EGU General Assembly Online
NP5.4 Session - 8th May 2020

Correcting for Model Changes in Statistical Post-Processing - An approach based on Response Theory

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Model Output Statistics techniques

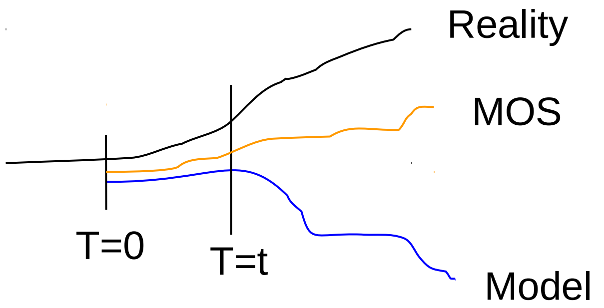
Statistical Post-processing of forecasts in developed to improve their quality based on information gathered from past forecasts

- ‘Deterministic’ approach: Linear techniques (Classical MOS, perfect prog), Kalman filtering
- ‘Deterministic’ approach: Nonlinear techniques (Neural networks, nonlinear fits, Machine Learning)
- Probabilistic approaches: use of deterministic precipitation forecasts
- (True) Probabilistic approaches: Calibration of the ensemble forecasts.

The Linear MOS technique

Linear regression between a set of observables of forecasts and observations

$$X_C(t) = \alpha(t) + \sum_{i=1}^{n} \beta_i(t) V_i(t)$$



$$J(t) = \sum_{k=1}^{M} \left(X_{C,k}(t) - X_k(t)\right)^2$$

M past forecasts

Minimization of J(t)

n=1

$$\alpha(t) = \langle X(t) \rangle - \beta(t) \langle V(t) \rangle$$

$$\beta(t) = \frac{\langle X(t)V(t) \rangle - \langle X(t) \rangle \langle V(t) \rangle}{\langle V(t)^2 \rangle - \langle V(t) \rangle^2}$$

Error in Variable MOS

$$V = \varsigma + \delta$$

$$X = \alpha + \beta\varsigma + \kappa$$

$$J(t) = \sum_{k=1}^{M} \frac{(V_k(t) - \varsigma_k(t))^2}{\sigma_\delta^2(t)} + \sum_{k=1}^{M} \frac{(X_k(t) - (\alpha + \beta\varsigma_k(t)))^2}{\sigma_\kappa^2(t)}$$

Intermediate cost function:

$$J(t) = \sum_{k=1}^{M} \frac{(\overbrace{(\alpha(t) + \beta(t)V_k(t))}^{X_{c,k}(t)} - X_k(t))^2}{\sigma_\kappa^2(t) + \beta^2(t)\sigma_\delta^2(t)}$$

One ‘free’ parameter:

$$\lambda = \frac{\sigma_\delta^2}{\sigma_\kappa^2} \text{ fixed to } \frac{\sigma_V^2}{\sigma_X^2}$$

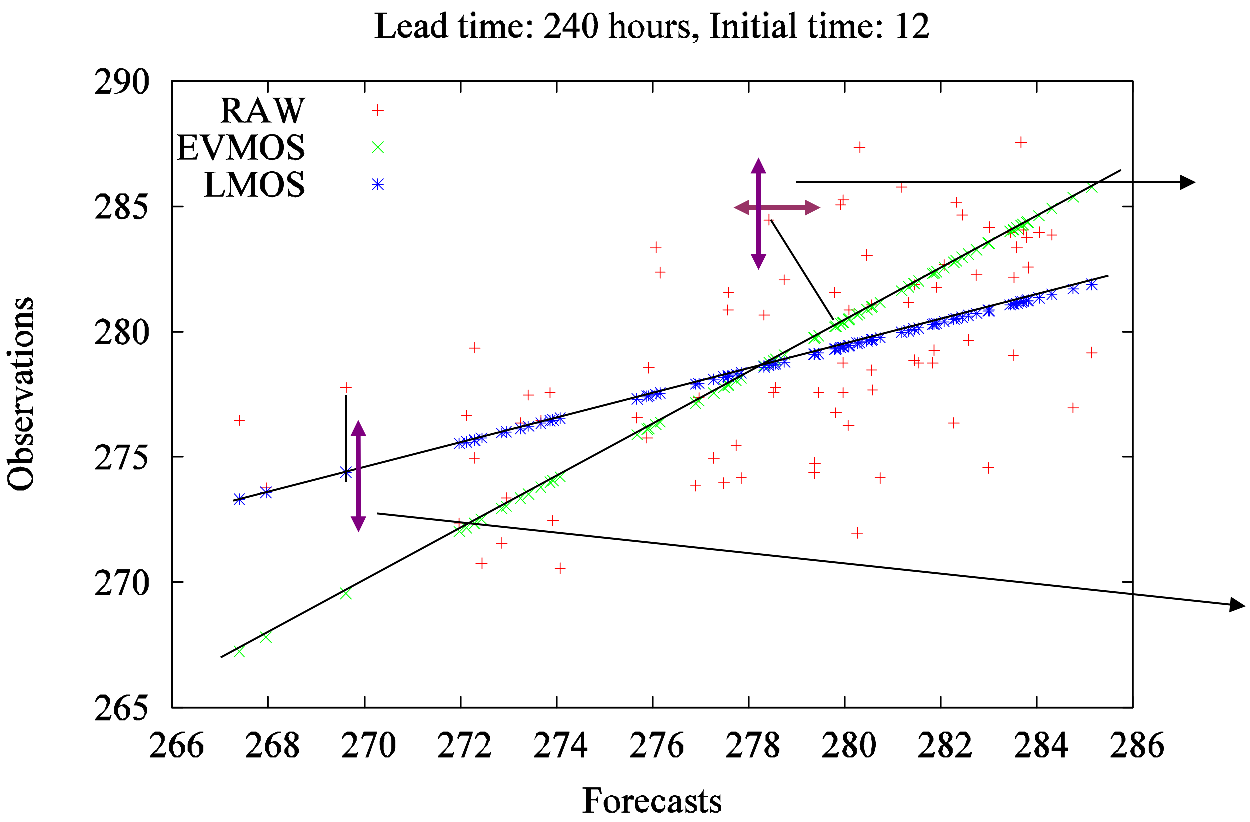
Needs some knowledge about the sources of errors

Minimization

$$\alpha(t) = <X(t)> - \beta(t) <V(t)>$$

$$\beta(t) = \sqrt{\frac{<X(t)^2> - <X(t)>^2}{<V(t)^2> - <V(t)>^2}} = \sqrt{\frac{\sigma_X^2(t)}{\sigma_V^2(t)}}$$

Illustration



Total least square Error-in-Variables regression

Classical linear regression

Vannitsem, 2009, QJRMS

Forecasting system changes

ECMWF

Implementation date	Summary of changes	Resolution	Full IFS documentation
11-Jun-2019	Cycle 46r1	Unchanged	CY46R1
05-Jun-18	Cycle 45r1	Unchanged	CY45R1
05-Nov-2017	ECMWF’s new long-range fo recasting system SEAS5	Unchanged	Documentation
11-Jul-17	Cycle 43r3	Unchanged	CY43R3
22-Nov-16	Cycle 43r1	Ocean (Horizontal & vertical)	CY43R1
08-Mar-16	Cycle 41r2	HRES/ENS/WAVE (Horizontal)	CY41R2
12-May-15	Cycle 41r1	Unchanged	CY41R1
1-Dec-13	Tropical cyclone trajectory	Unchanged	
19-Nov-13	Cycle 40r1	ENS (Vertical)	CY40R1
26-Jun-13	Cycle 38r2	HRES (Vertical)	

How to deal with model changes?

