The Modeler’s Mantra

This is the best available information, so it must be of value.
Everyone knows the limitations. Everyone understands the implications of these assumptions.
This is better than nothing.
No one has proven this is wrong.
There is no systematic error, on average. The systematic errors don't matter.
The systematic errors are accounted for in the post processing.
Normality is always a good first approximation. In the limit, it has to be normally distributed, at least approximately.
Everyone assumes it is normally distributed to start with.
Everyone makes approximations like that.
Everyone makes this approximation.
We have more advanced techniques to account for that.
The users demand this. The users will not listen to us unless we give them the level of detail they ask for.
We must keep the users on-board.
If we do not do this, the user will try and do it themselves.
There is a commercial need for this information, and it is better supplied by us than some cowboy.
Refusing to answer a question is answering the question.
Refusing to use a model is still using a model.
Even if you deny you have a subjective probability, you still have one. All probabilities are subjective.
The model just translates your uncertainty in the inputs to your rational uncertainty in the future.
Sure this model is not perfect, but it is not useless.
No model is perfect.
No model is useless if interpreted correctly. It is easy to criticise.
This model is based on fundamental physics.
The probabilities follow from the latest developments in Bayesian statistics.
Think of the damage a decision maker might do without these numbers.
Any rational user will agree.
Things will get better with time, we are making real progress.
You have to start somewhere. What else can we do? It might work, can you deny that?
What damage will it do?

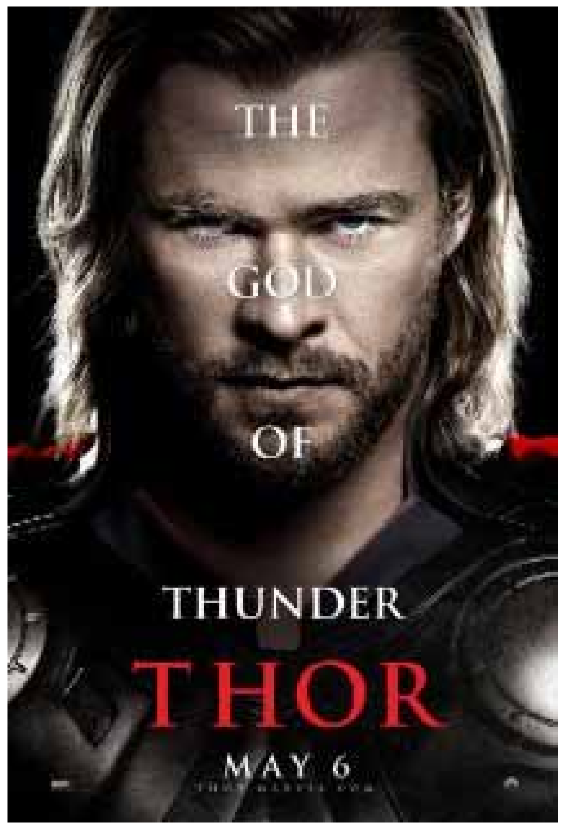
Predictability + School on Data Assimilation

from 26 April 2011 to 27 May 2011 Nordita

Predicting the unpredictable is a challenge that is common to various physical systems whose dynamics is governed by the equations of fluid dynamics. The oldest example is weather prediction and was developed since the 1950s by various people including the Norwegian meteorologist Ragnar Fjörtoft. Other examples include climate prediction, space weather forecast, and solar cycle forecast. The mathematics developed for these applications is extremely interesting and deserves more detailed understanding, so that these techniques can be used also in other areas where the application of this technique is less well developed.

A major difference between weather forecasting and climate or solar cycle forecasting is the long time scale and an additional shortage of diagnostic data. Climate models are also more complex and involve coupling between atmosphere and oceans. Solar cycle modeling, on the other hand, is still only at a rather exploratory level. It was only recently that a proper data assimilation method using the so-called Ensemble Kalman Filter to take into account uncertainties of dynamo model and measurements has been used for solar cycle prediction However, significant progress is expected within the next few years.


Mind the gap between
the training and reality.


THE
GOD
OF
THUNDER
THOR
MAY 6

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Internal (in)consistency… Model Inadequacy

www.lsecats.ac.uk

http://www2.lse.ac.uk/CATS/publications/Publications_Smith.aspx

Internally Coherent Data Assimilation (UQ/ME) in Maths, Physics, Forecasting and Decision Support

Leonard A Smith

LSE CATS/Grantham

Pembroke College, Oxford

Not possible without:

H Du, A. Jarman, K Judd, A Lopez,

D. Stainforth, N. Stern & E Suckling

Grantham Research Institute on Climate Change and the Environment

Which problem do you want to attack?

Maths **Physics (Science)** **Forecasting** **Decision Support**

Linearity
Perfect Model Class
Stochastic/Deterministic
Probability Theory
Epistemology
(Ethics)

Things that interest me include:

Model Improvement (Imperfection errors, Pseudo orbits)

Model Evaluation (Shadowing)

Forecast Evaluation (Scores and Communication)

Forecast Improvement (Model, Ensemble, Interpretation, Obs)

Nonlinear Data Assimilation (imperfect model, incomplete obs)

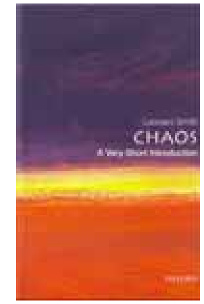
Relevance of Linear Assumption (Ensemble Formation and Adaptive Obs)

Decision Support (Value vs Skill, "Best available" vs "Decision Relevant")

**Relevance of Bayesian Way/
Probability Theory in Nonlinear Systems**

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Things that interest me:



Model Improvement (Imperfection errors, Pseudo orbits,Parameters)

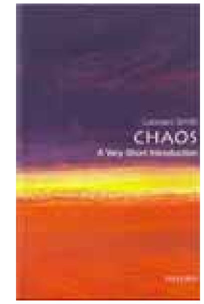
K Judd, CA Reynolds, LAS & TE Rosmond (2008) The Geometry of Model Error. Journal of Atmospheric Sciences 65 (6), 1749-1772.

LAS, M.C. Cuéllar, H. Du, K. Judd (2010) Exploiting dynamical coherence: A geometric approach to parameter estimation in nonlinear models, Physics Letters A, 374, 2618-2623

K Judd & LA Smith (2004) Indistinguishable States II: The Imperfect Model Scenario. Physica D 196: 224-242.

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Things that interest me:



Model Evaluation (Shadowing)

L.A. Smith, M.C. Cuéllar, H. Du, K. Judd (2010) Exploiting dynamical coherence: A geometric approach to parameter estimation in nonlinear models, Physics Letters A, 374, 2618-2623

LA Smith (2000) 'Disentangling Uncertainty and Error: On the Predictability of Nonlinear Systems' in Nonlinear Dynamics and Statistics, ed. Alistair I Mees, Boston: Birkhauser, 31-64.

Things that interest me:

Forecast Evaluation (Scores)

J Bröcker, LA Smith (2007) Scoring Probabilistic Forecasts: The Importance of Being Proper Weather and Forecasting, 22 (2), 382-388.

J Bröcker & LA Smith (2007) Increasing the Reliability of Reliability Diagrams. Weather and Forecasting, 22(3), 651-661.

A Weisheimer, LA Smith & K Judd (2005) A New View of Forecast Skill: Bounding Boxes from the DEMETER Ensemble Seasonal Forecasts, Tellus 57 (3) 265-279.

LA Smith & JA Hansen (2004) Extending the Limits of Forecast Verification with the Minimum Spanning Tree, Mon. Weather Rev. 132 (6): 1522-1528.

MS Roulston & LA Smith (2002) Evaluating probabilistic forecasts using information theory, Monthly Weather Review 130 6: 1653-1660.

D Orrell, LA Smith, T Palmer & J Barkmeijer (2001) Model Error in Weather Forecasting, Nonlinear Processes in Geophysics 8: 357-371.

Things that interest me:

Forecast Evaluation (Communication)

R Hagedorn and LA Smith (2009) Communicating the value of probabilistic forecasts with weather roulette. *Meteorological Applications* 16 (2): 143-155.

MS Roulston & LA Smith (2004) The Boy Who Cried Wolf Revisited: The Impact of False Alarm Intolerance on Cost-Loss Scenarios, *Weather and Forecasting* 19 (2): 391-397.

N Oreskes, DA Stainforth, LA Smith (2010) Adaptation to Global Warming: Do Climate Models Tell Us What We Need to Know? *Philosophy of Science*, 77 (5) 1012-1028

Things that interest me:

Forecast Improvement

J Bröcker & LA Smith (2008) From Ensemble Forecasts to Predictive Distribution Functions Tellus A 60(4): 663.

M S Roulston & LA Smith (2003) Combining Dynamical and Statistical Ensembles, Tellus 55 A, 16-30.

K Judd & LA Smith (2004) Indistinguishable States II: The Imperfect Model Scenario. Physica D 196: 224-242.

Things that interest me:

Nonlinear Data Assimilation (im/perfect model, incomplete obs)

H. Du (2009) PhD Thesis, LSE (online, papers in review)

Khare & Smith (2010) Monthly Weather Review in press

K Judd, CA Reynolds, LA Smith & TE Rosmond (2008) The Geometry of Model Error . Journal of Atmospheric Sciences 65 (6), 1749-1772.

K Judd, LA Smith & A Weisheimer (2004) Gradient Free Descent: shadowing and state estimation using limited derivative information, Physica D 190 (3-4): 153-166.

K Judd & LA Smith (2001) Indistinguishable States I: The Perfect Model Scenario, Physica D 151: 125-141.

Things that interest me:

Relevance of Linear Assumption **(Adaptive Obs)**

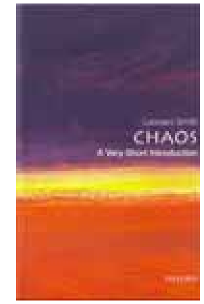
I Gilmour, LA Smith & R Buizza (2001) Linear Regime Duration: Is 24 Hours a Long Time in Synoptic Weather Forecasting? *J. Atmos. Sci.* 58 (22): 3525-3539.

JA Hansen & LA Smith (2000) The role of Operational Constraints in Selecting Supplementary Observations, *J. Atmos. Sci.*, 57 (17): 2859-2871.

PE McSharry and LA Smith (2004) Consistent Nonlinear Dynamics: identifying model inadequacy, *Physica D* 192: 1-22.

CENTRE FOR THE ANALYSIS OF TIME SERIES

Things that interest me:



Decision Support

Probabilities vs Odds (with Roman Frigg, in preparation)

Science for Decision Support (with Nick Stern, in preparation)

MS Roulston, DT Kaplan, J Hardenberg & LA Smith (2003) Using Medium Range Weather Forecasts to Improve the Value of Wind Energy Production, Renewable Energy 29 (4)

MS Roulston, J Ellepola & LA Smith (2005) Forecasting Wave Height Probabilities with Numerical Weather Prediction Models, Ocean Engineering 32 (14-15), 1841-1863.

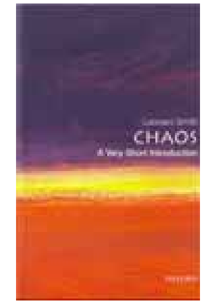
MG Altalo & LA Smith (2004) Using ensemble weather forecasts to manage utilities risk, Environmental Finance October 2004, 20: 8-9.

MS Roulston & LA Smith (2004) The Boy Who Cried Wolf Revisited: The Impact of False Alarm Intolerance on Cost-Loss Scenarios, Weather and Forecasting 19 (2): 391-397.

R Hagedorn and LA Smith (2009) Communicating the value of probabilistic forecasts with weather roulette. *Meteorological Applications 16 (2): 143-155.*

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Things that interest me:



Relevance of Bayesian Way/ Probability Theory to Real Nonlinear Systems

LA Smith, (2002) What Might We Learn from Climate Forecasts? *Proc. National Acad. Sci.* USA 4 (99): 2487-2492.

LA Smith (2000) 'Disentangling Uncertainty and Error: On the Predictability of Nonlinear Systems' (PDF) in Nonlinear Dynamics and Statistics, ed. Alistair I Mees, Boston: Birkhauser, 31-64.

DA Stainforth, MR Allen, ER Tredger & LA Smith (2007) Confidence, uncertainty and decision-support relevance in climate predictions, *Phil. Trans. R. Soc. A*, 365, 2145-2161.

DA Stainforth, T Aina, C Christensen, M Collins, DJ Frame, JA Kettleborough, S Knight, A Martin, J Murphy, C Piani, D Sexton, L Smith, RA Spicer, AJ Thorpe, M.J Webb, MR Allen (2005) Uncertainty in the Predictions of the Climate Response to Rising Levels of Greenhouse Gases *Nature* 433 (7024): 403-406.

PE McSharry and LA Smith (2004) Consistent Nonlinear Dynamics: identifying model inadequacy, *Physica D* 192: 1-22.

Definitions

Weather-like: decisions made very often, we can learn from mistakes.

large forecast-outcome library
“interpolation” in state space
nontrivial out-of-sample library
(some) user memory of pain

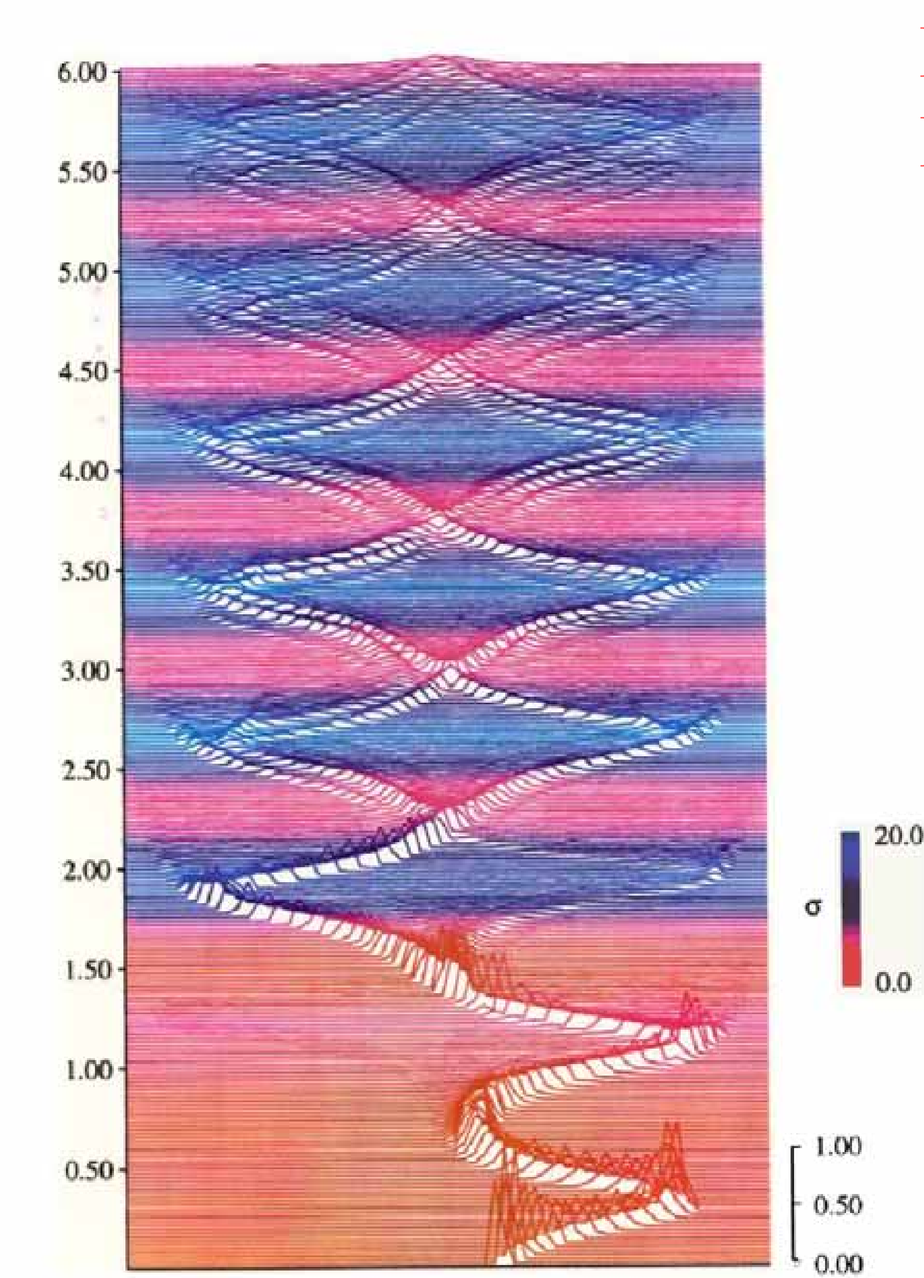
Climate-like: new information arrives very slowly

model lifetime << forecast lead time
extrapolation into the unobserved
strong contrarian pressures (well intended)
(sometimes) anti-science lobby

Ensembles:

Monte Carlo sampling of initial conditions and parameters in R^M

Grand Ensembles: opportunistic constrained weird sampling of deployable model manifold in ???



Smith (2002) Chaos and Predictability in *Encyc Atmos Sci*

Lyapunov Exponents Do Not Indicate Predictability!

Even with a perfect deterministic model, *the future* is, at best, a probability density function.

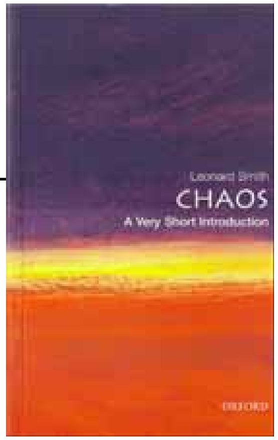
The limit of predictability reflects the leadtime our forecast PDF is "worse" than climatology.

And RMS forecast error is at best irrelevant. McSharry & Smith, PRL, (1999) Better nonlinear models from noisy data: Attractors with maximum likelihood,

What skill scores should we be using?
J Bröcker, LA Smith (2007) Scoring Probabilistic Forecasts: The Importance of Being Proper *Weather & Forecasting*, 22 (2), 382-388.

Ignorance: Good, 1952; MS Roulston & LA Smith (2002) Evaluating probabilistic forecasts using information theory, *Monthly Weather Review* 130 6: 1653-1660.)

Lyapunov Exponents Do **Not** Indicate Predictability!



C Ziehmann, LA Smith & J Kurths (2000), Localized Lyapunov Exponents and the Prediction of Predictability, Phys. Lett. A, 271 (4): 237-251.

LA Smith (2000) 'Disentangling Uncertainty and Error: On the Predictability of Nonlinear Systems' in Nonlinear Dynamics and Statistics, ed. Alistair I Mees, Boston: Birkhauser, 31-64.

LA Smith, C Ziehmann & K Fraedrich (1999) Uncertainty Dynamics and Predictability in Chaotic Systems, Quart. J. Royal Meteorol. Soc. 125: 2855-2886.

LA Smith (1997) The Maintenance of Uncertainty. Proc International School of Physics "Enrico Fermi", Course CXXXIII, 177-246, Societ'a Italiana di Fisica, Bologna, Italy.

LA Smith (1994) Local Optimal Prediction. Phil. Trans. Royal Soc. Lond. A, 348 (1688): 371-381.

Fallacy of Misplaced Concreteness

"The advantage of confining attention to a definite group of abstractions, is that you confine your thoughts to clear-cut definite things, with clear-cut definite relations. …

The disadvantage of exclusive attention to a group of abstractions, however well-founded, is that, by the nature of the case, you have abstracted from the remainder of things. ... it is of the utmost importance to be vigilant in critically revising your *modes* of abstraction.

Sometimes it happens that the service rendered by philosophy is entirely obscured by the astonishing success of a scheme of abstractions in expressing the dominant interested of an epoch."

A N Whitehead. Science and the Modern World. Pg 58/9

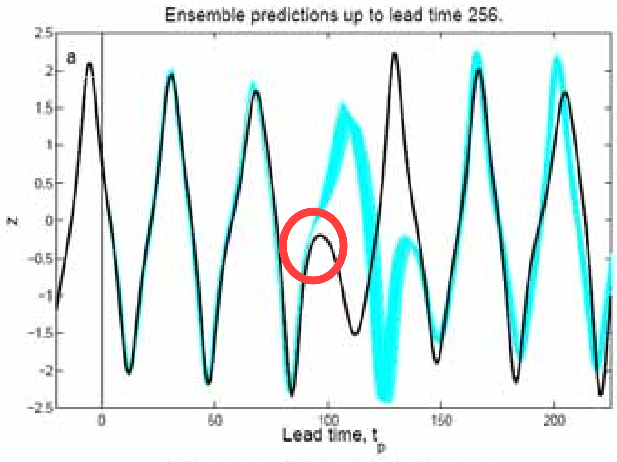
Probability forecasts based on model simulations provide excellent realisations of this fallacy, drawing comfortable pictures in our mind which correspond to nothing at all, and which will mislead us if we carry them into decision theory.

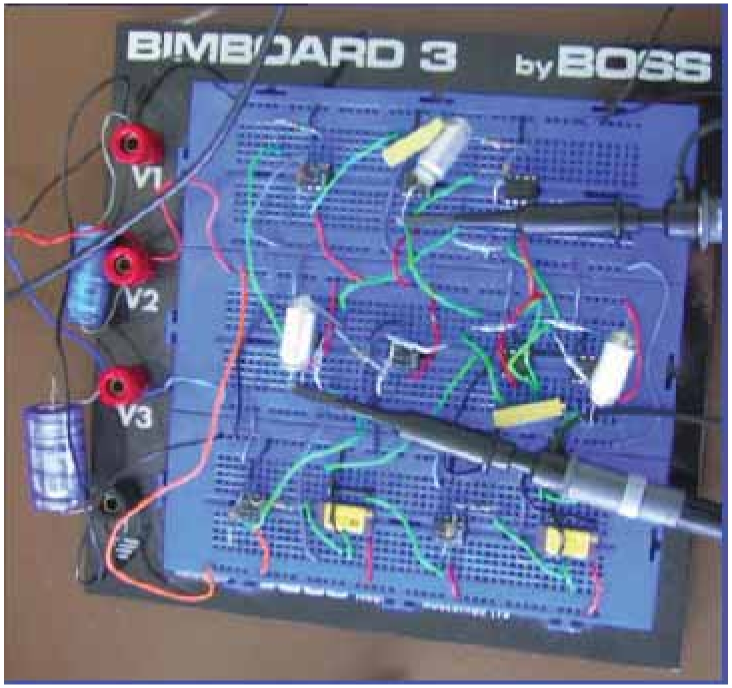
And today that is dangerous!

You don't have to believe everything you compute!

Betting on the future voltage in this circuit.

Model 1





Betting on the future voltage in this circuit.

Model 1

Model 2

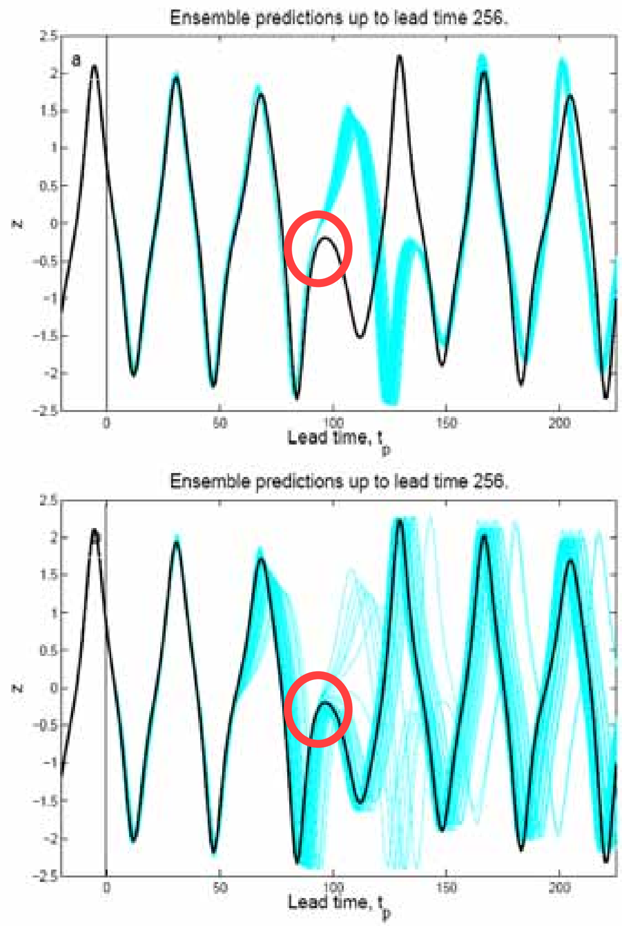
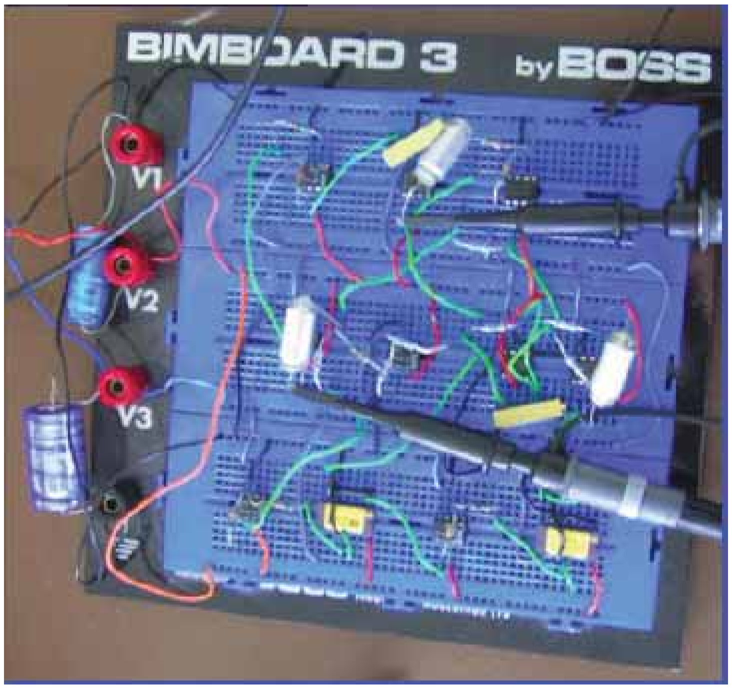
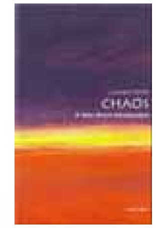


Figure 7: Ensemble predictions using (a) model 1 and (b) model 2. The



Moore-Spiegel Circuit (by Reason Machette)



One Initial State — Another Initial State

Model 1

Model 2

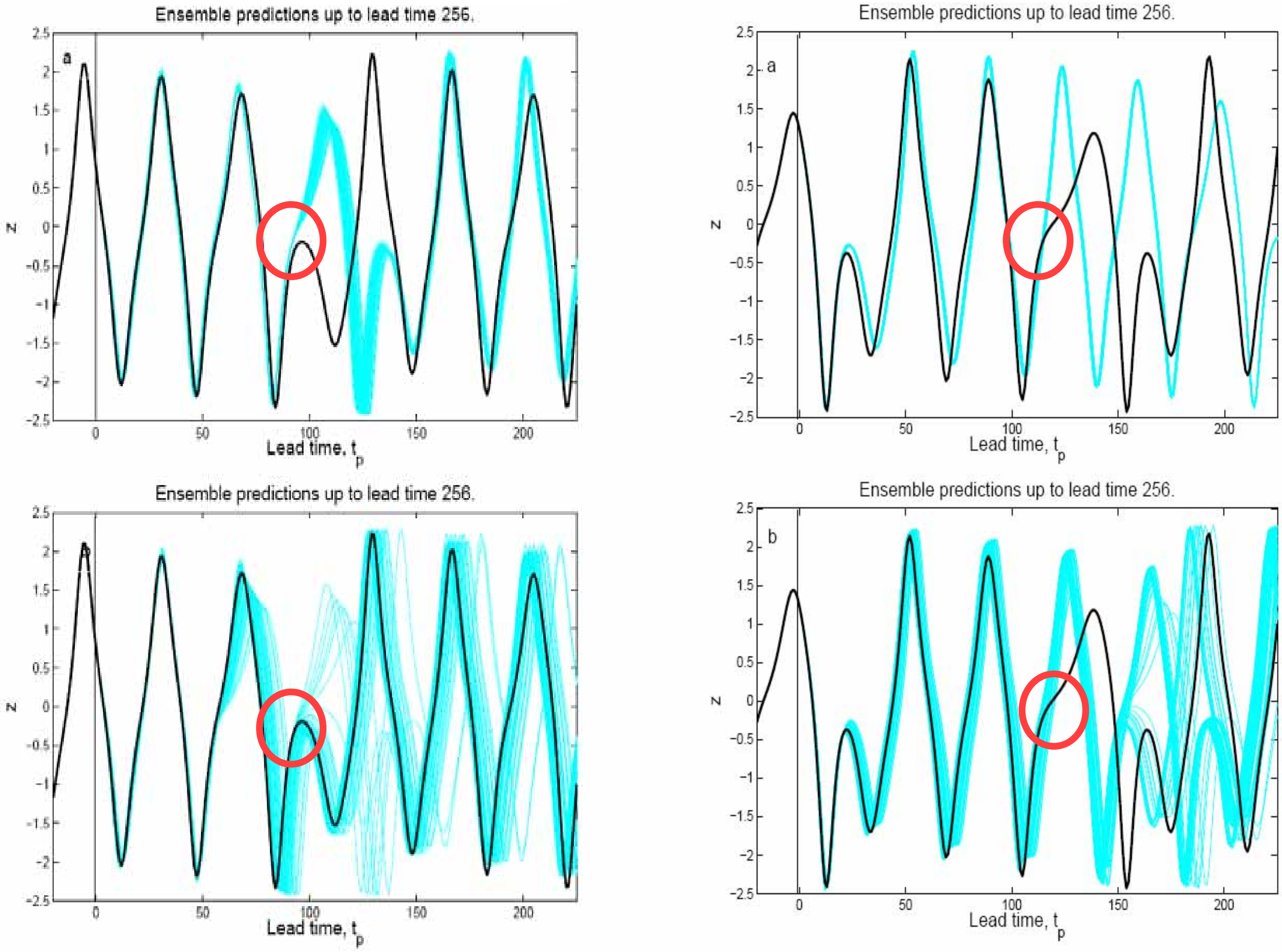
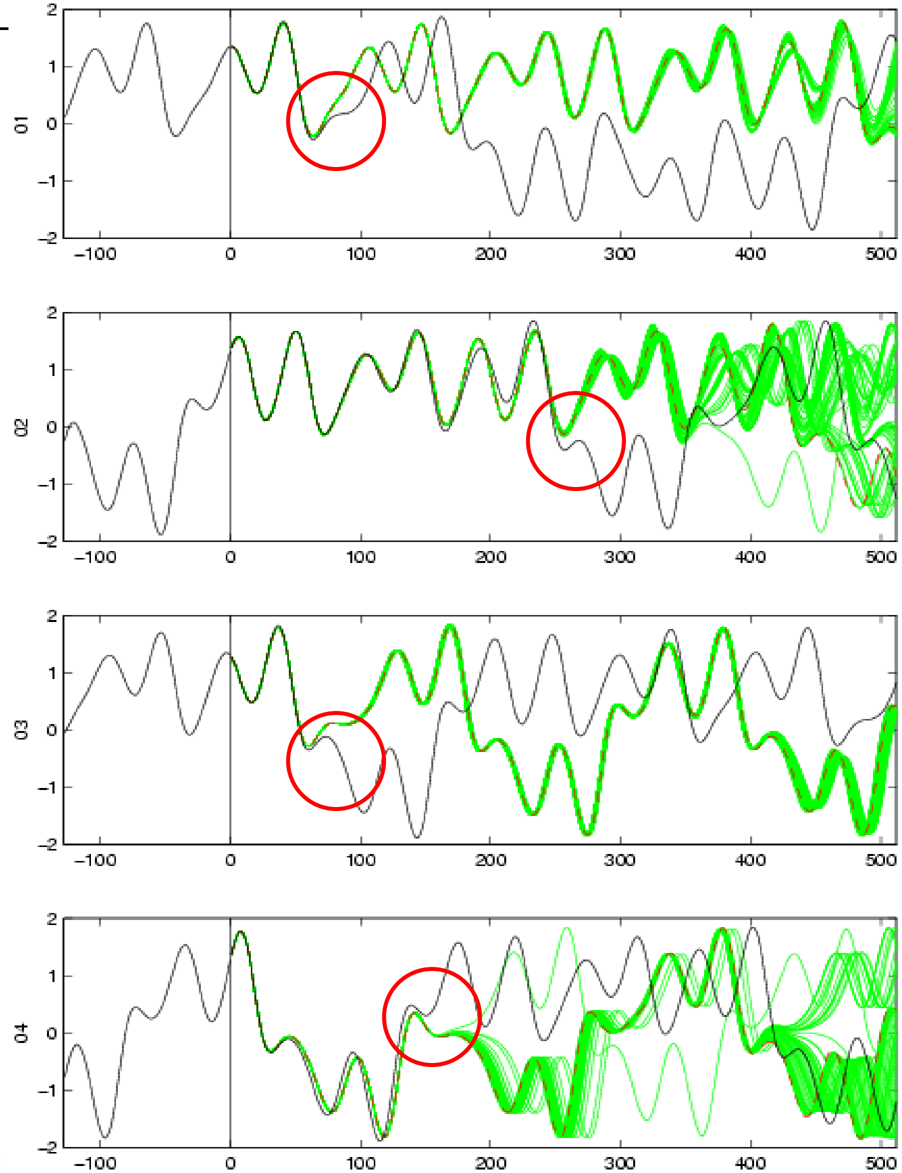


Figure 7: Ensemble predictions using (a) model 1 and (b) model 2. The2: Ensemble predictions using (a) model 1 and (b) model 2. T

Forecasts busts in a Chaotic Circuit



512 member ensembles
Best known 1-step model
512 step free running forecasts

So wait until we know the future, then look for model trajectories that "shadow" the obs to within the noise.

(But what is noise, really?)

There is no stochastic fix:

After a flight, the series of control perturbations required to keep a by-design-unstable aircraft in the air look are a random time series and arguably are Stochastic.

But you cannot fly very far by specifying the perturbations randomly!

Think of WC4dVar/ ISIS/GD perturbations as what is required to keep the model flying near the observations: we can learn from them, but no "stochastic model" could usefully provide them.

With the Eurofighter Typhoon, in subsonic flight the pressure point lies in front of the centre of gravity, therefore making the aircraft aerodynamically unstable, and is why Eurofighter Typhoon has such a complex Flight Control System – computers react quicker than a pilot.

When Eurofighter Typhoon crosses into supersonic flight, the pressure point moves behind the centre of gravity, giving a stable aircraft.

The advantages of an intentionally unstable design over that of a stable arrangement include greater agility – particularly at subsonic speeds - reduced drag, and an overall increase in lift (also enhancing STOL performance).

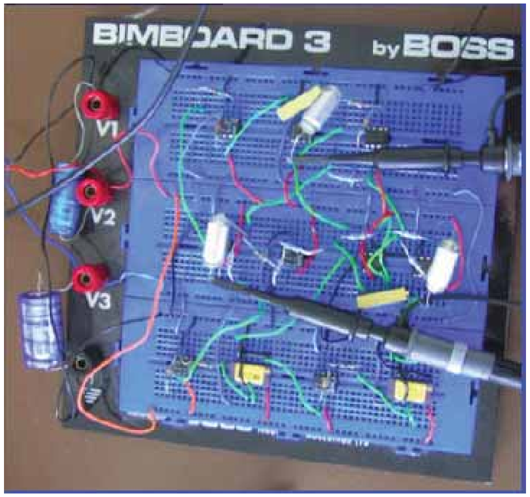
Which is NOT to say stochastic models are not a good idea:
Physically it makes more sense to include a realization of a process rather than it mean!
But a better model class will not resolve the issue of model inadequacy!

It will not yield decision-relevant PDFs!

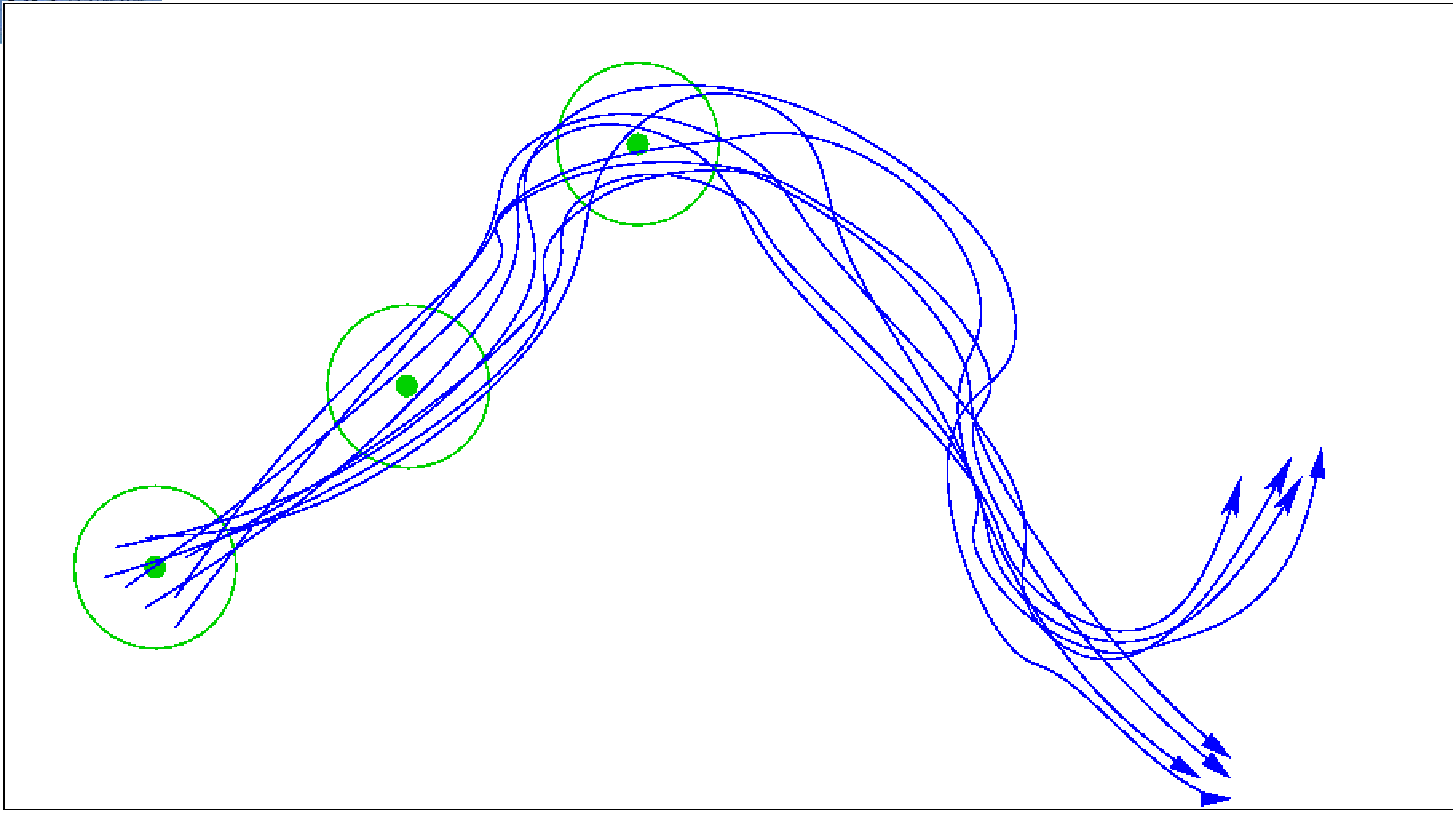
Definitions

Useful(1): log(p) scores much better than unconditioned distribution, μ
Useful(2): yields insight of use in making better policy decisions
Useful(3): enhances scientific understanding of the system

Wrong(1): empirically adequate (effectively perfect, wrong on a technicality)
Wrong(2): shadowing time long (useful forecasts: chaos *per se* not deadly)
Wrong(3): qualitatively dissimilar (useful for scientific understanding)

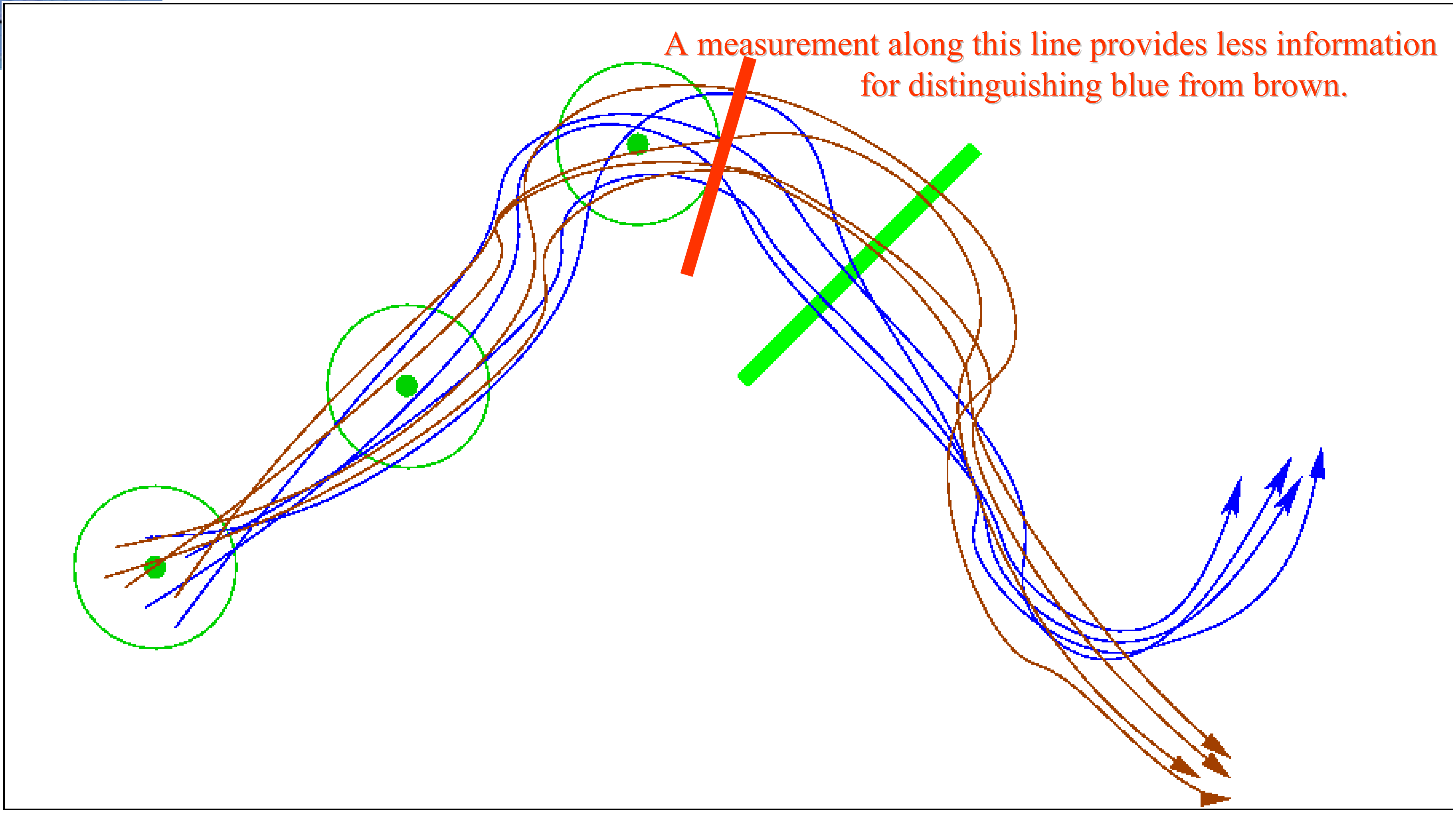


Simple Geometric Approaches…



Suppose we wish to distinguish two sets of simulations (say, storm/no storm); in terms of indistinguishable states, the AO question is simply "Which observations are most likely to separate these sets?"

To do this, merely color the trajectories in each set, and determine the observation in space and time (post ‘now’) that is likely to yield the most relevant information.



No linearization,
No implicit perfect model assumption,
And the ability to update the AO in light of scheduled obs without rerunning the simulations.

Model Inadequacy and Data Assimilation

Inside the perfect model scenario, I know what I am looking for:

The model and the system are effectively identical.
There is a state ("Truth") that is defines the future of the system.

In chaotic systems "Truth" is not identifiable given noisy observations.

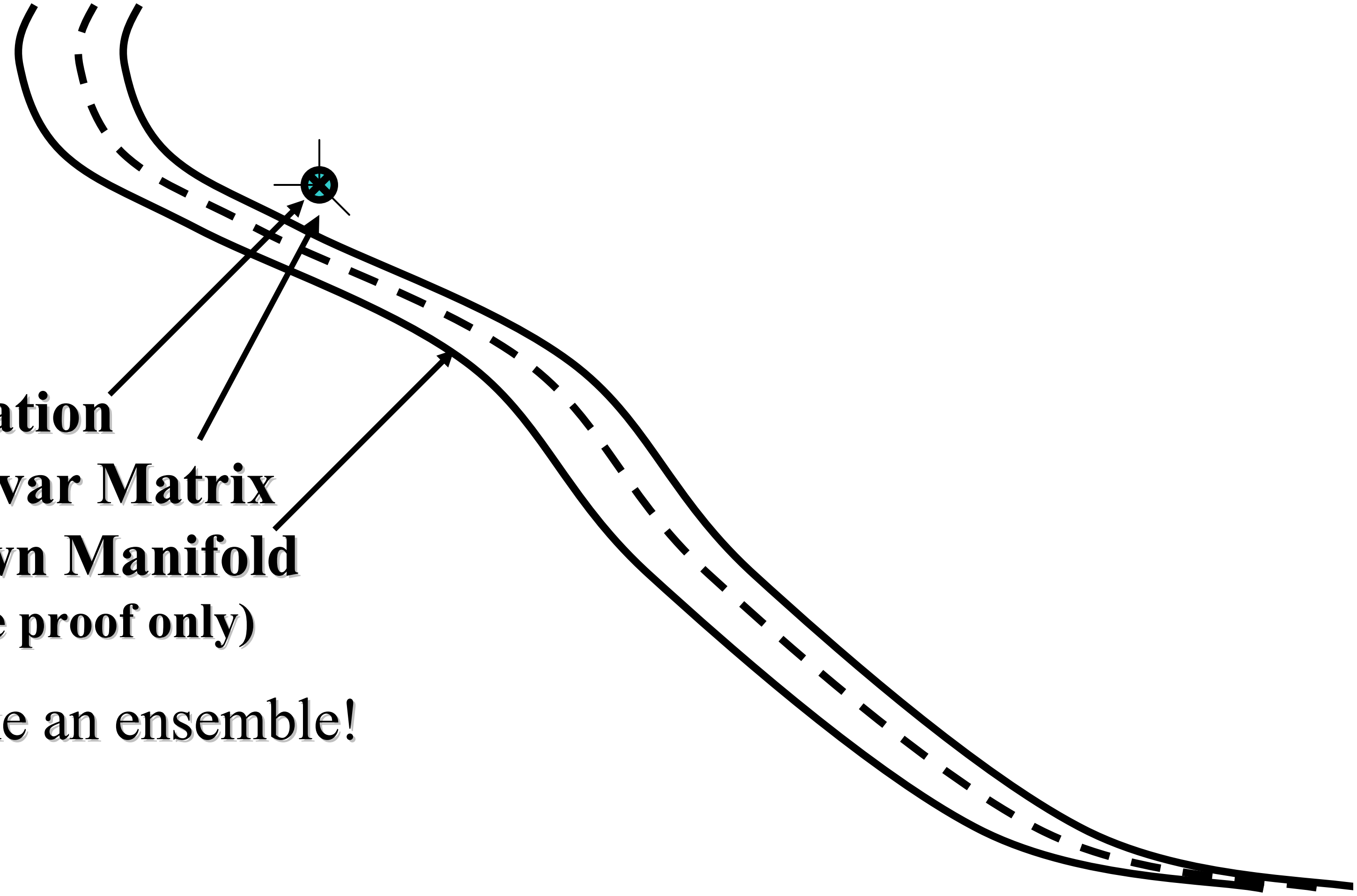
The most likely state, given with observations (and the noise model) will fall in the set H(x), the indistinguishable states of x, which are in turn a subset of the unstable manifold of x.

