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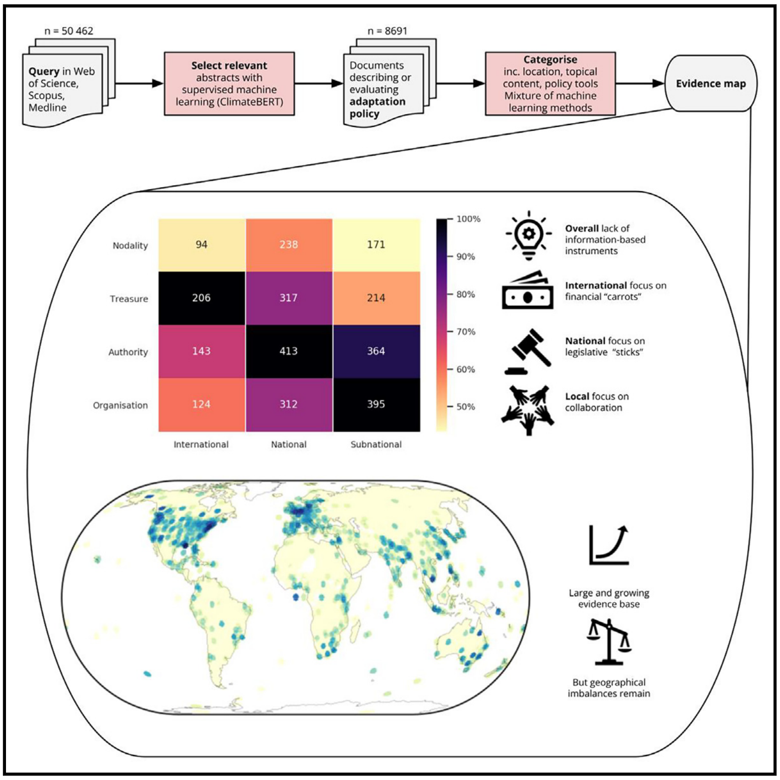
Machine learning evidence map reveals global differences in adaptation action

Graphical abstract



Highlights

- Use of machine learning to create a dataset of scientific adaptation policy literature
- The policy tools studied differ considerably by governance level and location
- Some of the most vulnerable countries are under studied
- Limited evidence for a shift in adaptation policy after the Paris Agreement and SDGs

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In brief

Governments are increasingly creating policies to adapt to the impacts of climate change. Tracking these policies globally is difficult with traditional methods, but we can use recent advances in machine learning to create an "evidence map" from scientific articles on adaptation policy. This highlights how governments around the world use different tools at different levels and in different regions. Most of this evidence, however, comes from the Global North, and we also see relatively few studies on information-based policies overall.

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Machine learning evidence map reveals global differences in adaptation action

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SCIENCE FOR SOCIETY As the impacts of climate change are increasingly felt around the world, tracking if and how adaptation is taking place is crucial; it enhances transparency and accountability while also showing where current efforts are falling short. This work adds to an emerging body of literature that uses machine learning to this end. In theory, such methods can provide a nuanced and detailed picture of large datasets. This allows the evidence map created here to be expansive, covering scientific publications from multiple databases globally and also including articles that could not be considered with manual- or keyword-based approaches.
Moreover, an explicit link is made to public administration theory—in particular, the NATO typology of policy tools—alongside more common characteristics, such as the type of climate impact a policy is responding to and the geographic location of studies and their authors. This results in a rich data set, which could be a fertile basis for further analyses.

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 categorizing 8,691 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, emphasize financial instruments, whereas national policies, particularly in Europe and Oceania, favor 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.

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, policymakers 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 adaptation evidence synthesis projects have been undertaken, including large-scale international efforts by the scientific community,[5,6] 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 that 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 policymakers on "what works?",[9,10] focusing instead on "what has been done?" or "are we doing enough?",[11] and even then, it can be difficult to provide comprehensive and policy-relevant syntheses.

