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# A Machine Learning-based Analysis of Climate Change

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**_Abstract_**

*Climatic variations are a pressing global challenge that demands immediate and comprehensive attention. A wealth of articles has been published on climate change mitigation and adaptation, yet there remains a need for innovative methods to explore the complexities of climatic variations and to devise more efficient and effective strategies for adjustment and alleviation. With technological advancements, machine learning (ML) and deep learning (DL) approaches have derived significant popularity across various fields, including climatic variations research. The objective of this paper is to investigate the most prevalent ML and DL approaches implemented to climatic variations mitigation and adaptation. Additionally, it seeks to identify the utmost common mitigation and adaptation measures, with a particular focus on urban areas, that have been investigated utilizing machine learning and deep learning methodologies. To fulfill these aims, this study utilizes word frequency analysis and topic modelling, specifically employing the Latent Dirichlet Allocation (LDA) algorithm as a machine learning tool. The findings indicate that Artificial Neural Networks (ANNs) are the predominant ML technique in both climate change mitigation and adaptation endeavours. Moreover, within various research domains concerning climate change, geoengineering and investigations into land surface temperature stand out as the fields that have most extensively employed ML and DL algorithms.*

**Keywords:** Clustering, machine learning, greenhouse gas, finite-time thermodynamics, climate change.

## INTRODUCTION

The effects of climate change, encompassing hurricanes, droughts, wildfires, and inundations, have heightened and become more frequent (Field et al..[1]) The United Nations (2018) cautions that unless global greenhouse gas (GHG) emissions are markedly diminished within the next three decades, the Earth will confront severe repercussions (IPCC, 2018). Despite this urgency, GHG emissions continue to escalate annually (Rolnick et al.,[2]). Tackling climate change presents a multifaceted scientific dilemma (Hunting ford et al., [3]) involving both mitigation (lowering emissions) and adaptation (preparing for inevitable impacts).

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Mitigation endeavors prioritize enhancing the effectiveness of energy grids, transportation systems, infrastructure, industry, and land utilization, diminishing dependence on non-renewable energy sources, and amplifying carbon absorption (Sharifi, [4]). Conversely, adaptation underscores the importance of resilience planning and disaster response to confront climate change impacts (Nalau and Verrall, [5]; Rolnick et al., [2]). Despite extensive exploration into climate change adaptation and mitigation, achieving unequivocal success remains challenging. The escalating intricacy and magnitude of climate data necessitate sophisticated technological instruments for proficient analysis (Koc and Acar, [6]).

 

Policy makers, municipal authorities, urban and regional strategists, and residents pursue efficient climate strategies customized to their governmental, economic, and environmental circumstances (Hermwille et al.,[7]; Milojevic-Dupont and Creutzig, [8]; Reckien et al., [9]; Shan et al., [10]). Planning endeavors to fulfill societal requirements optimally while taking into account socioeconomic and environmental elements (Abduljabbar et al., [11]).

Technological advancements, including model simulations, sensors, and observational tools, have significantly increased the availability of climate data (Faghmous and Kumar, [12]; Koc and Acar, [6]). Concurrently, developments in computer science, mathematics, and processing power provide the necessary tools for data analysis (Milojevic-Dupont and Creutzig, [8]). These new technologies have proven beneficial for addressing the challenges of future cities (Nosratabadi et al., [13]).

Machine learning (ML) and deep learning (DL), components of artificial intelligence (AI), have surged in popularity for their capacity to scrutinize vast datasets and discern trends (Abduljabbar et al., [11]; Huntingford et al., [3]; Koc and Acar, 2021[6]; Vapnik, [14]). ML is especially advantageous for comprehending intricate networks, extracting insights from extensive data, and making prognostications (Koc and Acar, [6]). ML methodologies find extensive use across diverse domains including traffic management, urban design, resource allocation, energy consumption prediction, food safety, and air quality surveillance (Audu et al. [15], 2020; Nosratabadi et al., [13]; Wataya and Shaw,[16]).

Due to the intricate nature of climate change, ML techniques are increasingly employed to comprehend and forecast climate-related phenomena (Koc and Acar, [6]). ML can be categorized into supervised and unsupervised learning (Murphy, [17]). Supervised learning associates inputs with outputs based on predefined response variables, while unsupervised learning uncovers novel relationships within the data (Abduljabbar et al., [11]; Sun and Scanlon, [18]; Ullah et al.,[19] ML approaches can capture robust nonlinearities, offering insights into aspects of global warming inaccessible to traditional regression methods (Dijkstra, [20]).

