






REVIEW

Geosciences

Assessing forest fragmentation and biodiversity impacts in sub-Saharan Africa: Methodological challenges and conservation strategies for small-scale agricultural landscapes

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Abstract

Tropical forests in sub-Saharan Africa (SSA) harbor around one-third of the world's species but are becoming more fragmented due to the expansion of human settlements and small-scale agricultural (SCA) areas. This study systematically reviewed the approaches and methods used to analyze forest fragmentation and its impact on biodiversity in SSA, with a focus on their suitability in SCA landscapes. The main findings revealed that most studies in SSA employed generalized approaches to assess fragmentation, failing to account for the distinct contributions of various land cover changes. The other key findings indicate that the majority of studies (i) depended on low-resolution remote sensing imagery, (ii) neglected to assess landscape metrics accuracy, and (iii) had limited focus on socioeconomic aspects. These limitations impede precise and thorough evaluation of SCA's contribution to forest fragmentation. To address these gaps, we recommend the following: (i) adoption of high-resolution images, (ii) integration of socioeconomic data, and (iii) rigorous validation of landscape metrics. Concerning biodiversity implications, 55.2% (21 out of 38) of the reviewed studies reported negative impacts, and 68.2% (26 out of 38) exhibited a taxonomic bias toward avian and tree/plant species. We recommend the

Abbreviations: AVHRR, advanced very high resolution radiometer; CNN, convolution neural network; DL, deep learning; ED, edge density; GIS, geographic information system; GEOBIA, geographic object-based image analysis; LiDAR, light detection and ranging; MODIS, moderate resolution imaging spectroradiometer; NAIP, National Agriculture Imagery Program; RADAR, radio detection and ranging; REDD+, reducing emissions from deforestation and forest degradation; SPOT, Satellite Pour l'Observation de la Terre; SCA, small-scale agricultural; SSA, sub-Saharan Africa.

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following: (i) enhanced utilization of remote sensing data for biodiversity monitoring, (ii) greater emphasis on neglected taxa (e.g., small mammals and amphibians), and (iii) focused conservation initiatives for small forest fragments, which are essential for biodiversity conservation, and reducing emissions from deforestation and forest degradation in SSA.

Plain Language Summary

The study found that small farm growing larger is the main reason animals and plants are disappearing in parts of Africa. We wanted to find ways to measure how these small farms break up forests and hurt wildlife, plants, and other living organisms. We learned that many studies have used poor-quality pictures from space and other general methods which miss important details found in small agriculture farms. Additionally, most studies on plants and animals in Africa have only focused on birds and trees. They ignore other types of creatures such as bees and frogs. Therefore, the study recommends (i) using better pictures from space and including information about people to understand how small farms affect nature, (ii) studying animals that are not often looked at, such as rats, rabbits, and frogs. Moreover, small patches of forest left between farms are important. They give birds, frogs, and rabbits a place to live and provide oxygen to breathe.

1 | INTRODUCTION

Forests are the dominant terrestrial ecosystem, covering approximately 30% of our planet's surface area (Arroyo-Rodríguez et al., 2020). Tropical forests in sub-Saharan Africa (SSA) provide habitat to one-third of the world's species and contain eight of the 34 global biodiversity rich areas (Archer et al., 2018; Chapman et al., 2022; Primack, 2014). However, 10%–30% of tropical forest biodiversity, which includes plants, mammal, bird, and amphibian species, is threatened by both forest loss and fragmentation (Achiso, 2020; Perrings & Halkos, 2015). Up to 50% of the total biodiversity in SSA is threatened due to continuous forest loss and fragmentation (Mohammed, 2020). Between 1990 and 2018, SSA lost approximately 98.7 million ha of forested areas, creating approximately 44 million small forest fragments (Fischer et al., 2021).

The primary drivers of such high forest fragmentation values in SSA are small-scale agricultural (SCA) area and settlement expansion, which pose a threat to the region's biodiversity (Chisanga et al., 2024; Perrings & Halkos, 2015; Phiri et al., 2019). Numerous studies in SSA have quantified landscape/forest fragmentation using land cover maps derived from Landsat satellite imagery (Dimobe et al., 2017; Fitz et al., 2022; Kowe et al., 2020; Mulatu et al., 2024; Ojoyi et al., 2016). These studies effectively measured the spatial and temporal impacts of land cover change

on landscape/forest fragmentation and observed an increase in landscape fragmentation. Their findings have informed landscape management strategies, which have focused on improving landscape connectivity, developing corridors for animals, and supporting ecological processes, such as pollination (Newmark et al., 2017; Riggio & Caro, 2017; Tiang et al., 2021). However, studies on landscape fragmentation in SSA often generalize or amalgamate the impact of all land cover changes on forest fragmentation. As a result, these studies fail to capture each land cover change driver's unique contribution to forest fragmentation, particularly relating to SCA areas. Given that SCA is a dominant and expanding driver of fragmentation in the region, this oversimplification obscures critical insights needed for targeted forest conservation strategies.

SCA-related expansion creates unique heterogeneous landscape patterns of several small agricultural fields with sizes of less than 2 ha and even smaller isolated forest fragments (Apraku et al., 2021; Siqueira et al., 2021; Wingate et al., 2024). However, the dominant use of Landsat imagery's in SSA to measure landscape fragmentation often overlooks and generalizes SCA fields and small forest fragments inside the fields, hence limiting its applicability in such areas (Singh et al., 2024). This demonstrates how traditionally used satellite data, such as the use of Landsat images, in studying landscape fragmentation, cannot accurately analyze forest fragmentation in SCA landscapes. Other standard approaches

used when conducting landscape fragmentation analysis that influence the accurate assessment of forest fragmentation in SCA areas are as follows:

- (i) Landscape representation model (Rahimi et al., 2022).
- (ii) Image classification algorithm (Donkor et al., 2022; Kanmani et al., 2023).
- (iii) Accuracy of land cover maps (Frazier & Kedron, 2017; Olofsson et al., 2014).

Landscape fragmentation significantly affects species such as birds, animals, and microorganisms, which rely on forests as their habitat (Fletcher et al., 2018; Haddad et al., 2015). Accordingly, several studies have measured the impact of landscape fragmentation on biodiversity (Kouagou et al., 2019; Mohandass et al., 2014; Ochungo et al., 2022; Ojoyi et al., 2016; Zungu et al., 2020). These included studies conducted in landscapes surrounding forest reserves (Alohou et al., 2017; Kouagou et al., 2019; Webala et al., 2019) and in urban areas (Muderere et al., 2020; Zungu et al., 2020). Few studies conducted in SSA included SCA areas in their study (Mboru & Mutua, 2023; Mulwa et al., 2021). For example, a study by Mboru and Mutua (2023) in Kenya examined the impact of fragmentation in a landscape that included savanna shrubs, woodland, and combined SCA areas and settlement areas. Due to the analysis of SCA areas in landscapes with other land covers, the impact on forest fragmentation specifically related to SCA areas was not assessed and remains limited.

While several global reviews on the impact of fragmentation on biodiversity exist, they are geographically biased toward countries in Europe, America, and Asia (Deikumah et al., 2014; Fletcher et al., 2018; Tan et al., 2023) and are not contextualized to SCA areas in SSA. This limits the applicability of such global reviews to inform research on the impacts of SCA-induced forest fragmentation on biodiversity in SSA. Therefore, this review aimed to answer the following research questions:

- What are the appropriate methods/approaches for measuring forest fragmentation applicable to SCA areas in SSA?
- What approaches/methods are relevant for assessing the impact of forest fragmentation on biodiversity specifically applicable for SCA-fragmented areas in SSA?

2 | CONCEPTUAL FRAMEWORKS

To provide a guiding framework to address our review's two research questions, we conceptualized the forest fragmentation process related to SCA area expansion (Figure 1). Figure

Core Ideas

- In sub-Saharan Africa (SSA), landscape fragmentation is often studied using broad methods and low-resolution images such as Landsat. Such approaches are usually ineffective in small-scale agriculture (SCA) areas in SSA.
- The adoption of high-resolution images, integration of socioeconomic data, and rigorous validation of landscape metrics are critical for the accurate, detailed, and comprehensive assessment of forest fragmentation in SCA areas.
- Biodiversity monitoring is enhanced by integrating remotely sensing data to complement the costly and time-consuming field-based data-collection approaches in SSA.
- The conservation of small forest fragments in SCA areas is crucial for mitigating the impacts of forest fragmentation, biodiversity conservation, and reducing emissions from deforestation and forest degradation (REDD+) initiatives in SSA.

1 illustrates how SCA expansion drives forest fragmentation, and its impact on biodiversity. Typically, landscapes begin with large, continuous forested areas with few surrounding SCA fields. However, rapid agricultural expansion has fragmented these forests into smaller and isolated patches (Collinge, 2009). Although fragmentation generally threatens biodiversity (Perrings & Halkos, 2015), the remaining small forest fragments still play a critical role in biodiversity conservation (Ancorenaz et al., 2021; Siqueira et al., 2021). They preserve landscape connectivity and provide habitats for birds, small mammals, amphibians, and insects (Mulwa et al., 2021; Siqueira et al., 2021; Wingate et al., 2024). In addition, small forest fragments offer ecosystem services such as pollination, seed dispersal, and soil fertility (Ancorenaz et al., 2021; Proesmans et al., 2019). They also provide local communities with food, wood, medicinal herbs, shade, control on water supply, and quality (Decocq et al., 2016). Thus, despite fragmentation pressures, small forest patches remain vital for biodiversity conservation, local community livelihoods, and sustainable agriculture.

