Climate Change Adaptation Policy Across Scales: a Machine Learning Evidence Map

Summary

Climate change adaptation policies are urgently needed, but the large volume and variety of evidence limits the ability of practitioners to make informed decisions. Here, we create an evidence map of adaptation policy research, selecting and categorising 8691 documents using state-of-the-art Transformers-based machine learning models. We combine policy-relevant categories, such as the NATO-typology and governance levels, with automatically extracted locations and a Structural Topic Model to provide a detailed global assessment of the tools governments are using to address climate change risks and impacts. We find that international-level policies, as well as policies in North America and much of the Global South emphasise financial instruments, whereas national policies, particularly in Europe and Oceania, favour authority-based legislation. Collaborative approaches are most common at the local level. Despite a rapidly expanding evidence base overall, we note persistent geographic inequalities and limited evidence on information-based policies, policy implementation and structural reforms.

Keywords: climate change, adaptation policy, Natural Language Processing (NLP), climateBERT, supervised machine learning, topic modelling, unsupervised machine learning, Big Data, evidence synthesis, Paris Agreement

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Introduction

Increasingly, governments around the world are adapting to the risks posed by climate change[1]. While the broad range of available adaptation policy options[2] may be seen as encouraging, in practice, policy makers often face considerable knowledge deficits on the design, implementation and evaluation of specific adaptation policies[3,4].

High quality and up-to-date overviews of scientific evidence on adaptation are thus crucial both to illustrate what adaptations are feasible and effective, and to identify where knowledge gaps remain. To this end, several large-scale international adaptation evidence synthesis efforts have been undertaken by both the scientific community[5,6], by governments themselves (e.g. the Global Stocktake under the Paris Agreement), and combinations of both[1]. Findings here suggest that most national governments have one or more adaptation policies in place and this number is growing; however, adaptation action lags behind mitigation, and current efforts are likely insufficient to adequately address accelerating climate impacts[1,7]. Additionally, although there is a considerable literature on the feasibility of individual adaptations, general statements on efficacy and comparisons between different adaptation options can be challenging[2,5]. As a consequence, evidence synthesis efforts struggle[5,8] to inform policy makers on “what works?”[9,10] focusing instead on “what has been done” or “are we doing enough?”[11]

The reasons for these synthesis difficulties are myriad and are reviewed elsewhere,[11,12] with two major reasons being the fragmented nature of adaptation research and the sheer volume of evidence. Underlying reasons for the fragmentation are differences in the definition of adaptation and of what constitutes successful adaptation;[10,13-15] moreover, literature from fields such as disaster risk reduction may use different terminology from an “adaptation framing”, but is often closely related.[16,17] Such a fragmented field with fuzzy system boundaries means there is no such thing as *the* adaptation literature; however, regardless of what exact definition is used, it is clear that the literature on adaptation to current and future impacts of climate change is extensive: even a relatively simple query in scientific databases results in many thousands of articles,[18] while a more comprehensive adaptation query incorporating more synonyms and terms from closely-related fields will result in tens of thousands of articles with varying degrees of relevance.[5,9]

Machine learning advances offers promising ways to better handle both these difficulties that are typical of “Big Literature”:[19] sophisticated models can recognise and categorise relevant documents, even if the parlance differs, and these algorithms can easily handle large datasets. Efforts have been undertaken herein to modify the traditional systematic review process to incorporate machine learning elements[20-22] and there is an emerging body of studies using machine learning to systematically assess the state of knowledge and progress in an adaptation context.[5,9,23-25]

A distinction can be made in this work on the types of documents analysed. Some directly analyse political documents, such as political speeches and municipal archives,[23] national policy papers[24] or submissions to the United Nations Framework Convention on Climate Change (UNFCCC).[25] Such analyses can provide an indication of shifting attitudes and practices among policy makers, the topics and actions they prioritise or shifts in political discourse, for example. Other studies have focussed on scientific papers, producing overviews of the evidence on topics such as expected climate impacts,[26] implemented adaptations[5,27] and the wider adaptation-related literature.[9] These analyses, alongside more traditional bibliometric work[18] and systematic reviews,[28] provide insight into how adaptation knowledge is developing, but it can be difficult to relate these trends in academic publications to policy making on the ground.

Here, we create a global evidence map of studies that evaluate adaptation policies, providing an overview of the kinds of tools governments worldwide are using to address the risks posed by climate change, as well as identifying places where evidence is lacking. Notably, we take a much broader view of what constitutes adaptation than traditional review methods or bibliometric studies would allow. In particular, we include literature that responds to climate-attributable impacts, even if the authors do not mention climate change or adaptation explicitly, and we include policies from all levels of government. This expansive scope is made possible by the use of cutting-edge supervised machine learning methods, which we use to select relevant documents at scale.

We further connect our findings to established literature on policy analysis by categorising the policies that are discussed in these documents, again using supervised machine learning. These categories include the NATO typology of policy tools[29] which describes four different types of policy: Nodality - providing information or conducting research; Authority – aws and regulations; Treasure – financial investments or risk underwriting; and Organisation – creating institutions or changing the functioning of existing governmental bodies. We also record information on the level of implementation – international, national or subnational – and the types of physical climate risks responded to. We combine this topic modelling, an unsupervised machine learning method, as well as a pre-trained model which extracts geographic locations. Taken together, this gives us a highly detailed view of the state of adaptation policy. More details can be found in the Experimental Procedures. Furthermore, as our approach is relatively easy to replicate, it could be seen as a first step towards establishing a living evidence platform for adaptation policies.

Results

Quickly growing literature on diverse adaptation policies

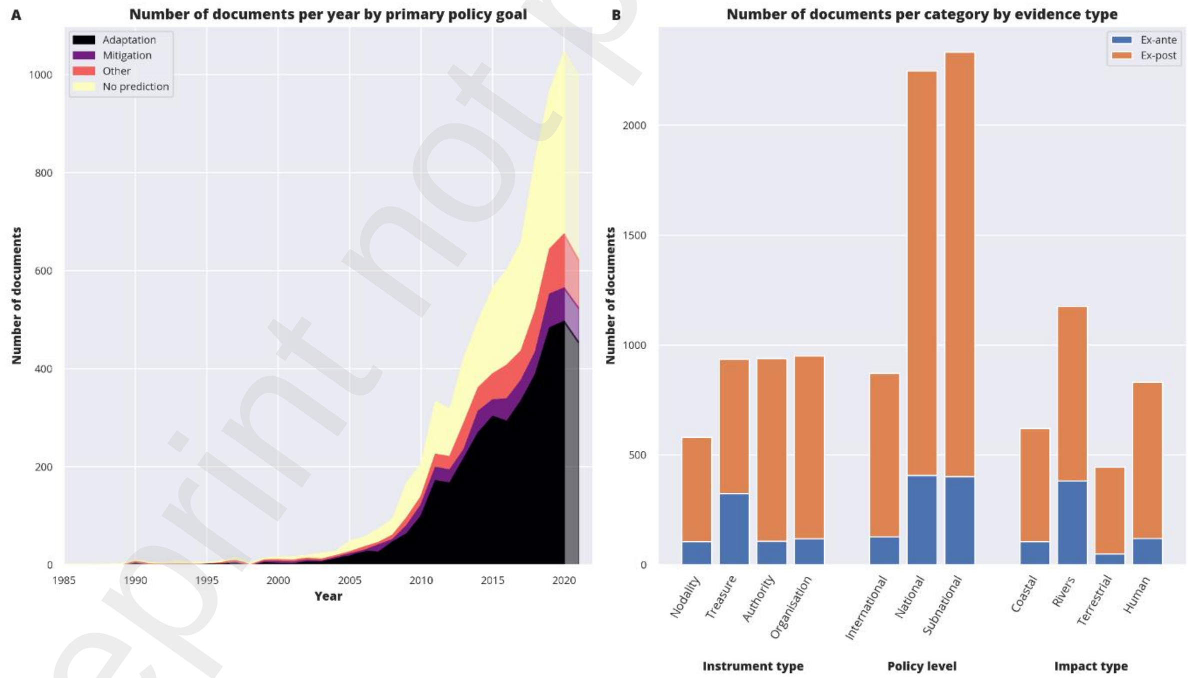

Figure 1: *Overview of the number of documents per category for the full dataset. In figure A, the number of new relevant documents is given per year, where colours represent the primary policy goal. In cases where multiple goals were detected, for example because multiple policies were discussed concurrently, the prediction with the highest confidence was taken. In Figure B, the number of documents for the remaining categories is given, sub-divided by evidence type.*

We find 8691 documents relevant to adaptation policies within our search of 50 462 documents (17.2%), which was conducted in October 2021. This literature is growing quickly, as shown in Figure 1, with the majority (n = 5468, 62.9% of selected documents) being published in or after 2016. This classifier on relevance showed excellent performance, with F1 scores on the test set for the selected hyper parameters of 92.2%, a precision of 92.5% and recall of 92.0%. We are therefore highly confident that our dataset includes the majority of adaptation policy analyses published in Scopus, Web of Science Core Collection and Medline.

The classifier performance for all 5 categories in Figure 1 was lower, with F1 scores ranging from 45.3% to 75.1% (see Supplementary Materials Table 1). Lower scores are to be expected: having multiple categories means there are more ways to make mistakes and distinctions become more granular. Indeed, we saw a drop in inter-coder reliability of human coded document to around 70% for most categories based on our double coding, implying the computer struggles to make classifications where humans struggle too. Moreover, these category classifiers are only trained on the subset of documents that were hand-labelled as relevant (irrelevant documents do not belong to any category), meaning there are far fewer examples to learn from. This is an especially pressing problem for rare categories, notably, *Nodality* for instruments and *Terrestrial* for impact type, which are largely responsible for the low-end of the performance scores. For all categories, we weighted labels relative to their prevalence, which essentially prioritises rare categories, thus improving precision (ranging from 65.7% to 90.1%) over recall (33.7% to 64.8%). In other words, we likely have a substantial number of false negatives for most categories, but false positives are comparatively rare.

Notably, relatively few studies describe policies with indirect or secondary adaptation effects (i.e. *Mitigation* or *Other* environmental policies), suggesting there is a lack of evidence on adaptation co-benefits. A similar imbalance can be seen for the study type, with relatively few *Ex-ante studies* (Figure 1 B). Based on the topic maps (Supplementary Materials Figures 7-9), most *Ex-ante* studies are cost estimates and impact models, often related to insurance, direct investment in flood defence, or management of river dams under different climate scenarios. Finally, international-level policies are far less common in our dataset than national or sub-national policies. Moreover, the international policies cover a much smaller range of topics, focussing on international funding streams.

National sticks, international carrots, subnational collaboration

Variations in policy instruments between different levels of government and location (Figure 2) provide an indication of the types of adaptation actions different actors take, which may reveal under-utilised options and issues of alignment.[30,31] For the distribution of specific topics between different levels of governance and policy instruments, see the topic maps in the Supplementary Materials (Figures 7-9).

At the international level, we find that *Treasure* instruments are the most common type, making up 36.3% of all *International* policies where any tool could be identified. This typically refers to projects supported by the international climate finance architecture (e.g. Global Environment Facility, Global Climate Fund, Adaptation Fund, multilateral development banks). Most of these policy instruments apply to countries in the Global South; combined with direct investments in adaptive infrastructure (e.g. flood defences), this makes studies of *Treasure* instruments especially common in Africa (32.4%), Asia (34.2%) and South America (31.3%). Instruments related to insurance and risk underwriting on the other hand are primarily from North America, where *Treasure*-based policies make up 29.3% of the total in our dataset.

Authority instruments are most common (32.2%) at the *National* level, which aligns with the expectation that national governments are the primary legal authority in most countries and are in large part responsible for designing (national) adaptation strategies. Still, evidence on these instruments is common at all levels, with a substantial literature on international conventions such as the Paris Agreement, as well as local regulations on a broad range of topics, including water management and urban governance. Geographically, *Authority* instruments make up a disproportionate number of policies in Europe (35.0%) and Oceania (34.9%). Given that authority instruments are “harder”, this corresponds well to the relatively ambitious climate targets and climate policy packages set by the European Union especially.

By contrast, *Subnational* policies most commonly (34.5%) rely on the “softer” *Organisation* instruments. This may be a result of the facilitative role played by subnational institutions that need to create implementing organisations and ensure societal support. Many of these policy instruments are related to stakeholder involvement and vulnerability, which may explain the relative abundance of *Organisation* instruments used in Africa. For North America, the overall mix of instruments is relatively evenly distributed, but the socio-political preference for a small government in the United States of America especially may be a contributing factor to the larger frequency of *Treasure* and *Organisation* over *Authority* instruments (29.3% and 29.1% against 22.5% respectively).

Evidence on *Nodality* instruments proved most difficult to find. The small number of nodality studies may therefore be an underestimation, though given the low precision for this particular label (53.8% on the test set with selected hyper-parameters), an overestimation appears equally likely. The few hundred studies in this category are mostly focussed on early warning systems and information on the health effects of climate change.

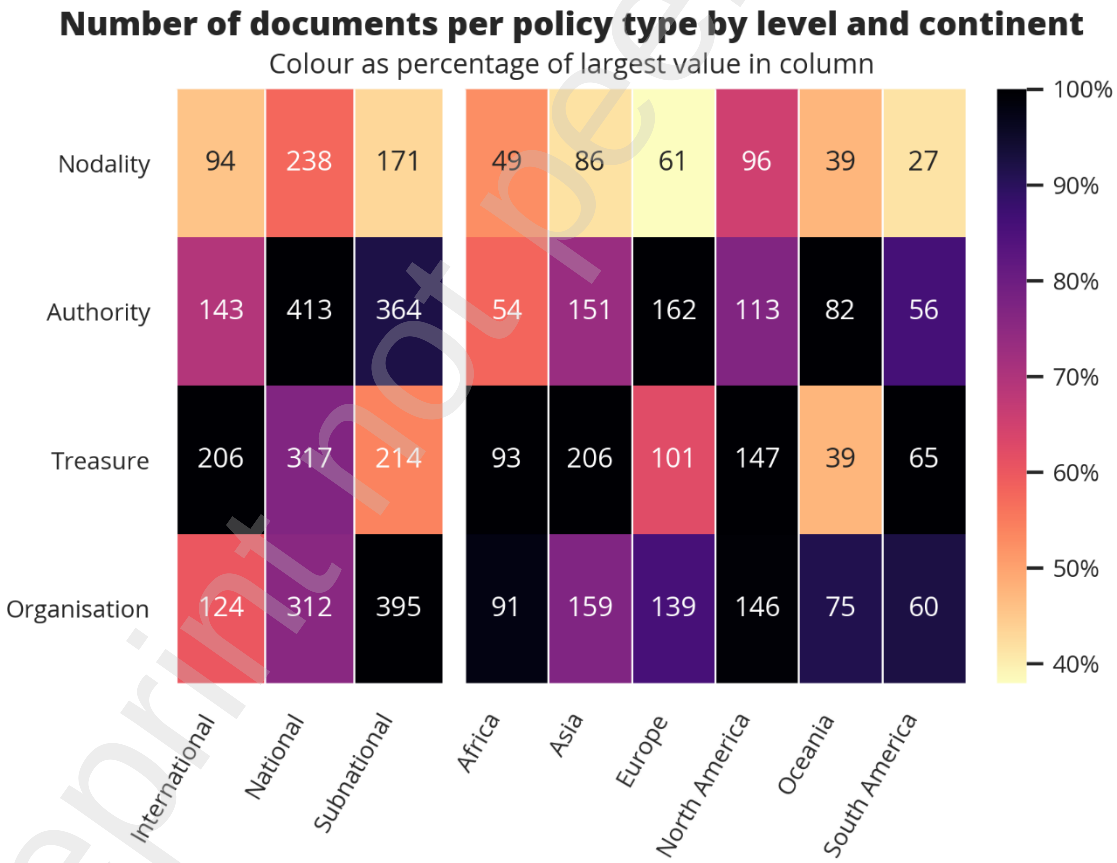

Figure 2: *Heatmap of policy instruments at different governance levels and in different continents. In this heatmap, the value represents the number of documents where categories occur together. For example, the classifier categorised 94 documents as being about a Nodality policy and at the international level. Since the total number of documents per category varies considerably, the colour represents a normalised value relative to the highest number of documents in a column.*

It is worth noting that the NATO model can be used to describe policy mixes[30] – i.e. which combinations of tools are used. However, in our dataset, we found few examples where multiple types of tools were identified in the same document, except for combinations with *Organisation* (co-occurrence with *Authority*: n=239; *Treasure*: n = 111, *Nodality*: n=121). *Organisation* instruments, such as stakeholder involvement or the establishment of a new governmental body, are in this case used as a supportive measure for other instruments.

