

Article

Marine Mammal Monitoring Research from 2014 to 2023: A Bibliometric Analysis of Collaboration, Technological Trends and Research Themes

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Abstract

Marine mammal monitoring research has expanded considerably alongside developments in acoustic, remote-sensing, telemetry, molecular, and computational approaches. This study used bibliometric analysis to characterise the structure and evolution of research published between 2014 and 2023. A total of 2586 peer-reviewed publications retrieved from the Web of Science Core Collection were analysed using CiteSpace to examine publication trends, collaboration networks, keyword co-occurrence, temporal clusters, and citation bursts. Annual publication output increased from 155 articles in 2014 to a peak of 362 in 2022, while collaboration networks revealed prominent research hubs across North America, Europe, Asia, and Oceania. Passive acoustic monitoring remained a persistent and highly connected theme, alongside habitat modelling, environmental impact assessment, and conservation research. Temporal and keyword analyses indicated increasing attention to machine learning, artificial intelligence, remote sensing, and environmental DNA, reflecting a broader movement towards automated and multimodal monitoring approaches. These patterns demonstrate an increasingly interdisciplinary research landscape but do not establish the effectiveness or operational uptake of individual technologies. Challenges remain regarding method-specific limitations, data integration, standardisation, validation, and geographical coverage. This study provides a quantitative basis for identifying major research themes and informing future methodological priorities.

Keywords: marine mammals; bibliometric analysis; passive acoustic monitoring; machine learning; remote sensing; environmental DNA; conservation



Academic Editor: Azizur Rahman

Received: 17 September 2026

Revised: 12 October 2026

Accepted: 14 October 2026

Published: 17 October 2026

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1. Introduction

Marine mammals perform diverse ecological functions within marine ecosystems, including influencing trophic interactions, redistributing nutrients through feeding, excretion, and movement, and transferring organic matter and nutrients across marine habitats and water-column strata [1,2]. They can also act as indicators of environmental change and ecosystem health [3]. Monitoring their occurrence, distribution, abundance, movements, and behaviour is therefore important for understanding ecosystem dynamics, assessing anthropogenic pressures, and informing conservation and management. Conventional visual surveys from vessels or aircraft remain fundamental to marine mammal monitoring but are constrained by factors including weather, daylight, sea state, observer availability,

and animal detectability [4]. These limitations are particularly relevant in remote environments and under low-visibility conditions and have contributed to the development and increasing use of complementary monitoring technologies.

Passive acoustic monitoring (PAM) has become an important component of marine mammal research and monitoring. By detecting species-specific or taxon-specific vocalisations, PAM can provide continuous, non-invasive observations over extended temporal scales and under conditions in which visual monitoring may be ineffective. Advances in autonomous recording systems, signal processing, and automated detection and classification have further increased the volume and complexity of acoustic data that can be collected and analysed [5]. Machine-learning approaches, in particular, are increasingly being applied to large acoustic datasets to support automated detection and classification. Nevertheless, acoustic monitoring remains dependent on factors such as vocal activity, signal propagation, sensor configuration, and analytical performance and therefore represents one component of a broader monitoring framework rather than a universal substitute for other methods.

A range of complementary technologies has also expanded the marine mammal monitoring toolkit. Active acoustic systems, including specialised sonar and scientific echosounders, can provide detections independently of animal vocalisation [4,6]. Satellite telemetry and biologging can provide information on individual movements, habitat use, diving behaviour, and migration [7], while radar and thermal imaging offer additional detection capabilities under particular environmental and operational conditions [4]. Environmental DNA (eDNA) and automated analytical approaches have also created additional opportunities for detecting species presence and integrating biological observations with environmental information [8]. Combining acoustic, visual, telemetry, molecular, and environmental datasets may therefore provide a more comprehensive representation of marine mammal occurrence and ecology than any individual method alone.

The rapid diversification of monitoring approaches has, however, generated challenges as well as opportunities. Monitoring methods differ in spatial and temporal coverage, detection probability, taxonomic resolution, operational constraints, and data requirements. Increasing data volumes also create challenges for storage, processing, validation, standardisation, and integration across platforms and monitoring programmes. Geographic inequalities in research effort remain important, particularly in remote, deep-water, polar, and less intensively studied regions. These challenges provide context for interpreting the development of the research field but are not themselves directly quantified by the bibliometric methods used here. Keyword co-occurrence, temporal, and citation-burst analyses can identify the representation, relationships, and changing visibility of terms associated with topics such as data integration or standardisation within the published literature, but they cannot determine the extent to which these challenges have been resolved in monitoring practice. Consequently, understanding the development of marine mammal monitoring requires consideration not only of individual technologies but also of how research priorities, analytical approaches, and scientific collaborations have evolved.

Bibliometric analysis provides a quantitative framework for examining such changes across a large body of scientific literature. By analysing publication metadata, keywords, citation patterns, and collaboration networks, bibliometric methods can identify the structure and development of a research field, including major research themes, changes in thematic representation over time, and patterns of scientific collaboration [9]. Importantly, bibliometric indicators characterise patterns within the published literature rather than directly measuring the effectiveness, performance, or operational adoption of individual monitoring technologies. This distinction is particularly relevant in a rapidly developing field, where increasing publication activity around a method does not necessarily demonstrate corresponding improvements in monitoring performance or implementation.

Against this background, the present study provides a bibliometric analysis of peer-reviewed marine mammal monitoring research published between 2014 and 2023. Using records retrieved from the Web of Science Core Collection and analysed with CiteSpace, we examine (i) temporal trends in research output; (ii) country, institutional, and co-authorship collaboration networks; (iii) the co-occurrence and temporal development of major research themes; and (iv) topics exhibiting concentrated periods of increased citation activity identified through citation-burst analysis. The objective is to characterise how the structure and thematic emphasis of marine mammal monitoring research evolved over this ten-year period and to identify major research areas and changes in their representation over time, while recognising the methodological and inferential limitations inherent in bibliometric evidence.

2. Materials and Methods

2.1. Data Source and Search Strategy

Bibliographic records were retrieved from the Web of Science (WoS) Core Collection to characterise marine mammal monitoring research published between 2014 and 2023. WoS was selected because it provides structured bibliographic and citation metadata suitable for bibliometric and network analyses.

The literature search was conducted on 19 November 2024 using a publication-date window from January 2014 to December 2023. The 2014–2023 interval was retained as a fixed ten-year retrospective period comprising complete calendar years rather than being extended to include the partial 2024 publication year. Because retrieval occurred almost 11 months after the end of the final calendar year, the search incorporated records indexed during much of 2024 that were associated with the defined search window. Nevertheless, no subsequent repeat search was conducted after 19 November 2024, and residual effects of delayed indexing cannot therefore be excluded. The study should therefore be interpreted as a retrospective bibliometric analysis of the fixed 2014–2023 publication period, rather than as a continuously updated assessment of the literature available at the time of manuscript submission.

The search combined terms identifying marine mammals, monitoring or tracking activities, and monitoring methods or related research topics. The final topic search was:

TS = ((marine mammal* OR whales OR dolphins OR seals OR Cetaceans OR Pinnipeds) AND (monitoring OR tracking) AND (acoustic OR sonar OR radar OR infrared OR seismic OR visual OR satellite OR habitat OR migration OR survey)) NOT ("optimization algorithm" OR "sealing" OR "leakage" OR "manufacturing" OR "blade surface" OR "robotics").

The search expression was structured into three conceptual blocks combined using the Boolean operator AND: (i) marine mammal taxonomic terms; (ii) general monitoring or tracking terms; and (iii) a set of alternative terms representing monitoring methods, observational approaches, and broader spatial, ecological, and survey contexts. Terms within each block were connected by OR. Consequently, individual terms such as 'acoustic', 'radar', 'seismic', or 'visual' were not mandatory search terms; a record could satisfy the third block through any one of the listed alternatives. The third block was designed to provide broad thematic coverage by including terminology associated with acoustic and sonar-based methods, radar, infrared and visual observation, seismic applications, satellite-based approaches, habitat and migration studies, and surveys. The resulting strategy was intended to retrieve a broad cross-section of marine mammal monitoring research while retaining sufficient thematic specificity for bibliometric analysis. The NOT clause was used to reduce retrieval of records in which broadly applicable monitoring or technological terms, including expressions such as 'optimization algorithm', 'robotics', and 'leakage', occurred in unrelated industrial, engineering, or computational contexts. The excluded

expressions were therefore treated as semantic exclusion terms rather than as monitoring approaches considered irrelevant to marine mammal research.

