Santander Meteorology Group

A multidisciplinary approach for weather & climate

Assessing model dependency in CMIP5 and CMIP6 based on their spatial dependency structure with probabilistic network models

Catharina E. Graafland* & José M. Gutiérrez

Instituto de Física de Cantabria (Universidad de Cantabria-CSIC), Santander, Spain

*catharina.graafland@unican.es

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- **Ensembles of Global Climate Models (GCMs)** are the main tool available to study the future evolution of climate (e.g. CMIP5 and CMIP6).

- However, **the problem of model interdependency** (Boe, 2018) poses limitations for the application of multi-model simulations in practical applications.

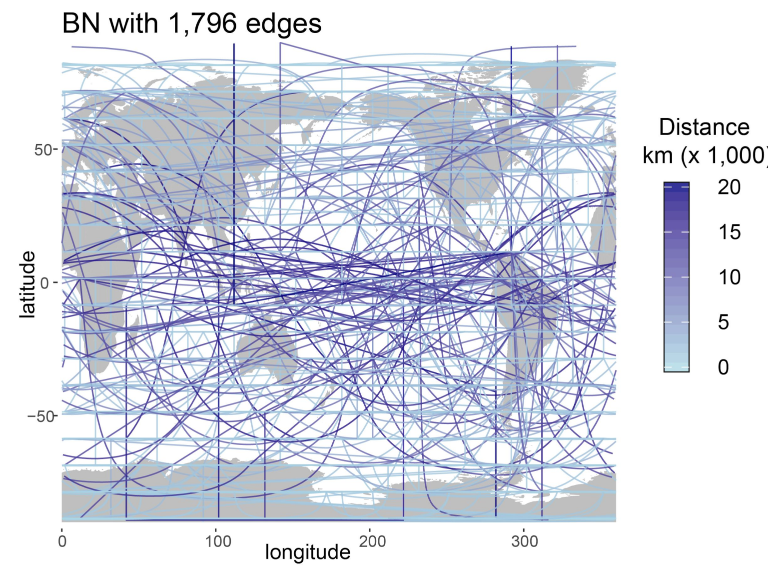
- There is a need of **automatic methods for assessing similarity of GCMs.**

Assessing model dependency in CMIP5 and CMIP6 based on their spatial dependency structure with probabilistic network models

We propose the use of **Directed Probabilistic Networks (DPNs)**

- **DPNs** have proven effective in learning the **spatial structure** underlying climate data using a complex network and encoding it as a multivariate probabilistic model (Graafland et al.,2020).

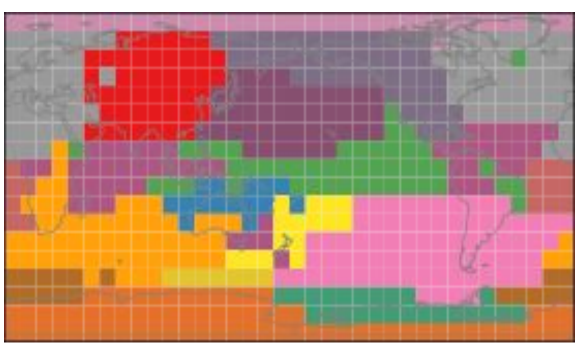
$$P(X_1, \ldots, X_N) = P(X_1|\Pi_{X_1}) \times \ldots \times P(X_N|\Pi_{X_N})$$



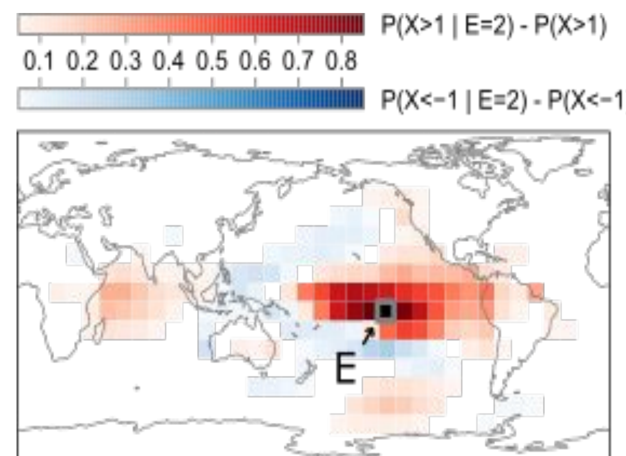
This DPN is constructed from **monthly mean surface temperature data** from a reanalysis dataset (ERA-Interim) for the 1981-2010 period interpolated to a 10 degrees grid with bilinear interpolation.

- **DPNs provide the spatial backbone of complex data**, modeling spatial dependencies between variables (in contrast to global statistical field measures such as mean, standard deviation) and **only include significant dependencies** (in contrast to networks based on correlation).

The backbone can be analysed with **complex network measures** like community structure detection:



but one is also able to extract **probabilistic features** like conditional probabilities given some evidence E.



Assessing model dependencies with DPNs

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- We have **monthly mean surface temperature data** from **three reanalysis** (ERA-Interim, NCEP-NCAR, and JRA55) from historical simulations from **33 GCMs participating in CMIP5** and from **24 GCMs participating in CMIP6** (Eyring, 2016), for the 1981-2010 period. The original resolutions of the datasets vary from 1 to 3 degrees. All datasets are interpolated to a 10 degrees grid with bilinear interpolation.

