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Review

# Machine Learning Applications in Sustainable Construction Materials: A Scientometrics Review of Global Trends, Themes, and Future Directions

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## Abstract

The integration of machine learning (ML) into sustainable construction materials research, particularly focusing on construction and demolition waste (CDW), has accelerated in recent years, driven by the dual need for digital innovation and environmental responsibility. This study presents a comprehensive scientometric analysis of the global research landscape on ML applications for predicting the performance of sustainable construction materials. A total of 542 publications (2007–2025) were retrieved from Scopus and analyzed using VOSviewer (V1.6.20) and Biblioshiny (Bibliometrix R-package, V5.1.1) to map publication trends, leading sources, key authors, keyword co-occurrence, and emerging thematic clusters. The results reveal a sharp rise in publications after 2018, peaking in 2024, in parallel with the growing global emphasis on the circular economy and the UN Sustainable Development Goals. Leading journals such as *Construction and Building Materials*, the *Journal of Building Engineering*, and *Materials* have emerged as key publication venues. Keyword analysis identified core research areas, including compressive strength prediction, recycled aggregates, and ML algorithm development, with recent trends showing increasing use of ensemble and deep learning methods. The findings highlight three thematic pillars—Performance Characterization, Algorithmic Modeling, and Sustainability Practices—underscoring the interdisciplinary nature of the field. This study also highlights regional disparities in research output and collaboration, underscoring the need for more inclusive and diverse global partnerships. Overall, this study provides a comprehensive and insightful view of the rapidly evolving ML-CDW research landscape, offering valuable guidance for researchers, practitioners, and policymakers in advancing data-driven, sustainable solutions for the future of construction.

**Keywords:** machine learning; scientometric analysis; bibliometric mapping; artificial intelligence; sustainability; predictive modeling



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## 1. Introduction

Construction makes a significant contribution to the economic potential of the country; it forms tangible assets and is an integral part of the wealth of the nation [1]. According to Alaloul et al. [2], the sector accounts for USD 1.7 trillion worldwide, and in most countries, it impacts 5–7% of the total Gross Domestic Product (GDP). Several investigations have demonstrated that any variation in the construction sector has a direct impact on all related sectors [2–4]. It has a significant role in the economy; therefore, its influence on a country's economy is associated with forward and backward linkages with other sectors [2]. Due to its higher significance role in the economy, it has been reported that most countries are investing in research and development (R&D) to develop sustainable techniques for the construction sector [2,5,6]. Hence, revolutionizing the construction sector will ensure sustainable development [2].

Regardless of its importance, the construction industry faces mounting challenges in several aspects, such as escalating demand for infrastructure, volatile raw-material costs, and growing concerns over environmental impacts. In particular, concrete, the most widely used construction material, drives significant resource consumption, CO<sub>2</sub> emissions, and waste generation. Cement manufacturing accounts for 5–8% of global CO<sub>2</sub> emissions [7,8], whereas the extraction of aggregates depletes natural reserves and alters ecosystems [9,10]. At the same time, the generation of construction and demolition waste (CDW) is increasing significantly [11]. An assessment reveals that the construction industry is responsible for 35% of global waste disposed of in landfills with related environmental consequences [12]. The European Union (EU) alone is responsible for generating approximately 850 million tonnes of construction and demolition waste (CDW) per year [13], and emerging economies are facing similar surges as urbanization intensifies.

In response to the above challenges, researchers and practitioners are exploring sustainable pathways to incorporate CDW into new concrete. As demonstrated by several investigations, recycled aggregates, recycled cement, recycled concrete powder, and other CDW derivatives have shown promise in reducing environmental burdens and preserving natural resources [14–16]. However, the heterogeneous nature of CDW—characterized by variability in composition, particle size, and contaminants poses significant mix-design challenges [17–19]. Traditional concrete mixture proportioning methods, which are typically based on a trial-and-error process, do not objectively provide the optimal setting of components to multiple performance criteria simultaneously [20–25]. The diverse properties and compositions of the concrete ingredients often make it difficult for conventional mix design methods to address the related complexities fully. Thus, to determine the proportions of ingredients that meet the required properties, an intelligent guess based on the predefined relationships must eventually be made. To overcome these limitations, researchers have increasingly turned to data-driven methods.

Recently, artificial intelligence (AI), specifically machine learning (ML) algorithms, has demonstrated remarkable potential in addressing these multivariate problems. As substantiated by various investigators [26–31], they can effectively capture the nonlinear behavior of concrete ingredients, enabling the development of optimized mixtures that achieve both strength and sustainability targets in the construction industry. It is also worth noting that these intelligent models help to alleviate the costly laboratory testing and improve the efficacy of engineering projects [23].

ML techniques can detect the implicit patterns among numerous features and establish intricate relationships without necessitating explicit knowledge [24]. Over the last two decades, ML algorithms such as artificial neural networks (ANN), gene expression programming (GEP), multi-expression programming (MEP), decision trees (DT), gradient boosting (GB), among others, have been widely used to predict the mechanical properties

of concrete owing to their capabilities of advanced and extremely powerful yielding of solutions to nonlinear and complex problems [23,32]. Accurate prediction models enable informed decision-making and ensure the desired properties are achieved [33].

While these algorithms are widely applied, their dominance is shaped by both methodological advantages and the specific properties of CDW-influenced concrete. ANNs are prevalent due to their strong ability to capture nonlinear and complex relationships, making them particularly effective for predicting compressive strength and durability in situations where multiple interacting variables exist [34,35]. Support Vector Machines (SVMs) are often adopted when datasets are relatively small, as they offer robustness and reliable predictions [35–37]. More recently, ensemble methods such as GB have become popular due to their high accuracy, robustness, and reduced risk of overfitting. By combining predictions from multiple models rather than relying on a single one, they are also able to handle heterogeneous CDW data effectively [36–38]. However, no single model consistently excels across all performance indicators; ANNs may overfit small datasets, SVMs can struggle with very high-dimensional data, and ensemble models require substantial computational resources. This variation highlights the importance of comparative evaluations and hybrid approaches in advancing the predictive capabilities of ML for recycled concrete research.

Additionally, ML algorithms can assist in characterizing concrete ingredients by analyzing their physical and chemical properties [39] and classifying waste materials based on their potential to contribute to desirable properties in a mixture. Furthermore, these methods can be leveraged to perform environmental assessments of different mixture designs, identifying more sustainable combinations of components and thereby strengthening the industry's ability to move toward a circular and low-carbon future [40,41].

Several bibliometric and review studies have mapped the role of ML in concrete research. For example, Khan et al. [42] conducted a broad scientometric analysis of ML in concrete technologies, spanning conventional, recycled, geopolymer, and fiber-reinforced concretes. Gamil [43] reviewed ML applications in concrete technology, focusing on areas such as durability, crack detection, and life-cycle prediction, while providing a bibliometric overview of global contributions. These studies provide valuable insights but are either broad in scope or application-driven, without focusing specifically on recycled concrete and sustainability-oriented ML research.

While these studies have contributed valuable insights, their coverage and focus differ substantially from the present study. Table 1 summarizes the distinctions between prior bibliometric reviews and this study in terms of scope, methodology, key insights, and contributions. As shown in Table 1, the novelty of this study lies in its focused scientometric examination of the intersection between ML, recycled concrete, and sustainability—an area only superficially addressed in prior bibliometric reviews.

This study builds on that foundation by presenting a scientometric analysis that is focused on the intersection of ML, recycled concrete, and sustainability. Unlike earlier works, it concentrates specifically on recycled-material concretes, systematically integrates sustainability considerations, and provides a structured mapping of interdisciplinary linkages, research gaps, and collaboration trends. This study advances the field by offering a focused scientometric overview that consolidates fragmented evidence, highlights sustainability-oriented trends, and identifies the emerging role of ML in shaping circular concrete practices.

**Table 1.** Comparison of previous bibliometric studies and the present study.

SN	Study	Title	Scope	Methodology	Key Insights	Contribution of Present Study
1	Khan et al. [42]	A Systematic Review of the Research Development on the Application of Machine Learning for Concrete	Comprehensive review of ML in concrete, including conventional, recycled, geopolymers, and fiber-reinforced concretes	Systematic review combined with scientometric mapping (Scopus; VOSviewer)	Mapped global publication trends, leading authors, and research communities in ML–concrete studies	Builds upon this work by highlighting ML applications specifically in recycled concrete and integrating sustainability perspectives
2	Gamil [43]	Machine learning in concrete technology: A review of the current research, trends, and applications	ML applications in concrete technology (durability, crack detection, life-cycle prediction)	Narrative review with supplementary bibliometric overview (Scopus)	Highlighted main application areas and global research contributions in ML for concrete	Extends this review by systematically mapping ML applications in recycled concrete and considering sustainability frameworks
3	Oshodi et al. [44]	A bibliometric analysis of recycled concrete research (1978–2019)	Bibliometric mapping of recycled concrete research across four decades	Scopus-based bibliometric analysis using Bibliometrix	Identified publication growth, key authors, and collaboration networks in recycled concrete research	Complements this analysis by incorporating ML applications and sustainability considerations
4	Li & Radlińska [45]	Artificial intelligence in concrete materials: A scientometric view	Broad AI applications in concrete materials research (1990–2020)	WoS-based scientometric mapping (co-citation and keyword analysis)	Explored structural evolution of AI-related research themes in concrete materials	Focuses on recycled concrete with sustainability lens, providing a more targeted AI application scope
5	All Noman et al. [46]	Machine Learning and Artificial Intelligence in Circular Economy: A Bibliometric Analysis and Systematic Literature Review	Role of AI/ML in advancing circular economy practices	Bibliometric analysis (Scopus) combined with systematic review of selected studies	Identified thematic clusters, research gaps, and AI's role in circular economy adoption	Applies similar analytical approaches specifically to circular concrete practices, bridging ML, recycled materials, and sustainability
6	Present Study	Machine Learning Applications in Sustainable Construction Materials: A Scientometrics Review of Global Trends, Themes, and Future Directions	Targeted focus on ML applications in recycled concrete with explicit integration of sustainability	Scientometric analysis (co-citation, keyword dynamics, collaboration networks; sustainability lens)	Maps interdisciplinary linkages, highlights sustainability-oriented research gaps, and identifies ML's role in shaping circular concrete practices	Offers a focused tri-axis perspective (ML + recycled concrete + sustainability), providing insights not previously synthesized in one study

To provide a clear framework for the rest of this paper, Section 2 presents the research gap and clearly defines the study's objectives. Section 3 outlines the methodology employed for conducting the scientometric analysis. Section 4 delivers a comprehensive presentation and analysis of the results, covering publication trends, leading sources, keyword networks, thematic evolution, top authors, citation impacts, geographic contributions, and collaboration patterns. Section 5 offers an in-depth discussion of the key findings and their implications. Section 6 concludes the paper by summarizing the main insights. Finally, the last section (Section 7) outlines the gap in the current literature on machine learning applications in recycled concrete research, the limitations of this investigation, and recommendations for future research.

## 2. Research Gap and Aim

Despite a sharp increase in publications on ML-based optimization of concrete incorporating CDW, there is no consolidated view of how this research domain has evolved. Existing studies often focus narrowly on algorithm performance or material behavior, with little attention to the broader research structure. Fundamental questions remain: What are the dominant themes? Which countries and authors are driving innovation? How have methods evolved?

To address these gaps, this study conducts a scientometric analysis of ML applications in predicting and optimizing concrete properties using CDW. By analyzing publication patterns, thematic clusters, and collaboration networks, the study aims to provide a comprehensive overview of the field's development and offer strategic insights for future research.

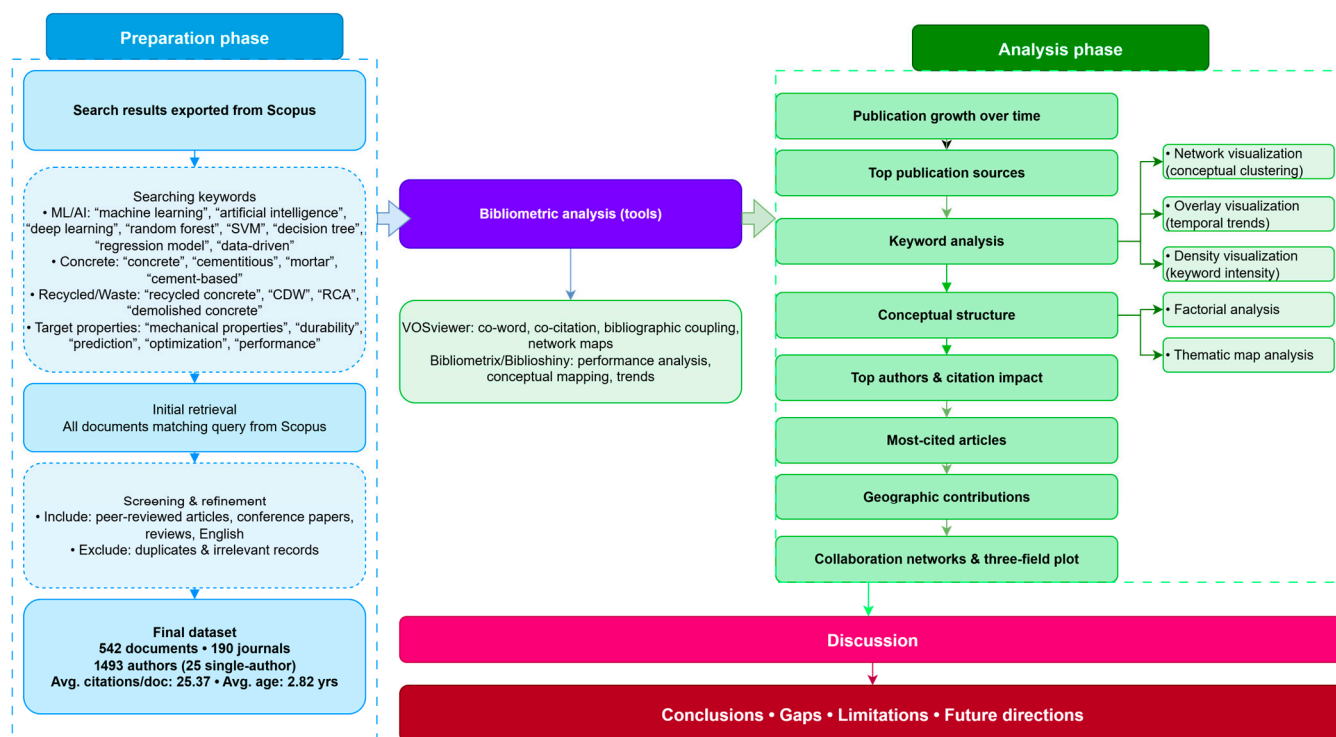
Specifically, this paper seeks to

- i. Quantify the growth of publications and identify the most influential journals, authors, and countries;
- ii. Map keyword co-occurrence patterns to reveal emerging topics and methodological shifts;
- iii. Examine collaboration networks and conceptual structures through co-citation and thematic evolution analysis.

