Forecasting Flow Reversals in a Chaotic Toy Climate

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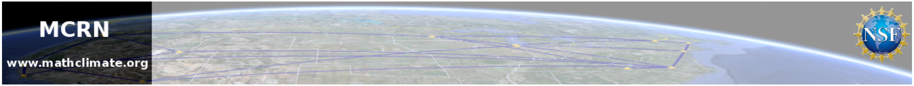


Outline

1. Study methodology
   - Thermosyphon
   - Experimental setup
2. The forecasting problem
   - Data assimilation
   - Model tuning
3. Results
   - DA – state estimation
   - Flow reversal forecasting
4. Conclusions

Lorenz (1963) system physical analog

Natural convection

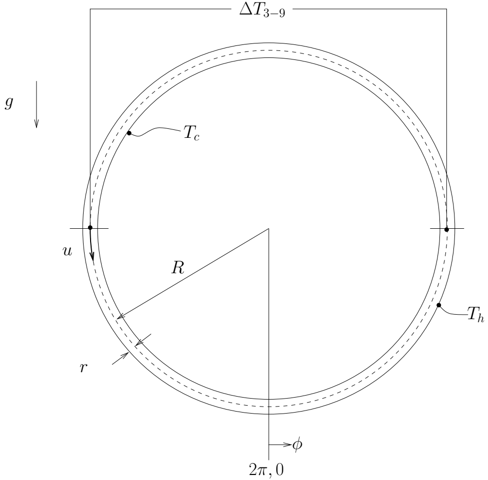
- Rayleigh-Bénard (2 plates)
- thermosyphon (loop, pipes)
- dynamical equations of Ehrhard & Müller (1990)
- "toy climate"

EM state vars:

$x_1 \propto u$, velocity

$x_2 \propto \Delta T_{3-9}$, horiz

$x_3 \propto \Delta T_{6-12}$, vert



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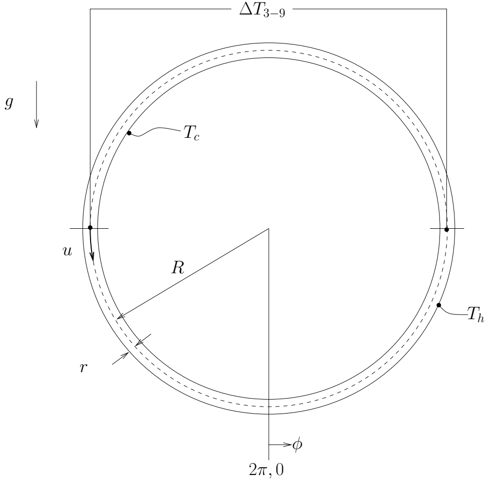

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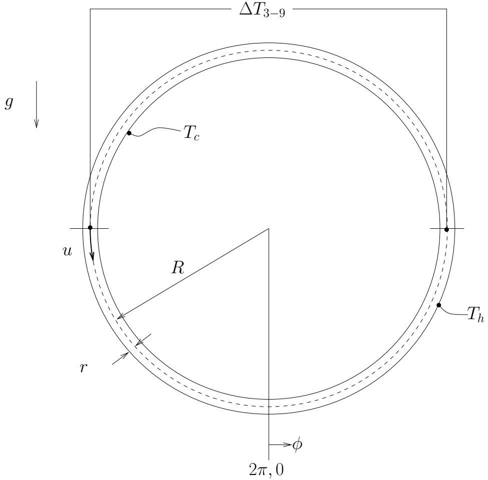

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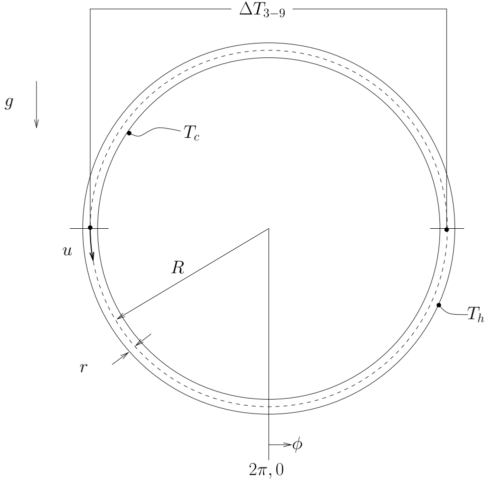