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- We **compute Climate DPNs** corresponding to the reanalysis and CMIP6 simulations and assume that **similar CMIP5/CMIP6/Reanalysis models** yield similar dependency structures and **close DPNs**:

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DPN 1

$$P_{M1} = p(W|X,Z)p(Z|X,Y)p(Y)p(X)$$

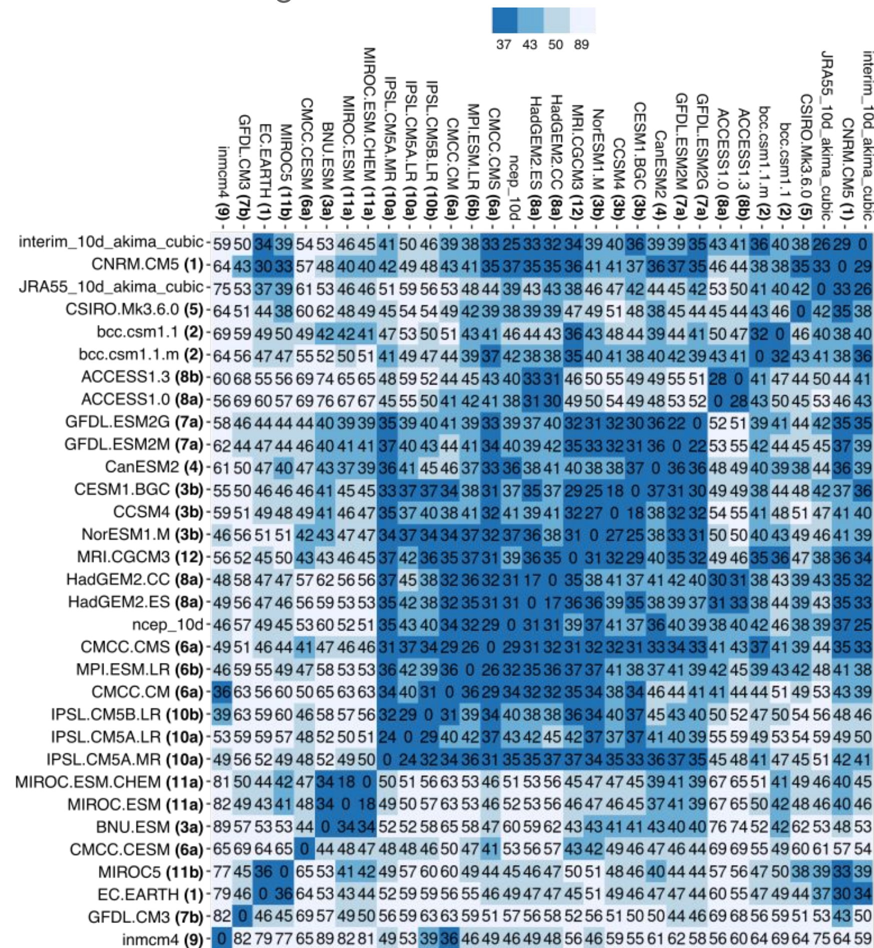
Bhattacharya distance between DPNs

$$d_B(P_{M1}, P_{M2}) = -\log \int_{\mathcal{R}} \sqrt{\mathrm{p}_{M1}(\mathrm{x})\mathrm{p}_{M2}(\mathrm{x})}\mathrm{dx}$$

DPN 2

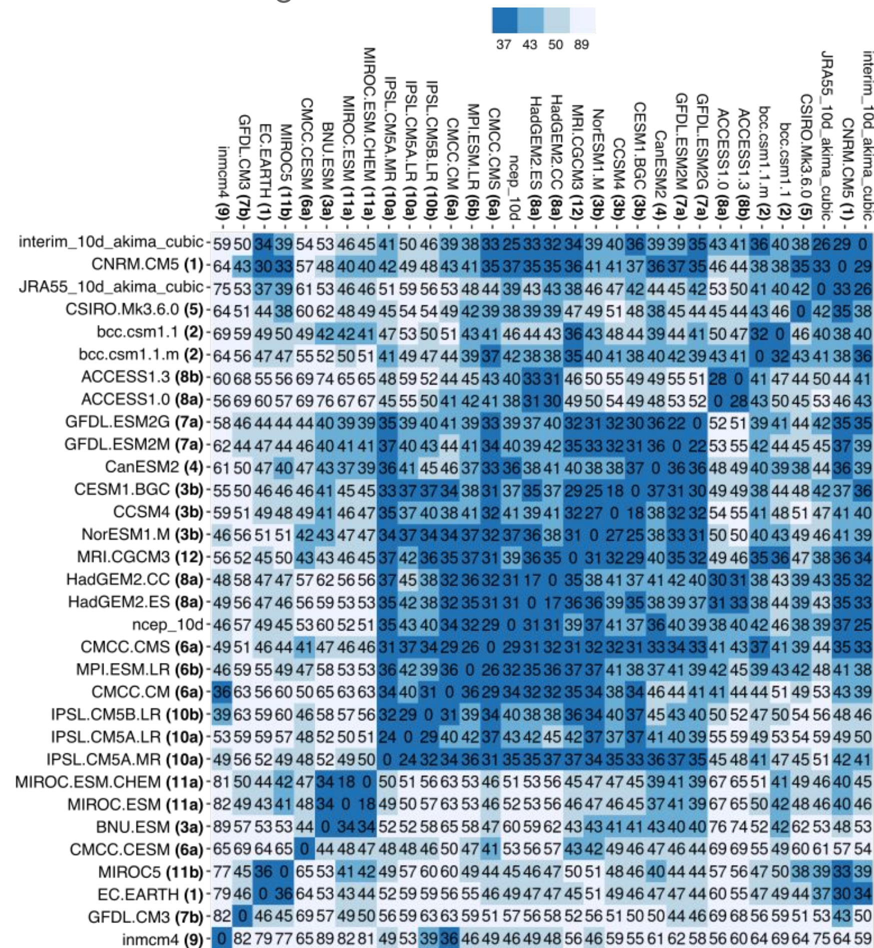
$$P_{M2} = p(W|X,Z)p(Z|X)p(Y)p(X)$$

- **Example:** resulting sub-matrix of pairwise Bhattacharya distances for CMIP5



- **Example:** resulting sub-matrix of pairwise Bhattacharya distances for CMIP5.

- Matrix of pairwise distance between DPNs of CMIP5 and Reanalysis.



