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Toxicological Impacts of River Chemical Spills in Affected West Virginia Counties

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This is to certify that the doctoral dissertation by

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2024

Abstract

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Dissertation Submitted in Partial Fulfillment

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Abstract

Factors such as geographical location/proximity and exposure to external environmental events, as well as poor regulatory processes, are known to increase the risk for cancers among affected populations. There is still a gap in the literature related to the incidence of cancers in specific regions with heavy industrialization and environmental health hazards. In West Virginia, chemical contamination events have occurred in or near water systems. The goal of this quantitative, retrospective study was to discover whether there were any differences in the incidence of disease or adverse health effects and cancers due to chemical contamination in four counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and in bordering counties. The conceptual framework was the epidemiological triangle. Secondary, archived data regarding incidence of cancers was primarily collected from the state Department of Health and Human Resources. Using analysis of variance, results revealed a significant association between proximity to chemical contamination and kidney cancer in Kanawha and Mingo counties, as well as breast and soft tissue cancers in Putnam County. Implications for positive social change include providing key insights for rural-dwelling individuals and/or communities directly or indirectly affected by environmental contamination events that can potentially reduce risk of certain diseases.

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Dedication

I dedicate my dissertation to my family and friends that have encouraged me along the way. A special feeling of gratitude to my father, James Peters. He became a widower when I was younger and still yet, he never wavered in being a good man and a great father. He has always believed that I could anything that I set my mind to and has encouraged me every step of the way.

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Chapter 1: Introduction to the Study

Introduction

Health can be impacted by environmental influences (e.g., man-made, pollution, etc.) that human beings come into contact daily. Factors such as geographical location/proximity and exposure to external environmental events, as well as poor regulatory processes, are known to increase the risk for cancers among affected populations. There is still a gap in the literature related to the incidence of cancers in specific regions with heavy industrialization and environmental health hazards, such as the U.S. state of West Virginia, where chemical contamination events have occurred in or near water systems. This study could illuminate positive social change by addressing environmental contamination and geographical location to such instances, as well as for rural dwelling individuals and/ or communities directly/indirectly impacted by such events.

In Chapter 1, the significance of this study is highlighted in the background. The need for this study is discussed in the problem section by examining instances of chemical contamination in the Elk, Ohio, Kanawha, and Tug Fork Rivers in WV. The intent behind this study is further discussed in the purpose section. Next, the research questions and hypotheses are listed, and in the conceptual framework section, its significance to this study is discussed. The study’s design is highlighted in the nature of the study section, and important definitions are listed. The assumptions, limitations, and delimitations of this study are then discussed. Chapter 1 concludes with a discussion of the significance of this study, as well as a summary of the information presented within this chapter.

Background

External elements that have the capability of causing detrimental health outcomes, such as water or soil contamination, air pollution, and/or occupational exposures, are simple, yet vital examples of how regulatory policies concerning the environment are weak; often, populations that are considered high risk will feel the ramifications of such health determinants due to improper policies, geographical location/proximity, and so forth (Listorti & Doumani, 2001; Perera, 1997). Rural Appalachia has some of the highest cancer mortality rates in the United States, up to 36% higher in comparison to other areas (Gilpin & Lofton, 2017). According to Perera (1997), the prevalence of cancer and other adverse health conditions and diseases is significantly associated with environmental exposure (e.g., benzene) based on geographical location/proximity; thus, preventative measures towards cancer should address environmental conditions.

Rural West Virginia/Appalachian Contamination Events

Particularly in rural, coal mining areas of West Virginia, Hitt and Hendryx (2010) suggested that the ecological integrity of streams would serve as an indicator of human cancer mortality rates. The researchers examined ecological integrity by using an index of benthic macroinvertebrate community structure (West Virginia Stream Condition Index) and quantified human cancer mortality rates using county-level data from the Centers for Disease Control and Prevention (CDC). They found that numerous factors (poverty, smoking, urbanization, etc.) were significant in explaining cancer mortality;

spatial (cancer clusters in coal mining areas) and regression analyses yielded significant associations between public health in WV and ecological integrity. However, the researchers noted that the need to monitor the surrounding environment (aquatic) in these high-risk areas is essential, and larger scale and/or similar studies should be conducted to further the understanding of ecological integrity in relation to geographical location.

Numerous chronic health conditions disproportionately experienced across the Central Appalachian region have been associated with environmental contaminants (Hoover et al., 2020). This is mainly due to the areas' historical economic reliance on agriculture, mining, and additional industries; such dependence has incited concerns about how disparities in regional health may be attributed to environmental contaminant exposures (Hoover et al., 2020). Arcipowski et al. (2017) noted that "local environment, the air we breathe, and the water we drink, can enhance or harm the health risk and disease burden of a community" (p. 2). In comparison to 85% of the United States, the Appalachian Regional Commission estimated that only 75% of the Appalachian region is served by municipal water systems (Krometis et al., 2017).

Residents in the other 25% of the region may use private water systems (springs, wells, and cisterns); these systems typically do not employ and/or require treatment prior to consumption, which can leave individuals susceptible to environmental contamination. In 2019, three environmental groups—the Natural Resources Defense Council, the Environmental Justice Health Alliance, and Coming Clean—reported that more than half of WV's counties ranked worst in the nation regarding violations that protect water quality; 36 of WV's 55 counties ranked among the top third of the worst-offending counties in the United States (Fedinick et al., 2019). In addition to water contamination, exposure to air pollution is associated with a range of adverse health effects (e.g., chronic obstructive pulmonary disease, asthma, lung cancer, stroke, etc.; Krometis et al., 2017).

On December 8, 2020, an explosion occurred at the Optima Chemicals Company facility in Belle, WV; the plant is located beside the Kanawha River (Trager, 2020). During the explosion, three individuals were injured, and one employee was killed (Trager, 2020). The explosion was reportedly caused by chlorinated dry bleach (sodium dichloroisocyanurate, a calcium hypochlorite) interacting with methanol; once dispersed into the air, hypochlorite can interact with water to form chlorine gas (Slater, 2020). Even though a shelter-in-place order was issued for a 2-mile radius, it only lasted for several hours, after which officials stated that the air and water quality were safe; West Virginia American Water's Kanawha Valley water treatment facility is located along the Elk River and not the Kanawha River (Slater, 2020). According to the safety data sheet from South Charleston-based water treatment chemical manufacturer, Clearon Corporation, sodium dichloroisocyanurate (CDB-63) is highly combustible and can cause eye damage, as well as severe skin burns (Tony, 2020). To date, there has been no known research regarding the possible environmental and health impacts of this explosion, not even for those employees working at Optima Chemicals Company.

Researchers have found that intratracheal instillation in rats of 10 microns or less of particulate matter obtained near an active mountaintop removal mining site in WV induced mitochondrially driven apoptosis in heart tissue and microvascular dysfunction. The particulate matter showed possibly carcinogenic effects on human lung cells; in contrast, the control particulate matter collected in another WV rural, Appalachian area with no mining activity that was 160 km away did not display such impacts (Krometis et al., 2017). Further research utilizing secondary data sources revealed that coal mining in Appalachia was correlated with lung cancer, higher adjusted mortality rates for total mortality, and chronic forms of kidney, respiratory, and cardiovascular disease; health disparities were present for women and men, as well as highest in areas where coal mining was more prevalent (Hendryx, 2015). In eastern Appalachian Kentucky, an additional study focusing on incidence displayed higher adjusted rates of lung cancer incidence rates in counties with high coal production (Hendryx, 2015). Members of the C8 Science Panel reviewed prior research on perfluorooctanoic acid (PFOA) involving longitudinal studies. They collected state health data and medical records with data on self-reported diseases among residents of WV and the mid-Ohio Valley. The studies suggested a possible correlation between PFOA exposure and higher rates of cancer (testicular, thyroid, and kidney), ulcerative colitis, and high cholesterol (Steenland et al., 2020). Although the purpose of this study is to focus on environmental contamination in communities in rural WV, particularly those within the Appalachian Mountains, there are additional regions that have been impacted by environmental contamination as well.

Additional U.S. and Global Contamination Events

Another community impacted by PFOA contamination is Hoosick Falls, New York. In 2014, residents of Hoosick expressed their concerns about PFOA and possible water contamination, but state officials did not officially investigate until 1 year later; federal officials at the U.S. Environmental Protection Agency (EPA) subsequently deemed the water unsafe for cooking and drinking (Reilly, 2017). Located on the Hoosick River, the culprit of the contamination was the Saint-Gobain Performance Plastics plant. Cohn et al. (2017) conducted a mixed-methods study in which they analyzed previously reported health data and concerns, as well as performed surveys, site visits, and semistructured interviews. Half of their respondents expressed they had health issues associated with PFOA exposure. More than half of those who underwent blood testing had PFOA blood levels exceeding 50 ppb, which is 25 times the national average (Cohn et al., 2017). Results also showed that the more concerned an individual was regarding PFOA health-related issues, the more likely they were to support policy changes; however, despite the health concerns associated with PFOA, 52% of respondents would not leave Hoosick Falls (Cohn et al., 2017).

Camp Lejeune is a military training facility in Jacksonville, North Carolina, that experienced water contamination for over 30 years (Reilly, 2017). Between 1952 and 1987, chemicals such as benzene, trichloroethylene, and perchloroethylene contaminated the drinking water from toxic substances being disposed of on the military base (Reilly, 2017). These chemicals or industrial solvents are known carcinogens (Green-Lott et al., 2020). Bove et al. (2014) conducted a retrospective cohort study using archived and self-reported data to assess the mortality among base personnel exposed to contaminated water. The researchers compared the specific causes of death for 4,647 full-time workers employed at Camp Lejeune (exposed) and 4,690 full-time workers employed at Camp Pendleton (not exposed) from 1973 to 1985. They found that in comparison to Camp Pendleton, Camp Lejeune had elevated mortality risks for cancers (kidney, prostate, cervical, rectal, liver, esophageal, Hodgkin lymphoma, and multiple myeloma) and Parkinson's disease (Bove et al., 2014).

Green-Lott et al. (2020) conducted a case-cohort study on a 59-year-old veteran who was stationed at Camp Lejeune for 5 years during the 1970s and who had developed a rare form of lymphocytic leukemia, hairy cell leukemia. By examining reported exposure, medical history, and presentation, the researchers concluded that this individual represented a possible link between hairy cell leukemia and exposure to trichloroethylene and benzene. Additional research has shown a potential correlation between pregnant women exposed to the contaminated water at Camp Lejeune and having a higher risk of a child born with noncancerous health risks (i.e., immune system disorders and heart problems; Agency for Toxic Substances and Disease Registry [ATSDR], 2017).

In 2014, due to the pending construction of a new pipeline, leaders of Flint, Michigan, which is located in Genesee County, switched from the city's water supply (Lake Huron (via the Detroit Water and Sewerage Department) to the Flint River (Reilly, 2017). Shortly after the water switch, General Motors' engine plant staff noticed that the water was corroding parts; by Fall 2014, officials allowed the car manufacturer to switch back to the original water source. It was not until September 2015 that officials finally issued a lead advisory and switched off the Flint River water source (Grossman & Slutsky, 2017). The Flint River is highly corrosive to iron and lead plumbing due to its high chloride content; therefore, the high chloride levels eroded the pipes in Flint and caused the leaching of lead into the water. Exposure to lead can lead to nervous system issues, seizures, hair loss, impaired cognitive and behavioral disorders, as well as brain and kidney damage (Reilly, 2017).

For their quantitative study, Grossman and Slutsky (2017) collected data from the University of Michigan-Flint Geographic Information Systems (GIS) Center, the Michigan Department of Community Health, and the Michigan Vital Records and Health Statistics Division. Their research revealed that from 2008 to 2015, fetal death rates increased by 58%, fertility rates decreased by 12%, and overall health at birth declined in comparison to other cities in the state of Michigan (Grossman & Slutsky, 2017). However, the water in Flint was contaminated with more than lead. Other researchers hypothesized that from June 2014 to November 2014, there would be an increase in reported cases of Legionnaires' disease in Genesee County, MI (Rhoades et al., 2017). Due to the corrosiveness of the Flint River, this led to 1.3–2.2 times more water main breaks and more iron released, which is a significant *Legionella* nutrient. After Flint switched back to the Detroit Water system, *Legionella spp.* and *Legionella pneumophila* decreased (Nelson et al., 2020; Rhoades et al., 2017).

In a community/regional health study, Liaw et al. (2008) conducted what was considered the first study aimed at childhood cancer mortality and high concentrations of arsenic in drinking water. For roughly 50 years, they assessed the importance of environmental factors regarding one's health by examining children (< 20 years of age) within five regions of Chile known to have arsenic-contaminated drinking water. Liver cancer mortality rates were higher, particularly among females, children (< 19 years of age) exposed early in life, and those living within the exposed region of Chile (Liaw et al., 2008).

Problem Statement

The Elk, Ohio, Kanawha, and Tug Fork Rivers in WV have experienced many instances of chemical contamination, resulting in environmentally and toxicologically induced health impacts on the surrounding population (Allen, 2019; Baxter, 2014; Mistich, 2014). Despite the growing interest in environmental contaminants and their potential impact on a population's health due to various factors (geographical location, proximity, and exposure), there is still a gap in current literature related to specific regions (WV counties). Such counties are recognized for heavy industrialization and environmental health hazards (i.e., chemical contamination), as well as increases in adverse health outcomes or incidences of reported health conditions/diseases (e.g., cancer rates). I also examined race/ethnicity and gender to further examine county-level incidences of reported health conditions or diseases (e.g., cancer rates).

Although 4-methylcyclohexane methanol (4-MCHM), a foaming, coal preparation, and washing agent, would make headlines in January 2014 when it leaked into the Elk River of Charleston, WV, there may have been a public health issue near this area several years prior concerning coal slurry (Allen, 2019; Baxter, 2014; Mistich, 2014). In July 2011, a 7-year-old mass tort was settled between Massey Energy Co. and roughly 700 residents of Mingo County, WV, regarding the underground disposal of coal slurry in an abandoned mine, which would ultimately lead to the contamination of groundwater. A year later, in 2012, more than 350 residents of Boone County would also reach a settlement concerning the contamination of groundwater from coal slurry (Fuchs, 2011; Sheppard, 2014). Due to a lack of effluent guidelines and/or strict regulatory actions, such contamination occurred for many years.

In February 1977, a South Charleston plant, Food Machinery Corporation (FMC), spilled 70–80 tons of carbon tetrachloride (CCl_4) into the Kanawha River. The spill would not only contaminate the water systems for those living within South Charleston but also those of the residents residing along the Ohio River in Cincinnati, Ohio, and Louisville, Kentucky (Douthat, 1977, p. 3). Within a few days, three more tons of this chemical would again be discarded into the Kanawha River. As a volatile organic compound, CCl_4 can cause environmental and health-related issues when exposure to high concentrations occur; the National Institute of Occupational Safety and Health and other organizations have attributed stratospheric ozone depletion (as a halogenated hydrocarbon), as well as toxic and carcinogenic human health effects, to this volatile substance (Evans & Puckrin, 1996; Moghadam et a., 2013). No major regulations existed for this chemical, but the EPA and WV's state government set a daily disposal (or dumping) limitation on this plant, which FMC had exceeded (Douthat, 1977, p. 3). According to Douthat (1977), FMC had been dumping CCl_4 into the Kanawha River since the 1920s (p. 3).

In August 2008, an explosion occurred at a Bayer CropScience plant in Institute, a community in Kanawha County, that released methomyl, or methyl isocyanate (MIC). The explosion killed two plant employees and caused damage up to 7 miles away from the site of the explosion (Mattise, 2015). Prior to this incident, MIC not only had an immediate impact on the lives of individuals on a global scale, but also over time (Mattise, 2015; National Research Council, 2012). In addition, MIC may raise environmental concerns (National Research Council, 2012). In 1951, DuPont’s Washington Works Plant, nestled on the banks of the Ohio River, began using PFOA, also known as C8; the company knew the chemical was toxic by the early 1960s (Mordock, 2016). By the late 1980s and early 1990s, DuPont was aware of the links to increased cancer rates and PFOA/C8. Even so, DuPont failed to inform its employees, the public at large, and the EPA (Sisk, 2020).

Purpose of the Study

The purpose of this study was to examine whether there were any differences in the incidence of disease or adverse health effects (i.e., reproductive issues, neurological disorders, respiratory disease, autoimmune disease, endocrine issues, and pulmonary edema) and cancer (i.e., non-Hodgkin's lymphoma, soft tissue sarcoma, liver, kidney, thyroid, ovarian, prostate, and testicular, etc.) rates pre- and post-exposure to chemical contamination, as measured by blood concentration level (BCL) of PFOA, 2,3,7,8-tetrachlorodibenzo-p-dioxin (TCDD), MIC, and 4-MCHM in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and in bordering counties. The study was quantitative in nature and involved secondary analysis of archived data at the state and federal level (e.g., WV and the CDC). The data, which were in the public domain, depicted the adverse toxicological impacts for counties bordering (at least one side bordering a river and/or intersected by the river) and/or in proximity (within 1 mile) to the Elk, Ohio, Kanawha, and Tug Fork Rivers, and compared to the additional counties in WV that border these four counties of interest. Variables of interest included:

- increased incidence rates of cancer in the four counties bordering and/or in proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers, versus the surrounding WV counties
- the BCLs of the measured chemicals (4-MCHM, MIC, PFOA, and TCDD); and
- gender and race/ethnicity.

Research Questions and Hypotheses

I addressed the following research questions (RQs) and hypotheses:

RQ1: Is there an association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers?

$H_0$1: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

H_a1: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

RQ2: Is there an association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River?

$H_0$2: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

H_a2: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

RQ3: Is there an association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River?

$H_0$3: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

H_a3: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

RQ4: Is there an association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River?

$H_0$4: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

H_a4: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

Conceptual Framework

The conceptual framework for this study was the epidemiological triangle (Gulis & Fujino 2015; Rivier University, n.d.). Human beings are a rather complex and variable species and, consequently, make repeatable and consistent results problematic for researchers to acquire (ChangingMinds.org, n.d.). Therefore, it is imperative to build upon previous studies' suggestions and theoretical constructs or frameworks to examine any associations between environmental aspects and negative health outcomes. Understanding that the incidence of adverse health events and diseases is not random within a population is an essential foundation of epidemiology (CDC, 2012b). Instead, disease and health events are more likely to transpire in specific individuals within a population due to an uneven distribution of risk factors; this is because some individuals are at a greater risk of being affected by certain factors than others (CDC, 2012b). However, modern epidemiology focuses on chronic noncommunicable diseases (i.e., diseases that are not directly transmissible or contagious), which do not appear to be attributable to any solitary causative factor (Broadbent, 2009).

The simplest of models regarding disease causation is the epidemiologic triangle, or epidemiological triad (CDC, 2012b). Disease causation models, such as the epidemiologic triangle, mainly focus on pathogens causing the disease and/or condition, as well as how it replicates and spreads (CDC, 2018; Rivier University, n.d.). This tool consists of three corners, or vertices: agent (the pathogen, or “what” causes disease or injury), host (the organism, or “who” harbors the agent) and environment (the “where”, or external factors that cause or permit injury or disease transmission; CDC, 2018; Rivier University, n.d.). With respect to time and research, the corner, agent, has developed to include both physical (e.g., repetitive forces related to carpal tunnel syndrome) and chemical (e.g., L-tryptophan contaminant responsible for eosinophilia-myalgia syndrome) causes of injury or disease (Allen et al., 2011; CDC, 2012b). Therefore, the three vertices that I examined were chemicals/contaminants (agent), individuals within the four WV counties of interest (host), and the four rivers that border or run through the four WV counties (environment).

Disease causation models can be utilized to focus on physical surroundings (environment) and socioecological factors (e.g., interactions or responses to environment), which can assist in examining organizational, policy, and community influences on health outcomes (Sallis et al., 2008). Stakeholders can use the epidemiologic triangle to reshape policies related to the use of possible contaminants (i.e., chemicals), safety or chemical regulations, and zoning regulations, as well as producers disclosing hazardous information regarding chemicals to businesses, other stakeholders, and the public (Wilson & Schwarzman, 2009). Interventions, knowledge, and policy changes may result from undertaking all three corners of the triangle; however, researchers may choose to focus only on one corner, such as the host and how to improve their resistance to agents (Gulis & Fujino, 2015). Such changes and interventions may aid in protecting both environmental and public health as it relates to pollution and exposure (Magarey & Trexler, 2020).

