

RESEARCH ARTICLE

Revisiting and Updating the Calculation of the Integrated Moisture Index

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ABSTRACT

The integrated moisture index (IMI) was developed to indicate long-term soil moisture potential from data collected in southeastern Ohio. Like the topographic wetness index, the IMI is derived from terrain characteristics that influence the downslope movement of water, with the addition of soil water-holding capacity. The combination of terrain and soil characteristics provides improved mapping of potential soil moisture. Since the development of the IMI, advances in soil data and geographic information systems warrant revisiting the original methods and modifying the calculation. I provide background information about soil moisture metrics while incorporating new data and techniques to calculate the IMI. Evaluating the transferability of the index to other regions by comparisons to ecological patterns among soil drainage, landforms, and existing vegetation may increase its use for other applications. The resulting IMI is comparable to the original but provides continuous data values and has a broader application than the data from Ohio.

1 | Introduction

Soil moisture can be a limiting factor that influences competition among vegetation (Dyer 2009) and regulates impacts of drought (Dai 2011) and flooding (Hodges 1997). Several topographic indices and metrics have been developed to represent the downslope flow and accumulation of water in various terrains. The hydrological forecasting model (TOPMODEL) developed by Beven and Kirkby (1979) for variable size contributing areas represents water storage based on the area drained and the slope angle of the focal unit. The main component of TOPMODEL is the topographic wetness index (TWI) (Sørensen et al. 2006), a widely used metric that represents soil moisture and overland flow. Digital terrain models have been used to map the influence of the topographic index from TOPMODEL at various spatial resolutions to evaluate potential limitations (Quinn et al. 1995). To address some limitations of defining soil moisture by slope and area, the topographic relative moisture index (TRMI) defines potential soil moisture content using slope aspect, slope configuration, slope steepness, and topographic position to estimate soil

moisture influenced by topography (Parker 1982). Accounting for processes that influence soil moisture, such as soil and geological characteristics, solar radiation, or vegetation, could help to refine estimates across complex landscapes (Dyer 2019).

Satellite derived soil moisture is available from several sources described by Mohanty et al. (2017). However, most datasets have coarse resolutions that is, greater than 1 km, which does not provide useful information for local management decisions. Additionally, high resolution satellite products often have short time series (i.e., less than 20 years) due to recent deployments which may not provide sufficient information to develop long-term trends, although the information obtained is valuable. As these datasets mature it is useful to consider more process-based and physiological approaches.

Many topographic soil moisture indices have been developed and applied to various landscapes, but most tend to exclude information about soil characteristics and rely more on the influence of terrain to determine soil moisture levels.

For overland flow, terrain derived estimates may be accurate, but underestimate potential soil moisture by ignoring the influence of percolation and subsurface flow (Buchanan et al. 2014; Frankenberger et al. 1999). The integrated moisture index (IMI) developed by Iverson et al. (1995, 1997) uses curvature, flow accumulation, and hillshade derived from elevation along with soil water-holding capacity to represent potential soil moisture. These four components are easily obtained, and each provide information about the movement of soil moisture. Curvature is a simplistic representation of topographic position, either concave or convex, while flow accumulation indicates the paths of water downslope and amount of pooling. Hillshade represents the influence of solar radiation and aspect, and soil water-holding capacity indicates how much water a particular soil component retains. The IMI values potentially range from 0 to 100 with higher values indicating wetter sites and lower values drier sites. By incorporating information about the soil characteristics into the IMI, the derived values more appropriately represent soil moisture potential rather than the accumulation of water resulting from overland flow. The TWI, TRMI, and IMI metrics are useful as each provides different information about water movement and storage influenced by terrain within a landscape. However, the IMI attempts to additionally account for water moving through a surface and not just over it.

The IMI was initially developed from elevation and soil moisture data obtained from a 475-ha section of the Vinton Furnace State Experimental Forest (VFSEF) in Vinton County, Ohio. This highly dissected landscape in southeastern Ohio has less than 100m of total relief. The IMI was developed for a small, forested region within the VFSEF to examine its effect on forest composition (Iverson et al. 1995, 1997; Iverson and Prasad 2003), and the index has been applied across New Jersey, Ohio, and Pennsylvania to examine wildfire hazards (Peters et al. 2013; Peters and Iverson 2017). The underlying process to calculate the IMI has not changed since its initial development; however, as data quality has improved and geographic information systems provide newer tools, it is useful to evaluate the methodology and see where improvements can be applied.

For this study, the IMI was calculated using digital elevation and gridded soil data across a large region of the eastern United States spanning parts of 36 states to examine site conditions among soil Pedon sampling locations (NCSS 2019). One potential improvement to the IMI calculation is to use scaling functions which result in continuous values instead of interval reclassification. I revisit the original method of calculation to provide some context for how terrain values were reclassified and compare the output from a subregion to data that were reclassified using scaling functions. I also propose masking out water features as these locations will deviate from the potential soil moisture content of neighboring landscapes. The goal is to (1) provide context to the development of the original index, (2) create IMI values which are continuous and may visually represent spatial and ecological patterns over the landscape more accurately, and (3) evaluate newer tools and datasets to facilitate the transferability of the original IMI to other landscapes. The IMI will be evaluated against soil drainage, landforms, and existing vegetation types to

determine if the range of values aligns with ecological concepts of soil moisture.

2 | Methods

The study region used to calculate the integrated moisture index (IMI) is defined by the spatial extent (east of approximately 102° W and between 32.26° N and 47.54° N) of data processing performed as part of another analysis (Nave et al. 2024, 2025) which evaluated IMI and soil organic carbon (Figure 1A). A subregion of ~220 × 366 km (80,298.25 km²) in the central Appalachians (Figure 1), that includes topographic features similar to sites used by Iverson et al. (1997) and spans an elevational range, was defined to reduce computational processing. This subregion was used to evaluate new scaling functions applied to the full study region for each terrain component (Figure 1B–D) to calculate the IMI (Figure 1E). All data processing was performed using ArcGIS Pro version 2.9 (ESRI 2022), except for the soil data which was processed with ArcGIS 10.7.1 (ESRI 2019) and may differ when performed using other software. The IMI is calculated from curvature, flow accumulation, hillshade, and soil available water supply (AWS) as:

$$\text{IMI} = (\text{Curvature} \times 0.1) + (\text{Flow Accumulation} \times 0.3) + (\text{Hillshade} \times 0.4) + (\text{AWS} \times 0.2) \quad (1)$$

where curvature, flow accumulation, hillshade, and AWS have been scaled 0–100 so that the final output has a similar range. The component weights are described by Iverson et al. (1995) as well as alternative weights when AWS is not available. In this study AWS is equal to AWC described in Iverson et al. (1995, 1997) and accounts for soil water-holding capacity among soil horizons. For many regions digital gridded soil data (e.g., Hengl et al. 2017; Soil Survey Staff 2023) are available.

