Constraining
Sea–air CO_2 Fluxes
from
Surface-Ocean Carbon Data

Christian Rödenbeck

Max Planck Institute for Biogeochemistry, Jena

D. C. E. Bakker, P. Landschützer,
R. Keeling, and M. Heimann

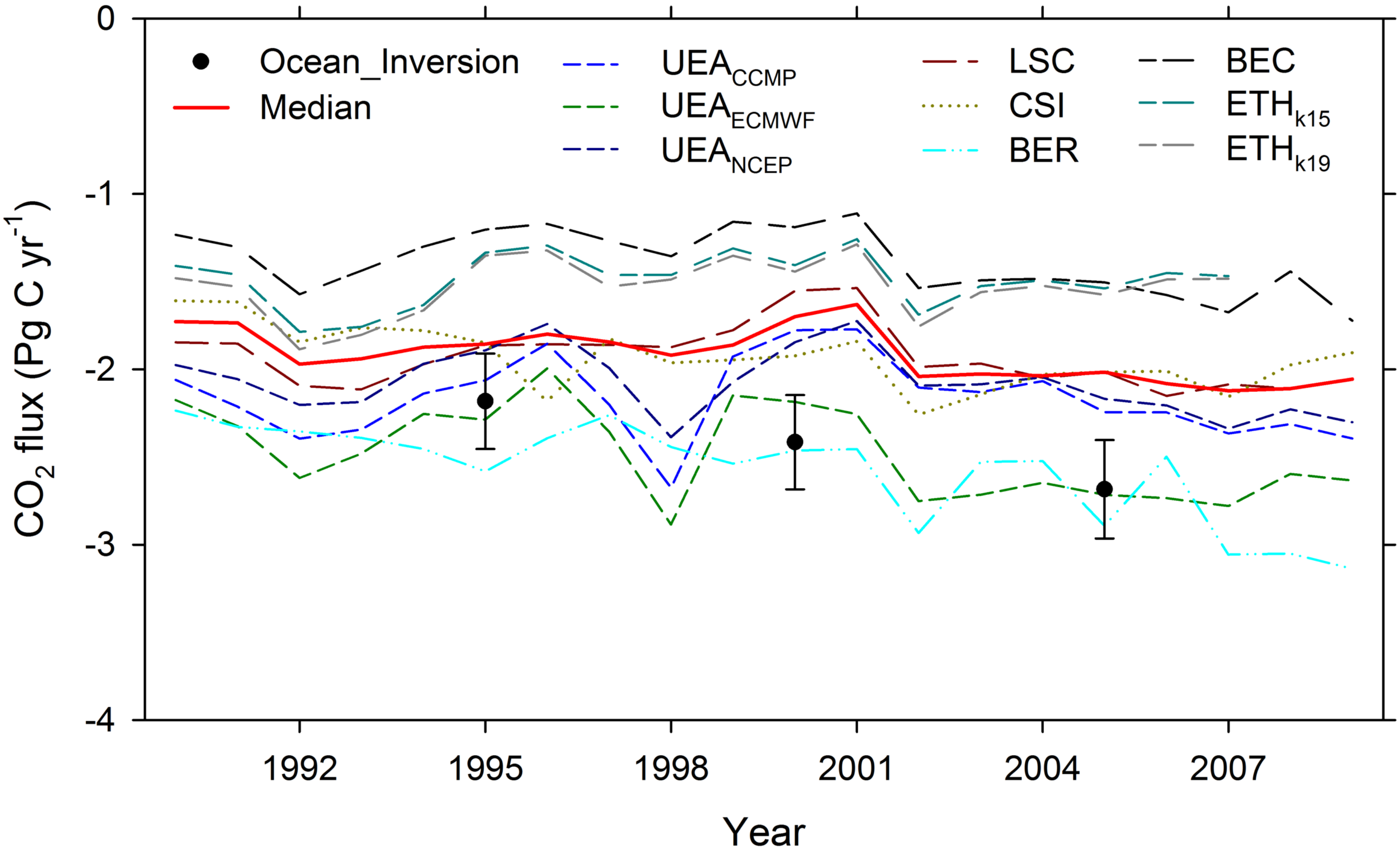
In collaboration with

N. Gruber, Y. Iida, A.R. Jacobson, S. Jones,
N. Metzl, S. Nakaoka, A. Olsen, G.-H. Park,
P. Peylin, K.B. Rodgers, T.P. Sasse,
U. Schuster, J.D. Shutler, V. Valsala,
R. Wanninkhof, J. Zeng

Many thanks to:

Data contributors, DKRZ, CarboChange, IMBER / SOLAS

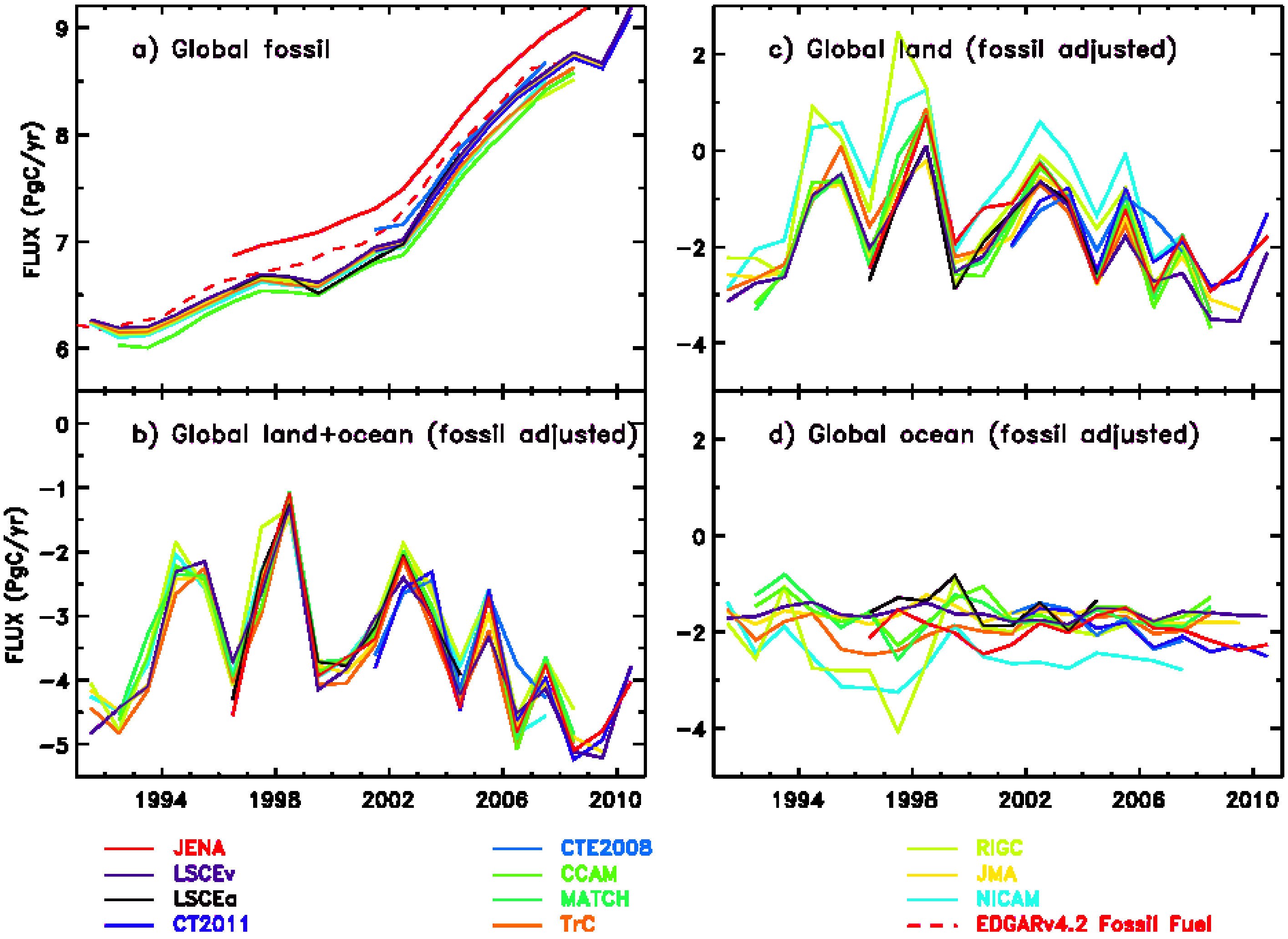
Motivation



Ocean process models

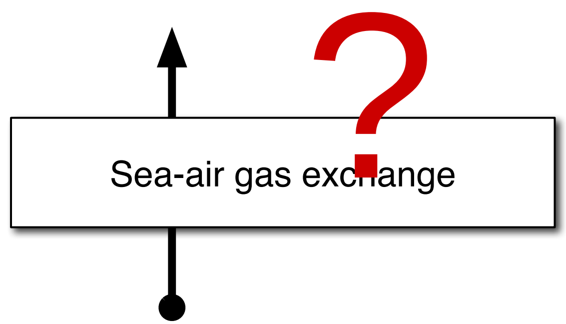
[Wanninkhof et al., RECCAP (2013)]

Motivation

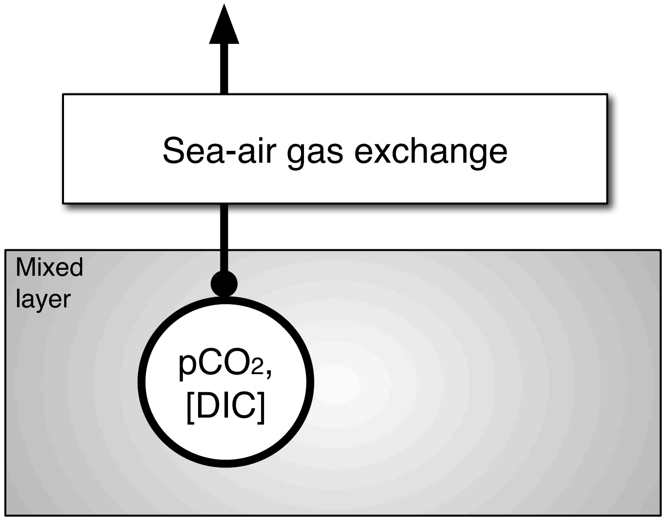


Atmospheric inversions

[Peylin et al., RECCAP (2013)]



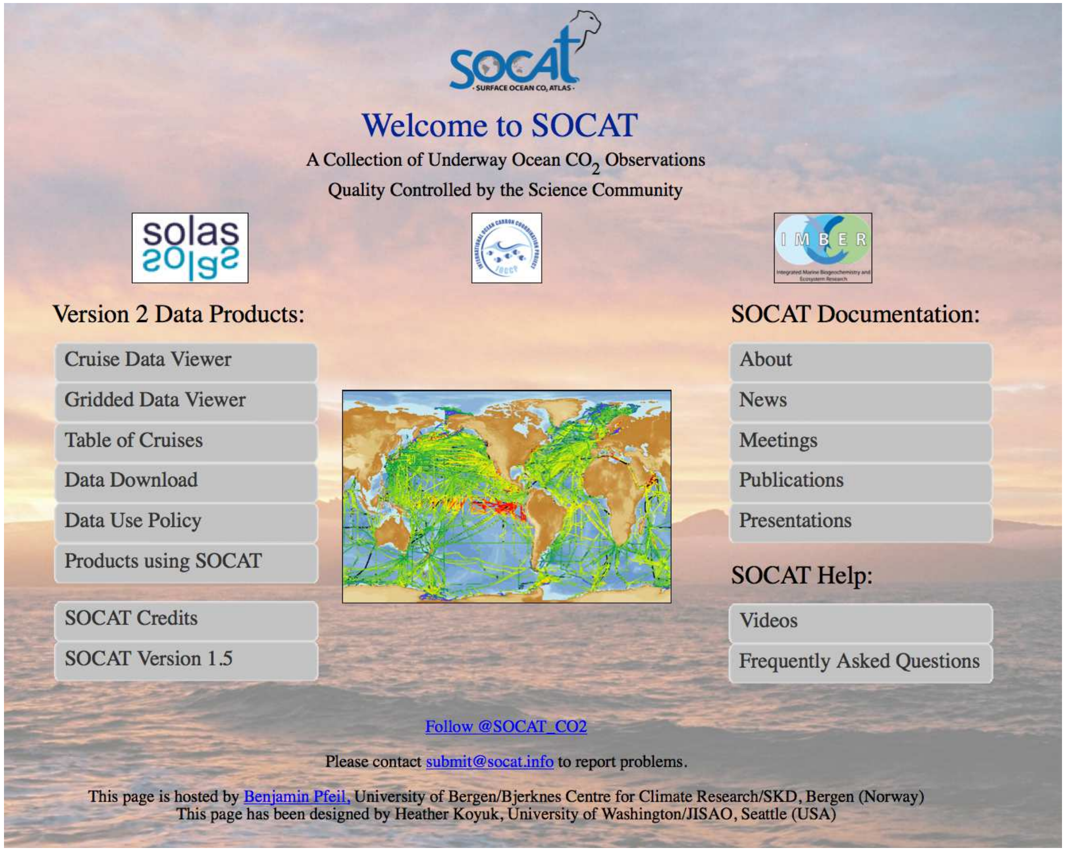
Carbon



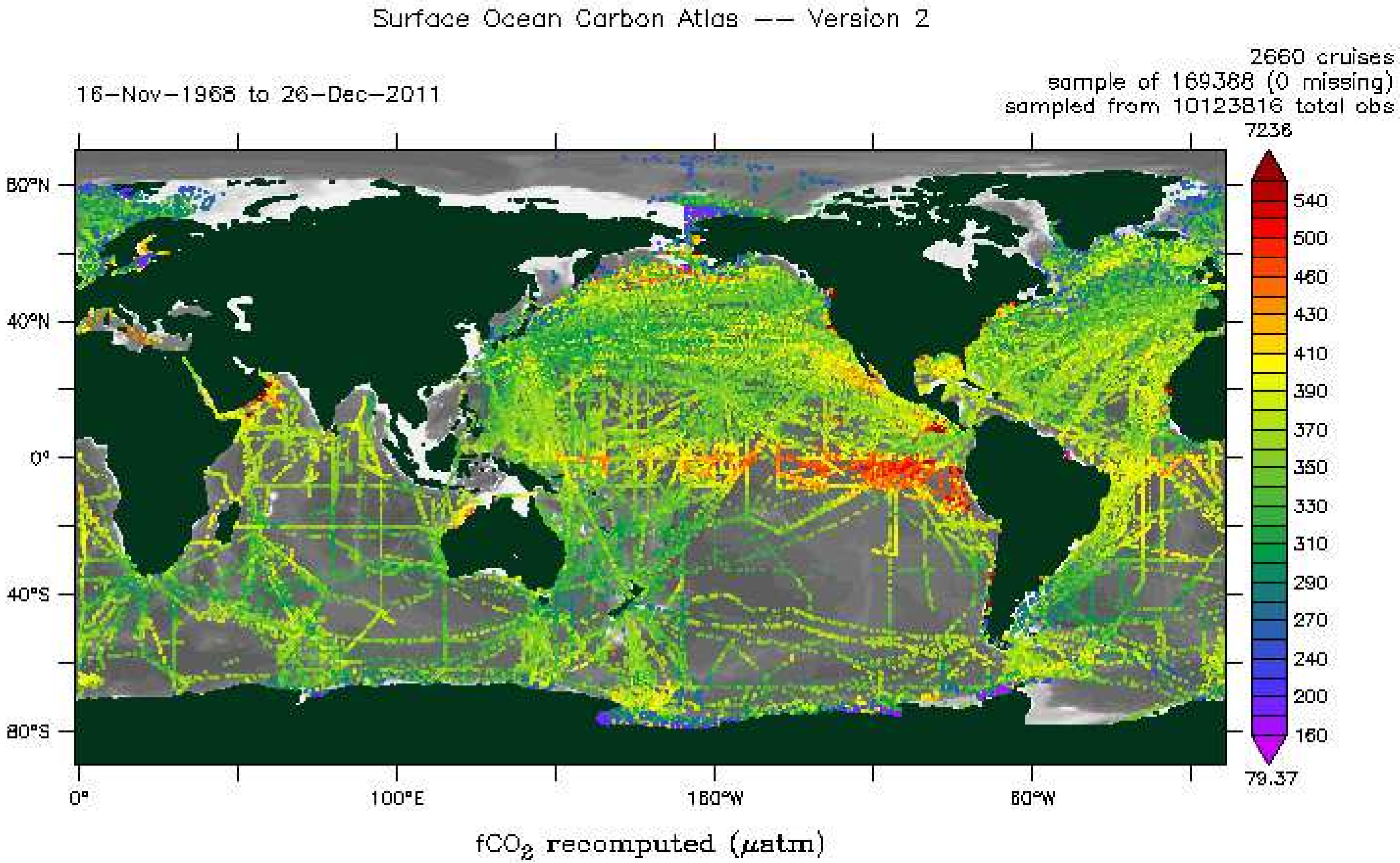
Carbon

Ocean carbon data collections:

– **SOCAT** v3 pCO_2 *[www.socat.info/]*
– **LDEO** v2014 pCO_2 *[cdiac.ornl.gov/oceans/LDEO_Underway_Database/]*
– **GLODAP** v2 [DIC], [Alk] *[cdiac.ornl.gov/oceans/glodap/]*



Data density / distribution



[www.socat.info]

