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ABSTRACT
The Appalachians, and Central Appalachia in particular, have a long history of resource extraction including coal mining. In the past half century, the region experienced a shift from underground to surface mining, which leaves highly visible changes on the landscape. This study presents an analysis of changes in surface mining extents between 1984 and 2015 using remote sensing techniques, and tests the methods of previous research over a broader study area. The authors found that 3070 km² (7.1%) of land within the central Appalachian coalfield was classified as mined land through the study period, and that the rate of newly mined land, as well as total mined land has decreased in recent years. The overall classification accuracy was 0.888 and the kappa coefficient was 0.880. Study results indicate that previously developed methods for identifying surface mines in a sub-region of Central Appalachia can successfully be applied over the broader region. The resulting surface mining datasets will be applied to a future study examining the potential human health impacts of surface mining.

KEYWORDS
Appalachian Coalfield, Surface Mining Extent, Time Series Analysis

INTRODUCTION
The landscape of Appalachia reflects the varied history of the region along with the numerous land use/land cover changes (LULCC) that the region has experienced since human settlement began. Appalachia in general, and Central Appalachia in particular, have in more recent history been subjected to intensive natural resource extraction such as timber harvesting and mineral extraction. Both became important agents of environmental change in the early 1800s, and large-scale coal mining began in earnest in the early 1900s; 80% of the nation’s coal was sourced from the region by 1930 (Yarnell, 1998). The impacts of underground mining on the landscape were visually apparent with large swaths of vegetation cleared around mine entrances and the creation of waste piles, as well as changes to aquatic environments. During the mid-1900s, the shift from underground to surface mining resulted in even greater permanent alteration of the landscape (Rouse & Greer-Pitt, 2006).

During surface mining, large swaths of vegetation are removed, exposing barren ground. As the process of accessing coal seams continues, mountaintops are typically removed and nearby valleys filled with that overburden in order to reach coal beneath the surface (Environmental Protection Agency, 2016). As the coal supply is exhausted from a section of the mined area, the ground is...
regraded and eventually revegetated, as operations move on to another part of the area permitted for coal removal. For the purposes of this research, we define “surface mining extents” as areas identified on satellite imagery as disturbed, barren lands within the USGS-defined Appalachian coalfield region that have experienced vegetation removal but have not yet seen revegetation occur. The Surface Mining Control and Reclamation Act of 1977 requires that a mined area be returned to the “approximate original contours.” These landscape alterations associated with surface mining, particularly removal of vegetation to expose bare ground and then the return to a vegetated state, are readily visible on the landscape with the use of remotely sensed data.

This research is part of a larger study responding to a need for the analysis of fine-scale individual-level human health impacts of surface mining in Central Appalachia (Krometis et al., 2017), which requires a reconstruction of historical surface mining extents. In particular, the broader study seeks to examine environmental exposures and human health outcomes associated with surface mining, as mining processes can result in air pollution and water contamination in the vicinity of a mine; minimal research has focused on premature mortality, adverse birth outcomes, and other human health concerns that could potentially be tied to surface mining (Hendryx 2015; Krometis et al., 2017). Therefore, the objective of this study is to delineate the annual extent of active surface mining within Central Appalachia for 1984-2015 to contribute to the body of research examining mining delineation within the region, and to meet our applied need as we examine human health impacts of surface mining. Li et al. (2015) developed a methodology, with a focus on the accurate identification of surface mines as compared to non-mined areas, for identifying surface mines using Landsat data and remote sensing techniques in a subset of Central Appalachia, and we respond to their suggestion to test their methods over a broader study area by applying them to the full coalfield region within Central Appalachia.

BACKGROUND

The identification of mined areas is a common application in remote sensing (Campbell & Wynne, 2011), but with a few exceptions, there has been minimal study of changes in the extent of surface mining across all of Central Appalachia, where there is a long history of land disturbance due to mining. Slonecker and Benger (2002) thoroughly reviewed the extent of research using remote sensing to evaluate surface mining through the end of the 1990s and determined that it is an effective way to examine mining and its impacts. More specific to our region of interest, Townsend et al. (2009) presented an examination of changes in surface mining extent and reclamation over time using Landsat in a coalfield region of Appalachia, with accuracy levels above 85%. A combination of LiDAR-derived data and satellite imagery in the coalfields of southern West Virginia proved to be an effective way to classify land cover within a mine-permitted area (Maxwell, Warner, Strager, & Pal, 2014). Although these studies proved that their methods were effective at identifying surface mining extents, both examined relatively small regions within the Appalachian coalfield.

