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Abstract

Preventing the materialization of climate change is one of the main challenges of our time. The involvement of the financial sector is a fundamental pillar in this task, which has led to the emergence of a new field in the literature, climate finance. In turn, the use of Machine Learning (ML) as a tool to analyze climate finance is on the rise, due to the need to use big data to collect new climate-related information and model complex non-linear relationships. Considering the proliferation of articles in this field, and the potential for the use of ML, we propose a review of the academic literature to assess how ML is enabling climate finance to scale up. The main contribution of this paper is to provide a structure of application domains in a highly fragmented research field, aiming to spur further innovative work from ML experts. To pursue this objective, first we perform a systematic search of three scientific databases to assemble a corpus of relevant studies. Using topic modeling (Latent Dirichlet Allocation) we uncover representative thematic clusters. This allows us to statistically identify seven granular areas where ML is playing a significant role in climate finance literature: natural hazards, biodiversity, agricultural risk, carbon markets, energy economics, ESG factors & investing, and climate data. Second, we perform an analysis highlighting publication trends; and thirdly, we show a breakdown of ML methods applied by research area.

Keywords: climate finance, machine learning, literature review, Latent Dirichlet Allocation.

JEL classification: C6, Q55, Q5.

Resumen

Evitar la materialización del cambio climático es uno de los principales retos de nuestro tiempo. En esta tarea, el sector financiero desempeña un papel fundamental, motivando a economistas académicos a desarrollar un nuevo campo de investigación, las finanzas climáticas. A la vez, el uso de tecnologías de aprendizaje automático (ML, por sus siglas en inglés) se ha popularizado para analizar problemas relacionados con las finanzas climáticas, debido principalmente a la necesidad de gestionar un volumen elevado de datos relacionados con el clima, y para modelizar relaciones no lineales entre variables climáticas y económicas. De esta manera, proponemos una revisión de la literatura académica para explorar cómo esta tecnología está posibilitando el crecimiento de las finanzas climáticas. Para ello, primero realizamos una búsqueda sistemática de estudios en esta materia en tres bases de datos científicas. Luego, usando un modelo de identificación automática de temas *(Latent Dirichlet Allocation),* identificamos estadísticamente siete áreas del conocimiento donde el ML está desempeñando un papel relevante: catástrofes naturales, biodiversidad, riesgo agrícola, mercados de carbono, energía, inversión responsable y datos climáticos. Para finalizar, hacemos un análisis de las principales tendencias de publicación, así como una clasificación de los modelos estadísticos utilizados en función del área de estudio. La principal contribución de este artículo es la provisión de una estructura de temas o problemas solventados gracias al uso del ML en finanzas climáticas, lo cual esperamos que facilite a expertos en esta tecnología la comprensión de las principales fortalezas y limitaciones de dicha tecnología aplicada en este campo de investigación.

Palabras clave: finanzas climáticas, sostenibilidad, cambio climático, aprendizaje automático.

Códigos JEL: C6, Q55, Q5.

1. Introduction

The financial sector has the potential to become an important ally in alleviating the adverse consequences of climate change. This was recognized by The Paris Agreement (UNFCCC, 2015), as the financial system will be crucial in mobilizing capital towards new (green) assets for climate mitigation and adaptation purposes. In fact, since that moment, the breadth of topics and the amount of articles on economics, finance and sustainabiliby increased dramatically[1]. The recognition of the role of finance in the fight against climate change has led to the emergence of a new field in the literature called climate finance[2], that focuses on *"the tools of financial economics designed for valuing and managing risk which can help society assess and respond to climate change"* (Giglio et al., 2021). High quality economic journals now dedicate special issues to climate and sustainable finance topics.[3]. This new prolific academic work has also been accompanied by international financial regulators and supervisors who have been actively working recently within and across institutions[4] to scale up climate finance to develop a new financial architecture that properly incorporates and manages climate-related opportunities and risks, specially a demand for climate information disclosures and risk management that is not easy to achieve taking into account the lack of (standardized) data.

One characteristic of climate finance literature is how fragmented the research is. This is not only a bibliographic concern, as it also makes it difficult to join efforts from different academic profiles in order to develop specific research. In a literature review performed by Cunha et al. (2021), the authors highlight the difficulty of defining the field and differentiating it from traditional finance, due to the poor theorization of the concept of "sustainability", an opinion shared by several other experts (Capelle-Blancard and Monjon, 2012; Zhang et al., 2019; Talan and Sharma, 2019; Liang and Renneboog, 2021; Giglio et al.,

[1] The sudden interest on the topic exploded from 2015 onwards, as reported by Malhotra and Thakur (2020). However, the three top finance journals (Journal of Finance, Journal of Financial Economics and Review of Financial Studies) did not publish a single article related to climate finance between January 1998 and June 2015, as indicated by Diaz-Rainey et al. (2017).

[2] The inception of the field, initially known as resource economics, is usually linked to the seminal work of Nobel Laureate William Nordhaus, who modeled the interactions between climate change and the economy. From there, more specifically on finance, early work on sustainability mainly addressed concerns on corporate governance and social investing (Capelle-Blancard and Monjon, 2012).

[3] For instance, the Review of Financial Studies, in March 2020 (Hong et al., 2020). Or the Journal of Corporate Finance, in April 2022 (Calvet et al., 2022). Also, thematic journals on environmental, climate and resource economics appear on top rankings like IDEAS/RePEc.

[4] Just as an example, the European Central Bank (ECB) set up in 2021 a dedicated Climate Center and the USA Federal Reserve joined the Network for Greening the Financial System (NGFS) in late 2020.

2021). This calls for a precautionary need to define the scope of our survey on climate finance. We will rely on the aforementioned definition provided by Giglio et al. (2021). Although we will use the term climate finance in this paper, we acknowledge that three concepts are used indistinctly in the academic literature, such as green finance, climate finance and carbon finance (Zhang et al., 2019). Similarly, we will leave out of our scope any work not touching upon climate change, and exclusively focusing on social topics, like corporate governance, impact investing, social investing and financial inclusion, which would fall under the label of sustainable finance. Though, a limitation exists as some studies do not disentangle environmental from governance and social factors, for instance, those focusing on the impact of Environmental, Social & Governance (ESG) scores on corporate performance. In this sense, inevitably some work from sustainable finance will be included.

Another characteristic of climate finance as a research field is the difficulties experts have to face in order to perform a solid empirical analysis. To name some of them: the still limited reliability of a growing amount of climate data, and the statistical complexity to model the non-linear behavior of climate change. These problems create profound mathematical challenges for making inference about the real climate (Stephenson et al., 2012) and its relationship with the economy. In fact, Diaz-Rainey et al. (2017) conclude that methodological constraints could explain previous lack of climate finance research in top finance and business journals. Additionally, classical problems like the presence of endogeneity is cornerstone in climate finance, as the impact of climate on the economy is two-folded due to the existence of a feedback loop. This has been widely recognized by policy makers, academics and financial supervisors (Gourdel et al., 2022). As we will see, all these issues justify the recourse to ML from researchers and experts as this technology is particularly well suited to deal with these problems.

While several surveys cover a wide range of climate finance papers (Kumar et al., 2022b; Cunha et al., 2021), many of them still use traditional statistical modeling tools to analyze the impact of climate change, existing only a subset of (emerging) studies harnessing ML to solve new emerging topics in this field. Taking into account the novelty and the heterogeneity in the use of ML in general and particularly in finance it is relatively complicated to monitor all this literature. Therefore, based on the proliferation of articles in climate finance, the fragmentation of the literature, and an increasing use of ML in finance (Goodell et al., 2021) and the financial industry (Jung et al., 2019), in this article we propose a systematic review of studies that rely on ML to solve climate finance problems. To face the challenge of heterogeneity of topics within the field, this review leverages on Natural Language Processing (NLP), in particular we implement a Latent Dirichlet Allocation (LDA) model, to statistically uncover latent topics which we are then able to successfully identify as relevant application domains. To the best of our knowledge this is the first work that systematically covers ML-based studies in climate finance[5], building a unique set of papers from different public databases, such as Web of Science, Google Scholar and Dimensions.ai. Notably, we make an effort to map which ML methods are mostly used in each climate finance topic, aiming to facilitate a profound understanding of how ML can enable climate finance to grow as a research field. This could be useful for future researchers interested in joining this academic debate, as well as policy makers looking for ways to better design climate finance instruments and policies. Indeed, the value of academic research in the overall innovation process has been widely investigated (Quatraro and Scandura, 2019), and in climate finance this has been recently recognized in the last Conference of the Parts (COP26), where it has been stated that Artificial Intelligence (AI) and ML can play a key role in important climate-related topics like prediction, mitigation, and adaptation, in ways we cannot afford to ignore (Clutton-Brock et al., 2021).

Our results support the relevance of ML as a driver of the publication trend in climate finance, a hypothesis that was starting to gain traction within economic and financial journals (Musleh Al-Sartawi et al., 2022), but still required empirical evidence. We positively observe that ML is covering the majority of research areas within current research in climate finance, however, with heterogeneous interest from scientific journals and expert knowledge domains. Notably, Economic journals pay lower attention to physical risks, a topic that is more mature in terms of peer-reviewed publications (usually in Environmental or Computer Science tabloids), while other topics like ESG factors & investing, or climate data, are still emerging. Finally, we appreciate a wide variety of methods applied in each topic, finding that most complex ones, like Artificial Neural Networks, do not lead in all thematic areas, as either the datasets available do not have the proper characteristics, or policy requirements require more interpretable model specifications.

