The First Generation of Machine Learning Applications for Tracking Climate Change Adaptation

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Declaration of authorship

The candidate confirms that the work submitted is their own, except where work which has formed part of jointly authored publications has been included. The contribution of the candidate and the other authors to this work has been explicitly indicated below. The candidate confirms that appropriate credit has been given within the thesis where reference has been made to the work of others.

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Rationale for submitting the thesis in alternative format

This thesis begins by outlining a broad problem: the practical difficulties of designing a meaningful adaptation tracking system. The potential solution presented is broad too: using modern machine learning methods to analyse large volumes adaptation-relevant information. Within this wide gamut, three concrete and distinct applications of machine learning methods to real-world data were developed, each of which require a separate introduction and discussion to properly addresses the specific characteristics of the dataset and methods used. These applications were therefore conceived as three separate publications, each of which was also subject to topic-specific peer review. Additionally, a fourth publication is included that aims to place the previous findings in a broader perspective, as well as describing how the findings can be used to improve machine learning applications for adaptation tracking going forward. This work aims to contribute to a broader discussion within the adaptation community; to maximise its potential impact, this too was submitted separately to a scientific journal with wide readership. This thesis binds together these four publications and reflects on their wider lessons in its final chapter. While each chapter has been edited for inclusion in this thesis, in order to maintain the independence of each piece of work, there is inevitably some overlap between chapters.

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Abstract

In the Information Age, datasets are getting too large and diverse for conventional synthesis methods. This is especially true for climate change adaptation: projects are highly context-dependent and information sources are numerous but scattered. At the same time, tracking progress on adaptation is vital: it shows if sufficient progress is being made, enables practitioners to learn from prior experiences and highlights where resources are most needed. In this thesis, I contribute to an emerging literature which uses machine learning for adaptation tracking. I explore how a combination of methods like Structural Topic Modelling and various supervised learning models can be used to map and analyse adaptation evidence at scale. First, I use inquisitive evidence mapping to systematically assess the breath of adaptation-relevant evidence in the peer-reviewed literature, finding it has developed rapidly and shows signs of maturing. However, long-standing problems persist, including significant Global North/South biases. The findings closely align with the results of semi-structured expert interviews, supporting the validity of my approach. Second, I focus on adaptation policies, using a Transformers-based machine learning model to identify and classify policy studies in the scientific literature. Here too, I note substantial geographical differences; moreover, I see few signs of progress on policy implementation and structural reforms. Third, I investigate how political framings influence the executive summaries of country-level reporting to the United Nations Framework Convention on Climate change. I find evidence that countries highlight local priorities in their executive summaries; however, attention to adaptation or climate action has not meaningfully increased since the adoption of the Paris Agreement. Finally, I critically assess the first generation of machine learning applications for adaptation. I note that most efforts are encouraging but fall short of their transformative potential. I then provide suggestions for improvement and argue that the adaptation community should treat machine learning as a paradigmatic shift, rather than an extension of business as usual.

Table of contents

List of figures

List of tables

Abbreviations

AI	Artificial Intelligence
AR	Assessment Report (of the IPCC)
BERT	Bidirectional Encoder Representations from Transformers
CCB	Cross Chapter Box (in IPCC reports)
COP	Conference of the Parties (to the UNFCCC)
CRI	Climate Risk Index
ES	Executive Summary
FAO	Food and Agriculture Organization
GROBID	GeneRation Of Bibliographic Data
IAV	impact, adaptation and vulnerability
INFORM	Index for Risk Management
IPCC	Intergovernmental Panel on Climate Change
LDA	Latent Dirichlet Allocation
LLM	Large Language Model
ML	Machine Learning
MRV	Measurement, Reporting and Verification
NACSOS	NLP Assisted Classification, Synthesis and Online Screening
NAMA	Nationally Appropriate Mitigation Actions
NATO	Nodality, Authority , Treasure and Organisation
NC	National Communication (to the UNFCCC)
NDC	Nationally Determined Contribution (under the UNFCCC)
(ND-)GAIN	(Notre Damme) Global Adaptation Initiative
NLP	Natural Language Processing
OECD	Organisation for Economic Co-operation and Development
PA	Paris Agreement
SIDS	Small Island Developing States
SPM	Summary for Policy Makers (in IPCC reports)
STM	Structural Topic Model

SVM	Support Vector Machine
TF-IDF	Term Frequency – Inverse Document Frequency
t-SNE	t-Distributed Stochastic Neighbourhood Embedding
UN	United Nations
UNDP	United Nations Development Program
UNEP	United Nations Environment Program
UNFCCC	United Nations Framework Convention on Climate Change
WG	Working Group (of the IPCC)
WHO	World Health Organization
WRI	World Risk Index

1 Introduction

1.1 Research rationale

This thesis is a response to two developments: first, the increasing likelihood that climate change will have serious and lasting effects to which people will need to adapt; and second, the rapid improvements in the ability of machine learning methods to handle large and complex datasets. The overarching aim is to examine how machine learning methods might be used to track how and where adaptation to climate change is taking place.

The importance of anthropogenic climate change at this point scarcely needs to be explained as it has been clear for decades (e.g. IPCC, 1992, World Meteorological Organization, 1979): human activities are causing an increase in the atmospheric concentrations of various greenhouse gasses, chiefly CO_2 and methane, which is causing global temperatures to increase, among other changes to the climate. An increase in the average global surface temperature of more than 1.5 °C above the pre-industrial average could have devastating effects for many ecosystems and people around the world (IPCC, 2018). Current levels of warming are approaching this limit and changes to the climate are already affecting every corner of the earth (IPCC, 2022b): in 2022, the planet had heated by an average 1.1 °C and temperatures are likely to continue climbing in the near future (National Aeronautics and Space Administration, 2023).

In other words: climate change is a current and global problem. People and governments will have to take action, including mitigation – i.e. decreasing the emission of greenhouse gasses – but also adaptation – i.e. how to adjust to the effects of climate change (IPCC, 2014b). Moreover, as the "climate crisis" (see: Feldman and Hart, 2021, Kunelius and Roosvall, 2021) accelerates, accurate information on how to respond is increasingly vital.

This is where machine learning can be of added value. As a field of research, machine learning, too, is decades old (Carbonell et al., 1983). However, it has grown rapidly in recent years in response to so-called "Big Data", which typically refers to large datasets (high volume) that change rapidly (high velocity) and are often about a mixture of topics in relatively unstructured formats (high variety). Taken together, these three factors mean that such datasets are difficult or impossible to analyse by hand (Kitchin and McArdle, 2016, Laney, 2001). The complexity of Big Data, combined with the decreasing costs of computational power and increasingly sophisticated models means that machine learning is now used in an ever-expanding variety of contexts (Fradkov, 2020).

As I will expand upon below, adaptation has all the hallmarks of a Big Data problem too: it is a highly varied field where increasingly large volumes of information need to be processed to address an urgent crisis. It seems therefore that machine learning methods are, at least in theory, well-suited to analysing adaptation data (Ford et al., 2016, Cheong et al., 2022). When I started my PhD research in 2019, this idea was largely untested, but since then, there has been a wave of computational research in the adaptation community. In particular, machine learning methods are being used to track international progress on adaptation. My work fits into this larger context of adaptation tracking.

I will expand upon this topic below, but here, at the very start of this thesis, I wish to briefly zoom out to the bigger picture and underline once more the urgency and the magnitude of this crisis. Climate change is causing people to flee their homes (Abel et al., 2019, Hoffmann et al., 2020). It is killing people (Vicedo-Cabrera et al., 2021, Carleton et al., 2022, Park et al., 2020). Human actions are causing more species to go extinct now than at any point in our history – a sixth mass extinction may be underway (Cowie et al., 2022, Sills et al., 2018) – and climate change is among the main driving factors (Purvis et al., 2019). Humanity has been slow to respond, but now, it seems "climate action" is on everyone's lips. Governments and companies alike routinely issue reports on all the great works they have done. Yet to me, much of this appears to be, in the words of Bingler et al. (2022) "cheap talk and cherry picking."

If we truly want to bring about lasting systemic change, part of the puzzle is finding objective ways to see where progress is being made, as well as where more needs to be done. That is what I hope to contribute to with this thesis.

1.2 Research context: adaptation tracking

A history of differing definitions

The practical goal of this thesis is to improve the global understanding of adaptation. This places my thesis squarely in the field of **adaptation tracking**, which seeks to develop and apply "*systematic approaches to assess progress on adaptation efforts over time and space, and between and across populations and sectors*" (Berrang-Ford et al., 2019p. 440). To understand why this is difficult to do in practice, it is first necessary to understand why adaptation is a complex and contentious concept. In the following sections, I will expand upon the political and historical roots of this complexity.

The term adaptation originally came from biology and ecology but was adopted by the climate change community to describe the different ways in which humans make themselves less vulnerable to climate change (Smit and Wandel, 2006, Smit and Pilifosova, 2003). More specifically, the Intergovernmental Panel on Climate Change (IPCC) defines **adaptation** as "*[t]he process of adjustment to actual or expected climate and its effects in order to moderate harm or exploit beneficial opportunities*" (IPCC, 2022a, Box TS.1). Although this definition does not preclude adaptation by non-humans, in the context of this thesis, as within much of the literature, the focus is on human adaptation.

Both scientifically and especially politically, adaptation has long been overshadowed by mitigation. Decreasing greenhouse gas emissions was the main goal of most early climate legislation, including for example the United Nations Framework Convention on Climate Change (UNFCCC) and the Kyoto Protocol, which was negotiated under this Convention (Schipper, 2006, Kuyper et al., 2018, Khan and Roberts, 2013). At this early stage, the degree to which a country could adapt was largely taken as a given, rather than as something that could be increased through intentional actions (Schipper, 2006). Additionally, the belief was that adaptation would not be necessary if mitigation was successful – or, more cynically, acknowledging the need for adaptation could be seen as an admission of guilt from industrialised[1] countries that their emissions are causing harm (Schipper, 2006, Pielke et al., 2007).

In the early 2000's, political pressure to take adaptation seriously grew for two main reasons: first, it became increasingly clear that countries were not mitigating their emissions enough to keep climate change within safe bounds, so adaptation would be necessary; second, the scientific community emphasised the importance of adaptation in a few landmark reports, including the IPCC's third and fourth assessment reports, published in 2001 and 2007 respectively (Bassett and Fogelman, 2013, Kuyper et al., 2018). These reports showed a growing interest in adaptation as conscious, possibly government-initiated processes (Beck, 2011). Further, although the effects of climate change are felt on the local scale and studies therefore by and large rely on local case studies (Biesbroek et al., 2013, Eisenack et al., 2014), the IPCC reports also showed that there were transferable lessons to be learned when these case are studies considered in the aggregate (Beck, 2011). Taken together, this not only made adaptation a viable subject for global policy debates, but it also started to remove the impression that adaptation was an issue purely for the Global South (Khan et al., 2020). Under the UNFCCC process, the increased pressure lead to a few adaptation decisions (see Singh and Bose, 2018 for a full list), including the establishment of a separate Adaptation Fund (decision 5/CP.7), the Bali Action Plan (1/CP.13) and the Cancún Adaptation Framework (1/CP.16), which made adaptation nominally equally important as mitigation.

Notably, the interpretation of adaptation that developed during this period on the international stage is somewhat different from how the concept is understood in the scientific community. Industrialised countries, who were asked to supply funding for adaptation, pushed for a relatively narrow interpretation of adaptation where it only refers to concrete actions, often of a technical nature, taken in response to risks and impacts that would not be present without climate change (Khan and Roberts, 2013, Sherman et al., 2016). This

[1] Generally, I will use Global North and Global South, as these terms do not imply a hierarchy the way for example developed/developing countries do. However, in the context of the UNFCCC, it is especially important to emphasise (historical) greenhouse gas emissions, which is why "industrialised countries" is used in this section, broadly equating to UNFCCC Annex II countries.

discussion primarily revolves around the definitions of "attributable to climate change" and "additionality", with especially the US arguing that funding can only be accessed if the supported actions are a proven direct response to climate change and thus separate from general development (Fujikura, 2022, Donner et al., 2016).

In practice however, that distinction is often difficult to make (Schipper et al., 2020, Sherman et al., 2016, Leiter and Pringle, 2018, Fankhauser and Burton, 2011). As a quick example, consider the paving of an existing unpaved road. The new road is likely to be more resistant to flooding and floods might increase due to climate change, so this project has an adaptation component. However, one could argue that the existing road would likely have been repaired anyway, so rather than counting the whole project as adaptation, only the added cost of paving should be counted. To make matters more complex, without climate change, floods might still have happened, so perhaps only a part of the paving costs should be counted. Or only (part of) the cost for including extra drainage, as this is a more direct and specific response to the changes in the climate, whereas paving also has economic benefits.

By contrast, in most parts of the scientific community, adaptation took on a broader meaning (Beck, 2011, Sherman et al., 2016), which leans less on singular events and actions, but rather recognises that climate change introduces additional variability in a wider system and can have complex interactions with a variety of social, cultural, political and economic factors, in addition to the direct physical impacts (e.g. Smit and Wandel, 2006, Smit and Pilifosova, 2003). During this time, the IPCC, too, explicitly recognises that sustainable development in the broadest sense can decrease a community's vulnerability to climate change (IPCC, 2007).

"Vulnerability" here is one of a few terms that are closely related to adaptation and therefore important to define. Although disagreement on their exact interpretation continues to this day (Saxena et al., 2018, Schipper et al., 2020, Ishtiaque et al., 2022), in its 5th Assessment Report (AR), the IPCC (2014b) sought to unify most of these terms into an overarching risk framework. More exactly, risk is divided into three overlapping concepts: hazards, vulnerability and exposure; these can manifest as impacts; see Figure 1.1. For full definitions, see the glossary of the IPCC (2022a).

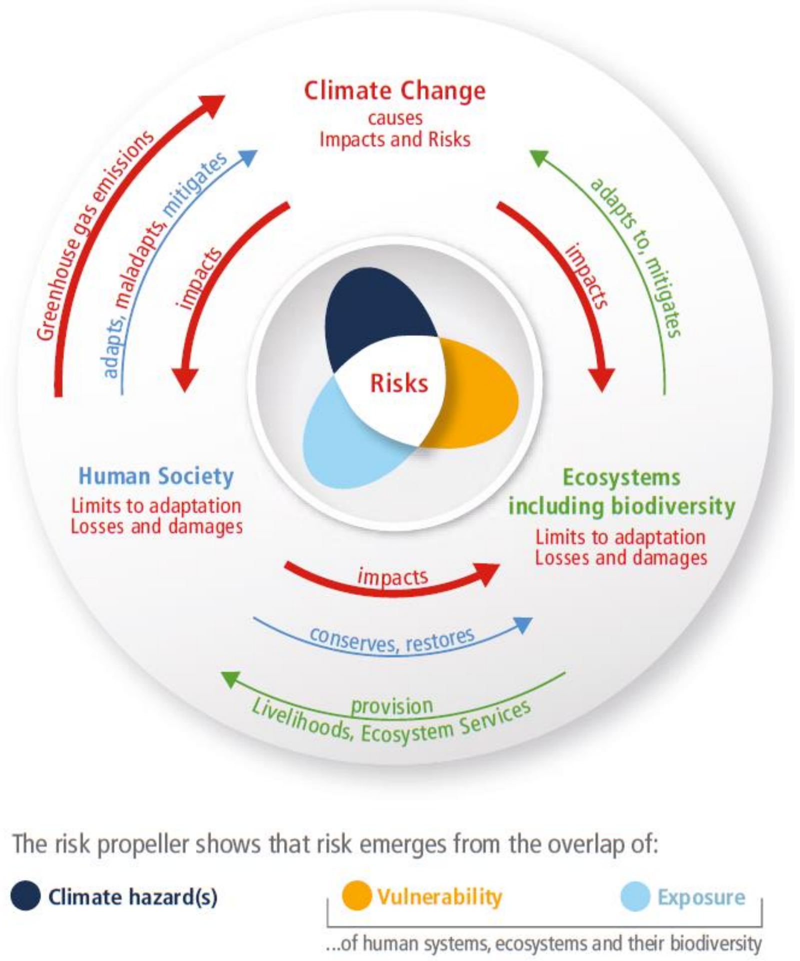


Figure 1.1: *The risk propeller, as proposed by the IPCC. It summarises how the concepts of hazard, vulnerability and exposure combine to create climate risks, and how these concepts depend on both human and natural systems. Figure adapted from IPCC (2022a figure TS.2)*

In brief:

- **Hazard** refers to the climatic driver, meaning the physical event that is caused or partially caused by climate change.
- **Vulnerability** is broader than just a component of climate risk, but it denotes the predisposition of a population or system to be adversely affected by climate change. This includes both their sensitivity to the effects of climate change and their capacity to respond, which is sometimes called "adaptive capacity."
- **Exposure** describes what exactly would be impacted, for example the number of people living in an area, the presence of industry or important ecosystems.
- **Impacts** are the consequences once a risk manifests and its magnitude depends on the previous three points.

To give an example of how these interact, climate change can increase the severity of flooding in an area (hazard). In an uninhabited piece of coastline without much value to ecosystems (low exposure), the risk is less severe than if that same flood would hit a city (high exposure), especially if that city faces socio-economic challenges and is unable to build flood defences or otherwise coordinate an effective response (highly vulnerable, low adaptive capacity). Actions the city takes to decrease their flood risk are adaptations and the negative consequences once a flood does happen are called impacts.

It is worth stressing that all these terms in practice are highly context-dependant. This in no small part explains why research into **Impacts, Adaptation and Vulnerability** (IAV) tends to rely on studies focussed on a particular region or sector, as I noted earlier (Biesbroek et al., 2013, Eisenack et al., 2014). One can for example find a substantial literature specifically focussed on adaptation strategies in the context of glacier tourism (Salim et al., 2021); this literature is obviously very different from the numerous studies about rice production in Asian delta's, as reviewed by Schneider and Asch (2020). Note also that this review follows a fairly typical order, first describing the current social- and physical environment (including vulnerabilities and potential exposure), followed by the main climate-related threats (hazards and potential impacts) and ending with possible responses (adaptations). Crucially, although these factors are obviously inter-related, most studies focus on only one part of this process. This means that while there is a substantial literature that self-identifies as being about adaptation – that is, the authors themselves use the word adaptation – the literature that is *relevant to* adaptation is considerably larger still – a policy maker may be very interested in climate impacts for their particular region and sector, even if the study itself does not discuss potential responses. As I will return to later, this makes reviewing or tracking adaptation progress more complex. A recurring theme throughout this thesis is determining if the literature is progressing from describing the current status and potential impacts to describing concrete adaptation actions.

Now, let us return to how the concept of adaptation changed over time. In addition to stressing complex inter-relations, AR5 used much stronger language overall than previous

IPCC reports, which put pressure on countries to increase their climate ambitions (Gao et al., 2017). The Kyoto Protocol had been extended a few years prior to include a second commitment period, but this was slated to end fairly soon, in 2020, and overall, a more comprehensive overhaul of the international climate regime seemed necessary (Streck et al., 2016, Kuyper et al., 2018).

Ultimately, this takes the form of the Paris Agreement. This Agreement was signed at the 21st Conference of the Parties (COP) and it greatly increases the importance of adaptation (Kuyper et al., 2018, Lesnikowski et al., 2017, Singh and Bose, 2018, Streck et al., 2016): it is depicted as an integral part of climate action, with the Agreement stating that all countries shall “engage in adaptation planning processes and the implementation of actions” (Article 7.9). Countries also pledge additional support for the most vulnerable countries especially. In part, this is an extension of an earlier promise to mobilise 100 billion US dollars per year for climate action, with a “balance between adaptation and mitigation” (Article 9.4).

As an aside, in this case, it is the Global South that pushes for a narrower interpretation of adaptation, or, more exactly, a narrower interpretation of adaptation *finance*. As stated earlier, it can be difficult to distinguish between adaptation and development (Schipper et al., 2020, Sherman et al., 2016). Some countries in the Global South accused industrialised countries of making access to finance difficult by requiring strict proof that the averted risks are attributable to climate change, while at the same time the funds in practice were taken from existing development assistance, rather than being new and additional adaptation-specific funds (Fujikura, 2022, Donner et al., 2016). Arguably, this issue is still not resolved, hindering the8ffecttive tracking of adaptation finance (Pauw et al., 2022).

Related to the *tracking* of adaptation specifically, the Paris Agreement makes a few crucial steps forward too. Most notably, it sets a global goal for adaptation (Article 7); it further establishes the Enhanced Transparency Framework (Article 13), which includes new requirements around the reporting of adaptation actions; and it calls for a Global Stocktake (Article 14) to periodically assess progress towards the goals of the Agreement. Negotiations on how exactly the Paris Agreement should be implemented continued for a few more years, but agreements on most issues were reached by the end of the COP 26 in Glasgow, just over a year and a half ago at the time of writing, and the Agreement is now in effect.

In the meantime, a few adaptation-related terms have garnered considerable additional attention between IPCC AR5 and AR6 (Magnan et al., 2022, Magnan et al., 2020, Adger et al., 2018). These terms include “transformational adaptation” and “adaptation limits” (e.g. IPCC, 2014a Box TS.8). Transformational adaptation seeks to be a radical departure from business-as-usual, as opposed to more traditional “incremental adaptation” (Few et al., 2017, Magnan et al., 2020). Limits to adaptation can be physical – i.e. beyond a certain level of warming, no technology can maintain a standard of living – but they can also be social and cultural – i.e. the required changes to adapt to a climatic change would entail a significant loss of culture or identity (Adger et al., 2009). Theoretical discussions on limits are far from new, but more practical and policy-oriented studies are emerging only now (Berkhout and Dow, 2023). Further, adaptations can have unintended negative consequences, for example if a focus on short-term incremental adaptation hinders necessary transformational adaptation later, or if adaptations lead to the emission of additional greenhouse gasses. Where this leads to an overall undesirable outcome, this is known as “maladaptation” and the risk of maladaptive responses has increased since AR5 (IPCC, 2022b). In other cases, it is better to speak of a “trade-off”: desalination plants and rainwater harvesting can lead to significant greenhouse gas emissions for example, but in places, their adaptive benefits may be more important. Conversely, it is also possible for adaptation actions to positively impact mitigation, or vice versa. This is known as “co-benefits” or “synergies”. As climate action is increasing, such practical concerns about interaction effects are increasingly relevant (Sharifi, 2020, Berry et al., 2015).

Further, there are myriad emerging terms and themes in research that are less explicitly related to adaptation, but which are still influencing current understandings of adaptation. I will highlight three sets of terms. First, I described earlier that climate risks are seen as an interplay of many social and physical factors; in recognition of this, recent research has started to focus on feedback effects and how risks can compound each other, which could lead also to “tipping points”(Rising et al., 2022, Pescaroli and Alexander, 2018). In other words, climate change can have unpredictable consequences because changes in one system can lead to a variety of effects in other systems and it is possible that such “cascading risks” push a particular climate-related system past a point from where the system starts to spin out of control, even if external forcings stop. Second, there can be a “residual risk” after adaptation limits have been reached and in places, climate impacts have already led to irreversible negative consequences. Some countries, especially in the Global South, are seeking compensation for or insurance against this so-called “Loss and Damage,” which under the UNFCCC is subject to ongoing negotiations (Naylor and Ford, 2023), but has so far resulted in the Warsaw Mechanism for Loss and Damage, as well as provisions under the Paris Agreement (Boda et al., 2021, Gewirtzman et al., 2018). Finally, I already noted the possibility for trade-offs and co-benefits, but it is important to understand that this need not be limited to climate-related effects only. Present-day adaptation research often places climate action in the broader context of “sustainable development,” hereby incorporating a broad range of issues such as biodiversity and economic inequality. IPCC AR6 for example evaluates the potential synergies and negative effects of specific adaptation actions on the Sustainable Development Goals (Ley et al., 2022).

Overall, the long road to the Paris Agreement shows a few fault lines that have serious consequences for adaptation tracking. Although it has historically received less attention than mitigation, adaptation has developed into a complex concept alongside a few closely related and equally complex concepts. Consequently, it is difficult to delineate exactly when something is adaptation and when it isn’t, with different communities maintaining different definitions and interpretations. Due to political tensions, these differences are unlikely to be resolved in the near future. This means that, although there now is a global goal on adaptation, it is still unclear what this goal would look like in practice, as well as how progress towards this goal should be measured (e.g. Craft and Fisher, 2018, Tompkins et al., 2018a).

The what, why and why not of adaptation tracking

So far, we focussed on adaptation, but only briefly mentioned adaptation tracking. For tracking, too, there are myriad competing frameworks and methodologies (e.g. Berrang-Ford et al., 2019, Craft and Fisher, 2018, Njuguna et al., 2022, Olhoff et al., 2018, Magnan and Chalastani, 2019). Within this multiplicity, Ford and Berrang-Ford (2016) describe "the 4Cs" which high-quality adaptation tracking should strive for:

- **Consistency**: any tracking method needs to determine what counts and what does not count as adaptation in a consistent manner. Researchers need to consider multiple viewpoints on adaptation and work towards a single operationalisation that they apply uniformly throughout their project. To ensure that the study is transparent and replicable, the criteria for inclusion and exclusion should be detailed and explicit.
- **Comparability**: tracking requires a comparable unit of analysis, which in most cases will mean defining a spatial limit – e.g. comparing the adaptation actions of two cities is likely to be more meaningful than comparing adaptation actions from a city to the actions of a country. Moreover, tracking efforts should not just compare *between* different units of analysis, but also *within* them to assess progress – e.g. how has the adaptive capacity of a country changed within the last 5 years?
- **Comprehensiveness**: trends and patterns are only meaningful if they are derived from data that adequately captures reality. Adaptation tracking therefore should rely on data that is as comprehensive as possible, using sampling methods where appropriate.
- **Coherence**: the chosen indicators should be coherent with the current understanding of adaptation. This means the indicators should have strong theoretical underpinnings as well as reflecting the complexities of adaptation on the ground.

To be clear, these 4Cs are to some degree aspirational; they capture a "gold standard" which is challenging to apply in practice. They can even be at odds with each other. For example, there is likely to be a trade-off between coherency on the one hand and comparability and comprehensiveness on the other: coherent data, such as in-depth case studies, are likely less abundant and can make comparisons more difficult than simpler measures such as counting the number of adaptation projects in a region.

Given such tensions and the conceptual differences mentioned earlier, some authors have questioned if tracking adaptation at the global scale is possible at all (Singh et al., 2022, Fisher and Craft, 2016, Leiter and Pringle, 2018, Dilling et al., 2019). These authors stress that adaptation is a local context-dependant process, so it is impossible to find a definition or measure of successful adaptation that fits all these situations. This in turn means that a unified global measurement will necessarily distort reality. Or, in terms of the 4Cs: a consistent measure that allows for comparisons will be incoherent with any practical understanding of adaptation. In this view, adaptation knowledge is only meaningful when it is considered in context, which makes any aggregate measure virtually meaningless.

In itself, I find this argument not particularly convincing, if only because measuring anything by its very nature is reductive. Famously, the only complete map of a place is the place itself, which, although perfectly accurate, is perfectly useless. A large part of good science is finding ways to represent an aspect of reality in a smaller but insightful manner. Adaptation science is no different.

However, the anti-tracking argument cannot be separated from its political context. One fear, predominantly of the most vulnerable countries (see e.g. Möhner, 2018), is that an unequal metric will become the basis for decision making, rather than listening to the countries and communities themselves (Dilling et al., 2019). For example, one could argue that the Adaptation Fund should prioritise projects with the most impact and therefore should allocate funding based on a given adaptation index. For both practical and political reasons however, no single index will satisfy all countries (Klein, 2009, Klein and Möhner, 2011). In a similar vein, some countries are already struggling to meet reporting requirements; having to collect additional data and going through a strictly standardised application process so that an index can be calculated would hinder access especially for the countries who need support the most (Leiter and Pringle, 2018).

I do not want to brush these fears and criticisms aside. Adaptation decision making should not be based on any single metric. Researchers and practitioners alike should work with communities and take their concerns seriously.

Still, there is space to do both: we can try to track adaptation *and* understand it qualitatively. An over-reliance on tracking efforts can lead to overly technocratic and bureaucratic decision-making, but equally, an over-reliance on context-specific studies can lead to a narrow understanding of adaptation. The fact that no perfect system exists is an argument to be cautious, not to categorically dismiss all tracking efforts. Moreover, there are positives to the tracking adaptation at scale too. It can serve at least three important functions.

First, a global overview improves accountability and, by extension, trust (Gupta and van Asselt, 2019, Frey and Burgess, 2022). International institutions like the UNFCCC work through consensus and collaboration rather than coercion, which mean they rely heavily on "naming and shaming" (Kinley, 2017). On the mitigation side, the "mitigation gap" and extensive greenhouse gas reporting has proven useful to this end; analogous efforts for adaptation could have similar benefits (see also: Magnan and Ribera, 2016, Berrang-Ford et al., 2019, Siders, 2019, Christiansen et al., 2020, Olhoff et al., 2018). To be sure, "Are we adapting to climate change?" (Berrang-Ford et al., 2011) is a hard question to quantify exactly – more on this later. Still, large long-standing efforts such as the Adaptation Gap Reports (UNEP, 2022) at least make a credible case that we are not adapting *enough,* pushing communities and countries to increase their efforts. Framed more positively, actors are more likely to trust a process if they can see that others are doing their fair share. Staying at the international level, this is one of the intended functions of the Enhanced Transparency Framework under the Paris Agreement (Weikmans et al., 2021, Frey and Burgess, 2022).

A second function of adaptation tracking would be to identify and prioritise needs (Olhoff et al., 2018, Berrang-Ford et al., 2019). The Global Stocktake is especially interesting in this light (Christiansen et al., 2020): a high-quality overview of the current state of play does not just allow us to see how much more needs to be done, but also what and where (Magnan et al., 2020).

Thirdly and relatedly, effective tracking can help to identify and share lessons learned. Practitioners often do not know what adaptation policy would be best suited for their situation (Kuhl, 2021, Ryan and Bustos, 2019). More broadly, adaptation science is missing a central place where data and information are shared and systematically organised, as well as a body that can coordinate researchers efforts based on the available evidence (Magnan et al., 2022). The IPCC is probably the closest analogue, but its mandate is to synthesise and assess climate science, not lead it. Moreover, because the IPCC generally only presents their summary, not the underlying studies, it is of limited value for practitioners looking for detailed insights. Adaptation tracking could be the basis for a more up-to-date and comprehensive platform where adaptation actions and outcomes are made easily accessible, so that practitioners can find relevant evidence and build on prior experiences.

In sum, despite some fundamental criticisms, the core motivation of this paper is that it would be beneficial to track adaptation at the international scale in a consistent, comparable, comprehensive and coherent manner. This could help build accountability and trust among actors, as well as identifying where action is needed and more effectively building on past efforts. However, this turns out to be difficult to achieve in practice. Such practical considerations will be discussed subsequently.

Practical issues with tracking

A major practical problem for adaptation tracking relates to the unit of measurement. Ideally, an adaptation tracking system could say "because of adaptation action X, climate risk was reduced by Y." But what is the unit of Y? For an individual climate impact, finding a suitable proxy may be easy – e.g. for flooding: "m^2 of inundated land" or "number of destroyed houses" etc. – but these generally do not translate to other impacts and risks of climate change. Still, as Ford and Berrang-Ford (2016) point out, different fields have faced similar problems; in health sciences, for example, Disability Adjusted Life Years are widely as a unified measure of different health impacts. For climate impacts, some have argued for using metrics like monetary damages and lives lost (Eckstein et al., 2019, Michaelowa and Stadelmann, 2018), but these still struggle to measure climate effects evenly; moreover, it can be difficult to say if an impact or risk was reduced due to a certain action, and if so, by how much. As such, how to measure adaptation generally, and adaptation effectiveness in particular, is still an open question (Dilling et al., 2019, Singh et al., 2022).

The de-facto solution generally is to side-step this issue: instead of measuring the outcomes – i.e. risk reduction – it may be easier to measure processes – i.e. is some form of adaptation taking place? (Fisher and Craft, 2016, Garschagen et al., 2022). In practice, this means using indicators such as the number of adaptation projects and policies or international funding flows (e.g. Berrang-Ford et al., 2019, UNEP, 2022, Craft and Fisher, 2018, Tompkins et al., 2018b, Lesnikowski et al., 2016). While methodologically easier, such efforts often rely on self-reported data and can struggle to separate statements and intentions from actual actions and outcomes (Berrang-Ford et al., 2021a, Owen, 2020, Biesbroek et al., 2018).

Most other practical problems with adaptation tracking relate to data. High-quality adaptation datasets are rare (Olhoff et al., 2018, Garschagen et al., 2022). Although governments are increasingly tracking adaptation within their countries (UNEP, 2022), tracking systems are generally not intended for global comparisons (Magnan et al., 2022). Reporting to the UNFCCC in theory could be the basis for a global-level overview – the Global Stocktake for example will largely be based on national reports submitted to the UNFCCC (Christiansen et al., 2020, Craft and Fisher, 2018, Tompkins et al., 2018b). In practice however, these reports are an imperfect source of data: they are used as political instruments to advance positions in the climate negotiations, rather than as instruments of accountability (Gupta and van Asselt, 2019, Weikmans et al., 2021). Other well-established data sources tend to focus on specific aspects, for example cataloguing climate-related development aid (Fujikura, 2022, OECD, 2023) or climate change laws (Grantham Institute and Sabin Center for Climate Change Law, 2022). Although useful, the limited nature of these data sources means they provide an incomplete image of adaptation; a more comprehensive tracking system would need to collect data independently (Magnan et al., 2022).

Collecting data however is also not straightforward. For text-based tracking systems, it can for example be difficult to create a comprehensive list of keywords. Given the large number of closely related terms, arguably, one would need to include keywords around terms like vulnerability, resilience, climate impacts and disaster risk reduction. Some of this literature may not mention climate change explicitly but can be highly relevant – e.g. papers on hurricane responses – while others might mention adaptation explicitly but focus mostly on another aspect – e.g. a paper on vulnerability mentioning that adaptation might be needed without further details. As a result, one can either focus on documents that self-identify as adaptation (e.g. Nalau and Verrall, 2021, Wang et al., 2018), accepting that the overview will be incomplete, or one can use a more extensive list of search terms and either accept that some results will be irrelevant or find a way of filtering the documents later (e.g. Berrang-Ford et al., 2021a).

In light of this, **systematic review** (Berrang-Ford et al., 2015) and **evidence mapping** methods (for guidance: Haddaway et al., 2018, White et al., 2020) are worth highlighting. Both methods aim to obtain an overview of available evidence that is transparent, replicable and as comprehensive as possible. For a systematic review, the aim is usually to answer a specific question, whereas evidence maps cover a wider evidence base and are more exploratory, cataloguing what evidence is available, as well as where there are knowledge gaps (James et al., 2016). Both methods start with a systematically developed search query, usually in multiple databases, after which the retrieved documents are screened based on explicitly defined criteria. Relevant documents are then critically assessed and catalogued.

Because these approaches rely on scientific databases, they share a few strengths and problems: on the one hand, scientific databases are relatively well-structured, including for example information-dense abstracts and high-quality meta-data, as well as extensive search functionalities (Gusenbauer, 2022, Gusenbauer and Haddaway, 2020); on the other hand, disciplinary coverage varies between databases (Gusenbauer, 2022) and most databases are biased towards the Global North, in particular towards English-speaking countries, excluding non-academic sources that may better describe practical projects and activities in the Global South (González-Alcaide, 2021, Marsolek et al., 2021).

For evidence mapping on adaptation it is important also to realise how many different disciplines are involved here. For the purposes of this thesis, **discipline** refers to a community of researchers working within a given paradigm, meaning they broadly share epistemological values – what knowledge is (scientifically) valuable and what methods can be used to create such knowledge -- and study a given subject based on a set of facts and beliefs that are widely held within the community (Bird, 2022, Palsson et al., 2013). While adaptation researchers commonly hold similar views on the basic facts of climate change – e.g. as contained in the IPCC Working Group 2 reports – there are important distinctions with respect to first part of that definition. Broadly, one can distinguish between on one hand those who focus on quantitative methods, often with a natural sciences background – this includes many modellers, climate risk researchers and engineers; and on the other hand, those who prioritise qualitative knowledge, often with a humanities or social sciences background – this includes researchers engaged in community-based research, vulnerability researchers and traditional document analyses (Eriksen et al., 2015, Moore et al., 2015, see also: Palsson et al., 2013). As I will expand upon in the next chapter, there is a tension, too, between academic objectives and adaptation practice: while science is predominantly devoted to the pursuit of knowledge, many in the adaptation community also wish to make a concrete impact, pursuing projects that lead to adaptive outcomes and making the researcher part of the adaptive process, rather than its observer (Eriksen et al., 2015, Lemos and Morehouse, 2005, Castro and Sen, 2022).

Of course these are generalisations: disciplines are not static and adaptation researchers from different disciplines can and do collaborate (Schipper et al., 2021), with varying levels of integration. In particular, it is useful to distinguish between **multi-disciplinary** collaboration – where actors maintain their own disciplinary beliefs but work on a shared project – and **inter-disciplinary** collaboration – where actors integrate knowledge from their own domains into new, shared knowledge (Sonnenwald, 2007). The latter is obviously more difficult, but regularly touted as essential to successful adaptation (Moore et al., 2015, Schipper et al., 2021). For adaptation tracking in general and evidence mapping in particular, both the diversity in disciplinary perspectives as well as the overlap and integration of those perspectives can difficult: social science journals tend to have different standards from natural sciences ones and quantifying distinguishing between trans- and interdisciplinary research is hard for single papers, let alone the scale of a typical evidence map. This also means that it becomes extra important to start off with a wide and inclusive search.

In sum, although evidence mapping methods are an imperfect proxy for adaptation action as the data are not comprehensive, such methods can still capture a broad range of activities and, when done well, they are relatively consistent and comparable.

In this thesis, as well as in a few related papers, evidence maps are created for adaptation-relevant contexts (Berrang-Ford et al., 2021b, Callaghan et al., 2021, Callaghan et al., 2020, Chausson et al., 2020). These efforts underline a problem that is prevalent in climate change as a whole: the volume of data is overwhelmingly massive. From scientific papers (Callaghan et al., 2020) to twitter posts (Effrosynidis et al., 2022) to newspaper articles (Chinn et al., 2020), searches for climate change related content all result in at least tens of thousands of results. As will become clear from my research also, adaptation-related content makes up an increasingly large share of this deluge of information. Clearly, with these kinds of numbers, manual analysis is only possible for limited sub-topics, not for a high-level overview.

Data considerations will be discussed more extensively in the papers included in this thesis. For now, the main points to realise are that adaptation tracking generally seeks to quantify processes over outcomes; that data is difficult to obtain in a structured format; that keyword-based selection of data will lead to incomplete results; and that datasets are likely to be too large to analyse by hand. This is where computer-based methods can be of added value; modern machine learning methods in particular are able to make fine-grained distinctions in large and messy datasets. This will be discussed in the subsequent section.

1.3 Methods in context: machine learning

Key concepts

Like adaptation, computer science is a field of many competing concepts that partially overlap and that can be interpreted in different ways. For the purposes of this thesis, the historical and epistemological reasons for these differences are largely unimportant, but it is useful to have an understanding of five of these broader concepts, namely: data science, Artificial Intelligence, machine learning, Big Data and Natural Language Processing.

The first and arguably broadest term is **data science.** This describes a collection of separate but connected fields of research, including parts of computer science and statistics (Emmert-Streib and Dehmer, 2019). These fields share and continue to develop a systematic process for analysing digital and numerical data, which includes data collection, data cleaning, an iterative stage of data exploration, modelling and interpretation (Emmert-Streib et al., 2016).

Artificial Intelligence (AI) is one of the tools in the data science toolkit, though AI has many other applications too. The field of AI, as its name suggests, attempts to develop computer-based systems that exhibit intelligent behaviour. What is considered intelligent is somewhat of an open question; generally, computer scientists say a system is intelligent if it can perform tasks that would normally require a human, but there also ideas for AI systems that would (far) surpass human intelligence (Haenlein and Kaplan, 2019).

Some AI systems, including most of the ones used in this thesis, make use of **machine learning**. These kinds of methods "*improve their performance at certain tasks on the basis of observed data*" (Ghahramani, 2015). In other words, a machine learning system adapts to information it is given; it "learns" how to perform a task, rather than explicitly being told to how to do so. We can distinguish here between the machine learning algorithm – meaning the lines of code that contain the instructions for how to learn; and a machine learning model – meaning that the algorithm has been applied to a dataset so that it has learned certain attributes.

As an aside, the distinction between AI and machine learning can get blurry. There certainly are systems that fall under AI but not machine learning – e.g. "expert systems" are in essence a long list of rules, but with enough smart rules, these systems can still perform tasks that otherwise would require human intelligence. Machine learning is therefore often considered a subset of AI (e.g. Helm et al., 2020, Jakhar and Kaur, 2020). However, this implies that all of machine learning is also AI, which is debatable: it is possible to create a system which adapts to its input data, making it machine learning, but which is also too simple to be called intelligent (Bishop, 2006). Most of the methods used in this thesis are clearly machine learning and I will generally use that term: even if these models could be considered AI too, I am mostly concerned with evaluating their utility, not their intelligence. Still, it is important to realise that just because a system can learn, that does not necessarily mean it is also good at its job.