2.1 | Elevation Derivatives

A digital elevation model at 30-m resolution was obtained from the National Elevation Dataset (U.S. Geological Survey 2022) and processed to calculate curvature, flow direction, a prerequisite to calculate flow accumulation, and hillshade. Prior to processing the elevation derivatives, all sink cells (e.g., depressions), those which have direct neighbors above the focal elevation and height differences less than 2m were filled to determine flow direction. Neighboring cells with height differences greater than 2m were assumed to be valid topographic features. Curvature, which indicates concavity or convexity and represents water collection or movement, was then calculated and required no additional parameters. Both flow direction and flow accumulation were calculated using the D-Infinity flow method (Tarboton 1997), which was not available in previous formulations of the IMI (Iverson et al. 1995, 1997), which considers downslope flow from the steepest neighbor using facets from the focal cell. Hillshade was calculated without modeling shadows, using an azimuth of 22.5° (i.e., light source from NNE), and an altitude of 45° from the horizon. The resulting hillshade surface values ranged from 0 to 255, represents shaded areas with lower

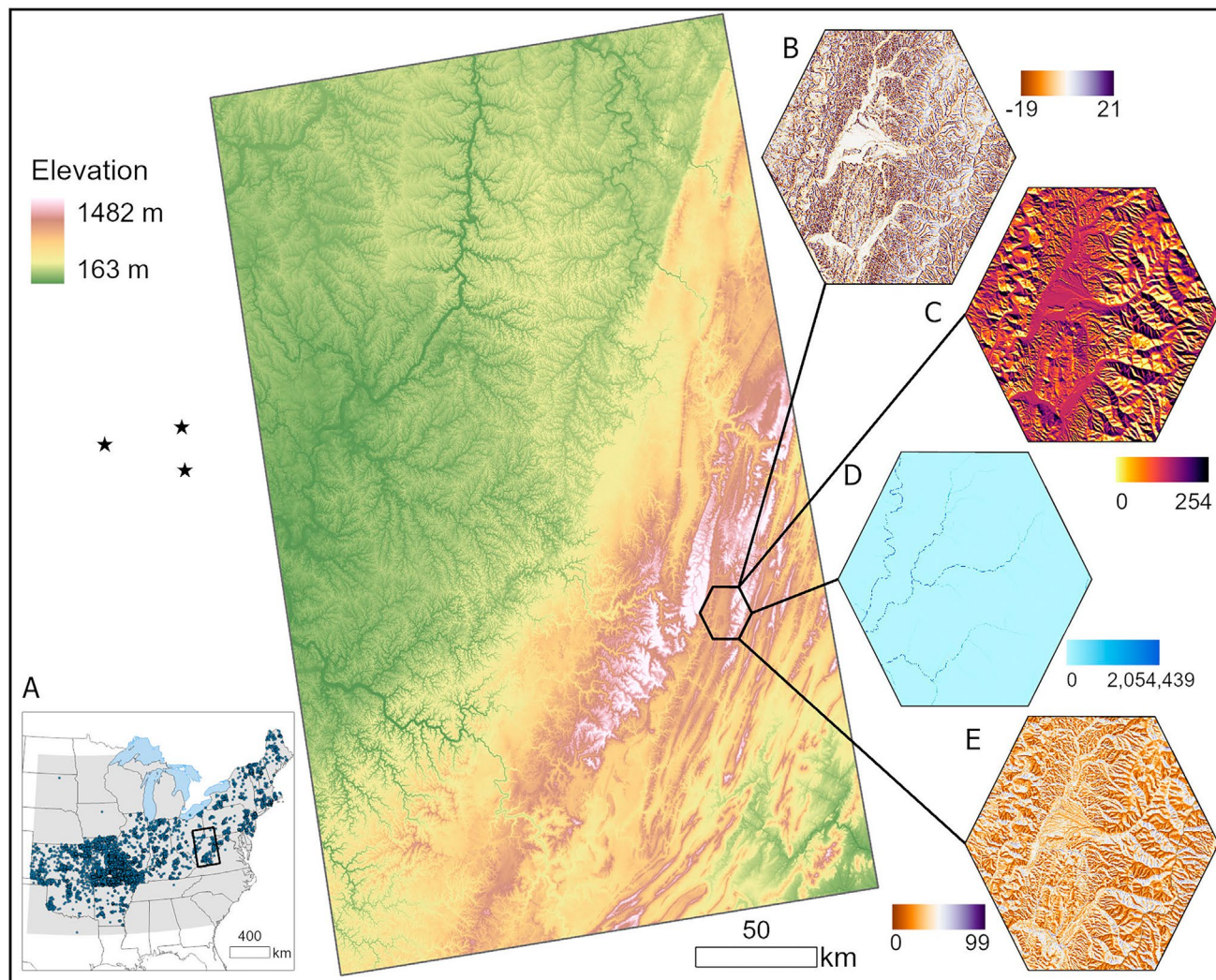


FIGURE 1 | A subregion used to test scaling functions to reclassify terrain components of the integrated moisture index (IMI) near the Vinton Furnace State Experimental Forest and other sites (stars) sampled by Iverson et al. (1995). Insets show (A) the extent for which IMI was calculated (gray) and soil Pedon sampling locations (blue), (B) curvature derived from elevation, (C) hillshade calculated from elevation at an azimuth of 22.5° with an altitude of 45° from the horizon, (D) flow accumulation calculated using the D-infinity algorithm, and (E) resulting IMI values.

values and brighter areas, those facing the specified azimuth and illuminated by the light source, with higher values (Figure 2).

