate at a Glance," and individual station data from the Applied Climate Information System. The temperature change data was retrieved from amazonaws.com (https://ccentralassets.s3.amazonaws.com/presents/2021EarthDay_data.zip)). It is calculated from the temperature change from 1970 to 2020.

2.2 Measures

In the model analysis, recorded occurrences of pediatric asthma, labeled as PediAsthma in the model, occurrences of adult asthma as AdultAsthma, and occurrences of lung cancer cases as LungCancer, are dependent variables. All are from year 2020.

The independent variables include temperature change from 1970 to 2020 as TempChange, average temperature from 2015 to 2020 as TempMean, unhealthy days for sensitive groups 2020 as UnhealthyDays2018, number of unhealthy days of nitrogen dioxide of year 2018 as DaysNO2, number of unhealthy days of particulate matter with radii of 2.5 micrometers in 2020 as DaysPM25, and number of unhealthy days of particulate matter with radii of 10 micrometers in 2020 as DaysPM10, number of unhealthy days for with harmful effects from Ozone 2020 as DaysOzone.

3. Results and Analysis

R studio is used to analyze the data; the three regression models results are listed (Tables 1, 2, and 3). R script is also attached as appendix at the end of the paper.

	TempChange	*TempMean*	*PediAsthma*	*AdultAsthma*	*LungCancer*	*UnhealthyDays2018*	*DaysNO2*	*DaysOzone*	*DaysPM25*	*DaysPM10*
TempChange	1									
TempMean	0.3179	1								
PediAsthma	0.1589	0.3795	1							
AdultAsthma	0.1492	0.2931	0.9673	1						
LungCancer	0.1203	0.1866	0.1475	0.1398	1					
UnhealthyDays2018	0.3355	0.4298	0.5452	0.5495	0.1954	1				
DaysNO2	0.3729	0.2507	0.2115	0.1990	-0.0434	0.4340	1			
DaysOzone	0.1833	-0.2231	-0.2243	-0.2116	-0.1193	0.0979	0.1079	1		
DaysPM25	-0.1955	0.1760	0.1523	0.0970	0.0444	-0.1817	-0.1729	-0.8548	1	
DaysPM10	0.2116	0.2036	0.3696	0.4643	0.2096	0.3509	-0.0285	0.0670	-0.3639	1

Figure 1. Correlation Matrix.

Figure 1 indicates that the correlation coefficients between independent variables are low enough (mostly <0.4) to include them in a regression model so no worries of multicollinearity, which is bad for linear regression analysis. There is high correlation between independent and dependent variables, which is good. DaysOzon and DaysPM25 are highly negatively correlated (-0.8548), which means they almost cancel out effects from each other. I decide to just include DaysPM25 in the models.

Table 1. Pediatric Asthma

Model 1: PediAsthma over TempChange+TempMean+UnhealthyDays2018+DaysNO2+DaysPM25+DaysPM10

Call: lm(formula = PediAsthma ~ TempChange + TempMean + UnhealthyDays2020 +DaysNO2 + DaysPM25 + DaysPM10, data = climatedata)

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-7648.35	18133.08	-0.422	0.67562
TempChange	-1344.43	4359.24	-0.308	0.75950
TempMean	74.38	244.76	0.304	0.76291
UnhealthyDays2018	411.64	145.29	2.833	0.00742 **
DaysNO2	134.62	204.78	0.657	0.51498
DaysPM25	84.37	33.64	2.508	0.01664 *
DaysPM10	164.69	69.09	2.384	0.02238 *

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

Residual standard error: 12870 on 37 degrees of freedom. Multiple R-squared: 0.4549, Adjusted R-squared: 0.3665. F-statistic: 5.146 on 6 and 37 DF, p-value: 0.000623

Table 1 shows the results about the relationships between occurrences of Pediatric Asthma and the independent variables. A regression of number of cases of Pediatric asthma is done over these independent variables. Significantly low p-values are marked with asterisks (*).

F-statistic: 5.146 on 6 and 37 degree of freedom, and p-value: 0.000623, mean that overall model fitness is very good. Multiple R-squared: 0.4549, meaning 45% of the variations in pediatric asthma can be explained by these variables. P-values for unhealthydays2020, DaysPM2.5, and DaysPM10 are significant, meaning unhealthy days of ozone and particle pollution levels have huge impacts on pediatric asthma occurrences.

