

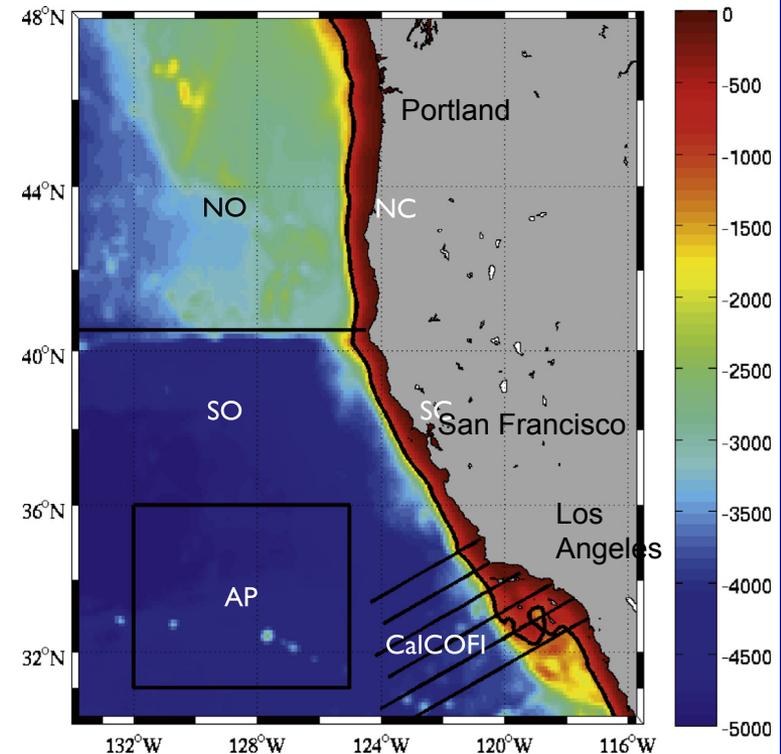
Impact of assimilating physical oceanographic data on modeled ecosystem dynamics in the California Current System

Christopher A. Edwards, University of California Santa Cruz

*K. Raghukumar, N. L. Goebel, G. Broquet, M. Veneziani, A. M. Moore, J. P. Zehr
H. Song, P. Mattern*

GODAE OceanView
Joint DA-TT & MEAP-TT Workshop
*Santa Cruz, CA
July 11-13, 2016*

Most results from Kaustubha et al. (2015)



Examples of assimilating systems

Main characteristics of selected GODAE/GOV forecasting systems

System	Ocean model	Biogeochemical model	Configuration	Data assimilation scheme		Assimilated data		System status
				PHYS ⁽¹⁾	BGC ⁽²⁾	PHYS	BGC	
FOAM-HadOCC	NEMO3.2-CICE	HadOCC	global, 1/4°cos(lat) resolution, 75 vertical layers	3D-Var	analysis correction + multi-variate balancing	satellite SLA, SST, sea ice, in situ SST, T/S profiles	chlorophyll-a or pCO ₂	pre-operational (BGC) operational (PHYS)
FOAM-ERSEM	NEMO3.2	ERSEM	Atlantic Margin, 7km resolution, 32 hybrid vertical layers	analysis correction	no	SST	no	operational
TOPAZ-NORWECOM	HYCOM	NORWECOM	North Atlantic and Arctic (Bering Strait), 50 km resolution 28 vertical layers	DEnKF	DEnKF & Gaussian anamorphosis	satellite SLA, SST, sea ice	chlorophyll-a	pre-operational
TOPAZ-NORWECOM	HYCOM	NORWECOM	same but 12 km resolution	DEnKF	no	satellite SLA, SST, sea ice, in situ T/S profiles	no	operational
MERCATOR-OCEAN/BIOMER	NEMO 3.1	PISCES (NEMO3.2) off-line coupled ⁽³⁾	global, 1/4°cos(lat) resolution, 50 vertical layers	SAM2V1	no	satellite SST, SSH, in situ T/S profiles	no	operational
MFS	NEMO3.4 + waves + atm.pressure	BFM (OPATM) off-line coupled ⁽³⁾	Mediterranean Sea (1/16°), 72 vertical layers	3D-Var	3D-VAR	Satellite SSH, in situ T/S profiles	chlorophyll-a	operational
CANOVA-GSBM	OPA9-LIM2	GSBM	East-Canadian shelf (1/12°), 46 vertical layers	no	no	no	no	non-assimilative hindcast

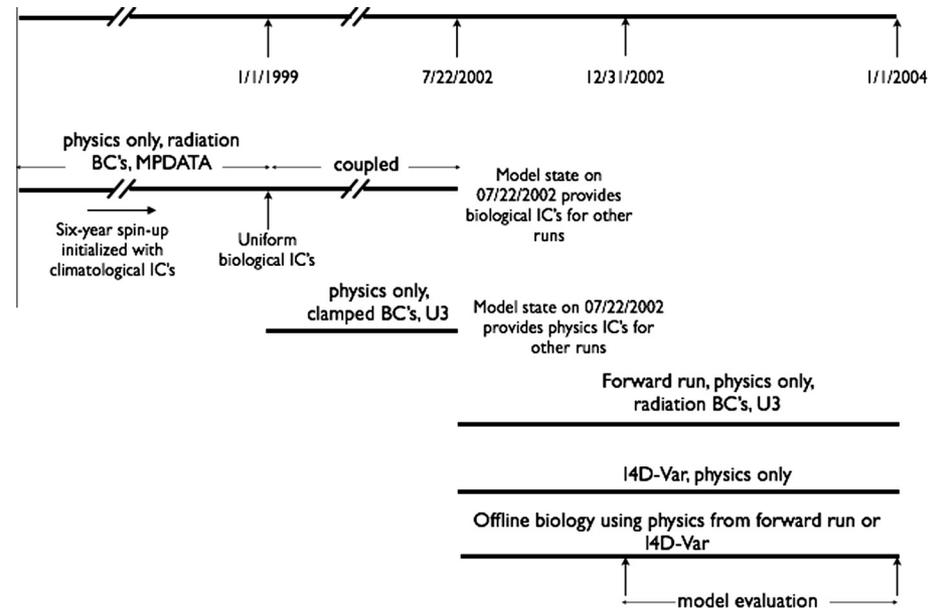
⁽¹⁾PHYS = physics; ⁽²⁾BGC = biogeochemistry; ⁽³⁾ biogeochemical model coupled off-line (run sequential) to physical model;

Gehlen et al. (in press)



Assimilation Details

- Incremental Strong Constraint 4D-Var
- ROMS-CCS
- 1/10 degree
- 42 levels
- Data assimilated
 - SSH (gridded)
 - SST (along track)
 - EN3 hydrography
- 14-day assimilation cycle
- Univariate covariances
- NPZD model run offline
- Daily saved snapshots

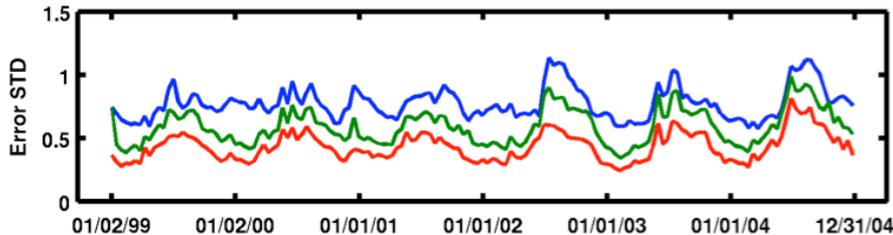
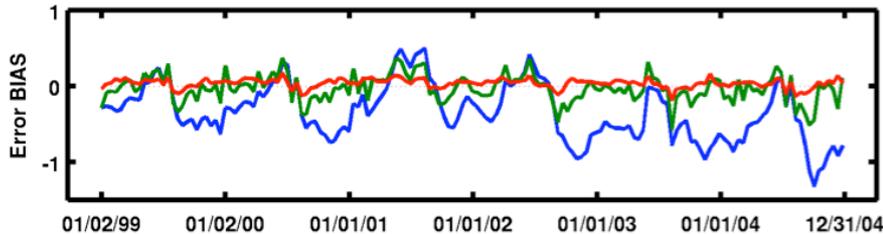
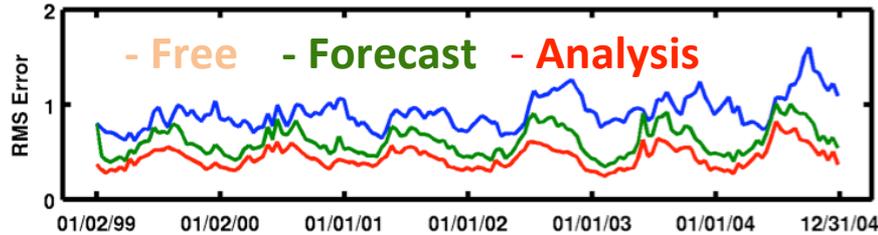


