



Advancing forest fragmentation analysis: a systematic review of evolving spatial metrics, software platforms, and remote sensing innovations

Sanjana Dutt · Tarmo K. Remmel ·
Carlos A. Rivas · Adriano Mazziotta ·
Mieczysław Kunz

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Abstract

Context Forest fragmentation, defined as the spatial configuration of habitat within landscapes, has been quantified using an expanding range of metrics and analytical workflows. Although methodological diversity has increased rapidly with advances in remote sensing and computational capacity, comparability and ecological interpretability remain uneven.

Objectives This review advances forest fragmentation analysis by systematically tracking the evolution of methodological families from 1990 to 2025 and

identifying structural constraints that limit transferability across regions and scales.

Methods We synthesized 138 studies and quantitatively analyzed an operational subset of 127 methodological and hybrid papers. Studies were grouped into twelve methodological families, and their proportional representation was evaluated across four temporal periods. Study level classification and complete search details are provided in the supplementary materials to ensure transparency and reproducibility.

Results Patch–mosaic metrics remain the analytical backbone of fragmentation research. Over time, analytical approaches have expanded from early patch-based measures toward connectivity-oriented, density-based, and emerging three-dimensional formulations. This trajectory reflects cumulative methodological expansion rather than paradigm replacement. Across methodological families, recurring constraints include sensitivity to spatial support, context-dependent parameterization, uneven validation of automated or global products, limited linkage to biological responses, and inconsistent reporting of methodological settings.

Conclusions Progress in fragmentation analysis is likely to depend less on introducing new indices and more on strengthening comparability through explicit documentation of habitat definitions, spatial resolution, connectivity rules, edge settings, window supports, and change detection parameters. By clarifying methodological trajectories and emphasizing transparent reporting, this review provides a structured

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S. Dutt (✉) · M. Kunz
Faculty of Earth Sciences and Spatial Management,
Nicolaus Copernicus University, Toruń, Poland
e-mail: sanjana.dutt@doktorant.umk.pl

T. K. Remmel
Faculty of Environmental and Urban Change, York
University, Toronto, ON, Canada

C. A. Rivas
Department of Forestry Engineering, Mediterranean Forest
Global Change Observatory (GLOBAM), DigiFoR+—
ERSAF, University of Córdoba, Campus de Rabanales,
Crta. IV Km 396, 14071 Córdoba, Spain

A. Mazziotta
Natural Resources Institute Finland (Luke),
Latokartanonkaari 9, 00790 Helsinki, Finland

foundation for more transferable and ecologically grounded fragmentation research.

Keywords Forest fragmentation · Landscape metrics · Connectivity · Scale sensitivity · Methodological evolution · Reproducibility

Introduction

Forest fragmentation, defined as the subdivision of continuous forest into smaller and more isolated patches, reshapes ecological processes, modifies edge environments, and can contribute to biodiversity loss (McGarigal and Marks 1995; Heilman et al. 2002; Riitters et al. 2007; Bennett and Radford 2008). The sensitivity of these metrics to spatial scale was established in foundational work that first quantified the effects of grain and extent on landscape patterns (Turner et al. 1989) and examined the stability of metrics across different pixel resolutions (Wickham and Riitters 1995). Globally, more than two thirds of forests occur within 1 km of an edge (Haddad et al. 2015; Siegel et al. 2024), with the strongest pressures observed in tropical and subtropical regions (Lung and Schaab 2006; Giriraj et al. 2010).

Fragmentation is conceptually distinct from habitat loss. Habitat loss reduces total forest area, whereas fragmentation concerns how a given amount of forest is spatially arranged in terms of patch size, shape, and isolation. This distinction is critical because many landscape metrics are strongly coupled to habitat amount, potentially confounding ecological inference. Recent work demonstrates that indices intended to capture fragmentation or edge effects may primarily reflect habitat amount rather than configuration, emphasizing the importance of explicitly defining what fragmentation metrics quantify (Martin et al. 2025). Connectivity, defined as the degree to which landscape structure facilitates or restricts movement, adds a further interpretive dimension (Bogaert et al. 2000; Vogt et al. 2007; Lausch et al. 2015). Although local edge effects are well documented, landscape scale ecological responses do not always follow directly from patch scale patterns. This highlights the need for scale explicit and methodologically transparent assessments that can be linked to ecological processes where possible.