Data science methods in general, and machine learning methods in particular, are useful especially in the context of **Big Data.** As mentioned in the introduction, Big Data refers to relatively modern phenomenon where data is available in high volumes, with considerable variety and a high velocity, meaning it changes rapidly (Kitchin and McArdle, 2016, Laney, 2001). These three "three V's" of Big Data are both an opportunity – one can find information on issues that until recently were opaque – as well as a challenge – finding the *right* information can be difficult. In recent years, additional descriptors of Big Data have been added, expanding the term to as many as 7 V's (Khan et al., 2014), 10 key characteristics (Sun et al., 2018) or even 56 V's (Hussein, 2020). The two most prominent of these additional terms are veracity and value (Geerts et al., 2018, Reimer and Madigan, 2019). Big Data is usually user-generated and/or from public sources, which means the data can be of questionable veracity, in the sense that it may be incomplete, ambiguous, deceptive or simply false. This introduces additional uncertainty. Further, simply because data is plentiful does not mean that it is also useful. The goal of Big Data analytics should be to find insights that have a measurable impact – i.e. they are of value.

In this thesis, most of the data is in text form. This means the techniques I use are mostly taken from **Natural Language Processing** (NLP). In short, NLP is a subset of AI that "*explores how computers can be used to understand and manipulate natural language text or speech to do useful things*" (Joseph et al., 2016). This definition encompasses a broad range of tasks from translation to creating chatbots to checking grammar. I will expand upon the specific NLP methods used in this thesis below.

Before we consider these specific methods though, it is worth highlighting just how quickly all of the above fields are developing. AI, machine learning and NLP each go back to at least the 1940s (Haenlein and Kaplan, 2019, Joseph et al., 2016) and since then, research in these fields has gone through cycles of great expectations and progress, followed by an "AI winter"

(Hendler, 2008, Mitchell, 2021). Whether the current optimism will also prove temporary remains to be seen, but right now, the pace is frantic, with enormous amounts of money and human resources being invested; at the time of writing, ChatGPT for example has inspired something akin to an arms race between some of the biggest companies in the world, all trying to build the most useful and powerful implementation of a large language model (Roose, 2023).

Practically, this means developments around all the concepts discussed here have been so rapid recently that other fields are struggling to keep up. By the time researchers have found a way to implement a given machine learning model, the model is already outdated. I will return to this dynamic in my fourth paper and in the discussion section of this thesis; for now, it is enough to understand that a machine learning application can be considered novel in a particular field in the sense that it has never been tried before, even if that same application might be considered outdated in the machine learning community because a newer model has already been developed.

Natural Language Processing methods used in this thesis

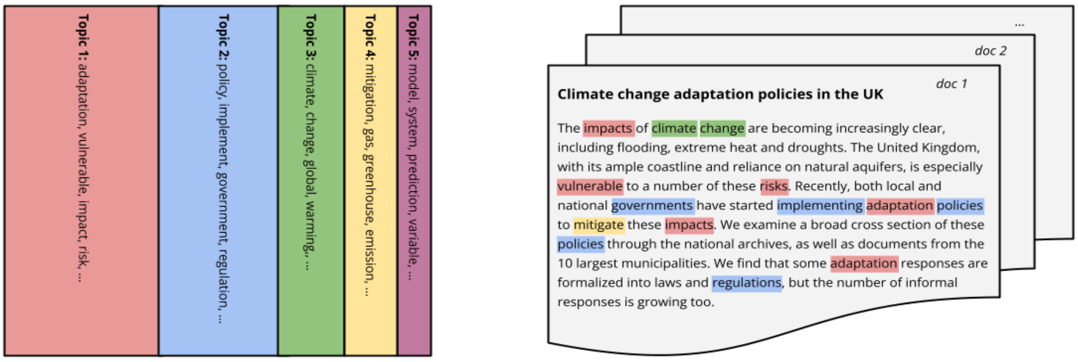
The majority of methods used within this thesis are machine learning methods from NLP. Broadly speaking, there are two types of machine learning. Firstly, **supervised learning** makes use of examples to learn. For example, in this thesis, I make use of supervised learning to identify documents which should be included in the evidence maps. To do so, I provide hand-labelled data which contain both positive examples (relevant documents that should be included) and negative examples (irrelevant that should be excluded). These original examples are called the training data. By providing enough training data, a model can be taught to perform a specific tasks. Supervised methods are especially useful if: a) training data exist or can be created; and b) the users knows what specific task is required. In the second paper of this thesis for example, I define categories of interest *a priori* and train a supervised model to categorise relevant documents.

Creating *a priori* categories is not always possible or useful; knowledge of the data may for example be limited. In other cases, training data are not available and would be too resource intensive to create. This is when we might use **unsupervised learning**, which does not need training data because it finds patterns in the data itself. Unsupervised algorithms are not made specifically for a dataset, but they will change some of their parameters automatically to best suit that data– i.e. they learn. Because there is no training data, unsupervised methods are generally quicker and easier to use than their supervised counterparts. However, the trade-off is that they generally also are more difficult to "steer" in a particular direction: if a user for example wants to classify documents, supervised methods can learn from examples of the different classes, while it is unknown (and in many cases unlikely) if an unsupervised algorithm will find a pattern that corresponds to the desired *ex-ante* classification. As such, unsupervised methods are most useful for data exploration. In this thesis, the wide variety of topics the lack of high-quality data, makes supervised learning impractical for gaining fine-grained insights into adaptation evidence. Instead, I will use topic modelling to explore the content of the selected documents.

At its most basic, a **topic model** takes a set of documents as its input and then outputs two list, the first containing 'topics', wherein each topic is described by a few keywords; the second detailing how much of each topic is present in each document – See Figure 1.2 for a more technical explanation. In practice, any topic model needs to find a balance within two factors:

a) words that are relatively distinctive for a document: unique words are more likely to describe the specific focus of the document, but the model searches for topics that are shared among a subset of documents, so the words cannot be too unique either; and
b) words that often occur within the same document: documents are likely to repeat words that are closely related to their main topics, but very general terms are also likely to be repeated.

For example, a user could instruct a topic model to find 5 topics in a document set about climate change. The model could find that words like vulnerability and adaptation are often used together in the same document, while mitigation and emissions are used by other documents. Another group of words around modelling is used by both mitigation and adaptation literature but is relatively separate from policy-related terms. The model ignores



	Topic 1	Topic 2	Topic 3	Topic 4	Topic 5
doc 1	0.31	0.26	0.18	0.14	0.11
doc 2	...	...	...	...	...
doc 3	...	...	...	...	...
...	...	...	...	...	...

Document-Topic Matrix

×

	national	climate	risk	...
Topic 1	0	0.72	3.6	...
Topic 2	8.96	0	0	...
Topic 3	0	9.46	0	...
...	...	...	...	...

Topic-Term Matrix

≈

	national	climate	risk	...
doc 1	2	1	1	...
doc 2	...	...	...	...
doc 3	...	...	...	...
...	...	...	...	...

Document-Term Matrix

Figure 1.2: *A figurative representation of a topic model, showing an example document where terms that are closely related to one of the topics are highlighted in the corresponding colour. Here, the Document-Term Matrix is a "bag-of-words": the numbers in each row represent how often each word occurs in the document. For* D *documents with* W *unique terms, this has the dimension* D×W, *which is likely to be very large. The model will try to find two smaller matrices that still capture as much information of the input as possible. Specifically, the Topic-Term matrix has the dimensions* T×W, *where* T *is the number of topics, and the values roughly correspond to the probability that the given word belongs to the given topic. Each document is assumed to contain a mixture of topics, described in the Document-Topic matrix, which has dimensions* D×T, *where the values represent the share of the topic within each document. In other words, if the list of topics per document and the list of words per topic are taken together, they should be similar to the input matrix. Figure adapted from Callaghan (2021).*

words like "and", "can", "is", because such terms are roughly equally common in all documents, but it does find a final general climate change topic, which is used by my many documents in varying amounts, while words around methodologies are too different between all the documents to show up as a separate topic.

There are a variety of ways to create such a model (for a recent comparisson, see: Egger and Yu, 2022). Non-negative Matrix Factorization (NMF) for example uses linear algebra to calculate the output matrices (Xu et al., 2003). Other methods use embeddings (explained later) to identify clusters of documents that use closely-related words and then calculate topics based on the documents within each cluster (Grootendorst, 2022, Esposito et al., 2016). The most popular topic modelling method is Latent Dirichlet Allocation (LDA), which is somewhat similar to NMF, but it is probabilistic: it uses probability distributions to denote the chance that a word belongs to a given topic, as well as the chance that a document contains a given topic (Blei et al., 2001, for a relatively accesible explanation, see Wesslen, 2018).

Despite its popularity, there are number of problems with LDA, some of which have since been addressed in range of LDA-derived models. For example, under the hood, LDA takes many different small steps, each with a random component. This makes the model flexible, but also slow for large datasets and models with many topics. WarpLDA (Chen et al., 2015) optimises random access for much faster performance, allowing researchers to for example build models with over a thousand topics from over 25 thousand research articles on sustainable energy (Bickel, 2019). As discussed, unsupervised models in general are hard to "steer" in a particular direction, and LDA is no exception, so a large share of the topics found by an LDA model are often not relevant for the analysis. There are however ways to make LDA "weakly supervised": one can suggest terms that the algorithm will then use as seed words to find topics (Jagarlamudi et al., 2012). This has for example been used to study press releases of cities, highlighting themes the authors *a priori* thought are central to climate action (Boussalis et al., 2019).

The actual topic models used in this thesis are **Structural Topic Models** (STM), which are technically also similar to LDA-based topic models, but they make some key alterations, which make them especially suited to social science research in general (Roberts et al., 2019, Roberts et al., 2014, Roberts et al., 2013) and this thesis in particular. The most important change for our purposes is the inclusion of prevalence co-variates. In simple terms, an LDA assumes that all documents are unrelated, so the chances of any document containing a given topic are equal when the model starts. An STM on the other hand allows the researcher to incorporate meta-data as a prevalence co-variate, in essence telling the model to start out with the assumption that documents with similar meta-data will have similar topic distributions. This is not only more realistic, but it also allows STM to simulate how the incorporated meta-data affects the size of the topic. By running multiple simulations, STM can also estimate an error range for these effect sizes.

Crucially, the latter also allows researchers to formally test hypotheses, which I do in the first paper. There is a strong tendency to be descriptive in most attempts to analyse large volumes of literature, including topic models (Effrosynidis et al., 2022, Huo et al., 2021) but also bibliographic analysis (Giupponi and Biscaro, 2015, Kim et al., 2021) and to a lesser degree systematic maps (Chausson et al., 2020, Salas et al., 2022). Most provide a general overview of the field, sometimes combined with observations on the changes over time, but the limited analytical power of such tools does not allow them to say if any observations are structural or significant. This in turn makes it difficult to critically investigate specific issues, which is why projects often only result in general observations. By contrast, with an STM, one can formulate a hypothesis – e.g. a topic is studied more in the Global North – then incorporate information as a co-variate in the model – e.g. the geographic location of the author of each document – and see if the estimated effect sizes show a significant difference. In short, topic models are often largely descriptive, but an STM allows researchers to be more analytical. In my first paper, I combine this with a systematic search and selection process, which together can be called "inquisitive systematic mapping" (Callaghan, 2021).

Aside from topic models, I make use of one more unsupervised machine learning method, namely **t-Distributed Stochastic Neighbourhood Embedding** (t-SNE), which is a dimensionality reduction algorithm developed by Van der Maaten and Hinton (2008). This algorithm is used to create visualisations of the topic models. As explained above, one of the outcomes of a topic model is a Document-Topic matrix, which has a width equal to the number of topics in the model (T) and a length equal to the number of documents (D). This matrix contains a lot of information on how different documents relate to each other – in essence, similar scores on similar topics imply similar documents – but because the matrix is so wide, it is difficult to plot. t-SNE can reduce this matrix from $D \times T$ to $D \times 2$, meaning every document gets an x and a y-coordinate. Crucially, the algorithm tries to maintain local structures, such that documents which were similar in T-dimensional space remain close together in the 2-dimensional outcome.

So far, I have described technique to inspect the context and content of documents, as well as to visualise the outcome, but in my thesis, machine learning also plays a role in finding those documents in the first place. For the first two papers included in this thesis, the documents I use in the STM are selected in a two-step process, starting with a systematic search, as is common for an evidence map. As I explained before, systematic queries for adaptation are either precise, but lack recall; or they have good recall but are rather imprecise. This is why I use Supervised machine learning methods in the second step. In other words, I start with a broad, inclusive query and then train a model to select the relevant documents. In the second paper, such methods are also used to classify the selected documents.

Specifically, in the first paper, I make use of a **Support Vector Machine** (SVM), the basic structure of which was developed in the 1990s (Cortes and Vapnik, 1995), after which it has been expanded to cover a broader range of optimisation problems (Chang and Lin, 2011). SVMs are used to categorise data – in our case, the SVM separates relevant documents from irrelevant documents. The basic functioning of the algorithm is relatively easy to understand in two dimensions (Figure 1.3). An example of such a two-dimensional problem would be to count how often two words occur in each of the text – e.g occurrences of "adaptation" on the x-axis and "mitigation" on the y-axis. In the training stage, the SVM would then try to find the best line to separate all the data points labelled relevant from all the data points labelled irrelevant. To then make predictions, the unseen documents would be plotted in the same way; if a document is plotted on the "relevant" side, it is predicted to be relevant and vice versa, where the distance to the line can be used as a proxy for how certain the classifier is.

In reality, instead of using two words, all the words in the document set are used, so for a vocabulary of size n, the algorithm places datapoints in n-dimensional space and draws a "line" with dimensions $n-1$. This still requires the texts to be "vectorized" – i.e. made into numbers that form the "coordinates" of the point. Instead of using the simple count of each word, I use Term-Frequency Inverse Document-Frequency (TF-IDF), which highlights distinctive terms in a document by dividing the number of times a word occurs in the given document by the number of times this same word occurs in all of the documents. A word

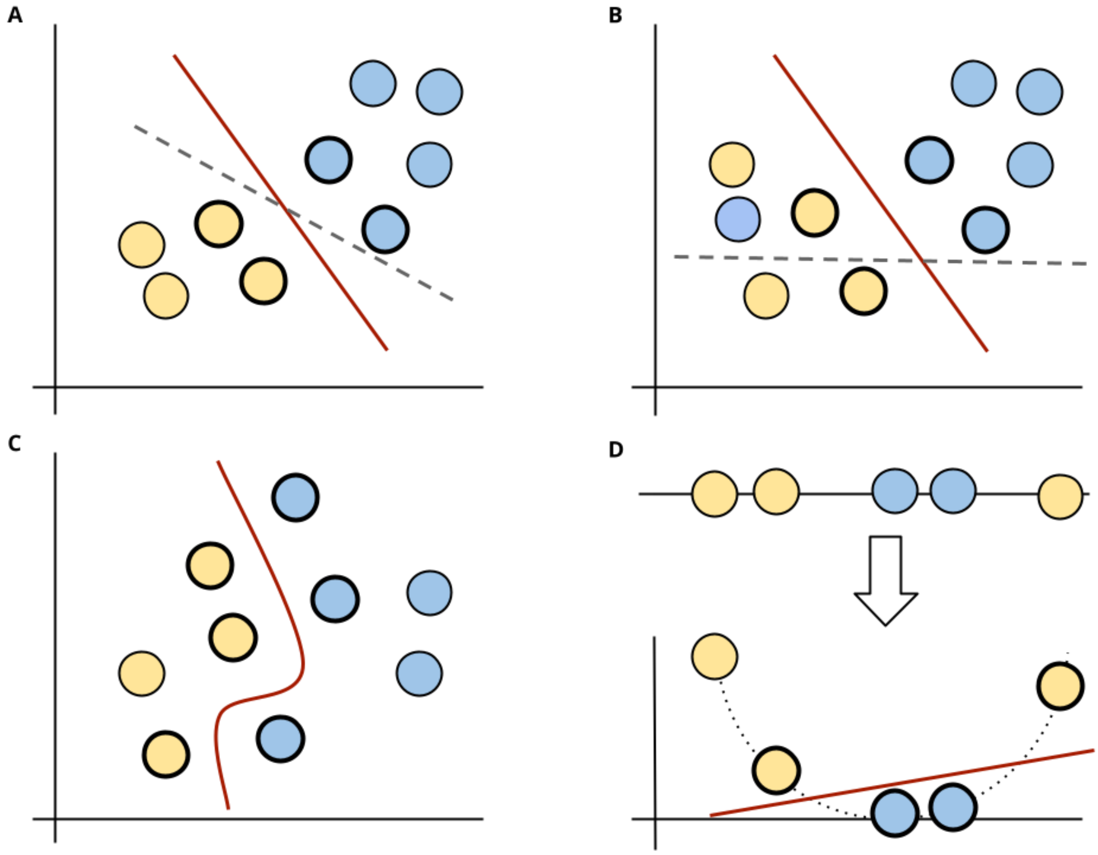


Figure 1.3: *The workings of a Support Vector Machine (SVM) in two dimensions, meaning the SVM draws a line (one dimensional) that separates all points in one class (blue) from the points in another class (yellow). If there are multiple ways to do this (panel A), the algorithm will maximise the distance between the line and the data points that are closest to the line. In this case will pick the solid red line over alternatives like the dotted grey line. These closest points (in bold) are called the support vectors as they determine the exact placement of the line. If a separating line is impossible (panel B), an SVM will choose a best fit still, incorporating a penalty for any outliers. In other cases where a linear separation is impossible (panel C), a non-linear kernel may be used to draw for example a sigmoid instead of a straight line. Alternatively, (panel D), separating the points may be made possible by increasing the dimensionality of the data itself – in this case, data on a straight line (one dimension) is transformed into a parabola (two dimensions), after which the separating line (one dimension) can be drawn.*

like "and" likely occurs a few times in a document, but because it also occurs often in many other documents, it's TF-IDF score would not be very high (large number divided by large number). By contrast, a word like "legislation" may occur a few times in a policy-related document, but it is not common in climate research in general, so it will have a high TF-IDF score (medium number divided by small number).

The second paper uses a more sophisticated and recent model known as a **Large Language Model** (LLM). One simplified way to look at a LLM is as a way to convert words into numbers, like the TF-IDF vectorization. Unlike that vectorization, LLMs are pre-trained on a large collection of texts (e.g. all of Wikipedia) to create a so-called embedding, where similar words are encoded as a similar vector – e.g. a word like “king” will have a similar vector to “queen”, but a very different vector from “car”.

There are different types of LLMs, but the one used here is a transformers-based model. At the moment, transformer-based models are the state-of-the-art. They outperform virtually all other methods for most NLP tasks (Gillioz et al., 2020, Greco et al., 2022) and research interest in these models is only increasing (Casola et al., 2022). The sheer size of these models means they can address issues that until recently were extremely difficult to solve. For example, if a word has two different meanings (“stand” as a verb or as a noun; “bank” as financial institution or the bank of a river, etc.), these models have enough context-awareness to have, in simplified terms, separate embeddings for their separate meanings.

What really sets transformers-based models apart is their ability to incorporate contextual meanings of words. In addition to the sheer size of such models, this is also an effect of how these models are trained, which is by predicting the missing word in a sentence. For example, for the sentence “I carry water in a [blank]”, words like bucket, bottle or glass are all likely predictions. In a bi-directional model, the algorithm also takes into account words that occur after the missing word: for “I carry water in a [blank] in my bag”, the words bucket and glass are no longer likely options, whereas bottle is. Such models can also have a second training step where the algorithm has to choose between two sentences: one is chosen at random, the other is the actual next sentence in the training text. This forces the model to, in a sense zoom out, which provides even more contextual awareness. Finally, the model can be fine-tuned for a specific task and collection of texts so it can learn domain-specific meanings.

Importantly for this thesis, relatively small projects (1000s of labelled samples) can benefit from these models especially. In my second paper, I try to make fine-grained distinctions between different types of policy. Given also the size of the initial query, it becomes extremely time-intensive to find good examples of each type of policy, so the model will have to be able to extrapolate from a relatively small training set. In the previously discussed TF-IDF + SVM model, if a word was not present in the training data, the classifier would not be able to take this word into account at all. Similarly, if a word was used in an unusual way in the training data, this could significantly skew results. LLMs prevent such problems by allowing users to in a sense import a rich understanding of language, so the model can make use of both context clues and its knowledge of similar words to make good classifications for a broad range of applications. In addition, in this thesis I make use of a specific LLM called ClimateBERT (Webersinke et al., 2021). This is a transformer-based bi-directional model that was trained specifically on climate change research, which should further increase the predictive power of the model.

1.4 Research objectives & structure

In the above, I have described both a need for more insights into adaptation progress globally, as well as a range of opportunities offered by modern machine learning methods. Before discussing how this translates to the concrete objectives of each paper, however, it may be fruitful to look at the sum of all the building blocks I introduced so far – in other words, a variety of perspectives and methods have been discussed, but how do these fit together into a coherent approach that is shared between the papers that make up the core of this thesis?

The place of this thesis in the larger literature landscape

So far, I have argued that: 1) adaptation is complex and varied but also urgent; 2) tracking adaptation therefore is also complex but if done well, it can provide insights that lead to better adaptation decision making; 3) there are many existing tracking approaches, but all have to make pragmatic choices which entail trade-offs among the 4Cs of idealised adaptation tracking; 4) a variety of machine learning methods exist which can help analyse large and diverse datasets; and 5) these methods continue to develop rapidly, but even older methods present untested potential for adaptation tracking purposes. What was left mostly implicit in all this, is that machine learning approaches can help particular kinds of tracking in particular ways. The focus of this thesis is on maximising these benefits.

The most obvious benefit here relates to comprehensiveness: as stated before, machine learning is often used to gain insights from large datasets, so the increasing importance of adaptation and the associated increasing flow of data are more easily managed when using computational methods. Maximising this benefit means taking an inclusive view of what is considered adaptation so that I might provide an overview that is as comprehensive as possible. In line with this, I do not limit myself to literature that uses the word 'adaptation' to describe itself but include also other relevant parts of the wider IAV and climate risk literature.

Although my focus on NLP is partially personally motivated – these are the tools I know best – it is also a good moment to focus on text-based methods. I have briefly mentioned the rapid increase in adaptation policies and research on the one hand; on the other hand, NLP methods are improving quickly too, making this an opportune moment to test their efficacy. This is not to say that other machine learning applications are useless for adaptation tracking, but rather that text-based tracking methods are an area where particularly large improvements seem likely.

Further, if the aim is to maximise synergies between methodological advancements and useful insights, we should also *who* needs those insights. As this is an academic thesis, other adaptation researchers are a key target audience, but in my view, tracking ultimately should serve practitioners. Concretely, this means incorporating non-academic stakeholders, focussing my analysis on policy-relevant questions and stressing in particular issues around implementation of adaptation.

There is a notable tension here: while I believe that machine learning could in theory benefit the tracking of adaptation *outcomes*, the required data would be complex to obtain. To put it bluntly, I could either invest my time in obtaining these data or explore more cutting-edge methods; I did not have the resources to do both. I opted to prioritise the methodological contribution, and as a consequence, focus largely on tracking adaptation *processes.* As I will expand upon in the final chapters of my thesis, other efforts at using AI for adaptation tracking have made a broadly similar calculus, which is defensible for a first generation of methodological proof-of-concepts. My contribution, apart from the scale, is also to identify

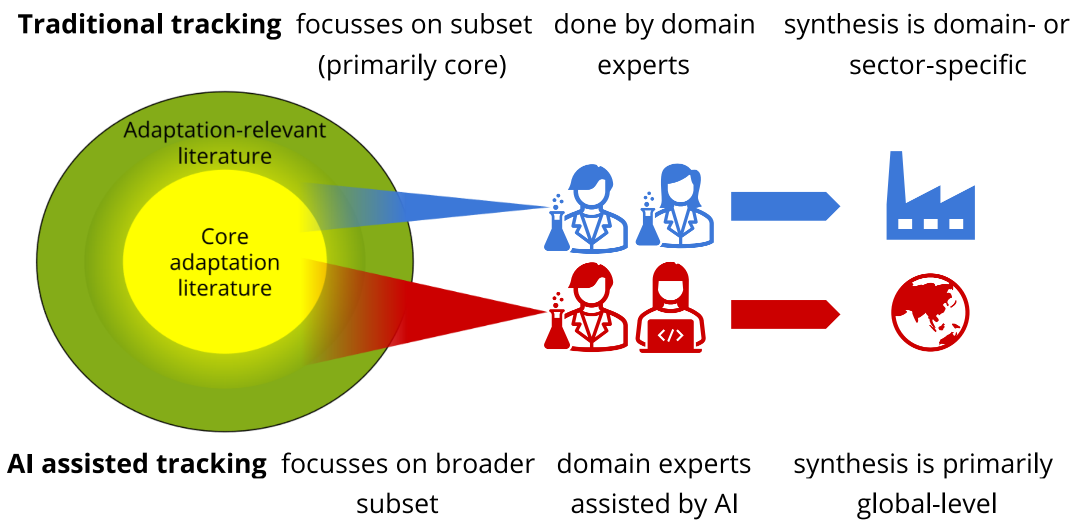


Figure 1.4: *the difference in approach between traditional tracking of adaptation and tracking that is assisted by Artificial Intelligence (AI). Neither approach can give a complete image of all adaptation, but traditional tracking, because of the sheer volume of adaptation-relevant information tends to be limited to sub-topics within adaptation, whereas AI-assisted approaches are better suited to general global overviews.*

policies. The next grand challenge for the adaptation community will be to combine different approaches together.

Similarly, although much of the adaptation literature focusses on specific sectors and types of adaptations, I focus here on the global level, asking “how is the world as a whole progressing on adaptation?” This large scope aligns well with the previously noted ability of machine learning to handle large datasets. Again though, there is an argument to be made that this will not result in the most practice-relevant information, as practitioners need localised information. As I set out under the section Practical Issues with Tracking, I partially agree with such criticisms, but do not believe they negate the need for tracking entirely. Moreover, it is theoretically possible to use a larger scale overview as the basis from which to “zoom in” to a specific issue. Just how far one can zoom depends on how fine-grained the distinctions are that can be made between data points, which is part of the methodological questions this thesis hopes to contribute to.

Thus, my approach to adaptation tracking can be summarised as follows (see also Figure 1.5): the purpose of adaptation tracking is to create high-level overviews of adaptation-relevant processes and, where possible, outcomes in a systematic way. What gets counted as "relevant" is subject to debate, but any meaningful definition can ultimately be traced back to actions that reduce the present or future risks of climate change. Competing outlooks herein can lead to meaningfully different overviews, but this does not invalidate tracking – rather, it highlights the need for openness about one's basic assumption. In particular, there is a trade-off between on the one hand being specific and sensitive to local contexts, and on the other, being comprehensive and inclusive. Machine learning assisted tracking offers ways that benefit especially the latter side, while still allowing for relatively nuanced distinctions. Given the relative novelty of such methods, these types of tracking efforts should be explored first in projects where adaptation relevance is defined broadly and large amounts of data can be obtained. Once they have proven to be useful, more challenging analyses can be attempted, but machine learning methods should always be used alongside more traditional adaptation tracking efforts, rather than replacing them.

Objectives per paper

In the first paper, I aim to build an evidence map of scientific literature on adaptation, defined broadly, in order to assess where progress is being made. To this end, the sub-objectives are:

- To identify key benchmarks for scientific progress in adaptation research;
- To identify where machine learning can provide reasonable proxies for these benchmarks, and, where possible, include uncertainty estimates so that hypotheses can be more formally assessed;
- To assess if qualitative assessments by experts align with the quantitative findings using machine learning methods.

The second paper builds on the first, again building an evidence map, but this time I aim to answer a narrower question by focussing on adaptation policies, defined here as any action that is either instigated or directly supported by a government at any level. The types of classifications I make in this paper are much more specific, necessitating the use using more sophisticated models and more sources. Exactly how granular the distinctions are that can be made this way is difficult to say *a priori*, so in parts, a hierarchical categorisation will be used. This way, results for the 'top level' (a handful of categories) can be reported, and I can also attempt classifications for subsets within those broad categories. The sub-objectives are:

- To assess what the most granular distinctions are that can be made at scale by modern supervised machine learning and how this compares to more established methods;
- To identify how the policy tools used by governments to adapt to climate change differ by geographic location, by government level, and over time;
- To evaluate whether the Paris Agreement has been successful at creating a shift away from assessing the magnitude of the climate crisis and towards implementing adaptation solutions.

In the third paper, I take on a different dataset, namely reporting to the UNFCCC. These reports are potentially a good global-level dataset for assessing progress on climate action, but they are published as part of a highly politicised process. I interrogate this political element by focussing on the framing of the reports in their executive summaries. The sub-objectives are:

- To determine whether the framing of a country's reporting is influenced by national priorities, specifically their greenhouse gas emissions and their vulnerability to climate change;
- To identify if a significant shift has occurred in national reporting since the Paris Agreement, specifically if there is increased attention for either climate solutions or for impacts, adaptation and vulnerability topics.

In my fourth paper, I aim to draw lessons from these previous experiences, as well as experiences from similar projects and an overview of the literature. I argue that machine learning applications for climate change adaptation are a promising solution to many of the issues in adaptation tracking, but simultaneously, that such efforts to date are insufficient to realise that promise. The sub-aims are:

- To assess where the first generation of machine learning methods have already made meaningful contributions towards adaptation tracking, as well as where efforts to date have fallen short;
- To identify how improvements can be made in the use of machine learning methods for adaptation tracking;
- To explore if a more radical departure from existing adaptation tracking methods may be better suited to incorporating machine learning methods.

Finally, although the fourth paper already synthesises some of my work, I will do so more extensively in the closing chapter of this thesis. I will combine this with my recommendations for further research and reflections on how to solve some of the more structural problems identified in this work.

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2 Progress in Climate Change Adaptation Research

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Abstract

The scientific literature on climate change adaptation has become too large to assess manually. Beyond standard scientometrics, questions about if and how the field is progressing thus remain largely unanswered. Here we provide a novel, inquisitive, computer-assisted evidence mapping methodology that combines expert interviews (n=26) and Structural Topic Modelling to evaluate open-ended research questions on progress in the field. We apply this to 62,191 adaptation-relevant scientific publications (1988-2020), selected through supervised machine learning from a comprehensive climate change query. Comparing the literature to key benchmarks of mature adaptation research, our findings align with trends in the adaptation literature observed by most experts: the field is maturing, growing rapidly, and diversifying, with social science and implementation topics arising next to the still-dominant natural sciences and impacts-focused research. Formally assessing the representativeness of IPCC citations, we find evidence of a delay effect for fast-growing areas of research like adaptation strategies and governance. Similarly, we show significant topic biases by geographic location: especially disaster and development-related topics are often studied in Southern countries by authors from the North, while Northern countries dominate governance topics. Moreover, there is a general paucity of research in some highly vulnerable countries. Experts lastly signal a need for meaningful stakeholder involvement. Expanding on the methods presented here would aid the comprehensive and transparent monitoring of adaptation research. For the evidence synthesis community, our methodology provides an example of how to move beyond the descriptive towards the inquisitive and formally evaluating research questions.

2.1 Introduction

To achieve the goal of limiting the increase in global average temperature to well below 2°C, ambitious mitigation action will be required (IPCC, 2018b). Even if this goal is met, human livelihoods and ecosystems will still be exposed to substantial climate risks, and many countries in the Global South are especially vulnerable (IPCC, 2018b). In this context, adaptation—defined as *"[t]he process of adjustment to actual or expected climate and its effects"* (IPCC, 2014a)—is particularly important. Adaptation typically occurs in response to a specific climate risk or impact, but it is also useful to know if and where progress is being made in the aggregate; doing so in a systematic and transparent manner is the goal of so-called adaptation tracking (Berrang-Ford et al., 2019, Ford and Berrang-Ford, 2016, Olhoff et al., 2018).

Given the sheer diversity of adaptation, tracking efforts typically focus on one particular source, such as policy documents (Berrang-Ford et al., 2019) or financial information (Donner et al., 2016). Considering the Global Stocktake under the Paris Agreement and the upcoming Intergovernmental Panel on Climate Change's (IPCC) sixth Assessment Report (AR6), a comprehensive overview of the *scientific* literature on adaptation is essential too: it can better enable knowledge sharing and help assess progress in understanding as well as identifying persistent knowledge gaps, which in turn assists policy makers in prioritising future investments (Lesnikowski et al., 2017, Berrang-Ford et al., 2019, Siders, 2019). In sum, such a science-focussed tracking exercise should help the adaptation community understand in what areas we have strong evidence, where we are making progress, and where more needs to be done.

A number of reviews over the last decade have attempted to document trends in understanding on climate change adaptation and related fields (Biesbroek et al., 2018, Berrang-Ford et al., 2015). Systematic reviews, in particular, are increasingly common (Berrang-Ford et al., 2015), although the majority of reviews focus on specific regions or issues within adaptation, reviewing a corpus of literature that rarely extends beyond 100 documents (e.g. Lwasa, 2015, Owen, 2020, Berrang-Ford et al., 2011, Ford and Pearce, 2010, c.f. Bisaro et al., 2018, Lesnikowski et al., 2015). Evidence mapping may typically consider an order of magnitude more articles (Nakagawa et al., 2019, c.f. Haddaway et al., 2020), but even this may not be large enough when considering the sheer volume of literature: Callaghan et al. (2020b) find around 50,000 new papers on climate change in 2018 alone, and adaptation is a quickly growing field herein (Wang et al., 2018, Haunschild et al., 2016). The advent of such "Big Literature" (Nunez-Mir et al., 2016) makes it impossible for researchers to keep up with all available information and hinders synthesis efforts, including IPCC reports (Callaghan et al., 2020b, Minx et al., 2017a, Nunez-Mir et al., 2016).

Crucially, although Big Literature is a problem for current, largely manual methods, it is also an opportunity for machine learning (Cheng et al., 2018, Nakagawa et al., 2019, Lamb et al., 2019, Rolnick et al., 2019). Text mining methods, for example, use machine learning to uncover patterns in large text-based datasets; in the context of adaptation they have recently been applied to examine policy documents (Biesbroek and Delaney, 2020, Lesnikowski et al., 2019) and narratives from researchers and practitioners (Lesnikowski et al., 2019). Furthermore, some recent evidence maps (McKinnon et al., 2015, Collaboration for Environmental Evidence, 2018, Haddaway et al., 2020) have made use of machine learning to examine issues such as carbon dioxide removal (Minx et al., 2018, Minx et al., 2017b), mitigation in cities (Lamb et al., 2019), climate change governance strategies (Hsu and Rauber, 2021) and the climate change literature as a whole (Callaghan et al., 2020b).

For adaptation, the closest analogy to a comprehensive map of the literature is the bibliometric analysis by Wang et al. (2018), together with similar work on related concepts (Siders, 2019, Di Matteo et al., 2018, Wang et al., 2014, Einecker and Kirby, 2020). Like most evidence maps (Nakagawa et al., 2019), these analyses are mainly descriptive; they typically do not examine concrete research questions and their chosen methods often do not allow for formal evaluation of hypotheses. Moreover, work to date relies on relatively coarse-grained heuristics to describe the actual content of adaptation research. As such, it is of limited use for assessing *progress* in adaptation research. As a consequence, despite the rapidly increasing body of research on adaptation, persistent gaps remain in our knowledge of how the field is maturing (Ford and Berrang-Ford, 2016).

In this article, we develop a new methodology for computer-assisted, inquisitive evidence mapping. We apply this to adaptation-relevant research published over the last 32 years, in order to formally evaluate where progress is (and is not) being made. To this end, we first use expert interviews with researchers and practitioners (n=26) to identify benchmarks of a mature adaptation research field. We then assess progress towards these benchmarks, capitalising on the opportunities afforded by machine learning to add to the extant literature in two key ways. First, we create a dataset of adaptation-relevant literature; here, taking a machine learning approach allows us to define this in a broad way as *any study which focusses on the impacts of climate change on human systems or adjustments to those impacts.* This breadth is essential given the diversity of ways in which adaptation research is defined (Dupuis and Biesbroek, 2013, Preston et al., 2015b, Siders, 2019), and allows us to place literature which self-defines as adaptation in the wider landscape of impact, adaptation, and vulnerability (IAV) studies. Second, we analyse this dataset using Structural Topic Modelling (STM) (Roberts et al., 2014), which enables us to assess progress towards the benchmarks in a more formal way than other more descriptive evidence mapping methods (see methods). We augment STM results with scientometric approaches and insights from the interviews. Overall, this first foray into using machine learning to assess progress in adaptation research can serve as a steppingstone from which to continue analysing this rapidly expanding field.

2.2 Methods: Expert-informed, inquisitive computer-assisted systematic mapping

Our approach follows three interactive phases, as outlined in Figure 2.1. Note that the findings used in the interview phase were based on a preliminary, somewhat smaller dataset. We will attempt to describe the machine learning methods for a non-technical audience, but given the limited space, will refer to other sources for more detailed explanations (e.g. Lesnikowski et al., 2019, Roberts et al., 2016)

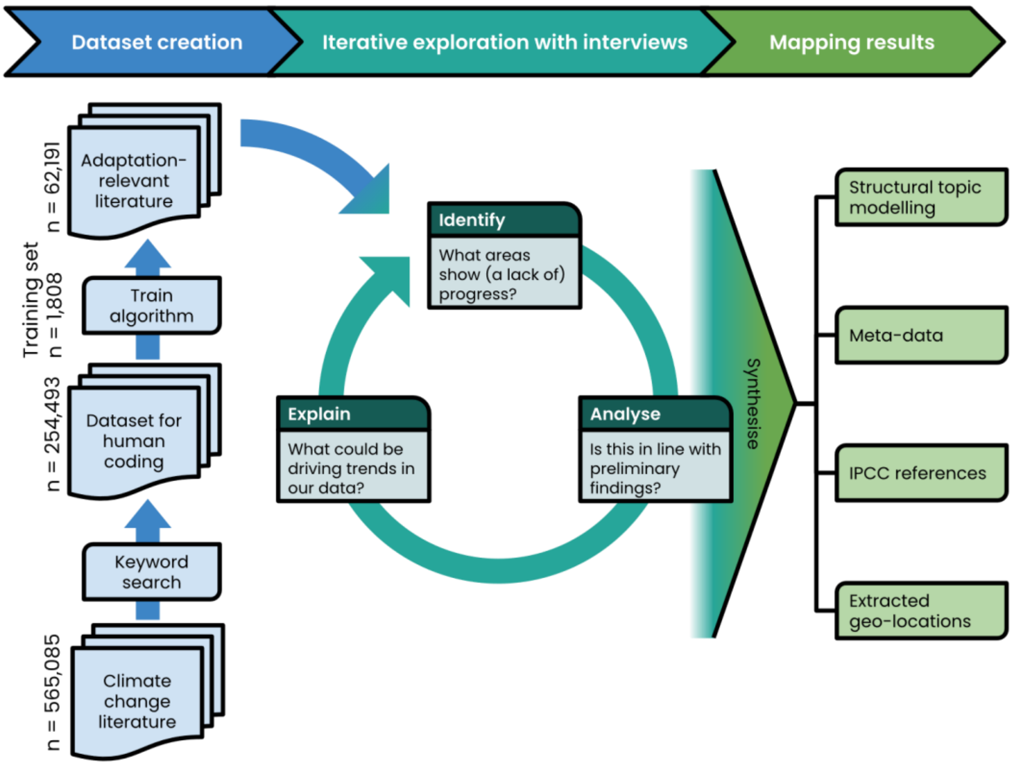

Figure 2.1: *Schematic overview of the research process. The number of included documents is given for each step of the dataset creation phase.*

Dataset: Supervised machine learning to select adaptation-relevant documents

Here we use a methodology rooted in supervised machine learning to identify a corpus of adaptation-relevant publications. Scientometric studies typically develop their datasets from comparatively simple search queries (e.g. Wang et al., 2018, Wang et al., 2014, Einecker and Kirby, 2020) to avoid including irrelevant literature. By contrast, systematic reviews and maps conduct extensive high-quality searches (Collaboration for Environmental Evidence, 2018). Like such gold-standard queries, our approach incorporates many synonyms for adaptation-relevant terms, except these are "learned" by an algorithm, allowing for many more documents to be considered. As an added advantage, this allows us to quantify the quality of the dataset. Our dataset is based on the general climate change dataset created by Callaghan et al. (2020b). This dataset uses abstracts, titles and metadata (no full text) from the Web of Science Core Collections databases. We update their search to create a dataset with 565,085 documents published between 1985 and 13 August 2020. These documents are imported using a platform called NACSOS: NLP Assisted Classification, Synthesis and Online Screening (Callaghan et al., 2020a), which also includes machine learning tools. In this dataset, we first conduct a broad keyword search and then use supervised machine learning to select adaptation-relevant literature. Specifically, we use a Support Vector Machine (SVM) (Chang and Lin, 2011, using Pedregosa et al., 2011), which is an algorithm that aims to mimic human decisions in classification tasks (here: adaptation-relevant or not) based on a so-called training set (here: 1,808 hand-coded documents). Explicit inclusion/exclusion criteria were created *a priori* and amended iteratively when the classification of a document was unclear.

