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A Systematic Review and Bibliometric Study of Climate Change Sentiment Analysis: Trends and Approaches

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Abstract.
Purpose: This study aims to map research trends in sentiment analysis on the climate change topic from the beginning of 2020 to the middle of 2025 by utilizing a Systematic Literature Review (SLR) method, along with bibliometric analysis. Climate change represents a worldwide challenge that profoundly affects both the environment and human social interactions, making it essential to comprehend public perceptions of this issue thoroughly. The escalating use of social media is driving an increase in research related to sentiment analysis, which is utilized to gain insights into public opinions and emotions.
Methods: Data was collected from six leading databases such as Scopus, ScienceDirect, Taylor and Francis, IEEE Xplore, Sage Journals, and ProQuest, resulting in 3,326 articles. After a screening process using the PRISMA 2020 framework, 42 articles were selected for further analysis.
Result: The findings suggest that Twitter is the predominant platform for climate change sentiment analysis, referenced in 32 articles, while Sina Weibo is mentioned in nine articles, Reddit in two articles, and both Facebook and YouTube in one article each. Of the four approaches assessed, the leading approaches identified in this research are Machine Learning and Deep Learning. In the Machine Learning category, Naïve Bayes is the predominant approach, appearing in 18 articles, followed by Naïve Bayes, cited in 17 articles. Furthermore, Logistic Regression and Random Forest are each mentioned in 13 articles. In the field of Deep Learning methodologies, 10 articles used Convolutional Neural Networks (CNNs), nine articles featured Bi-LSTMs, six articles featured LSTMs, and 13 articles referenced Transformer-based models, particularly BERT. Furthermore, model validation primarily used cross-validation techniques, and the most referenced evaluation metrics were accuracy, recall, and F1-score in 33 articles and precision in 32 articles.
Novelty: The novelty of this research lies in the time of information collection for research on climate change sentiment analysis, spanning 2020 to the middle of 2025. The latest research on a related issue was conducted from 2008 to 2022. Furthermore, this study provides insights into research trends and includes the distribution of articles by country, separating them into Single-Country Publications (SCPs) and Multi-Country Publications (MCPs). This research also presents information on social media platforms, classification approaches, and commonly employed validation and evaluation tools, which differentiate it from prior studies. This analysis is conducted on six leading databases, producing valuable findings for researchers and policymakers.

Keywords: Climate change, Sentiment analysis, Machine learning, Deep learning, Hybrid, Lexicon, Social media, Bibliometric, Systematic literature review
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INTRODUCTION

Over the last few years, social media has emerged as the leading platform for individuals to share their insights and perspectives on various events and occurrences. This transformation has fundamentally altered our methods of communication, information sharing, and involvement in large-scale events [1], [2]. Social media has become the most extensively utilized tool across the entire region [3]. According to the Digital 2024 Global Overview Report, there are over 5 billion social media users worldwide. Through social media, people can access interactive media, enabling social media users to articulate various viewpoints.

Concerns regarding climate change and its consequences have become a key focus of dialogue on social media platforms [1]. It is widely acknowledged that climate change and its consequences present one of the most pressing threats to both human society and the natural environment. The impact of climate change has become more evident, characterized by severe weather phenomena such as hurricanes, tornadoes, hail, lightning, fires, and floods [4]. For instance, in early 2025, wildfires occurred in Southern California, and

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floods hit Mecca, Saudi Arabia, and Bekasi, Indonesia. The ramifications of climate change exacerbate existing inequalities and present new challenges for governments, industries, and individuals [5].

The issue of climate change is complex, and there is no immediate solution to resolve it. Thus, it is essential to comprehend the challenge by leveraging technological advancements, including social media, to find solutions [6]. Social media generates a vast amount of sentiment-laden information through various formats, including tweets, status updates, blog posts, comments, and reviews [7]. The sheer volume of data produced by users is substantial and beyond the capacity for detailed analysis. Therefore, automation is required to manage this situation. To effectively and efficiently address this challenge, sentiment analysis has been implemented as a solution [8], [9].

Sentiment analysis, often referred to as opinion mining, is a significant area within Natural Language Processing (NLP) that focuses on identifying and classifying opinions conveyed in textual material [10]. Some researchers categorize sentiment analysis into three main categories: positive, neutral, and negative. However, there are instances where public opinion is further divided into four categories: agree, neutral, disagree, and the most accurate news [3].

Several studies have explored sentiment analysis associated with climate change. The analysis of public perceptions related to climate change through social media platforms has now been widely performed. For instance, some researchers used twitter data to investigate the social debate and conference regarding the climate crisis [1], [2], to capture the public and leaders' opinion about global warming [11], to understand people's emotions during a disaster [12], [13], and to illustrate the conduct and beliefs of the populace before, during, and after flood situations [14]. Some researchers also utilized other social media platforms to analyze climate change topics, including YouTube [13], Weibo [15], and Reddit [16].

Several studies on this topic applied approaches such as Lexicon [1], [2], Machine Learning [11], and Deep Learning [12], [14], [17] in conducting sentiment analysis on social media. Researchers often compare these approaches to identify the most efficient method for sentiment analysis.

