Scaling up assessments of regional impacts of climate change: a rapid, computer-assisted systematic map

Max Callaghan, Jan Minx, Carl-Friedrich Schleussner, Gerrit Hansen, Quentin Lejeune, Shruti Nath, Emily Theokritoff, Marina Andrijevic, Robert Brecha, Michael Hegarty, Chelsea Jones, Kaylin Lee, Agathe Lucas, Nicole van Maanen, Inga Menke, Peter Pfleiderer, Burcu Yesil

August 25, 2020

Context

Systematic assessments of the evidence on Climate Change like those conducted by the IPCC are vital.

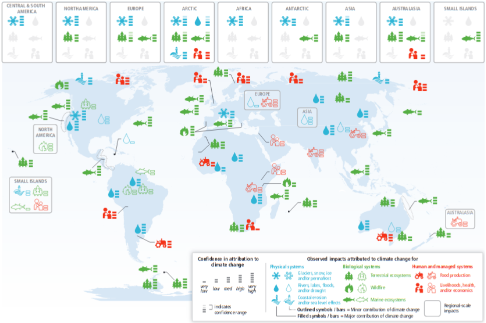

Figure 18-3 | Global patterns of observed climate change impacts reported since AR4. Each filled symbol in the top panels indicates a class of systems for which climate change has played a major role in observed changes in at least one system within that class across the respective region, with the range of confidence in attribution for those region-wide impacts indicated by the bars. Regional-scale impacts where climate change has played a minor role are shown by outlined symbols in a box in the respective region. Sub-regional impacts are indicated with symbols on the map, placed in the approximate area of their occurrence. The impacted area can vary from specific locations to broad areas such as a major river basin. Impacts on physical (blue), biological (green), and human (red) systems are differentiated by color. This map represents a graphical synthesis of Tables 18-5, 18-6, 18-7, 18-8, and 18-9. Absence of climate change impacts from this figure does not imply that such impacts have not occurred.

1011

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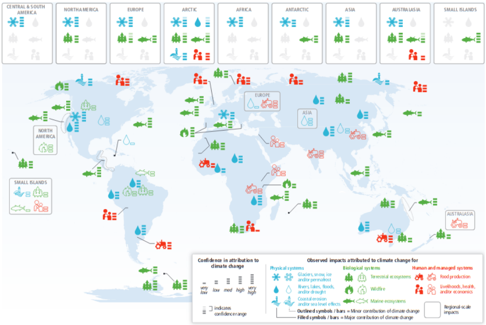

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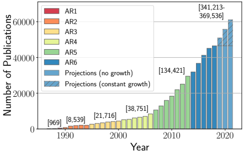

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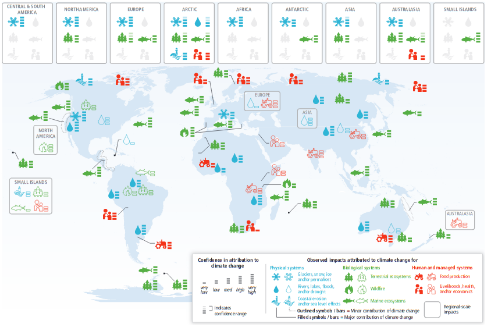

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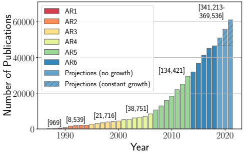
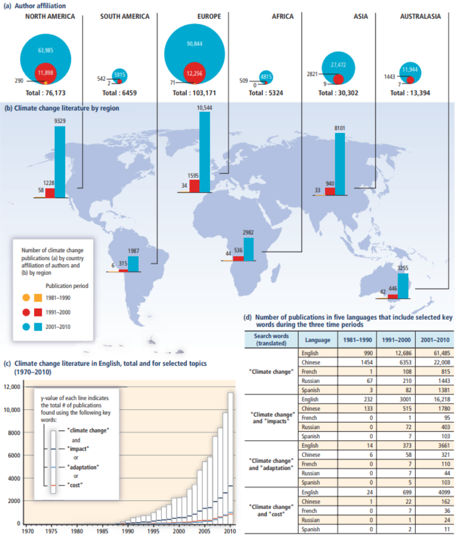


- These are challenged by big literature Callaghan et al. (2020)
- They do not account for uncertainty about what literature is available

Quantifying the literature

- AR5 WGII started with a basic bibliometric analysis of climate change (and impacts and adaptation) literature
- The literature has doubled again since then
- We can do more than this