Broquet et al. (2009), Raghukumar et al. (2015)



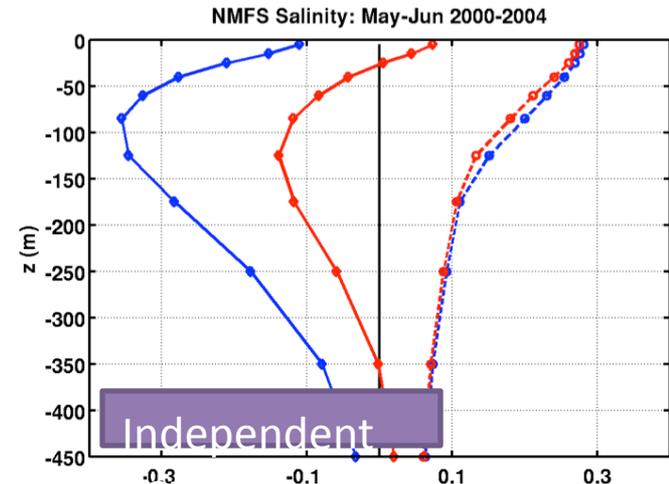
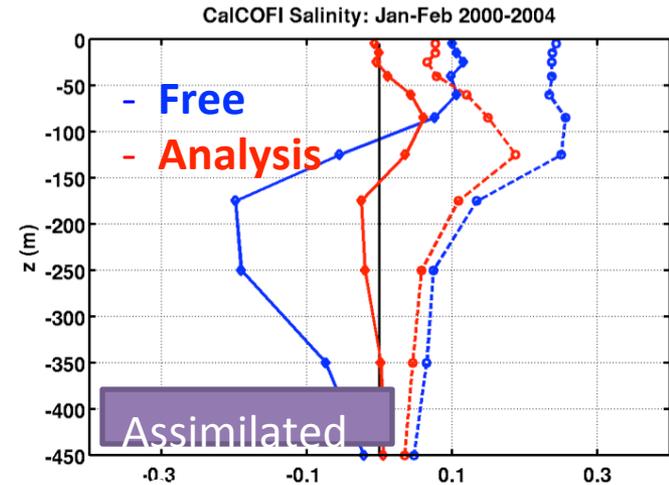
UCSC California Current (physical) 4D-Var Assimilation System assimilating SSH/SST/CalCOFI/GLOBEC

Diagnostics relative to observations



Error statistics for COAMPS SST for each 14d assimilation cycle

$$(\text{RMS Error})^2 = (\text{Error bias})^2 + (\text{Error STD})^2$$

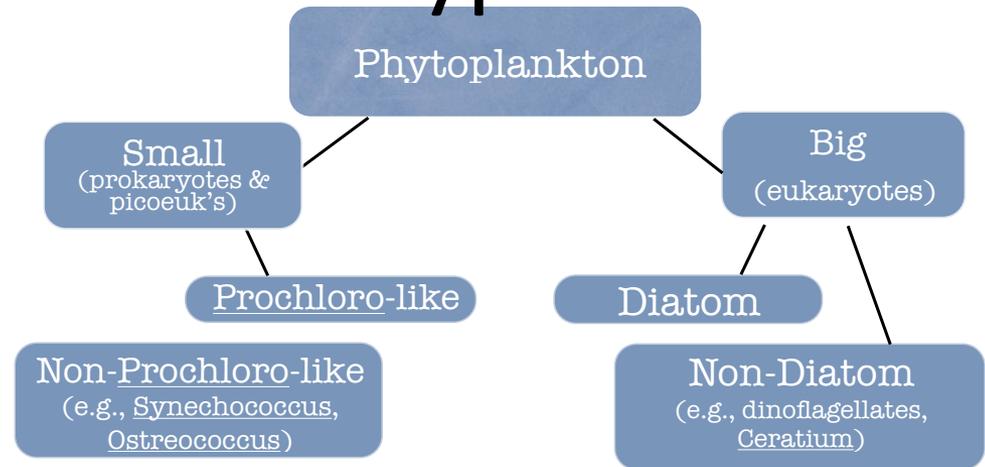
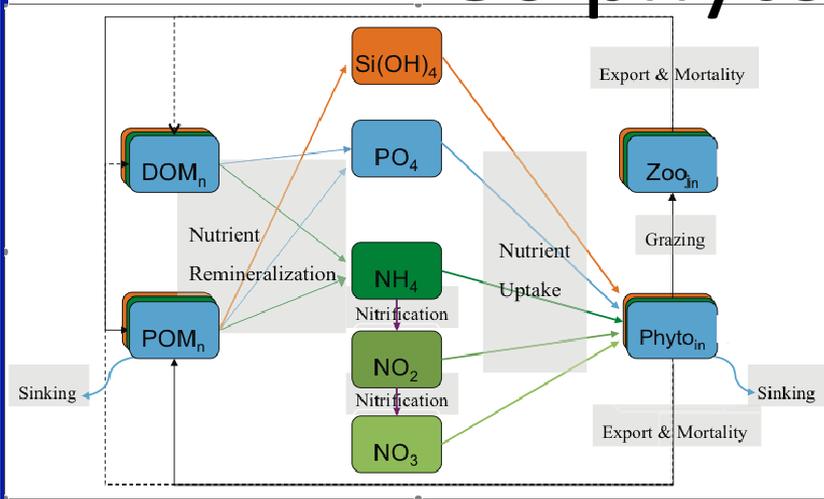


Broquet et al. (2009)

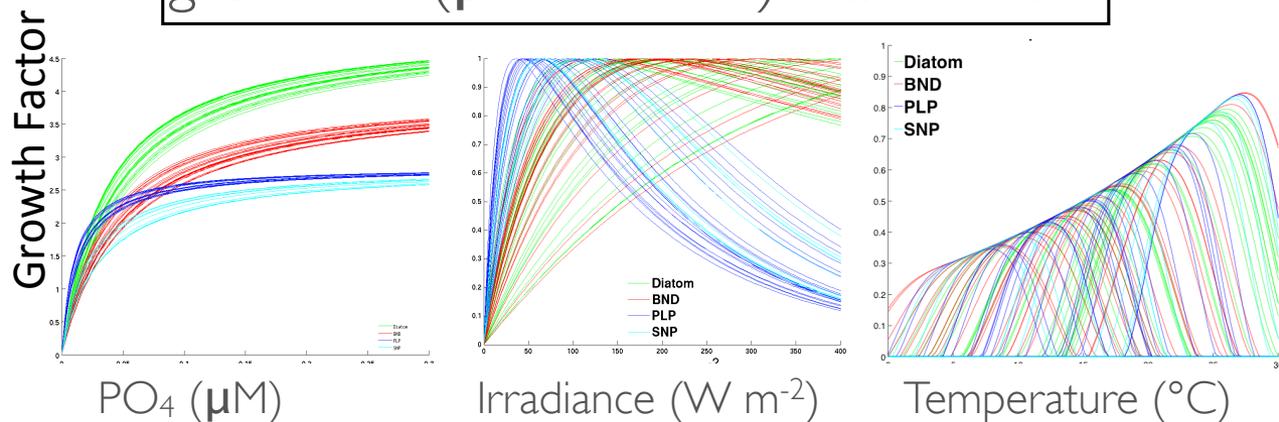


Self-Assembling Ecosystem Model

~80 phytoplankton types



$$\text{growth} = (\mu_{\max} * N_{\text{lim}}) * I_{\text{lim}} * T_{\text{lim}}$$

