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Gil-Clavel, Sofia; Wagenblast, Thorid; Akkerman, Joos; Filatova, Tatiana

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Review

Patterns in reported adaptation constraints: insights from peer-reviewed literature on floods and sea-level rise

Sofia Gil-Clavel[1,2,*], Thorid Wagenblast[1,†], Joos Akkerman[1,‡] and Tatiana Filatova[1,§]

Understanding climate change adaptation constraints for different actors — governments, communities, individuals, and households — is essential, as adaptation turns into a matter of survival. Though rich qualitative research reveals constraints for diverse cases, methods to consolidate knowledge and elicit patterns in adaptation constraints for various actors are scarce. Therefore, this work analyzes associations between different adaptations and actors' constraints to climate-induced floods and sea-level rise. Our novel approach derives textual data from peer-reviewed articles (published before February 2024) by using natural language processing, thematic coding books, and network analysis. The results show that social capital, economic factors, and government support are constraints shared among all actors.

Addresses
[1] Faculty of Technology, Policy and Management, Delft University of Technology, Jaffalaan 5, 2628 BX Delft, the Netherlands
[2] Vrije Universiteit Amsterdam, Faculty of Communication Science, De Boelelaan 1105, 1081 HV Amsterdam, the Netherlands

Corresponding authors: Gil-Clavel, Sofia (B.S.GilClavel@vu.nl, B.S.GilClavel@tudelft.nl), Filatova, Tatiana (t.filatova@tudelft.nl)
[*] https://orcid.org/0000-0003-4707-849X
[†] https://orcid.org/0009-0003-5324-3778
[‡] https://orcid.org/0009-0000-7877-9788
[§] https://orcid.org/0000-0002-3546-6930

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Introduction

The climate crisis is one of the most pressing challenges of the 21st century. The committed economic losses due to procrastination on climate mitigation are so dear that climate change adaptation (CCA) becomes a matter of survival [1]. Whether or not we will be able to successfully adapt will make a big difference [2]. Therefore, CCA increasingly becomes a priority for governments, communities, individuals, and households worldwide. CCA encompasses a wide range of measures ranging from soft to hard and taking a form of either incremental or transformational responses [3]. Despite CCA being critical for climate-resilient development, massive adaptation gaps are reported at the country and continental levels [4,5], and significant adaptation deficits — that is, lower adaptation than would be optimal — at the individual and community scales [6,7].

These adaptation gaps can be attributed to various adaptation constraints. Such constraints arise from a wide range of factors, such as physical, ecological, social, economic, financial, educational, technological, and governance [8–10]. Furthermore, the prevalence of these constraints is specific to the adapting actor or the location of the climate impact [8,11]. This specificity of the constraints can also be seen in the rich empirical evidence on CCA [4,10], which reports a wide range of adaptation constraints and drivers that play out for different types of CCA performed by various actors in diverse (geographical) contexts.

While there is rich literature eliciting the adaptation behavior of various actors and their diverse constraints across geographies, this knowledge is fragmented across disciplines and is largely qualitative. This makes it difficult to systematize globally and to identify any generic patterns across locations. Furthermore, scientific understanding of which adaptation constraints and drivers manifest for different actors is hindered by a lack of open-access standardized databases that could allow multilevel analysis across actors. Nevertheless, understanding which constraints manifest for different CCA measures and actors is essential for the design of effective CCA policies as climate-induced damages accelerate.

The challenge of gathering and analyzing information on CCA constraints and limits is approached from different angles. Reviews like Thomas et al. [10] or Biesbroek et al. [12] systematically extract articles and rely on people reading the full texts and encoding those in databases. With these databases, they provide an overview of barriers in various categories (e.g. institutional or social) and their origin (climate vs nonclimate related). It is in this context where machine learning (ML) is a cost-effective way to automatically annotate text. As such, ML has been used to identify CCA-relevant corpuses of publications [13,14] and to track where and how CCA is taking place [13]. This is done by training classifiers that help speed up filtering out irrelevant articles and to detect and assign variables' values depending on the text. Another way to study CCA consists of gathering empirical data to estimate adaptation constraints [15]. Adger et al. [16] start with statements on the CCA topic and complement them with insights from, among others, history, sociology, and economics, concluding that culture, social values, risk, and knowledge shape CCA limits. Such insights can then be used to inform simulation studies. For instance, agent-based models can be calibrated using empirical findings and micro-data (see e.g. [6]), which are increasingly available. This allows exploring how individual adaptation constraints (awareness, social norms, and so on besides pure economic constraints) dynamically interact with the wider system and affect aggregate outcomes, like regional residual damages and their distributional impacts [7].

