

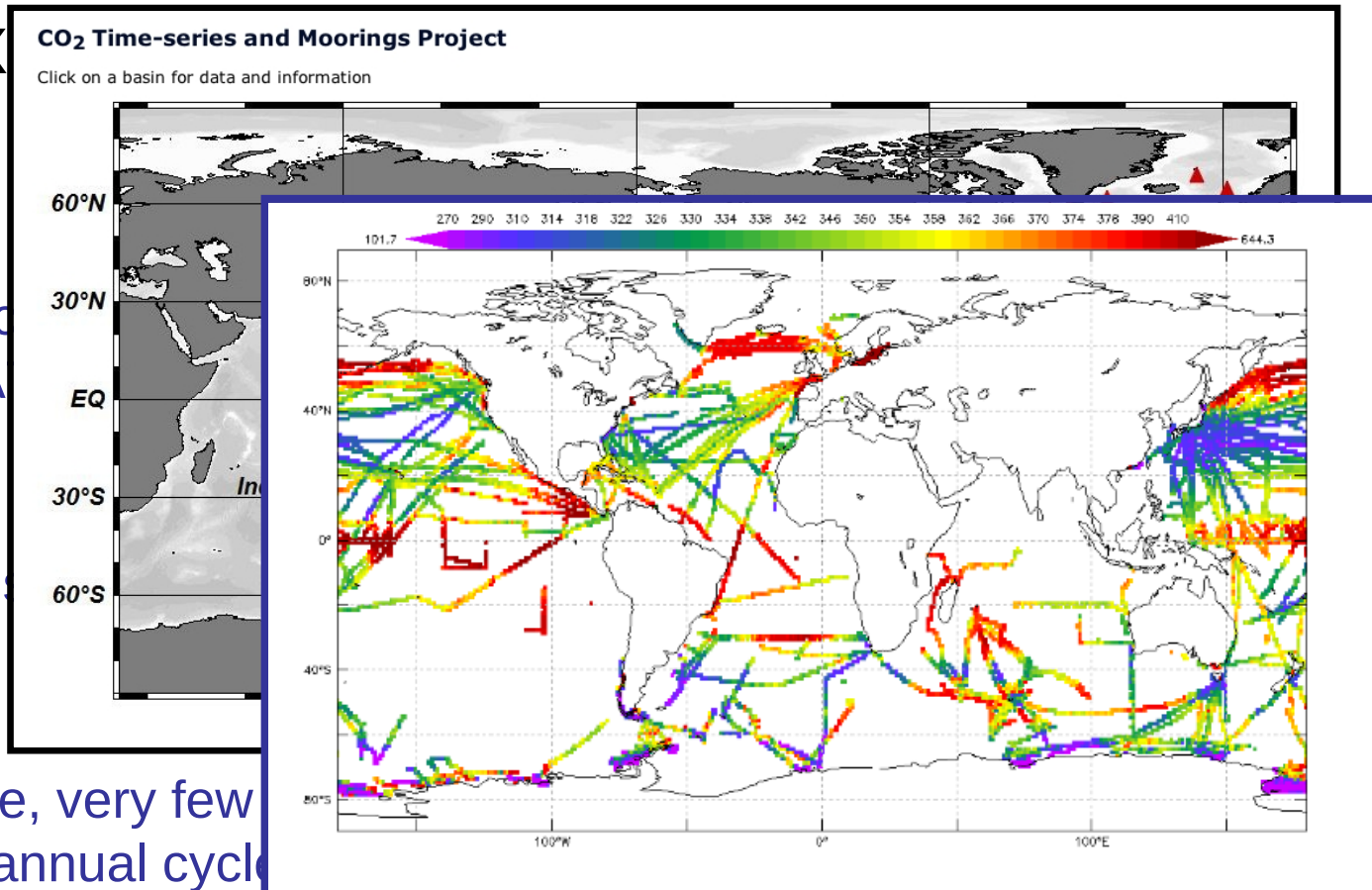
Prediction of ocean carbon dioxide levels at observational time series nodes using satellite ocean remote sensing products