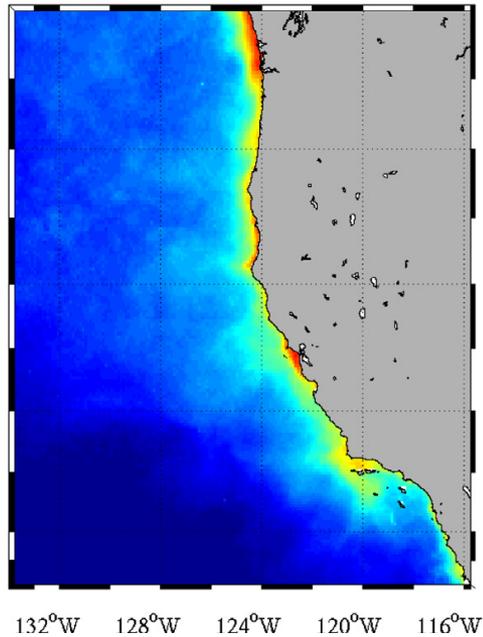


Follows et al. (2007), Goebel et al. (2010)

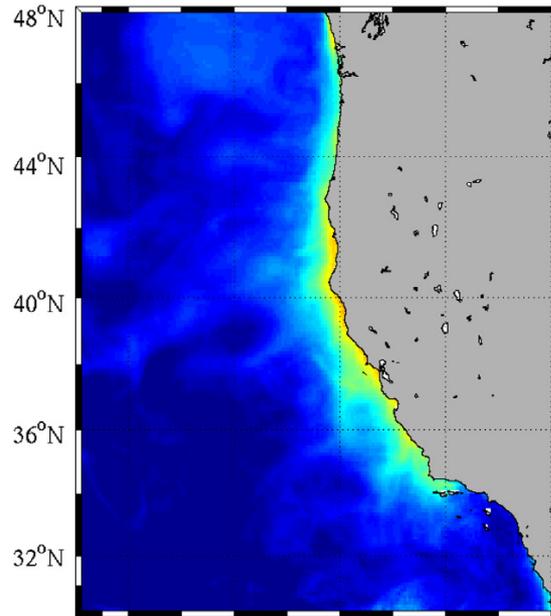


Annual Mean Surface $\log_{10}(\text{Chlorophyll})$

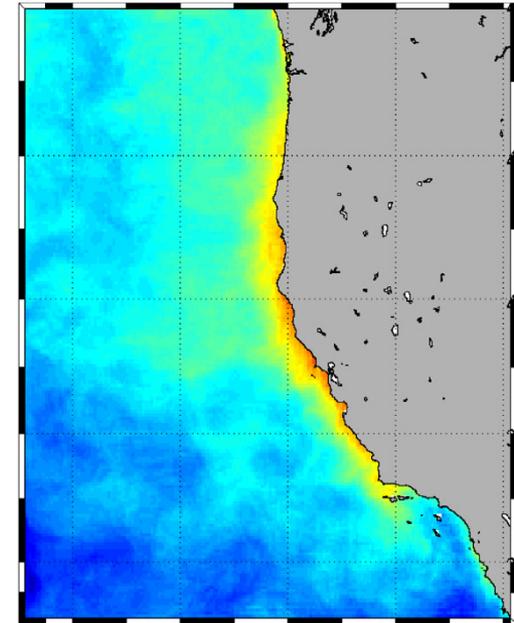
(d) Chl (SeaWiFS)



(a) Chl (Fwd)



(b) Chl (DA)



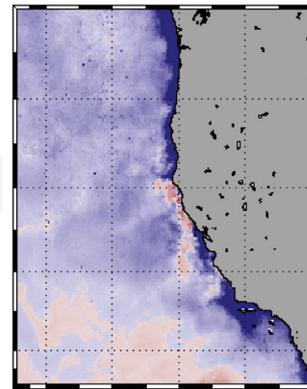
Bias (model-data) and Correlations

Table 1

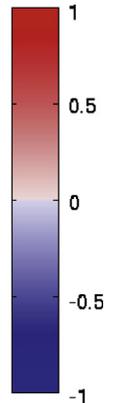
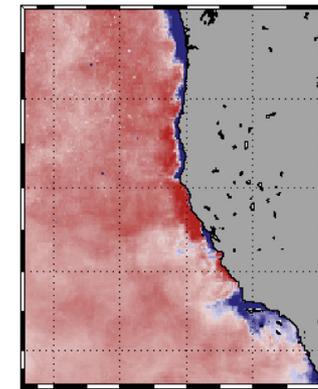
Mean error biases (mg Chl cm⁻³) and mean statistically significant correlations of modeled surface chlorophyll compared to satellite estimates for the forward run and data assimilation without/with a one-week overlap between assimilation cycles.

	Bias			Correlation		
	Forward	DA	DA-O	Forward	DA	DA-O
Domain	-0.11	0.25	0.14	0.19	0.42	0.38
Coast	-0.59	-0.02	-0.15	0.26	0.14	0.14
N. Coast	-0.86	-0.21	-0.39	0.41	0.46	0.45
S. Coast	-0.41	-0.17	0.00	0.16	-0.05	-0.05
Offshore	-0.06	0.27	0.16	0.19	0.44	0.40
N. Off.	-0.10	0.33	0.19	0.40	0.70	0.67
S. Off.	-0.05	0.24	0.14	0.08	0.31	0.27

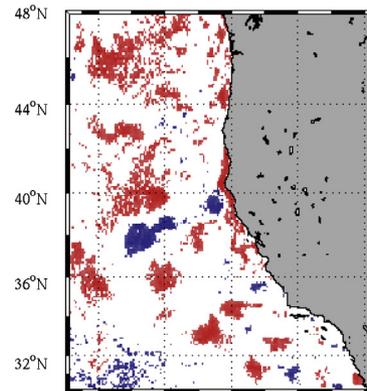
(a) Bias (Fwd)



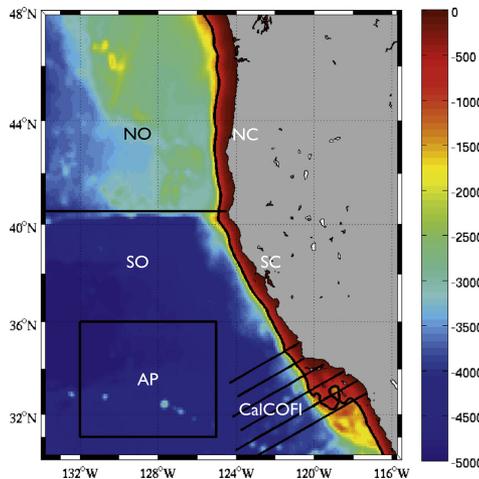
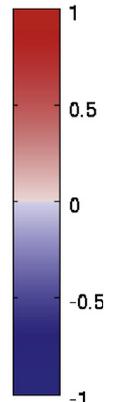
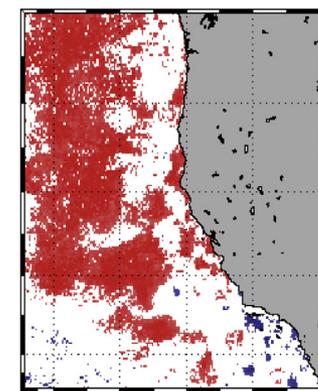
(b) Bias (DA)



(d) Correlation (Fwd)