All in all, we notice that the growing academic interest in ML and climate finance is also aligned with the nascent concern from financial authorities on understanding the potential application of new technologies to resolve operational problems identified in climate-related financial topics. We refer for example to Fintech Hackcelerator for a greener financial system sponsored in 2021 by the Monetary Authority of Singapore, or the 2021 Green Fintech Challenge, hosted by the Federal Conduct Authority in UK. Significantly, with a longer term view,

[5]This systematic review complements and extends the work of Ghoddusi et al. (2019), Ullah et al. (2021) and de Souza et al. (2019), probably the closest studies to this one, but, notably, we assemble a significantly larger set of studies, covering the whole field of climate finance.

the Bank of International Settlements has created a series of Innovation Hubs (BISIH) worldwide, and a Network (BISIN) who are experimenting and monitoring new developments in technology, and how it could be useful for Central Banks, being climate finance innovation one the key areas of interest. Finally, the success of ML applied to climate finance issues is also corroborated by a new wave of projects and market-driven solutions which are flourishing in the private sector, giving birth to a new market segment currently labeled as "green fintechs" (Macchiavello and Siri, 2022). Notwithstanding this, ML & AI is an energy consuming technology, therefore any analysis on its potential shall always be complemented with its carbon footprint, a concern by itself that has been given the name of "Green AI", as we will note later on.

The remaining part of this paper is organized as follows. Section 2 explores the role of ML in climate finance. Section 3 explains the methodology of the survey based on topic modeling, and the data collection process. Section 4 details the findings from the clustering of topics. Section 5 includes some analysis on ML methods used, and publication trends. Section 6 concludes.

2. The role of Machine Learning in Climate Finance

According to the pioneer researcher Athey (2018), ML is *"a field that develops algorithms designed to be applied to datasets, with the main areas of focus being prediction, classification, and clustering or data processing"*. While conventional statistical and econometric techniques, such as a regression, often work well in several circumstances, there are idiosyncratic methodological problems that may benefit from using different tools. This is particularly relevant in climate-related issues.

First, the usual large size of the datasets involved in climate finance may require more powerful statistical manipulation tools. In recent years, the quantity and granularity of economic data in general has improved dramatically. On the one hand, the sudden explosion of micro-level datasets offers an unparalleled insights into the inner workings of the economy and the financial system. On the other hand, datasets are increasingly more complex to deal with (López de Prado, 2019). As an example of this complexity, we can mention the great differences between the temperature predictions of the 20 global climate models, from various laboratories around the world, that inform the Intergovernmental Panel on Climate Change (IPCC), with data for over 100 years (Monteleoni et al., 2011). Moreover, some of the most interesting datasets in climate finance are not only highly dimensional, but also unstructured, including information from news articles, voice recordings or satellite images, which along with the complexity of the phenomena they measure, means that many of these datasets are beyond the grasp of usual econometric analysis.

Second, big datasets may contain non-linear relationships between the variables that are not suitable for simple linear models. It has been largely recognized that ML techniques such as decision trees, support vector machines, neural networks, and so on, may allow for more effective ways to model complex financial and economic relationships (Varian, 2014; Athey, 2018; Athey and Imbens, 2019). The key advantage of many ML methods is that they use data driven model selection, treating the data-generating process (DGP) as unknown, allowing researchers to deal with large datasets without imposing restrictive assumptions. On the other hand, as described by Breiman (2001), traditional model-driven statistical community (like econometrics) assumes that the data are generated by a given stochastic process, being able to better understand the relationship between the variables. As very illustratively explained by Huntingford et al. (2019), and Castle and Hendry (2022), shared characteristics of financial and climate time series make ML tools appropriate for studying many aspects of observational climate-change data and its economic impact. For instance, green-house gas emissions are a major cause of climate change as they accumulate in the atmosphere. As these emissions are currently mainly due to economic activity, financial and climate time series have commonalities, including considerable inertia, stochastic trends, possible non-linearities, omitted variables and abrupt distributional shifts. Moreover, both disciplines lack complete knowledge of their respective DGPs, so data-driven model search allowing for shifting distributions is important, and ML offers a rigorous route to analyzing such complex data. In this context, the appeal of ML is that it manages to uncover generalizable patterns. In fact, the success of ML is largely due to its ability to discover non-trivial relationships that were not specified in advance. Moreover, it manages to fit very flexible functional forms to the data without simply over-fitting, working well out-of-sample (Mullainathan and Spiess, 2017).

Therefore, ML in climate finance offers the opportunity to explain relationships that have the potential for huge societal impact (Hoepner et al., 2021). Indeed, the effects of climate change are increasingly visible, usually represented as tail risks, or low-probability and high-impact events with material impact on the economy and well-being of people. Storms, droughts, fires, and flooding have become stronger and more frequent (Kruczkiewicz et al., 2022). Global ecosystems are changing, including the natural resources and agriculture on which humanity depends. Yet, year after year, these emissions rise, giving only a pause during Covid-19 lock-down. In the well-known "Tragedy of the Horizons", Mark Carney (2015) showed us that the environmental impact of climate change translates into substantial financial risks to global assets measured in the trillions of dollars. However, it is hard to forecast where, how, or when climate change will impact the stock price of a given company, or even the debt of an entire country. Financial short-termism fails to incentivize the prediction of medium or long-term risks, which include most climate change-related exposures such as the physical impact on assets like factories or premises. As we will see, ML can help us to close this "inter-temporal" gap. A very illustrative example is given by researchers from the Quebec AI Institute (2021), who warned during the last COP26 that preventing climate–related catastrophic consequences will require changes in both policy-making and individual behaviors. However, many cognitive biases (like abstraction and myopic term discount) might prevent us from taking action today. To tackle this market failure, they developed *"This Climate does not Exist"*, a research project that harness ML (in particular Generative Adversarial Networks, or GANs) to create images of personalized climate impacts which will be especially powerful in overcoming the barriers to action and raising climate change awareness.

But the set of topics in climate finance where ML is being utilized is much broader. Recent literature reviews on sustainable finance, like Rolnick et al. (2022), show how ML can contribute, for instance, in climate investment, applying deep learning both for tilting portfolio selection towards low carbon emitting corporates, and investment timing. In fact, as concluded by the authors, this climate-aligned investment strategy is creating major shifts in certain sectors of the market towards renewable energy alternatives, which are seen as having a greater growth potential than traditional fossil fuels. Other authors (Akomea-Frimpong et al., 2021) focus on the determinants of banks' green products and strategies. This is another example of the high impact of climate-related problems. Due to dependencies from several nations on Russian oil and gas, the green transition has gained a further sense of emergency, having its implications on the future regulation of energy markets (e.g.: RePowerEurope). We could further elaborate on the overlapping issue between green public policies and digitization. For instance, Gailhofer et al. (2021) specifically discuss about the role of AI in the European Green Deal, Bag et al. (2021) study the role of public institutions on the adoption of big data analytics and AI technology, and how this affects sustainable manufacturing and circular economy, and Plakandaras et al. (2018) use ML techniques to model climate change as a geopolitical risk, forecasting its impact on several financial assets.

As a conclusion, the emerging use of AI and ML is disrupting and transforming the financial industry (Wall, 2018). Climate finance is a particular area where innovation is growing fast and having big impact, as acknowledged by academics, policy makers, and market participants. As an example, in a position paper Kaack et al. (2020) hope that recent breakthroughs in ML can help us get closer to achieving the UN SDGs, and Kumar et al. (2022a) think that new-age technologies applied to sustainability can make significant contributions to the green transition. Both Al-Sartawi et al. (2021) and Avgouleas (2021) suggest that cutting-edge financial technology encompassing AI, ML and blockchain can be critical in terms of boosting sustainable finance. And for Inampudi and Macpherson (2020) there is a great potential for AI to contribute towards global economic activity, especially ESG investing. In fact, the digitization of climate finance has led to the birth of a FinTech sector that comprises technology-backed innovative business models for finance, something that has been given the name of “Green Fintech” (see GDFA (2022) for a taxonomy devoted to classify market-driven green fintech business solutions). However, there are limits to the potential of ML in climate finance. A good example is Nguyen et al. (2022), who found low predictive capabilities of ML models to estimate indirect carbon emissions (known as Scope3) of corporates, due to high level of missing, and incomplete data. Technology cannot improve badly reported data, however AI-driven technologies offer great potential to capture and validate climate-related information (Huntingford et al., 2019; Rolnick et al., 2022), improving notably its quality, a lesson which should be taken by policy makers and regulators.

Last but no least, two important caveats hold. First, this article is not a claim supporting ML at the expense of other statistical modeling techniques, like econometrics. Finance is a field where notions like causality are of greater importance, not only predictive accuracy. Therefore, we understand ML as a tool to add value, which might assist researches achieving some particular objectives in climate finance. A great example of this cooperation between both statistical modeling approaches is given by DeepAg (Gurrapu et al., 2021), a framework that employs econometrics to determine the relationship between financial indices and production of agricultural commodities and then uses Artificial Neural Netowrks to identify and measure the effect of outliers events on the global economy, based on interdependent relationships.

Second, we feel responsibly obliged to bring to this discussion the other side of the impact of ML on climate change, as well. New technologies do not only bring us opportunities. Kaack et al. (2020) explain ways in which AI and ML can be detrimental to efforts addressing climate change, warning of those uses that might harm our planet. AI or AI-driven technologies can become pollutants and net emitters of greenhouse emissions, depending on the types of applications and the circumstances of their deployment. For example, remote sensing algorithms for satellite image analysis can be used to gather information on agricultural productivity, but can also be used to accelerate oil and gas exploration. Self-driving cars can make driving more efficient, but they could also increase the amount people drive. And finally, ML include computationally expensive programming, which is an energy intensive activity. This final concern has minted the term “Green AI”, which we will further investigate in the following Section, referring to responsible and low carbon intensive coding and good practices relating the training and deployment of complex algorithms in the academic industry (Strubell et al., 2019; Hershcovich et al., 2022).