The combined use of ML and simulations is already helping to predict climate and forecast extreme weather events, as well as to identify and leverage relationships between climate variables [17]. This is because ML helps to build (simulation) models that continuously learn from regularly generated sources of data (e.g. satellite images). However, ML falls short when the aim is to elicit more nuanced information on the relation between CCA measures and different economic, demographic, and psychological factors. It is here where tools like natural language processing (NLP) can be exploited, which, despite their great advantages, to our knowledge, there are few works using NLP to study CCA [18].

This paper aims to bring new insights from the recent empirical literature on adaptation constraints by analyzing the associations between different CCA measures and factors (constraints and drivers) of various actors: governments, communities, or individuals and households. Specifically, we derive a database of qualitative findings from peer-reviewed articles, published before February 2024, using a novel algorithm grounded in NLP. We analyze the elicited connections between actors–adaptations–constraints using network visualizations. Our analysis is focused on CCA to floods and sea-level rise (SLR). Among all climate-induced hazards, we focus on different types of floods — pluvial, fluvial, and coastal — which are the costliest and most widespread worldwide, accounting for 69% of all global damages [19], making it important to understand which constraints to adapt to them manifest for what type of actors. Furthermore, climate change is observed to increase the extent, frequency, and intensity of flood events. This increased impact of flooding is projected, in combination with socioeconomic developments, to increase global damages by a factor of 1.2–1.8 (4.–5.) for 2°C (4°C) of warming with respect to 1.5°C, with even higher damages under no-adaptation scenarios. A large share of the increase in damages is concentrated in lower-income countries, with Africa and Asia being particularly exposed [20]. This showcases the need for additional adaptation action, and as such, it is important to understand which constraints manifest for what type of actors.