## 3. Methodology

Scientometrics is a cutting-edge analytical approach that leverages quantitative methods and visualization techniques to elucidate the evolution, structural framework, and intricate relationships within complex scientific knowledge domains [47,48]. By integrating established scientometric methodologies with powerful visual mapping tools, scientometrics offers unparalleled insights into research dynamics and intellectual landscapes.

This study followed a rigorous, multi-step approach, as illustrated in Figure 1, which presents the research workflow and methodological sequence. The first critical step was selecting the appropriate bibliographic database. Several previous investigations [49–56] have used both Scopus and Web of Science for this type of analysis across a wide range of disciplines. Among these, Scopus stands out as one of the most comprehensive databases, providing broader document and more up-to-date document coverage than its counterparts, particularly for recent publications [57–60]. In addition, Scopus is widely recognized as a premier source of peer-reviewed literature, offering the highest number of citations and abstracts [60,61]. Notably, Mongeon and Paul-Hus [57] demonstrate that Scopus provides the widest coverage of construction-related academic research compared to other databases such as Google Scholar, Web of Science, and PubMed. Based on these considerations, Scopus was selected as the optimal platform to retrieve relevant literature for this study.



**Figure 1.** Research workflow illustrating the sequential methodological steps employed in this study.

After selecting the database, the next task was to identify relevant keywords pertaining to the topic “Machine Learning Applications in Predicting and Optimizing Concrete Properties Incorporating Waste Concrete Materials.” Keywords were carefully structured using Boolean operators to capture all relevant studies while excluding unrelated papers. To assess the robustness of the search query, several keyword variations were systematically tested by adding and removing terms. Each variation was applied in Scopus, and the retrieved datasets were exported as CSV files for comparison. The three runs yielded 433, 435, and 542 publications, respectively. The query producing 542 publications was selected for analysis, as it provided the widest coverage while including all highly relevant and frequently cited studies in the field. This iterative validation process ensured that the final dataset is both comprehensive and representative (see Supplementary Material, File S1: Scopus dataset of 542 publications).

In addition, to further ensure the relevance of the dataset, we conducted a random manual check of several publications from the final query results, which confirmed that the included records were highly consistent with the study scope. We also verified the inclusion of benchmark papers frequently cited in this field. For example, Wang et al. [62], “A Comprehensive Review on Recycled Aggregate and Recycled Aggregate Concrete,” appeared across all three query runs, while Naderpour et al. [63], which applied ANN to predict the compressive strength of eco-friendly concrete, was retrieved in the 433 and 542 publication runs but not in the 435 publication run. Since all records from the smaller datasets were contained within the 542-publication dataset, the final selection ensured comprehensive coverage of highly cited and representative studies.

The Scopus search query was structured as follows:

- **Machine Learning/AI terms:** “machine learning” OR “artificial intelligence” OR “deep learning” OR “neural network” OR “random forest” OR “support vector machine” OR “decision tree” OR “regression model” OR “data-driven”.
- **Concrete-related terms:** “concrete” OR “cementitious” OR “mortar” OR “cement-based”.

- **Recycled/waste material terms:** “recycled concrete” OR “construction and demolition waste” OR “CDW” OR “recycled aggregate” OR “RCA” OR “demolished concrete” OR “waste concrete”.
- **Target property terms:** “mechanical properties” OR “durability” OR “strength prediction” OR “performance” OR “optimization” OR “modelling” OR “prediction”.

Following the keyword search, additional refinement options were applied to exclude irrelevant articles. Only articles, conference papers, and review documents were considered. The source type was set to include all categories: journals, conference proceedings, book series, books, trade journals, and reports, to ensure both high-quality content and greater relevance. The analysis was restricted to English-language documents to maintain consistency and coherence throughout the review. There was no restriction on the year of publication, allowing for a broad-based analysis over time. Furthermore, no limitations were set on the subject area, enabling comprehensive coverage of all related fields of study.

The refined dataset, exported as a CSV file, contained 542 documents. Figure 2 illustrates the key attributes of the dataset, revealing an impressive annual growth rate of 26.92% and an average of 25.37 citations per document. The total number of contributing authors was 1493, of whom 25 authored single-authored papers. These documents originated from 190 source journals and span the years 2007 to 2025. The average document age is 2.82 years, indicating that, on average, the publications appeared 2.82 years prior to the analysis year (2025). This reflects the recency of the dataset, with most documents published in the last few years.



**Figure 2.** Main information of the extracted documents.

Two complementary bibliometric tools were employed to conduct this investigation: VOSviewer (V1.6.20) [64] and Bibliometrix (V5.1.1) [65] via RStudio (V2024.12.0+467). Developed by Nees Jan van Eck and Ludo Waltman at Leiden University, VOSviewer excels in co-word, co-citation, and bibliographic coupling analyses, providing advanced clustering and sophisticated graphical visualizations of scientific networks [47,64]. Its strength lies in its intuitive and informative mapping of complex research relationships. In relation to the number of publications, co-citation analysis becomes more robust as the dataset size increases, since larger datasets allow stronger co-citation links and more precise identification of influential works. VOSviewer does not impose a strict limit on the number of publications included; however, very large datasets may lead to highly dense maps that reduce readability and computational efficiency. In parallel, the open-source bibliometric software Biblioshiny was used to conduct the bibliometric analysis. Biblioshiny offers a complete suite of statistical techniques and visualization tools, making it especially suitable for performance analysis and conceptual mapping of the field [66,67].

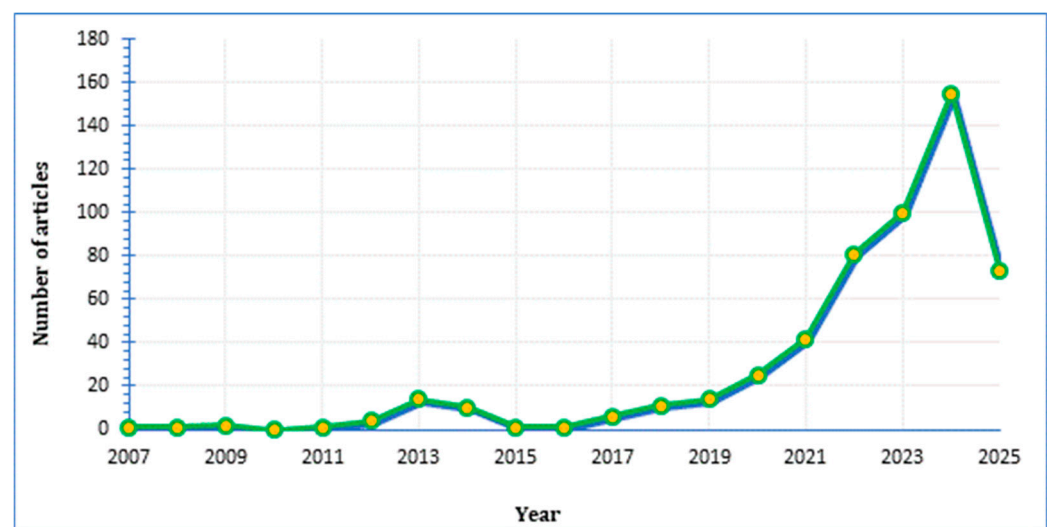
Together, these tools created a powerful analytical synergy: VOSviewer's network visualization capabilities complemented Bibliometrix's robust statistical and conceptual analyses. This dual-tool approach ensured cross-validation and enriched insights, enabling a multidimensional and holistic exploration of publication trends, thematic clusters, author networks, and international collaboration. The methodology was thus deliberately designed to systematically chart the intellectual terrain of machine learning applications in sustainable concrete technology, directly addressing the study's core research aims.

#### 4. Results and Analysis

This section presents the results of the scientometric analysis on ML applications in predicting and optimizing concrete properties incorporating waste concrete materials. Drawing on data extracted from the Scopus database and analyzed using Biblioshiny and VOSviewer, the section explores publication growth trends, leading sources, author and country contributions, keyword networks, thematic evolution, and influential articles. Each subsection highlights key patterns and interprets how these findings reflect the field's development, collaborative landscape, and emerging research priorities.

##### 4.1. Publication Growth over Time

Figure 3 depicts the annual growth of publications in the field of ML applications for predicting the performance of sustainable concrete utilizing waste concrete materials, as analyzed with the Biblioshiny application.



**Figure 3.** Publication growth over time.

An evident exponential development pattern in the number of publications over time indicates the increasing importance and interest in this field of study. The peak around 2013 corresponds with growing awareness of circular economy practices and initial efforts to incorporate CDW into concrete. The subsequent decline until 2016 may be linked to a limited availability of large, high-quality datasets and the slow adoption of ML techniques in construction materials research.

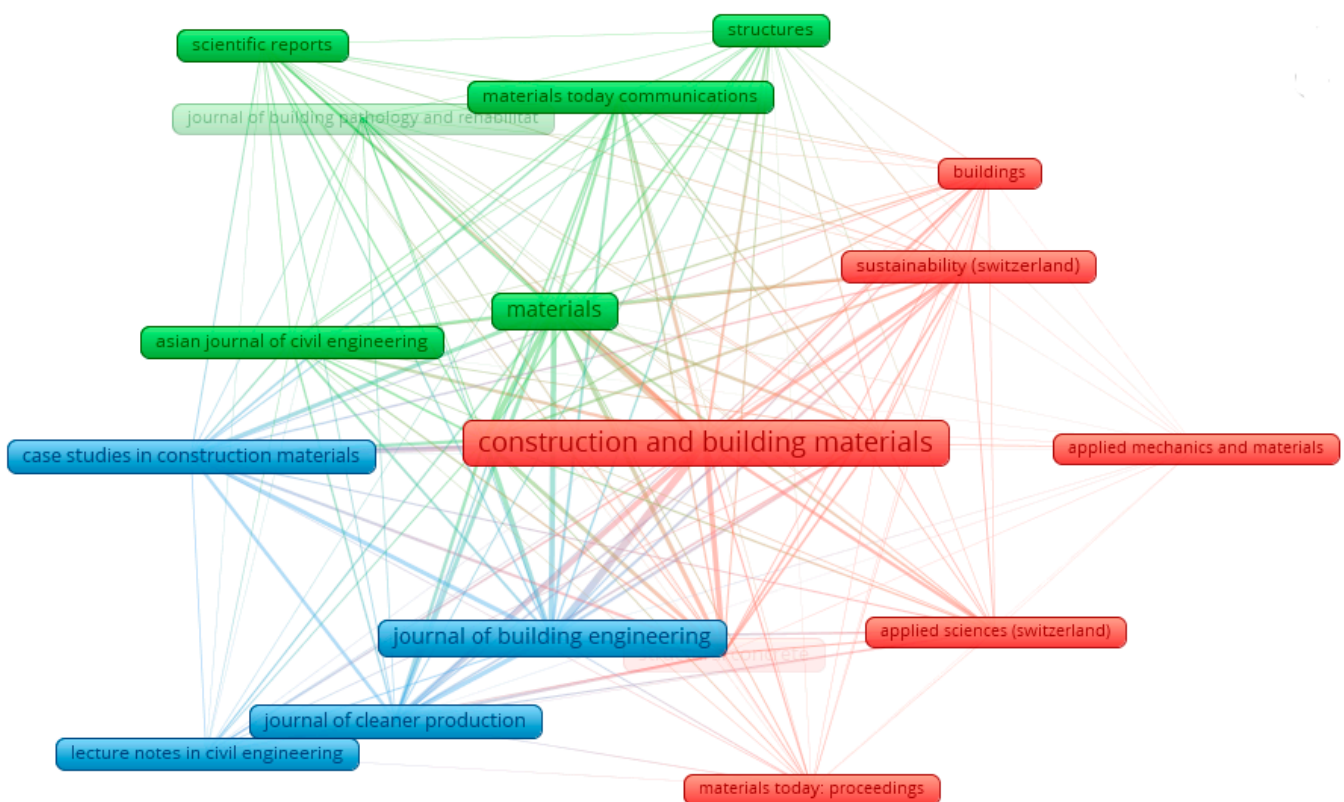
From 2017 onward, there has been a sharp rise in publications, likely driven by several converging factors: wider adoption of ML algorithms across engineering disciplines, increased emphasis on sustainable construction by governments and funding agencies, and the growing accessibility of CDW datasets. The peak in 2024, with approximately 160 articles, suggests that ML-based approaches for predicting concrete performance are

now recognized as central to advancing sustainable construction practices, particularly in data-driven material optimization.

