Climate change detection based on smooth temporal patterns

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Introduction

Definition (IPCC, 2007) : detection, attribution

Detection is the process of demonstrating that an observed change is significantly different than can be explained by natural internal variability.

Basic ideas
Definition (IPCC, 2007) : detection, attribution

Attribution of causes of climate change is the process of establishing the most likely causes for the detected change with some defined level of confidence.

Attribution of the change $X$ to the cause $Y$ requires:

- detection of $X$,
- $X$ is consistent with the expected response to $Y$,
- $X$ is not consistent with alternative, physically plausible causes.

Basic ideas
**Introduction**

**Definition (IPCC, 2007) : detection, attribution**

**Basic ideas**
- One tries to quantify the response to each external forcing,
- D&A involve statistical tests applied to observed data.
Classical approach for D&A

Statistical model:

\[ Y_{s,t} = \sum_{k=1}^{K} \beta^{(k)} g^{(k)}_{s,t} + \epsilon_{s,t}, \]

- \( Y \): climate variable (data),
- \( g^{(k)} \): the estimated response to the forcing \( k \) (known),
- \( \beta^{(k)} \): a real amplitude coefficient (unknown),
- \( \epsilon_{i} \): internal climate variability (random).

Statistical method:
Classical approach for D&A

Statistical model:

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Statistical method:

Classical approach for D&A

**Statistical model:**

\[ Y_{s,t} = \sum_{k=1}^{K} \beta^{(k)} g^{(k)}_{s,t} + \varepsilon_{s,t}, \]

**Statistical method:**


Requires to know the responses (or signals \( g^{(k)} \)), and the statistical properties of the internal variability (\( \varepsilon \)).
Motivations

The spatial structure of both signal and noise may be difficult to simulate accurately (particularly at the regional scale).

Introduce a method for detecting the anthropogenic forcing:

- based on simplified responses to external forcings (here: only temporal patterns),
- that avoids challenging simulations by climate models for evaluating the internal climate variability.
Statistical framework and assumptions

- Climate change signal
- Internal variability $\varepsilon$
- Tested statistical hypothesis
Statistical framework and assumptions

Climate change signal

\[ Y_{s,t} = m_s + Y_{s,t}^{(cc)} + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

- Additivity

Internal variability \( \varepsilon \)

Tested statistical hypothesis
Statistical framework and assumptions

Climate change signal

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

- Additivity
- Space-time separability

Internal variability \( \varepsilon \)

Tested statistical hypothesis
Statistical framework and assumptions

Climate change signal

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

- Additivity
- Space-time separability
- Smoothness over time

Internal variability \( \varepsilon \)

Tested statistical hypothesis
**Statistical framework and assumptions**

**Climate change signal**

\[ Y_{s,t} = m_s + g_s \mu_t + \epsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

**Internal variability** \( \epsilon \)

- Gaussian distribution

**Tested statistical hypothesis**
Statistical framework and assumptions

**Climate change signal**

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

**Internal variability** \( \varepsilon \)

\[ \text{Cov}(\varepsilon_{s,t}, \varepsilon_{s',t'}) = C_{s,s'} \Sigma_{t,t'} \]

- Gaussian distribution
- Space-time separability

**Tested statistical hypothesis**
Statistical framework and assumptions

Climate change signal

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

Internal variability \( \varepsilon \)

\[ \text{Cov}(\varepsilon_{s,t}, \varepsilon_{s',t'}) = C_{s,s'} \alpha^{|t-t'|} \]

- Gaussian distribution
- Space-time separability
- The covariance in time is the one of an auto-regressive process of the first order (AR1)

\[ \varepsilon_{s,t} = \alpha \varepsilon_{s,t-1} + \tilde{\varepsilon}_{s,t} \]

Tested statistical hypothesis
Statistical framework and assumptions

Climate change signal

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

Internal variability \( \varepsilon \)

\[
\text{Cov}(\varepsilon_{s,t}, \varepsilon_{s',t'}) = C_{s,s'} \delta_{t,t'}
\]

- Gaussian distribution
- Space-time separability
- The covariance in time is the one of an auto-regressive process of the first order (AR1)

\[ \varepsilon_{s,t} = \alpha \varepsilon_{s,t-1} + \tilde{\varepsilon}_{s,t} \]

Pre-whitening, one has \( \Sigma = I \)
Statistical framework and assumptions

Climate change signal

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t}, \quad s = 1, \ldots, S, \quad t = 1, \ldots, T. \]

Internal variability \( \varepsilon \)

\[ \text{Cov}(\varepsilon_{s,t}, \varepsilon_{s',t'}) = C_{s,s'} \delta_{t,t'} \]

