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Review

Trends in Oil Spill Modeling: A Review of the Literature

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Abstract

Oil spill simulation models are essential for predicting the oil spill behavior and movement in marine environments. In this study, we comprehensively reviewed a large and diverse body of peer-reviewed literature obtained from Scopus and Web of Science. Our initial analysis phase focused on examining trends in scientific publications, utilizing the complete dataset derived after systematic screening and database integration. In the second phase, we applied elements of a systematic review to identify and evaluate the most influential contributions in the scientific field of oil spill simulations. Our analysis revealed a steady and accelerating growth of research activity over the past five decades, with a particularly notable expansion in the last two. The field has also experienced a marked increase in collaborative practices, including a rise in international co-authorship and multi-authored contributions, reflecting a more global and interdisciplinary research landscape. We cataloged the key modeling frameworks that have shaped the field from established systems such as OSCAR, OIL-MAP/SIMAP, and GNOME to emerging hybrid and Lagrangian approaches. Hydrodynamic models were consistently central, often integrated with biogeochemical, wave, atmospheric, and oil-spill-specific modules. Environmental variables such as wind, ocean currents, and temperature were frequently used to drive model behavior. Geographically, research has concentrated on ecologically and economically sensitive coastal and marine regions. We conclude that future progress will rely on the real-time integration of high-resolution environmental data streams, the development of machine-learning-based surrogate models to accelerate computations, and the incorporation of advanced biodegradation and weathering mechanisms supported by experimental data. These advancements are expected to enhance the accuracy, responsiveness, and operational value of oil spill modeling tools, supporting environmental monitoring and emergency response.

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Academic Editors: Chunpeng Chen, Ce Zhang and Wenting Wu

Received: 16 June 2025
Revised: 30 July 2025
Accepted: 30 July 2025
Published: 2 August 2025

Citation: Vasconcelos, R.N.; Lima, A.T.C.; Lentini, C.A.D.; Miranda, J.G.V.; de Mendonça, L.F.F.; Costa, D.P.; Duverger, S.G.; Cambui, E.C.B. Trends in Oil Spill Modeling: A Review of the Literature. *Water* **2025**, *17*, 2300. https://doi.org/10.3390/w17152300

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Keywords: oil spills; synthetic aperture radar—SAR; oil spill modeling; simulations; oil dispersion

1. Introduction

Oil spills pose significant threats to the environment, marine ecosystems, and local economies. Assessing the potential behavior of spills is essential for implementing timely preventive measures and reducing negative impacts [1–5]. Identifying potential spill scenarios and simulating their evolution can improve preparedness and response strategies, thereby protecting vulnerable ecosystems [2,6,7]. Continuous research in this area is vital for enhancing our ability to anticipate and manage these catastrophic events [1,8,9].

State-of-the-art simulation models are crucial for predicting the trajectory and spread of oil spills in marine environments [8,10–12]. These models involve physical simulations of fluid dynamics, advanced numerical algorithms for movement estimations, the statistical analysis of historical data, and hybrid approaches that integrate multiple techniques [10,13]. The knowledge gained from these diverse methodologies is crucial for developing effective strategies to minimize the impacts of oil spills [14–16].

In the past, oil spill trajectory simulations were based on basic models and empirical methods [10,12,17]. Advancements in technology have led to the development of more sophisticated forecasting tools [10,12,17]. These tools now utilize computational fluid dynamics simulations, machine learning algorithms, and numerical models that consider environmental factors, such as wind patterns and sea currents [10,12,17]. As a result, our understanding of oil spill dynamics has significantly improved, thereby enhancing our ability to respond effectively [10,12].

Numerical modeling and simulations play a pivotal role in oil spill response and contingency planning, providing real-time forecasts based on environmental data such as the wind velocity and surface currents [10,12]. They are used to simulate the trajectory of oil spills by considering various ecological factors, such as wind patterns, sea currents, and the physical properties of the oil [3,18]. These models are customized to address specific challenges in various environments, considering the interactions between environmental characteristics [10,12]. By integrating these factors, simulation models provide a comprehensive understanding of oil spill behavior, enabling authorities to make informed, real-time decisions that minimize damage and safeguard marine resources [12]. Accurate oil spill forecasting is crucial for effective recovery operations and the protection of marine resources [10].

Recent reviews have highlighted the importance of incorporating environmental variables such as three-dimensional flow fields, turbulence, wind guidance, transport, and wave breaking into forecast models [12,17,19,20]. Technological advancements have enabled the development of sophisticated tools for simulating oil spill trajectories, including computational fluid dynamics simulations, machine learning algorithms, and numerical models that account for environmental factors [12,17,19,20]. There is a growing interest in developing and utilizing these simulation models, which have demonstrated effectiveness in forecasting oil drift paths, evaluating affected areas in the presence of wind and currents, and integrating with biochemical models [12,17,19,20].

An integrated approach analysis, utilizing both qualitative and quantitative tools [21–24], facilitates an understanding of the evolution and influence of research across disciplines [22,25–27]. By examining integrated-type literature reviews, researchers gain comprehensive insights into the scientific patterns of the oil spill simulation field, which are crucial for developing effective prevention, mitigation, and response strategies. This

analysis identifies critical research areas and knowledge gaps to enhance understanding and spur further developments in oil spill modeling through diverse methodologies and perspectives.

This study aims to analyze the scientific field of oil spill simulation by focusing on key publishing trends and the predominant methodological approaches found in the most cited documents. Our objective is to understand the evolution of citation trends in oil spill simulation studies, identify the leading journals in terms of the document output, and determine the most employed simulation models in these highly cited works. Additionally, we seek to identify the frequently used variables that represent these processes in the top-cited documents. By uncovering the patterns that have influenced the development of this research area and highlighting emerging directions, this study will provide insights into methodological diversity, identify leading researchers and influential publications, and trace the progression of the research output over time based on the most cited documents. Ultimately, we aim to deliver a comprehensive overview of the evolution of this field and offer valuable guidance to support future advancements in oil spill modeling. Additionally, this study highlights recent methodological trends involving genetic algorithms for oil spill analysis, multi-objective evolutionary algorithms for oil spill detection, and quantum immune fast spectral clustering for automatic spill identification, recognizing their growing relevance and presenting complementary contributions to the current state of the art of the oil spill scientific field.

2. Materials and Methods

The methodological approach employed in this study combines traditional bibliometric analyses with both qualitative and quantitative descriptors, as well as systematic review techniques, to facilitate effective information extraction. Key activities involved selecting appropriate databases, formulating specific queries, and applying relevant filters, notably utilizing Scopus and Web of Science for data collection. The search was centered on pertinent semantic terms related to oil spill simulation. We included the most widely represented document types, encompassing a variety of formats, including journal articles, Article/Book Chapters, Article/Proceedings, paper books, book chapters, conference papers, proceedings papers, reviews, review/books, and chapter books, to ensure a comprehensive compilation of scholarly contributions (Figure 1).

We subsequently applied filters to narrow our search to publications up to 2024. Following this, we undertook a thorough manual screening of the refined dataset. We reviewed titles and abstracts to ensure they aligned with our primary objective of assessing the oil spill simulation domain. In instances of ambiguity, we conducted full-text evaluations to confirm relevance. This screening process was essential for preserving the precision and integrity of our study.

Building on the dataset compiled in stage 1, we conducted a series of analyses, including general statistical overviews, trend tracking over time, and author productivity measurements. In stage 2, we employed systematic review methods elements to identify prevailing trends in oil spill simulation research. The total citation count served as a proxy for influence, informing our selection of these highly impactful studies. To refine our dataset, we concentrated on the most cited documents, which account for approximately 12.2% of the dataset collected. Each document in this subset was examined for details such as the models employed, primary variables measured, data visualization techniques, geographic focus, and overall citation metrics.

Figure 1 illustrates the data sources and analytical methods employed in this research, thereby enhancing the clarity and methodological rigor of our investigations.

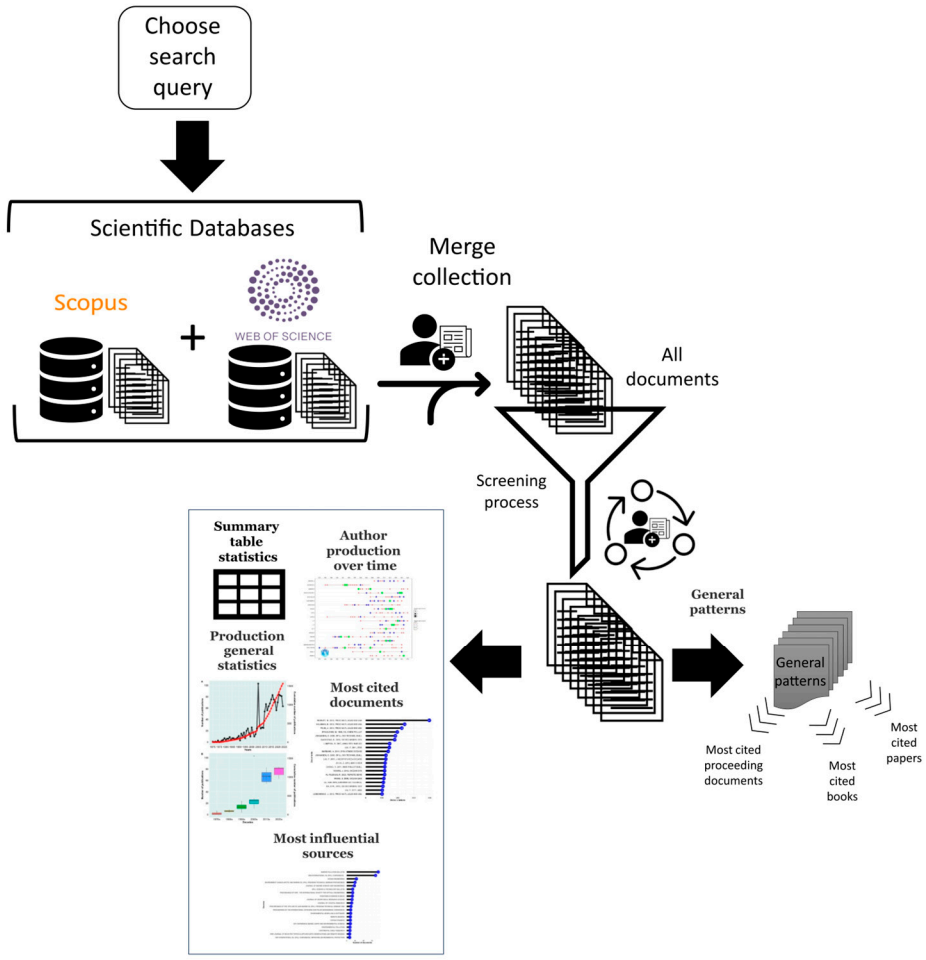


Figure 1. The diagram shows the sequence of procedures implemented at each stage of this study.

2.1. Bibliographic Base

Our research draws upon two primary bibliographic databases, Scopus and Web of Science, to ensure comprehensive coverage of the relevant literature. Scopus, launched by Elsevier in November 2004 [28], is a wide-ranging resource encompassing scientific outputs from various domains. It provides citation analysis data extending back to 1996, thus offering a detailed overview of global research trends [28]. Scopus currently includes over 53 million published references derived from more than 24,000 scientific journals [28]. Its web-based interface presents users with an array of tools for efficient literature searches, facilitating both basic and advanced queries [28]. By enabling rapid and consistent information retrieval, Scopus provides a comprehensive view of scientific developments [28].

In parallel, we utilized WoS, a platform maintained by Clarivate Analytics and recognized for its extensive coverage of peer-reviewed literature [29]. WoS consolidates multiple citation indexes, including the Science Citation Index Expanded (SCIE), the Social Sciences Citation Index (SSCI), and the Arts and Humanities Citation Index (AHCI), thereby offering a robust dataset for bibliometric analysis [29]. WoS currently includes over 53 million published references derived from more than 24,000 scientific journals [28].

By integrating both Scopus and WoS into our methodology, we maximize the likelihood of retrieving pertinent studies related to our research scope, while also enhancing the reliability and completeness of our literature review (see Figure 1).

2.2. Search Query

A detailed search query was formulated, utilizing targeted keywords, phrases, and Boolean operators to yield accurate and relevant results, thereby ensuring a robust foundation for encompassing a wide range of salient literature on the subject matter.

In our search strategy, we implemented various filtering criteria to maintain methodological consistency. We began by including all available document types identified in our database queries, such as journal articles, chapters from articles and books, conference papers, proceedings papers, reviews, and review chapters. This inclusive approach was designed to capture the full range of contributions to the field of oil spill modeling.

