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The Link Between Habitat Suitability and Landscape Connectivity in a Changing Climate: A Bibliometric Assessment

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Abstract

Species distribution models (SDMs) estimate how climate change may alter habitat suitability. Connectivity models quantify how landscape structure facilitates or constrains species movement among habitat patches. However, links between the two approaches are uncertain. This study assessed their integration and the use of SDM outputs in connectivity analyses. Records from 2010 to 2025 were retrieved from Scopus and Web of Science. The records were grouped into three corpora: SDM-only, connectivity-only, and integrated. Publication trends were compared with negative-binomial models. Concept dictionaries identified main themes, and pathway classification distinguished forms of methodological integration. Of 5715 records, only 244 integrated both approaches (5.3% of the SDM literature; 17.9% of the connectivity literature). The integrated corpus increased by 21.7% per year, faster than connectivity-only (13.9%; $p = 0.001$) but comparable to SDM-only (19.1%; $p = 0.266$). Integrated records formed a larger share of the connectivity literature than of the SDM literature in all 16 years (median difference: 11.2 percentage points; $p < 0.001$); because the two shares have a common numerator and unequal denominators, this contrast describes the relative weight of integrated work in each literature and does not by itself establish the direction of methodological transfer. Metadata consistent with the use of projected habitat-suitability surfaces as a connectivity input were identified in 38.1% of integrated records. The strongest keyword link paired SDMs with landscape connectivity ($n = 61$), but this pair is imposed by the search vocabulary; among pairs not required by the query, SDM concepts linked most often to habitat fragmentation and to dispersal or range shifts ($n = 29$ each). Despite the rapid expansion of the literature, methodological integration is still limited. Stronger links require explicit and transparent transfer of SDM outputs into corridor, resistance, and network models.

Keywords: species distribution; landscape connectivity; climate change; ecological corridors; range shift; bibliometric analysis

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1. Introduction

Climate change alters the spatiotemporal dynamics of habitat suitability and, consequently, the geographic distributions of species [1–4]. These changes can cause expansion, contraction, or redistribution of suitable habitat relative to current species ranges [5,6]. The direction and pace of observed range shifts can differ from climatic niche projections because realized redistribution also depends on movement and landscape configuration [7,8].

A projection of climatic suitability therefore does not establish realized occupancy [9–11]. Species-specific traits and the arrangement, isolation, and permeability of habitat patches can limit realized range shifts [12,13]. Landscape connectivity and habitat accessibility vary among species and landscape configurations [14,15]. Habitat fragmentation and landscape resistance disrupt connections among habitat patches, reduce gene flow, and isolate populations from potential climate refugia [16–18]. In turn, they increase local extirpation risk [19,20]. Stepping-stone habitats (non-contiguous, discrete patches that link core habitat patches) can maintain connections between current ranges and future suitable habitats in a landscape matrix [21,22]. A distribution projection that ignores this movement component describes potential suitability, not realized occupancy [23–25].

Species distribution models (SDMs), also known as ecological niche models, combine species occurrence data with environmental variables to characterize species–environment relationships [26–31]. They utilize these relationships to estimate habitat suitability [32,33]. Climate change applications extend this framework: SDMs use climate data with projections from global climate or Earth system models under alternative emissions pathways (e.g., RCPs or SSPs) [34,35]. Model outputs provide continuous estimates of environmental suitability for specified taxa, periods, and climate scenarios [36–38]. At regional and continental extents, this framework enables consistent comparisons among species and future periods [39,40]. Advances in biodiversity informatics, Earth observation, fine-grain climate products, and ensemble methods have increased both the taxonomic coverage and spatial resolution of SDM applications [41,42]. In terrestrial ecosystems, these SDM outputs support climate-vulnerability assessments, protected-area evaluation, restoration priorities, and targeted field surveys [43,44]. SDM output is commonly proposed as the spatial input for connectivity evaluation among suitable areas [45,46]. The frequency of this integration in the published literature has not been quantified.

Landscape connectivity analyses quantify how landscape composition and configuration influence movement capacity among habitat patches [47,48]. Structural connectivity describes the spatial arrangement of habitat patches without consideration of species behavior [49–51]. Functional connectivity accounts for species-specific dispersal and behavioral responses to the landscape matrix [52,53]. Resistance surfaces assign relative costs to landscape elements [54,55]. Least-cost methods identify paths with minimum total resistance [54,56]. Circuit theory estimates connectivity by simulating current flow within a resistance landscape and identifies areas of high current density, or pinch points [57,58]. Graph theory represents habitat patches as nodes and potential connections as weighted edges [44,59–61]. Network metrics quantify cohesion, node centrality, and the relative importance of individual patches. Connectivity metrics differ in the landscape attributes and functional processes they represent, and their values depend on resistance values, dispersal thresholds, spatial grain, and patch definition. Under climate change, comparisons between current and projected habitat-suitability maps can reveal changes in corridor location, network cohesion, and accessibility [45,62–64]. Connectivity analyses provide the movement information needed to complement the habitat-suitability projections generated by SDMs [64,65].

The ecological link between habitat suitability and movement potential underpins the integrated use of SDMs and landscape connectivity analyses [66,67]. SDM projections can define habitat patches, identify source and destination areas, or assign resistance values to landscape elements [68,69]. Connectivity analyses that use SDM projections reveal whether a future suitable habitat is isolated or connected to the habitat network [70,71]. They can also identify habitat patches whose conservation value derives from their position within a future network [72,73]. Conservation priorities may consequently differ when assessments consider habitat suitability and network position. However, methodological integration

requires an analytical link between SDMs and connectivity analyses. Some studies apply separate habitat-suitability and connectivity analyses to the same conservation problem. The defining criterion is whether the connectivity analysis uses an SDM output. Without this analytical link, the relationship between the approaches is conceptual rather than methodological [74–76].

Forest ecosystems concentrate a large share of terrestrial biodiversity and provide ecosystem services that include carbon sequestration, hydrological regulation, and soil retention [77,78]. These ecosystems are particularly exposed to the combined pressures of climate change and habitat fragmentation, since tree species and forest-dependent fauna often have limited dispersal capacity relative to the pace of climatic change [79,80]. Forest fragmentation from land-use change also reduces landscape permeability and amplifies the dispersal limitation already caused by climate-driven range shifts. Silvicultural and conservation planning in forest systems therefore depends on projections that combine future habitat suitability with realistic assessments of species movement capacity. Forest management decisions (e.g., reserve design, corridor placement, and assisted colonization) have consequences across spatial and temporal scales, so the SDM–connectivity link is important [81–84]. Despite this relevance, forest-specific applications of SDMs and connectivity analyses have developed within largely separate research traditions, a divide that parallels the broader disciplinary separation described above [85,86]. Forest ecosystems have high conservation value, and their responses to climate change are well documented. A synthesis of the forest literature can quantify the use of SDM outputs in connectivity assessments and distinguish conceptual overlap from methodological integration. Prior reviews of SDM performance and of landscape connectivity have rarely focused specifically on forest systems as a unit of analysis. This gap leaves the scale and consequences of this disciplinary divide within forest ecology largely undocumented. This study therefore restricts its bibliometric scope to forest ecosystems. The restriction allows direct comparison of publication trends, thematic composition, and methodological pathways within a single, ecologically coherent literature [87–89].

This study quantifies the extent, relative weight, and form of integration between SDMs and landscape connectivity analyses in climate change research published from 2010 to 2025. Studies were grouped by analytical focus into three categories: SDMs without connectivity, connectivity without SDMs, and integration of the two approaches. Publication trends are compared among these three corpora. Relative measures compare the share of the connectivity literature accounted for by integrated studies with the corresponding share of the SDM literature. Because the two literatures differ substantially in size, these shares describe the weight of integrated work within each field rather than the direction of methodological transfer between them. The analysis also examines temporal changes in thematic emphasis and the uses of SDM outputs within connectivity analyses. Keyword relationships describe the main conceptual links between the fields. Here, two research questions were explored: (1) To what extent have SDMs and landscape connectivity analyses been integrated in climate change research? (2) To what extent have SDM outputs been used as inputs in landscape connectivity analyses? The findings can inform forest conservation planning by clarifying how future habitat-suitability projections are incorporated into connectivity analyses.

2. Materials and Methods

2.1. Data Sources and Literature-Search Strategy

Literature searches were conducted in Scopus and Web of Science (WoS) for studies published between 2010 and 2025 [90]. Three complementary searches were performed. The first targeted species distribution modeling (SDM) studies conducted in forest or ecosystem

contexts under climate change. The second identified studies on landscape connectivity within the same thematic and temporal scope, without requiring an explicit reference to SDMs. The third search required both SDM and connectivity terms and therefore identified studies that explicitly combined the two research domains.

Each search consisted of three main term groups: the analytical approach, the ecological context, and climate change. The SDM group covered species distribution model, habitat suitability model, ecological niche model, and their common abbreviations. The connectivity group covered connectivity and landscape connectivity. Forest- and ecosystem-related terms defined the ecological context, while climate change, global warming, and future scenarios defined the climatic context. Scopus searches were applied to titles, abstracts, and keywords. WoS searches were applied to the Topic field. Records indexed under the keyword Animals were excluded. The complete database-specific search strings are provided in Appendix A Table A1.

The SDM search returned 3732 records from Scopus and 2302 from WoS, giving 6034 records before cross-database duplicate removal. The independent connectivity search returned 743 records from Scopus and 850 from WoS, for a total of 1593 records before duplicate removal. The combined SDM–connectivity search returned 182 records from Scopus and 156 from WoS, giving 338 records before cross-database duplicate removal. After the Scopus and WoS outputs were merged, this search contained 245 candidate records. A post-merge check detected one residual duplicate, leaving 244 unique publications in the combined SDM–connectivity corpus. Records were matched across exports by DOI where available and, where no DOI was present, by normalized title and publication year, with titles lowercased, punctuation and diacritics removed, and whitespace collapsed. No manual relevance or eligibility screening was applied beyond these query-level criteria, and every record returned by a search entered the corresponding corpus. Eligibility was therefore defined by the search strings, the publication window, and the exclusion of records indexed under the keyword Animals. This follows the convention of bibliometric mapping, in which the retrieved corpus is itself the object of study rather than a sample of eligible evidence, and it differs from the eligibility screening applied in systematic reviews. Identification, deduplication, and corpus assignment are summarized in Figure 1 following the PRISMA 2020 reporting structure; because no post-retrieval eligibility screening was applied, no records were excluded at that stage.

As mentioned above, records from Scopus and Web of Science formed three mutually exclusive corpora: SDM-only, connectivity-only, and integrated. The analyses assessed publication growth, the direction and extent of integration between the two fields, temporal shifts in concept prevalence, and the methodological pathways within integrated studies. Keyword relationships were also examined at both the network and concept-pair levels to define the comparative fingerprint of SDM–connectivity integration. Figure 2 summarizes the complete analytical workflow, from the database search and record consolidation to the pathway classification and the comparative keyword fingerprint. To ensure transparency and reproducibility, the completed PRISMA 2020 checklist is provided in the Supplementary Materials.

2.2. Methods

2.2.1. Annual Publication Output and Growth-Rate Analysis

Annual publication counts were calculated for each mutually exclusive corpus from 2010 through 2025. Let S_y, C_y, and I_y denote the number of SDM-only, connectivity-only and integrated publications in year y, respectively. Annual totals for the two broader literatures were defined as:

$$\mathrm{SDM}_y = S_y + I_y$$

and

$$\text{Connectivity}_y = C_y + I_y$$

The combined literature in a given year was defined as:

$$\text{Combined}_y = S_y + C_y + I_y$$

Differences in temporal growth among the three mutually exclusive corpora were evaluated using a negative-binomial generalized linear model. Negative-binomial regression was selected because publication counts are non-negative integers and bibliometric count data commonly exhibit variance exceeding the mean, making a conventional Poisson model potentially inappropriate [91]. Overdispersion was not tested formally in these series. The negative-binomial model was specified a priori because it nests the Poisson distribution and remains valid whether or not the variance exceeds the mean, so the specification is conversative rather than contingent on a diagnostic. The dispersion parameter estimated from the data (149.1, Section 3.2) implies a variance close to the mean at the observed counts, which indicates that these series depart only slightly from equidispersion and that the fitted model lies near its Poisson limit. The choice of error distribution in therefore unlikely to be consequential for the growth-rate contrasts reported in Section 3.2.

