A Topography of Climate Change Research

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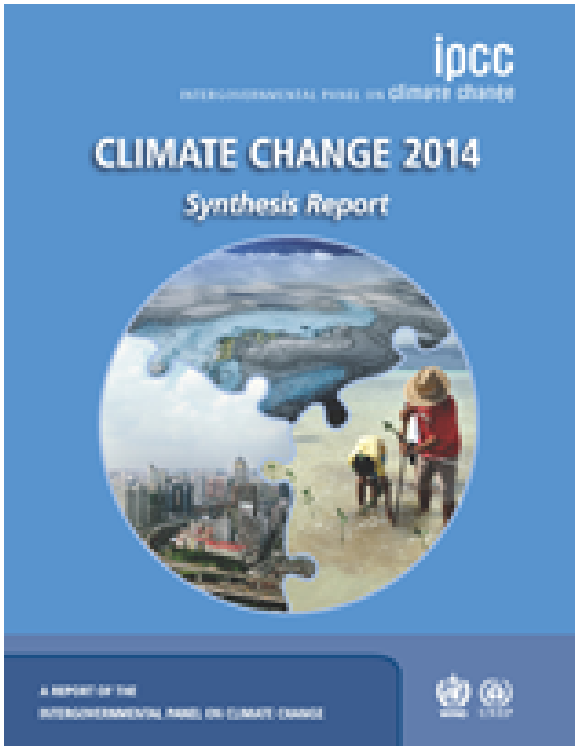
Context



- To contribute evidence-based policy-making on climate change, the IPCC aims to *comprehensively* assess
- These assessments should be aim to balance legitimacy, credibility and relevance (Cash and Clark, 2001)

Motivation

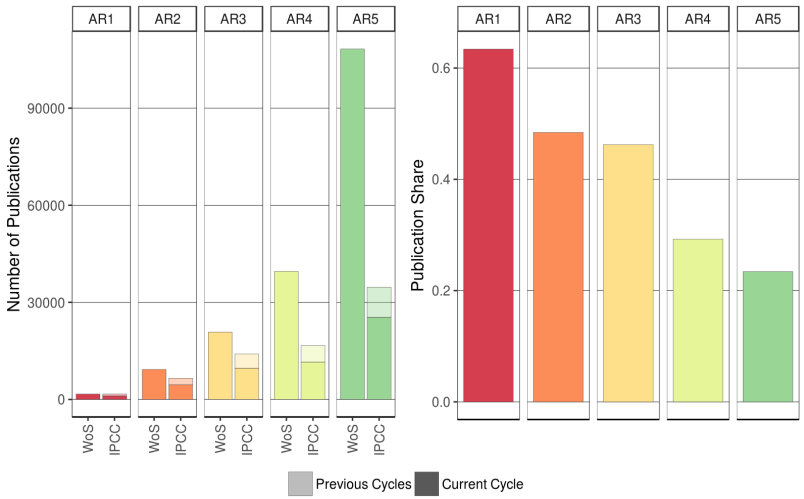


Figure: Source: Minx et al. (2017)

- Comprehensive, credible and relevant assessments become more challenging as the literature grows

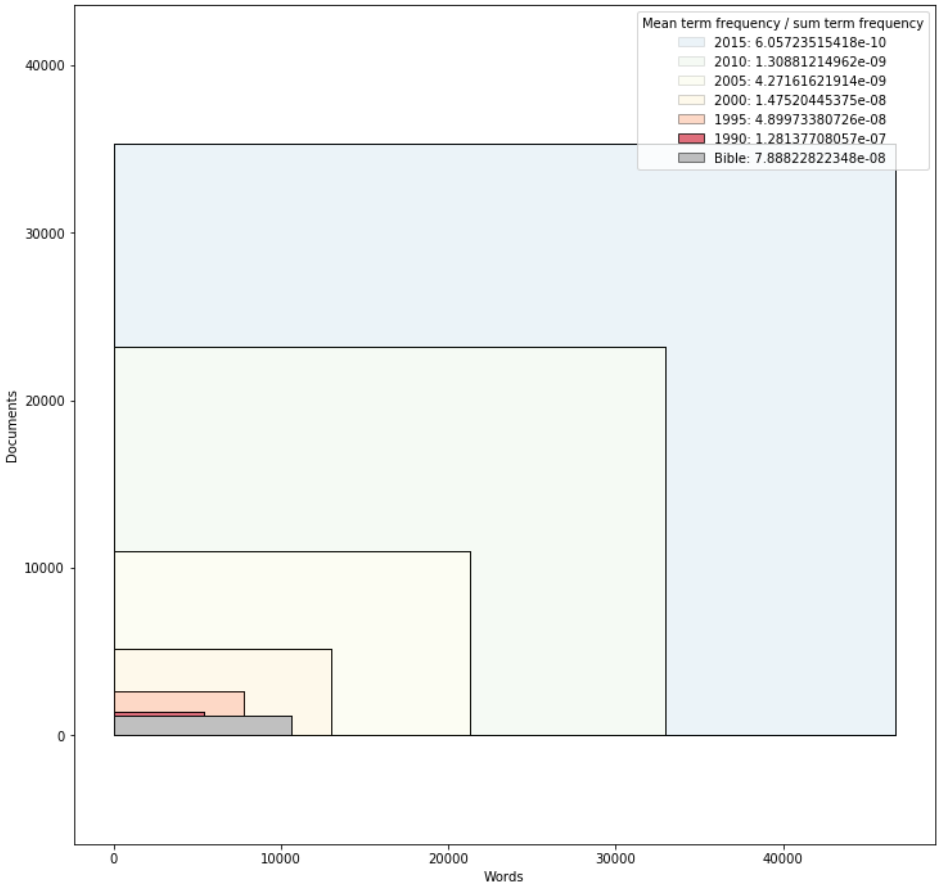
To understand, and to aid, scientific assessments of climate change, we need to machine read the literature