- Reforecasts (ECMWF, NOAA…)
- Using an adaptive method which progressively improve when more new forecasts are issued (e.g. UMOS, Wilson & Vallée, 2002)
- Other methods?
    - Linear Response Theory (Ruelle, 1998)

↓

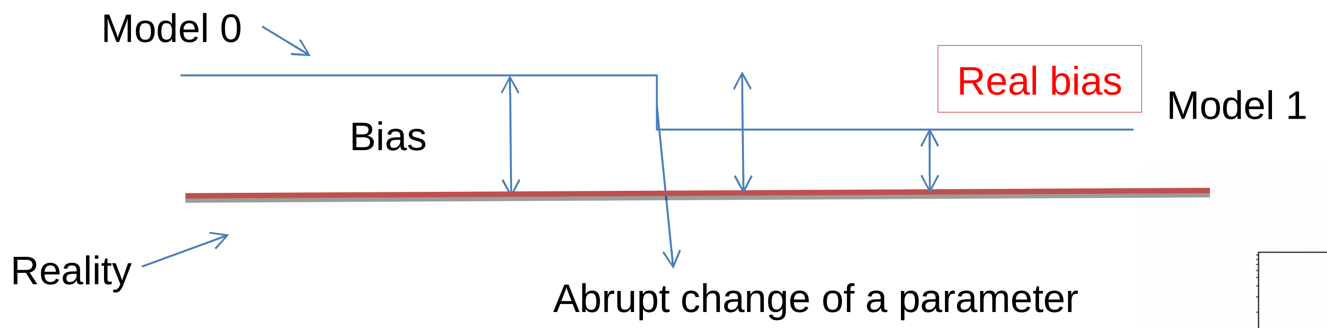
Objective of the current presentation

Reforecasts are expensive

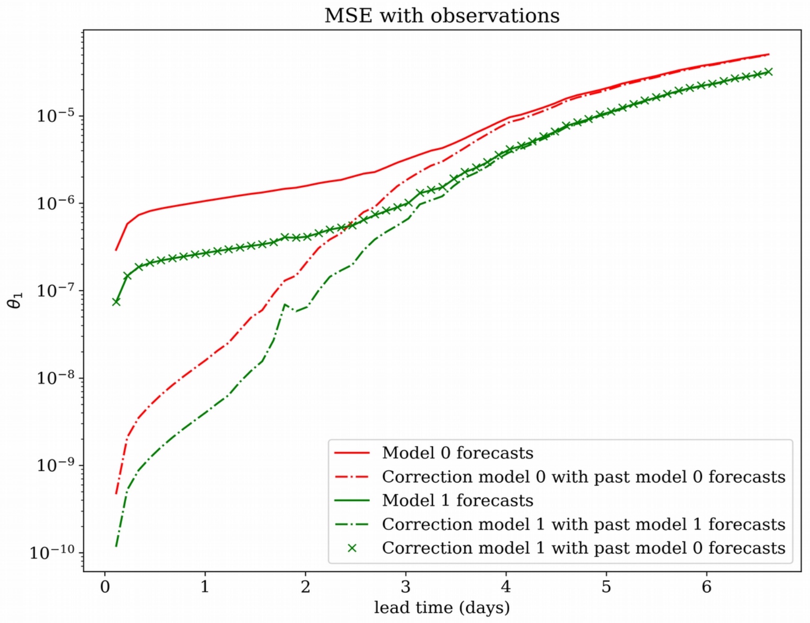
Done on a global scale by ECMWF and NOAA (GEFS model)

Is it possible to approach the problem in a different way?
Can we avoid using and computing reforecasts?

Impact of model changes



Given a model change (model 0 → model 1):



A new approach to avoid reforecasting

RMI

… while still taking the model change into account: <u>Response theory</u>

Idea:

- Given a model change (model 0 → model 1)
- assuming the model change is an analytic function Ψ , perform a sensitivity analysis

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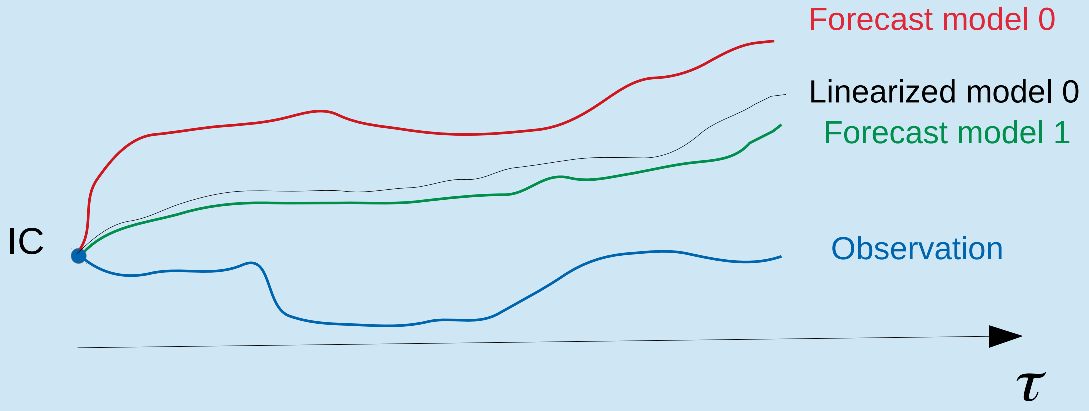
Model 0 : $\dot{y} = F(y)$

Model 1 : $\dot{\hat{y}} = \hat{F}(\hat{y}) = F(\hat{y}) + \Psi(\hat{y})$

1st-order perturbation by Ψ:

$$\left.\begin{aligned} \delta\dot{y} &= \nabla F(y)\cdot\delta y + \Psi(y) \\ \delta y(0) &= 0 \end{aligned}\right\} \quad y + \delta y \approx \hat{y}$$



Sensitivity with respect to Ψ, not IC !

Response theory and post-processing

RMI

Post-processing typically involves statistical moments !

e.g. Error-in-variables MOS

For a variable x(τ) and a predictor y(τ)

$$x_C(\tau) = \alpha(\tau) + \beta(\tau)\ y(\tau)$$ Corrected variable

with

$$\alpha(\tau) = \langle x(\tau)\rangle - \beta(\tau)\,\langle y(\tau)\rangle$$
$$\beta(\tau) = \sqrt{\frac{\sigma_x^2(\tau)}{\sigma_y^2(\tau)}}$$

(τ ≡ lead time)

Vannitsem, QJRMS 2009

Response theory

For an observable A: $\langle A(\tau)\rangle_{\hat{y}} = \langle A(\tau)\rangle_y + \delta\langle A(\tau)\rangle + \ldots$

with

$$\delta\langle A(\tau)\rangle = \Big\langle\ \delta y(\tau)\cdot\nabla A(y(\tau))\ \Big\rangle_{y(0)}$$

Ruelle, Physics Letters A 1998

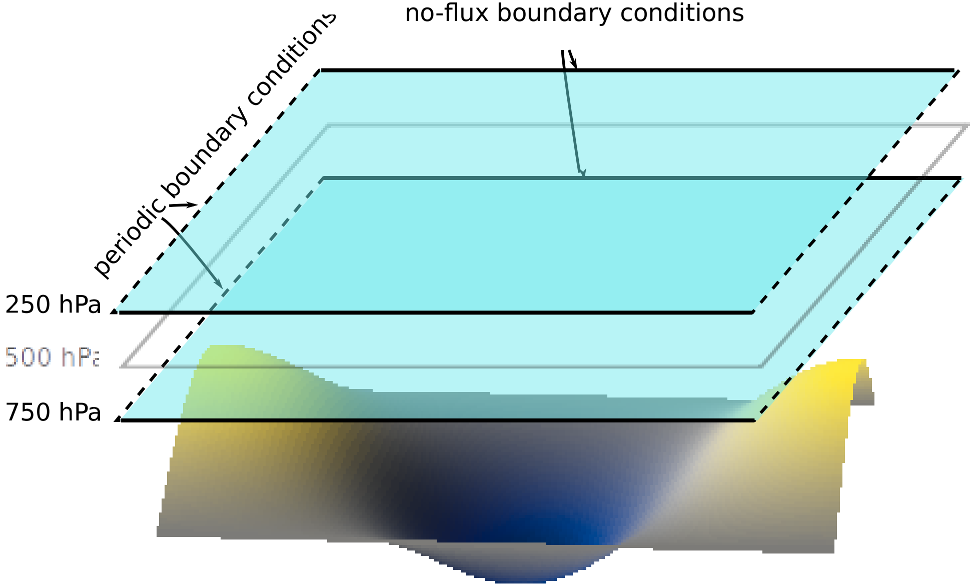
Sensitivity of the moments = average over linearized trajectories

Allow to compute variation of 1st moment (A=y), 2nd moment (A=y²), … due to model change.