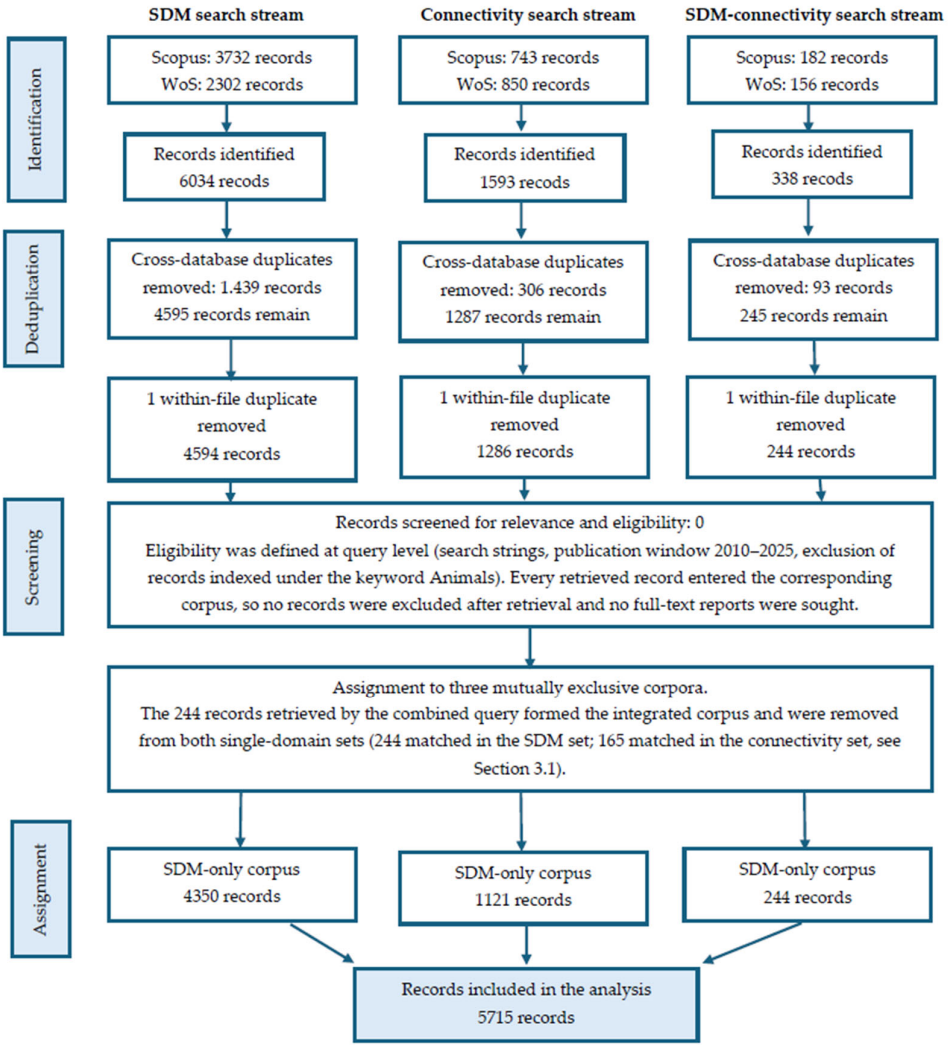


Figure 1. Identification, deduplication, and corpus assignment, reported following the PRISMA 2020 flow structure. Eligibility was defined at the query level, so no records were excluded after retrieval, and the screening stage reports no exclusions.



Figure 2. Analytical workflow of the study. Steps 1–5 correspond to the search and corpus-construction procedures described in Section 2.1 and summarized in Figure 1; steps 6–12 correspond to the analyses described in Sections 2.2.1–2.2.6, in the order in which they are presented.

For corpus g and publication year y, the model was specified as:

$$N_{g,y} \sim \mathrm{NB}(\mu_{g,y}, \theta),$$

with the linear predictor:

$$\log(\mu_{g,y}) = \beta_0 + \beta_1 t_y + \beta_{2,g} + \beta_{3,g} t_y$$

where $N_{g,y}$ is the annual publication count; $t_y = y - 2010$ is the centered publication year; and g represents the SDM-only, connectivity-only, or integrated corpus. The corpus-by-year interaction tested whether temporal growth rates differed among the three corpora.

An omnibus likelihood-ratio test compared the full corpus-by-year interaction model with a reduced additive model containing only corpus and year main effects. Group-specific annual growth rates were derived from the corresponding log-scale year coefficients as:

$$G_g = 100\left[\exp(b_g) - 1\right]$$

where b_g is the estimated annual slope for corpus g. These quantities represent model-based annual multiplicative changes rather than simple compound growth rates calculated from only the first and final years. Logarithmic scaling used for graphical presentation did not affect model fitting; the negative-binomial model was fitted to the original annual counts.

2.2.2. Measurement of SDM–Connectivity Integration Within Each Literature

Integration was evaluated relative to both of the disciplinary literatures because the SDM and connectivity corpora differed substantially in size. The proportion of the SDM literature that also addressed connectivity was calculated for each year as:

$$P_{\text{SDM}\rightarrow\text{ Connectivity},y} = 100 \times \frac{I_y}{S_y + I_y}$$

The arrow notation used in the two expressions below identifies which literature supplies the denominator; it does not denote a transfer of models or data between fields. Conversely, the proportion of the connectivity literature that also addressed SDM was calculated as:

$$P_{\text{Connectivity}\rightarrow\text{SDM},y} = 100 \times \frac{I_y}{C_y + I_y}$$

The annual share of integrated publications in the complete combined literature was calculated as:

$$P_{\text{Combined},y} = 100 \times \frac{I_y}{S_y + C_y + I_y}$$

These measures address different questions. The first quantifies how frequently SDM research incorporated connectivity, whereas the second quantifies how frequently connectivity research incorporated SDM. The combined-literature measure describes the overall prevalence of studies identified through the explicitly integrated query.

2.2.3. Relative Representation of Integrated Records in the Two Literatures

The annual difference between the two shares was quantified as:

$$\Delta_y = P_{\text{Connectivity}\rightarrow\text{SDM},y} - P_{\text{SDM}\rightarrow\text{ Connectivity},y}$$

Positive values indicate that integrated publications formed a larger share of the connectivity literature than of the SDM literature in that year. The two percentages share a numerator and have unequal denominators, so the difference is bounded below by the difference in corpus size and cannot by itself identify the direction of methodological transfer between the two fields. It is reported here as a measure of the relative weight of integrated work within each literature. The median annual difference was used to summarize the magnitude of this gap across the 16-year study period.

The consistency of the sign of this difference across years was assessed using an exact two-sided sign test. Under the null hypothesis, the probability of a positive annual difference was assumed to be 0.5:

$$K \sim \text{Binomial}(n, 0.5)$$

where K is the number of years with a positive difference and n is the number of non-zero annual differences. The sign test evaluates whether the direction of the difference is consistent across years; it does not test the magnitude of the difference or the existence of a temporal trend [92]. Because the connectivity corpus was smaller than the SDM corpus in every year of the series, a positive annual difference is expected on arithmetic grounds; the test therefore establishes the consistency of that difference across years rather than a property of methodological practice.

2.2.4. Keyword-Based Thematic Profiling and Methodological Pathway Classification

The thematic and methodological profiles of the three mutually exclusive corpora—SDM-only ($n = 4350$), connectivity-only ($n = 1121$), and integrated ($n = 244$)—were

compared using a predefined dictionary of SDM-, connectivity-, and climate-related concepts. For each publication, the title, abstract, author keywords, Keywords Plus, and available index keywords were converted to lowercase and combined into a single searchable text field. Conceptually equivalent expressions were grouped using regular-expression dictionaries. The evaluated concepts comprised species distribution modeling, MaxEnt, machine learning, habitat suitability, landscape connectivity, corridor or least-cost approaches, circuit or resistance modeling, habitat fragmentation, dispersal or range shift, and climate projection. For example, "species distribution model", "species distribution modeling", "ecological niche model", "habitat suitability model", "SDM", and "ENM" were grouped under the species distribution modeling concept. Similarly, corridor variants and least-cost terminology, circuit-theory and resistance-surface terminology, and dispersal and range-shift terminology were consolidated into their corresponding methodological categories. The concept categories were not mutually exclusive; a publication could contain and therefore contribute to more than one term category.

Term prevalence was calculated separately within each corpus as:

$$P_{g,t} = 100 \times \frac{n_{g,t}}{N_g},$$

where $n_{g,t}$ is the number of publications in corpus g containing term category t at least once, and N_g is the total number of publications in that corpus. Repeated occurrences of a term within the same publication were counted only once. Percentages were calculated relative to each corpus's own size, allowing corpora of substantially different sizes to be compared. For visualization, prevalence values were rounded to the nearest whole percentage, while unrounded values were retained in the analytical output.

Temporal changes in the integrated corpus were evaluated using four consecutive periods: 2010–2013, 2014–2017, 2018–2021, and 2022–2025. Four-year periods were used instead of annual values because the integrated corpus was small during the early years, making annual percentages highly sensitive to individual publications. Following reduplication, the four periods contained 15, 23, 73, and 133 publications, respectively. Within each period, term prevalence was calculated as the percentage of publications containing the corresponding normalized concept. These temporal summaries were treated as descriptive indicators of changes in terminology and methodological emphasis rather than as evidence of statistically stable temporal trends.

Publications in the integrated corpus were additionally assigned to mutually exclusive methodological pathways using a hierarchical, rule-based classification of titles, abstracts, and keyword fields. First, evidence of an SDM-derived output was identified using expressions such as "species distribution model", "ecological niche model", "habitat suitability", "climatic suitability", "suitability map", "predicted distribution", "potential distribution", "MaxEnt", "SDM", and "ENM". Records containing an SDM-output expression with circuit-theory, Circuitscape, Omniscape, Linkage Mapper, resistance-surface, cost-surface, current-density, least-cost, cost-distance, graph-theory, or network-analysis terminology were assigned to the network/resistance-based category. Records containing an SDM-output expression and corridor-planning, corridor-design, corridor-model, habitat-corridor, wildlife-corridor, ecological-corridor, or related corridor terminology, but not already assigned to the network/resistance category, were classified as corridor/least-cost application.

Among the remaining records, a publication was classified as a climate-projected suitability input when SDM-output terminology occurred together with both connectivity terminology and explicit future-climate terminology. Future-climate evidence included expressions such as "future climate", "climate scenario", "climate projection", "projected climate", "future scenario", "RCP", "SSP", "CMIP" "general or global circulation model",

and "range shift". Connectivity evidence included "landscape connectivity", "functional connectivity", "structural connectivity", "connectivity analysis", and "connectivity model". Records retrieved by the combined search but lacking sufficient metadata-level evidence for any of these methodological pathways were assigned to the co-occurrence/unclear category. Because this classification was based on bibliographic metadata rather than complete methodological descriptions, it was interpreted as a reproducible screening-level assessment of integration rather than definitive full-text confirmation of model-to-model data transfer.

2.2.5. Cross-Domain Keyword Co-Occurrence Analysis

A cross-domain co-occurrence analysis was conducted using the 244 unique publications in the integrated corpus. Unlike the broader thematic profiling, which also incorporated titles and abstracts, this analysis was restricted to author keywords, Keywords Plus, and available index keywords to retain the conventional bibliometric meaning of keyword co-occurrence. The original combined export contained 245 records; one duplicate publication appeared twice with minor differences in title formatting and was removed through normalized-title matching, leaving 244 unique records.

Keyword variants were consolidated using a predefined synonym dictionary. The SDM-related family comprised species distribution modeling, MaxEnt, habitat suitability, ecological niche, and machine learning. The connectivity-related family comprised landscape connectivity, corridor, least-cost path, circuit theory, resistance surface, habitat fragmentation, and dispersal or range shift. Each normalized concept was counted no more than once per publication, regardless of whether it appeared in multiple keyword fields. Terms were eligible for inclusion when they occurred in at least four integrated-corpus publications.

For every eligible SDM-related term i and connectivity-related term j, document-level co-occurrence was calculated as:

$$C_{ij} = \sum_{d=1}^{N} I_{di} I_{dj},$$

where $I_{di} = 1$ if publication d contained term i and 0 otherwise, and I_{dj} was defined equivalently for connectivity term j. Only cross-domain pairs occurring together in at least two publications were retained. To limit visual congestion, a maximum of the 28 strongest cross-domain pairs, ranked by raw co-occurrence count, was displayed. Association strength was also calculated as

$$AS_{ij} = \frac{NC_{ij}}{f_i f_j},$$

where N is the number of integrated publications, and f_i and f_j are the document frequencies of the corresponding terms. Association-strength values were retained in the analytical outputs for sensitivity assessment, whereas raw co-occurrence counts were used as the more directly interpretable ribbon weights [93].

The cross-domain relationships were visualized as an undirected chord diagram using the circlize package in the R environment [94]. SDM-related sectors were represented in blue and connectivity-related sectors in orange. The number reported for each sector represented the number of unique publications containing that term. Ribbon width represented the number of unique publications in which the corresponding SDM and connectivity terms co-occurred. Because co-occurrence does not establish directionality, ribbons were assigned a neutral purple-gray color rather than the color of either term family. Ribbon opacity increased moderately with co-occurrence frequency, while width remained the primary representation of relationship strength. The two term families were separated by enlarged angular gaps, and terms within each family were ordered by decreasing document frequency.