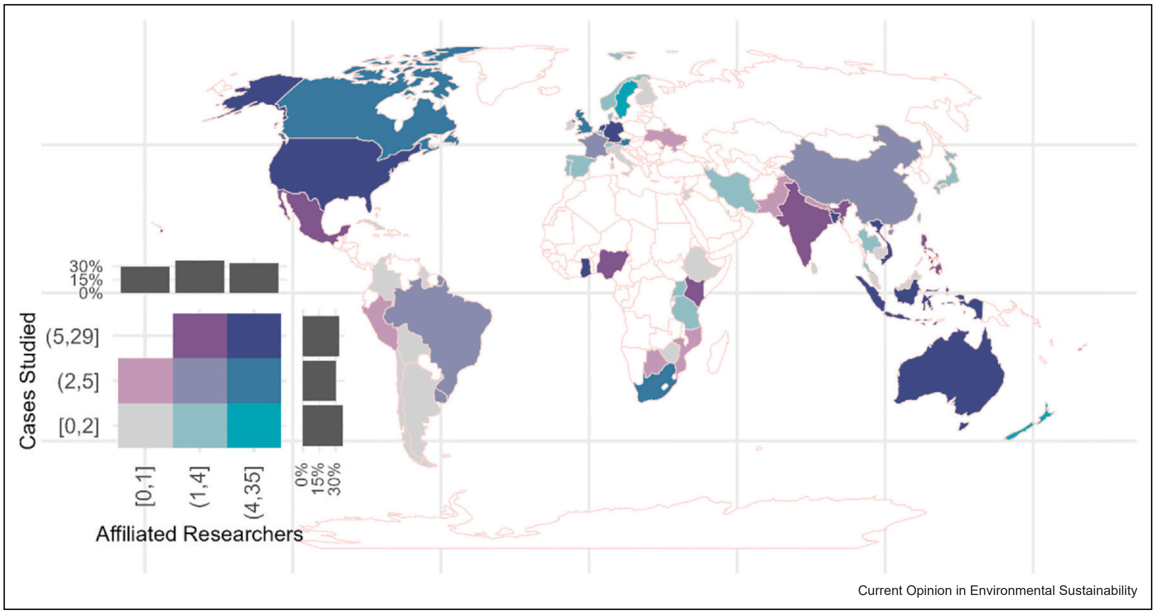
Data and methods

To identify articles potentially useful for the database, we combine a systematic literature review with unsupervised and supervised learning [21]. This delivered us a database with 240 articles that are about floods and SLR. Leveraging on the power of ML and NLP, we were able to screen the entire text of the articles (contrasted with abstracts/keywords/title only typically done in bibliometric analysis) to extract relationships between measures and factors[5] instead of the conventional terms counting. This enabled us to screen large amounts of qualitatively reported relationships between various constraints and CCA for various actors. Appendix B contains detailed data and methodological explanations.

Figure 1 shows the number of affiliated authors and the count of articles researching cases in each country (see Appendix B for their derivation). To allocate countries, we assigned countries' number of affiliated authors and article cases to their respective quantiles. The quantile intervals are [0,0.33], [0.33,0.66], [0.66,1]. Figure 1 shows that many Western European and Anglophone countries belong to the upper quantiles. This indicates researchers and cases based in Anglophone countries are more heavily represented in the literature. This bias could be due to our use of English articles from Scopus [22]. However, the data set also contains highly researched nations in Asia (Indonesia, Bangladesh, and Vietnam) and Sub-Saharan Africa (Ghana, Kenya, and South Africa). While the currently available literature unequally treats different nations, the current data set does contain findings on multiple (vulnerable) regions and

[5] In this context, a factor is understood as a variable that either drives or constrains the adoption of a CCA measure (Appendix D provides the full list of factors identified in our search). Empirical and theoretical work on CCA has identified many factors that could potentially affect CCA decisions. As we show later in the manuscript, we relied on previous classifications.

Figure 1



Distribution of articles about CCA to floods and SLR by researchers' affiliation and cases studied. Categories represent the quantiles [0, 0.33], (0.33, 0.66], and (0.66, 1]. The gray histograms represent the percentage of countries in each category.

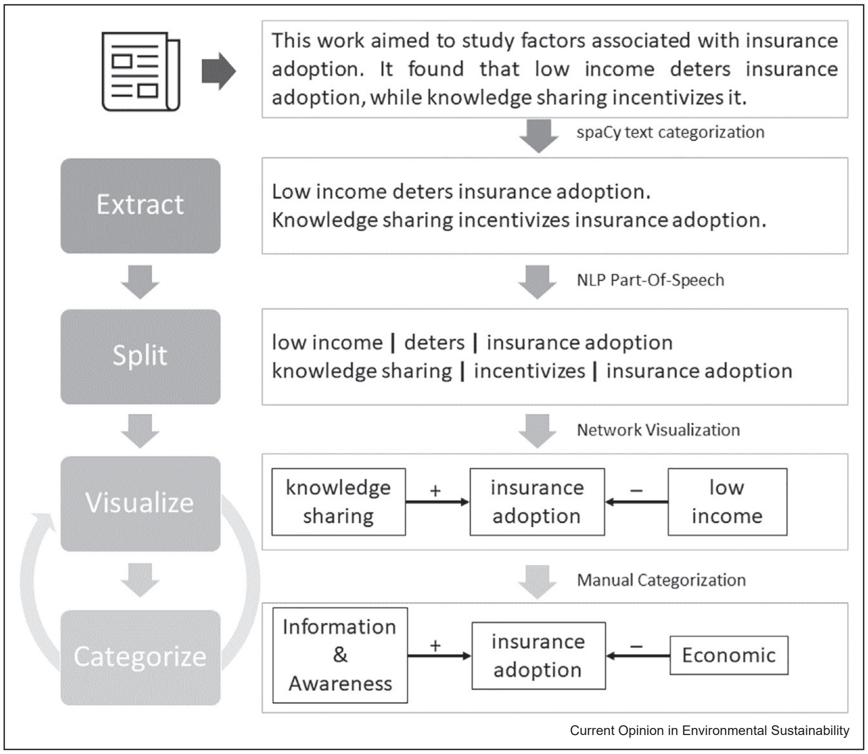
can therefore capture adaptation constraints in a wide range of socioeconomic circumstances.