Gives $\delta\alpha\ ,\ \delta\beta$

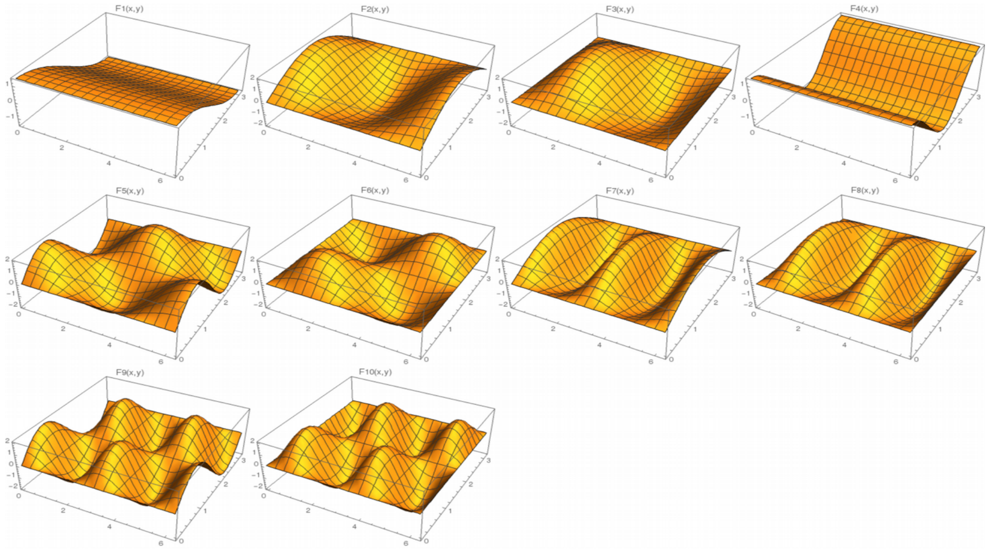
Application to an idealized atmospheric model