2.2.6. Concept Prevalence and Cross-Domain Term Pairs in the Keyword Fields

To characterize the thematic composition of the three mutually exclusive corpora, keyword-based term prevalence was calculated for the SDM-only, connectivity-only, and integrated datasets. This analysis differs from the profiling described in Section 2.2.4 in one respect: the text field was restricted to author keywords, Keywords Plus, and index keywords, excluding titles and abstracts, so that the results retain the conventional bibliometric meaning of keyword-based prevalence. Normalization and the ten-concept dictionary were otherwise identical to those defined in Section 2.2.4 and are not repeated here. Each concept was coded as present or absent once per document, irrespective of how many times it occurred or in how many keyword fields it was identified. For each corpus and concept, prevalence was calculated as the number of unique records containing the concept divided by the total number of records in that corpus and expressed as a percentage. Circle area was scaled to this within-corpus prevalence, while exact percentages were retained as numerical labels.

Cross-domain methodological coupling was examined within the integrated corpus using a binary document-by-term incidence matrix. All Cartesian combinations between the five SDM-related and five connectivity-related concepts were evaluated, producing 25 possible cross-domain term pairs. For each pair, raw co-occurrence was calculated as the number of unique integrated-corpus records in which both concepts were detected. Co-occurrence was additionally expressed as a percentage of the integrated corpus by dividing the pair count. The complete set of pairwise results was displayed as a matrix in which color intensity represented the raw co-occurrence count and each cell reported both the count and corresponding corpus percentage. The three pairs with the highest raw co-occurrence counts, selected after requiring at least two co-occurring records, were highlighted to facilitate interpretation. Because raw co-occurrence is influenced by the marginal prevalence of individual terms, pairwise counts were interpreted with the corpus-level prevalence profiles rather than as normalized effect sizes. The analysis was descriptive: co-occurrence indicates that two concepts were used within the same bibliographic record but does not establish a directional relationship, causal association, or confirmed analytical workflow.

3. Results

3.1. Data Sources and Literature-Search Strategy

The three exports contained 4595 SDM records, 1287 connectivity records, and 245 combined-query records. Within-file reduplication removed one record from each export. The reduplicated source sets therefore contained 4594, 1286, and 244 records, respectively. The 244 combined-query records formed the integrated corpus. These records were removed from the two single-domain sets. The final SDM-only corpus contained 4350 records. The final connectivity-only corpus contained 1121 records. The three mutually exclusive corpora contained 5715 records in total. The two single-domain sets did not lose the same number of records. All 244 integrated records were present in the reduplicated SDM export, which fell by exactly that number, whereas the reduplicated connectivity export fell by 165, leaving 79 integrated records that the independent connectivity search had not retrieved. This difference follows from the composition of the context term group in the Scopus strings: the SDM and combined searches both included the term ecosystem, whereas the connectivity search did not (Appendix A Table A1). Records whose only context match was that term were therefore retrieved by the combined and SDM searches but not by the connectivity search. The WoS strings used an identical context group across the three streams and did not contribute to the difference. Because corpus assignment was governed by the combined query, this asymmetry does not alter the composition of the

three mutually exclusive corpora or the annual counts reported below; its effect on the denominators used in Section 3.3 is examined there.

3.2. Annual Publication Output and Growth

The SDM-only corpus contained the largest number of publications in every year (Figure 3). Annual publications increased from 30 in 2010 to 188 in 2017, 379 in 2021, and 770 in 2025. The connectivity-only corpus increased from 16 publications in 2010 to 179 in 2025. The integrated corpus contained no more than six publications per year between 2010 and 2017. This number increased to 17 in 2018 and ranged from 13 to 27 between 2018 and 2024. In 2025, the integrated corpus reached its highest annual count of 63 publications.

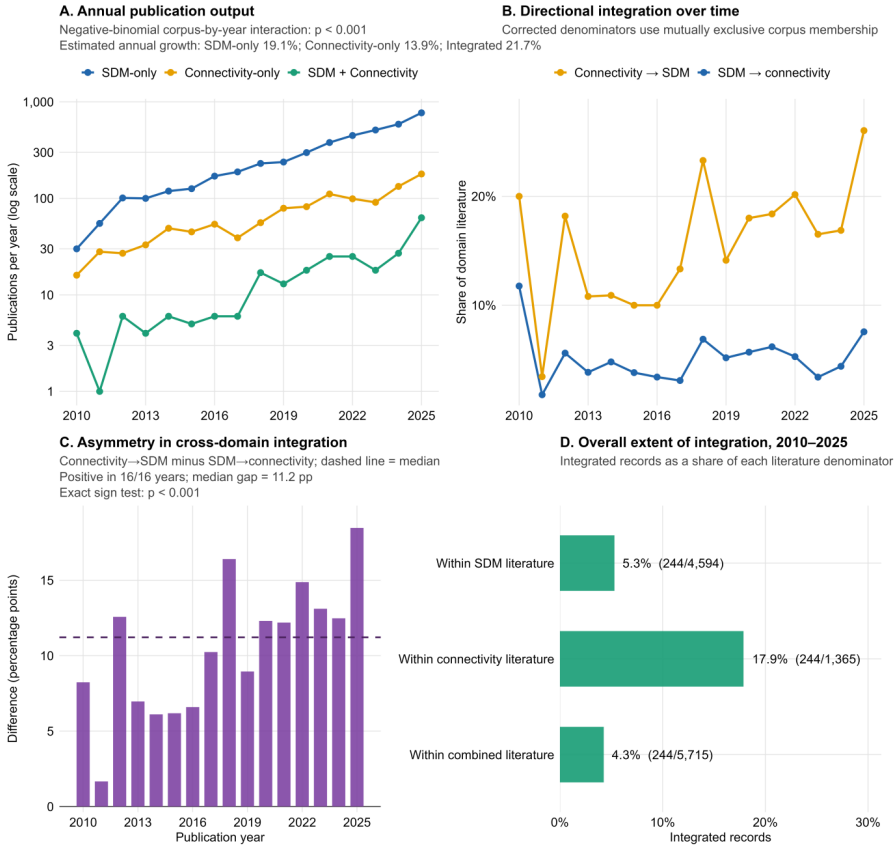


Figure 3. Extent, temporal dynamics, and relative representation of SDM–connectivity integration, 2010–2025: (**A**) annual publication output across the mutually exclusive SDM-only, connectivity-only, and integrated corpora; (**B**) annual integrated-corpus shares within the SDM and connectivity literature; (**C**) yearly difference between the two integration shares, with the dashed line denoting the median difference; the panel labels drawn inside the figure use the word asymmetry, but this difference compares two literatures of unequal size and does not indicate the direction of methodological transfer (Section 2.2.3); (**D**) overall proportion of integrated records within the SDM, connectivity, and combined literature denominators.

The negative-binomial corpus-by-year interaction was significant. The likelihood ratio statistic was 16.55 with two degrees of freedom (p = 0.000255). The full interaction model had a log-likelihood of −178.08. The additive model had a log-likelihood of −186.36. The fitted dispersion parameter was 149.1. The annual rate ratio was 1.191 for SDM-only records. Its 95% confidence interval was 1.176–1.206. This corresponded to 19.1% annual growth. The annual rate ratio was 1.139 for connectivity-only records. Its 95% confidence interval was 1.120–1.159. This corresponded to 13.9% annual growth. The annual rate ratio was 1.217 for integrated records. Its 95% confidence interval was 1.174–1.261. This

corresponded to 21.7% annual growth. Connectivity-only growth differed from SDM-only growth (Table 1). Integrated growth also differed from connectivity-only growth. Integrated growth did not differ from SDM-only growth.

Table 1. Linear contrasts of annual publication rates from the negative-binomial corpus-by-year model (delta beta is the difference between corpus-specific log-rate slopes; the ratio of rate ratios is exp[delta beta]; and a value of 1 denotes equal annual slopes).

Annual-Rate Contrast	Delta Beta	SE	z	Ratio of Rate Ratios	95% CI	*p*
Connectivity-only vs. SDM-only	−0.0444	0.0108	−4.124	0.957	0.937–0.977	<0.001
Integrated vs. SDM-only	0.0215	0.0193	1.112	1.022	0.984–1.061	0.266
Integrated vs. connectivity-only	0.0659	0.0201	3.277	1.068	1.027–1.111	0.001

3.3. Relative Representation of Integrated Records in the Two Literatures

Across 2010–2025, integrated records represented 5.3% of the SDM literature. The numerator was 244. The denominator was 4594. Integrated records represented 17.9% of the connectivity literature. The denominator was 1365. They represented 4.3% of the combined literature. The denominator was 5715 (Figure 4). The annual combined-literature integration indices for 2010–2013 were 8.0%, 1.2%, 4.5%, and 2.9%. The values for 2014–2017 were 3.4%, 2.8%, 2.6%, and 2.6%. The values for 2018–2021 were 5.6%, 3.9%, 4.5%, and 4.9%. The values for 2022–2025 were 4.4%, 2.9%, 3.6%, and 6.2%. The annual SDM-to-connectivity shares for 2010–2013 were 11.8%, 1.8%, 5.6%, and 3.8%. The values for 2014–2017 were 4.8%, 3.8%, 3.4%, and 3.1%. The values for 2018–2021 were 6.9%, 5.2%, 5.7%, and 6.2%. The values for 2022–2025 were 5.3%, 3.4%, 4.4%, and 7.6% (Figure 3B). The annual connectivity-to-SDM shares for 2010–2013 were 20.0%, 3.4%, 18.2%, and 10.8%. The values for 2014–2017 were 10.9%, 10.0%, 10.0%, and 13.3%. The values for 2018–2021 were 23.3%, 14.1%, 18.0%, and 18.4%. The values for 2022–2025 were 20.2%, 16.5%, 16.9%, and 26.0%. The share of integrated records within the connectivity literature exceeded the share within the SDM literature in all 16 years. The annual gaps for 2010–2013 were 8.2, 1.7, 12.6, and 7.0 percentage points. The gaps for 2014–2017 were 6.1, 6.2, 6.6, and 10.2 points. The gaps for 2018–2021 were 16.4, 9.0, 12.3, and 12.2 points. The gaps for 2022–2025 were 14.9, 13.1, 12.5, and 18.5 points (Figure 3C). The minimum annual gap was 1.7 percentage points in 2011. The maximum gap was 18.5 points in 2025. The median gap was 11.2 points. The mean gap was 10.5 points. The exact two-sided sign test included 16 positive differences and no negative differences. Its p value was 0.000031. Because the two shares have a common numerator and the connectivity corpus was smaller than the SDM corpus in every year, this consistency is expected on arithmetic grounds and is reported as a description of relative weight rather than of directional transfer between the fields. A sensitivity check addressed the denominator asymmetry described in Section 3.1 by restricting the integrated corpus to the 165 records that the independent connectivity search also retrieved. Under this restriction, integrated records represented 3.7% of the SDM literature (165 of 4515) and 12.8% of the connectivity literature (165 of 1286). Both values are lower than in the primary analysis, and the difference between the two shares persists.

3.4. Comparative Thematic and Methodological Profile

Species distribution model terms occurred in 82% of SDM-only records. They occurred in 0% of connectivity-only records. They occurred in 88% of integrated records (Figure 4). MaxEnt occurred in 42%, 1%, and 30%, respectively. Machine learning occurred in 15%, 8%, and 10%. Habitat suitability occurred in 45%, 4%, and 54%. Landscape connectivity

occurred in 0% of SDM-only records. It occurred in 100% of connectivity-only records. It occurred in 100% of integrated records. Corridor or least-cost terms occurred in 2%, 15%, and 23%, respectively. Circuit or resistance terms occurred in 0%, 5%, and 10%. Habitat fragmentation occurred in 5% of SDM-only records, 26% of connectivity-only records, and 32% of integrated records. Dispersal or range-shift terms occurred in 17%, 19%, and 38%, respectively. Climate projection terms occurred in 51%, 10%, and 48%.

