

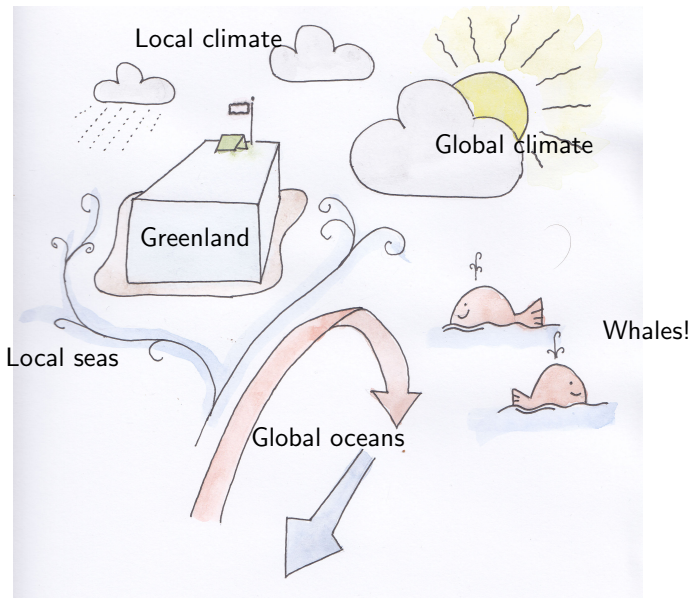
Assessing Model Limitations

Jonathan Rougier

Department of Mathematics
University of Bristol, UK

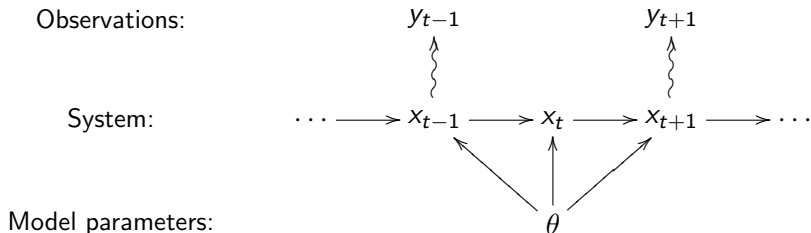
Bristol, Thu 13 May 2010

Illustration: the Greenland ice-sheet



Two different approaches

The current approach (deterministic model):



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Observations:

y_{t-1}

y_{t+1}

System:

$\dots \longrightarrow x_{t-1} \longrightarrow x_t \longrightarrow x_{t+1} \longrightarrow \dots$

Model parameters:

θ

Learning

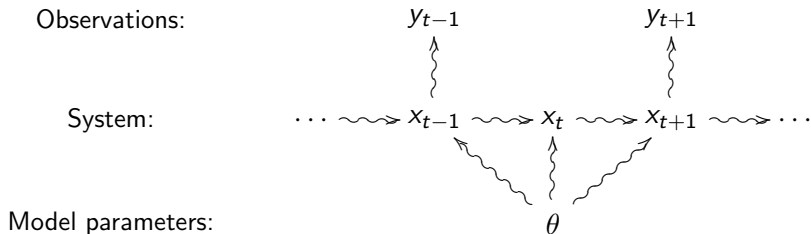
The initial state x_0 and the model parameters θ are jointly estimated by minimising the sum of squared deviations between the observations and the model output ('maximum likelihood').



Not expected to perform well.

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The *statistical* approach (*stochastic* model):



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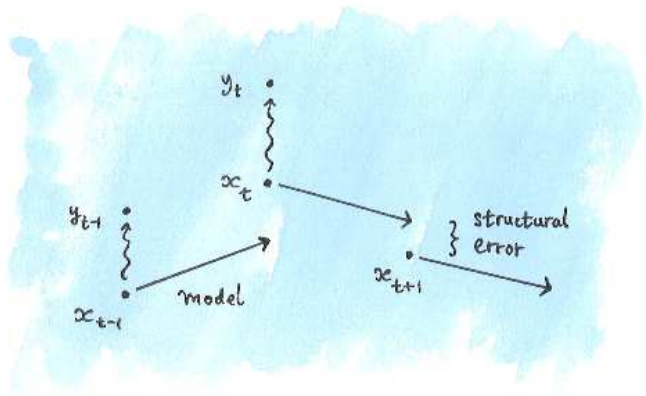
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Learning

The joint distribution of the state trajectory x_0, x_1, \dots and the model parameters θ is updated by the observations $\{y_t\}$. The result is represented as a set of samples of $(x_0, x_1, \dots, \theta)$.

 *Hard to do: call a statistician!*

Structural error on the time-step



Why is it so important to 'noise up' the model?



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- ▶ In environmental science, the dominant source of uncertainty is structural limitations in the model, and this uncertainty lives in the propagation of the state vector from x_{t-1} to x_t .

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- ▶ If we are interested in quantifying uncertainty, then, for our analysis to be defensible, the uncertainty must be sourced correctly.
- ▶ In environmental science, the dominant source of uncertainty is structural limitations in the model, and this uncertainty lives in the propagation of the state vector from x_{t-1} to x_t .
- ▶ We cannot simply add on some uncertainty to the solution of a deterministic model, because **non-linearities** in the model imply that *deterministic and stochastic solutions have fundamentally different characters*.