It is important to note that the apparent drop in publications in 2025 does not reflect reduced research activity; this study was conducted mid-year, and several studies are still in progress or awaiting publication. The final publication count for 2025 is therefore expected to surpass previous years.

#### 4.2. Top Publication Sources

Understanding the leading journals, conference proceedings, and publishing sources within a research domain is essential for understanding where scientific dialogues are focused and how knowledge is shared. Within the framework of ML applications for concrete, including waste materials, identifying leading sources helps expose the primary sites generating innovation, guiding research priorities, and so attracting the most influential work [68,69]. Figure 4 depicts the science mapping visualization of the major publication sources, generated with VOSviewer. A bibliometric coupling study was performed using a minimum threshold of 5 documents per source. Out of 190 sources initially retrieved, only 20 met the minimum threshold of 5 documents and were included in the analysis. The threshold of 5 was selected to ensure that only sources with a meaningful number of contributions were considered, providing a balance between inclusiveness and interpretability while reducing noise from marginally represented sources.

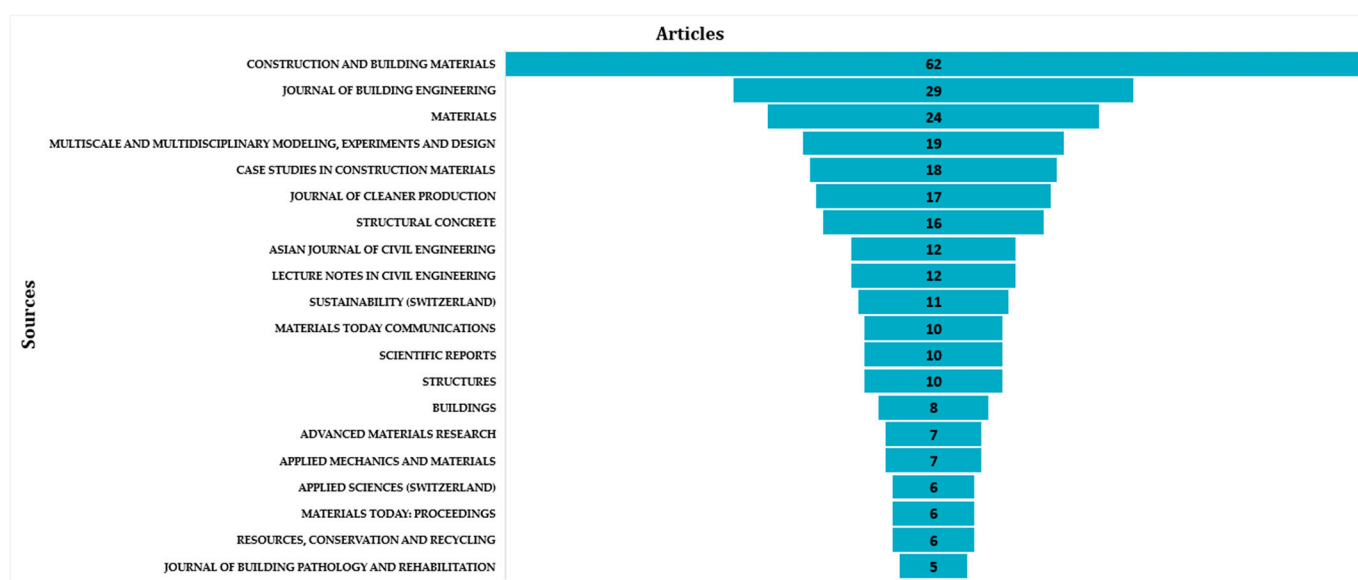


**Figure 4.** Science mapping visualization of top publication sources, highlighting leading journals that drive research dissemination and showing the relative influence of each source in the field.

In the network visualization, each journal is represented as a node, with node size reflecting its publication volume. The relative distances between nodes are determined based on the similarity of their citation patterns, calculated using VOSviewer’s association strength algorithm—closer nodes indicate stronger citation relationships. Notably, the *Journal of Construction and Building Materials* and the *Journal of Building Engineering* emerge

as dominant sources, evidenced by their larger node sizes. These journals play a prominent role in disseminating knowledge and linking citations within the field, substantially shaping the research landscape. Aside from the size of the node distribution, the network is divided into three distinct clusters—red, green, and blue—each color-coded to signify different thematic or topical groups. This grouping identifies journals with strong theme overlaps and citation linkages within the same cluster. For example, the red cluster focuses on *Construction and Building Materials*, demonstrating its widespread influence across related journals such as *Sustainability* (Switzerland) and *Buildings*.

Figure 5 quantitatively supports these observations by showing the number of articles per source. *Construction and Building Materials* leads with 62 publications, followed by the *Journal of Building Engineering* (29) and *Materials* (24). This quantitative evidence reinforces the journals' dominance in the domain.



**Figure 5.** Relevant sources with their publication count.

In terms of scholarly impact, Figure 6 displays the h-index values of these journals, as analyzed by Biblioshiny. *Construction and Building Materials* continues to lead with an h-index of 33, followed by the *Journal of Building Engineering* and *Materials*, which has h-indices of 16 and 15, respectively. This displays not just the volume of publications, but also their scientific importance and citation strength within the field.

In addition to these impact metrics, it is important to consider the potential influence of the year of origin of these journals on their observed dominance in the field. Older journals naturally have had more time to accumulate publications, citations, and stronger network linkages, which can partly explain their leading positions in both the science mapping and impact analyses. For instance, *Construction and Building Materials*, founded in 1987, and *Materials*, established in 2008, have had varying durations to build their reputations and scholarly impact. In contrast, relatively newer journals, such as the *Journal of Building Engineering* (launched in 2015), have shown rapid growth and increasing influence despite their relatively short history. Thus, while the science mapping and bibliometric indicators highlight these sources as central to the domain, part of their dominance can reasonably be attributed to their longer presence and established position in the field.

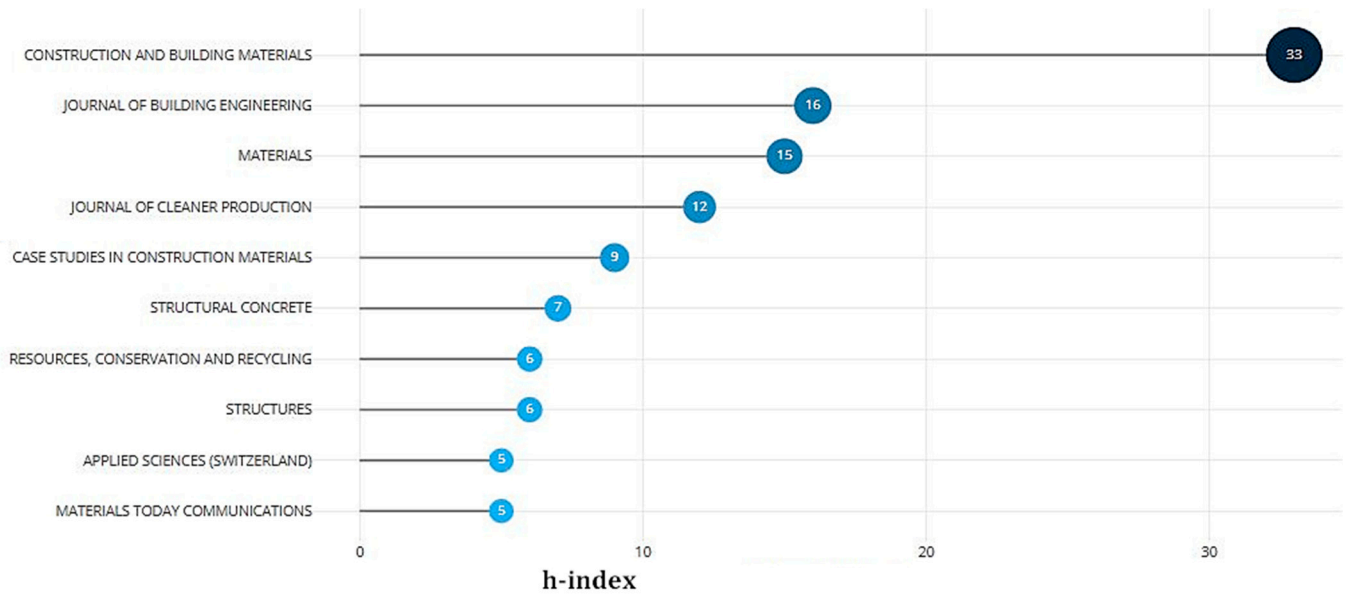


Figure 6. H-index values of leading journals, showing their scholarly impact within the field.

Furthermore, Figure 7 depicts the journals’ annual publishing trends, demonstrating a consistent and considerable growth in the number of publications over time. The trend is especially noticeable for *Construction and Building Materials*, which has a higher annual growth rate than other journals. This trend reflects the growing scholarly engagement driven by global imperatives surrounding sustainability, innovative construction practices, and the reuse of materials.

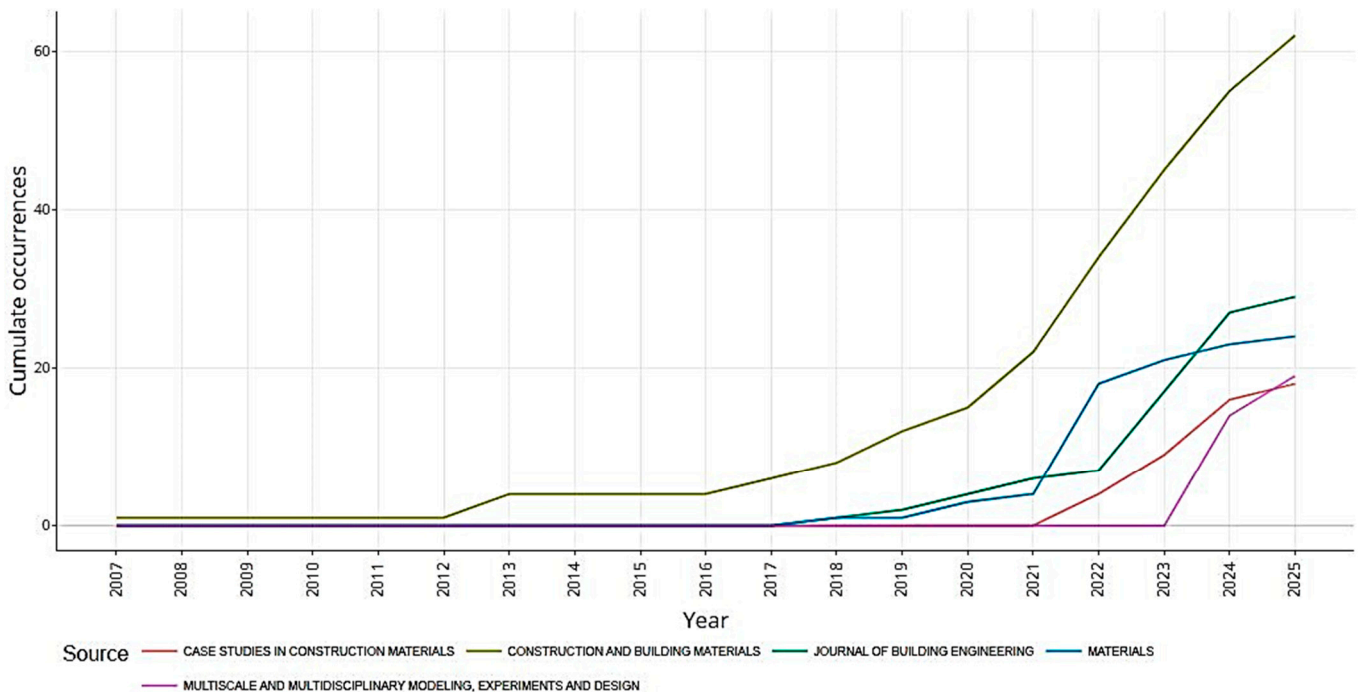


Figure 7. Source production over time.

### 4.3. Keyword Analysis

Analyzing the most frequently used keywords in a research field offers valuable insight into its main topics, emerging trends, and underlying conceptual structure [70,71]. This subsection presents the resulting network, overlay, and density visualizations, focusing on the most common keywords that shape the research landscape. Co-occurrence





**Table 2.** Top 10 most frequently occurring keywords in the field.

Rank	Keyword	Occurrences	Total Link Strength
1	Machine learning (Machine-learning)	279	2207
2	Recycling	259	2224
3	Concrete aggregates	263	2203
4	Compressive strength	248	1904
5	Recycled aggregate concrete	213	1591
6	Forecasting	138	1279
7	Recycled aggregates	126	1024
8	Neural networks	91	767
9	Concrete mixtures	82	760
10	Cements	41	373

“Compressive strength” (248, 1904), “concrete aggregates” (263, 2203), and “recycling” (259 occurrences, 2224 link strength) are additional terms that serve as the foundation for the study landscape. Significant correlations between “neural networks” (91, 767), “forecasting” (138, 1279), and “recycled aggregate concrete” (213, 1591) underscore the growing use of artificial intelligence and predictive technologies in designing and optimizing construction materials. The presence of “concrete mixtures” (82, 760) and “recycled aggregates” (126, 1024) highlights a sustained focus on material performance and sustainability.