More recently, Li et al. (2015) developed an approach of examining time series of Landsat-derived vegetation indices for detecting surface mining in the Central Appalachian coalfield, with a specific focus on southwestern Virginia. Specifically, Li, Zipper, Donovan, Wynne, and Oliphant (2015) determined that the normalized difference vegetation index (NDVI; Rouse Jr, Haas, Schell, & Deering, 1974) was best at distinguishing bare ground from vegetation during leaf-on periods (i.e., the growing season) when compared to the Normalized Burn Ratio (NBR; Key & Benson, 1999), the Normalized Difference Moisture Index (NDMI; Hardisky, Klemas, & Smart, 1983), the tasseled cap greenness-brightness (TC-GB; Kauth & Thomas, 1976) difference index, and the “Red” band, and the “Near Infrared” (NIR) Band. NDVI, which quantifies photosynthetic activity, has been widely used in change detection research (e.g., Lunetta, Knight, Ediriwickrema, & Worthy, 2006; Shao, Taff, Ren, & Campbell, 2016). Li et al. (2015) found that 8% of the region experienced mining over the 28-year period with a kappa coefficient of 0.9252. Furthermore, Li et al. (2015) suggested that the Appalachian coalfield is ideal for examining surface mine detection techniques due to the intensive
mining that has occurred within the region in recent decades; the study aimed to provide an approach for detecting surface mines with high accuracy and recommends applying the method across the Appalachian coalfields. Lastly, Pericak et al. (2018) contributed to this body of research in the region with an examination of surface mining extents with an approach that combines Landsat imagery and Google Earth Engine. In particular, the study delineated areas with low NDVI (i.e., barren earth) within the region as surface mines, which contrasted with high-NDVI areas that represent vegetated land with forest or herbaceous cover, and found that 2900 km² was newly mined between 1985 and 2015 with kappa coefficients ranging from 0.62 to 0.93 in each year.

For this research, we ultimately decided to extend the work of Li et al. (2015) in southwestern Virginia by applying their methods to an expanded study area of the coalfield region of Central Appalachia. Our goal was to determine whether those methods remain viable over the full coalfield region.

DATA AND METHODS

Study Area

The area of study for this research is the Central Appalachian coalfield (Figure 1), which we define as the portion of the Appalachian Regional Commission (ARC)-defined Central Appalachian subregion that intersects the United States Geological Survey (USGS)-defined Appalachian coalfield (East, 2013; Table 1). The study-defined Central Appalachian coalfield is 43407 km² and is comprised of all or portions of 58 counties within the states of Kentucky, Tennessee, Virginia, and West Virginia. According to a characterization of the study area using the 2011 National Land Cover Database (NLCD) data, which was made available by Jin et al. (2013), ~33680 km² (77.6%) of the study area is classified as forest land cover, while ~5600 km² (12.9%) is classified as pasture or grassland. The remaining 9.5% of the study area is predominantly classified as developed (open space and low intensity) or as barren land.

The Central Appalachia coalfield was selected following a similar rationale used by Li et al. (2015), that the Appalachian coalfield is ideal for examining surface mine detection techniques due to the intensive mining that has occurred within the region in recent decades. According to data gathered from the Kentucky Department for Natural Resources; the Tennessee Department of Environment and Conservation; the Virginia Department of Mines, Minerals, and Energy Surface Mining; and the West Virginia Department of Environmental Protection’s Division of Mining and Reclamation, 7092 km² (16.3%) of the study area was permitted for surface mining through the year 2015. However, in any given year, mining typically occurs within a small area of any given zone that is permitted for mining; as coal is extracted, previously mined areas are revegetated, and mining moves on to another part of the permitted zone. Of the four states that comprise the study region, Kentucky has the largest area of land permitted for mining (5549 km²), followed by West Virginia (953 km²), Virginia (301 km²), and Tennessee (289 km²).