Maller et al. (2006) noted that public health researchers should attempt to understand the health benefits of being in contact with nature because it can increase health promotion and prevention as well as provide a foundation for an environmental public health socioecological approach. Researchers use such an approach to integrate environmental sustainability while also enhancing the understanding and well-being of individuals and the health of communities (Maller et al., 2006). Often, studies that focus on environmental aspects have incorporated additional elements (e.g., community-level factors), and, therefore, a more complex and multilevel approach (i.e., one that considers multifactorial causes, socioecological factors, etc.) is generally required. Liaw et al. (2008) emphasized the importance of this theory by targeting community and regional health and assessing the surrounding environment within Chile, which yielded the conclusion that liver cancer mortality rates were higher among children in the region exposed to arsenic. Villanueva et al.'s (2007) community-level study showed that the relationship between bladder cancer and long-term exposures to trihalomethanes can vary due to routes of exposure, as well as by geographical region. I used the epidemiologic triangle, which is a disease causation model, in this correlational, quantitative study to explore the relationship between an individual's environment (e.g., zoning regulations, chemical and safety regulations, etc.) and their health status (i.e., incidence of disease, adverse health effects, and cancer rates) due to pre- and post-contamination (i.e., chemical) of water in four WV counties that border the Elk, Ohio, Kanawha, and Tug Fork Rivers.

Nature of the Study

This was a quantitative, nonexperimental study with a retrospective, correlational focus using public-domain archived data. Nonexperimental forms of inquiry are an essential component of quantitative designs, which can be employed to compare or find correlations among sample characteristics (Creswell, 2009; Laureate Education, 2010). Quantitative, correlational studies tend to be flexible while also allowing for the exploration of the linear strength, relationship, and/or direction between two or more variables of interest (Campbell & Stanley, 1963). A retrospective study (i.e., a study that involves working backward) was essential in reexamining and understanding a known outcome (i.e., immediate and trending health effects and/or associated rates in cancer) of interest within this geographical area of interest because chemical contaminations have already transpired (see Fink, 2013). Therefore, I chose to perform a secondary data analysis on previously collected data, which allowed for assessments among groups (see Frankfort-Nachmias & Nachmias, 2008). Such an analysis allowed for the determination of whether a correlation potentially existed among adverse health effects for those four counties bordering and/or in proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers (see National Institutes of Health [NIH], 2003). This was a quantitative study rooted in descriptive epidemiology. The study was an ecologic, retrospective, correlational study that considered previously collected data on the population level. Correlation analyses were performed to examine the associations between pre- and post-chemical contamination (before and after chemical contamination was identified) exposure, and acute and/or chronic illnesses or conditions (i.e., cancer; see Peters, 2014c).

Definitions

Blood concentration level (BCL): The level of concentration of the contaminants 4-MCHM, MIC, PFOA, and TCDD in residents' blood.

Border counties: The following four counties were of interest in this study due to their location and/or proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers: Kanawha, Mingo, Putnam, and Wood.

Incidence rates of cancer: The prevalence of cancer in surrounding counties due to known toxicological events (i.e., chemical contamination) and industrialization occurring at and/or near the Elk, Ohio, Kanawha, and Tug Fork Rivers; there is a potential for residents in these counties to be at an increased risk for various cancers (Brender, Maantay, & Chakraborty, 2011).

Gender: In this study, identification as either male or female. Data were collected on residents in all 55 counties to determine whether there were differences in the incidence of diseases, adverse health effects, and cancer rates pre- and post-exposure to chemical contamination.

Race/ethnicity: In this study, identification as Hispanic/Latino or not Hispanic/Latino, as well as European American, African American, Asian, Native Hawaiian/Pacific Islander, and/or American Indian/Alaskan Native. Data were collected on residents in all 55 counties to determine whether there were differences in the incidence of diseases, adverse health effects, and cancer rates pre- and post-exposure to chemical contamination.

Toxicological impacts: Influences that can affect an individual's and/or populations' health, such as poor environmental living conditions due to chemical contamination.

Assumptions

I assumed that the secondary data were properly and ethically collected, as well as unbiased in nature. In addition, I assumed that the employed methods and sampling instruments were applicable for evaluating the variables of interest. Due to geographical proximity and environmental/contamination events, I assumed that certain counties of WV would display higher rates of individuals with increased adverse health effects and cancer.

Scope and Delimitations

The use of the conceptual framework, the epidemiologic triangle, was helpful in outlining the scope for this particular study. A county's geographical location and/or proximity to an event (i.e., chemical contamination) served as the independent variable and, therefore, also defined the scope of the study.

Limitations

Although there are positive aspects to utilizing secondary data sources (e.g., the conservation of time and money), such sources can be limited in terms of the information they provide (e.g., variables) (Tripathy, 2013). Also, some data sources may not be accessible and/or permission may need to be granted, which takes time. Secondary data sources can also have issues stemming from human error—for instance, in the sampling and analysis procedures that were used. Therefore, it is necessary to employ relevant, unbiased, and accessible secondary data sources that are also reputable (Tripathy, 2013). For this study, the main sample consisted of the four counties of interest in WV, which is a relatively small sample size. The WV counties surrounding the four counties of interest were assessed for health comparison reasons.

Significance

When strategies, ideas, and actions are not only employed but also created in order to promote dignity, progress, and worth amongst these levels where both social and human conditions are improved upon, it is commonly referred to as “positive social change” (Walden University, n.d.-b). Using secondary data sources, I sought to provide insights into the differences, if any, in the incidence of adverse health effects and cancer rates between (a) four WV counties that border, or are in proximity to, the chemically contaminated Elk, Ohio, Kanawha, and Tug Fork Rivers, and (b) surrounding counties. The results may potentially be used by stakeholders to develop improved policies, regulations, and safe chemical use information, which may promote positive social change.

Summary

Given the vital role that the environment plays in human health and vice versa, the purpose of this study was to discover if there were any differences in the incidence of disease, adverse health effects, and/or cancer pre- and post-exposure to chemical contamination in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and in counties that do not border one of these rivers. In this chapter, I provided an overview of the study. In Chapter 2, I review existing literature regarding environmental contamination and human health. In Chapter 3, a description of the methodology for this study is provided. The researcher's role, research design and rationale, population of interest, data collection, data analysis, and ethical procedures are the main components within this chapter. The rationale for the study's research design, as well as the sampling procedures, is provided. I also provide overviews of the data collection procedures, instrumentation, and data analysis techniques.

In Chapter 4, I will discuss the methodology, sample, instrumentation, and analysis I used to assess the incidence of disease and cancer pre- and post-contamination. In Chapter 5, county health data will be summarized, and the findings from this study will be presented. I will further discuss the limitations of this study. Last, in the final chapter, I will also highlight the study's implications for positive social change and offer recommendations for future research not only within this area of interest but also in other geographical locations where similar environmental events have occurred and/or are currently transpiring.

Chapter 2: Literature Review

Introduction

Various regions in WV have experienced many instances of chemical contamination, resulting in environmentally and toxicologically induced health impacts on the surrounding population (Allen, 2019; Baxter, 2014; Mistich, 2014). There is still a gap in current literature related to specific regions (WV counties) due to environmental contaminants and their potential impact on a population's health due to various factors (geographical location, proximity, and exposure). Therefore, the purpose of this quantitative study was to examine whether there were any differences in the incidence of disease or adverse health effects (i.e., reproductive issues, neurological disorders, respiratory disease, autoimmune disease, endocrine issues, and pulmonary edema) and cancer (i.e., non-Hodgkin's lymphoma, soft tissue sarcoma, liver, kidney, thyroid, ovarian, prostate, and testicular, etc.) rates pre- and post-exposure to chemical contamination, as measured by blood concentration level (BCL) of PFOA, 2,3,7,8-tetrachlorodibenzo-p-dioxin (TCDD), MIC, and 4-MCHM in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and in bordering counties.

Chapter 2 will highlight research regarding exposure and proximity to PFOA, 2,3,7,8-tetrachlorodibenzo-p-dioxin (TCDD), MIC, and 4-MCHM, as it pertains to possible increases in adverse health effects and cancer rates. This chapter will also discuss how other chemical contaminates have led to particular adverse health effects and cancer rates due to proximity. Chapter 2 commences with discussing the literature search strategies employed by the researcher and the conceptual framework for this study; specifically how prior studies have used conceptual frameworks in order to examine how chemical contaminants and proximity to such contaminants can impact one's health. This chapter's literature review then discuss key variables and concepts, as well as how such literature relates to the current dependent and independent variables. Chapter 2 concludes by focusing on prior and recent chemical contamination events in WV and literature review to support these events, which further supports the research questions and hypotheses.

Literature Search Strategy

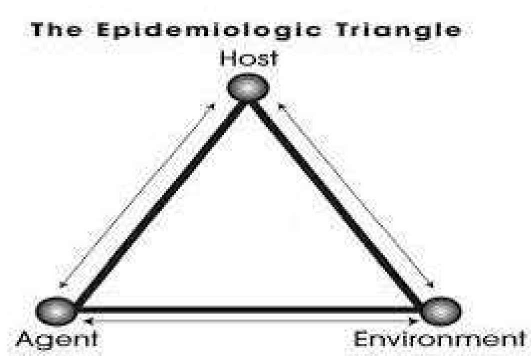
Literature was found by searching on Google, Google Scholar, ProQuest, ScienceDirect, Walden University's Library, etc. However, some of the sources that were used, were already available to the researcher (i.e., books from Walden University). Depending on the reason, particular search terms were used to find relevant resources (e.g., contamination, water contamination, Appalachia, rural, environmental health, cancer incidence rates, geographical location/proximity, etc.). Particular/known contamination events were also searched for by using the exact name of the contamination and/or the area in which it had occurred; certain chemicals were searched for as well. In addition, government websites such as the CDC, U.S. Chemical Safety and Hazard Investigation Board, National Institutes of Health (NIH), and so forth, were accessed ~~in order~~ to obtain vital information on chemical contamination, proximity to contamination events, and possible adverse health effects. Mostly, the researcher looked for resources that were within the past five years. However, in some instances, older research must be used due to availability; but these resources were also used based on their relevancy to the study.

Conceptual Framework

As previously stated, the conceptual framework for this study is the Epidemiological Triangle. It has three corners, or vertices: agent, host, and environment (Figure 1). The three vertices this research aims to examine are: chemicals/contaminants (agent), individuals within the four W.Va. counties of interest (host), and the four rivers that border/run through the four W.Va. counties (environment). Other research has used the epidemiologic triangle to examine whether or not exposure to contaminates has an impact on their health. For instance, Villanueva et al.'s (2007) community-level study showing the relationship between bladder cancer and long-term exposures to trihalomethanes (THMs) can vary due to routes of exposure, as well as by geographical region. Although the results were considered to be non-significant, Naji (2015) also incorporated the epidemiologic triangle. Naji (2015) examined if exposure to bisphenol A (BPA), a chemical in plastic, was associated with BPA in urine and the reporting of cardiovascular diseases (CVD). A study conducted by the Danish National Birth Cohort (DNBC) examined exposure to PFOSA and an increased risk for breast cancer; the researchers found that women younger than 40 years of age who had been exposed to PFOSA, especially during early pregnancy, were significantly associated with the development of breast cancer (Bonefeld-Jorgensen et al., 2014). Therefore, a disease causation model, such as the Epidemiological Triangle, could assist this correlational, quantitative study by expanding upon the knowledge of an individual's environment (i.e., zoning regulations, chemical regulations/safety, etc.) regarding aspects of their health status (i.e., incidence of disease/adverse health effects and cancer rates) due to pre- and post-contamination (i.e., chemical) of water in four West Virginia counties that border the Elk, Ohio, Kanawha, and Tug Fork Rivers (geographical location/proximity).

Figure 1

The Epidemiological Triangle



Note. From "Understanding the Epidemiologic Triangle through Infectious Disease," by CDC, 2018, (https://www.cdc.gov/healthyschools/bam/teachers/documents/epi_1_triangle.pdf).

Literature Review Related to Key Variables and/or Concepts

The Role of the Environment in the Distribution of Human Diseases

In a broader sense regarding individual susceptibility, environmental factors such as lifestyle, diet, and additional non-genetic components are thought to be implicated in most human cancers (Perera, 1997). However, this concept of environmental influences should also frequently incorporate various other elements that human beings encounter daily. To be more specific, humans continuously encounter natural and/or manufactured environmental exposures (e.g., soil, outdoor/indoor air pollution, etc.) that are potentially carcinogenic (Boffetta & Nyberg, 2003). Inhalation, absorption, and/or ingestion are just a few transmission routes for environmental contaminants. Various *vectors* (e.g., water contamination) that we as humans may depend upon for survival can be a direct reflection of the surrounding environment's stability (Morris, 1995). Thus, through the progression of technology and molecular epidemiologic studies, evidence has shown that certain population groups are considered to be at a higher risk for environmental carcinogens, especially in conjunction with predisposing genetic traits (Perera, 1997).

It is also imperative that the geographical location of known carcinogen clusters be further examined in terms of these environmental exposures. Reducing exposure to such environmental factors (even behavioral) could assist in preventing the global and regional burden of disease-related deaths (Danaei et al., 2005; Ezzati et al. 2002). For instance, developing and/or low- and middle-income countries mostly endure higher cancer rates and resulting deaths based upon modifiable risk factors versus developed/high-income nations; however, subpopulations within high-income regions usually are at a higher risk for such risk factors as well (Danaei et al., 2005; Ezzati et al., 2002). Even though a patient's outcome regarding cancer can also be directly impacted by their access to care, Onega et al., (2008) noted that sparse evidence still exists surrounding geographical location and accessibility to care, as well as population aspects and contributing environmental factors.

As society continuously transforms, so does the environment in which humans live. Environmental factors and the distribution of diseases are just two crucial elements that have and will continue to influence the field of epidemiology and public health (Ness et al., 2009). In order to make greater strides in public health, potentially hazardous and harmful to human health environmental components need to be identified and further examined (Morris, 1995). In doing so, environmental primary preventive measures can assist in decreasing the risk of cancer. Additional preventative methods (e.g., lifestyle) for numerous populations should also be considered, as well as both the roles of acquired and genetic susceptibility (Danaei et al., 2005; Perera, 1997). Furthering research in these areas can potentially assist benefit and even protect certain populations from possible environmental carcinogens through the progression of public health, environmental safety, and regulation policies (Perera, 1997; Peters, 2015).

Air Pollution

Air and water are vital elements to sustaining numerous life forms, yet both can and do contain pollutants. According to the EPA (n.d.), air pollution is defined as "one or more chemicals or substances in high enough concentrations in the air to harm humans, other animals, vegetation, or materials. Such chemicals or physical conditions (such as excess heat or noise) are called "air pollutants" and/or "the presence of contaminants or pollutant substances in the air that interfere with human health or welfare or produce other harmful environmental effects" (p. 1). It is believed that contaminants released into the air are more hazardous than those dispersed into the land and/or water; thus, air pollution is a great contributor to respiratory diseases, and 80% of lung diseases are due to pollution (e.g., emission from buses, trucks, cars, businesses, etc.; Conserve Energy Future, n.d.). However, the effects of air pollution can be historically witnessed with the 1952 Great Smog that impacted London and killed roughly 8,000 people. In today's society, individuals are at a greater risk for indoor (2-5 times) air pollution than outdoor, but air pollution due to traffic can increase one's chances of having a heart attack; living near busy roads, cities, and so forth put people at a greater risk for developing bronchitis, asthma, some cancers, and heart disease (Conserve Energy Future, n.d.). In Asia, 65% of deaths are due to air pollution, while there are 25% of air contaminated deaths in India. For over 3 months, methane was emitted from the Aliso Canyon, a natural gas storage facility located in California; according to researchers, this methane leak was the largest in U.S. history (Wilson, 2016).

A new disease has been coined in Beijing due to the rise in air pollution, and it is simply referred to as the "Beijing cough." It is estimated that 6,000,000 individuals will die annually by 2050 from exposure to air contaminants (Conserve Energy Future, n.d.). Switching from more solid, biomass fuels (BMFs) to more efficient and cleaner fuels can reduce individuals' exposure to air pollution (Conserve Energy Future, n.d.). Research has shown a possible increased risk for TB due to air pollution. Even though very few studies exist on associations at the individual level, there appears to be a relationship between the use of BMFs and the rates of TB infection in global geographic regions (Laumbach & Kipen, 2012). Even though studies have shown an increased risk of self-reported TB infection with BMF use (OR 2.58, CI 1.98–3.37), this still may not be accurate due to additional factors (smoking) not being taken into consideration (Laumbach & Kipen, 2012). However, traffic-related air pollution and TB associations can impair macrophage function, and therefore, such a correlation could be biologically plausible (Laumbach & Kipen, 2012).

Water Contamination

Although air pollution is of great concern, the focus of this study is to further understand the possible correlation between water contamination and adverse health effects. According to the World Health Organization (2002), 3.1% of global deaths and 3.7% of global disability-adjusted life years are due to a lack of sanitation, poor hygiene, and inadequate or unsafe water. Roughly 15% of annual childhood deaths can be attributed to diarrhea, and unclean/unsafe water results in 4,000,000,000 cases of diarrhea annually (Ross, 2010). Daily, roughly 2,000,000 tons of sewage and agricultural/industrial waste are discharged and released into the world's waters (Ross, 2010). This can clearly have health impacts not only in underdeveloped and developing countries but also in developed countries. In France, 97% of groundwater samples did not meet nitrate standards, and, within the United States, Colorado had roughly 23,000 abandoned mines that have polluted 2,300 km of streams (Ross, 2010).

The ingestion of drinking water with high levels of inorganic arsenic (> 1,000 μg/L) has been associated with chronic diseases, such as coronary heart disease; thus, when a case-cohort study was conducted in Colorado, the results revealed that lifetime exposure to low-level (< 100 μg/L) inorganic arsenic in drinking water was also associated with an increased risk for coronary heart disease (James et al., 2015). After the introduction of a more corrosive water source, the people of Flint, Michigan, were susceptible to drinking water that contained lead; individuals (i.e., children) exposed to lead are at a greater risk for developing cognitive, behavioral, and neurological issues versus their counterparts (Bianchi, 2015; Cecil et al., 2011; Hanna-Attisha et al., 2016).

The blood lead levels for children younger than the age of 5 years increased from 2.4% to 4.9%, while certain impoverished neighborhoods witnessed a 6.6% increase (Hanna-Attisha et al., 2016). Since contaminants impact the environment through essential life-sustaining substances, various factors need to be taken into consideration regarding their distribution and frequency.

Factors That May Influence Population Health

When conducting research, especially regarding population health, it is vital to take additional considerations into account. These are considerations/factors that can theoretically aid in the explanation of occurrences, rates, and possible increases in certain health conditions and/or diseases. For this study, factors such as geographical location, at-risk populations, and potential health effects related to exposure are essential in understanding how certain events may impact population health.

Geographical Location

As technology has developed, so have advancements surrounding epidemiology and environmental public health, such as enhanced analytical technology, developments in exposure science (e.g., detection and quantification technology), and enhanced methods for understanding potential environmental impacts on population health (e.g., temporal analytical techniques) (Ness et al., 2009). GIS is one such technological advancement in the field of surveillance, and this scientific tool is utilized to incorporate information and manage geographic associations (CDC, 2006). This method has been used to monitor and assess policies/programs within certain environments and track any GIS modifications (Nykiforuk & Flaman, 2011). With the employment of technology-based surveillance such as GIS, estimates (concentrations) surrounding exposure to environmental contaminants can be produced; this method is becoming a relatively common exposure assessment regarding proximity to hazardous events (e.g., waste sites), exposure to pesticides, and modeled concentrations of contaminants in soil, air, and water (Meliker & Sloan, 2011).

GIS can assist researchers to examine the health status of rural and urban populations regarding their external environment. Through a meta-analysis, Po et al. (2011) displayed that exposure to BMF had detrimental health impacts via respiratory diseases. The results of 25 articles pertaining to respiratory illnesses of rural women and children showed that children were three times more likely to develop acute respiratory infections due to BMF exposure, while women were 2.4 times as likely to develop chronic obstructive pulmonary disease when exposed to BMF in comparison other fuels; when smoking was controlled for, women were still 1.5 times more likely to develop chronic bronchitis (CB) (Po et al., 2011). A pooled effect size (OR 3.53, 95% CI 1.94 to 6.43) was produced for children exposed to BMF in rural areas, and it was relatively larger than the OR (OR 1.78, 95% CI 1.45 to 2.18) for the association between solid fuel and pneumonia in children (Po et al., 2011). Generally, those living within overcrowded, urban (metropolitan) areas tend to be at a higher risk for environmental exposures, such as ambient air nitrogen dioxide (NO_2) concentrations (Padilla et al., 2014; Peters, 2015).

At-Risk Populations

Various populations are considered at a higher risk and/or more susceptible to the health consequences of environmental impacts. One factor that may put certain populations at a higher risk is their proximity and/or geographical location to an event. However, additional factors play a vital role in determining whether one is considered to be at a higher risk for such environmental health determinants, such as age and being immunocompromised. Barouki et al. (2012) stated that environmental toxin effects and nutrients can have relatively the same impact on the development of non-communicable diseases; the prevalence of such diseases has increased over the past 40 years. Therefore, with the use of the developmental origins of health and disease concept, the authors aimed to study the environmental exposure (and nutritional) impacts during the developmental stages of an individual’s life (Barouki et al., 2012).