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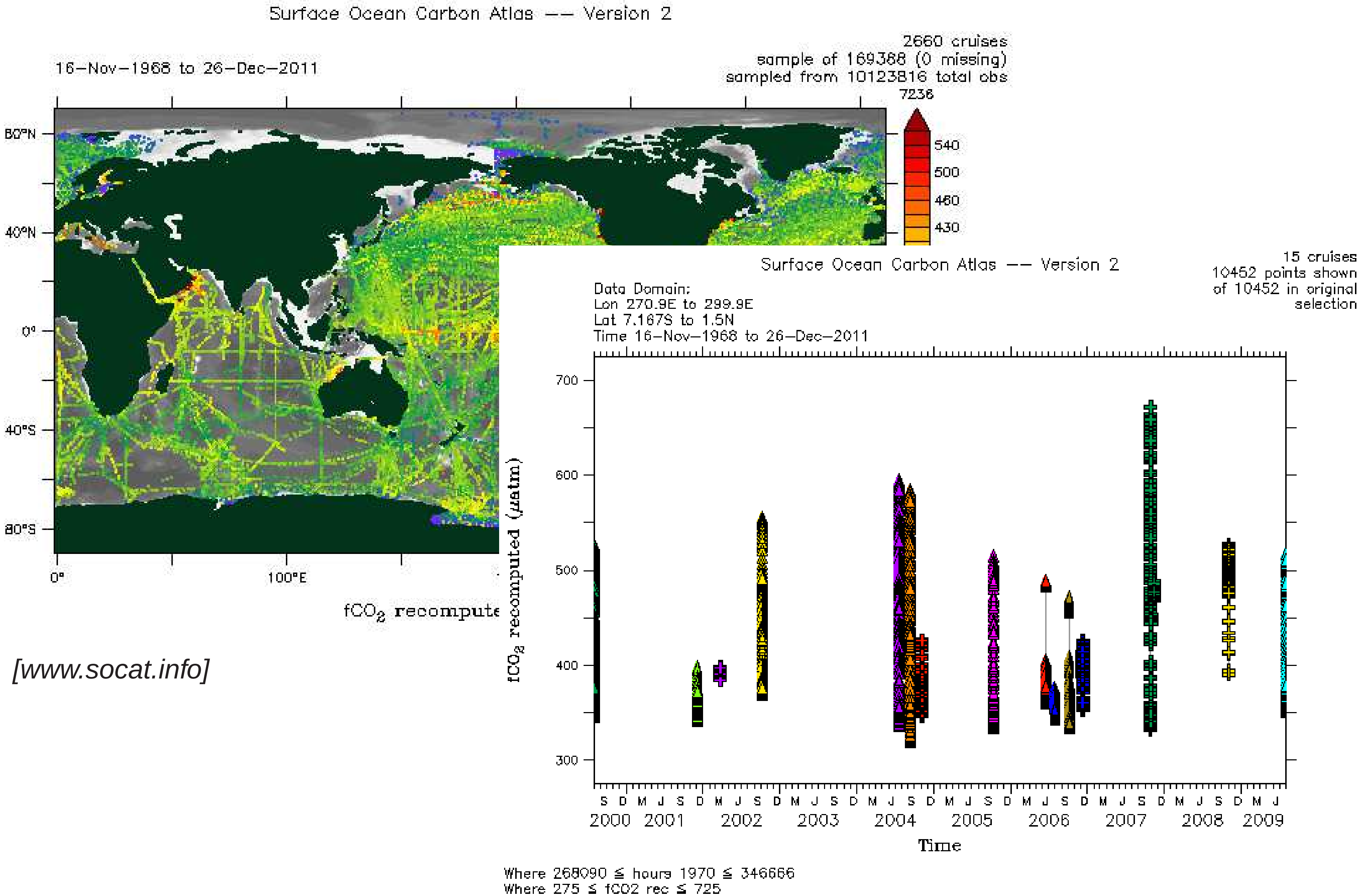

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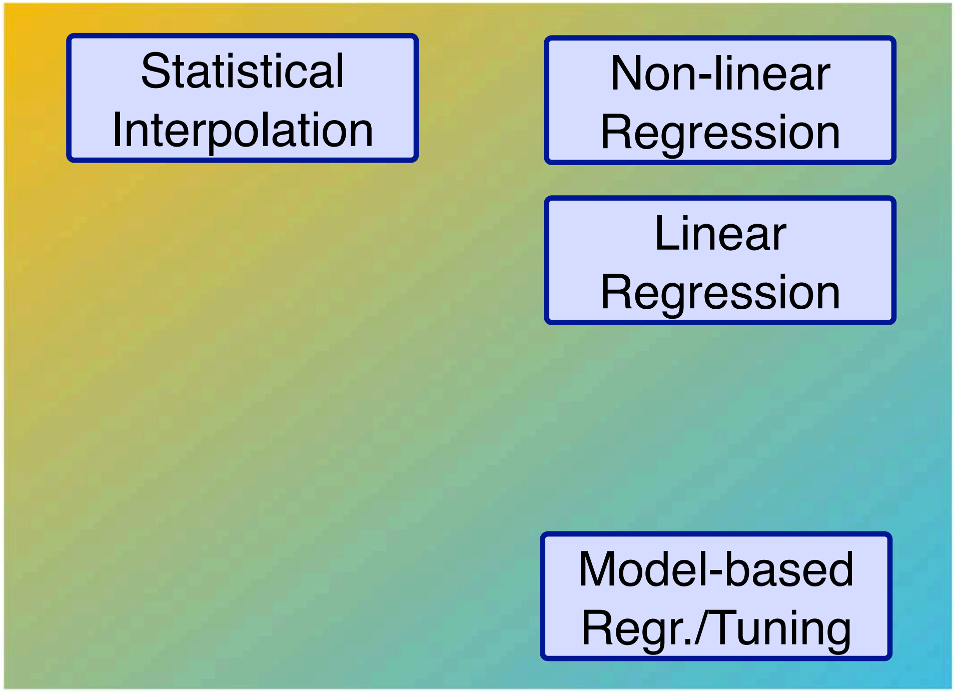
Mapping methods



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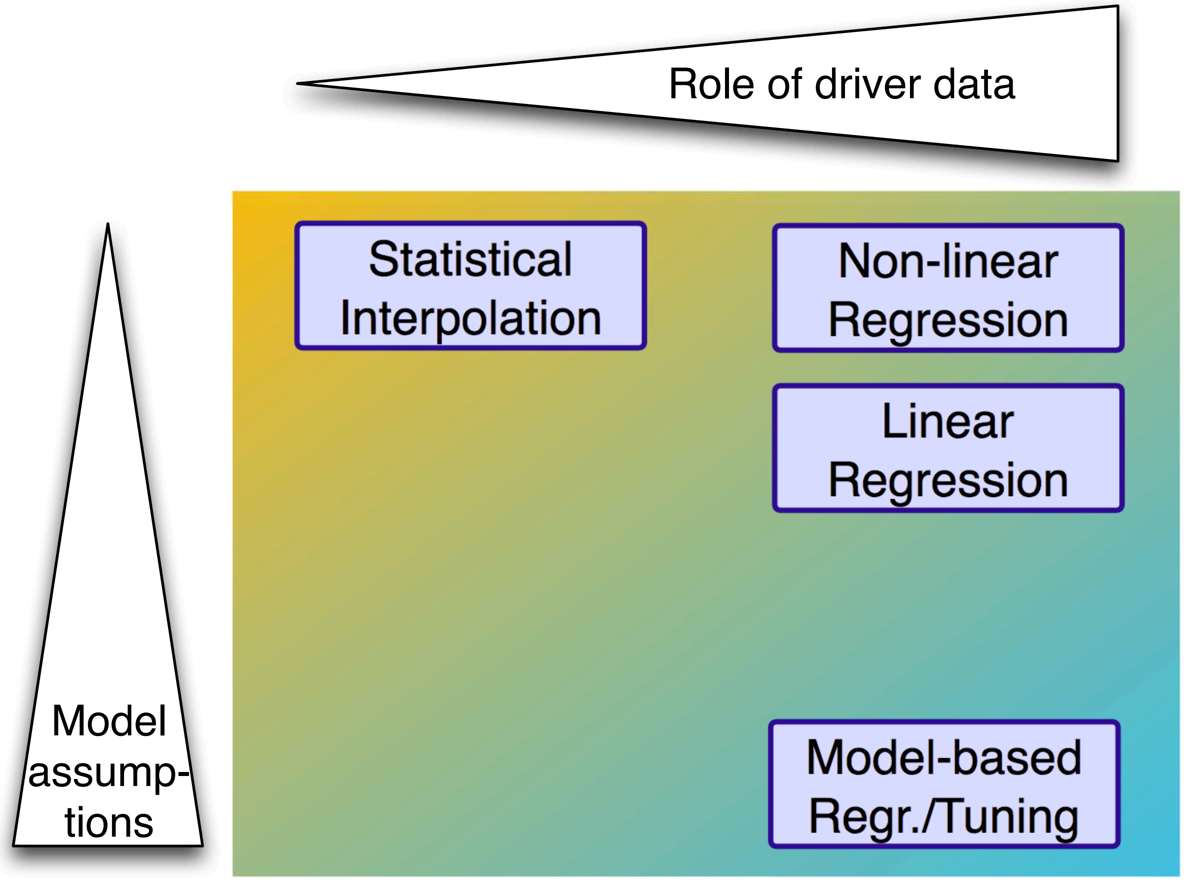

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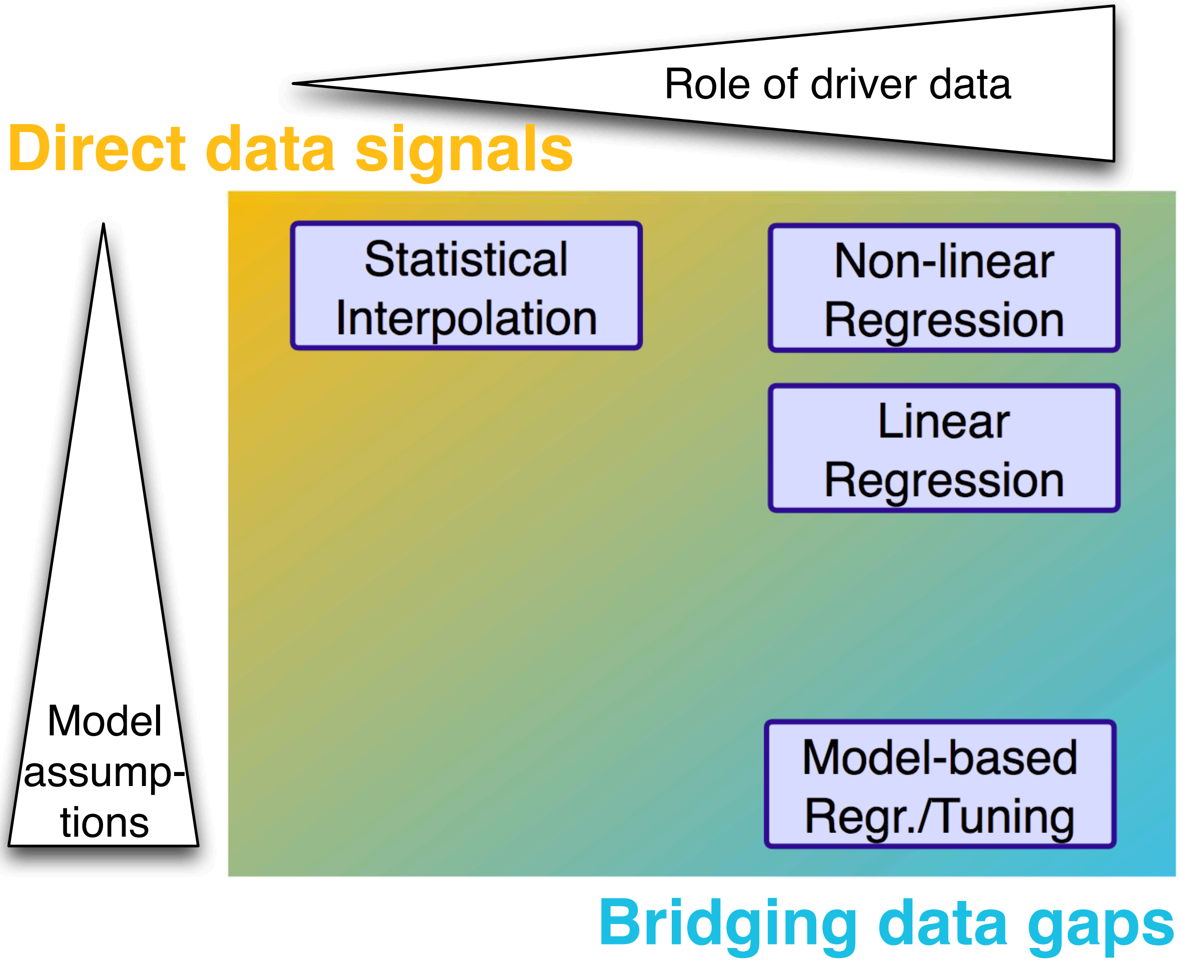


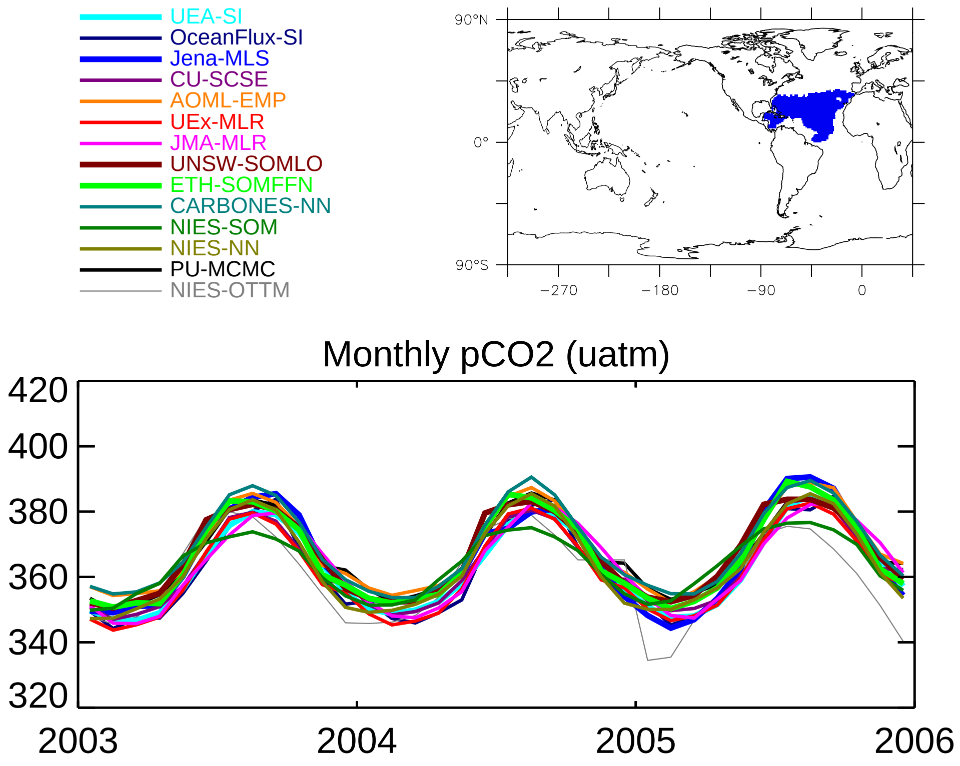
$\longrightarrow$ **Interesting complementarity**

$\longrightarrow$ **Extracting robust features**

SOCOM: Collating 14 mapping methods

SOCOM SURFACE OCEAN pCO_2 MAPPING INTERCOMPARISON

First results [Rödenbeck et al., BG (2015)]



Seasonality:

Most methods roughly agree on phasing and amplitude

(also to Takahashi et al., 2009)

→ *Seasonality well constrained from data*

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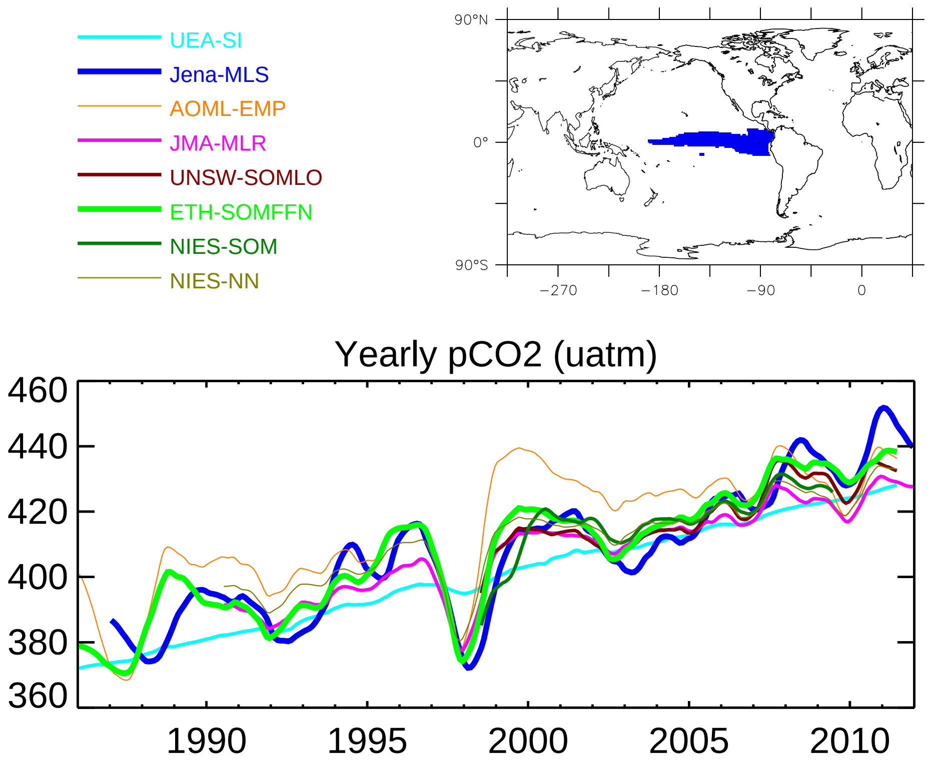

Interannual Variations (IAV):

– secular rise

– Tropical Pacific:

* Biome with largest IAV
* Link to ENSO

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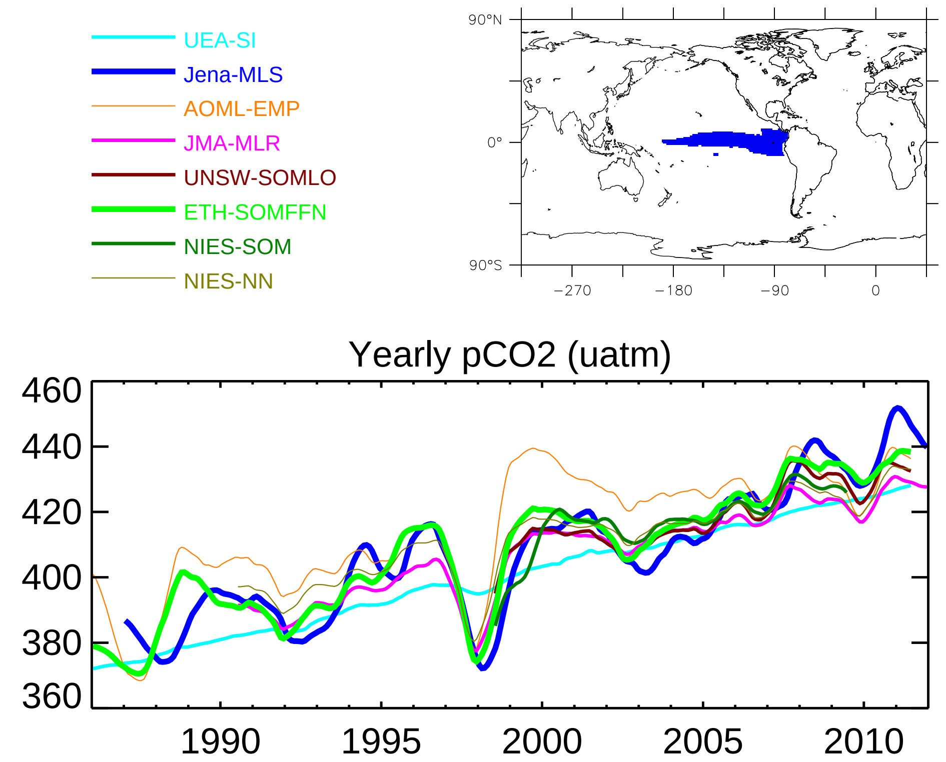

