Mapping Forward-Looking Mitigation Studies at Country Level

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Abstract

We provide a first survey of the rapidly expanding literature on country-level mitigation pathways using systematic mapping techniques. We build a database of 4691 relevant papers from the Web of Science and Scopus. We analyze their abstracts and metadata using text mining and natural language processing techniques. To discover common topics within the abstracts, we use an innovative and fully reproducible topic modeling approach based on two machine-learning models. We find number of papers per country well correlated with current levels of GHG emissions, with few papers for (current) low emitters, notably in Africa. Time horizons of 2030 and 2050 each account for one third of the papers, with the former actually more frequent in recent years, spurred by interest in the (Intended) Nationally Determined Contributions. Topic modeling analysis of the dataset reveals that forward-looking mitigation papers encompass all dimensions of mitigation, save for finance issues, that are lacking. However, energy and to a lesser degree land use, land use change and forestry (LULUCF) are very dominant relative to other sectors. Topics are unevenly addressed across countries, reflecting national circumstances and priorities, but also pointing to gaps in the literature. The limited number of forward-looking papers in (currently) low-emitting countries raises questions of lack of research capacity in support of the construction of domestic climate policies.

Keywords: Mitigation Pathway, Forward-looking, National, Topic Modeling, Natural Language Processing

1 Introduction

The Paris Agreement signed in 2015 emphasizes nationally determined contributions (NDCs) as the building block of global action against climate change, today and over time as countries are expected

to ramp up their ambition over time in subsequent NDCs. An increasing number of countries have also communicated long-term low greenhouse gas emission development strategies under Article 4 of the Agreement and/or adopted mid-century mitigation goals.

Though there exist principles for mitigation that are general enough to apply everywhere (e.g., decarbonize electricity, electrify end-uses, promote energy efficiency, enhance carbon sinks), building effective mitigation strategies at country level requires to take into account local economic, social, technological, institutional and cultural circumstances, all the more so when mitigation objectives are ambitious. To inform such a process, country-specific analysis is required (Fragkos et al. 2021).

While country-level assessment of ambitious climate objectives have been conducted for many countries, via both individual exercises and multi-country projects (such as the Deep Decarbonization Pathways project (Waisman et al. 2019), CD-LINKS (CD-LINKS 2019) COMMIT (COMMIT 2019) or ENGAGE (`https://www.engage-climate.org/`), there exists to our knowledge no comprehensive survey of this literature despite its relevance for policy-making. This may be explained by the large number of countries, the large number of research teams with diverse backgrounds (energy, macroeconomics, environment, etc.) working on national mitigation pathways, and by the lack of institutions that would bring them together. By contrast, the literature on mitigation pathways at global level originates from a limited number of research teams worldwide and benefits from well-developed institutions such as the global mitigation scenario databases hosted by the International Institute for Applied Science Analysis or the Integrated Assessment Modeling Consortium. It has been extensively surveyed, in particular in the IPCC 4th and 5th Assessment Reports.

In this paper, we bridge this gap by providing a comprehensive overview of the literature on mitigation pathways at country level. Specifically, we ask: How comprehensive is the geographical coverage of this literature? Up to what time horizons does it consider mitigation strategies? What models do these analysis use? And what are the main aspects of mitigation it addresses?

To do so, we harvest forward-looking mitigation papers at country level from the Web of Science (WoS) and Scopus databases, resulting in a dataset of 4,691 abstracts and other paper metadata. We use language processing techniques to extract additional information from the abstracts, such as country, time horizon of the analysis or name of the model used. Finally, we use topic modeling techniques to identify the main issues discussed in each paper in the database. We improve the method proposed by Lamb et al. (2019) by reducing subjectivity bias and by optimizing the parameters of the method so as to maximize the explanatory power of the topics.

Overall, our paper contributes to a growing literature that mobilizes big data and machine learning techniques to analyse the academic literature on climate change (Lamb et al. 2019, Callaghan et al. 2020, Aleixandre-Benavent et al. 2017, Belter & Seidel 2013, Haunschild et al. 2016, Li & Zhao 2015, Wang et al. 2014).

Besides our main findings presented below, the dataset of papers and related topics produced in this research is of interest on its own as it allows researchers, policymakers and stakeholders to 'zoom in' on particular topics and/or countries of interest to inform policy processes and/or identify research gaps. We have striven here to provide the method and results in a clear, transparent and

fully reproducible way, with view to making the results easier to communicate (Donnelly et al. 2018, Haddaway & Macura 2018, Minx et al. 2017).

The rest of this article is structured as follows : section 2 details our methodology, section 3 presents and discusses our results and section 4 concludes.

2 Methodology

2.1 Database construction

To find mitigation pathway(s) at the national level, we search the academic databases WoS and Scopus for papers that meet the following three conditions: (i) include the name of a country in the title,[1] (ii) include "mitigation" or a synonym in the title, abstract, or keywords,[2] and (iii) include a year in the period [2025-2100] in the title, abstract or keywords.

The two selections are then merged into one database, and duplicates are eliminated. Due to differences in coverage of peer-reviewed journals, results of the searches from WoS and Scopus differ significantly, with 944 references that appear only in Scopus and 574 only in WoS. The search expressions and the resulting database of 4691 papers, obtained November 14, 2020, can be found in the supplementary materials to this article.

Limiting the search for country names to the title of the reference is based on the observation that papers focusing on national mitigation pathways typically have the name of the country in the title. Conversely, attempts using search equations with country names in the abstract led to harvesting too many irrelevant papers. Finally, adding a year is critical to restricting the search to papers devoted to future pathways. Without this condition, the vast literature on current mitigation policies, for instance, would also be embarked in the search.

While the search string is precise and encompasses all countries, our identification strategy has two shortcomings . First, we focus on papers in English only, although there are relevant papers on forward-looking mitigation at country level in other languages. Second, we search two major databases (WoS and Scopus), while other relevant paper may be indexed elsewhere. Overall, however, we think that our approach provides an extensive view of the available literature.

2.2 Additional treatments

The database is post-treated using the Pandas library (Wes McKinney 2010) of the Python software. We search country names, demonyms and acronyms in the title to associate each paper to a country. When the title of a paper contains more than one country name (which occurs for 153 papers), one

[1] We use the list of countries of the United Nations Statistics Division (https://unstats.un.org/unsd/methodology/m49/overview/), supplemented with demonyms, acronyms and the terms 'European Union' and 'EU'.

[2] We search for the following synonyms to mitigation: "low carbon", "decarboni*ation", and ("carbon" OR "CO2" OR "GHG" OR "greenhouse gas") NEAR/3 "reduc*". The last expression means that one of the words in parentheses must be separated by a maximum of three words from the term "reduc*".

entry is created for each. The resulting extended database contains 4884 rows. We use it to analyze the geographical coverage of our dataset.

Two additional parameters are added. First, we search the title, keywords and abstracts of each paper for an horizon year in the [2025; 2100] range. If more than one number are found, we retain the largest one. Second, we search for model names, again duplicating entries if several models are identified.

We use a combined list of models from the comparative review of scenario modeling tools for national pathways to the Sustainable Development Goals by Allen et al. (2016), the list of models documented by the IAMC, as well as the generic expressions "computable general equilibrium" and "integrated assessment model". The database with one entry for each combination of paper, country and model has 4996 rows.

2.3 Topic modeling

2.3.1 Overview

Topic modeling is a machine learning method aimed at discovering common topics within a corpus of documents, here the abstracts of the papers selected above. Specifically, we use the Non-negative Matrix Factorization (NMF) classification method (Lee & Seung 1999). The starting point is to build the so-called Term Frequency-Inverse Document Frequency (TF-IDF) matrix, in which each row corresponds to a paper and each column to a word, and in which coefficients measure the frequency of a given word in the abstract of a given paper, weighted by the frequency of that particular word in the whole corpus.

The next step is to decompose the TF-IDF matrix, i.e., to search for the combination of matrices W and H such that their product W x H best approximates TF-IDF. The columns of matrix W, also the rows of matrix H, can then be interpreted as topics. Matrix H indicates the weight of each word in each topic, while matrix W indicates the weight of each topic in each abstract.

The outcome of the method is sensitive to the number of topics (the number of columns of matrix W and the number of rows of matrix H) as well as to other parameters of the optimization process. Previous studies using the NMF classification method have explored several number of topics and selected the value based on expert judgment (Lamb et al. 2019, Callaghan et al. 2020). Here, we reduce the risk of arbitrariness and subjectivity bias by selecting exogenous parameters from a topic coherence measure (O'callaghan et al. 2015), based on the Word2vec word embedding algorithm (Mikolov, Sutskever, Chen, Corrado & Dean 2013, Mikolov, Chen, Corrado & Dean 2013). The following details each step.

2.3.2 Corpus identification

To identify the corpus, abstracts are pre-treated. All characters are put in lower case, punctuation signs, connectors and commonly used words are deleted, and words are grouped according to common radicals. Since the country scope and time horizon of each paper is already identified through the

search equation, country names and time horizons are deleted. Terms related to mitigation listed in the search equation are also deleted, since by construction of the database each abstract contains at least one of them. Finally, we exclude terms that are either too rare (i.e., that appear in less than 1% of the abstracts) or too frequent (i.e., that appear in more than 95% of the abstracts). The final corpus contains 1300 terms.

2.3.3 TFI-DF matrix construction

We measure the weight of each term using the $TFIDF$ index, defined for each abstract a and each term t as follows (Salton & Buckley 1988):

$$TFIDF_{at} = \frac{tfidf\,(a,t)}{\sqrt{\sum_{i=1}^{T} tfidf\,(a,i)^2}} \tag{1}$$

Where

$$tfidf\,(a,t) = tf\,(a,t) \times \left[\log\left(\frac{A}{df(t)}\right) + 1\right] \tag{2}$$

With $tf\,(a,t)$ the number of occurrences of term t in abstract a and $df(t)$ the number of abstracts containing term t. The TF-IDF index thus weighs a particular term in a particular abstract if it appears frequently in that abstract but not frequently in the rest of the corpus.

2.3.4 Topic identification

We use the Non-negative Matrix Factorization (NMF) method to identify relevant clusters of words (hereafter topics). The algorithm searches for the set of K topics such that the product of the non-negative matrices abstract-topic $W_{A\times K}$ and topic-terms $H_{K\times T}$ best approximates $TFIDF_{A\times T}$. The W matrix can be interpreted as the weight of each topic in each abstract, while the H matrix represents the weight of each term in each topic.