Additionally, we narrowed the temporal scope of the search to encompass all documents published before 2025. This was explicitly specified in the search strings using the syntax particular to each database (Scopus: PUBYEAR < 2025; Web of Science: PY = (<2025)).

After the initial retrieval, we conducted a screening phase that involved evaluating titles, abstracts, and keywords as defined by the authors. When necessary, we conducted full-text reviews to determine the relevance of individual studies to our research objectives. This multi-stage filtering process was designed to eliminate unrelated records and refine the dataset, ensuring a closer alignment with the thematic scope of our study.

For the review of the systematic elements approach, we implemented a targeted selection strategy focused on total citation counts, choosing the most cited papers to represent the conceptual and methodological core of the field. This decision is elaborated upon in a subsequent section.

The searches were conducted in the Scopus and Web of Science (WOS) databases on 9 May 2025. As outlined in the search strings, all peer-reviewed documents published before 2025 were included in our analysis.

For our exploration in Scopus, we crafted the search query to maximize its effectiveness as follows: TITLE-ABS-KEY ((“Oil spill*” OR “Oil slick*”) AND (“Model*” OR “Simulat*” OR “Predict*” OR “Forecast*”) AND (“Traject*” OR “Propagat*” OR “Track*”)) AND PUBYEAR < 2025. This thoughtfully constructed query enabled us to identify pertinent peer-reviewed documents that tackle the complexities of oil spill modeling and their environmental repercussions. Likewise, we tailored the search query for Web of Science (WOS) to fit their specific framework, resulting in the following structure: TS = ((“Oil spill*” OR “Oil slick*”) AND (“Model*” OR “Simulat*” OR “Predict*” OR “Forecast*”) AND (“Traject*” OR “Propagat*” OR “Track*”)) AND PY = (<2025). This adjustment ensured consistency and comprehensiveness across the different databases.

Through these queries, we successfully isolated and gathered peer-reviewed documents that examine various facets of simulations, predictions, and forecasting techniques concerning oil spill trajectories. This approach allowed us to compile a comprehensive and scientifically sound body of research that serves as the foundation for our study.

2.3. Data Analysis

Our analysis consisted of two primary components for data processing. In the first section, we examined various facets of the progression and trends in scientific publications, concentrating on the most influential documents, key sources, and prominent authors. To achieve this, we utilized the complete documents acquired during the screening stage, as well as integrated datasets from both the Scopus and Web of Science databases.

In the second processing component, we implement a systematic review element approach aimed at identifying and evaluating the most influential documents in the field of oil spill simulation. This analysis involved selecting a range of scientific publications, encompassing all document types retrieved from the overall dataset (i.e., articles, review

papers, conference proceedings, book chapters, and books). A detailed citation frequency analysis served as a crucial indicator of each publication's impact and relevance. In total, we selected 188 documents, which account for approximately 12.2% of the entire dataset collected during our comprehensive search phase.

The data were gathered by thoroughly reading and reviewing each selected publication, ensuring that all information was sourced directly from the original works to uphold the authenticity and accuracy of our findings. We carefully documented several key aspects, including the models utilized, which ranged from atmospheric and hydrodynamic to biogeochemical models.

Furthermore, we documented the key variables integrated into these models, imaging techniques employed, and the geographic locations associated with each study. This approach enabled us to compile a comprehensive collection of information that highlights the diversity and complexity inherent in the scientific research surrounding oil spill simulation.

We utilized the Bibliometrix package [25] to conduct a quantitative and statistical analysis of publication trends. This library enabled us to examine author productivity, temporal trends, and the evolution of author output over time, as well as to identify the most cited documents [30]. All analytical figures and analyses were performed using R version 4.0.4 [30,31] and the RStudio IDE version [32], alongside the ggplot2 version 3.3.5 [33] and Bibliometrix version 3.1.4 libraries [25,33].

3. Results

3.1. Publishing Trends

The bibliographic database underwent a thorough screening, filtering, and refinement process, resulting in the identification of 1541 documents on oil spill simulation spanning from 1970 to 2024. An analysis of publication trends by decade indicates that the most significant proportion of these documents was published during the 2010s, totaling 667 documents, followed by the 2020s with 363 documents. Earlier decades saw a progressive decline in contributions, with 299 documents from the 2000s, 157 from the 1990s, 40 from the 1980s, and 15 from the 1970s.

The distribution pattern reveals a notable increase in the scholarly output over time, as evidenced by an overall annual growth rate of 7.81% from 1970 to 2024. A closer examination of the data presented in Table 1 further reinforces the consistent upward trajectory of the published research on oil spill simulations across all decades, with the most pronounced increase occurring in the post-1970s period. Our analysis of publication trends from 1970 to 2024 (refer to Table 1 and Figure 2A,B) reveals significant fluctuations in the annual number of publications related to oil spill simulation.

The variations presented highlight the growing interest in oil spill simulation research and the long-term impact of major spill events. Over the 55 years studied (1970–2024), a total of 1541 publications were identified, resulting in an average of approximately 28.0 ± 29.5 papers per year. A decade-by-decade analysis reveals a significant increase in the average annual output: from 1.5 ± 1.7 papers per year in the 1970s, it rose to 4.3 ± 2.0 in the 1980s, 16.1 ± 7.8 in the 1990s, 30.3 ± 26.6 in the 2000s, 68.3 ± 11.7 in the 2010s, and 72.6 ± 10.0 in the partial 2020s. This upward trend highlights the increasing importance of oil spill research, particularly over the last two decades (Figure 2A,B).

An examination of specific publication peaks further illustrates the field's responsiveness to technological advancements, policy changes, and environmental crises. The five most prolific years in the dataset were 2005 (101 publications), followed by 2016 (82), 2015 (81), 2021 (81), and 2022 (79).

Table 1. Summary table statistics on publication sources, authorship, and collaborative patterns.

Main Information							
Timespan	1970:1979	1980:1989	1990:1999	2000:2009	2010:2019	2020:2024	1970:2024
Sources *	14	34	67	127	385	211	730
Documents	15	40	157	299	667	363	1541
Annual growth rate %	-	-	-	-	-	-	7.81
Paper contents							
AUTHORS							
Authors	34	71	233	675	1928	1406	3756
Authors of single-authored docs	2	5	21	31	39	16	96
Authors collaboration							
Co-authors per doc	2.40	2.5	2.73	3.39	4.37	4.79	4.04
International co-authorships %	0.00	0.00	2.54	7.02	14.39	19.83	12.52

Note(s): * The same source may be included multiple times within the 1970–2024 period.

In terms of authorship, a total of 3756 distinct authors contributed to these publications. There were 96 single-authored works, with distributions across the decades as follows: 2 in the 1970s, 5 in the 1980s, 21 in the 1990s, 31 in the 2000s, 39 in the 2010s, and 16 in the early 2020s.

Collaboration metrics indicate a burgeoning research community, as evidenced by the average number of co-authors per document increasing from 2.40 $\pm$ 5.3 in the 1970s to 4.79 $\pm$ 47.3 between 2020 and 2024. Decade-specific averages reveal figures of 2.50 $\pm$ 4.6 in the 1980s, 2.73 $\pm$ 23.1 in the 1990s, 3.39 $\pm$ 86.9 in the 2000s, and 4.37 $\pm$ 79.4 in the 2010s, culminating in an overall mean of 4.04 across all documents. Additionally, international co-authorship has experienced significant growth, soaring from 0.00% in the 1970s and 1980s to 20.05% in the 2020s. Intermediate rates were recorded at 2.54% in the 1990s, 7.02% in the 2000s, and 14.39% in the 2010s, with an average of 12.52% throughout the entire period.

The publication and collaboration patterns in oil spill simulation research reveal a complex landscape, primarily characterized by journal articles, conference contributions, reviews, book chapters, and books, which provide greater depth. Notable peaks in production occurred in 2005, 2011, 2020, and 2022, reflecting a responsiveness to environmental disasters, technological advancements, and evolving scientific priorities. This diversity in publication formats and collaborative efforts highlights the interdisciplinary nature and increasing significance of the field within environmental science and policy.

Journal articles play a critical role in scholarly communication, averaging 13.6 publications per year and reaching a peak of 60 articles in 2022. They constitute the majority of annual outputs in oil spill simulation research, underscoring their significance in disseminating new findings and methodologies.

Conference and proceedings papers also make notable contributions to scholarly exchange, with an average of 3.56 $\pm$ 4.17 papers published annually. The year 1997 saw a peak of 17 papers, likely in response to pivotal environmental events or prominent scientific gatherings. Over the years, production has stabilized at a similar average, reflecting the ongoing importance of conferences in presenting preliminary research, fostering interdisciplinary dialog, and facilitating future collaborations.

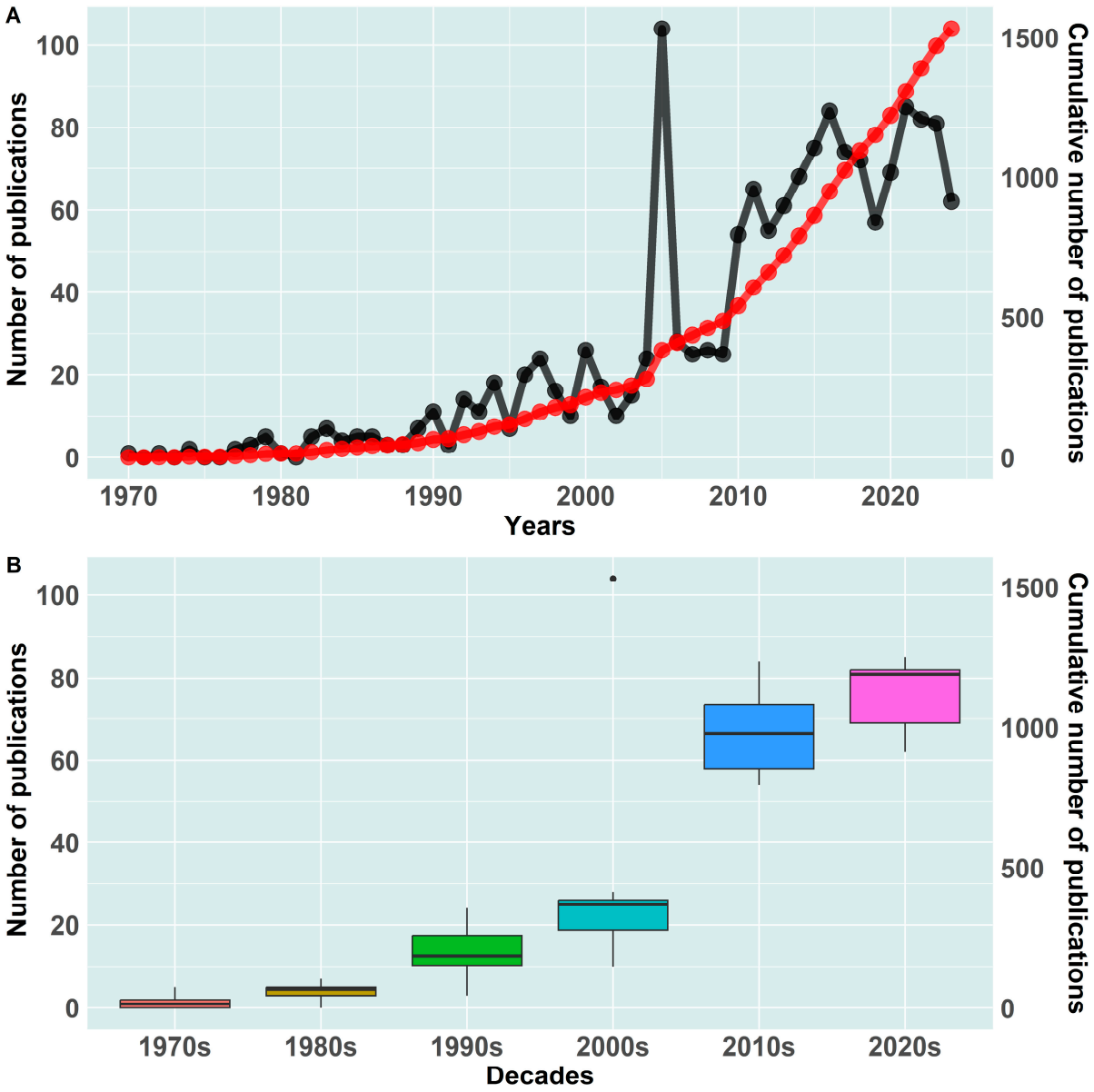


Figure 2. The figure describes the annual growth trend of oil spill simulation publications (black curve, left *y*-axis) in panel (**A**), compared with the cumulative number of publications over time (red curve, right *y*-axis) for the period of 1970–2024. In panel (**B**), the number of publications is grouped by decades, with each box plot represented in a different color. Diamond symbols indicate the median, while the height of the box plot represents the interquartile range (IQR), and the whiskers extend to the 95th percentile.