Interannual Variations (IAV):

– secular rise

– Tropical Pacific:

  * Biome with largest IAV

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Methods selected / weighted by relative IAV mismatch to SOCATv2

better match to data
$\rightarrow$ also closer mutual agreement

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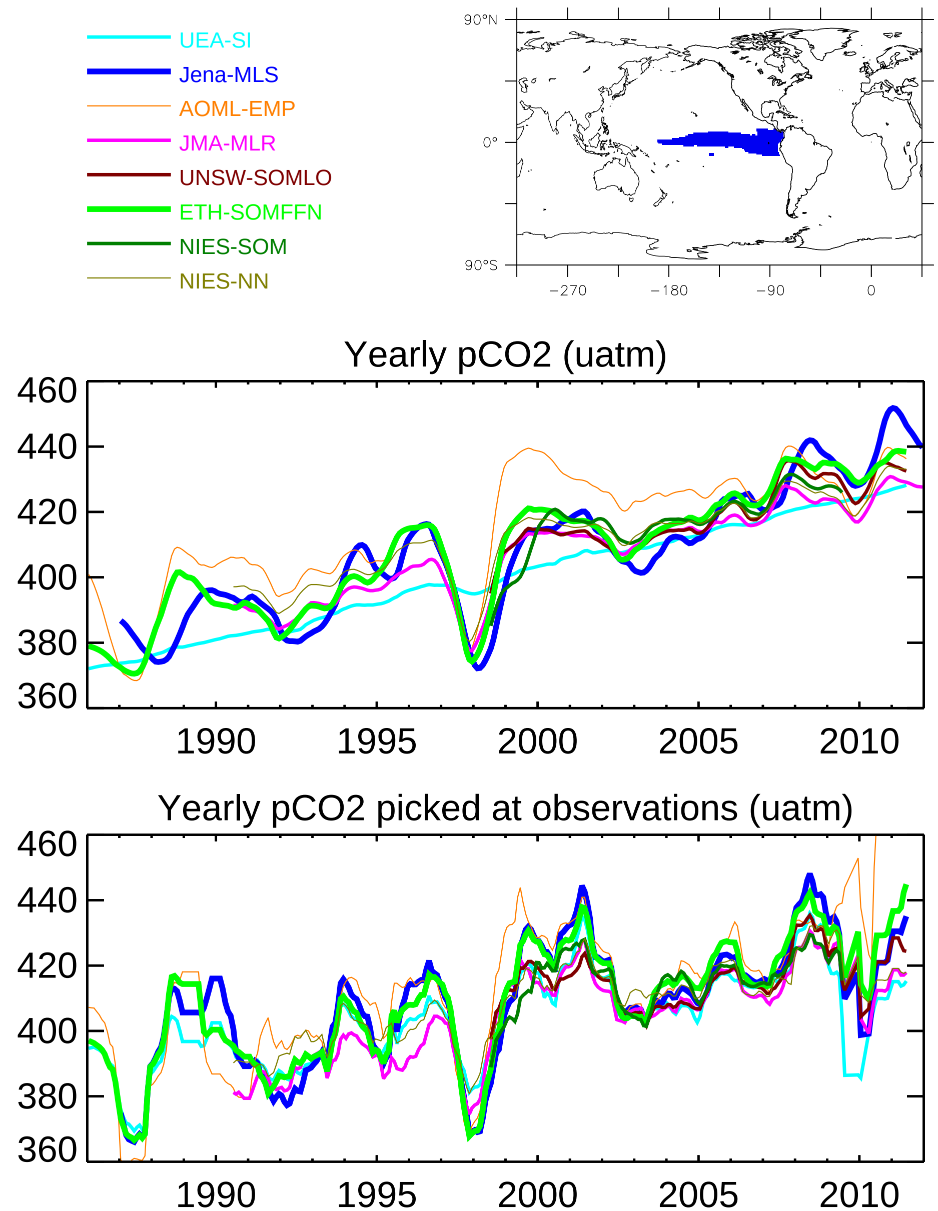

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– secular rise

– Tropical Pacific:

  * Biome with largest IAV

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Data-covered pixels only: (SOCAT v2)

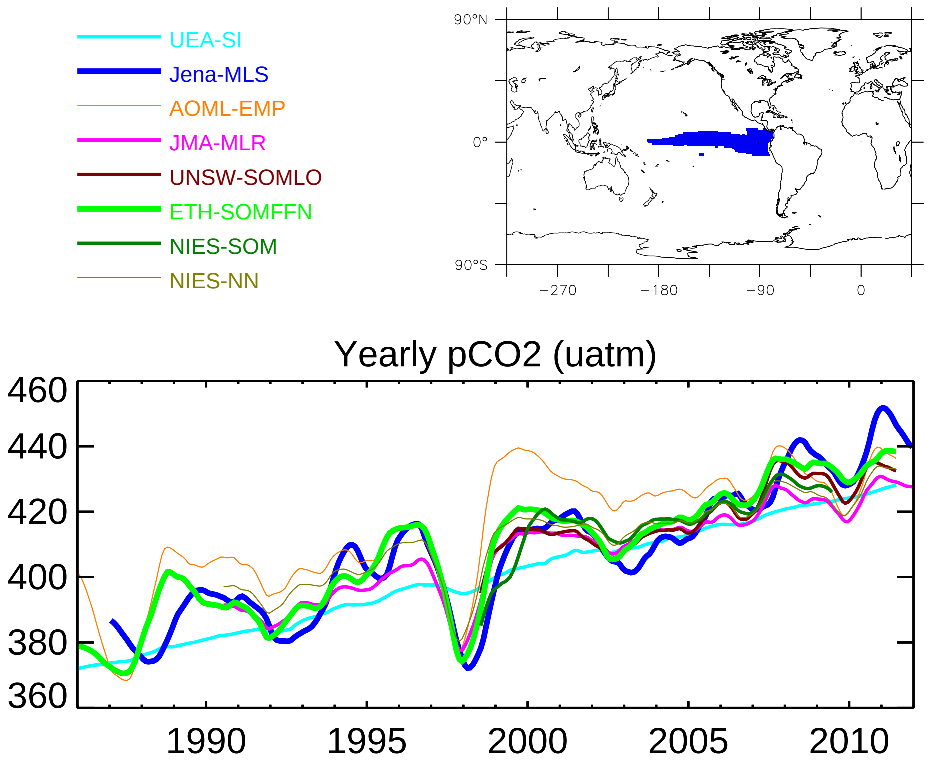
– Smaller ensemble spread

– Altered time variations

  → sampling bias (seasonally, spatially)

  → challenge for mapping

First results: Sea–air CO_2 fluxes [Rödenbeck et al., BG (2015)]



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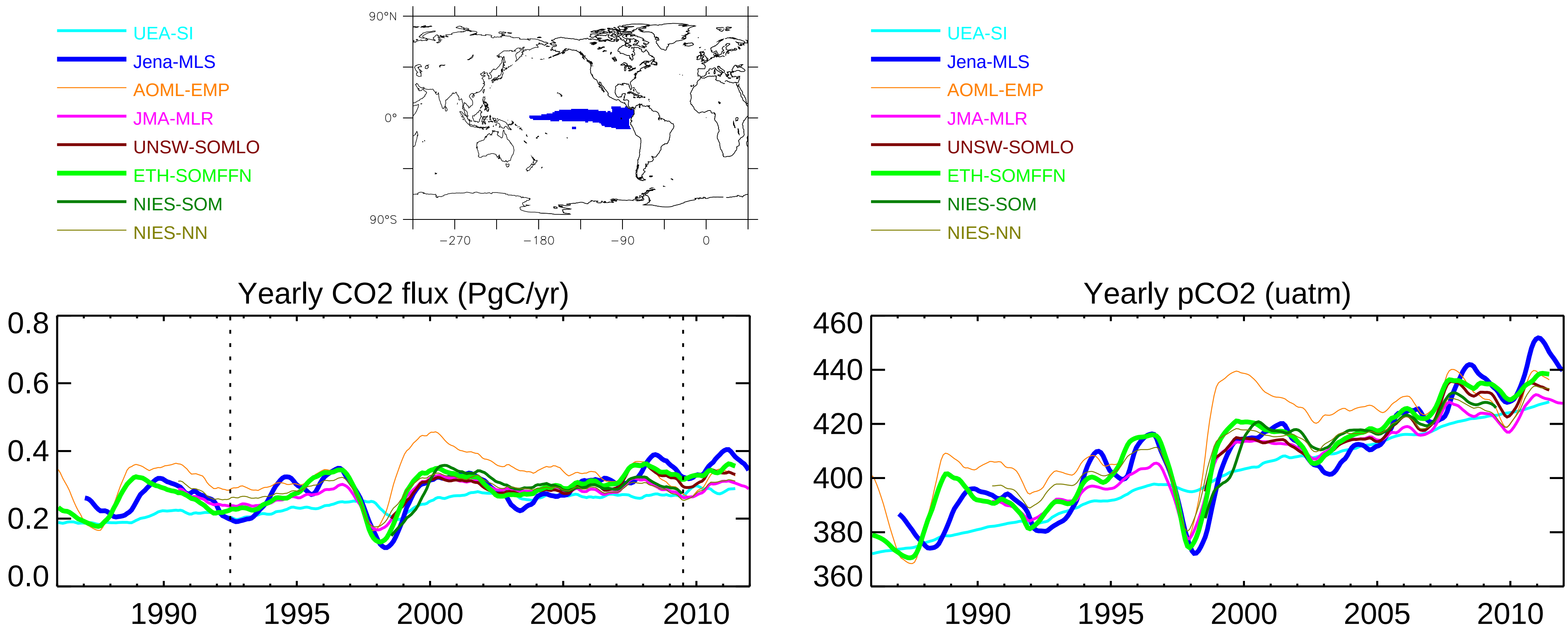

$$f = k(u^2) \cdot \varrho L \cdot (p\mathrm{CO}_2 - p\mathrm{CO}_2^{\mathrm{atm}})$$

$\rightarrow$ *Flux IAV dominated by* $p\mathrm{CO}_2$ *IAV*

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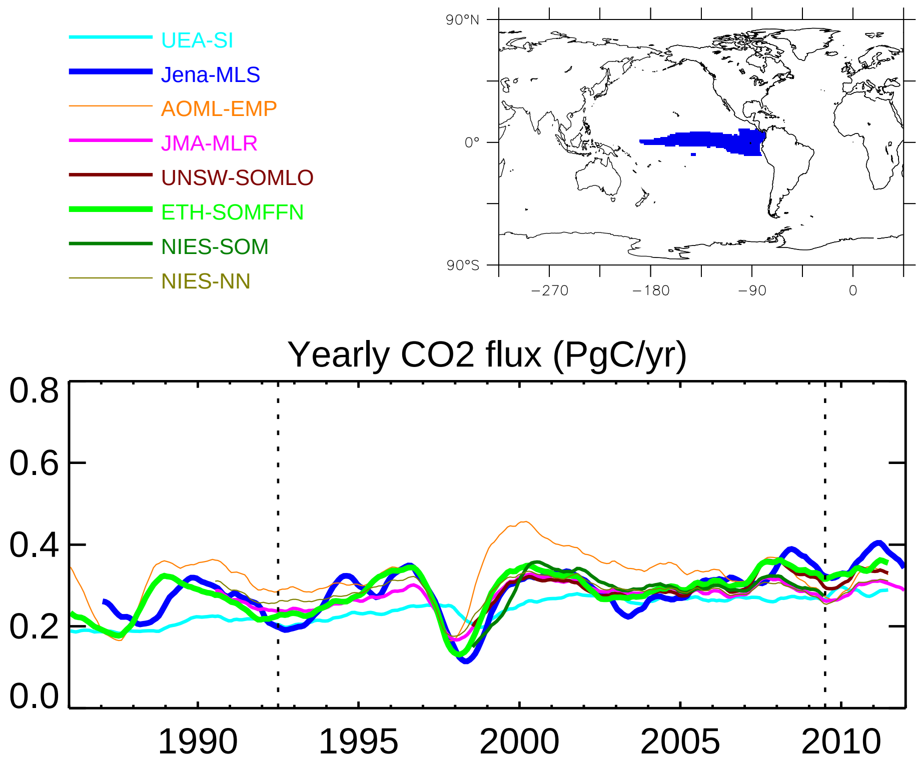

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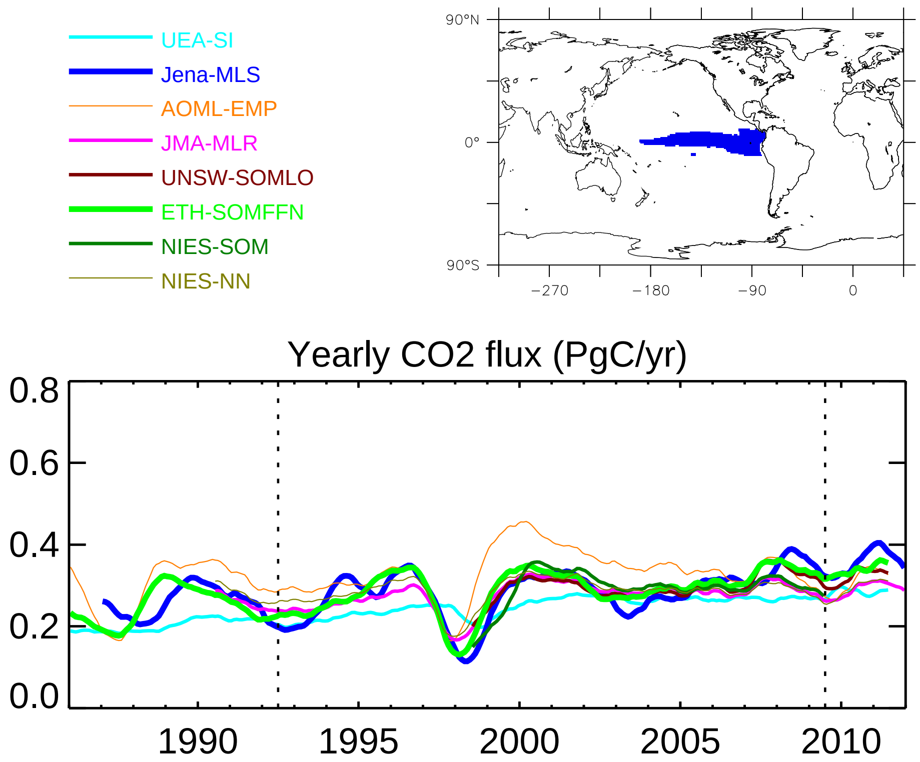