2.1. Green AI

Recently artificial intelligence has encountered such dramatic progress that it is seen as a tool of choice to solve environmental issues, such as greenhouse gas emissions (GHG). At the same time the ML researchers began to realize that training models with more and more parameters required a lot of energy and, as a consequence, GHG emissions, questioning the complete environmental impacts of AI methods for the environment (Schwartz et al., 2020). Based on this concern, Ligozat et al. (2021) propose to study the possible negative impact of AI systems often presented as a solution to climate change, presenting different methodologies used to assess this impact, in particular life cycle assessment. For instance, recent advances in large Transformer models have raised public concerns on their environmental footprint at the time of designing and developing the models (Zhang et al., 2022).

However, as we are seeing in our study, a large variety of ML methods are used in Climate Finance, making sense to extend the concern on the environmental footprint of ML more broadly. In 2019, researchers (Strubell et al., 2019) in a pioneer paper estimated the consumption of large NLP models, comparing it in CO2 equivalents with illustrative general life examples. They conclude that training a big Transformer with neural architecture search can emit up to six times what a car produces (including fuel) in its lifetime. Therefore, the authors recommend to grant researches equitable access to computation resources, and suggest to prioritize computationally efficient hardware and algorithms. In another work, these pioneering researchers (Strubell et al., 2020) extend their work to modern language models like BERT, or GPT-2.

Overall, a common conclusion is that we need accurate reporting of energy and carbon usage. It is essential for understanding the potential climate impacts of ML research to incentivize responsible research. To this purpose, Henderson et al. (2020) introduce a framework that makes this easier by providing a simple interface for tracking ML models' real-time energy consumption and carbon emissions, making carbon accounting easier. Lacoste et al. (2019) present as well a *Machine Learning Emissions Calculator* as a tool for researches to better understand the environmental impact of training their models. In a position paper Schwartz et al. (2020) advocates a practical solution by making efficiency an evaluation criterion for research alongside accuracy and related measures, like Hershcovich et al. (2022) who propose a climate performance model card with the primary purpose of being practically usable with only limited information about experiments and the underlying computer hardware, in order to increase awareness about the environmental impact of NLP research.

A big challenge remains on new methods being currently developed to make ML trustworthy and scalable. For instance, challenges like model interpretability require computationally expensive ad-hoc techniques like SHAP (Lundberg and Lee, 2017), which is a key concern for financial supervisors (Alonso Robisco and Carbó Martínez, 2022; Dupont et al., 2020) or the cost of differential privacy is often a reduced model accuracy and a lowered convergence speed producing a higher carbon footprint due to either longer run-times or extensive experiments (Tornede et al., 2021). Similarly, this happens with Automated ML (AutoML), a discipline that provides methods and processes to make ML available for non-Machine Learning experts, where this problem is amplified due to large scale experiments conducted with many datasets and approaches, each of them being run with several repetitions to rule out random effects (Naidu et al., 2021).

3. Methodology

We adopt and implement the Scientific Procedures and Rationales for Systematic Literature Reviews (SPAR-4-SLR) protocol, which consists of three major stages, namely assembling, arranging, and assessing of articles (Paul et al., 2021). We include in Table A.6 in the Appendix a full description of this process.

Our final collection of documents adds up to 217 research articles, from which we extract the abstracts, which will comprise the sample of texts (corpus) in our study. Our goal will be to discover the hidden or latent (unobservable) topics in the corpus of documents (observable), using a ML-technique, Latent Dirichlet Allocation (Blei et al., 2003). This will help us understand documents analyzing the presence of words. Often the term "topic" is used in a technical, statistical sense, but ultimately the last phase of any topic modeling approach involves expert analysis to uncover through inspection a more usual theme that aligns with each topic, allowing to label each of them with a more economic meaningful name. In addition, we aim to rank the topics according to their prevalence (Sievert and Shirley, 2014), which we find to be a convenient visualization tool for the exploration and presentations of the topics.

3.1. Data collection

To assemble the corpus of articles on ML-based climate finance, we identified relevant keywords relating to climate finance from a preliminary assessment of literature reviews on both sustainable (carbon, or green) finance, energy economics and ML in finance (Kumar et al., 2022a; Ghoddusi et al., 2019; Aziz et al., 2022)[6]. Following the identification of these words in climate finance

[6] After determining a reasonable combination of words we experimented with some other variations of terms for both ML and climate change, finding no meaningful number of articles variation, suggesting we got a good convergence on a suitable corpus of identified research.

and ML (this led to a combination of 20 keywords[7]) we conducted the search of articles using an advanced search string in the category ALL ("article title, abstract, and keywords"), and AB ("abstract only") on Google Scholar, Web of Science, and Dimensions.ai[8], as shown in **Expression 1**. The start date was selected to be 1st January 1999, being the last update as of April 22nd, 2022.

Expression 1

ALL= ("climate change" OR "ESG" OR "sustainable finance" OR "green finance" OR "climate finance") AND AB = (finance OR "financial market" OR bond* OR investment* OR corporate* OR funding OR financing) AND ALL= ("lasso" OR "random forest*" OR "extreme gradient" OR "xgboost" OR CART OR "deep learning" OR "neural network" OR "machine learning")*

The data was collected using a "Human-In-the-Loop" (HIL) approach. It consists of proceeding to a purely automated data collection with an ex-post validation based on human field expertise. For instance, a total of 45 search pages (showing 10 items each) were screened in Google Scholar by an expert, while the process of checking potential duplicates between different databases was performed automatically using the software OneNote. Contrary to other literature reviews, we aim to focus on a narrow definition of ML in climate finance. This means our results should be familiar to economists and not relying too heavily on environmental or engineering science with no connection of the research question or conclusion to an economic (or finance) theme or discourse.[9] It is important to highlight that our approach, incorporating a screening phase in Google Scholar, allows a richer understanding of a research field that is growing so fast, and therefore relevant research is still in working paper status, waiting to be published by peer-reviewed journals, and consequently does not appear in the results retrieved from more standardized databases like WoS or D.AI yet.

3.2. Topic modeling

Topic modeling assumes a person approaches writing a document with a collection of topics in mind and the words chosen will represent this topic mixture. For instance, a climate finance researcher applying ML to solve a problem will, for example, write a paper with a topic mixture of 50% climate change, 30% finance, and 20% ML modeling. The key task for the topic modeling researcher is therefore to reverse engineer the latent topics from the observed words. Currently, a widely accepted approach for topic modeling is Latent

[7]The symbol * is used to capture singular and plural forms of the words.

[8]As a robustness check we verified that all the studies tagged as "climate finance and economics" in the expert network hosted in `https://www.climatechange.ai/` were included.

[9]This was actually a drawback appreciated in other literature reviews like Warin and Stojkov (2021), or Kumar et al. (2022b), where on the other hand, the size of the corpus analyzed was one order of magnitude bigger.

Dirichlet Allocation (LDA), developed by Blei et al. (2003). The key practical advantage of LDA is that it allows documents to be a mixture of different topics, while topics are presented as a mixture of words. This fits the reality observed in climate finance studies, since different topics can partially overlap within a document. We apply the Gensim implementation of LDA in Python (Rehurek and Sojka, 2010). The procedure for extracting the topics consist of a variety of steps required for training, tuning, and applying the resulting LDA model to the corpus. We briefly describe the most important ones, leaving further explanations in the Appendix section [10].

After processing the data[11], we count with D documents that together contain N unique tokens that we can represent by an N x D matrix W with entries $w_{n,d}$ that are the number of occurrences of token n in document d. Thus, the total number of tokens in document d is $N_d = \sum_{n=0}^{N} w_{n,d}$. The LDA model consists of two matrices, $\beta_{N\times K}$ and $\theta_{K\times D}$, where K is the total number of topics. For topic k, the vector β_k contains the N token weights, which act as the probabilities $P(n|k)$ that the token n contribute to a document's bag of words, conditional on the topic k contributing to the document. That is, $P(n|k) = \beta_k$, i.e.: the weight of token n in topic k. Therefore, $\sum_{n=1}^{N} \beta_{n,k} = 1$. For document d, the vector θ_d contains the K topic weights – which act as the probabilities $P(k|d)$ that the topic k appear in the document. Thus, $P(k|d) = \theta_{k,d}$, i.e.: the weight of topic k in document d. Similarly, $\sum_{n=1}^{N} \theta_{k,d} = 1$. When these probabilities are significant, we may say that a topic k is relevant in document d. Finally, this setting allows us to decompose in the next equation the probability of a token n in a document d as Hofmann (2001):

Eq.1

$$P(n|d) = \sum_{k=1}^{K} P(n|k) \cdot P(k|d) = \sum_{k=1}^{K} \beta_{n,k} \cdot \theta_{n,d}$$

Topic modeling involves reducing the dimensions of these matrices to end up with the same number of rows (documents) but a restricted number of columns

[10] Regarding the relevance of topics, and suitable selectors of optimal number of topics (Figures A.2 and A.3)

