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ORIGINAL PAPER

Cancer incidence and proximity to coal ash impoundments in the United States

Charlie H. Zhang · Mahmuda Mohammed · Natalie C. DuPré · Brian Guinn · Michael E. Egger · Kristina M. Zierold

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Abstract Across the United States (U.S.), many communities experience disproportionate exposure to environmental health hazards due to their proximity to coal-fired power plants and associated coal ash disposal sites. These facilities release toxic heavy metals such as arsenic, mercury, and lead into the surrounding environment, posing serious public health risks. Although prior research has documented adverse health effects of coal-fired power plants, few studies have specifically examined the relationship between cancer incidence and proximity to coal ash impoundments, as well as exposure to elevated concentrations of toxic constituents in coal ash. Using complementary contingency table analyses, bivariate spatial association techniques, and spatial regression methods, this study finds consistent evidence that counties containing or adjacent to coal ash impoundments exhibit significantly higher cancer incidence rates compared to more distant counties, even after adjusting for potential confounders. Incidence rates for both total cancer and lung cancer were significantly associated with smoking, drinking, and physical inactivity, corroborating prior research on these behavioral risk factors. The lung cancer model further revealed significant positive associations between cancer incidence and $PM_{2.5}$, arsenic concentrations, and airborne cancer risk scores, highlighting specific environmental risk factors for the disease. These findings strengthen the evidence linking coal ash exposure to adverse health outcomes and underscore the urgent need for robust enforcement and compliance measures to protect communities from coal ash contamination.

Keywords Coal-fired power plants · Coal ash impoundments · Proximity · Heavy metals · Cancer incidence · United States

C. H. Zhang (✉)
Department of Geographic and Environmental Sciences, College of Arts & Sciences, University of Louisville, Louisville, KY 40292, USA
e-mail: c.zhang@louisville.edu

C. H. Zhang · N. C. DuPré · B. Guinn
Center for Integrative Environmental Health Sciences (CIEHS), University of Louisville, Louisville, KY 40202, USA

M. Mohammed
Department of Urban and Public Affairs, College of Arts & Sciences, University of Louisville, Louisville, KY 40292, USA

N. C. DuPré · B. Guinn
Department of Epidemiology & Population Health, School of Public Health & Information Sciences, University of Louisville, Louisville, KY 40202, USA

M. E. Egger
Department of Surgery, Division of Surgical Oncology, University of Louisville, Louisville, KY 40202, USA

K. M. Zierold
Department of Public Health, University of Mississippi, Oxford, MS 38677, USA

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Introduction

Coal ash, also known as Coal Combustion Residuals (CCR), is primarily a byproduct of burning coal for electricity generation (Deonarine et al., 2023). The U.S. Environmental Protection Agency (EPA) estimates that approximately 70 million tons of coal ash are produced annually in the United States (U.S.), the second largest types of industrial waste after mining operations (American Coal Ash Association, 2023; U.S. Environmental Protection Agency, 2025a). Coal ash typically contains higher concentrations of heavy metals than the original coal, as the combustion process enriches these toxic elements in the residual ash (Altıkulaç et al., 2022; Deonarine et al., 2015; Zierold et al., 2021). Although the U.S. EPA has not classified coal ash as hazardous, chronic exposure to these substances has been linked to increased rates of lung cancer, cardiovascular disease, birth defects, and other serious health outcomes in nearby populations (Amster, 2021; Daouda et al., 2021; Gottlieb et al., 2010; Ruhl et al., 2009; Tomlinson et al., 2024).

Coal ash is commonly disposed of in open-air storage impoundments or landfills located near coal-fired power plants because on-site disposal is less costly and subject to fewer regulatory constraints (Sears & Zierold, 2017; U.S. Environmental Protection Agency, 2025b). There are approximately 1400 coal ash storage sites across 45 U.S. states, collectively holding over 3 billion tons of coal ash (Sierra Club, 2014). Many of these facilities lack critical safety infrastructure—such as proper landfill capping and impoundment lining—leaving surrounding communities exposed to significant environmental and health risks. Coal ash can contaminate the environment through airborne particle dispersal or by leaching into nearby soil and water sources. In addition to chronic exposure risks, catastrophic events such as the 2008 Kingston Fossil Plant spill and the 2014 Dan River breach have demonstrated the potential for large-scale environmental and public health disasters (Gaffney, 2018).

Existing research indicates that communities living near coal-fired power plants face elevated cancer risks primarily due to long-term exposure to heavy metals (e.g., arsenic, cadmium, lead, etc.) in coal ash, many of which are known carcinogens that contribute to tumor development and progression (Khlifi & Hamza-Chaffai, 2010; Kravchenko & Lyerly, 2018; Kumari et al., 2023; Whiteside & Herndon, 2018). The International Agency for Research on Cancer (IARC) identifies arsenic and cadmium compounds as Group 1 carcinogens, indicating they are proven to cause cancer in humans (Waalkes, 2019). Exposure to these substances is linked to a higher risk of several cancers, with lung cancer being particularly prominent. Lead is classified as a probable human carcinogen and is linked to cancers of the kidney, brain, and lung (Balali-Mood et al., 2021). According to the EPA, individuals living near certain unlined coal ash ponds and relying on groundwater for drinking face a 1 in 50 risk of developing cancer due to arsenic contamination—an exposure level 2000 times higher than the EPA's acceptable cancer risk threshold and even greater than the risk associated with smoking a pack of cigarettes daily (U.S. Environmental Protection Agency, 2010b). A later study examining the spatial disparities in residence at the time of cancer diagnosis in relation to coal-fired power plants in South Korea found significant higher levels of esophageal, stomach, liver, and lung cancer incidence among females residing near power plants (Han et al., 2024). Additionally, particulate matter released from coal-fired power plants or contained in coal ash is another major carcinogenic factor (Munawer, 2018). The fine particles in coal ash can be inhaled deep into the lungs, where they can cause inflammation, oxidative stress, and tissue damage, potentially leading to the development of lung cancer over time (Kentros et al., 2024; Lockwood & Evans, 2014).