Deep learning (DL) methodologies, including deep multi-layer architectures, have elevated ML efficacy by acquiring high-level representations from data (LeCun et al., [21]). DL techniques augment prediction precision and diminish reliance on human involvement (Sun and Scanlon, [18]). DL is progressively integrated into studies encompassing business, management, and data analytics (Najafabadi et al.,[22]).

Mastering and deploying these diverse techniques necessitate considerable expertise, as highlighted by Cheng et al. [23] who observed that most of these methods are tailored for proficient users such as data analysts and ML specialists. Nevertheless, the widespread adoption of ML and DL across various domains has acquainted researchers with some of the most utilized techniques.

The utilization of ML and DL in climate change mitigation and adaptation is still in its nascent stages. These approaches are anticipated to gain more prominence owing to the abundance of extensive datasets, their capability to model nonlinear dynamics, and their adaptability to novel data (Koc and Acar, [6]; Milojevic-Dupont and Creutzig, [8]; Rolnick et al., [2]). The ISO 14090 standard on climate change adaptation (Nalau and Verrall, 2021[5]) and the IPCC's 2018 special report on limiting global warming to 1.5°C (IPCC, 2018) underscore the immediacy of climate action.[24] Major corporations, such as Google, are also leveraging ML for addressing climate challenges.

This study endeavors to furnish an outline of ML and DL applications in climate change mitigation and adaptation. It tackles two primary inquiries: (i) What are the prevalent ML and DL methodologies in climate change investigation? (ii) In which particular domains of climate change mitigation and adaptation, notably in urban settings, are ML and DL approaches frequently employed? To address these queries, the study employs word frequency analysis and topic modeling to scrutinize keywords extracted from scholarly articles.

 

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## MATERIALS AND METHODS

### Search Principles

This study utilized various prominent databases and digital repositories to identify the most pertinent research papers employing machine learning (ML) and deep learning (DL) methodologies for climate change mitigation and adaptation. Specifically, we leveraged resources such as Web of Science (WoS), Science Direct, and the digital libraries of both the Association for Computing Machinery (ACM) and the Association for Computational Linguistics (ACL). The search was conducted on November 10, 2021, and involved combinations of specific terms:

- *Keywords:* "climate change adaptation" OR "climate adaptation" OR "climate change mitigation" OR "climate mitigation"
- *Techniques:* "ML" OR "DL" OR "neural machine translation" OR "convolutional neural network (CNN)" OR "long short-term memory" OR "Bidirectional encoder representation from transformers" OR "linear discriminant analysis" OR "natural language processing"

Only original research articles were considered, with review articles, encyclopedias, book chapters, and conference abstracts excluded to focus solely on primary research. Recognizing the multifaceted and multidisciplinary nature of climate change, articles from a diverse array of fields were included, encompassing Environmental Science, Energy, Agricultural and Biological Science, Social Science, Earth and Planetary Science, Engineering, Business Management and Accounting, Computer Science, and Decision Science.

The search yielded a total of 832 articles from Science Direct, 129 from Web of Science, four from the ACM digital library, and six from ACL Anthology. Following the screening of titles, abstracts, and keywords, and the removal of duplicates, the final dataset comprised 254 articles. This selection process is depicted in Figure 1, following the guidelines of the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework.

### Data Analysis and Trends

The quantity of publications regarding the utilization of ML and DL in climate change mitigation and adaptation has notably surged in recent times. As depicted in Figure 2, the volume of publications on these subjects remained modest until 2014, with merely 10 papers published. However, by 2020, the number of publications had escalated to 63, and it further rose to 85 in 2021.