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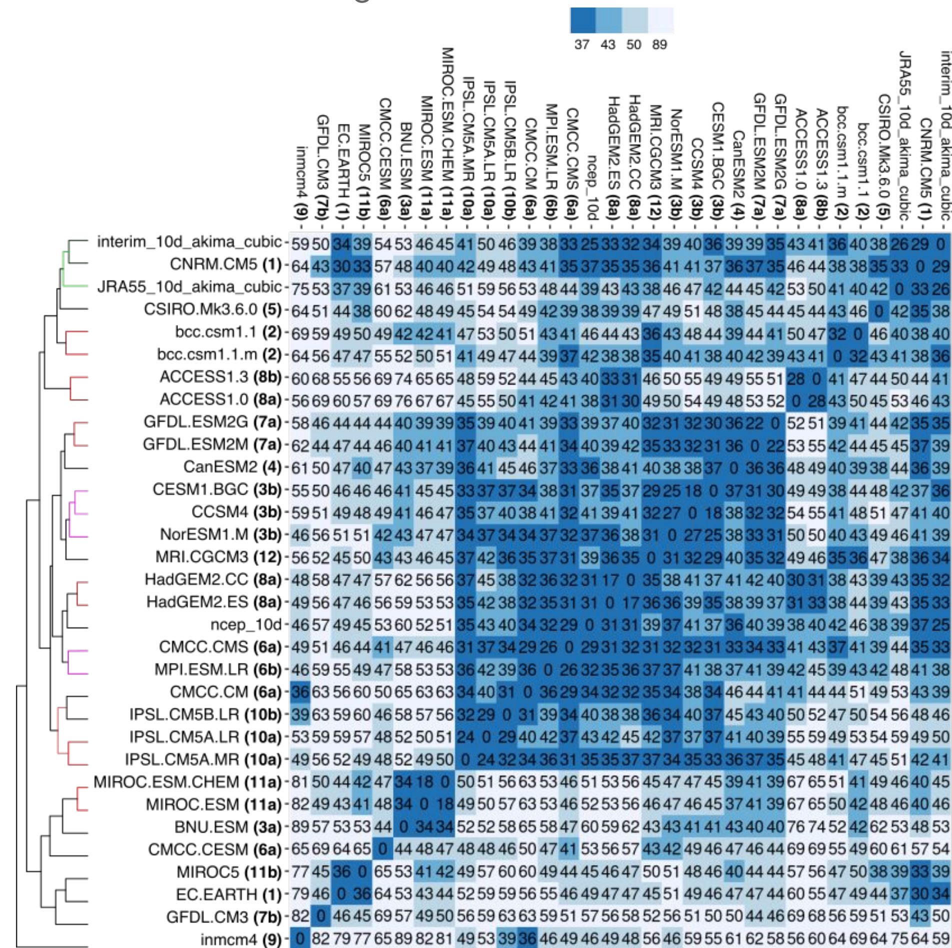
- Matrix of pairwise distance between DPNs of CMIP5 and Reanalysis.

- Hierarchical clustering of close DPNs



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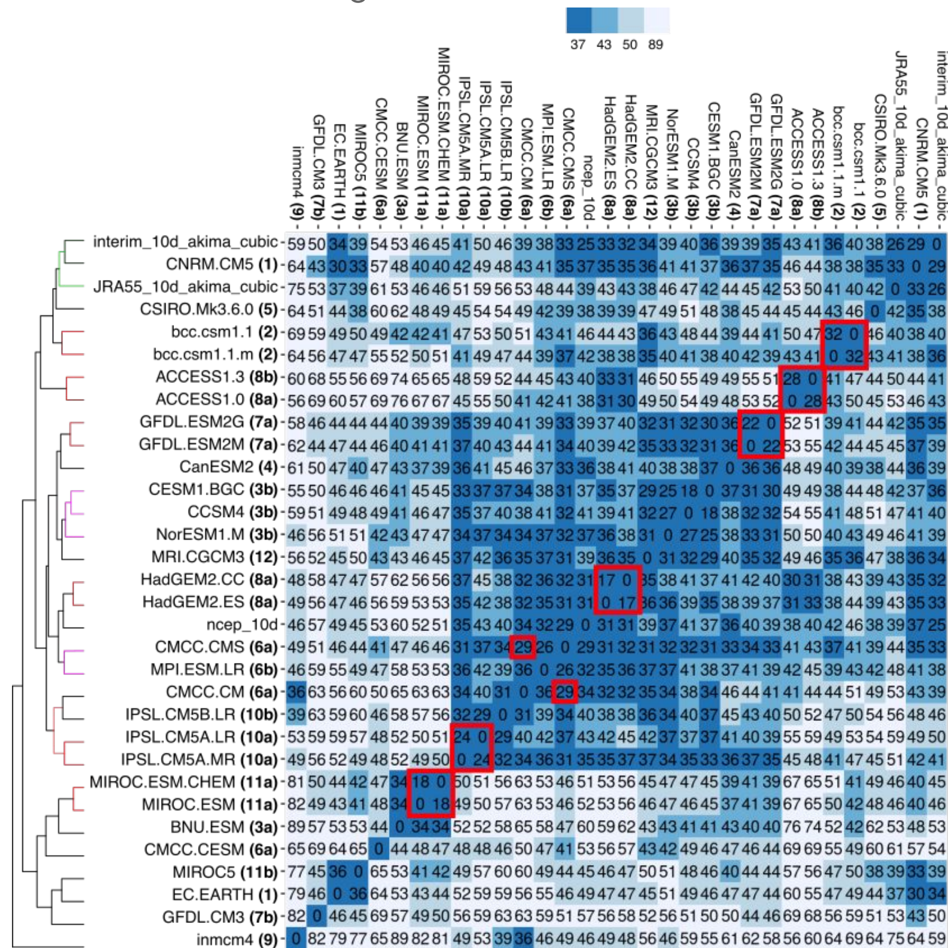
- **Uncover interdependencies**