Spectral 2-layer QG model on a β-plane with an orography at mid-latitude



10 modes → 20 var. Ordinary Differential Equations

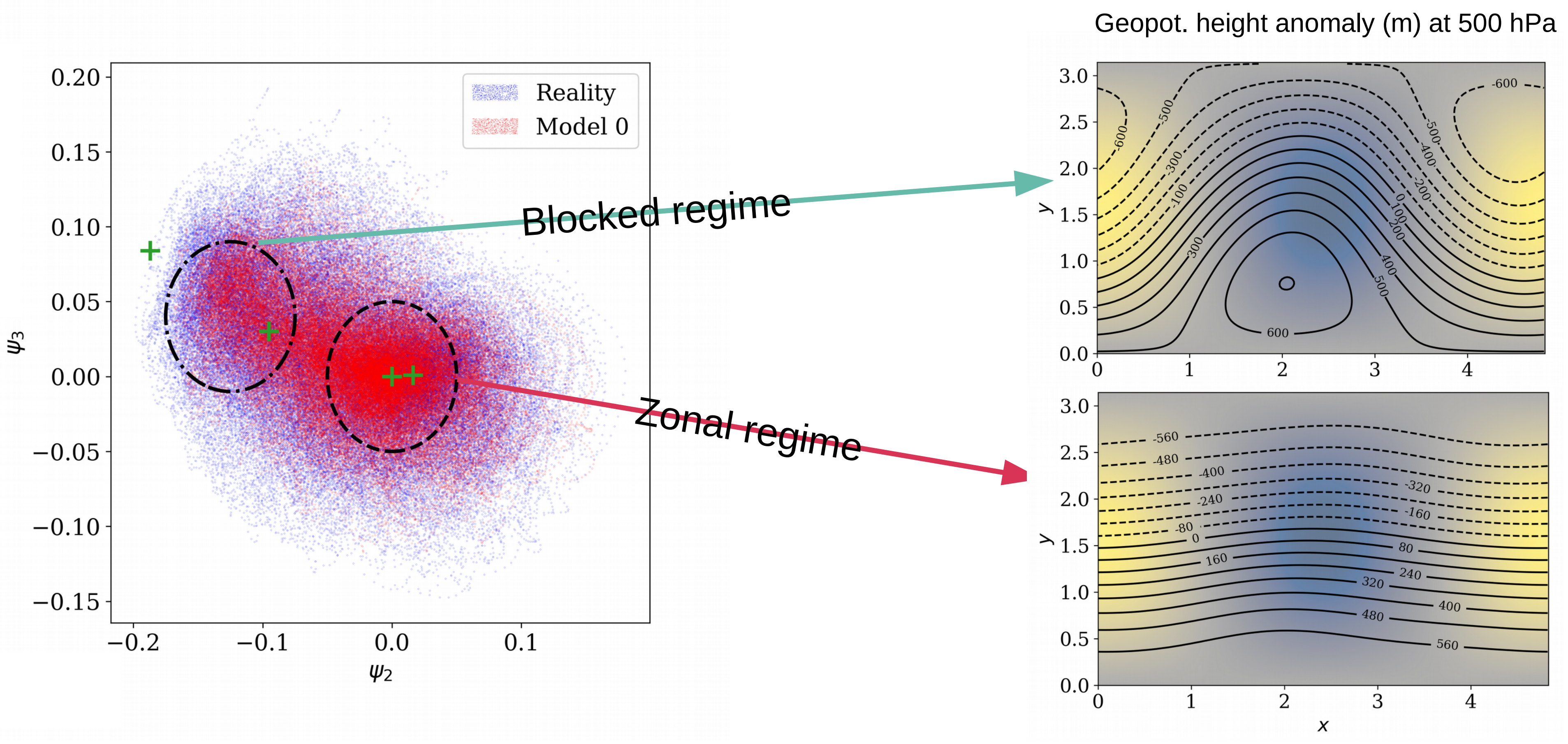
Streamfunction + Temperature



Reinhold & Pierrehumbert, Monthly Weather Review 1982

Computed with the qgs model: https://github.com/Climdyn/qgs

Dynamics of the idealized atmospheric model



Post-processing experiments

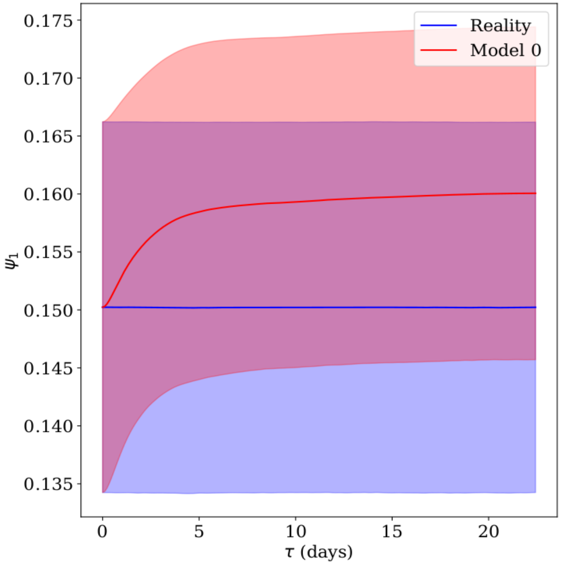
2 ≠ experiments

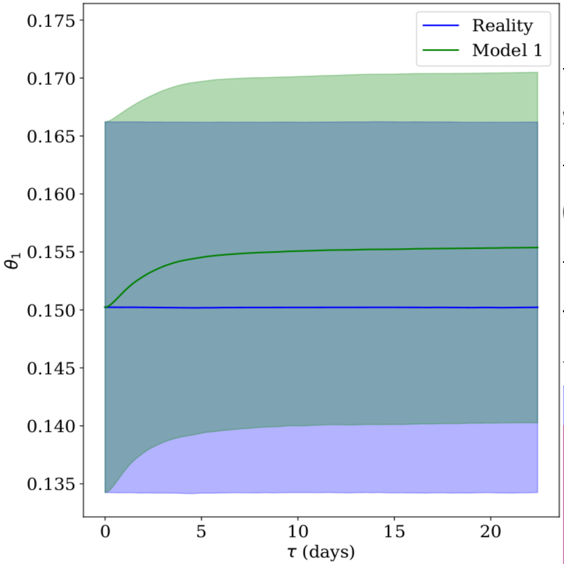
Parameter description \ Experiment			Newtonian cooling modification		Friction coefficient modification	
	Symbol \ System	Reality	Model 0	Model 1	Model 0	Model 1
Newtonian cooling coefficient	h_d	0.3	0.33	0.315	0.3	
Atm. layers friction	k_d	0.1	0.1		0.12	0.11
Bottom layer friction	k'_d	0.01				
Domain aspect ratio	n	1.3				
Meridional temperature gradient	θ_2^*	0.2				
Mountain ridge altitude	h_2	0.4				

3 versions of the model
with one ≠ parameters:

- Reality (observations)
- Model 0
- Model 1

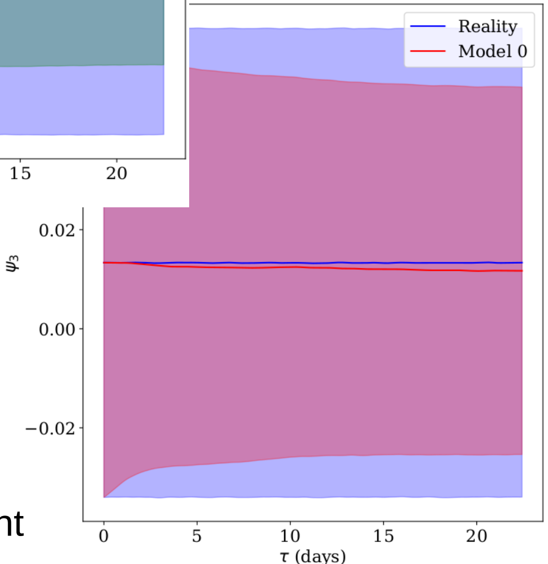
Post-processing experiments

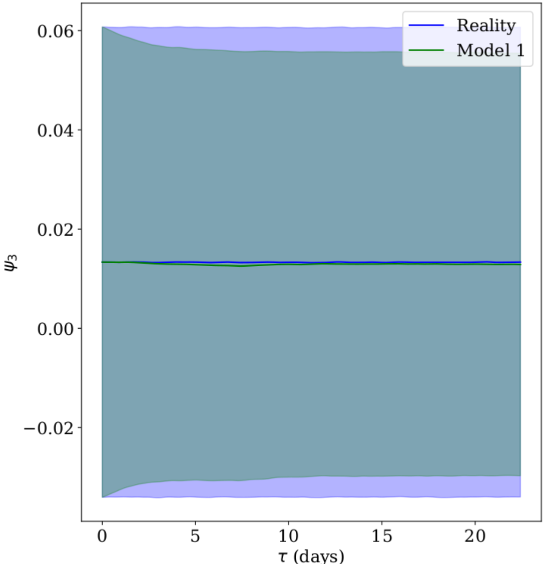




2 ≠ experiments

ian cooling modification		Friction coefficient modification	
0	Model 1	Model 0	Model 1
	0.315	0.3	
0.1		0.12	0.11





3 versions of the model with one ≠ parameters:

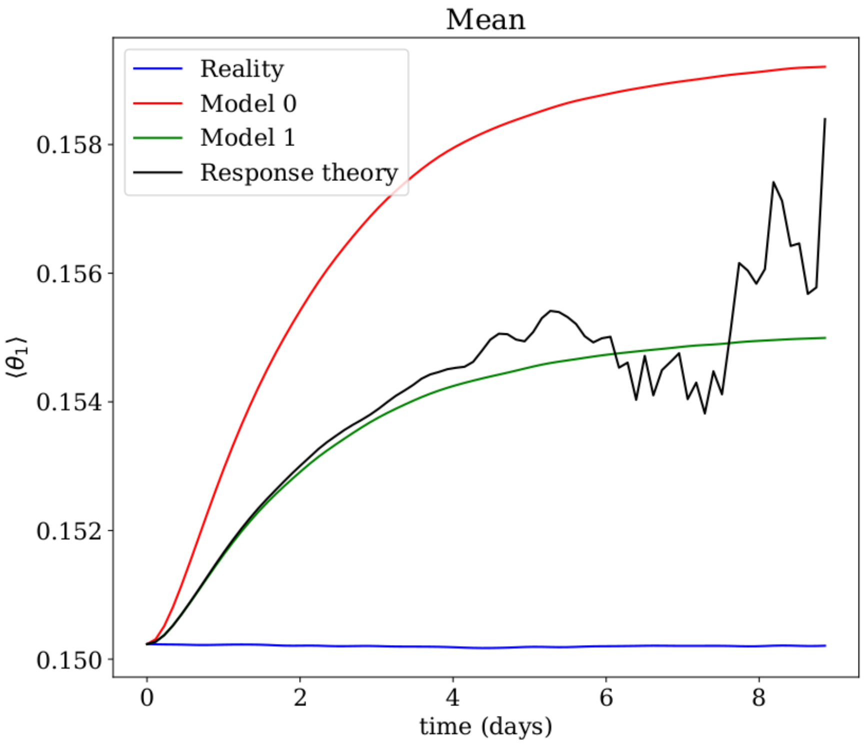
- Reality (observations)
- Model 0
- Model 1

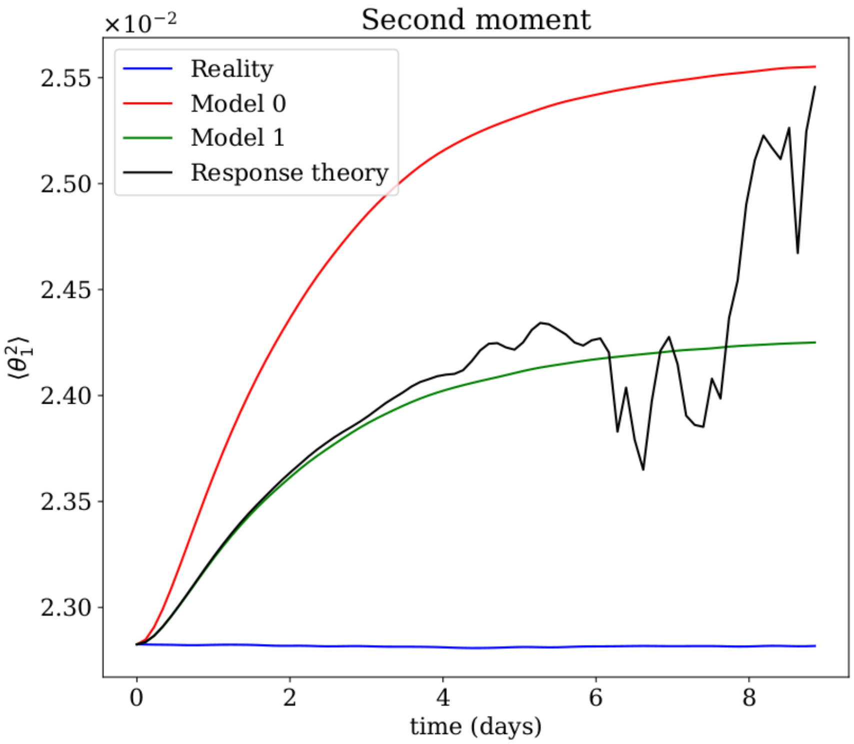
Here : Results for the friction experiment