2.2 | Soil Data

Soil AWS to a depth of 150 cm, the maximum depth sampled and which likely accounts for most of the rooting zone of trees—however, see Schenk and Jackson (2002), Negri et al. (2003), and Fan et al. (2017) for potential maximum rooting depths—was obtained from gridded NATSGO data and processed using the USDA Natural Resource Conservation Service Soil Data Development Tools (Soil Survey Staff 2023). The gridded NATSGO data has a spatial resolution of 30 m for the conterminous United States and integrates local soil, county surveys, and state surveys where available. While the gridded soil surveys provide an extensive dataset of various soil characteristics and properties, the data has been shown to include biased values, often along county or state boundaries

(Thompson et al. 2012). When mapped across the 36 state study region, soil AWS contained a few spatial discontinuity issues as described by Thompson et al. (2012) but appeared to be minor as data values between map units did not greatly vary. Inspection of some mapping units with discontinuous AWS value among neighboring counties or across state boundaries revealed that the soil series or the sampling depths, due to restrictive layers, were different suggesting that values could be valid. Soil AWS, which accounts for 20% of the IMI, represents the potential total volume of water in centimeters which could be available to plants when the soil is at field capacity and ranged from 0 to 90 cm.

2.3 | Data Scaling

Originally, Iverson et al. (1995, 1997) scaled the elevation components by first reclassifying the values based on histograms of the data and assigning corresponding bins to ordinal numbers.

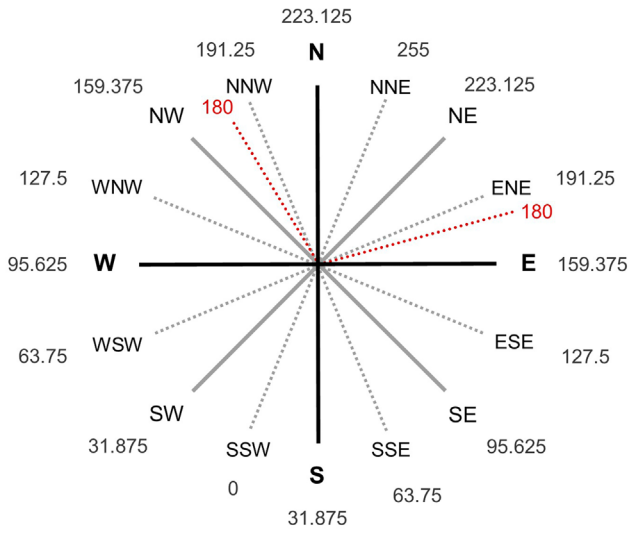


FIGURE 2 | Compass rose with cardinal (bold lines), intercardinal (gray lines), and secondary intercardinal (dashed lines) directions. Numeric values indicate the hillshade digital number resulting from a light source originating at 22.5° (NNE) with an altitude of 45° from the horizon. The dotted red line indicates a hillshade value of 180 representing the original midpoint of reclassified hillshade values (Iverson et al. 1995, 1997).

While the bins were influenced by the frequency of values occurring within the VFSEF, the rationale for specific thresholds was based on ecological principles, such as hillshade values greater than 180 representing north and northeastern aspects, and lower values indicating northwestern to southeastern aspects. The hillshade component serves as a proxy for aspect and solar radiation, since the direction of the light source was set to northeast, which receives less solar radiation. Other ecological principles included lower and upper limits for curvature which used a 2:1 ratio of vertical distance to horizontal distance. Once values were assigned to classes, which for curvature, flow accumulation, and hillshade consisted of seven, 10, and 11, each class was scaled to a range of 0–100 by the corresponding elevation component equation:

$$\text{Hillshade} = (\text{reclassified_value} - 1) \times 10 \quad (2)$$

where *reclassified_value* is an ordinal number from 1 to *N* representing each class.

$$\text{Curvature} = (100 - (16.67 \times (\text{reclassified_value} - 1))) \quad (3)$$

$$\text{Flow Accumulation} = (\text{reclassified_value} - 1) \times 11.1111 \quad (4)$$

While this approach was useful for southeastern Ohio, the data values applied to the histograms may not be representative of other regions and the scaled values were not continuous. Therefore, using the Rescale by Function tool within ArcGIS Pro, a logistic decay function was applied to the curvature surface with the Y-intercept percent set to 99, so values below –0.6 were set to 100, and values above 0.6 were set to 0, which rescaled curvature to a 0–100 range. Flow accumulation values were rescaled using a logarithm function with the input *shift*

and *factor* parameters set to -1×10^{-7} and 1 respectively, which were the default values for the data, and an upper threshold of 200. A linear function was applied to hillshade with a lower and upper threshold of 139 and 221 respectively, so values below the lower were set to 0 and those above upper were set to 100. These thresholds for curvature and hillshade follow the same range described in internal documentation by Iverson et al. (1997), but allow the rescaled values to be continuous rather than grouping values into intervals specific to Equations (2) and (3). Another major change from the original reclassification was that hillshade values of 180 were not assigned to a separate class as indicated by the histogram for VFSEF data (Iverson et al. unpublished data). The logistic decay curvature values, logarithm flow accumulation values, and linear hillshade values were used in Equation (1).

Soil AWS to a depth of 150cm or to the depth of a restrictive layer or the water table if these occurred above 150cm was rescaled and used in Equation (1). A logic of if-else statements (Appendix A) was used to evaluate values of AWS and the two soil depths to apply a min-max normalization:

$$\text{AWS} = x \times 100 / \text{AWS}_{\text{maximum}} \quad (5)$$

where *x* is the focal value of soil AWS, and the maximum AWS value was determined by the potential depth of the survey. The maximum AWS was set to 150cm or the depth indicated by the restrictive layer or water table when these were less than 150cm.

2.4 | No Data Mask

The soil AWS data contained values of no data where soil surveys have not been performed and where exposed bedrock and waterbodies (e.g., ponds, lakes, streams, etc.) prohibit surveys. These missing values were combined with cells of flat elevation, derived by calculating aspect, and locations of waterbodies, obtained from the National Hydrological Dataset (NHD; U.S. Geological Survey 2023), to indicate pixels where the IMI cannot be accurately calculated. Generally, areas of flat to low topographic relief do not produce reliable IMI values, especially if the pixel is occupied by water.

NHD polygons representing lakes/ponds and reservoirs were selected within the study region and converted to a 30-m raster data layer to mask IMI values where permanent water occurs. The no data mask was then removed from the final IMI surface to remove inaccurate data values.

