



In partnership with



Weak Constraint 4D-Var Data Assimilation in the Regional Ocean Modeling System (ROMS) using a Saddle-Point Algorithm

Andy Moore, UC Santa Cruz

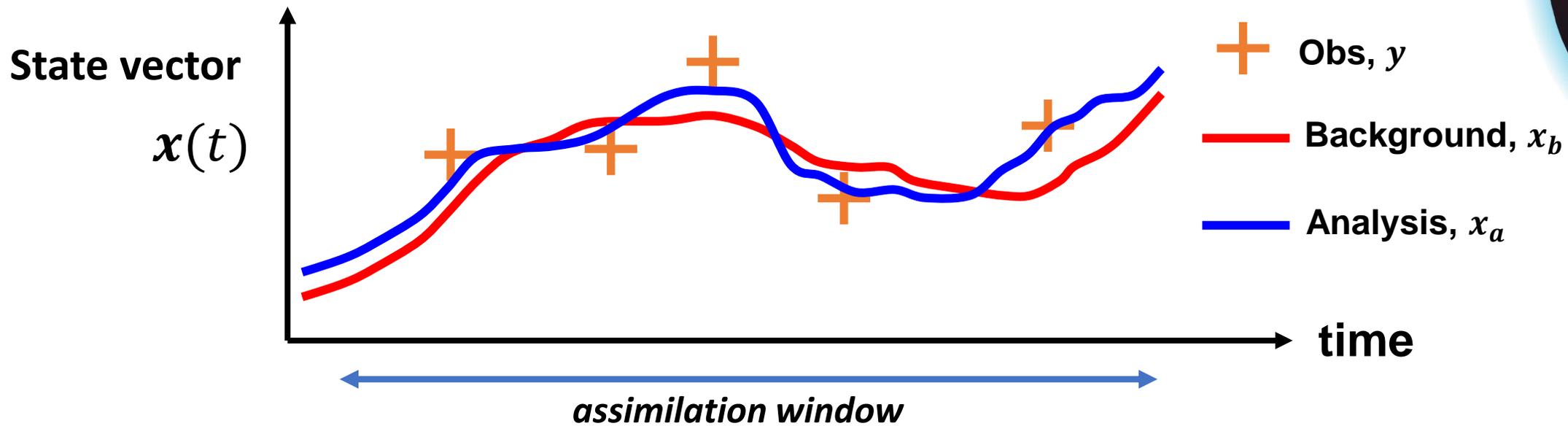
Hernan Arango, Rutgers University

John Wilkin, Rutgers University

Chris Edwards, UC Santa Cruz



4-Dimensional Variational (4D-Var) Data Assimilation



4D-Var employs variational calculus to minimize a cost function.

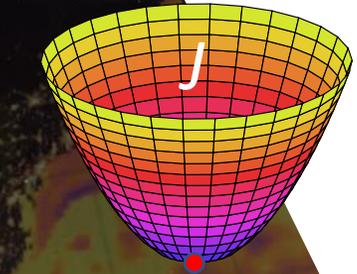
Forecast model:
$$\overset{\text{state vector}}{\mathbf{x}_k} = \overset{\text{forecast model}}{\mathcal{M}_k}(\mathbf{x}_{k-1}) + \overset{\text{model error}}{\mathbf{q}_k} \quad k = 1, n$$

Prior assumption: “perfect” model ($\mathbf{q}_k = 0$) → Strong constraint DA
“imperfect” model ($\mathbf{q}_k \neq 0$) → Weak constraint DA

Motivation: Increase the efficiency of the iterative 4D-Var cost function minimization.

Incremental Weak Constraint 4D-Var Fisher and Gürol (2017)

Incremental \rightarrow linearize about the background $x_b \rightarrow \delta x_k = x_k - (x_b)_k; \delta q_k = q_k - (q_b)_k$