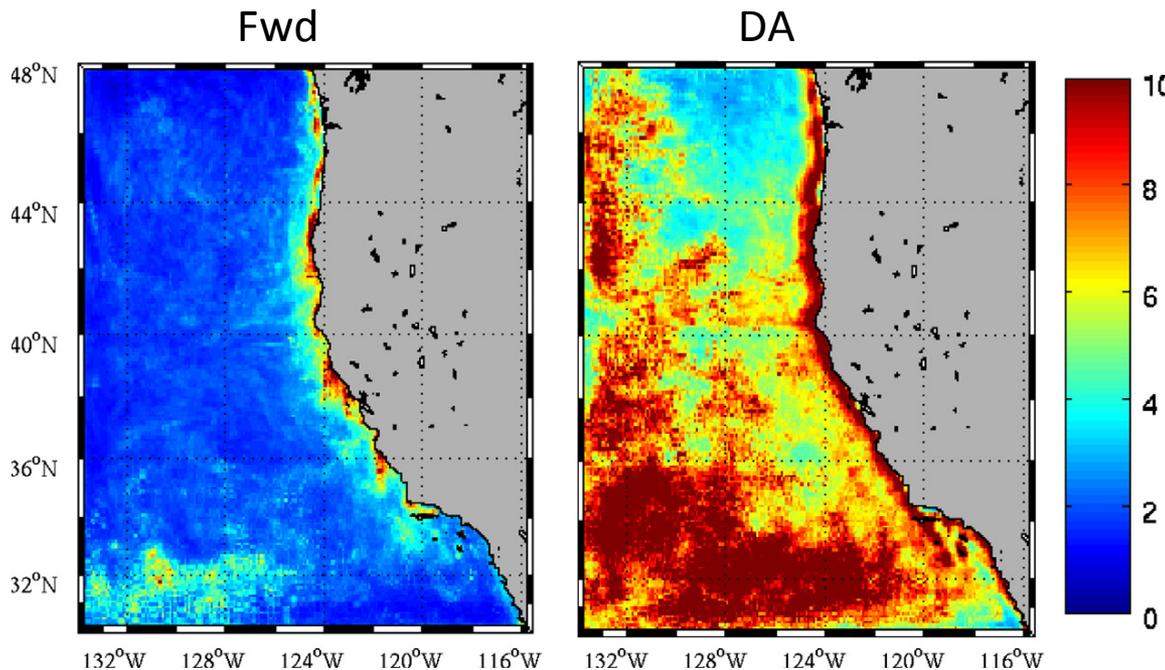


(e) Correlation (DA)



Causes of excess production: (1) Assimilation shocks

RMS(w) at 50 m



- Direct application of sequential physical DA results in shocks.
- Unbalanced portion of cycle initial conditions yields gravity wave adjustment to physical fields.
- Not a major problem for physical fields.
- Major issue for ecosystem fields due to biological rectification.



Nitrate Budget shows DA drives a large vertical eddy flux divergence (Forward, DA)

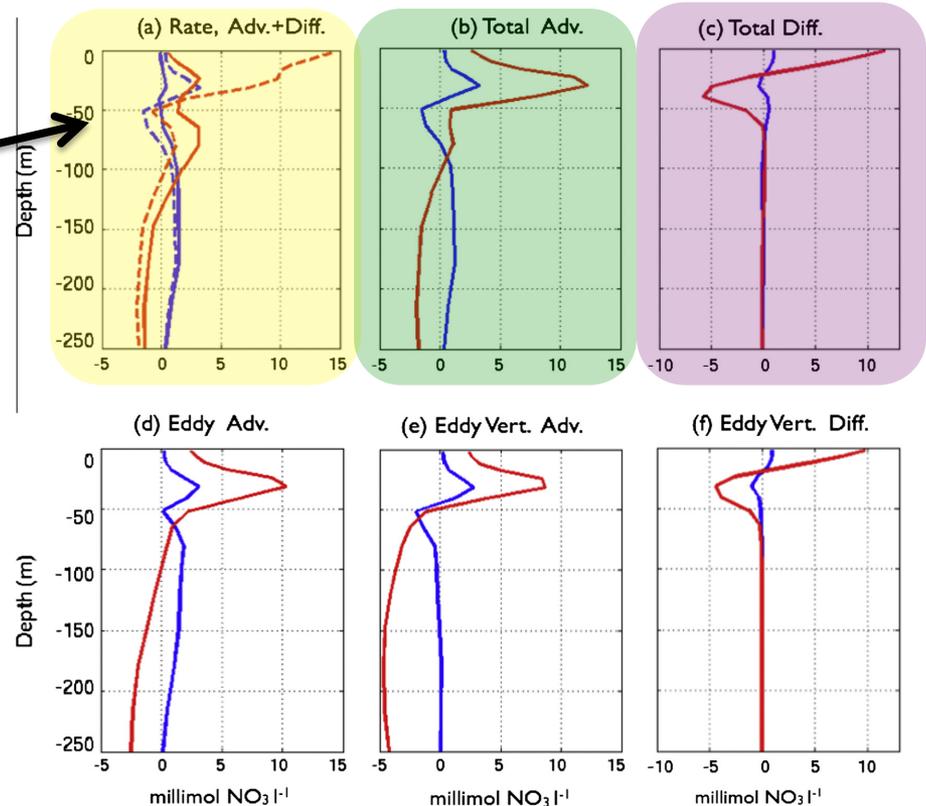
rate of change = sum of advective and diffusive flux divergences and source/sink terms

$$\frac{\partial [N]}{\partial t} = -\frac{\partial}{\partial x}(u[N]) - \frac{\partial}{\partial y}(v[N]) - \frac{\partial}{\partial z}(w[N]) + \frac{\partial}{\partial x}\left(K_H \frac{\partial [N]}{\partial x}\right) + \frac{\partial}{\partial y}\left(K_H \frac{\partial [N]}{\partial y}\right) + \frac{\partial}{\partial z}\left(K_V \frac{\partial [N]}{\partial z}\right) + \mathcal{S},$$

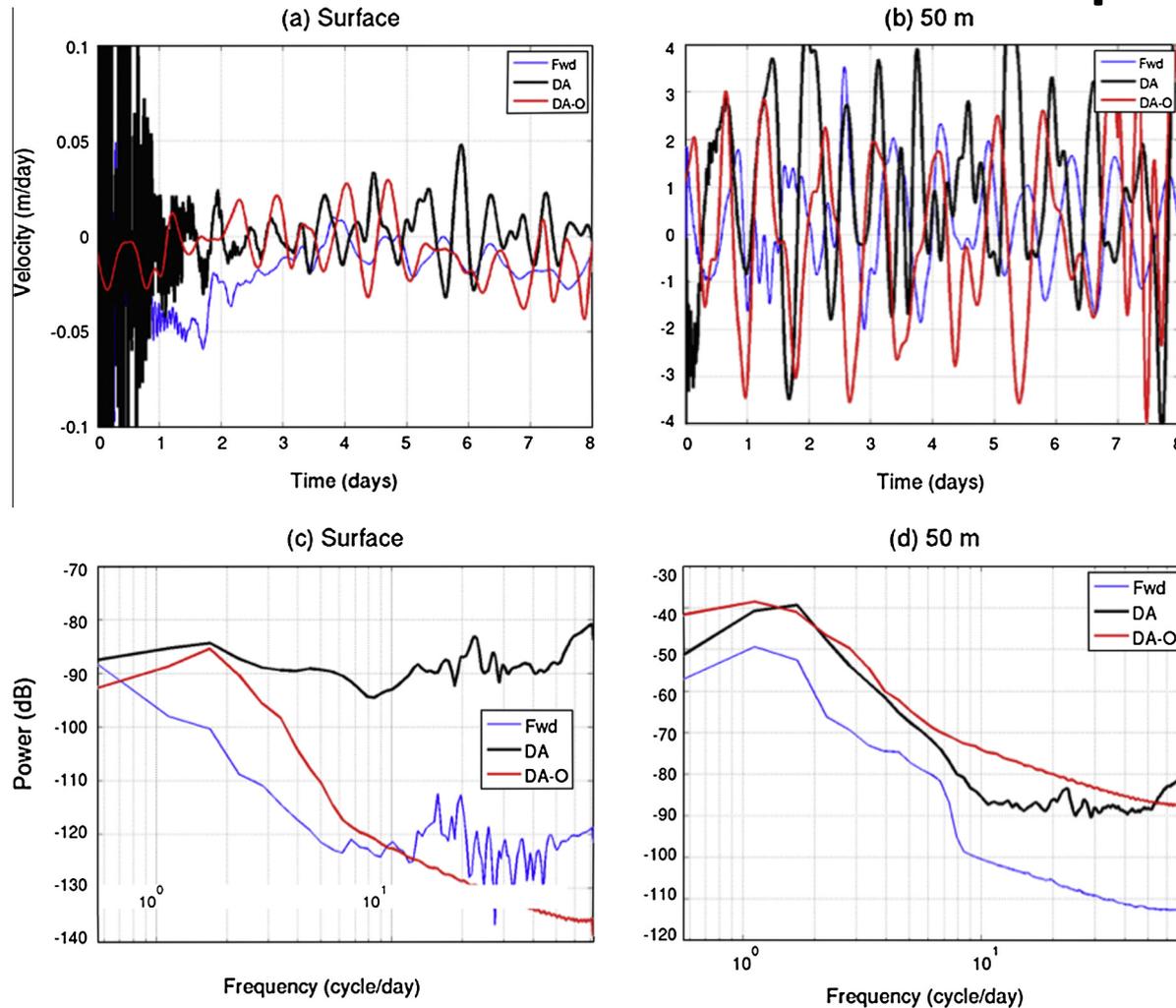
Difference between dashed and solid lines is the net sources/sinks

