

# **ASSESSING THE BIODIVERSITY SUPPORT POTENTIAL OF FOREST PATCHES FOR CONSERVATION PLANNING**

by

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## Abstract

Biological diversity is a critical component controlling ecosystem function and resiliency, yet it remains difficult to measure at the spatial and temporal scales relevant to conservation. Recently, biodiversity surrogates have emerged as a potentially useful tool for estimating the ability of a habitat patch to support biological diversity over the long-term, termed *biodiversity support potential*. The objective of the present study was to assess the biodiversity support potential of forest habitat patches in North Carolina. I used the diversity of unique land cover types and biophysical conditions as surrogates for biodiversity. Biophysical conditions were captured through the use of terrain-based indices: a topographic convergence index, potential radiation load, and elevation; these were indexed and combined to generate unique environmental conditions affecting the distribution of plant community types. Modeled estimates of soil moisture were ground-truthed to verify that topographic convergence is a reasonable index of soil moisture. *Natural Heritage Element Occurrences* were used to weight discrete environmental conditions and land covers according to their current biodiversity value. Finally, *Significant Natural Heritage Areas* were used as a reference to assesses whether biodiversity surrogates effectively capture habitats presumed to have the highest biodiversity value, and thus, whether surrogates are capable of evaluating existing networks of protected lands and identifying conservation priorities. The study revealed that both environmental settings and vegetation community types may be effectively used as surrogates for biodiversity. While surrogate assessment suggests that current biodiversity value (as estimated by weighted metrics) should be considered distinct from biodiversity support potential (as estimated by unweighted zip code diversity), both metrics are relevant and should be incorporated into large-scale conservation planning initiatives. Using geospatial tools developed in this study, estimates of biodiversity

support potential and value can be generated for all regions of the United States using existing, publicly available data. Environmental settings may be adjusted to capture the most relevant characteristics of each ecoregion, especially as additional data sets (including fine-scale soils data) becomes nationally available. Biodiversity surrogates may also be readily calibrated through the use Natural Heritage data, and I call for increased cooperation and data-sharing in future conservation planning and implementation efforts. Prioritization of land for conservation will continue to move toward the inclusion and overlay of multiple ecosystem services; biodiversity surrogates should be used to ground these initiatives with biologically relevant priorities.

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## **Introduction**

The character of conservation is changing. From a narrow focus on the conservation of biodiversity, in which society was considered a separate, disruptive part of the landscape, conservation is shifting in an effort to capture multiple objectives, both natural and societal. In particular, it seeks to value and conserve biodiversity as a critical element in the provision of ecosystem services, which broadly describe the suite of biotic and abiotic processes by which material and energy flows through the environment are regulated (Naeem et al., 1999). By providing ecosystem goods and sustaining biodiversity, these processes provide both direct and indirect benefits to human welfare (Costanza et al., 1998). These goods generally include the maintenance of air and water quality and the sequestration of atmospheric carbon, but may also include the provision of recreational opportunity, aesthetic beauty, and other less tangible benefits (Daily et al., 1997; Naeem et al., 1999). Indeed, conservation organizations and state wildlife agencies are under growing pressure to protect and/or restore land with the greatest potential for maintaining biodiversity and providing ecosystem services in the long-term.

Unfortunately, many of these services are not considered in traditional market economies, nor are the role of ecosystem services in producing market goods recognized. Consequently, they are often undervalued by society (Daily et al., 1997). The tendency to overlook and/or undervalue ecosystem services is a major driver behind the degradation or conversion of natural systems (Daily et al., 1997). Their valuation and integration into market economies necessarily depends on developing systems for quantifying and comparing the spatial provision of services, as habitat types differ in their ability to support biodiversity, sequester carbon, or protect watershed integrity (Balvanera et al., 2001). These efforts must independently evaluate and subsequently overlay services in order to generate a more complete measure of ecosystem value. Despite the

inherent difficulty and a high degree of uncertainty, such efforts are beginning to be incorporated into conservation planning initiatives. By examining the character and spatial variability of habitats across the landscape, conservation planning may direct resources toward regions with the greatest potential for providing and sustaining the most valuable suite of ecosystem services.

While biodiversity itself is not typically considered an ecosystem service, recent studies have demonstrated that ecosystem function and resilience are directly tied to the number and composition of resident species (Naeem et al., 1998; Naeem et al., 1999). Therefore, biodiversity must, in some form, be integrated into techniques for valuing ecosystem services. However, the biological diversity of an individual habitat patch, defined here as a discrete block of contiguous habitat, remains difficult to assess directly. The data needed to estimate biodiversity are not typically available at the spatial and temporal scales relevant to conservation planning and management decisions. Further, limited knowledge of species life history traits, distribution, and abundance makes fine-scale distribution modeling of species and/or communities difficult (Schumaker, 1996) and more susceptible to limited sample size (Ferrier, 2002). Given these difficulties, some have begun to argue in favor of using biodiversity surrogates to inform conservation planning (Ferrier, 2002). Surrogates typically include unique habitat types or biophysical settings; rather than seeking to estimate the number of species within a particular habitat patch, biodiversity surrogates estimate the ability of a habitat patch to support and maintain biodiversity in the face of future environmental change. Thus, surrogates capture what may be termed biodiversity support potential.

There are two primary classes of biodiversity surrogates, both of which are derived from remotely sensed data. First, classified land cover types are used to estimate the diversity of dominant habitat types (e.g., unique forest and/or wetland communities) within a habitat patch;

in theory, conservation resources should be directed so as to maximize the area and diversity of these habitats. The approach assumes that the majority of species typically associated with each habitat or community type will be conserved through the protection of that habitat (Ferrier, 2002). The second approach is to estimate unique ‘environmental settings’ that effectively capture the primary biophysical constraints relevant to plant species and communities (Araujo et al., 2001; Ferrier, 2002; Stephenson, 1990 & 1998; Urban et al., 2000). In addition to directly controlling the distribution and abundance of plant communities, these constraints may also indirectly control the distribution of wildlife species, as many species tend to rely on particular vegetative community types. Settings typically include temperature and the availability of both water and light, and may provide a measure of biodiversity support potential in the face of shifting temperature, precipitation, and disturbance regimes. If derived from current, readily available geospatial data, surrogates enable estimation of biodiversity support potential at large spatial scales (Kintsch and Urban, 2002). However, Ferrier (2002) suggests that surrogates must be informed by biological inventories if they are to become ecologically meaningful measures of biodiversity support.

These approaches are not without criticism. Araujo et al. (2001) maintains that environmental diversity is generally a poor predictor of species diversity, though he notes that plant species do exhibit consistent patterns of representation. The notion that environmental diversity provides a useful surrogate stems from the assumption that species distributions are at equilibrium with governing environmental factors. But, surrogates may ignore the significant roles that extinction, speciation, dispersal barriers, and biotic interactions play in determining the biological diversity of a site (Araujo et al., 2001). Further, biophysical proxies do not capture either disturbance or

land use history, each of which may be an important determinant of species composition and diversity in many regions.

Despite these criticisms, there remains a critical need to identify and prioritize habitat for conservation. While an individual species approach has been largely successful in protecting endangered species, these efforts tend to be expensive and do not always provide tangible benefits for the great majority of non-target, ecologically significant species. Accurate measures of biodiversity are not currently available at the scales necessary for planning and implementing conservation initiatives, and biodiversity surrogates probably constitute the most feasible method for estimating the biodiversity support potential of habitats at scales relevant to the human landscape. Surrogates that rely on unique habitat types and/or environmental settings will likely offer the principal approach, especially if these measures are informed by biological inventories. If combined with relevant landscape-scale metrics (connectivity, patch area and configuration, etc.), biodiversity surrogates have the potential to more fully capture the buffering capacity of habitat patches.

A review of the recently released state Wildlife Action Plans (Lerner et al., 2006) found that forty-nine states are focusing on the conservation of particular habitat types as the primary strategy for conserving priority species. Recent shifts in political support for climate change action may also encourage the use environmental settings, which may provide a better measure of biodiversity value under changing climate regimes. Toward that end, I seek to develop a conservation planning tool capable of assessing the biodiversity support potential of habitat patches across North Carolina. I use a suite of biodiversity surrogates, including both biophysical proxies and land cover types, as potential measures of biodiversity support. The model is then

applied to a sample watershed to assess the ability of the tool to accurately predict regions of high biodiversity value, and thus, whether surrogates may be effectively used to evaluate and prioritize lands for conservation. The tool is part of a larger project to quantify and value a suite of ecosystem services, including watershed protection, carbon sequestration, and recreational/scenic value. The ultimate objective is to provide a conservation planning tool set that overlays spatially explicit, valued services in the identification of conservation priorities. Further, I seek to develop a tool that may be readily learned and applied by land conservation organizations across the contiguous United States, reducing the need for specialized technical training and planning support.