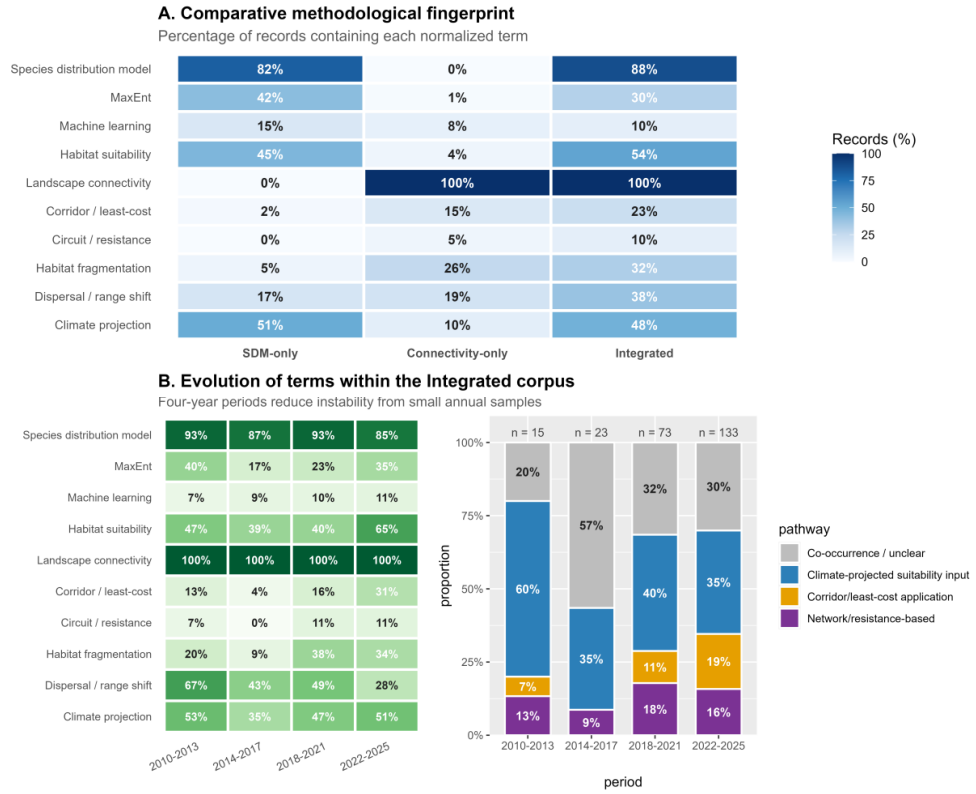


Figure 4. Comparative thematic composition and methodological pathways of SDM–connectivity integration: (**A**) prevalence of normalized SDM-, connectivity-, and climate-related terms across the mutually exclusive SDM-only, connectivity-only, and integrated corpora; left of (**B**) four-year variation in term prevalence within the integrated corpus; right of (**B**) proportional composition of co-occurrence/unclear, climate-projected suitability input, corridor/least-cost application, and network/resistance-based pathways, with period-specific record totals shown above the bars.

The integrated-minus-SDM-only differences were positive for seven of the ten terms. They were negative for MaxEnt, machine learning, and climate projection. The integrated-minus-connectivity-only differences were positive for nine terms. The difference for landscape connectivity was zero (Table 2).

Table 2. Percentage-point differences in term prevalence between the integrated corpus and the two single-domain corpora (values are percentage-point differences calculated from the whole-number prevalence values displayed in the comparative fingerprint. The last column compares the integrated value with the larger of the two single-domain values).

Normalized Term	Integrated Minus SDM-Only	Integrated Minus Connectivity-Only	Integrated Minus Larger Single-Domain Value
Species distribution model	+6	+88	+6
MaxEnt	−12	+29	−12
Machine learning	−5	+2	−5
Habitat suitability	+9	+50	+9

Table 2. *Cont.*

Normalized Term	Integrated Minus SDM-Only	Integrated Minus Connectivity-Only	Integrated Minus Larger Single-Domain Value
Landscape connectivity	+100	0	0
Corridor/least-cost	+21	+8	+8
Circuit/resistance	+10	+5	+5
Habitat fragmentation	+27	+6	+6
Dispersal/range shift	+21	+19	+19
Climate projection	−3	+38	−3

3.5. Temporal Composition of the Integrated Corpus

The four publication periods contained 15, 23, 73, and 133 integrated records, respectively (Figure 3B,C). The first two periods contained 38 records in total, whereas the last two periods contained 206 records. In 2010–2013, species distribution model terms were identified in 14 of 15 records (93.3%), with MaxEnt appearing in 6 records (40.0%). Machine learning was reported in 1 record (6.7%), whereas habitat suitability was found in 7 records (46.7%). Landscape connectivity was present in all 15 records. Meanwhile, corridor or least-cost terms were recorded in 2 records (13.3%), and circuit or resistance terms appeared in 1 record (6.7%). Habitat fragmentation was identified in 3 records (20.0%). Dispersal or range shift was documented in 10 records (66.7%), while climate projection was reported in 8 records (53.3%). In 2014–2017, species distribution model terms were identified in 20 of 23 records (87.0%), with MaxEnt appearing in 4 records (17.4%). Machine learning was reported in 2 records (8.7%), whereas habitat suitability was found in 9 records (39.1%). Landscape connectivity was present in all 23 records. In contrast, corridor or least-cost terms were recorded in 1 record (4.3%), whereas circuit or resistance terms did not appear. Habitat fragmentation was identified in 2 records (8.7%). Dispersal or range shift was documented in 10 records (43.5%), and climate projection was reported in 8 records (34.8%). In 2018–2021, species distribution model terms were identified in 68 of 73 records (93.2%), with MaxEnt appearing in 17 records (23.3%). Machine learning was reported in 7 records (9.6%), whereas habitat suitability was found in 29 records (39.7%). Landscape connectivity was present in all 73 records. Meanwhile, corridor or least-cost terms were recorded in 12 records (16.4%), and circuit or resistance terms appeared in 8 records (11.0%). Habitat fragmentation was identified in 28 records (38.4%). Dispersal or range shift was documented in 36 records (49.3%), while climate projection was reported in 34 records (46.6%). In 2022–2025, species distribution model terms were identified in 113 of 133 records (85.0%), with MaxEnt appearing in 46 records (34.6%). Machine learning was reported in 15 records (11.3%), whereas habitat suitability was found in 86 records (64.7%). Landscape connectivity was present in all 133 records. Meanwhile, corridor or least-cost terms were recorded in 41 records (30.8%), and circuit or resistance terms appeared in 15 records (11.3%). Habitat fragmentation was identified in 45 records (33.8%). Prevalence values for dispersal or range shift and for climate projection in this period are shown in left of Figure 4B.

3.6. Methodological Pathway Composition

The categories below record the evidence available in bibliographic metadata rather than confirmed model-to-model data transfer (Section 2.2.4). Across the full integrated corpus, metadata consistent with a climate-projected suitability input were identified in 93 records (38.1%). Co-occurrence or unclear cases accounted for 79 records (32.4%). Network or resistance-based pathways accounted for 38 records (15.6%). Corridor or least-cost applications accounted for 34 records (13.9%). In 2010–2013, climate-projected

suitability input accounted for 9 of 15 records (60.0%). Co-occurrence or unclear cases accounted for 3 records (20.0%). Network or resistance-based pathways accounted for 2 records (13.3%). Corridor or least-cost applications accounted for 1 record (6.7%). In 2014–2017, climate-projected suitability input accounted for 8 of 23 records (34.8%). Co-occurrence or unclear cases accounted for 13 records (56.5%). Network or resistance-based pathways accounted for 2 records (8.7%). No record was classified as a corridor or least-cost application. In 2018–2021, climate-projected suitability input accounted for 29 of 73 records (39.7%). Co-occurrence or unclear cases accounted for 23 records (31.5%). Network or resistance-based pathways accounted for 13 records (17.8%). Corridor or least-cost applications accounted for 8 records (11.0%). In 2022–2025, climate-projected suitability input accounted for 47 of 133 records (35.3%). Co-occurrence or unclear cases accounted for 40 records (30.1%). Network or resistance-based pathways accounted for 21 records (15.8%). Corridor or least-cost applications accounted for 25 records (18.8%).

3.7. Cross-Domain Keyword Co-Occurrence

Keyword-only screening retained 11 terms at the minimum occurrence threshold (Figure 5). Twenty-four cross-domain pairs met the minimum pairwise threshold. Species distribution model and landscape connectivity co-occurred in 61 records. Species distribution model also co-occurred with habitat fragmentation and dispersal or range shift in 29 records each. Likewise, habitat suitability and landscape connectivity co-occurred in 26 records. Ecological niche and landscape connectivity co-occurred in 22 records. Meanwhile, MaxEnt and landscape connectivity co-occurred in 16 records. Species distribution model and corridor co-occurred in 12 records. In addition, ecological niche and habitat fragmentation and habitat suitability and habitat fragmentation each co-occurred in 10 records. Ecological niche and dispersal or range shift co-occurred in 8 records. Habitat suitability and corridor also co-occurred in 8 records. MaxEnt and habitat fragmentation likewise co-occurred in 8 records. Next, machine learning and landscape connectivity co-occurred in 7 records. Habitat suitability and dispersal or range shift co-occurred in 6 records. Moreover, habitat suitability and circuit theory, MaxEnt and corridor, and MaxEnt and dispersal or range shift each co-occurred in 4 records. Machine learning and dispersal or range shift co-occurred in 3 records. Species distribution model and circuit theory also co-occurred in 3 records. Species distribution model and least-cost path likewise co-occurred in 3 records. Finally, four pairs co-occurred in 2 records. These were ecological niche–corridor, ecological niche–least-cost path, machine learning–circuit theory, and MaxEnt–least-cost path. These counts require one qualification. Every record in the integrated corpus satisfies a query that required both an SDM term and the terms connectivity or landscape connectivity, so any pair formed between an SDM-family term and those two terms is imposed by the search design and carries no information about methodological practice. The frequency-normalized association strengths in Appendix A Table A2 show this directly: species distribution model with landscape connectivity has an association strength of 1.015, and ecological niche with landscape connectivity 1.045, both indistinguishable from chance. The pairs that exceed chance involve terms absent from the search strings, led by machine learning with circuit theory (3.486), MaxEnt with least-cost path (2.169), ecological niche with least-cost path (2.033), habitat suitability with circuit theory (1.914), and habitat suitability with corridor (1.823). These association strengths rest on small counts, in two cases on a single pair of records, and are reported as descriptive rather than as evidence of preferred method pairings.

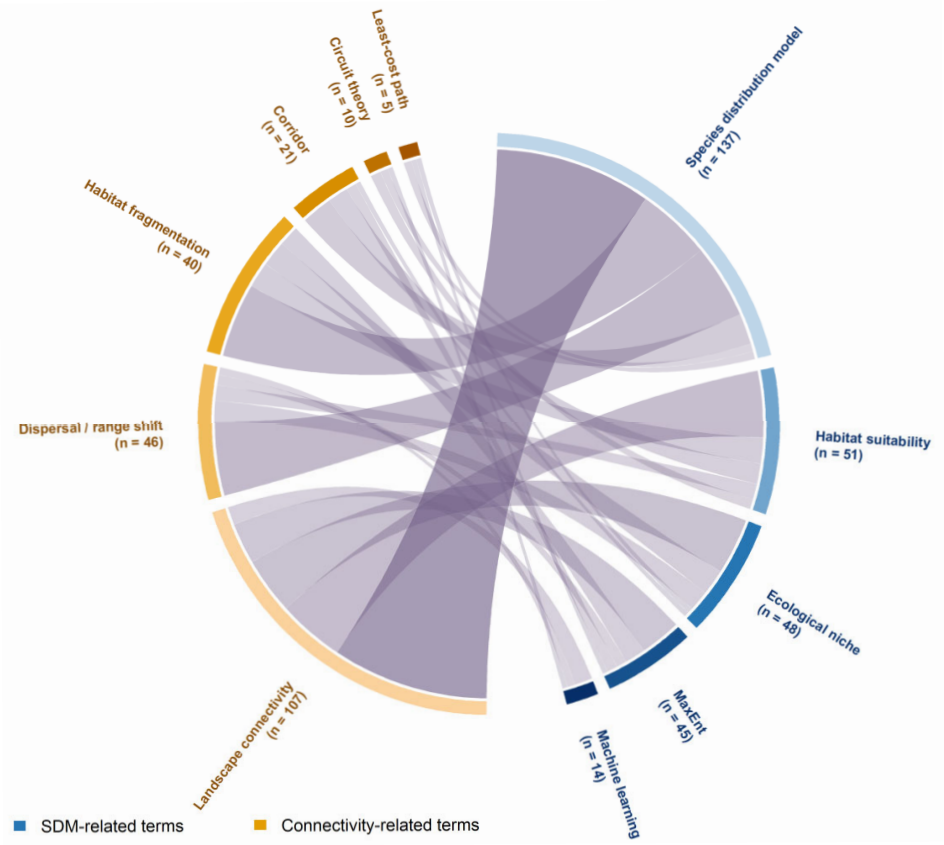


Figure 5. Cross-domain keyword co-occurrence structure within the integrated corpus. Ribbons linking an SDM-related term to landscape connectivity are imposed by the combined search query, which required both vocabularies in every retrieved record, and are not interpreted as evidence of methodological practice; see Section 3.7 and Appendix A Table A2.

