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Original Contribution

Ecological Integrity of Streams Related to Human Cancer Mortality Rates

Nathaniel P. Hitt[1] and Michael Hendryx[2]

[1]*Department of Fisheries and Wildlife Sciences, Virginia Polytechnic Institute and State University, Blacksburg, VA 24061*
[2]*Department of Community Medicine, West Virginia University, One Medical Center Drive, P.O. Box 9190, Morgantown, WV 26506*

Abstract: Assessments of ecological integrity have become commonplace for biological conservation, but their role for public health analysis remains largely unexplored. We tested the prediction that the ecological integrity of streams would provide an indicator of human cancer mortality rates in West Virginia, USA. We characterized ecological integrity using an index of benthic macroinvertebrate community structure (West Virginia Stream Condition Index, SCI) and quantified human cancer mortality rates using county-level data from the Centers for Disease Control and Prevention. Regression and spatial analyses revealed significant associations between ecological integrity and public health. SCI was negatively related to age-adjusted total cancer mortality per 100,000 people. Respiratory, digestive, urinary, and breast cancer rates increased with ecological disintegrity, but genital and oral cancer rates did not. Smoking, poverty, and urbanization were significantly related to total cancer mortality, but did not explain the observed relationships between ecological integrity and cancer. Coal mining was significantly associated with ecological disintegrity and higher cancer mortality. Spatial analyses also revealed cancer clusters that corresponded to areas of high coal mining intensity. Our results demonstrated significant relationships between ecological integrity and human cancer mortality in West Virginia, and suggested important effects of coal mining on ecological communities and public health. Assessments of ecological integrity therefore may contribute not only to monitoring goals for aquatic life, but also may provide valuable insights for human health and safety.

Keywords: Ecological integrity, cancer, coal mining, streams, benthic macroinvertebrates

INTRODUCTION

Over the last 25 years, assessments of ecological integrity have become commonplace in biological conservation, but their role in public health analysis remains largely unexplored. Nonetheless, ecological integrity assessments can provide inferences about environmental quality that are relevant for understanding environmentally mediated human disease (Rapport, 1999; Torres and Monteiro, 2002; Sala et al., 2009). Moreover, the lack of integrated research hinders the development of holistic strategies to protect ecological and human health (Wilcox et al., 2004). In this article, we evaluated the relationships between ecological integrity and human cancer mortality in West Virginia, USA.

Karr and Dudley (1981) defined ecological integrity as an ecosystem state that "support[s] and maintain[s] a

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Correspondence to: Nathaniel P. Hitt, e-mail: nhitt@usgs.gov

balanced, adaptive community of organisms having a species composition, diversity, and functional organization comparable to that of natural habitats within a region.'' In practice, ecologists often quantify ecological integrity by sampling biological communities and calculating metrics that indicate known environmental quality gradients (Karr and Chu, 2000). In freshwater ecosystems, ecological integrity assessments have provided insights that were not available from water chemistry assays (e.g., Yoder and Rankin, 1998), because biota are exposed to multiple physical and chemical conditions simultaneously and therefore provide an integrated measure of environmental quality.

Environmental conditions clearly affect human cancer incidence and mortality rates. Genetic factors may predispose individuals to cancer risk but are thought to be secondary to the overriding role of environmental conditions (Fearon, 1997; Perera, 1997). For example, Lichtenstein et al. (2000) evaluated cancer incidence between 44,788 pairs of twins (i.e., controlling for genetic influences) and concluded that environmental factors had the principal role in causing sporadic cancers. However, the authors noted that some types of cancers, such as prostate and colorectal cancers, showed greater heritability than other cancer types (Lichtenstein et al., 2000).

Globally, cancer is one of the leading causes of death (WHO, 2009) and accounts for over 23% of annual deaths in the United States (ACS, 2010). Communities in the Appalachian region (i.e., the mountainous region from New York to Mississippi as defined by the Appalachian Regional Commission) suffer from higher rates of cancer incidence and mortality than the rest of the nation, and rates are particularly high for lung, colorectal, and cervical cancer (Barnett et al., 2000; Huang et al., 2002; Halverson et al., 2004; Cakmak et al., 2006). The elevated cancer rates are generally thought to result from high-risk behaviors, such as smoking and physical inactivity, as well as poor access to medical care (Huang et al., 2002).

However, elevated cancer mortality rates are concentrated in coal mining regions of Appalachia (Lengerich et al., 2005; Hendryx et al., 2008). These elevated rates are partly the result of the persistent socioeconomic disadvantages that characterize coal mining areas, but even after statistical adjustment for education, poverty, smoking rates, physician supply, and other risks, some forms of cancer mortality remain elevated (Hendryx et al., 2008). Moreover, elevated rates of heart, lung, and kidney disease are associated with coal mining in Appalachia, after controlling for other risk variables (Hendryx et al., 2007; Hendryx and Ahern, 2008; Hendryx, 2009). We reasoned that if environmental contamination from coal mining was a contributing factor for human disease, ecological integrity should be negatively related to cancer and coal mining.

Methods

Ecological Integrity

We characterized ecological integrity using the West Virginia Stream Condition Index (SCI), an index of stream benthic macroinvertebrate community structure (Gerritsen et al., 2000). Benthic macroinvertebrates are invertebrate animals that dwell on the bottom of streams (''benthic'') and are visible to the unaided eye (''macro''). These organisms exhibit important interspecific differences in their physiological and behavioral responses to pollution (Merritt and Cummins, 1996) and, therefore, are widely used in ecological integrity assessments (e.g., USEPA, 2002). Since 2002, the West Virginia Department of Environmental Protection (WVDEP) has used the SCI to assess compliance with the U.S. Clean Water Act (Huffman, 2009), and the SCI has been used to evaluate the ecological consequences of mining (Palmer et al., 2010).

