A scoping review on climate change education

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Abstract

Escalating climate impacts predicted in the past decades are now a reality almost everywhere on the planet, and the time-critical dimension of the climate crisis means that the coming years will be instrumental in securing a climate resilient future for generations to come. Education is central to promoting climate action, yet the role that climate change education plays in advancing climate awareness, action and advocacy, and helping to enhance resiliency for young generations and the public at large is poorly understood. Here, we provide a first-of-its kind mapping of the literature on climate change education to better understand topic relationships and spatial distribution, and highlight potential new avenues for research on climate education. Machine learning methods including semantic analysis, geoparsing and topic modeling are used to support our study. Topic modeling shows that climate change education is a very interdisciplinary field of research well embedded in key climate change research topics including climate change adaptation, disaster risks and education, mitigation and sustainability, with the bulk of the literature situated in social science research, followed by topics on agricultural and adaptation, and education topics including methodologies, paradigm shifts, and research methods. Central to climate change education is the methodological dimension of teaching and educating either through formal or informal methods. Topic clustering reveals that topics including energy, renewable energy, fossil fuel and emissions are visibly far from topics school, teacher and science. As expected, social research lies in the middle and overlaps at the periphery with most other topic clusters, except with topics of energy mitigation, disaster risk, and medical health. Through geoparsing, country mentions and case studies are largely skewed towards the English speaking countries and in particular the United States– though this is not always the case when we look at more specific topics. This study should stimulate more targeted research into the specific topics that have emerged. Our findings also call for a strong incentive for governments to react on funding for further research into climate change education, also stimulating a global exchange of ideas through support and incentives for open science. More broadly, climate change education should be compulsory at all levels of formal education, ensuring a comprehensive curriculum of all relevant topics.

Author summary

Veruska Muccione contributed to the conceptualization, data curation, investigation, coding, models, visualization, writing – original draft and writing – review and editing. Tracy Ewen contributed to the conceptualization, investigation, visualization, writing – original draft and writing – review and editing. Saeid Vaghefi contributed to the conceptualization, investigation, models, writing – original draft, and writing – review and editing.

Introduction

The climate crisis is making headlines every day [1, 2]. Escalating impacts and consequences of risks predicted in the past decades are now a reality almost everywhere on the planet [3]. The latest reports of the IPCC emphasize the time-critical dimension of the climate crisis and that the coming years will be instrumental in securing a climate resilient future for generations to come [3, 4]. The already noticeable and widespread impacts of climate change have led to increasing climate anxiety in young generations across the globe [5]. Feelings of uncertainty, anger, helplessness, and guilt are negatively affecting the daily lives of youth and call for a need to action. In the past five years, young people globally have taken the climate crisis upon themselves, and to the streets, they have made numerous appeals to decision makers, and are energetically driving actions [6, 7]. Children and young adults are internalizing the problem, and in trying to find solutions and ways to cope, are integrating different sources of information into their learning perspective [8]. This critical knowledge has prompted significant action and a new mindset that is empowering youth to solve the challenges of the climate crisis, with prominent young climate activists voicing their views with generational connection, and received as moral authority among existing climate policy actors [7].

It is not fully clear however how adults and children alike access and consume information to develop knowledge and understanding to be better equipped to handle these challenges. Social media platforms, blogs, and a growing number of communication channels have made it possible for science to have a more immediate, and broader reach and influence outside of the academic sphere [7, 9, 10]. The channels have however also led to the spread of misconceptions and fake news amongst the general public, slowing down positive action [11–13]. Yuan et al. [14] have analyzed more than 7 million tweets about climate change between 2019-2020 and found that aggressive tweets (although a small proportion of total tweets) were more likely to be retweeted and politicised.

To counteract misinformation and bolster action, interventions at the level of communications and education have been deemed essential [15]. Climate change education refers to the process of teaching and learning about the causes, consequences, and potential solutions to climate change [4]. Climate change education aims to enhance public awareness, understanding, and engagement in climate change issues, as well as foster adaptive capacity and support for climate action [16, 17]. Recent developments in university education are moving in the direction of including modules on climate change and the climate crisis as part of compulsory study programmes as a result of activism and public dialogue [18–21]. There are good examples of initiatives and online platforms that provide a broader scope of resources on climate or climate focused environmental education. For example, the EU education and training sector focus on green education [1]; the Office of Climate Education, under the auspices of UNESCO [23]; or initiatives like the GLOBE (Global Learning and Observations to Benefit the Environment) Program, supported by US governmental agencies, which gives students and the public

[1] https://education.ec.europa.eu/focus-topics/green-education [22]

the opportunity to contribute to observations, research and analysis of global environmental data [24]. Existing successful models of climate-focused project-based learning have resulted in increased climate awareness and overall carbon reduction [25]. For example, significant carbon reduction was measured through student-consumer choices after five years of taking a university climate change course, indicating that even a small amount of climate change information and awareness introduced into school curricula has the potential to result in a significant effect [21].

Climate change education comes in many different forms, from formal educational systems, such as school curricula, universities, and vocational qualifications to informal settings like media and social media platforms [20, 26]. Communication and engagement strategies, such as experiential learning, climate games, and online courses have been described as effective and useful methods for reaching diverse audiences and fostering climate literacy [9, 27]. As a result, research is paying increasingly more attention to the role that education in its different forms plays on its power to catalyse action and empower citizens [28]. Some studies have found that although learning leads to knowledge and skills, the type of information and learning experience can have a profound effect on the outcomes of successful learning and behaviour change and whether there is lasting impact; this is especially true for climate change information where personal relevance to the issue or an engaged learning experience can be critical to solidifying a lasting change, especially for children and young people [18, 20, 21, 29]. Along these lines, scholars have reported the considerable challenges when moving from climate change education to effective climate action, therefore arguing that there is still a gap and misconceptions within the teaching and student communities when it comes to climate change [30].

Evidence on climate change education is rich and emerging and yet there has been limited synthesis and assessment on the extent to which education and climate change are interrelated topics. Whereas education appears to be instrumental for climate action or lack thereof, depending on the sources of information and learning, we have little knowledge of the different research angles that explore or invoke a role for climate change education. Furthermore, education has been so far sidelined in large environmental assessments such as the recent IPCC reports. The Summary for Policy Makers of the Working Group 2 on Impacts, Adaptation and Vulnerability mentions "education" four times, whereas the Summary for Policy Makers of the Working Group 3 on Mitigation mentions it three times. These summaries are the first policy stop for decision makers and therefore plays a key role in leading to policy changes, which might apply to education policy. A recent study that examined how climate issues are integrated into classrooms, in nearly 50 countries found that more than half make no reference to climate change in their primary and secondary school educational curriculums, indicating a clear need for more policy interventions in basic formal education at both national and international levels [31].

In this paper we provide a first-of-its kind scoping of the literature on climate change education using systematic mapping of the literature. Systematic mapping is an approach that seeks to give an overview of an area of research [32]. It is different from a systematic review whose scope it is to synthesize evidence, identifying strengths and weaknesses, usually with a very specific formulated goal [33]. We explore the main research topics in climate change education to find topic associations, their spatial distribution, and to highlight potential new avenues for further research on climate change education, as well as to gain more insight into the role that education plays in advancing climate awareness. Owing to the exponentially growing number of publications on climate change, the methods for systematic mapping of the literature is situated in the context of big data and big literature [34–36]. The paper is organised as follows. The next section, Methods describes the methodological approach for data collection and analysis as well as the data set used in our analysis. The Results and Discussion sections summarize and discuss the main findings of the paper, as well as offer some insight on future directions. Finally, we end with Conclusions.

