Land Use Features Driving Human Health: A Zip Code Analysis in California

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A Zip Code Analysis in California

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Abstract

Land cover has been linked to local health effects both positive and negative (Patz 2004; Kamp & Davies 2008; Holgate et al., 1999; Stansfelt, 2000; Mace et al., 2004). For example, aircraft and urban noise-scapes altered from natural land cover have been linked to mental health issues and cardiovascular disease along with elevated levels of stress (Kryter, 2009; Holgate, 1999; Kamp & Davies, 2008). Mining and industrial coal factories also deviating from natural land cover have been linked to increased mortality (Hendryx, 2016; Epstein, 2011; Buonocore, 2016). Conversely, community access to green-space, parks, and higher biodiversity areas appear to be linked to increased health (Velarde, 2009; Pretty, 2005; Karjalainen, 2010; Ostfeld, 2006).

However, research is lacking to map a correlation between local human disease incidence and vegetative land cover. Land cover data can be compared as samples at the zip code grain via GIS government databases and correlated via regression analysis to local health markers of the common diseases.

The central research question I addressed was: Can land cover type be correlated to human health indicators? As an interesting case study example to be included also in the analysis, the EPA List of Toxic Waste sites was also be regressed against cancer and heart disease to see if a high proportion of land cover that have been highly altered from natural land cover drives poor health.

To model if natural land cover promotes or lessens human health, samples of zip codes in California State were used from government data. The regression analysis

accounted for confounding factors of gender, income, race, education, employment, and access to healthcare, which are the factors that are also expected to affect health (WHO, 2019). A multiple regression analysis was performed to examine Statistical correlations between land cover and health by using a proxy of the two most common diseases, cardiovascular diseases and cancers. Based on previous research, the expected hypothesis was that more vegetative land cover will correlate to decreased local cardiovascular disease and cancer disease while abundant land cover types such as forests and vegetated areas will correlate to increased health. This predicted correlation between local land cover and human health was not statistically supported, perhaps due to multicollinearity showing among variables and missing variables in the equation. More research might be needed to more rigorously test the hypothesis.

The second hypothesis that a higher incidence of waste sites and toxic sites within a zip code area will correlate with decreased human health in the form of more cancer and cardiovascular disease was also not able to be statistically supported, probably also due to multicollinearity and additional variables were missing from the equation.

In the future, research of this type may be useful so that social or regulatory pressure could guide taxes or penalties placed on new developments of land that affect community health via altering natural types of land cover or creating waste sites.

Acknowledgments

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[MOU1]

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Chapter I

Introduction

A growing body of research suggests that local land cover acts as a driver of human health (Patz et al., 2004; Dister, Fish, Bros, Frank, & Wood, 1997; Foster & Gilligan, 2007). For an example of a land use type correlated with health effects, agriculture has been linked as a driver of poor human health (Bowler, 2010; Votsi, Mazaris, Kallimanis, Drakou, & Pantis, 2014). Humans draw on natural resource areas of high vegetation land cover for health via regulating, provisioning, cultural and supporting services (Xu, plus 2007). Though studies have correlated the presence of a variety of vegetative land cover features such as green-spaces, parks, agricultural areas, airports, urban areas, and highways to local health impacts (Patz et al, 2004; Kamp & Davies, 2008; Holgate, 1999; Stansfelt, Haines, & Brown, 2000; Mace, Bell, & Loomis 2004), there has been limited research into land cover patterns as an overall driver of local disease at a fine grain of study such as zip code boundaries.

Research Significance and Objectives

The primary goal of this study was to investigate if independent variables of land cover are correlated with dependent variables of local human disease of cardiovascular diseases and cancer. I investigated this with samples defined by zip codes within California. California was chosen for its varied population, varied terrain and microclimates, and its being a complex and varied economy with many land cover types.

This research will be a step toward understanding whether land cover and presence of vegetation can be associated with the "environmental externality" of local human health[MOU2]. Conversely, is there is an association between an increase in a disease after destroying land cover for a building development? Correlations found could be investigated in future research projects.

Background

According to World Health Organization (WHO, 2005), the very definition of health describes the need for physical, mental, and social well-being dependent on a state of local environmental quality (Kingsley, 2009). It is widely acknowledged that land use is likely to affect human health (Aguirre, Ostfeld, Tabor, House, & Pearl, 2002). Xu et al. (2008) described how regulating, provisioning, cultural, and supporting services are provided by the forest environment of highly vegetative land cover to feed into local human health and wellbeing. Pinder, Kessel, Green, and Grundy(2009) reveled that in the context of community forestry, environment and health were not discrete but one interwoven and inseparable resource system. It appears from previous study that humans depend on areas of high vegetation land cover and vegetation for health.

Unhealthy Landscapes

The presence or absence of vegetative land cover has been indicated in a wide range of studies, and some data support individual land cover features interplaying into human health markers locally. Likewise, in a study of systems models of land use change, Patz et al. (2004) dissected land cover changes and their effect on human health including infectious disease. They first defined the term "unhealthy landscapes" as a series of land cover changes such as coastal zone degradation, mining, road construction, fragmentation of forest, and agriculture that increase the risk of infectious disease transmission and affect public health.

Many studies have correlated individual health conditions to individual stressors from these altered low land cover environments, typically urban or industrial via a variety of mechanisms. Patz et al.(2004) traced land use changes linked to increased infection risks of disease such as Lyme and malaria. Agricultural development that alters natural vegetative land cover and disease emergence were also linked in this analysis. Stressors of human land use deviations from natural cover such as air and noise pollution have been linked by Holgate (1999) to not only respiratory and nervous system malfunctions, along with heart irritations but also to mental health problems, stress, and depression. Stansfelt et al. (2000) showed that there is a noise link to mental health while Gidlof-Gunnarson and Ohrstrom (2007) correlated road traffic noise and wellbeing. Kamp and Davies (2008) correlated non-natural environmental noise with to cardiovascular diseases. Cohen, Janicki-Deverts and Miller (2007) linked environmental auditory stress to higher localized cancer, HIV, and cardiovascular disease.

When lands use differs from natural land cover, environmental health quality appears to systematically affect multiple human senses. Non-natural, ambient stressors in reduced cover areas are linked in multiple studies to disease. Kryter (1990) showed that aircraft noise induces psychological stress. Noise sources were shown by Mace et al. (2004) to increase human annoyance and stress levels. Landscape distribution and mental health were linked by Bluhm, Nordling and Berglind (2004), who showed that road traffic annoyance led to increases in sleep disturbances. De Coensel and Bolteldooren (2006) found that urban soundscapes increased annoyance and sleep deprivation. Urban sprawl decreases heath markers (Benfield, Bell, Troup, & Soderstrom, 2009). Speldewinde, Cook, Davies and Weinsten (2011) presented the hidden health burden including higher suicides, depression, heart disease, and asthma, from the environmental degradation processes leaving local drylands in the place of land cover. In summary, artificial noise and other factors accompanying human-constructed land use types that deviate from natural landscapes and land cover appear to affect health poorly.

Healthy or Therapeutic Landscapes

Likewise, positive correlations have been found between human health and natural landscapes that include large areas of natural land cover. Natural high land cover areas of vegetation called "therapeutic landscapes" show positive effects on human health such as reduction of stress (Velarde et al., 2007). Bowler (2010) linked conservation of biodiversity, as found in high land cover areas, to better health mental outcomes.

High vegetation land cover forests provide biodiversity and ecosystem services thus promoting mental and physical health as well as stress reduction (Karjalainen, Sarjala, & Raitio, 2010). Residents with access to natural areas of land cover have better metal and physical health (Pretty, Peacock, Sellens, & Griffin, 2005), benefitting from green spaces to exercise for mental and physical. wellbeing Maas, Verheii, Groenewegen, De Vries and Spreeuwenberg (2006) linked urban green space to health benefits as well.

Conservation area and health correlations were found by Barbosa et al. (2007), leading them to conclude that access to green space health benefits overall health markers. Holgate (1999) linked exercise availability and artificial land use types effect on health. Cohen et al. (2007) showed that park exercise provides a health benefit to residents. The term "therapeutic landscape" was coined by Gesler (1992) who advocated that green areas of land cover vegetation may need policy changes to protect their health benefits, and require cost benefit analysis to determine their additional worth to the local community before land use changes are made. Additionally, research suggests that land use areas mapped as of high biodiversity of species such as forests seen in high vegetation land cover areas may additionally play a role in creating a healthy landscape via regulation of air quality: "Trees and forests in the conterminous US removed 22.4 million tons of air pollution in 2010 with human health effects valued at US$ 8.5 billion" (Nowack, Hirabayashi, Bodine, & Greenfield, 2014, p. 119). Research has also directly linked air quality to mortality and hospitalizations (WHO, 2014).

In summary, the body of research available appears to correlate high land cover and corresponding high biodiversity areas with health benefits to humans. This suggests that the presence of high vegetation land cover greenspaces, land in natural states, and parks[MOU3] will be associated with better local human health.

Spatial Mapping of Landscape Features and Human Health.

Methods to map land cover type were first described by Forman (1995), who first proposed models to categorize spatially formatted land. Forman noted that changes in land cover have been documented to alter species composition, providing favorable conditions for some organisms and not for others. He described how the mechanisms of agricultural development, urbanization, deforestation, population movement can cause introduction of novel disease pathogens, water and air pollution, biodiversity loss, eutrophication, hydrological alterations, animal intensive production systems, monoculture crops, habit fragmentation, and road building -- all factors which then can cause macro and micro environmental changes. However, Patz et al. (2004) called for a clearer picture to be investigated in order for increased interdisciplinary cooperation, particularly among policymakers.