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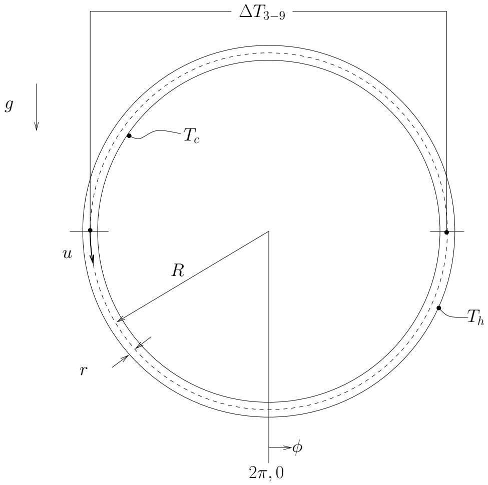

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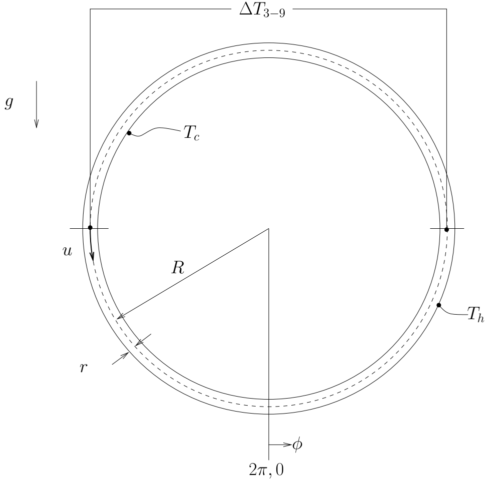
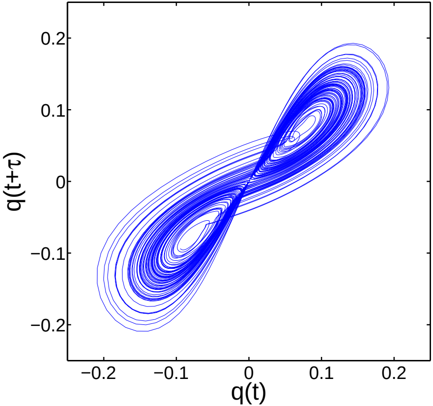


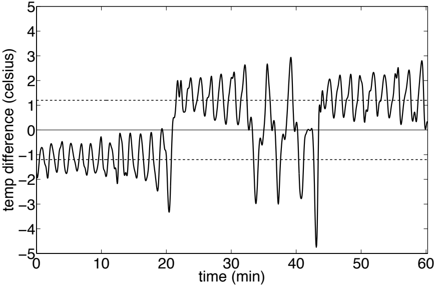
Flow reversals in action, from Ridouane et al. (2009)

(LoadingMovie)

A familiar attractor



60 s time-delay reconstruction mass flow rate (kg/s) in simulated thermosyphon



timeseries of horizontal temperature difference for laboratory thermosyphon

- we call zero-crossings flow reversals

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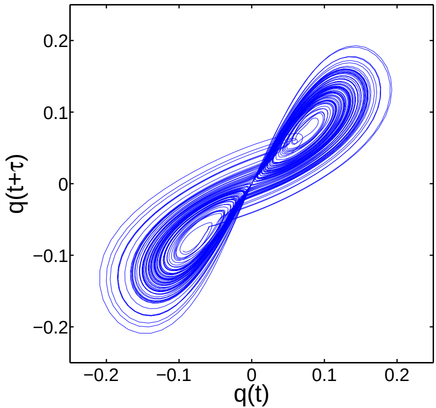

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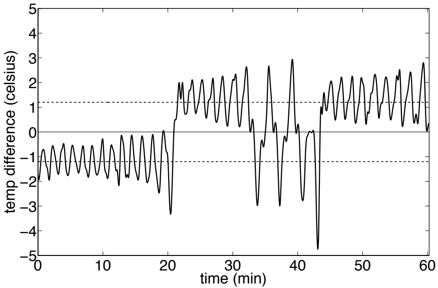

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Flow reversal significance

Example of regime changes,
transition between inherently different behaviors
(in thermosyphon: CW vs. CCW)

Other important examples:

- climate shifts (glacial vs. interglacial)
- weather patterns (El Niño, PDO)
- desertification