There are some bibliometric analysis studies focusing on climate change topics. Dilaver et al. [18] examine the relevance of climate change to non-communicable diseases through the use of bibliometric analysis. Baidya et al. [19] conducted a bibliometric analysis to examine the trends associated with climate change and sustainable growth. Liu et al. [20] employed bibliometric analysis to examine the features of climate change risk. There's also research conducted by Ajibade et al. [21] that performed a bibliometric analysis to comprehensively evaluate the publication landscape of Machine Learning and Climate Change research, relying on documents published in Scopus from 2008 to 2022. Moreover, this study exclusively discusses the trend of Machine Learning in Climate Change, focusing on publication growth patterns, while neglecting social media platforms, classification approaches, and the validation and evaluation tools that are frequently used.

Despite extensive research on this subject, there is a lack of recent studies that conduct bibliometric analyses and literature reviews focused on sentiment analysis related to this topic. Specifically, those that examine the types of social media platforms, classification approaches, and the validation and evaluation tools that are regularly used, rather than focusing solely on patterns of publication growth. Therefore, it is essential to analyze the latest advancements in sentiment analysis related to climate change and establish a foundation for future research initiatives in this field.

This research presents a bibliometric analysis of 42 studies focused on sentiment analysis related to climate change, drawn from six databases such as Scopus, ScienceDirect, Taylor and Francis, IEEE Xplore, Sage Journals, and ProQuest, over the last five years (2020-2025). The objective of this research is to respond to the ensuing research questions:

RQ 1: What are the trends in sentiment analysis for the topic of climate change?

RQ 2: What social media platforms and dataset sources are applied in sentiment analysis focused on climate change discussions?

RQ 3: What are the prevalent sentiment classification approaches utilized in relation to climate change?

RQ 4: What methods of validation and evaluation tools are employed in sentiment analysis approaches associated with climate change discussions on social media?

The remaining part of the research article is summarized below. Section 2 detailed a review of the literature focusing on sentiment analysis in relation to climate change and relevant studies. The methodology utilized for the research is detailed in Section 3, and Section 4 provides analysis reports of the chosen dataset. Section 5 describes the research summary and suggestions for further researchers.

METHODS

To achieve the study's objective of providing empirical insights into climate change, two methods were utilized: the Systematic Literature Review (SLR) method and bibliometric analysis. This section outlines the research process conducted using the Systematic Literature Review (SLR) and data analysis.

First, a thorough analysis of the literature data was carried out using the Systematic Literature Review (SLR) methodology, guided by the principles of the PRISMA 2020 framework. There are three stages in PRISMA flowcharts: identification, screening, and inclusion [22]. Among these three phases, most articles were eliminated during the screening phase. This occurred for various reasons: the research was considered unrelated to sentiment analysis of climate change, it did not use social media as a data source, it was not presented in a journal or conference format, the article was not entirely accessible, and data were duplicated.

To evaluate and measure the quality of each literature obtained in inclusion, it is necessary to conduct a quality assessment adapted from Kitchenham's guidelines. The evaluation of quality is conducted to maintain the standards of the selected literature [23]. This assessment of quality features several checklists that are used to evaluate studies, where each response is marked as "Yes = 1" or "No = 0" [24]. Two reviewers conducted this process. Disagreements regarding the assessment were resolved through discussion.

Table 1. Checklist for Quality Assessment

Checklist	Questions
C1	Does the paper effectively articulate the goals of the research?
C2	Does the paper offer a comprehensive literature review, in addition to providing the background and context for the study?
C3	Does the paper include references to prior research to highlight the key contributions of the current study?
C4	Does the paper provide details about the architecture or methodology that has been proposed?
C5	Does the paper include findings from research?
C6	Does the paper offer conclusions that are significant to the research questions or challenges outlined?
C7	Does the paper suggest any recommendations for future research or enhancements?
C8	Is the paper included in the Scopus database (Q1/Q2/Q3/Q4/unindexed)?

Data that has been gathered and has passed through the Quality Assessment phase will proceed to a data extraction process utilizing a structured template that encompasses bibliographic details (article title, year, journal name, and country), research attributes (research objectives, datasets, and social media platforms utilized), methodologies or approaches, along with the validation and evaluation tools employed.

Identification

The search was carried out on several distinguished literature and journal platforms that researchers frequently use. The databases utilized include Scopus, Science Direct, Taylor and Francis, IEEE Xplore, Sage Journal, and ProQuest.

After selecting the databases for the search, the formulation of the search strategy required the establishment of search keywords that originated from the research questions. These keywords were interconnected using "AND" to associate the primary keywords and "OR" to include synonyms or alternative expressions.

On August 10th, 2025, the specified search string TITLE-ABS-KEY criteria (("climate change" OR "global warming" OR "extreme weather" OR "climate effect" OR "climate variability") AND ("sentiment analysis") AND ("social media" OR "social network" OR "online")) was executed. The year filter was activated for 2020 and 2025 on the search engine. It is ensured that all research obtained at this stage is fully accessible and written in English. The result of this phase leads to the identification of 3,326 pieces of literature.

Screening

In the screening phase, the title and abstract are selected. The selected title and abstract must relate to the analysis's sentiment regarding the subject of climate change.

The researcher also ensured there were no duplicate files and proceeded with the study selection process. The criteria for both inclusion and exclusion have been determined and are represented in Table 2. Considering the results obtained from the inclusion and exclusion criteria, there are 118 articles that have been selected.