K Judd & LA Smith (2001) Indistinguishable states I: the perfect model scenario *Physica D* 151: 125-141

Even if you do not believe in the mathematical niceties of Indistinguishable States, if you are aiming to make decisions PDFs from ensembles, you must be targeting something similar! (No?)

What is a manifold?
"Utter and Senseless Destruction of Dynamical Information?"

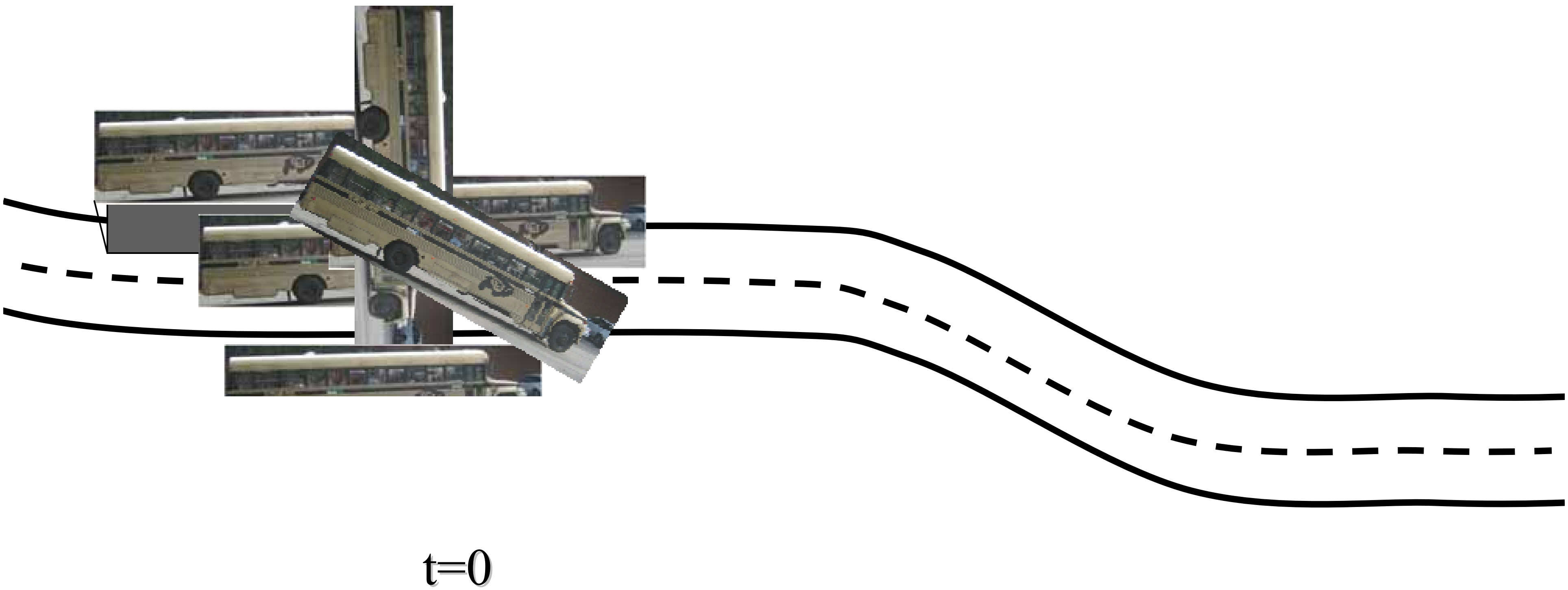
M=11
(x,y,z,u,w,v…)



Observation
Obs-Covar Matrix
Unknown Manifold
(existence proof only)

Lets make an ensemble!

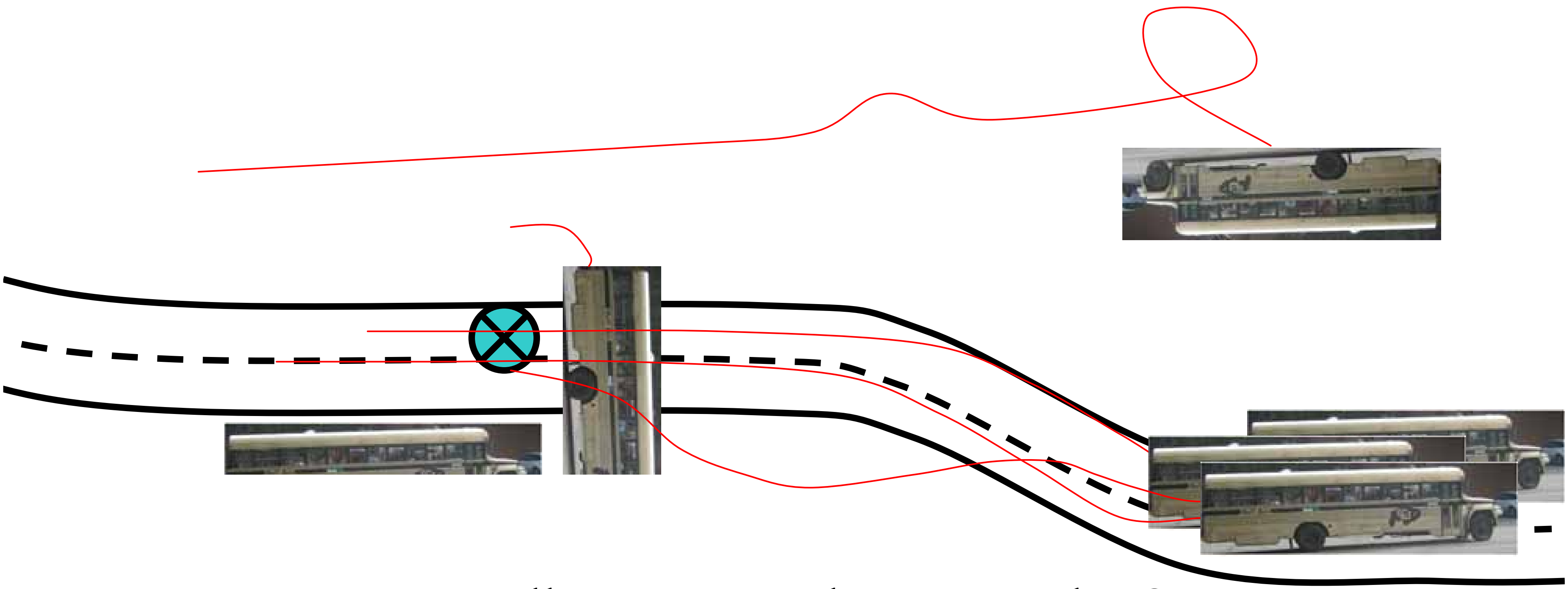
Now evolve the ensemble under the (perfect) model:



Lets make an ensemble!

Now evolve the ensemble under the (perfect) model:

And get a new observation…



Do I really want to make a KF update?

-or-

Can I use the fact that the model dynamics (stochastic or deterministic) trace out the manifold I know exists but cannot sample directly?!?

t=1

How does this compare with En KF :Shree (student of JA))

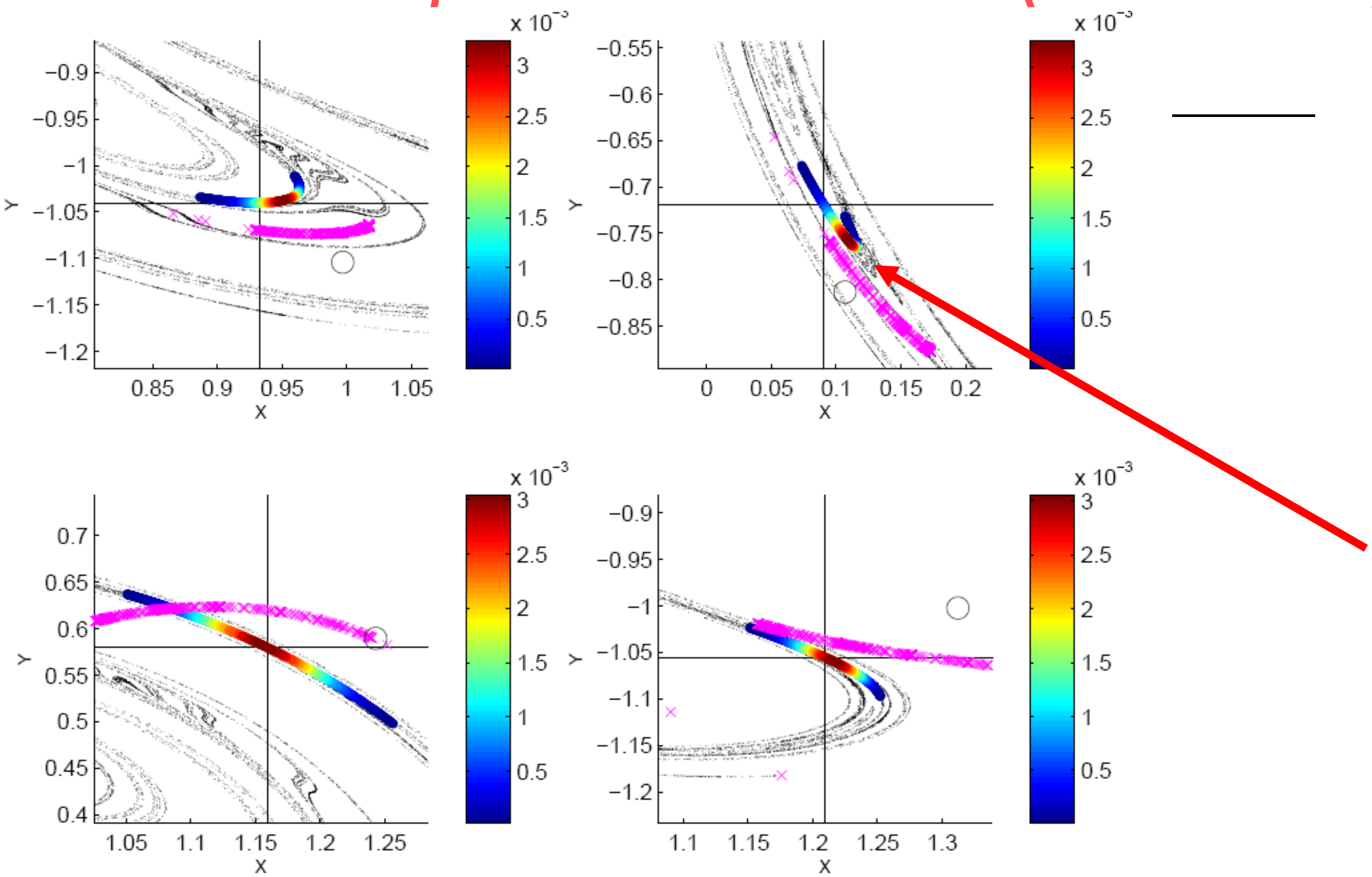


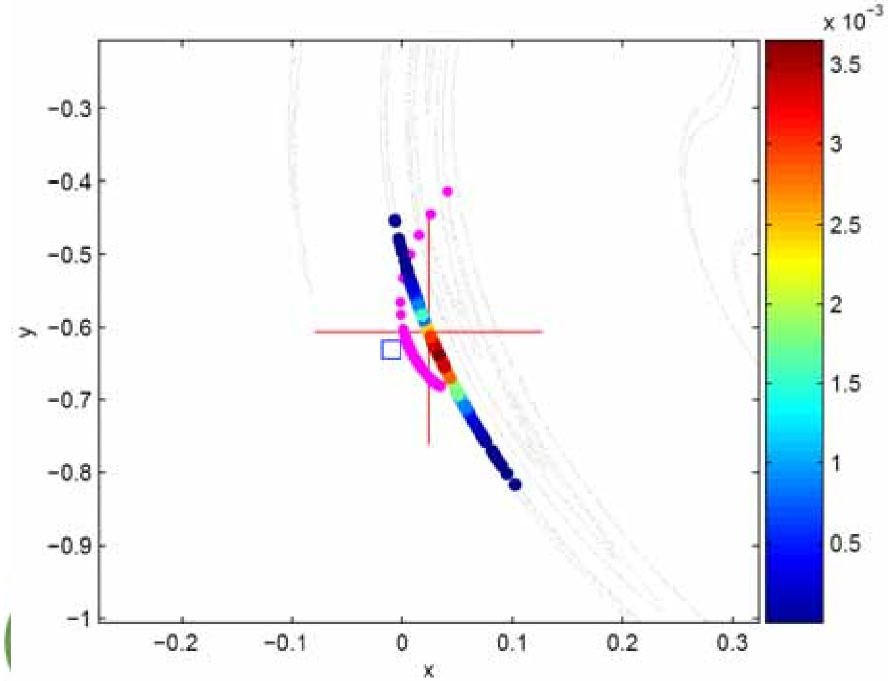
FIG. 7. Results for the Ikeda model. The upper left panel consists of a snapshot of $K = 1000$ member IS and EN ensembles. The target is located at the intersection of the two lines, where as the observation is depicted by the circle. The EN ensemble is depicted by the 1000 magenta crosses. The EN ensemble members are equally likely and are therefore given the same color. The colored dots depict the weighted ensemble obtained via the IS method. The coloring indicates their relative likelihood given observations from t_{992} to t_{1001}. The upper right, lower left and lower right panels depict ensembles for the next 3 observation times.

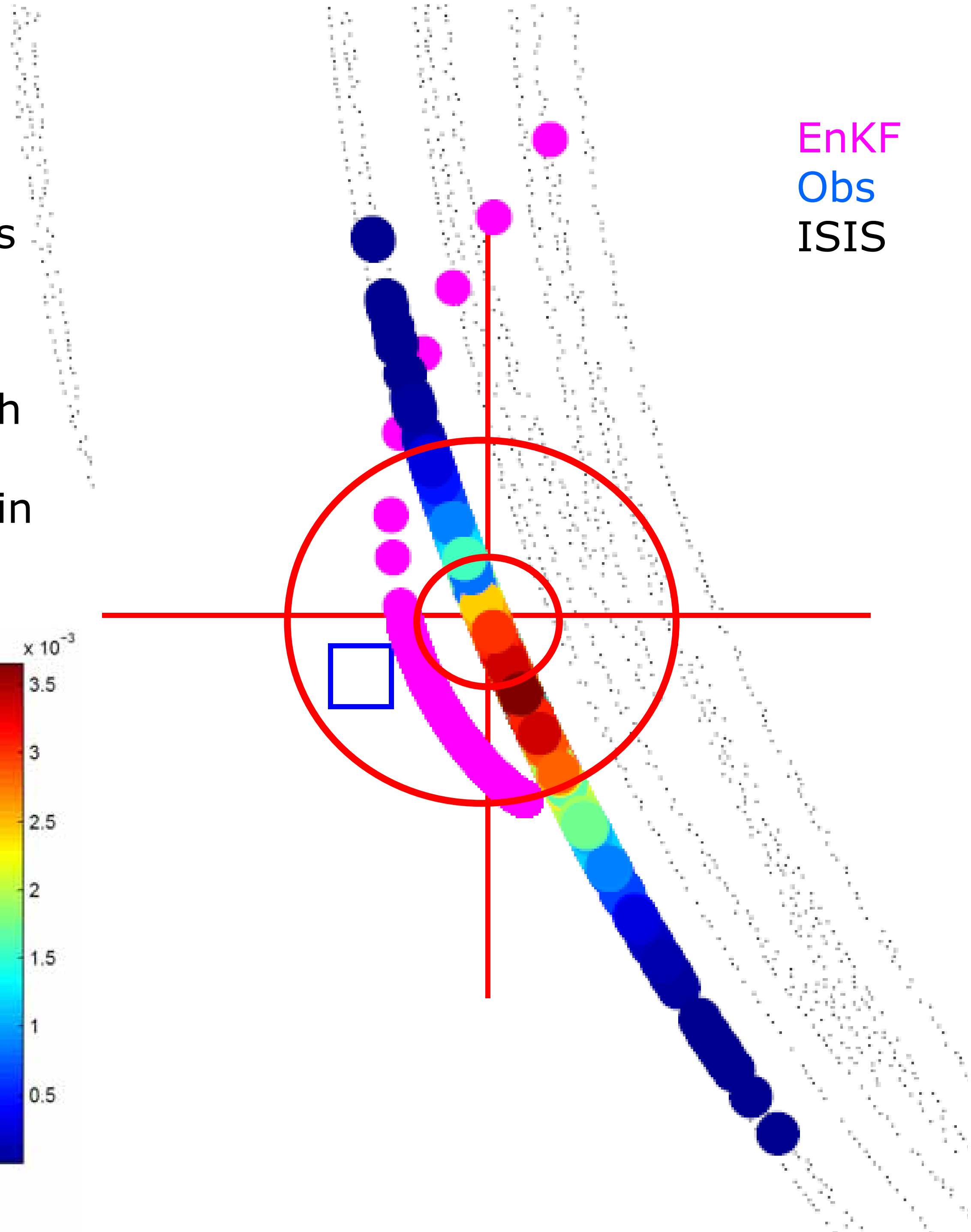
Khare & LAS, in press MWR

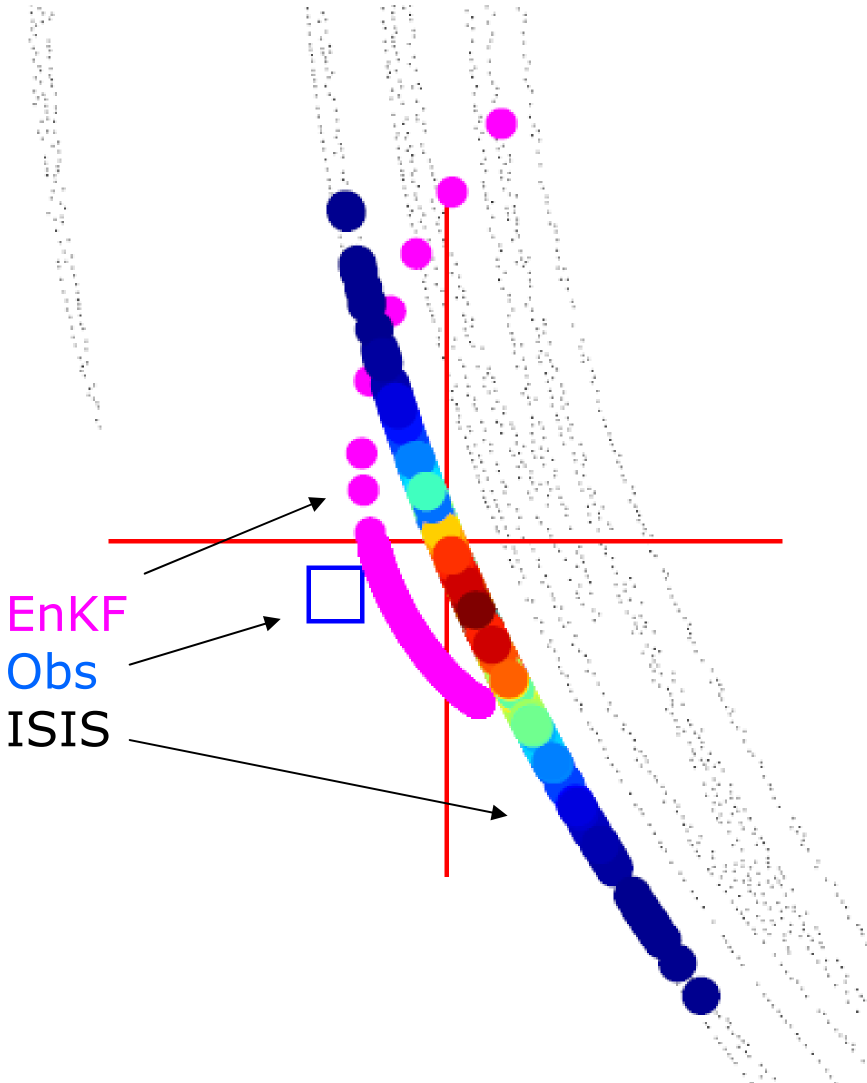
The ε-ball method

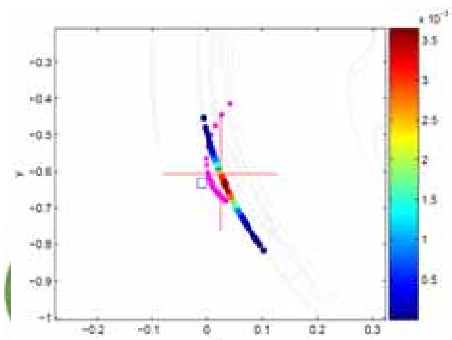
Consider a series of spheres of radius ε ("ε –balls") centred on "Truth."

Count how many times each method "wins" by putting more probability mass within ε of the "Truth" (as a function of ε)









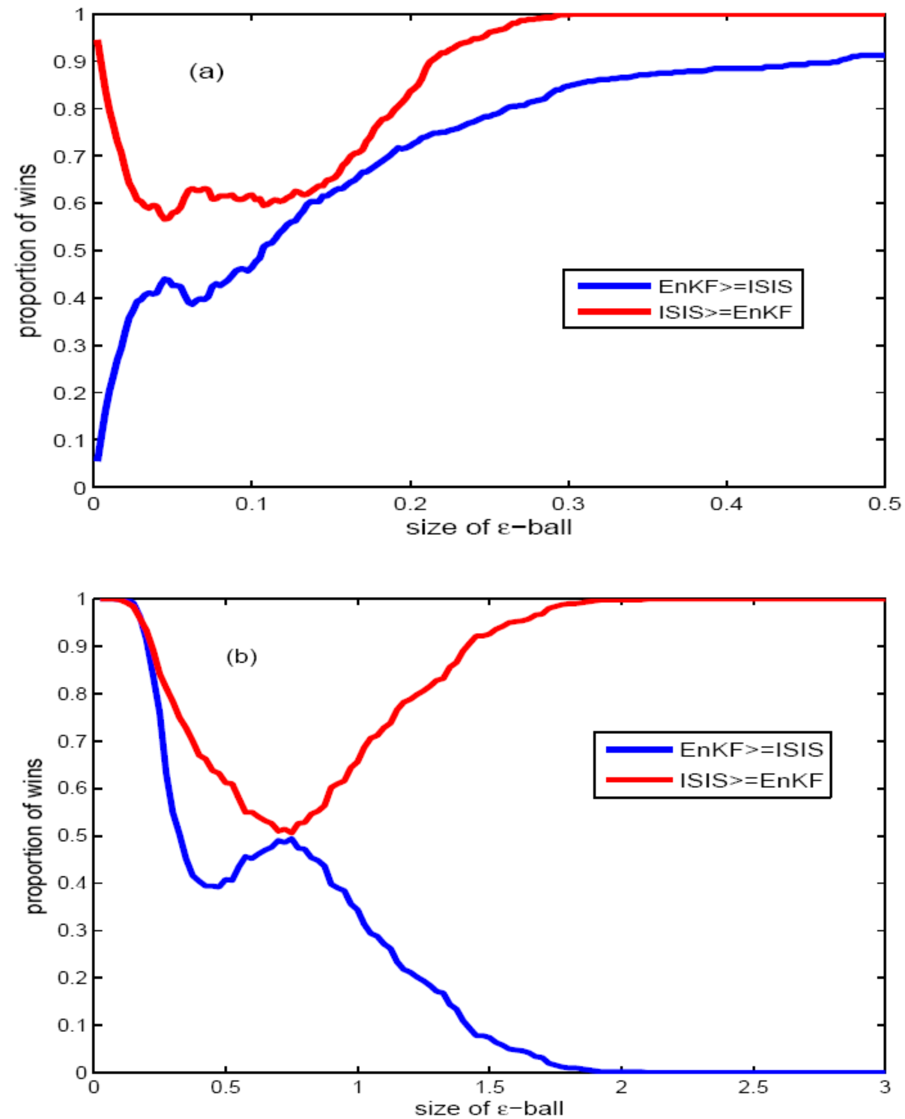
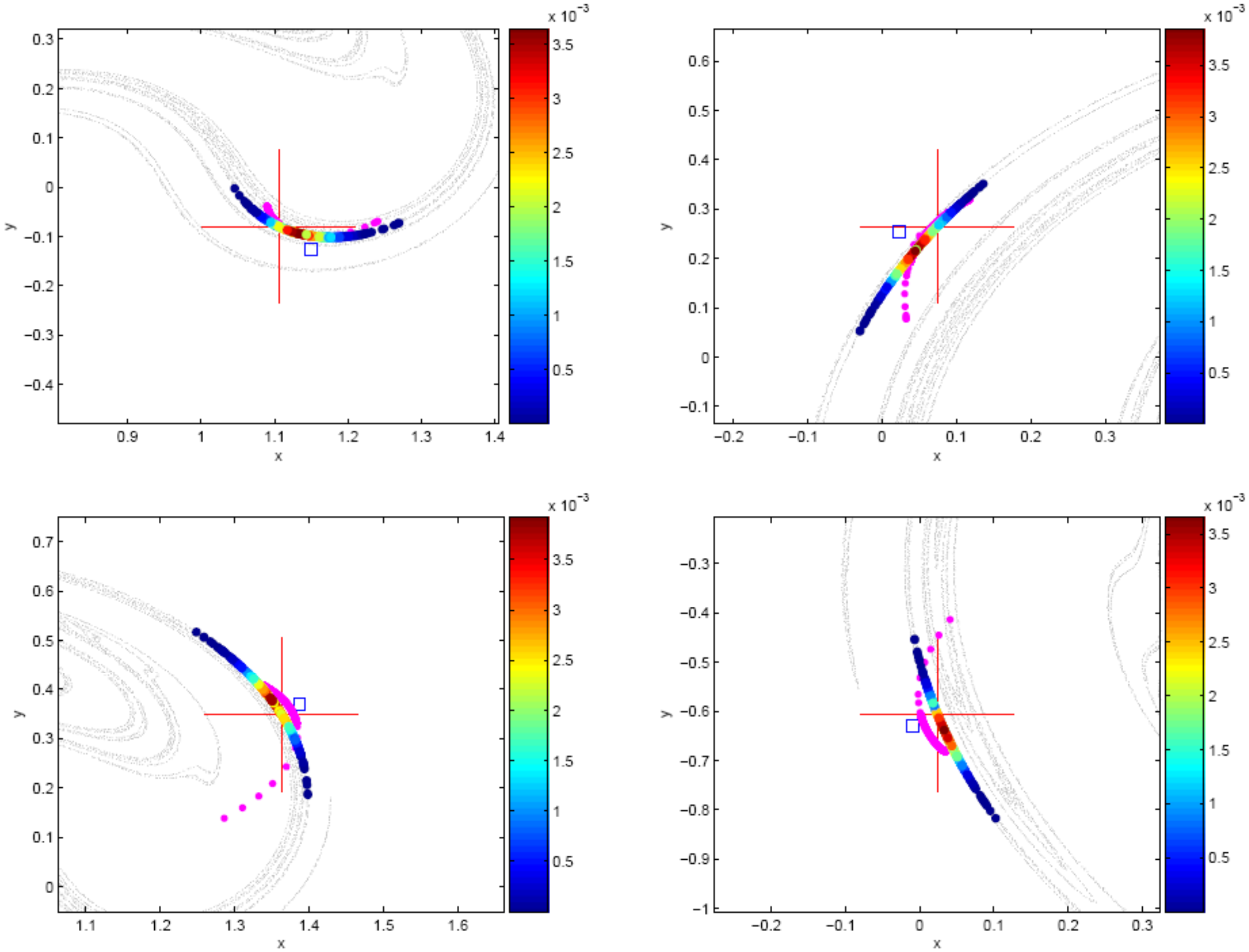


Figure 3.6: Compare the EnKF and ISIS results via ϵ-ball, the blue line denotes the proportion of EnKF method wins and the red line denotes the proportion of ISIS method wins a) Ikeda experiment, Noise level 0.05 (Details of the experiment are listed in Appendix B Table B.3); b) Lorenz96 experiment, Noise level 0.5 (Details of the experiment are listed in Appendix B Table B.4)

How does this compare with En KF (Du after Anderson)



ISIS ensemble from the indistinguishable states of an estimate of x.

Figure 3.5: Ensemble results from both EnKF and ISIS for the Ikeda Map (Experiment C). The true state of the system is centred in the picture located by the cross; the square is the corresponding observation; the background dots indicate samples from the Ikeda Map attractor. The EnKF ensemble is depicted by 512 purple dots. Since the EnKF ensemble members are equally weighted, the same colour is given. The ISIS ensemble is depicted by 512 coloured dots. The colouring indicates their relative likelihood weights. Each panel is an example of one nowcast.

Du (2009)

With En KF in an M=12 Lorenz 96 system (Shree)

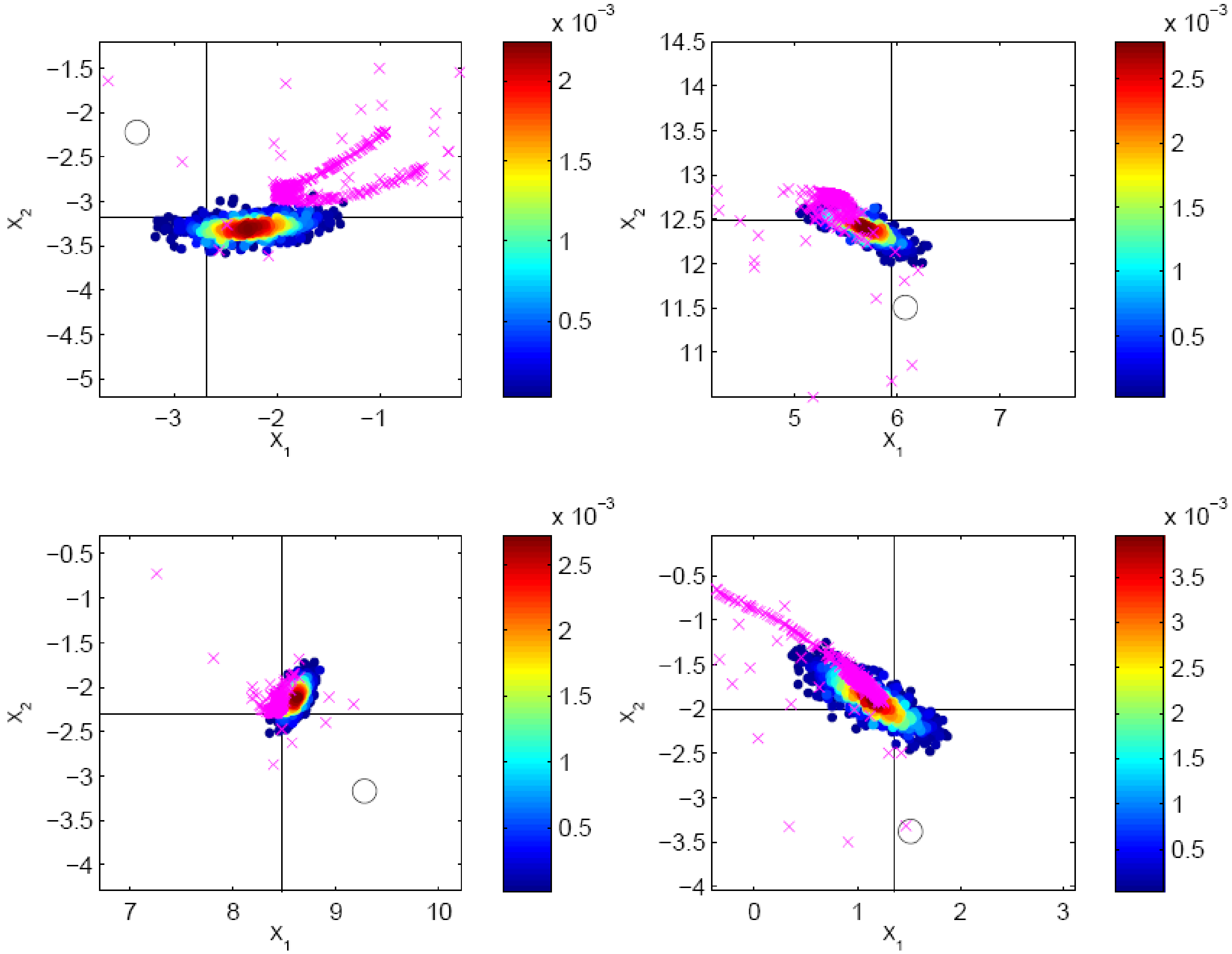
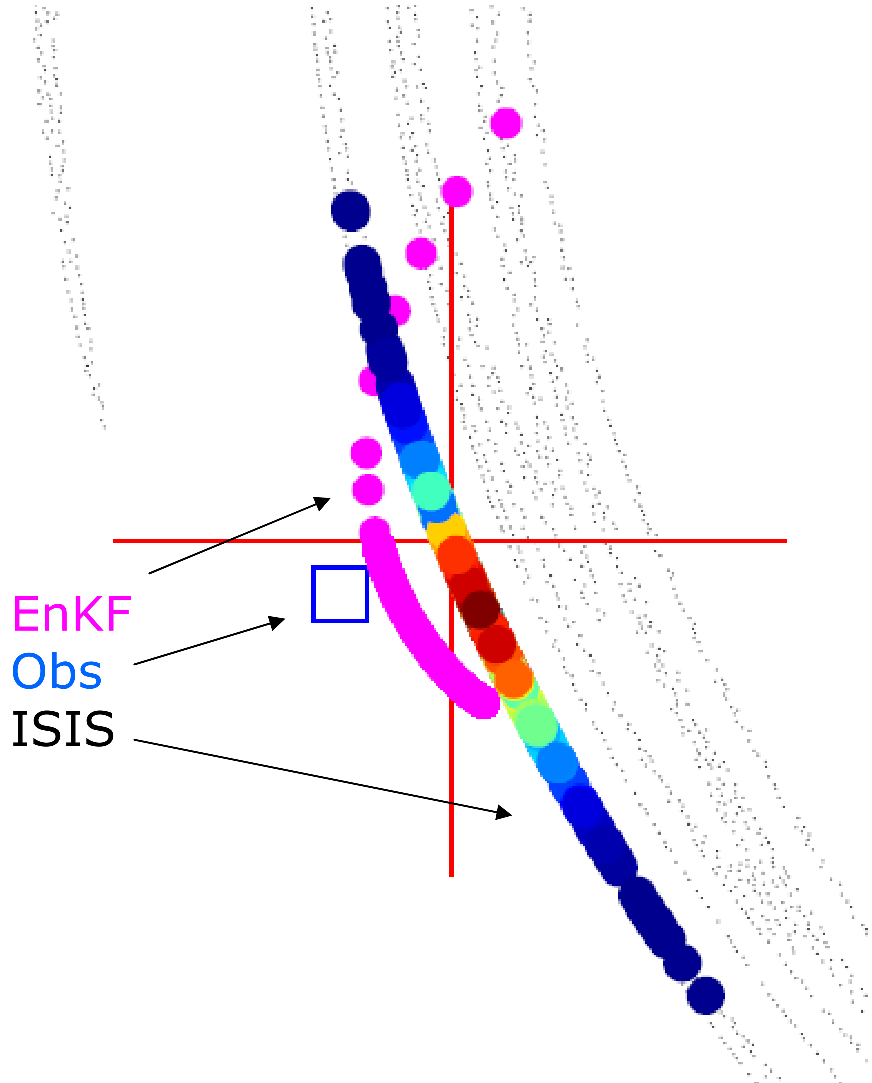


FIG. 10. Results for the 12-variable Lorenz 1996 model. The upper left panel consists of a snapshot of $K = 1000$ member IS and EN ensembles at assimilation time t_{1001}. The target is located at the intersection of the two lines, where as the observation is depicted by the circle. The EN ensemble is depicted by the 1000 magenta crosses. The EN ensemble members are equally likely and are therefore given the same color. The colored dots depict the weighted ensemble obtained via the IS method. The coloring indicates their relative likelihood given observations from t_{982} to t_{1001}. The upper right, lower left and lower right panels depict ensembles for the assimilation times t_{1011}, t_{1021} and t_{1031} respectively.

Khare & LAS, in press

Grantham Research Institute on Climate Change and the Environment



But the point here is that all the grey dots, the target for PDF forecasting, go away when the model is imperfect!

Given an imperfect model, we can test against additional observations in "now cast" mode, but the aim of a relevant (PDF) ensemble has vanished.
(and would be a function of lead-time if resurrected!)

(See Du's thesis for much discussion and examples)

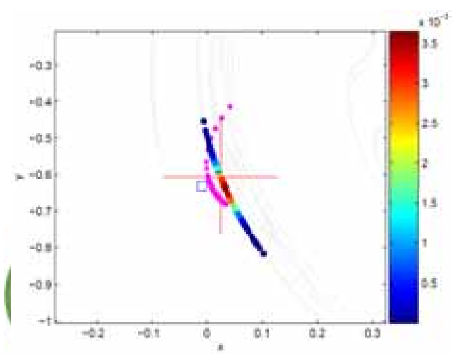
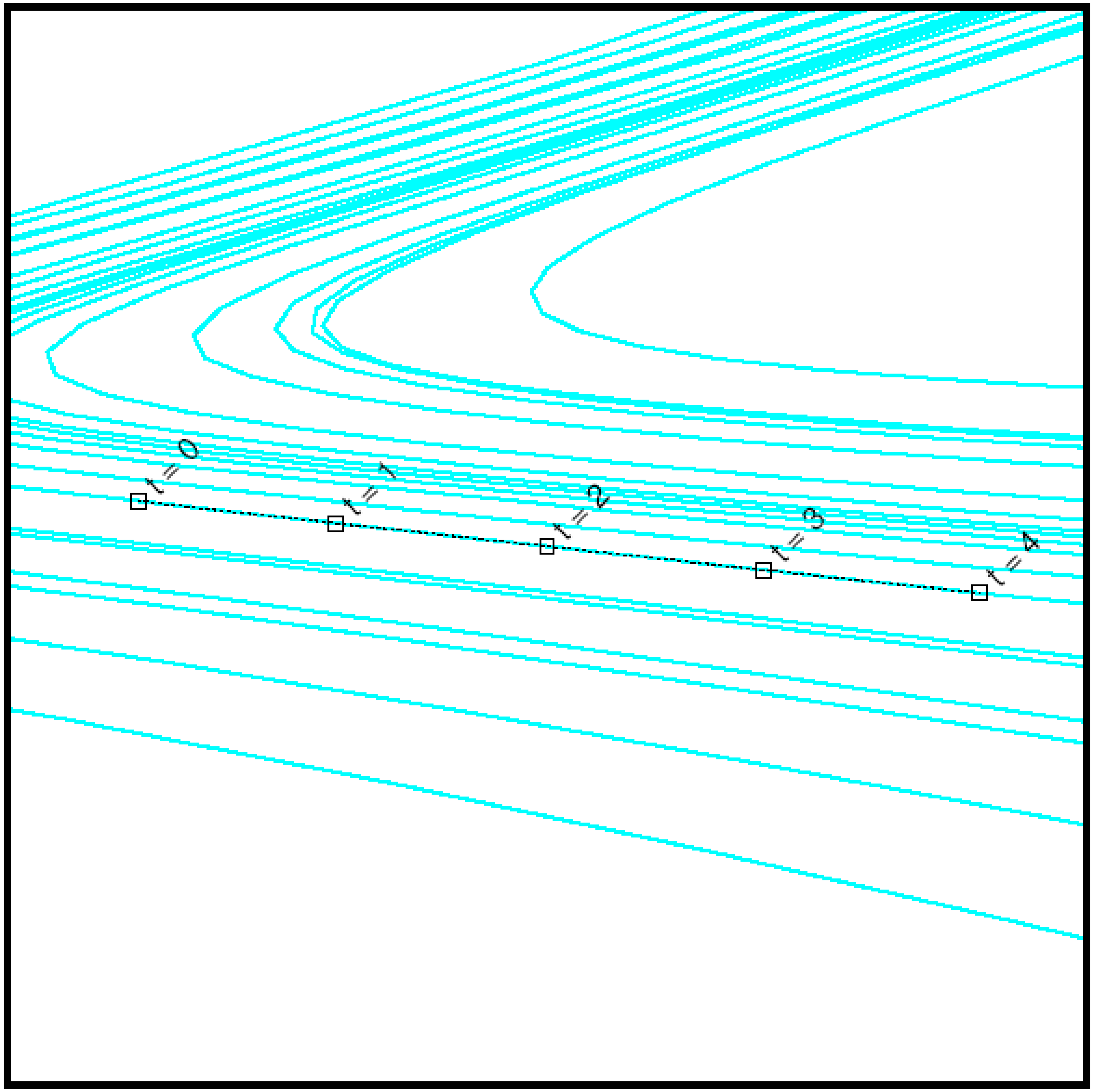


Figure 3.6: Compare the EnKF and ISIS results via ϵ-ball, the blue line denotes the proportion of EnKF method wins and the red line denotes the proportion of ISIS method wins a) Ikeda experiment, Noise level 0.05 (Details of the experiment are listed in Appendix B Table B.3); b) Lorenz96 experiment, Noise level 0.5 (Details of the experiment are listed in Appendix B Table B.4)

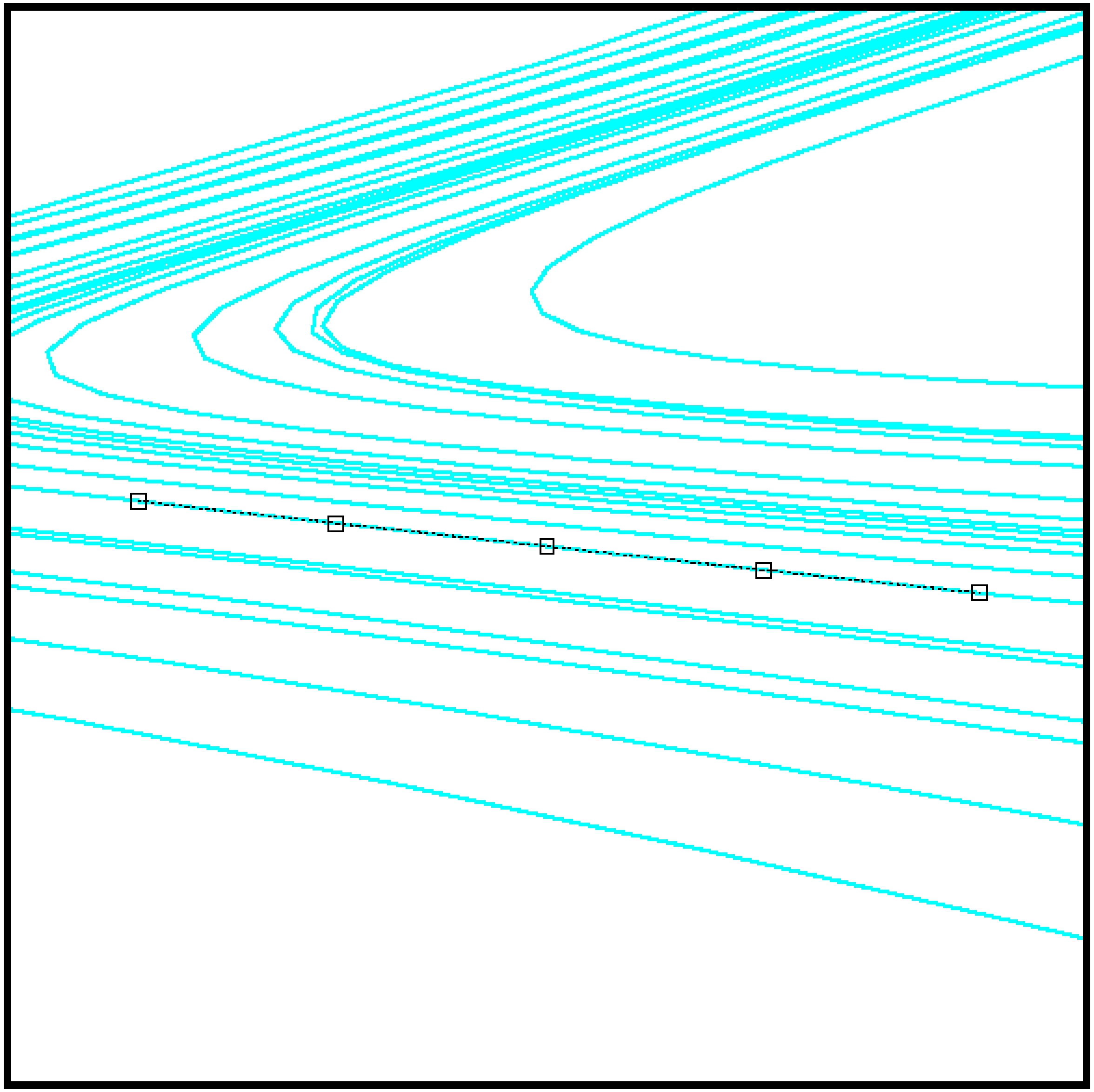
So how does this work?