Closely related, proceedings paper publications derived from conference presentations were produced moderately, averaging 0.44 ± 0.96 documents per year, with a production peak observed in 2011 (4 documents). This trend suggests concentrated phases of thematic attention, often tied to major scientific assemblies aiming to formalize and disseminate cutting-edge research outputs. The trajectories of conference and proceedings publications illustrate the dynamic and responsive nature of research dissemination, particularly during periods marked by environmental emergencies and technological advancements.

While less common, book chapters and full-length books make significant contributions to the field by providing in-depth explorations of specific topics. On average, book chapters were published at a rate of 0.11 ± 0.69 per year, with a peak of 5 chapters released in 2011. This trend likely reflects collaborative efforts to compile knowledge into the-

matic volumes during critical periods of conceptual growth. In contrast, books, averaging 0.07 ± 0.26 publications annually, reached their high point in 1996 with the publication of 3 titles. The lower frequency and greater investment required for book production underscore their strategic importance in delivering integrative and foundational perspectives aimed at a wider academic and policy-making audience.

Additional hybrid formats, including Articles/Book Chapters and Articles/Proceedings Papers, have emerged, albeit infrequently. Articles/Book Chapters appeared sporadically, with only five instances recorded in 2011, indicating brief moments of intensified collaboration surrounding collective volumes. Likewise, Articles/Proceedings Papers were rare, peaking at four publications in 2011, often associated with the formalization of significant scientific gatherings into structured outputs.

Review articles, although published less frequently, have significantly influenced the intellectual development of the field. On average, they accounted for 0.6 ± 2.6 publications per year, peaking with 17 reviews published in 2011. The increase in review activity during certain periods indicates efforts to reassess established paradigms, incorporate recent methodological advancements, and synthesize fragmented knowledge bases, particularly in response to emerging environmental challenges and advancements in monitoring and modeling technologies.

The minor category of Review/Book Chapters, which merges the formats of reviews and chapters, remained exceedingly rare, with occurrences in only two years, 2011 and 2015, and never exceeding a single document in any given year.

Collectively, these publication patterns illustrate a complex landscape of scientific dissemination in oil spill simulation research. While journal articles and conference-related outputs dominate in terms of volume and frequency, other formats such as reviews, book chapters, and books offer crucial depth and perspective. Notable peaks in publication activity, particularly in 1997, 2011, and 2022, suggest that the field is highly responsive to external influences, including environmental disasters, technological advancements, and evolving scientific priorities. This dynamic interplay of publication types highlights the interdisciplinary nature of the field and its increasing significance within the broader context of environmental science and policy.

The rise in oil spill incidents has generated considerable concern among scientists and the public. A prominent example is the Deepwater Horizon disaster in the Gulf of Mexico in 2010, which released approximately 4.9 million barrels of oil and spurred an increase in oil spill research. Similarly, major spills in the Sundarbans, Bangladesh, in 2014 and off the coast of Galveston, Texas, in 2015 underscored the urgent need for advanced modeling techniques and coordinated mitigation strategies.

3.2. Most Cited Documents

An updated bibliometric assessment, utilizing a carefully curated dataset of 1541 publications spanning from 1970 to 2024, disclosed a cumulative total of 19,681 citations. The overall mean stands at 12.77 citations per document ($\pm$27.78). The citation distribution within the dataset is noticeably skewed, highlighting a concentration of scholarly recognition among a select group of highly influential publications (Figure 3). This uneven distribution reflects a typical long-tail pattern, where a minority of documents accounts for a significant portion of the total citations, indicating the presence of cumulative advantage dynamics in the field of oil spill modeling research (Figure 3).

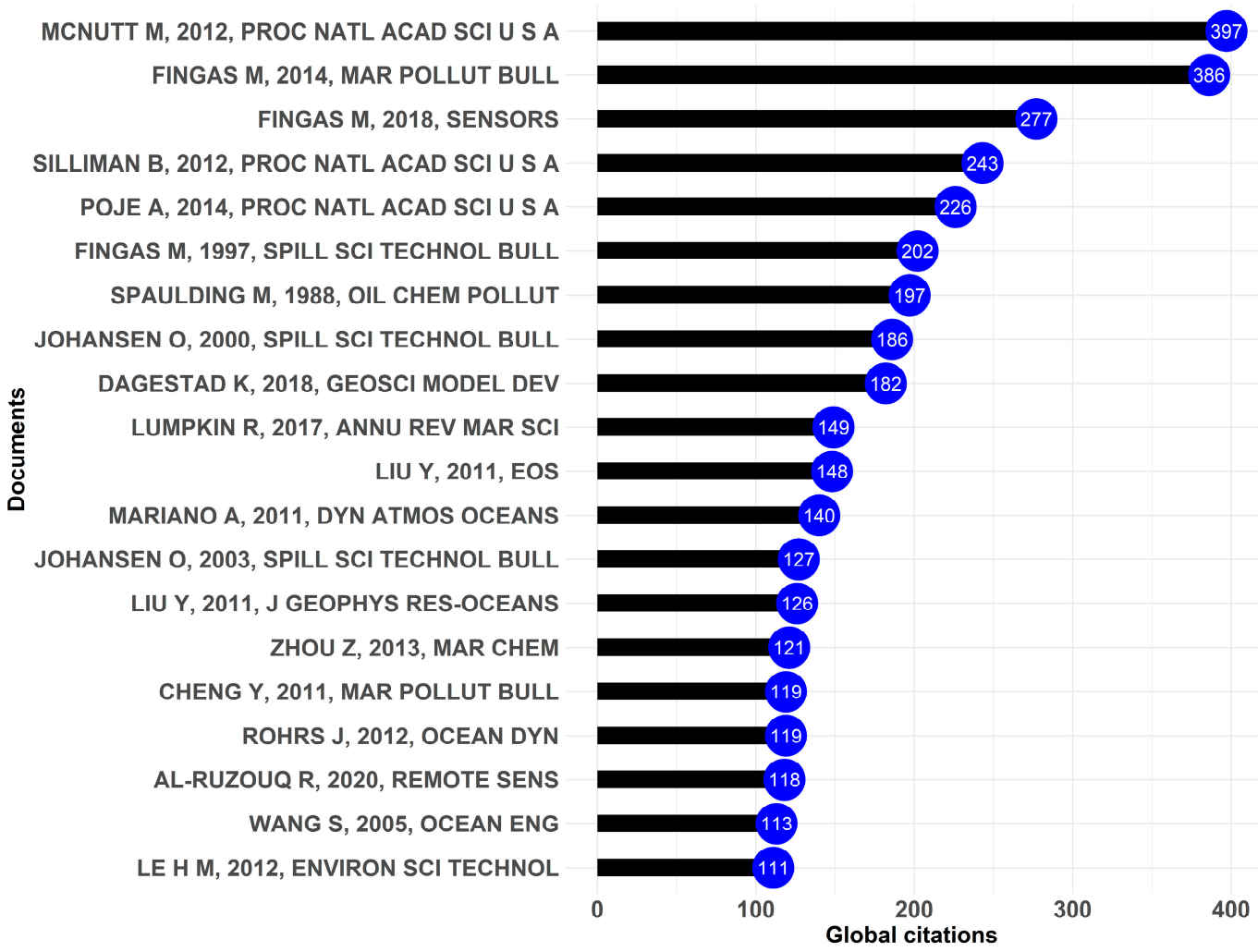


Figure 3. The figure illustrates the top twenty most impactful documents based on total citations. The respective citation numbers are represented by blue circles on the right side.

A thorough analysis of the 20 most cited publications supports this observation. Although these works constitute just 1.30% of the entire corpus, they collectively account for 3687 citations, representing 18.73% of all recorded citations. On average, each of these top 20 documents received 184.35 citations, which is more than 14.44 times the overall average for the dataset. This concentration underscores their foundational significance in shaping the intellectual trajectory of the field, as they serve as recurrent references for subsequent studies and exert a lasting methodological and conceptual influence (Figure 3).

At the forefront of citation counts is the work of McNutt, M. (2012) (Proc. Natl. Acad. Sci. U.S.A.) [34] which has accumulated 397 citations, representing 2.02% of the total. It is closely followed by Fingas M (2014, Mar. Pollut. Bull.) [35] with 386 citations (1.96%), and Fingas M (2018, Sensors) [36] which has garnered 277 citations (1.41%). Other notable contributions include Silliman B, 2012 (Proc. Natl. Acad. Sci. U.S.A.) [37] with 243 citations (1.23%), Poje A, 2014 (Proc. Natl. Acad. Sci. U.S.A.) [38], at 226 citations (1.15%), and Fingas M, 1997 (Spill Sci. Technol. Bull.) [39] with 202 citations (1.03%). Additionally, Spaulding, M. (1988). Oil Chem. Pollut. [40] remains a significant reference with 197 citations (1.00%).

The list further includes the following notable contributions: Johansen O, 2000 (Spill Sci. Technol. Bull.) [41] with 186 citations (0.95%); Dagestad K, 2018 (Geosci. Model Dev.) [42] with 182 citations (0.92%); Lumpkin R, 2017 (Annu. Rev. Mar. Sci.) [43] with 149 citations (0.76%); Liu Y, 2011 (EOS) [44] with 148 citations (0.75%); Mariano A, 2011 (Dyn. Atmos. Oceans) [45] with 140 citations (0.71%); Johansen O, 2003 (Spill Sci. Technol.

Bull.) [46] with 127 citations (0.65%); Liu Y, 2011 (J. Geophys. Res.–Oceans) [47] with 126 citations (0.64%); Zhou Z, 2013 (Mar. Chem.) [48] with 121 citations (0.61%); Röhrs J, 2012 (Ocean Dyn.) [49] with 119 citations (0.60%); Cheng Y, 2011 (Mar. Pollut. Bull.) [50] with 119 citations (0.60%); Al-Ruzouq R, 2020 (Remote Sens.) [51] with 118 citations (0.60%); Wang S, 2005 (Ocean Eng.) [52] with 113 citations (0.57%); and Le H M, 2012 (Environ. Sci. Technol.) [53] with 111 citations (0.56%). Collectively, these works represent the foundational elements of oil spill modeling, shaping research priorities and offering both theoretical and computational frameworks for further advancements.

The most frequently cited documents represent a diverse range of research themes and methodological advancements, including turbulence parameterization, Lagrangian trajectory modeling, subsurface blowout simulations, the integration of remote sensing, operational forecasting, and a synthesis based on reviews. These works exemplify the methodological rigor and technological advancements that characterize the evolution of this field.

When categorized by document type, journal articles overwhelmingly lead in scholarly impact, comprising 72.30% of all citations with an average of 18.64 $\pm$ 28.3 citations per article. In contrast, review articles, while accounting for only 9.24% of the total citations, demonstrate the highest citation intensity, with an average of 67.48 $\pm$ 110 citations each.

Conference papers account for 6.69% of citations, and their average of 2.98 $\pm$ 6.5 citations per paper highlights a more modest impact compared to journal-based outputs. Proceedings papers contribute 1.99% of citations, with an average of 2.00 $\pm$ 3.5 citations each, reflecting their role in the early dissemination of research.

Book chapters represent 1.16% of all citations, averaging 8.77 $\pm$ 10.8 citations per chapter, while standalone books contribute 0.82% of citations, with a mean of 14.73 citations each. This indicates that when books are published, they can achieve a significant reach. Editorial materials comprise only 0.07% of citations, averaging 3.50 $\pm$ 10.5 citations, while letters account for a minimal share of 0.04%, although they have an average of 8.00 citations.

Several hybrid and niche formats exhibit distinct citation profiles: "Article/Book Chapter" documents account for 3.25% of citations, "Article/Proceedings Paper" formats contribute 3.09% of citations, "Review/Book Chapter" outputs represent 1.03% of citations, and "Editorial Material/Book Chapter" items constitute 0.32% of citations. Notably, formats such as early-access articles, conference reviews, and meeting abstracts recorded no citations in this dataset.

These patterns illustrate that while journal and review articles dominate the scholarly attention, hybrid and book-based formats can achieve similarly high per-document impacts, underscoring the diverse ways in which foundational oil spill modeling research is disseminated and acknowledged.