Cost function J

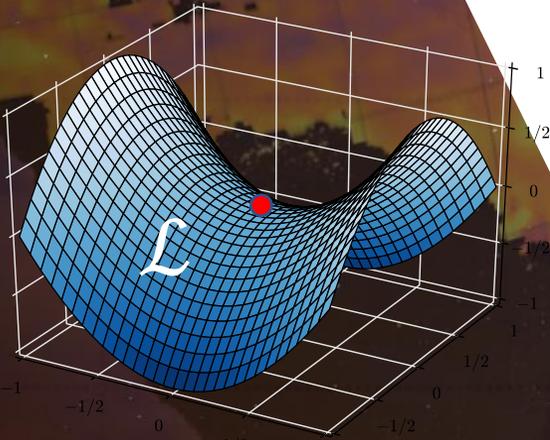
Forcing Formulation

Minimize the usual cost function J

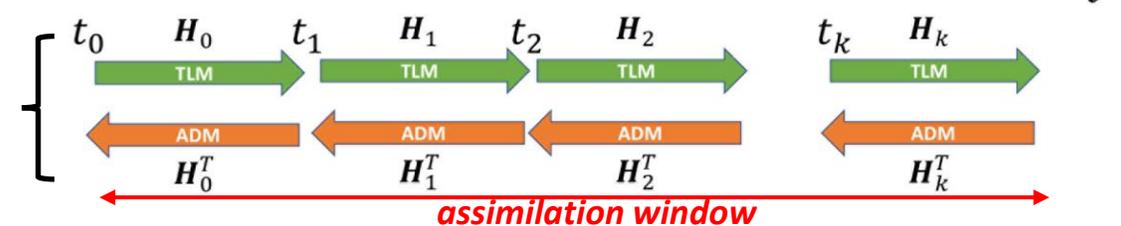
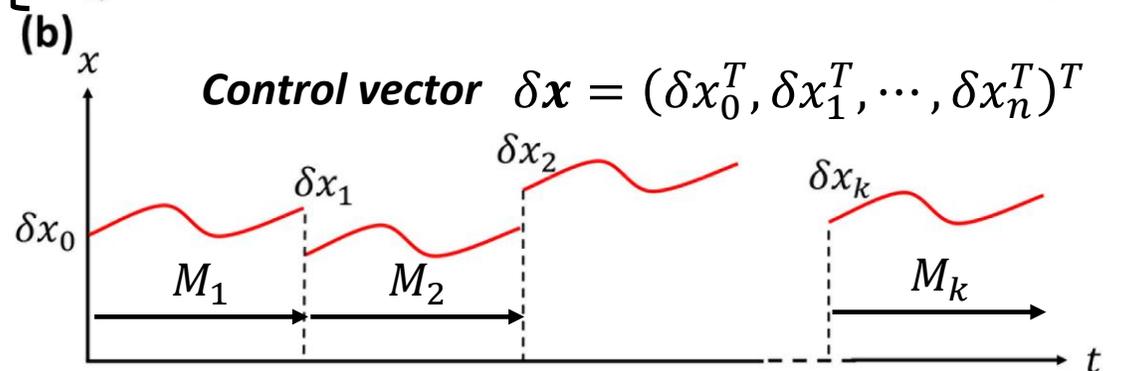
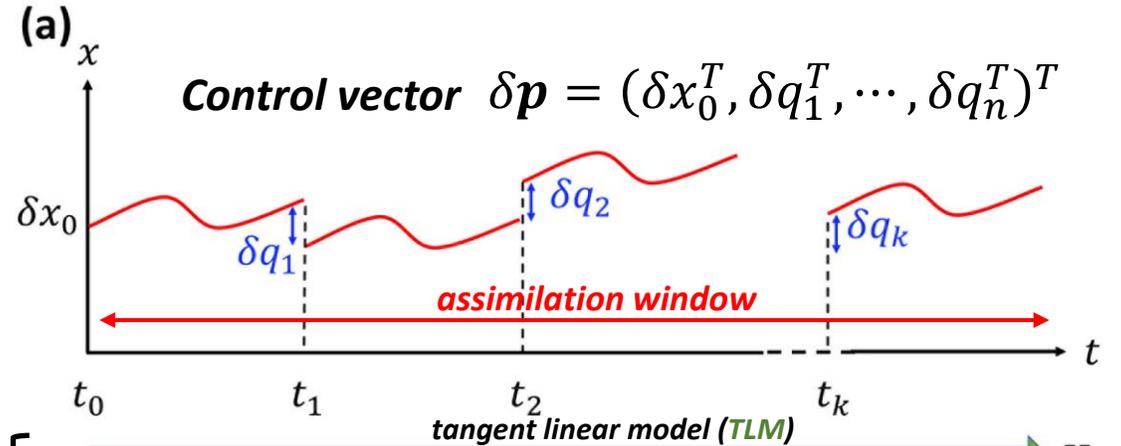
Time sequential