The conceptual framework (Figure 1) highlights the key characteristics of SCA-fragmented landscapes. They consist of several SCA fields and numerous small, complex shaped forest fragments in and around agricultural fields, driven by nonspatial factors such as population increase and income. The expansion of the SCA leaves several small forest fragments that provide benefits to biodiversity and local communities. These identified characteristics provided us with a framework to assess the approaches and methods used to

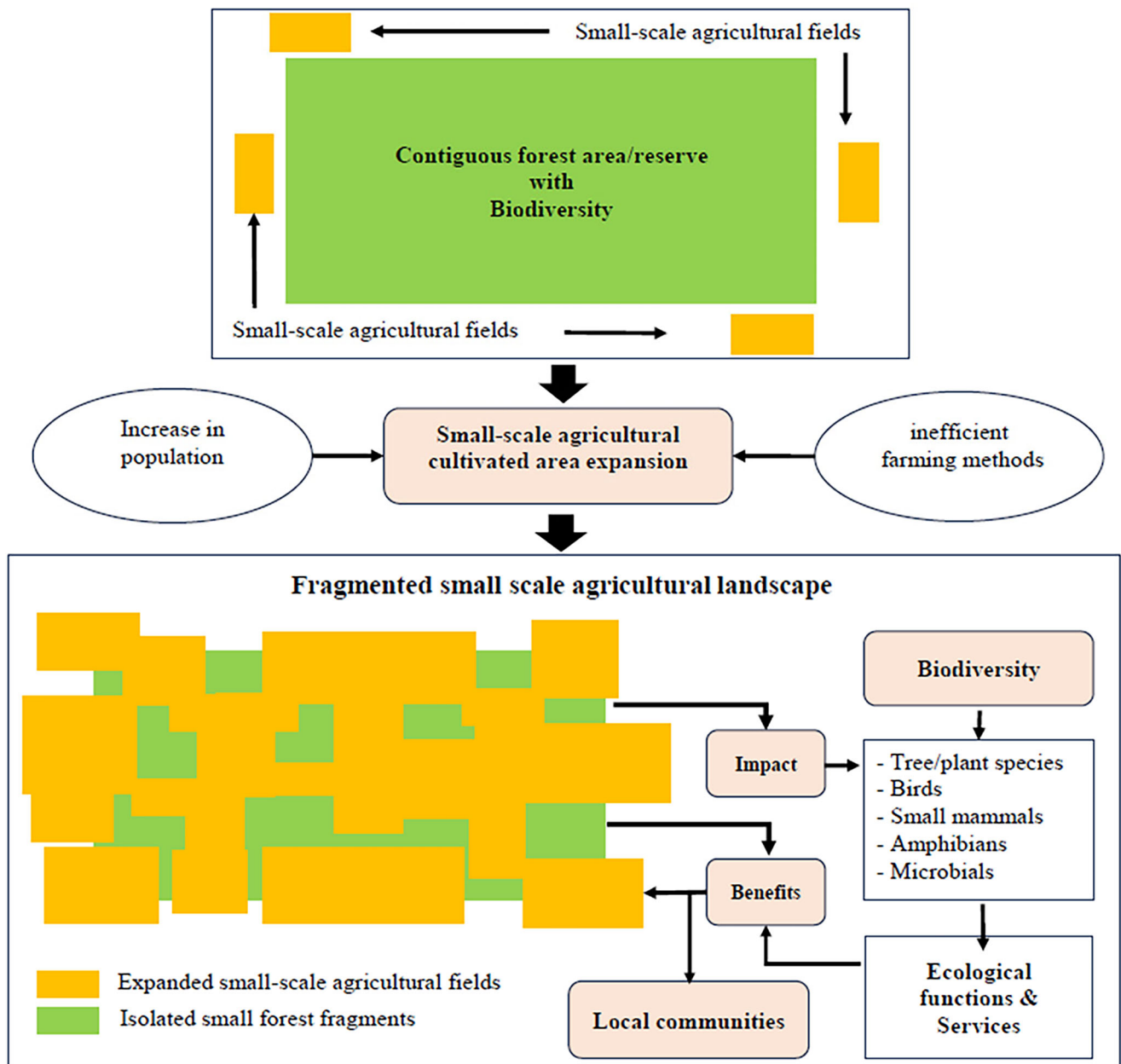


FIGURE 1 Conceptual framework showing how small-scale agricultural expansion drives forest fragmentation.

analyze forest fragmentation and its impact on biodiversity for their suitability for use in SCA landscapes found in SSA.

3 | MATERIALS AND METHODS

This study undertook a comprehensive review of existing research on forest fragmentation and its impact on biodiversity within SCA areas in SSA. To achieve this, a systematic and structured approach was employed to identify, extract, and analyze relevant studies from various databases. The methodology was designed to ensure that the selected studies were both relevant and of high quality, thereby providing

robust insight into the topic under investigation. The following subsections outline the detailed literature search, screening process, extraction process, data classification, data analysis, and interpretation.

3.1 | Search criteria and strategy

The search for studies used in this review was based on Google Scholar, SCOPUS, Semantic Scholar, Environmental Science Collection, Research4Life, and JSTOR databases. The search aimed to identify studies addressing these two questions, specifically studies that clearly specify their approaches or

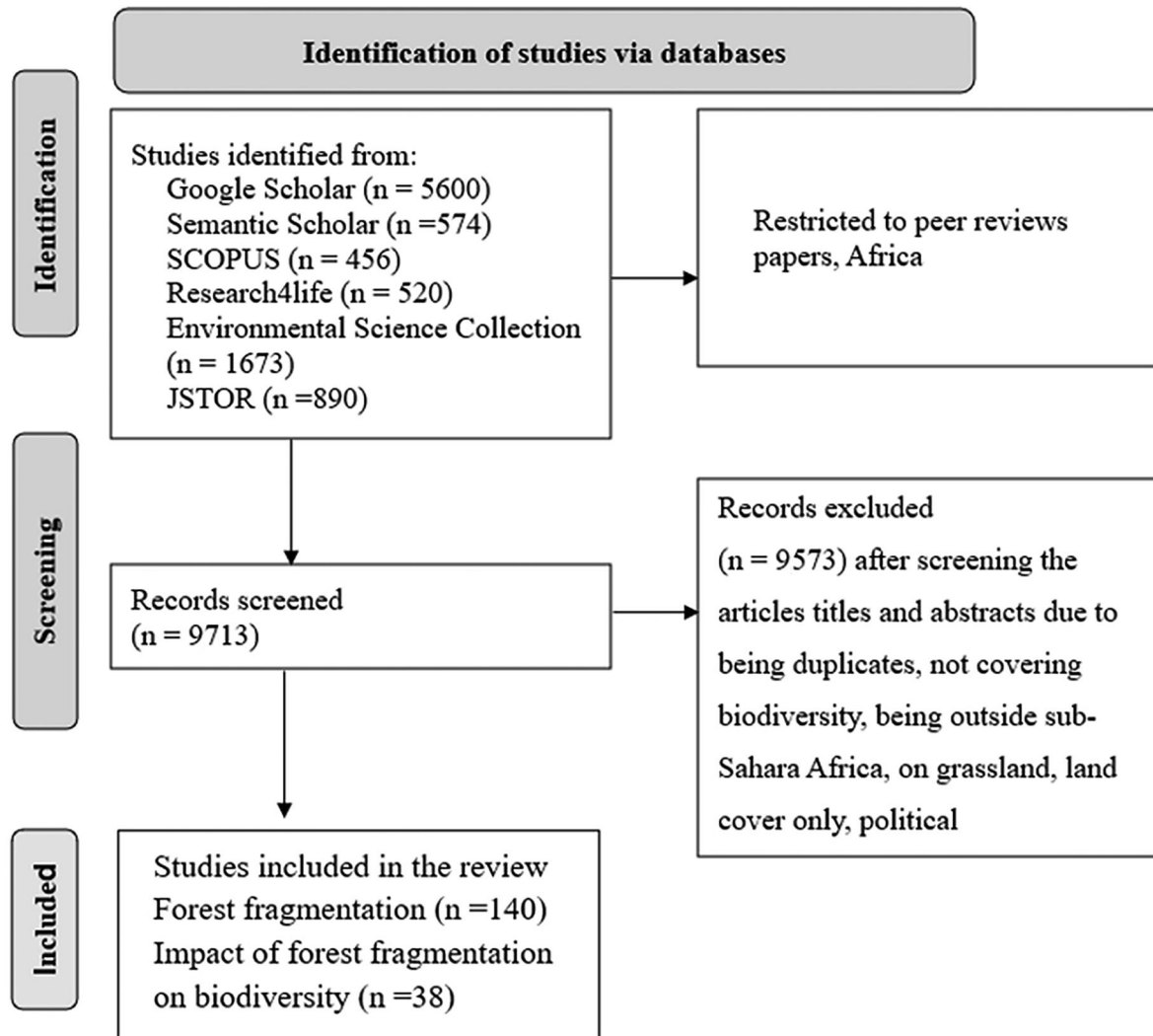


FIGURE 2 Study retrieval, screening, and inclusion.

methods used in (i) analyzing forest fragmentation and (ii) analyzing the impact of forest fragmentation on biodiversity in SSA. The main search strings were “Forest fragmentation in Africa,” “impact of fragmentation on biodiversity from Africa,” “habitat fragmentation in Africa,” “small-scale agriculture and effect in sub-Saharan Africa,” “landscape change in sub-Saharan Africa,” “effect or impact of landscape fragmentation in Africa,” and “fragmentation AND biodiversity in SSA AND Africa” on the original article title and abstract.

