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A Hierarchical Binary Process Model to Assess Deviation from Desired Ecological Condition across a Broad Forested Landscape in Alabama

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Abstract: This work describes the development and analysis of a spatially explicit environmental model to estimate the current, ecological, condition class of a managed forest landscape in the southern United States. The model could be extendable to other similar temperate forest landscapes, yet is characterized as a problem-specific, hierarchical, binary process model given the explicit relationships it recognizes between the management of southern United States pine-dominated natural forests and historical ecological conditions. The model is theoretical, based on informed proposals of the landscape processes that influence the ecological condition, and their relationship to perceived ecological condition. The modeling effort is based on spatial data that describe the historical forest community classes, forest plan provisions, fire history, silvicultural treatments, and current vegetation conditions, and six potential ecological condition classes (ECC) are assigned to lands. A case study was provided involving a large national forest, and validation of the outcomes of the modelling effort suggested that the overall accuracy when predicting the exact ecological condition class was about 46%, while the overall accuracy ±1 class was about 81%. For large, heterogeneous forest areas, issues remain in estimating the input variables relatively accurately, particularly the pine basal area.

Keywords: binary process model; temperate forests; pine ecosystems; ecological condition

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1. Introduction

Vast expanses of forests within the southern United States were historically subject to periodic fires that were initiated by both humans and natural events [1]. Fire has therefore historically shaped the character and composition of the southern pine forests [2–4]. Due in part to the expansion of the human population across the southern landscape, the growth of wood-using industries, and public policies concerning the control of wildfires, the character and composition of southern pine forests has changed since the onset of European colonization [5]. One recent estimate of land use in the southern United States suggested that the landscape consisted of about 42% tree cover, 14% rangeland and scrubland, 14% cropland, 12% pasture, 6% grass (lawns and other mainly non-native grassy areas), and 3% developed and roaded areas [6]. While much (87%) of the forested lands today are privately owned or owned by corporations or industries, there are also substantial public lands in the southern United States, and nearly one-quarter of these are national forests [7], where the restoration of native ecological forested systems is a current major priority [8–11].

The increased human use of resources prompts a need for measurable indicators to evaluate ecological conditions and assess a system's sensitivity or resilience to disturbance [12]. An understanding of the current ecological condition of a landscape can inform management efforts aimed at restoration activities [10]. When considering potential forest management activities on public lands, it may therefore be important to assess the ecological condition, and how human intervention can alter the stage or gradient of forest development [13]. Further, the magnitude of the deviation from a reference state may be described through a quantitative system of evaluation [14–16]. Linking empirical data that describe an ecosystem with estimates of ecological condition is therefore important in informing or prioritizing restoration actions that may enhance the ecological function of a forested system [17]. An assessment of management goals that is based on measurable indicators of ecological conditions can address the desired future conditions of a forest [18], which often involve measures of forest structure and composition and are general enough to allow one to evaluate progress toward achievement [19].

As a result of an increased public awareness of environmental issues, advances in environmental science, and advances in computer systems, a number of process models have been developed recently to help evaluate the ecological condition of landscapes (e.g., [16,20–22]). This type of work involves the characterization of land, and a comparison of its state to the reference conditions desired by land managers; therefore, one objective of our research was to develop a model to assess the ecological condition classes of forested stands (groups of trees in 2–50 ha patches). Technically, the model may be described as a theoretical, problem-specific, hierarchical, binary process model, given the explicit relationships we acknowledge between current forest conditions, historical ecological conditions, and the potential management of southern United States pine-dominated natural forests. The model can also be described as a spatial decision support system; spatial data are provided as input, logic is applied, and analyses are conducted to ideally support forest management decisions [23]. A second objective of the research was to apply the ecological condition class model to a large heterogeneous forest area, the Talladega National Forest in Alabama. From a managerial perspective, the outcomes of estimates of ecological condition can inform forest management decisions, can help assess whether goals are being achieved, and can serve as a sociological tool for considering the capacity for prescribed fire and timber management activities within lands where these activities are allowed. Additionally, the model can be used to describe where sufficient management activities have already occurred, where the desired future conditions have been achieved, and where additional management activities are needed to address restoration goals.

2. Materials and Methods

Although perhaps generalizable to the broader Piedmont and southern Coastal Plain regions of the southern United States, the model described here, while designed to operate on a landscape scale, is place-specific and focuses on locally important ecological processes [24,25].