Limited evidence on policies from the Global South

Given persistent problems around the representation of the Global North in adaptation literature more broadly[9] as well as the considerable variation in adaptive capacity and vulnerability of countries,[32] we assess the global spread of our dataset and combine these locations with the topic model results to identify regionally dominant topics (Figure 3). It is readily apparent that evidence is unequally divided, with the majority of studies mentioning places in the Global North. The UNFCCC has divided its signatories into Annex I and non-Annex I countries, which roughly equate to the Global North and Global South respectively. Annex I countries represent a minority of countries and people but make up 54.3% (n=3961) of the places mentioned in abstracts and titles in our dataset, with places in the USA being by far the most common (n=2172, 29.8%).

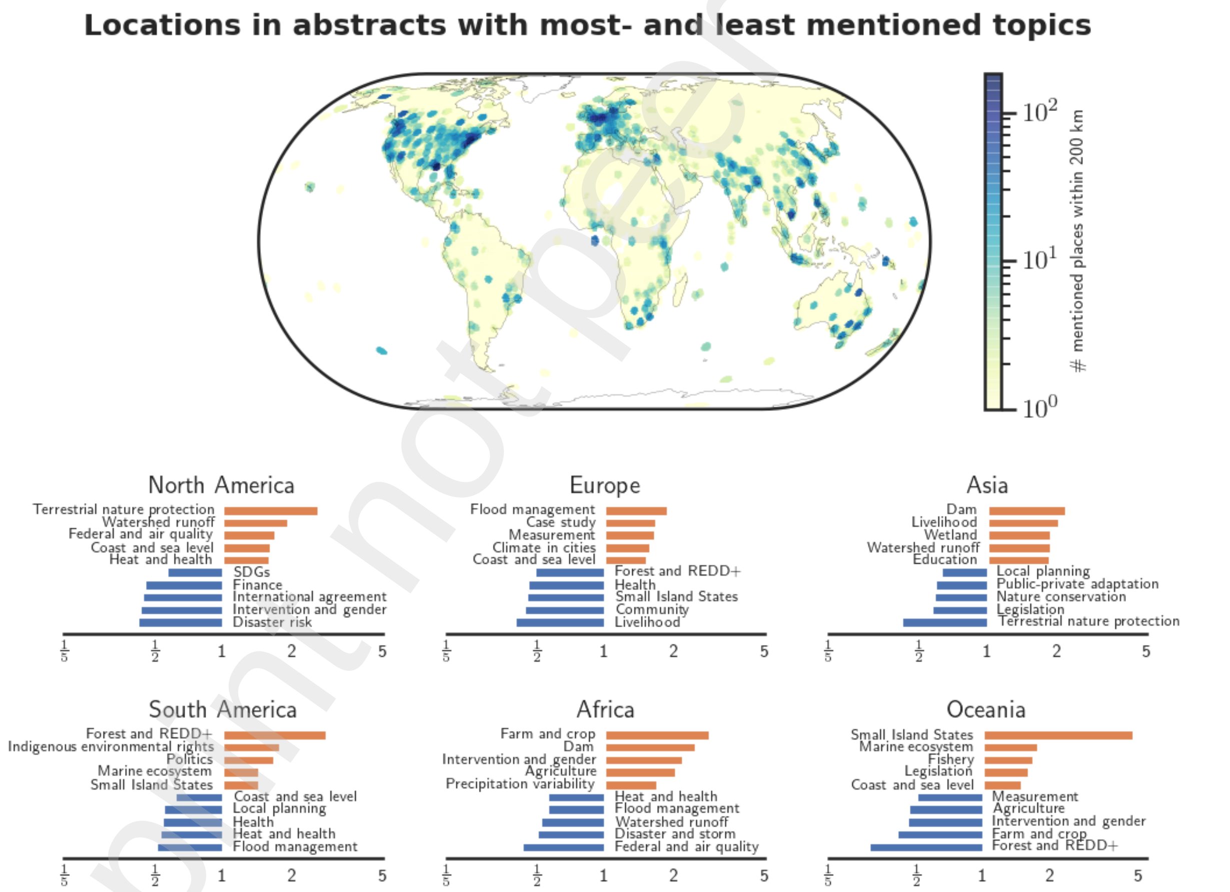

Figure 3: *Map of locations of research, as well as most- and least-mentioned topics. On the map, locations extracted from the title and abstract have been marked by a circle. References to a country or area are placed in the middle of that country or area. If multiple places within the same country were mentioned in one document, only the most specific location is used. The bar graphs below give the topics that are most over- and under- represented in documents from the given continents, relative to the average of all documents.*

A comparatively high number of studies from South-East Asia, especially China (n=414, 5.7%) and India (n=399, 5.5%), mean that one cannot say categorically that more vulnerable countries are studied less (alongside problems on the different operationalisations of vulnerability; see Supplementary Materials Figure 5). However, especially Latin America, much of the Middle East, and most countries in Africa are rarely mentioned in adaptation policy research and many countries in these regions are highly vulnerable.

Importantly, the low numbers of documents in our dataset do not necessarily mean that there are fewer climate policies in these regions. In the Climate Change Laws database[33] for example, Brazil is among the countries with the most adaptation policies listed. Language and location biases likely play a role, as we focus on peer-reviewed journals with an English-language abstract here. However, it is also notable that the Global Adaptation Mapping Initiative,[5] which categorized evidence from implemented adaptation actions, has a higher proportion of Global South literature, despite using the same scientific databases. This suggests that Southern literature has a relatively high proportion of individual projects from non-governmental organisations, while policies are understudied.

Despite the geographical imbalance, the topic model results suggest that the content of the literature generally aligns with the climate priorities of the region. Note that the numbers given in Figure 3 are normalised relative to the average size of each topic, while the in-text numbers are estimated effect sizes based on a linear regression with uncertainty ranges from 25 simulations and the effect size given as a percentage and positive (negative) values describing an increase (decrease). See Supplementary Materials Figure 3 for the corresponding plot.

North America, Oceania and Europe all have a substantial literature on water management issues, with *Coast and sea level* being over-represented in North America (estimated effect: 201.2% , 0.95 confidence interval: 133.9–265.6%) Oceania (175.0%, 68.0–279.6%) and Europe (135%, 63.9–221.0%); in the latter, *Flood Management* (162.6% 93.4–232.7%) and *Case Study* (108.8%, 89.4–130.8%) are notable outliers too, while in Oceania, ocean-related topics receive special attention, including *Small Island States* (247.5%, 168.5–317.0%). *Marine ecosystem* is a relatively small topic, so the effect is not significant (29.3%, -46.6-133.7%), but noteworthy relative to the other regions. In addition to water topics, research in North America also emphasises *Terrestrial Nature Protection* (122%, 73.7–125.4%), which includes keywords on conservation areas. It is also notable that *Intervention and gender* is under-represented in North American literature (-77.1%, -92–-50.2%). In Asia, rather than the more general *Flood management,* the topic *Dam* is relatively most common (99.9%, 57.5–143.6%), in keeping with the earlier emphasis on direct (infrastructure) investments in this region. The latter may also help explain the emphasis on the economic terms captured by the *Livelihood* topic (151.8%, 105.6–197.2%).

For the remaining regions, error estimates are substantially larger, due to the relatively small literature. In South America, notable topics include *Forest and REDD+* (230.1%, 117.4–339.4%; the latter term being the United Nations programme on reforestation), in keeping with the important role of the Amazon rainforest. *Indigenous environmental rights* also make up an outsized proportion of South American literature, but the effect is not significant (18.8%, -12.0–51.6%). Policy research from Africa focusses primarily on food-related issues, with *Farm and crop* (315.0%, 227.1–412.1%), as well as *Agriculture* (95.7%, 49.4–144.6%) being relatively over-represented.

At the same time, geographical imbalances appear even more pronounced when looking at cross-country collaborations (Figure 4). Among the subset of papers with authors from two or more countries (n = 1944 documents), almost half of the first authors (45.6%) are from a European country. It is also notable that for most continents, a substantial percentage of

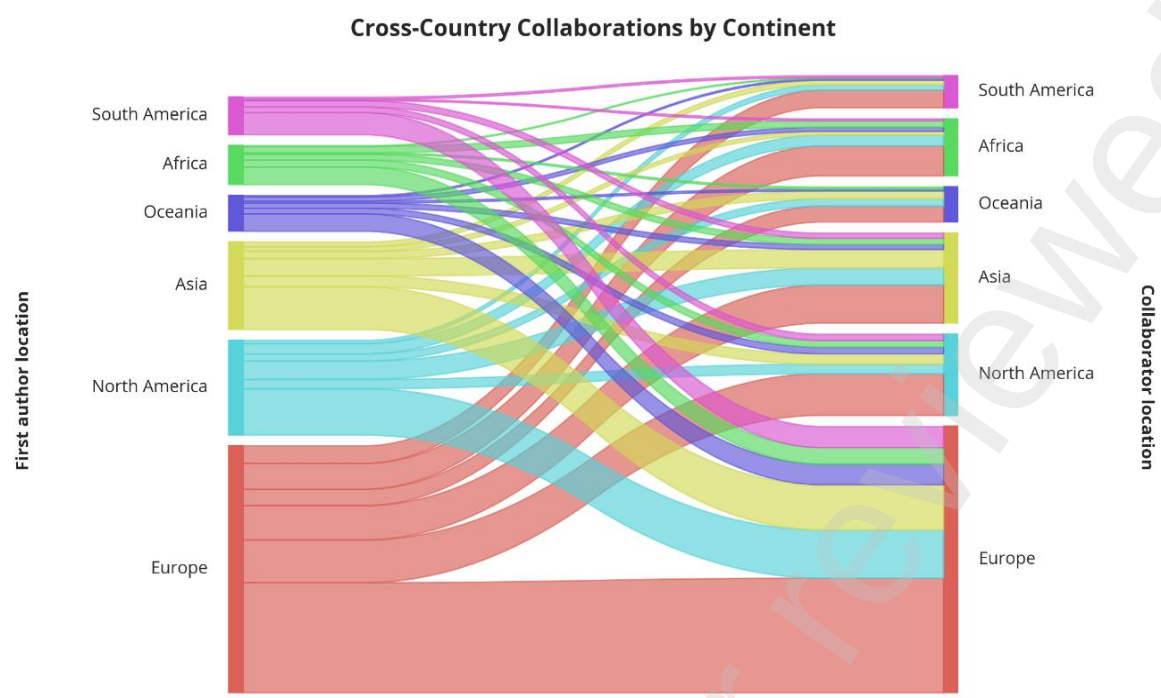

Figure 4: *how often papers are written by authors from different countries, sub-divided by continent. The locations are based on the affiliation of the authors, with first authors on the left and any co-authors on the right. Only papers where the location of the first author as well as of at least one co-author could be identified by the geoparser are represented here. Authors with multiple listed affiliations were counted proportionally -- e.g. when one affiliation was in Europe and one in Asia, both Asia and Europe are counted as a half for this author.*

collaborations is within the same continent. The exception here is North America, but this is because there are only three countries in North America (the Caribbean is counted as part of South America); in other words, while authors from especially the United States and Canada contribute substantially to the adaptation policy literature, they often collaborate with authors from the same country, and are therefore not counted in Figure 4.

In addition, despite persistent calls for South-South collaborations[34] and the important role such collaborations have played in advancing international climate policy,[35] South-South collaborations appear rare in scientific projects. Collaborations between only Annex I countries appear to be extremely scarce (n=385 unique documents) – far fewer than the number of purely Annex I collaborations (n=1051) and less also than North-South collaborations: 500 documents have at least one Non-Annex I author as well as an Annex I author. Still, within these documents, in almost all cases, the majority of authors was based in an Annex I country (n=414, 82.8% of North-South collaborations).

Development topics are gaining ground

The Paris Agreement was adopted in late 2015 and elevated the importance of adaptation on the international stage, emphasising the need for rapid implementation of policies[14,36]. Around the same time, the Sustainable Development Goals (SDGs) were also adopted, highlighting the need for adaptation to incorporate broader sustainability terms to be successful long-term.[37,38] Given the importance of these international agreements, we may expect to see a shift in topics in a similar direction.

Our results show research on a few development-related topics has increased in recent years (Figure 5). This broadly corresponds to the type of shift one would expect in a field where the

SDGs are gaining importance; however, given that most of the decreasing topics are fairly general, it may in part also be a reflection of increasing complexity and maturation of the field of adaptation research, combined with increased research from the Global South.

In line with the latter explanation, the most policy-focussed topics are not among the quickest growing topics. In the full table (Supplementary Materials Figure 10), some topics, like *Programme evaluation* (19.5% increase; confidence interval 9.8–28.7%) and *Implementation and barriers* (18.4%, 10.2–26.5%) do show a statistically significant increase post-Paris Agreement, but we see no significant effect either way for topics such as *Climate governance* (4%, -9.2–18.2%)*,* *Finance* (4.0%, -15.8–25.2%) and *National Policy* (2.3%, -8.7–14.4%)*;* topics like *Legislation* (-20.7%, -36.2–-5.1%) and *Climate strategy* (-16.0%, -24.2–-7.6%) meanwhile show a decrease of a similar magnitude. This suggests that the Paris Agreement's focus on policy implementation is not (yet) resulting in major shifts in research content, even if the volume of research is increasing.

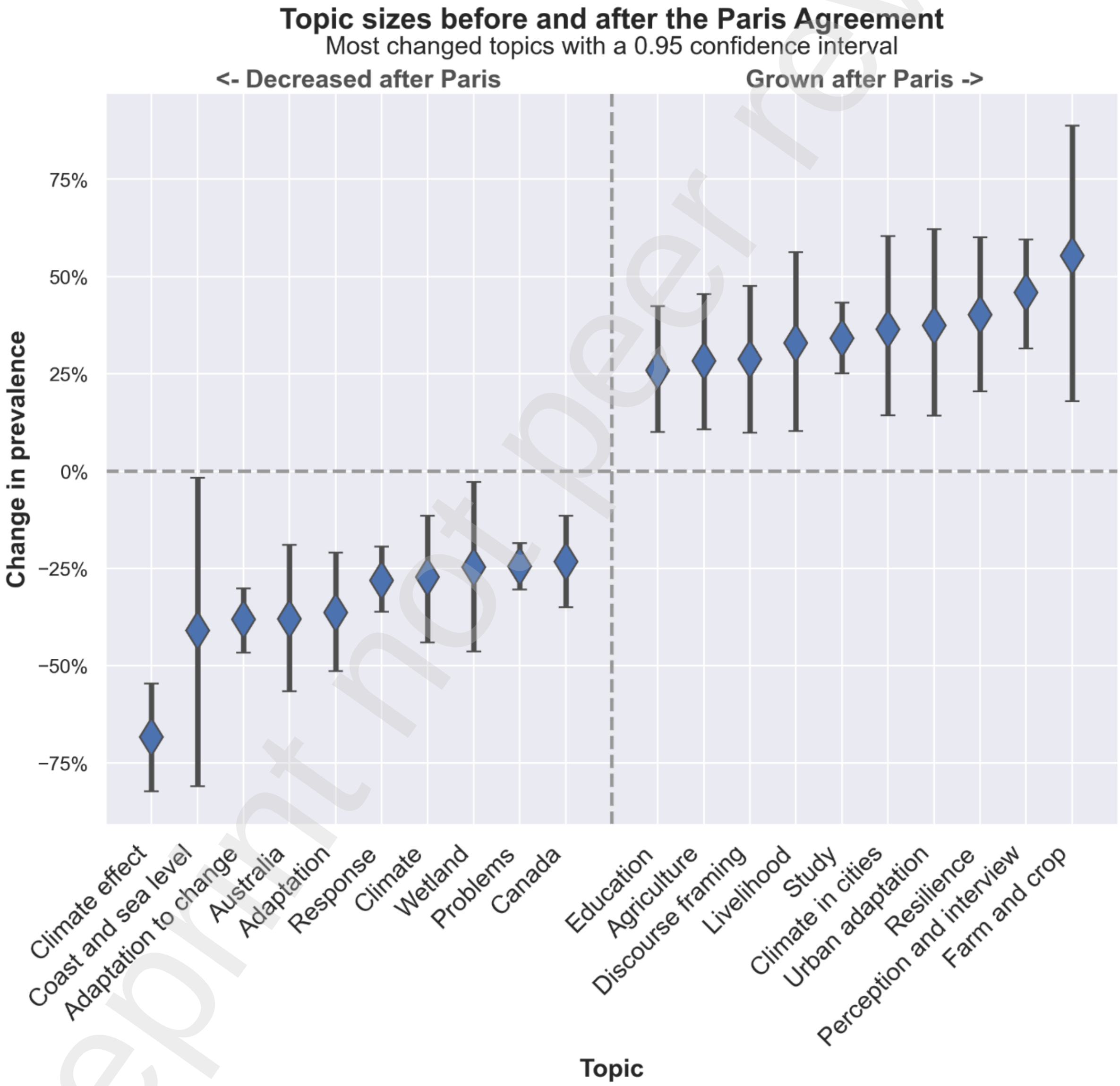

Figure 5: *estimates for how often topics in our Structural Topic Model are discussed in documents published after 2015 relative to before. Only the 5 most-grown and 5 most-decreased topics are given, and non-statistically significant topics are left out too.*

It is also notable that *Resilience* is the third-quickest growing topic (40.2% increase, 18.0–88.7%) while *Vulnerability* is shows a small decrease (-8.4%), though the latter is not statistically significant (conf. -24.2–7.1%). A similar trend was found in a bibliometric analysis of adaptation papers[39] where resilience replaced vulnerability as the most-used keyword. Given the considerable ambiguity around the exact meaning of both these two terms[40,41] one should be careful not to over-interpret this shift; still, it does suggest that adaptation policy studies are increasingly focused on a more immediate and mechanistic understanding of risk, rather than on structural differences and power relationships that form the root causes for climate risks, consistent with arguments made by others. [42,43]

Recent priority issues rarely reflected in policy analyses

Given the size of our dataset, our chosen model with 105 topics provides relatively granular information. However, even in this model, issues like capacity-building, mainstreaming, gender issues, barriers to implementation, health effects (other than heat and air pollution) and nature-based solutions are all relatively small and often share a topic in the model with other issues. This may be surprising given the considerable attention given to all these issues in recent years in the broader adaptation literature, including for example in the latest IPCC assessment report.[6] One should, however, remember that we selected papers where adaptations were supported or instigated by a government entity. In this policy literature, these topics appear to be in their infancy.