We then estimate the performance of the SVM using 10 k-fold cross-validation, resulting in an overall accuracy of 90% (± 3.4%) and an F_1 score of 81% (± 7.1%). In simpler terms, although this score is comparable to the results of similar work on different documents (Hsu and Rauber, 2021), it also implies that nearly 20% of relevant data is missed and that a similar percentage of papers is a false positive. However, the accuracy did not improve substantially with a larger training set. Note also that this error is not random: the algorithm generally excludes completely irrelevant documents, but struggles where human coders had difficulties consistently identifying relevant articles. We therefore posit that the relatively high error rate is a reflection of assigning binary scores in a field with substantial conceptual "slipperiness" (Ford and Berrang-Ford, 2016, for similar issues: Berrang-Ford et al., 2021). Systematic reviews try to ameliorate this through strict selection criteria, but here too a substantial number of documents will not fall unambiguously in either the inclusion or exclusion category (e.g. Owen, 2020). A similar error would therefore likely be present – but not quantified – if all selection was done by hand rather than machine. Further limitations of our study include the exclusion of grey literature and studies not indexed in English.

Expert interviews: Scoping expert perceptions of the state of adaptation research

The expert interviews served the dual purpose of both identifying key characteristics of a mature research field (i.e. benchmarking) and 'ground-truthing' the findings of the preliminary analyses, which required a relatively flexible exploratory kind of interview. We

Table 2.1: Details of expert interview participants

	Number of experts	
IPCC Affiliation (if any)	Coordinating Lead Author: 10 Lead Author: 9	Contributing author/other: 4
Non-IPCC affiliation	Academic: 17 NGO and intergovernmental: 6	Government: 3
Current location	Europe: 10 Latin America & Caribbean: 6 North America: 5	Africa: 3 Asia: 2
Gender	Man: 14	Woman: 12

therefore conducted semi-structured expert interviews (Fielding and Thomas, 2008, Horton et al., 2004).

Initially, experts were approached based on their IPCC affiliation, with most experts being either a Lead Author or a Coordinating Lead author for at least one chapter — mostly chapters in AR5 Working Group II (IPCC, 2014a, IPCC, 2014b) and the Special Report on 1.5°C (IPCC, 2018a). To get perspectives, including non-academic perspectives, further experts were later added through snowball sampling, though experts from Oceania and the Middle East are lacking. In total, 26 experts were interviewed, details of whom can be found in Table 2.1

Although the content of the interview changed as the analysis developed, each interview was divided into two main sections: First, an open-ended section to let the expert describe the main challenges and developments within the adaptation field in their own words; second a more focussed discussion on specific topics on adaptation, including comments on trends identified through our preliminary analyses. Recurring themes in the interviews were used to iteratively create a list of areas of interest. Once all interviews had concluded, each interview was analysed again in light of the major themes that emerged and the new analyses that had since taken place. The resulting key characteristics of a mature adaptation research were: providing specialist, practice-relevant information; interdisciplinary understanding, including in the IPCC; broad representation; and connection to practice. These form the benchmarks for our evidence map.

Inquisitive systematic mapping

Systematic maps have been highly descriptive in nature. It is the ambition here to provide a methodological framework that allows to formally assess the research landscape, which we term "inquisitive, computer-assisted systematic mapping". For example, Lamb et al. (2019) point towards differences in research themes across different regions, but it is hard to say whether these differences are statistically meaningful.

To facilitate an inquisitive approach to systematic mapping we root our analysis in Structural Topic Modelling (STM) (Roberts et al., 2014), which is an unsupervised machine learning method that identifies themes in large text corpora. STM is similar to the more standard Latent Dirichlet Allocation (LDA) in that both find clusters of words which frequently occur in the same documents, but STM can also incorporate the effect of a set of covariates on the respective topic distributions — e.g. language shifting over time or authors from different countries using different language. Moreover, once the topic model has been created, the effect of the meta-data per topic can be estimated, which allows us to move beyond descriptions of the research field into more formal assessments of progress benchmarks, including indicators for statistical significance.

A range of models with between 50 and 220 topics were created. A higher number of topics means a more granular picture of the literature, but also fragments topics that should stay together. After a first selection, 3 candidate topic models were discussed by multiple authors, striving to find the lowest number at which a majority of major themes from the interviews still had a clearly defined topic in the model, and setting the final number of topics at 105 by consensus – see also (Müller-Hansen et al., 2020). Labels for the topics were decided on using both the most associated words using various metrics (see Annex) and the most closely associated documents for each topic.

One way to visualise the final topic model is by using a dimensionality reduction algorithm. We use t-distributed Stochastic Neighbour Embedding (t-SNE) (Maaten and Hinton, 2008). In essence, the topic model assumes that each document is comprised of multiple topics; for each document, it calculates topic scores for every topic. For n documents and k topics, this results in an $n \times k$ matrix. t-SNE can reduce this to $n \times 2$, while 'trying' to keep points that are similar in k-dimensional space (similar topics) close in 2-dimensional space (similar coordinates). The result can then be plotted, showing clusters of documents which discuss similar topics.

Further, one of the main interests arising from the interviews was the geographic distribution of the literature. We therefore use a pre-trained named entity recognition algorithm (Halterman, 2017) to determine where a place name is mentioned in an abstract or title. A dictionary method (Martinez Palenzuela, 2018) was used to extract the location of the first author as author affiliations are not given in a sentence and therefore may not always be identified correctly by the pre-trained algorithm.

Callaghan et al. (2020b) already included data on if papers in the dataset were cited in IPCC Assessment Reports. We matched references from IPCC Special Reports as well, using a pre-trained machine learning algorithm called GeneRation Of BIbliographic Data (GROBID) (GROBID, 2020) to identify references and csvmatch (Harlow, 2020) to do fuzzy matching.

Lastly, the Web of Science database includes information on the research field, which is based on the journal. These were too specific for our purposes and were therefore converted to more general categories based on the Organisation for Economic Co-operation and Development (OECD) category scheme (OECD, 2012).

2.3 *Results*

We identify 62,191 adaptation-relevant peer reviewed articles published between 1988 and August 2020 (Figure 2.2 a). Between 2009—2019, the literature output on average grew by 20.6% per year – faster than the broader climate change field (Callaghan et al., 2020b, Haunschild et al., 2016). Subsequently, we present an assessment of progress in adaptation research based on this dataset, using quotes and insights from the expert interviews to provide a more qualitative understanding. An overview of our findings is given in Table 2.2.

Table 2.2: *Summary of results with respect to our selected benchmarks of maturity. The description of these benchmarks includes sub-components, were applicable, and cites work that highlights the importance of these benchmark for mature adaptation research. In the maturity column, we provide a qualitative evaluation by the authors of (progress towards) maturity based on the results below.*

Benchmark	Description	Maturity
Specialist, applicable information	Information provided by researchers should be able to provide specialist answers to practice-relevant questions (Klein et al., 2017, Mustelin et al., 2013, Bohman et al., 2018)	Significant progress
Interdisciplinary understanding	The interdisciplinary nature of the climate change problem necessitates **integration** between disciplines (Klein et al., 2017, Nesshöver et al., 2017, Preston et al., 2015b, Eigenbrode et al., 2014, Feola et al., 2015) …	Mixed
	… and the **IPCC** should represent evidence from different disciplines fairly (Victor, 2015, Beck and Mahony, 2018, Carraro et al., 2015)	Mostly mature
Broad representation	There is an imbalance between the Global North and South in terms of **quantity** (Janssen, 2007, Janssen et al., 2006, Haunschild et al., 2016, Wang et al., 2018)…	Some progress; gaps remain
	… and **thematic focus** (Bulkeley et al., 2013, Wamsler and Lawson, 2012, Chandra et al., 2018) of the research base which should be addressed.	Gaps remain
Connection to practice	A meaningful connection between research and practitioners, especially local stakeholders, is essential for successful adaptation in practice (Bohman et al., 2018, Lynch et al., 2008, Preston et al., 2015a)	Mixed on politics, stakeholders insufficient

Vulnerability dominates but the adaptation field is specialising & moving to solutions

A mature adaptation research field should provide an evidence base that can inform decision making through targeted and specialised information (Klein et al., 2017, Mustelin et al., 2013, Bohman et al., 2018). Our analysis reveals a rapidly expanding and specialising evidence base with increased attention for implementation-related topics especially (Figure 2.2).

Although these developments point towards a maturing field, at present, natural science journals dominate publishing, accounting for 70.0% of research. A caveat here is that some explicitly interdisciplinary journals are classified (OECD, 2012) as natural sciences, including *Climatic Change*, the most frequent publication (n=1,961). Still, the topics from STM (Table 2.3) also predominantly point to highly technical subjects (e.g. climate modelling).

While social science topics are also represented (e.g. governance, migration), adaptation-relevant research often focusses on what needs to be adapted to as opposed to what *responses*

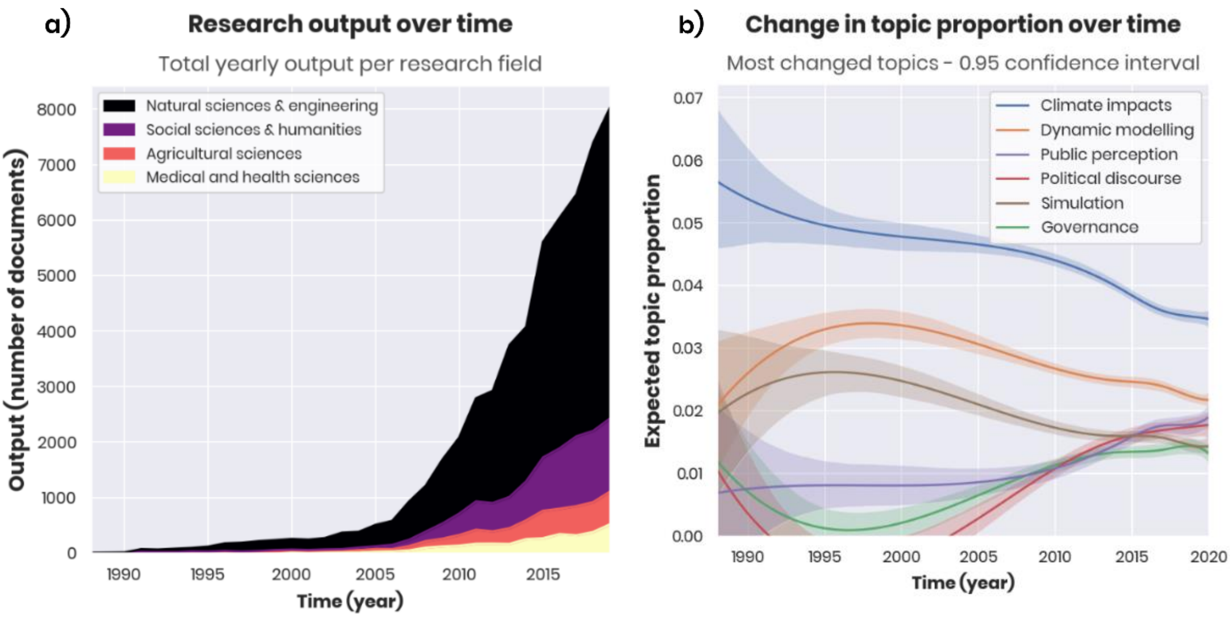

Figure 2.2: *Changes in papers over time. a) shows the output per year (19889—2019), sub-divided by field, based on the Web of Science categories. b) shows the topic proportion over time for the 3 most- and 3 least increased topics since 2000. In layman's terms, a high value means that the texts in the dataset from around that year contain more words related to that topic.*

are needed. Research in the "problem space" including impacts and vulnerability studies, is thus more common than research in the "solution space" (Haasnoot et al., 2020).

Relatedly, research appears to be specialising. The most prominent topic in the topic model overall is on general Climate Change Impacts. However, the relative prevalence of this topic and the other general climate change topics have decreased markedly in the last two decades (Figure 2.2). By contrast, some of the fastest growing topics are Political Discourse, Public Perception, and Urban Issues. This suggests that the literature is increasingly focused on more specialised issues within adaptation (noting that these are relative proportions, so the absolute output will be increasing for many topics, even if their relative share has decreased).

Experts further stated that the previously noted dominance of research in the problem space may be decreasing for three main reasons: solutions are emphasised under the Paris Agreement; the effects of climate change are becoming more apparent, especially in the

Table 2.3 (next page): *Results of the Structural Topic Model where the topics are grouped in overarching categories for ease of reference. A more extensive version of this table which includes the most closely associated keywords per topic can be found in the Annex.*

CATEGORY	TOPIC LABEL		
General Climate Change	Climate Impacts	Global Warming	Global Challenge
Meteorology	Heatwave	In-/decrease (water)	Weather Trend
	Temperature	Seasonality	Rainfall
	Seasonality (ENSO)	Precipitation	
Modelling & Mapping	Simulation	Dynamic Modelling	Downscaling
	Future Projection	Future & Past	Remote Sensing
	Coupled Model	Emission Scenario	
Methods & Methodology	Bias	Uncertainty	Variable
	Research	Review Study	Key Finding
	Ethics		
Physical Environment	Coastal Zone	Sea Level Rise	Sea Level (Deltas)
	SIDS	Watershed	Stream Flow
	River Basin	Glacier & Lake	Ice Surface
	Snow/Alpine	Soil	Forestry
Biology	Nature conservation	Ecosystem Services	Species Distribution
	Land use		
Urban & Infrastructure	Urban	Green Building	Design
	Sewers & Roads		
Food & Agriculture	Agriculture	Farmer	Food Security
	Livestock	Fisheries	Crop Yield
	Cultivars	Quality of Produce	Crop genetics
	Plant Stress		
Water & Water Management	Groundwater	Water Availability	Flood Insurance
	Drought	Irrigation	Hydrology
Extreme Events	Extreme Event	Wildfire	Disaster
	Storm Surge		
Adaptation-Related Concepts	Adaptation Strategy	Resilience	Hazard
	Vulnerability Assessment	Sustainable Development	
Governance & Programmes	Governance	International Policy	Political Discourse
	Decision Making (Stakeholders)	Roles in Discourse	
Health	Infectious Disease	Public Health	Vector-borne Disease
	Mortality & Hospital	Affected Groups	
Socioeconomic Factors	Economics	Tourism	Socioeconomics
	Damage	Social Mobilisation	Education
	Public Perception	Environmental Migration	Resource Management
Communities	Tradition/Indigenous	Household	Local Community
Countries & Places	Africa	Canada	United States
	China (Grassland)	India (Rice)	Europe
	Australia		
Other/mixed	Mixed (Flash Flood, Asia)	Mixed (Conclusions, Consequences)	Mitigation
	Energy		

Global South; and concrete adaptations and adaptation policies are increasingly being implemented (IPCC, 2018a, Ch. 4), meaning they can be evaluated. In line with this, we find increased attention for most topics related to implementation and policy, while the relative share for all modelling topics has been decreasing.

Experts on the policy side, however, indicated that, while there may be an increase in quantity, the quality of research on governance has not progressed as much. One interviewee questioned if in recent years, we have made "*any progress beyond knowing that there are some technical measures, that it is important to involve stakeholders, and that there are various barriers and opportunities? I think personally that we have moved a little, but not as much and not as fast as we had initially thought.*"

Topics are largely distributed along disciplinary boundaries but IPCC reports provide a largely representative synthesis

While specialist knowledge is necessary, cross-disciplinary understanding of the broader adaptation field is also important for mature adaptation research (Klein et al., 2017, Nesshöver et al., 2017, Preston et al., 2015b) — indeed, disciplinary understandings of adaptation can limit the effectiveness of adaptation in practice as they can lead to oversimplified solutions to multidimensional problems (Eigenbrode et al., 2014, Feola et al., 2015). Our analysis documents evidence of a more integrated assessment for some topics, but most topics in our model remain dominated by one discipline (Figure 2.3).

The mapping of our topic model corresponds well to the expert interviews and earlier findings (Einecker and Kirby, 2020). The natural sciences are particularly dominant for topics related to modelling and geography. Articles in social science journals use dissimilar language and focus on topics around economics and politics predominantly. Agricultural topics have strong links to the natural sciences, though topics like food security are highly interdisciplinary. There is an interdisciplinary cluster of articles centred around the health effects of heatwaves, but overall, the health literature is relatively distinct from the rest of adaptation-relevant research, with clusters on vector-borne diseases and public health.

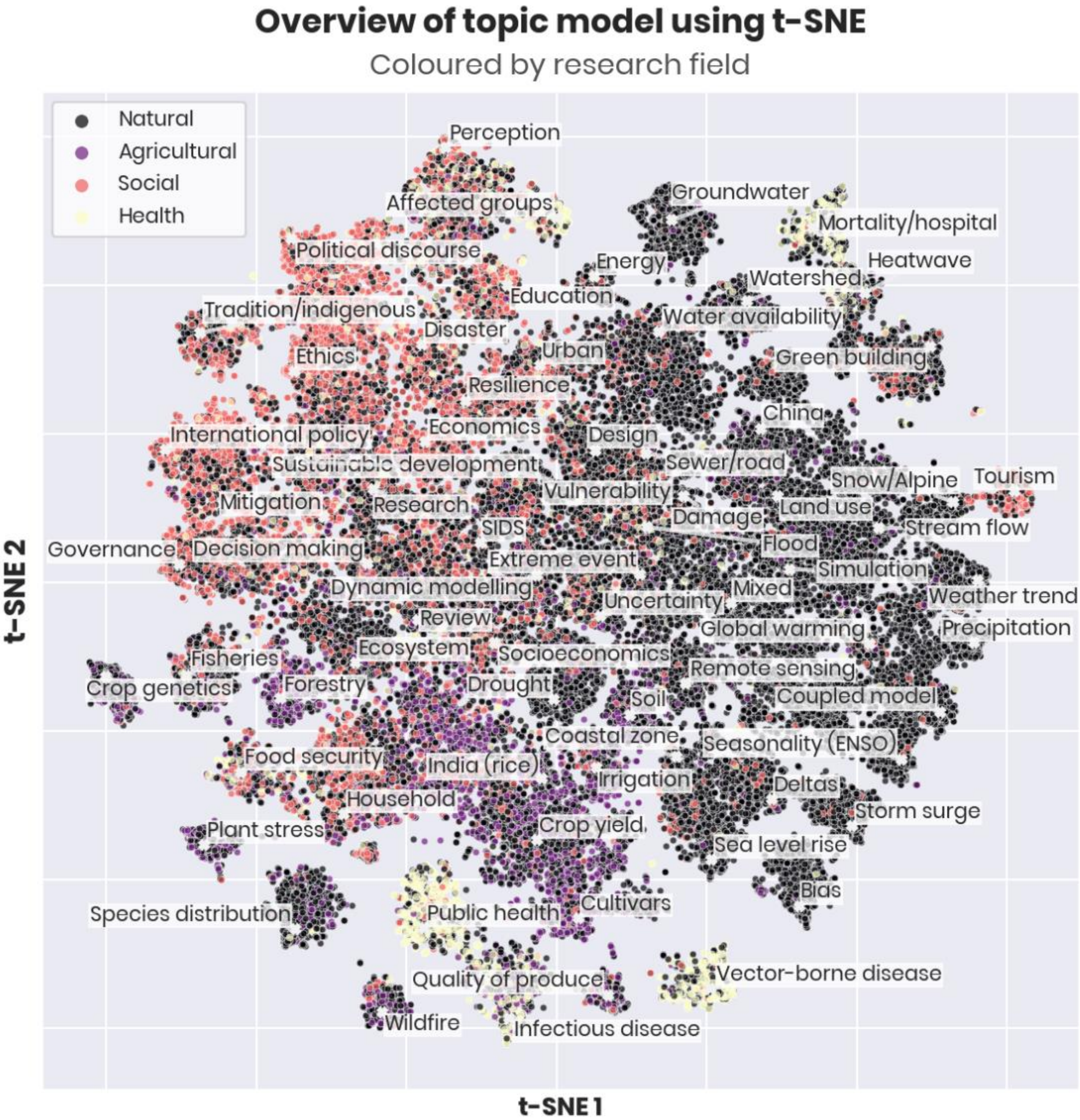

Figure 2.3: *A mapping of the topic model. The 105 dimensions of the topic model are reduced to two so that each document can be plotted as a single dot, where the algorithm attempts to keep documents with a similar topic distribution close together. Dots are then coloured by research field with labelling for locally dominant topics; areas of same-coloured dots around a label therefore imply that most publishing on this topic is from journals in the same field. Due to the dimensionality reduction, the axes have no meaningful unit — see methods.*

Further, an interdisciplinary cluster of articles is centred around the health effects of heatwaves.

Relatedly, a disconnect between scientists and healthcare practitioners was noted by one expert: "*The challenge is, this [practical experience] is not then put into the research community. (…) All of those health risks [of climate change] are current problems. All of those health risks have*

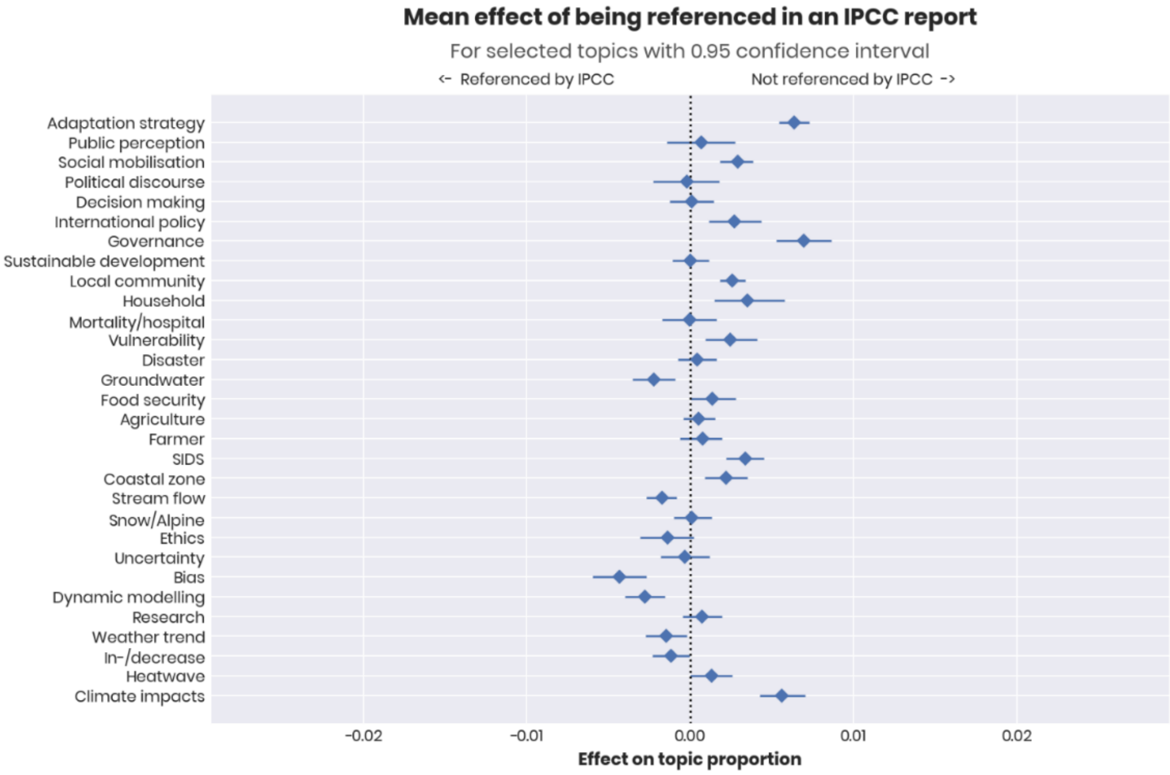

***Figure 2.4**: Effect of meta-data on the topic prevalence for selected topics in our topic model, here comparing documents that are cited in IPCC reports to the rest of the dataset. In essence, values further to the left (right) mean that a topic is more (less) likely to occur in documents cited by the IPCC compared to the documents that are not cited. A value in the middle means that the topic is equally represented in both. Axes are identical to Figure 2.6 for easy comparison.*

policies and programmes to manage them. Until recently, none of those policies and programmes explicitly incorporated climate change."

Inter/transdisciplinary communication more broadly was also identified as a challenge by multiple experts. One stated that, as a social scientist, they at times felt like they were added to a project "*to explain the results,*" rather than being integrated in the project cycle. By contrast, experts commented that the representation of social sciences in IPCC reports is increasing, in line with earlier findings (Callaghan et al., 2020b). The establishment of a shared vocabulary between disciplines was noted to have taken time to develop but is proving useful, especially for Working Group II. This assertion is especially interesting given both past criticisms (Bjurström and Polk, 2011, Victor, 2015) and current calls for an integrated assessment of adaptation progress (Siders, 2019, Magnan and Chalastani, 2019).

To test the representativeness of IPCC reports, 4,922 IPCC Working Group II (AR 1–5) and Special Report references were matched to documents in the dataset and the effect of this meta-data on the topic proportions examined (Figure 2.4). Generally, this literature has similar topic proportions to the other literature in our dataset. With the exception of the climate impacts topic, under-represented topics are predominantly identical to those identified as fast-growing above; it therefore seems plausible that this may be addressed in the upcoming AR6. Note also that interviewed IPCC authors almost universally agreed that non-scientific publications and non-English publications can be highly relevant, but that these are too often not seen by researchers and rarely included in IPCC reports — nor are they in our dataset. When it comes to representing scientific research however, apart from some delay effects, IPCC reports appear to fairly represent disparate fields of research.

Both the amount and the content of research differs by region

Experts and literature (Janssen, 2007, Janssen et al., 2006, Haunschild et al., 2016, Wang et al., 2018) alike pointed to unequal representation between the Global North and South as a persistent problem within the adaptation field. One expert remarked for example that they would expect the Global North to "*dominate the funding and the first author. And the last author.*" This is broadly supported by the geographic information extracted from our data, though there are large differences within the North-South division.

The location of the first author could be extracted for 52,977 papers (85.1% — Figure 2.5), of which the largest group was located in the United States (n= 11,749) followed by China (n= 5,475). Grouping by Annex I status, 69.4% (n= 25,490) of the documents originate from Annex I countries. It should be noted here though that many researchers have international backgrounds. Authors from an Annex I institution may therefore originate from a non-Annex I country.

By identifying geographical locations in the title or abstract of our dataset, we estimate where studies are taking place. At least one location was identified in 39,509 papers (63.5%). The imbalance is smaller for these locations: the US is still most prominent (n= 7,469), but the gap with China (n= 4,938) is smaller. Half (49.5%, n = 19,575) of identified places are in Annex

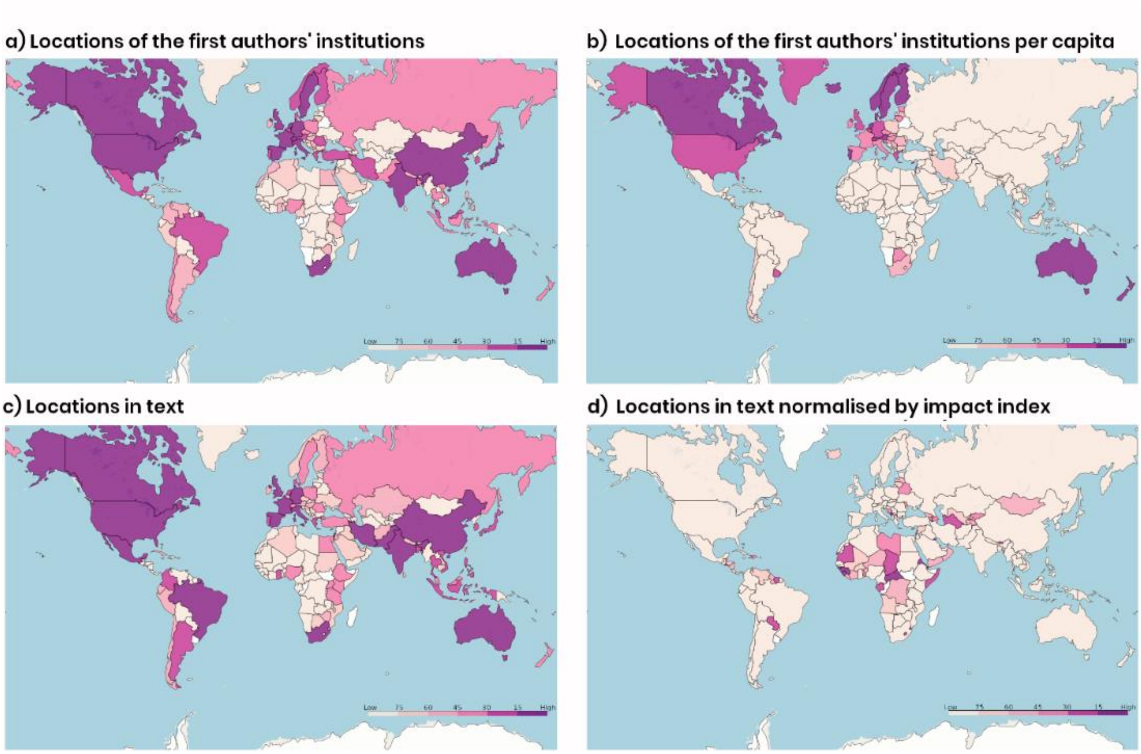

Figure 2.5: *The geographic spread of the number of publications, where the location is based on the country of the first author (a and b) and the location identified in the abstract and title (c and d). b) is normalised by the country's population; d) is normalised by the ND-GAIN index, which ranks countries based on a climate impact score. Colours represent 5 consecutive groups of 15 countries each.*

I countries. For 31.2% (n= 6,229) of all research taking place in non-Annex I countries, the primary author is based in an Annex I country.

In interviews, funding imbalances are named most often as driving these inequalities, though there may be increasing awareness from funding agencies around this. Correspondingly, if we consider only the literature since 2015, the trend is towards fewer Annex I authors (64.6%) and more research in non-Annex I countries (55.6%).

Further, Latin American experts highlighted that international funding applications often require a vulnerability assessment; however, middle income countries cannot always produce this as the initial funding for these vulnerability assessments was focused on Least Developed Countries (LDCs — notably, for National Adaptation Programmes of Action through 5/CP.7 (UNFCCC, 2002) and for National Adaptation Plans through 5/CP.17 (UNFCCC, 2012)). There is some evidence for such a "*middle income gap*," especially in parts of Latin America, Eastern Europe, and the Middle East.

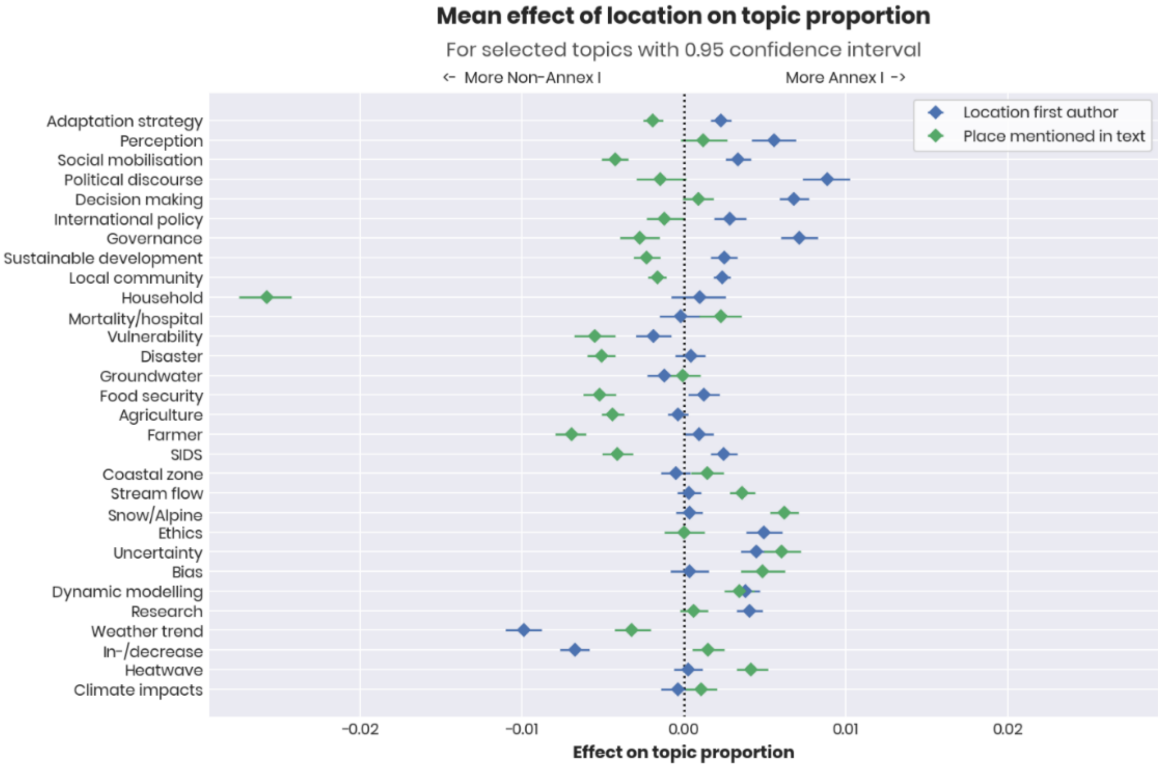

Figure 2.6: *Effect of meta-data on the topic prevalence for selected topics in our topic model, here comparing the country identified in the abstract and of the country of the first author, where the countries are grouped by UNFCC Annex I status.In essence, values further to the left (right) mean that a topic is more (less) likely to occur in documents on the given topic from Non-Annex I countries, compared to Annex I countries. A value in the middle mean that the topic is equally represented in both.*

Vulnerability does not always translate into more research. Combining place name mentions with indices of vulnerability to climate change (Chen et al., 2015 — data from 2018, Eckstein et al., 2019) highlighted a subset of African and South American countries and Small Island Developing States (SIDS), as well as the Balkans and Central Asia, as understudied — i.e. highly vulnerable, but few papers. However, differences within regions and country groups can be substantial, such as Tonga (n=4) and the Solomon Islands (n=144). Overall, there is no consistent relationship between vulnerability and research output.

We can consider North-South inequalities also in terms of the topics of research. Here, a somewhat controversial criticism of the field from one of the experts was that "*theories come from the North, evidence comes from the South*" — meaning that studies which define key terms tend to come from Northern countries, which are then applied in case studies in the South

(Alatas, 2003, Ergin and Alkan, 2019). While difficult to operationalize, STM does allow us to calculate the effect of both the location of the author and places mentioned in the text on topic distributions (Figure 2.6). This reveals that many governance-related and conceptual topics are discussed somewhat more by authors based in Annex I countries, but that these topics do not necessarily mention places in Annex I countries. This suggests that a substantial part of this research is conducted by Annex I authors in non-Annex I countries.

A similar but shifted trend is observed for topics with a strong development link: research here more often takes place in non-Annex I countries, but authors are not necessarily based there. The Household topic is associated with words like smallholder [farms], but also Ghana and Kenya, which explains why this effect is so pronounced for this topic especially. More generally, the importance of agriculture for the economies of many Southern countries led experts to expect agricultural topics to be overrepresented in Non-Annex I countries, which also corresponds to our data.

By contrast, subjects around modelling and natural sciences tend to be slightly more present in literature from Annex I countries — though the effect is less consistent. The resources and technical knowledge required for this type of research is often higher and more difficult to find in the Global South. One expert, for example, noted that most countries in Central America lack graduate programmes in climatology, as well as the computing power to run state-of-the-art climate models.

Experts signal the need for connection to practice if not politics

Academic experts had mixed opinions on how their scientific work connected to practice and politics. Some experts found that scientific concepts do at times inform the international negotiations: Loss and Damage was cited as a prime example of this. *Vice versa*, concepts from the policy side can enter the scientific discourse, especially when they are connected to funding. Together, this points to a feedback loop where researchers are incentivised to use politically salient terminology and decision makers in turn may adopt scientific concepts to substantiate their choices. Although the motivations of authors cannot be gleaned from a topic model, this dynamic likely contributed to the prevalence of many closely related terms such as vulnerability and resilience in our topic model. Underlying this feedback loop is the pressure many experts feel to produce work that is politically relevant. Some experts stated they were uncomfortable with this, as it may have a bearing on the (perceived) impartiality of research. Such reservations fit into a wider and longstanding debate in the literature (e.g. Klein et al., 2005), wherein some for example have highlighted the importance of professional ethics for adaptation researchers (Lacey et al., 2015).

Other experts put forward that many adaptation researchers want to make a positive difference, especially for the most vulnerable communities – see also the previously noted prevalence of Annex I researchers in non-Annex I countries. Although this does not always necessitate a close connection to politics, connections with local communities and meaningful stakeholder involvement are widely seen as important for adaptation research to make such a positive difference in the long term (Bohman et al., 2018, Lynch et al., 2008, Preston et al., 2015b). As one expert focussing on marine and coastal issues noted: *"Building and strengthening local capacity is absolutely critical (…) The best long-term stewards of those coastlines, will be those who live along them and whose lives depend on the oceans and stand the most to lose from projected changes. They are at the frontline. We need to invest in them so they have the skills and knowledge to best prepare them for what is to come."*

Despite this need, as stated before, findings from practice are not widely taken up by the research community. Conversely, practitioner interviewees stated that they were in no position to keep up with the scientific literature; some felt a lack of guidance from the scientific community on basic implementation issues especially; in essence, "*what works where?*"

2.4 Progress in adaptation research

In this paper we present an expert-informed, computer-assisted and inquisitive method for systematic mapping. We demonstrate how machine learning can be used to build a broad corpus of adaptation-related research. We develop existing approaches to computer-assisted systematic mapping (Callaghan et al., 2020b, Creutzig et al., 2019, Haddaway et al., 2020) by rooting our methodology in structural topic modelling which allows us to formally assess open-ended research questions emerging from the expert interviews. In our opinion, this is an important step in systematic mapping, which has remained largely descriptive in character (Nakagawa et al., 2019, Callaghan et al., 2020b, Wang et al., 2018, Haunschild et al., 2016, Fisch-Romito et al., 2020, Lamb et al., 2019), instead using inquisitive research questions as the foundation for evidence mapping.

We find a wide variety of topics are increasingly being assessed, and research is moving towards implementation of adaptation actions, indicating a maturing research field where researchers are progressively moving into more specialised sub-topics. Moreover, criticisms that the IPCC under-represents especially the social sciences (Bjurström and Polk, 2011, Victor, 2015) we find are likely a reflection of the quick growth of social science topics and the dominance of natural sciences in adaptation research more broadly, not of a bias within the IPCC.

At the same time, some long-standing issues still need to be resolved. Integration between natural and social sciences continues (Bjurström and Polk, 2011) to be a challenge, and parts of health research appear to be especially separated from mainstream work on adaptation. Research agendas should aim to break down silos, not just between disciplines but also between research and practice (Klein et al., 2017). There is also a clear need for work that includes local communities and practitioners and/or that has clear transferable results; projects which take a holistic approach can facilitate knowledge sharing between both different disciplines and groups of stakeholders, even if those project can be more difficult to implement (Eigenbrode et al., 2014, Feola et al., 2015). Arguably, such projects could also help meet recent calls for practice-relevant recommendations from the IPCC (Beck and Mahony, 2018, Victor, 2015, Carraro et al., 2015).

There is limited progress towards decreasing the well-established (Janssen, 2007, Janssen et al., 2006, Haunschild et al., 2016, Wang et al., 2018) gap in research output between the Global North and South. We find the gap extends to the topics of research, not just to the quantity. The paucity of research in some highly vulnerable countries is also noteworthy. In response, funding structures may have started to shift, but more needs to be done to ensure that funds are distributed justly (Ciplet et al., 2013) and that they meet local needs (Colenbrander et al., 2018), including supporting multi-sector solutions long term (Chu et al., 2016).

Overall, given both these persistent challenges and the signs of increasing maturity, "reflexive adaptation" (Preston et al., 2015b) continues to be crucial. Large-scale quantitative approaches can help especially for relatively exploratory analyses; these should augment rather than replace qualitative reflexions (Nakagawa et al., 2019, Berrang-Ford et al., 2015). To play an effective role in such critical discussions, the evidence mapping community should move beyond descriptive work and instead further develop methods and approaches that will allow for formal hypothesis testing. We take some tentative steps in that direction here.

It is worth highlighting again that our approach should be seen as a first step. We took a broad view of what could be considered adaptation-relevant, thus providing insights into larger trends. This capitalises on the ability of machine learning methods to handle large datasets, but the trade-off is that we cannot address more detailed questions. Moreover, even this large dataset is not comprehensive (see methods). Further machine learning work may for example focus on the evidence for adaptation solutions, incorporating also non-academic data sources, and contribute to a comprehensive tracking of adaptation actions around the globe as a foundation for urgently needed progress both in science and policy (Berrang-Ford et al., 2019, Lesnikowski et al., 2015, Siders, 2019, Craft and Fisher, 2018, Lesnikowski et al., 2017). Ultimately, like any tool, machine learning methods have limitations.