2.1. Study Area

This research was conducted in the Talladega Mountains of Alabama (USA), on lands managed by the Talladega National Forest (approximately centered at 33.51° N, 85.80° W). The Talladega National Forest is located in northeastern Alabama (Figure 1), which is situated within the Piedmont and Ridge and Valley ecoregions of the United States. This area of the southern United States has a humid subtropical climate, where hot, humid summers and mild winters are common, and annual precipitation is about 1260 mm. Historically, the land area of the Talladega National Forest was composed mainly of coniferous tree species (*Pinus* spp.) [26], and the location and character of these were heavily influenced by the occurrence of fire [27]. Places on the landscape dominated by deciduous tree species were often located in bottomlands and ravines, where, if fires occurred, lower intensity fires were common [27]. The elevations range from approximately 160 m to 735 m above sea level, and the highest point in Alabama is located here. Longleaf pine (*Pinus palustris* Mill.) and shortleaf pine (*Pinus echinata* Mill.) were commonly found on south- and southwest-facing upper slopes and summits [28], and less frequently intermixed with chestnut oak (*Quercus montana* Willd.) on very steep north-facing slopes [29]. While perhaps not as prevalent today, the longleaf pine was a very common species nearly a century ago on southern aspects, up to about 580 m (1900 feet) in elevation, where other pines (e.g., loblolly pine, *Pinus taeda* L.) were also found [30]. Fires maintained mountain longleaf pine woodlands, and fires typically had a return interval of 1 to 5 years [31]. Although the longleaf pine ecosystem has been subject to logging and species conversion since the mid-18th century, reductions in the extent of the longleaf pine ecosystem were most rapid during the post-World War II economic boom [32]. The Talladega National Forest had a modest degree of forest management activity beginning in 1936, when it was established through proclamation [33], through the early 2000s, coinciding with its expansion through land purchases from private individuals and timber companies made possible under the authority of the Weeks Act (Chapter 186, 36 Stat 961) and other proclamations. During this period of time, forests on many upland sites were harvested and planted with loblolly pine. Today, the national forest is composed of 93,694 ha of land and contains a mosaic of vegetation types. Currently, even-aged stands of four pine tree species (loblolly pine, longleaf pine, shortleaf pine, and Virginia pine (*Pinus virginiana* Mill.)) compose about 52% of the national forest lands. In the last few decades, the estimated fire return interval has been 5–6.5 years [25], although historically it has ranged from about 2.6–3.2 years [34,35].

Figure 1. The location of the Talladega National Forest in northeast Alabama, USA.

2.2. Analysis Methods

The desired future conditions of the Talladega National Forest focus on maintaining and restoring forest health [9,11,36,37]. The desired conditions focus on the development of a mosaic of forest stands with variable-sized openings in the forested canopy. The desired pattern of vegetation ideally would resemble the footprint of natural disturbances, as they are currently understood. In transforming the current landscape to these desired conditions, certain outcomes (timber products) are by-products of management activities designed to meet other resource objectives (e.g., those related to wildlife habitat, old growth, and forest health). The ecological condition classes described here represent the conceptual distance in ecological status that each forested area is away from optimum conditions. The estimation of ecological condition class can inform managers of those places across the landscape where restoration activities are necessary to achieve desired future conditions, as well as those areas that are of the desired condition and should be maintained. The model outcomes can account for planning and progress towards the desired future conditions if used consistently when management actions or disturbances occur on the landscape.

An ecological condition class (ECC) model was developed to estimate the stand-level forest condition as it relates to reference ecological conditions. As with other models that characterize landscape condition (e.g., [8]), the ECC model is data-driven, and uses logic to develop inferences about ecological integrity. However, in contrast to other models, the ECC model was developed to operate at a fine scale (stand-level, where stands average 14.6 ha), using local knowledge and readily available spatial data. Environmental models are of value to society to assist in the comprehension of complex ecological systems that have distinct spatial dynamics [38]. The ECC model we describe is an attempt to represent real-world ecological conditions through the manipulation of spatial information across a broad scale (93,694 ha) and the creation of a mathematical analogue. The model was decomposed into different elements that were considered important in describing ecological condition. The ranges of the corresponding appropriate values of these elements to ecological condition were based on local knowledge of the system, and six potential ecological condition classes (Tiers) were assigned to each stand. Given this, the ECC model could be characterized as a problem-specific, hierarchical, binary process model that integrates knowledge to evaluate environmental systems [38,39]. The outcomes of the model are class values, essentially a *yes* or *no* answer as to whether a piece of land falls within a certain ecological condition class. Logical expressions (i.e., if-then-else statements) within a hierarchical system are used to select the appropriate condition class from the data. For example, the ECC model allows the user to determine a range of fire frequencies and basal area estimates (Figure 2) to determine which ecological condition class a stand may fall within. This implies that a piece of land, given all of the criteria employed, will be assigned to one condition class, regardless of its stature within the different classes (i.e., one class may suggest a higher Tier, while another suggests a lower). The ECC model has other general characteristics. For example, the model uses existing conditions to express or predict current ecological condition, yet does not predict into the future what these conditions might be, which would require integration with a forest growth and yield model, and a model to simulate future management activities. The ECC model is also purely deterministic and contains no stochastic processes. Further, the ECC model does not emphasize any potential interactions among the various input data. Finally, the ECC model is also considered to be inductive, as results are obtained from empirical data and field observations [39]. In one sense, the ECC model is theoretical, as it is based on proposals of landscape processes that influence ecological condition and, based on these relationships, a hierarchical mathematical system is developed to assign the class values to the various pieces of the landscape [40].