Over the past three decades, methodological practice in fragmentation analysis has evolved substantially. Broadly, this evolution has progressed from patch-based landscape metrics toward morphology-based diagnostics, connectivity-oriented approaches, and more recent data-driven and three-dimensional analyses enabled by advances in remote sensing and computational environments. Early studies focused on descriptive patch, edge, and shape metrics that quantify landscape pattern, as formalized in the widely used *FRAGSTATS* framework developed by McGarigal and Marks (1995) and discussed in regional landscape assessments by O'Neill et al. (1999). Tools such as *FRAGSTATS* and *Patch Analyst* subsequently provided standardized environments for calculating landscape metrics and comparing fragmentation across regions (Elkie et al. 1999). These patch-mosaic approaches were later complemented by morphology-based diagnostics and connectivity-oriented frameworks. For example, Vogt et al. (2007) introduced morphological spatial pattern analysis (MSPA), which classifies landscape elements into structural roles such as core, edge, bridge, and corridor; these approaches were later operationalized through tools such as *GuidosToolbox* (Riitters et al. 2009; Vogt and Riitters 2017). Advances in remote sensing further expanded fragmentation analysis. Airborne laser scanning and Light Detection and Ranging (LiDAR) data have been integrated with landscape metrics to characterize forest structure (Maier et al. 2006; Zald et al. 2016), while time-series change detection algorithms using Landsat data allow consistent monitoring of disturbance trajectories (Zhu and Woodcock 2014; Kennedy et al. 2018). Similarly, terrestrial laser scanning (TLS) enables detailed three-dimensional characterization of canopy structure in fragmented forests (Nunes et al. 2022). At the same time, cloud platforms such as *Google Earth Engine* (GEE) and open-source analytical ecosystems including the R package *landscapemetrics* and the Python library *PyLandStats* support increasingly reproducible workflows for landscape analysis (Gorelick et al. 2017; Hesselbarth et al. 2019; Bosch 2019). Neutral landscape models further enable controlled experimentation by separating habitat composition from spatial configuration and testing the sensitivity of fragmentation metrics to methodological choices (van Strien et al. 2016; Justeau-Allaire et al. 2022).

Despite these advances, several challenges continue to limit comparability and ecological interpretation across studies. Fragmentation metrics remain sensitive to spatial scale and are often confounded with habitat amount, as noted in empirical studies of species–habitat relationships (Hargis et al. 1999) and later methodological evaluations (Long et al., 2010a, 2010b). Parameter choices and thresholds are frequently region dependent, and hidden methodological settings—such as pixel resolution, neighborhood size, or edge definitions—can strongly influence metric outcomes (Ostapowicz et al. 2008; Hernando et al. 2017). As demonstrated by Zatelli et al. (2019), even the size of the computational neighborhood used in metric calculations can significantly affect fragmentation estimates. Empirical validation also remains uneven, particularly for large-scale applications and emerging three-dimensional indicators derived from LiDAR data (Zald et al. 2016; Rimmel 2022). Moreover, links between fragmentation indicators and biological responses are not always straightforward, as emphasized in broader discussions of fragmentation effects on biodiversity (Fahrig 2003, 2019; Fletcher et al. 2018). Finally, methodological settings and analytical workflows are often inconsistently reported, limiting reproducibility and cross-study comparison (Hesselbarth et al. 2021). Recent approaches—including fixed-window density measures such as Forest Area Density, morphology combined with graph-based connectivity metrics, and voxel-based three-dimensional indicators—address some of these issues but also introduce additional assumptions that require explicit evaluation (Wickham et al. 2008; Lin et al. 2021; Rimmel 2022).

The main aim of this study is to advance forest fragmentation analysis by synthesizing methodological developments and identifying pathways to improve interpretability, reproducibility, and transferability across spatial and ecological contexts. To achieve this, we systematically review 138 methodological studies published between 1990 and 2025 with three objectives: (i) to trace the evolution of fragmentation metrics from early patch based measures toward connectivity, density based, and emerging three dimensional approaches; (ii) to evaluate how remote sensing inputs, time series and change detection workflows, and analytical environments influence the accuracy and comparability of fragmentation indicators; and (iii) to identify recurring methodological

limitations and summarize key reporting elements that support robust and transferable fragmentation analysis.

Methodology

Literature search

This review followed the PRISMA 2020 framework (Page et al. 2021) to ensure transparency and reproducibility. We focused on methodological developments in forest fragmentation and included peer reviewed journal articles published between 1990 and 2025.

Literature searches were conducted between 3 October 2024 and 9 September 2025 using Publish or Perish (Harzing, 2010), a bibliometric retrieval tool for structured queries in Google Scholar. Complementary searches were performed directly in Scopus and Web of Science to ensure comprehensive coverage. Searches were restricted to English language journal articles; conference proceedings, theses, book chapters, and reports were excluded.

Search queries combined mandatory, alternative, and excluded terms targeting forest fragmentation methods while filtering unrelated thematic contexts. Complete search strings for all databases are provided in Supplementary Table S1.