These findings highlight a pronounced Matthew effect, where a select few high-impact studies attract significant academic attention, while the majority see limited citation engagement. This phenomenon reflects not only a cumulative advantage but also the field's reliance on a small number of cornerstone studies for theoretical grounding and methodological validation. Furthermore, external events, such as the Deepwater Horizon oil spill in 2010, act as catalytic moments that spur bursts of scholarly production and citation activity, particularly evident in the spike of top cited publications in the following years (2011–2012). Overall, while oil spill modeling continues to evolve and diversify, the field remains anchored to a relatively narrow set of influential works that define research paradigms and drive innovation.

3.3. Influential Sources

The analysis indicates that a relatively small number of publication venues disproportionately influence the overall literature. *The Marine Pollution Bulletin* stands out as the leading source, producing 93 articles (6.04%), underscoring its ongoing significance in the fields of marine pollution and oil spill science. Following closely are the 2005 International Oil Spill Conference (IOSC) proceedings, which contributed 84 documents (5.45%), emphasizing the vital role that specialized conferences play in sharing applied, operational, and policy-relevant insights. *Ocean Engineering* ranks third, with 28 publications (1.82%), focusing on advancements in spill modeling and response strategies within the fields of coastal and marine engineering.

Figure 4 illustrates the comprehensive distribution of scholarly outputs related to oil spill simulations, encompassing a wide range of publication venues. The dataset comprises 730 distinct sources, collectively encompassing 1541 documents, yielding an average of 2.11 ± 5.24 publications per source. This pattern highlights both the extensive dissemination of research and the concentration of activity within a select group of high-impact platforms.

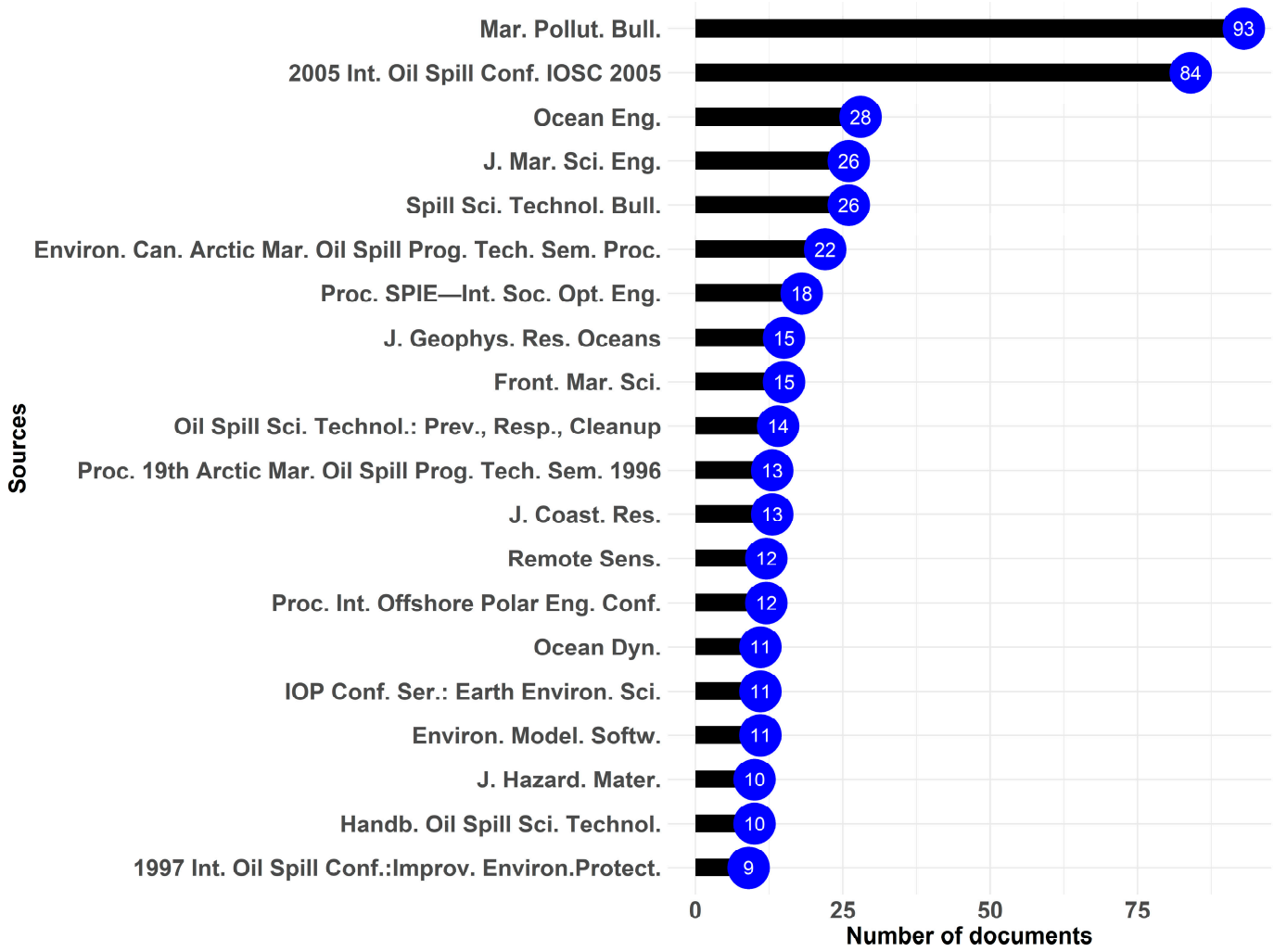


Figure 4. The figure presents the top twenty most impactful sources, along with the corresponding number of documents, as indicated by the blue circles on the right side.

The remaining leading sources further illustrate the multidisciplinary nature of the field. These include the *Journal of Marine Science and Engineering* and the *Spill Science & Technology Bulletin*, each contributing 26 documents (1.69%), as well as the Environment Canada

Arctic and Marine Oil Spill Program (AMOP) Technical Seminar Proceedings, which added 22 documents (1.43%). Additionally, the proceedings of the SPIE—The International Society for Optical Engineering—published 18 documents (1.17%), highlighting the significance of optical remote sensing technologies. Both *Frontiers in Marine Science* and the *Journal of Geophysical Research: Oceans* published 15 articles each (0.97%), emphasizing the connection between environmental sensing and geophysical modeling.

Specialized venues such as Oil Spill Science and Technology: Prevention, Response, and Cleanup (13 articles, 0.84%), **Remote Sensing** and Proceedings of the International Offshore and Polar Engineering Conference (each contributing 12 articles, 0.78%), and *Environmental Modelling & Software* (11 articles, 0.71%) rank among the most prolific outlets. Other noteworthy contributors include the *IOP Conference Series: Earth and Environmental Science* and *Ocean Dynamics* (both with 11 articles, 0.71%), as well as the *Handbook of Oil Spill Science and Technology* and the *Journal of Hazardous Materials* (each featuring 10 articles, 0.65%). The *1997 International Oil Spill Conference: Improving Environmental Protection* also made its mark with nine articles, accounting for 0.58%.

The top 20 sources collectively account for a significant portion of the overall scholarly output, consolidating a substantial share of methodological advancements, case studies, and modeling innovations within the field. The notable standard deviation in the document count per source (5.24) suggests a skewed distribution, wherein a few high-output venues act as essential repositories of knowledge. In contrast, the majority of sources make more modest contributions.

This concentrated yet varied dissemination landscape underscores the dynamic and interdisciplinary character of oil spill simulation research. The significant presence of specialized journals, technical symposia, and conference proceedings illustrates the dual focus of the field on advancing theoretical modeling and enhancing operational spill response strategies. These sources function not only as platforms for academic discourse but also as crucial conduits for translating modeling advancements into practical insights for environmental risk assessment and mitigation.

3.4. Authors Contributing

Among the various contributors to research in oil spill modeling, the top 20 most prolific authors exhibit a remarkable blend of academic productivity and citation impact (see Figures 5 and 6). Collectively, these authors have produced 420 publications, which account for 27.2% of the total 1541 documents, and have garnered 8432 citations, representing 42.8% of all citations within the dataset (refer to Figures 5 and 6).

At the forefront of this group is Fingas M, who has authored 82 publications and accumulated 2412 citations (with a citation index of approximately 29.41), with his publication activity spanning from 1977 to 2021. In second place is Spaulding M, with 32 publications and 562 citations (index ≈ 17.56), active from 1979 to 2021. Following closely is Reed M, who has 25 publications and 557 citations (index ≈ 22.28), contributing to the field from 1986 to 2019 (see Figures 5 and 6).

Anderson E ranks fourth with 24 publications and 215 citations (index ≈ 8.96), with a publication span from 1982 to 2005. Li Y follows in fifth place, having 22 publications and 215 citations (index ≈ 9.77), with an active publishing period from 2000 to 2024 (see Figures 5 and 6). Johnson W has authored 21 publications, garnering 249 citations (index ≈ 11.86), and was active from 1992 to 2020. Simecek-Beatty D produced 20 publications and received 72 citations (index ≈ 3.60), with contributions spanning from 1994 to 2021. Barker C made 19 publications and achieved 135 citations (index ≈ 7.11), with a publication window from 1999 to 2024 (see Figures 5 and 6).

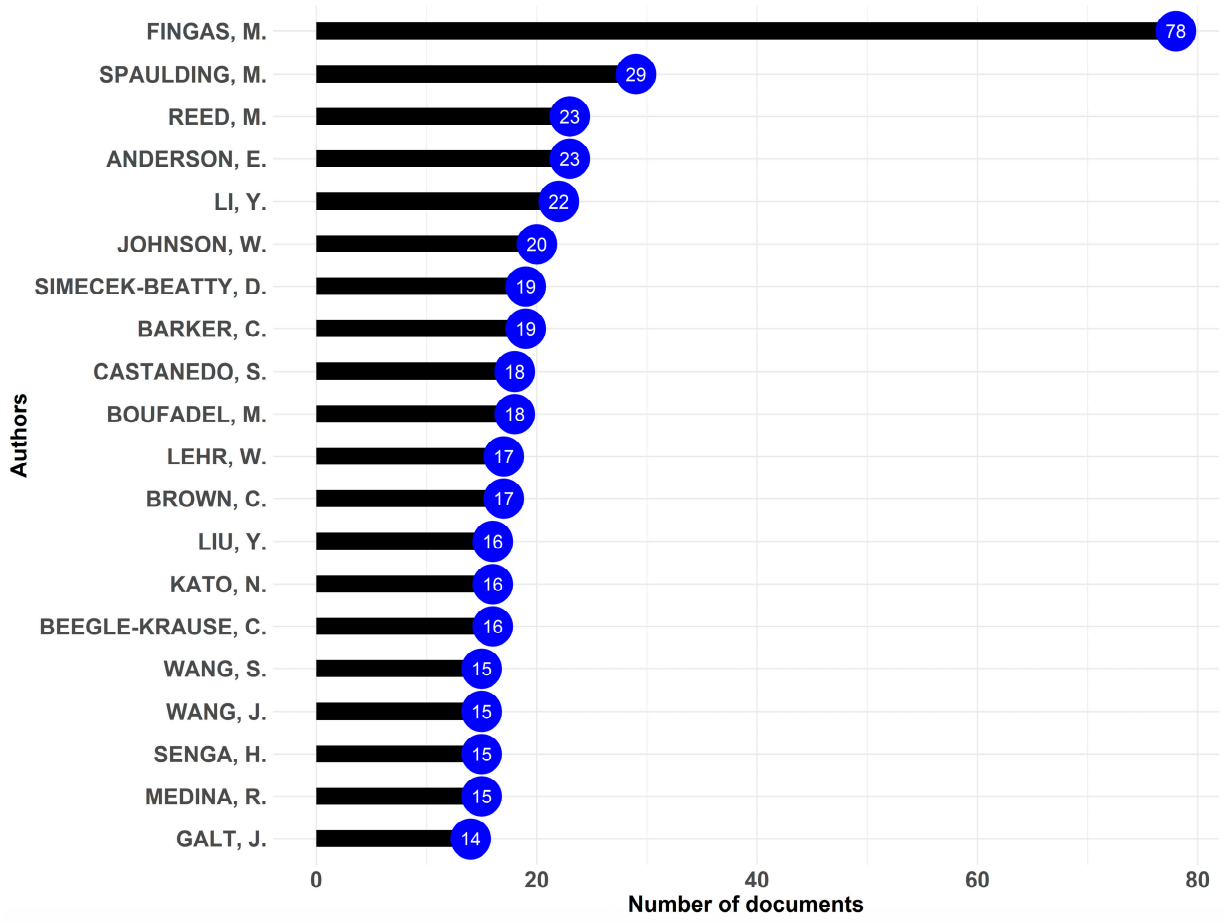


Figure 5. Top 20 most prolific authors in oil spill modeling research, ranked by number of published documents. Black horizontal bars show each author's total publications, and blue markers indicate the exact count next to each bar.