It is logical that because humans depend on the environment for health, changes in the environmental systems will affect humans. Research has linked potential mechanisms of action for better land cover type mapping. One example is how Schmidt and Ostfeld (2001) documented that forest fragmentation, urban sprawl and biodiversity loss associated with the resulting decreases in natural, vegetative land cover increase Lyme disease risk. Seventy-five percent of human diseases are zoonotic and linked to wildlife or domestic animals: thus, changes in species distribution due to land use will affect infectious disease health. Ostfeld (2005) documented that decreasing biodiversity and productivity of ecosystems leads to less ecosystem resilience thus infectious vector borne diseases increase. One can imagine the public cost of increasing local diseases that create health care costs and debilitate workers locally.

Previous attempts to map “unhealthy” versus “healthy” landscapes to present include Jackson et al. (2008), who engaged in tranquility mapping, a methodology to map the visual landscape stimuli in Scotland Wales using GIS weighted markers of perceived “naturalness of landscape cover,” such as open space, plants, wildlife, and fresh air linked to perception of tranquility, versus features such as roads, airports, trucks, and power lines. Jackson's work summarized the need to advocate for greater value being put on the value of high land cover, tranquil places for national health, and wellbeing. Consideration of land cover types into health policy and planning has been called for in many studies (Wight, 2011). Pauleitnet[MOU4] (2011) at a Mersey, UK site also studied urban land cover change effects to show urban sprawl areas on a map of lower environmental quality with ill effects on local community.

For an example of this process of land use mapping as linked to heath, Votsi et al. (2014) assessed a tranquility map of 39 classes of natural land cover types in Italy associated with tranquility and five markers of human health (mental health disorders, diseases of circulatory system, diseases of musculoskeletal system disease of respiratory system) for 10 years period of hospital record data. The result was a quantitative spatial map of life-quality and its relation to the health of Italian citizens. Local increases in distribution of agricultural types of land cover were found to be a major driver of poor local health quality. The study concluded to say that the role of natural tranquil areas with undisturbed land cover should be put foremost in environmental health policies to protect human health (Votsi et al., 2014).

To summarize, high land cover areas including green space, parks, increased biodiversity, and forest features have been tied to better health locally. Airports, artificial noise, mining, industrial waste, industrial energy, road traffic, and agricultural land use types, correlated with low and altered land cover have been tied to poor local health. However, the effects of multiple land use types on human disease remains poorly investigated at a fine grained, local level.

Case Studies: Industrial Land Use Externalities

Industrial land use such as waste sites where land cover is minimal and with artificially constructed structures and chemicals, are good examples of a land use feature tied to poor local human health. The first Superfund waste site at Love Canal, NY, provides an excellent case study illustrating how failure to account for the externality of industrial land use's effect on local health can be disastrous both for the landowners and community. As industrial chemical company profits are high, if industrial land use types owned by chemical companies were profiled by profit alone without including the externality of long-term potential community health effects, this land cover decision may appear most attractive. However, over the life cycle of this type of land use, the land use project value is much less attractive when health externalities are included.

Love Canal was created near Niagara Falls, NY in the 1920s by the creation of a municipal and chemical dumpsite near a residential area. The Hooker Chemical Company in 1953 had covered its industrial dumpsite and sold it to the local community for $1. Not long after, local residents began having birth defects and health issues from the industrial waste seeping into their neighborhoods, one of which was benzene, a known carcinogen (Beck, 1979). NY State was forced to buy the homes near the site for $7 million dollars to relocate families and help alleviate the crisis.

Instead of Hooker Chemical being fiscally responsible from its large profits for the environmental remediation of Love Canal in the full land use life cycle, responsibility and costs fell upon the local community and the government via tax fund grants from the EPA's Resource Conservation and Recovery Act. Thus, rather than the offending corporate landowner's responsibility through the life cycle of land use, generally EPA waste sites are now the responsibility of "Superfund", a United States federal government program designed to fund the cleanup of sites contaminated with hazardous substances and pollutants.

Superfund law allows the US EPA to sue potentially responsible corporate parties such as Hooker Chemical to force them to clean up hazardous waste sites or to back pay for the cleanup. Many PRPs countersue the local municipalities to force them to shoulder some of the costs as well. Such lawsuits lead to inevitable delays in cleanup while local resident health suffers.

A recent review of Superfund sites concluded that "since 1980…something between 30 and 60 percent (of funds) had gone for legal expenses" to deny corporate responsibility (Hedeman, 1991). This process appears highly inefficient. This overview of the Superfund crisis demonstrates the importance of explicitly calculating land use trade-offs such as reducing natural, vegetative land cover and increasing artificial constructs up front when planning or regulating land use in communities (Viscusi, 1998).

Local residents are ultimately those who pay with their health, and more often than not the government rather than the company responsible funds most of the land cleanup, which still may not fully account for its full health effects or their costs. In one study, the rate of cancer incidence increased by more than 6% in counties with Superfund sites (Kirkpin, 2016[MOU5]). However, in a sample of the 150 Superfund sites in the US, at the majority of sites the expected number of cancers averted by remediation is less than 0.1 cancers per site and that cost per cancer case averted is over $100 million (Vicusi, 1998). Often, the legal proceedings process to place the responsibly on the offending corporation land owner is so lengthy and costly that these corporations go bankrupt, leaving the state and the local residents to clean up alone. Health care bills are often displaced and paid by employers of those harmed or the state for those on disability.

According to the Medical Expenditure Panel Survey from the Agency for Healthcare Research Quality, cancer care costs an average of $85,201 per patient in 2010-2011 (AHRQ 2018). The National Institute of Health estimated that the overall costs of cancer in 2009 were more than $216 billion. This included $86.6 billion for direct medical costs – the total of all health expenditures, and $130.0 billion for indirect mortality costs – the cost of lost productivity due to premature death (AHRQ 2018). If the scale of industrial operations that create projects that convert natural areas of high land cover can be correlated with increased cases of illness such as cancers, this correlation should ultimately be quantifiable in terms of health care dollars, and research may quantify this dollar amount creating penalties or taxes for those operations that decrease naturally occurring, vegetative land cover in favor of industrial waste sites or landscapes deviating from natural cover.

In an ever more transparent world where customers now have increasing access to GIS and Google Maps, companies or land owners that engage in land use choices that appear over their life cycles to be "unhealthy" to the local community may feel social pressure to do better business while owning land use types that have been associated with human harm. Conversely, should this or future research demonstrate a health link to land cover, landowners private or corporate who create or preserve land cover conducive to human health may be able to ask for tax benefits or credits.

Research Questions, Hypotheses and Specific Aims

The central research question I addressed was: Can land cover type be correlated to human health? My hypothesis was that a greater percent of vegetative cover will be associated with better human health in the form of less disease incidence. I also hypothesized that as a case study, zip code areas with more toxic waste sites would be correlated with more disease of cancer and cardiovascular origin.

Specific Aims

To test these hypotheses, I completed the following:

1. Collected data on health markers of cardiovascular and cancer disease incidence per zip code in California.
2. Collected data on the land cover types in each zip code.
3. Included data from zip codes in a regression equation to account for confounding factors also influencing health: gender, race, employment, education, income, and access to healthcare.
4. Used regression analysis to examine the data for significant relationships between land cover type and local cardiovascular disease and cancer focused on waste sites from the EPA's List of Toxic Waste sites in California.

Chapter II

Methods

This project sought to identify relationships between land use and human effects on land and the local health of residents at the zip code level. The question the study sought to answer was: How does human actions on a landscape shape local human health? The study made use of a number of variables relating to landcover and toxic sites in a regression models to examine how they impacted local health outcomes with a focus on cancer, stroke and heart disease. Demographic factors were also taken into account because of their modifying effect on health outcomes.

Datasets

Data on land use were summarized at the zip level using the zonal statistics tool in ArcGIS 10.7. The landcover data is in a raster format with each land use type assigned a particular pixel. The land use landcover layer was sourced from the NLCD geoportal (http://portal.gis.ca.gov/geoportal/catalog/main/home.page). The land use data was classified into various land use classes for ease of analysis. Because the landcover was nominal, dummy variables were created for each landcover class. Each dummy variable represented one category of the landcover variable and was coded with 1 if the case falls in that category and with 0 if not. For example, in the dummy variable for built area, all cases in which the variables are landcover were coded as 1 and all other cases, in which the variable is either farmland etc., are coded as 0. This allowed me to enter the landcover values as numerical.

The analysis also made use of data on the location of hazardous waste sites sourced from CIESIN (https://sedac.ciesin.columbia.edu/data/set/superfund-atsdr-hazardous-waste-site-ciesin-mod-v2). This data came in the form of polygons and was converted to points and spatially joined to the zip code shapefile using the zip code as the unique ID for joining. This helped to track how many points (waste sites) fell within any zip code.

Demographic data from the latest census results for California were extracted and used in the analysis. These included data on educational level with focus on the lowest and highest levels of education, and data on race, access to healthcare facilities, income levels (highest and lowest levels of income) and gender. Access to healthcare was measured as density of health facilities in the study area. Gender was viewed in terms of the total number of males and females, as opposed to 1 for male and 0 for females. These demographic factors affect health at the local level and hence had to be accounted for in the regression equation.

Data on health outcomes was sourced from the California Health and Human Services Open Data Portal (https://data.chhs.ca.gov/dataset/leading-causes-of-death-by-zip-code). These data consisted of counts of cancer, heart diseases and stroke cases at the zip code level for the entire state of California for the year 2013. The data were in MS Excel format and were joined to the shapefile of California using the "Join By Attribute" tool with the zip code as the common field. Because cancer, stroke and heart disease account for a vast majority of human diseases and data were available at the zip level, they were viewed as good proxies for local human health.

Datasets came in different formats and had to be harmonized for purposes of the analysis. The cancer and heart disease/stroke data were in CSV format and were summarized at the ZIP level using pivot tables in MS Excel.