2.2. Dataset Selection

The initial WoS search returned 2787 records. The results were restricted by document type to Articles and Review Articles, resulting in the final dataset of 2586 publications. Of these records, 2465 (95.3%) were classified as Article-type publications and 121 (4.7%) as Review-type publications. The two document categories were analysed together because the study was designed to characterise the structure and thematic development of the retrieved research literature as a whole, rather than to compare bibliometric patterns between publication types. No additional language-based exclusion was applied to the exported dataset; 2573 records (99.5%) were indexed by WoS as English and 13 (0.5%) as other languages. The scope of the dataset was determined primarily by the bibliographic search expression and document-type restriction described above. Conference abstracts, standalone book chapters, grey literature, and other document types outside the Article and Review Article categories were not included in the analysed dataset.

Full bibliographic records and cited references for the 2586 retained publications were exported from WoS in plain-text format in six sequential batches of up to 500 records for subsequent processing in CiteSpace. The batches represented non-overlapping segments of the same WoS result set. Verification of record identifiers across the exported files confirmed 2586 unique WoS accession numbers and no duplicate records. The literature retrieval and dataset-selection process is summarised in Figure 1.

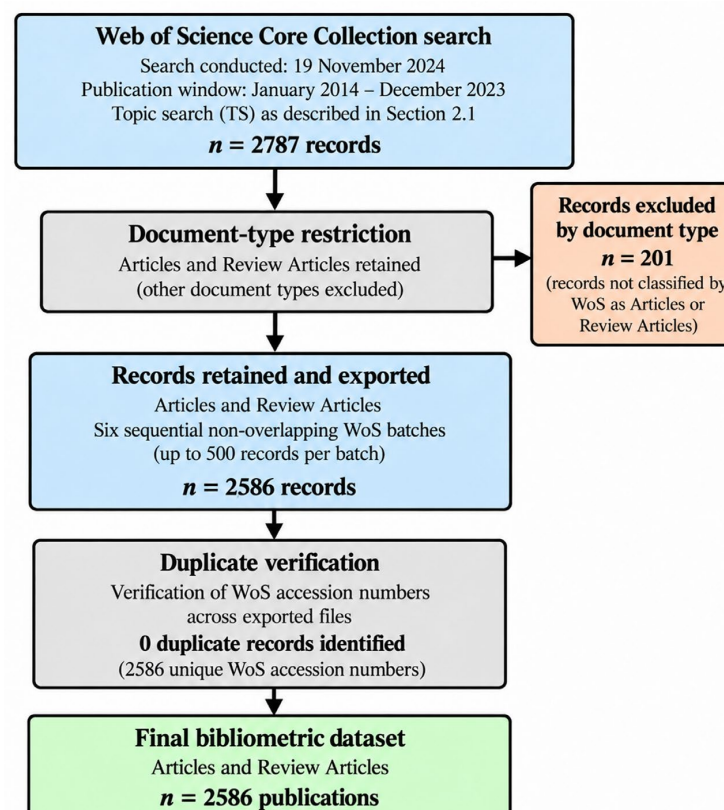


Figure 1. Bibliographic record retrieval and dataset-selection workflow for the bibliometric analysis.

2.3. Data Preprocessing and Term Normalisation

Prior to network analysis, synonymous or closely related terms were consolidated using the CiteSpace 6.3.R1 Alias function to reduce artificial fragmentation of the

bibliographic networks. Normalisation included singular and plural forms, common and scientific species names, British and American spelling variants, abbreviations, semantically equivalent or closely related terms, and alternative representations of institutional names. For example, *bottlenose dolphin* and *bottlenose dolphins*, *common dolphin* and *Delphinus delphis*, and *eDNA* and *environmental DNA* were consolidated. Institutional variants referring to the same organisation were similarly harmonised where appropriate. This preprocessing was applied to improve consistency in keyword and institutional representation before network construction.

2.4. Bibliometric and Network Analysis

Data processing, network construction, and visualisation were performed using CiteSpace version 6.3.R1 without additional analytical code [10,11]. Network analyses were conducted for country, institution, author, and keyword node types, according to the analytical objective of each network. The g-index was used as the node-selection criterion because it provides a citation-sensitive approach to selecting influential items within each time slice and is recommended for node selection in CiteSpace [10]. Unlike fixed Top N or Top N% criteria, which retain a predetermined number or proportion of the most highly cited items per slice, g-index selection is based on cumulative citation performance, with the scaling factor k controlling the size of the selected set. In the present analysis, k was adjusted during network construction to control network size while maintaining approximately 200 nodes. The exact run-specific values of the g-index scaling factor k and the complete parameter configurations for the original CiteSpace analyses were not preserved in the analytical records. Consequently, settings that could not be independently verified, including any additional threshold or link-selection parameters, are not reported retrospectively from software defaults. Pathfinder pruning, pruning of sliced networks, and pruning of the merged network were enabled to reduce redundant links and improve network interpretability. Cluster visualisations were generated using the static cluster display. All temporal analyses covered the defined 2014–2023 study period; however, the original run-specific time-slicing configuration was not preserved and is therefore not reconstructed retrospectively. Temporal cluster visualisations were interpreted descriptively; no inference regarding cluster quality was based on modularity or silhouette statistics. Four complementary analyses were applied to characterise the structure and temporal development of the research field:

1. Collaboration network analysis. Country, institutional, and co-authorship networks were examined to characterise the geographical and organisational structure of marine mammal monitoring research. Nodes represent countries, institutions, or authors, while links represent collaborative relationships. Publication counts were used to describe the relative representation of countries, institutions, and authors in the retrieved literature. Network visualisations were used to illustrate collaborative relationships, while numerical centrality measures were reported for authors where available. Country- and institution-level findings were interpreted descriptively, without inferring comparative network centrality or citation impact from publication counts alone.
2. Keyword co-occurrence analysis. Relationships among co-occurring keywords were examined to identify major research themes and associations among monitoring methods, ecological topics, analytical approaches, and conservation-related research. Keyword nodes were interpreted comparatively within the network on the basis of their relative frequency and connectivity. No fixed frequency or centrality threshold was used to classify individual terms as ‘prominent’; rather, these network properties were used to describe relative differences among terms represented in the analysis.

3. Temporal and cluster analysis. Temporal visualisations of keyword clusters were used to examine how major research themes developed during 2014–2023. These analyses were interpreted to distinguish persistent research areas from themes that became more prominent later in the study period. A technology-focused keyword time-zone visualisation was additionally used to examine the chronological appearance and connectivity of monitoring and analytical approaches.
4. Citation-burst analysis. Citation-burst detection was used to identify terms or publications exhibiting marked increases in citation activity over defined periods. Citation bursts were interpreted as indicators of rapidly increasing research attention rather than direct measures of technological effectiveness or operational adoption.

These indicators were interpreted according to their distinct bibliometric meanings rather than as interchangeable measures of thematic importance or temporal development. Frequency measures were interpreted as counts of the corresponding bibliographic items or terms represented in the relevant analysis; network connectivity and centrality characterised their structural relationships within the corresponding networks; temporal visualisations described changes in representation across the study period; and citation bursts identified concentrated periods of increased citation activity. No single indicator, or fixed combination of indicators, was used to classify a topic formally as ‘emerging’.

The resulting network and temporal visualisations were considered collectively to characterise collaboration patterns, major research themes, and changes in thematic representation over the analysed period. Interpretation was restricted to patterns represented within the bibliographic dataset; no causal relationship between publication trends and the effectiveness or operational implementation of monitoring technologies was inferred.

3. Results

3.1. Publication Output and Geographical and Institutional Collaboration

The analysed dataset comprised 2586 records retrieved using the defined 2014–2023 search window. Annual publication output based on the final WoS publication-year field (PY) generally increased from 155 records in 2014 to a maximum of 362 in 2022 (Figure 2). The corresponding counts were 186 in 2015, 211 in 2016, 239 in 2017, 235 in 2018, 257 in 2019, 269 in 2020, 343 in 2021, 362 in 2022, and 301 in 2023. An additional 28 records retrieved within the search window had been published online as Early Access before the end of 2023 but were subsequently assigned a final publication year of 2024 in WoS. These records were retained in the original analytical corpus, giving a total of 2586 records. Because the search was conducted on 19 November 2024 and was not subsequently repeated, residual delayed indexing of records associated with the final study year cannot be excluded. The lower count at the end of the series should therefore not be interpreted as evidence of a substantive decline in research output.