The reasons for these 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] Similarly, there is a long-standing debate on if and how adaptation can be separated from general development.[18,19] 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,[20] 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 offer promising ways to better handle both these difficulties that are typical of "big literature"[21]: sophisticated models can easily handle large datasets while remaining sensitive to specific contexts and different research traditions. Recognizing this potential, efforts have been undertaken to modify the traditional systematic review process to incorporate machine learning elements,[22–24] and there is an emerging body of studies using machine learning to systematically assess the state of knowledge and progress in an adaptation context.[5,9,25–27]

Machine learning efforts to date can be divided based on the types of documents they analyze. Some use political documents, such as political speeches and municipal archives,[25] national policy papers,[26] or submissions to the United Nations Framework Convention on Climate Change (UNFCCC).[27] Such analyses can provide an indication of shifting attitudes and practices among policymakers, the topics and actions they prioritize, or shifts in political discourse, for example. However, reporting on adaptation is both relatively infrequent and open to politically motivated interpretations,[28,29] making it difficult to draw objective and generalizable conclusions from such data. Other studies have instead focused on scientific papers, producing overviews of the evidence on topics such as expected climate impacts,[30] implemented adaptations,[5,31] and the wider adaptation-related literature.[9] These analyses, alongside more traditional bibliometric work[20] and systematic reviews,[32] provide insight into how adaptation knowledge is developing, but it can be difficult to relate these trends in academic publications to policymaking on the ground.

Here, we create a global evidence map of the scientific literature that evaluates 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 determining how research on adaptation policies is shifting over time and identifying places where evidence is lacking. Notably, the use of machine learning methods allows us to take a much broader view than traditional review methods or bibliometric studies would allow. More specifically, we use supervised machine learning to identify and classify adaptation policy research at scale, which we combine with topic modeling to gain detailed insights into the content of this research. The resulting dataset created could be used for more detailed, qualitative enquiries into any (combination) of the topics and categories we discuss here at the global level. Similarly, since our approach is relatively easy to replicate, it could serve as a first step toward establishing a living evidence platform for adaptation policies.

RESULTS AND DISCUSSION

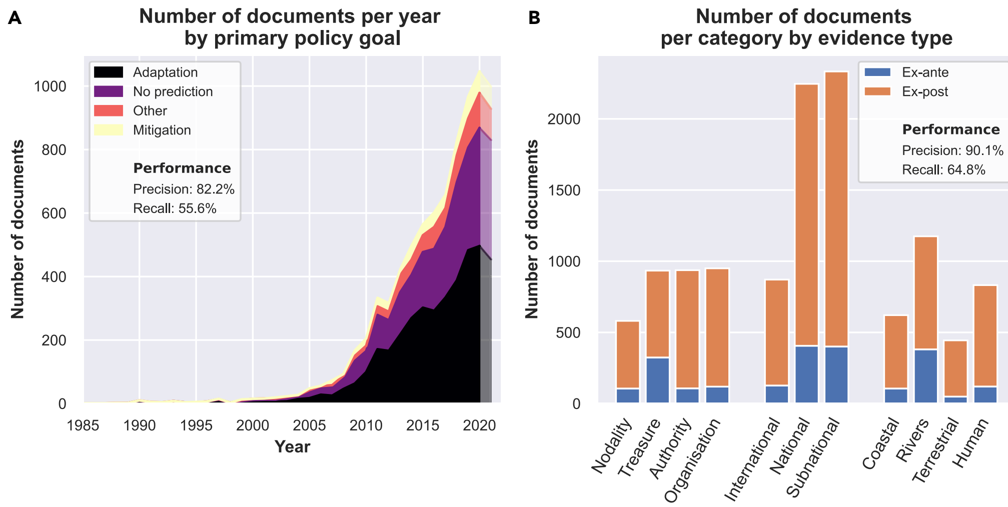
Machine learning methods summary and performance

More detailed descriptions of our methods, including technical details and an overview of our process, can be found in the experimental procedures. For clarity, we include non-technical descriptions of the data selection and categories here too. Additional details, including exact inclusion/exclusion criteria for all categories, are also available in the study protocol.[33]

We use a query that combines climate, policy, and adaptation keywords to download scientific articles at the abstract level from three major databases. To select the relevant articles, we train a binary classifier. Such a classifier does not rely on keywords but rather "learns" a nuanced understanding of what a relevant article looks like based on examples. This means that studies that respond to climate-attributable impacts can be included even if the authors do not mention climate change or adaptation explicitly; similarly, the scalability of machine learning methods allows us to include policies from all levels of government. The first classifier is used to identify articles that substantially discuss or evaluate at least one action that reduces or aims to reduce climate risks and that was instigated or supported by a government body at any level.

We find 8,691 documents (i.e., abstracts of articles found in Web of Science, Medline, or Scopus) that meet this standard 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 = 5,468, 62.9% selected documents) being published in or after 2016. This classifier on relevance showed excellent performance, with an F1 score on the test set for the selected hyperparameters of 92.2%, a precision of 92.5%, and a 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.

