## Covariance Propagation in Data Assimilation: A Continuum Analysis of Advective Systems

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## Motivation: Addressing Variance Loss in Data Assimilation

## Data Assimilation as a Discrete Problem

Daley (1991), Kalnay (2003), Evensen (2009), etc.

$$
\boldsymbol{P}_{k+1}=\boldsymbol{M}_{k+1, k}\left(\boldsymbol{M}_{k+1, k} \boldsymbol{P}_{k}\right)^{T}+\boldsymbol{Q}_{k}
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Maybeck (1982) Ch. 9.2, Anderson and Anderson (1999), Mitchell and Houtekamer (2000), etc.

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Ménard et al. (2000), Ménard and Chang (2000), Lyster et al. (2004), Pannekoucke et al. (2016, 2021), Ménard et al. (2021).

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## Continuum Analysis of

 Covariance PropagationReturn to the continuum in an effort to uncover the underlying cause of variance loss in the propagation step.

## An Exploration of Covariance Propagation in Advective Systems

Part I: Analyze the continuum covariance propagation and uncover a discontinuous change in dynamics,

Part II: Derive the dynamics approximated by numerical schemes along the covariance diagonal.

## Part I:

Continuum Covariance Propagation

## Part I: Generalized Advective Dynamics

Define $q=q(\boldsymbol{x}, t)$ for $\boldsymbol{x} \in S_{r}^{2}$ with $q_{0}$ stochastic with mean $\bar{q}_{0}, \boldsymbol{v}=\boldsymbol{v}(\boldsymbol{x}, t)$ the (deterministic) velocity field, and $b=b(\boldsymbol{x}, t)$ a (deterministic) scalar,

$$
\begin{gathered}
q_{t}+\boldsymbol{v} \cdot \nabla q+b q=0, \\
q\left(\boldsymbol{x}, t_{0}\right)=q_{0}(\boldsymbol{x}) .
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Let $\mathbb{E}\{\cdot\}$ denote the expectation operator, and define the covariance $P=P\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}, t\right)=\mathbb{E}\left\{\left[q\left(\boldsymbol{x}_{1}, t\right)-\overline{q\left(\boldsymbol{x}_{1}, t\right)}\right]\left[q\left(\boldsymbol{x}_{2}, t\right)-\overline{q\left(\boldsymbol{x}_{2}, t\right)}\right]\right\}$,

$$
\begin{gathered}
\text { Continuum Covariance Evolution Equation } \\
P_{t}+\boldsymbol{v}_{1} \cdot \nabla_{1} P+\boldsymbol{v}_{2} \cdot \nabla_{2} P+\left(b_{1}+b_{2}\right) P=0 \\
P\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}, t_{0}\right)=P_{0}\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}\right)
\end{gathered}
$$

## Part I: Dynamics Along the Hyperplane $x_{1}=x_{2}$

$$
\begin{gathered}
\left(\mathcal{P}_{t} f\right)\left(\boldsymbol{x}_{1}\right)=\int_{S_{r}^{2}} P\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}, t\right) f\left(\boldsymbol{x}_{2}\right) d \boldsymbol{x}_{2}, f \in L^{2}\left(S_{r}^{2}\right) \\
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spatially correlated (continuous) $q_{0}$
$P_{0}\left(x_{1}, x_{2}\right)=\sigma_{0}\left(x_{1}\right) C_{0}\left(x_{1}, x_{2}\right) \sigma_{0}\left(x_{2}\right)$

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$$
\sigma_{t}^{2}+\boldsymbol{v} \cdot \nabla \sigma^{2}+2 b \sigma^{2}=0
$$

$$
\sigma^{2}\left(\boldsymbol{x}, t_{0}\right)=P_{0}(\boldsymbol{x}, \boldsymbol{x})
$$