same institute



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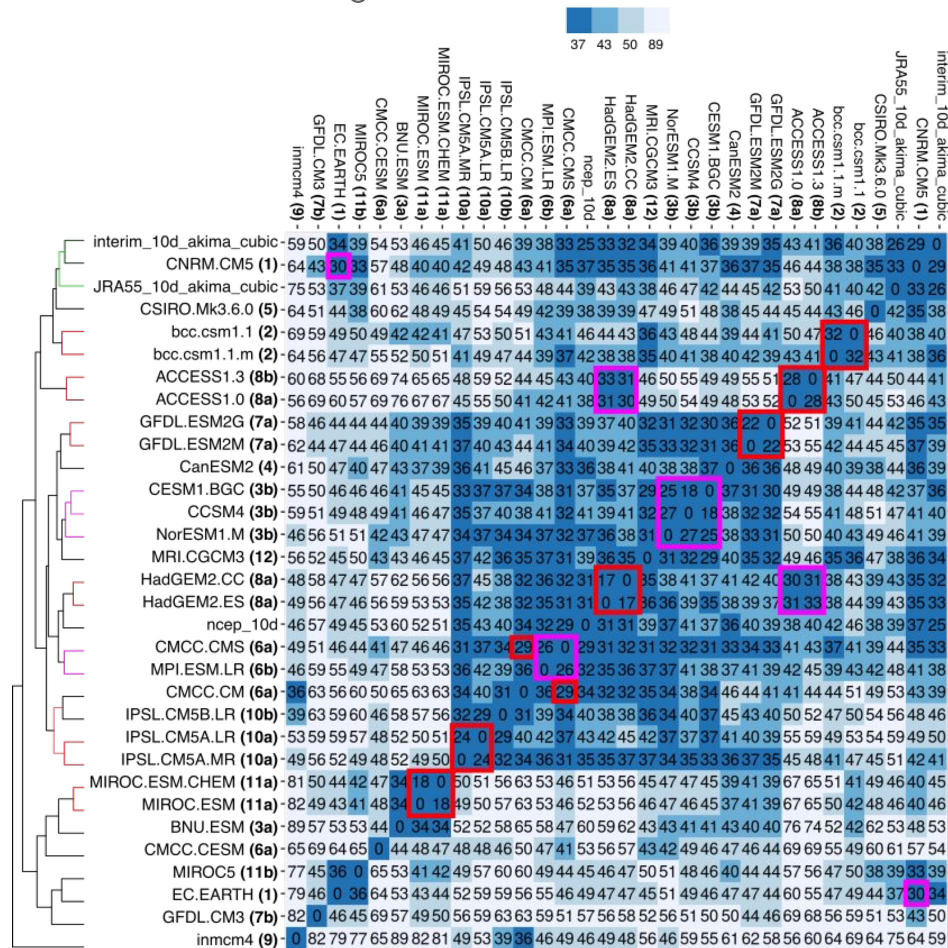

- Matrix of pairwise distance between DPNs of CMIP5 and Reanalysis.
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- **Uncover interdependencies**

same institute

same atmospheric model

- **Example:** resulting sub-matrix of pairwise Bhattacharya distances for CMIP5

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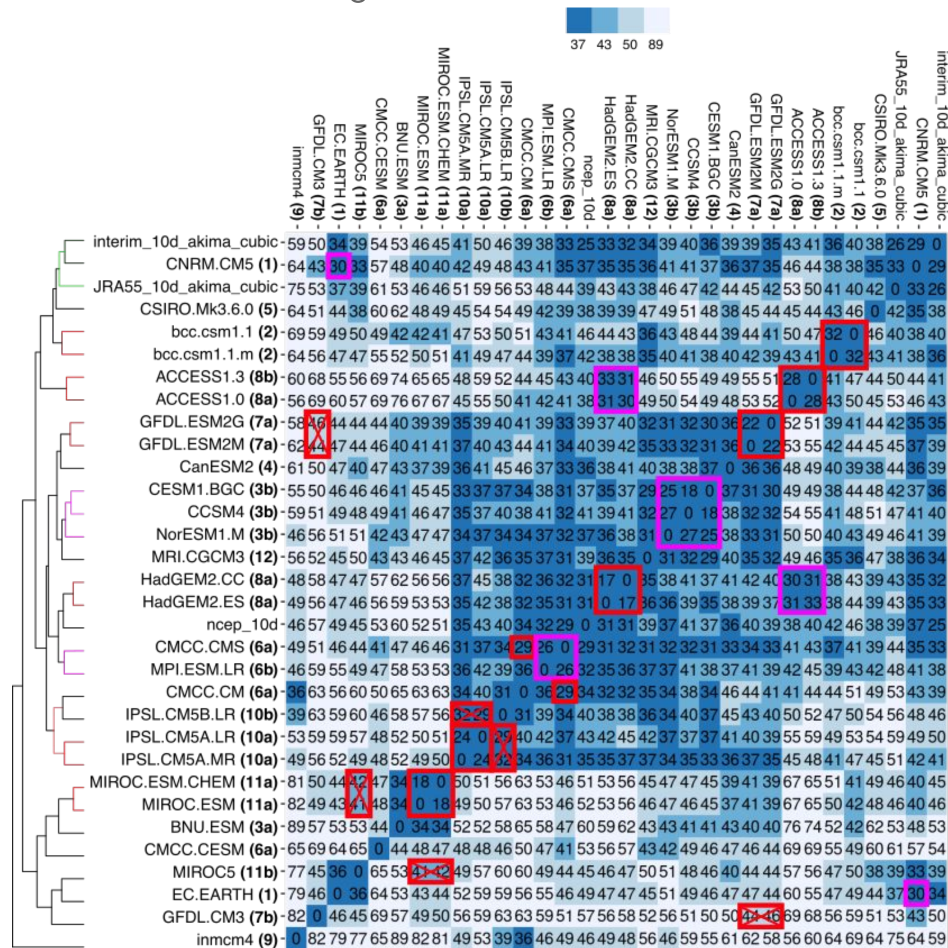
same institute