In the systemic review of literature conducted by Karagas et al. (2012), the main objective was to not only understand current knowledge of the impacts of low-level methylmercury (MeHg) on health but also to further the knowledge through risk assessments that employed factors such as birth outcomes and infant growth, neurocognitive/behavioral outcomes, cardiovascular outcomes, and immunologic outcomes. Therefore, 68 articles that specifically had measurements for low-level MeHg were retrieved via PubMed (National Library of Medicine 2012) and ScienceDirect (Karagas et al., 2012). According to the authors, low levels of MeHg may have influences on fetal growth and development; such influences have continued within their first 2 years of life, especially for susceptible subgroups. However, the results surrounding the factor immunologic effects were inconsistent regarding low-level MeHg. In addition, there were no clear patterns established for low-level MeHg effects on cardiovascular disease, but this did vary due to sex, age, and timing of exposure when neurological outcomes were taken into consideration (Karagas et al., 2012). For instance, in Europe and Israel, when low levels of MeHg (0.36 μg/g) were found in toenails, there was a positive association with myocardial infarction; in contrast, the Health Professionals Study and Nurses' Health Study found that there was no relation to toenail MeHg and incident to cardiovascular disease (Karagas et al., 2012). Thus, more studies are needed surrounding low-level exposure to MeHg, as well as those considered to be at risk.

Health Effects of Exposure

Exposure to such sources can have adverse health effects, and many may have long-term impacts. When pollutants/contaminants enter the environment, many may not simply dissipate and/or break down; in contrast, biomagnification and bioaccumulation can occur. Such interactions with contaminants and the environment can thereby produce human-environment interactions; to be more specific, gene-environment interactions. These interactions can be further explained by proximal (biological/downstream exposures) and distal (societal/upstream influences) risk factors (Shi & Singh, 2011). Even though GIS has been quite influential in the public health realm, advanced surveillance of human (gene)-environment (exposure) interaction is needed, especially based upon proximity to exposure (e.g., gene-environment and GIS). In addition, the gene-environment interaction can be limiting at the individual-level; thus, clustering can display proximal and distal factors as influencing disease risk (Shah, 2004; Zhu, 2014).

In northern Chile, more than 250,000 individuals were exposed to high levels of arsenic in their drinking water when a water treatment plant was installed from 1958-1970 (Steinmaus et al., 2013). Since many individuals are exposed to arsenic-contaminated water on a global scale, the authors conducted a population-based case–control study in northern Chile, which revealed that both bladder and lung cancers were found up to 40 years after the highest levels of exposure had ceased; meaning, arsenic levels are still high in this area and having continuing health impacts (gene-environment) (Steinmaus et al., 2013). What does this mean for current environmental issues? The Animas River in Colorado has been polluted for years by abandoned mines, but a recent spill of stored, chemical-laced water by the EPA has only made matters worse (Turkewitz, 2015). Among other metals, the wastewater contained lead and arsenic (Turkewitz, 2015). Thus, the importance of living in a healthier and greener environment has been recommended for short- and long-term impacts. Health (mental and physical) and well-being can occur from living within greener environments, and thus, this notion can lead to parks and natural reserves playing a much larger role, influence, and scope within various societies; particularly urban communities (Maller et al., 2006; Peters, 2015).

Notable Contamination Cases in West Virginia

Because an individual’s environment, geographical location, and even proximity to an event can play a vital role in observed health issues, certain geographical locations and populations within them may experience higher rates of diseases and conditions (Peters, 2014a). A range of health issues/conditions (e.g., adverse health effects, cancer, etc.) may also be viewed as health inequities/inequalities, because they could affect individuals globally due to poverty and unfortunate circumstances (location/proximity) (Peters, 2014b). However, health inequalities such as the increase in diseases and/or conditions associated with geographical location and/or proximity to an event (or events), do not only take place in developing countries, but also in the United States; especially rural, remote areas like the Appalachian Mountains (Erwin, 2008). Various counties within the state of WV have witnessed such health inequalities simply based upon their geographical location/proximity to incidents (i.e., chemical contamination) that are of great public health and environmental concern.

Food Machinery Corporation

FMC leaked 70–80 tons of CCl_4 into the Kanawha River, which would not only contaminate the water of South Charleston (see Figure 2), but also the water system for those along the Ohio River in Cincinnati, Ohio, and Louisville, Kentucky (Douthat, 1977, p. 3). Due to insufficient guidelines, three more tons of this chemical would be spilled into the same water system within a few days. However, over roughly 55 years prior to that incident in 1977, FMC had already been improperly disposing of this volatile chemical (Douthat, 1977, p. 3).

Carbon Tetrachloride. Classified as a volatile organic compound, CCl_4 (molecular wt. = 153.8 g/mol) is a colorless, transparent, very stable, and volatile chlorinated hydrocarbon that does not occur naturally (i.e., is manufactured; ATSDR, 2011; National Center for Biotechnology Information [NCBI], n.d.). The hydrocarbon, which tends to smell sweet and can be detected at lower levels, is also referred to as benziform, carbon chloride, perchloromethane, tetrachloroethane, or methane tetrachloride (ATSDR, 2011). This chemical is used as a solvent for resins, varnishes, oils, lacquers, rubber waxes, fats, and as the foundation for the manufacturing of organic compounds (NCBI, n.d.). Based on prior carcinogenicity discovered in experimental research on animals, CCl_4 is classified as being reasonably anticipated to be a human carcinogen (NCBI, n.d.).

In humans, CCl_4 is thought to mainly affect the liver, central nervous system, cardiovascular system, and kidneys (ATSDR, 2011; NCBI, n.d.). Acute, short-term symptoms associated with oral and inhalation exposures to CCl_4 are vomiting, headache, lethargy, nausea, and weakness; both kidney and liver damage appear to be the primary health issues associated with acute exposures to higher levels and long-term, chronic exposures (inhalation and oral) to CCl_4 (NCBI, n.d.). Therefore, the EPA has classified this chemical as a probable human carcinogen (Group B2) (NCBI, n.d.). Even so, there is limited human data/inadequate evidence pertaining to the carcinogenic impacts of CCl_4 (NCBI, n.d.). The hydrocarbon was once used in pesticides and the manufacturing of refrigerants, cleaners, fire extinguishers, and so forth; based on its toxicity and other harmful effects, it is no longer used for such household purposes, but it is still employed for industrial use (ATSDR, 2011).

Massey Energy Co.

In July 2011, a 7-year-old mass tort was settled among Massey Energy Co. and roughly 700 residents of Mingo County, WV, concerning the underground and abandoned mine disposal of coal slurry (Fuchs, 2011). The Tug Fork River is a tributary of the Big Sandy River and is part of the Mississippi River watershed by means of both the Big Sandy and Ohio Rivers (U.S. Geological Survey, n.d.; see Figure 2). Although this river is notoriously known for being the dividing line between the quarrelling

Hatfields and McCoys, it has also been the host for other issues (i.e., chemical contamination) (Shepherd, 2019). The Tug Fork River borders and separates the county of Mingo from the State of Kentucky (U.S. Geological Survey, n.d.). Lick Creek, Rawl, Merrimac, and Sprigg communities accused a Massey subsidiary (Rawl Sales & Processing Co.) of contaminating their groundwater between 1978 and 1987 by dropping 1,400,000,000 gallons of coal slurry into abandoned mines (Fuchs, 2011). In June 2012, more than 350 residents of Boone County also reached a settlement over claims of coal slurry contamination and tainted groundwater (Sheppard, 2014).

Coal Slurry. This fluid (waste) is simply the product created when coal is washed with water and chemicals prior to shipping the coal to market; this procedure aids in the reduction of non-combustible materials (e.g., sulfur) from the coal (Herter, 2012). The coal cleaning process yields waste that contains coarse-size fractions (i.e., coarse refuse) and small particles (i.e., fine refuse) (Aken et al., 2014). The aqueous suspension of fine refuse (or coal slurry) contains the chemicals used in coal washing and potentially additional toxic substances, including hydrocarbons and heavy (Aken et al., 2014). Coal slurry is disposed of by using underground injection (e.g., abandoned underground mines) and/or stored in surface impoundments (Aken et al., 2014; Herter, 2012). Such disposal techniques raise concerns, and it is often feared that this can contaminate both the environment and nearby drinking water, as well as additional water sources (Azad, 2017).

Although the exact chemical composition of coal slurry is mainly unknown and may vary, various elements and compounds (organic and inorganic) are known contributors to this fluid; in addition, high levels of lye, diesel fuel, caustic starch, sulfates, nitric and sulfuric acids, as well as flocculants, patented industrial coagulants, and surfactants have been found in coal slurry (Herter, 2012). Several of these compounds are identified as being genotoxic, neurotoxic, and carcinogenic; chronic exposure to the metals found in coal slurry can also be quite damaging to the human body, resulting in potential health issues such as miscarriages, birth defects, neuropathy, kidney and liver failure, cancer, and brittle bones among others (Herter, 2012).

Bayer CropScience Plant

On August 28, 2008, an explosion occurred at a Bayer CropScience plant in Institute in Kanawha County, WV, as a result of MIC (Mattise, 2015; see Figure 2). The plant is located near the Kanawha River. Today, it is owned by Union Carbide, which is now a part of Dow Chemical Company. The explosion killed two plant employees, injured eight, and caused damage up to 7 miles away from the site of the explosion (Mattise, 2015). The U.S. Chemical Safety and Hazard Investigation Board (CSB, 2011) stated the following:

> Although Bayer CropScience reported that no toxic chemicals were released because they were consumed in the intense fires, the CSB later confirmed that the only air monitors suitably placed near the unit to detect toxic chemicals were, in fact, not operational at the time of the incident. No reliable data or analytical methods were available to determine what chemicals were released or predict any exposure concentrations. (p. 2)

According to the final investigative report, Bayer personnel did not perform the standard prestartup safety review, the personnel were not appropriately trained, and the equipment was not properly functioning (CSB, 2011).

The Kanawha Valley harbors various facilities that handle large quantities of hazardous materials, and some of these are highly toxic (CSB, 2011). The Bayer CropScience facility in Institute, WV, is the only one in the United States that not only stores but also uses large amounts of MIC (CSB, 2011). Roughly 24 years prior, in 1984, more than 40 tons of MIC would also be responsible for the immediate deaths of 3,800 individuals in Bhopal, India, and would later significantly contribute to morbidity and premature death rates for thousands more, as well as present environmental concerns (Broughton, 2005; Vijayan, 2010). Pulmonary edema was the apparent cause of death for many individuals, while countless others died from secondary respiratory infections; those who survived have and still experience damage to the eyes and lungs, while the number of stillbirths and spontaneous abortions also increased after this incident in India (EPA, 2016). When the incident occurred in India, many in the Kanawha Valley attempted to reduce and/or eliminate the use of MIC by convincing the owners of the Institute facility of its' toxicity and potential danger (CSB, 2011). Thus, the 2008 explosion only revived community concern and pressure to reduce the MIC risk to the public (CSB, 2011).

Methomyl. MIC is an organic compound with the molecular formula C_2H_3NO; isocyanatomethane, methyl carbylamine, and MIC are all synonyms for this compound (Delaware Health and Social Services, 2016; EPA, 2016). It serves as an intermediate chemical in the production of carbamate pesticides (such as carbaryl, carbofuran, methomyl, and aldicarb) while also being utilized in the production of both rubbers and adhesives (Delaware Health and Social Services, 2016; EPA, 2016). This highly toxic and irritating material is considered extremely hazardous to human health, especially from acute (short-term) exposure (EPA, 2016). According to the Delaware Health and Social Services (2016):

> Methyl isocyanate, classified as a choking/pulmonary agent, is a water reactive liquid at room temperature. Methyl isocyanate is irritating and corrosive to the eyes, skin, and respiratory tract, including asthma-like allergy. Exposure to methyl isocyanate can result in cough, difficulty breathing, chest pain, excessive tearing (lacrimation), swelling of the eyes, and unconsciousness. (para. 1)

Symptoms emerging over the next 24 to 72 hr. (or late-stage exposure) after exposure to MIC can include cardiac arrest, acute lung injury, and even death; therefore, sanitization of those exposed is unequivocally necessary (Delaware Health and Social Services, 2016). It was the primary toxicant in the Bhopal disaster, which initially killed nearly 2,259 people, and ultimately, 3,787 people in total (EPA, 2016).

Pharmacia (aka Monsanto Company)

Pharmacia, previously known as Monsanto Company, was located in Nitro, WV, nestled right beside of the Kanawha River (EPA, 2017). Nitro is a city that straddles the border between Putnam and Kanawha Counties (see Figure 2). Monsanto Company was operational from 1934 to 2000. From 1948 to 1969, this facility in Nitro manufactured a key element of Agent Orange, 2,4,5-trichlorophenocyacetic acid (EPA, 2017). A hazardous byproduct of this herbicide, TCDD, was found at the facility (Fiorito & De Martino, 2014; Institute of Medicine Committee to Review the Health Effects in Vietnam Veterans of Exposure to Herbicides, 1994). Pharmacia (Monsanto) is believed to be the main culprit behind TCDD contamination within the Kanawha River.

2,3,7,8-tetrachlorodibenzo-p-dioxin (TCDD). Dioxins belong to the group of persistent organic pollutants, and they can be highly toxic environmental pollutants. Unfortunately, due to their chemical stability, dioxins can last 7 to 11 years (half-life) inside the human body (primarily stored in fat tissue). Humans are mainly exposed to dioxins via their accumulation within the food chain (consumption of meat, dairy, fish, etc.; World Health Organization, 2016). Water contaminated with TCDD impacts not only the surrounding environment but also food sources (food chain).

The Kanawha River and additional water systems within WV are contaminated with TCDD. The State standards for WV specify that dioxin levels in the Kanawha River should not exceed 0.014 pg/L. Based on the data collected, dioxin levels consistently exceed the State's water quality standard (Limno-Tech, 2000). However, exposure to TCDD does not only occur through food and water; individuals can also be directly exposed to this dioxin. On March 8, 1949, occupational exposure to TCDD occurred at the Monsanto Company. TCDD escaped through a chimney and inside the plant when the pressure inside an autoclave manufacturing this dioxin exceeded safety limits (Institute of Medicine Committee to Review the Health Effects in Vietnam Veterans of Exposure to Herbicides, 1994). Dioxins, such as TCDD, can act as a carcinogen and increase one's risk for cardiovascular, metabolic, developmental, endocrine, and reproductive issues (Fiorito & De Martino, 2014; World Health Organization, 2017).

DuPont's Washington Works Plant

In 1948, DuPont built the Washington Works plant in Parkersburg, WV (Blake, 2018). Parkersburg is a city located in Wood County, WV (see Figure 2); this city is positioned at the confluence of the Little Kanawha and Ohio Rivers (National Association of Counties [NACO], n.d.). In 1951, DuPont began purchasing PFOA, also known as C8, from 3M to manufacture Teflon at its Washington Works plant, which quickly became the largest global producer of Teflon (Mordock, 2016); by 1961, the company knew that PFOA/C8 was toxic (PFAS Project Lab, n.d.). In 1981, DuPont removed female workers from working directly with Teflon due to evidence of birth defects in babies born to female employees of the Washington Works plant (PFAS Project Lab, n.d.). After an increase in various health issues (i.e., cancers) reported by employees of the WV plant and numerous lawsuits, the plant moved PFOA/C8 production to Fayetteville, North Carolina (Mordock, 2016).

Perfluorooctanoic Acid. PFOA, also known as C8, is a manufactured perfluorochemical and a byproduct in the production of fluoropolymers. Perfluorochemicals are utilized to create manufactured fluoropolymer coatings that are nearly frictionless (non-stick), as well as resistant to heat, stains, grease, water, and oil (CDC, 2017). Teflon is the brand name used for a group of manufactured chemicals (fluoropolymer), and thus, PFOA is the consequence of such a formation (American Cancer Society, 2020). Even though levels of PFOA/C8 in drinking water are typically low, they can be higher in specific areas, such as those neighboring chemical plants that utilize PFOA/C8.

PFOA/C8 can impose significant health concerns due to its ability to stay within the environment and human body for long periods of time. In 2005, years after PFOA/C8s original introduction into the City of Parkersburg, residents' PFOA/C8 blood levels within 2 miles of the plant far exceeded the EPA's guidelines (Mordock, 2016). Research involving both animals (laboratory) and humans (living near or working in PFOA-related facilities) exposed to PFOA shows increases in the risk of testicular, prostate, liver, breast, pancreas, kidney, thyroid, ovarian, and bladder cancers (American Cancer Society, 2020).

Freedom Industries' 2014 Leak Into the Elk River

Freedom Industries is the industrial plant responsible for leaking the chemical 4-MCHM into the Elk River (see Figure 2). Roughly 1 month prior to the January 9, 2014, chemical leak, Freedom Industries was formed on December 13, 2013 (Barrett, 2014). This formation was due to a merger between Crete Technologies, Etowah River Terminal, and Poca Blending (Barrett, 2014).

4-Methylcyclohexane Methanol

Information pertaining to 4-MCHM is sparse and therefore, both short- and long-term health impacts of this substance are still unknown, specifically regarding human health (Lan et al., 2015). However, its environmental impacts are also vastly unknown, and assessments and monitoring are also needed. Lan et al. (2015) noted this sparse information issue surrounding 4-MCHM and, therefore, via an innovative quantitative toxicogenomics approach, assessed the mechanistic toxicity of 4-MCHM and its metabolites. The research, using both yeast (proteomics analysis) and human cells (transcriptional analysis), showed that 4-MCHM metabolites were more likely to be harmful than 4-MCHM in both types of cells; overall, this chemical is associated with genotoxicity due to DNA damage-related biomarkers being induced within human cells (Lan et al., 2015). Prior research underpinned this study to address negative health outcomes that can potentially arise due to long-term/routine exposure to harmful environmental conditions. Thus, further research is needed concerning the possible influences of 4-MCHM.

Whelton and McMillan (2015) conducted a cross-sectional study to better understand WV residents' perceptions 2 weeks following the January 2014 chemical spill of 4-MCHM into the Elk River of WV; this was accomplished via rapid in-home surveys and water testing. According to prior medical and survey data, flushing could possibly lead to adverse health effects (Whelton & McMillan, 2015). Out of the 16 households surveyed, 14 of these reported smelling an odor coming from their tap water for up to at least 2 weeks after the chemical spill; seven of the households reported that at least one individual from their household became ill during this time frame. Overall, concentrations of 4-MCHM differed from home to home, and flushing reduced 4-MCHM levels within the majority of homes (Whelton & McMillan, 2015).

Propriety Mixture

On January 21, 2014, an additional chemical was discovered in the environment and was identified as a proprietary mixture mainly composed of propylene glycol phenyl ether and dipropylene glycol phenyl ether (CDC, 2014). This mixture was in the same tank as the 4-MCHM and although it entered the Elk River at the same time, it was in much smaller amounts (CDC, 2014).

Figure 2

Map of West Virginia Counties and Rivers

Note. From “West Virginia Lakes, Rivers, and Water Resources,” by B. Cole, n.d., (https://geology.com/lakes-rivers-water/west-virginia.shtml). Copyright 2005–2024 by Geology.com.

Summary and Conclusions

The literature review engaged with the issue of chemical contamination on population and environmental health. Air and water are both vital elements to sustaining numerous life forms, yet both can and do contain pollutants. Potentially toxic chemicals can enter the environment via means of accidental leaks/poor containment, insufficient guidelines, ignoring the issue, explosions, and so on. Such chemicals can contaminate water and/or air sources of communities and, thus, potentially cause health and environmental issues; typically, these companies/facilities responsible for these chemical leaks/exposures are one of the main, if not the leading employers within the impacted communities. Such chemicals have the possibility of staying within the environment and impacting different generations (e.g., intergenerational, food chain, etc.).

In rural regions, such as certain WV counties within the Appalachians, ecological integrity (an ecosystem that supports/maintains the biota) of waterways can serve as an indicator of human cancer mortality rates (Hitt & Hendryx, 2010). The majority of prior research pertaining to chemical exposure has focused primarily on immediate/acute impacts and not necessarily long-term impacts of exposure, especially if chronic exposure is through air, water, and so forth. Therefore, despite the growing interest in environmental contaminants and their potential impact on a population's health due to various factors (e.g., geographical location, proximity, and exposure), there is still a gap in the current literature related to WV counties. Specifically, regions that are recognized for heavy industrialization and environmental health hazards (i.e., chemical contamination), as well as increases in adverse health outcomes or incidences of reported adverse health conditions/diseases (e.g., cancer rates) where such influences have previously transpired and/or have not been publicly acknowledged by studying a particular time frame, (i.e., pre- and post-contamination/exposure; Hoover et al., 2020).

