Uncertainties too large to predict tipping times of major Earth system components from historical data

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PIK

ClimTip

Expanded presentation with more text

Observation- based Early warning signals

Boers & Rypdal 2021

Boers et al. 2021
Michel et al. 2022
Ditlevsen & Ditlevsen 2023
Ben-Yami et al. 2023

Lu et al. (in review)

Boulton et al. 2022
Blaschke et al.
(in review)

Smith et al. 2022
Smith et al. 2023

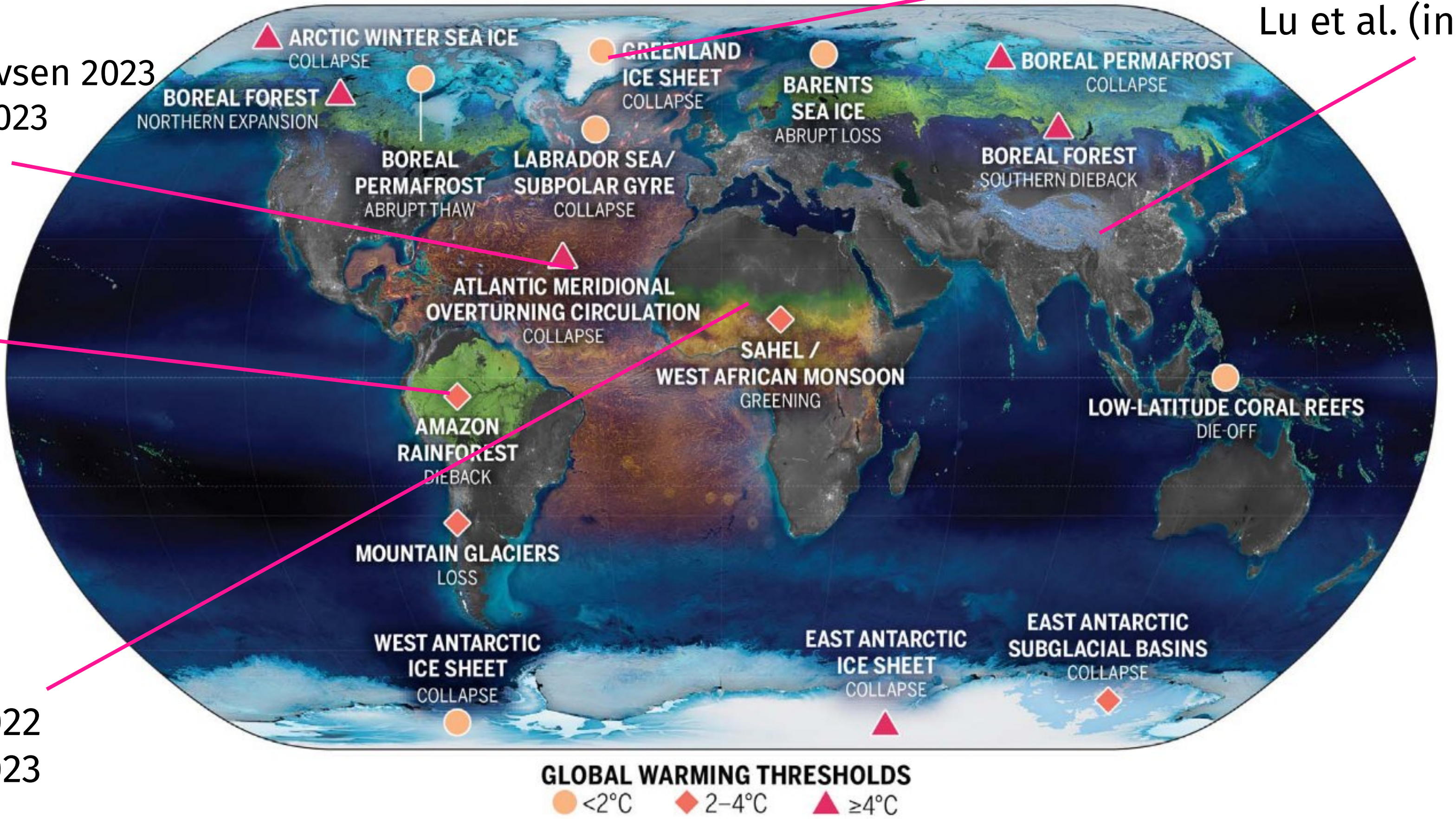
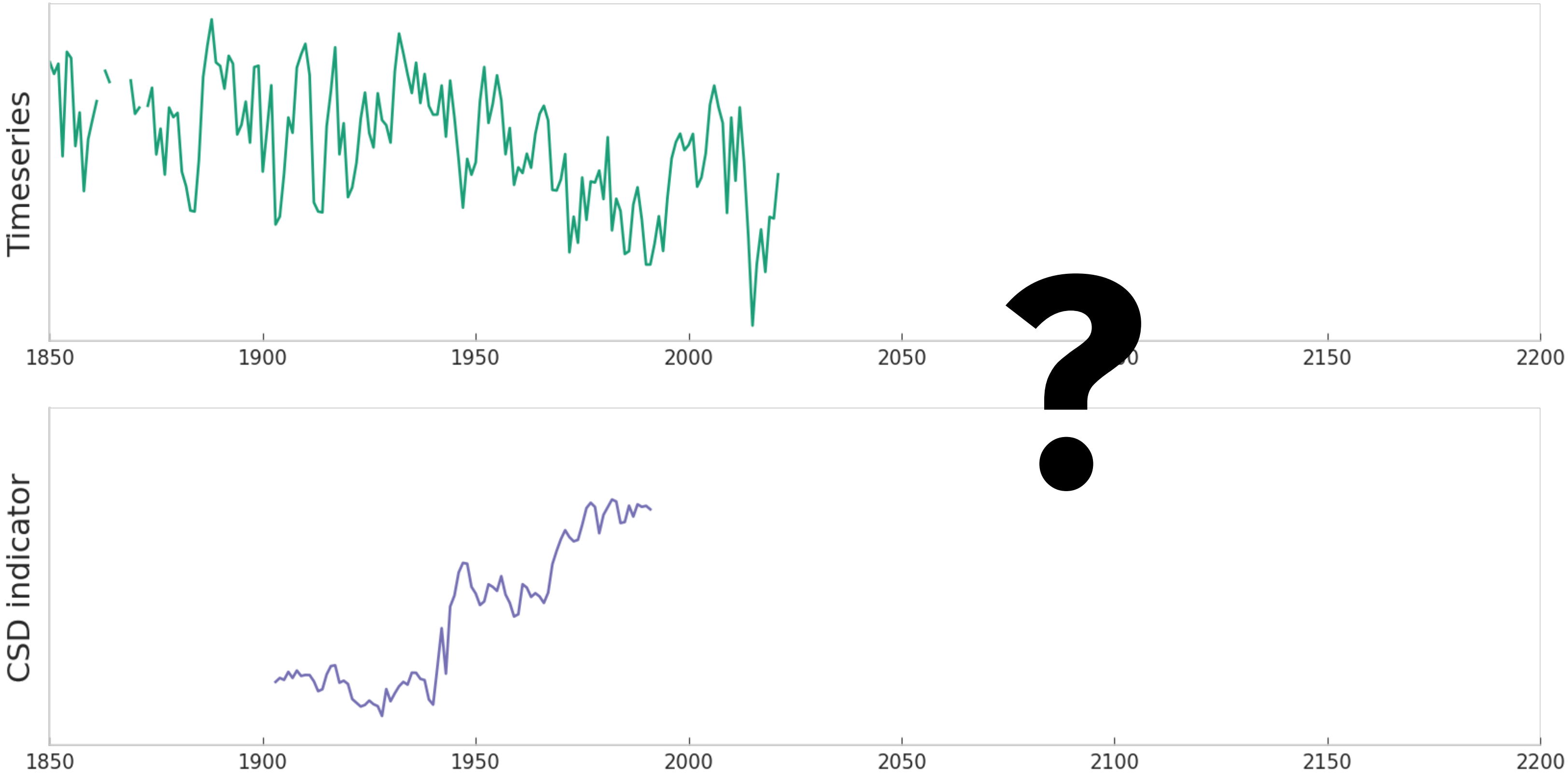


Figure: Armstrong-Mckay et al. 2022

- Critical slowing down (CSD) indicators can tell us that the system is becoming less stable and potentially approaching a critical transition
- This can make us think - can extrapolate this information into the future and predict the time that the system will tip?