The Geometry of Model Error



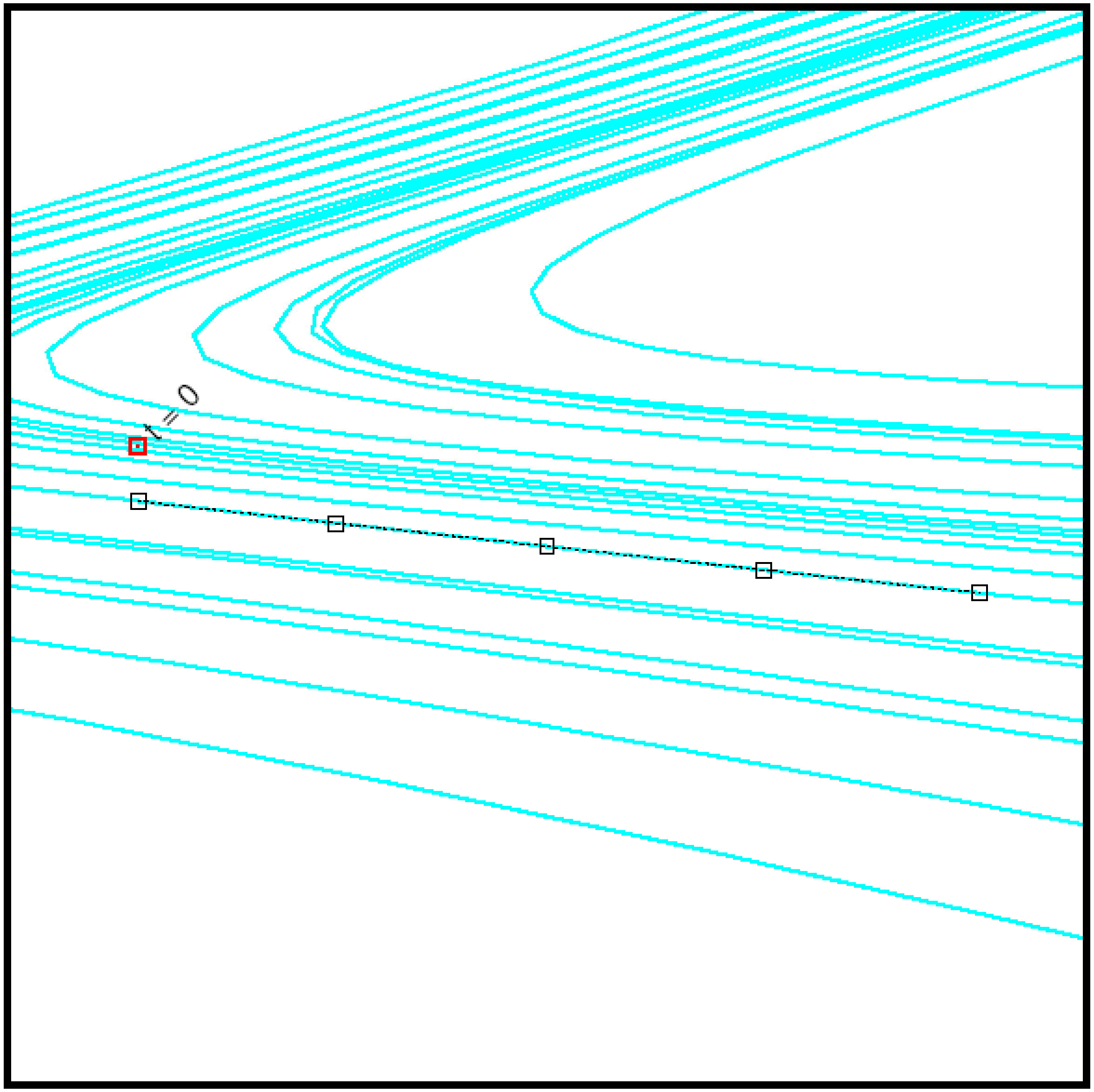
Here is a trajectory segment of Lorenz 63

The Geometry of Model Error

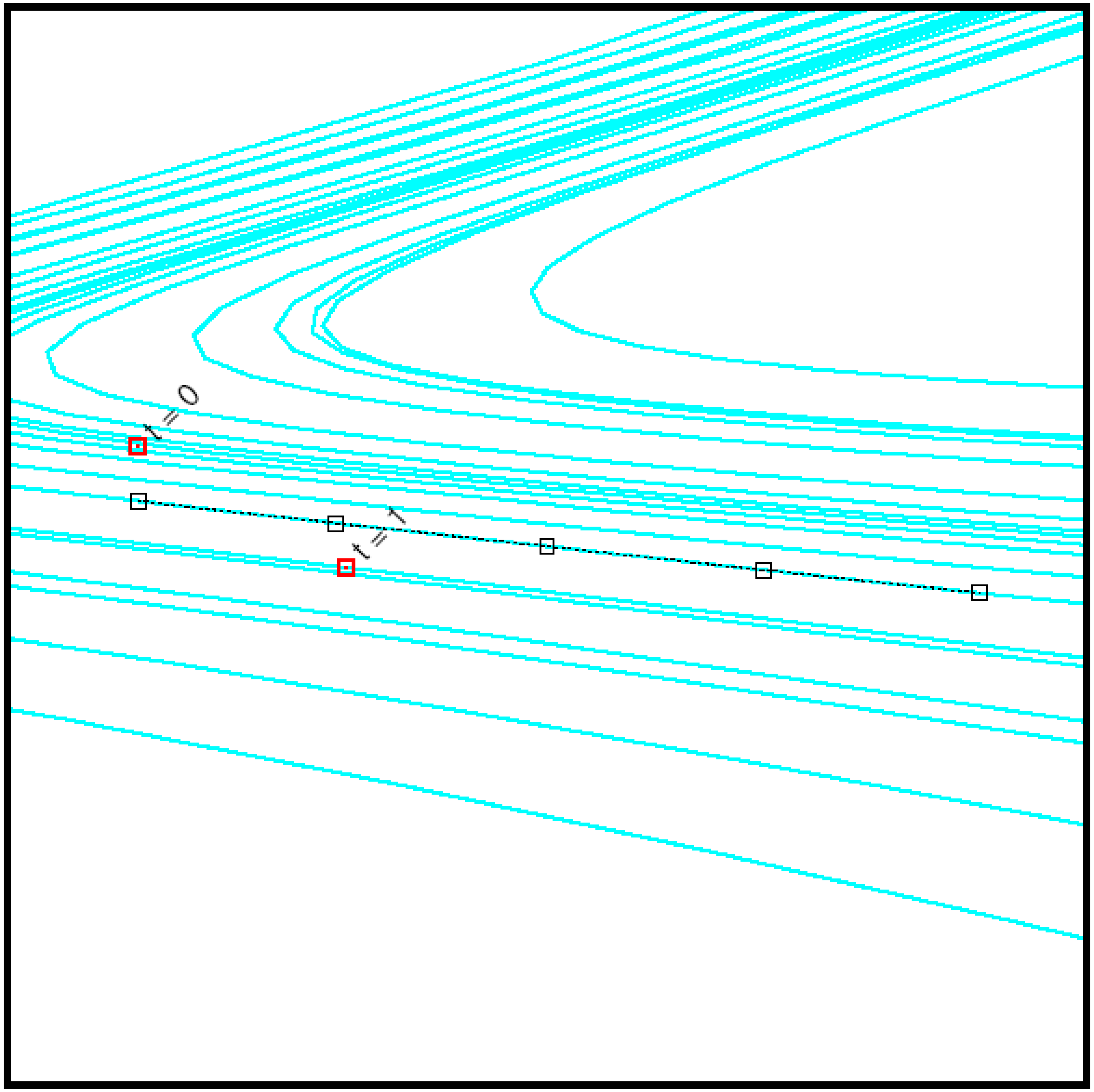


Making observations

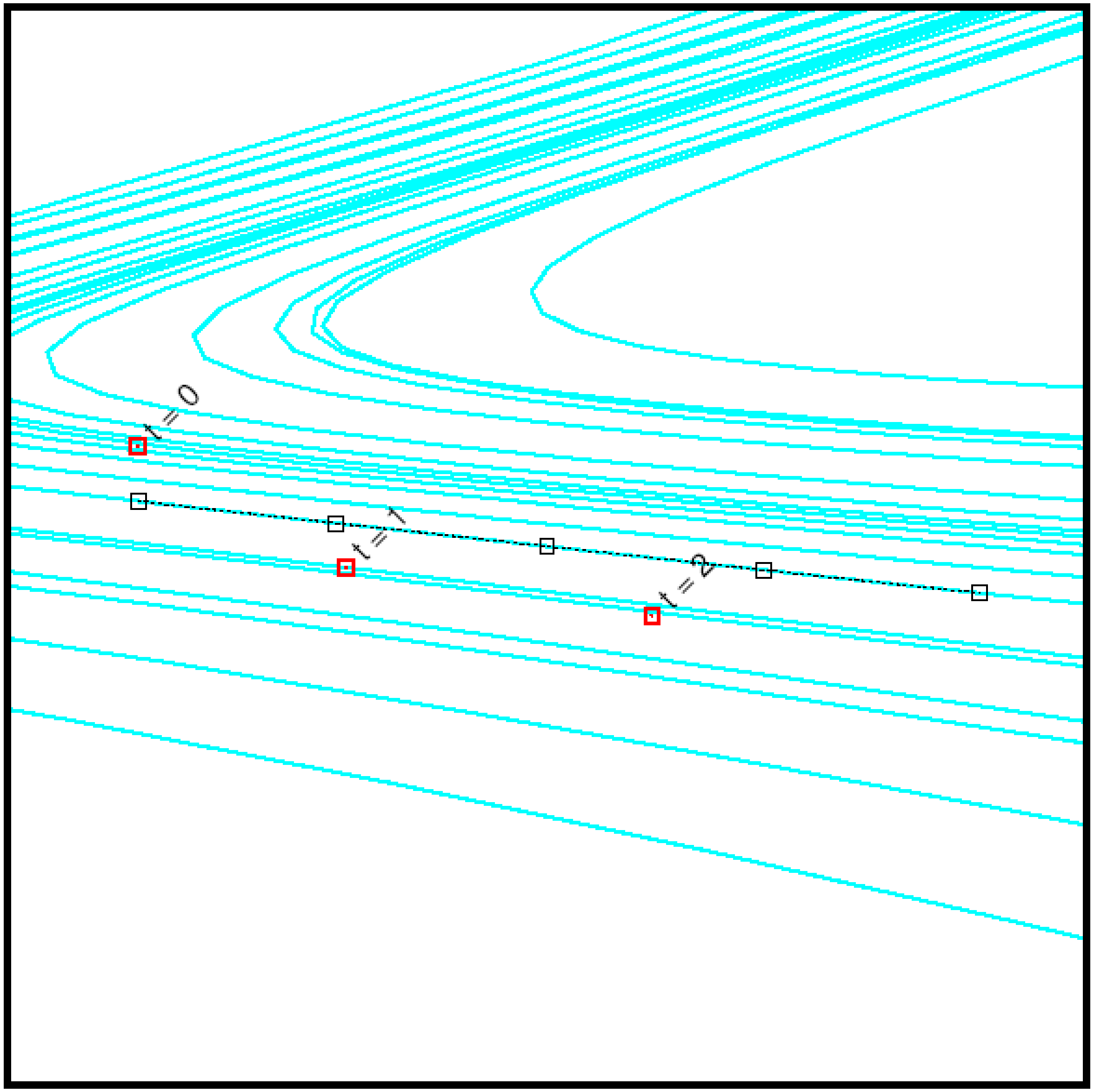
The Geometry of Model Error



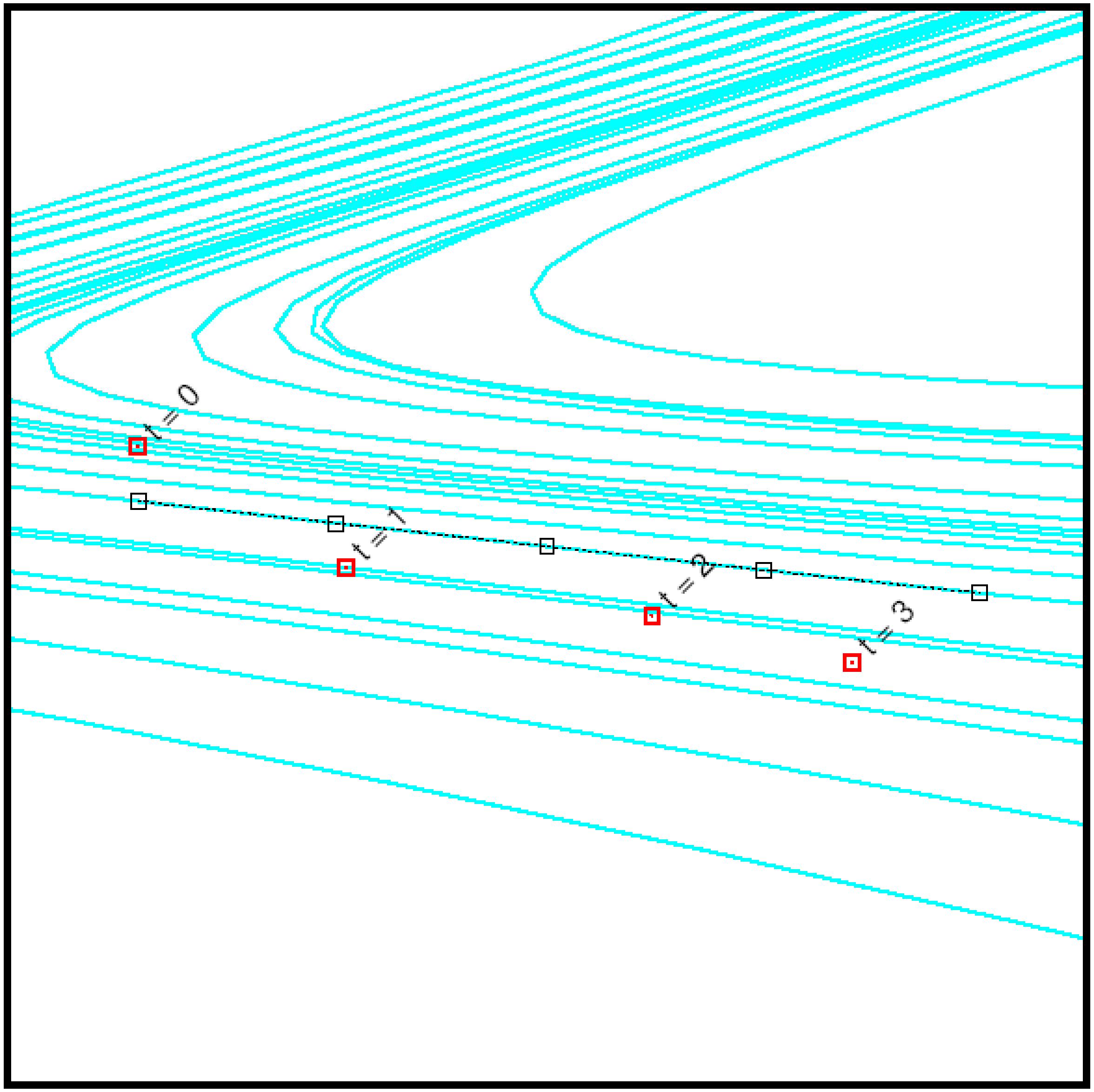
The Geometry of Model Error

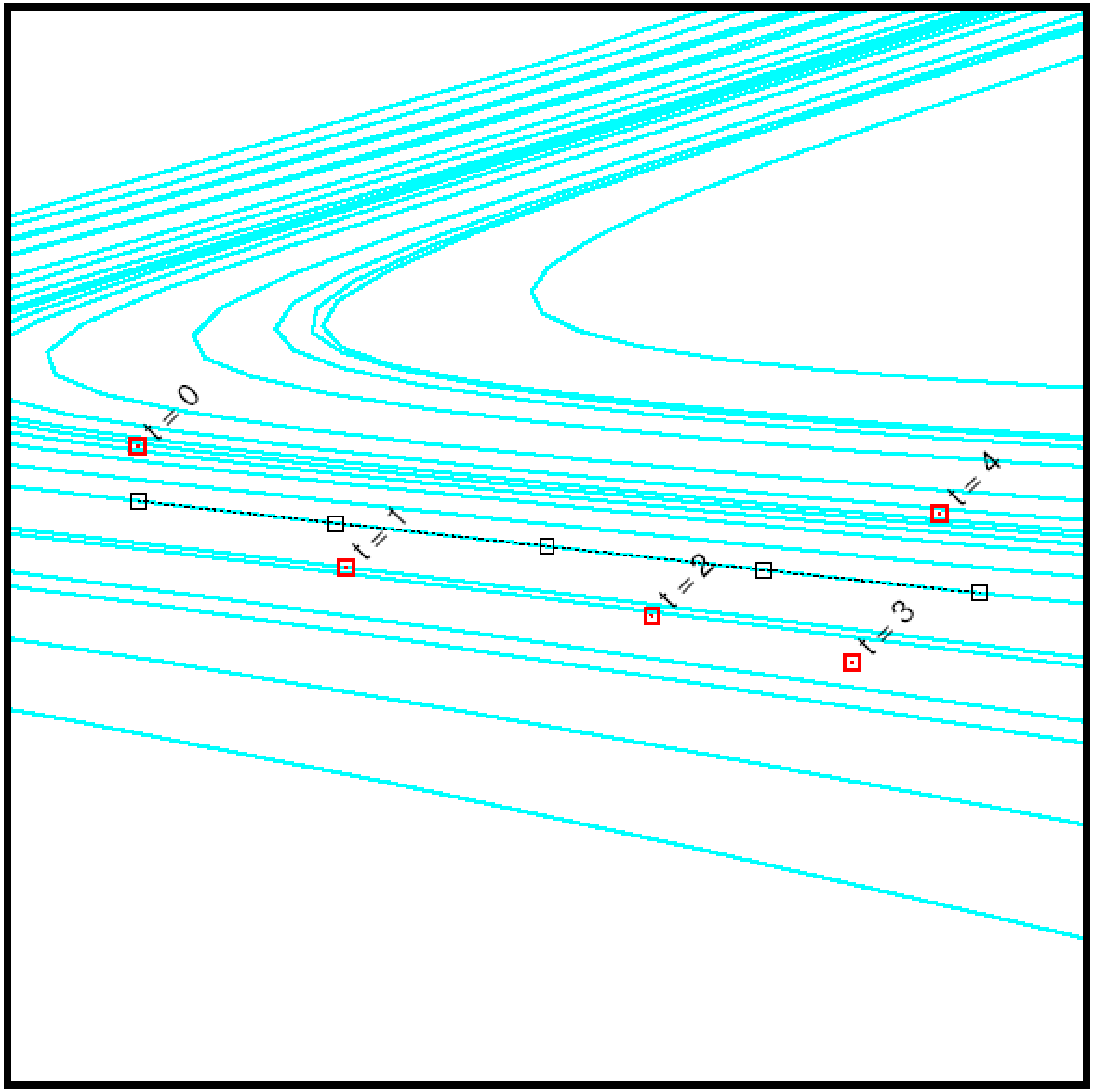


The Geometry of Model Error



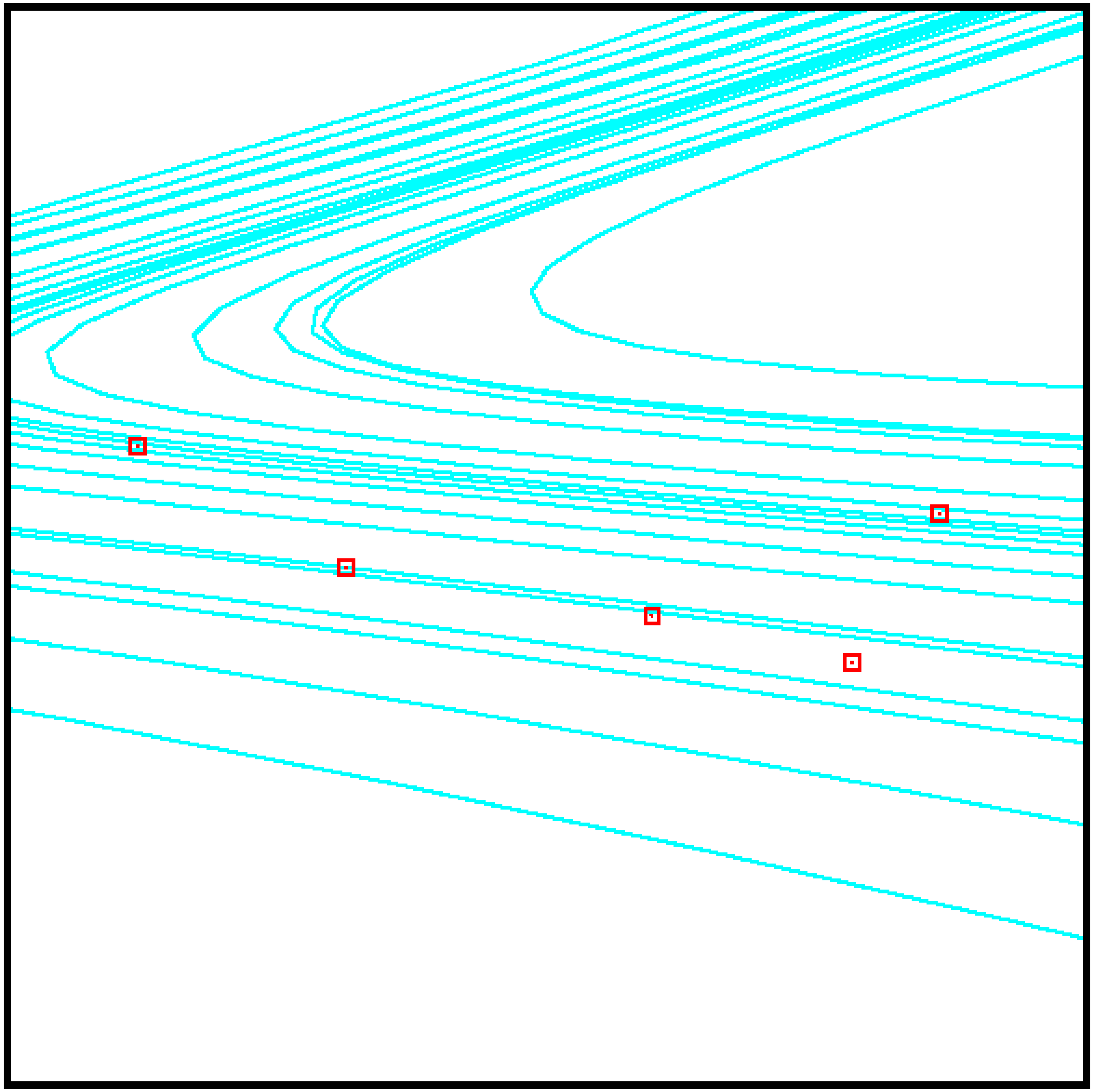
The Geometry of Model Error





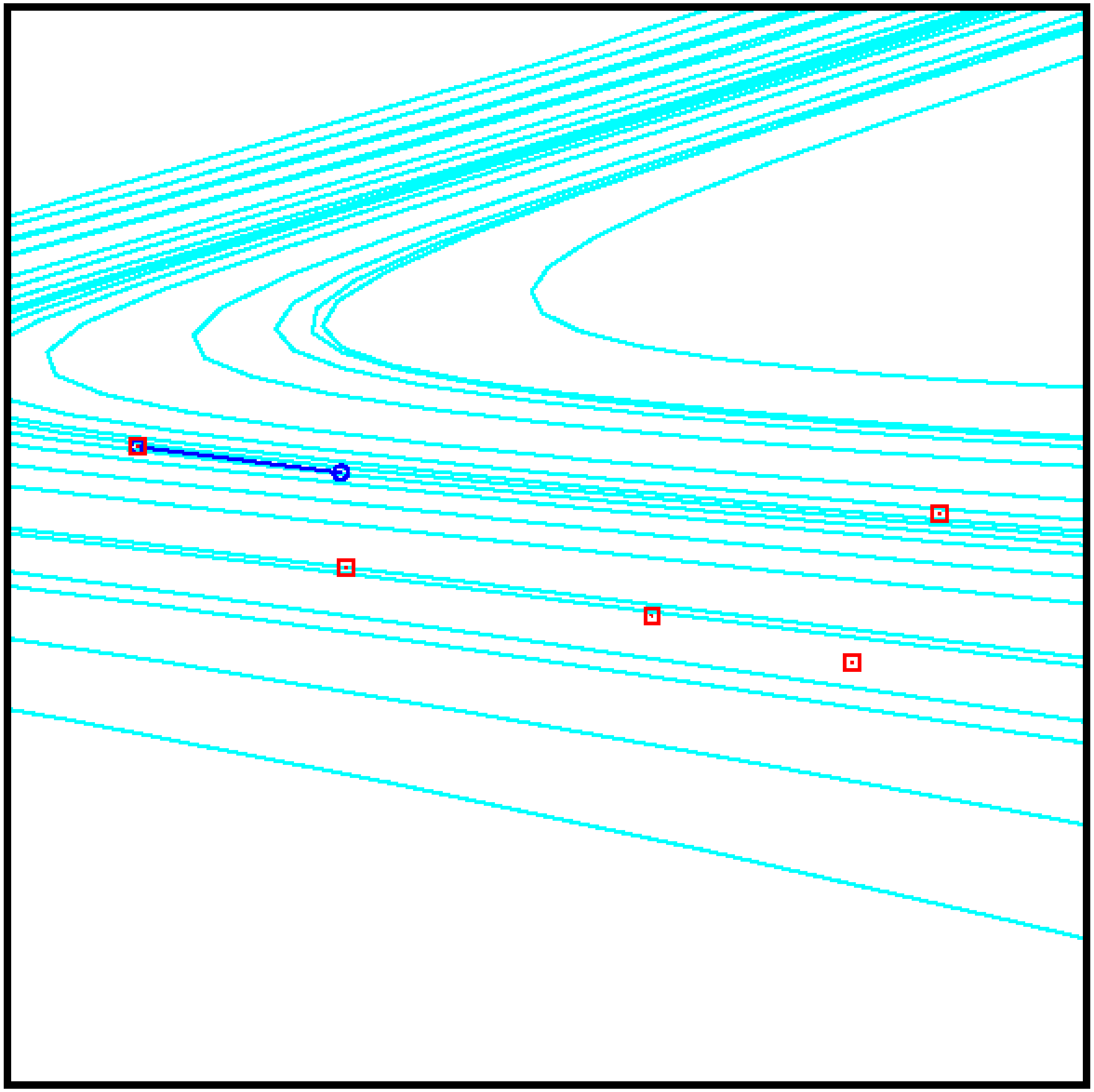
Five observations

The Geometry of Model Error

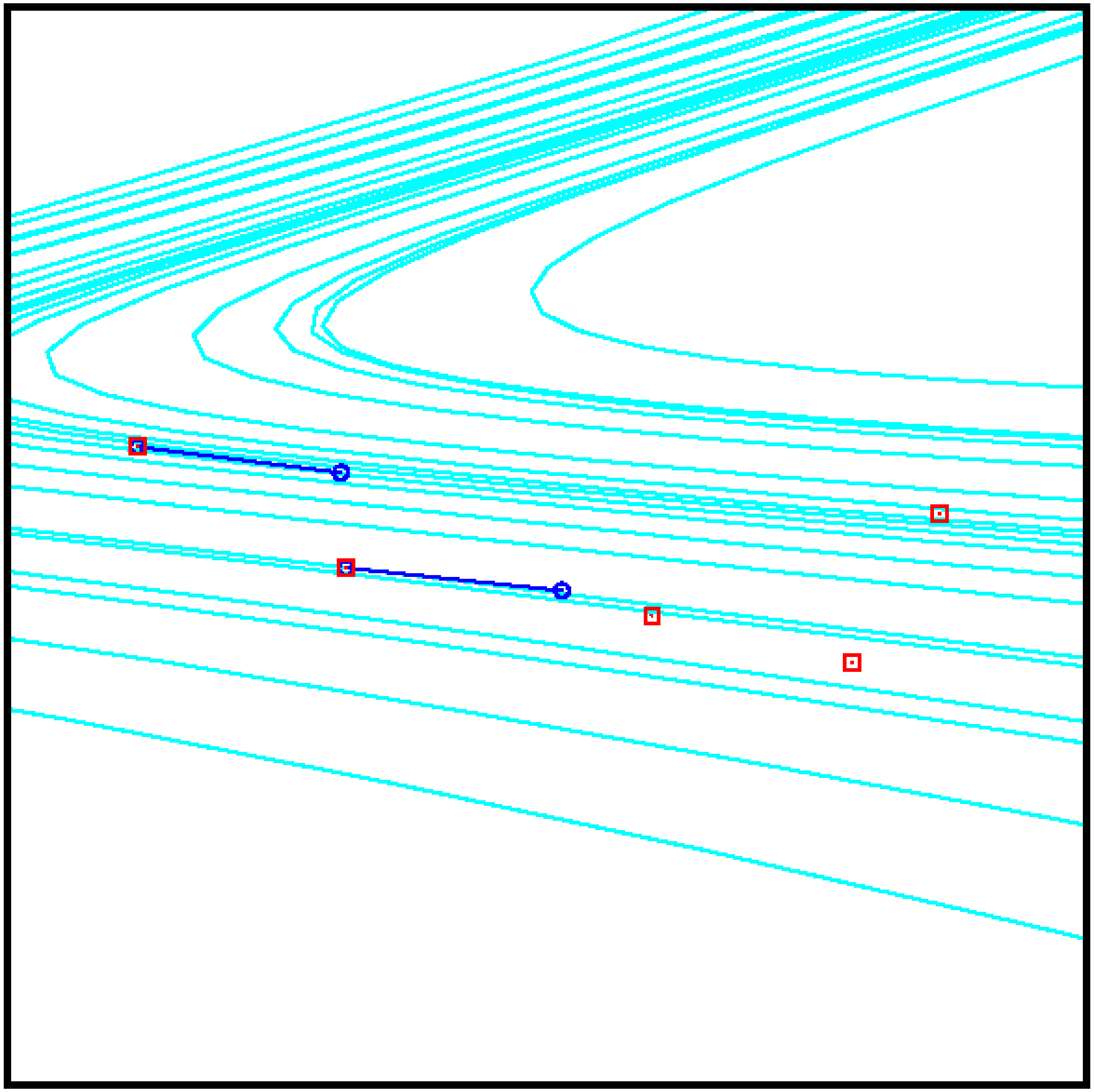


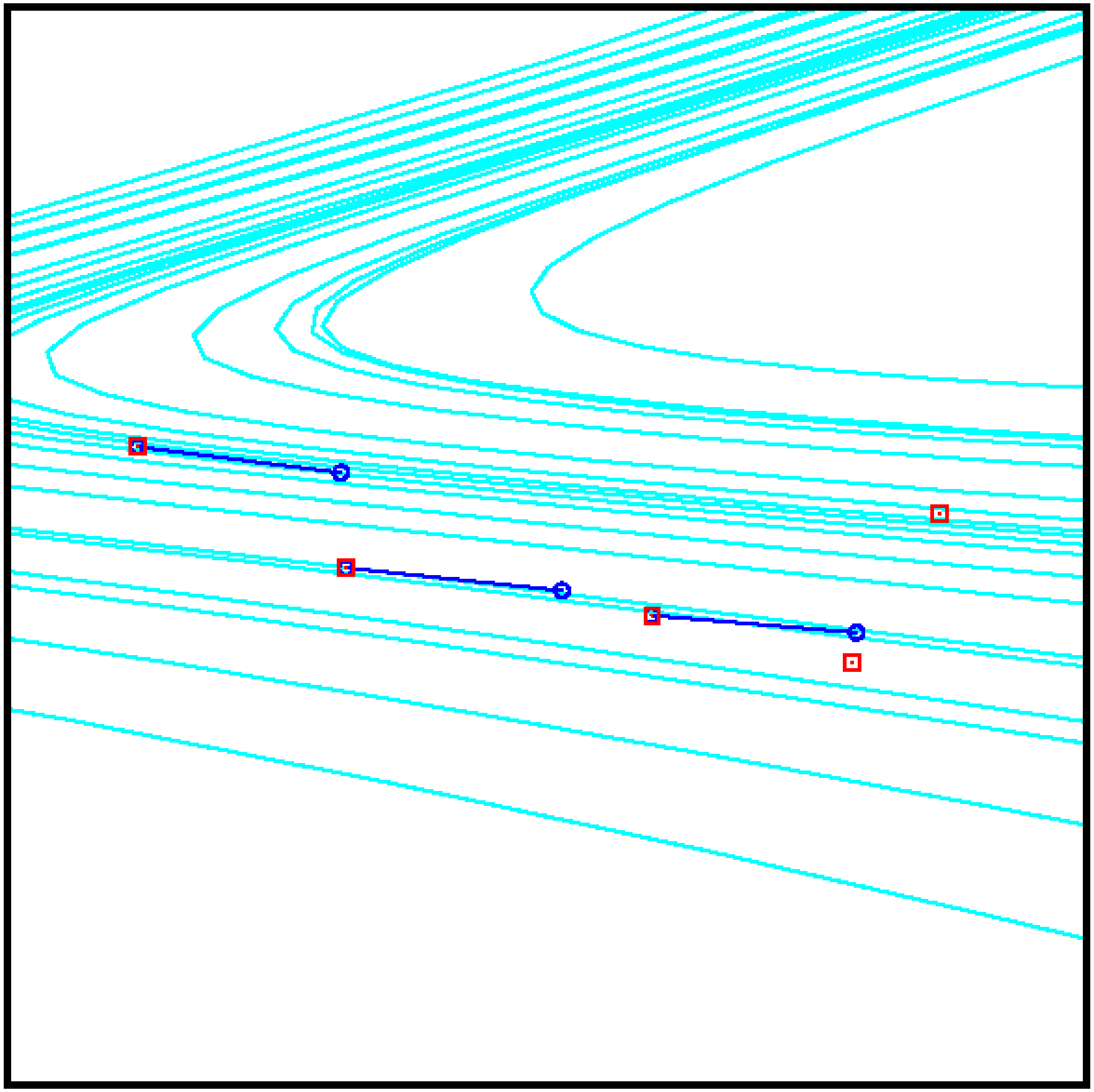
All we have are observations

The Geometry of Model Error

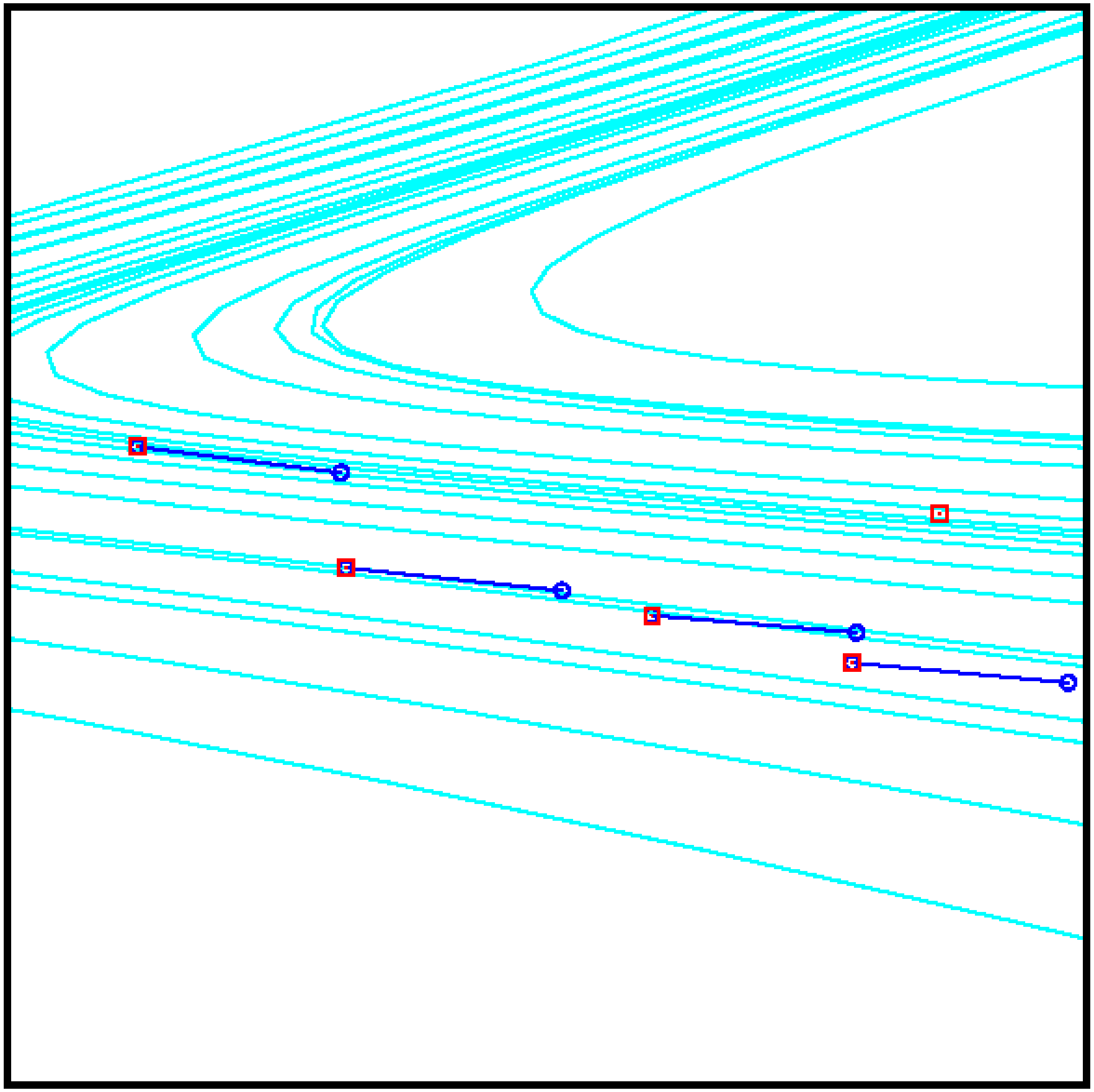


The Geometry of Model Error

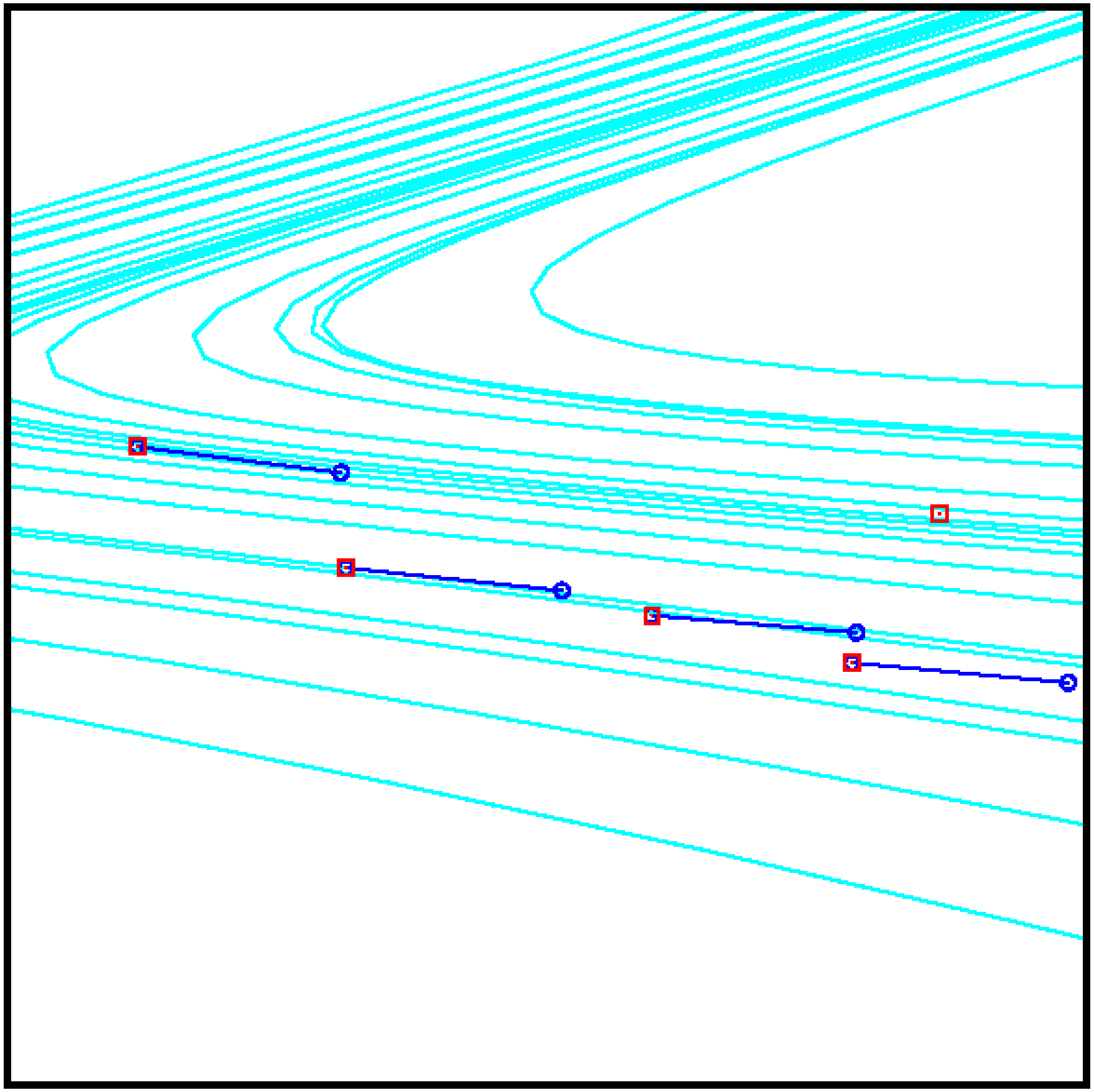




The Geometry of Model Error

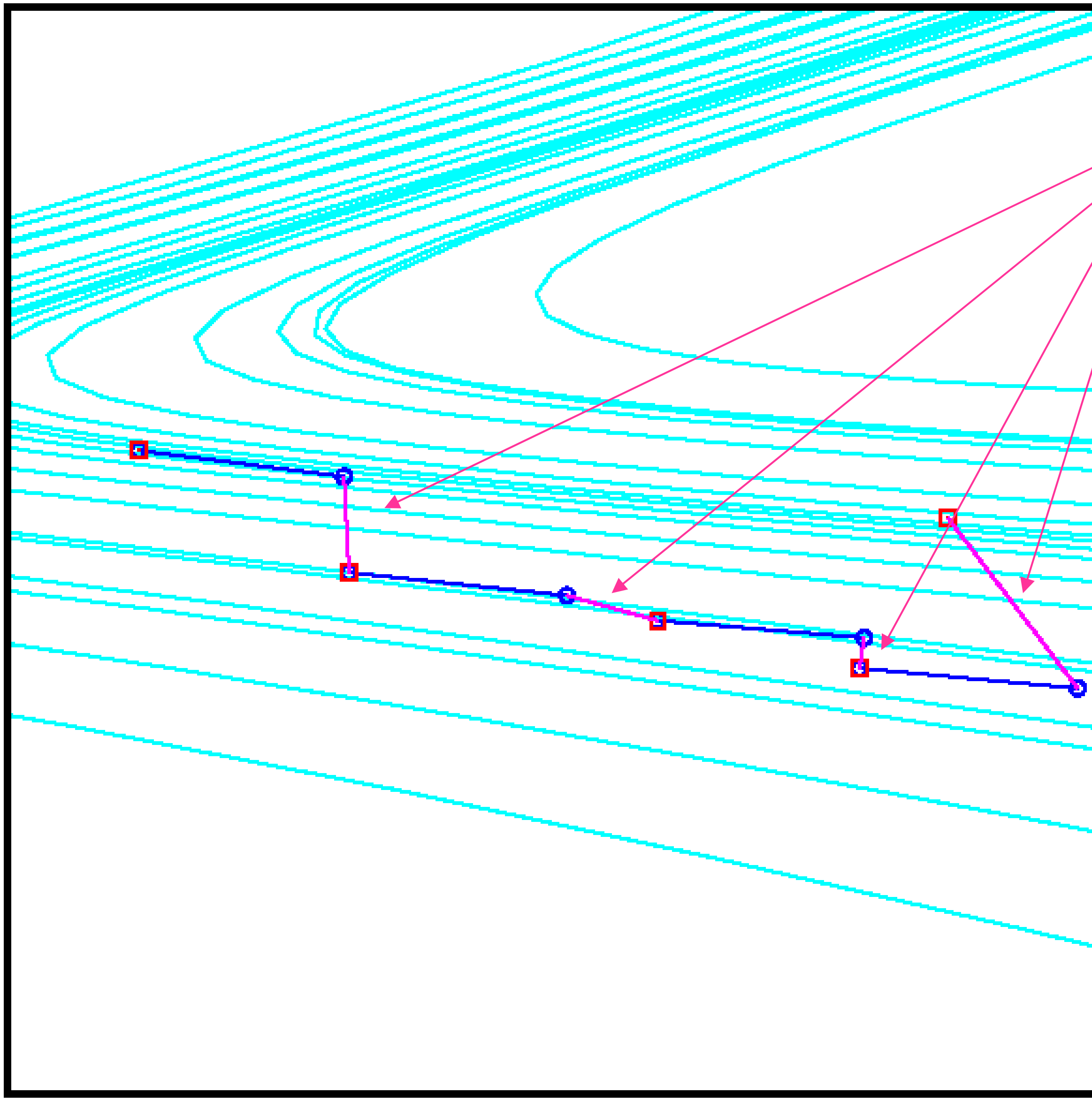


Forecasts from observations



Apply shadowing filter

The Geometry of Model Error

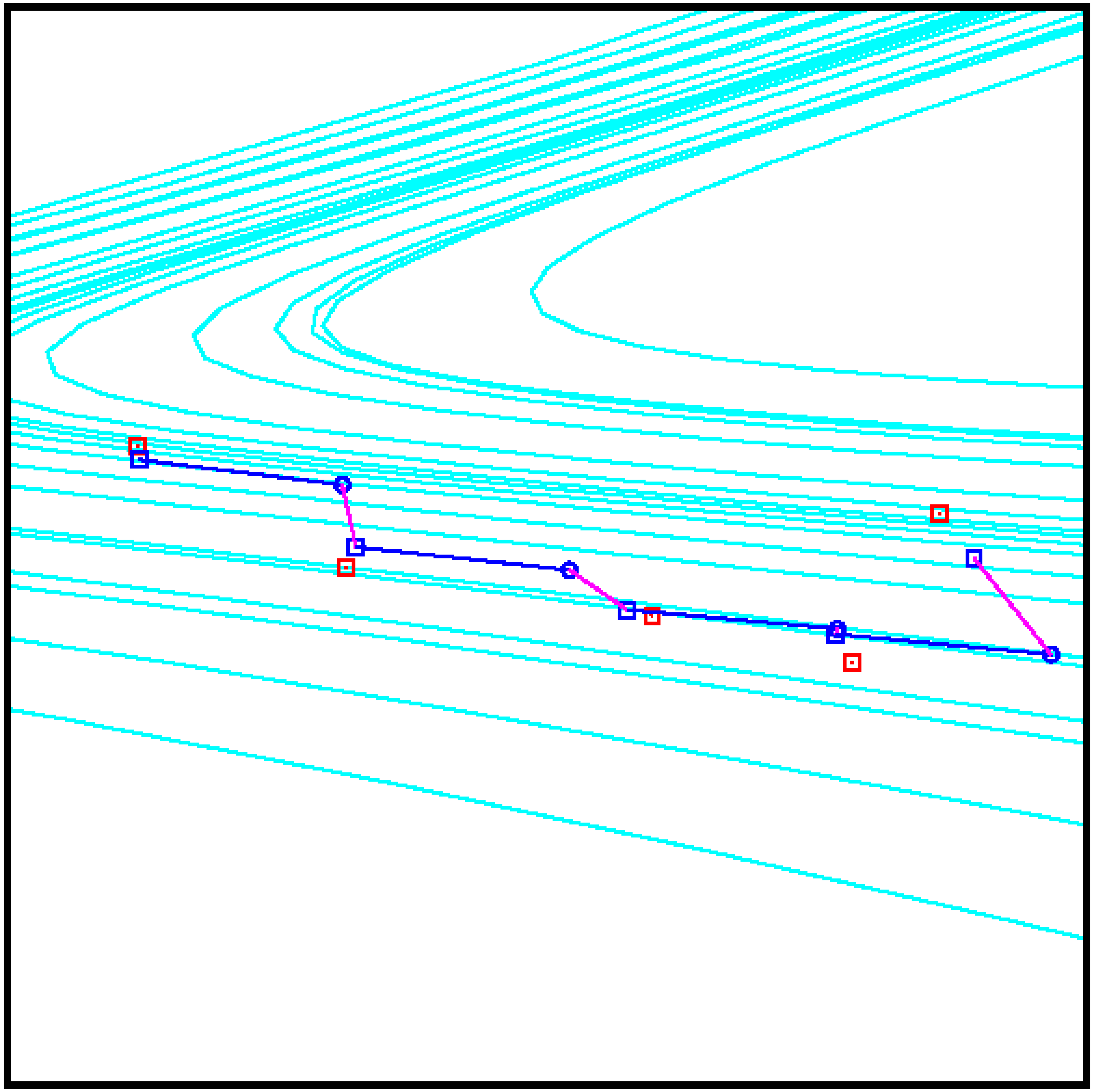


The aim is to minimize the mismatches simultaneously.