## **Methods**

I began by exploring the geographic region used as a setting for model development and application, and then outline how biophysical settings were generated and defined within the model. As models rely heavily on the use of proxies, I field-tested the variability of modeled settings to verify their use at landscape scales. I next examine the development of biodiversity models, including the delineation of forest patches and the development of proxies for biodiversity support potential. Particular attention is given to the components and creation of biophysical proxies at large spatial scales. I next describe the process by which both biophysical proxies and land cover types were used to estimate biodiversity support potential at the patch level. Finally, I outline methods for evaluating the success of surrogates in capturing regions of high biodiversity support and apply the procedure to a sample watershed to assess tool performance. Verification relies on a comparison of tool outputs with the distribution of *Significant Natural Heritage Areas* (or *SNHAs*), “an area of land or water identified by the



Natural Heritage Program as being important for conservation of the state's biodiversity" (North Carolina Natural Heritage Program, 2008).

### ***Study Area***

Biodiversity support tools were developed to function at ecoregional scales, as delineated by The Nature Conservancy in 2000. Both the application of the model in generating patch-level biodiversity support estimates and the validation of model accuracy necessitated the use of smaller spatial scales. The Pigeon watershed in western North Carolina was selected for this purpose (Figure 1). Falling completely within the Southern Blue Ridge ecoregion, the Pigeon was chosen primarily because it is heavily forested and contains feasible sites for the field-based portion of the study (e.g., eastern portion of Great Smoky Mountain National Park). The Pigeon also contains a fairly high proportion of Significant Natural Heritage Areas, which were used as a reference in validating estimates of biodiversity support potential. Alternative datasets, and fine-scale soils data in particular, will also soon be available for the watershed. Though not currently available for the entire country, soil characteristics are an important determinate of plant community distribution and may be incorporated into future tool iterations to further refine biophysical proxies.

Great Smoky Mountains National Park, located within the northwestern region of the Pigeon along the North Carolina and Tennessee border, was selected for assessment of soil moisture surrogates (Figure 1). The Park is nearly 525,000 acres in area, spans a wide elevation gradient (from 875 to 6,643 feet), and receives between 55 and 85 inches of precipitation (valleys and peaks, respectively) each year. The Park also supports a wide range of community types, from low-elevation deciduous forests to the highly imperiled spruce-fir forests at higher elevations. While resident ecosystems have been shaped by previous land use practices, and in particular, by

extensive logging prior to park establishment in 1934, they have been under legal protection for nearly 75 years. Indeed, the Park has been noted for its concentration of rare species (primarily plant and aquatic species) endemic to the Blue Ridge ecoregion, and was designated an International Biosphere Reserve by the United Nations. Thus, the Park seems to provide a contiguous, healthy suite of habitats suitable for estimating soil moisture gradients at landscape scales. Logistically, it also houses one or more representatives of each unique environmental setting identified by the biophysical surrogate tools, many of which may be readily accessed via road and trail. Finally, nearly a third of the Park is located within the Pigeon watershed; with a fairly large concentration of *Significant Natural Heritage Areas*, it provided an ideal proof of concept for assessing the performance of biodiversity support tools.

### ***Data Sources***

A suite of publicly available GIS data layers were used in the development, application, and validation of biodiversity support tools. Thirty-meter resolution digital elevation models (DEM), available as part of the National Elevation Dataset (NED), were used to generate biophysical proxies (including elevation, potential radiation load, and topographic convergence). Watershed and stream catchment boundaries were obtained from the National Hydrography Dataset (NHD+). Catchments, which represent stream reach contributing area and are typically between 1 and 10 km<sup>2</sup>, were used to delineate maximum patch size. Land cover types from the North Carolina Gap Analysis Program (NC-GAP, 2008) were also used; the distribution and diversity of plant community types are classified at thirty-meter resolution to the alliance level using dominant species. I also obtained modeled species abundance and distributions from NC-GAP, which uses known Element Occurrences (see below) and expert review to predict bird, mammal, reptile, and amphibian ranges. While not publicly available, the North Carolina Natural Heritage

Program provided Element Occurrence data; Element Occurrences, which are collected by Natural Heritage Programs and are available for every state, describe the distribution of rare species and community types across the landscape. Maps of *Significant Natural Heritage Areas*, which were used in tool assessment, were also obtained from the NC Natural Heritage Program.

### ***Components of Modeled Biophysical Settings***

Gradient analysis has revealed that vegetation types vary as a function of unique environmental conditions, and in particular, along temperature and moisture gradients (Stephenson, 1990; McCune and Grace, 2002). Indeed, Whittaker (1956 & 1967) demonstrated that temperature and plant-available moisture constitute the two most important factors controlling the distribution of plant communities in the Great Smoky Mountains. Temperature, relative soil moisture, and relative radiation loading were selected as the primary proxies for environmental heterogeneity; these represent the most plant-relevant environmental factors in mountainous regions. These conditions are captured using estimates of elevation, topographic convergence, and potential solar radiation, respectively; it is important to note that these proxies provide estimates of relative difference. To develop a simple index of local site conditions, I created a system for classifying these conditions into ecologically meaningful ranges.

Elevation is an important determinant of both temperature and precipitation, with temperature tending to decrease with increasing elevation and precipitation generally exhibiting the opposite pattern (Urban, 2000). Because it plays so prominent a role in determining both temperature and precipitation, elevation was divided into five distinct classes, each approximately 350 meters in height. It is important to note that these effects may be more pronounced in regions of strong orographic lifting. In regions with minimal topographic relief, such as North Carolina's Piedmont and Coastal Plain ecoregions, elevation would likely play a less significant role in

controlling the distribution of plant species and communities. Thus, fewer classes would be necessary or other, more plant-relevant variables (including geology or relevant soil characteristics) might be used.

Topographic convergence, derived from estimates of slope and upslope contributing area, measures the tendency of water to drain to or away from a point. It has been widely used by hydrologists (Moore et al., 1990), but is increasingly used by plant ecologists to estimate relative soil moisture across the landscape (Lookingbill and Urban, 2005; Urban et al., 2000 & 2002). Using digital elevation models, topographic convergence was estimated for each cell in the DEM as a function of both the upslope area contributing to flow accumulation ( $a$ ) and local slope ( $b$ ), after Urban (2000):

$$\text{Topographic Convergence} = \ln [a / (\tan b)] \quad (1)$$

Topographic convergence was divided into three classes, with the two extremes characterized by dry, divergent areas and moist, convergent areas; moisture estimates intermediate the extremes were placed into a third soil moisture class.

The potential radiation load at a given elevation depends largely on the slope and aspect of the land surface, and can be computed rather simply from terrain data (Pierce et al., 2005). Intuitively, southwest-facing slopes tend to receive more radiation than northeast-facing slopes; thus, they also tend to experience higher temperatures and higher evaporative demand. Potential solar radiation was estimated by transforming aspect (see equation 2), as adapted by Lookingbill and Urban (2005) from Beers et al. (1966):

$$\text{Potential Solar Radiation} = -\cosine (\text{Aspect} - 45) \quad (2)$$

Potential solar radiation was divided into three classes, in which the two extremes delineate warmer, southwest-facing slopes and cooler, northeast-facing slopes; potentials intermediate the two extremes were placed into a third class.

Rather than applying evenly spaced class breaks, I instead used Element Occurrences to identify more ecologically meaningful thresholds. While the spatial coverage of Element Occurrences is relatively small relative to the scales considered here, they represent an important and widely available empirical basis for making biophysical proxies more ecologically meaningful. Because terrestrial plants are more likely to vary according to biophysical constraints than many wildlife species, I limited our use of Element Occurrences to terrestrial and wetland plants and plant communities. As Natural Heritage data are characterized by varying degrees of accuracy regarding the spatial location of occurrences, I removed from subsequent analyses all occurrences with an error greater than one kilometer. Remaining Element Occurrences were then sampled for each of the three environmental variables. The process appends each occurrence with the value of each biophysical variable at the corresponding sampling location. A natural Jenk's breaks classification (ArcGIS 9.3) was applied to divide the occurrences into the appropriate number of classes and identify class thresholds for each of the three biophysical variables. North Carolina is divided into three distinct ecoregions - the Coastal Plain, Piedmont, and Southern Blue Ridge. To more accurately capture the unique and variable character of the state's ecoregions, thresholds for each biophysical variable were defined independently for each.

Having identified appropriate, ecologically meaningful thresholds and divided the three biophysical variables into distinct classes, I next assigned each class a unique numerical code. Elevation classes were assigned numbers from 1 to 5, while both topographic convergence and

radiation assigned numbers between 1 and 3. Classes were subsequently combined algebraically in order to create a simple, three-digit *zip code* that unambiguously indexes the environmental conditions at any point on a landscape (Figure 2). Forty-five unique environmental zip codes were generated according to the following equation:

$$\text{Environmental Zip Code} = (\text{Elevation} * 100) + (\text{TCI} * 10) + (\text{Solar Radiation}) \quad (3)$$

Here, higher numbers represent higher elevation, higher radiation load, and greater soil moisture; for example, a “531” would represent a moist high-elevation site on a shady, northeast-facing cove, while a “113” would represent a low-elevation, relatively dry southwest-facing slope.