Table 2. Criteria for Inclusion and Exclusion in This Systematic Literature Review

Inclusion Criteria	Exclusion Criteria
Publications focused on sentiment analysis regarding climate change as expressed on social media.	Publications that are not relevant to sentiment analysis regarding climate change on social media or only discuss opinions in general.
Published within the last five years (2020–2025).	Publication outside the specified time period.
Publications written in English.	Publications are not written in English.
Publications in the form of journals or proceedings.	Publications in forms other than journals or conferences.
Fully accessible publications.	Publications are not fully accessible.

Inclusion

In the inclusion phase, the selected articles must answer the research questions. Therefore, researchers screened the entire text content. Following the various selection and filtration processes, we identified 42 pieces of literature that were examined to address the Research Questions. Figure 1 illustrates a flow diagram that follows the PRISMA 2020 guidelines for this research.

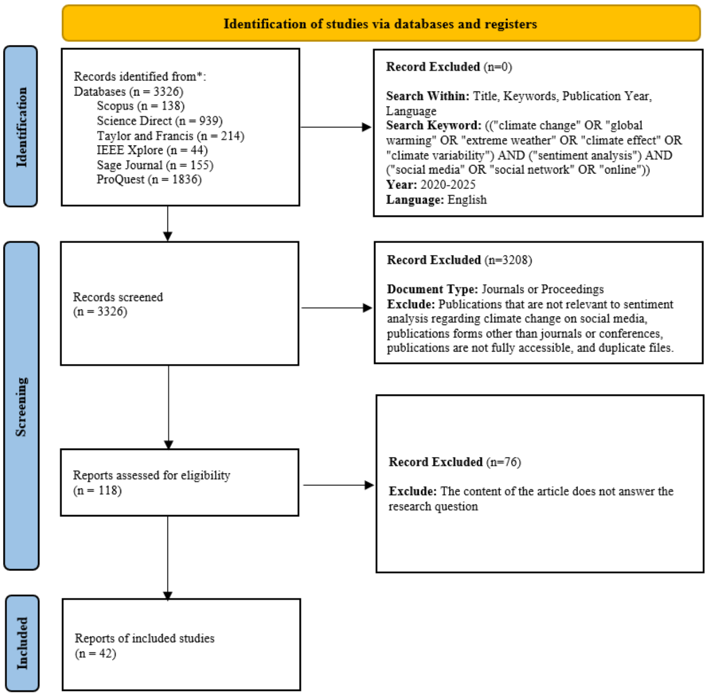


Figure 1. Research Selection Flow Diagram based on PRISMA 2020

Figure 1. illustrates the PRISMA 2020 flow diagram applied in this research, depicting the systematic research selection process across three stages: identification, screening, and included. The review began with 3,326 articles sourced from six major academic databases. After removing 3,208 articles based on relevance

to the topic, publication type, and full accessibility, 118 articles proceeded to the screening stage. Following document types and content checks, we are removing 76 articles. In summary, 42 full-text articles were examined for eligibility and complied with all inclusion criteria for extensive analysis.

Data Analysis

A Bibliometric analysis was carried out to explore citation networks, keyword co-occurrences, and also co-authorship [21]. Throughout the phase of bibliometric analysis concerning the data, the results of the evaluation were expressed in numerical terms and percentages linked to categorical variables [18].

In the network or relationship visualization of the data, we also used VOSviewer version 1.6.20. VOSviewer is an innovative software that enables users to visualize networks or connections by leveraging a text-mining function while engaging in problem-referencing tasks [19]. This software represents data by tags and a circle. The extent of an item's depiction, characterized by the scale of its label and the scale of its circle, is directly linked to its related weight. The cluster influences the color of every element it is associated with, and the lines that connect the elements denote the relationships [18].

In this study, we filtered data from articles obtained from six different databases and then entered them into the Mendeley application. This resulted in the use of the Vosviewer application being less than optimal. Because the exported data was in RIS format, we only display research keywords related to sentiment analysis regarding the subject of climate change.

RESULT AND DISCUSSION

The previously selected literature will be the main reference to answer the four research questions that have been submitted previously. The findings of the Research Questions pertaining to sentiment analysis on the climate change topic will be reported in this section.

[RQ1] Trends in sentiment analysis for the topic of climate change

1. Articles published by year

To determine the number of articles related to sentiment analysis on climate change, we used six different databases. The search results and filtering through the PRISMA Framework revealed that this topic has been increasingly featured as a research topic over the years.

In 2020, three articles addressed this topic. Then, in 2021, the number of articles increased to four, but then remained unchanged in 2022. Furthermore, in 2023, there was a significant increase in research on this topic, resulting in 12 articles. The growth in sentiment analysis research on climate change from 2022 to 2023 was predominantly driven by the increasing diversity and urgency of the subjects explored, ranging from public reactions to flooding and extreme weather to their connections to the Sustainable Development Goals (SDGs). Then, in 2024, it rose again to 15 articles on this topic. Lastly, only four research articles are relevant to this field in 2025. This is attributed to the fact that data collection was limited to the period up to August 2025. Therefore, it does not reflect a decrease in interest. Figure 2 displays the number of research articles that have been published regarding this topic.