Since the selected number of topics is small relative to the total number of abstracts (typically less than 5%), there is no algorithm of polynomial complexity that converges to a unique solution.[3] However, one can iteratively converge to local solutions by solving the optimization problem (3), in which $||.||_{Fro}$ and $||.||_1$ are the Frobenius and L_1 norms respectively, and where $\alpha \geq 0$ and $0 \leq l_1 \leq 1$ are coefficients.

$$\min_{W,H\geq 0} \frac{1}{2}||X - WH||^2_{Fro} + \alpha\left[l_1\left(||W||_1 + ||H||_1\right) + (1-l_1)\left(||W||^2_{Fro} + ||H||^2_{Fro}\right)\right] \tag{3}$$

The first term in equation (3) ensures the convergence of the WH product towards $TF-IDF$,

[3]NMF methods are still preferred to principal component analysis methods (for which such algorithm exists) for textual analysis because in the former, several topics can apply to a single abstract.

while the second imposes additional constraints on the structure of W and H. The L_1 regularization (second term) favors the presence of null coefficients in the matrices, thereby limiting the number of topics each abstract is related to, and limiting the number of terms each topic contains. The minimization of the L_2 regularization (third term), on the other hand, tends to limit differences across coefficients in the matrixes.

We initialize the NMF algorithm using the Non-Negative Double Singular Value Decomposition method (Boutsidis & Gallopoulos 2008, Belford et al. 2018). To ensure that our results are reproducible, we set the random seed of the algorithm to 1511.

2.3.5 Parameter optimization in the NMF method

The set of topics identified with the NMF method is contingent on the choice of K (number of topics), α (intensity of regularization relative to the optimization criteria) and l_1 (regularization parameter). We thus build a performance measure for each set of topic, and then select the triplet (K,α,l_1) that produces the highest ranking set. To our knowledge, this is the first time that the algorithm below is used to select the best triplet (it has previously been used to select K only (O'callaghan et al. 2015)).

The index we use is called "coherence". It measures how similar the semantic environments of each of the terms that compose a given topic are. The higher the index, the more consistent are the words that compose the topic. The coherence of a set of topics is the average of the coherence of each individual topic.

Following O'callaghan et al. (2015), we produce a vectorial representation of the semantic environment of each term within the corpus of abstracts using the Word2vec word embedding algorithm (Mikolov, Sutskever, Chen, Corrado & Dean 2013, Mikolov, Chen, Corrado & Dean 2013). Word2vec is a two-layer neuronal network that maps words into vectors that account for the semantic environment of the word. Words that share similar contexts are characterized by similar multi-dimensional vectors.

We use the Skip-Gram method to train the neural network. This approach seeks to predict the semantic context of a term. The error is computed based on the corrected prediction of the words surrounding this term. The coherence of each topic coherence is then the mean of the pairwise cosine similarities between the terms that characterize the topic. Precisely, for a topic k, the coherence index $TCW2V_k$ is computed as follows:

$$TCW2V_k = \frac{1}{\binom{N}{2}} \sum_{j=2}^{N} \sum_{i=1}^{j-1} similarity\left(wv_{tj}, wv_{ti}\right) \tag{4}$$

Where N is the number of terms that we choose to characterize each topic,[4] wv_{kj} is the vector associated to term j characterizing topic k, wv_{ki} is the vector associated to term i characterizing

[4]For each topic, we retain the five terms with the highest ranking score in the topic - terms matrix H.

topic k and $similarity(A, B)$ is the cosine similarity of vectors A and B, defined as:

$$similarity(A, B) = \frac{\sum_{i=1}^{D} A_i B_i}{\sqrt{\sum_{i=1}^{D} A_i^2}\sqrt{\sum_{i=1}^{D} B_i^2}} \tag{5}$$

We assign the set of topics resulting from each triplet (K,α,l_1) with the mean of the scores obtained by each individual topic.

We systematically explore the set of triplets (K, α, l_1) in the range $[2, 40]\times([0.00, 0.31]\, U\, [0.40, 1.00])\times [0.0, 1.0]$ (with increments of $1, (.01; 0.1)$ and 0.1 respectively). For each combination, we perform the NMF algorithm and compute the coherence index of the resulting set of topic. The highest score is obtained for the triplet $(39, 0.1, 0.9)$, which we retain for the remainder of the study.

2.4 Relationship across topics

To visualize how topics relate to each other (Figure A6), we use *LDAvis* (Sievert & Shirley 2014), a system initially developed to explore topic-term relationships in a fitted Latent Dirichlet Allocation (LDA) model. The intertopic distance is based on the Jensen Shannon divergence calculated from the H matrix coefficients characterizing the topic-terms relationships. Principal Components Analysis (PCA) then projects the set of intertopic distances onto two dimensions. In online supplementary material, the interactive visualization is available and represents the individual terms that are the most useful for interpreting each topic. In particular, it enables to look at the corpus-wide frequency of a given term as well as the topic-specific frequency of the term.

2.5 Relationship between abstracts and topics

The W matrix links topics to abstracts. However, it has too many non-zero coefficients, and a threshold is required to ascribe a topic to an abstract. This in turn requires that the weights of each topic in each abstract be comparable across abstracts.

We normalize the W matrix so that the sum of the coefficients of each row is equal to one. This way, each line of the matrix can be interpreted as shares of each topic in a given abstract. To do so, we transform each coefficient in the W matrix such as :

$$W^*_{ak} = \frac{W_{ak} \times \sum_{i=1}^{T} H_{ki}}{\sum_{i=1}^{T} WH_{ai}} \tag{6}$$

We then ascribe topic k to abstract a if $W_a k^* > 0.02$, as per Lamb et al. (2019)).

To check how relevant the resulting mapping is, we build another mapping based on titles. Specifically, we ascribe topic k to abstract a if $W^*_{ak} > 0.02$ and if at least one of the 5 terms best characterizing topic k appears in the title of the paper. Figure A5 presents the number of papers per topics in each mapping. As the Figure illustrates, these distributions are similar, the one on the bottom

being scaled down from the one on top. Since the presence of a word characterizing a topic in the title of a paper is a strong indication that the paper is indeed related to that particular topic, the comparison between the two mappings is a good indication that our initial mapping is relevant.

3 Results

3.1 Papers are distributed in proportion to countries GHG emissions

Overall, 136 countries (plus the European Union) appear in the database (Figure 1. However, the geographic distribution of papers is particularly skewed. China accounts for 24.3% of all papers. Distant second are the US (9.0%), followed by the UK (6.0%), the EU as a region (5.3%) (this figure excludes papers related to individual EU Member States), and India (4.9%). Region-wise,[5] nearly half of the papers (46.5%) focus on Asia, a little more than a quarter on Europe (28.4%) and a sixth on the Americas (17.3%, of which 7.0% on Latin America and 10.3% on North America). The other regions each accounts for less than 5% of the papers. Africa, in particular, is very poorly represented (4.4%), with all but 7 countries in the region with less than 10 papers, and nearly half with no paper at all.

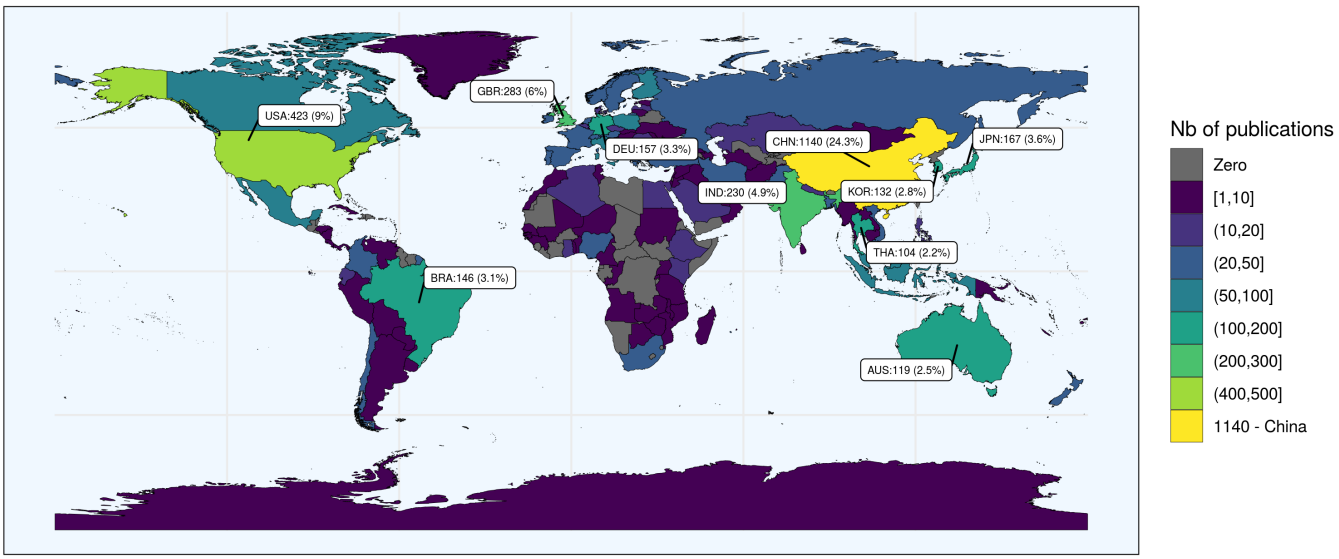

Figure 1: Geographical distribution of papers in the database. Papers related to the EU as a whole are not represented. (Source: Authors).

The representation of each country in the database appears well correlated with its GHG emissions (Figure 2). This is not surprising since the larger the problem, the more likely it is to attract the attention of the (domestic and foreign) research community, either suo motu or at the request of governments or of other interested parties. A prominent exception is the UK, which features much

[5]When a paper is devoted to countries in different regions (e.g., China and the US), it is attributed the region of the first country to appear in the list. There are only 72 such papers in the database so we consider the potential bias negligible.

more frequently in the database than its GHG emissions would suggest. This may translate the strength of the UK research community on mitigation, and/or the fact that with the adoption of the Climate Change Act in 2008, the UK has a longer history of national climate policies than most high-emitting countries.