Since we aim to give insights into flood and SLR adaptation constraints that different actors face, we classify the articles depending on who is adapting or is supposed to adapt. Following the Intergovernmental Panel on Climate Change [20], we define three types of actors: Government (GOV), Communities (COM), and Individuals&Households (IHH). Governments represent various formal institutional actors that play a crucial role in providing both 'hard' protection measures and infrastructure and 'soft' measures like financing and information provision. However, public government-led CCA is often insufficient [23], making understanding private CCA a key priority [4]. Furthermore, adaptation is inherently local requiring elaborate knowledge of local conditions and actors. At local scales where adverse climate-induced impacts manifest, COM are important facilitators of collective location-specific and inclusive adaptation action. This also holds for IHH who adapt their own properties, physical environment, and practices to local idiosyncratic circumstances. To differentiate between actors, each member of our team independently categorized articles attributing CCA to specific actors and refined the labeling during a thorough cross-check procedure finalized with the label agreed upon by the majority. From here, 83, 76, and 39 articles were classified as IHH, GOV, and COM, respectively. The last 42 covered multiple actors or levels of participation; therefore, they were classified as belonging to all categories.

Our methodology analyses the abstract, results, conclusions, and/or discussion of the 240 articles. For this, we follow four steps (Figure 2, Appendix B contains a more detailed explanation). First, to *Extract Findings*, we trained a spaCy text categorization model [24]. Second, *Split Sentence* refers to extracting the subject, verb, and object from each finding following Ref. [25]'s algorithm. This algorithm extracts the subject, verb, and object from the sentences using parts of speech. The algorithm transforms the subject and object into network's nodes, and verbs into links, marking the type of relation between the nodes (positive, negative, or neutral association). For example, the sentence 'knowledge sharing incentivizes insurance adoption' would be transformed into two nodes connected by a positive link. A positive link implies that a factor is a driver of CCA, a negative link denotes a CCA constraint, and a neutral link may mean both depending on specific context or conditions.

Finally, to *Categorize*, we visually inspect the networks to find the measures and factors associated with CCA to floods and SLR. In general, it is always good to start this iteration by already having a research-informed dictionary (our dictionaries of measures and factors are in Appendices C and D, respectively). To classify the adaptation measures, we rely on the four types of adaptation to floods [26] – resist (protect), accommodate,

Figure 2



Methodology workflow.