Search words (translated)	Language	1981–1990	1991–2000	2001–2010
"Climate change"	English	990	12,686	61,485
	Chinese	1454	6353	22,008
	French	1	108	815
	Russian	67	210	1443
	Spanish	3	82	1381
"Climate change" and "impacts"	English	232	3001	16,218
	Chinese	133	515	1780
	French	0	1	95
	Russian	0	72	403
	Spanish	0	7	103
"Climate change" and "adaptation"	English	14	373	3661
	Chinese	6	58	321
	French	0	7	110
	Russian	0	7	44
	Spanish	0	5	103
"Climate change" and "cost"	English	24	699	4099
	Chinese	1	22	162
	French	0	7	36
	Russian	0	1	24
	Spanish	0	2	11

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- Predict in what way relevant documents are relevant:
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  - What type of evidence do they provide?
  - In which locations is there evidence

Once we can do that, we can draw a rough map of the available evidence, and aid the production of an *assessment* of the available evidence

Distribution of labour between humans and machines

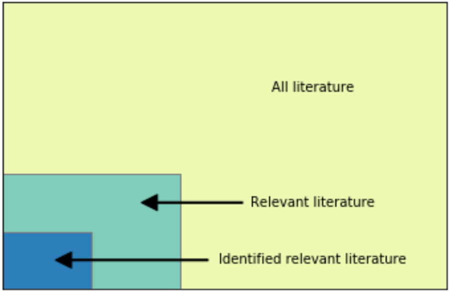
A human expert or a team of human experts is best placed to answer those questions for any single document, but they can't look at all potentially relevant documents

We can use labels generated by humans to try to teach a computer what a relevant document looks like, and how to decide in what way it is relevant.

If this works well, we can predict, with some uncertainty, how much evidence there is, and where and on what topic it is.

Building a query

We built a query using the documents from the tables in AR5 WGII Chapter 18. The ideal query should contain *all* documents included in those tables, along with *all* additional relevant documents (untestable) and a hopefully minimal amount of irrelevant documents



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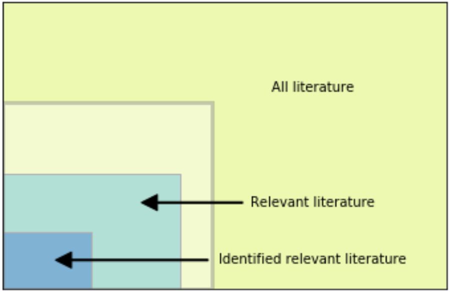

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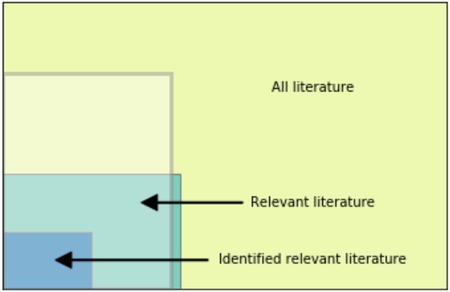

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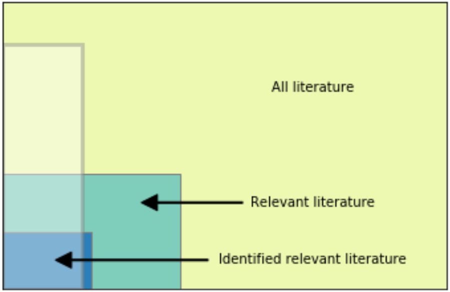


Our query contained a list of climate variables, a list of impacts, and a list of words narrowing down the literature on observed impacts

Climate

TS=("climate model" OR "elevated* temperatur" OR "ocean* warming" OR "saline* intrusion" OR "chang* climat" OR "environment* change" OR "climat* change" OR "climat* warm" OR "warming* climat" OR "climat* varia" OR "global* warming" OR "global* change" OR "greenhouse* effect" OR "snow cover" OR "extreme temperature" OR "cyclone" OR "ocean acidification" OR "anthropogen*" OR "sea* level" OR "precipitation variabil*" OR "precipitation change*" OR "temperature* impact" OR "environmental* variab" OR "weather* pattern" OR "weather* factor*" OR "climat*") OR TS=("change* NEAR/5 cryosphere" OR "increase* NEAR/3 temperatur*"))