Methods

Systematic reviews and mapping have been valuable assets to synthesize various key topics from the literature on climate change [37–40]. As the amount of literature on climate change has increased exponentially, machine assisted assessments of the literature have started complementing human efforts [34]. Machine learning has been used in assessing progress on human adaptation [35], to map the literature on climate change and health [41], to highlight global adaptation limits [42], for impact attributions [36] and to give insights on the topology of climate change research [34]. This paper adds to the mapping of climate change literature by focusing on climate change education. The notebooks and data used can be found on GitHub [43].

Data collection, search and screening

Publications on the Dimensions API [2] and the Web of Science, Core Collection [3] were screened based on titles, abstracts and key words until June 30, 2022 using the string searches detailed in S1 Fig. To be included, publications had to be indexed in English and be of the type article or book. Dimensions search returned 12698 records and Web of Science returned 9920. We excluded records that did not have an abstract or DOI and removed duplicates. Finally, only papers having both a non null abstract and DOI were selected. After merging the two database datasets and removing duplicates, 16438 records were retained for the machine learning supervised task.

Supervised learning is a type of machine learning algorithm where the model learns to make predictions by being trained on labeled examples [44]. The algorithm is given a set of input-output pairs, where the inputs are the features or attributes of the data and the outputs are the corresponding labels or target values. The goal of the algorithm is to learn a mapping between the inputs and outputs, so that it can make accurate predictions on new, unseen data [45, 46]. About 10% of the selected records (1644) was randomly sampled and put aside to create the training and test set. The authors team manually labelled 1636 abstracts as either relevant or non-relevant (eight records had to be removed from the train-test sample due to unreadable abstracts). Papers on ”school environment” or ”school climate” were labelled non-relevant because they had no relation with climate change or global warming. For some papers the relevance was not immediately clear. These papers were therefore labelled and reviewed separately by different authors until agreement was reached on their inclusion or exclusion. The proportion of papers labelled as relevant corresponds to about 40%.

Various supervised machine learning techniques were applied for the supervised task using the Scikit-Learn pipeline [47, 48]. We first employ a selection of pipelines, where each pipeline performs the same set of concatenated steps but each pipeline has a different classifier [44]. In the first step, a count vectorizer transforms each document in a feature vector. Afterwards, term-frequency times inverse document frequency (TF-IDF) transforms the document-feature matrix to scale down the impact of words (or tokens) which occur very frequently in a corpus but are not very informative. TF-IDF is a statistical approach for text mining and information retrieval from a large corpus of documents [49]. Term Frequency (TF) measures how frequently a term (word) appears in a document. It is calculated as the number of times a word appears in a

[2] https://www.dimensions.ai/
[3] https://www.webofscience.com/

document divided by the total number of words in the document. Inverse Document Frequency (IDF) measures how important or rare a word is across all documents in the corpus. It is calculated as the logarithm of the total number of documents in the corpus divided by the number of documents that contain the word. A classifier is then instantiated, the training data are fed through the pipeline, and finally predictions are made on the test set. Each classifier is trained on about 70% of the data and performance is tested on the remaining 30%.

Further to this, a Generative Pre-Trained Transformer GPT-2 for climate change related topics (climate-GPT-2 models) is used for the supervised task [50]. The difference between the classifiers and the GPT-2 models lies in their foundational methodologies. Classifiers are based on traditional machine learning algorithms and require explicit feature engineering. In contrast, climate-GPT-2, a decoder transformer, uses the final token of the input sequence to predict the subsequent token. In climate-GPT-2 architecture the last token of the input sequence contains all the necessary information for prediction tasks. We utilized this information to make a prediction in a classification task rather than a generation task. In other words, instead of using the first token embedding to make a prediction like we normally do in encoder transformer models, we used the last token embedding to make a prediction (here in a classification task).

The performance of each model is assessed using a confusion matrix and classification report [51]. In a binary classification problem like the one here, the confusion matrix is a square matrix of the type $\begin{pmatrix} TN & FP \\ FN & TP \end{pmatrix}$ where TN = True Negative, TP = True Positive, FP = False Positive and FN = False Negative. The classification report provides the weighted averages for precision, recall, F1-Score and accuracy, where accuracy is the sum of the true predicted instances divided by the sum of all instances; precision represents the positive predictive value and is given by TP divided by the sum of TP and FP; recall represents the true positive rates and is given by TP divided by the sum of TP and FN. F1-Score is the harmonic mean of precision and recall. For a dataset like ours which is reasonably well balanced between positive and negative instances, accuracy is a good predictor of the model performance. The classification report is given in Table 1. Cross-validation with k-folds is also implemented. In this case, classification is performed on samples of different sets of data for testing and training each time (or for each fold) [47]. The k-fold increases performance of each classifier by a factor between 0.02-0.04. Climate-GPT-2 outperforms all other classifiers in terms of accuracy, whereas the other parameters are similar across all classifiers except Random Forest and Multinomial Naïve-Bayes. Therefore, we select Climate-GPT-2 to make predictions on the whole data corpus.

	Precision	Recall	F1-Score	Accuracy
Multinomial Naïve-Bayes	0.72	0.66	0.56	0.66
Linear Support Vector Classification	0.81	0.81	0.81	0.81
Random Forest	0.79	0.79	0.79	0.79
Multi-layer Perceptron Classifier	0.80	0.80	0.80	0.80
Nonlinear Support Vector Classification	0.80	0.81	0.80	0.80
Climate-GPT-2	0.80	0.81	0.80	0.85

Table 1. This table gives a summary of the performance of each classifer model expressed as Precision, Recall, F1-Score and Accuracy.

Data analysis

The first step of our data analysis is a simple bibliographic analysis to get a sense of the distribution of publications over time, the journal scope and the distribution of citations. In the next step we make use of the spaCy library to lemmatize the abstracts. SpaCy is an open source natural language processing library for information extraction from a large volume of text [52]. The lemmatized abstracts are passed to the TF-IDF instantiated model for various tasks, as for example to allow visualization of words in a world cloud.

To map the scope of the literature we used topic modeling. Topic modeling is a type of unsupervised learning method for text mining based on Bayesian probability which extracts meaningful topics from short and long texts [53, 54]. It requires domain knowledge to make sense of the topic clustering and it has been successfully deployed for topic mapping of the climate change literature [34, 36, 41]. Topic modelling allows to cluster the distribution of words into representative topics [41]. There are different algorithms to implement topic modelling. Here we follow an approach implemented in [34] and use non-negative matrix factorisation (NMF) [53]. In a nutshell NMF takes the TF-IDF vectorized text matrix and breaks it down in a feature matrix which contains the topics and a weight matrix which contains the weights of those topics. Based on the feature matrix, each abstract is labelled to the topic with the highest weight [55]. To improve the reliability of the topic modelling results, we performed several experiments with a different number of topics and aimed at convergence between 1) the domain knowledge of the authors refined through an analysis of the abstracts in the human classification task and 2) the coherence score which measures the relative distance of words within a topic [56]. The coherence score algorithm predicted 15 as the best number of topics in our corpus. The second best score predicted by the algorithm was 10 which also happens to give a more satisfactory clustering of topics following the human classification task. T-distributed Stochastic Neighbor Embedding (t-sne) is then employed as a dimensional reduction technique to visualize the topic scores in a two dimensional space [34, 57, 58]. Finally, Geoparsing is implemented to collect information on where in the world the studies take place and how the topics are geographically distributed. Geoparsing is a technique that can determine the geolocation in unstructured text and has been used previously in the context of climate change impact attribution [36] and for climate health literature mapping [41]. We used the open source software Geotext to extract cities and country mentions from text [59].