[11] A necessary first step in topic modeling is processing the corpus of documents by tokenizing each document into a collection of their individual words where order is unimportant (i.e.: each document is treated as a "bag of words"). Then, stop-words that have no topic context (such as "and", "of", "the"), are removed, as well as common terms that are highly repeated in the corpus, which we identify because they appear in more than half of the documents, or rare terms for which we set a threshold of being in less than two documents. We deem that both categories of terms contain little meaning to contribute to a relevant topic. Remaining words in a document are stemmed to generate the words' root, and accurately capture unique terms usage. This means suffixes are removed to create common stem terms, e.g.: finance, financial and finances might be reduced to the common "financ" root. In theory, a token can have any number of words (usually monograms are used, but we could have bi- and trigrams). For simplicity, we keep our analysis to single word tokens as we find that it allows us to easily label the topics at the final stage.

which represent the topics. To this purpose LDA assumes a particular Dirichlet distribution that can be used to produce probability vectors β_k and θ_d, that allow an assumption to be made about how topics are distributed across tokens and documents. Using two external inputs, α and β as Dirichlet priors, we can determine the generative process in the LDA (Blei, 2012; Blei et al., 2003) α is a parameter that determines θ_d or per-document topic distribution, and β is a parameter that determines β_k or per-topic token distribution. The LDA posteriors are a result of the trade-off between two inherently conflicting goals. Firstly, that only a relatively small number of topics are expected in a well-written document, and secondly that only high probability should be assigned to a small number of tokens that belong to highly informative topics. The trade-off exists because if we assign, for instance, a single topic to a single document, thus succeeding at the first goal, the second goal becomes difficult to achieve because all tokens in the document must have a relatively high probability of belonging to that topic. The estimation of the LDA model requires a Bayesian updating from its initial semi-random allocation of topics to tokens and documents, to converge to a probabilistic distribution of topics across documents. Technically, the process will be completed when we find matrices $\beta_{N\times K}$ and $\theta_{K\times D}$ that most likely have produced the observed data W. [12]

4. Results

As we mentioned, LDA becomes a useful approach to cluster similar documents together from a large disparate literature, as it is the case of ML-based climate finance. To select the number of topics for our final model, multiple models with different topic numbers were produced and relevance scores were compared, following Equation 2 (see Appendix).

A challenge with topic modeling is that topics that make ML-sense do not necessarily make human sense. Therefore, in order to label the resulting topics we do a qualitative check with human expert judgment to ensure that the words determined for each topic make sense within the existing climate finance literature. When the LDA model is estimated, we inspect the topics in three ways: first, we look at the tokens with the highest probability per topic β_k; second, we sample d =20 documents and check whether the highest probability $\theta_{K\times D}$ of each document d belonging to a topic k matches the thematic area identified by a human expert in advance (who read the abstract)[13]; and finally we look at the tokens ranked according to topic relevance as defined by Sievert and Shirley (2014).

[12] In our case, the Gensim implementation, based on a Bayesian approach, finds the best configuration of the model automatically as well as several settings related to numerical efficiency (Hofmann, 2001). In order not to stop at a local optimum we use a high enough number of iterations, in particular we needed 40,000 passes to reach a stable solution.

[13] All results present herein pass this test, with a threshold of at least 50% success rate.

Arguably, there is no easy way to find the optimal number of topics. To this purpose, in the literature several scores are suggested, like Perplexity or Coherence. Increasing the number of topics usually improves these statistical measures during topic modeling, however we must at the same time account for a higher computational cost of training the model as the number of topics increase, and more importantly, the complexity for a human to discern the economic meaning of more topics will also increase. In our case, we decide to estimate our LDA model with 10 topics, as informed by the Rate of Perplexity Change (Zhao et al., 2015), as shown in Figure A.2 in the Appendix[14]. After inspection, we are able to label a total of 7 comprehensive and economically reasonable topics, having to discard 3 of them (see TableA.2).[15]

Inspecting these keywords, we can initially label each topic, resulting this process in the following research areas in climate finance that rely on ML-methods: (i) natural hazards, (ii) biodiversity, (iii) carbon markets, (iv) agricultural risk, (v) ESG factors & investing, (vi) energy economics, and (vii) climate data. To confirm the economic sense of each topic, and their interdependencies, we plot the visualization of the clustering in 7 meaningful topics.[16]

We successfully arrive after inspection of the relevance scores of key tokens per topic to a meaningful understanding of the concepts covered by each one. For instance, using as example Figure 1 for Topic 9, in the right hand side panel, we find highly ranked (nearly) exclusive terms like “energi”, “emiss”, “carbon”, “ghg” or “greenhous”, as well as overlapping terms like “predict”, “carbon”, and “build”. Varying the values of , we can easily label this topic as Energy economics, understanding this as a cluster of research papers dealing with ML to solve problems, for instance, related to GHG emissions, air pollution, carbon price, energy forecasting, energy consumption or buildings efficiency. For further reference we leave in the Appendix the visualization of the remaining topics, being able to confirm that the labeling makes economic sense after inspection of the respective relevance rankings, allowing us to fine-tune the final name of each topic in detail.

5. Publication Trends and Analysis

From a total of 217 unique documents, out of the 7 identified latent topics, we can group them in three overarching areas, well known in climate finance

[14]We include in Figure A.3 in the Appendix the same plot using the Coherence score, from which we extract similar conclusions.

[15]We find that their composition is either mainly comprised of methodological terms (e.g.: in topics 1 and 3 we encounter tokens like “activ”, “correl”, “signific”, “algorithm”, “term”, “price”, “differ”, etc.) or repetitive with other topics (e.g.: in topic 5 we find concepts related to carbon markets like “emiss”, “carbon” and “soil”, but commingled with low relevant tokens like “studi”, “result” and “forecast”.

[16]The remaining analysis of relevance per topic is included in the Appendix in Figures A.8, A.7, A.4, A.9, A.5, A.6.

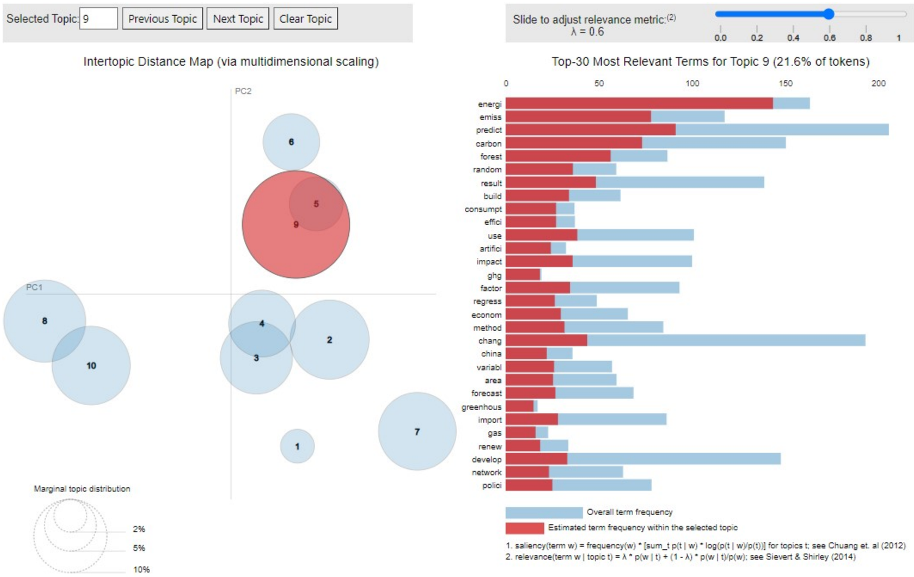

Figure 1: Visualization of Topic 9 (Energy Enconomics)

literature (Kumar et al., 2022b): Physical risks, Transition risks and Corporate & Social Responsibility (CSR), noticing that they capture a similar share of total publications. See Table 1 with a summary of descriptive statistics.

Table 1: Descriptive statistics of the corpus

		Journal	Working Paper	Conf. Proceeding	Phd Dissertation	Book Chapter	Total
Physical Risks	**Biodiversity**	15	6	3	0	0	24
	Natural Hazards	19	2	3	1	0	25
	Agricultural risk	17	4	3	0	1	25
Transition Risks	**Energy economcis**	44	10	2	1	1	58
	Carbon Markets	12	2	1	2	1	18
Corporate & Social Responsibilty	**ESG factors & investing**	17	14	2	0	0	33
	Climate data	12	13	6	3	0	34
Total		136	51	20	7	3	217

We observe that physical risk is a mature research area as the majority of publications are in peer-reviewed journals. This contrasts with other areas that seem to be emerging and relying still more on working paper format, especially two, Climate data, where more than half of the research articles gathered are still not published in a journal, and ESG factors & investing, where notably close to half of the documents belong to this class.

From our results, we extract some stylized facts.

Finding #1 *"ML covers most climate finance topics"*

> We observe that currently ML is applied for a majority of topics related to climate change in finance. For instance, we identify relevant studies covering five out of the seven topics listed in Kumar et al. (2022b), [17] and four out of six topics identified in Debrah et al.

[17]Seven clusters were identified in this study, namely: Socially responsible investing, Climate financing, Green financing, Impact investing, Carbon financing, Energy financing, Governance of sustainable financing and investing. Inspecting their uncovered tokens per topic, we find coincidence of terms in all of the clusters but Green financing, and Governance of sustainable financing and investing.

(2022) [18], which could serve as a benchmark survey describing the field of sustainable finance as a whole.

Finding #2 *"Starting with physical risk, going into market-related topics"*

From being initially applied to solve physical risks problems, like weather and natural hazards forecasting, and issues related to energy economics, currently a relevant number of studies are using ML for responsible investing, ESG factors and measuring corporate's compliance with climate data regulatory disclosures. See Figure A.10 in the Appendix.