While previous studies have explored the associations between coal-fired power plants and cancer risk (Benedetti et al., 2001; Collarile et al., 2017; Han et al., 2024; Ige et al., 2024), relatively few have specifically examined the spatial relationship between cancer incidence and proximity to coal-ash storage facilities (Kravchenko & Lyerly, 2018), as well as its connection with heavy metal exposure (Hagemeyer et al., 2019; Zhang & Zierold, 2024). More importantly, government regulation of coal ash and public awareness of the health risks posed by coal ash in the U.S. remains limited (U.S. Environmental Protection Agency, 2010a). Many residents living near coal ash disposal sites are unaware that the ash contains hazardous contaminants or that exposure can occur via air, water, and soil (Gaffney, 2023). This study seeks to address these gaps by analyzing the ecological associations between proximity to coal ash impoundments and cancer incidence across the U.S., using national datasets and advanced geospatial statistical methods.

Data and methods

Data and variables

Data on the locations (latitude and longitude) of coal-fired power plants and attributes of their affiliated coal ash storage facilities across the U.S. were acquired from Earthjustice (https://earthjustice.org/feature/coal-ash-contaminated-sites-map). This dataset compiles information reported by coal-fired power plants in compliance with the 2015 Coal Combustion Residuals Rule—the first federal regulation aimed at controlling coal ash pollution.

Airborne cancer risk scores and exposure concentrations for three toxic heavy metals: arsenic, cadmium, and lead were downloaded from the EPA's 2014 National Air Toxics Assessment (NATA, https://www.epa.gov/national-air-toxics-assessment/2014-nata-assessment-results) (U.S. Environmental Protection Agency, 2018), considering the long latency period between exposure to environmental risk factors and cancer diagnosis (Carpenter & Bushkin-Bedient, 2013; Steinmaus et al., 2014; Triebig, 2010). The EPA's 2014 NATA estimated chemical exposure concentrations by integrating modeled ambient concentrations with census data and human activity patterns, providing screening-level estimates for inhalation exposure based on assumptions about emissions, dispersion, and population behavior (U.S. Environmental Protection Agency, 2018).

Cancer risk scores are expressed as probabilities, specifically, the estimated number of additional cancer cases per million people exposed to a particular toxic air pollutant over a lifetime. For example, a cancer risk score of 1 in a million suggests that one additional case is expected per million people exposed. Unlike previous studies that relied on ambient concentrations (Hart et al., 2018), we used exposure concentrations, which could offer a more accurate estimate of the actual pollutant dose individuals receive—an essential factor in evaluating health risks using exposure concentrations might be more scientifically sound for cancer risk studies (Robinson et al., 2024). Nevertheless, ambient concentration remains valuable for broader public health assessments and for identifying areas with high pollution levels that warrant further investigation (Kramer et al., 2025; Tomlinson et al., 2024; U.S. Environmental Protection Agency, 2024).

County-level cancer incidence data were obtained from the National Cancer Institute (NCI)'s Surveillance, Epidemiology, and End Results (SEER) cancer registry program (https://statecancerprofiles.cancer.gov/map/map.noimage.php). The age-adjusted cancer incidence rates by county, based on the most recent 5-year average (2017–2021) include all cancer types, across all racial and ethnic groups, both sexes, and all age categories. We limited our analysis to the 48 contiguous states, as no CCR facilities are in Alaska and Hawaii. Counties in Indiana and Kansas were also excluded due to unavailable data. Additionally, 12 which had low case counts (i.e., less than 16 records), were suppressed in accordance with standard data privacy practices established by the U.S. Centers for Disease Control and Prevention—CDC). As a result, our analysis was restricted to 2901 counties across the contiguous U.S. Using age-adjusted cancer rates allows for more accurate geographic comparisons than crude incidence rates, as it accounts for differences in population age structures. This adjustment ensures that observed variations in cancer rates are not simply attributable to disparities in age distribution across populations (Ige et al., 2024; Jagai et al., 2017). In addition to total cancer incidence, we also obtained data specifically for lung cancer—one of the leading causes of cancer-related deaths—because direct exposure of airborne pollutants significantly increases the likelihood of cellular damage in lung tissues compared to other organs (Collarile et al., 2017; Poulson et al., 2024). To be consistent with the overall cancer analysis, the lung cancer dataset includes all racial and ethnic groups, both sexes, and all age categories.

Additionally, data on health risk behaviors measures (i.e., smoking, binge drinking, obesity, physical inactivity, poverty, and lack of health insurance) were obtained from the CDC Population Level Analysis and Community Estimates (PLACES) database, which uses the national Behavioral Risk Factor Surveillance System (BRFSS) data and a small-area estimation method to generate data for small area units such as counties, census tracts and ZIP Code

Tabulation Areas (Kong & Zhang, 2020; Wang et al., 2017).

Spatial statistical analyses

We calculated straight-line distance from each county to the nearest power plant using *ArcGIS Pro* to assess proximity to coal ash storage facilities, which are typically located on power plant properties for logistic, economic, and regulatory reasons (EarthJustice, 2024b). To measure the straight-line distance from a point (e.g., power plant) to a polygon (e.g., county), one must first identify the closest edge (or line segment) of the polygon to the point. Then, the shortest distance from the point to that specific edge can be calculated. If a power plant is located within a county, the distance is zero; if a power plant is outside a county, the distance is positive. To investigate the association between proximity to coal ash sites and county level cancer incidence rates, three cumulative spatial statistical analyses including contingency table analysis, bivariate spatial association, and multiple linear regression were performed with statistical significance evaluated at three levels: $p < 0.05$, $p < 0.01$, and $p < 0.001$ (2-tailed).