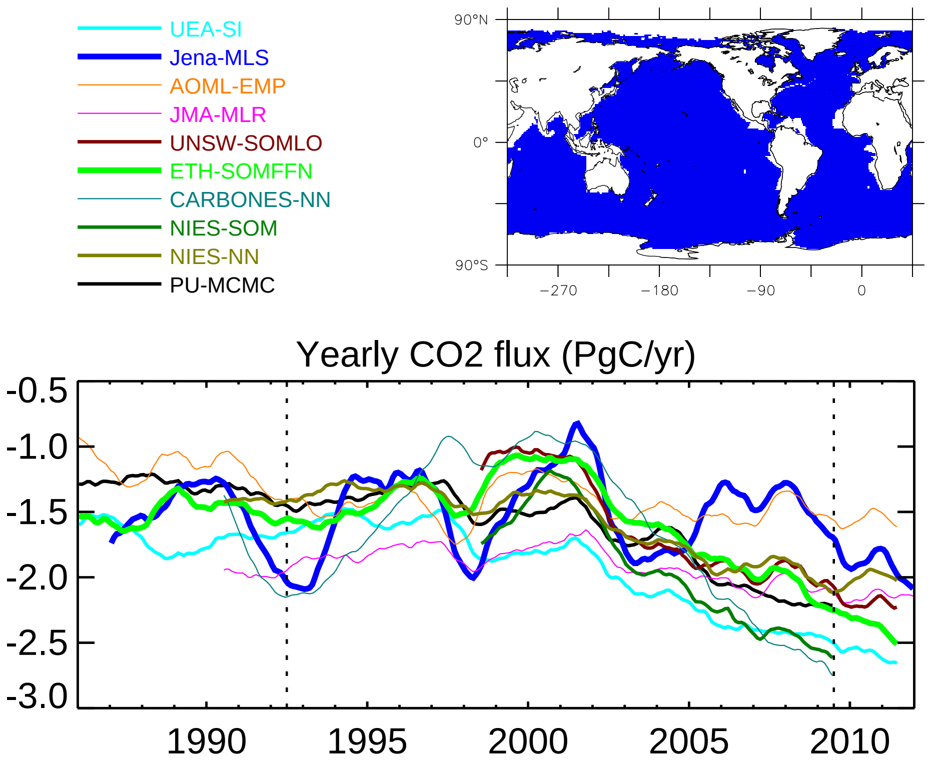

Little decadal change Increasing sink

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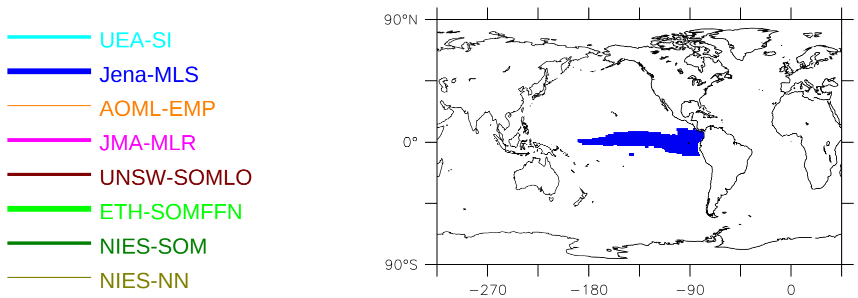
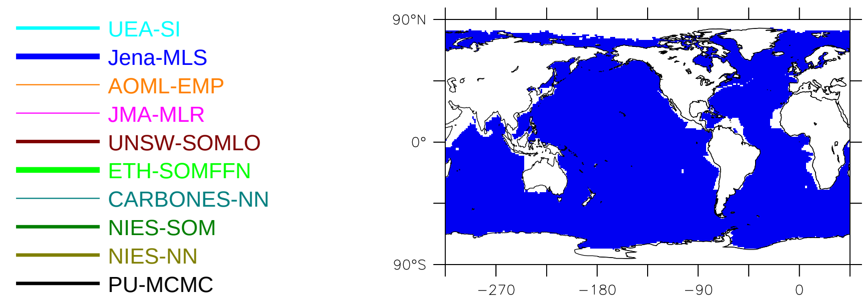
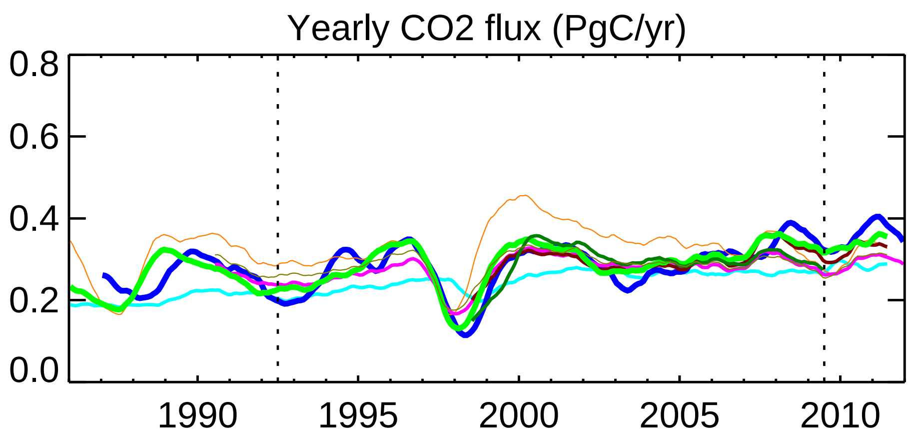
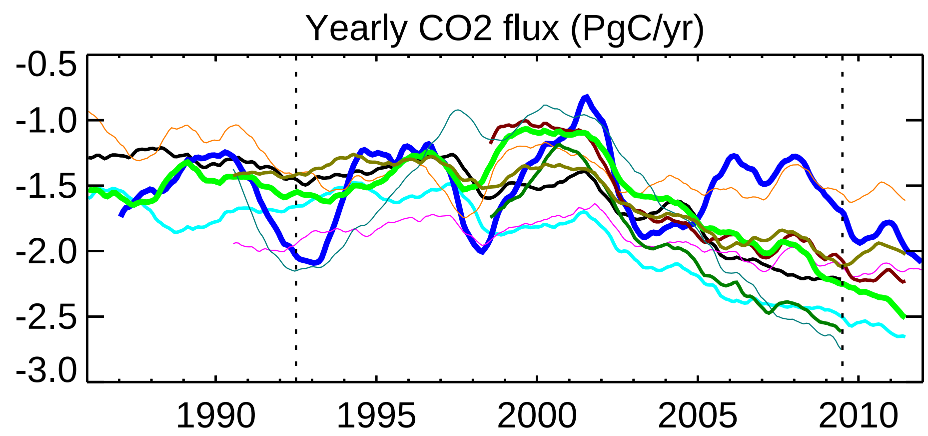




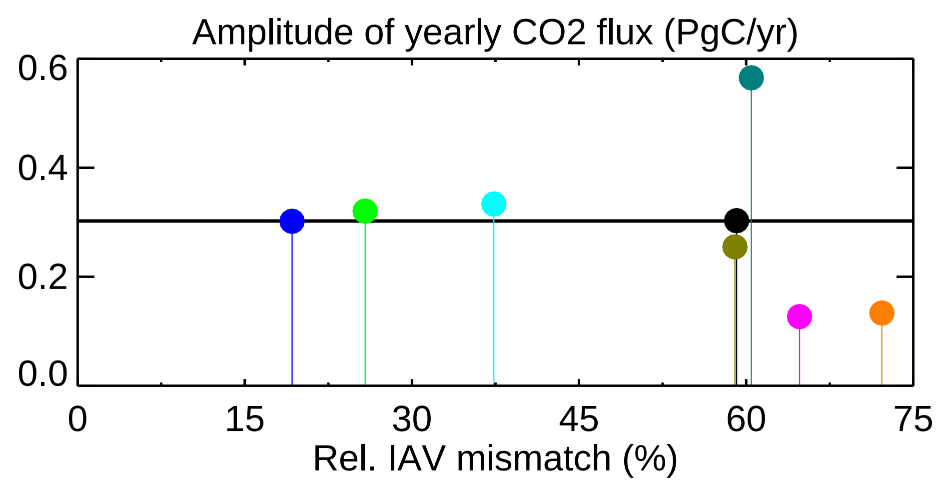




Weighted mean

global IAV amplitude: $0.31\,\mathrm{PgC\,yr^{-1}}$

$\rightarrow$ *Underestimated by process models*



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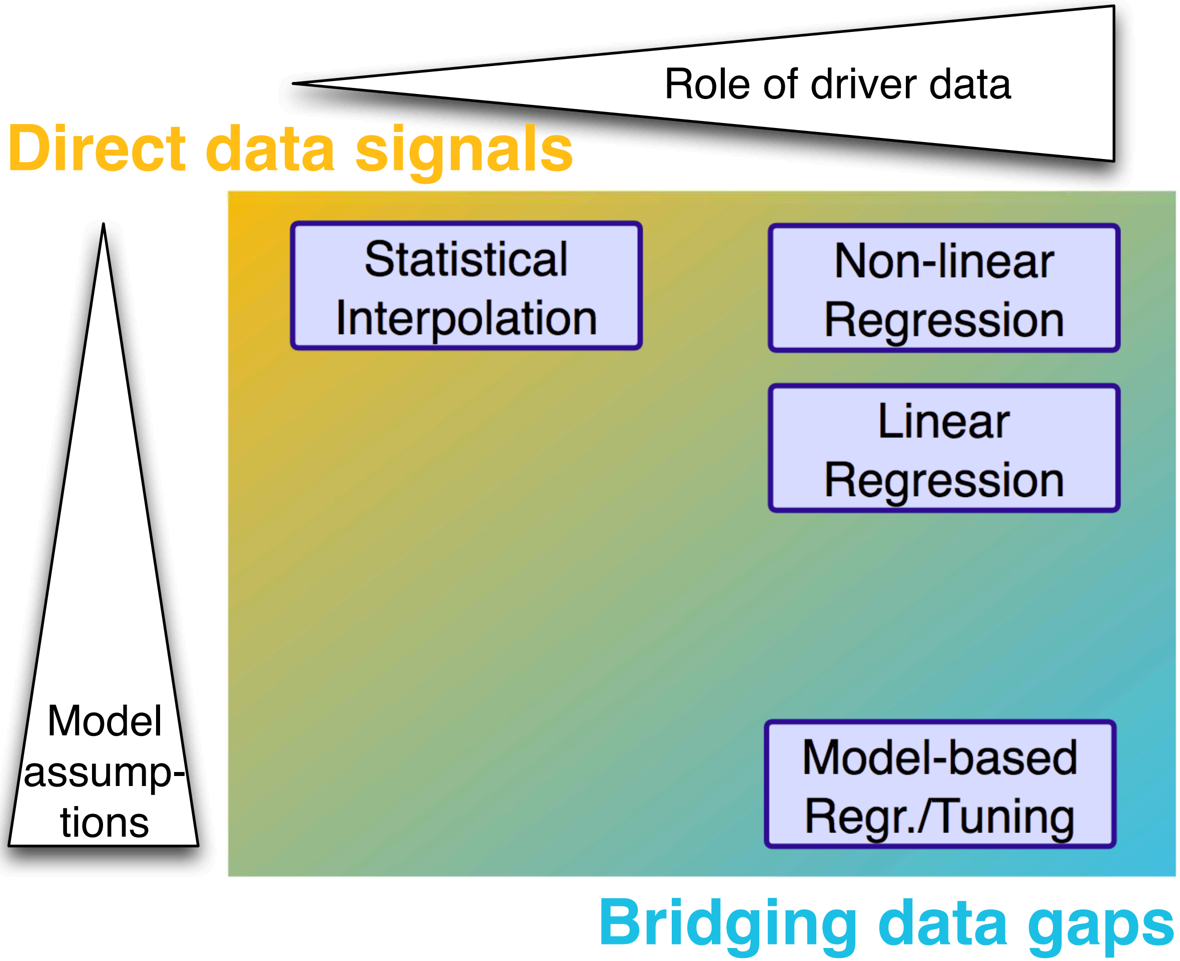


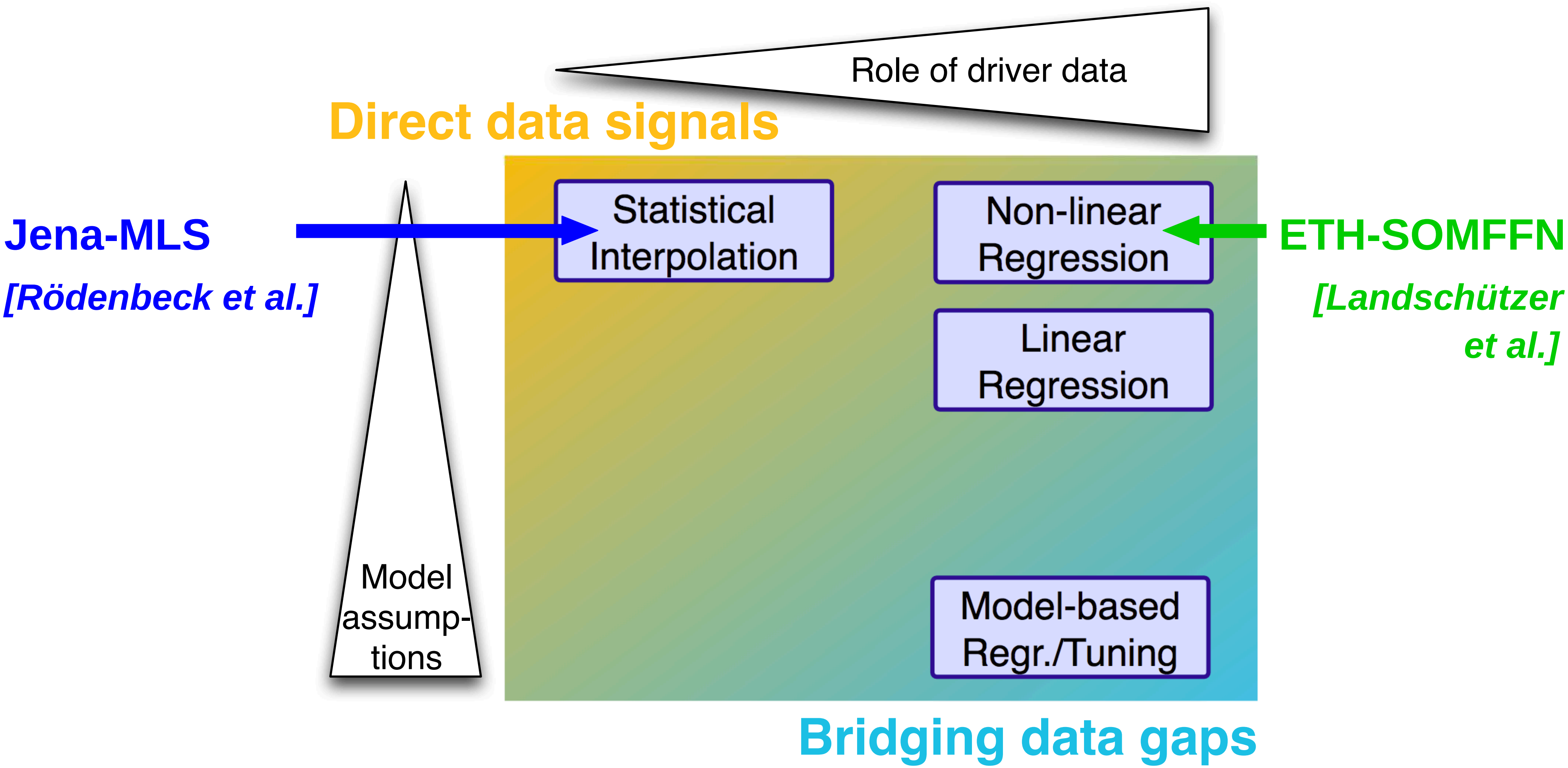
⟶ **Interesting complementarity**

⟶ **Extracting robust features**

SOCOM: Collating 14 mapping methods

SOCOM
SURFACE OCEAN pCO_2 MAPPING INTERCOMPARISON

Mapping methods



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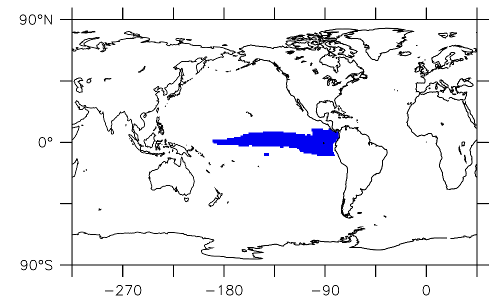
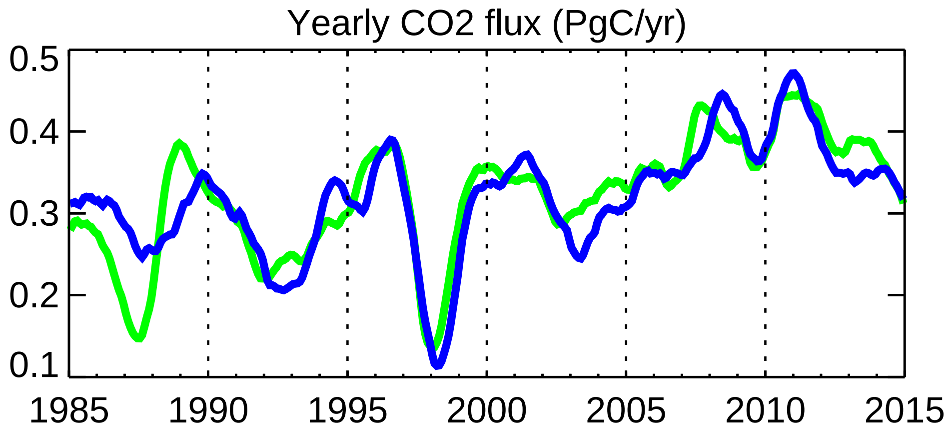
SURFACE OCEAN pCO_2 MAPPING INTERCOMPARISON

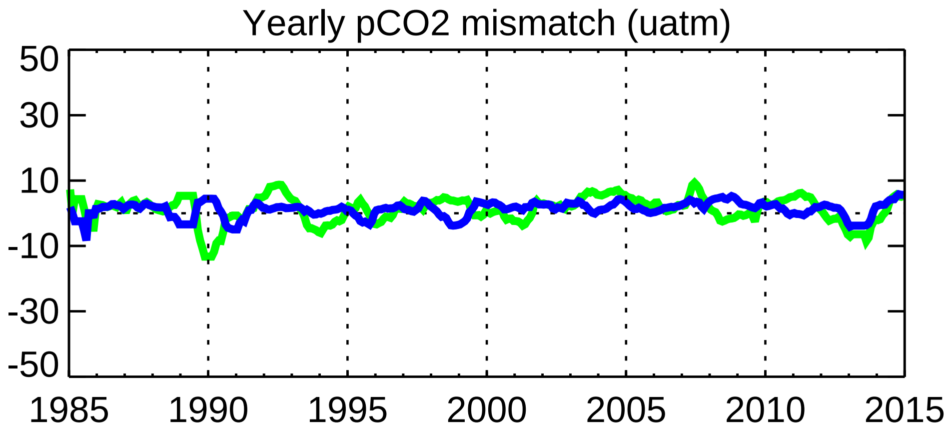
Cross Validation

(18.%) Jena oc_v1.4S

(28.%) ETH-SOMFFN2016







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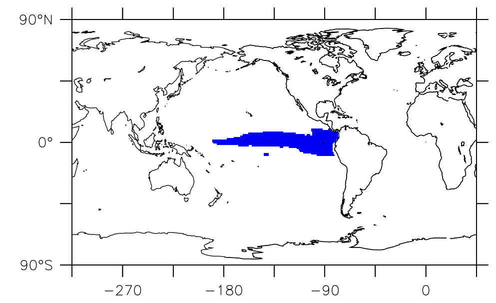

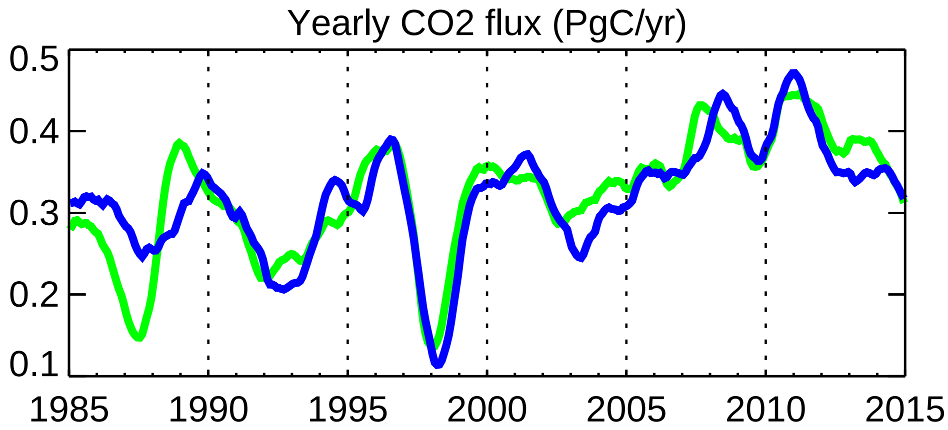

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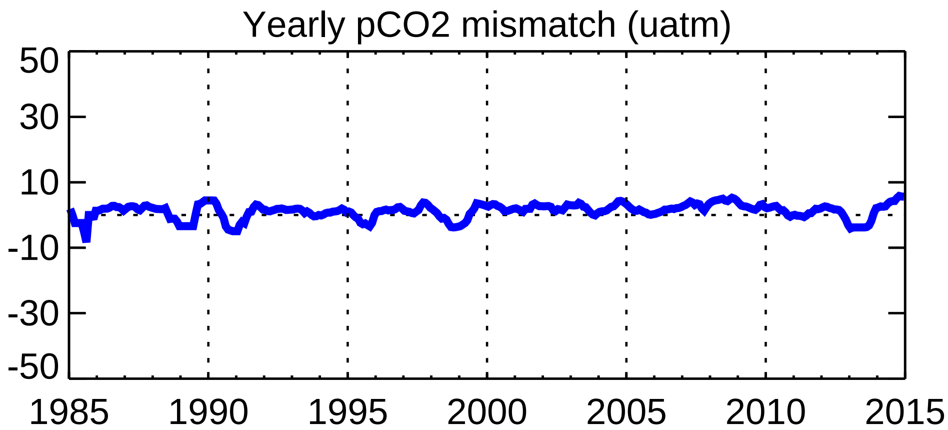