Lehr W has authored 19 publications, garnering a total of 112 citations, resulting in an index of approximately 5.89, with contributions spanning from 1983 to 2021. Castanedo S also has 19 publications but boasts a significantly higher impact, with 520 citations, yielding an index of around 27.37, demonstrating a noteworthy influence from 2005 to 2021 (see Figures 5 and 6).

Brown C is particularly notable, with 18 publications and an impressive 1064 citations, achieving the highest citation-per-publication index on the list at approximately 59.11, published between 1993 and 2018. Kato N, who also has 18 publications, has accumulated 124 citations, resulting in an index of about 6.89 from 2007 to 2017. Senga H contributed 17 publications and collected 122 citations, yielding an index of approximately 7.18, within the same time frame of 2007 to 2017 (see Figures 5 and 6).

Additionally, Brown C stands out with 17 publications and an impressive total of 1041 citations, achieving the highest citation per publication index in this context at approximately 61.24, between 1993 and 2018. Meanwhile, Kato N, who also published 17 articles, accumulated 121 citations, resulting in an index of around 7.12 from 2007 to 2017. Senga H contributed 16 publications, garnering 119 citations and yielding an index of roughly 7.44 over the same period (see Figures 5 and 6).

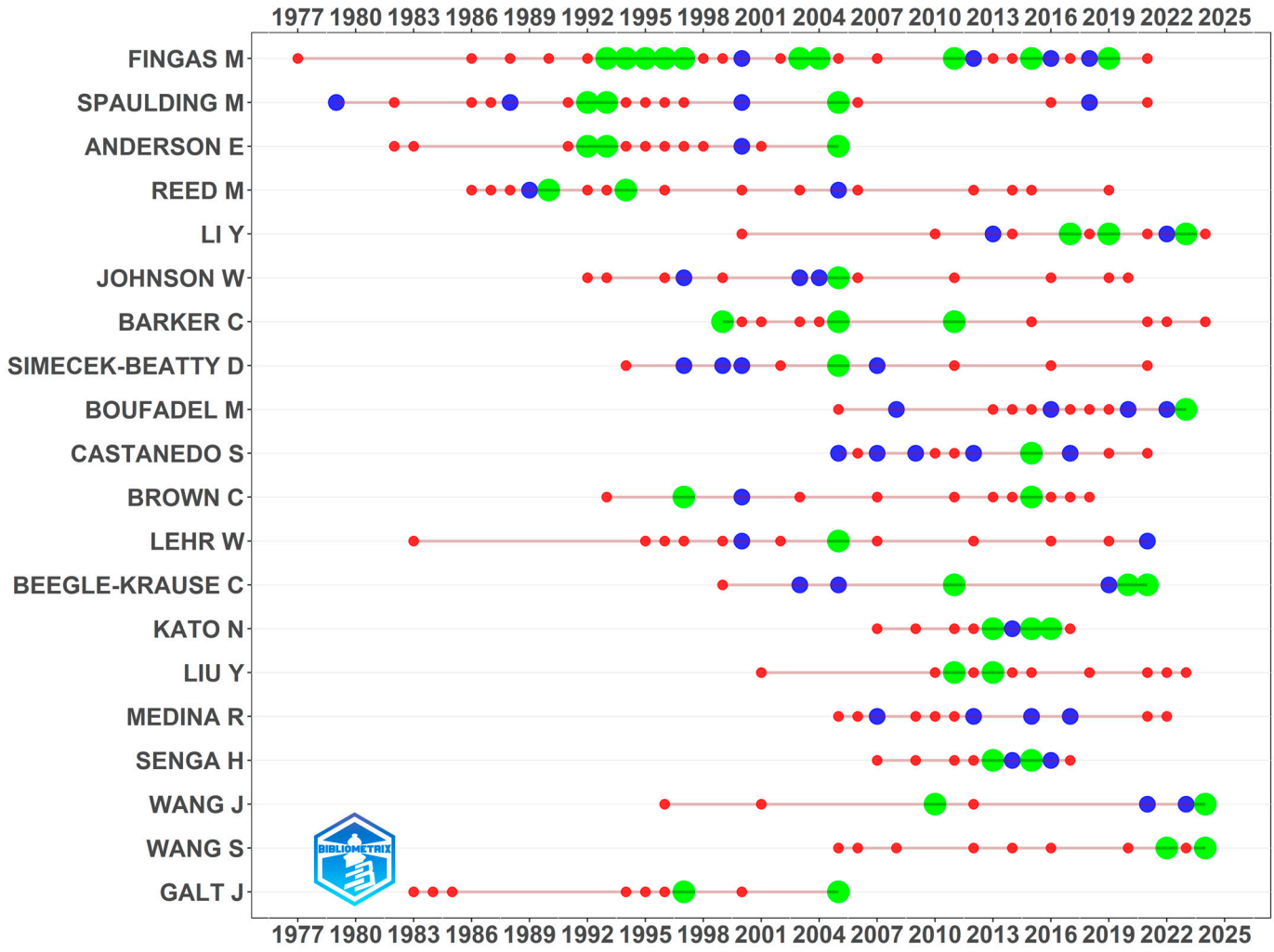


Figure 6. Temporal trends of key authors are visualized using colored circles to represent the number of published papers and red lines to show the temporal distribution of publications over time for each author. The size of the circles indicates the number of papers published in a given year, categorized into three levels (1, 2, and 3 papers), as shown in the legend. The color of the circles represents the total number of citations received by the publications in that year.

Beegle-Krause C has authored 17 publications, accumulating a total of 219 citations, resulting in an index of approximately 12.88, from 1999 to 2021. Liu Y stands out with 16 publications and an impressive 645 citations, yielding a remarkably high impact index of around 40.31, covering the period from 2001 to 2022. Medina R has also contributed 16 publications, which received 412 citations, with an index of approximately 25.7 and active between 2005 and 2022 (see Figures 5 and 6). Boufadel M is similarly noted for 16 publications, garnering 288 citations and an h-index of approximately 18 from 2005 to 2022. Li Z authored 15 publications, which have garnered 161 citations, resulting in an index of roughly 10.73, with contributions spanning from 2010 to 2022. Lee K has produced 14 publications that accumulated 244 citations, yielding an index of about 17.43, active from 2005 to 2024. Lastly, Wang J concludes the top 20 with 14 publications and 98 citations, resulting in an index of approximately 7.00, active from 1996 to 2024 (refer to Figures 5 and 6).

The publication periods of these top 20 authors span from as early as 1977 to as recent as 2024, highlighting their long-term dedication and significant impact on the evolution of oil spill modeling. This group of researchers is pivotal in the development

and dissemination of scientific knowledge within the field, establishing a foundation for methodological advancements and future innovations.

3.5. Trends in the Most Influential Publications

3.5.1. Prominent Oil Spil Modeling and Integrative Components

An analysis of the top 188 most influential publications reveals significant trends and detailed insights into oil spill modeling. Table S1 provides a summary that contains specific information.

The reviewed documents identify several widely used oil spill models in the field. Among the prominent models is the OSCAR (Oil Spill Contingency and Response Model), developed by SINTEF. This three-dimensional model effectively addresses both surface and subsurface releases, calculating the fate and effects of oil and gas spills.

The text encompasses algorithms for spreading, evaporation, natural dispersion, emulsification, dissolution, and volatilization. Noteworthy among these are OILMAP and SIMAP, developed by ASA for managing surface and subsurface hydrocarbon releases. These systems provide algorithms for oil spreading, evaporation, emulsification, entrainment, and shoreline–seabed interactions, while also considering tidal influences. MEDSLIK-II, which operates in the Mediterranean region, features a built-in database of over 220 oil types and has been utilized to forecast the fate and transport of oil during various emergencies. OpenOil, founded on the OpenDrift framework, incorporates algorithms for wave entrainment, vertical mixing, resurfacing, and emulsification and is actively used in Norway for contingency planning and search-and-rescue missions. Additionally, models like DeepBlow (which simulates deepwater blowout plumes), GNOME (General NOAA Operational Modeling Environment), and JETLAG (focused on submerged oil jets and plume behavior) are frequently referenced, alongside specialized applications for electromagnetic scattering, oil droplet dynamics, and remote sensing data assimilation.

Across the 188 studies examined, an average of 1.62 ± 1.37 models were employed per study, with some papers incorporating as many as 8 different frameworks simultaneously. This trend reflects a growing inclination toward multimodel integration under complex environmental conditions.

In terms of model types, hydrodynamic models were predominant, appearing in 94 instances (approximately 50.0%), followed by biogeochemical models (15 occurrences; around 8.0%), oil-spill-specific models (14; approximately 7.4%), wave models (12; nearly 6.4%), and atmospheric models (6; roughly 3.2%). Additionally, more specialized categories emerged, including particle tracking models (4; about 2.1%) and trajectory models (2; around 1.1%). This underscores the interdisciplinary integration of oceanography, meteorology, environmental chemistry, and computational physics.

The primary physical and biogeochemical variables incorporated into these models were referenced 774 times, yielding an average of 4.78 ± 4.10 mentions per study. The most frequently cited variables included the wind speed (13 mentions), evaporation (12), wind (11), ocean currents (9), current velocity (8), and temperature (7). Additional variables such as salinity, droplet size distributions, and dispersion coefficients further underscore the multiphase complexity inherent in oil spill forecasting.

Observational and remote sensing datasets were recorded 425 times, averaging 2.62 ± 3.01 mentions per study. While 55 studies did not specify a data source, the most commonly utilized sources were MODIS imagery (8 mentions), along with ENVISAT ASAR, MERIS, SAR, and Landsat 8 (each with 3 mentions), as well as various other satellite and in situ measurements.

Study area information was recorded in 192 entries, encompassing a wide range of regions. The Gulf of Mexico emerged as the most frequently reported focus, featuring in

15 studies, followed by mentions of "China" in 7 studies, the Bohai Sea in 5, the Arabian Gulf in 4, and the East China Sea in 3. Additionally, 18 studies did not specify a geographic area, highlighting the potential for enhancing the spatial context in future research.

The integration of these elements into oil spill models marks a significant advancement in the field, equipping researchers and practitioners with powerful tools to simulate and comprehend complex spill dynamics. However, this overview also emphasizes the ongoing necessity for the broader adoption of diverse observational datasets, the continual development of integrated multimodel frameworks, and improved geographic reporting to enhance predictive accuracy and support adequate environmental protection and disaster responses.

3.5.2. Critical Variables and Emerging Trajectories in Oil Spill Modeling

An analysis of 188 influential publications revealed that a diverse range of environmental and physicochemical variables is integrated into oil spill models, thereby enhancing their inferential capabilities and improving the predictive accuracy. The dataset documented 840 instances of variable integration, averaging 4.54 ± 3.96 variables per study. This trend highlights the growing shift toward multi-factorial and multidimensional modeling approaches in simulating oil spill dynamics, as models increasingly incorporate a broader spectrum of environmental factors.

Among the most significant factors identified, ocean currents were emphasized as crucial for assessing the movement and dispersion of oil spills. Data on currents, primarily sourced from hydrodynamic models such as HYCOM and products from the Copernicus Marine Service, appeared in approximately 46.5% of the reviewed documents. Models like the OSCAR and SIMAP consistently integrate data on the current velocity and direction to accurately predict oil transport patterns, highlighting the essential role of ocean circulation within oil spill modeling frameworks.

Wind-related variables, particularly the wind speed and direction, were included in approximately 46.0% of the studies, underscoring their significant impact on the surface drift of oil slicks. Atmospheric data from systems like NOAA's Global Forecast System (GFS) and the European Centre for Medium-Range Weather Forecasts (ECMWF) are used to feed models such as GNOME. This integration allows for robust simulations of pollutant advection in marine environments, thereby enhancing the reliability of forecasts for coastal response operations.

Wave dynamics, including the wave height, frequency, and direction, accounted for approximately 16.8% of the cited variables. These parameters are essential for accurately modeling processes such as oil dispersion, emulsification, and entrainment into the water column. Wave models, such as WAM, provide critical data that is integrated into systems like MEDSLIK-II and OpenOil, enabling simulations of how sea state conditions affect the behavior of oil slicks across various meteorological scenarios.

Temperature, including both air and sea surface temperatures, was incorporated into approximately 13.5% of the models. Precise thermal fields enable the simulation of variations in oil viscosity, evaporation rates, and the efficiency of microbial biodegradation. Models such as the Spill, Transport, and Fate Model (STFM) rely heavily on these parameters to accurately represent the thermodynamic behavior of oil under various environmental conditions and to predict the phase transitions of spilled hydrocarbons.