Data

Past research indicates that moderate resolution Landsat imagery is appropriate for delineating surface mining extent at an annual temporal scale (Li et al., 2015; Pericak et al., 2018; Townsend et al., 2009). Landsat data are available at a 16-day temporal resolution and a 30-meter spatial resolution. To identify surface mining extent annually across the study region from 1984 to 2015, the “best available” Landsat data were downloaded from the USGS (Table 1) for each of the seven scenes (WRS II grid system: Path 18/Row 33, Path 18/Row 34, Path 19/Row 33, Path 19/Row 34, Path 19/Row 35, Path 20/Row 34, Path 20/Row 34) that intersect the study area (Figure 2). The criteria used to select the “best available” Landsat image for each scene and year is the same that was used by Li et al. (2015). Namely, the highest quality (i.e., minimal cloud cover) image that was acquired
during peak growing season - defined here as June 1 – September 30 - was downloaded for each scene and year. When a suitable image was not available during the peak growing season (scene < 85% complete), it was extended to October 15. By using images during the peak growing season, the distinction between barren (i.e., mined) land and vegetated land is most obvious. Specifically, level 1T (terrain corrected) Landsat products were used for this study. These data are co-registered by the Earth Resources Observation and Science Center and Landsat 5 and 7 data are processed with the Landsat Ecosystem Disturbance Adaptive Processing System (LEDAPS; Masek et al., 2006), while Landsat 8 data are processed using the Landsat Surface Reflectance Code (LaSRC; Vermote, Justice, Claverie, & Franch, 2016). This processing includes a surface reflectance correction, a water and snow mask, and a cloud shadows mask for each acquisition date. Following the methods of Li et al. (2015), no post-2003 Enhanced Thematic Mapper (ETM+) images were used to avoid data gap issues caused by the scan line corrector problem. As such, no Landsat images were downloaded for the 2012 growing season. The first five bands for each of the “best available” Landsat images (31 years X 7 scenes) were stacked and the cloud and water masks for each Landsat image were used to eliminate poor quality pixels from the analysis.

To support our identification of surface mines, we used three supplemental datasets: mine permit boundaries, land cover data, and aerial photography. Mining permit boundaries were gathered from the Kentucky Department for Natural Resources; the Tennessee Department of Environment and Conservation; the Virginia Department of Mines, Minerals, and Energy Surface Mining; and the West Virginia Department of Environmental Protection’s Division of Mining and Reclamation (Table [Table reference]).

Figure 1. The study area consists of parts of the USGS-defined Appalachian coalfield that intersect with ARC-defined Central Appalachia. Also shown are the historical (through 2015) mine permit boundaries across the study area.
The mining permit boundaries for all states were merged to create a single shapefile of historical (through 2015) permits. As noted by past research (e.g., Li et al., 2015; Townsend et al., 2009), these boundaries contain most, but not all mined land within the central Appalachian region. Land cover data for the study region were obtained from the National Land Cover Dataset (NLCD) for 2001 (NLCD 2001; Homer et al., 2007), 2006 (NLCD 2006; Fry et al., 2011), and 2011 (NLCD 2011; Jin et al., 2013). These data are available at a 30-meter spatial resolution. Additionally, high-resolution aerial imagery was downloaded from the United States Department of Agriculture’s (USDA) National Agricultural Imagery Program (NAIP; Table 1). NAIP images are available at the county level from 2003 to 2015, and at a temporal resolution of approximately two years.

### Methods

Past research has shown that land-cover classification accuracy increases with training sample size (e.g., Shao & Lunetta, 2012). Therefore, we followed guidance from similar research (e.g., Li et al., 2015) to choose an adequate number of training points. Specifically, 500 points were randomly placed within the mining permit boundaries of six randomly selected counties (Figure 2; counties 1 – 6). Likewise, 100 points were placed in urban areas (NLCD 2011: Developed, low intensity; Developed, medium intensity; Developed, high intensity) within the six randomly selected counties. It is important to note that the 600 training points were placed across the six counties using a stratified random sampling design. For each year in the study period, each point was classified as bare ground or vegetated. Classification was performed by visually inspecting all available NAIP imagery for the six counties, in addition to all Landsat images displayed using bands 2, 3, and 4 (3, 4, 5 for Landsat 8). For consistency, abbreviations used hereafter will be the same as those used by Li et al. (2015). Based on the time series of classifications, each of the 600 points was then given a classification. Those points classified as vegetation for all years in the study period were given a classification of persistent vegetation (PV). Otherwise, the point was classified as disturbed and assigned a second classification. The training pixels that were disturbed by mining activities were classified as EM; meaning that the pixel was disturbed by mining at one or more times over the observation period, and the remaining pixels were classified as OD; meaning that vegetation disturbances other than mining (e.g., clear-cutting or land development) occurred during the study period.