2.5 | Evaluation

To evaluate whether newer scaling functions were effective in creating a continuous surface that had a range of values from 0 to 100, the mean and standard deviation for the testing subregion (Figure 1) were compared among the original and the current methods. Histograms for the three elevational components and the resulting IMI surface within the testing subregion were graphed to compare the original and current scaling methods. Across the full study region, the distribution of IMI values was evaluated among three independent datasets: (1) soil drainage classes, (2) topographic landforms, and (3) existing vegetation

types by spatially combining each of these 30-m datasets with the IMI. Additionally, a visual inspection of various locations was performed to examine whether spatial patterns differed between the two methods. Soil drainage class of the dominant component, the highest percent composition within the soil map unit, from the NATSGO database was compared to IMI values. Drainage classes describe the frequency and duration of wet periods assessed from observations of water tables, soil wetness, landscape position, and soil morphology (Soil Survey Staff 2023). Boxplots were evaluated against the assumption that IMI values would increase along a gradient of excessively drained to very poorly drained classes. The subaqueous class was excluded since it corresponded to water features that were masked out from the IMI data.

Geomorphon landforms (Jasiewicz and Stepinski 2013) were derived from the 30-m filled DEM using a 0.2 degrees threshold for flat terrain, a 7-cell search distance, and a 1-cell skip distance. The search and skip distances define the area of an annulus neighborhood used to classify terrain into landforms (flat, peak, ridge, shoulder, spur, slope, hollow, footslope, valley, and pit). The slope class was further differentiated by flat, northeastern, and southwestern aspects. While landforms do not account for soil moisture, the expectation of IMI values to represent drier ridges and wetter valleys should occur. The 12 landforms were used to calculate boxplot statistics of IMI values.

Similar to the analysis of tree species and IMI values performed by Iverson et al. (1995, 1997), the LANDFIRE existing vegetation type (EVT) dataset (LANDFIRE 2022) was used to evaluate IMI values across the study region. LANDFIRE EVTs are defined by machine learning trained with field surveys, Landsat, elevation, and biophysical data to represent terrestrial ecological systems. Thirty of the 53 forest vegetation type groups with areas greater than or equal to 0.2% of the study region were used to calculate boxplot statistics of IMI values. The expectation is that certain vegetation groups would be associated with either drier or moist sites. The managed tree plantation class was excluded from the analysis as soil moisture on these sites is likely influenced by active management, whereas the ruderal forest and introduced upland vegetation-treed classes were included as these sites were once managed and abandoned at some point prior to forest establishment. Trees associated with these two classes consist of conifers (e.g., *Juniperus virginiana* and several *Pinus*) and hardwoods (e.g., *Acer*, *Amelanchier* spp., *Betula*, *Liquidambar styraciflua*, *Liriodendron tulipifera*, *Quercus nigra*, and others) typical of eastern forests (see Appendix B and Supporting Information for details) (NatureServe 2017). For the seven drainage classes, 12 landforms, and 30 EVT groups, an ANOVA and Tukey honest significant difference test were performed to assess whether the mean IMI values were significantly different between classes and identify which classes were different using a 95% confidence interval, respectively.

3 | Results

The use of scaling functions to reclassify curvature, hillshade, and flow accumulation and calculate an IMI was developed within an 80,298.25-km² testing region in the eastern US (Figure 1) and applied to the study region (Figure 1A).

Waterbodies from the NHD occupied 0.4% of the testing region and combined with flat areas accounted for an additional 0.1% where IMI values are likely not accurate. IMI values range from 0 to 100 representing a gradient of drier to wetter potential soil moisture conditions influenced by topographic features and soil characteristics. For each elevational component the mean and standard deviation (std) of scaled 0–100 values were similar between the original and the current methods for the testing subregion. Curvature had a mean of 49.4 and 49.6 with std of 33.1 and 34.1, hillshade had a mean of 44.6 and 44.6 with std of 30.6 and 30.9, and flow accumulation had a mean of 20.5 and 30.3 with std of 25.6 and 26.0 for the original and current methods respectively. The resulting IMI surface within the testing subregion had a mean of 31.6 and 34.9 with std of 15.2 and 15.6 for the original and current methods, respectively. Histograms comparing the original and current methods displayed similar trends when the continuous values were binned according to the original classes (Figure 3). While the shape of the two histograms was similar, the current hillshade greatly differed from the original for values in the 50–59 class due to unscaled values of 180 not being reclassified as a separate class (Figure 3A). Curvature displayed minimal differences with the first and sixth classes having the greatest among the two methods (Figure 3B). Both the original and current scaled flow accumulation values exhibit a logarithmic trend; however, the current scaling method shifts more values to the middle of the range (Figure 3C). When IMI is split into quarters, minor differences occurred throughout the testing subregion; however, there is an apparent shift in the current values where approximately 6.8% of the testing region had higher IMI values (Figure 3D).

The elevational components and IMI values derived from the original reclassification and newer scaling functions appear to visually produce the same general spatial patterns and features (Figure 4). However, for each component nuanced differences are detectable upon close inspection. Specifically, the scaling functions result in more pixels between the original interval classes due to the continuous values. For example, the pale orange area that appears whitish in the upper left of Figure 4A,D,H for curvature, or the intensity of blue for Figure 4C,F,J for some flow accumulation networks. Among IMI values derived from the original reclassification and the newer scaling functions, spatial patterns across the landscape are present; however, the continuous values appear to change the distribution when compared to the original gradient where values representing moist sites appear drier (Figure 4G,K).

The comparison of boxplots of IMI values across the full study area to soil drainage class indicates that IMI values tended to increase as soil drainage becomes more restricted (Figure 5A). Soil drainage classes within the full study region included well drained (51.7%), moderately well drained (15.9%), somewhat poorly drained (11.4%), poorly drained (9.5%), somewhat excessively drained (4.2%), very poorly drained (3.7%), excessively drained (3.6%), and subaqueous (<0.1%) which was excluded because of a small sample size. The ANOVA (26,502,202.7; $p < 0.001$) indicated significant differences between classes and the Tukey test identified each class as significantly different (Supporting Information). The 12 landforms tended to represent drier IMI classes among ridges and southwestern slopes, while lower and northeastern slopes corresponded to wetter IMI