We use Jupyter Notebook for our classification tasks and analysis. Our scripts are available on GitHub [43].

Results

After performing the supervised tasks and adding to the training-test sample with relevant data, a final dataset comprising a total of 5917 papers was retained for all remaining analyses. The split between relevant and irrelevant paper can be visualised in Fig. S2 Fig). The data-set with the relevant papers contains the following bibliometric information: article title, abstract, list of authors, publication year, journal title, DOI and number of citations.

Bibliographic and content analysis

The literature on climate change education started to appear more markedly around the last decade of the 20th century and the number of publications has increased two orders of magnitude in the past two decades (Fig.1 and S3 Fig). The number of publications recorded in 2022 reflects only the first six months, and the trend of high publication output continued in 2022 (not shown). Given the relative paucity of papers before 2005, we focus our analysis on papers for the period 2006-2022 for the remainder of the study.

Fig 1. Publication per year. Publications per year for the period Jan 2006 - June 2022.

In order to infer the influence that specific source titles have on the overall research domain we look at the number of publications per source title as well as the average number of citations (Fig. 2). To assess who engages with this type of research, the top twenty journals per number of citations (top panel) and number of papers (bottom panel) are shown. In the climate focused research, high impact journals such as Climatic Change and Nature Climate Change score very high in number of citations, as well as does the topical journal Environmental Education Research. However, most of these climate focused titles score relatively low in number of publications (while the topical journal Environmental Education Research scores high) inferring that climate change education is rather a subtopic in the broader landscape of climate and climate change research. It also emerges that both proportion of publication and citation are very scattered with many titles representing less than 0.5% of the total citations.

Fig 2. Proportion of publications and citations. Top 20 journals based on the number of citations per title (top) and number of papers per title (bottom). For the sake of clarity on the top 20 journals are shown

We produced a word cloud showing the first 500 most frequent words with the size of the word indicating the relative weight as obtained from the TFIDF abstracts lemmitized using SpaCy (Fig. 3). We see that *student* has the highest occurrence (the largest word shown), followed by *environmental*, *science*, *study* and *research*. Other words with high occurrence are also *health*, *knowledge*, *teacher*, *development*, *school* and *sustainability*. It is worth noting that although *school* has a reasonably high occurrence, *student* and *teacher* are higher (with *student* being by far the highest), *university* is also less frequent, as opposed to *research* which scores very high. The word *child* or any reference to K-12 or young people have comparatively low occurrence.

Fig 3. Most frequent single words. The word cloud shows the first 500 most frequent words, with the size of the word indicating the relative weight of the each words whose frequency is obtained from the TFIDF abstracts lemmitized using SpaCy.

Topics and clustering

During the human coding process we determined that the literature tended to fall within five broad thematic areas, i.e. 1) strictly climate change education focused, or education in the context of 2) climate change mitigation and sustainability, 3) climate change adaptation adaptation, 4) climate impacts and disasters, and 5) climate health education. Combining the knowledge gained from the coded abstracts with the results of the coherence score, we defined ten topic clusters. A summary of the first 10 most common words per topic is given in Table 2.

The proportion of the 10 different topics across our corpus of abstracts is shown in Fig. 4, with Topic 1: Social_Research being the highest with 20%, followed by Topic 4: Adaptation_Agriculture, 14%, and School_Student, 13%. If we look at the ten most prevalent words in Topic 1, it includes many broad and more general terms which likely reflects its high score: research, social, challenge, learning, approach, community, new,

Topic	First ten most prevalent words
Topic 1 Social_Research	research, social, challenge, learning, approach, community, new, world, problem, project
Topic 2 Health_Medical	health, medical, nursing, public, nurse, environmental, professional, care, impact, human
Topic 3 School_Student	student, use, school, study, course, learning, learn, science, research, knowledge
Topic 4 Adaptation_Agriculture	adaptation, farmer, perception, knowledge, study, information, level, impact, public, use
Topic 5 Sustainability_Sustainable	sustainability, sustainable, development, university, research, esd, environmental, paper, approach, student
Topic 6 Environment_Behavior	environmental, behaviour, environment, student, issue, child, study, human, problem, nature
Topic 7 Energy_Mitigation	energy, renewable, technology, emission, use, fuel, student, sustainable, fossil, solar
Topic 8 Physical_Geography	geography, physical, entry, dictionary, soil, discipline, cover, biogeography, ocean, hydrology
Topic 9 Teacher_Science	science, teacher, scientific, student, school, study, research, use, knowledge, issue
Topic 10 Disaster_Risk	disaster, risk, community, flood, reduction, hazard, resilience, natural, school, management

Table 2. The table shows the topic number and name, with the corresponding ten most common words associated with each topic.

world, problem, project. It was surprising to us that Topic 8: Physical_Geography was only about 1%, since we assume that many climate topics would be included in a physical geography curriculum, and this would be reflected in our dataset. However, since our initial search string includes "change", this maybe leads to many papers with a physical geography focus to be excluded (although climate topics are taught, perhaps climate change is less referred to).

Fig 4. Proportion of papers per topic. The proportion shows the argmax of the NMF which is calculated based on the most probable topic assignment for a given document.

To understand the relationship between the topics, we performed a topic clustering. Figure 5 shows the topic clustering where each color corresponds to a distinct topic. The ten topics are reasonably well separated although for some papers there are clear overlaps. Topics including energy, renewable energy, fossil fuel and emissions (Topic 7: Energy_Mitigation) are visibly far from topics school, teacher and science (i.g. Topics 3 and 9: School_Student and Teacher_Science, respectively). School education gravitates closer to impacts and adaptation than to mitigation. Papers on system learning and social research, Topic 1: Social_Research, are in the centre of the diagram which indicates that they are distinct from the other topics, but also relatively close to most of them. Again, this is likely since Topic 1 includes more general, and less specific, terms. Health and medical education are close to the topic of adaptation but relatively far from all the others. Fig. S4 Fig shows the temporal evolution of the cluster of topics over a five-year interval. It can be noted that more papers on sustainability, SDG and university have emerged in the last five years which are closer to the school teacher and science cluster (and in fact are even overlapping). However, apart from a clear increase in the amount of literature in the last decade for all clusters, there are no visible shifts or changes in the shape of the cluster landscape.

Fig 5. Topic clustering using t-sne. Each dot corresponds to a paper in a two dimensional space. The different colors depict the ten different topics.

The heatmap in Fig. 6 confirms that indeed the topics are weakly correlated, and many are weakly anticorrelated. Those showing the highest correlation, albeit a weak correlation, are papers on learning, school and student with school, teacher and science. Given the proximity of the words identified within the topics this is expected. However, it is striking that system learning and social research topics are (weakly) anticorrelated with the topic represented by the words learning, school, science and teaching. Extant research has confirmed that climate change education is strongly rooted in the natural sciences. This is an historic artefact, and on the other hand it highlights how the interdisciplinary dimension of climate change is still underdeveloped at least when it comes to education.

Fig 6. Topic correlation. The heat map shows the Pearson correlation amongst the ten different topics. The heatmap is generated using seaborn and the color and annotated number within each cell indicate the strength of the correlation [60].

Geographic distribution of studies

To gain better insight into which countries were more actively involved in publishing literature on climate change education, we tagged country mentions in our analysis. Results are shown in Fig.7, Fig. S5 Fig. Less than 40% of the abstracts however specifically mention countries and/or location. Amongst those abstracts that have explicit geolocations, the large majority are in the United States, followed by the United Kingdom and Australia (Fig. 7 and Fig. S5 Fig). It is worth mentioning that the Geotext as setup here does not recognise political unions such as the European Union or EU. Therefore, if the EU is mentioned instead of the countries, it will not be tagged at the level of countries. It will be only identified at the continental level. Most of the countries and world regions are mentioned in at least one study, there are noticeable gaps for African countries. The continental distribution shows that Asia has the highest proportion of studies, with North America and Europe sharing a similar proportion and South America having the least studies. It emerges that again Africa as a continent is poorly represented.