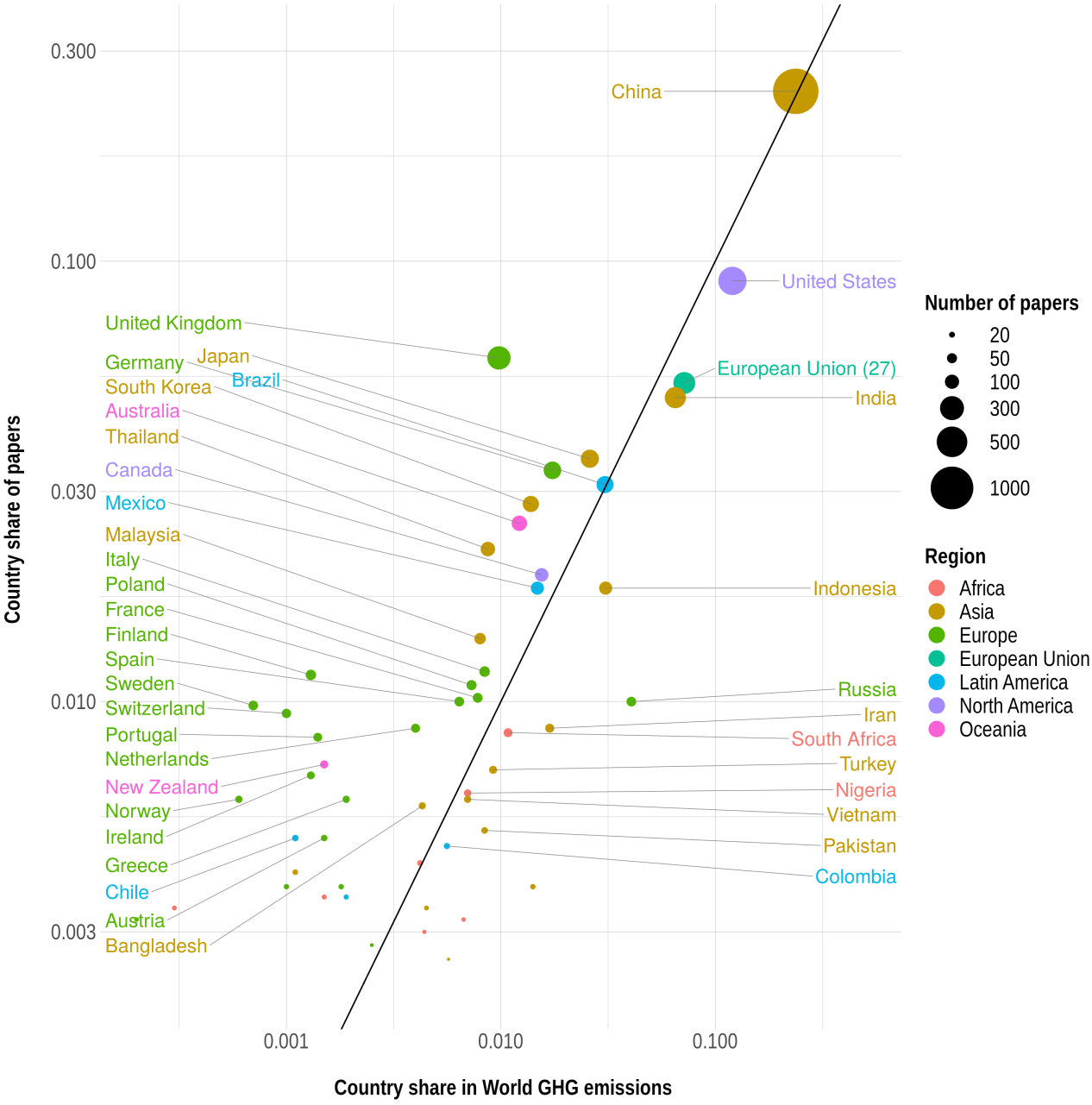

Figure 2: Country share of papers in the database (y-axis) against country share in World GHG emissions (x-axis). Oblique line the x=y line. Sources: Authors, 2016 GHG emissions data (including emissions from land use, land-use change and forestry) from the CAIT database.

Another exception is Russia, with significantly fewer papers than its share of emissions would suggest. This might reflect the fact that our search is confined to papers written in English. It might also point to a research community that has invested more on other priorities than mitigation.

Amongst countries with middle- or low-emissions, OECD countries, particularly in Europe (e.g., Finland, Switzerland, Sweden) have more papers in the database than their shares of GHG emissions would suggest. Developing countries, on the other hand, tend to be closer to the line or below.

The tail of the distribution is also relevant for policy making. Of a total of 197 Parties to the UN Framework Convention on Climate Change, 143 have less than 10 papers in the database, 127 less than 5, and 65 have none. In their survey of urban climate mitigation case studies, Lamb et al. (2019) similarly find a very uneven distribution of papers by country. While it is difficult to determine a threshold below which the number of forward-looking publications on mitigation would be "insufficient" to inform policies, 10 papers or less (to be compared with 39 major topics in the database, see below) leaves little chance that even the different sectoral aspects of mitigation be adequately covered. Policymakers and stakeholders in Africa, in particular, have for the most part scant scientific literature to rely on, despite rapidly increasing emissions. Informing strategies to limit growth in GHG emissions (and ultimately start reducing them) while continuing to other development goals needs a major shift in the focus of research towards the continent.

3.2 Paris Agreement has spurred increased attention to 2030 time horizon

The distribution of time horizons of papers (Figure 3.b) presents two very clear peaks in 2030 and 2050 respectively, each accounting for 34% of all papers. Only 14% of all papers have a time horizon beyond 2050, a major difference with the literature on mitigation at the global level, in which 2100 is the norm. This translates a difference in research questions. Forward-looking mitigation studies at the global level are typically conducted to assess mitigation scenarios against long-term temperature goals, whereas forward-looking studies at the national level have typically the objective to assess more detailed policy packages. For that purpose, 2050 is already a long time horizon.

Figure 3.a presents papers by publication year and by time horizon. It shows a rapid expansion of the forward-looking mitigation literature at country level over the past two decades, with a clear inflexion point around 2014: The annual increment of publications is markedly higher in the 2014-2020 period than in the 2007-2013 period. Such inflexion does not appear when looking at the climate change literature as a whole. When doing so, on the contrary, Callaghan et al. (2020) find annual increments more or less constant over the whole 2007-2020 period. The timing of the inflexion point (2014) suggests that the prior negotiation and adoption of the Paris Agreement [6], with its strong emphasis on national-level mitigation, may have spurred increased interest in national-level mitigation.

This hypothesis is further supported by the fact that 2014 also marks an inflexion in the distribution of time horizons across papers. As can be seen in Figure 3.a, the share of papers with a time horizon up to 2030 was decreasing before 2014. But from 2014 onward, this trend is reversed. Since 2030 is the time horizon of nearly all the Intended NDCs communicated in 2015 (and of most the

[6]The Paris Agreement was signed in 2015. However, Parties to the UNFCCC were asked to submit Intended Nationally Determined Contributions at COP19 in Warsaw (Poland) in November 2013.

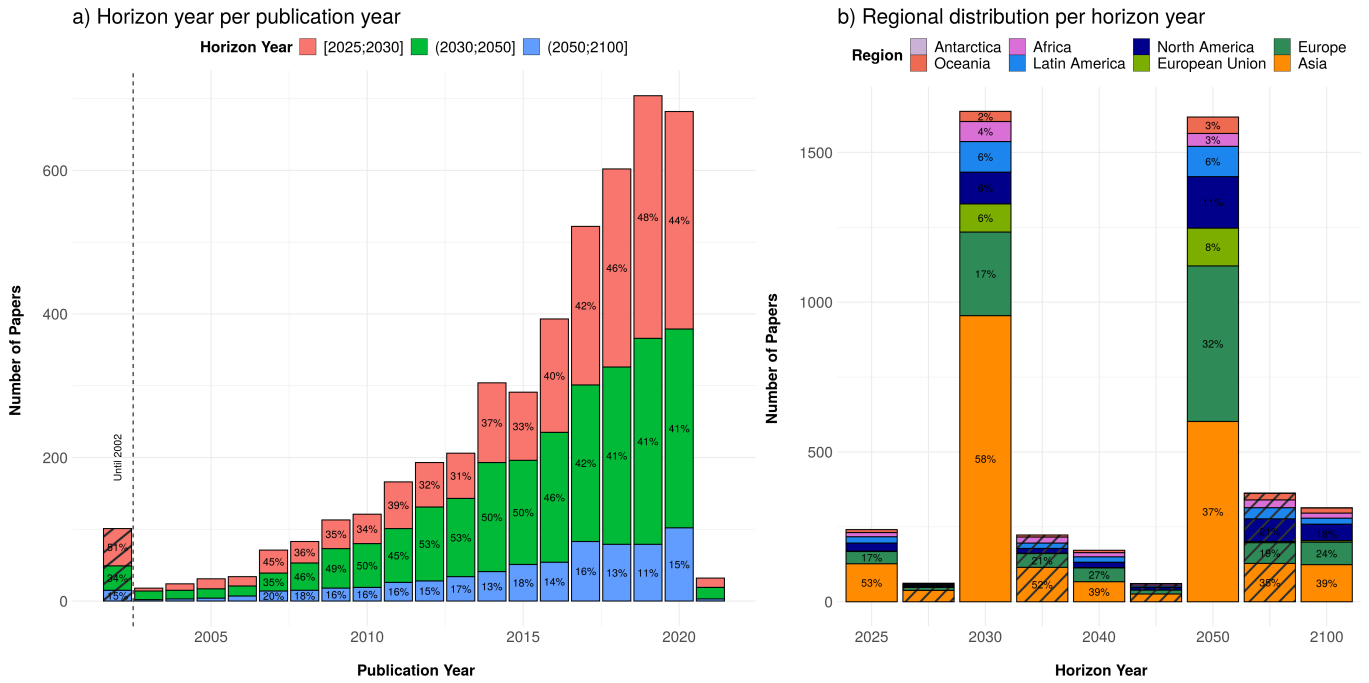

Figure 3: Distribution of papers in the database by publication year and time horizon (a); and by time horizon and region (b). On panel a, the first bar accounts for all the papers in the database published prior to 2003. On panel b, plain bar plots indicate number of papers with a 2025, 2030, 2050 or 2100 time horizons, while cross-hatched bar plots aggregate all the papers with time horizons in between these bounds. On panel b, papers referring to European Union as a whole are accounted separately from those referring to individual European countries.

NDCs to date), this finding suggests again that the negotiation and signature of the Paris Agreement has spurred increased interest in mitigation at the national level. The adoption of the Sustainable Development Goals (SDGs) in 2015, also with a 2030 as a time horizon, may also have played a role, though mitigation is only one of the 17 SDGs.[7]

Finally, Figure 3.b shows that the distribution of time horizons differs by region. Europe and North America represent more 62% of the literature with a 2050 time horizon, against 25% of the literature with a 2030 time horizon. Conversely, Asia represents 68% of the literature with a 2030 time horizon, against 40% up to 2050. This suggests that research in Europe and North America is already focused on mid-century time horizons, consistent with the mid-century mitigation strategies that several European countries and the EU have adopted. Whereas the focus in Asia would be more on the conditions under which NDCs can be achieved by 2030. If this explanation is correct, then we should soon see an increase in the share of papers about 2050 and 2060 time horizons in Asia following the recent announcement of the long-term mitigation objective by China.

[7]A breakdown of papers by publication year and by region (Figure A1) shows a rapid increase in the share of papers on Asian countries since 2016, mostly driven by China. This is consistent with the hypothesis that the Paris Agreement spurred increased interest in national level mitigation, given the prominent attention given to the Chinese NDC.

3.3 Studies offer a comprehensive but uneven coverage of major mitigation issues

Table 1 presents the outcome of the topic modeling analysis described in Methods. Topics are ranked by numbers of papers attached (column T0.02), and characterized by their five most relevant words (column Terms).[8] The "title" attached to each topic (column Topic) is our own work.