same institute + significant atmospheric model change

same atmospheric model



- **Example:** resulting sub-matrix of pairwise Bhattacharya distances for CMIP5

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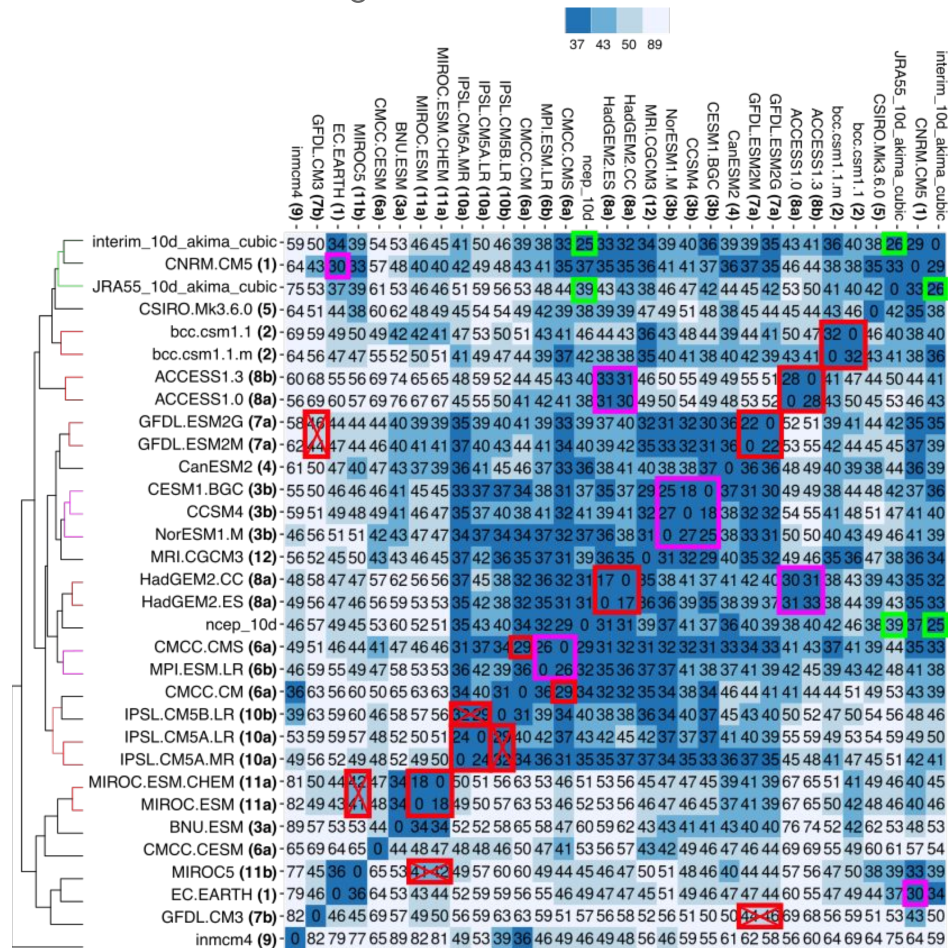
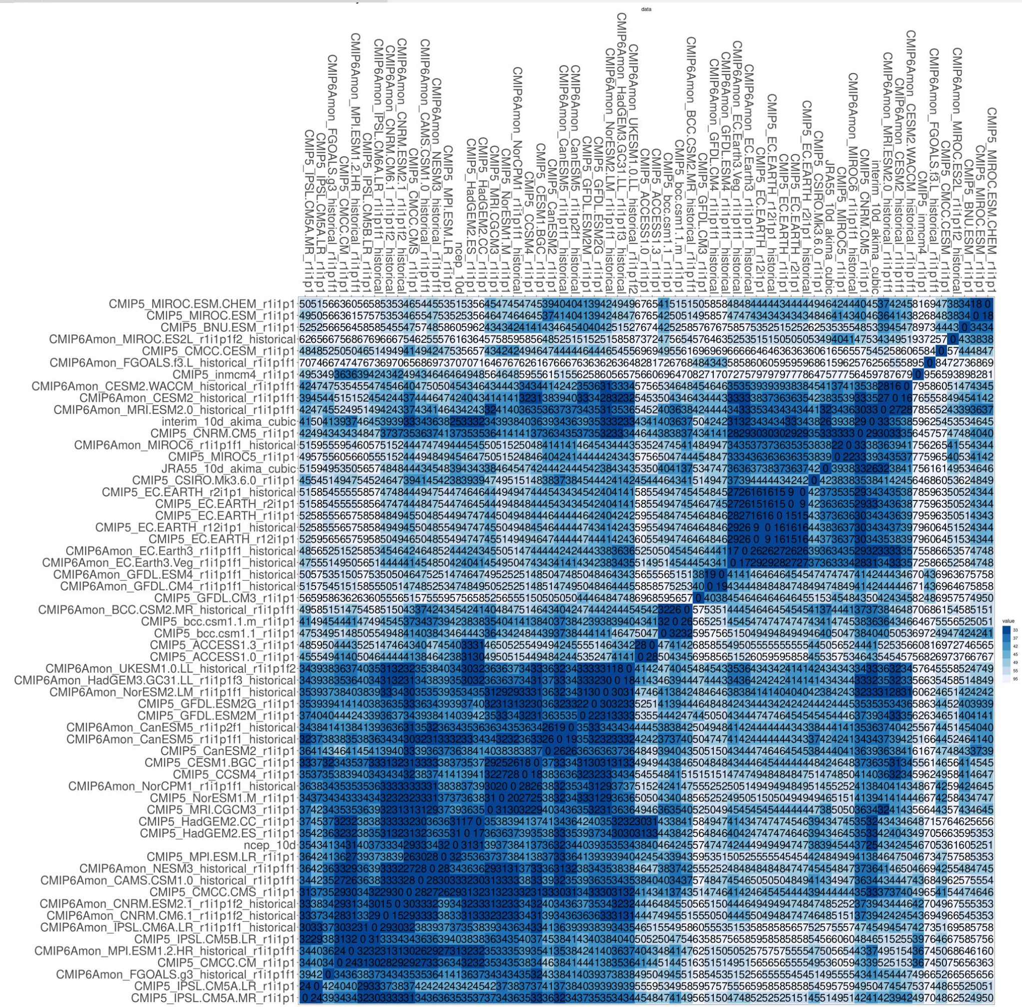
reanalysis vs reanalysis