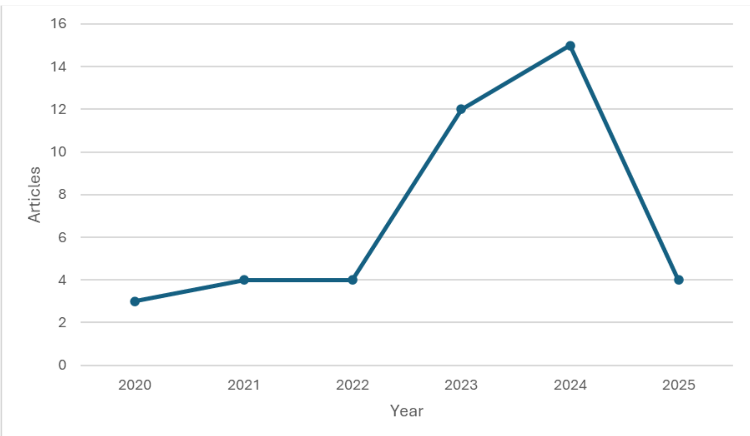
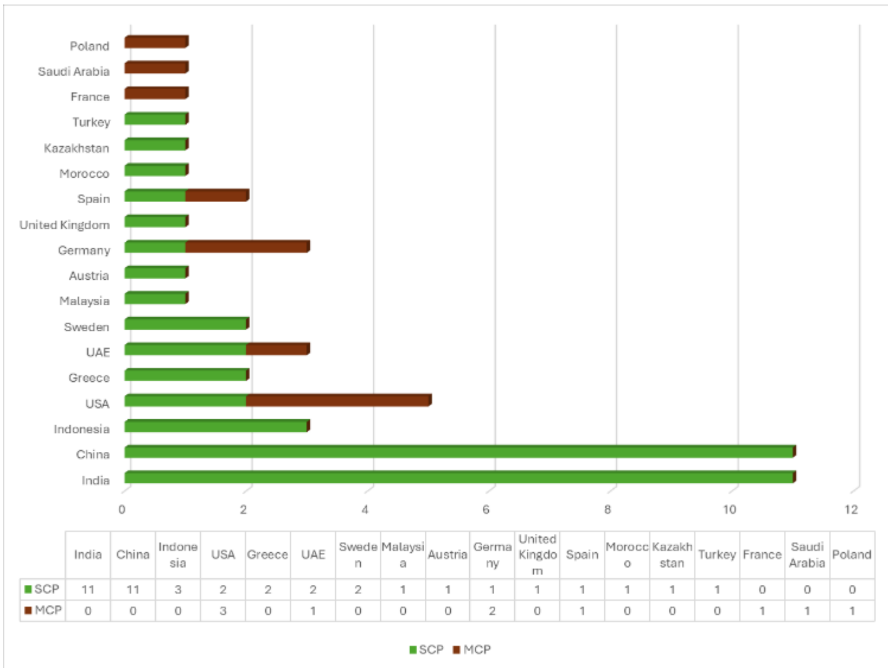


Figure 2. Growth Trajectory of Published Documents on Sentiment Analysis of Climate Change Topic Research (From Early 2020 to Mid 2025)

2. Articles distribution by country

The allocation of articles among different countries was meticulously examined. Figure 3 illustrates the leading countries with the highest quantity of publications based on the nationality of the corresponding author. The green bar which signifies Single-Country Publications (SCPs), indicates the ratio of publications in which all authors are from the same country as the corresponding author. In contrast, the brown bar denoting Multi-Country Publications (MCPs), indicates the ratio of articles that feature at least one author from a country distinct from that of the corresponding author [18].



	India	China	Indonesia	USA	Greece	UAE	Sweden	Malaysia	Austria	Germany	United Kingdom	Spain	Morocco	Kazakhstan	Turkey	France	Saudi Arabia	Poland
SCP	11	11	3	2	2	2	2	1	1	1	1	1	1	1	1	0	0	0
MCP	0	0	0	3	0	1	0	0	0	2	0	1	0	0	0	1	1	1

Figure 3. Article Distribution by Country

3. The inventory of keywords for each cluster

The results were visualized using VOSviewer to emphasize the keywords that appear most frequently. Figure 4 provides a visual representation of the network maps for author keywords in the sentiment analysis of climate change research. In the analysis of author-related keywords, a total of 121 author keywords were assessed, with each keyword having a minimum of two occurrences. Six clusters were established, each consisting of 23 keywords that have strong links to one another.

The default setting of VOSviewer features topics that are labeled and symbolized as circles. A keyword is classified as necessary when its frequency of occurrence is elevated, resulting in a larger circle [25]. The width of the lines indicates the level of collaboration among keywords [18]. Sentiment analysis stands out as the highest frequency occurrence, depicted by the biggest circle.

Cluster 1 represents the integration of social media platforms and Natural Language Processing (NLP) techniques, with "Social Media" emerging as the central node. Cluster 2 focuses on "Sentiment Analysis" and is closely related to the "Climate Change" topic. Cluster 3 then highlights the growing use of alternative platforms, particularly Reddit, and the growing adoption of deep learning architectures, including CNNs. Cluster 4 addresses dominant data platforms and behavioral analysis. Cluster 5 then reflects research streams related to the public discourse on "Global Warming." Finally, Cluster 6 focuses on a more general AI-based perspective, linking "Machine Learning" with "Artificial Intelligence".