Early warnings crucial for preventing catastrophes

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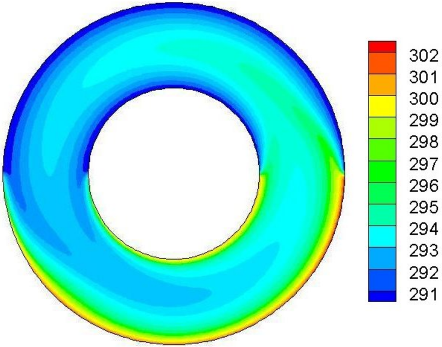
Forecasting scheme

1. CFD simulations represent thermosyphon "truth"
   - 2-D, $\mathcal{O}(10^4)$ discretization of Navier-Stokes equations, implemented in FLUENT package
   - observations made of mass flow rate q (scalar)
2. EM (imperfect) model makes the forecasts
3. simplest realistic DA experiment



Steady temperature profile.
Image credit: Ridouane et al. (2009)

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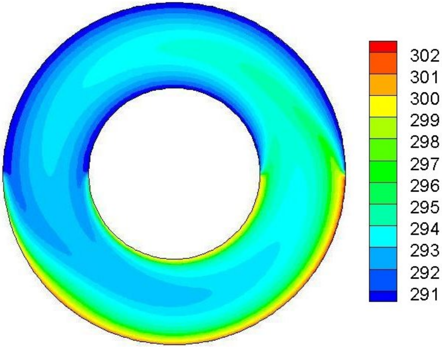

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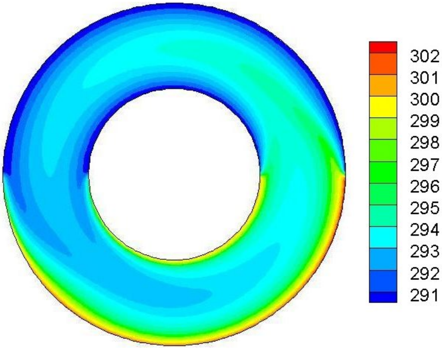

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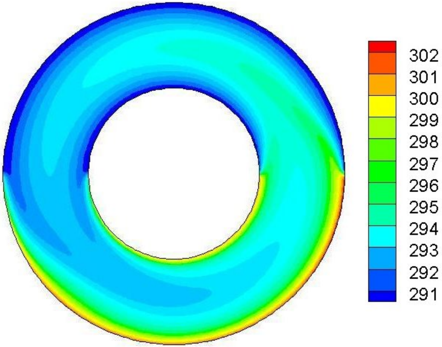

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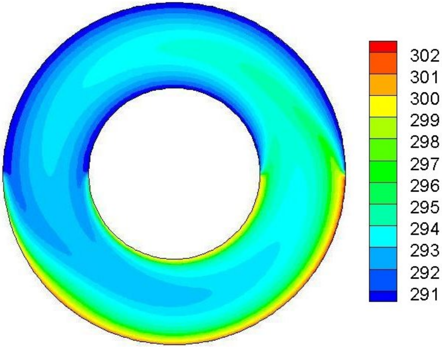

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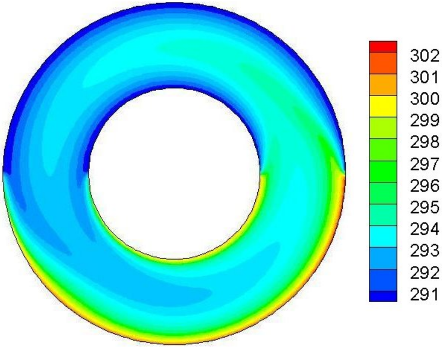

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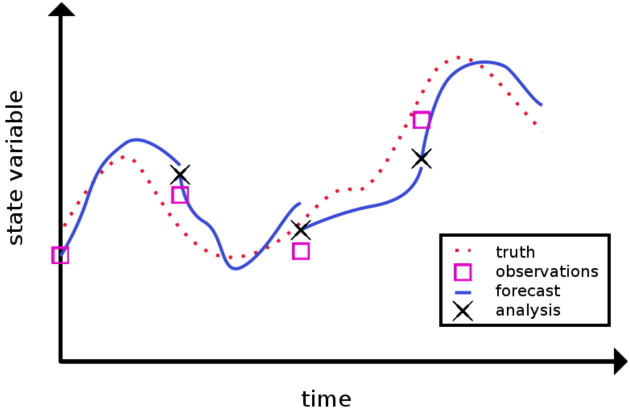
The initial value problem

Data assimilation (DA) estimates the current state that minimizes future forecast error, using past forecasts and observations