Variance Equation

$$
\begin{gathered}
P\left(x_{1}, x_{2}, t\right)=\sigma\left(x_{1}, t\right) C\left(x_{1}, x_{2}, t\right) \sigma\left(x_{2}, t\right) \\
\left(\mathcal{P}_{t} f\right)\left(x_{1}\right)=\int_{S_{r}^{2}} P\left(x_{1}, x_{2}, t\right) f\left(x_{2}\right) d x_{2}
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$$
\begin{gathered}
\text { spatially uncorrelated } q_{0} \\
P_{0}\left(\boldsymbol{x}_{1}, x_{2}\right)=P_{0}^{c}\left(\boldsymbol{x}_{1}\right) \delta\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}\right) \\
\downarrow \\
P_{t}^{c}+\boldsymbol{v} \cdot \nabla P^{c}+(2 b-\nabla \cdot \boldsymbol{v}) P^{c}=0 \\
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Continuous Spectrum Equation

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\end{gathered}
$$

## Part I: Variances Extracted from Full Rank Covariance Propagation

Covariance (CN M) Diagonals for $C_{0}=\mathrm{GC}, \sigma_{0}(x)=\sin (3 x) / 3+1$, as $c \rightarrow 0$ at Final Time (T=3.979)


Figure 1: Exact solutions to the variance equation ( $\sigma^{2}$, black dashed) and continuous spectrum equation ( $P^{c}$, brown solid) at time $T$ (slightly after a full period) for a spatially-varying initial condition. The state dynamics satisfy the continuity equation $\left(b=v_{x}\right)$ with velocity $v(x)=\sin (x)+2$.

The variance, $\sigma^{2}$ (black dashed), and continuous spectrum, $P^{c}$ (brown solid), are distinct when the velocity field varies in space.

## Part I: Variances Extracted from Full Rank Covariance Propagation

Covariance (CN M) Diagonals for $C_{0}=\mathrm{GC}, \sigma_{0}(x)=\sin (3 x) / 3+1$, as $c \rightarrow 0$ at Final Time (T=3.979)


Figure 2: Diagonals extracted from covariances matrices propagated forward to time $T$ (slightly after a full period) using the Crank-Nicolson finite difference scheme for covariances with different initial correlation lengths (linearly proportional to $c$ in legend).

As correlation lengths shrink, the numerically propagated diagonals are approximating something, though it is unclear what is being approximated.

## Part I: Concluding Thoughts, Insights, and Lingering Questions

- Key Insight: The discontinuous change in the continuum dynamics causes problems when propagating covariance diagonals in discrete space.
- Both spurious loss and gain of variance are observed.
- What is $M(M P)^{\top}$ trying to approximate along the covariance diagonal?


## Part II:

Error Analysis of $M(M P)^{T}$

## Part II: $M(M P)^{T}$ and the Covariance Diagonal

$$
\begin{gathered}
\text { Covariance propagation, } \\
\boldsymbol{P}_{k+1}=\boldsymbol{M}_{k+1, k}\left(\boldsymbol{M}_{k+1, k} \boldsymbol{P}_{k}\right)^{T}
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How does approximating the covariance diagonal with off-diagonal elements impact the dynamics being approximated along the diagonal?

## Part II: Semi-Discretization for the Covariance Diagonal Propagation

Consider the generalized advection equation in flux form on the unit circle $\left(S_{1}^{1}\right), v>0$,

$$
q_{t}+(v q)_{x}+\left(b-v_{x}\right) q=0
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Apply a first-order upwind spatial discretization for $x_{i}=i \Delta x, i=1,2, \ldots, N, \Delta x=\frac{2 \pi}{N}$,

$$
\frac{d}{d t} q_{i}(t)=\frac{1}{\Delta x}\left[v_{i-1}(t) q_{i-1}(t)-v_{i}(t) q_{i}(t)\right]-\left[b_{i}(t)-\left(v_{x}\right)_{i}(t)\right] q_{i}(t)
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$$