In addition, to further understand the impacts of chemical contamination on a population, it is essential to examine categorical data such as gender and race/ethnicity. For instance, such categorical data can assist researchers in determining if certain individuals may be at a higher risk due to occupational exposure (e.g., TCDD contamination) and/or physiological. According to the United Nations Development Programme (2011):

> For instance, in agricultural communities in developing countries, men may be at higher risk of direct exposure to chemical pesticides during application, while women (and sometimes children) may be more likely to be indirectly exposed during planting and harvesting. At the same time, biological factors–notably size, physiological, hormonal, and enzyme differences between women and men, and between adults and children–also influence susceptibility to health damage from exposure to toxic chemicals. (p. 3)

Thus, such data can assist in revealing county demographics as it pertains to adverse health outcomes or incidences of reported health conditions/diseases (e.g., cancer rates). To further our understanding of potential health and environmental impacts (immediate and long-term) caused by contamination events, it is vital to examine one's proximity to such events. Therefore, further research into quantifying the mechanisms of contaminant toxicity to humans/living organisms is imperative for a better understanding of their role in the environment for those individuals directly impacted, as well as future generations. Chapter 3 will discuss the researcher's role, methodology, population, data collection process/procedures, and research design and rational, as well as threats to reliability and validity.

Chapter 3: Research Method

Introduction

The main sections of this chapter are the researcher's role, research design and rationale, methodology, and threats to validity. The study's research design and rationale reflected the chosen research design and rationale behind its selection. An overview of this study's population of interest was given, as well as the sampling procedures employed. Last, a description of the data collection process, instrumentation, and data analysis procedures was also provided.

The purpose of this study was to attempt to discover if there are any differences in the incidence of disease/adverse health effects and cancer rates pre- and post-exposure to chemical contamination, in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and counties that do not border one of these rivers. The study is purely quantitative in nature, using public domain secondary archived data at the state and federal level (e.g., WV and the CDC), depicting the adverse toxicological impacts for counties bordering and/or in proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers, and compared against all other counties in the WV. Variables of interest include increased incidence rates of cancer and reported disease/adverse health effects in counties bordering and/or in proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers vs. the surrounding WV counties, and the variables of gender and race/ethnicity that might or might not have been affected.

Role of the Researcher

I did not directly interact with participants who live in the specified areas to collect data; instead, archival data will be collected from published sources available to the public. Collection of data is not restricted and is published by the state for researcher consumption. I used Microsoft Excel and Statistical Package for the Social Sciences (SPSS) Version 28 to organize and analyze the data.

I collected archival data on cancer rates in WV. I collected and analyzed all the published data I could find. This means that sampling did not occur. The population is defined as all counties in the state of WV. Access to data is not prohibited or restricted. Data has been published and is available on the state of WV, CDC, and National Institutes of Health (NIH)/National Cancer Institute websites. Only aggregated data were collected. This means that individual data on subjects was not available and was not sought by the researcher. Rather, cancer rates were obtained and analyzed according to research protocol. Aggregate cancer data on subjects from WV counties were obtained from published sources maintained by the CDC. Data from 55 WV counties was collected and processed. Sampling was not conducted; rather, all data published on cancer rates was obtained.

Research Design and Rationale

The intended nature of this non-experimental study design was quantitative with a correlational (i.e., retrospective) focus, using public domain archived data. Select strategies of inquiry (non-experimental) are an essential component to quantitative designs, which can be employed to compare or find correlations among sample characteristics (Creswell, 2009; Laureate Education, Inc., 2010). Quantitative, correlational studies tend to be flexible in various areas, while also displaying the linear strength, relationship, and/or direction, between two or more variables of interest (Campbell & Stanley, 1963). A retrospective study (working backward) can be essential in reexamining and understanding a known outcome (i.e., immediate and trending health effects or associated rates in cancer) of interest within this geographical area of interest since a history of certain events (i.e., chemical contaminations) have already transpired (Fink, 2013). Therefore, a secondary data analysis (assessment among groups) was performed on the previously collected data, which allowed assessments among groups (Frankfort-Nachmias & Nachmias, 2008). Such an analysis was utilized to determine if a relationship potentially exists among adverse health effects for those four counties bordering and/or in proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers (NIH, 2003). A retrospective, correlational research design can be beneficial to this environmental health study by not only building upon what current literature exists but also by performing a secondary data analysis regarding the comparison of residents' health statuses within a specific location (i.e., 55 counties of WV) that have experienced certain environmental contamination events (Peters, 2014c).

The quantitative portion of this study was a comparative design where the aim was to explore differences in cancer rates between specified counties. In comparative, non-experimental studies, variables occur naturally in a setting, meaning that the researcher will not impose manipulation or random selection. Comparative research designs are used to obtain information about the current status of the phenomena and to describe what exists with respect to cancer rates between counties. This study incorporated a cross-sectional approach, meaning that data will be collected at a single point in time rather than across time.

Advantages and Disadvantages of the Research Design

The main advantage of quantitative research is the ability to obtain data at a single point in time. This facilitates data collection and provides the means to obtain information on individuals that may otherwise be difficult to get. Comparative non-experimental designs usually involve comparing aggregate data. Because data is typically archival in nature, data can be easily obtained through data mining techniques rather than via primary sources.

The main disadvantage of using quantitative research involves the lack of depth of information. That is, in quantitative research, observations are generally coalesced into numerical values or propositional phrases that have been pre-defined by the researcher. This feature of quantitative research usually restricts information from developing or involving and can, therefore, affect the external validity of the study. Furthermore, in a non-experimental comparative study, when aggregated data is being used, the researcher does not have the means to drill down into the data to find nuances that may support conclusions and enhance the interpretation of findings.

Methodology

The target population for this study consisted of residents in the four WV counties of interest (Kanawha, Mingo, Putnam, and Wood counties), who are considered to be at risk, due to their geographical location, for diseases and adverse health effects (i.e., reproductive issues, neurological disorders, respiratory disease, autoimmune disease, endocrine issues, and pulmonary edema) and certain cancers (i.e., non-Hodgkin's lymphoma, soft tissue sarcoma, kidney, thyroid, ovarian, prostate, and testicular). I attempted to collect health data/cancer incidence rates on the four counties of interest during the contamination events, as well as 10 years prior and 10 years after such events. Since every resident within the four counties of interest will not have been equally exposed to the contaminants, exposure will be confirmed via BCL among those residents who were tested and exposed to 4-MCHM, PFOA, MIC, and TCDD. The 51 additional WV counties are considered to not be at risk (geographically non-exposed) and will be used for toxicological comparison. Therefore, increases in incidences of disease/adverse health conditions and/or cancer rates for the four WV counties (pre- and post-exposure/events) of interest and those additional counties that border them were ultimately evaluated.

Population

The population consisted of all individuals who live in WV. Data on both sexes were obtained. Filters for age, income, and socioeconomic status were not available and, therefore, were not a condition for inclusion. Data sampling did not occur since cancer rates are reported by county; that is, the four counties of interest and their surrounding counties in the state of WV was targeted. As of 2022, the reported population of WV was 1,775,156, with a median age of 42.6. In 2021, WV's median household income was $27,302 (Data Commons, n.d.).

A priori sample determination was assessed by conducting a formal power analysis. Three factors were measured when conducting the analysis, including the effect size of the phenomena, the intended power of the study, and the level of significance to be used in rejecting the null hypotheses (alpha). Study power is the probability of rejecting a false null hypothesis. As a common guideline, the adequate power to reject a false null hypothesis is .80 (Kuehl, 2000). Effect size is an estimate measurement of the strength of the relationship between variables in the study (Cohen, 1988). The effect size was characterized by Cohen (1988) as Cohen's f^2 small, medium, and large, where each level is associated with a specified effect size. Thus, a small effect = .10, medium = .25 and large = .40.

There are no formal standards for power (referred to as π), or alpha (referred to as α). In most cases, researchers assess the power of their tests using π=0.80 and significance using α = .05 as a standard for adequacy. These two conventions imply a four-to-one trade-off between β-risk and α-risk (β is the probability of a Type II error; α is the probability of a Type I error, 0.2 and 0.05 are conventional values for β and α) (Ellis, 2010).

Alpha is defined as how confident one is when rejecting the null hypothesis. As a matter of convention, Social Science research suggests that alpha should be set at .05 (Faul, Lang, & Buchner, 2007). However, when sampling is not being conducted, and all data points will be used, a minimum of 30 data points is recommended, given the central limit theorem. Therefore, the sample size for this study was 385 respondents. This sample size was calculated from an unknown population size by utilizing a 95% confidence interval and the following equation (Thakur, n.d.):

$$\text{Sample Size} = \frac{(\text{Z-score})^2 \times p \times (1-p)}{(\text{margin of error})^2}$$

$$\text{Sample Size} = \frac{(1.96)^2 \times 0.5 \times (0.5)}{(0.05)^2}$$

$$\text{Sample Size} = 384.16$$

Sampling and Sampling Procedures

It is nearly impossible to study every individual (i.e., target population) residing within these four WV counties of interest, and a longitudinal study would be both costly and time-consuming. Therefore, sampling procedures can assist researchers in ascertaining a sample representative of the target population (whole population of interest); in turn, such deductions, based on relevant characteristics, can be relayed back to the target population. Reliability and validity aid the determination of how the sample results can be generalized to the target population. Researchers should be mindful when selecting a sampling procedure/technique (i.e., archived data) based on the unit(s) being analyzed (i.e., WV county residents). This affects the instruments utilized in collecting information from the sample and how such data is ultimately analyzed.

Procedures for Recruitment, Participation, and Data Collection

Archival and/or secondary data sources were used for this study. Data sources in the public domain from the West Virginia Department of Health and Human Resources (DHHR) and the CDC can be easily retrieved for this research. In addition, secondary data sources from NIH's National Cancer Institute, such as GIS, cluster analysis, demographics, and so forth, were accessed and utilized. I used Excel and SPSS to process the collected data.

Instrumentation

Processed data in the form of ratios was obtained from the state of WV, CDC, and NIH/National Cancer Institute websites. Incidence, considered a measure of disease, allows researchers to determine an individual's probability of being diagnosed with a disease during a particular time frame; thus, the quantity of newly detected cases of a disease is incidence (New York State Department of Health, 1999). An incidence rate is the ratio (frequency) of the sum of new cases of a disease divided by the population (sum of persons) at risk for the disease (New York State Department of Health, 1999). The numerator is the number of new cases of disease(s) during a specific time frame and/or period of observation, while the denominator is the observed person-years or number of persons at risk for a disease in a population during a specific time frame (CDC, 2012a; Marcus, 2019). The numerator is divided by the denominator to obtain an incident rate. Therefore, the National Cancer Institute (n.d.) defines cancer incident rate as:

> the number of new cancers of a specific site/type occurring in a specified population during a year, usually expressed as the number of cancers per 100,000 population at risk. That is: Incidence rate = (New cancers / Population) × 100,000 (para. 1).

No instruments were used in the study. Surveys were not employed.

Data Analysis Plan

To analyze the data, I used the SPSS Version 28 software program. Data analysis was accomplished using the analysis of variance (ANOVA). An ANOVA test is a statistical procedure conducted to determine differences in a continuous scaled dependent variable (defined in the equation as “y”) between a categorical scaled variable (“x”) with at least two levels. Assumptions for ANOVA include linearity, normality, independence of error, and homogeneity of variance. For this study, the dependent variable was certain contamination events within four WV counties and their possible correlation to higher rates/increases in adverse health effects and cancer. The four WV counties bordering the Elk, Ohio, Kanawha, and Tug Fork Rivers versus the counties that do not border these rivers will be the independent variables.

ANOVA is used to compare means across two or more independent groups to determine if they differ significantly. During the 1920s and 1930s, a geneticist and statistician named R. A. Fisher, developed ANOVA; it is commonly referred to as Fisher’s ANOVA (Lindman, 1974). The ANOVA equation is simply the sum of squared differences between groups divided by the sum of squared differences within groups (i.e., between mean squares ÷ within mean squares). This basic calculation indicates the variation in scores found between groups and divides that by the variation in scores found within groups. The subsequent ratio (designated by F) measures the strength of independence; F is always positive and always greater than 0. Also, a measure of the strength of independence, eta squared, is calculated using the following equation:

Eta squared = Sum of squares between groups ÷ Total sum of squares

Eta squared is typically referred to as an effect size, which is characterized by the following scale developed by Cohen (1988): .01 = Small, .06 = Medium, and .14 = Large. Thus, the two measures of validity, *F* and *Eta squared*, will be utilized to determine effect size. Once ANOVA has been completed and if any of the group means are significantly different, a post hoc test will be conducted for this study. When there are three or more groups, a post hoc test (e.g., Tukey's post hoc test) is necessary when the null hypotheses have been rejected; post hoc tests allow researchers to see where the significant differences among the groups reside (Tipton & Morgan, 2018).

Threats to Validity

Reliability

In research, assessments are considered reliable if they produce the same results on a consistent (inter-item consistency) basis; this is assumed if what is being measured is not being altered (Trochim, 2006). According to Tabachnick and Fidell (2007), researchers have the capability of studying the properties of measurement scales and the items that compose such scales via reliability analysis. A reliability coefficient, which ranges from 0 to 1, is calculated/produced from the Cronbach's alpha reliability analysis; this coefficient is grounded upon the average inter-item association. In addition, if the coefficient is ≥ 0.60, then scale reliability is assumed. Based on the given characteristics of the data, reliability is not applicable, implying that such (reliability) data cannot be obtained from single-value ratio information.

Validity

Validity refers to the assumption that the cancer rates obtained measures the cancer rate of a specified population. Validity of the data is assumed, given that the data has been screened, processed, and analyzed under instruction of the state of WV, CDC, and NIH/National Cancer Institute. Furthermore, the design is appropriate for the study, the sample is assumed to be representative of the population, sample methodology does not contain biases, and statistical procedure is applicable for what is being analyzed. Data collection is appropriate, and the instruments are assumed to accurately measure what is supposed to be measured.

Ethical Procedures

Generally, it is assumed that ethical issues do not greatly pertain to secondary data analysis versus primary data analysis. Because secondary data were utilized for this study, it is imperative to consider the potential ethical issues that can impact secondary data analysis and, therefore, should be properly addressed. Even though a secondary data analysis was conducted, Walden University (n.d.-a) requires institutional review board approval prior to any form of data collection, which I obtained (approval no. 09-14-22-0474481). First and foremost, it is essential to understand if the data set/database is accessible and/or if permission is needed; for this research in question, a public data set will be utilized, and thus, permission will not be necessary ("The Research Ethics Guidebook", n.d.). Certain criteria (i.e., methodology, time frame of collection, and purpose of data collection) pertaining to the data used will be evaluated and deemed both relevant and acceptable to the study (Tripathy, 2013). As the primary researcher, there was no conflict of interest regarding the population of interest. Based on the variables selected and the results, it is vital to mention that it is not the intent of the researcher to depict a bias (i.e., higher risk for certain health outcomes) towards rural-dwelling individuals. It is also imperative to note that no participants will be identifiable and/or recognizable in the original data set.

Summary

The purpose of this quantitative study was to attempt to discover if there are any differences in the incidence of disease/adverse health effects and cancer rates pre- and post-exposure to chemical contamination in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and counties that do not border one of these rivers. This non-experimental, quantitative study design with a correlational (i.e., retrospective) focus was warranted for this research. By utilizing a retrospective approach, the researcher examined secondary archived data from the state and federal levels, such as the CDC and the State of West Virginia's Health Department.

The population of interest and sample were identified by known contamination events occurring in four of the 55 WV counties. Therefore, the surrounding WV counties are considered to not be at risk (geographically non-exposed) and will be used for toxicological comparison by comparing their incidences of disease/adverse health conditions and/or cancer rates to the four counties (pre- and post-exposure/events) of interest; however, for this study, only the counties surrounding the four counties will be used for comparison. The researcher attempted to discover and retrieve secondary data on the four counties of interest, paying special attention to general cancer incidence rates during the contamination events, as well as 10 years prior and 10 years after such events. Therefore, counties lacking retrievable cancer incidence rates for at least 10 years prior and 10 years after the contamination event could be considered a limitation for this study, and statistical findings should be deduced with caution.

I answered the RQs by comparing two or more independent groups through utilizing the ANOVA. The null hypotheses will be rejected if the p-value for each correlation is less than the commonly accepted alpha value ($\alpha = .05$). This chapter concluded with a discussion surrounding possible threats to reliability, validity, and ethical considerations. Chapter 4 will display the results of the data analysis based on the methodology, sample, instrumentation, and analysis techniques that were utilized to perform the assessment of the incidence of disease and cancer rates pre- and post-contamination (i.e., chemical).

Chapter 4: Results

Introduction

The resolution of this study is to attempt to discover if there are any differences in the incidence of disease/adverse health effects and cancer rates pre- and post-exposure to chemical contamination in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and counties that do not border one of these rivers. There was one primary research question tested for this study. From this question, four null and four alternative hypotheses were generated. Therefore, the following research questions were employed to further investigate the purpose of this study:

RQ1: Is there an association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers?

$H_0$1: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

H_a1: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

RQ2: Is there an association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River?

$H_0$2: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

H_a2: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

RQ3: Is there an association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River?

$H_0$3: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

H_a3: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

RQ4: Is there an association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River?

$H_0$4: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

H_a4: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

Data Collection

Various forms of secondary data and prior articles have been collected for quite some time now. However, as the trajectory of the research changed, so did the need for these particular data. I was unable to find specific incidents of adverse health effects pre- and post-contamination) Kanawha, Mingo, Putnam, and Wood counties, or for other WV counties. Therefore, I made several attempts to reach out to DHHR. During June 2023, the researcher was directed by DHHR to the necessary secondary data (vital statistics) for the years 2011–2020. The DHHR had to mail the additional, archived data, which displayed the vital statistics for the years 1996–2010; I did not receive these data until early August 2023. Further specific county data had to be personally provided by DHHR via email; this was finally received by the end of September 2023. Last, additional data for Kanawha County and 4-MCHM was retrieved via the CDC/Community Assessment for Public Health Emergency Response (CASPER).

Descriptive Statistics

Upon obtaining the data, tables were created for each county of interest. Such tables display the time frame, surrounding county data, incidence rates, gender, age, race, diseases/adverse health effects (e.g., non-Hodgkin's lymphoma, soft tissue sarcoma, kidney, liver, thyroid, ovarian, prostate, and testicular cancers, etc.), and data specific to the county of interest and chemical contaminate. In addition to tables being created to display the data, calculations were also manually done by the researcher.

Tables 1–14 display the descriptive statistics for specific cancers in the four counties of interest, as well as their surrounding counties. Additional data for Kanawha, Mingo, Putnam, and Wood counties are shown in Appendices A–D. Tables A1–AD exhibit the population for Kanawha, Mingo, Putnam, and Wood counties, respectively, for 1993–2020. Tables A2 and A3 are different in that the data regarding Kanawha County were gathered from a different source. Tables A2 and A3 display data specific to 4-MCHM; of the 39 households reporting members with acute health issues or symptoms, the most frequently reported symptoms were rash (n = 21, 53.9%), skin irritation/itching (n = 17, 43.6%), respiratory illness/cough (n = 6, 15.4%), other (n = 9, 23.1%), and both diarrhea and nausea (n = 5, 12.8%; CDC, 2014, 2016; Thomasson et al., 2017). Age at death in the four counties of interest are shown in Tables A7, B5, C6, and D10, whereas Tables A6, B4, C5, and D9 reveal the number of deaths associated with gender and race. Tables A4, A5, B2, B3, C2, C3, C4, and D2–D8 display the incidence of particular cancer rates known to be associated with certain chemicals.