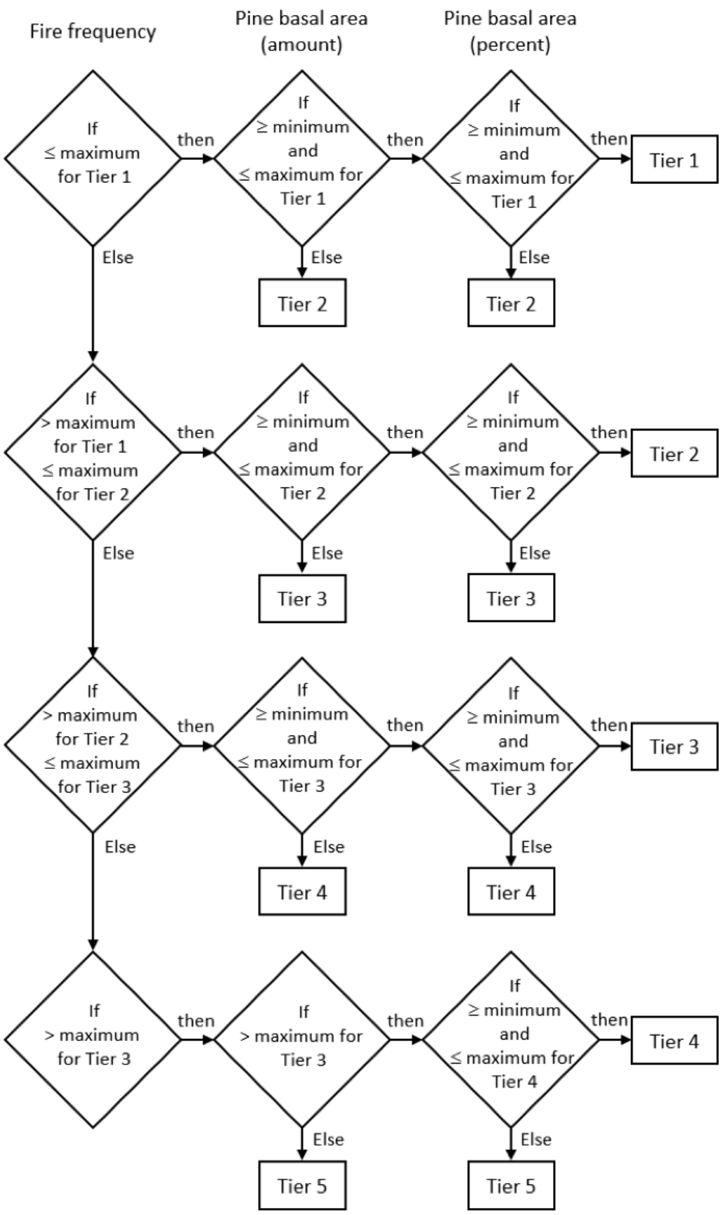

Figure 2. Logic model used to assign ecological condition class to each historically pine-dominated area of forest in the Talladega National Forest. Tier 6 is predominantly deciduous forest located in coves, along streams, and on steep north- and northwest-facing slopes.

2.3. GIS Data

The ECC model was developed using Python 2.7 and is accessed through ArcMap's ArcGIS Toolbox. The geospatial inputs needed include four vector databases (forest stand boundaries, property boundaries, operable area mask, and historical fire occurrence) and one raster database representing a historical community classification. Rather than using a system such as classification trees to identify the key factors in predicting the ecological status of parts of a landscape (as in [41]), a logic model (Figure 2) was developed to arrive at an ecological condition class (Tier 1 = near reference condition, Tier 5 = far from reference condition) for each stand in the national forest, in a manner similar to Trager et al. [10]. The logic model was based on expert opinion, which was informed by knowledge and history of the ecosystem and relevant scientific reports (e.g., [27,34,42]). In many cases, a well-defined reference condition is unavailable from the scientific literature [43]; therefore, reference conditions for this study were determined using local knowledge of the landscape and expert opinion, and were informed by associated research [25].