First, a contingency table analysis using the chi-square test was conducted to examine if there is a significant relationship between proximity to coal ash impoundments and cancer incidence levels, with both variables treated categorically. Chi-square tests are widely used to evaluate both differences and associations in categorical data (Bewick et al., 2004; Teye et al., 2021). To categorize cancer incidence for each county, we used the national median cancer incidence rate (459.9 per 100,000 population during 2017–2021) as the threshold. Counties with rates below the median were classified as having "Low" cancer incidence, while those at or above the median were classified as "High." For proximity, counties were divided into two groups: "Proximity" and "Non-proximity." The proximity group included counties with coal ash ponds located within a specified distance threshold (equal or less than threshold), while the non-proximity group included counties with no coal ash ponds or those located beyond the threshold. A series of distance thresholds (5 km, 10 km, 15 km, and 20 km) were applied to classify all 2684 counties into proximity and non-proximity groups based on their distance from coal ash impoundments. This approach allows us to evaluate the sensitivity of the contingency table analysis to varying proximity definitions, thereby enhancing the robustness and reliability of our findings (Bauleo et al., 2019; Casey et al., 2018; Zhang & Zierold, 2024).

Second, a bivariate spatial association analysis using Lee's L statistic was performed to explore how the relationship between cancer incidence and distance to coal ash impoundments varies spatially across the U.S. . While the contingency table analysis provides a global assessment of the statistical association between cancer incidence and county-level proximity to coal ash sites, it does not provide information about the direction or magnitude of the relationship. Lee's L—implemented in *ArcGIS Pro*—offers a more in-depth analysis of spatially varying patterns in this relationship. Moreover, unlike the global Pearson correlation coefficient, Lee's L enables the assessment of spatial associations between two continuous variables by providing both global and local Lee's L statistics (Lee, 2001; Tao & Thill, 2025). The application of spatial statistical methods is grounded in the first law of geography or principle of spatial autocorrelation, which is inherent in geographically referenced data such as county-level cancer incidence rates and proximity to power plants in this study (Gesler, 1986; Griffith, 2018; Tobler, 1970). In the context of this study, Lee's L statistic was instrumental in identifying regions where cancer incidence rates were spatially associated with the distance to coal ash impoundments. Specifically, it helped detect areas where high or low cancer rates corresponded with either close or distant proximity to CCR sites. This spatial statistical measure provided valuable insight into localized patterns of environmental exposure and health outcomes, revealing clusters of elevated or reduced cancer risk.

Finally, we employed multiple linear regression (both ordinary least squares or OLS and spatial lag models) to examine the relationship between cancer incidence rates and proximity to coal ash impoundments, while controlling for potential confounding factors. Spatial lag regression works by including spatially lagged values of cancer incidence rates from neighboring counties to address spatial autocorrelation (Anselin & Rey, 1991; Kuo et al., 2019), as adjacent areas tend to exhibit similar cancer incidence levels, thereby violating the basic assumption of linear regression. Age-adjusted incidence rates for all cancer types and for lung cancer specifically were used as the dependent variables in separate models. Independent variables included straight-line distance to the nearest coal ash storage site, average $PM_{2.5}$ concentration, cancer risk scores, and exposure concentrations for three heavy metals. Distance was used as a proxy for proximity to coal ash storage facilities associated with coal-fired power plants. Incorporating NATA assessments for cancer risk scores and exposure concentrations of arsenic, cadmium, and lead helps account for toxic airborne emissions from coal-fired power plants and other industrial facilities in regression models. The NATA database models emissions and dispersion of hazardous air pollutants from coal-fired power plants; however, it does not account for emissions from coal-ash landfills and impoundments. Additionally, covariates such as poverty, lack of health insurance, lack of leisure time physical activity (physical inactivity), and binge drinking among adults (defined as % adults who reported having ≥ 5 drinks (men) or ≥ 4 drinks (women) on ≥ 1 occasion during the previous 30 days) (Bagnardi et al., 2015; White et al., 2017) were considered. Other covariates included smoking (defined as adults who have smoked ≥ 100 cigarettes in their lifetime and currently smoke every day or on some days) (Mokdad et al., 2017; Myers et al., 2020) and obesity prevalence (%) (Moss et al., 2025; Pati et al., 2023). Numerous studies have utilized county-level data and advanced geospatial statistical methods to examine associations between environmental risk factors and population-based health outcomes (Chang et al., 2017; Martinez-Morata et al., 2022; Moore et al., 2018).