Correction of the moments

10000 linearized trajectories

First mode of the temperature
→ Meridional temperature gradient

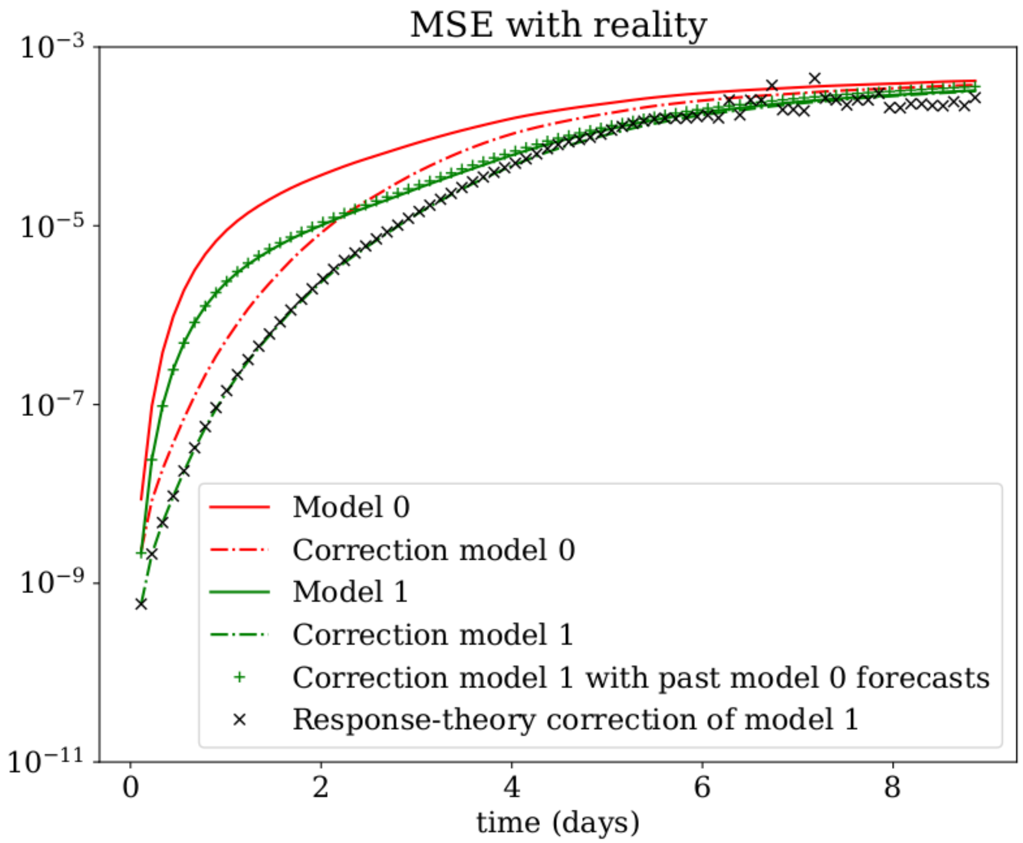




EVMOS α , β

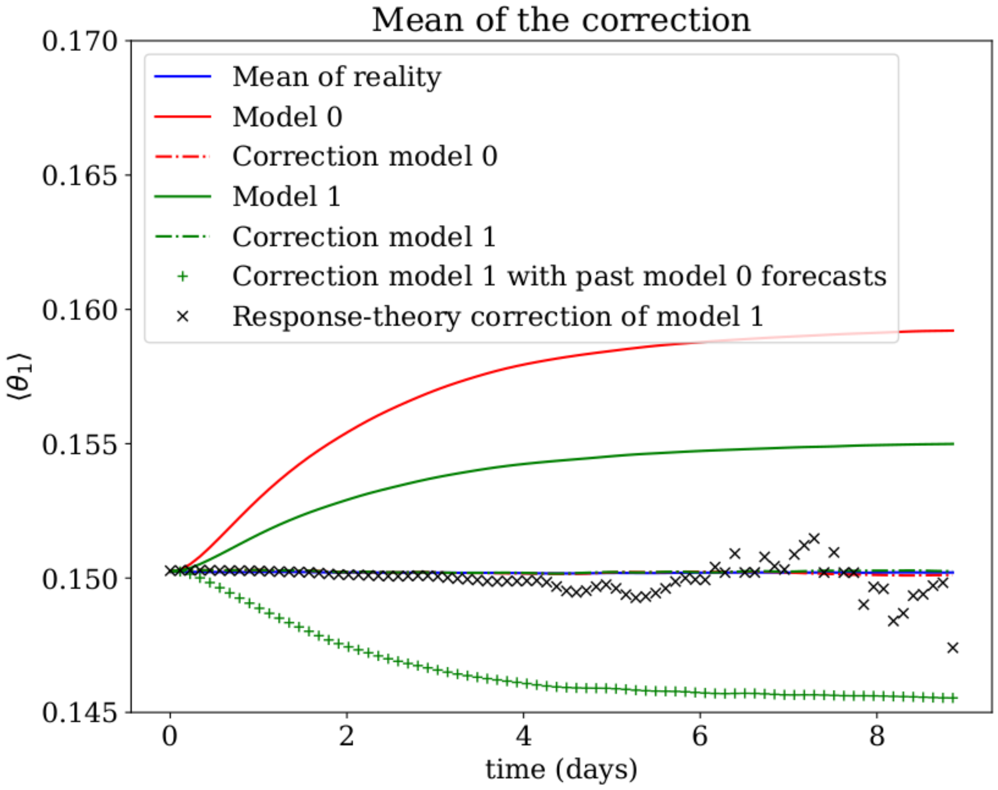
Correction of the moments → Post-processing