Studies were eligible if they proposed, evaluated, or systematically applied methods for quantifying forest fragmentation. This included structural and configurational metrics, Morphological Spatial Pattern Analysis (MSPA), graph based connectivity approaches, fixed window density measures, change detection workflows feeding fragmentation indicators, and emerging three dimensional or voxel based methods. Purely ecological case studies without methodological contribution were excluded.

The database search returned 1,160 records. Citation tracing using Litmaps and Connected Papers, together with expert recommendations, identified 46 additional studies, resulting in 1,206 records prior to deduplication. The screening and selection process is summarized in Fig. 1.

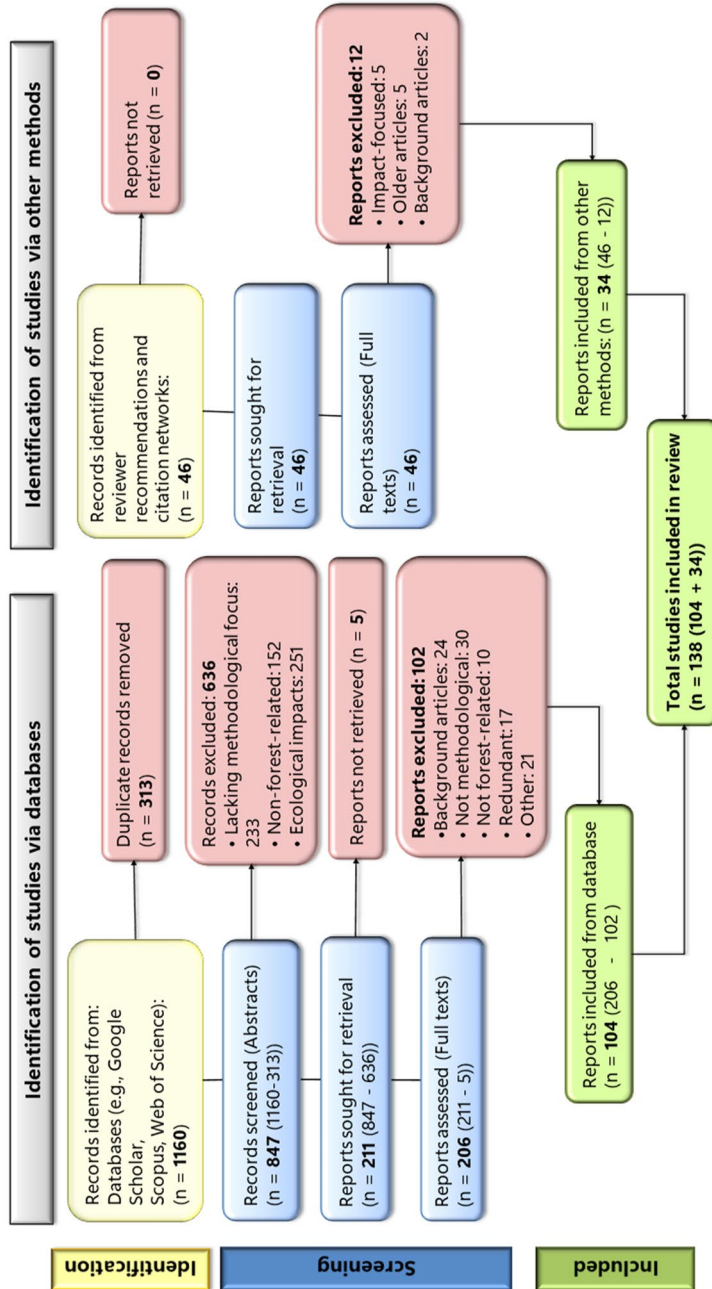


Fig. 1 PRISMA 2020 flow diagram showing study identification, screening, eligibility, and inclusion for the systematic review of forest fragmentation methodologies (1990–2025). The final dataset comprised 138 studies

Screening and eligibility assessment

Duplicate removal using Rayyan, a web based systematic review screening tool (Ouzzani et al. 2016), eliminated 313 records, leaving 847 unique studies. Title and abstract screening excluded studies lacking methodological focus, forest relevance, or fragmentation methods components.

A total of 211 articles were sought for full text retrieval; five could not be obtained, leaving 206 for assessment. In parallel, 46 additional studies from citation tracing were evaluated at full text stage.

Of the 206 database sourced studies, 102 were excluded due to lack of methodological novelty, absence of forest focus, repeated application of established workflows without innovation, or insufficient methodological detail. This yielded 104 studies from database searches. Among the 46 supplementary studies, 12 were excluded for similar reasons, resulting in 34 additional inclusions. A complete list of all 138 studies, including those analyzed as data sources but not explicitly cited in the narrative text, is provided in Supplementary Table S2 and the Supplementary References.

