The Impact of Research on Carbon Dioxide Removal and its Potential for the Public Use of Science
Master's Thesis Exposé
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1 Introduction

Climate change is one of the most pressing issues of the current time and mitigation and adaption require immediate action (IPCC, 2022a). While consequences of rising temperatures are becoming more prevalent through heat waves or extreme weather, pressure is rising to find effective measures (Moriarty and Honnery, 2022). In recent years, Carbon Dioxide Removal (CDR) has received rising attention. It describes a variety of approaches to remove carbon dioxide from the atmosphere to reach net-zero emission as agreed on in the Paris agreement (Smith et al., 2024).

While literature on CDR has grown rapidly over the past years, only few systematic approaches on impact and spill-over effects have been conducted. Spill-over is defined as the attention a research article receives from the count of citations, patents and mentions in media. The higher the spill-over, the higher the societal impact of the research article (Tripodi et al., 2024).

In this thesis, I want to identify the impact of different CDR methods using scientific papers and their citations, patents based on the research paper and the mentions in the public debate using the altmetrics score[1]. Altmetrics are counts of mentions of the research in news, social media and policies (Altmetric, 2025). I will analyze which group of CDR methods contributes most to the public debate. This will be achieved by assembling a dataset on CDR literature including patents and meta data using a finetuned Large Language Model (LLM) to first identify relevant research papers from a large text corpus and then predict their CDR type. Afterwards, their spill-over effect is analyzed using different methods.

2 Related Work

2.1 Carbon Dioxide Removal

CDR describes a range of methods to reduce CO_2 levels in the atmosphere and store carbon dioxide for decades to millenia (Keller et al., 2018; Smith et al., 2024). CDR can be achieved by convential methods, which are afforestation, reforestation, agroforestry, forest management, peatland and coastal wetland restoration, soil carbon sequestration

[1]https://www.altmetric.com/, accessed May 7th, 2025

(SCS) in croplands and grasslands and durable wood products. Novel CDR technologies are biochar, mineral products, enhanced rock weathering, biomass burial, bio-oil storage, bioenergy with carbon capture and storage (BECCS), direct air carbon capture and storage (DACCS), ocean fertilisation, ocean alkilinity enhancement (OAE), biomass sinking and direct ocean carbon capture and storage (Smith et al., 2024).

The latest report by the Intergovernmental Panel on Climate Change (IPCC) states that CDR is needed to limit global warming to 2°C (IPCC, 2022b).

The State of Carbon Dioxide Removal report analyzes current research, deployment, innovation and barriers with regards to meeting the targets of the Paris agreement (Smith et al., 2024). The authors find that CDR is currently deployed on a low level using mostly conventional methods, although the share of novel methods has grown rapidly. However, proposals of CDR deployment by governments are currently insufficient to reduce emissions in line with the 1.5°C target.

2.2 Literature Analyses in Climate Science

Many scholars undertook systematic literature analyses in the past. Tripodi et al. (2024) analyze the public use of CDR research. They use data on scientific publications from 1998 to 2017 from Web of Science, Reliance on Science, Microsoft Academic Graph and Altmetric to identify articles based on keywords, titles and abstracts to quantify the possibility of scientific progress in different CDR categories. They analyze the mentions in research articles, patents and public discussions up to 2021 which are determined by mentions and citations normalized over time and compare it to a control technology. Their study finds that CDR research persistently generates larger impact than its control group across all dimensions. Direct air capture is cited and patented most often. Blue carbon and BECCS gains most mentions in the public debate. The study also identifies geographic clusters by CDR type.

With the advent of LLMs, many researchers in climate science have done automated literature screenings with the support of this technology. Lück et al. (2024b) conducted a systematic evidence synthesis on policy and governance of CDR. They use a fine-tuned ClimateBert model to first classify papers on and off CDR from a large pool of CDR papers found in Web of Science and Scopus. Subsequent to this, papers classified as CDR are then categorised into distinct CDR types. Another paper by Lück et al. (2024a) assembled a dataset in CDR using a language model. The authors retrieved about 70,000 documents from Scopus and Web of Science using search queries and then annotated about 6000 documents by hand on whether it is a CDR technology or not and if yes, which CDR technology. Then, they used the annotated documents to train a classifier and applied it on the unseen papers. The final count of retrieved studies was 28,976, representing the most extensive collection of research in this domain to date.