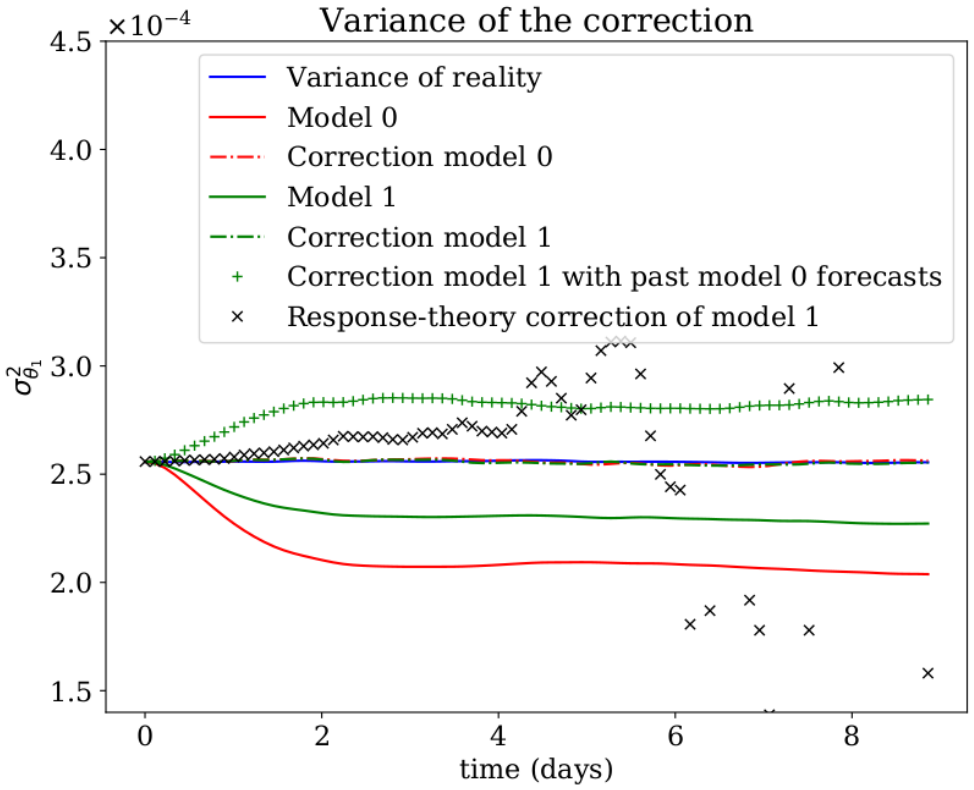
EVMOS α , β



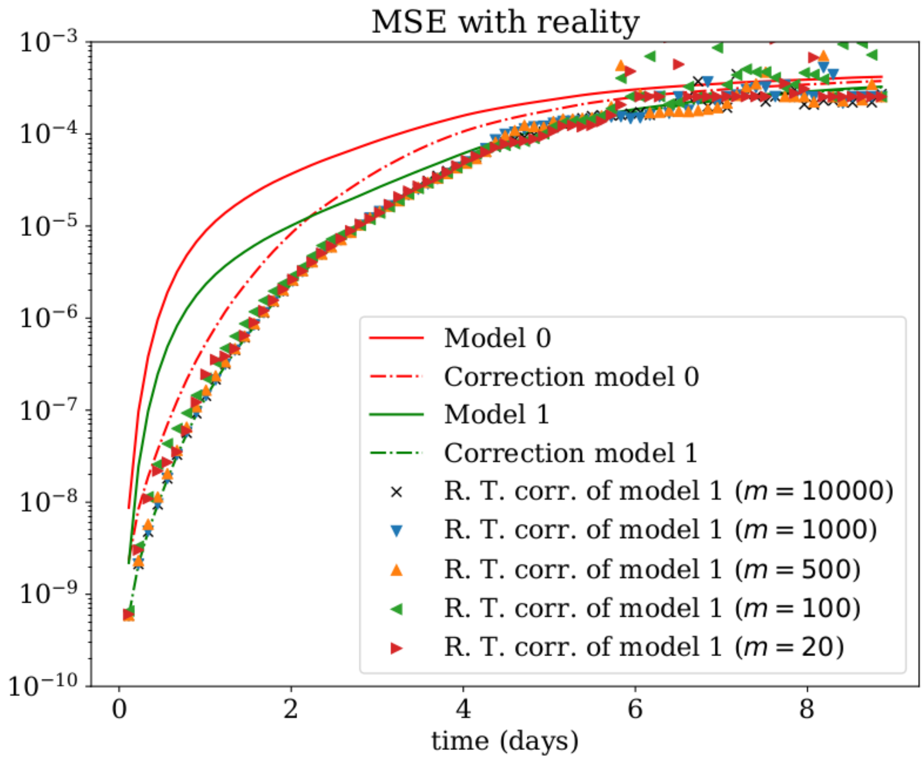
Correction of the mean and the variance

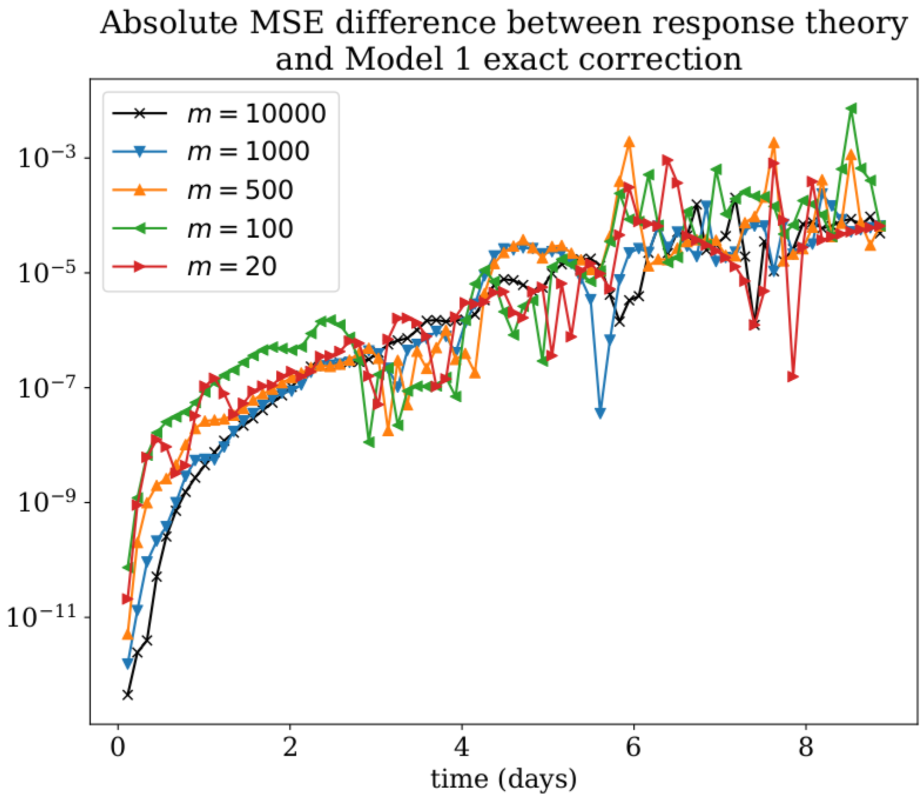
Good but Response Theory deteriorates after 4 days





Impact of the number m of trajectories





Good results even with 20 linearized trajectories → Open question: competitive with reforecasts?

Conclusions & Outlook

- Response theory allows to correct model changes in PP schemes accurately
- Needs a linearized model (tangent model)
- Alternative to reforecasts
- Can be extended to ensemble forecasts and other methods
- Results published in:

Demaeyer, J. and Vannitsem, S.: *Nonlin. Processes Geophys. Discuss.*, in review, 2019.

https://doi.org/10.5194/npg-2019-57

What next?

- Test in operational setups? → Competitiveness with direct reforecasts?
- Other PP frameworks

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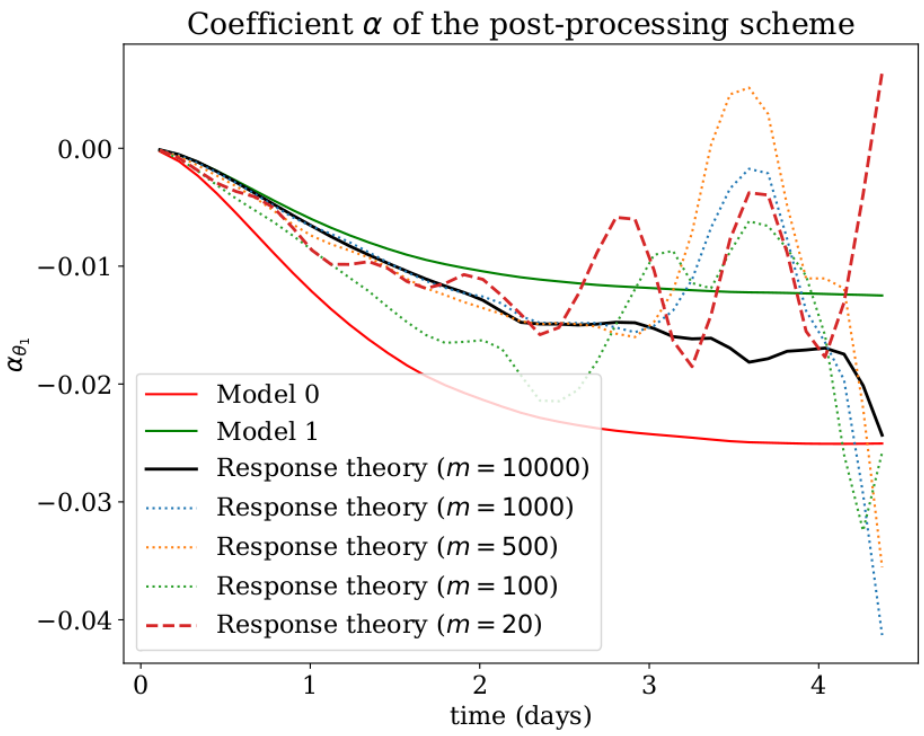
Computation performed with the new qgs model.