Finding #3 *"Mature vs emerging research topics"*

As shown by higher ratios of peer-reviewed publications versus working papers format, topics like Agricultural risk, Natural hazards, Biodiversity, and Energy economics are more mature. Though, Climate data and ESG factors & investing are emerging, younger topics. See Figure A.11 in the Appendix.

Finding #4 *"Low attention to physical risk in Economic journals"*

We identify publications in very heterogeneous knowledge domains, like journals from environmental sciences, computer sciences, or economics and finance journals. We observe that Economic and Finance journals still pay more attention to topics related to CSR and Transitions risks, lagging behind other scientific journals that publish more work on Physical risk and its socioeconomic impact using ML. See Figure A.12 in the Appendix.

Finding #5 *"Artificial neural networks do not always lead"*

Some ML models standout within each field of interest. Overall, Random forests and Artificial Neural Networks are the mostly used ones, but for instance, in Physical risk we appreciate a strong usage of image recognition tools, usually associated with the need to handle newly available (unstructured) data from remote sensing, text, and satellites, relying therefore heavily on Convolutional Neural Networks and Random forests. However, in Transition risks, Artificial Neural Networks dominate within our subset of documents, usually benefiting from access to a big datasets to study energy-related top-

[18]Six clusters were identified in this study, namely: Green bond market and greenium, Green credit, Carbon investment and market, Green banking, Market stress, and Climate finance policies. Inspecting their uncovered tokens per topic, we find coincidence of terms in all of the clusters but Green banking, and Market stress.

ics. Finally, in CSR, interestingly the access to bigger amounts of data is still challenging, and the requirements on the specifications of the models and the interpretability of results push towards more linear techniques like Ridge and/or Elastic net regularization in multiple types of regressions, together with a notable share of studies introducing techniques from explainable AI (xAI) like Shapley values (Lundberg and Lee, 2017). See Figures A.13, A.14 and A.15 in the Appendix with the respective breakdowns, and Tables A.3, A.4 and A.5 with a detailed list of papers analyzed in the corpus and references to the ML methods used, per research area.

6. Conclusion

We aim to shed some light on the value of ML within climate finance, in order to understand its potential to drive innovative work in this knowledge area. To this purpose we assemble a corpus of relevant articles and we estimate a Latent Dirichlet Allocation (LDA) model to uncover latent topics in the literature, finding seven granular application domains which we are able to label with economic meaning that significantly describe where ML is being used within climate finance. To the best of our knowledge this is the first study that relies on Natural Language Processing (NLP) to automatically review this highly heterogeneous research field, offering academics, market experts and policy makers a means to assess emerging topics, and well as knowledge gaps. We hope this will enable a better knowledge of this innovative field, aiding climate finance to scale up in order to become mainstream in the near future.

As a bottom line, climate finance literature has been growing fast, and we have been able to gather evidence supporting the importance of ML in this field. We uncover up to seven research topics that are coherent with current sustainable finance literature reviews, and illustrate the areas where ML methods are adding more value (for instance, climate data seems to be a novel area that is arising thanks to ML). We also identify topics (i.e.: physical risk) that remain mainly covered by Environmental journals, while Economic journals seem to prioritize research on ESG factors & investment and Carbon markets, having therefore to acknowledge that the relevance of climate finance is still a work in progress in the top economic forums. Some of these findings seem to be a concern shared by financial authorities like the ECB as stated by Tuominen (2022), from the Supervisory Board, referring to its recent report (March, 2022) on banks' progress towards transparent disclosure of their climate-related and environmental risk profiles noted that *"although both physical and transition risks are becoming increasingly material, banks continue to focus their strategies more on transition risks than on physical risks."*

Last but not least, two additional lessons can be taken from this study. First, ML is not capable of solving problems when available data is of poor quality, therefore, more emphasis should be put by financial authorities on promoting new technologies to collect and validate climate-related data (Huntingford et al., 2019; Rolnick et al., 2022); and secondly, ML is an energy consuming activity and therefore, its usage should be promoted in a environmental responsible way, and area that remains of high interest for further research Henderson et al. (2020); Strubell et al. (2020).

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Appendix A. Appendix

Relevance of tokens.

The relevance r of token n to topic k, given a tuning parameter λ is given in by:

Eq. 2

$$r(n,k|\lambda) = \log\left(\beta_{N\times K}\right) + (1-\lambda)\cdot\log\left(\frac{\beta_{N\times K}}{\sum_{k=1}^{K}\beta_{N\times K}}\right)$$

Where the term $\log\left(\frac{\beta_{N\times K}}{\sum_{k=1}^{K}\beta_{N\times K}}\right)$ is called token's lift. The higher the marginal probability of token n over the corpus, the higher is its lift and the more exclusive a token is for a topic. With $\lambda = 1$, tokens of top relevance equals the top words, even if these do not show up exclusively in that particular topic. With $\lambda = 0$, tokens of top relevance are the ones exclusive to the given topic. By varying $\lambda\epsilon\,(0,1)$ and studying the different resulting ranking of tokens, we get a good understanding of the words that contribute to a topic. Following the recommendation of Sievert and Shirley (2014) we fix $\lambda = 0.66$ in order to label them with an economic meaningful name.

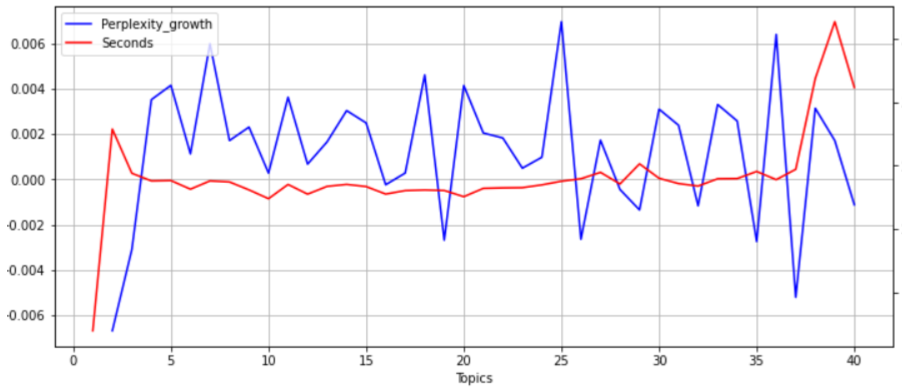

Figure A.2: Rate of Perplexity Change and latency of training

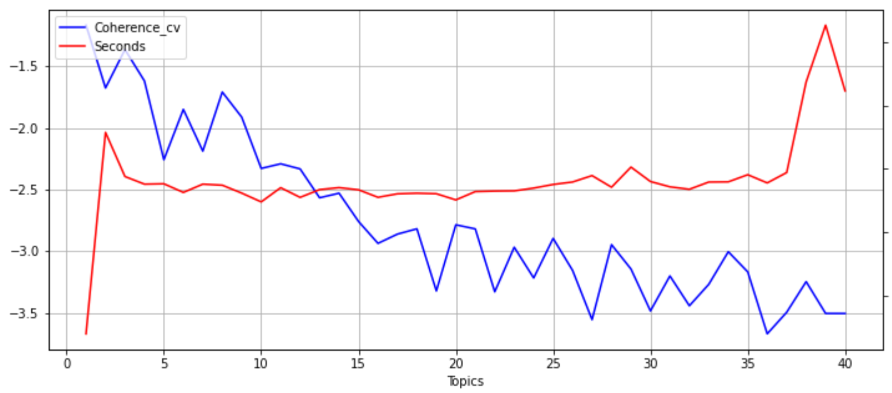

Figure A.3: Coherence score and latency of training

Table A.2: Probabilities of tokens, per topic.

LDA Topic	1		2		3		4		5	
	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)
	activ	0.026	risk	0.026	sustain	0.018	biodivers	0.012	carbon	0.028
	csr	0.017	flood	0.023	chang	0.011	financi	0.012	soil	0.024
	valu	0.012	algorithm	0.012	studi	0.01	green	0.011	invest	0.016
	flood	0.01	predict	0.011	method	0.009	base	0.011	predict	0.011
	storag	0.01	price	0.01	financ	0.009	develop	0.01	power	0.011
	correl	0.01	term	0.009	polici	0.009	invest	0.01	polici	0.011
	corpor	0.01	differ	0.007	research	0.008	resourc	0.01	emiss	0.01
	signific	0.01	impact	0.007	topic	0.008	cost	0.009	studi	0.01
	avail	0.009	provid	0.007	inform	0.008	conserv	0.008	result	0.009
	base	0.009	studi	0.007	train	0.008	research	0.008	forecast	0.009
Econ. Label	*discarded*		Natural hazards		*discarded*		Biodiversity		*discarded*	

LDA Topic	6		7		8		9		10	
	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)	Tokens	Probability of token per topic (_k)
	carbon	0.026	chang	0.027	esg	0.07	energi	0.03	compani	0.02
	price	0.023	crop	0.024	invest	0.024	predict	0.019	corpor	0.019
	market	0.02	yield	0.019	rat	0.022	emiss	0.016	report	0.018
	emiss	0.018	futur	0.014	social	0.021	carbon	0.015	financi	0.018
	firm	0.016	agricultur	0.013	portfolio	0.021	forest	0.012	disclosur	0.017
	green	0.015	adapt	0.011	compani	0.013	result	0.01	csr	0.016
	financ	0.013	product	0.011	perform	0.013	chang	0.009	perform	0.014
	paper	0.012	hybrid	0.011	stock	0.013	use	0.008	risk	0.013
	stock	0.01	project	0.01	risk	0.012	random	0.008	relat	0.012
	sector	0.01	suitabl	0.01	score	0.012	impact	0.008	environment	0.011
Econ. Label	Carbon markets		Agricultural risk		ESG factors investing		Energy economics		Climate data	