Using a second machine learning classifier, the relevant articles are then further categorized to connect our findings to established literature on policy analysis (see Figure 1). We first classify by instrument type using the NATO typology of policy tools,[34] which has been applied to adaptation by other authors.[35,36] Broadly speaking, this typology describes 4 different



	Instrument type	Policy level	Impact type
Precision	65.7%	84.0%	84.0%
Recall	40.3%	59.6%	33.7

Figure 1. Overview of the number of documents per category for the full dataset

(A) The number of new relevant documents is given per year, where colors represent the primary policy goal. In cases where multiple goals were detected, for example because multiple policies were discussed concurrently, only the prediction with the highest confidence prediction was counted.

(B) The number of documents for the remaining categories is given, subdivided by evidence type. For each of the classifiers (document selection and the 5 categories), the precision and recall scores are also given. These are standard machine learning performance measures. Precision is calculated by dividing the number of correctly classified positive examples in a category by the total number of documents labelled as that same category (i.e., how "clean" the results are). Recall describes the proportion of all true positive documents that are classified by the algorithm as relevant (i.e., how comprehensive the results are).

types of actions governments can take to further a policy objective, namely:

- Nodality: providing information or conducting research, including, for example, awareness campaigns or information platforms.
- Authority: laws and regulations, which can be either binding or non-binding and includes, for example, quotas, international conventions, and safety standards.
- Treasure: financial investments or risk underwriting, including direct spending and government-supported insurance.
- Organization: creating institutions or changing the functioning of existing governmental bodies, including formalizing stakeholder involvement and creating new government bodies such as a national climate commission.

We also classify articles by policy level—i.e., whether the government body involved is international, national, or subnational. Further, articles are classified by climate impact type that the policy responded to, in a manner similar to Callaghan et al.,[30] distinguishing between coastal impacts (e.g., hurricanes, sea-level rise), rivers (e.g., fluvial flooding, irrigation), and terrestrial (e.g., deforestation, ecosystem degradation) and impacts on human systems (e.g., health, urban issues). As adaptation can also be a secondary effect of a policy, we also record the primary policy goal, which can be either adaptation, mitigation, or other non-climate policies. For the latter two, the adaptation co-benefit needs to be named explicitly. Finally, we categorize articles according to evidence type, with *ex ante* referring to studies that use models and projections, while *ex post* studies evaluate an ongoing or completed policy. Categories are not mutually exclusive and can also be left blank if there is insufficient information in the abstract.

The classifier performance for all 5 categories was lower, with F1 scores ranging from 45.3% to 75.1% (also see Table S1). 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 the inter-coder reliability of human-coded documents to around 70% for most categories based on our double coding, implying that 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 labeled 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 prioritizes rare categories, thus improving over recall. 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 that 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 1B). Most *ex ante* studies are cost estimates and impact models,

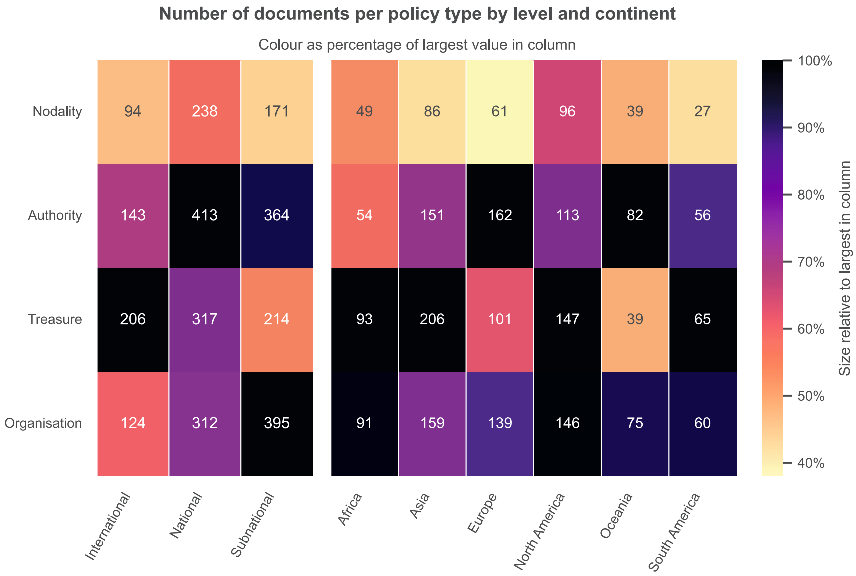


Figure 2. Policy instruments at different governance levels and in different continents

In this heatmap, the value represents the number of documents where categories occur together. For example, the classifier categorized 94 documents as being about a nodality policy and at the international level. Since the total number of documents per category varies considerably, the color represents a normalized value relative to the highest number of documents in a column—i.e., dark purple to blue cells suggest that the given policy tool is favored at the given level or in the given region. For example, at the international level, there is a relative abundance of research on treasure instruments; in absolute numbers, this is roughly equal at the subnational level. However, there is more subnational research overall, especially in authority and organization instruments, so treasure instruments are less of a focus here.

often related to insurance, direct investment in flood defense, or management of river dams under different climate scenarios (see the results of the topic model in Table S2 and corresponding topic maps in Figures S1–S3). Finally, international-level policies are far less common in our dataset than national or subnational policies. Moreover, the international policies cover a much smaller range of topics, focusing on international funding streams.