Calculation notebooks: https://github.com/jodemaey/Postprocessing_and_response_theory_notebooks

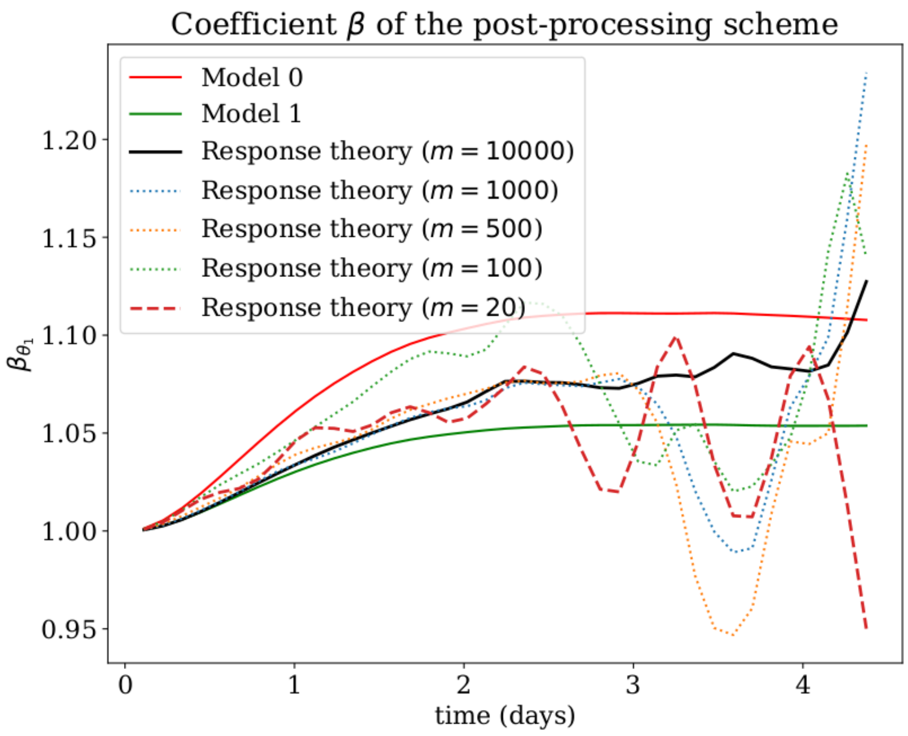
Model freely available at: https://github.com/Climdyn/qgs https://qgs.readthedocs.io/en/latest/