Saddle-point Formulation

Minimize J subject to additional constraints \rightarrow Lagrange function



Lagrange function \mathcal{L}



Time parallel

Saddle-Point 4D-Var in the California Current System using the Regional Ocean Modeling System (ROMS)

Two ROMS configurations:

- 1/3rd degree resolution, 42 σ -levels
- COAMPS surface forcing
- ECCO open boundary conditions
- Observations:
 - satellite SST
 - Aviso altimetry
 - Argo profiling floats
- 4-day 4D-Var windows
- Standard test case (WC13)

- 1/10th degree resolution, 42 σ -levels
- ERA surface forcing
- Global HYCOM open boundary conditions
- Observations:
 - satellite SST
 - Aviso altimetry
 - Argo profiling floats
- 8-day 4D-Var windows



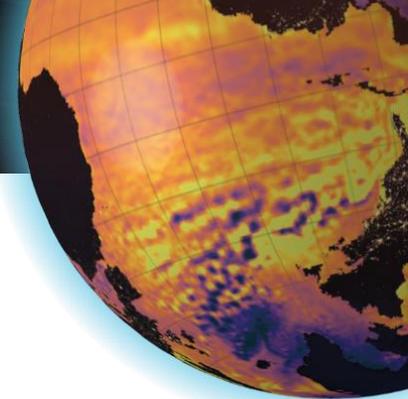
Forcing formulation: RBCG (Restricted B-preconditioned CG)

Saddle-point formulation: SP4DVAR

Single 4d-Var cycle:

1 outer-loop, $n=8$ sub-intervals, $Q=0.2B$

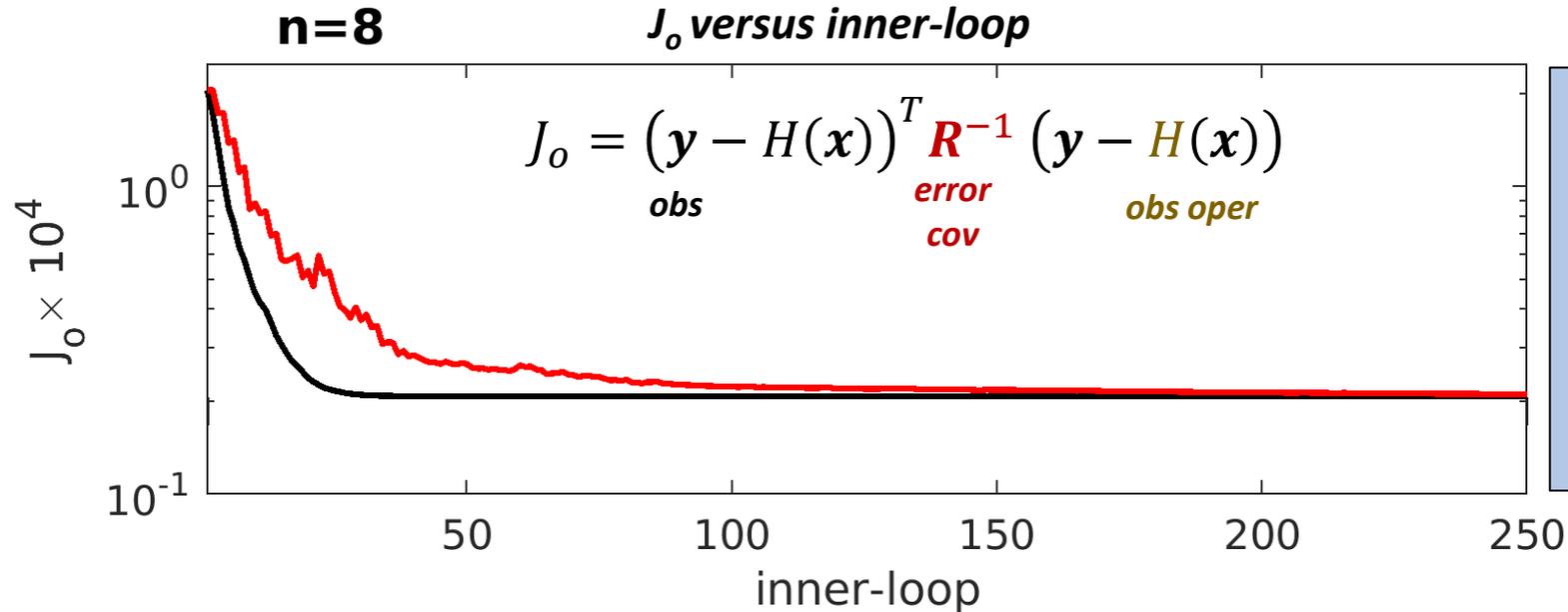




Convergence Validation

1/3rd degree resolution, 4-day assimilation window, 3-7 Jan 2004

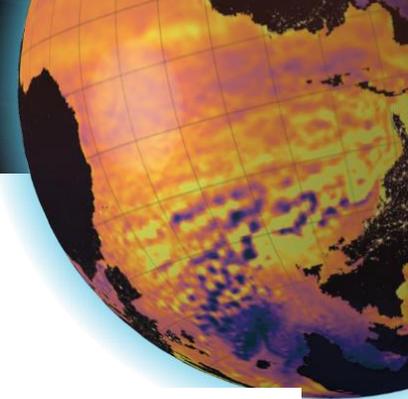
1 outer-loop, 4-day window, $n=8$ sub-intervals, $Q=0.2B$



- SP4DVAR & RBCG yield the same solution.
- SP4DVAR converges more slowly than RBCG, **but** SP4DVAR benefits from time parallelization → less wall clock time

- RBCG (forcing formulation of 4D-Var)
- SP4DVAR (saddle-point formulation)

Obs: Blended SST, SSH (Aviso),
in situ T & S (XBT, CTD, Argo)



Termination before Convergence

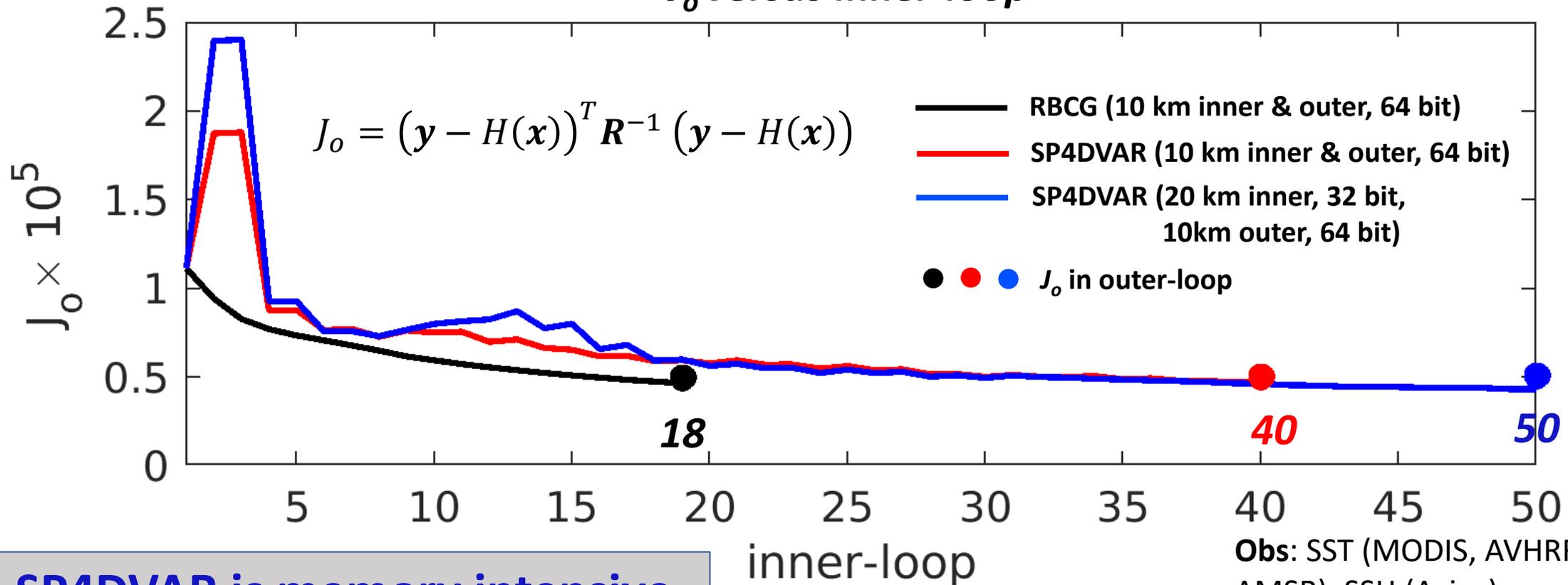
1/10th degree resolution, 8-day assimilation window, 3-11 Jan 2004