The grid cells in the historical communities raster GIS database were assigned to one of five historical community class values (three coniferous, two deciduous). While the middle and lower slopes of the hills within the national forest might once have supported mixed pine-hardwood forests [27], two general deciduous forest communities dominated: (a) yellow-poplar (*Liriodendron tulipifera* L.) dominated forests in the stream bottoms and low-lying wet areas; and (b) chestnut oak forests on the steep north- and northwest-facing slopes [42]. These two historical communities were considered Tier 6 in the classification process. We used a digital elevation model (DEM), a landform index [44] derived from this, and a raster version of the national forest's soils database to help estimate the distribution of the historical communities. A landform index of 25 or greater was assumed to indicate a bottomland area, the main areas for locating the yellow-poplar community. The chestnut oak community were assumed to be those areas with high slopes, north- and west-facing aspects, and ridgetops [45]; therefore, we assumed that the slope class (40% or greater) and the aspect (north or northwest) were the variables to identify the chestnut oak historical community. Womack and Carter [42] suggested that each of three pine communities would be found in areas where the landform index was about 25 or lower. Topographically, these are generally areas away from creeks, on slopes, or ridge tops. Womack and Carter [42] suggested that the longleaf pine—sassafras (*Sassafras albidum* Nutt.)—community type would be found on steeper slopes and associated with soils that had the lowest calcium levels in the A horizon. We assumed that this historical community would be found in areas where the slope was greater than 30%, and included eight soil management units that most closely related to those suggested by Womack and Carter [42]. The shortleaf pine—black cherry (*Prunus serotina* Ehrh.)—community was suggested to be located on more gentle slopes, where the soils have the greatest calcium levels. Therefore, we assumed that these areas included lands where the slope was less than 20% and included ten soil management units. The longleaf pine—shortleaf pine community—was assumed to have slopes ranging between 20 and 30%, and included five soil management units where the calcium levels were neither very high nor very low. Since the historical community class database contained raster data, the majority value of the historical community class values within each stand was stored as an attribute in the forest stand boundaries GIS database.

The forest stand boundaries GIS database is a vector database including an estimate of basal area for each forest stand. The need for basal area estimates across the national forest (Figure 3) is an important input; the basal area information for the forest was developed over time using stand exams (from timber cruises) and expert opinion based on using aerial photographs. Updating the basal area information using LiDAR data was not possible at this time, given the heterogeneity of the forests (natural, planted, mixed species, etc.), and the need for high quality plot samples with precise coordinates that span the range of this heterogeneity. As we note later, the quality of this information is important in estimating the ecological condition classes. The operable area mask was a polygon GIS database used to delineate the areas that are generally available for forest management activities. Output from the ECC tool only included those places within the operable area mask where management activities can occur. Ground slope (35%) was the main factor for determining where management activities can occur, as well as Streamside Management Zones and Riparian areas, as defined in the Forest Plan. The fire occurrence GIS database contained overlapping polygon features that represented individual fires (wild and prescribed) that occurred in Talladega National Forest over the last four decades. Fire return interval data were derived using a geospatial tool developed for the national forest [25] that uses the number of months between the first and last fire associated with each polygon and the total number of fires in the fire database. The tool converts multipart (overlapping) fire polygons into individual polygons representing single fires across the national forest and assigns a fire return interval to each polygon.