The shapefile containing population information and zip codes was clipped to the boundaries of California and formed the main dataset of the analysis as all the other data were joined to it using the zip code as the common field.

Land Cover Data

The landcover data set was downloaded from the USGS website and contained landcover information for the entire United States. These data were clipped to the boundaries of California and reclassified to four land cover classes.

The workflow for clipping a raster layer using a polygon was:

Click on Arc Tool Box and navigate to Dat4a Management Tools > Raster Processing > Clip.

The reclassification was necessitated by the fact that many landcover classes would have led to an increase in the number of variables to be used for the analysis. The landcover data was reclassified into four broad classes: bare areas, forested areas, built-up areas and vegetated areas. In ArcGIS, the workflow for reclassification was as follows:

In ArcMap, open the Arc toolbox navigate to Spatial Analyst > Reclass and select Reclassify (Figure 1).

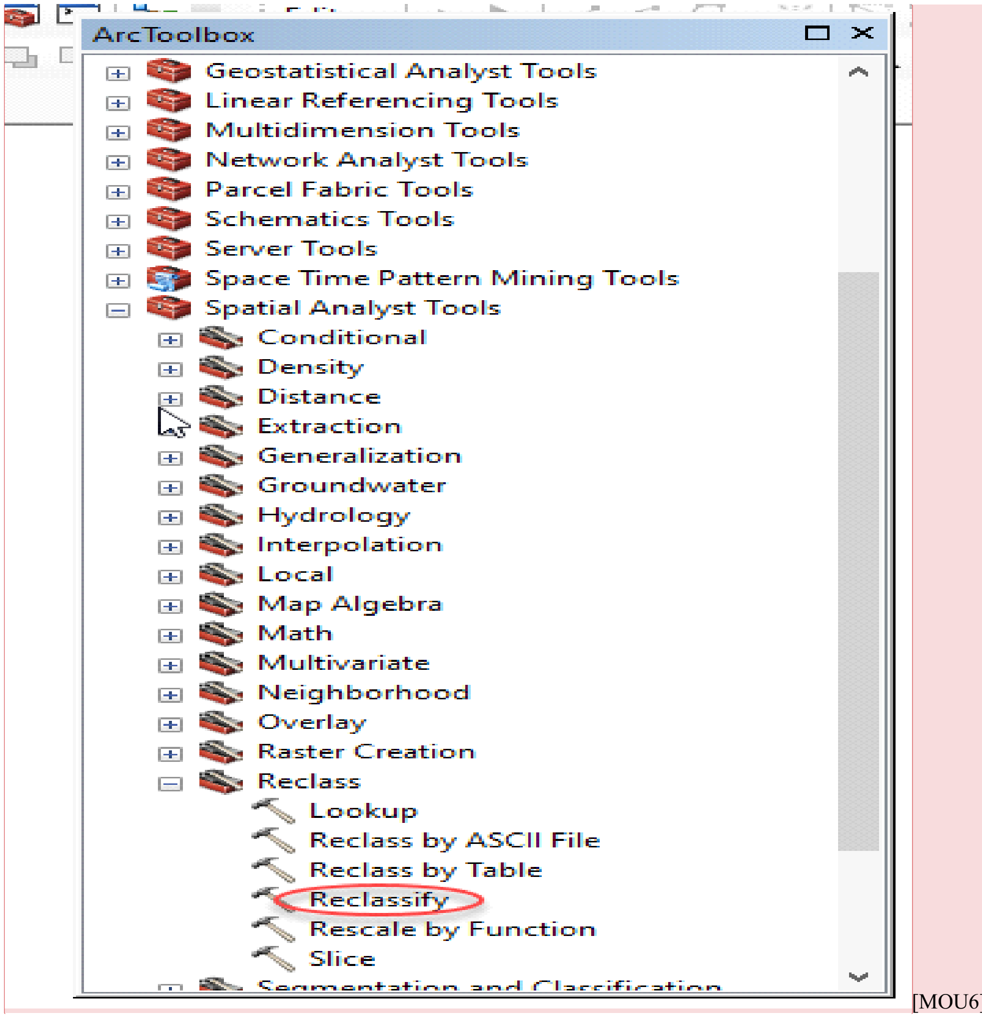


Figure 1. Dialog box for the reclassification tool in ArcGIS spatial analyst toolbox.

The classes were then assigned to each zip code using the zonal statistics tool in ArcMap. This tool works by Summarizing the values of the Land Use raster within the zip zones of the California dataset and reports the results as a table that was then joined to the California shapefile using the zip codes. The procedure was as follows:

In ArcMap, open the Arc toolbox navigate to Spatial Analyst tool and within it click on Zonal and select Zonal Statistics as a Table (Figure 2).

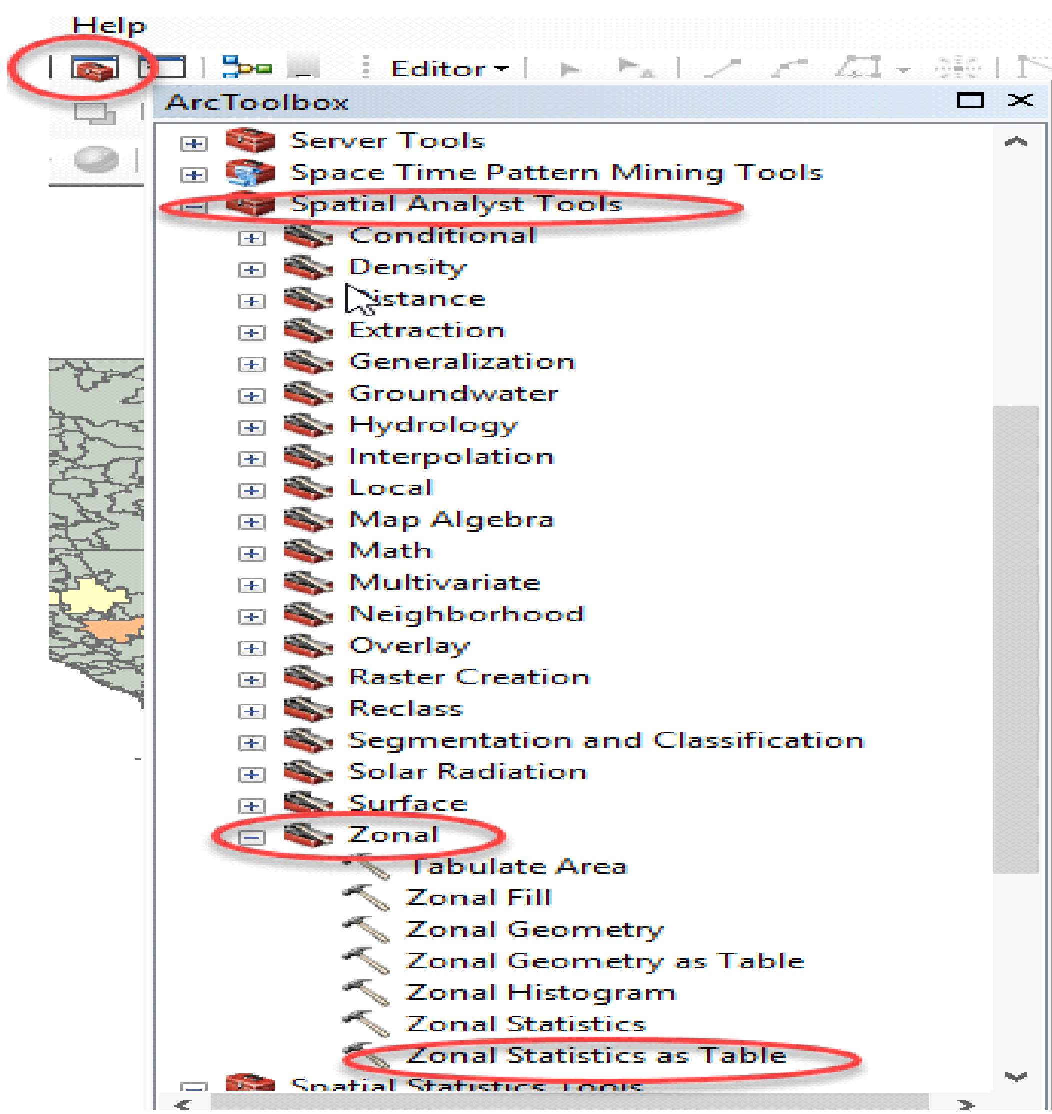


Figure 2. Dialog box for the zonal statistics as a table tool in ArcGIS spatial analyst toolbox.

This procedure brings up the dialog where one enters the necessary information and runs the tool (Figure 3). The output of the analysis was a table that can then be joined back to the California shapefile using a common field.

