# Some Issues in Reduced Model Problem 

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## Outline

(1) Description of the reduced model problem
(2) Linear case
(3) Numerical experiments

We assume that the true model is

$$
\begin{align*}
d x & =F_{1}(x, y) d t+\sigma_{x} d W_{x}  \tag{1}\\
d y & =\frac{1}{\epsilon} F_{2}(x, y) d t+\frac{\sigma_{y}}{\sqrt{\epsilon}} d W_{y}  \tag{2}\\
y_{n}^{o} & =h_{1}\left(x_{n}\right)+h_{2}\left(y_{n}\right)+\xi_{n} \tag{3}
\end{align*}
$$

where the equations for $x$ and $y$ form the prior model.
Equation (3) is the true observational model.

## The role of $\epsilon$

- x is the slow process that we can build a model to resolve;
- $y$ is the fast process that we can not model.


## Goal:

- build a model for $x$ without explicitly modeling for $y$;
- build an observational model that only involves $x$.

$$
\begin{align*}
d x & =F(x) d t+\widetilde{\sigma}_{x} d \widetilde{W}_{x}  \tag{4}\\
y^{o} & =h(x)+\widetilde{\xi}_{n} \tag{5}
\end{align*}
$$

## Question:

How to choose $F, \widetilde{\sigma}_{x}, h$ and $\widetilde{\xi}_{n}$, so that the analysis/short forecast of the state $x$ using reduced models is as close as possible to those of the true models.

## Some partial results:

$$
\begin{array}{rlrl}
d x & =F_{1}(x, y) d t+\sigma_{x} d W_{x} & d x=F(x) d t+\widetilde{\tau} \\
d y & =\frac{1}{\epsilon} F_{2}(x, y) d t+\frac{\sigma_{y}}{\sqrt{\epsilon}} d W_{y} & y^{o}=h(x)+\widetilde{\xi}_{n} \\
y_{n}^{o} & =h_{1}\left(x_{n}\right)+h_{2}\left(y_{n}\right)+\xi_{n} & &
\end{array}
$$

1, We need to significantly modify $F, \widetilde{\sigma}_{x}, h$ and $\widetilde{\xi}_{n}$. Inparticular, $h$ could be very different from $h_{1}, \operatorname{Var}\left(\widetilde{\xi}_{n}\right)$ is no longer the instrumental error variance;
2, We may need to assume some nonzero correlation between the system noise $d \widetilde{W}_{x}$ and the observational noise $\widetilde{\xi}_{n}$;
3, When observations are frequently taken, we may need to assume an extremely large $\operatorname{Var}\left(\widetilde{\xi}_{n}\right)$.

## Linear case

We consider the following system (true model):

$$
\begin{align*}
d x & =a_{11} x d t+a_{12} y d t+\sigma_{x} d W_{x}  \tag{6}\\
d y & =\frac{a_{21}}{\epsilon} x d t+\frac{a_{22}}{\epsilon} y d t+\sigma_{y} d W_{y}  \tag{7}\\
y_{n}^{o} & =h_{1} x_{n}+h_{2} y_{n}+\sqrt{R} v_{n} \tag{8}
\end{align*}
$$

We also asumme a linear reduced model:

$$
\begin{align*}
d x & =\alpha x d t+\widetilde{\sigma}_{x} d \widetilde{W}_{x}  \tag{9}\\
y_{n}^{o} & =h x_{n}+\sqrt{r} \widetilde{v}_{n} \tag{10}
\end{align*}
$$

First we convert the prior model to a discrete time system:

$$
\begin{align*}
x_{n+1} & =F_{11} x_{n}+F_{12} y_{n}+\sqrt{q_{x}} W_{x}  \tag{11}\\
y_{n+1} & =F_{21} x_{n}+F_{22} y_{n}+\sqrt{q_{y}} W_{y}  \tag{12}\\
y_{n}^{o} & =h_{1} x_{n}+h_{2} y_{n}+\sqrt{R} v_{n} \tag{13}
\end{align*}
$$

and the reduced model:

$$
\begin{align*}
x_{n+1} & =\widetilde{F} x_{n}+\sqrt{\widetilde{q}} \widetilde{W}_{x}  \tag{14}\\
y_{n}^{o} & =h x_{n}+\sqrt{r} \widetilde{v}_{n} \tag{15}
\end{align*}
$$

Question: How to find those parameters in the reduced model?

Write

$$
\begin{equation*}
y_{n}=I_{n} x_{n}+\eta_{n} \tag{16}
\end{equation*}
$$

for some constant $I_{n}$, such that $\eta_{n}=y_{n}-I_{n} x_{n}$ and $x_{n}$ are uncorrelated. $I_{n}=\frac{\operatorname{Cov}\left(x_{n}, y_{n}\right)}{\operatorname{Var}\left(x_{n}\right)}$.
Then

$$
\begin{align*}
x_{n+1} & =F_{11} x_{n}+F_{12} y_{n}+\sqrt{q_{x}} W_{x} \\
& =F_{11} x_{n}+F_{12}\left(I_{n} x_{n}+\eta_{n}\right)+\sqrt{q_{x}} W_{x} \\
& =\left(F_{11}+F_{12} I_{n}\right) x_{n}+\left(F_{12} \eta_{n}+\sqrt{q_{x}} W_{x}\right) \tag{17}
\end{align*}
$$

This suggests $\widetilde{F}=F_{11}+F_{12} I_{n}$ and $\widetilde{q}_{x}=F_{12}^{2} \operatorname{Var}\left(\eta_{n}\right)+q_{x}$.