The SCI is calculated from six metrics of benthic macroinvertebrate community structure, each of which has been independently tested for its sensitivity to environmental degradation: (1) the sum of taxonomic groups present; (2) the sum of individuals in the orders Ephemeroptera, Plecoptera, and Trichoptera (i.e., EPT taxa); (3) the percentage of EPT individuals in the total sample; (4) the percentage of individuals in the family Chironomidae; (5) the percentage of individuals in the top-two dominant taxa (i.e., taxonomic evenness); and (6) the Hilsenhoff Biotic Index (HBI) (Hilsenhoff, 1988; Gerritsen et al., 2000). Metrics of taxonomic diversity, chironomid abundance, and EPT taxa generally decrease with increasing pollution. In contrast, taxonomic evenness typically increases with degradation (Merritt and Cummins, 1996). The HBI also increases in response to organic pollutants in streams (Hilsenhoff, 1988).

SCI calculations required several steps. First, WVDEP biologists collected a sample of stream benthic macroinvertebrates using a standardized kick-net protocol during baseflow conditions (Gerritsen et al., 2000). Second, organisms were sorted and preserved in ethanol. A random

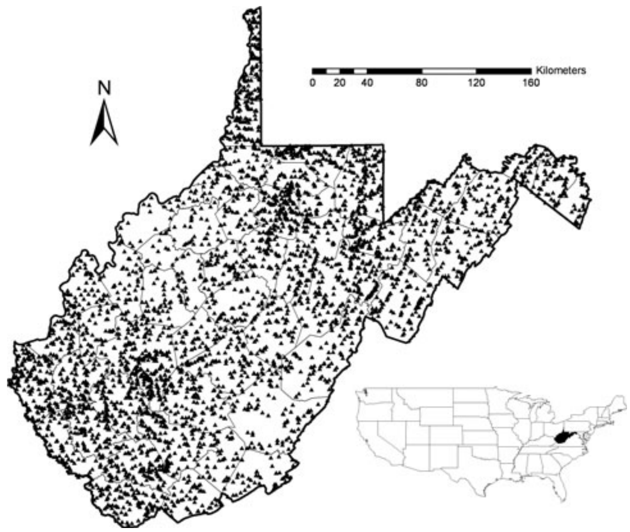


Figure 1. Sampling sites (triangles) for stream condition index (SCI) data in West Virginia, USA.

subset of 200 organisms was then selected for analysis (Gerritsen et al., 2000). In the laboratory, organisms were identified to the family-level and enumerated. The six metrics (listed above) were then calculated, standardized on a 0–100 scale so that all metrics increase with increasing site quality, and averaged (Gerritsen et al., 2000). The SCI therefore ranges from 0 to 100, with high values indicating a condition of high ecological integrity and vice versa.

The SCI dataset consisted of 4718 sampling locations in West Virginia (Fig. 1) which were sampled from 1996 to 2006. We aggregated the SCI data to the county-level to permit comparisons with public health data. The minimum number of samples per county was 15 (Pleasants County) and the maximum number was 277 (Kanawha County); 50% of the counties supported at least 70 samples (Fig. 1, Appendix A). The number of samples per county was not related to mean SCI values (Pearson's $r = 0.07$), thus permitting an evaluation of SCI data while avoiding potentially confounding effects of sampling effort.

Public Health

Cancer mortality data for West Virginia were obtained from the Centers for Disease Control and Prevention database (CDC, 2008). We used county-level, age-adjusted total cancer mortality rates per 100,000 people for the combined years 1979–2005. We also evaluated cancer rates by diagnosis, including respiratory, digestive, oral, genital, urinary, breast, and "other" cancer types. We further divided genital cancer by sex to assess prostate cancer for males, and cervical, ovarian, and uterine cancer for females. We only considered females for breast cancer rates. These groups were based on International Classification of Diseases coding criteria (ICD-9 for the years 1979–1998 and ICD-10 for the years 1999–2005) (Table 1).

Coal Mining

We quantified coal mining intensity for each county in two ways. First, we calculated an area-adjusted measure of coal production (1000 tons/km^2) with data from the West Virginia Geologic and Economic Survey (WVGES, 2009). Second, we developed a coal mining index (CMI) to characterize the associated impacts of mining (e.g., coal processing, slurry injection) as well as potential inter-county effects of mining (e.g., a mine draining into an adjacent county).

The CMI was calculated from spatial analyses of coal mining and associated activities. First, we developed statewide maps of surface and underground coal mines, point locations of coal slurry impoundments, permitted coal slurry injection sites, and coal processing facilities. We mapped mine boundary centroids whose permit dates ranged from 1979 to 2005 ($n = 2924$). We mapped slurry injection sites (i.e., coal processing waste injected underground as a means of disposal) from National Pollution Discharge Elimination System data ($n = 270$). Spatial datasets were obtained from WVDEP and the U.S. Environmental Protection Agency.

Second, we mapped census block groups within the study area (US Census, 2000) and converted block groups into raster data of 30 m^2 cells. Third, we calculated the inverse mean distance between each grid cell and the nearest mine, impoundment, injection site, and coal preparation plant. These distances were then averaged across type of activity and block group to the county-level. CMI values were then standardized to a mean of 50 and a standard deviation of 10 (Table 1), so that increasing values indicated increasing proximities to coal mining activities. Spatial analyses were performed in ArcGIS (versions 9.2 and 9.3; ESRI, Redlands, CA).

