Landscape Ecology

https://doi.org/10.1007/s10980-026-02347-6

Article in Press

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Received: 24 Sep 2025

Accepted: 29 Mar 2026

Published online: 09 April 2026

**Cite this article as: Csikós, N., Gudmann, A., Szabó, S. *et al.* The BreakPointIndex: a new angle-based landscape metric for quantifying patch shape and boundary complexity. *Landsc Ecol* (2026). https://doi.org/10.1007/s10980-026-02347-6**

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# The BreakPointIndex: A new angle-based landscape metric for quantifying patch shape and boundary complexity

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## Abstract

### *Context*

Shape-related landscape metrics are fundamental in landscape ecology, as patch geometry and boundary complexity directly influence species diversity through edge effects and the tolerance of organisms to environmental conditions and change. Patch boundaries often exhibit strong contrasts with adjacent land-cover types, giving rise to important ecological processes, particularly along sharp transitions such as forest–pasture edges. While classical metrics—such as the shape index, fractal dimension, and edge density—effectively characterize overall patch geometry, they provide limited capacity to capture local geometric properties, including vertex-level angular discontinuities.

### *Objectives*

We introduce the BreakPointIndex (BPI), a novel landscape metric that quantifies the angular complexity along polygon boundaries. Our aims were to (i) provide a tool for detecting and mapping breakpoints using user-defined angular thresholds, and (ii) examine how threshold choice and land cover characteristics influence BPI values at the patch and shared boundary levels.

### *Methods*

The BPI tool identifies breakpoints along polygon edges based on specified angular thresholds, generates a breakpoint point layer, computes breakpoint counts and densities (perimeter and area), and quantifies shared breakpoints and shared edge lengths between neighboring polygons. The outputs included updated shapefiles and TXT/HTML summary reports. The tool was demonstrated using the 2018 Urban Atlas dataset and applied three angular threshold ranges (5°–160°, 20°–160°, and 40°–140°). In addition, scale sensitivity was quantitatively evaluated by analyzing BPI responses across multiple levels of boundary detail.

### *Results*

The number and distribution of breakpoints were significantly affected by the angular threshold parameters. Wider thresholds captured finer-scale irregularities, especially in natural and semi-natural classes, such as forests, pastures, and permanent crops, whereas narrower thresholds highlighted major directional changes and emphasized more regular, urban patterns. Patch-level BPI values and variability differed across land cover types, and shared-breakpoint analysis revealed structurally contrasting interfaces, such as those between forests and pastures or between agricultural and built-up areas. The scale-sensitivity analysis revealed a non-linear and class-dependent response of BPI, with many natural land cover classes showing an initial increase followed by a decline as geometric detail was reduced.

***Conclusions***

BPI complements conventional landscape metrics by offering a flexible, vertex-based measure of boundary complexity. It provides detailed information on polygon geometry and shared edges, supporting applications in edge analysis and habitat assessment. As the BPI is scale-dependent and sensitive to data generalization, its interpretation should consider the mapping resolution and dataset provenance. Overall, the BPI tool offers a reproducible framework for integrating boundary geometry into landscape ecological analyses. The results confirm that BPI exhibits structured and interpretable scaling behavior, supporting its application in comparative landscape analyses.

**Keywords**: landscape metrics, shape complexity, angular threshold, land cover, GIS

## 1. **Introduction**

Landscape metrics have become fundamental tools for quantifying and describing spatial patterns of landscapes, with wide-ranging applications in ecology, land-use planning, and conservation (Turner 1990; Margules and Pressey 2000; Cushman and McGarigal 2002; Uuemaa et al. 2009, 2013; Walz 2011; Fahrig et al. 2011; Lausch et al. 2015; Duflot et al. 2017; Csorba et al. 2024). A variety of metrics had been invented to describe landscape structure at different spatial scales and levels of organization, including the entire landscape, individual land cover classes, and single patches, since the innovative work of (McGarigal and Marks 1995) and the development of the FRAGSTATS software. The evolution of these metrics from raster-based to vector-based implementations has led to greater flexibility for users and the ability to avoid cumbersome data conversions. Tools such as Patch Analyst, V-LATE, and ZonalMetrics have successfully extended the calculation of these metrics within user-defined vector zones or tessellations, supporting both regular (e.g. grids, hexagons) and irregular (e.g. administrative, ecological units) delineations (Elkie et al. 1999; Lang and Tiede 2003; Adamczyk and Tiede 2017). Ecological studies have shown that organisms respond differently to structurally contrasting boundaries, such as forest–pasture transitions, highlighting that boundary geometry can shape habitat conditions and species interactions (Martínez-Falcón et al. 2018).

Landscape metrics remain central to quantifying spatial patterns and form-function relationships in landscape ecology (Uuemaa et al. 2009, 2013; Csorba and Szabó 2012; Singh et al. 2015). Most existing landscape metrics primarily focus on quantifying properties such as area, perimeter, edge density, shape complexity, and class-level diversity (e.g. Shannon’s Diversity Index, Shape Index, Fractal Dimension Index). A basic breakpoint-based metric with an adjustable angle threshold was already available in ArcView in 2003, but its functionality was limited compared to the BPI and lacked tools for quantifying breakpoint density or analyzing shared boundaries (Moser et al. 2002). Furthermore, due to software obsolescence and ArcView's own discontinuation, this tool has not been functioning or supported for over fifteen years. Consequently, there was a growing need for updated and more versatile approaches to patch shape analysis in modern GIS environments. Certain spatial features, such as the density and distribution of breakpoints (i.e., vertices describing abrupt changes in polygon boundaries), remained underexplored, even though these features may offer critical insights into landscape fragmentation, edge complexity, or anthropogenic alteration. Building on these foundational insights, the method focuses on breakpoints, performing landscape pattern analysis by explicitly incorporating breakpoint detection, thereby filling a critical gap by quantifying nuanced polygon boundary complexity.