Table 1

Liver Cancer Incidence in Kanawha County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	6.76666	3.258491	.615797	5.50315	8.03017	2.425	13.094
2	28	6.16934	7.236852	1.367636	3.36318	8.97550	.000	33.246
3	28	5.62362	8.220837	1.553592	2.43591	8.81133	.000	28.966

4	28	6.92323	5.090726	.962057	4.94925	8.89721	.000	15.793
5	28	6.34468	5.964778	1.127237	4.03178	8.65758	.000	21.533
6	28	4.52874	3.773416	.713109	3.06556	5.99192	.000	12.405
Total	168	6.05938	5.831292	.449894	5.17117	6.94759	.000	33.246

Note. *CI* = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 2

Kidney Cancer Incidence in Kanawha County

	N	*M*	*SD*	*SE*	95% *CI* for *M*		Minimum	Maximum
					LL	*UL*		
1	28	22.45197	6.973047	1.317782	19.74810	25.15583	12.070	37.645
2	28	20.19260	14.493303	2.738977	14.57269	25.81252	3.783	61.743
3	28	23.60146	16.545812	3.126865	17.18566	30.01726	.000	59.868
4	28	19.25491	7.795005	1.473118	16.23232	22.27749	8.348	37.062
5	28	18.46663	12.638330	2.388420	13.56600	23.36727	.000	50.244
6	28	20.77654	9.426756	1.781489	17.12122	24.43185	6.211	40.499
Total	168	20.79068	11.800306	.910413	18.99328	22.58809	.000	61.743

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 3

Liver Cancer Incidence in Mingo County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	5.38731	4.036297	.762788	3.82220	6.95243	.000	15.815
2	28	5.62982	4.991016	.943213	3.69451	7.56513	.000	17.804
3	28	7.74443	6.295769	1.189788	5.30319	10.18568	.000	27.091
4	28	6.33378	4.277620	.808394	4.67509	7.99247	.000	14.605
5	28	6.25057	5.465878	1.032954	4.13113	8.37002	.000	19.244
Total	140	6.26918	5.073293	.428771	5.42143	7.11694	.000	27.091

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 4

Kidney Cancer Incidence in Mingo County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	6.18	2.994	.566	5.02	7.34	1	12
2	28	9.14	4.759	.899	7.30	10.99	2	22
3	28	5.21	2.573	.486	4.22	6.21	1	11
4	28	9.32	4.092	.773	7.73	10.91	3	20
5	28	5.50	2.912	.550	4.37	6.63	1	13
Total	140	7.07	3.945	.333	6.41	7.73	1	22

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 5

Breast Cancer Incidence in Putnam County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	88.31001	16.132445	3.048746	82.05450	94.56552	62.630	128.789
2	28	99.02135	12.265484	2.317959	94.26529	103.77740	77.569	133.025
3	28	89.52144	17.661245	3.337661	82.67312	96.36976	53.184	129.479
4	28	74.51984	14.471037	2.734769	68.90855	80.13112	49.550	102.798
5	28	80.09672	18.095183	3.419668	73.08014	87.11330	46.332	126.539
6	28	101.81894	7.272566	1.374386	98.99893	104.63894	84.869	112.393
Total	168	88.88138	17.467786	1.347669	86.22072	91.54204	46.332	133.025

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 6

Non-Hodgkin's Lymphoma Incidence in Putnam County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	22.55937	5.949806	1.124408	20.25227	24.86646	8.831	33.422
2	28	23.10336	5.429260	1.026034	20.99812	25.20861	14.480	33.609
3	28	25.58018	10.861016	2.052539	21.36872	29.79164	3.838	46.265
4	28	24.93313	8.578396	1.621165	21.60678	28.25949	4.625	40.330
5	28	25.96535	10.902374	2.060355	21.73785	30.19285	4.020	48.120
6	28	25.08723	5.473724	1.034437	22.96474	27.20971	16.370	38.847
Total	168	24.53810	8.192775	.632086	23.29019	25.78601	3.838	48.120

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 7

Soft Tissue Cancer Incidence in Putnam County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	2.87963	2.426070	.458484	1.93890	3.82036	.000	7.347
2	28	2.85195	1.722210	.325467	2.18414	3.51975	.000	5.459
3	28	4.63119	4.353036	.822646	2.94326	6.31912	.000	17.574
4	28	3.93347	4.438621	.838821	2.21235	5.65458	.000	13.480
5	28	25.96535	10.902374	2.060355	21.73785	30.19285	4.020	48.120
6	28	3.46267	1.356059	.256271	2.93685	3.98850	1.473	6.806
Total	168	7.28738	9.887597	.762845	5.78131	8.79344	.000	48.120

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 8

Non-Hodgkin's Lymphoma Incidence in Wood County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	25.15963	5.981270	1.130354	22.84033	27.47892	11.394	35.495
2	28	24.84018	19.424771	3.670937	17.30804	32.37232	.000	66.667
3	28	20.99002	13.039624	2.464257	15.93378	26.04626	.000	58.377
4	28	21.62076	17.930267	3.388502	14.66813	28.57340	.000	69.037
5	28	25.58018	10.861016	2.052539	21.36872	29.79164	3.838	46.265
Total	140	23.63815	14.226074	1.202323	21.26095	26.01536	.000	69.037

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 9

Testicular Cancer Incidence in Wood County

	N	*M*	*SD*	*SE*	95% CI for M		Minimum	Maximum
					LL	*UL*		
1	28	2.76596	1.554397	.293754	2.16323	3.36869	.000	6.958
2	28	3.35347	7.834463	1.480574	.31558	6.39136	.000	26.734
3	28	1.76030	3.846981	.727011	.26860	3.25201	.000	10.467
4	28	3.14583	6.875923	1.299427	.47963	5.81204	.000	18.519
5	28	2.67079	3.575906	.675783	1.28420	4.05738	.000	14.046
Total	140	2.73927	5.218938	.441081	1.86718	3.61137	.000	26.734

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 10

Prostate Cancer Incidence in Wood County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	77.20324	13.373267	2.527310	72.01763	82.38885	52.182	106.522
2	28	86.87046	36.367376	6.872788	72.76866	100.97225	27.027	173.333
3	28	74.77999	28.141840	5.318308	63.86772	85.69226	9.709	123.633
4	28	73.63457	42.410990	8.014924	57.18931	90.07984	.000	172.414
5	28	84.09151	18.213788	3.442082	77.02894	91.15408	56.537	128.118
Total	140	79.31595	29.781549	2.517000	74.33940	84.29251	.000	173.333

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 11

Thyroid Cancer Incidence in Wood County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	10.04963	5.761800	1.088878	7.81544	12.28382	2.273	25.448
2	28	9.10461	9.723619	1.837591	5.33418	12.87503	.000	27.972
3	28	11.60117	9.289538	1.755558	7.99907	15.20328	.000	29.140
4	28	12.24600	16.642483	3.145134	5.79271	18.69928	.000	50.839
5	28	13.10412	9.575725	1.809642	9.39104	16.81720	.000	37.962
Total	140	11.22111	10.738803	.907595	9.42663	13.01558	.000	50.839

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 12

Kidney Cancer Incidence in Wood County

	N	M	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	21.69058	7.131088	1.347649	18.92543	24.45573	10.369	44.302
2	28	21.92003	18.211262	3.441605	14.85844	28.98163	.000	66.605
3	28	21.85292	17.424962	3.293008	15.09622	28.60961	.000	61.387
4	28	26.78731	16.755357	3.166465	20.29027	33.28436	.000	68.859
5	28	22.78092	12.102534	2.287164	18.08805	27.47379	3.784	51.767
Total	140	23.00635	14.832588	1.253582	20.52780	25.48491	.000	68.859

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 13

Breast Cancer Incidence in Wood County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	95.89666	14.719820	2.781785	90.18891	101.60441	59.688	115.198
2	28	88.09574	45.631197	8.623486	70.40181	105.78967	13.177	169.403
3	28	82.36678	26.815772	5.067705	71.96871	92.76485	42.110	150.270
4	28	83.17888	40.810447	7.712449	67.35424	99.00352	16.722	169.463
5	28	89.52144	17.661245	3.337661	82.67312	96.36976	53.184	129.479
Total	140	87.81190	31.533999	2.665109	82.54251	93.08130	13.177	169.463

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Table 14

Ovarian Cancer Incidence in Wood County

	N	*M*	*SD*	*SE*	95% CI for *M*		Minimum	Maximum
					LL	*UL*		
1	28	8.90969	3.483533	.658326	7.55892	10.26046	3.435	16.262
2	28	9.99102	11.230396	2.122345	5.63633	14.34572	.000	40.000
3	28	9.43105	8.988110	1.698593	5.94582	12.91627	.000	29.435
4	28	7.38499	11.872825	2.243753	2.78119	11.98879	.000	34.740
5	28	7.77357	6.001346	1.134148	5.44649	10.10065	.000	20.902
Total	140	8.69807	8.826030	.745936	7.22322	10.17291	.000	40.000

Note. CI = confidence interval; *LL* = lower limit; *UL* = upper limit.

Results

Research Question 1

The independent variable, county, was classified as 1 = Kanawha, 2 = Boone, 3 = Clay, 4 = Fayette, 5 = Roane, and 6 = Putnam. The results were not significant liver cancer [$F(5, 162) = 0.631$, $p = 0.677$], but kidney cancers [$F(5, 162)=202.426$, $p < .001$] was significant in Kanawha County. There also appears to be differences among the means for the dependent variable, kidney cancer (eta square = 0.862), but not for the dependent variable, liver cancer (eta square = 0.019). A post hoc test (Tukey) was conducted to evaluate disparities for only kidney cancer incidence across the six counties, especially in comparison with the Kanawha County. The Tukey pairwise comparison for kidney cancer between Kanawha County and its surrounding counties (Boone, Clay, Fayette, Roane, and Putnam), is also significant. A Tukey pairwise comparison was not conducted for liver cancer due to the ANOVA analysis not being significant.

Research Question 2

The independent variable, county, was classified as 1 = Mingo, 2 = Logan, 3 = McDowell, 4 = Wayne, and 5 = Wyoming. For Mingo County, and its surrounding counties, the results were not significant for liver cancer [$F(4, 135) = 0.914$, $p = .458$], but was significant for kidney cancer [$F(4,135)=8.863$, $p < .001$]. There also appears to be differences among the means for the dependent variable, kidney cancer (eta square = 0.208), but not for liver cancer (eta square = 0.026). A post hoc test (Tukey) was conducted to evaluate disparities of kidney cancer incidence across the five counties, especially in comparison with the Mingo County. The Tukey pairwise comparison for kidney cancer between Mingo County and its surrounding counties of Logan and Wayne, appears to be significant. A Tukey pairwise comparison was not conducted for liver cancer due to the ANOVA analysis not being significant.

Research Question 3

The independent variable, county, was classified as 1 = Putnam, 2 = Cabell, 3 = Jackson, 4 = Lincoln, 5 = Mason, and 6 = Kanawha. The results were significant for both breast [$F(4, 162) = 14.193$, $p = < .001$] and soft tissue cancers [$F(5, 162)= 84.079$, $p < .001$] in Putnam County, as well as the surrounding counties. However, the results for non-Hodgkin's lymphoma [$F(5, 162) = 0.792$, $p = 0.557$] were not significant between Putnam County and its surrounding counties. There also appears to be differences among the means for the dependent variables: breast cancer (eta square = 0.304) and soft tissue cancer (eta square = 0.722), but not for non-Hodgkin's lymphoma (eta square = 0.024). A post hoc test (Tukey) was conducted to evaluate disparities of breast and soft tissue cancers incidence across the six counties, especially in comparison with the Putnam County; a Tukey pairwise comparison was not conducted for non-Hodgkin's lymphoma due to the ANOVA analysis not being significant. The Tukey pairwise comparison for breast cancer between Putnam County and its surrounding counties of Lincoln and Kanawha, are significant. However, as it relates to soft tissue carcinoma, the mean difference is solely significant for the surrounding county of Mason in comparison to all other surrounding counties, as well as the county of interest, Putnam.

Research Question 4

The independent variable, county, was classified as 1 = Wood, 2 = Pleasants, 3 = Ritchie, and 4 = Wirt. For Wood County, and its surrounding counties, the results were not significant for non-Hodgkin's lymphoma [$F(4, 135) = 0.637$, $p = 0.637$], testicular [$F(4, 135) = 0.380$, $p = 0.822$], prostate [$F(4, 135) = 1.085$, $p = 0.366$], thyroid [$F(4, 135)= 0.636$, $p = 0.638$], kidney [$F(4, 135) = 0.584$, $p = 0.674$], breast [$F(4, 135) = 0.837$, $p = 0.504$], and ovarian cancers [$F(4, 135) = 0.427$, $p = 0.789$]. There also appears to be no differences among the means for the dependent variables: non-Hodgkin's lymphoma (eta square = 0.019), testicular cancer (eta square = 0.011), prostate cancer (eta square = 0.031), thyroid cancer (eta square = 0.019), kidney cancer (eta square = 0.017), breast cancer (eta square = 0.024), and ovarian cancer (eta square = 0.012). Therefore, a post hoc test (Tukey) was not conducted to evaluate disparities of non-Hodgkin's lymphoma, testicular, prostate, thyroid, kidney, breast, and ovarian cancers incidence across the four counties, especially in comparison with Wood County.

Summary

The purpose of this quantitative study was to attempt to discover if there are any differences in the incidence of disease/adverse health effects and cancer rates pre- and post-exposure to chemical contamination in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and counties that do not border one of these rivers. This non-experimental, quantitative study design with a correlational (i.e., retrospective) focus was warranted for this research. By utilizing a retrospective approach, the researcher examined secondary archived data from the state and federal levels, such as the CDC and the State of West Virginia's Health Department.

The population of interest and sample were identified by known contamination events occurring in four of the 55 WV counties. Therefore, the surrounding WV counties are considered to not be at risk (geographically non-exposed) and were used for toxicological comparison by comparing their incidences of disease/adverse health conditions and/or cancer rates to the four counties (pre- and post-exposure/events) of interest; however, for this study, only the counties surrounding the four counties will be used for comparison. The researcher attempted to discover and retrieve secondary data on the four counties of interest, paying special attention to general cancer incidence rates during the contamination events, as well as 10 years prior and 10 years after such events. Secondary data were primarily retrieved from DHHR.

Therefore, counties lacking retrievable cancer incidence rates for at least 10 years prior and 10 years after the contamination event could be considered a limitation for this study, and statistical findings should be deduced with caution. The research questions were addressed by comparing two or more independent groups through utilizing the ANOVA. The null hypotheses will be rejected if the p-value for each correlation is less than the commonly accepted alpha value ($\alpha = .05$). This chapter concluded with a discussion and portrayal surrounding descriptive statistics and statistical analysis. Chapter 5 will display the interpretation of results, how such results relate to the epidemiologic triangle, possible limitations, recommendations, and potential social change related to this study.

Chapter 5: Discussion, Conclusions, and Recommendations

Introduction

The purpose of this study was to attempt to discover if there were any differences in the incidence of disease/adverse health effects (i.e., reproductive issues, neurological disorders, respiratory disease, autoimmune disease, endocrine issues, and pulmonary edema) and cancer (i.e., non-Hodgkin's lymphoma, soft tissue sarcoma, kidney, thyroid, ovarian, prostate, and testicular) rates pre- and post-exposure to chemical contamination as measured by BCL of PFOA, TCDD, MIC, and 4-MCHM in the four WV counties (Kanawha, Mingo, Putnam, and Wood) that border the Elk, Ohio, Kanawha, and Tug Fork Rivers, and counties that do not border one of these rivers. This quantitative study utilized an ecologic, retrospective, correlational approach that considered previously collected data on the population level. Secondary data from WV's DHHR and Casper was used to explore any possible relationships among the independent variable, the four WV counties of interest bordering/in proximity to the Elk, Ohio, Kanawha, and Tug Fork Rivers versus the counties that do not border these rivers and the dependent variable, certain contamination events within the four WV counties and their possible correlation to higher rates of cancers. Chapter 5 provides a detailed summary and discussion regarding the subsequent research questions:

RQ1: Is there an association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers?

$H_0$1: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

H_a1: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

RQ2: Is there an association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River?

$H_0$2: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

H_a2: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

RQ3: Is there an association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River?

$H_0$3: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

H_a3: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

RQ4: Is there an association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River?

H_04: There is no statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

H_a4: There is a statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

Interpretation of the Findings

Research Question 1

Regarding RQ1, the p-value for kidney cancer was less than 0.05. Therefore, the null hypothesis is rejected that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers. The p-value for liver cancer was greater than 0.05. Therefore, the null hypothesis is accepted that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Kanawha County and additional bordering counties adjacent (or in proximity to) to the Elk and Kanawha Rivers.

Research Question 2

For RQ2, the p-value for kidney cancer was less than 0.05. Therefore, the null hypothesis is rejected that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River. The p-value for liver cancer was greater than 0.05. Therefore, the null hypothesis is accepted that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Mingo County and additional bordering counties adjacent (or in proximity to) to the Tug Fork River.

Research Question 3

For RQ3, the p-value for breast and soft tissue cancers was less than 0.05. Therefore, the null hypothesis is rejected that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River. The p-value for non-Hodgkin's lymphoma was greater than 0.05. Therefore, the null hypothesis is accepted that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Putnam County and additional bordering counties adjacent (or in proximity to) to the Kanawha River.

Research Question 4

For RQ4, the p-value for non-Hodgkin's lymphoma, testicular, prostate, thyroid, kidney, breast, and ovarian cancers was greater than 0.05. Therefore, the null hypothesis is accepted that there is no statistically significant association between the events of chemical contamination and cancer incidence rates in Wood County and additional bordering counties adjacent (or in proximity to) to the Ohio River.

The Findings in Relation to the Conceptual Framework

The conceptual framework for this study was the epidemiologic triangle (Gulis & Fujino 2015; Rivier University, n.d.). This is a disease causation model that can assist in clarifying how an individual's or population's environment can gravely impact their health via the utilization of three vertices: agent, host, and environment (CDC, 2018; Rivier University, n.d.). Peters et al. (2021), hypothesized that exposure to chemical and environmental stressors can impact public health via occupational and household settings, as well as contaminated soil, food, air, and water; thus, human health can be impaired due to environmental insults. Similarly, this research also found that there is a significant association between the incidence of certain adverse health effects and cancers, and particular chemical contaminants that are associated with such issues. Furthermore, the research found that one's environment (county location/proximity) to chemical contamination (agent) is significantly associated with an increased incidence of cancer (i.e., kidney, breast, and soft tissue) within humans (host). Therefore, the relationship between chemical contamination (agent) and proximity to such events (environment) can potentially lead to higher incidence rates of cancer and other cancers within a particular population (host).

Limitations

Although this study has its strengths, it would be careless, not to mention the limitations it may harbor. There are positive aspects to utilizing secondary data sources (e.g., conserves time and money), such sources can be limiting in specific information (variables); also, some data sources may not be accessible and/or permission may need to be granted, which takes time. Secondary data sources can also have issues surrounding human error embedded within them, such as sampling and analysis procedures. For this research, some of the secondary data were not readily available; the remaining data had to be mailed and/or emailed to the researcher, which, in this case, did not conserve time. Some of the data provided by WV DHHR were different from the vital statistics data provided by DHHR. Therefore, there appeared to be slight discrepancies between what was reported and what was given to the researcher. For instance, in Table 1, the data provided goes all the way back until 1993, but the data provided in the vital statistic reports only goes back until 1996. Therefore, the researcher had to obtain additional population data from other sources to further verify the validity of the earlier data.

In addition, there were missing and/or scarce data. Several of the reports provided by DHHR were missing yearly data, and it was unclear whether data were simply not reported for the years in question. DHHR was unable to provide BCLs data regarding possible exposure to chemical contaminations, as well as possible modes of transport/contact (e.g., air, direct contact, water, etc.). Having such data would have provided more validity to the study in terms of knowing emphatically if a person was in contact with such chemical contaminants and how they were exposed. Data were also provided by DHHR, which depicted the race/ethnicity and gender diagnosed with particular cancers. However, the overwhelming majority of subjects were White or European American, as well as male (see Table C3). Therefore, it was not necessary to examine the categorical variables of gender and race/ethnicity.

When asked, DHHR was also unable to provide data regarding adverse health effects (e.g., respiratory issues, etc.). There was sparse data provided on such health effects in DHHR's vital statistic reports. However, the data were vague and all-consuming; it did not define specific adverse health effects. Therefore, using such data would not have been credible for this research. Although some of the data provided by DHHR listed information for 1993, the vital statistic reports only ranged from 1996 to 2020. Thus, the researcher was unable to examine pre- and post-exposure to chemical contaminants by comparing data from 10 years prior to contamination events and 10 years after said events. Only four counties of interest were examined, as well as their surrounding counties. Thus, this may have greatly limited the sample size. Last, it is important to note that chemical contaminants may not have been a true representation of all possible risk factors.

Recommendations

There was a statistically significant association between geographical location/proximity to chemical contaminations and an increase in the incidence of cancer rates, especially regarding kidney cancer in Kanawha and Mingo counties, as well as soft tissue and breast cancers in Putnam County. There are additional considerations when interpreting the results of this study, previous studies, and planning for future studies of these techniques. For instance, some researchers (Hendryx, 2015; Yuan et al., 2018) have found statistically significant associations between one's environment, proximity to contamination, and their health, whereas other researchers (Vargas et al., 2020) has found no significance. Thus, future research is needed on this matter, as well as proper data collection on the modes of transport/contact and dispersal amongst the population. In addition to modes of transportation, local governments and/or the companies responsible for contamination should encourage data collection in terms of medical testing (i.e., BCLs).

It is also vital for future data collection to display if individuals are diagnosed with particular adverse health effects and cancer, to specify whether or not if such individuals are traveling to the county/area of interest on a regular basis (i.e., traveling for work, etc.). A disease causation model, such as the epidemiologic triangle, could assist in future correlational, quantitative studies by expanding upon the knowledge of an individual's environment (i.e., zoning regulations, chemical regulations/safety, etc.) regarding aspects of their health status (i.e., incidence of disease/adverse health effects and cancer rates) due to pre- and post-contamination (i.e., chemical) of water in four WV counties that border the Elk, Ohio, Kanawha, and Tug Fork Rivers (geographical location/proximity).

