Assessing Future Energy Development across the Appalachian Landscape Conservation Cooperative

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EXECUTIVE SUMMARY

Global demand for energy has increased by more than 50 percent in the last half-century and a similar increase is projected through 2030. Energy development is projected to continue its steep upward trajectory and encompass more than 200,000 km^2 (49 million acres) in the U.S. alone by 2035. How we choose to meet U.S. and global demands for energy will have significant implications both for biodiversity and human well-being. The purpose of this report is to:

1. Identify areas across the Appalachian Landscape Conservation Cooperative (LCC) most likely to undergo changes in land cover as a result of the development of wind, shale gas, and coal resources; and,
2. Show how these areas intersect with places likely to support important habitat for species conservation, and ecosystem services such as drinking water and recreation.

The Appalachian LCC is 62% forested, and its Temperate Conifer and Broadleaf forests are among the most threatened habitats on Earth: nearly half of the original extent of this forest type has been converted. The region's complex terrain, temperate climate, and the millions of years over which species have evolved free of the disturbance of glaciation have combined to make the Appalachian region a recognized biodiversity hotspot (Figure 1). The Appalachian's extensive forests and healthy streams also provide drinking water for over 22 million people as well as prime hunting, fishing, and recreational opportunities.

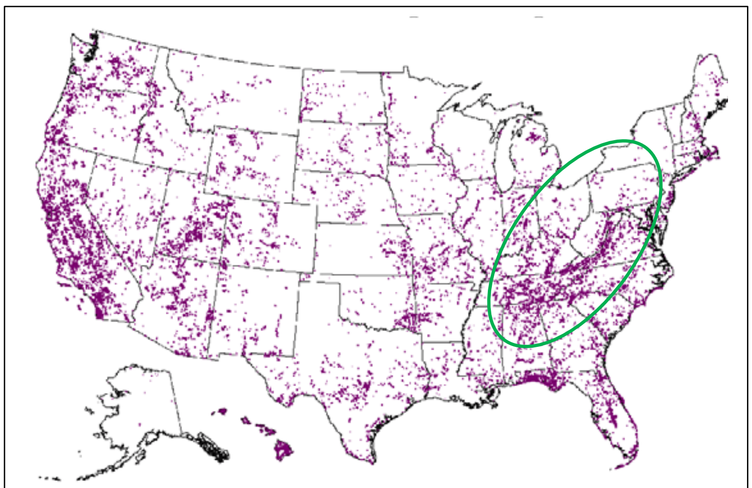

Figure 1: Distribution of Imperiled Species in the U.S. The green oval approximates the area within the APPLCC. Source: Chaplin et al 2000.

The biologically rich Appalachians are also the energy resource hub of the eastern United States. Coal mining has defined the Appalachians for generations and remains a major industry despite its uncertain future. "Unconventional" shale gas extraction now vies with coal on the Appalachian landscape. Within the Central Appalachians, the Marcellus and Utica shale gas plays alone may yield over 120 trillion cubic feet of gas - potentially enough to meet the needs of every household in the United States for approximately 18 years. The broad southwest-to-northeast tending ridges that extend from western Pennsylvania to eastern West Virginia are some of the windiest spots east of the Mississippi River. These ridges are being developed for wind energy facilities that could help Eastern states meet renewable energy standards.

We developed a risk assessment for future energy development to quantify the potential impacts on forest and aquatic resources across the 15 eastern states (146 million acres) comprising the Appalachian LCC. First we developed spatially explicit models predicting the probability of wind development, shale gas development, and surface coal mining for the entire study area and the probability of wet shale gas development within the Utica play. We then selected areas where energy development was most likely to occur and calculated impacts to forest cover and natural communities. We also calculated the cumulative risk scores for interior forest habitat patches (forest cores) and watersheds across the Appalachian LCC. Finally, to estimate potential cumulative impacts of energy development to people and wildlife, we intersected the energy probability layers and forest and watershed cumulative risk scores with GIS layers of conservation priorities and ecosystem services.

Our analysis determined that nearly 31,000 km^2 (7.6 million acres) within the Appalachian LCC have a high probability of energy development from one or more sources (Figure 2). These areas are concentrated in the eastern portion of the Appalachian LCC, on the Allegheny and Cumberland plateaus. Pennsylvania alone supplies nearly half (44%) of the total high energy development area, while West Virginia contributes 21%. This constitutes approximately 11% of the total land area in each of the two states.

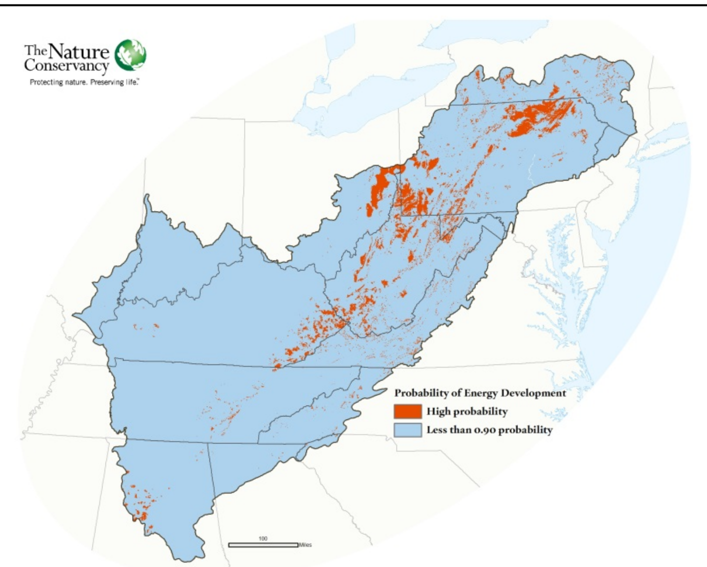

Figure 2: Distribution of High Probability Energy Development Areas across the Appalachian LCC.

Although 7.6 million acres is a relatively small part of the sprawling study area (6%), it is a very important portion. Our analysis indicates that energy development will occur disproportionally in areas covered with natural vegetation. Nearly three-quarters (71%) of the area at potentially highest risk from energy development - an area larger than the state of Maryland – is forested (22,000 km^2 or 5.4 million acres), encompassing 10% (19,000 km^2 or 4.6 million acres) of the Appalachian LCC's remaining intact patches of interior forest habitat. Similarly, 80% of the wind, 65% of the shale gas, and 75% of the coal high-probability development areas overlap natural forest habitats.

Forest cover is a key determinant of water quality, specifically turbidity and water temperature. These are key habitat attributes for iconic species such as eastern brook trout. Changes in land cover also affect flow regimes (the timing, duration, and frequency of different levels of water flows) which are a powerful determinant of aquatic system health and richness. We found that nearly 16% of the LCC's small watersheds at highest potential risk from energy development have been identified by The Nature Conservancy as essential to the conservation of the region's native aquatic wildlife. Forest cover is also important to the maintenance of healthy cave and karst habitats that support many species not found outside the Appalachian LCC. We found that 12% (474) of the watersheds in the Appalachian LCC that potentially support cave and karst species are at highest potential risk of energy development.

Natural systems provide essential services to water utilities, businesses, and communities—from water flow regulation and flood control to water quality and air temperature regulation. We found that 75% (5,559) of the watersheds in the Appalachian LCC are ranked among the top quartile of watersheds nationally in their ability to produce clean water. Sixteen percent (153) of these important drinking water watersheds are within the area identified as at highest potential risk for energy development. Currently, 82% of the watersheds in the study region have less than 2% impervious cover; however, 15% of these are at highest potential risk of energy development. Loss of permeable forest land is associated with increases in non-point source pollution and sedimentation, which can lower the quality of surface drinking water.

We suggest that the status quo of permit-by-permit, project-by-project energy development is poorly suited to maintaining the Appalachian's extensive forests and rivers, the unique biological heritage they support, and the drinking water and recreational values they provide to people. Rather, to achieve the desired outcomes of efficient infrastructure development *and* the conservation of healthy forests and clean rivers we need to:

1. Understand where energy development is most likely to occur;
2. Identify other biological resources and ecosystem services present in those areas;
3. Undertake detailed conservation planning in areas where high energy development probability and other high resource values co-occur, and
4. Identify strategies to avoid, minimize and fully compensate for impacts ensuring no net loss of functions and values.

The datasets we have created depict future potential risks from the development of coal, natural gas, and wind energy across the Appalachian LCC to key ecological features, such as forest cores and intact watersheds. Through the online mapping tool developed as part of this project the datasets can be accessed by industry, land managers, NGOs, regulators, and the public to use for project screening, regional planning and assessment, and mitigation. By producing these analyses and working with the Appalachian LCC to further their use, we hope to provide the basis for constructive conversations among the Cooperative's partners and with industry, regulatory agencies, and the public on developing a forward-thinking framework that values energy development alongside clean air, clean water, and the multitude of other benefits that people derive from nature. Such a framework could include voluntary practices, comprehensive planning, and sensible regulation so that the region's highly desirable energy resources may be extracted in ways that also preserve the region's high-quality forests and rivers.

INTRODUCTION

Background and Purpose

Global demand for energy has increased by more than 50 percent in the last half-century and a similar increase is projected through 2030 (IEA 2009). In the United States, technological advances and concerns about CO^2 emissions and energy security have spurred a rapid increase in alternative and unconventional energy production over the last decade. Because of this mounting demand, overall energy development is projected to continue its steep upward trajectory and encompass more than 200,000 km^2 (49 million acres) in the U.S. alone by 2035 (IEA 2009, McDonald et al. 2009). Clearly, how we choose to meet U.S. and global demands for energy will have significant implications both for biodiversity and human well-being. Anticipating and mitigating these impacts will be among our greatest conservation challenges in coming decades (Kiesecker et al. 2010).

The purpose of this report is to communicate the results of an effort to model areas within the Appalachian Landscape Conservation Cooperative (LCC) that have the highest probability of experiencing changes in land cover as a result of the development of wind, shale gas, and coal resources, and to illustrate how these models can be used to assess potential risk to species, habitats and ecological services at a regional scale. The analyses conducted here build on previous assessments conducted by The Nature Conservancy in the Appalachians Landscape (Johnson 2010; Evans and Kiesecker 2014). This report supports the Appalachian LCC's goal to "create and deliver a landscape-level data sharing strategy and scalable toolsets" (APPLCC 2012). The report also helps meet the identified need for science that will improve decision-making by increasing people's understanding of potential land-use changes, economic impacts, and pressures on the resources of the Appalachian LCC region (APPLCC 2011). The specific objectives for this project were the following:

1. Examine how potential future energy development in the Appalachians overlaps with important natural areas that support biodiversity, healthy ecological systems, and drinking water resources;
2. Illustrate the potential consequences of energy development on the region's biodiversity and ecological services by assessing the impacts of development on forests, and watersheds;
3. Strengthen the capacity of the Appalachian LCC members to better understand and effectively communicate to others how areas with a high potential for energy development may intersect with

intact forests and watersheds in order to increase the potential for development outcomes that avoid, minimize, and compensate for unintended harm to human and natural communities.

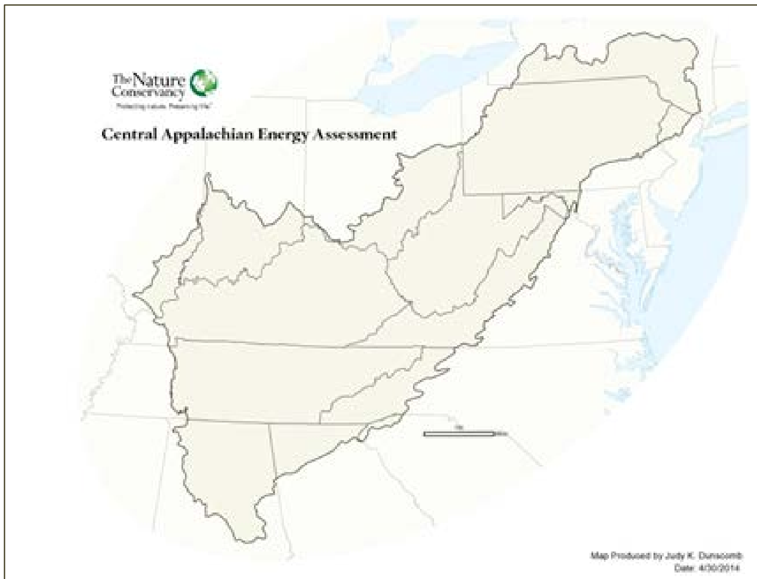

Figure 3: Appalachian Landscape Conservation Cooperative

This report includes the following contracted deliverables:

1. Models that predict the probability of development for wind energy, multiple shale gas plays, and surface coal mining across the Appalachian LCC, and a model that predicts the probability of wet shale gas development within the Utica Shale gas play;

2. Assessment of potential cumulative impacts of energy development on natural resources, using indicators such as forest fragmentation and ecosystem services (in this case, water availability) to illustrate potential regional impacts, which we reported using metrics such as percent loss of important resource areas; and,

3. A series of GIS layers depicting energy probability models and cumulative impact assessments delivered via a web-based map visualization and data server developed as part of this study. This web-based mapping tool allows the public access to data for downloading and viewing and is accessible from TNC and the Appalachian LCC web sites

The Appalachian LCC Region

Landscape Conservation Cooperatives such as the Appalachian LCC were founded in recognition of the scale and complexity of threats in the 21st century (USFWS 2014). Many ecologists and organizations have recognized that effective conservation requires collaborative planning for species populations and habitats across large geographic areas (Trombulak and Baldwin 2010; USFWS 2014).