Statistical Analyses

We used multiple linear regression and spatial analyses to evaluate the relationships among cancer mortality, ecological integrity, and coal mining. We used linear regression techniques to model predictors of ecological

Table 1. Environmental and cancer summary statistics for counties in West Virginia, USA ($N = 55$)[a]

Category	Variable	Mean	SD	Minimum–maximum
Ecological integrity	Stream condition index (SCI)[b]	66.2	8.2	49.2–81.1
Cancer	Total	217.2	19.0	161.6–271.3
	Digestive	48.7	4.8	38.3–59.8
	Breast (female)	27.2	3.4	18.2–36.2
	Genital (female)	18.5	3.3	8.7–29.1
	Genital (male)	30.9	4.1	20.4–37.4
	Oral	5.8	1.7	1.0–9.2
	Respiratory	71.7	12.2	36.4–110.3
	Urinary	9.7	1.6	6.4–14.7
	"Other"	25.1	3.5	15.2–34.8
Coal mining	Coal mining index (CMI)[c]	50	10	41.5–83.7
	1000 tons/km^2	48,174	87,991	0–412,689
Covariates	Smoking rate	27.8	4.0	21.1–39.0
	Urbanization[d]	5.6	3.4	1–12
	Poverty rate	17.2	4.9	9.0–35.5

[a]Cancer variables are expressed as age-adjusted mortality per 100,000 people.
[b]Higher SCI values indicate greater ecological integrity.
[c]Higher CMI values indicate greater potential influences of coal mining.
[d]Higher values indicate lower potential influences of urbanization.

integrity and cancer mortality, and to evaluate socioeconomic covariates. Based on prior research (Hendryx and Ahern, 2008; Hendryx et al., 2008; Hendryx 2009), we evaluated county-level data on poverty, access to health care providers, extent of urbanization, education, and smoking (US Census, 2000; USDHSS, 2006; CDC, 2007).

Poverty was expressed as the average percent of the county population below the federal poverty threshold for years 2000–2002 (USDHSS, 2006). We quantified access to health care providers as the number of active primary-care physicians per 1000 people from data in year 2000 (USDHSS, 2006). Urbanization was represented by ordinal data ranging from 1 to 12, where high values indicated low urbanization levels during 2003 (USDHSS, 2006). Education was quantified as the percent of the county population aged 25 years and older that had completed at least 4 years of college (US Census, 2000). We quantified smoking rates as the percent of adults in each county who reported being current smokers (CDC, 2007). These socioeconomic data represented some of the most recent information available for counties within the study area.

We used multiple linear regression analysis with backwards-selection to reduce the set of covariates with a $P < 0.10$ retention criterion (Seber and Lee, 2003). Based on these analyses, we retained poverty rate, smoking rate, and urbanization for the cancer model, and urbanization for the ecological integrity model. We then included these covariates in linear regression models of cancer mortality and ecological integrity (Huynen et al., 2004).

We used spatial analysis techniques to evaluate the geographic structure of study variables at two spatial scales. At the state-level, we calculated global Moran's I values to assess patterns of spatial autocorrelation across the study area (Moran, 1950). Positive values would indicate that nearby counties are more similar to each other than expected by chance (and negative values would indicate that nearby counties are more different from one another than expected by chance). At the county-level, we calculated local Moran's statistics to map spatial clusters (Anselin, 1995). Local Moran's methods compare observations for each county to each of its neighbors, thus producing maps of spatial clusters of low- and high-value regions (Anselin, 1995). Moran's statistics were calculated with ArcGIS toolbox applications (version 9.3; ESRI). We reasoned that if human cancer mortality increased with ecological disintegrity, cancer clusters and SCI clusters would also exhibit inverse spatial associations.

We used partial Mantel tests to evaluate the possible effects of spatial autocorrelation on associations between SCI, CMI, and cancer mortality (see Hitt et al., 2003; Oden, 2005). Mantel tests are distance-based matrix correlations that use permutation procedures to establish statistical significance (Mantel, 1967). Partial Mantel tests permit the analysis of bivariate associations while controlling for the effects of additional covariates (Legendre, 2000). To develop the correlation matrices, we used Bray–Curtis distances (Bray and Curtis, 1957) of SCI, CMI, and total cancer mortality. We then expressed spatial autocorrelation as a matrix of county-wise Euclidean distances among centroids and included this matrix as a covariate in partial Mantel tests (Legendre, 2000). We assessed the significance of Mantel correlation coefficients using two-tailed P-values from 10,000 permutations. Distance matrices and Mantel tests were calculated using the ecodist package in R (Goslee and Urban, 2007).

Results

Ecological integrity (SCI) was inversely correlated to age-adjusted cancer mortality rates (Table 2). Cancer types exhibited distinct relations to ecological integrity. Digestive, breast, respiratory, and urinary cancer mortality rates were significantly correlated to SCI, whereas mortalities from female or male genital cancer, oral cancer, and "other" cancers were not (Table 2). Regression models revealed that poverty, smoking, and urbanization were significant predictors of total cancer mortality but did not account for the observed relation between ecological integrity and cancer mortality (Table 3).

Table 2. Relations between cancer mortality, ecological integrity, and coal mining intensity in West Virginia, USA[a]

Cancer type	Ecological integrity	Coal mining	
	SCI	1000 tons/km^2	CMI
Total	−0.50**	0.42**	0.51**
Digestive	−0.42**	NS	NS
Breast (female)	−0.47**	NS	NS
Genital (female)	NS	NS	NS
Genital (male)	NS	NS	NS
Oral	NS	NS	NS
Respiratory	−0.44**	0.47**	0.53**
Urinary	−0.27*	NS	NS
"Other"	NS	0.40**	0.45**

[a]Pearson correlation coefficients are given for relations between cancer mortality rates and stream condition index (SCI) values, coal mining intensity (1000 tons/km^2), and a coal mining index (CMI). Cancer was expressed as age-adjusted cancer mortality per 100,000 people. Correlation coefficients with * or ** indicate $P < 0.05$ or $P < 0.01$, respectively.