Study classification and analytical subset

The 138 included studies were classified into three categories: Conceptual ($n=11$), Hybrid conceptual methodological ($n=15$), and Methodological ($n=112$). Conceptual studies provided theoretical clarification or methodological critique. Hybrid studies combined conceptual framing with operational implementation. Methodological studies primarily developed or applied analytical workflows.

For quantitative assessment of temporal methodological trends in Sect. "Results", analyses were restricted to the operational subset of 127 studies (112 Methodological plus 15 Hybrid). Conceptual studies were retained for theoretical synthesis but excluded from proportional calculations. Study level classification is documented in Supplementary Table S2.

Review limitations

This review was limited to English language peer reviewed journal articles, which may exclude some

regional contributions. The search strategy emphasized methodological terminology, which may favor software explicit studies; citation tracing and expert recommendations were used to reduce this bias. Screening was conducted by a single reviewer using predefined criteria, with co author oversight during final inclusion. All counts align with the PRISMA diagram, and full search strings and study lists are provided in Supplementary Table S1 and Supplementary Table S2.

Results

Literature structure and analytical subset

The final corpus comprised 138 studies published between 1990 and 2025 (Supplementary Table S2). As described in Sect. "Methodology", these were classified as Conceptual ($n=11$), Hybrid conceptual–methodological ($n=15$), and Methodological ($n=112$).

Quantitative assessment of temporal methodological trends was conducted using the operational subset of 127 studies (112 methodological and 15 hybrid contributions). Purely conceptual studies were retained for theoretical context but were excluded from proportional calculations. Similar systematic reviews of fragmentation research have demonstrated that datasets of comparable size are sufficient for identifying temporal patterns and methodological shifts (Fardila et al. 2017; Feleha et al. 2025). Figure 2 synthesizes the temporal distribution of methodological families and situates them within broader analytical and computational environments.

Method family classification

The 127 operational studies were assigned to twelve methodological families (Table 1). These families represent recurring analytical strategies and are not mutually exclusive. Patch mosaic metrics encompass categorical landscape indices commonly implemented in *FRAGSTATS* (McGarigal and Marks, 1995), including area, edge, shape, contagion, and nearest neighbour measures. Morphological analysis refers to Morphological Spatial Pattern Analysis and related implementations that classify