Cluster 1, which is marked with a red circle, contains six items. The most frequently occurring keyword in this cluster is ‘Social Media’ with 12 occurrence of keywords, 14 links and a total link strength of 25. Accompanied by ‘Natural Language Process’ featuring six occurrence of keywords, 11 links and 16 total link strength; ‘BERT’ featuring three occurrence of keywords, five links and eight total link strength; ‘Disaster Management’ featuring three occurrence of keywords, five links and five total link strength; ‘Sina Weibo’ featuring two occurrence of keywords, five links and an five total link strength; and ‘Spatiotemporal Analysis’ featuring three occurrence of keywords, three links and four total link strength.

Cluster 2, which is marked with a green circle, has five items. The most frequently occurring keyword in this cluster is 'Sentiment Analysis', which has 26 occurrences of keywords, 21 links and 71 total link strength. In conjunction with 'Climate Change' which has 20 occurrence of keywords, 19 links and 59 total link strength; 'Text Mining' which has three occurrence of keywords, seven links and 12 total link strength; 'Random Forest' which has two occurrence of keywords, five links and seven total link strength; and 'Naïve Bayes' which has two occurrence of keywords, three links and five total link strength.

Cluster 3, which is marked with a blue circle, has four items. The most frequently occurring keyword in this cluster is 'Reddit' which contains two occurrences of keywords, nine links and 11 total link strength. Accompanied by 'Deep Learning' that contains three occurrences of keywords, six links and eight total link strength; 'Convolutional Neural Network' that contains two occurrences of keywords, six links and eight total link strength; and 'Text Classification' that contains two occurrences of keywords, seven links and seven total link strength.

Cluster 4, which is marked with a yellow circle, has three items. The most frequently occurring keyword in this cluster is 'Twitter' that contains eight occurrences of keywords, 13 links and 31 total link strength. Accompanied by 'Emotion Analysis' that contains two occurrences of keywords, seven links and nine total link strength and 'Latent Dirichlet Allocation' that contains two occurrences of keywords, four links and four total link strength.

Cluster 5, which is marked with a purple circle, has three items. The most frequently occurring keyword in this cluster is 'Global Warming' which has five occurrences of keywords, 11 links and 16 total link strength. Accompanied by 'Opinion Leaders' which has two occurrences of keywords, four links and six total link strength and 'Social Media Analytics' which have two occurrences of keywords, four links and six total link strength.

Cluster 6, which is marked with a aqua circle, has two items. The are 'Machine Learning' that contains six occurrences of keywords, eight links and 16 total link strength and 'Artificial Intelligence' that contains two occurrences of keywords, three links and three total link strength.

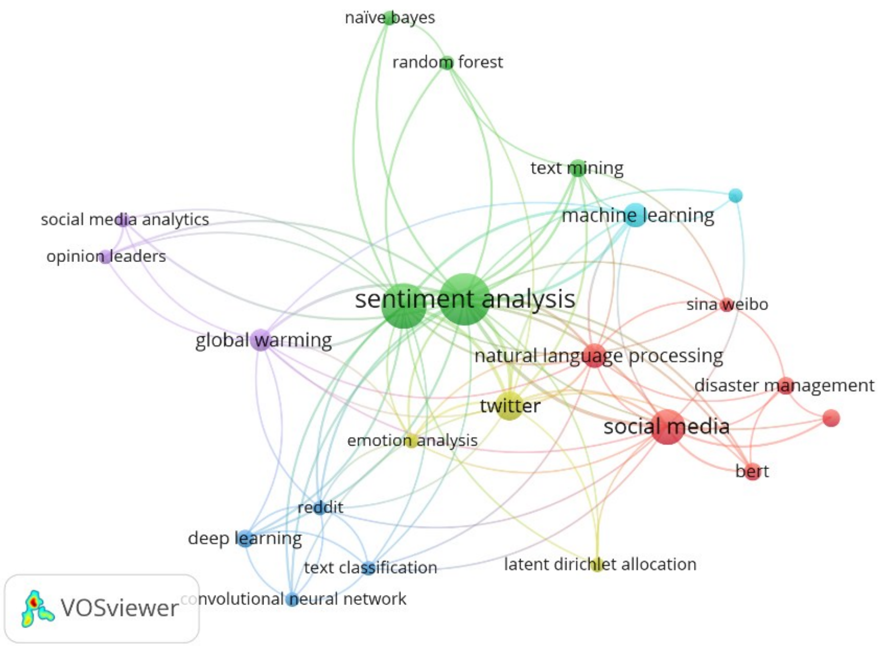


Figure 4. Applying VOSviewer for Network Visualizations in the Sentiment Analysis of Climate Change Research

4. The 10 most frequently cited publications regarding the climate change topic research

In bibliometric research, highly cited publications often reflect significant influence and contributions to the development of a field. Analysis of the most cited publications provides insight into the core literature that researchers primarily refer to.

In this study, we provide information about the top 10 most frequently cited publications on Sentiment Analysis of Climate Change Topic Research in the 2020-2025 period. The citation process in this paper was carried out by manually checking the number of citations of 42 papers obtained through Google Scholar and journal websites.

The results of this review revealed that research conducted by Yuan et al. [26] called "Social media for enhanced understanding of disaster resilience during Hurricane Florence" had the largest quantity of citations, with 106 of the total citations. Alongside research executed by Uthirapathy et al. [27] with 105 total citations and research conducted by Barachi [28] with 98 total citations. Further information about this can be seen in Table 3.