3.8. Keyword-Only Comparative Fingerprint

The keyword-only analysis produced a second corpus comparison (Figure 6). In SDM-only records, species distribution model occurred in 54.4%. MaxEnt occurred in 26.9%. Machine learning occurred in 8.6%. Ecological niche occurred in 15.8%. Habitat suitability occurred in 17.3%. In the same SDM-only records, landscape connectivity occurred in 0.0%. Corridor or least-cost occurred in 0.4%. Circuit or resistance occurred in 0.0%. Habitat fragmentation occurred in 2.4%. Dispersal or range shift occurred in 8.3%. In Connectivity-only records, species distribution model occurred in 0.1%. MaxEnt occurred in 0.3%. Machine learning occurred in 4.6%. Ecological niche occurred in 0.7%. Habitat suitability occurred in 1.2%. In the same connectivity-only records, landscape connectivity occurred in 42.4%. Corridor or least-cost occurred in 7.0%. Circuit or resistance occurred in 3.0%. Habitat fragmentation occurred in 15.1%. Dispersal or range shift occurred in 10.4%. In integrated records, species distribution model occurred in 56.1%. MaxEnt occurred in 18.4%. Machine learning occurred in 5.7%. Ecological niche occurred in 19.7%. Habitat suitability occurred in 20.9%. In the same integrated records, landscape connectivity occurred in 43.9%. Corridor or least-cost occurred in 9.8%. Circuit or resistance occurred in 4.9%. Habitat fragmentation occurred in 16.4%. Dispersal or range shift occurred in 18.9%. The grouped co-occurrence matrix contained 25 SDM–connectivity term pairs. For species distribution model, the counts across landscape connectivity, corridor or least-cost, circuit or resistance, habitat fragmentation, and dispersal or range shift were 61, 14, 4, 29, and 29. The corresponding percentages were 25.0%, 5.7%, 1.6%, 11.9%, and 11.9%. For MaxEnt, the five counts were 16, 5, 1, 8, and 4. The corresponding percentages were 6.6%, 2.0%, 0.4%,

3.3%, and 1.6%. For machine learning, the counts were 7, 1, 2, 1, and 3. The percentages were 2.9%, 0.4%, 0.8%, 0.4%, and 1.2%. For ecological niche, the five counts were 22, 4, 3, 10, and 8. The corresponding percentages were 9.0%, 1.6%, 1.2%, 4.1%, and 3.3%. For habitat suitability, the counts were 26, 8, 4, 10, and 6. The percentages were 10.7%, 3.3%, 1.6%, 4.1%, and 2.5%.

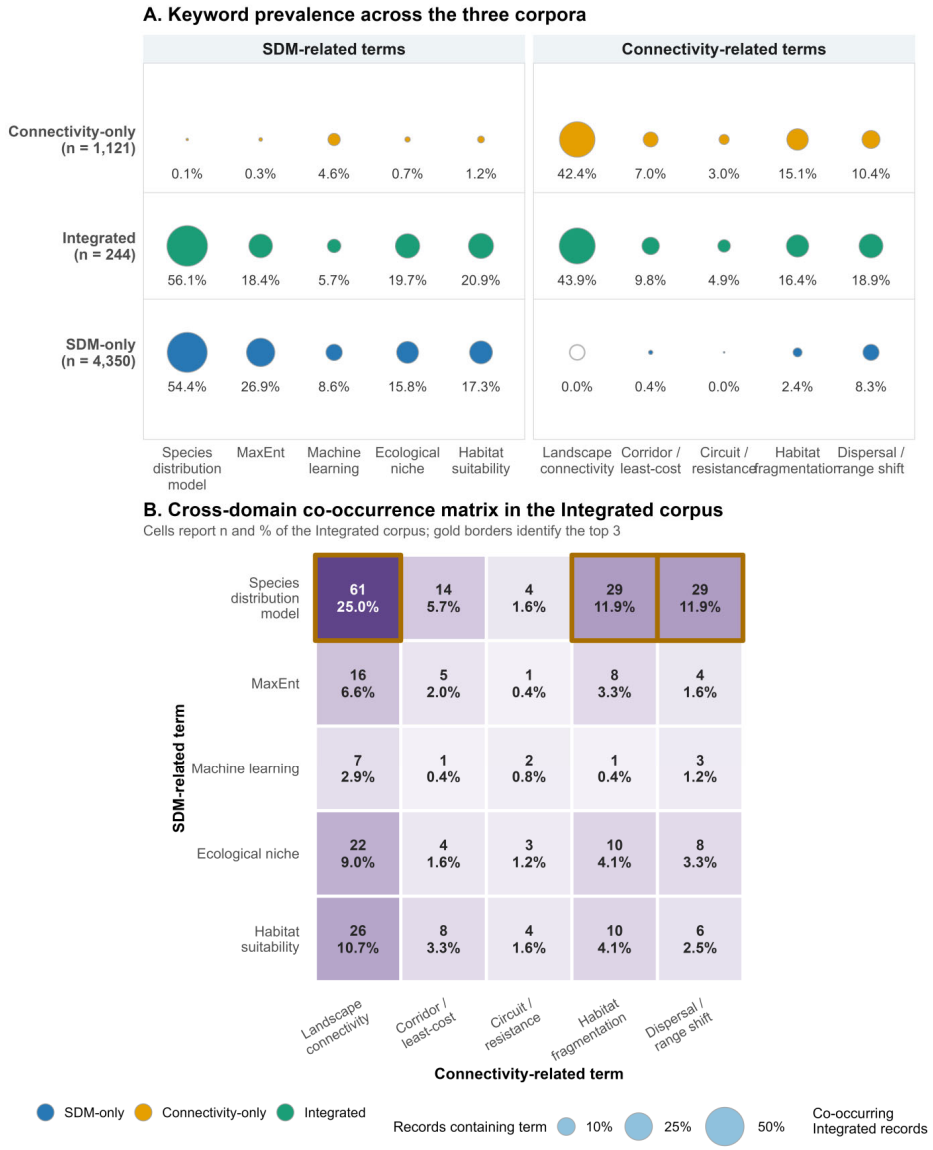


Figure 6. Comparative keyword fingerprint and cross-domain co-occurrence structure: (**A**) record-level prevalence of normalized SDM-related and connectivity-related terms across the mutually exclusive SDM-only, connectivity-only, and integrated corpora, with circle size proportional to within-corpus prevalence; (**B**) complete 5 × 5 matrix of SDM–connectivity term pairs within the integrated corpus, with cells reporting raw co-occurrence counts and percentages of integrated records and gold borders identifying the three largest pairwise counts.

4. Discussion

This study shows that habitat-suitability assessment and landscape-connectivity analysis are still rarely combined in studies of forest responses to climate change. This lack of integration is important because climatic suitability indicates potential habitat, but dispersal and establishment also determine occupancy. As outlined in the Introduction, a future habitat has limited management value if species cannot reach it or maintain gene flow with source populations. SDMs estimate potential habitat suitability, yet their outputs require

ecological interpretation before they can inform distributional responses [27,28]. Connectivity contributes to this context because it considers patch arrangement, matrix permeability, and species-specific dispersal [10,51]. The low level of methodological integration found in this study shows that much of the literature still evaluates climatic opportunity and spatial access as separate problems. This result does not reduce the value of SDMs or connectivity models as individual tools. Instead, it identifies a gap between ecological process and analytical practice in forest climate studies. In response to RQ1, methodological integration increased during the study period but still represented a small part of the literature.

Publication output for integrated studies rose rapidly during the study period. This rise indicates that the link between suitability and connectivity now receives increased attention. However, the low share of integrated records shows that publication growth has not made methodological integration common practice. The much larger SDM-only corpus provides a sound basis for this interpretation: SDMs were commonly applied without an explicit connectivity component. At the same time, conservation studies have called for climate-responsive connectivity for more than a decade [22,95,96]. These two lines of study have developed with limited methodological exchange. This helps explain why integrated output can rise rapidly yet stay uncommon. The pattern indicates expansion from a small base, not field-wide integration. More complete integration would require connectivity questions during SDM design, before threshold choice or map production.

Integrated work occupies a larger fraction of the connectivity literature than of the SDM literature in every year of the series. This contrast follows in part from the difference in corpus size, since the two shares have a common numerator, and it should not be read as a measure of borrowing between the fields. One reading that the present data cannot test relates it to the requirements of each method. Connectivity analyses need habitat nodes, resistance values, or destination areas, so SDM output can enter as a ready spatial input. An SDM may end with a suitability map without considering connectivity between habitat patches. Climate-connectivity studies demonstrate how environmental surfaces, land cover, and movement costs can identify links between present and future conditions [97,98]. This account remains a hypothesis. The only direction-informative evidence in the present study comes from the pathway classification, which identifies the suitability surface as the upstream product in those records where a workflow could be reconstructed from metadata. For forest applications, this dependency becomes important when long generation times and fragmented populations delay access to new climatic habitat [52,66].

The thematic profile adds detail to the same interpretation. Integrated records gave greater prominence to habitat suitability, fragmentation, dispersal, range shifts, corridors, and least-cost concepts than the single-domain corpora. These themes correspond to the ecological steps that connect potential habitat with spatial access. However, climate-projection, MaxEnt, and machine learning terms occurred at similar frequencies in the integrated and SDM-only corpora. This result challenges the assumption that integration mainly follows algorithmic novelty. MaxEnt settings affect model response and transfer, but algorithm selection cannot determine ecological connectivity [36,98]. Likewise, a more accurate suitability surface can still yield weak corridor priorities if thresholds, dispersal limits, or resistance rules lack ecological justification [99,100]. A defensible integrated study must explain how suitability becomes a node, a resistance value, a corridor endpoint, or another connectivity input [75].

The pathway classification indicates which forms of integration are detectable in bibliographic metadata. Records reporting a climate-projected suitability input formed the largest group, and network, resistance, corridor, and least-cost applications formed smaller ones. The later rise of corridor and least-cost applications points to greater diversity in the questions posed by integrated studies. Least-cost analysis identifies a minimum-cost

connection under assigned resistance values [54]. Circuit theory evaluates multiple possible connections and can locate zones where alternatives are scarce [58]. Graph models evaluate patch roles and network cohesion [61,101]. Habitat-availability indices add patch area and dispersal probability to network assessment [44]. The pathway results support question-led method selection because future stands, climate refugia, corridor placement, and network vulnerability require different outputs. In response to RQ2, projected suitability surfaces were the most frequently detected point of connection in the bibliographic record; explicit network, resistance, corridor, and least-cost pathways were detected less often. Because the classification rests on titles, abstracts, and keywords, these proportions describe what integrated studies report rather than what they necessarily did.

The dominance of climate-projected suitability as an input indicates that most explicit integration followed a sequential workflow: the SDM was completed first, and its output then entered a connectivity model. This sequence is practical, but each assumption in the suitability model carries into the next stage. A binary threshold can alter patch boundaries, node number, and the distance between suitable areas. A conversion from suitability to resistance also assumes a defined relation between habitat preference and movement cost. That relation requires ecological justification because suitability and resistance are not interchangeable concepts [100,102]. Temporal correspondence adds another concern when future climate surfaces are combined with current land-cover conditions. As a result, two studies may both be classified as integrated yet differ substantially in ecological interpretation and uncertainty. A stronger workflow would report the transfer rule, compare reasonable alternatives, and retain SDM uncertainty in the connectivity estimates [75].

In the pathway classification, 32.4% of records fell into the co-occurrence or unclear category, which points to incomplete workflow reporting. Many titles, abstracts, and keywords did not state how an SDM output entered the connectivity analysis. This ambiguity prevents reproduction of the analytical chain and weakens comparison among studies. Small changes in resistance values, suitability thresholds, dispersal limits, or patch definitions can alter link locations and patch ranks [99,100]. Resistance parameterization also requires empirical or expert justification, and no universal transformation from suitability to resistance exists [102]. A future climate surface paired with present land cover contains an assumption that land cover will stay constant. SDM uncertainty should enter connectivity outputs and should not disappear at a binary threshold [33,75]. Explicit documentation of source data, scale, time period, threshold, dispersal value, resistance rule, and uncertainty would make integrated studies reproducible and easier to compare.

The keyword network also separates conceptual proximity from methodological integration. SDM and landscape-connectivity terms formed the clearest cross-domain link, followed by fragmentation and dispersal concepts. Links between algorithm names and specific connectivity methods were rare. The established definition of connectivity includes landscape effects on movement, but the term can refer to distinct spatial and functional properties [10,51]. Habitat fragmentation also carries a broad meaning and does not confirm that a study built a connectivity model [7,12]. For the same reason, a strong normalized association based on few records should not be read as a preferred method pair. The keyword results are useful as a map of conceptual proximity, but pathway classification provides the stronger test of integration. Future studies should keep these two levels separate so terminology does not substitute for workflow documentation.

The temporal meaning of connectivity also deserves attention. Present-day connectivity links habitat patches that are suitable at the same time, but climate connectivity may connect current populations with areas expected to become suitable later. These are different planning problems. A static corridor can maintain present-day connectivity yet fail to link a population with future climatic habitat. Connectivity with future habitat may

also depend on stepping-stone habitats that become suitable at different times or on staged restoration. Studies of climate connectivity have shown the value of linking present and future climatic conditions within the same spatial analysis [97,103]. The limited number of explicit corridor and least-cost pathways found here suggests that this temporal connection is still uncommon in the indexed literature. Future studies should distinguish current network cohesion, access to future habitat, and the sequence of suitable areas over time [96].

The forestry implications below are derived from the cited adaptation literature and interpreted in relation to the bibliometric patterns; they are not direct management findings of this study. A suitability map can identify current and future climatic habitats for tree species, forest communities, or habitat types. Connectivity analysis can then assess links among source stands, future habitat, and refugia under land-use constraints. For trees, seed dispersal, pollen flow, demographic lag, and local adaptation can make the accessible area much smaller than the climatically suitable area [25,52,66]. Forest managers can apply integrated outputs to corridor restoration, stepping-stone placement, reserve extension, and protection of permeable matrix areas [22,43]. Silvicultural options may include retained canopy, riparian woodland, mixed stands, and restoration of small habitat patches, but each action needs a stated species or habitat objective. Where natural range expansion appears too slow, connectivity results can inform assisted gene flow or assisted migration, subject to genetic and ecological risk assessment [52,73]. In this role, integration converts broad climate exposure into spatial priorities that can enter forest plans and adaptive management [104].