1 outer-loop, 8-day window, $n=8$ sub-intervals, $Q=0.2B$

$n=8$

J_o versus inner-loop

$$J_o = (y - H(x))^T R^{-1} (y - H(x))$$



- RBCG (10 km inner & outer, 64 bit)
- SP4DVAR (10 km inner & outer, 64 bit)
- SP4DVAR (20 km inner, 32 bit, 10km outer, 64 bit)
- ● ● J_o in outer-loop

18

40

50

inner-loop

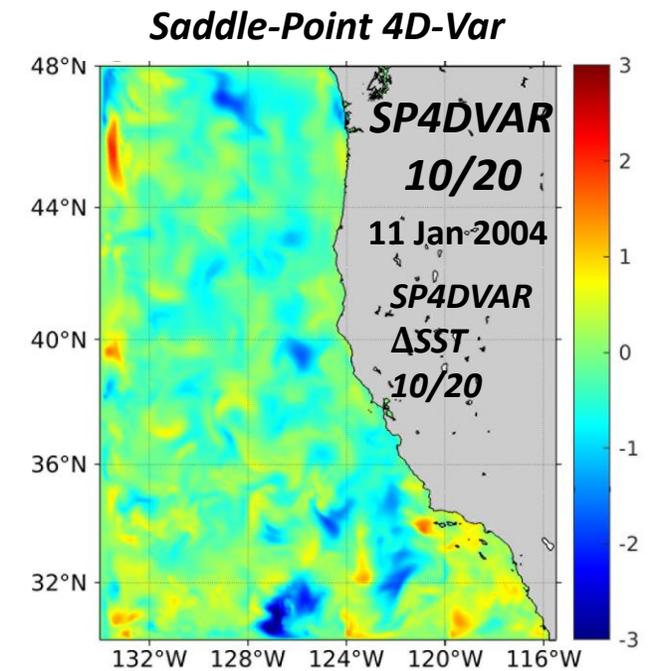
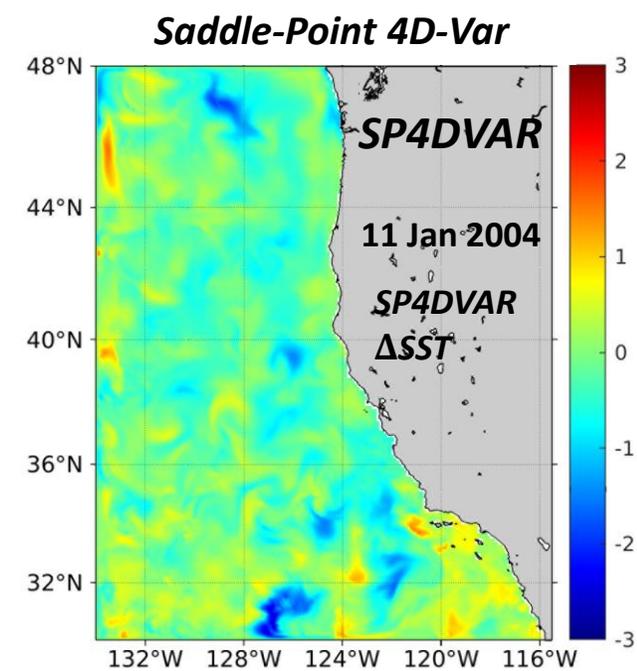
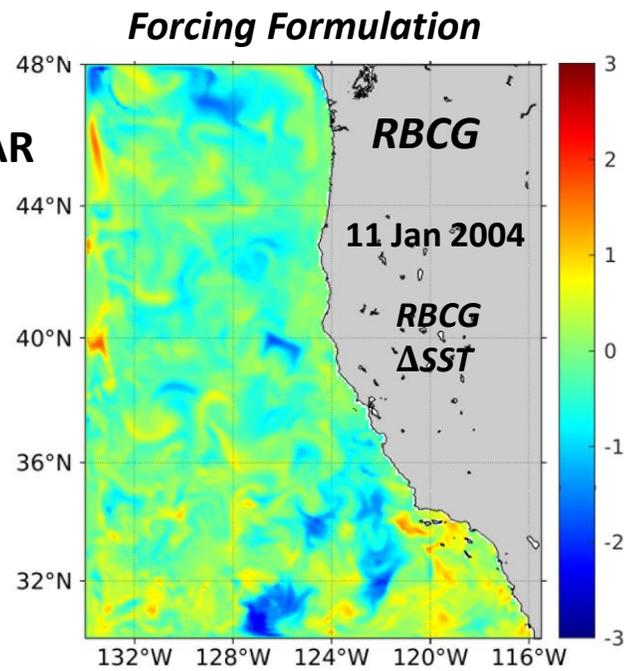
Obs: SST (MODIS, AVHRR, GOES, AMSR), SSH (Aviso), in situ T & S (XBT, CTD, Argo)