Given the rapid growth of and developments in many research fields though, they are necessary tools. Manual assessment practices, especially global environmental assessments like those by the IPCC or the Intergovernmental Science-Policy Platform on Biodiversity and Ecosystem Services (IPBES) are increasingly challenged by Big Literature; the related science-policy discussion offers few ideas on how to secure credibility, transparency and rigour in the scientific landscape of the 21st century (Minx et al., 2017a, Nunez-Mir et al., 2016). This paper contributes to a growing body of literature that uses data science tools to help keep abreast of the available science and efficiently summarize the available science (Callaghan et al., 2020b, Berrang-Ford et al., 2021, Creutzig et al., 2019, Hsu and Rauber, 2021). Along with similar efforts to embed machine learning components into evidence synthesis methods (Nakagawa et al., 2019, Haddaway et al., 2020), we believe that such data science tools cannot only prepare global environmental assessments for the age of Big Literature, but also lift them to a higher level of comprehensiveness, timeliness and transparency.

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Annex to Chapter 2: topic model keywords

CATEGORY	Topic label	
General Climate Change	Climate Impacts	Prob: climat, chang, impact, effect, respons,
		FREX: climat, chang, impact, respons, effect,
		Lift: climat, chang, non-clim, impact, change-induc,
		Score: climat, chang, impact, respons, effect,
	Global Warming	Prob: global, warm, degre, increas, limit,
		FREX: warm, global, degre, latitud, warmer,
		Lift: low-warm, gmt, preindustri, warm, gwls,
		Score: warm, global, degre, increas, latitud,
	Global Challenge	Prob: challeng, global, world, emerg, face,
		FREX: challeng, world, crisi, emerg, face,
		Lift: covid-, mankind, loom, atom, donald,
		Score: challeng, global, emerg, world, crisi,
		Prob: challeng, global, world, emerg, face,
Meteorology	Heatwave	Prob: heat, wave, hot, stress, heatwav,
		FREX: heat, heatwav, hot, uhi, wbgt,
		Lift: hws, hvi, heat-health, non-heat, wbgt,
		Score: heat, wave, uhi, heatwav, hot,
		Prob: heat, wave, hot, stress, heatwav,
	Temperature	Prob: temperatur, degre, increas, air, maximum,
		FREX: temperatur, minimum, air, night, maximum,
		Lift: tnp, tmax, tmin, t-max, work-rel,
		Score: temperatur, degre, air, maximum, minimum,
	Seasonality (ENSO)	Prob: season, dri, wet, pattern, associ,
		FREX: oscil, enso, nino, wet, dri,
		Lift: enso, nio-southern, -hpa, dipol, enso-driven,
		Score: dri, season, wet, enso, oscil,
	In-/decrease (water)	Prob: increas, decreas, annual, runoff, chang,
		FREX: decreas, annual, evapotranspir, runoff, evapor,
		Lift: etp, eto, penman, priestley-taylor, aet,
		Score: runoff, evapotranspir, decreas, annual, evapor,
	Seasonality	Prob: season, winter, summer, spring, period,
		FREX: spring, winter, autumn, phenolog, frost,

		Lift: rgp, phenophas, nec, ncp, frost,
		Score: winter, spring, season, summer, phenolog,
	Precipitation	Prob: precipit, indic, intens, day, increas,
		FREX: precipit, consecut, percentil, heavi, day,
		Lift: sdii, rxday, prcptot, drought-flood, etccdi,
		Score: precipit, day, extrem, daili, percentil,
	Weather Trend	Prob: trend, signific, station, observ, show,
		FREX: trend, station, mann-kendal, detect, seri,
		Lift: theil-sen, m-k, pre-whiten, morlet, mann-kendal,
		Score: trend, station, mann-kendal, detect, annual,
	Rainfall	Prob: rainfal, rain, intens, use, heavi,
		FREX: rainfal, rain, raini, idf, trmm,
		Lift: fournier, raingaug, chirp, kiremt, persiann-cdr,
		Score: rainfal, rain, raini, idf, heavi,
Modelling & Mapping	Simulation	Prob: model, simul, use, data, perform,
		FREX: simul, calibr, valid, model, error,
		Lift: glam, rrmse, rmse, marksim, split-sampl,
		Score: simul, model, calibr, valid, perform,
	Future Projection	Prob: futur, project, rcp, repres, current,
		FREX: futur, rcp, project, pathway, repres,
		Lift: rcps, futur, rcp, project, pathway,
		Score: futur, project, rcp, pathway, rcps,
	Coupled Model	Prob: centuri, region, model, project, forc,
		FREX: cmip, intercomparison, twenty-first, centuri, aerosol,
		Lift: isimip, annual-mean, pgw, signal--nois, intercomparison,
		Score: cmip, centuri, intercomparison, model, ensembl,
	Dynamic Modelling	Prob: model, dynam, scale, develop, assess,
		FREX: dynam, scale, comput, complex, model,
		Lift: iam, danubia, agent-bas, abm, meta-model,
		Score: model, dynam, integr, scale, approach,
	Future & Past	Prob: futur, project, rcp, repres, current,
		FREX: futur, rcp, project, pathway, repres,
		Lift: rcps, futur, rcp, project, pathway,

		Score: futur, project, rcp, pathway, rcps,
	Emission Scenario	Prob: scenario, impact, emiss, chang, climat,
		FREX: scenario, baselin, sres, emiss, ipcc,
		Lift: afi, scenario, giss, uktr, bau,
		Score: scenario, emiss, sres, ipcc, baselin,
	Downscaling	Prob: downscal, model, climat, ensembl, gcms,
		FREX: gcms, gcm, sdsm, downscal, rcms,
		Lift: gcms, mpi-esm-mr, sdsm, mri-cgcm, narccap,
		Score: downscal, gcms, gcm, ensembl, circul,
	Remote Sensing	Prob: data, map, use, monitor, inform,
		FREX: satellit, remot, map, sens, sensor,
		Lift: sentinel-, uav, hyperspectr, space-bas, unman,
		Score: data, map, satellit, remot, sens,
Methods & Methodology	Bias	Prob: bias, statist, method, daili, resolut,
		FREX: correct, bias, grid, resolut, reanalysi,
		Lift: inter-vari, correct, distribution-bas, quantile-bas, k-nearest,
		Score: bias, correct, daili, grid, resolut,
	Research	Prob: research, understand, knowledg, focus, paper,
		FREX: research, gap, interdisciplinari, literatur, topic,
		Lift: bibliometr, scientometr, transdisciplinar, research, transdisciplinari,
		Score: research, scienc, review, gap, literatur,
	Ethics	Prob: problem, human, concept, societi, way,
		FREX: ethic, geoengin, concept, think, idea,
		Lift: theolog, geoengin, philosoph, wick, ethic,
		Score: ethic, human, concept, geoengin, problem,
	Uncertainty	Prob: uncertainti, estim, method, differ, use,
		FREX: uncertainti, robust, assumpt, probabilist, uncertain,
		Lift: aleatori, rdm, carlo, mont, bns,
		Score: uncertainti, estim, probabilist, robust, method,
	Review Study	Prob: review, studi, report, assess, impact, systemat, literatur
		FREX: systemat, report, review, summar, search, panel, intergovernment

		Lift: eia, lca, nox, scopus, full-text, sciencedirect, proquest
		Score: review, report, systemat, pollut, literatur, ipcc, panel
	Variable	Prob: variabl, variat, factor, spatial, relationship,
		FREX: variabl, correl, variat, regress, linear,
		Lift: hfmd, gwr, krige, correl, idw,
		Score: variabl, correl, regress, variat, spatial,
	Key Finding	Prob: import, can, includ, also, provid,
		FREX: import, includ, particular, key, well,
		Lift: key, import, particular, crucial, well,
		Score: import, includ, can, provid, develop,
Physical Environment	Coastal Zone	Prob: coastal, zone, area, coast, along,
		FREX: coastal, coast, gulf, inland, coastlin,
		Lift: abras, iczm, risc-kit, rra, coastal,
		Score: coastal, coast, zone, coastlin, inund,
	SIDS	Prob: island, tropic, small, cyclon, pacif,
		FREX: atol, sid, fiji, caribbean, tcs,
		Lift: atol, fiji, kiribati, micronesia, samoa,
		Score: island, cyclon, tropic, hurrican, pacif,
	River Basin	Prob: river, basin, discharg, upper, lower,
		FREX: basin, river, upstream, brahmaputra, sub-basin,
		Lift: headstream, brahmaputra, yichang, jinsha, midstream,
		Score: river, basin, discharg, yangtz, yellow,
	Snow/Alpine	Prob: snow, mountain, elev, cover, alpin,
		FREX: snow, snowfal, alpin, switzerland, ski,
		Lift: snowfal, snowmak, switzerland, sublim, swe,
		Score: snow, mountain, ski, alpin, snowmelt,
	Sea Level Rise	Prob: sea-level, rise, slr, beach, shorelin,
		FREX: sea-level, slr, mangrov, beach, shorelin,
		Lift: bruun, ice-sheet, loggerhead, oceanfront, shorefac,
		Score: sea-level, slr, beach, shorelin, mangrov,
	Watershed	Prob: watersh, qualiti, sediment, load, pollut,
		FREX: watersh, phosphorus, load, nitrat, suspend,

		Lift: ammonium, coliform, non-point, nonpoint, bod,
		Score: watersh, sediment, qualiti, load, pollut,
	Glacier & Lake	Prob: lake, glacier, mountain, dam, valley,
		FREX: glacier, lake, himalaya, debri, outburst,
		Lift: hindu, hkh, morain, proglaci, everest,
		Score: lake, glacier, dam, mountain, permafrost,
	Soil	Prob: soil, moistur, eros, content, carbon,
		FREX: soil, soc, moistur, tillag, leach,
		Lift: rusl, soc, wepp, soil, loami,
		Score: soil, moistur, eros, tillag, soc,
	Sea Level (Deltas)	Prob: level, sea, rise, delta, salin,
		FREX: subsid, delta, sea, estuari, marsh,
		Lift: vmd, psu, caspian, dinh, mmi,
		Score: sea, rise, level, delta, tidal,
	Stream Flow	Prob: flow, regim, stream, low, peak,
		FREX: flow, stream, california, low-flow, regim,
		Lift: ucrb, pnw, freshet, crb, joaquin,
		Score: flow, stream, regim, california, peak,
	Ice Surface	Prob: surfac, human, activ, cycl, storag,
		FREX: storag, surfac, cycl, freshwat, anthropogen,
		Lift: grace-deriv, gws, tws, storag, gldas,
		Score: surfac, storag, human, freshwat, cycl,
	Forestry	Prob: forest, tree, forestri, deforest, redd,
		FREX: forestri, timber, redd, pine, beech,
		Lift: windthrow, aspen, beech, picea, ponderosa,
		Score: forest, tree, redd, forestri, plantat,
Biology	Nature conservation	Prob: conserv, protect, landscap, biodivers, wetland,
		FREX: conserv, wetland, biodivers, landscap, protect,
		Lift: waterfowl, hydroperiod, natura, geodivers, pothol,
		Score: conserv, wetland, landscap, biodivers, protect,
	Land use	Prob: land, use, cover, area, chang,
		FREX: land, lulc, land-us, cropland, cover,
		Lift: clue-, luc, lulc, land-usecov, useland,
		Score: land, cover, land-us, lulc, cropland,

	Ecosystem Services	Prob: ecosystem, servic, ecolog, restor, provid,
		FREX: ecosystem, servic, restor, ecolog, provis,
		Lift: pes, disservic, ess, eba, ipb,
		Score: ecosystem, servic, ecolog, restor, provis,
	Species Distribution	Prob: speci, distribut, suitabl, potenti, area,
		FREX: speci, invas, suitabl, extinct, nich,
		Lift: butterfli, miroc-h, climex, reptil, amphibian,
		Score: speci, suitabl, habitat, invas, distribut,
Urban & Infrastructure	Urban	Prob: urban, citi, area, infrastructur, develop,
		FREX: urban, citi, metropolitan, megac, nbs,
		Lift: eco-c, city--c, hcmc, nbs, city-scal,
		Score: urban, citi, metropolitan, smart, infrastructur,
	Sewers & Roads	Prob: system, network, transport, drainag, road,
		FREX: system, sewer, rainwat, road, drainag,
		Lift: rwh, freight, tank, rail, sewer,
		Score: system, network, drainag, transport, road,
	Green Building	Prob: build, green, space, thermal, built,
		FREX: green, roof, built, residenti, overh,
		Lift: energyplus, hvac, cfd, cibs, facad,
		Score: build, green, thermal, comfort, hous,
	Design	Prob: design, propos, infrastructur, oper, framework,
		FREX: engin, propos, oper, design, infrastructur,
		Lift: cyber, eco-engin, nsga-ii, multi-attribut, inexact,
		Score: infrastructur, design, oper, engin, propos,
Food & Agriculture	Agriculture	Prob: agricultur, practic, technolog, adopt, improv,
		FREX: agricultur, climate-smart, csa, agroecolog, fertil,
		Lift: csa, urea, climate-smart, agricultur, agroecolog,
		Score: agricultur, fertil, technolog, crop, agroforestri,
	Livestock	Prob: product, livestock, produc, increas, pest,
		FREX: feed, cattl, pollin, forag, product,
		Lift: aflatoxin, mycotoxigen, mycotoxin, deoxynivalenol, aspergillus,
		Score: product, livestock, pest, anim, weed,
	Cultivars	Prob: cultivar, date, sow, stage, potato,

		FREX: potato, cotton, sorghum, sow, bean,
		Lift: lint, boll, peanut, cropgro, rzwqm,
		Score: cultivar, sow, potato, cotton, sorghum,
	Plant Stress	Prob: plant, stress, respons, growth, effect,
		FREX: leaf, plant, transpir, stress, photosynthesi,
		Lift: mycorrhiz, rhizospher, prolin, rhizobacteria, stomat,
		Score: plant, stress, leaf, physiolog, growth,
	Farmer	Prob: farmer, farm, bangladesh, incom, profit,
		FREX: bangladesh, farm, farmer, profit, shrimp,
		Lift: flevoland, whole-farm, prawn, shrimp, bangladesh,
		Score: farmer, farm, bangladesh, profit, incom,
	Fisheries	Prob: marin, fisheri, fish, ocean, stressor,
		FREX: fisheri, fisher, fish, acidif, marin,
		Lift: fisheri, hab, shark, gbr, trutta,
		Score: fisheri, marin, fish, reef, coral,
	Quality of Produce	Prob: qualiti, coffe, wine, fruit, zealand,
		FREX: coffe, wine, grape, viticultur, grapevin,
		Lift: coffea, huglin, oliv, vineyard, alentejo,
		Score: wine, coffe, grape, viticultur, grapevin,
	Food Security	Prob: food, secur, insecur, nutrit, trade,
		FREX: food, secur, insecur, nutrit, hunger,
		Lift: undernourish, overweight, fsi, hunger, agrifood,
		Score: food, secur, insecur, nutrit, trade,
	Crop Yield	Prob: crop, yield, wheat, maiz, product,
		FREX: wheat, maiz, corn, yield, soybean,
		Lift: miscanthus, wheat-produc, virgatum, switchgrass, sugarcan,
		Score: crop, yield, wheat, maiz, grain,
	Crop genetics	Prob: crop, varieti, genet, breed, divers,
		FREX: genet, trait, toler, gene, genom,
		Lift: germplasm, marker-assist, proteom, qtl, qtls,
		Score: crop, breed, genet, seed, toler,
	Groundwater	Prob: groundwat, aquif, recharg, area, studi,
		FREX: aquif, groundwat, recharg, hydrogeolog, pump,

Water & Water Management		Lift: aquif, galdit, groundwater-level, hydrogeolog, hydrogeospher,
		Score: groundwat, aquif, recharg, pump, intrus,
	Drought	Prob: drought, index, sever, indic, standard,
		FREX: spi, drought, spei, index, standard,
		Lift: spei, z-index, pdsi, precipitation-evapotranspir, spi,
		Score: drought, index, spi, spei, pdsi,
	Water Availability	Prob: water, resourc, suppli, avail, demand,
		FREX: water, scarciti, reus, shortag, suppli,
		Lift: greywat, desalin, reus, iwrm, scarciti,
		Score: water, resourc, suppli, scarciti, demand,
	Irrigation	Prob: irrig, water, use, effici, requir,
		FREX: irrig, wue, deficit, schedul, save,
		Lift: irrigation-induc, irrig, sprinkler, nir, drip,
		Score: irrig, water, wue, crop, effici,
	Flood Insurance	Prob: flood, insur, increas, measur, floodplain,
		FREX: insur, flood, flood-pron, floodplain, england,
		Lift: nfip, policyhold, frm, property-level, flood-pron,
		Score: flood, insur, floodplain, dike, flood-pron,
	Hydrology	Prob: hydrolog, catchment, streamflow, reservoir, runoff,
		FREX: catchment, hydrolog, rainfall-runoff, streamflow, reservoir,
		Lift: vattenbalansavdeln, grj, xaj, pre-chang, simhyd,
		Score: hydrolog, streamflow, catchment, reservoir, runoff,
Extreme Events	Extreme Event	Prob: extrem, event, weather, frequenc, occurr,
		FREX: event, extrem, weather, frequenc, occurr,
		Lift: rainfall-trigg, ewe, event, extrem, thunderstorm,
		Score: extrem, event, weather, frequenc, landslid,
	Storm Surge	Prob: storm, surg, wind, wave, height,
		FREX: surg, storm, wind, height, overtop,
		Lift: slosh, adcirc, overtop, usac, wind-wav,
		Score: storm, surg, wave, wind, height,
	Wildfire	Prob: fire, wildfir, burn, area, increas,

		FREX: fire, wildfir, burn, amazon, bushfir,
		Lift: wildland-urban, fire, fire-pron, fire-rel, flammabl,
		Score: fire, wildfir, burn, amazon, bushfir,
	Disaster	Prob: disast, natur, conflict, respons, prepared,
		FREX: disast, humanitarian, drr, post-disast, violenc,
		Lift: climate-conflict, disaster-resili, post-disast, violent, rebel,
		Score: disast, conflict, drr, natur, prepared,
Adaptation-Related Concepts	Adaptation Strategy	Prob: adapt, strategi, measur, option, implement,
		FREX: adapt, strategi, option, measur, cope,
		Lift: -regret, adapt, mal-adapt, strategi, maladapt,
		Score: adapt, strategi, option, measur, implement,
	Vulnerability Assessment	Prob: vulner, assess, indic, capac, high,
		FREX: vulner, capac, rank, indic, score,
		Lift: indicator-bas, svi, sovi, vulner, ccva,
		Score: vulner, exposur, index, assess, capac,
	Resilience	Prob: plan, resili, framework, enhanc, concept,
		FREX: resili, plan, strateg, planner, cca,
		Lift: resilience-build, resili, resilience-bas, plan, cca,
		Score: resili, plan, cca, framework, concept,
	Sustainable Development	Prob: sustain, develop, achiev, innov, integr,
		FREX: sustain, innov, goal, achiev, transit,
		Lift: wef, sdgs, bioeconomi, water-energy-food, sustain,
		Score: sustain, innov, develop, transform, technolog,
	Hazard	Prob: hazard, loss, natur, expos, potenti,
		FREX: hazard, loss, port, expos, asset,
		Lift: seaport, multi-risk, multihazard, hazard, seismic,
		Score: hazard, loss, asset, port, exposur,
		Prob: hazard, loss, natur, expos, potenti,
Governance & Programmes	Governance	Prob: govern, institut, capac, barrier, actor,
		FREX: govern, institut, actor, organis, arrang,
		Lift: cross-level, polycentr, multi-actor, devolut, subsidiar,
		Score: govern, institut, actor, barrier, capac,
		Prob: inform, decis, use, stakehold, process,

	Decision Making (Stakeholders)	FREX: stakehold, decision-mak, decis, expert, maker,
		Lift: co-design, decision-support, backcast, user-ori, decision-mak,
		Score: stakehold, decis, inform, decision-mak, tool,
	International Policy	Prob: polici, nation, develop, intern, countri,
		FREX: polici, cooper, unfccc, commit, intern,
		Lift: ndcs, non-annex, oda, indc, relevanceth,
		Score: polici, intern, nation, countri, cooper,
	Roles in Discourse	Prob: role, issu, climat, play, attent,
		FREX: play, role, attent, issu, question,
		Lift: contrarian, wire, wcc, litig, clim,
		Score: role, issu, play, articl, attent,
	Political Discourse	Prob: polit, articl, frame, argu, discours,
		FREX: discours, narrat, polit, frame, contest,
		Lift: populist, post-polit, discurs, foucault, techno-manageri,
		Score: polit, discours, justic, narrat, frame,
Health	Infectious Disease	Prob: diseas, pathogen, infect, infecti, outbreak,
		FREX: tick, pathogen, zoonot, infecti, cholera,
		Lift: brucellosi, burgdorferi, helminth, host-parasit, inoculum,
		Score: diseas, pathogen, infect, infecti, virus,
	Mortality & Hospital	Prob: mortal, associ, increas, effect, death,
		FREX: admiss, mortal, hospit, respiratori, cardiovascular,
		Lift: cardiorespiratori, -caus, admiss, case-crossov, circulatori,
		Score: mortal, hospit, death, respiratori, morbid,
	Public Health	Prob: health, public, human, care, impact,
		FREX: health, care, medic, public, healthcar,
		Lift: hia, ncds, noncommunic, lancet, ecohealth,
		Score: health, public, human, medic, healthcar,
	Affected Groups	Prob: peopl, live, age, resid, mental,
		FREX: worker, mental, nurs, children, child,
		Lift: post-traumat, ptsd, distress, posttraumat, adolesc,
		Score: mental, children, worker, peopl, nurs,

	Vector-borne Disease	Prob: malaria, incid, transmiss, dengu, vector,
		FREX: malaria, dengu, mosquito, aed, aegypti,
		Lift: anophel, aegypti, malari, plasmodium, schistosoma,
		Score: malaria, dengu, mosquito, transmiss, vector,
Socio-economic Factors	Economics	Prob: econom, cost, benefit, invest, market,
		FREX: invest, cost, incent, financi, regulatori,
		Lift: actioncrit, contextsther, policykey, succeedeffect, ppps,
		Score: cost, econom, invest, market, financi,
	Damage	Prob: caus, damag, structur, due, prevent,
		FREX: damag, failur, caus, catastroph, safeti,
		Lift: hydrotechn, corros, armenia, geotechn, damag,
		Score: damag, caus, failur, structur, prevent,
	Public Perception	Prob: percept, survey, perceiv, individu, behavior,
		FREX: percept, perceiv, belief, attitud, behavior,
		Lift: social-psycholog, pmt, pro-environment, wtp, willing,
		Score: percept, perceiv, attitud, belief, behavior,
	Tourism	Prob: tourism, park, tourist, japan, destin,
		FREX: tourism, tourist, park, destin, visitor,
		Lift: ecotour, tourism, visitor, tourism-rel, scenic,
		Score: tourism, tourist, destin, park, japan,
	Social Mobilisation	Prob: social, capit, mobil, dimens, gender,
		FREX: social, mobil, inequ, capit, gender,
		Lift: adaptacion, cambio, esta, politica, una,
		Score: social, gender, women, inequ, capit,
	Environmental Migration	Prob: environment, environ, migrat, forc, degrad,
		FREX: environment, migrat, refuge, migrant, displac,
		Lift: palestinian, climate-migr, binat, gec, environment,
		Score: environment, migrat, environ, migrant, refuge,
	Socioeconomics	Prob: popul, countri, develop, growth, econom,
		FREX: popul, million, socioeconom, countri, billion,
		Lift: lecz, ssps, gdp, hdi, ssp,
		Score: popul, countri, growth, million, econom,

	Education	Prob: learn, communic, educ, scienc, program,
		FREX: student, communic, learn, teach, game,
		Lift: pre-servic, classroom, teach, teacher, curricula,
		Score: learn, educ, communic, student, engag,
	Resource Management	Prob: manag, resourc, integr, practic, implement,
		FREX: manag, integr, resourc, implement, practic,
		Lift: nrm, manag, climate-inform, natural-resourc, management-,
		Score: manag, resourc, practic, integr, implement,
Communities	Tradition/	Prob: cultur, tradit, indigen, knowledg, arctic,
	Indigenous	FREX: arctic, indigen, archaeolog, heritag, cultur,
		Lift: inuvialuit, tek, hunter-gather, iqaluit, archaeologist,
		Score: cultur, arctic, indigen, heritag, tradit,
	Household	Prob: household, livelihood, rural, studi, use,
		FREX: household, smallhold, livelihood, ghana, kenya,
		Lift: agro-pastoralist, farmer--farm, male-head, female-head, farm-household,
		Score: household, livelihood, smallhold, rural, ghana,
	Local Community	Prob: local, communiti, rural, mine, initi,
		FREX: communiti, local, community-bas, mine, council,
		Lift: frack, communiti, community-bas, photovoic, local,
		Score: communiti, local, community-bas, mine, rural,
Countries & Places	Africa	Prob: south, africa, west, east, asia,
		FREX: africa, south, african, sahel, sub-saharan,
		Lift: sadc, africa, african, niamey, sahel,
		Score: africa, south, african, west, east,
	China (Grassland)	Prob: china, veget, region, area, arid,
		FREX: plateau, china, npp, ndvi, mongolia,
		Lift: mongolia, qinghai, three-riv, hexi, songnen,
		Score: china, veget, arid, plateau, ndvi,
	Australia	Prob: predict, australia, use, australian, accur,
		FREX: australia, queensland, australian, predict, neural,
		Lift: anfi, perceptron, queensland, svm, svr,
		Score: predict, australia, australian, neural, queensland,
	Canada	Prob: canada, canadian, franc, british, columbia,

		FREX: ontario, des, quebec, les, canada,
		Lift: aux, avec, des, etud, ont,
		Score: canada, canadian, franc, les, des,
	India (Rice)	Prob: rice, india, district, pakistan, indian,
		FREX: india, rice, pradesh, paddi, lanka,
		Lift: aman, kerala, ludhiana, rice-grow, uttar,
		Score: rice, india, pakistan, paddi, monsoon,
	United States	Prob: state, unit, across, counti, usa,
		FREX: rangeland, state, brazil, unit, graze,
		Lift: syrup, contermin, rancher, grazier, ceara,
		Score: state, unit, rangeland, counti, pastur,
	Europe	Prob: region, europ, central, area, european,
		FREX: european, europ, mediterranean, itali, turkey,
		Lift: czech, european, poland, hungarian, turkey,
		Score: region, europ, mediterranean, european, itali,
Other/mixed	Mixed (Flash Flood, Asia)	Prob: distribut, period, studi, return, area,
		FREX: flash, curv, nonstationari, taiwan, return,
		Lift: log-pearson, guangdong, zhejiang, pmf, hec-ra,
		Score: flash, curv, return, inund, probabl,
	Mixed (Conclusions, Consequences)	Prob: will, like, need, mani, current,
		FREX: will, alreadi, continu, come, like,
		Lift: alreadi, soon, come, nato, will,
		Score: will, like, need, alreadi, requir,
	Energy	Prob: energi, demand, generat, power, consumpt,
		FREX: energi, renew, electr, hydropow, fossil,
		Lift: thermoelectr, photovolta, run--riv, energy-rel, blackout,
		Score: energi, demand, hydropow, electr, power,
	Mitigation	Prob: mitig, sector, industri, emiss, carbon,
		FREX: ghg, compani, gas, sector, greenhous,
		Lift: smes, disclosur, csr, scc, ghg,
		Score: emiss, sector, carbon, industri, greenhous,

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

Anne J. Sietsma, Emily Theokritoff, Robbert Biesbroek, Iván Villaverde Canosa, Adelle Thomas, Max Callaghan, Jan C. Minx, James D. Ford

Abstract

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.

3.1 Introduction

Increasingly, governments around the world are adapting to the risks posed by climate change (United Nations Environment Programme, 2022). While the broad range of available adaptation policy options (Ley et al., 2022) may be seen as encouraging, in practice, policy makers often face considerable knowledge deficits on the design, implementation and evaluation of specific adaptation policies (Kuhl, 2021, Ryan and Bustos, 2019).

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 (Berrang-Ford et al., 2021, Intergovernmental Panel on Climate Change, 2022), by governments themselves (e.g. the Global Stocktake under the Paris Agreement), and combinations of both (United Nations Environment Programme, 2022). 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 (Nachmany et al., 2019, United Nations Environment Programme, 2022). 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 (Ley et al., 2022, Berrang-Ford et al., 2021). As a consequence, evidence synthesis efforts struggle (Berrang-Ford et al., 2019, Berrang-Ford et al., 2021) to inform policy makers on “what works?” (Sietsma et al., 2021, Runhaar et al., 2018) focusing instead on “what has been done” or “are we doing enough?” (Garschagen et al., 2022) and even then, it can be difficult to provide comprehensive an policy-relevant syntheses.

The reasons for these difficulties are myriad and are reviewed elsewhere (Ford and Berrang-Ford, 2016, Garschagen et al., 2022), 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 (Craft and Fisher, 2018, Runhaar et al., 2018, Tompkins et al., 2018, Singh et al., 2022); moreover, literature from fields such as disaster risk reduction may use different terminology from an "adaptation framing", but is often closely related.(Busayo et al., 2020, Rana, 2020). Similarly, there is a long-standing debate on if and how adaptation can be separated from general development (Schipper et al., 2020, Leiter and Pringle, 2018). 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 (Wang et al., 2018), 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 (Berrang-Ford et al., 2021, Sietsma et al., 2021).

Machine learning advances offers promising ways to better handle both these difficulties that are typical of "Big Literature" (Nunez-Mir et al., 2016): sophisticated models can easily handle large datasets, while remaining sensitive to specific contexts and different research traditions. Recognising this potential, efforts have been undertaken to modify the traditional systematic review process to incorporate machine learning elements (Haddaway et al., 2020, Nakagawa et al., 2019, van de Schoot et al., 2021) and there is an emerging body of studies using machine learning to systematically assess the state of knowledge and progress in an adaptation context (Sietsma et al., 2021, Berrang-Ford et al., 2021, Lesnikowski et al., 2019a, Biesbroek et al., 2020, Biesbroek et al., 2022).

Machine learning efforts to date can be divided based on the types of documents they analyse. Some directly use political documents, such as political speeches and municipal archives,(Lesnikowski et al., 2019a) national policy papers(Biesbroek et al., 2020) or submissions to the United Nations Framework Convention on Climate Change (UNFCCC) (Biesbroek et al., 2022). 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. However, reporting on adaptation is both relatively infrequent and open to politically motivated interpretations (Gupta and van Asselt, 2019, Weikmans et al., 2021), making it difficult to draw objective and generalisable conclusions from such data. Other studies have instead focussed on scientific papers, producing overviews of the evidence on topics such as expected climate impacts (Callaghan et al., 2021), implemented adaptations (Berrang-Ford et al., 2021, Ulibarri et al., 2022), and the wider adaptation-related literature (Sietsma et al., 2021). These analyses, alongside more traditional bibliometric work (Wang et al., 2018) and systematic reviews (Naulleau et al., 2021), 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 the scientific literature which 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 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 are introduced below. We combine this with 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. Furthermore, the dataset created here could be used for more detailed, qualitative enquiries into any (combination) of the topics and categories we discuss here at the global level. Similarly, as our approach is relatively easy to replicate, it could serve as a first step towards establishing a living evidence platform for adaptation policies.

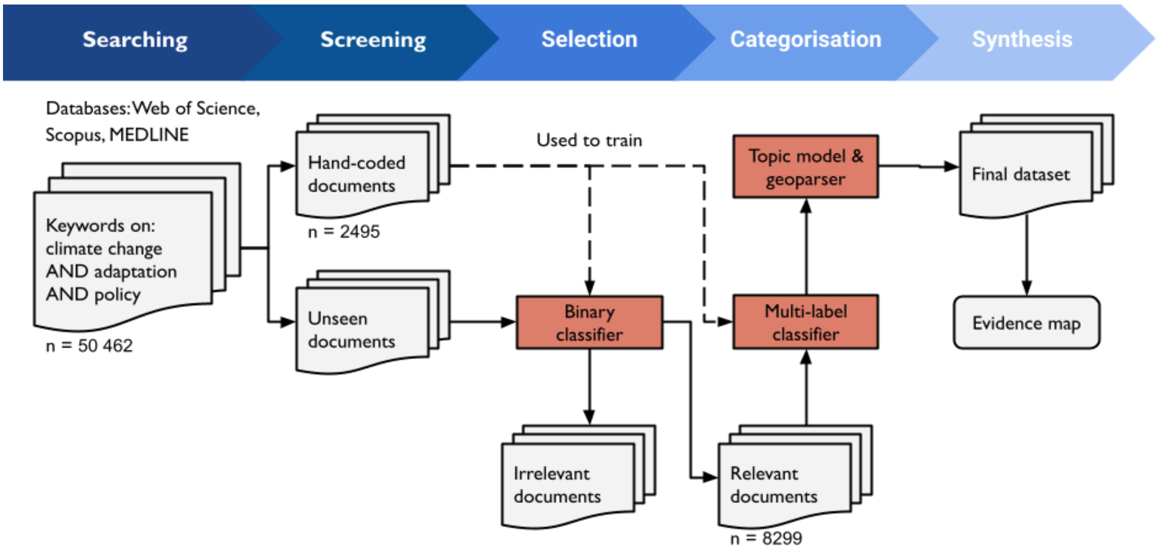


Figure 3.1: An overview of the research process in 5 steps. Machine learning components are given in red.

3.2 Experimental procedures

Our methodology was published in a separate protocol (Sietsma et al., 2022) 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 3.1): 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. (2020b) 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.

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. (Callaghan et al., 2020a) 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 (Webersinke et al., 2021) through HuggingFace (Wolf et al., 2019). 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 (Callaghan et al., 2021) 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** (Hood, 1983). 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. (2021): 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** (Halterman, 2017) 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 (Hickisch et al., 2019, Mongeon and Paul-Hus, 2016), 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) (Roberts et al., 2019) 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.

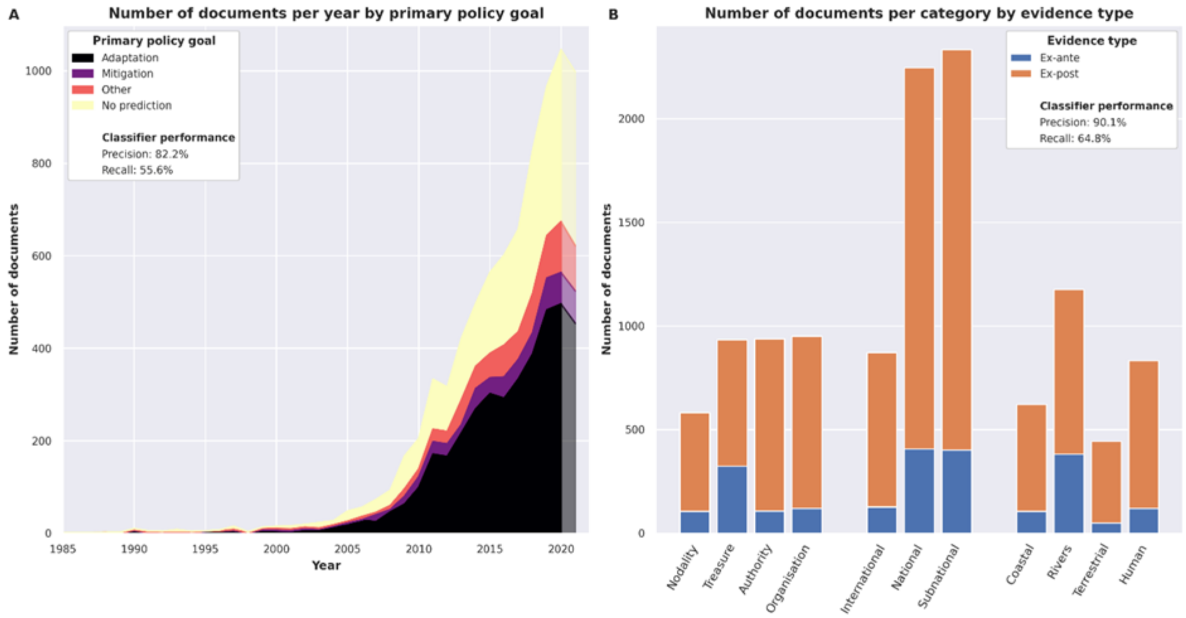
Each topic was then named based on their most-associated keywords (see Annex 1) and highest scoring documents. For geographical analyses, topics with geographical keywords (e.g. country names) were removed manually.

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 Annex 2 Figure A3.1 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 (Lesnikowski et al., 2017), while others have argued that adaptation policies should align with the targets set in the SDGs to be successful long-term (Fuldauer et al., 2022b, Fuldauer et al., 2022a). By



	Document selection
Precision	92.5%
Recall	92.0%

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

***Figure 3.2**: 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, only the prediction with the highest confidence was counted. In Figure B, the number of documents for the remaining categories is given, sub-divided 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 reflects the proportion of the documents labelled relevant by the algorithm that true positives (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).*

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.

3.3 Results

Quickly growing literature on diverse adaptation policies

The first classifier is used to identify articles which substantially discuss or evaluate at least one action that reduces or aims to reduce climate risks and which was instigated or supported by a government body at any level. We find 8691 documents (i.e. abstracts of articles found in Web of Science, Medline or Scopus) relevant 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 3.2, 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 3.2 was lower, with F1 scores ranging from 45.3% to 75.1% (see Annex 2 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 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 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 3.2 B). 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.

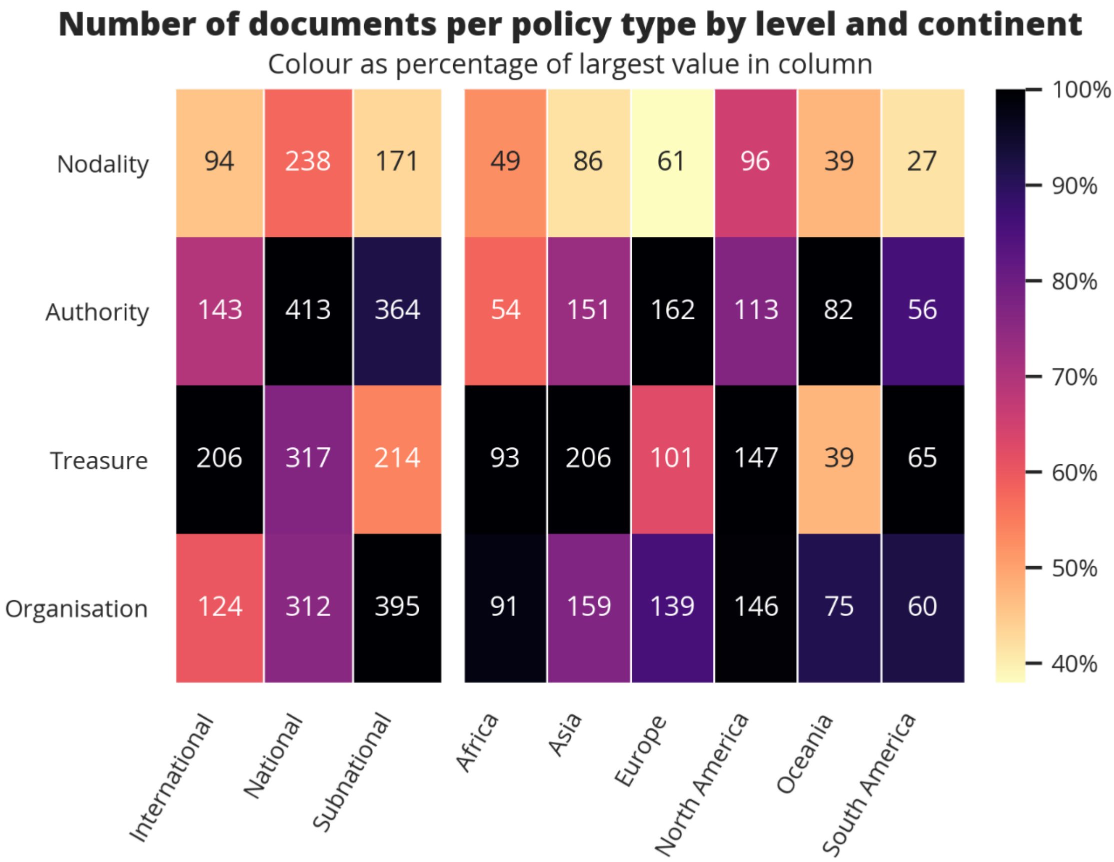


Figure 3.3: *Heatmap of policy instruments at different governance levels and in different continents. In this heatmap, the value represents the number of documents where categories occur together. For example, the classifier categorised 94 documents as being about a Nodality policy and at the international 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.*

National sticks, international carrots, subnational collaboration

Variations in policy instruments between different levels of government and location (Figure 3.3) provide an indication of the types of adaptation actions different actors take, which may reveal under-utilised options and issues of alignment (Lesnikowski et al., 2019b, Biesbroek, 2021). Locations here are based on the results of the pre-trained geoparser.

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 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.