DA algorithms tested

- 3D-Var
  - constant background error
  - simple and efficient
  - operational many places
- Extended Kalman Filter (EKF)
  - background error propagated with adjoint model
  - numerically costly, only for small models
- Ensemble Kalman Filters (ETKF, EnSRF)
  - ensemble of states represents current state + uncertainty
  - no need for adjoint model
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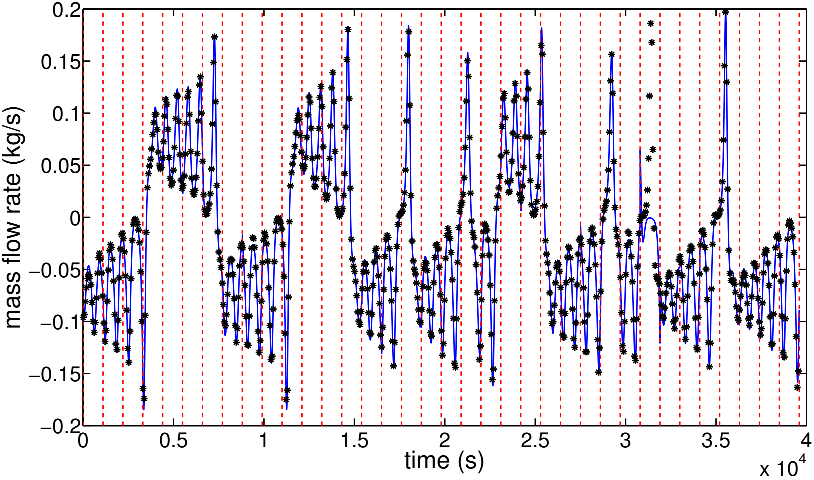
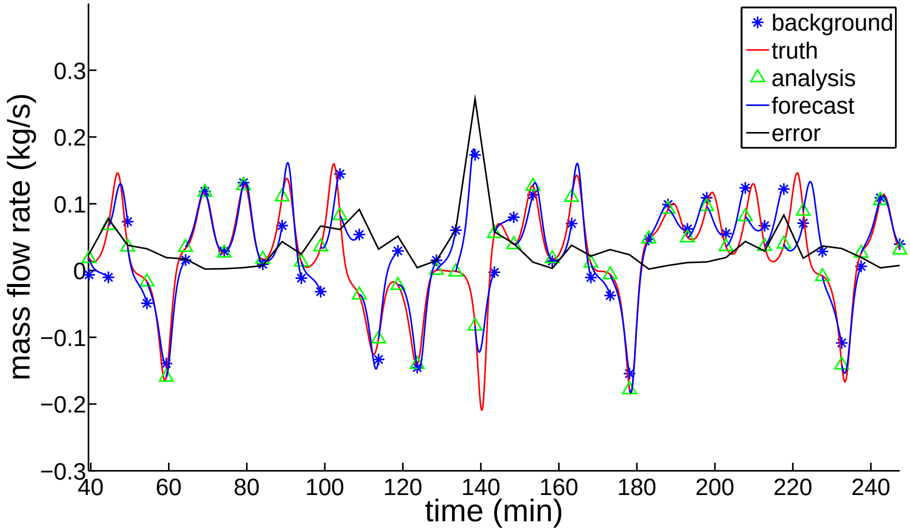
Multiple shooting parameter estimation



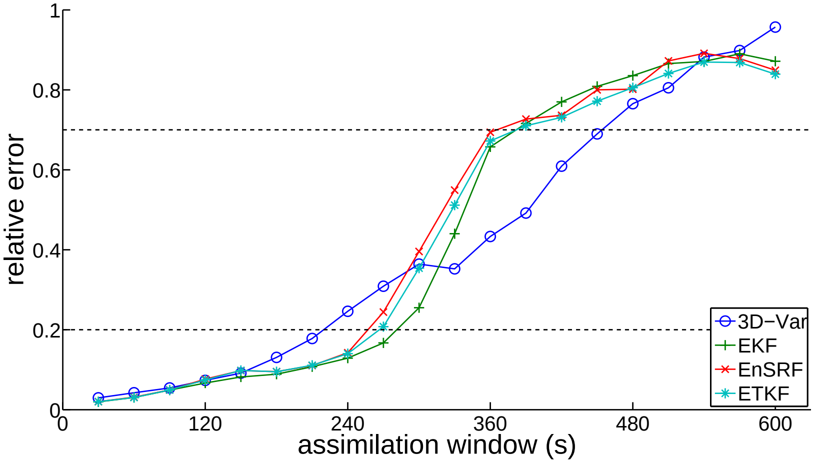
$\alpha = 7.99$, $\beta = 27.3$, $K = 0.148$,