#### 4.3.1. Network Visualization: Conceptual Clustering

Figure 8 illustrates the co-occurrence relationships between keywords, where node size reflects frequency [72] and edge thickness denotes the strength of co-occurrence [73]. The analysis reveals four major clusters, each identified by a distinct color, suggesting thematically cohesive research streams. These clusters were generated using VOSviewer’s modularity-based algorithm, which groups keywords with stronger co-occurrence links into the same cluster, highlighting closely connected research themes. Cluster 1 (Red) emphasizes types of materials and mechanical parameters, comprising keywords such as “compressive strength,” “elastic modulus,” “regression analysis,” “split tensile strength,” and “recycled aggregates.” Cluster 2 (Green) is centered around algorithms and their roles in predictive modeling, featuring terms such as “machine learning,” “forecasting,” “adaptive boosting,” “support vector machines,” and “decision trees.” Cluster 3 (Blue) focuses on core materials, including “concrete,” “fly ash,” “recycled concrete,” “construction and demolition waste,” and “sustainable development.” Cluster 4 (Yellow) represents emerging trends like “learning algorithm,” “neural-learning,” and “optimization.” Together, these clusters reflect the convergence of the field of recycled concrete research toward three major pillars: material performance characterization, advanced computational modeling, and sustainable construction practices.

#### 4.3.2. Overlay Visualization: Temporal Research Trends

The overlay visualization in Figure 9 reveals the chronological development of key themes in the domain by color-coding keywords according to their average year of publication. Yellow nodes represent recently emerging areas, while purple-to-blue nodes reflect older, more established topics [74,75].

Recent keywords, such as “gradient boosting,” “machine learning models,” “adaptive boosting,” and “deep learning,” are highlighted in yellow, indicating a notable increase in the application of ensemble learning and artificial intelligence techniques over the last

few years. These terms are primarily located within Cluster 2 (see Figure 8), which, as previously noted, are algorithms and their roles in predictive modeling.

In contrast, foundational terms such as “elastic moduli,” “splitting tensile strength,” and “aggregates” appear in purple colors, suggesting that while still relevant, their peak relevance was in an earlier period of the field’s development. This temporal trend reflects a shift from traditional material characterization toward computational performance prediction, as evidenced by the increasing presence of terms such as “machine learning” and “forecasting.” The integration of these techniques demonstrates both enhanced analytical capacity and the evolving priorities of researchers in optimizing concrete design.

These trends also reflect broader changes in the field driven by technological advances and shifting research priorities. The increasing attention to ensemble learning methods, neural networks, and predictive modeling underscores the growing integration of artificial intelligence in construction research. At the same time, keywords related to recycled aggregates and sustainable materials indicate a continued focus on environmentally conscious practices and material optimization. Together, these trends highlight how methodological innovation and sustainability considerations are shaping current directions in recycled concrete research.

#### 4.3.3. Density Visualization: Keyword Intensity Mapping

As shown in Figure 10, the density map illustrates the concentration of keyword activity, with red denoting regions of high frequency and relevance. Here, the highest-density zones are occupied by dominant keywords like “compressive strength,” “machine learning,” “concrete aggregates,” “forecasting,” and “recycling.” They play a crucial role in several studies, as evidenced by their central location and color intensity.

Medium-density terms such as “neural networks,” “regression analysis,” “recycled aggregate concrete,” and “mechanical properties,” on the other hand, imply secondary but still significant ideas that reinforce and broaden the field’s fundamental body of knowledge. This mapping of intensity demonstrates how research on recycled concrete is becoming more interdisciplinary and data-driven. Both materials-related terms (such as “aggregates,” “cements,” and “fly ash”) and computational keywords (such as “support vector machines,” and “random forests”) are highly prevalent, indicating a broadening of focus that combines sustainability, construction materials, and artificial intelligence.

#### 4.4. Conceptual Structure

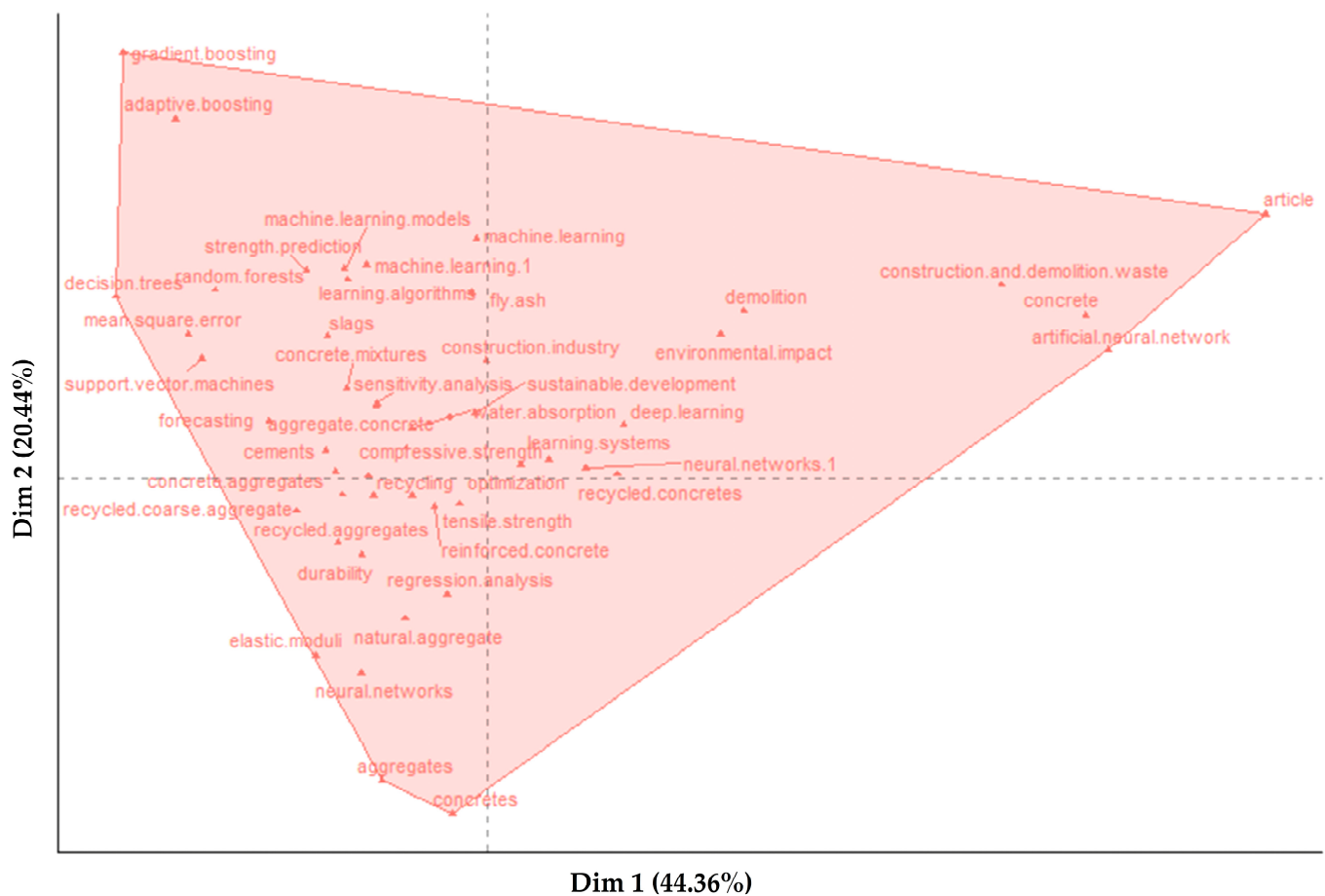
Exploring the conceptual structure of a research field helps to identify its core topics, methodologies, and the relationships between key ideas. Conceptual structure analysis aims to map the intellectual organization of a field by uncovering major concepts, theories, and the connections among them. This approach provides a clear view of how knowledge is structured and how various themes interact within the research domain [76].

To analyze the conceptual structure of this study area, a thematic map and factorial analysis were conducted using Biblioshiny. The thematic map categorizes topics into four quadrants—motor themes, niche themes, basic themes, and emerging or declining themes—based on their development (density) and relevance (centrality) [77,78]. Factorial analysis, specifically Multiple Correspondence Analysis (MCA), was used to identify major conceptual clusters, revealing how keywords and concepts are grouped and interconnected within the literature [78,79].

##### 4.4.1. Factorial Analysis

The factorial analysis, based on MCA, revealed three distinct conceptual clusters that characterize the current structure of the research domain, as shown in Figure 11. The first cluster is centered on predictive modeling in concrete science and includes terms such as

machine learning, regression analysis, support vector machine, random forest, and strength prediction, which indicates the increasing integration of data-driven and algorithmic approaches in evaluating and forecasting concrete properties. The second cluster consists of fundamental concrete properties and material-related terms such as compressive strength, durability, recycled aggregates, and optimization, which represent the experimental core of research in recycled concrete. Lastly, the third cluster reflects the broader sustainability and industrial context, including terms such as construction and demolition waste, recycling, and sustainable development. This shows that environmental considerations and industry applications form a meaningful background to technical research. It is also worth noting that the term “article” appears in isolation near the “artificial neural network” on the far right of the MCA space. This reflects its role as a general bibliometric or metadata term rather than a conceptually meaningful keyword within the thematic structure and thus may not hold substantive relevance in the context of research clustering.

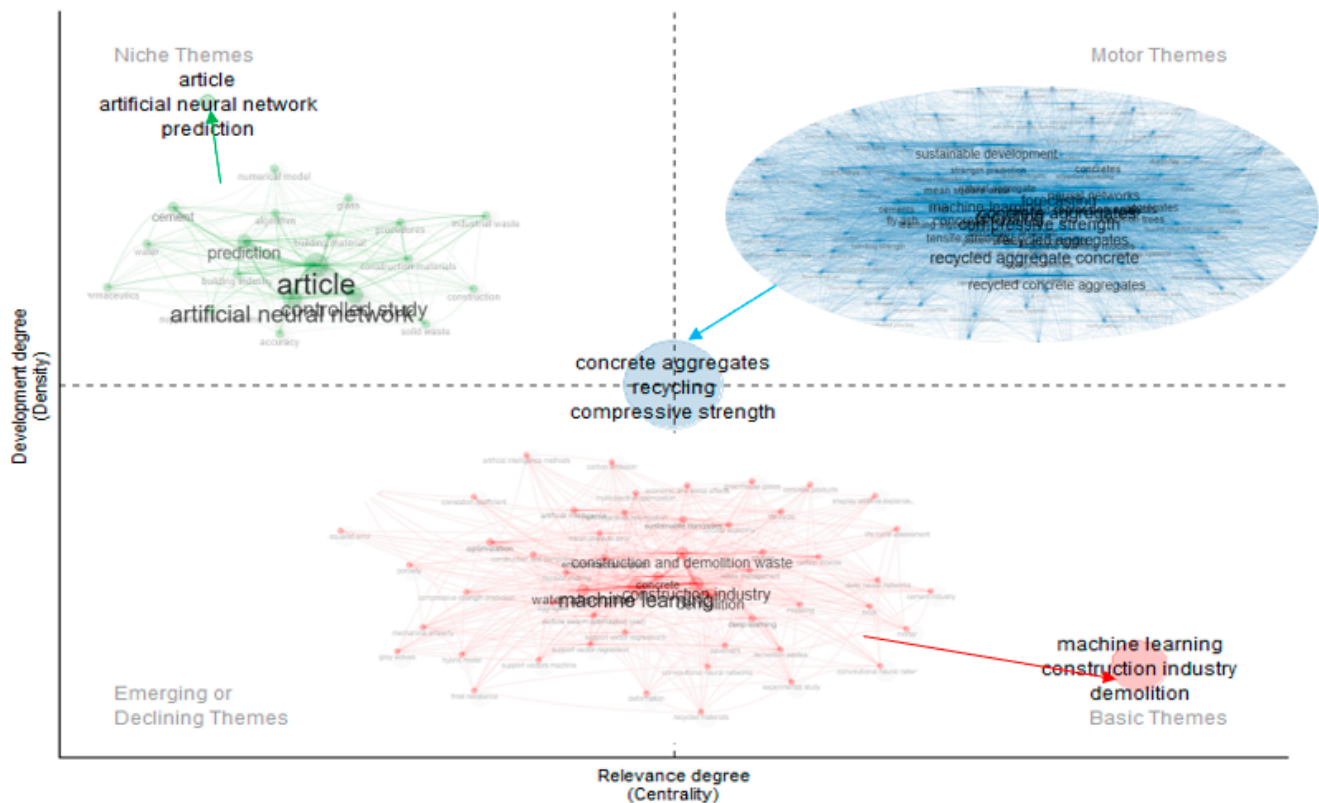


**Figure 11.** Factorial analysis of research themes using MCA. Dashed vertical and horizontal lines mark the origin (0,0) of Dim 1 and Dim 2 and split the plot into four quadrants.