Motivation - Update 2018

Now that 2017 has ended, I have update the query to include papers from 2017 as well.

These extra 36,000 papers take the total number of documents to 309,697.

Approach - Words, words, words



- Topic modelling is a way of reducing the dimensionality of a corpus of documents
- A large matrix of documents x words is factorised by a matrix of topics x words and a matrix of topics x documents (Lee and Seung, 1999)
- Topics describe the latent structure of the document corpus

Approach - Words, words, words

$$V_{i\mu}$$

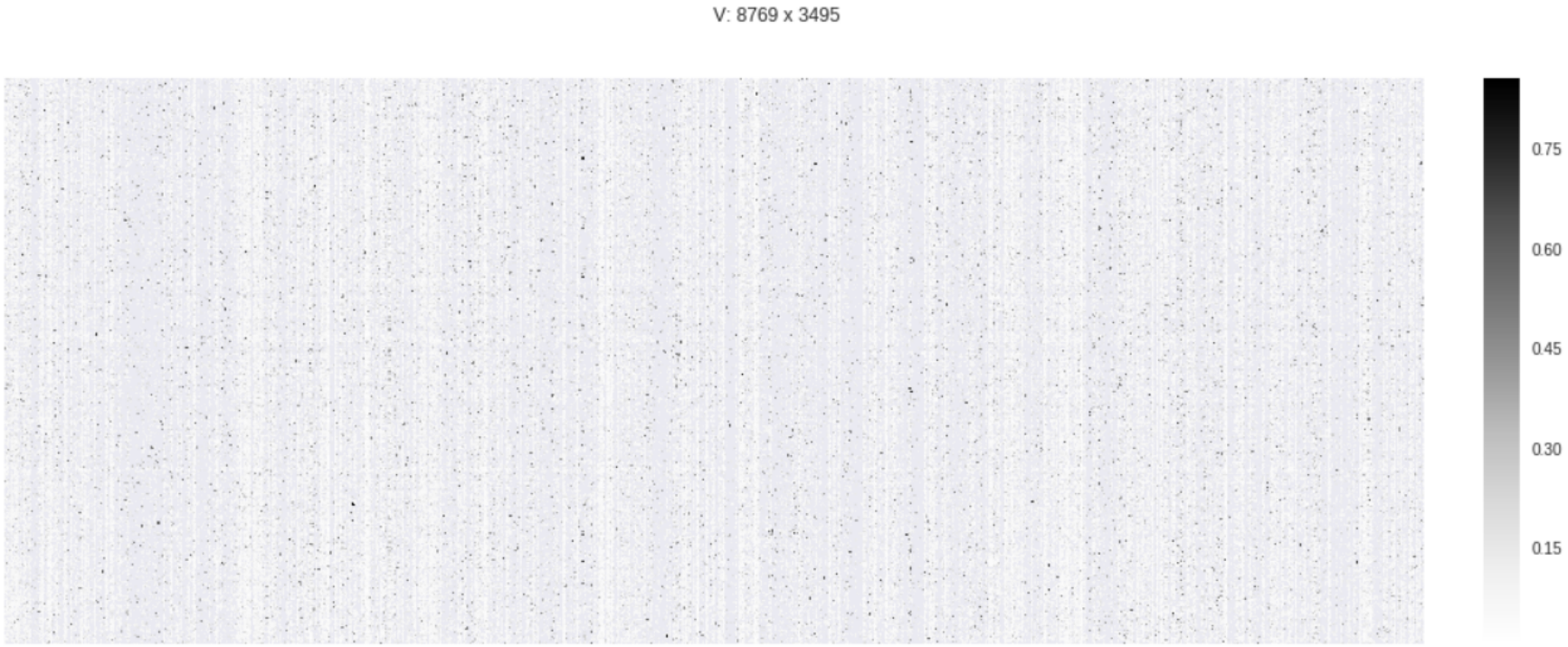
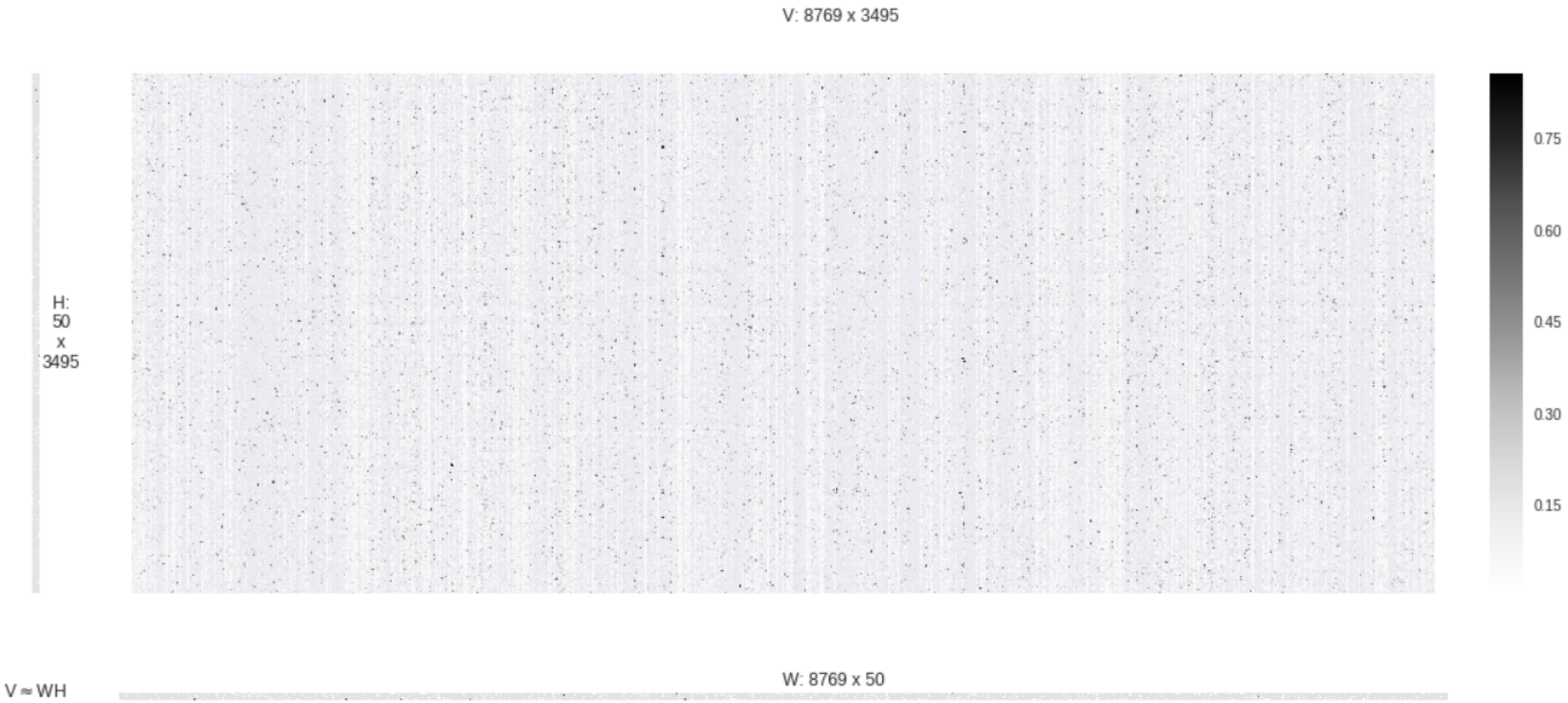


Figure: A topic model of 3495 documents on climate change from the year 2000

Approach - Words, words, words

$$V_{i\mu} \approx (WH)_{i\mu} = \sum_{a=1}^{r} W_{ia} H_{a\mu}$$



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Research Questions

- What is the thematic structure of the literature on climate change, and how has this changed over the five assessment periods of the IPCC
- What can this modelled thematic structure tell us about the past and future relationship between the IPCC and scientific literature on climate change?

Methodology - Dynamic Topic Modelling

The topic models above assume that the topics, and the words that make them up, are stable over time. Two approaches to better model dynamic topics:

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Where the size and variety of the literature we want to model has increased exponentially, we need an approach that allows for the emergence of new topics.

Dynamic NMF

Dynamic NMF - application to climate change

- Choosing the number of window topics is non-trivial. Data-driven approaches are limited (see below), and human selection is time consuming.
- To facilitate the description of trends over the assessment periods of the IPCC, and to minimize the number of modelling decisions, I consider each IPCC assessment period as a time window.