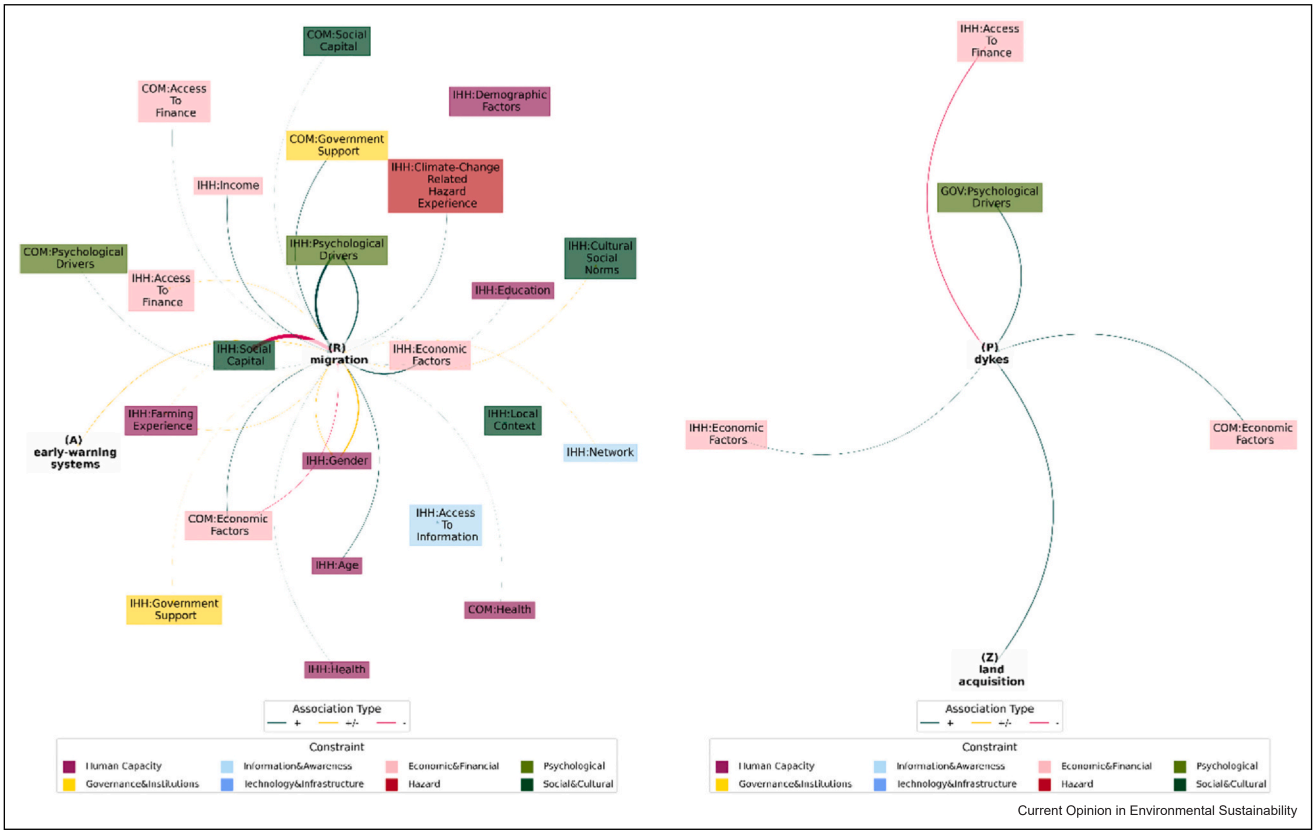
avoid (zoning), and retreat. We further expanded this list with behavioral adaptation measures to represent both structural and nonstructural CCA [27]. These were incorporated into the initial five-categories list. We define factors driving or hindering CCA, drawing from behavioral flood adaptation literature [28,29] and wider institutional factors [4,10]. We further classify our list of 27 factors into eight types of adaptation constraints/drivers inspired by Thomas et al. [10] and revised for our purpose: human capacity, psychological, economic&financial, social&cultural, hazard, information&awareness, governance&institutions, technology&infrastructure. We repeated steps 3 and 4 until all nodes were categorized. By applying this method to the literature reporting adaptations of various actors to floods and SLR worldwide, we derived a data set that could be used to, for example, elicit various adaptation constraints reported to play a frequently positive (+), negative (–), or neutral (+/–) role in CCA.

Results

Before discussing patterns in reported adaptation constraints per actor, first, we demonstrate two networks resulting from our constructed data set, focusing on two CCA measures, to illustrate typical outcomes of our algorithm applied to the floods and SLR articles' findings. We then proceed with presenting the full network of adaptation constraints associated with CCA measures for each actor.

Figure 3 shows the network visualization of two of the CCA measures: migration (Figure 3a) and dykes (Figure 3b). This means that we constrained to only findings that were about migration and dykes, respectively. In Figure 3, the nodes represent either a CCA measure or a factor reported to facilitate or hinder CCA for either of the actors in our database of articles' findings. The CCA measures are noncolored nodes in bold text. The factors are colored nodes, where the colors represent the adaptation constraint group with which the CCA factors associate. The edge colors represent the type of association that was most frequently mentioned between the nodes. The edge colors green, yellow, and red represent positive, neutral, and negative associations. The edge thickness represents the frequency the connection appeared, where the thicker the more frequent. In the middle of the cluster appears the term that has the highest number of connections with the rest of the terms; that is, it is the node with the highest degree (migration in Figure 3a, dykes in Figure 3b). From there, the further away a node is from the center, the smaller its degree, that is, the less the term appears in the findings.

Figure 3



Network of constraints associated with **(a)** migration and **(b)** dykes as an adaptation option for all actors in our data set. The factors are colored nodes for each of the eight adaptation constraints/drivers types. Adaptation measures are noncolored nodes in bold text, where (A): Avoid, (P): Protect, (R): Retreat, and (Z): Zoning.