Several design limits qualify these interpretations. Titles, abstracts, and keywords may omit a link present in the full text, so some studies may have entered the unclear category. Dictionary-based coding can miss synonyms and cannot judge ecological quality. The rule-based pathway classifier was not validated against a manually coded subsample, so its precision and recall are unknown, and the pathway proportions should be read as screening-level evidence from bibliographic metadata rather than as confirmed analytical workflows. The exclusive pathway hierarchy also assigns one label to studies that may contain several linked analyses. Scopus and Web of Science differ in journal coverage, language, and regional representation [90]. The exclusion of records indexed under Animals sharpened the focus on forest plants, habitats, and ecosystems, but it also limits inference about fauna. For that reason, fauna-specific movement validation falls beyond the corpus defined by the search, and it should not appear as a central recommendation here. These limits do not negate the observed corpus patterns, but they restrict claims to the literature visible under the stated search and classification rules. Three further limits follow from the search design. First, the combined query required the literal terms connectivity or landscape connectivity, so a publication that transferred an SDM output into a resistance surface or a least-cost corridor without using either term in its title, abstract, or keywords would have been assigned to the SDM-only corpus; the reverse omission is also possible. The reported prevalence of integration is therefore a lower bound, and a query built on a broader connectivity vocabulary would be expected to return a larger integrated corpus. Second, forest scope was defined operationally by retrieval under the forest term group, with no manual verification of the study system and no restriction on taxon, forest type, ecological process, or spatial grain; the corpus consequently mixes stand-level and continental analyses of tree species, forest-dwelling plants, and forest habitat types. The bare term ecosystem in the Scopus SDM and combined strings widened this definition further, admitting records with no explicit forest term, as noted in Section 3.1. Third, the directional measures compare shares computed on denominators of very different size and are reported as relative representation rather than as evidence about the direction of methodological transfer.

Future studies should begin with full-text classification of the transfer from suitability output to connectivity input. A common extraction protocol could record thresholds, patch rules, dispersal values, resistance transformations, temporal correspondence, validation data, and uncertainty. Comparative studies could apply least-cost, circuit, and graph methods to the same SDM ensemble and examine changes in forest priorities. Forest landscape models could add succession, harvest, fire, drought, and land-use change, because static land cover can misrepresent future access [86]. Genetic data, occurrence records, seed-dispersal observations, and recruitment surveys could test predicted links in plant and forest systems [18,25]. Future studies should also carry climate and SDM uncertainty into patch ranks and corridor priorities [33,75]. The main conclusion is that rapid publication growth has not yet resolved the analytical separation identified in the Introduction. Forest climate assessment will become more informative when habitat suitability and landscape access are evaluated as one linked study question.

5. Conclusions

This study shows that the rapid growth of SDM and connectivity research has not yet led to broad methodological integration. Only 244 of 5715 records combined the two approaches, and integrated work formed a larger share of the connectivity literature than of the SDM literature, a contrast that reflects the relative weight of integrated studies in each field rather than the direction of methodological transfer. Projected suitability surfaces were the point of connection most often detectable in the bibliographic record, while explicit application in corridor, resistance, least-cost, and network models was reported less often. The large group of co-occurrence or unclear cases also shows that many publications did not explain how suitability estimates entered the connectivity workflow. For forest conservation, this distinction matters because future suitable habitat has limited value if it is isolated from current populations or cannot be reached under existing landscape conditions. Future studies should state how SDM outputs define habitat patches, resistance values, corridor endpoints, or network nodes and should retain model uncertainty in the final connectivity estimates. A more transparent link between habitat suitability and landscape access would produce results that are easier to compare and more useful for forest planning under climate change.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/f17091024/s1; File S1: PRISMA_2020_checklist.

Author Contributions: Conceptualization, J.V., D.G. and S.E.H.; methodology, D.G.; software, D.G.; validation, S.E.H., formal analysis, D.G.; investigation, A.S.Ö.; resources, S.E.H. and D.G.; data curation, S.E.H.; writing—original draft preparation, S.E.H.; writing—review and editing, D.G., A.S.Ö., S.E.H. and J.V.; visualization, D.G.; supervision, J.V.; project administration, J.V.; funding acquisition, J.V. All authors have read and agreed to the published version of the manuscript.

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Data Availability Statement: The data presented in this study are available on request from the corresponding author.

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Conflicts of Interest: The authors declare no conflicts of interest.

Abbreviations

The following abbreviations are used in this manuscript:

ASCII	American Standard Code for Information Interchange
CI	Confidence interval
CMIP	Coupled Model Intercomparison Project
ENM	Ecological niche model
EXACTKEYWORD	Exact keyword field in Scopus
MaxEnt	Maximum entropy
PUBYEAR	Publication year field in Scopus
RCP	Representative concentration pathway
RQ	Research question
SDM	Species distribution model
SE	Standard error
SSP	Shared socioeconomic pathway
TITLE-ABS-KEY	Title, abstract, and keyword fields in Scopus
TS	Topic field in Web of Science
WoS	Web of Science

Appendix A

Table A1. Database-specific search strings, record yields, and consolidation outcomes for the species distribution modeling, landscape connectivity, and combined SDM–connectivity searches in Scopus and Web of Science.

Search Stream	Database	Complete Search String	Records Retrieved	Record Consolidation
Species distribution modeling (SDM)	Scopus	TITLE-ABS-KEY (“species distribution model” OR “habitat suitability model” OR “ecological niche model” OR “SDM” OR “ENM” OR “maxent”) AND TITLE-ABS-KEY (“forest species” OR “forest” OR “ecosystem” OR “forest ecosystem” OR “forestry” OR “forest habitat”) AND TITLE-ABS-KEY (“climate change” OR “global warming” OR “future scenarios”) AND PUBYEAR > 2009 AND PUBYEAR < 2026 AND EXCLUDE (EXACTKEYWORD, “Animals”)	3732	Scopus and WoS produced 6034 records before cross-database duplicate removal.
Species distribution modeling (SDM)	Web of Science	TS = (“species distribution model” OR “habitat suitability model” OR “ecological niche model” OR “SDM” OR “ENM”) AND TS = (“forest species” OR “forest” OR “forestry” OR “forest ecosystem” OR “forest habitat”) AND TS = (“climate change” OR “global warming” OR “future scenarios”) NOT TS = (“animal”)	2302	
Landscape connectivity	Scopus	TITLE-ABS-KEY (“connectivity” OR “landscape connectivity”) AND TITLE-ABS-KEY (“forest species” OR “forest” OR “forest ecosystem” OR “forest habitat” OR “forestry”) AND TITLE-ABS-KEY (“climate change” OR “global warming” OR “future scenarios”) AND PUBYEAR > 2009 AND PUBYEAR < 2026 AND EXCLUDE (EXACTKEYWORD, “Animals”)	743	Scopus and WoS produced 1593 records before duplicate removal.

Table A1. *Cont.*

Search Stream	Database	Complete Search String	Records Retrieved	Record Consolidation
Landscape connectivity	Web of Science	TS = (“connectivity” OR “landscape connectivity”) AND TS = (“forest species” OR “forest” OR “forestry” OR “forest ecosystem” OR “forest habitat”) AND TS = (“climate change” OR “global warming” OR “future scenarios”) NOT TS = (“animal”)	850	Scopus and WoS produced 1593 records before duplicate removal.
Combined SDM and landscape connectivity	Scopus	TITLE-ABS-KEY (“species distribution model” OR “habitat suitability model” OR “ecological niche model” OR “SDM” OR “ENM” OR “maxent”) AND TITLE-ABS-KEY (“connectivity” OR “landscape connectivity”) AND TITLE-ABS-KEY (“forest species” OR “forest” OR “forestry” OR “ecosystem” OR “forest ecosystem” OR “forest habitat”) AND TITLE-ABS-KEY (“climate change” OR “global warming” OR “future scenarios”) AND PUBYEAR > 2009 AND PUBYEAR < 2026 AND EXCLUDE (EXACTKEYWORD, “Animals”)	182	Scopus and WoS produced 338 records in total. After cross-database consolidation, 245 candidate records remained. One residual duplicate was removed, leaving 244 unique records.
Combined SDM and landscape connectivity	Web of Science	TS = (“species distribution model” OR “habitat suitability model” OR “ecological niche model” OR “SDM” OR “ENM”) AND TS = (“connectivity” OR “landscape connectivity”) AND TS = (“forest species” OR “forest” OR “forestry” OR “forest ecosystem” OR “forest habitat”) AND TS = (“climate change” OR “global warming” OR “future scenarios”) NOT TS = (“animal”)	156	

Table A2. Frequency-normalized association strengths for all retained cross-domain keyword pairs in the integrated corpus (association strength = N × Oij/(fi × fj), where N = 244, Oij is the observed pair count, and fi and fj are the marginal term frequencies. The $\log_2$ column reports $\log_2$ (association strength). Figure 5 uses raw co-occurrence for ribbon width).

Rank	SDM-Related Term	Connectivity-Related Term	Association Strength	$\log_2$ Strength
1	Machine learning	Circuit theory	3.486	1.802
2	MaxEnt	Least-cost path	2.169	1.117
3	Ecological niche	Least-cost path	2.033	1.024
4	Habitat suitability	Circuit theory	1.914	0.937
5	Habitat suitability	Corridor	1.823	0.866
6	Species distribution model	Habitat fragmentation	1.291	0.368
7	Ecological niche	Habitat fragmentation	1.271	0.346
8	Habitat suitability	Habitat fragmentation	1.196	0.258
9	Habitat suitability	Landscape connectivity	1.163	0.218
10	Machine learning	Landscape connectivity	1.140	0.189
11	Machine learning	Dispersal/range shift	1.137	0.185
12	Species distribution model	Dispersal/range shift	1.123	0.167
13	MaxEnt	Habitat fragmentation	1.084	0.116
14	Species distribution model	Least-cost path	1.069	0.096
15	Ecological niche	Landscape connectivity	1.045	0.064
16	MaxEnt	Corridor	1.033	0.047
17	Species distribution model	Corridor	1.018	0.026
18	Species distribution model	Landscape connectivity	1.015	0.021
19	Ecological niche	Dispersal/range shift	0.884	−0.178
20	MaxEnt	Landscape connectivity	0.811	−0.302

Table A2. *Cont.*

Rank	SDM-Related Term	Connectivity-Related Term	Association Strength	$\log_2$ Strength
21	Habitat suitability	Dispersal/range shift	0.624	−0.680
22	Species distribution model	Circuit theory	0.534	−0.905
23	Ecological niche	Corridor	0.484	−1.047
24	MaxEnt	Dispersal/range shift	0.471	−1.086