632 s/(time unit), 0.0136 (kg m/s)/(x_1 unit)

3D-Var results for 300 s assimilation window

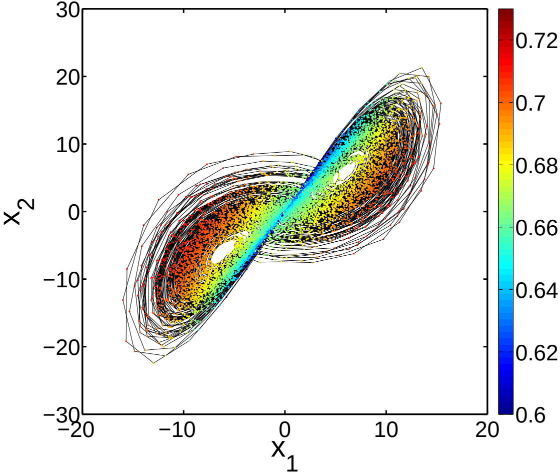


Comparing DA algorithms – background error



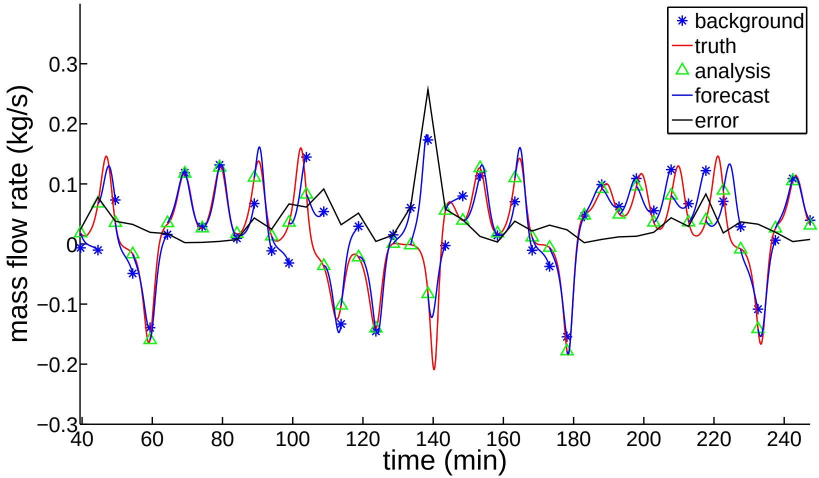
- Error relative to RMS mass flow rate
- Dashed lines for “perfect” and “useless” forecasts

Assimilated thermosyphon attractor



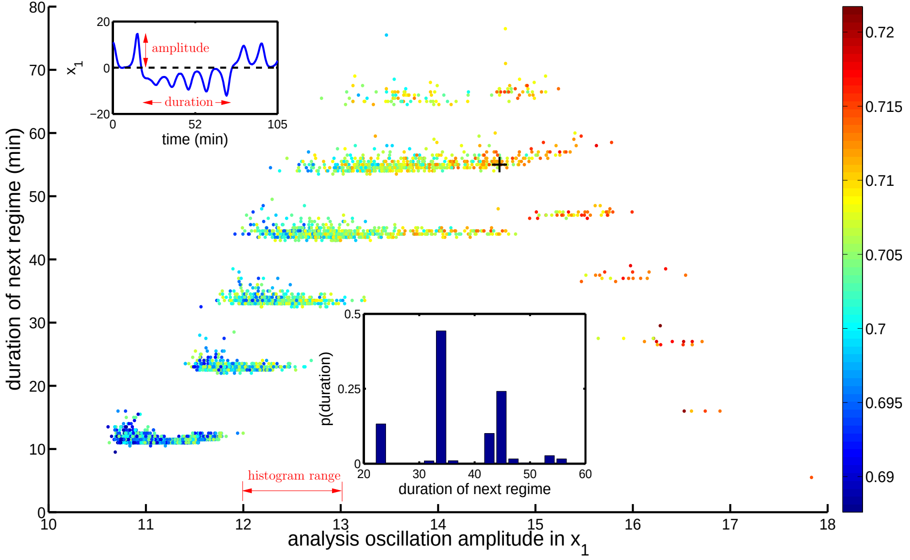
Color indicates bred vector growth rate, 30 s window