Table 2. Adult Asthma

Model 2: AdultAsthma over TempChange+TempMean+UnhealthyDays2018+DaysNO2+DaysPM25+DaysPM10

Call: lm(formula = AdultAsthma ~ TempChange + TempMean + UnhealthyDays2018 +DaysNO2 + DaysPM25 + DaysPM10, data = climatedata)

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	10945.1	62015.0	0.176	0.86087
TempChange	-5375.6	14908.6	-0.361	0.72047
TempMean	-453.1	837.1	-0.541	0.59155
UnhealthyDays2018	1491.1	496.9	3.001	0.00480 **
DaysNO2	592.7	700.3	0.846	0.40281
DaysPM25	313.5	115.0	2.725	0.00976 **
DaysPM10	795.5	236.3	3.367	0.00178 **

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 44010 on 37 degrees of freedom.
Multiple R-squared: 0.4968,Adjusted R-squared: 0.4152.
F-statistic: 6.089 on 6 and 37 DF, p-value: 0.000166

Table 2 is the result from the regression of AdultAsthma on the independent variables. It displays the relationships between occurrences of Adult Asthma and the independent variables. Same conclusions can be made. F-statistic: 6.089, and p-value: 0.000166. Overall model fitness is very good. Multiple R-squared: 0.4968, meaning about 50% of the variations in adult asthma can be explained by these variables. P-values for unhealthydays2020, DaysPM2.5, and DaysPM10 are significant, meaning number of unhealthy days and particle pollution levels have huge impacts on adult asthma occurrences.

Table 3 shows the result from the regression of LungCancer on the independent variables. This table displays the relationships between occurrences of Lung Cancer and the independent variables. F-statistic: 0.6778, and p-value: 0.6683. Overall model fitness is not good. The variables seem not valid in explaining the occurrence of lung cancer. All P-values are too big to be significant. Notice there are no significantly low p-values for any of the relationships between the occurrences of lung cancer and the independent variables.

Table 3. Lung Cancer

Model 3: LungCancer over TempChange+TempMean+UnhealthyDays2020+DaysNO2+DaysPM25+DaysPM10

Call: lm(formula = LungCancer ~ TempChange + TempMean + UnhealthyDays2018 +DaysNO2 + DaysPM25 + DaysPM10, data = climatedata)

Coefficients:

	Estimate	Std. Error	t-value	Pr(>|t|)
(Intercept)	-1408.341	2183.194	-0.645	0.523
TempChange	242.702	524.846	0.462	0.646

TempMean	11.616	29.469	0.394	0.696
UnhealthyDays2018	14.061	17.492	0.804	0.427
DaysNO2	-18.169	24.655	-0.737	0.466
DaysPM25	2.401	4.050	0.593	0.557
DaysPM10	6.911	8.318	0.831	0.411

Residual standard error: 1549 on 37 degrees of freedom.
Multiple R-squared: 0.09903, Adjusted R-squared: -0.04707.
F-statistic: 0.6778 on 6 and 37 DF, p-value: 0.6683

The three dependent variables in the research were studied to be affected at least in some way by some of the independent variables. So, it was interesting to see that the occurrence of lung cancer had no significant relationships with any of the independent variables. One reason is that cancer is a result of long-term development. So, it is less associated with one-year data of air pollution. Pediatric and adult asthma were both shown to be significantly affected by unhealthy levels of ozone, particulate matter 2.5, and particulate matter 10 as asthma is often more acute and can attack suddenly by even one-day deterioration of weather and air conditions.

The days of Ozone pollution is not included in the models as the variable cancels impacts from Unhealthy days of PM 2.5. I tried a regression by replacing DaysPM25 with Days Ozone in the model 1. The result gets worse, not as good as with DaysPM25 included. The coefficient of Days Ozone is negative as opposite to that of DaysPM25. A regression by replacing DaysPM25 with Days Ozone was assessed in the model 2. The coefficient of Days Ozone is negatively large. Both regressions confirm what the correlation between DaysPM25 with Days Ozone tells.

4. Discussion and conclusions

In this study it is easy to see those unhealthy days for sensitive groups, PM 2.5 pollution, and PM 10 pollution have considerable influence on adult and pediatric Asthma. The coefficients of these variables in models 1 and 2 are big, have significantly low p-values, indicating that the relationship was unlikely to be caused by chance. The results of this study are concurrent with a statement made in the CDC's Asthma and Air Pollution Tool Kit, "Long-term exposure to ozone and particle pollution has been found to injure the lungs and has been shown to cause asthma in children" [18]. Therefore, to protect the environment is important. Any policies, technologies, and investment to reduce emission and pollution should be encouraged and supported. Governments and businesses, societies, and communities all over the world should work together, work hard, and team together to reduce the impacts from climate changes. The limits in this research are: 1) the data was only collected from 43 metropolitan areas in the United States. A bigger sample size certainly make analysis better, especially if the data can be retrieved from other continents. But the data collection is always the most challenging job for this type of research. 2) There should be other factors of concern, which can also affect these respiratory system related diseases. Future analysis should try to include more variables with a bigger data set. 3) the impacts from Ozone pollution are a myth from the data, worth further research with larger data sets.

References

[1] Climate Central. "AMERICAN WARMING: The Fastest-Warming Cities and States in the U.S." 17 Apr. 2019, www.climatecentral.org/news/report-american-warming-us-heats-up-earth-day.

[2] "NOAA Climate.gov: Science & Information for a Climate-Smart Nation." NOAA.

[3] Air Quality Index - A Guide to Air Quality and Your Health, airnow.gov/index.cfm?action=aqi_brochure.index.