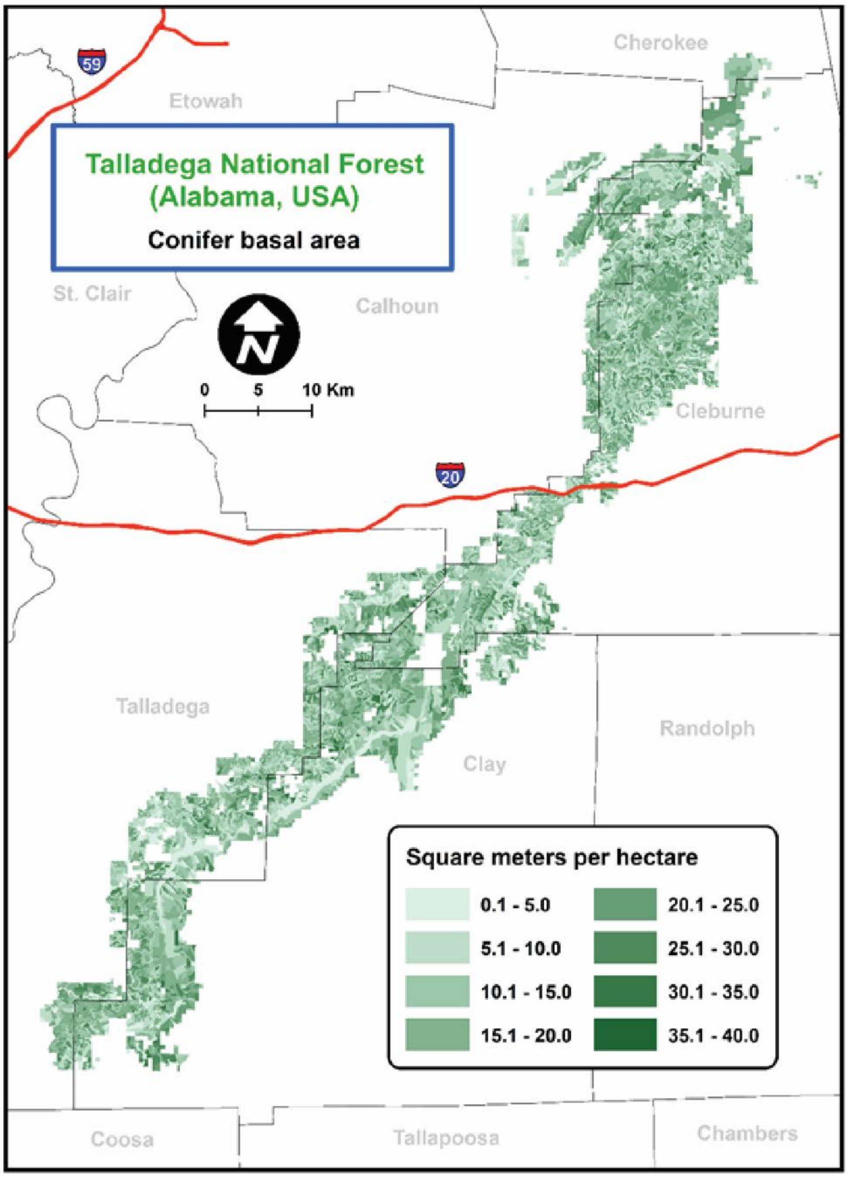

Figure 3. Estimated pine basal area (m^2) per hectare in the Talladega National Forest, Alabama, USA.

Using the property boundary GIS database, each of the input database features were clipped to the same data extent, to avoid any issues related to misregistration. Using the fire occurrence database, a raster database was created, based on the fire return interval. Using a zonal statistics process, the most commonly occurring fire return interval value within each stand boundary was attributed to each stand. Using the same zonal statistics function, the most frequently occurring historical community class was then assigned to each stand.

The variables and associated ecological thresholds for the ECC modeling process require expert opinion on the minimum and maximum ranges of basal area for each condition class (Table 1), the percentage of pine species' basal area appropriate for each class, and the mean fire return interval appropriate for each class. While the model was in development, repeated iterations of the process by a biologist familiar with the landscape were used to examine and compare the model outcomes to local knowledge. These repeated iterations were used to calibrate the modeling process, and to determine the appropriate variables and threshold values to use in the ECC process. While the model is flexible in allowing different levels of pine tree species basal area and fire return intervals to define the Tiers, we assume the values for the ranges of the pine basal area (m^2/ha) and percent pine basal area in Table 1 for the case study that we present here. Independent evaluations of ecological condition by other experienced ecologists were then used to validate the assignment of the condition class to landscape features. These observations consisted of a different set of data than that used in the calibration process. A validation of the process uses an omission–commission matrix to compare the modelled assignment of ecological condition classes to expert opinion of the current ecological condition class gained from in situ visual assessments of 173 forested stands. This provides an assessment of the overall accuracy (predicted vs. observed) of the classification process, as well as an estimate of the associated Kappa coefficient, which represents how well the assignment of ecological condition classes may agree with the reference information, even though an interpretation of the Kappa coefficient value may suffer from interpretation and definition issues [46,47]. Further, user's and producer's accuracy of the ecological condition class assignments were derived from this analysis. The producer's accuracy provides an estimate of the error of omission from the perspective of the reference set of data, and indicates the percentage of stands in each Tier of the reference set that were actually classed accordingly in the ECC modeling effort. The user's accuracy expresses the error of commission from the perspective of the classified stands from the modeling effort, and provides an estimate of the percentage of stands classified as a certain Tier that were actually assigned to that Tier in the reference set.

Table 1. Parameters used in the case study analysis assigning ecological condition class values to the forests of the Talladega National Forest in Alabama, USA.