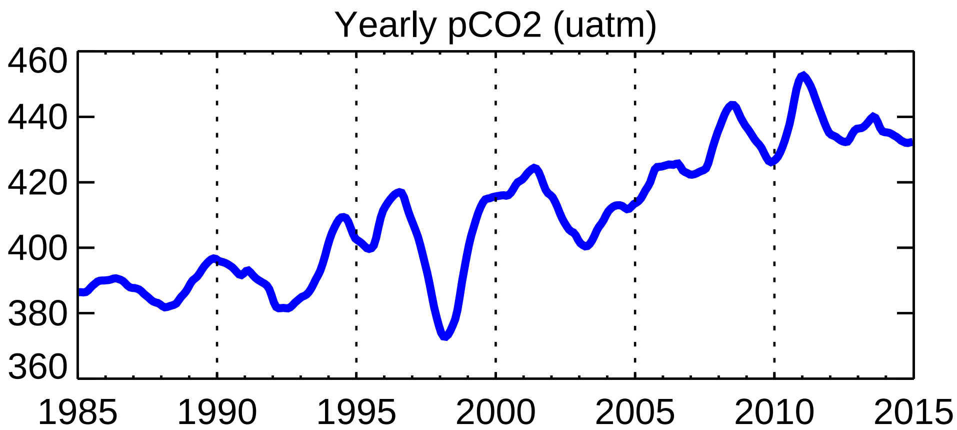

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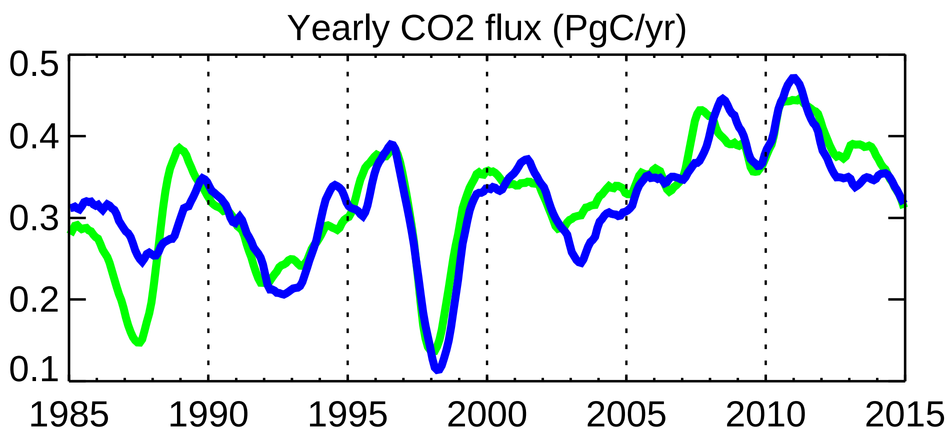
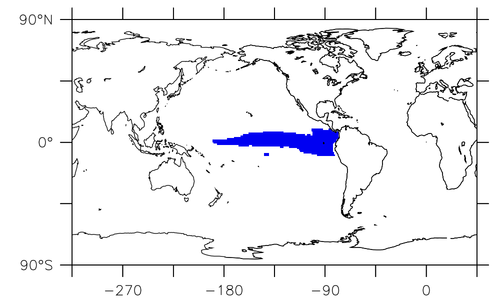




"Benchmark":

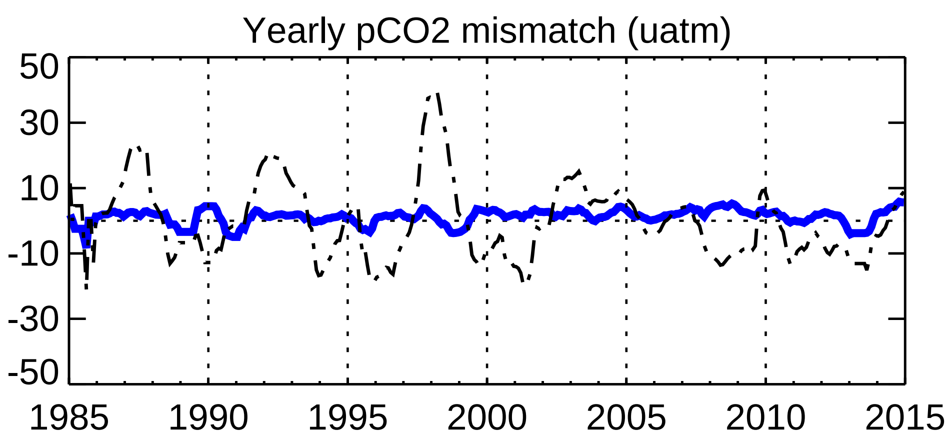
Keep seasonality+trend, but **no IAV**

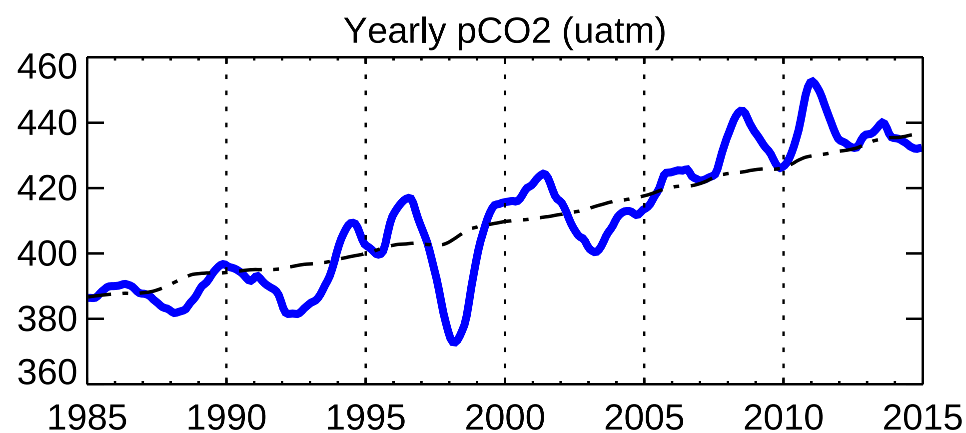
→ Mismatch ≈ signal size

→ "100% error"

(18.%) Jena oc_v1.4S

(100.%) Jena oc_v1.4S Benchmark





Cross Validation

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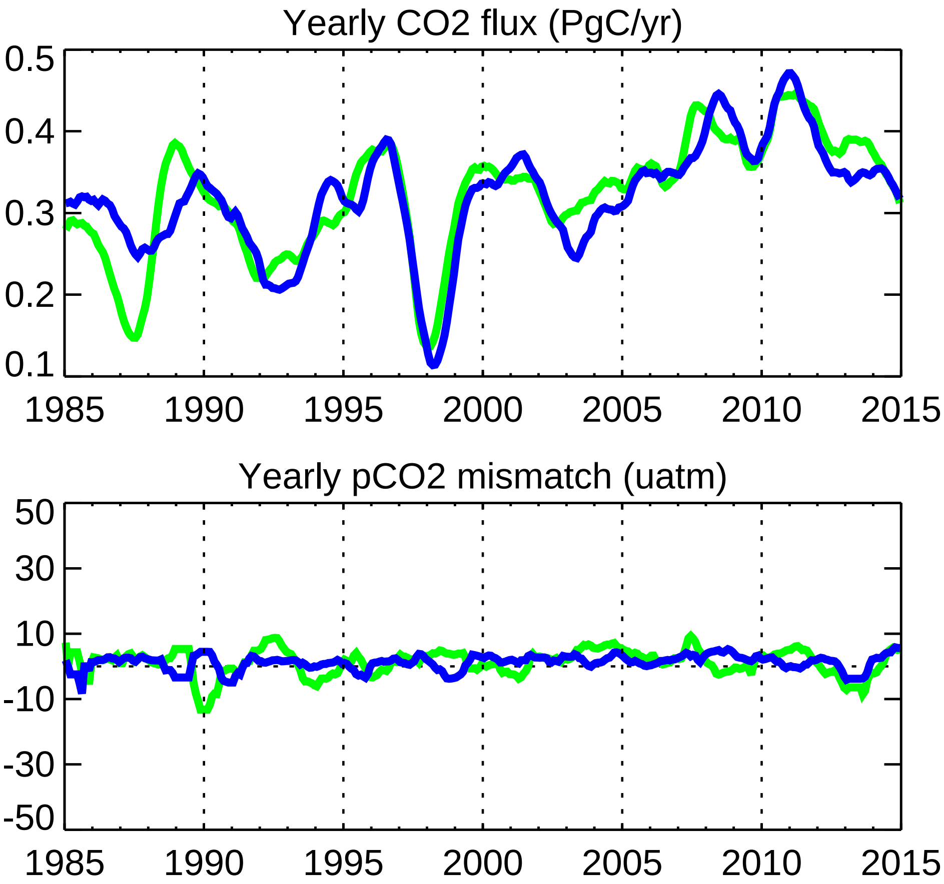

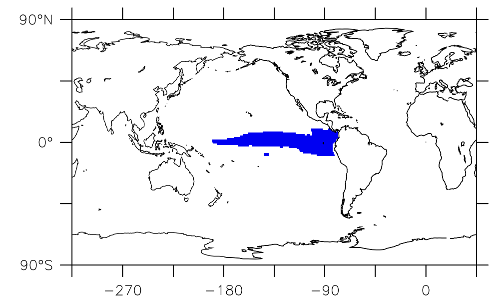

Interpolation:

Time-dep. DoF's

$\rightarrow$ Any IAV possible

Regression:

Constant DoF's

$\rightarrow$ IAV from drivers

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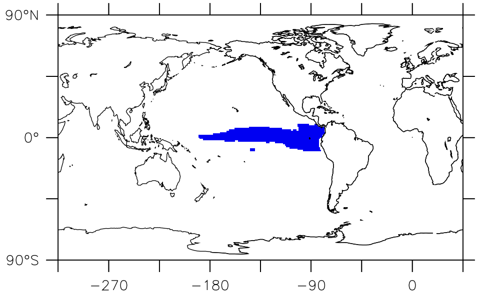

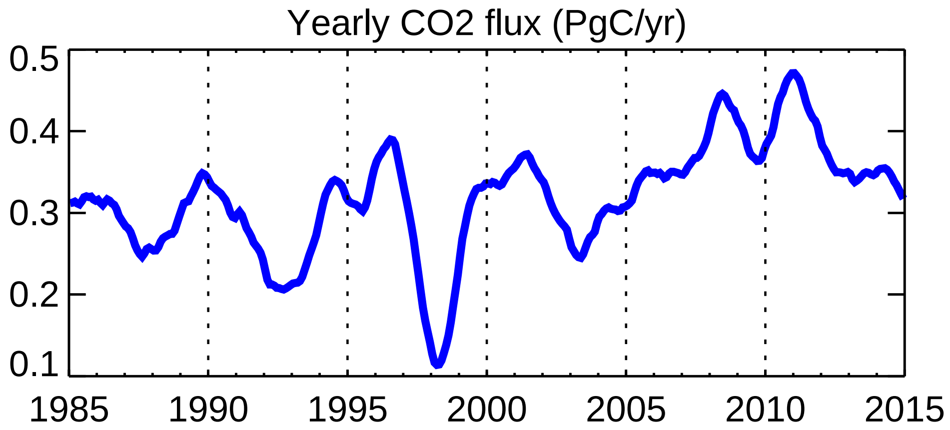

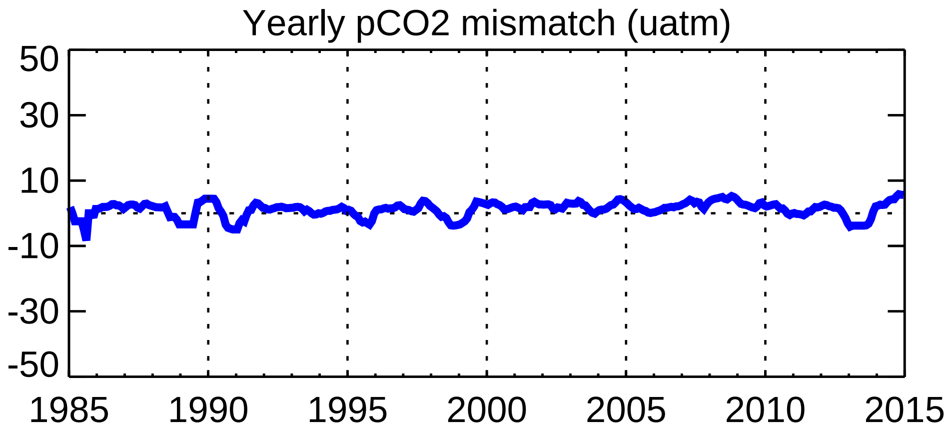

Cross Validation

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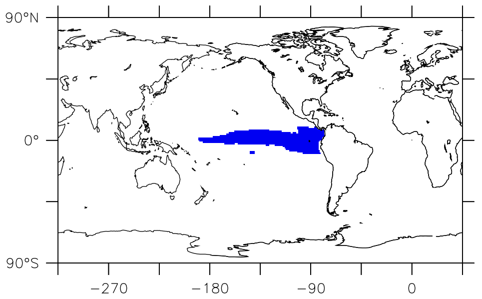
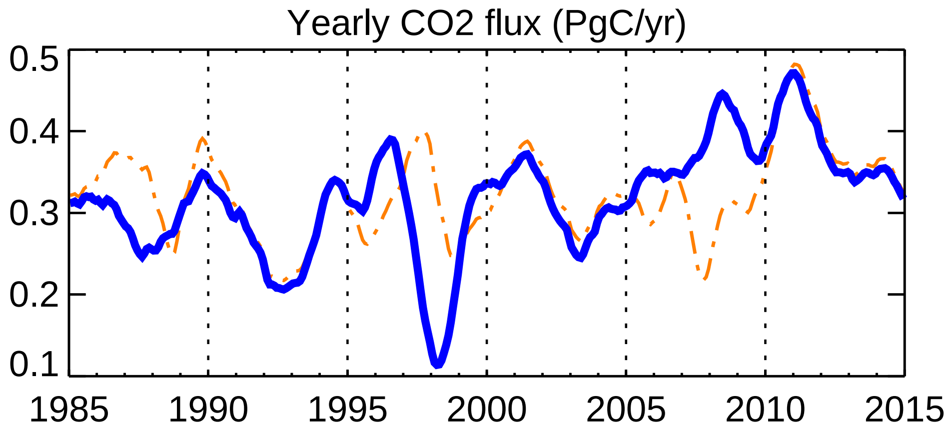
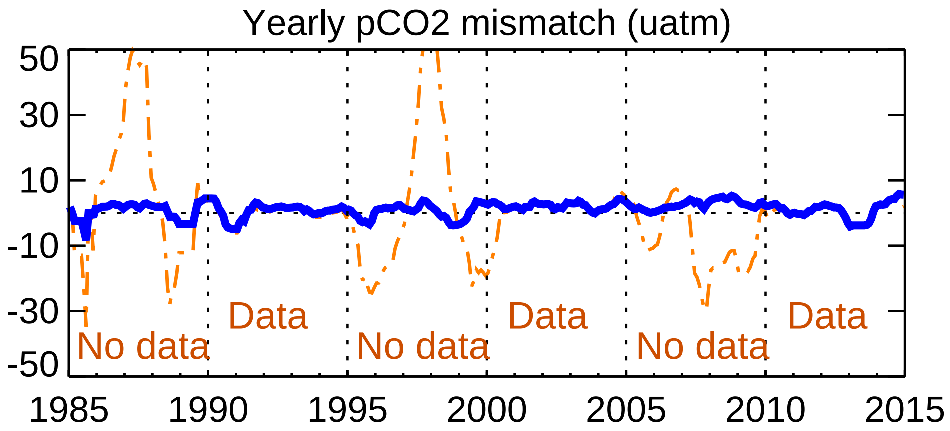
(121.%) Jena oc_v1.4S (CrossVal5yr0)

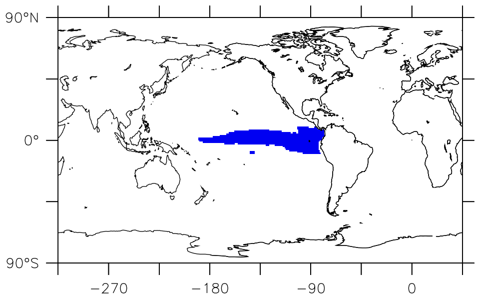






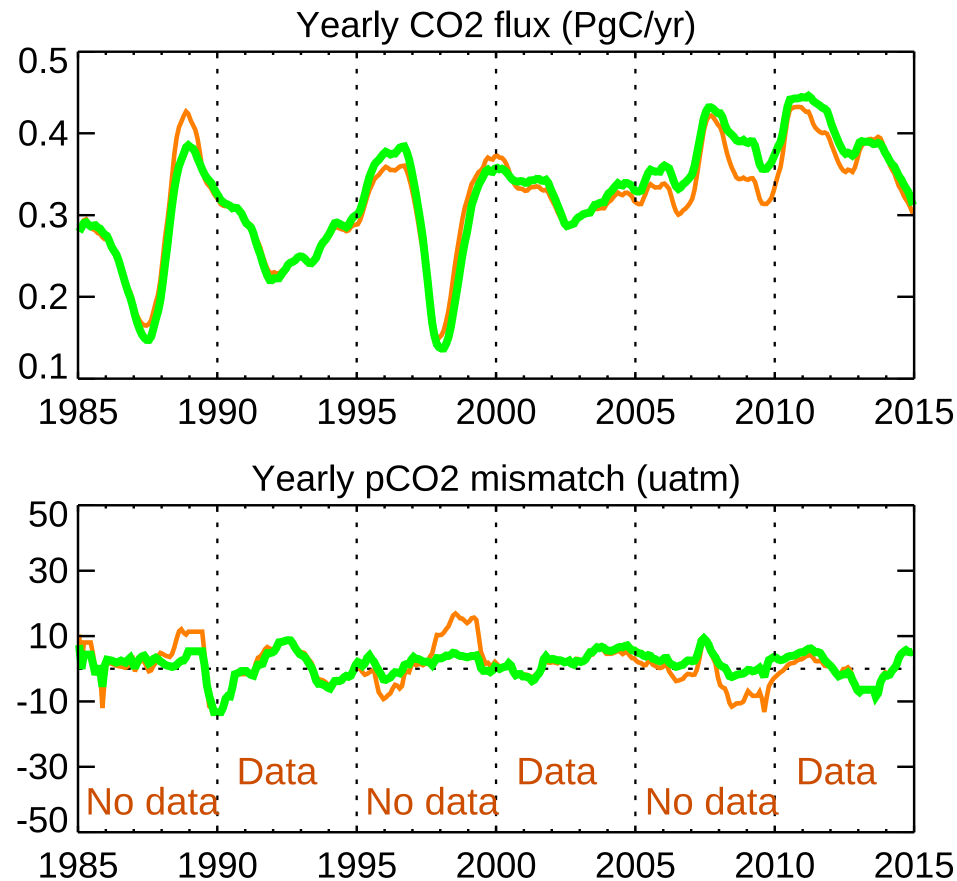
→ Data-only interpolation cannot bridge multi-year gaps