Nearly all the papers in the database (4687 out of 4691) are related to topic No.1, characterized by the words "policy - develop - econom - countri - use". This is not surprising, since papers on mitigation scenarios at country level typically discuss policy implications, including in the abstract. More interesting is the fact that the corpus is then split nearly in half between papers related to topic No.2 (*Climate Change*) and papers related to topic No.3 (*Energy Efficiency*). The two ensembles are largely disjointed, as can be seen from the mapping of the strength of the pairwise combinations of topics (Figure A7). Papers associated with topic No.2 (*Climate Change*) tend to be also associated with topics such as *Drought*, *Flood*, *Water*, *Crop Yield*, *Forest*, *Land Use*, *Agriculture* or *Air Pollution*. Whereas papers associated with topic No.3 (*Energy Efficiency*) tend to be associated with topics such as *Hydrogen*, *Steel/Iron*, *Nuclear*, *Peak*, *Oil*, *CCS*, *Wind/Solar* or *Buildings*. The other topics can be organized in five groups: (i) methods (*Scenarios* and *Systems*), (ii) policies (e.g., *Costs* or *Targets/INDC*), (iii) sectors ; (iv) air pollution; and (v) climate change impacts (*Drought*, *Flood* and *Crop Yield*). The latter are not all primarily about mitigation, as the search equation also picks forward looking impact assessment or adaptation study at the national level that have in the abstract the word "mitigation" or a demonym.

Using the outline of the IPCC Working Group III 6th Assessment Report as a rough mapping of the topics associated with mitigation (Table 1, column 5), one can see that the forward-looking mitigation papers at the national level cover all IPCC WGIII AR6 sectoral chapters (6 to 11) as well as issues related to demand (5), policies (13) and innovation (16). The absence of international policies (Chapter 14) is understandable since the search equation focuses on mitigation at the national level. The absence of a topic related to finance (Chapter 15), on the other hand, confirms anecdotal evidence that few forward-looking national mitigation pathways have been analyzed along that lens so far. Finally, the lack of a standalone topic dedicated to SDGs (Chapter 17) may be related to the fact that if individual SDGs are discussed in the abstracts, it may be in a diffuse way that does not get picked up in a topic (except for *Air Pollution*). Among the sectors that are represented there is considerable imbalance: energy is the one with the largest number of related papers (27%) followed by LULUCF (9%), while the other sectors are much less represented. Though the attribution of topics to particular sectors may be debatable in some cases (for example, bioenergy could also be related to LULUCF), and though sector-specific information may also be present in the body of the papers, the observation of an imbalance between sectors appears robust.

[8] Topics are characterized by word stems rather than by full words. For example, the word stem corresponding to «country» or « countries » is "countri". We use the stemming algorithm from the library stemming.porter2 (https://pypi.org/project/stemming/1.0/).

Topic	Terms	Category	Sector	Relevant IPCC WG3 chapter	T0.02	T0.02 Title
Policy-Dvlpt-Eco	polici_develop_econom_countri_use	context			4,687	1,324
Climate change	climat_chang_temperatur_futur_project	context			2,000	1,038
Energy efficiency	energi_effici_consumpt_save_demand	context			1,732	1,018
Scenario	scenario_model_bau_refer_three	method			1,428	553
Consumption	intens_structur_consumpt_factor_growth	other		5	936	221
Electricity	electr_generat_demand_grid_suppli	sectoral	energy	6	904	471
Power	power_generat_plant_sector_capac	sectoral	energy	6	797	416
Costs	cost_abat_option_benefit_margin	policy		12	761	229
Target/INDC	target_achiev_indc_meet_ndc	policy		13	706	200
Air Pollution	air_pollut_pm2_qualiti_health	other		17	674	252
Fuel	fuel_fossil_diesel_altern_biofuel	sectoral	energy	6	586	157
Transport	transport_sector_road_passeng_freight	sectoral	transport	10	567	298
System	system_model_transit_integr_pathway	method			543	339
Renewable Energies	renew_energi_sourc_share_res	sectoral	energy	6	540	359
Cement	industri_cement_sector_product_process	sectoral	industry	11	497	301
Technology	technolog_advanc_deploy_low_clean	technology		16	421	168
Land Use	land_use_soil_area_chang	sectoral	landuse	7	420	253
Permit market	price_et_market_trade_polici	policy		13	419	241
Vehicle	vehicl_fleet_car_hybrid_passeng	sectoral	transport	10	387	227
Coal	coal_fire_plant_natur_phase	sectoral	energy	6	360	126
Buildings	build_residenti_stock_sector_construct	sectoral	buildings	8	356	180
Agriculture	agricultur_food_product_livestock_farm	sectoral	landuse	7	351	188
Bioenergy	biomass_bioenergi_biofuel_residu_wood	sectoral	energy	7	345	160
Urban	urban_citi_area_popul_develop	policy		8	331	197
Wind/Solar	wind_solar_capac_instal_photovolta	sectoral		6	324	107
Forest	forest_sequestr_wood_sink_stock	sectoral	landuse	7	314	188
Crop yield	crop_yield_soil_wheat_fertil	sectoral	landuse	7	302	113
Water	water_resourc_basin_river_irrig	impacts		WG2	291	133
Flood Risk	flood_risk_coastal_sea_disast	impacts		WG2	284	127
Heat Pump	heat_pump_district_cool_boiler	sectoral	buildings	9	272	94
CCS	ccs_storag_captur_geolog_plant	technology		6	251	127
Waste	wast_landfil_solid_municip_treatment	sectoral	waste	11	222	73
Tax	tax_revenu_polici_equilibrium_model	policy		13	213	117
Oil	oil_product_crude_natur_export	sectoral	energy	6	200	72
Peak	peak_around_reach_earlier_non	policy		3	173	65
Nuclear	nuclear_plant_power_mix_new	sectoral	energy	6	160	87
Steel/Iron	steel_iron_product_materi_save	sectoral	industry	11	105	70
Hydrogen	hydrogen_cell_chain_produc_product	sectoral	energy	6	94	60
Drought	drought_precipit_sever_frequenc_index	impacts		WG2	89	39

Note: pm2 is the word stem resulting from «PM2.5» after text preprocessing.

Table 1: Description of the 39 topics, including short name (column Topic), 5 most relevant words (column Terms), type of topic (column Category), sector when relevant, related IPCC WG3 AR6 chapter for classification purpose when relevant, and number of related papers with threshold of 0.02 (column T0.02) and with threshold of 0.02 plus keywords in title (column T0.02 Title) (see Methods and Figure A5).

3.4 Topics reflect country circumstances

The distribution of countries for individual topics mostly reflects the overall distribution of countries in the database (see Figures A3 and A4). At one end of the spectrum, China has the largest number of papers for all topics except *Heat Pump* (preceded by the UK), *Nuclear* (preceded by Japan, the UK and South Korea) and *Hydrogen* (preceded by Germany, Japan and the UK). At the other, African countries appear only once in the top 5 for a topic (Ethiopia for *Drought*). There are, however, differences across topics. Forward-looking mitigation studies about industrial sectors (*Cement* or *Steel-Iron*) have been conducted predominantly for China, while the distribution of papers across countries is much more balanced for topics such as *Renewable Energy* or *Buildings*. The imbalance in research across countries in the *Urban* topic is particularly surprising, since urban development issues are not confined to China. It is however, consistent with the finding of Lamb et al. (2019) that urban case studies in China overwhelmingly dominate the literature.

Figure 4 maps the distribution of topics for the 55 most-represented countries in the database. The number in each cell is the number of papers devoted to country x and related to topic k. The shade of the cell indicates the share of the topic in the total number of papers devoted to the country. Reading the Figure vertically provides a view of the relative importance of a given topic across countries.

Patterns emerge. Some topics appear in 10% or more of the papers in nearly all 55 countries, such as *Energy Efficiency*, *Electricity* or *Power*). Others stand out only in a limited set of countries, such as *Oil* in Saudi Arabia, Kuwait, Canada, Malaysia, Indonesia, Ecuador, Mexico, and Austria, *Coal* in China, India, Australia, Malaysia, Poland, South Africa, Viet Nam, Chile and Czechia or *Nuclear* in Japan, Korea, France, and Romania. It is not surprising that topics that are related to country-specific circumstances (e.g., fossil fuel endowments or share of nuclear in electricity mix) appear in a smaller set of countries than topics that relate to broadly shared elements of mitigation (e.g., the electricity grid or the power sector). However, the list of countries where "specialized" topics appear suggests gaps in the literature. For example, the *Oil* topic does not stand out in major oil exporting countries such as Nigeria, Russia or Norway. Regarding the 'policy' topics, *Costs* and *Target/INDC* appear evenly distributed across countries. *Permit market* is often present, notably in papers devoted to the EU. On the other hand, *Tax* is poorly represented (five countries present this topic in more than 10% of related publications), reflecting at least a higher degree of attention in the academic literature to the former relative to the latter.

Reading the Figure horizontally provides a country by country snapshot of the issues identified by the academic literature as most important in the context of future mitigation. Some countries have balanced literature that cover nearly every topics, while other have much more 'specialized' literature. For instance, literature on Indonesia is balanced, with three major topics (*Energy Efficiency*, *Target/INDC* and *Land Use*) plus eight other topics including power generation, forest and oil. The literature on Poland, on the other hand, is more focused on *Power*, *Costs*, *Renewable Energies* and *Coal*. Although the former are mostly countries with large number of papers attached (China, the U.S., the EU) and the latter are by construction mostly countries with smaller number of papers,

the relationship does not necessarily hold everywhere. Portugal or Ireland, for example, have smaller yet more balanced literature than Japan (with a higher than average number of papers devoted to *Nuclear* and *Hydrogen*) or Brazil (*Forest*, *Land Use*, *Agriculture*).