The CMI was positively correlated with total cancer mortality (Table 2) and negatively related to ecological integrity (Table 3). Coal mining was correlated with increasing respiratory cancer and "other" cancer mortalities in the study area (Table 2). The simple measure of coal mining (i.e., 1000 tons/km^2) showed a similar relationship to total cancer rates and to respiratory and "other" cancer types, but the correlation coefficient magnitudes were smaller than for CMI (Table 2). We therefore used CMI for subsequent regression and spatial analyses. Urbanization was a significant predictor of SCI, but did not account for the observed relation between coal mining and ecological integrity (Table 3).

Cancer mortality exhibited significant spatial structure in the study area. Total cancer mortality rates were generally higher in the southwest portion of the state and lower in the northeast (Fig. 2), resulting in significant spatial autocorrelation among counties (Table 4). Local Moran's statistics revealed a low-cancer cluster in the northeast portion of the state (Grant, Hardy, Pendleton, Tucker, and Randolph Counties) and a high-cancer cluster in the southwest portion of the state (Boone, Lincoln, Logan, and Mingo Counties).

Cancer types also exhibited distinct spatial structure. County-level respiratory cancer rates were highly spatially autocorrelated (Table 4), generally increasing from northeast to southwest portions of the study area (Fig. 3). As observed with the total cancer mortality, respiratory cancer exhibited a low-cancer cluster among several northeastern counties (Grant, Hardy, Pendleton, and Tucker Counties) and a high-cancer cluster among several southwestern counties (Boone, Kanawha, Lincoln, Logan, Mingo Counties) (Fig. 4). "Other" cancer rates also exhibited spatial autocorrelation among counties (Table 4), with a high-cancer cluster located in southwest (Lincoln and Logan Counties) and a low-cancer cluster in the central portion of the state (Calhoun, Gilmer, and Wirt Counties) (Fig. 4). In contrast, mortality rates for female breast cancer, digestive cancer, female or male genital cancer, oral cancer, and urinary cancer did not exhibit significant spatial structure among counties (Table 4; Fig. 3).

Ecological integrity exhibited significant spatial structure in the study area. SCI values were highest in the eastern portion of the state (Fig. 2). Significant spatial autocorrelation among counties yielded a high-integrity cluster in the

Table 3. Linear regression models testing the relationship of ecological integrity (stream condition index, SCI) to total age-adjusted cancer mortality per 100,000 people (model 1) and relationship of coal mining (coal mining index, CMI) to SCI (model 2) while controlling for covariates[a]

Model	Dependent variable	Independent variables	Unstandardized coefficient	SE	*P*
1[b]	Total cancer mortality	Intercept	204.49	25.24	<0.0001
		SCI	−0.61	0.27	0.028
		Poverty	1.47	0.47	0.003
		Urbanization	−1.84	0.74	0.017
		Smoking	1.37	0.53	0.013
2[c]	SCI	Intercept	75.41	4.98	<0.001
		CMI	−0.30	0.09	0.002
		Urbanization	1.07	0.27	<0.001

[a]Covariates were identified by a priori analyses (see text).
[b]$F = 12.75$ (df $= 4, 50$), adjusted $R^2 = 0.47$, $P < 0.0001$.
[c]$F = 13.04$ (df $= 2, 52$), adjusted $R^2 = 0.31$, $P < 0.0001$.

eastern portion of the state, including Grant, Pendleton, Pocahontas, Randolph, Tucker, and Webster Counties (Table 4; Fig. 4). However, SCI exhibited no significant multi-county clusters in other portions of the state.

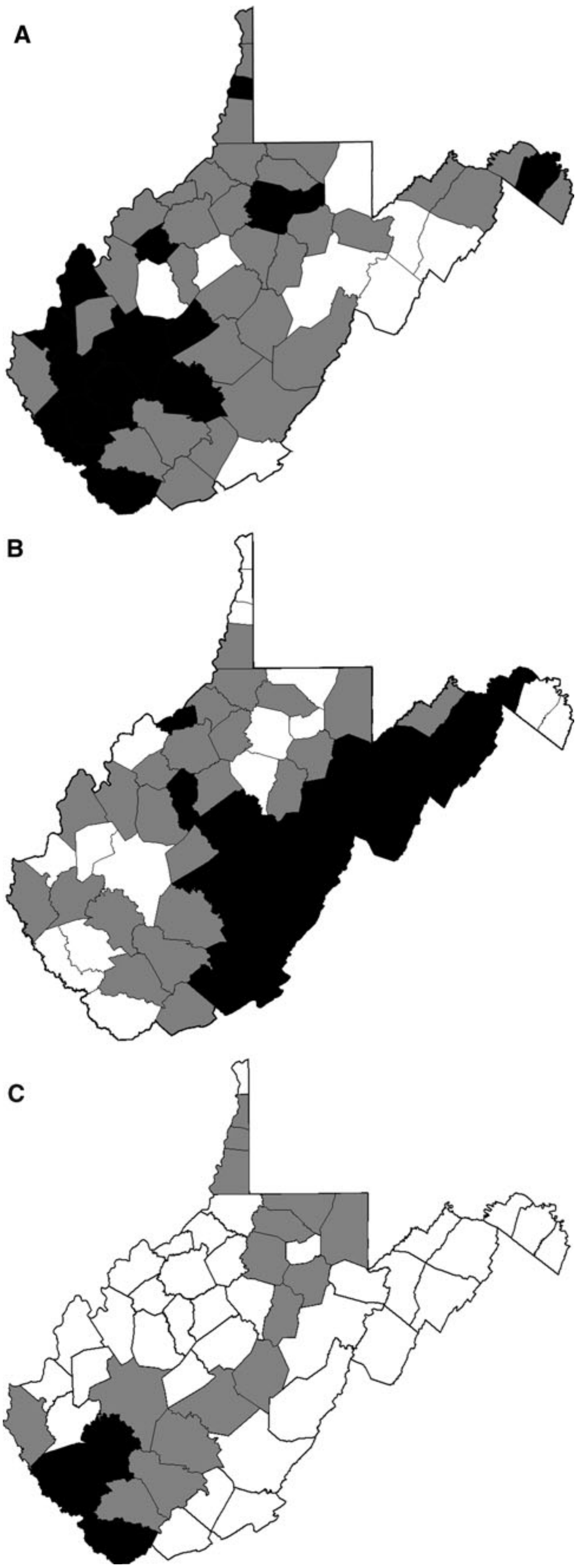
The coal mining index showed highest values in the southwest region of the state (Fig. 2) and exhibited significant spatial autocorrelation among counties (Table 4). High-coal clusters were detected in the northern part of the state (Monongalia County) and the southwest (Boone, Logan, McDowell, Mingo, and Wyoming Counties) (Fig. 4). One low-coal cluster was located in the central portion of the state, encompassing Ritchie and Wirt Counties (Fig. 4).