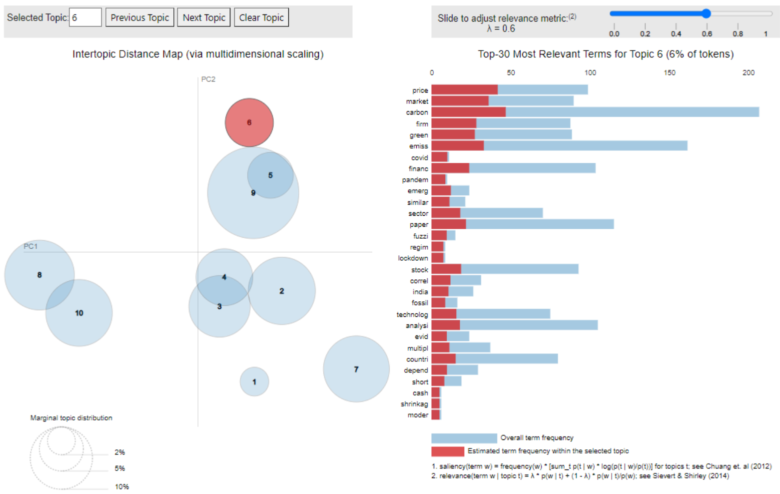

Figure A.4: Visualization of topic 6 (carbon markets)

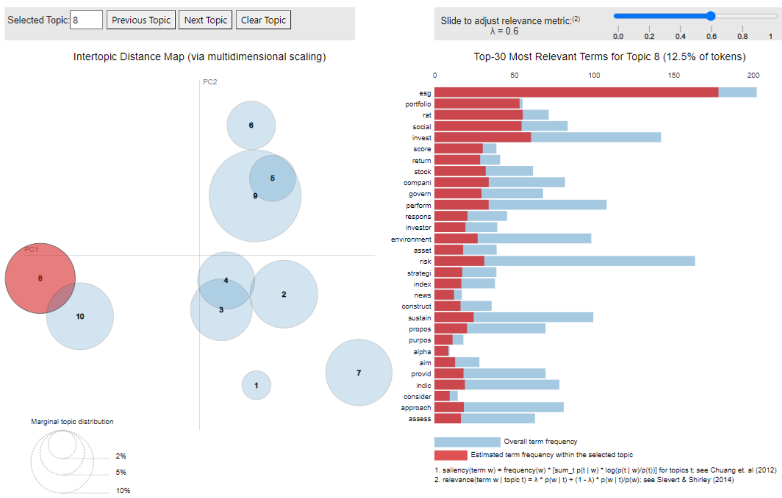

Figure A.5: Visualization of topic 8 (ESG factors & investing)

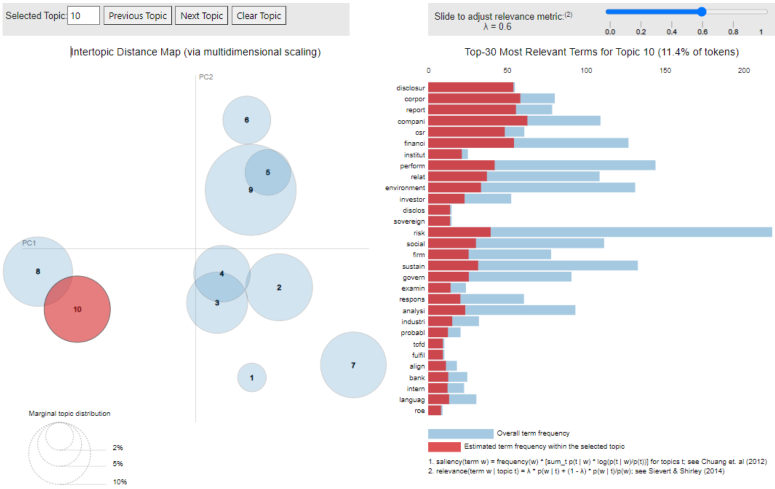

Figure A.6: Visualization of topic 10 (Climate data)

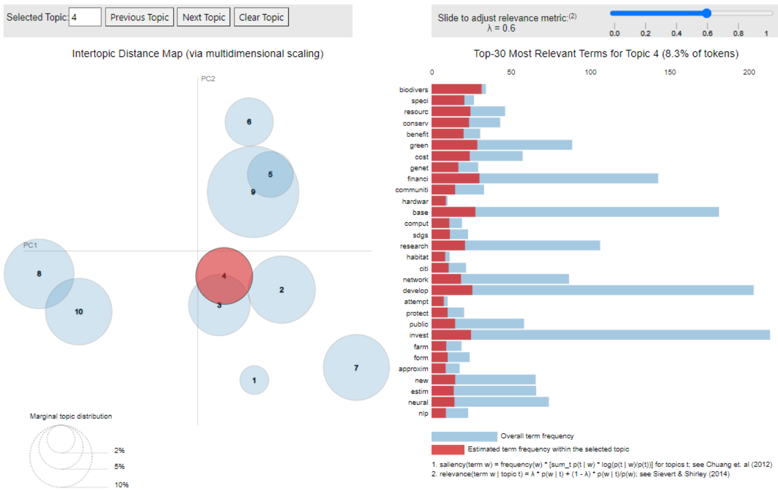

Figure A.7: Visualization of topic 4 (Biodiversity)

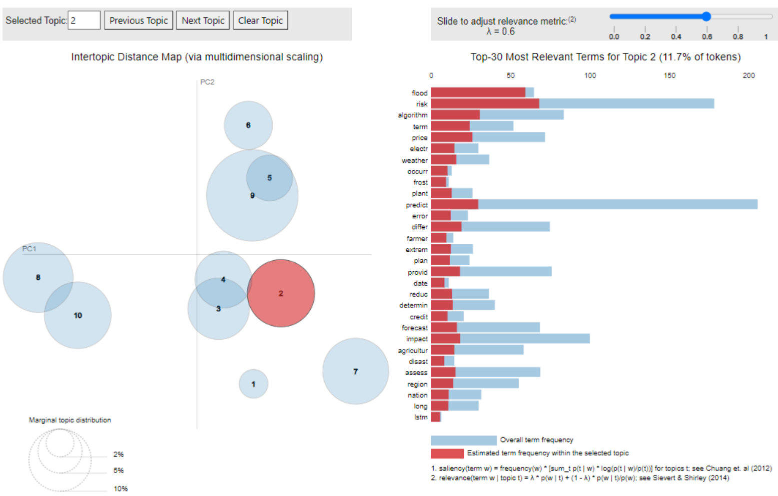

Figure A.8: Visualization of topic 2 (Natural hazards)

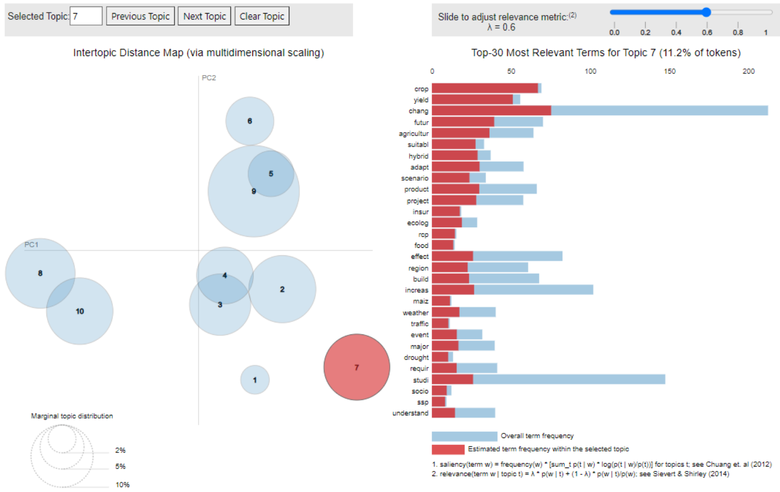

Figure A.9: Visualization of topic 7 (Agricultural risk)