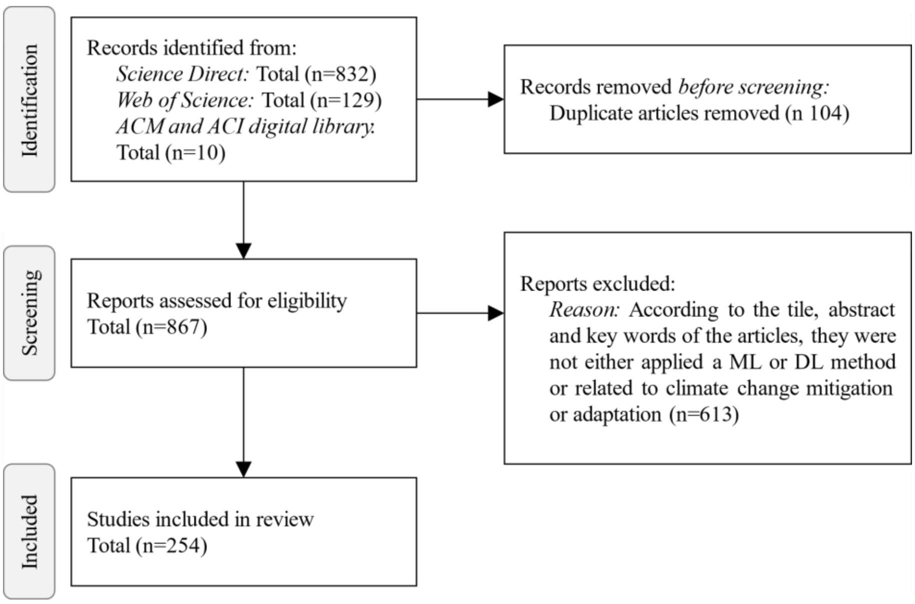


**Figure 1.** PRISMA framework for gathering articles, adapted from (Moher et al., 2009).


**Figure 2.** The predominant machine learning and deep learning techniques utilized for climate change adaptation and mitigation.

Environmental Science emerged as the primary domain of focus among the articles, followed by Agricultural and Biological Science, Energy, and Earth and Planetary Science. Additionally, there has been a discernible uptick in publications from the fields of Engineering and Computer Science in recent years, signifying an increasing interest among engineers and computer scientists in applying their expertise to address climate change challenges.

The swift expansion in the volume of publications mirrors the escalating prominence and significance of ML and DL techniques in climate change investigation. This trajectory is projected to persist as these technologies advance and as more data becomes accessible. The interdisciplinary character of the research underscores the collaboration between environmental scientists, engineers, and computer scientists in tackling the intricate challenges of climate change mitigation and adaptation.

Subsequent sections delve into the research methodology and elaborate on the study's outcomes, culminating in a conclusion that encapsulates the findings and delineates their implications for future research and policy formulation.

 

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**Word Frequency Analysis**

Word frequency analysis is a widely employed technique in bibliometric studies to pinpoint primary research themes and focal areas based on the recurrence of keywords or topic phrases in the literature. This analysis offers insights into the principal research points within a particular field by examining the frequency of specific words in research articles.

***Data Preparation***

Following the retrieval of relevant documents (articles) from the initial search, an Excel file was crafted containing crucial details such as the title, year of publication, abstract, keywords, and journal title. While the abstract section provides comprehensive information on ML and DL methods, it often encompasses numerous irrelevant words that could distort the outcomes of a word frequency analysis. Moreover, words may be reiterated multiple times within an abstract, compromising the reliability of the analysis. Hence, the keywords section, typically comprising both methodologies and topics, was chosen for more precise analysis.

***Text Preprocessing***

The keywords were amalgamated into a corpus (a compilation of text documents) and imported into Python, a programming language well-suited for text analysis. Text preprocessing was executed using the Natural Language Toolkit (NLTK) library in Python. The preprocessing steps encompassed:

1. *Text normalization*: This phase entailed cleansing the data by:
   i. Eliminating punctuation
   ii. Omitting numbers
   iii. Discarding white spaces
   iv. Excluding stop words (commonly occurring words typically filtered out in text processing)
   v. Eliminating non-English words
   vi. Converting all letters to lowercase
2. *Tokenization:* This process involved segmenting the text into smaller units, such as individual words, to establish meaningful phrases. Tokenization aids in analyzing text data at a granular level.