The country-level collaboration network showed contributions from multiple regions and numerous international links (Figure 3). Descriptive counts derived from the WoS affiliation data showed that the USA had the highest publication representation (1146 records; 44.3% of the corpus), followed by Canada (382; 14.8%), Australia (310; 12.0%), Scotland (308; 11.9%), and England (277; 10.7%). France, Germany, the People’s Republic of China, Italy, and Spain completed the ten countries/regions with the highest publication counts (Table 1). Because publications involving multiple countries were attributed to each represented country, these percentages describe representation within the corpus rather than mutually exclusive shares of total output. The collaboration network additionally illustrates the relationships among these contributors and the wider international research structure (Figure 3).

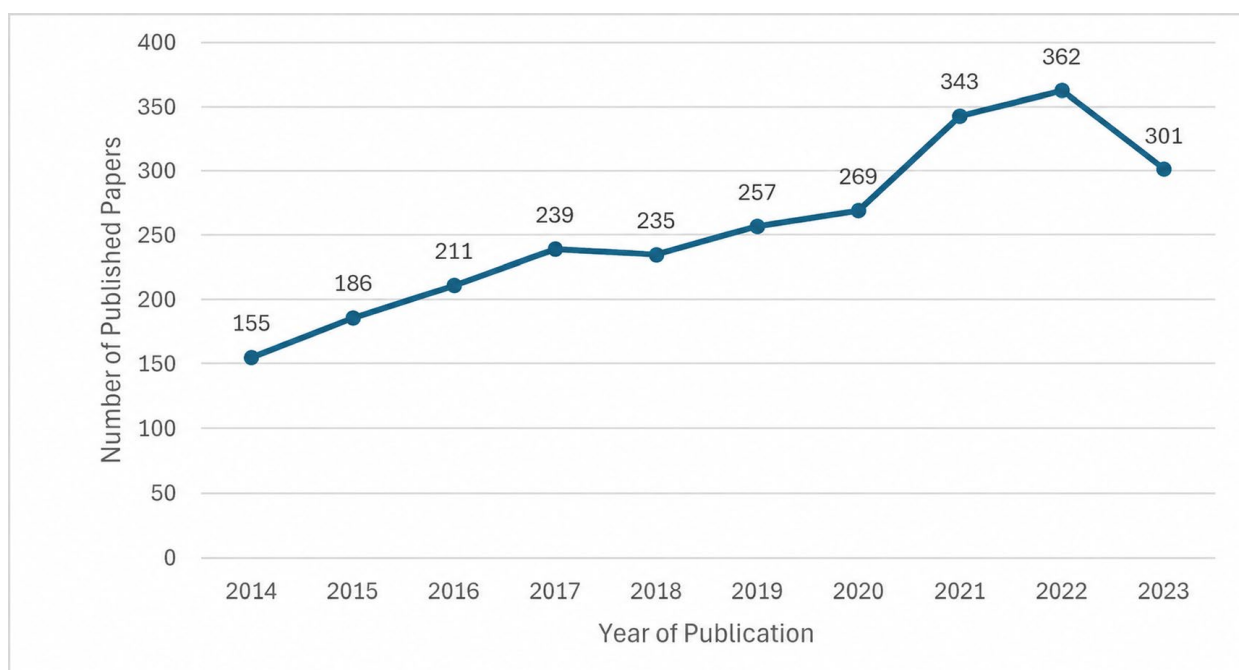


Figure 2. Annual publication output in marine mammal monitoring research from 2014 to 2023, based on the final publication year (PY) recorded in the Web of Science Core Collection. The 28 Early Access records subsequently assigned to 2024 are not represented in the annual series.

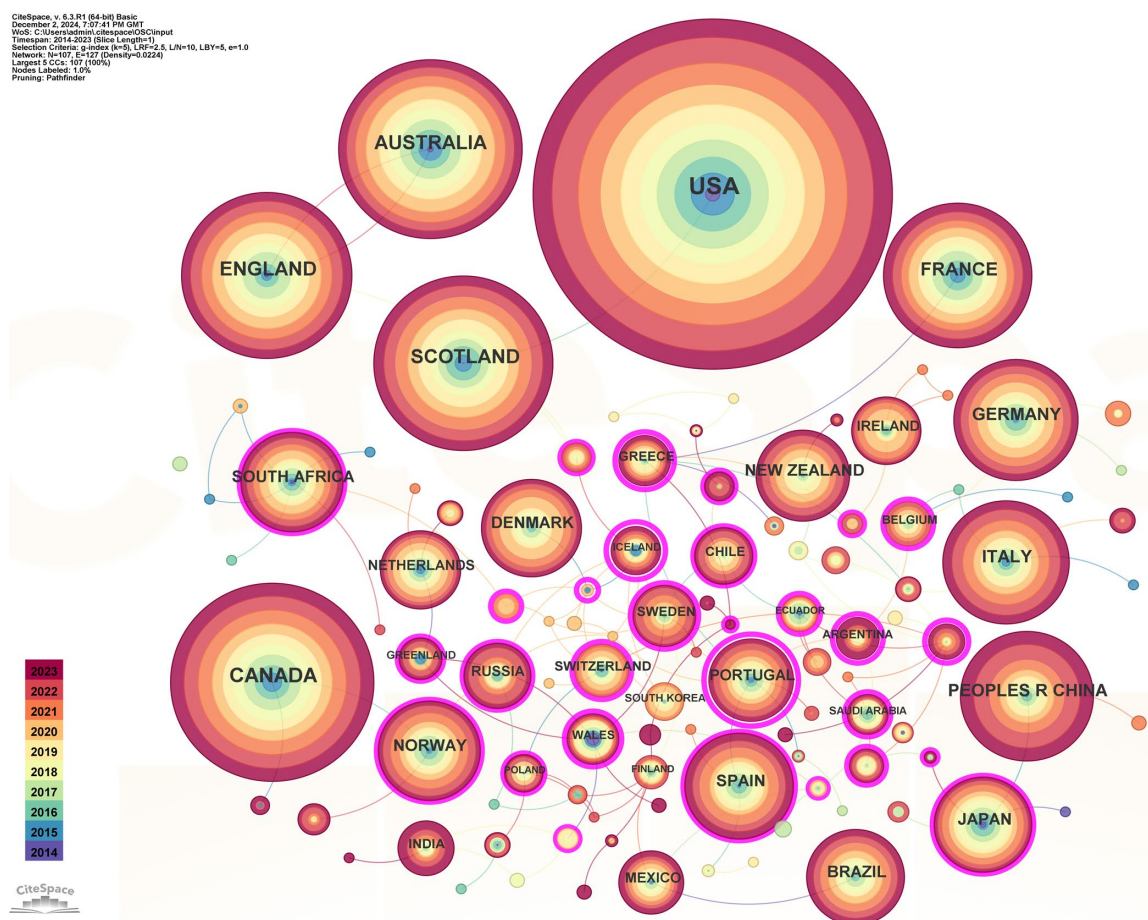


Figure 3. Global map of country publication volume and cooperation network for marine mammal monitoring research, 2014–2023.

Table 1. Countries most frequently represented in the 2586-publication dataset. Publication counts represent the number of records containing at least one author affiliation from the corresponding country; a publication may therefore be counted for more than one country. Percentages are relative to the complete dataset and are not mutually exclusive.

Country/Region as Recorded by WoS	Publications	% of Corpus
USA	1146	44.3%
Canada	382	14.8%
Australia	310	12.0%
Scotland	308	11.9%
England	277	10.7%
France	213	8.2%
Germany	159	6.1%
China	157	6.1%
Italy	152	5.9%
Spain	116	4.5%

The distribution of links among country nodes indicates extensive international co-authorship, with particularly visible connectivity among major contributors in North America, Europe, and the Asia-Pacific region.

The institutional collaboration network showed contributions from universities, government agencies, and research organisations across several regions (Figure 4). Descriptive counts derived from the WoS affiliation data identified NOAA as the institution with the highest publication representation (220 records; 8.5% of the corpus), followed by the University of St Andrews (208; 8.0%), the University of Washington (122; 4.7%), Fisheries and Oceans Canada (121; 4.7%), and Oregon State University (115; 4.4%). The University of California, Santa Cruz; the Woods Hole Oceanographic Institution; the University of California, San Diego; Aarhus University; and Cornell University completed the ten institutions with the highest publication counts (Table 2). Because publications involving multiple institutions were attributed to each represented institution, these percentages describe institutional representation within the corpus rather than mutually exclusive shares of total output. The collaboration network complements these descriptive counts by illustrating relationships among institutions represented in the analysed literature.

Table 2. Institutions most frequently represented in the 2586-publication dataset. Publication counts represent the number of records containing at least one author affiliation from the corresponding institution; a publication may therefore be counted for more than one institution. Percentages are relative to the complete dataset and are not mutually exclusive.