Results

Results from the contingency table analysis assessed the relationship between proximity to coal ash impoundments and cancer risk levels (Table 1). For example, of the 526 counties having a coal-fired power plant or within a 10 km radius, 212 counties had lower cancer levels, while 314 counties had higher cancer levels than the national median . In contrast, of the 2374 counties beyond the 10 km threshold, 1227 counties had lower cancer levels, while 1147 counties had higher cancer incidence levels. This distribution produced a statistically significant chi-square value of 22.310 ($p < 0.001$), indicating that counties closer to coal ash storage facilities were more likely to exhibit cancer incidence rates above the national median. The analysis using alternative distance thresholds (5, 15, and 20 km) yielded similar outcomes, indicating that counties near coal ash storage sites were more likely to have higher cancer

Table 1 Contingency table: difference in cancer incidence levels between counties near coal-fired power plants and those farther away cancer incidence levels*

Distance thresholds	County groups	Low cancer level < national median	High cancer level ≥ national median	Total
5 km	Proximity (≤ 5 km)	165 (196.0)	230 (199.0)	395
	Non-proximity (> 5 km)	1274 (1243.0)	1231 (1262.0)	2505
	Total	1439	1461	2900
	Chi-square = 11.268, $p < 0.001$			
10 km	Proximity (≤ 5 km)	212 (261.0)	314 (265.0)	526
	Non-proximity (< 5 km)	1227 (1178.0)	1147 (1196.0)	2374
	TOTAL	1439	1461	2900
	Chi-square = 22.310, $p < 0.001$			
15 km	Proximity (≤ 5 km)	254 (312.1)	375 (316.9)	629
	Non-proximity (> 5 km)	1185 (1126.9)	1086 (1144.1)	2271
	TOTAL	1439	1461	2900
	Chi-square = 27.427, $p < 0.001$			
20 km	Proximity (≤ 5 km)	314 (379.6)	451 (385.4)	765
	Non-proximity (> 5 km)	1125 (1059.4)	1010 (1075.6)	2135
	TOTAL	1439	1461	2900
	Chi-square = 30.564 ($p < 0.001$)			

*Each cell of the table contains the observed frequency count, followed by the expected frequency count, in parentheses rates than those farther away or the potential harmful effects of exposure to coal ash emitted from coal ash impoundments.

A visualization of the geographic distribution of cancer incidence and coal ash impoundments suggests that most coal ash impoundments are concentrated in the eastern United States—particularly in the Midwest, Ohio Valley, and the South, which have historically been major coal producers, leading to the establishment of nearby power plants (Fig. 1). Nationwide, there are 741 coal ash storage impoundments associated with 302 coal-fired power plants, with Indiana, Texas, Illinois, Kentucky, and Missouri ranking as the top five states by number of impoundments. Results from the spatial autocorrelation analysis using global Moran's I supported our visualization, indicating that both age-adjusted cancer incidence rates (Moran's I $= 0.45$, $p < 0.001$) and proximity to coal-fired power plants (Moran's I $= 0.91$, $p < 0.001$) were spatially clustered.

The results from the more detailed bivariate spatial association analysis provided a clearer and more nuanced illustration of the spatial relationship between distance to coal ash impoundments and cancer incidence (Fig. 2). A global negative correlation was observed between cancer incidence and distance to coal-fired impoundments (Pearson's r $= -0.237$, $p = 0.002$; Lee's L $= -0.235$), indicating that counties closer to these sites tend to have higher cancer rates. This finding was further supported by 449 counties that exhibited statistically significant negative local associations between distance to CCR sites and cancer incidence. These counties were highlighted in dark red and labeled "Near - High" in the legend, signifying high cancer rates in areas near coal ash impoundments.

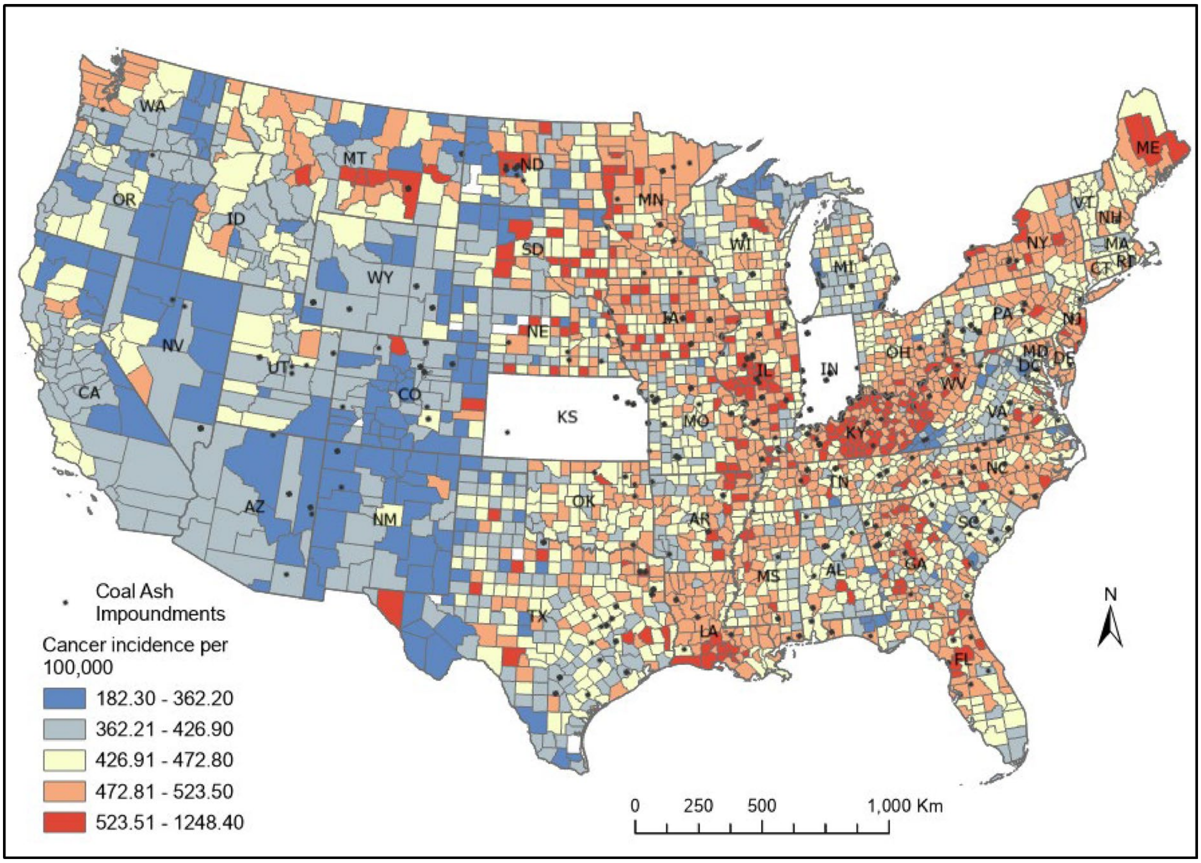

Fig. 1 Annual average age-adjusted cancer incidence (2017–2021) for 2684 U.S. counties using data downloaded from the National Cancer Institute (NCI)

