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

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Expanded presentation with more text
Observation-based Early warning signals

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

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

Smith et al. 2022
Smith et al. 2023

Boers & Rypdal 2021
Lu et al. (in review)

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

1. **Modelling assumptions** have to be made to extrapolate from past data to future outcomes.
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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 height
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.
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→ 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:

\[ 3 \times 10^{-3} \ FNF + WN + LinForc \]

The MLE method works
1. Modelling assumptions

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.

The system can tip.

The model is a fold-normal form.

The noise is white.
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:

\[
\times 10^{-3} \times (\text{FNF} + \text{RN} + \text{LinForc})
\]

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- True tipping time $t_c$
- Tipping before 1000
- Tipping after 5000
- No tipping predicted
- DD23 MLE method

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:

![Graph showing distribution with tips at different time points]

- True tipping time $t_c$
- Tipping before 1000
- Tipping after 5000
- No tipping predicted

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.
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:

<table>
<thead>
<tr>
<th></th>
<th>optimal p</th>
<th>p=0</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPG-2xGMT HadISST</td>
<td>2037.5</td>
<td>2053.7</td>
</tr>
<tr>
<td>SPG-2xGMT ERSSTv5</td>
<td>3047.7</td>
<td>3047.7</td>
</tr>
<tr>
<td>SPG-2xGMT HadCRUT5</td>
<td>2131.6</td>
<td>2168.9</td>
</tr>
<tr>
<td>SPG-1xGMT HadISST</td>
<td>2064.7</td>
<td>2084.2</td>
</tr>
<tr>
<td>SPG-1xGMT ERSSTv5</td>
<td>4780.9</td>
<td>4780.9</td>
</tr>
<tr>
<td>SPG-1xGMT HadCRUT5</td>
<td>2314.6</td>
<td>2314.6</td>
</tr>
<tr>
<td>Dipole HadISST</td>
<td>2085.2</td>
<td>2123.9</td>
</tr>
<tr>
<td>Dipole ERSSTv5</td>
<td>3285.4</td>
<td>3285.4</td>
</tr>
<tr>
<td>Dipole HadCRUT5</td>
<td>2915.5</td>
<td>2914.3</td>
</tr>
</tbody>
</table>

Tipping times using the HadCRUT5 200 member uncertainty ensemble:

<table>
<thead>
<tr>
<th></th>
<th>p=0</th>
<th>optimal p</th>
</tr>
</thead>
<tbody>
<tr>
<td>SPG-2xGMT</td>
<td>2158.3-3072.8</td>
<td>2120.9-3072.8</td>
</tr>
<tr>
<td>SPG-1xGMT</td>
<td>2249.8-2992.6</td>
<td>2249.8-2600.7</td>
</tr>
<tr>
<td>Dipole</td>
<td>2428.2-8065.1</td>
<td>2359.1-inf</td>
</tr>
</tbody>
</table>

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