#### 4.4.2. Thematic Map Analysis

Figure 12 depicts thematic map analysis, which divides topics into four quadrants based on their development and relevance. The lack of motor themes, those that are both central and well-developed, demonstrates that no single topic now dominates the area in terms of maturity and influence. This suggests that the field of research is still evolving or remains fragmented. Although well developed in terms of methodology, specific subjects such as artificial neural networks and prediction remain on the periphery, demonstrating specialization rather than greater integration. In contrast, essential concepts such as demolition, construction, and machine learning are very central but low in density. Although

these topics are basic and extensively applicable, they require additional methodological refinement to emerge and become robust study disciplines. The center cluster of concrete aggregates, recycling, and compressive strength on the map indicates their role as underlying issues that support a broad spectrum of study. The absence of themes in either the emerging or decreasing quadrants indicates that the themes are stable and that no locations are changing rapidly.



**Figure 12.** Thematic map analysis of research on ML applications in recycled concrete, showing topic distribution across four quadrants based on development and relevance.

#### 4.5. Top Authors and Citation Impact

As emphasized by Yu and Hayes [80], a researcher's influence should be evaluated not only by the number of publications but also by the citation impact of their work, offering a comprehensive view of both productivity and scholarly influence within the research community. To assess the most influential contributors in the field of ML applications for predicting and optimizing concrete properties using waste materials, authorship analysis was conducted using Biblioshiny. Accordingly, this section discusses the most relevant authors based on the number of documents published, authors' productivity over time, author productivity patterns modeled through Lotka's Law, and the local impact of authors as measured by the H-index.

Figure 13 illustrates the ten most relevant authors ranked solely by the number of publications. WANG Y, XU J, and ZHANG Y are identified as the most prolific, each contributing between 9 and 17 documents. These authors appear to be leading figures in the domain of sustainable concrete and ML applications. Others, such as AHMAD W, BEHNOOD A, and AHMAD A, also demonstrate notable productivity, albeit at a slightly lower level. This frequency-based analysis highlights the key contributors shaping the literature in this niche research area.

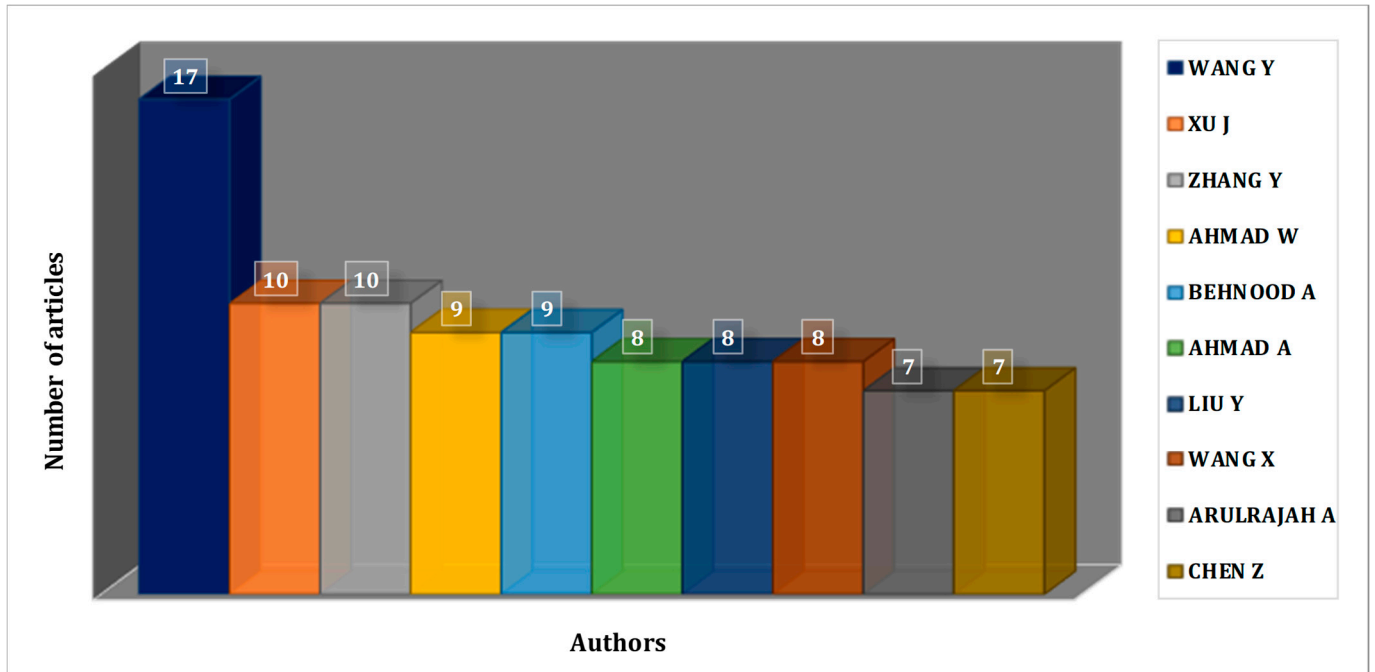


Figure 13. Most relevant authors by number of documents.

Figure 14 provides a time-series visualization of the annual publication trends of top authors, with bubble sizes indicating the total citations per year (TC/year). Authors such as WANG Y, XU J, and ZHANG Y demonstrate consistent scholarly output over the past decade, with significant peaks in both publication count and citation impact between 2018 and 2022. In contrast, authors like ARULRAJAH A and CHEN Z have emerged more recently with fewer articles, suggesting their role as rising contributors in the field.

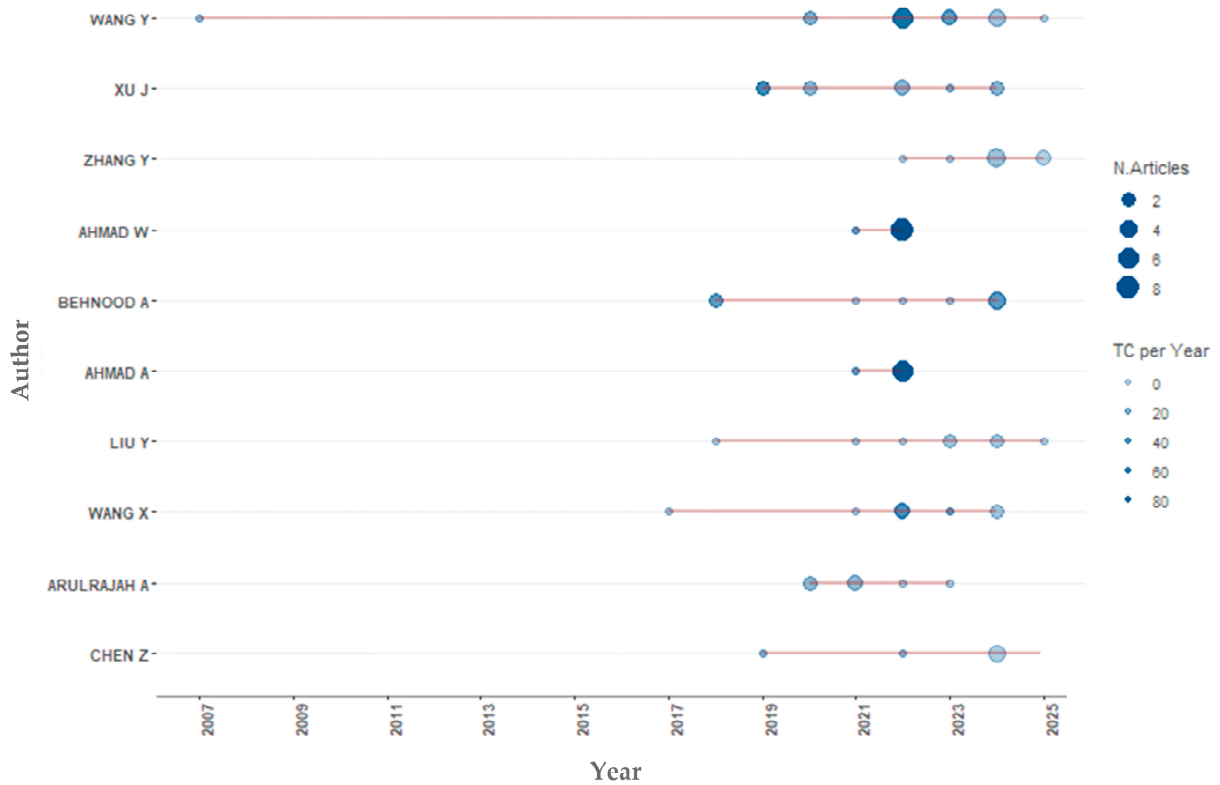
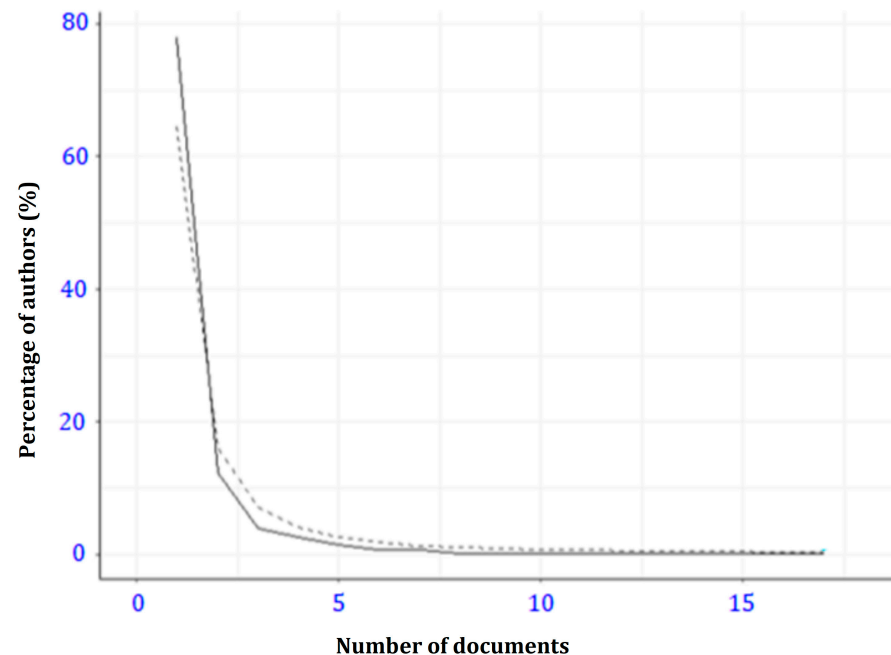


Figure 14. Author production over time.

Figure 15 models author productivity in accordance with Lotka's Law, which posits that the number of authors publishing  $n$  articles is inversely proportional to  $n^2$  [81]. The steep curve confirms this distribution: a small cohort of authors is responsible for a large portion of the publications, while the majority contribute only once or twice. Very few authors have published more than 10 documents, underscoring the dominance of a highly productive core group. This pattern is characteristic of many scientific domains and demonstrates the inequality in publication frequency [82].

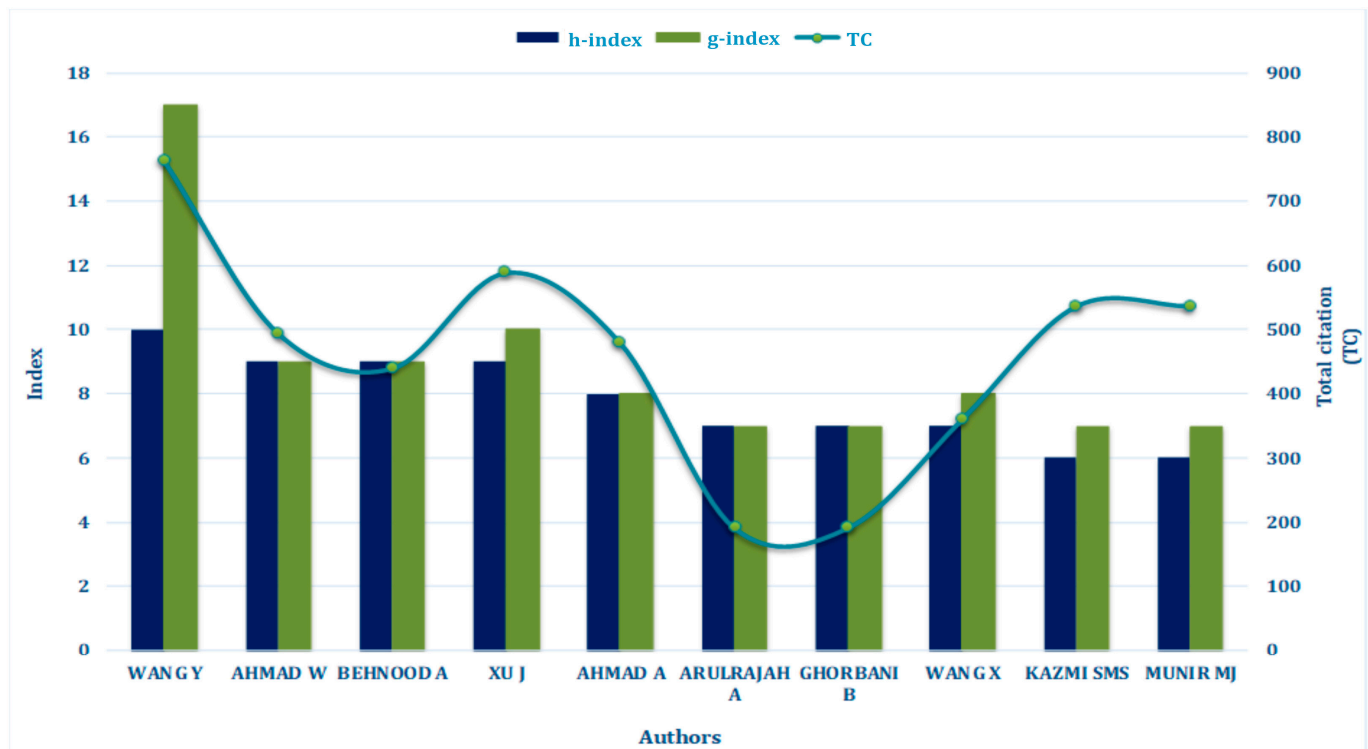


**Figure 15.** Authors productivity through Lotka's law. The solid line shows the observed distribution (% of authors with  $n$  publications), while the dashed line shows the theoretical Lotka fit ( $\sim 1/n^2$ ) for comparison.