Institution	Publications	% of Corpus
NOAA	220	8.5%
University of St Andrews	208	8.0%
University of Washington	122	4.7%
Fisheries and Oceans Canada	121	4.7%
Oregon State University	115	4.4%
University of California, Santa Cruz	91	3.5%
Woods Hole Oceanographic Institution	88	3.4%
University of California, San Diego	78	3.0%
Aarhus University	74	2.9%
Cornell University	63	2.4%

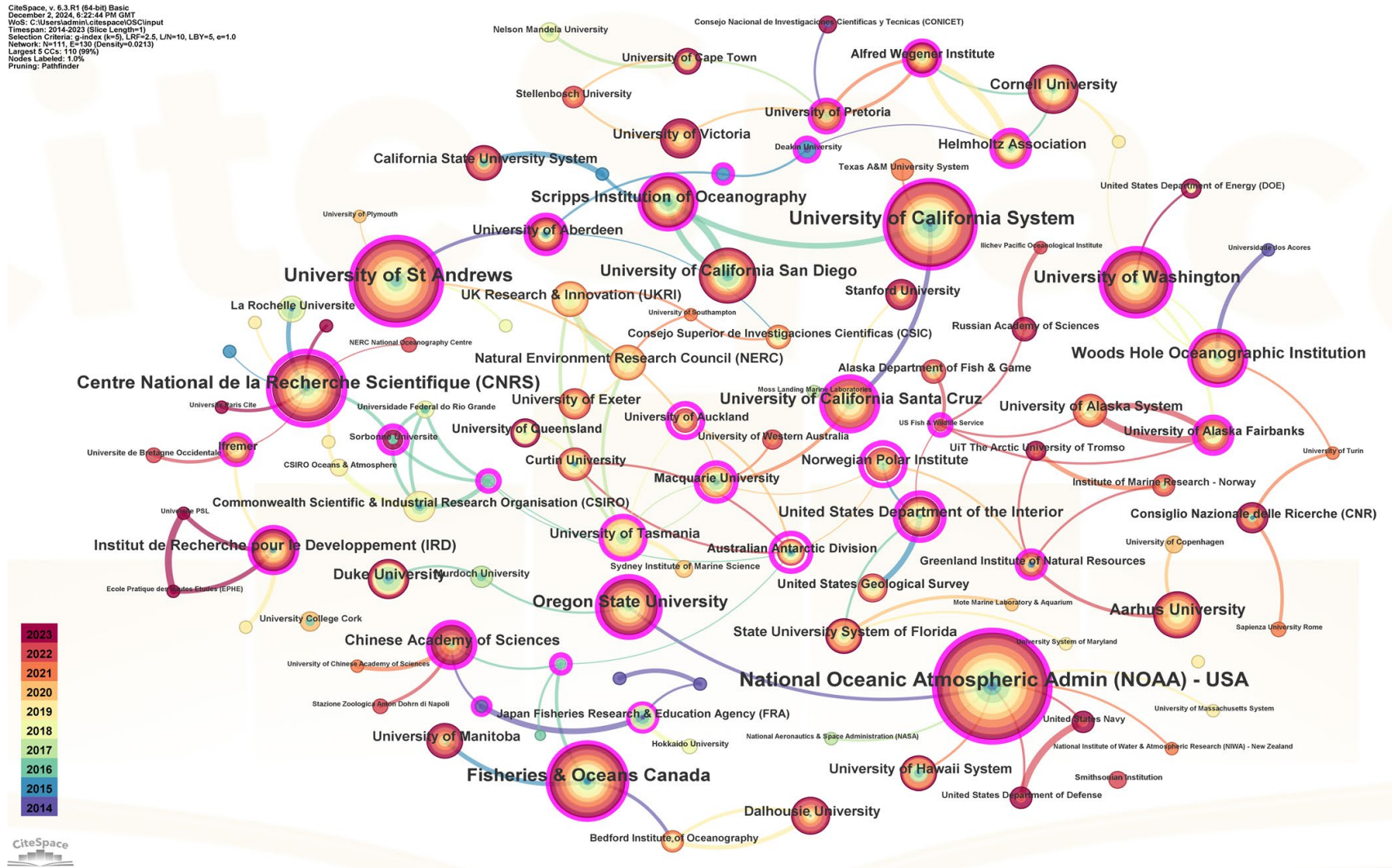


Figure 4. Institutional publication output and collaboration network, 2014–2023.

Overall, the country- and institution-level networks show that marine mammal monitoring research during 2014–2023 was distributed across multiple geographical regions and involved collaborative links among numerous research organisations.

3.2. Co-Authorship Network

The co-authorship analysis identified a network of recurring contributors and collaborative author groups (Figure 5). Table 3 presents the authors with the highest publication counts in the analysed dataset together with their network centrality values. Among the prominent authors represented in the network were Sofie M. Van Parijs, John A. Hildebrand, Simone Baumann-Pickering, Holger Klinck, Steven H. Ferguson, Christophe Guinet, Mark A. Hindell, Kathleen M. Stafford, Daniel P. Costa, and Tomonari Akamatsu.

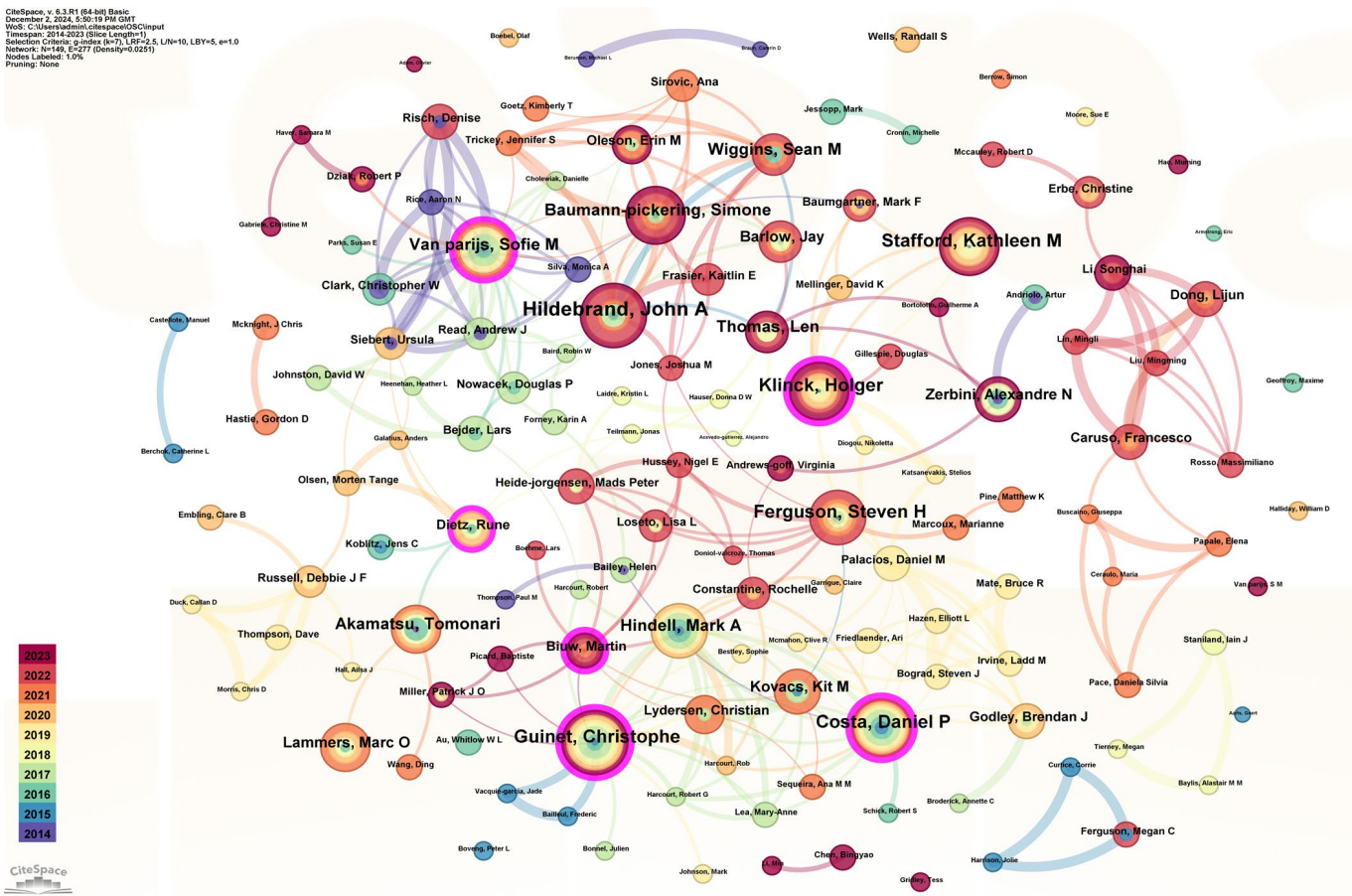


Figure 5. Co-authorship network of researchers in marine mammal monitoring. Larger nodes indicate authors with more publications; connecting lines indicate co-authorship relationships.