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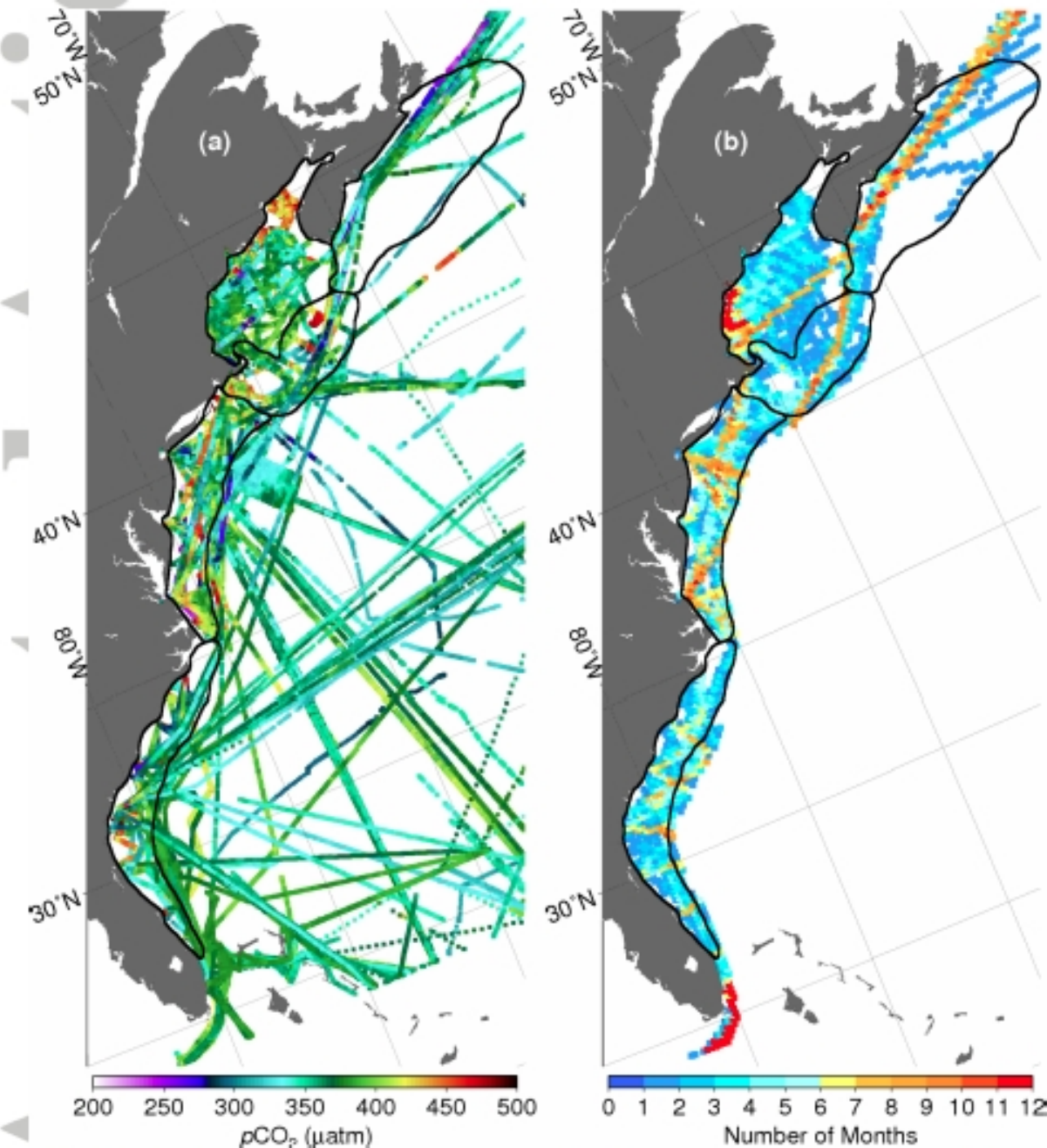
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Mass flux



- Standard approach (Takahashi/SOCA, CTracker)
- **Pros:** increasing mean global and (more points)
- **Cons:**
 - time coverage, very few for even one annual cycle
 - spatial coverage, many basins (e.g. SO, Indian Ocean, and S. Pacific & Atlantic are very sparsely sampled)



US East Coast
example from
Signorini et al 2013

More than 800,000
indiv. samples,
1987-2011

Few pixels with
monthly coverage

Fig. 3. Color-coded SOCAT surface ocean $p\text{CO}_2$ cruise tracks (a) and corresponding coastal binned data (b) with associated color-coded temporal coverage in months. The highest temporal coverage corresponds to the most travelled routes (in orange to red), i.e., most frequent destination ports (Boston, New York, Norfolk, Miami) used by

Objective – global space/time $\Delta p\text{CO}_2$ estimator at daily-to-weekly time step

- Current state of the art:
 - Using satellite or model estimates of key controlling factors (SST (1st order), Chl/SSS/ML) + ship-based CO₂ measurements to develop empirical models
 - Recent examples: Signorini et al. 2013; Liu-JPL with SVR; Chierici et al. 2012; Hales et al., 2012; Lohrenz & Cai, 2006; Zhu et al., 2009; Gledhill et al., 2009
 - Regionally < 5-25 uAtm rms, globally higher

Objective – global space/time $\Delta p\text{CO}_2$ estimator

- Issues:
 - Is the ocean $p\text{CO}_2$ data sampling coverage (time & space) sufficient to train a model
 - Validation can be tenuous (how to determine sample independence?)
 - Choice of inputs: often not mechanistic (e.g. lat, long, time_day, time_year) nor sufficient
 - Is upper ocean $p\text{CO}_2$ too variable for such global or even regional models?
 - What level of accuracy needed for gas transfer rate investigations and flux products?

Our approach – focus on time series

- Assumption: without time resolved algorithm training datasets, pCO₂ prediction is likely under-constrained
- Desired training sets - continuous in situ pCO₂ data with sub seasonal sampling and limited regional span

Ocean pCO₂ time series data for algo input

- Goal: Obtain virtual and actual time series data
- Requirements
 - sub seasonal resolution
 - at least one complete annual cycle
 - select several diverse ocean regions and apply consistent algorithm development approach



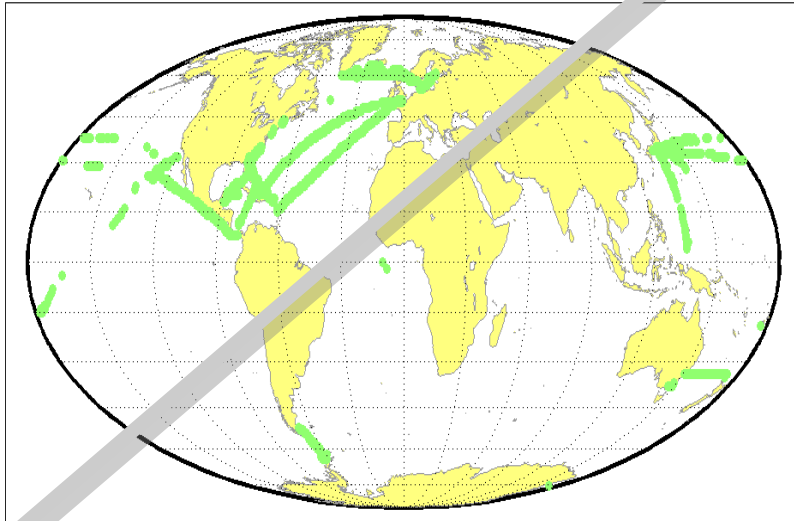
MOORED



VIRTUAL (SOCAT)