Similarly

$$
\begin{align*}
y_{n}^{o} & =h_{1} x_{n}+h_{2} y_{x}+\sqrt{R} v_{n} \\
& =h_{1} x+h_{2}\left(I_{n} x_{n}+\eta_{n}\right)+\sqrt{R} v_{n} \\
& =\left(h_{1}+h_{2} I_{n}\right) x_{n}+\left(h_{2} \eta_{n}+\sqrt{R} v_{n}\right) \tag{18}
\end{align*}
$$

This suggests $h=h_{1}+h_{2} I_{n}$ and $r=h_{2}^{2} \operatorname{Var}\left(\eta_{n}\right)+R$.

In sum, we rewrite the dynamics of $x$ and the observational model as:

$$
\begin{align*}
x_{n+1} & =\left(F_{11}+F_{12} I_{n}\right) x_{n}+\left(F_{12} \eta_{n}+\sqrt{q_{x}} W_{x}\right)  \tag{19}\\
y_{n}^{o} & =\left(h_{1}+h_{2} I_{n}\right) x_{n}+\left(h_{2} \eta_{n}+\sqrt{R} v_{n}\right) \tag{20}
\end{align*}
$$

where the "reduced" system noise is $\left(F_{12} \eta_{n}+\sqrt{q_{x}} W_{x}\right)$, and the "reduced" observational noise is $\left(h_{2} \eta_{n}+\sqrt{R} v_{n}\right)$. They are correlated! The correlation is $F_{12} h_{2} \operatorname{Var}\left(\eta_{n}\right)$.

The only shortcoming of the decomposition above is that the "reduced" system noise and observational noise are no longer white. This effect is significant when observations are frequently taken.

## Numerical results

Consider the following system (true model):

$$
\begin{align*}
d x & =-x d t+y d t+2 d W_{x}  \tag{21}\\
d y & =-\frac{1}{\epsilon} x d t-\frac{1}{\epsilon} y d t+\frac{2}{\sqrt{\epsilon}} d W_{y}  \tag{22}\\
y_{n}^{o} & =0.8 x_{n}+0.5 y_{n}+\sqrt{R} v_{n} \tag{23}
\end{align*}
$$

where $R=0.1 \operatorname{Var}(x)$. Observations are taken for every $\Delta t=0.1$ time units. $\left(x_{n}=x(0.1 n), y_{n}=y(0.1 n)\right)$.

## h-r plot

Contour plot of the error in percentage for varying $h$ and $r$ and fixed $\widetilde{F}, \widetilde{q}_{x}$ and $c=0$.


## h-r plot

Contour plot of the error in percentage for varying $h$ and $r$ and fixed $\widetilde{F}, \widetilde{q}_{x}$ and $c=0$.


## h-c plot

Contour plot of the error in percentage for varying $h$ and $c$ and fixed $\widetilde{F}, \widetilde{q}_{x}$ and $r$.


## h-c plot

Contour plot of the error in percentage for varying $h$ and $c$ and fixed $\widetilde{F}, \widetilde{q}_{x}$ and $r$.


## h-r plot for $\Delta t=0.01$ and $\Delta t=0.001$.

Contour plot of the error in percentage for varying $h$ and $r$ and fixed $\widetilde{F}, \widetilde{q}_{x}$ and $c=0$.


Question: why do we need a large $r$ when $\Delta t$ is small?

Recall the reduced model:

$$
\begin{equation*}
y_{n}^{o}=\left(h_{1}+h_{2} I_{n}\right) x_{n}+\left(h_{2} \eta_{n}+\sqrt{R} v_{n}\right) \tag{24}
\end{equation*}
$$

where $\eta_{n}=y_{n}-I_{n} x_{n}$.
$\eta_{n}$ is not a white noise!
When $\Delta t=0.01$ or $0.001, \eta_{n}$ and $\eta_{n+1}$ are highly correlated.

## A mathematical justification

Suppose at a fixed time point $t$, we have two observations $y_{n, 1}^{0}$ and $y_{n, 2}^{0}$ which are drawn from the same observational model. Now assume that they are the same (i.e. they have correlation 1). Two ways to assimilate these two observations:

1, only assimilate one of $y_{n, 1}^{0}$ and $y_{n, 2}^{0}$ and use the instrumental R;
2, assimilate these two observations one by one but use an inflated $r$.

## Lemma

Using $r=2 R$ in the second way we can get the same result by the first way.

Consider the system:

$$
\begin{align*}
& d x=-x d t+2 d W_{x}  \tag{25}\\
& d y=-y d t+2 d W_{y}  \tag{26}\\
& y_{n}^{o}=0.8 x_{n}+0.5 y_{n}+\sqrt{R} v_{n} . \tag{27}
\end{align*}
$$

There is a natural way of choosing the reduced prior model:

$$
\begin{equation*}
d x=-x d t+2 d W_{x} \tag{28}
\end{equation*}
$$

And it is natural to assume for this model that the reduced observational noise and the system noise are uncorrelated. Hence the only parameters left to determine are $h$ and $r$.

## h-r plot for $\Delta t=0.1,0.01,0.001$.



## Summary

1, We need to significantly modify $F, \widetilde{\sigma}_{x}, h$ and $\widetilde{\xi}_{n}$. Inparticular, $h$ could be very different from $h_{1}, \operatorname{Var}\left(\widetilde{\xi}_{n}\right)$ is no longer the instrumental error variance;
2, We may need to assume some nonzero correlation between the system noise $d \widetilde{W}_{x}$ and the observational noise $\widetilde{\xi}_{n}$; 3, When observations are frequently taken, we may need to assume an extremely large $\operatorname{Var}\left(\widetilde{\xi}_{n}\right)$.