Governance levels: Sticks, carrots, and collaboration

Variations in policy instruments between different levels of government and location (Figures 2 and S4) provide an indication of the types of adaptation actions different actors take, which may reveal underutilized options and issues of alignment.[36,37] For the distribution of specific topics between different levels of governance and policy instruments, see the topic maps in the supplemental information (Figures S1–S3). Locations here are extracted using a pre-trained geoparser.[38]

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, Green 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 defenses), 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 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" Organization instruments. This may be a result of the facilitative role played by subnational institutions that need to create implementing organizations and ensure societal support. Many of these policy instruments are related to stakeholder involvement and vulnerability, which may explain the relative abundance of organization 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 USA especially may be a contributing factor to the larger frequency of Treasure and Organization 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 hyperparameters), an overestimation appears equally likely. The few hundred studies in this category are mostly focused on early warning systems and information on the health effects of climate change.

It is worth noting that the NATO model can be used to describe policy mixes[36]—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 Organization (co-occurrence with Authority: n = 239, Treasure: n = 111, and Nodality: n = 121). Organization 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.

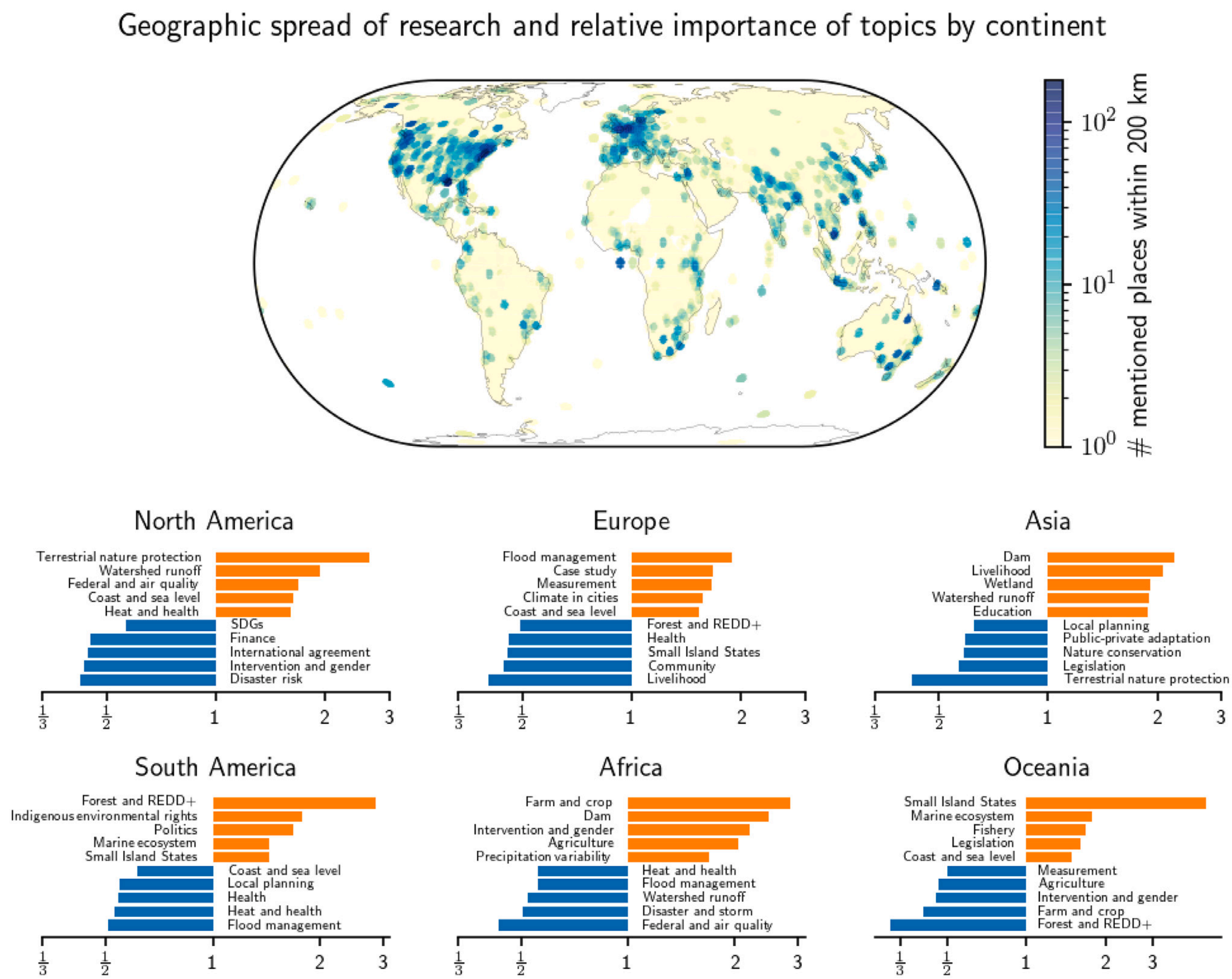


Figure 3. Map of locations of research, as well as most- and least-mentioned topics
On the map, locations extracted from the title and abstract have been marked by a circle. References to a country or area are placed in the middle of that country or area. If multiple places within the same country were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

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,[39] we assess the global spread of our dataset and combine these locations with the topic model results to identify regionally dominant topics (Figures 3 and S5–S7 for additional regions). 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 the Global South, respectively. Annex I countries represent a minority of countries and people but make up 54.3% (n = 3,961) of the places mentioned in the abstracts and titles in our dataset, with places in the USA being by far the most common (n = 2,172, 29.8%).