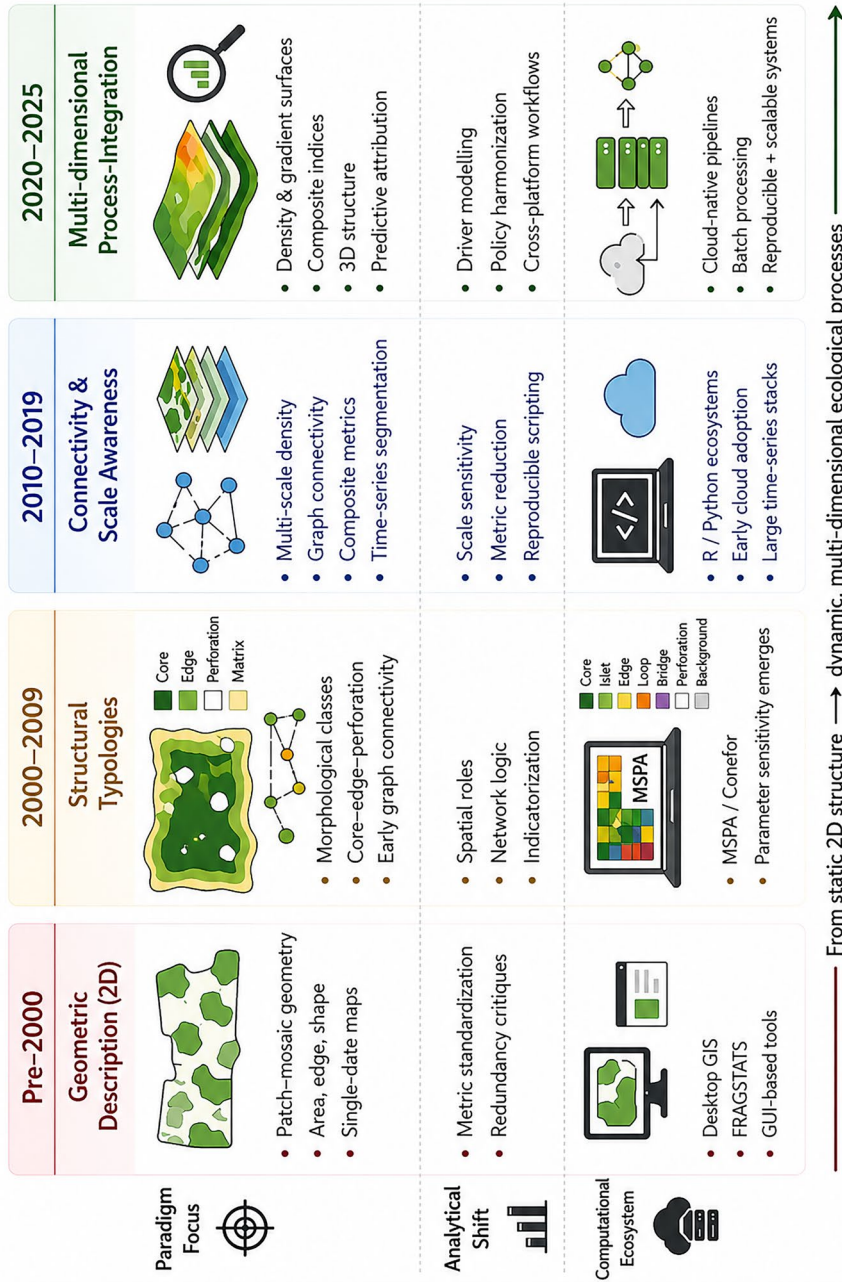


Fig. 2 Paradigm expansion in forest fragmentation analysis (1990–2025). From patch-mosaic geometry to multi-dimensional, scale-aware, and process-integrated workflows, integrating methodological families and computational ecosystems derived from the operational subset

Table 1 Temporal distribution of forest fragmentation methodological families (operational subset, $n=127$)

Methodological family	Pre-2000 ($n=10$)	2000–2009 ($n=23$)	2010–2019 ($n=46$)	2020– 2025 ($n=48$)
Patch–mosaic metrics (PMM)	80%	70%	72%	77%
Morphological analysis (MOR)	0%	22%	15%	19%
Graph-based connectivity (GRA)	0%	17%	13%	15%
Density / gradient approaches (DEN)	0%	17%	9%	17%
Information-theoretic methods (INF)	0%	0%	2%	10%
Simulation and generative models (SIM)	10%	4%	11%	10%
Composite / index synthesis (COMP)	30%	4%	11%	15%
Time-series segmentation (TS)	0%	4%	17%	13%
Three-dimensional structure (3D)	0%	9%	4%	13%
Vector-based frameworks (VECTOR)	0%	0%	11%	8%
Scripted and modular workflows (pipe)	0%	0%	15%	33%
Cloud-native platforms (CLOUD)	0%	0%	2%	10%

(Percentages may exceed 100% because individual studies can belong to multiple methodological families)

landscapes into structural roles such as core, edge, and perforation (Vogt et al. 2007; Riitters et al. 2009). Graph based connectivity includes network derived metrics such as the Probability of Connectivity (PC) and the Integral Index of Connectivity (IIC) implemented in *Conefor* (Saura and Torné, 2009).

Density and gradient approaches include moving window forest proportion metrics such as Pf and Pff (Riitters et al., 2000; Wickham et al., 2007), Forest Area Density, and related continuous surface formulations. Information theoretic methods rely on divergence based pattern comparison using Kullback Leibler or Jensen Shannon metrics (Nowosad and Stepinski 2019; Rimmel 2020). Simulation and generative models include neutral landscape models and cellular automata Markov frameworks used to generate controlled configurations (van Strien et al. 2016; Justeau Allaire et al. 2022).

Composite approaches apply factor reduction techniques such as principal component analysis to derive integrated fragmentation indices (Zhen et al., 2023). Time series segmentation includes disturbance detection algorithms such as Vegetation Change Tracker (VCT) (Huang et al. 2010), Continuous Change Detection and Classification (CCDC) (Zhu and Woodcock 2014), and LandTrendr (Kennedy et al. 2018). Three dimensional structure refers to Light Detection and Ranging derived structural metrics and voxel based morphology (Nunes et al. 2022; Rimmel 2022). Vector based frameworks compute topology

preserving metrics directly from parcel data (Yao et al. 2022).

Computational families include scripted and modular workflows implemented in *R*, *Python*, and geographic information system scripting environments (Hesselbarth et al. 2019; Bosch 2019; Wegmann et al., 2018), as well as cloud native platforms such as *GEE* and *FAO SEPAL* that enable distributed processing (Kennedy et al. 2018; Vogt et al. 2022).