Tier	Minimum Pine Basal Area (m^2/ha)	Maximum Pine Basal Area (m^2/ha)	Minimum Pine Basal Area (%)	Maximum Pine Basal Area (%)	Maximum Fire Return Interval (years)
1	9.2	18.4	80	100	3
2	11.5	18.4	60	80	5
3	18.4	27.6	40	60	7
4	27.6	—	20	40	>7
5	—	27.6	—	—	>7

3. Results

The spatial extent of the estimated ecological condition classes (Figure 4), using the assumptions of parameters from Table 1, indicates that there are four or five areas of the national forest that contain forest conditions that may be near (in an ecological sense) the desired future conditions, as defined by experts familiar with the historical conditions of this area of Alabama. One reason may be that these areas are deemed as favorable locations for periodic prescribed fires, based on the terrain and the distance from developed areas. From a management perspective, the risks involving the use of prescribed fire near major roads, developed areas, and in steep terrain may outweigh the desire to transform the ecological condition of a forest with fire. This may likely be the reason for lower Tiers (4 and 5) being assigned to the land areas near the Interstate Highway (I-20) and other areas in the north of the national forest, and along a ridge line that weaves southward through Clay and Talladega Counties. Certainly, other options, such as timber harvests (partial or final), may also be used to manage coniferous and deciduous tree species basal area at desired levels. These efforts may be limited by access, market conditions, budgets for sale preparation activities, and available personnel. However, a map of the estimated ecological condition classes can act to inform future management planning activities. Both the location and extent of the deviations of current forest conditions from desired forest conditions can be assessed through this product. Associated budgets for prescribed fire activities and other management actions can be better informed, as can the amount of personnel needed to implement these actions.

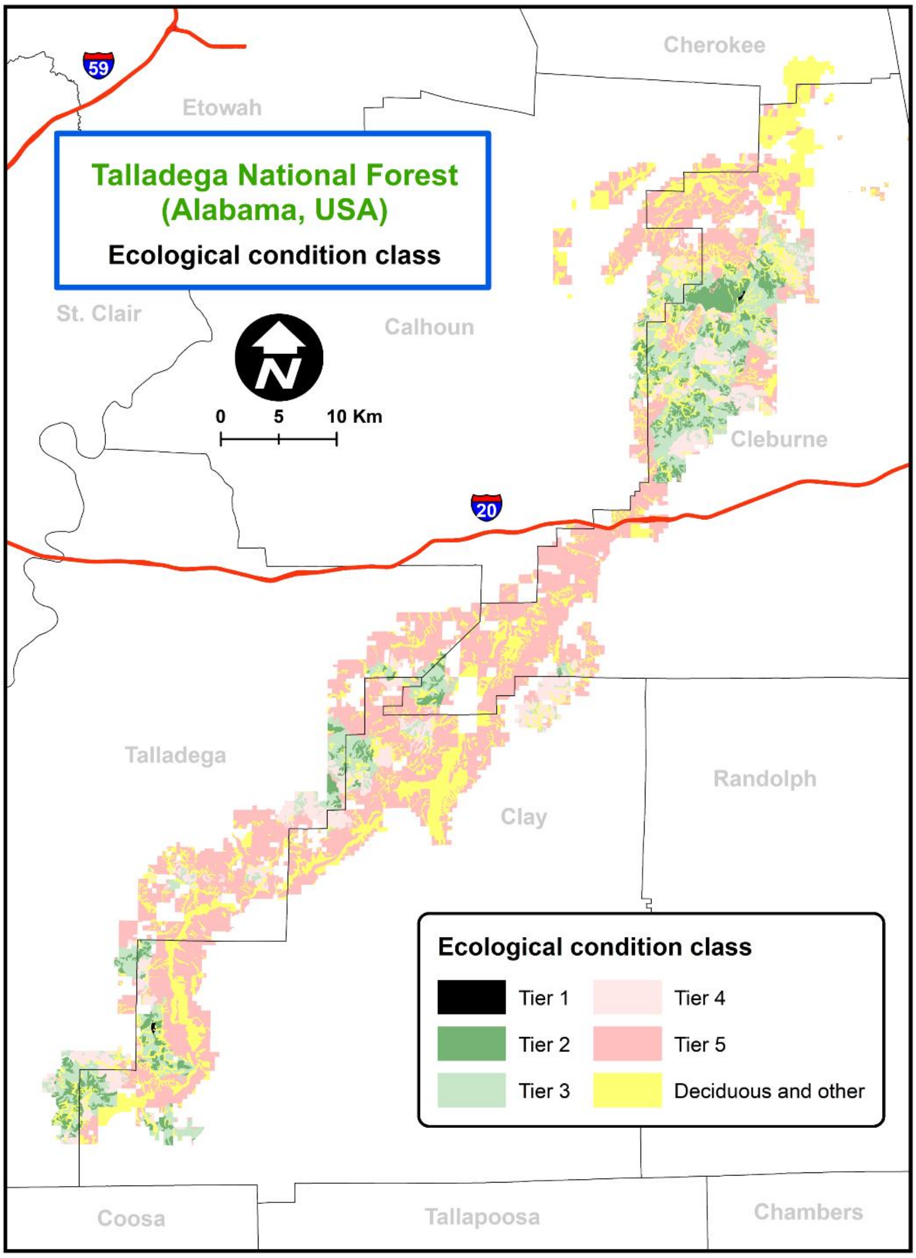

Figure 4. Estimated ecological condition class for a case study on the Talladega National Forest, Alabama, USA.