Forecast error during flow reversals



Flow reversal occurance and regime duration hard to predict

Thermosyphon "weathermap" – regime duration



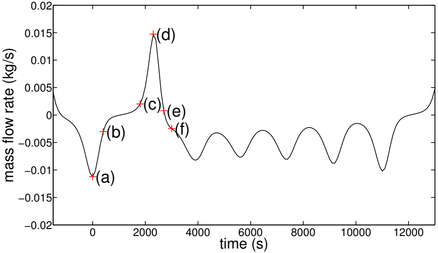
Key result

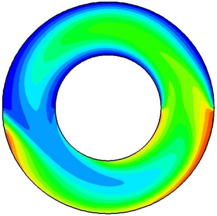
There is a trend:

large x_1-amplitudes lead to longer regimes

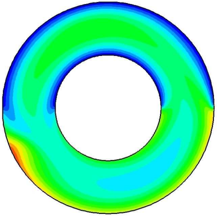
(immediately preceding new flow regime) (up to a point)

Understanding the physical mechanism

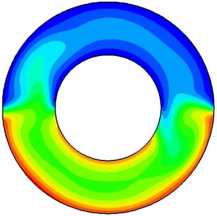




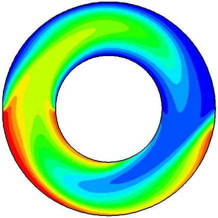
(a) t=0 s



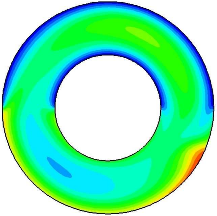
(b) 400 s



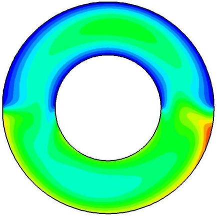
(c) 1800 s



(d) 2300 s

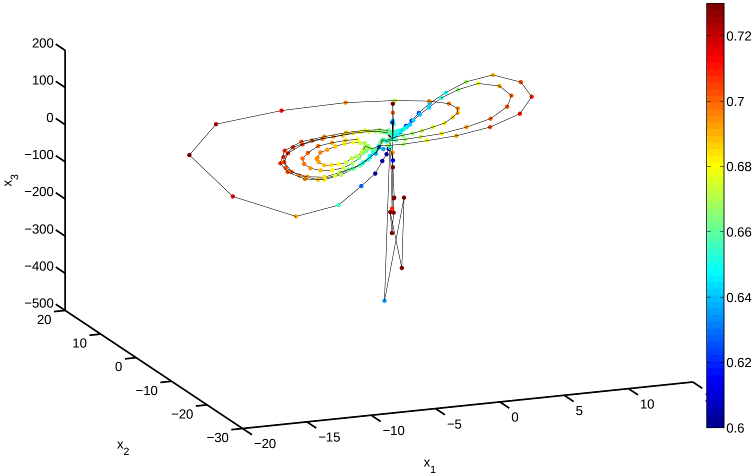


(e) 2700 s



(f) 3000 s

EKF assimilated perfect “storm”



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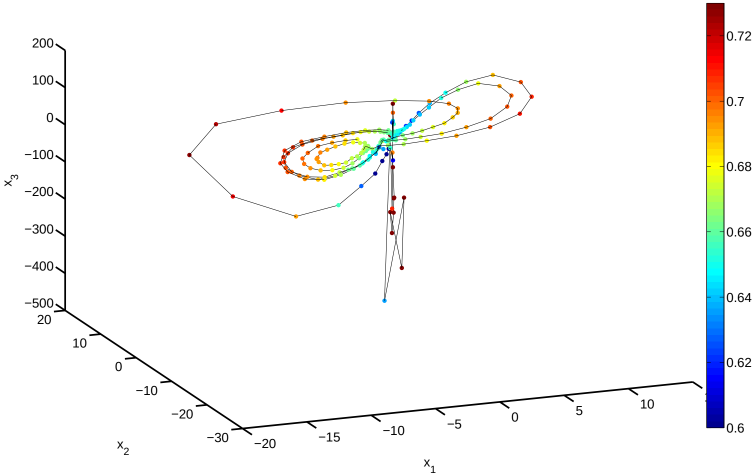

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Flow reversal early warning

3 different tests:

1. Lead: lead forecast state moves into other regime
2. Bred vector: growth rate threshold
3. Slope:
   - slope of linear fit of x_2 vs. x_1, from analysis
   - inspired by hypothesis of viscous vs. thermal feedback, dates to Welander (1967)