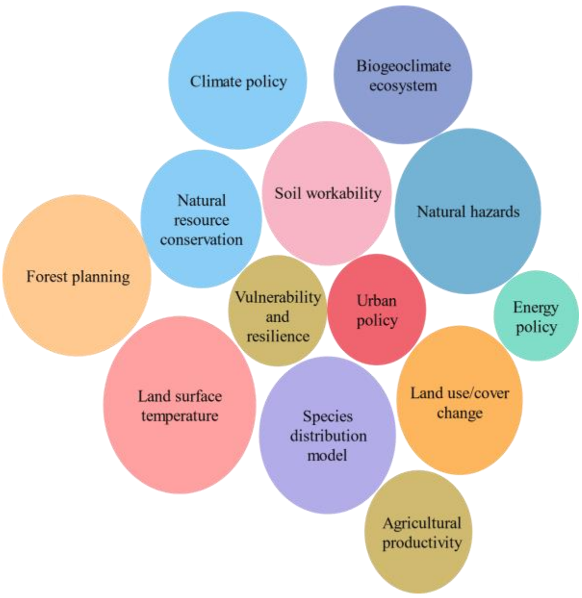
**Frequency Matrix Generation**

Post preprocessing, a matrix was constructed containing the words and their frequencies for each article. This matrix encompassed single words, as well as two- and three-part phrases, identified by the code employed in this study. To concentrate specifically on ML and DL methodologies, the extracted words were refined to gather only those relevant to these methodologies.

**RESULTS**

The analysis depicted in Figure 2 reveals that the most utilized machine learning (ML) and deep learning (DL) methods in studies pertaining to climate change mitigation and adaptation encompass artificial neural networks, random forests, support vector machines, and gradient boosting. In addition, other prevalent techniques in climate change adaptation include boosted regression trees, fuzzy inference systems, MaxEnt, topic modeling, and CART. For climate change mitigation, additional frequently employed methods comprise convolutional neural networks (CNNs), decision trees, topic modeling, long short-term memory networks (LSTMs), and logistic regression.

The findings from the Latent Dirichlet Allocation (LDA) analysis for climate change adaptation, as depicted in Figure 3, reveal 13 primary themes alongside their corresponding frequency percentages and 10 associated keywords. These results underscore the prevalent utilization of ML and DL methodologies in studies centred on land surface temperature (11.8%). Other noteworthy topics in climate change adaptation encompass forest management, natural calamities, and species distribution models, each accounting for approximately 10% frequency (Figure 4). Additional significant themes include alterations in land cover and land use, soil suitability, and the integration of climate policy (each




| Topic | Frequency (%) | Words |
|---|---|---|
| Land surface temperature | 11.8% | System, temperature, adapt, global, temperature_global, carbon_emission, model, land, heat, pathway_quantile |
| Forest planning | 10.6% | Agriculture, forest, secure, migration, ecosystem_forest, model, drought, model_assist, reforestation, assist_migration |
| Natural hazards | 10.6% | Model, water, flood_protect, urban, hydrology, forecast, manage, drought, heat_island, storm |
| Species distribution model | 9.4% | Species, ensemble_species, temperature, species_distribution, ensemble, model, distribution, network, land, use |
| Land use/cover change | 8.2% | Adapt, use, system, land, evapotranspiration, soil, plan, effect, land use, cover |
| Soil workability | 8.2% | Soil, organ_carbon, landsat, carbon_soil, moisture, landsat_indice, plastic_limit, content, clay_content, soil_hydraulic |
| Mainstreaming climate policy | 8.2% | Adapt, policies, analysis, site, quantitative_text, mainstream, mainstream_intelligence, decision_make, text, text_analysis |
| Biogeoclimate ecosystem | 7.1% | Network, ecosystem, classification, program, agriculture, assist, bioclimate, biogeoclimate_ecosystem, biogeoclimate, distance |
| Natural resource conservation | 7.1% | River, network, grand, grand_river, water, river_discharge, conservation, resource, wind, hydrology |
| Agricultural productivity | 5.9% | Adapt, data, gene, product, express, vegetation, rice, crop_adapt, upland_rice, growth |
| Vulnerability and resilience | 4.7% | Carbon, resilience, soil, chrono_function, risk_management, coastal, vulnerability, chronofunction_coastal, land, adaptation |
| Urban policy | 4.7% | Planning, model, pavement, risk_maxent, infrastructure, ssp_risk, urban_heat, urban, crowd, rcp_ssp |
| Energy policy | 3.5% | Energy, analysis, data, adapt, cost, model, use_energy, generation, cities_scale, circular |

**Figure 3.** Themes related to climate change adaptation, identified using machine learning (ML) and deep learning (DL) methods, along with 10 associated words for each topic obtained from LDA topic modelling.