Cross Validation



(28.%) ETH-SOMFFN2016

(48.%) ETH-SOMFFN2016 (CrossVal5yr0)



→ Regression against drivers (SST, SSS, Chl-a, atm. CO_2) offers some bridging capacity

Cross Validation

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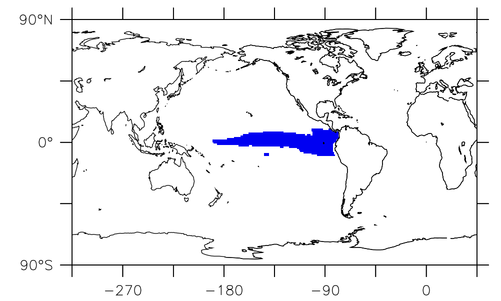

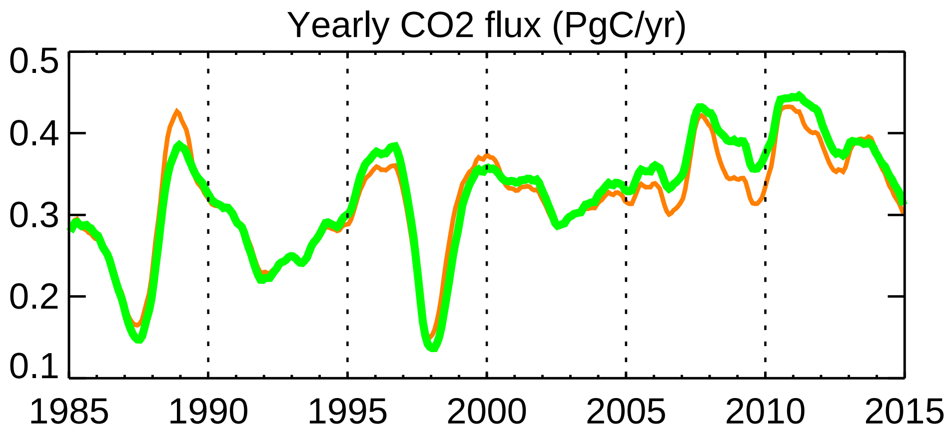

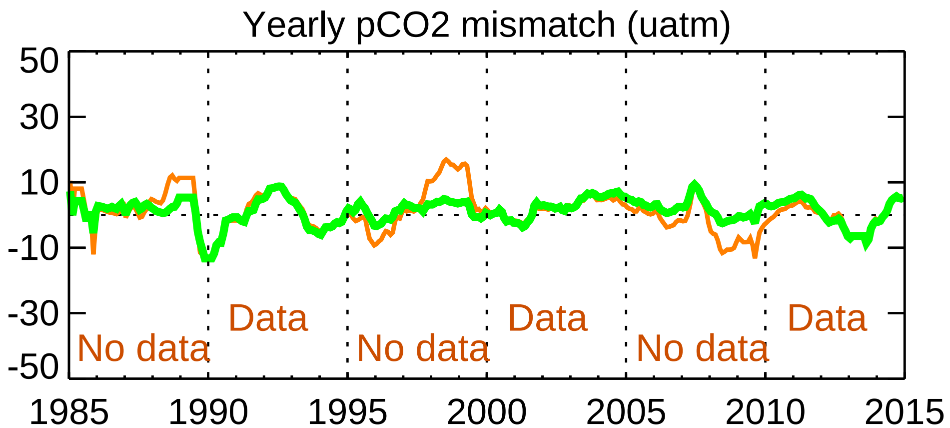

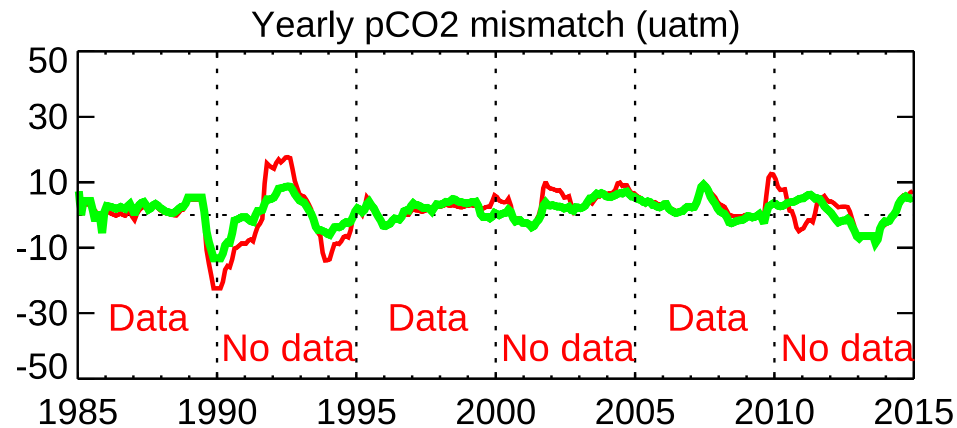

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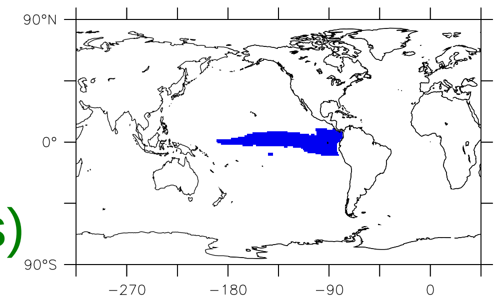
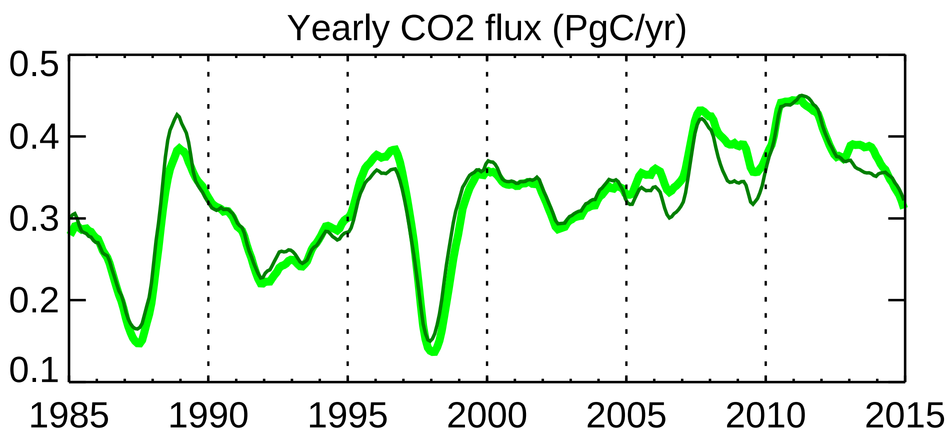
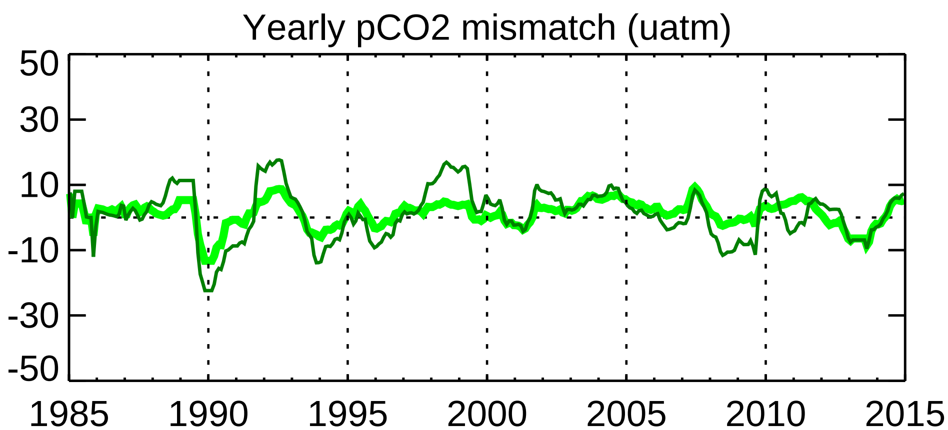


(28.%) ETH-SOMFFN2016

(62.%) ETH-SOMFFN2016 (Unconstrained periods)





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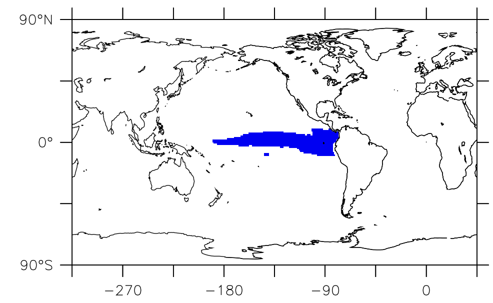
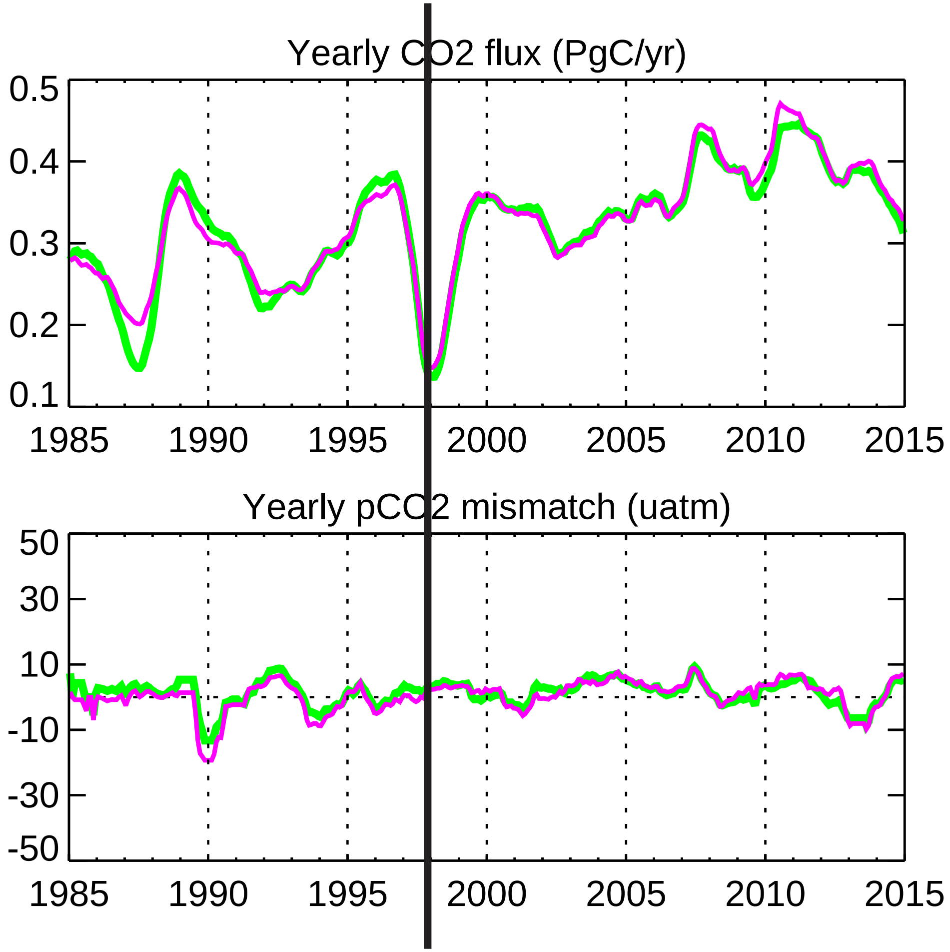


(28.%) ETH-SOMFFN2016

(35.%) ETH-SOMFFN2016, regr. SST & SSS



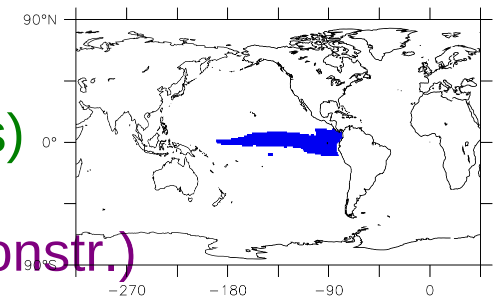
Chl-a data only available since 1998

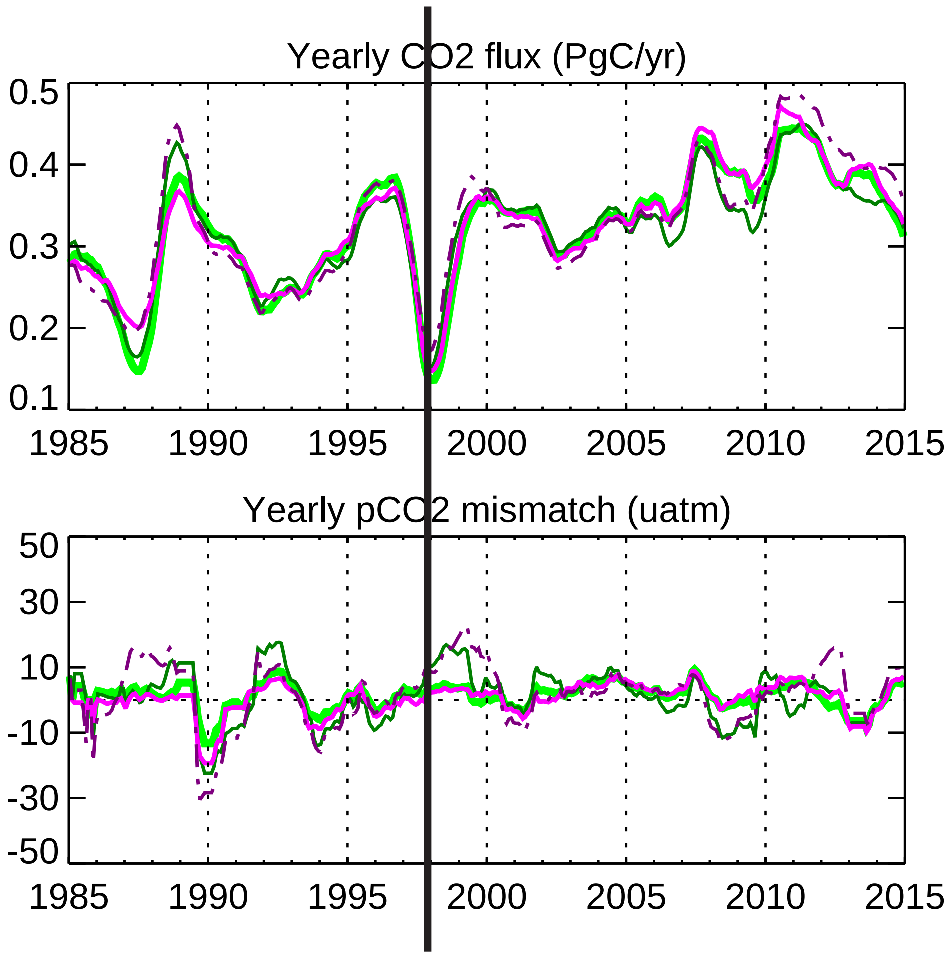
– do SST and SSS suffice?

→ Less fitting capacity
(but main modes similar)

Cross Validation

(28.%) ETH-SOMFFN2016
(62.%) ETH-SOMFFN2016 (Unconstrained periods)
(35.%) ETH-SOMFFN2016, regr. SST & SSS
(77.%) ETH-SOMFFN2016, regr. SST & SSS (Unconstr.)