Table 3. Top 10 most prolific authors in marine mammal monitoring research (2014–2023), with publication counts and network centrality measures.

Rank	Author	Publications	Centrality
1	Hildebrand, John A	34	0.05
2	Guinet, Christophe	31	0.18
3	Hindell, Mark A	29	0.14
4	Stafford, Kathleen M	27	0.09
5	Costa, Daniel P	25	0.1
6	Akamatsu, Tomonari	24	0.03

Table 3. Cont.

Rank	Author	Publications	Centrality
7	Ferguson, Steven H	24	0.04
8	Klinck, Holger	24	0.09
9	Baumann-Pickering, Simone	23	0.03
10	Van Parijs, Sofie M	22	0.14

The network contained multiple clusters of connected authors rather than a single, uniformly connected collaboration structure. Several highly represented authors were linked to multiple co-authorship groups, indicating connections among otherwise differentiated parts of the network.

3.3. Keyword Co-Occurrence Network

Passive acoustic monitoring (PAM) was strongly represented in the keyword network (Figure 6). Examination of the underlying WoS Author Keywords showed that the exact term ‘passive acoustic monitoring’ occurred in 262 publications. For comparison, ‘marine mammal’ and ‘marine mammals’, considered together as singular/plural variants, occurred in 180 publications, while the exact methodological terms ‘satellite tracking’ and ‘remote sensing’ occurred in 36 and 31 publications, respectively. These descriptive frequencies provide a directly reproducible measure of keyword representation in the source corpus and should not be interpreted as CiteSpace degree or centrality values, which additionally depend on term normalisation, node selection, and network pruning.

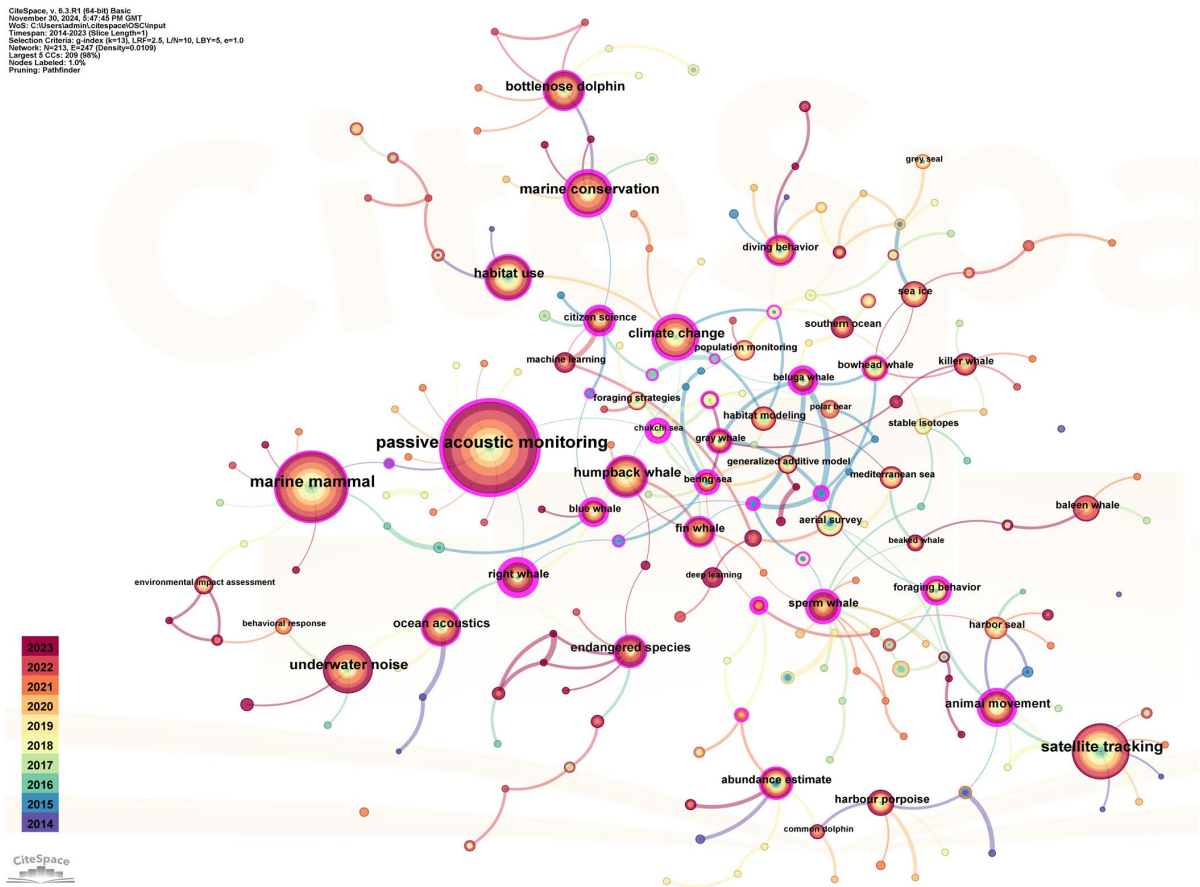


Figure 6. Keyword co-occurrence network for marine mammal monitoring research, 2014–2023.

A separate but connected group of computational terms included machine learning, deep learning, and artificial intelligence. Other portions of the network contained keywords associated with conservation and individual marine mammal taxa, as well as terms related to habitat use, habitat modelling, climate change, diving behaviour, and environmental variables.

The network also included keywords associated with polar and sub-polar research and with monitoring or modelling approaches applied across different ecological contexts. Taken together, the co-occurrence structure shows simultaneous representation of acoustic monitoring, computational methods, species- and conservation-focused research, habitat analysis, and environmental change within the literature.

3.4. Temporal Development of Research Themes

The temporal cluster visualisation was interpreted descriptively to examine differences in the timing and persistence of research themes represented during the study period (Figure 7). The PAM cluster was represented from the beginning of the 2014–2023 interval and persisted throughout much of the analysed period. Terms associated with this cluster included convolutional neural network and feature extraction, reflecting connections between acoustic monitoring and computational analysis within the bibliographic network.

Clusters associated with habitat modelling and endangered species were also represented across the temporal network, while artificial intelligence- and machine-learning-related terms became more prominent during the later part of the study period. The temporal clusters are therefore interpreted as descriptive structures within the CiteSpace visualisation rather than as quantitatively validated cluster partitions.

3.5. Technology-Related Keyword Time-Zone Analysis

The technology-related time-zone visualisation shows the chronological distribution of monitoring and analytical keywords across 2014–2023 (Figure 8). During the earlier part of the study period, represented terms included passive acoustic monitoring, habitat modelling, environmental impact assessment, fisheries sonar, and midfrequency active sonar.

During the middle portion of the study period, machine learning and hidden Markov model appeared together with analytical terms including feature extraction and cross-correlation function. In the later portion of the time-zone network, computational terms including computer vision and artificial intelligence were represented, together with camera traps, offshore wind energy area, and eDNA.

The time-zone analysis therefore indicates a chronological broadening of the terminology represented in the literature, from established acoustic, survey, and habitat-related approaches towards a wider set of computational, visual, molecular, and applied monitoring topics.

3.6. Citation-Burst Analysis

Citation-burst analysis identified terms that exhibited concentrated periods of increased citation activity during 2014–2023 (Figure 9). Earlier bursts included aerial survey, state-space model, and minke whale. During subsequent years, bursts were associated with machine learning, habitat modelling, and seismic survey. Terms appearing among the later bursts included deep learning and eDNA, with deep learning showing a burst during 2022–2023.