To address this methodological gap, a novel breakpoint-oriented landscape pattern index was developed that can be fully automated within both the ArcGIS Pro and QGIS frameworks. In contrast to traditional shape metrics, the BreakPointIndex (BPI) operates at the vertex level by identifying abrupt changes in direction, so-called 'breakpoints', based on user-defined angular thresholds. This vertex-based approach enables a more localized and threshold-sensitive detection of morphological irregularities, making BPI a promising tool to highlight overgeneralized polygon geometries, edge-related artifacts, and structurally complex land use patterns. Although the commonly used ZonalMetrics tool can accurately calculate the total length and percentage of shared boundaries between two specified category pairs within a landscape, it is limited to analyze only one category pair at a time, which can be time-consuming for datasets with numerous categories (Adamczyk and Tiede 2017). In contrast, the BPI can address these gaps by quantifying not only the extent but also the geometric complexity of shared polygon edges.

The implementation builds on recent calls in the landscape ecology literature to expand the repertoire of metrics available for class-level analysis, thereby supporting more nuanced ecological assessment, planning, and monitoring. Parameters, such as angular thresholds for breakpoint identification, can be interactively specified, enabling tailored analyses that better capture the geometric and ecological heterogeneity of polygon boundaries at multiple scales. By filling the methodological gaps noted in earlier studies regarding scale-dependence and the operational limitations of zone- or patch-based metrics, the BPI advances landscape pattern analysis toward greater ecological relevance and practical utility. BPI provides a more comprehensive assessment by capturing not only the extent but also the geometric complexity of shared boundaries, enabling deeper insights into habitat heterogeneity and landscape structure (Manolis et al. 2002; Marozas 2014; Alignier et al. 2014; Bereczki et al. 2015; Akresh et al. 2024).

This implementation offers an open-source landscape metric platform but with specialized functionality for analyzing breakpoint patterns in vector- based (polygonal) landscape data. Specifically, the BPI toolbox addresses several key needs in vector-based landscape structure analyses: (i) detects breakpoints along the polygon edges using user-defined angular thresholds; (ii) generates a breakpoint point layer and maps their spatial distribution; (iii) calculates breakpoint counts and densities (perimeter-and area-based); identifies shared breakpoints and shared edge lengths between neighboring polygons; (v) produces updated shapefiles and TXT/HTML summary reports.

## 2. Methods

The BPI script offers a highly customizable and user-friendly approach for analyzing the geometric complexity of polygonal boundaries (habitat patches) within landscape data. Users have direct control over key parameters: the detection of breakpoints is governed by two angle thresholds, lower and upper limits (for example, 20° and 160°), allowing the analyst to precisely define which turns or directions along a boundary are considered significant (Figure 1). This enables a sensitivity adjustment tailored to either very subtle edge undulations or only major changes in direction, fitting the resolution or ecological interpretation required.

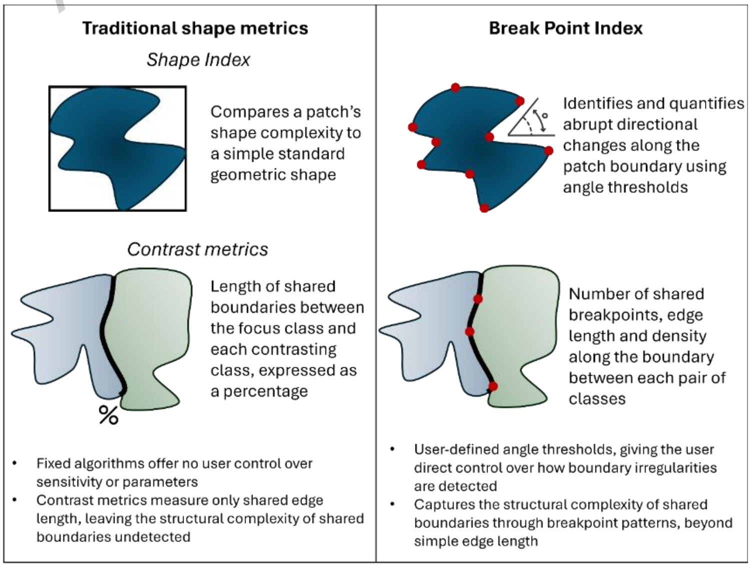

*Figure 1. Illustration of traditional shape/contrast metrics (V-Late and Zonal metrics tools) versus the BreakPointIndex (BPI)*

A thorough explanation of each input parameter that the developed tool requires, including its purpose, data type, and whether it is essential or optional in the process, offers a deeper understanding of BPI (Table 1). These parameters govern the detection, storage, and quantification of breakpoints and determine the structure of the resulting outputs.

*Table 1. Summary of input parameters and their functions*

| Parameter | Description | Data type | Type |
|---|---|---|---|
| *Input polygons* | Polygon feature class that will be analyzed | Feature layer | Required |
| *Output points* | Point feature class that will store vertices with angles within the specified thresholds. | Feature class | Required |
| *Lower Angle Threshold* | Minimum angle (in degrees) to be considered a breakpoint. Default is 20°. Cannot be smaller than 0°. | Double | Required |
| *Upper Angle Threshold* | Maximum angle (in degrees) to be considered a breakpoint. Default is 160°. It cannot be smaller than value of Lower Angle Threshold. | Double | Required |
| *Include Inner Rings* | If checked, inner rings (holes) will also be analyzed. | Boolean | Optional |
| *ID Field* | Optional field from the input polygons to transfer as an identifier to the output points. | Field | Required |
| *BPI Field Name* | The column name in the attribute table that stores the calculated BPI value, e.g., BPI 20–160. | String | Optional |
| *perimeter field* | Optional name of the field to store breakpoint count per unit perimeter. | String | Optional |
| *area field* | Optional name of the field to store breakpoint count per unit area. | String | Optional |
| *Field of Category Pairs* | Metrics are calculated for category pairs that share a common boundary, counting their shared BPI values (e.g., "Forest–Grassland"). | Field | Required |
| *Output txt file* | Specify the path and name of the output text file. This file will contain a summary of the shared breakpoints statistics, including the number of shared points and shared edge lengths between polygons — optionally grouped by category if specified. | File | Required |

The tool checks polygon attributes, identifies breakpoints along boundaries (optionally including inner rings), calculates their counts and densities, and records them in the polygon layer (Figure 2). It also detects shared breakpoints between neighboring categories and summarizes the results as text and HTML reports. The tool efficiently processes large datasets with progress reporting and error handling, producing spatial and tabular outputs that are ready for use.