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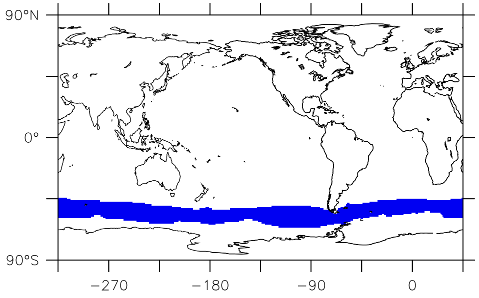
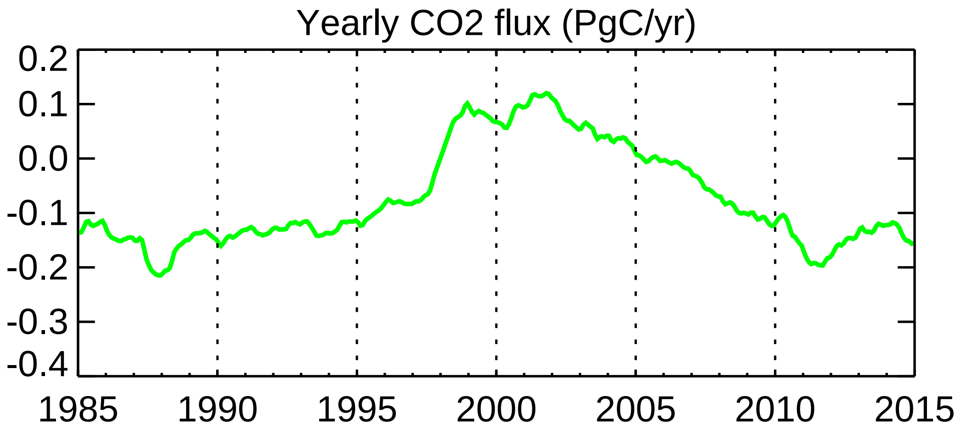
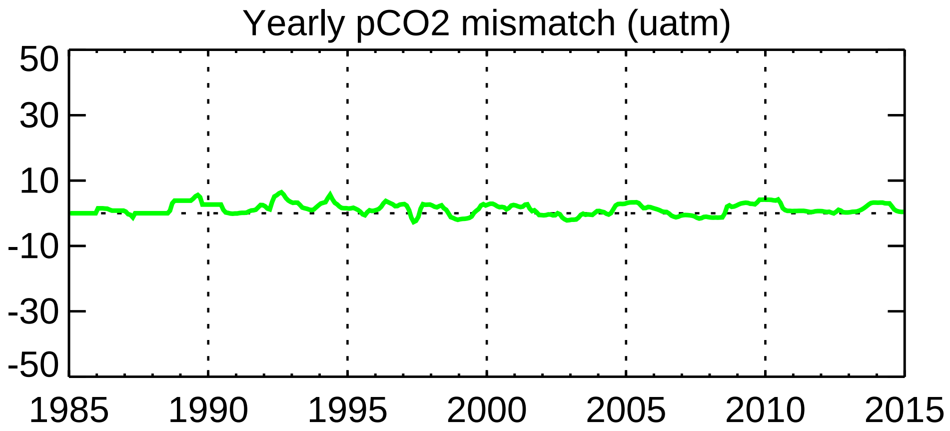


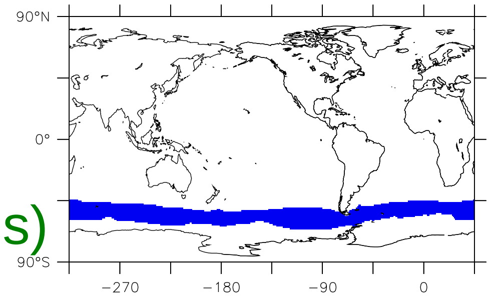
—— (47.%) ETH-SOMFFN2016





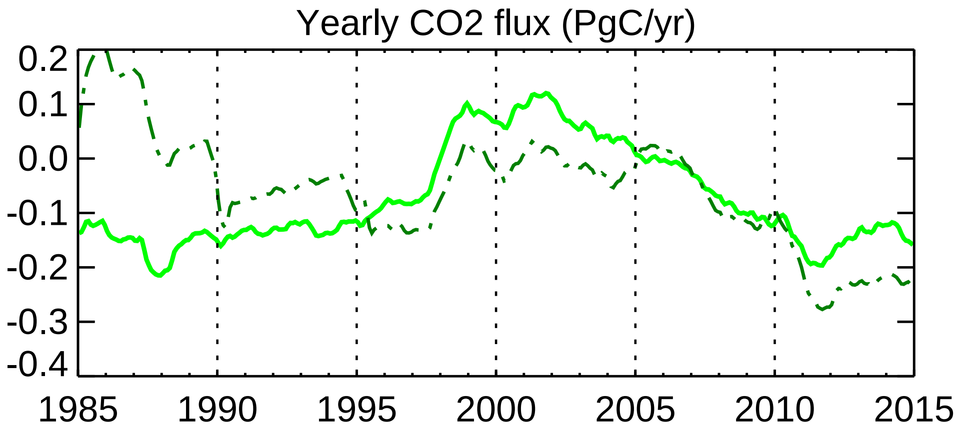
Southern Ocean – sparse data

Cross Validation

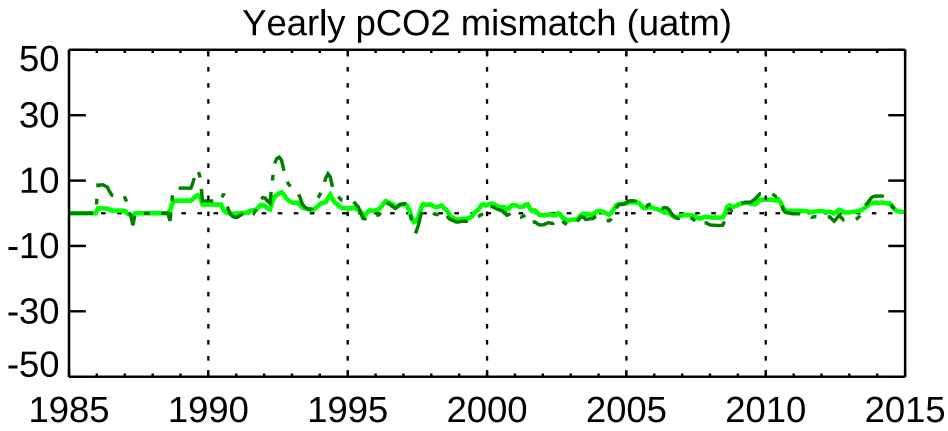


—— (47.%) ETH-SOMFFN2016

–·– (106.%) ETH-SOMFFN2016 (Unconstrained periods)

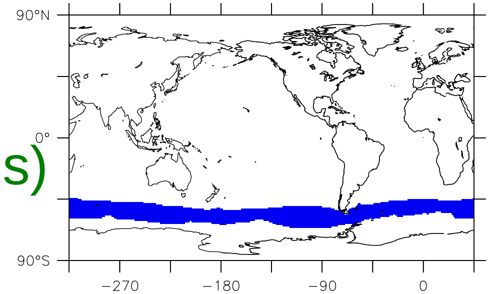


Southern Ocean – sparse data



→ Bridging difficult &
difficult to test

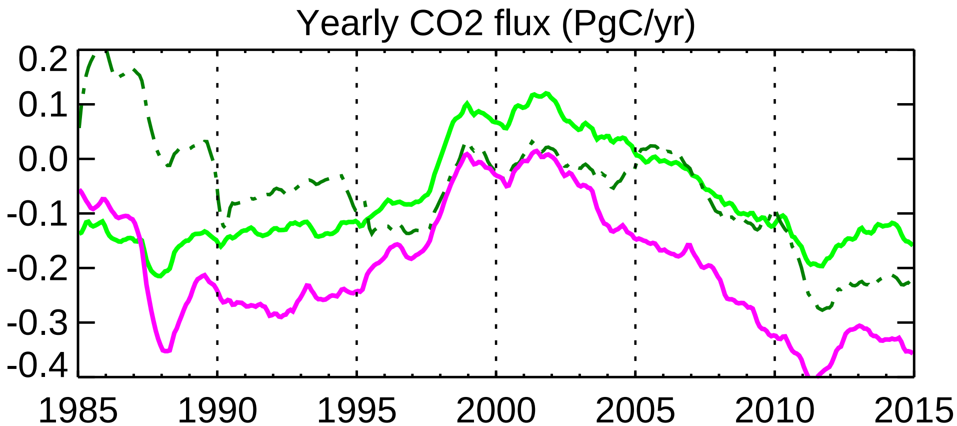
Cross Validation

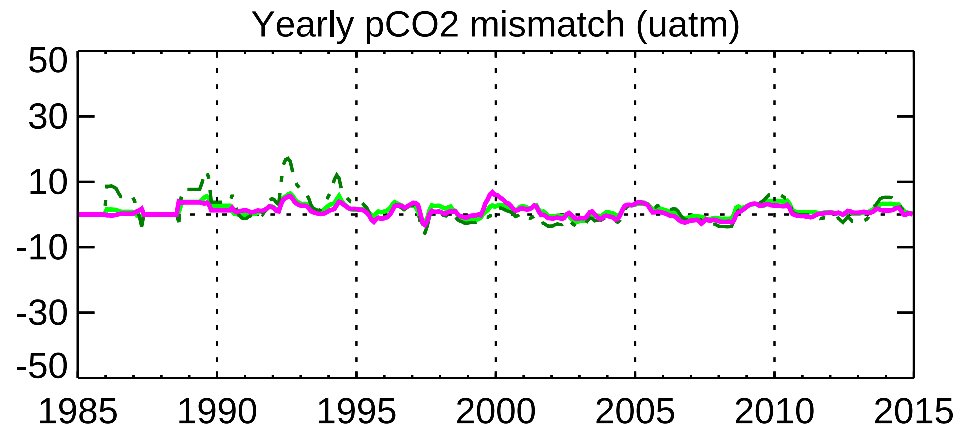


—— (47.%) ETH-SOMFFN2016

– · – (106.%) ETH-SOMFFN2016 (Unconstrained periods)

—— (53.%) ETH-SOMFFN2016, regr. SST & SSS





Southern Ocean – sparse data

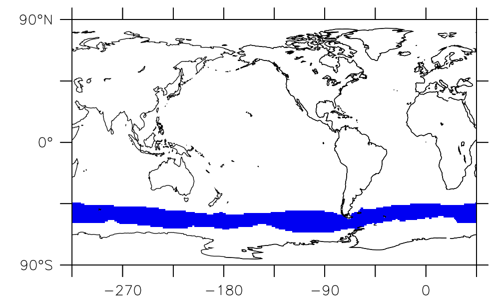
→ Bridging difficult &
difficult to test

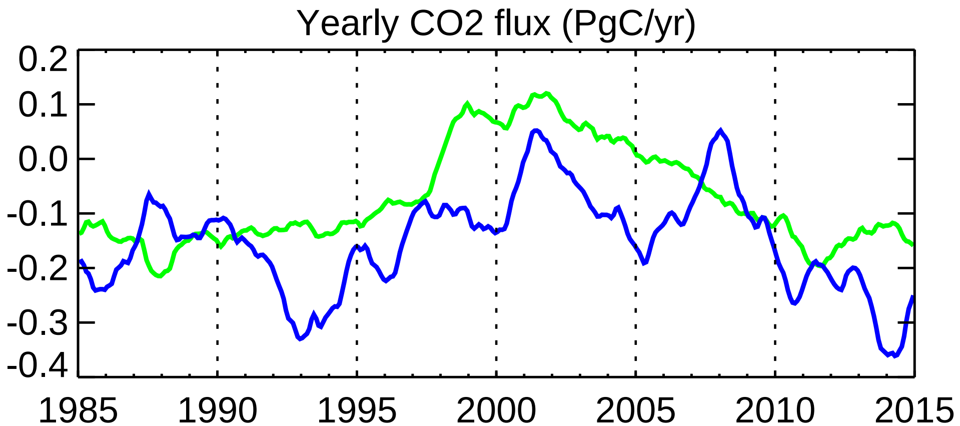
→ again main modes similar w/o Chl-a

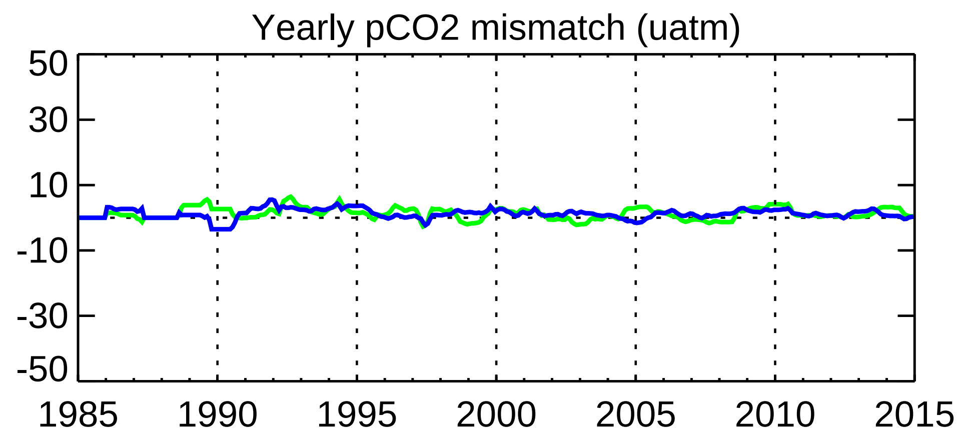
Cross Validation

(37.%) Jena oc_v1.4S

(47.%) ETH-SOMFFN2016







Southern Ocean – sparse data

→ Bridging difficult &
difficult to test

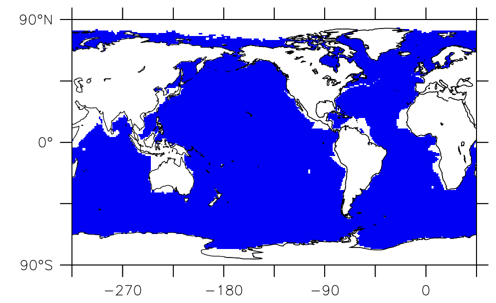
→ again main modes similar w/o Chl-a

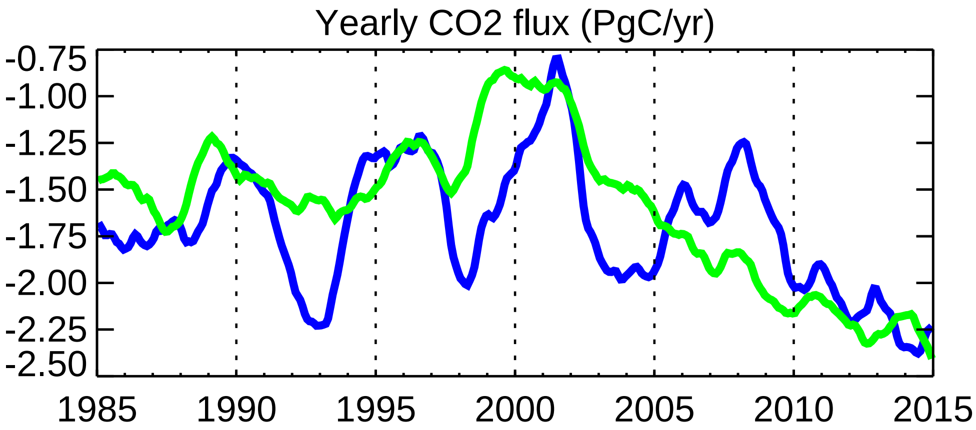
→ Decadal trends also from data directly

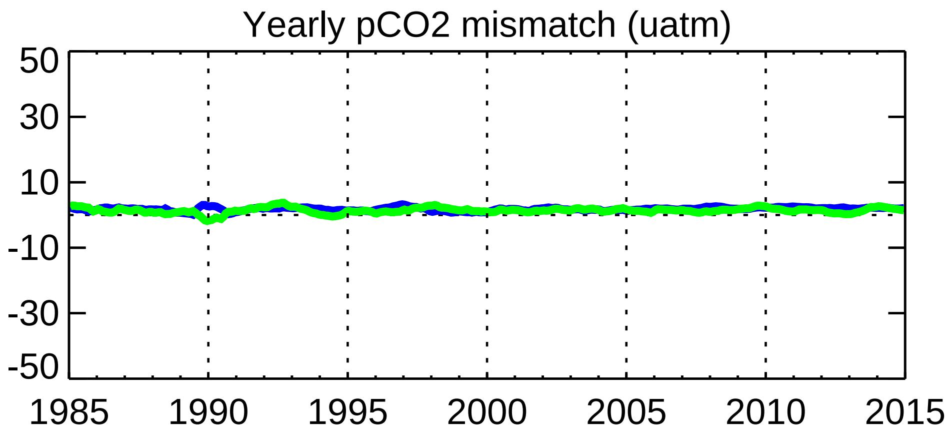
Cross Validation

(25.%) ETH-SOMFFN2016

(18.%) Jena-MLS14SSS

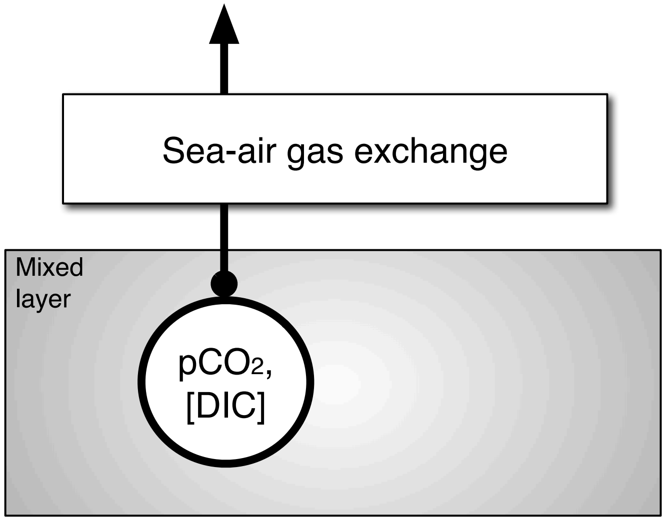






Global Ocean flux
– affected by data-sparse regions

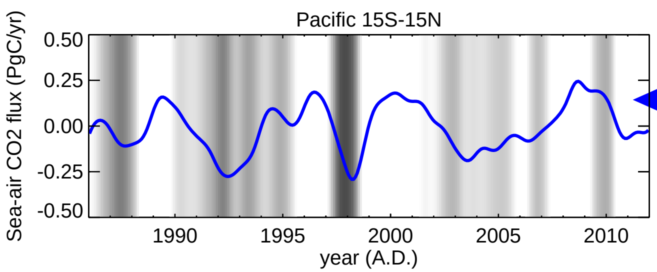
→ Complementary mapping methods
(interpolation, regression)
help to assess robustness