Salinity, although less frequently represented (5.4% of studies), remains a pivotal variable influencing oil buoyancy, dispersion, and emulsification thresholds. Salinity fields, often coupled with temperature profiles, enhance the ability of hydrodynamic models to simulate vertical stratification and its implications for oil spreading and sedimentation processes.

Biogeochemical variables, including nutrient concentrations and planktonic biomass, were incorporated in approximately 3.2% of the cases. These parameters, derived from biogeochemical forecasting systems, are crucial for informing biodegradation modules by characterizing the environmental conditions that facilitate the microbial breakdown of hydrocarbons, especially in nutrient-enriched or biologically productive regions.

Oil-specific physical properties, such as the density, viscosity, and chemical composition (including distinctions between light and heavy crude oils), were featured in about 15.1% of the studies. Accurate characterization of these properties is essential for models like OILMAP and SIMAP, as it enables the simulation of key processes, including spreading behavior, weathering rates, emulsification thresholds, and long-term degradation dynamics.

Sediment interactions were referenced in approximately 2.2% of the studies, primarily in relation to coastal and shallow-water spills. Data on the sediment type and distribution facilitate the modeling of oil adhesion to particulate matter, sedimentation dynamics, resuspension events, and risks of seabed contamination. These factors are crucial for evaluating nearshore environmental impacts and developing effective remediation strategies.

Sunlight exposure and ultraviolet radiation were included in about 0.5% of the studies, highlighting their significant role in the photolytic degradation of surface oil layers. Incorporating solar radiation data is crucial for accurately simulating weathering pathways, particularly in low-latitude regions with intense solar exposure, where photo-oxidation significantly contributes to the natural attenuation of oil.

Freshwater contributions, including river discharges and precipitation events, were incorporated in only about 0.5% of the reviewed models. These factors play a crucial role in influencing salinity gradients, nutrient fluxes, and the physical oceanographic conditions that dictate the horizontal and vertical distribution of oil spills, especially in estuarine and nearshore environments.

The integration of observational datasets has increasingly gained traction in both operational and research modeling frameworks. A total of 453 instances of remote sensing and in situ data integration were identified, resulting in an average of 2.45 ± 2.86 datasets integrated per study. Various sources were frequently utilized, including satellite imagery from sensors such as MODIS, VIIRS, MERIS, and SAR; spectral reflectance data (Rrc); Floating Algae Index (FAI) products; HF radar-derived surface currents; and drifter deployments. These datasets are essential for model initialization, boundary condition updates, assimilation processes, and forecast validation, significantly enhancing the accuracy and responsiveness of oil spill simulations.

The spatial analysis indicated that the Gulf of Mexico was the most frequently studied region, with 33 studies (17.8%), followed by the Arabian Gulf with 8 studies (4.3%), and the Bohai Sea with 7 studies (3.8%). The Bay of Biscay had five studies (2.7%), while the East China Sea and Black Sea each accounted for four studies (2.2%). The Shetland Islands had two studies (1.1%), and there were single-study locations, including the Sea of Oman and the Ohmsett wave tank, each representing 0.5%. This broad geographic distribution highlights the variety of environmental conditions examined across these studies.

The integration of diverse variables and data sources highlights the shift toward multiphysical, multiscale, and multidisciplinary frameworks for oil spill modeling. By incorporating environmental forcing factors, chemical weathering parameters, biological response processes, and observational data streams, modern oil spill models are delivering increasingly robust, comprehensive, and operationally relevant predictions of spill behavior.

Looking ahead, the future of oil spill modeling is focused on several key aspects. A critical priority is the integration of high-resolution, near-real-time environmental forcing data from various background models, including hydrodynamic, meteorological, wave, and biogeochemical systems, to enhance the reliability of operational models. Concurrently,

there is a significant push towards developing advanced biodegradation algorithms, refined through real-time laboratory and field experimental results to more accurately represent the microbial processes and hydrocarbon breakdown across diverse marine environments.

Ongoing advancements in modeling oil weathering processes, specifically evaporation, emulsification, dissolution, and photo-oxidation, are expected. These enhancements aim to provide more accurate, dynamic, and environmentally sensitive simulations of oil spill behavior under varying conditions. Emerging modeling frameworks are increasingly incorporating dynamic oil property modules that adapt the physical and chemical characteristics of oil in response to the exposure time, weathering stages, and environmental factors.

In addition to advancing the physics and chemistry of models, there is a distinct focus on improving computational efficiency and scalability. The growing scale and complexity of oil spill simulations require robust parallel computing solutions that can effectively manage extensive spatial domains and prolonged temporal forecasts while preserving high-spatial and -temporal resolutions. Enhancements in numerical optimization, adaptive mesh refinement, and the integration of machine-learning-based surrogate models are expected to be crucial in addressing these computational challenges.

Finally, real-time data assimilation from remote sensing and in situ observation networks is emerging as a vital area of development. By incorporating continuous observational updates into operational models, researchers can significantly enhance the reliability, responsiveness, and accuracy of oil spill trajectory forecasts and environmental impact assessments. The integration of live satellite imagery, surface drifter trajectories, HF radar data, and ocean buoy information is anticipated to become standard practice in next-generation operational oil spill models.

Overall, the field of oil spill modeling is rapidly evolving, driven by technological advancements, scientific discoveries, and an urgent societal need to protect marine ecosystems better. These ongoing developments are crucial in enhancing our collective capacity to respond effectively to oil spills and to protect the resilience of our coastal and oceanic environments.

4. Discussion

4.1. General Patterns

4.1.1. Historical Growth and Research Relevance

Over the past decades, oil spill modeling has evolved into a mature and dynamic research field. Our analysis reveals several key patterns underpinning this development: the sustained growth in the publication output, episodic surges triggered by major spill events, the diversification in publication types, increasing international collaboration, and the integration of advanced technologies. Collectively, these trends reflect the field's responsiveness to external drivers and its trajectory toward methodological and institutional consolidation.

The volume of publications on oil spill modeling has increased steadily throughout the study period. In the 1970s and early 1980s, only a few studies were published annually, whereas by the 2010s, the annual output had risen to dozens of publications [54–56]. This long-term growth is indicative of rising environmental awareness, increasing regulatory demands, and a broader recognition of the ecological and economic consequences of oil spills. By the early 21st century, the field had transitioned from a niche topic to a prominent research domain, as reflected by the accelerating publication rate.

Superimposed on this general growth trend are sharp surges in research activity following major oil spill incidents. For example, the 1989 Exxon Valdez disaster coincided with an increase in modeling studies, and the 2010 Deepwater Horizon (DWH) blowout triggered an unprecedented spike in the publication output. Following the DWH event, the number of related publications roughly doubled relative to prior years, representing

the most substantial short-term increase observed in our dataset. Other large-scale spills, such as the 1979 Ixtoc I blowout, the 1991 Gulf War oil release, and the 2002 Prestige spill, also aligned with more minor but discernible peaks in scholarly output. Although none matched the scale or duration of the DWH-driven surge, these episodes consistently demonstrate that catastrophic oil spills serve as catalysts for rapid research mobilization. They also underscore the tendency for scientific agendas to be shaped by environmental crises, reinforcing the importance of sustained, proactive investigation, even in the absence of significant events [19,57,58].

The dissemination of findings has evolved in tandem with the field's expansion [10]. Throughout the study period, peer-reviewed journal articles comprised the majority of publications, accounting for approximately half of all outputs. Conference papers and proceedings made up a substantial portion, around 40%, highlighting the role of professional events in facilitating rapid dissemination. Notably, during the mid-2000s, conference contributions spiked, likely due to major international spill conferences or symposia that produced comprehensive proceedings. In recent years, the dominance of journal articles has increased, indicating a shift toward more archival and peer-reviewed dissemination as the field matures.

In addition to research articles and conference papers, the literature comprises a modest yet notable body of review articles, books, and book chapters. These publication types have primarily emerged since the early 2000s, with review articles becoming increasingly common after 2010. This pattern reflects a growing effort to synthesize accumulated knowledge and critically evaluate the state of the art. Likewise, the appearance of books and book chapters, especially from the mid-2000s onward, demonstrates the development of comprehensive reference materials as the knowledge base deepens. The presence of such works is characteristic of a maturing scientific discipline, serving to organize dispersed findings, consolidate theoretical frameworks, and guide future research directions.

Recent increases in the publication volume, particularly in 2023, may be partially attributed to the 2019–2020 oil spill along the Brazilian coast, one of the most severe environmental disasters in the region. This event prompted scientific initiatives aimed at understanding the origin, dispersion, and environmental consequences of the spill. Notably, studies by Sbragio et al. [59] and Tessarolo et al. [60] applied advanced modeling approaches to simulate oil transport along the South Equatorial Current, emphasizing the complexities of subsurface and surface dispersion, as well as concerns regarding long-term contamination. This renewed wave of research activity contributes to the observed rise in publications during the current decade and exemplifies how environmental crises continue to drive scientific innovation and inquiry.

These events have not only stimulated research but have also fostered greater engagement among scientists, regulatory bodies, and industry stakeholders. At the same time, technological advancements such as improved computational power, enhanced remote sensing platforms, and the growing use of machine learning have enabled more sophisticated and integrated modeling frameworks.

Another salient trend is the steady increase in collaborative research. Early publications often featured one or two authors from a single institution or country. In contrast, recent works commonly involve large, multi-author teams spanning institutions and nations. This shift is especially evident after the Deepwater Horizon incident, which led to the formation of extensive research consortia and cross-sector collaborations. The resulting co-authorship network reflects a transition from isolated research efforts to a globally interconnected community.

This collaborative shift carries important implications. Oil spill modeling is inherently interdisciplinary, requiring the integration of oceanography, meteorology, chemistry, engi-

neering, and ecology. Larger, multi-institutional teams facilitate this integration, enabling comprehensive models that can simulate oil dispersion, degradation, and ecological impacts simultaneously. International partnerships also promote methodological convergence and comparative analysis, allowing lessons learned in one region to inform spill responses elsewhere. For instance, standardized modeling frameworks and community-developed tools have emerged as products of this global collaboration.

The field of oil spill modeling has undergone a significant transformation. The field has evolved from a reactive, event-driven discipline into a proactive and methodologically robust research area. The convergence of sustained publication growth, post-disaster surges, expanded dissemination modes, technological advancement, and rising global collaboration defines the present landscape of oil spill modeling and sets the stage for future advances.

4.1.2. Key Publications, Journals, and Influential Authors

The bibliometric patterns observed in this study reveal central dynamics shaping the evolution of oil spill modeling research, aligning with broader trends in scientific development. Key findings include a highly skewed citation distribution, the dominance of a few core journals, increasing interdisciplinarity and collaboration, and the catalyzing role of environmental disasters in steering research agendas.

Our analysis shows a markedly unequal citation distribution, with a small number of publications accounting for the majority of citations. This Pareto-like pattern exemplifies the Matthew effect in science, whereby the early recognition of a study reinforces its long-term prominence. Seminal modeling papers and comprehensive reviews, particularly those addressing pioneering trajectory models or early assessments of the Deepwater Horizon, have become foundational references in the field. While this visibility facilitates the diffusion of validated methodologies and datasets, it may also bias research toward established topics, limiting the emergence of novel approaches or underrepresented issues. Such concentration reflects both a consolidation of the core knowledge and a potential barrier to diversification. Recognizing this imbalance is critical for the research strategy, as it highlights the need for targeted support for innovative or regionally specific studies that might otherwise be eclipsed by canonical literature.

Similarly, the concentration of publications within a small number of journals reflects a structured pattern of scientific communication. A few high-impact journals in environmental science and marine technology dominate both the volume of articles and citation counts in the dataset. This distribution aligns with Bradford's Law, which states that a core set of journals produces most of the influential literature. These outlets not only offer wider visibility and rigorous peer review but also shape research priorities through editorial selection. While centralization facilitates knowledge accumulation and discoverability, it may inadvertently marginalize valuable insights published in lesser-known venues. Thus, researchers and information professionals must remain attentive to the broader landscape of the literature to avoid overlooking peripheral yet significant contributions.

A notable trend is the increasing prevalence of interdisciplinary and collaborative research. Recent publications often feature large author teams spanning multiple institutions and disciplines, integrating oceanography, engineering, ecology, chemistry, remote sensing, and socio-economic analysis. This shift mirrors broader developments in environmental sciences, where addressing complex problems increasingly requires cross-disciplinary expertise. Many of the most cited studies in our dataset reflect this trend, involving coordinated efforts between domain specialists such as ocean modelers, biologists, and remote sensing analysts. The post-2010 period, particularly following the Deepwater Horizon incident, witnessed the emergence of international consortia and team-based research as the

norm. These collaborative structures have enabled more holistic models, such as coupling physical dispersion dynamics with ecological impact assessments, and improved the policy relevance of oil spill science. However, they also necessitate mechanisms to overcome communication barriers and coordinate methodologies across diverse fields. Our findings support the view that environmental crisis research has evolved into a form of convergence science, becoming increasingly reliant on collaborative networks to produce integrative, high-impact knowledge.