Partial Mantel tests revealed that associations between SCI, CMI, and total cancer mortality were robust to effects of spatial autocorrelation among counties (Table 5). When accounting for inter-county distances, ecological integrity (SCI) was significantly related to mining (CMI) and cancer mortality, and CMI was significantly related to total cancer mortality (Table 5). The association between ecological integrity and mining was somewhat stronger than the association between ecological integrity and cancer (i.e., Mantel $r = 0.226$ and 0.120, respectively; Table 5). Similarly, total cancer mortality revealed a somewhat stronger association with mining than ecological integrity (Mantel $r = 0.230$ and 0.120, respectively; Table 5).

Discussion

Our analysis revealed important relations among ecological integrity, human cancer mortality, and coal mining in West Virginia (Table 2). Smoking, poverty, and urbanization were important predictors of cancer mortality, but did not account for the significant association between ecological integrity and public health (Table 3). It is well known that smoking and poverty are associated with increased risks of disease and mortality (Anderson et al., 1997; Waitzman and Smith, 1998), and our results provided additional support for this conclusion. Our study also contributed a new insight for eco-epidemiology: Stream benthic macroinvertebrate communities provided an indicator of human cancer mortality rates (Table 3), probably as a result of multiple direct and indirect exposure pathways. Although WVDEP conducts benthic macroinvertebrate sampling to assess the biological integrity of streams (Huffman, 2009), our study reveals that these assessments may also improve our understanding of human health in nearby areas. As a result, biological monitoring and assessment may provide important social benefits.

Our results demonstrated significant relationships between increasing coal mining (CMI), decreasing ecological integrity (SCI), and increasing cancer mortality (Tables 2 and 3). These results suggest, but cannot prove, a causal link between coal mining and cancer mortality. This contention is supported by prior research demonstrating that coal mining and processing may increase carcinogenic contamination of air and water in nearby areas (Griffith et al., 2004; McAuley and Kozar, 2006; Ghose, 2007; Ghose and Majee, 2007). For example, the West Virginia Geologic and Economic Survey tracks 59 impurities present in West Virginia coal, including carcinogens such as arsenic and cadmium (WVGES, 2007). Arsenic in drinking water is a



◂ **Figure 2.** Total age-adjusted cancer mortality, ecological integrity, and coal mining intensity in West Virginia, USA: **a** total cancer, **b** stream condition index (SCI), **c** index of coal mining (CMI). All variables are mapped as one of three classes (Jenks' natural breaks) with low, medium, and high levels indicated as white, gray, and black polygons, respectively. Numerical breakpoints are presented in Appendix B.

Table 4. Spatial cluster analysis of cancer mortality, ecological integrity (stream condition index, SCI), and coal mining (coal mining index, CMI) in West Virginia[a]

Category	Variable	Moran's *I*	*z* score	*P*
Cancer mortality	Total*	0.268	3.065	0.002
	Breast (female)	0.029	0.502	0.616
	Digestive	−0.030	−0.116	0.907
	Genital (female)	0.106	1.331	0.183
	Genital (male)	−0.013	0.055	0.956
	Oral	−0.064	−0.477	0.633
	Respiratory*	0.456	5.091	<0.001
	Urinary	−0.065	−0.498	0.618
	"Other"*	0.204	2.363	0.018
Ecological integrity	SCI*	0.257	2.875	0.004
Coal mining	CMI*	0.560	6.244	<0.0001

[a]Cancer was expressed as age-adjusted cancer mortality per 100,000 people. Moran's *I* values were calculated using the inverse distance method and Euclidean distances. Positive Moran's *I* values indicate spatial autocorrelation among counties. Variables indicated with * show $P < 0.05$ and are mapped with local Moran's statistics (Fig. 4).

causal factor for lung cancer (Ferrechio et al., 2000) and skin cancer (Landrigan, 1982; Vahter et al., 2002; Jarup, 2003). Cadmium exposure is linked to many cancer types including lung, breast, and pancreatic cancer (Huff et al., 2007).