But! There are large uncertainties in tipping time prediction

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2. **Indirect fingerprints** are used because there are no direct observations of a sufficiently long time span.

Satellite data for vegetation indices

Sea surface temperatures for AMOC strength

Ice-core derived melt rates for ice sheet hight

But! There are large uncertainties in tipping time prediction

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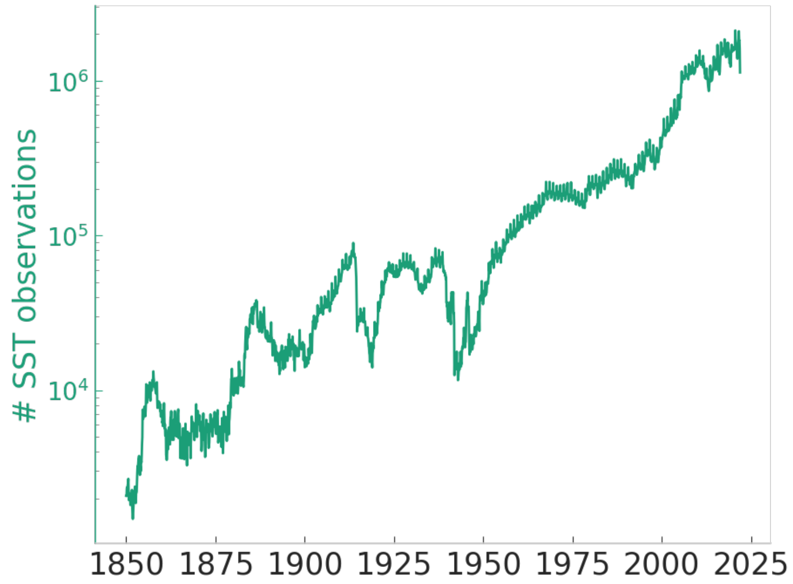
2. **Indirect fingerprints** are used because there are no direct observations of a sufficiently long time span.
3. **Observational dataset uncertainties** propagate to the tipping time prediction. For example, uncertainties arising from the bias and preprocessing in observational datasets with measurement uncertainties and gaps.



But! There are large uncertainties in tipping time prediction

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3. **Observational dataset uncertainties** propagate to the tipping time prediction. For example, uncertainties arising from the bias and preprocessing in observational datasets with measurement uncertainties and gaps.

→ In our paper, we discuss these uncertainties in general and for three different tipping time prediction methods. In this presentation, we focus on the MLE method introduced by Ditlevsen & Ditlevsen 2023, and apply it to the Atlantic Meridional Overturning Circulation, as they do in their paper.

1. Modelling assumptions

The assumptions we investigate are:

the system can tip	the model is a fold-normal form	the noise is white	the forcing is linear

We define models for which different combinations of this assumptions hold. We then generate 10^4 time series from each model, and calculate a tipping time for these time series using the MLE method. This gives us a distribution of tipping times.