Ji et al. (2025) analyzed the results of using different LLMs in climate science on the quality of their results. They evaluate the use of LLMs to identify future research fields in environmental sciences. They analyzed a selection of 34,034 journal articles and conducted a word cloud visualization, topic modeling visualization using vector representations and clustering as well as an LLM-based text analysis with GPT-3.5, ChatGPT and GPT-4. It has been demonstrated that, in particular, GPT-3.5 has the capacity to identify more comprehensive and recent analyses of environmental science. Quilodrán-Casas et al. (2024) examined further usages for LLMs. The authors used the OpenAlex[2] database described by Priem et al. (2022). They investigated title-abstract pairs of scientific papers on three dimensions: climate change mitigation potential, stage of technological development and readiness for deployment. impact to climate change mitigation potential, their stage of technological development and readiness for deployment using GPT4-o. Their research finds that the LLM approach can identify overlooked innovations more effectively compared to human expertise.

2.3 Artificial Intelligence and Explainable AI

In the scope of this thesis, neural networks will be used as a method of Artificial Intelligence (AI) to detect patterns in the dataset. Explainable AI (XAI) will be used to analyze these patterns.

AI refers to extract patterns from data, learn these patterns, and apply that knowledge to new data by adapting in a flexible manner (Kaplan and Haenlein, 2019). In research settings, AI is especially valuable for projects that seek to integrate concepts across diverse scientific disciplines and, as a result, demand familiarity with multiple streams of literature that can be challenging for humans to process (Islam et al., 2022).

However, decision processes of AI models are often unclear, raising questions about trust and accountability (Kalasampath et al., 2025). With increased usage of AI technologies, the demand for explainability rises. Ongoing research in XAI aims to clarify how AI systems work, promote ethical and responsible technology use, and enable society to effectively engage with evolving AI technologies (Adadi and Berrada, 2018; Islam et al., 2022).

A variety of XAI methods exist for different purposes. SHAP (SHapley Additive exPlanations) values have been introduced by Lundberg and Lee (2017) and are a model-

[2]https://openalex.org/, accessed May 4th, 2025

independent game theoretic approach and assign each feature an importance variable for their individual prediction. The method interprets features as players in a coalition game. The Shapley value, the payoff, is the additive measure of importance in every combination of features, thus allowing global and local interpretations of a model (Angelov et al., 2021).

Another global methodology of XAI is Global Attribution Mapping (GAM) for features with precise semantic definitions. It can explain non-linear representations of subpopulation granularity, provides tunable granularity for different amounts of subpopulations and can also provide global explanations for individual samples. GAMs use a pair-wise rank distance matrix between features and group similar local feature importances into clusters using a K-medoids algorithm. The detected medoid summarizes its recognized pattern to a cluster of global attribution (Ibrahim et al., 2019; Angelov et al., 2021).

A local methodology is Local Interpretable Model-Agnostic Explanations (LIME). LIME trains a surrogate model to allow for interpretations of local behavior of the global model. Input data is altered and the model evaluates how the alterations change the prediction. The methodology uses a weighted linear model to adjust the data. The weighting is based on how close the pertubed data is to the original input data (Angelov et al., 2021; Kalasampath et al., 2025).

3 Problem Statement and Objectives

In recent years, literature on CDR has grown as shown in figure 1 (Smith et al., 2024). Lück et al. (2024a) point out that the amount of research articles on CDR is growing faster than for research related to climate change in general. Several studies and reviews analyze current research (Minx et al., 2017), assessed trends on large data sets (Lück et al., 2024a&b) or assessed impact and spillover effects (Tripodi et al., 2024). However, the amount of scientific literature on CDR has be come too large to be analyzed manually (Lück et al., 2024a).