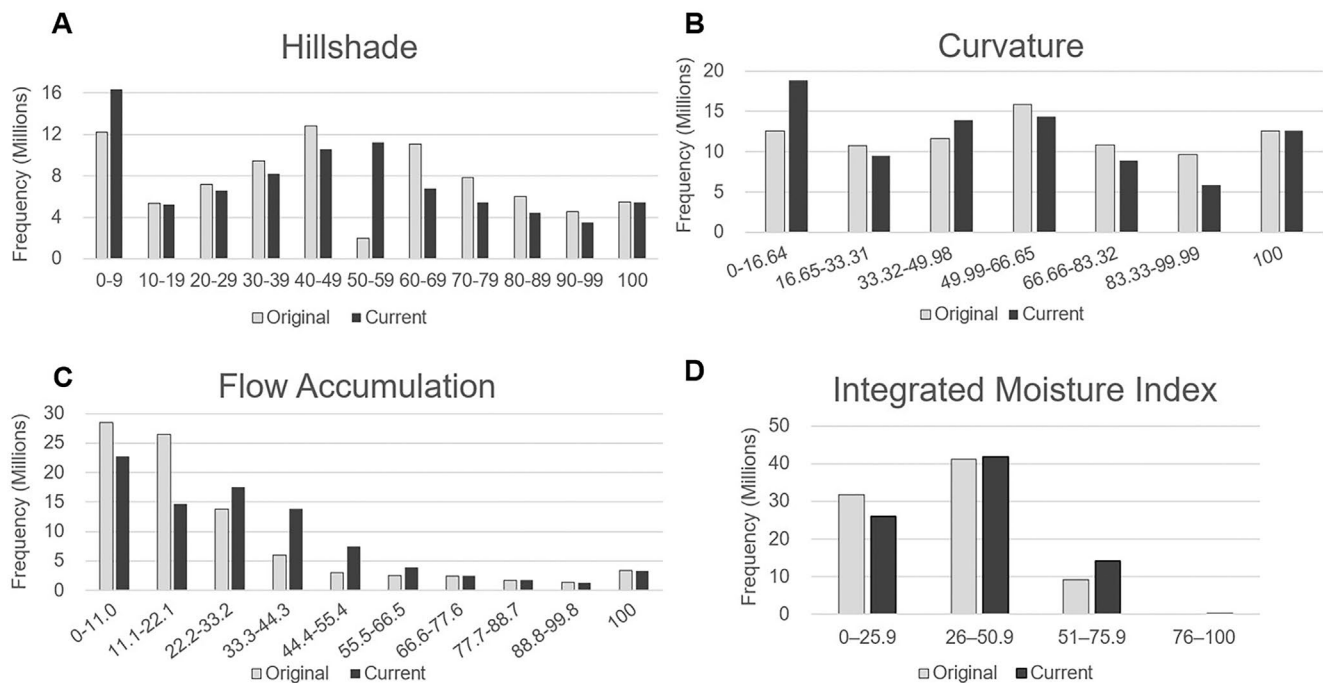


FIGURE 3 | Histograms of the scaled 0–100 values from the test region for (A) hillshade, (B) curvature, (C) flow accumulation, and (D) the integrated moisture index with break points as equal fourths. The original methods (Iverson et al. 1995, 1997) and current Rescale by Function tool are combined for comparison.

values (Figure 5B). Landforms across the full study area corresponding to IMI values consisted of 17% southwestern slopes, 16% spurs, 14% flat slopes, 13% valleys, 12% ridges, 12% hollows, 4% northeastern slopes, 4% flat, 3% footslopes, 2% shoulders, 2% peaks, and 1% pits. The ANOVA (97,675,749.4; $p < 0.001$) indicated significant differences between classes and the Tukey test identified each class as significantly different (Supporting Information). The study region coincided with 30 EVT groups covering 0.2% or greater and representing forest types that accounted for 90.6% of the 39.3% of forested area. Managed tree plantations (3.1%) were excluded as these sites may have altered hydrological and vegetation regimes compared to natural environments (Figure 5C). While each of the 30 EVT classes contain data points along the IMI gradient, focusing on the value range between the whiskers ignores outlier values. The ANOVA (2,763,846.4; $p < 0.001$) indicated significant differences between classes and the Tukey test identified each class as significantly different (Supporting Information). Tree species generally associated with dry sites, for example, oaks and hickories have median IMI values among the drier and intermediate classes, while species found on wetter sites, for example, maples, spruce, and riparian forest, tend to be within intermediate values.

4 | Discussion

Several indices developed to represent potential soil moisture (i.e., TWI, TRMI) do not include soil characteristics that can influence water retention. The IMI was developed to include soil information, when available, to more accurately represent moist sites due to soil properties rather than only indicating the flow of water down slope (Iverson et al. 1995, 1997). The conceptual process developed from a small region in southeastern Ohio was

applied to a large region of the eastern United States producing similar values when compared to the original methods. While some differences resulted in the scaled hillshade and flow accumulation surfaces, these differences do not appear to impact the overall representation of IMI as evident by the similar frequencies within the testing subregion (Figure 3). In addition to updating the IMI calculation to include rescaling functions, using newer techniques such as the D-Infinity flow method and newer data sets like the gridded NATSGO soil data help to improve the representation of potential soil moisture by accounting for the complex process of water movement down slope and through soils. The use of rescaling functions offers two benefits in that it (1) can account for the distribution of the data and (2) removes the somewhat subjective interval class breaks defined by the original data for Ohio. These benefits help to improve the transferability of the index within the eastern United States. However, the boxplots for soil drainage, landforms, and EVT groups revealed that the median IMI values tended to be skewed towards the drier end of the gradient rather than distributed across the gradient as suggested by Iverson et al. (1997). The EVT groups are intended to define a range of potential vegetation occurring within a 30-m pixel and the geomorphon landforms were created with a simple parameterization for this analysis and might benefit from regional refinements. Thus, defining cutoffs for xeric and mesic values seems challenging given the intent of the IMI is to represent potential soil moisture content along a gradient relative to the surrounding landscape.

One goal of this study was to create continuous IMI values. The original reclassification equations do not result in a continuous gradient of 0–100, as curvature, flow accumulation, and hillshade consisted of seven, 10, and 11 unique values respectively. If these components were continuously scaled from 0 to 100, the