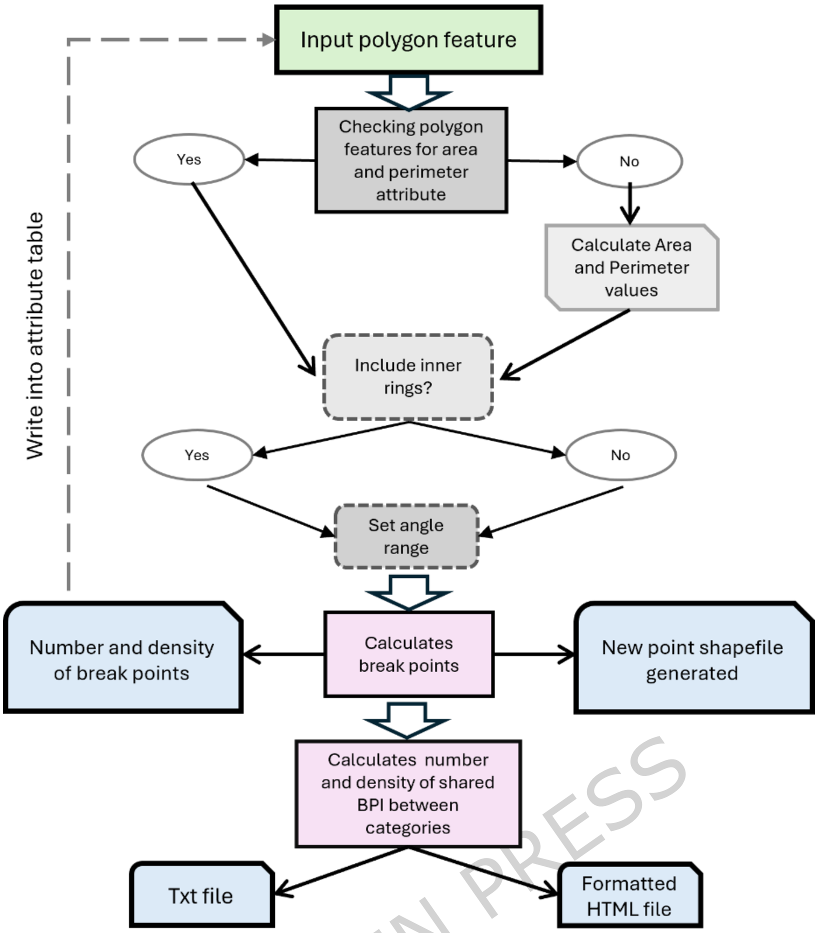

*Fig 2. Workflow diagram illustrating the processing steps for breakpoint index calculation*

To quantitatively assess the scale sensitivity of the BPI, a multi-level analysis was conducted by systematically modifying the geometric detail of polygon boundaries. BPI values were recalculated across five levels of spatial detail corresponding to simplification tolerances of 0, 2, 5, 10, and 20 m (Douglas-Peucker algorithm). These levels were selected to represent a gradual reduction in boundary complexity while remaining consistent with the geometric resolution of the dataset.

The analysis focused on mean BPI values across representative land cover classes, including agricultural, natural, wetland, and urban categories. This approach enabled the identification of scaling relationships and class-specific responses of BPI to changes in geometric detail, allowing a direct evaluation of its scale-dependent behavior.

Statistical analyses were performed on the complete dataset (n = 14,184). Due to the large sample size and the skewed distribution of BPI values, non-parametric statistical tests were applied. Differences in BPI values among the three angle ranges were assessed using the Friedman test, the non-parametric equivalent of repeated-measures ANOVA. Pairwise comparisons were conducted using Wilcoxon signed-rank tests with Bonferroni correction.

For comparative analysis, shape index values were derived using the V-Late extension in ArcMap and compared with the proposed BPI metric.

The developed BPI calculation tool is publicly available; details and access links are provided in Supplementary Material.

## 3. Results

To demonstrate and evaluate the BPI method, we used the 2018 Urban Atlas dataset for the city of Nyíregyháza, Hungary (EEA 2021). Urban Atlas is a vector-based land cover dataset developed within the European Union’s

Copernicus program. It is updated every six years and provides harmonized, high-resolution urban land use information. The dataset provides a detailed and thematically rich representation of urban and surrounding rural land cover, enabling the testing of the method across various spatial configurations. The study area was selected because of its diverse urban landscape, which includes both compact and more fragmented land use patterns (Figure 3): contains both larger homogeneous patches and smaller, complex polygon structures, making it suitable for assessing the sensitivity and applicability of the BPI in different spatial contexts. Three threshold ranges were selected to represent a practical spectrum of sensitivity: a wide window (5°–160°) capturing nearly all directional changes, a balanced setting (20°–160°), and a narrow window (40°–140°) isolating only major directional shifts. This allowed us to illustrate how parameter choice shapes BPI behavior and provides guidance for selecting threshold values in relation to data resolution and research aims. While these configurations serve as illustrative examples, the angular thresholds are user-defined and can be freely adjusted.

