Introduction	Results from Synthetic Data	Results from real observations and CMIP5 simulations	Summary
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New Cointegration Methods for Detection and Attribution of Climate Trends

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Detection and At	tribution defined		

Detection

IPCC defined detection of climate change as a process of demonstrating that climate or a system affected by climate has changed in some defined statistical sense without providing a reason for that change

Attribution

Attribution is a process of evaluating the relative contributions of multiple causal factors to a change or event with an assignment of statistical confidence.

Reliable detection and attribution of changes in climate is fundamental in enabling decision makers to manage climate-related risk (Hegerl et al., 2010).



Introduction

Results from Synthetic Data

Results from real observations and CMIP5 simulations

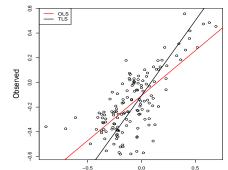
The OLS and TLS fits

Summary

Methodological Approaches

Existing regression approach

The ordinary least squares (OLS) and/or total least squares (TLS) regression methods have been employed in detection-attribution studies (Allen and Stott, 2003; Stott et al., 2003).



Modelled

 $\begin{array}{lll} \text{OLS}: \mathbf{y} = & \mathbf{X}\beta + \epsilon_t \\ \text{TLS}: \mathbf{y} = & (\mathbf{X} - \mathbf{w})\beta + \epsilon_t \end{array} \right\} \begin{array}{l} \mathbf{y} - \textit{observed}, \mathbf{X} - \textit{modelled}, \\ \epsilon - \textit{climate noise } \& \mathbf{w} - \textit{model uncertainty} \end{array}$

Detection: reject $H_0: \beta = \mathbf{0}$ Attribution: reject $H_0: \beta_f = 0$ for a particular forcing f





- Most climatic time series are non-stationary.
- Non-stationary time series can lead to spurious regressions (Granger and Newbold, 1974).
- Better to see if one time series x can be used to detrend another time series y
- Vector autoregressive (VAR) models are useful in capturing the linear interdependencies among multiple time series.



Introduction

Results from Synthetic Data

Methodological Approaches

Cointegrating time series model: VAR(2) model

VAR(2)

For a bivariate vector
$$\mathbf{z}_t = \begin{pmatrix} y_t \\ x_t \end{pmatrix}$$
, we use a VAR(2) model:

$$\mathbf{z}_t = \mathbf{\Pi}_1 \mathbf{z}_{t-1} + \mathbf{\Pi}_2 \mathbf{z}_{t-2} + \boldsymbol{\epsilon}_t, \qquad t = 1, 2, ..., T$$

VECM

The vector error correction model, VECM

$$\Delta \mathbf{z}_t = \mathbf{\Pi} \mathbf{z}_{t-1} + \mathbf{\Gamma} \Delta \mathbf{z}_{t-1} + \boldsymbol{\epsilon}_t$$

is estimated using Johansen's maximum likelihood method.

Given the rank of $\pmb{\Pi}$ matrix is 1, the long-run coefficient β can be estimated from

$$\Pi = \alpha \beta'$$





Simple "toy" models are used to generate synthetic data.

$$\begin{array}{ll} c_t = & e + c_{t-1} + \varepsilon_t \\ y_t = & \alpha_0 + \alpha_1 c_t + \xi_t \\ x_t = & \gamma_0 + \gamma_1 c_t + \nu_t \end{array} \right\} \begin{array}{l} c_t - CO_2 \text{ in year } t, e - emissions, \\ y_t - \text{observed temperature}, x_t - \text{modelled temp} \end{array}$$

Parameters estimated using the 20^{th} century annual observation from HadCRUT3 and GISS model simulations.

Historical near surface temperature (Brohan et al., 2006) and 16 of the models included in CMIP5 simulations are also used.



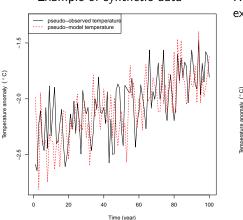
Introduction ○○○○○● Results from Synthetic Data

Results from real observations and CMIP5 simulations

Summary

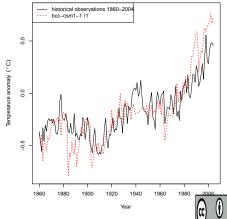
The Data

Time series of synthetic and real data



Example of synthetic data

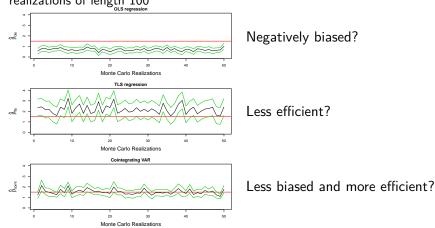
Historical global mean temperature and example of CMIP5 simulation



 \Rightarrow Non-stationary

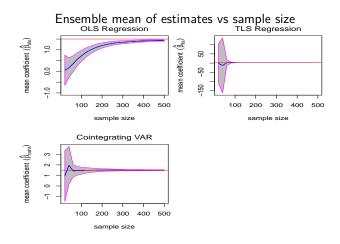
Estimates for 50 MC realizations

Estimates for 50 Monte Carlo realizations of length $100_{\text{outs repression}}$





Sampling properties of the estimators



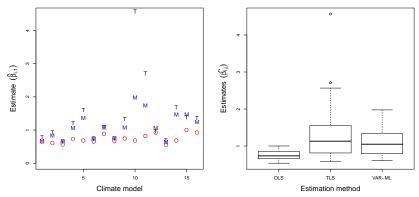


 \Rightarrow OLS-biased, TLS-very uncertain, VAR-ML-better than the two

Distribution of estimates: using real observations and CMIP5 simulations

Estimates-one run from each model: O-OLS, M-VAR-ML, and T-TLS

Distribution of estimates: for all realizations



 \Rightarrow The cointegrating VAR estimates are not biased to either extremes. \Rightarrow The pattern/distribution of estimates do back results from synthetic data.



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Summarv			

- The static regression methods could end-up with spurious results for non-stationary climatic variables- high risk of misleading policy makers.
- The dynamic VAR based MLE are less biased and more efficient than those of the OLS and TLS estimates of static regression.
- We can do better with cointegrating VAR method in detection and attribution studies.



Introduction	



Thank you

Questions?

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