Our results are consistent with documented effects of mining on stream ecosystems in Appalachia. Several studies have demonstrated substantive differences in benthic macroinvertebrate communities between streams that flow from coal surface-mines and those that do not. For example, the extirpation of a taxonomic order of macroinvertebrates (i.e., mayflies [*Ephemeroptera*]) has been reported in mining-affected streams (Pond et al., 2008; Palmer et al., 2010; Pond, in press). Such biological changes have been attributed to changes in water quality, water quantity, and physical habitat in streams draining mining operations in Appalachia (Phillips, 2004; Hartman et al.,

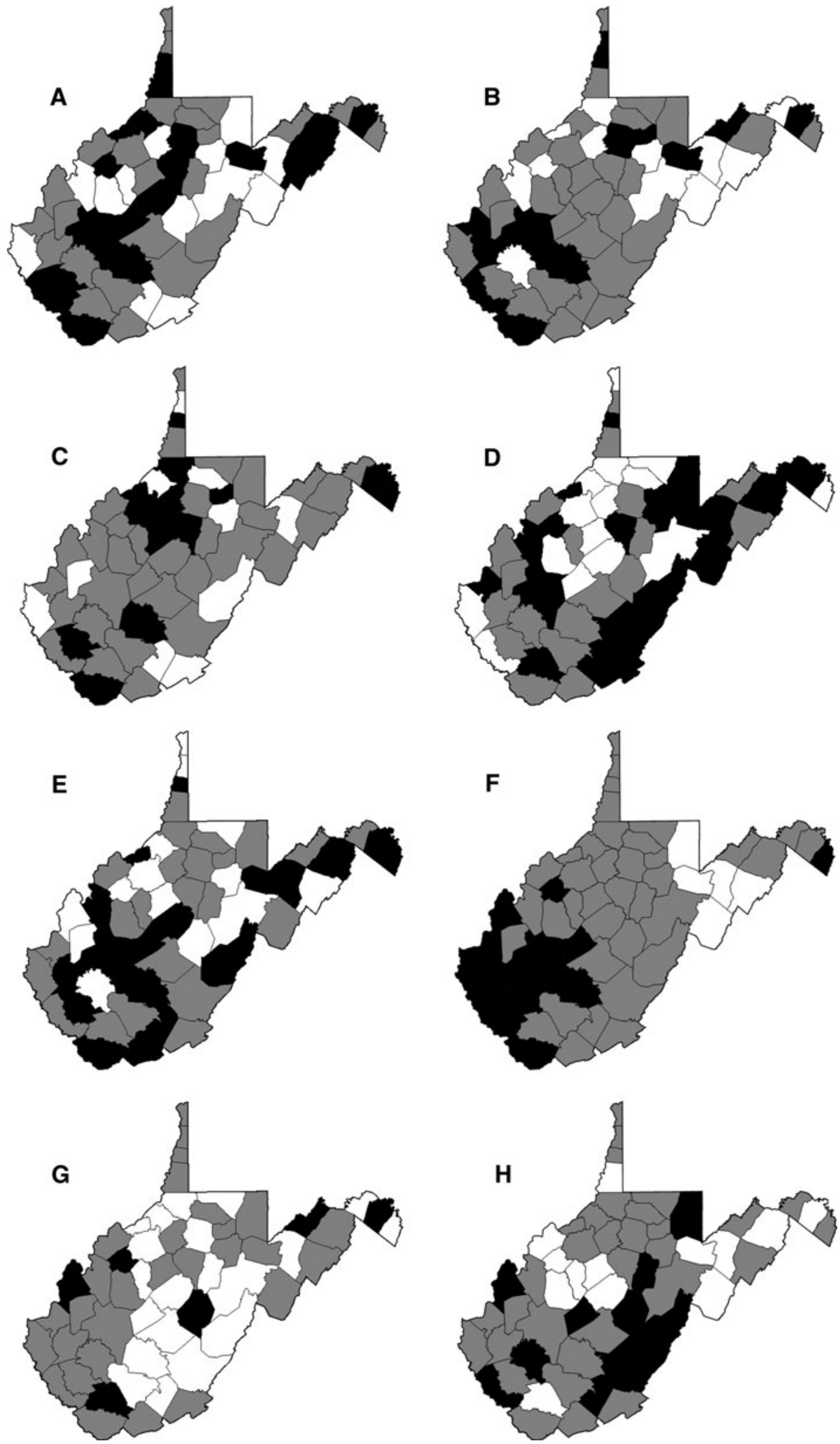


Figure 3. Spatial distribution of cancer types: **a** digestive; **b** breast (female), **c** genital (female), **d** genital (male), **e** oral, **f** respiratory, **g** urinary, **h** "other" cancer. All variables are mapped as one of three classes (Jenks' natural breaks) with low, medium, and high levels indicated as white, gray, and black polygons, respectively. Numerical breakpoints are presented in Appendix B.

2005; Negley and Eshleman, 2006; Pond et al., 2008; Palmer et al., 2010).

Some coal-mediated effects on benthic macroinvertebrates may be linked to human cancer mortality, but others may not. For example, it is improbable that hydrological effects of coal surface-mining (Phillips, 2004; Negley and Eshleman, 2006) could influence human health, but benthic macroinvertebrate communities clearly respond to