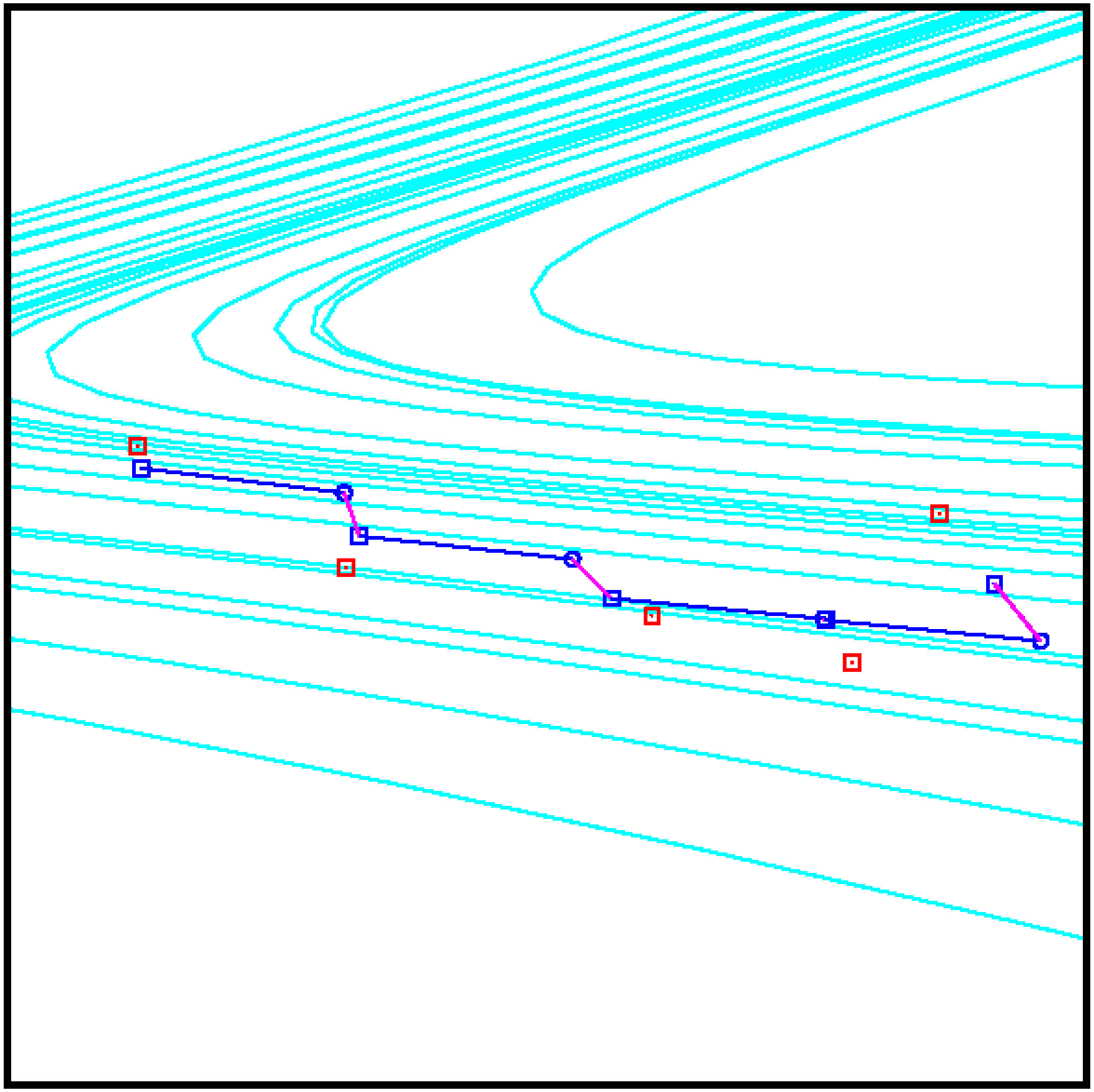
This is simply gradient decent, in a N*M (=15) dimensional space, towards unique global minima which form the trajectory manifold.

After using them to define the starting point, we ignore the observations during the (initial) decent.

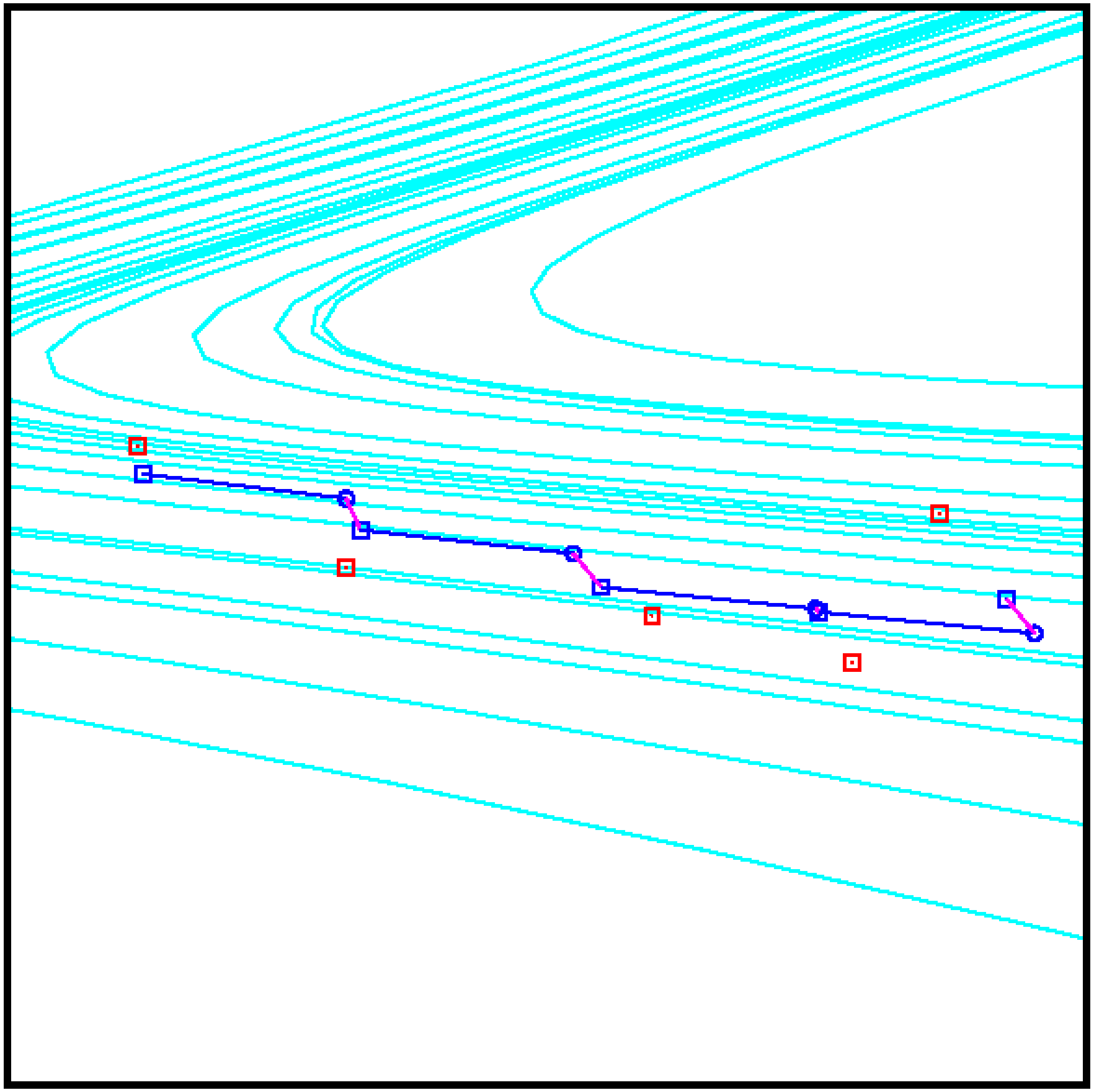
The Geometry of Model Error



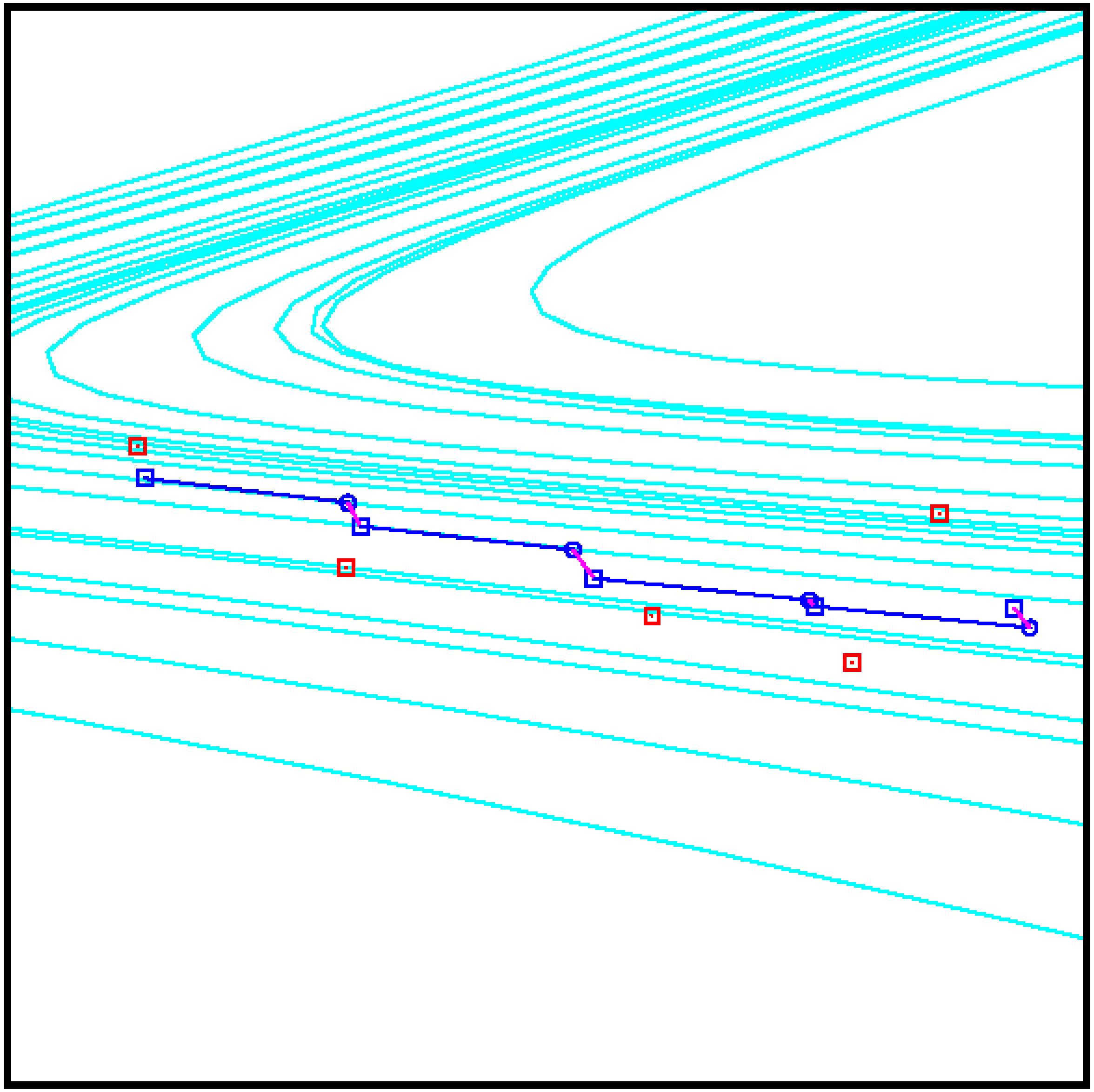
Iterate 1



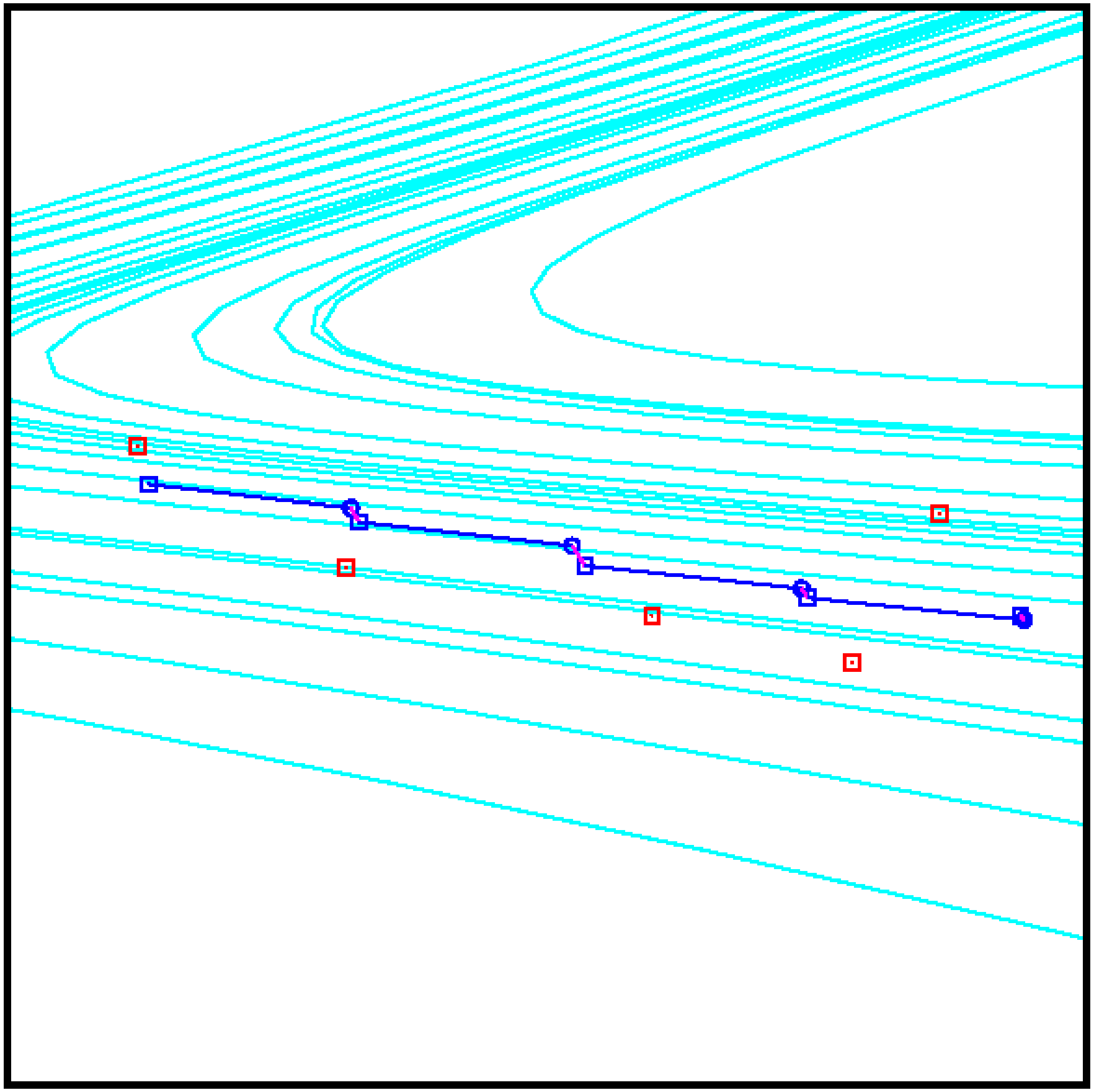
Iterate 2



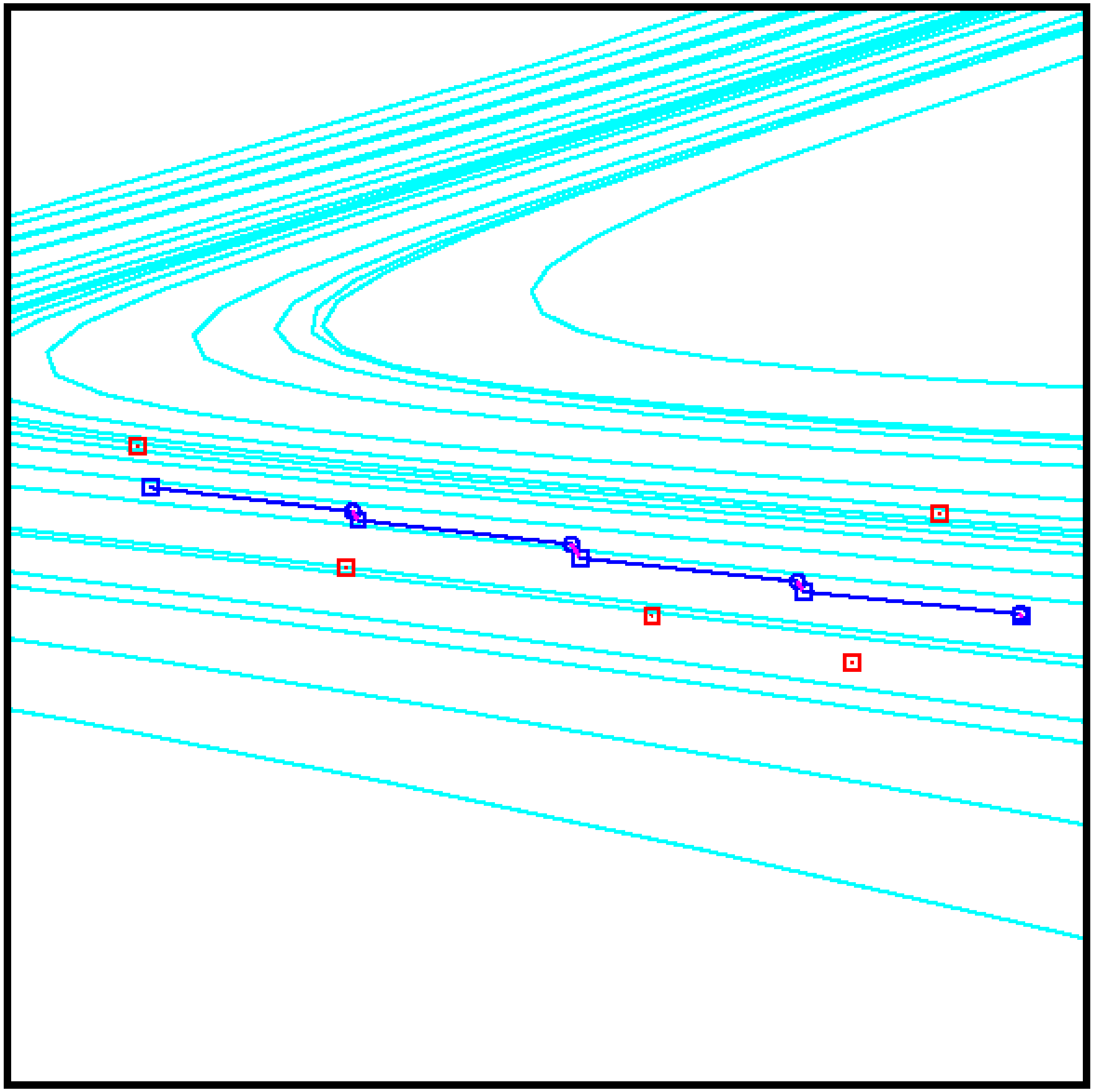
Iterate 3



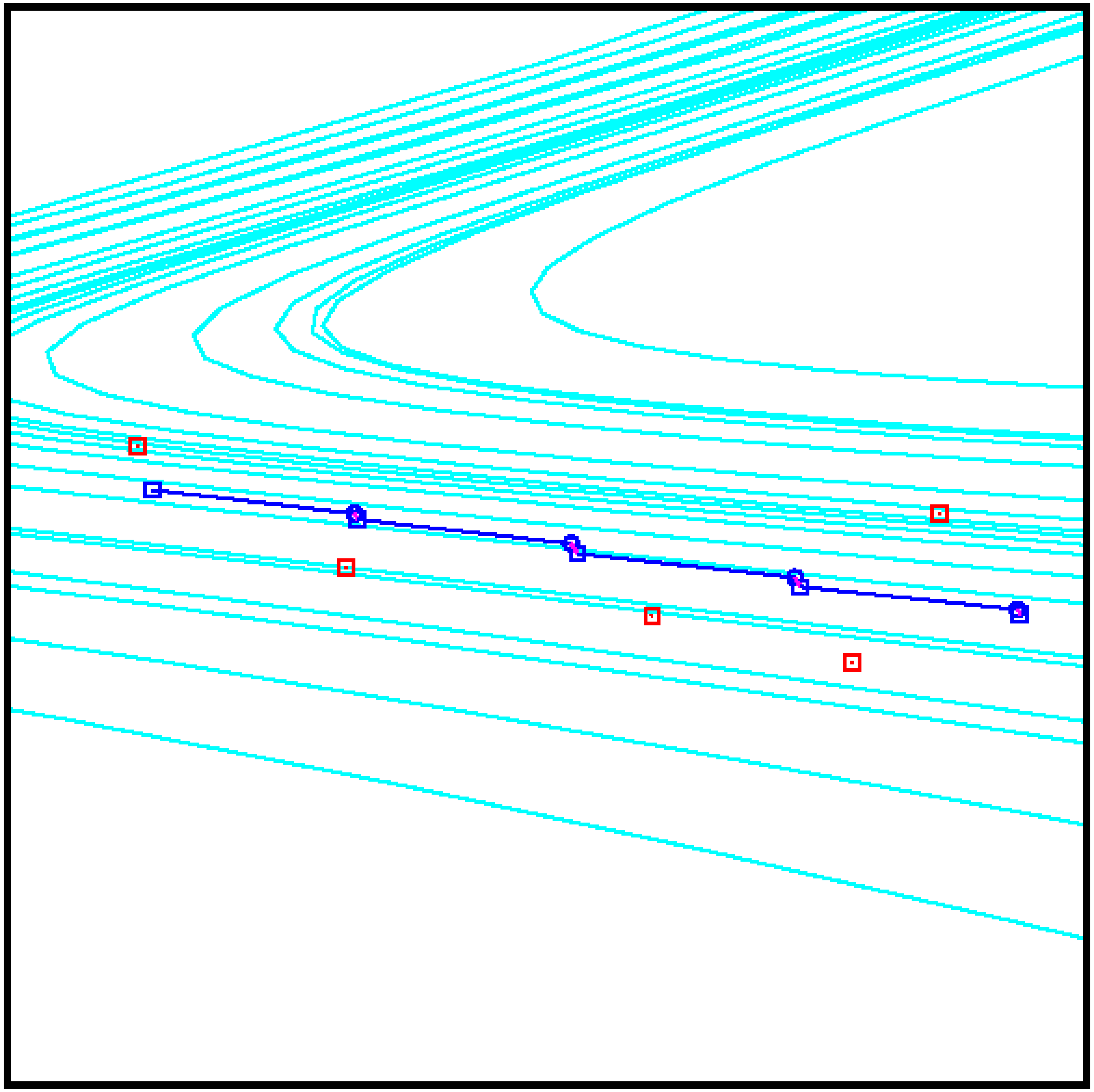
Iterate 4



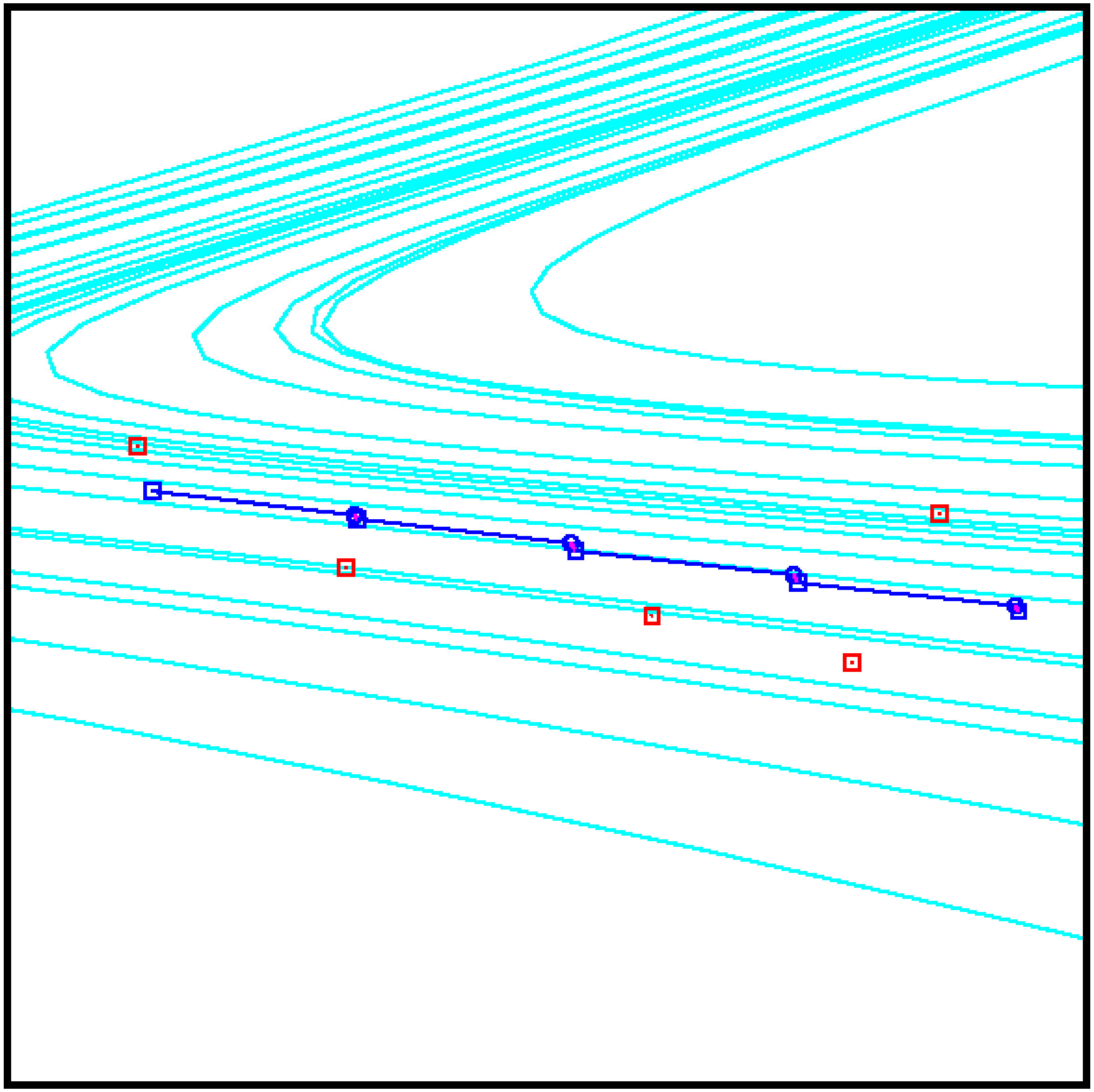
Iterate 5



Iterate 6

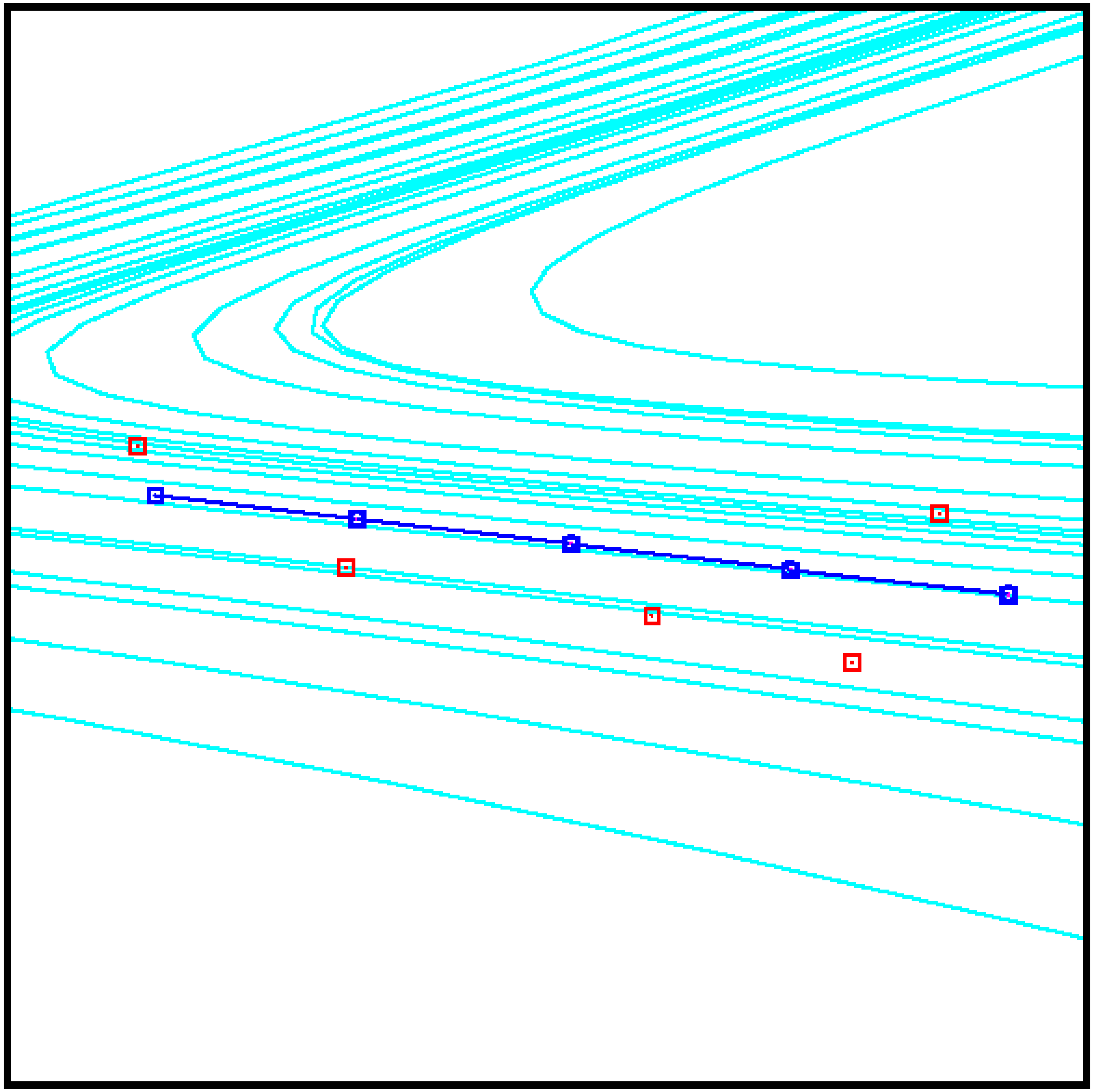


Iterate 7



Iterate 8

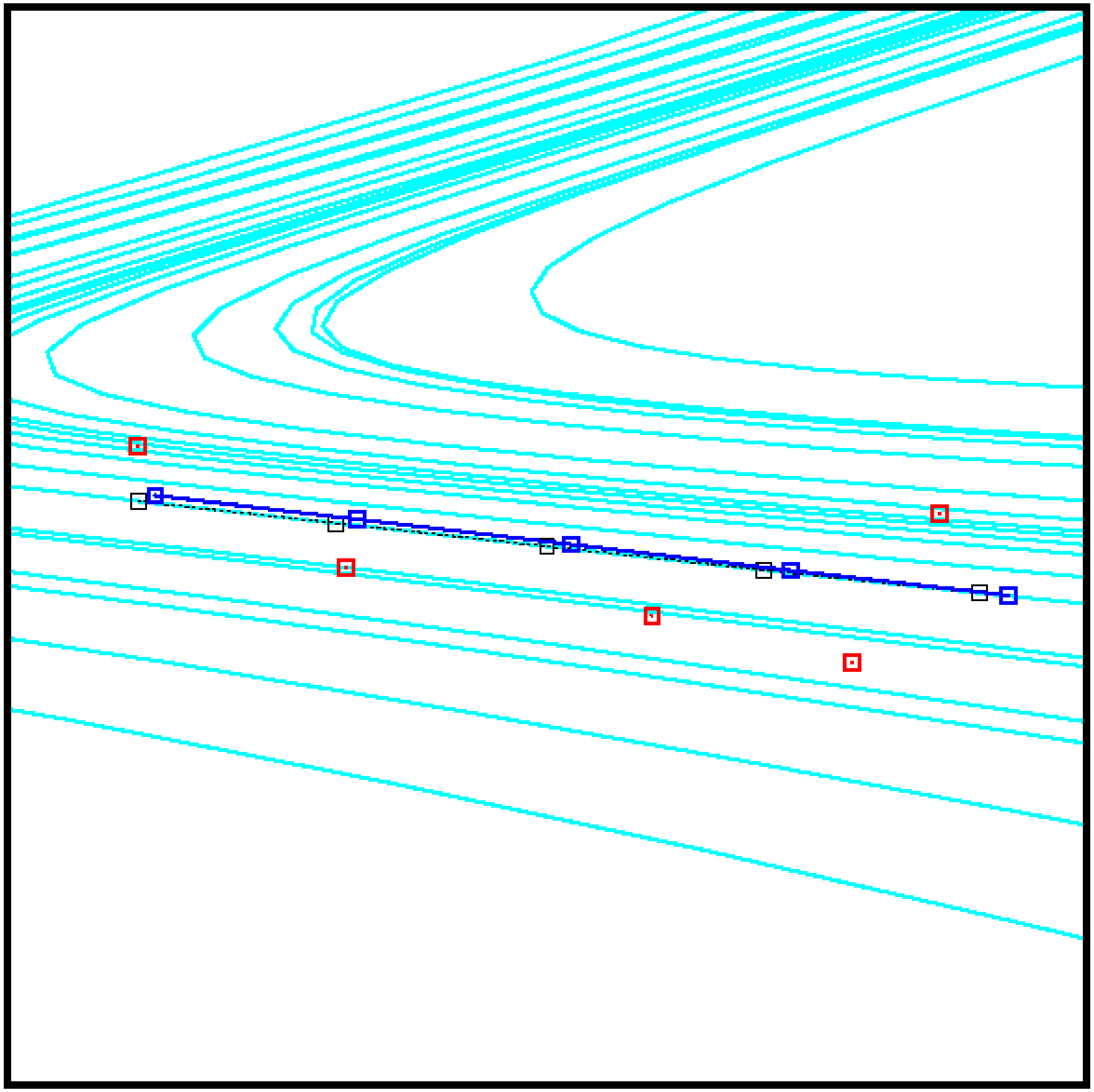
The Geometry of Model Error



Convergence toward a trajectory.

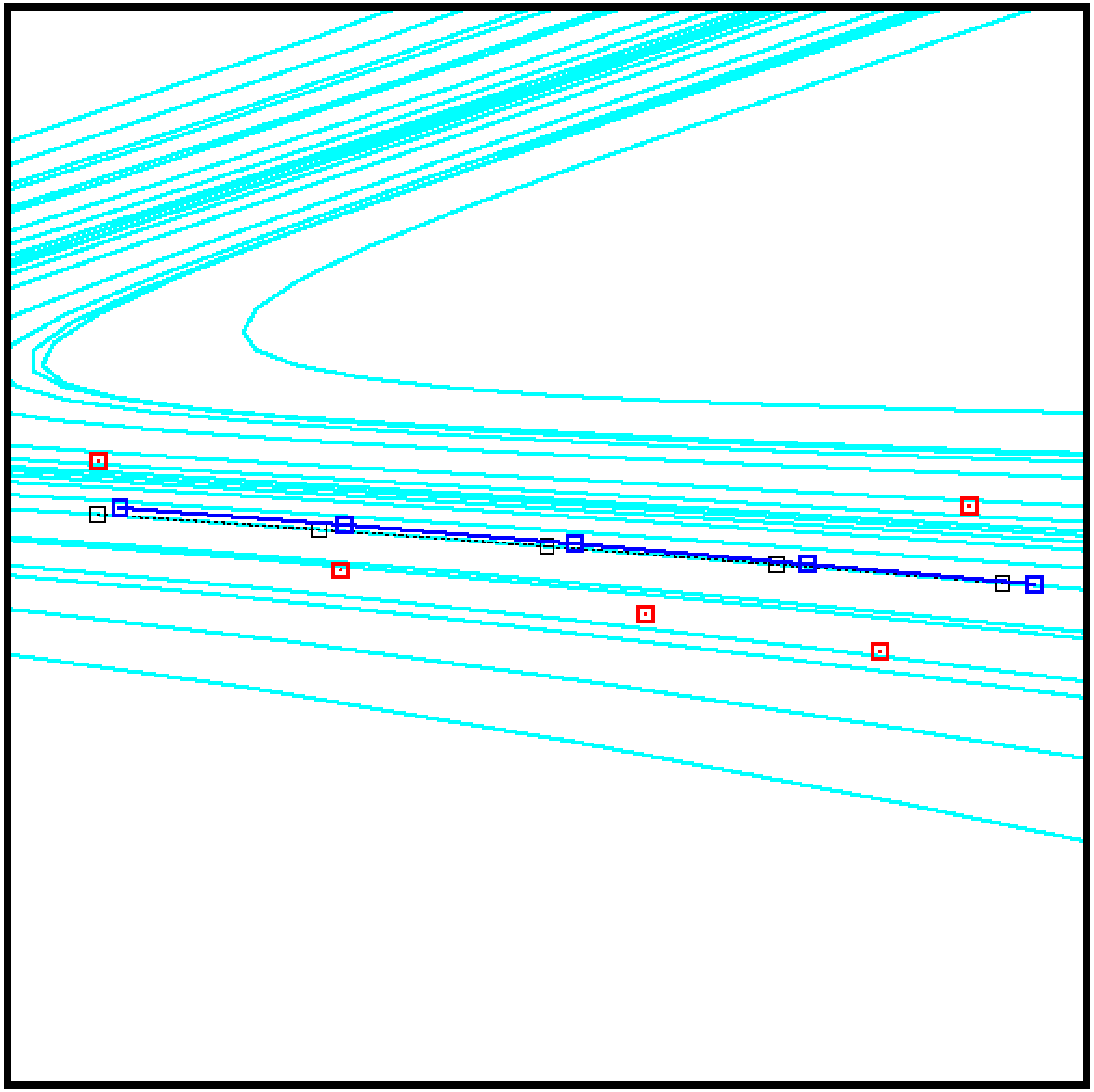
Once very close, the trajectory passing through any point on the psuedo-orbit can be used/contrasted with other trajectories.