Very few regions yielding a time series, even using recent SOCAT

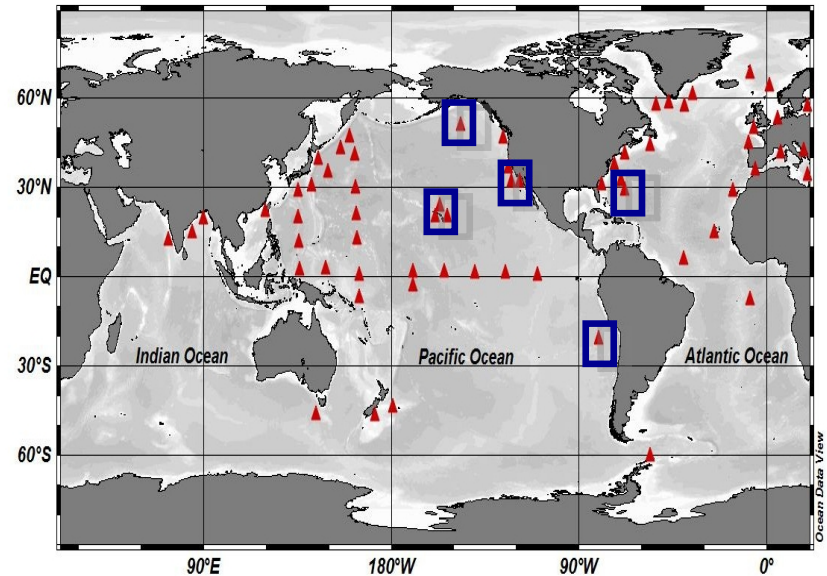
Pixels with at least 8 months data for 2 years: 2005 and 2006



Several (few) of the global network have multi-month time sets online

CO₂ Time-series and Moorings Project

Click on a basin for data and information



Methods overview

5 site training sets: Satellite matchups + buoy
pCO₂

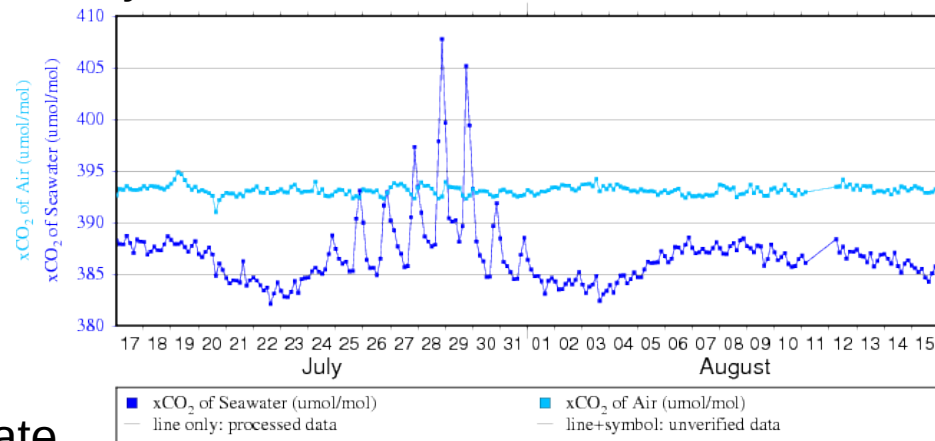
LS regression modeling
Multiple Linear Regression
Neural Network

Mechanistic modeling (e.g. 1-D temp-normalized pCO₂ vs. DIC_{bio}, carbonate closure with TA(SSS)) NOT DISCUSSED HERE

Similar methodology at each sites, 3 N Pac, 1 S Pac, 1 N. Atlantic + an overall model for experimentation

Validation

xCO₂ of Seawater & xCO₂ of Air @ Stratus (85W,20S)
[Date: 2013-07-17 to 2013-08-16]



Overall matchup dataset creation, site-by-site

Type	Source	Time	Spatial Res.
In situ SST	Mooring	sub-daily	m
In situ SSS	Mooring	sub-daily	m
In situ pCO ₂	Mooring	sub-daily	m
Sat. Chl _a	GlobColour	daily	9 km
Sat. SST & PAR	Aqua-MODIS	daily	9 km
Sat. NPP	OSU/MODIS	8-day	9 km
Model MLD	OSU/hycom	8-day	9 km

pCO₂, in situ and satellite data used for algorithm training

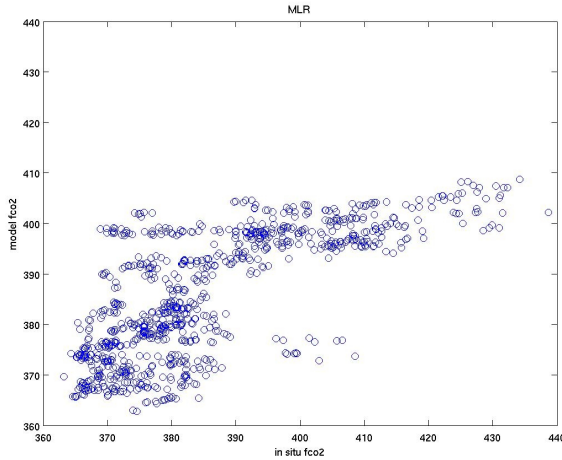
Total buoy measurements and coincident cloud-free satellite data

Source	Type	Region	Time period	# total points (daily/native)	# satellite extractions (all reqd)
Stratus	Buoy	S. Pacific	2006-2008	1185/9543	339
Papa	Buoy	N. Pacific	2007-2010	809/6343	68
CCE1	Buoy	West coast	2008-2010	559/4468	162
WHOTS	Buoy	HOTS	2007-2009	598/4803	287
BATS	Buoy	N. Atl.	2005-2007	709/5345	384
SHIPBOARD					
Clivar	Ship	Atlantic	1997,2007	4556	701
Carina	Ship	N. Atl.
SOCAT	Ship	N. Atl.	1998-2001		30040
VOCALS	Ship	S. Pac.	2008-2009		6094