3.2 | Literature search, extraction, and screening

Based on the search keywords above (in Section 3.1), 9713 articles were retrieved from the following databases and collections: SCOPUS (456), Google Scholar (5600), Semantic Scholar (574), Research4life (520), environmental collection (1673), and JSTOR (890), as shown in Figure 2. SCOPUS

is one of the most widely accepted and comprehensive data sources for research (Pranckutė, 2021). Google Scholar provides a valuable resource for researchers in regions such as SSA, with poor access to scientific literature, ensuring comprehensive coverage (Bramer et al., 2017; Singh et al., 2023). Semantic Scholar, Research4life environmental collection, and JSTOR databases supplemented SCOPUS and Google Scholar databases. Studies from these databases were retrieved between July and September 2024, covering publications from 1995 to 2024 with a focus on SSA. The inclusion criteria comprised original, peer-reviewed articles in English that addressed forest fragmentation in SSA. Articles were excluded if they (i) focused on other continents (e.g., Asia, Europe, and the Americas), (ii) examined themes unrelated to forest fragmentation and its biodiversity impacts, or (iii) discussed political fragmentation, grassland fragmentation, water biodiversity, standalone land use and land cover, or biodiversity studies. Figure 2 presents the literature search and screening process, as depicted in the PRISMA-P flow

diagram (Medeiros et al., 2021), offering a clear overview of record identification, screening, eligibility assessment, and inclusion.

3.3 | Data classification and extraction process

The studies selected for the review were divided into two groups: (i) those addressing forest fragmentation, and (ii) those examining its impact on biodiversity. For studies on forest fragmentation, a data extraction list was generated to capture critical methodological approaches, including country, year, landscape representation model (patch or surface-based), landscape metrics, remote sensing imagery, image classification algorithms, and accuracy assessment methods.

The landscape model was included in the data extraction list because of its influence on accurate representation of fragmented landscapes. For instance, patch-based models are appropriate for discrete heterogeneous landscapes, whereas surface/gradient models better represent continuous landscapes (Rahimi et al., 2022). Remote sensing data theme was included in the data extraction list because the spatial resolution of remotely sensed images significantly affects the accuracy and detail of fragmentation analysis (Fynn & Campbell, 2019; Hernando et al., 2017). This is essential, particularly for mapping SCA fields of less than 0.5 ha (Hampwaye et al., 2007; Mosomtai et al., 2020) and small forest fragments with individual trees (Siqueira et al., 2021). Furthermore, SCA areas exhibit spectral characteristics similar to those of bare soil and grassland, resulting in occasional misclassification (Esch et al., 2014; Simwanda & Murayama, 2017). Given these challenges, the data extraction list also included image classification algorithms and accuracy assessment techniques for land cover maps and landscape metrics.

A separate extraction checklist was employed for studies on biodiversity impacts, which included author, year, country, data collection methods (field or remote sensing), species taxa, and reported biodiversity effects. The data collection approach variable was included on the data extraction list because SCA area expansion creates millions of small forest fragments (Fischer et al., 2021), which requires efficient and cost-effective data collection approaches (Rocchini et al., 2016; Rossi et al., 2022; Shamaoma et al., 2022). The species taxa and effect variables were included on the list informed by prior reviews on the impact of forest fragmentation on biodiversity (Deikumah et al., 2014; Fahrig, 2017; Teixido et al., 2020).

3.4 | Quality assessment of studies

Following the creation of the data extraction list (Section 3.3), each study was systematically reviewed and recorded in

Microsoft Excel table. Studies which did not clearly specify their methods or approaches were excluded from the analyses pertaining to those particular methods, but were included in other analyses where information on the methods used was available. For example, studies on forest fragmentation that utilized pre-classified land cover maps without specifying the classification algorithm used (e.g., Gumede et al., 2022; Smith et al., 2018) were excluded from the image classification algorithm analysis but included in other relevant assessments.

Additionally, we created a Microsoft Excel checklist for studies examining the effects of fragmentation on biodiversity, documenting details, such as country, data collection methods, landscape metrics, biodiversity indices, and response themes. Likewise, studies that failed to report methodological details were excluded from that method-specific analyses but incorporated into other applicable evaluations where sufficient information was available. Therefore, only studies that clearly described the methods and approaches used were included in the respective review sections.

3.5 | Data analysis and interpretation

Following the thematic classification of the studies, the data were systematically summarized and recorded in a Microsoft Excel spreadsheet. Regarding forest fragmentation, key variables included landscape representation models (patch or surface), landscape metrics (composition and configuration), and remote sensing data (e.g., Landsat and Sentinel-2) and accuracy assessment techniques. To evaluate the impact of fragmentation on biodiversity, extracted variables included data collection methods (remote sensing or field-based), biodiversity effects (positive, negative, neutral, and mixed), and species (birds, trees/plants, mammals, small mammals, microorganisms, insects, and amphibians). The resulting graphs were interpreted narratively and contextualized to assess their suitability for measuring forest fragmentation in SCA areas, as well as their implications for biodiversity in SSA.

4 | RESULTS AND DISCUSSION

This section examines a wide range of studies published between 1995 and 2024 to identify the key approaches and methods used in forest fragmentation studies across SSA. Additionally, we reviewed a subset of studies that focused on the impact of forest fragmentation on biodiversity. Sections 4.1 and 4.2 present our findings on the trends, applied methods, and approaches used to study forest fragmentation and its impact on biodiversity in SSA. These results are

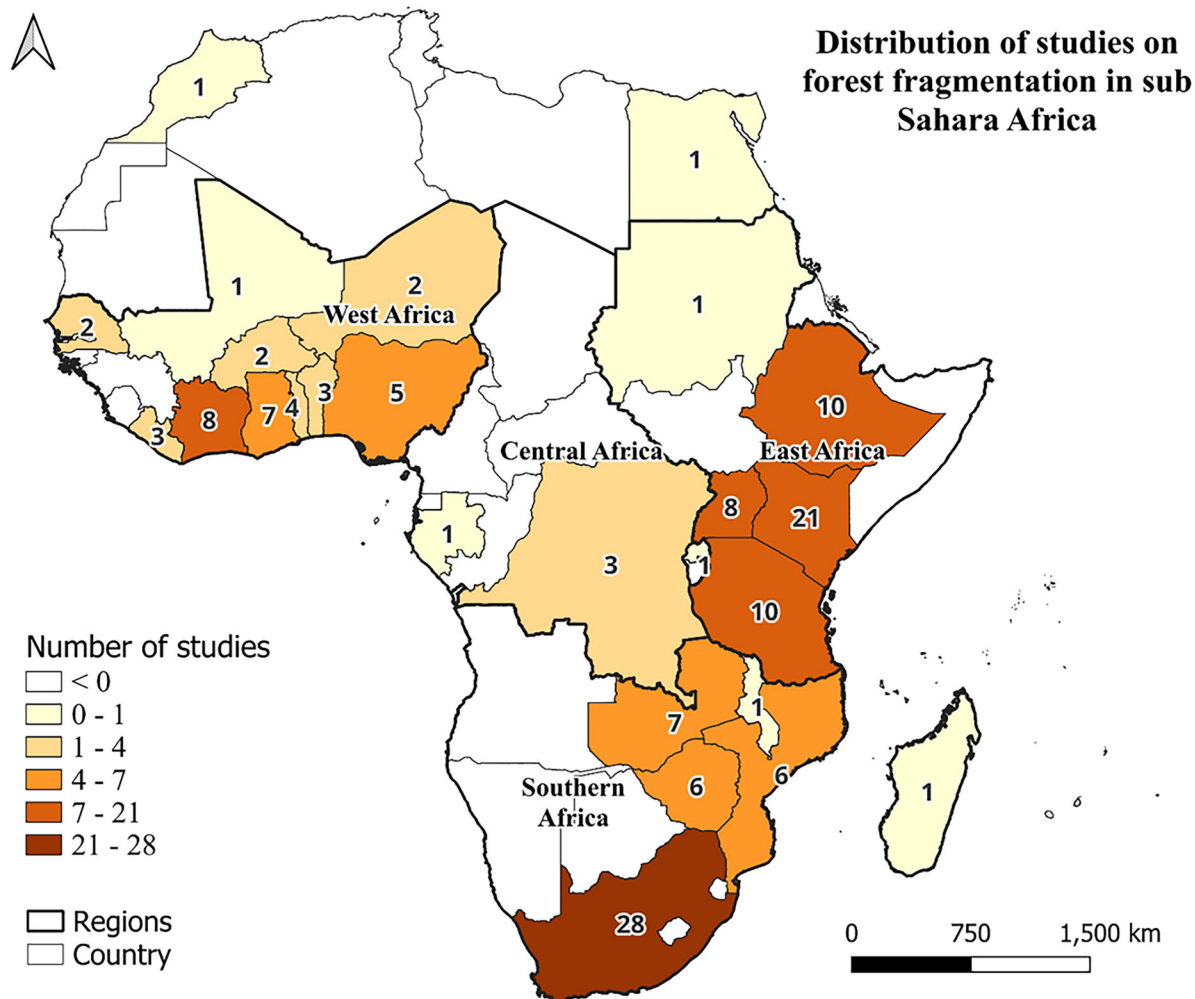


FIGURE 3 Distribution of studies reviewed on forest fragmentation in sub-Saharan Africa.

further discussed to assess their applicability to SCA fragmented areas in SSA.