A comparatively high number of studies from South East Asia, especially China (n = 414, 5.7%) and India (n = 399, 5.5%), means that one cannot say categorically that more vulnerable countries are studied less (alongside problems on the different operationalizations of vulnerability; see Figure S8). 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,[40] 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 (GAMI),[5] which categorized evidence from implemented adaptation actions, has a higher proportion of Global South literature, despite using the same scientific databases. The GAMI, however, focused on implemented adaptation actions, which did not need to be the result of a policy. This therefore

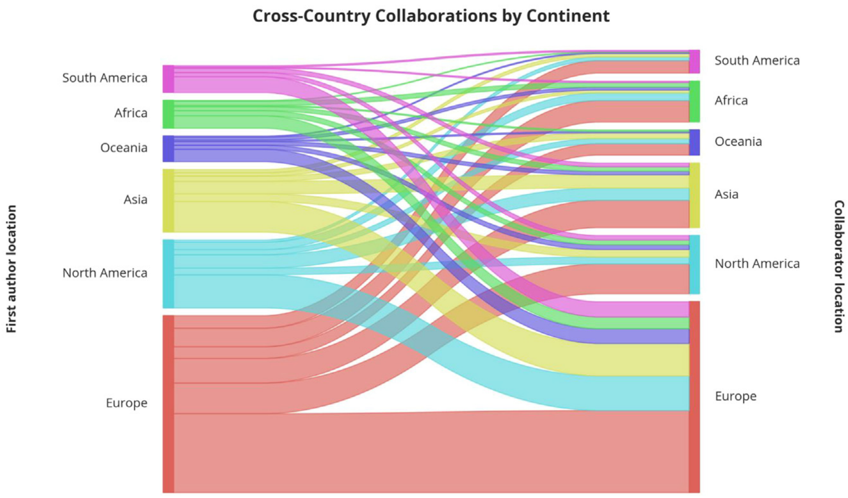


Figure 4. Authorship teams from multiple countries, subdivided by continent

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 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 were counted as a half for this author.

suggests that Southern literature has a relatively high proportion of individual projects from non-governmental organizations, while policies are understudied in this context.

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 normalized 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 Figure S5 for the corresponding plot.

North America, Oceania, and Europe all have 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 to 133.7%) but is noteworthy relative to the other regions. In addition to water topics, research in North America also emphasizes 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% to 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 program 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% to 51.6%). Policy research from Africa focuses 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). This is important for two reasons: first, international collaborations require resources and that those resources should be allocated equitably; second, the discourse on South-South and North-South collaborations within adaptation often suggest that such efforts can be used for knowledge transfer and dissemination of best practices.[41–43] Among the subset of papers with authors from two or more countries (n = 1,944 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 collaborations are 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 USA 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[43] and the important role such collaborations have played in advancing international climate policy,[44] South-South collaborations appear rare in scientific projects. Collaborations between only annex I countries appear to be extremely scarce (n = 385 unique documents; see also Figure S9)—far fewer than the number of purely annex I collaborations (n = 1,051) 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 were based in an annex I country (n = 414, 82.8% 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, emphasizing the need for rapid implementation of policies.[14,45] Around the same time, the Sustainable Development Goals (SDGs) were also adopted, highlighting the need for adaptation to incorporate