SP4DVAR is memory intensive

SST 4D-Var Increments: 10km resolution, 3-11 Jan 2004

SST increments:
RBCG vs SP4DVAR

1 outer-loop
8-day cycle
 $n=8, Q=0.2B$



Outer-loop J_o :

$$J_o = 5.03 \times 10^4$$

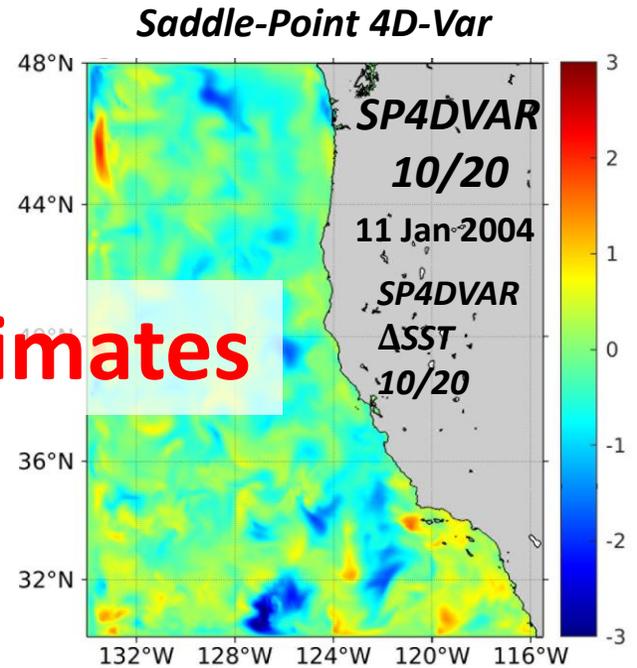
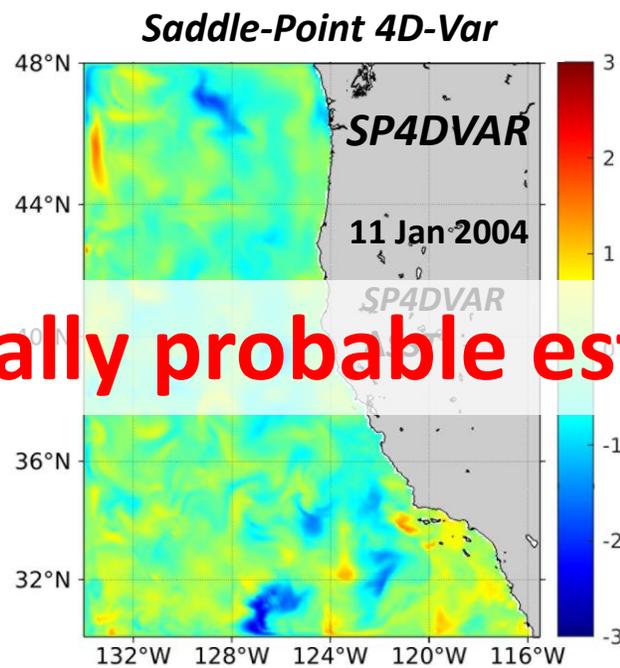
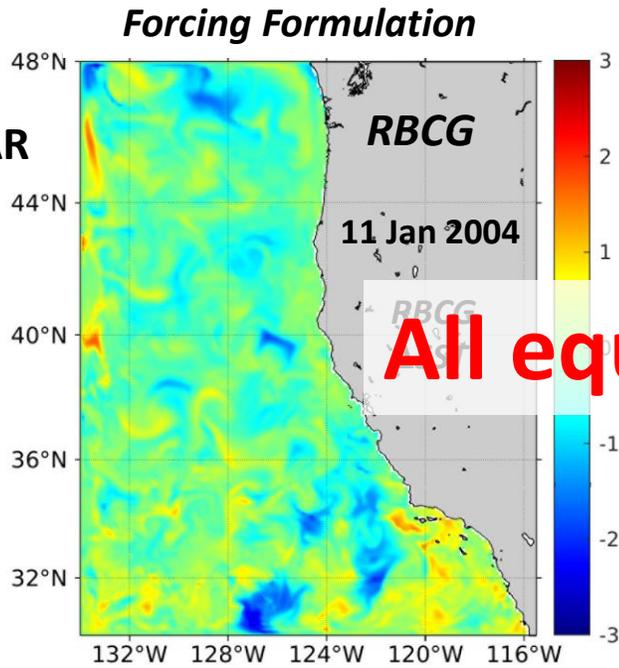
$$J_o = 5.04 \times 10^4$$