Pre-2000: Geometric configuration and metric standardization

Prior to 2000, forest fragmentation analysis was dominated by patch–mosaic metrics, which were implemented in 80% of studies (Table 1). Fragmentation was typically quantified using categorical land-cover maps and *FRAGSTATS*-derived metrics (McGarigal and Marks 1995), including area, edge, shape complexity, contagion, and nearest-neighbour distance (Ripple et al. 1991; Jaeger 2000). Several studies examined metric behaviour and redundancy, testing sensitivity to grain and spatial extent (Hargis et al. 1999; O'Neill et al. 1999). Simulation models were present in 10% of studies, and composite metric reduction approaches in 30%.

No studies in this period implemented morphological spatial pattern analysis, graph-based connectivity indices, density-based moving-window approaches, time-series segmentation, three-dimensional structural

metrics, programmable pipelines, or cloud platforms (Table 1). Analyses were conducted primarily within desktop geographic information system environments, including early *ArcView/ArcInfo* implementations, *GRASS GIS*, and standalone *FRAGSTATS* workflows (Fig. 2). Overall, this period reflects a methodological focus on geometric patch configuration, with fragmentation primarily characterized through categorical landscape metrics implemented in desktop GIS environments.

2000–2009: Structural classification and connectivity metrics

Between 2000 and 2009, patch–mosaic metrics remained widely used (70%; Table 1), but additional methodological families were introduced. MSPA and related tools were implemented in 22% of studies (Vogt et al. 2007; Riitters et al. 2009). These methods classified landscapes into structural types based on image morphology (connectivity and relative position).

Graph-based connectivity metrics were implemented in 17% of studies, particularly following the release of *Conefor* (Saura and Torné 2009). The Probability of Connectivity (PC) and Integral Index of Connectivity (IIC) quantified patch importance and habitat availability under specified dispersal thresholds. Density-based moving-window metrics were also present in 17% of studies, including forest proportion metrics such as Pf and Pff. Time-series segmentation was limited (4%).

This period therefore reflects the coexistence of geometric patch metrics, structural typologies, and network-based connectivity measures (Fig. 2). Implementations were primarily desktop based, typically through *ArcGIS* and *QGIS* extensions, standalone *FRAGSTATS* and *Conefor* tools, and early morphology software, with limited scripting or workflow automation. Consequently, fragmentation analysis expanded beyond patch geometry to include structural classification and connectivity-based representations of landscape structure.

2010–2019: Temporal reconstruction and programmable analysis

From 2010 onward, fragmentation analysis diversified while retaining patch–mosaic metrics (72%;

Table 1). Time-series segmentation increased to 17%, supported by algorithms such as VCT (Huang et al. 2010), CCDC (Zhu and Woodcock 2014), and LandTrendr (Kennedy et al. 2018). These methods reconstructed annual disturbance histories from Landsat time series.

Morphological analysis (15%) and graph-based connectivity (13%) remained present. Density and gradient approaches were implemented in 9% of studies. Information-theoretic pattern comparison gained traction during this period (2%) (Nowosad and Stepinski 2019; Rimmel 2020). Vector-based topology-preserving approaches were introduced (11%).

Programmable and reproducible workflows increased to 15%, reflecting adoption of scripting environments in R, Python, and *GRASS GIS* (Hesselbarth et al. 2019; Bosch 2019; Wegmann et al. 2018). Cloud-based platforms appeared in 2% of studies. These developments indicate a transition toward temporally explicit and programmable analytical workflows that allowed fragmentation patterns to be linked with disturbance histories.

2020–2025: Multi-method integration and scalable infrastructures

In the most recent period, patch–mosaic metrics remained common (77%; Table 1) but were frequently integrated with other approaches. Morphological analysis (19%), density-based metrics (17%), and graph-based connectivity (15%) were often combined. Composite index synthesis increased to 15%. Information-theoretic approaches increased to 10%, and three-dimensional structure-based metrics to 13% (Nunes et al. 2022; Rimmel 2022).

Programmable analytical pipelines expanded substantially (33%), incorporating scripting, batch processing, and integration with statistical or machine learning frameworks. Cloud-native platforms increased to 10%, including *GEE* and related distributed infrastructures (Osewe et al. 2022; Vogt et al. 2022). Figure 2 summarizes these temporal patterns across methodological families and computational environments. Collectively, these developments reflect a shift toward integrated multi-method frameworks supported by scalable computational infrastructures.

Discussion

A cumulative expansion rather than replacement of paradigms

Across the four time periods, patch–mosaic landscape metrics remained the most persistent analytical backbone, but their role shifted from being the primary output to becoming one component within multi-method workflows (Table 1; Supplementary Table S2). Early studies largely operationalized fragmentation as two-dimensional geometry derived from categorical maps, supported by the standardization of landscape metrics in *FRAGSTATS* (McGarigal and Marks 1995) and early sensitivity critiques that highlighted redundancy and scale dependence (Hargis et al. 1999; O’Neill et al. 1999). Rather than being displaced, these metric families were progressively complemented by approaches that made landscape structure more interpretable in terms of spatial roles and connections.