Larger, more systemic issues also appear to be discussed less in the context of policy. This includes for example climate resilient development, maladaptation and co-benefits as well as trade-offs, none of which show up in the model. As noted earlier, the lack of policies that were classified as being primarily focussed on mitigation or other non-adaptation goals similarly indicates a lack of research on co-benefits and trade-offs. Current funding structures could be an explanatory factor here: when resources are scarce – relative to the size of the problem anyway[1] – and allocated on a project-basis, the majority of research will focus on smaller, more concrete policies and projects.

Conclusion

Our results support the broader Big Literature trend we described at the outset: literature on adaptation policies is growing quickly. Given that more than a thousand new studies are published per year now and given also the wide variety of topics within adaptation, the use of machine learning methods seems increasingly necessary. Here we show that such a machine learning pipeline for policy-specific documents is feasible and can be used to distinguish macro-level trends and evidence gaps.

These trends paint a mixed picture of adaptation policy research. On the one hand, the volume and variety of research continues to increase, covering a broad range of different instruments and contexts. Evidence from North America, most of Europe and South- and South-East Asia is especially plentiful, and at the international level, projects supported by the international climate finance architecture are a frequent subject of study. At the same time, considerable evidence gaps persist. Three main areas are especially noteworthy.

First, there is a need for assessments of policies that explicitly include components like gender, nature-based solutions and adaptation as a component of structural or transformative changes towards sustainable development. For each of these topics, there is a substantial literature on their theoretical importance,[9,44-47] as well as an increasing amount of practical evidence, mostly from individual projects,[48-50] but it is unclear if, where and how policy makers are incorporating them into laws, regulations and governance more broadly.

Relatedly, our findings support concerns[51] about the lack of research into comprehensive policies. In particular, we find that few evaluated policies use a mixture of tools and that topics within research are not meaningfully more focussed on policy implementation in recent years. An important caveat here is that our work uses abstracts of scientific publications, which are an imperfect proxy for actions on the ground; analysis of full texts and other data sources may uncover more nuanced mixtures of policy instruments.[30] Still, considering how much has been written about "mainstreaming"[10] and about the Paris Agreement as a turning point for adaptation,[36,52] our results provide a sharp contrast, suggesting instead that adaptation policies – or at least studies of policies – often take the form of a specific intervention aimed at solving a single climate impact using a single instrument. Given that a just response to the climate crisis will require a system-level transition and an increased pace of policy implementation,[1] this narrow scope is problematic.[51] To address this gap, it seems prudent to borrow established methods and theories from fields such as political and policy sciences, which have a longer history of evaluating socio-political transformations.

Lastly, geographical imbalances remain a key problem in scientific publishing more broadly,[53,54] but are especially pressing for adaptation research, given the vulnerability of many places in the Global South. The so-called "grey literature," including for example project evaluations by donors and government-led studies, may have better coverage in the Global South, but can be difficult to assess systematically.[5,55,56] In addition to addressing persistent funding inequalities,[57] the adaptation community should therefore prioritise systematic assessments and categorisation of non-academic adaptation evidence especially.

Taken together, these findings suggest that it can still be difficult to find relevant evidence for specific subtopics and for specific contexts. On the technical side, we are butting up against the limitations of current models and data: there simply are not that many studies to learn from and these are difficult to find. For example, for the *Nodality* instruments and *Terrestrial* impacts categories the machine learning classifiers would likely have benefited from a larger training set (i.e. more hand-labelled documents), but finding examples proved extremely time-intensive, requiring the screening of around 100 random documents per example. More detailed classifications – as envisioned in our original coding scheme – could not be made reliably for similar reasons. Advances in few-shot learning (e.g. [58]) may help alleviate this in the future, but at present, the literature is likely simply too small relative to the overall number of publications on adaptation policy.

More practically, this puts adaptation practitioners in a difficult position. Given the context-dependent nature of adaptation, evidence likely needs to meet some specific parameters to be relevant; the consequence is that a large number of studies need to be done to cover different scenarios, yet it is this same deluge of information that makes relevant information like the proverbial needle in an expanding haystack. Moreover, in line with Berrang-Ford, et al. [5], the fast majority of documents from our query did not describe any adaptation policies at all, making policy-relevant information even harder to find. Broad categories and topic maps are essential to document larger trends, but they cannot compensate for a lack of high-quality studies and they do not diminish the need for in-depth assessments.

Importantly however, global assessments do not hinder such in-depth studies; in fact, they can help facilitate them by segmenting the "haystack" into smaller, more focussed classifications. In this way, global assessments can also form the basis for interactive evidence platforms, which would allow practitioners to focus on their specific areas of interest more easily by combining different layers of information – for example, a city official selecting all documents belonging to urban topics which use a *Treasure* instrument in their region. Further, reviews can be set up as a so-called living evidence map, meaning the map can be improved and extended as additional evidence becomes available. This greatly reduces the need for repeated reviews on ever-more specific topics, but it requires long-term support.

To enable high-quality (living) evidence maps, the adaptation community has work to do: researchers and practitioners alike need to become more "machine learning literate" and think strategically on the types of data sources and categories they need to accelerate their work. To be sure, manual qualitative evidence synthesis will remain important for the foreseeable future too, but given the deluge of information, it is increasingly untenable to rely on such methods alone. Machine learning methods, such as those developed here and elsewhere,[5,9,24,26] provide a promising way forward. Given also the increasingly severe impacts of climate change, reliable and scalable ways to synthesise evidence will be instrumental to improving adaptation planning and reducing the harms caused by climate change.

Experimental Procedures

Our methodology was published in a separate protocol[59] where more details can be found. Note that some of the categories mentioned in the protocol proved to be unfeasible in practice; these are not mentioned below. Broadly, our strategy consists of 5 stages (Figure 6): searching, screening, selection, categorisation and synthesis.

Search

The aim for our search was to be as comprehensive as possible to best use the opportunities offered by machine learning. This means that the search results in a substantial number of irrelevant documents which are removed through the screening and selection steps.

We conduct our search in three major scientific databases: Web of Science Core Collection, Scopus and Medline. Our search string has three main components: 1) climate change, with keywords modified from Callaghan, et al. [60] and added recognised climate impacts based on IPCC's AR6 Table 12.2; 2) adaptation, including adaptation-adjacent terms and specific adaptation actions from AR6 WG2's Cross Chapter Box FEASIB; and policy, including terms around governance and terms related to the UNFCCC process. Documents need to match at least one keyword from all three major components – i.e. they are linked by a boolean AND. The majority of keywords for each sub-components are internally linked by a boolean OR.

We retrieve the title, abstract, and meta-information for all documents. No full-texts were retrieved.

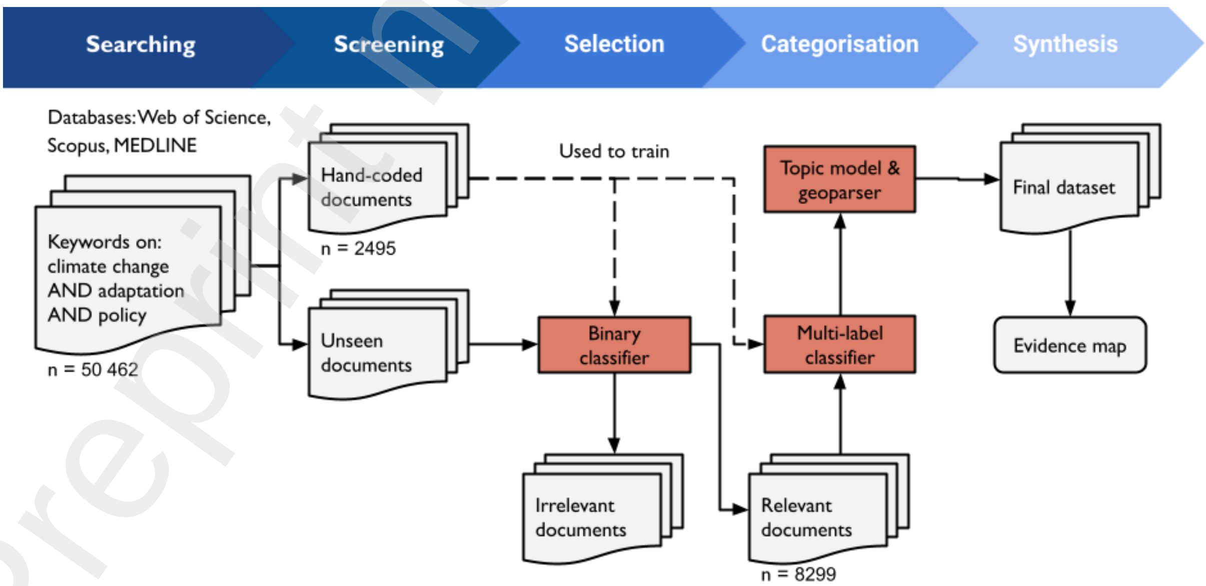

Figure 6: *An overview of the research process in 5 steps. Machine learning components are given in red.*

Screening and selection

The basic premise of supervised machine learning is that a computer can "learn" to mimic human decision making based on examples. We use supervised machine learning both to select relevant documents and to categorise them, but in both cases, no examples exist to learn from. Therefore, in the screening step, AJS, ET, AT and IVC manually labelled 2495 documents. This was done using the NLP Assisted Classification, Synthesis and Online Screening (NACSOS) platform. [61] To ensure consistency, 15% of documents were double coded.

For each document, the human labellers had to decide if it was relevant. A document was considered relevant if it met two criteria: 1) it must include a substantial focus on a response to climate change or to a weather phenomenon wherefore changes can confidently be attributed to climate change, as determined by the IPCC AR6 Table 12.2. Note that neither climate change nor adaptation need to be mentioned explicitly. 2) the adjustment must be either enabled by, supported by, or a direct result of at least one policy. In simpler terms, the document must analyse an adaptation policy.

The majority of documents for labelling were randomly selected, but keyword-based searches and preliminary results of the machine learning classifier were used to increase the number of positive examples for a few categories to reduce screening times.

The labelled documents were used to train a machine learning classifier based on ClimateBERT[62] through HuggingFace.[63] Such Transformers-based language models are at the cutting edge of current NLP methods. This model in particular has been specifically trained to work well on climate change-related texts. Nested cross-validation[26] with four outer loops and three inner loops is used to optimize hyperparameters and measure the accuracy of the classifiers. Given the substantial training times for BERT models, we do not conduct a full grid search for hyper parameters, but instead use Optuna with a Tree-structured Parzen Estimator (TPE) sampler doing 75 trails per inner loop.

Categorisation: supervised learning

If a document was labelled as relevant, further category labels were added in the screening process. These labels were used to train additional classifiers in the same manner as described above, except with a custom loss function to enable class weights, as classes were generally unbalanced. Each of these classifiers was used to make predictions only on the subset of documents that was either labelled as relevant or predicted to be relevant. For the labelling process, each of the categories has multiple options, which are not mutually exclusive. If the document contained insufficient information to assign one of the categories, this category was left blank.

We categorise policies according to the well-established **NATO typology of policy instruments**.[29] The typology has 4 components: *Nodality* involves producing or providing information, including research programmes and information campaigns. *Authority* instruments generally take the form of laws, regulations or agreements, which may or may not be legally binding. *Treasure* involves the spending of public money or the government taking on some form of financial risk, for example by investing in infrastructure or through an insurance scheme. Finally, *Organisation* policies either create a new organisation or change how an existing organisation is governed, for example, the setting up of a governmental committee or involving stakeholders in decision making. The use of this typology allows us to connect our findings to policy research literature, gaining better insights into the types of tools governments favour in different contexts.

There are four more categories for which we hand-label documents. First, some policies have adaptation effects without this being the **primary goal**. Such policies are included, as long as it explicitly mentions an adaptation component or a change in a recognised climate impact. Note that this includes both co-benefits and co-harms/maladaptation. We distinguish between three groups: primarily *adaptation*, primarily *mitigation*, or any *other* policy with adaptation benefits, which includes for example general environmental policies like the creation of a nature conservation area that also has adaptive affects for humans.

Second, the **policy level** refers to what level of the government is responsible for the implementation of the policy and is divided into three options: I*nternational*, including for example the UNFCCC, the European Union and any other multi-country collaborations; *National* refers to any government institution with influence over a whole country, which for federated nations is the federal government; and *Subnational* is any governmental body below national, including municipal or provincial governments, as well as state governments for federated nations and collaborations between different sub-national governments within a country. Although adaptation is often said to be location-specific, adaptation policies are made at all three levels, and the levels may depend on each other – e.g. the Paris Agreement is international legislation, but it requires national governments to submit plans which may require local governments to undertake actions.

Third, the climate **impact type** was recorded. In simple terms, this denotes what type of environmental change the adaptation policy is responding to. Although we started with an extensive list of impacts based on AR6 Table 12.2, we later combined these labels into four options based on Callaghan, et al. [26]: C*oastal,* including sea level rise and coastal flooding, as well as coastal storms; *Rivers*, including fluvial flooding and non-coastal storms, *Terrestrial,* including forests and desertification, and *Human,* including health impacts, agriculture and urban areas.

Finally, the **evidence type** of studies is labelled too. Here, there are two options: E*x-ante* and *Ex-post*. This refers to the kind of study that was conducted, where the former denotes studies based on forecasts or models, and the latter encompasses all evidence based on ongoing or completed projects. Distinguishing between the two is important as ex-post studies indicate that policies are being implemented, not just discussed, whereas some ex-ante studies are likely also necessary to ensure that adaptation policies meet predictions of climate change.

Categorisation: pre-trained and unsupervised learning

In addition to the hand-coded categories described above, we also use a pre-trained **geoparser**[64] to identify geographic locations in the documents, as well as in the affiliations of authors. Since the geoparser does not recognise country adjectives (e.g. "German" instead of "Germany"), we also use a dictionary method to find these words. Language and location bias likely influence the geographic spread of evidence,[65,66] but it is still important to establish where in the world evidence is lacking and to compare the content of policies to location-specific effects of climate change.