$$J_o = 5.10 \times 10^4$$

SST 4D-Var Increments: 10km resolution, 3-11 Jan 2004

SST increments:
RBCG vs SP4DVAR

1 outer-loop
8-day cycle
 $n=8, Q=0.2B$



All equally probable estimates

Outer-loop J_o : $J_o = 5.03 \times 10^4$

$J_o = 5.04 \times 10^4$

$J_o = 5.10 \times 10^4$

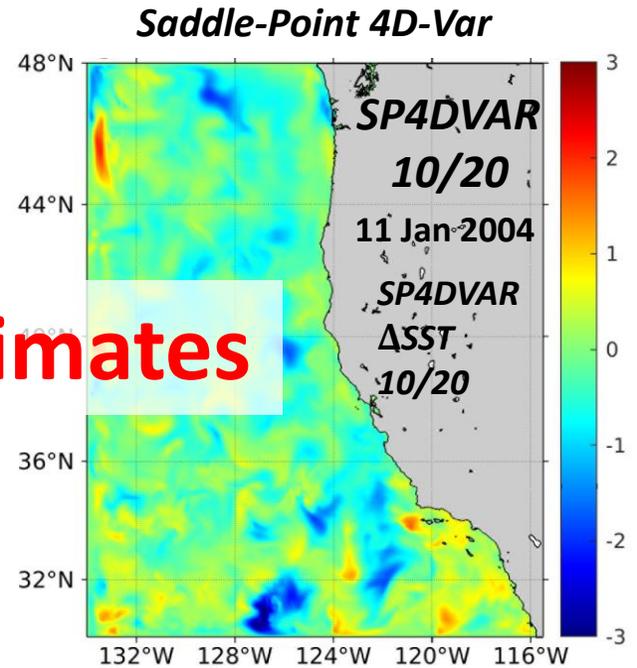
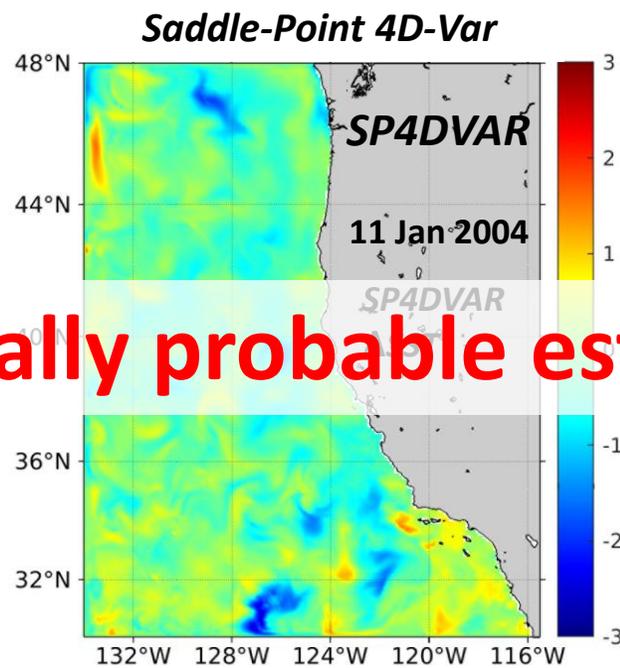
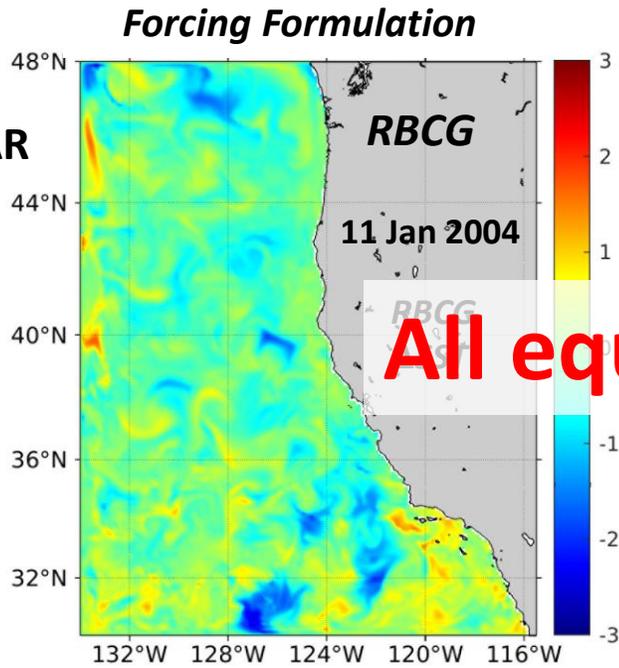
$$J_o = (\mathbf{y} - H(\mathbf{x}))^T \mathbf{R}^{-1} (\mathbf{y} - H(\mathbf{x}))$$