Illustration: the van der Pol oscillator

Has a 'slow' response x and a 'fast' response \dot{x} , related by

$$\ddot{x} + \dot{x} + (\alpha - x^2)x = \sigma x \xi$$

where ξ is white noise. Here $\theta = (\alpha, \sigma)$; we'll take $\alpha = 1$.

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As a model for glacial cycles

Deterministic, $\sigma = 0$

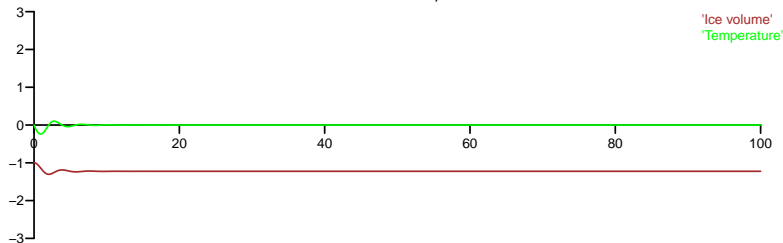


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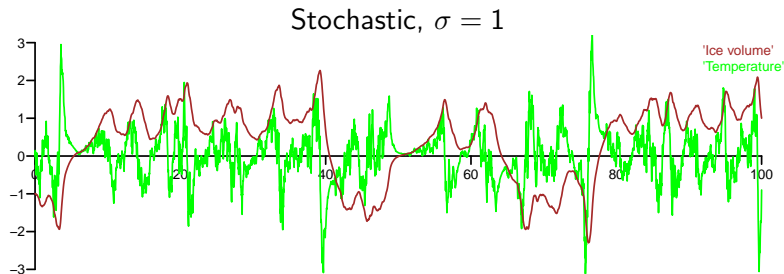


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Stochastic, $\sigma = 1$

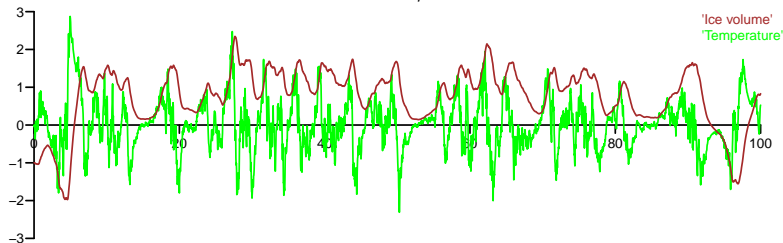


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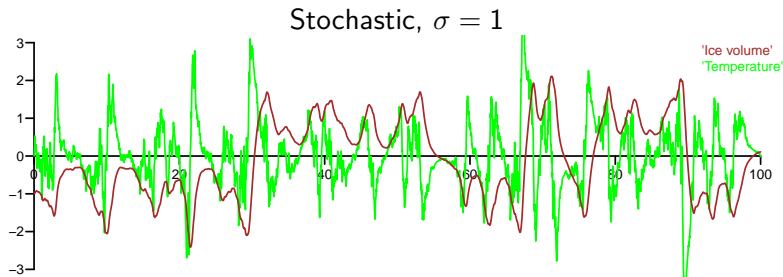


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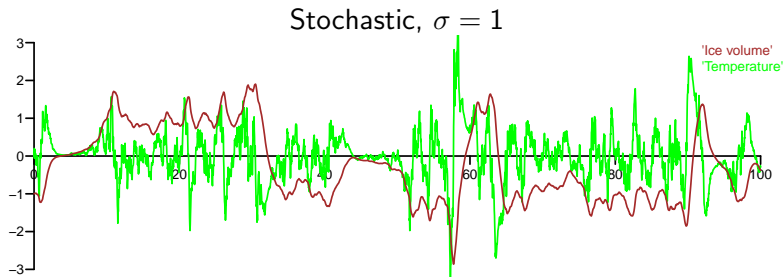


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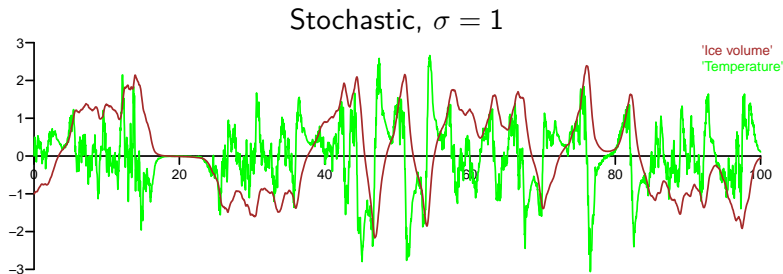


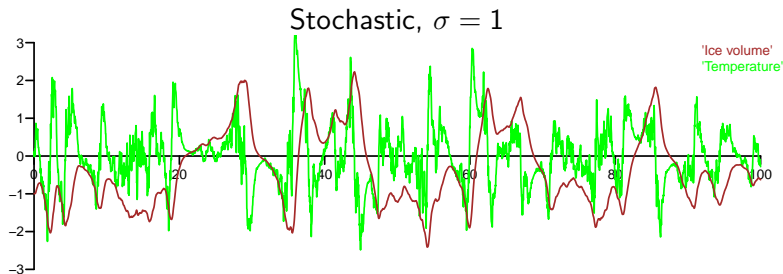
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And, some time soon,

4. Call in a statistician and noise up your model!