Note: from 7 M pCO₂ samples down to few hundred samples per site

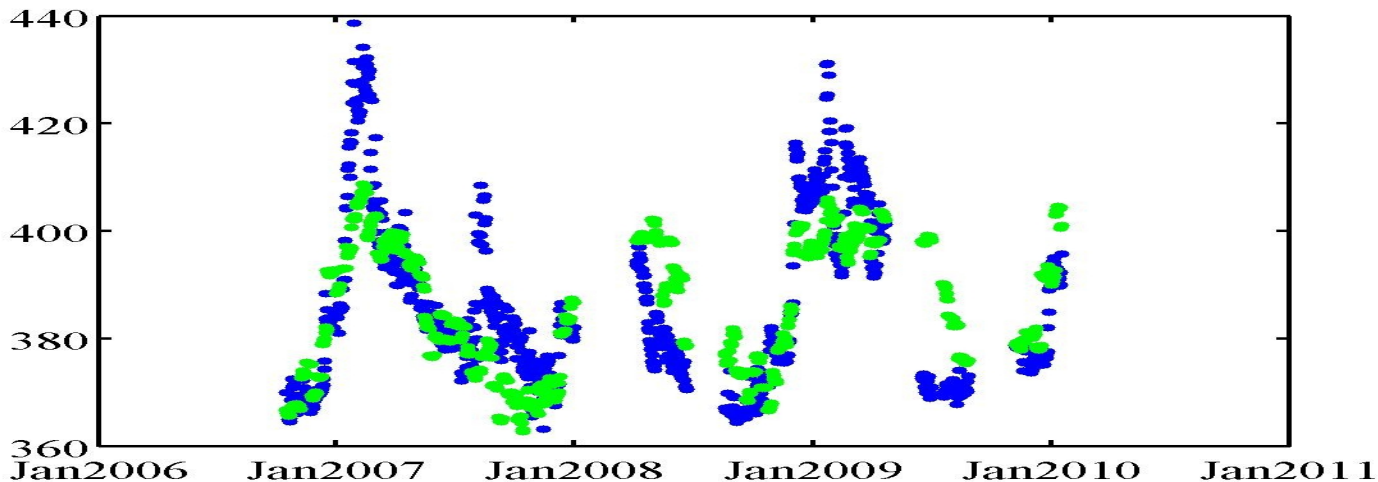
Site-specific multiple linear regression

– what inputs help?



Stratus Time series pCO₂ modeling

Inputs	RMS (uatm)	# pts *
SST, MLD	17.8	339
SST, MLD, SSS	12.3	339
SST, MLD, SSS, Chl	14.8	339
SST, MLD, SSS, NPP	11.3	339
SST, MLD, SSS, NPP, bbp/Chl	10.0	339
SST, MLD, SSS, NPP, bbp/Chl, CDM	8.7	62



Salinity drives largest variance reduction

Ocean color also contributes

Similar at each site
PAPA, BATS, HOTS

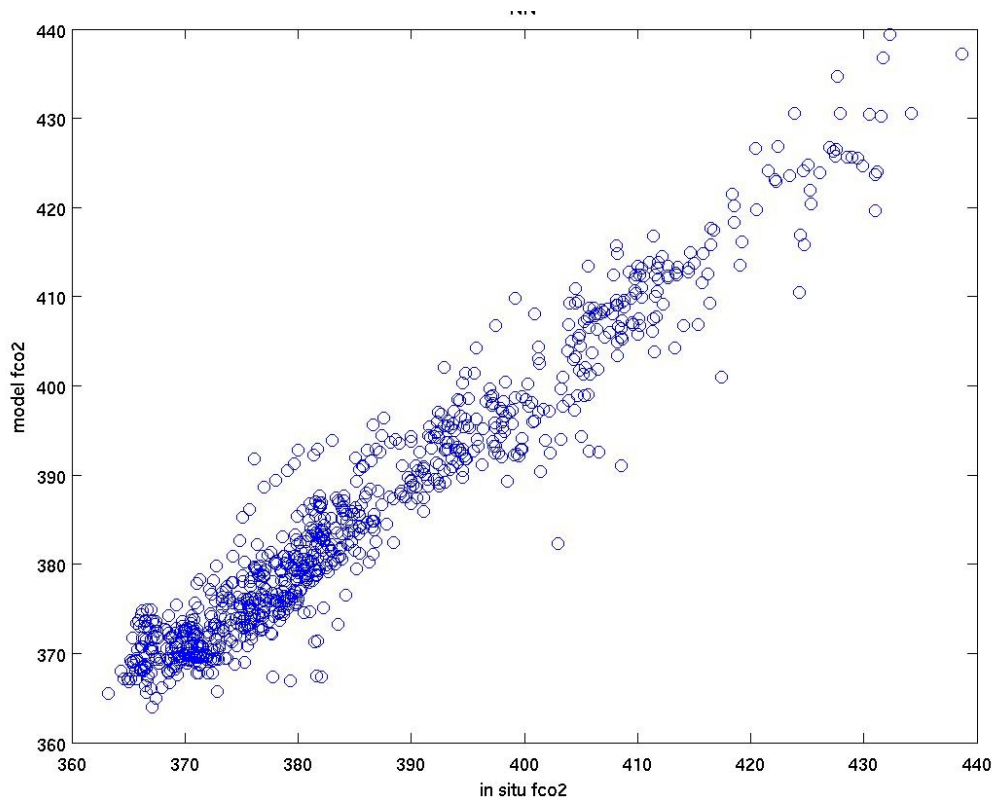
Neural Network – factor 2 improvement

Stratus Time series pCO₂ modeling - NN

Inputs	RMS (uatm)	# pts
SST, MLD	7.4	339
SST, MLD, SSS	4.9	339
SST, MLD, SSS, Chl	4.4	339
SST, MLD, SSS, NPP	3.8	339
SST, MLD, SSS, NPP, bbp/Chl	4.2	339
SST, MLD, SSS, NPP, bbp/Chl, CDM	4.8	62