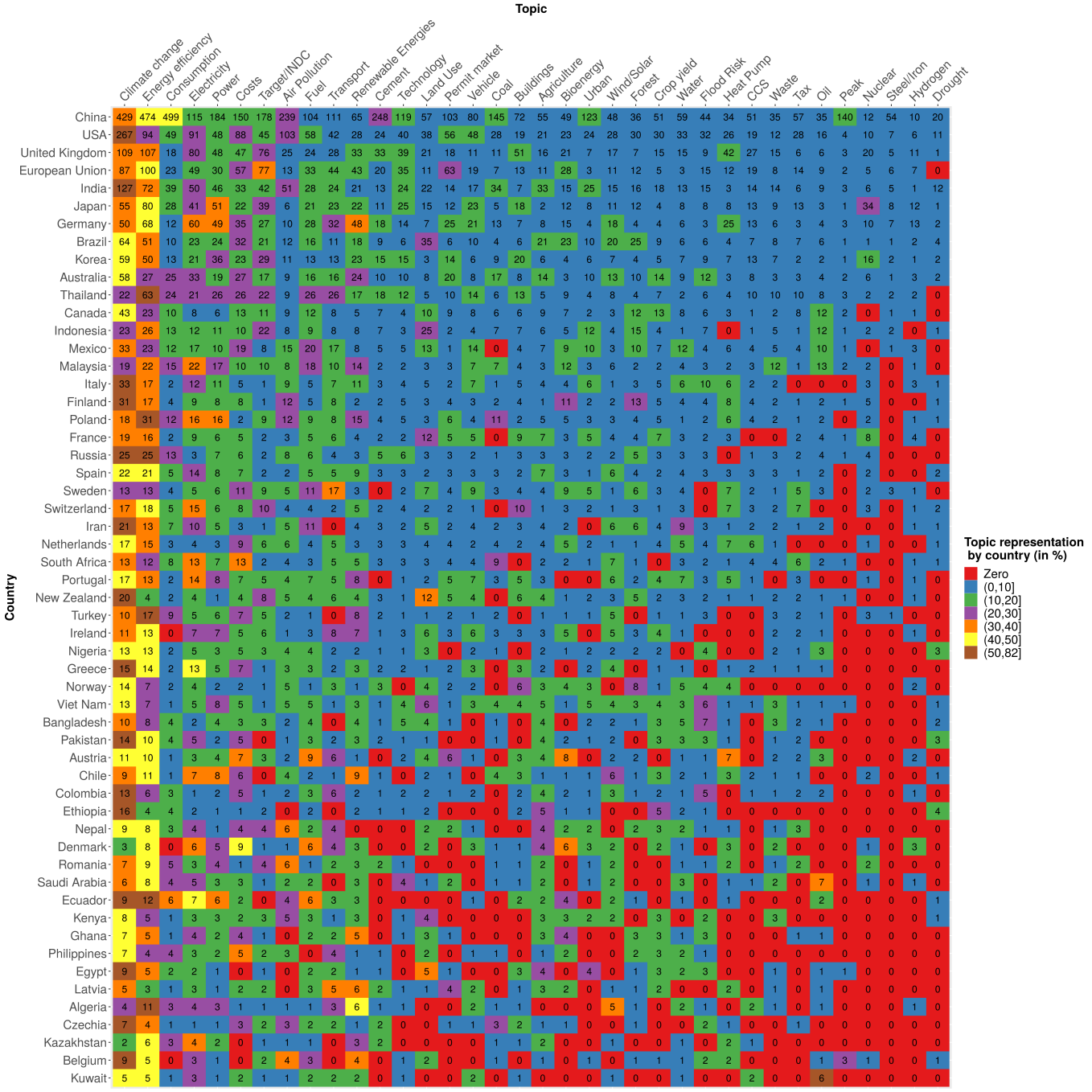

Figure 4: Topic distribution in the 55 most represented countries in the database. Topics, from left to right, and countries, from top to bottom, are presented in descending order of their representation in the database. Topic representation per country (in %) is the number of country-studies associated to the topic divided by the total number of country-studies. Since individual papers can be associated to several topics, the sum of the topic representations is not equal to 100. The *Policy-Devlpt-Eco* topic is not included, since it is present is almost every paper. The *Scenario* and *System* topics are also not included since they refer to the method of the paper rather than to the issues that the paper addresses.

Patterns of countries also emerge, based on natural resource endowments (e.g., Brazil, Canada, Indonesia, Finland, New Zealand, Norway and Ghana all having higher-than-average papers on *Forest* and LULUCF-related topics), technology (e.g., Japan, Germany, Italy, France, Denmark and Norway on *Hydrogen*), or specific policies (e.g., *Tax* in South Africa and Switzerland). Forward-looking studies related to impacts of climate change are particularly frequent (in relative terms) in some countries, mostly in the global south (e.g., Ethiopia, Pakistan, Bangladesh, Nigeria for *Drought*). Finally, for each country, it is also interesting to examine the topics that are not addressed. Some may just be less relevant in that particular context (e.g., *Coal* in France). Others may point to gaps in the literature. For instance, one may argue that given their importance for the French 2050 net zero target, *Forest* and *Bioenergy* are currently under represented in the literature on France.

3.5 Models are mainly identified in studies devoted to Asia

Finally, we attempt to analyze the methods used in the papers to study mitigation at country level. This is not easy given the limited amount of information present in the metadata. We focus on models, checking metadata against a database of 80 scenario modeling tools for national pathways to the Sustainable Development Goals (Allen et al. 2016) and the list of 48 models documented by the IAMC. We identify model names in only 16% of the abstracts (734). Compared with the country coverage of the overall dataset (Figure 1), Asia is even more represented (60.3%) in this subset. For example, Thailand is three times more represented than in the general database (6.2% against 2.2%) (see Figure A8). At the other end of the spectrum, Africa is scarcely present (4.7%) with only 13 countries represented. Model-wise, Computable General Equilibrium (CGE) model is the most common category of models in the corpus. The three individual models that dominate, LEAP, TIMES and MARKAL are all bottom-up. They are highly used for Asia and Europe (Figure A9). Unsurprisingly, these three models are mainly used for energy-related questions (top 3 for topics *Energy Efficiency*, *Electricity*, *Power*, *Fuel*, *Transport*, *Vehicle*, *Renewable Energies*) (Figure A10). Finally, it is interesting to note that the Japanese AIM model is present in 62 publications (of which 59 in Asia, given its many regional spin-offs AIM Korea, AIM Viet Nam etc.), illustrating the importance of regional clusters.

However, these findings are limited to the arguably small sample of papers that name their model (or model type) in the abstract and whose models are state-of-the-art tools in our reference list. The term "model" is actually present in 52% (2446) abstracts and characterizes mainly, as well as the terms "scenario", "bau", "refer", and "three", the topic *Scenario*. This topic is represented in 30% (1428) publications from the database and associated to the "Method" category as it characterizes papers detailing the methodology in the abstract. To better identify the modeling tools used in these studies, a deeper analysis of the publications based on the full text is needed. Although limited to a small sample of papers, these findings nonetheless emphasize again the inequalities between countries.

4 Conclusion

In this paper, we provide a first mapping of the forward-looking mitigation literature at country level, using systematic mapping techniques. We find number of papers per country well correlated with current levels of GHG emissions, with few papers for (current) low emitters. Time horizons of 2030 and 2050 each account for one third of the papers, with the former actually more frequent in recent years, spurred by interest in the (I)NDCs. Topic modeling analysis of the dataset reveals that forward-looking mitigation papers encompass all dimensions of mitigation, save for finance issues, that are lacking. However, energy and to a lesser degree Land Use, Land Use Change and Forestry (LULUCF) are very dominant relative to other sectors. Topics are unevenly addressed across countries, reflecting national circumstances and priorities, but also pointing to gaps in the literature.

From a methodological point of view, the paper builds upon and improve on Lamb et al. (2019) by providing a systematic way to maximize the accuracy of the topic modeling. It also illustrates how topic modeling can complement traditional methods of evidence synthesis. Precisely, most systematic reviews are based on a search query that yields thousands of publications. These are then screened to set irrelevant papers aside and scale down the number of papers to a manageable level. Here topic modeling is used to help the screening process and to provide an overview of the publications identified along all the steps of the database construction.

This paper has three main limitations. First, the term mitigation (or its demonyms) that we use in the search equation harvests too broad a set of papers, since papers about impacts and adaptation to climate change may still refer to mitigation in the abstract. The deep interactions between mitigation and adaptation make this limitation difficult to overcome. Next, despite instructions by Journals, abstracts remain written in very different ways across papers. For the purpose of textual analysis, abstracts that are as close as possible to the method and key findings of the paper are preferable, though that may come at the expense of readability. General sentences providing context about climate change may be easily recognizable as such in a full paper (of which they would only represent a tiny fraction), whereas in an abstract they may be confused with a substantive result of the paper. The ubiquitousness of the *Climate Change* topic is a demonstration of that risk. Third, as all analysis based on metadata (abstract, title and keywords), we may miss relevant material that does not make it to the abstract. For example, we cannot rule out that non-energy sectors (e.g., industry or transport) are discussed more frequently in the body of the papers than the abstracts suggest.

Our attempt to survey the methods used for conducting forward-looking mitigation studies is limited by the fact that detailed methods, let alone model names, are not systematically presented in the abstracts. An overview of national mitigation models, similar to the overview of global mitigation models supported by the Integrated Assessment Modeling Consortium, would be helpful to complement this first attempt.

Finally, our paper has policy implications, as forward-looking mitigation studies typically aim at informing decision, notably in the context of the Paris Agreement. Where we find such papers

scarce, policymakers and stakeholders do not benefit from this source of insights. This is all the more regrettable as these countries, typically with low emissions at present, may still have options to avoid getting into high emissions paths. Possible explanations for our finding include lack of domestic research capacity, lack of data, or lack of interest or incentive for foreign research teams to work on other national contexts. In any case, our paper adds quantitative evidence to existing qualitative analysis of capacity to prepare forward-looking climate policies (e.g., UNFCCC (2019)). And it also provides a basis to further explore the reasons for the discrepancies across countries.

Acknowledgments

We warmly thank two anonymous reviewers who contributed to improve the quality of the manuscript. Claire Lepault acknowledges funding from the French environment and Energy Management Agency (Ademe) (research Contract 18MAR000099186715 'State of the Art of prospective modeling', 2018-2019).

Data Availability

The data that support the findings of this study are openly available at https://github.com/ClaireLepault/Mapping-country-mitig-pathways, with the exception of the abstracts from Scopus and Web of Science, that can not be published for copyright reasons. However, code and explanations are fully provided to reproduce the analysis and get the complete databases. In particular, a tutorial on systematic search on Scopus and Web of Science at https://github.com/ClaireLepault/systematic-search-wos-scopus shows how to download the initial metadata databases from WoS and Scopus.

Code Availability

The code used to produce this paper is completely available in Jupyter notebook format. All the process, from the search query to the figures is explained and clearly reproducible using Python and R at https://github.com/ClaireLepault/Mapping-country-mitig-pathways.

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Appendices

Supplementary Figures

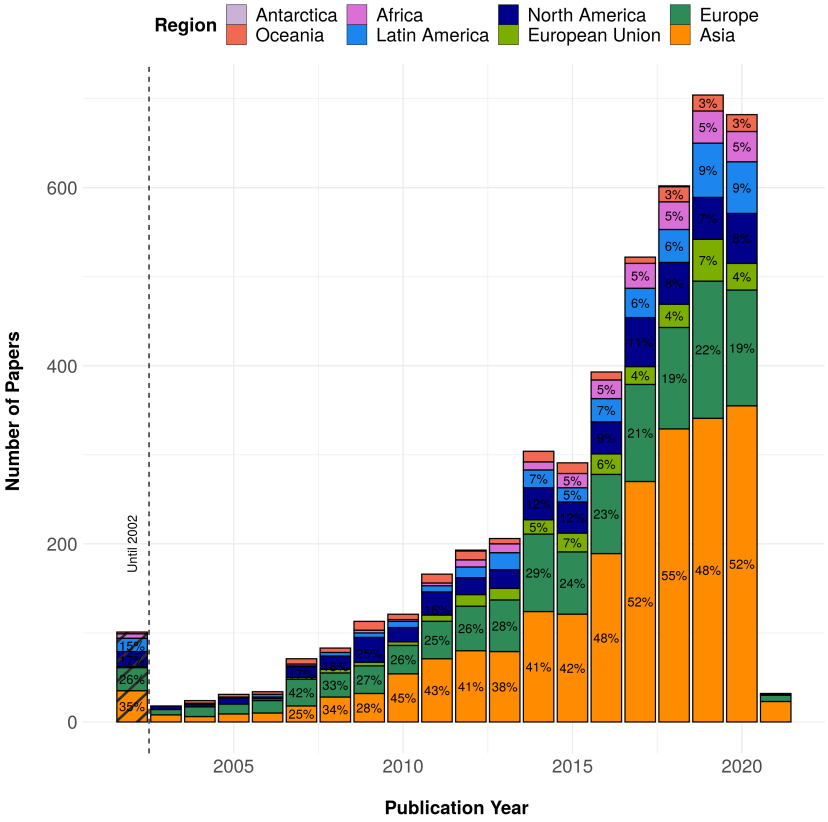


Figure A1: Papers in the corpus by region and publication year. For ease of reading, all papers published up to 2002 are associated to year 2002.