Lastly, we use a **topic model** to gain a more fine-grained understanding of the content of the selected documents. Topic models are an unsupervised machine learning method, meaning they do not use labels but instead infer a structure from the input data autonomously. In simple terms, a topic model tries to find clusters of words that frequently occur together in different documents. For each document, it then calculates a score for each of the topic clusters.

We use a Structural Topic Model (STM)[67] as it allows for the incorporation of meta-data and more formal hypothesis testing by estimating error ranges. Standard pre-processing was done using Quanteda, including stopword removal and stemming. We use single words, but also include bigrams (e.g. "climate change" or "adaptation policy" are kept together instead of being treated like separate terms), as we found this made a substantial difference to the interpretability of our topic model. Single words had to occur at least 10 times and occur in a maximum of 95% documents; for bigrams the minimum frequency was increased to 100 to decrease computation times.

Topic models were ran for 50, 75, 85, 100 and 125 topics initially. The range between 100 and 125 appeared to include an appropriate level of detail without resulting in too many "junk topics". We then ran additional models for 100, 105, 110 and 120 topics, and finally used STM's modelselection feature with 60 initial runs to create a range of models with 105 topics, selecting the model with the best exclusivity and semantic coherence for our final model. Each topic was then named based on their most-associated keywords (see Supplementary Materials Table 2) and highest scoring documents. For geographical analyses, topics with geographical keywords (e.g. country names) were removed manually.

Synthesis

In our analysis, we focus on three different factors: combinations of different categories, geographical variations, and changes in the discourse over time. The first is relatively straight forward: heatmaps are created by counting the number of documents for different combinations of categories.

To identify locally dominant topics, for all topics, we calculate the average topic score of the documents from each region, where the regional information is taken from the geoparser. These regional topic scores are then divided by the global average to find relative over- and under-representations. We also conduct the same analysis using STM's built-in effect estimation function, which incorporates error ranges. These are reported only in the Supplementary Materials (Figure 3) as the resulting topics are similar and the numerical values more difficult to interpret than a ratio.

To investigate how the discourse has changed over time, we focus on differences between the literature pre-2016 versus all papers published since. Although more detailed analyses on shifts over time are possible in theory, yearly variation is substantial for many topics, leading to considerable error ranges for most topics and no significant trends at the yearly level. The dataset may simply be too small relative to the detail in our topic model: even in the most recent years, around 1000 documents were published, meaning that in a model with 105 topics, a dozen papers on a given topic may create a large swing. By treating the publication year as a categorical variable instead, we can distinguish significant changes. The specific time periods (pre- and post-2016) were chosen as this divided the dataset in roughly equal parts and because both the Paris Agreement and the SDGs were adopted in late 2015. The Paris Agreement greatly increased the importance of adaptation at the global stage [36], while others have argued that adaptation policies should align with the targets set in the SDGs to be successful long-term [37,38]. By seeing which topics have shifted significantly between the two periods, and which topics have not, we find an indication if these international policies have led to a corresponding shift in the academic literature.

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Author contributions

Conceptualisation, AJS, RB, MC, JCM and JDF; Methodology, AJS, ET, RB, AT, MC, JCM and JDF; Software: AJS and MC; Investigation, AJS, ET, AT and IVC; Data Curation, AJS; Writing

– Original Draft, AJS; Writing – Reviewing & Editing, AJS, ET, RB, AT, JCM and JDF; Visualization, AJS and MC; Supervision, JCM and JDF.

Declaration of interests

The authors declare no competing interests.

Data and code availability

All original code and document data will be deposited at Zenodo and made publicly available as of the date of final publication. At time of first submission however, this has not yet been published. Reviewers who wish to see the code or data, please contact eeajs@leeds.ac.uk

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Supplementary Materials

Climate Change Adaptation Policy Across Scales: a Machine Learning Evidence Map

Model performance

Table 1: Performance of the different classifiers based on nested cross-validation. Averages are calculated from the test sets in the outer loop. The hyper-parameters which resulted in the highest F1 score were then used to re-train on the complete labelled dataset; this score is given as 'selected'. Categories marked with an asterisk had one outer loop where the tests scores were near 0, indicating that, for that this loop the model was over-fitting. Given that these hyper-parameters were disregarded for the full prediction, performance for these categories especially is likely to be closer to the selected score than to the average.

Category	F1	Precision	Recall
Inclusion	Average: 89.1% Selected: 92.2%	Average: 89.6% Selected: 92.5%	Average: 89.1% Selected: 92.0%
NATO	Average: 39.7% Selected: 49.3%	Average: 60.1% Selected: 65.7%	Average: 30.6% Selected: 40.3%
Primary policy aim*	Average: 46.2% Selected: 65.6%	Average: 59.5% Selected: 82.3%	Average: 38.3% Selected: 55.6%
Governance level	Average: 62.1% Selected: 69.4%	Average: 79.9% Selected: 84.0%	Average: 51.9% Selected: 59.6%
Impact responded to*	Average: 31.9% Selected: 45.3%	Average: 59.9% Selected: 84.0%	Average: 22.9% Selected: 33.7%
Study type	Average: 61.9% Selected: 75.1%	Average: 78.9% Selected: 90.1%	Average: 51.2% Recall: 64.8%

Topic model

Table 2: top keywords using STM's standard range of metrics for each topic.

Topic name	Notes	Top keywords
Sustainable development		Highest Prob: develop, sustain, climat_develop, chang_develop, develop_climat, develop_chang, growth
		FREX: sustain, chang_develop, develop, sustain_develop, sustain_climat, develop_chang, climat_develop
		Lift: sustain_develop, develop_sustain, climat_sustain, sustain_climat, chang_sustain, develop_chang, sustain
		Score: develop, sustain, climat_develop, chang_develop, develop_climat, sustain_develop, develop_develop
Plays a role	Junk	Highest Prob: role, import, effort, play, play_role, attent, can
		FREX: play, play_role, role, effort, role_climat, import, role_chang
		Lift: play, play_role, role_chang, role_climat, chang_effort, climat_effort, role
		Score: role, play, play_role, effort, import, role_climat, role_adapt
Precipitation variability	ENSO = El Nino Souther Oscilation	Highest Prob: drought, rainfal, year, increas, area, variabl, period
		FREX: drought, landslid, rainfal, water_drought, record, plain, season
		Lift: geo-hydrolog, enso, drought, 1979, aqueduct, drought-rel, nino
		Score: drought, rainfal, landslid, water_drought, season, dri, variabl
Stakeholder involvement		Highest Prob: process, stakehold, tool, decision-mak, participatori, can, context
		FREX: process, stakehold, adapt_process, decision-mak, tool, participatori, process_climat
		Lift: adapt_process, ccfms, process, process_climat, chang_process, iter, climat_process
		Score: process, stakehold, decision-mak, tool, participatori, adapt_process, process_climat
Legislation		Highest Prob: new, law, legal, articl, regul, legisl, regulatori
		FREX: law, legal, legisl, zealand, chang_new, regulatori, new
		Lift: diagon, law, court, legal, chang_new, zealand, tabasco
		Score: law, legal, new, legisl, regul, regulatori, zealand
Climate effect		Highest Prob: chang, will, climat, effect, futur, current, affect
		FREX: effect_chang, climat_chang, climat_will, will, chang_will, chang_chang, climat_effect
		Lift: chang_will, climat_will, chang_affect, climat_chang, effect_chang, climat_affect, chang_requir
		Score: chang, will, climat, climat_will, effect_chang, effect, climat_chang

Topic name	Notes	Top keywords
Dam	MCM = Milion Cubic Metre; Aswan for Aswan Dam, GLOF = Glacial Lake Outburst Flood; GERD = Grand Ethiopian Renaissance Dam	Highest Prob: dam, reservoir, oper, lake, hydropow, storag, regul
		FREX: dam, reservoir, hydropow, nile, indus, lake, glacier
		Lift: ibi, mcm, aswan, glof, snowpack, dam, gerd
		Score: reservoir, dam, hydropow, lake, nile, downstream, mcm
Study	Science lingo without much meaning	Highest Prob: studi, result, analysi, base, show, method, compar
		FREX: result, show, method, studi, base, analysi, index
		Lift: index, weight, method, attribut, result, show, multi-criteria
		Score: studi, analysi, result, show, method, index, base
Flood management		Highest Prob: flood, flood_manag, increas, protect, area, damag, flood_flood
		FREX: flood_flood, flood, flood_manag, manag_flood, chang_flood, flood_increas, adapt_flood
		Lift: adapt_flood, flood_area, flood_flood, chao, manag_flood, phraya, flood_chang
		Score: flood, flood_manag, flood_flood, risk_flood, flood_climat, floodplain, chang_flood
Climate in cities	There is also a separate adaptation and urban topic	Highest Prob: citi, citi_climat, climat_citi, adapt_citi, chang_citi, citi_chang, plan_citi
		FREX: citi_climat, climat_citi, adapt_citi, chang_citi, citi_chang, citi_adapt, citi_citi
		Lift: bandar, citi_adapt, citi_chang, citi_climat, superblock, adapt_citi, chang_citi
		Score: citi, citi_climat, climat_citi, adapt_citi, chang_citi, citi_chang, plan_citi
Challenge	Fairly generic	Highest Prob: challeng, address, face, opportun, futur, present, includ
		FREX: challeng, challeng_chang, face, challeng_climat, address, opportun, climat_challeng
		Lift: challeng_chang, challeng_climat, challeng, address_challeng, climat_challeng, chang_challeng, face_challeng
		Score: challeng, address, challeng_chang, challeng_climat, face, opportun, chang_challeng
Capacity building		Highest Prob: capac, build, enhanc, strengthen, capac_climat, capac_chang, build_capac
		FREX: capac, capac_climat, capac_chang, build_capac, build, capac_adapt, strengthen
		Lift: capac_climat, build_capac, capac_chang, capac, dar, enhanc_capac, salaam
		Score: capac, build, capac_climat, capac_chang, build_capac, capac_adapt, enhanc_capac
SDGs	Unsure why China (inc. lake Taihu) and Japan are in this.	Highest Prob: goal, china, achiev, implement, sustain_goal, agenda, progress
		FREX: sustain_goal, sdgs, china, goal, achiev_goal, chines, japan
		Lift: dah, mdgs, sdgs, sustain_goal, taihu, achiev_goal, sdg

Topic name	Notes	Top keywords
	MDGs = Milenium Development Goals	Score: china, goal, sdgs, sustain_goal, chines, japan, sdg
Uncertain decision making	RDM = Robust Decision Making; DAPP = Dynamic Adaptive Policy Pathways; ATP = Adaptation Tipping Points	Highest Prob: decis, uncertainti, futur, make, long-term, pathway, robust
		FREX: uncertainti, decis, robust, pathway, flexibl, uncertain, maker
		Lift: rdm, signpost, dapp, atp, uncertainti, uncertainti_climat, uncertainti_chang
		Score: uncertainti, decis, pathway, flexibl, robust, futur, uncertainti_climat
System	Sic seems to have been used as a filler word for unknow characters	Highest Prob: system, sic_sic, complex, social-ecolog, system_climat, sic, system_chang
		FREX: sic_sic, sic, system, system_chang, system_climat, adapt_system, social-ecolog
		Lift: adapt_system, system_chang, sic, sic_sic, system_climat, ses, system_adapt
		Score: system, sic_sic, sic, social-ecolog, system_climat, system_chang, adapt_system
Greeenhouse gas emissions		Highest Prob: emiss, transport, greenhous, gas, carbon, reduc, greenhous_emiss
		FREX: greenhous, greenhous_emiss, transport, gas, ghg, emiss, reduc_emiss
		Lift: intermod, greenhous, greenhous_emiss, usiji, gase, ghg, reduc_emiss
		Score: emiss, greenhous, gas, greenhous_emiss, transport, carbon, ghg
Climate strategy		Highest Prob: strategi, climat_strategi, chang_strategi, strategi_climat, strategi_chang, develop_strategi, adapt_strat
		FREX: climat_strategi, chang_strategi, strategi_climat, strategi, strategi_chang, develop_strategi, strategi_adapt
		Lift: climat_strategi, strategi_climat, chang_strategi, develop_strategi, strategi_adapt, strategi_chang, strategi
		Score: strategi, climat_strategi, chang_strategi, strategi_climat, strategi_chang, adapt_strategi, develop_strategi
Programme evaluation		Highest Prob: program, evalu, effect, data, overal, includ, util
		FREX: program, evalu, data, nation_program, use_data, util, effect
		Lift: program, acquisit, evalu, catarina, nation_program, 0.001, beef
		Score: program, evalu, data, effect, nation_program, use_data, util
Research and innovation	CXC = ClimateXChange (Scottish programme); CCS = carbon caputure and storage	Highest Prob: research, innov, work, field, technolog, highlight, gap
		FREX: research, innov, field, research_climat, climat_research, work, chang_research
		Lift: cxc, chang_research, research_climat, research, ccs, climat_research, innov
		Score: research, innov, field, technolog, research_climat, work, climat_research
Land use		Highest Prob: use, land, area, can, chang_use, climat_use, spatial

Topic name	Notes	Top keywords
		FREX: chang_use, use, climat_use, land_chang, use_climat, use_studi, use_chang Lift: chang_use, use_chang, land_chang, studi_use, use, land_plan, use_climat Score: use, land, land_plan, land_chang, chang_use, climat_use, use_climat
Europe	CCOP = Coordinating Committee for Geoscience Programmes in East and SE Asia -- unsure why it ended up with this topic, but there are only two papers; MSFD = Marine Strategy Framework Directive	Highest Prob: european, europ, main, aim, union, germani, direct FREX: european, union, europ, germani, franc, itali, portug Lift: ccop, czech, european, hungari, serbia, slovenia, msfd Score: european, europ, union, germani, itali, franc, poland
Social and cross-cutting success	NBS= nature based solutions	Highest Prob: social, success, outcom, multipl, benefit, object, solut FREX: success, multipl, outcom, social, solut, rang, object Lift: nbs, multipl, success, outcom, nature-bas, accept, solut Score: social, success, solut, outcom, benefit, multipl, nbs
Public-private adaptation	Mostly public? RDWA = Rural Drinking Water Associations; SMEs = Small and Medium Enterprises	Highest Prob: public, privat, author, public_climat, public_adapt, climat_public, adapt_public FREX: public_adapt, public, public_climat, privat, adapt_public, chang_public, climat_public Lift: second-ti, public_adapt, rdwa, vienna, smes, adapt_public, public Score: public, privat, public_climat, public_adapt, adapt_public, climat_public, chang_public
Framework	MDPI = the publisher with an office in Basel whose copyright message was not fully removed	Highest Prob: framework, propos, appli, relev, structur, administr, concept FREX: framework, administr, element, relev, propos, appli, develop_framework Lift: develop_framework, climat_framework, switzerland, administr, basel, mdpi, chang_framework Score: framework, propos, administr, concept, relev, appli, structur
Disaster risk	DRR = Disaster Risk Reduction; CCA = climate change adaptation	Highest Prob: disast, reduct, disast_reduct, risk, drr, cca, disast_manag FREX: disast_reduct, drr, cca, climat_disast, risk_drr, disast_drr, sendai Lift: climat_disast, cca, disast_reduct, drr, hyogo, risk_drr, chang_cca Score: disast, disast_reduct, drr, cca, reduct, disast_manag, risk_drr
Small Island States	SIDS = small island developing states	Highest Prob: island, small, pacif, state, sid, small_state, caribbean FREX: sid, small_state, island_state, small_develop, island, vanuatu, pacif