Figure 16 highlights the citation impact of the top 10 most influential authors in the field by presenting their local H-index, g-index, and total citation counts. Among them, WANG Y leads with an H-index of 10, followed closely by AHMAD A, BEHNOOD A, and XU J, each with an H-index of 9. These values reflect not only the quantity of their published work but also the consistent academic recognition it has received, indicating strong and sustained influence.

In addition to the H-index, the g-index is also shown in Figure 16. This metric places greater emphasis on highly cited publications, offering a more nuanced view of academic impact. WANG Y again stands out with the highest g-index of 17, confirming that his most-cited works have made a significant impact. XU J and BEHNOOD A both record g-indices of 11, exceeding their H-indices and suggesting that their influence is driven in part by a few exceptionally well-cited papers.

Finally, the figure also illustrates each author's total citation (TC) count, which provides a broader measure of cumulative impact. WANG Y again leads with 764 citations, well ahead of his peers. He is followed by XU J with 589 citations, while MUNIR MJ, KAZMI SMS, and AHMAD W follow closely with 537, 537, and 495 citations, respectively. These numbers reinforce the significant and influential contributions these researchers have made to the field.



**Figure 16.** Authors' local impact by H-index.

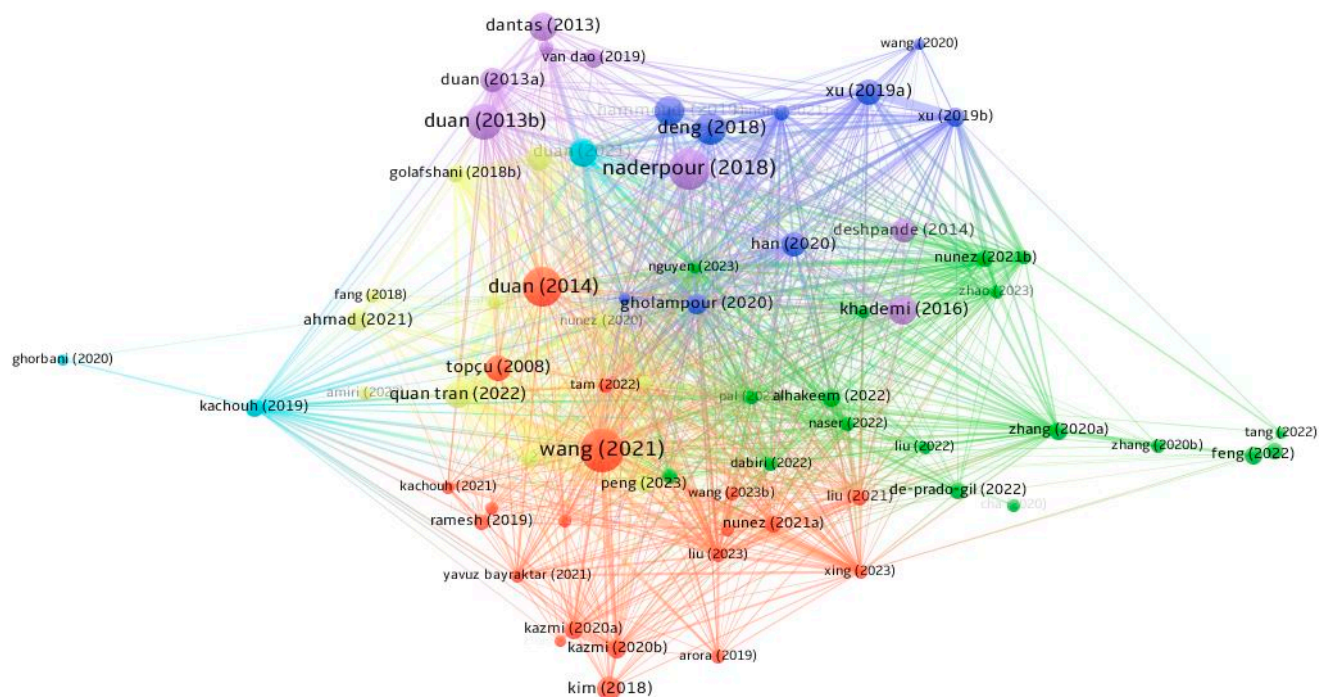
#### 4.6. Most-Cited Article

The number of citations a publication receives is a widely accepted indicator of its scholarly influence and contribution to a field [83,84]. To explore the intellectual structure and citation dynamics in the area of ML applications for predicting and optimizing concrete properties using waste materials, a bibliographic coupling analysis was conducted using VOSviewer, with the unit of analysis set to “documents.” A minimum citation threshold of 25 was applied. The most influential works in the field were highlighted by the 138 documents out of 542 that satisfied this criterion.

The top ten most-cited articles in the field are listed in Table 3. With 588 citations and a total link strength (TLS) of 290, Wang et al. [62] article, “A Comprehensive Review on Recycled Aggregate and Recycled Aggregate Concrete,” published in *Resources, Conservation and Recycling*, is at the top of the list. Represented by the biggest node in Figure 17 (red cluster), this article, whose exhaustive synthesis of recycled aggregate concrete (RAC) research covers topics from recycling processes and mechanical performance to the integration of artificial intelligence models and sustainability policies, particularly those framed within the European Union’s Green Deal and Circular Economy Action Plan, serves as a central reference point. Unlike predictive modeling studies, Wang et al. [62] primarily provide a broad review that maps the field’s intellectual structure. Based on the coupling network shown in Figure 17, highly cited works form well-separated clusters (red, green, blue, purple), reflecting specialized but overlapping research directions.

**Table 3.** Details of the top 10 most-cited articles in the field.

SN	Authors	Documents	Title	Year	Source	Cited by	TLS	Ref.
1.	Wang B.; Yan L.; Fu Q.; Kasal B.	wang (2021)	A Comprehensive Review on Recycled Aggregate and Recycled Aggregate Concrete	2021	<i>Resources, Conservation and Recycling</i>	588	290	[62]
2.	Naderpour H.; Rafiean A.H.; Fakharian P.	naderpour (2018)	Compressive strength prediction of environmentally friendly concrete using artificial neural networks	2018	<i>Journal of Building Engineering</i>	548	132	[63]
3.	Duan Z.H.; Poon C.S.	duan (2014)	Properties of recycled aggregate concrete made with recycled aggregates with different amounts of old adhered mortars	2014	<i>Materials and Design</i>	488	125	[85]
4.	Duan Z.H.; Kou S.C.; Poon C.S.	duan (2013)	Prediction of compressive strength of recycled aggregate concrete using artificial neural networks	2013	<i>Construction and Building Materials</i>	416	173	[86]
5.	Deng F.; He Y.; Zhou S.; Yu Y.; Cheng H.; Wu X.	deng (2018)	Compressive strength prediction of recycled concrete based on deep learning	2018	<i>Construction and Building Materials</i>	330	140	[87]
6.	Hammoudi A.; Moussaceb K.; Belebchouche C.; Dahmoune F.	hammoudi (2019)	Comparison of artificial neural network (ANN) and response surface methodology (RSM) prediction in compressive strength of recycled concrete aggregates	2019	<i>Construction and Building Materials</i>	287	138	[88]
7.	Khademi F.; Jamal S.M.; Deshpande N.; Londhe S.	khademi (2016)	Predicting strength of recycled aggregate concrete using Artificial Neural Network, Adaptive Neuro-Fuzzy Inference System and Multiple Linear Regression	2016	<i>International Journal of Sustainable Built Environment</i>	267	113	[89]
8.	Duan J.; Asteris P.G.; Nguyen H.; Bui X.-N.; Moayedi H.	duan (2021)	A novel artificial intelligence technique to predict compressive strength of recycled aggregate concrete using ICA-XGBoost model	2021	<i>Engineering with Computers</i>	261	194	[90]
9.	Dantas A.T.A.; Batista Leite M.; De Jesus Nagahama K.	dantas (2013)	Prediction of compressive strength of concrete containing construction and demolition waste using artificial neural networks	2013	<i>Construction and Building Materials</i>	261	84	[91]
10.	Tam V.W.Y.; Tam C.M.; Wang Y.	tam (2007)	Optimization on proportion for recycled aggregate in concrete using two-stage mixing approach	2007	<i>Construction and Building Materials</i>	253	0	[92]



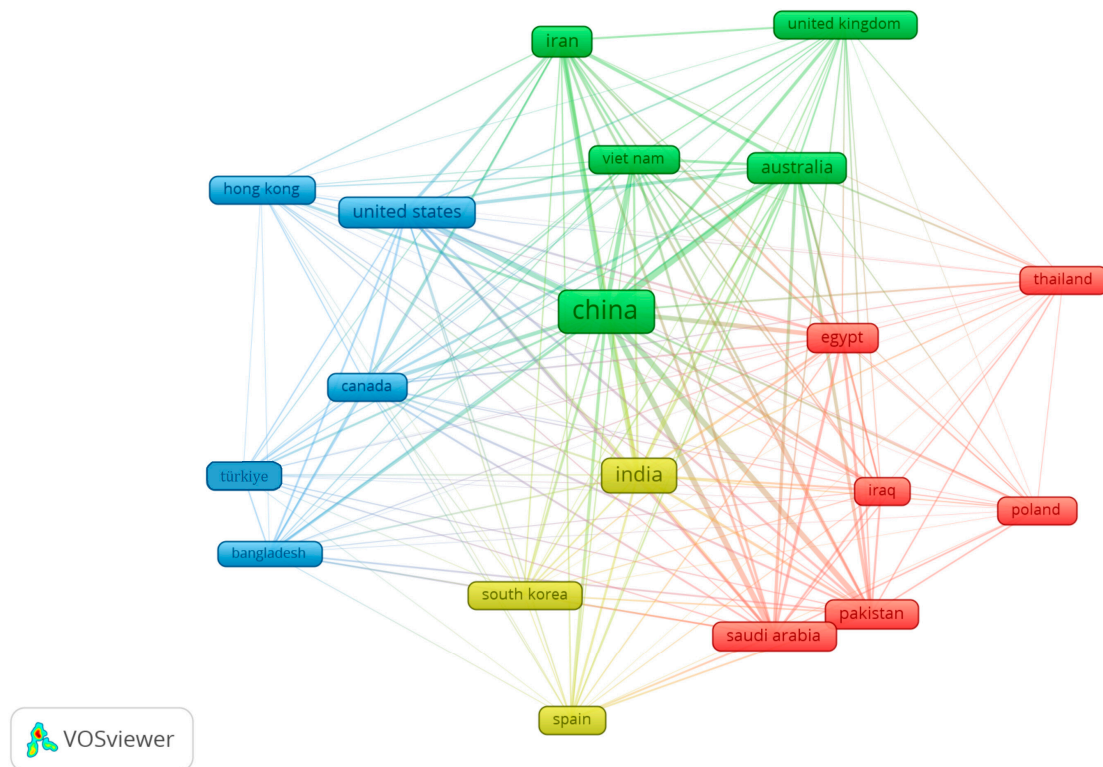
**Figure 17.** Bibliographic coupling network showing the most-cited articles in the field. Node size reflects citation counts, while colors indicate distinct clusters of related research.

With 548 citations and a TLS of 132, Naderpour et al. [63] come in second, focusing on the use of ANN to predict the compressive strength of environmentally friendly concrete. Their study includes data preprocessing—such as normalization and selection of relevant input parameters—and rigorous model validation performance metrics such as  $R^2$  and RMSE.

Another prominent contributor is Duan, with two highly cited works: Duan & Poon [85], which examines RAC properties based on old adhered mortar content and compares experimental results with predicted results using ANN, receiving 488 citations; and Duan et al. [86], which received 416 citations and develops ANN models for compressive strength prediction. These studies demonstrate a progression from broad reviews to specific predictive modeling approaches. They differ in their focus, methodology, and validation strategies, highlighting complementary contributions: Wang et al. [62] offer a holistic synthesis and policy perspective, whereas Naderpour et al. [63] and Duan & Poon [85] provide empirical modeling insights that advance predictive applications of ML in sustainable concrete research.

#### 4.7. Geographic Contributions

Figure 18 provides a detailed scientometric overview of the global research landscape on ML applications in estimating and optimizing concrete properties incorporating waste concrete materials. For this analysis, a bibliographic coupling analysis was conducted using VOSviewer, with the unit of analysis set to “countries.” The minimum number of documents per country was set to 10, and 19 countries met this criterion out of 69.