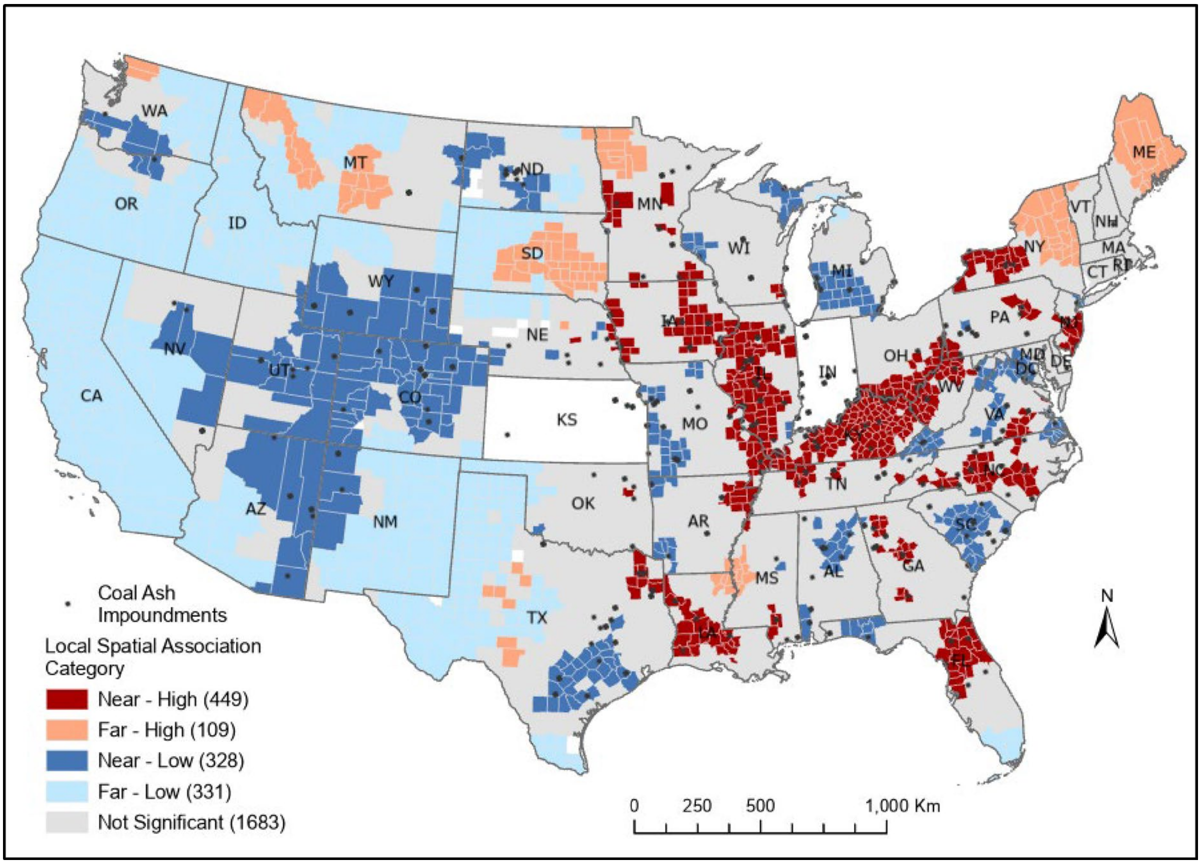

Fig. 2 Map of bivariate spatial association between cancer incidence and proximity to coal ash impoundments across the U.S

The two largest clusters of these counties span across Iowa, Illinois, Missouri, Tennessee, Kentucky, Ohio, West Virginia, and Pennsylvania. Additional smaller clusters were identified in central Louisiana, southern Mississippi, northeastern Florida, western Georgia, southern North Carolina, upstate New York, New Jersey, and central Pennsylvania. Among the 449 counties, local correlations were significant at the 99% confidence level in 45 counties, at the 95% level in 232 counties, and at the 90% level in 172 counties (Table 2).

In contrast, 109 counties showed significant positive local correlations, labeled "Far - High" and mapped in pink. These counties, despite being far from coal ash impoundments, exhibited high cancer levels, suggesting that other environmental or

Table 2 Number of counties by significance of bivariate spatial association between cancer incidence and distance to CCR (n = 2900)

Category	Count of counties by significant level of bivariate correlation			
	99% significant	95% significant	90% significant	Significant at all levels
Near—High	45	232	172	449
Far—High	61	34	14	109
Near—Low	112	133	83	328
Far—Low	211	85	35	331
Not significant				1683

socioeconomic risk factors may be contributing to cancer incidence. Additionally, 328 counties near CCR sites showed low cancer incidence rates, while 331 counties located farther away also exhibited low cancer rates.