Topic name	Notes	Top keywords
		Lift: pep, pic, small_develop, atol, ikm, island_state, kiribati
		Score: island, pacif, sid, small_state, island_state, small_develop, small
Discourse framing	NGDOs = Non-Governmental Development Organisation	Highest Prob: frame, actor, discours, debat, interest, narrat, influenc
		FREX: discours, frame, narrat, debat, domin, normat, arena
		Lift: ngdos, kingdon, discours, frame, discurs, cork, epistem
		Score: discours, frame, actor, narrat, discurs, debat, agenda
Groundwater		Highest Prob: water, suppli, demand, water_water, groundwat, scarciti, chang_water
		FREX: climat_water, groundwat, water_water, chang_water, adapt_water, water_system, aquif
		Lift: aquif, overdraft, inter-basin, climat_water, water-suppli, adapt_water, recharg
		Score: water, water_water, groundwat, suppli, water_manag, climat_water, chang_water
Africa		Highest Prob: africa, south, african, asia, ghana, east, west
		FREX: africa, african, asia, kenya, ghana, south, cape
		Lift: africa, african, asia, cape, ssa, sadc, mozambiqu
		Score: africa, south, african, asia, sub-saharan, ghana, kenya
Renewable energy		Highest Prob: energi, renew, electr, effici, technolog, power, generat
		FREX: electr, energi, renew, solar, oil, biofuel, compani
		Lift: biodiesel, gcc, photovolta, biofuel, feedstock, olnpp, electr
		Score: energi, electr, renew, solar, biofuel, gcc, oil
Watershed runoff	BMPs = Best Management Practices; LID = Low Impact Development; SuDS = Sustainable Drainage System; SWMM = Stormwater Management Model; WWTPs = Wastwater Treatment Plants	Highest Prob: watersh, runoff, drainag, stormwat, hydrolog, area, rainfal
		FREX: runoff, drainag, spong, bmps, lid, discharg, sud
		Lift: swmm, wwtps, infiltr, lid-bmp, rwh, sud, bmp
		Score: runoff, stormwat, drainag, spong, watersh, discharg, lid
Collaboration	IGCP = International Geoscience Programme; c2c	Highest Prob: network, organ, particip, engag, collabor, activ, actor
		FREX: organ, collabor, engag, network, particip, partnership, share
		Lift: igcp, c2c, sna, collabor, organ, forum, geoscienc

Topic name	Notes	Top keywords
	= city to city; SNA = Social Network Analysis	Score: network, collabor, organ, particip, engag, actor, partnership
Urban adaptation	SUWM = Sustainable Urban Water Management	Highest Prob: urban, area, climat_urban, settlement, growth, metropolitan, urban_chang
		FREX: urban, urban_climat, chang_urban, urban_polici, climat_urban, adapt_urban, metropolitan
		Lift: dhaka, suwm, pathumthani, urban_polici, megac, urban_climat, chang_urban
		Score: urban, climat_urban, urban_chang, chang_urban, urban_manag, urban_climat, adapt_urban
United States and wildfires		Highest Prob: state, unit, fire, california, wildfir, counti, state_climat
		FREX: wildfir, fire, state, california, unit, chang_state, state_climat
		Lift: eft, oklahoma, wine, cedar, firefight, burn, maryland
		Score: state, fire, wildfir, unit, california, state_climat, eft
Environmental improvement		Highest Prob: improv, integr, environ, provid, establish, oper, within
		FREX: improv, environ, integr, establish, comprehens, oper, provid
		Lift: environ, improv, comprehens, unifi, oper, integr, establish
		Score: integr, improv, environ, oper, comprehens, applic, provid
Coast and sea level	ICZM = Integrated Coastal Zone Management	Highest Prob: coastal, rise, sea, sea_rise, zone, coast, protect
		FREX: sea_rise, climat_coastal, shorelin, sea-level, coastal, slr, beach
		Lift: iczm, dune, landward, marsh, schleswig-holstein, sea_rise, set-back
		Score: coastal, sea, sea_rise, sea-level, rise, beach, coastal_manag
Agriculture	CSA = Climate Smart Agriculture	Highest Prob: agricultur, food, secur, product, climat_agricultur, csa, insecur
		FREX: csa, climat_agricultur, climate-smart, food, agricultur, chang_agricultur, agricultur_climat
		Lift: cocoa, csa, climate-smart, agri-food, climat_agricultur, cgiar, agricultur_chang
		Score: agricultur, food, csa, secur, climat_agricultur, climate-smart, chang_agricultur
Institutional arrangement		Highest Prob: institut, arrang, formal, mechan, institut_climat, institut_adapt, depend
		FREX: institut, institut_climat, institut_chang, chang_institut, institut_adapt, arrang, formal
		Lift: institut_chang, chang_institut, institut, acm, institut_climat, institut_govern, seq
		Score: institut, arrang, institut_climat, institut_adapt, institut_chang, adapt_institut, formal
Literature review		Highest Prob: review, literatur, group, document, focus, discuss, organis
		FREX: literatur, review, organis, document, group, academ, systemat

Topic name	Notes	Top keywords
		Lift: cannabi, literatur, organis, climat_review, informa, review, academ
		Score: group, review, document, literatur, organis, systemat, academ
Sector and integration	CPI = climate policy integration; CCD = climate compatible development	Highest Prob: sector, integr, synergi, integr_chang, coher, coordin, integr_adapt
		FREX: integr_chang, sector_climat, integr_adapt, adapt_sector, integr_climat, sector, synergi
		Lift: sector_climat, cpi, ccd, integr_chang, sector_adapt, adapt_sector, integr_adapt
		Score: sector, integr, integr_chang, synergi, integr_adapt, sector_climat, adapt_sector
Local municipality		Highest Prob: local, municip, climat_local, local_climat, local_adapt, adapt_local, chang_local
		FREX: local_chang, municip, local_adapt, chang_local, local_govern, local, adapt_local
		Lift: inter-municip, tmcns, ewmus, local_chang, swedish, local_govern, develop_local
		Score: local, municip, local_climat, local_adapt, climat_local, adapt_local, chang_local
Livelihood		Highest Prob: livelihood, household, reloc, peopl, bangladesh, resid, rural
		FREX: bangladesh, reloc, livelihood, villag, resid, household, retreat
		Lift: gandhi, mahatma, vunidogoloa, kivalina, bangladesh, khulna, reloc
		Score: reloc, livelihood, bangladesh, household, resettl, resid, villag
Nature conservation		Highest Prob: conserv, protect, area, biodivers, speci, habitat, natur
		FREX: conserv, biodivers, habitat, protect, speci, refugia, biolog
		Lift: amphibian, refugia, taxa, wilder, smma, bird, tsavo
		Score: conserv, biodivers, protect, speci, habitat, area, refugia
Modelling		Highest Prob: model, scenario, futur, simul, optim, result, combin
		FREX: scenario, model, simul, climat_scenario, use_model, model_use, optim
		Lift: rcp4.5, scenario, rcp8.5, use_model, simul, model, climat_scenario
		Score: scenario, model, simul, climat_scenario, use_model, model_use, futur
Project	Projections are also stemmed to project, but with pilot and mainstream also in the mix, this is likely about projects	Highest Prob: project, mainstream, climat_project, project_climat, project_chang, pilot, mainstream_adapt
		FREX: project, project_climat, climat_project, mainstream_adapt, chang_project, adapt_project, mainstream
		Lift: adapt_project, mainstream_adapt, project_climat, chang_project, climat_project, project, mainstream_chang
		Score: project, mainstream, climat_project, project_climat, mainstream_adapt, project_chang, mainstream_chang
Climate plan		Highest Prob: plan, climat_plan, spatial, chang_plan, adapt_plan, plan_climat, plan_chang

Topic name	Notes	Top keywords
		FREX: chang_plan, plan, climat_plan, adapt_plan, plan_chang, plan_plan, plan_climat
		Lift: chang_plan, plan_plan, plan_chang, plan, adapt_plan, climat_plan, plan_adapt
		Score: plan, climat_plan, chang_plan, adapt_plan, plan_climat, plan_chang, plan_plan
Implementation and barrier		Highest Prob: implement, support, barrier, lack, identifi, limit, key
		FREX: barrier, support, lack, overcom, constraint, support_adapt, implement
		Lift: barrier_adapt, support_adapt, overcom, barrier, support, support_chang, lack
		Score: barrier, support, implement, barrier_adapt, support_adapt, lack, constraint
Measurement		Highest Prob: measur, implement, prevent, climat_measur, chang_measur, implement_measur, technic
		FREX: climat_measur, chang_measur, measur, implement_measur, adapt_measur, measur_climat, measur_chang
		Lift: chang_measur, climat_measur, measur_chang, implement_measur, measur_adapt, measur_climat, adapt_meas
		Score: measur, climat_measur, chang_measur, implement_measur, measur_climat, measur_chang, adapt_measur
Conflict and displacement	Displacement covers both migrants and refugees	Highest Prob: conflict, migrat, human, intern, displac, mobil, popul
		FREX: migrat, refuge, displac, conflict, migrant, cdm, humanitarian
		Lift: jewish, peacebuild, refuge, migrant, migrat, ucdm, camp
		Score: migrat, displac, refuge, conflict, resettl, cdm, migrant
Heat and health	HWIS = Heat Warning and Information System	Highest Prob: heat, hous, warn, earli, wave, mortal, temperatur
		FREX: heat, mortal, warn, earli_system, hous, wave, heat-rel
		Lift: heat, hwis, mortal, tod, earli_system, heat-health, indoor
		Score: heat, hous, warn, mortal, wave, heat-rel, earli_system
Health	HIA = Health Impact Assessment	Highest Prob: health, diseas, health_climat, climat_health, health_chang, human, chang_health
		FREX: health_climat, climat_health, health_chang, chang_health, health_health, health, diseas
		Lift: dengu, health_chang, countdown, hia, infect, infecti, lancet
		Score: health, health_climat, climat_health, health_chang, diseas, chang_health, health_health
Politics	Mostly about political power structures	Highest Prob: polit, argu, power, articl, way, relat, structur
		FREX: polit, argu, tension, power, neoliber, elit, critiqu
		Lift: hydrosoci, postcoloni, neoliber, elit, polit, technocrat, dispossess
		Score: polit, power, argu, neoliber, tension, elit, contest
Marine ecosystem		Highest Prob: marin, ocean, reef, ecosystem, mangrov, mpas, protect

Topic name	Notes	Top keywords
	MPA = Marine Protected Area; ABNJ = Areas Beyond National Jurisdiction (i.e. international waters); CCAMLR = Commission on the Conservation of Marine Living Resources	FREX: reef, mangrov, mpas, marin_area, mpa, ocean, marin
		Lift: antarct, mpa, abnj, bleach, ccamlr, ebm, lsmpas
		Score: marin, mpas, reef, ocean, mpa, marin_area, coral
Disaster and storm	Idai and Katrina both names of storms; SRH = sexual and reproductive health, which is studied as part of vulnerability; Swap as part of risk swap or land swap as an adaptation	Highest Prob: disast, hazard, natur, recoveri, prepared, emerg, respons
		FREX: recoveri, cyclon, typhoon, hurrican, hazard, prepared, evacu
		Lift: idai, latino, srh, swap, tsunami, typhoon, katrina
		Score: disast, hazard, cyclon, recoveri, hurrican, prepared, typhoon
Adaptation to change	EBA = Ecosystem-based adaptation; one of two generic adaptation topics	Highest Prob: adapt_chang, adapt, adapt_climat, chang, paper, chang_adapt, adapt_paper
		FREX: adapt_chang, adapt_climat, challeng_adapt, adapt_paper, eba, approach_adapt, adapt_also
		Lift: eba, challeng_adapt, adapt_chang, adapt_climat, adapt_challeng, adapt_paper, adapt_also
		Score: adapt_chang, adapt_climat, adapt, eba, chang_adapt, adapt_paper, approach_adapt
Indigenous environmental rights		Highest Prob: environment, right, indigen, human, peopl, tradit, cultur
		FREX: environment, right, indigen, climat_environment, environment_climat, chang_environment, peru
		Lift: marriag, climat_environment, environment, right, indigen, chang_environment, environment_climat
		Score: environment, right, indigen, climat_environment, chang_environment, peopl, human
Water and resource management	IWRM = Integrated Water Resource Management	Highest Prob: resourc, natur, water_manag, natur_manag, manag_resourc, chang_resourc, resourc_climat
		FREX: resourc, integr_resourc, iwrm, resourc_climat, chang_resourc, manag_resourc, natur_manag
		Lift: iwrm, integr_resourc, arequipa, resourc_climat, resourc, burkina, faso
		Score: resourc, water_manag, iwrm, integr_resourc, manag_resourc, chang_resourc, natur_manag
Infrastructure and greenspace	GSI = Green Stormwater Infrastructure; UGI = Urban Green Infrastructure	Highest Prob: infrastructur, green, space, road, new, korea, urban_infrastructur
		FREX: infrastructur, green, urban_infrastructur, korea, road, space, neighbourhood
		Lift: greenspac, gsi, ugi, infrastructur, urban_infrastructur, green, korean

Topic name	Notes	Top keywords
		Score: infrastructur, green, urban_infrastructur, road, space, stormwat, korea
Mitigation		Highest Prob: mitig, climat_mitig, mitig_chang, climat, mitig_climat, chang_mitig, chang_adapt
		FREX: mitig, mitig_climat, chang_mitig, climat_mitig, mitig_chang, polici_mitig, mitig_polici
		Lift: chang_mitig, mitig_climat, polici_mitig, mitig, adapt_mitig, mitig_polici, climat_mitig
		Score: mitig, climat_mitig, mitig_chang, mitig_climat, chang_mitig, mitig_polici, mitig_adapt
Insurance		Highest Prob: insur, scheme, market, financi, transfer, properti, incent
		FREX: insur, buyout, premium, market, subsidi, contract, scheme
		Lift: buyout, micro-insur, policyhold, weather-index, wtp, crs, insur
		Score: insur, buyout, premium, market, scheme, subsidi, nfip
International agreement		Highest Prob: intern, agreement, climat, convent, pari, unfccc, framework_chang
		FREX: framework_chang, convent_chang, unfccc, unit_convent, nation_convent, pari, unit_framework
		Lift: cop26, cbdr, convent_chang, nation_convent, nmm, post-pari, unit_convent
		Score: unfccc, convent_chang, pari, nation_convent, unit_framework, unit_convent, agreement
Australia		Highest Prob: australia, australian, reform, council, paper, queensland, bushfir
		FREX: australia, australian, queensland, bushfir, melbourn, reform, victoria
		Lift: australia, ngn, queensland, brisban, bushfir, australian, lis
		Score: australia, australian, bushfir, queensland, reform, murray-darl, melbourn
Community	CBOs = Community-based Organisations	Highest Prob: communiti, rural, community-bas, nepal, communiti_climat, communiti_chang, adapt_communiti
		FREX: communiti_climat, communiti, adapt_communiti, communiti_chang, chang_communiti, communiti_adapt, ne
		Lift: cbos, communiti_climat, adapt_communiti, chang_communiti, communiti_adapt, communiti_chang, climat_communiti
		Score: communiti, nepal, community-bas, rural, communiti_climat, communiti_adapt, communiti_chang
Level		Highest Prob: level, chang_level, adapt_level, nation_level, level_climat, level_adapt, local_level
		FREX: adapt_level, chang_level, level_adapt, level, level_climat, polici_level, climat_level
		Lift: adapt_level, cross-level, chang_level, level_adapt, polici_level, climat_level, level_chang
		Score: level, adapt_level, chang_level, level_adapt, local_level, nation_level, climat_level
Resilience		Highest Prob: resili, build, resili_chang, enhanc, resili_climat, can, increas
		FREX: resili, resili_chang, climat_resili, build_resili, resili_climat, increas_resili, resili_adapt

Topic name	Notes	Top keywords
		Lift: increas_resili, resili, resili_chang, build_resili, climat_resili, resili_adapt, chang_resili
		Score: resili, resili_chang, resili_climat, climat_resili, build_resili, urban_resili, increas_resili
Information	NMHSs = National Meteorological and Hydrological Services	Highest Prob: inform, knowledg, servic, scienc, scientif, provid, understand
		FREX: knowledg, inform, scienc, scientist, scientif, climat_inform, use_inform
		Lift: nmhss, co-product, few, climat_inform, science-polici, knowledg, knowledg_climat
		Score: inform, knowledg, scienc, servic, scientif, climat_inform, use_inform
Response		Highest Prob: respons, issu, chang, relat, respond, climat, respons_chang
		FREX: respond_chang, respons_chang, respons_climat, climat_respons, respons, issu, issu_chang
		Lift: climat_respons, respond_chang, respons_climat, respons_chang, chang_issu, issu_chang, chang_respons
		Score: respons, issu, respons_chang, respond, climat_respons, respond_chang, climat_issu
Region		Highest Prob: region, region_climat, chang_region, climat_region, adapt_region, region_chang, region_adapt
		FREX: region_climat, chang_region, climat_region, adapt_region, region, region_chang, region_adapt
		Lift: climat_region, adapt_region, compatriot, region_climat, chang_region, region_adapt, region_chang
		Score: region, region_climat, climat_region, chang_region, adapt_region, region_chang, region_adapt
Research paper	Mostly science-jargon again	Highest Prob: paper, approach, design, implic, find, valu, methodolog
		FREX: methodolog, implic, india, design, paper, purpos, design_approach
		Lift: neld, design_approach, methodolog, india, purpos, emerald, origin
		Score: india, design, paper, methodolog, approach, purpos, valu
Federal and air quality	SUMP = Sustainable Urban Mobility Plan; NEPA = National Environmental Policy Act; Nurs is stem of nurse/nursing etc.	Highest Prob: feder, qualiti, pollut, air, standard, u., american
		FREX: feder, air, qualiti, pollut, american, u., standard
		Lift: sump, nepa, nurs, air, feder, drug, contamin
		Score: feder, air, qualiti, pollut, u., nurs, standard
Canada		Highest Prob: option, canada, north, feasibl, canadian, usa, northern
		FREX: canada, canadian, option, columbia, british, north, quebec
		Lift: nunavut, alberta, canadian, okanagan, princ, saskatchewan, scotia
		Score: canada, option, canadian, columbia, ontario, north, quebec
		Highest Prob: context, explor, analysi, understand, complex, three, interact