Carry out Reynolds decomposition to get mean and eddy flux divergences

$$\overline{wN} = \overline{w}\overline{N} + \overline{w'N'}$$

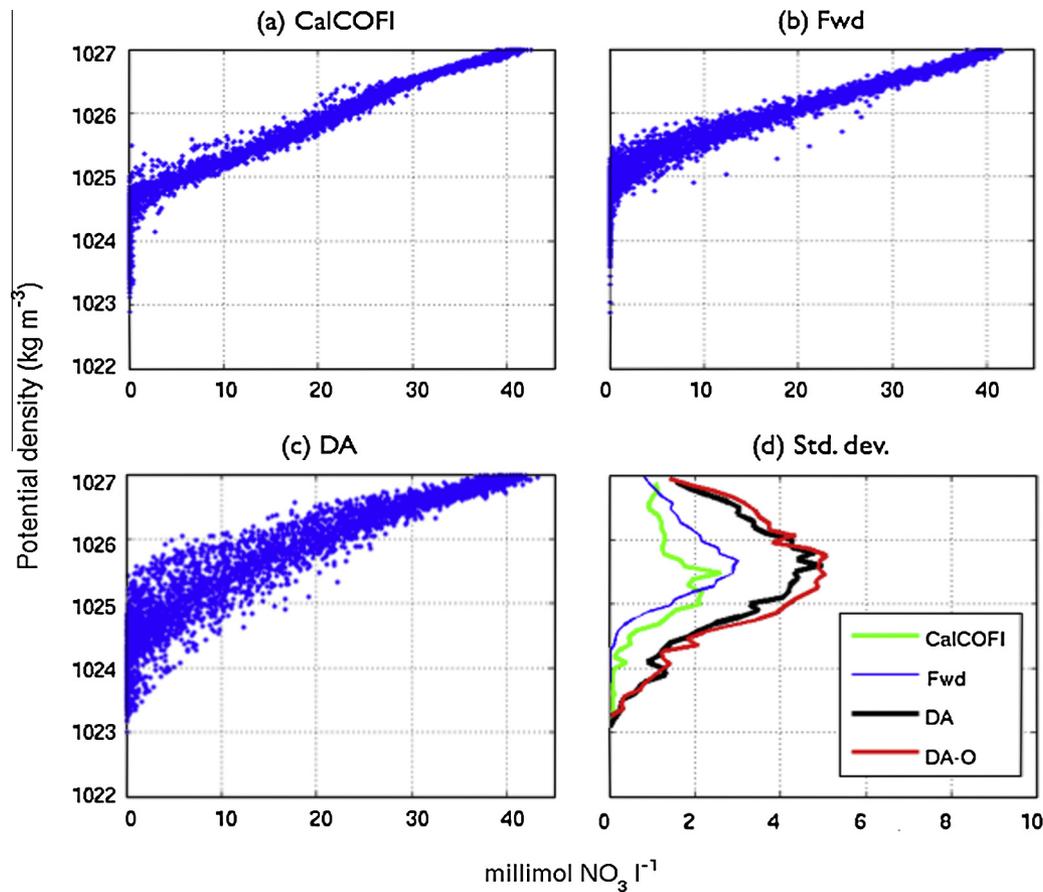


Shocks and power in vertical velocity field at Surface and 50 m depth



Causes of excess production:

(2) Increased nitrate variance on density surfaces



Summary

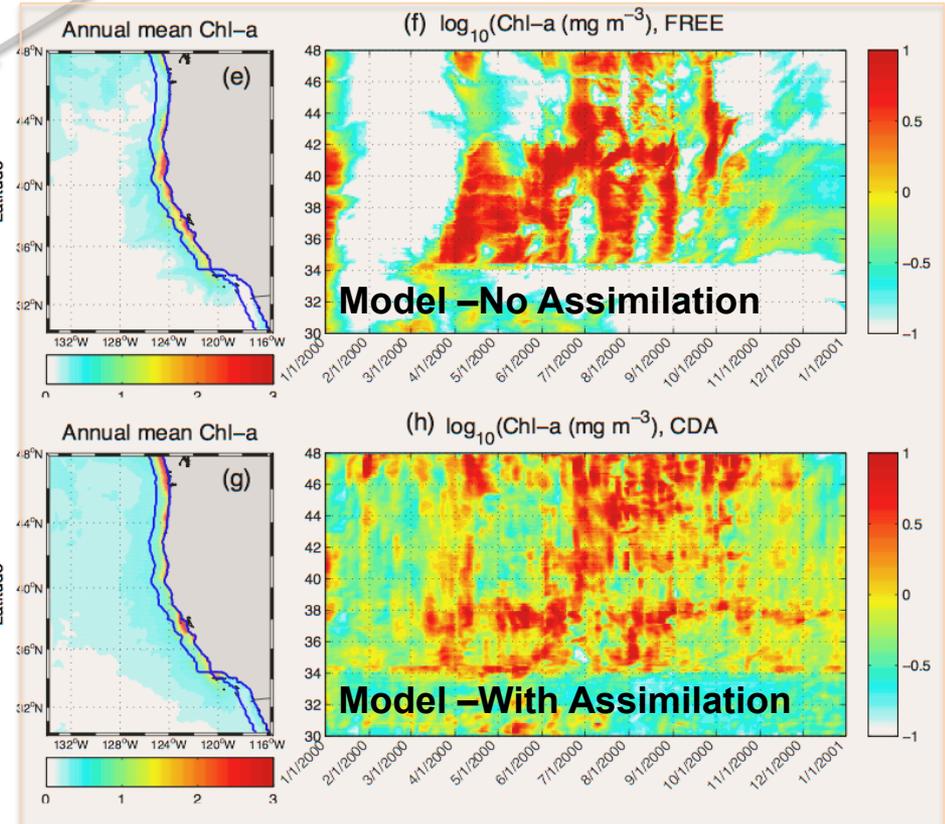
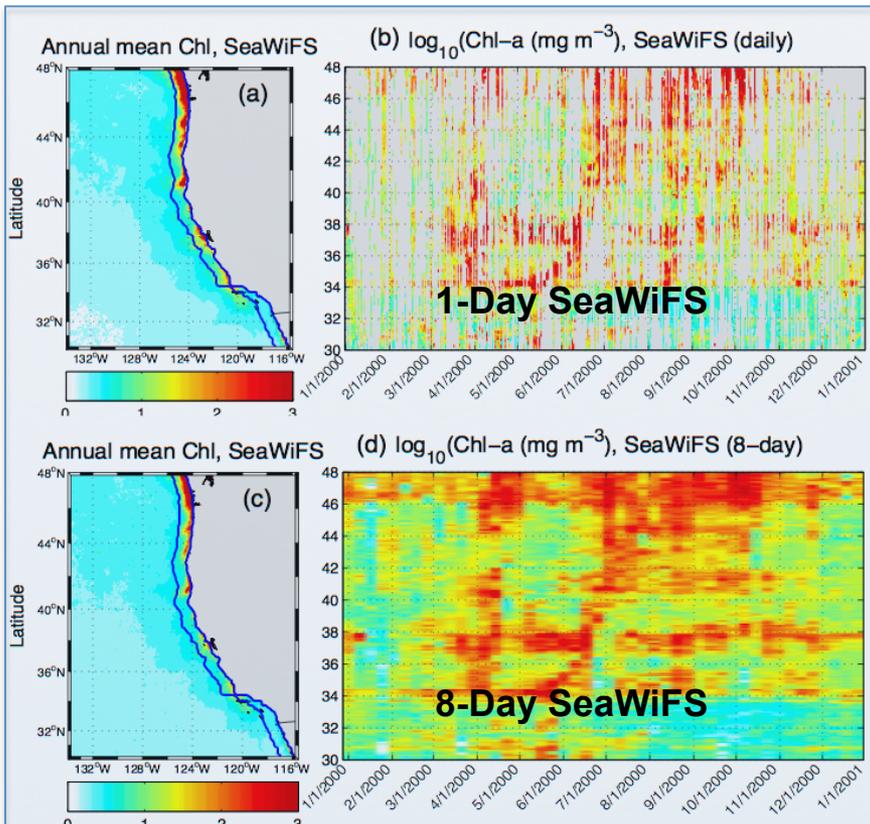
- Physical assimilation alone results in both positive and negative influences on biogeochemical models
 - Positive: Improved correlation of surface chlorophyll relative to satellite observations in areas where chlorophyll is strongly linked to slowly evolving physical features.
 - Negative: increased standing stock (helpful in a few places but mostly deleterious)
- At least 2 mechanisms identified
 - Assimilation shocks
 - Increased nutrient variance on density surfaces due to updates to density surfaces but not nutrient fields
- Issue is not biogeochemical model/dependent, although magnitude of effect is dependent on the model (not shown)
- Possible mitigation:
 - Avoid start of cycle (did not meaningfully reduce bias)
 - Improve balance operator to reduce shocks
 - Adjust nitrate fields along with T/S
- Argues for fully coupled physical/biogeological assimilation