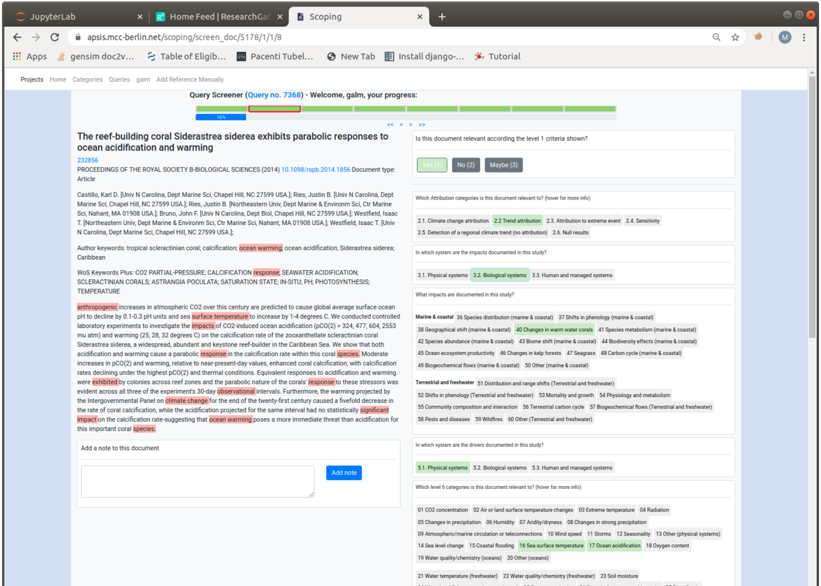
Impacts

AND (TS=("migration" OR "impact*" OR "specie*" OR "mortality*" OR "health" OR "disease*" OR "ecosystem*" OR "mass balance" OR "flood*" OR "drought" OR "disease*" OR "adaptation" OR "malaria" OR "fire" OR "water scarcity" OR "water supply" OR "permafrost" OR "biological response" OR "food availability" OR "food security" OR "vegetation dynamic*" OR "cyclone*" OR "yield*" OR "gender" OR "indigenous" OR "conflict" OR "inequality" OR "snow water equival*" OR "surface temp*") OR TS=("glacier* NEAR/3 melt*" OR "glacier* NEAR/3 mass*" OR "erosion* NEAR/5 coast*" OR "glacier* NEAR/5 retreat*" OR "rainfall* NEAR/5 reduc*" OR "coral* NEAR/5 stress*" OR "precip* NEAR/5 *crease*" OR "river NEAR/5 flow"))

Observed

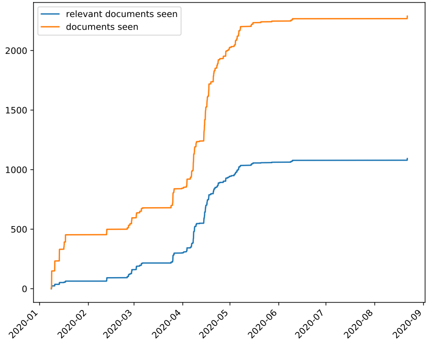
AND (TS=("recent" OR "current" OR "modern" OR "observ*" OR "evidence*" OR "past" OR "local" OR "region*" OR "significant" OR "driver*" OR "driving OR "respon*" OR "were responsible" OR "was responsible" OR "exhibited" OR "witnessed" OR "attribut*" OR "has increased" OR "has decreased" OR "histor*" OR "correlation" OR "evaluation"))

We set up our platform to record the relevance and lots of other information about each document



Screening and coding

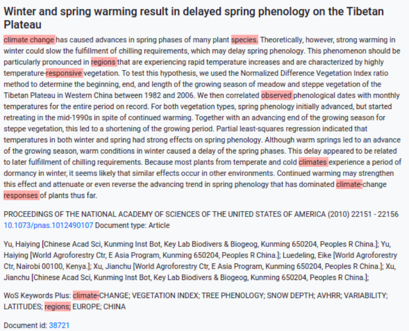
- 1 large random sample (unbalanced)
- 1 sample of documents predicted to be relevant (unbalanced)
- iterative small samples of documents predicted to be relevant to each category (over-hasty generalisation)
- iterative samples of documents containing words and phrases designed to pick up under-represented (subject to human bias and error)



To which we added the papers included in AR5 WGII Chapter 18 (coded as relevant and with their corresponding impact category).

Feature space - text as data

The set of features is a TFIDF weighted set of unigrams and bigrams from the documents' abstracts


Winter and spring warming result in delayed spring phenology on the Tibetan Plateau