Table 3. The 10 Most Frequently Cited Publications Regarding the Climate Change Topic Research (From Early 2020 to Mid 2025)

Authors	Publication titles	Key findings	Journal titles	Number of citations
Yuan et al. [26]	Social Media for Enhanced Understanding of Disaster Resilience during Hurricane Florence	An analysis was conducted of public responses to Hurricane Florence, a natural disaster that struck the United States in September 2018. Public sentiment was classified into three groups: positive, negative, and neutral, to identify differences in responses across demographic groups. The demographic analysis included a study comparing sentiment across different racial and ethnic groups (White, Black, Hispanic, Asian) and genders (Male and Female).	International Journal of Information Management	106
Uthirapathy et al. [27]	Topic Modelling and Opinion Analysis on Climate Change Twitter Data Using LDA and BERT Model	Classifying public opinion on climate change into four specific categories: pro news, support, neutral, and anti.	International Conference on Machine Learning and Data Engineering	105
Barachi [28]	A Novel Sentiment Analysis Framework for Monitoring the Evolving Public Opinion in Real-Time: Case Study on Climate Change	This research looks into the transformation of Greta Thunberg's emotions over a period of time and the public's reaction to her tweets (support, strong support, opposite, strong opposite).	Journal of Cleaner Production	98
Effrosynidis et al. [29]	The Climate Change Twitter Dataset	Analyzing public perception or opinion regarding climate change via Twitter (stance: believer, denier, neutral), sentiment (positive/negative/neutral), language aggressiveness, discussion topics, and linking them to location data, gender, and temperature anomalies.	Expert Systems With Applications	95
Sham et al. [30]	Climate Change Sentiment Analysis Using Lexicon, Machine Learning, and Hybrid Approaches	Discover the optimal approach for performing sentiment analysis related to climate change tweets and relevant domains through an evaluative comparison of diverse sentiment analysis approaches.	Sustainability	67
Saura et al. [31]	Impact of Extreme Weather in Production Economics: Extracting Evidence from User-Generated Content	Identify the major consequences of extreme weather events on the production economy based on User-Generated Content (UGC) analysis on Twitter.	International Journal of Production Economics	58

Rosenberg et al. [32]	Sentiment Analysis on Twitter Data Towards Climate Action	Understanding public sentiment on climate change issues related to the Sustainable Development Goals (SDGs) established by the United Nations: Sustainable Development Goal 7 – Affordable and Clean Energy, Sustainable Development Goal 11 – Sustainable Cities and Communities, and Sustainable Development Goal 13 – Climate Action.	Results in Engineering	54
Kirelli et al. [33]	Sentiment Analysis of Shared Tweets on Global Warming on Twitter with Data Mining Methods: A Case Study on Turkish Language	Determining the sentiment intensity (positive, negative, neutral) of tweets about global warming in Turkish using a Machine Learning approach.	Computational Intelligence and Neuroscience	51
Bryan-Smith et al. [34]	Real-Time Social Media Sentiment Analysis for Rapid Impact Assessment of Floods	Developing a multimodal (text + image) sentiment analysis model to measure flood impact in real-time.	Computers and Geo-sciences	48
Wu et al. [35]	Spatio-Temporal Difference Analysis in Climate Change Topics and Sentiment Orientation: Based on LDA and BiLSTM Model	Analyze public perception and distribution of sentiment (positive, neutral, and negative) towards the issue of climate change.	Resources, Conservation & Recycling	41

[RQ 2] Social media platforms and dataset sources are applied in sentiment analysis focused on climate change discussions

On the internet, there are several social media platforms as places for users to share their thoughts. The thoughts they share are generally in the form of text, so that research related to sentiment analysis uses a lot of text-based social media. Researchers can use one or more social media to conduct sentiment analysis.

This is also seen in the results of the analysis of the selected literature, 32 of them using social media Twitter in conducting sentiment analysis [3], [6], [7], [10], [11], [26], [27], [28], [29], [30], [31], [32], [33], [34], [36], [37], [38], [39], [40], [41], [42], [43], [44], [45], [46], [47], [48], [49], [50], [51], [52], [53]. One of the key factors contributing to Twitter's prominence as the leading platform is its user-friendly access to Application Programming Interfaces (APIs), which simplifies the process of locating, combining, and utilizing data from multiple external sources. Meanwhile, nine literature use Weibo [35], [54], [55], [56], [57], [58], [59], [60], [61], two literature use Reddit [49], [62], one literature uses Facebook and YouTube [36], [49].

The finding that much of the discussion about climate change takes place on social media, particularly Twitter, suggests that policymakers and environmental institutions should use these platforms as primary channels for public communication, monitoring misinformation, and evaluating public acceptance of climate policies in real time. For more details, it is shown in Figure 5.