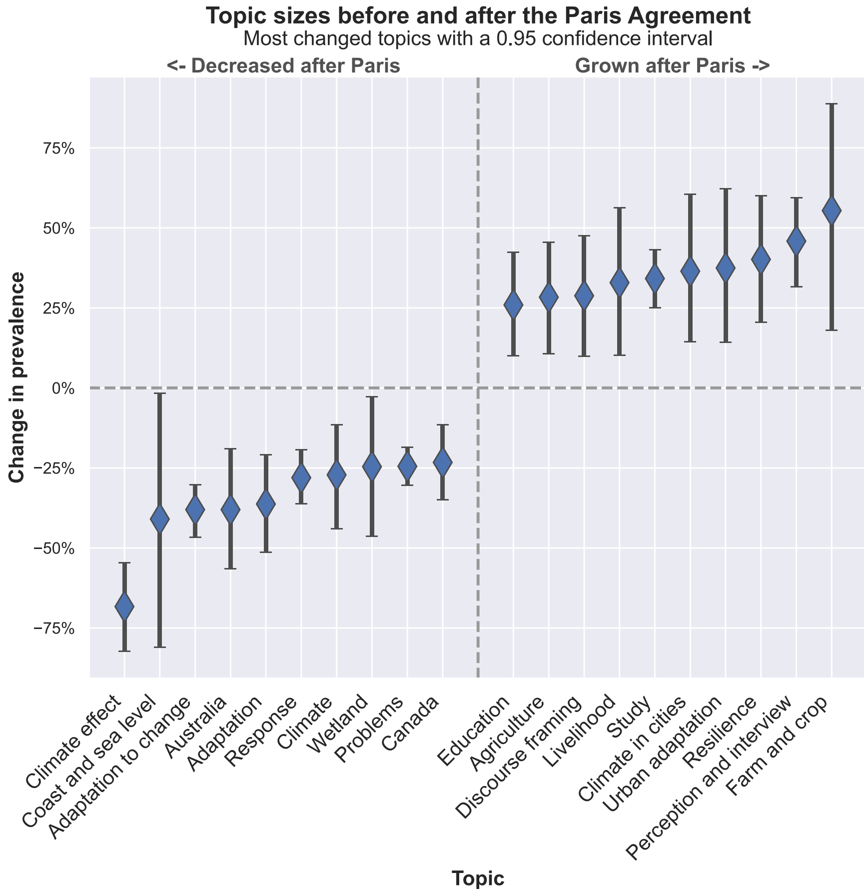


Figure 5. Changes in topic prevalence since the Paris Agreement

Estimates for how often topics in our structural topic model are discussed in documents published after 2015 relative to before. Only the 5 most-increased and 5 most-decreased topics are given, and non-statistically significant topics are left out too.

broader sustainability terms to be successful long term.[46,47] Importantly, these agreements do not stand on their own: there is extensive literature on the connections between development and adaptation; the Paris Agreement and SDGs are the products of a more wholistic understanding of sustainability, vulnerability, and climate action that researchers had increasingly promoted in the preceding years.[48–50] Therefore, we may expect to see a shift in topics over time in a similar direction.

Our results show that 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-focused topics are not among the quickest-growing topics. In the full table (Figure S10), some topics, like program 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% to 18.2%), finance (4.0%, −15.8% to 25.2%), and national policy (2.3%, −8.7% to 14.4%); topics like legislation (−20.7%, −36.2% to 5.1%) and climate strategy (−16.0%, −24.2% to 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.

It is also notable that resilience is the third quickest-growing topic (40.2% increase, 18.0%–88.7%), while vulnerability shows a small decrease (−8.4%), though the latter is not statistically significant (confidence interval −24.2% to 7.1%). A similar trend was found in a bibliometric analysis of adaptation papers,[51] where resilience replaced vulnerability as the most-used keyword. Interpreted positively, this could signify a move away from disempowering concepts focused on victims of climate change; conversely, the concept of resilience has been critiqued for an overly mechanistic understanding of risk and for overlooking power relationships that a vulnerability lens typically does acknowledge.[52–55] The latter reading would go against the broader increased importance of development-related topics we noted earlier. Given also the considerable ambiguity around the exact meaning of both these two terms,[56,57] one should be careful not to overinterpret this shift.

Recent priorities 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 focused 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 continue 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 toward sustainable development. For each of these topics, there is substantial literature on their theoretical importance,[9,58–61] as well as an increasing amount of practical evidence, mostly from individual projects,[62–64] but it is unclear if, where, and how policymakers are incorporating them into laws, regulations, and governance more broadly.