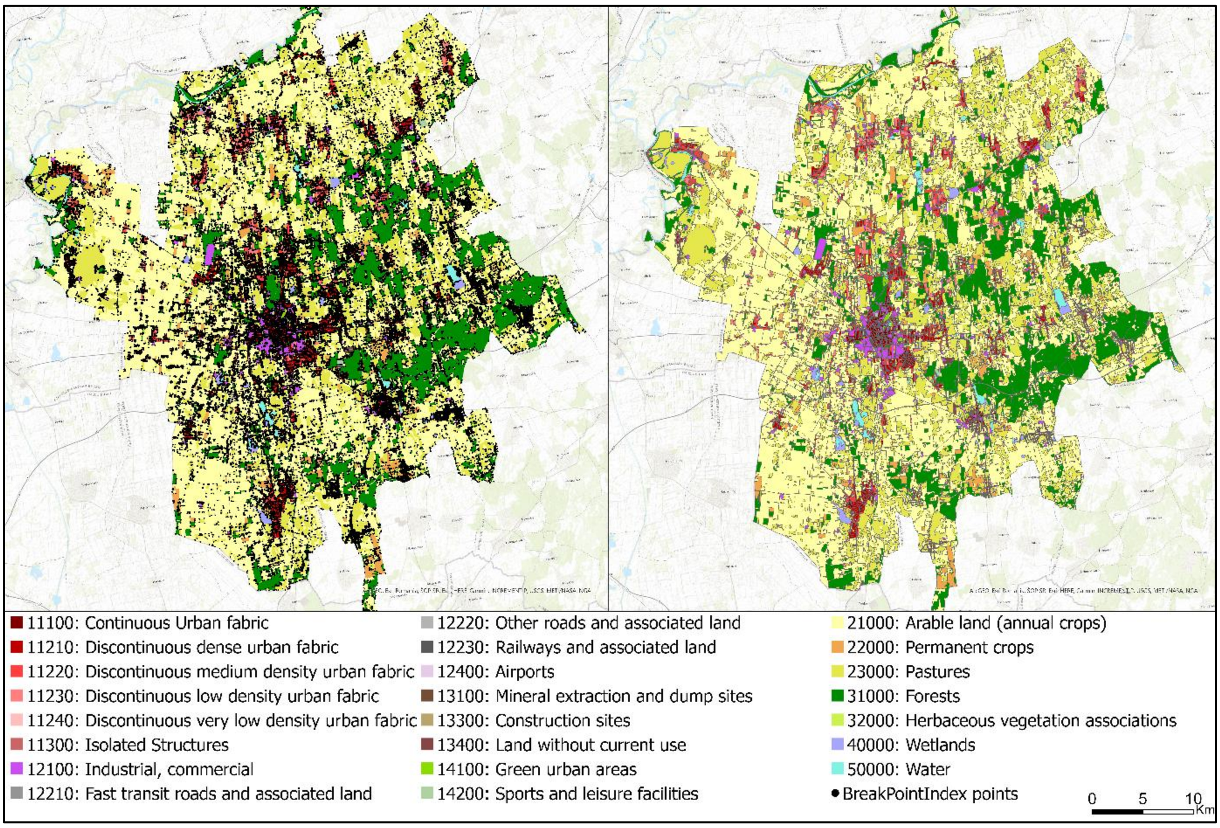

*Figure 3. The city of Nyíregyháza, Hungary, as represented by the 2018 Urban Atlas dataset. The overlaid points (left) represent the results of the BPI calculation using angular thresholds of 20° (lower) and 160° (upper).*

The most selective configuration was experienced with the narrow angle range (Figure 4A), resulting in the fewest BPI points (147,477 across the study area), which were mostly aligned with well-defined, narrow landscape transitions. Balanced angle range captured more transitions (200,325 BPI points), including broader and more complex edges (Figure 4B), while the wide angle range of 5–160° identified the highest number of BPI points (700,531), often detecting more diffuse and subtle changes (Figure 4C).