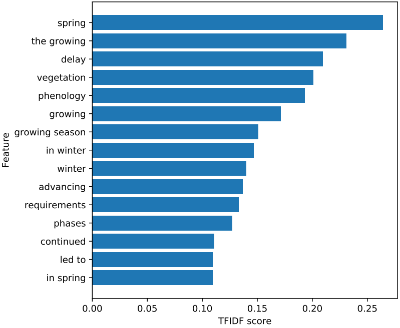
climate change has caused advances in spring phases of many plant species. Theoretically, however, strong warming in winter could slow the fulfillment of chilling requirements, which may delay spring phenology. This phenomenon should be particularly pronounced in regions that are experiencing rapid temperature increases and are characterized by highly temperature-responsive vegetation. To test this hypothesis, we used the Normalized Difference Vegetation Index ratio method to determine the beginning, end, and length of the growing season of meadow and steppe vegetation of the Tibetan Plateau in Western China between 1982 and 2006. We then correlated observed phenological dates with monthly temperatures for the entire period on record. For both vegetation types, spring phenology initially advanced, but started retreating in the mid-1990s in spite of continued warming. Together with an advancing end of the growing season for steppe vegetation, this led to a shortening of the growing period. Partial least-squares regression indicated that temperatures in both winter and spring had strong effects on spring phenology. Although warm springs led to an advance of the growing season, warm conditions in winter caused a delay of the spring phases. This delay appeared to be related to later fulfillment of chilling requirements. Because most plants from temperate and cold climates experience a period of dormancy in winter, it seems likely that similar effects occur in other environments. Continued warming may strengthen this effect and attenuate or even reverse the advancing trend in spring phenology that has dominated climate-change responses of plants thus far.

PROCEEDINGS OF THE NATIONAL ACADEMY OF SCIENCES OF THE UNITED STATES OF AMERICA (2010) 22151 - 22156
10.1073/pnas.1012490107 Document type: Article

Yu, Haiying [Chinese Acad Sci, Kunming Inst Bot, Key Lab Biodivers & Biogeog, Kunming 650204, Peoples R China.]; Yu, Haiying [World Agroforestry Ctr, E Asia Program, Kunming 650204, Peoples R China.]; Luedeling, Eike [World Agroforestry Ctr, Nairobi 00100, Kenya.]; Xu, Jianchu [World Agroforestry Ctr, E Asia Program, Kunming 650204, Peoples R China.]; Xu, Jianchu [Chinese Acad Sci, Kunming Inst Bot, Key Lab Biodivers & Biogeog, Kunming 650204, Peoples R China.];

WoS Keywords Plus: climate-CHANGE; VEGETATION INDEX; TREE PHENOLOGY; SNOW DEPTH; AVHRR; VARIABILITY; LATITUDES; regions; EUROPE; CHINA

Document id: 38721

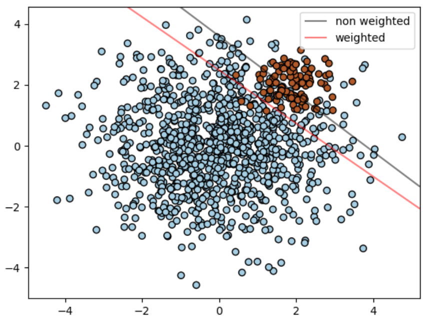


We discard very uncommon and very common features, leaving us with a vocabulary of 7,394 unique features.

Setup

We need two types of classifiers:

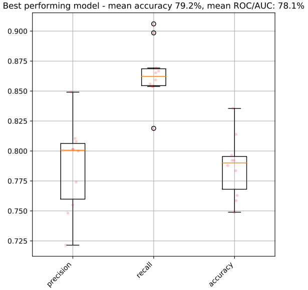
- A binary, include/don't include classifier
- Various multilabel classifiers for impact types, attribution categories and climate drivers

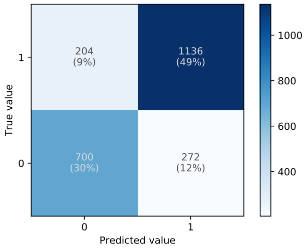


We use Support Vector Machines (SVMs), which draw hyperplanes through the feature space which best separate the classes

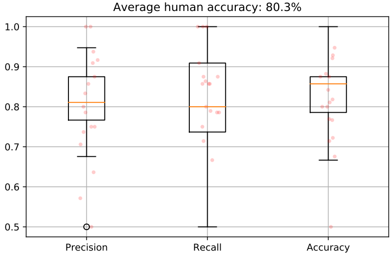
Note that a state of the art language model such as BERT may outperform SVMs, but these are resource and data hungry, and less transparent

We predict the relevance of a document most of the time





Scores are comparable or better than individual human performance in choosing the mode classification



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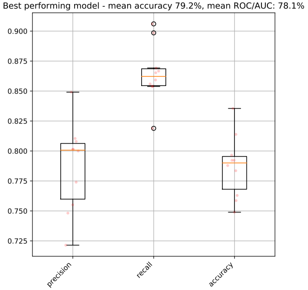

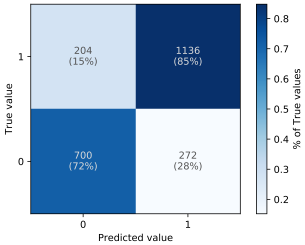

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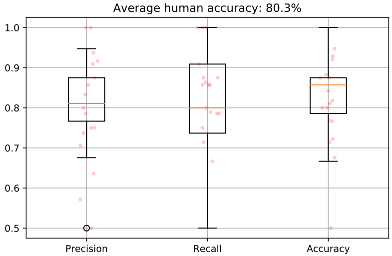