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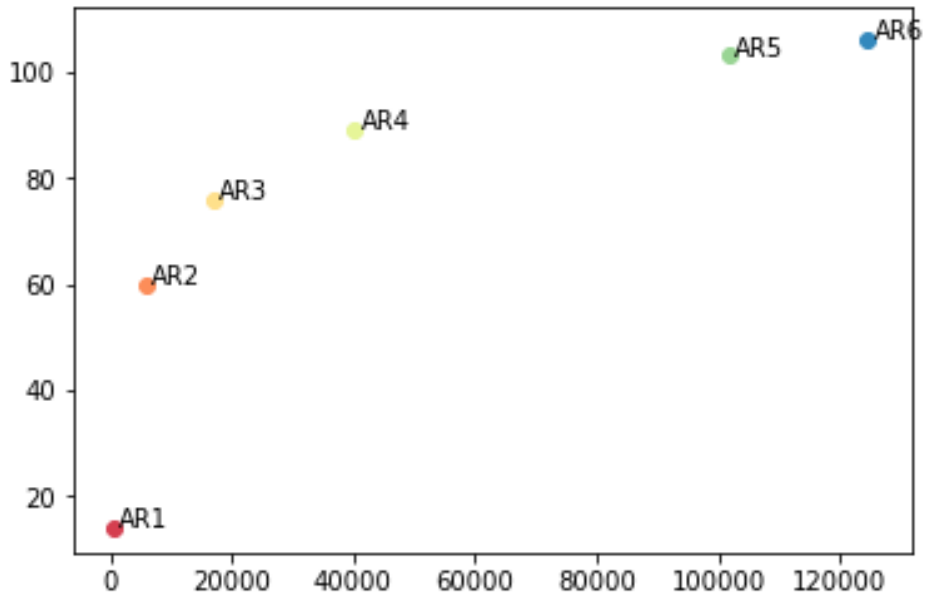
- To facilitate the description of trends over the assessment periods of the IPCC, and to minimize the number of modelling decisions, I consider each IPCC assessment period as a time window.

- Starting from a logarithmic relationship between the number of documents and the ideal topic number, I compare 5 runs with varying numbers of topics for each window