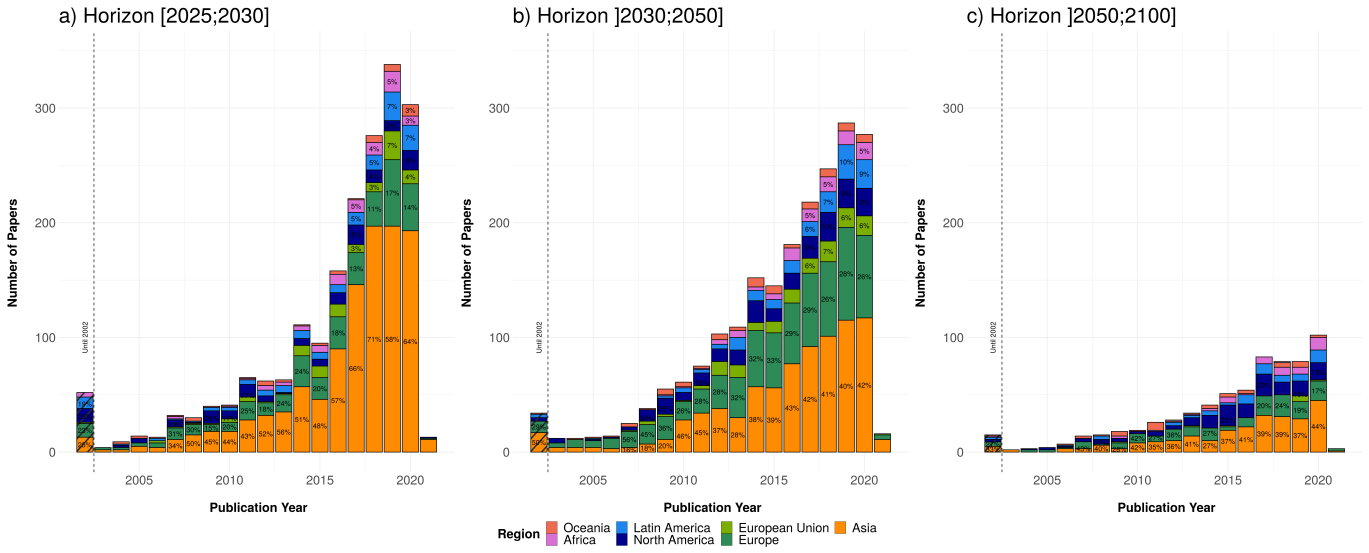


Figure A2: Comparison of the regional distribution of papers according to horizon year and publication year;

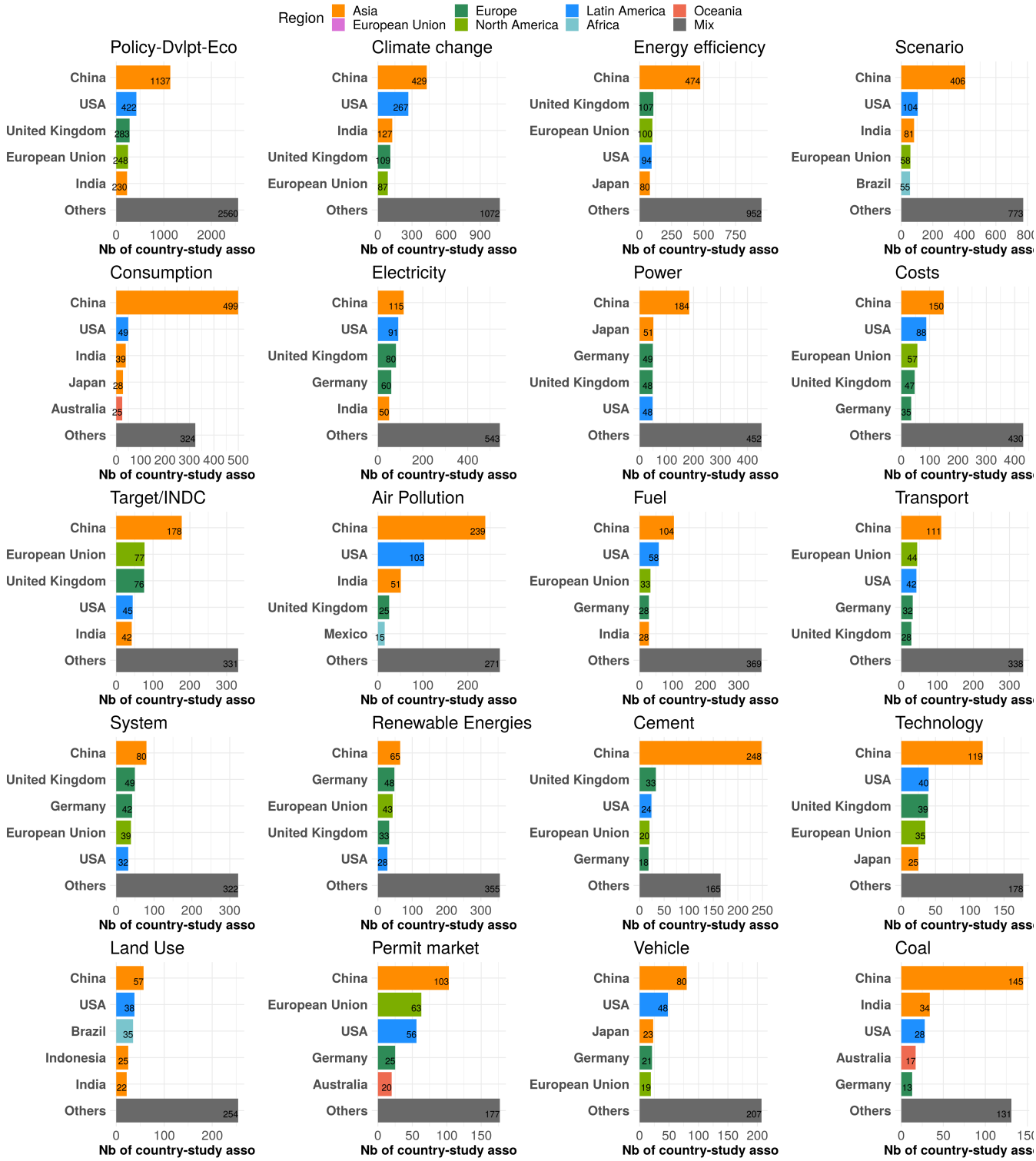


Figure A3: Top 5 countries representing each topic. From left to right, and from top to bottom, topics are presented in the descending order of their representation in the whole database.

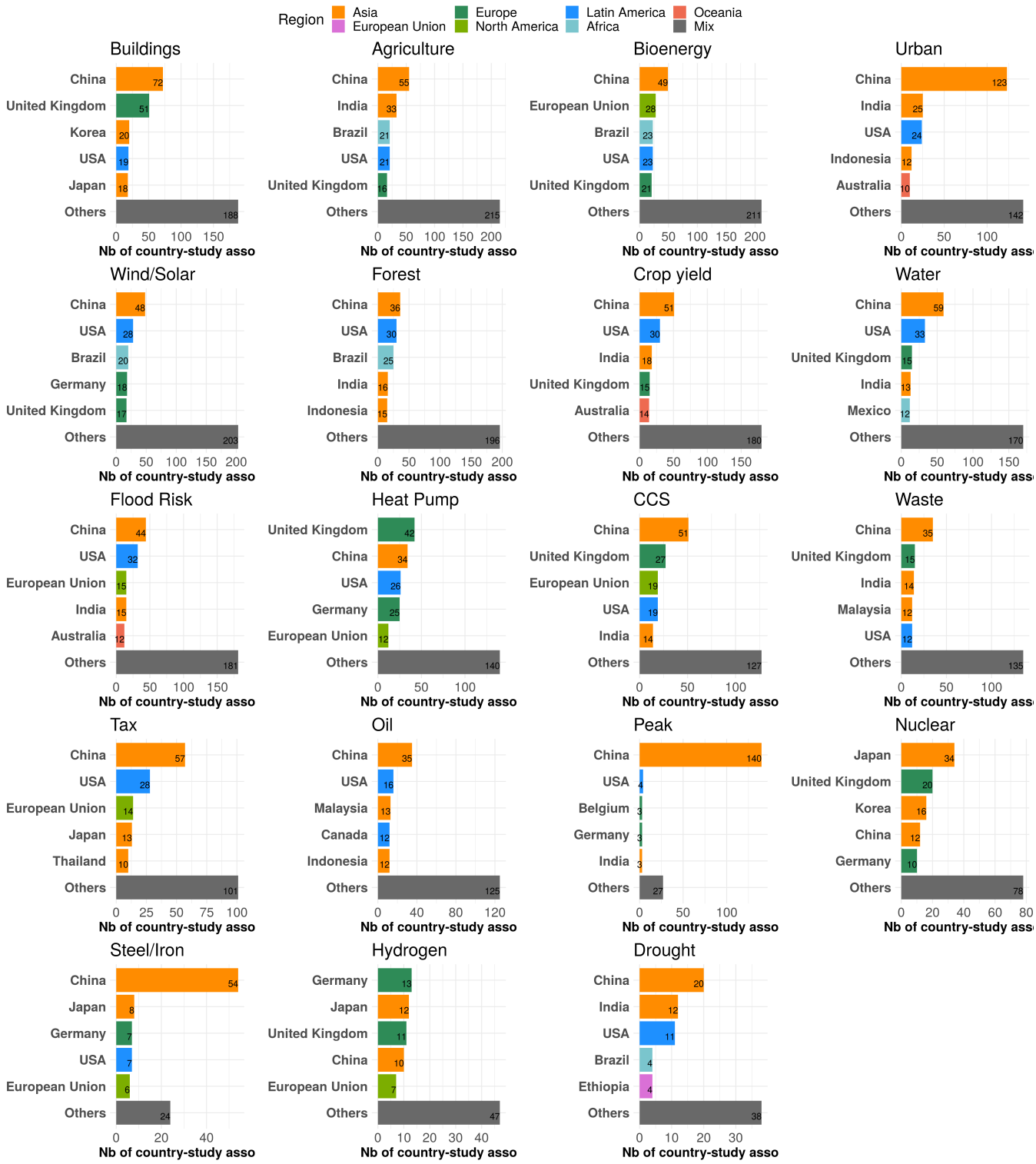


Figure A4: Top 5 countries representing each topic. From left to right, and from top to bottom, topics are presented in the descending order of their representation in the whole database.