Descriptive statistics for the multiple regression models are presented in Table 3. Cancer incidence rates varied widely across U.S. counties, ranging from a minimum of 182.3 to a maximum of 1248.4 cases per 100,000 population, with a mean of 459.2 and a standard deviation of 59.1. The minimum distance to coal ash impoundments was 0 km, indicating counties with CCR sites located within their boundaries, while the maximum distance was 581.7 km, with an average of 73.1 km. Airborne cancer risk scores also showed substantial variation: the county with the highest score (465.1) had a value nearly 50 times greater than that of the county with the lowest score (8.8).

As expected, county-level age-adjusted incidence rates for all cancer types were negatively correlated with distance to coal ash storage sites and positively correlated with airborne cancer risk scores, exposure to arsenic, smoking, obesity, physical inactivity, and poverty rate, as indicated by the bivariate linear correlation (Pearson's r) analysis (Table 4). However, lack of health insurance showed unexpected negative correlation with cancer incidence, while $PM_{2.5}$, exposure to cadmium and lead, and binge drinking were not significantly correlated with cancer incidence.

Results of the multiple regression model for all cancer types supported the negative correlation between cancer incidence and distance to CCR, indicating a positive association with proximity to CCR locations. Positive associations were also observed for airborne cancer risk scores, smoking, binge drinking, and physical inactivity. Although not statistically significant, $PM_{2.5}$, exposure to the three heavy metals, and obesity exhibited the expected positive coefficients with cancer incidence. In contrast, poverty and lack of health insurance showed unexpected negative associations with cancer incidence. Overall, the model explained 17% of the variance in overall cancer incidence, as indicated by the adjusted R-squared value. The results of spatial lag model improved the explanatory power of the OLS model indicated by a larger R-square value (0.296) and the significant spatially lagged incidence rates from nearby counties, which represents spatial autocorrelation. Moreover, it is noteworthy that distance remained significant in the spatial lag model after spatial autocorrelation and other confounding factors have been adjusted.

The OLS regression model for lung cancer incidence revealed expected associations with proximity to CCR locations, $PM_{2.5}$ concentrations, exposure to arsenic, smoking, binge drinking, and lack of physical activity (Table 5). Conversely, airborne cancer risk score and lead exposure were not significant. Unexpected inverse associations were observed for cadmium exposure, obesity, poverty, and lack of health

Table 3 Descriptive statistics of cancer incidence, proximity to power plants, and covariates (n = 2313)

Variables	Min	Max	Mean	S.D
Dependent variable				
All cancer incidence rates per 100,000	182.3	1248.4	459.2	59.1
Independent variables				
Distance to coal ash storage facility (km)	0	581.7	73.1	91.3
$PM_{2.5}$ (μg/m^3)	1.3	39.1	7.7	2.1
Airborne cancer risk score (per million)	8.8	465.1	27.5	13.4
Exposure concentration of arsenic (ng/m^3)	0.001	0.9	0.03	0.03
Exposure concentration of cadmium (ng/m^3)	0.0005	1.7	0.001	0.04
Exposure concentration of lead (ng/m^3)	0.011	3.3	0.2	0.1
Smoking rate among adults (%)	9.1	40.3	21.7	4.1
Binge drinking among adults (%)	9.8	27.2	18.1	3.2
Obesity rate among adults (%)	15.7	50.1	35.2	4.6
Lack of physical activity among adults (%)	10.0	44.9	27.4	5.4
Poverty rate (%)	0	49.4	10.9	5.5
Lack of health insurance (%)	6.3	46.6	16.0	5.5

Table 4 Results of multiple regression of age-adjusted all cancer incidence rates against proximity to ash storage facilities and other environmental risk factors

Variables	Pearson's r with all cancer rates	OLS model for all cancer rates (n = 2313)		Spatial lag model
		Coefficient	Std. error	
Intercept	n.a	268.668***	18.216	147.044***
Distance to coal ash storage sites (km)	−0.241***	−0.086***	0.014	−0.053***
Airborne cancer risk scores (per million)	0.120***	0.412***	0.100	0.247**
$PM_{2.5}$ (μg/m^3)	−0.002	0.768	0.614	0.638
Exposure concentration of arsenic (ng/m^3)	0.053*	45.485	39.665	46.391
Exposure concentration of cadmium (ng/m^3)	0.019	23.782	30.593	23.505
Exposure concentration of lead (ng/m^3)	0.030	10.726	8.050	9.310
Smoking rate among adults (%)	0.266***	1.642**	0.531	1.224*
Binge drinking among adults (%)	−0.034	3.172***	0.540	2.372***
Obesity rate among adults (%)	0.243***	0.491	0.404	0.593
Physical inactivity among adults (%)	0.257***	3.827***	0.545	2.209***
Poverty rate (%)	0.083***	−1.223***	0.339	−0.730*
Lack of health insurance (%)	−0.072***	−1.598***	0.277	−0.559*
Spatially lagged cancer rates (per 100,000)	n.a.	n.a.	n.a.	0.366***
Adjusted R-Squared		0.170		0.296
Global Moran's I among residuals		0.336 ($p < 0.001$)		

*Denotes statistically significant at the 0.05 level while **denotes at the 0.01 level and ***denotes at the 0.001 level. Multicollinearity among the independent variables was not a concern, as all variance inflation factor (VIF) values were below 7.5

Table 5 Results of multiple regression of age-adjusted lung cancer incidence rates against proximity to ash storage facilities and other environmental risk factors