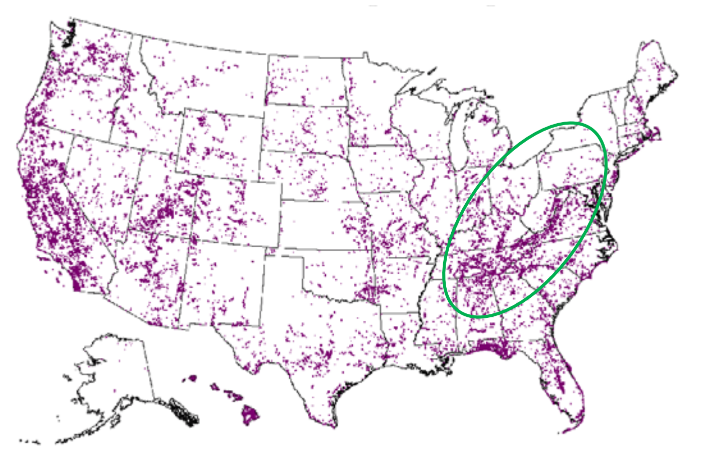

Figure 4: Distribution of Imperiled Species in the U.S. The green oval approximates the area within the APPLCC. Source: Chaplin et al 2000.

The Appalachian LCC covers approximately one-third of the land area of the contiguous U.S. and extends from New York south to Alabama and west to Illinois, spanning 146 million acres across fifteen U.S. states (Figure 3). A complex mosaic of ridges, valleys, and rolling plains, the Appalachian LCC is 62% forested and largely coincides with the Temperate Conifer and Broadleaf Forest biome. This type of forest is among the most threatened habitats on Earth (Olson and Dinerstein 1998; Hannah et al. 1995) with more than 46% of its original extent having been converted out of natural land cover (Hoekstra 2005). The region's complex terrain, temperate climate, and the millions of years over which species have evolved free of the disturbance of glaciation have combined to make the Appalachian region a recognized biodiversity hotspot (Figure 4).

For example, the Tennessee-Cumberland river system that lies at the heart of the Appalachian LCC is the nation's richest in aquatic fauna and includes more endemics than any other North American river basin (Jenkins et al. 1972). Biologists have identified the Tennessee-Cumberland as a global center of salamander diversity, and documented numerous imperiled species including freshwater mussels, fishes, cave invertebrates, plants, and amphibians (Chaplin et al. 2000). In addition, the Appalachian LCC encompasses two of the three major eastern cave regions (the Appalachian and the Interior Low Plateau, and is a global center of cave species diversity (Figure 5, Christman et al. 2005). The

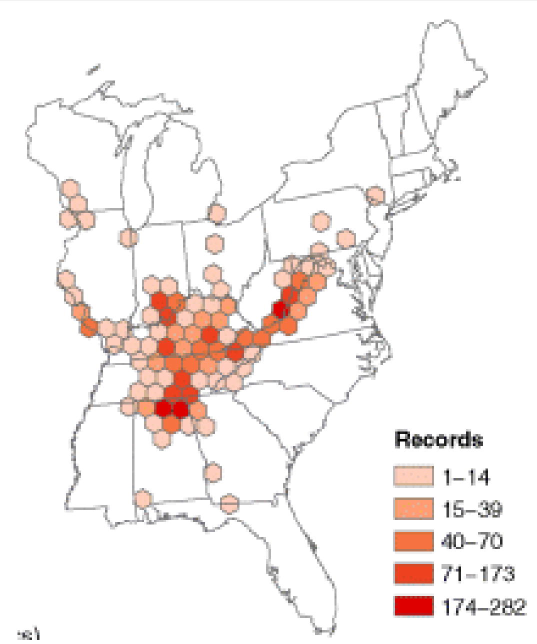

Figure 5: Records for Cave Obligate Organisms in the Eastern U. S. Source Christman et al 2005

Appalachian's extensive forests and healthy streams also provide drinking water for over 22 million people as well as prime hunting, fishing, and recreational opportunities.

The biologically rich Appalachians are also the energy resource hub of the eastern United States. Coal mining has defined the Appalachians for generations and remains a major consideration even though its future is uncertain. There is a complex, dynamic relationship between the price of coal and the relatively high cost of recovering Appalachian coal from its remaining thin seams. Policies that call for a reduction in greenhouse gas emissions may also reduce the demand for thermal coal. Despite these obstacles, the Appalachian region produced 292 million short tons of coal in 2012, which is just under one-third of total U.S. production. Of this output, about one-third was surface mined (EIA 2013). The U.S. Energy Information Administration (EIA) projects that total U.S. coal production will grow 4.1% to 1,024 million short tons in 2014 but decline slightly in 2015. Notably, Appalachian coal production is projected to decline by 2.7% whereas production in the central portion of the U.S. is expected to remain steady (EIA 2014).

Two new forms of energy compete with coal on the Appalachian landscape. Miles beneath the surface, formations of gas-rich shale laid down in deep anoxic waters around 400 million years ago are being tapped using recently developed hydraulic fracturing techniques. The mining of this large, ''unconventional'' source of gas dispersed in shale is expected to be a key component of energy production in the next several decades (Wood et al. 2011). Within the Central Appalachians, the Marcellus and Utica shale gas plays alone may yield over 120 trillion cubic feet of gas (Kirschbaum et al. 2012; Coleman et al. 2011). According to statistics on annual consumption by gas customers from the American Gas Association (2014) and from the U.S. Census Bureau (2014), this is enough gas to meet the needs of every household in the United States for approximately 18 years.

The broad southwest-to-northeast tending ridges that extend from western Pennsylvania to eastern West Virginia, known as the Allegheny Front, offer a third and potentially rich source of energy—wind. As some of the windiest spots east of the Mississippi River, these ridges are attractive for wind farms that could help heavily populated Eastern states meet renewable energy standards. Timeframes across states vary, but the U.S. Department of Energy has a stated goal of producing 20%

of U.S. electricity, or 241 gigawatts, from terrestrial wind energy development by 2030 (U.S. DOE 2008).

We posit that the status quo of permit by permit, project by project energy development is poorly suited to maintaining the Appalachian's extensive forests and rivers, the unique biological heritage they support, and the drinking water and recreational values they provide to people. Rather, to achieve the desired outcomes of efficient infrastructure development *and* the conservation of healthy forests and clean rivers we need to:

1. Understand where energy development is most likely to occur;
2. Identify other biological resources and ecosystem services present in those areas;
3. Undertake detailed conservation planning in areas where high energy development probability and other high resource values co-occur, and identify strategies to avoid, minimize and fully compensate for land protection or other actions to ensure no net loss of functions and values.

METHODS

General Approach

We developed a risk assessment for future energy development to estimate the potential impacts on forest and aquatic resources across the 15 eastern states comprising the Appalachian LCC (Figure 3). We developed spatially explicit models predicting the probability of wind development, development of multiple shale gas plays across the LCC, and surface coal mining for the entire study area and the probability of wet shale gas development within the Utica play. Because our primary objective was to look at the land-use impacts of energy development, we did not attempt to estimate the probability of underground coal mining. The modeling approach we chose uses "presence

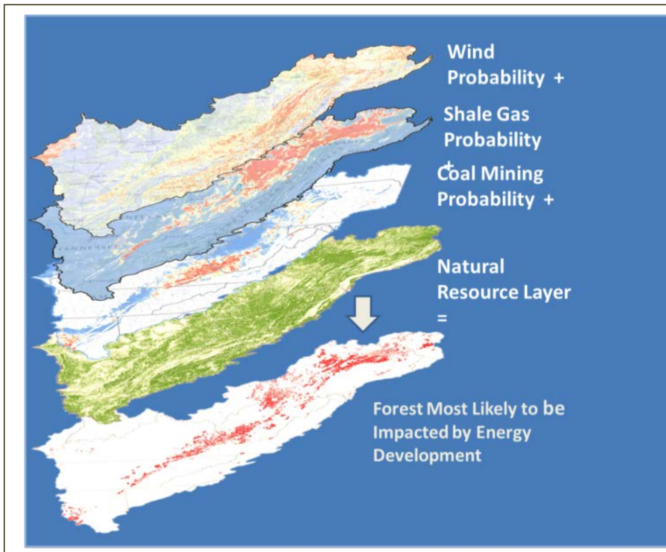

Figure 6: Illustration of intersecting energy and resource layers.

points" of actual gas wells, wind turbines, and surface coal mines along with independent variables associated with each form of energy development, such as thermal maturity, wind speed, and coal geology to predict where future energy development is more or less likely to occur. We imposed a threshold of $p \geq 0.90$ on the model output so as to select areas where energy development was most likely to occur. We then intersected that subset with data layers for forest cover and natural communities to identify areas potentially affected by energy development (Figure 6). We also calculated the cumulative potential risk scores for interior forest habitat patches (forest cores) and 12-digit hydrologic units (watersheds) across the Appalachian LCC. Finally, to estimate some potential cumulative impacts of energy development to people and wildlife, we intersected the energy probability layers and forest and watershed cumulative potential risk scores with GIS layers of important natural habitat areas and ecosystem services (i.e. drinking water and recreation).

Statistical Models

We compiled spatial databases of wind energy development (projects submitted for permitting by the FCC and installed turbine locations), shale gas development (permitted and drilled shale gas wells) and coal mining (surface coal mining permits) along with covariates identified through a multidisciplinary scoping process as likely to influence development (Table 1). The probability of surface coal mining was modeled only for areas within the Appalachian LCC that correspond to coal supply regions mapped by the U.S. Energy Information Administration in 2013 (Figure 7).

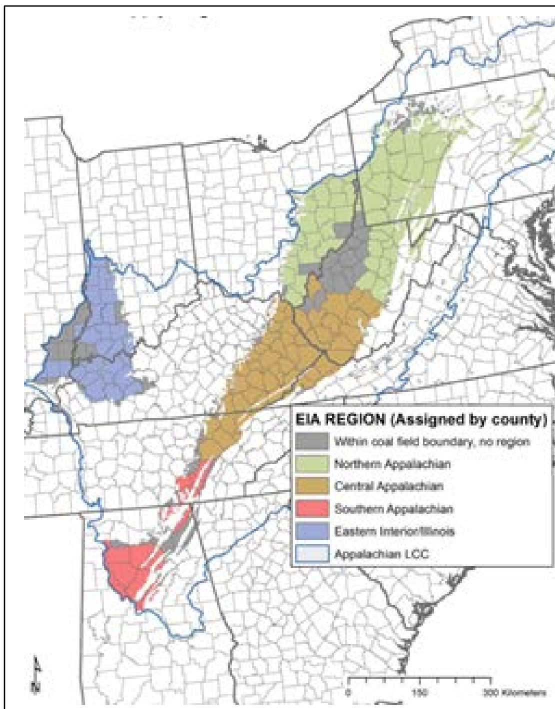

Figure 7: Coal Model Extent. The area modeled for probability of coal mining was limited to the U.S. Energy Information Administration Coal Supply Regions within the Appalachian LCC.

We utilized a class of statistical models referred to as "weak" or "ensemble" learners (Hastie et al. 2009). These are a very powerful class of non-parametric models that rely on multiple realizations of the data to fit an optimal predictor. We utilized the Random Forests algorithm (Breiman 2001) as the specific partitioning statistic in our predictive models for coal, shale, and wind. This statistical approach is a very robust model for classifying high-dimensional (large number of independent variables) multivariate data particularly with dependent variables exhibiting a Bernoulli [0,1] distribution (Evans et al. 2011). Nonparametric models do not require assumptions of normality, and the Random Forests algorithm can handle mixed variable types, is robust to over fit and autocorrelation effects and automatically accounts for high-dimensional interactions (Evans et al. 2011). The Random Forests algorithm generates an ensemble of models using an iterative bootstrap (or sampling of) the data. Recursive hierarchal partitions are created for each data subsample using a Classification and Regression Tree algorithm with an entropy splitting equation.

This approach is ideal for data where the classes may overlap, making it extremely useful for a model where we are forced to use random data for the null class or where the data is inherently noisy. Model estimates are made through a plurality votes matrix and probabilities are derived by looking at the poster distribution of the votes matrix (Evans and Cushman 2009).

Because the Random Forests algorithm only uses a subset of the data in each model iteration (the bootstrap sample), some of the data are withheld. The withheld data are called out-of-bag (OOB) data. In order to assess the importance of a predictor variable in the model, the variable is withheld and the model is rerun without the variable present. The OOB data are classified. The mean decrease in accuracy for the classification of the OOB data, once the variable is removed from the model, provides an estimate of the importance of that variable. By back-predicting to the withheld data, the OOB also provides a measure of model fit without the need for an independent data withhold, simplifying the process of model evaluation (Breiman 2001).

Model Specification

Surface Coal Mining

For the coal model a binominal dependent variable was specified using classified presence of surface mining [1] or absence of surface mining [0] using mine permit centroids. Only mines permitted after the year 2000 were considered to ensure that we were capturing active mines that are using current surface mining techniques. Predictor variables were analyzed with the dependent variable of location of active surface mine permits. Surface mining permit locations were obtained from individual state agencies for the ten coal-producing states within the study area (AL, IL, IN, KY, MD, OH, PA, WV, VA). Mining permits were further limited to active surface mining permits by excluding underground mines and permits associated with inactive or historical mines. In certain states, if permit status (active/inactive) was not indicated, permits were limited to those with dates from the year 2000 to the present in an attempt to limit the analysis to current, active mines.

In order to create more variability and to decrease correlation in the model, we generated five separate sets of absence data. First, we generated random points across the coal extent of the study area, and removed all random points occurring within a mine permit or within 0.5 miles of a surface mine centroid. We then drew five separate random samples. For each set of training data we used an equal number of presence and absence points (5,165 of each and 10,330 total). The same presence data were used in each set with a different set of absence points. All of the predictor variables were assigned to the training points from the raster cell at that location using the software tool Geospatial Modeling Environment (Beyer 2014).

The data were then read into the statistical package R and the Random Forests algorithm run using the Random Forest package (Liaw and Wiener 2002). A separate model was generated for each of the five training sets. For each model 1,000 trees were generated, and the number of randomly selected predictor variables sampled in each tree was set to 3 (the square root of the number of bands, which is the default setting). All five of the models were then combined to produce a model containing 5,000 trees. Using the final combined model, all 1 km^2 pixels in the coal extent study area were classified and the probability of the pixel being a surface mine was predicted to a 1km^2 raster surface using the RandomForest raster package (Hijmans 2014).

