A Rapid Computer-assisted Systematic Map of Regional Climate Impacts



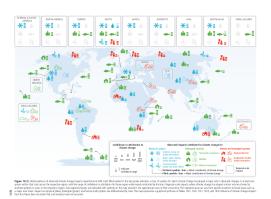
March 9, 2020

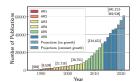
Systematic assessments of the evidence on Climate Change like those conducted by the IPCC are vital.



Figure 11-1 (Gialul pattern of devended chase of experimental properties of

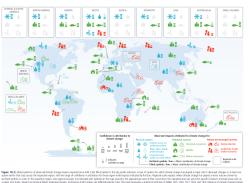
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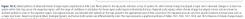


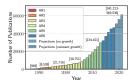


 These are challenged by big literature

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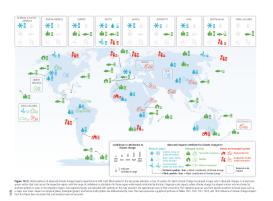


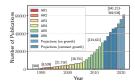




- These are challenged by big literature
- With more research out there, we need to be more systematic in assessing it

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- These are challenged by big literature
- With more research out there, we need to be more systematic in assessing it
- Machine learning can help

Rapid, Computer-assisted Systematic Mapping



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 We produced a systematic map of the literature on urban mitigation

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- We produced a systematic map of the literature on urban mitigation
- Using topic models (unsupervised learning) we were able to describe the thematic content of research and show how that varied by region

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- We produced a systematic map of the literature on urban mitigation
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With regional impact attribution literature, we have specific categories we are looking for, and a small dataset of labelled documents

Proposal

We plan to use the labelled data from AR5 WGII Table 18-5 - 18-9 to train a classifier that can identify literature relevant to the different impact categories, in the corresponding map.

This will require more screening, for the generation of further validation and training data

The results can

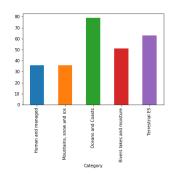
- contribute to the production of the map in AR6
- inform us about research gaps
- enhance our understanding of the what literature what was included in the last map, and what, if any, other information could have been included

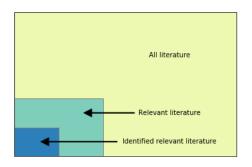
AR5 Data

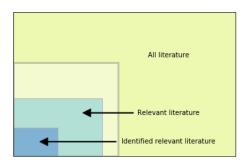
Table 16.1 (Convenience of climate durage reported sizes AAA or more trains, rose, and ex, over the pairs several decises, across may reader elegans, with occupants of climate changes in the decision of climate changes in the

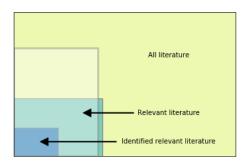
	Mountains, snow and ice	References	Confidence in detection	Role of climate	Climate driver	Reference behavior	Confidence in attribution
Africa	Retreat of tropical highland glaciers in East Africa	M64g et al. (2008, 2012); Taylor et al. (2009)	Very high	Major	Warming, drying	No change	High
Europe	Retreat of Alpine, Scandinavian, and Icelandic glaciers	WGI ARS Section 4.3.3; Bauder et al. (2007); Björnsson and Pilsson (2008); Paul and Habberli (2008); WGMS (2008); Zemp et al. (2009); Andreassen et al. (2012); Marzeion et al. (2012); Gandner et al. (2013)	Vary high	Major	Warning	No change	High
	Increase in rock slope failures in western Alps	Sections 18.3.1.3 and 23.3.1.4; Fischer et al. (2012); Huggel et al. (2012a)	riigh	Major	Warming	No change	Medium
Asia	Permafrost degradation in Siberia, Central Asia, and the Tibetan Plateau	WGI ARS Section 4.7.2; Section 24.4.2.2; Romanovsky et al. (2010); Yang et al. (2013)	High	Major	Warming	No change	High
	Shrinking mountain glaciers across most of Asia	WGI ARS Section 4.3.3; Section 24.4.1.2; Box 3-1; Bolch et al. (2012); Cogley (2012); Gardelle et al. (2012); Kääb et al. (2012); Yao et al. (2012); Gardner et al. (2013); Stelon et al. (2013)	High	Major	Warming	No change	Medium
Australasia	Substantial reduction in ice and glacier ice volume in New Zealand	WGI ARS Section 4.3.3; Table 25-1; Chinn et al. (2012)	Righ	Major	Warming	No change	Medium
	Significant decline in late-season snow depth at three out of four alpine sites in Australia 1957–2002	Table 25-1; Nicholis (2006); Hennessy et al. (2008)	High	Major	Warming	No change	Medium
North America	Shrinkage of glaciers across western and northern North America	WGI ARS Section 4.3.3; Gardner et al. (2013)	High	Major	Warming	No change	High
	Decreasing amount of water in spring snowpack in western North America 1960–2002	Stewart et al. (2005); Mote (2006); Barmett et al. (2008)	High	Major	Warming	No change	Migh
South and Central America	Shrinkage of Andean glaciers	WGI ARS Section 4.3.3; Section 27.3.1.1; Table 27-3; Vaille et al. (2008); Bradley et al. (2009); Jonnéli et al. (2009); Poveda and Pineda (2009); Marzeion et al. (2012); Gardiner et al. (2013); Ruband et al. (2013)	High	Major	Worming	No change	High
Polar regions	Decreasing Arctic sea ice cover in summer	WSI ARS Section 4.2.2.1; ACIA (2005); AMAP (2011)	Very high	Major	Air and ocean warming, change in ocean circulation	No change	High