### ***Verifying Model Components***

The variability of environmental gradients remains difficult to assess at landscape scales (Lookingbill and Urban, 2005). While the use of elevation and potential solar radiation as proxies are widely accepted, topographic convergence remains somewhat uncertain. Soil moisture is highly variable across both space and time, making it difficult to assess whether topographic convergence accurately captures moisture gradients. Toward that end, I designed a field study to assess whether topographic convergence provides an accurate surrogate for soil moisture at landscape scales.

*Field Assessment* – In order to assess the accuracy of modeled topographic convergence, I conducted ground measurements of soil moisture across a range of environmental gradients within Great Smoky Mountain National Park during the summer of 2007. I sampled the three unique topographic convergence classes across a range of elevation and potential radiation conditions (see description of environmental zip codes, above) to establish relative differences in

soil moisture. Assessing soil moisture does not necessitate sampling all possible combinations of moisture, elevation, and potential radiation, however, so soil moisture classes were sampled randomly across elevation and radiation gradients. Sampling locations were accessed on foot with the aid of a portable GPS unit and compass, and three soil moisture readings were taken at each location using a portable soil moisture probe.

Prior to field assessment, I applied a GIS-based decision-tree model to reduce potential sampling area. Given the difficult nature of park terrain, all regions located further than 200 meters from park roads and trails were excluded from analysis. Similarly, as sampling areas were to be accessed on foot, regions located further than 10 miles away (a reasonable half-day walk) from easily accessible park entrances were removed. Finally, zip code patches with an area less than 0.5 hectares were removed; small patches are more difficult to accurately locate in the field and are more likely to be a remnant of estimation error. Even under these relatively strong constraints on potential sampling area, at least one representative for 43 of the 45 total zip codes was found within the feasible sampling area. The two outliers were found deep within the park's interior and were excluded from sampling efforts.

Having identified a reasonable set of potential sampling areas within the park, sampling design was adjusted to incorporate an additional logistical limitation. Soil moisture is heavily dependant on a number of factors, including time of day, the intensity and time since the last precipitation event, terrain slope, soil type, etc., all of which make between-site comparisons challenging. Sampling soil moisture at fixed reference plots across a diverse suite of locations enables between-site comparisons by reducing these sources of error. Thus, reference stations were set up at five, fairly evenly spaced access points around the perimeter of the park. To establish

relative differences in soil moisture among the reference stations, all stations were sampled over the course of a single morning on four consecutive, rainless days. The approach enabled estimation of mean soil moisture, as well as the slope of the drawdown curve, within each reference plot. Drawdown curves were fit to each reference station via regression analysis; subsequent measurements at each reference station established where on the drawdown curve the station was on a specific sampling day, and by extrapolation, the approximate soil moisture at each of the other four reference stations.

There is also considerable change in soil moisture on a daily time-scale. Temperatures increase and peak during the afternoon, and plant evapotranspiration begins to reduce soil water in the late morning as temperature and radiation reach threshold levels. To reduce error introduced by daily drawdown, soil moisture measurements were only collected between sunrise (approximately 6:30 a.m.) and 11:00 a.m. each morning and reference stations were measured at the start of each sampling day. Soil moisture measurements collected within the park were compared with their respective reference station, which in turn enabled comparison with moisture estimates collected at other reference stations (and sampling locations) through time.

*Analyses* – Analyses revealed that topographic convergence does accurately capture soil moisture gradients at the landscape level. Moisture class one, representing areas with lowest soil moisture, possessed a mean of  $19.4 \text{ cm}^3 \text{ water per m}^3 \text{ soil}$  ( $\text{cm}^3/\text{m}^3$ ). Moisture class two had a mean of  $23.3 \text{ cm}^3/\text{m}^3$  and moisture class three, representing areas of highest soil moisture, possessed a mean of  $27.0 \text{ cm}^3/\text{m}^3$ . One-way analysis of variance revealed significant differences among each of the three TCI classes ( $p=0.027$ ,  $F_{\text{crit}}=3.13$ ); evaluation of between-group differences was also significant for all class comparisons. Having verified the use of topographic



convergence as an accurate proxy for soil moisture, I next consider the development and application of biodiversity support tools.

### ***Model Development and Application***

Two distinct tool sets were developed to estimate the biodiversity support potential of terrestrial habitats in North Carolina. The first uses the diversity of unique biophysical conditions, while the second uses the diversity of land cover types (as classified by NC-GAP) across the landscape. Unweighted and weighted metrics (using biological inventories from the North Carolina Natural Heritage Program) were designed for each tool set, for a total of four different measures of biodiversity support potential. Each tool generated a map of all habitat patches within an ecoregion, ranked according to their relative biodiversity support potential.

*Patch Delineation* – In many regions, blocks of contiguous habitat can extend across areas so large as to be effectively irrelevant to conservation and management. Much of western North Carolina, for example, is heavily forested; when patch size remains unconstrained, the western section of the state (within the Southern Blue Ridge ecoregion) falls into three vast blocks of essentially contiguous forest. To make tools more directly usable, I chose to limit the spatial scale of analysis by setting an upper limit on patch size. Size constraints were derived from stream reach catchments as delineated by the National Hydrography Dataset. Catchments were typically several hundred hectares in area, provided a more convenient spatial scale for analysis, and enabled integration with the watershed evaluation tools also developed as part of the larger study. As a proof of concept, I further limited analyses to regions of contiguous forest by removing all non-forested habitats from the NC-GAP land cover maps.

*Estimating Biodiversity Support Potential* – All points on the landscape were assigned a unique environmental zip code; similarly, all pixels were assigned a unique land cover classification according to the distribution of primary vegetative community types (NC-GAP). The simplest measure of diversity is the total number or richness of zip codes or land cover classes within a forest patch, which may be easily calculated within ArcGIS. The richness of zip codes represents the diversity of unique environmental settings within a particular patch; land cover richness measures the diversity of vegetative habitat types. Patches with a greater richness score should possess greater environmental/habitat diversity, which in turn should support a greater number of species over the long-term. While total richness is an important measure of diversity, it is critical to account for the relative area of each zip code or cover class and provide a diversity measure sensitive to dominance (e.g., when one zip code or cover class occupies a disproportionate area of the patch). The Shannon Diversity Index, provided below, was used for this purpose (Brower 1977).

$$H' = - \sum p_i \cdot \log p_i \quad (4)$$

Here,  $p_i = \frac{n_i}{N_i}$ , where  $n_i$  is the area of particular cover or zip code richness and  $N_i$  is the total area of the patch itself. Increased dominance of one or more cover or zip code classes reduces the overall diversity score of that patch. Patches with low dominance have zip codes or land cover classes with a fairly even area distribution and should possess a greater biodiversity support potential than a patch with a similar richness score but a higher degree of dominance. The area-weighted index cannot be used alone, however, because estimates of dominance vary according to the number of classes. For example, a patch with three zip codes might receive a higher biodiversity rank than another in which ten zip codes are present (where the three primary zip

codes possess the same relative area, but in which the seven minor zip codes raise the dominance score). Therefore, I averaged the richness and area-weighted diversities to create single metrics for both environmental zip codes and land cover classes; each unweighted metric generates single, patch-level estimates of biodiversity support potential, which may then be used to compare the relative biodiversity support potential of patches across larger spatial scales.

It is also important to examine whether particular environmental settings or vegetative habitat types tend to support greater species richness than others. Thus, Element Occurrences were used to calculate the frequency with which rare and endangered species and communities are associated within each zip code or land cover class. The frequency of Element Occurrences, however, should be correlated with the area of each zip code or cover class, with larger areas tending to capture a larger number of occurrences. To correct for this bias, I estimated the density of Element Occurrences per unit zip code or cover class area. Each zip code or cover class was subsequently reclassified according to estimated density of occurrences per unit area (or pixel) associated with each. By assigning each pixel type a predicted number of Element Occurrences, the total number of predicted Element Occurrences within each patch may be estimated given the composition and area of the environmental settings or cover classes found there. In other words, the procedure assigns a weight to each patch based on the estimated capacity of each setting or cover type to support rare or endangered species or community types. Patches with environmental settings or land covers containing a greater predicted Element Occurrence density should possess a greater current biodiversity value; as above, these weighted metrics may be used to compare biodiversity value among patches at larger scales (Figure 3).