We also take a look at the distribution of topics per country. For the sake of clarity we only show the 20 most relevant countries per topic in Fig. S6 Fig. The plots confirm that the majority of studies include the United States for most of the topics. However, there are some noticeable exception. For example, the topic Disaster_Risk is dominated by studies in Indonesia, which is not surprising given that Indonesia has one of the

Fig 7. Geographical distribution of studies. The left panel shows the geographical distributions of studies based on ISO country codes; the right panel shows the proportion of studies per continent based on ISO continent codes. AF = Africa, AQ = Antarctica; AS =Asia; EU = Europe; NA = North America; OC = Oceania; SA = South America.

highest rates of natural disasters in the world, with earthquakes, tsunamis, floods, landslides, drought, and forest fire risks being relatively high compared to other countries [61]. It is positive to see that this is reflected in the literature. If we look beyond the United States in first place, we can also see that Australia and United Kingdom are high for several topics including Social_Research, and Health_Medical (also including Canada), whereas Energy_Mitigation is high for Asian countries, including China, Japan and India.

Discussion

There is a clear urgent need for educators and governments to strongly support the immediate integration of climate change in school curricula, as well as bolstering other effective ways of engaging students and lay people, and provide them with critical thinking skills necessary to navigate the flood of information. Addressing these needs is an essential and time-critical part of the solution to climate change [62]. The knowledge generated in both the classroom and outside will help to form the next generations of climate leaders, scientists and policy makers, while also having a wider reaching impact and be available to everyone [63]. There is compelling evidence that people around the world are listening to science and that they are doing this out of their own interest and concerns [64]. On this premise, strengthening climate change education and engagement has been identified as one of six social tipping dynamics to activate disruptive change towards positive societal transformation [65]. Given the importance of climate change education and an absence of a systematic and broad assessment of the literature to date, we have embraced a mapping approach to track the field of climate change education.

In this analysis we have given a first of its kind assessment of the typology of literature on climate change education as well as its evolution, main topics, geographical distribution and relationships. From our analysis it emerges that climate change education is well represented in main stream climate topics ranging from climate change adaptation, energy and mitigation, health, and sustainable development. A considerable share of the literature is situated in the context of social research, for example in terms of climate change challenges and learning approaches (Topic 1). Climate change education resonates clearly with environmental related terms, including research, students and science. However, a noticeable finding in our analysis is also the diversity of keywords that emerge from the textual analysis in Fig. 3. Climate education is not exclusively associated with natural science terms (including physical geography) or education terms, but other important terms include community, sustainable, development and health. This diversity is also apparent from the results of the topic modelling (see Table 2, Fig. 4 and Fig. S4 Fig).

Although a lot has been published on climate change education, and over many different domains, as it can be inferred from Fig. 1 and Fig. 4, climate change education still remains a niche when it comes to promoting new educational policies which address the climate crisis [66–68]. Furthermore, there is an apparent disconnect between the rich literature on the topic of climate change education that we find here and the implementation of education driven solutions into adaptation and mitigation strategies and plans [28, 65].

Looking more closely at the results of the topic modeling, we see some overlap across topics for example between the social and more methodological research on education with that on environmental and behavioural science as well as with adaptation (Fig. 5). This proximity confirms the central role of education in shaping environmental behaviours [69, 70]. Two clearly, and again unexpected, separated topics appear from the topic clustering analysis, i.e. the climate health education literature (Topic 2) and that of disaster risk reduction (Topic 10) Fig. 6. It can be inferred from the key word analysis that Topic 2 is mainly about how to integrate climate change literacy into nursing and medical schools and curriculum, rather than addressing health impacts and risks which would have been positioned more closely to the risks and disasters topic. In general, the evidence of harm to health from climate related disasters remains scattered and often focused on weather related displacement, whereas the large majority of health literature is mostly concentrated on heat health impacts and vector-borne diseases [71].

Our analysis also shows that sometimes intuitively linked topics are shown to be separated in the climate change literature, although these topics should (and do) fall under the broader topic of climate change education more generally. On the one hand, climate change has been traditionally taught within the natural sciences, and only emergingly taught in other sub-disciplines (e.g. sustainability and health) and on the other hand it highlights how the interdisciplinary dimension of climate change still remains underdeveloped at least when it comes to education. This perhaps motivates a paradigm shift in the way we might implement climate education into our portfolio of strategies to mitigate or adapt to climate change – teaching these topics as a whole with the introduction of a class dedicated to climate change education should be mandatory, addressing all these topics in their own right, and not as tack-on topics in other core curriculum courses. A global shift in the way we even think about teaching climate topics has already been previously advocated and is clearly needed, and will need to be remade from the bottom up [72, 73].

An important caveat to this study is that a lot of the primary literature or material on climate change education may be classified as other literature types (governmental reports, white papers, curriculum documents, and the like) rather than as peer reviewed publications or books [31], as we've addressed here. This is naturally due to the nature of climate change education and how this is written about or documented, and dominated by each country's own language (it is obviously more useful for teachers, lecturers and educators to have curriculum documents in their own language). The number of publications is also likely strongly related to the amount of governmental funding for academics in any given country (as well as the number of academics working on these topics), where countries that allocate more spending on these topics will rank higher in number of publications, and will likely also have research focused on case studies or other methods (e.g., US, particularly NSF funding which tops the list when we look at the top funding agencies and grant amounts for our publication dataset S1 Table). We believe our findings here also call for a strong incentive for governments to react on funding for research into climate change education more generally, as has also been previously proposed [74]. If we are to have a global exchange of ideas on how best to tackle climate change education into our portfolio of strategies, then we also need to support and incentivize open science to this end. Policies need to be backed by strong, and global, research. As we saw in our analysis, although there are a few high impact, climate focused, journals that score very high in number of citations, these titles score relatively low in number of publications overall, indicating that climate education is rather a subtopic in the broader landscape of climate research, and this needs to change.

There are of course some limitations in the approach used here. First, the mapping of the literature did not allow us to more deeply explore some themes that emerged in the analysis, for example why certain countries are more prevalent than others.

Secondly, the classification algorithm, although it performs very well, still miss-classifies a small percentage of the papers. This is a recurrent limitation when doing reviews in big data fashion, and a topic that has already been highlighted in previous research [34–36]. We have, however, generated a data set with annotated abstracts and multi-labels for each topic which will certainly serve the community and be used for further analyses. Thirdly, we focused on only the abstracts from each publication, which gives only a cursory summary of each paper and may have missed publications with keywords mentioned only in the full text. In a further step, the whole manuscript could be processed as part of the dataset. State of the art AI frameworks such as the LangChain [75] which interacts with the text and enables numerous applications could then be used on the bulk of the literature for downstream tasks such as question answering (QA) and text summarization [76].