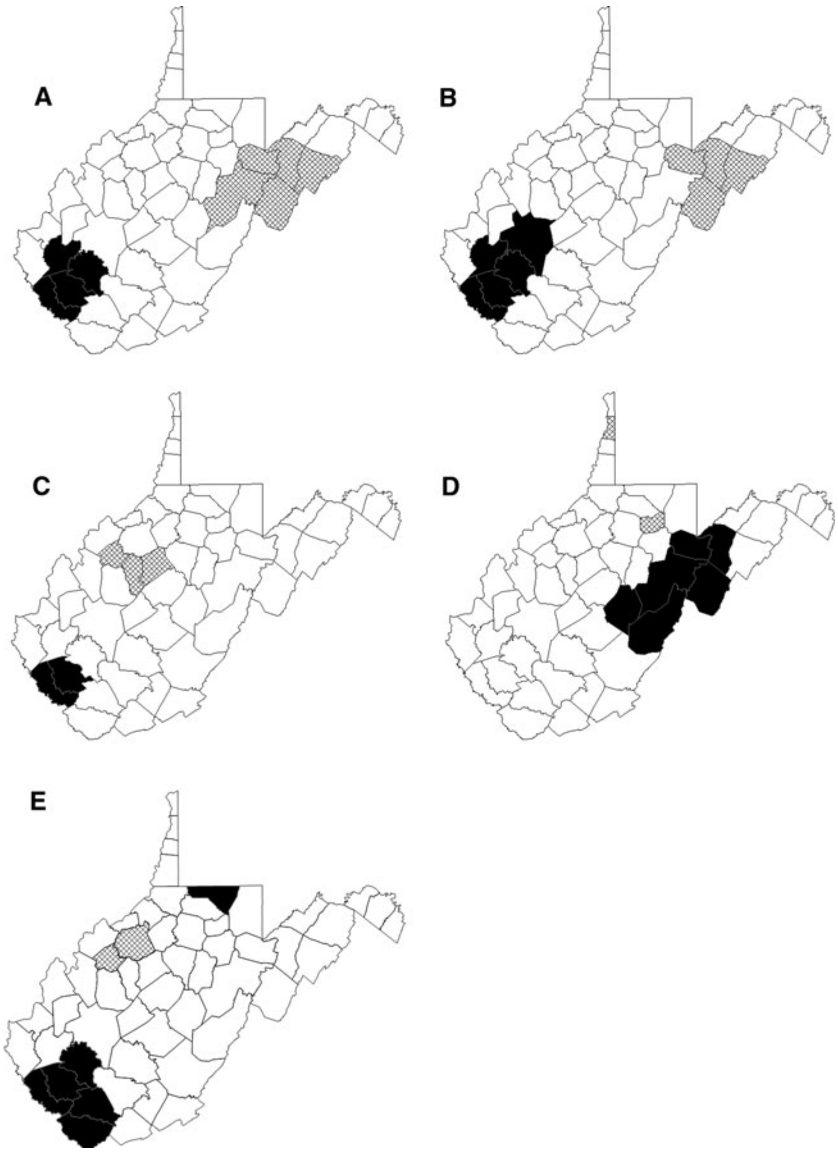


Figure 4. Local Moran's I statistics for **a** total age-adjusted cancer morality, **b** respiratory cancer, **c** "other" cancer, **d** stream condition index (SCI), and **e** coal mining index (CMI). Cross-hatched areas indicate values lower than the mean. Filled areas indicate areas higher than the mean. Counties with $P < 0.10$ are shown (see Table 4).

Table 5. Partial Mantel Correlations of total age-adjusted cancer mortality per 100,000 people, ecological integrity (stream condition index, SCI), and coal mining (coal mining index, CMI) in West Virginia[a]

	SCI	CMI	Total cancer mortality
SCI	–	0.226	0.120
CMI	0.002	–	0.230
Total cancer mortality	0.068	0.021	–

[a]Upper diagonal cells indicate partial Mantel r correlation coefficients; lower diagonals indicate associated P-values. Partial Mantel correlations were calculated while controlling for spatial autocorrelation (i.e., Euclidean distances among county centroids [see text]).

hydrological variation (Bunn and Arthington, 2003). In contrast, transport of dissolved metals from coal mining and processing areas may present a human exposure pathway through well-water, poorly treated municipal water, or consumption of metal-contaminated fish. Moreover, the sensitivity of mayflies to dissolved metals (Yuan and Norton, 2003), and the loss of mayflies in mining-affected streams (Palmer et al., 2010), suggest that metal contamination may be a concern for human communities in downstream areas. Our analysis does not evaluate waterborne exposure pathways directly, and we recognize that other possible exposure pathways may be of equal or greater importance for human disease (e.g., dust from mining and processing sites; Ghose and Majee, 2007).

Inferences from our study were limited by the spatial and temporal resolution of available data. The public health data in this study were limited to the county-level, and thus required averaging thousands of ecological integrity observations (Fig. 1) into 55 county averages. We also combined temporal data for SCI (1996–2006), CMI (1979–2005), and cancer mortality (1979–2005). In each case, data aggregation will tend to diminish dose–response signals because our statistical models cannot control for heterogeneity within counties and among years. Moreover, our treatment of counties as observational units (i.e., an ecologic study sensu Morgenstern [2008]) does not imply that individuals within counties have predictable epidemiological exposures or responses. As a result, our results should not be used to estimate per-capita health risks but instead should be interpreted as an exploratory treatment of possible cause-and-effect relationships.

New research is needed to better understand the causal relations between ecological integrity and human health. First, individual-based studies are needed to quantify per-capita cancer risks with respect to ecological integrity and socioeconomic factors. Second, analyses of macroinvertebrate genera and species are needed to understand possible mechanistic links to public health and to apply laboratory-based physiological research to field-based bioassessment survey results. For example, the SCI was calculated from family-level data, but macroinvertebrate genera have shown greater sensitivity to stressors in the Central Appalachians (Waite et al., 2004). Third, spatial analyses of human health and ecological integrity are needed across larger geographic extents to evaluate the generality of the results presented here. The recent development of a continental-scale ecological integrity dataset (Paulsen et al., 2008) provides this opportunity in North America. Our results suggest that such a continental-scale analysis would be feasible and may provide important insights.

Conclusion

It is intuitive that ecological integrity and human health are intrinsically linked (e.g., Rapport, 1999; Di Giulio and Benson, 2002; Tabor, 2002). However, global analyses have shown weak or statistically insignificant relations between ecological integrity and human health (Sieswerda et al., 2001; Huynen et al., 2004). In contrast, our analysis demonstrated a significant association between ecological disintegrity and human cancer mortality in West Virginia, USA. We detected significant influences of known socioeconomic risk factors (smoking, poverty, and urbanization) on cancer mortality, but these factors did not account for the observed integrity–cancer relationship. Nor could we explain our observations as a statistical effect of spatial autocorrelation within the study area. Instead, our study demonstrated that the ecological integrity of streams was significantly related to public health in nearby areas. Although the macroinvertebrate data evaluated in this study were collected to assess the quality of aquatic life, our study revealed that these assessments may also contribute an improved understanding of human health and safety.