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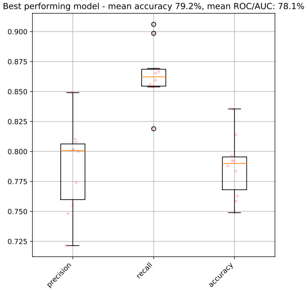

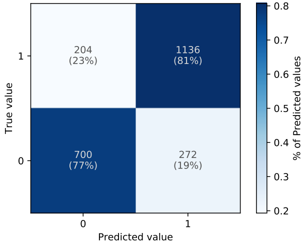

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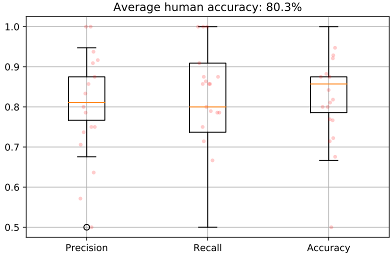
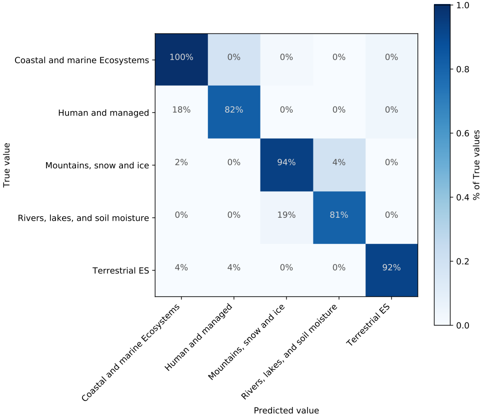
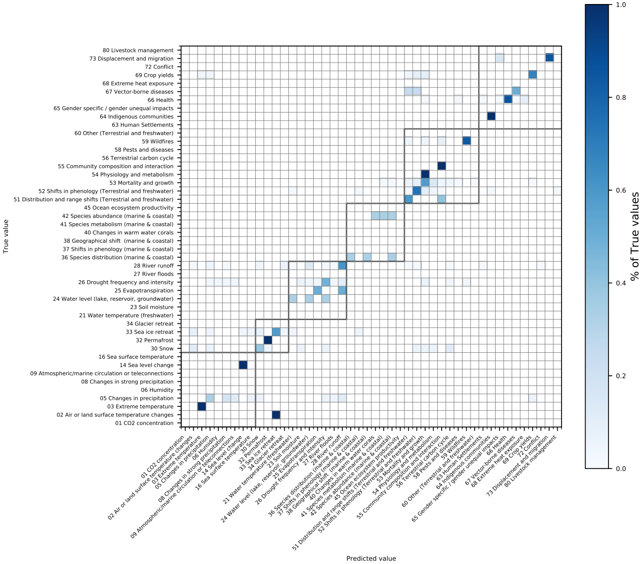


We are even better at predicting what sector impacts occured in



We even have some success at predicting specific impacts

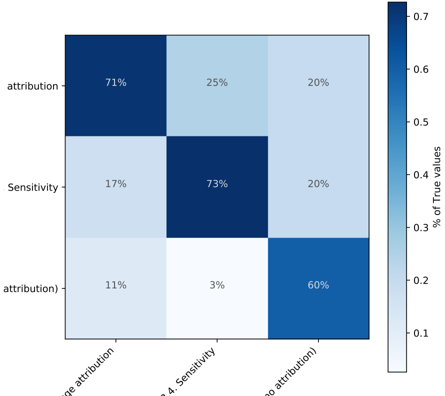


But we need more labelled data to do this properly

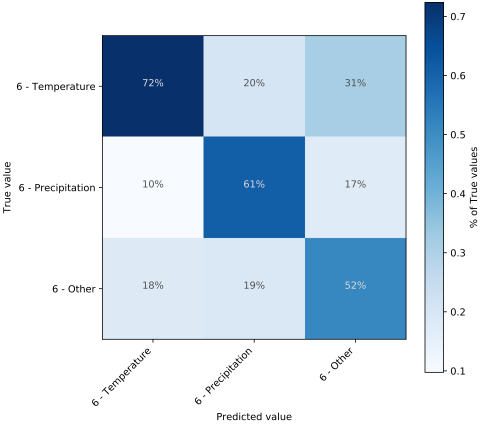
Our machine could not tell the difference between Climate change attribution and long term trend attribution

Climate change attribution describes impacts driven by trends or events attributable to human influence on the climate