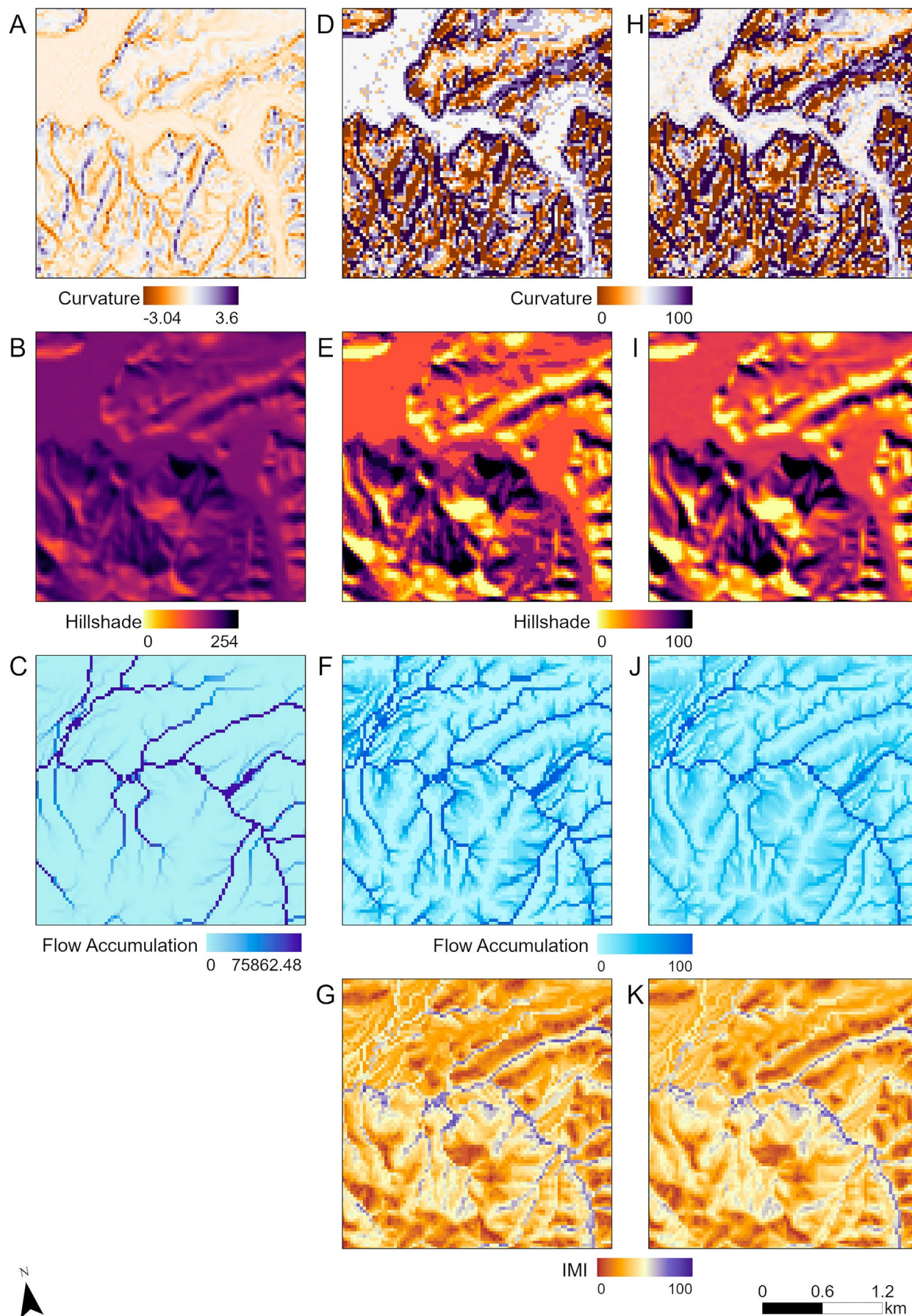


FIGURE 4 | Legend on next page.

FIGURE 4 | A comparison of the three elevation derivatives (A–C) between the original reclassification scheme (D–F) and the scaling functions (H–J) for a portion of the subregion within the test region displayed in insets of Figure 1. Scaling functions consisted of logistic decay for curvature (H), linear for hillshade (I), and logarithm for flow accumulation (J) to calculate the integrated moisture index (IMI, G and K). The data legends for curvature (A) and flow accumulation (C) were truncated to values within the displayed extent for visualization purposes where values range from –19 to 21 and 0 to 2,054,439 respectively, within the test region.

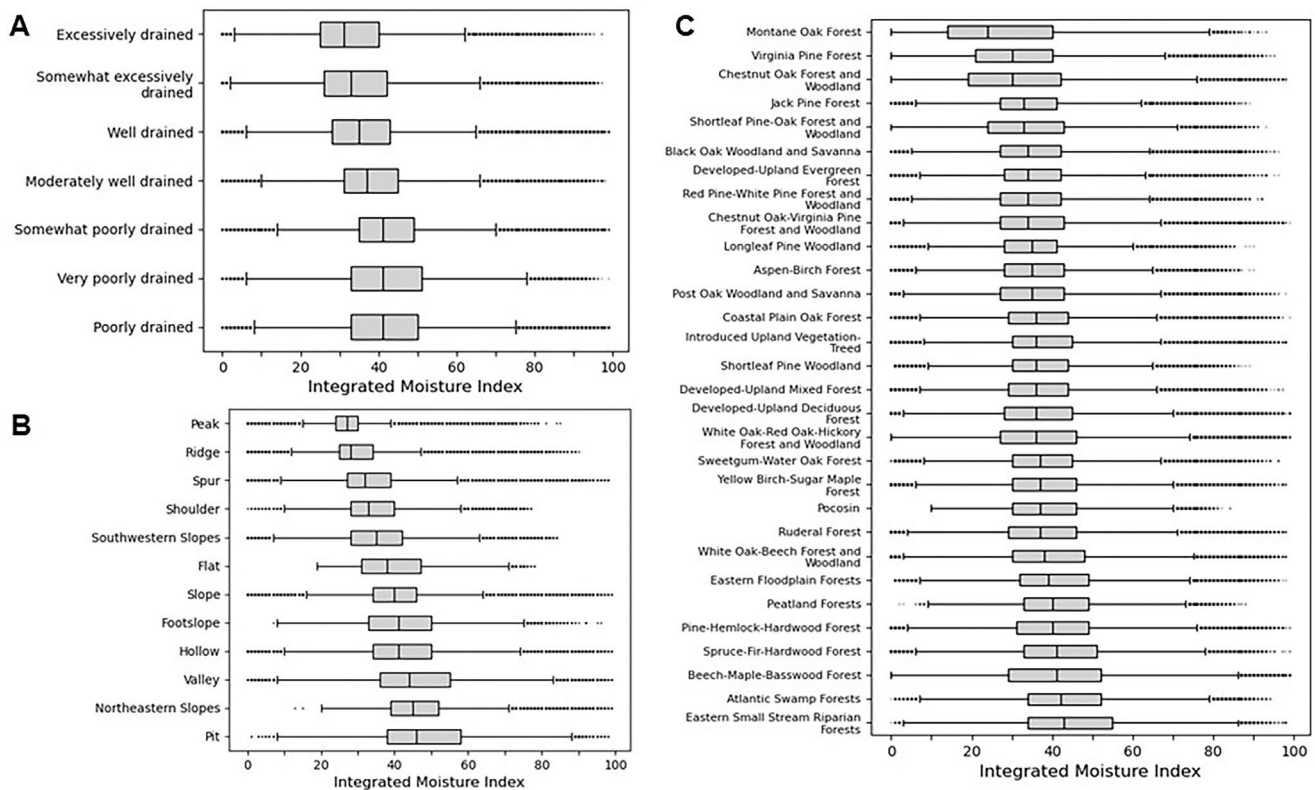


FIGURE 5 | Boxplots of integrated moisture index values across the study region (A) among (A) soil drainage classes, (B) geomorphon landforms and (C) 30 LANDFIRE Existing Vegetation Types (EVT) groups that account for 90.6% of the 39.3% of forested area. Forest classes from the EVT data have been cross-walked with forest types defined by the Society of American Foresters, see Appendix B.