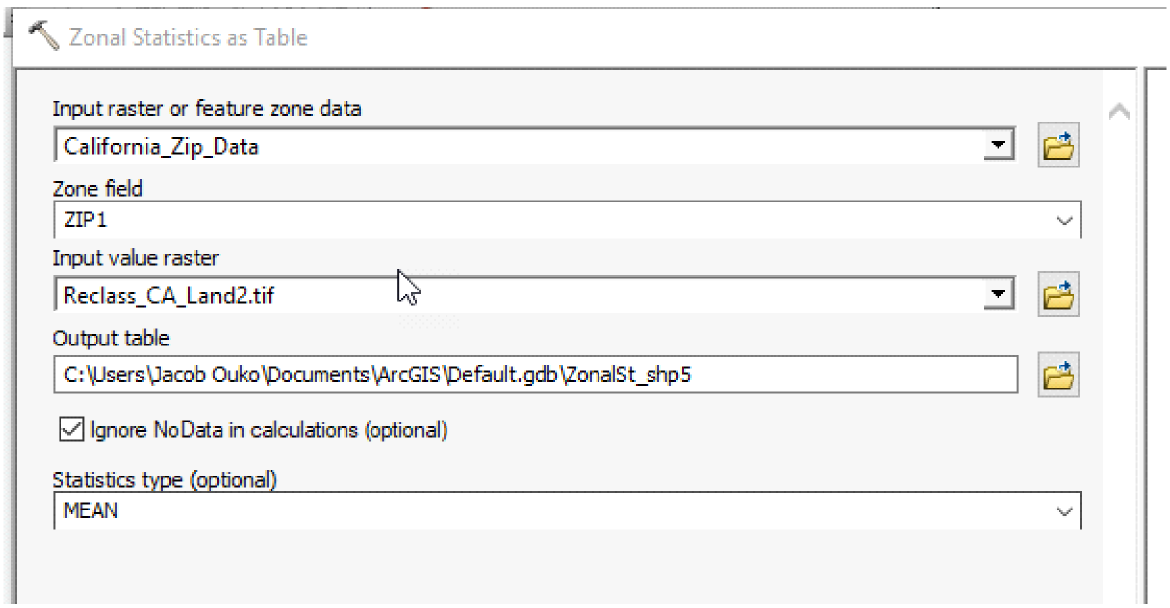


Figure 3. Input fields for the zonal statistics as a table tool.

Waste Sites Layer

The Hazardous waste layer was downloaded from the sedac website (https://sedac.ciesin.columbia.edu) and is a polygon of all the waste sites in the United States. It seeks to provide an easily accessible, corrected data set of polygons for hazardous waste sites in the United States which can be used to identify nearby populations and assess their potential risk. This data came complete with zip codes and was clipped to the boundaries of California and joined to the California shapefile using the spatial join functionality. For purposes of this analysis, the number of waste sites falling within each zip code was used as the unit for analysis.

Data Analyses

Multiple analyses were carried out with the dependent variables being cancer, stroke and heart disease cases while the explanatory variables were landcover and toxic sites together with the demographic variables.

The residuals of each analysis were mapped and the relationships between the various factors analyzed. The study made use of Multiple Regression Ordinary Least Squares (0LS) available in ArcGIS. The equation assumed the formula:

$$Y = \beta_0 + \Sigma_{j=1..p}\, \beta_j X_j + \varepsilon$$

where Y is the dependent variable, β_0, is the intercept of the model, X_j corresponds to the j^{th} explanatory variable of the model (j= 1 to p), and e is the random error with expectation 0 and variance σ^2

Multiple Ordinary Least Squares was preferred because it allows the analysis to take into account multiple explanatory variables, as was the case in this analysis. This type of regression was also preferred because it takes into account all the elements of diverse scales in a sample and for the simplicity of its operation. It also makes very efficient use of the data and generates good results even with relatively small data sets.

After generating the regression equation, the outcome was assessed against a number of factors such as:

- Multiple R-Squared and Adjusted R-Squared values that are measures of model performance.
- Coefficient, Probability or Robust Probability, and Variance Inflation Factor (VIF) for each explanatory variable.
- The spatial autocorrelation of the residuals.

The OLS tool also produces an output feature class and optional tables with coefficient information and diagnostics. The output feature class is automatically added to the table of contents, with a hot/cold rendering scheme applied to model residuals. Dependent and explanatory variables should be numeric fields containing a variety of values. For this reason, derived values for the landcover variable were coded with numeric values

The Unique ID field links model predictions to each feature. Consequently, the Unique ID values must be unique for every feature, and typically should be a permanent field that remains with the feature class. In this analysis, the unique value was the Zip ID as all the analysis was at the zip level.

Procedure for the Analysis

The procedure was to Open Arc toolbox and navigate to the Spatial Statistics tool box, then open the Measuring Spatial Relationships tool and click on Ordinary Least Squares tool (Figure 4).

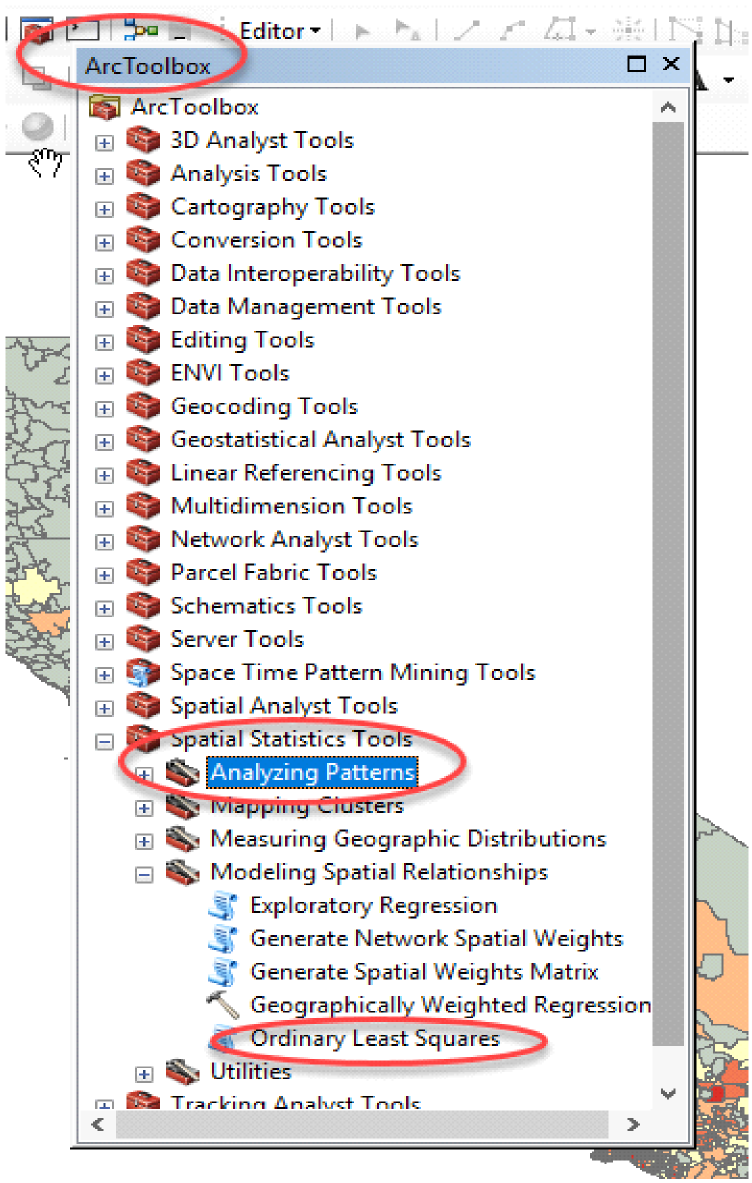


Figure 4. Dialog box for the ordinary least squares' regression in ArcGIS spatial statistics toolbox.

This opens up the dialog box for the ordinary least squares' regression (Figure 5). This allows one to input the Analysis Dataset, the Unique Field, Output Feature Class, Dependent Variables, and the Explanatory Variables.

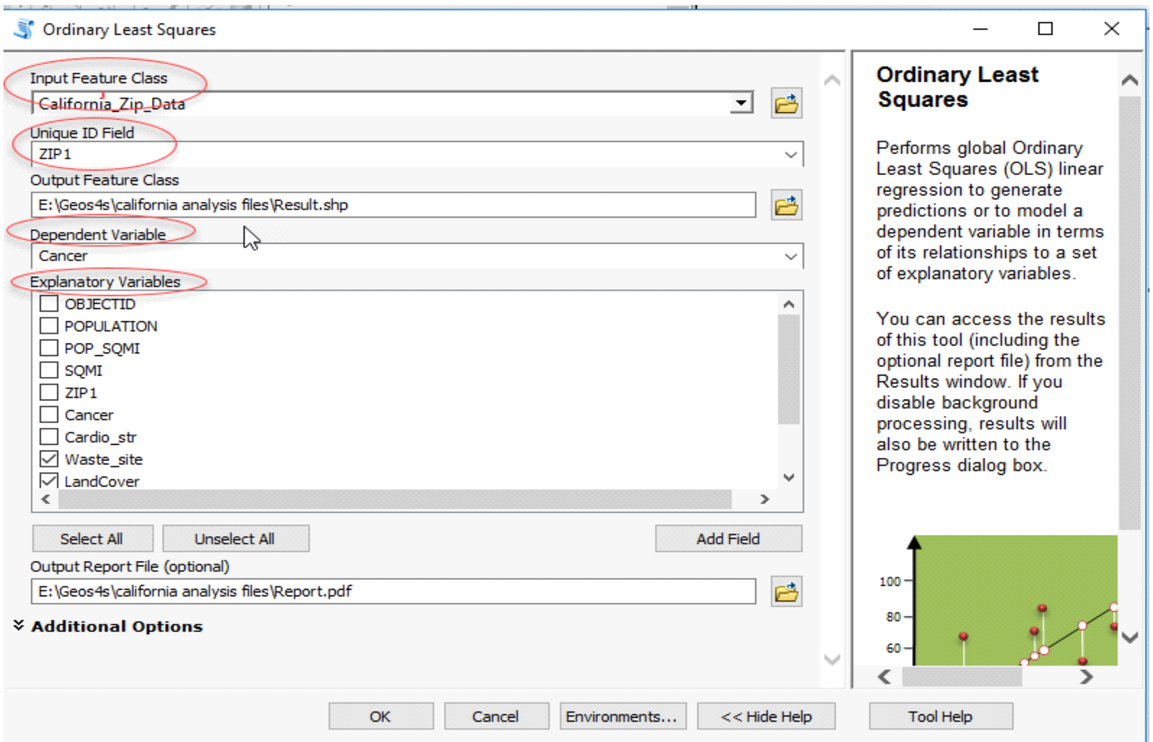


Figure 5. Input field for the ordinary least squares regression tool.