Coal Kriging Models

We implemented Ordinary Kriging models for creating 1km^2 sulfur and ash raster surfaces (Cressie 1991). We examined the data for normality and spatial trends, and we fit an experimental semiovariogram. Because coal geology follows unique ridge and topographical synclines, directional variation (anisotropy) was examined for all the models. For the ash model, we found improved fit by specifying anisotropy parameters at an angle of 44.6 and a 45 degree tolerance. The sulfur model did not require any adjustments for anisotropy. The BTU model was specified using a Simple Kriging model. A log transformation was applied to the BTU values to make the variances more constant throughout the study area and make the variable normally distributed. We explicitly modeled directional variation (anistropy) and incorporated it into the model. Models were validated using the root mean squared error from the cross-validation prediction errors. Modeling was conducted using the Geostatistical Analyst extension in ArcGIS 10.1 (Johnston et al. 2001).

Shale and Wind Models

We generated two shale gas models (one for wet gas in the Utica shale play and one for multiple plays across the entire Appalachian LCC) and one wind model for the entire Appalachian LCC. To do this we developed a new non-parametric modeling approach that provides robust estimates of the probability of resource development at each pixel based only on known locations (Evans and Kiesecker 2014). To develop this approach we first created random observations to act as the "absence" class in the model utilizing an isotropic density estimate (Diggle 2003). The probability density values of the random sample allowed us to weight the random sample, thus providing a more likely random sample the further away it is from a known well or turbine and providing a conditional sample based on the spatial process of the known locations. The "presence" class was represented by known observations. In a given iteration of the model, the number of random observations generated was the same size as the number known observations.

A model was then built using the Random Forests algorithm (Breiman 2001; Evans et al. 2011) and the probabilities were predicted back to the training data. The estimated probabilities were set aside, a new set of random points created, and the process repeated. At each iteration where the modeling process was repeated, the new model was combined with the previous ones and the new probability estimated based on the ensemble. This was repeated until the resulting probability distribution was unchanged when compared to previous model iterations using a Kolmogorov-Smirnov distributional equality test (Birnbaum and Tingey 1951) at a p=0.001 confidence. Once the model converged, it was predicted to the final set of raster surface variables identified in the model. We then predicted a 1km^2 raster surface of the resource development probabilities.

This method provides two distinct advantages. First, it has been demonstrated that bootstrap approaches converge on stable probability distributions that are comparable to Bayesian methods such as Monte Carlo Markov Chains (MCMC). Second, given the condition that the parameters are fixed, these models can be run as a series of independent models with different data and combined into a new ensemble. This new ensemble is justified because the theory of weak learning is based on combining a series of models based on randomized subsets of data. This can easily be extended to incorporate random models across several independent ensemble models constructed using different training data with a fixed set of parameters.

Table 1: List of Independent Variables, Associated Model, Data Source, and Brief Description

Variable name	Model	Source	Description
Surface dissection	Wind	USGS	Dissection of elevation in (3x3 window)
Wind Production Classes	Wind	DOE-NREL	NREL Wind production classes
Distance to transmission	Wind	Ventyx	Euclidian distance to power transmission
Topographic Roughness	Wind	USGS	Variance of elevation in (9x9 window)
Bouguer Anomalies	Shale, Utica	USGS	Gravitational anomalies (Bouguer)
Isograv Anomalies	Shale, Utica	USGS	Gravitational anomalies (Isogravitational)
Magnetic Anomalies	Shale, Utica	USGS	Gravitational anomalies (Magnetic)
Shale Depth	Utica	Ohio Dept. Natural Resources	Depth (m) of shale
Shale Thickness	Utica	Ohio Dept. Natural Resources	Thickness (m) of Utica shale
Surface geology	Utica, Shale	USGS	Formation type
Topographic Roughness	Shale	USGS	Variance of elevation in (3x3 window)
Coal supply region	Coal	EIA	Coal supply regions for Appalachians
Mountaintop removal region	Coal	EPA	Mountaintop removal mining regions
Coal geology type	Coal	USGS	Generalized coal fields
Sulfur percentage of coal	Coal	USGS Coal Quality database	Percentage of sulfur in coal indicating ash yield
BTU Content of Coal	Coal	USGS Coal Quality database	BTU content indicating energy output
Distance to coal fired power plants	Coal	EIA/ESRI	road distance to coal-fired power plants
Distance to intermodal transportation facilities	Coal	BTS/ESRI	road distance to freight transfer stations
Distance to inland ports	Coal	BTS/ESRI	road distance to inland shipping ports
Distance to rail	Coal	EIA/ESRI	Euclidian distance to railroads
Population density	Coal	U.S. Census Bureau/ESRI	Density of human population

Based on previous shale modeling efforts in the Marcellus shale formation (Evans and Kiesecker 2014), we specified ten potential predictor variables in the Utica wet gas model. Following model selection procedures in Murphy et al. (2010), we identified seven variables that explained model fit (Table 1). Unfortunately, two of these variables (shale depth and thickness) were based on deep-well monitoring data that were not available for the full extent of the Appalachian LCC. We therefore specified the Appalachian LCC shale plays model using the five remaining variables representing gravitational anomalies (Bouguer, isogravimetric, magnetic), topographic variability, and surface geology. For the Utica Wet Shale gas model, we also used shale depth and thickness. Modeling was conducted using ArcGIS (ESRI), Geomorphometrics and Gradient Modeling Toolbox (Evans et al. in prep), R (R core team) and RandomForest R package (Liaw and Wiener 2002).

To simplify and improve the prediction of impacts associated with shale gas development, we combined the model of multiple shale gas plays across the Appalachian LCC and the Utica-specific wet shale gas models with a third model we previously generated for the Marcellus play, which exhibited very high accuracy (Evans and Kiesecker 2014). We overlaid the three model rasters and used the maximum modeled probability score of each cell to create the "LCC Max Gas" model, which was used in all resource intersections.

Resource Layers

In addition to mapping probability of energy development, a desired outcome of this study was to illustrate the intersection between areas of concern for natural resource conservation and with high probability of energy development. Natural resource values considered important for the region were forest habitat, aquatic habitat, cave and karst habitat, and ecosystem services including drinking water and protected lands. We evaluated potential natural resource data sets according to three criteria: relevance to resource conservation; likelihood of being affected by activities associated with energy development; and availability of documentation describing the methods used to generate layer and the consistency and replicability thereof. Ten data sets met our specification criteria and are described in Table 2.

Table 2: Natural Resource Layers Evaluated for Risk from Energy Development

Resource Layer Name	Source	Description
NLCD Forest Cover	USGS	30m raster of forested land cover
Nature Serve Ecological Systems	USGS	30m raster of vegetation types
Interior Forest Cores	The Nature Conservancy	shapefile of interior forest patches greater than 500 acres
Protected Areas Database	USGS	shapefile of areas with some degree of conservation management restrictions
12-Digit HUCs	National Hydrography Dataset	small watersheds
Important Surface Drinking Watersheds	U.S. Forest Service	National ranking of watersheds' ability to provide clean drinking water
Watershed Impervious Cover	USGS	30m raster of impervious cover
TNC Aquatic Portfolio	The Nature Conservancy	Aquatic habitat conservation prioritization
USGS Karst Dataset	USGS	shapefile of cave and karst geology

Analysis of Energy Development Impacts - Raster Datasets

To determine energy development probability of forest cover and ecological systems, we selected ≥ p=0.90 as a threshold for high energy development probability. We tested the appropriateness of this threshold by calculating the area with p=0.90 or greater, and comparing it with published energy development projections from federal agencies to ensure that the acreage indicated by the ≥ p=0.90 threshold was consistent with those projections (U.S. DOE 2011, Coleman 2011, Kirschbaum 2012, EIA 2013b).

<u>Forest Cover</u> – We elected to evaluate the intersection between energy development and forest cover because the Appalachian LCC is within the temperate deciduous forest biome, and forest is the dominant habitat type in the region (62% of land cover). Forest cover is a class in the 2006 National Land Cover Database (NLCD) that is dominated by either deciduous or evergreen trees generally greater than 5 meters tall and greater than 20% of total vegetation cover (Fry et al. 2011). NLCD is a 16-class land cover classification scheme that has been applied consistently across the conterminous United States at a spatial resolution of 30m. To assess potential impacts to forest cover from energy development, we extracted the forest cover class from 2006 NLCD and intersected it with development probabilities ≥ p=0.90).

<u>Ecological Systems</u> – The National Vegetation Classification System is a national ecological map that represents recurring groups of biological communities that are found in similar physical environments and are influenced by similar dynamic ecological processes, such as fire or flooding

(Comer et al. 2003). We utilized a 30m dataset of terrestrial ecological system units developed by NatureServe (USGS 2011b) and intersected it with development probabilities ≥ p=0.90 for each energy type to identify the 30m cells at high potential risk of energy development.

Analysis of Energy Development Impacts - Feature Datasets

We defined the "potential energy development risk" within forest cores and watersheds by summarizing cumulative risk scores for each polygon. This was done to better reflect potential risk to natural resources that may overlap with lower probability energy resource areas but where other constraints not accounted for in the energy probability models may still render the area desirable for energy development. Through previous simulation work (Breiman 2001) and as indicated in probability theory (Hastie et al. 2009) a critical threshold of p=0.65 is supported as being indicative of a high likelihood of the processes being true. We adopted this known threshold and set all values < p=0.65 to zero, to provide a non-influencing constant value. We then calculated the cumulative probability for each unit using the following equation:

Equation 1

$$f_p(p) = \left[\frac{\sum p_{ij}}{a/\max(a)}\right] / \max\left[\frac{\sum p_{ij}}{a/\max(a)}\right]$$

where; p_{ij}=cumulative probability of patch, and a=area, which normalizes for differences in area among polygons and sets the final value within a range from 0 to 1.

We then used percentiles to classify relative potential risk scores for forest cores and watersheds into categories: (None = 0, Low < 0.50, Moderate 0.50 – 0.75, High 0.75– 1).

Forest Cores – Forest cores are areas of interior forest habitat within forest patches where forest patches are defined as areas of contiguous natural cover bound by non-natural edge or linear fragmenting features (roads, railroads, transmission lines, natural gas pipelines). We utilized a dataset created by The Nature Conservancy to derive forest cores (Appendix 1). To delineate interior forest cores, we applied a negative 100 meter buffer around all patches to represent that portion of the patch that contained interior forest habitat. The 100m buffer was based on the body of research regarding the comparative success of breeding songbirds relative to their distance from the edge of the occupied habitat patch (Paton 1994; Chalfoun et al. 2002; Manolis et al. 2002; Weakland and Wood 2005). Cores that were divided into multiple parts by the buffering process were treated as separate patches. The resolution of the energy probability rasters is 1km^2 (247.11 acres) so we eliminated all cores less than 500 acres to reduce the error created by partial pixel intersection. In order to reflect the area that would reduce the size of the interior forest core, we re-buffered the remaining polygons by 100m. We then calculated the cumulative relative potential risk using eq. 1.

Watersheds – Watersheds are a useful unit of analysis for assessing impacts to aquatic habitats because they integrate the effects of all land uses occurring within the area that drains to a common body of water, such as a stream. We used the smallest unit-definition in the hierarchy of hydrologic units (12-digit HUCs) using the National Hydrography Watershed Boundary Dataset (USGS 2014). We then calculated the cumulative relative potential risk (eq. 1) for each watershed.

To determine the relative potential risk of energy development to resources of concern, we intersected resource data layers with either forest cores or watersheds and attributed the resource layer with the relative potential risk score of the intersecting polygon.

Protected Areas – The Protected Areas Database of the United States (PAD-US) is the national inventory of U.S. terrestrial and marine protected areas that are dedicated to the preservation of biological diversity and to other natural, recreation and cultural uses, and managed for these purposes through legal or other effective means. Lands in PAD-US are mainly open space/resource lands owned by agencies and non-profits. The current data set includes the "gap ranks" of these lands, indicating how they are being managed for conservation purposes. (USGS 2012) Gap ranks range from 1-4. Only GAP Status Codes 1 and 2 meet the definition of protected by IUCN (USGS 2011a). Many areas included in the PAD-US are available for energy development, including areas with GAP status 1 and 2 which may have severed gas or mineral rights. Since we were unable to distinguish between protected areas on which energy development was prohibited, and those on which it was not, we included all protected lands in our assessment of potential energy development risk.

Forest habitat conservation is generally the greatest conservation concern on protected lands in the Eastern United States. We therefore evaluated the potential impacts of energy development on forests on protected lands by selecting all forest cores that intersect with the protected lands layer and by calculating the number and area of forest cores at potential risk for energy development.

Important Surface Drinking Watershed – The U.S. Forest Service's Forest to Faucets analysis indicates the relative importance of watersheds to drinking water, based on the potential amount of water produced and the number of people who use that water (Barnes et al. 2009). We selected the upper quartile of total percent-forest and private percent-forest (national weighted importance ≥ 0.75) as important for drinking water production and intersected that subset of watersheds with the combined potential energy risk layer. From this we calculated the number and location of watersheds exhibiting important characteristics for drinking water that are potentially at risk for energy development.

Watershed Impervious Cover – Impervious cover represents the percent of impervious surface, at 30m resolution, for the conterminous United States and is part of the NLCD dataset (Greenfield et al. 2009). Impervious cover is used as a metric for predicting how much water will infiltrate soil versus how much will run off as overland flow. Forests are considered to be completely permeable to rainfall; in contrast, roads, pipelines, well and turbine pads, and reclaimed mined lands all have different infiltration capacities. We calculated percent impervious cover for each 12-digit HUC and then applied King's impervious cover model (undisturbed, 0 < 0.5%; low impacts, 0.5-2%; moderately impacted, 2-10%; highly impacted, >=10%) to classify the watersheds (King et al. 2011). We evaluated the intersection of the two lowest impervious cover classes with the cumulative potential energy risk to each HUC to identify watersheds at highest potential risk of transitioning upwards toward these higher class designations (Hilderbrand 2010).