To identify annual surface mining extent across the study area from 1984 – 2015 (minus 2012), a multi-step approach similar to that developed by Li et al. (2015) was employed.

### First Step: Vegetation Index Selection and Scene Mosaicking

As the data and methods used for this research are similar to those used by Li et al. (2015), and based on the success past research has shown using NDVI to delineate mined land from non-mined

### Table 1. Data source information for the data used during this research

<table>
<thead>
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<tr>
<td>West Virginia</td>
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land, NDVI was selected as the vegetation index for this study. For each of the seven Landsat scenes across the study area, an NDVI image was generated for each year (1984 – 2015) using the Red and Near Infrared bands from the “best available” image for that year. The NDVI images for scenes acquired between October 1 and October 15 were normalized to the long-term NDVI average of each respective scene. An annual NDVI composite of the study area was then generated for each year in the study period. As a portion of each Landsat scene intersects with adjacent scenes, a maximum value NDVI mosaic of the study area was generated for each year using ArcGIS’s cell statistic tool. This decision follows guidance from past land cover classification research (e.g., Olthof et al., 2005). It is important to note that this procedure did not result in spatially complete mosaics (Figure 3). However, the study area data completeness is above 85% for every year in the historical record, and similar data completeness is also exhibited for areas within mining permit boundaries (Figure 3).

Second Step: CART Classification

Li et al. (2015) noted that inter-annual variation of NDVI values due to changes in vegetation “greenness” does not support the computation of a single bare ground threshold. As such, a bare ground threshold was computed for each year using Classification And Regression Trees (CART) regression (Therneau, Atkinson, & Ripley, 2018). For this, NDVI values from the time series of mosaics were extracted for all 600 classified (bare ground or vegetated) training points. CART classification was then conducted to compute a bare ground threshold for each year (Figure 4). Next, the NDVI mosaic for each year was reclassified to 0 for bare ground or 1 for vegetated land cover. The reclassified
images were summed using ArcGIS’s cell statistics tool and those pixels with vegetated land cover through the entire study period (31 years) were classified as PV. Otherwise, the pixel was classified as disturbed.

Third Step: Surface Mine Detection Across Central Appalachia

The final step was to separate mined land (EM) from land that experienced other disturbances (OD) through the study period, such as clear-cutting or industrial development. As noted by Li et al. (2015), the mining permit boundaries do not always contain the mined areas completely. It is important to note that this could simply be artifact of human error in digitizing the permit boundaries, rather than an indication of illegal mining activities. Through their analysis, Li et al. (2015) determined that an NDVI time series of EM-disturbed land generally has a lower minimum NDVI value and also exhibits greater variability than that of NDVI values representing OD lands. As such, standard deviation values were computed for time series of NDVI values for each pixel within the study area. Those values, along with the minimum NDVI values, were then extracted for the training pixels classified as EM, and for those classified as OD. CART classification was once again used to compute the minimum NDVI and NDVI standard deviation thresholds. Using a time series minimum NDVI of 0.4195 and a time series standard deviation threshold of 0.1710, the non-PV pixels were classified as OD or EM. Specifically, using the arcpy Python site package, the time series of each non-PV pixel was examined and those located within a mining permit boundary with a minimum NDVI value less than 0.4195, or outside of a permit boundary with a minimum NDVI value less than 0.4195 and a standard deviation greater than 0.1710 were classified as EM. Otherwise, the pixel was classified as OD. The use of these thresholds to detect EM land was possible due to the relatively low variability in the time series of scene NDVI values (Figure 4).

An additional procedure was applied to correct several errors that were visually apparent. All land areas that were classified by the NLCD 2011 as Developed (low, medium, and high) were reclassified from EM to OD. This procedure was also used by Li et al. (2015), who noted that the time series of NDVI values representing some OD lands exhibited relatively high variability across the study area.
period, and ultimately misclassification (OD instead of EM). Through further visual inspection of the results, it was apparent that some agricultural land was being misclassified as EM land. This is not surprising, as agricultural practices during the growing season could lead to greater variability in time series of NDVI values, as well as relatively low minimum NDVI values. Therefore, pixels that were persistently defined as agriculture (Pasture/Hay, Cultivated Crops) by NLCD 2001, NLCD 2006, and NLCD 2011 were reclassified from EM to OD. The time series of NDVI values for those pixels classified as EM were processed again to determine year of initial disturbance, and the year in which mining activities ceased. For each pixel, the disturbance date was tagged to the year that a pixel’s NDVI time series was lower than the CART computed bare ground threshold. Conversely, the end-of-mining date was tagged to the year that a pixel’s NDVI time series became greater than the CART determined bare ground threshold.