The Geometry of Model Error

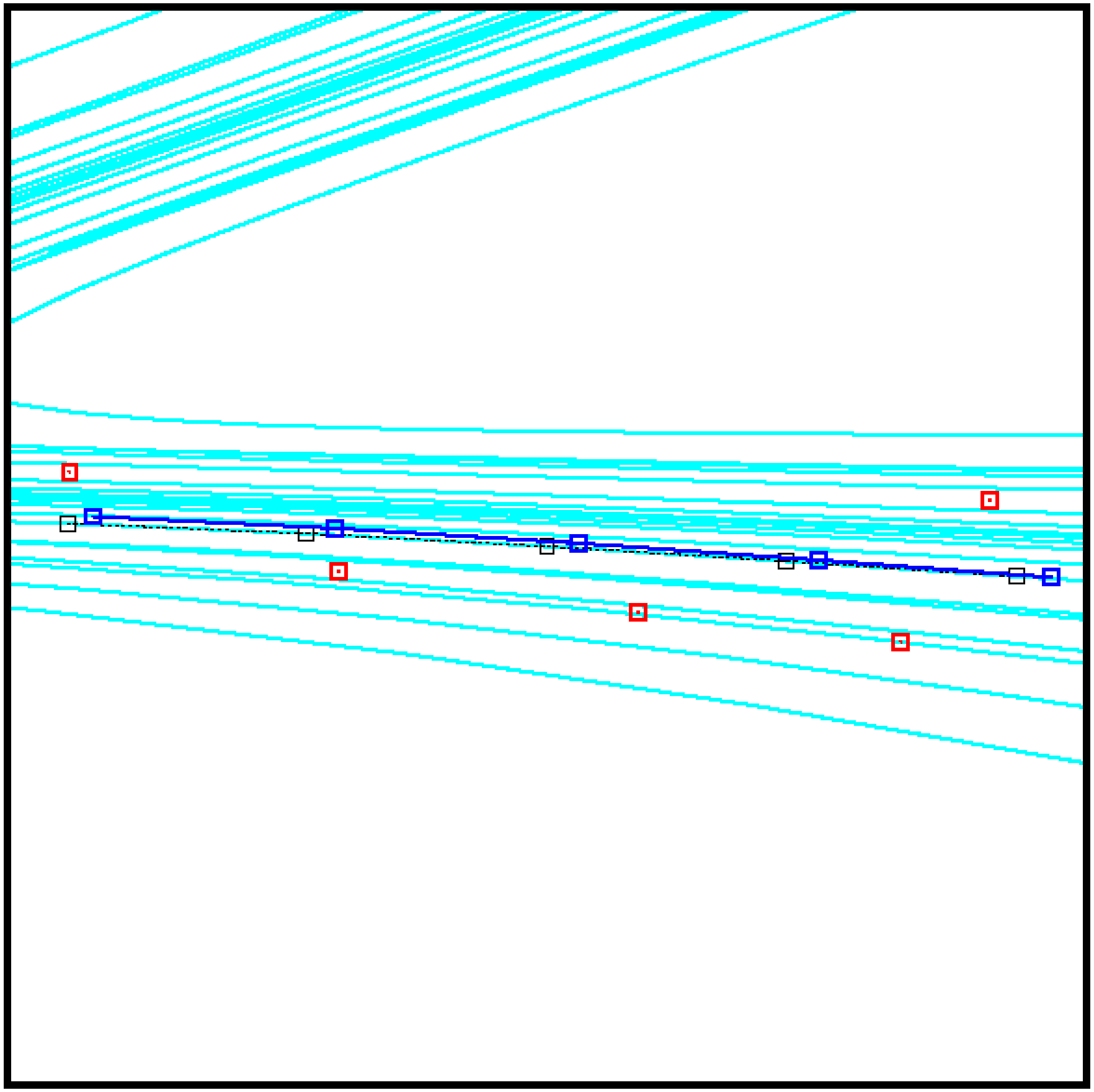


Near Truth, but not Truth

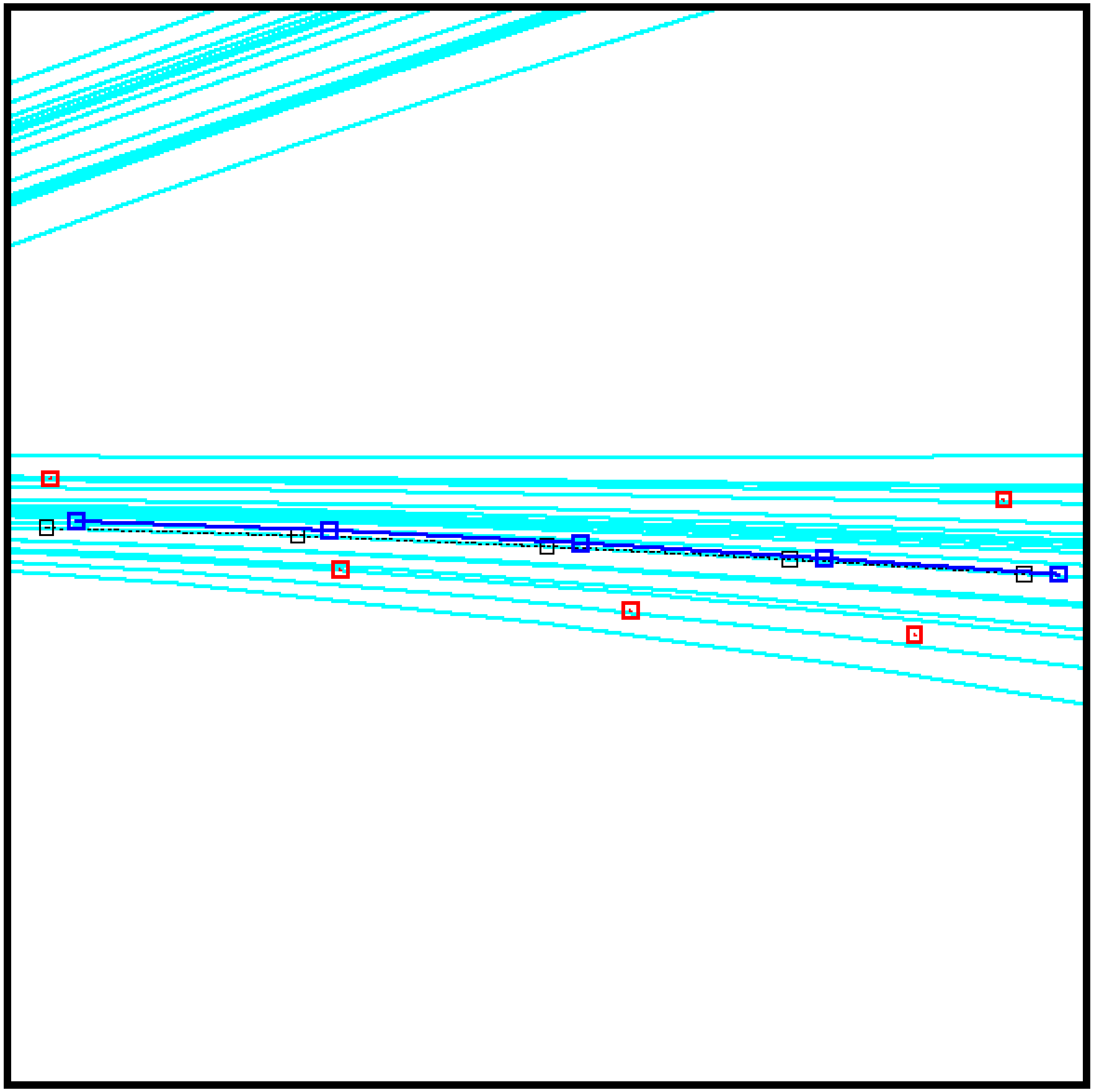
The Geometry of Model Error



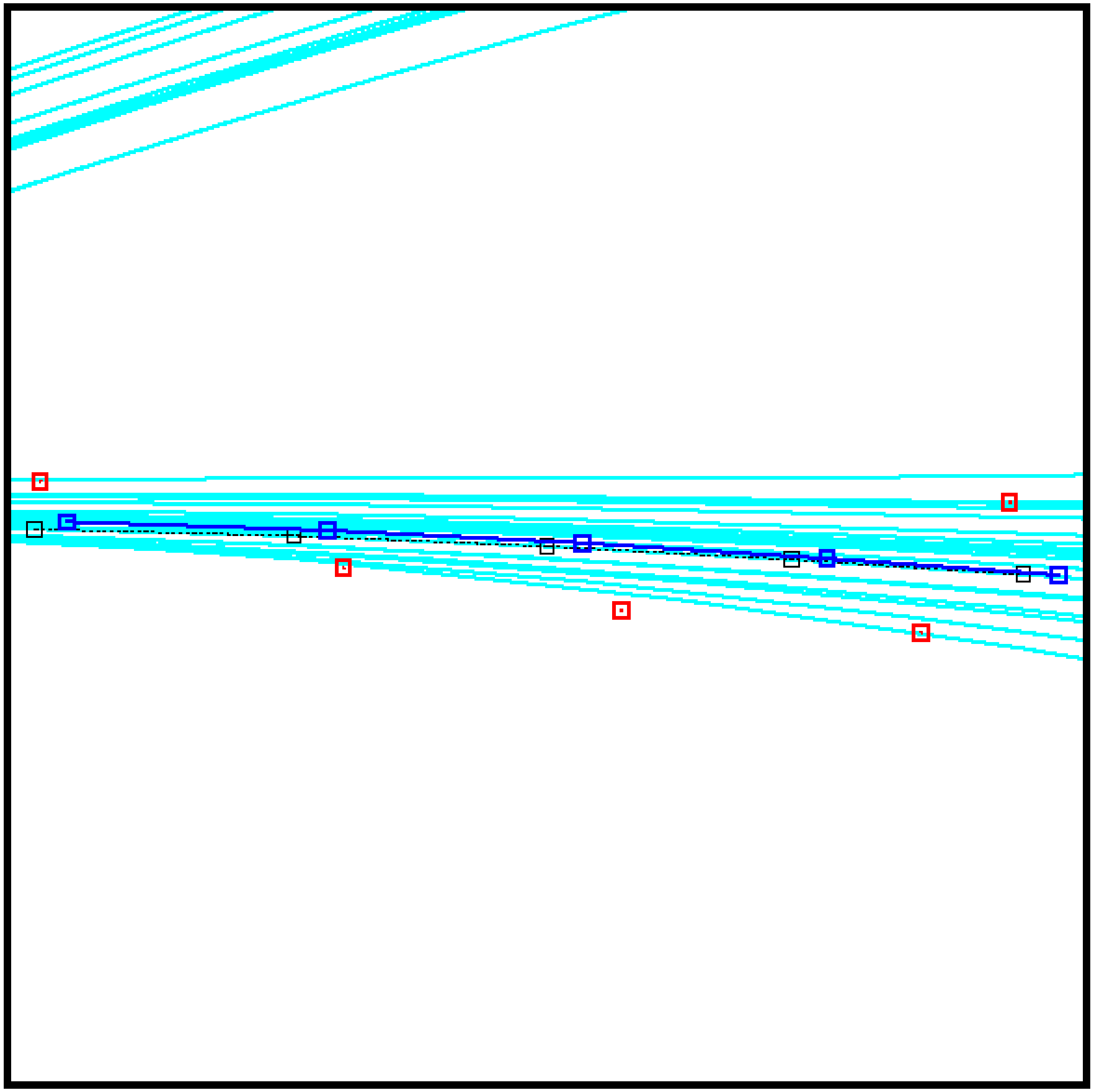
The Geometry of Model Error



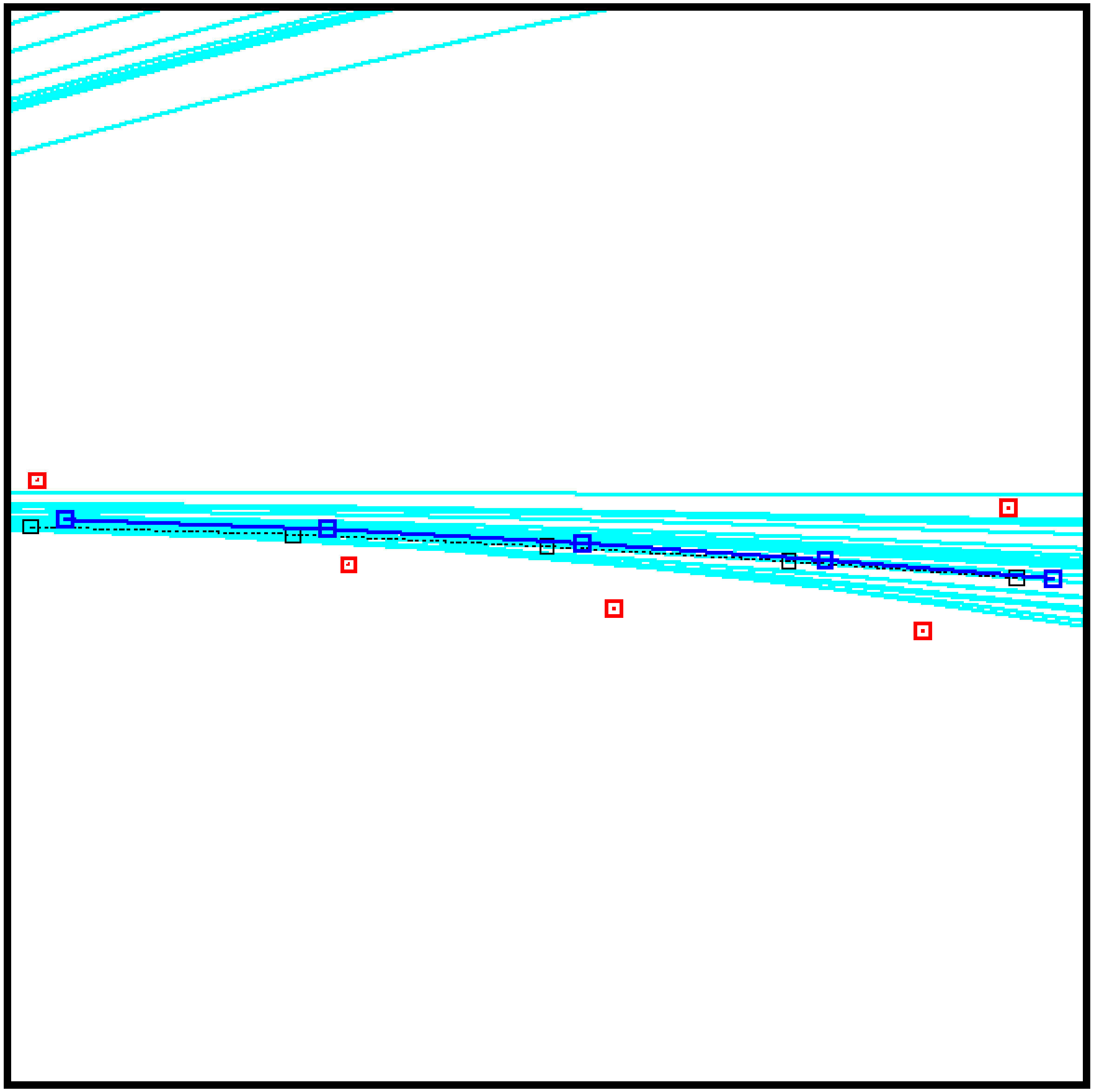
The Geometry of Model Error



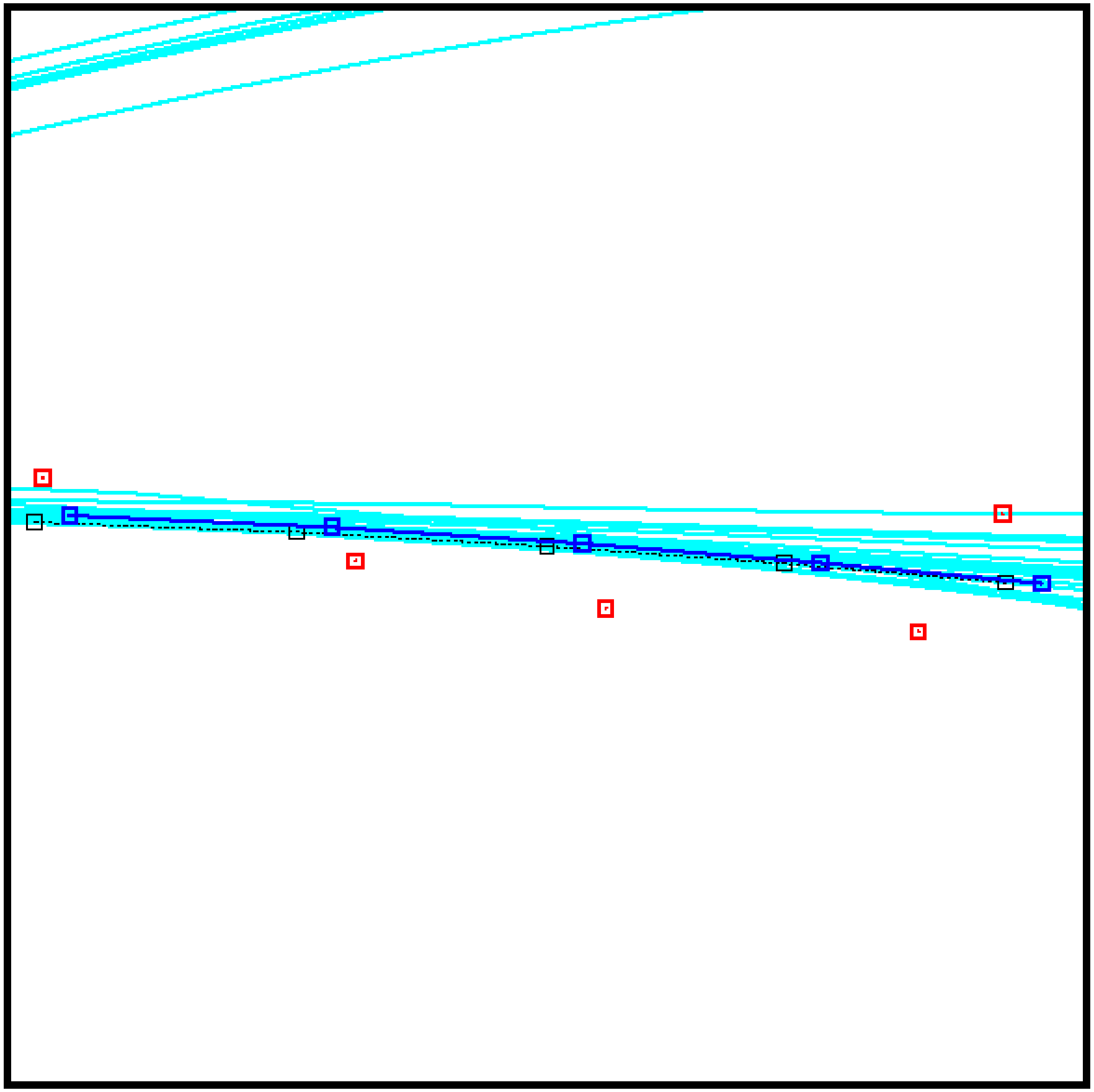
The Geometry of Model Error

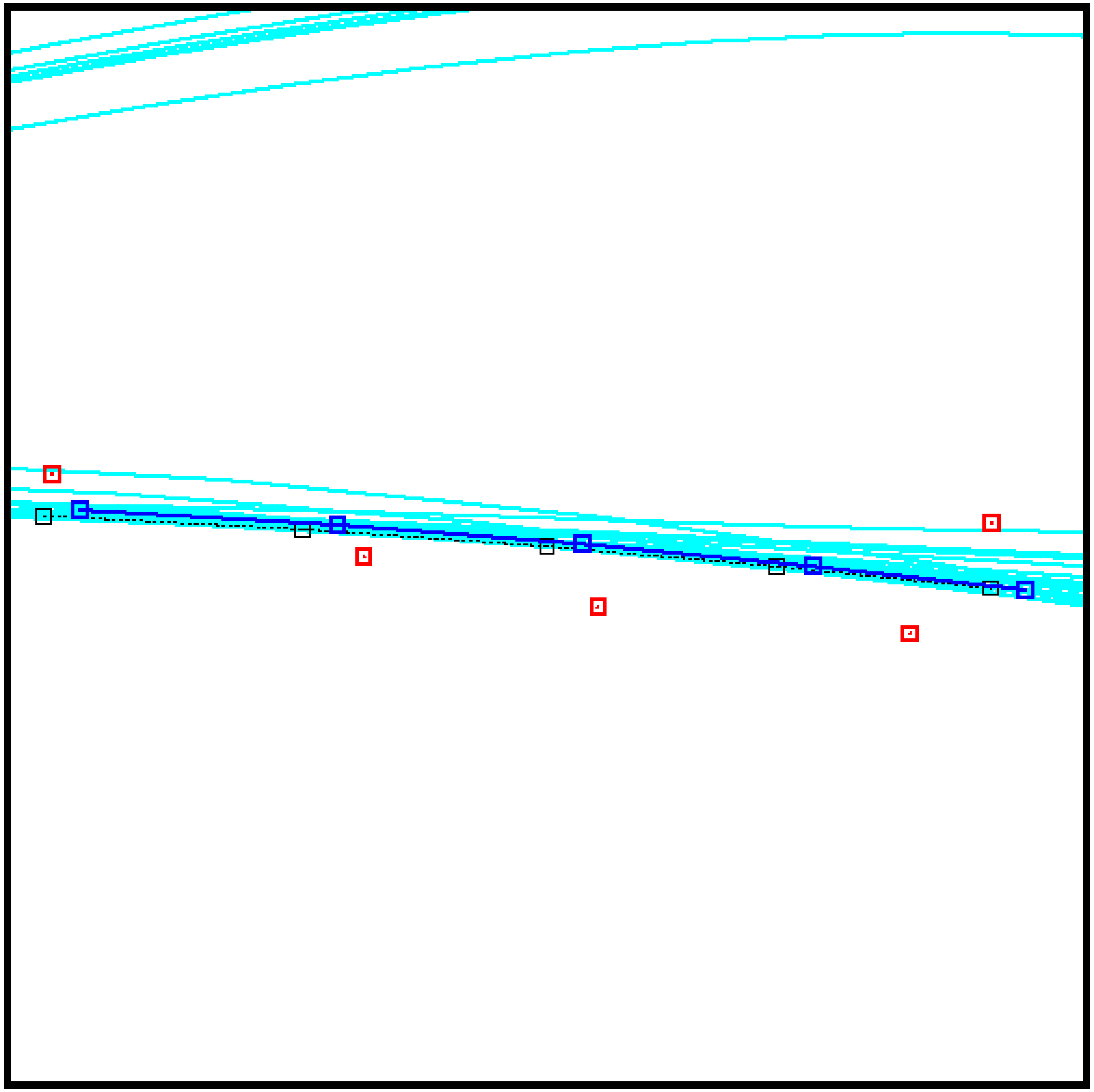


The Geometry of Model Error

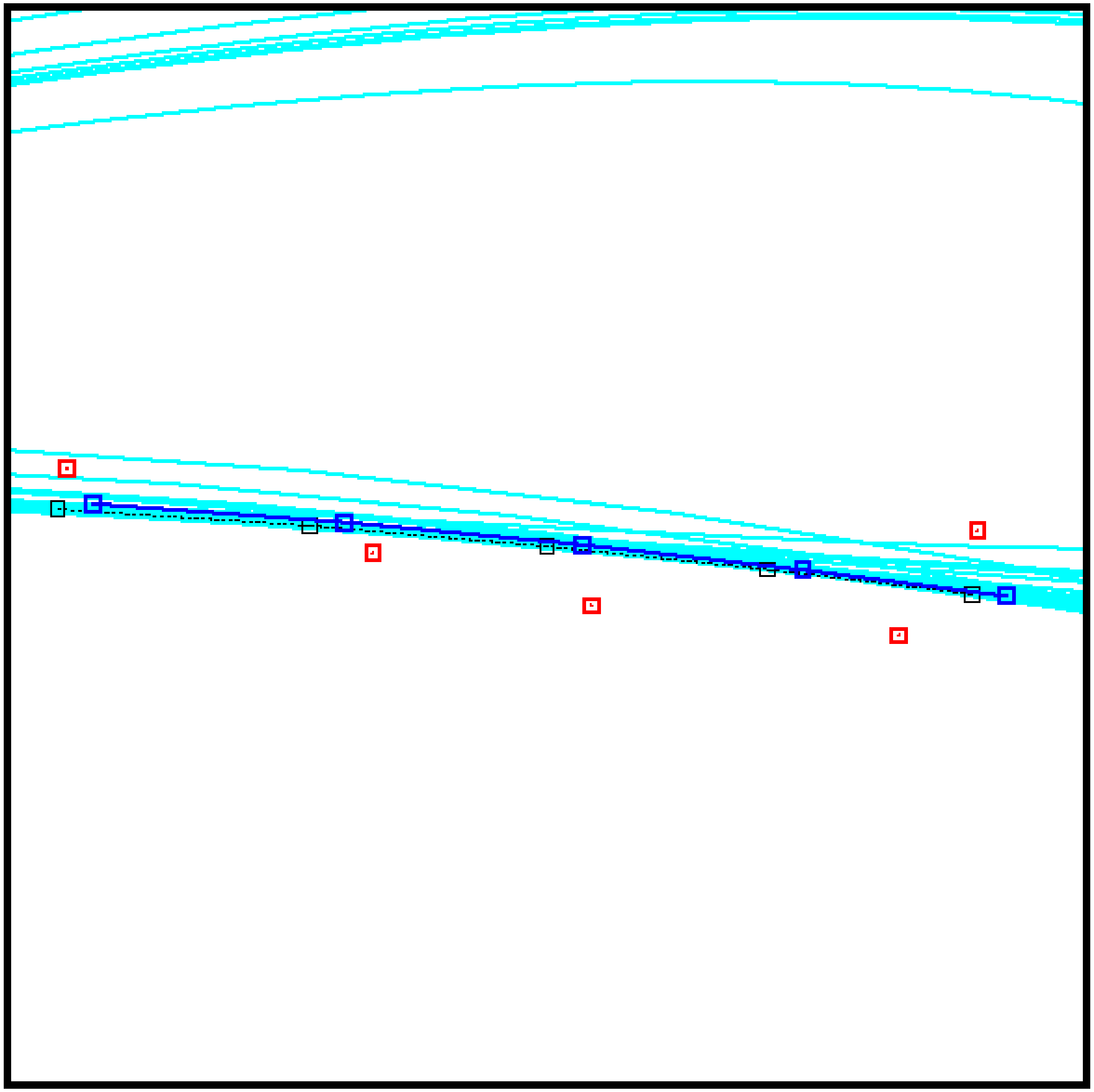


The Geometry of Model Error





The Geometry of Model Error

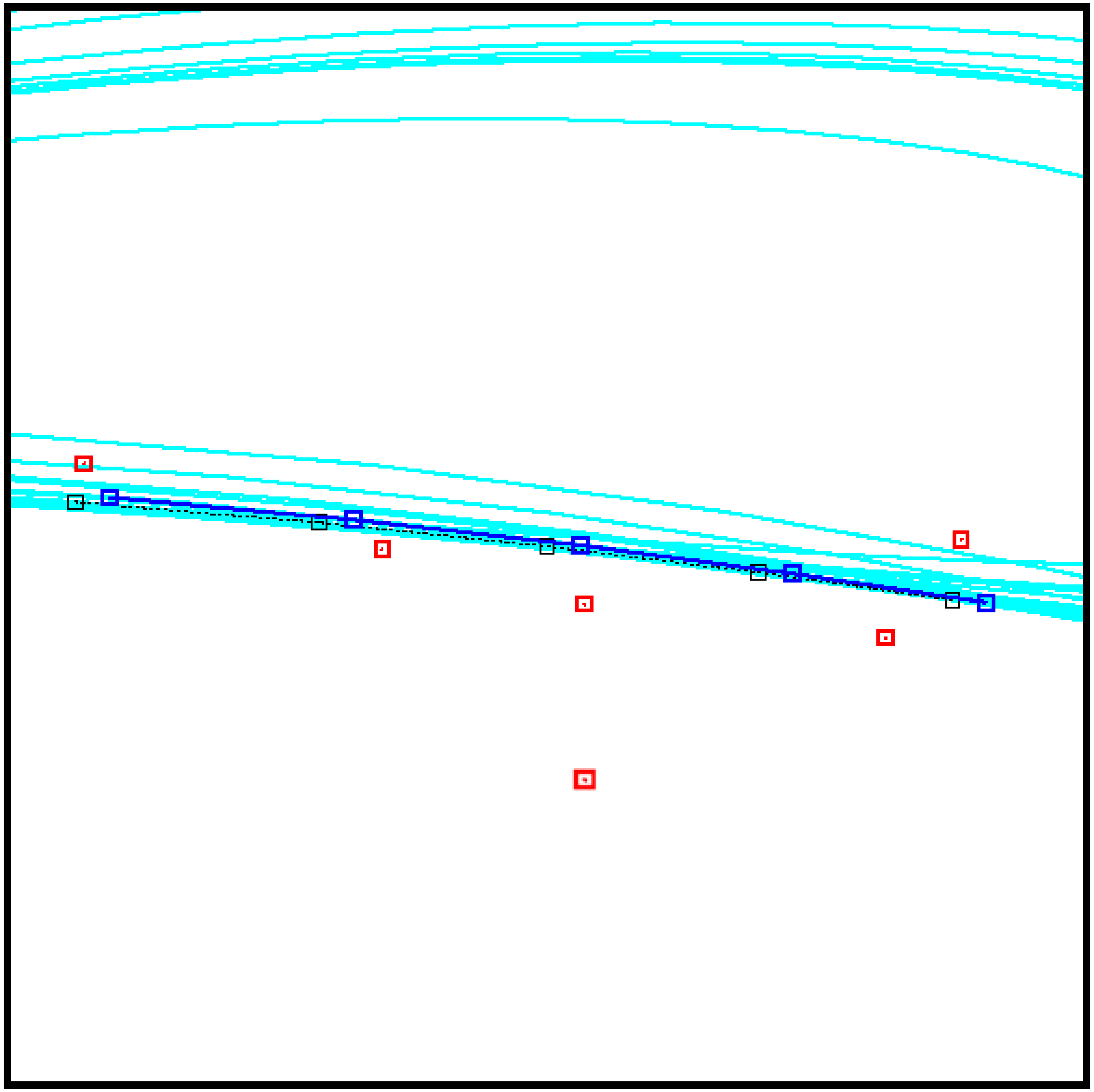


The trajectory is near the natural manifold; the obs are not!

(Near defined rather poorly using the noise model!)

The trajectory is also near to (but different from) the segment of truth that generated the obs.

The Geometry of Model Error

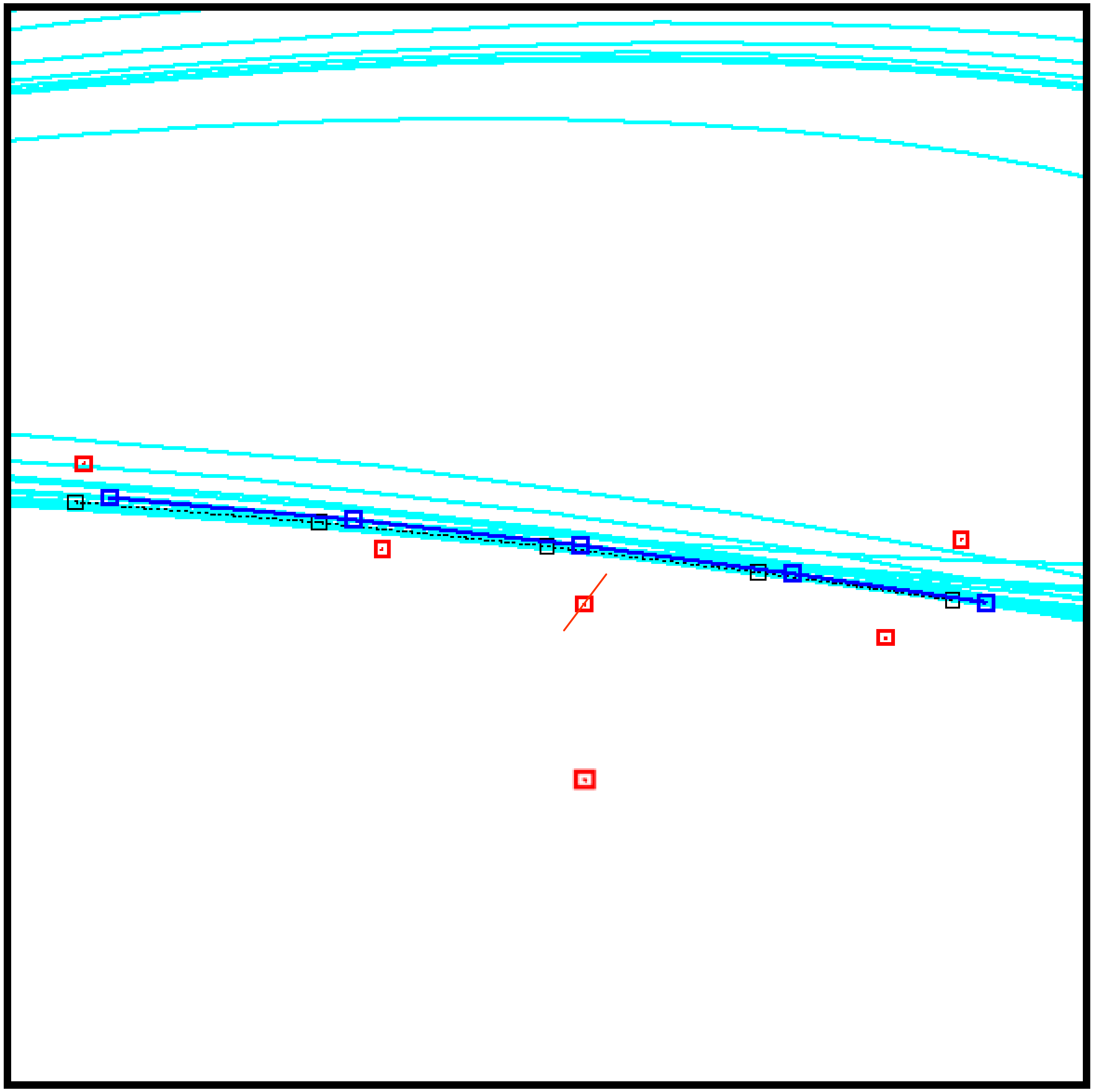


This is achieved by paying more attention to the dynamics over the window. Statistical properties of the trajectory from the observations are secondary.

This proves remarkably robust either:

- when the model is perfect
- in high-dimensional spaces

The Geometry of Model Error

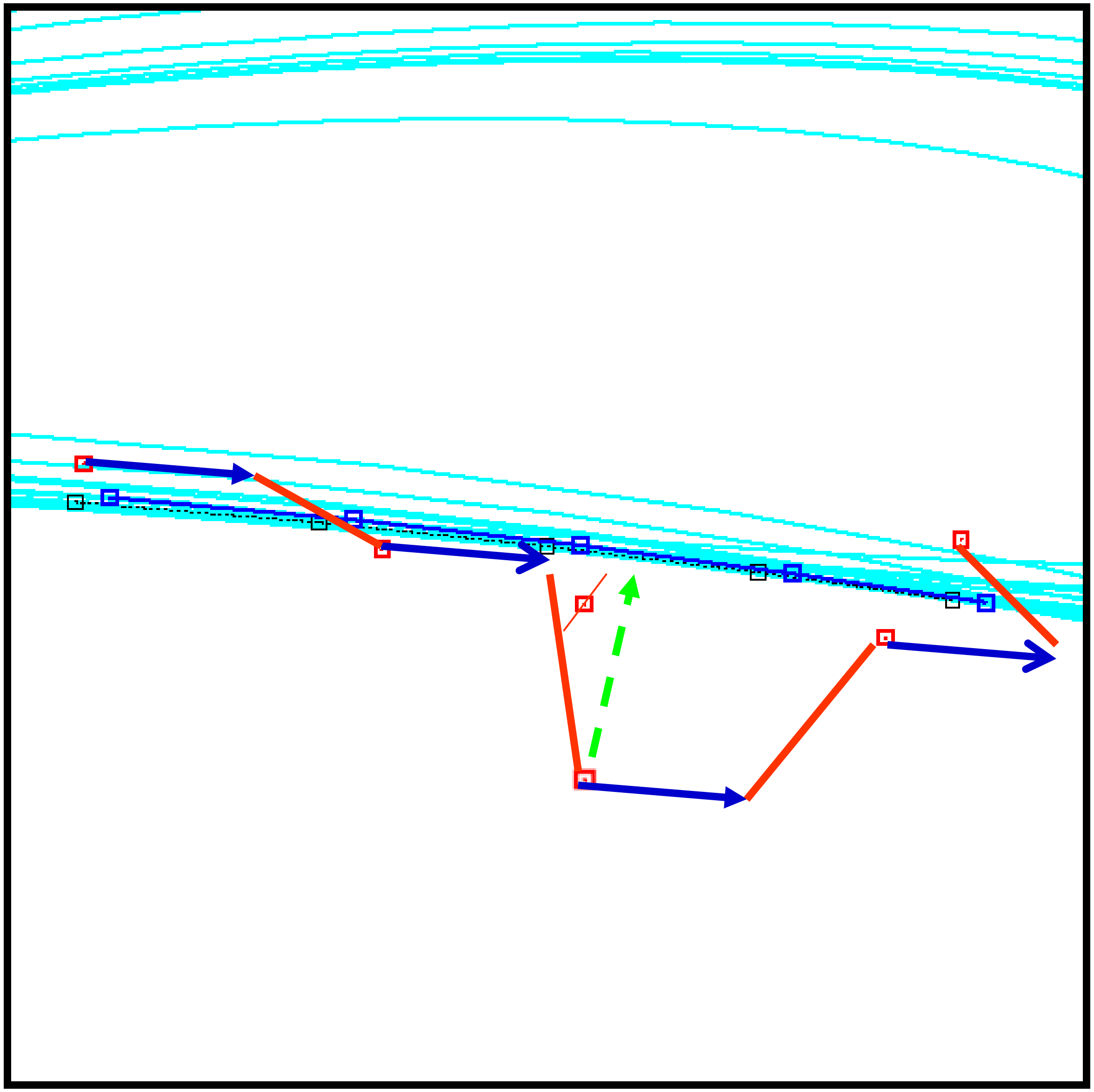


Suppose the observation at t=3 had been significantly in error.

The shadowing filter can recover using observations from t=4 and beyond, in a manner that sequential filters cannot.

In the shadowing filter, the mismatch at t=3 and t=4 is decreased by bringing the estimated state at t=3 back toward the model manifold

The Geometry of Model Error



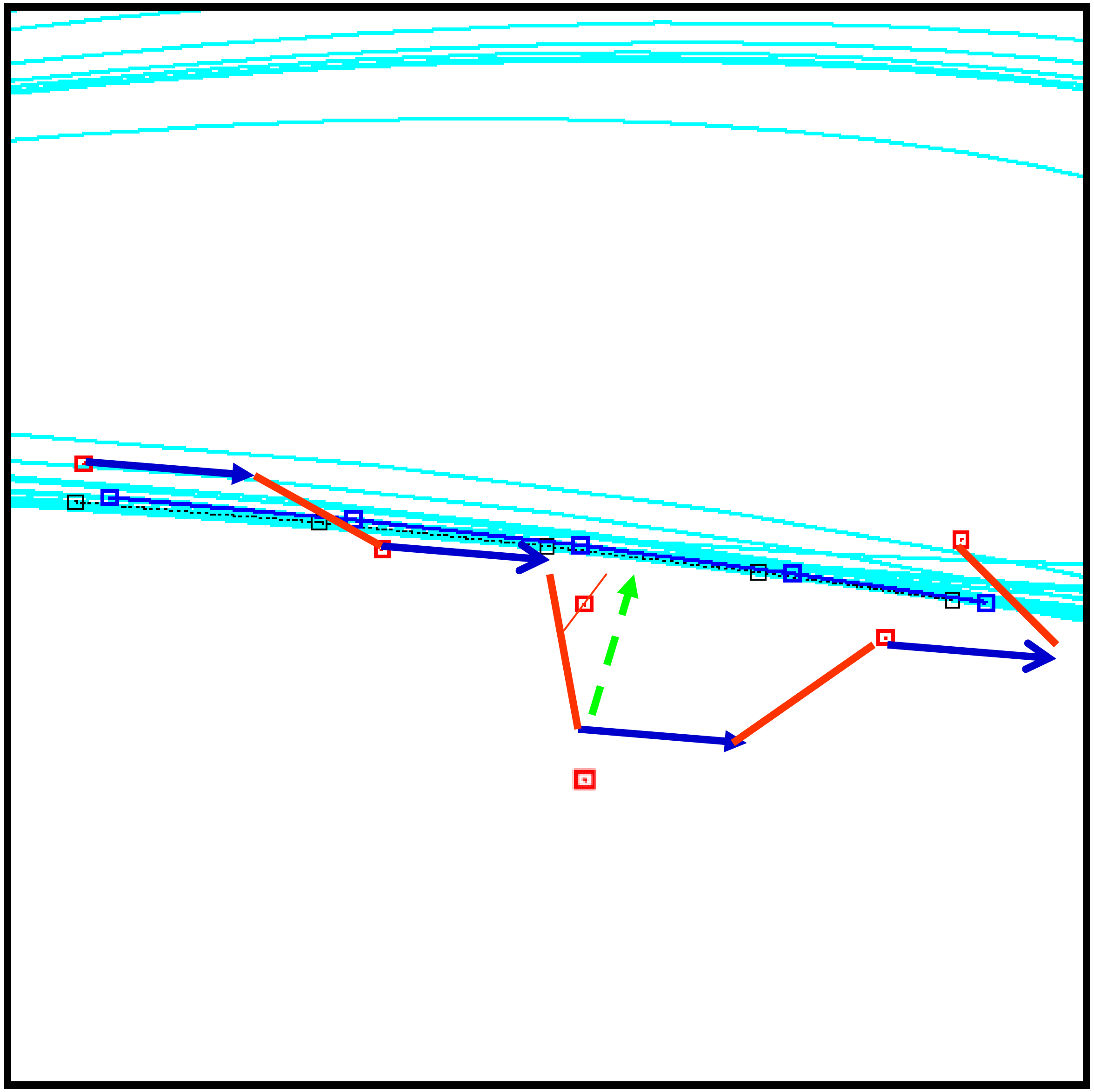
Suppose the observation at t=3 had been significantly in error.

The shadowing filter can recover using observations from t=4 and beyond, in a manner that sequential filters cannot.

In the shadowing filter, the mismatch at t=3 and t=4 is decreased by bringing the estimated state at t=3 back toward the model manifold

Sequential filters do not have access to this multi-step information.

The Geometry of Model Error



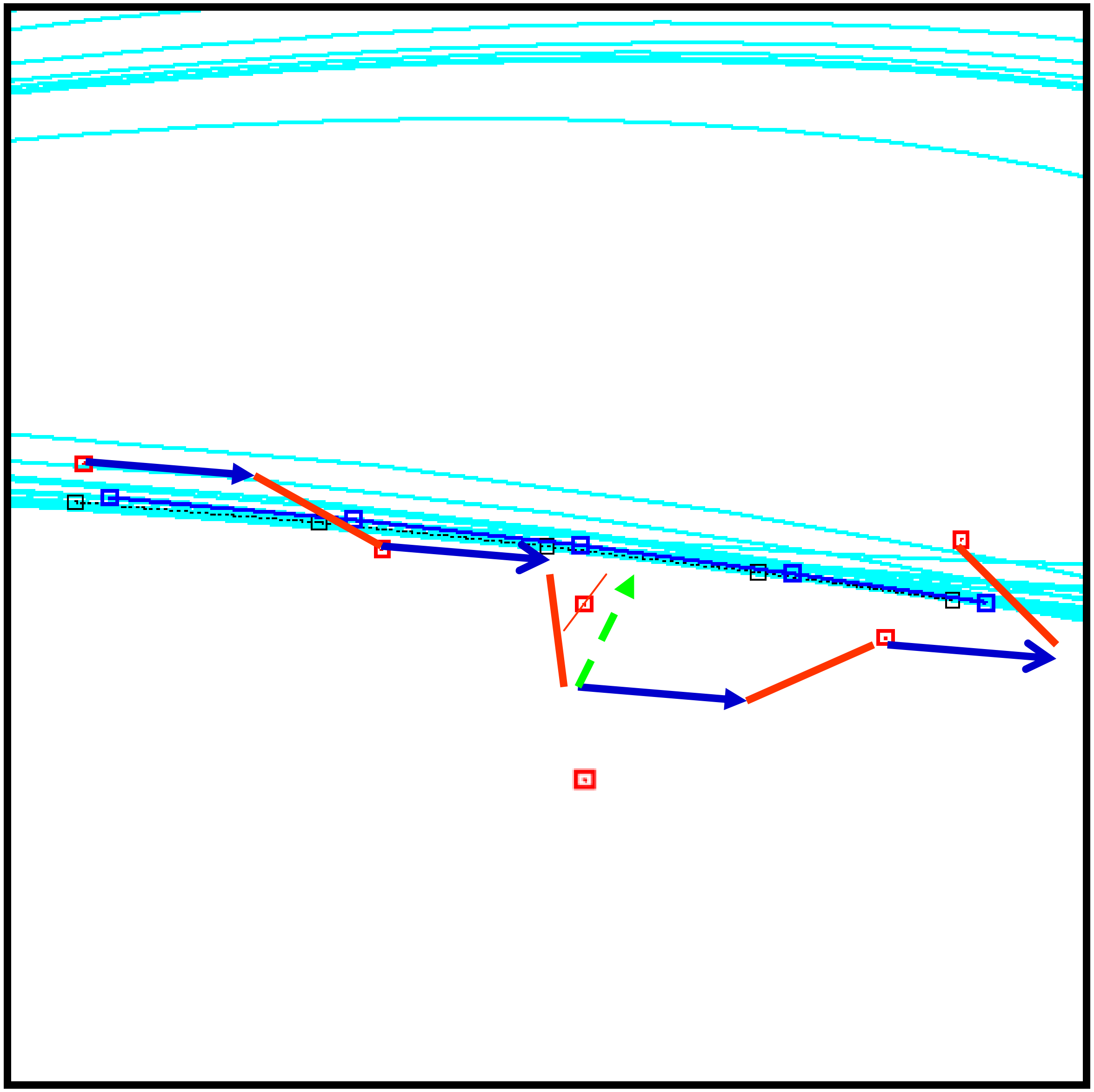
Suppose the observation at t=3 had been significantly in error.

The shadowing filter can recover using observations from t=4 and beyond, in a manner that sequential filters cannot.

In the shadowing filter, the mismatch at t=3 and t=4 is decreased by bringing the estimated state at t=3 back toward the model manifold

Sequential filters do not have access to this multi-step information.

The Geometry of Model Error



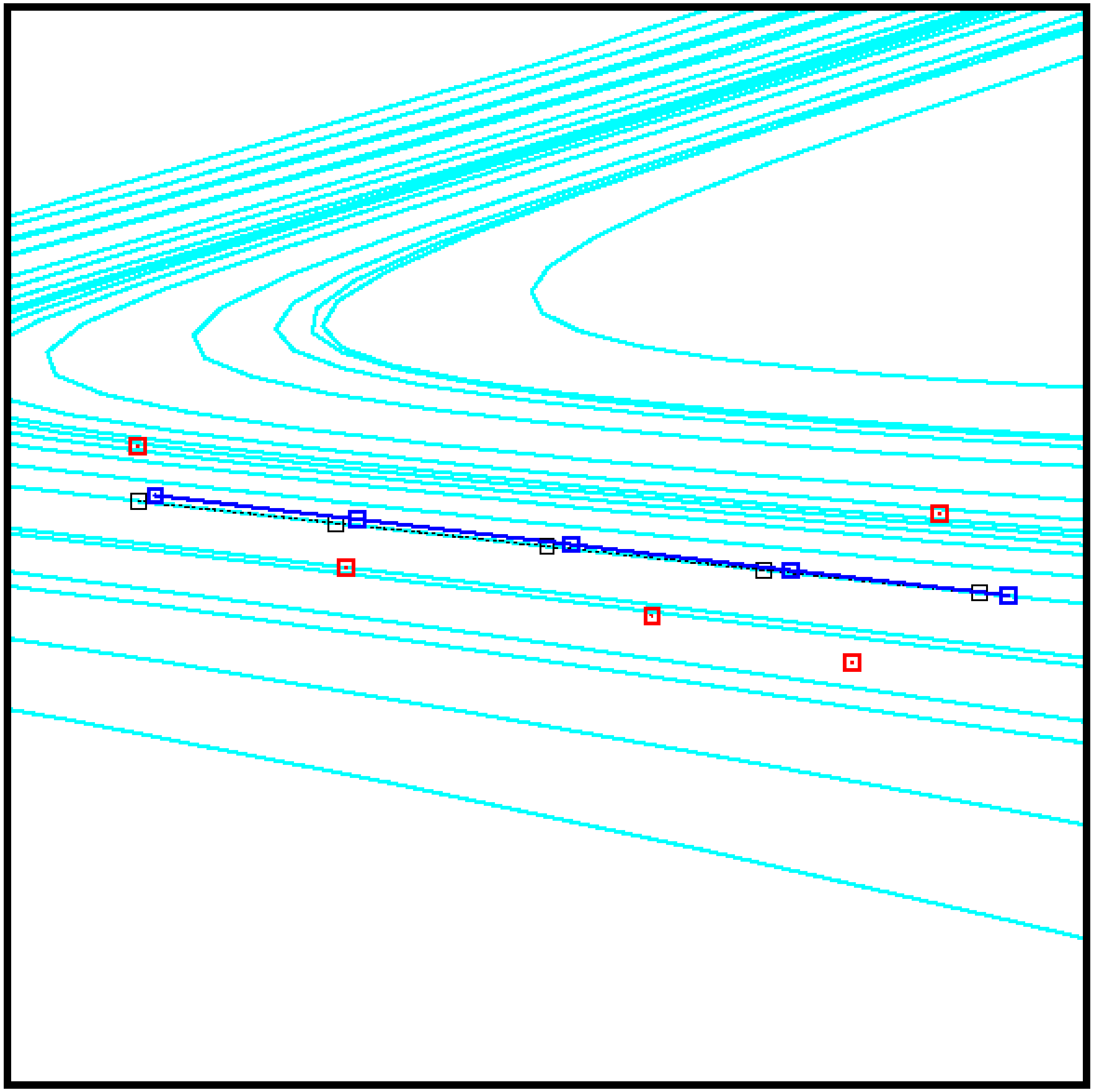
Suppose the observation at t=3 had been significantly in error.

The shadowing filter can recover using observations from t=4 and beyond, in a manner that sequential filters cannot.

In the shadowing filter, the mismatch at t=3 and t=4 is decreased by bringing the estimated state at t=3 back toward the model manifold

Sequential filters do not have access to this multi-step information.

The Geometry of Model Error



Given that we can find one such trajectory near the obs, we can create an ensemble form the set of indistinguishable states of that (and similar) trajectories, and then draw from that set conditioned on how well each member compares with the observations.

(Judd & Smith, Physica D Indistinguishable States I, 2001 Indistinguishable States II, 2004)

The aim of data assimilation in this case is an accountable probability forecast:

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

How does this compare with En KF :Shree (student of JA))

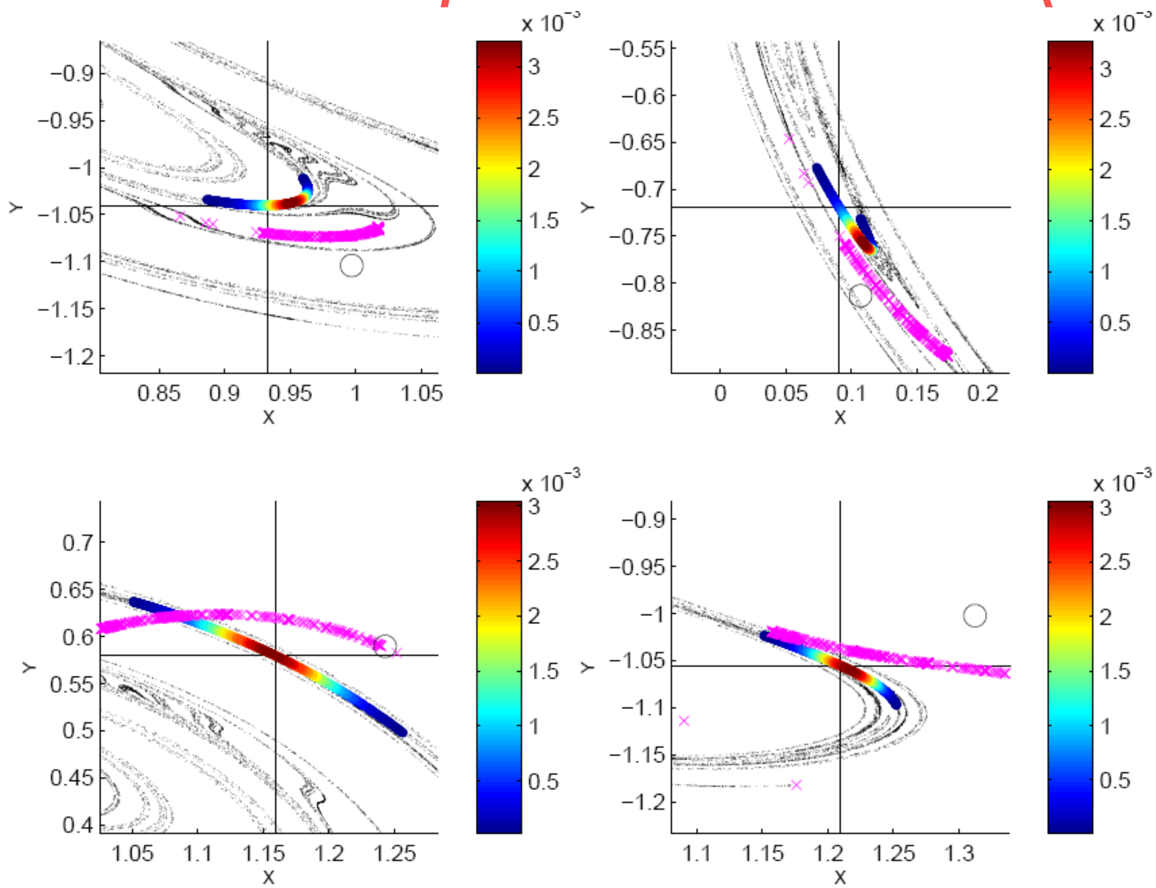


FIG. 7. Results for the Ikeda model. The upper left panel consists of a snapshot of $K = 1000$ member IS and EN ensembles. The target is located at the intersection of the two lines, where as the observation is depicted by the circle. The EN ensemble is depicted by the 1000 magenta crosses. The EN ensemble members are equally likely and are therefore given the same color. The colored dots depict the weighted ensemble obtained via the IS method. The coloring indicates their relative likelihood given observations from t_{992} to t_{1001}. The upper right, lower left and lower right panels depict ensembles for the next 3 observation times.

Khare & LAS, in press MWR

Grantham Research Insti
Climate Change ar
the Environment

Deployed: m=2, m=18, T20/T21, NOGAPS

K Judd, CA Reynolds, TE Rosmond & LA Smith (2008) The Geometry of Model Error . *Journal of Atmospheric Sciences 65 (6), 1749-1772.*

[74] J Bröcker & LA Smith (2008) From Ensemble Forecasts to Predictive Distribution Functions *Tellus A 60(4): 663.*

Chemical Engineering Research and Design, **82**(A), 1-10 SCI 4. Abstract

[66] K Judd & LA Smith (2004) Indistinguishable States II: The Imperfect Model Scenario. *Physica D* **196**: 224-242.

PE McSharry and LA Smith (2004) Consistent Nonlinear Dynamics: identifying model inadequacy, *Physica D 192: 1-22.*

K Judd, LA Smith & A Weisheimer (2004) Gradient Free Descent: shadowing and state estimation using limited derivative information, *Physica D 190 (3-4): 153-166.*

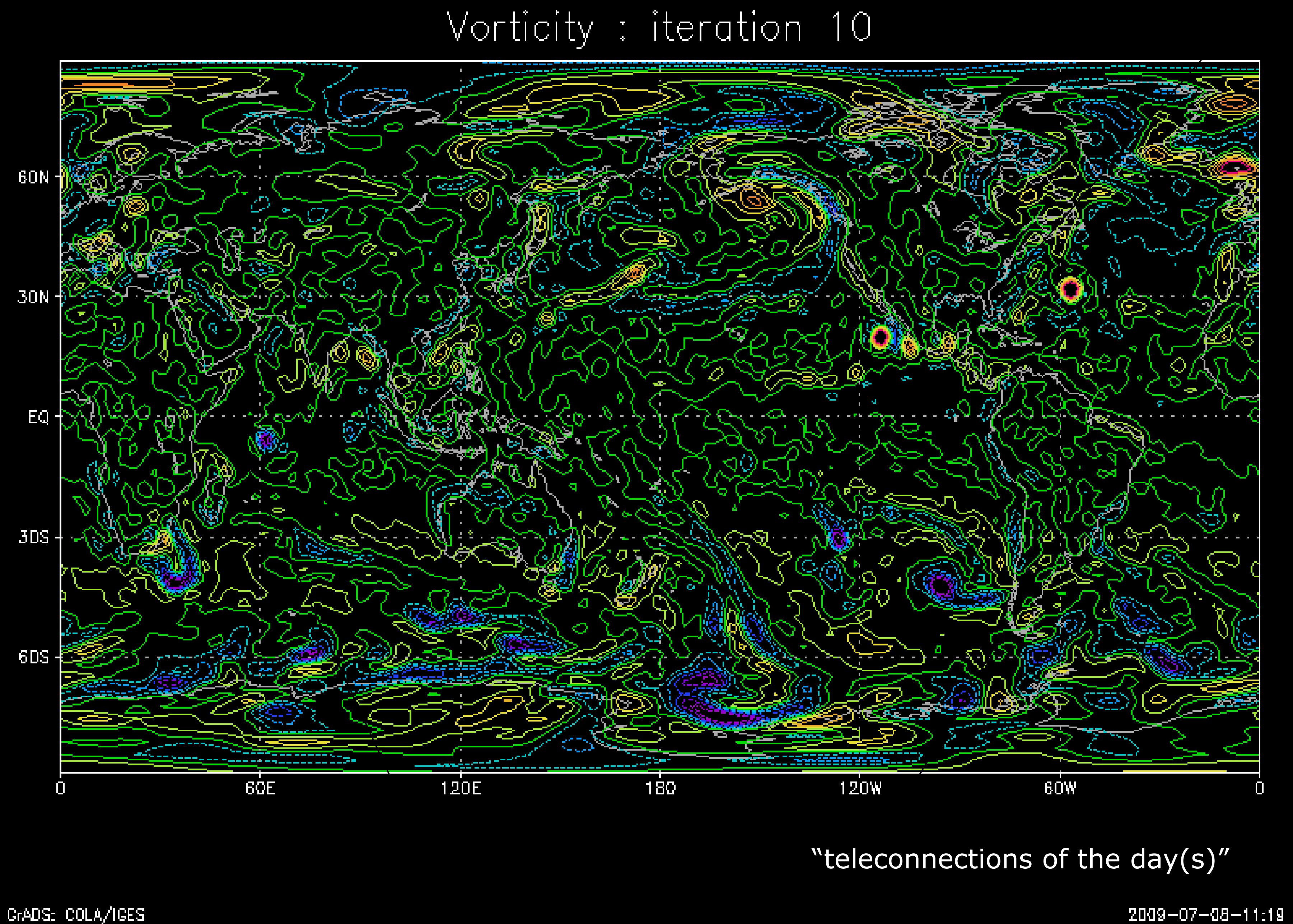
LA Smith (2003) Predictability Past Predictability Present. In 2002 ECMWF Seminar on Predictability. pg 219-242. ECMWF, Reading, UK.