Define $P_{i, j}(t)=\mathbb{E}\left\{\left[q_{i}(t)-\bar{q}_{i}(t)\right]\left[q_{j}(t)-\bar{q}_{j}(t)\right]\right\}$ and take $i=j$,

$$
\frac{d}{d t} P_{i, i}(t)=\frac{1}{\Delta x}\left\{v_{i-1}(t)\left[P_{i-1, i}(t)+P_{i, i-1}(t)\right]-2 v_{i}(t) P_{i, i}(t)\right\}-2\left[b_{i}(t)-\left(v_{x}\right)_{i}(t)\right] P_{i, i}(t)
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$$

Averaging across the diagonal to approximate $P_{i-1 / 2, i-1 / 2}(t)$

## Part II: Approximated Dynamics Along the Covariance Diagonal

$$
\begin{gathered}
\text { Variance Equation } \\
\sigma_{t}^{2}=-\left(v \sigma^{2}\right)_{x}-\left(2 b-v_{x}\right) \sigma^{2}
\end{gathered}
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Continuous Spectrum Equation
$P_{t}^{c}=-\left(v P^{c}\right)_{x}-\left(2 b-2 v_{x}\right) P^{c}$

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P_{t}^{c}=-\left(v P^{c}\right)_{x}-\left(2 b-2 v_{x}\right) P^{c}
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First-Order Upwind:

$$
\begin{aligned}
\frac{d}{d t} P\left(x_{i}, x_{i}, t\right) & =-\left.(v P)_{x}\right|_{x_{1}=x_{2}=x_{i}}\left[1-\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}\right]-\left[2 b\left(x_{i}, t\right)-2 v_{x}\left(x_{i}, t\right)\right] P\left(x_{i}, x_{i}, t\right) \\
& -v_{x}\left(x_{i}, t\right) P\left(x_{i}, x_{i}, t\right)\left[1-\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}\right]-\frac{1}{\Delta x} \frac{\Delta x^{2}}{4 L^{2}\left(x_{i}, t\right)} v\left(x_{i}, t\right) P\left(x_{i}, x_{i}, t\right) \\
& +\tilde{G}_{u}\left(x_{i}, t\right)+\tilde{H}_{u}\left(x_{i}, t\right) .
\end{aligned}
$$

## Part II: Approximated Dynamics for First- and Second-Order Schemes

First-Order Upwind:

$$
\begin{aligned}
\frac{d}{d t} P\left(x_{i}, x_{i}, t\right) & =-\left.(v P)_{x}\right|_{x_{1}=x_{2}=x_{i}}\left[1-\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}\right]-\left[2 b\left(x_{i}, t\right)-2 v_{x}\left(x_{i}, t\right)\right] P\left(x_{i}, x_{i}, t\right) \\
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& +\tilde{G}_{u}\left(x_{i}, t\right)+\tilde{H}_{u}\left(x_{i}, t\right)
\end{aligned}
$$

Second-Order Centered Difference:

$$
\begin{aligned}
\frac{d}{d t} P\left(x_{i}, x_{i}, t\right)= & -\left.(v P)_{x}\right|_{x_{1}=x_{2}=x_{i}}\left[1-\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}\right]-\left[2 b\left(x_{i}, t\right)-2 v_{x}\left(x_{i}, t\right)\right] P\left(x_{i}, x_{i}, t\right) \\
& -v_{x}\left(x_{i}, t\right) P\left(x_{i}, x_{i}, t\right)\left[1-\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}\right] \\
& +\tilde{G}_{c}\left(x_{i}, t\right)+\tilde{H}_{c}\left(x_{i}, t\right)
\end{aligned}
$$

## Part II: Significance of $\Delta x^{2} / 8 L^{2}(x, t)$

Solutions $\frac{\Delta x^{2}}{8 L^{2}(x, t)}$ for $L_{t}+v L_{x}-v^{\prime} L=0, L_{0}=c \sqrt{0.3}, v=\sin (x)+2, T=2 \pi / \sqrt{3}$


Figure 3: Time series snapshots of the ratio $\Delta x^{2} / 8 L^{2}(x, t)$ for different initial correlation lengths and grid lengths (uniform discretization of the unit circle).