We approached the validation of the assignment of the ecological Tiers to individual stands across the landscape from two perspectives: exact correspondence with expert opinion; and a fuzzy approach that suggests that the assigned Tier may be ±1 class off, due to data quality limitations noted earlier. Using the first approach, comparing exact correspondence with expert opinion about the state of forest conditions, the overall accuracy of the modeling approach was 44.5% (Table 2). With the exception of Tier 5, the farthest from the desired conditions, both producer's and user's accuracies were low (less than 52%), and the Kappa coefficient of agreement was estimated to be about 29%. The model seemed to frequently estimate a condition class Tier for stands that was 1 class below the expert opinion for the stands used in the validation effort. Using the second approach, where the assigned Tier may be ±1 class off, the overall accuracy of the modeling approach was 84.4% (Table 3). In this case, both the producer's and user's accuracies were quite good (above 81%), except in the cases involving the assignment of Tier 1 stands (based on expert opinion) to a model estimate of Tier 3. In this second case, allowing an assigned Tier to be ±1 class off, the Kappa coefficient of agreement was estimated to be about 80%. Given uncertainties in the input data (particularly the basal area estimates for each stand), this second case appears to be more suitable in validating the modeling approach.

Table 2. Omission–commission matrix for validating the ecological condition class modeling effort based on the parameters used in Table 1.

Modeled	Reference Tier (Expert Opinion)						User's
Tier	**1**	**2**	**3**	**4**	**5**	**Total**	**Accuracy (%)**
1	1	0	0	0	0	1	100.00
2	11	23	8	5	0	47	48.9
3	9	14	10	4	1	38	26.3
4	0	5	12	10	0	27	37.0
5	0	2	5	20	33	60	55.0
Total	21	44	35	39	34	173	
Producer's Accuracy (%)	4.8	52.3	28.6	25.6	97.1		

Table 3. Omission–commission matrix for validating the ecological condition class modeling effort based on the parameters used in Table 1 and allowing ±1 modeled Tier.

Modeled	Reference Tier (Expert Opinion)						User's
Tier	**1**	**2**	**3**	**4**	**5**	**Total**	**Accuracy (%)**
1	1	0	0	0	0	1	100.00
2	11	23	8	5	0	47	89.4
3	9	14	10	4	1	38	73.7
4	0	5	12	10	0	27	81.5
5	0	2	5	20	33	60	88.3
Total	21	44	35	39	34	173	
Producer's Accuracy (%)	57.1	84.1	85.7	87.2	97.1		

4. Discussion

The ecological condition classes estimated through the ECC model represent the relative distance that each forested stand in the Talladega National Forest is from a desired reference condition, based on its fire history, basal area, composition, and an estimate of historical forest condition. Reference conditions represent the highest quality, lowest maintenance forests where natural regeneration of the desired tree species occurs, and minimal inputs occur to sustain and perpetuate the systems. In other words, reference conditions represent the most resilient systems that we currently know to have evolved on these landscapes. Using native minimally disturbed stands for reference allows us to gain an understanding of the elements needed to develop structural thresholds, and the prescribed fire and timber management needed to perpetuate these ecological conditions. The distance then, in ecological terms, of a stand of trees from a desired ecological state may be measured in a discrete manner by the conditions under which the thresholds have been crossed [48], but a disadvantage of this approach is that a slight deviation (e.g., 0.01 m^2 per ha of pine basal area) above or below a threshold shifts the assigned Tier to a stand of trees one full class away. Therefore, the ecological condition classes described in the outcomes of these analyses should not be viewed directly as the ecological thresholds, given the abrupt change in the assignment of quality or characteristics to an ecosystem, when one moves from one class to the next.

Depending on the complexity of the resource management issue, landscape-level spatial decision support systems can be of value in informing management decisions. Evaluations of landscape management options can be perplexing to management teams, when priorities and resource conditions need to be assessed at the same time [49]. Therefore, an integrated spatial decision support system, such as the model described here, can assist in the assessment of feasible management options and the achievement of ecological goals, by reducing complex issues to manageable, logical criteria applied to current conditions [20]. Models such as these can also allow land managers to better understand the spatial extent of meeting ecological landscape goals (or alternatively, landscape degradation), which can then inform project-level planning processes and monitoring efforts [10]. Considering the financial resources required for restoration efforts in the southeastern United States, some modest monitoring and planning would allow more precise estimates of the need and effort. However, landscape-level spatial decision support systems are not perfect, as the quality of the outcomes can vary depending on the quality of the inputs and how resources are classified [22].