To the best of my knowledge, no study thus far has used a dataset in which the input data has used a LLM to identify CDR and non-CDR publications as well as the type of CDR for a systematic analysis of citations, patents and altmetrics. I expect that the size of the input data set will be significantly larger than the input data by Tripodi et al. (2024).

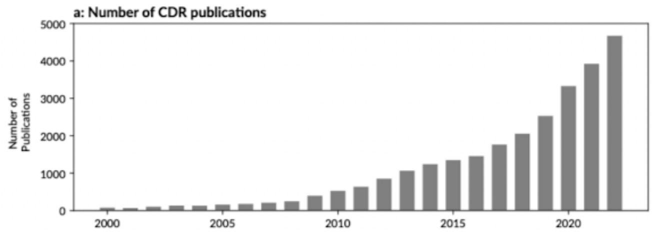

Figure 1: Number of publications on CDR; Source: Smith et al. (2024)

The objective of this thesis is three-fold: First, I will replicate the study by Tripodi et al. (2024) with a dataset of which the input data and CDR type has been classified by a fine-tuned ClimateBert model which is described in Lück et al. (2024a). Then, a GLM is trained on this data as in Tripodi et al. (2024). This serves the purpose of identifying deviations in the GLM in comparison to Tripodi et al. (2024) which are due to the dataset and also serves as a baseline for further analyses. Secondly, I will train Feed-Forward Neural Networks (FFNN) to predict the counts of citations, patents and altmetrics with input data as specified in section 4.1. Then, I will analyze drivers of studies with a high impact using XAI. Finally, I will compare the results of the neural networks with the GLMs.

Therefore, I formulate the following research questions:
RQ1: Do the results of this analysis yield the same results as the previous study by Tripodi et al. (2024) while using a significantly larger dataset?
RQ2: What are the drivers of high impact papers on CDR?
RQ3: How do spill-over effects by location of authors or patent holders differ?

4 Methodology and Data

To conduct a systematic analysis of the impact of existing literature on CDR, I want to follow the proposed methodology by Tripodi et al. (2024) and improve it in three ways: Firstly, I will be using a larger input data set, secondly, I will construct a different control data set and finally, I will train a FFNN and conduct a XAI analysis on the model. The whole process is visualized in figure 2.

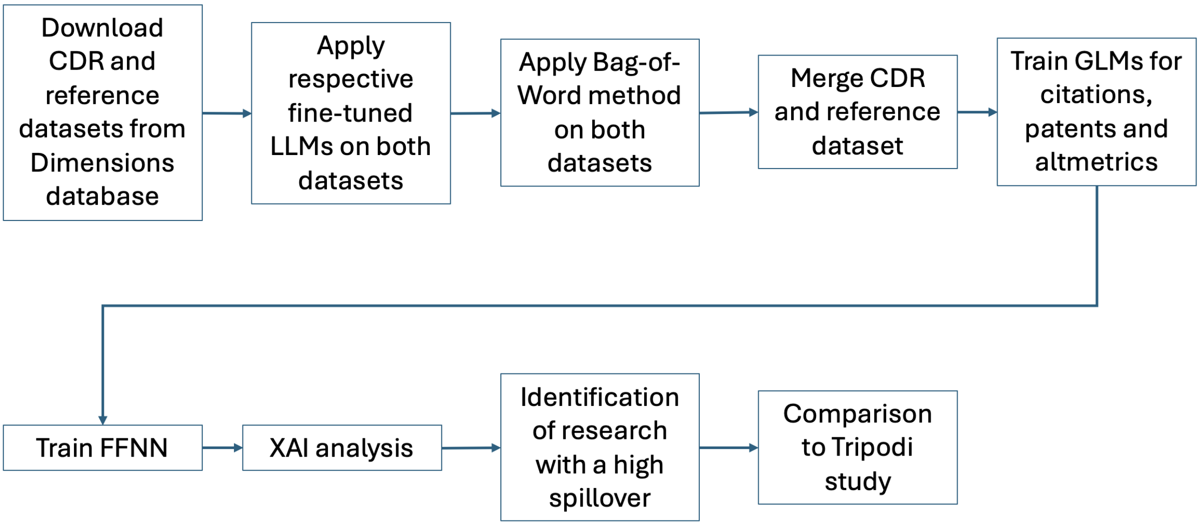

Figure 2: Research Process

4.1 Input data

I will use input data from the Dimensions database[3]. Dimensions is a scholarly database which includes scientific publications (research articles, books, book chapters and conference proceedings) as well as citations, grants, patents, clinical trials, policy documents and altmetric information (Hook et al., 2018). The database holds 98 million publications and 150 million patents (Dimensions, 2025).