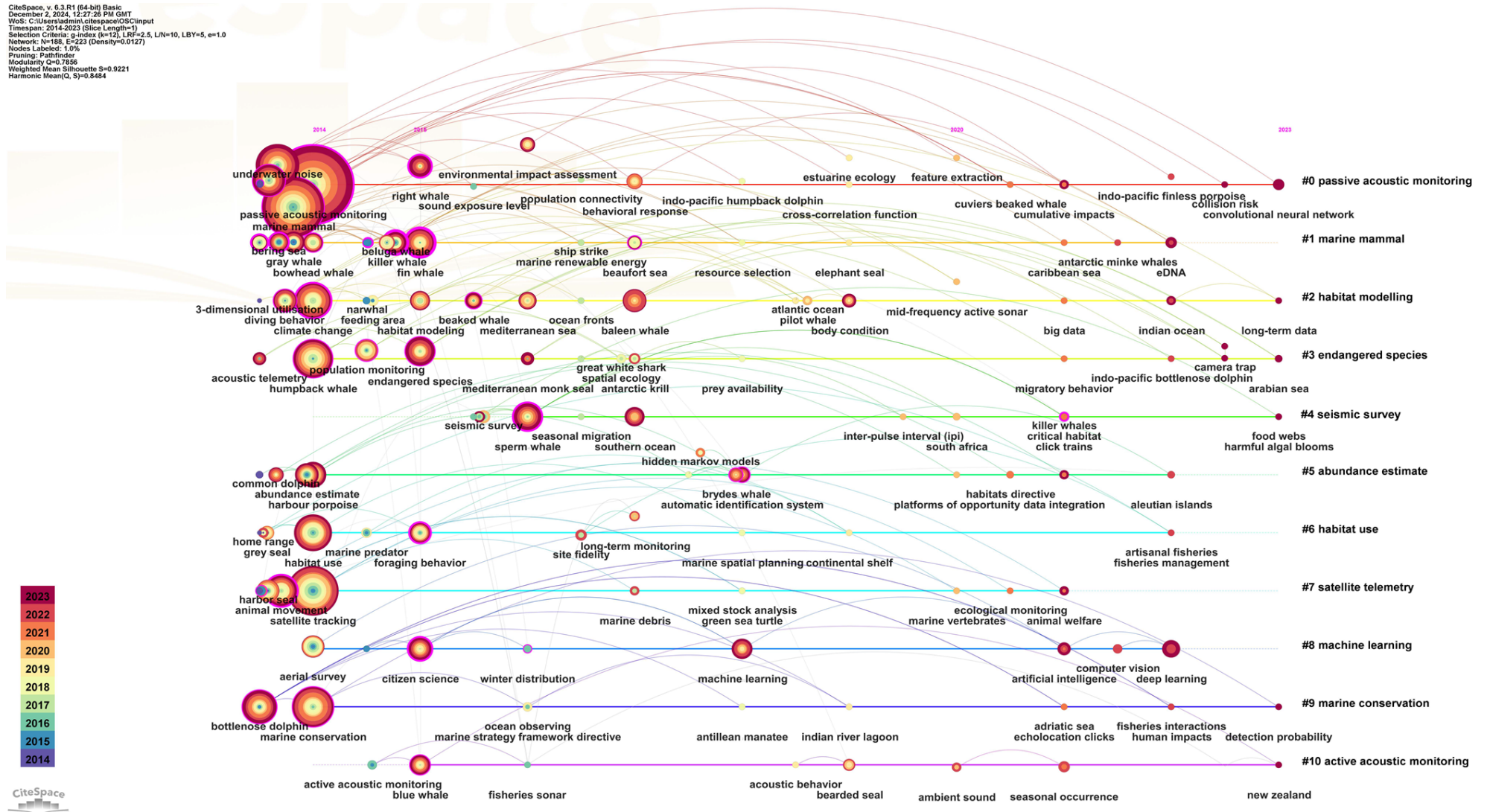


Figure 7. Temporal co-occurrence network of clustered keywords, 2014–2023.

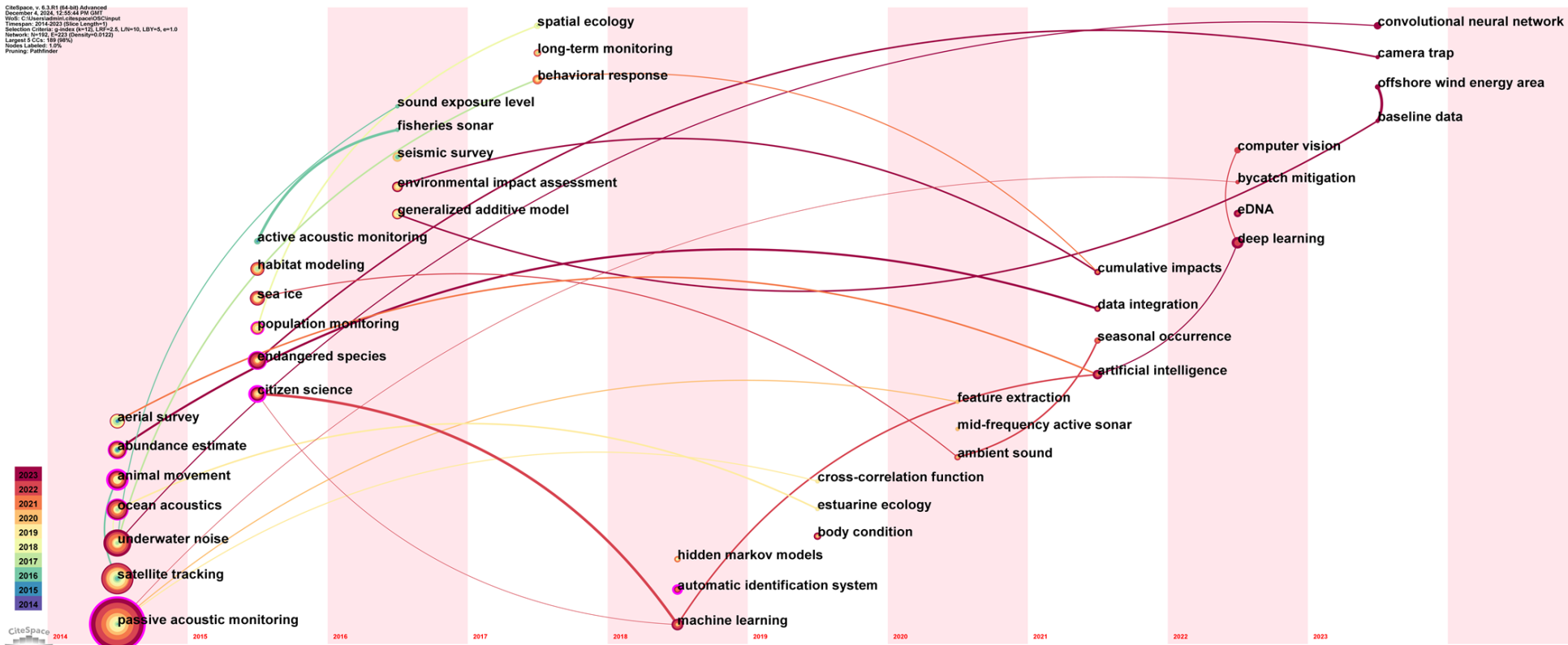


Figure 8. Technology keyword co-occurrence time-zone network, 2014–2023.

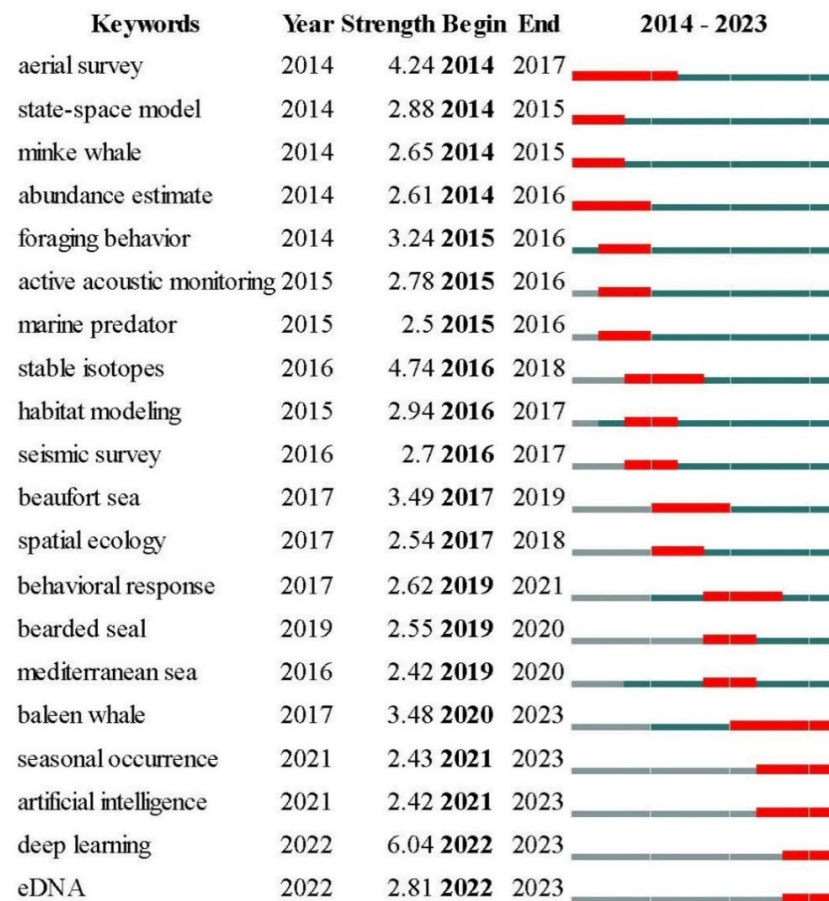


Figure 9. Citation-burst detection of keywords, 2014–2023.