Assessing model dependencies with DPNs

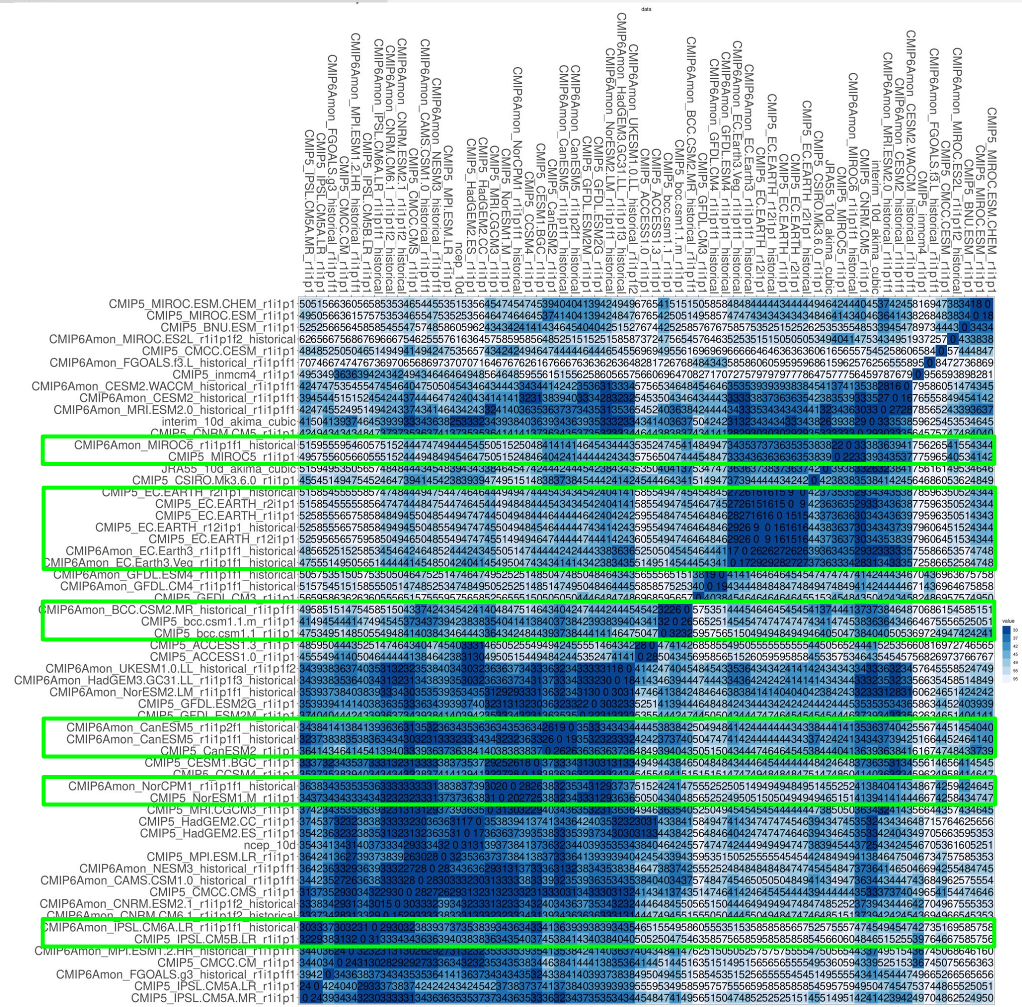
- We extend the analysis adding CMIP6 models to identify significant **model changes** that underwent **CMIP5 GCMs in their transition to CMIP6**.

- Matrix of pairwise distance between DPNs of CMIP5 and CMIP6 and Reanalysis.



- Matrix of pairwise distance between DPNs of CMIP5 and CMIP6 and Reanalysis.