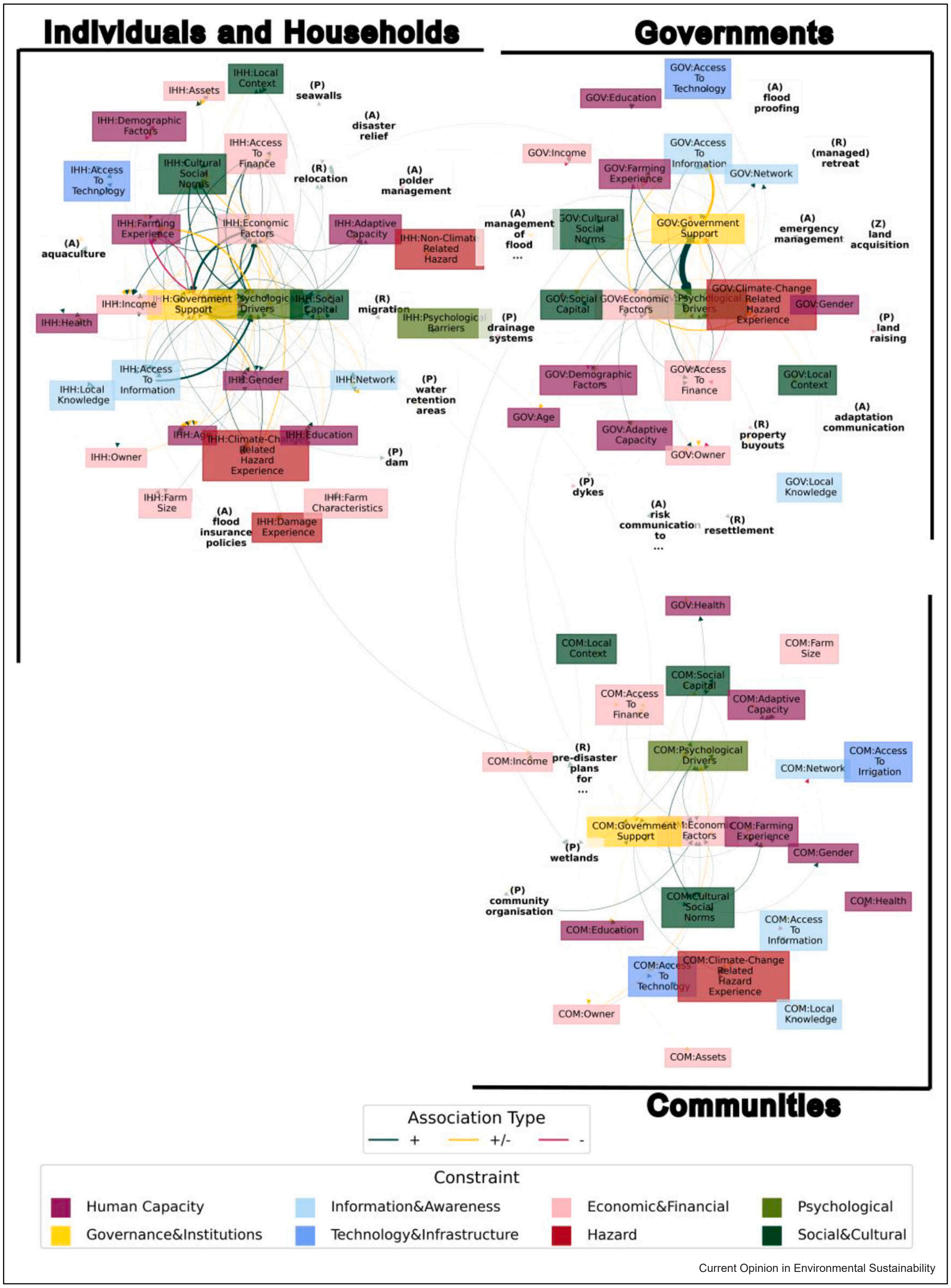
Accordingly, Figure 3a elicits that in the articles, migration tends to appear more often connected with the factors social capital, psychological drivers, economic factors, and gender falling under social&cultural, psychological, economic&financial, and human capacity adaptation constraints, respectively. The color and direction of the edges reveal that economic factors tend to be positively associated with migration, meaning that in the literature, economic factors are frequently reported as drivers of migration (both for COM and IHH). However, the inverse is not necessarily true, as migration appears neutrally (IHH) or negatively (COM) associated with economic factors, implying that literature reports no clear evidence on whether migration as a CCA measure leads to actors' improved economic situation.