I also used modeled species richness developed by the North Carolina Gap Analysis Program to weight both environmental zip codes and land cover types. Species distributions and richness, derived from biophysical associations, Natural Heritage data, and expert opinion, have been generated for an extensive suite of birds, mammals, reptiles, and amphibians. To weight each land cover type or zip code, modeled richness for all species were aggregated to generate estimates of total species richness. Land covers and zip codes were subsequently weighted according to the total predicted species richness per unit area; densities were then used to calculate patch-level estimates of biodiversity support potential. As subsequent accuracy assessment revealed, using modeled species richness as a weighting factor does not seem to accurately capture biodiversity value. Patch-level estimates remained largely uniform after applying the weighting procedure, indicating that modeled richness does not vary significantly as a function of either land cover class or biophysical setting. The approach was therefore discarded and will not be considered further.

### ***Model Validation***

To assess the accuracy of the biodiversity tools, I generated watershed maps in which all forest patches were ranked according to their biodiversity support potential. Having generated four biodiversity metrics (weighted and unweighted zip code and land cover diversity), assessment required four watershed maps. I then examined differences in the biodiversity support potential of patches located within *Significant Natural Heritage Areas (SNHAs)* compared with a random selection of patches from the Pigeon (see Figure 3, left, for example map). *SNHAs* should identify regions with high biodiversity value; while they do not capture all biologically significant areas, they represent a minimum reference area for comparison.

*Randomization Procedure* – As data were not normally distributed, a non-parametric randomization procedure (see below) was used to examine differences in mean biodiversity support potential. Two random sample sets were taken initially, with 100 samples drawn with replacement from patches located within *SNHAs* (for each biodiversity metric, separately). Samples from each set were paired and the difference in biodiversity support between each sample pair calculated for each of the 100 pairs; the average difference provides an estimate of ‘within-group’ (e.g., patches located within *SNHAs*) biodiversity support variability. Next, two additional random, paired 100-sample sets were collected, the first from within-*SNHA* patches and the second from all patches within the watershed. The average difference between each sample pair provides an estimate of ‘between-group’ variation; the magnitude of ‘between-group’ variation was then compared to ‘within-group’ variation. If patches within *SNHAs* have a higher biodiversity support potential than patches drawn at random from the watershed, ‘within-group’ variation should be consistently smaller. The procedure above was replicated 10,000 times; the frequency with which ‘within-group’ variation was smaller than ‘between-group’ variation was tallied and divided by the total number of replications to generate a probability. This probability may be interpreted as a p-value; probabilities greater than 0.95 or 95% revealed that the mean biodiversity support potential for patches within *SNHAs* was significantly different than a random selection of patches. In cases where there was a significant difference, I examined the mean biodiversity support potential for both patch classes to identify the greater of the two. I also used the procedure outlined above to compare within-*SNHA* patches to those found outside these designated regions.

It is important to note that patch area should be correlated with biodiversity support potential (Ferrier, 2002), and analyses must account for this relationship. As a result of tool design, larger

patches tend to house a greater number of unique land cover types and environmental settings simply because they cover a more extensive area. Interestingly, while unweighted metrics *are* highly correlated with patch area, weighted biodiversity metrics do not exhibit this relationship. In order to reaffirm the independence of both metric types from patch area, analyses of both were corrected for area-related effects. Toward that end, patches were divided into five unique area classes using two distinct approaches in order to examine the effect of classification method (Table 1). In the first, patches were separated into five area classes so that each contained approximately the same number of patches, though each class did not necessarily cover the same area range. In the second, a natural Jenk's breaks classification (as specified in ArcGIS 9.3) was used to generate five classes with approximately the same area range but an uneven number of patches. The randomization procedure detailed above was applied within each area class independently, largely removing area-related effects from the analysis. Because area classes still cover a specific, albeit greatly reduced area range, these effects do generate a limited degree of bias. Further, because the first approach generates five classes with significantly different area ranges, the Jenk's breaks method may be a more consistent method for removing area-related effects. As the Jenk's method is probably more appropriate, and because both classification schemes generate fairly similar results, I limited examination of results to the Jenk's method.

*Tiered Procedure* – It is useful to approach research questions from multiple avenues in order to confirm trends. Thus, I also examined the proportion of within-*SNHAs* patches that occupy the top tiers of the biodiversity support distribution. For example, of the nearly 1200 patches found within the Pigeon watershed, the 60 patches with the highest biodiversity support potential would represent the 'best' five percent of habitat patches. Of course, the identity of these patches will likely shift depending on which metric is examined. Therefore, I calculated the proportion of best

patches located within *SNHAs*, generating another measure of how well each of the biodiversity support metrics captures *SNHAs*. In addition to looking at the best five percent of habitat patches for each of the four metric types, I repeated the analysis for patches within the best 10, 25, and 50%. I also flipped the analysis and examined the ‘worst’ habitat patches – those patches falling within the lowest 5, 10, 25, and 50% regarding estimated biodiversity support potential. It is important to note that the number of forest patches within *SNHAs* (approximately one-third of the total) is far less than the number of patches outside of these areas; results must be evaluated with an awareness of this difference.

## Results

*Randomization Procedure* – Analyses revealed that biodiversity support potential, as measured by unweighted land cover diversity, was significantly less for patches within *SNHAs* relative to those outside (Table 2 and Figure 4). This finding holds for all but the smallest area classes (those smaller than 82.5 hectares in area), which did not show a significant difference. Comparison of patches within *SNHAs* to a random selection of patches from across the watershed did not reveal consistent trends, though findings suggest that unweighted land cover diversity is generally less for within-*SNHA* patches. Assuming that biodiversity is effectively captured by land cover diversity, these findings would suggest that *SNHAs* possess a reduced diversity of species and/or communities. Land cover diversity also tended to increase with patch area for all patch groupings, reaffirming the need to remove area-related biases from measures of biodiversity support potential (Figure 4). Interestingly, the overall mean of unweighted land cover diversity was greater for within-*SNHA* patches, which seems inconsistent with the findings above. However, *SNHAs* contain a greater number of large, intact patches; larger patches tend to have higher biodiversity support potential when unweighted metrics are used. Thus, while

biodiversity support potential was greater for patches outside of *SNHAs* within each specific area class, the trend was masked at more coarse scales of analysis by the fact that within-*SNHA* patches are generally larger (mean of 150.5 hectares) than non-*SNHA* patches (mean of 65.9 hectares).

Weighting land cover diversity using Element Occurrences generates quite different suite of findings. Patches within *SNHAs* have significantly greater biodiversity support potential than those outside *SNHAs* for all area classes (Figure 5). Similarly, patches within *SNHAs* have higher biodiversity support values relative to a random selection of patches; however, the degree of significance diminishes with increasing patch area until differences are no longer significant for the largest patch areas. The differential success of weighted and unweighted metrics suggests that the use of biological inventories to weight surrogates is an effective method for strengthening their ability to capture conservation value. While there is a noticeable area-related affect on the magnitude of differences, weighted land cover diversity does not show the clear correlation with patch area shown by unweighted metrics. This suggests that weighted metrics may be more resistant to area-related biases.

Unweighted zip code diversity for within-*SNHA* patches was generally greater than for those located outside, although these differences were not consistently significant except for patches greater than 279 hectares in size (Figure 6). Similarly, patches within *SNHAs* had a higher biodiversity support than patches drawn at random from the watershed; again, this only holds for patches greater than 279 or less than 82.5 hectares in size. The figure again reveals that biodiversity support potential increased with increasing patch area, confirming that unweighted metrics were highly correlated with patch area. Findings for weighted zip code diversity were



similar to those of weighted land cover diversity; for all area classes, biodiversity support potential was significantly greater for within-*SNHA* patches compared with those outside (Figure 7). Similarly, patches within *SNHAs* had a higher biodiversity support relative to a random selection of patches. Again, the degree of significance lessened with increasing patch area until differences were no longer significant for the largest area class. As with the land cover surrogates, weighted zip code diversity more accurately captured *SNHAs* (and thus, conservation value) than did unweighted measures. Weighted zip code diversity and patch area were only slightly correlated, again confirming that weighted metrics are less affected by patch area.

*Tiered Procedure* – The proportion of within-*SNHA* patches that occupy the top tiers of the biodiversity support distribution were examined next. For unweighted land cover diversity, only between 31 and 41% of the best patches (from all categories) fell within *SNHAs* (Figure 8). This proportion was approximately equal to the proportion of patches within *SNHAs* across the entire watershed (at 34%), suggesting that patches outside *SNHAs* have an equal likelihood of having high land cover diversity. These proportions were significantly lower than those derived for the three other biodiversity support metrics for tiers within the top 25%. Examining patches with the lowest support potentials (Figure 9), within-*SNHA* patches account for between 17 to 25% of the total, which is similar to proportions observed for unweighted zip diversity but relatively high compared with either of the weighted metrics. Thus, *SNHA* patches were spread out fairly evenly across the distribution of land cover diversity estimates, reaffirming the relative ineffectiveness of unweighted land cover diversity in identifying patches with high conservation value. With weighted land cover diversity, on the other hand, between 85 and 60% of the best patches fell within an *SNHA*, though the proportion fell consistently as lower quality patches were included (Figure 8). The opposite trend was observed for low value patches, as the proportion increased

from 2 to 10% as patch quality increased (Figure 9). The differences between unweighted and weighted land cover diversity observed here again suggest that weighting biodiversity surrogates improves their ability to identify lands with high conservation value.