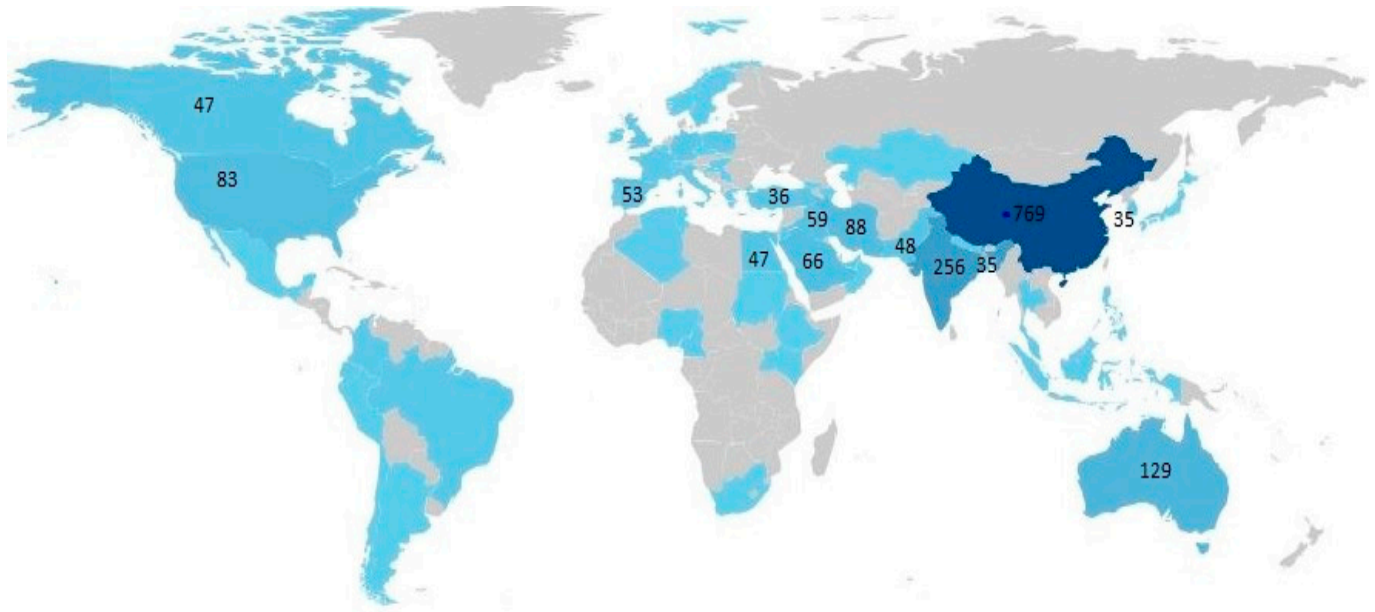


**Figure 18.** Network visualization of top contributing countries.

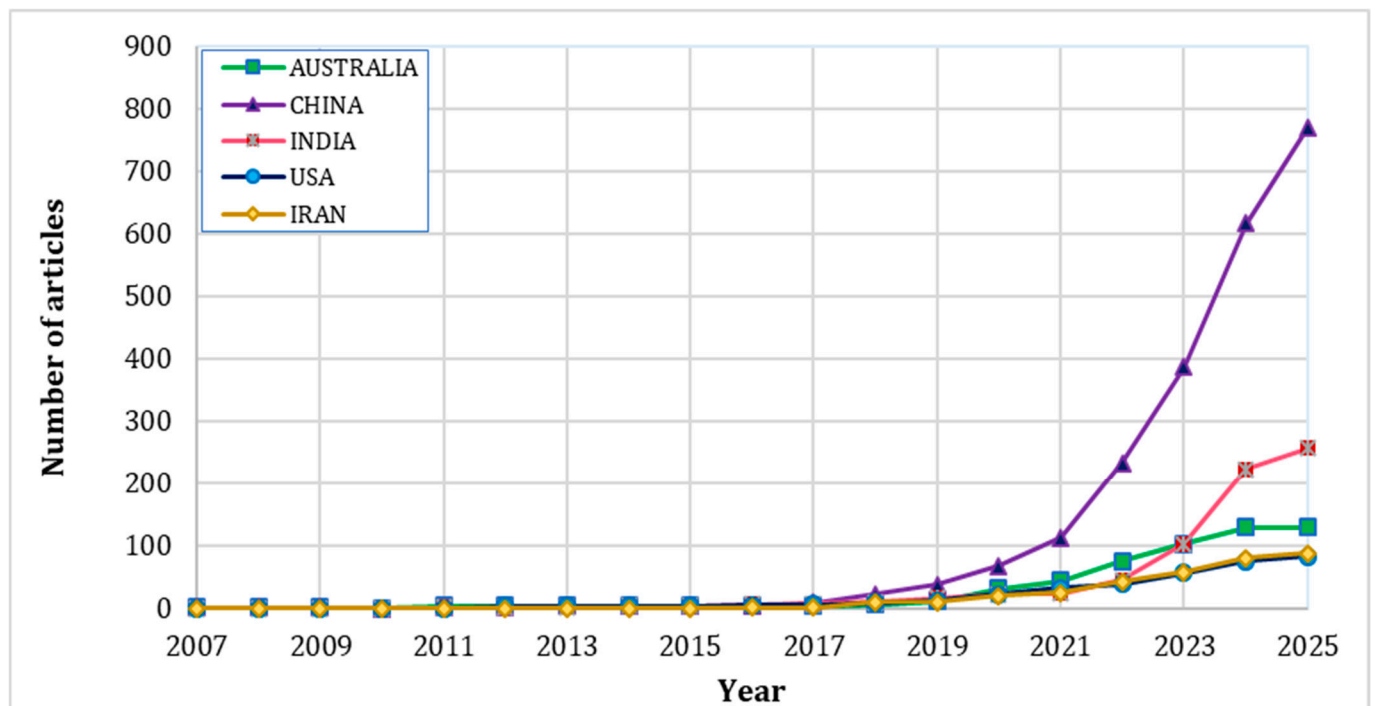
The co-authorship network map in Figure 18 reveals four color-coded collaboration clusters that shape the global ML-for-concrete landscape. While the green cluster, led by Australia and comprising China, Iran, the United Kingdom, and Viet Nam, emphasizes strong Asia-Pacific and European ties, the red cluster—which includes Egypt, Iraq, Pakistan, Poland, Saudi Arabia, and Thailand—reflects a close-knit regional partnership. In a blue cluster spanning North America and Asia, the United States and Canada collaborate closely with Bangladesh, Hong Kong, and Türkiye. Finally, the yellow cluster, centered on India, extends its ties primarily to Spain and South Korea. The fact that China has by far the largest node highlights both the depth of its international connections and its highest research output. It connects several clusters, most notably with Australia, the United Kingdom, the United States, and Türkiye, underscoring its critical role in advancing global ML-based concrete research.

The world map in Figure 19 further reinforces the geographic contribution patterns in Figure 18, showing that China leads in publication count with a total of 769 articles, followed by India (256), Australia (129), Iran (88), Saudi Arabia (59), South Korea (53), and the United States (83). This indicates a strong concentration of research activity in Asia, with China acting as the primary engine driving this field. Western nations like the USA and UK, though contributing fewer papers, still maintain a visible influence through collaborative ties and research quality.

Figure 20 illustrates country production over time, highlighting the rapid growth of publications after 2016, particularly from China, which exhibits exponential increases, reaching over 700 articles by 2025. India showed a noticeable upward trajectory starting around 2018, reflecting growing national efforts to apply ML techniques in sustainable concrete research. Meanwhile, Australia and the USA show a slower but steady increase, suggesting consistent long-term contributions.



**Figure 19.** Collaboration world map. Numbers show each country's publication count; darker shades indicate higher volumes, lighter shades lower.

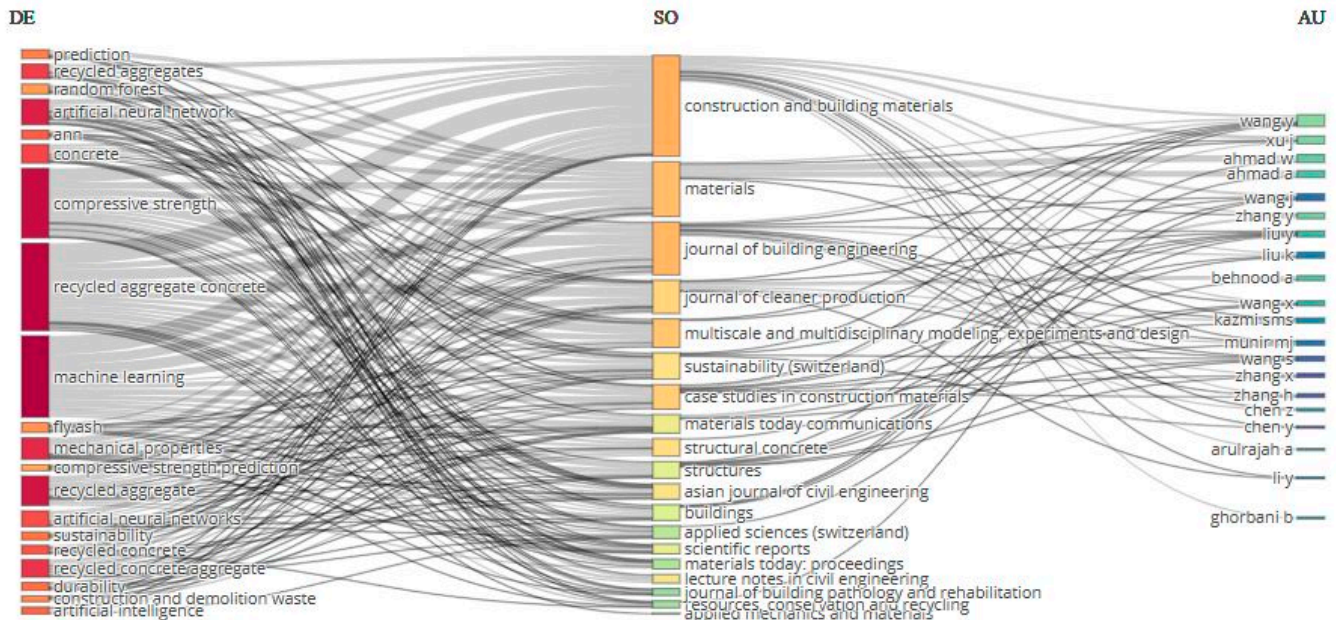


**Figure 20.** Country's production over time.

#### 4.8. Collaboration Networks and Three-Field Plot

To better visualize the relationships between key research themes, journals, and authors, a three-field plot (3FP) analysis was conducted using the Biblioshiny app. The primary intellectual and cooperative trends forming the field of study are illustrated by this analysis, which links authors, journals, and keywords. As a result, Figure 21 shows a comprehensive 3FP linking the most widely used keywords (DE), journals (SO), and authors (AU) in this field of study. According to the dominating keywords, fly ash, machine learning, recycled aggregate concrete, compressive strength, ANN, prediction, random forest, durability, and sustainability, the field is heavily focused on enhancing

material performance and predictive modeling. *Construction and Building Materials* is the leading publication, followed by *Materials*, *Journal of Building Engineering*, *Journal of Cleaner Production*, and *Sustainability* (Switzerland). These journals serve as important knowledge hubs, concentrating a significant portion of the research and facilitating the dissemination of key findings.



**Figure 21.** 3FP showing the interconnected relationships between keywords, journals, and authors.

Relevant authors are also mapped by the 3FP; Wang Y, Xu JY, Ahmad W, and Ahmad A are prominently featured. These authors are strongly connected to high-impact journals and recurring topics such as recycled aggregates, machine learning (ML), ANN, and compressive strength prediction. Their prominence indicates the formation of dominant institutional hubs driving research in predictive modeling and sustainable construction materials.

Keyword co-occurrence and clustering reveal the flow of knowledge from foundational topics—like ANN-based compressive strength prediction—to emerging ML techniques, including ensemble methods, and deep learning. This evolution suggests an interdisciplinary expansion, as researchers increasingly integrate computational intelligence with sustainable construction material design. Furthermore, the proximity of keywords related to durability, sustainability, and fly ash signals growing interest in linking performance optimization with environmental and life-cycle considerations.

Overall, the 3FP not only maps the structural relationships among authors, journals, and keywords but also provides insights into the direction of the field: strong institutional hubs guide knowledge dissemination, while emerging interdisciplinary patterns indicate a shift toward diverse ML applications and sustainability-focused research.