Skill scores (in %):

	lead	BV	slope
TS	84	63	73
HR	97	97	77
FAR	13	36	7

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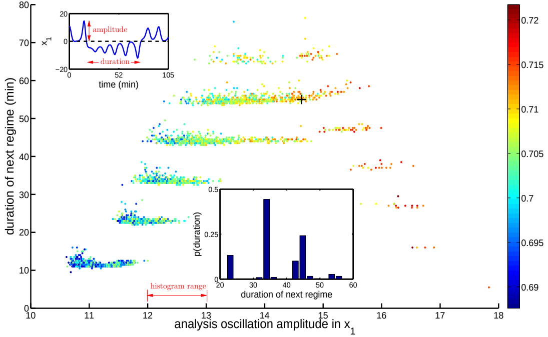
Window of stability: predicting regime duration



1. measure maximum x_1 amplitude of the analysis/forecast state at the time a flow reversal is (correctly) forecast
2. calculate likelihood of durations (discrete) using weathermap
3. probabilistic forecast of regime duration $\Longrightarrow$

Duration forecast skill

Test	RPS
lead	51%
BV	63%
slope	48%

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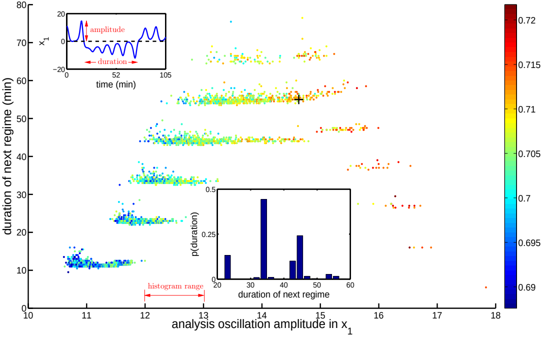

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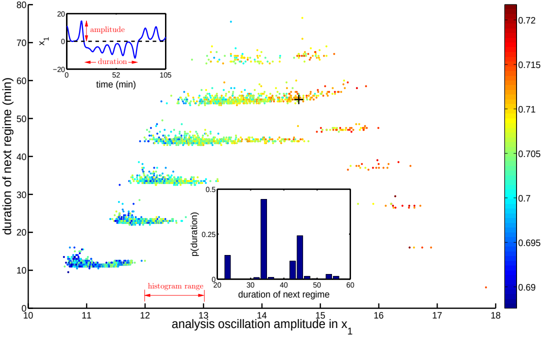

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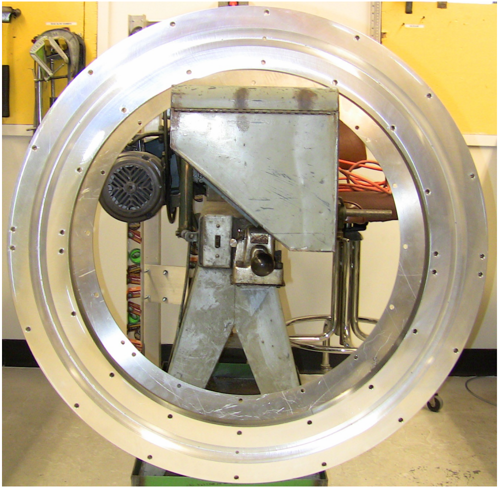
Wrapping up

- DA effectively couples a low-dimensional, approximate model to complex direct numerical simulations of the thermosyphon
- Empirical techniques based on physics best predict flow reversals and subsequent duration
- Preprint available at my personal website http://uvm.edu/∼kharris/papers/thermosyphon-da.pdf

Laboratory thermosyphon



Our techniques should be applicable to thermosyphon experiments

Acknowledgments

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Thanks to El Hassan Ridouane, Floyd Vilmont, Darren Hitt, Ashley McKhann, Nick Allgaier, and Ross Lieb-Lappen.