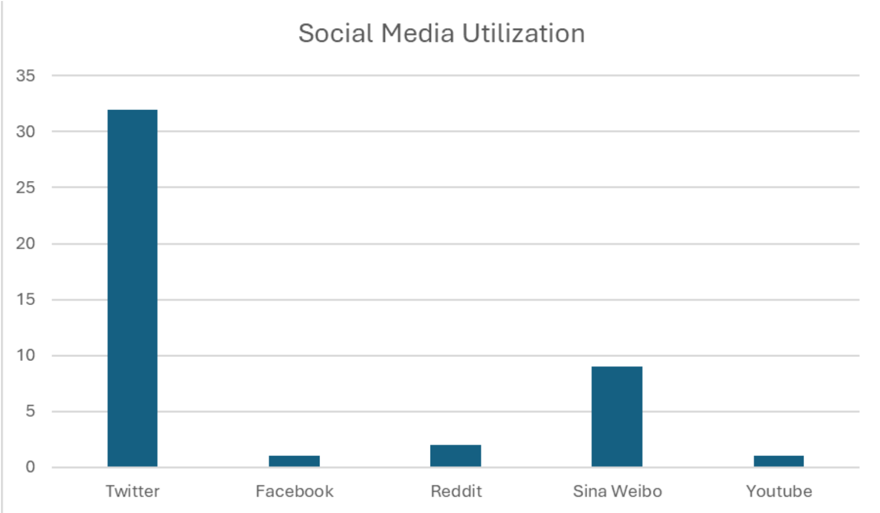


Figure 5. Social Media Utilization

In the analysis conducted on the selected literature, the dataset sources obtained were mostly from Kaggle [3], [7], [27], [30], [37], [39], [42], [46], [50], [62], Twitter [6], [10], [11], [26], [28], [29], [30], [31], [32], [33], [34], [36], [37], [38], [40], [41], [43], [44], [45], [46], [47], [48], [49], [51], [52], [53], Sina Weibo [35], [54], [55], [56], [57], [58], [59], [60], [61], Reddit [49], [62], Facebook posts [36] and YouTube public comments [49].

[RQ 3] The prevalent sentiment classification approaches utilized in relation to climate change

We can classify the approaches to Sentiment Analysis into four primary groups. First is a Machine Learning-based approach, second is a Deep Learning Approach (Deep Learning and Transformers), third is a Lexicon-based approach, and the last is a hybrid approach. Table 4. summarizes the classification approaches that are commonly used in climate change topics.

Table 4. Overview of the Classification Approaches Applied to Climate Change Issues

Research area	Classifier	References
Machine Learning	Support Vector Machine (SVM)	[3], [6], [27], [29], [30], [31], [33], [37], [40], [41], [42], [45], [46], [48], [51], [54], [55], [60]
	Naïve Bayes	[3], [7], [11], [29], [30], [31], [33], [38], [39], [40], [41], [45], [46], [48], [52], [54], [60]
	Logistic Regression (LR)	[6], [7], [30], [31], [32], [37], [38], [39], [41], [46], [48], [51], [54]
	Linear Discriminant Analysis (LDA)	[26], [27], [29], [31], [35], [37], [43], [51], [55], [56]
	Random Forest	[6], [7], [31], [37], [38], [39], [41], [45], [46], [51], [52], [54], [55]
	K-Nearest Neighbors (K-NN)	[7], [27], [33], [39], [46], [54]
	Decision Tree	[6], [39], [54]
	Linear Support Vector Classifier (LSVC)	[7], [39]
	XGBoost	[3], [37], [38], [55]
	Adaptive Boosting (AdaBoost)	[54]
	Ridge Classifier	[39]
	Extra Trees Classifier	[39]
Deep Learning	Deep Neural Network (DNN)	[41]
	Convolutional Neural Networks (CNN)	[27], [29], [36], [38], [44], [45], [46], [48], [51], [62]

	Recurrent Neural Networks (RNN)	[36], [38], [62]
	Fully Connected Neural Network (FCNN)	[46]
	Long Short-Term Memory (LSTM)	[27], [28], [29], [34], [38], [46]
	Bi-LSTM	[27], [28], [35], [44], [47], [50], [57], [58], [61]
	Multi-Layer Perceptron (MLP)	[54]
Deep Learning (Transformers)	Bidirectional Encoder Representations from Transformers (BERT)	[6], [27], [29], [32], [38], [45], [48], [53], [56], [57], [58], [59], [61]
	ClimateBERT	[6]
	DistilBERT	[38]
	RoBERTa	[10], [34], [38], [43], [47]
	BERTweet	[43], [47]
	BERTopic	[43], [49], [56]
	SentiBERT	[44]
	Word BERT (WBERT)	[47]
	Sentence BERT (SBERT)	[47]
	Contrastive Language-Image Pretraining (CLIP)	[34]
Lexicon-Based	VADER	[10], [26], [29], [30], [32], [34], [36], [37], [42], [43], [47], [51]
	SentiWordNet	[30]
	TextBlob	[29], [30], [31], [32], [37], [42], [47]
	National Research Council Canada Lexicon (NRC)	[40]
Hybrid	VADER and Logistic Regression (LR)	[30]
	VADER and Support Vector Machine (SVM)	[30]
	VADER and Naïve Bayes	[30]
	SentiWordNet and Logistic Regression (LR)	[30]
	SentiWordNet and Support Vector Machine (SVM)	[30]
	SentiWordNet and Naïve Bayes	[30]
	TextBlob and Logistic Regression (LR)	[30]
	TextBlob and Support Vector Machine (SVM)	[30]
	TextBlob and Naïve Bayes	[30]

An analysis of 42 studies revealed a methodological shift from traditional machine learning to deep learning approaches in social media-based climate change sentiment analysis research. In 2020-2021, traditional algorithms such as Support Vector Machine (SVM), Naïve Bayes, K-Nearest Neighbors, Logistic Regression, etc. still dominated research, often combined with TF-IDF-based text representations, bag-of-words approaches, or lexicon-based approaches such as VADER and TextBlob. This year, deep learning began to emerge through models such as CNN and Bi-LSTM.