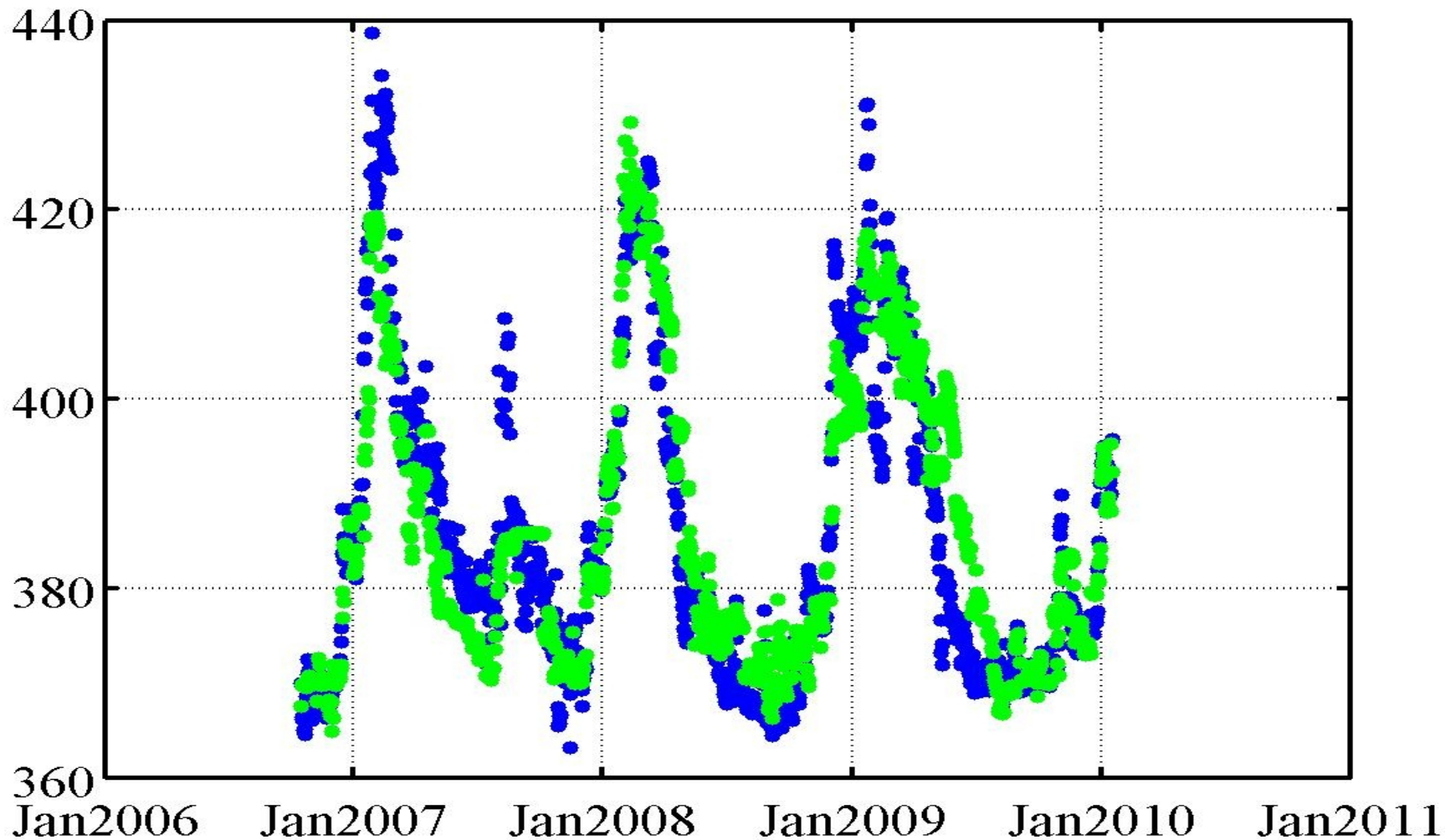


- Neural network solutions superior at each site
- Similar rms reduction as variables added up to 4 inputs (chosen best case)
- Similar reduction and results site-by-site