Unweighted zip code diversity also performs fairly well, with proportions increasing from 50 to 85% as higher quality patches were included (Figure 8). Except for the best biodiversity support class (top 5%), unweighted zip code diversity did not perform as well as either of the weighted metrics. This also holds true for the lower tiers; between 18 and 25% of the worst patches fell within an *SNHA*, trends that were fairly similar to those observed for unweighted land cover diversity. Weighted zip code diversity performed almost as well as weighted land cover diversity, with between 81 and 55% of patches falling within an *SNHA* (Figure 8). Again, the proportion of capture fell consistently as lower quality patches were included in the analysis. With between 7 and 20% of low quality patches falling within an *SNHA*, weighted zip code diversity does not perform as well as weighted land cover diversity but consistently better than either of the unweighted metrics (Figure 9).

Finally, the proportion of within-*SNHA* patches occupying the top tiers of the biodiversity support distribution were examined when the three best biodiversity metrics (weighted land cover diversity and both weighted and unweighted zip code diversity) were averaged to generate a combined estimate of biodiversity support potential (Figure 8). Interestingly, this combined biodiversity metric performed better than any of the individual metrics when examining the best 5 and 10% of patches. More specifically, 98 and 88% of the best patches are located within an *SNHA*, respectively, compared with 83 and 85% for weighted land cover diversity (the most effective individual metric). For the top 25 and 50% of patches, however, the combined measure

performed less well than weighted land cover diversity, capturing 69 and 54% of the best patches compared with 73 and 59% for weighted land cover diversity. The finding suggests that it may be possible to aggregate biodiversity estimates to produce more robust measures of conservation value.

## Discussion

The study suggests that forest patches located outside of *Significant Natural Heritage Areas* tend to possess higher land cover diversity, which contradicts what would be expected if land cover diversity were an effective surrogate for biodiversity support potential. If *SNHAs* do represent biodiverse regions, it appears that a greater number of land cover types will not necessarily capture this potential. These findings confirm Ferrier's (2002) assertion that the diversity of remotely sensed land cover types, by itself, does not constitute an effective surrogate for biodiversity. The success of weighted land cover diversity in capturing these regions suggests that using biodiversity inventories to weight land cover surrogates does enable for the capture of current biodiversity value. Land cover types clearly vary in the degree to which they support rare and endangered species and communities, and should be weighted by species-level data if they are to be effectively applied as surrogates in conservation planning initiatives. Although weighted land cover diversity appears to be an effective surrogate, it is important to remember that many places (especially outside of the United States) do not possess detailed estimates of land cover.

Biophysical surrogates, on the other hand, may be used more widely. Unweighted zip code diversity is also a more effective proxy for biodiversity support potential than unweighted land cover diversity in regions where biological inventories are not available. Of course, its

effectiveness is limited to patches of larger area. Weighting a biodiversity surrogate using biological inventories increases its success in capturing regions of high biodiversity value, as unique biophysical conditions similarly seem to vary in the degree to which they support rare and endangered species and communities. Weighting environmental zip codes using Natural Heritage data is an effective method of accounting for this variation. The usefulness of biological inventories is fortunate, as Element Occurrences are collected by Natural Heritage programs within every state and represent a broadly applicable, cost-effective approach. Biophysical surrogates offer the added advantage of enabling a more flexible approach, potentially able to better capture the factors most relevant to a particular ecoregion. For example, elevation is less important than soil type and/or quality within North Carolina's Piedmont and Coastal Plain ecoregions. Incorporating appropriate soil characteristics (e.g., pH, % sand or clay, plasticity) into a unique zip code scheme would enable capture of the environmental constraints most relevant to resident plant species and communities, which could again be locally calibrated using biological inventories.

Despite the relative success of biodiversity surrogates in capturing lands with high biodiversity value, potential weaknesses in the assessment approach must also be considered. In particular, we must consider whether biodiversity value, as represented by *Significant Natural Heritage Areas*, also represents regions with high biodiversity support potential. Unweighted surrogates themselves do not measure current biodiversity value, but instead represent the ability of a habitat patch to buffer biodiversity; they capture the long-term resiliency of a forest patch and its ability to support biodiversity through time. While I have thus far assumed that these two measures are sufficiently similar to warrant direct comparison, results suggest that they may be distinct. In particular, unweighted measures of zip code diversity seem to capture what I have

termed biodiversity support potential. On the other hand, weighted measures (including both zip code and land cover diversity) may represent measures of current biodiversity value. Indeed, weighted measures were more effective than unweighted measures in capturing *Significant Natural Heritage Areas*, designated for biodiversity value and not biodiversity support potential. Interestingly, findings also suggest that combining these distinct metrics into a single measure may provide a more powerful surrogate, capturing both biodiversity value and support potential. Estimates of biodiversity support potential may also be combined with relevant landscape-scale metrics (connectivity, patch area and configuration, etc.) to generate a more complete measure of conservation value.

The study also relies heavily on the assumption that *Significant Natural Heritage Areas* have higher biodiversity value than surrounding lands. *SNHAs* are designated in order to identify and prioritize “high-quality or rare natural communities, rare species, and special animal habitats” (North Carolina Natural Heritage Program, 2008). However, the designation of these regions seems inherently biased, with many areas located within regions less impacted by human activity. Examining the distribution of *SNHAs* within western North Carolina, for example, reveals that many fall within already protected, publicly owned lands well removed from urban development centers. Although *SNHAs* represent a more spatially contiguous set of habitats, it is likely that these areas represent an incomplete coverage of lands with high biodiversity value. Many other public lands have *not* been designated, despite already existing legal protection and connectivity to adjacent protected lands. This suggests that, while *Significant Natural Heritage Areas* were clearly designated with some consideration given to the current condition and habitat connectedness, it is likely that their distribution is not limited by the legal status of lands; thus, they do represent relative biodiversity value.

Indeed, other regions with potentially high biodiversity value may have escaped designation; and lands outside of *SNHAs* may or may not support high levels of biodiversity. While this observation may be perceived as a shortcoming of the model validation approach, the possibility of incomplete coverage actually speaks to the power of the model in capturing the areas that *have* been identified. *SNHAs* provide an accurate, albeit spatially limited measure of biodiversity value. While both weighted biodiversity metrics tend to effectively capture *Significant Natural Heritage Areas*, the model also identifies many forested patches located outside of *SNHAs* as having high biodiversity support potential (Figure 10). These lands have escaped designation but may still possess high biodiversity value or support potential; thus, such lands represent conservation priorities that should merit closer examination.

Unweighted environmental settings may also help identify opportunities for landscape-scale restoration. Land use history and current ecosystem condition may have been factored into decisions regarding the designation of *Natural Heritage Areas*. While some of these lands may be currently degraded, restoration initiatives could successfully restore ecosystem function within patches best able, due to their unique biophysical characteristics, to maintain and support biological diversity in the long-term. Degraded patches with high biodiversity support potential would then also represent regions of high restoration potential. While of less immediate concern than the purchase of lands or land development rights, restoration will likely become a more prominent conservation tool as land acquisition efforts become increasingly expensive.

## **Conclusions**

Unique environmental settings and land cover types were effectively used to assess the biological diversity of habitats at ecoregional scales. Although surrogate assessment suggests

that biodiversity value (as estimated by weighted metrics) is distinct from biodiversity support potential (as estimated by unweighted zip code diversity), both metrics are ecologically relevant and should be incorporated into conservation planning initiatives. Both surrogate types can be generated for the entire United States using existing, publicly available data. Further, surrogates may be readily calibrated using Natural Heritage data; land cover diversity, in particular, *must* be so weighted in order to accurately capture regions of high biodiversity value. Environmental settings may also be adjusted to capture the most relevant characteristics of each ecoregion. The effectiveness of these surrogates will likely improve, especially as additional data sets (including fine-scale soils data and more widespread biological inventories) become nationally available. Thus, it is likely that increased data sharing and cooperation will become an increasingly important component of future conservation planning and implementation efforts. Prioritization of land for conservation is steadily moving toward the inclusion and overlay of multiple ecosystem services; this study demonstrates that biodiversity surrogates may be used to ground these initiatives in biologically relevant priorities.