TNC's Aquatic Portfolio – The Nature Conservancy developed a methodology for identifying the set of stream reaches that would need to be conserved to protect all the representative native biodiversity in a given aquatic ecoregion. The general approach is to select and set conservation goals for a set of fine filter (G1 and G2 species) and coarse filter (aquatic ecological systems) targets that combined represent the native biodiversity of an aquatic ecoregion. Known occurrences of these targets are mapped and evaluated for viability, and occurrences are selected to meet goals based on the principles of efficiency and complementarity. The output of this assessment process is called a freshwater ecoregional portfolio (Higgins and Esselman 2010). We compiled the portfolios resulting from freshwater ecoregional assessments within the study region (Smith et al. 2002, TNC 2012) along with supplemental portfolio streams identified by the Indiana, Illinois, Kentucky, and Ohio operating units. The latter consisted of the Whitewater River (IN and OH), Middle Fork Kentucky River (KY), and Tygarts Creek (KY). We then selected all HUC-12s that intersected a portfolio stream segment to create and aquatic portfolio layer for this study. Finally, we intersected the aquatic portfolio layer with the HUC-12 cumulative relative potential risk layer to the locate priority watersheds for aquatic conservation at highest potential risk from potential energy development.

Karst Geology – The USGS has published a report and GIS database describing and delineating areas underlain by soluble rocks that have potential for karst development. Distribution of areas of mature surface karst in the contiguous United States is primarily dependent on the presence of soluble rocks at or near the land surface and mean annual precipitation above approximately 30 inches. In the humid parts of the United States, most karst features such as caves and sinkholes occur in carbonate (limestone and dolomite) rocks. Carbonate rocks at or near the land surface in humid regions are typically karstified and contain varying densities of sinkholes, caves, and other karst features. Carbonate rocks buried beneath 50 feet of glacially derived insoluble sediments commonly produce cover-collapse sinkholes in areas where karst is overlain by loess or other cohesive unconsolidated deposits (Weary and Doctor 2014). We intersected the data layers for carbonate rocks at or near the land surface and carbonate rocks buried beneath 50 feet of glacially derived insoluble sediments with the cumulative potential energy risk probability for each HUC-12 and calculated the location and number of watersheds with karst producing geology that were at potential risk for energy development.

RESULTS

Coal Model

The highest modeled probability for future surface mining (Figure 8) is found in the Central Appalachian region, particularly throughout southwestern West Virginia and eastern Kentucky. Other pockets of higher probability are found in western Kentucky and central Alabama, and to a lesser extent, north central West Virginia and the bituminous coal region of Pennsylvania and Ohio.

The final Random Forests model scenario included a total of ten predictor variables. We considered removing low-performing variables from the final model, based on variable contribution to the overall result. However, alternative models with fewer variables did not perform as well as the full model, producing higher classification error rates. As estimated by the out-of-bag mean decrease in accuracy, the coal geology type and the sulfur content were found to be the most important predictor variables in the model, though all variables contributed. For each training dataset, the out-of-bag error estimate was around 15% and the misclassification of presence and absence points were evenly balanced. Plotting the error rate against the number of trees generated suggests that 1,000 bootstrap replicates were more than ample to stabilize the error.

Model significance was tested versus randomly generated models and was found to be significant with a p- value of 0.0101. The total area within each EIA coal supply region with relatively high probability (≥

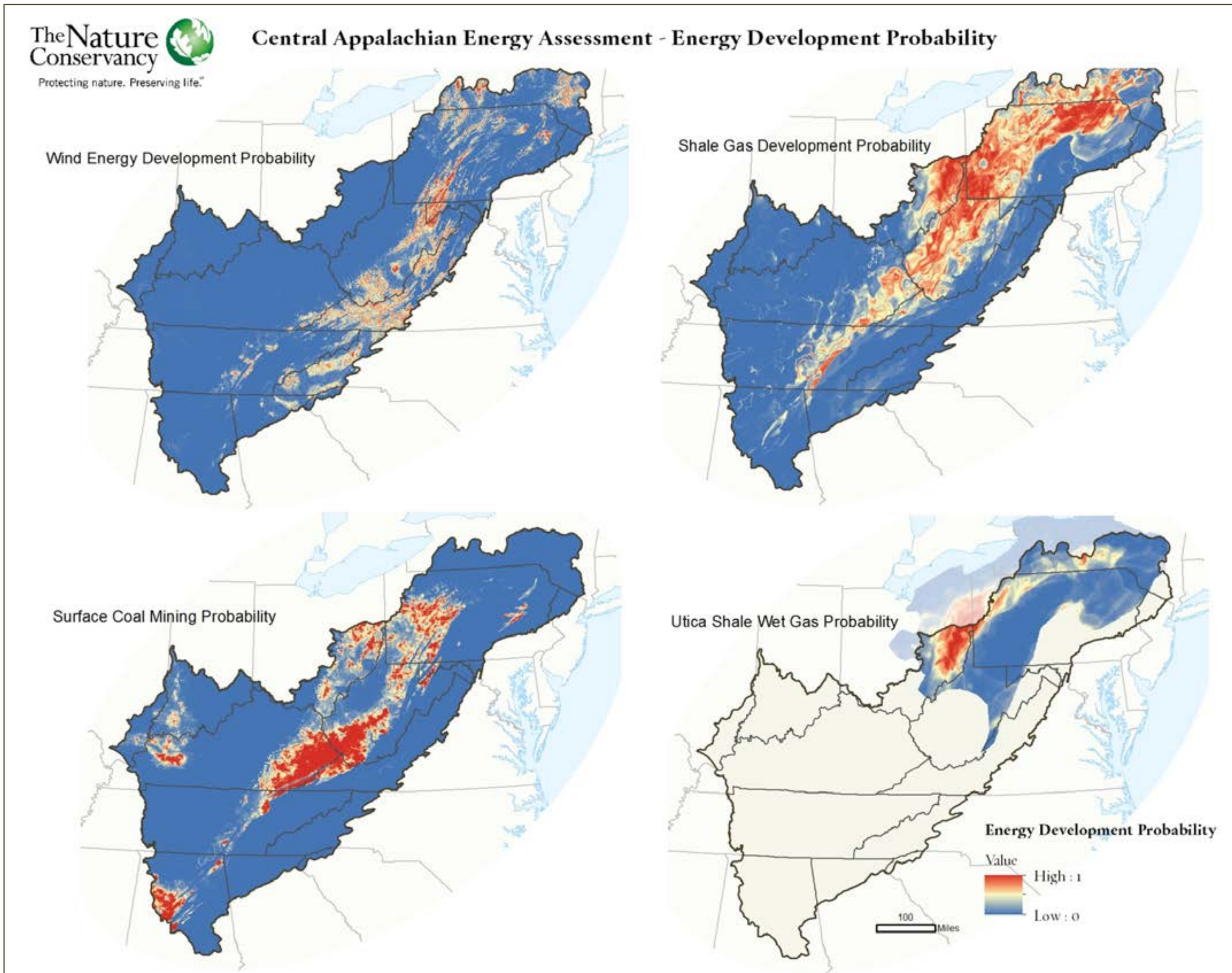

Figure 8: Results for Four Energy Probability Models.

p=0.90) is listed in Table 3. The Central Appalachian region has the highest percentage of high probability areas for the four regions, while the Northern Appalachian and Eastern Interior/Illinois regions have a very small percentage. Note that while the Northern, Central and Southern Appalachian coal supply regions lie completely within the current study boundary (Appalachian LCC), the Eastern Interior/Illinois coal supply region also includes production in portions of western and central Illinois and Mississippi that are not included in the study area for this project. Based on the most recent available coal production statistics from 2011 (EIA 2012), there are a total of six counties in the Eastern Interior/Illinois region that produce coal but are located outside of the project study region. For 2011, these six counties accounted for 11.7% of the total surface coal production for the Eastern Interior/Illinois region (so approximately 11-12% of coal production in this region will not be accounted for in our model results and projections). Strager et al. performed additional scenario analyses on the relative footprint of surface coal mining within each of the coal supply regions which were not incorporated in to this report (see Strager et al. 2013 for details and results).

Table 3: U.S. Energy Information Administration Coal Supply Regions, with Area of Relatively High (≥ P=0.90) Probability of Future Surface Coal Mining Based on Random Forests Model Results

Region Name	Regional Area (acres)	Area < p=0.90 (acres)	Area ≥ p=0.90 (acres)	% of Region < p=0.90	% of Region ≥ p=0.90
Northern Appalachian	17,013,673	16,898,275	115,398	99.32	0.68
Central Appalachian	13,291,284	12,199,080	1,092,204	91.78	8.22
Southern Appalachian	3,571,903	3,369,277	202,626	94.33	5.67
Eastern Interior/Illinois	6,955,264	6,930,801	24,463	99.65	0.35

Shale and Wind Models

Both the combined shale and wind models exhibited high predictive power with Kappa (k=0.87, k=0.77) and area under the receiver operating characteristic curve (AUC) (α=0.96, α=0.94) respectively. A randomization test (n=9999) supported the models at a significance level of p=0.001. Whereas the models are statistically well supported, data on drilling activity were only available for the Marcellus shale as the other Appalachian plays are just starting to be developed – an issue we anticipated when we submitted our proposal to the Appalachian LCC. Consequently, extrapolation of the probabilities in the southern portion of the study area is highly uncertain. We also found that probabilities correspond well with more specific shale models (Utica wet gas and Marcellus). To model the entire Appalachian

LCC, we chose to develop a model that represents general shale gas potential across the region by using all available data spanning both the Marcellus and Utica formations (Utica wells n=321, Marcellus wells n= 10,419) as well as a specific Utica shale model (Figure 8). Whereas we expect the Appalachian LCC-wide model will illustrate potential hotspots of gas development across the study area, we believe that the uncertainty associated with the spatial prediction in the southern portion is too high to support any scenario development or to be used to guide decision making. The available Utica well data is from wells producing wet gas, which contains less than 85% methane and has a higher percentage of liquid natural gasses (LNG's) such as ethane and butane. LNG's have multiple commercial uses which makes drilling of new wet gas wells more profitable in the current market where prices for methane (dry natural gas) are relatively low. Consequently, the Utica shale gas model largely represents the probabilities of wet gas development, rather than all gas development in the play. Low probabilities therefore do not necessarily represent low potential development of the dry gas resources.

Patterns of Energy Development

Our energy models identify 30,778 km^2 (7,605,552 acres) as having a high probability of energy development (≥ *p*=0.90). Shale gas accounts for nearly 60% of this area with 18,312 km^2 (4,525,078 acres) with a high probability of development. Wind accounts for only about 22%, or 7,018 km^2 (1,734,218 acres), and coal accounts for approximately 18%, or 5,788 km^2 (1,430,273 acres) (Table 4).

Pennsylvania and West Virginia have much larger percentages of high-probability (≥ *p*=0.90) energy development for all sources (44% and 21%, respectively) than do other states within the study area. Ohio has the third largest percentage for all sources (10%), to which shale gas makes the largest contribution (16%). Kentucky is fourth and has the largest percentage of high-probability coal development (45%). These four states plus New York support 90% of the high-probability energy development area for all energy sources.

Table 4: Percent of High Energy Development Probability Area within Each Appalachian LCC State

State	% of Appalachian LCC Area	% Total High Wind Probability Area	% Total High Shale Gas Probability Area	% Total High Surface Coal Mining Probability Area	% Total High Probability Area for all Sources
Pennsylvania	16.38%	31.55%	60.48%	3.37%	43.54%
West Virginia	10.64%	21.99%	17.15%	33.52%	21.41%
Ohio	5.52%	0.00%	15.80%	1.03%	9.53%
Kentucky	16.84%	0.28%	0.45%	45.42%	8.68%
New York	6.20%	14.94%	4.52%	0.00%	6.00%
Virginia	6.78%	17.68%	0.03%	0.78%	4.04%
Alabama	7.76%	0.00%	0.00%	14.36%	2.62%
Maryland	0.75%	7.28%	0.00%	0.12%	1.62%
Tennessee	13.87%	1.54%	1.57%	1.37%	1.51%
North Carolina	3.61%	4.07%	0.00%	0.00%	0.89%
Georgia	2.76%	0.36%	0.00%	0.00%	0.08%
South Carolina	0.31%	0.31%	0.00%	0.00%	0.07%
Illinois	1.83%	0.00%	0.00%	0.02%	0.00%
Indiana	6.08%	0.00%	0.00%	0.00%	0.00%
New Jersey	0.66%	0.00%	0.00%	0.00%	0.00%

Below we examine the potential consequences of development by exploring the intersection of high-potential development areas with selected resource layers.

Resource Layers

<u>Forest Cover</u> – We found there to be 368,031 km^2 (90,942,658 acres) of forest cover within the Appalachian LCC study area, of which 21,750 km^2 (5,374,643 acres) or 6% is within the area identified as having a greater than p=0.90 probability of energy development. Within that 6% approximately half of the forest acreage that is potentially affected is from shale gas development, with wind and coal affecting 2% and 1% of forest cover, respectively (Figure 9).

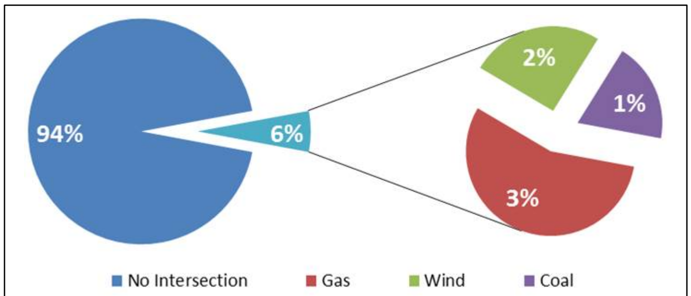

Figure 9: Percent of Forest Land Cover Intersecting ≥p=0.90 Energy Development Areas

<u>Ecological Systems</u> – The vast majority of ecological systems that intersect high probability (≤ p=0.90) energy development areas are in a "natural" vegetation class (Comer et al. 2003), as shown in Table 5. Totals for each

energy type intersecting a natural vegetation class are: wind, 83%; gas, 66%; and coal, 86%. Forest to Open Woodland is the natural system most frequently intersected: with more than 82% of high probability wind development areas, 65% of high probability gas development areas, and 76% of high probability coal development areas in this system type.