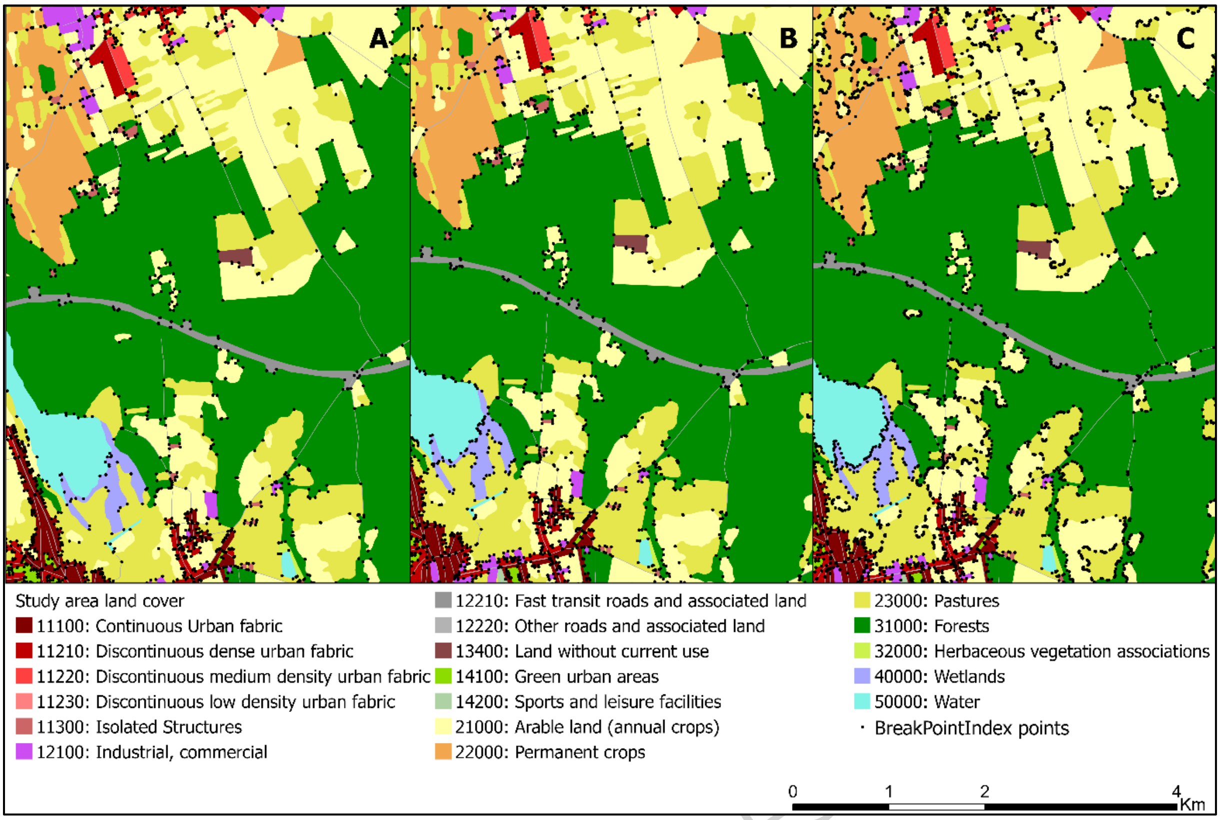

*Figure 4. Zoomed-in comparison of BreakPointIndex (BPI) results for three different angular threshold settings in a selected sub-area of the Nyíregyháza study site. The base layer was derived from the 2018 Urban Atlas land cover dataset. (A) 40–140° angle threshold, (B) 20–160° angle threshold, and (C) 5–160° angle threshold. The black dots represent the identified BPI points.*

Importantly, the appropriate choice of angle threshold depends not only on the landscape context but also on the quality and resolution of the input vector data. In highly generalized or coarsely digitized polygon layers, narrow thresholds may miss relevant transitions, whereas overly inclusive settings may highlight artifacts originating from digitization noise.

*Table 2. Most frequent land cover category pairs with shared BreakPointIndex (BPI) points under different angle thresholds. Narrow 40–140°, balanced 20–160°, wide 5–160°.*

| Category 1 | Category 2 | Shared break-points | Shared edge length (m) | Density (points / 100m) |
|---|---|---:|---:|---|
| **Narrow angle threshold** | | | | |
| Arable land (annual crops) | Pastures | 11469 | 51676787 | 0.02 |
| Arable land (annual crops) | Forests | 7277 | 29542616 | 0.02 |
| Arable land (annual crops) | Discontinuous dense urban fabric (S.L.: 50% - 80%) | 5409 | 13301976 | 0.04 |
| Discontinuous dense urban fabric (S.L.: 50% - 80%) | Other roads and associated land | 4270 | 14783388 | 0.03 |
| Discontinuous dense urban fabric (S.L.: 50% - 80%) | Pastures | 4046 | 11900173 | 0.03 |
| Pastures | Forests | 3824 | 20114347 | 0.02 |
| **Balanced angle threshold** | | | | |
| Arable land (annual crops) | Pastures | 21978 | 86323686 | 0.03 |
| Arable land (annual crops) | Forests | 10453 | 40482164 | 0.03 |
| Pastures | Forests | 5732 | 28208622 | 0.02 |
| Arable land (annual crops) | Discontinuous dense urban fabric (S.L.: 50% - 80%) | 5666 | 14451082 | 0.04 |
| Discontinuous dense urban fabric (S.L.: 50% - 80%) | Other roads and associated land | 5082 | 17313600 | 0.03 |
| Discontinuous dense urban fabric (S.L.: 50% - 80%) | Pastures | 4327 | 13493165 | 0.03 |
| **Wide angle threshold** | | | | |
| Arable land (annual crops) | Pastures | 200387 | 1003191873 | 0.02 |
| Arable land (annual crops) | Forests | 29109 | 92364449 | 0.03 |
| Pastures | Forests | 14957 | 54039540 | 0.03 |
| Pastures | Permanent crops (vineyards, fruit trees, olive groves) | 11977 | 11644015 | 0.10 |
| Arable land (annual crops) | Permanent crops (vineyards, fruit trees, olive groves) | 10314 | 7835683 | 0.13 |
| Discontinuous dense urban fabric (S.L.: 50% - 80%) | Other roads and associated land | 8035 | 22742354 | 0.04 |

The results demonstrated that the number of shared BPI points were highly dependent on the applied angular thresholds (Table 2). The shared breakpoint and shared edge length columns report summary values expressed as totals, whereas the density column represents mean values. In the case of the widest threshold range (5–160°), we detected substantially more transitions related to narrower settings, especially between agricultural categories, such as ‘arable lands’ and ‘pastures’ (200,387 shared points). This wide range also revealed transitions that were not prominent at narrower thresholds, e.g. in case of ‘permanent crops’ and ‘pastures’, with particularly high BPI densities (up to 0.13 points per 100 m). In contrast, the narrow range captured fewer shared points overall but emphasized clearer boundaries in more compact, urban, or well-structured areas, such as transitions involving discontinuous dense urban fabric. These findings suggest that the choice of angular thresholds significantly influences both the quantity and spatial characteristics of the identified land cover transitions, and that threshold settings may need to be adapted depending on the digital quality and structural complexity of the vector layer. For example, the arable land–forest increased from 7,277 shared breakpoints (narrow) to 10,453 (balnced) and finally to 29,109 (wide), illustrating how wider thresholds amplify subtle geometric transitions along natural boundaries. Meanwhile, urban boundary pairs such as Discontinuous dense urban fabric–Other roads increased only moderately (4,270 → 5,082 → 8,035), reflecting their more consistent and rectilinear morphology. These patterns show that natural and semi-natural boundaries respond much more strongly to threshold adjustments than urban ones.