It is worth noting that the NATO model can be used to describe policy mixes (Lesnikowski et al., 2019b) – 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(Sietsma et al., 2021) as well as the considerable variation in adaptive capacity and vulnerability of countries,(Feldmeyer et al., 2021) we assess the global spread of our dataset and combine these locations with the topic model results to identify regionally dominant topics (Figure 3.4). 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%).

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 Annex 2 Figure A3.2). 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 (Grantham Institute and Sabin Center for Climate Change Law, 2022) for example, Brazil is among the countries with the most adaptation policies listed. Language and location biases likely play a

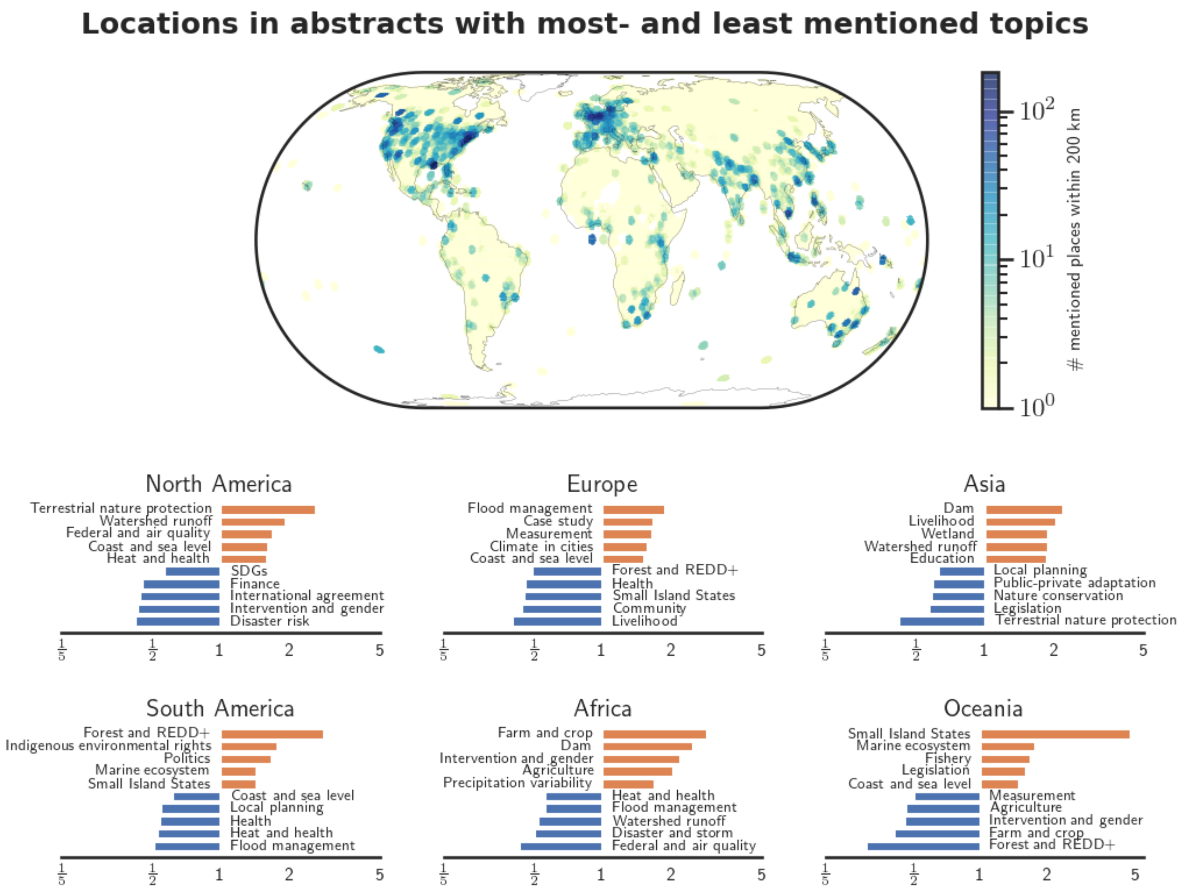


Figure 3.4: *Map of locations of research, as well as most- and least-mentioned topics per continent. On the map, locations extracted from the title and abstract have been marked by a circle. References to a country or area are placed in the middle of that country or area. If multiple places within the 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.*

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 (Berrang-Ford et al., 2021), which categorized evidence from implemented adaptation actions, has a higher proportion of Global South literature, despite using the same scientific databases. That project however focussed on implemented adaptation policies, which did not need to be the result of a policy. This therefore suggests that Southern literature has a relatively high proportion of individual *projects* from non-governmental organisations, while *policies* are understudied in this context. Further substantiating this impression is the relative emphasis on *Treasure* instruments in Africa, for example – these may be internationally funded projects, or direct investments. Legal *Authority*-based instruments, are not routinely subject of scientific publications.

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 3.4 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 Annex 2 Figure A3.1 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,

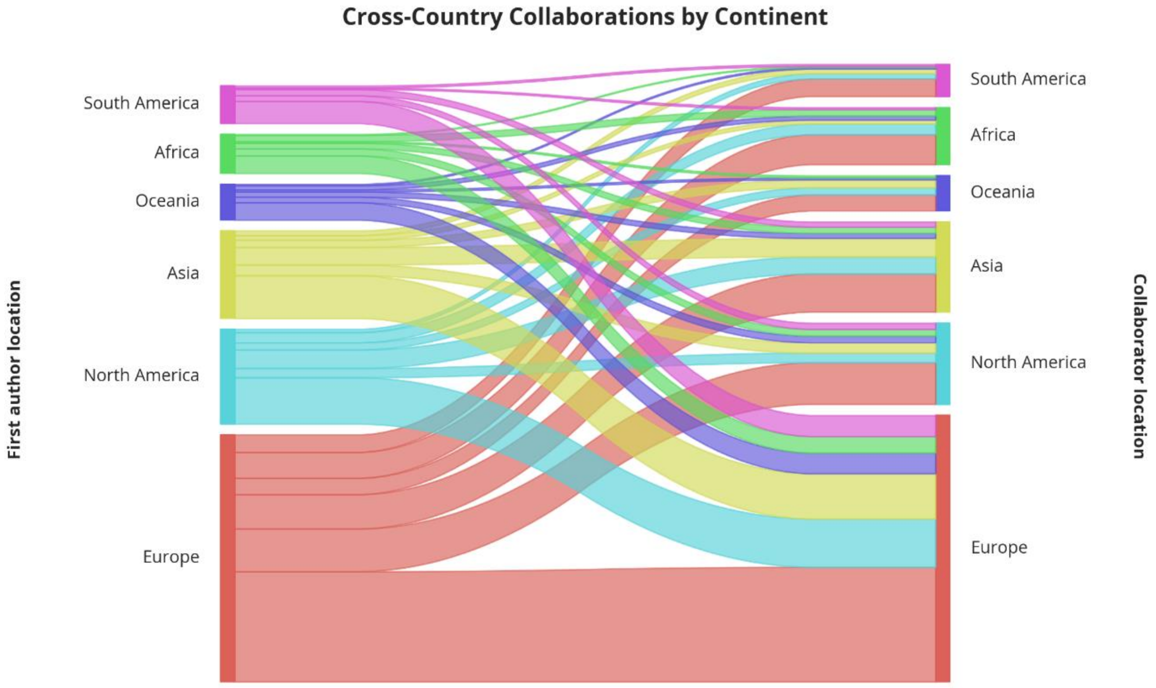


Figure 3.5: *Diagram of how often papers are written jointly by authors from different countries, sub-divided by continent. The locations are based on the affiliation of the authors, with first authors on the left and any co-authors on the right. Only papers where the location of the first author as 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.*

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 3.5). This is important for two reasons: first, international collaborations require resources and those resources should be allocated equitably; second, the discourse on South-South and North-South collaboration within adaptation often suggest that such efforts can be used for knowledge transfer and dissemination of best practices(Saric et al., 2019, Lal, 2019, Tan et al., 2021). 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 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 3.5.

In addition, despite persistent calls for South-South collaborations (Tan et al., 2021)and the important role such collaborations have played in advancing international climate policy (Weber and Kopf, 2018), 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 (Lesnikowski et al., 2017, Tompkins et al., 2018). 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 (Fuldauer et al., 2022a, Fuldauer et al., 2022b). Importantly, these agreements do not stand on their own: there is an extensive literature on the connections between development and adaptation; the Paris Agreement and SDGs are the product of a more wholistic understanding of sustainability, vulnerability and climate action which researchers had increasingly promoted in the preceding years (Kuyper et al., 2018, Möhner, 2018, Sherman et al., 2016). Therefore, we may expect to see a shift in topics over time in a similar direction.

Our results show research on a few development-related topics has increased in recent years (Figure 3.6). 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.

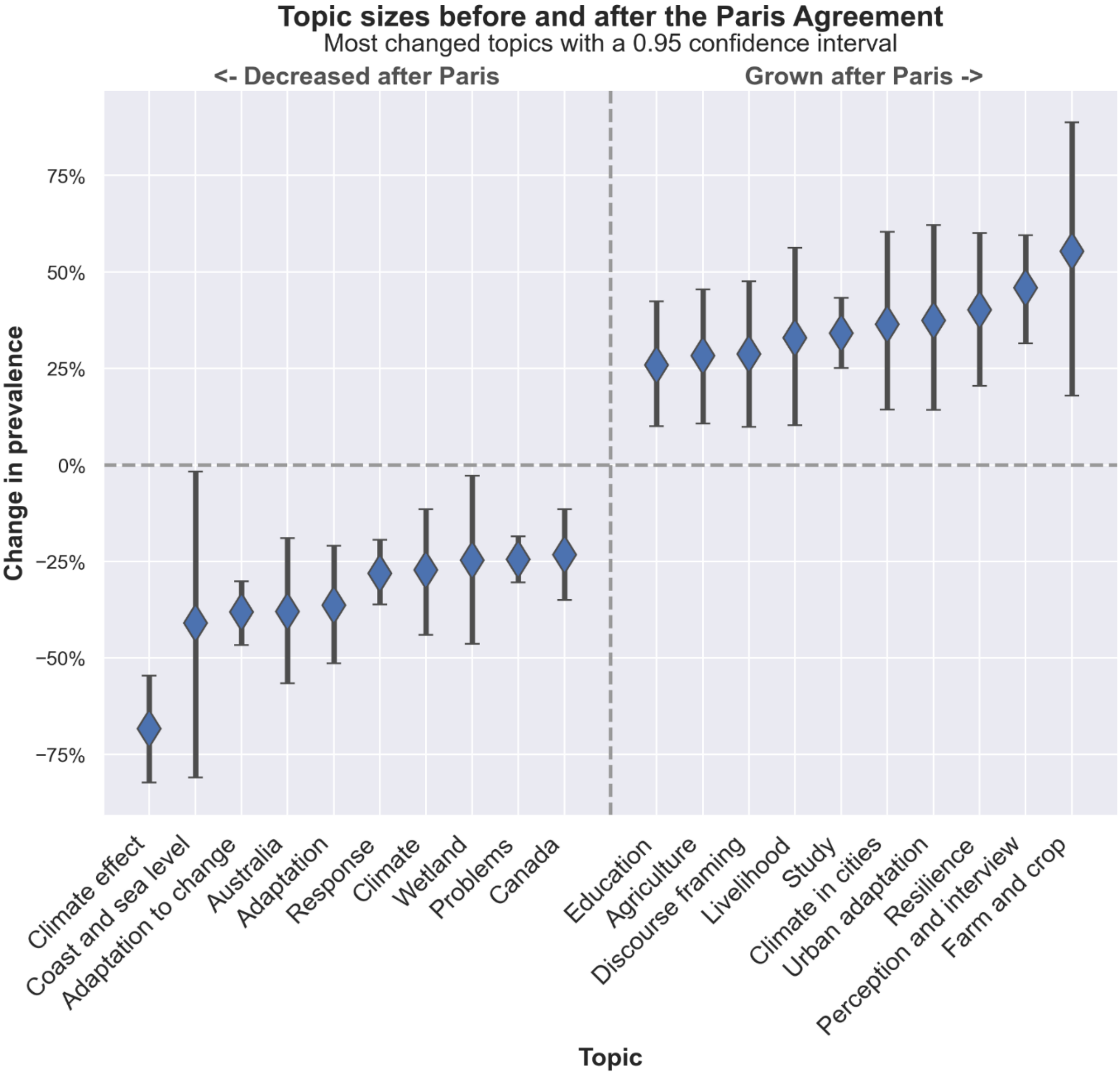


Figure 3.6: *estimates for how often topics in our Structural Topic Model are discussed in documents published after 2015 relative to before. Only the 5 most-grown and 5 most-decreased topics are given, and non-statistically significant topics are left out too.*

In line with the latter explanation, the most policy-focussed topics are not among the quickest growing topics. Outside of the topics included in the figure, 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.

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 (Nalau and Verrall, 2021) where resilience replaced vulnerability as the most-used keyword. Interpreted positively, this could signify a move away from disempowering concepts focussed 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 (Ribot, 2022, Ford et al., 2018, Kelman et al., 2016, Naylor et al., 2020). 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 (Joakim et al., 2015, Cutter, 2016) one should be careful not to over-interpret this shift.

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 (Intergovernmental Panel on Climate Change, 2022). 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 (United Nations Environment Programme, 2022) – and allocated on a project-basis, the majority of research will focus on smaller, more concrete policies and projects.

3.4 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 (Sietsma et al., 2021, Seddon, 2022, Wester and Lama, 2019, Pearse, 2017, Scoones et al., 2020), as well as an increasing amount of practical evidence, mostly from individual projects (Chausson et al., 2020, Roy et al., 2022, Vermeulen et al., 2018), 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 (Magnan et al., 2022) 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, like other machine learning approaches (Berrang Ford et al., 2021, Berrang-Ford et al., 2021, Callaghan et al., 2021, Callaghan et al., 2020b, Sietsma et al., 2021), 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 (Lesnikowski et al., 2019b), while our analysis is more suited to highlighting the main points of projects which authors wish to emphasise. 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 analyse the larger texts.

Data issues notwithstanding, considering how much has been written about "mainstreaming" (Runhaar et al., 2018) and about the Paris Agreement as a turning point for adaptation (Kinley, 2017, Lesnikowski et al., 2017), 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 (United Nations Environment Programme, 2022), this narrow scope is problematic (Magnan et al., 2022). 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 (Gusenbauer, 2022, Khanna et al., 2022), 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 (Haddaway et al., 2015, Adams et al., 2016, Berrang-Ford et al., 2021). In addition to addressing persistent funding inequalities (Khan et al., 2020), and the previously mentioned need for full-text analysis at scale, 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. Tunstall et al., 2022) 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. (2021), 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 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, as the classifications need to be re-run periodically in this case and additional hand-labelled 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 (Callaghan et al., 2021, Berrang-Ford et al., 2021, Sietsma et al., 2021, Biesbroek et al., 2020), 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.

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Annex 1 to Chapter 3: topic model keywords

Topic name	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	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	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
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	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	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	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	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
	Score: china, goal, sdgs, sustain_goal, chines, japan, sdg
Uncertain decision making	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	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_strategi
	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	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
	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	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	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	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	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	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	Highest Prob: island, small, pacif, state, sid, small_state, caribbean
	FREX: sid, small_state, island_state, small_develop, island, vanuatu, pacif
	Lift: pep, pic, small_develop, atol, ikm, island_state, kiribati
	Score: island, pacif, sid, small_state, island_state, small_develop, small
Discourse framing	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	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	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
	Score: network, collabor, organ, particip, engag, actor, partnership
Urban adaptation	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	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	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
	Lift: cannabi, literatur, organis, climat_review, informa, review, academ
	Score: group, review, document, literatur, organis, systemat, academ
Sector and integration	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	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
	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_measur
	Score: measur, climat_measur, chang_measur, implement_measur, measur_climat, measur_chang, adapt_measur
Conflict and displacement	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	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	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	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
	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	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	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	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	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
	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	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, nepal
	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
	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	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	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	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
Explore context and theory	Highest Prob: context, explor, analysi, understand, complex, three, interact
	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	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
	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	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
	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
	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	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
Global change	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	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	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

Annex 2 to Chapter 3: additional figures

Table A3.1: *Performance of the different classifiers based on nested cross-validation with scores from the outer-loop. The hyper-parameters which resulted in the highest F1 score in the outer loop were 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, implyings over-fitting. 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%

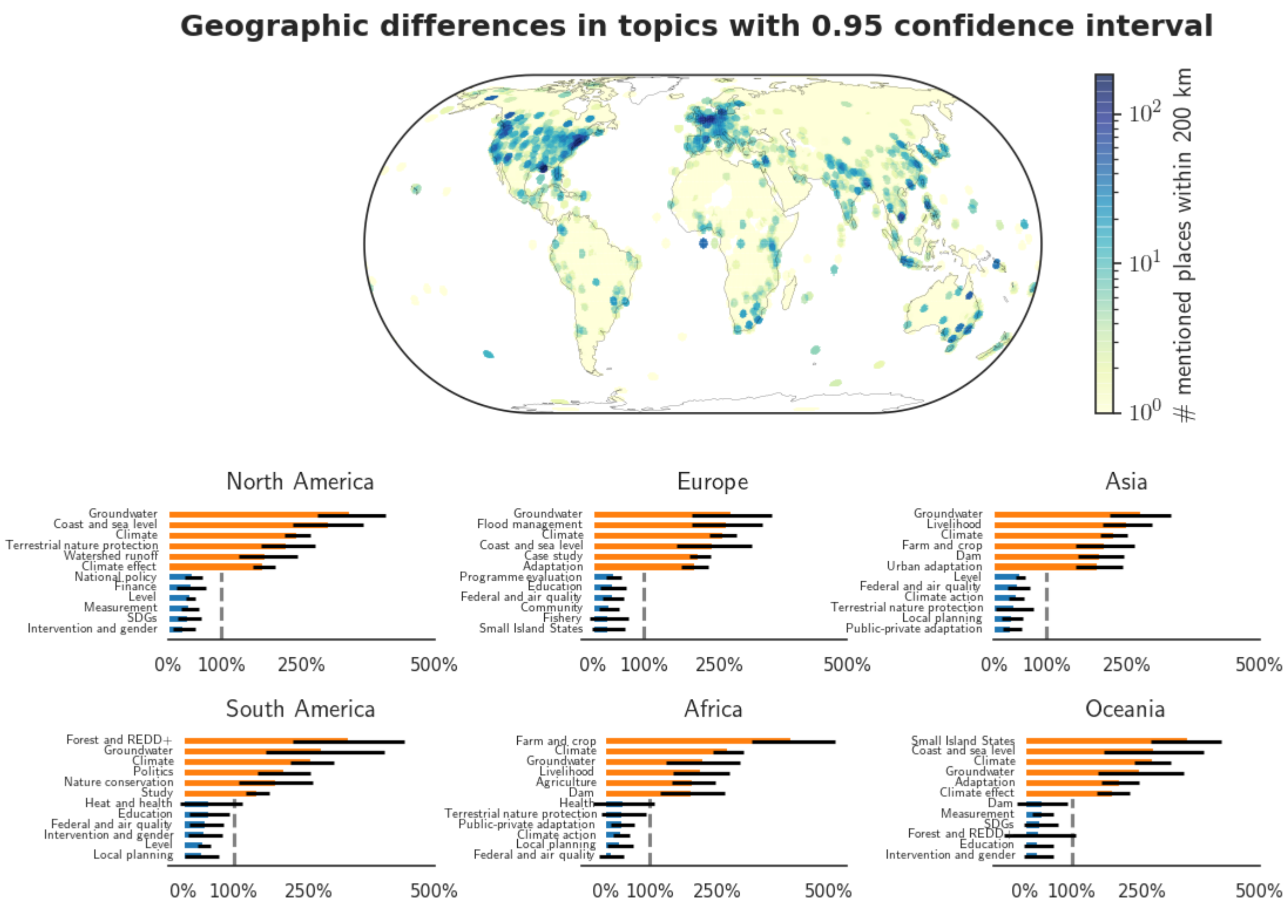

Figure A3.1: *locally dominant topics by continent from linear regressions with error estimates at 0.95 confidence interval.*

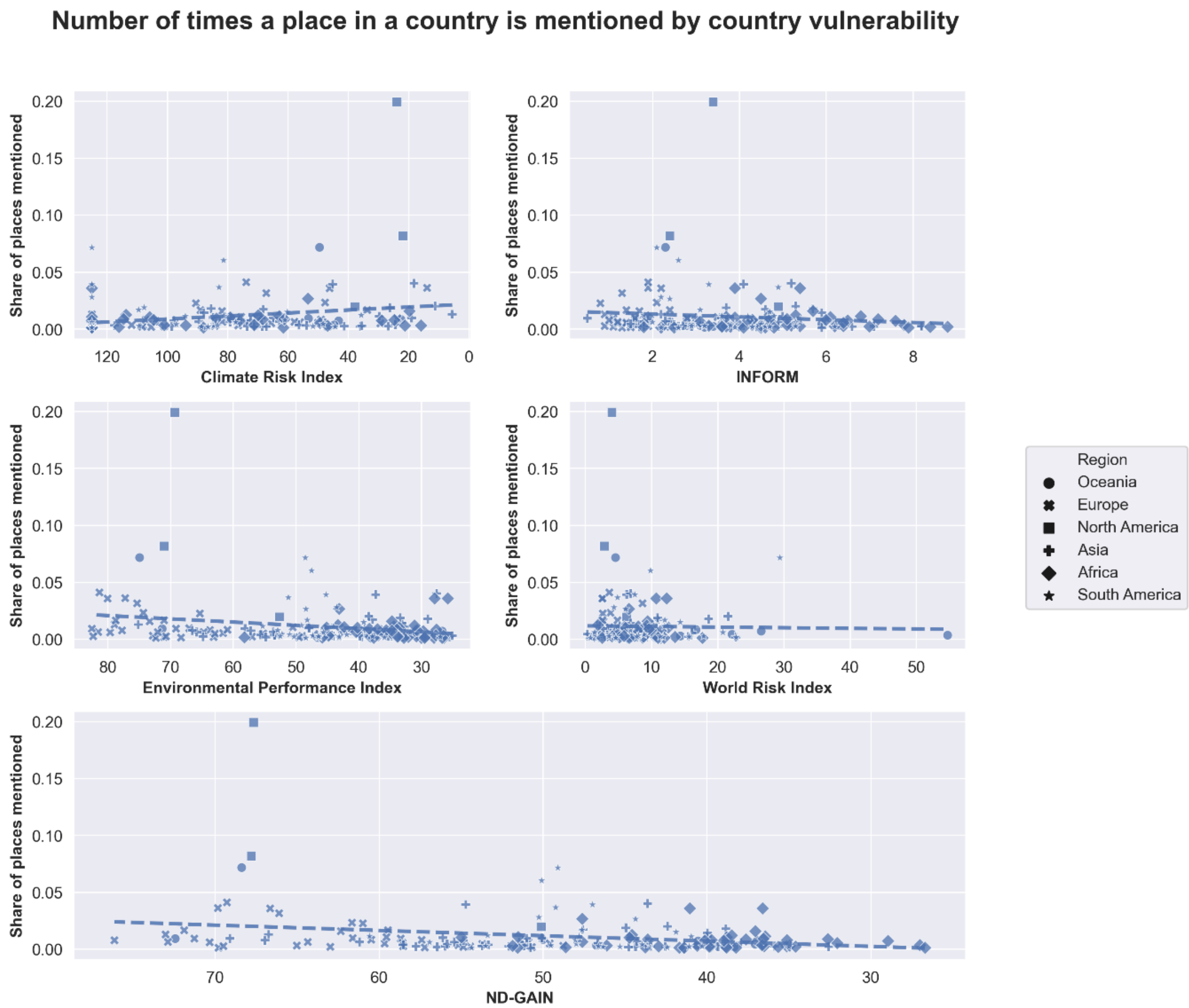

Figure A3.2: *the number of places mentioned per country as a share of the total number of places plotted against various indices, namely the Climate Risk Index (Eckstein et al., 2019), which includes measures on the real impacts of climate change per country; the INFORM Risk Index, which combines proxies 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 yearly 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 (the USA's high score in the climate risk index index is due to costly hurricane impacts), while many of the most at-risk countries are among the least studied, including many SIDS for example. None of these figures are meant to provide a normative assessment of where most research* should *take place.*

4 How do countries frame climate change? A global comparison of adaptation and mitigation in UNFCCC National Communications

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Abstract

Self-reporting is an important mechanism of the UNFCCC to collect information about what countries are doing to achieve their climate change mitigation and adaptation targets and how much progress has been made. Here we empirically test four hypotheses about what countries prioritise in their self-reporting through the National Communications. Using quantitative text analysis methods (Structural Topic Modelling and keyness statistics), we analyse over 600 submissions (from 1994-2019) and find evidence that vulnerable countries highlight impacts, vulnerability and adaptation rather than mitigation targets, whereas high emitting countries tend to focus their messaging more on mitigation. Despite the Paris Agreement being considered as a "watershed moment", we find no statistically significant increase in focus on climate solutions post-Paris, and no significant increase in attention to adaptation. Our global assessment and the methods used offer a novel perspective to understand what gets framed as important by governments. Finally, we provide reflections on how self-reporting mechanisms can be used for global stocktaking of progress on climate action.

4.1 Introduction

The United Nations Framework Convention on Climate Change (UNFCCC) recognizes that transparency and accountability are essential elements for the negotiations (Kinley et al., 2021). Generally, agreements under the UNFCCC typically prefer ‘public shaming’ over ‘policing’ to ensure compliance (Kinley et al., 2021). In such a governance-by-disclosure approach, self-reporting serves as a basis to hold governments accountable (Gupta and van Asselt, 2019, Van Asselt et al., 2015), especially for countries seeking and receiving international funding (Biermann and Gupta, 2011, Rai et al., 2019, UNEP, 2021). Transparent reporting is also key to assessing progress to achieve the UNFCCC targets, to improving policy by learning from prior experiences (Aldy and Pizer, 2014, Jacoby et al., 2017), as well as gaining insights into to legitimacy, equity and justice issues (Bäckstrand et al., 2018).

Because reporting plays such a central role in the UNFCCC system, it is perhaps unsurprising that many different reporting structures exist. Countries were already asked to regularly provide information in the original Convention (UNFCCC Article 12), and requirements increased under the subsequent Kyoto Protocol and the Paris Agreement (PA). This information is provided through various plans and documents, including, National Adaptation Plans for Action, Nationally Appropriate Mitigation Actions (NAMA), Biennial (update) Reports, National Communications (NCs), Nationally Determined Contributions (NDCs), Adaptation Communications, among others.

Reporting under the Convention is typically considered a technical exercise where governments follow guidelines to provide requested information; in practice however, this reporting is inherently political. Most reporting requirements are designed to offer a substantial amount of flexibility to countries (Weikmans et al., 2021). Given the substantial stakes in the UNFCCC negotiations, governments have both the motive and the opportunity to highlight national priorities and position themselves in the international arena. For example, some countries might highlight their structural vulnerabilities, whereas others might frame their reporting around progress on reducing greenhouse gas (GHG) emissions.

Recent studies have seen the proliferation of reports and policy documents as a promising data source to study progress on climate action, for instance, regarding ambition levels, alignment to national policies, Measurement, Reporting and Verification (MRV), climate education (McKenzie, 2021, Rosenstock et al., 2019, Tørstad et al., 2020). Yet, most studies using UNFCCC reporting are qualitative in nature and focus on limited topics (e.g. McKenzie, 2021, Rosenstock et al., 2019). Given the large number of documents available, attempting a comprehensive assessment would be too time consuming using traditional qualitative approaches. Moreover, reporting requirements to the UNFCCC are only increasing, with additional information to be submitted under the Paris Agreement's Enhanced Transparency Framework; similarly, submissions to the Global Stocktake have not yet closed, but they number over a thousand documents, many of which are hundreds of pages long (see: UNFCCC, 2023). In short, while reporting can be a useful source of data, its sheer volume is making it increasingly difficult to use this reporting for global-level assessments using established manual review methods.

Computer-based quantitative approaches can form part of the solution here, but those methods so far are only rarely used in the context of UNFCCC reporting. Only in the last few years, a handful of studies have started using machine learning approaches to analyse reports such as NCs and NDCs (Biesbroek et al., 2022, Hsu and Rauber, 2021, Lesnikowski et al., 2019a). These studies use reporting as a proxy to assess progress on a given topic, but do not address the political narratives. In our view, this is an oversight, given the aforementioned political nature of this reporting.

In this paper, we aim to increase our understanding of what countries consider important in reporting to the UNFCCC. More specifically, we test four prevalent hypotheses in the scientific literature about vulnerability, emissions and the impact of the Paris Agreement that help us to better understand the political messaging of these reports (see section 4.2).

To explore messaging, we focus on the Executive Summaries (ES) of NCs. An ES is highly visible, intended to be read by a broad range of stakeholders, such as donors, potential partners and governmental actors. This means governments have a large incentive to not only summarise the whole document's narrative and content, but also to emphasise their main political messages in the ES. The ES are therefore arguably the best place to unpack the nation's climate priorities. To analyse the ES, we apply Natural Language Processing (NLP) tools to test our hypotheses.

Our study represents an important step in assessing how governments frame their political messages and what they decide to report on. These aspects of self-reporting are key to understanding the usefulness of governance-by-disclosure. As such, our work can inform the international negotiations on climate change, especially given the new transparency requirements under the PA, for which countries will submit their first reports at the end of 2022.

4.2 Policy attention to climate change: hypotheses

To identify drivers in countries' messaging, we focus here on two groups of hypotheses: national and international level.

National level hypotheses: vulnerability and emissions

Although we acknowledge that exact definitions in the field are sometimes contested (Dewulf, 2013), vulnerability to climate change can broadly be understood as the propensity to be adversely affected by the impacts of climate change, and typically include measurements of exposure, sensitivity, and adaptive capacity (IPCC, 2022a). Many non-climatic drivers such as poverty and governance influence human vulnerability to climate change; especially the most vulnerable countries are already experiencing severe impacts attributed to climate change (IPCC, 2022a).

Vulnerability to climate impacts forms an integral part of international climate policy making; adaptation is even named explicitly in the original Convention. Other early examples include the Adaptation Fund (5/CP.7) and the National Adaptation Plan of Action process (4/CP.7), both established at COP7, 2001. The importance of adaptation was emphasised also in key agreements such as the Bali Action Plan (1/CP.13) and the Cancun Adaptation Framework (1/CP.16), which nominally placed adaptation on equal footing with mitigation (Article 2b; see also Singh and Bose, 2018). Notably, many of these agreements emphasise the vulnerability and adaptation needs of the Global South, calling on Annex I countries to provide support.

Governments can prioritise a high vulnerability framing by mentioning more topics around vulnerability, and mentioning each of these topics more often in their ESs. This can have benefits for countries in future negotiations by effectively emphasising the need for international finance and support (Betzold and Weiler, 2017). Placing much emphasis on vulnerability can also have negative implications, however. For example, it may discourage investments in the region by calling attention to the risks posed by climate change; similarly, it may call into question the success of prior adaptation investments. Yet, given the sustained call for "new and additional finance" for adaptation within the UNFCCC (Donner et al., 2016; Khan et al., 2020), the benefits may outweigh the negatives for vulnerable countries. We therefore hypothesise that:

> **Hypothesis 1:** *Highly vulnerable countries focus more on impacts, adaptation and vulnerability (IAV) than less vulnerable countries.*

Previous studies have shown the dominance of mitigation topics over adaptation throughout NCs (Biesbroek et al., 2022). However, it seems plausible that there are significant differences within country groups as the current and historical GHG emissions by countries are widely diverse. Typically, the most vulnerable countries are least responsible for current and accumulated GHG emissions (IPCC, 2022b). Conversely, countries with high emissions have the moral (Knutti and Rogelj, 2015) and legal responsibility to drastically reduce emissions. Given this difference in responsibility, it seems likely that the highest emitting countries will spend a larger share of their NCs highlighting their mitigation efforts.

There are, however, political reasons why this may not be the case: if a country's mitigation efforts are seen as insufficient, the ES could emphasise other issues instead to distract from this topic. In other words, countries that have cut emissions most have an incentive to emphasise mitigation compared to countries that have not made much progress.

Since higher emitting countries have a greater responsibility to act, they are more likely to emphasise any actions taken to reduce emissions in their ESs. We therefore hypothesise that:

> **Hypothesis 2:** *Countries with high GHG emissions place more emphasis on mitigation to limit global warming than less emitting countries.*

International level hypotheses: Paris Agreement effect

Although adaptation has always been a component of global climate policy (e.g. Article 4 of the Convention), early landmark agreements such as the Kyoto Protocol largely treated adaptation as an issue for developing countries (Khan et al., 2020). Particularly during the early years, adaptation was considered admittance that global efforts to reduce GHG emissions failed (Schipper, 2006). Although this discourse gradually changed, it was not until the PA that adaptation was consistently mentioned as an integral element of climate action and thus firmly placed on equal footing with mitigation (Lesnikowski et al., 2017a). To be clear, the reasons for this are not exclusively political, but also reflect the increasingly noticeable impacts of climate change around the globe (Kuyper et al., 2018, Lesnikowski et al., 2017b, Singh and Bose, 2018, Streck et al., 2016).

Regardless of motivation, the increased attention to adaptation is notable, with countries committing to substantial text-based reporting on adaptation. The Paris Agreement Article 7.2 states that "adaptation is a global challenge faced by all" and that it "is a key component of and makes a contribution to the long-term global response to climate change". Further, Article 7.9 states that "Each Party shall, as appropriate, engage in adaptation planning processes and the implementation of actions, including the development or enhancement of relevant plans, policies and/or contributions". The PA also flags the importance of Loss and Damage, transboundary risks, the need for collective efforts to adapt, and the involvement of non-state actors, among other issues. We would expect to see this increased attention reflected in the ESs and therefore hypothesise that:

> **Hypothesis 3:** *Countries paid more attention to climate change impacts, adaptation and vulnerability after the Paris Agreement was adopted.*

In addition to placing greater emphasis on adaptation, the PA has been characterised as an important shift in framing from problems towards solutions (Haasnoot et al., 2020{Du, 2022 #2411). This shift is in part a reflection of scientific progress. The IPCCs 5th Assessment Report (AR), published just before COP21, called global warming "unequivocal" (2014 p. 4) and found it "extremely likely that human influence has been the dominant cause" (2014 p. 17). Meanwhile, advances in technology made adaptation and mitigation options more accessible. This meant the decisions adopted in Paris shifted from understanding the problem and exploring options, to emphasise the urgency for accelerated implementation of climate change adaptation and mitigation solutions.

Since the PA, the above trend has continued, as is reflected in the literature (Kinley, 2017, Sietsma et al., 2021), in subsequent IPCC reports using stronger language on the need for immediate climate action, and in increasing investments in climate technologies (IPCC, 2022a, IPCC, 2022b). We therefore hypothesise that:

> **Hypothesis 4:** *Countries paid more attention to climate solutions after the Paris Agreement was adopted.*

4.3 Methods

Machine learning techniques are becoming increasingly popular in social and political sciences since they allow the processing of large volumes of text-based data in speed and breadth not feasible using manual methods (Berrang-Ford et al., 2021). This is also true for climate policy, where large amounts of literature are becoming rapidly available, and the number of studies applying machine learning to analyse these documents is expanding (Biesbroek et al., 2018, Ford et al., 2016, Hsu and Rauber, 2021). Here we used two NLP tools: word-frequency comparison and topic modelling.

Data collection & pre-processing

The dataset is based on Biesbroek et al. (2022) and included all officially submitted NCs published before and through 2019. We manually extracted the ES for all documents, creating a corpus of 606 ES. These were annotated with the following meta-data: publication year, geographic region and Annex I status. Standard pre-processing procedures were applied using

Quanteda (Benoit et al., 2018), including stemming and stopword removal. We used two lower thresholds: words needed to occur at least 120 times and in at least 30 documents. We manually removed place names to obtain topics that centre around concepts and biomes rather than nations or regions. The final vocabulary consisted of 1511 unique words. More details can be found in the methods and supplementary sections of Biesbroek et al. (2022).

Data analysis - identifying key terms and topic modelling

To identify differences in the content of the ES, we use topic modelling for all 4 hypotheses. This is a widely used unsupervised machine learning method to discover the hidden semantic structures across a body of documents (Roberts et al., 2019). In simple terms, it assumes that each text contains a mixture of a few topics and uses an algorithm to identify clusters of words which are frequently used together (e.g. a text containing “apple” is more likely to also contain “pear” than “car” or “road”); these clusters of terms then represent topics which are labelled by the researcher (e.g. “fruit” and “transport”). Topic modelling is increasingly used in climate change contexts (Hsu and Rauber, 2021, Lesnikowski et al., 2019b, Sietsma et al., 2021) and is particularly useful in cases where data is unstructured and where no *ex-ante* categories exist. For a more detailed yet accessible explanation, please refer to Lucas et al. (2015), Grimmer and Stewart (2013).

We ran a Structural Topic Model using the STM package in R (Roberts et al., 2019). STMs are especially adept at creating meaningful topic models for comparative social science (Lucas et al., 2015). To determine the k-value (i.e. number of topics), we follow standard practice (e.g. Sietsma et al., 2021, Tvinnereim et al., 2017, Callaghan et al., 2020) by creating models for a range of k-values and comparing them qualitatively. Specifically, the model was run at k=5, 10, 15, 20, 25, 30, 40, and 50 to show a wide range of results. These were qualitatively assessed for coherence, accuracy and breadth of representation of the original documents. The 25-35 range was chosen as most promising, as most topics here had a clear focus, without many “junk” topics, and with generally clear distinctions between IAV and mitigation topics. Within this, k=33 had the highest semantic coherence (a standard quantitative measure for topic quality) and was chosen as our final model.

Topics were labelled based on keywords and the most closely associated documents per topic. One topic was qualitatively assessed as incoherent and was thus removed. The remaining 32 topics were then classified by the researchers in an ordinal scale ranging from "highly mitigation related" to "neutral / both mitigation and adaptation" to "highly IAV related". This informed the qualitative clustering of topics into five classes: Strong Adaptation, Weak Adaptation, Strong Mitigation, Weak Mitigation, and Cross-cutting Themes. These classes were quantitatively validated using the Topic Correlates function.

Testing the hypotheses

To test the first two hypotheses, we took the mean prevalence of IAV topics and mitigation topics per ES and compared these metrics against the country's vulnerability score (H1) and emissions data (H2) in the year preceding the report's submission. If our first hypothesis is true, countries with a higher vulnerability should also have a higher prevalence of IAV-related topics. Similarly for the second hypothesis, high-emission countries should have a higher prevalence of mitigation topics.

As no global quantification method of country-level vulnerability is universally accepted, we used the four most established global indices of national climate risk and vulnerability: the Notre Dame Global Adaptation Initiative (ND-GAIN), the World Risk Index (WRI), INFORM and the Climate Risk Index (CRI). Earlier analyses have found considerable differences as well as overlap between the indices (Feldmeyer et al., 2021, Garschagen et al., 2021). Given space constraints, as well as data availability especially for earlier years, we present the results of the ND-GAIN and the WRI. Further descriptions of these indices can be found in the Annex to this chapter, where we also include additional indices.

For emissions data, we use the most recent version of the Global Carbon Project (Andrew and Peters, 2021). The database includes both per-capita and total emissions. Given that historical emissions play a significant role in the UNFCCC negotiations, we compare these yearly emissions to the cumulative emissions per country since 1750.

We calculate r-squared and Spearman correlations for hypotheses 1 and 2, characterising the relationships between vulnerability (GAIN & WRI) vs. IAV/mitigation topic prevalence and emissions (total & per capita) vs. IAV/mitigation topic prevalence. In all cases, vulnerability and emissions data from the year preceding the report submission is used, or the first available value for NCs published prior to the range covered by the indices. We combine this numerical baseline with qualitative observations to note broader trends in the data.

To test whether the PA caused a shift in framing political priorities, we made use of the same mitigation-adaptation topic classification as above. Additionally, all topics were manually classified on whether they are "solution-oriented", noting which topics were geared towards action and practical implementation, often including terms such as "program," "policy," and verbs relating to planning and implementation. To determine solutions-oriented topic classes, two classification rounds were done independently by the researchers and the average score was taken to ensure consistency in the classification. The topic prevalence of reports submitted directly prior to the PA (2007-2015) were then compared against the scores of reports submitted afterwards (2016-2019). The first period is longer to reflect the lower number of submissions pre-Paris and the cut-off aligns with reporting guideline changes published in 2007 (Breidenich, 2011). We would expect to see an increase in reporting on both IAV topics (H3) and solutions-related topics (H4) after the PA was adopted.

In addition to topic modelling, we make use of word-count-based statistics. Although relatively simple, these have been shown to be highly effective at identifying how different sides in a debate frame their arguments by highlighting key terms (Risi and Proctor, 2020, Supran and Oreskes, 2021). Here, we used a chi-square test to identify words which are significantly under- or over-represented in a subset of the corpus to test hypotheses 3 and 4. We divided the texts in two ways: 1) NCs from Annex I countries compared to NCs from non-Annex I countries, where we expected to see mitigation-related terms being over-represented in Annex I submissions and IAV terms in non-Annex I submissions; and 2) comparing submissions post-Paris Agreement to those before, where we expected to see an over-representation of both IAV and solutions-related terms in the post-Paris texts. To test the robustness of this method, we include the same statistics for random subsets of the dataset, as well as using log-likelihood instead of chi-square; this can be found in the supplementary materials.