[4] "Air Pollution Diseases." Environmental Pollution Centers (EPC), www.environmentalpollutioncenters.org/air/diseases/.

[5] "Air Quality and Climate Change Research." EPA, Environmental Protection Agency, 14 Nov. 2019, www.epa.gov/air-research/air-quality-and-climate-change-research.

[6] "Climate Basics for Kids." Center for Climate and Energy Solutions, 12 July 2019, www.c2es.org/content/climate-basics-for-kids/.

[7] "Climate Basics for Kids." Center for Climate and Energy Solutions, 12 July 2019, www.c2es.org/content/climate-basics-for-kids/.

[8] Olivier Deschênes and Enrico Moretti, "Extreme Weather Events, Mortality, and Migration," Review of Economics and Statistics 91 (2009): 659–81, doi: 10.1162/rest.91.4.659.

[9] The Case for Theory-Guided Data Science." Big Data, Mary Ann Liebert, Inc. 1 Sept. 2014,

www.ncbi.nlm.nih.gov/pmc/articles/PMC4174912/.

[10] Green, Josie. “25 Most Polluted Cities in the US.” 247wallst.Com, 247wallst.com/special-report/2019/06/03/25-most-polluted-cities-in-the-us/6/.

[11] David Albouy et al., “Climate Amenities, Climate Change, and American Quality of Life,” Working Paper no. 18925 (National Bureau of Economic Research, Cambridge, MA, 2013.

[12] Deschênes,Olivier “Temperature, Human Health, and Adaptation: A Review of the Empirical Literature,” Energy Economics 46 (2014): 606–19, doi: 10.1016/j.eneco.2013.10.013.

[13] Faghmous, James H, and Vipin Kumar. “A Big Data Guide to Understanding Climate Change.

[14] Katharina Janke, Carol Propper, and John Henderson, “Do Current Levels of Air Pollution Kill? The Impact of Air Pollution on Population Mortality in England,” Health Economics 18 (2009): 1031–55, doi: 10.1002/hec.1475.

[15] Walton H., Dajnak D., Evangelopoulos D., Fecht D. Impact Assessment of Air Pollution on Asthma in London. King’s College London; London, UK: 2019. https://www.london.gov.uk/sites/default/files/asthma_kings_report_april_2019_final.pdf.

[16] National Climatic Data Center, “Quick Links.” www.ncdc.noaa.gov/data-access/quick-links.

[17] “Sources of Greenhouse Gas Emissions.” EPA, Environmental Protection Agency, 13 Sept. 2019, www.epa.gov/ghgemissions/sources-greenhouse-gas-emissions.

[18] CDC, https://www.cdc.gov/nceh/multimedia/infographics/asthma_air_pollution.html.

[19] Currie, Janet et al., “Does Pollution Increase School Absences?” Review of Economics and Statistics 91 (2009): 682–94, http://doi: 10.1162/rest.91.4.682.

[20] Michael Oppenheimer and Jesse K. Anttila-Hughes, “The Science of Climate Change,” Future of Children 26, no. 1 (2016): 11–30.

[21] Nicholas J. Sanders, “What Doesn’t Kill You Makes You Weaker: Prenatal Pollution Exposure and Educational Outcomes,” Journal of Human Resources 47 (2012): 826–50, doi: 10.3368/jhr.47.3.826.

[22] Oppenheimer, Michael and Anttila-Hughes, Jesse K. “The Science of Climate Change,” Future of Children 26, no. 1 (2016): 11–30.

Appendix

R scripts for data analysis	*Software package*

#Read the climate data in .csv from disk to an R console session as dataframe climate-data
climatedata<-read.csv("climatedata.csv")
 	
#Verify the data is in the session and display the column names of the data set.
colnames(climatedata)
 	
#modify the output width to 220
options(width=220)
 	
#Use cor()function to calculate the coorelation matrix of the columns concerned.
cor(climatedata[,4:12])
 	
#use lm() to run regression of climate variables on pediAsthma, adultAsthma and Luncancer separately
#Model1 uses PediAsthma as the dependent variable
cldmo-del1<-lm(PediAsthma~TempChange+TempMean+UnhealthyDays2018+DaysNO2+DaysPM25+DaysPM10, data=climatedata)
summary(cldmodel1)
 	
#Model2 uses AdultAsthma as the dependent variable
cldmo-del2<-lm(AdultAsthma~TempChange+TempMean+UnhealthyDays2018+DaysNO2+DaysPM25+DaysPM10, data=climatedata)
summary(cldmodel2)
 	
#Model3 uses PediAsthma as the dependent variable
cldmo-del3<-lm(LungCancer~TempChange+TempMean+UnhealthyDays2018+DaysNO2+DaysPM25+DaysPM10, data=climatedata)
summary(cldmodel3)
	https://cran.r-project.org/
	
	https://cran.r-project.org/web/packages/neuraln et/neuralnet.pdf,
	
	https://www.rstudio.com/