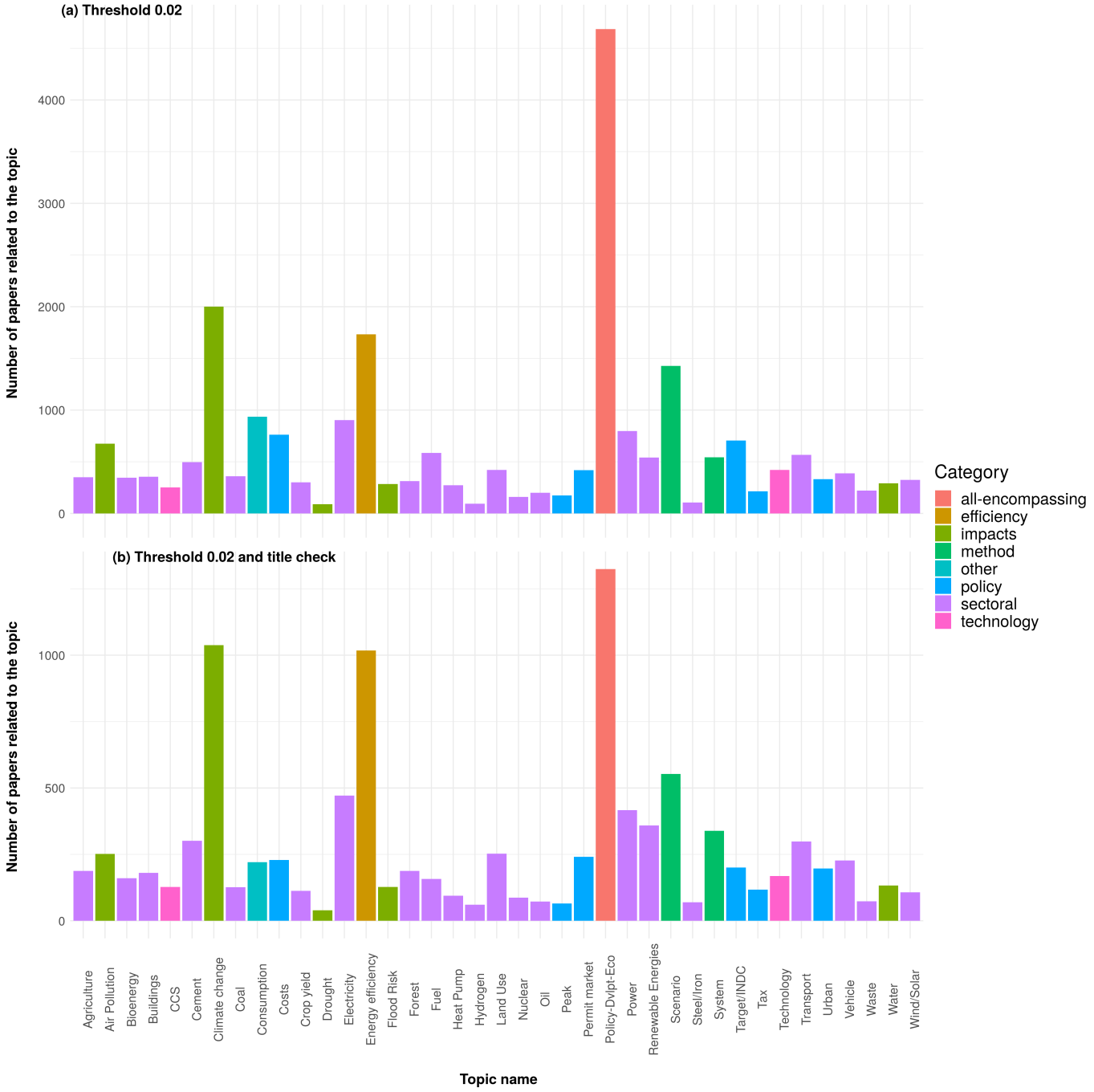
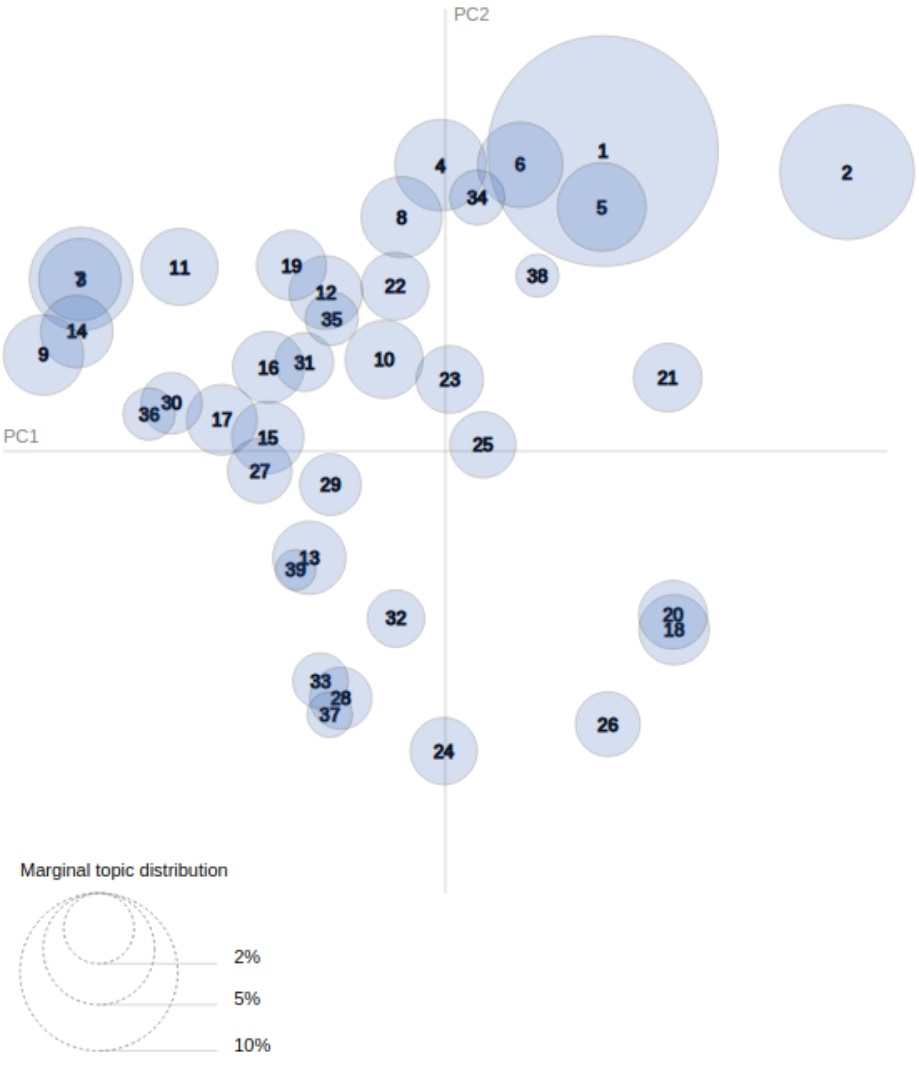


Figure A5: Distribution of topics when papers : are are selected with $t = 0.02$ (a); are selected with $t = 0.02$ **and** contains in the title one of the five term characterizing the topic (b)



	Topic
1	Policy-Dvlpt-Eco
2	Climate change
3	Energy efficiency
4	Scenario
5	Air Pollution
6	Consumption
7	Electricity
8	Target/INDC
9	Power
10	Costs
11	Transport
12	System
13	Cement
14	Renewable Energies
15	Technology
16	Buildings
17	Fuel
18	Forest
19	Vehicle
20	Land Use
21	Flood Risk
22	Permit market
23	Urban
24	Agriculture
25	Water
26	Crop yield
27	Coal
28	Bioenergy
29	CCS
30	Wind/Solar
31	Heat Pump
32	Waste
33	Oil
34	Tax
35	Peak
36	Nuclear
37	Steel/Iron
38	Drought
39	Hydrogen

Figure A6: Intertopic Distance Map (via multidimensional scaling)

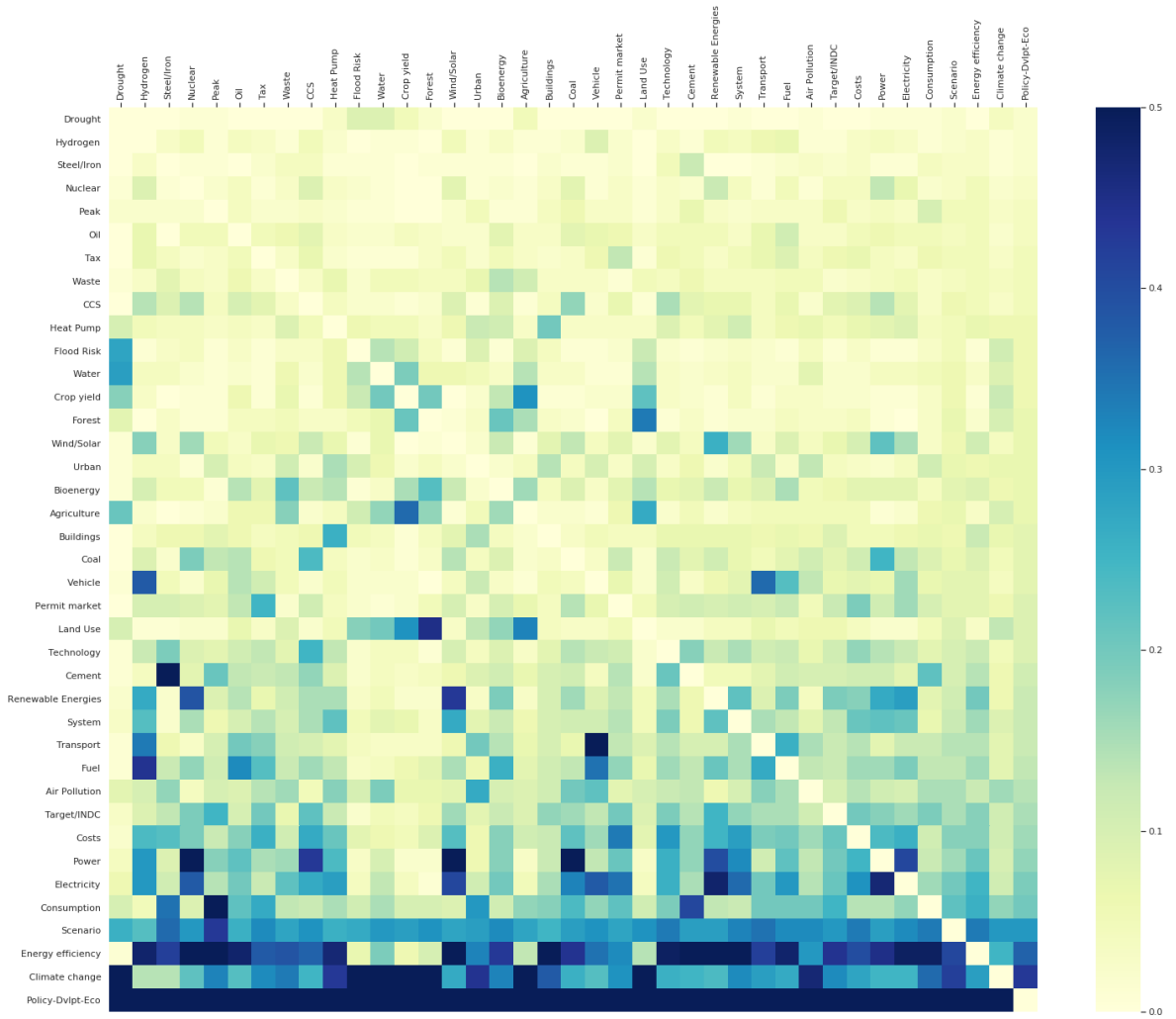


Figure A7: Heatmap of the papers common accross topics (each cell corresponds to the number of common papers to both topics (row and column) on the total number of papers related to the topic-column)