Implications

When strategies, ideas, and actions are not only employed but also created to promote dignity, progress, and worth amongst these levels where both social and human conditions are improved upon, it is commonly referred to as "positive social change"

(Walden University, n.d.-b). Through evidence-based data, this study can improve positive social change by addressing environmental contamination and geographical location to such instances, as well as for rural-dwelling individuals and/or communities directly/indirectly impacted by such events. The data provided in this study may influence individuals living in Kanawha, Mingo, Putnam, and Wood counties to be more aware that they are possibly at a higher risk for developing particular cancers, as well as potentially adverse health effects, even though data were not available for this. The public should be encouraged to report any possible encounters with chemical contamination and/or any possible side effects. For those who may be unable to report for various reasons (fear of losing one's job, unable to physically go and seek assistance, and so forth); anonymity needs to be reassured, and in some cases, physically going (surveying) to people to report incidences. Proper follow-up over time with individuals suspected of being contaminated, collection of biohazards (e.g., BCLs) information, and additional information when necessary; all of these suggestions can also aid in the collection of more viable data. The results of this study, and others similar, may be used to change and develop improved policies, regulations, and safe chemical use information; thereby, promoting positive social change.

In addition, the findings of this study can possibly contribute to public health interventions to reduce cancer (and potentially adverse effects) disparity by addressing the risk factors and encouraging social change within the population. The epidemiologic triangle can assist in reforming policies surrounding the use of possible contaminants (i.e., chemicals), safety or chemical regulations, and zoning regulations, as well as producers disclosing hazardous information regarding chemicals to businesses, other stakeholders, and the public (Wilson & Schwarzman, 2009). Interventions, knowledge, and policy changes can result from undertaking all three corners of the triangle; however, researchers may choose to focus only on one corner, such as the host and how to improve their resistance to agents (Gulis & Fujino, 2015). Such changes and interventions will aid in the protection of both environmental and public health as it relates to pollution and exposure (Magarey & Trexler, 2020).

Conclusion

This research involved quantitative, non-experimental research methods with a retrospective, correlational focus. Secondary, archived data from DHHR and CDC/CASPER was employed to conduct this study. The independent variable, the four WV counties of interest bordering the Elk, Ohio, Kanawha, and Tug Fork Rivers versus the counties that do not border these rivers/surrounding counties, was found to be significantly associated with the dependent variable, certain contamination events within the four WV counties and their possible correlation to higher rates/increases in cancer(s) (i.e., kidney, breast, and soft tissue cancers). The conceptual framework, the epidemiologic triangle, details how an environment can bring the agent and host together. This study’s results reinforced this conceptual framework, displaying statistically significant results between proximity (environment) to contamination events and the public (host) and the chemical contagion (agent); thus, revealing higher incidence of cancer rates in certain populations closest to chemical contamination. There are particular regions (WV counties) that are known for heavy industrialization and environmental health hazards (i.e., chemical contamination), as well as increases in adverse health outcomes or incidences of reported adverse health conditions/diseases (e.g., cancer rates) where such influences have previously transpired and/or have not been publicly acknowledged by studying a particular time frame, (i.e., pre- and post-contamination/exposure). Despite the growing interest in environmental contaminants and their potential impact on a population's health due to various factors (e.g., geographical location, proximity, and exposure), there is still a gap in current literature related to such regions. Thus, further research examining such time frames and even longitudinal studies can not only bring awareness to the importance of one's environment on their overall health, but also illicit changes in policies and how the public responds to such contamination events.

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Appendix A: Kanawha County Data

Table A1

Kanawha County Population, 1995 – 2020

Year	Total	Year	Total
1995	206,200	2008	191,018
1996	207,700	2009	191,663
1997	203,600	2010	193,063
1998	202,000	2011	192,315
1999	199,300	2012	192,179
2000	200,073	2013	191,275
2001	197,338	2014	190,223
2002	195,790	2015	188,332
2003	195,413	2016	186,241
2004	195,218	2017	183,293
2005	193,559	2018	180,454
2006	192,419	2019	178,124
2007	191,306	2020	176,253

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table A2

Households with members with reported health issues/symptoms related to the 4-MCHM spill and age of affected.

	Frequency (n=171)	Weighted % (95% CI)
Health Issues/symptoms[a]		
Yes[b]	39	21.7 (14.4-28.9)
No	126	75.0 (67.5-82.6)
Don't know	5	2.6 (0.0-5.3)
Refused	1	0.7 (0.0-2.1)
Age of affected household members[c]		
Less than 18 years	6	14.9 (3.4-26.5)
18 years or older	35	89.6 (78.7-100.0)

[a]SurveyRespondents(n=171).

[b]Households reporting members with health issues/symptoms (n=39).

[c]Of the households (n=39) reporting members with health issues/symptoms.

Note. The data for households with members with reported health issues/symptoms related to the 4-MCHM spill and age of affected are from *Acute Health Effects after the Elk River Chemical Spill, West Virginia, January 2014*, by Thomasson et al., 2017 (https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5349493/).

Table A3

Health Symptoms and Onset

Symptom reported[b]	Frequency (n=39)[a]	% of interviewed households (95% CI)	Projected number of households (95% CI)	Weighted % (95% CI)
Rash	21	53.9 (37.2-69.9)	13,632 (8,419-18,846)	53.2 (32.9-73.5)
Skin irritation/itching	17	43.6 (27.8-60.4)	10,671 (5,291-16,053)	41.6 (20.6-62.6)
Respiratory illness/cough	6	15.4 (5.9-30.5)	4,127 (674-7,581)	16.1 (2.6-29.6)
Diarrhea	5	12.8 (4.3-27.4)	3,787 (520-7,053)	14.8 (2.0-27.5)
Nausea	5	12.8 (4.3-27.4)	3,350 (394-6,307)	13.1 (1.5-24.6)
Sore Throat	4	10.3 (2.9-24.2)	2,864 (97-5,631)	11.2 (0.4-22.0)
Headache	4	10.3 (2.9-24.2)	2,767 (164-5,370)	10.8 (0.6-21.0)
Vomiting	2	5.1 (0.6-17.3)	1,699 (0-4, 187)	6.6 (0.0-16.3)
Abdominal Pain	2	5.1 (0.6-17.3)	1,262 (0-3,113)	4.9 (0.0-12.2)
Eye irritation/pain	2	5.1 (0.6-17.3)	1,165 (0-2,785)	4.6 (0.0-10.9)
Other*	9	23.1 (11.1-39.3)	6,214 (2,882-9,547)	24.3 (11.2-37.3)
Symptom onset				
Before the "do not use" order	6	15.4 (5.9-30.5)	3,932 (841-7,022)	15.4 (3.3-27.4)

During the "do not use" order	18	46.2 (30.1-62.8)	12,525 (7,081-17,971)	48.9 (27.6-70.1)
After the "do not use" order	19	48.7 (32.4-65.2)	11,593 (6,931-16,258)	45.2 (27.0-63.4)

[a]Households that reported experience health symptoms.

[b]Household respondents could select more than one answer/symptom from the survey.

*Other symptoms reported included dizziness (n=3), dry skin (n=2), cellulitis (n=1), "chest on fire" (n=1), rapid heat beat (n=1), and unspecified (n=1).

Note. The data for acute health symptoms and onset due to 4-MCHM are from *Disaster Response and Recovery Needs of Communities Affected by the Elk River Chemical Spill, West Virginia*, by CDC, 2014 (https://dhhr.wv.gov/News/2014/Documents/WVCASPERReport.pdf).

Table A4

Diagnosis of Liver Cancer by Surrounding Counties: Kanawha County

County	Kanawha	Boone	Clay	Fayette	Roane	Putnam
Year of Diagnosis						
1993	7	2		3		0
1994	10			1	1	1
1995	5	1				1
1996	8	1				0
1997	8	1		3	2	3
1998	10	1		1	2	1
1999	9		1	4		2
2000	8			1		1
2001	5	1		2		1
2002	10	3	3	2	1	0
2003	9	1		4		1
2004	13			2	1	0
2005	9			1		2
2006	9		1	1	1	1
2007	12	1	1	2	1	1
2008	9	1		3	1	3
2009	16	3	2	5	1	2
2010	9	2		3	1	4
2011	15	2		7		4
2012	17		1	3	2	4
2013	18	1	1	7	2	7
2014	16	4			1	2
2015	20	4	1	7		5
2016	21	2	1	7	2	5
2017	24		1	5	1	6
2018	22	1		5	3	1
2019	19	2		6	2	5
2020	23	7	2	3	1	7
Grand Total	**361**	**41**	**15**	**88**	**26**	**70**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table A5

Diagnosis of Kidney Cancer by Surrounding Counties: Kanawha County

County	Kanawha	Boone	Clay	Fayette	Roane	Putnam
Year of Diagnosis						
1993	27	1	4	4	1	7
1994	25	2		6	2	4
1995	26	1		8		6
1996	33	3	1	9		5
1997	31	5	1	8	2	5
1998	27	2	4	7	3	3
1999	31	3		5	2	4
2000	29	3	2	8	1	6
2001	43	3	2	4	1	6
2002	35	1	2	7	1	9
2003	34	6	2	8	1	12
2004	36	7	1	8	5	6
2005	51	5	3	9	4	15
2006	43	2	1	7	4	15
2007	52	5		6	1	12
2008	46	4	3	5	2	10
2009	52	3	6	14	4	17
2010	48	4	2	5	3	12
2011	49	8	2	11	2	17
2012	43	5	3	17	3	19
2013	48	5	5	14	3	18
2014	51	4	3	10	6	11
2015	58	4	2	11	5	16
2016	61	11	1	15	1	13
2017	69	10	4	9	4	23
2018	56	10	2	13	7	19
2019	55	5	4	8	4	17
2020	46	13	3	11	4	11
Grand Total	**1205**	**135**	**63**	**247**	**76**	**318**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table A6

Number of Deaths by Race, Gender, and County of Residents: Kanawha County 1996-2020

Year	Gender	White or European American	Black or African American	All other races	Unknown	Total
1996	M	1,094	90	1	*	2,435
	F	1,172	76	2	*	
1997	M	1,100	78	2	*	2,452
	F	1,199	71	2	*	
1998	M	1,170	72	1	*	2,555
	F	1,217	93	2	*	
1999	M	1,153	66	0	*	2,518
	F	1,205	91	3	*	
2000	M	1,096	62	1	*	2,504
	F	1,263	79	3	*	
2001	M	1,087	70	3	*	2,553
	F	1,316	74	3	*	
2002	M	1,136	71	0	*	2,510
	F	1,227	72	4	*	
2003	M	1,058	84	0	*	2,496
	F	1,251	75	1	*	
2004	M	1,087	55	3	*	2,463
	F	1,237	79	2	*	
2005	M	1,113	72	0	*	2,489
	F	1,216	84	4	*	
2006	M	1,153	76	2	*	2,398
	F	1,088	77	2	*	
2007	M	1,135	70	4	*	2,439
	F	1,153	73	4	*	
2008	M	1,164	85	4	*	2,572
	F	1,231	83	5	*	
2009	M	1,143	65	6	*	2,454
	F	1,160	74	6	*	
2010	M	1,155	65	4	*	2,467
	F	1,170	70	3	*	
2011	M	1,075	63	3	*	2,388
	F	1,181	64	2	*	
2012	M	1,058	90	4	0	2,398

_	F	1,167	71	6	2	_
2013	M	1,146	68	2	*	2,489
	F	1,189	79	4	*	
2014	M	1,133	68	4	*	2,433
_	F	1,161	64	3	*	_
2015	M	1,144	85	4	*	2,523
	F	1,204	82	4	*	
2016	M	1,149	94	2	*	2,520
	F	1,193	73	6	*	
2017	M	1,188	71	4	*	2,598
	F	1,239	88	6	*	
2018	M	1,221	94	5	*	1,320
	F	1,285	66	7	*	1,358
2019	M	1,216	101	15	*	1,332
	F	1,111	65	5	*	1,181
2020	M	1,412	107	8	*	1,527
	F	1,339	75	7	*	1,421

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table A7

Age at death by Kanawha County Residence, 1996-2020

								Age in years								
Year	Total	Rate*	< 1	1 to 4	5 to 9	10 to 14	15-19	20-24	25-34	35-44	45-54	55-64	65-74	75-84	85+	Average age at death
1996	2,435	11.8	17	1	1	3	6	9	38	70	159	248	579	755	549	72.8
1997	2,452	12	11	1	3	4	12	8	33	63	141	262	541	803	569	73.3
1998	2,555	12.6	13	2	3	4	11	15	33	93	144	267	566	811	593	72.9
1999	2,518	12.6	9	4	1	5	11	23	25	76	164	253	557	766	624	73.2
2000	2,504	12.5	18	2	5	3	14	16	27	96	186	238	494	765	640	72.7
2001	2,553	12.9	17	4	1	0	3	14	25	94	189	243	473	800	690	73.6
2002	2,510	12.8	20	2	4	3	13	25	30	82	176	253	437	801	664	73
2003	2,469	12.6	15	2	0	2	18	21	35	78	173	240	450	767	668	73.2
2004	2,463	12.6	14	3	2	4	9	18	29	70	162	281	409	796	666	73.5
2005	2,489	12.9	18	5	2	2	11	16	34	85	196	259	416	800	645	72.9
2006	2,398	12.5	12	3	3	0	15	17	45	85	202	319	408	716	573	71.7
2007	2,439	12.7	18	5	1	1	7	15	43	68	180	301	408	739	653	72.8
2008	2,572	13.5	19	7	0	2	7	22	32	87	200	306	402	758	730	73
2009	2,454	12.8	26	2	0	4	10	11	35	71	196	303	406	707	683	72.7
2010	2,467	12.8	11	3	0	4	8	16	41	66	206	336	420	657	699	72.8
2011	2,388	12	15	1	1	0	5	11	53	68	208	303	386	666	671	72.8
2012	2,398	12.5	19	4	4	5	6	9	53	62	188	323	427	614	684	72.4
2013	2,489	13	13	1	2	1	11	9	59	58	183	356	469	619	708	72.7
2014	2,433	12.8	11	0	2	3	10	16	48	83	175	365	464	584	672	72.1
2015	2,523	13.4	4	3	0	1	10	25	59	84	180	383	465	579	730	72.3
2016	2,520	13.5	14	4	1	0	5	20	60	91	167	389	476	598	695	71.9
2017	2,598	14.2	17	1	4	1	5	25	63	98	163	393	495	594	739	71.9
2018	2,678	14.8	15	2	0	2	8	19	71	94	174	357	558	655	723	72
2019	2,513	14.1	17	2	2	3	6	14	71	92	157	393	512	575	669	71.6
2020	2,948	16.7	15	2	0	3	7	15	76	131	181	402	683	720	713	71.4

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table A8

Selected causes of resident deaths: Number & Rate in Kanawha County, 1996-2004*

Year	1996	1997	1998	1999	2000	2001	2002	2003	2004
Selected causes of death									
Non-Hodgkin's Lymphoma									
Soft tissue sarcoma									
Liver cancer									
Kidney cancer									
Testicular cancer									
prostate cancer	45 & 21.8	27 & 13.3	30 & 14.9	31 & 15.6	30 & 15.0	26 & 13.2	29 & 14.8	30 & 15.4	17 & 8.7
Breast cancer	49 & 23.7	42 & 20.6	51 & 25.2	34 & 17.1	49 & 24.5	31 & 15.7	30 & 15.3	31 & 15.9	38 & 19.5
Ovarian cancer	29 & 14.0	17 & 8.3	20 & 9.9	13 & 6.5	11 & 5.5	23 & 11.7	16 & 8.2	15 & 7.7	17 & 8.7
Thyroid Cancer									
All other cancers	146 & 70.6	146 & 71.7	123 & 60.9	164 & 82.3	151 & 75.5	139 & 70.4	145 & 74.1	147 & 75.2	38 & 67.3
Pulmonary Edema	143 & 69.2	121 & 59.4	126 & 62.4						
Endocrine gland disorders (diabetes)	77 & 37.3	96 & 47.2	102 & 50.5	93 & 46.7	90 & 45.0	108 & 54.7	98 & 50.1	96 & 49.1	49 & 86.8
Upper respiratory diseases									
Autoimmune disorders									

Lower respiratory diseases	31 & 15.0	28 & 13.8	26 & 12.9	139 & 69.7	176 & 88.0	153 & 77.5	146 & 74.6	143 & 73.2	38 & 67.3
Neurological disorders									
Reproduction/Childbirth (fetal deaths)	12 & 5.0	17 & 6.9	7 & 2.9	17 & 6.8	17 & 7.1	19 & 8.2	13 & 5.4	23 & 9.7	23 & 9.4
Exposure to Noxious Substances/external substances	20 & 9.7	19 & 9.3	23 & 11.4	19 & 9.5	20 & 10.0	16 & 8.1	16 & 8.2	23 & 11.8	9 & 15.9

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table A9

Selected causes of resident deaths: Number & Rate in Kanawha County, 2005-2012*

Year	2005	2006	2007	2008	2009	2010	2011	2012
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	23 & 11.9	25 & 13.0	22 & 11.5	27 & 14.1	26 & 13.6	23 & 11.9	27 & 14.0	20 & 10.4
Breast cancer	39 & 20.1	32 & 16.6	41 & 21.4	43 & 22.5	38 & 19.8	28 & 14.5	38 & 19.8	43 & 22.4
Ovarian cancer	10 & 5.2	12 & 6.2	7 & 3.7	12 & 6.3	10 & 5.2	11 & 5.7	13 & 6.8	11 & 5.7

Thyroid Cancer								
All other cancers	139 & 71.8	141 & 73.3	149 & 77.9	143 & 74.9	137 & 71.5	139 & 72.0	121 & 62.9	139 & 72.3
Pulmonary Edema								
Endocrine gland disorders (diabetes)	92 & 47.5	77 & 40.0	92 & 48.1	74 & 38.7	71 & 37.0	86 & 44.5	73 & 38.0	66 & 34.3
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	155 & 80.1	132 & 68.6	130 & 68.0	163 & 85.3	177 & 92.3	151 & 78.2	147 & 76.4	147 & 76.5
Neurological disorders								
Reproduction/Childbirth (fetal deaths)	17 & 7.5	18 & 7.8	6 & 2.5	16 & 6.7	20 & 8.8	7 & 3.2	5 & 2.3	11 & 5.0
Exposure to Noxious Substances/external substances	27 & 13.9	15 & 7.8	18 & 9.4	16 & 8.4	20 & 10.4	21 & 10.9	14 & 7.3	13 & 6.8

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table A10

Selected causes of resident deaths: Number & Rate in Kanawha County, 2013-2020*

Year	2013	2014	2015	2016	2017	2018	2019	2020
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								

prostate cancer	23 & 12.0	15 & 7.9	20 & 10.6	29 & 15.6	11 & 6.0	25 & 13.9	19 & 10.7	35 & 19.9
Breast cancer	20 & 10.5	37 & 19.5	33 & 17.5	28 & 15.0	10 & 5.5	33 & 18.3	23 & 12.9	23 & 13.0
Ovarian cancer	13 & 6.8	14 & 7.4	13 & 6.9	13 & 7.0	32 & 17.5	8 & 4.4	9 & 5.1	15 & 8.5
Thyroid Cancer								
All other cancers	124 & 64.8	142 & 74.6	113 & 60.0	128 & 68.7	125 & 68.2	118 & 65.4	98 & 55.0	109 & 61.8
Pulmonary Edema								
Endocrine gland disorders (diabetes)	97 & 50.7	85 & 44.7	96 & 51.0	83 & 44.6	83 & 45.3	86 & 47.7	128 & 71.9	146 & 82.8
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	178 & 93.1	153 & 80.4	184 & 97.7	149 & 80.0	163 & 88.9	202 & 111.9	162 & 90.9	161 & 91.3
Neurological disorders								
Reproduction/Childbirth (fetal deaths)	11 & 4.9	8 & 3.7	10 & 4.9	13 & 6.6	9 & 4.7	11 & 5.9	5 & 2.9	14 & 8.2
Exposure to Noxious Substances/external substances	17 & 8.9	20 & 10.5	19 & 10.1	21 & 11.3	15 & 8.2	19 & 10.5	21 & 11.8	21 & 11.9

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Appendix B: Mingo County Data

Table B1

Mingo County Population, 1995 – 2020

Year	Total		Year	Total
1995	33,600		2008	26,352
1996	33,900		2009	26,387
1997	32,600		2010	26,839
1998	31,900		2011	26,563
1999	31,500		2012	26,103
2000	28,253		2013	25,900
2001	27,714		2014	25,716
2002	27,561		2015	25,292
2003	27,585		2016	24,647
2004	27,389		2017	24,127
2005	27,210		2018	23,785
2006	27,100		2019	23,424
2007	26,755		2020	22,951

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table B2

Diagnosis of Kidney Cancer by Surrounding Counties: Mingo County

County	Mingo	Logan	McDowell	Wayne	Wyoming
Year of Diagnosis					
1993	2	2	7	6	1
1994	6	5	7	5	1
1995	3	5	10	13	5
1996	4	3	3	9	4
1997	2	7	4	7	8
1998	1	8	6	7	2
1999	6	4	7	7	7
2000	1	5	2	3	4
2001	7	5	1	12	6
2002	6	9	4	6	3
2003	9	6	4	11	3
2004	4	5	6	7	5
2005	7	10	3	10	5
2006	5	10	6	10	3
2007	7	7	9	4	4
2008	3	10	4	10	9
2009	5	7	2	9	5
2010	6	12	11	3	5
2011	9	10	4	8	8
2012	12	14	4	16	10
2013	9	22	5	8	6
2014	7	8	5	13	13
2015	9	12	2	14	4
2016	11	10	6	11	9
2017	10	19	10	10	7
2018	10	17	6	20	3
2019	6	12	5	6	10
2020	6	12	3	16	4
Grand Total	**173**	**256**	**146**	**261**	**154**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table B3