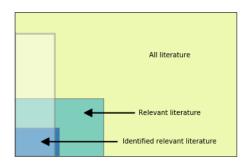
257 Documents available in Web of Science from AR5 WGII Table 18-5 - 18-9











I built a query that returns all identified documents by assembling keywords on three themes

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 "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

TS=("impact*" OR "specie*" OR "mortality*" 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 "vield*" 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")

Attribution

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

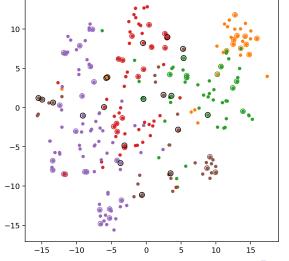
Even after excluding sensible words that occurred in the query, but not in the AR5 references, we have 318,885 documents

Machine Learning Approach

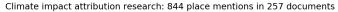
- We use the text of the documents to train a model to categorise the documents we know the categories for
- We use that model to predict the categories of documents we haven't seen yet
- ▶ We screen these documents, providing validation and more training data

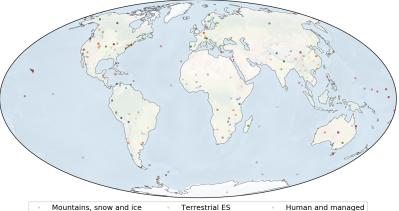
Proof of Concept

- Mountains, snow and ice: accuracy 92.21%, precision 81.82%, recall 69.23%
- Rivers lakes and moisture: accuracy 89.61%, precision 87.50%, recall 50.00%
- Terrestrial ES: accuracy 92.21%, precision 100.00%, recall 72.73%
- Oceans and Coasts: accuracy 96.10%, precision 95.00%, recall 90.48%
- Human and managed: accuracy 90.91%, precision 100.00%, recall 30.00%



Proof of Concept

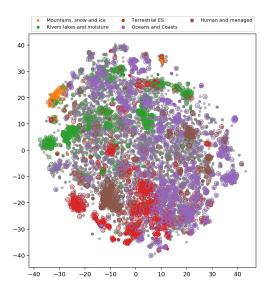




- Rivers lakes and moisture
- Oceans and Coasts

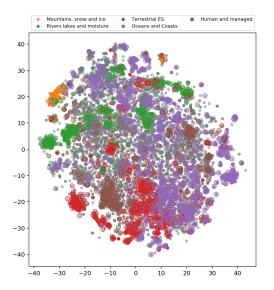
We view the same documents in the context of a sample of 10,000 new documents

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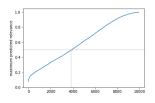


We can train the model on the known documents, and use it to predict the categories of the unseen documents

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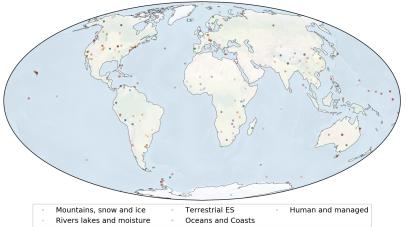


- We can train the model on the known documents, and use it to predict the categories of the unseen documents
- About 40% of documents are predicted to be relevant (!), but the model is only trained on positive cases



Recall the orignal map of places mentioned in the AR5 documents

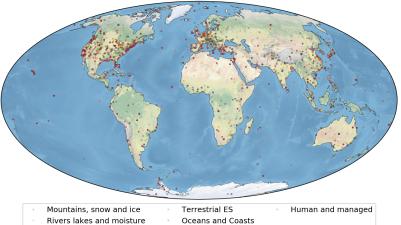
Climate impact attribution research: 844 place mentions in 257 documents



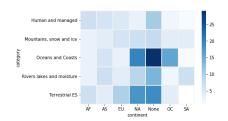
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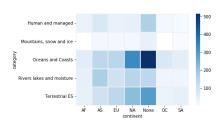
In just a sample of 10,000 documents, we have a lot more places mentioned, and regional concentrations are clearer

Climate impact attribution research: 29431 place mentions in 9963 documents



Proof of Concept - regional aggregation





Next Steps

Take a random sample of the new documents, assess their relevance to different categories, and record geographical focus (expertise and time needed!).

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Outputs:

- What does this tell us about the new literature?
- What does this tell us about the available literature from before, and what was included or not?

References

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