The first major broadening involved morphology-based structural typologies, particularly MSPA, which reframed fragmentation as the distribution of core, edge, perforated, and patch components rather than only patch statistics (Vogt et al. 2007; Riitters et al. 2009). In parallel, graph-based connectivity approaches formalized fragmentation-relevant habitat availability using network indices such as the PC and IIC, operationalized in tools such as *Conefor* (Saura and Torné 2009). These developments made explicit that fragmentation assessments often depend on assumptions about connectivity thresholds and the spatial support over which structure is evaluated, bringing parameterization to the foreground.

From 2010 onward, methodological diversification increasingly reflected the realities of remote-sensing time series and the demand for scalable, repeatable analysis. Time-series segmentation approaches such as the VCT and CCDC enabled disturbance histories to be reconstructed from dense Landsat stacks (Huang et al. 2010; Zhu and Woodcock 2014), while later implementations of LandTrendr in cloud environments lowered computational barriers for large-area applications (Kennedy et al. 2018). Alongside these detectors, continuous density and gradient-based formulations—such as moving-window forest proportion indices (Pf/Pff) and related density surfaces provided alternatives to strict patch delineation and

made scale dependence explicit rather than implicit (Wickham et al. 2007). More recent work extended fragmentation logic into information-theoretic and similarity-based comparisons, treating landscapes as distributions of configurations or signatures rather than a set of individual indices (Nowosad and Stepinski 2019; Rimmel 2020; Nowosad 2021).

Together, these shifts support the interpretation synthesized in Fig. 2: forest fragmentation analysis has expanded from geometric description toward structural typologies, network connectivity, scale-aware continuous surfaces, and increasingly process-linked workflows, without abandoning its early metric foundations.

The pipeline shift: why scripted and cloud-native environments matter

One of the clearest recent developments is not a single new metric family, but the transition from “single-step metric calculation” toward scripted and modular analytical pipelines (Table 1). These pipelines integrate preprocessing, metric computation, sensitivity testing, and visualization in parameter-explicit workflows. In *R*, packages such as *landscapemetrics* support reproducible computation of *FRAGSTATS*-type metrics in tidy workflows (Hesselbarth et al. 2019), while Python ecosystems provide parallel capacity for batch processing and integration with modeling (Bosch 2019). Importantly, pattern-based spatial analysis tools such as *motif* do not reproduce *FRAGSTATS* indices, but instead represent local landscapes using spatial signatures derived from co-occurrences and compare these signatures using distance measures for tasks such as clustering, search, and change detection (Nowosad 2021). This distinction is consequential because it reflects a conceptual move toward comparing patterns as multivariate structures rather than as collections of single-number indices.

Cloud-native platforms have amplified this pipeline shift by enabling time-series processing and large-scale fragmentation monitoring without bespoke infrastructure. Implementations of disturbance segmentation on GEE illustrate how detector outputs can be linked directly to downstream fragmentation characterization in scalable workflows (Kennedy et al. 2018; Osewe et al. 2022). At the same time, cloud deployment heightens the importance

of reporting parameter choices such as compositing rules, edge definitions, window sizes, and detector settings because defaults can strongly shape inferred change trajectories and fragmentation states (Francini et al. 2023; Zatelli et al. 2019). The methodological implication is that reproducibility is now defined less by the name of a software tool and more by whether an analysis is described as a re-runnable pipeline with explicit spatial support and sensitivity constraints.

Persistent constraints and implementable reporting standards

Despite methodological expansion, several constraints recur across the literature and limit transferability across regions and scales. First, most fragmentation indicators remain sensitive to grain, extent, neighbourhood rules, and window sizes, which can confound ecological inference when spatial support is not explicit or tested (Turner et al. 1989; Hargis et al. 1999; Ostapowicz et al. 2008; Zatelli et al. 2019). These scale-related challenges are fundamentally rooted in the Modifiable Areal Unit Problem (MAUP), where conclusions shift based on how units are aggregated or zones are defined (Jelinski and Wu 1996). Our review confirms that modern indicators still exhibit the predictable Type I, II, and III scaling responses first categorized in empirical scalograms, which remain more consistent for changes in grain than for changes in extent (Wu et al. 2002; Wu 2004).