- Under CMIP6 some models hold a similar spatial dependency structure



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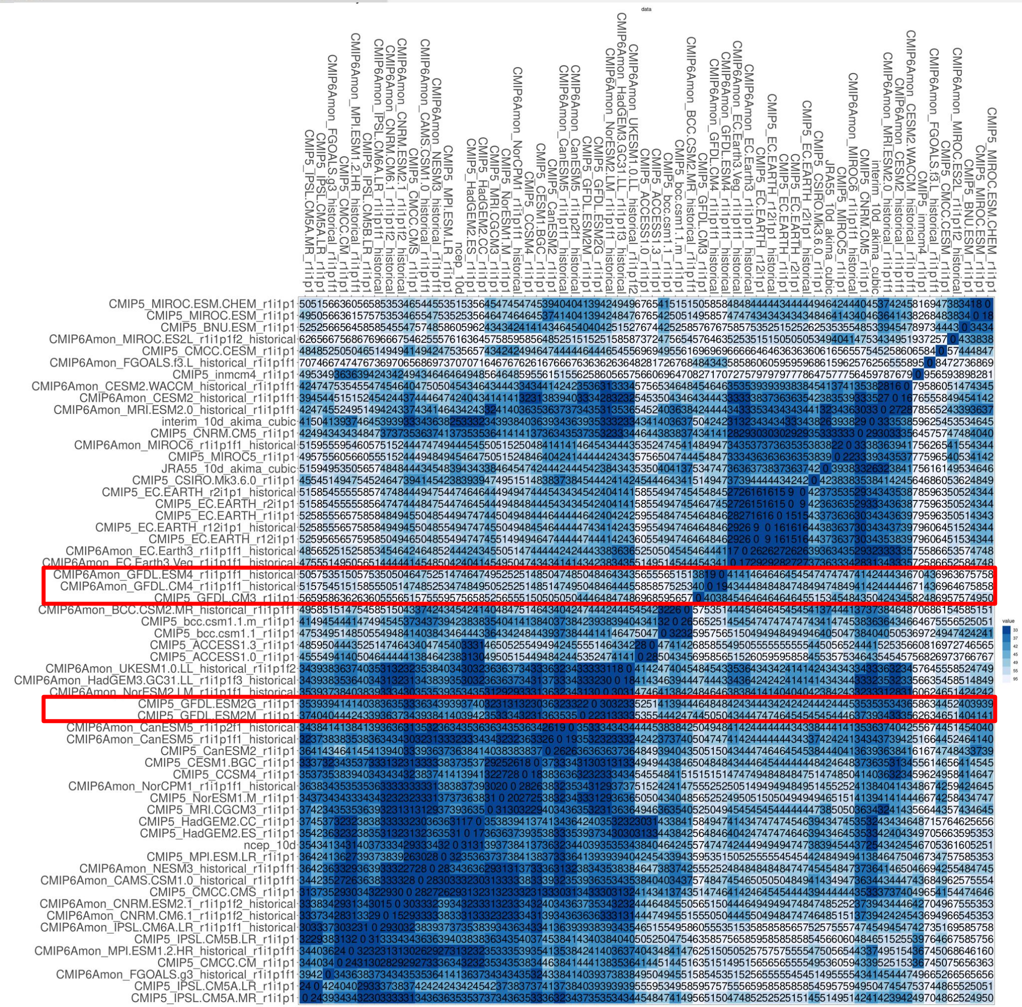
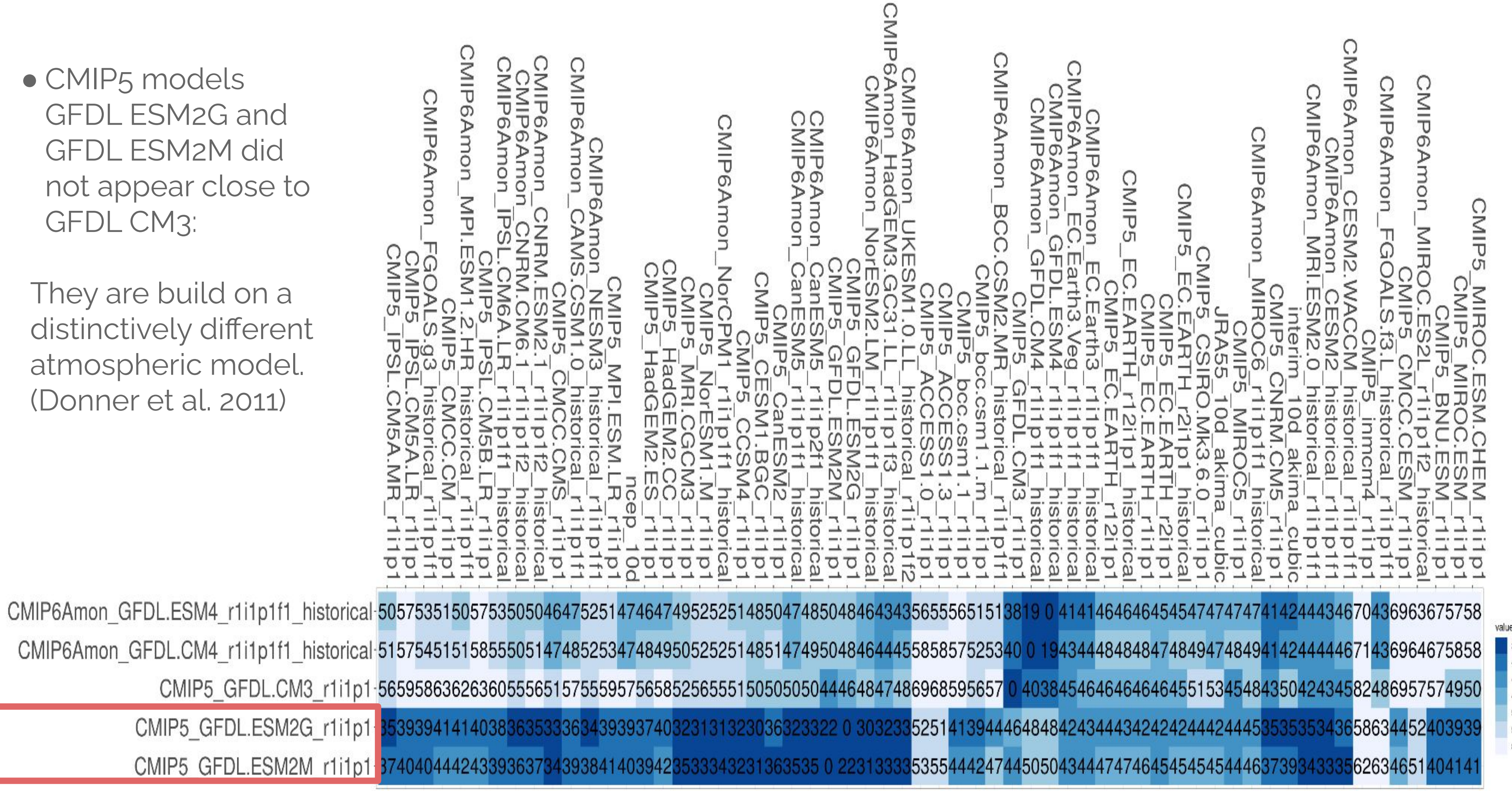