Dynamic NMF - number of topics

Human topic number criteria

- Intelligibility

Data-driven topic number criteria

- Reconstruction accuracy
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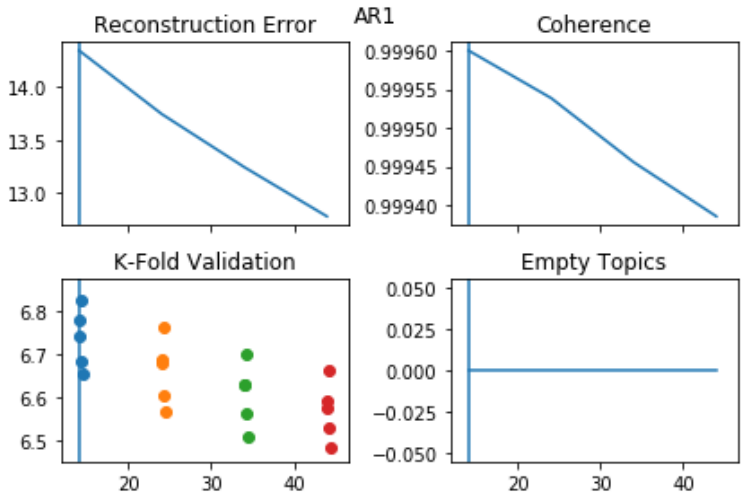
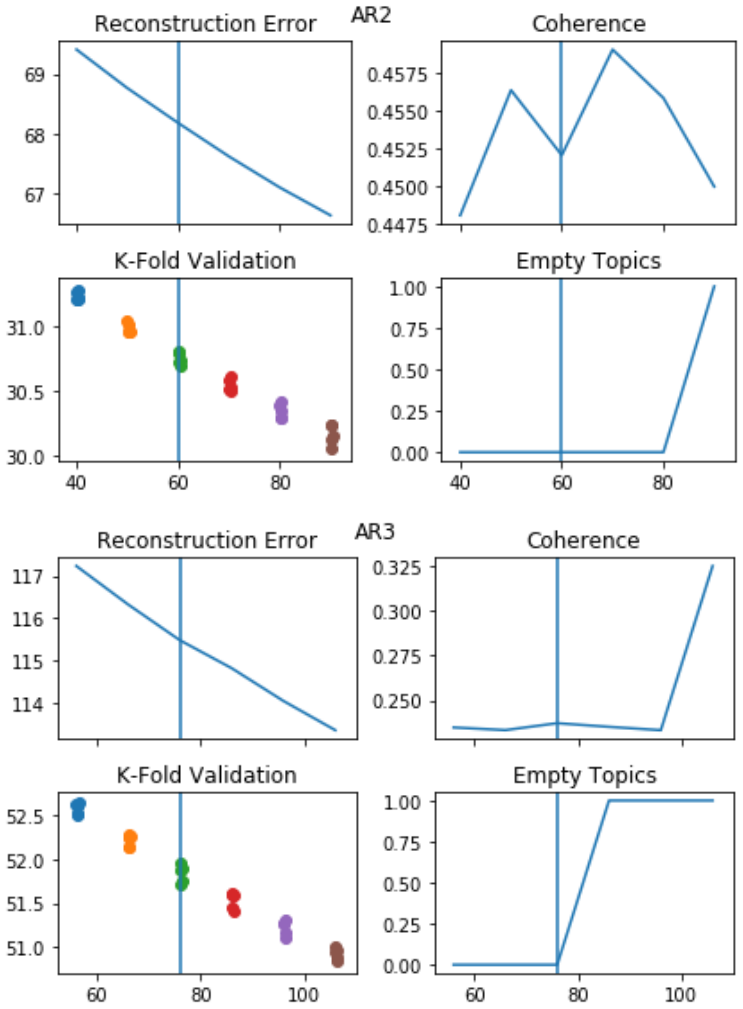
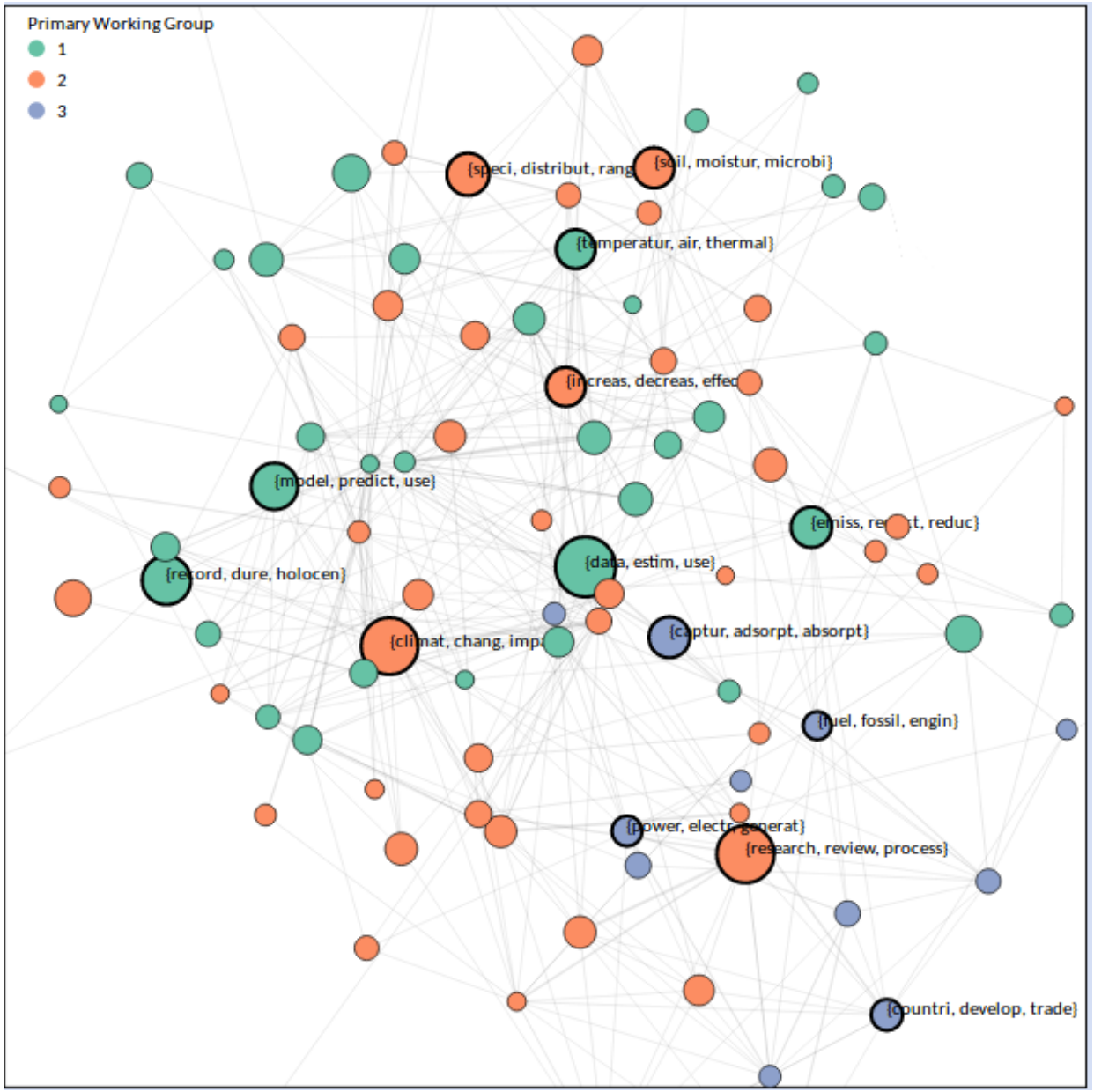