Conclusions

This research provides a global mapping of climate change education literature which combines supervised and unsupervised machine learning methods assisted by human coding of the abstracts. We manually annotated 1636 papers from a corpus of over 16'000 papers obtained from Dimensions and Web of Science literature database. Using supervised learning we selected more than 5000 relevant records which we then analysed using various text mining tools ranging from semantic analysis to topic modeling and geoparsing [34–36, 41]. Our study reveals that climate change education is a very interdisciplinary field of research well embedded in key climate change research topics such as climate change adaptation, disaster risks and education, mitigation and sustainability. The bulk of the literature is situated in the social science research with a high amount of the literature exploring topics including education methodologies, paradigm shifts in education, and the analysis of traditional and non traditional research methods. There are however, disconnects across topics that would intuitively fit together such as health and disaster risk. Furthermore, the geographical distributions shows that English speaking countries produce the largest share of the research literature when it comes to case studies or country mentions. This could be an interesting topic to investigate further in order to guide policy, by looking more closely at the share of research funds for climate change education across the globe. With this study, we have provided a first annotated and large database on climate education topics to better understand topic relationships and spatial distribution within the literature, and highlight potential new avenues for research on climate education. We expect our dataset will be useful for further disaggregation and analysis by the research community, in the full spirit of open and fair research [77, 78], and help to guide the first step in a much needed paradigm shift in the way we might implement climate education into our portfolio of strategies to mitigate or adapt to climate change.

Supporting information

S1 Fig. Search string applied to two databases. Web of Science (WOS) Core Collection and Dimensions, with the total number of papers retained after exclusions. We excluded records that did not have an abstract or DOI, and all duplicates. Also shown is the total number of papers which were manually coded.

S2 Fig. Paper split. The barplot shows the split between relevant and irrelevant papers from the total collection of papers.

S3 Fig. Publications per year 1966-2022. Publications per year for the entire period from 1966 - 2022 (June 2022).

S4 Fig. Five years interval t-sne clustering. t-sne clustering over a five year interval starting from 2005. We start from 2005 instead of 2006 to keep the interval regular until 2021 and drop 2022 given that only half year is included. The clustering has not changed over time although the number of paper in each clustering has increased considerably.

S5 Fig. Proportion of countries tagged in the abstracts. The figure shows the proportion of papers mentioning a given country out of the total of the papers mentioning any country. The total of the paper mentioning a country or more in its abstract is 2261.

S6 Fig. Proportion of countries tagged in the abstracts per topic. The figure shows the proportion of papers mentioning per country and per topic.

S1 Table The top funding agencies per country and grant amounts. The table shows the top funding agencies per country with the total number of grants, and aggregated funding amount for our publication dataset obtained with our search from the Dimensions API 2 S1 Fig. Only funding amounts over 10 Million are shown (for the top 40 organizations).

S1 Appendix. Codes and dataset. The code and models are available through the GitHub repository [43]. The raw dataset and labelled dataset can be made available upon requests.

Acknowledgments

V.M. and S.A.V. acknowledge support of the Digitalization Initiative of the Zurich Higher Education Institutions (DIZH). We also acknowledge support of dimension.ai through the project DIM-152.

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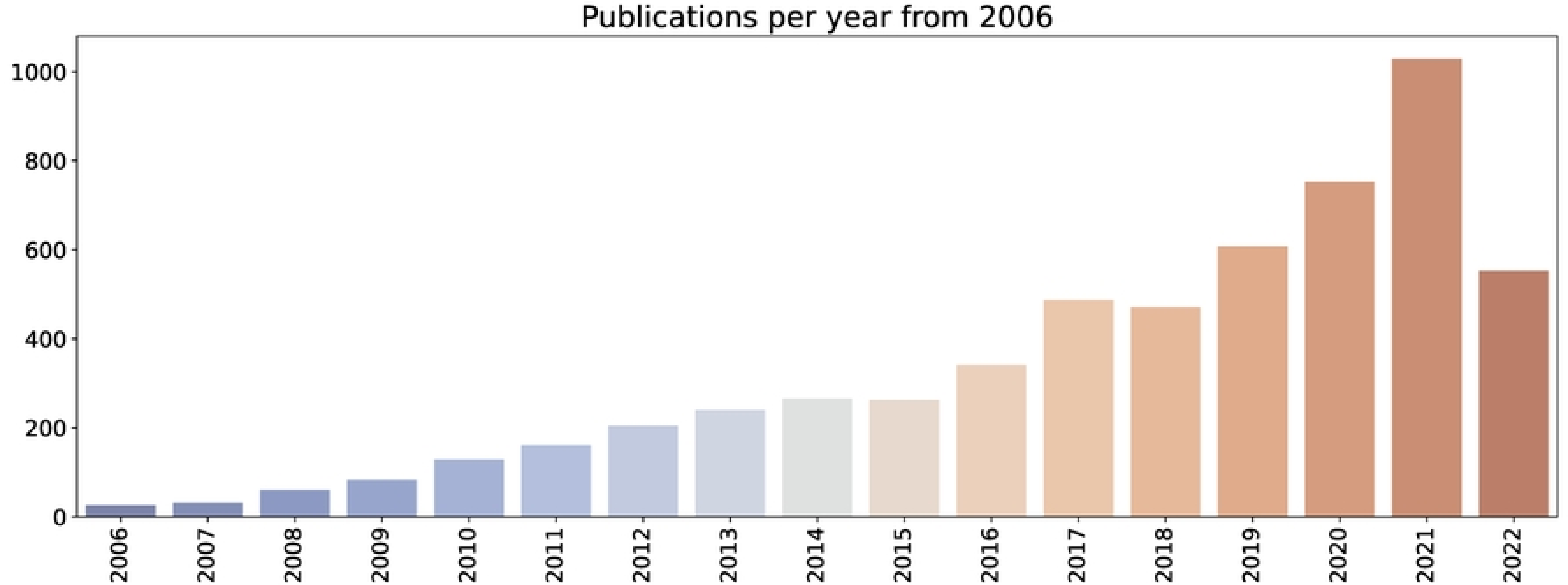
Publications per year from 2006
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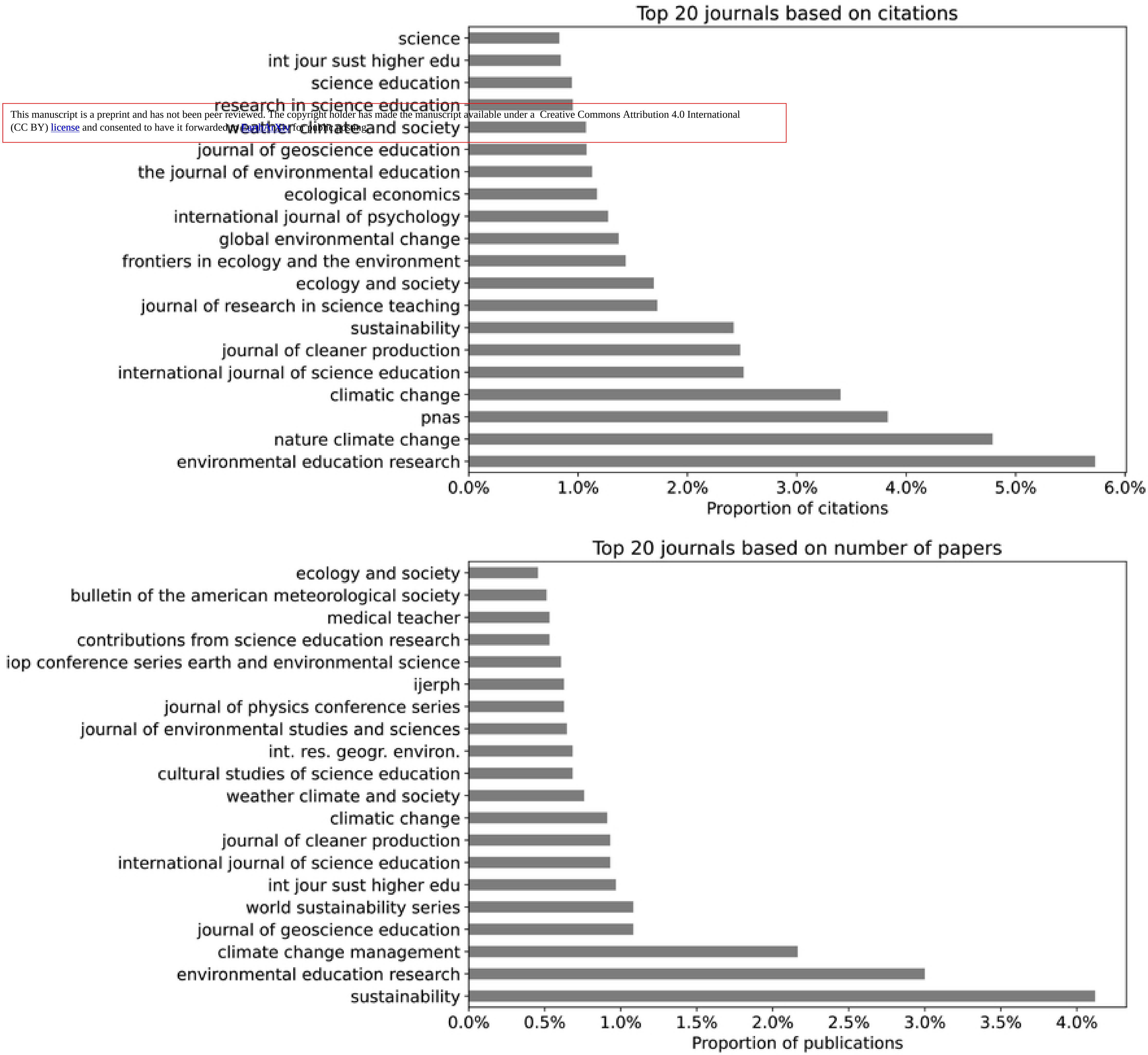
Fig 1