4.1 | Landscape fragmentation in SSA

4.1.1 | The geographic distribution and biases

The geographic distribution (Figure 3) showed a strong concentration of studies in South Africa (28 studies). East Africa was well-represented by Kenya (20 studies), Tanzania (10 studies), Ethiopia (nine studies), and Uganda (eight studies). While West African countries such as Nigeria (five studies), Togo (four studies), Liberia (three studies), Senegal (three studies), and Sierra Leone (two studies) were under-represented. Other countries, such as Central Africa, Chad, South Sudan, Congo, Somalia, and Eritrea had no studies represented. Hence, future research should prioritize these countries with a low number of studies to ensure a more

comprehensive understanding of forest fragmentation and its impact across SSA. Additionally, taxonomic biases were evident in the reviewed studies (Figure 7; Section 4.2.3), with a disproportionate focus on avian species (15 studies) and tree/plant species (11 studies) compared to amphibians (one study), small mammals (four studies), insects (three studies), and other organisms (four studies). This aligns with prior reviews that noted similar biases (Awoyemi & Ibáñez-Álamo, 2023; Deikumah et al., 2014; Fahrig, 2017; Fardila et al., 2017; Tan et al., 2023), underscoring the need for broader taxonomic coverage in fragmentation research.

4.1.2 | Generalized approach of analyzing landscape fragmentation

Most landscape fragmentation studies reviewed in SSA employed land cover maps derived from remotely sensed imagery (Chileshe et al., 2023; Dimobe et al., 2017; Fitz et al., 2022; Ojoiy et al., 2016; Yohannes et al., 2020). Although

these land cover maps enable spatial and temporal analyses of landscape fragmentation, they often fail to separate the effects of SCA area expansion on forest fragmentation. Instead, landscape fragmentation is typically assessed and generalized at larger scales using established boundaries, such as administrative units (Chileshe et al., 2023; Phiri et al., 2019; Shapiro et al., 2016), watersheds (Badjana et al., 2015; Chisola et al., 2020; Muleta & Biru, 2019; Murunga et al., 2024; Yohannes et al., 2020), and forest reserves (Dimobe et al., 2017; Fitz et al., 2022; Muluneh et al., 2021). A key limitation of this approach is the amalgamation of SCA areas with other land-cover/land cover/uses, concealing its unique contribution to forest fragmentation. For instance, Fitz et al. (2022) analyzed forest fragmentation in Cross River National Park but combined agricultural areas with shrubs and disturbed forests, complicating the assessment of the effect of forest fragmentation specifically attributable to SCA areas. Similarly, Murunga et al. (2024) examined landscape metrics covering the Koitobos River Basin in Trans-Nzoia, Kenya, without isolating SCA areas from other agricultural systems. Therefore, methodological developments are necessary to explicitly link SCA area expansion to forest fragmentation, which is a key driver of forest fragmentation in SSA (Laurance et al., 2014; Perrings & Halkos, 2015).

4.1.3 | Methods for analyzing forest fragmentation in SCA landscapes

Two complementary approaches can be explored to assess forest fragmentation specifically linked to SCA. The first method involves geographic information system (GIS)-based analysis using QGIS or ArcGIS to extract forest and agricultural land cover classes, and then isolating SCA fields based on size thresholds (2–10 ha) and morphological characteristics such as irregular shapes (Apraku et al., 2021; Bey et al., 2020; Trivedi et al., 2023). Additionally, the novel global agricultural fields boundary data (Field of the World) extracted from Sentinel-2 and image segmentation, which include SSA countries (South Africa, Kenya, and Rwanda), can be also explored to identify SCA fields (Kerner et al., 2025). Once the SCA fields are identified and extracted, they can be overlaid with the forest class classified from remotely sensed imagery to identify forest fragments associated with the SCA fields. Subsequently, landscape metrics pertaining to forest fragments specific to SCA can be calculated. The second approach could combine local knowledge from agricultural officials with visual interpretation of high spatial resolution imagery to identify the location of SCA fields, followed by typical forest fragmentation analysis in the identified area. Collectively, these approaches can provide a focused evaluation of forest fragmentation that is distinctively related to SCA areas, thereby enabling methodological cross-validation.

4.1.4 | Landscape fragmentation representation models

Landscapes are typically spatially represented using patch-based (discrete) or surface-based (continuous) models (Gustafson, 2019). Patch-based models use land cover maps as inputs and are suitable for representing discrete and heterogeneous landscapes (Frazier & Kedron, 2017). On the other hand, the surface-based models employ gridded data such as vegetation indices and digital elevation models which measure phenomena, which vary within a landscape (Frazier & Kedron, 2017; Mondal, 2011). All reviewed studies utilized patch-based models of landscape representation (Chileshe et al., 2023; Dimobe et al., 2017; Fitz et al., 2022; Mosomtai et al., 2020; Ocloo et al., 2024; Ojoyi et al., 2016). This preference for patch-based models stems mainly from the model's simplicity and temporal tracking capabilities (Frazier & Kedron, 2017; Rahimi et al., 2022), and is particularly suitable for analyzing forest fragmentation driven by SCA. Patch-based models effectively delineate the distinct boundaries associated with SCA expansion, in contrast to surface models, which provide less interpretable results for fragmentation analysis and hinder temporal comparisons (Mondal 2011; Rahimi et al., 2022).

4.1.5 | Landscape fragmentation metrics

Landscape metrics are quantitative measures for analyzing spatial patterns and structures in fragmented landscapes, particularly when using patch-based models (Arora et al., 2021; Frazier & Kedron, 2017). Landscape metrics are categorized into two main types: composition metrics (e.g., patch size and Shannon's diversity index) that measure the abundance and diversity of habitat fragments, and configuration metrics (e.g., proximity index and contagion index) that assess their spatial arrangement (Frazier, 2019; Frazier & Kedron, 2017). Our review found that both composition (56.1%) and configuration landscape metrics (43.6%) were utilized almost equally in SSA, although there was a slight preference for composition metrics (Figure 4). This bias toward composition metrics is noteworthy given recent critiques that they often fail to differentiate forest fragmentation from habitat loss, which are distinct but frequently conflated processes (Collinge, 2009; Fahrig, 2017; Riva et al., 2024).

For instance, forest/habitat fragmentation involves breaking contiguous habitats into smaller, isolated fragments, which reduces landscape connectivity and configuration (Collinge, 2009; Riva & Fahrig, 2023). Habitat loss involves area reduction or perforation of homogenous habitats/forests without necessarily breaking them into small and isolated fragments (Collinge, 2009; Riva & Fahrig, 2023).

Configuration and composition landscape metrics

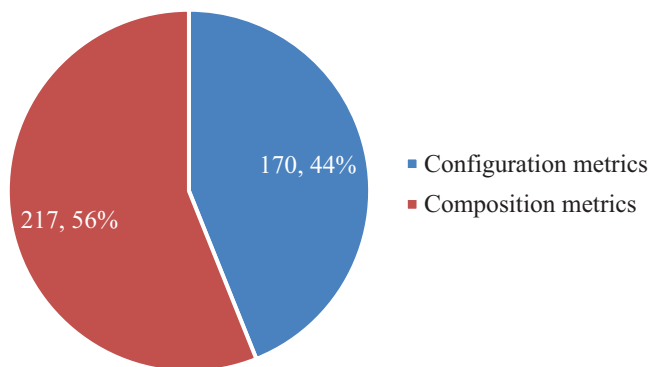


FIGURE 4 Comparison between composition and configuration metrics.

Understanding these distinctions is crucial for developing effective targeted conservation strategies, as their implications on biodiversity differ significantly. By addressing forest fragmentation and habitat loss separately, researchers can develop targeted interventions that promote ecological resilience. These targeted interventions can help to preserve critical habitats and ensure the survival of various species, ultimately contributing to the overall health of ecosystems. Moreover, effective communication of these differences to policymakers and the public is essential for fostering support for conservation efforts. Therefore, configuration metrics are recommended for measuring actual forest fragmentation related to SCA as well as for other heterogeneous landscapes (Riva & Fahrig, 2023).

4.1.6 | Remote sensing data

Having established the limitations of current landscape metrics, we evaluated the use of remotely sensed data to measure forest fragmentation. Our review found that forest fragmentation studies in SSA employed diverse optical satellite imagery with varying spatial, spectral, and temporal resolutions (Table 1). These include the following:

- Low-resolution imagery (greater than 30 m): moderate resolution imaging spectroradiometer (MODIS), advanced very high resolution radiometer (AVHRR), and project for on-board autonomy-vegetation (PROBA-V).
- Medium-resolution (5–30 m): Landsat and Sentinel-2.
- High resolution (1–5 m): satellite pour l'Observation de la terre (SPOT), IKONOS, RapidEye, and PlanetScope (PS).
- Very high resolution (less than 1 m): Worldview.

Spatial resolution critically influences the ability to detect SCA fragmentation, particularly fields <0.5 ha (Hampwaye

et al., 2007) and isolated tree fragments (Siqueira et al., 2021). Although low-resolution (MODIS and AVHRR) and medium-resolution imagery (Landsat and Sentinel-2) are freely accessible, their low spatial resolution limits their applicability to fine-scale fragmentation analysis in SCA areas (Wingate et al., 2024). Conversely, high-resolution images (e.g., PS [3 m], SPOT [1.5 m]) and very high-resolution sensors (e.g., Worldview [30–50 cm]) offer enhanced detailed mapping, enabling more accurate mapping of SCA fields and associated small forest fragments.