## **Acknowledgements**

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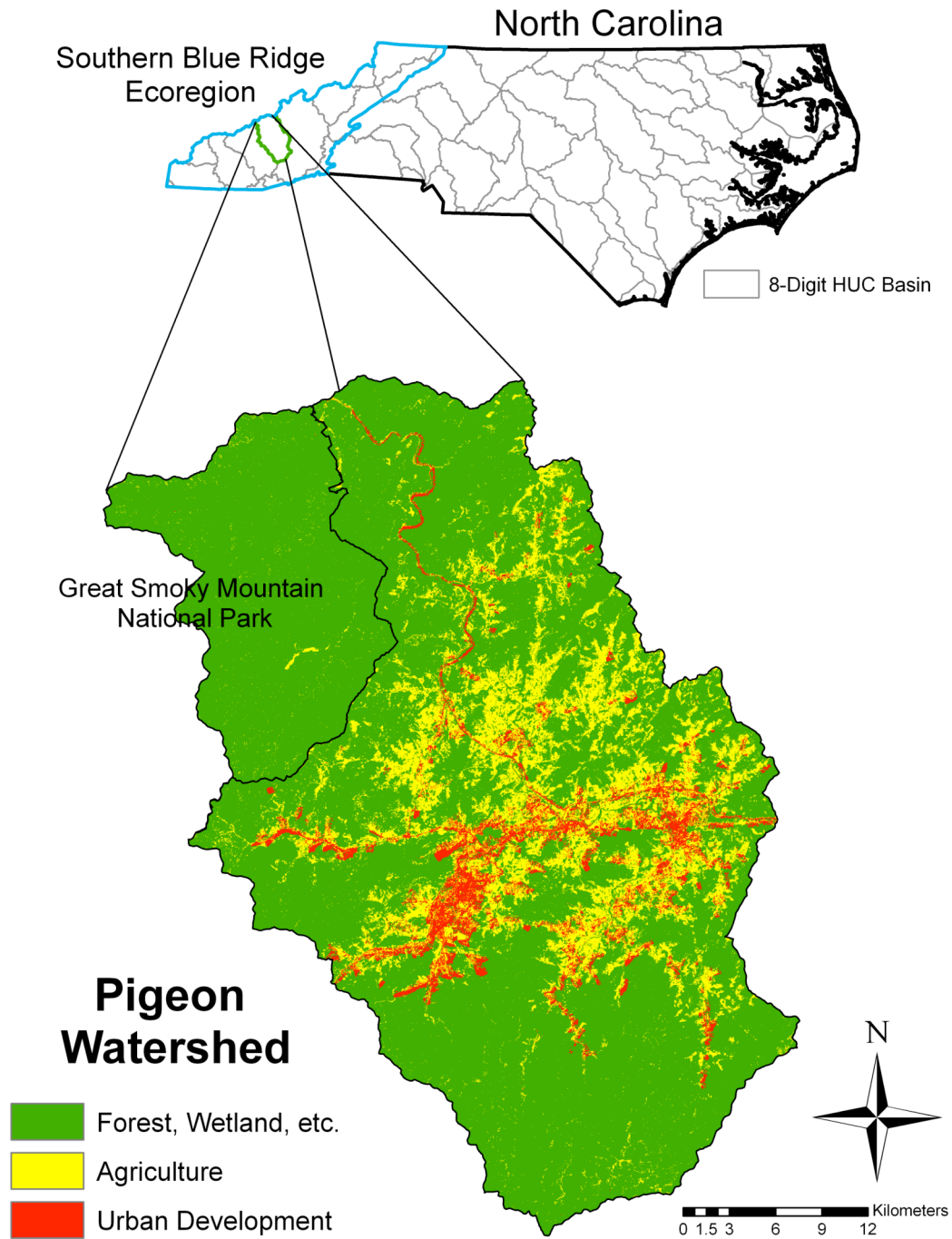
## Tables and Figures

**Table 1:** Classification of patches into five distinct area classes using two unique approaches.

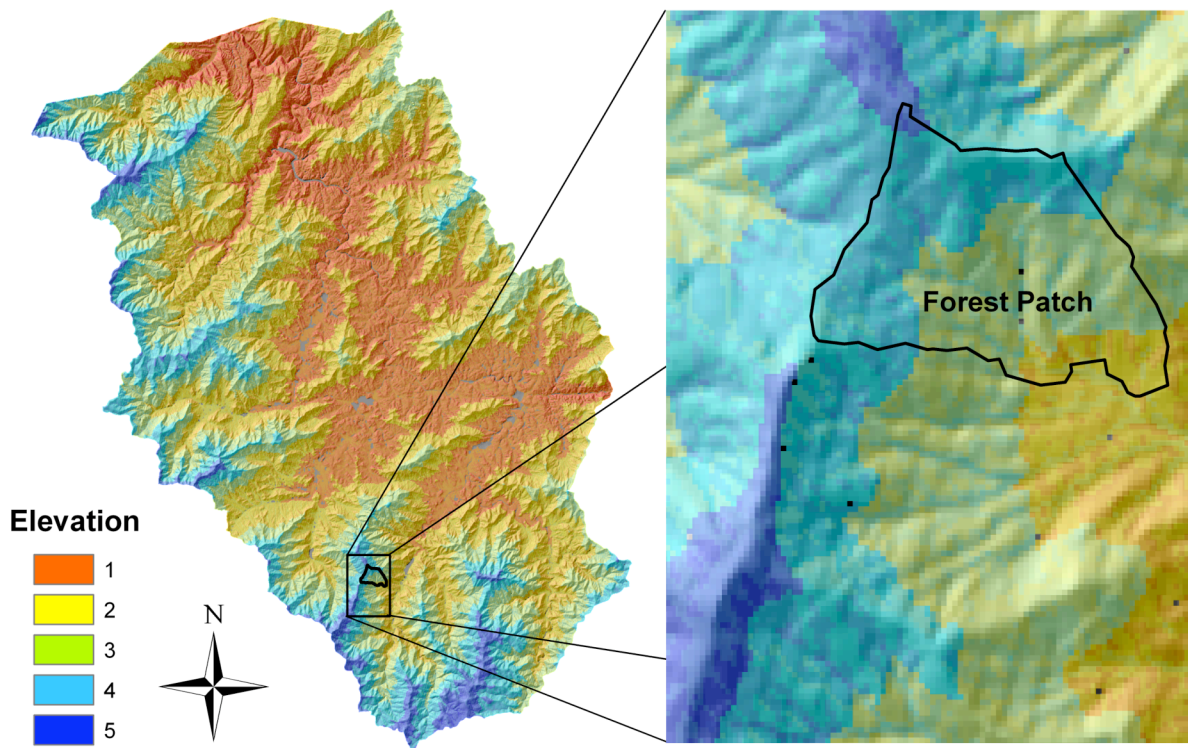
	Area Class	Area (Ha)	Patches Within <i>SNHAs</i>	Patches Outside <i>SNHAs</i>	Total Patch Number
Equal Number Classes	1	0.1 - 5.0	39	198	237
	2	5.0 - 18.9	45	196	241
	3	19.2 - 83.1	67	171	238
	4	83.5 - 179.6	117	123	240
	5	180.5 - 699.6	144	95	239
Jenks Classes	1	0.1 - 82.3	150	562	712
	2	82.5 - 166.7	107	112	219
	3	169.9 - 278.9	82	71	153
	4	279.5 - 432.7	55	33	88
	5	444.6 - 699.6	18	5	23

**Table 2:** Comparisons between within-*SNHA* patches and two additional patch categories: a random selection of patches from across the watershed (“Random”), and patches found outside of *SNHAs* (“Outside”). Values represent relevant p-values for between patch comparisons, and highlighted values identify statistically significant differences; red highlights where within-*SNHA* patches have higher biodiversity support value, while blue highlights where within-*SNHA* patches have lower values.