Preliminary results - structure



- A network of comprehensible topics is generated with 100 topics
- Topics can be matched to the IPCC working group from which the majority of the topic documents are referenced in
- Topics from the same working group are **significantly** more likely to be correlated with each other than those which are not

Preliminary results - Inter-working Group topics - WG 1 and 3

IPCC Coverage	Primary WG	Topic Title	WG 1	WG 2	WG 3
0.16%	1	{rainfal, monsoon, rain}	0.50%	0.50%	0.00%
0.10%	2	{veget, ndvi, cover}	0.41%	0.59%	0.00%
0.16%	1	{snow, cover, winter}	0.59%	0.41%	0.00%
0.17%	2	{region, local, scale}	0.41%	0.59%	0.00%
0.16%	1	{coastal, mangrov, rise}	0.57%	0.42%	0.01%

Preliminary results - Inter-working Group topics - WG 1 and 3

IPCC Coverage	Primary WG	Topic Title	WG 1	WG 2	WG 3
0.09%	3	{gas, coal, greenhous}	0.30%	0.15%	0.56%
0.10%	3	{transport, vehicl, road}	0.24%	0.12%	0.64%
0.13%	1	{emiss, reduct, reduc}	0.45%	0.21%	0.34%
0.09%	1	{methan, oxid, methanotroph}	0.63%	0.16%	0.20%
0.13%	3	{ghg, greenhous, gas}	0.15%	0.09%	0.75%

Preliminary results - Inter-working Group topics - WG 2 and 3

IPCC Coverage	Primary WG	Topic Title	WG 1	WG 2	WG 3
0.11%	2	{sustain, develop, resourc}	0.04%	0.51%	0.46%
0.08%	3	{build, construct, design}	0.03%	0.38%	0.59%
0.11%	2	{environment, impact, life}	0.06%	0.58%	0.36%
0.19%	3	{polici, tax, govern}	0.02%	0.32%	0.66%
0.16%	2	{urban, citi, plan}	0.07%	0.55%	0.38%

Preliminary results - gaps in coverage

How can we get a sense of which topics are better covered in IPCC reports?

- Each document d either matches or does not match an IPCC reference
- For each topic h, we can sum the scores for each category of document
- The "IPCC proportion" of each topic is the proportion of the sum of the document score accounted for by documents which match IPCC references.

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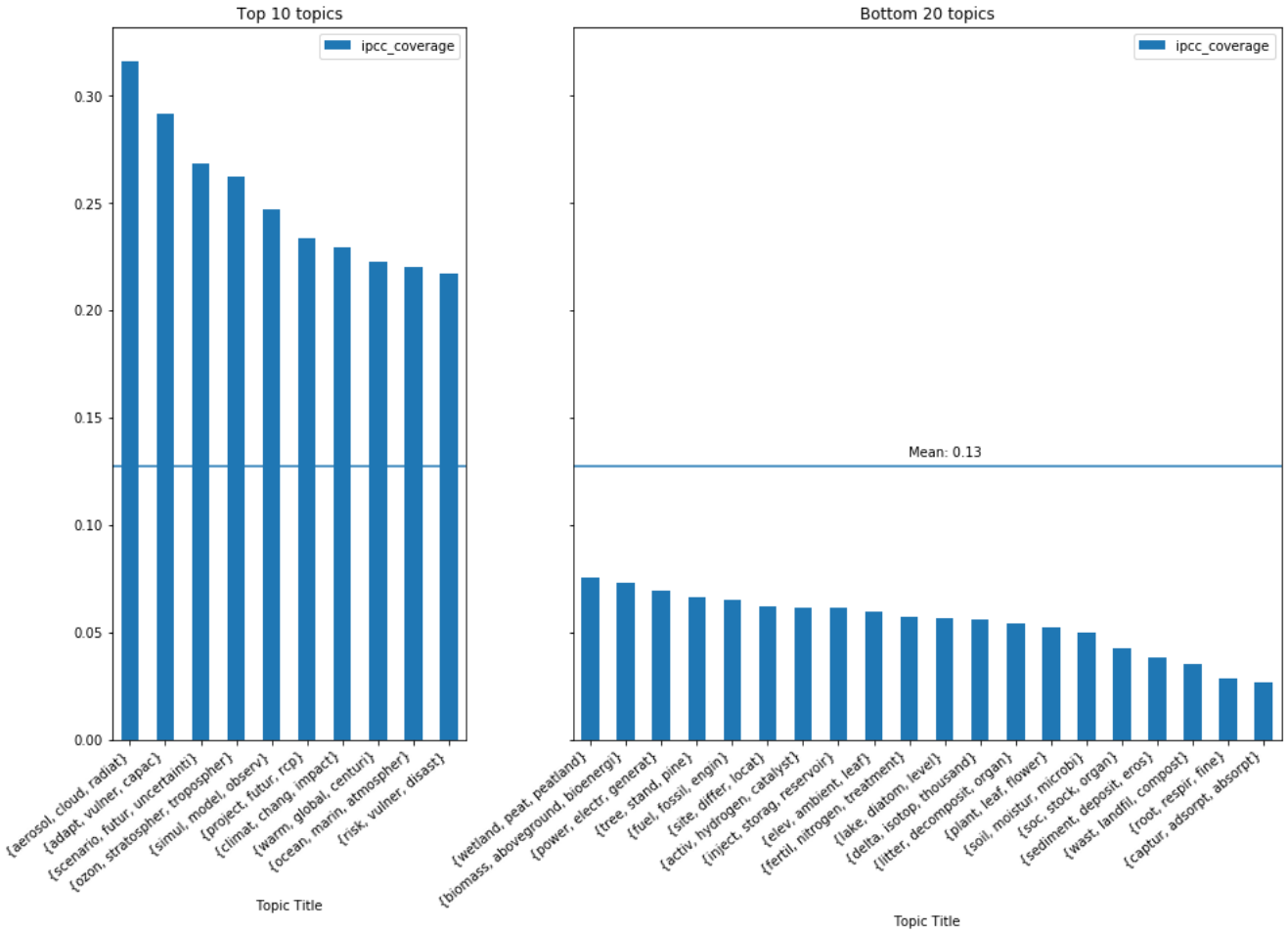