Second, connectivity and typology approaches often require thresholds or assumptions (e.g., edge depth or dispersal distance) that are context-dependent and may not be portable across biomes without calibration (Wickham and Riitters 1995; Saura and Torné 2009; Lin et al. 2021). These sensitivities are compounded by uneven ecological coverage in the methodological literature. Many widely used fragmentation frameworks were developed and validated primarily in temperate forest systems where long-term monitoring data and high-resolution remote sensing products are available. As noted in global syntheses of fragmentation research (e.g., Haddad et al. 2015) and systematic assessments of landscape ecology studies (Fardila et al. 2017), empirical applications remain geographically biased toward Europe and North America, while tropical and disturbance-dominated systems are comparatively underrepresented.

Consequently, fragmentation metrics and parameterizations derived from well-instrumented landscapes may require recalibration when applied to forests with different disturbance regimes, canopy structures, or land-use pressures. Third, the growing reliance on global products and automated disturbance detectors increases the risk of omission and commission errors in regions where canopy change is subtle or cyclical, reinforcing the need for targeted validation (Hansen et al. 2013; Nunes et al. 2022). Characterizing these multiscale characteristics through explicit scaling functions remains the most precise way to ensure that fragmentation indicators are both robust and transferable across diverse spatial contexts (Wu 2004).

A practical outcome of this review is therefore the need for a minimal reporting standard that is independent of method family. At a minimum, studies should explicitly state: (i) the habitat definition and minimum mapping unit, (ii) pixel size and neighbourhood rule, (iii) edge width (where applicable), (iv) the spatial support of moving-window or density-based indices, and (v) parameter settings for change-detection and compositing when time-series outputs feed fragmentation indicators. Making these settings explicit would improve comparability across studies regardless of whether fragmentation is quantified using patch metrics, morphology, connectivity, density surfaces, or signature-based approaches.

Boundary conditions: fragmentation pattern, fragmentation process, and fragmentation per se

Finally, the literature reviewed here spans both *fragmentation as pattern* and *fragmentation as process* intertwined with habitat loss. *Fragmentation as pattern* refers to the spatial configuration of habitat patches, *fragmentation as process* describes the ecological or land-use dynamics that generate these patterns, and *fragmentation per se* denotes configuration effects independent of habitat amount. This distinction is central because many commonly used indicators respond jointly to habitat amount and configuration, and temporal change metrics may conflate changes in habitat quantity with changes in *fragmentation per se* (Fahrig 2003; Long et al. 2010). At the extremes of habitat amount, configuration becomes uniform and fragmentation effectively disappears, illustrating the theoretical limits

of configuration-based indicators. The methodological families identified in Table 1 include approaches designed to separate composition from configuration, but these separations are not uniformly implemented across application domains. Clarifying whether a study targets *fragmentation as pattern*, *fragmentation as process*, or *fragmentation per se* is therefore necessary for interpreting metrics consistently and for aligning methodological choices with ecological questions.

Summary statements

Over the past three decades, forest fragmentation analysis has evolved from primarily geometric descriptions of patch configuration toward structurally explicit, connectivity-aware, and increasingly scale-conscious analytical systems. Rather than replacing earlier approaches, successive methodological families have accumulated around a persistent patch–mosaic backbone. Morphological typologies, graph-based connectivity, density and gradient surfaces, time-series segmentation, information-theoretic comparisons, and emerging three-dimensional formulations now coexist within integrated workflows.

This review advances fragmentation analysis by making that cumulative structure explicit. By grouping operational studies into comparable methodological families and tracking their temporal trajectories, we show that shifts in the field have been driven as much by computational environments and data availability as by conceptual innovation. The transition toward scripted, modular pipelines and cloud-enabled processing has particularly altered how fragmentation metrics are implemented, reproduced, and scaled.

At the same time, methodological expansion has not eliminated persistent constraints. Fragmentation indicators remain sensitive to spatial support and parameterization; connectivity formulations depend on context-specific assumptions; and time-series outputs propagate detector choices into downstream pattern metrics. The practical implication is not the need for entirely new indices, but for greater precision in how existing ones are specified, validated, and reported.

Future progress will likely depend less on inventing additional metrics and more on strengthening comparability and transferability. Explicit

documentation of habitat definitions, spatial resolution, connectivity rules, edge settings, window supports, and detector parameters would substantially improve cross-study synthesis. Integrating complementary families—such as morphology with network indices, or density surfaces with structural information—offers a pragmatic path toward reducing composition–configuration conflation. Where feasible, coupling fragmentation outputs with independent validation or biological response data will further strengthen ecological inference.

Forest fragmentation remains a central concept in landscape ecology and conservation planning. By clarifying how its analytical tools have evolved—and by identifying the reporting and validation practices that most strongly influence interpretation—this review provides a structured foundation for more transparent, transferable, and ecologically grounded fragmentation research in the decades ahead.

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Declarations

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