Apart from optical imagery, two studies (Figure 5) integrated optical imagery with active remote sensing (light detection and ranging [LiDAR] and radio detection and ranging [RADAR]) to measure forest fragmentation (Shapiro et al., 2016, 2023). However, LiDAR imagery are rarely used in forest fragmentation studies in SSA because of the high cost and complexity of interpreting 3D forest fragmentation metrics (Rahimi et al., 2022). Conversely, Sentinel-1 RADAR data are useful in filling data gaps in cloud-prone regions such as the Congo Basin (Shapiro et al., 2023). Furthermore, the use of RADAR images can complement optical imagery by reducing misclassification errors (e.g., by distinguishing SCA fields from bare soil or grassland) (Choukri et al., 2024; Dobrinić et al., 2020). For example, a study by Forkuor et al. (2014) in Benin demonstrated that the combination of RapidEye with synthetic aperture radar improved the agricultural area image classification accuracy by 10%–15%. This shows that the integration of high-resolution imagery with RADAR images can enhance fragmentation analysis, particularly in SCA landscapes.

4.1.7 | Trade-off between low and high spatial resolution imagery

Deciding on which satellite imagery to use involves deciding between using freely available coarser resolution imagery and costly high-resolution imagery. This decision mainly depends on factors such as cost, size of the area to be covered, and temporal and spatial resolution (Li & Roy, 2017). Coarser imagery such as Landsat imagery (30 m) and MODIS (250 m) are practical and cost-effective for large-scale forest fragmentation assessments (Forget et al., 2018; Mosomtai et al., 2020). They are also beneficial for global, regional, and national applications, where precision in small object mapping is less critical (Munawar et al., 2022). However, coarse-resolution images have significant drawbacks when it comes to detecting small objects. For example, the spatial resolution of Landsat (30 m) and MODIS (250 m) can mask smaller forest fragments and limit the effectiveness of the analysis, particularly in SCA landscapes where small objects are interspersed with complex backgrounds (Singh et al., 2024). Studies have demonstrated that small features or specific agricultural

TABLE 1 Remotely sensed data used in forest fragmentation.

Spatial resolution	Sensors	Spatial resolution	Temporal resolution	Cost/availability	Suitability for to capture SCA areas	Examples of studies
Low resolution	MODIS, AVHRR, PROBA-V	250 m–1 km	Daily	Free Complete coverage	Too coarse for individual fields Good for context	(Ocloo et al., 2024; Traoré et al., 2024)
Medium resolution	Landsat, Sentinel-2	5–30 m	5–30 days	Free Extensive archive	Limited by the spatial resolution to capture SCA fields of (>0.5 ha) Extensive temporal coverage	(Chapungu et al., 2014; Chileshe et al., 2023a; Chisola et al., 2020; Kowe et al., 2020; Mosomtai et al., 2020; Mulatu et al., 2024; Ochungo et al., 2022; Ojoi et al., 2016; Osewe et al., 2022)
High resolution	SPOT, IKONOS, RapidEye, PlanetScope Pleiades	1–5 m	1–5 days	Moderate (\$1–\$15/km ²) Growing archive	Good for capturing SCA field boundaries (>0.5 ha) and single tree forest fragments Balanced cost-effectiveness	(Ehlers Smith et al., 2018; Maseko et al., 2020; Mosomtai et al., 2020; Mulwa et al., 2021; Zungu et al., 2020)
Very high resolution	Worldview, Aerial Photograph	<1 m	1–5 days (on demand)	High cost (\$15–\$50/km ²) Limited archive	Excellent for small agricultural fields (<0.5 ha), including single tree patches Limited by cost for large areas	(Cho et al., 2015; Ndao et al., 2021; Wu et al., 2000)
RADAR	PALSAR (Sentinel-1)	10 m	5 days	Freely available after 2016	Limited by the spatial resolution to capture SCA fields of (>0.5 ha) Extensive temporal coverage	(Shapiro et al., 2023)
LiDAR	Varies	Mean point density of 2/m ²	On demand	High such as \$100–\$2000/km ²	Provide 3D metrics, such as height, but limited in representation heterogeneous landscape in SCA areas.	(Shapiro et al., 2016)

Abbreviations: AVHRR, advanced very high resolution radiometer; LiDAR, light detection and ranging; MODIS, moderate resolution imaging spectroradiometer; PROBA-V, project for on-board autonomy-vegetation; RADAR, radio detection and ranging; SCA, small-scale agricultural; SPOT, Satellite Pour l'Observation de la Terre.

Number of studies per remote sensing imagery

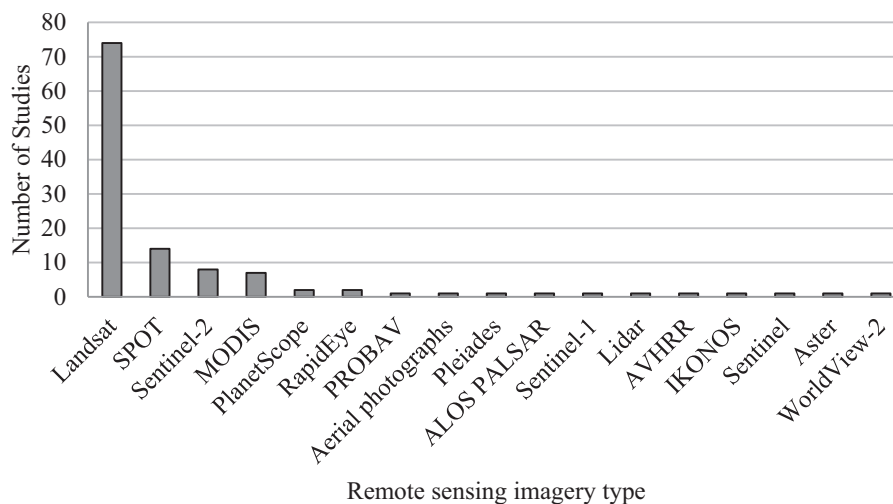


FIGURE 5 Remote sensing satellite imagery types used for forest fragmentation studies in sub-Saharan Africa (SSA).

practices are often indistinguishable in lower resolution imagery (Singh et al., 2024), leading to inaccurate assessments of forest fragmentation. High-resolution imagery provides the granularity needed to effectively monitor small landscape features and allows for accurate assessments of detailed land cover changes and forest fragmentation (Rampheri et al., 2023).

Nevertheless, high-resolution imagery often comes with substantial financial costs and reduced temporal resolution due to limitations in satellite overpasses. For example, a new image collection for Worldview costed \$27.50 per km² in 2020, which is beyond the budgets of most SSA countries (Duporge et al., 2021). Moreover, the availability of images can be sporadic, which may result in gaps in the temporal analysis of forest fragmentation, which is essential for capturing historical changes (Munawar et al., 2022; Singh et al., 2024). The detailed mapping of small objects is crucial in SCA landscapes; hence, the spatial resolution of imagery carries more weight than the rich historical image archives, temporal resolution, and cost. Hence, the most affordable or available high-resolution imagery such as SPOT, Worldview, and PS (3 m) should be used to ensure detailed and accurate measurement of forest fragmentation in SCA landscapes. Moreover, PS images are becoming more affordable for use in SSA, costing approximately \$1.50 per km² (Apollo Mapping, 2022). However, in situations where research funds are still not available, Sentinel-2 (10 m) imagery can be used as a fair compromise, especially that it is underutilized in landscape fragmentation studies in SSA as shown in Figure 5. Because Sentinel-2 is freely available, it has a higher spatial, temporal, and spectral resolution than the most used Landsat imagery in the region.

4.1.8 | Land use/cover classification methods

Research on forest fragmentation in SSA predominantly employs land cover maps classified using satellite imagery. Different image classification algorithms are typically used to produce the land cover maps used in forest fragmentation analysis in the SSA (Figure 6). Our review observed that maximum likelihood algorithm was the most used image classification algorithm in forest fragmentation analysis (36 studies) in the region. This was followed by random forest (14 studies), support vector machines (five studies), K-nearest neighbor (four studies), density slicing algorithm (three studies), and nearest neighbor classification (two studies). The other algorithms include ISODATA (one study), regression tree (one study), rule-based classifier (one study), and moving window analysis (one study) (Figure 6).

Despite not being the most commonly used image classification algorithm in forest fragmentation studies in SSA, the random forest classifier (Kanmani et al., 2023) and support vector machine (Donkor et al., 2022; Thamaga et al., 2022) usually outperform other pixel-based classifiers in terms of image classification accuracy. For example, Kanmani et al. (2023) compared the image classification accuracy of different algorithms in a study in India. They observed that the random forest algorithm achieved the highest image classification accuracy of 92%, outperforming the maximum likelihood algorithm at 85% and the maximum distance and K-nearest neighbor classifiers, both at 81%. Similarly, Donkor et al. (2022) compared the accuracy of different image classification algorithms in a study conducted in a cocoa plantation in Ghana and observed that the support vector machine algorithm achieved the highest image classification accuracy of

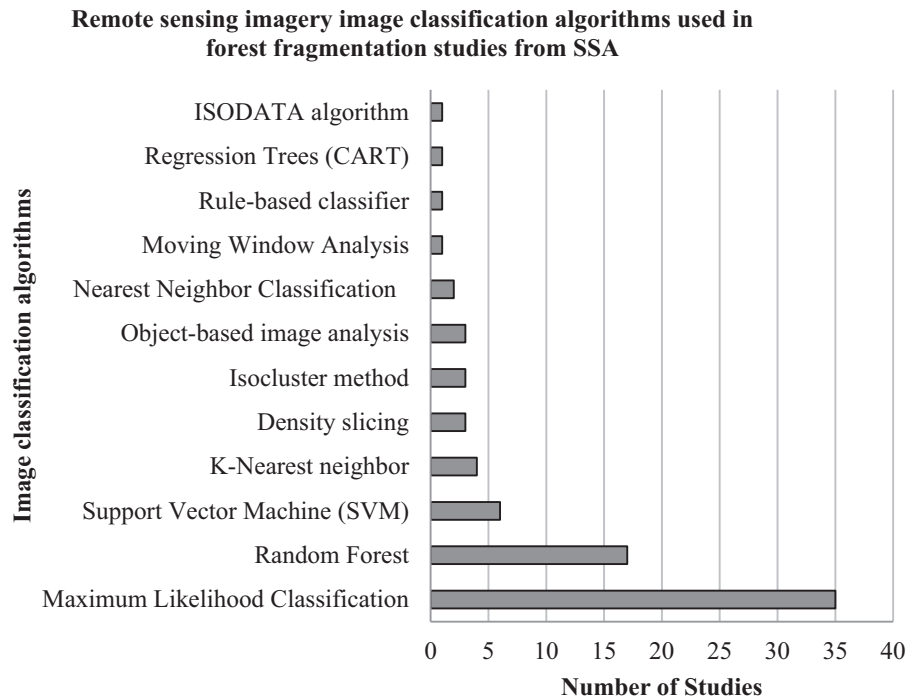


FIGURE 6 Types of image classification algorithm used in small-scale agricultural (SSA) to analyze forest fragmentation.