- The physical science aspects of climate change, as well topics on impacts, adaptation and scenarios are well covered by the IPCC
- Topics on specific technological solutions (particularly NETs), as well as soils, are less well covered

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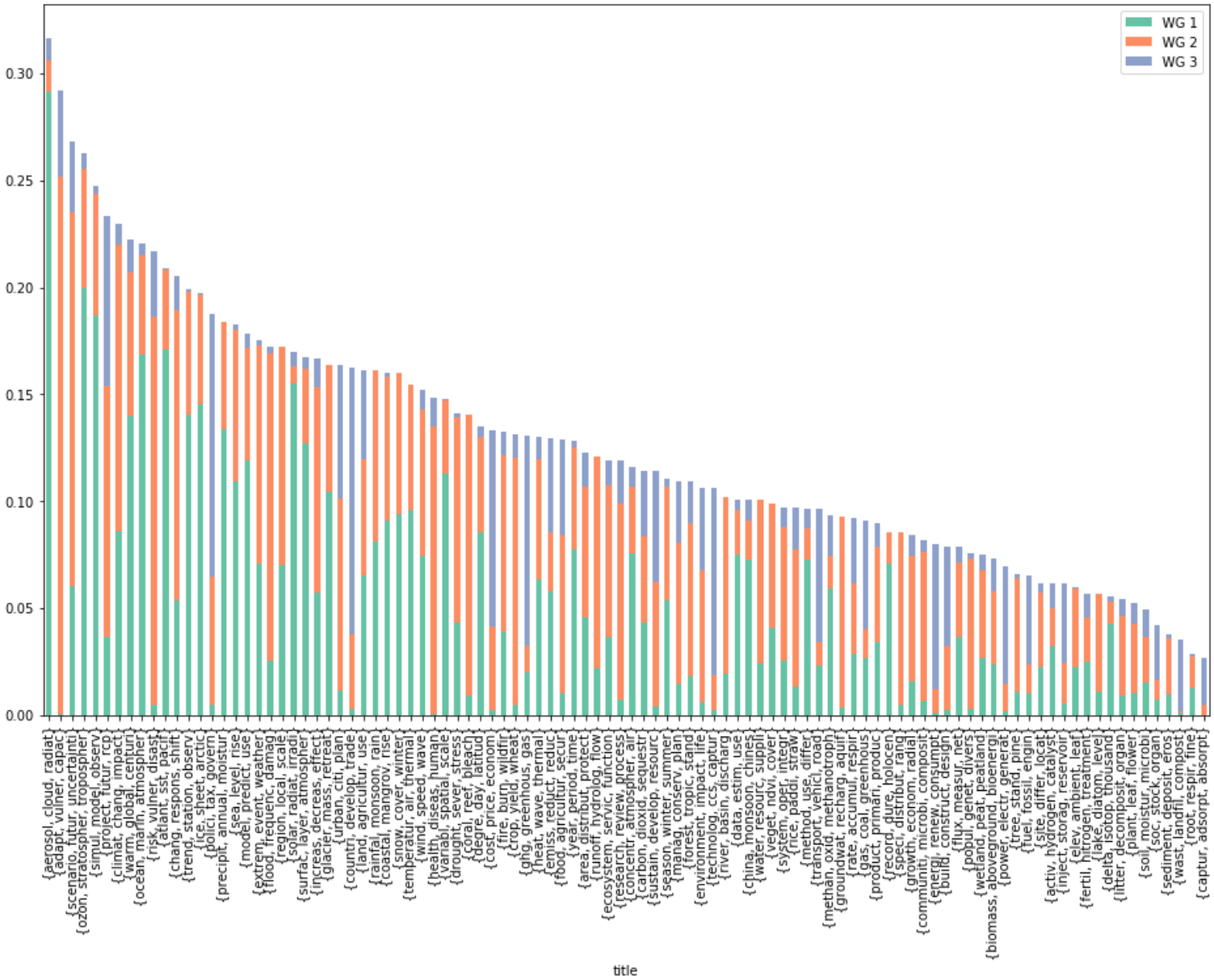