Conditional probability:
 $J_o \propto -\ln(P(\mathbf{x}|\mathbf{y}))$

SST 4D-Var Increments: 10km resolution, 3-11 Jan 2004

SST increments:
RBCG vs SP4DVAR

1 outer-loop
8-day cycle
 $n=8, Q=0.2B$



All equally probable estimates

Outer-loop J_o :

$$J_o = 5.03 \times 10^4$$

$$J_o = 5.04 \times 10^4$$

$$J_o = 5.10 \times 10^4$$

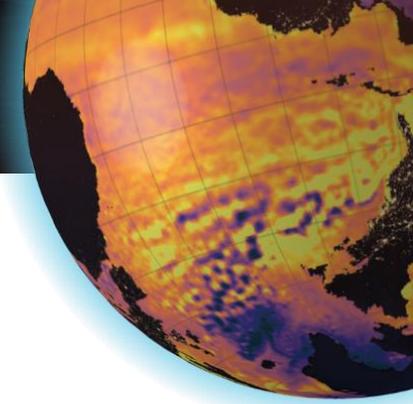
Relative CPU time per inner-loop:

100%

12%

1.6%

Scales as $\sim(2n)^{-1}$



Summary and Conclusions

- Saddle-point 4D-Var has the potential to be a game-changer!
- Saddle-point 4D-Var will run ***much*** faster than RBCG on very large HPC systems
- Outstanding performance issues in ROMS-SP4DVAR:
 - improve efficiency of adjoint model
 - solution assembly & GMRES overhead
 - preconditioning
- Ongoing work: specification of model error covariances, **Q** (ML?)

Moore, A.M., H.G. Arango, J. Wilkin and C.A. Edwards, 2023: Weak constraint 4D-Var data assimilation in the Regional Ocean Modeling System (ROMS) using a saddle-point algorithm: Application to the California Current Circulation. Ocean Modelling, <https://doi.org/10.1016/j.ocemod.2023.102262>.

SYM POSIUM IUM



OP' 24

ADVANCING OCEAN PREDICTION
SCIENCE FOR SOCIETAL BENEFITS

Thank you!