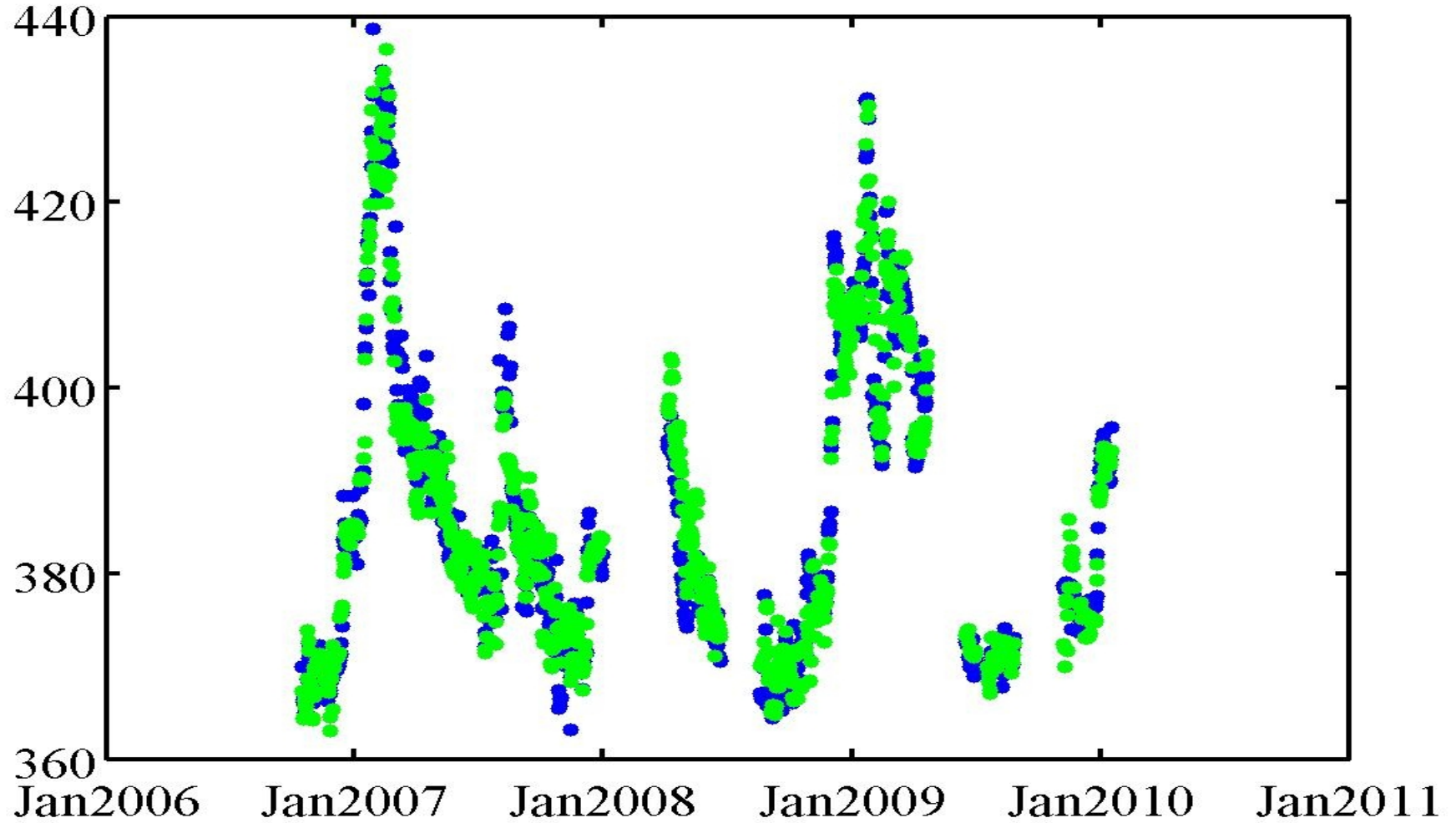
Stratus Time series pCO₂ model

NN (SST, MLD)



Stratus Time series pCO₂ model

NN (SST, MLD, SSS, NPP)

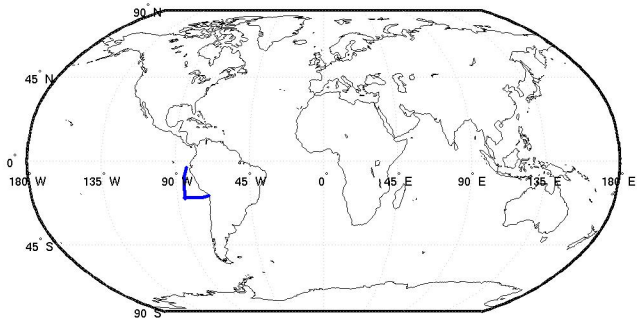


assessment with ship data – near Stratus

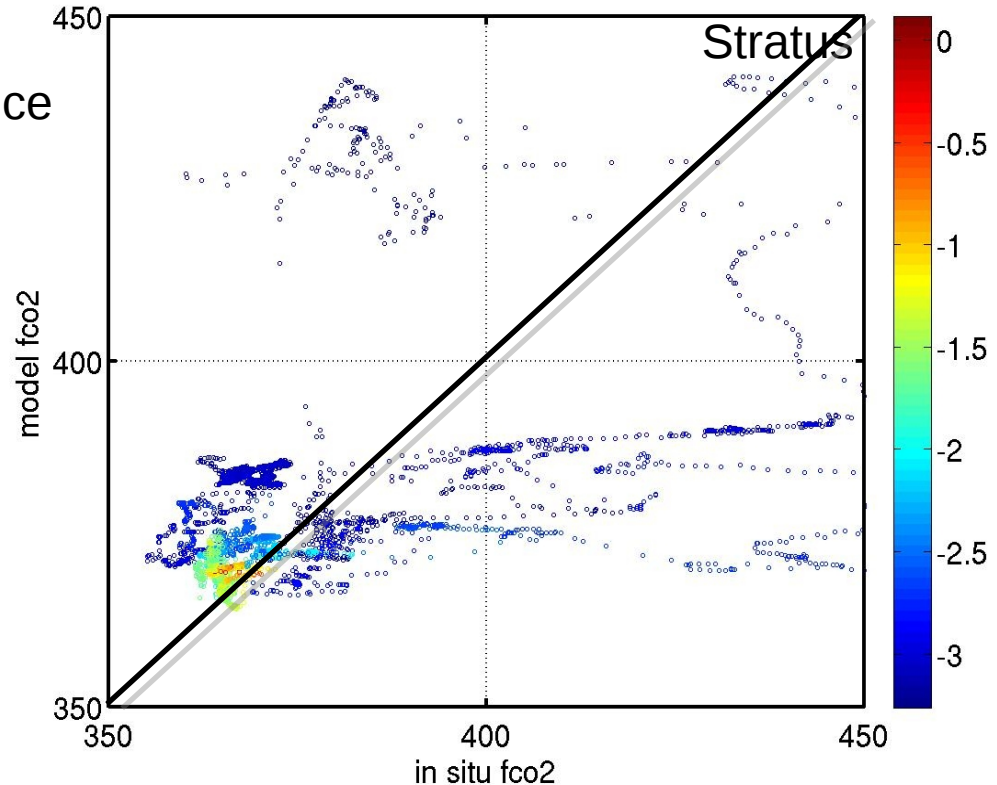
Use independent ship data surrounding
the site with same satellite matchups