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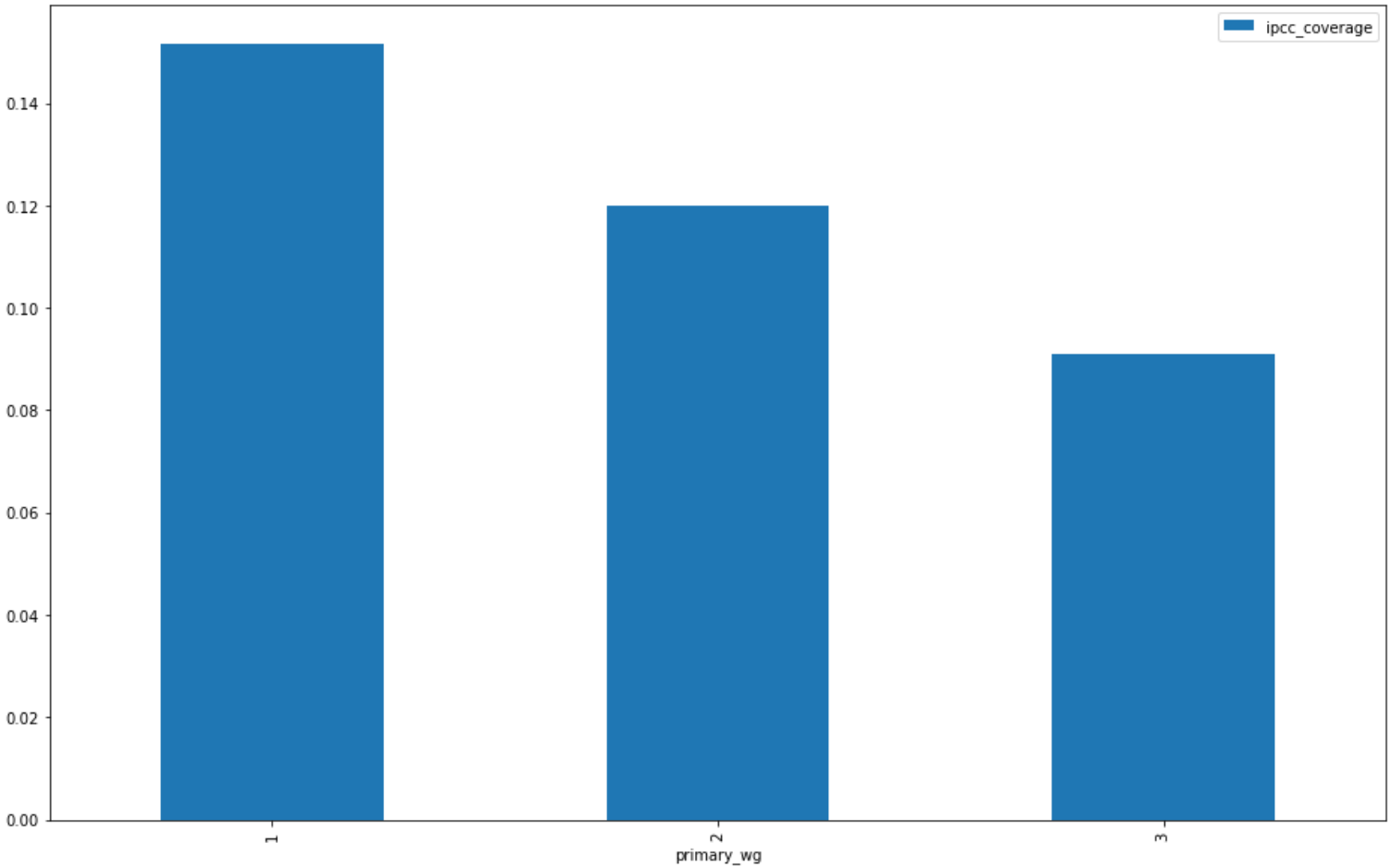

Next steps

- Adjusting second stage of model to give more weight to topics with many documents (to better capture emergence)
- Further analysis of new model
- (Manual) comparison of (AR6) topics with AR6 outline

Blei, D. M. and Lafferty, J. D. (2006). Dynamic Topic Models. *International Conference on Machine Learning*, page 113âĂŞ120.

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