The distribution of citation bursts varied in both timing and duration. Some acoustics-related terms were represented over comparatively extended periods, whereas computational and molecular terms occurred among the more recent bursts. These results identify changes in the concentration of citation activity across research topics during the study period.

4. Discussion

4.1. Growth and Collaborative Structure of Marine Mammal Monitoring Research

The bibliometric record for 2014–2023 indicates sustained growth in marine mammal monitoring research, with annual publication output more than doubling between 2014 and the maximum observed in 2022. The increase in publication output observed during the study period indicates growing representation of marine mammal monitoring research within the analysed WoS corpus. However, this pattern should not be interpreted solely as evidence of growth in the underlying research activity, because bibliometric publication counts may also be influenced by factors external to the field, including changes over time in overall scientific publication volume and database coverage. These broader publishing and indexing trends were not quantified in the present analysis and therefore cannot be separated from field-specific growth. The present analysis therefore characterises the development of the published research field rather than the operational performance of marine mammal monitoring programmes.

Country-, institution-, and author-level networks indicate that this growth occurred within an internationally connected research landscape. Strong representation of institutions in North America and Europe was accompanied by contributions from the Asia-

Pacific region, Africa, and elsewhere. International collaboration is particularly relevant to marine mammal research because many species and populations occur across large geographical ranges and multiple jurisdictions, while monitoring programmes can involve combinations of field infrastructure, long-term datasets, and specialised analytical expertise. Nevertheless, the geographical distribution of publications should not be equated with the geographical distribution of marine mammal populations or monitoring need. Bibliometric prominence may also be influenced by differences in research capacity, publication practices, and representation within WoS-indexed English-language journals.

The co-authorship network similarly showed multiple collaborative groups and recurrent connections among productive authors. These patterns are most appropriately interpreted as evidence of the collaborative organisation of the published research field rather than as measures of the scientific importance of individual researchers. The thematic diversity identified elsewhere in the bibliometric analysis, encompassing bioacoustics, habitat and movement studies, environmental assessment, remote sensing, and computational approaches, further indicates that marine mammal monitoring research draws upon multiple methodological domains.

4.2. Persistent Importance of Passive Acoustic Monitoring and Diversification of Monitoring Approaches

Passive acoustic monitoring (PAM) was one of the most persistent and highly connected themes identified across the keyword co-occurrence and temporal analyses. Its association with underwater noise, behavioural response, environmental impact assessment, and marine mammal taxa is consistent with the established use of acoustic monitoring in marine mammal research and anthropogenic-noise assessment [12–14]. PAM can provide extended temporal coverage and operate during darkness and other conditions that constrain conventional visual observations, making it particularly useful for monitoring vocalising species and for collecting long-duration datasets [4,12].

Its prominence in the bibliometric network should nevertheless not be interpreted as evidence that PAM is universally superior to other monitoring methods. Acoustic detectability depends on whether animals vocalise, the characteristics and directionality of their signals, source–receiver geometry, propagation conditions, ambient and anthropogenic noise, hydrophone characteristics and configuration, and the performance of detection and classification procedures. Consequently, an acoustic non-detection cannot generally be interpreted as evidence of animal absence. Detection range and taxonomic resolution can also vary substantially among species, call types, environments, and recording systems [4,13]. These constraints are especially important when PAM is used to support abundance estimation, behavioural inference, or real-time mitigation rather than to document acoustic presence alone.

The occurrence of active acoustics, visual and remote-sensing approaches, telemetry, and other monitoring terms alongside PAM reflects a broader diversification of the methodological landscape. These approaches address different observational dimensions rather than providing interchangeable measurements. Active acoustic systems can detect targets independently of vocal activity, although detection and classification depend on factors including target characteristics, range, system configuration, and environmental conditions [4,6]. Visual surveys can provide species identification, group-size estimates, behavioural observations, and direct contextual information, but remain affected by availability and perception biases as well as visibility, sea state, observer performance, and survey design [6]. Telemetry and biologging provide detailed information on individual movement, diving behaviour, and habitat use [7], while population-level inference may be constrained by sample size, deployment duration, potential tagging effects, and the representativeness of tagged individuals [15,16].

The bibliometric results therefore indicate methodological diversification rather than replacement of established methods by newer technologies. Selection of an appropriate monitoring approach remains dependent on the biological or management question, target species, spatial and temporal scale, environmental conditions, operational setting, and required detection or inference endpoint. The increasing representation of multiple monitoring approaches in the literature consequently supports consideration of their complementary capabilities and limitations rather than a simple hierarchy among technologies.

4.3. Machine Learning, Artificial Intelligence, and Increasing Automation

Machine learning, deep learning, and artificial intelligence became increasingly visible in the later part of the analysed period. Their occurrence alongside PAM, feature extraction, computer vision, and related analytical terms is consistent with increasing attention to automated processing of large acoustic and image datasets. Long-duration autonomous monitoring can generate data volumes that are impractical to inspect manually, creating a role for automated detection and classification systems [17,18]. Applications include acoustic call detection and species classification [5,17], image-based detection [19], and analysis of movement and environmental datasets [20].

The bibliometric evidence, however, demonstrates increasing research attention to these approaches, not a general improvement in monitoring accuracy or operational reliability. Performance reported for machine-learning systems depends on the composition and quality of training and validation datasets, annotation accuracy, class balance, recording or imaging conditions, model architecture, and the degree to which evaluation data are independent of training data [21]. Models developed using data from one region, sensor configuration, species assemblage, or noise environment may not retain the same performance when transferred to another [22]. Rare species and uncommon call types can present particular difficulties because representative training data may be limited.

False-positive and false-negative rates are consequential in ecological and mitigation applications, and high performance under controlled validation does not necessarily imply equivalent performance during continuous field deployment [23]. Independent validation, transparent reporting of training datasets and performance metrics, assessment of domain transfer, and retention of expert review where appropriate therefore remain important. These considerations are particularly relevant to deep-learning models, for which the processes underlying individual predictions may not be readily interpretable, highlighting the importance of explainability and transparent model evaluation [24,25].

The increasing representation of AI-related terms during 2014–2023 should consequently be interpreted cautiously. The analysis captures a period in which these approaches were becoming increasingly represented in the literature; it cannot establish their eventual contribution to marine mammal monitoring or predict their future predominance. This distinction is particularly important given the rapid development of computational methods after the endpoint of the present dataset.

4.4. Increasing Representation of Multimodal and Molecular Approaches

The later or increasing representation of terms such as computer vision, camera traps, remote sensing, and eDNA in the temporal analyses should not necessarily be interpreted as indicating the emergence of entirely new research activities. Examination of the underlying Author Keywords showed that some of these terms were already present at low frequencies earlier in the study period. For example, ‘remote sensing’ was represented from 2015 onwards, while eDNA-related keywords occurred from 2016 but became more frequent towards the end of the study period. Camera-trap terminology was also distributed across the study period rather than being confined to its later years. Computer vision showed a

pattern more strongly concentrated towards the end of the analysed period, with Author Keyword occurrences concentrated in 2021–2023; however, computer-vision applications in animal ecology pre-date this pattern [26]. Accordingly, later visibility in the bibliometric network is interpreted here as increased representation within the analysed literature rather than, by itself, evidence of technological novelty or first adoption [26,27].

Environmental DNA (eDNA) provides a complementary means of detecting marine mammal species without requiring direct visual or acoustic observations. Applications include species-specific detection, biodiversity assessment, and genetic characterisation, although their suitability depends on assay design, sampling procedures, and the availability of appropriate reference sequences [8]. Detection performance also depends on sampling effort and environmental conditions; consequently, non-detection cannot necessarily be interpreted as evidence of species absence, as illustrated by the limited cetacean detections obtained using low-volume eDNA transect sampling [28]. These constraints highlight the importance of interpreting molecular observations in conjunction with other monitoring information rather than treating eDNA as a direct substitute for established survey methods.