86.47%, outperforming both the artificial neural network at 85.15% and random forest algorithms at 84.04%. Therefore, employing random forest and support vector machine classifiers for classifying SCA areas is recommended to ensure the production of highly accurate land cover maps necessary for the accurate assessment of forest fragmentation. Recently, the use of random forest in landscape fragmentation analysis is becoming more common in SSA (Onaolapo et al., 2022; Salem & Tsurusaki, 2024; Traoré et al., 2024).

Although not used in any of the reviewed studies on forest fragmentation, deep learning (DL) has recently gained considerable attention (Bosco et al., 2021; Lynda et al., 2021; Uwizera et al., 2022). This is because of the recent push toward the use of artificial intelligence approaches. DL has been tested in SSA, including in SCA areas and promises improved image classification results (Lynda et al., 2021; Rustowicz et al., 2019). For instance, Lynda et al. (2021) tested the accuracy of DL and convolution neural network (CNN) in SCA areas in Ghana and South Sudan using PS, Sentinel-1, and Sentinel-2 images. In this study, CNN algorithm achieved an overall accuracy of 69.7% in Ghana and 85.3% in South Sudan test sites. Uwizera et al. (2022) tested DL in East Africa to classify economic areas for urban planning, and achieved an accuracy (F1-score) of 99%. Despite the ability of DL to improve image classification, DL algorithms are not yet widely used as mainstream approaches in image classification in forest fragmentation studies in SSA. DL's high requirements, such as its reliance on high computation capacity, high quality (spatial and spectral) images, technical expertise, and

limited availability of training data, hinder its wider use in SSA (Lynda et al., 2021).

4.1.9 | Geographic object-based image analysis

Geographic object-based image analysis (GEOBIA) is another method used to classify remotely sensed imagery into land cover maps that are used as input in forest fragmentation analysis. GEOBIA image classification approach clusters pixels into meaningful objects or features based on their spectral, spatial, and contextual characteristics rather than individual pixel spectral values alone (Gevaert et al., 2016; Matarira et al., 2022; Shamaoma et al., 2006). This allows for a more accurate classification of complex heterogeneous landscapes such as highly fragmented SCA landscapes. Despite the ability of the GEOBIA image classification approach to improve image classification, it has only been used by a few studies to produce land cover maps used as inputs in forest fragmentation analysis in SSA (Muderere et al., 2020; Ndao et al., 2021; Nyamugama & Kakembo, 2015). For example, Muderere et al. (2020) integrated GEOBIA image classification approach while classifying SPOT (5 m) imagery in a study in Zimbabwe to produce land cover maps with an 89.7% image classification accuracy. Similarly, Ndao et al. (2021) incorporated the GEOBIA classification approach to classify heterogeneous agricultural landscapes in Senegal and achieved an accuracy of 88%. Although GEOBIA offers

significant advantages for the accurate image classification of complex heterogeneous SCA landscapes, its application remains limited in SSA. This highlights the need for the broader adoption of GEOBIA to enhance forest fragmentation analysis in SCA landscapes.

4.1.10 | Accuracy assessment of land cover maps

The accuracy assessment of land use and land cover maps used in forest fragmentation analysis is essential for achieving credible and dependable results. It provides important information on the accuracy and reliability of land cover maps before they can be used in various applications, such as deforestation and forest fragmentation assessment (Olofsson et al., 2014; Stehman & Foody, 2019). The error confusion matrix and Kappa coefficient assessment approaches are commonly used to measure the accuracy of land cover maps before they are used for any application (Olofsson et al., 2014; Stehman & Foody, 2019). The error confusion matrix compares the classified land cover map against the reference data to determine the number of correctly classified pixels for each land cover class (Gunathilaka & Fernando, 2022). Based on the error matrix results for each land cover class, the overall accuracy of the land cover map is calculated as the ratio of correctly classified pixels to the total number of sampled pixels. The kappa coefficient is a statistical measure used to measure the reliability of the agreement between classified land cover maps and reference data (Olofsson et al., 2014; Stehman & Foody, 2019). Even with extreme care, the classification of land cover maps is rarely 100% accurate. However, the aim of remote sensing analysis is typically to produce land cover maps with an overall accuracy that meets the acceptable minimum accuracy threshold between 65% and 85% (Dzurume et al., 2022; Sibanda et al., 2016).

Subsequently, landscape fragmentation analysis primarily utilizes land cover maps, which are typically not 100% accurate, but fall within acceptable accuracy thresholds. This accuracy assessment information must be reported to demonstrate the credibility of land cover maps before they can be used in any analysis (Olofsson et al., 2014). Following this requirement, the majority of studies on forest fragmentation in SSA have assessed the accuracy of their land cover maps (Adepoju & Salami, 2017; Chibeya et al., 2021; Mohamed et al., 2021; Ndao et al., 2021; Ochungo et al., 2022). However, several other studies have not reported accuracy assessment results for the land cover maps used in their forest fragmentation analysis (Chapman et al., 2022; Chapungu et al., 2014; Chileshe et al., 2023; Lemenkova, 2024; Muderere et al., 2020; Ojoyi et al., 2016). Failure to report the accuracy assessment results of the land cover maps used in fragmentation analysis undermines the credi-

bility of their fragmentation analysis. Without information on the image classification accuracy, there is no way to determine the credibility of forest fragmentation results derived from such land cover maps. This could potentially lead to incorrect conclusions regarding forest fragmentation results (Frazier & Kedron, 2017), and therefore could not be reliable for landscape conservation planning.

4.1.11 | Accuracy assessment for landscape fragmentation metrics

Although numerous studies in SSA have reported the accuracy on land cover maps used for fragmentation analysis (Adepoju & Salami, 2017; Chibeya et al., 2021; Mohamed et al., 2021; Ndao et al., 2021; Ochungo et al., 2022), the accuracy of fragmentation landscape metrics remains undetermined. Frazier and Kedron (2017) in their review identified this as a weakness in landscape fragmentation studies that used land cover maps in their analysis. Assessing the accuracy of landscape metrics is important for reporting uncertainty and enhancing the validity and credibility of fragmentation results, especially in SCA areas. This occurs because SCA-related fragmentation creates small forest fragments that may be missed, generalized, or misclassified as other land cover types. This can result in varying or inaccurate forest fragmentation analysis (Hernando et al., 2017; Fynn & Campbell 2019).

For example, Fynn and Campbell (2019) compared edge density (ED) and largest patch index landscape metrics calculated from land cover maps classified from different remotely sensed imagery with varying spatial resolutions in Blacksburg, VA. The remotely sensed imagery assessed were Landsat (30 m), Sentinel-2 (10 m), national agriculture imagery program (NAIP [0.25 m]), and unmanned aerial system (UAS [0.03 m]). In this study, substantial differences in the ED landscape metric values were observed: 0.55 for Landsat, 0.70 for Sentinel-2, 256.99 for NAIP, and 346.97 for UAS. The results showed that higher spatial resolution imagery, such as UAS and NAIP imagery, yielded higher detailed ED values, whereas coarser spatial resolution imagery, such as Landsat, produced lower ED values. However, these remote sensed imagery capture ED at varying spatial scales and are relevant for different purposes. For example, Landsat captures ED at a coarse scale, which is relevant for analysis conducted at large scale, such as at global (Haddad et al., 2015), national (Shapiro et al., 2016), district (Chileshe et al., 2023). In contrast, UAS imagery captures ED at a fine scale, which is suitable for detailed local-scale analysis. This demonstrates that using high spatial resolution remote sensing imagery is necessary to obtain local detailed forest fragmentation patterns (Wickham & Riitters, 2019). This is especially important for analyzing forest

fragmentation related to SCA expansion, which creates forest fragments which are small, have complex shapes and edges, and where detailed detecting of edges is required.