Diagnosis of Liver Cancer by Surrounding Counties: Mingo County

County	Mingo	Logan	McDowell	Wayne	Wyoming
Year of Diagnosis					
1993		1	2	2	
1994		1			2
1995	1		2	5	1
1996	1	1	4	1	1
1997	1	1			2
1998			3	1	
1999	1	3	3	2	1
2000	2		1		3
2001		1	1	2	
2002	1		1	3	2
2003	1	3	2		2
2004	1		2	3	1
2005	2	2		3	
2006	1	1	3	3	2
2007	4	3	1	3	
2008	2		3	6	2
2009	3	1		1	
2010	2	4	1	2	2
2011	1	5	1	3	1
2012	1	1	3	2	3
2013	2	5		1	
2014	2	3	1	4	
2015	4	3	2	4	2
2016	1	6	2	3	3
2017	2	2	5	5	3
2018	2	2	3	4	4
2019	1	4	3	5	3
2020	1	3	1	5	1
Grand Total	**40**	**56**	**50**	**73**	**41**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table B4

Number of Deaths by Race, Gender, and County of Residents: Mingo County 1996-2020

Year	Gender	White or European American	Black or African American	All other races	Unknown	Total
1996	M	161	8	0	*	335
	F	162	4	0	*	
1997	M	192	5	0	*	371
	F	170	3	1	*	
1998	M	168	5	0	*	337
	F	160	4	0	*	
1999	M	156	2	0	*	317
	F	150	9	0	*	
2000	M	152	2	0	*	333
	F	174	5	0	*	
2001	M	159	5	0	*	318
	F	151	3	0	*	
2002	M	168	12	0	*	331
	F	151	0	0	*	
2003	M	168	2	0	*	365
	F	192	3	0	*	
2004	M	186	3	0	*	337
	F	142	5	1	*	
2005	M	163	2	0	*	335
	F	165	5	0	*	
2006	M	198	5	0	*	391
	F	182	6	0	*	
2007	M	172	5	0	*	352

	F	170	5	0	*	
2008	M	192	4	0	*	380
	F	181	3	0	*	
2009	M	187	2	0	*	371
	F	180	2	0	*	
2010	M	186	1	0	*	360
	F	170	3	0	*	
2011	M	196	6	0	*	371
	F	162	7	0	*	
2012	M	177	12	0	1	348
	F	153	4	1	0	
2013	M	193	5	0	*	368
	F	163	7	0	*	
2014	M	220	1	1	*	402
	F	177	3	0	*	
2015	M	167	3	1	*	333
	F	160	2	0	*	
2016	M	154	4	2	*	340
	F	176	4	0	*	
2017	M	200	6	0	*	371
	F	156	9	0	*	
2018	M	192	2	1	*	195
	F	148	3	0	*	151
2019	M	199	3	1	*	203
	F	173	4	0	*	177
2020	M	224	5	0	*	229
	F	179	3	0	*	182

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table B5

Age at death by Mingo County Residence, 1996-2020

			Age In Years													
Year	Total	Rate*	< 1	1 to 4	5 to 9	10 to 14	15-19	20-24	25-34	35-44	45-54	55-64	65-74	75-84	85+	Average age at death
1996	335	9.9	3	1	0	0	6	4	13	14	24	45	84	77	64	68.1
1997	371	11.4	5	2	1	2	0	5	7	15	40	47	94	94	59	67.5
1998	337	10.6	3	1	0	1	1	4	6	15	21	47	80	98	60	69.8
1999	317	10.1	1	1	0	1	3	1	11	11	31	48	73	76	60	68.8
2000	333	11.8	2	0	0	0	2	1	7	19	29	50	77	87	59	69.3
2001	318	11.5	5	0	0	1	1	5	7	15	24	37	73	90	60	69.2
2002	331	12	7	1	1	1	1	4	5	15	26	49	66	106	49	68
2003	365	13.2	1	0	0	0	3	1	8	23	30	39	87	99	74	70.2
2004	337	12.3	1	1	0	1	5	2	10	19	37	37	71	94	59	68.3
2005	335	12.3	5	0	0	1	0	5	15	18	33	38	71	89	60	67.5
2006	391	14.4	4	0	0	0	2	8	12	15	41	65	78	97	69	67.7
2007	352	13.2	5	0	0	0	0	5	12	14	44	45	85	79	63	67.6
2008	380	14.4	5	2	0	0	1	1	7	24	33	65	81	98	63	67.8
2009	371	14.1	3	1	0	1	1	0	10	19	34	75	76	87	64	67.9
2010	360	13.4	4	1	0	0	1	5	11	20	34	63	82	84	55	66.9
2011	371	14	2	1	0	0	0	4	8	16	49	74	70	83	64	67.3
2012	384	13.3	1	1	0	1	1	2	10	24	27	62	70	88	61	68
2013	368	14.2	6	1	0	0	0	2	7	20	35	65	76	84	72	68.1
2014	402	15.6	5	2	0	0	1	2	15	22	41	67	100	80	67	66.7
2015	333	13.2	1	0	0	4	0	2	5	15	42	61	63	82	58	68.2
2016	340	13.8	1	2	0	0	2	0	13	16	33	72	77	72	52	66.8
2017	371	15.4	2	0	0	0	1	2	10	17	35	78	82	78	66	68.3
2018	346	14.5	1	0	0	0	0	0	8	10	45	54	80	93	55	69.4
2019	380	16.2	1	0	0	0	3	2	6	26	34	60	105	77	66	68.6
2020	411	17.9	2	1	0	0	1	1	6	30	32	80	108	99	51	67.6

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table B6

Selected causes of resident deaths: Number & Rate in Mingo County, 1996-2003*

Year	1996	1997	1998	1999	2000	2001	2002	2003
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	2 & 5.9	3 & 9.2	2 & 6.3	1 & 3.2	2 & 7.1	3 & 10.8	3 & 10.9	2 & 7.3
Breast cancer	1 & 2.9	1 & 3.1	3 & 9.4	7 & 22.2	6 & 21.2	6 & 21.6	2 & 7.3	5 & 18.1
Ovarian cancer	1 & 2.9	1 & 3.1	5 & 15.7	0 & 0.0	2 & 7.1	0 & 0.0	1 & 3.6	1 & 3.6
Thyroid cancer								
All other cancers	13 & 38.3	17 & 52.1	17 & 53.3	14 & 44.4	15 & 53.1	12 & 43.3	15 & 54.4	21 & 76.1
Pulmonary Edema	23 & 67.8	33 & 101.2	28 & 87.8					
Endocrine gland disorders (diabetes)	12 & 35.4	12 & 36.8	20 & 62.7	13 & 41.3	10 & 35.4	8 & 28.9	15 & 54.4	11 & 39.9
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	6 & 17.7	2 & 6.1	1 & 3.1	27 & 85.7	35 & 123.9	29 & 104.6	23 & 83.5	29 & 105.1
Neurological disorders								

Reproduction/Childbirth (fetal deaths)	2 & 5.2	5 & 11.4	2 & 5.1	3 & 7.4	3 & 8.3	3 & 8.0	1 & 2.6	2 & 5.3
Exposure to Noxious Substances/external substances	4 & 11.8	6 & 18.4	8 & 25.1	4 & 12.7	5 & 17.7	2 & 7.2	7 & 25.4	10 & 36.3

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table B7

Selected causes of resident deaths: Number & Rate in Mingo County, 2004-2012*

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
Selected causes of death									
Non-Hodgkin's Lymphoma									
Soft tissue sarcoma									
Liver cancer									
Kidney cancer									
Testicular cancer									
prostate cancer	5 & 18.3	5 & 18.4	2 & 7.4	0 & 0.0	3 & 11.4	1 & 3.8	2 & 7.5	3 & 11.3	0 & 0.0
Breast cancer	3 & 11.0	12 & 44.1	4 & 14.8	2 & 7.5	4 & 15.2	1 & 3.8	4 & 14.9	4 & 15.1	6 & 23.0
Ovarian cancer	2 & 7.3	1 & 3.7	3 & 11.1	1 & 3.7	3 & 11.4	0 & 0.0	4 & 14.9	6 & 22.6	1 & 3.8
Thyroid cancer									
All other cancers	14 & 51.1	17 & 62.5	16 & 59.0	17 & 63.5	24 & 91.1	20 & 75.8	17 & 63.3	21 & 79.1	16 & 61.3
Pulmonary Edema									
Endocrine gland disorders (diabetes)	14 & 51.1	21 & 77.2	21 & 77.5	7 & 26.2	21 & 79.7	24 & 91.0	16 & 59.6	10 & 37.6	16 & 61.3

Upper respiratory diseases									
Autoimmune disorders									
Lower respiratory diseases	32 & 116.8	21 & 77.2	40 & 147.6	31 & 115.9	38 & 144.2	31 & 117.5	32 & 119.2	26 & 97.9	37 & 141.7
Neurological disorders									
Reproduction/Childbirth (fetal deaths)	1 & 2.7	3 & 8.1	1 & 2.7	2 & 5.1	2 & 5.7	1 & 2.7	1 & 2.6	0 & 0.0	1 & 2.8
Exposure to Noxious Substances/external substances	4 & 14.6	7 & 25.7	18 & 66.4	6 & 22.4	5 & 19.0	9 & 34.1	7 & 26.1	6 & 22.6	7 & 26.8

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table B8

Selected causes of resident deaths: Number & Rate in Mingo County, 2013-2020*

Year	2013	2014	2015	2016	2017	2018	2019	2020
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	2 & 7.7	4 & 15.6	4 & 15.8	1 & 4.1	1 & 4.1	2 & 8.4	3 & 12.8	4 & 17.4
Breast cancer	5 & 19.3	5 & 19.4	3 & 11.9	6 & 24.3	2 & 8.3	3 & 12.6	5 & 21.3	3 & 13.1
Ovarian cancer	1 & 3.9	2 & 7.8	2 & 7.9	2 & 8.1	0 & 0.0	2 & 8.4	0 & 0.0	0 & 0.0
Thyroid cancer								

All other cancers	19 & 73.4	17 &66.1	18 & 71.2	20 & 81.1	15 & 62.2	14 & 58.9	16 & 68.3	15 & 65.4
Pulmonary Edema								
Endocrine gland disorders (diabetes)	20 & 77.2	14 & 54.4	9 & 35.6	5 & 20.3	15 & 62.2	11 & 46.2	24 & 102.5	12 & 52.3
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	35 & 135.1	39 & 151.7	30 & 118.6	24 & 97.4	35 & 145.1	36 & 151.4	30 & 128.1	39 & 169.9
Neurological disorders								
Reproduction/Childbirth (fetal deaths)	1 & 3.2	2 & 5.8	3 & 9.4	1 & 3.7	1 & 3.1	1 & 3.6	2 & 7.2	2 & 7.1
Exposure to Noxious Substances/external substances	4 & 15.4	5 & 19.4	3 & 11.9	4 & 16.2	3 & 12.4	3 & 12.6	3 & 12.8	4 & 17.4

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Appendix C: Putnam County Data

Table C1

Putnam County Population, 1995 – 2020

Year	Total	Year	Total
1995	48,900	2008	55,488
1996	47,900	2009	55,673
1997	48,900	2010	55,486
1998	48,300	2011	56,008
1999	51,900	2012	56,435
2000	51,589	2013	56,650
2001	51,680	2014	56,770
2002	52,230	2015	56,848
2003	53,035	2016	56,941
2004	53,836	2017	56,792
2005	54,443	2018	56,682
2006	54,982	2019	56,450
2007	55,001	2020	56,428

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table C2

Diagnosis of Breast Cancer by Surrounding Counties: Putnam County

County	Putnam	Cabell	Jackson	Lincoln	Mason	Kanawha
Year of Diagnosis						
1993	33	82	27	21	19	184
1994	32	75	24	14	15	195
1995	34	94	19	16	20	175
1996	30	91	20	11	21	221
1997	33	99	19	11	16	213
1998	39	94	23	13	12	227
1999	40	92	20	16	24	224
2000	48	77	30	17	20	222
2001	45	90	27	12	14	216
2002	49	89	15	14	17	195
2003	49	89	24	17	33	192
2004	46	81	22	16	21	209
2005	44	90	28	23	20	198
2006	52	95	28	14	19	201
2007	46	100	28	17	21	214
2008	40	92	24	18	23	187
2009	60	86	33	20	26	179
2010	49	90	28	17	31	200
2011	47	102	33	17	15	202
2012	55	129	27	21	19	196
2013	59	114	21	17	27	185
2014	66	83	19	17	19	208
2015	46	106	22	12	23	186
2016	49	97	30	19	20	180
2017	44	109	23	17	20	174
2018	73	107	30	15	27	180
2019	65	103	37	13	25	195
2020	59	85	28	19	21	169
Grand Total	**1332**	**2641**	**709**	**454**	**588**	**5527**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table C3

Diagnosis of non-Hodgkin's Lymphoma by Surrounding Counties: Putnam County

County	Putnam	Cabell	Jackson	Lincoln	Mason	Kanawha
Year of Diagnosis						
1993	4	18	1	1	1	42
1994	8	14	6	5	5	38
1995	7	18	5	5	4	35
1996	9	30	8	5	10	34
1997	9	31	5	5	5	41
1998	9	16	11	6	5	52
1999	9	18	5	4	8	40
2000	8	22	6	3	8	45
2001	9	24	13	9	4	43
2002	12	15	7	6	4	46
2003	11	21	10	4	10	42
2004	15	29	6	5	5	50
2005	15	28	9	2	9	43
2006	16	18	4	9	6	54
2007	12	23	11	6	9	64
2008	10	19	13	8	6	50
2009	14	32	3	5	8	49
2010	15	18	4	7	9	75
2011	16	20	9	4	5	52
2012	17	17	9	7	6	48
2013	9	27	6	5	5	60
2014	15	21	10	6	13	45
2015	19	22	8	6	11	41
2016	16	29	9	7	12	46
2017	16	18	4	7	7	64
2018	14	22	5	6	9	51
2019	12	26	5	3	4	60
2020	16	20	11	6	3	44
Grand Total	**342**	**616**	**203**	**152**	**191**	**1354**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table C4

Diagnosis of Soft Tissue Cancer by Surrounding Counties: Putnam County

County	Putnam	Cabell	Jackson	Lincoln	Mason	Kanawha
Year of Diagnosis						
1993	2		1		1	4
1994		3		1	5	5
1995		2			4	5
1996		3			10	5
1997	2	2	1	2	5	3
1998	1		1		5	4
1999		1	2	1	8	11
2000			1		8	6
2001	1	4			4	13
2002	1	5	1	3	4	4
2003		1			10	7
2004	1	3	1		5	5
2005	4	2	3		9	10
2006		2	5	1	6	6
2007	3	5		2	9	7
2008	2	3	1		6	13
2009	3	4	2	2	8	10
2010	3	4	3	1	9	7
2011	3	3	1		5	6
2012	2	5	3	2	6	6
2013	1	4		2	5	5
2014	1	2	2	2	13	5
2015		4		2	11	7
2016	3	2	1	2	12	7
2017	3	1	2		7	6
2018	1	1	2		9	7
2019	3	5	3		4	8
2020	4	5	1	1	3	5
Grand Total	**47**	**76**	**37**	**24**	**191**	**187**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table C5

Number of Deaths by Race, Gender, and County of Residents: Putnam County 1996-2020

Year	Gender	White or European American	Black or African American	All other races	Unknown	Total
1996	M	241	1	0	*	448
	F	204	2	0	*	
1997	M	199	0	1	*	427
	F	225	2	0	*	
1998	M	199	0	0	*	417
	F	218	0	0	*	
1999	M	204	1	1	*	436
	F	230	0	0	*	
2000	M	223	0	0	*	445
	F	219	2	1	*	
2001	M	188	0	0	*	419
	F	230	1	0	*	
2002	M	201	0	0	*	450
	F	249	0	0	*	
2003	M	236	0	0	*	488
	F	251	1	0	*	
2004	M	228	2	0	*	464
	F	233	1	0	*	
2005	M	229	1	0	*	480
	F	250	0	0	*	
2006	M	215	1	0	*	451
	F	233	2	0	*	
2007	M	218	4	2	*	471
	F	246	1	0	*	
2008	M	283	1	0	*	536
	F	251	1	0	*	
2009	M	257	0	0	*	505
	F	246	2	0	*	
2010	M	252	1	1	*	505
	F	248	3	0	*	
2011	M	268	0	0	*	510
	F	239	2	1	*	
2012	M	295	3	1	0	583

	F	283	1	0	0	
2013	M	275	0	4	*	548
	F	267	0	2	*	
2014	M	307	3	0	*	578
	F	266	1	1	*	
2015	M	290	1	1	*	568
	F	276	0	0	*	
2016	M	342	2	1	*	625
	F	278	1	0	*	
2017	M	324	1	1	*	631
	F	302	1	1	*	
2018	M	304	2	1	*	307
	F	295	0	1	*	296
2019	M	326	2	2	*	330
	F	322	3	1	*	326
2020	M	354	5	2	*	361
	F	333	1	0	*	334

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table C6

Age at death by Putnam County Residence, 1996-2020

			Age in Years													
Year	Total	Rate*	< 1	1 to 4	5 to 9	10 to 14	15-19	20-24	25-34	35-44	45-54	55-64	65-74	75-84	85+	Average age at death
1996	448	9.4	4	0	0	2	7	1	4	10	27	60	114	128	91	71.5
1997	427	8.5	3	0	0	1	1	1	8	12	24	41	91	139	106	73.4
1998	417	8.1	2	2	0	0	3	3	9	15	33	49	102	121	78	70.3
1999	436	8.4	3	2	1	2	3	7	10	12	23	44	87	134	108	71.8
2000	445	8.6	3	1	0	1	2	4	8	15	34	45	100	126	106	71.8
2001	419	8.1	8	1	2	0	5	5	7	11	20	54	80	126	100	70.8
2002	450	8.6	4	0	0	1	2	3	6	12	28	47	86	140	121	73.4
2003	488	9.2	5	1	1	1	3	5	6	19	33	64	100	127	123	71.3
2004	464	8.6	8	0	1	2	6	4	5	16	35	51	91	149	96	70.5
2005	480	8.8	4	0	1	1	4	3	7	18	28	60	100	139	115	71.9
2006	451	8.2	3	1	1	0	1	3	9	10	29	57	96	130	111	72.6
2007	471	8.6	3	1	0	2	1	3	10	20	40	51	75	131	134	72
2008	536	9.7	3	1	0	0	1	7	14	9	37	82	104	156	122	71.6
2009	505	9.1	0	1	0	1	2	5	13	23	40	63	79	127	151	72.1
2010	505	9.1	5	1	0	1	2	6	8	8	34	65	87	153	135	72.6
2011	510	9.1	4	0	0	2	1	0	12	15	36	51	102	131	156	73.4
2012	583	10.3	4	1	1	0	1	4	6	14	36	81	132	149	154	72.8
2013	548	9.7	7	0	1	0	0	2	13	14	43	69	100	143	156	72.4
2014	578	10.2	3	2	2	0	0	5	9	20	34	83	118	145	157	72.3
2015	568	10	4	0	0	0	2	2	12	12	36	69	115	156	160	73.4
2016	625	11	1	1	1	0	4	3	14	24	38	81	129	168	161	72.2
2017	631	11.1	0	0	1	1	3	1	22	21	40	71	133	162	176	72.8
2018	603	10.6	2	0	0	2	0	4	11	22	38	82	133	150	159	72.4
2019	656	11.6	4	1	0	1	2	5	15	12	31	90	137	181	177	73.2
2020	695	12.3	3	0	0	1	2	2	20	27	30	76	135	193	206	73.6

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table C7

Selected causes of resident deaths: Number & Rate in Putnam County, 1996-2003*

Year	1996	1997	1998	1999	2000	2001	2002	2003
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	5 & 10.4	8 & 15.9	6 & 11.7	1 & 1.9	6 & 11.6	2 & 3.9	5 & 9.6	3 & 5.7
Breast cancer	8 & 16.7	4 & 8.0	5 & 9.8	4 & 7.7	13 & 25.2	9 & 17.4	9 & 17.2	7 & 13.2
Ovarian cancer	2 & 4.2	0 & 0.0	4 & 7.8	3 & 5.8	0 & 0.0	4 & 7.7	0 & 0.0	3 & 5.7
Thyroid cancer								
All other cancers	29 & 60.5	24 & 47.8	26 & 50.8	21 & 40.5	21 & 40.7	17 & 32.9	34 & 65.1	25 & 47.1
Pulmonary Edema	24 & 50.1	18 & 35.9	23 & 44.9					
Endocrine gland disorders (diabetes)	19 & 39.7	12 & 23.9	15 & 29.3	16 & 30.8	15 & 29.1	16 & 31.0	17 & 32.5	24 & 45.3
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	8 & 16.7	3 & 6.0	4 & 7.8	19 & 36.6	25 & 48.5	21 & 40.6	27 & 51.7	31 & 58.5
Neurological disorders								