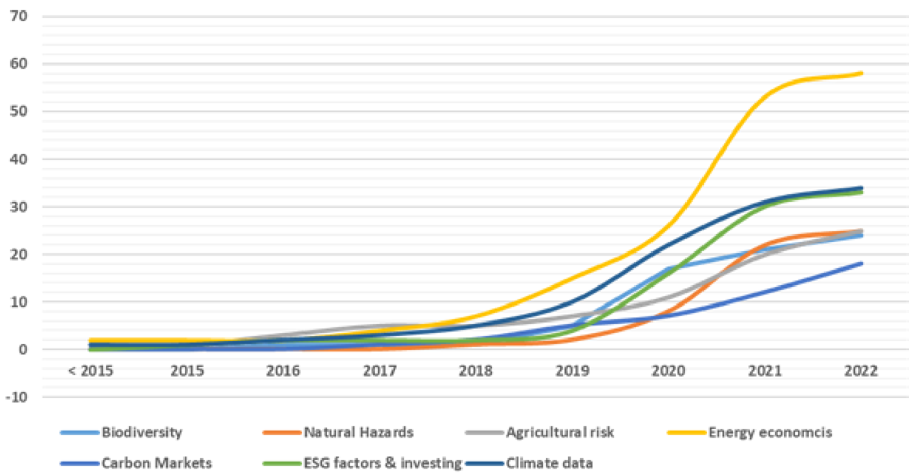

Figure A.10: Number of publication (cumulative), per year and topic

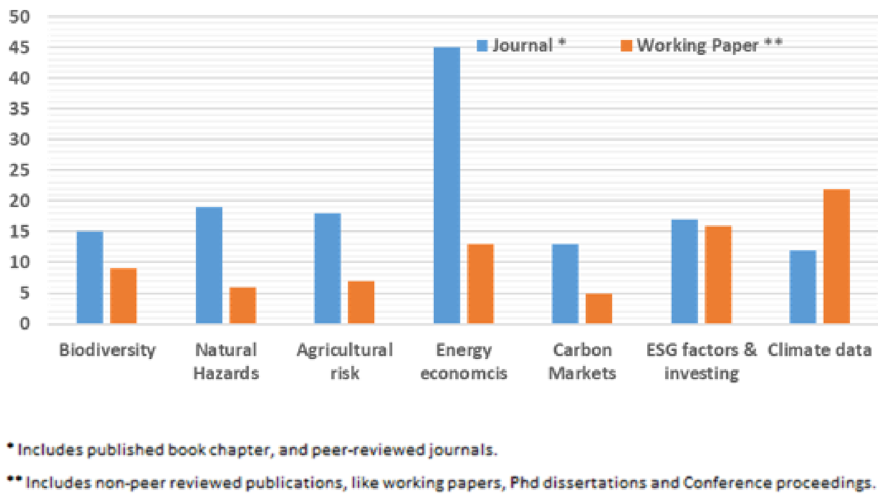

Figure A.11: Total number of publication, by type of journal

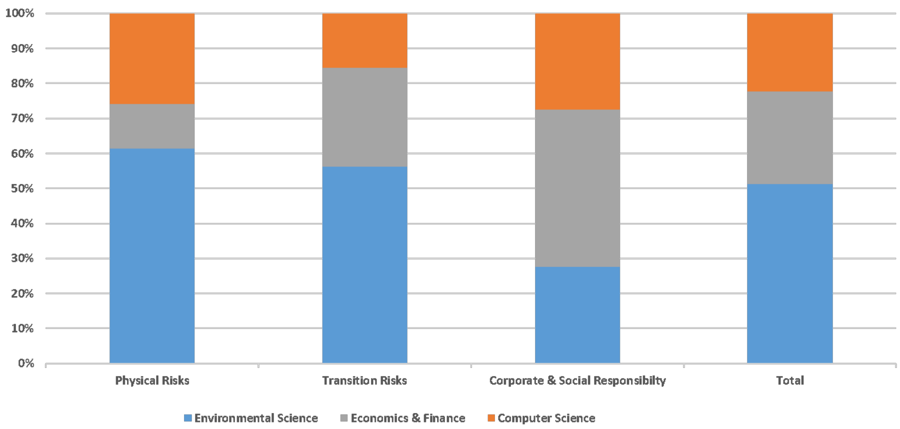

Figure A.12: Total number of publication, by type of publication science

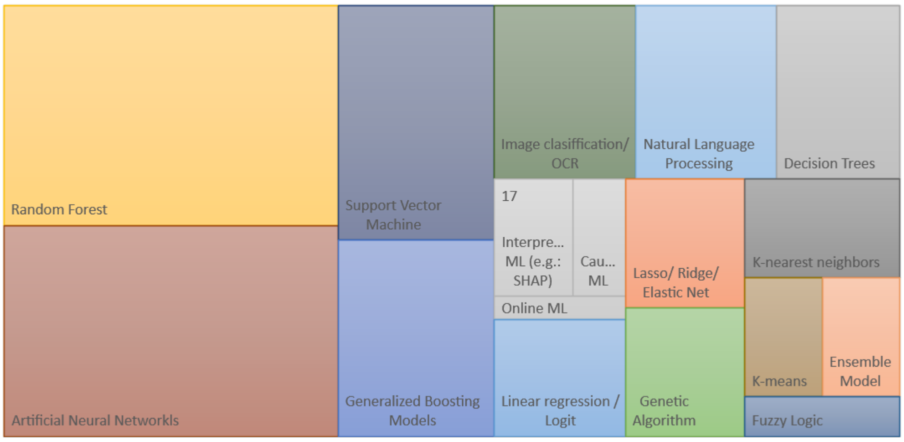

Figure A.13: Type of model used: Physical risk

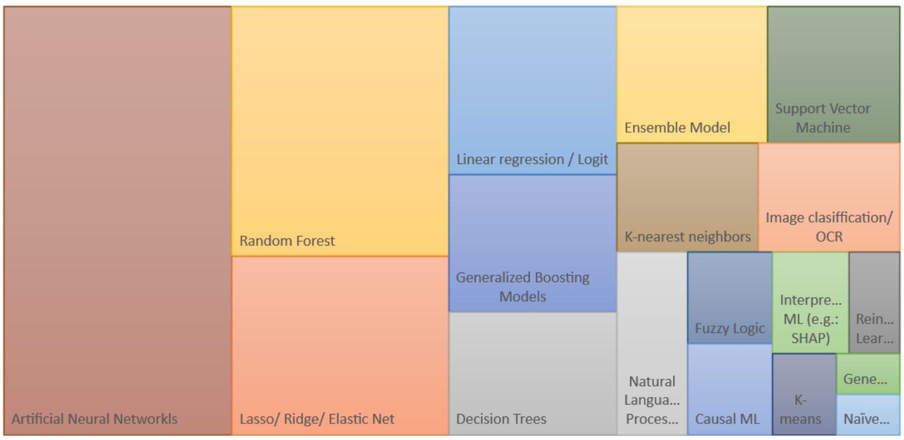

Figure A.14: Type of model used: Transition risk

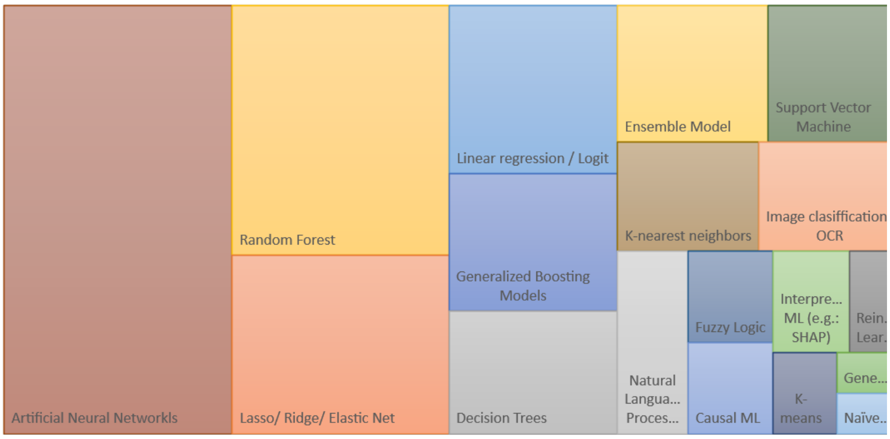

Figure A.14: Type of model used: Transition risk

Table A.3: Corpus of documents. ML methods, by topic (Physical Risk).

Application domain		List of papers	List of ML models
Physical Risks	Natural Hazards	Bayle et al. (2020), Manandhar et al. (2020), Biffis and Chavez (2017), Chen et al. (2020), Cesarini et al. (2021), Lyubchich et al. (2019), Hoang et al. (2020), Inyang et al. (2020), Bjånes et al. (2021), Nti et al. (2021), Rohayani et al. (2021), Avand et al. (2021), Shu et al. (2022), Yang et al. (2021), Diniz et al. (2021), Best et al. (2021).	Markov-CA (deep learning), Image classification, Random forest, Genetic algorithms, K-means, ANN, SVM, XGBoost, LSTM (Recurrent Neural Network), Extra trees, , Regression model, CART (Decision Trees), Multi-layer Perceptron (deep learning), Adaptive Neuro Fuzzy Inference System, Back-propagation Neural Network, Ensemble model.
	Biodiversity	Floreano and de Moraes (2021), Wang et al. (2018), Dao et al., Lima et al. (2022), da Silveira et al. (2021), Keys et al. (2021), Macadam et al. (2021), Pearson et al. (2020), Dao et al. (2019), Santamaria et al. (2020), Reiersen et al. (2021), Rakova and Winter (2020), Hou et al. (2020), Seidl et al. (2020), Evans et al. (2011), Bastien-Olvera and Moore (2021).	Linear Regression, Decision Tree, Naive Bayes, Support Vector Machine, Random forest, Artificial Neural Network (ANN), K-Nearest Neighbours, Boosting Ensemble meta-algorithm, Reinforcement learning, Deep multi-agent reinforcement learning, Kernel Extreme Learning Machine, Stacked denoising autoencoders, Wavelet Neural Network, Genetic Algorithm, Particle Swarm Optimization, Bagging, Causal Direction from Dependency (D2C) algorithm, LightGBM (Gradient boosted decision trees), CatBoost, XGBoost, SHAP, Optical Character Recognition (OCR), Natural Language Processing (NLP), Interpretable trees, K-means, LSTM (Recurrent Neural Network), Double debiased ML, Radial Artificial Neural Network, Lasso, Causal forest, Causal boosting, Local Interpretable Model-Agnostic Explanation (LIME), Passive Aggressive Regressor, Linear Regression, Box-Cox, K-NN, Multilayer perceptron, Ridge, Elastic Net, RidgeCV, Least Angle Regression, Extra Trees, AdaBoost, Gradient Boosting, Failing rule (decision tree) Stacking, SHAP.
	Agricultural Risk	Feng et al. (2019), Porfirio et al. (2017), Dhokley et al. (2018), Tidake et al. (2020), Ben Ayed and Hanana (2021), Talukdar et al. (2022), Ghaffarian et al. (2022), Liu and Zhan (2019), Coca-Castro et al., Gümüşçü et al. (2020), Vishwakarma (2019), Belhadi et al. (2021), Sabu and Kumar (2020), Paul et al. (2020), Cortés and López-Hernández (2021), Müller et al. (2016), Haro et al. (2021).	Random forest, SVM, C4.5 classifier, Decision Trees, Gradient Boosting, Random forest, Multi-layer Perceptron (deep learning), SVM, Logit Boosting, Rotation Forest, Genetic algorithm, Multiple linear regression, Bayesian network, Convolutional Neural Network, Least-squares SVM, Extreme machine learning (feed-forward neural network), Ensemble model, LSTM (Recurrent Neural Networks), K-NN, ANN, Fuzzy logic, K-means, Generalized Boosted Regression, AdaBoost, Gradient Boosting Machines, Radial Basis Function Neural Network, Bagging, Boosting.