*Table 3. Mean and standard deviation of patch-level BPI values by land cover class under three different angle threshold settings (narrow: 40–140°, balanced: 20–160°, and wide: 5–160°).*

| | **Mean** | | | **Standard deviation** | | | **Mean Shape Index** |
|---|---|---|---|---|---|---|---|
| **Land cover category / Thresholds** | **Narrow** | **Balanced** | **Wide** | **Narrow** | **Balanced** | **Wide** | |
| Airports | 13.00 | 16.00 | 16.00 | n.a. | n.a. | n.a. | 1.38 |
| Arable land (annual crops) | 15.24 | 22.14 | 109.00 | 24.65 | 37.79 | 255.17 | 1.55 |
| Construction sites | 5.00 | 6.63 | 13.75 | 1.85 | 2.83 | 18.87 | 1.20 |
| Continuous urban fabric | 6.96 | 7.44 | 9.09 | 6.90 | 7.03 | 8.22 | 1.32 |
| Discontinuous dense urban fabric | 7.19 | 7.81 | 9.56 | 5.63 | 6.06 | 7.84 | 1.34 |
| Discontinuous low density urban | 6.24 | 7.03 | 8.44 | 3.65 | 4.64 | 6.41 | 1.22 |
| Discontinuous medium density urban | 6.14 | 6.82 | 8.26 | 3.46 | 4.02 | 5.44 | 1.25 |
| Discontinuous very low density urban | 5.24 | 5.80 | 7.15 | 1.95 | 2.46 | 5.01 | 1.11 |
| Fast transit roads and associated land | 14.96 | 22.70 | 36.89 | 11.15 | 17.48 | 26.59 | 2.97 |
| Forests | 14.66 | 20.52 | 51.35 | 25.17 | 36.29 | 119.58 | 1.46 |
| Green urban areas | 8.22 | 9.26 | 11.61 | 7.49 | 8.80 | 11.81 | 1.29 |
| Herbaceous vegetation associations | 9.75 | 14.25 | 35.00 | 9.29 | 15.32 | 33.27 | 1.40 |
| Industrial, commercial | 6.02 | 6.93 | 8.52 | 3.46 | 4.34 | 6.36 | 1.15 |
| Isolated structures | 4.70 | 5.71 | 6.49 | 1.39 | 2.99 | 3.84 | 1.08 |
| Land without current use | 6.75 | 7.46 | 8.84 | 3.65 | 4.43 | 5.82 | 1.23 |
| Mineral extraction and dump sites | 7.14 | 8.82 | 11.27 | 5.82 | 7.85 | 10.15 | 1.15 |
| Other roads and associated land | 521.52 | 717.61 | 1288.1 | 2702.8 | 3722.2 | 6598.6 | 18.66 |
| Pastures | 9.35 | 14.25 | 80.41 | 14.83 | 22.26 | 159.30 | 1.51 |
| Permanent crops | 8.05 | 13.77 | 75.73 | 9.23 | 17.14 | 111.77 | 1.39 |
| Railways and associated land | 5.15 | 6.35 | 11.33 | 3.66 | 4.95 | 10.95 | 4.56 |
| Sports and leisure facilities | 6.44 | 7.67 | 9.47 | 3.94 | 5.47 | 7.35 | 1.22 |
| Water | 7.79 | 14.05 | 25.74 | 6.34 | 13.98 | 28.53 | 2.61 |
| Wetlands | 11.88 | 21.53 | 39.56 | 12.14 | 22.92 | 43.29 | 1.39 |

The analysis of patch-level BPI values revealed considerable differences across land cover categories and angle thresholds settings (Table 3). Narrow angle threshold yielded lower average BPI values with smaller standard deviations, whereas the wide threshold resulted in significantly higher values, especially for more fragmented or complex land covers such as ‘pastures’, ‘permanent crops’, ‘forests’, and ‘arable land’ (annual crops). For instance, ‘pastures’ increased from a mean BPI of 9.35 (narrow) to 14.25 (balanced) and 80.41 (wide), whereas ‘permanent crops’ increased from 8.05 to 13.77 to 75.73 across the same thresholds. ‘Arable land’ showed an even steeper increase (15.24 → 22.14 → 109.00). These shifts quantify how wider thresholds capture the fine-scale curvature and small directional deviations that are typical of organically evolving boundaries. In contrast, urban categories (e.g., discontinuous urban fabric) displayed relatively stable and low BPI values across thresholds, implying more compact and regular boundary patterns. For example, the ‘discontinuous dense urban fabric’ showed only modest changes (7.19 → 7.81 → 9.56), and the ‘continuous urban fabric’ followed a similarly narrow range (6.96 → 7.44 → 9.09). This stability reflects the planned rectilinear structure of built environments, where polygon boundaries contain fewer subtle angular fluctuations. One notable exception was the ‘other roads and associated land’ category, which consistently showed extremely high average BPI values and standard deviations regardless of the threshold setting, likely due to the segmented and branching geometry of road networks. This class's mean BPI values were 521.52 (narrow), 717.61 (balanced), and 1,288.1 (wide), with standard deviations that were far higher than 2,700, 3,700, and 6,500, respectively, which illustrates how linear infrastructure polygons inherently produce an unusually large number of directional changes per unit boundary length. The pronounced contrast between natural and artificial boundary structures suggests considerable potential for ecologists to interpret the related processes, particularly for transitions that are known to influence species behavior, edge permeability, and landscape connectivity.

BPI values differed significantly among the three angle ranges (Friedman test: $\chi^2(2) = 20{,}897$, $p < 0.001$; $n = 14{,}184$). Median BPI values were lowest for the narrow angle range (median = 5, IQR = 6), followed by the balanced range (median = 7, IQR = 8), while the highest values were observed for the wide range (median = 14, IQR = 34). Bonferroni-corrected Wilcoxon signed-rank tests indicated significant differences between all pairwise comparisons ($p < 0.001$ for all).