In situ vs. predicted colored by distance
($\log_{10}(\text{distance}^{-1})$)

agreement not impressive



VOCALS cruise
data



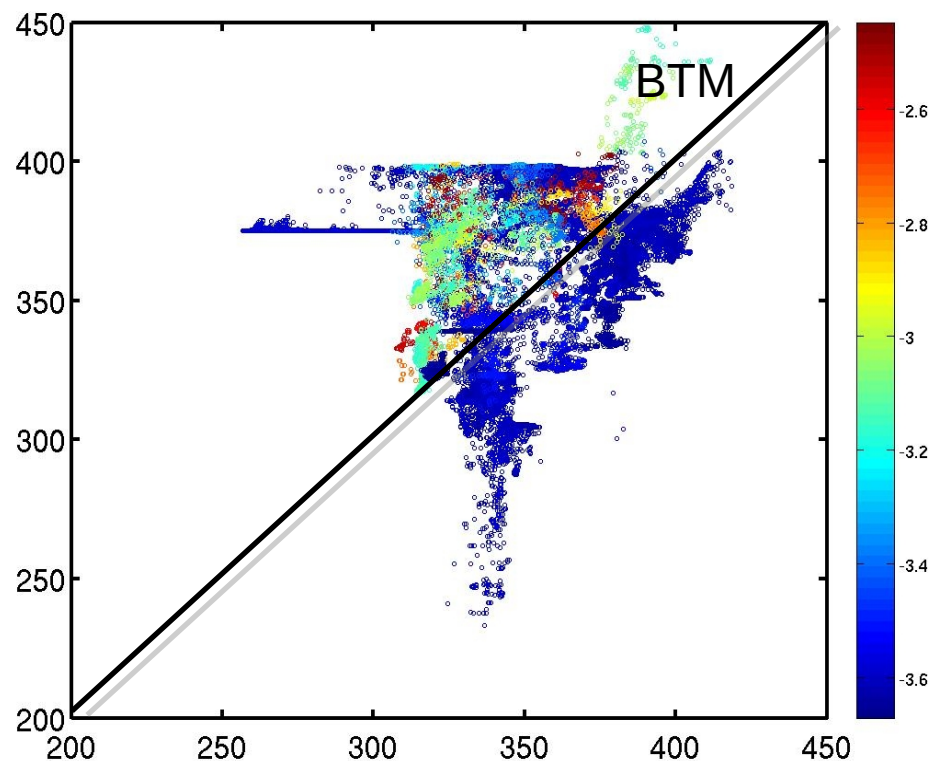
assessment with ship data – near BATS

Use independent ship data surrounding
the site with same satellite matchups

In situ vs. predicted colored by distance
($\log_{10}(\text{distance}^{-1})$)



SOCAT + Clivar
cruise data



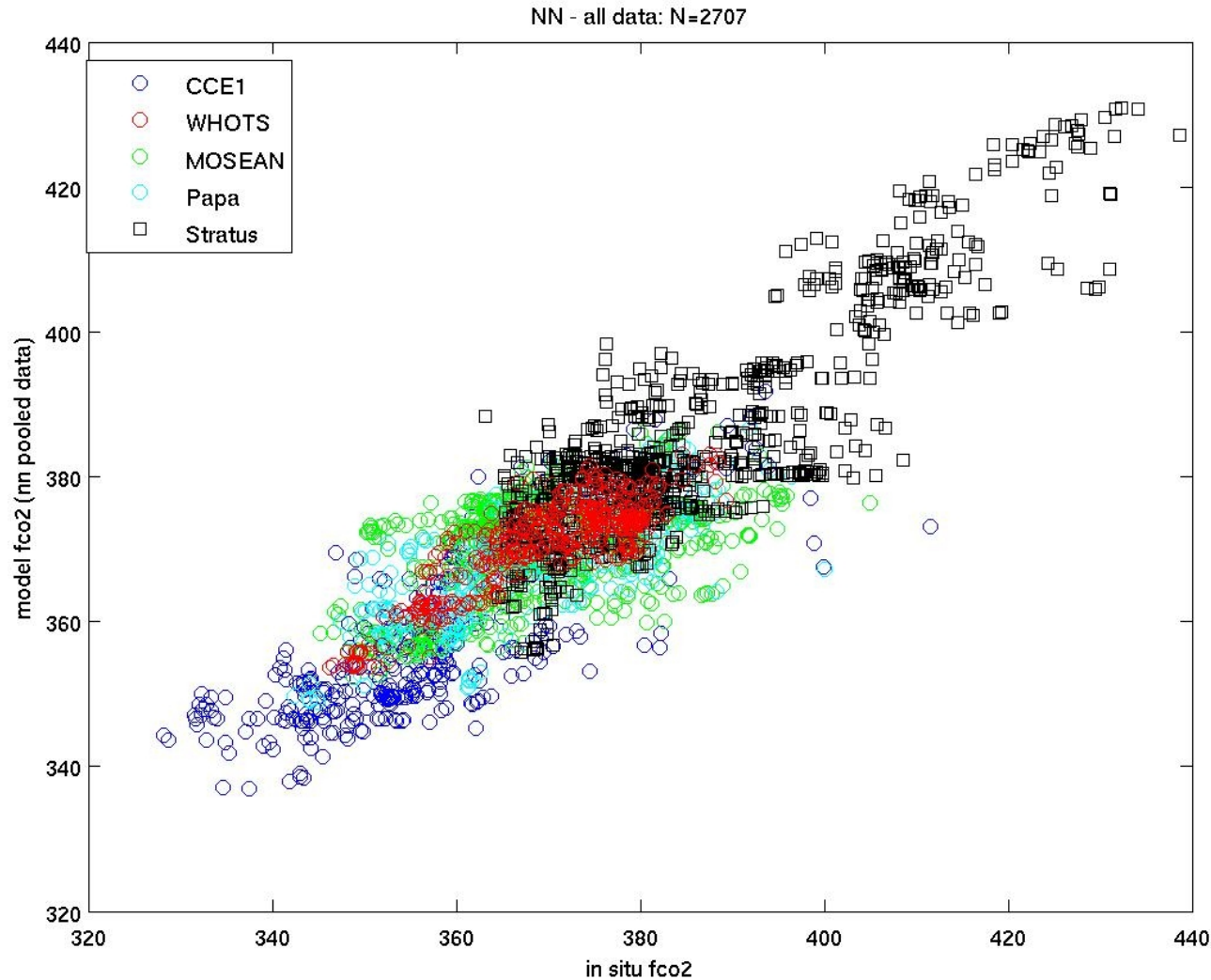
further assessment
required

Future? Multi-site algorithm

why, why not, how successful at each site and elsewhere?