Temporal trends also indicate that major environmental disasters serve as inflection points for research surges. The 1989 Exxon Valdez spill spurred extensive investigations in the 1990s, while the 2010 Deepwater Horizon disaster produced an unprecedented wave of scientific activity. The latter event triggered substantial funding, most notably through the USD 500 million Gulf of Mexico Research Initiative, and catalyzed diverse studies on deep-sea plume modeling, shoreline impacts, and long-term ecosystem recovery. Our data reflects a sharp increase in the publication volume and topical breadth following this event. Such surges correspond to what is known in policy studies as the "issue–attention cycle," where crises temporarily elevate the public and political focus, mobilizing scientific resources. While this pattern can generate rapid innovation, it may also lead to a decline in attention once the crisis subsides. Hence, reactive bursts of research must evolve into sustained programs addressing both immediate impacts and long-term preparedness. In oil spill modeling, this translates into the need for continuous monitoring systems and methodological refinement independent of acute events.

Taken together, these findings have significant implications. The dominance of highly cited papers and core journals reflects a well-defined but rigid knowledge structure, requiring deliberate efforts to foster emerging areas and avoid reinforcing closed citation loops. The prevalence of interdisciplinary and collaborative studies is a positive signal of the field's responsiveness to complexity, though it requires sustained institutional and financial support. Moreover, the reactive nature of research following disasters highlights the need for a more proactive and resilient scientific culture, one that builds a cumulative capacity before, during, and after crises. For oil spill modeling, this entails investing in long-term model development, cross-disciplinary training, and continuous validation using observational data. By addressing these structural dynamics, the research community can enhance its capacity to respond effectively to future environmental emergencies while advancing the foundational science.

4.2. Literature Trends

4.2.1. Modeling Frameworks, Critical Variables, and Future Prospects

The evolution of oil spill simulation research over the past few decades is marked by an increasing complexity, the integration of multidisciplinary processes, and a growing reliance on observational data. Early models were simplistic, using two-dimensional empirical formulas or vector computations to estimate spill trajectories. In contrast, current approaches rely on three-dimensional numerical models coupled with meteorological, hydrodynamic, and wave models, embedded within operational forecasting systems. This advancement has been catalyzed by both computational improvements and high-impact events such as the 2010 Deepwater Horizon and 2011 Penglai spills, which exposed model limitations and prompted a transition toward multiphysical, multiscale frameworks.

Modern oil spill models incorporate met-ocean forcings (currents, winds, waves) alongside comprehensive oil fate algorithms. Tools like SINTEF's OSCAR simulate both surface and subsurface dynamics, integrating advection, turbulent dispersion, and weathering processes (e.g., spreading, evaporation, emulsification, dissolution, biodegradation). ASA's SIMAP and OILMAP systems further extend capabilities, coupling transport and

weathering with environmental impact assessments. These models, validated against major spill events such as Exxon Valdez, demonstrate robustness and are widely used in planning and response operations.

Open-source platforms such as NOAA's GNOME and MEDSLIK-II have broadened access to high-quality modeling tools. GNOME, through its Python 3 interface (PyGNOME), supports ensemble runs and uncertainty quantifications. MEDSLIK-II and OpenOil allow flexible integration with external oceanographic and atmospheric models. These community-driven systems emphasize transparency, adaptability, and real-time application, fostering a broad adoption in operational contexts.

Specialized modules have emerged to simulate deepwater blowouts, a scenario where traditional surface models fall short. Near-field models, such as JETLAG, DeepBlow, and TAMOC (Texas A&M Oilspill Calculator), handle plume dynamics, including gas dissolution, hydrate formation, and droplet rise. When coupled with far-field models like OILMAPDEEP, they enable seamless multiscale simulations from the wellhead to the surface, exemplifying the field's integrated, multidisciplinary approach.

The fidelity of any oil spill simulation relies on an accurate representation of environmental drivers, primarily the ocean currents and wind. These govern transport trajectories, with the surface wind drift typically accounting for 3–5% of the wind speed. Wave dynamics also play a critical role via Stokes drift and turbulence-induced dispersion. The high-resolution forcing data, often derived from external forecasts or observational networks, is essential for simulating coastal eddies, sea breezes, and other small-scale features that affect spill pathways. Accurate environmental inputs are thus prerequisites for reliable trajectory forecasts.

In addition to physical drivers, physicochemical and biogeochemical parameters significantly influence the fate of oil. The sea surface temperature modulates the oil viscosity and evaporation, while salinity affects the emulsion formation. Sunlight exposure leads to photo-oxidation, altering oil chemistry and persistence. Biodegradation, which is dependent on the nutrient levels, microbial communities, and oxygen availability, is typically modeled using first-order kinetics; however, many models still underrepresent this process. Tools like SIMAP explicitly include biodegradation, offering greater realism for long-term fate assessments. Moreover, oil-specific properties (e.g., density, volatility, emulsion potential) sourced from libraries like NOAA's ADIOS are increasingly used to parameterize simulations.

The geomorphological context also shapes spill outcomes. The shoreline type, sediment load, and coastal bathymetry influence oil stranding and sedimentation. Models like OILMAP simulate shoreline accumulation and incorporate shoreline-specific weathering and removal rates. Sediment suspension in shallow waters facilitates oil–particle aggregation and eventual seabed deposition, a process explicitly modeled in SIMAP. These interactions, although complex and uncertain, are crucial for predicting the oil persistence and its ecosystem impact.

A key advance in recent years has been the assimilation of observational datasets into modeling workflows. Satellite remote sensing (SAR, optical), aerial surveys, HF radar, and GPS drifters provide real-time or near-real-time data on the spill extent and ocean dynamics. Assimilation methods ranging from simple parameter adjustments to ensemble Kalman filters are now routinely used to update forecasts and reduce uncertainty. NOAA's GNOME incorporates assimilation routines to nudge model outputs toward observations, improving the alignment with actual slick positions. Ensemble modeling further enhances forecast robustness, generating probabilistic outputs that capture the scenario variability and guide emergency responses.

Operational infrastructures, such as NOAA's GOODS (GNOME Online Oceanographic Data Server) and European systems linked to Copernicus, ensure continuous access to updated environmental datasets. These platforms facilitate the near-real-time coupling of models and observations, transforming oil spill forecasting into a dynamic, responsive system akin to weather prediction. The result is a more accurate and timely modeling capacity, essential for crisis response.

Geographical patterns in the publication density reflect both historical spill occurrences and the perceived environmental risk. The Gulf of Mexico stands out due to the Deepwater Horizon incident, with the Gulf of Mexico Research Initiative (GoMRI) driving regional advancements in deep plume modeling, ecological impact assessments, and operational forecasting. East Asia (e.g., Bohai and East China Seas) has seen similar spikes following incidents like Penglai, Sanchi, and Tasman Spirit, with localized adaptations of models such as MEDSLIK-II and GNOME. In Europe, the Black Sea, North Sea, and Baltic Sea receive attention due to persistent shipping activity and regional vulnerabilities; models like OILTOX have been tailored for local conditions. The Middle East, particularly the Arabian Gulf, presents unique challenges, e.g., high salinity and evaporation rates requiring scenario-specific simulations for contingency planning.

The model validation through controlled experiments complements real-world case studies. Facilities like the Ohmsett wave tank enable researchers to study oil behavior under repeatable conditions, informing model parameterization. For example, Ohmsett tests have refined algorithms for emulsification, photo-oxidation, and droplet size distributions, directly enhancing models like GNOME. Field-scale trials, including Arctic spills and drifter deployments, further enhance model realism by providing empirical ground truth data.

Recent work underscores the convergence toward fully coupled, multiphysical, and multiscale modeling systems. Rather than treating oil transport as an isolated process, future frameworks aim to integrate met-ocean, biogeochemical, and ecological components within unified environments. Nested, two-way coupled systems enable downscaling from ocean basin to estuarine and shoreline scales, capturing interactions ranging from deep-sea plumes to coastal stranding. Demonstrations by institutions like the U.S. Navy already showcase these capabilities in forecasting systems.

The future of oil spill modeling is unambiguously interdisciplinary. Accurate biodegradation modeling, for instance, requires input from microbiologists on hydrocarbon degradation rates under varying conditions, while ecotoxicological impacts call for integrations with ecosystem and food web models. Some post-Deepwater Horizon studies have begun to incorporate biological exposure metrics. A few initiatives are even linking oil spill models to socio-economic impact assessments (e.g., fisheries closures, tourism losses), pointing toward broader decision support applications.

The oil spill modeling scientific field has evolved from simple trajectory tools to comprehensive, interdisciplinary frameworks that can simulate the full complexity of spill dynamics. This evolution is driven by improvements in computational capacity, the increased availability of observational data, collaborative research, and the pressing need for effective environmental responses. The continued integration of physical, chemical, biological, and socio-economic modules will further enhance the relevance and accuracy of future models.

4.2.2. Relevant Issue Perspectives

Although genetic algorithms for oil spill analysis, multi-objective evolutionary algorithms for oil spill detection, and quantum immune fast spectral clustering for automatic oil spill identification were not the primary focus of our evaluation, we would like to highlight some recent general trends related to these approaches in this section.

Genetic algorithms (GAs) have been employed to tackle various challenges in oil spill modeling and detection. In spill trajectory modeling, GAs serve as powerful optimization tools to calibrate model parameters, thus improving prediction accuracy [61]. One of the tendencies in literature involves integrating a GA with a Lagrangian oil spill model to automatically adjust key parameters (such as wind drift factor and diffusion coefficients) and maximize the overlap between simulated oil slicks and observed spill extents. After many generations of evolution, the GA-tuned model showed significantly reduced discrepancies between model results and observations of a real spill, yielding more accurate oil slick predictions than manual calibration methods [61]. This demonstrates that GAs can efficiently navigate complex, non-linear parameter spaces, finding near-optimal solutions that enhance model reliability in varied environmental conditions [61].

Beyond modeling, GAs have also been applied to remote sensing data for automatic oil spill detections. Marghany (2014) [62] introduced a GA-based approach to identify oil slicks in Synthetic Aperture Radar (SAR) imagery from RADARSAT-2. In this method, GA operations (especially crossover and mutation) evolve candidate segmentations of the SAR image to isolate true oil spill "dark spots" from look-alike features. The GA effectively generated accurate oil spill patterns, as confirmed by the receiver operating characteristic (ROC) analysis [62]. Notably, the GA approach achieved about a 90% detection confidence for actual oil slick footprints, outperforming surrounding environmental false targets [62]. These results highlight that GAs can serve as robust automatic detectors in remote sensing, reducing the reliance on labor-intensive visual interpretations. In summary, recent advances show GAs to be versatile in oil spill analysis from optimizing simulation models to enhancing image-based spill detection by intelligently searching large solution spaces for optimal or near-optimal configurations [62].

Single-objective methods may struggle to balance competing criteria in oil spill detection (e.g., maximizing true positives while minimizing false positives and misclassifications such as look-alikes). Multi-objective evolutionary algorithms (MOEAs) address this by optimizing multiple goals simultaneously using a Pareto-based selection. Marghany (2014) [63] demonstrated one such approach using a Multi-Objective Evolutionary Algorithm to detect oil spills in COSMO-SkyMed SAR data [63]. This algorithm evolved a population of solutions to simultaneously maximize oil slick identification and minimize confusion with look-alike phenomena (like low-wind areas or algal blooms). The outcome was an accurate and well-discriminated oil spill mapping, with the algorithm correctly classifying \~96% of oil spill pixels while misidentifying only\~1% as look-alikes and\~3% [63] as sea roughness. Such a performance, evaluated via ROC curves, underscores the advantage of MOEAs in achieving a high detection rate and low false alarm rate concurrently.

A key advancement of multi-objective approaches is their ability to produce a set of Pareto-optimal solutions, giving analysts flexibility to choose a suitable trade-off between sensitivity and specificity. In practice, applying an MOEA like NSGA-II to oil spill SAR images enables the simultaneous optimization of multiple features or entropy measures that distinguish oil slicks from the background [64]. The evolutionary process naturally preserves solutions that balance these objectives, thus improving the overall reliability of the detection. Studies have noted that such algorithms can even differentiate thick oil slick regions from thinner sheen areas, which is valuable for response prioritization. Although research on MOEAs for spill detection is still emerging, early results indicate they can outperform single-objective methods by handling the inherent trade-offs in spill identification tasks effectively. This represents a significant step forward in automated oil spill surveillance, as multi-objective evolutionary frameworks yield more robust and accurate detection outcomes under varying conditions [64].