D Orrell, LA Smith, T Palmer & J Barkmeijer (2001) Model Error in Weather Forecasting, *Nonlinear Processes in Geophysics 8: 357-371.*

K Judd & LA Smith (2001) Indistinguishable States I: The Perfect Model Scenario, *Physica D 151: 125-141.*

L.A. Smith, M.C. Cuéllar, H. Du, K. Judd (2010) Exploiting dynamical coherence: A geometric approach to parameter estimation in nonlinear models, Physics Letters A, 374, 2618-2623

Thanks to Kevin Judd



"teleconnections of the day(s)"

Mismatch Directions Reveal Model Error

(a)

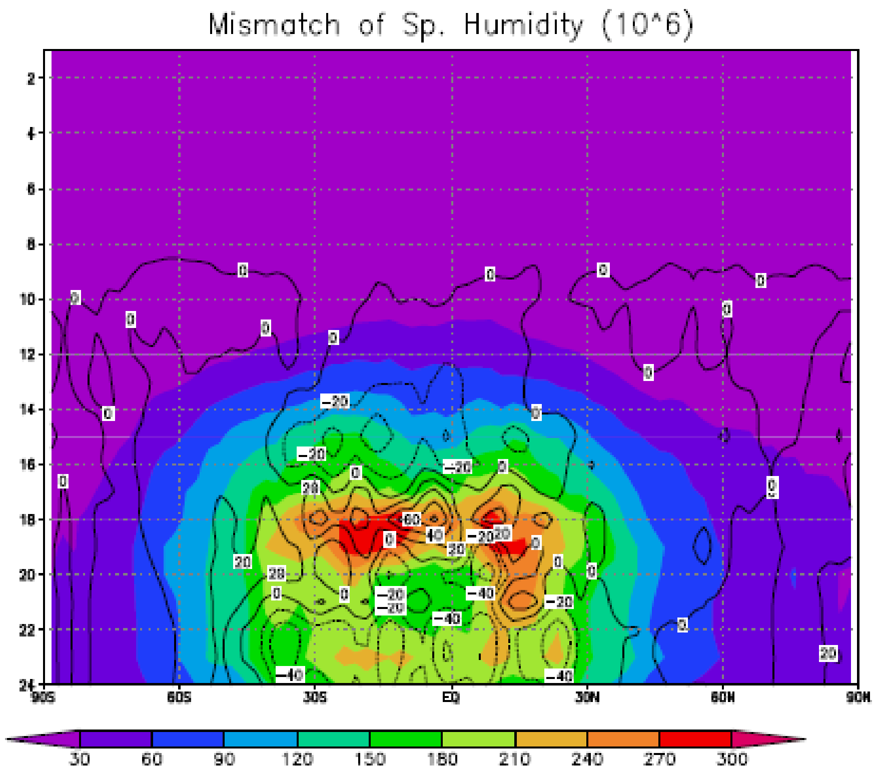


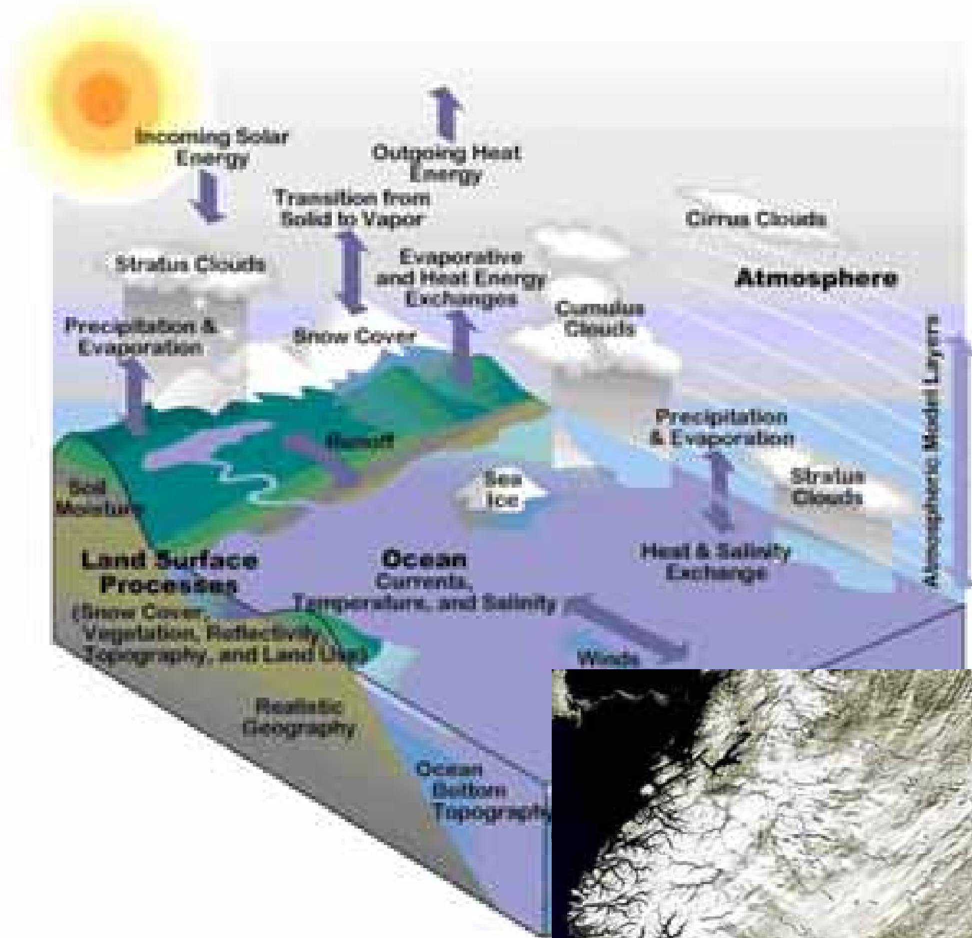
Figure 10: *Direction error for T47L24 and T79L30 models. Contour lines show mean error and shading shows standard deviation. Details as in figure9*

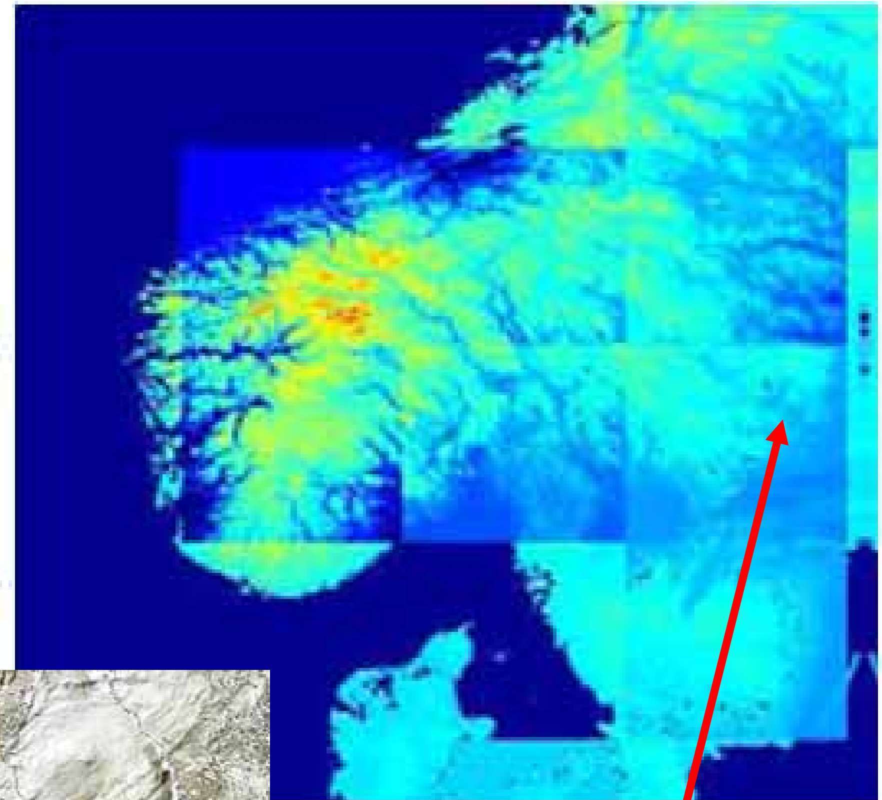
Grantham Research Institute on Climate Change and the Environment

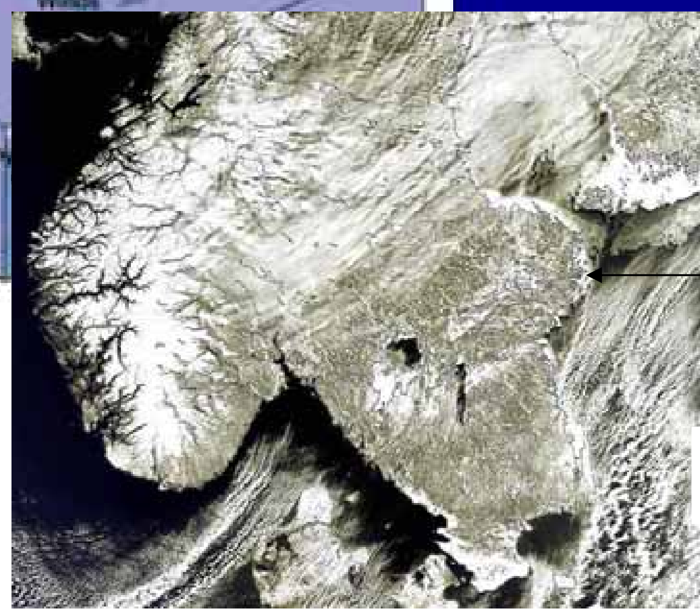
K Judd, CA Reynolds, LA Smith & TE Rosmond (2008) The Geometry of Model Error . Journal of Atmospheric Sciences 65 (6), 1749-1772

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

When a model looks too good to be true…







You are not here!

… it probably isn't.

Nordica 3 May 2011

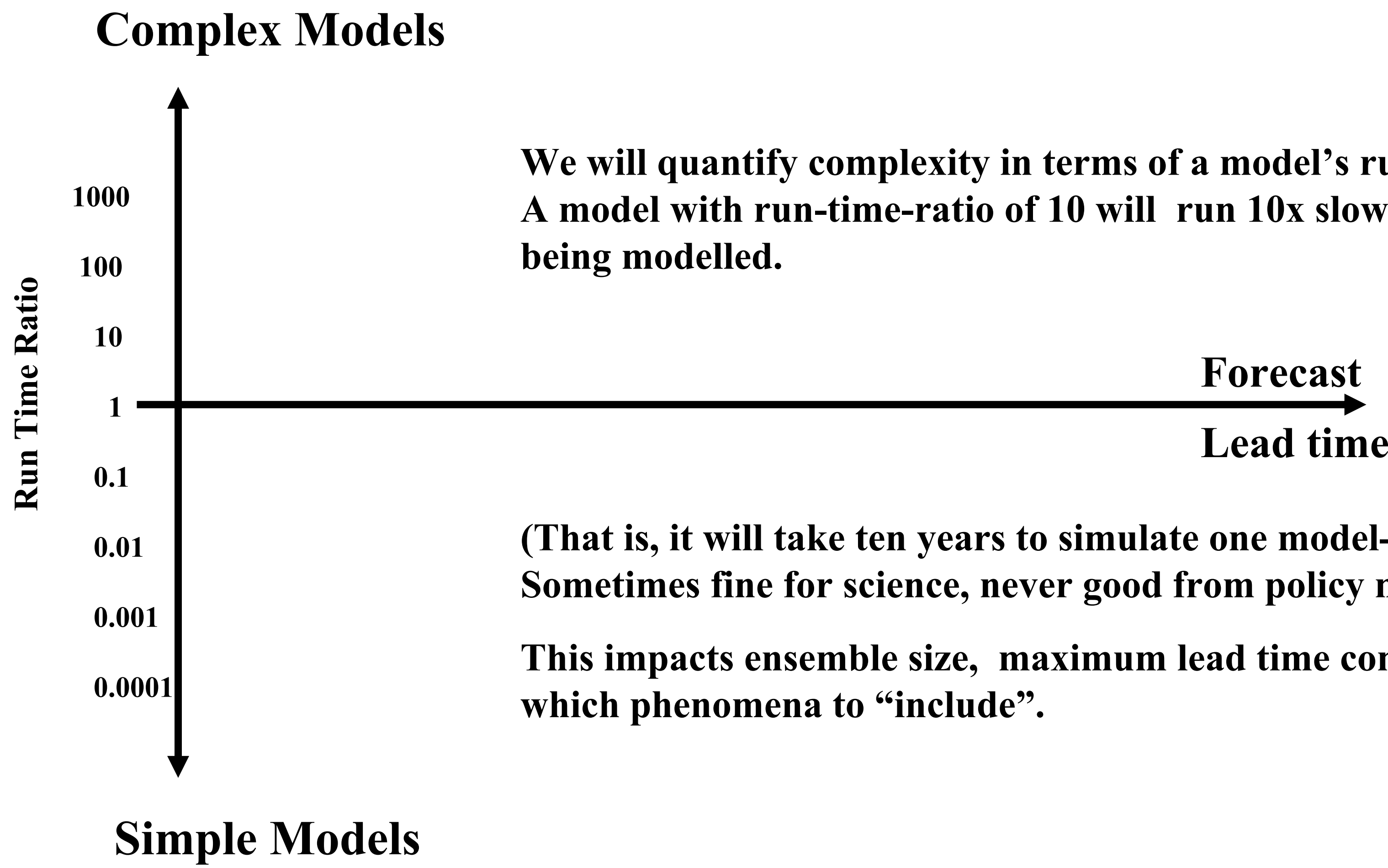
Grantham Research Institute on Climate Change and the Environment

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

How would you design a "climate" model?

What are you constrained by?

For decision support, the model has to run faster than real time.
The larger the lead time, the fewer ensemble members you can run to examine sensitivity.



We will quantify complexity in terms of a model's run-time-ratio. A model with run-time-ratio of 10 will run 10x slower than the system being modelled.

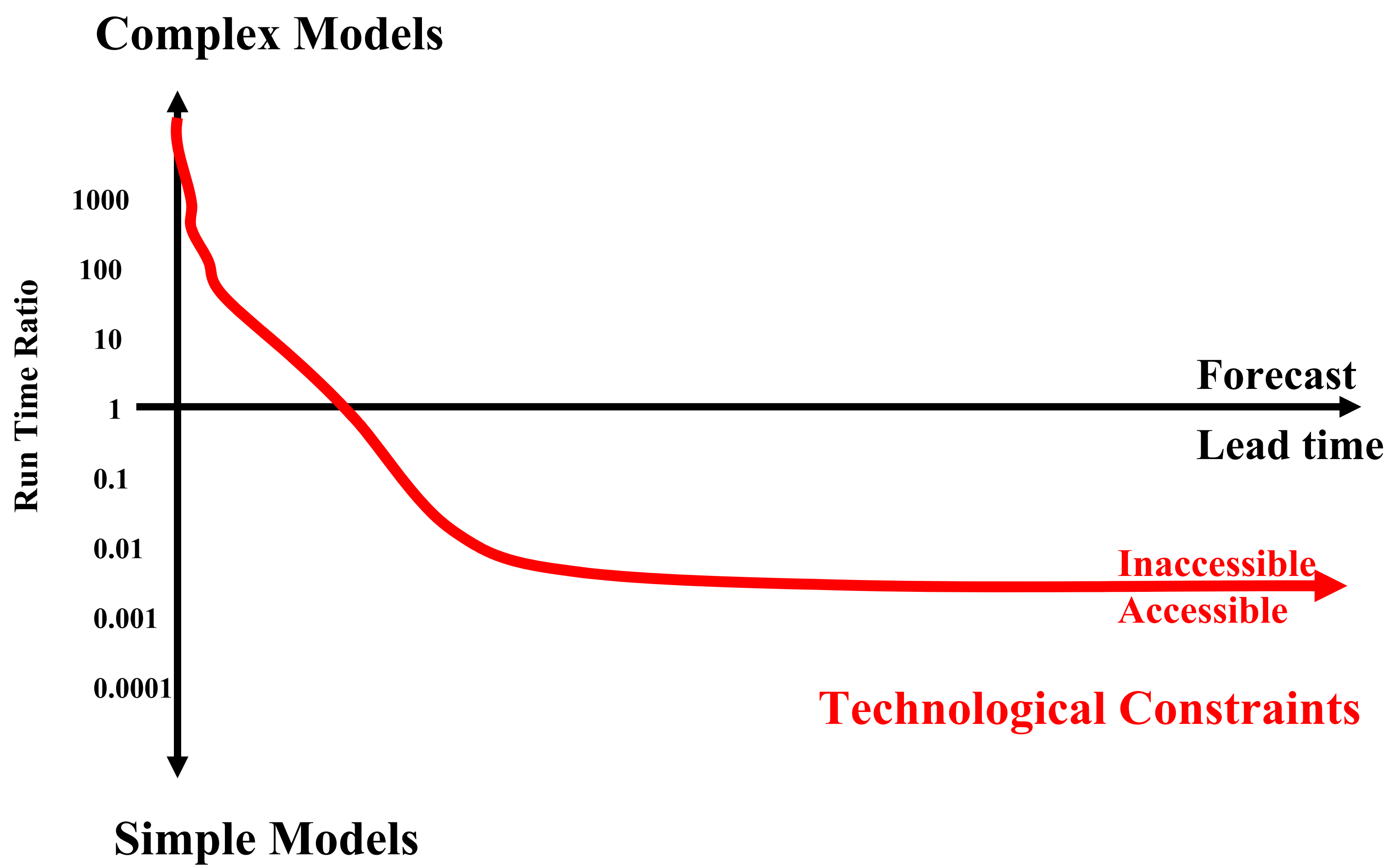
(That is, it will take ten years to simulate one model-year. Sometimes fine for science, never good from policy makers.)

This impacts ensemble size, maximum lead time considered, and which phenomena to "include".

How would you design a climate model?

What are you constrained by?

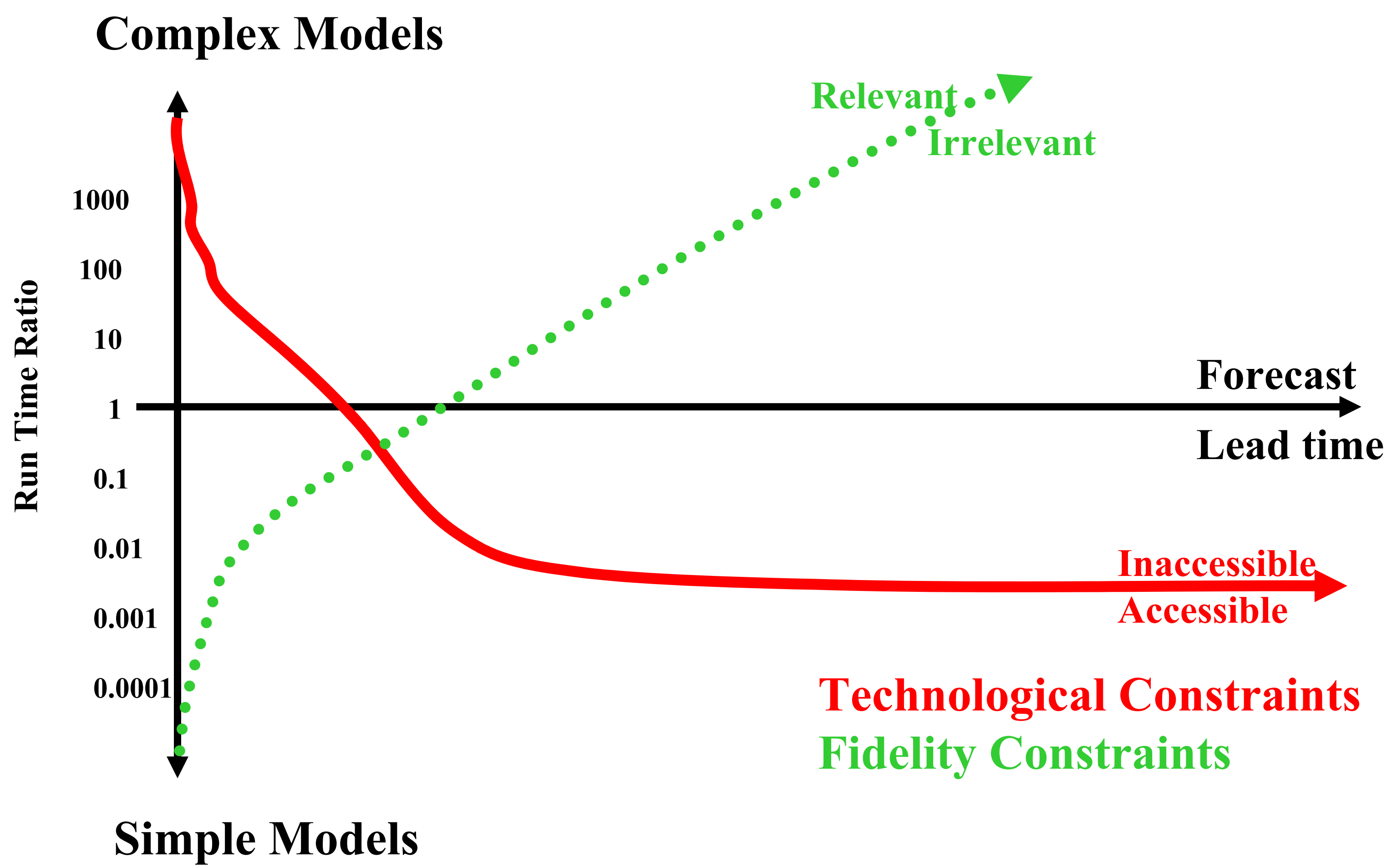
Complex models may not fit in current hardware, even if you know what you would build. And the more complex your model, the fewer "simulation hours" you will have.



How would you design a climate model?

What are you constrained by?

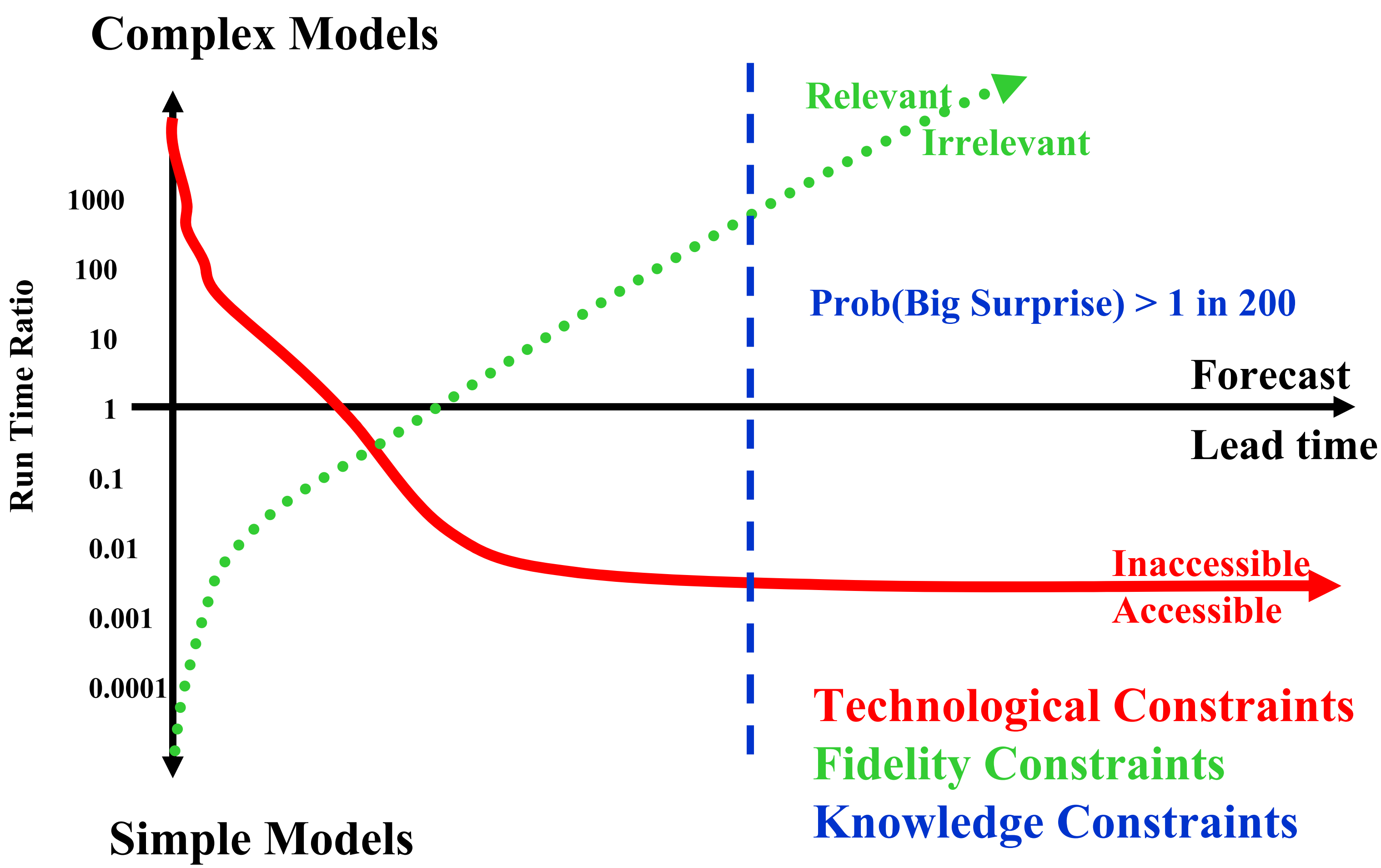
Requirements for model fidelity sets a lower bound on the complexity with lead time. Almost always, the model is required to grow more complex at larger lead times.



How would you design a climate model?

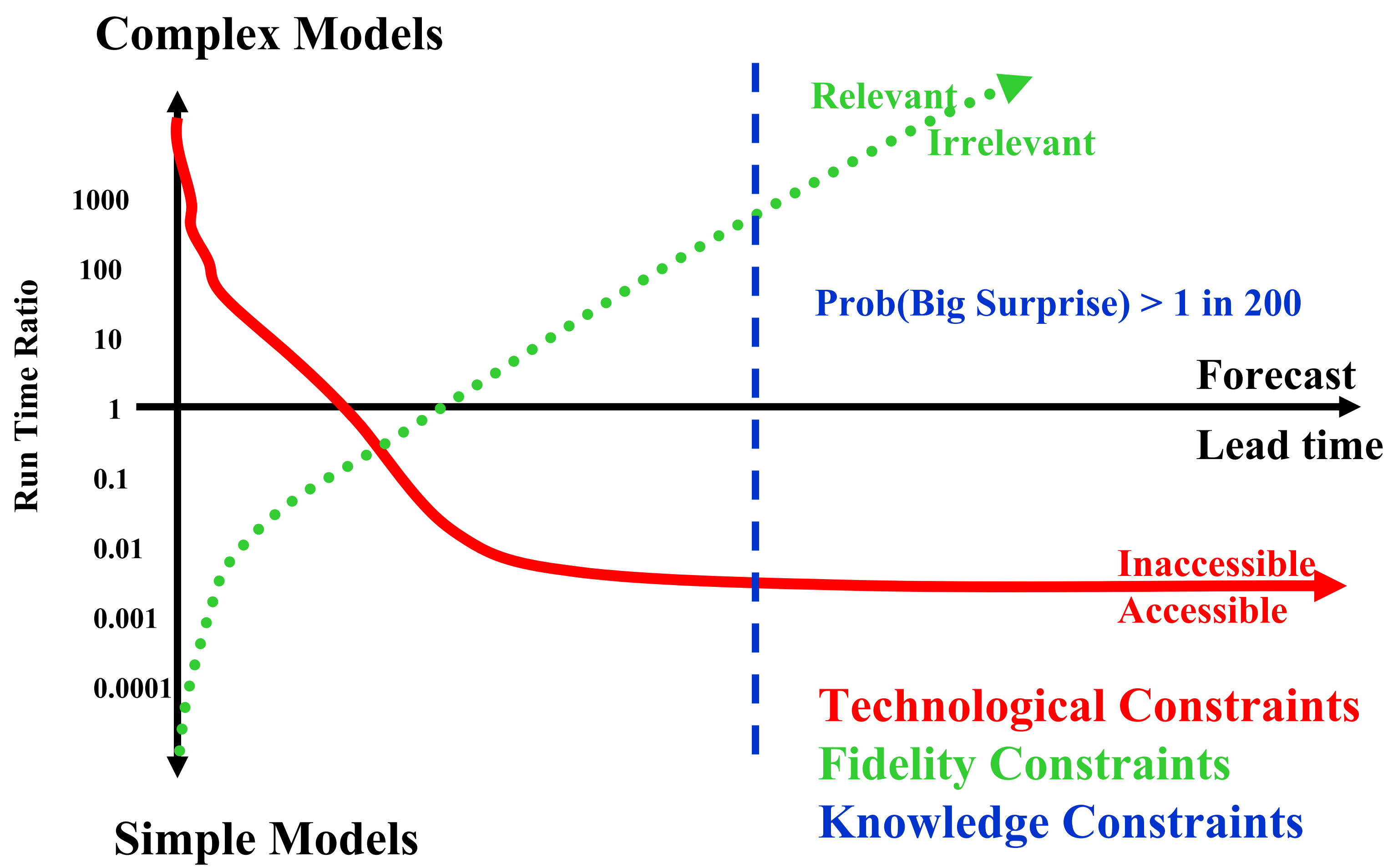
What are you constrained by?

Limits of current scientific/mathematical knowledge mean the model may *be expected to* prove inadequate.
Following the financial sector, we will tolerate this as long as the Prob(Big Surprise) < 0.05



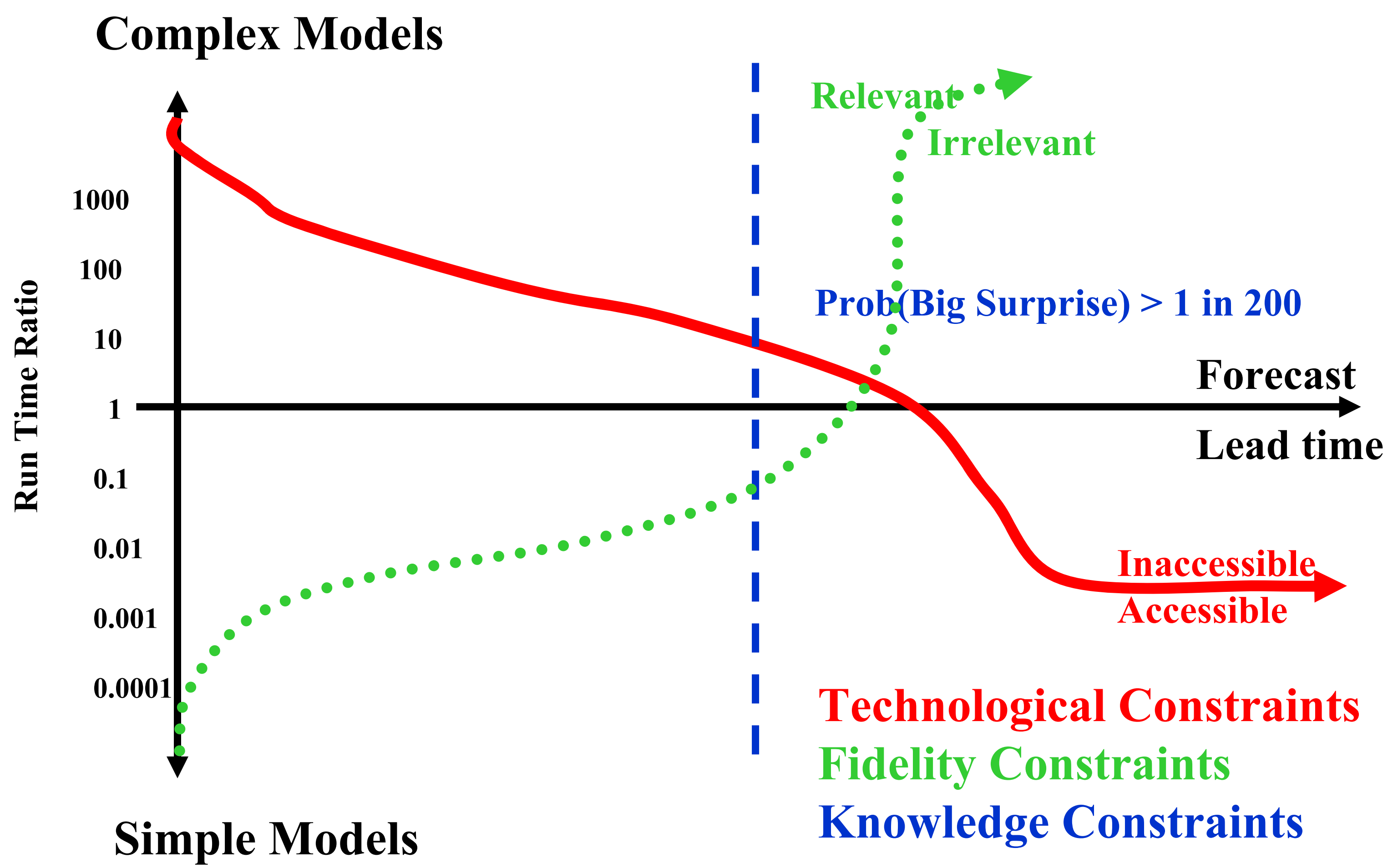
How would you design a climate model?

The decision you take will depend on how these three curves lie.



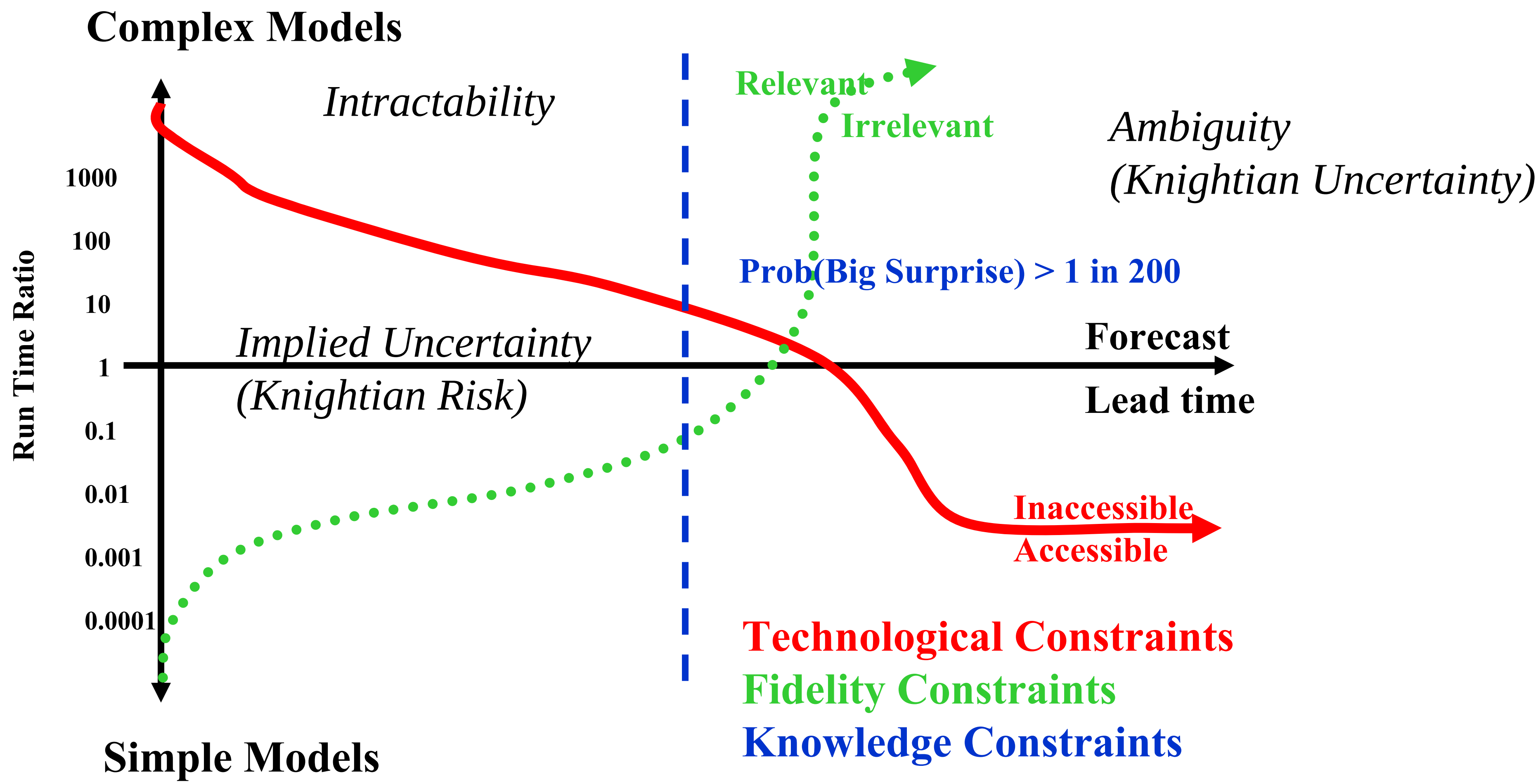
How would you design a climate model?

The decision you take will depend on how these three curves lie.



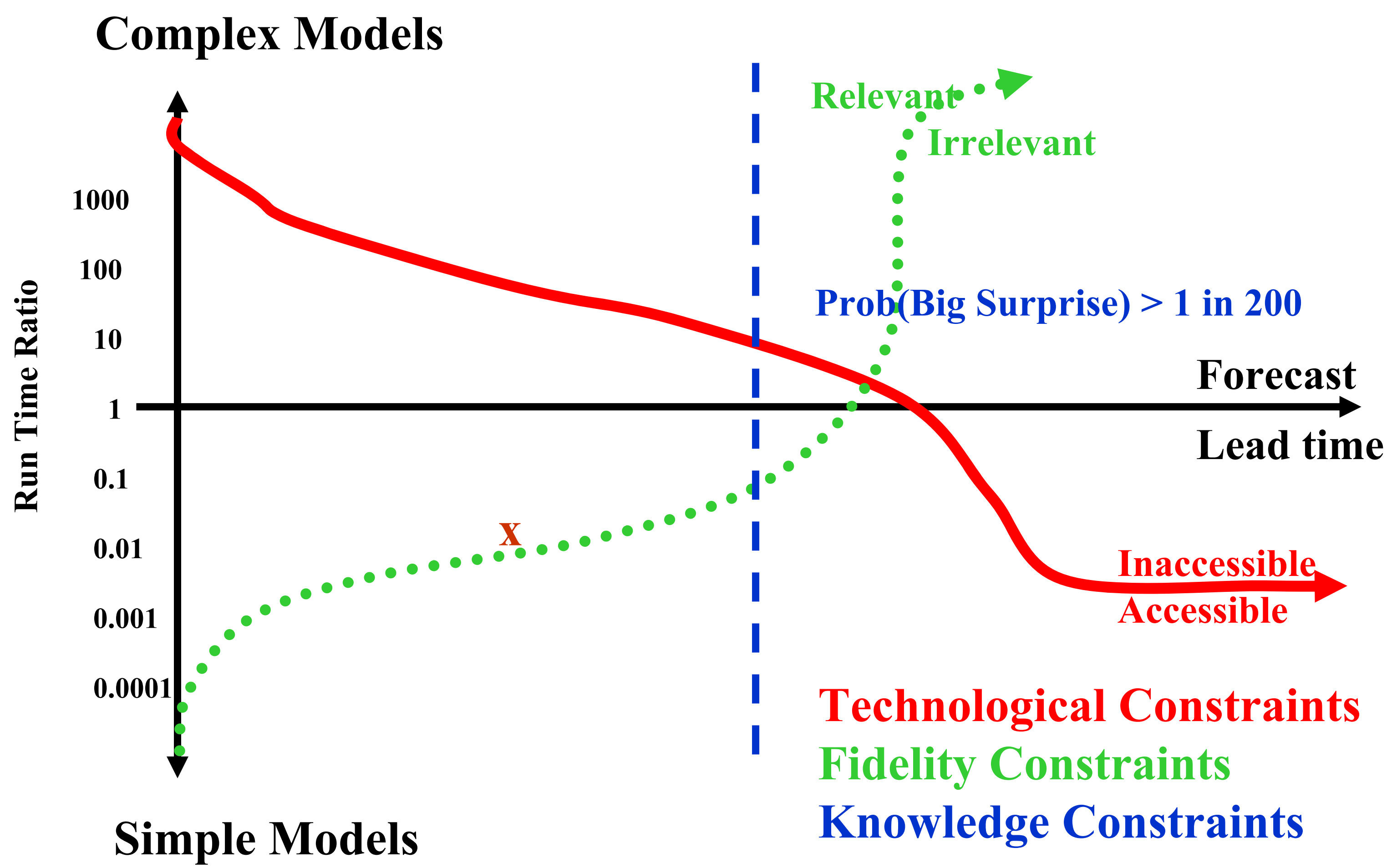
How would you design a climate model?

What are the challenges we face with interpreting model simulations in different regions of this schematic?



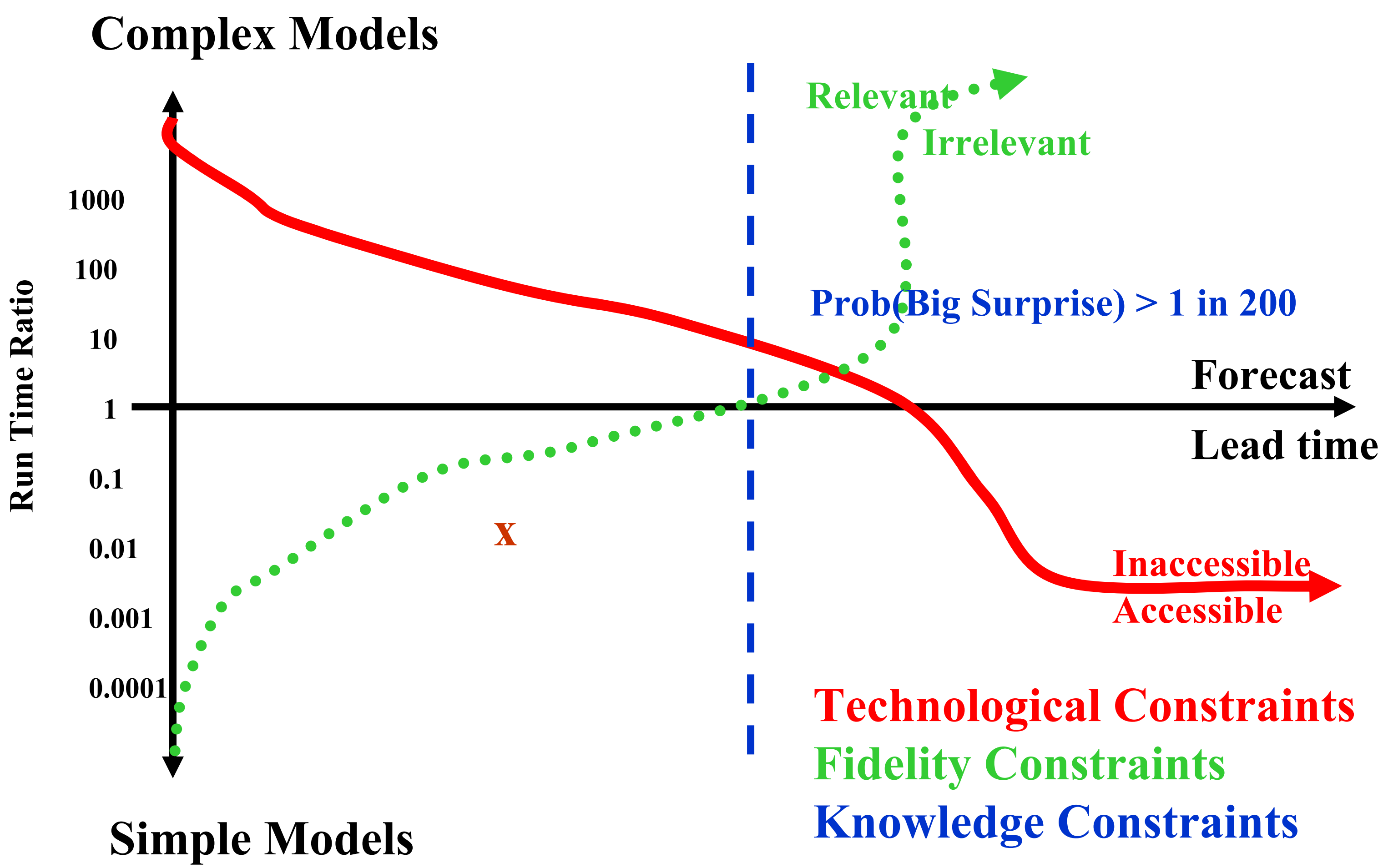
How would you design a climate model?

We need to be above the green line, below the red, and to the left of the blue.
So we could make a relevant 100 year simulation and have it a year from now.