The download from Dimensions is based on queries. Similar to Tripodi et al. (2024), I will include scientific publications as a basis and use their respective citations, patents and altmetrics. Afterwards, as described in Lück et al. (2024a), I will use a finetuned ClimateBert model to first distinguish studies relevant for CDR and then to predict the CDR type as described in Lück et al. (2024a). This model yielded a F1 score of 0.91 and ROC-AUC score of 0.85 and is trained on the following CDR types: afforestation/reforestation, restoration of landscapes/peats, agroforestry, SCS, blue carbon management, enhanced weathering, OAE, ocean fertilisation/artificial upwelling, BECCS, DACCS, biochar as well as general literature on CDR not focussing on a particular technology. Additionally, a Bag-of-Word (BOW) model will be trained on the dataset. The BOW model will serve as a baseline for the accuracy of predictions.

I expect that this method will retrieve a dataset of a size similar to Lück et al. (2024a), which would be about 29,000 studies.

[3]https://www.app.dimensions.ai, accessed May 4th, 2025

As also done by Tripodi et al. (2024), counts of citations, patents and mentions are computed. As in Tripodi et al. (2024), I will create a control data set which uses data of a different climate technology to compare against CDR. The control technology of choice is renewable energy. The input data will be downloaded from the Dimensions database and I will retrieve the same features as for CDR. A LLM is used to distinguish irrelevant studies returned by the query from relevant ones. This will be done by another finetuned ClimateBert model[4], which is finetuned on textual information on renewable energies and has first been introduced by Deng et al. (2023). The purpose of the control dataset to find out if CDR has a larger societal impact than a control technology. To find the most suitable matching article, criteria for the same year of publication, a similarly ranked journal and a similarly ranked first author as a CDR article.

I will use the data sets of CDR and control technology to train Generalized Linear Models (GLM) and FFNNs. It will receive the following input features:

- CDR type (binary variable)
- publication years of the research article (binary variable)
- region (one-hot encoder)
- H-index of first author
- journal rank

4.2 Generalized Linear Model

In a first step, four GLMs will be trained to estimate the impact of research paper citations, patents and altmetrics as well as total counts of a research paper and its attached patents and altmetrics. This serves the purpose of analyzing deviations to the impact study of Tripodi et al. (2024) and also serves as a baseline for further steps. If deviations appear, I assume these are due to the significantly larger input data set.

4.3 Model Training and Explainable AI Analysis

Further, I will train four FFNNs to predict the counts of citations, patents, altmetrics and total counts for CDR and the control technology.

To analyze drivers of impacts of CDR and non-CDR research articles, I will employ methodologies of XAI. SHAP or GAM will be applied to analyze feature importance of the model globally. For an analysis of outliers (e.g., particular high impact values), I will apply LIME.

[4]https://huggingface.co/climatebert/renewable, accessed May 21st, 2025

4.4 Results

Resulting models of this thesis will be four GLMs and four FFNNs. I will use the GLMs to replicate the study by Tripodi et al. (2024) and analyze whether possible deviations are due to the significantly larger dataset I use in this thesis. I will use methods of XAI to examine the results of the FFNNs and find drivers of high impact of CDR research and the control group. Finally, I will investigate deviations in the results of the GLMs and the FFNNs.

Ideally, I will retrieve a dataset suitable for CDR and control technology studies. From this data set, I will train a FFNN that outperforms the GLM baseline model and is suitable for finding drivers of impactful CDR studies using XAI.

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