Across land cover categories, BPI values showed a co-variation with the mean shape index, indicating that land cover types characterized by higher geometric complexity according to BPI also tended to be more complex in terms of shape metrics.

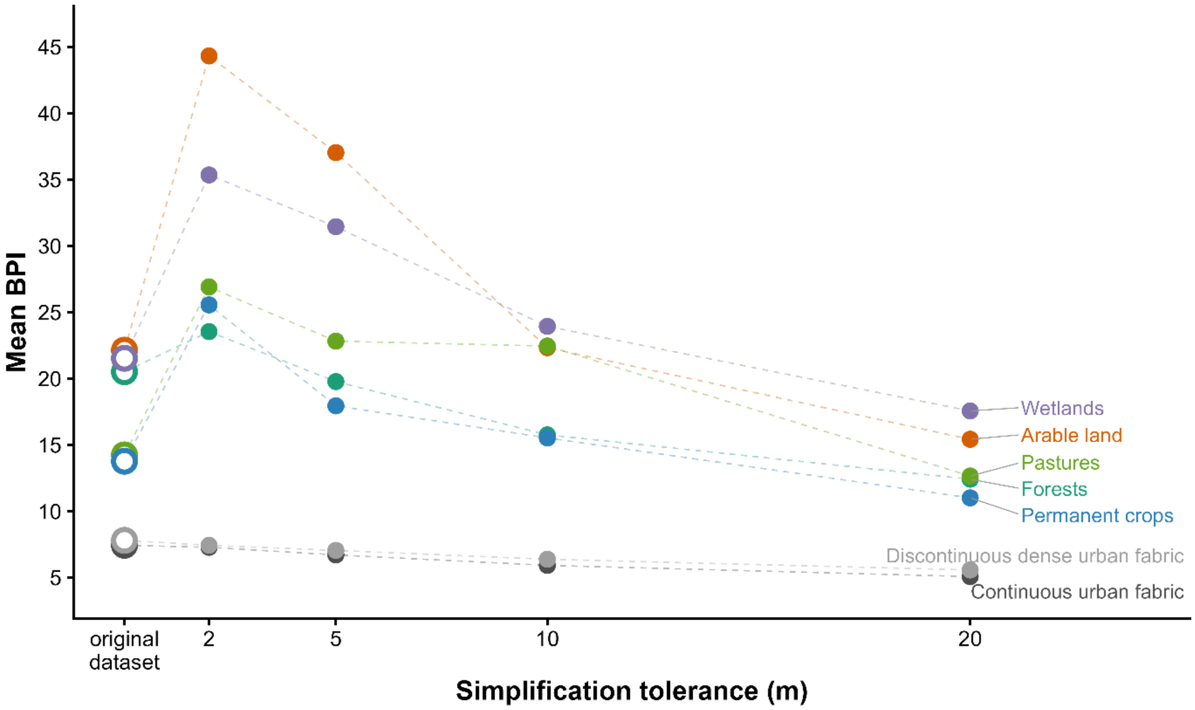

Figure 5. Scale sensitivity of the BreakPointIndex (BPI) across selected land cover classes under increasing levels of boundary generalization (0–20 m simplification tolerance).

The scale-sensitivity analysis revealed that BPI exhibits a consistent and non-linear response to changes in boundary detail (Figure 5). Across most land cover classes, BPI values increased at low levels of simplification (2 m), followed by a gradual decline as the level of simplification increased. This indicates that BPI is not a monotonic function of scale, but instead reflects the balance between noise reduction and structural simplification.
The observed pattern was particularly pronounced in natural and semi-natural land cover classes. Arable land showed a strong increase from 22.14 to 44.33 between 0 and 2 m, followed by a decrease to 15.43 at 20 m. Wetlands and pastures exhibited similar peak-shaped responses, while permanent crops also showed a clear non-linear trend. These results indicate a high sensitivity of BPI to geometric detail in organically structured landscapes.
In contrast, urban categories displayed a more stable and gradually decreasing behavior. Continuous urban fabric decreased from 7.44 to 5.08, and discontinuous dense urban fabric from 7.81 to 5.58 across the examined scale range. This suggests that BPI is less sensitive to scale changes in landscapes characterized by regular, rectilinear boundaries.

## 4. Discussion

We demonstrated that the BPI provides a sensitive and flexible means of quantifying polygon boundary complexity, thereby filling an important methodological gap in landscape pattern analysis. While traditional metrics, such as shape index, fractal dimension, or edge density, had been applied to describe spatial configuration (Turner 1990; Csorba and Szabó 2012; Lausch et al. 2015; Jafari et al. 2017; Tian et al. 2023; Verma et al. 2024), they typically rely on global descriptors that summarize overall geometric form. In contrast, BPI offers a localized, vertex-based approach that captures abrupt directional changes. Our findings highlight that incorporating angular information into boundary analysis yields novel insights into structural heterogeneity and ecological interpretations. Because BPI measures geometry at a fine resolution, its values inevitably depend on the accuracy and generalization level of the input data, which means that datasets with different mapping standards may yield systematically different breakpoint densities.

The comparison of the three angular threshold settings (wide, balanced, and narrow) revealed that BPI values are highly sensitive to the angular range. Wider thresholds consistently produced greater numbers of breakpoints and higher patch-level BPI values, particularly in natural and semi-natural categories, such as forests, pastures and permanent crops. These categories are known to possess more irregular, organically shaped boundaries owing to ecological processes and land management patterns (Griffith et al. 2002; Ries et al. 2004; Midha and Mathur 2010; Szilassi et al. 2017). Therefore, widening the threshold window amplified subtle morphological variations that would otherwise be smoothed out or remain undetected. In contrast, the urban categories displayed consistently low BPI values across all thresholds, reflecting their more regular anthropogenic boundary patterns. The low BPI values were observed for urban categories aligned with the geometric regularity in built environments, where the borders represent designed structures like parcel lines, roadways, and building blocks (Zhang et al. 2017). The clear contrast between natural and artificial patterns justifies that the BPI can serve as a discriminative metric for characterizing different landscape types.