Pooling time series data and model training to create a single multi-site algorithm

RMS goes up factor of 1.5-2 at each site (Still all less than 8 uAtm)



Future? - Liu et al. support vector regression algorithm**

- Adding geography and time in the input suite

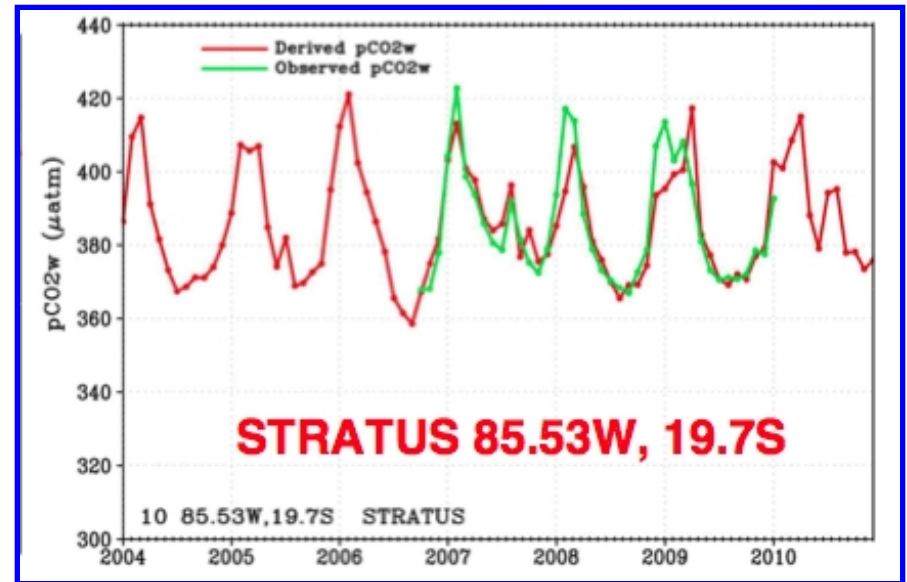
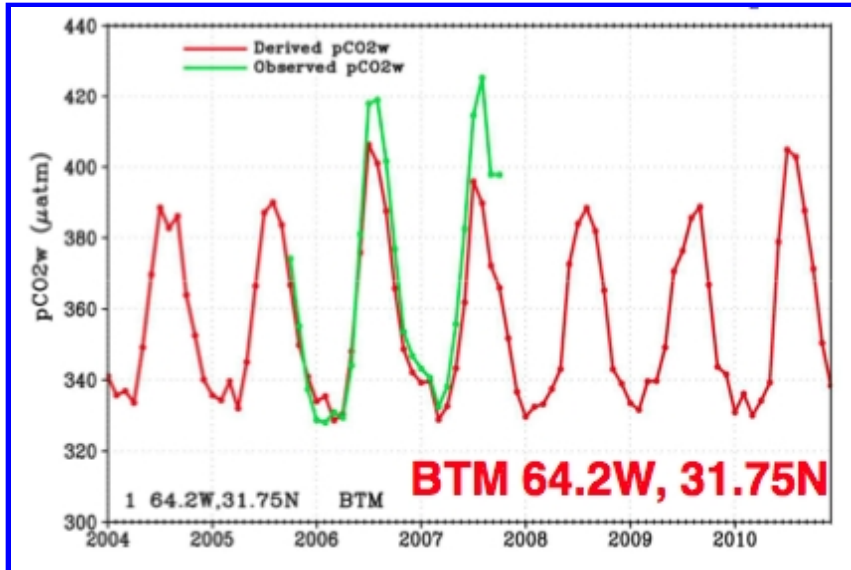
- 16 uAtm rms against withheld validation data

- Very dependent on good pCO₂ data coverage in space/time (200 k + SOCAT samples used)

□ Input (3-day): sin(day), cos(day), lat, sin(lon), cos(lon), SST (AMSR-E), Chl-a (SeaWiFS+MODIS TERRA+MODIS Aqua), SSS (Levitus climatology), Mixed layer depth (GODAS).

** http://aquarius.umaine.edu/docs/aqsci2012_WGC-02-Timothy.pdf

Future? - Liu et al. support vector regression algorithm**



- Doing quite well even on time series nodes that are not in the data set
- Some 10-15 uAtm overshoot in summer

** http://aquarius.umaine.edu/docs/aqsci2012_WGC-02-Timothy.pdf

Summary

- First steps at time series pCO₂ sites and their utility for improving ocean pCO₂ prediction models
- Contributions - a) methodical means for evaluating satellite inputs and their value in the inversion, b) revisiting pCO₂ training and validation datasets
- Neural networks outperforming Multiple Linear regression
- After SST and MLD, improvements with SSS, satellite-derived NPP (PAR)
- Our site-based algorithms yield < 5-6 uAtm rms, all-site NN < 8 uAtm
- BUT do they not appear to travel well, even within the region ???

FUTURE

- Can apply/expand any aspect within the OAFlux Cloud matrix to test further (e.g. SMOS SSS, GlobColour)
- Bringing in geography & time inputs + more data (cf. Liu approach) may indeed be the path forward at global scale (but is it better than climatology for SOLAS?)
- More gas flux evaluation at time series nodes?

*** We wish to acknowledge the use of field and satellite data from NOAA, WHOI, SOCAT, and the space agencies. ****