Relatedly, our findings support concerns[65] 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 focused on policy implementation in recent years. An important caveat here is that our work, like other machine learning approaches,[5,9,30,66,67] uses abstracts of scientific publications, which are an imperfect proxy for actions on the ground—manual systematic reviews typically remove a substantial number of articles in full-text screening, so we may be overestimating the volume of information, although it should be noted that we applied stricter criteria at the abstract level than a manual review would. Either way, given the limited information in abstracts, the analysis of full texts and other data sources may uncover more nuanced mixtures of policy instruments,[36] while our analysis is more suited to highlighting the main points of projects that authors wish to emphasize. Further studies may wish to explore how full-text analysis can be done at the global level—such work will need to overcome the hurdles of publisher paywalls and differing institutional access, in addition to requiring substantially more computational power to analyze the larger texts.

Data issues notwithstanding, considering how much has been written about "mainstreaming"[10,68,69] and about the Paris Agreement as a turning point for adaptation,[45,70] 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.[65] 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. Working with established frameworks, such as the NATO typology we used here, can help bring relevance and intercomparability to adaptation research.

Lastly, geographical imbalances remain a key problem in scientific publishing more broadly[71,72] but are especially pressing for adaptation research given the vulnerability of many places in the Global South. The so-called "gray 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.[5,73,74] In addition to addressing persistent funding inequalities[75] and the previously mentioned need for full-text analysis at scale, the adaptation community should therefore prioritize systematic assessments and categorization 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-labeled 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., Tunstall et al.,[76] 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] our query required documents to use at least one policy-relevant keyword, but based on the classifier results, many of these documents did not substantially discuss 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 focused classifications. Because they are easily repeatable, machine learning assessments in particular 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

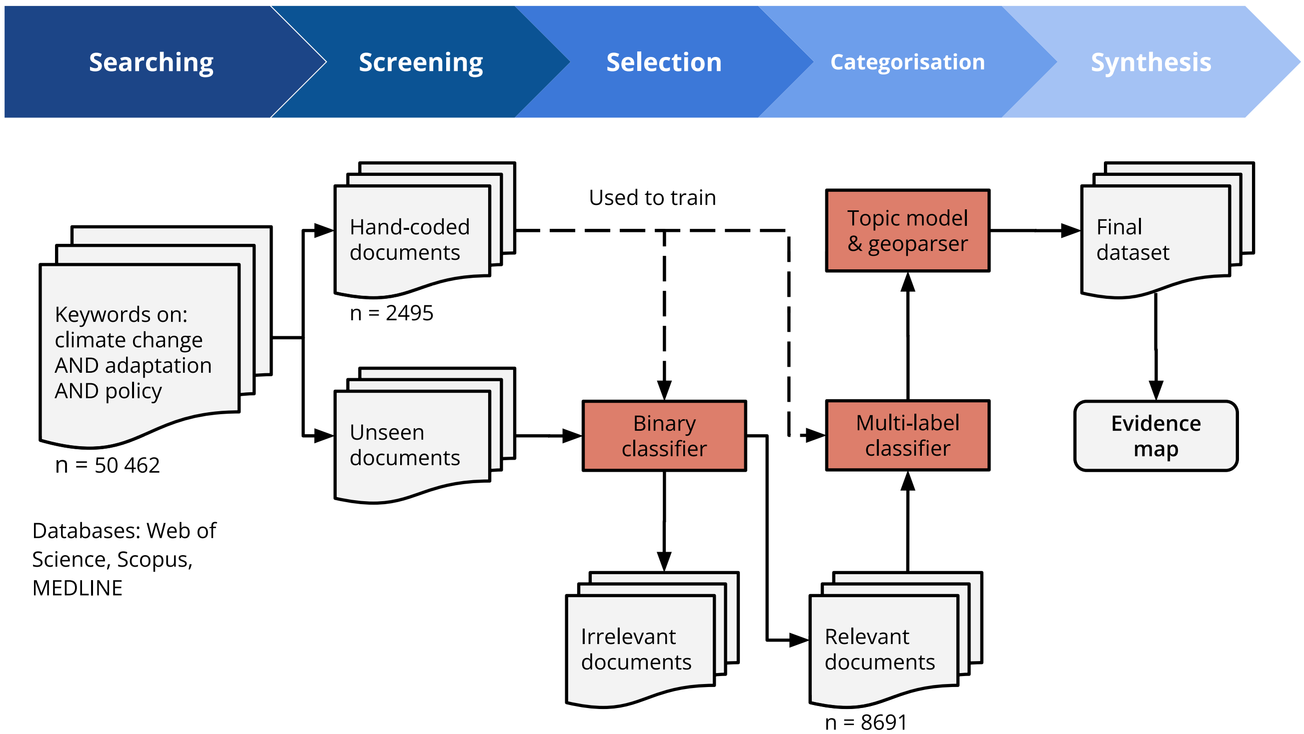


Figure 6. Schematic representation of the research process

The overview is broken down into 5 steps. Machine learning components are given in red.