Accuracy Assessment

A validation dataset consisting of 2250 points within ten randomly selected counties (Figure 2; 7 - 16) was created. This validation dataset was created by randomly placing 500 points within lands identified as PV, 200 points within OD classified pixels, and 50 points within each of the EM annual categories (31 years). Following the accuracy assessment methodologies of Li et al. (2015), the initial disturbance year was used to assign an EM annual category. Validation points were manually deleted if more than one point was located within a homogenously classified pixel group. The validation dataset consisted of 2024 points after this procedure, and these points were then manually classified using a suite of validation datasets. Specifically, using NAIP imagery, the NLCD 2011 dataset, and all Landsat images (displayed as bands 2, 3, 4) were used to classify the validation points as PV, OD, or EM. A confusion matrix was constructed based upon the accuracy assessment and the overall accuracy, kappa coefficient, user’s accuracies, and producer’s accuracies were computed.
RESULTS AND DISCUSSION

Accuracy

The overall classification accuracy is 0.888, and the kappa coefficient is 0.880 (Table 2). The producer’s accuracy of all classes is between 0.693 (OD) and 0.976 (EM-2015). The user’s accuracy is between 0.755 (EM-2014) and 0.979 (EM-1993). The impact of missing data (Figure 3) appears to have had a negligible impact on producer’s and user’s accuracies for this study. The relatively low percent of usable data for 1985 did coincide with relatively low producer’s accuracy for EM-1985 (Figure 3; Table 2). However, the producer’s and user’s accuracies for other years with relatively low usable data (e.g., 1993, 1998, and 2013) were seemingly not impacted by missing data. In agreement with past studies (e.g., Li et al., 2015), many of the errors tended to be along the edges of mined land. For example, although NAIP imagery showed no appreciable change in a mining extent for one surface mine, the NDVI of a boundary pixel that was classified as vegetated for the year of disturbance, was classified as bare ground the following year. Additionally, errors were noted within the western portion of the study area where agricultural land was misclassified as EM land. It is also worth noting that PV pixels adjacent to those masked out of the analysis by cloud cover were sometimes misclassified as OD, as the NDVI time series values became lower than the bare ground threshold. Overall, the accuracies of this study are similar to those of Li et al. (2015), indicating that the methods they developed are well-suited for identifying EM lands across a larger, and more physiographically diverse, study area.

Total EM Extent

A total of 3070 km² (7.1%) of land within the Central Appalachian coalfield was classified as EM from 1984 – 2015 (Figure 5). Kentucky has historically experienced the greatest surface mining, with 1817 km² of land classified as EM within the Central Appalachian coalfield portion of the state. Within the Central Appalachia region of West Virginia, Virginia, and Tennessee, a total of 716 km², 298 km², and 238 km², respectively, were classified as EM. Within our study region, West Virginia was the most intensively mined state, as 8.2% of the state located within the central Appalachian coalfield was classified as EM from 1984 – 2015. A total of 37723 km² (86.9%) of land within the study region was classified as PV through the study period, while 2438 km² (5.6%) was classified as OD (Figure 5). The total EM extent (3070 km²) found by this study from 1984 – 2015 is slightly larger than the 2900 km² land classified as mined by Pericak et al. (2018) from 1985 to 2015. It is important to note that discrepancies between the results of this research and that of Pericak et al. (2018) were expected, as they examined the entire central Appalachian region (not just the coalfield portion) from 1985 – 2015.

EM Land Through Time

From 1984 to 2015, an average of 99 km² of land that was previously PV was converted to EM. Newly converted EM land ranges from 294 km² (1984) to 25 km² (2015). The relatively high value of new EM land in 1984 is at least partially due to that year being the first year examined by this research. After removing 1984, the average conversion of non-EM land to EM land is 92 km² (Figure 4). This rate of conversion from non-EM to EM per year is similar to the annual rate of 87 km² found by Pericak et al. (2018).