Variables	Pearson r with lung cancer rates	OLS model for lung cancer rates (n = 2163)		Spatial lag model
		Coefficient	Std. error	
Intercept	n.a	−9.286*	4.321	−22.196***
Distance to coal ash storage facility (km)	−0.307***	−0.026***	0.003	−0.012***
Airborne cancer risk score (per million)	0.119***	0.014	0.023	−0.010
$PM_{2.5}$ (μg/m^3)	−0.026	0.502**	0.156	0.364**
Exposure concentration of arsenic (ng/m^3)	0.011	23.370*	9.088	19.933*
Exposure concentration of cadmium (ng/m^3)	−0.051*	−8.824	6.961	−1.846
Exposure concentration of lead (ng/m^3)	−0.045*	0.669	1.845	1.119
Smoking rate among adults (%)	0.665**	2.304***	0.127	1.710***
Binge drinking among adults (%)	−0.267***	0.299*	0.128	0.437***
Obesity rate among adults (%)	0.467***	−0.208*	0.094	−0.065
Physical inactivity among adults (%)	0.590***	1.263***	0.128	0.691***
Poverty rate (%)	0.346***	−0.546***	0.083	−0.324***
Lack of health insurance (%)	0.062**	−0.414***	0.066	−0.052
Spatially lagged lung cancer incidence	n.a.	n.a.	n.a.	0.416***
Adjusted R-squared		0.514		0.611
Global Moran's I among OLS residuals		0.339 ($p < 0.001$)		

insurance. Overall, the lung cancer model explained more than 51% of the variance in incidence rates across U.S. counties. The inclusion of spatially lagged values of lung cancer incidence from nearby counties improved model performance, while the negative correlation between cancer incidence and distance, as well as the positive correlations with smoking, drinking and physical inactivity, remained significant.

Discussions

This national study of the spatial associations between cancer incidence rates and proximity to coal-fired power plants and their affiliated coal ash impoundments has the following scientific merits: First, conducting a geographic study using national datasets (i.e., NCI's cancer registries, EPA, and CDC PLACES) allows us to detect broad spatial patterns, especially the disparities in cancer rates between counties in proximity to coal-ash impoundments and counties that are farther away. Second, the research design of incorporating three complementary spatial analysis approaches—contingency table analysis, bivariate spatial association, and multiple regression—provides a rigorous framework for hypothesis testing. Third, the ecological approach facilitates hypotheses generation (e.g., whether cancer incidence is elevated near clusters of impoundments), which can justify more resource-intensive individual-level studies in the future. Moreover, because both exposure and health outcomes are measured at the population level, findings from this study directly inform public health burden and policy decisions (e.g., land use zoning, remediation priorities), issues that regulators typically address first. Importantly, given the toxic nature of coal ash, its widespread distribution across thousands of communities (Longest et al., 2022), and the absence of strict EPA regulation, national research on this topic provides critical evidence to support stronger regulatory measures and remediation efforts aimed at preventing environmental contamination and protecting the health of nearby residents.

The results of contingency table analysis indicate that counties that contain or near coal ash impoundments were significantly more likely to exhibit higher cancer incidence levels than counties farther away, regardless of the distance thresholds applied. Bivariate spatial associations further revealed clusters of counties with significant positive local correlations between proximity to coal ash sites and cancer incidence. These findings align with previous studies that have documented the adverse impacts of proximity to coal-fired power plants and cancer clusters across the U.S. (Goodman et al., 2012; Guo et al., 2024; Luo et al., 2025; Moore et al., 2017; Reynolds et al., 1996). For example, a study in the Appalachian Coal-Mining Region identified three clusters of counties with higher-than-expected cancer rates. One of these clusters included several counties in the Louisville, Kentucky, metropolitan area (Christian et al., 2011).

While the spatial regression model explained less than 30% of the variance in total cancer incidence, it explained over 61% of variance in lung cancer incidence. The substantial increase in explanatory power underscores the value of focusing on specific cancer types using disaggregated data in future research. In both the total cancer and lung cancer models, distance to coal ash impoundments showed significant and negative associations, even after adjusting for other confounding factors and spatial autocorrelation. These findings support our hypothesis that proximity to coal ash impoundments is linked to increased cancer risks. Furthermore, cancer incidence for both total cancer and lung cancer were significantly associated with smoking, drinking, and physical inactivity, which corroborate prior research on these relationships (Guo et al., 2024; Moss et al., 2025). The lung cancer model demonstrated significant positive associations between cancer incidence and $PM_{2.5}$, arsenic concentration, as well as airborne cancer risk scores, highlighting specific environmental risk factors for the disease.

Several potential explanations may account for the weak associations observed between heavy metal exposure and cancer incidence. First, the data on metal exposures were assessed for a single year, rather than using long-term cumulative measures. Cancer typically develops because of chronic exposure to risk factors over extended periods. Second, EPA's NATA data model only airborne exposure, overlooking other critical pathways such as contaminated drinking water and soil. Industry data indicates that approximately 90% of coal ash impoundments contribute to groundwater contamination by nearly two dozen heavy metals, often exceeding health thresholds set by the EPA (Sierra Club, 2014). To fully reveal the health impacts of coal ash exposure, future research should incorporate comprehensive cumulative exposure assessments that capture long-term contamination across multiple environmental pathways including air, water, and soil (Bailey et al., 2025). Such integrative approaches are critical for evaluating aggregate risks from coal ash constituents, particularly toxic heavy metals.

The findings in this study were inconsistent with the existing studies that suggest linkages between cancer incidence and poverty and lack of health insurance (Boscoe et al., 2014; Hall et al., 2022). Although it may seem counterintuitive, U.S. counties with higher poverty rates and lower health insurance coverage often report lower cancer incidence rates. This pattern is largely attributable to underdiagnosis resulting from limited access to healthcare and preventive services such as screening (Marlow et al., 2009). Certain cancers—like cervical, liver, and Kaposi sarcoma—are more prevalent in low-income areas due to factors such as infectious agents, environmental exposures, and inadequate vaccination or screening (Amboree et al., 2024). In contrast, cancers such as melanoma, thyroid, and testicular are more commonly diagnosed in wealthier populations, likely reflecting lifestyle differences and greater access to early detection (Wagle et al., 2025).