Reproduction/Childbirth (fetal deaths)	2 & 3.5	3 & 5.1	2 & 3.4	4 & 6.4	8 & 13.7	5 & 7.8	7 & 11.9	4 & 5.9
Exposure to Noxious Substances/external substances	2 & 4.2	2 & 4.0	3 & 5.9	2 & 3.9	5 & 9.7	3 & 5.8	2 & 3.8	5 & 9.4

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table C8

Selected causes of resident deaths: Number & Rate in Putnam County, 2004-2012*

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
Selected causes of death									
Non-Hodgkin's Lymphoma									
Soft tissue sarcoma									
Liver cancer									
Kidney cancer									
Testicular cancer									
prostate cancer	4 & 7.4	5 & 9.2	4 & 7.3	1 & 1.8	3 & 5.4	7 & 12.6	5 & 9.0	5 & 8.9	5 & 8.9
Breast cancer	3 & 5.6	3 & 5.5	6 & 10.9	8 & 14.5	7 & 12.6	8 & 14.4	8 & 14.4	10 & 17.9	7 & 12.4
Ovarian cancer	2 & 3.7	1 & 1.8	8 & 14.6	2 & 3.6	6 & 10.8	2 & 3.6	1 & 1.8	2 & 3.6	5 & 8.9
Thyroid cancer									
All other cancers	32 & 59.4	34 & 62.5	35 & 63.7	21 & 38.2	32 & 57.7	27 & 48.5	32 & 57.7	37 & 66.1	33 & 58.5
Pulmonary Edema									

Endocrine gland disorders (diabetes)	17 & 31.6	16 & 29.4	18 & 32.7	13 & 23.6	20 & 36.0	19 & 34.1	10 & 18.0	14 & 25.0	20 & 35.4
Upper respiratory diseases									
Autoimmune disorders									
Lower respiratory diseases	32 & 59.4	40 & 73.5	26 & 47.3	20 & 36.4	41 & 73.9	28 & 50.3	25 & 45.1	27 & 48.2	36 & 63.8
Neurological disorders									
Reproduction/Childbirth (fetal deaths)	1 & 1.5	6 & 9.3	1 & 1.6	2 & 3.1	6 & 9.8	1 & 1.7	3 & 5.1	3 & 4.9	1 & 1.7
Exposure to Noxious Substances/external substances	2 & 3.7	7 & 12.9	6 & 10.9	3 & 5.5	6 & 10.8	4 & 7.2	2 & 3.6	3 & 5.4	4 & 7.1

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table C9

Selected causes of resident deaths: Number & Rate in Putnam County, 2013-2020*

Year	2013	2014	2015	2016	2017	2018	2019	2020
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	3 & 5.3	4 & 7.0	7 & 12.3	9 & 15.8	9 & 15.8	6 & 10.6	7 & 12.4	6 & 10.6

Breast cancer	6 & 10.6	12 & 21.1	3 & 5.3	11 & 19.3	12 & 21.1	7 & 12.3	8 & 14.2	8 & 14.2
Ovarian cancer	4 & 7.1	4 & 7.0	3 & 5.3	1 & 1.8	3 & 5.3	3 & 5.3	1 & 1.8	2 & 3.5
Thyroid cancer								
All other cancers	37 & 65.3	38 & 66.9	38 & 66.8	34 & 59.7	27 & 47.5	34 & 60.0	34 & 60.2	24 & 42.5
Pulmonary Edema								
Endocrine gland disorders (diabetes)	18 & 31.8	11 & 19.4	14 & 24.6	23 & 40.4	21 & 37.0	22 & 38.8	27 & 47.8	30 & 53.2
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	34 & 60.0	46 & 81.0	34 & 59.8	40 & 70.2	36 & 63.4	31 & 54.7	54 & 95.7	38 & 67.3
Neurological disorders								
Reproduction/Childbirth (fetal deaths)	1 & 1.6	1 & 1.6	2 & 3.3	1 & 1.8	0 & 0.0	2 & 3.9	2 & 3.6	3 & 5.8
Exposure to Noxious Substances/external substances	4 & 7.1	4 & 7.0	10 & 17.6	4 & 7.0	5 & 8.8	2 & 3.5	5 & 8.9	4 & 7.1

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Appendix D: Wood County Data

Table D1

Wood County Population, 1995 – 2020

Year	Total	Year	Total
1995	88,300	2008	86,204
1996	88,000	2009	86,888
1997	87,000	2010	86,956
1998	86,800	2011	87,120
1999	86,300	2012	86,701
2000	87,986	2013	86,569
2001	87,541	2014	86,237
2002	87,306	2015	86,452
2003	87,336	2016	85,643
2004	87,100	2017	85,104
2005	87,047	2018	84,203
2006	86,597	2019	83,518
2007	86,088	2020	82,938

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D2

Diagnosis of Breast Cancer by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	68	7	6	3
1994	67	1	10	3
1995	77	10	10	4
1996	79	5	10	6
1997	67	6	7	8
1998	97	7	8	8
1999	94	3	5	7
2000	61	10	8	6
2001	99	1	8	2
2002	85	4	8	2
2003	77	5	8	4
2004	92	7	7	7
2005	89	7	14	7
2006	99	3	6	1
2007	78	1	6	3
2008	87	10	11	5
2009	76	2	11	4
2010	91	10	11	2
2011	52	5	6	2
2012	80	9	8	3
2013	88	4	6	10
2014	77	9	8	4
2015	82	13	15	6
2016	95	9	8	4
2017	81	8	6	2
2018	97	11	7	7
2019	95	6	13	8
2020	91	12	4	6
Grand Total	**2321**	**185**	**235**	**134**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D3

Diagnosis of Kidney Cancer by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	18		1	1
1994	15			2
1995	11	1		2
1996	10		1	2
1997	11	2		2
1998	9			1
1999	14	2	4	2
2000	15	2	3	
2001	17		2	1
2002	14	3	2	1
2003	20		3	2
2004	22		1	1
2005	16	1	3	2
2006	16		1	3
2007	24	2		4
2008	20	2	5	3
2009	20	2	3	3
2010	21	2	4	1
2011	14	1	1	2
2012	22	2	1	
2013	22	3	2	1
2014	22	2	6	1
2015	29	3	2	1
2016	21	1	3	1
2017	22	3	6	1
2018	22	5	4	2
2019	37	3	2	1
2020	20	4	2	
Grand Total	**524**	**46**	**62**	**42**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D4

Diagnosis of non-Hodgkin's Lymphoma by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	15		2	1
1994	10	2	3	
1995	18	4	1	
1996	23		4	1
1997	18			
1998	25		3	2
1999	21	5	5	2
2000	15	1	2	1
2001	18	1	2	2
2002	26	3	6	1
2003	31	1	3	2
2004	19	2	1	1
2005	20	1	1	1
2006	22	2	3	2
2007	28	2	1	
2008	23	3		2
2009	21	2	2	2
2010	24	4	3	2
2011	19	3	1	2
2012	22		1	
2013	28	4	2	1
2014	21		3	
2015	20	2	1	3
2016	28		2	2
2017	27	2	2	4
2018	26	3	2	
2019	28	3	2	1
2020	13	2	2	
Grand Total	**609**	**52**	**60**	**35**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D5

Diagnosis of Prostate Cancer by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	55	9	8	5
1994	58	4	12	2
1995	54	8	8	3
1996	78	13	10	1
1997	63	3	1	6
1998	69	2	7	2
1999	75	5	5	10
2000	76	5	11	7
2001	89	8	9	8
2002	93	8	7	7
2003	74	5	13	5
2004	70	12	11	4
2005	67	8	9	2
2006	66	8	11	5
2007	67	4	9	6
2008	83	6	7	2
2009	65	8	4	5
2010	66	5	6	7
2011	82	9	10	4
2012	59	5	4	3
2013	49	7	6	2
2014	45	3	3	2
2015	50	5	8	2
2016	58	6	9	5
2017	58	3	6	8
2018	69	5	8	4
2019	68	10	9	2
2020	65	8	3	
Grand Total	**1871**	**182**	**214**	**119**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D6

Diagnosis of Testicular Cancer by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	2			
1994	3	2		
1995	3			1
1996	4		1	1
1997	3			
1998	2			
1999	4			
2000				
2001	2			
2002		1		
2003	1			
2004	3			
2005	4			
2006	2			
2007	3	1	1	
2008	2		1	
2009	3			
2010	3			
2011	2			
2012	1		1	
2013	3			
2014	6			
2015	2			1
2016	1			1
2017	1			
2018	2	2		1
2019	1	1	1	
2020	4			
Grand Total	**67**	**7**	**5**	**5**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D7

Diagnosis of Ovarian Cancer by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	6		1	
1994	6	2	3	
1995	14	3	1	
1996	11			
1997	13	1	1	
1998	7	1	1	
1999	11	2	1	
2000	7			1
2001	12	1		
2002	7		3	
2003	3	2		1
2004	6		1	2
2005	7		2	
2006	6		2	
2007	14			
2008	7	1	2	2
2009	8	1		1
2010	10	1		
2011	5	1	1	1
2012	8			1
2013	5	1	2	
2014	4		2	
2015	3	2	1	2
2016	8	1	1	
2017	5		1	
2018	7		1	1
2019	9			
2020	7	1		
Grand Total	**216**	**21**	**27**	**12**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D8

Diagnosis of Thyroid Cancer by Surrounding Counties: Wood County

County	Wood	Pleasants	Ritchie	Wirt
Year of Diagnosis				
1993	3		1	
1994	3			
1995	7			
1996	2	1		
1997	5		2	2
1998	3			
1999	4			1
2000	10			
2001	3		1	
2002	6		1	3
2003	7	1		
2004	5	1	1	1
2005	9		2	
2006	9	1	1	2
2007	11	1	1	
2008	9	2	2	
2009	10	1	2	1
2010	11		3	
2011	11	1	3	2
2012	10	1	1	
2013	11		2	3
2014	16	1	1	
2015	22	2	2	
2016	18	1	2	2
2017	14	1	2	1
2018	13		1	1
2019	8	2		1
2020	3	2	2	
Grand Total	**243**	**19**	**33**	**20**

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D9

Number of Deaths by Race, Gender, and County of Residents: Wood County 1996-2020

Year	Gender	White or European American	Black or African American	All other races	Unknown	Total
1996	M	441	2	2	*	910
	F	461	4	0	*	
1997	M	485	1	0	*	1,026
	F	536	3	1	*	
1998	M	455	6	0	*	950
	F	484	5	0	*	
1999	M	446	5	0	*	1,011
	F	554	5	1	*	
2000	M	494	2	0	*	1,043
	F	542	5	0	*	
2001	M	449	3	2	*	1,001
	F	542	5	0	*	
2002	M	466	2	1	*	1,002
	F	530	3	0	*	
2003	M	475	4	0	*	992
	F	509	4	0	*	
2004	M	439	4	1	*	931
	F	482	4	1	*	
2005	M	461	1	0	*	939
	F	474	2	1	*	
2006	M	446	4	2	*	935
	F	477	3	3	*	
2007	M	435	7	0	*	948
	F	501	4	1	*	
2008	M	498	6	0	*	1,020
	F	515	1	0	*	
2009	M	486	4	1	*	1,020
	F	524	4	1	*	
2010	M	460	8	5	*	989
	F	512	4	0	*	
2011	M	489	5	0	*	1,039
	F	543	1	1	*	
2012	M	451	2	0	2	976

	F	512	6	2	1	
2013	M	512	5	1	*	1,045
	F	519	7	0	*	
2014	M	531	6	3	*	1,097
	F	553	3	1	*	
2015	M	540	6	3	*	1,068
	F	511	6	1	*	
2016	M	513	5	1	*	1,108
	F	587	2	0	*	
2017	M	560	5	0	*	1,094
	F	524	4	1	*	
2018	M	573	6	2	*	581
	F	553	3	1	*	557
2019	M	548	5	1	*	554
	F	548	7	3	*	558
2020	M	622	5	5	*	632
	F	570	2	1	*	573

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx).

Table D10

Age at death by Wood County Residence, 1996-2020

			Age in Years														
Year	Total	Rate*	< 1	1 to 4	5 to 9	10 to 14	15-19	20-24	25-34	35-44	45-54	55-64	65-74	75-84	85+	Average age at death
1996	910	10.3	6	1	0	1	6	4	8	19	54	107	196	247	261	73.8
1997	1,026	11.8	10	1	0	0	3	5	7	33	69	103	201	316	278	73.9
1998	950	10.9	6	1	2	0	1	4	14	35	43	82	199	311	252	73.9
1999	1,011	11.7	7	1	1	0	6	4	9	34	47	88	202	304	308	74.9
2000	1,043	11.9	6	2	0	0	5	6	12	20	55	109	201	318	309	75
2001	1,001	11.4	8	3	2	1	3	3	14	37	56	100	177	316	281	73.8
2002	1,002	11.5	9	2	1	0	5	6	12	23	67	99	163	321	294	74
2003	992	11.4	4	0	0	2	2	6	8	26	63	106	169	320	286	74.7
2004	931	10.7	10	1	1	0	2	6	6	31	44	98	183	297	252	73.8
2005	939	10.8	10	2	0	0	2	4	12	17	64	94	175	287	272	74.3
2006	935	10.8	8	1	0	1	4	5	15	24	68	97	135	314	263	73.9
2007	948	11	14	2	0	2	3	3	12	13	69	117	163	265	285	73.4
2008	1,020	11.8	5	1	0	1	2	3	13	28	69	117	187	319	275	73.9
2009	1,020	11.7	10	2	0	1	2	6	11	20	71	137	184	273	303	73.5
2010	989	11.4	8	3	2	0	0	5	14	20	49	133	214	250	291	73.6
2011	1,039	11.9	9	1	0	1	2	3	16	25	67	131	190	278	316	73.8
2012	976	11.3	6	4	0	0	2	5	13	21	78	126	176	280	265	73.1
2013	1,045	12.1	9	1	0	3	1	6	19	27	75	134	200	255	315	73
2014	1,097	12.7	10	2	1	2	6	10	12	27	82	157	203	277	308	72.4
2015	1,068	12.4	6	1	0	0	1	5	18	30	64	145	219	284	295	73.3
2016	1,108	12.9	8	2	0	1	3	4	28	41	76	143	220	270	312	72.3
2017	1,094	12.9	4	1	1	2	0	9	25	33	66	141	224	280	308	72.9
2018	1,138	13.5	6	1	1	1	3	8	27	20	65	155	244	310	297	73
2019	1,112	13.3	6	0	0	1	0	8	12	43	75	162	211	314	280	72.6
2020	1,205	14.5	4	4	1	0	1	6	29	33	73	160	253	339	302	72.6

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table D11

Selected causes of resident deaths: Number & Rate in Wood County, 1996-2003*

Year	1996	1997	1998	1999	2000	2001	2002	2003
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	14 & 15.9	10 & 11.5	8 & 9.2	7 & 8.1	13 & 14.8	9 & 10.3	10 & 11.5	12 & 13.7
Breast cancer	17 & 19.3	10 & 11.5	9 & 10.4	8 & 9.3	10 & 11.4	14 & 16.0	14 & 16.0	8 & 9.2
Ovarian cancer	6 & 6.8	12 & 13.8	10 & 11.5	4 & 4.6	5 & 5.7	3 & 3.4	11 & 12.6	1 & 1.1
Thyroid cancer								
All other cancers	52 & 59.1	72 & 82.8	60 & 69.1	59 & 68.4	43 & 48.9	76 & 86.8	42 & 48.1	62 & 71.0
Pulmonary Edema	47 & 53.4	49 & 56.3	39 & 44.9					
Endocrine gland disorders (diabetes)	34 & 38.6	33 & 37.9	33 & 38.0	32 & 37.1	31 & 35.2	47 & 53.7	42 & 48.1	40 & 45.8
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	14 & 15.9	14 & 16.1	10 & 11.5	54 & 62.6	57 & 64.8	63 & 72.0	45 & 51.5	68 & 77.9
Neurological disorders								
Reproduction/Childbirth (fetal deaths)	5 & 4.7	10 & 9.8	9 & 8.5	5 & 5.2	2 & 1.9	6 & 5.9	6 & 5.9	7 & 6.9

Exposure to Noxious Substances/external substances	3 & 3.4	1 & 1.1	6 & 6.9	7 & 8.1	6 & 6.8	5 & 5.7	5 & 5.7	4 & 4.6

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table D12

Selected causes of resident deaths: Number & Rate in Wood County, 2004-2012*

Year	2004	2005	2006	2007	2008	2009	2010	2011	2012
Selected causes of death									
Non-Hodgkin's Lymphoma									
Soft tissue sarcoma									
Liver cancer									
Kidney cancer									
Testicular cancer									
prostate cancer	7 & 8.0	6 & 6.9	8 & 9.2	8 & 9.3	8 & 9.3	12 & 13.8	7 & 8.1	6 & 6.9	4 & 4.6
Breast cancer	17 & 19.5	13 & 14.9	7 & 8.1	14 & 16.3	16 & 18.6	11 & 12.7	19 & 21.9	21 & 24.1	14 & 16.1
Ovarian cancer	6 & 6.9	2 & 2.3	5 & 5.8	4 & 4.6	5 & 5.8	1 & 1.2	2 & 2.3	8 & 9.2	3 & 3.5
Thyroid cancer									
All other cancers	53 & 60.8	51 & 58.6	46 & 53.1	42 & 48.8	68 & 78.9	49 & 56.4	53 & 61.0	52 & 59.7	57 & 65.7
Pulmonary Edema									
Endocrine gland disorders (diabetes)	40 & 45.9	28 & 32.2	25 & 28.9	37 & 43.0	30 & 34.8	29 & 33.4	38 & 43.7	36 & 41.3	23 & 26.5
Upper respiratory diseases									
Autoimmune disorders									

Lower respiratory diseases	57 & 65.4	62 & 71.2	53 & 61.2	53 & 61.6	71 & 82.4	69 & 79.4	57 & 65.6	69 & 79.2	75 & 86.5
Neurological disorders									
Reproduction/Childbirth (fetal deaths)	9 & 9.1	8 & 7.8	5 & 5.1	9 & 8.6	5 & 5.2	1 & 1.0	2 & 2.1	13 & 13.1	4 & 4.5
Exposure to Noxious Substances/external substances	5 & 5.7	2 & 2.3	2 & 2.3	6 & 7.0	5 & 5.8	7 & 8.1	5 & 5.8	5 & 5.7	3 & 3.5

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.

Table D13

Selected causes of resident deaths: Number & Rate in Wood County, 2013-2020*

Year	2013	2014	2015	2016	2017	2018	2019	2020
Selected causes of death								
Non-Hodgkin's Lymphoma								
Soft tissue sarcoma								
Liver cancer								
Kidney cancer								
Testicular cancer								
prostate cancer	9 & 10.4	7 & 8.1	10 & 11.6	8 & 9.3	8 & 9.4	17 & 20.2	5 & 6.0	6 & 7.2
Breast cancer	8 & 9.2	23 & 26.7	21 & 24.3	12 & 14.0	14 & 16.5	16 & 19.0	10 & 12.0	15 & 18.1
Ovarian cancer	6 & 6.9	2 & 2.3	5 & 5.8	3 & 3.5	6 & 7.1	4 & 4.8	2 & 2.4	4 & 4.8
Thyroid cancer								

All other cancers	56 & 64.7	58 & 67.3	50 & 57.8	52 & 60.7	60 & 70.5	65 & 77.2	65 & 77.8	61 & 73.5
Pulmonary Edema								
Endocrine gland disorders (diabetes)	40 & 46.2	36 & 41.7	36 & 41.6	38 & 44.4	45 & 52.9	52 & 61.8	50 & 59.9	55 & 66.3
Upper respiratory diseases								
Autoimmune disorders								
Lower respiratory diseases	69 & 79.7	65 & 75.4	77 & 89.1	69 & 80.6	81 & 95.2	82 & 97.4	78 & 93.4	74 & 89.2
Neurological disorders								
Reproduction/Childbirth (fetal deaths)	4 & 3.8	3 & 2.9	5 & 5.1	5 & 5.3	2 & 2.2	3 & 3.3	1 & 1.2	4 & 5.1
Exposure to Noxious Substances/external substances	8 & 9.2	9 & 10.4	8 & 9.3	4 & 4.7	2 & 2.4	3 & 3.6	6 & 7.2	7 & 8.4

Note. Vital statistics data is from the West Virginia Department of Health & Human Resources [DHHR], n.d. (https://dhhr.wv.gov/HSC/SS/Vital_Statistics/Pages/Vital_Statistics.aspx). *Rates for total deaths are per 1,000 population. Rates for fetal deaths, deaths under 1 year and deaths under 28 days are per 1,000 live births. All other rates are per 100,000 population unless otherwise noted.