The factors connected to dykes look different. Dykes is associated with land acquisition, another adaptation measure (Figure 3b), indicating that these two often go hand in hand. Dykes is positively related to economic factors (COM, IHH), implying that there is a positive interaction between dykes and economic development, whereas access to finance (IHH) has a negative relation. Psychological drivers (GOV) are also positively associated with dykes, hinting at barriers that need to be overcome to adapt with dykes.

Figure 4 shows the network visualization applied to all the CCA measures and factors. To facilitate its reading, we simplified the network by only showing the edges that appear in the 0.75 quantile and then applying a sigmoid function to calculate their weight. The three clusters represent the CCA measures and corresponding adaptation constraints and drivers for each group of actors: IHH, GOV, and COM. Appendix E provides similar networks of elicited relationships between CCA measures and adaptation factors (i.e. constraints or drivers) for each actor individually (Figures 1E to 3E).

In terms of the CCA measures, we see that for the GOV cluster, the measures are done primarily and exclusively by the governments. This is not necessarily true for IHH (e.g. dam and seawalls are not performed by IHH), but they could affect the implementation of the measure (see measures with (R), this is better displayed in Figure 1e, Appendix E).

Figure 4



CCA measures and factors clustered by actor. The factors are colored nodes where colors represent the eight types of adaptation constraints/drivers. Adaptation measures are noncolored nodes in bold text, where (A): Avoid, (P): Protect, (R): Retreat, and (Z): Zoning.

Figure 4 shows certain patterns across actors; for example, certain constraints are frequently mentioned for all actors. As such, social capital, from the social&cultural constraints, is very frequently mentioned across all actors. Furthermore, constraints from governance (government support), psychological (psychological drivers), and economic constraints (economic factors) are relatively central to all three actors. Slightly less central, climate change–related hazard experience plays a role for all actors.

Different adaptation strategies are associated with different actors (Figure 4 or Figures 1E to 3E in Appendix E for more detailed figures for each actor). Government is related to different policies (e.g. risk communication, managed retreat, relocation), emergency management (emergency management, early warning systems, disaster relief), and structural changes in the environment (e.g. beach nourishment, dykes, dam, seawalls). IHH show more individual adjustments like flood insurance or aquaculture but also resettlement (migration, relocation), which are strongly related with government support. COM show the least adaptation measures related to them. This could be because the community often does not implement the adaptation measure but rather a government body or individual [30].

In terms of shared CCA constraints, we see that social capital, economic factors, and government support are the most frequently mentioned regardless of the actor. This is an interesting insight, as social capital is commonly conceptualized as an IHH's adaptation factor [31], possibly less relevant for GOV. However, this reviewed empirical evidence reveals that government-led CCA also relies on social capital, probably for policy support. All three actors rely on climate change–related hazard experience, confirming earlier results that hazard experience is important to trigger action on both individual, communal, and governmental levels (e.g. [32,33]) but can also hinder adaptation if the experience is less severe [34] or too frequent so people cannot recover from it. For IHH, psychological and social&cultural constraints are reported to play a major role, followed by economic&financial confirming previous results (e.g. [30]). Communities are reported to be constrained by social&cultural factors, governance& institutions and information&awareness. According to the reviewed literature, governments' CCA relies on existing/ past governance&institutions, economic&financial factors, psychological, and social&cultural constraints, with the latter likely related to acceptable risks and policies. Furthermore, it is associated with sociodemographic factors involving individuals like gender, education, or age, hinting that these factors still play a role in CCA.

Finally, in terms of the connections between the CCA measures and factors, Figure 4 shows some interesting insights. For IHH, climate change–related hazard experience is positively associated with migration, implying that reviewed articles frequently reports IHH hazard experience as a driver of migration.