This study has several additional limitations. First, the results may be affected by under-reporting of coal ash storage sites, as data are based on disclosures required under the 2015 Coal Ash Rule.

Following years of legal battles and grassroots pressure, the U.S. EPA implemented a new regulation in 2024 that expanded federal oversight and cleanup mandates to include hundreds of older coal ash landfills and ponds previously exempt, many of which had been contaminating groundwater with toxic waste. This new rule closes loopholes in the 2015 Coal Ash Rule, which had left about half of all coal ash unregulated and allowed coal-fired power plants nationwide to sidestep cleanup responsibilities. *EarthJustice* has identified as many as 1271 "legacy coal ash sites scattered in 30 states which were not regulated by the 2015 Coal Ash Rule (EarthJustice, 2024a). Legacy coal ash sites refer to CCR impoundments—such as ponds and landfills—located at power plants that ceased operation before October 19, 2015. Moreover, residents and communities experiencing multiple types of exposure may face heightened risks compared to those exposed only to coal-fired power plants and coal ash storage facilities. Explicitly incorporating these potential confounders and effect modifiers will enhance the rigor and validity of the study.

Second, using distance as a proxy for proximity to coal ash impoundments is limited by the arbitrary nature of distance thresholds used to define "proximity" and the challenge of determining a single "safe" distance. Factors such as meteorological and hydrological conditions (e.g., wind direction and speed, precipitation, and soil permeability) and plant-specific characteristics, including emissions controls and the lining or capping status of coal ash storage facilities, can significantly influence exposure risk. For example, Müller et al. (2022) indicates a carcinogenic risk associated with arsenic exposure extending up to nearly 10 km from the coal-fired power plant, while Yang et al. (2017) suggested that the health risk of power-fired power plants could reach as far as 20–30 miles away. While coal-fired power plants contribute to air pollution linked to increased lung cancer risk, a study in Kansas found that proximity alone was not a significant predictor of age-adjusted lung cancer incidence rates when controlling other factors like smoking, age, poverty, and wind patterns (Ige et al., 2024).

Third, reliance on aggregated county-level cancer incidence data obscures within-county variability and limits access to detailed covariates such as race, age, gender, lifestyle factors, and other socioeconomic risk determinants, making it difficult to fully control for confounding. Furthermore, cancer registries may experience delays or underreporting in certain counties. Future research should incorporate individual-level data through community-based studies to obtain more precise measures of cancer diagnosis and environmental exposures. In particular, future studies should examine racial/ethnic disparities in cancer incidence in relation to exposure to coal ash, as the environmental injustice literature has long highlighted that communities of color and economically disadvantaged populations face disproportionate exposure to environmental pollutants, exacerbating racial health disparities including cancer (Buzzelli & Jerrett, 2003; Chakraborty & Maantay, 2011; Daouda et al., 2021; Moore et al., 2018). For example, analyses using disaggregated cancer incidence rates have indicated elevated cancer rates among Black populations, who predominantly reside in segregated neighborhoods (Poulson et al., 2024).

Despite its limitations, this study reinforces existing evidence of elevated cancer risks among communities located near coal-fired power plants and associated coal ash impoundments, likely due to chronic exposure to coal ash contaminants containing carcinogenic heavy metals. To address these weaknesses, future research should employ more accurate and representative measures of proximity and exposure to better assess the adverse health impacts of coal ash. Beyond heavy metals, future studies should also investigate the radiological risks of coal ash, as recent research has raised concerns about health hazards associated with its reuse in products such as cement, concrete, and landscaping material (Turhan & Jamasali, 2024). Likewise, emerging proposals to extract rare earth elements from coal ash may introduce additional environmental and health risks if not carefully managed (Briffa et al., 2020; Slavković-Beškoski et al., 2024).

Conclusion

Across the United States, many communities face environmental health challenges due to their proximity to coal-fired power plants and associated coal ash disposal sites, which release toxic substances such as arsenic, mercury, and lead into the environment. Limited national-level research has investigated if residential proximity to coal ash impoundments was related to elevated risks of cancer. Building on the existing literature, this study examined the linkages between cancer incidence and proximity to coal ash storage facilities as well as exposure to airborne heavy metals while accounting for other socioeconomic, environmental, and behavioral risk factors. The findings of this empirical analysis shed new light on the link between exposure to coal ash and cancer risk, offering valuable insights that can inform public health policies and help address the disproportionate challenges faced by communities near coal ash storage sites, which are more vulnerable than those farther away.

Given the toxic nature of coal ash, the U.S. EPA only recently mandated coal-fired power plants to properly manage and dispose of it, including the safe closure of coal ash impoundments in favor of cleaner and more sustainable approaches (Kumar & Reddy, 2024). Although coal-fired power plants have been gradually phased out in favor of cleaner energy sources, thousands of coal ash storage facilities including both active and legacy sites continue to pose long-term environmental and health risks to nearby communities due to inadequate treatment and regulatory oversight. Therefore, there is an urgent need for additional research and stronger policy interventions to mitigate the environmental health risks associated with coal ash, given the enduring legacy of coal-fired power generation.

Author contribution CHZ and KMZ composed research design; NCD, BG, and MEE participated in the discussions of the data analysis; CHZ and MM conducted the data analysis and interpretation of the results. All authors proofread the final version of the manuscript.

Data Availability All the data used in this study are obtained from publicly available data sources.

Declarations

Conflict of interest The authors declare no competing interests.

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