Top 20 journals based on citations
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science education
research in science education
weather climate and society
journal of geoscience education
the journal of environmental education
ecological economics
international journal of psychology
global environmental change
frontiers in ecology and the environment
ecology and society
journal of research in science teaching
sustainability
journal of cleaner production
international journal of science education
climatic change
pnas
nature climate change
environmental education research
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Proportion of citations
Top 20 journals based on number of papers
ecology and society
bulletin of the american meteorological society
medical teacher
contributions from science education research
iop conference series earth and environmental science
ijerph
journal of physics conference series
journal of environmental studies and sciences
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cultural studies of science education
weather climate and society
climatic change
journal of cleaner production
international journal of science education
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world sustainability series
journal of geoscience education
climate change management
environmental education research
sustainability
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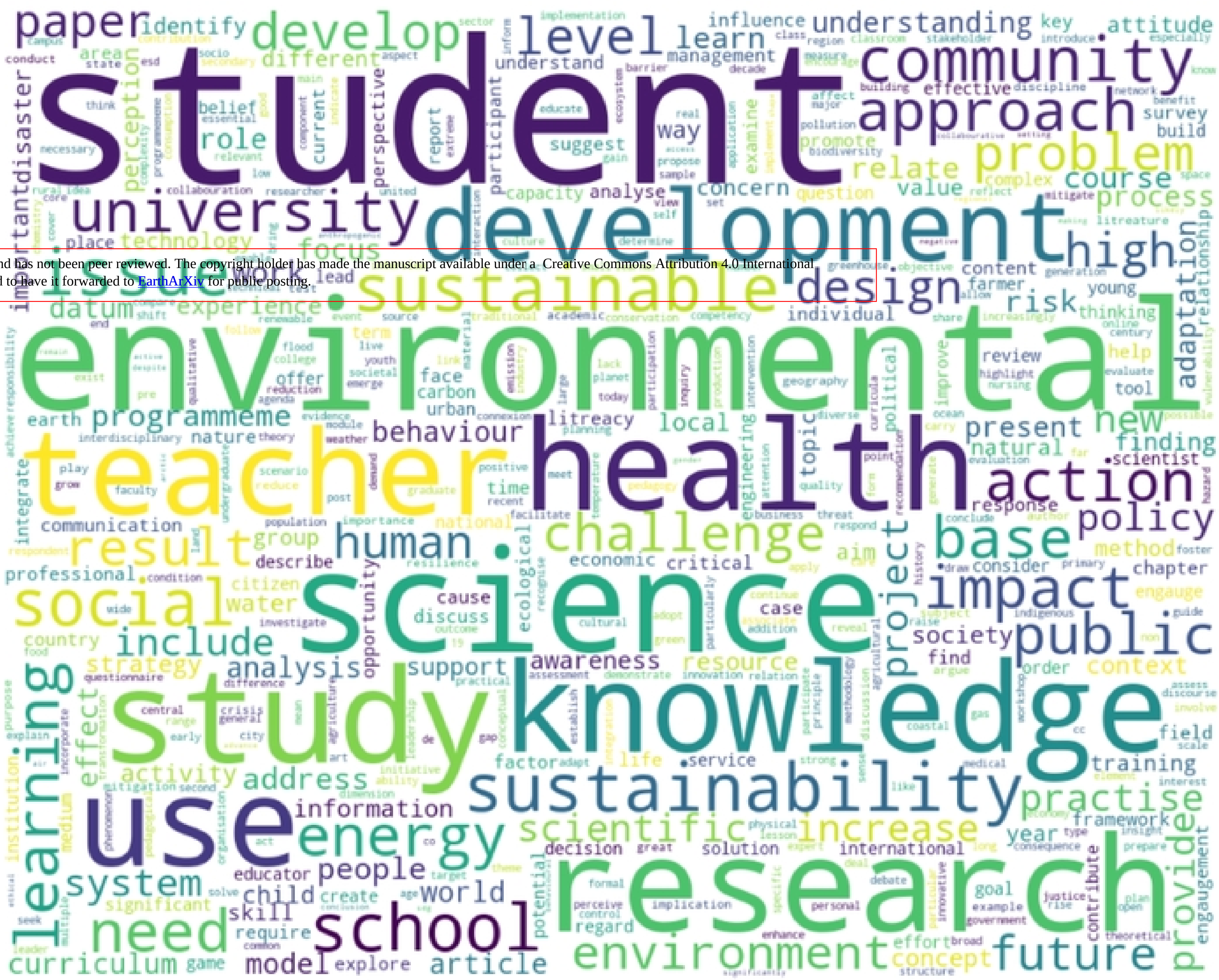
Proportion of publications