selecting all documents belonging to urban topics that 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, as the classifications need to be re-run periodically in this case and additional hand-labeled data may be required in time to ensure that the machine learning models can accurately interpret new developments in adaptation science.

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,[5,9,26,30] provide a promising way forward. Given also the increasingly severe impacts of climate change, reliable and scalable ways to synthesize evidence will be instrumental in improving adaptation planning and reducing the harms caused by climate change.

EXPERIMENTAL PROCEDURES

Resource availability

Lead contact

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Materials availability

This study did not generate new unique materials.

Data and code availability

All original code has been deposited at Zenodo under the DOI https://doi.org/10.5281/zenodo.7893023. This also contains the core dataset of the publication in tabular format and is publicly available as of the data of publication.

General methodology

Our methodology was published in a separate protocol, 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, categorization, 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.[67] and added recognized 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 subcomponents are internally linked by a Boolean "OR." We retrieve the title, abstract, and meta-information for all documents. No full texts were retrieved.

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 categorize them, but in both cases, no examples exist to learn from. Therefore, in the screening step, A.J.S., E.T., A.T., and I.V.C. manually labeled 2,495 documents. This was done using the NLP Assisted Classification, Synthesis and Online Screening (NACSOS) platform.[77] To ensure consistency, 15% documents were double coded.

For each document, the human labelers 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, a main subject of the document must be an adaptation policy.

The majority of documents for labeling 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 labeled documents were used to train a machine learning classifier based on ClimateBERT[78] through HuggingFace.[79] Such Transformers-based language models are at the cutting edge of current natural language processing (NLP) methods. This model in particular has been specifically trained to work well on climate-change-related texts. Nested cross-validation[30] 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 hyperparameters but instead use Optuna with a tree-structured Parzen estimator (TPE) sampler doing 75 trails per inner loop.

Categorization: Supervised learning

If a document was labeled 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 were either labeled as relevant or predicted to be relevant. For the labeling 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 categorize policies according to the well-established NATO typology of policy instruments.[34] The typology has 4 components: nodality involves producing or providing information, including research programs 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, organization policies either create a new organization or change how an existing organization 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 favor 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 they explicitly mention an adaptation component or a change in a recognized 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: international, including, for example, the UNFCCC, the European Union, and any other multicountry 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 subnational 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 that 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.[30]: Coastal, 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 labeled too. Here, there are two options: *ex 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, and a high number of *ex post* studies also indicates that the evidence base is more likely to include practical on-the-ground experiences. At the same time, *ex ante* studies can inform policymakers about a range of options, including options under different climate change scenarios, so they are necessary to ensure that adaptation policies meet the challenges of future climate change.

Categorization: Pre-trained and unsupervised learning

In addition to the hand-coded categories described above, we also use a pre-trained geoparser[38] to identify geographic locations in the documents, as well as in the affiliations of authors. Since the geoparser does not recognize 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,[80,81] 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),[82] 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 run 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 Table S2) 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 supplemental information (Figure S4), 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 1,000 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,[45] while others have argued that adaptation policies should align with the targets set in the SDGs to be successful long term.[46,47] By seeing which topics have shifted significantly between the two periods, and which topics have not, we find an indication of whether these international policies have led to a corresponding shift in the academic literature.

SUPPLEMENTAL INFORMATION

Supplemental information can be found online at https://doi.org/10.1016/j.oneear.2023.12.011.

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AUTHOR CONTRIBUTIONS

Conceptualization, A.J.S., R.B., M.C., J.C.M., and J.D.F.; methodology, A.J.S., E.T., R.B., A.T., M.C., J.C.M., and J.D.F.; software, A.J.S. and M.C.; investigation, A.J.S., E.T., A.T., and I.V.C.; data curation, A.J.S.; writing – original draft, A.J.S.; writing – review and editing, A.J.S., E.T., R.B., A.T., J.C.M., and J.D.F; visualization, A.J.S. and M.C.; supervision, J.C.M. and J.D.F.

DECLARATION OF INTERESTS

The authors declare no competing interests.

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