Topic name	Notes	Top keywords
Explore context and theory		FREX: explor, interact, theori, empir, context, complex, understand
		Lift: theori, theoret, operation, interact, empir, proposit, explor
		Score: theori, empir, analysi, interact, explor, complex, context
Farm and crop		Highest Prob: farmer, crop, farm, product, irrig, smallhold, adopt
		FREX: farmer, crop, farm, rice, smallhold, maiz, farmer_climat
		Lift: cultivar, maiz, farmer_climat, sorghum, cotton, farmer, farmersâ
		Score: farmer, crop, farm, irrig, smallhold, rice, maiz
Education		Highest Prob: educ, district, provinc, popul, higher, pakistan, school
		FREX: school, district, pakistan, educ, provinc, youth, student
		Lift: school, teacher, cce, khyber, pakhtunkhwa, student, youth
		Score: pakistan, educ, school, district, provinc, youth, student
Case study		Highest Prob: case, differ, two, perspect, approach, studi, instrument
		FREX: perspect, case, differ, illustr, two, netherland, question
		Lift: dutch, netherland, perspect, illustr, case, answer, societ
		Score: case, netherland, differ, dutch, perspect, instrument, two
Climate risk		Highest Prob: risk, climat_risk, risk_chang, risk_climat, chang_risk, manag_risk, adapt_risk
		FREX: climat_risk, manag_risk, risk_adapt, risk, risk_chang, chang_risk, risk_plan
		Lift: crm, risk_adapt, climat_risk, manag_risk, risk_strategi, address_risk, assess_risk
		Score: risk, risk_chang, risk_climat, manag_risk, climat_risk, chang_risk, adapt_risk
Climate governance		Highest Prob: govern, govern_climat, climat_govern, govern_chang, chang_govern, govern_adapt, adapt_govern
		FREX: climat_govern, govern_chang, govern, chang_govern, adapt_govern, govern_adapt, govern_climat
		Lift: climat_govern, govern_chang, govern_govern, adapt_govern, chang_govern, govern_adapt, govern
		Score: govern, govern_climat, govern_chang, climat_govern, adapt_govern, govern_adapt, chang_govern
Terrestrial nature protection	BLM = Bureau of Land Management; NWR = National Wildlife Refuge	Highest Prob: forest, park, tree, mountain, reserv, speci, wildlif
		FREX: park, wildlif, biospher, reserv, tree, nativ, alaska
		Lift: kelp, spruce, blm, easement, geoconserv, geodivers, nwrs
		Score: forest, park, speci, wildlif, tree, mountain, reserv
Vulnerability		Highest Prob: vulner, reduc, vulner_chang, social, justic, vulner_climat, exposur

Topic name	Notes	Top keywords
		FREX: vulner_chang, vulner, vulner_climat, climat_vulner, justic, vulner_adapt, exposur
		Lift: vulner_chang, climat_vulner, vulner_adapt, vulner, vulner_climat, reduc_vulner, adapt_vulner
		Score: vulner, vulner_chang, justic, vulner_climat, climat_vulner, vulner_adapt, chang_vulner
Finance		Highest Prob: countri, fund, financ, develop, aid, financi, climat
		FREX: financ, fund, adapt_countri, countri, countri_climat, chang_countri, climat_countri
		Lift: disburs, gef, mdbs, chang_countri, ldcs, climat_countri, adapt_countri
		Score: countri, financ, fund, countri_climat, adapt_countri, climat_countri, aid
Initiative		Highest Prob: need, initi, toward, scale, requir, approach, across
		FREX: toward, initi, scale, need, transit, requir, wider
		Lift: toward, bottom-up, initi, wider, scale, top-down, forward
		Score: need, initi, scale, toward, approach, transit, requir
Learn from practice		Highest Prob: practic, learn, transform, experi, emerg, lesson, divers
		FREX: learn, practic, transform, lesson, experi, chang_practic, boundari
		Lift: transform, learn, regen, lesson, practic, transdisciplinari, chang_practic
		Score: practic, learn, transform, lesson, experi, emerg, boundari
Assessment		Highest Prob: assess, indic, report, monitor, trend, status, detail
		FREX: indic, report, monitor, assess, trend, detail, databas
		Lift: cbm, indic, monitor, report, databas, trend, inventori
		Score: assess, monitor, indic, report, trend, status, detail
Policy		Highest Prob: polici, climat_polici, chang_polici, polici_climat, polici_chang, adapt_polici, develop_polici
		FREX: climat_polici, polici_climat, chang_polici, polici_polici, polici, polici_chang, implement_polici
		Lift: polici_polici, polici_climat, climat_polici, chang_polici, polici_studi, polici_chang, implement_polici
		Score: polici, climat_polici, polici_climat, chang_polici, polici_polici, polici_chang, adapt_polici
Problems	Also not meaningful: a problem that needs to be solved	Highest Prob: consid, mani, one, exist, problem, particular, part
		FREX: mani, problem, consid, part, one, general, take
		Lift: mani, general, take, part, problem, still, consid
		Score: problem, consid, mani, one, take, account, part
Terrestrial ecosystem		Highest Prob: ecosystem, restor, ecolog, landscap, servic, land, soil

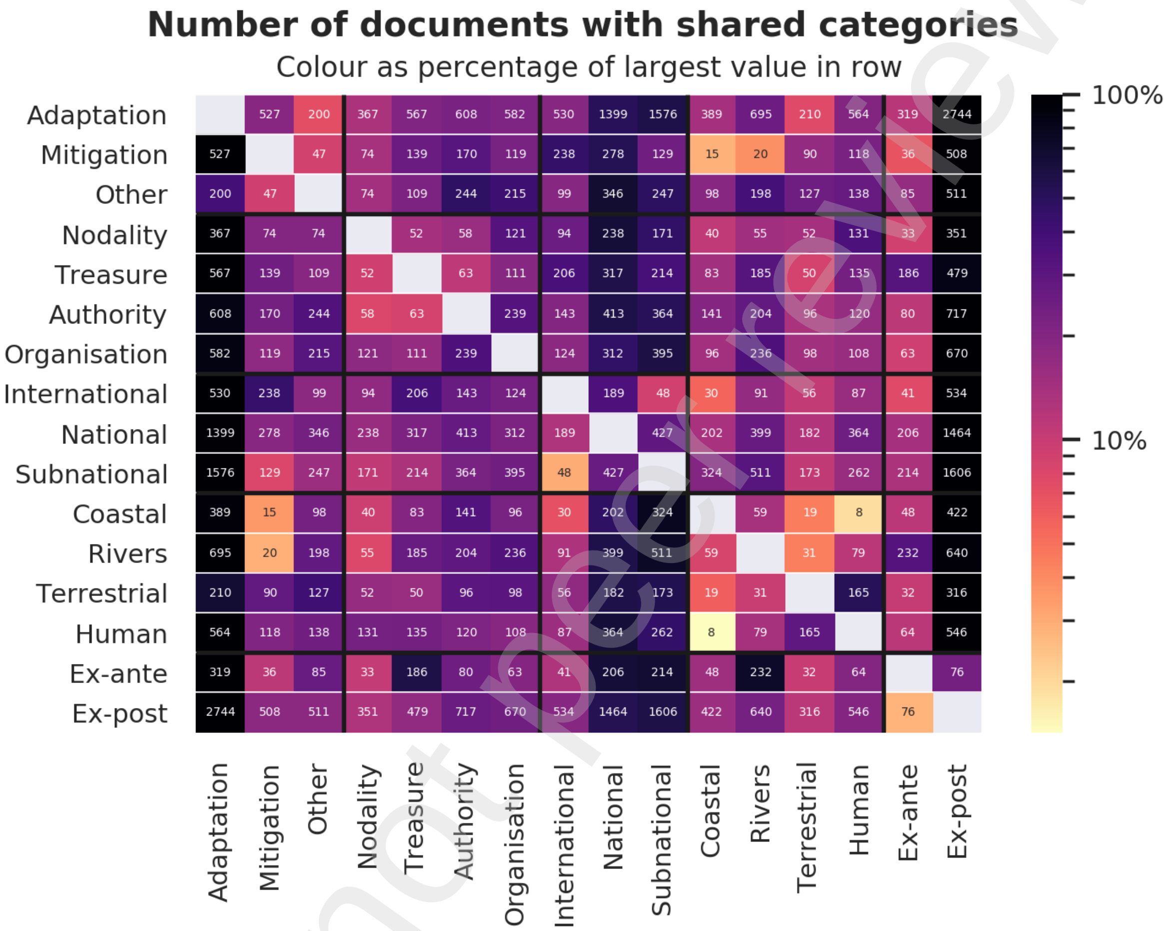
Topic name	Notes	Top keywords
		FREX: restor, grassland, veget, landscap, soil, pes, desertif
		Lift: brr, beaver, cerp, ewu, grassland, ldn, loess
		Score: restor, ecosystem, soil, landscap, veget, land, ecolog
Local planning		Highest Prob: author, local_plan, local, local_polici, polici_local, adopt, local_action
		FREX: local_plan, local_polici, polici_local, local_action, plan_local, com, mayor
		Lift: com, ccp, ccps, trans-loc, local_plan, local_polici, iclei
		Score: local_plan, local_polici, polici_local, local_action, plan_local, mayor, com
Management		Highest Prob: manag, manag_chang, manag_climat, adapt_manag, manag_adapt, chang_manag, integr_manag
		FREX: manag_chang, manag_climat, manag, manag_adapt, manag_manag, climat_manag, adapt_manag
		Lift: manag_manag, manag_chang, manag_climat, approach_manag, climat_manag, manag_adapt, manag
		Score: manag, manag_chang, adapt_manag, manag_climat, manag_manag, chang_manag, manag_adapt
Awareness and agency		Highest Prob: increas, agenc, concern, awar, associ, communic, rais
		FREX: awar, agenc, communic, concern, rais, citizen, profession
		Lift: climigr, awar, rais, communic, citizen, agenc, concern
		Score: agenc, awar, communic, citizen, increas, concern, rais
Climate		Highest Prob: climat, chang, climat_adapt, chang_climat, climat_climat, address_chang, chang_studi
		FREX: climat_climat, chang_climat, climat_can, address_chang, climat_case, climat_studi, chang_studi
		Lift: climat_climat, climat_becom, examin_climat, climat_case, climat_can, paper_climat, address_chang
		Score: climat, chang, climat_adapt, climat_climat, chang_climat, address_chang, chang_studi
Extreme event		Highest Prob: event, extrem, weather, extrem_event, increas, frequenc, sever
		FREX: extrem, extrem_event, event, weather, climat_extrem, frequenc, taiwan
		Lift: extrem_event, climat_extrem, extrem, weather, event, weather-rel, taipei
		Score: event, extrem, weather, extrem_event, frequenc, climat_extrem, taiwan
Intervention and gender		Highest Prob: intervent, programm, gender, women, indonesia, agroforestri, equal
		FREX: gender, programm, women, intervent, agroforestri, indonesia, equal
		Lift: gender, women, programm, indonesian, gender-sensit, agroforestri, men
		Score: intervent, gender, programm, women, agroforestri, indonesia, ethiopia
Adaptation		Highest Prob: adapt, climat_adapt, adapt_adapt, develop_adapt, adapt_develop, implement_adapt, adapt_studi

Topic name	Notes	Top keywords
		FREX: adapt_adapt, effect_adapt, adapt_studi, adapt_identifi, adapt_can, adapt_use, adapt_case
		Lift: adapt_identifi, adapt_adapt, case_adapt, adapt_differ, adapt_studi, effect_adapt, paper_adapt
		Score: adapt, climat_adapt, adapt_adapt, develop_adapt, adapt_studi, implement_adapt, adapt_develop
Perception and interview		Highest Prob: studi, interview, survey, percept, influenc, data, factor
		FREX: percept, interview, survey, qualit, perceiv, semi-structur, questionnair
		Lift: islamabad, percept, questionnair, semi-structur, interview, perceiv, transcript
		Score: interview, percept, survey, qualit, perceiv, data, semi-structur
Forest and REDD+		Highest Prob: forest, redd, deforest, forestri, carbon, reduc, degrad
		FREX: redd, deforest_degrad, cameroon, deforest, reduc_deforest, emiss_degrad, emiss_forest
		Lift: cameroon, cbfm, deforest_degrad, forest-rel, reduc_deforest, slaveri, deadwood
		Score: forest, redd, deforest, deforest_degrad, reduc_deforest, emiss_degrad, emiss_forest
River basin		Highest Prob: basin, river, irrig, water, alloc, flow, transboundari
		FREX: basin, water_irrig, water_river, irrig, river, river_manag, irrig_water
		Lift: ebro, heih, hydro-polit, laja, orange-senqu, rbmp, ibt
		Score: basin, irrig, river, water, water_irrig, flow, irrig_water
Fishery		Highest Prob: fisheri, fish, aquacultur, co-manag, ecosystem, lake, stock
		FREX: co-manag, fisheri, aquacultur, fish, fisher, catch, comanag
		Lift: turf, abalon, rfmos, tuna, co-manag, lmb, songkhla
		Score: fisheri, fish, aquacultur, co-manag, marin, fisher, lake
Investment cost		Highest Prob: cost, invest, benefit, increas, estim, total, year
		FREX: cost, per, invest, estim, billion, averag, total
		Lift: cge, conservacion, miri, que, manejo, cost, per
		Score: cost, invest, estim, per, billion, benefit, million
Economy and tourism	AZRF = Arctic Zone of the Russian Federation (mentioned by one paper on economic developments there) ; ADM = Agricultural	Highest Prob: econom, term, economi, activ, industri, tourism, long
		FREX: term, econom, tourism, economi, long, industri, econom_climat
		Lift: azrf, adm, tourism, term, econom_climat, russia, econom
		Score: econom, tourism, arctic, term, industri, economi, long

Topic name	Notes	Top keywords
	Drought Management or Adaptive Delta Management	
Global change	Intersting to see COVID popping up	Highest Prob: global, world, global_chang, crisi, warm, becom, global_climat
		FREX: global_chang, global, global_climat, climat_global, chang_global, world, crisi
		Lift: chang_global, global_chang, coronavirus, climat_global, global_climat, global, pandem
		Score: global, global_chang, global_climat, world, covid-19, pandem, climat_global
National policy	NDCs = Nationally Determined Contributions; NSAs = Non-state and sub-national actors; TNA = Technology Needs Assessment; NAP = National Adaptation Plan	Highest Prob: nation, nation_polici, intern, countri, contribut, nation_plan, prioriti
		FREX: nation, ndcs, climat_nation, nation_chang, chang_nation, nation_polici, nation_plan
		Lift: ndcs, nsas, ndc, tna, nation_contribut, nap, nation_chang
		Score: nation, ndcs, nation_polici, nation_chang, climat_nation, nation_plan, chang_nation
Climate action		Highest Prob: action, climat_action, action_climat, cultur, climat, action_chang, adapt_action
		FREX: climat_action, action_climat, action, action_chang, chang_action, adapt_action, action_adapt
		Lift: climat_action, action_climat, action_chang, chang_action, action, action_adapt, ireland
		Score: action, climat_action, action_climat, action_chang, adapt_action, chang_action, heritag
Wetland	Only place where Loss and Damage appear too, but often also "loss of wetlands/habitat/…"	Highest Prob: wetland, loss, delta, vietnam, damag, mekong, salin
		FREX: wetland, delta, turkey, salin, mekong, vietnam, loss
		Lift: delta, vmd, wetland, tre, 19th, seawe, mississippi
		Score: wetland, delta, mekong, loss, vietnam, salin, sediment
South America		Highest Prob: analyz, perform, brazil, mexico, brazilian, main, chile
		FREX: brazil, analyz, chile, mexico, brazilian, paulo, rio
		Lift: cistern, paulo, brazil, meso-institut, sao, universidad, chile
		Score: brazil, analyz, brazilian, chile, amazon, mexico, rio
Impact		Highest Prob: impact, impact_chang, assess, climat_impact, chang, potenti, climat
		FREX: climat_impact, impact_chang, impact, assess_climat, impact_climat, chang_impact, adapt_impact
		Lift: assess_impact, climat_impact, assess_climat, adapt_impact, impact_chang, chang_impact, impact_climat
		Score: impact, impact_chang, climat_impact, assess, impact_climat, assess_climat, chang_impact

Heatmap

Figure 1: A heatmap of co-occurring categories with all categories on both axes. The number represents the number of documents where both categories are present; colours are based on the percentage of the highest value in each row and are on a logarithmic scale.