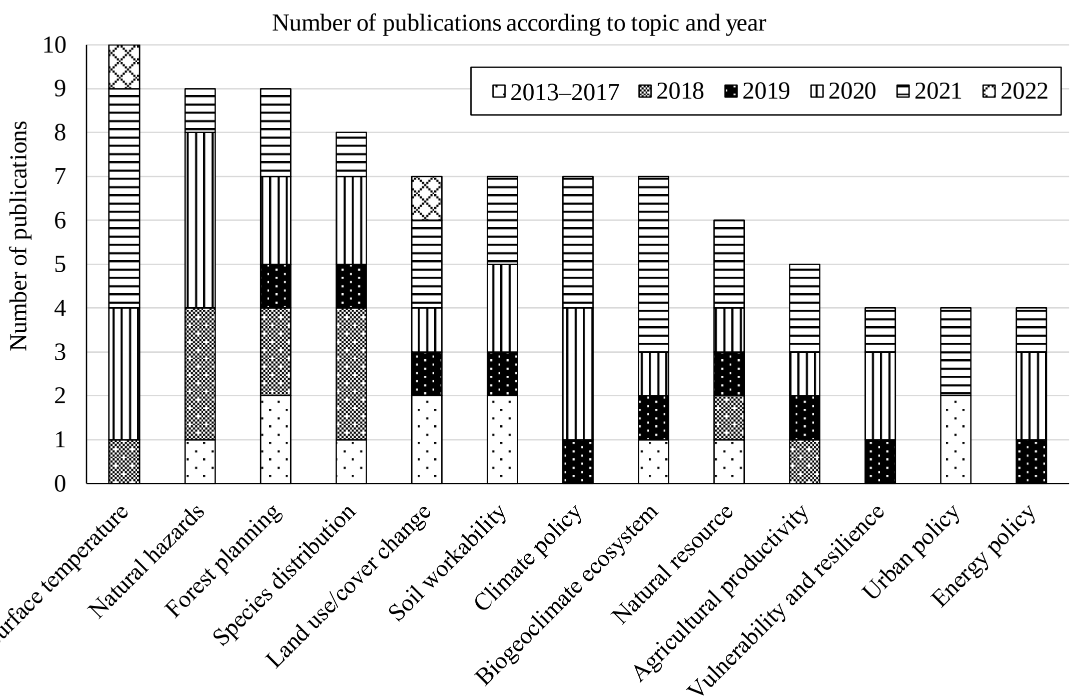
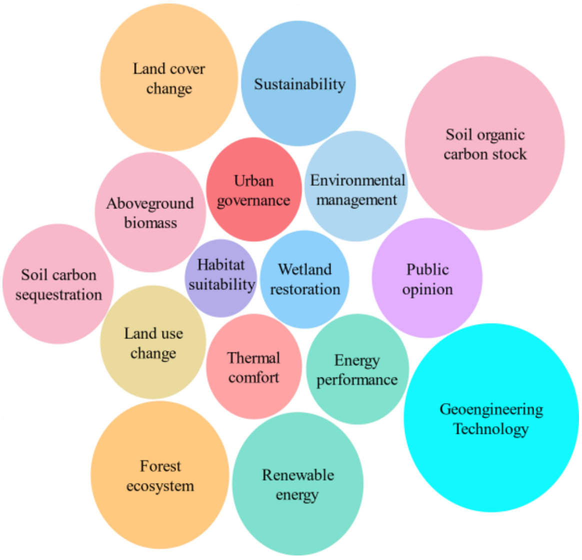



**Figure 4.** Prominent climate change adaptation subjects from 2013 to 2022.

with an 8.2% frequency), bio geoclimatic ecosystems and the preservation of natural resources (each with 7.1%), agricultural yield (5.9%), susceptibility and resilience, urban governance (each with 4.7%), and energy policy (3.5%).