Additional materials

EVMOS α and β

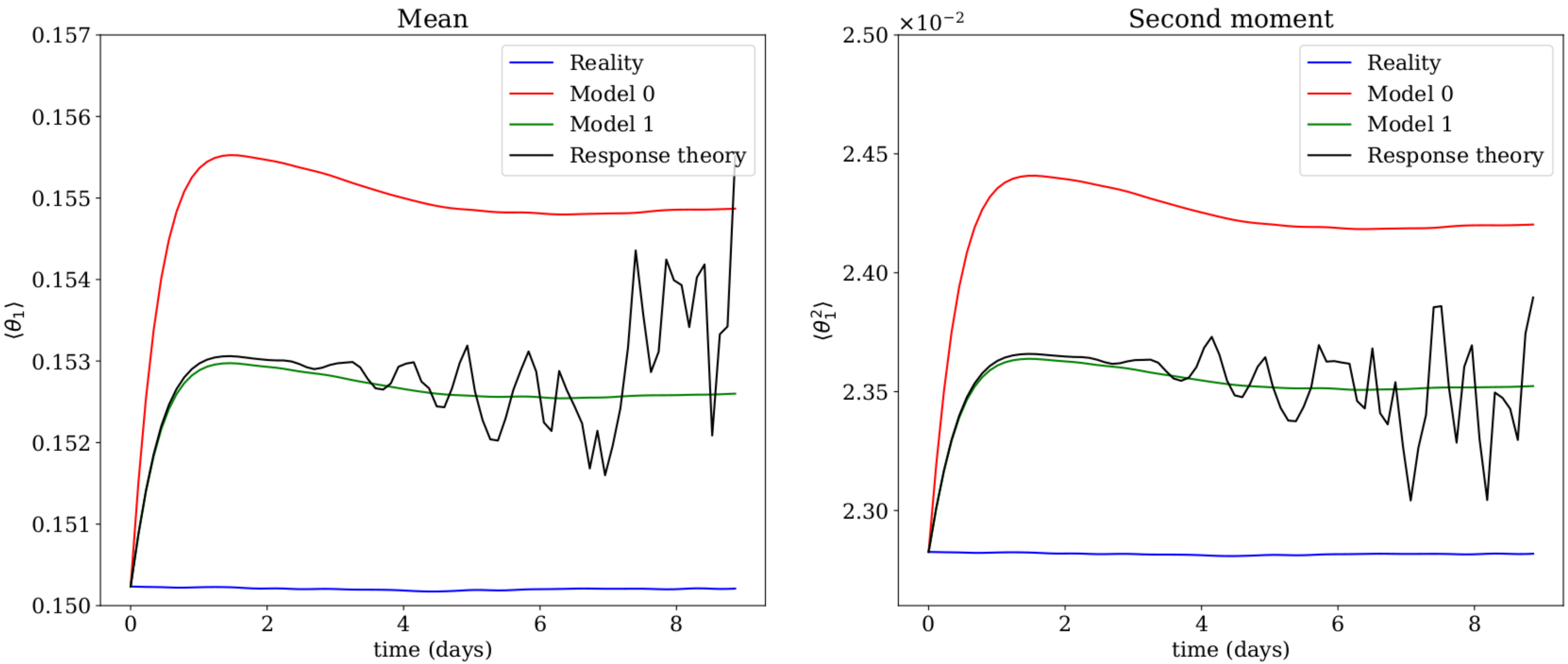


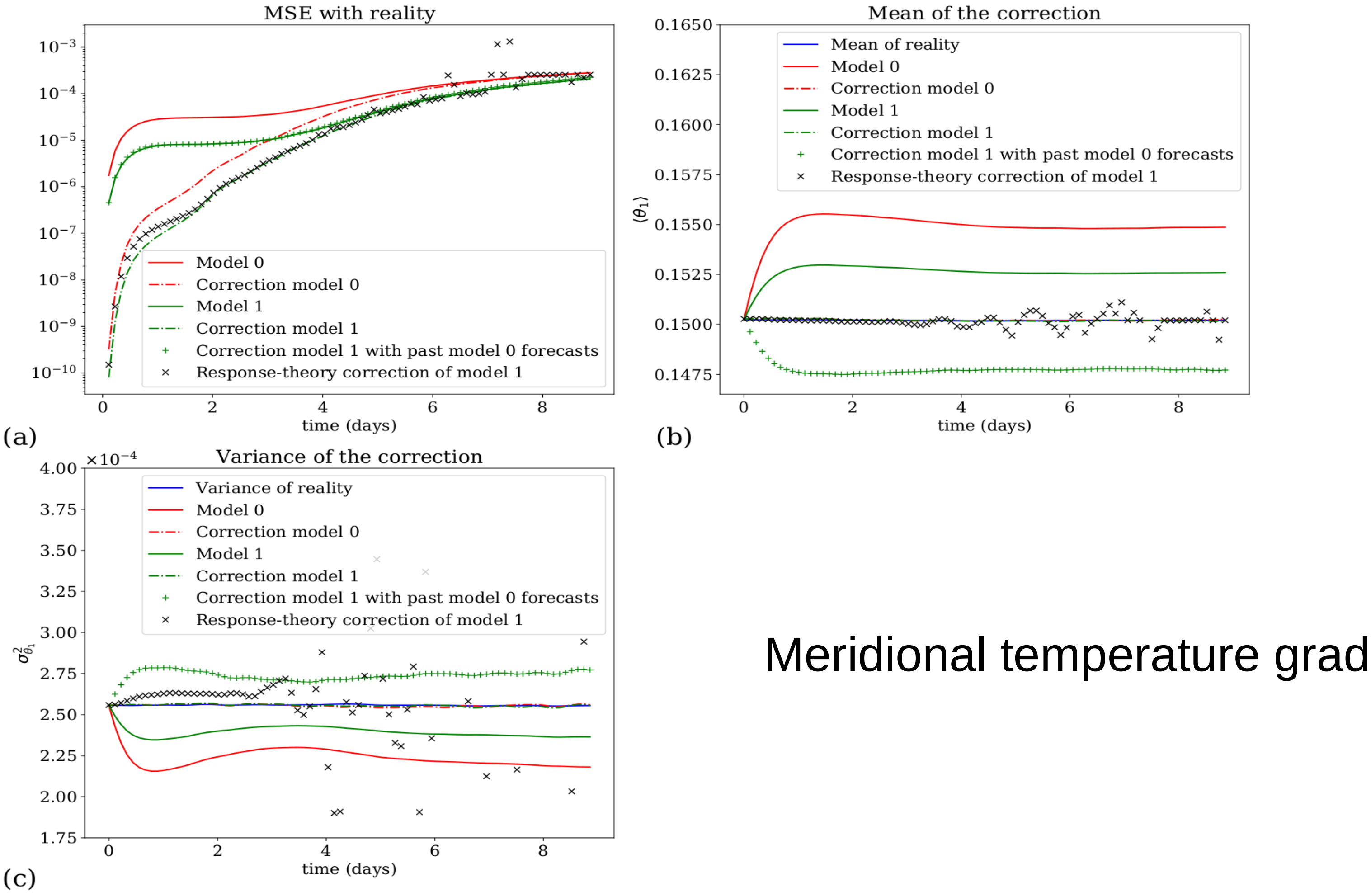
Coefficient α of the post-processing scheme
0.00
−0.01
−0.02
−0.03
−0.04
α_{θ_1}
0
1
2
3
4
time (days)
Model 0
Model 1
Response theory ($m = 10000$)
Response theory ($m = 1000$)
Response theory ($m = 500$)
Response theory ($m = 100$)
Response theory ($m = 20$)



Coefficient β of the post-processing scheme
1.20
1.15
1.10
1.05
1.00
0.95
β_{θ_1}
0
1
2
3
4
time (days)
Model 0
Model 1
Response theory ($m = 10000$)
Response theory ($m = 1000$)
Response theory ($m = 500$)
Response theory ($m = 100$)
Response theory ($m = 20$)

Meridional temperature gradient experiment





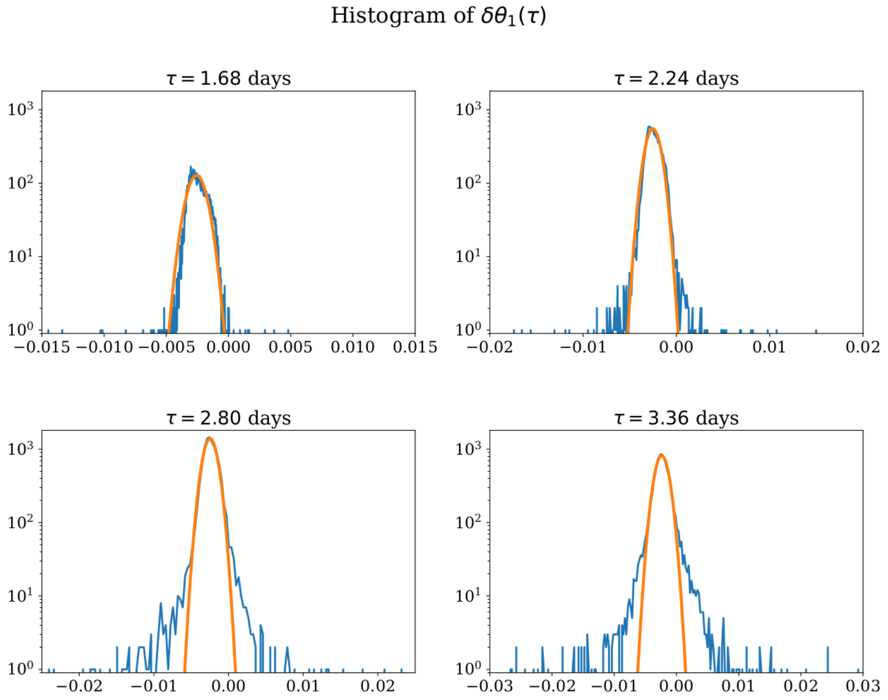
RMI

Meridional temperature gradient experiment

Why the response deteriorate after 4 days?

$$\begin{cases} \dot{y} = F(y) \\ \delta\dot{y} = \nabla F(y)\cdot\delta y + \Psi(y) \\ \delta y(0) = 0 \end{cases}$$

Histogram of $\delta\theta_1$



Fat tails in the distribution !

Estimation of the moments is complicate.

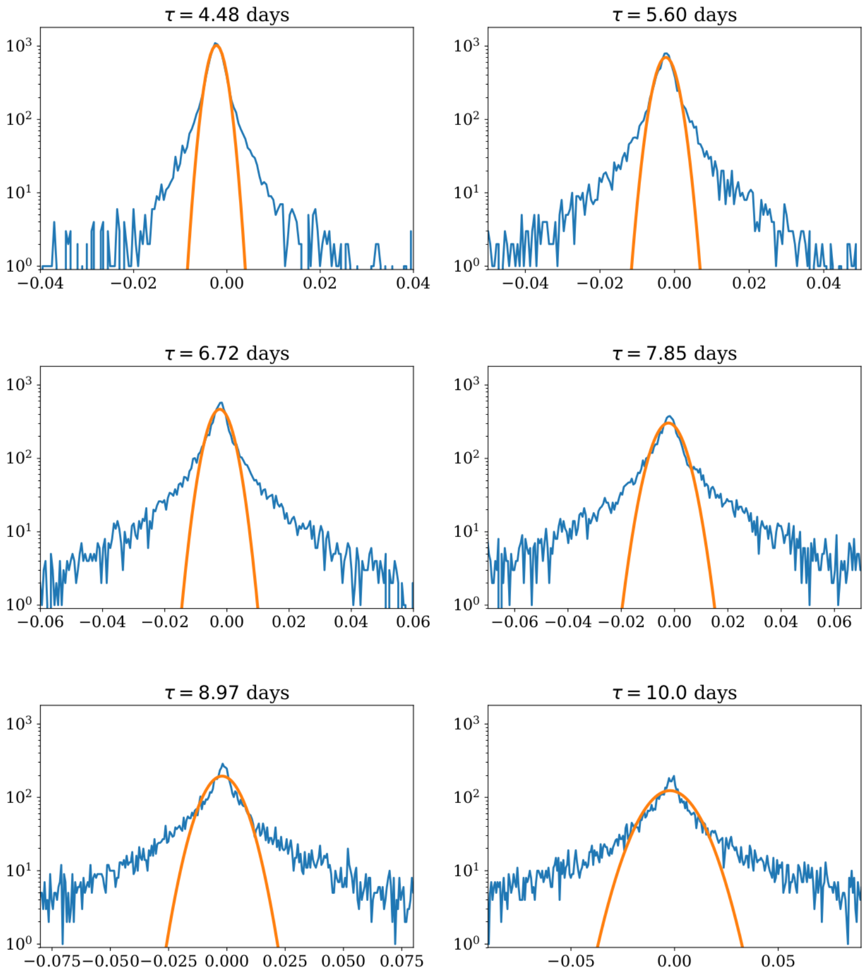
Why the response deteriorate after 4 days?

$$\dot{y} = F(y)$$

$$\delta \dot{y} = \nabla F(y) \cdot \delta y + \Psi(y)$$

$$\delta y(0) = 0$$

Histogram of $\delta \theta_1$



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