Detailed lists of the specific systems that intersect high-probability energy development areas

Table 5: Distribution of Natural Vegetation Classes Intersecting High Probability (≥*p*=0.90) Energy Development Areas

National Vegetation Classification: Class	% of Wind Area	% of Gas Area	% of Coal Area
Natural Habitats (Forest, Shrublands, Rock)	81%	66%	87%
Agricultural Areas	12%	24%	4%
Modified Vegetation and Developed Lands	7%	10%	8%
Quarries/Strip Mines/Gravel Pits	0%	0%	1%

can be found in Appendix 2. The Forest to Open Woodland Systems that most frequently intersect high-probability energy development are oak and northern hardwood forest types. Shale gas was the only type of energy development that intersected a non-natural system over more than 10% of the study area: 16% of potential high probability shale gas development areas were classified as pasture or hay fields.

Forest Cores – Our analysis found 92,649 km^2 (44,894,286 acres) of interior forest habitat within the Appalachian LCC, distributed among 18,174 cores that contain 500 or more acres of interior forest. Cores are mainly concentrated along the eastern portion of the Appalachian LCC (Figure 10). Nearly 10% of the cores are potentially at highest risk for energy development, nearly 13% are potentially at some risk, and nearly 27% are at potentially low risk (Table 6)

Table 6: Summary of Potential Energy Risk to Forest Cores

Buffered Forest Cores	Wind Forest Acres		Shale Gas Forest Acres		Coal Forest Acres		Summary Risk	
	km^2	% Wind	km^2	% Gas	km^2	% Coal	km^2	% All Forest
Highest Risk (≥75%)	11,439	19.69%	11,114	26.59%	4,376	27.25%	18,769	10.33%
Some Risk (≥50% < 75%)	14,743	25.38%	12,018	28.75%	5,170	32.19%	22,863	12.58%
Low Risk (>0 <50%)	31,900	54.92%	18,671	44.66%	6,515	40.56%	48,254	26.56%
No Risk = 0							91,794	50.53%

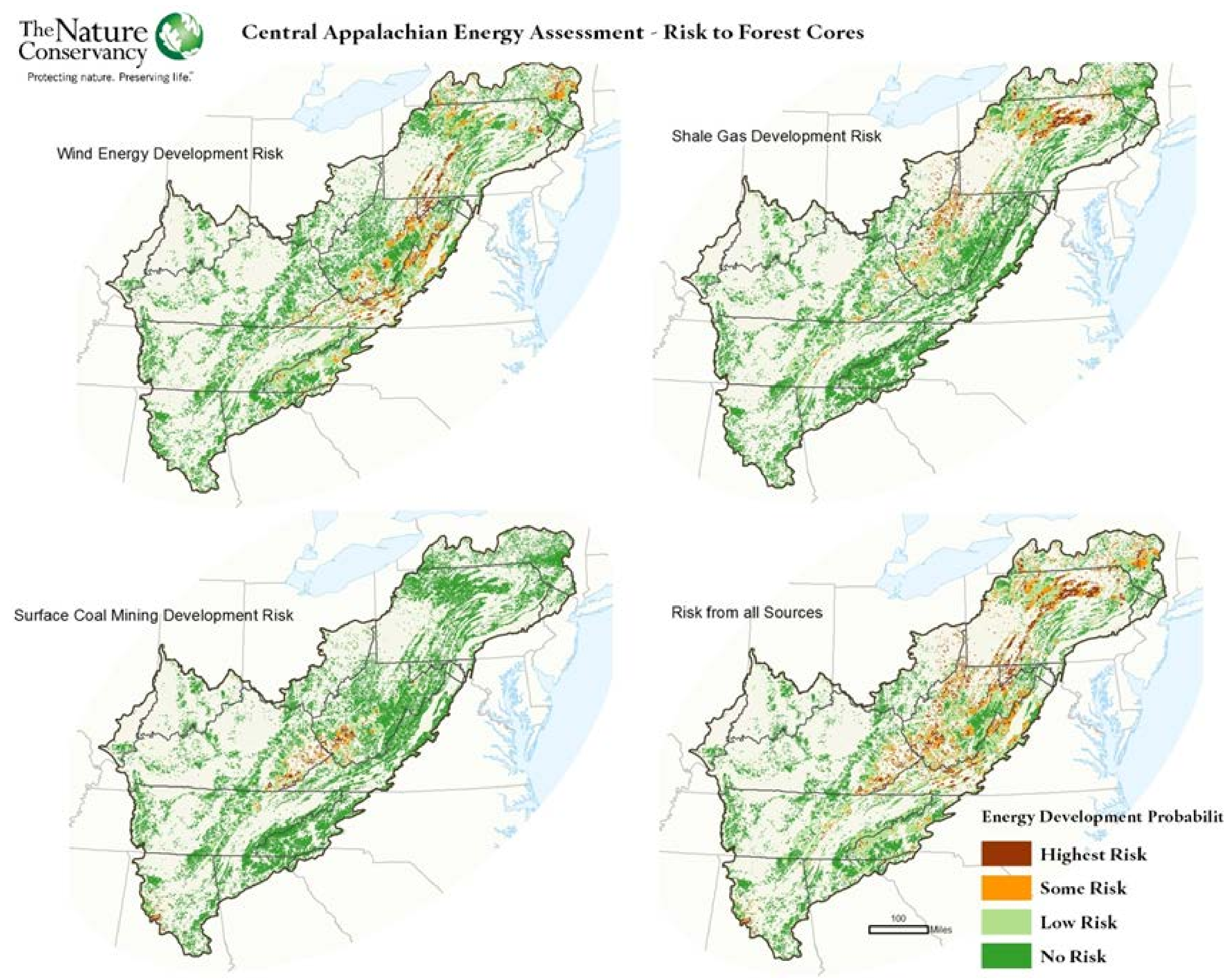

Figure 10: Cumulative Risk of Energy Development to Forest Cores

Table 7: Percent of Area in Protected Cores at Highest Potential Risk for Energy Development, by Ownership.

Protected Landowner	% Area
State	64%
Federal	22%
Private	10%
Local Government	2%
Other	2%

<u>Protected Areas</u> – Over 105,000 km^2 (26 million acres) of interior forest within the Appalachian LCC fall into some category of protected lands, constituting 59% of all interior forest habitat. Of the protected interior forest cores, 10% or about 10,000 ^{2} (2.4 million acres) are potentially at highest risk of energy development; 13% or more than 14,000 km^2 (3.5 million acres) are potentially at some risk; and 31% or about 33,000 km^2 (8.2 million acres) are potentially at low risk. The remaining 46% or nearly 50,000 (12.2 million acres) had cumulative

potential risk scores of zero. Sixty-four percent of forest cores at highest potential risk of energy development are owned by states; the Federal Government owns 22% (Table 7).

Watersheds – We analyzed 7,416 12-digit hydrologic units within the Appalachian LCC (Figure 11). More than 15% of these are potentially at highest risk from energy development, approximately 7% potentially at some risk, and nearly 19% potentially at low risk (Table 8).

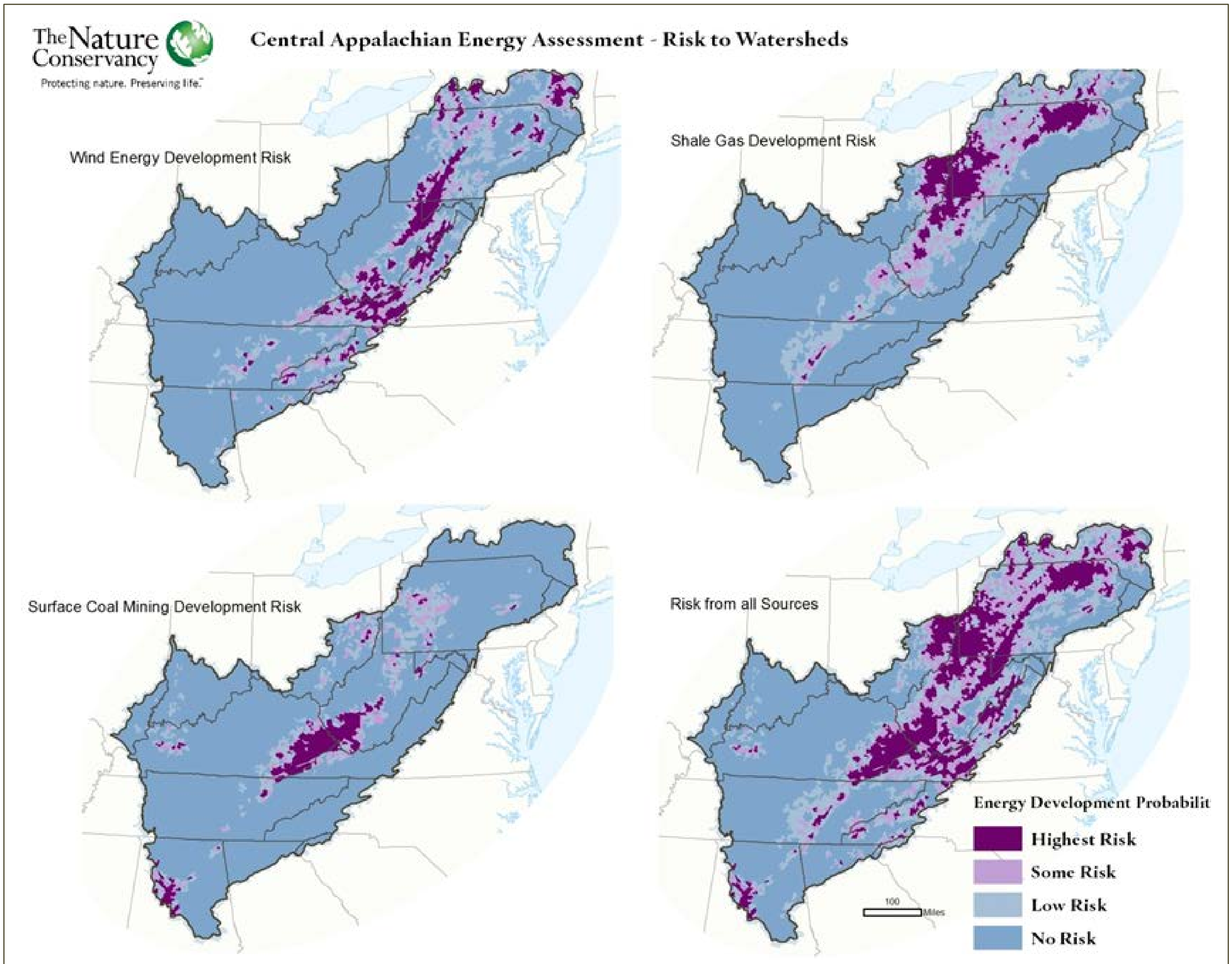

Figure 11: Cumulative Risk of Watersheds (12-Digit HUCs) to Energy Development

Table 8: Potential Energy Risk to Watersheds within the Appalachian LCC

Watersheds	Watershed Wind Risk		Watershed Shale Gas Risk		Watershed Coal Risk		Summary Watershed Risk	
	# HUCs	% Wind	# HUCs	% Gas	# HUCs	% Coal	# HUCs	% All
Highest Risk (≥75%)	600	34%	798	40%	472	46%	1154	16%
Some Risk (≥50% < 75%)	514	29%	550	28%	281	28%	873	12%
Low Risk (>0 <50%)	673	38%	633	32%	263	26%	1310	18%
No Risk = 0							4079	55%

Surface Drinking Water Supply – Seventy-five percent of watersheds within the Appalachian LCC were in the top quartile of important watersheds nationally. We further found 969 watersheds (13% of study region) in the top quartile of forest importance to drinking water, and 282 (4% of study region) in the top quartile of the index of private forest importance to drinking water. These represent 83,647 km^2 (20,669,682 acres) and 22,977 km^2 (5,677,900) acres, respectively (Table 9). Twelve percent of watersheds important to drinking water are potentially at highest risk from energy development (Figure 12).

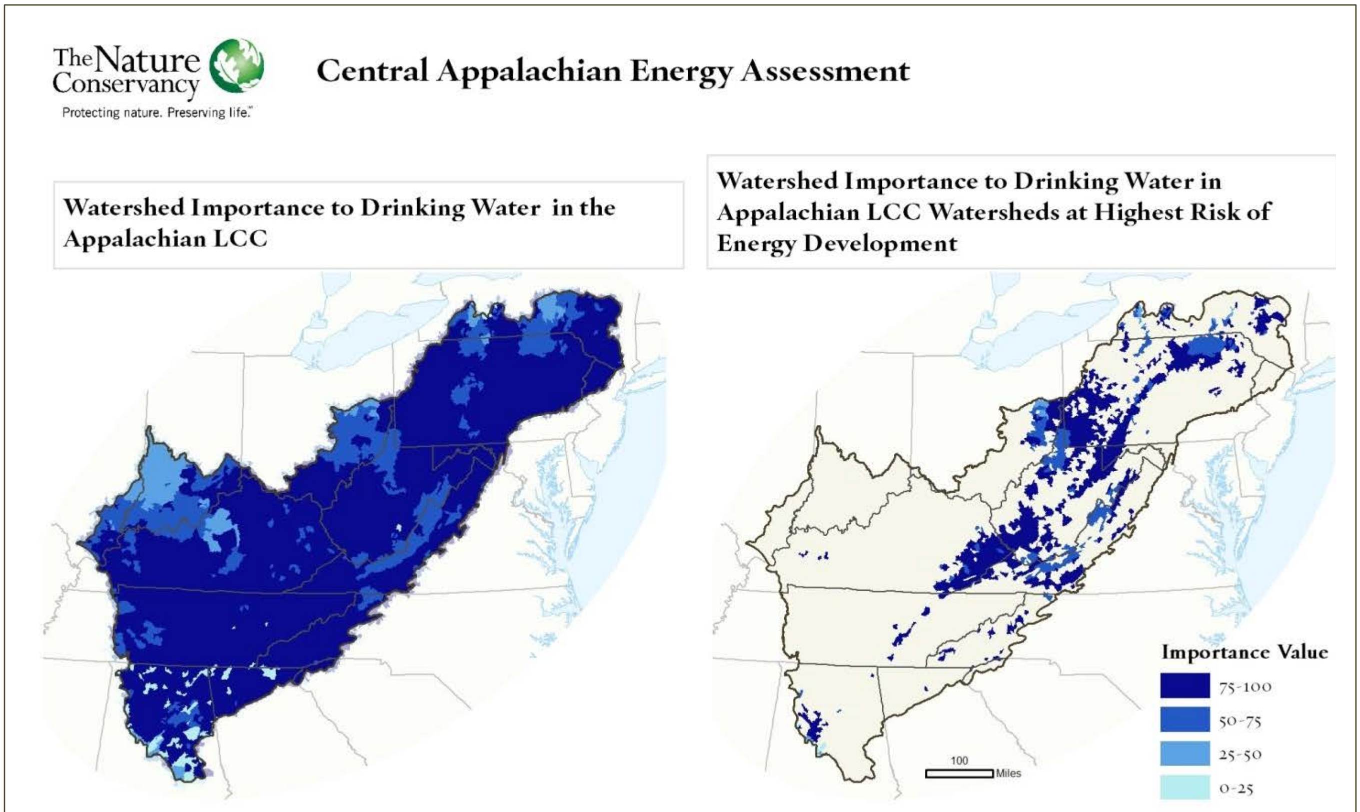

Figure 12: Important Drinking Watersheds

Table 9: Potential Energy Risk to Watersheds Important to Surface Drinking Water Supply