| Topic | Frequency (%) | Words |
|---|---|---|
| Geoengineering technology | 13.7% | Image, inventory, geologic, model, landsat_image, inventory_site, satellite, computing, nation, photogrammetry_ensemble |
| Soil organic carbon stock | 11.3% | Soil, organ_carbon, soil_organ, carbon, organ, map, assess, stock, carbon_stock, soil_map |
| Land cover change | 8.3% | Mitigation, data, agriculture, land_cover, soil, ann, waste, vegetation, carbon_sequestration, |
| Forest ecosystem | 8.3% | Deforestation, aboveground, map, forest_ecosystem, data, spatial_model, ecosystem, component_analysis, land, resource_economic |
| Renewable energy | 7.7% | Carbon, energy, structure, pca_svr, analysis, solar_thermal, text, emission, renewable, |
| Sustainability | 6.0% | Environmental, service, ecosystem, sustainable, energy, vegetation, ecosystem_service, lidar, mitigation |
| Soil carbon sequestration | 5.4% | Carbon, energy, sequestration, carbon_sequestration, soil, network, analysis, manage, index, land |
| Aboveground biomass | 5.4% | Analysis, carbon, vehicle, aboveground_biomass, biomass, inventories, forest, balance, nutrient, agriculture |
| Public opinion | 5.4% | Public, text, biomass, analysis, emission, topic, topic_model, policy, dirichlet_allocation, build |
| Environmental management | 4.8% | Environment, carbon, energy, data, network, governance, integration_tropic, data_integration, pollution |
| Energy performance | 4.8% | Carbon, energy, management, conservation, system, build, efficiency, airborne_observatory, land, svm_k |
| Land use change | 4.8% | Service, environment, land, land_use, use, organization, transform, network, household, landscape |
| Thermal comfort | 4.8% | Ground, island, heat_flux, problem, carbon, optimum, thermal, human_activity, transit, temperature_object |
| Urban governance | 4.8% | Spatial, forecast, urban, use, land, policy, management, transform, wavelet_transform, city_network |
| Wetland restoration | 3.6% | Energies, wetland, network, resolution, greenhouse, restoration, species, phragmite, ensemble, coastal |
| Habitat suitability | 2.4% | Species, distribution, trend, land, water, habitat, species_distribution, model, classification, ecosystem |

**Figure 5.** Themes concerning climate change mitigation, identified through the application of machine learning (ML) and deep learning (DL) methods, along with 10 associated words for each topic derived from LDA topic modelling.

Figure 5 presents the number of publications on each topic from 2013 to 2022, showing that 2021 had the most publications on land surface temperature, biogeoclimatic ecosystems, natural resources, and agricultural productivity, while 2020 saw more papers on natural hazards and energy policy.

In the domain of climate change mitigation, as demonstrated in Figure 6, geoengineering technology (13.7%) and soil organic carbon stock (11.3%) emerge as the predominant themes employing ML and DL methods [25]. Other associated topics encompass land cover change, forest ecosystems, and renewable energy (each comprising approximately 8% frequency), sustainability (6%), soil carbon sequestration, aboveground biomass, environmental management, energy performance, land use change, thermal comfort, and urban governance (each with roughly 5% frequency) [26–28]. Conversely, the least popular topics for mitigation utilizing these techniques are wetland restoration (3.6%) and habitat suitability (2.4%).

The distribution of publications on climate change mitigation by topic and year (depicted in Figure 6) indicates that geoengineering technology garnered the highest number of publications in 2019 [30–34]. Conversely, carbon stock, renewable energy, carbon sequestration, urban governance, and habitat suitability emerged as the most popular topics in 2021. Notably, in 2020, there was a notable increase in articles published on land cover change and sustainability.

In the realm of urban climate change adaptation, ML and DL techniques predominantly target areas such as land surface temperature, urban heat island mitigation, and natural hazard management [35].