Tested statistical hypothesis

\[ H_0 : \text{“} g = 0 \text{”} \quad \text{vs} \quad H_1 : \text{“} g \neq 0 \text{”} \]
Evaluating the temporal patterns $\mu$

Evaluation is:

- done from climate model runs (20CM3 and A1B scenario),
- based on an “indicator” of climate change $\theta$,
- performed requiring smoothness.
Evaluating the temporal patterns $\mu$

For each CMIP3 model
Evaluating the temporal patterns $\mu$

For each CMIP3 model
Evaluating the temporal patterns $\mu$

Set of 24 CMIP3 models
Statistical test
The Hotelling test (MANOVA)

- Statistical model

\[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t} \]

- Parameters: \( m, g, C \).
Statistical test
The Hotelling test (MANOVA)

- Statistical model
  
  \[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t} \]

- Parameters : \( m, g, C \).

- Least-Square Estimates : \( \hat{m}, \hat{g}, \hat{\varepsilon} \), then \( \hat{C} \).
Statistical test
The Hotelling test (MANOVA)

- Statistical model
  \[ Y_{s,t} = m_s + g_s \mu_t + \varepsilon_{s,t} \]

- Parameters: \( m, g, C \).

- Least-Square Estimates: \( \hat{m}, \hat{g}, \hat{\varepsilon} \), then \( \hat{C} \).

- Test’s variable:
  \[ v = \hat{g}' \hat{C}^{-1} \hat{g} \sim_{H_0} F(S, T - S - 1). \]
Observations
We used a dataset of homogenised temperatures and precipitation covering France, over the 1900-2006 period.

Models
We used 24 CGCMs from CMIP3.
Annual mean temperatures over France (1)
Complete dataset

**Figure 1:** Time evolution of the $p$-value of the detection test, applied to annual mean temperatures over France.
Figure 1: Time evolution of the $p$-value of the detection test, applied to annual mean temperatures over France.
Annual mean temperatures over France (2)
After removing the mean over the spatial domain

**Figure 2:** Time evolution of the $p$-value of the detection test, applied to annual mean temperatures over France, after removing the spatial mean.
Annual mean temperatures over France (2)
After removing the mean over the spatial domain

**Figure 2:** Time evolution of the $p$-value of the detection test, applied to annual mean temperatures over France, after removing the spatial mean.
Annual mean temperatures over France (3)
Estimated spatial pattern \( \hat{g} \)

\textbf{FIGURE 3}: Change of the annual mean temperature, estimated over the 1900-2006 period (\( \hat{g} \)).
Annual mean temperatures over France (3)
Estimated spatial pattern $\hat{g}$

The spatial distribution of the change is significantly:

\[ \hat{g} \]

\[ 6^\circ W \quad 3^\circ W \quad 0^\circ \quad 3^\circ E \quad 6^\circ E \]

\[ 42^\circ N \quad 44^\circ N \quad 46^\circ N \quad 48^\circ N \quad 50^\circ N \quad 52^\circ N \]

\[ 1.6 \quad 1.55 \quad 1.5 \quad 1.45 \quad 1.4 \quad 1.35 \quad 1.3 \quad 1.25 \quad 1.2 \quad 1.15 \]

\[ ^\circ C \]

**Figure 3:** Change of the annual mean temperature, estimated over the 1900-2006 period ($\hat{g}$).
The spatial distribution of the change is significantly:

- non zero,
- 

**Figure 3**: Change of the annual mean temperature, estimated over the 1900-2006 period ($\hat{g}$).
Annual mean temperatures over France (3)
Estimated spatial pattern $\hat{g}$

The spatial distribution of the change is significantly:

- non zero,
- non zero mean,
- 

**Figure 3:** Change of the annual mean temperature, estimated over the 1900-2006 period ($\hat{g}$).
The spatial distribution of the change is significantly:

- non zero,
- non zero mean,
- non uniform.

**Figure 3**: Change of the annual mean temperature, estimated over the 1900-2006 period ($\hat{g}$).
Annual rainfall over France

**Figure 4:** Time evolution of the $p$-value of the detection test, and estimated spatial pattern of change (1900-2006).
Conclusions

The temporal optimal detection (TOD) method:
- is based on smooth temporal patterns,
- takes into account the spatial properties of the investigated field,
- avoids a challenging estimation of spatial patterns of changes and spatial properties of the internal climate variability from climate models,
- is well-suited for regional studies.

The application of the TOD method over France highlights new results about climate change detection over the country.