A similar principle applies to multimodal monitoring more generally. Acoustic, visual, telemetry, molecular, oceanographic, and remote-sensing approaches provide different forms of information, potentially addressing some of the observational limitations associated with individual methods [4,27]. The complementary use of underwater optical imaging and eDNA metabarcoding, for example, has been shown to broaden biodiversity detection in marine environments, although applications reviewed to date have predominantly concerned taxa and ecosystems other than marine mammals [29]. Integrating heterogeneous monitoring data nevertheless presents methodological challenges because individual approaches differ in their spatial and temporal coverage, observation processes, detection probabilities, and associated uncertainties. Such differences must be explicitly considered before combined observations can support robust ecological inference [30].

The increasing bibliometric representation of multiple monitoring modalities should thus not be interpreted as evidence that an integrated monitoring framework has already been achieved across the field. Rather, the results identify an increasingly heterogeneous methodological landscape in which interoperability and validation become more important as the number and complexity of data streams increase. Establishing when different data sources are genuinely complementary, rather than simply available simultaneously, represents an important methodological question for future monitoring programmes.

4.5. Study Limitations and Research Priorities

Several limitations affect interpretation of the present bibliometric analysis. First, the dataset was derived exclusively from the Web of Science (WoS) Core Collection and was restricted by document type to Articles and Review Articles. The retrieved corpus was overwhelmingly English-language, although a small number of records indexed in other languages were retained in the dataset. Relevant research indexed only in other bibliographic databases or contained in reports and other grey literature was therefore not represented, while literature published in languages other than English may have been incompletely represented. Database selection and document-type restrictions are recognised considerations in bibliometric research because they influence the coverage and composition of the resulting dataset [9]. Articles and Review Articles were analysed jointly, with the latter accounting for 4.7% of the corpus. No Article-only sensitivity analysis was conducted; consequently, the extent to which the inclusion of Review Articles may have influenced citation patterns, keyword co-occurrence or network clustering remains undetermined. The relatively small proportion of Review Articles should not be interpreted as

evidence that their inclusion had no effect on these results. The exclusion of grey literature is particularly relevant to applied marine mammal monitoring, as the present analysis does not capture methodological and operational information published exclusively in government, industry, consultancy, or conservation reports.

Second, the composition of any bibliometric dataset is sensitive to the search strategy [9]. Although the search incorporated a broad combination of marine mammal, monitoring, and methodological terms, no single query can capture every relevant publication while excluding all peripheral material. Relevant studies using terminology not represented in the search expression may therefore have been omitted. The search strategy was not independently validated against a benchmark set of relevant publications, and the effects of individual NOT-clause exclusions on corpus composition were not quantified. Consequently, the possibility of relevant records having been omitted through the inclusion or exclusion criteria cannot be ruled out. The resulting networks should consequently be understood as representations of the literature retrieved under the defined search strategy rather than exhaustive maps of all marine mammal monitoring activity.

Third, term normalisation was required to consolidate synonyms, spelling variants, scientific and common names, abbreviations, and institutional variants before network construction. Such preprocessing reduces artificial fragmentation but also involves analytical judgement. Particularly where related but not strictly identical concepts are consolidated, normalisation can affect node frequencies and network structure. The results should therefore be interpreted at the level of broad research patterns rather than as precise measurements of conceptual boundaries.

An additional methodological limitation concerns the reproducibility of the original CiteSpace analyses. Although the software version, node-selection criterion and principal pruning procedures are documented in Section 2.4, the complete run-specific parameter configurations, including the exact g-index scaling factors, time-slicing settings and any additional threshold or link-selection parameters, were not preserved. As these settings can influence network construction, node selection, clustering and temporal representations, exact computational reproduction of the original network analyses cannot be assured. This constitutes a significant limitation of the study, particularly for the independent verification and replication of network-derived results. Accordingly, the associated findings should be interpreted as descriptive patterns within the analysed corpus, subject to the documented methodological constraints.

Bibliometric indicators also measure characteristics of scientific publication and citation. Keyword frequency, network centrality, co-occurrence, and citation bursts do not directly measure the accuracy, effectiveness, technological maturity, field adoption, or conservation value of a monitoring method. Similarly, the later appearance of a term does not necessarily establish that the underlying technology itself is new; it may instead reflect changes in terminology, publication frequency, indexing, or application within marine mammal research. These distinctions are consistent with the need to select and interpret bibliometric techniques according to the research questions they are intended to address [9].

A further limitation concerns the temporal coverage of the study, which ends in December 2023. The analysis therefore provides a defined ten-year retrospective view rather than a description of developments occurring after that date. This limitation is especially relevant to rapidly developing areas such as artificial intelligence and machine learning. The temporal patterns identified here can indicate increasing research attention to particular topics within 2014–2023, but they should not be extrapolated as evidence or predictions of subsequent technological development. Because bibliographic databases may continue to update records after a search has been performed, residual delayed indexing of publications associated with the final study year cannot be excluded.

Within these constraints, the bibliometric patterns identified in this study highlight several areas warranting further attention in marine mammal monitoring research. These include independent validation and transparent reporting of monitoring performance; explicit characterisation of detection uncertainty and method-specific biases; improved interoperability and standardisation across monitoring platforms; and evaluation of the conditions under which multimodal approaches provide additional information relative to individual methods. Greater representation of regions currently under-represented in the analysed literature and improved accessibility of monitoring datasets and associated metadata would also support comparative and large-scale research. Future bibliometric studies could extend the present analysis by incorporating additional bibliographic databases and relevant grey literature and by examining whether the patterns identified during 2014–2023 persist as computational, molecular, and integrated monitoring approaches continue to develop.

5. Conclusions

This bibliometric analysis characterised the development of marine mammal monitoring research between 2014 and 2023 using 2586 publications retrieved from the Web of Science Core Collection. Annual publication output increased from 155 in 2014 to a peak of 362 in 2022, indicating substantial growth in the literature during the study period. Country-, institution-, and author-level networks revealed an internationally connected research landscape, with prominent contributions from North America, Europe, Asia, and Oceania. These patterns describe the organisation and geographical representation of the published research field, although they do not necessarily reflect the distribution of monitoring effort or conservation needs worldwide.

Keyword co-occurrence and temporal analyses identified passive acoustic monitoring as a persistent and highly connected research theme, alongside habitat modelling, environmental impact assessment, and conservation-related research. The increasing visibility of machine learning, artificial intelligence, remote sensing, and environmental DNA indicated diversification of the methodological topics represented in the literature, particularly towards the latter part of the study period. These findings document changes in research attention rather than demonstrating improvements in detection performance, operational adoption, or the effectiveness of individual monitoring technologies.

The results provide a quantitative basis for identifying major research themes and examining changes in their representation over time, as well as how collaboration and methodological interests developed within the literature captured by the search strategy. They also highlight priorities for further investigation, including independent validation of monitoring methods, transparent reporting of detection uncertainty, improved interoperability between data sources, and assessment of the circumstances in which multimodal approaches provide additional ecological information. Given the restrictions associated with database coverage, search terms, document selection, term normalisation, and the study endpoint, the findings should be interpreted as a retrospective characterisation of the retrieved literature rather than an exhaustive assessment of marine mammal monitoring practice. Future studies incorporating additional bibliographic sources and more recent publications could establish whether the patterns identified here persist and how the representation of different monitoring approaches changes over time.

Author Contributions: Conceptualisation, V.L.G.T.; Methodology, M.M.R.J. and V.L.G.T.; Investigation, M.M.R.J. and V.L.G.T.; Resources, V.L.G.T.; Writing—Review and Editing, M.M.R.J. and V.L.G.T.; Supervision, V.L.G.T.; Project Administration, M.M.R.J. and V.L.G.T. All authors have read and agreed to the published version of the manuscript.

Funding: This research received no external funding.

Data Availability Statement: The bibliographic data analysed in this study were obtained from the Web of Science Core Collection. The relevant bibliographic files have been provided to the journal for editorial assessment. The complete exported records have not been deposited in a public repository because permission for their public redistribution has not been established. The search strategy, retrieval date, and selection criteria are provided in the Materials and Methods section.

Acknowledgments: The authors gratefully acknowledge the support of the Joint Industry Sound & Marine Life Programme, under which this study was developed as part of a broader research effort addressing marine mammal monitoring under low-visibility conditions. The programme provided the framework for investigating monitoring approaches and their development, including the bibliometric assessment presented here. The authors also acknowledge William L. Wu for assistance in the original bibliometric analyses and generating the associated network visualisations, and Charlotte Waugh for her assistance with figure formatting and editorial preparation.

Conflicts of Interest: Mario M. Rollo Jr. is employed by Ocean Science Consulting Ltd, and Victoria L. G. Todd is a Director of the company. The authors declare no other financial or non-financial conflicts of interest in relation to this research.

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