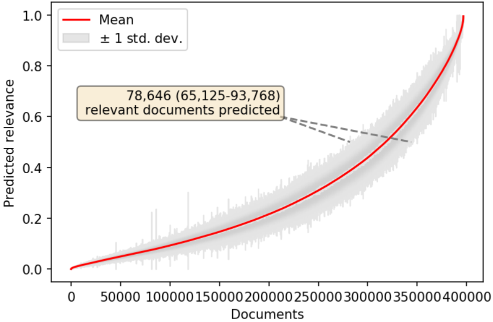
But we can fairly well distinguish between a merged attribution category, sensitivity, and detection only



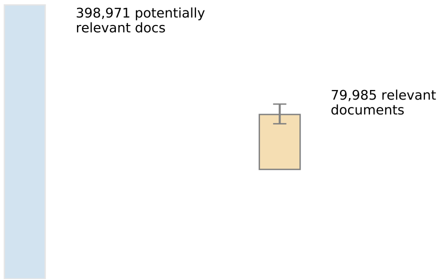
Finally, we are also able to distinguish between broad categories of climate drivers

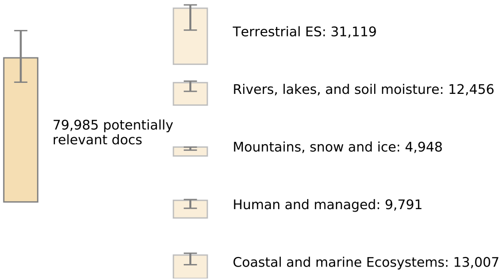


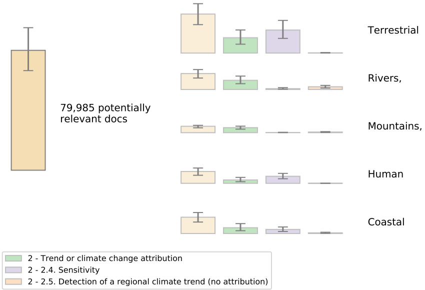
We predict tens of thousands of additional documents relevant according to the criteria we defined



- We train 10 classifiers on random partitions of the labelled dataset
- This gives us 10 estimates for each unseen document
- The mean and standard deviation of these estimates give us an idea, with some uncertainty, of how many documents are in each category


398,971 potentially
relevant docs
79,985 relevant
documents

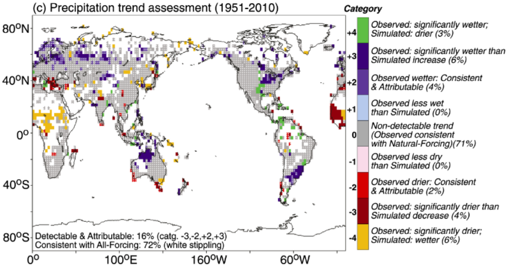

79,985 potentially relevant docs
Terrestrial ES: 31,119
Rivers, lakes, and soil moisture: 12,456
Mountains, snow and ice: 4,948
Human and managed: 9,791
Coastal and marine Ecosystems: 13,007

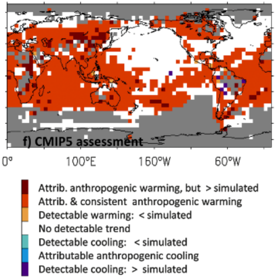

79,985 potentially relevant docs
Terrestrial
Rivers,
Mountains,
Human
Coastal
2 - Trend or climate change attribution
2 - 2.4. Sensitivity
2 - 2.5. Detection of a regional climate trend (no attribution)

Synthesizing impacts evidence with quantitative detection and attribution evidence

We know from detection and attribution studies whether observed trends in temperature and precipitation are attributable to human influence on the climate.

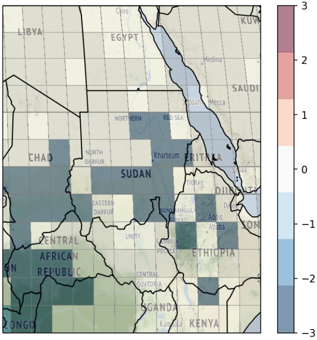
Knutson et al. (2013); Knutson and Zeng (2018) show this on a grid cell level

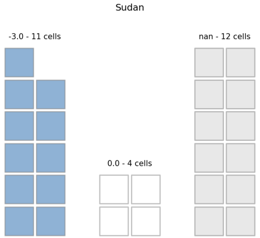




We can combine this with information from our database of impacts evidence, in which the locations, and the climate drivers have been predicted