Limitations

A number of limitations arise from the methodology and data used. Shortcomings of using NCs to track adaptation have been discussed elsewhere (Biesbroek et al., 2018, Ford and Berrang-Ford, 2016). Whilst our dataset offers a global perspective, some countries are underrepresented in the submitted NCs, for example due to different submission times or resource constraints. In order to address this we grouped NC submissions in regular time frames to smooth breaks in data distribution. Additionally, the UNFCCC guidelines are not detailed enough to ensure consistent reporting between countries and over time (Ford and Berrang-Ford, 2016) creating some variation in what is reported. Furthermore, NCs represent national reporting, therefore, their analysis may overlook sub-regional differences, such as urban or local particularities, as well as specific sectors or population groups (Araos et al., 2016, Ford and King, 2015). Lastly, by relying on the dataset of Biesbroek et al. (2022), NDCs in 2020 or later are missing.

4.4 Results

General impressions of data

The 32 topics that emerged were clustered into five classes, see Figure 4.1. In total, 7 topics were classified as Strong Adaptation, 3 as Weak Adaptation, 7 as Cross-cutting Themes, 1 as Weak Mitigation, and 14 as Strong Mitigation. Generally, the proportion of each class remains relatively stable over time.

Using these categories, Figure 4.1a-b highlights differences in class proportion by Annex countries. Annex I countries discuss Strong- and Weak-Mitigation topics and Cross-cutting Themes more than topics in either of the Adaptation classes. Non-Annex I countries place significantly ($p<0.05$) more attention on adaptation and less on mitigation topics than Annex I nations. This matches the results from the term-frequency comparison shown in Figure 4.1c-d, showing that the top words for Annex I are aligned with mitigation topics (e.g. greenhouse,

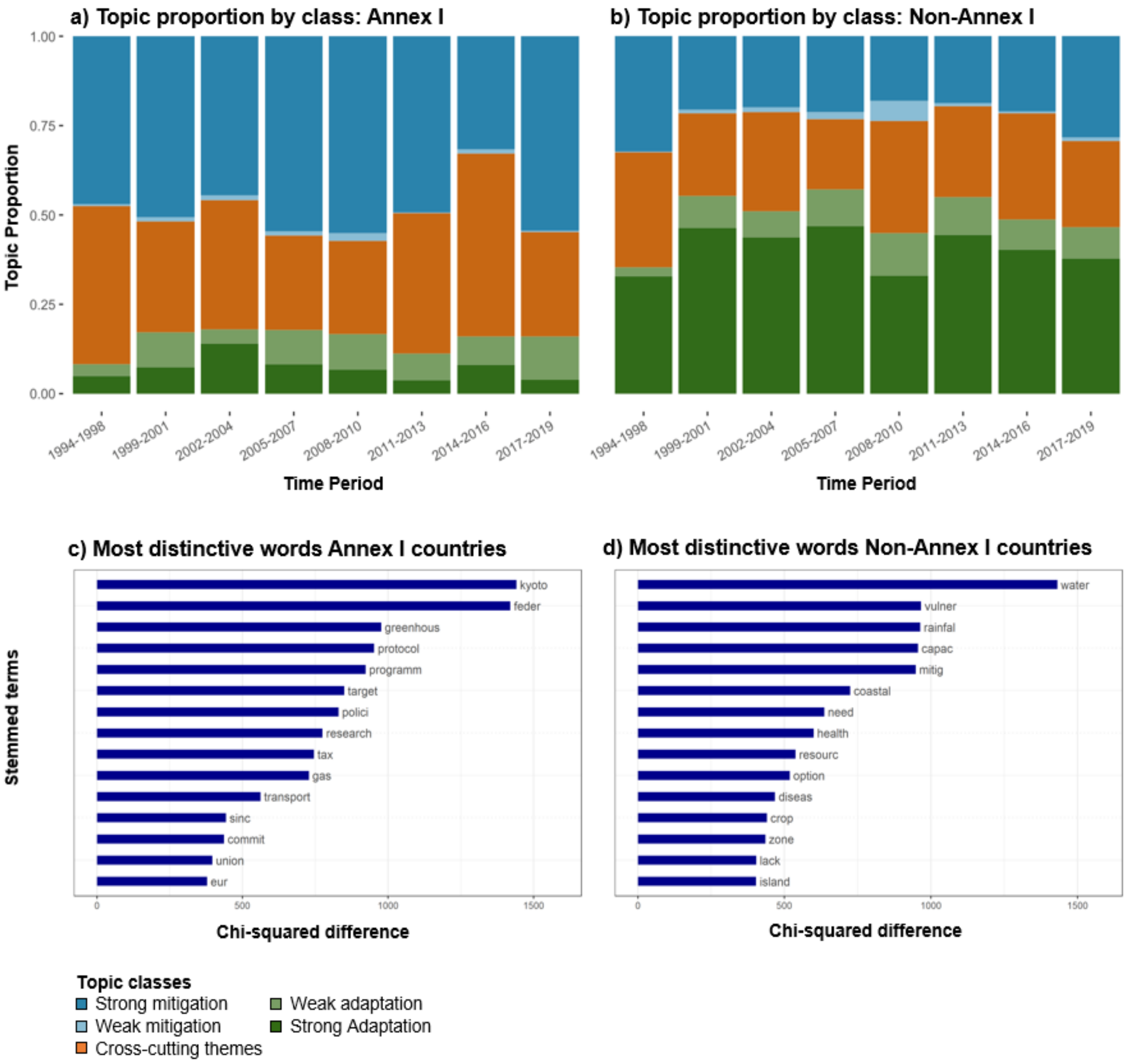

Figure 4.1: *Proportion of the five topic classes over time, by Annex I status (a-b) and most distinctive words by Annex status (b-c). Keywords are stemmed so that different word-forms are counted together. All documents were considered here (n = 347 for non-Annex I, n = 259 for Annex I).*

transport) while top Non-Annex I words are linked to IAV topics (e.g. vulnerability, capacity). A key exception here is the term mitig*, which is also over-represented in non-Annex I reports; note however that in many cases this refers to "mitigating risks" rather than decreasing emissions.

Overall, the distribution between all topic groups has remained relatively stable over time. There are some notable shifts for individual topics. For Annex I countries, *Innovations & programs* and *Research & observations* increase the most over time, while *Federal energy & transportation* and *Macroeconomics* topics decrease. For Non-Annex I countries, *GHG reporting* increases most significantly over time while *Macroeconomics*, *Global conventions*, and

Mitigation financial instruments decrease. Changes of individual topics within these groups are discussed in more detail in relation to H3-4 below.

The topic model group results broadly overlap with the key terms, see Figure 4.3: some of the most-distinguishing words are related to IAV (e.g. resilience, adapt*) and others to solutions (e.g. action, plan, program). Yet overall, the recently dominant words relate to new programmes with their associated acronyms and terminology.

Topic proportion and dominance can be further broken down by global region, which shows similar distribution as between Annex I and Non-Annex I countries. For example, adaptation related topics such as *Rural responses* and *Livelihoods & water resources* are extremely dominant in Africa while less significant in other world regions. Similarly, in North and Central America, major topics include *Projected livelihood impacts*, *Adaptive capacity*, *Coastal & island impacts*, but also *Green programs*. In contrast, Europe shows more prominence in topics such as *Macroeconomics*, *Kyoto & GHG*, and *Measurements*. Major topics in Asia include diverse issues as *Instruments & programs*, *Hydrological impacts*, and *Greenhouse gases*. South America is dominated by *Projected livelihood impacts*. *Rio programs* is large at the beginning of the study time period, falling off in more recent years. *Forest management & programs* does the opposite, starting small and becoming dominant in the most recent time periods. In Oceania, *Coastal & island impacts*, *Mitigation governance*, and *Adaptive capacity* stand dominant.

Results by hypothesis

Linkage between IAV and vulnerability (H1)

In line with our hypothesis, more vulnerable countries tend to discuss IAV more extensively in their ES, compared to less vulnerable nations who put more emphasis on mitigation. Subtracting the mitigation score from the IAV score to get one single metric for the balance between this topic, the correlation is statistically significant ($p<0.01$) and moderately strong (ND-GAIN: -0.67; for WRI: 0.46). Similarly, some of the most-distinguishing words for Non-Annex I countries are related to IAV.

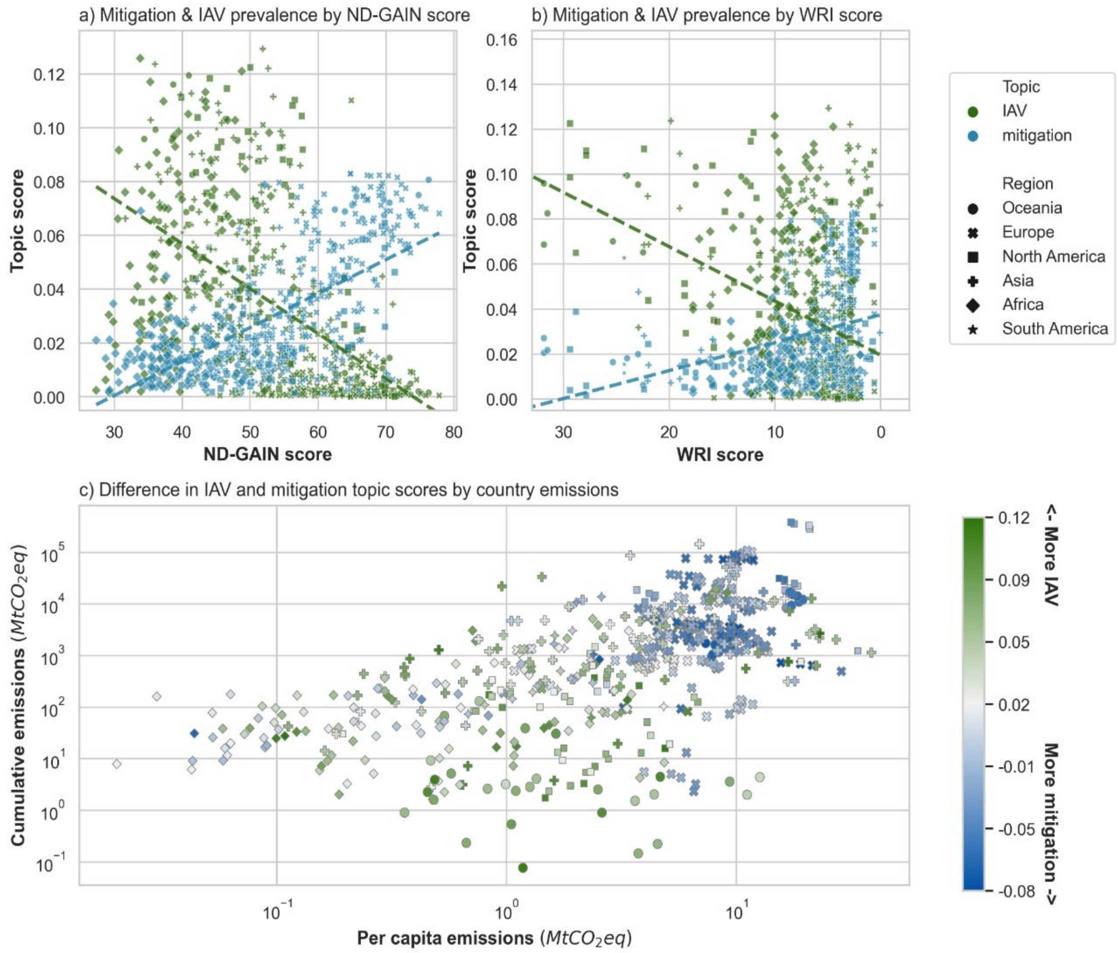

Figure 4.2: *The mean prevalence of topics per report is calculated for two categories of topics: Impacts Adaptation & Vulnerability (IAV) and mitigation topics. The resulting score is plotted against two vulnerability indices: ND-GAIN (a) and WRI (b). Lines of best fit (least squares) are included. IAV proportion and the vulnerability indices are moderately correlated (ND-GAIN - Spearman r: -0.61, p<0.01; WRI - Spearman r: 0.42, p<0.01). A moderately positive correlation was found between mitigation proportion and per capita and cumulative emissions (Spearman r 0.51 and 0.42 respectively, both p<0.01). Note that the x-axis for b) is flipped so that more vulnerable countries are plotted on the left, in line with a). In b), two reports by Vanuatu (1999 and 2016) were removed to improve legibility as the country's WRI scores were extreme outliers (55.9 and 56.6 respectively). In c), the same topic scores are used, but the mitigation score is subtracted from the IAV score so that the colour represents the balance between the two topic groups. The position is determined by the country's cumulative versus per-capita GHG emissions. All documents are considered here (n = 606).*

At the topic level, the same general trend holds (see Figure 4.2a,b). The effect is especially pronounced for Small Island Developing States (SIDS), who submitted half of the top-20 most IAV-focussed ES. By contrast, European countries tend to be among the less vulnerable countries and have a low prevalence of IAV-related topics. For Asian and South American countries, the effect is less pronounced, but more vulnerable countries in these two regions overall do discuss IAV more. Notably, some highly vulnerable African countries have low topic scores for both IAV and mitigation as these focus instead on the more process-oriented cross-cutting topics.

The results are highly dependent on the vulnerability index used. ND-GAIN scores are fairly evenly distributed, making the effect more visible. Almost all low-vulnerability countries discuss more mitigation topics here; generally, more vulnerable countries emphasise IAV but this effect is less consistent. By contrast, WRI shows a large cluster of low vulnerability countries, most of which are in Europe. Broadly, these countries report extensively about mitigation, but some also discuss IAV. The differences in topic scores appear more pronounced for the small group of countries with a very high WRI score (i.e. highly vulnerable). In part, the more clustered appearance of the WRI plot may be due to data availability: Annex I countries have reported considerably more frequently than Non-Annex I countries, so there are less data points for high-scoring countries.

The two other widely used vulnerability indicators are included in the Annex, alongside plots using only sub-components of the indices. The INFORM scores are similar to the WRI scores, though some low-ranked Asian and North American countries still emphasise IAV. The CRI scores do not appear to correlate with mitigation or IAV topics. This may be due to the lack of historical CRI scores; given that this index is based on climate-related disasters in a given year, it may also indicate that messages in the ES are not influenced by single events.

Overall, we see general support for hypothesis 1 from both the topic model results at the country level and the word-frequency differences between Annex-I and non-Annex I countries.

Linkage between mitigation and emissions (H2)

Results for the second hypothesis are similar to those of the first: at the word-level, mitigation-related words are especially prevalent for Annex I countries (Figure 4.1c,d). For the topic model results, the top-20 most mitigation-focussed ES were almost exclusively submitted by

European countries, with two NCs from New Zealand (2017 and 1994) and one from Tunisia (2019) being the only exceptions.

For mitigation too, it matters which metric is used. Per-capita emissions show a moderately strong positive relationship with mitigation scores (Spearman r: 0.51, $p<0.01$). Almost all countries with very low emissions emphasise IAV topics while mostly or completely disregarding mitigation in their abstracts. European countries especially tend to emphasise mitigation topics, even for the countries where per-capita emissions are close to the median of 4.4 MtCO2eq. Some of these countries do have fairly high cumulative emissions though, lending some support to our hypothesis.

More broadly, we see a weaker effect for cumulative emissions (Spearman r: 0.43, $p<0.01$) and counting absolute emissions cumulatively or yearly does not lead to large differences (see Appendix Figure A4.3). In both cases, the data is unevenly distributed - i.e. most countries have fairly low absolute emissions, relative to the few large outliers (notably, the US, China, Germany and the UK). For these outliers, the mitigation scores are generally higher than the IAV scores. Within the large group of lower-emitting countries, IAV topics are over-represented generally, but there are outliers here from all regions.

We find limited support for hypothesis 2: high per capita emissions broadly correlate with emphasis on mitigation in the countries' ES, but this is most apparent for the largest emitters; the effect is also less pronounced for absolute emissions compared to per-capita. We do see significant differences in word-use between Annex I and Non-Annex I countries, though it is unclear whether this reflects a larger focus on mitigation action or on mitigation-related procedural terminology.

Effect of the Paris Agreement on Impacts Adaptation and Vulnerability (H3)

Figure 4.4 shows the size and growth rate of topics comparing submitted data before (2007-2015) and after (2015-2020) the PA. Comparing the global average size of topics over both periods, mitigation topics are overall slightly larger than IAV topics. Largest mitigation topics comprise *National GHG inventories, Mitigation governance* and *GHG reporting*, while largest

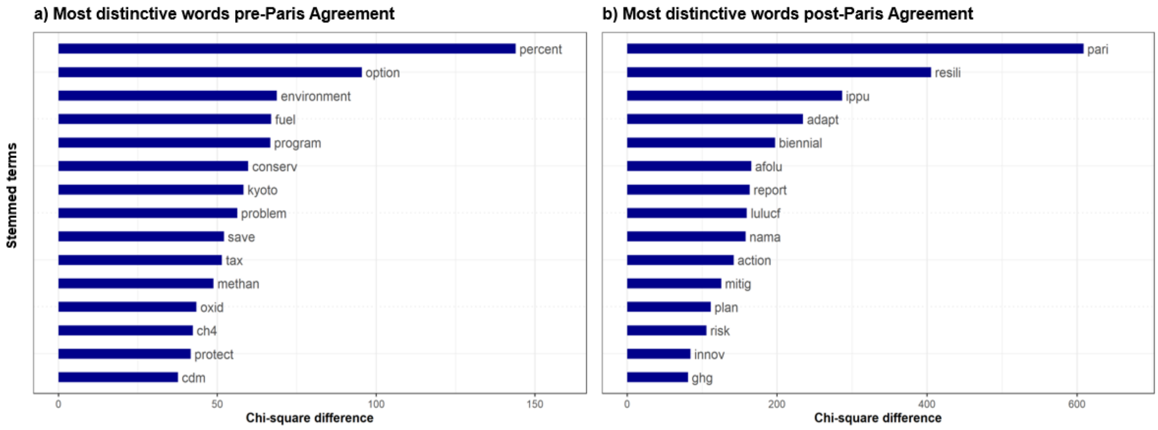

Figure 4.3: *Most distinctive words pre-Paris (a) and post-Paris (b). A few terms are acronyms, mostly related to different types of greenhouse gas (GHG) emissions: IPPU stands for Industrial Processes and Product Use; AFOLU refers to Agriculture, Forestry and Other Land Use; LULUCF is short for Land Use, Land Use Change and Forestry. Two further acronyms relate to international programmes: NAMA here means Nationally Appropriate Mitigation Actions; CDM is the acronym for Clean Development Mechanism, a mitigation credit system originally established under the Kyoto Protocol. Note that the number of submissions in both periods is unevenly distributed, with 116 out of 606 documents having been submitted post-Paris Agreement.*

IAV topics are *Adaptive capacity* and *Coastal & island impacts.* Meanwhile, the largest cross cutting topic is by far *Forest management & programs.*

Globally, the largest topics are also the ones with higher growing rates after the PA. The highest growing rates are observed for *GHG reporting*, and *Geography*, followed by *Forest management & programs*, *National GHG inventories*, *Mitigation financial instruments*, and *Kyoto & GHGs*. Large topics as *Adaptive capacity*, *Livelihoods & water resources*, among other adaptation topics, have remained stable. Medium large topics as *Country characteristics*, *Global conventions*, and *Innovations & programs* have even decreased. Overall, mitigation topics show the highest rates of growth after Paris compared to IAV topics. Cross cutting themes tend to remain stable or decrease.

Average topic size and growth rate are driven by large regional differences. Oceania's largest topic is *Mitigation governance,* which contributes heavily to its global share. Europe and Asia contribute to larger topic size of mitigation topics, such as *GHG reporting* and *National GHG inventories.* In contrast, the largest adaptation topics seem to be driven by Oceania's *Coastal & island impacts* as well as *Adaptive capacity*, followed by *Projected livelihoods & impacts* in South

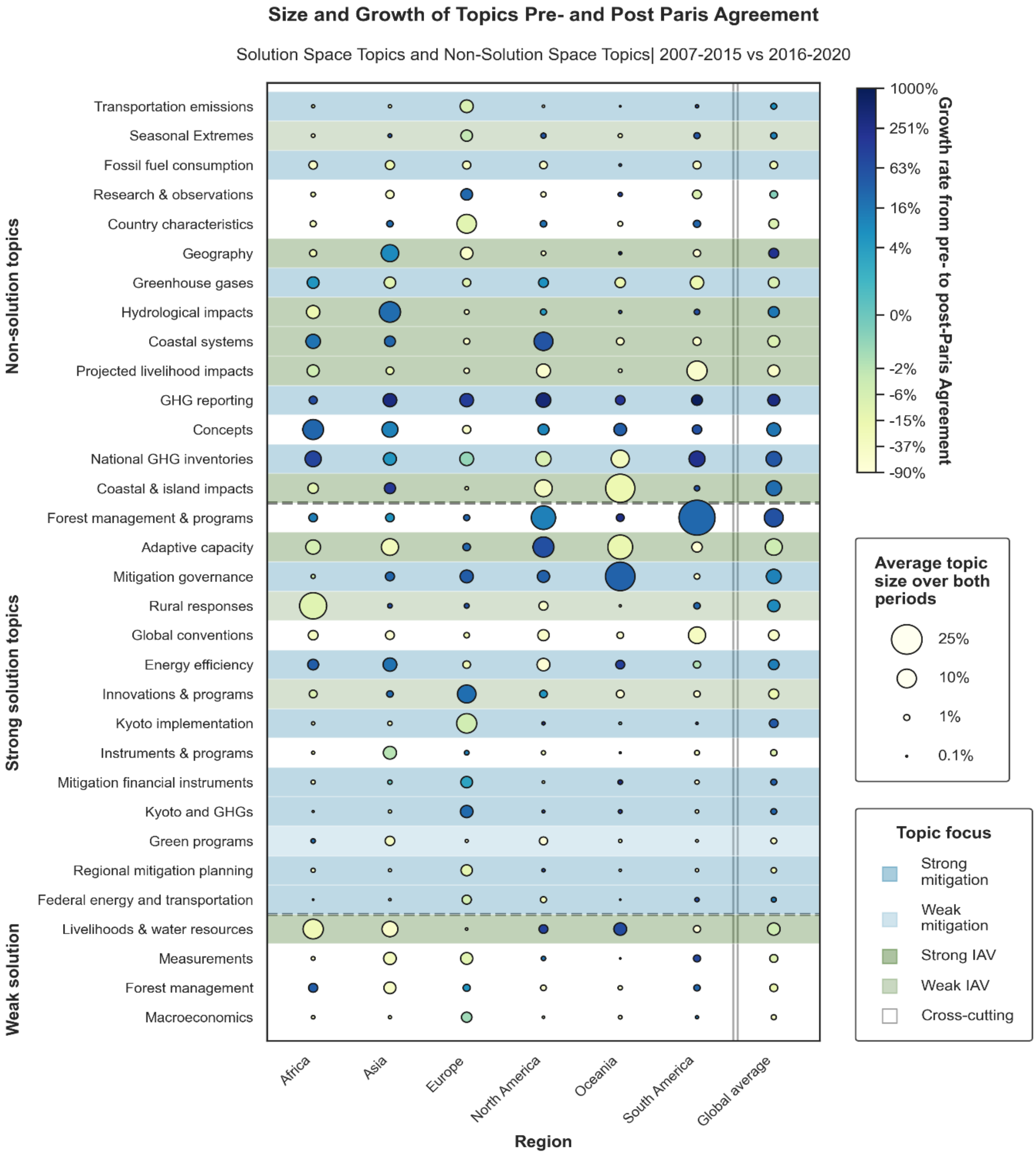

Figure 4.4: *Comparison of topic prevalence over time. All countries with at least one report in either the pre-Paris (2007-2015) and the post-Paris (2015-2019) time periods are selected, using the reports furthest from the time split if there are multiple reports from one country in one period. (Resulting number of reports considered per region: Africa – 42 pre-Paris, 22 post-Paris; Asia – 38 pre, 25 post; Europe – 45 pre, 39 post; North America – 14 pre, 12 post; Oceania – 9 pre, 6 post; South America – 10 pre, 9 post). The average topic score for both periods is then calculated, depicted here as the size of the circle. The growth rate of these topics from pre-Paris is also calculated and determines the circle's colour. Topics are grouped by whether they are solution-oriented; rows are coloured by topic classification (IAV or Mitigation).*

America and *Livelihoods & water resources* in Africa. Cross-cutting themes also show huge regional differences. *Forest management & programs* is not only the dominant issue in South America and less in North America but shows additionally a high growth rate after Paris. Further regional differences stand out for *Rural responses,* which is the dominant topic in Africa, and *Country characteristics* which is larger in Europe.

Looking at the topic growth rates after Paris, it stands out that mitigation, followed by cross-cutting topics, grew more in all regions except for North America, compared to IAV topics. The latter grew more only in North America and Asia, and for individual topics, in Oceania and South America.

For the most distinct words in documents before and after the PA, as shown in Figure 4.3, variations on the words adaptation and resilience prove strong in more recent documents. This supports the notion that IAV holds more prominence since Paris. Yet, *mitig** and *GHG*, as well as terms related to sectoral emissions, are also present.

To summarise, we see mixed evidence for hypothesis 3: while some individual IAV-related words do tend to be used more post-Paris, overall, IAV topics do not show a consistent growth over time nor regions. Instead, mitigation topics continue to dominate the discussion.

Increasing solution-oriented focus in reporting (H4)

Solution-oriented topics were considered as those involving and pointing towards action and implementation, including decision making and funding. Of the topics strongly pointing towards solutions, 7 belong to the mitigation class, 6 to cross cutting themes and only 1 explicitly to IAV. The non-solutions topics are composed of 5 mitigation, 5 IAV topics and 4 cross-cutting themes.

The non-solutions class shows, on average, slightly larger topic sizes than both the strong and weak solutions classes. Among the largest strong-solutions topics and with moderate to high growth rate after Paris, we find *Forest management & programs, Mitigation governance, Rural responses* and *Energy efficiency*. Yet, equally large but fastest growing topics are found in the non-solutions class. These comprise, for instance, *Coastal & island impacts, National GHG* *inventories*, *Concepts* and *GHG reporting*. The smallest topics overall belong to the strong solutions class, for example *Federal energy & transportation* and *Regional mitigation planning*.

Large regional differences in size and growth rate of topics are observed. Solutions largely differ per region, broadly in line with regional priorities. While one or two regions tend to dominate certain topics - also with moderate to high growth after Paris - most topics remain very small. For instance, Africa and South America show only one very large solution topic (*Rural responses* and *Forest management & programs* respectively). For North America and Oceania, *Adaptive capacity* is dominant alongside *Forest Management* and *Mitigation governance* respectively. By contrast, in Asia and Europe, solutions topics are slightly larger in size and we see a larger diversity of topics.

Conversely, there are no large regional outliers for the non-solutions topics. Moreover, they show a moderate to high growth rate after Paris. In other words, regions tend to discuss equally and diversely on non-solutions topics. An exception are the topics related to climate impacts: they are generally non-solution topics.

To summarise, strong solutions topics are biased towards mitigation and present large regional variations, with a couple of dominant topics per region. In contrast, non-solution topics are more constant in size, growth rate and regional distribution. The most homogenous and straightforward post-Paris impact seems to be the growth of the non-solutions topics *GHG reporting* and *Concepts*. Overall, we find that regional priorities may influence the reporting on individual topics, but we see no evidence for our hypothesis that solutions-focussed topics are increasing in prominence.

4.5 Discussion

Reporting to the UNFCCC is an important mechanism to capture how countries are progressing towards the global goals on mitigation and adaptation. We demonstrate how some of this reporting is used to frame issues by highlighting some topics and excluding others. Here we highlight three key findings and what they tell us about the future of climate policy tracking.

First, our results show that NCs broadly reflect national and regional priorities in mitigation or adaptation, largely supporting our first two hypotheses. We observe that more vulnerable countries focus more attention in their NCs towards IAV than less vulnerable countries, in line with previous findings (Biesbroek et al., 2022). We also find that high emitters tend to place more attention in their NCs on mitigation than lower emitters. These results are perhaps unsurprising, but this work is one of the first large-scale empirical confirmation that countries highlight nationally important issues.

Second, we find limited evidence on the effect of the Paris Agreement on the solutions focus. The PA stands as a key milestone in the evolution of climate policy and action, producing many aspirational targets and calling for an increase in solutions-focused thinking. While highly ambitious national policies are being formulated across the world, there is little knowledge on whether progress is being made towards achieving those ambitions (c.f. Meinshausen et al., 2022, UNEP, 2022). Our analysis indicates that implementation post-Paris is not clearly visible across NCs' summaries; although our approach does not allow us to distinguish between a lack of reporting and a lack of action, both are cause for concern. In addition to providing transparency, reporting should help countries learn from each other's experiences, but when reporting on actions is limited, this learning will also be limited. Further, a lack of action would be consistent with the findings of earlier authors who noted an "implementation gap" (Runhaar et al., 2018, Roelfsema et al., 2020). This is worrisome not just because it implies that countries are failing to live up to their collectively agreed goals, but more importantly, because of what those goals represent: they are a recognition that rapid and inclusive climate action is necessary to address future climate impacts as well as current ones.

Third, we find limited evidence towards the effect of the PA on focusing on adaptation. Our analysis did not indicate the increase of adaptation topics and a corresponding reduction in prominence of mitigation topics in the NCs. This is surprising, given first, the growing evidence on climate change, especially on increased frequency and severity of extreme weather events induced by climate change, as well as on their actual and potential impacts

(James et al., 2019, Otto et al., 2016, IPCC, 2022a); and second, the high expectations of those within the IAV community. Magnan and Ribera (2016) for example argued that the PA may lay "foundations for a new era for climate change adaptation".

Here, too, it is difficult to distinguish between under-reporting and in-action. For adaptation, this fits into a larger pattern: even large-scale collaborative efforts must rely on relatively crude heuristics to determine whether progress is being made in adaptation (UNEP, 2021, UNEP, 2022). Some degree of under-reporting appears likely, as several authors have discussed the difficulties around setting adaptation goals and indicators, e.g. the difficulty for defining measurable and comparable indicators, as well as for building Monitoring & Evaluation systems, and for designing a framework to take stock adaptation progress (Ford and Berrang-Ford, 2016, Ford et al., 2015, Lesnikowski et al., 2016). Whilst the NCs provide valuable insights in country progress, intra-country progress on adaptation will be difficult to extract across UNFCCC reports. The adaptation communications and further guidelines for stocktaking may play a critical role in overcoming these challenges and creating adaptation reporting that is more consistent; however, given the subjective nature and fuzzy concept of adaptation, it seems likely that countries will continue to use their reporting not just as a tool for transparency, but also for political ends accountability (Gupta and van Asselt, 2019, Weikmans et al., 2021). This raises the question how meaningful conclusions can be drawn from reporting that is large in both volume and variety.

How and when to use computer-based tools should be part of these discussions. As our results illustrate, these methods may be especially useful for high-level assessments and to identify big-picture patterns in large corpora of text data.

Computer-based tools are easiest to apply when data is available in comparable formats. The recent adoption of "common tabular formats" (FCCC/PA/CMA/2021/L.21) is especially interesting to create coherent, consistent and comparable data. These are mostly centred around emissions and mitigation, but they should provide information on progress towards Nationally Determined Contributions as a whole, which includes adaptation as well. During the negotiations at COP26 in Glasgow, some countries appeared to fear losing flexibility as a result of standardised formats (see also FCCC/PA/CMA/2021/L.21 paragraph 5).

The real issue however may not be one of flexibility, but of reporting capacity and funding, particularly for the Global South. This is also an issue in our database as many Non-Annex I countries have submitted 3 or less NCs, while most Annex I countries have submitted 7. In other words, based on NCs, we can get a far less granular understanding of priorities and progress in many countries that are most vulnerable to climate change. The increases in required reporting under the Paris Agreement aims to address this, but these intentions will fall flat if they are not matched with funding and support.

Despite these methodological limitations, tracking whether progress towards achieving the high ambitions set in the Paris Agreement is critical to hold governments accountable and to ensure timely and adequate responses to exacerbating climate change challenges. Global assessments, such as those presented here, are an important way for the scientific community to help improve transparency in global progress on climate action.

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Annex to chapter 4: additional figures

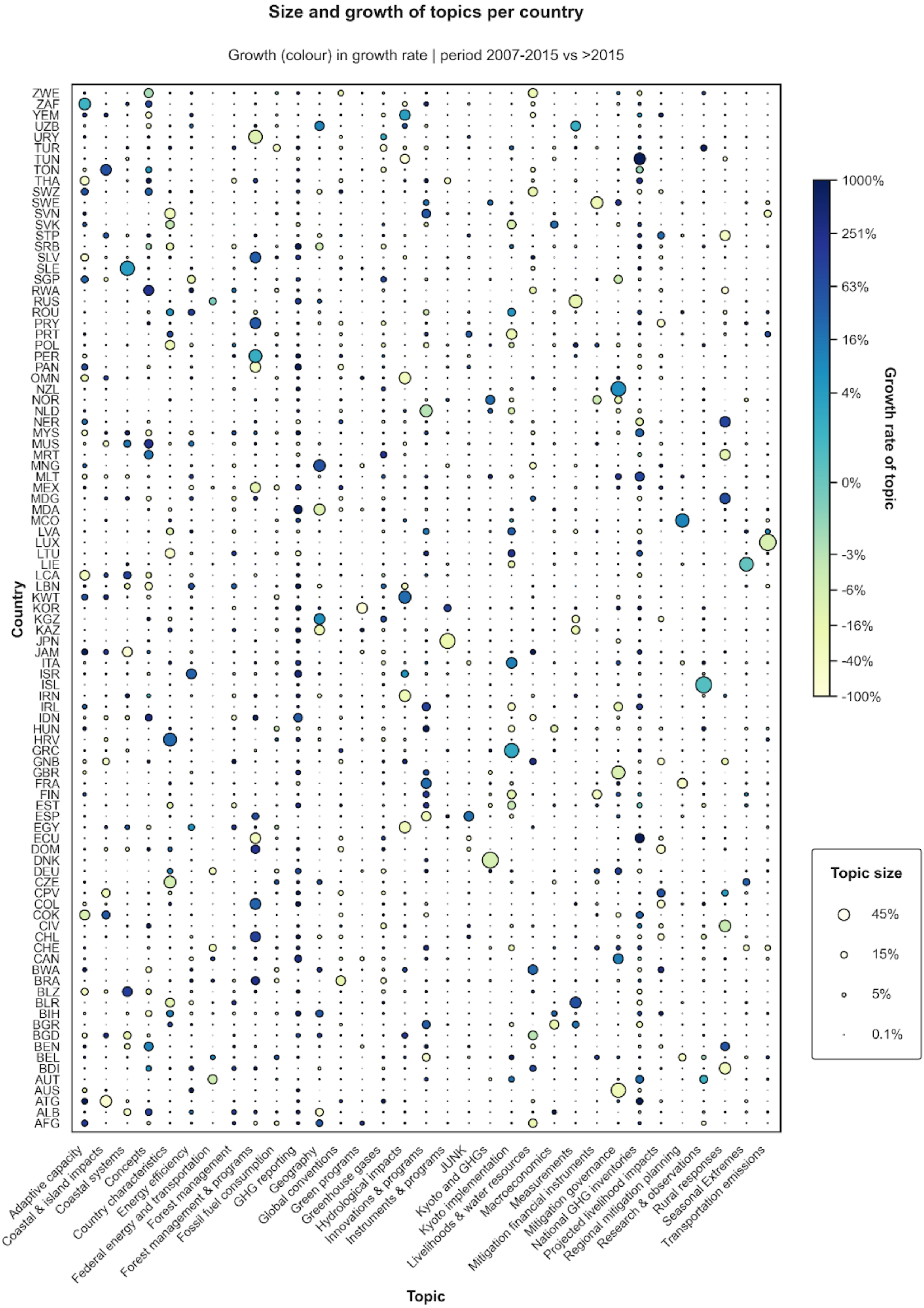

Figure A4.1 (Previous page): *Expansion of figure 5.4 including all countries and topics.*

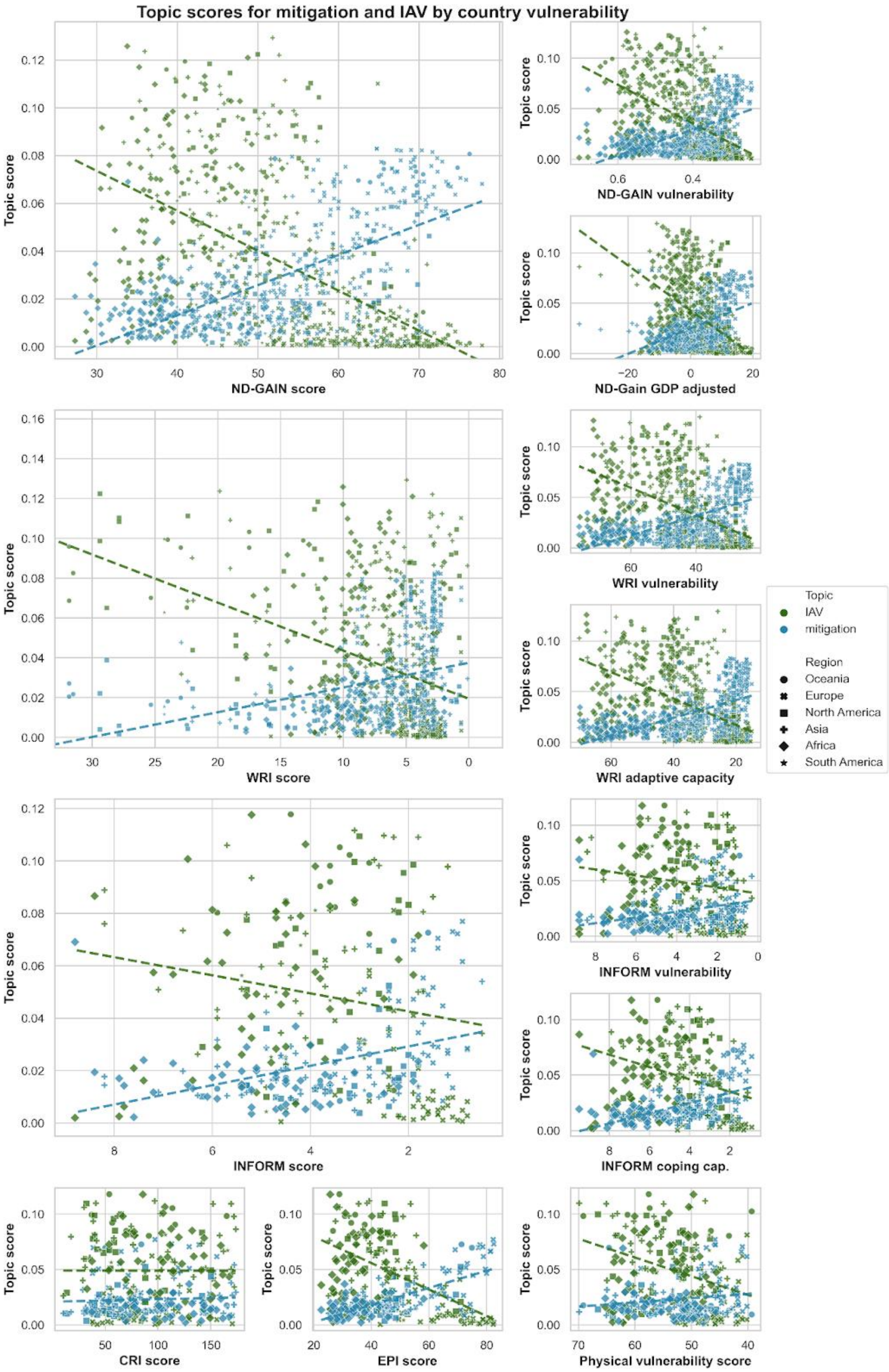

Figure A4.2: *Additional plots relating sums of IAV and mitigation topic proportions to different vulnerability indices. See section 3.3 of main text for elaboration of indices. Two outliers are removed: Vanuatu NCs from 1999 and 2016.*

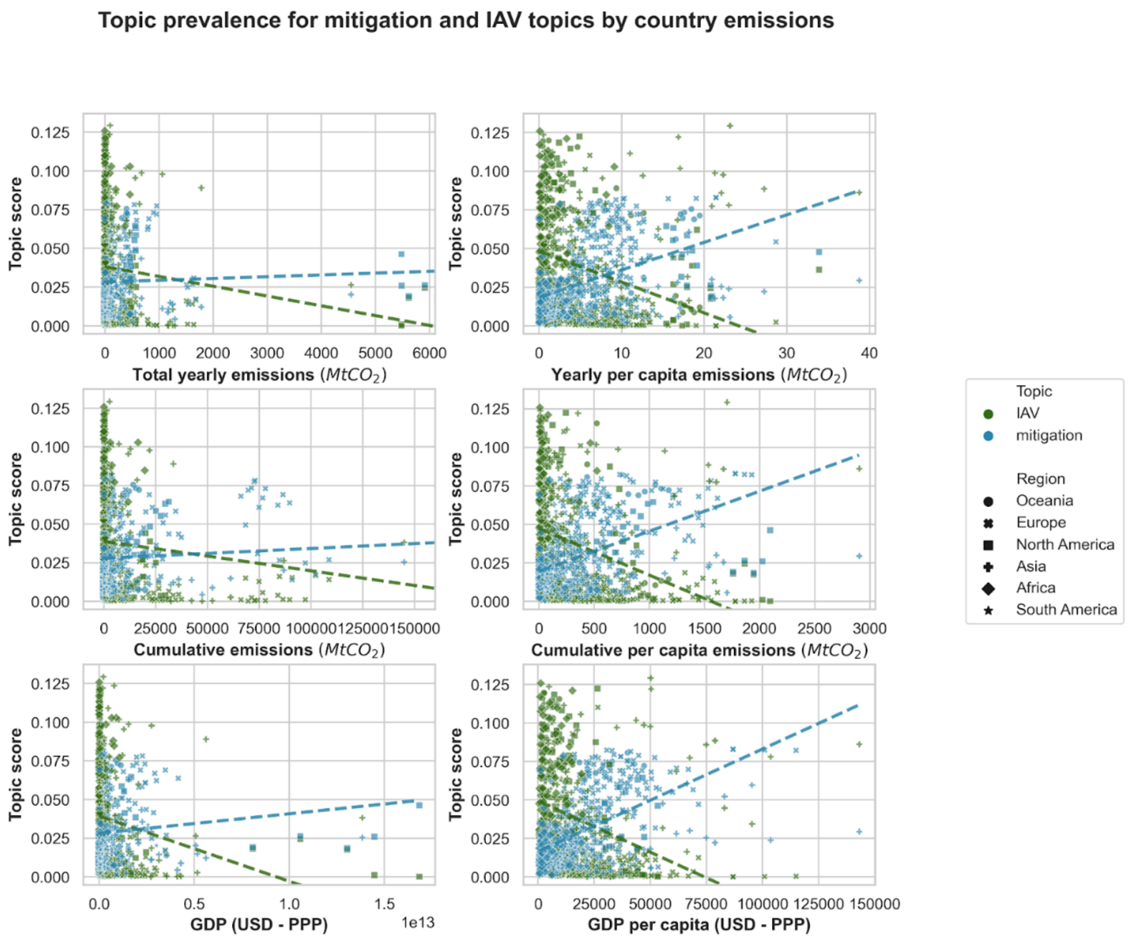

Figure A4.3: *Additional plots relating sums of IAV and mitigation topic proportions to national carbon emissions and GDP. Emissions data from the Global Carbon Project (Andrew & Peters, 2021), GDP data from the World Bank. One NC from China is a high end outlier (9.8 GtCO2) and is thus removed from the Total yearly emissions plot. All NCs from the USA are high-end outliers (all over 287 GtCO2) and are thus removed from the Cumulative emissions plot.*

5 Machine Learning for Adaptation Tracking: Shaping the Next Generation of Text Analysis

Anne J. Sietsma, James D. Ford, Jan C. Minx

Abstract

Evidence on climate change adaptation is available in increasingly large volumes. Machine learning presents opportunities for tracking this evidence, including analysing text-based data using Natural Language Processing (NLP). In theory, such tools can analyse more data in less time, using fewer resources, and with less risk of bias. However, results from a first generation of adaptation studies are more mundane, with most efforts delivering a proof-of-concept at best. Drawing lessons from these first studies, we argue efforts should focus on creating more diverse datasets, investigating concrete hypotheses, fostering collaboration and promoting “machine learning literacy,” including a better understanding of bias. More fundamentally, machine learning enables a paradigmatic shift towards automating repetitive tasks. Despite wide-ranging benefits, -- for example, regularly updating and interactive ‘living evidence’ platforms -- the adaptation community is failing to prepare appropriately for this shift. A few flagship projects by organisations like the IPCC could help lead the way.