Fig 2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increase
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content
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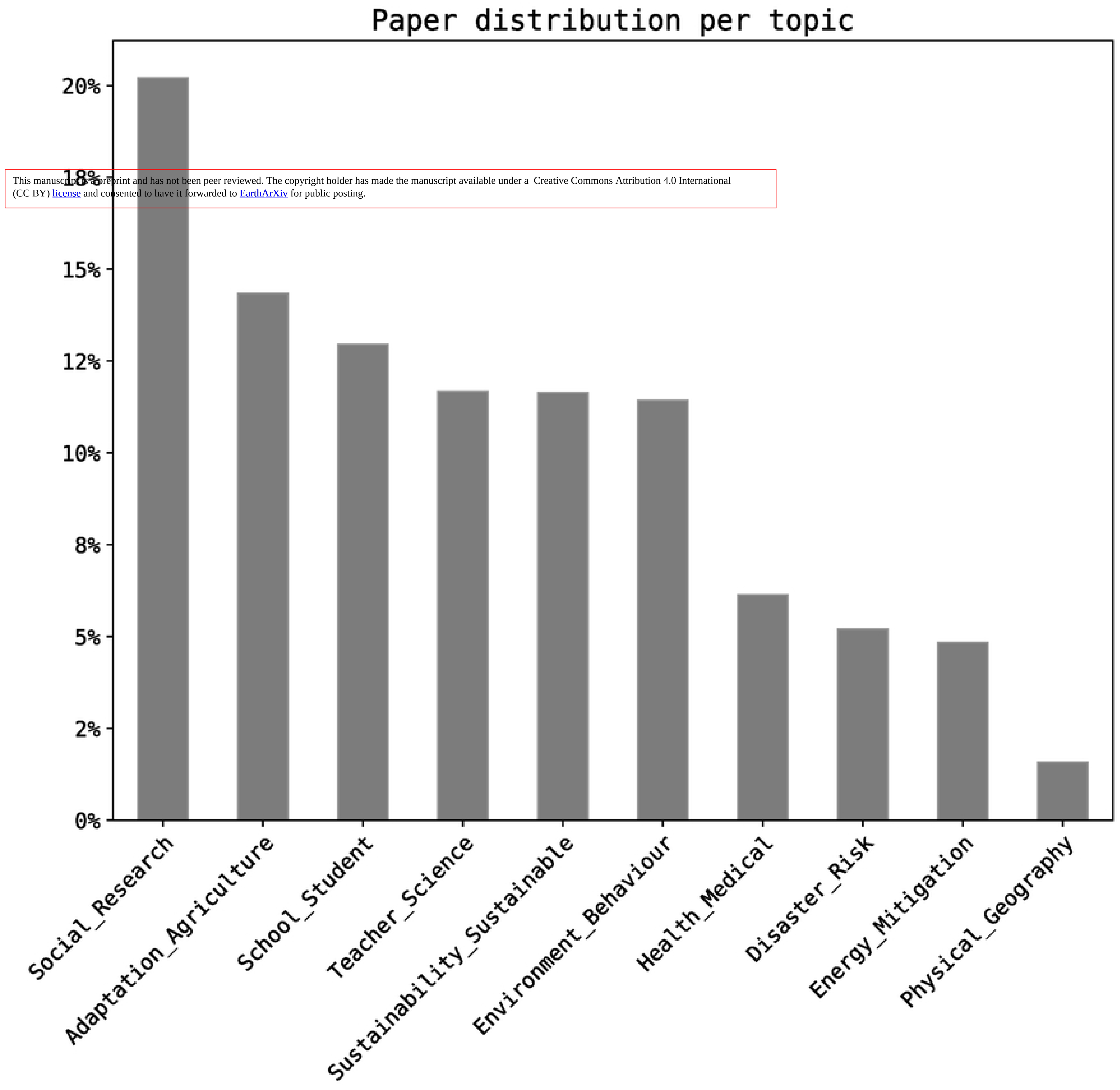
Fig 3



Paper distribution per topic
20%
18%
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8%
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Social_Research
Adaptation_Agriculture
School_Student
Teacher_Science
Sustainability_Sustainable
Environment_Behaviour
Health_Medical
Disaster_Risk
Energy_Mitigation
Physical_Geography

Fig 4

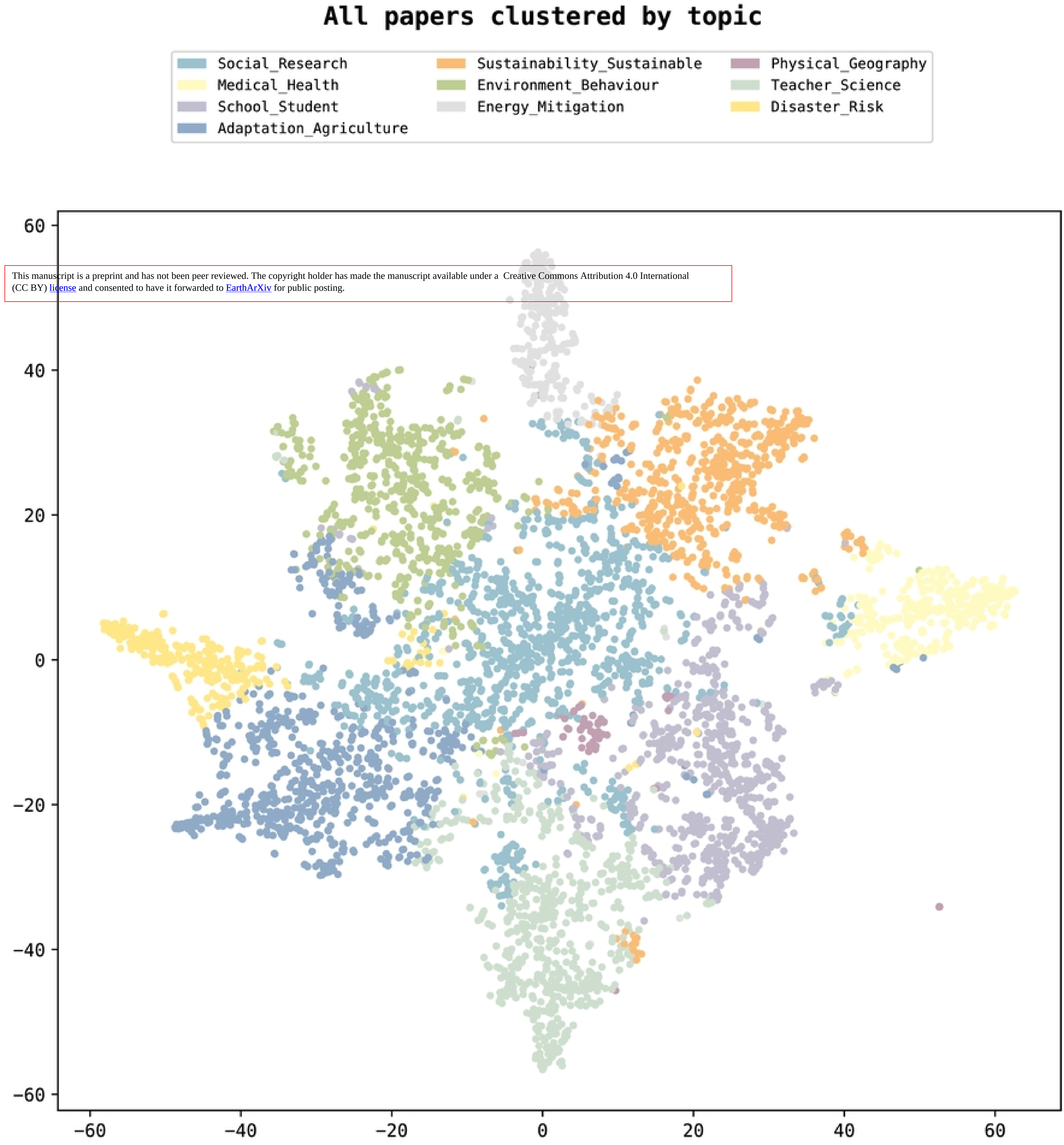
All papers clustered by topic
Social_Research
Medical_Health
School_Student
Adaptation_Agriculture
Sustainability_Sustainable
Environment_Behaviour
Energy_Mitigation
Physical_Geography
Teacher_Science
Disaster_Risk
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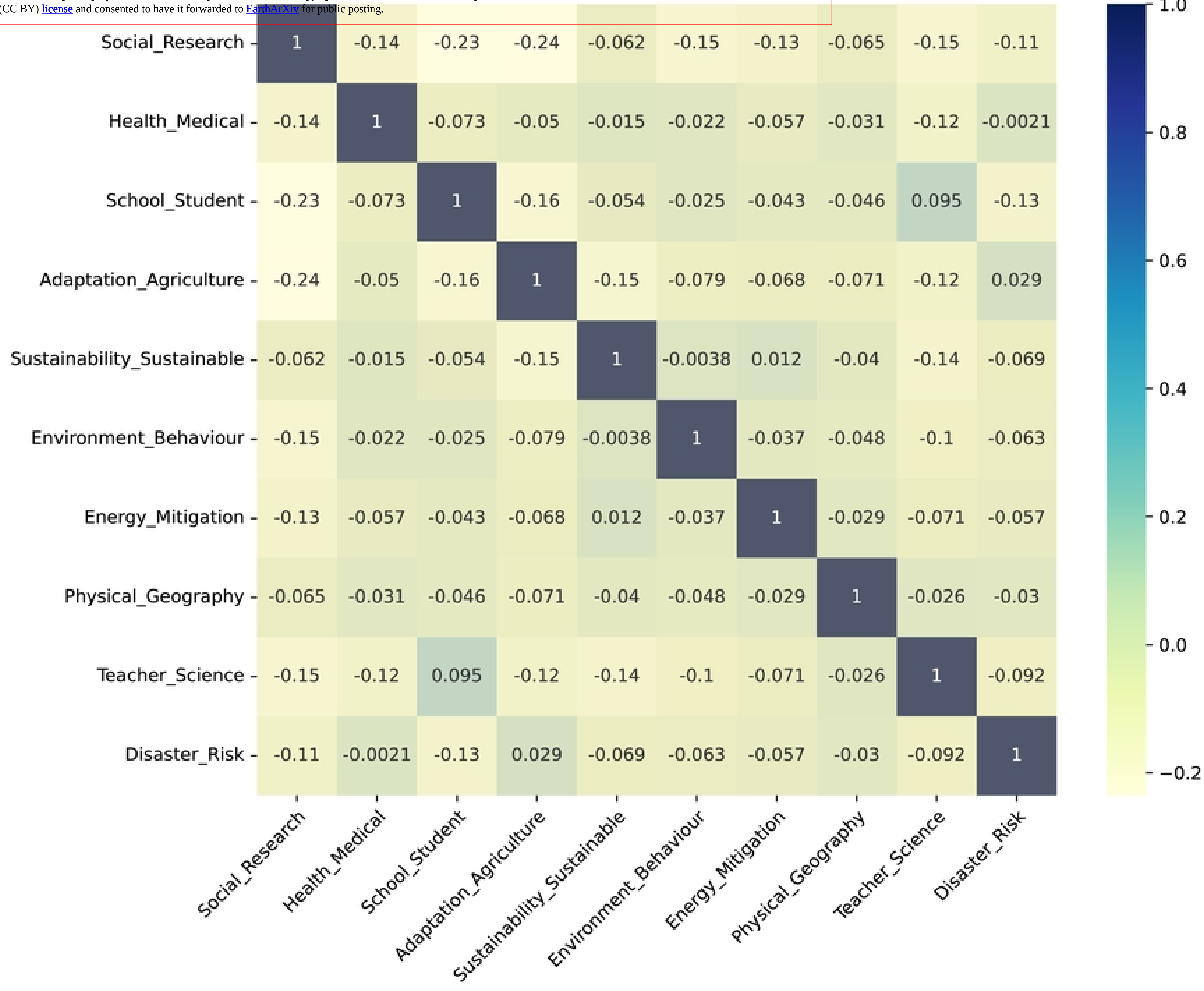
Fig 5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Environment_Behaviour
Energy_Mitigation
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Disaster_Risk
1 -0.14 -0.23 -0.24 -0.062 -0.15 -0.13 -0.065 -0.15 -0.11
-0.14 1 -0.073 -0.05 -0.015 -0.022 -0.057 -0.031 -0.12 -0.0021
-0.23 -0.073 1 -0.16 -0.054 -0.025 -0.043 -0.046 0.095 -0.13
-0.24 -0.05 -0.16 1 -0.15 -0.079 -0.068 -0.071 -0.12 0.029
-0.062 -0.015 -0.054 -0.15 1 -0.0038 0.012 -0.04 -0.14 -0.069
-0.15 -0.022 -0.025 -0.079 -0.0038 1 -0.037 -0.048 -0.1 -0.063
-0.13 -0.057 -0.043 -0.068 0.012 -0.037 1 -0.029 -0.071 -0.057
-0.065 -0.031 -0.046 -0.071 -0.04 -0.048 -0.029 1 -0.026 -0.03
-0.15 -0.12 0.095 -0.12 -0.14 -0.1 -0.071 -0.026 1 -0.092
-0.11 -0.0021 -0.13 0.029 -0.069 -0.063 -0.057 -0.03 -0.092 1
1.0
0.8
0.6
0.4
0.2
0.0
−0.2