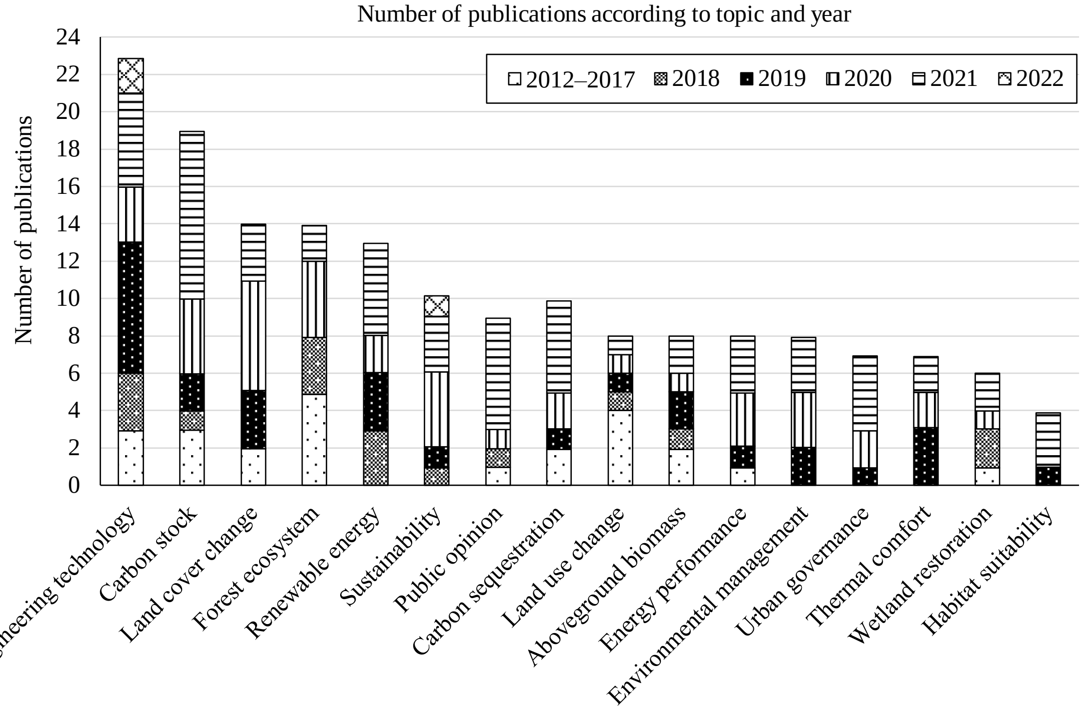



**Figure 6.** Frequent climate change mitigation themes spanning from 2013 to 2022.

Conversely, in urban climate change mitigation studies, these methods are chiefly directed towards urban land use/cover change and energy consumption. The subsequent sections offer a concise overview of the application of ML and DL methods in climate change adaptation and mitigation topics, with a specific focus on urban studies. While ML and DL techniques hold potential for application across various urban sectors (e.g., transportation, waste, and water) to achieve climate change objectives, this summary concentrates on primary applications related to selected urban issues due to space limitations.

## CONCLUSION

The increasing prominence of machine learning (ML) and deep learning (DL) methodologies in climate change research underscores their significance and efficacy in delivering robust and accurate predictions. This study has scrutinized research applying ML and DL techniques in climate change mitigation and adaptation to delineate the prevailing methods in these domains.

This investigation aimed to ascertain the foremost ML and DL methods employed in climate change mitigation and adaptation research. Furthermore, it identified primary topics within these realms, particularly in urban locales, that recurrently leverage these techniques. To attain these objectives, word frequency analysis was employed to ascertain the prevalent ML and DL methodologies. Topic modeling, specifically employing the latent Dirichlet allocation (LDA) technique, was utilized to delineate the topics based on word frequency in the corpus of articles. The outcomes reveal that Artificial Neural Networks, Random Forest, Support Vector Machines, and Gradient Boosting are the most prevalent ML and DL techniques in climate change research. Additionally, for climate change mitigation, commonly utilized methods encompass CNNs, Decision Trees, Topic Modeling, and Logistic Regression. In contrast, for climate change adaptation, Boosted Regression Trees, Fuzzy Inference Systems, and MaxEnt are frequently employed.

Critical topics in climate change mitigation commonly explored through ML and DL techniques include geoengineering, soil organic carbon stock, land cover change, and forest ecosystems. In urban areas, these techniques predominantly address land use and land cover change and energy consumption, pivotal for climate change mitigation. Regarding climate change adaptation, ML and DL techniques are chiefly applied to subjects such as land surface temperature, forest planning, natural hazard management, and species distribution models. In urban studies, prevalent topics encompass land surface temperature, urban heat islands, and natural hazards.

The study leveraged the Web of Science (WoS), Science Direct, and ACM and ACL digital libraries to uncover relevant papers. Future endeavors could broaden the scope by integrating additional databases to attain more comprehensive findings. Moreover, focusing on specific topics pertaining to climate change mitigation or adaptation could furnish more nuanced insights into the frequently employed ML and DL methodologies. Furthermore, delving into the abstract or methodology sections of studies could yield deeper insights into the applied techniques.

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