resulting combinations, ignoring AWS, could consist of more than 1 million integer pairs representing 999 unique values at one decimal; and not 770 pairs with 257 one decimal values as the original reclassification has the potential to produce. This exponential increase in potential value pairs further distributes the representation of soil moisture along the index. As exhibited by the boxplots of drainage, landforms, and EVT classes each corresponding to a wide range of IMI values. While it may seem that the IMI has misclassified excessively drained soils with high values, information about the corresponding landforms is unknown. In this case, if the excessively drained soil occurs in a hollow, valley, or pit, the higher IMI value could be valid. Similarly, peaks, ridges, or spurs having poorly drained soils are likely more influenced by downslope flow but could have higher IMI values.

While not tested in this study, the source DEM resolution should not influence the rescaling of intermediate components and IMI values. The use of 30m elevation data was based on data availability, computational feasibility, and storage capacity for the study region. Elevation data is available at

1 and 10 m resolutions for some regions and better define the topographic patterns across the landscape but would not impact the value reclassification greatly, which is based on ecological principles. For example, the original lower and upper breakpoints for curvature (e.g., ± 0.6) had some physical basis in that it represents a change of 60 vertical units for one horizontal unit between each pixel. Depending on the data resolution, the threshold for curvature could be modified based on local topography, but generally for 30m data a 60-unit change could be sufficient to describe how concave or convex the landscape is within the pixel compared to the eight surrounding neighbors. For finer resolutions, a similar ratio of 2:1 may provide a useful starting point when defining the lower and upper breakpoints, as a 20-unit change over 10m should be more than sufficient to determine the flow or pooling of surface water. Additionally, the upper threshold of 200 for flow accumulation values represents a contribution area of 0.18 km² based on 30-m grids. Soil moisture is likely not influenced by such areas, except along streams, however, accounting for intermittent headwater channels that do not contribute to downslope soil moisture can be informative.

Removing IMI values where permanent water occurs on the landscape can be helpful, although the soil AWS may omit some unsampled areas covered by water and influence values assigned to the wetter end of the gradient. In areas of flat terrain, the resulting IMI values exhibit linear features as the downslope flow of soil moisture is difficult to model. For small lakes, ponds, and streams, these patterns do not occur as the topographic influence directs soil moisture to these features. However, when large water features or flat terrain are present in the source data, these features are more noticeable. Instead of masking out water features, one could include this information within the final IMI dataset as a separate value. Likewise, there could be other information (e.g., impervious surfaces, developed landscapes, etc.) in which to mask or filter the IMI values depending on the analysis or dataset purpose.

5 | Conclusion

The integrated moisture index (IMI) was developed from a highly dissected landscape in southeastern Ohio based on ecological principles to indicate long-term potential soil moisture. The index includes soil characteristics, not considered in some other topographic moisture indices, to add soil moisture retention to topographic information. The IMI is intended to identify soil moisture as a gradient of dry to wet conditions irrespective of current precipitation or seasonality, for example, snowmelt or drought.

As a gradient index, missing value combinations can misrepresent information among environmental conditions. Therefore, in revisiting the methodology and updating how each component is scaled, the resulting IMI values are fully continuous from 0 to 100 providing improved representation of soil moisture and data visualization. Additionally, data scaling based on functions informed by the distribution of values has likely improved the transferability of the index from the original information by reducing the somewhat arbitrary breakpoints derived from a small region in Ohio. Among drainage classes and landforms, IMI values appear to represent drained soils and ridges as lower values and less drained soils and valleys as higher values. The simplistic input requirements of the IMI allow it to be calculated for any region with terrain data providing potential information on soil moisture, which can be attractive if satellite products are too coarse.

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Disclosure

The use of trade, firm, or corporation names in this publication is for the information and convenience of the reader. Such use does not constitute an official endorsement or approval by the U.S. Department of Agriculture or the Forest Service of any product or service to the exclusion of others that may be suitable. The findings and conclusions in this publication are those of the individual author and do not necessarily

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Conflicts of Interest

The author declares no conflicts of interest.

Data Availability Statement

All source data was publicly available. Elevation data was accessed from <https://nationalmap.gov/elevation.html>, gridded soil data was accessed from <https://nrscs.app.box.com/v/soils>, hydrology data was accessed from <https://www.usgs.gov/national-hydrography/access-national-hydrography-products>, and existing vegetation type was accessed from <https://www.landfire.gov/>. While these datasets were used for this study, the method and application can be applied to any elevational dataset. A replacement for the Soil Data Development Tools is being developed and accessible from <https://www.nrscs.usda.gov/resources/data-and-reports/ssurgo-portal>.

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Supporting Information

Additional supporting information can be found online in the Supporting Information section. **Table S1:** Results from an analysis of variance and Tukey honest significant difference test for integrated moisture index values among seven USDA Natural Resource Conservation Service soil drainage classes. **Table S2:** Results from an analysis of variance and Tukey honest significant difference test for integrated moisture index values among 12 geomorphon landforms. **Table S3:** Results from an analysis of variance and Tukey honest significant difference test for integrated moisture index values among 30 LANDFIRE existing vegetation type groups. LANDFIRE Existing Vegetation Type (EVT) Groups: descriptions of each of the 30 EVT groups providing the corresponding EVTs.

Appendix A

Logic to determine soil available water supply depth.