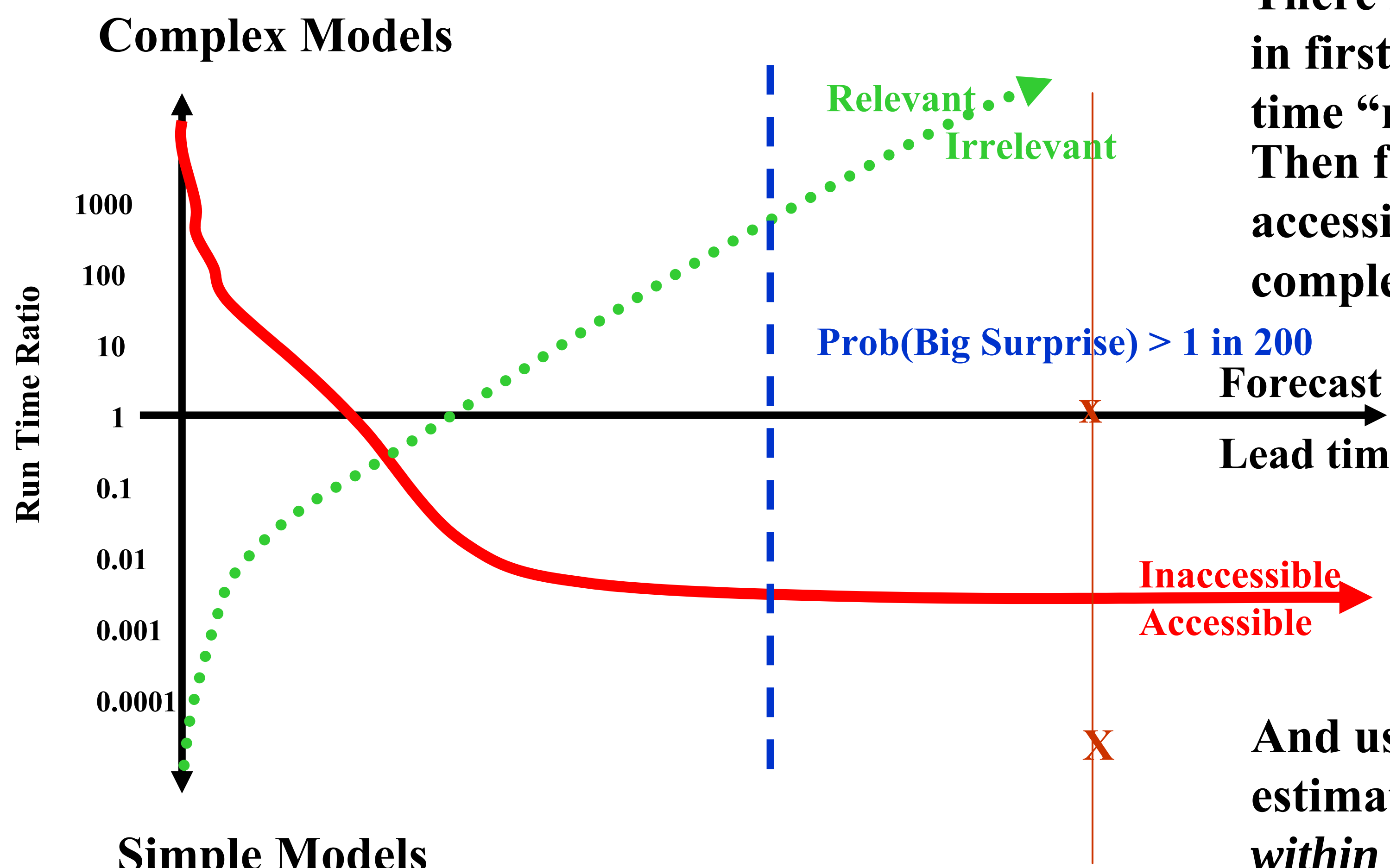
How would you design a climate model?

But in this case, this “100 year” model is out of our reach.
Of course we can build it anyway, call it “best available” knowing it is both best and irrelevant; and pass it on (saying clearly that Prob(B.S.)~1)



Technological Constraints
Fidelity Constraints
Knowledge Constraints

Decision Support Model Model (Design to deliver)

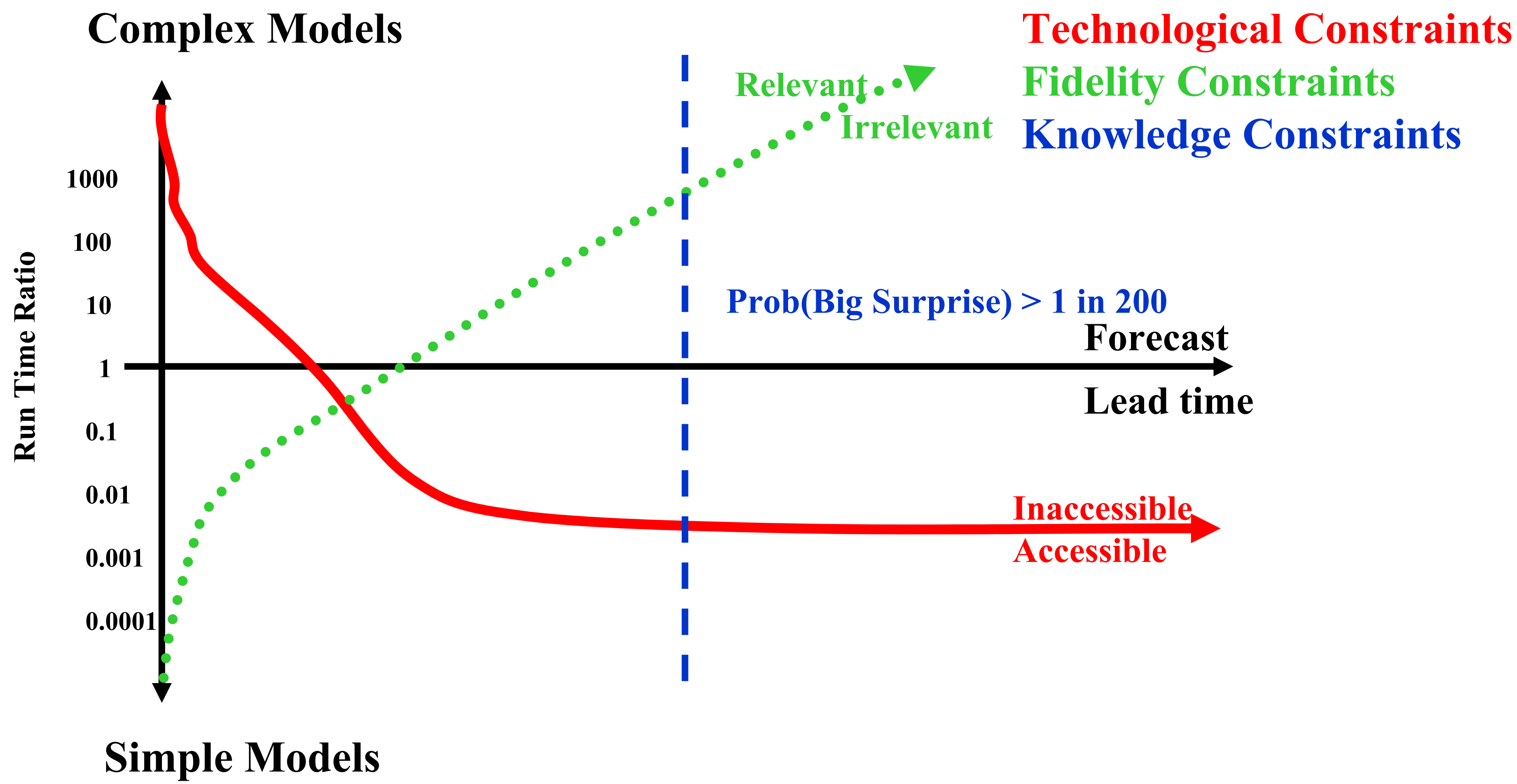


There is some danger in first picking the lead time "required." Then finding an accessible level of complexity

And using ensembles to estimate "uncertainty" *within* an irrelevant model.

Technological Constraints
Fidelity Constraints
Knowledge Constraints

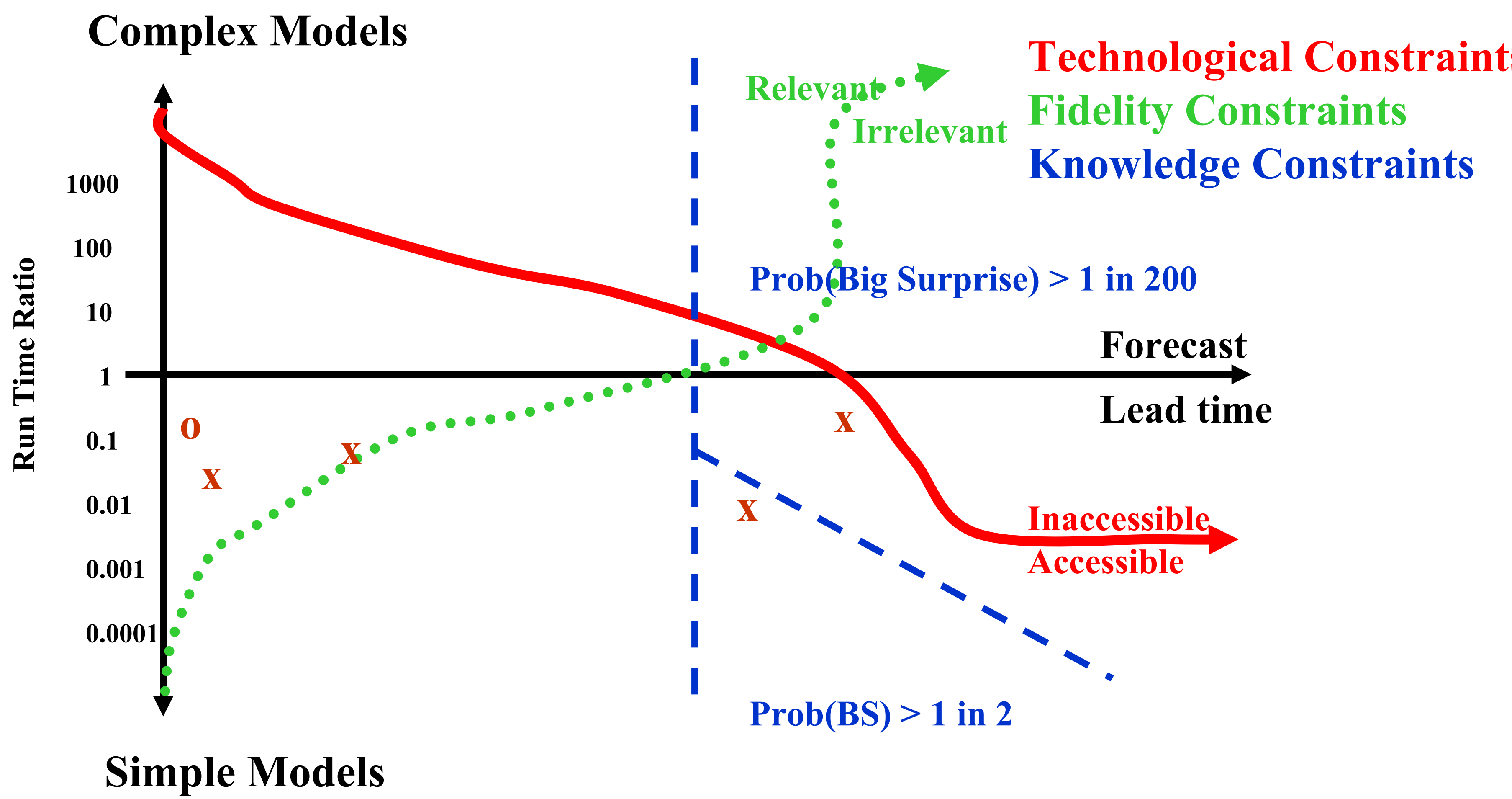
Is designing the "art of the solvable" so different?



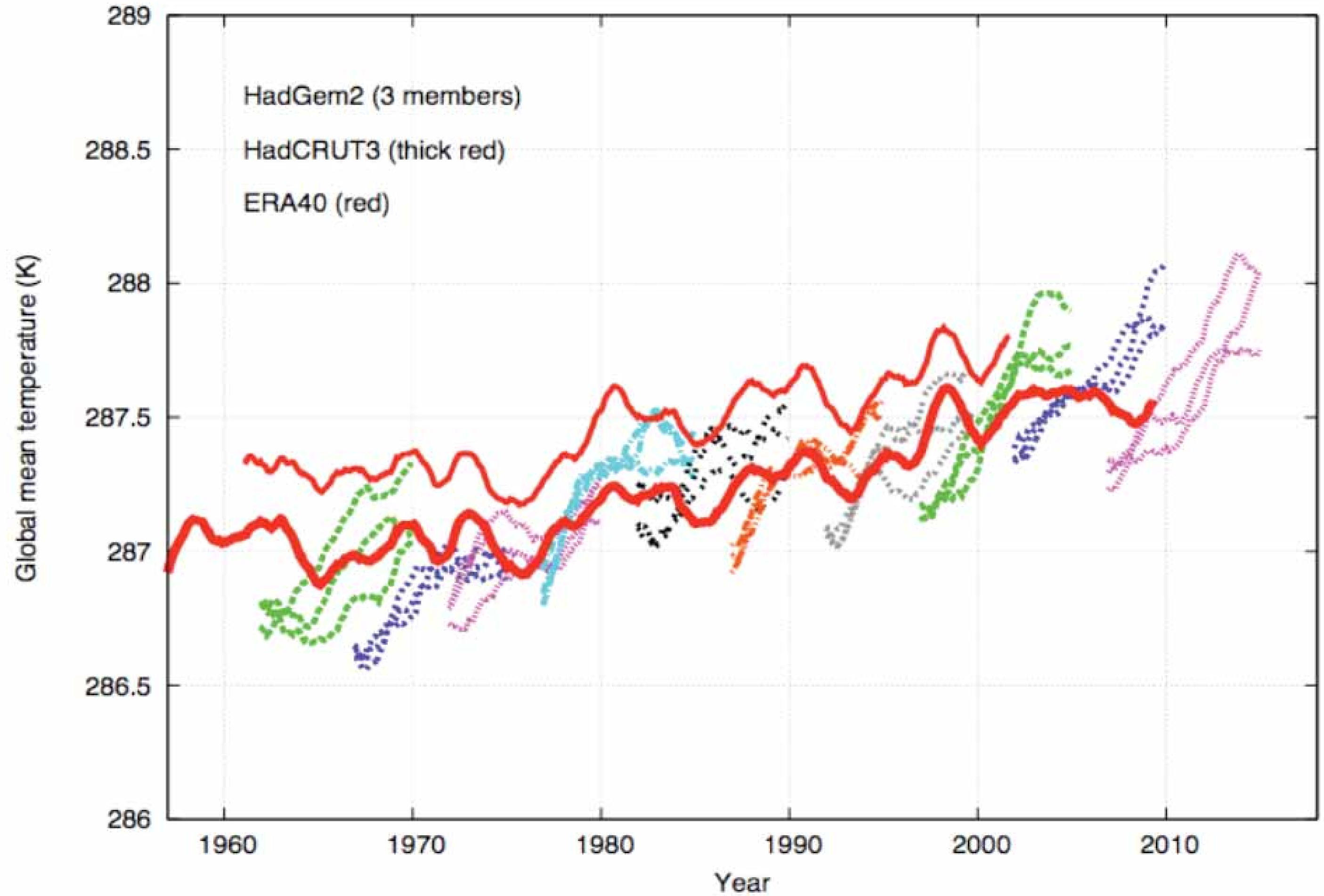
Other than the fact that identifying a big surprise in this case means tenure!

Where have we designed operational models?

A subjective view of operational weather (< 10 days), seasonal (< 18 months), GCM (<100 years) and hi-res Climate (< 80 years) models each fall.



Decadal Forecasting ***at global scales.***



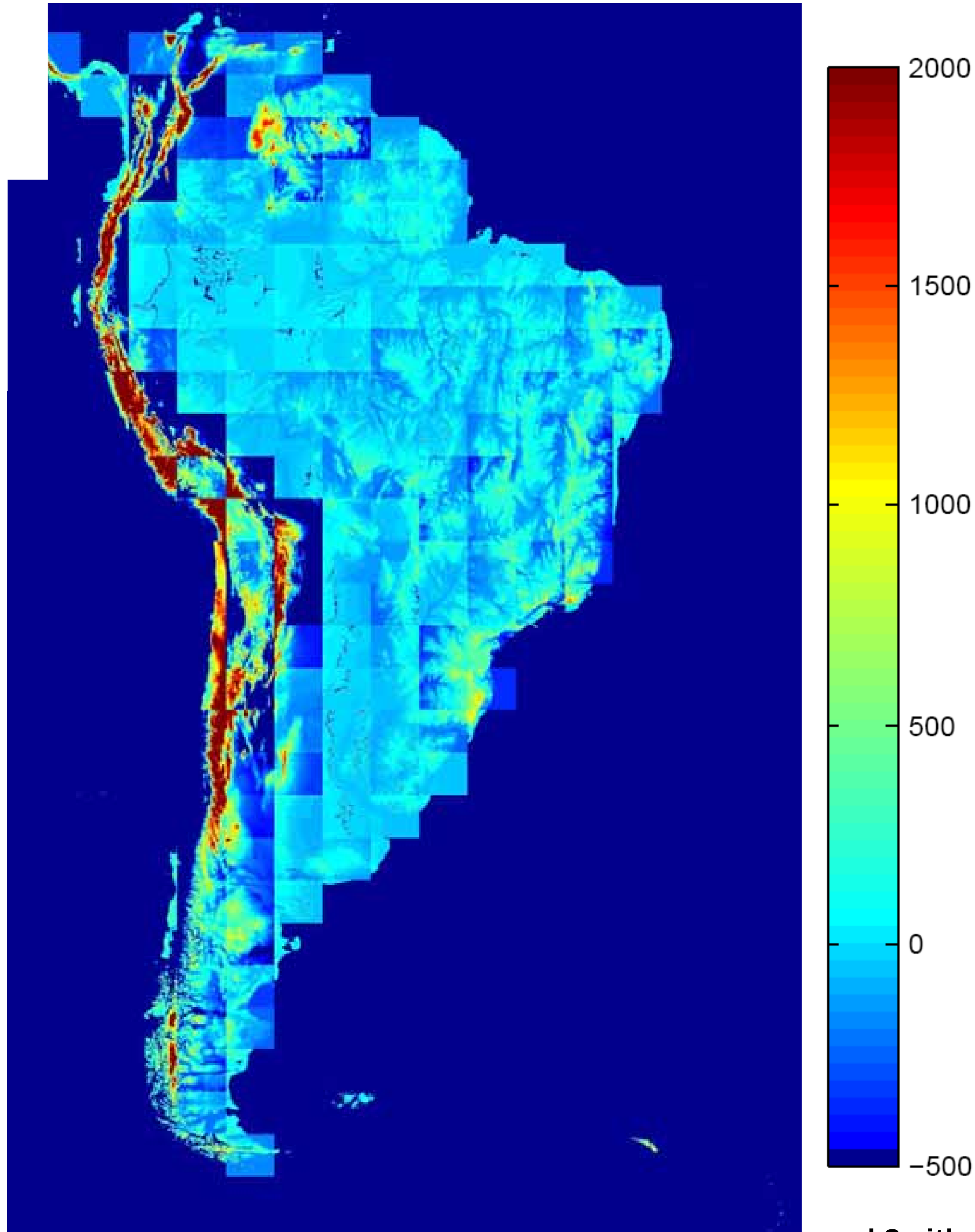
Back off on "Laws of Physics" justification if post processing is required.
Transparent forecast evaluation in empirical units of interest.
Careful (true) cross-validation. (And some *arguably* true out-of-sample)
Quantitative documentation of historical forecasts (for intercomparison)

There are also less direct errors: Missing mountain ridges:

And resulting long term feedbacks (bio-feed backs, albedo, …)

One-way coupled regional models **cannot** account for missing physics or inactive feedbacks.

At what lead times do inadequacies in downstream flow (or precipitation) result in feedbacks with beyond local impacts?



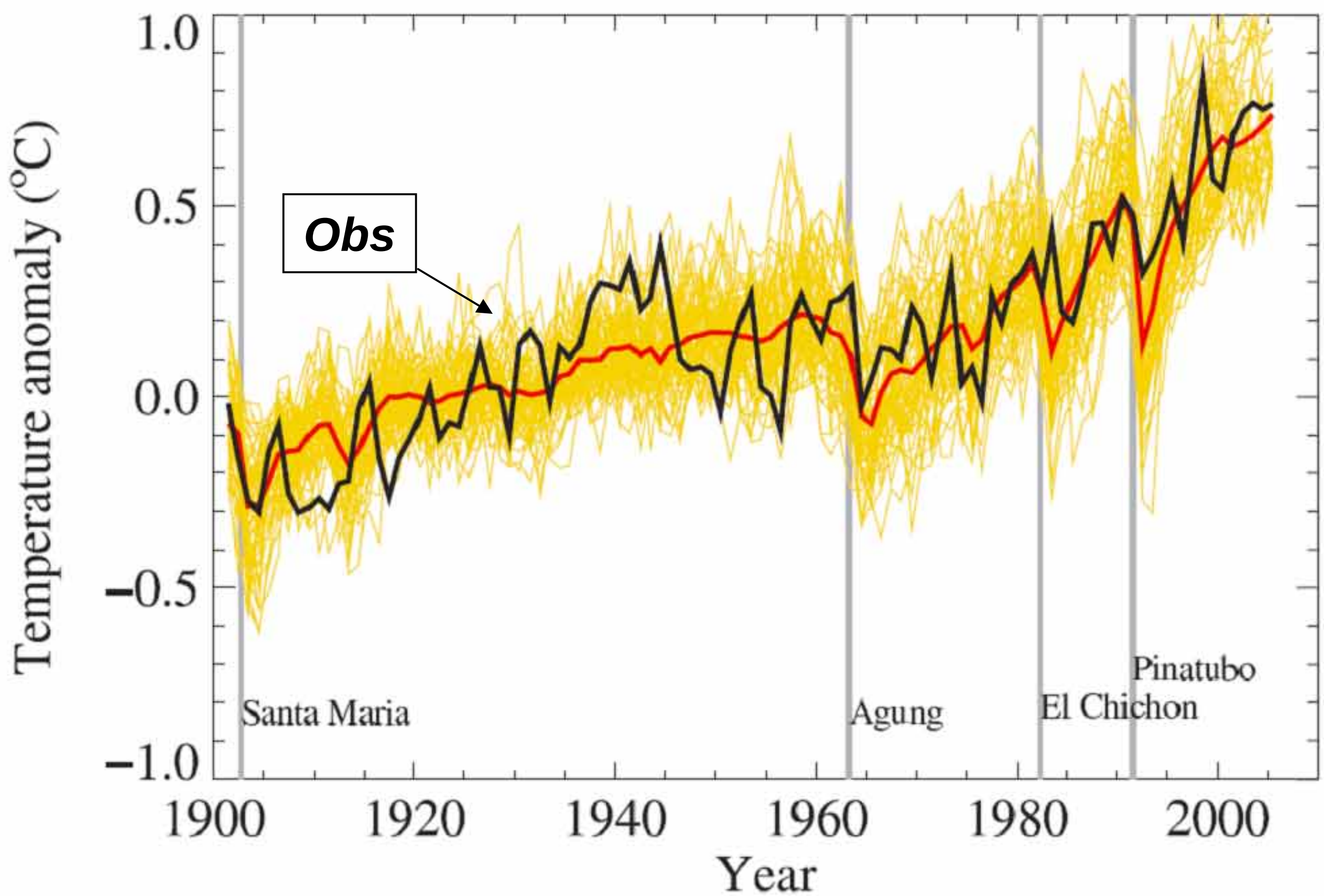
Grantham Research Institute on Climate Change and the Environment

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

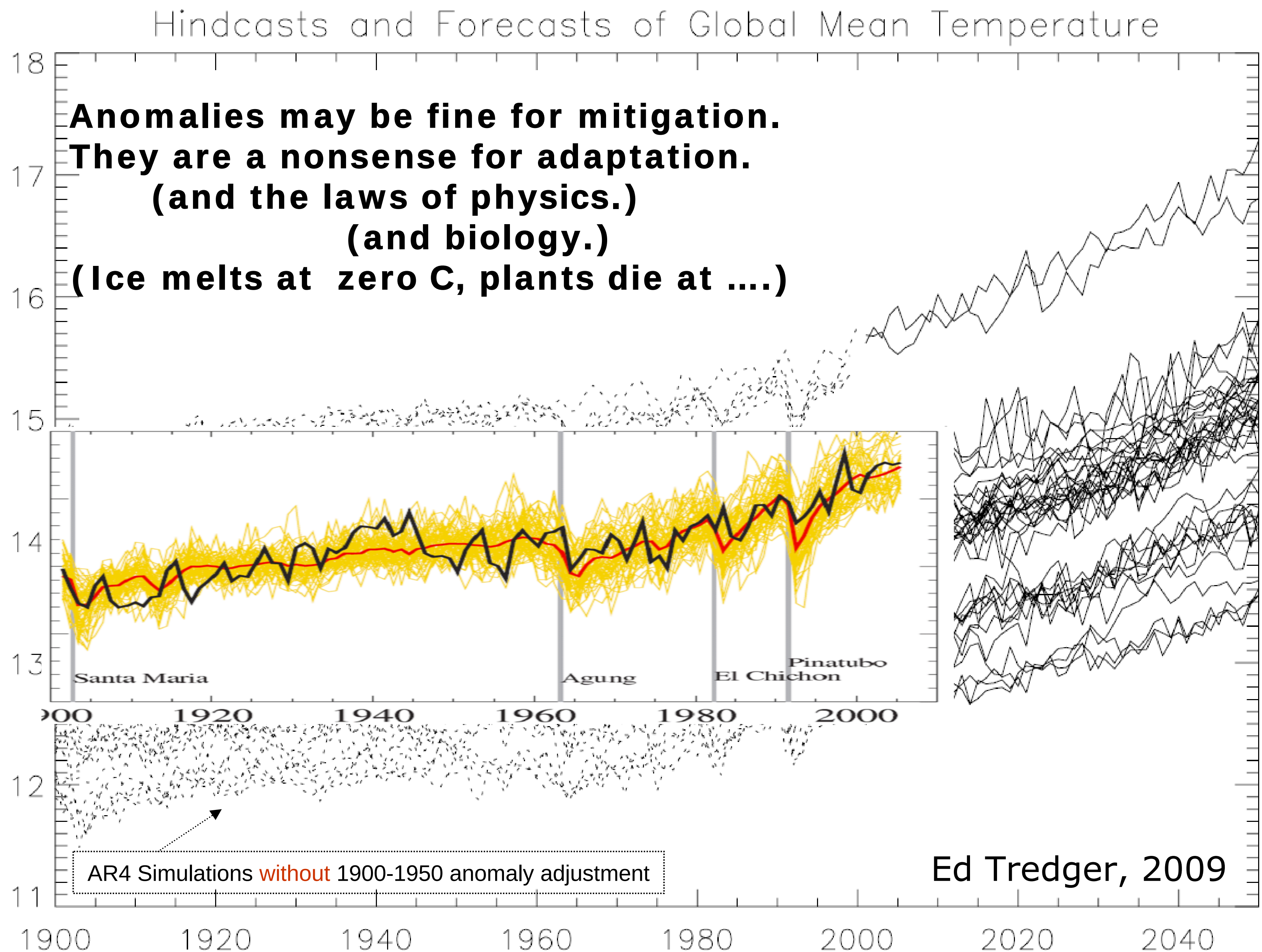
Anomalies: Misrepresentation and Confusion

Post-processing removes the systematic error in each model.

FAQ 8.1, Figure 1. *Global mean near-surface temperatures over the 20th century from observations (black) and as obtained from 58 simulations produced by 14 different climate models driven by both natural and human-caused factors that influence climate (yellow). The mean of all these runs is also shown (thick red line). Temperature anomalies are shown relative to the 1901 to 1950 mean. Vertical grey lines indicate the timing of major volcanic eruptions. (Figure adapted from Chapter 9, Figure 9.5. Refer to corresponding caption for further details.)*



Grantham Research Institute on Climate Change and the Environment


Hindcasts and Forecasts of Global Mean Temperature
Anomalies may be fine for mitigation.
They are a nonsense for adaptation.
(and the laws of physics.)
(and biology.)
(Ice melts at zero C, plants die at ....)
Santa Maria
Agung
El Chichon
Pinatubo
AR4 Simulations without 1900-1950 anomaly adjustment
Ed Tredger, 2009
18
17
16
15
14
13
12
11
1900
1920
1940
1960
1980
2000
2020
2040

10

This risk of overconfidence is well known and well founded.

Global Climate Projections

The effects of uncertainty in the knowledge of Earth system processes can be partially quantified by constructing ensembles of models that sample different parametrizations of these processes. However, some processes may be missing from the set of available models, and alternative parametrizations of other processes may share common systematic biases. Such limitations imply that distributions of future climate responses from ensemble simulations are themselves subject to uncertainty (Smith, 2002), and would be wider were uncertainty due to structural model errors accounted for. 797

One would be exposed to significant losses/costs if distributions which are not decision-support relevant probabilities are interpreted as if they were.

The IPCC itself might say this a bit louder/earlier.

LA Smith, (2002) What Might We Learn from Climate Forecasts? Proc. National Acad. Sci. USA 4 (99): 2487-2492

And if one must give numbers, include the probability of model irrelevance with lead time.

If precip over the Amazon (or Okeefenokee) is badly simulated, the biomass will be badly simulated, this missing/extra feedback may lead to model irrelevance… First local, then global.

Timescales for such things may be sound science!

No scientific forecast is complete without one.

Spatial Scales

metres

km

1000km

Target Lead-time

hours weeks years decades centuries

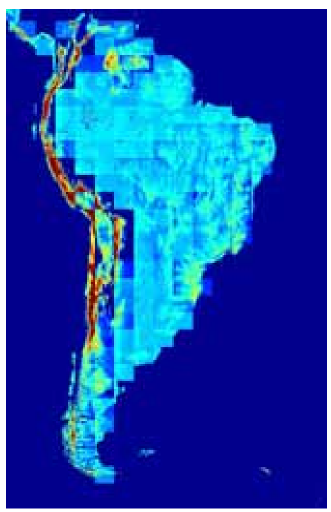
Prob(Big Surprise)

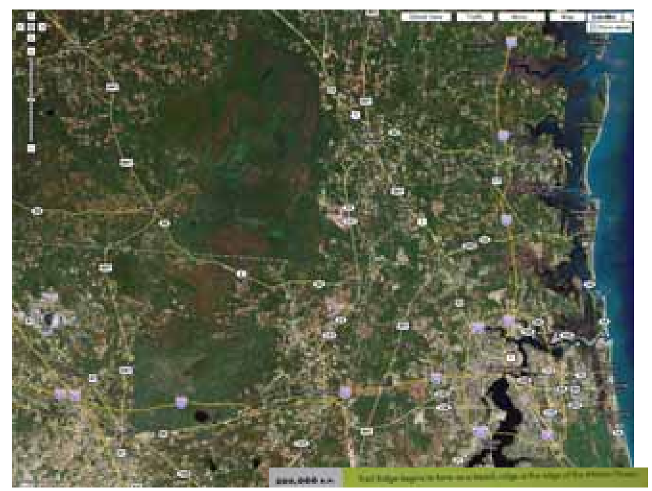
years

weeks

day

Temporal Average Scale





Nordica

3 May 2011

Grantham Research Institute on Climate Change and the Environment

Where did we get the idea of model-based PDFs?
What about insight and *understanding* (without PDFS)

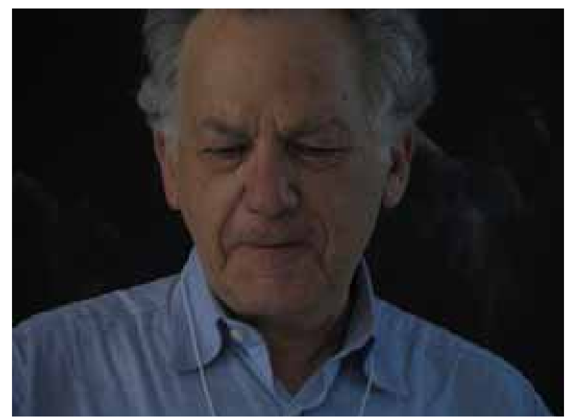
When did the idea that climate models could provided quantitative insight regarding the probability of future worlds come about?
Was it a philosopher who suggested (or failed to deprecate) this idea?

Because of the various simplifications of the model described above, it is not advisable to take too seriously the quantitative aspect of the results obtained in this study. Nevertheless, it is hoped that this study not only emphasizes some of the important mechanisms which control the response of the climate to the change of carbon dioxide.

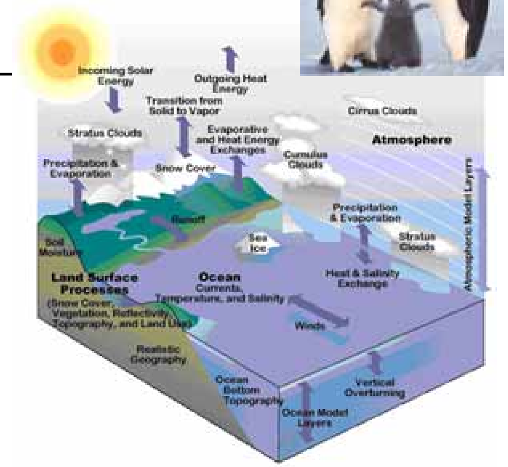
The Effects of Doubling the CO_2 Concentration on the Climate of a General Circulation Model[1]

SYUKURO MANABE AND RICHARD T. WETHERALD
Geophysical Fluid Dynamics Laboratory/NOAA, Princeton University, Princeton, N.J. 08540
(Manuscript received 6 June 1974, in revised form 8 August 1974)

Mechanisms == Insight



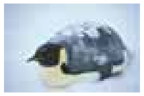
Moving Forward:
Plausible Planets or Implausible Earths?



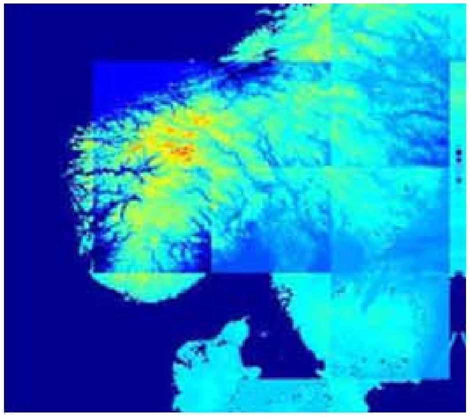
How can we best develop our models as the available computational power increases?

A) Simulate potentially real planets that get more and more Earth-like while omitting any Earth-relevant process for which the model cannot provide coherent physical drivers on Earth-like scales. (no suggestion of linear superposition intended!)

Does water vapour come after mountains?
Does vegetation come after water vapour?



Do we avoid the penguin effect? (until it is simulated realistically)



B) Via an hodgepodge of unphysical/unbiological simulations resembling no planet that could possibly exist, but "including" every phenomena we can think of that might be important (including penguins), and hoping the simulated planets will suddenly become Earth-like at some resolution in an ill-defined higgledy-piggledy way.

One might argue physical intuition is more effective in evaluating plausible planets, as there is physics to intuit in that case. (and at least a few examples.)

Grantham Research Institute on Climate Change and the Environment

Watch out for the Penguin Effect

The challenge of climate change will be with us for some time.

Can we maintain parallel streams: pure research to apply in 2050, and applied research to improve the modelling position we are in when we get there?

When selecting a thesis problem: do you suggest something important, like understanding cloud dynamics (better)?

Or to be the first person in the world to include the penguin effect in a global model? (and thereby all but assured a job at a rival modelling centre?)

(Similar effects plague economics and statistics)

THERE IS NO PENGUIN EFFECT

(My prior on this effect is zero)

It is a joke regarding climate,

but sadly not career paths!

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

?What year did climate prediction move beyond understanding to quantitative forecasting?

The basic insight here is not new

When in doubt, **distrusting the indications, or inferences from them (duly considered on purely scientific principles, and checked by experience), the words "*Uncertain*," or "*Doubtful*," may be used, without hesitation.**

Fitzroy, 1862

Dr. Platzman

I may add to this another point mentioned by Dr. Charney, a somewhat philosophical comment concerning model experiments. I think that I agree with Dr. Charney's suggestion that machines are suitable for replacing model experiments. But I think it is also necessary to remember that there are in general two types of physical systems which one can think of modeling. In one type of system one has a fairly good understanding of the dynamical workings of the system, involved. Under those conditions the machine modeling is not only practical but probably is more economical in a long run. Typical examples of this kind, I think, are problems where you are concerned, let's say, with wave action in harbors, in general a whole class of engineering problems of that kind. But there is another class of problem where we are still far from a good understanding of the dynamical properties of the system. In that case laboratory models, I think, are very effective and have a very important place in the scheme of things.

PROCEEDINGS
OF
THE INTERNATIONAL SYMPOSIUM
ON NUMERICAL WEATHER
PREDICTION IN TOKYO

NOVEMBER 7–13, 1960

Because of the various simplifications of the model described above, it is not advisable to take too seriously the quantitative aspect of the results obtained in this study. Nevertheless, it is hoped that this study not only emphasizes some of the important mechanisms which control the response of the climate to the change of carbon dioxide, but also identifies the various requirements that have to be satisfied for the study of climate sensitivity with a general circulation model.

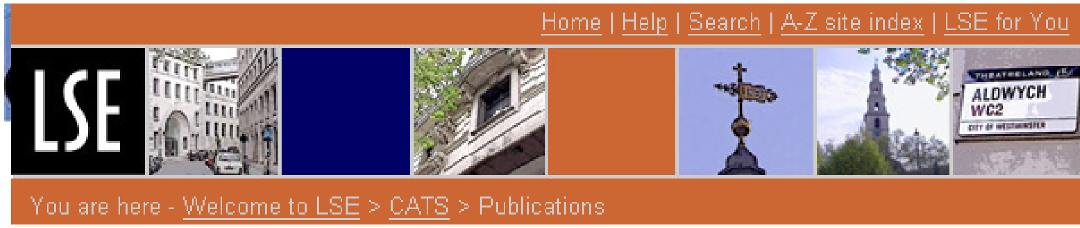
The Effects of Doubling the CO_2 Concentration on the Climate of a General Circulation Model[1]

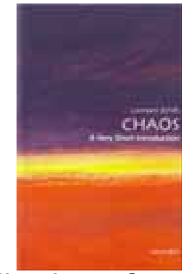
SYUKURO MANABE AND RICHARD T. WETHERALD

Geophysical Fluid Dynamics Laboratory/NOAA, Princeton University, Princeton, N.J. 08540

(Manuscript received 6 June 1974, in revised form 8 August 1974)

Grantham Research Institute on Climate Change and the Environment





Papers

R Hagedorn and LA Smith (2009) Communicating the value of probabilistic forecasts with weather roulette. *Meteorological Applications*16 (2): 143-155. Abstract

K Judd, CA Reynolds, TE Rosmond & LA Smith (2008) The Geometry of Model Error (DRAFT). *Journal of Atmospheric Sciences* 65 (6), 1749--1772. Abstract

K Judd, LA Smith & A Weisheimer (2007) How good is an ensemble at capturing truth? Using bounding boxes for forecast evaluation. *Q. J. Royal Meteorological Society*, **133** (626), 1309-1325. Abstract

J Bröcker, LA Smith (2008) From Ensemble Forecasts to Predictive Distribution Functions *Tellus A* 60(4): 663. Abstract

J Bröcker, LA Smith (2007) Scoring Probabilistic Forecasts: On the Importance of Being Proper *Weather and Forecasting* 22 (2), 382-388. Abstract

J Bröcker & LA Smith (2007) Increasing the Reliability of Reliability Diagrams. *Weather and Forecasting*, 22(3), 651-661. Abstract

MS Roulston, J Ellepola & LA Smith (2005) Forecasting Wave Height Probabilities with Numerical Weather Prediction Models *Ocean Engineering*, 32 (14-15), 1841-1863. Abstract

A Weisheimer, LA Smith & K Judd (2004) A New View of Forecast Skill: Bounding Boxes from the DEMETER Ensemble Seasonal Forecasts, *Tellus* **57** (3): 265-279 MAY. Abstract

PE McSharry and LA Smith (2004) Consistent Nonlinear Dynamics: identifying model inadequacy, *Physica D* 192: 1-22. Abstract

K Judd, LA Smith & A Weisheimer (2004) Gradient Free Descent: shadowing and state estimation using limited derivative information, *Physica D* 190 (3-4): 153-166. Abstract

MS Roulston & LA Smith (2003) Combining Dynamical and Statistical Ensembles *Tellus 55 A*, 16-30. Abstract

MS Roulston, DT Kaplan, J Hardenberg & LA Smith (2003) Using medium-range weather forecasts to improve the value of wind energy production *Renewable Energy* 28 (4) April 585-602. Abstract

MS Roulston & LA Smith (2002) Evaluating probabilistic forecasts using information theory, *Monthly Weather Review* 130 6: 1653-1660. Abstract

LA Smith, (2002) What might we learn from climate forecasts? *Proc. National Acad. Sci.* USA 4 (99): 2487-2492. Abstract

D Orrell, LA Smith, T Palmer & J Barkmeijer (2001) Model Error in Weather Forecasting *Nonlinear Processes in Geophysics* 8: 357-371. Abstract

JA Hansen & LA Smith (2001) Probabilistic Noise Reduction. *Tellus 53 A* (5): 585-598. Abstract

I Gilmour, LA Smith & R Buizza (2001) Linear Regime Duration: Is 24 Hours a Long Time in Synoptic Weather Forecasting? *J. Atmos. Sci.* 58 (22): 3525-3539. Abstract

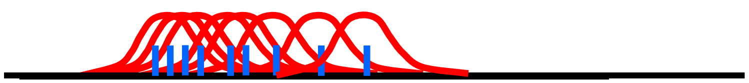
K Judd & LA Smith (2001) Indistinguishable states I: the perfect model scenario *Physica D* 151: 125-141. Abstract

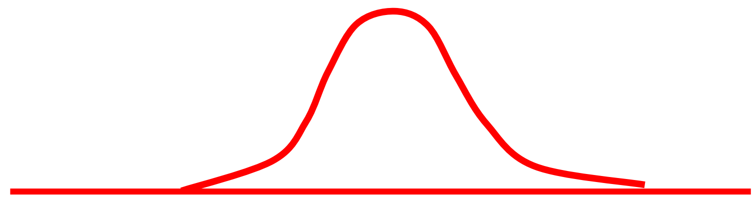
LA Smith (2000) 'Disentangling Uncertainty and Error: On the Predictability of Nonlinear Systems' in *Nonlinear Dynamics and Statistics*, ed. Alistair I. Mees, Boston: Birkhauser, 31-64. Abstract

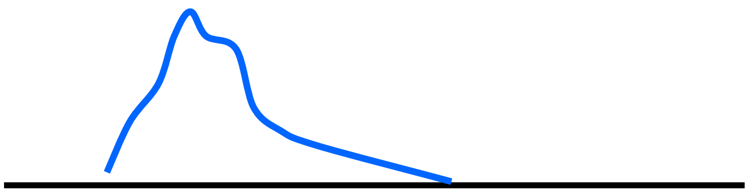
Ensembles Members In - Predictive Distributions Out

(1) Ensemble Members to Model Distributions

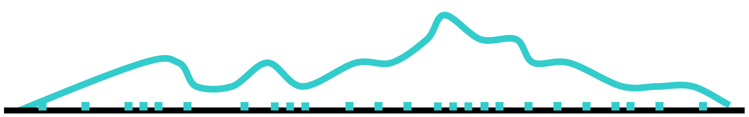
K is the kernel, with parameters σ,δ (*at least*)







$$P_1(x)=\sum_{i=1}^{n_{eps}} K(x,s_i^1)/n_{eps}$$



$$P_{clim}=\sum_{i=1}^{n_{clim}} K(o_i)/n_{clim}$$

Kernel & blend parameters are fit *simultaneously* to avoid adopting a wide kernel to account for a small ensemble.

One would always dress (K) and blend (α) a finite ensemble, even with a perfect model and perfect IC ensemble.

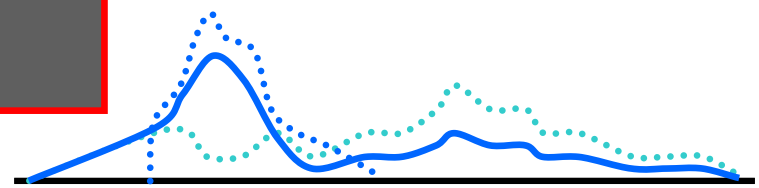
Forecast busts and lucky strikes remain a major problem when the archive is small.

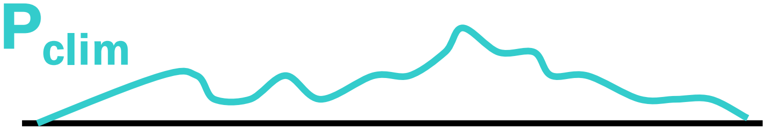
J Bröcker, LA Smith (2008) From Ensemble Forecasts to Predictive Distribution Functions *Tellus A* 60(4): 663.

Ensembles Members In - Predictive Distributions Out

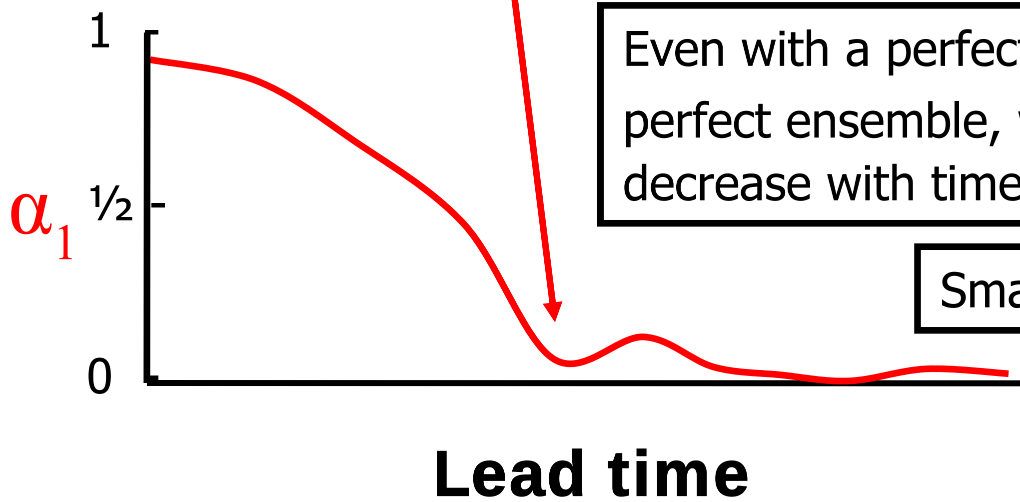
For a fixed ensemble size α decreases with time

And if $\alpha_1 \approx 0$, can there be any *operational* justification for running the prediction system.





$$M_1 = \alpha_1 P_1 + (1-\alpha_1) P_{clim}$$



Even with a perfect model and perfect ensemble, we expect α to decrease with time for small n_{eps}

Small :: $n_{eps} << n_{clim}$

Grantham Research Institute on Climate Change and the Environment

J Bröcker, LA Smith (2008) From Ensemble Forecasts to Predictive Distribution Functions *Tellus A* 60(4): 663.

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Demonstrations of local skill against climatology on EQUIP timescales (months).