The quantum immune fast spectral clustering (QIFSC) algorithm is an innovative method that blends principles from quantum computing, artificial immune systems, and spectral clustering to identify oil spills in remote sensing data. Introduced by Marghany in the context of a polarimetric SAR analysis, QIFSC aims to overcome limitations of conventional clustering by exploiting quantum-inspired operations to achieve a faster and more discerning image segmentation [65]. In this approach, image features (e.g., polarization signatures of slicks vs. water) are encoded and clustered in a high-dimensional space using immune system metaphors (maintaining diversity of solutions) combined with quantum bit superposition principles. This allows the algorithm to search the solution space at a granular (sometimes described as "subatomic") level, enhancing its ability to detect subtle differences between true oil spills and look-alike features [65].

A notable advancement of QIFSC is its efficiency and accuracy in handling complex SAR datasets. By optimizing feature clustering with quantum-inspired techniques, QIFSC can rapidly isolate oil spill pixels even in quad-polarized SAR data, where the feature space is large. Marghany's work demonstrated that QIFSC achieved an improved automatic detection of oil spills in RADARSAT-2 fully polarimetric images, successfully distinguishing oil slicks with a higher confidence than prior methods [65]. This quantum immune approach effectively reduces misclassification by ensuring that the clustering process is both robust (through immune diversity preservation) and finely tuned (through quantum state search) to the characteristics of oil slicks [65]. One practical limitation, however, is the reliance on quad-pol SAR data, which is not always freely available or operationally accessible. Despite this, QIFSC represents a cutting-edge development: it is among the first to incorporate quantum computing concepts in oil spill remote sensing, pointing toward a new frontier of algorithms that can handle detection tasks with exceptional speed and precision [65]. As sensor technology and data availability improve, such hybrid quantum-inspired techniques could greatly augment our capabilities for automatic oil spill identification and monitoring [65].

4.2.3. Future Prospects and Limitations

Oil spill simulation modeling has evolved substantially, progressing from basic two-dimensional trajectory estimations to advanced three-dimensional frameworks that integrate weathering dynamics, real-time data assimilation, and multiphysics coupling. The most influential publications analyzed in this study reflect this progression and outline emerging directions that will likely shape the field's next phase.

High-resolution modeling and real time data integration are at the forefront of future developments. Advancements in the computational capacity and the proliferation of near-real-time environmental data from high-resolution satellites and UAVs are enabling oil spill models to operate at finer spatial and temporal scales. These inputs are expected to drive the adoption of dynamic forecasting systems that adjust continuously using live observations. Sophisticated data assimilation techniques, including four-dimensional variational assimilation (4D-Var) and ensemble-based methods, will further reduce the latency between observations and model corrections. Automated pipelines for processing remote sensing inputs (e.g., satellite imagery, SAR) into model-ready formats will become essential for operational use, enabling real-time adaptations during the critical early stages of a spill.

Enhanced weathering and biodegradation algorithms are another area of active research. While evaporation and emulsification are routinely included, other key processes such as dissolution, photo-oxidation, and biodegradation remain underrepresented in many models. Recent advances incorporate the oil droplet size and chemical composition into dissolution parameterizations, which is crucial for accurately simulating subsurface

plume dynamics. Biodegradation modules are moving beyond simple decay constants, integrating the microbial community behavior, hydrocarbon structure, temperature, and nutrient levels. Experimental and field data are now being used to calibrate these sub-models, enhancing predictions of the oil property evolution (e.g., viscosity, density, water content), which in turn influence transport and fate. Machine learning (ML) approaches are also being applied to estimate droplet size distributions, particularly for evaluating the dispersant efficiency and biodegradation potential under varying conditions.

Computational efficiency and emerging technologies are critical as models become more data-intensive. Parallelization, GPU acceleration, and cloud computing are transforming simulation workflows, enabling large ensemble runs that support probabilistic forecasting. ML is increasingly used not only for image-based oil detection but also for developing surrogate models, parameter optimization, and the prediction of spill impacts. Hybrid frameworks that combine physics-based modeling with ML components are poised to enhance both speed and accuracy, particularly in operational contexts.

Ensemble forecasting techniques, inspired by numerical weather prediction, are becoming standard in oil spill modeling. Methods such as ensemble Kalman filtering and stochastic ensemble generation allow probabilistic outputs that account for uncertainty in both model parameters and environmental forcings. These approaches support robust scenario-based planning and improve response effectiveness.

Real-time emergency response tools represent a strategic vision for the field. Future operational systems will offer intuitive interfaces, a seamless integration with global metocean datasets, and rapid setups for diverse spill scenarios. Capabilities such as interactive "what-if" simulations testing dispersants, skimming, or in situ burning will enhance strategic decision-making. Increasingly, outputs will depict uncertainty as probability fields rather than deterministic trajectories. Models will also guide the deployment of physical assets, such as drifters, gliders, and UAVs, for in situ data acquisition, thereby transforming simulation systems into central command tools during emergencies.

Despite the notable progress, several limitations persist. Many operational models still oversimplify or neglect long-term processes such as sedimentation, photo-oxidation, and biodegradation. The underrepresentation of these mechanisms undermines the predictive accuracy, particularly in long-term impact assessments. Future systems must incorporate calibrated sub-models for these processes to improve reliability.

Artificial Intelligence (AI) offers significant potential for advancing oil spill modeling. Beyond supporting rapid image analysis and classification, AI can optimize parameter tuning, generate high-speed surrogate models, and enhance real-time data assimilation. Its integration into operational frameworks promises smarter, adaptive simulation systems.

The model selection and application must also be context-dependent. Models such as OSCAR, SIMAP, and MEDSLIK-II offer high-resolution, physics-based simulations suitable for environmental impact assessments and contingency planning. Conversely, tools like OILMAP, GNOME, and OpenOil emphasize computational efficiency and adaptability, making them ideal for real-time operations. Selecting the appropriate tool based on the event scale, environment, and response time is crucial for achieving an optimal performance.

This review primarily focused on publications indexed in Scopus and Web of Science, encompassing a diverse array of document types, including journal articles, conference papers, book chapters, and reviews. The integration of these two leading databases, along with a structured screening process, guaranteed a thorough overview of the literature on oil spill modeling. During the systematic phase of this review, a focused subset of 188 documents was chosen from an initial pool of 1541 publications. Although this selection constitutes only a fraction of the total dataset, it was adequate to provide both analytical depth and thematic consistency. The chosen publications were meticulously examined

to extract comprehensive information on modeling approaches, environmental variables, geographic applications, and methodological advancements. While a larger sample may offer additional insights, the volume analyzed aligns with best practices for systematic reviews, facilitating a thorough and meaningful synthesis. Therefore, despite this numerical limitation, this review effectively captures the key scientific patterns, prevailing trends, and conceptual advancements in the field, providing a reliable and representative perspective on the evolution of oil spill modeling research.

A critical gap remains in Arctic oil spill modeling, as sea ice significantly alters the behavior of spills. The scarcity of highly cited Arctic studies suggests a need for expanded research on modeling in ice-covered waters. Future reviews should aim for a broader source inclusion and consider a wider array of environmental contexts to foster a more complete understanding.

Although the self-citation bias is a common challenge in bibliometric analyses, our assessment did not find a significant distortion among top cited works. Nevertheless, an ongoing scrutiny of citation practices remains essential to preserve analytical integrity.

In that sense, the results point to a study that transcends a traditional bibliometric synthesis by shedding light on the scientific and technological forces that have shaped oil spill modeling over the past five decades. It underscores how external events, especially major spill disasters, have driven methodological shifts, catalyzed technological innovation, and fostered interdisciplinary collaboration. Looking ahead, the field is advancing toward high-resolution, real-time, and ML-enhanced simulation platforms. These innovations will improve prediction capabilities, strengthen emergency responses, and support more effective environmental risk mitigation.

Ultimately, oil spill modeling plays a crucial role not only in advancing scientific understanding but also in enhancing operational readiness and environmental resilience. As global offshore activities expand and climate change exacerbates risks, the continued refinement and deployment of advanced modeling frameworks will be vital for protecting marine and coastal ecosystems against future disasters.

5. Conclusions

This study combines a bibliometric analysis with systematic review elements to examine the development and trends in the literature on oil spill simulations, providing insights into academic contributions, analytical techniques, and evaluation methods in the field.

Our bibliometric analysis reveals that the oil spill modeling discipline evolved into a prolific scientific field in the 1970s and 1980s, particularly following major spill incidents. The formats of publications have diversified, with journal articles and conference proceedings representing approximately half of the output and conference proceedings accounting for nearly 40%. Moreover, the notable increase in review papers and books from the early decades reflects a concerted effort to consolidate knowledge in this area. Collaboration in oil spill modeling has evolved into large, interdisciplinary consortia, increasing the authorship and fostering global networks for consensus-building. Future progress depends on proactive research, ongoing monitoring, integrating emerging technologies, and exploring underrepresented scenarios. Consolidating advanced tools and datasets will enhance the accuracy and responsiveness of oil spill models, improving preparedness and mitigation strategies.

Our study demonstrates that oil spill modeling has progressed from two-dimensional trajectory estimates to fully coupled, three-dimensional, and multiphysical frameworks. Early models relied on empirical formulas and vector calculations, whereas contemporary systems integrate hydrodynamic, atmospheric, wave, chemical weathering, and, increasingly, biogeochemical processes within operational forecasting environments. Key model

families such as OSCAR, OILMAP/SIMAP, GNOME, and MEDSLIK-II now simulate the surface slick evolution, subsurface plumes, emulsification, evaporation, natural dispersion, and, in some cases, biodegradation and sedimentation, reflecting a marked expansion in the process coverage. Major spill events have catalyzed advances in near-field plume modeling and spurred the coupling of plume outputs to far-field drift models. Integrating high-resolution metocean forcings driven by HF radar, satellite SAR/optical imagery, and drifter deployments have proven essential for accurate trajectory forecasts, particularly in complex coastal regimes. Recent developments in real-time data assimilation (e.g., 4D-Var, ensemble Kalman filters) and ensemble forecasting enhance predictive skills and quantify uncertainty, enabling probabilistic guidance for emergency responses.

Looking forward, four priorities emerge: (1) the further coupling of met–hydro–wave–biogeochemical modules within nested, multiscale architectures; (2) the incorporation of advanced weathering sub-models (photo-oxidation, dynamic biodegradation, droplet-size prediction) informed by laboratory and field experiments; (3) the adoption of high-performance computing, parallelization, and machine-learning-based surrogates to support ensemble and real-time applications; and (4) the expansion of multidisciplinary interfaces linking ecological, socio-economic, and operational decision support tools.

Supplementary Materials: The following supporting information can be downloaded at: https://www.mdpi.com/article/10.3390/w17152300/s1, Table S1: The table describes the 188 most influential publications on oil spill simulation. The table includes study titles, descriptions of the numerical and dispersion models used (including model types), variables applied, remote sensing or observational datasets, study areas, digital identifiers (DI), document title (TI). References [34–53,66–232] are cited in the Supplementary Materials.

Author Contributions: Conceptualization, R.N.V., C.A.D.L., A.T.C.L., D.P.C., S.G.D., J.G.V.M. and L.F.F.d.M.; methodology, R.N.V., C.A.D.L., A.T.C.L., J.G.V.M. and D.P.C.; software execution, R.N.V., D.P.C. and S.G.D., writing—original draft preparation, R.N.V., C.A.D.L., J.G.V.M., L.F.F.d.M. and J.G.V.M.; writing—review and editing, R.N.V., C.A.D.L., A.T.C.L. and E.C.B.C.; supervision, R.N.V., C.A.D.L. and A.T.C.L.; funding acquisition, C.A.D.L. and A.T.C.L. All authors have read and agreed to the published version of the manuscript.

Funding: This work is funded by the Brazilian Ministry of Defense, Management, and Operational Center of the Amazon Protection System (CENSIPAM) TED 001/2022. The first two authors, J.G.V.M. (grant #307828/2018-2) and R.N.V. (grant #81330/2021-4), would like to thank the CNPq for the research fellowships. Additionally, this manuscript contributes to the AtlantECO project, funded by the European Union's Horizon 2020 research and innovation program, under grant agreement n° 862923, and to the INCT IN-TREE for Technology in Interdisciplinary and Transdisciplinary Studies in Ecology and Evolution n°#465767/2014-1.

Data Availability Statement: Not applicable.

Acknowledgments: We appreciate comments and suggestions from the anonymous reviewers that helped improve the quality and presentation of the manuscript.

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

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