Fully coupled, strong constraint 4D-Var physical/biogeochemical assimilation

- 1 year (2000) SeaWiFS ocean color assimilation
- along with SST, SSH, in situ hydrography
- NPZD model

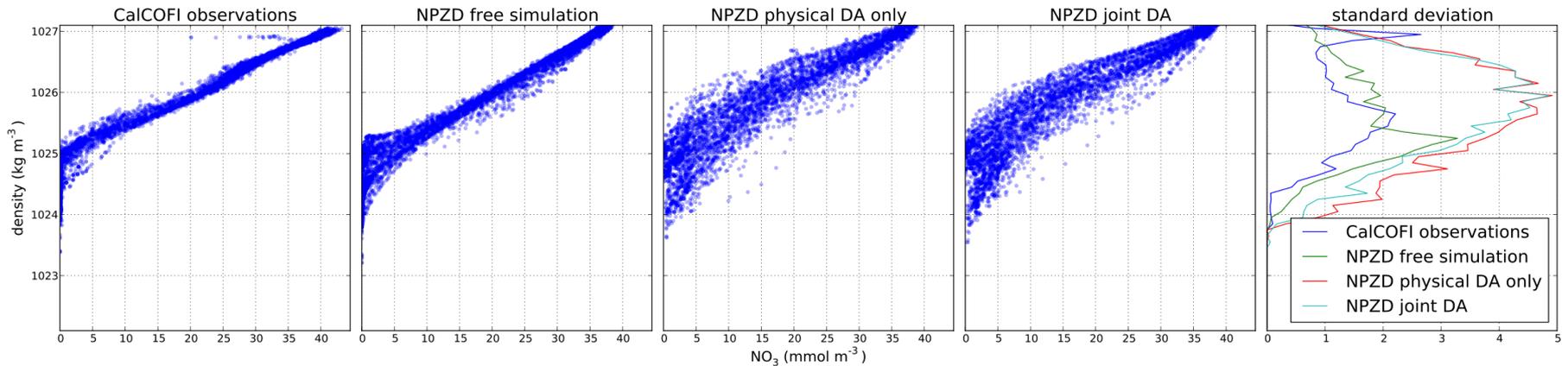
Gray color indicates cloud cover



Song et al. (in press), and P. Mattern's talk yesterday



Chl assimilation does not fix the subsurface nitrate problem



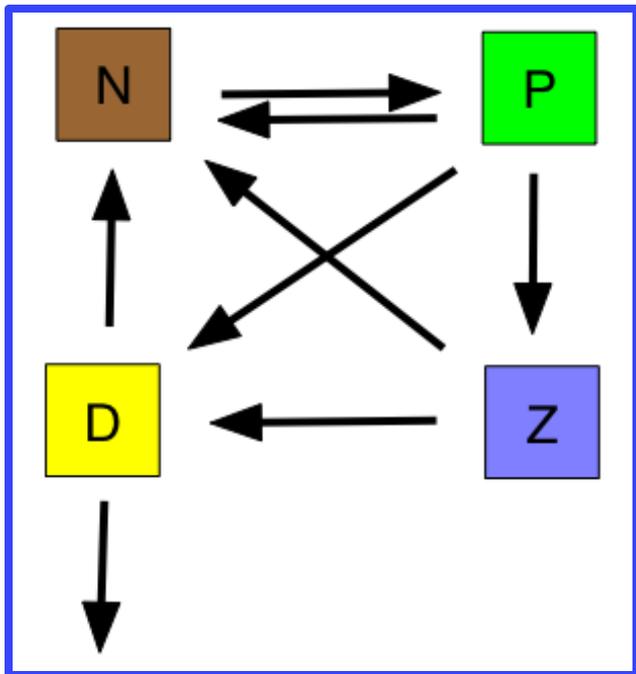
- Possible solutions
 - Balance operator
 - Multivariate error covariances
 - Climatological constraints
 - Nitrate sensors



Can work with more complex Ecosystem Models

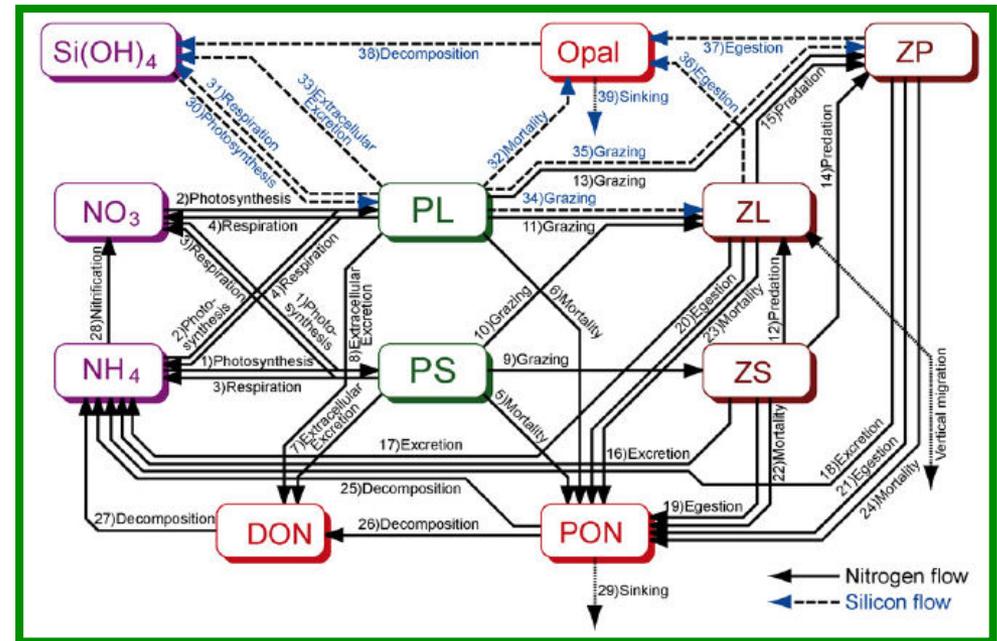
NPZD

(Powell et al. 2006)