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Appendices

Appendix A. West Virginia stream condition index (SCI) summary statistics by county[a]

County	*n*	Mean	SEM	Range	Minimum	Maximum
Barbour	51	62.6	2.4	68.7	21.2	89.9
Berkeley	80	59.4	2.1	75.6	15.7	91.3
Boone	143	63.9	1.1	78.3	19.5	97.8
Braxton	63	72.8	1.6	56.0	36.6	92.6
Brooke	52	55.2	2.2	67.2	12.1	79.3
Cabell	57	56.4	2.5	75.1	15.5	90.6
Calhoun	23	72.4	2.1	40.8	51.7	92.5

Appendix A. continued

County	*n*	Mean	SEM	Range	Minimum	Maximum
Clay	55	68.5	2.0	60.2	33.5	93.7
Doddridge	39	70.5	2.0	57.3	39.3	96.5
Fayette	128	64.3	1.6	77.3	17.8	95.1
Gilmer	62	62.2	1.7	65.0	27.5	92.5
Grant	81	73.4	1.8	56.7	40.3	97.0
Greenbrier	91	79.6	1.1	58.9	39.6	98.5
Hampshire	98	75.0	1.1	57.6	37.7	95.3
Hancock	40	59.1	2.7	65.0	25.4	90.4
Hardy	88	73.1	1.6	65.5	29.1	94.5
Harrison	151	49.2	1.0	60.0	13.7	73.7
Jackson	46	70.2	2.1	55.3	39.2	94.4
Jefferson	25	52.8	2.7	56.7	29.7	86.5
Kanawha	277	57.7	1.0	85.3	11.0	96.2
Lewis	65	57.6	1.8	61.8	26.4	88.3
Lincoln	100	68.9	1.6	73.3	24.1	97.4
Logan	122	57.6	1.8	79.0	15.8	94.8
Marion	56	54.7	2.3	82.3	10.6	92.9
Marshall	116	68.4	1.6	82.3	15.3	97.7
Mason	79	66.8	1.8	69.1	23.7	92.8
McDowell	120	64.4	1.6	71.4	23.2	94.5
Mercer	63	68.1	2.0	70.8	20.1	90.9
Mineral	58	69.2	2.3	86.5	9.8	96.3
Mingo	73	55.0	1.9	70.8	18.9	89.8
Monongalia	134	53.0	1.7	83.3	9.8	93.0
Monroe	52	71.8	1.8	55.2	38.2	93.4
Morgan	59	76.6	1.5	61.1	31.7	92.8
Nicholas	132	75.6	1.2	71.5	24.8	96.3
Ohio	63	54.0	2.0	70.7	12.1	82.9
Pendleton	132	74.2	1.1	56.5	39.1	95.5
Pleasants	15	71.5	3.2	45.8	51.3	97.1
Pocahontas	119	80.6	1.0	52.2	44.0	96.2
Preston	178	66.8	1.6	88.0	9.8	97.8
Putnam	59	61.1	2.4	78.4	12.5	90.9
Raleigh	156	64.1	1.3	75.2	16.5	91.7
Randolph	216	80.4	0.8	87.8	11.8	99.6
Ritchie	34	66.7	2.5	56.2	36.2	92.4
Roane	51	66.8	2.5	75.0	18.1	93.1
Summers	44	74.8	1.8	78.9	18.7	97.6
Taylor	31	56.0	2.2	43.3	33.0	76.3
Tucker	137	80.8	1.0	69.3	27.9	97.2
Tyler	43	69.3	1.9	51.7	41.1	92.8
Upshur	70	70.1	2.0	75.8	21.3	97.1
Wayne	176	63.6	1.4	82.6	13.0	95.6
Webster	79	81.1	1.1	59.2	38.3	97.4
Wetzel	70	68.0	1.6	65.0	27.0	92.0

Appendix A. continued

County	*n*	Mean	SEM	Range	Minimum	Maximum
Wirt	17	64.2	3.5	60.9	24.3	85.2
Wood	16	56.7	4.1	54.8	29.5	84.3
Wyoming	133	64.7	1.2	68.4	23.7	92.1

[a]SCI values range from 0 to 100, with increasing values corresponding to increasing levels of ecological integrity. Raw data are available from the West Virginia Department of Environmental Quality.

Appendix B. Numerical breakpoints mapped in Figs. 2 and 3[a]

Figure	Variable	Category 1	Category 2	Category 3
1A	Total cancer	161.6–200.4	200.4–223.7	223.7–271.3
1B	Stream condition index	49.2–61.1	61.1–70.5	70.5–81.1
1C	Index of coal mining	41.5–49.8	49.8–64.3	64.3–83.7
2A	Digestive cancer	38.3–45.1	45.1–50.8	50.8–59.8
2B	Breast cancer (female)	18.2–24.8	24.8–29.2	29.2–36.2
2C	Genital cancer (female)	8.7–16.0	16.0–20.0	20.0–29.1
2D	Genital cancer (male)	20.4–28.1	28.1–32.5	32.5–37.4
2E	Oral cancer	1.0–4.5	4.5–6.6	6.6–9.2
2F	Respiratory cancer	36.4–58.2	58.2–77.7	77.7–110.3
2G	Urinary cancer	6.4–9.1	9.1–11.3	11.3–14.7
2H	"Other" cancer	15.2–22.7	22.7–27.6	27.6–34.8

[a]Breakpoints were defined from Jenks' natural breaks and calculated in ArcGIS (version 9.3; ESRI, Redlands, CA).

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