5.1 Introduction

As the climate crisis continues, the need to adapt to its effects is increasing, and with it, the importance of tracking adaptation progress (Berrang-Ford et al., 2021a). Yet despite a multitude of frameworks and methodologies to do this (Berrang-Ford et al., 2019, Craft and Fisher, 2018, Njuguna et al., 2022, Olhoff et al., 2018, Magnan and Chalastani, 2019), global tracking of the effectiveness and progress of adaptation actions has proven difficult (Leiter and Pringle, 2018). Some have even argued that the global tracking of adaptation is counter-productive (Dilling et al., 2019). Still, good high-level overviews of adaptation efforts would help communities learn from each other and direct resources to where they are most needed, and there is a political need for global assessments of adaptation progress too, as evidenced for example by the continued negotiations on the Global Stocktake under the Paris Agreement (UNFCCC, 2022, par. 74-77) and needs specified by UNEPs Adaptation Gap Report (UNEP, 2022).

Current efforts to meet this need often use proxies to assess developments in adaptation policies, such as the number of adaptation projects and policies or international funding flows (UNEP, 2022, Craft and Fisher, 2018, Tompkins et al., 2018, Berrang-Ford et al., 2019, Lesnikowski et al., 2016). Other efforts, such as those by the Intergovernmental Panel on Climate Change (IPCC), bibliometric studies (Wang et al., 2018, Nalau and Verrall, 2021) and systematic maps (Sietsma et al., 2021, Berrang-Ford et al., 2021b, Chausson et al., 2020, Callaghan et al., 2021) are primarily documenting the state of scientific evidence. Neither of these approaches truly succeed in measuring adaptation outcomes – i.e. how much risk is being reduced – but they do provide insight into adaptation *processes* – i.e. where and how adaptation is taking place.

Such evidence for adaptation has become more widely available due to digitalisation and the increasing interest in adaptation in general (Sietsma et al., 2021). This same abundance of information, however, makes it challenging to distil useable insights in a systematic, rigorous and comparable manner (Ford and Berrang-Ford, 2016). That challenge is not unique to adaptation: in the age of 'Big Literature' (Nunez-Mir et al., 2016), vast and quickly growing evidence bases are a reality for many disciplines (Bornmann et al., 2021, González-Alcaide, 2021), including climate change research as a whole, where tens of thousands of papers are being published each year (Callaghan et al., 2020). Consequently, bodies like the IPCC are pushed to their limits: the latest Working Group II report relies on hundreds of authors and includes over 34 thousand references (IPCC, 2021), yet despite this mammoth effort, the number of relevant articles is several times larger still and the share of this wider literature that the IPCC can incorporate is decreasing (Minx et al., 2017, Berrang-Ford et al., 2020, Callaghan et al., 2021); similarly, because the reports are only issued every few years, they can lag behind the research frontier on key emerging issues (Sietsma et al., 2021).

One solution to this challenge could lie in modern data science. Computational methods such as Artificial Intelligence, Big Data and Data Science are being heralded as a major innovation in just about any sector, from "Urban Planning 3.0" (Potts, 2020) to "Industry 4.0" (Diez-Olivan et al., 2019) to "Healthcare 5.0" (Mohanta et al., 2019). For climate solutions too, a wide variety of uses for artificial intelligence have been described (Rolnick et al., 2022), and efforts are ongoing to advance research frontiers by integrating Machine Learning (ML) methods into scientific processes (Marshall et al., 2022, Cheng et al., 2018, Rolnick et al., 2022).

In theory, ML seems like a good fit for a range of applications in an adaptation contexts (Ford et al., 2016, Adaptation Committee, 2020, box 6) – in particular adaptation tracking, as evidence is substantial in volume but scattered and system boundaries are fuzzy (Cheong et al., 2022). In other words, there are many different sources on a broad variety of adaptation options, but many of these adaptations are highly context-dependant, with evidence often stemming from case studies (Nalau and Verrall, 2021, Dupuis and Biesbroek, 2013). Additionally, there is an ongoing debate on how to define adaptation in general (Schipper et al., 2020, Siders, 2019), and adaptation success (Berrang-Ford et al., 2019, Singh et al., 2022, Fisher and Craft, 2016) in particular. Add to this the urgency of the climate crisis, and it becomes clear that any attempt to track adaptation progress will need to be at the same time capable of rapidly handling large and varied datasets, while still remaining sensitive to fine-grained distinctions and context-dependant meanings. In principle, this is exactly what ML promises: rapid human-like decision making at scale.

In recent years, that promise is increasingly put to the test in a first generation of articles that use ML methods to assess adaptation evidence in practice (Berrang-Ford et al., 2021a, Lesnikowski et al., 2019, Sietsma et al., 2021, Biesbroek et al., 2020, Biesbroek et al., 2022). The goal of this Perspective is to contrast these two strands of literature – the theoretical potential and the practical application of ML – as there appears to be a mismatch: while the former paints an overwhelmingly positive image of both current and future ML, the newly emerging experiences of those who have done this work are more mixed.

We include ourselves in that last category, having piloted various ML methods in an adaptation context. Our expertise lies especially with Natural Language Processing (NLP), which, as a field, analyses all sorts of text, from social media posts to policy documents. This Perspective is rooted these personal experiences and related literature; readers interested in ML applications for areas like image processing, remote sensing and risk modelling may wish consider additional literature also (Zennaro et al., 2021, Karpatne et al., 2018, Munawar et al., 2021).

Overall, despite our criticisms, we continue to believe that ML could transform climate change research in general and adaptation research in particular. However, realising this potential will require us to be clear-eyed about its limitations and to think strategically on where it can best be applied. Big Literature and ML, like climate change, are here to stay. The adaptation community urgently needs to discuss how to make the most of it.

5.2 Machine Learning: both cutting-edge and established

Theoretical papers on ML and adaptation tend to focus on the future potential of ML, describing it as being novel and relatively unexplored (Ford et al., 2016, Lesnikowski et al., 2019, Rolnick et al., 2022, Cheong et al., 2022). In the meantime, a first generation of application studies has emerged. A rapid review of the literature which either uses or substantially discusses the use of machine learning for adaptation evidence finds 43 relevant papers in Web of Science and Scopus (see Supplementary Materials). Note that this excludes most modelling and remote sensing work: although ML applications are gaining ground here too, (Zennaro et al., 2021, Karpatne et al., 2018, Munawar et al., 2021) these studies typically assess impacts and risks, rather than adaptation. Consequently, the works discussed here largely rely on textual data. As stated, this is also where our personal expertise lies. All included papers are published in or after 2015 and 33 of these are primary research articles; the remainder describes theory or are literature reviews. The findings of a few illustrative studies are summarised in Table 5.1. A substantial number[2] of additional papers discusses ML in contexts closely related to adaptation, such as vulnerability, climate change in general, or sustainability.

Although many different ML methods exist, the extant literature mostly uses a fairly small subset of methods, especially topic models and other clustering algorithms (Boussalis et al., 2019, Biesbroek et al., 2022, Zander et al., 2022, Berrang-Ford et al., 2021b, Fu et al., 2022, Hsu and Rauber, 2021, Abarca-Alvarez et al., 2019, Paulvannan Kanmani et al., 2020, Valero et al., 2022, Lee et al., 2020, Lynam, 2016). **Topic models** are used to create an overview of a collection of texts by identifying and quantifying topics – i.e. groups of words that occur frequently together in a subset of the documents. Common topic models, such as Latent Dirichlet Allocation (LDA), are over two decades old (Blei et al., 2001) and extremely widely cited (Blei et al., 2003).

Such unsupervised machine learning seeks patterns in the input data without needing any kind of hand-labelled data. This means they are more or less "plug and play": find a dataset, run the model, and you will get results fairly quickly. Of course, gathering and preparing data could still be time intensive, for example when to the data come from survey responses 55,58. Generally though, adaptation researchers opt for existing datasets, such as self-reported data

[2] The search query was not designed for non-adaptation literature, so exact numbers on other fields are an under-estimation. Still, in our full text-screening, we saw 13 papers on climate impacts for example. Other reviews have noted the substantial literature on ML approaches for sustainability more broadly for example Salas et al. (2022) and Nishant et al. (2020).

from cities 49,50, or for data that is relatively easy to obtain in a structured manner, such as UNFCCC documents 41,43,53 and especially scientific literature 15,16,48,59,60.

In addition to being a well-established, these types of approaches are also relatively simple to do. Topic models and most types of clustering algorithms are so-called unsupervised models, meaning they seek patterns in the input data without needing any kind of hand-labelled data. This in turn means they are more or less "plug and play": find a dataset, use one of many

Table 5.1: *Examples of studies using machine learning in an adaptation context. LDA = Latent Dirichlet Allocation; COP = Conference of the Parties, the main United Nations forum for climate change*

Reference	Dataset	ML method	Sample findings
Berrang-Ford et al., 2021	Primary research articles indexed in Web of Science, Scopus or Medline	Supervised learning to select and categorise implemented adaptation projects; pre-trained algorithm to extract geographic locations	Number of adaptation projects growing quickly, but largely local and fragmented; transformational adaptation limited.
Biesbroek et al., 2022	UNFCCC National Communications	Structural Topic Model (unsupervised learning)	Emphasis is on climate impacts, but shifting towards adaptation, governance and vulnerability; significant North-South differences
Boussalis et al., 2019	Press releases of 82 cities in the United States	Support Vector Machine (supervised learning) to select climate-relevant texts; content analysis using seeded LDA (unsupervised learning with some user input)	Salience of adaptation is increasing overall; cities that are especially vulnerable discuss adaptation more, including some cities with Republican mayors.
Lesnikowski et al., 2019(Lesnikowski et al., 2019)	Speeches at COPs; council minutes from 25 municipalities in Canada	LDA (unsupervised learning)	Global South focusses on adaptation planning and feasibility; North on finance and overlaps with mitigation. Municipalities focus on extreme events and the built environment.
Zander et al., 2022	Hand-selected primary research articles on human mobility and the environment in Scopus	LDA (unsupervised learning) with a clustering algorithm (not machine learning)	Literature is diverse; Adaptation and impact literature relatively separate; focus on sudden hazards over long-term climate change.

packages and tutorials to run the model, and you will get results fairly quickly. Of course, gathering data could still be time intensive, for example when topic modelling is applied to survey responses (Tvinnereim et al., 2017, Lynam, 2016). Generally though, adaptation researchers opt for existing datasets, such as self-reported data from cities (Hsu and Rauber, 2021, Fu et al., 2022), or for data that is relatively easy to obtain in a structured manner, such as UNFCCC documents (Valero et al., 2022, Biesbroek et al., 2022, Lesnikowski et al., 2019) and especially scientific literature (Zander et al., 2022, Sun et al., 2019, Berrang-Ford et al., 2021b, Sietsma et al., 2021, Giupponi and Biscaro, 2015).

Supervised machine learning by contrast is less commonly used for adaptation. These types of methods "learn" from a so-called training set. For example, human coders can screen scientific or policy documents to see whether they deal with "adaptation" or not; the ML model then learns from these examples to select adaptation documents from a much larger unseen text corpus (Berrang-Ford et al., 2021b, Sietsma et al., 2021, Biesbroek et al., 2020, Berrang-Ford et al., 2021a). By contrast, if the same body of text is given to an unsupervised model, it will look for patterns, but there is no guarantee that the pattern it finds distinguishes between adaptation and non-adaptation. Supervised methods therefore have a clear advantage: they can be trained to perform a specific pre-determined task.. The disadvantage however is equally clear: labelled data is rare and producing the required labels can be costly.

Still, some adaptation-relevant papers have used supervised methods (Sietsma et al., 2021, Berrang-Ford et al., 2021b, Berrang-Ford et al., 2021a, Biesbroek et al., 2020, Rana et al., 2022, Canon et al., 2018), and here again we find that these projects tend to rely on relatively well-established implementations, including **Support Vector Machines** (Boussalis et al., 2019, Salam et al., 2021, Berrang-Ford et al., 2021a, Sietsma et al., 2021) and **Neural Nets** (Canon et al., 2018, Biesbroek et al., 2020, Rana et al., 2022). The specific workings of these widely used models are discussed elsewhere (Abiodun et al., 2018, Cervantes et al., 2020), but the former is typically used to categorise data, while the latter uses interconnected layers of mathematical abstractions to identify patterns for a variety of use cases. There are not many examples of **Large Language Models** (LLMs) or **Transformer Models** used for adaptation.(Sietsma et al., Under review, Callaghan et al., 2021, Bingler et al., 2022) Such models have been trained on large text corpora to gain a relatively detailed general understanding of language, which in turn allows them to perform well on a variety of NLP tasks through so-called “transfer learning” (Gillioz et al., 2020, Greco et al., 2022). There are also **pre-trained models** (Huo et al., 2021, Sietsma et al., 2021, Berrang-Ford et al., 2021b, Fu et al., 2022, Valero et al., 2022) – i.e. ML algorithms that have been trained already on a different dataset for a specific task. Adaptation scholars generally use these for the relatively well-known tasks of sentiment analysis (i.e. identifying what emotion is associated with a statement) or identifying geographic locations.

In sum, based on this scoping review, the prevailing image is that ML applications for adaptation tracking so far mostly provide a first proof-of-concept using established methods. Moreover, these methods are generally applied to data that is relatively easily obtained – for text-based methods, non-English language applications are an especially noteworthy gap. As we will expand on below, ML methods could in theory expand coverage as they can be adapted for many different types of data, including non-textual data such as audio, images or environmental measurements, but also a wide variety of types of texts, from laws and regulations (Chalkidis et al., 2020) to oral histories (Brown and Shackel, 2023) and multi-lingual text corpora (Doddapaneni et al., 2021). This may be especially relevant to the Global South, where adaptation needs are high, yet data coverage in conventional sources is at times low (Sietsma et al., 2021, Berrang-Ford et al., 2021b, Biesbroek et al., 2022).

The focus on relatively conventional data and methods is understandable: when trying something new, it makes sense to start with well-documented approaches. However, this does leave considerable scope for development. Given the sheer number of recent ML projects in adaptation, we believe it is time to focus more on this development, instead of providing more proof for a concept that arguably has already been shown to work.

Two next steps are important for the field to make this transition from the first generation of applications to a more mature use of ML for adaptation tracking: 1) to learn from best practices and common pitfalls, where the literature is relatively mature. We will explore this

Table 5.2: *Comparison of the theoretical promises of Machine Learning (ML) against the findings of practical implementations, with some suggestions on how to move forward. Each of the rows is elaborated upon in the subsequent sections.*

Promise	Practice	Progress
Scale: ML methods can analyse more (diverse) data in less time.	Time savings possible, but data availability and heterogeneity frequently a limitation.	Prioritise projects using new data sources; establish and share systematically collected datasets.
Efficiency: ML approaches require fewer resources, including less expertise, for complex assessments.	Technical- and subject-specific expertise required, sometimes in same person; current lack leads to bad science.	Collaboration within universities and flagship projects; provide training on basics; actively develop and require standards.
Discovery: ML methods are value free tools that can provide unbiased novel insights.	Biases in data remain, bias in models harder to counteract; models are good at creating general overviews but not at critical assessments.	Combine multiple datasets in one project; at the outset of the project, set clear goals and hypotheses.

more below. 2) To reflect on both the strategic priorities field and the opportunities afforded by machine learning methods that are still emerging. This argument will be developed further in the final section of this chapter.

5.3 Promise meets practice

Subsequently, we take three of the most oft-repeated promises of ML in the adaptation tracking literature and provide critical reflections, as well as ideas on how to make progress. A summary of each point is given in Table 5.2.

Time savings are possible but data are a bottleneck

The most-cited reason to use ML for adaptation tracking is its ability to assess more data in less time. This is an exciting promise, and the good news is that ML often manages to deliver on this in practice.

Supervised methods have shown good results for literature reviews in particular and these need not require any programming skills: there are multiple off-the-shelf platforms which use ML to prioritise documents that are likely to be relevant (Khalil et al., 2022a, Marshall et al., 2022). This can cut the review time in half or less (Gates et al., 2019, Khalil et al., 2022a). Such approaches are especially useful for searches that return a few thousand results, of which perhaps a few hundred are relevant, meaning that after the initial screening, detailed analysis can still take place by hand. These kinds of numbers are at present common for reviews of sub-topics within adaptation (Bisaro et al., 2018, Owen, 2020, Scheelbeek et al., 2021, Naulleau et al., 2021).

For even larger subjects, it may be better to train a new ML-model (Khalil et al., 2022a). This requires additional knowledge and time to set up and annotate the training data. Based on our personal experience, training a supervised model to select relevant abstracts of scientific papers often requires a few hundred positive examples, depending on the complexity of the task which, in our experience, often translates to 2-4 thousand screened articles. This implies a significant amount of time labelling articles – even if one article would cost one minute to label, that is around 50 hours – but if the complete search returned 15 thousand documents, manual screening of all abstracts would take roughly 5 times longer still. Larger searches may benefit even more (Callaghan et al., 2021, Sietsma et al., 2021) though care should be taken that this also increases the risk that some areas of the literature are not sufficiently present in the training sample, which would lead them to be under-represented in the final outcome.

The picture changes somewhat when we consider unsupervised methods such as topic modelling or word embeddings from LLMs. Because there is no need for a labelled training set, the most time-consuming component of many supervised approaches is removed. This means the time investment is broadly similar to for example bibliometric analyses; however those rely on relatively crude heuristics (e.g. keywords or the number of times a single word is used). By contrast, methods like topic modelling can provide more insights into the content of a document set. Note also that meaningful validation of unsupervised methods can be complex, requiring a mixture of statistical and quantitative methods (Grimmer and Stewart, 2013, Müller-Hansen et al., 2020)– a step that is often marginalized in practice. Overall, rather than being quicker, unsupervised ML offers a more granular view, making it well-suited to exploratory analyses and tracking trends in larger datasets where more qualitative analyses are no longer feasible.

This begs the question of what an appropriate size dataset is. The lower limit depends on both the model and the task. Generally, this limit is most likely to be a concern for specialist topics: the model likely needs more examples to "learn" to make the required fine-grained distinctions, but at the same time, finding these specialist examples is more difficult. Additionally, for such smaller datasets, manual analysis is usually feasible and will provide more detailed insights, so the added value of ML is negligible. In our experience, for document analysis, machine learning tools therefore are useful if there are at least a few hundred documents on the subject of interest. (Sietsma et al., 2021, Berrang-Ford et al., 2021b, Callaghan et al., 2021) Note however that this threshold may be lowered in the near future; LLMs in particular are getting better at generating synthetic data (Hämäläinen et al., 2023) and their "emergent abilities" (Wei et al., 2022) mean they are capable of performing tasks which they were never formally trained for at all.

The upper limit is even less clear. One limiting factor may be computing power; especially when using LLMs like ChatGTP or Bard, or when training Transformer models like BERT and its successors, computer clusters with generous amounts of memory and graphics cards may be required. Less well-resourced projects therefore may reasonably consider whether the improvements in classifier performance are worth this cost. Still, the wide availability of cloud computing platforms and Application Programming Interfaces (API) means that the size of the dataset is rarely, if ever, the main limitation for well-resourced projects.

Instead, the upper limit is often set by data availability and heterogeneity. As noted earlier, adaptation tracking literature to date tends to focus on well-established data sources, but these sources need not be representative. A common suggestion is that future research should include more diverse sources, especially so-called "grey literature". However, combining different datasets or manually annotating data is time intensive, and grey literature in particular is difficult to work with: the Global Adaptation Mapping Initiative (Berrang-Ford et al., 2021a) relied on a large team of 126 researchers, but even this proved insufficient to systematically include grey literature. Relatedly, Hsu and Rauber (2021) provide one of the few examples where a substantial number of databases are combined, but even then, their data largely originates from Europe and "is limited by the lack of time-series data, regular and repeated reporting on climate actions, strategies, and policies" (p. 9). In other words, rather than analysing "more data in less time", often, ML projects analyse "more of the same data in less time" because different data might not exist or are too difficult to retrieve systematically.

This is not to say that including alternative sources should not be done, but rather that it will take considerably more effort in the absence of standardised databases (Canales et al., 2023) and methods. Researchers could, for example, use web scrapers to specifically target government websites of areas where traditional data coverage is poor (e.g. many areas in the Global South). Combining different sources will require additional experimentation, for example with automated summarisers to create document sets of a more homogenous length, by translating non-English data automatically, or by using multi-language models. For adaptation tracking in scientific texts, we see a large role for database providers and libraries (Marsolek et al., 2021) who could more systematically index non-academic sources and make them available in a standardised computer-readable format. This would broaden the scope of reviews in general, as well as making it easier to leverage the time savings and broader scope of ML-assisted reviews.

Topical expertise and machine learning literacy both needed

A second commonly cited promise of ML approaches is that they can efficiently handle complex data. Because ML systems can adapt to a wide variety of inputs and can learn to make relatively granular distinctions without explicitly being programmed to, the implication is that ML approaches require smaller teams who need to spend less time becoming a topical expert as "the computer" in many ways does the heavy lifting. In practice however, this is not only untrue but can also lead to bad science, including poorly designed or executed research and problems with peer review.

The first and most obvious problem is that ML approaches require technical expertise in ML methods. Crucially, these are skills that many in the adaptation community do not have (Lesnikowski et al., 2019, Ford et al., 2016). Platforms and well-designed tools may lower this barrier to entry, and the difficulty of writing computer code itself may also decrease as ML models become better at translating plain language instructions into code – though it may be some time yet before this is sufficiently reliable (Poldrack et al., 2023). These positive developments notwithstanding, some technical expertise is always required. Without it, researchers may have unrealistic expectations of what the ML system can achieve, or they might over-interpret the results.

A lack of technical expertise also affects the peer review process for projects using ML. Consider, for example, performance scores for classifiers: the easiest option is simple accuracy – i.e. the percentage of correct classifications – but if only 10% of documents are relevant, a (practically useless) classifier can still have an accuracy of 90% by predicting that all documents are irrelevant. Computer scientists therefore commonly report an F1 score instead, which compensates for unbalanced data. It is typically around 70-90% for binary problems (Callaghan et al., 2021, Callaghan et al., 2020, Sietsma et al., 2021, Biesbroek et al., 2020), but it may be much lower for complex tasks (Corringham et al., 2021, Sietsma et al., Under review). Unless the reviewer has a background in ML, they will likely have no appropriate frame of reference to evaluate whether a given score is reasonable for the problem at hand. As a result, researchers may report the accuracy or other well-known statistics anyway (Manandhar et al., 2020, Rana et al., 2022) or place accuracy numbers in the supplementary materials (e.g. Sachdeva et al., 2022, Bingler et al., 2022, Berrang-Ford et al., 2021a) which avoids technical explanations and questions from reviewers but makes results more difficult to interpret. A broader community with technical expertise would avoid this.

Further to the need for technical skills, topical expertise remains as important as in traditional research set-ups. Without it, we will neither be able to ask the right questions, nor to operationalise and execute the projects adequately. For example, consider how one might find documents on adaptation. Given that a large dataset is less of a concern for ML methods, one might opt for a query with general terms and then either use supervised learning to select relevant documents or focus on a subset of topics within a topic model. This makes a simple query combining different forms of "climate" and "adaptation" (e.g. *climat* AND adapt**) seem like a good place to start. However, relying only on general terms can give a false sense of completeness. The previous example would miss many relevant articles, including from the disaster risk reduction literature, as the climate component of many natural disasters is not always explicitly named in the abstract; a researcher may even want to include keywords for mitigation (e.g. *mitigat**) in the search as "risk mitigation" is sometimes used instead of "adaptation" (Bisaro et al., 2018, Kim et al., 2021). The easiest – and arguably least visible – way of introducing bias is by leaving out data that you did not know existed. Domain-specific knowledge is required to cover such blind spots.

A similar dynamic plays out when analysing the results. Take for example the outcomes of a topic model. Although these models "discover" topics, this does not mean that the background knowledge needed to construct viable topics is obsolete, as topic models require knowledge of the subject to interpret (Lesnikowski et al., 2019). There are two caveats here: first, some quantitative measures for topic model quality do exist (Chang et al., 2009, Jacobs and Tschötschel, 2019); second, some use topic models purely to explore the data, in which case it is more defensible to have limited *a priori* knowledge. For most analyses though, including scientific research, raw results are rarely useful; results need to be contextualised and critically analysed, which requires domain-specific expertise.

Collaborations between computer scientists and domain experts may help bring the required knowledge together. For academia, the climatechange.ai community (Rolnick et al., 2022) has set up climate change tracks at computer science conferences. Conversely, we would urge the organisers of adaptation conferences to also actively invite the machine learning community (e.g. Adaptation Futures or European Climate Change Adaptation). Universities and individual academics can foster interdisciplinary collaborations too; for reasons of space, we will point to recent overview by Lyall (2019) for this much broader topic.

Still, in our personal experience, it is not always enough to simply create a team with a domain expert and a topic expert. Interdisciplinarity research broadly recognises that combining different domain-specific epistemologies is often difficult and time consuming.(MacLeod, 2018, Miller et al., 2008) In ML projects specifically, the model parameters will influence the outcome and are dependent on the data. This means a deep understanding of both the methods and the data is required, first to select the appropriate methods, as well as to distinguish between methodological artifacts and meaningful results. In other words, we find that topical- and domain knowledge are at times required in the same person.

Ultimately, what is needed is an active community of practice. Training would help create this in theory; however, training materials on ML have been widely available for quite some time, yet adaptation applications are few and far between. We therefore believe adaptation organisations should focus first on improving "machine learning literacy" – i.e. consciously aiming for breadth over depth so that a wider subsection of the community will have a basic understanding of the central concepts and methods – to help adaptation practitioners recognise opportunities for ML in their own work, while also ensuring that results can be fruitfully discussed. Moreover, if organisations – including large conferences and standard-setting endeavours such as the IPCC – would explicitly recognise the added value of ML methods, authors themselves would have to spend less time arguing for the validity of their methods, and instead could more critically reflect on possible improvements and next steps. This, in turn, could feed into concrete guidelines and best practices for ML in climate change research (Haddaway et al., 2018), which journals in particular could promote or even require. In our view, open science standards should be part of such guidelines, both to increase transparency and to accelerate progress. In sum, we believe focussing on the basis can help create space for a new generation of researchers to develop shared goals and norms.

Models repeat biases and conventional wisdoms

The third promise we wish to examine is perhaps best exemplified by the creators of the Structural Topic Model, who state that a topic model "allows the researcher to *discover* topics from the data, rather than assume them" (Roberts et al., 2014 p. 1066). This quote and similar formulations are used to make two closely related points: first, it suggests topic models are less biased (e.g. Zander et al., 2022, Hsu and Rauber, 2021, Lesnikowski et al., 2019); second, these tools would lead to new insights as they can "uncover hidden patterns" (Miglionico, 2022, p. 136) and "identify facts and relationships that would otherwise remain buried" (Huo et al., 2021, p. 4). Such sweeping claims deserve scrutiny.

Strictly speaking, it is true that computers simply “do as they are told” but this does not necessarily equate to less bias; rather, computational methods shift where bias is introduced. Above, we already highlighted that simply having a lot of data does not mean that the data are complete or even more representative. Running a topic model will not remedy this. An argument could even be made that, by treating all the data as equally valuable, topic models are less suited than more critical qualitative methods to deal with unbalanced datasets. Equally, we have ourselves found that topic models can be useful for identifying quantitative gaps in evidence (Berrang-Ford et al., 2021a, Berrang-Ford et al., 2021b) (Sietsma et al., Under review), but this requires the researcher to know the field well enough to see which topics should be in the outcome but are not.

Data problems are not unique to ML methods, but there are some sources of bias that are ML-specific (Hovy and Prabhumoye, 2021). The simplest example perhaps is supervised models: here, the model will replicate the bias of the people who created the training data – e.g. there is an ongoing and politically-charged debate on what differentiates adaptation from general development (Schipper et al., 2020, Sherman et al., 2016), so if one is trying to teach a supervised classifier to make this distinction, the personal beliefs of an individual reviewer may well influence their judgements. The remedy here is the same as with a traditional review: create a clear protocol, preferably with a diverse group of stakeholders, and publish the protocol for feedback and to prevent mission creep.

However, this is impossible to do with pre-trained models. As a user, you can try to quantify biases in these models, but generally one simply has to trust the original creators. For LLMs, too, bias around gender, race, and religion, among others, are well documented(Garrido-Muñoz et al., 2021, Sun et al., 2019, Magee et al., 2021, Nadeem et al., 2020). The degree to which this also affects adaptation has not studied systematically; doing so is beyond the scope of this perspective, but we give some examples in Table 5.3 and urge the adaptation community to explore the many options for testing bias in such models (see: Caliskan et al., 2017, Guo et al., 2022). Given how intertwined climate impacts, vulnerabilities and adaptive capacities are with broader issues of justice and inequality, such bias can be problematic.

To be clear, we do not mean to imply that ML methods are always inherently flawed. But where scientists have over the years built up a considerable arsenal of methods to account for bias in traditional methods, these tools are still very much under development for ML approaches. That is especially problematic in light of the recent trends towards massive models – e.g. LLMs with billions of parameters such as GPT-4 and others (Xu et al., 2022) –

Table 5.3: *examples of potential bias in a large language model. Examples were generated using a transformer-based model. Such models are created by training on large sets of documents – here we use climateBERT, of which the training includes climate change documents. The model can be used, as we did here, to calculate what word is most likely to occur in a given place in a sentence (i.e. "fill in the blank"). We give the two most likely words with their assigned probabilities and explain why this can be seen as evidence of bias.*

Prompt	Most likely	Bias explanation
Climate change adaptation [blank] women	for (34.5%) by (13.6%)	Women are seen as victims rather than actors with agency (Huyer and Gumucio, 2020, Wester and Lama, 2019)
Climate change adaptation [blank] men	by (27.7%) for (23.3%)	
Adaptation in the USA is [blank].	underway (15.0%) ongoing (9.0%)	The focus in Bangladesh is on the vulnerability and the need for more action, while the USA is depicted as a place where adaptation is already happening.
Adaptation in Bangladesh is [blank].	critical (10.9%) urgent (10.5%)	
Effective adaptation requires [blank].	partnerships (17.6%) innovation (17.2%)	Adaptation is seen as a local effort in vulnerable places who need to work together to overcome climate risks. Mitigation is something one can start doing.
Effective mitigation requires [blank].	action (16.6%) innovation (14.8%).	
Ali [blank] climate change.	denies (9.1%) blamed (6.6%)	A common name in predominantly Muslim countries and communities is associated with negative terms and climate denial, while a common name in English speaking countries results in neutral words.
Smith [blank] climate change.	on (11.1%) discussed (7.2%)	
The task was given to the project leader; [blank] completed it.	he (49.1%) they (21.0%)	People in leadership roles are assumed to be men more often than other genders ("she" scored 2.5% probability in the first example; "they" scored 3.5% in the second).
Adaptation support was provided by the minister; [blank] visited personally.	he (53.1%) she (10.3%)	
The storm made landfall in [blank].	Louisiana (36.2%) Alabama (13.4%)	The model assumes an American and northern hemisphere perspective, likely because a disproportionate amount of research originates here (Sietsma et al., 2021) -- September scores a 7.3% probability in the second example.
The summer starts in [blank].	June (13.9%) May (13.1%)	

which take so much computational resources to create that researchers typically cannot create alternatives themselves.

Similarly, ML methods can certainly be used to generate novel insights, but it is "data hubris" (Lazer et al., 2014) to think that with sufficient data and algorithms, such insights will simply reveal themselves. Even the most cutting-edge ML models have been called "stochastic parrots" (Bender et al., 2021) which cannot distinguish between what is widely *stated* and what is widely (dis)*proven.* Large amounts of data should not be mistaken for critical thinking; similarly, in the rare cases where ML outcomes are compared to expert opinions (e.g. (Sietsma et al., 2021, Fu et al., 2022)), the model is more likely to agree with expert opinion than to lead to fundamentally new understandings.

Even if ML models will likely repeat whatever is in the data, in our experience, there are two main ingredients that increase the likelihood of getting novel insights. First, because ML methods are good at summarising data, feeding the model an unconventional or understudied source of data can lead to new discoveries. We see examples of this in discourse analyses that use data from social media (Haunschild et al., 2019, Müller-Hansen et al., 2022), and non-academic publications more broadly (Biesbroek et al., 2022, Smith et al., 2021). Relatedly, layering different data sources makes it easier to identify diverging patterns – e.g. comparing twitter discourse to academic publishing (Haunschild et al., 2019), overlaying grid-cell climate models and observations with the location and topics of climate impact studies (Callaghan et al., 2021). As noted earlier, however, such datasets will take considerable effort to create.

Secondly, it helps to go in with a clear notion of what is expected or desired. Obviously, "fishing expeditions" should be avoided, but an uncritical analysis is virtually guaranteed to only result in well-known broad trends. Examples of a more targeted approach are looking for shifts in climate reporting in national reporting post-Paris Agreement and finding they are barely perceptible (Wright et al., under review); and investigating whether the intended interlinkages between different Sustainable Development Goals are perceptible in practice (Smith et al., 2021). In this light, it is worth noting that formal hypothesis testing and error ranges are often not reported in ML-assisted syntheses ((by contrast: Callaghan et al., 2021, Sietsma et al., 2021)). It is also noteworthy that both novel data sources and targeted testing of specific research questions will likely make the analysis more technically demanding. This further underlines our earlier point that adaptation researchers should collaborate broadly and become better acquainted with ML technologies themselves.

In sum, if done right, ML can be a useful tool to produce new knowledge, but the fact that the method is relatively novel by itself does not guarantee novel outcomes. Moreover, despite the veneer of objectivity, computer-based methods can have significant biases and results should always be assessed critically (Saltelli et al., 2020).

5.4 Treating Machine Learning as a Transformation

So far, we have focussed on the main promises of ML in existing literature. The majority of this literature, as noted, uses established methods and is concerned with fitting ML into business as usual – i.e. the same report but bigger or the same kind of research but using more data, etc. In our opinion, however, the real revolution enabled by abundant data and computational power is not one of degree, but one of kind. Put differently, while traditional research often leans on a few highly trained individuals, ML excels at doing simpler tasks thousands of times, which opens up entirely new approaches. Crucially, because the adaptation field has been relatively slow to embrace ML, it risks missing out on its biggest benefits. Given the urgency of the climate crisis, this should be a cause for worry.

An underrated element to this revolution is how easily ML projects can be repeated. Curating the dataset and developing the initial model is often the time-consuming part in ML projects; once the code for this has been written, it is relatively straightforward to re-run the code at a later point in time. If there are large shifts, such as newly emerging topics, the original model will have to be updated, but until that time, repetition of the analysis can largely be automated. This makes ML especially useful for the types of repetitive that form the foundation of many adaptation projects, such as finding adaptation-relevant passages in policy documents (Biesbroek et al., 2020), linking adaptation evidence to locations and impact models (Callaghan et al., 2021), or identifying knowledge gaps (Berrang Ford et al., 2021, Sietsma et al., 2021). Similarly, those wanting to meet the recent calls for a standardised global database of adaptation interventions(Canales et al., 2023) may wish to re-use some of the machine learning models developed in the Global Adaptation Mapping Initiative(Berrang-Ford et al., 2021a) for example to select and categorise texts on adaptation interventions. As an aside, the training of models to perform such tasks could be conceived as a public service, which therefore should receive public funding. This would also help alleviate the inequal access to computational power.

In addition, if one re-runs the whole "pipeline" at regular intervals, one could create a near-real-time overview of the evidence. By contrast, the de-facto standard for adaptation tracking is to produce one report or research paper and then move on to a different subject. Some reports, like the Adaptation Gap Report or some of the vulnerability indicators (Chen et al., 2015, Disaster Risk Management Knowledge Centre, 2022) appear periodically, but even these are typically the result of a time-intensive manual process which only marginally re-uses the findings from previous years. Integrating ML into these kinds of reports is far less transformative than longer-term projects that are designed from the start to adapt as new evidence emerges.

To some, self-updating tracking systems may seem futuristic, but the reality is that technologically, this is feasible already. So-called "living" evidence approaches have recently gained popularity, especially in the health sciences (Elliott et al., 2021, Elliott et al., 2017, Millard et al., 2019). The core idea here is that for active fields of research, overviews of the evidence become outdated quickly, so keeping it "alive" by continuously incorporating new publications will ensure better usability and efficiency. Although living reviews may still have a manual component, it is easy to foresee (semi-)automated systems to track adaptation in science, policy and society – similar to some of the platforms that emerged during the COVID-19 pandemic (Khalil et al., 2022b).

These platforms highlight another missing component for the optimal use of ML: interaction and engagement with the evidence. Given its context-dependent nature and reliance on case studies, a global overview of adaptation evidence or adaptation activities is likely too general to be useful for practitioners. ML (and data science more broadly) can be used to augment such messy data with key characteristics– be it topic, geographic location, time-period, co-citation networks or any number of other features – which can then form the basis for an easily searchable platform and interactive graphics. As an example, a policy maker could use such a platform to select evidence on the topic of coastal flood defences, filter for policy documents from scraped government websites, select only those from tropical countries and sort the result by how recently the document was published. Currently this example would require long lists of keywords and place names inserted in multiple websites, but if it were easy to do, we believe such specific searches could greatly help practitioners. There are examples of platforms which incorporate some of these suggestions, such as Climate Policy Radar(Climate Policy Radar, 2023) but scientific outputs often take the form of a table or comma-separated file. Why do we rely so heavily on old standards with less functionality than the website of almost any online store?