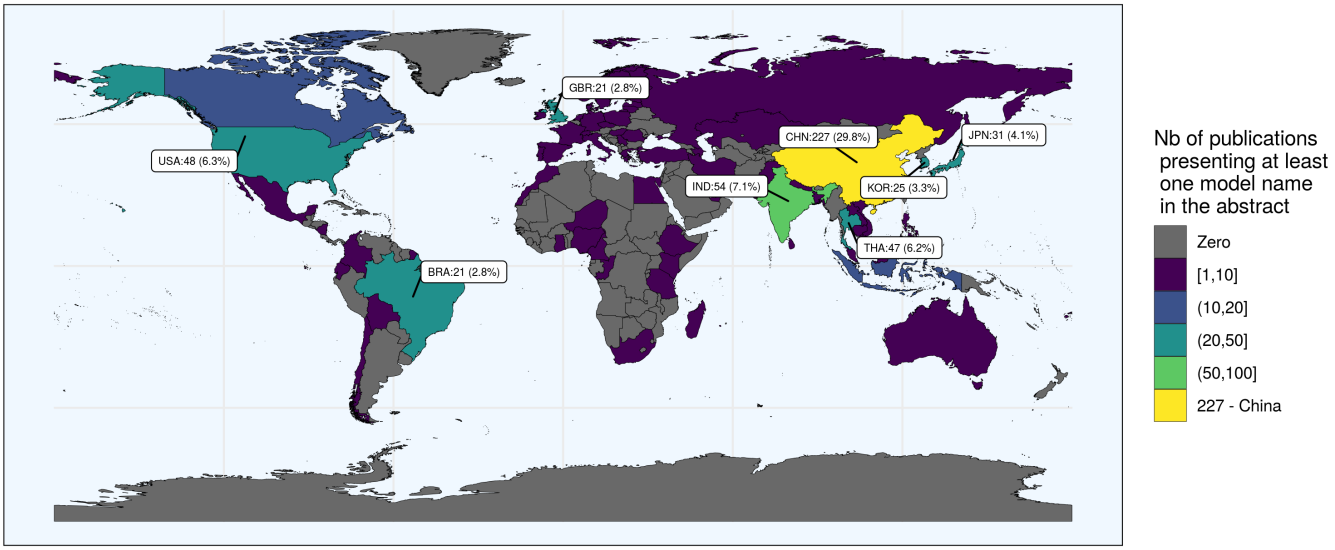


Figure A8: Country distribution of studies mentioning at least one model in the abstract. As the map is at the country level, papers related to the European Union are not represented in this figure.

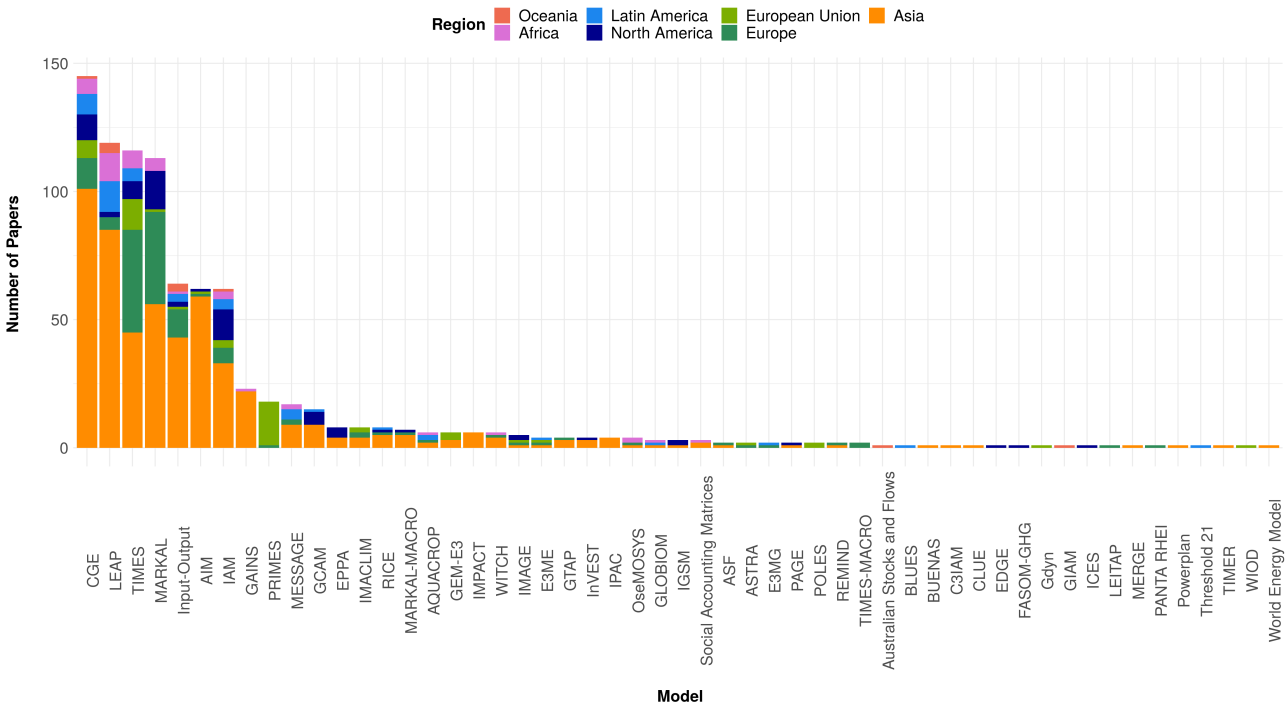


Figure A9: Histogram of the number of model-study associations

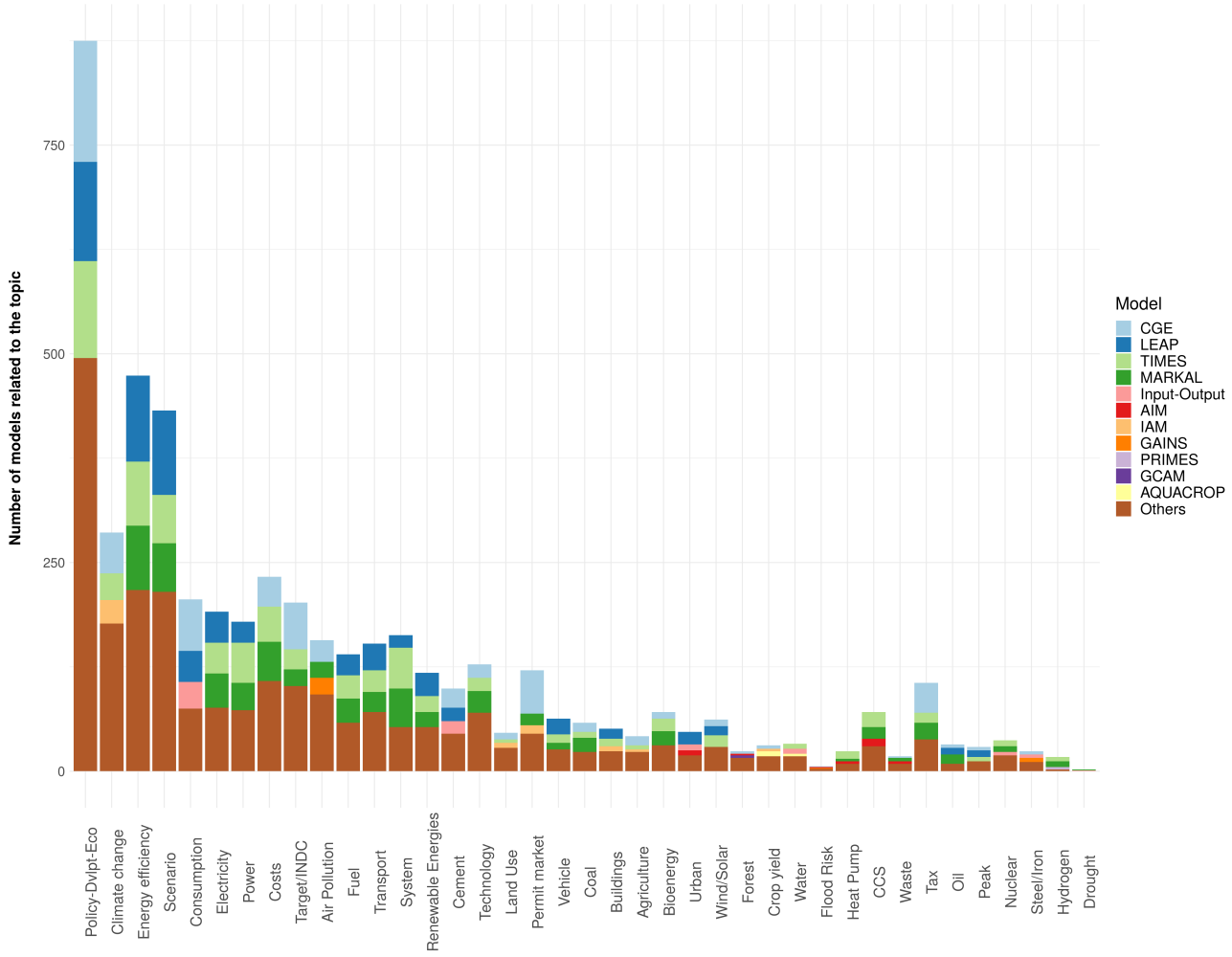


Figure A10: Histogram of the number of model-study association per topic. Topics, from left to right, are presented in the descending order of their representation in the whole database. For each topic, only the three most represented models are in distinct colors.

Supplementary Table

Number of topics	Number of papers	
	Threshold 0.02	Threshold 0.02 and title check
0	0	367
1	31	1104
2	238	1410
3	648	1050
4	956	539
5	972	177
6	832	37
7	517	5
8	283	2
9	136	0
10	56	0
11	18	0
12	2	0
13	2	0

Table A 1: Number of topics characterizing papers. For each paper in the database, the NMF algorithm provides the weight of each topic. We consider that a particular paper is related to a particular topic if the normalized weight of the topic in the paper is greater than 0.02 (column Threshold 0.02). To check the robustness of this method, we consider a second attribution process in which papers are linked to a topic if at least one of the five top words (the words most important in the topic) figures in the title of the paper (column Threshold 0.02 and title check).