Correlation lengths $L(x, t)$ satisfy

$$
L_{t}+v L_{x}-v_{x} L=0
$$

For the first-order upwind discretization, the term $-\frac{1}{\Delta x} \frac{\Delta x^{2}}{4 L^{2}\left(x_{i}, t\right)} v\left(x_{i}, t\right) P\left(x_{i}, x_{i}, t\right)$ can become large even when $\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}$ is small.

## Part II: Higher Order Average Approximations

Linear Combinations of $P_{i, i+1}+P_{i+1, i}, P_{1}\left(x_{i+1 / 2}, t\right), P_{2}\left(x_{i+1 / 2}, t\right)$ vs. $2 \sigma^{2}\left(x_{i+1 / 2}, t\right)$ (exact, solid) for $\sigma_{0}^{2}=1, v=\sin (x)+2$, FOAR Correlation Function


Figure 4: Time series snapshots of higher order average approximations (dashed)
Higher order average approximations do not always result in better approximations of the covariance diagonal. compared to the exact solution (solid).

## Part II: Concluding Thoughts, Lingering Questions, and Further Investigation

- Key Insight: Approximating the diagonal with off-diagonal elements changes the dynamics

$$
\boldsymbol{P}_{k+1}=\boldsymbol{M}_{k+1, k}\left(\boldsymbol{M}_{k+1, k} \boldsymbol{P}_{k}\right)^{T}
$$ approximated along the covariance diagonal.

- For advective systems, the approximated dynamics depend on ratio of the grid resolution to the correlation length, $\frac{\Delta x}{L}$.
- What does this suggest about covariance propagation practiced in current data assimilation schemes?



## Acknowledgements and Questions

For more information or further discussion, contact Shay at shay.gilpin@colorado.edu
Relevant work:
Gilpin, Matsuo, and Cohn, (2022): Continuum covariance propagation for understanding variance loss in advective systems, SIAM/ASA JUQ.

The presenter would like to thank the National Science Foundation (NSF) for supporting this work through the NSF Graduate Research Fellowship.

## Extra Slides

## Motivation Spurious Loss of Variance in 2D Transport Model

a) variance from $M(M P)^{\top}$

b) variance forecast


Figure 1 from Ménard et al. (2000), illustrating the variances $\sigma^{2}(\boldsymbol{x}, t)$ associated with the covariance $P\left(\boldsymbol{x}_{1}, \boldsymbol{x}_{2}, t\right)$ on an isentropic surface of Earth's atmosphere governed by

$$
P_{t}+\boldsymbol{v}_{1} \cdot \nabla_{1} P+\boldsymbol{v}_{2} \cdot \nabla_{2} P=0
$$

(a) variance extracted from the discrete covariance propagation $M(M P)^{T}$, (b) variance obtained by solving the associated equation for the variance,

$$
\sigma_{t}^{2}+\boldsymbol{v} \cdot \nabla \sigma^{2}=0, \sigma_{0}^{2}=1
$$

## Motivation: Spurious Loss of Variance in 3D Transport Model



Figure 5: Figure 5 from Ménard et al. (2021) depicting the total error variance as a function of time for different ensemble experiments in a $3 D$ chemical transport model (chemistry turned off, advection only).

FIGURE 5 Total error variance evolution using ERA-Interim winds for different initial correlation length using 20 and 100 members

## Part I: The Hyperplane $x_{1}=x_{2}$ is a Characteristic Surface

The characteristic equations for $\boldsymbol{x}_{1}$ and $\boldsymbol{x}_{2}$ both satisfy

$$
\begin{gathered}
\frac{d \boldsymbol{x}}{d t}=\boldsymbol{v}(\boldsymbol{x}, t), \\
\boldsymbol{x}\left(t_{0}\right)=\boldsymbol{s}
\end{gathered}
$$

where $\boldsymbol{x}_{i}=\boldsymbol{x}\left(t ; \boldsymbol{s}_{i}\right)$ for the initial coordinate $\boldsymbol{s}_{i}, i=1,2$.