Geographical spread of topics

Additionally figures here are based on geographic locations extracted from the titles and abstracts of documents. Note that the numbers given in Figure 3 and 4 are normalised relative to the average size of each topic and plotted on a log scale, while the numbers in Figure 2 are estimated effect sizes based on a linear regression (i.e. STM's "estimate effect" functionality) with uncertainty ranges from 25 simulations and the effect size given on a linear scale as a percentage with values larger (smaller) than 100% describing an increase (decrease). For each of the maps, only the highest scoring topics are given.

The geographic spread suggests that many highly vulnerable areas do not attract much research attention. To investigate this more formally, we plot vulnerability indices against the number of documents per country in Figure 5.

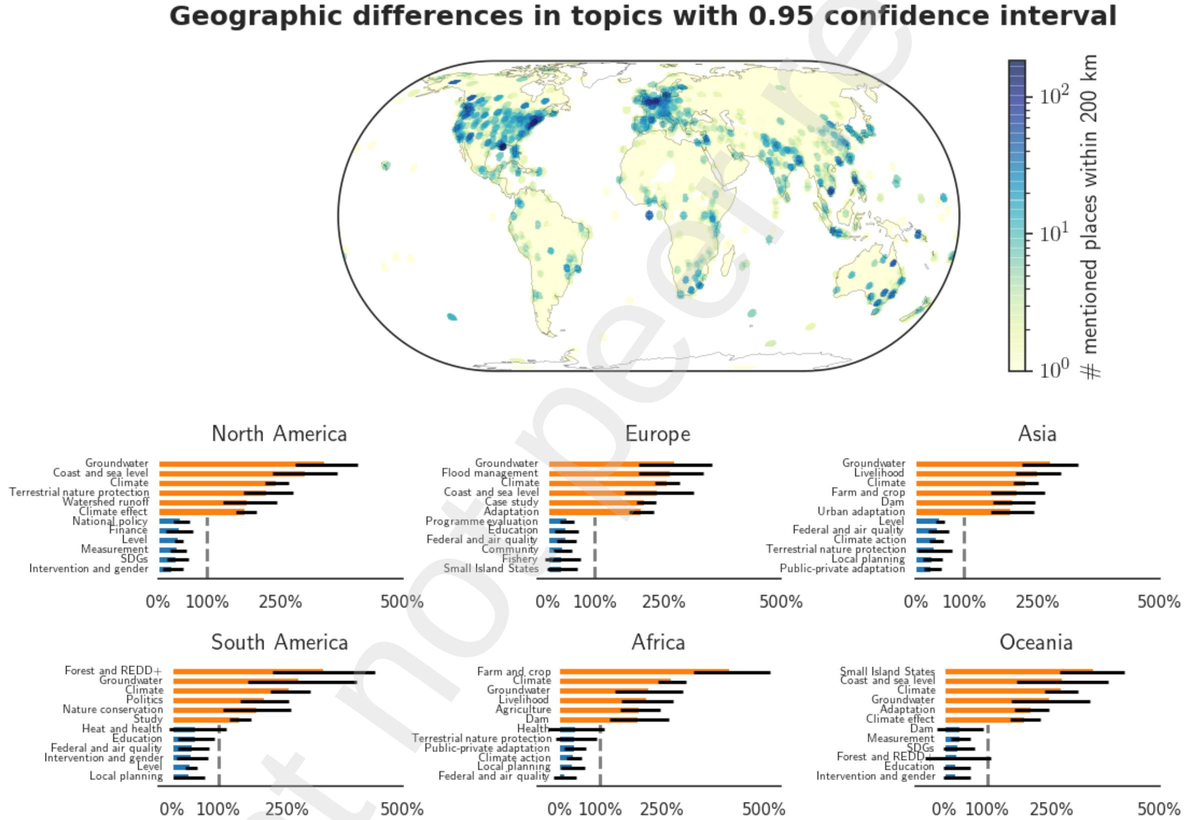
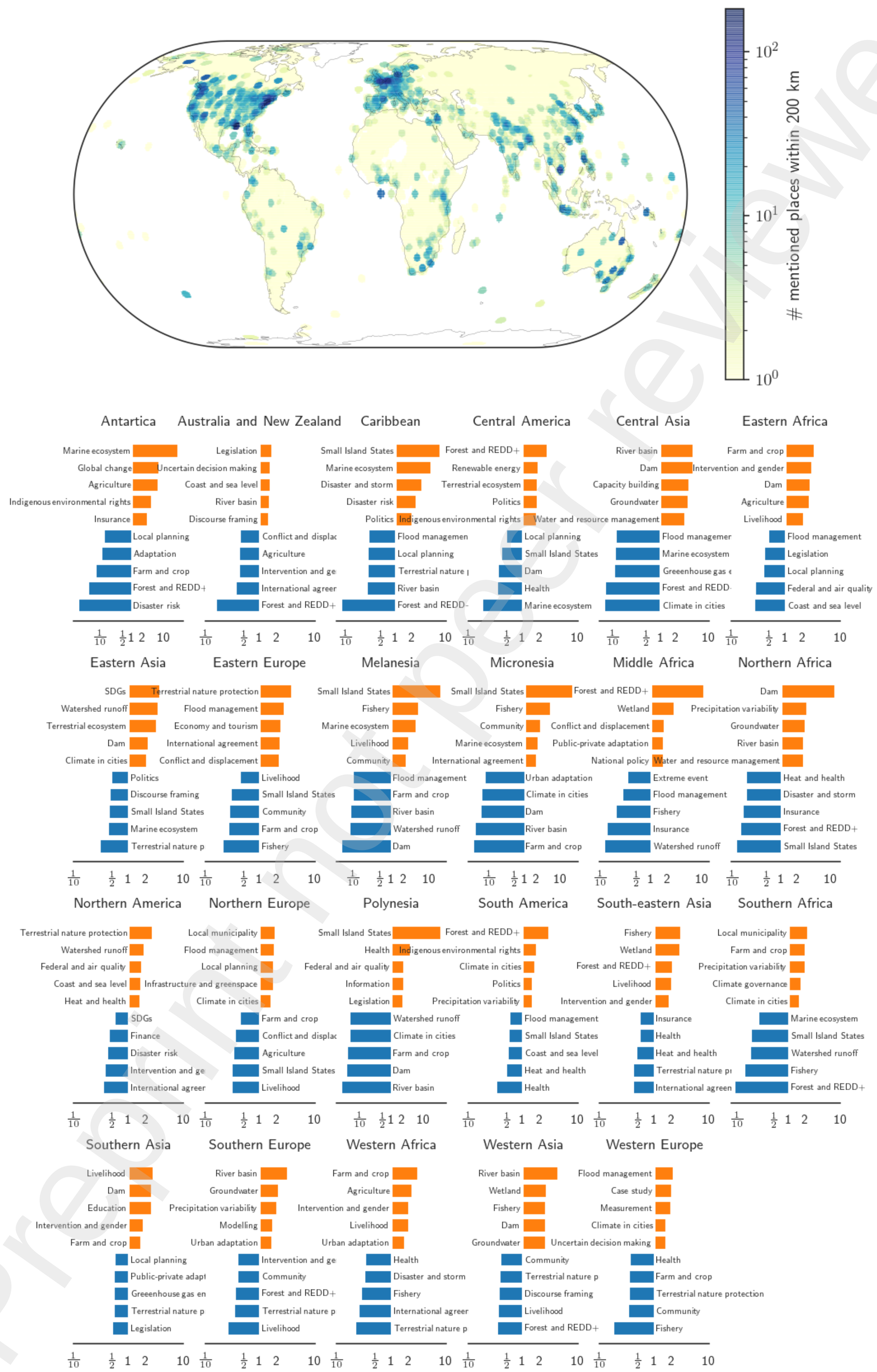


Figure 2: locally dominant topics by continent from linear regressions with error estimates at 0.95 confidence interval.

Figure 3 (next page): most over- and under- represented in documents by UN-statistical region, relative to the average of all documents. Note that while the findings generally align well with expectations, for many of these areas, the graph is based on a low (<100) number of documents, meaning that effects are generally not statistically significant at this scale, except for most topics in Australia and New ZXealand, Northern America, Northern Europe, South-Eastern Asia, Southern Asia, Southern Europe and Western Europe.

Most- and least mentioned topics by UN statistical region



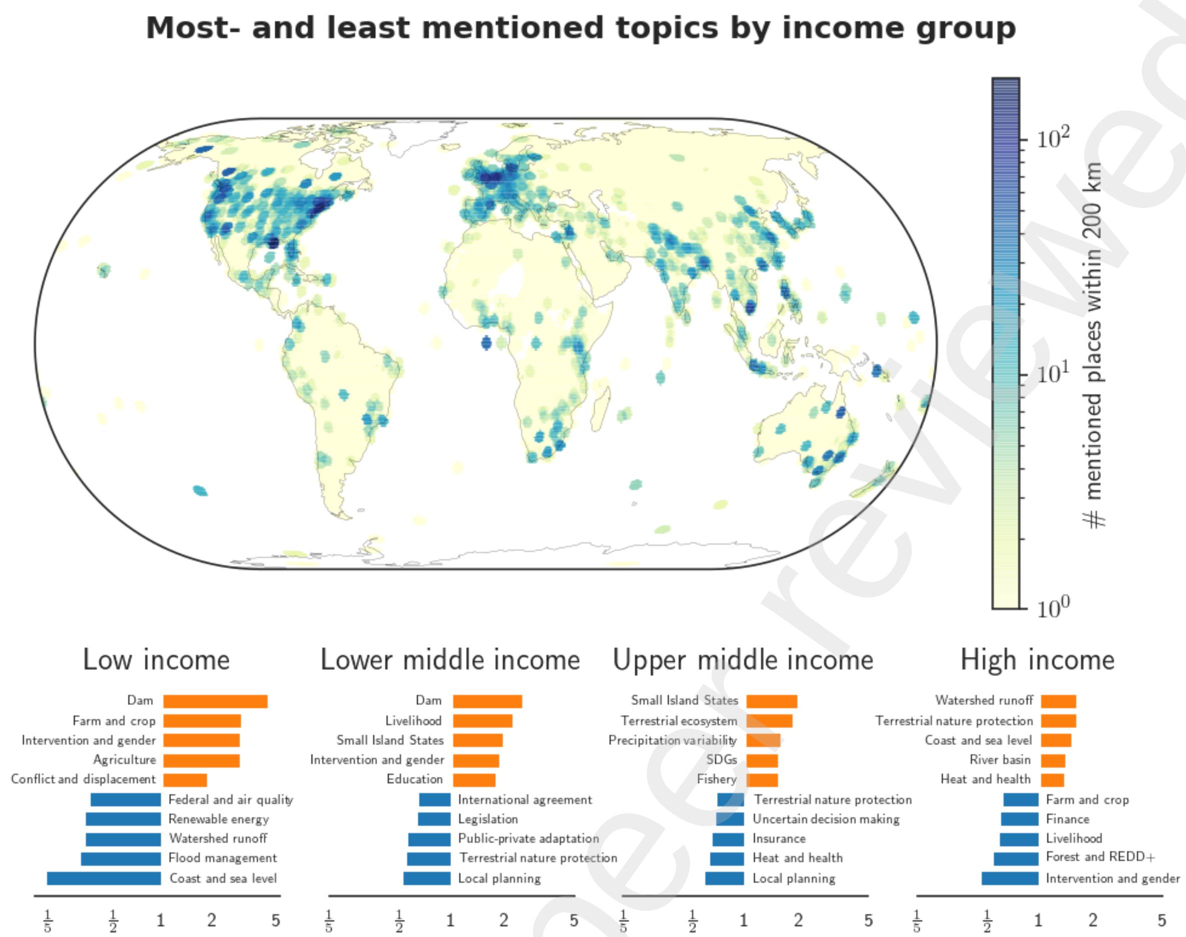


Figure 4: most over- and under- represented in documents by World Bank income group, relative to the average of all documents.

Figure 5: the number of places mentioned per country as a share of the total number of places plotted against various indices, namely the Climate Risk Index (Eckstein et al., 2019), which includes measures on the real impacts of climate change per country; the INFORM Risk Index, which combines proxies for hazard & exposure, vulnerability and lack of coping capacity; the Environmental Performance Index (Wolf et al., 2022), which uses a wide variety of environmental sustainability indicators, including climate change performance and various ecosystem vitality proxies; the World Risk Index (Welle and Birkmann, 2015), which includes many natural risks, including climate-related risks, and the ND-GAIN index (Chen et al., 2015), which ranks countries based on a combination of vulnerability and readiness to adapt. The indices on the x-axis are given such that lower performing and more vulnerable countries are always placed on the left, flipping the axis where needed. If available, the index value for the year preceding the publication of the document was used. The scores and place name mentions are then averaged per country. The trendline is based on a least-squares regression, but is not statistically significant. However, it is notable that most of the extremely highly scoring countries (e.g. the USA making up almost a fifth of all placename mentions) are generally considered less at risk, while many of the most at-risk countries are among the least studied. One should remember too however that the publication numbers here are not scaled by population, so e.g. many small island states are highly vulnerable in most indices, but also have only a relatively small number of people living on them. None of these figures are meant to provide a normative assessment of where most research *should* take place.

Geographical spread of authors

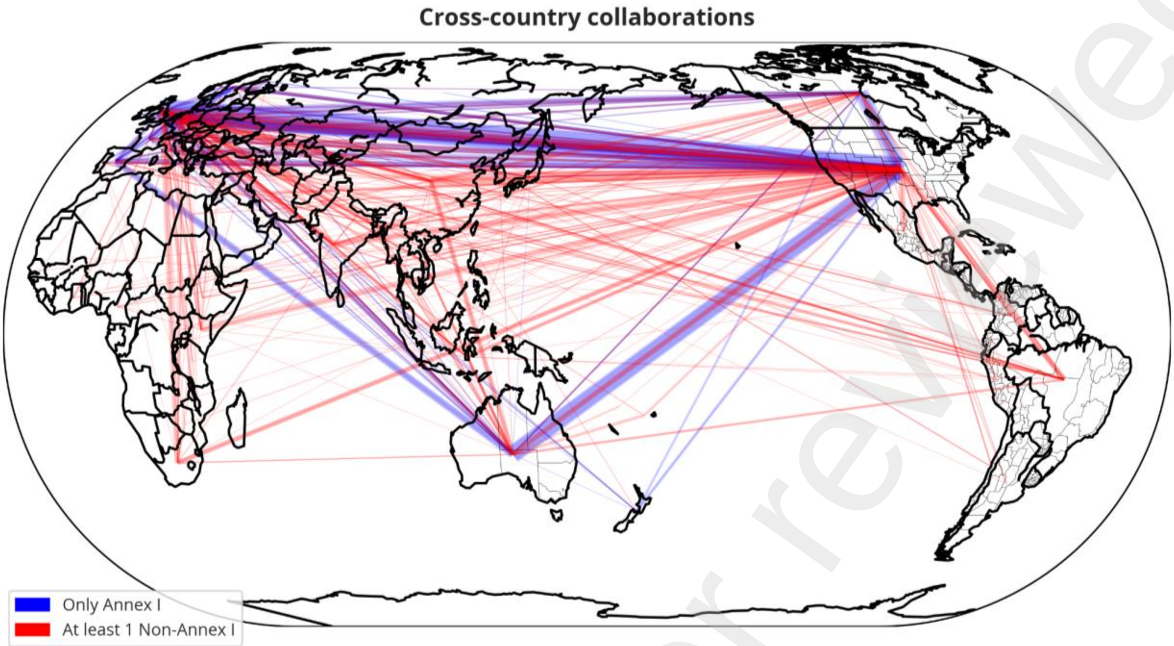


Figure 6: collaborations between authors from different countries, based on geographic locations extracted from the author affiliations. A line is drawn between the country of each primary author and the country of their co-authors, with wider lines indicating more frequent collaborations. If any of the authors' primary affiliation was in a Non-Annex I country, the line is red; if all listed institutions were in Annex I countries instead, the line is coloured blue. The non-standard longitudinal positioning of the map was chosen to better highlight the lack of collaborations with authors from Africa and Latin America.