Threshold >75%	Importance to Drinking Water			Forest Importance to Drinking Water			Private Forest Importance to Drinking Water		
	# HUCs	%	% all	# HUCs	%	% all	# HUCs	%	% all
	5,559		75%	969		13%	282		4%
Highest Risk Areas	903	16%	12%	153	16%	2%	48	17%	1%
Some Risk Areas	707	13%	10%	100	10%	1%	26	9%	0%
Low Risk Areas	1,037	19%	14%	174	18%	2%	50	18%	1%
No Risk Areas	2,912	52%	39%	542	56%	7%	158	56%	2%

TNC's Aquatic Portfolio – We found that nearly half (46%) of the 12-digit HUCs within the Appalachian LCC coincide with the Conservancy's aquatic portfolio. Of these, 16% (7% of all HUCs analyzed) are potentially at highest risk for energy development, 12% are potentially at some risk, and 17% are potentially at low risk, while 55% of priority HUCs had a cumulative potential risk score of zero and are assumed to have a negligible risk of energy development (Figure 13).

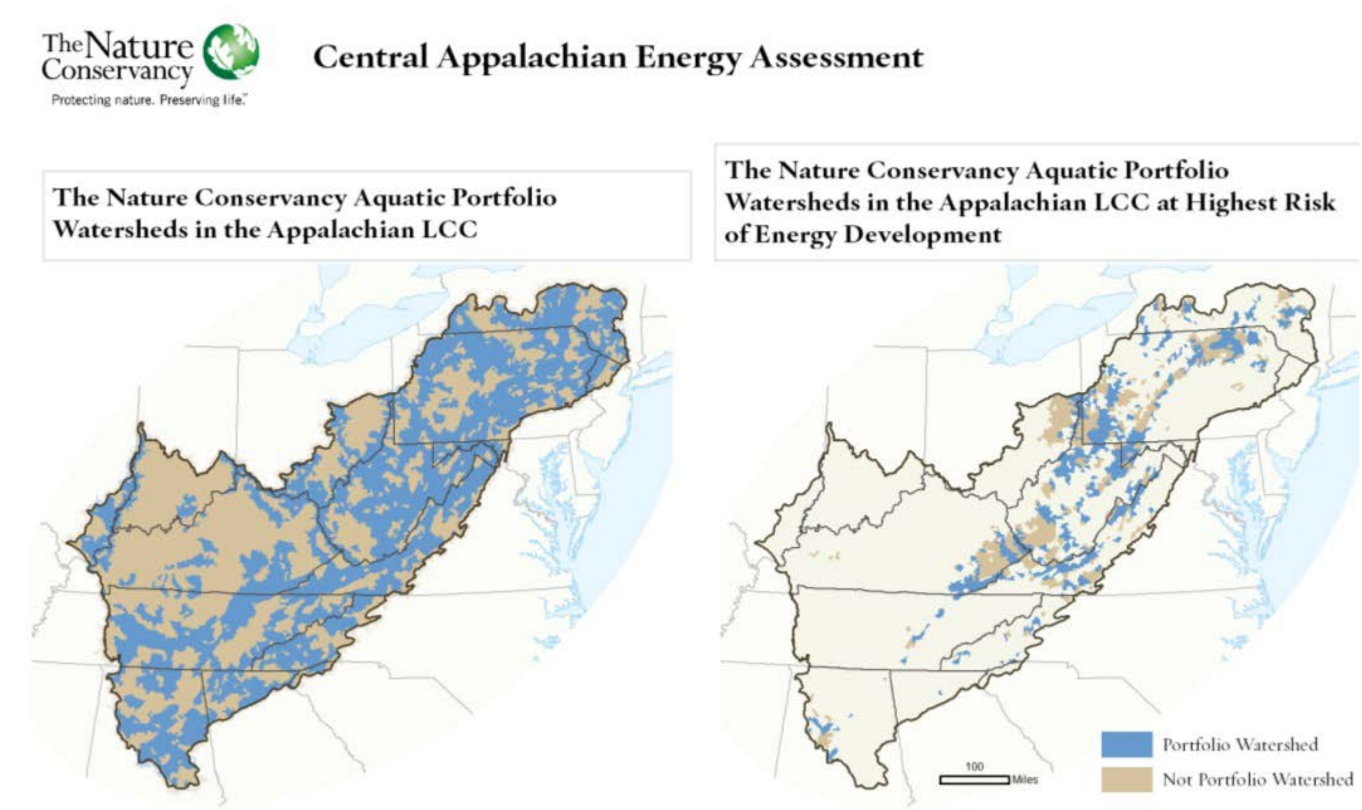

Figure 13: The Nature Conservancy Aquatic Portfolio

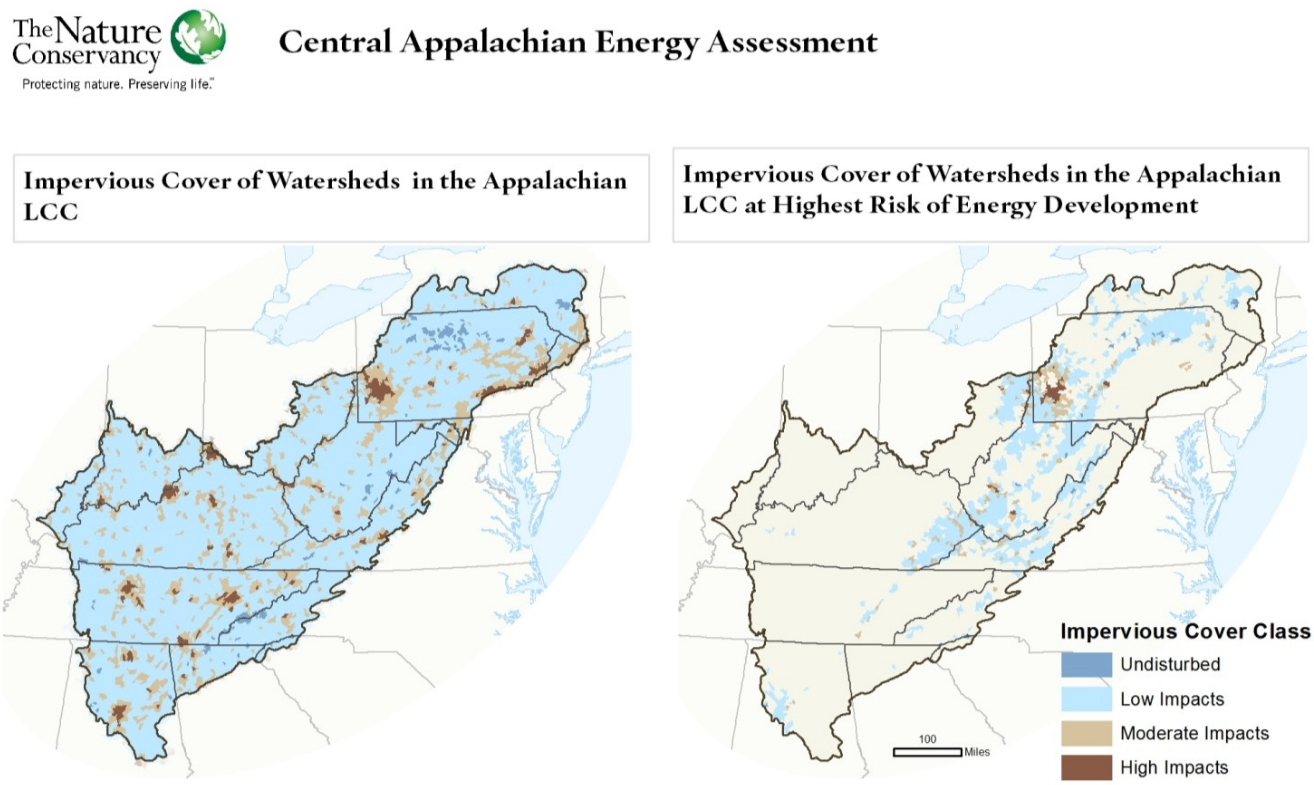

Figure 14: Impervious Cover Classes of Watersheds in the Appalachian LCC

<u>Impervious Cover Watersheds</u> – We determined that 82% (6,095) of the 12-digit HUCs in the study area had impervious cover values of 2% or less. This equates to an area of 129,981,894 acres. Of those watersheds with 2% or less impervious cover, we found that 15% are potentially at highest risk of energy development (Figure 14), 12% are potentially at some risk of energy development, and 18% are potentially at low risk of energy development. The remaining 55% is assumed not to be at risk for energy development.

<u>Karst Geology</u> – We found that 52% (3,824) of all watersheds within the Appalachian LCC support karst geology and that 12% of these are potentially at highest risk for energy development. Eight percent are potentially at some risk for energy development and 13% are potentially at low risk. Sixty-seven percent of watersheds that contain karst geology had zero cumulative risk scores for energy development and are assumed to have no risk.

DISCUSSION AND CONCLUSIONS

Potential Impacts of Energy Development in the Appalachian LCC

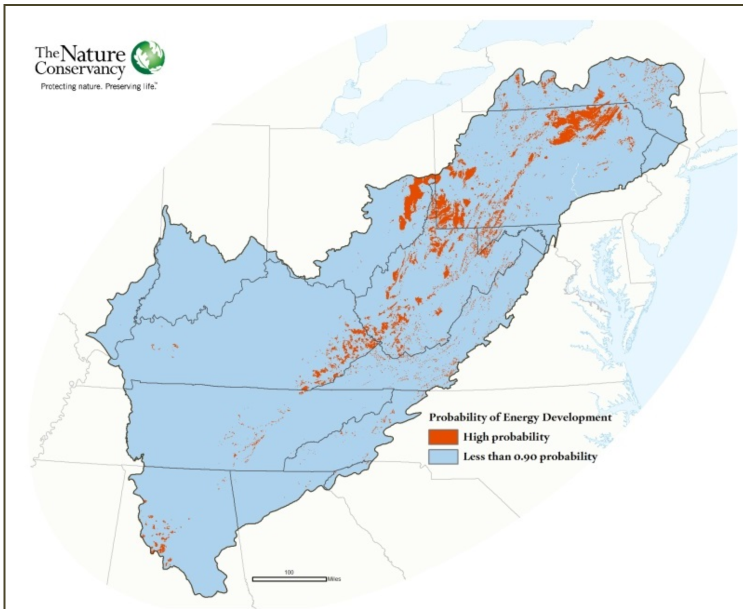

Figure 15: Distribution of High Probability Potential Energy Development Areas across the Appalachian LCC.

Our energy forecast modeling and analysis determined that 31,000 km^2 (7.6 million acres) within the Appalachian LCC have a high probability of potential energy development from one or more sources. Rather than being evenly distributed across the study area, however, the acres with a high probability for development are concentrated in the eastern portion of the Appalachian LCC, on the Allegheny and Cumberland plateaus (Figure 15). Pennsylvania alone supplies nearly half (44%) of the total high energy development area, while West Virginia contributes 21%. This acreage constitutes approximately 11% of the total land area in each of the two states.

Not only are the potential impacts of energy development concentrated geographically, but our analysis shows they also fall disproportionately within ecologically important land. Although 7.6 million acres is a relatively small part of the sprawling study area (6%), it is a very important portion, as explained below. Our analysis indicates that energy development may occur disproportionally in areas covered with natural vegetation. Nearly three-quarters (71%) of the area at highest potential risk from energy development - an area larger than the state of Maryland – is forested (22,000 km^2 or 5.4 million acres), encompassing 10% (19,000 km^2 or 4.6 million acres) of the Appalachian LCC's remaining intact patches of interior forest habitat. Similarly, potentially high energy development risk areas intersect natural ecological systems for 80%, 66%, and 85% of wind, gas, and coal models, respectively. The habitat most frequently intersected by high potential energy development risk is forest, with the Forest to Open Woodland ecological system the most likely to coincide with energy development: 80% of the wind, 65% of the shale gas, and 75% of the coal potential high energy development risk areas overlap this system.

Forest cover is a key determinant of the ability of water to infiltrate soil rather than run off as overland flow. The relationship between surface runoff and the loss of water quality, specifically turbidity and water temperature (Gartner et al. 2013), is well demonstrated. Both qualities are important habitat attributes for iconic species such as eastern brook trout (Hudy et al. 2008) and other aquatic species (Gergel 2002, Allan et al. 2003). Changes in land cover also affect flow regimes (the timing, duration, and frequency of different levels of water flows) which are a powerful determinant of aquatic system health and richness (Poff et al. 1997). We found that nearly half (46%) of the 12-digit HUCs within the Appalachian LCC coincide with The Nature Conservancy's Aquatic Portfolio. This dataset was designed to delineate a minimum set of stream habitats that, if conserved, would protect all the representative aquatic species within the planning region. Sixteen percent of these priority watersheds are potentially at highest risk for energy development, which could have profound implications for the success of efforts to conserve the region's aquatic biodiversity.