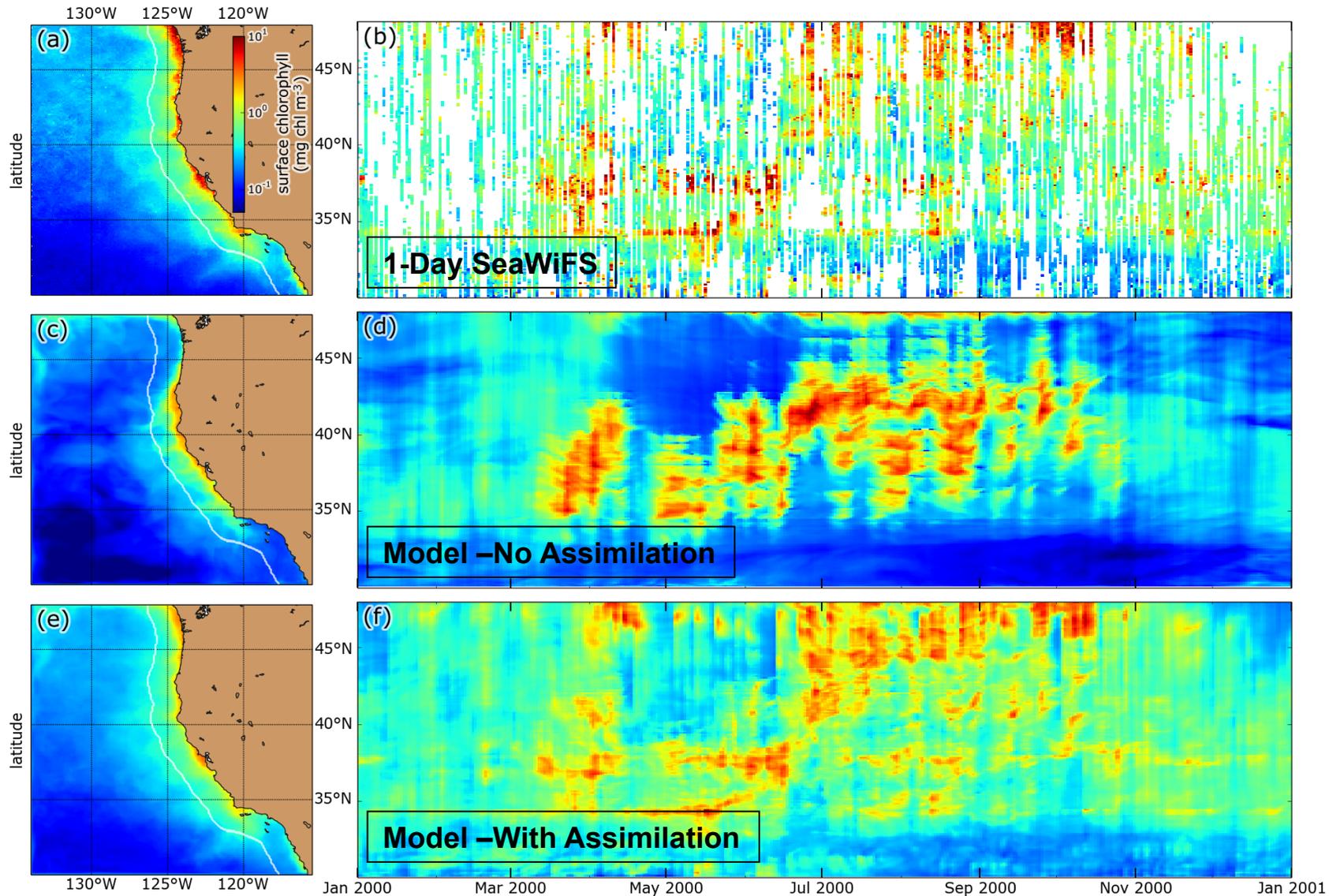


NEMURO

(Kishi et al. 2011)