Standardizing Variables

All the raw variables were standardized for purposes of the analysis using the Descriptives command in SPSS software. Standardization was necessitated by the fact that there existed high levels of multicollinearity within the independent variables and hence it was necessary to reduce this. Multicollinearity refers to independent variables that are correlated. This problem can obscure the statistical significance of model terms, produce imprecise coefficients, and make it more difficult to choose the correct model.

The standardization method used for normalizing the data was the Z-score method that rescales an original variable to have a mean of zero and standard deviation of one.

Handling of Redundant Variables in the Analysis

Redundant variables were identified and dropped from the analysis to reduce multicollinearity among the explanatory variables, especially among the demographic variables. An initial regression analysis was run and all variables with a Variance Inflation Factor (VIF) greater than 7.5 were dropped from the analysis. Variables that had a VIF>7.5 included; Total Population, Male Population, Female Population, Black Race, White Race, Asian Race, Other Races, Educational Achievement and High Income (Table 1).

Table 1. Summary of OLS results for all explanatory variables. Variables with a VIF greater than 7.5 were later dropped from the analysis.

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-1.044552	0.434335	-2.404945	0.016268*	0.489622	-2.133387	0.033023*	--------
Landcover	0.701623	0.584539	1.200301	0.230192	0.132417	5.298599	0.000000*	1.009619
Health Facilities	-0.586243	0.034818	-16.837271	0.000000*	0.100452	-5.836052	0.000000*	1.525100
Total_Pop	5924.623180	2392457.0164	0.002476	0.998023	4052420.5228	0.001462	0.998833	> 1000.0
HH_pop	-1.831240	0.822454	-2.226555	0.026093*	0.881172	-2.078186	0.037831*	850.962642
Male_Pop	-2945.514378	1188884.2424	-0.002478	0.998022	1969903.8626	-0.001495	0.998806	> 1000.0
Female_Pop	-2986.351083	1206891.0672	-0.002474	0.998025	2013789.3639	-0.001483	0.998816	> 1000.0
HighSchool	0.792244	0.141551	5.596881	0.000000*	0.158898	4.985851	0.000001*	25.206485
Graduate	0.138080	0.107421	1.285406	0.198834	0.120197	1.148777	0.250808	14.516670
Low_Income	0.253946	0.058358	4.351495	0.000018*	0.075609	3.358688	0.000817*	4.284442
High_Income	0.035777	0.099569	0.359319	0.719416	0.097776	0.365906	0.714496	12.471885
HH_Income	-0.007636	0.043947	-0.173760	0.862066	0.032642	-0.233937	0.815063	2.429695
White	0.634829	0.234687	2.705004	0.006897*	0.254604	2.493395	0.012737*	69.289112
Black	0.087585	0.081669	1.072434	0.283671	0.096991	0.903020	0.366630	8.390821
American_Indian	0.064689	0.050644	1.277331	0.201668	0.049616	1.303791	0.192492	3.226608
Asian	0.161495	0.122210	1.321454	0.186539	0.138534	1.165744	0.243882	18.788850
Other_races	0.000004	0.000016	0.244927	0.806545	0.000018	0.217547	0.827807	248.867535

Explanatory variables retained were: American Indian Race, Low Income, Household Income, and Health Facilities. These were in addition to the landcover and waste sites, which were used as explanatory variables.

Analysis of Scenarios.

Several scenarios were examined through GIS analysis:

- Cancer to land cover type by zip code: This explores the relationship between land cover type and cancer rates in a given zip code.

- Heart disease/stroke to land cover type by zip code: This explores the relationship between land cover type and heart disease/stroke in a given zip code.
- Case study of toxic waste site to cancer by zip: This explores the relationship between human created toxic waste sites to local cancer rates within a zip code.
- Case study of toxic waste site to cardiovascular disease and stroke by zip: This explores the relationship between human created toxic waste sites to local cardiovascular disease within a zip code.

Chapter III

Results

Figure 6 shows the results of the ordinary least squares regression where cancer is the independent variable with landcover, number of health facilities, race, income level and waste sites being the explanatory variables. The standard residuals were mapped at the zip code level and the zip codes mapped red had the highest standard deviations. In the resultant model (Table 2), Household income, being an American Indian and the number of health facilities returned statistically significant values ($p<0.05$) as evidenced by the * associated with them (Table 2).

OLS Regression Results

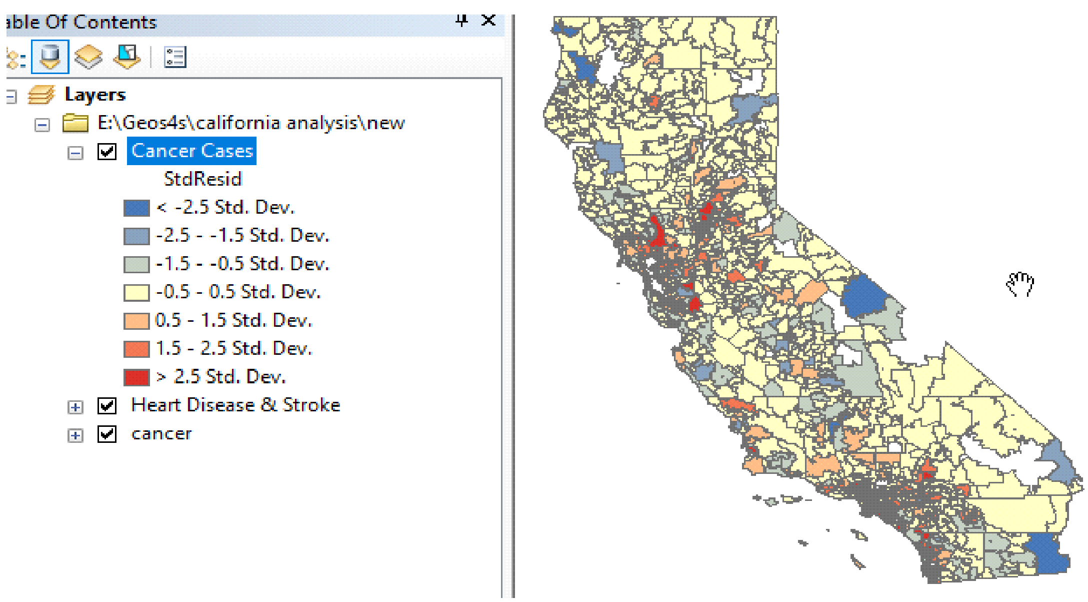


Figure 6. Mapped residuals for cancer cases against landcover, waste sites, income, health facilities and race. The resulting standard deviations are mapped at the zip code level.

Table 2. OLS model results for cancer cases against landcover, waste sites, income, health facilities and race

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	0.093771	0.166568	0.562958	0.573545	0.114020	0.822409	0.410947	--------
LC_Forest	-0.215359	0.169583	-1.269937	0.204288	0.115148	-1.870281	0.061617	23.455080
LC_Developed	-0.022749	0.168353	-0.135124	0.892516	0.116619	-0.195067	0.845358	42.607697
LC_Bare_Land	-0.331756	0.311442	-1.065225	0.286917	0.175460	-1.890780	0.058823	1.398420
LC_Vegetated	-0.121316	0.167711	-0.723360	0.469551	0.115063	-1.054340	0.291869	41.676512
Waste Sites	-0.018302	0.012850	-1.424251	0.154572	0.012068	-1.516598	0.129570	1.013570
Health_Facilities	0.102289	0.015451	6.620432	0.000000*	0.020969	4.878129	0.000002*	1.465294
Low_Income	0.327565	0.019981	16.393491	0.000000*	0.044288	7.396303	0.000000*	2.450711
HH_Income	0.364944	0.013825	26.396516	0.000000*	0.018330	19.909699	0.000000*	1.173273
American_Indian	0.352203	0.017473	20.156840	0.000000*	0.049310	7.142666	0.000000*	1.874043

OLS Diagnostics

Input Features:	data1	Dependent Variable:	ZCANCERS
Number of Observations:	1700	Akaike's Information Criterion (AICc) [d]:	2652.890340
Multiple R-Squared [d]:	0.724674	Adjusted R-Squared [d]:	0.723207
Joint F-Statistic [e]:	494.241098	Prob(>F), (9,1690) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	3246.936490	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	277.685335	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Jarque-Bera Statistic [g]:	2087.424116	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Landcover type and the presence of waste sites did not show statistically significant relationships with the occurrence of cancer and they all returned a negative coefficient. Land cover (developed areas) together with the demographic explanatory variables together explained 72.5% of the occurrence of cancer cases in California by zip code as shown by the multiple R squared of 0.7247.

The Moran I test of autocorrelation (Figure 7) showed that there is a relatively high rate of autocorrelation among the explanatory variables meaning that local clustering is taking place. Moran's I Test outputs 0.46 with a z score of 9.7 and $p < 0.001$ (Figure 7).