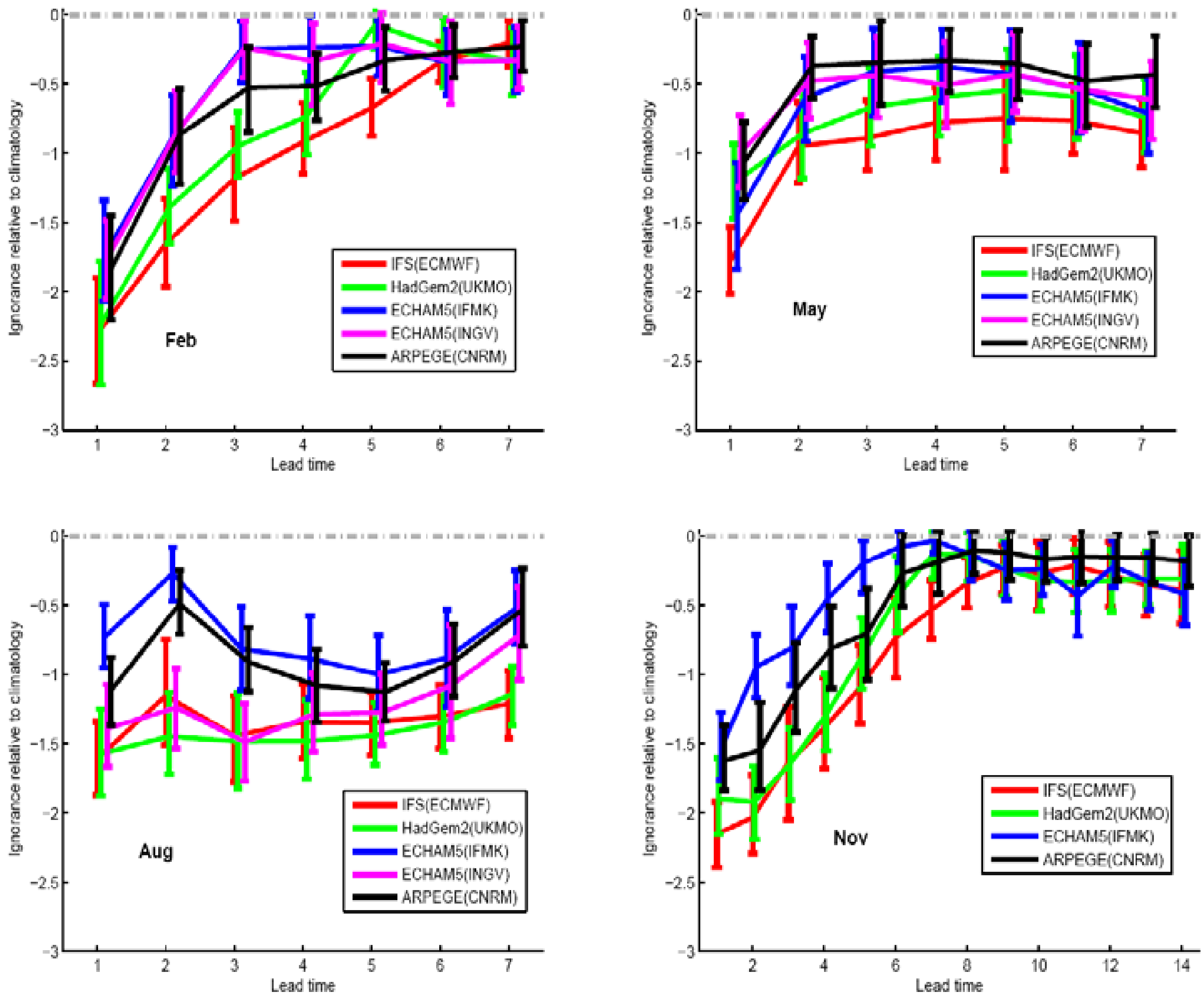


Fig 1: Ignorance score of each model forecast of SST in the Nino3.4 region

The ε-ball score is not "Proper"

$IGN = -log(p(X))$ *Good(1952)*

$S(p(x), X) = \int p(z)2\, dz - 2\, p(X)$ *???? first*

Ignorance and the proper linear score are proper scores, but require first dressing and blending the ensemble.

The ε-ball score is not proper, but when one method wins decisively, it has the advantage of evaluating the ensemble directly.

What other alternatives might you suggest?

J Bröcker, LA Smith (2007) Scoring Probabilistic Forecasts: On the Importance of Being Proper *Weather and Forecasting* 22 (2), 382-388

How would *you* design a climate model?

Suppose a newly rich nation rang up your philosophy department and asked for assistance in designing a new "Earth Systems" model from scratch. A philosophically sound model.

How complicated/complex a model should you attempt?

How will you communicate your results?

You would still face some constraints, although money is no object!

You can use the best computer technology of 2011
You can use the best scientific understanding of 2011
You can provide uncertainty information, even PDFs. (Numerate user)
You can provide information as far into the future as you can provide information.
Guidance is needed "quickly", but the exact cost of delay is part of the project!

You are not constrained by:

•Legacy code
•Legacy domain specialists
•Blatant Political Interference

What are you constrained by?

Why is this difficult in climate science?

Define Climate
See how models grow
Ask what is in the science already
Look at what an ensemble really does
Ask how to plug leaking probability mass!
Illustrate danger of post-processing for presentation.
Aiming for insight
Alternative paths forward

See also Radio 4’s GQT!

What is climate?

Climate is what you expect, Weather is what you get.

Robert Heinlein (1973)

The climate system is a complex, interactive system consisting of the atmosphere, land surface, snow and ice, oceans and other bodies of water, and living things. The atmospheric component of the climate system most obviously characterises climate; climate is often defined as ‘average weather’. Climate is usually described in terms of the mean and variability of temperature, precipitation and wind over a period of time, ranging from months to millions of years (the classical period is 30 years).


GLOSSARY OF METEOROLOGY

climate—“The synthesis of the weather” (C. S. Durst); the long-term manifestations of weather, however they may be expressed. More rigorously, the climate of a specified area is represented by the statistical collective of its weather conditions during a specified interval of time (usually several decades).

Climate is a distribution of multivariate time series!
(It’s not just a number or two)
And for policy and (most) decision support:
“All Climate is Local”

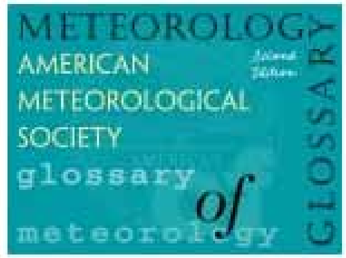
Definition of Climate Changed!

This definition more or less rules out many physically interesting "extreme events" a priori.

GLOSSARY OF METEOROLOGY

A B C D E F G H I J K L M N O P Q R S T U V W X Y Z

Home | Browse Terms | Help



Search Definitions
Search
case sensitive

First Edition Preface Second Edition Preface Acknowledgments

- **climate**—The slowly varying aspects of the atmosphere–hydrosphere–land surface system.
  It is typically characterized in terms of suitable averages of the climate system over periods of a month or more, taking into consideration the variability in time of these averaged quantities. Climatic classifications include the spatial variation of these time-averaged variables. Beginning with the view of local climate as little more than the annual course of long-term averages of surface temperature and precipitation, the concept of climate has broadened and evolved in recent decades in response to the increased understanding of the underlying processes that determine climate and its variability. *See also* climate system, climatology, climate change, climatic classification.

- **variability**—Mathematically, same as spread.

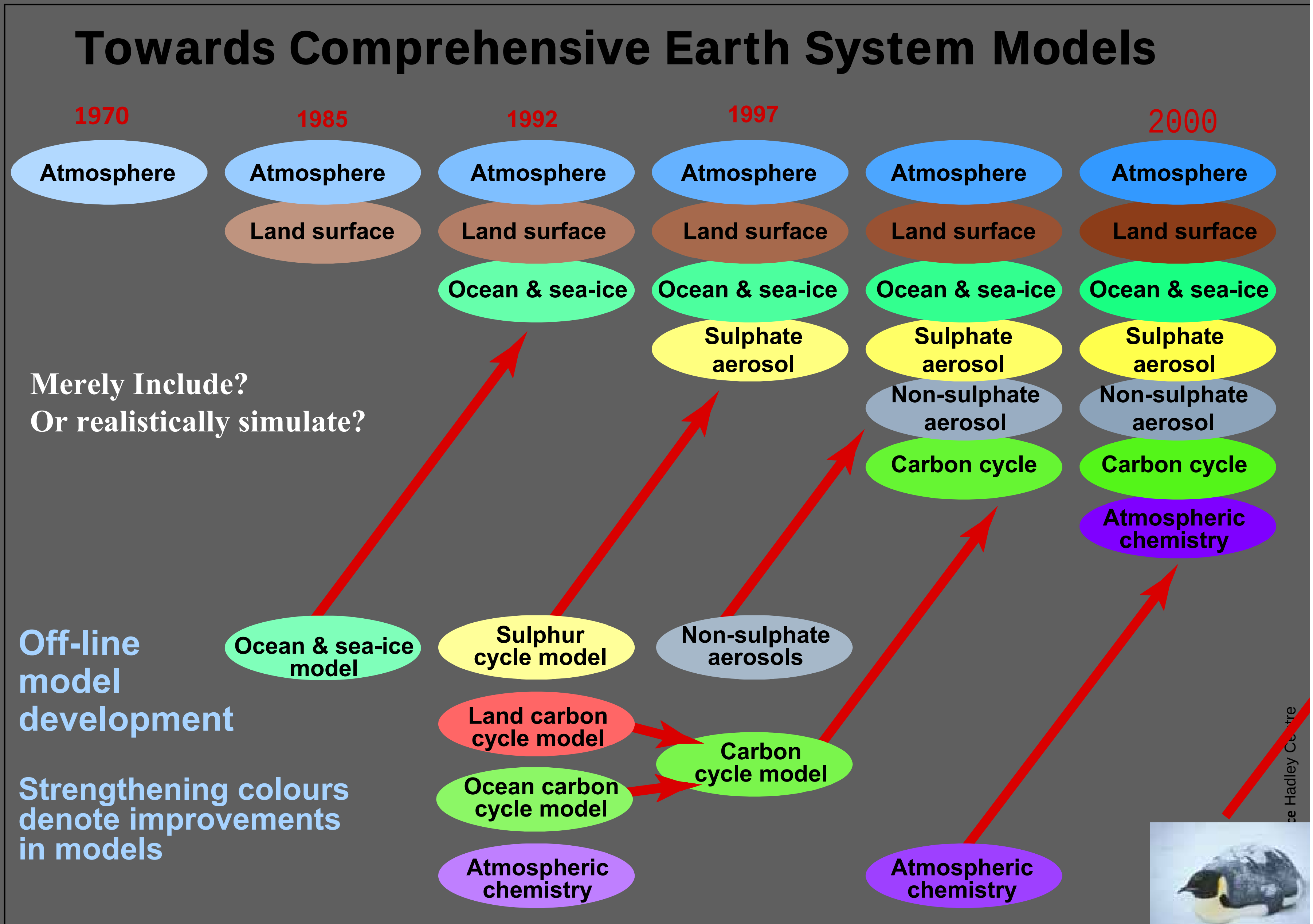
- **spread**—1. (Also called variability.) The general departure of individual values from central tendency.
  Spread is reflected geometrically in the probability curve as the width of the region over which the probability density is appreciable. *See* scatter, variance. 2. Popular contraction for dewpoint spread.

- **central tendency**—In statistics, the general level, characteristic, or typical value that is representative of the majority of cases.
  Among several accepted measures of central tendency employed in data reduction, the most common are the arithmetic mean (simple average), the median, and the mode.

http://amsglossary.allenpress.com/glossary/search?id=climate1

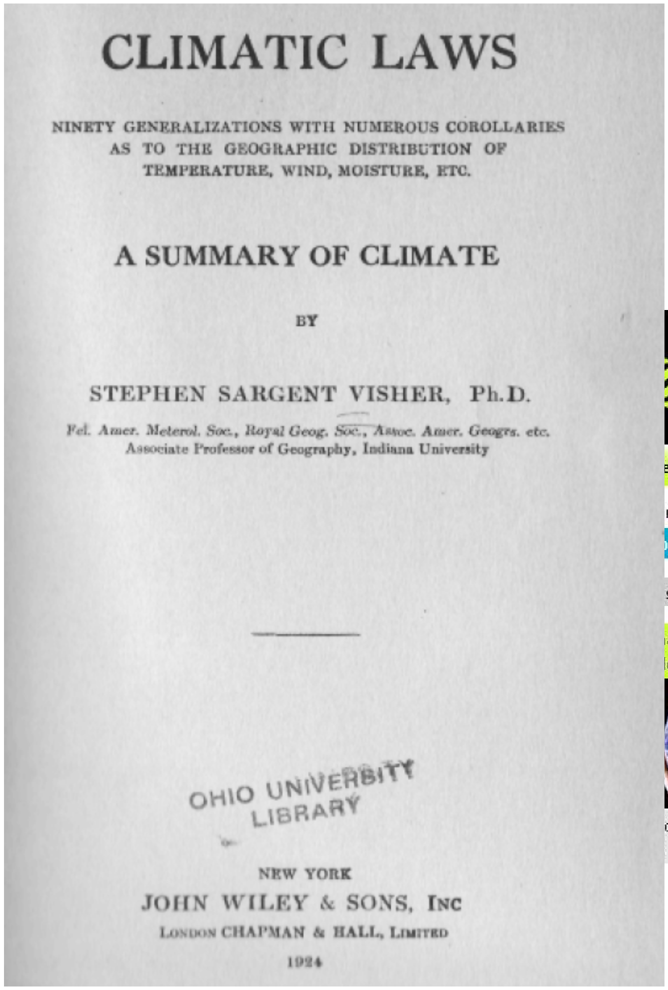
What do you include in your big model?

Climate Science must do this, taking care to avoid “over-parameterizationing”



CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

What will your big model add?



CLIMATIC LAWS

NINETY GENERALIZATIONS WITH NUMEROUS COROLLARIES AS TO THE GEOGRAPHIC DISTRIBUTION OF TEMPERATURE, WIND, MOISTURE, ETC.

A SUMMARY OF CLIMATE

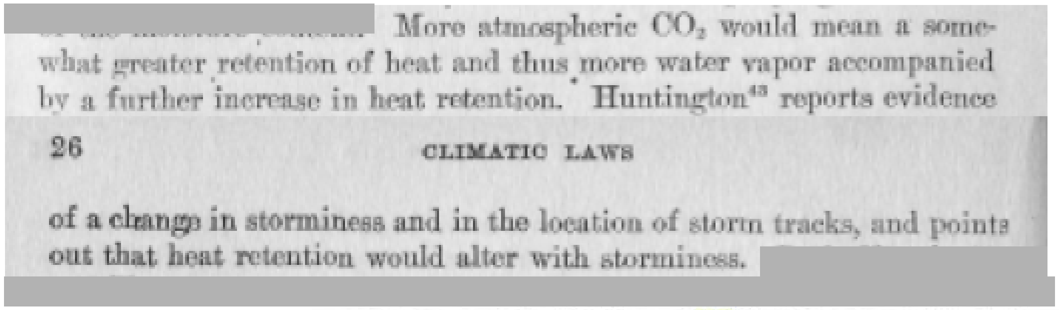
BY

STEPHEN SARGENT VISHER, Ph.D.

Fel. Amer. Meterol. Soc., Royal Geog. Soc., Assoc. Amer. Geogrs. etc.
Associate Professor of Geography, Indiana University

NEW YORK
JOHN WILEY & SONS, INC
LONDON CHAPMAN & HALL, LIMITED
1924

1924



More atmospheric CO_2 would mean a somewhat greater retention of heat and thus more water vapor accompanied by a further increase in heat retention. Huntington[43] reports evidence

26 CLIMATIC LAWS

of a change in storminess and in the location of storm tracks, and points out that heat retention would alter with storminess.

?Confidence?

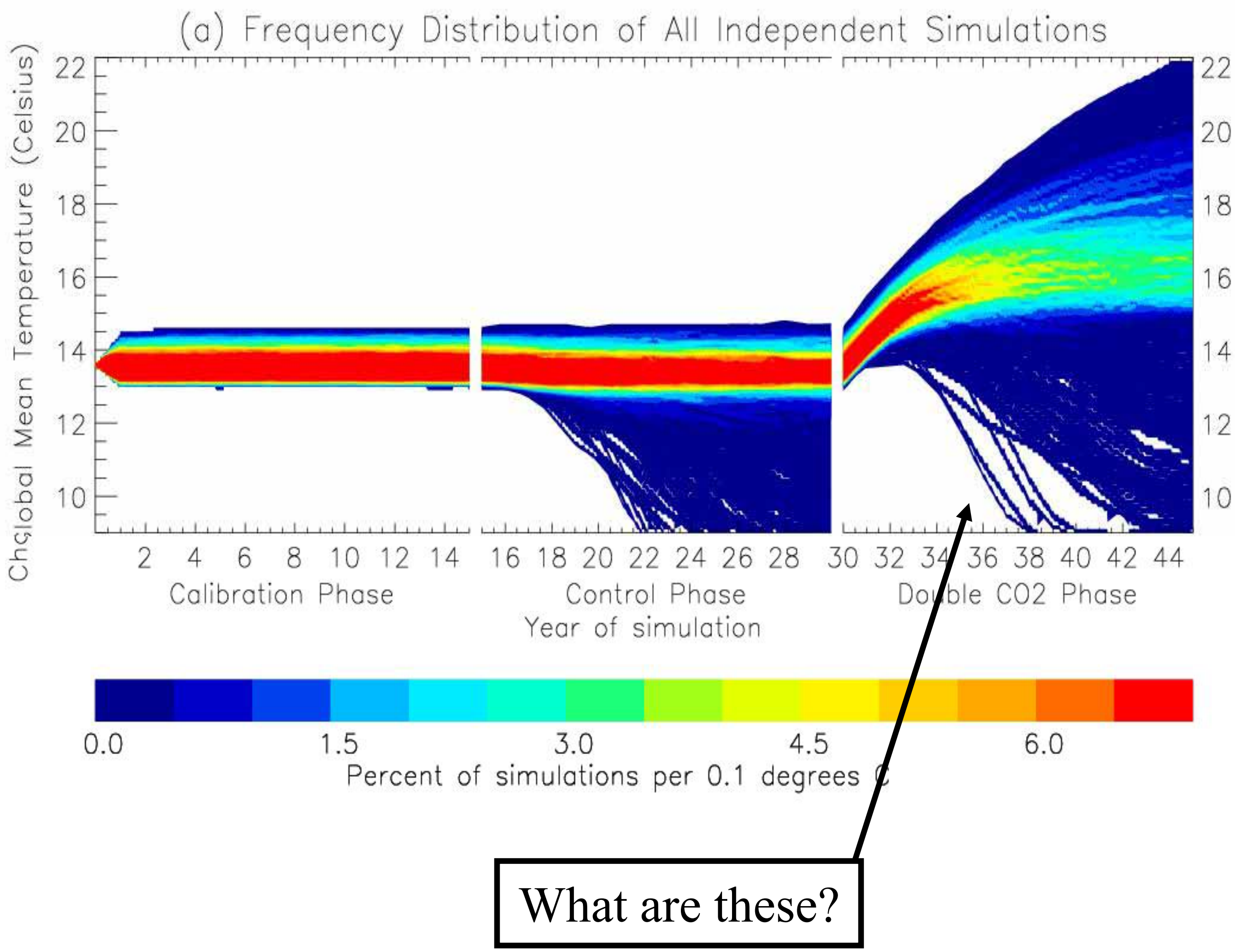
?Insight?

?Numbers per Postcode?

http://www.metoffice.gov.uk/climatechange/guide/what/

Grantham Research Institute on Climate Change and the Environment

Another problem I cannot solve: Area 51 issues. Ensembles yield diversity info within the model!…



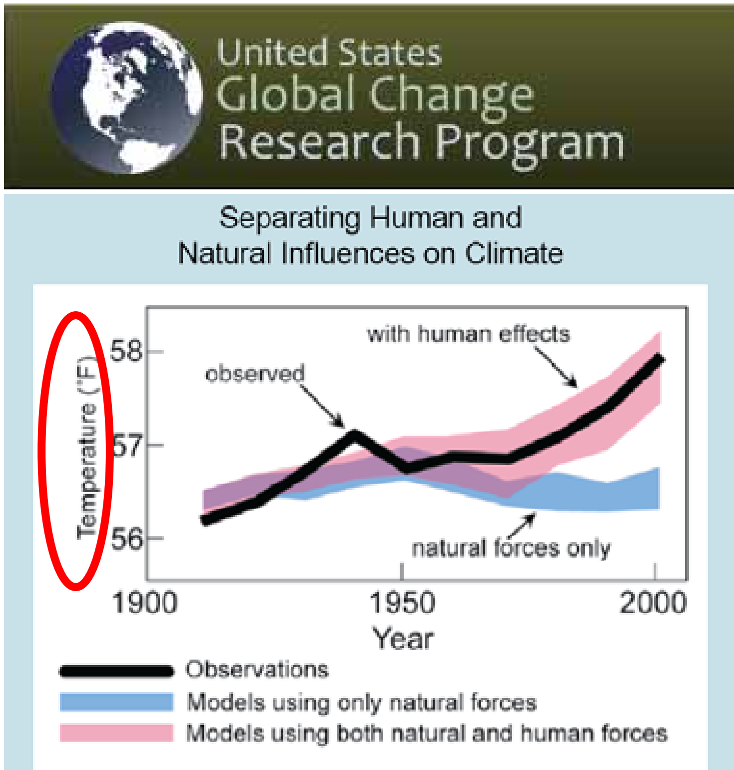
Leaking Probability

I am running a large ensemble under one model which can only be adequate under certain general conditions.
(Like the linear approximation to σT^4, changes in sea ice)

As I extrapolate to 2100, 20% of my models first venture into some known-to-be-unphysical regions, and then crash.

How do I account for this probability mass when speaking to a policy maker?

Can model diversity be connected to uncertainty in the future?
How?



As the blue band indicates, without human influences, global average temperature would actually have cooled slightly over recent decades. With human influences, it has risen strongly (black line), consistent with expectations from climate models (pink band).

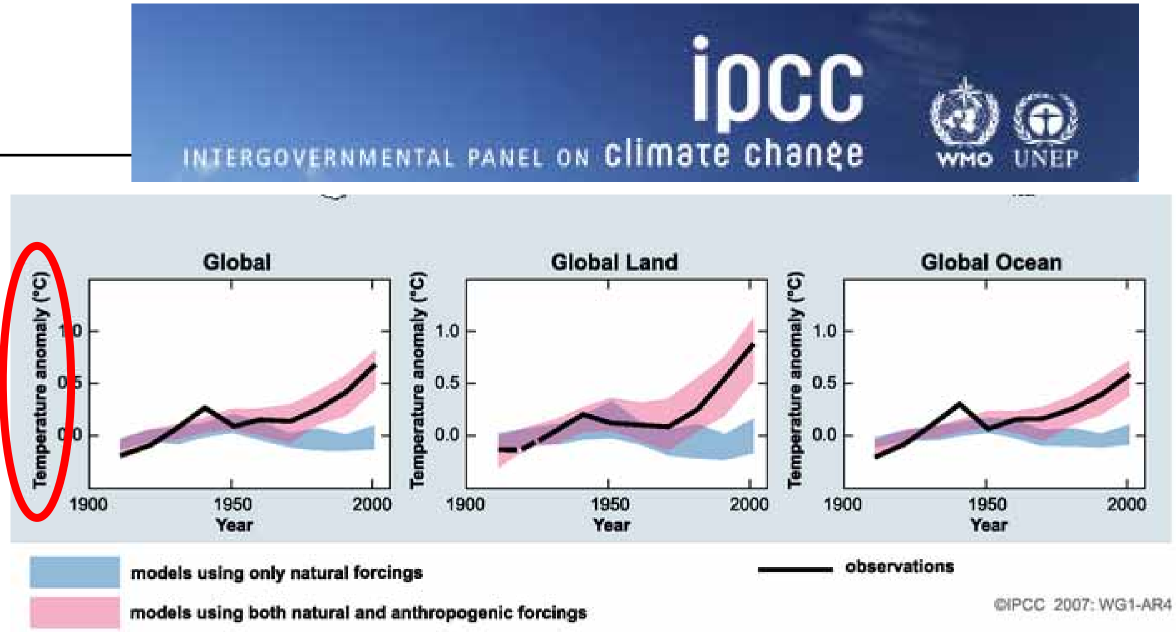


Figure SPM.4. Comparison of observed continental- and global-scale changes in surface temperature with results simulated by climate models using natural and anthropogenic forcings. Decadal averages of observations are shown for the period 1906 to 2005 (black line) plotted against the centre of the decade and relative to the corresponding average for 1901–1950. Lines are dashed where spatial coverage is less than 50%. Blue shaded bands show the 5–95% range for 19 simulations from five climate models using only the natural forcings due to solar activity and volcanoes. Red shaded bands show the 5–95% range for 58 simulations from 14 climate models using both natural and anthropogenic forcings. {FAQ 9.2 Figure 1}

http://www.ipcc.ch/publications_and_data/ar4/wg1/en/figure-spm-4.html

http://www.globalchange.gov/images/cir/pdf/20page-highlights-brochure.pdf

Statistical post-processing: These are anomalies, not temperatures. Parameterization of cloud formation is a bit of a distraction when we are missing two kilometre tall walls of rock…

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Perhaps we might aim for Insight and not numbers when the model is wrong?

Policy-making tracks actions by people to impacts on people: our models are but a small piece of that chain.

Communicating plausible outcomes and the limits of our understanding are more valuable than model-based probabilities, when the model is wrong. And, of course: all models are wrong.

Scientific Speculation can be of great value to policy makers, given with all the qualifications required to make the scientist comfortable.

(How did we get comfortable NOT doing this with model-based speculation?)

Other Questions

Nonlinearity
Signal and Noise; Natural variability and climate.

What is the model? Equations+code+compiler+machine?
Which perfect parameterizations could we not drive well -> timescale

Accuracy: Evolution (chaos), Driving Feedbacks (known), Feedbacks (unknown)

Policy Targets: "A 50% chance of less than 2 degree warming

Can we get necessary, never sufficient, tests of model relevance?

Extrapolation: there is no "out of sample" test.

A model might be dangerous if it…

…looks too good
…can sell newspapers
…is *required* for important decisions
…statistical post-processing is obscured
…is sold on in-sample tests
…is applied to extrapolation
…is nonlinear and evaluated with RMS
…looks too good to be true
…the one who made it thinks it might be

Watch out for the Penguin Effect

Credibility and Obfuscation (ESPN)

If you examine how meteorologists promoted weather forecasting in the 60's, it was based on aiding understanding and guidance.

Platzman (1962)

If you examine how meteorologists promoted climate modelling in the 80's, it was based on aiding understanding and guidance.

Manabe & Wetherall (1975) **&c**

NWP became decision-relevant only after it aided, then surpassed statistical forecasting, in real time.

By construction, Climate prediction cannot demonstrate skill out-of-sample! But if it fails in fair tests against statistical methods in-sample, it might be well advised to return to "aiding understanding."

?What year did climate prediction move beyond understanding to quantitative forecasting?

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Overview(1)

Climate GCMs are large nonlinear models.

Robustness of warming to model structure is a plus.

It is a nonsense to assume anomalies are informative for local details
(if the laws of physics respected such transformations,
we would not need such big nonlinear models: water freezes at…)

Is it not a nonsense to assume such models can be scientifically informative on time scales where local feedbacks are nontrivial?

Presenting anomalies in such misleading ways begs misinterpretation.
(not to mention risking our credibility)

So what are we to do given such large systematic errors?

1) **Aim for insight, not numbers.**
2) **Quantify the probability of model irrelevance (with lead time).**
3) **Demonstrate that they can, in fact, shadow the obs. (after projection)**

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

Are Projections just Predictions?

All predictions are conditioned on something(s); if we ran2011 models in 2050 would they admit shadowing trajectores?

Met Office

Hadley Centre
for Climate Predictions and Research

http://www.metoffice.gov.uk/publications/HCTN/HCTN_20.pdf

GLOSSARY OF METEOROLOGY

A B C D E F G H I J K L M N O P Q R S T U V W X Y Z

Home | Browse Terms | Help

METEOROLOGY GLOSSARY
AMERICAN METEOROLOGICAL SOCIETY
glossary of meteorology
Second Edition

Search | Search Definitions | case sensitive

First Edition Preface | Second Edition Preface | Acknowledgments

- **climate prediction**—The prediction of various aspects of the climate of a region during some future period of time.
  Climate predictions are generally in the form of probabilities of anomalies of climate variables (e.g., temperature, precipitation), with lead times up to several seasons (*see* climate anomaly). The term "climate projection" rather than "climate prediction" is now commonly used for longer- range predictions that have a higher degree of uncertainty and a lesser degree of specificity. For example, this term is often used for "predictions" of climate change that depend on uncertain consequences of anthropogenic influences such as land use and the burning of fossil fuels.

Grantham Research Institute on Climate Change and the Environment

As we move to smaller spatial scales, when, where and at what lead-times will simulation models lose their relative skill?

As more and more statistical models are tested, how do we quantify the statistical significance of the n^{th} model?

(What level of performance can we expect in real time?)

Good experimental design is required (i.e. specifying the order of locations examined) if statistical significance is to be assigned to local predictions.

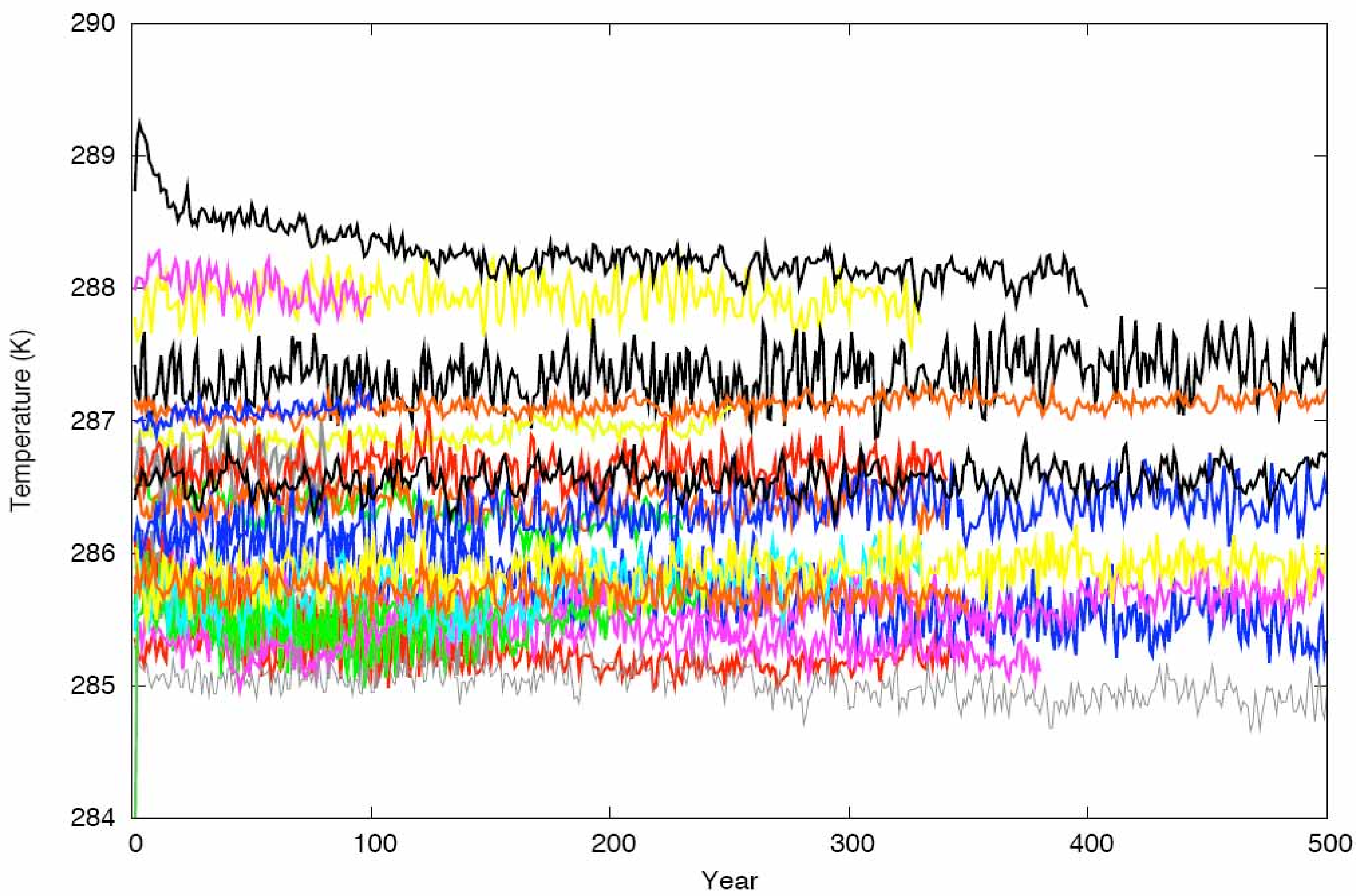
(Scanning the globe for regions of skill is a nonsense)

CATS CENTRE FOR THE ANALYSIS OF TIME SERIES

"Control Runs"

WCRP CMIP3 Multi-Model Data

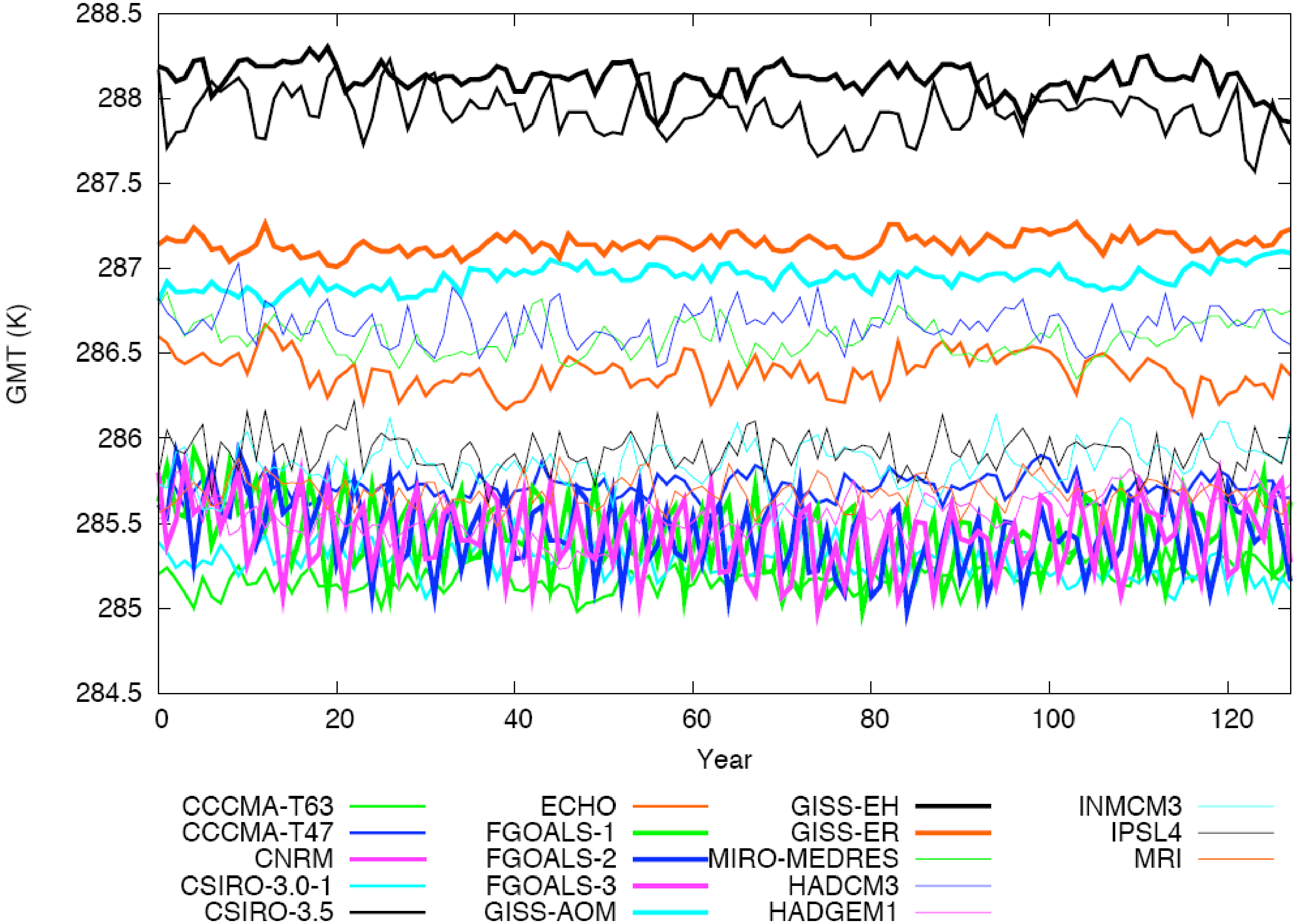
Home Data About ESG Login



Controls

WCRP CMIP3 Multi-Model Data

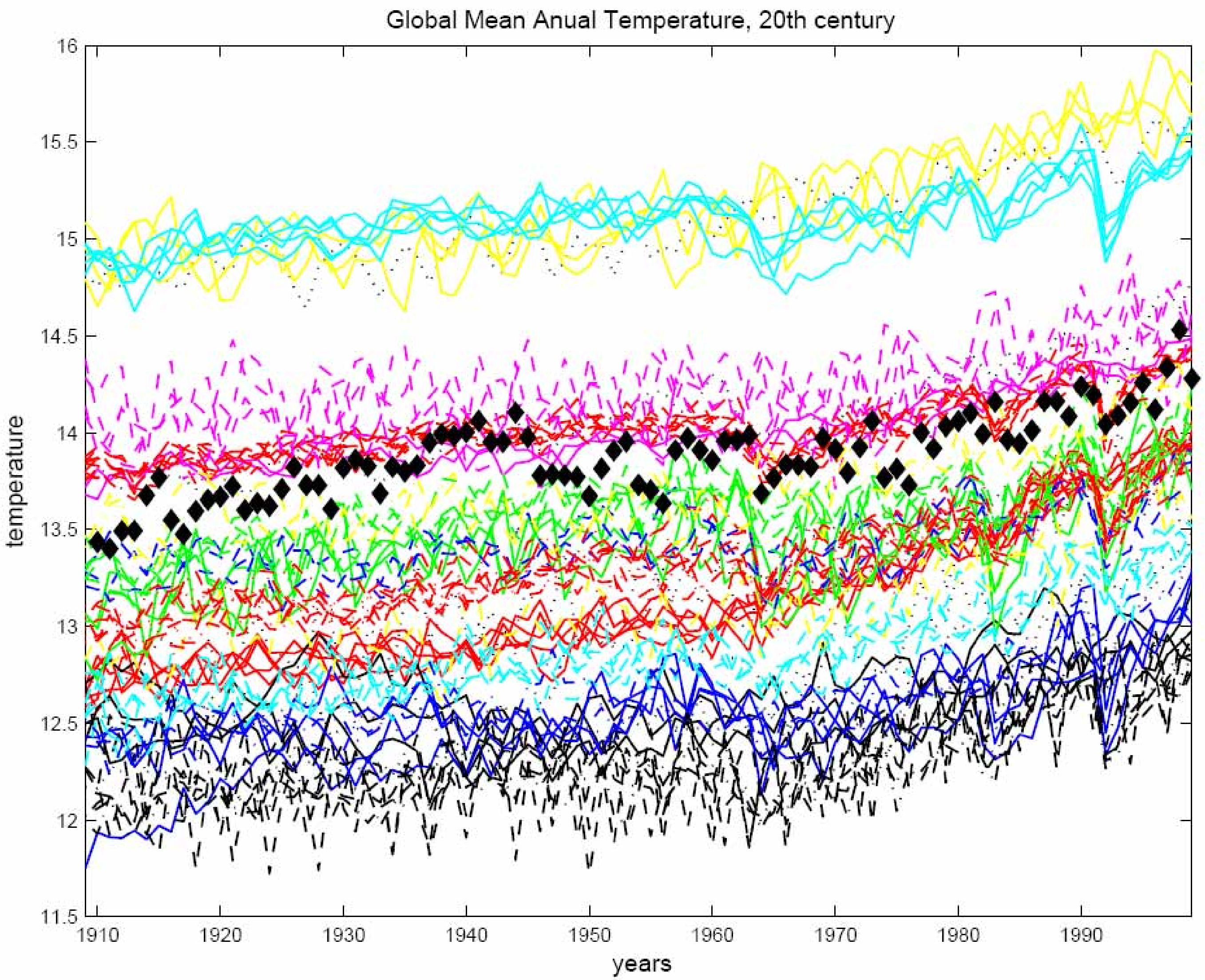
Home Data About ESG Login



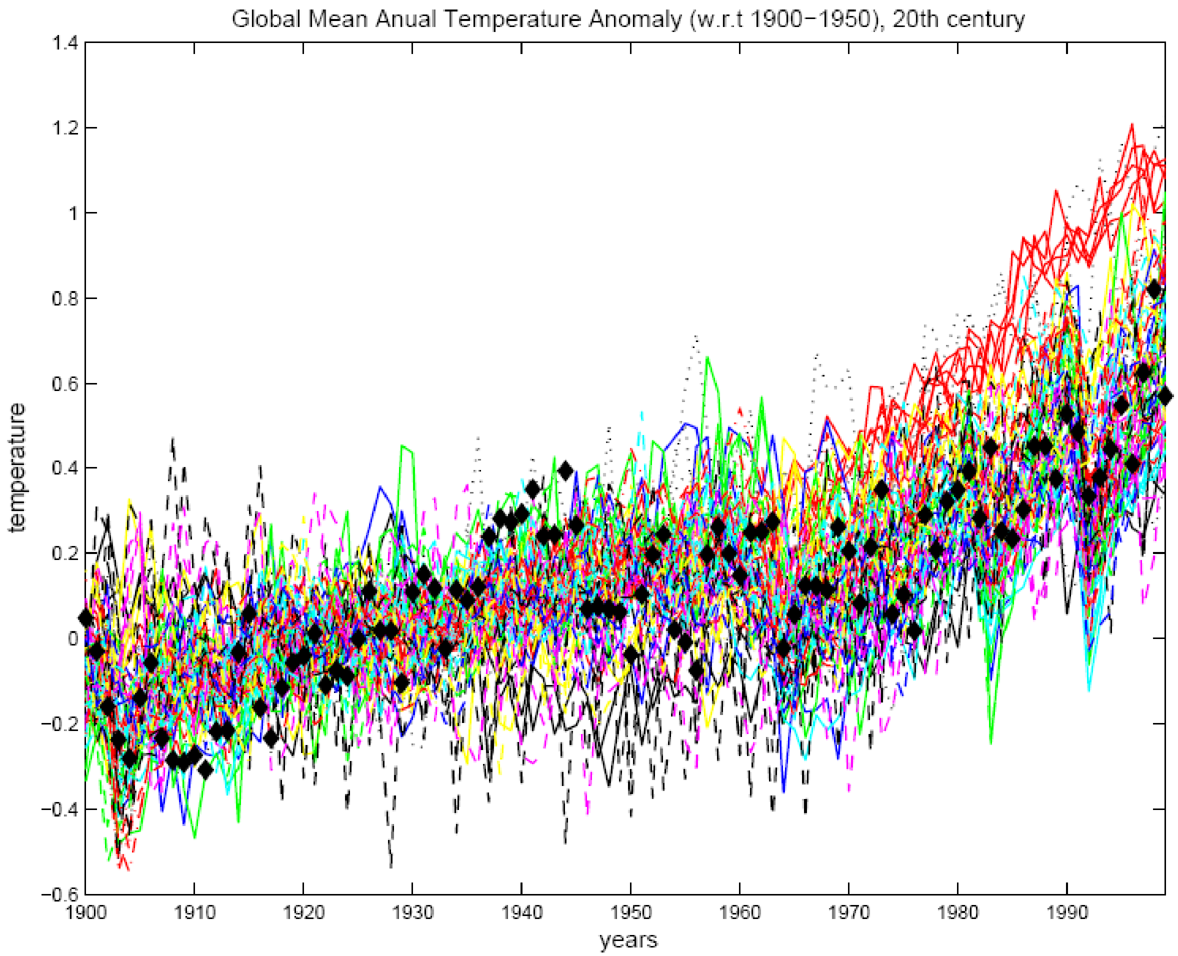
"Pink Runs"

WCRP CMIP3 Multi-Model Data

Home Data About ESG Login



What do we do given such systematic errors?



Climate change detection, and forecasting (1937)

THE ARTIFICIAL PRODUCTION OF CARBON DIOXIDE AND ITS INFLUENCE ON TEMPERATURE

By G. S. CALLENDAR

(Steam technologist to the British Electrical and Allied Industries Research Association.)

(Communicated by Dr. G. M. B. DOBSON, F.R.S.)

[Manuscript received May 19, 1937—read February 16, 1938.]

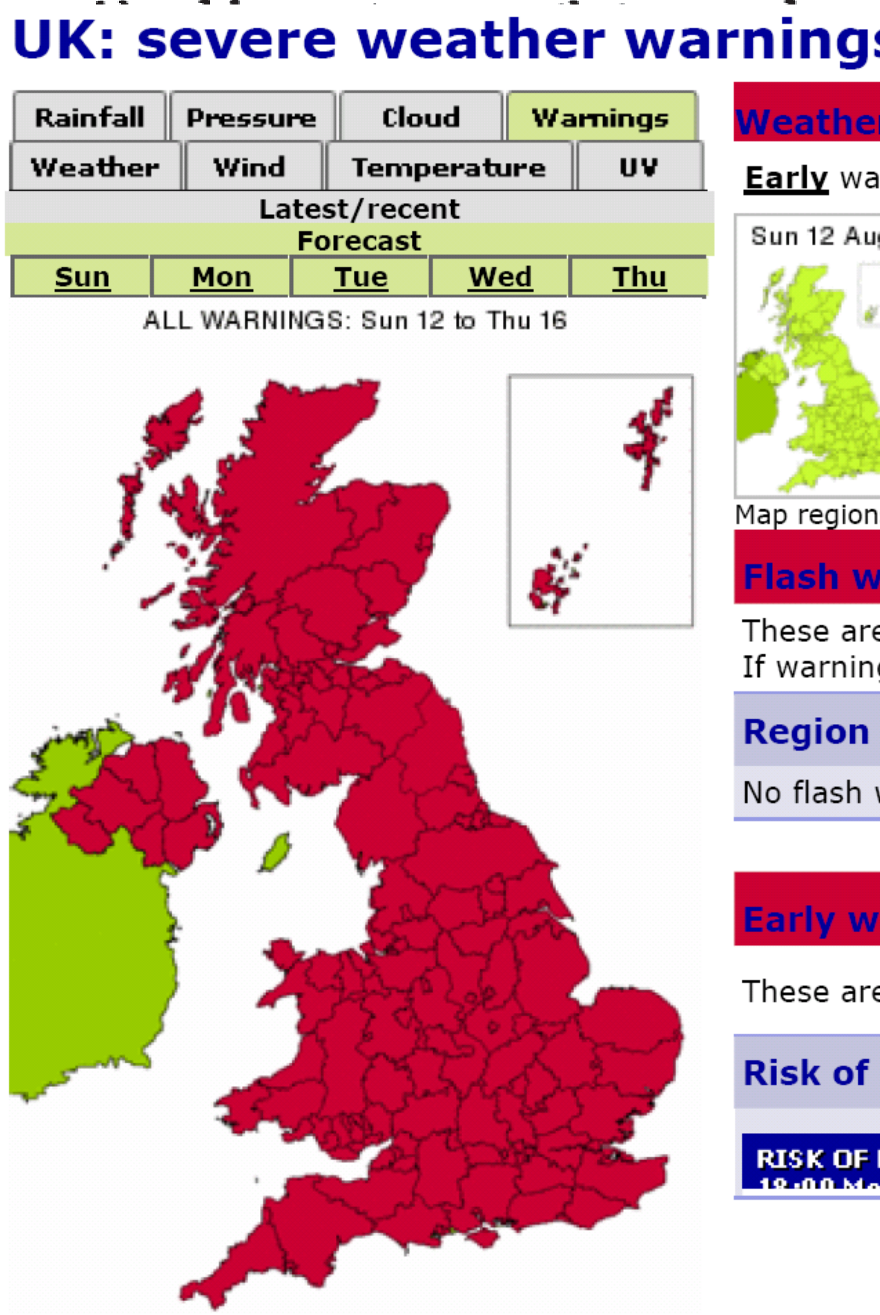
The radiation absorption coefficients of carbon dioxide and water vapour are used to show the effect of carbon dioxide on " sky radiation." From this the increase in mean temperature, due to the artificial production of carbon dioxide, is estimated to be at the rate of 0·003°C. per year at the present time.

It is well known that the gas carbon dioxide has certain strong absorption bands in the infra-red region of the spectrum, and when this fact was discovered some 70 years ago it soon led to speculation on the effect which changes in the amount of the gas in the air could have on the temperature of the earth's surface. In view of the much larger quantities and absorbing power of atmospheric water vapour it was concluded that the effect of carbon dioxide was probably negligible, although certain experts, notably Svante Arrhenius and T. C. Chamberlin, dissented from this view.

In the following paper I hope to show that such influence is not only possible, but is actually occurring at the present time.

That would be **1937**

Objection has been taken to such forecasts, because they cannot be always exactly correct,—for all places in one district. It is, however,



nprehensive expressions, in
endent judgments from the
g their immediate vicinity,
be very useful, as well as
erwise uninformed person,
bable cannot be otherwise
ay *bound* to act in accord-
dgment.
uld be merely *cautionary*
here over these islands,—
sory, or interfering arbi-
viduals.
ons may be incorrect—our
the signs afforded to man,
n is the real deficiency.

Fitzroy, 1862