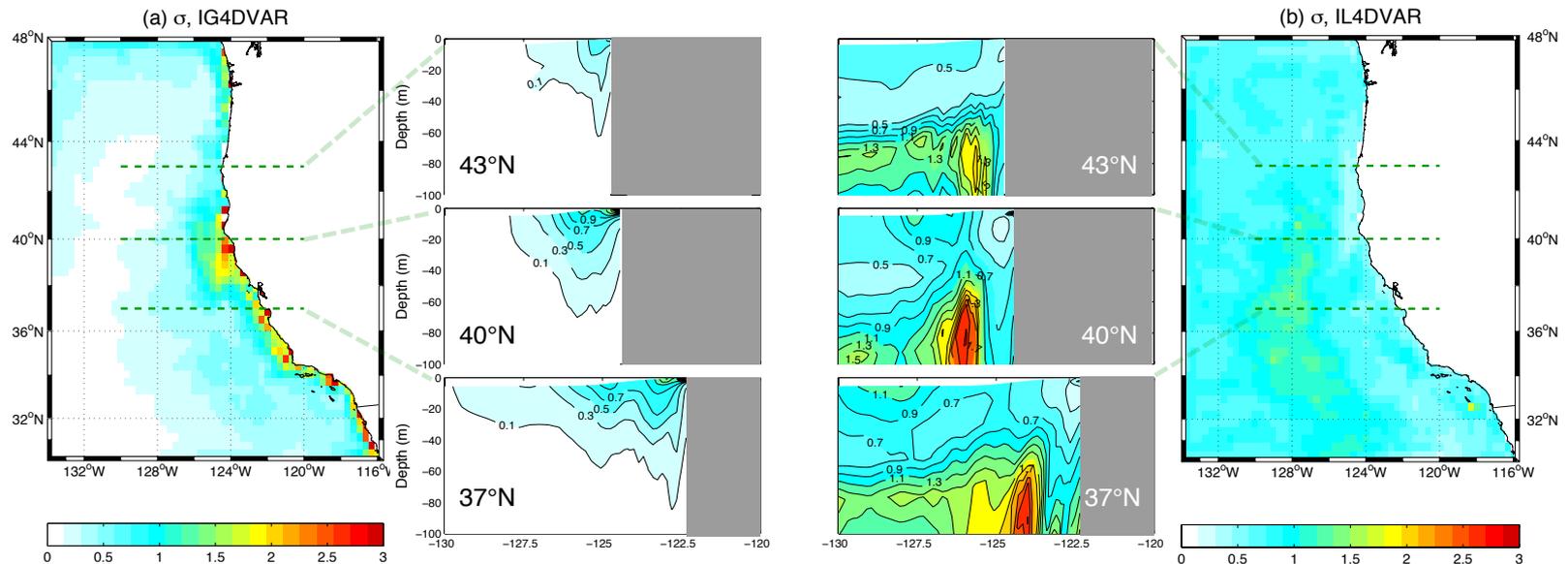


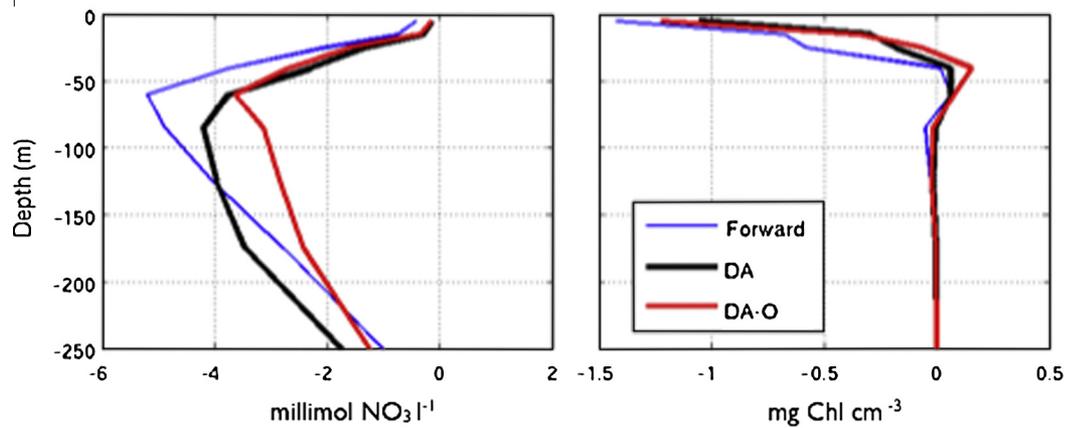
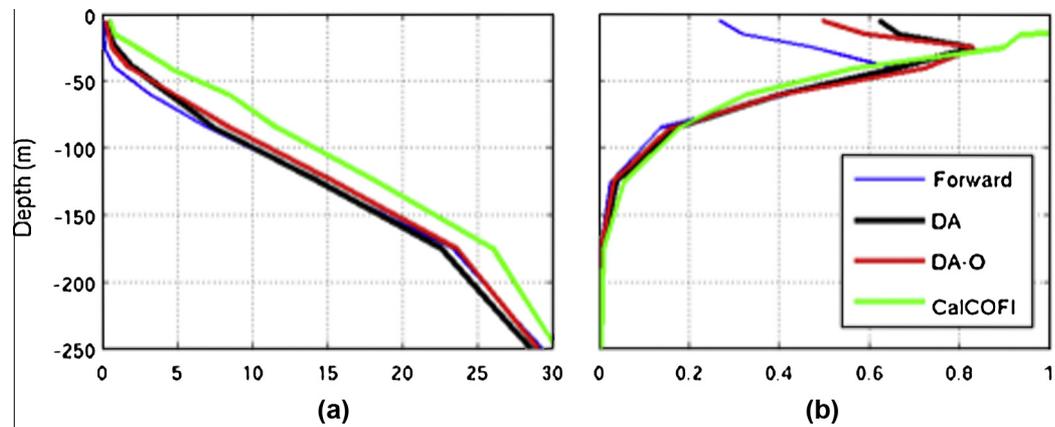
Example using the NEMURO model



Potential Issue: sensitivity at depth

- Standard deviation of P used shows high uncertainty in log space at depth
- May be an issue in future with subsurface obs



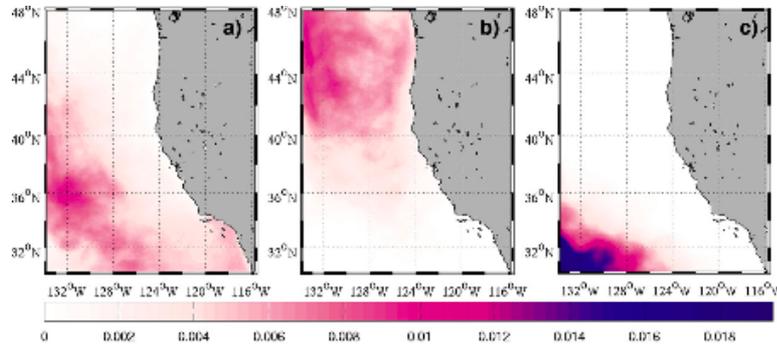
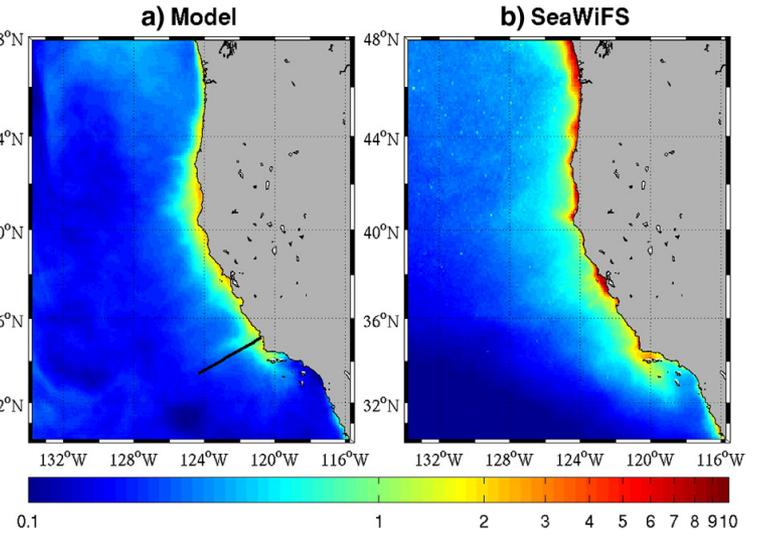
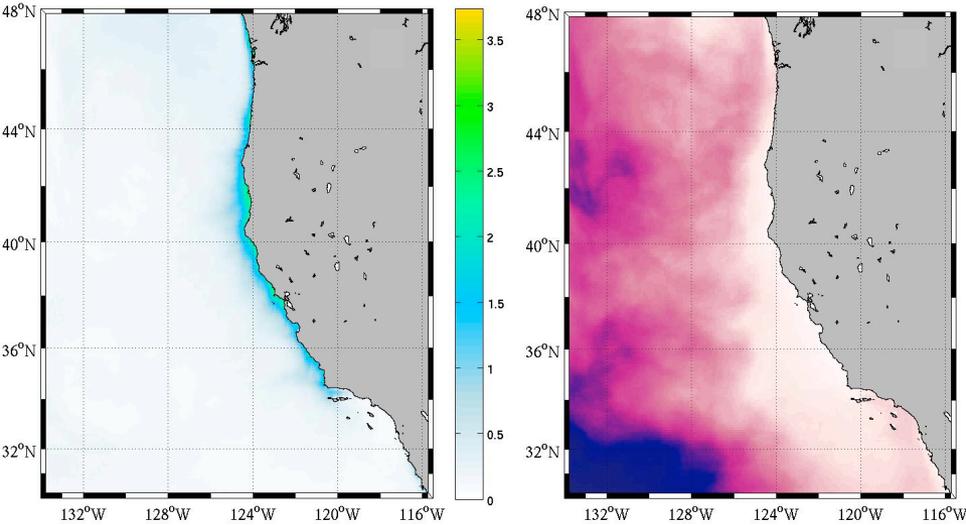


Surface Biogeography

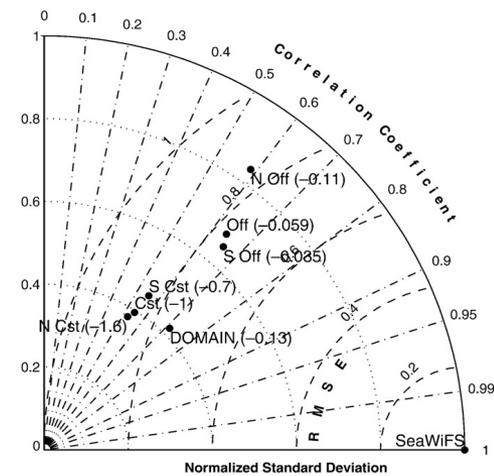
Diatoms

Prochlorococcus-like

Chlorophyll Biomass



a) Annual Averages for Regions (Bioseed 33)



A slide shamelessly lifted from Emlyn Jones (MEAP-TT 2015)

Table 1.2. Assimilation effect on chl-a and nutrients.

better, worse, similar=less than 10% change



Region (partner)	ME	% MB	PCC	RMSE
Baltic (DMI)	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4
NE_Atlantic (PML)	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4
Mediterranean (HCMR)	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4
Mediterranean (OGS)	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4	Chl NO3 PO4

- ME: model efficiency; %MB: percentage model bias; PCC: Pearson correlation coefficient; RMSE: root mean square error
- In most regions the reanalysis simulations demonstrated improved skill for the assimilated variable(s)
- For non-assimilated variables the assimilation improved the skill of some variables and degraded others.