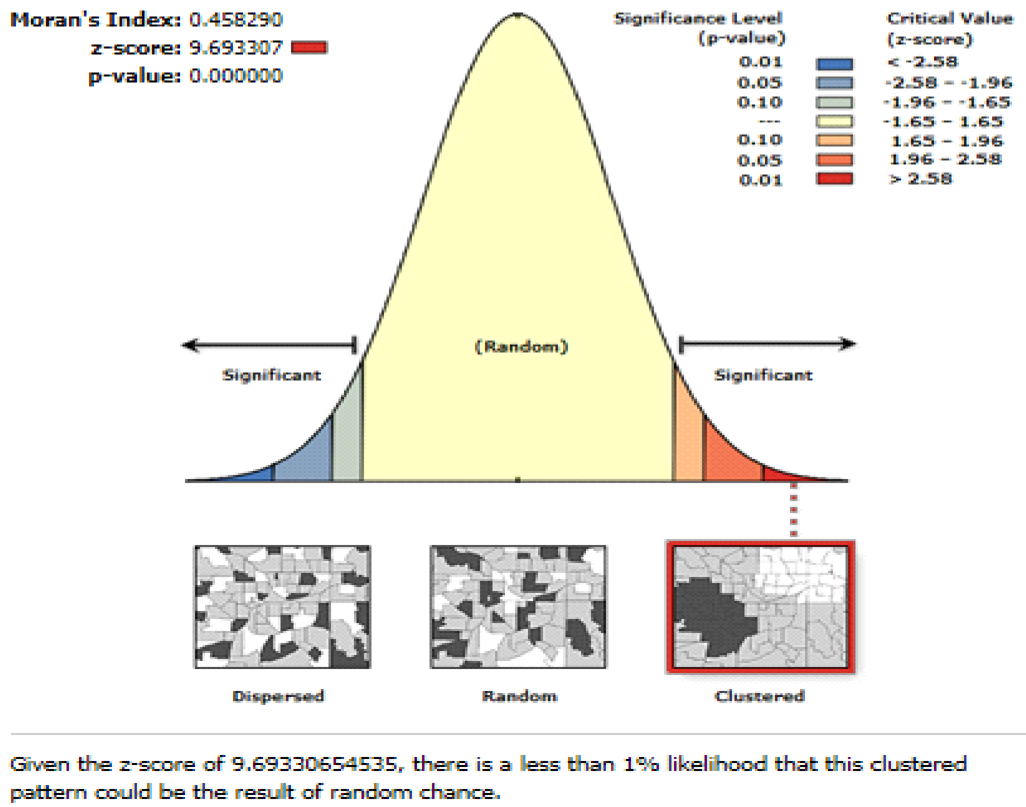
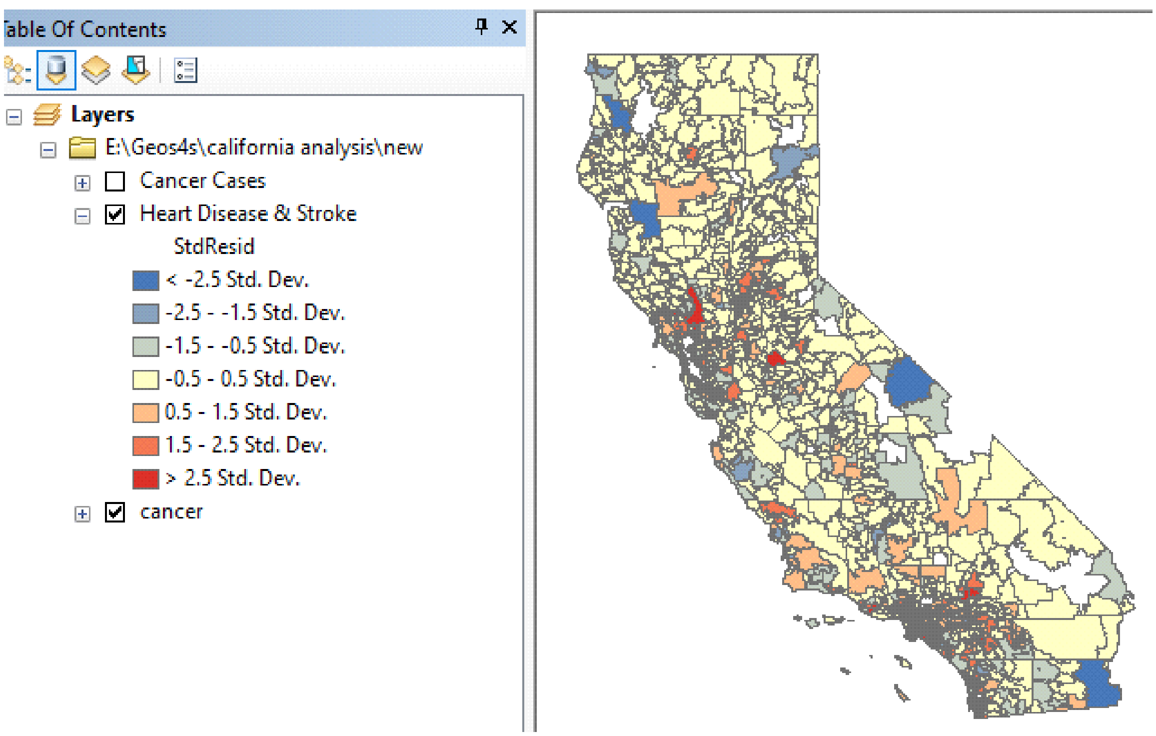


Figure 7. Moran's test results for cancer cases that show a high rate of spatial autocorrelation among the explanatory variables.

Moran's I test is a correlation coefficient that measures the overall spatial autocorrelation of the data set, meaning how one object is similar to others surrounding it. Moran's I Test value between 0-1 as in 0.47 here means objects are attracted by each other in a clustered pattern. The z score being positive at 9.7 can be interpreted as meaning objects are positively attracted or correlated to nearby objects. This indicates that the observations are not independent. Therefore, more data or clarification of data is needed for this regression equation to have independent zip codes as spatial units for statistical validity. It is most likely that unknown variables are missing from the equation, and future additional work is needed to clarify the relationships.

Heart Disease & Stroke Cases

Figure 8 shows the results of the standard deviations of the ordinary least squares regression where heart disease and stroke were the independent variables with landcover, number of health facilities, race, income level and waste sites being the explanatory variables. The standard residuals were mapped at the zip code level and the zip codes mapped red had the highest standard deviations.



[MOU7]

Figure 8. Mapped residuals for heart disease & stroke against landcover, waste sites, income, health facilities and race. The resultant standard deviations are mapped at the zip code level.

Household income, being an American Indian, the number of health facilities, waste sites and bare land returned statistically significant values ($p<0.05$) as evidenced by the * associated with these variables (Table 3).

Table 3. OLS model results for heart disease & stroke against landcover, waste sites, income, health facilities and race.

OLS Diagnostics

Input Features:	data1	Dependent Variable:	ZHEARTD_SK
Number of Observations:	1700	Akaike's Information Criterion (AICc) [d]:	2829.680822
Multiple R-Squared [d]:	0.694499	Adjusted R-Squared [d]:	0.692873
Joint F-Statistic [e]:	426.878328	Prob(>F), (9,1690) degrees of freedom:	0.000000*
Joint Wald Statistic [e]:	2714.390892	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Koenker (BP) Statistic [f]:	229.951243	Prob(>chi-squared), (9) degrees of freedom:	0.000000*
Jarque-Bera Statistic [g]:	2750.626251	Prob(>chi-squared), (2) degrees of freedom:	0.000000*

Summary of OLS Results - Model Variables

Variable	Coefficient [a]	StdError	t-Statistic	Probability [b]	Robust_SE	Robust_t	Robust_Pr [b]	VIF [c]
Intercept	-0.050464	0.175451	-0.287623	0.773679	0.085429	-0.590708	0.554800	--------
LC_Forest	-0.114728	0.178712	-0.641970	0.520979	0.087418	-1.312396	0.189574	23.475613
LC_Developed	0.159343	0.177237	0.899037	0.368746	0.089640	1.777589	0.075657	42.558879
LC_Bare_Land	-0.272842	0.328268	-0.831157	0.405988	0.133071	-2.050343	0.040474*	1.400149
LC_Vegetated	0.002582	0.176698	0.014615	0.988335	0.086709	0.029783	0.976233	41.693353
Waste Sites	-0.025165	0.013532	-1.859656	0.063108	0.012582	-2.000100	0.045641*	1.012982
Health_Facilities	0.159440	0.016253	9.810120	0.000000*	0.030885	5.162380	0.000001*	1.461237
Low_Income	0.448337	0.021326	21.022630	0.000000*	0.045961	9.754733	0.000000*	2.515994
HH_Income	0.175917	0.014423	12.197301	0.000000*	0.012405	14.181106	0.000000*	1.150702
American_Indian	0.326748	0.018459	17.701475	0.000000*	0.046087	7.089785	0.000000*	1.884876

Forested areas, developed areas and vegetated areas did not show statistically significant relationship with the occurrence of heart disease and stroke with forested areas returning a negative coefficient. Land cover (developed areas) together with the demographic explanatory variables together explains 69.5% of the occurrence of heart disease and stroke cases in California by zip code, as shown by the multiple R squared of 0.695 (Table 3).

The Moran I test of autocorrelation (Figure 9) showed that there was a relatively high rate of autocorrelation among the model's residual error displayed. Additional factors not accounted for in this regression model that were clustering the data at the local level, and driving health outcomes. Moran's I Test value between 0-1 as in 0.55 here means objects are attracted by each other in a clustered pattern. The z score being positive at 11.7 can be interpreted meaning objects are positively attracted or correlated to nearby objects. This means that the observations are not independent.