BPI's suitability for studying edge complexity has been demonstrated by the examination of the shared breakpoints between categories. Differences in shared BPI densities across land cover pairs revealed not only the irregularity of given categories but also the structural contrasts between them. This aligns with ecological findings that boundary characteristics, such as the sharpness, complexity, or permeability of edges, strongly influence ecological interactions and species responses (Manolis et al. 2002; Banks-Leite et al. 2010; Marozas 2014; Szilassi et al. 2017; Martínez-Falcón et al. 2018; Akresh et al. 2024; Negrello-Oliveira et al. 2025). ‘Forest’–‘pasture’ boundaries are ecologically important because organisms may respond differently to their structural contrast. Martínez-Falcón et al. (2018) showed that dung beetles vary across such ecotones, indicating that boundary structures can influence habitat conditions. Thus, the BPI offers a simple geometric descriptor for these sensitive transitions.

BPI is a flexible tool as angle ranges can be specified by the users, fitting the parameters to the given aims, ignoring small changes of the edges and focusing only on the large complexity or considering even the small edge-variations. The user-defined angular thresholds and vertex-level analysis of the patch edges, the BPI extends the available methodological repertoire; however, its performance must be understood within the constraints imposed by the dataset geometry. Over-generalized polygon boundaries may underrepresent true structural variations, whereas over-digitized boundaries may introduce artificial breakpoints. Thus, interpreting BPI outcomes requires attention to the provenance and digitization practices of the data.

These findings highlight the broader significance of BPI in landscape ecology. By quantifying boundary complexity at a fine geometric resolution, this metric allows researchers to detect structural patterns to which traditional indices are not sensitive. This enables an improved assessment of habitat heterogeneity, supports the identification of ecologically important edge types, and enhances landscape-level interpretations of connectivity, fragmentation, and land-use intensity. As such, the BPI introduces a novel and practically relevant dimension to the analytical toolkit used for understanding landscape structure.

The scale-sensitivity analysis provides a quantitative characterization of how BPI responds to changes in geometric detail. Similar to previously described scaling relationships in landscape metrics (Wu et al. 2002; Wu 2004; Frazier 2016), BPI exhibited a systematic but non-monotonic response to scale. In several land cover classes, low levels of simplification led to an increase in BPI values, which can be interpreted as the removal of geometric noise while preserving dominant structural features, whereas at higher levels of simplification BPI values declined as boundary complexity was progressively reduced.

Importantly, most previous studies on scaling behavior in landscape metrics have been conducted using raster-based data, where scale is typically defined by cell size. In contrast, BPI operates on vector-based geometries, where scale is governed by boundary detail and vertex configuration. This fundamental difference implies that scaling responses may not be directly comparable between raster- and vector-based approaches.

These results indicate that BPI does not simply depend on scale, but responds to it in a structured and interpretable manner. The observed class-specific differences further suggest that BPI captures intrinsic properties of boundary organization, distinguishing between organically evolving and highly structured landscapes.

Limitation of the analysis is that we applied Urban Atlas data (EEA 2021), which captures broad landscape patterns but may omit fine-scale boundary variation, which means that BPI values primarily reflect meso-scale geometry. These scale and accuracy effects reflect known dependencies in other landscape metrics (Cushman and McGarigal 2002; Uuemaa et al. 2005; Lausch et al. 2015).

Regarding the BPI, it uses vector data, and sensitive for the scale, and the number of vertices, the land cover maps, classified from satellite images and then transformed from raster to vector, are not appropriate inputs for the analyses, as all pixels may represent a vertex; accordingly, edge-generalization should be used, which also can raise questions. Best inputs are the vectorized maps.

## Conclusion

We aimed to develop a landscape metric tool (BreakPointIndex, BPI), which can reveal the patch complexity, and the contrasts between category pairs. The new Python-based tool is implemented into ArcGIS Pro and QGIS to facilitate the usage into ecological analysis, and we tested its performance with Urban Atlas data and with three different angle ranges (wide, balanced, and narrow). We found that the BPI offers valuable data on edge complexity at both the patch and class levels. The number of breakpoints helped in identifying the complex patch boundaries as an index and as a map showing the hotspots spatially. Testing of three angle ranges justified that BPI can be efficient for several tasks, focusing on regular shapes (e.g., built-in areas) or complex forms (e.g., forests, grasslands), so can be used both in urban and natural areas, too. Shared edges (points and length) and breakpoint density are new metrics in landscape ecology, and our analysis in the study are confirmed that the outputs are valid, the BPI values reflect real functional meanings in ecological investigations. BPI provides new opportunities for understanding spatial heterogeneity and its ecological consequences, supporting more nuanced habitat modeling, biodiversity assessment, and effective landscape management decisions.

## Funding

This research APC was funded by the University of Szeged Open Access Fund (grant number: 8120); SS was supported by the KKP 144068 project.

## Author contributions

N.C. developed the concept, implemented the programming, designed the methodology, carried out the testing, and wrote the first draft of the manuscript. A.G. contributed to programming. S.S. provided review and feedback. P.S. contributed to concept development and review. All authors contributed to writing and approved the final version of the manuscript.

## Competing interest

The authors have no relevant financial or non-financial interests to disclose.

## Data Availability

The datasets generated during and/or analysed during the current study are available from the corresponding author on reasonable request.

## Supplementary material

The developed BPI calculation tool is publicly available through the following platforms:

ArcGIS Pro toolbox, downloadable via ArcGIS Online: https://arcg.is/1GCO8a3

QGIS plugin: https://plugins.qgis.org/plugins/break_pointer

Open-source code (GitHub): https://github.com/gudmandras/Break-Point-Index.git

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