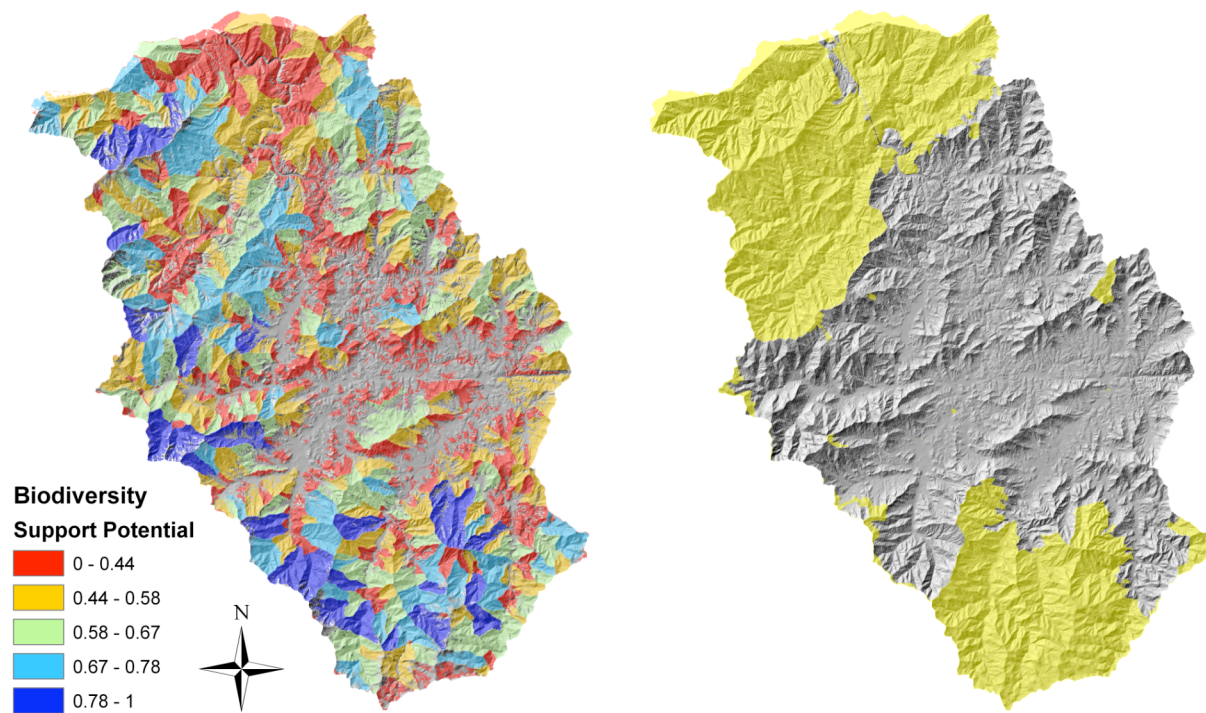
Area Class	Land Cover Diversity		Weighted Cover Diversity		Zip Code Diversity		Weighted Zip Diversity	
	Random	Outside	Random	Outside	Random	Outside	Random	Outside
1	0.58	0.60	1.00	1.00	0.99	0.93	1.00	0.99
2	0.95	1.00	0.99	1.00	0.91	0.93	1.00	1.00
3	0.90	1.00	0.99	1.00	0.80	0.84	0.99	1.00
4	0.98	1.00	0.98	1.00	0.96	1.00	0.98	1.00
5	0.65	1.00	0.94	1.00	1.00	1.00	0.91	1.00



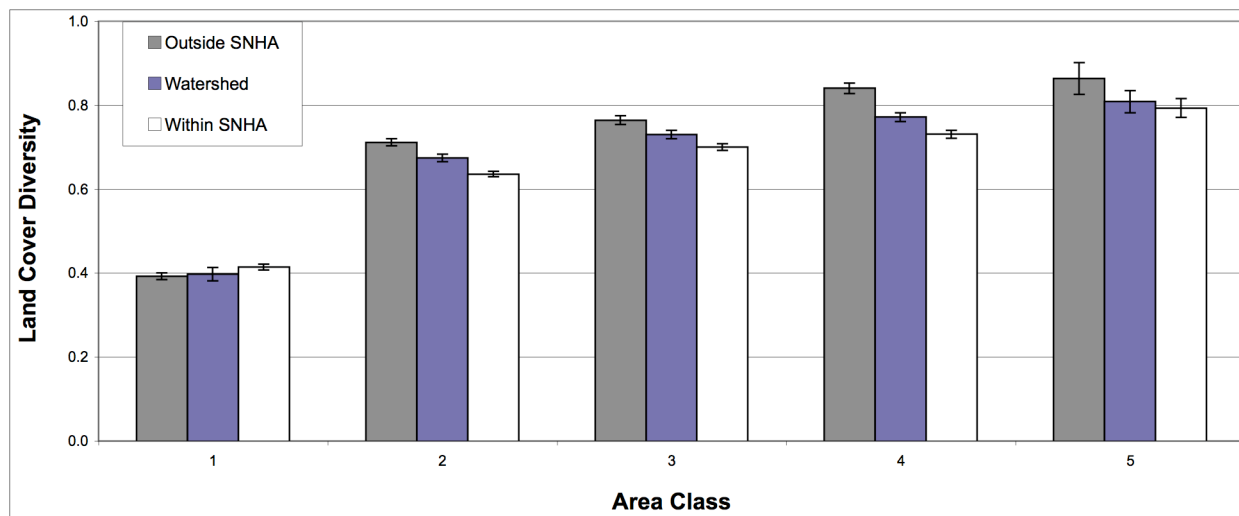
**Figure 1:** Above: North Carolina and its major hydrologic basins, including the Southern Blue Ridge ecoregion and the Pigeon Watershed. Below: A more detailed view of the Pigeon and its associated land cover types (derived from NC-GAP).



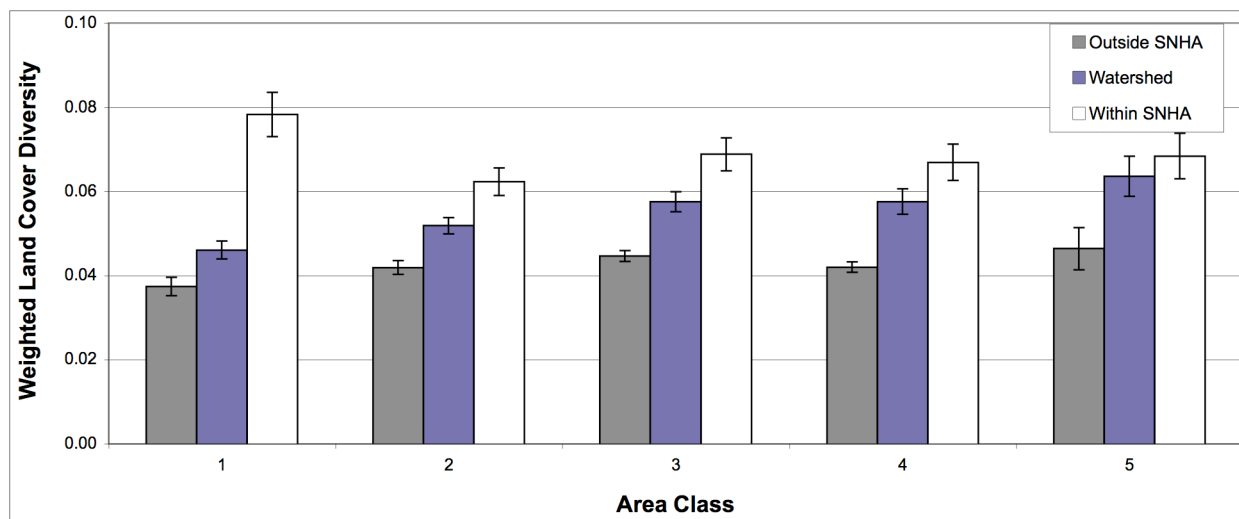
**Figure 2:** Left: Environmental settings or ‘zip codes’ within the Pigeon Watershed, delineated by the five elevation classes. Right: A detail of zip codes in and around a sample forest patch; discrete zip codes are seen as fine gradations of color within each band.



**Figure 3:** Left: Biodiversity support potential, as measured by weighted zip code diversity, for forest patches within the Pigeon Watershed. Right: Distribution of *SNHAs*, shown in yellow.

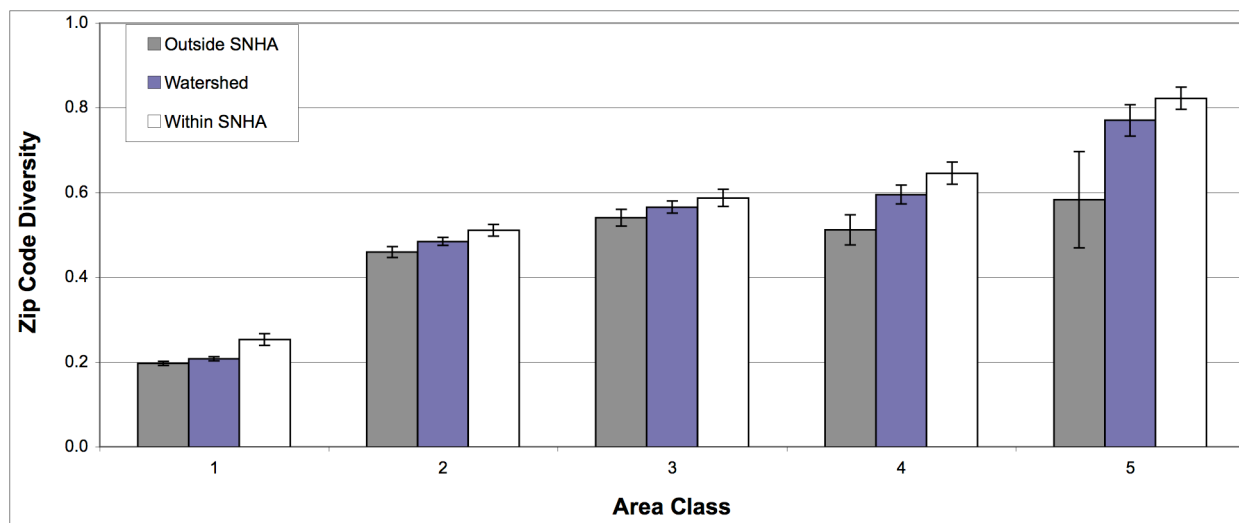


**Figure 4:** Mean land cover diversity (and standard error) for all patches within the watershed, patches within *SNHAs*, and patches outside *SNHAs*.