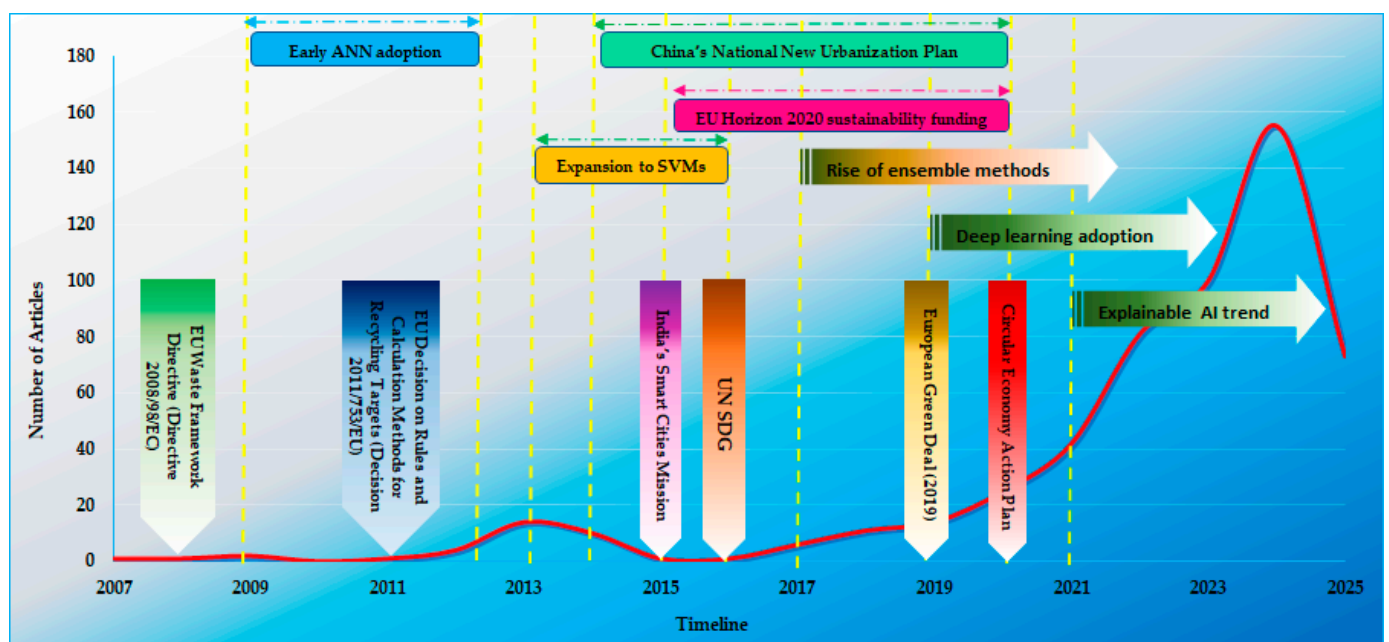
## 5. Discussion

Building on the foundational role of scientometric and bibliometric analyses in uncovering research dynamics, this study applies these tools to examine how ML techniques are shaping advancements in sustainable construction materials research—particularly focusing on CDW. Through the integration of VOSviewer and Biblioshiny, the analysis provides both network visualizations and quantitative insights. The combined use of these tools enhances the reliability of the identified clusters and thematic trends, highlighting the effectiveness of mixed-method scientometric approaches in mapping emerging areas. The

following discussion contextualizes the main findings concerning the study's objectives and situates them within broader developments in sustainable construction and data-driven materials science.

The publication trend in ML applications for sustainable construction materials shows distinct phases shaped by technological, regulatory, and sustainability drivers, as illustrated in Figure 22, which highlights key milestones influencing research activity over time. An early peak around 2013 reflects initial efforts to incorporate CDW into concrete and the adoption of circular economy principles following the EU Waste Framework Directive (2008/2011), which introduced the waste hierarchy and promoted high-quality recycling. For instance, Pacheco et al. [93] show that recycled aggregates derived from CDW can replace natural aggregates in concrete, aligning with directive aims to use CDW as a resource. Similarly, Zhang et al. [94] analyze how the waste hierarchy framework has guided development of advanced CDW treatment technologies, particularly for waste concrete.

The subsequent decline until 2016 likely resulted from limited high-quality datasets and slower uptake of advanced ML methods. A study by Regona et al. [95], identifies data quality and availability as major obstacles to AI adoption in the construction industry. The research emphasizes that AI systems depend on extensive datasets to train and operate effectively. In the construction sector, data collection is often inconsistent and fragmented, leading to challenges in implementing AI solutions [95].



**Figure 22.** Publication trends in ML for sustainable construction with policy and technological milestones [96–102].

From 2017 onward, publications rose sharply, culminating in a peak of approximately 160 articles in 2024. This surge reflects the growing maturity of ML techniques, including deep learning and ensemble learning approaches capable of handling heterogeneous materials data, and aligns with intensified global sustainability efforts, such as the UN Sustainable Development Goals (Goal 11 on sustainable cities and Goal 12 on responsible consumption and production) [96,97]. Regulatory initiatives such as the European Green Deal (2019), which targets at least a 50% emissions reduction by 2030, and the Circular Economy Action Plan (2020), which addresses product life cycles, further accelerated research funding and industry uptake of low-carbon construction solutions. Overall, this upward trend marks a transformation from predominantly empirical studies to more

sophisticated, data-centric approaches, where ML enables the identification of hidden patterns, quantification of complex relationships, and accurate prediction of material properties. The apparent dip in 2025 is a mid-year artifact rather than a true decline in research activity.

The strong presence of specialized journals such as *“Construction and Building Materials,” “Journal of Building Engineering,”* and *“Materials”* underscores the interdisciplinary nature of this transformation. These journals collectively provide a key platform for disseminating research that merges materials science and computational techniques, reflecting the growing recognition that data-driven methods can drive innovations in both the design and application of recycled materials.

Keyword co-occurrence and factorial analyses further elucidate the field’s transformation by revealing clusters of research themes that converge on material performance characterization, advanced computational modeling, and sustainable construction practices. This thematic progression corresponds with an increasing adoption of advanced methods, signaling a shift toward more sophisticated, multi-objective optimization frameworks. Technically, early studies predominantly applied ANNs for compressive strength prediction before expanding to SVMs, which proved effective for smaller datasets and niche property prediction. More recently, ensemble and deep learning approaches have been employed to manage heterogeneous CDW data, enabling multi-objective predictions that integrate mechanical performance with durability and sustainability indicators. These developments reflect a clear shift from single-target, trial-and-error approaches toward robust, explainable, and integrated ML frameworks. Foundational topics, including mix-design variability and experimental validation, nonetheless remain essential, underscoring the continued need for hybrid strategies that combine laboratory testing with computational modeling. Reflecting this evolution, post-2017 literature increasingly incorporates terms such as “deep learning,” “ensemble learning,” “gradient boosting,” and “Explainability” [98–100]. At the same time, policy and regulatory agendas have reinforced the prominence of keywords like “optimization,” “forecasting,” and “recycled aggregates,” while sustainability-oriented terms, including “life cycle,” “low-carbon,” and “sustainable development,” highlight the field’s alignment with broader global initiatives. Collectively, these patterns demonstrate that the trajectory of the field is being shaped not only by technological innovation but also by regulatory frameworks and sustainability imperatives.

The geographic and collaborative patterns revealed by the co-authorship network and country production data reflect the key role that certain regions—particularly China, India, and Australia—are playing in shaping this field. Regional policy frameworks such as China’s National New Urbanization Plan (2014–2020), India’s Smart Cities Mission (2015), and EU sustainability funding programs (2020) appear to have influenced these research hubs [101,102]. The strong clusters of collaboration within the Asia-Pacific and European regions suggest that policy priorities, industrial needs, and research funding mechanisms may be influencing the formation of specialized knowledge hubs. Nonetheless, the limited collaboration between continents underscores an opportunity to foster more international partnerships, particularly with underrepresented regions in Africa and Latin America. Such collaborations could broaden the applicability of ML methods across different materials, mix designs, and environmental conditions, strengthening the robustness and generalizability of the models.

Furthermore, the most-cited articles and authors identified in this study underscore the foundational role of key contributors who have successfully integrated ML techniques into materials research. The extensive citations of Wang et al. [62] and Naderpour et al. [63] reflect their methodological innovations—particularly in developing, validating, and interpreting ML models—which have profoundly influenced subsequent investigations in

this area. Importantly, their work highlights the necessity of employing explainable and trustworthy methods to enable practitioners and regulators to interpret and apply these models with confidence.

## 6. Conclusions

This study conducted a comprehensive scientometric analysis of the application of ML techniques in sustainable construction materials research, particularly focusing on CDW. By employing a combination of VOSviewer and Biblioshiny, this inquiry maps the intellectual structure, collaboration patterns, and thematic trends that have defined this rapidly growing field. The key conclusions arising from this analysis are as follows:

- **Rapid and sustained growth of the field:** The analysis revealed a rapid growth in research output, with 542 documents published between 2007 and 2025 and an average annual growth rate of 26.9%. Research activity was minimal before 2013 and declined slightly between 2013 and 2016, but it accelerated significantly after 2017, reaching a record high of around 160 papers in 2024.
- **Journals as key knowledge hubs:** The analysis highlights the role of specialized journals in shaping and disseminating ML-related research on recycled concrete. *Construction and Building Materials* (62 papers, h-index = 33), *Journal of Building Engineering* (29 papers, h-index = 16), and *Materials* (24 papers, h-index = 15) emerge as central platforms for both high-impact and high-output contributions. These journals have become central platforms for disseminating ML-related concrete research, serving both as high-volume and high-impact sources.
- **Dominant thematic clusters:** Keyword and thematic analysis revealed four main clusters of inquiry within this domain: material performance and characterization, predictive modeling techniques, sustainability, core materials, and emerging computational approaches. Machine learning, recycling, compressive strength, and recycled aggregates were the most frequently occurring terms, reflecting a strong focus on developing robust, data-informed models to predict and enhance material properties while addressing environmental and sustainability goals.
- **Concentration of influence:** The distribution of authors' contributions reveals a small group of prolific and highly cited contributors who have profoundly influenced the trajectory of the field. Wang Y stands out as the most prolific and influential researcher, with an h-index of 10 and 764 citations, followed by A. Ahmad, A. Behnood, and J. Xu, each with an h-index of 9. These authors have shaped the direction and momentum of the field through their widely cited works.
- **Highly cited seminal works:** Certain key publications have become cornerstones for subsequent investigations and applications. Wang et al. [62] (588 citations), Naderpour et al. [63] (548 citations), and Duan & Poon [85] (488 citations) are the most frequently cited, reflecting their methodological innovations and their utility in developing and validating ML models for recycled aggregate concrete.
- **Geographic and collaborative patterns:** the geographic distribution of publications highlights a strong regional concentration, with China leading the output (769 publications), followed by India, Australia, Iran, the USA, Saudi Arabia, and South Korea. The collaboration network underscores the formation of prominent regional clusters such as China–Australia–UK–USA and India–Spain–South Korea, highlighting both the dominance of Asia-Pacific countries and the significance of cross-border research partnerships.

## 7. Gaps, Limitations, and Future Directions

This scientometric analysis reveals several critical gaps in the current body of literature on ML applications in sustainable construction materials research, particularly focusing on CDW. The field is heavily focused on predicting compressive strength, while other essential properties such as durability, creep, shrinkage, and permeability are significantly under-explored. Similarly, most studies emphasize recycled aggregates, overlooking alternative CDW materials such as ceramic, glass, or mixed waste. Advanced ML techniques—such as deep learning, ensemble learning, and hybrid models—have only recently begun to appear in the literature, indicating a missed opportunity to enhance prediction accuracy and model robustness.

Several methodological and data-related limitations should be acknowledged. First, this study relied exclusively on English-language publications indexed in Scopus, which may have excluded relevant findings from non-English sources and regional journals or conferences. While Scopus provides broad coverage and a very high degree of overlap with Web of Science (WoS), with recent analyses showing that about 99% of WoS-indexed journals are also covered by Scopus [103], differences in document coverage remain. Previous comparative studies indicate that the overlap between Scopus and WoS varies by discipline, often ranging between 80% and 90% [61,103,104], with WoS being more selective and Scopus including a larger number of regional and niche journals [103,104]. Consequently, a degree of under-coverage bias cannot be ruled out, particularly for WoS-exclusive publications, and future reviews could benefit from integrating multiple databases to achieve more comprehensive representation.

Beyond database-related considerations, additional methodological issues also warrant attention. Many ML studies are constrained by small or homogeneous datasets, which can lead to overfitting and reduce the generalizability of models. Furthermore, dataset quality and completeness vary widely. The field is also heavily concentrated in a small number of journals and countries, highlighting potential publication bias and challenges in applying findings across different regional contexts. In addition, the country assignment in bibliometric mapping attributes multi-authored papers to all listed countries, which may inflate publication counts and introduce discrepancies in country-level comparisons. Collectively, these issues underscore the need for more diverse, standardized, and internationally representative datasets, as well as rigorous methodological practices to improve the robustness, reproducibility, and applicability of ML models in sustainable construction materials research.

To advance the field, future research should broaden its scope to include a wider range of concrete properties and CDW materials. Embracing advanced ML methods and explainable AI will improve model interpretability and performance. Greater international collaboration—especially involving underrepresented regions—can enhance the diversity and relevance of research. Additionally, network-based relevance metrics, such as PageRank, Stirling index, and other network centrality measures (e.g., Degree, Betweenness, and Closeness centrality), could be employed to better evaluate influential publications and knowledge hubs in the field. Future studies should also focus on expanding dataset diversity, standardizing data collection protocols, and validating ML models across different regional contexts to enhance reproducibility and reliability. Integrating sustainability metrics, such as life-cycle assessment and embodied carbon, into ML frameworks is essential for promoting eco-friendly construction practices. Finally, future scientometric and systematic reviews should incorporate technical evaluations of model accuracy, reproducibility, and real-world sustainability impacts to provide a more comprehensive understanding of progress.

**Supplementary Materials:** The following supporting information can be downloaded at <https://www.mdpi.com/article/10.3390/su17188453/s1>. File S1: Scopus dataset of 542 publications.

**Author Contributions:** E.M.G.: Software, Formal analysis, Validation, Investigation, Resources, Data curation, Writing—original draft. W.Z.T.: Conceptualization, Formal analysis, Supervision, Validation, Writing—review & editing. L.E.-L.: Conceptualization, Supervision, Writing—review & editing. M.D.Y.: Conceptualization, Supervision, Validation, Project administration, Writing—review & editing. All authors have read and agreed to the published version of the manuscript.

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