1. Modelling assumptions

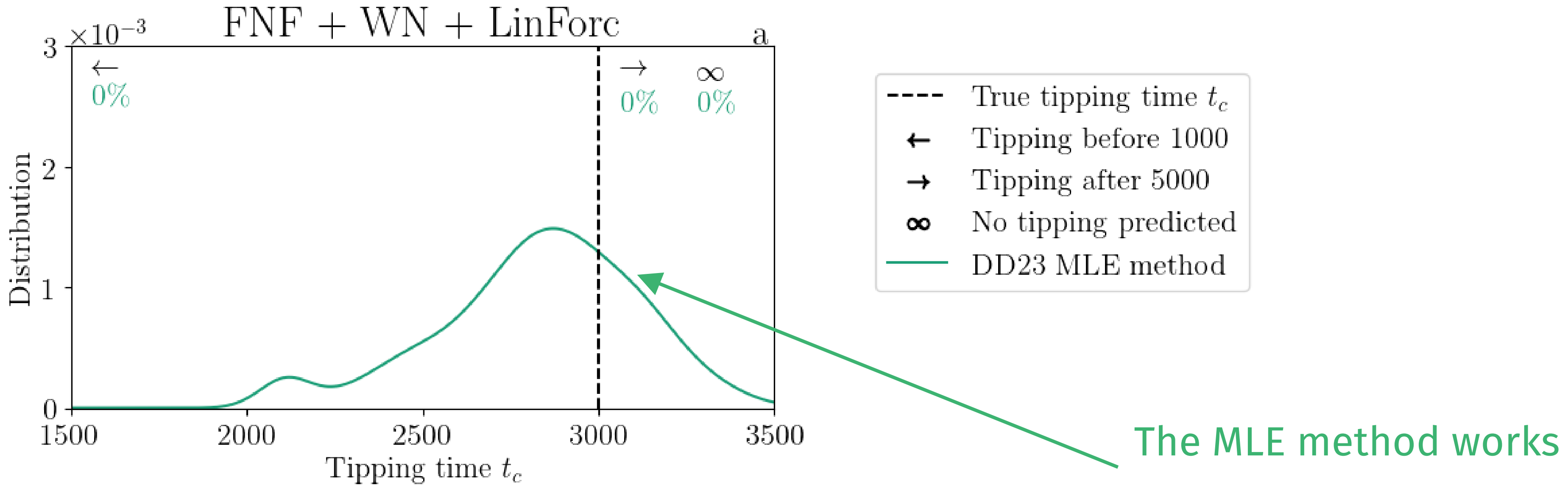
the system can tip

the model is a fold-normal form

the noise is white

the forcing is linear

Results when all the assumptions are true:



1. Modelling assumptions

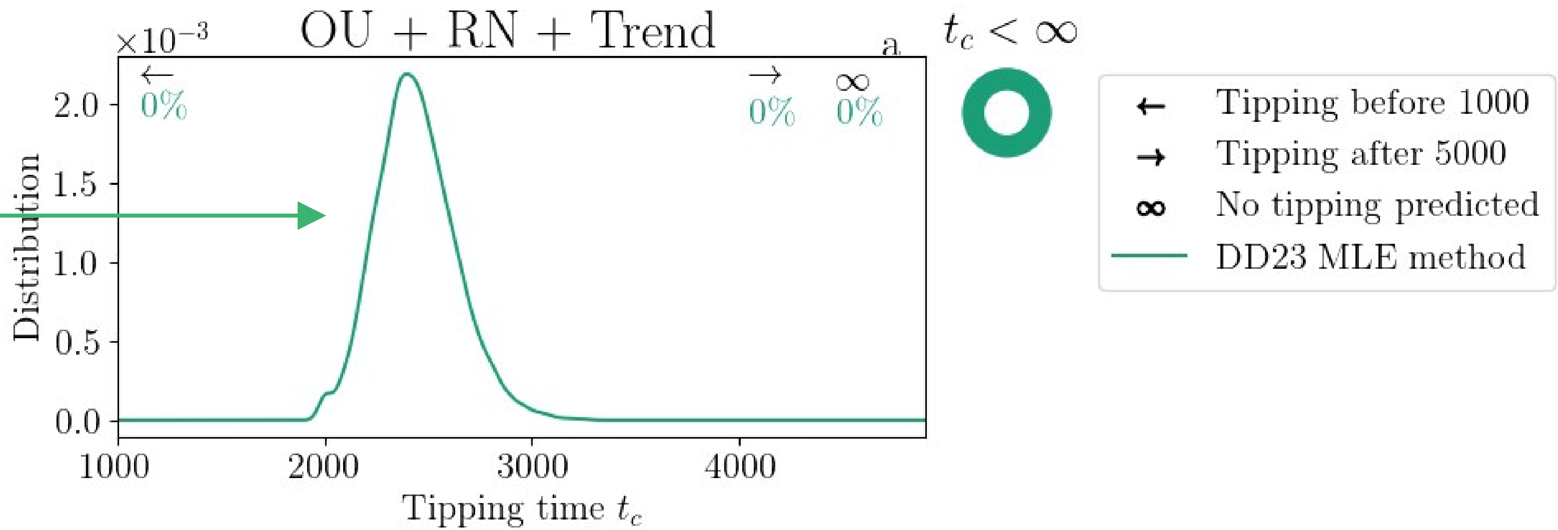
~~the system can tip~~

~~the model is a fold-normal form~~

~~the noise is white~~

We apply the MLE method to a linear model without any bifurcation but with an added mean trend, forced with red noise that increases in correlation strength

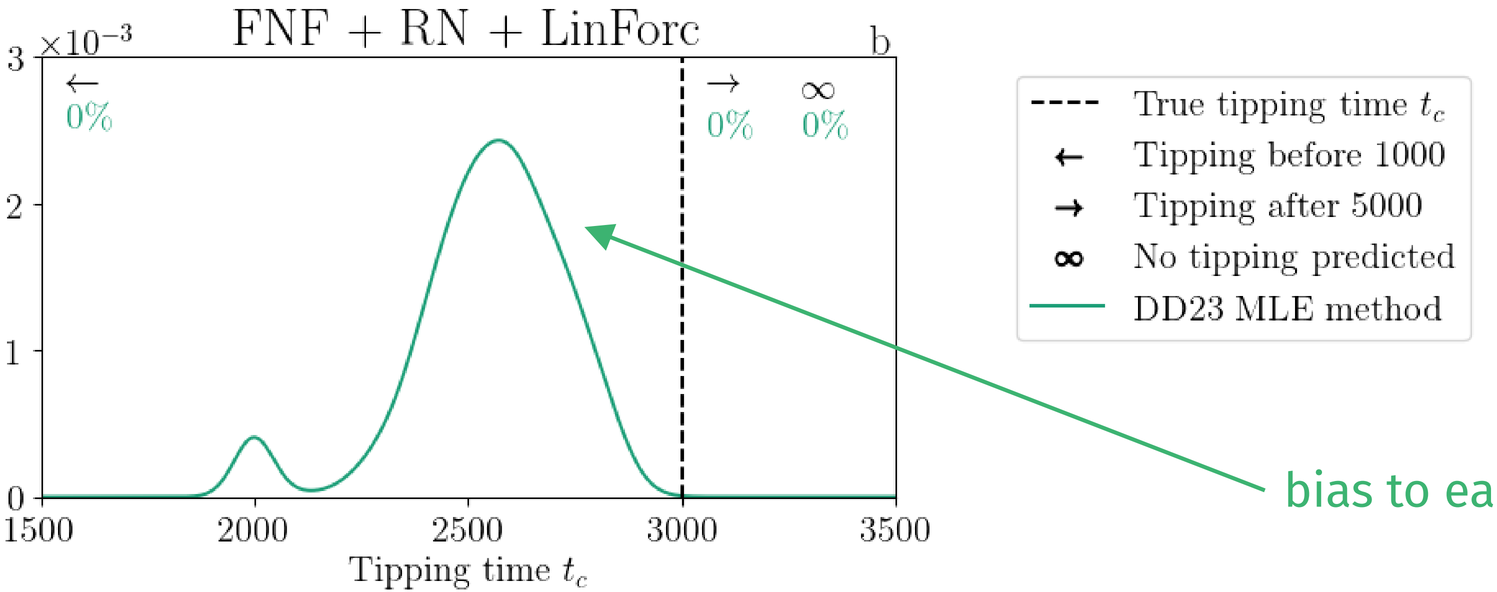
The MLE method predicts tipping



1. Modelling assumptions

the system can tip	the model is a fold-normal form	~~the noise is white~~	the forcing is linear

We apply the MLE method to a fold normal-form system driven by red noise with increasing correlation strength:



bias to earlier years!