Conclusions and discussion

This work aimed to uncover possible patterns that different actors share when adapting to CC-induced floods and SLR. We did so by analyzing the associations between different CCA measures and factors (constraints and drivers) of various actors — GOV, COM, or IHH — reported in CCA cases worldwide. We derived the data from the findings of peer-reviewed articles on different types of floods and on SLR using a novel algorithm grounded in NLP. Our analysis consisted of network visualizations where the nodes represent either measures or factors (grouped into eight types of CCA constraints/drivers) and the edges represent the most frequently reported association between them (neutral, positive, or negative). Our main findings show that certain CCA constraints are more frequently shared among actors, and certain CCA measures are more likely to be associated with specific actors.

In terms of shared CCA constraints, we see that social capital, economic factors, and government support are the most frequently mentioned regardless of the actor. This is an interesting insight, as social capital is commonly conceptualized as an IHH's adaptation factor, possibly less relevant for governments. However, this reviewed empirical evidence reveals that government-led CCA also relies on social capital, probably for policy support. For IHH, psychological and social&cultural constraints are reported to play a major role, followed by economic&financial confirming previous results (e.g. [29]). Communities are reported to be constrained by social&cultural factors, governance&institutions, and information&awareness. They are also more frequently associated with CC maladaptation, perhaps because specific adaptations may not consider externalities or long-term impacts that adversely affect community-level risks or vulnerabilities at the community scale [35]. According to the reviewed literature, governments' CCA relies on existing/past governance&institutions, economic&financial factors, psychological, and social&cultural constraints, with the latter likely related to acceptable risks and policies. Furthermore, it is associated with sociodemographic factors, involving individuals like gender, education, or age, hinting that these factors still play a role in CCA.

CCA is not an isolated action but a complex interplay of the different societal processes, including capacity building, institutional involvement, and financial abilities. There is a need to understand how to facilitate successful interaction best, and further research is needed into how this impacts micro to macro patterns.

Considering the current and future CC impacts, it is the responsibility of all actors, from individuals to governments and international cooperation, to ensure that windows of opportunities emerge and are used to reduce damages, vulnerabilities, and risk, and, eventually, save lives.

Our work contributes to the systematic analysis of CCA constraints [10] and adds two novel contributions. First, we automatically extract positive and negative relationships from articles' findings using NLP. This allows us to trace in a transparent manner the relationships between reported CCA measures, actors, and types of constraints/drivers. Second, we developed a novel data network visualization that enables eliciting nuanced associations and patterns in CCA measures and constraints/drivers, going beyond the aggregated counts that bibliometric studies typically deliver. Yet, our work is not without limitations. First, our methodology depends on dictionaries. These dictionaries can be incomplete or change over time depending on the literature considered. This means that they might omit some measures or might have missed some discipline-specific terms referring to the same factors. Also, it was not always possible to differentiate articles on the type of flooding (pluvial, fluvial, and coastal), though CCA measures could vary. Second, we relied on peer-reviewed articles in English retrieved from Scopus. This biases the results to research articles. Therefore, work on constraints to CCA to floods and SLR published as gray literature or as government documents was not considered. Finally, we acknowledge that our algorithm to visualize the networks can still be improved. The algorithm is still work in progress, and we aim to continue researching better ways to convey such multi-dimensional volumes of information.

Code Availability

The codes to replicate this work will be available upon publication of the article at: https://github.com/SC3-TUD/SC3_VIDI.

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CRediT authorship contribution statement

S. Gil-Clavel conceptualized the study. T. Filatova conceptualized and leads the research project within which this study is a critical pillar. S. Gil-Clavel and T. Filatova conceptualized the data extraction methodology. S. Gil-Clavel prepared the data, designed the NLP and visualization algorithms, and performed the formal analysis and visualization. S. Gil-Clavel, T. Wagenblast, and J. Akkerman performed the data curation. S. Gil-Clavel prepared the first draft of the article. T. Filatova, T. Wagenblast, and J. Akkerman co-wrote the article. All authors reviewed the manuscript.

Data Availability

The data come from articles text. Once the article is published, we will upload the list of articles and the code to replicate this work to our GitHub repository.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.cosust.2024.101502.

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- • of special interest
- •• of outstanding interest

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