Fig 6

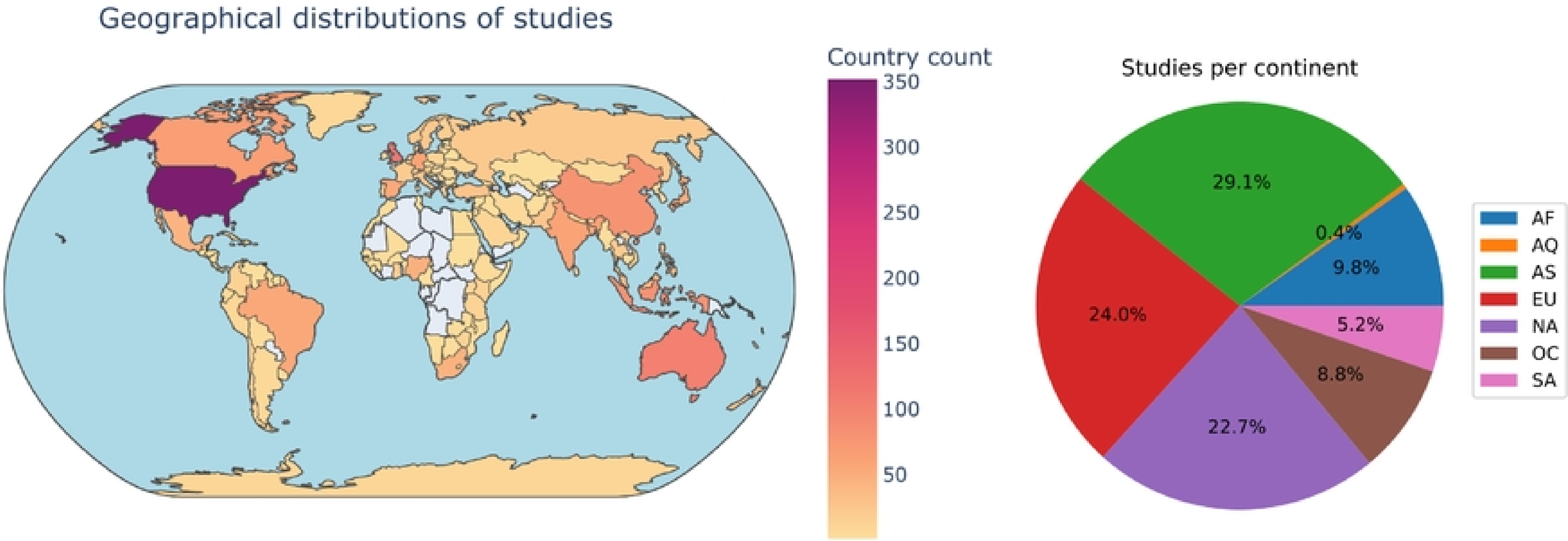
Geographical distributions of studies
Country count
350
300
250
200
150
100
50
Studies per continent
29.1%
0.4%
9.8%
24.0%
5.2%
8.8%
22.7%
AF
AQ
AS
EU
NA
OC
SA

Fig 7