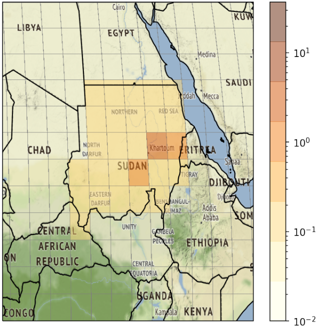
Synthesising impacts with D&A evidence

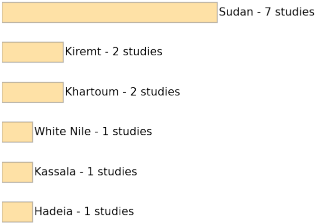




- 11 out of 27 gridcells in Sudan contain a reduction in rainfall attributable to human influence on the climate
- Each study referring to Sudan (as the smallest identifiable geographical entity) and predicted to document impacts driven by precipitation refers to a place where around 41% of the area is known to have anthropogenic changes in precipitation

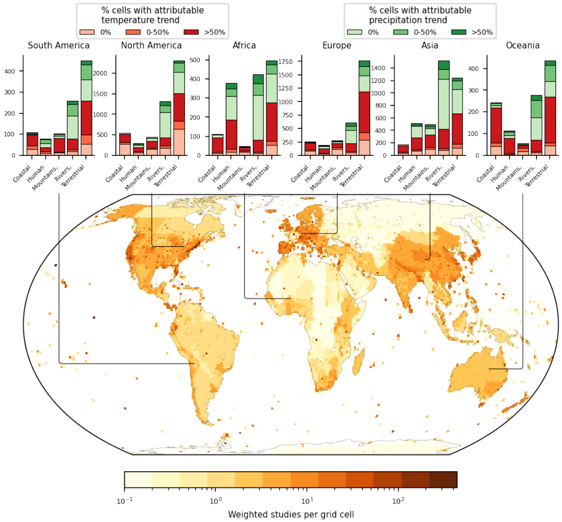
Synthesising impacts with D&A evidence





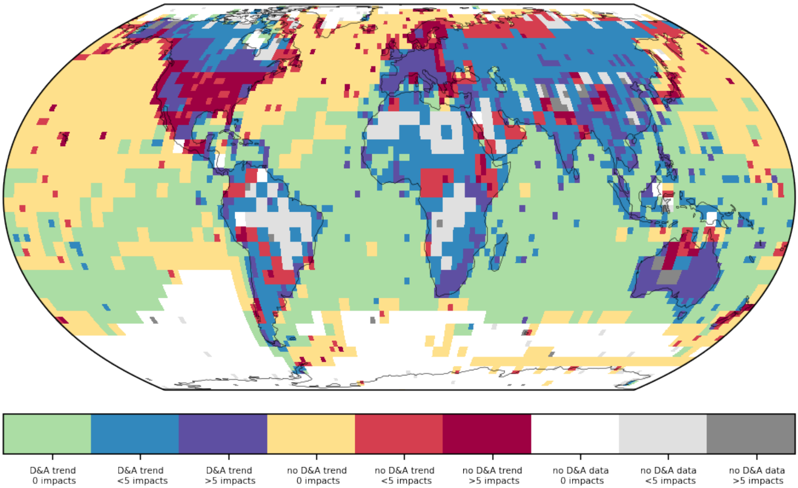
- 7 studies refer to Sudan (as the smallest identifiable geographical entity), and Sudan has 27 gridcells
- We apportion these studies to the relevant gridcells, calculating that each gridcell in Sudan has $\frac{7}{27}$ studies referring to it
- We do the same for each further geographical entity

We can show the amount of each type of study in each region

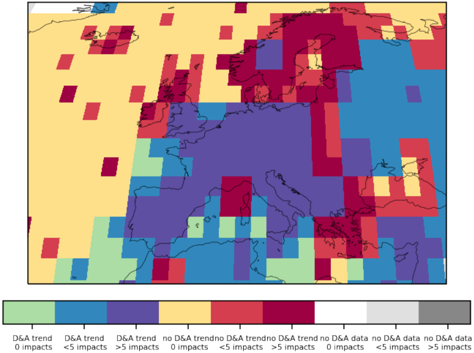


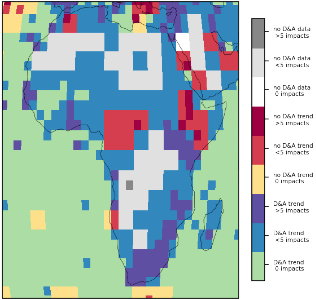
- In North America, most studies refer to places and drivers where a minority of gridcells show an attributable trend
- In Africa, the opposite is the case

The combination of evidence types at a grid cell level shows where we have lots or little evidence of each type