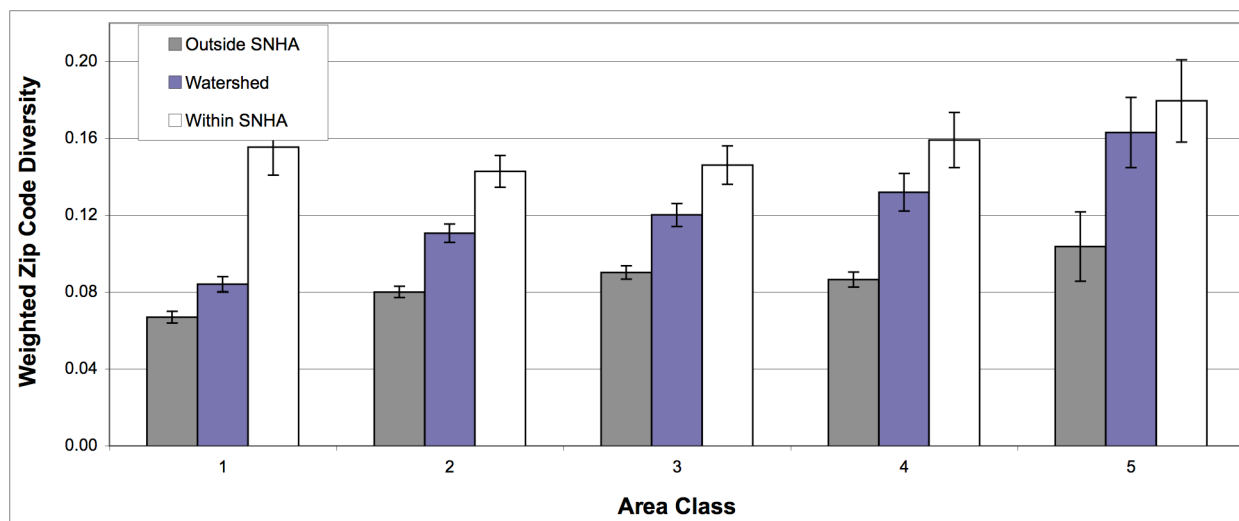


**Figure 5:** Mean weighted land cover diversity (and standard error) for all patches within the watershed, patches within *SNHAs*, and patches outside *SNHAs*.

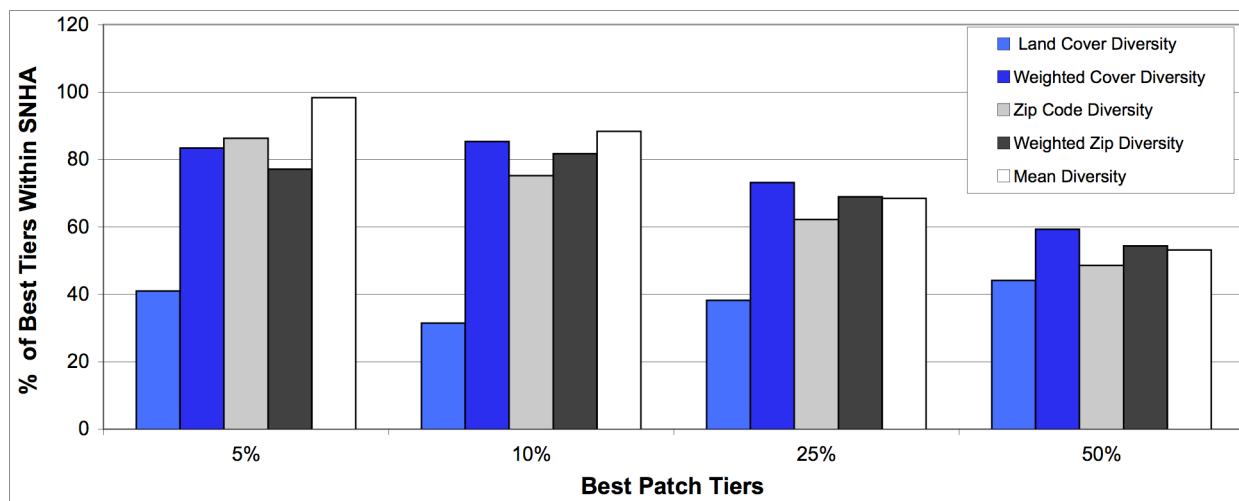




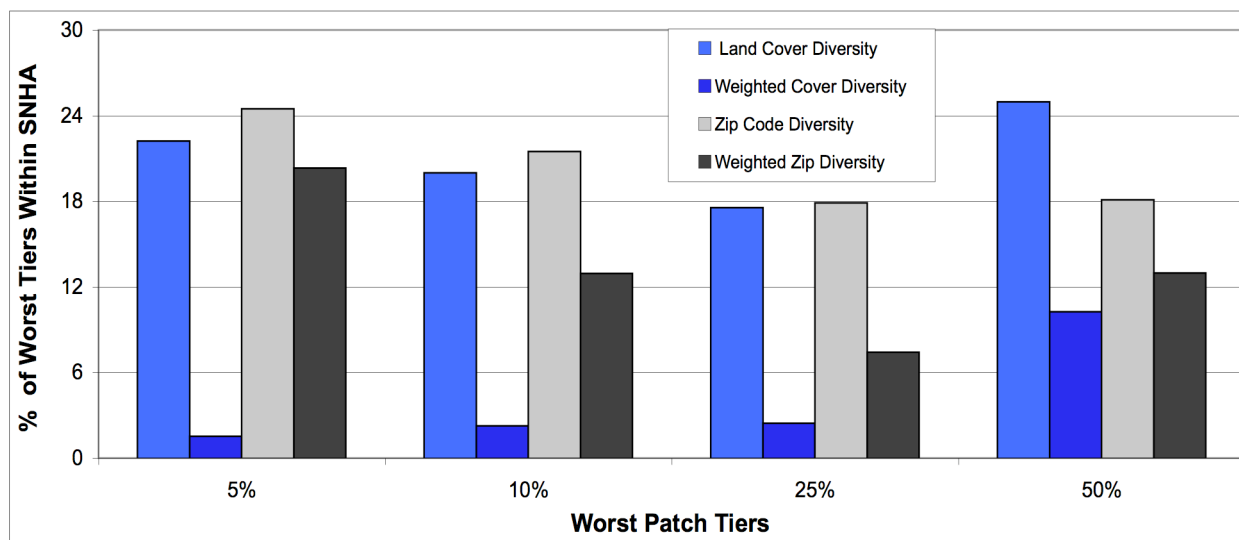
**Figure 6:** Mean zip code diversity (and standard error) for all patches within the watershed, patches within *SNHAs*, and patches outside *SNHAs*.



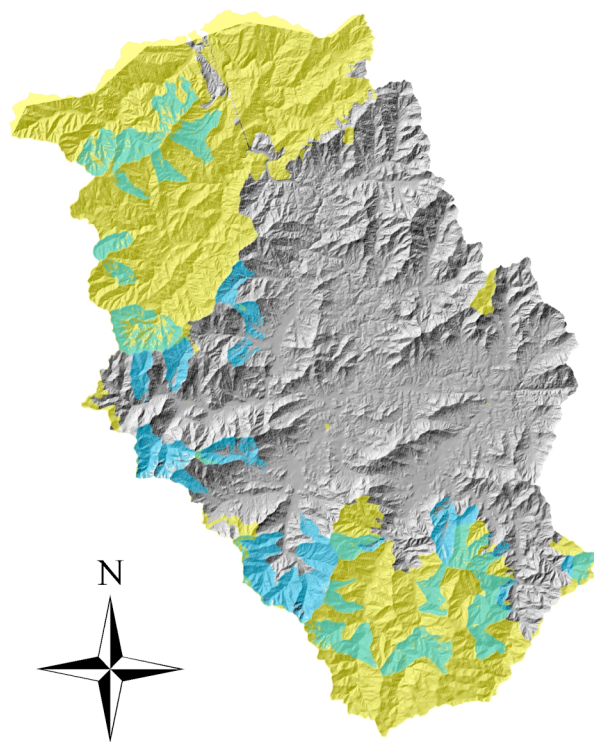
**Figure 7:** Mean weighted zip code diversity (and standard error) for all patches within the watershed, patches within *SNHAs*, and patches outside *SNHAs*.



**Figure 8:** Proportion of patches within *SNHAs* that occupy the top tiers of the biodiversity support potential distribution.



**Figure 9:** Proportion of patches within *SNHAs* that occupy the bottom tiers of the biodiversity support potential distribution.



**Figure 10:** Top 20% of patches, measured using the combined biodiversity support potential metric (blue), set over *SNHAs* (yellow and lighter blue) to identify gaps in the existing network of legally protected lands (darker blue).