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where $\boldsymbol{x}_{i}=\boldsymbol{x}\left(t ; \boldsymbol{s}_{i}\right)$ for the initial coordinate $\boldsymbol{s}_{i}, i=1,2$.
If $\boldsymbol{s}_{1}=\boldsymbol{s}_{2}$, then for $t \geq t_{0}$

$$
\boldsymbol{x}_{1}=\boldsymbol{x}\left(t ; \boldsymbol{s}_{1}\right)=\boldsymbol{x}\left(t ; \boldsymbol{s}_{2}\right)=\boldsymbol{x}_{2}
$$

solutions that start on the hyperplane $\boldsymbol{x}_{1}=\boldsymbol{x}_{2}$ remain on this hyperplane for all time.
As a result, there is a discontinuous change in covariance dynamics as initial correlation lengths tend to zero.

## Part I: The Fundamental Solution Operator

We can write solutions to the state equation as

$$
q(x, t)=\left(\mathcal{M}_{t} q_{0}\right)(x),
$$

where $\mathcal{M}_{t}: L^{2}\left(S_{r}^{2}\right) \mapsto L^{2}\left(S_{r}^{2}\right)$ is the fundamental solution operator

$$
\left(\mathcal{M}_{t} f\right)(x)=\int_{S_{r}^{2}} M(x, t ; \xi) f(\xi) d \xi, \quad f \in L^{2}\left(S_{r}^{2}\right),
$$

whose kernel $M=M(\boldsymbol{x}, t ; \boldsymbol{\xi})$ satisfies

$$
\begin{gathered}
M_{t}+v \cdot \nabla M+b M=0, \\
M\left(x, t_{0} ; \boldsymbol{\xi}\right)=\delta(x, \boldsymbol{\xi}) .
\end{gathered}
$$

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M\left(x, t_{0} ; \xi\right)=\delta(x, \xi) .
\end{gathered}
$$

We can also define the adjoint fundamental solution operator, $\mathcal{M}_{t}^{*}: L^{2}\left(S_{r}^{2}\right) \mapsto L^{2}\left(S_{r}^{2}\right)$, defined by

$$
\left(\mathcal{M}_{t}^{*} f, g\right)_{2}=\left(f, \mathcal{M}_{t} g\right)_{2} \quad \forall f, g \in L^{2}\left(S_{r}^{2}\right),
$$

which is also an integral operator,

$$
\left(\mathcal{M}_{t}^{*} f\right)(\xi)=\int_{S_{r}^{2}} M^{*}(\xi ; x, t) f(x) d x, \quad f \in L^{2}\left(S_{r}^{2}\right)
$$

## Part I: Continuum Covariance Propagation (Operator Formulation)

We can express the covariance $P\left(x_{1}, x_{2}, t\right)$ in terms of the kernels $M$ and $M^{*}$,

$$
P\left(x_{1}, \boldsymbol{x}_{2}, t\right)=\int_{S_{r}^{2}} \int_{S_{r}^{2}} M\left(\boldsymbol{x}_{1}, t ; \boldsymbol{\xi}_{1}\right) P_{0}\left(\boldsymbol{\xi}_{1}, \boldsymbol{\xi}_{2}\right) M^{*}\left(\boldsymbol{\xi}_{2} ; \boldsymbol{x}_{2}, t\right) d \boldsymbol{\xi}_{2} d \xi_{1}
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$$

or simply

$$
\mathcal{P}_{t}=\mathcal{M}_{t} \mathcal{P}_{0} \mathcal{M}_{t}^{*}
$$

where $\mathcal{P}_{t}: L^{2}\left(S_{r}^{2}\right) \mapsto L^{2}\left(S_{r}^{2}\right)$ is the covariance operator,