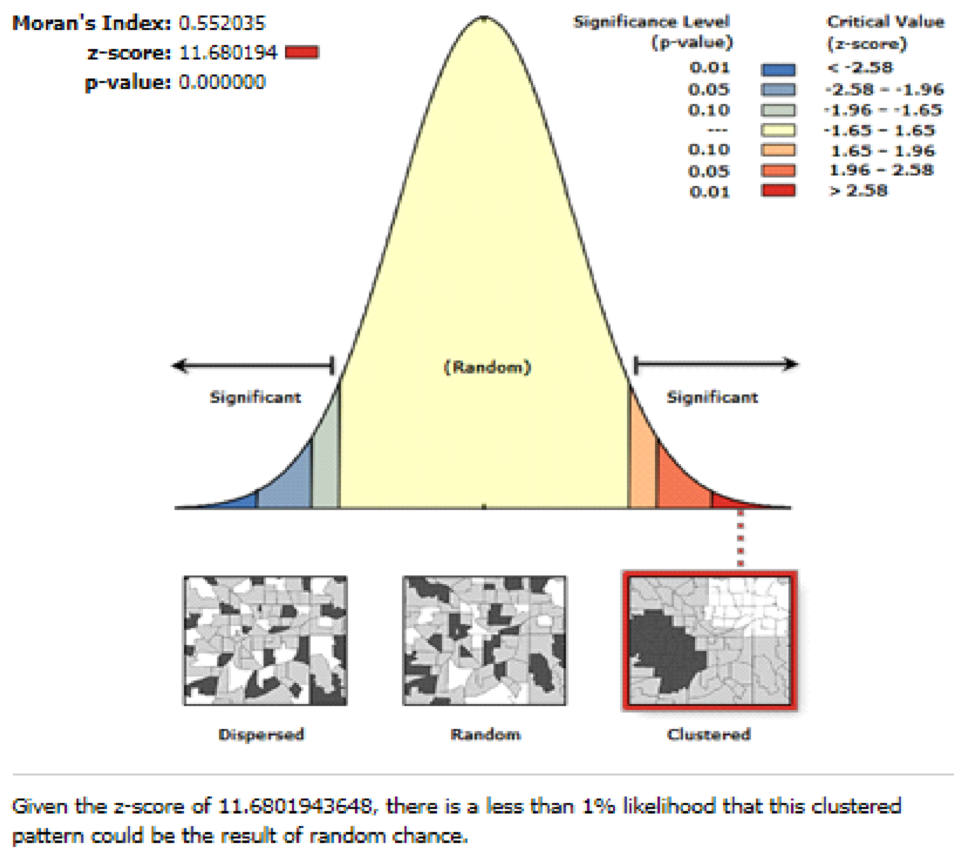


Figure 9. Results of the Moran's I test results for heart disease and stroke. The results showed a high rate of spatial autocorrelation among the explanatory variables.

Therefore, more data or clarification of data were needed for this regression equation to have independent variables and statistical validity. It is most likely that unknown variables were missing from the equation, and future additional work is needed to clarify the relationships.

Chapter IV

Discussion

The goal of the project was to examine if there were statistical correlations between natural land cover and local health markers of cancer and cardiovascular disease , using CA zip codes as a spatial sample unit. Unfortunately, the regression equation output indicated that these were not statistically corelated. We can infer that there are missing variables, not included in the analysis that explain the bulk of the local health markers of cancer and cardiovascular disease rates by zip code. For example, the type of food eaten may be a large contribution to health but this was not included in the equation variables.

My hypothesis that of land cover with increased naturally occurring vegetation were likely to correlate to less disease has not been substantiated by a statistically valid correlation. Forested areas, developed areas and vegetated areas did not show statistically significant relationship with the occurrence of heart disease and stroke with forested areas returning a negative coefficient. Furthermore, regarding my hypothesis that waste sites correlated to worse local health; this was not shown statistically that zip codes containing the most toxic waste areas correlated with more local disease.

It also appears that the variables are not independent; they are spatially clustered, meaning that they are groped locally closer to each other in clusters. Thus, this method of analyzing the available data did not yield usable results.

Research Limitations

Due to time constraints, this study was a snapshot of relationships. To truly study relationships between land use choices and human health, the study data would ideally be extended over time. Data ideally would be sampled every five and twenty years to see how changing land use has affected local zip code health data.

This project cannot account for confounding health data based on diet, as zip code residents eat food imported from different sites outside of the zip code. Perhaps future research may isolate residents living, working, and eating within the zip code to account for dietary and workplace factors.

Reflection on Methods Used

In retrospect, were the study to be repeated, I would use only one land cover feature at a time as a variable in the regression equation and one disease for a one to one correlation. For example, I would study airports and their link to cancer. Then, I would repeat the simple equation for as many land uses features as possible: roads, airports, waste sites, train stations, farms. I would link a one to one correlation first. Then, I would then do a systematic review of the correlated land use features and health markers to create a full picture of which can be used locally to boost or detract from health. This procedure would avoid the variables from being autocorrelated, and make sure variables that were missing were identified.

Future work could repeat the concepts used in this project to identify firm statistical correlation between local land use features and human health. That future research may answer the question, “What is the value of land cover type to human health?

Likewise, in the future this type of research on land cover type may assign a disease cost per person to the additional cases of disease correlated with decreasing vegetative land cover. With this data, a similar project may be able to estimate how much communities may be willing to pay in additional taxes to reward landowners that exhibit land use choices beneficial to the community health.

Conclusions

Landcover type and the presence of waste sites did not show statistically significant relationships with the occurrence of cancer; all returned a negative coefficient. Land cover (developed areas) together with the demographic explanatory variables together explained 72.5% of the occurrence of cancer cases in California by zip code as shown by the multiple R squared of 0.7247.

The presence of autocorrelation and clustering locally in the data indicates at this time it is not possible to make a full conclusion on any correlation between local land use features and local human health markers. There must be other missing exploratory variables that are responsible for the residual error. Further analysis is called for to determine the relationship between local land cover and waste sites to disease incidences of heart disease and cancer at the zip code level.

References

AHRQ: Agency for Healthcare Research and Quality. Medical Expenditure Panel Survey. 2018. US Dept of Health and Human Services. USA.gov. https://www.meps.ahrq.gov/mepsweb/

Aguirre, A.A., Ostfeld, R.S., Tabor, G.M., House, C., & Pearl, M.C. (Eds.) (2002). *Conservation Medicine: Ecological Health in Practice*. New York: Oxford University Press.

Barbosa, O., Tratalos, J. A., Armsworth, P. R., Davies, R. G., Fuller, R. A., Johnson, P., & Gaston, K. J. (2007). Who benefits from access to green space? A case study from Sheffield, UK. *Landscape and Urban Planning*, *83*(2-3), 187-195.

Benfield, J. A., Bell, P. A., Troup, L. J., & Soderstrom, N. (2010). Does anthropogenic noise in national parks impair memory? *Environment and Behavior*, *42*(5), 693-706.

Beck, E. C. (2016, September 22). The Love Canal Tragedy. Retrieved June 06, 2020, From https://archive.epa.gov/epa/aboutepa/love-canal-tragedy.html

Biodiversity, Air Quality, and Human Health Report. (2015). Connecting global priorities: biodiversity and human health: a state of knowledge review. World Health Organization and Secretariat of the Convention on Biological Diversity. Retrieved from https://www.fs.fed.us/nrs/pubs/jrnl/2015/nrs_2015_nowak_001.pdf

Bluhm, G., Nordling, E., & Berglind, N. (2004). Road traffic noise and annoyance-An Increasing environmental health problem. *Noise and Health*, *6*(24), 43.

Boadi, K. O., & Kuitunen, M. (2005). Environment, wealth, inequality and the burden of Disease in the Accra metropolitan area, Ghana. *International Journal of Environmental Health Research*, *15*(3), 193-206.

Bowler, D.E., Buyung-Ali, L.M., Knight, T.M. .... *(*(2010). A systematic review of evidence for the added benefits to health of exposure to natural environments. *BMC Public Health 10,* 456. https://doi.org/10.1186/1471-2458-10-456

Buonocore, J. J., Lambert, K. F., Burtraw, D., Sekar, S., & Driscoll, C. T. (2016). An Analysis of Costs and Health Co-Benefits for a U.S. Power Plant Carbon Standard. Retrieved June 06, 2020, from https://doi.org/10.1371/journal.pone.0156308

California Health and Human Services Open Data Portal. 2019. (https://data.chhs.ca.gov/dataset/leading-causes-of-death-by-zip-code)

Cohen, S., Janicki-Deverts, D., & Miller, G. E. (2007). Psychological stress and disease. *Jama*, *298*(14), 1685-1687.

Davies, H., & Van Kamp, I. (2012). Noise and cardiovascular disease: A review of the literature 2008-2011. *Noise and Health*, *14*(61), 287.

De Coensel, B., & Botteldooren, D. (2006). The quiet rural soundscape and how to characterize it. *Acta Acustica United with Acustica*, *92*(6), 887-897.

Dister, S. W., Fish, D., Bros, S. M., Frank, D. H., & Wood, B. L. (1997). Landscape characterization of peridomestic risk for Lyme disease using satellite imagery. *The American journal of tropical medicine and hygiene*, *57*(6), 687-692.

Doak, D. F., Bigger, D., Harding, E. K., Marvier, M. A., O'Malley, R. E., & Thomson, D. (1998). The statistical inevitability of stability-diversity relationships in community ecology. *The American Naturalist*, *151*(3), 264-276.

Fann, N., Nolte, C. G., Dolwick, P., Spero, T. L., Brown, A. C., Phillips, S., & Anenberg, S. (2015). The geographic distribution and economic value of climate change-related ozone health impacts in the United States in 2030. *Journal of the Air & Waste Management Association*, *65*(5), 570-580.

Gesler, W. M. (1992). Therapeutic landscapes: medical issues in light of the new cultural geography. *Social Science & Medicine*, *34*(7), 735-746.

Gidlöf-Gunnarsson, A., & Öhrström, E. (2007). Noise and well-being in urban residential environments: The potential role of perceived availability to nearby green areas. *Landscape and Urban Planning*, *83*(2-3), 115-126.

Goulder, L.H,. & Kennedy, D. (1997). Valuing ecosystem services: philosophical bases and empirical methods (pp. 23-47). Island Press, Washington, DC.

Hamilton, J. T., & Viscusi, W. K. (1999). How costly is "clean"? An analysis of the benefits and costs of Superfund site remediations. *Journal of Policy Analysis and Management: The Journal of the Association for Public Policy Analysis and Management*, *18*(1), 2-27.