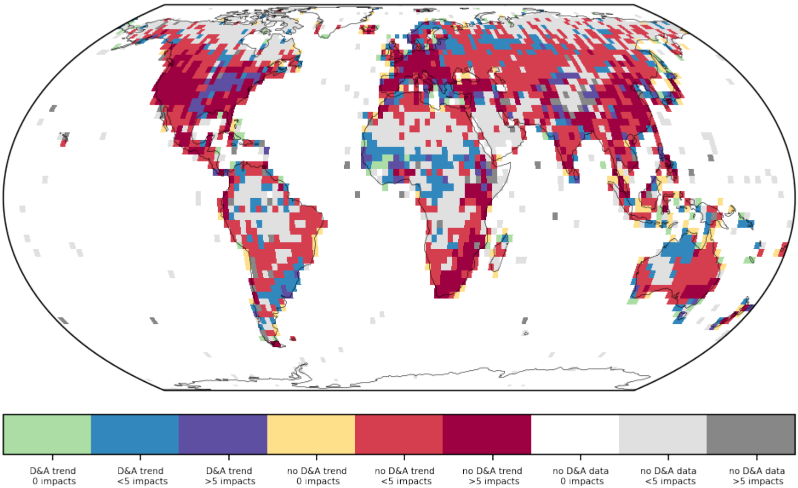
In Europe, we know a larger amount about sectoral impacts in areas we know are warming due to human influence on the climate than in Africa



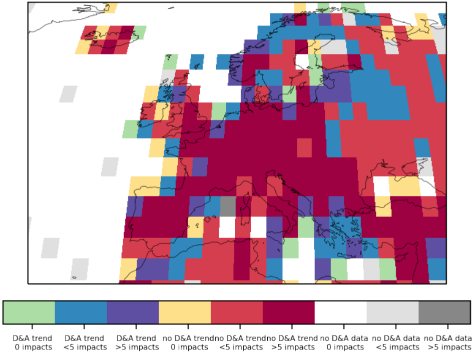


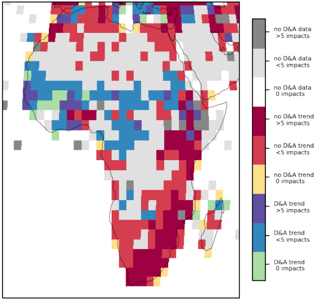
Further, impact studies on the effects of human-induced warming in Africa are concentrated in South Africa and East Africa

We are less certain about human influence on precipitation trends, but in China, Europe, Southern and Eastern Africa, and the US, the impacts of precipitation trends are frequently studied



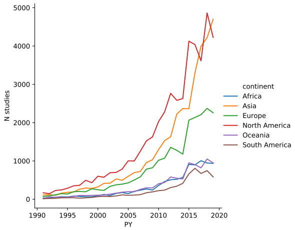
There are large parts of Africa we know are getting drier because of climate change, but we know little about the effects.

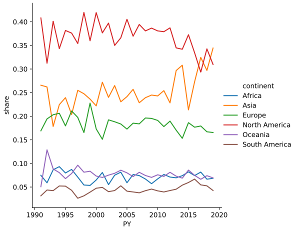




In Europe, the effects of precipitation change are more frequently studied, even where we cannot attribute changes to human influence.

A growing body of literature on impacts





- There are now hundreds of impacts studies published every year about every continent
- There has been huge growth in Asia over the last decade

Note that these are rough numbers, for about 27% of studies, no place could be found with confidence. A further 9% of studies referred to non-national or supranational geographical entities which could not be easily assigned to a continent.

Conclusions

- We identify a large body of evidence about climate impacts, including [x] studies documenting impacts in areas we know are changing due to human influence on the climate
- What we know about the effects of a changing climate on human and natural systems does not always match with what we know about how (and where) humans are driving changes in climate variables

But,

- Current results only show studies in Web of Science, so definitely do not show all relevant studies
- Although our query returned all papers in the relevant AR5 section, it may still miss potentially relevant literature.
- Study identification is approximate and uncertain
- Geoparsing is also inexact, and is unable to grasp fuzzy geographical content e.g. "Western China"
- In large parts of the world, we do not even know reliably if precipitation and temperature are changing

Outlook - an interactive atlas of climate impacts evidence

What can show here are static headline results. What would be most useful for assessment-makers is an interactive platform where evidence can be searched for by sector, type and location. We plan to create such a platform to accompany the paper.

Additionally, we are in the process of incorporating literature from Scopus and MEDLINE, and potentially lens.org.

Summary - Scaling up assessments of regional impacts of climate change: a rapid, computer-assisted systematic map

- In a large collaborative coding exercise, we examined thousands of papers *potentially* relevant to understanding observed impacts of climate change
- We used machine learning to identify tens of thousands of studies *likely* to be relevant.
- We predicted the sector, climate driver, evidence type and location for each of these studies
- We used the location and predicted climate driver to match each study with quantitative evidence on how and where human influence on the climate can be identified.

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