References

1. Chen, I.-C.; Hill, J.K.; Ohlemüller, R.; Roy, D.B.; Thomas, C.D. Rapid Range Shifts of Species Associated with High Levels of Climate Warming. *Science* **2011**, *333*, 1024–1026. [CrossRef]
2. Kelleher, S.; Guillera-Arroita, G.; Elith, J.; Briscoe, N.J. Twenty Years of Dynamic Occupancy Models: A Review of Applications and Look to the Future. *Ecography* **2026**, *2026*, e07757. [CrossRef]
3. Parmesan, C.; Yohe, G. A Globally Coherent Fingerprint of Climate Change Impacts across Natural Systems. *Nature* **2003**, *421*, 37–42. [CrossRef]
4. Root, T.L.; Price, J.T.; Hall, K.R.; Schneider, S.H.; Rosenzweig, C.; Pounds, J.A. Fingerprints of Global Warming on Wild Animals and Plants. *Nature* **2003**, *421*, 57–60. [CrossRef]
5. Pearson, R.G.; Dawson, T.P. Predicting the Impacts of Climate Change on the Distribution of Species: Are Bioclimate Envelope Models Useful? *Glob. Ecol. Biogeogr.* **2003**, *12*, 361–371. [CrossRef]
6. Thomas, C.D.; Cameron, A.; Green, R.E.; Bakkenes, M.; Beaumont, L.J.; Collingham, Y.C.; Erasmus, B.F.; De Siqueira, M.F.; Grainger, A.; Hannah, L. Extinction Risk from Climate Change. *Nature* **2004**, *427*, 145–148. [CrossRef]
7. Opdam, P.; Wascher, D. Climate Change Meets Habitat Fragmentation: Linking Landscape and Biogeographical Scale Levels in Research and Conservation. *Biol. Conserv.* **2004**, *117*, 285–297. [CrossRef]
8. With, K.A.; Gardner, R.H.; Turner, M.G. Landscape Connectivity and Population Distributions in Heterogeneous Environments. *Oikos* **1997**, *78*, 151–169. [CrossRef]
9. Biancolini, D.; Broennimann, O.; Guisan, A.; Rondinini, C. Global Patterns of Niche Changes in Alien Mammals: Potential Drivers and Significance for Invasion Projections. *Glob. Change Biol.* **2026**, *32*, e70755. [CrossRef]
10. Taylor, P.D.; Fahrig, L.; Henein, K.; Merriam, G. Connectivity Is a Vital Element of Landscape Structure. *Oikos* **1993**, *68*, 571–573. [CrossRef]
11. Vos, C.C.; Berry, P.; Opdam, P.; Baveco, H.; Nijhof, B.; O'Hanley, J.; Bell, C.; Kuipers, H.; Nijho, B. Adapting Landscapes to Climate Change: Examples of Climate-Proof Ecosystem Networks and Priority Adaptation Zones. *J. Appl. Ecol.* **2008**, *45*, 1722–1731. [CrossRef]
12. Fahrig, L. Effects of Habitat Fragmentation on Biodiversity. *Annu. Rev. Ecol. Evol. Syst.* **2003**, *34*, 487–515. [CrossRef]
13. Hannah, L.; Midgley, G.F.; Millar, D. Climate Change-integrated Conservation Strategies. *Glob. Ecol. Biogeogr.* **2002**, *11*, 485–495. [CrossRef]
14. Rudnick, D.; Ryan, S.J.; Beier, P.; Cushman, S.A.; Dieffenbach, F.; Epps, C.; Gerber, L.R.; Hartter, J.N.; Jenness, J.S.; Kintsch, J. *The Role of Landscape Connectivity in Planning and Implementing Conservation and Restoration Priorities*; Issues in Ecology; Ecological Society of America: Washington, DC, USA, 2012.
15. Turner, M. *Landscape Ecology in Theory and Practice: Pattern Process*; Springer: New York, NY, USA, 2001.
16. Haddad, N.M.; Brudvig, L.A.; Clobert, J.; Davies, K.F.; Gonzalez, A.; Holt, R.D.; Lovejoy, T.E.; Sexton, J.O.; Austin, M.P.; Collins, C.D.; et al. Habitat Fragmentation and Its Lasting Impact on Earth's Ecosystems. *Sci. Adv.* **2015**, *1*, e1500052. [CrossRef]
17. Keppel, G.; Van Niel, K.P.; Wardell-Johnson, G.W.; Yates, C.J.; Byrne, M.; Mucina, L.; Schut, A.G.T.; Hopper, S.D.; Franklin, S.E. Refugia: Identifying and Understanding Safe Havens for Biodiversity under Climate Change. *Glob. Ecol. Biogeogr.* **2012**, *21*, 393–404. [CrossRef]
18. Manel, S.; Schwartz, M.K.; Luikart, G.; Taberlet, P. Landscape Genetics: Combining Landscape Ecology and Population Genetics. *Trends Ecol. Evol.* **2003**, *18*, 189–197. [CrossRef]
19. Bellard, C.; Bertelsmeier, C.; Leadley, P.; Thuiller, W.; Courchamp, F. Impacts of Climate Change on the Future of Biodiversity. *Ecol. Lett.* **2012**, *15*, 365–377. [CrossRef]
20. Tilman, D.; May, R.M.; Lehman, C.L.; Nowak, M.A. Habitat Destruction and the Extinction Debt. *Biol. Conserv.* **1995**, *3*, 409. [CrossRef]
21. Beier, P.; Noss, R.F. Do Habitat Corridors Provide Connectivity? *Conserv. Biol.* **1998**, *12*, 1241–1252. [CrossRef]
22. Krosby, M.; Tewksbury, J.; Haddad, N.M.; Hoekstra, J. Ecological Connectivity for a Changing Climate. *Conserv. Biol.* **2010**, *24*, 1686–1689. [CrossRef]

23. Dobrowski, S.Z. A Climatic Basis for Microrefugia: The Influence of Terrain on Climate. *Glob. Change Biol.* **2011**, *17*, 1022–1035. [CrossRef]
24. Guisan, A.; Chevalier, M.; Adde, A.; Zarzo-Arias, A.; Goicolea, T.; Broennimann, O.; Petitpierre, B.; Scherrer, D.; Rey, P.-L.; Collart, F.; et al. Spatially Nested Species Distribution Models (N-SDM): An Effective Tool to Overcome Niche Truncation for More Robust Inference and Projections. *J. Ecol.* **2025**, *113*, 1588–1605. [CrossRef]
25. Sork, V.L.; Smouse, P.E. Genetic Analysis of Landscape Connectivity in Tree Populations. *Landsc. Ecol.* **2006**, *21*, 821–836. [CrossRef]
26. Araújo, M.B.; Guisan, A. Five (or so) Challenges for Species Distribution Modelling. *J. Biogeogr.* **2006**, *33*, 1677–1688. [CrossRef]
27. Elith, J.; Leathwick, J.R. Species Distribution Models: Ecological Explanation and Prediction Across Space and Time. *Annu. Rev. Ecol. Evol. Syst.* **2009**, *40*, 677–697. [CrossRef]
28. Guisan, A.; Thuiller, W. Predicting Species Distribution: Offering More than Simple Habitat Models. *Ecol. Lett.* **2005**, *8*, 993–1009. [CrossRef] [PubMed]
29. Guisan, A.; Zimmermann, N.E. Predictive Habitat Distribution Models in Ecology. *Ecol. Model.* **2000**, *135*, 147–186. [CrossRef]
30. Phillips, S.J.; Anderson, R.P.; Schapire, R.E. Maximum Entropy Modeling of Species Geographic Distributions. *Ecol. Model.* **2006**, *190*, 231–259. [CrossRef]
31. Soberon, J.; Peterson, A.T. Interpretation of Models of Fundamental Ecological Niches and Species' Distributional Areas. *Biodivers. Inform.* **2005**, *2*, 1–10. [CrossRef]
32. Thuiller, W.; Lafourcade, B.; Engler, R.; Araújo, M.B. BIOMOD—A Platform for Ensemble Forecasting of Species Distributions. *Ecography* **2009**, *32*, 369–373. [CrossRef]
33. Zurell, D.; Franklin, J.; König, C.; Bouchet, P.J.; Dormann, C.F.; Elith, J.; Fandos, G.; Feng, X.; Guillera-Arroita, G.; Guisan, A.; et al. A Standard Protocol for Reporting Species Distribution Models. *Ecography* **2020**, *43*, 1261–1277. [CrossRef]
34. Riahi, K.; Van Vuuren, D.P.; Kriegler, E.; Edmonds, J.; O'neill, B.C.; Fujimori, S.; Bauer, N.; Calvin, K.; Dellink, R.; Fricko, O. The Shared Socioeconomic Pathways and Their Energy, Land Use, and Greenhouse Gas Emissions Implications: An Overview. *Glob. Environ. Change* **2017**, *42*, 153–168. [CrossRef]
35. Van Vuuren, D.P.; Edmonds, J.; Kainuma, M.; Riahi, K.; Thomson, A.; Hibbard, K.; Hurtt, G.C.; Kram, T.; Krey, V.; Lamarque, J.-F.; et al. The Representative Concentration Pathways: An Overview. *Clim. Change* **2011**, *109*, 5–31. [CrossRef]
36. Araújo, M.B.; Peterson, A.T. Uses and Misuses of Bioclimatic Envelope Modeling. *Ecology* **2012**, *93*, 1527–1539. [CrossRef] [PubMed]
37. García del Barrio, J.M.; Guadaño-Peyrot, C.; Grivet, D.; Olsson, S.; Barba, D.; Auñon, F.; Chacón-Moreno, E.; Fernández-Pastor, M.; Gaitán, E.; Mateo, R.G. Vulnerability to Climate Change of Forest Genetic Conservation Units Assessed Through Species Distribution Models. *Land* **2026**, *15*, 890. [CrossRef]
38. Sara, S.; Wilfried, T.; Esther, G.; Thibaud, D.; Sylvain, G.; Daniel, F.M.; Claire, M.; Yvan, C.; Mickaël, H. Digging Deeper: Deep Joint Species Distribution Modeling Reveals Environmental Drivers of Earthworm Communities. *Soil Biol. Biochem.* **2026**, *212*, 110021. [CrossRef]
39. Kramer-Schadt, S.; Niedballa, J.; Pilgrim, J.D.; Schröder, B.; Lindenborn, J.; Reinfelder, V.; Stillfried, M.; Heckmann, I.; Scharf, A.K.; Augeri, D.M.; et al. The Importance of Correcting for Sampling Bias in MaxEnt Species Distribution Models. *Divers. Distrib.* **2013**, *19*, 1366–1379. [CrossRef]
40. Shen, C.; Chen, X.; Zhou, C.; Xu, L.; Qian, M.; Zhao, H.; Li, K. Predicting Suitable Spatial Distribution Areas for Urban Trees Under Climate Change Scenarios Using Species Distribution Models: A Case Study of Michelia Chapensis. *Land* **2025**, *14*, 638. [CrossRef]
41. Beck, J.; Böller, M.; Erhardt, A.; Schwanghart, W. Spatial Bias in the GBIF Database and Its Effect on Modeling Species' Geographic Distributions. *Ecol. Inform.* **2014**, *19*, 10–15. [CrossRef]
42. Tümer, Y.Ö.; Caglayan, I.; Yeşil, A.; Iverson, L. Two Decades of Species Distribution Modeling: A Systematic Review of Methods and Applications. *Ecol. Model.* **2026**, *513*, 111441. [CrossRef]
43. Heller, N.E.; Zavaleta, E.S. Biodiversity Management in the Face of Climate Change: A Review of 22 Years of Recommendations. *Biol. Conserv.* **2009**, *142*, 14–32. [CrossRef]
44. Saura, S.; Pascual-Hortal, L. A New Habitat Availability Index to Integrate Connectivity in Landscape Conservation Planning: Comparison with Existing Indices and Application to a Case Study. *Landsc. Urban Plan.* **2007**, *83*, 91–103. [CrossRef]
45. Bedson, C.P.E.; Payne, B.L.; Sutherland, C.; Greaves, D.J.; White, H.E.; Buchanan, F.; Crick, H.Q.P. Designing a Climate Change Resilient Landscape Connectivity Network from a Multi-Species Perspective. *Ecol. Evol.* **2025**, *15*, e71956. [CrossRef]
46. Hof, A.R.; Mina, M.; Mairota, P.; Aguilar, F.; Leitinger, G.; Br\uuna, J.; Koivula, M.; Klopčič, M.; Sjögren, J.; Vacchiano, G. A Perspective on the Need for Integrated Frameworks Linking Species Distribution and Dynamic Forest Landscape Models across Spatial Scales. *Front. Ecol. Evol.* **2024**, *12*, 1112712. [CrossRef]
47. Hanski, I. Metapopulation Dynamics. *Nature* **1998**, *396*, 41–49. [CrossRef]