Natural vegetative cover is also important to the maintenance of healthy cave and karst habitats (USFWS 2011; van Beynen et al. 2012). The Appalachian LCC is currently funding a project to map cave and karst resources within its boundaries. Although that layer was not available, we were able to analyze a USGS dataset that indicates the potential for cave and karst resources to occur (Weary and Doctor 2014). We found that cave and karst geology were potentially present in that 52% (3,824) of the watersheds in the Appalachian LCC, and that 12% (474) of these are at highest potential risk of energy development.

Natural systems provide essential services to water utilities, businesses, and communities—from water flow regulation and flood control to water quality and air temperature regulation (Gartner et al. 2013; Conte et al. 2011). Our findings underscore the importance of watersheds within the Appalachian LCC in providing valuable ecosystem services to human populations as well, both within and outside the region: 75% (5,559) of the watersheds in the Appalachian LCC are nationally ranked as among the top quartile of watersheds able to produce clean water (Figure 12). Nearly 1,000 of these watersheds, or more than one-fifth, are in the top quartile of watersheds based on the importance of forest to the quality of the drinking water they produce. Sixteen percent (153) of these important drinking water watersheds are within the area identified as potentially at highest risk for energy development. Loss of permeable forest land is associated with increases in non-point source pollution and sedimentation, which can lower the quality of surface drinking water (Gartner et al. 2013; Conte et al. 2011). Currently, 82% of the watersheds in the study region have less than 2% impervious cover; however, 15% are potentially at highest risk of energy development (Figure 14). Forest loss associated with high levels of energy development could shift these watersheds into an impervious cover category that will adversely affect aquatic species and surface drinking water (Barnes et al. 2009; Hilderbrand et al. 2010; King et al. 2011; Evans and Kiesecker 2014).

Assumptions, Uncertainties, and Data Limitations

Regional Scale. The analysis boundary for this study encompasses almost 1/3 of the United States. This allows for us to look at large scale patterns of overlap between potential energy development and other valuable natural resources, and to highlight where those intersections are concentrated so that action can be taken proactively to alleviate conflicts for the benefit of industry, agencies, regulators, NGOs and others. Guidance for how to apply these datasets to other regional analyses is given in Appendix 3. Unfortunately, the large scale at which this analysis was undertaken limits how much we can say about local impacts. A downscaled assessment using variables available within a smaller analysis unit such as an 8-digit HUC, or industrial land or lease holding, and refined with post hoc assessments of regulatory and local land use constraints is necessary to evaluate site specific impacts, and to inform project specific micro-siting decisions.

Energy Resources. Our models used the most current data to estimate shale gas, wind and coal development patterns in this region (U.S. DOE. 2008; EIA 2013b), but projections of development potential will likely need to be revised as more development location data becomes available. This is particularly the case for shale gas production in plays in the southern portion of the study region such as the Conasauga and Chattanooga, which are in very early development stages and for which well data was limited.

We were unable to obtain data on some factors considered to be important for new surface coal mining activity, including stripping ratios (overburden, coal bed thickness), coal reserves remaining, surface ownership patterns, and coal quality as related to market demand (US EPA 2005). Location and extent of past mining were not uniformly available for the entire study area, as mining datasets from individual states varied greatly in quality. Data related to stripping ratios (overburden, seam thickness) were available for some coal seams (Northern and Central Appalachian Basin Coal Regions Assessment Team 2001) and states in the study region (Illinois (ILSGS 2012); Indiana (INGS 2000); West Virginia (WVGES 2013); and Virginia (Virginia Tech 1999) but not others. Remaining coal reserves are available on a county-by-county basis for some states (see West Virginia Coal Association 2012 for example) or on a regional level from the U.S. (EIA 2012) but reserve data are not consistently published at a detailed enough spatial scale for the region in order to be included in the project. We used the mountaintop removal region delineated by the U.S. Environmental Protection Agency (US EPA 2005) as a surrogate for overburden, and this may have resulted in reduced modeled probabilities of coal productions in the Eastern Interior/Illinois coal production region.

The estimation of probable wind energy development patterns is also highly uncertain, and will be influenced by a number of factors, including investment in transmission, tax policy, fuel costs and emission regulations (McDonald et al. 2009; Kiesecker et al. 2011, Fargione et al. 2012). Despite these reservations several other studies have attempted to project future development patterns within portions of the LCC study area and our estimates of potential development footprints are consistent with those potential development patterns (Considine et al. 2011; U.S. DOE 2011; Kirschbaum, et. al 2012).

Energy Footprint. For this regional analysis, we calculate the area potentially affected by energy development as either the entire 1 km^2 grid cell with probability ≤ p=0.90 although we do not expect energy development will necessarily be distributed throughout the entire cell. In some cases this may overestimate the number of acres on which actual development infrastructure would be situated. This assumption was necessary because we did not have sufficiently detailed data on shale gas resource potential throughout the LCC to develop buildout scenarios that would have more accurately estimated the area likely to be impacted. Similarly, we report potential impacts for forest cores and watersheds based as if the entire polygon was affected. Again we lack adequate data to develop stable scenarios that would indicate which specific portions of these analysis units would be most affected. We consider these estimates reasonable however for the purposes of highlighting which resources are most likely to be adversely affected, and where in the study region impacts are likely to be concentrated.

Current technologies. There have been significant technological advances, such as lateral drilling technologies, that have substantially reduced surface impacts from energy extraction. We can expect that these technologies will continue to advance to further environmental goals while increasing our abilities to extract resources. However, we cannot account for future technological advances in this paper. All build out assumptions are based on current technology.

Model Uncertainties. In addition to potential uncertainties in projecting the amount of future energy development, model uncertainty is also a consideration. Without simulation, extrapolated models are notoriously difficult to validate, and the uncertainty must instead be inferred through model fit and cross validation. We have high confidence in the models that correspond to the Marcellus and wet gas within the Utica shale plays, but it is difficult to evaluate model performance for all shale plays across the entire Appalachian LCC study area. As mentioned above, we do not have much confidence of the shale probabilities in the southern portion of the LCC due to lack of data from those plays.

The wind model is highly supported; however we do note that some interior forest patches overlying areas of mapped high wind energy resource did not emerge as having potentially highest risk for energy development. This may be due to the inclusion of a covariate (distance to transmission). Because the covariate represents current installed infrastructure and not potential, it constrains the estimates to areas where transmission infrastructure exists regardless of wind suitability.

Another source of uncertainty is related to ancillary data utilized in the resource assessment. For example, it is known that NLCD underestimates regeneration forests (Sader and Legaard 2008) which may bias assessment of area impacted. However this error is likely smoothed out over an area as large as the Appalachian LCC.

Reducing Impacts of Energy Development

Our analysis indicates that energy development could challenge the ability of forests to provide important benefits to people due to the size of its potential footprint and how that footprint may impact forest cores, natural ecological systems, and key watersheds. However, the increased area in energy production may be compatible with biodiversity and drinking water if energy development is judiciously sited.

Patterns of shale gas and wind development provide an opportunity to illustrate how both the size and location of energy development differentially affect forests. Shale gas is potentially the dominant driver of increased deforestation because it accounts for 50% of the future potential energy footprint. At the same time, the areas with the highest modeled probability for wind energy development occur along high-elevation ridge tops, which tend to support large patches of interior forest. Consequently, although the area with a high-probability for wind development is much smaller than the area for combined shale gas (1.7 million vs 4.5 million acres), a much larger percentage of wind's high-potential area for development intersects with forest to open woodland in contrast to that for shale gas (80% vs 65%). Furthermore, wind development is more likely to intersect with remaining forest cores than will shale gas development (~2 million acres and ~1.9 million acres, respectively). The potential impact of projected energy development is not solely a function of total footprint but is related to the correspondence between the type of energy resource and intact natural habitat (Northrup and Wittemyer 2013).

The degree of flexibility in how different energy technologies are implemented also affects their impact on natural areas. For instance, shale gas well development has the largest potential extent of the three energy types we assessed. But development typically occurs using multiple lateral wells sited on a single pad. The lateral reach of shale gas wells means there is more flexibility in where pads and infrastructure can be placed (Johnson 2010, Rozell and Reaven 2012). This flexibility can be used to avoid or minimize impacts to natural habitats. Consolidation of more wells onto fewer pads also helps reduce the habitat fragmentation associated with linear features such as roads and pipelines (Johnson 2010). Consolidation was not explicitly accounted for in our probability models. In contrast, the best areas for wind development are atop ridge lines, which afford wind developers less flexibility in siting turbines in ways that will mitigate potential impacts to forests (Northrup and Wittemyer 2013).

Avoiding and Mitigating Impacts of Energy Development

Our analysis reveals that the potential cumulative impacts of multiple projects pose the greatest challenge for safeguarding biodiversity and biological resources. The term "cumulative impacts" refers to the combined effects of human activity on a resource or community. The potential impacts from individual gas wells/wind turbines or even those of a single wind farm, coal mine, or gas field are likely to be manageable and compatible with broader conservation priorities. As realized impacts accumulate over time and combine with the impacts from other sources, however, they can lead to significant overall degradation of resources.

Unfortunately assessments of environmental impacts are presently made well-by-well or gas-field-by-gas-field with little or no attempt to assess their cumulative impacts (Canter and Ross 2010). Furthermore, efforts to analyze and address cumulative impacts after the fact have proven challenging. In the case of air or water quality, for example, a single oil and gas well or even a small group of wells generally cannot be identified as exceeding a specific threshold—be it a health-based standard or a requirement to maintain concentrations of a substance in surface water sources at or below a set level. But this need not be the case. Tools exist for analyzing the cumulative impacts of development and for determining whether mitigation is needed on individual operations to avoid exceeding established standards (Thorne et al. 2009, Saenz et al. 2013). Incorporating these tools proactively into siting and mitigation decisions will help prevent incremental damage from accumulating to harmful proportions.

In light of the high potential for energy development that we project for this landscape in the coming decades, a major challenge for the Appalachian LCC will be understanding and mitigating the impacts of energy development in high-value forests and watersheds. Historically, most mitigation has been reactive and occurred at small spatial scales (Kiesecker et al. 2009). Now researchers and conservation practitioners concur that mitigation should be more proactive and comprehensive in order to effectively maintain healthy natural systems (Kiesecker et al. 2010; Kiesecker et al. 2013). Moving siting and mitigation decisions away from a permit-by-permit approach and towards decision making on the scale of a landscape allows stakeholders to perceive and assess the cumulative impacts. Armed with this knowledge they can avoid or minimize impacts, identify priority areas where compensation for remaining residual impacts can occur through conservation or restoration, and achieve energy development that is consistent with broader conservation goals and human quality of life (Pritchard 1993; Bartelmus 1997; Kiesecker et al. 2013). Without a landscape-scale vision, priorities become difficult to establish and resources may be squandered on inefficient planning and compensation that does not restore or maintain valued natural resources. Moving forward, we hope that our assessment will stimulate planners, regulators, and energy developers to think strategically about cumulative impacts and to develop practical guidelines for when and how cumulative impacts should be included in siting and mitigation decisions.

Future Directions

Ultimately our goal with these analyses was to bring scientific information based on predictive modeling to a dialogue on integrating the need for forest and stream conservation with energy development objectives. The report seeks to identify those areas within the Appalachian Landscape Conservation Cooperative that have the highest probability of energy development-driven land use change. Our models of energy development probability can be used to assess potential risk to species habitats and ecological services at a regional scale. The datasets we have created depict future potential risks from the development of coal, natural gas, and wind energy across the Appalachian LCC. Our analysis highlights key ecological features that may be affected, such as forest cores and intact watersheds, so that steps may be incorporated at the earliest stages of planning to avoid or minimize the impacts from energy development. Through the online mapping tool developed as part of this project the datasets can be accessed by industry, land managers, NGOs, regulators, and the public to use for project screening, regional planning and assessment, and mitigation. By producing these analyses and working with the Appalachian LCC to further their use, we hope to provide the basis for constructive conversations among the Cooperative's partners and with industry, regulatory agencies, and the public on developing a forward-thinking framework that values clean air, clean water, and the multitude of other benefits that people derive from nature alongside energy development. Such a framework could include voluntary practices, comprehensive planning, and sensible regulation so that the region's highly desirable energy resources may be extracted in ways that also preserve the region's high-quality forests and rivers.

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APPENDIX 1: METHODS FOR FOREST PATCH DELINEATION IN THE APPALACHIAN LANDSCAPE CONSERVATION COOPERATIVE (PLUS KY/NY/OH/PA/TN)

Prepared By Tamara Gagnolet, Misty Downing, and Matthew Long
October 2013

SUMMARY

This dataset represents forest patches greater than 50 acres in the broader Central Appalachian region. This **study area** represents the Appalachian Landscape Conservation Cooperative (LCC) boundary expanded to include the states of Kentucky, New York (minus Long Island), Ohio, Pennsylvania, and Tennessee in their entirety. (A 10-mile buffer was added to the southwestern portion of the Apps LCC boundary.) **Forest patches** are defined as areas of contiguous natural cover bound by non-natural edge or linear fragmenting features (roads, railroads, transmission lines, natural gas pipelines). The following land cover types were selected from the 2006 National Land Cover Database (NLCD) to define "natural cover": deciduous forest, coniferous forest, mixed [deciduous-coniferous] forest, scrub-shrub, woody wetland, and emergent wetland. Forest patches were delineated based on non-forest edge (from the NLCD) and the following linear fragmenting features:

- electric transmission lines (from Ventyx, LLC, August 2013),
- natural gas pipelines (from Ventyx, LLC, August 2013),
- railroads (from 2007 ESRI StreetMap data), and
- roads (from 2007 ESRI StreetMap data).

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METHODS

Analysis Boundary: Created an analysis boundary by combining the Appalachian Landscape Conservation Cooperative boundary and the state boundaries for NY, OH, and PA. (Note: Forest patches were delineated in two major batches, roughly north and south, and then combined by Misty Downing into a single, non-overlapping dataset.)

Land Cover: Clipped NLCD 2006 to the analysis boundary.

Transmission: Downloaded August 2013 Ventyx data (from TNC's ecadpubtest server) representing electric transmission lines and natural gas pipelines, clipped them to the analysis boundary, merged them, and reprojected them.

Railroads: Clipped ESRI StreetMap 2008 railroad data to the analysis boundary and reprojected the shapefile.