Table A.4: Corpus of documents. ML methods, by topic (Transition Risk).

Application domain		List of papers	List of ML models
Transition Risks	**Carbon Markets**	Zhu and Chevallier (2017), Zhou et al. (2018), Levi (2021), Reiersen et al. (2021), Qi et al. (2021), Morkner et al. (2022), Reed et al. (2019), Sun (2022), Shi et al. (2021), Biesbroek et al. (2020), Kulkarni (2021), Debnath and Bardhan (2020), Donner et al. (2016), Nay (2016), Pincet et al. (2019), Feng et al. (2021), Li et al. (2020), Jaycocks (2019), Schmidt et al. (2021), Abdullah et al. (2021), Caldecott et al. (2018), Nguyen et al. (2021), Han et al. (2021), Yao and Zhao (2022), Khan and Awasthi (2019), Li et al. (2021), Fang et al. (2021), Debone et al. (2021), Nunnari et al. (2004), Acheampong and Boateng (2019), Ma et al. (2021), Sun et al. (2021), Calvo-Pardo et al. (2022), Wei et al. (2018), Shi et al. (2020), Rahman et al. (2021).	Least Squares Support Vector Machines, Extreme learning machine (Deep learning), SVM, Natural language processing (NLP), Back-propagation Neural Network, OLS, Lasso, Genetic Algorithm, ANN, Random Forest, Decision Tree, Convolutional Neural Networks, Multiple Linear regression, OLS, Elastic Net, K-NN, Random forest, Extreme Gradient Boosting Decision Tree, Fuzzy logic, Multilayer perceptron, Multinomial logistic regression, Ensemble model, Convolutional-Long Short Term Memory, Artificial neural network with backpropagation, Gaussian Process Regression, Feed-forward neural network, Extreme machine learning, Lasso, Natural Language Processing (NLP), Latent Dirichlet Allocation (LDA), Machine-coding (Symbolic AI), Fuzzy comprehensive evaluation model, GAN.
	Climate data	Diggelmann et al. (2020), Schwabe et al., Nugent et al. (2020), Owusu (2020), Sautner et al. (2020), Li and Yu (2022), Antoncic (2020), Kheradmand et al., Luccioni and Palacios (2019), Moreno and Caminero (2022b), Friederich et al. (2021), Luccioni et al. (2020), Cojoianu et al. (2020), Miglionico (2022), Raghupathi et al. (2020), Bingler et al. (2022), Benites-Lazaro et al. (2018), Raman et al. (2020), Bala et al. (2015), Moreno and Caminero (2022a), Chen et al. (2021), Clarkson et al. (2020), Ehrhardt and Nguyen (2021), Wen (2018), Mansouri and Momtaz (2021).	Natural language Processing (NLP), Natural language understanding (NLU), Context-based algorithms, Keyword discovery algorithm, LDA, Word2vec, Doc2Vec (word embeddings), Text mining, Automated language systems, Text analytics, ClimateBert, Neural language modeling, SVM, Fully-connected neural network, Computer-based textual analysis, Logistic classifier, Lasso, Joint entity, Relation extraction, ANN.

Table A.5: Corpus of documents. ML methods, by topic (CSR).

Application domain		List of papers	List of ML models
Corporate & Social Responsibilty	**ESG factors & Investing**	Engle et al. (2020), Hilario-Caballero et al. (2020), Yu et al. (2022a), Lanza et al. (2020), Jha (2021), Margot et al. (2021), Klusak et al. (2021), Vo et al. (2019), Guo et al., Chen and Liu (2020), Erhardt et al. (2020), Zhang and Chen (2021), Sokolov et al. (2021a), Yu et al. (2022b), Bua et al. (2022), Cepni et al. (2022), Plakandaras et al. (2018), Taleb et al. (2020), Tiwari et al. (2022), Hisano et al. (2020), Drei et al. (2019), Chang et al. (2021), Coqueret et al. (2021), Škapa et al. (2022), De Lucia et al. (2020), Teoh et al. (2019), Sokolov et al. (2020), Mitsuzuka et al. (2017), Gupta et al. (2021), Sokolov et al. (2021b), Krappel et al. (2021), D'Amato et al. (2022), Svanberg et al. (2022), Lin and Bai (2022), Bouyé and Menville (2020), Berg et al. (2021), Citterio, Kluza et al. (2021), Natsume and Feng (2019), Ma (2019), Anders (2021), Yan and Meng (2021), Joshi and Chauhan (2021), Michalski and Low (2021), Dudás and Naffa (2020), Riad et al. (2019), Hong et al. (2022), Sharma et al. (2022).	Textual analysis, Genetic algorithm, Multiobjective evolutionary algorithms, Classification and Regression Trees, Random forest, ANN, SVM, Decision Trees, Support Vector Regression (SVR), Deterministic ML (Symbollic AI), Multivariate Bidirectional Long Short-Term Memory neural network, Deep reinforcement learning, Deep learning, Ensemble model, XGBoost, Fuzzy reasoning, K-NN, AdaBoost, OLS, Lasso, Elastic Net, PLS, Ordered Logistic regression, Ridge, K-NN, SVM, Naive Bayesian, Multilayer Perceptron (MLP) Neural Networks, Long Short-Term Memory (LSTM) Neural Networks, Natural language processing (NLP), Extremely randomized trees, Linear regression, Feed-forward neural network, AdaBoost, CatBoost, XGBoost, Ensemble model, Kohonen neural network, Naïve Bayes, Gradient boosting, Logistic regression, Radial basis function (RBF), SVM, SHAP, Classification tree, Lasso, SHAP.
	Climate data	Diggelmann et al. (2020), Schwabe et al., Nugent et al. (2020), Owusu (2020), Sautner et al. (2020), Li and Yu (2022), Antoncic (2020), Kheradmand et al., Luccioni and Palacios (2019), Moreno and Caminero (2022b), Friederich et al. (2021), Luccioni et al. (2020), Cojoianu et al. (2020), Miglionico (2022), Raghupathi et al. (2020), Bingler et al. (2022), Benites-Lazaro et al. (2018), Raman et al. (2020), Bala et al. (2015), Moreno and Caminero (2022a), Chen et al. (2021), Clarkson et al. (2020), Ehrhardt and Nguyen (2021), Wen (2018), Mansouri and Momtaz (2021).	Natural language Processing (NLP), Natural language understanding (NLU), Context-based algorithms, Keyword discovery algorithm, LDA, Word2vec, Doc2Vec (word embeddings), Text mining, Automated language systems, Text analytics, ClimateBert, Neural language modeling, SVM, Fully-connected neural network, Computer-based textual analysis, Logistic classifier, Lasso, Joint entity, Relation extraction, ANN.

Table A.6: SPAR-4-SLR protocol. Assembling, arranging and assessing.

Assembling	
Search Keywords:	
ALL=(”climate change” OR ”ESG” OR ”sustainable finance” OR ”green finance” OR ”climate finance”) AND AB=(finance OR ”financial market*” OR bond* OR investment*OR corporate* OR funding OR financing) AND ALL=(”lasso” OR ”random forest*” OR ”extreme gradient” OR ”xgboost” OR CART OR ”deep learning” OR ”neural network” OR ”machine learning”)	
Search Databases:	
1. Web of Science (WoS)	
2. Google Scholar (GS)	
3. Dimensions.ai (D.AI)	
Search Result:	
1. Web of Science (WoS): 125 documents	
2. Google Scholar (GS): 18,300 documents - 45 search pages screened , approx. 450 results.	
3. Dimensions.ai (D.AI): 127 documents	
Arranging	
Organizing Filters:	
Filetered Year for Inclusion:	1999-2022
Filtered Area for Inclusion:	Environmental Science, Computer Science, Economics Finance
Filtered Document Type for Inclusion:	Article
Filtered Publication Stage for Inclusion:	Final
Filtered Source Type for Inclusion:	Journal Article, Working Paper, Conference Proceedings, Book chapter.
Filtered Language for Inclusion:	English
Find duplicates:	Using Endnote bibliographic manager
Ex-post external validation:	Based on field expertise (Human-in-the-Loop).
Filtered Search Result:	217 documents
Assessing	
Analysis Methods:	
Performance analysis:	Publication trend, Evolution of model choice by topic, Breakdown of Journal and Publication type
Topic modelling	Latent Dirichtlet Allocation (LDA), using Python.
Agenda Proposal Method:	Reading of articles and and reflection of text extracts including mention on machine learning models.
Reporting Convention:	Figures, tables and words.
Limitations:	Accuracy of search results, specially in GS. Completeness of references in Environmental Science with a focus on finance.
Support:	No funding received

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