The average (1984 – 2015) annual total extent of EM land across the study region is 330 km². The magnitude of total land area disturbed by EM activities varied from a maximum of 554 km² in 2007 to a minimum of 211 km² in 1985 (Figure 6). There is noticeable year-to-year variability in the time series of annual EM extent across the study region (Figure 6). While a portion of this variability could be from misclassified pixels, we think that a majority is a result of pixels adjacent to those masked out of the analysis by cloud cover, but located within mining permit boundaries, whose NDVI time series values became lower than the bare ground threshold for a given year. Additionally, while executing the accuracy assessment we noted that it was not uncommon for mining activities to cease for several
years (allowing for re-vegetation) before continuing, which could also lead to short-term variability in the time series of total EM extent. It is also apparent that since 2010, the area of land disturbed by mining activities has decreased when compared to earlier in the study period. The general increase of land disturbed annually by EM activities from the mid-1980s through 2010, and the negative trend thereafter are generally in agreement with the results of Pericak et al. (2018). However, the magnitude of average annual total mining extent is markedly different from that determined by Pericak et al.

Table 2. The confusion matrix, which was generated using the design-based accuracy assessment. Shown are accuracy assessment results for PV, OD, and EM lands. EM lands were classified by date of initial disturbance.
(2018), as they suggested that value to be 940 km² from 1985 to 2015. One possible explanation for this difference is that their study region of Central Appalachia was 83000 km², which is much larger than the area of study used for this research, only the coalfield region of Central Appalachia (43407 km²). Another possible explanation for the difference, which Pericak et al. (2018) noted, is that their automated method is more lenient when defining active mining extent when compared to a supervised approach, which was used for this research.

**CONCLUSION**

The objective of this study was to delineate surface mining extent by year between 1984-2015 in the coalfield region of Central Appalachia. The results of this study represent an important contribution to the body of literature examining changes in surface mining extents in the understudied region of Central Appalachia, as we confirm that the methods of Li et al. (2015) can successfully be applied, with similar accuracy levels, across the full coalfield region of Central Appalachia, as recommended by their study. We determined that between 1984 and 2015, 3070 km² (7.1%) of land within the Central Appalachian region was disturbed by surface mining activities, and that the Central Appalachian coalfield portion of West Virginia has historically been the most intensively mined when compared to that within the states of Kentucky, Tennessee, and Virginia. The work presented here also determined that an average of 99 km² of previously vegetated land was converted to surface mining land each year from 1984 through 2015 (minus 2012), and that the average annual extent of surface mining
within the Central Appalachia coalfield was 330 km² through the study period. Differences between the results of this study and those of a previous study were discussed.

Accurate depictions of surface mining extents are important as researchers attempt to better understand the ways in which mining impacts human and ecological systems. This study importantly confirms the relatively high accuracy of Li et al’s (2015) methods by applying them to the entire coalfield region in Central Appalachia and contributes to the larger body of literature that seeks to remotely identify surface mining. The resulting surface mining layers from this study have numerous applications; in particular, the impact of mining on ecological, human, and community health at a fine spatial scale can be studied with the use of our results. As previously stated, this study is part of a larger project that seeks to consider how human health in Central Appalachia could be affected by surface mining. There is a dearth of research in that area (Krometis et al. 2017), and the application of our results, along with the potentially explanatory impacts of mining on air and water quality and in turn human health, will represent an important step forward. Hendryx (2015, pg. 820) reviewed the literature on potential human health impacts of surface mining and reported that studies examining surface mining and “environmental exposure, dose, and biological impact are urgently needed.” The use of explosives and heavy diesel equipment, and the presence of coal slurry near mines, for example, could contribute to elevated rates of cancer, cardiovascular disease, poor birth outcomes, and respiratory illness, to name a few adverse health outcomes, among those living near mines, after controlling for other variables (Hendryx 2015). While coal production has declined in the region as natural gas extraction has expanded (Bowen et al. 2018), coal is expected to have a continuing impact on the geography of Central Appalachian residents, ecosystems, and communities (Krometis et al. 2017); a recent study that combined a spatial model with demand forecasts estimated nearly 1000 km² of new mine development for the region in the coming decades (Strager et al. 2015). Therefore, the surface mining extents developed by this study could support future studies aiming to understand past and future implications of surface mining across Central Appalachia.
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*Korine Kolivras is an Associate Professor of Geography at Virginia Tech. As a medical geographer, her research examines the human health impacts of environmental variability, including land cover change and climate variability and change, using quantitative and geospatial approaches. Previous work focused on emerging infectious diseases, but she has recently expanded her research program to study the impacts of land cover change on residents of Central Appalachia as part of a broad collaboration in research, teaching, and outreach across public health, the humanities, social sciences, and engineering.*