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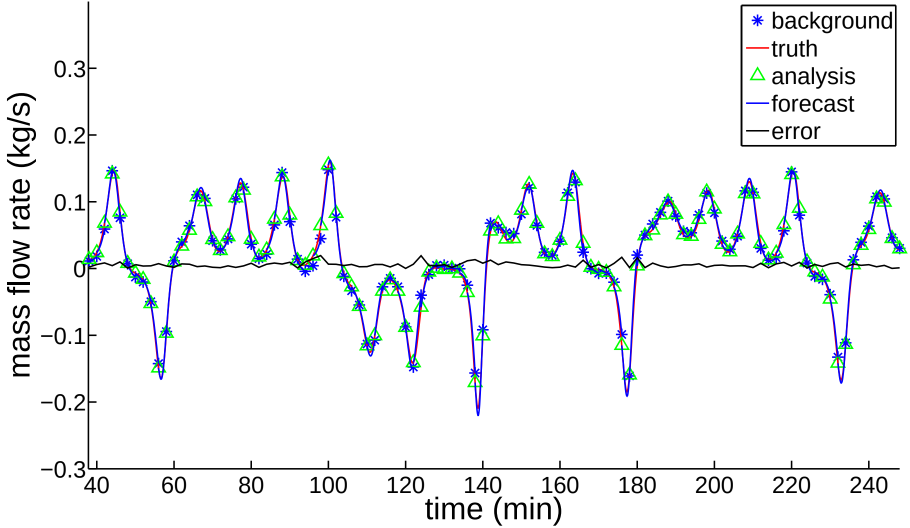
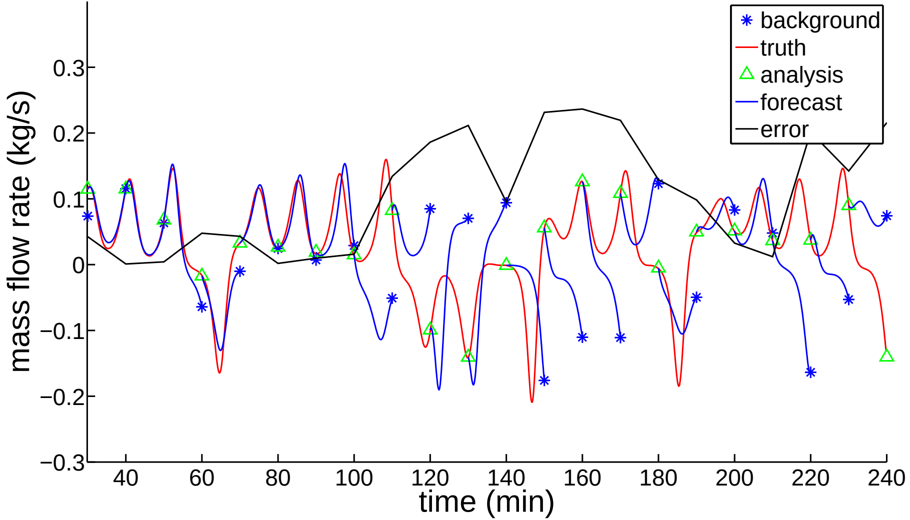
NSF

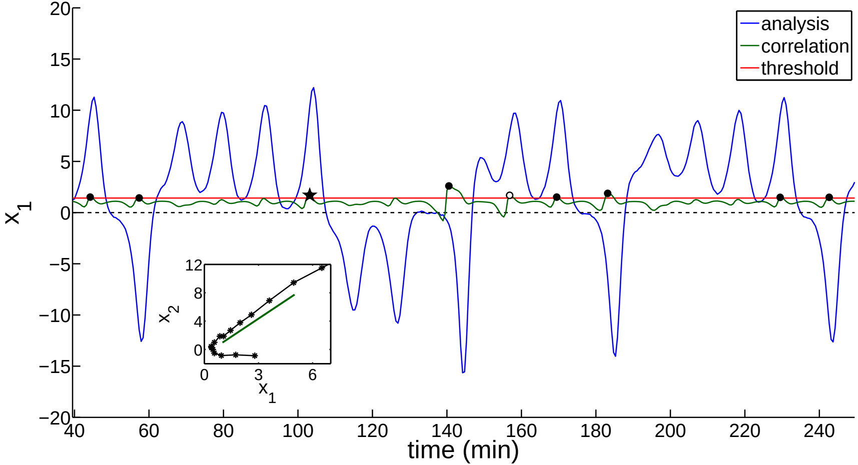
3D-Var results for 120 s assimilation window



3D-Var results for 600 s assimilation window



Early warning: more on the slope test



More flow reversal occurance stats

1. Lead:
   TS= 84%, FAR=13%,
   HR=97%, n=160542

		Observed	
		Yes	No
Fcast	Yes	4115	639
	No	135	155653

2. BV:
   TS= 63%, FAR=36%,
   HR=97%, n=124118

		Observed	
		Yes	No
Fcast	Yes	4131	2323
	No	119	122522

3. Slope:
   TS= 77%, FAR=7.1%,
   HR=82%, n=157978

		Observed	
		Yes	No
Fcast	Yes	3473	266
	No	777	153426