$$
\left(\mathcal{P}_{t} f\right)\left(x_{1}\right)=\int_{S_{r}^{2}} P\left(x_{1}, x_{2}, t\right) f\left(x_{2}\right) d x_{2}, \quad f \in L^{2}\left(S_{r}^{2}\right),
$$

where at $t=t_{0}$ we have

$$
\left(\mathcal{P}_{0} f\right)\left(x_{1}\right)=\int_{S_{r}^{2}} P_{0}\left(x_{1}, x_{2}\right) f\left(x_{2}\right) d x_{2}, \quad f \in L^{2}\left(S_{r}^{2}\right) .
$$

## Part II: Expanding the Averaging Term

$$
\frac{d}{d t} P_{i, i}(t)=\frac{1}{\Delta x}\left\{v_{i-1}(t)\left[P_{i-1, i}(t)+P_{i, i-1}(t)\right]-2 v_{i}(t) P_{i, i}(t)\right\}-2\left[b_{i}(t)-\left(v_{x}\right)_{i}(t)\right] P_{i, i}(t) .
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The natural choice is to expand about the half-grid point $x_{i-1 / 2}, x_{i-1 / 2}$.

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$$

The natural choice is to expand about the half-grid point $x_{i-1 / 2}, x_{i-1 / 2}$.

$$
\begin{aligned}
& P\left(x_{i-1}, x_{i}, t\right)+P\left(x_{i}, x_{i-1}, t\right)=2 P\left(x_{i-1 / 2}, x_{i-1 / 2}, t\right)+\left(\frac{\Delta x}{2}\right)^{2} P_{2}\left(x_{i-1 / 2}, t\right)+\mathcal{O}\left(\Delta x^{3}\right) \\
& P_{2}(x, t)=\left[\frac{\partial^{2} P}{\partial x_{1}^{2}}-2 \frac{\partial^{2} P}{\partial x_{1} \partial x_{2}}+\frac{\partial^{2} P}{\partial x_{1}^{2}}\right]_{x_{1}=x_{2}=x}=P(x, x, t) \log [P(x, x, t)]_{x x}-\underbrace{\frac{P(x, x, t)}{L^{2}(x, t)}}_{\text {correlation length }}
\end{aligned}
$$

## Part II: Semi-Discretization in Advection Form (Upwind)

Suppose we consider the state equation in advection form,

$$
q_{t}+v q_{x}+b q=0
$$

and discretize $q_{x}$ using a first-order upwind scheme,

$$
\frac{d}{d t} q_{i}(t)=\frac{v_{i}(t)}{\Delta x}\left[q_{i-1}(t)-q_{i}(t)\right]-b_{i}(t) q_{i}(t)
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The semi-discretization for the covariance diagonal is then,

$$
\frac{d}{d t} P_{i, i}(t)=\frac{v_{i}(t)}{\Delta x}\left\{\left[P_{i-1, i}(t)+P_{i, i-1}(t)\right]-2 P_{i, i}(t)\right\}-2 b_{i}(t) P_{i, i}(t)
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$$

The approximated dynamics (after expanding the averaging term) are

$$
\begin{aligned}
\frac{d}{d t} P\left(x_{i}, x_{i}, t\right)= & -v\left(x_{i}, t\right) P_{x}\left(x_{i}, x_{i}, t\right)\left[1-\frac{\Delta x^{2}}{8 L^{2}\left(x_{i}, t\right)}\right]-2 b\left(x_{i}, t\right) P\left(x_{i}, x_{i}, t\right) \\
& -\frac{1}{\Delta x} \frac{\Delta x^{2}}{4 L^{2}\left(x_{i}, t\right)} v\left(x_{i}, t\right) P\left(x_{i}, x_{i}, t\right)+A_{u}\left(x_{i}, t\right)+B_{u}\left(x_{i}, t\right)
\end{aligned}
$$