Then, in 2022-2023, there was a significant increase in the adoption of deep learning models. Bi-LSTM, CNN, and Transformer-based architectures began to be used more systematically. During this phase, traditional methods shifted from being primary models to benchmarking baselines to demonstrate the superiority of deep learning models.

Finally, from 2024 to mid-2025, Transformer-based models became a frequently applied approach in research on sentiment analysis, stance detection, information extraction, and spatiotemporal analysis. This approach simultaneously processes text, images, and spatial information. Traditional methods are still utilized, but their role as baseline data has become less prominent.

[RQ 4] Methods of validation and evaluation tools are employed in sentiment analysis approaches associated with climate change discussions on social media

It is crucial to assess model capabilities using validation techniques and evaluation tools to forecast new data that was not part of the estimation process. This approach assists in detecting challenges such as selection bias or overfitting and provides insights into how the model will perform when applied to an independent dataset, such as an unknown dataset derived from actual reviews [24].

1. Validation Methods

There are two validation techniques, namely train or test split and cross validation [63]. Based on the selected literature, there is a literature used train or test split as the validation methods where 80% for training and 20% for testing [11].

There are some literatures that use cross validation as a validation technique. In cross validation, there is k-fold cross-validation that refers to the process of randomly splitting the original dataset into k subsets that are uniform in size. This method is effective in avoiding overfitting and ensuring that the data remains unbiased, particularly in situations where the dataset is not evenly distributed [24]. The utilized datasets were primarily organized into 5 or 10 folders of equal size, similar to the approach taken in [29], [30], [36], [54].

2. Evaluation Tools

The performance of a supervised algorithm is determined by comparing its predicted results to the actual values [64]. In this literature, there are two types of evaluation tools that we examined: Classification Performance Metrics and Probabilistic Metrics.

For Classification Performance Metrics, accuracy is the most commonly utilized metric in studies related to climate change [3], [6], [7], [11], [27], [28], [29], [30], [31], [32], [33], [34], [35], [36], [37], [38], [39], [40], [41], [42], [46], [47], [49], [50], [51], [52], [53], [55], [56], [59], [60], [61], [62], then followed by Precision [3], [6], [7], [27], [28], [29], [30], [31], [32], [33], [34], [37], [38], [39], [40], [41], [42], [44], [45], [46], [47], [48], [49], [51], [53], [54], [56], [57], [58], [59], [60], [62], Recall [3], [6], [7], [27], [28], [29], [30], [31], [32], [33], [34], [37], [38], [39], [40], [41], [42], [44], [45], [46], [47], [48], [49], [51], [52], [53], [54], [56], [57], [58], [59], [60], [62], and F-measure atau F1-score [3], [6], [7], [28], [29], [30], [31], [32], [33], [34], [37], [38], [39], [40], [42], [43], [44], [45], [46], [47], [48], [49], [51], [52], [53], [54], [55], [56], [57], [58], [59], [60], [62].

For Probabilistic Metrics, there are some literatures that used Area Under Curve (AUC) [36], [46], [55] and Receiver Operating Characteristic (ROC) [46]. There are also some literatures that used other performance measures such as Pearson's Correlation, Kendall, Spearman Correlation [40], Cohen Kappa [37] and Root Mean Squared Error (RMSE) [41].

CONCLUSION

This study aims to map research trends related to sentiment analysis on the topic of climate change through an approach that combines a Systematic Literature Review (SLR) and bibliometric analysis. By analyzing 42 articles published in six leading databases, this study successfully identified research trends, social media platforms used, dominant sentiment classification methods, as well as validation methods and evaluation tools applied in previous studies. The findings indicate that this subject has garnered more research attention in recent years, with a significant increase in publications in 2023 and 2024. This research discovered that Twitter is the most extensively utilized social media platform in studies concerning sentiment analysis related to climate change, followed by Sina Weibo, Reddit, Facebook, and YouTube. From a methodological perspective, this research highlights a significant methodological evolution in the field of climate sentiment analysis, shifting from established machine learning approaches in 2020–2021 to a more extensive use of deep learning frameworks in 2022–2023, culminating in the increasing prominence of Transformer-based architectures from 2024 to mid-2025. Traditional algorithms are increasingly used as baselines, while advanced models enable more complex analytical tasks. From the evaluation side, metrics such as Accuracy, Precision, Recall, and F1-score are the most used evaluation tools, with validation methods in the form of cross-validation and train-test split. However, this study still has limitations. While it is relatively recent in the research period, the publication period of this study is narrow, less than five years. Furthermore, this study focused solely on social media-based sentiment analysis related to climate change, so the researcher's excluded articles on similar topics based on news or other sources. These findings serve as a foundation for the researchers to improve methodological choices, enhance model performance, and inform future experimental designs. For computer scientists, the shift towards Transformer-based models indicates a growing need for handling contextual nuances in environmental texts. By analyzing sentiments related to climate change, policymakers can create more impactful climate policies, awareness campaigns, and communication approaches. In further research, it is recommended to include literature in various languages to obtain a more comprehensive picture.

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