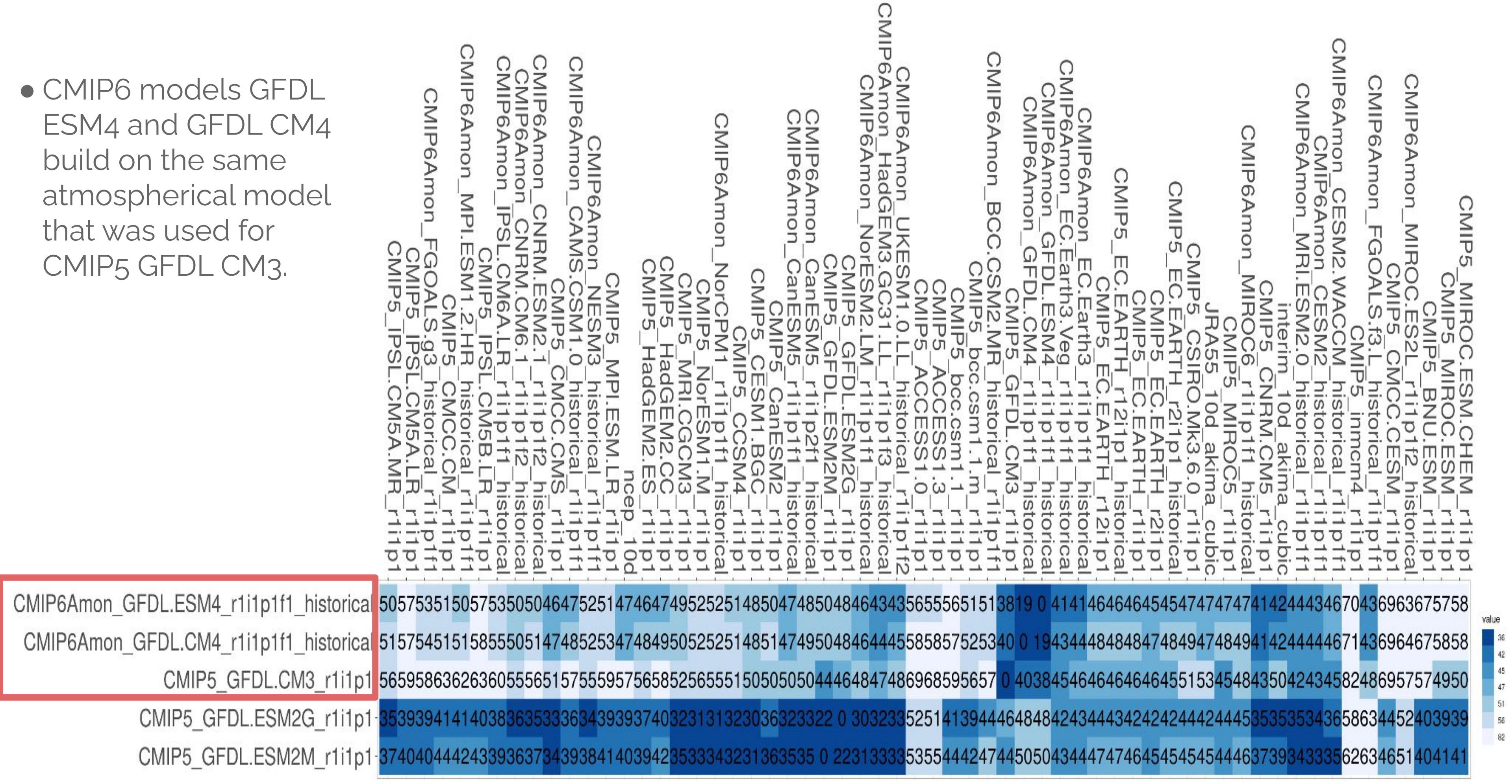
- Whereas other CMIP6 models show significant change in spatial dependency structure with respect to their predecessors

- CMIP5 models GFDL ESM2G and GFDL ESM2M did not appear close to GFDL CM3:

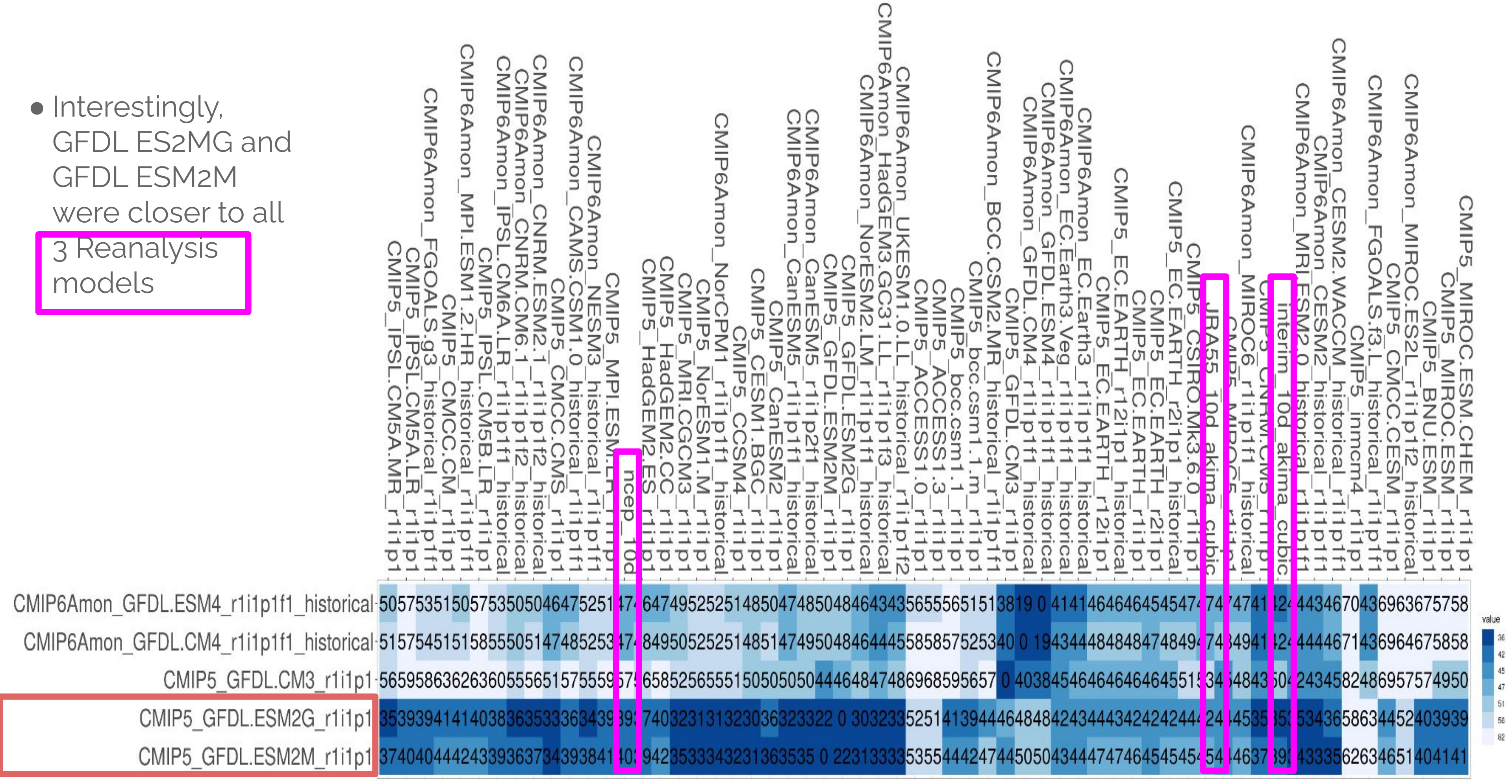
They are build on a distinctively different atmospheric model. (Donner et al. 2011)



- CMIP6 models GFDL ESM4 and GFDL CM4 build on the same atmospherical model that was used for CMIP5 GFDL CM3.



- Interestingly, GFDL ES2MG and GFDL ESM2M were closer to all 3 Reanalysis models



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