T-SNE dimensionality reduction of topic model

In the below figures, the topic model is represented using dimensionality reduction through T-SNE (Van der Maaten and Hinton, 2008). The basic idea is this: go from the full 105-topic model to a 2-dimensional representation where each dot represents a topic, and keep documents with a similar topic distribution (i.e. in 105-dimensional topic space) close together in the final plot (i.e. 2-dimensional cartesian coordinates). The colour of each dot represents the highest-scoring category for the document. Labels are then added by calculating the average position of each topic. The shape isn't necessarily important here; relative distances are. T-SNE is especially good at preserving local structures, so e.g. *Coast* being opposite *Terrestrial* is not especially meaningful, but *Coast* being close to *Flood* and *Insurance* is.

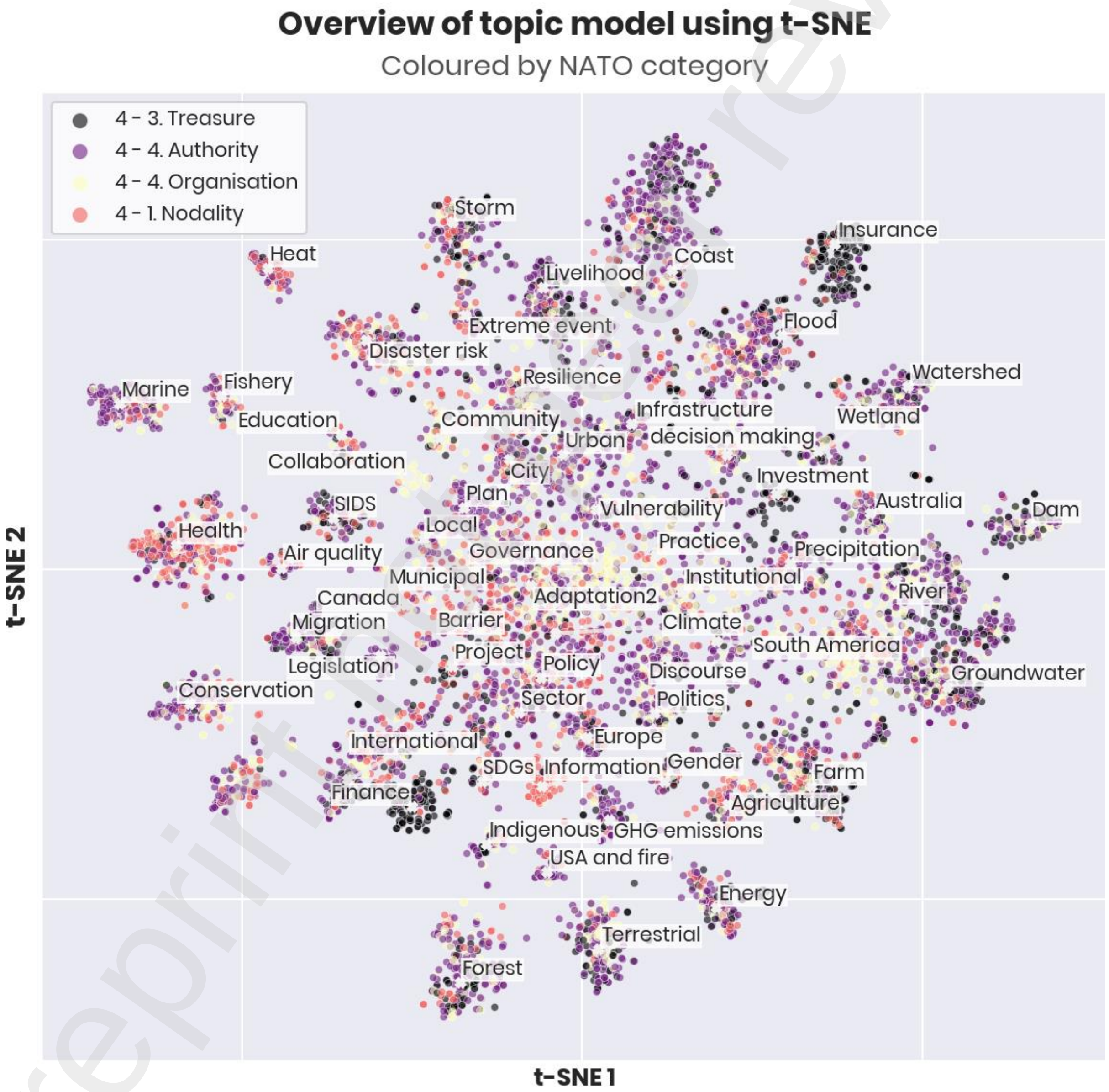


Figure 7: t-SNE dimensionality reduction of the topic model coloured by NATO category.

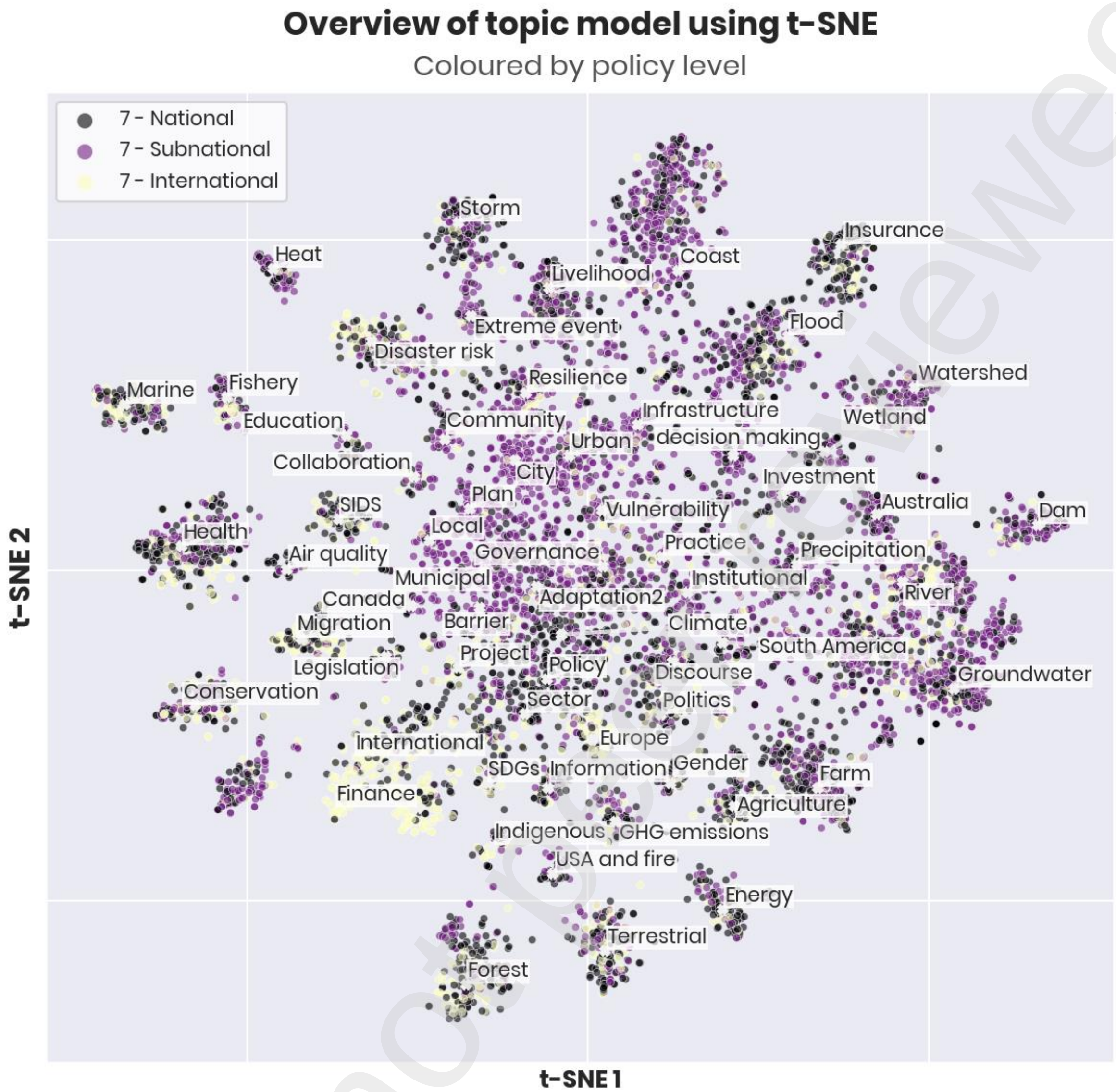


Figure 8: t-SNE dimensionality reduction of the topic model coloured by implementation level.

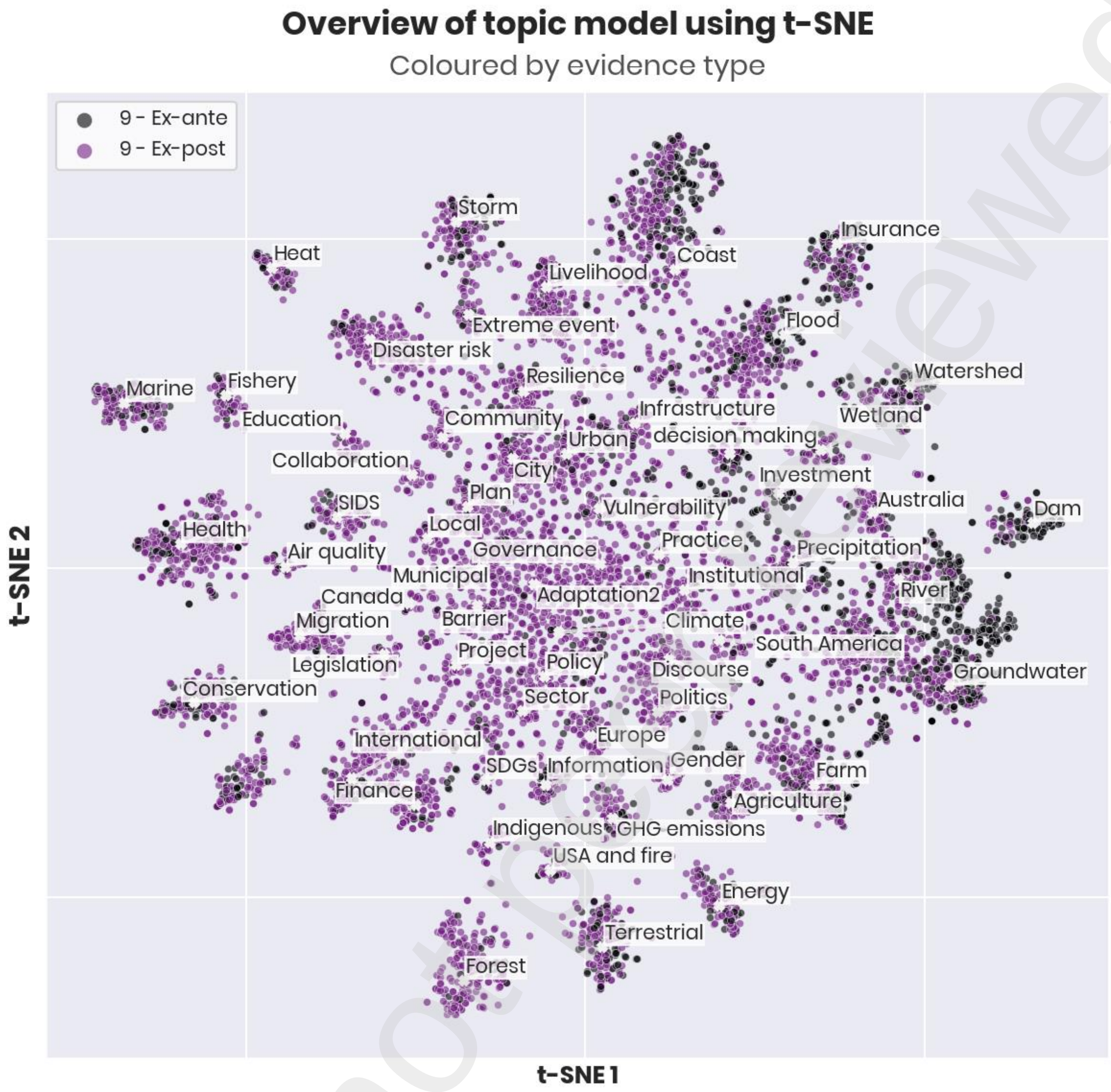


Figure 9: t-SNE dimensionality reduction of the topic model coloured by evidence type.

Topic changes over time

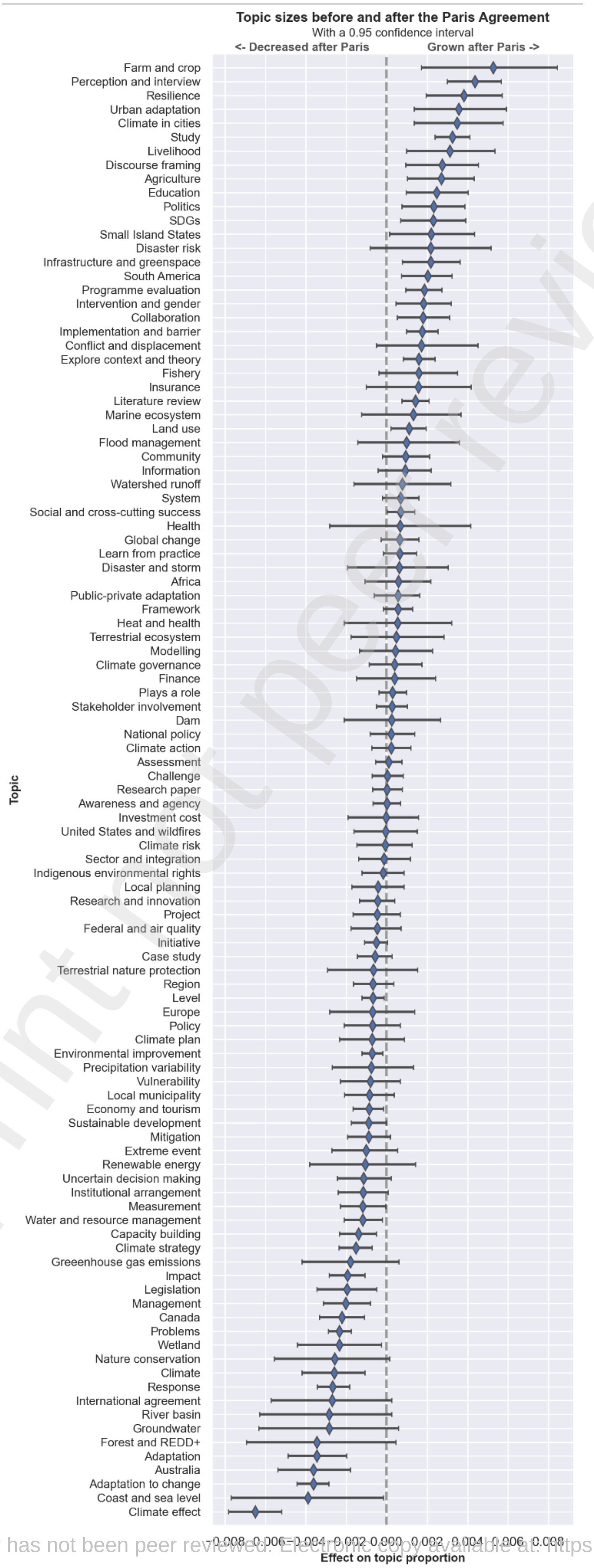


Figure 10 (previous page): effect of the publication year as a categorical variable (pre-2016 or after) on the topic proportion for all topics in the topic model. The bars represent a 0.95 confidence interval.

Additional references for the supplementary materials

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