48. Jennings, M.K.; Zeller, K.A.; Lewison, R.L. Supporting Adaptive Connectivity in Dynamic Landscapes. *Land* **2020**, *9*, 295. [CrossRef]
49. Lapin, K.; Oettel, J.; Braun, M.; Konrad, H. (Eds.) *Ecological Connectivity of Forest Ecosystems*; Springer Nature: Cham, Switzerland, 2025; ISBN 978-3-031-82205-6.
50. Martínez-Richart, A.I.; Zolles, A.; Oettel, J.; Petermann, J.S.; Essl, F.; Lapin, K. A Review of Structural and Functional Connectivity Studies in European Forests. *Landsc. Ecol.* **2024**, *40*, 10. [CrossRef]
51. Tischendorf, L.; Fahrig, L. On the Usage and Measurement of Landscape Connectivity. *Oikos* **2000**, *90*, 7–19. [CrossRef]
52. Aitken, S.N.; Whitlock, M.C. Assisted Gene Flow to Facilitate Local Adaptation to Climate Change. *Annu. Rev. Ecol. Evol. Syst.* **2013**, *44*, 367–388. [CrossRef]
53. Fahrig, L. Ecological Responses to Habitat Fragmentation per Se. *Annu. Rev. Ecol. Evol. Syst.* **2017**, *48*, 1–23. [CrossRef]
54. Adriaensen, F.; Chardon, J.P.; De Blust, G.; Swinnen, E.; Villalba, S.; Gulinck, H.; Matthysen, E. The Application of 'Least-Cost' Modelling as a Functional Landscape Model. *Landsc. Urban Plan.* **2003**, *64*, 233–247. [CrossRef]
55. Bai, H.; Zhang, Y.; Huang, J.; Chen, H. Constructing Ecological Networks and Analyzing Impact Factors in Multi-Scenario Simulation Under Climate Change. *Land* **2025**, *14*, 1120. [CrossRef]
56. Foltête, J.-C.; Vuidel, G. Landscape Graphs as Tools for Modelling and Managing Spatial Ecological Networks: Current Limits and New Challenges. *Environ. Model. Softw.* **2025**, *193*, 106594. [CrossRef]
57. Zhuge, M.; Wei, L.; Wang, J.; Hu, Y. Assessing the Impact of the G331 Highway on Three Types of Wildlife Groups' Habitat and Connectivity in Changbai Mountain Using a Multi-Model Framework. *Land* **2026**, *15*, 238. [CrossRef]
58. McRae, B.H.; Dickson, B.G.; Keitt, T.H.; Shah, V.B. Using Circuit Theory to Model Connectivity in Ecology, Evolution, and Conservation. *Ecology* **2008**, *89*, 2712–2724. [CrossRef]
59. Hashemi, R.; Darabi, H.; Hashemi, M.; Wang, J. Graph Theory in Ecological Network Analysis: A Systematic Review for Connectivity Assessment. *J. Clean. Prod.* **2024**, *472*, 143504. [CrossRef]
60. Lalechère, E.; Bergès, L. A Validation Procedure for Ecological Corridor Locations. *Land* **2021**, *10*, 1320. [CrossRef]
61. Urban, D.; Keitt, T. Landscape Connectivity: A Graph-theoretic Perspective. *Ecology* **2001**, *82*, 1205–1218. [CrossRef]
62. Brodie, J.F.; Gonzalez, A.; Mohd-Azlan, J.; Nelson, C.R.; Tabor, G.; Vasudev, D.; Zeller, K.A.; Fletcher, R.J. A Well-Connected Earth: The Science and Conservation of Organismal Movement. *Science* **2025**, *388*, eadn2225. [CrossRef]
63. Schumaker, N.H. A Rapid Assessment Methodology for Quantifying and Visualizing Functional Landscape Connectivity. *Front. Conserv. Sci.* **2024**, *5*, 1412888. [CrossRef]
64. Jackson, S.T.; Sax, D.F. Balancing Biodiversity in a Changing Environment: Extinction Debt, Immigration Credit and Species Turnover. *Trends Ecol. Evol.* **2010**, *25*, 153–160. [CrossRef]
65. Loarie, S.R.; Duffy, P.B.; Hamilton, H.; Asner, G.P.; Field, C.B.; Ackerly, D.D. The Velocity of Climate Change. *Nature* **2009**, *462*, 1052–1055. [CrossRef]
66. Corlett, R.T.; Westcott, D.A. Will Plant Movements Keep up with Climate Change? *Trends Ecol. Evol.* **2013**, *28*, 482–488. [CrossRef]
67. Wang, D.; Li, W.; Guo, N.; Li, C. Impacts of Climate Change on Habitat Suitability and Landscape Connectivity of the Amur Tiger in the Sino-Russian Transboundary Region. *Animals* **2025**, *15*, 2466. [CrossRef]
68. Esser, L.F.; Neves, D.; Jarenkow, J.A. Species Distribution Models to Help Integrate Community Ecology. *Austral Ecol.* **2025**, *50*, e70091. [CrossRef]
69. Riva, F.; Martin, C.J.; Galán Acedo, C.; Bellon, E.N.; Keil, P.; Morán-Ordóñez, A.; Fahrig, L.; Guisan, A. Incorporating Effects of Habitat Patches into Species Distribution Models. *J. Ecol.* **2024**, *112*, 2162–2182. [CrossRef]
70. Struebig, M.J.; Wenzler, M.; Runting, R.K.; Law, E.; Budiharta, S.; Seaman, D.; Kramer-Schadt, S. Connectivity Conservation to Mitigate Climate and Land-Cover Change Impacts on Borneo. *Biol. Conserv.* **2024**, *299*, 110838. [CrossRef]
71. Zeller, K.A.; Compton, B.W.; Finn, S.P.; Palm, E.C. Measuring Ecological Connectivity with Ecological Distance and Dynamic Resistant Kernels. *Landsc. Ecol.* **2024**, *39*, 95. [CrossRef]
72. Gonzalez, P.; Neilson, R.P.; Lenihan, J.M.; Drapek, R.J. Global Patterns in the Vulnerability of Ecosystems to Vegetation Shifts Due to Climate Change. *Glob. Ecol. Biogeogr.* **2010**, *19*, 755–768. [CrossRef]
73. McLachlan, J.S.; Hellmann, J.J.; Schwartz, M.W. A Framework for Debate of Assisted Migration in an Era of Climate Change. *Conserv. Biol.* **2007**, *21*, 297–302. [CrossRef]
74. Bourdouxhe, A.; Duflot, R.; Radoux, J.; Dufrêne, M. Comparison of Methods to Model Species Habitat Networks for Decision-Making in Nature Conservation: The Case of the Wildcat in Southern Belgium. *J. Nat. Conserv.* **2020**, *58*, 125901. [CrossRef]
75. De Kort, H.; Baguette, M.; Lenoir, J.; Stevens, V.M. Toward Reliable Habitat Suitability and Accessibility Models in an Era of Multiple Environmental Stressors. *Ecol. Evol.* **2020**, *10*, 10937–10952. [CrossRef]
76. Soret, M.; Moulherat, S.; Lenormand, M.; Luque, S. Implication of Modelling Choices on Connectivity Estimation: A Comparative Analysis. *arXiv* **2024**, arXiv:2407.09564.
77. Pan, Y.; Birdsey, R.A.; Fang, J.; Houghton, R.; Kauppi, P.E.; Kurz, W.A.; Phillips, O.L.; Shvidenko, A.; Lewis, S.L.; Canadell, J.G.; et al. A Large and Persistent Carbon Sink in the World's Forests. *Science* **2011**, *333*, 988–993. [CrossRef]

78. Saatchi, S.S.; Harris, N.L.; Brown, S.; Lefsky, M.; Mitchard, E.T.A.; Salas, W.; Zutta, B.R.; Buermann, W.; Lewis, S.L.; Hagen, S.; et al. Benchmark Map of Forest Carbon Stocks in Tropical Regions across Three Continents. *Proc. Natl. Acad. Sci. USA* **2011**, *108*, 9899–9904. [CrossRef]
79. Allen, C.D.; Macalady, A.K.; Chenchouni, H.; Bachelet, D.; McDowell, N.; Vennetier, M.; Kitzberger, T.; Rigling, A.; Breshears, D.D.; Hogg, E.T. A Global Overview of Drought and Heat-Induced Tree Mortality Reveals Emerging Climate Change Risks for Forests. *For. Ecol. Manag.* **2010**, *259*, 660–684. [CrossRef]
80. Bonan, G.B. Forests and Climate Change: Forcings, Feedbacks, and the Climate Benefits of Forests. *Science* **2008**, *320*, 1444–1449. [CrossRef]
81. Bohnett, E.; Oetting, J.; Noss, R.; O'Brien, M.; Frakes, R.; Smith, D.; Lockhart, S.; Mullinax, J.; Poor, E.E.; Scheick, B.; et al. Consolidating Diverse Modeling Methods and Spatial Prioritization for Multispecies Connectivity Planning. *Front. Conserv. Sci.* **2024**, *5*, 1406944. [CrossRef]
82. Rivas, C.A.; Palacios-Rodríguez, G.; Navarro-Cerrillo, R.M. Landscape Disruption in a Fragmented World: A Critical Global Analysis. *J. Environ. Manag.* **2026**, *411*, 130131. [CrossRef]
83. Wickenberg, B.; McCormick, K.; Olsson, J.A. Advancing the Implementation of Nature-Based Solutions in Cities: A Review of Frameworks. *Environ. Sci. Policy* **2021**, *125*, 44–53. [CrossRef]
84. Xu, D.; Peng, J.; Liu, M.; Jiang, H.; Tang, H.; Dong, J.; Meersmans, J. Bridging Climate Refuges for Climate Change Adaptation: A Spatio-Temporal Connectivity Network Approach. *Geogr. Sustain.* **2025**, *6*, 100235. [CrossRef]
85. Cramer, W.; Bondeau, A.; Woodward, F.I.; Prentice, I.C.; Betts, R.A.; Brovkin, V.; Cox, P.M.; Fisher, V.; Foley, J.A.; Friend, A.D.; et al. Global Response of Terrestrial Ecosystem Structure and Function to CO_2 and Climate Change: Results from Six Dynamic Global Vegetation Models. *Glob. Change Biol.* **2001**, *7*, 357–373. [CrossRef]
86. Seidl, R.; Thom, D.; Kautz, M.; Martin-Benito, D.; Peltoniemi, M.; Vacchiano, G.; Wild, J.; Ascoli, D.; Petr, M.; Honkaniemi, J. Forest Disturbances under Climate Change. *Nat. Clim. Change* **2017**, *7*, 395–402. [CrossRef]
87. Ahrens, D.; Benedikter, S.; Giessen, L. Rethinking Synergies and Trade-Offs at the Forest-Sustainable Development Goals (SDGs) Nexus—A Systematic Review. *Sustain. Dev.* **2025**, *33*, 5069–5090. [CrossRef]
88. Costa, J.R.S.; Brancalion, P.H.S.; Joly, F.-X.; Simões, L.H.P.; Bonfanti, J.; Le Maire, G.; Robin, A.; Guillemot, J. Forest Ecosystem Multifunctionality: A Systematic Review of Measures and Drivers. *Curr. For. Rep.* **2026**, *12*, 2. [CrossRef]
89. Genc, N.; Colak, H.E.; Baser, V. Towards Sustainable Futures: An Interdisciplinary Bridge—A Bibliometric Review on Climate Change, Agriculture, Land Management, and GIS. *Sustain. Dev.* **2025**, *33*, 5848–5873. [CrossRef]
90. Mongeon, P.; Paul-Hus, A. The Journal Coverage of Web of Science and Scopus: A Comparative Analysis. *Scientometrics* **2016**, *106*, 213–228. [CrossRef]
91. Ver Hoef, J.M.; Boveng, P.L. Quasi-Poisson vs. Negative Binomial Regression: How Should We Model Overdispersed Count Data? *Ecology* **2007**, *88*, 2766–2772. [CrossRef]
92. Dixon, W.J.; Mood, A.M. The Statistical Sign Test. *J. Am. Stat. Assoc.* **1946**, *41*, 557–566. [CrossRef]
93. Van Eck, N.J.; Waltman, L. How to Normalize Cooccurrence Data? An Analysis of Some Well-Known Similarity Measures. *J. Am. Soc. Inf. Sci. Technol.* **2009**, *60*, 1635–1651. [CrossRef]
94. Gu, Z.; Gu, L.; Eils, R.; Schlesner, M.; Brors, B. "Circlize" Implements and Enhances Circular Visualization in R. *Bioinformatics* **2014**, *30*, 2811–2812. [CrossRef] [PubMed]
95. Hodgson, J.A.; Thomas, C.D.; Wintle, B.A.; Moilanen, A. Climate Change, Connectivity and Conservation Decision Making: Back to Basics. *J. Appl. Ecol.* **2009**, *46*, 964–969. [CrossRef]
96. Littlefield, C.E.; Krosby, M.; Michalak, J.L.; Lawler, J.J. Connectivity for Species on the Move: Supporting Climate-Driven Range Shifts. *Front. Ecol. Environ.* **2019**, *17*, 270–278. [CrossRef]
97. Nuñez, T.A.; Lawler, J.J.; Mcrae, B.H.; Pierce, D.J.; Krosby, M.B.; Kavanagh, D.M.; Singleton, P.H.; Tewksbury, J.J. Connectivity Planning to Address Climate Change. *Conserv. Biol.* **2013**, *27*, 407–416. [CrossRef]
98. Merow, C.; Smith, M.J.; Silander, J.A., Jr. A Practical Guide to MaxEnt for Modeling Species' Distributions: What It Does, and Why Inputs and Settings Matter. *Ecography* **2013**, *36*, 1058–1069. [CrossRef]
99. Beier, P.; Majka, D.R.; Spencer, W.D. Forks in the Road: Choices in Procedures for Designing Wildland Linkages. *Conserv. Biol.* **2008**, *22*, 836–851. [CrossRef]
100. Zeller, K.A.; McGarigal, K.; Whiteley, A.R. Estimating Landscape Resistance to Movement: A Review. *Landsc. Ecol.* **2012**, *27*, 777–797. [CrossRef]
101. Rayfield, B.; Fortin, M.-J.; Fall, A. Connectivity for Conservation: A Framework to Classify Network Measures. *Ecology* **2011**, *92*, 847–858. [CrossRef]
102. Spear, S.F.; Balkenhol, N.; Fortin, M.-J.; McRae, B.H.; Scribner, K.I.M. Use of Resistance Surfaces for Landscape Genetic Studies: Considerations for Parameterization and Analysis. *Mol. Ecol.* **2010**, *19*, 3576–3591. [CrossRef]

103. McGuire, J.L.; Lawler, J.J.; McRae, B.H.; Nuñez, T.A.; Theobald, D.M. Achieving Climate Connectivity in a Fragmented Landscape. *Proc. Natl. Acad. Sci. USA* **2016**, *113*, 7195–7200. [CrossRef]
104. Millar, C.I.; Stephenson, N.L.; Stephens, S.L. Climate Change and Forests of the Future: Managing in the Face of Uncertainty. *Ecol. Appl.* **2007**, *17*, 2145–2151. [CrossRef]

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