However, obtaining very high spatial resolution imagery necessary for detailed and accurate assessment of forest fragmentation, is often unfeasible in SSA due to cost constraints (Lynda et al., 2021). Therefore, it is important to develop approaches for measuring the accuracy of landscape metrics, regardless of the remotely sensed imagery used, provided that the imagery meets the accuracy requirements of the study. One possible approach to measure the accuracy of landscape metrics would be to compare landscape metric values derived from classified forest fragments (from land cover maps) with those calculated from manually digitized versions of the same forest fragments. The differences between these two sets of landscape metric values can be calculated using the root mean square error and standard deviation as indicators of accuracy. This approach will contribute to increasing the validity and credibility of forest fragmentation results, especially in SCA areas, where more detailed fragmentation analysis results are necessary. Without clear accuracy measures, the calculated landscape metrics can misrepresent the actual landscape fragmentation patterns (Frazier & Kedron, 2017). This can lead to erroneous conclusions regarding the state of forest fragmentation, resulting in ineffective land management strategies and biodiversity conservation efforts.

4.1.12 | Limited focus of forest fragmentation research on socioeconomic factors

Research on forest fragmentation in SSA has predominantly utilized spatial data, such as land cover maps to analyze fragmentation patterns and temporal trends (Fitz et al., 2022; Lemenkova, 2024; Mohamed et al., 2021; Ojoyi et al., 2016; Shapiro et al., 2016). Although this approach has enabled valuable assessments of landscape changes, it focuses only on the spatial aspects of forest fragmentation. Recent studies on forest fragmentation in the region have continued to prioritize spatial aspects of fragmentation through the use of landscape metrics, such as patch size and patch density (Lemenkova, 2024; Mulatu et al., 2024; Olayiwola & Salau, 2024). For instance, Olayiwola and Salau (2024) assessed fragmentation in Nigeria using land cover derived landscape metrics, but ignored the socioeconomic factors driving fragmentation. Few studies have incorporated nonspatial data obtained through interviews to complement spatial analysis in their examination of forest fragmentation (Chapungu et al., 2014; Murunga et al., 2024). However, these studies did not conduct an in-depth analysis of the statistical influence of socioeconomic factors on forest fragmentation.

Moreover, socioeconomic factors such as population, income, land ownership, agricultural practices, and government policies affect forest fragmentation patterns (Mayele et al., 2024). Therefore, the influence of such socioeconomic factors on forest fragmentation should be investigated to understand how they affect forest fragmentation in SSA. The integration of socioeconomic data with landscape metrics will require the collection of socioeconomic data using GIS-based tools, such as the open data kit (ODK) and KoboToolbox. These mobile GIS data collection tools offer efficient ways to collect spatially referenced socioeconomic data (Nowak et al., 2020), which can be spatially linked to forest fragmentation landscape metrics. Linking such data with landscape metrics would enable researchers to assess the relationships between socioeconomic factors and spatial fragmentation patterns. This integrated approach will provide in-depth insights into how socioeconomic dynamics drive forest fragmentation in SSA. This supports the development of more effective and context-specific management strategies for biodiversity conservation in SCA landscapes.

4.2 | Impacts of forest fragmentation on biodiversity in SSA

4.2.1 | Impacts of forest fragmentation

The impacts of forest fragmentation on biodiversity have been extensively studied in SSA (Kouagou et al., 2019; Mohandass et al., 2014; Ochungo et al., 2022; Ojoyi et al., 2016; Zungu et al., 2020). Table 2 show a few selected study on the impact of forest fragmentation on biodiversity reviewed. Forest fragmentation predominantly exerts negative impacts on biodiversity by isolating species habitats and disrupting critical ecological processes such as nutrient cycles, pollination, and seed dispersal (Fletcher et al., 2018; Haddad et al., 2015). Our review observed a similar trend, with more than half of the studies reporting negative effects (21 out of 38) of forest fragmentation on biodiversity (Anyango et al., 2024; Ojoyi et al., 2016; Webala et al., 2019; Zungu et al., 2020). For instance, Anyango et al. (2024) found negative correlation between ED metric and tree species richness indices in Kenya. Similarly, Zungu et al. (2020) observed a negatively correlation between patch size metrics and mammals species richness indices in an urban South African landscape. In light of these findings, conservation efforts in SSA have largely prioritized large forest fragments in forest reserves and national parks (Allan et al., 2017; Tang & Adesina, 2022).

A few studies in our review reported mixed effects (3 out of 38), noting both negative and positive effects of fragmentation on biodiversity (Ehlers Smith et al., 2018; Mbora & Mutua, 2023; Mulwa et al., 2021). For instance, Mulwa et al. (2021) reported a negative correlation between the ED

TABLE 2 Summary of key studies on impact of fragmentation on biodiversity in small-scale agricultural (SSA).

Author	Study objective	Methods	Key finding
Muderere et al. (2020)	Influence of landscape structure on the diversity of avifauna species in tropical urban areas of Northeastern Zimbabwe.	Data were collected in grassland areas, forest areas, and built-up areas. Used size, shape, and isolation distance as landscape metrics and species diversity indices. The relation was determined using multivariate analysis techniques.	Land use/land cover composition influences the abundance of avifauna species in tropical urban landscapes. Forested areas had low species abundance.
Zungu et al. (2020)	Effects of landscape context on mammal richness in the urban forest mosaic.	Used remote-triggered camera traps to map presence and absence of mammals and determined the occupancy of mammals in 28 forest patches. The relationship was determined using multivariate analysis.	Larger patches close together supported higher species richness than small ones. Thus, indicating negative impact of landscape fragmentation.
Mulwa et al. (2021)	How disturbed/degraded landscape affects birds' communities.	Sampled near natural blocks, degraded forest plantation, and agricultural land. The clumpiness and cohesion landscape metrics and species richness and abundance were used.	Avifauna species diversity of woodland specialists was negatively correlated with the edge density metric of the low-urbanization forested. The disturbed forest fragments had higher (positive effects) species richness. Importance of preserving small forest patches.
Anyango et al. (2024)	Relationship between the edge density of the forest fragments and the tree species richness.	Studied the effect in SCA areas, used edge density and tree species richness.	Reduction in the number of tree species richness with increase in patch density (negative impact).
Ehlers Smith et al. (2018)	Investigates the habitat avian taxonomic and functional diversity changes across gradient.	Used patch size landscape metrics, taxonomical, and functional diversity.	Decrease in avian diversity with decrease in patch size. However, the study noted diversity of generalist avian species was as higher in small forest fragment <9 ha.

metric and specialist bird species diversity indices but higher bird species richness in disturbed forest fragments in Kenya. Similarly, Ehlers Smith et al. (2018) found reduced avian diversity with decreasing patch size but noted that small fragments (<9 ha) supported higher diversity of generalist bird species compared to larger patches. These findings underscore the importance of often-overlooked small forest fragments in maintaining biodiversity, particularly in highly fragmented landscapes. Protecting small forest fragments is crucial for the survival of various species because they serve as essential remaining habitats and corridors for wildlife, enabling movement and genetic exchange (Mulwa et al., 2021; Siqueira et al., 2021; Wingate et al., 2024).

Despite their ecological significance, small forest fragments, often found in SCA landscapes, are rarely recognized or prioritized for protection (Wingate et al., 2024). Yet, they serve as critical stepping stones for enhancing landscape con-

nectivity and supporting ecosystem services (Mulwa et al., 2021; Riva & Fahrig, 2022; Siqueira et al., 2021; Wingate et al., 2024). By recognizing the value of smaller habitats, conservation efforts can create a network of protected areas consisting of both small and large forest fragments that facilitate species movement and gene exchange in highly fragmented SCA landscapes. This interconnectedness supports individual species and strengthens the ecosystem's resilience to adapt to environmental changes and human impacts across the region. Furthermore, the protection of small forest fragments will contribute toward halting biodiversity loss and meeting the sustainable development goal (SDG) 15 on biodiversity and ecosystem protection (Huan & Zhu, 2022). Additionally, the protection of small forest fragments, which act as carbon sink, will contribute to the reduction of emissions from deforestation and degradation (REDD+) (Decocq et al., 2016; Dimobe et al., 2025; Wingate et al., 2024).

4.2.2 | Methods for data collection on biodiversity in fragmented landscapes

Studies on the impact of fragmentation on biodiversity in SSA have traditionally used field-based data-collection methods (Anyango et al., 2020; Gumede et al., 2022; Kouagou et al., 2019; Webala et al., 2019). However, field-based data collection methods are time-consuming and costly (Rocchini et al., 2016; Rossi et al., 2022; Shamaoma et al., 2022). In contrast, remote sensing imagery provides a cost-effective and efficient alternative for large-scale assessments, particularly in fragmented SCA landscapes where small forest patches dominate (Rocchini et al., 2016; Rossi et al., 2022; Shamaoma et al., 2022). Several studies in the region have used remotely sensed imagery, such as SPOT and Rapid Eye, to derive landscape metrics for evaluating the effects of forest fragmentation on biodiversity (Gumede et al., 2022; Muderere et al., 2020; Mulwa et al., 2021; Ojoyi et al., 2016; Zungu et al., 2020). For instance, Muderere et al. (2020) used SPOT imagery to quantify patch ED, patch size, and shape complexity, enabling an analysis of fragmentation impacts on bird species in the urban tropical landscapes of Northeastern Zimbabwe. Remotely sensed imagery provided a cost-effective way of measuring landscape metrics, especially for studies that required measuring landscape metrics for more than 100 forest fragments (Smith et al., 2018).

Despite its potential, none of the reviewed studies extended the use of remotely sensed images to estimate species richness and diversity. This represents a missed opportunity to enhance biodiversity monitoring by integrating remote sensing technology with field-based data-collection approaches. Recent advances in remote sensing data-collection techniques have demonstrated the feasibility of such approaches. For instance, Shamaoma et al. (2023) achieved 87% classification accuracy in mapping five dominant tree species in Zambia's Miombo woodlands using UAS. Nkya et al. (2024) successfully applied PS and UAS imagery to classify tree species in Tanzania's Tongwe Forest Reserve (achieving 72% accuracy). These studies highlight the effectiveness of UAS and PS imagery for tree species mapping in SSA. However, their applications have so far been limited to forest reserves, leaving untested potential in SCA landscapes, where forest fragmentation is most pronounced.