Soil depth to any restrictive layer and depth to water table were evaluated against 150 cm to determine the maximum value of soil available water supply (AWS) for each map unit. The following if-else statements were used to set the maximum AWS value to scale AWS to a range of 0–100 using Equation (5):

Let x = AWS of map unit, RD = depth to any restrictive layer, and WD = depth to water table so that:

if RD is null or $RD = 0$ and WD is null or $WD = 0$, set $AWS_{\max}$ to 150;

if $150 \leq RD$ and $150 \leq WD$ or $RD < x < WD$ or $WD < x < RD$, $AWS_{\max}$ to 150;

if RD is null and $150 > WD > x$, set $AWS_{\max}$ to WD ;

if WD is null and $150 > RD > x$, set $AWS_{\max}$ to RD ;

if $x < RD < WD \leq 150$ or $x < RD \leq 150 \leq WD$, set $AWS_{\max}$ to RD ;

if $x < WD < RD \leq 150$ or $x < WD \leq 150 \leq RD$, set $AWS_{\max}$ to WD ;

if $RD = WD$ and $150 > RD > x$, set $AWS_{\max}$ to RD ;

if $RD < x < WD < 150$, set $AWS_{\max}$ to WD ;

if $WD < x < RD < 150$, set $AWS_{\max}$ to RD ;

if $RD < x$ and $WD < x$, set $AWS_{\max}$ to x ;

else flag record.

Appendix B

LANDFIRE existing vegetation type: table of 30 dominant, by area, existing vegetation type (EVT) groups and the corresponding Society of American Foresters and Society for Range Management (SAF_SRM)

cover type (Eyre 1980) crosswalk. The EVT groups and SAF_SRM cover types are sorted in decreasing order by percentage of the region. This table excludes managed tree plantations, which accounted for 3.1%

of the overall forested land, as additional resources (e.g., fertilization, pest treatments, watering) could allow species to persist in sites with uncharacteristic integrated moisture index values associated with EVT.

EVT group	SAF_SRM cover type	Percent of region
White Oak-Red Oak-Hickory Forest and Woodland	SAF 52: White Oak-Black Oak-Northern Red Oak. SAF 53: White Oak.	5.2
Yellow Birch-Sugar Maple Forest	SAF 27: Sugar Maple. SAF 55: Northern Red Oak.	3.5
Chestnut Oak Forest and Woodland	SAF 44: Chestnut Oak.	3.0
Beech-Maple-Basswood Forest	SAF 60: Sugar Maple-Beech. SAF 58: Yellow Poplar-Eastern Hemlock. SAF 25: Sugar Maple-Beech-Yellow Birch. SAF 26: Sugar Maple-Basswood. SAF 52: White Oak-Black Oak-Northern Red Oak.	2.6
Pine-Hemlock-Hardwood Forest	SAF 60: Sugar Maple-Beech. SAF 24: Hemlock-Yellow Birch.	2.5
Introduced Upland Vegetation-Treed	LF 51: Introduced Upland Vegetation—Tree.	2.4
Atlantic Swamp Forests	SAF 39: Black Ash-American Elm-Red Maple. LF 46: Atlantic Coastal Plain Swamp. LF 72: Peatland Forests. SAF 33: Red Spruce-Balsam Fir. SAF 97: Atlantic White Cedar. LF 47: Gulf Coastal Plain Swamp. SAF 61: River Birch-Sycamore. SAF 88: Willow Oak-Water Oak-Diamondleaf Oak.	1.8
Chestnut Oak-Virginia Pine Forest and Woodland	SAF 59: Yellow Poplar-White Oak-Northern Red Oak. SAF 44: Chestnut Oak. LF 55: Appalachian Grass and Shrub Balds.	1.6
Post Oak Woodland and Savanna	SAF 40: Post Oak-Blackjack Oak. SRM 733: Juniper-Oak.	1.5
Ruderal Forest	LF 53: Ruderal Forest.	1.5
Eastern Floodplain Forests	SAF 61: River Birch-Sycamore. SAF 92: Sweetgum-Willow Oak. SAF 96: Overcup Oak-Water Hickory. SAF 39: Black Ash-American Elm-Red Maple. SAF 91: Swamp Chestnut Oak-Cherrybark Oak. SAF 94: Sycamore-Sweet Gum-American Elm.	1.4
Spruce-Fir-Hardwood Forest	SAF 33: Red Spruce-Balsam Fir. SAF 5: Balsam Fir. SAF 30: Red Spruce-Yellow Birch.	1.4
Developed-Upland Deciduous Forest	LF 20: Developed.	0.9
Eastern Small Stream Riparian Forests	SAF 92: Sweetgum-Willow Oak. SAF 61: River Birch-Sycamore. LF 42: Great Plains Riparian.	0.8
Shortleaf Pine-Oak Forest and Woodland	SAF 76: Shortleaf Pine-Oak.	0.6
White Oak-Beech Forest and Woodland	SAF 52: White Oak-Black Oak-Northern Red Oak. SAF 53: White Oak.	0.5
Red Pine-White Pine Forest and Woodland	SAF 15: Red Pine.	0.5
Coastal Plain Oak Forest	SAF 52: White Oak-Black Oak-Northern Red Oak. SAF 72: Southern Scrub Oak. SAF 89: Live Oak.	0.5
Developed-Upland Mixed Forest	LF 20: Developed.	0.4
Developed-Upland Evergreen Forest	LF 20: Developed.	0.4

EVT group	SAF_SRM cover type	Percent of region
Shortleaf Pine Woodland	SAF 82: Loblolly Pine-Hardwood. SAF 76: Shortleaf Pine-Oak. SAF 75: Shortleaf Pine.	0.3
Peatland Forests	SAF 13: Black Spruce-Tamarack.	0.3
Aspen-Birch Forest	SAF 16: Aspen.	0.3
Longleaf Pine Woodland	SAF 71: Longleaf Pine-Scrub Oak. SAF 70: Longleaf Pine.	0.3
Jack Pine Forest	SAF 15: Red Pine. SAF 1: Jack Pine.	0.3
Virginia Pine Forest	SAF 79: Virginia Pine.	0.2
Black Oak Woodland and Savanna	SAF 110: Black Oak. SAF 14: Northern Pin Oak.	0.2
Pocosin	LF 48: Pocosin.	0.2
Sweetgum-Water Oak Forest	SAF 92: Sweetgum-Willow Oak. SAF 59: Yellow Poplar-White Oak-Northern Red Oak. SAF 88: Willow Oak-Water Oak-Diamondleaf Oak. SAF 91: Swamp Chestnut Oak-Cherrybark Oak.	0.2
Montane Oak Forest	SAF 52: White Oak-Black Oak-Northern Red Oak. SAF 40: Post Oak-Blackjack Oak.	0.2