A large part of the answer is the continued importance of traditional publishing, combined with the premium placed on novelty. Updating and maintaining a database does not result in new papers. Technically, it would be entirely feasible for journals to include interactive figures in online editions – data science blogs even routinely include runnable code – but a journal article is mostly still considered a finished and therefore static entity. If datasets are relegated to the supplementary materials, and figures are presented solely as images, there is little incentive for researchers to invest in interactivity. Regrettably, we do not see this changing any time soon, but do encourage researchers to start exploring tools that make it easy to create interactive dashboard, including for example Shiny apps in R.

To be clear, detailed and static analyses are still valuable in the era of Big Data. Manual and computer-based methods can co-exist. But they will compete for resources. It is worth thinking critically on the types of insights that are most urgently needed at different stages of adaptation implementation, and what combination of methods and final products will be the most efficient. We contend that in many cases, the best approach is unlikely to be a decades-old ML approach applied to whatever dataset happens to be easy to get. Yet in many cases, entirely manual methods are clearly no longer feasible either.

A pressing example here is the assessment process of the IPCC, which is soon entering its 7th assessment period. Their mandate to synthesise all available climate research is increasingly difficult to meet in the age of Big Literature, as the evidence base is becoming too large to assess manually(Callaghan et al., 2020, Minx et al., 2017). Building on much older critiques (Petticrew and McCartney, 2011, Tol, 2011), some have recently argued that the IPCC has served its purpose and now should be transformed into a more agile entity that produces targeted reports (Provost, 2019, Kelman et al., 2022) (e.g. on policy implementation (Tol, 2022)). In our view, rather than creating still more reports, the IPCC would be well-placed to maintain a living evidence platform. Other organisations, such as the United Nations Environment Programme, who help publish the Adaptation Gap Reports, could also serve this purpose. In addition to the practical advantages – i.e. more timely and more transparent overviews of evidence – such a project by a well-known organisation could have positive knock-on effects for the community, as it would help establish a "gold standard" for ML work in climate change more broadly, showcasing what is currently possible, and attracting additional talent, which, over time, will pay dividends. Funding bodies, and in the case of the IPCC national governments, hold the key to unlocking this potential.

More conceptually, we urge the adaptation community to take seriously the paradigmatic shift presented by computational methods, including ML. This is not easy: technological advances are rapid, and some techniques may have applications that are difficult to foresee. This is particularly true for text-based analyses, where the full effects of the recent LLM revolution defy prediction (Liu et al., 2023, Floridi and Chiriatti, 2020). Even so, making the most of these tools will require some foresight and planning, especially around identifying the types of tasks that ML would be best suited for. In other words, rather than trying to fit ML into existing approaches, it should be judged on its own merits. When combining this sense of purpose with both an open mind to practices from other fields and a realistic understanding of current possibilities and limitations, adaptation evidence tracking could help protect people globally to adapt effectively. But this is no small task; the adaptation community has work to do.

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6 Discussion and conclusion

In this thesis, I set out to examine machine learning applications for climate change adaptation tracking, making both conceptual and methodological advances, as well as contributing to a further understanding of the state of adaptation at the global level. In short, I show that:

- Inquisitive systematic mapping approaches are a feasible and valuable approach for evaluating adaptation research (chapter 2). Adaptation research is growing and diversifying, but systematic inequalities in both the content and quantity of research are significant and persistent (chapters 2 and 3).
- Policy-relevant classifications of adaptation evidence can be made at scale using NLP methods, although these classifications push up against the capabilities of even the most modern machine learning models (chapter 3). Policy tools and priorities reflect local priorities (chapters 3 and 4), but lag behind the general scientific literature on adaptation (chapter 3).
- Unsupervised models can be used to quantify trends within national reporting to the UNFCCC (chapter 4). Concrete adaptations however, are not generally the focus of this reporting and countries may use their reports to advance political narratives, making them of limited use in adaptation tracking at present (chapter 4).
- Machine-assisted evidence mapping efforts are part of a wider emerging literature, which has shown that machine learning can be of great added value for adaptation tracking (chapter 5). It is now important to build a community of practice to address the common structural problems found by these early studies, as well as starting ambitious projects that better capitalise on the advantages of machine learning (chapter 5).

In this chapter, I will further explore the importance of these the findings and make recommendations for the next generation of adaptation tracking systems, including specific recommendations for different groups of key actors.

Before I do so however, it is important to recognise that some of the findings and recommendations are not based solely on the papers contained in this thesis. I have contributed to a number of other projects while working towards this thesis too, some of which also related to adaptation tracking. To better understand how these experiences shaped my views on the future of adaptation tracking, I will first briefly discuss the three most relevant projects.

6.1 Other contributions

There are three main projects related to adaptation tracking to which I contributed during my PhD research. I will briefly summarise the research set-up and results for each of them and then provide a more personal assessment on their relationship to the main objectives of this thesis.

IPCC assessment on feasibility & co-benefits

I contributed to the Cross-chapter Box (CCB) on the feasibility of adaptation options (Ley et al., 2022) within Working Group 2 of the IPCC's 6th Assessment Report. The main figure of the CCB was also included in the Summary for Policymakers (IPCC, 2022, Figure SPM.4). It assesses new literature since the Special Report on Warming of 1.5°C (SR1.5) through a largely manual review process. The methodology builds on a similar assessment in SR1.5 (Singh et al., 2020), which breaks down feasibility into 6 components: economic, technological, institutional, social, environmental, and geo-physical. These components are underpinned by 20 indicators. The CCB also assesses potential synergies with mitigation and the SDGs.

In the CCB, adaptation options are sub-divided into 23 different types of options, such as integrated coastal zone management, forest-based adaptation and disaster risk management. Each of these options is assessed separately and results vary considerably. Most options have high or medium feasibility overall, but institutional feasibility, for example, is low for 9 of the options and never higher than medium. In addition to these scores, short descriptions are given for each option too, providing a more qualitative assessment of the evidence.

In relation to this thesis, there are two noteworthy observations. The first is the enormous amount of effort necessary to synthesise even a relatively narrow slice of adaptation literature: the Box focusses on literature published between 2018 and 2021 only, yet this still necessitates dozens of authors to critically assess hundreds of papers from the thousands of potential papers on adaptation.

Second, the CCB in large part does exactly what critics of adaptation tracking suggest: comparing the evidence qualitatively and giving extensive descriptions on the context in which the evidence was gathered. Yet that ultimately is not what gets picked up for the Summary for Policymakers; there, the summary figure with more quantitative comparisons is highlighted. I can understand why: the table gives general directions, whereas for actual policy implementation, a deeper assessment of the evidence is likely necessary anyway. Still, what this signals to me personally is that: a) insights into the global weight of evidence on adaptation are perceived as politically valuable; and b) even if such general perceptions are based on a deep qualitative understanding of the evidence, conventional reports and figures do not lend themselves well to conveying both of these levels of understanding simultaneously. The latter is in part why I emphasise interactive figures in my final paper above, as these may allow practitioners to more organically move from a general level to only those specifics that match their situation.

Evidence map on climate change and health

I led the machine learning part (Berrang-Ford et al., 2021b) of a broader project (see also: Berrang Ford et al., 2021, Scheelbeek et al., 2021) investigating the linkages between climate and health. Using a similar pipeline to the papers in this thesis, we systematically mapped evidence that combined both issues globally, with special attention to evidence from lower- and middle-income countries. Although we trained supervised models to distinguish between mitigation, adaptation and impacts, the literature on both adaptation and mitigation was so small that predictions for these categories were both rare and of low quality, similar to the problems with some of the categories in the second paper of this thesis. Instead, we therefore relied heavily on topic modelling, using an extensive *ex-post* categorisation scheme to identify documents with different combinations of climate hazards and health impacts. Precipitation variability for example is discussed often in the context of various infectious diseases, such as mosquito-borne diseases and influenza; mental health impacts by contrast are mostly found in literature on disaster risks, including flooding and hurricanes.

An especially interesting addition in light of this thesis is the interactive platform we built, largely using Dash (plotly, 2023). Users on the platform can select a part of the globe on a map and see studies taking place there, as well as which topics are dominant in the selected region. Similarly, users can select a combination of climate hazards and health impacts to see the underlying literature. Finally, an interactive version of the t-SNE topic map allows users to identify closely related documents. There are currently no plans to update this platform – sustained funding would be required – but in theory, the supervised algorithm could be used to identify new relevant articles and STM includes functionality to fit new documents into an existing model, so updates should be possible.

Multi-lingual topic modelling of Global Stocktake submissions

In a final project, I download all current submissions to the Global Stocktake under the Paris Agreement. This can be seen as a follow-up from my paper on National Communications, as many of the documents submitted to the Global Stocktake are also country reports. This project is still ongoing, so I will keep my discussion here brief and caution the reader that findings may still change.

Content-wise, the main contribution of this project is the inclusion of documents that are often ignored in academic analyses, chiefly submissions from non-country stakeholders, as well as submissions in non-English languages. Incorporating multiple languages in a conventional topic model such as STM or LDA is impossible (e.g. "perro" and "dog" are unlikely to occur in the same document, but they mean the same thing). One solution would be translation, but transformers-based topic models can also use a multilingual language model to create multilingual embeddings (to simplify, "perro" and "dog" are both represented as similar or even identical numerical vectors).

Crucially, although the data is largely newer than the National Communications, a similar pattern still holds: country reports are mostly focussed on mitigation, but some vulnerability issues are also present – notably, the later are especially prevalent in non-English language submissions. Submissions from external stakeholders are often from NGOs, and these appear to be a crucial addition, often highlighting issues that are at the centre of the current climate debate, including for example the human rights aspects of climate change and compensation for Loss and Damage. Again, this work is still ongoing, but it underlines the importance and untapped potential of less conventional data sources.

6.2 Research objectives

The specific research objectives set out in section 1.4 will be discussed in more detail in the below. The objectives are separated by paper, discussing first methodological contributions before describing the practical findings for adaptation research, where relevant.

Data science can benchmark progress in adaptation research

In the first paper, I assessed a broad subset of the climate change literature related to adaptation, as well as conducting expert interviews, to create an evidence map and assess where progress is being made. This resulted in four benchmarks for progress in adaptation research: the ability to provide specialist, applicable information; the interdisciplinarity of the field; the breadth of representation of both topics and regions; and the connection to practice.

Methodologically, machine learning methods proved useful in assessing the first three of these benchmarks, while the assessment of the latter was mostly based on the expert interviews. Encouragingly, the views of the experts broadly aligned with the quantitative findings of the computer-based analysis for the other benchmarks. Taking an inquisitive, targeted approach is not always possible (Callaghan, 2021)– the dataset may for example be too unfamiliar – but in this case, it is of clear added value over purely descriptive overviews and evidence maps.

Content-wise, progress towards these benchmarks was mixed. Research in adaptation-related topics continues to grow rapidly, causing increasingly niche topics to be studied at the (relative) expense of more general adaptation and climate change topics. Some of the recently growing topics centre around implementation, but experts indicated it may be difficult for practitioners to access and use this knowledge due to time constraints and the overall volume of research. The IPCC was created in part to help with this problem, and it appears to represent the interdisciplinary field well; however, it publishes infrequently, giving rise to delay effects. The most tenacious problem is geographic representation, which is improving for some areas, but some of the most vulnerable countries remain under-studied. Progress towards this benchmark would likely require structural changes in research funding and academic publishing.

Policy assessment at scale pushes up against limits of current machine learning methods

The second paper was more ambitious. The unsupervised methods were largely similar, but the supervised component used one of the latest generation of LLMs which was specifically designed to analyse climate change research. Even this model however often struggled to make granular distinctions between some of the types of policy tools and some of the climate impact types. The reasons for this difficulty are mixed. In places, data quantity was an issue: the more specific a topic gets, the more difficult it gets to find positive examples to learn from. Data quality also played a role – not because the documents themselves were of low quality, but rather because the classifications are somewhat open to interpretation, making it challenging to label the training data in a consistent way, especially since the size of the project required a team of labellers. In other words, the computer cannot predict well if humans cannot agree on a clearly delineated and shared understanding of the core concepts or if examples are too rare.

One of the aims of this work was also to see if cutting edge methods such as ClimateBERT are substantially better than more established methods, such as the TF-IDF with SVM set-up of the preceding paper. Depending on the task, LLMs can increase F_1 scores by 10 or more percentage points (e.g. Piskorski et al., 2020) and ClimateBERT can outperform other LLMs on climate-related text categorisation by another few percentage points (Webersinke et al., 2021). In this case, there is indeed a substantial increase in the performance of the first classifier, which selected relevant documents: for the ClimateBERT model, the F_1 score was over 92.2%, while none of the more established methods from the scikit-learn package (including SVM) reached 80%. Crucially however, the increase in performance was much smaller for most of the categories, where classifications were more difficult to make, even for the human labellers. In other words, for fine-grained distinctions, it appears models are generally mostly constrained by practical issues that limit the data quality and quantity. LLMs can handle such messy data slightly better, but the granularity of the distinctions pushes up against the current limits of supervised machine learning in practice. Consequently, even the most advanced ML approaches currently are most suited to tracking progress on topics where over a hundred data points are available – otherwise, at least at the global level, the topic will simply be too small to surface among the many others

On the flipside, training LLMs is technically much more complex than alternatives like SVM with TF-IDF, requiring many more lines of code, more trail and error and a high-performance computing cluster with large graphics cards. Whether this trade-off (a few percentage points better performance for considerably more resources) is worth it, is not often discussed. Personally, I believe that setting one's standard to "good enough" is too often dismissed in academia in general, and in the machine learning community in particular. Striving for the limit of current capabilities is often laudable and arguably part of the nature of science, but it may not always be necessary and it does make machine learning more daunting for those without a background in the discipline or without the required resources.

In terms of adaptation tracking, some of the findings align well with the prior paper, including the under-representation of some of the most vulnerable regions in the world. In this second effort, the focus was on policies, and policy-related findings also broadly confirm to expectations. In line with the adage that adaptation is local, regional priorities were broadly reflected in the results of the topic model; furthermore, national- and sub-national level policies made up the majority of evidence, while international policies play a facilitative role by supplying funds and frameworks.

The most surprising and worrying results are around the Paris Agreement. The expectation was that implementation-related topics would be increasing substantially, with the Paris

Agreement ushering in a time of climate action; given the overall growth of the evidence base, there is some evidence for this in an absolute sense, but the relative importance of most policy- and implementation related topics did not increase significantly post-Paris. Also notable were the gaps in evidence: topics such as maladaptation and co-benefits, as well as systemic and transformational change, are the subject of considerable debate in the adaptation community, but this does not appear to translate into policies and policy evaluations (Adger et al., 2022, Berrang-Ford et al., 2021a).

UNFCCC reporting is political and shift to climate action is dubious

In the third paper, the main methodological difference is the choice of dataset – UNFCCC reports instead of scientific papers. Because these reports are often written by policy makers (e.g. ministries of environment), intuitively, this should result in findings that more closely relate to climate policy. In practice however, this political dimension is likely to be as much a hindrance as it is an advantage. Countries appear to use these texts as the basis for international negotiations, making them useful for identifying regional priorities, but equally making it difficult to distinguish between what is intended or desired versus what is actually made law or implemented.

Especially compared to the preceding paper, the methods used here are not novel. Word-count statistics in particular are relatively old, but interestingly, prove quite useful for documenting broad trends. Although they are less suitable for more complex inquiries, they are an easy way to quickly explore basic questions. This further bolsters my argument above that sometimes a "good enough" approach may be preferable over one that uses the lasest generation of machine learning methods.

Also in line with the previous paper, evidence for a shift towards climate action in the Post-Paris era is mixed at best. In part, this may be because of the dataset as the last two years were not included in the dataset. It is less clear to me what the choice to focus on executive summaries means in this regard: on the one hand, executive summaries will highlight politically salient points, which may encourage some countries to emphasise how much more needs to be done in an effort to put pressure on the political negotiations; on the other hand, the reports also function as an accountability mechanism towards donors, and countries will likely want to present themselves in the best light, both of which would suggest that the executive summaries should stress any climate action taken. Either way, information from Southern countries is generally less frequent. Increased reporting requirements under the Paris Agreement may help overcome this, but, given the difficulties many Southern countries currently have with reporting regularly, this will require additional support from the North. Without such support, UNFCCC reporting will continue to struggle to capture climate action in the most vulnerable regions.

First-generation machine learning applications show room to grow

In the fourth paper, I reflect on my own experiences and synthesise evidence from what I call the "first generation" of machine learning applications for adaptation tracking. I use this to make suggestions on how such applications can be made to work in practice, resulting in three key arguments: 1) this first generation broadly speaking has proven that machine learning can be of added value, though these efforts also share some common problems; 2) overcoming these problems will require efforts at a larger scale than the currently common insular proof-of-concept projects; and 3) to truly capitalise on the advantages of machine learning, a more radical departure from business as usual will be required.

The key advantage of using machine learning is that it enables large-scale projects that still address nuanced questions. Especially for projects that are big by manual synthesis standards, but small-to-medium by machine learning standards, user-friendly tools are also increasingly available, leading to real time savings. Unsupervised methods are increasingly easy to use as well; topic models in particular have shown to be a broadly reliably method for exploring and synthesising large volumes of texts, and they can form the basis of more complex analyses and insights too. These advantages are key in the age of Big Literature.

More critically, in theory, machine learning could also help address data gaps, but efforts to date are rarely used for this purpose, focussing instead on the same few data sources. Similarly, large-scale evidence synthesis projects are too often solely descriptive, which limits their added value compared to more targeted, inquisitive approaches that are also possible with machine learning methods. Further, biases in the data are often not addressed explicitly (Frampton et al., 2022), let alone investigated systematically. Current projects are too small to truly address these issues. Authors need to build on prior efforts, but this is difficult to do if the broader field of adaptation research still sees machine learning as an unproven tool for future use. A machine learning "community of practice" needs to emerge within adaptation research so that more ambitious projects can tackle the underlying issues uncovered by the first generation of machine learning-assisted adaptation tracking.

Finally, I note that the first generation of studies generally aims to integrate machine learning into existing approaches. Machine learning is particularly well-suited to repeating the same task, so a machine learning pipeline could be used as the basis for a living evidence platform. If large and ambitious projects do emerge over time, for example platforms that categorise and synthesise different data sources automatically, it is particularly important for adaptation that local and specific attributes of evidence still remain accessible. In simple terms, users should be able to zoom into a particular area of the overall literature landscape. I propose interactive figures as a means to this end. More generally, a paradigmatic shift will require the support of one or a few large players. A large flagship project could be both a service to the community and an impetus for new high-quality research.

6.3 Recommendations

Recommendations were scattered across my final paper, and some have been mentioned again in the above. Subsequently, I will expand upon some of these recommendations, as well as mentioning a few others in a more structured manner. I will start with the smaller suggestions, mostly for academia. Some current problems however would require more structural changes, which I will discuss afterwards.

Further research: data and technical tools

Data lie at the core of the most immediate problems for adaptation tracking. The two best-explored data sources are used in this thesis too; they are the various documents of the UNFCCC (Biesbroek et al., 2022, Genovese et al., 2022, Lesnikowski et al., 2019a, Valero et al., 2022) and academic databases (Berrang-Ford et al., 2021a, Giupponi and Biscaro, 2015, Sun et al., 2022), while some city-level collaborations have also produced substantial adaptation-relevant datasets (Lee et al., 2020, Hsu and Rauber, 2021, Abarca-Alvarez et al., 2019). Problematically, all these data sources have limited coverage in similar places, most notably highly vulnerable countries and communities in the Global South. There are three main ways this could be addressed in the near future:

The easiest, but also least-impactful option is to use alternative literature databases which include more grey literature; Google Scholar for example has a much broader coverage than either Web of Science or Scopus, even if its search functionality is strictly speaking too limited for systematic literature reviews (Gusenbauer, 2022, Gusenbauer and Haddaway, 2020, Haddaway et al., 2015). Other databases, such as Dimensions or Lens.org, cannot compete in terms of academic coverage (Harzing, 2019), but do incorporate factors like Wikipedia citations and offer functionalities like searching for related literature based on abstracts and scholarly networks which can help searches be more comprehensive (Gusenbauer, 2021). Moving away from academia, high-quality databases also exist for newspaper articles, including ProQuest (Ford and King, 2015) and projects that automatically extract information from newspapers. A prime example of the latter is the Global Database of Events, Language and Tone (Leetaru and Schrodt, 2013), which automatically translates news stories and then uses further NLP techniques to link articles to specific events; this may be especially helpful for analysing the response climate-related disasters (Lu et al., 2022).

Secondly, finding and collating new data sources independently is also an option. As mentioned, some UNFCCC documents have been analysed relatively extensively already, but there also public reports from bodies within the UNFCCC family that to date have received no attention, including technical reports to expert bodies such as the Paris Committee on Capacity Building and the Technology Executive Committee, as well as data from the so-called "financial instruments": the Global Environment Facility, the Green Climate Fund and the Adaptation Fund. Further, other United Nations agencies also publish on adaptation-related topics, most notably the UN Environment Program (UNEP), but also the UN Development Program (UNDP), World Health Organization (WHO) and the Food and

Agriculture Organization (FAO). One might expect there to be a database of all these documents, but the closest analogue are the UN search engine (search.un.org) and the UN's Official Document System (documents.un.org/prod/ods.nsf); however, neither allow bulk downloads. Still, depending on the chosen focus, the number of documents may well be small enough to download the reports manually within a reasonable timeframe. This also holds for multilateral and regional development banks. They have received some interest in the context of adaptation finance because they also fund adaptation projects (Fujikura, 2022, Savvidou et al., 2021), but their qualitative reporting has, to my knowledge, not been assessed at scale, even though this could help coverage in the Global South especially.

Finally, web crawlers can also be used to create new datasets. Such crawlers can go through extensive lists of web addresses and extract text data. They are rarely used in an adaptation context, but there are examples from climate change research more broadly, mostly to study public opinion – e.g. based on blogs (Elgesem, 2019) and comments on news websites (Lörcher and Taddicken, 2017) or forum posts (Jiang et al., 2018). Planas et al. (2022) however point out that web crawlers could also extract policies or policy-relevant information from government websites. For adaptation tracking, such a proposal still requires an extensive list of government websites, and even then, digital records are likely still unevenly distributed. Regardless, it could provide a meaningfully different view of adaptation in practice.

Importantly, the proposal of Planas et al. (2022) combines a web scraper with a variety of other NLP tools to create a complete policy analysis pipeline. This also includes automatic translation for non-English sources, as well as a summarizer to create information-dense texts and supervised learning – more specifically, named entity recognition – to extract geographic locations, people or the names of policies. This information would then be combined in a "knowledge graph", where key attributes of each text are stored. The sum of these efforts would be a central platform for all environmental policies.

While this is not as straightforward as the authors imply (see Structural changes below), I agree that many NLP tools are under-utilised by the environmental science community in general, and the adaptation community in particular. The value of machine translation and multilingual methods is worth underlining, as it could help fill common data gaps. This is especially true for policy studies (e.g. Biesbroek et al., 2022, Le, 2020), given that policies are typically published only in the local language. Translation, one could argue, is of limited added value for academic evidence mapping, given that only a tenth of publications in major databases are not English (Albarillo, 2014) and findings of systematic reviews typically remain the same when non-English articles are excluded (Nussbaumer-Streit et al., 2020). However, this argument does not translate across disciplines: smaller studies, projects conducted by local communities, as well as studies showing a limited effect of an intervention are more likely to be rejected by traditional publishers, introducing a systematic bias that may be especially problematic for environmental topics (Konno et al., 2020), including adaptation.

For many other NLP tools, the added value for academic inquiry may be less clear. What to think for example of generative AI, such as ChatGPT? A properly designed AI "co-pilot" may make it easier to write computer code (Cheng et al., 2022), but it is less well-equipped to generate critical and novel insights (Bender et al., 2021). Personally, I believe many of these tools will be especially useful towards end-users. For tasks like question answering, LLMs are proving to be a massive step forward (Hu et al., 2023, Zhao et al., 2020); if the climate change community can make sure the answers are transparent and based on reliable sources (Vaghefi et al., 2023, Pride et al., 2023), this could be a relatively intuitive way for even the lay public to interface with climate science.

If the current rapid developments in AI truly represent a paradigmatic shift, most likely, some uses of these tools will only become apparent with experimentation and time. There is a balance to be maintained here: if methodological experimentation is not goal-oriented, it can become a "method in search of a problem" (Kolb, 1991, p. 40). The adaptation community however, does not appear at risk of swerving too far in that direction, given that only a few dozen studies out of many thousands use any kind of machine learning at all. In other words, if all you have is a hammer, every problem will look like a nail; however, if you ignore the existence of the hammer despite other people around you using it, it becomes unnecessarily difficult to hit the nail on the head.

Further research: adaptation tracking

In addition to further exploring such technical tools, adaptation tracking researchers also should continue to strive towards the 4 C's of adaptation tracking (Ford and Berrang-Ford, 2016). Comparability appears to be an especially pressing problem. I propose three main avenues for further research.

First, adaptation researchers could address comparability within the primary data. More specifically, adaptation projects are generally individual interventions without a control group. This makes it especially hard to determine how different contextual variables influence outcomes (Berrang-Ford et al., 2021a, Biesbroek et al., 2018, Swart et al., 2014, Hunt and Watkiss, 2011). Similarly, longitudinal *ex-post* evaluations are rare (Owen, 2020): typically, a project is funded for a few years, which may be followed by an evaluation, but this is not a good indicator for an adaptation's long-term success (Mills-Novoa, 2023). In simple terms, the best way to disentangle why adaptations work in some places and not in others, is to either try the exact same approach in different places, or to try different approaches in the same place, and evaluate the results over a longer period of time. This would require a large investment, as long-term funding for multiple projects would need to be released together – but it may well be more efficient in the long run, as the results will be more informative than if the same funds were spent on individual projects.

Second, adaptation is sometimes presented as being uniquely context-dependant (Dilling et al., 2019, Eriksen et al., 2021), but many of the same issues that lead to low comparability within adaptation science are also common in other fields, including other environmental disciplines, but also for example parts of psychology and economics. These fields have longer histories, in which they have developed methods and tools to draw conclusions and synthesise knowledge regardless of the heterogeneity of the evidence; the adaptation community could benefit from adopting some of these practices. Systematic reviews are one such example, having shown to be of added value outside of their original medical sciences context, including adaptation (Berrang-Ford et al., 2015).

Similarly, adaptation scientists could borrow from political sciences to analyse and compare adaptation policies. To give but one example, the IPCC highlights that institutional factors often form a barrier to the effective implementation of adaptation (Ley et al., 2022). That in itself however is hardly actionable; political scientists have long since developed a shared understanding of specific institutional factors, as well as means to evaluate the alignment between specific policies and their institutional context (Njuguna et al., 2022). In my second paper, I took some steps towards embedding adaptation policy analysis into wider political science (building on: Henstra, 2016, Lesnikowski et al., 2019b). It would be interesting to extend this analysis by a) comparing the findings to a similar analysis for mitigation; and b) further investigating what national characteristics could be responsible for the observed differences.

This leads me to the third point: developing common standards – or at least, common understandings of what different standards mean. To be consistent, adaptation tracking should use a single understanding of adaptation. However, it is not clear what the consequences of choosing a particular perspective are in practice. Efforts to disentangle the different meanings of adaptation usually study which communities have adopted different concepts (Dewulf, 2013, Nalau et al., 2021, Calliari et al., 2020). It would be beneficial to the tracking community if this process could be flipped – i.e. given a list of potential characteristics of adaptation *a priori*, how do each of these choices influence the quality and quantity of evidence, funding and/or adaptation projects?

To give a practical example, one could take the 8 adaptation heuristics of Preston et al. (2015), which state that adaptation can be described as 1) local, 2) novel, 3) urgent, 4) participatory, 5) proactive responses to predictions, 6) win-win or no-regrets, 7) reactive, or 8) a means to handle residual risk after mitigation. These heuristics are not mutually exclusive and some may need refining to be operationalised (Nalau et al., 2021), but they should provide a good starting point. Then, a supervised model can be trained for each of the categories and applied to a systematic query, much like the first two papers of this thesis. The information may not always be available in the abstract, so it could be that for this proposal to work, one would also need to consider full texts. Still, the resulting evidence maps should provide some insight into how different types of adaptation definitions are used in practice and how meaningful the differences actually are.

So far, my suggestions can be seen in the light of a long-standing debate between those who maintain that adaptation research should strive to become more scientific, and those who emphasise the value of practice-led adaptation research (Swart et al., 2014, Moss et al., 2013, Füssel and Klein, 2006, Smit et al., 1999). Tracking efforts in particular would benefit from a more uniform approach to adaptation, so it is perhaps unsurprising that in the above, I mainly argue in favour of more scientific rigour. To be clear however, I am not advocating for an adaptation science that is strictly standardised, quantitative and orchestrated top-down. As I noted also in my first paper, many adaptation researchers value close connections to practice because they want to make a practical difference, especially for vulnerable communities; an exactly delineated definition is not needed to do this work, so it makes sense to focus on obtaining results on the ground, rather than on developing or choosing theoretical frameworks (Swart et al., 2014).

However, if no explicit adaptation framing is chosen, it is implicitly defined, often by the funders of the project, which can lead to maladaptive outcomes by emphasising Northern perspectives on development over local needs (Eriksen et al., 2021). In short, the exact definition of adaptation is a political choice, but that does not mean that researchers can avoid making this choice altogether. Researchers should state their choices explicitly, while striving for scientific objectivity and rigour where possible. This would help tracking, but more broadly, it would make the relevancy of any adaptation results easier to interpret.

Structural changes

Many of the major issues highlighted in this thesis ultimately require structural solutions that go much beyond the purview of any one researcher or discipline. In particular, I will expand upon two ideas I introduced in my final paper, namely the role of journals and that of funding bodies and governments, especially in their potential support for a living evidence platform.

Journal articles are the *de-facto* standard for academic publishing on climate change. Notably however, for computer science, the focus has long since shifted from journals to conference submissions (Freyne et al., 2010) and more recently, pre-prints and other public repositories (Hook et al., 2019). One reason for this is simple: journal timelines are unable to match the rapid speed of developments in the computer science field. If a submission takes a few months to get through peer review before it is published, the true cutting edge in machine learning may well have moved already. Pre-prints especially became a more common fixture for other research fields too during the COVID-19 pandemic (Else, 2020, Wittkopf et al., 2022). Journals, for their part, are increasingly offering pre-prints as part of their publication process now too. All of which is to say that the academic publishing industry can feel archaic and conservative, but it is able to change when put under sufficient pressure and when alternatives are readily available.

Publicly available pre-prints however, are but one aspect of how academic publishing should keep up with the times. Sopinka et al. (2020) for example, in their description of a “scientific paper of the future”, highlight various recent developments that journals could adopt, including freely accessible data and analytical code, possibly leading to interactive visualisations, as well as living evidence reviews, better representation of under-privileged groups, plain languages summaries and alternative metrics for impact. Especially the first few suggestions appear useful in the context of Big Data. In the interest of open science, making one’s computer code open source is a good first step, but it is also possible to share whole programming environments (e.g. through a docker image) or runnable “notebooks,” complete with explanations and runnable on an easily replicable virtual machine (Mendez et al., 2020, Hollaway et al., 2020), as well as machine learning models (Li et al., 2021), which would make it easier for researchers to build upon prior work. I have already discussed earlier how interactive figures can allow readers to make Big Data analyses more useful by selecting the components that are most important for their use cases and highlighted how living evidence practices could be transformational.

It is difficult to assess how quickly such changes could be adopted and my research does not address that question directly, so I will keep my discussion brief. If we take images as an example, there have been experiments with alternatives to static 2-dimensional figures for well over a decade, which, so far have received limited uptake in academia (Ard et al., 2022). Still, Figshare is a relatively well-established repository, and interactive figures are possible here already (Hyndman, 2019). Similarly, advocates for open science have long advocated for including executable code as part of scientific publications (Kauppinen and Espindola, 2011) but this is far from the norm. At computer science conferences however, it is increasingly common to use platforms like Google Colab or Binder. These types of services may not be sufficient for large machine learning models, but they can easily handle more basic data exploration (Carneiro et al., 2018) and would be relatively simple to integrate into digital publications, so perhaps computer science conferences could serve as an example.

Overall, changes to make academic publishing more suited to the Digital Age *could* come quickly – the tools are technically feasible and have been broadly tested. By themselves, those changes are therefore not structural, but incremental. The reason I discuss them here, and at some length, is because I believe that, taken together, they would greatly help increase the "machine learning literacy" of the climate change community. Not everyone needs to be fully proficient in a programming language, but it is possible to lower the barrier of entry enough that everyone who wants to can understand and apply basic data science methods. This may read like a catch-22 situation: if there are no users of these innovations, the journals have no reason to implement them, but without regularly encountering and using those tools in their own academic environment, there will not be many users. However, big publishers have journals for a wide range of audiences, including those with an established machine learning community. They may wish to incorporate some of the above suggestions for those journals first and then extend their use more widely over time.

My argument for a centralised living evidence synthesis platform follows a similar logic: if one institution can create such a platform, they could in the process set the gold standard for NLP applications in adaptation and broadly demonstrate how computer-based methods can be of added value, which may inspire others. This, of course, in addition to the primary benefit of having a trusted, current and shared source of adaptation evidence. Moreover, here too, the tools to build a comprehensive pipeline are technically feasible: one could combine a variety of supervised learning algorithms to pre-select different types of literature with unsupervised algorithms to provide an overview of the selected literature, as well as pre-trained named entity recognition models so these selections can be made at a granular level with relative ease (Planas et al., 2022). The Global Adaptation Mapping Initiative (Berrang-Ford et al., 2021a) is perhaps the closest project to date in this direction, as it has shown that a computer-assisted global evidence map can be the basis for many other more focussed analyses (Zvobgo et al., 2022, Scheelbeek et al., 2021, Leal Filho et al., 2022). Still, while this shows the value of the underlying data, the dataset is not easily accessible or searchable, nor is the data being updated. Moreover, even with these limitations, the project already required the help of over a hundred adaptation researchers. The central problem for establishing such a platform therefore is organisational: who would have both the sustained funding and the broad trust of the scientific community to create a broadly supported evidence platform, especially given how politically sensitive some adaptation issues are?

In my paper, I suggest that the IPCC may take up this role. The main reason for this is the IPCC's established reputation as the central but independent authority on climate research. Its close proximity to the UNFCCC process and recognition by practitioners would help ensure that an evidence platform – should it be established – is also used in practice. However, this same proximity to politics also brings practical problems. Presently, every IPCC report goes through multiple rounds of comments and the Summary for Policymakers is even approved line by line by governments. This process allows governments to some degree to control the narrative, although it should be noted that many comments are technical and constructive in nature (Palutikof et al., 2023). Changing the IPCC's assessment practices to incorporate machine learning and living evidence reviews would mean that its member countries can no longer assess all of the body's outputs. So far, the IPCC has mostly moved towards more control, not less (De Pryck, 2021), so my proposal may not have a high chance of succeeding. Still, with the IPCC's 6th assessment period coming to a close, now would be an opportune moment to establish such new initiatives and there appear to be few, if any, other ideas on how the Panel will be able to assess the full scope of climate literature (Callaghan et al., 2020, Minx et al., 2017, Kelman et al., 2022).

There are of course other institutions which could take on this role. The United Nations Environment Programme (UNEP) for example is already involved with the adaptation gap reports (UNEP, 2022). The Organisation for Economic Cooperation and Development (OECD) generally has a more limited geographical coverage, but they already collect data on overseas development aid (OECD, 2022), as well as climate-specific multilateral finance (OECD, 2023) and these data are regularly updated. Either way, sustained funding and long-term political support would be a pre-requisite for making any central adaptation data platform a success.

Finally, I am aware that adaptation finance is in short supply – or at least, that the "adaptation finance gap" continues to grow (IPCC, 2022). The adaptation community needs to prioritise its resources, yet I am unsure how to weigh the costs and benefits of more up-to-date and more accessible adaptation evidence against those of, say, coastal defence measures. Certainly, the benefits of the latter are more direct and more tangible and I do not wish to minimise the need for such adaptations. Rather, what I argue here, is that there are machine learning methods available that could make the process of knowledge discovery and synthesis in the adaptation field more efficient, more transparent and more inclusive, all at once. The benefits of that might be indirect, but they will only become more relevant if the pace of adaptation knowledge production continues to accelerate.

6.4 Conclusion

Before I make my concluding remarks, it is first worth reiterating the central problem I tried to address in thesis: keeping track of adaptation evidence is both increasingly difficult and increasingly urgent; however, to be useable, adaptation tracking should be both general and specific at the same time – that is to say, tracking efforts aim to provide a large-scale overview that is consistent, comparable and comprehensive, while still being sensitive to contextual factors and conceptual differences within the field (Ford and Berrang-Ford, 2016). In theory, this is exactly where machine learning excels: making decisions that human-like in their nuance, but at a large scale (Nunez-Mir et al., 2016, Zhong et al., 2021). Broadly speaking, in this thesis, I show that such an approach can also work practice, but in places, the complexity and ambiguity inherent to adaptation research also stretches current machine learning to its limits.

Cynically, I could conclude that by adopting machine learning methods, we are replacing one problem with another, going from having too much data to lacking structured and specific data. This is especially pressing for supervised learning methods: they can reliably make broad distinctions in large datasets, but they can struggle with more specific questions, as finding or creating enough training data is difficult. For some questions, it likely is impossible at present: while exact numbers will differ, as a rough estimate, a model can start making sufficiently exact predictions with around 100 positive examples to learn from, but that may well be the entire extant literature on a given question. If one would use unsupervised methods to tackle the same problem, one would not need to spend time finding and creating the training data, but it is still likely that the literature is too small and too similar to related topics, so the model will struggle to identify the relevant clusters. Frustratingly, it is exactly those specific questions that are of most interest to many adaptation researchers and practitioners (Leiter and Pringle, 2018, Magnan et al., 2020).

One response to this is that we should simply ask different questions. As I have argued, research to date often tries to integrate machine learning applications for adaptation into business-as-usual. Some of the classifiers I used certainly fall under this category as well: I am essentially asking the model to assume the role of a researcher in a literature review. While this worked in places, often, the more interesting findings came from playing to the method's strengths. In particular, combining different models into one pipeline proved fruitful (see also for example Callaghan et al., 2021). Linking location data with topic model results for example often gave interesting results, highlighting both regional priorities and research gaps by comparing the research within a region to all research globally on the same topic.

Similarly, the scale at which machine learning tends to work lends itself well to testing broadly held assumptions. The results here were often unsurprising in the sense that most assumptions proved to be true or plausible – I do not think any adaptation researcher is surprised for example that peer-reviewed research is scarce in many of the most vulnerable countries. This is an old problem that is deeply rooted in larger structures of inequality. Importantly however, with machine learning methods, such problems can be quantified and monitored.

Moreover, it should be noted here again that I, like most other adaptation tracking efforts, relied on data that is relatively well-studied. Finding something surprising here is simply not that likely. Data science methods such as webscraping here remain largely under-utilised and could help address some of the structural (data) inequalities that remain prevalent in adaptation research generally (Lahsen et al., 2010, Newell et al., 2021), and adaptation tracking in particular (Berrang-Ford et al., 2021a, Biesbroek et al., 2018, Garschagen et al., 2022).

Machine learning can also play a more facilitative role, especially for evidence synthesis efforts (Nakagawa et al., 2019). Researchers interested in questions that are too detailed to answer with current computational methods could still use the broader categorisations to find additional literature for example. Although machine learning tools are increasingly being integrated into scientific databases, the climate change community has specific needs too that general platforms are unlikely to meet. While it seems entirely plausible that the major scientific databases will start using geoparsers to allow users to select research taking place in specific countries, it seems less likely that they will also allow users to select research from coastal regions to name but one example. A climate-specific living evidence platform with such functionalities would be a considerable service to the community. Although the first generation of machine learning applications for adaptation laid bare a number of methodological issues and open questions, their results are also encouraging enough to warrant an ambitious effort, using the latest models and methods to make climate science more accessible and review processes more transparent.

Perhaps the largest argument to continue with the current line of inquiry however, is the lack of realistic alternatives. Adaptation tracking using manual methods such as the Adaptation Gap Reports certainly is useful, and those efforts should continue. Even so, unless the quality of data drastically improves – which is possible, but perhaps not likely under the Paris Agreement – these analyses to me seem destined to repeat similar findings. Again, these findings are useful, but they cannot tell the whole story. Analysing and synthesising diverse adaptation data at the global level remains challenging and this trend will likely only intensify.

Conversely, machine learning methods are rapidly getting better. Given firstly those improvements, secondly, the relative dearth of machine learning applications for adaptation to date, and thirdly the cautiously optimistic results from the few applications that do exist, it seems this is a fruitful direction for further research. In light of the accelerating impacts of climate change, it is a necessary one too.

In sum, both machine learning and climate action are at an inflection point, so the decisions we make now will have lasting consequences. I hope we choose wisely.

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