One of the main limitations of modeling efforts such as these, where large areas composed of thousands of small-scale features (stands) are employed, involves the quality of the input data. The fire history database used in this analysis is generally considered to be well-developed with respect to the timing and severity of fires. Some of the boundaries of fires were developed using GNSS or other methods, and therefore the accuracy of the lines that form the boundaries may be moderately good, although an accuracy assessment of these landscape features (fire boundaries) was not possible. The larger source of uncertainty in our input data, in our minds, involved the pine basal area estimates for each stand. These were developed through stand exams, some rather dated, and other means. Updating this information with new stand exams was not possible due to the cost involved. We are considering an analysis of high-quality LiDAR obtained in 2021, which may facilitate the development of better structural signatures of stands that could more accurately guide the modeling effort. This is an avenue for future work, as reference plots are needed to associate the signatures observed in LiDAR data to actual forest conditions, and since the cost of analysis also weighs on this option. The high structural variability within the forested stands on the Talladega National Forest further adds to the complexity of the analysis and the need for a large number of reference plots.

The availability of current resource information, particularly involving attributes of forested areas that are critical for assessing ecological condition, can be a critical factor in assessing environmental sustainability across large areas [50]. As others have noted, a key challenge for using ecological models, such as the one described here, involves the age of the resource information, and, if it were possible to acquire current information, a cost/benefit analysis of the trade-offs (time, cost, expertise) would seem necessary [51]. Assuming funds were available to pursue these efforts, it has been suggested that cost-efficient technology is available to develop from remotely sensed information certain fine-scale forest attributes across broad areas, although the data processing requirements may require additional time and expertise [52]. The availability of sound reference information is also important in using the models to assess environmental sustainability across large areas. In our study, we used the expert opinion of a seasoned professional who has long studied the biological aspects of forest succession in the study area. In other similar efforts, expert opinion has been used, and where more than one expert was involved, issues of subjectivity bias and conceptual drift may arise [53]. The use of expert opinion as landscape-level reference information is not new in ecological research; it can serve to link the knowledge of seasoned professionals and researchers to field observations of resource conditions, and to arrive at quantitative or qualitative rankings of ecological condition and risks [54]. As we found in this work, relating expert opinion to metrics that can be acquired through field observation and remote sensing can be very challenging, and methods to ensure that an analysis of ecological condition is robust, repeatable, and consistent may be of value [55].

Within the U.S. Forest Service organization, the successful integration of results from ecological models, such as these that use fine-scale data, with results obtained from mid-scale analyses obtained from national template models (e.g., [8]) remains to be seen. For example, the basic modeling units are clearly different with these two efforts, as the Talladega National Forest stands used in our analysis average 25 ha in size, while the land type associations used in mid-scale national models average 8000 ha in size. To facilitate the widespread use of a problem-specific, hierarchical, binary process model such as the one described here, a model should be designed in a manner that the outcomes or results are replicable, quantifiable, and credible for landscapes containing similar natural resources [24]. Further, an assessment and wise use of the resources (data, technology), costs, and organizational capacity to use models such as these for ecological assessment and to support planning processes are necessary to ensure the success of the system [24,56]. Knowledge of these needs would facilitate the planning and scoping of need across national forests, to assess capacity and place the resources needed to achieve desired future outcomes, as defined in forest-level land management plans.

5. Conclusions

The spatially explicit, hierarchical, binary process environmental model described in this work allows for the estimation of the deviation in the ecological condition of the southern United States pine forests from the reference conditions. The model provides land managers with information on the current ecological condition of a managed forest landscape, and facilitates discussions related to land management planning: where sufficient management activities have already occurred; where desired future conditions were achieved; and where additional management activities should be focused to address restoration goals. The model requires several GIS databases concerning the current condition of forests, and these may need attention. For example, we believe that the pine basal area estimates of the 94+ thousand hectare area need to be more closely assessed, as they seem to be the weakest link in the modeling chain. The model also requires expert opinions of the condition of the reference sites, spanning all of the ecological tiers, so that estimates of the ecological condition from the modeling effort can be quantitatively assessed. These expert opinions need to be made consistently, and the rules that drive the ECC model need to reflect them. Ultimately, the model described here could be extendable to other similar temperate forest landscapes, yet it is characterized as problem-specific, given the explicit relationships it uses to describe the difference between the current conditions of southern United States, pine-dominated, natural forests and historical reference conditions.

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