Roads: Selected the ESRI StreetMap 2001-2008 dataset features within the analysis boundary and exported the selection, then reprojected to Albers. Repaired geometry. Because the road dataset was so large for the entire analysis area, clipped the dataset into 5 overlapping subsets for conversion to raster. Finally, mosaicked the resulting five rasters into one raster.

Existing Energy Footprints: Used existing TNC analysis of well pads, surface mining, and wind turbines for the Central Apps region (old data now – see previous metadata documents). Added existing wind farm boundaries from Ventyx August, 2013, clipped to study area.

Processing steps for the above inputs:

1. Clipped each dataset to the analysis boundary and reprojected to regional Albers (USA_Contiguous_Albers_Equal_Area_Conic_USGS_version).
2. Added a new field to the infrastructure shapefiles called FRAG (type = short integer; precision = 4) and left it populated with zeros.
3. Convert to Raster: Used **Feature to Raster** tool with Value field = FRAG and Cellsize = equivalent to the clipped NLCD 2006 input raster. The roads layer required special attention. After checking and repairing the geometry, the roads shapefile was clipped into five pieces (using newly created rectangle shapefiles in the Albers projection that roughly

divided the study area into overlapping fifths). Each of those five pieces was converted to a raster separately, and then the resulting five rasters were mosaicked into one raster for the whole study area.

4. Export raster using Data Frame extent. After each vector feature was converted to raster, the resulting raster was exported using the extent of the Data Frame (which was zoomed out beyond the study area). This step ensured that all rasters covered the entire study area, regardless of the extent of the input data.
5. Reclassify NoData to 1s: Used **Reclassify** tool: reclass field = value

Old Values	New Values
0	0
NoData	1

6. Extract by Mask: each of the reclassified rasters was extracted using the clipped NLCD 2006 input raster as a Mask. This step has the dual purpose of ensuring that each of the rasters covers the exact same study area and also that the cells of the rasters are exactly aligned (Extract by Mask includes a sub-routine that automatically aligns the cells of the input raster and the mask).
7. Merge infrastructure rasters: Used **Raster Calculator** tool: multiplied all infrastructure rasters together ("elecebm" * "footebm" * "pipeebm" * "railsebm" * "roadebm" * "windebm") output = infracombo
8. Create natural vegetation raster: Use **Reclassify** tool on NLCD 2006; reclass field = value

Old Values	New Values
0 – 39	0
40 – 59	1
60 – 89	0
90 – 99	1
NoData	NoData

Output = natveg

9. Combine infrastructure and natural vegetation rasters: Used **Raster Calculator** tool: multiplied infrastructure raster ("infracombo") and natural vegetation raster ("natveg") together output = veginfracombo
10. Reclassify 0s to NoData: Used **Reclassify** tool: reclass field = value
    - Output = veginfcomrecl

Old Values	New Values
0	NoData
1	1

11. Convert to Polygon: Used **Raster to Polygon** tool: Field = value; simplify polygons box was checked.
12. Add ACREAGE Field (type = double) and Calculate Acreage.
13. Select forest patches >= 50 acres and create final dataset: **Apps_LCC_forest_patches_gt50acres.shp**
14. Create symbology file to display forest patches by size: Apps_LCC_forest_patches_gt50acres.

APPENDIX 2: DETAILED OUTPUT OF INTERSECTION OF HIGH PROBABILITY ENERGY DEVELOPMENT AREAS WITH THE NATIONAL NATURAL VEGETATION CLASSIFICATION.

Systems that intersect with High Probability (>=.90) Wind Energy Development

Code	System Name	NVC Class	Naturalness	% Wind
4109	Northeastern Interior Dry-Mesic Oak Forest	Forest to Open Woodland	Natural	20.29%
4313	Appalachian (Hemlock)-Northern Hardwood Forest	Forest to Open Woodland	Natural	19.75%
4124	Southern and Central Appalachian Cove Forest	Forest to Open Woodland	Natural	9.80%
4108	Laurentian-Acadian Northern Hardwood Forest	Forest to Open Woodland	Natural	8.88%
	Other[1]			8.56%
81	Agriculture - Pasture/Hay	Cultural Vegetation	Cultural	8.13%
4123	Allegheny-Cumberland Dry Oak Forest and Woodland	Forest to Open Woodland	Natural	6.43%
4312	Central Appalachian Dry Oak-Pine Forest	Forest to Open Woodland	Natural	6.27%
4121	Southern Appalachian Oak Forest	Forest to Open Woodland	Natural	4.76%
21	Developed-Open Space	Developed-Open Space	Cultural	3.18%
82	Agriculture - Cultivated Crops and Irrigated Agriculture	Cultural Vegetation	Cultural	2.32%
4126	Central and Southern Appalachian Montane Oak Forest	Forest to Open Woodland	Natural	1.64%

Systems that intersect with High Probability (>=.90) Shale Gas Development

Code	System Name	NVC Class	Naturalness	% Gas
4313	Appalachian (Hemlock)-Northern Hardwood Forest	Forest to Open Woodland	Natural	20.18%
81	Agriculture - Pasture/Hay	Cultural Vegetation	Cultural	16.15%
4127	South-Central Interior Mesophytic Forest	Forest to Open Woodland	Natural	14.38%
4108	Laurentian-Acadian Northern Hardwood Forest	Forest to Open Woodland	Natural	7.77%
82	Agriculture - Cultivated Crops and Irrigated Agriculture	Cultural Vegetation	Cultural	7.52%
4109	Northeastern Interior Dry-Mesic Oak Forest	Forest to Open Woodland	Natural	7.42%
4312	Central Appalachian Dry Oak-Pine Forest	Forest to Open Woodland	Natural	6.59%
21	Developed-Open Space	Developed-Open Space	Cultural	5.67%
	Other			3.73%
4124	Southern and Central Appalachian Cove Forest	Forest to Open Woodland	Natural	2.31%
8311	Ruderal Forest	Modified/Managed Vegetation	Semi-Natural	2.08%
9333	Central Appalachian River Floodplain	Forest to Open Woodland	Natural	1.78%
4308	Laurentian-Acadian Pine-Hemlock-Hardwood Forest	Forest to Open Woodland	Natural	1.70%
4123	Allegheny-Cumberland Dry Oak Forest and Woodland	Forest to Open Woodland	Natural	1.57%
22	Developed-Low Intensity	Developed-Low Intensity	Cultural	1.13%

[1] Systems that intersect potential high probability areas over less than 1% of the study area were combined into the category "Other"

Systems that intersect with High Probability (>=.90) Surface Coal Mining

Code	System Name	NVC Class	Naturalness	% Coal
4123	Allegheny-Cumberland Dry Oak Forest and Woodland	Forest to Open Woodland	Natural	53.52%
8301	Successional Shrub/Scrub	Shrubland & Grassland	Natural	9.48%
4127	South-Central Interior Mesophytic Forest	Forest to Open Woodland	Natural	7.23%
	Other			4.62%
4313	Appalachian (Hemlock)-Northern Hardwood Forest	Forest to Open Woodland	Natural	3.53%
4256	Southern Appalachian Low-Elevation Pine Forest	Forest to Open Woodland	Natural	3.32%
4124	Southern and Central Appalachian Cove Forest	Forest to Open Woodland	Natural	3.09%
4319	Southern Ridge and Valley / Cumberland Dry Calcareous Forest	Forest to Open Woodland	Natural	2.68%
21	Developed-Open Space	Developed-Open Space	Cultural	2.68%
81	Agriculture - Pasture/Hay	Cultural Vegetation	Cultural	2.66%
8514	Managed Tree Plantation	Managed Tree Plantation	Cultural	2.27%
32	Quarries/Strip Mines/Gravel Pits	Quarries/Strip Mines/Gravel Pits	Cultural	1.57%
4109	Northeastern Interior Dry-Mesic Oak Forest	Forest to Open Woodland	Natural	1.26%
82	Agriculture - Cultivated Crops and Irrigated Agriculture	Cultural Vegetation	Cultural	1.05%
22	Developed-Low Intensity	Developed-Low Intensity	Cultural	1.03%

APPENDIX 3: GUIDANCE FOR USING WATERSHED AND FOREST CORE ENERGY RISK DATASETS TO DETERMINE POTENTIAL ENERGY RISK TO PRIORITY AREAS

A complexity of the kind of risk assessments described here is that there is no absolute value for a high risk area. Instead, one must determine the potential risk of one area relative to other areas within the study boundary. For this project, we used an energy probability raster for the Appalachian LCC to calculate the summed risk of all the pixels within each forest core (patches of interior forest habitat) and watershed. We then calculated the quartile risk values for each energy source. To simplify subsequent analyses, we created fields within the data tables for the forest cores and watersheds to indicate the risk status and source for each polygon (Table A3-1). Finally, we created a field [ALLNRG_RSK] to identify those polygons that are at highest potential energy risk from one or more sources.

Energy Source	Level of Risk		
	Highest	Moderate	Low
Wind	1	2	3
Gas	10	20	30
Coal	100	200	300

Table A3-1. Energy development risk and source are uniquely coded in the Forest Core and Watershed Risk shapefiles. The units place designates the level of risk while the number of zeroes indicates the energy source.

Planners can use either the forest core or watershed data layers to assess how the potential risk of energy development within their priority interest areas compares to that of the region as a whole. For aquatic species, we recommend using the watershed database, and for terrestrial species we recommend using the forest core database. Note that we do not consider either of these layers appropriate to assess risk to isolated wetland or grassland habitats.

Example 1. Assessing risk to Aquatic Habitat Priorities within the Tennessee Cumberland Basin.

As part of the 2005 Tennessee State Wildlife Action Plan, occurrences of target aquatic species were assigned to watershed (12-digit Hydrologic Unit) boundaries, and statistics on species richness and conservation priority were calculated (TNC 2012). Using ArcGIS, We joined the data from this effort to our watershed risk layer using the 12-digit Hydrologic Unit code (Figure A3-1a). We then used a definition query to show species richness only for those watersheds at highest risk from energy development from one or more sources (Figure A3-1b). This allowed us to pinpoint quickly those watersheds where potential energy risk and biodiversity values coincide and where further planning is necessary.

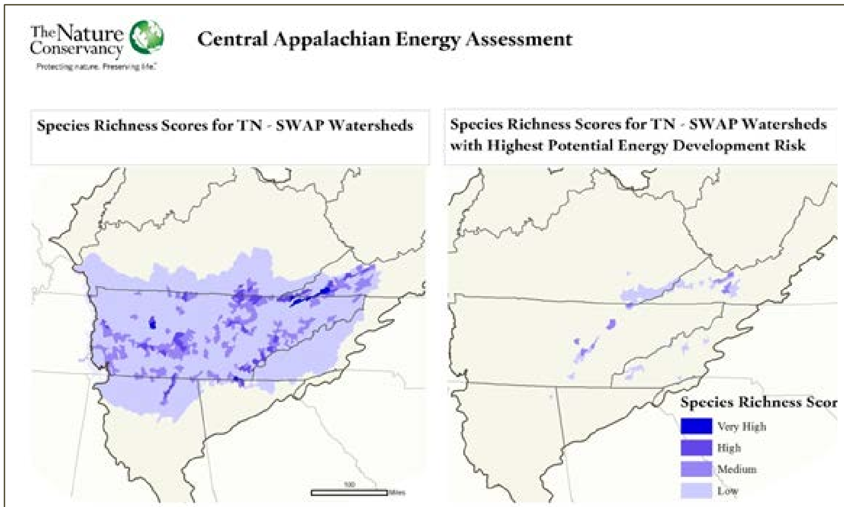

Figure A3-1 a) Species Richness Scores for the Tennessee and Cumberland River Basins; b) Species Richness Scores for high energy development probability watersheds in the Tennessee and Cumberland River Basins.

Example 2: Assessing Risk to National Audubon Society Atlantic Flyway Priority Forests

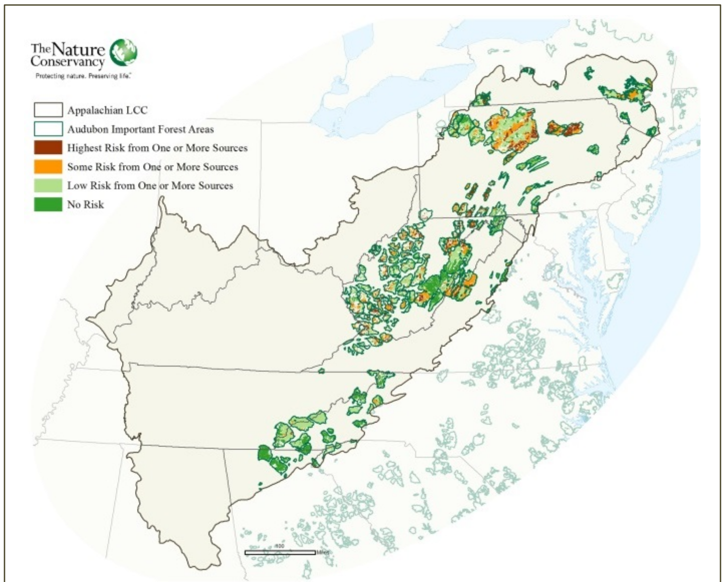

Figure A3-2: Potential Energy Development Risk to Forest Cores within National Audubon Society's Atlantic Flyway Priority Forests.

The National Audubon Society has worked to map the largest, most intact forested areas in the U.S. portion of the Atlantic Flyway (Maine to Florida) that support the highest richness and abundance of birds of regional conservation significance (Audubon 2012). We assessed the risk of energy development to the subset of these priority forests that overlap with the analysis boundary for the Appalachian LCC by intersecting them with the forest cores data layer. Figure A3-2 shows how simple mapping can allow planners to identify which priority forest blocks have a relatively proportion of forest cores with high potential energy development. These data can be quantitatively analyzed to determine the area of interior forest cores in each priority block that are at potentially highest risk of energy development, and from which sources. A simple approach within ArcGIS is to select forest cores that intersect the polygon of interest, and attribute those data records by adding a field and calculating the value of that field for the selected records to be 1. That data table can then be opened and analyzed in Excel.

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