4.2.3 | Taxa studied in forest fragmentation research

The effects of forest fragmentation on biodiversity in SSA have mostly been assessed using studies on birds/avians (15 studies) and trees/plants (11 studies) as response species (Figure 7). Avian species have attracted significant attention because of their vulnerability to habitat fragmentation and

essential ecological functions in pollination and seed dispersal (Awoyemi & Ibáñez-Álamo, 2023; Fardila et al., 2017; Wang et al., 2023). In the same vein, research on plant/tree species has been prioritized because they form the structural foundation of ecosystems, providing essential resources such as food and habitat for various organisms (Kalaba et al., 2010; Ross et al., 2018; Syampungani et al., 2021).

Nevertheless, considerable knowledge gaps exist regarding the effects of forest fragmentation on other ecologically relevant species such as small mammals (four studies), insects (three studies), amphibians (one study), and microorganisms (Figure 7). These species perform important ecological functions as follows:

- Small mammals facilitate seed dispersal, soil aeration, and serve as key prey species (Chaplin-Kramer et al., 2015; Imakando et al., 2023).
- Amphibians act as bioindicators, contribute to nutrient recycling, and regulate insect populations (Schneider-Maunoury et al., 2016; Thompson & Donnelly, 2018).
- Insects assist in pollination, decomposition, and soil fertility (Savilaakso et al., 2009).
- Microorganisms are crucial for nutrient recycling and organic matter decomposition (Källén et al., 2012).

The current study bias toward prominent birds/avian and plant/tree species neglects the ecological importance of smaller organisms that often survive in fragmented agricultural landscapes. Considering that several understudied species mostly reside in small forest fragments within agricultural landscapes, focused studies on their responses to fragmentation are necessary. Such research would provide essential insights for formulating successful conservation strategies in SCA systems, in which small forest fragments function as crucial biodiversity refuges.

4.2.4 | Strategies used to mitigate impacts of forest fragmentation

The impacts of forest fragmentation on biodiversity in SSA are predominantly negative (Anyango et al., 2024; Muderere et al., 2020; Mulwa et al., 2021; Zungu et al., 2020). Various strategies have been implemented to mitigate the negative impacts of forest fragmentation, with the aim of reestablishing ecological integrity and enhancing species and ecosystem resilience (Cushman et al., 2018; Riggio & Caro, 2017). Some of the strategies employed include the establishment of ecological corridors, forest habitat restoration plans, and sustainable land-use practices (Ajibade et al., 2023; Kalaba et al., 2010; Syampungani et al., 2021). Ecological corridors have been implemented to improve the landscape connectivity and species movement between forest fragments (Shapiro et al.,

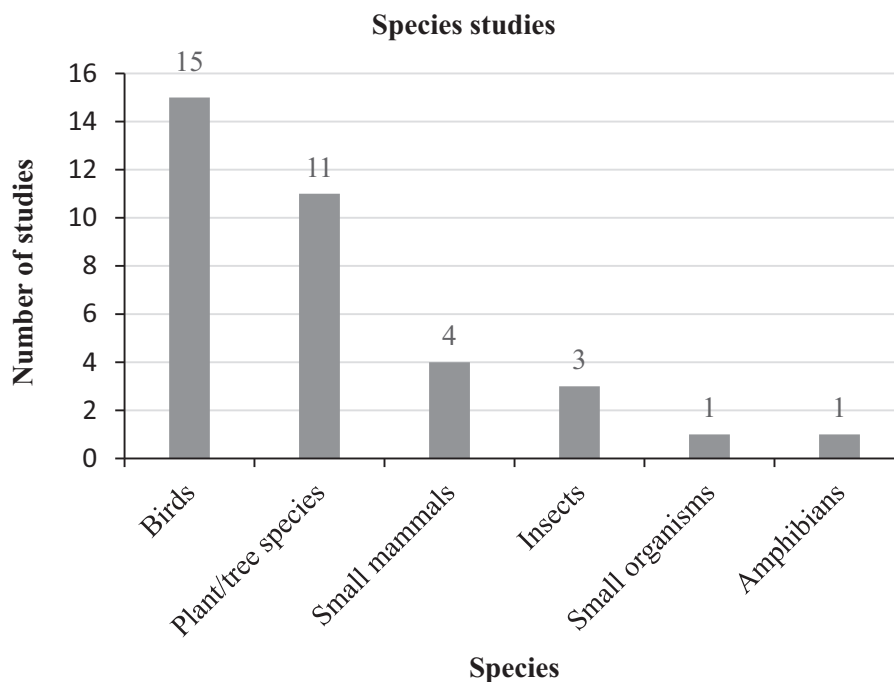


FIGURE 7 Number of studies against the species category.

2016). Whereas forest habitat restoration strategies reestablish vital habitats for various species to enhance biodiversity and ecosystem functioning (Newmark et al., 2017). However, both ecological corridors and restoration strategies have mainly been implemented around protected areas such as forest reserves and national parks (Cushman et al., 2018; Riggio & Caro, 2017). Thus, similar interventions should be implemented in other landscapes, such as SCA landscapes, where forest fragmentation is high.

Nonetheless, certain sustainable farming methods, such as agroforestry and conservation agriculture, have been implemented in SCA in SSA to promote biodiversity (Chirwa et al., 2024; Habanyati et al., 2020). These sustainable agricultural farming practices have been implemented to reduce degradation and mitigate the negative impacts of climate change (Ajibade et al., 2023; Bogale & Bekele, 2023; Syampungani et al., 2021). Sustainable land-use practices also have the potential to be implemented in spatial patterns that mitigate the negative impacts of forest fragmentation in SCA areas. However, the potential of these sustainable farming practices to alleviate the impacts of forest fragmentation on biodiversity due to SCA expansion has seldom been examined.

5 | CONCLUSION

This review highlights the importance of tailored approaches for accurate assessment of SCA-induced forest fragmentation across SSA. The results underscored the limitations of

using general methods such as low-resolution remote sensing images and landscape fragmentation analyses based on amalgamated land cover types. As such approach and methods fail to capture the unique spatial patterns and ecological effects of SCA-driven forest fragmentation in SSA. In addition, the review emphasized the importance of incorporating socioeconomic factors into forest fragmentation analyses to grasp the fundamental causes and develop context-specific conservation strategies. Regarding forest fragmentation implications, there has been a disproportionate focus on field-based data collection approaches and the use of avian and tree species in biodiversity studies. This has resulted in significant knowledge gaps regarding the effects of forest fragmentation on small mammals, amphibians, and insects, which are crucial for ecosystem functioning and resilience. To address the identified limitations of the methods used to analyze fragmentation and its impacts, we recommend the following methods/approaches as appropriate for SCA landscapes found in SSA:

Short term

Using high-resolution imagery and object-based classification approach to accurately assess forest fragmentation in the level of detail suitable for SCA areas (Donkor et al., 2022; Mulwa et al., 2021; Ndao et al., 2021; Wingate et al., 2024).

Integration of socioeconomic data in forest fragmentation analysis collected using mobile GIS data collection tools such as the ODK and KoboToolbox (Nowak et al., 2020). This will facilitate the analysis of the

spatial relationships between socioeconomic factors and fragmentation patterns.

Long-term

- Prioritizing the under-researched species, such as small mammals, amphibians, and insects. These rarely studied species are sensitive to environmental changes and inhabit small forest fragments found in SCA. Hence, appropriate to be used when analyzing the impacts of forest fragmentation on biodiversity (Källén et al., 2012; Savilaakso et al., 2009).

Research

- Develop approaches that uniquely identifies SCA expansion's contribution to forest fragmentation in SSA. This could yield different results from the current approaches that analyze fragmentation based on all land-use types present in the study area.
- Develop statistically robust approaches to measure the accuracy of landscape metrics used in forest fragmentation assessments. This will enhance the robustness of forest fragmentation assessments, thereby providing effective guidance for developing landscape management strategies appropriate for SCA areas in SSA.

Policy

- Increased funding to research institutions in SSA to enable procurement of high-resolution imagery such as SPOT (3 m) and Worldview (30 and 50 cm). This will facilitate an in-depth and accurate assessment of the forest fragmentation necessary for SCA areas.
- Integrate policies which promotes small forest fragment conservation within SCA landscapes strategies such as the existing community-led Community Forest Management Area (CFMA). CFMAs are community-driven projects within the REDD+ strategy, aimed at reducing deforestation (Pelletier et al., 2016). Besides, protecting small forest fragments supports SDGs 13 and 15 on biodiversity protection and climate change mitigation.

This review emphasizes the importance of adopting innovative robust methodologies to measure forest fragmentation induced by SCA expansion and its implication on biodiversity. Therefore, laying a foundation for improved conservation planning to sustain the resilience of SSA ecosystems amid the growing SCA expansion and climatic challenges.

AUTHOR CONTRIBUTIONS

Gillie Cheelo: Conceptualization; formal analysis; investigation; methodology; visualization; writing—original draft.

Hastings Shamaoma: Methodology; supervision; writing—review and editing. **Charles Bwalya Chisanga:** Supervision; writing—review and editing. **Jules Christian Zekeng:** Supervision; writing—review and editing. **Stephen Syampungani:** Conceptualization; funding acquisition; resources; supervision; writing—review and editing.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest

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