Hardin, G. (1968). The tragedy of the commons. S*cience*, *162*, 1243-1248.

Hedeman, W. N. , Johnathan Z., Cannon, & Friedland, D. M. (199). Superfund transaction costs: a critical perspective on the superfund liability scheme. *Environmental Law Reporter*, *10,* 413-10,426

Herrman, H., Saxena, S., & Moodie, R. (2005). *Promoting mental health: concepts, emerging evidence, practice: a report of the World Health Organization, Department of Mental Health and Substance Abuse in collaboration with the Victorian Health Promotion Foundation and the University of Melbourne*. World Health Organization.

Jackson, S., Fuller, D., Dunsford, H., Mowbray, R., Hext, S., MacFarlane R. & Haggett C. (2008). Tranquility Mapping: developing a robust methodology for planning support, Report to the Campaign to Protect Rural England, Centre for Environmental & Spatial Analysis, Northumbria University, Bluespace environments and the University of Newcastle upon on Tyne.

Karjalainen, E., Sarjala, T., & Raitio, H. (2010). Promoting human health through forests: overview and major challenges. *Environmental Health and Preventive Medicine*, *15*(1), 1.

Keesing, F., Belden, L. K., Daszak, P., Dobson, A., Harvell, C. D., Holt, R. D., ... & Myers, S. S. (2010). Impacts of biodiversity on the emergence and transmission of infectious diseases. *Nature*, *468*, 647-652.

Kingsley, M. T, Metting, F. B, Frederickson, J.K., & Siedler, R. J. (1993). Environmental Restoration Using Plant-Microbe Bioaugmentation. Presented at the In Situ Bioreclamation Symposium. U.S. Dept of Energy.

Kirpich, A., & Leary, E. (2017). Superfund locations and potential associations with cancer incidence in Florida. *Statistics and Public Policy*, *4*(1), 1-9.

Kryter, K. D. (1990). Aircraft noise and social factors in psychiatric hospital admission rates: a re-examination of some data. *Psychological Medicine*, *20*(2), 395-411.

Largo-Wight, E. (2011). Cultivating healthy places and communities: evidenced-based nature contact recommendations. *International Journal of Environmental Health Research*, *21*(1), 41-61.

Lelieveld, J., Evans, J. S., Fnais, M., Giannadaki, D., & Pozzer, A. (2015). The contribution of outdoor air pollution sources to premature mortality on a global scale. *Nature*, *525*, 367-371.

Levy, J. I., Buonocore, J. J., & Von Stackelberg, K. (2010). Evaluation of the public health impacts of traffic congestion: a health risk assessment. *Environmental Health*, *9*(1), 65.

Maas, J., Verheij, R. A., Groenewegen, P. P., De Vries, S., & Spreeuwenberg, P. (2006). Green space, urbanity, and health: how strong is the relation?. *Journal of Epidemiology & Community Health*, *60*(7), 587-592.

Mace, B. L., Bell, P. A., & Loomis, R. J. (2004). Visibility and natural quiet in national parks and wilderness areas: Psychological considerations. *Environment and Behavior*, *36*(1), 5-31.

Meadows, D. H. (2008). *Thinking in Systems: A Primer*. Chelsea Green Publishing.

Naeem, S., & Li, S. (1997). Biodiversity enhances ecosystem reliability. *Nature*, *390*, 507-509.

Naeem, S., Naeem, S., Thompson, L. J., Lawler, S. P., Lawton, J. H., & Woodfin, R. M. (1995). Empirical evidence that declining species diversity may alter the performance of terrestrial ecosystems. *Philosophical Transactions of the Royal Society of London. Series B: Biological Sciences*, *347*(1321), 249-262.

NIH. Air Pollution and Your Health. National Institute of Environmental Health Sciences. https://www.niehs.nih.gov/health/topics/agents/air-pollution/index.cfm

Nowak, D. J., Hirabayashi, S., Bodine, A., & Greenfield, E. (2014). Tree and forest effects on air quality and human health in the United States. *Environmental Pollution*, *193*, 119-129.

Ostfeld, R. S., Schauber, E., and Evans, A. (2005). What is the strongest predictor of annual Lyme disease: weather, mice, or acorns? *Ecological Applications*, *15.*

Ostfeld, R. S., & Keesing, F. (2000). Biodiversity series: the function of biodiversity in The ecology of vector-borne zoonotic diseases. *Canadian Journal of Zoology*, *78*(12), 2061-2078.

Patz, J. A., Daszak, P., Tabor, G. M., Aguirre, A. A., Pearl, M., Epstein, J., ... & Bradley, D. J. (2004). Unhealthy landscapes: policy recommendations on land use change and infectious disease emergence. *Environmental Health Perspectives*, *112*(10), 1092-1098.

Patz, J. A., Campbell-Lendrum, D., Holloway, T., & Foley, J. A. (2005). Impact of regional climate change on human health. *Nature*, *438*(7066), 310-317.

Pauleit, S., Ennos, R., & Golding, Y. (2005). Modeling the environmental impacts of urban land use and land cover change – a study in Merseyside, UK. *Landscape and Urban Planning*, *71,* 295-310.

Pielou, E. C. (1967). A test for random mingling of the phases of a mosaic. *Biometrics*, 657-670.

Pinder, R., Kessel, A., Green, J., & Grundy, C. (2009). Exploring perceptions of health and the environment: a qualitative study of Thames Chase Community Forest. *Health & Place*, *15*(1), 349-356.

Pope, C. A., Dockery, D. W., Holgate, S. T., Koren, H., Samet, J., & Maynard, R. L. (1999). Epidemiology of particle effects. Air Pollution and Health. *Holgate ST , Samet JM, Koren HS, Maynard RL*.

Powe, N.A. & Willis, K.G. (2004). Monetarising community benefits. Chapter 13: *SQW, Evaluation of the Impact of Community Engagement in the North East Community Forests, commissioned by North East Community Forests.*

Pretty, J., Peacock, J., Sellens, M., & Griffin, M. (2005). The mental and physical health outcomes of green exercise. *International Journal of Environmental Health Research*, *15*(5), 319-337.

Richmond, C., Elliott, S. J., Matthews, R., & Elliott, B. (2005). The political ecology of health: perceptions of environment, economy, health and well-being among 'Namgis First Nation. *Health & Place*, *11*(4), 349-365.

Salvi, S., Blomberg, A., Rudell, B, Kelly, F, Sandstrom, T, Holgate, S., & Frew, A. (1997). Acute inflammatory responses in the airways and peripheral blood after short term exposure to diesel exhaust in healthy human volunteers. *American Journal of Respiratory and Critical Care*, *159*.

Schmidt, K. A., & Ostfeld, R. S. (2001). Biodiversity and the dilution effect in disease ecology. *Ecology*, *82*(3), 609-619.

Selenide, P. C., Cook, A., Davies, P., & Weinstein, P. (2011). The hidden health burden of environmental degradation: disease comorbidities and dryland salinity. *Eco Health*, *8*(1), 82-92.

Stansfeld, S., Haines, M., & Brown, B. (2000). Noise and health in the urban environment. *Reviews on Environmental Health*, *15*(1-2), 43-82.

Townsend, M., Phillips, R., & Aldous, D. (2009). "If the land is healthy… it makes the people healthy": The relationship between caring for Country and health for the Yorta Yorta Nation, Boonwurrung and Bangerang Tribes. *Health & Place*, *15*(1), 291-299.

Tullo, A. (2017, November 1). Top 50 U.S. chemical producers of 2016 - cen.acs.org. Retrieved June 6, 2020, from https://cen.acs.org/articles/95/i19/Top-50-US-chemical-producers.html

Raheem, N., J. Talberth, S. Colt, E. Fleishman, P. Swedeen, K. J. Boyle, M. Rudd, R. D. Lopez, T., O'Higgins, C., Willer, & Boumans, R. M. (2009). The Economic Value of Coastal Ecosystems in California. U.S. Environmental Protection Agency, Washington, DC, EPA/600/F-09/046

Raeder, J., Larson, D., Li, W., Kepko, E. L., & Fuller-Rowell, T. (2008). Open GGCM simulations for the THEMIS mission. *Space Science Reviews*, *141*(1-4), 535-555.

Velarde, M. D., Fry, G., & Tveit, M. (2007). Health effects of viewing landscapes– Landscape types in environmental psychology. *Urban Forestry & Urban Greening*, *6*(4), 199-212.

Viscusi, K. & Hakes, J. (1998). Synthetic risks, risk potency, and carcinogen regulation. *Journal of Policy Analysis and Management*, *17.*

Votsi, N. E. P., Mazaris, A. D., Kallimanis, A. S., Drakou, E. G., & Pantis, J. D. (2014). Landscape structure and diseases profile: associating land use type composition with disease distribution. *International Journal of Environmental Health Research*, *24*(2), 176-187.

WHO. (2016). Ambient air pollution: A global assessment of exposure And burden of disease. Retrieved June 06, 2020, from http://www.who.int/phe/publications/air-pollution-global-assessment/en/

WHO. (2019). The Determinants of Health: Health Impact Assessment. Retrieved from https://www.who.int/hia/evidence/doh/en/

William, H. H., Jonathan, C. Z., & David, F. M. (2016). Superfund Transaction Costs: A Critical Perspective On the Superfund Liability Scheme. Retrieved June 06, 2020, from https://elr.info/sites/default/files/articles/21.10413.htm

Wilson, E. O., & Forman, R. T. T. (1995). Land mosaics: the ecology of landscape and regions.

Xu, J., Yang, Y., Li, Z., Tashi, N., Sharma, R., & Fang, J. (2008). Understanding land use, livelihoods, and health transitions among Tibetan nomads: a case from Gangga Township, Dingri County, Tibetan Autonomous Region of China. *EcoHealth*, *5*(2), 104.