1. Modelling assumptions

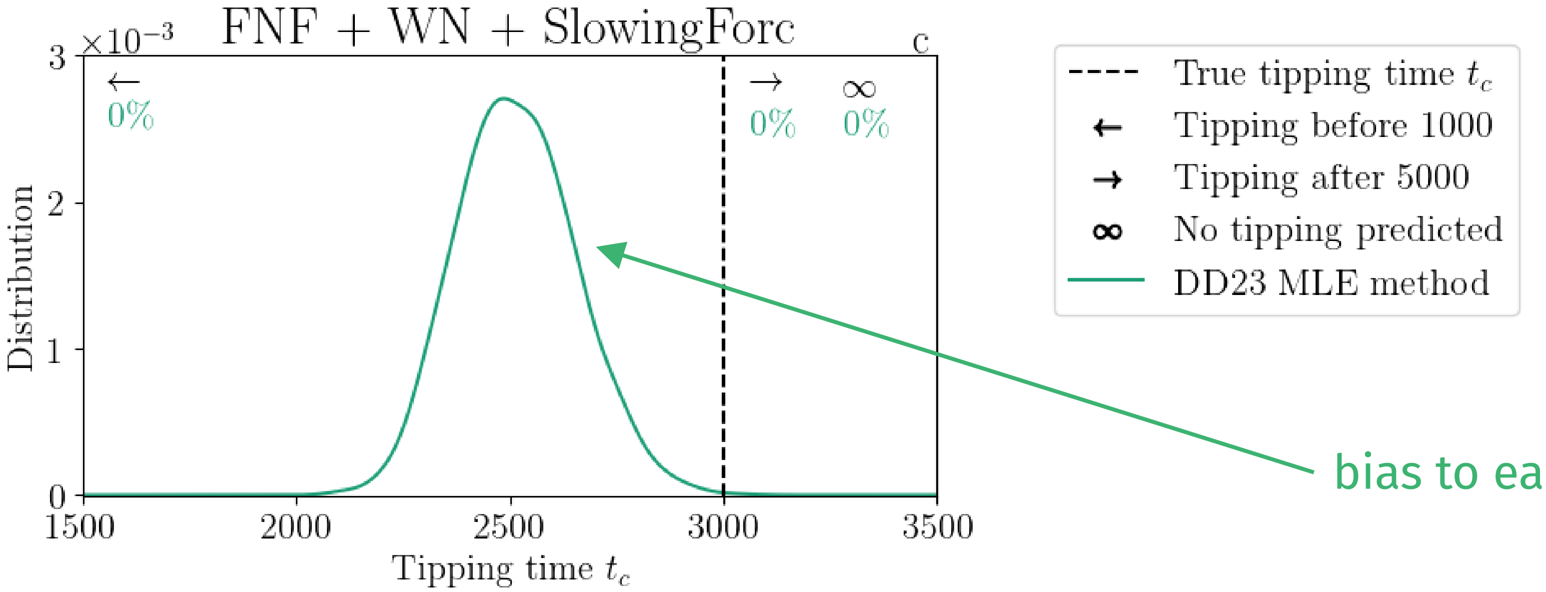
the system can tip

the model is a fold-normal form

the noise is white

~~the forcing is linear~~

We apply the MLE method to a fold normal-form system where the forcing decelerates in a non-linear manner:



bias to earlier years!

2. Indirect fingerprints

AMOC fingerprints:

Sea surface temperatures

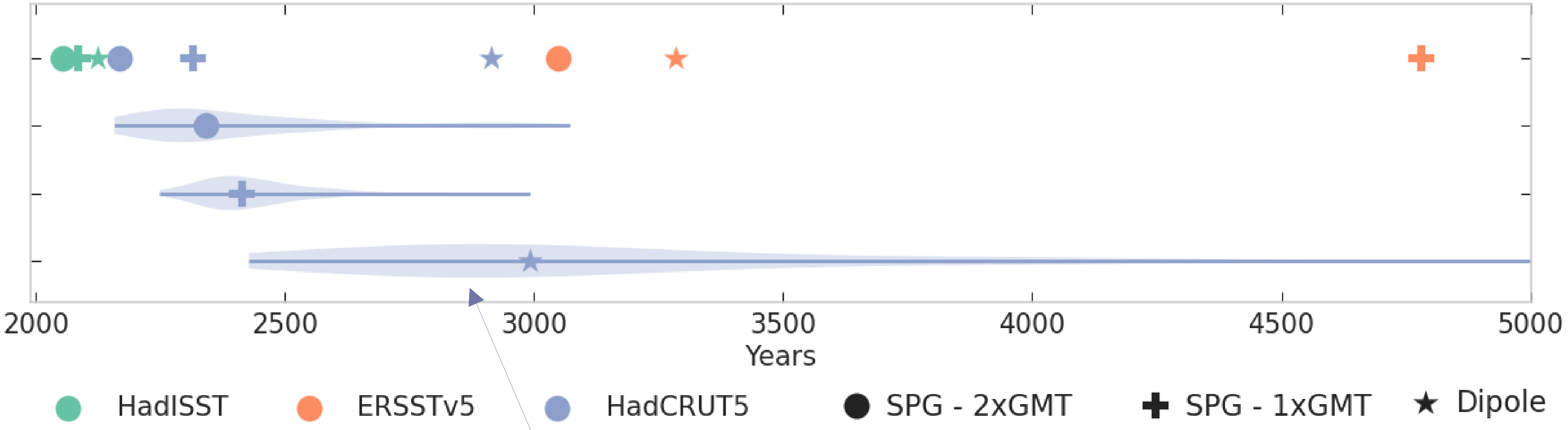
Sub-polar gyre SSTs – global mean SSTs

Sub-polar gyre SSTs – 2x(global mean SSTs)

Northern box SSTs – southern box SSTs

2. Indirect fingerprints
3. Observational dataset uncertainties

We use three different fingerprints + three different SST datasets, and apply the MLE method to individual time series as well as to the HadCRUT5 uncertainty ensemble



HadCRUT5 200 member uncertainty ensemble

Conclusions

The uncertainties in tipping time prediction are:

1. The **modelling assumptions** underlying the methods for tipping time estimation
2. The reliability of using **indirect fingerprints** to predict tipping times of climate tipping elements
3. The uncertainties that arise from the bias and preprocessing in **observational datasets** with measurement uncertainties and gaps

→ Some of these issues could improve with time, e.g. with another century of direct AMOC observations. However, it is unclear if the highly nonlinear and complex dynamics governing the proposed tipping elements can ever be reliably modelled at the accuracy needed for tipping time prediction. Finally, it will never be possible to know the change in future forcing, so any extrapolation will always be uncertain as it would assume a specific future scenario.

Conclusions

Key points:

⇒ the MLE method predicts a tipping time even for a linear red noise model

⇒ having red noise or non-linear forcing can also significantly bias the tipping time prediction

⇒ for the AMOC, using different fingerprints and SST datasets gives tipping times from 2050 to 4780 (8065 in the uncertainty ensemble)

We should not try to predict tipping times – the data just isn't good enough

Thank you!

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Tipping times using the different fingerprints and datasets:

	optimal p	**p=0**
SPG-2xGMT HadISST	2037.5	2053.7
SPG-2xGMT ERSSTv5	3047.7	3047.7
SPG-2xGMT HadCRUT5	2131.6	2168.9
SPG-1xGMT HadISST	2064.7	2084.2
SPG-1xGMT ERSSTv5	4780.9	4780.9
SPG-1xGMT HadCRUT5	2314.6	2314.6
Dipole HadISST	2085.2	2123.9
Dipole ERSSTv5	3285.4	3285.4
Dipole HadCRUT5	2915.5	2914.3

Tipping times using the HadCRUT5 200 member uncertainty ensemble:

	p=0	**optimal p**
SPG-2xGMT	2158.3-3072.8	2120.9-3072.8
SPG-1xGMT	2249.8-2992.6	2249.8-2600.7
Dipole	2428.2-8065.1	2359.1-inf

optimal p means that we use the optimization method introduces by Ditlevsen & Ditlevsen 2023, p=0 means we don’t