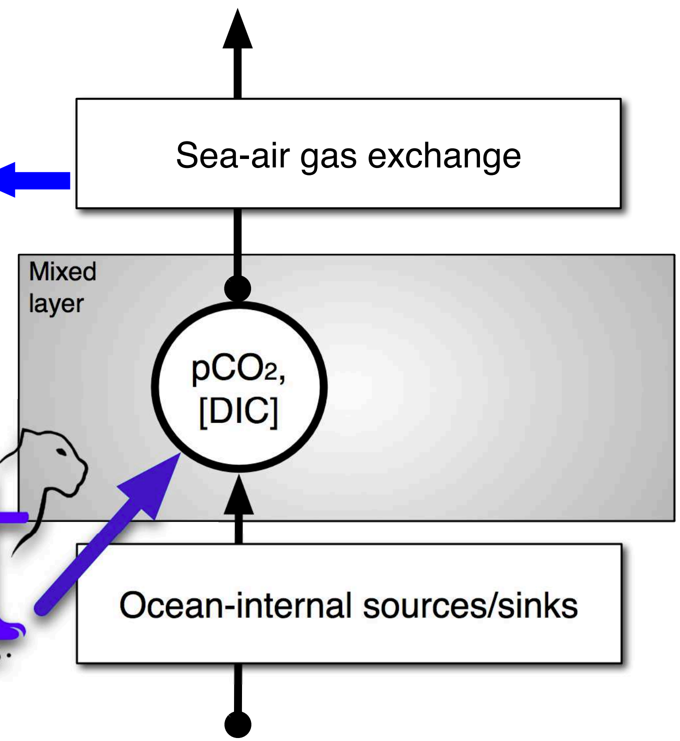


Carbon

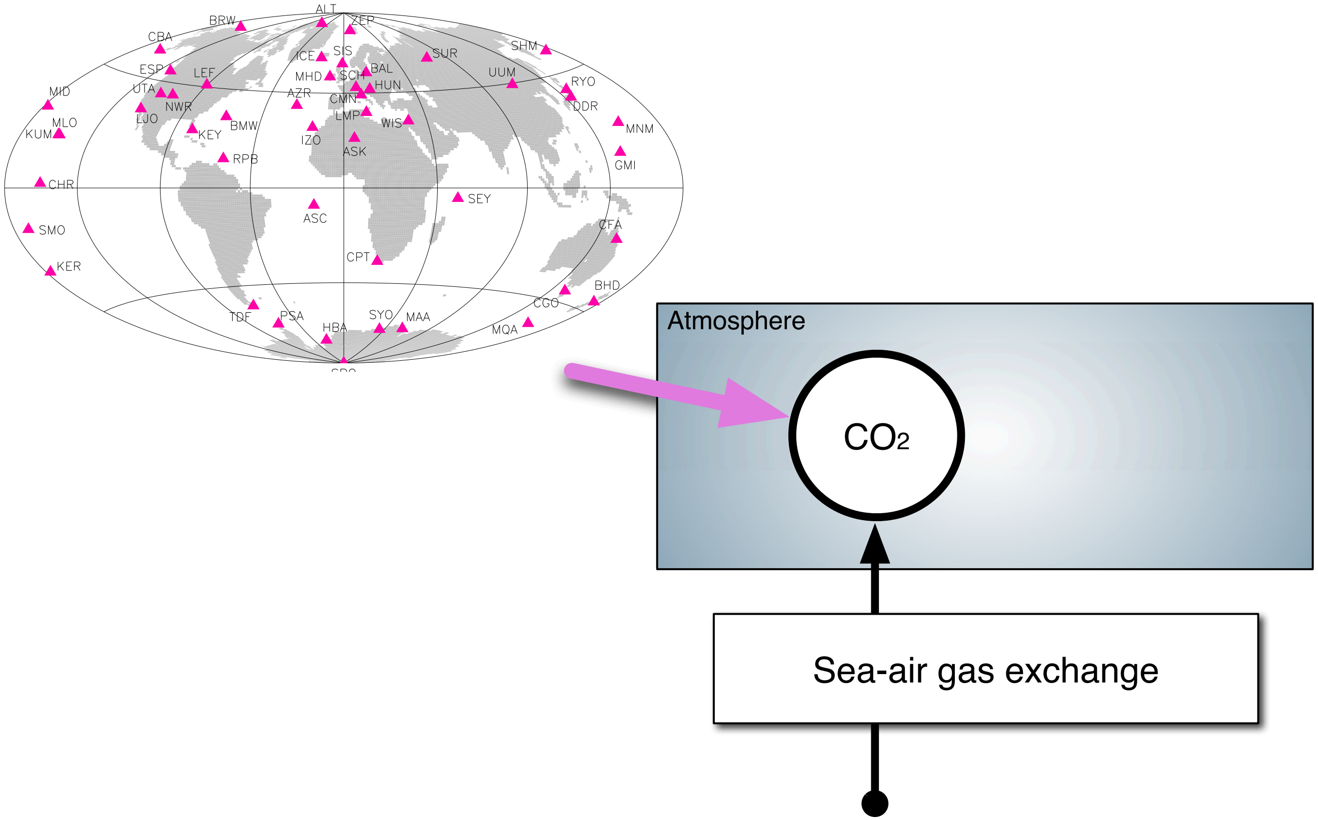
CO_2 **flux**

inferred from pCO_2 interpolation

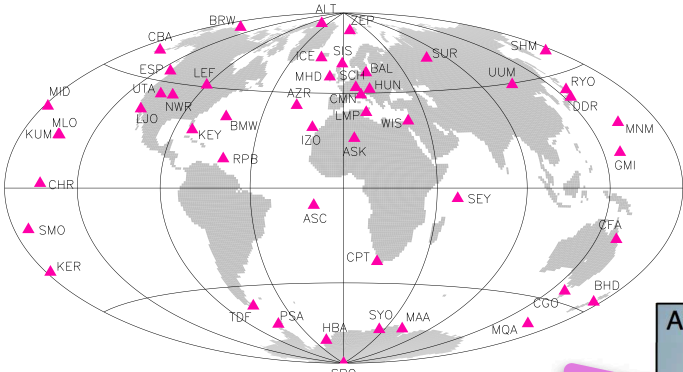




Carbon



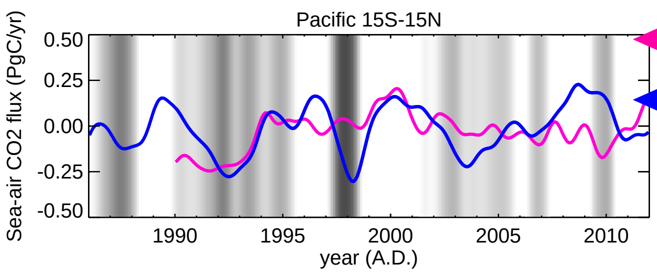
Carbon

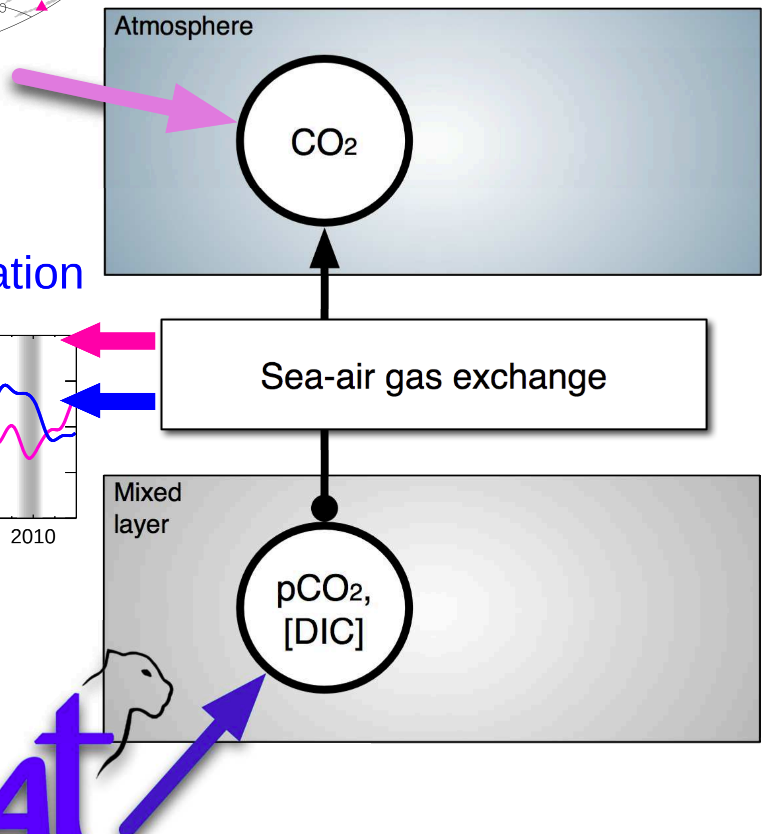


CO_2 **flux**

inferred from CO_2 inversion

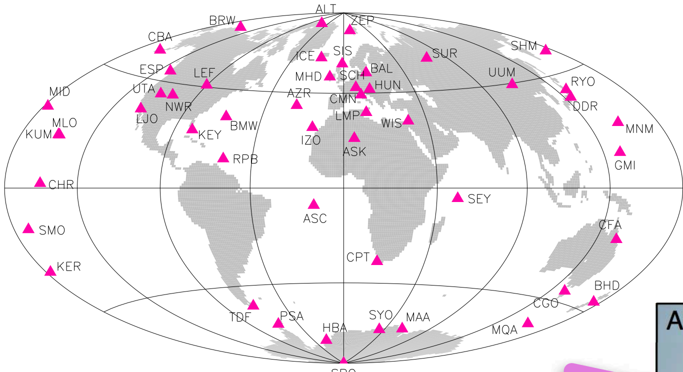
inferred from p CO_2 interpolation





SOCAT · SURFACE OCEAN CO_2 ATLAS ·

Carbon



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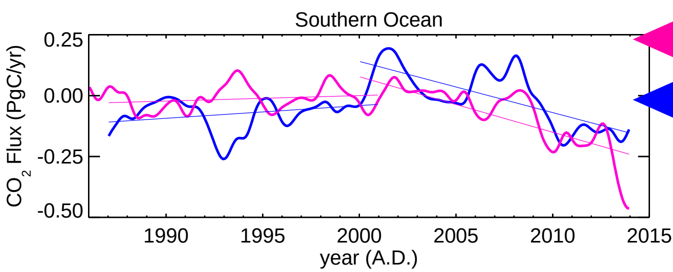
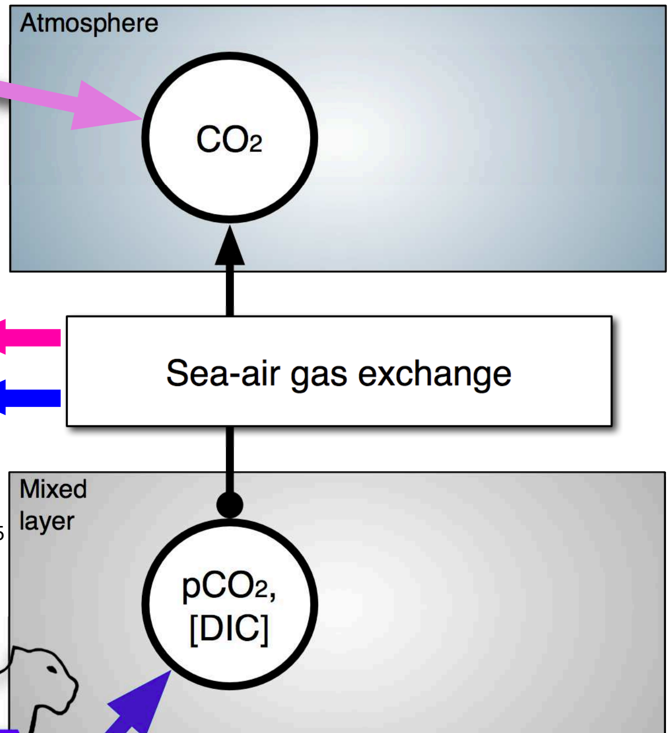
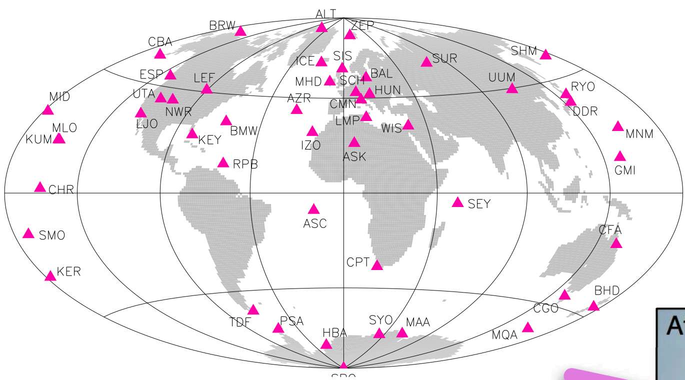
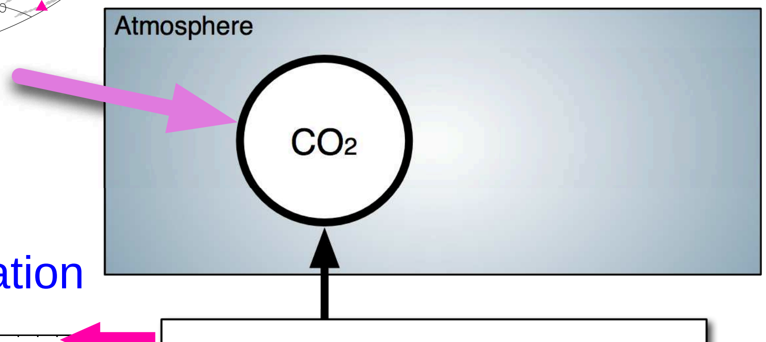




SOCAT · SURFACE OCEAN CO_2 ATLAS ·

Carbon





CO_2 **flux**

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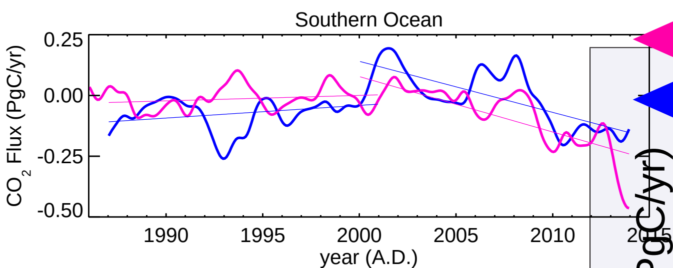
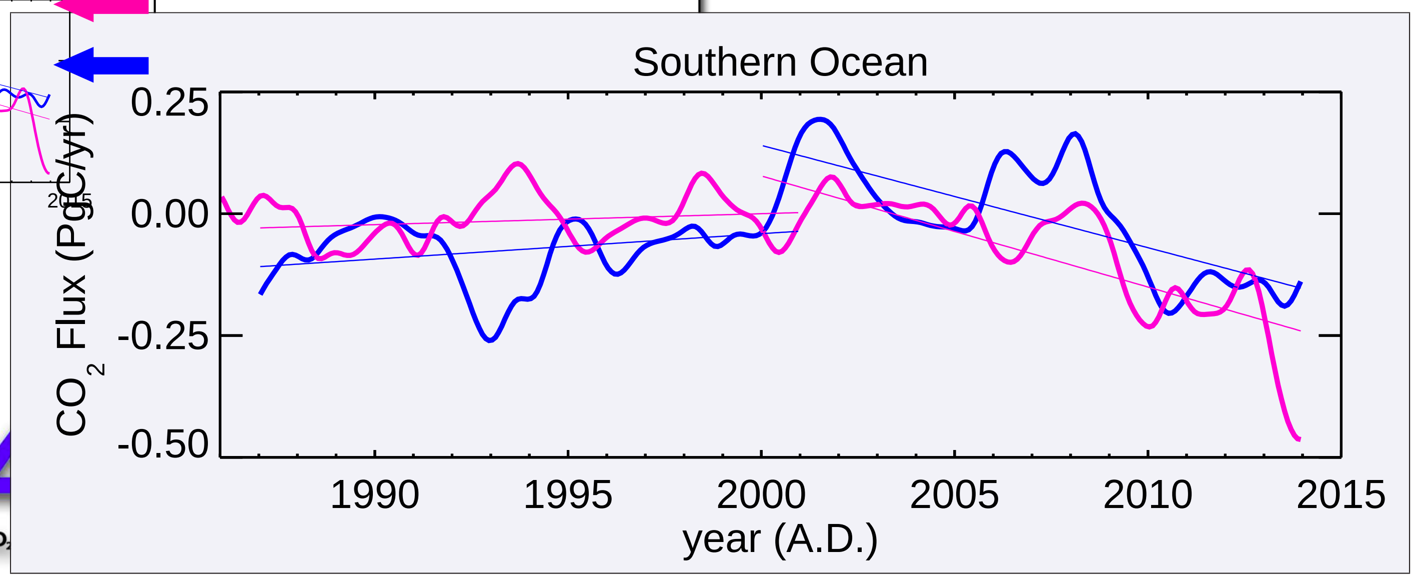
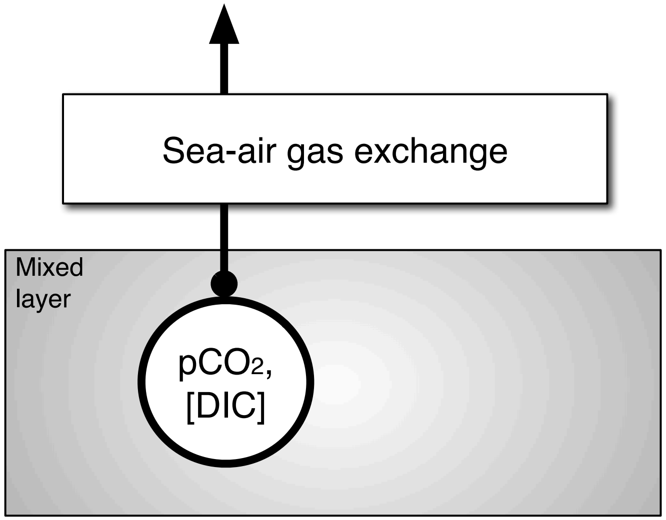
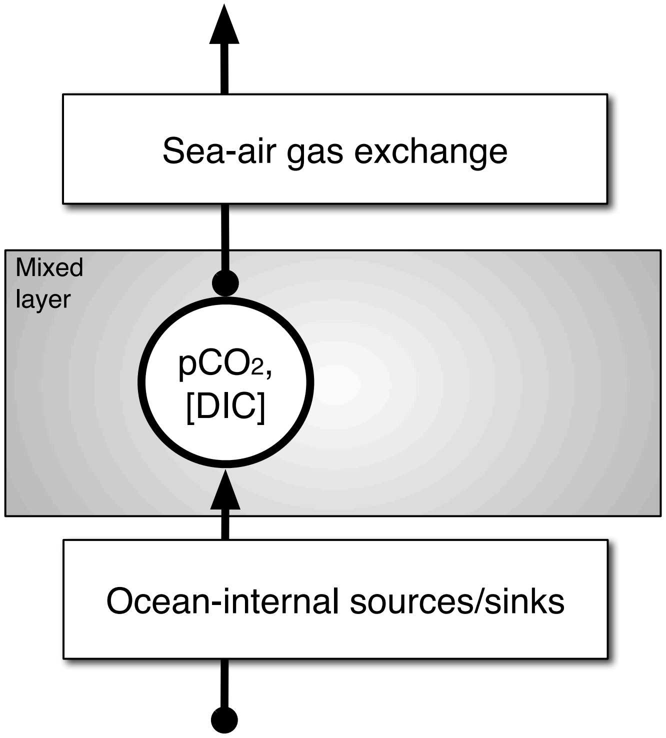




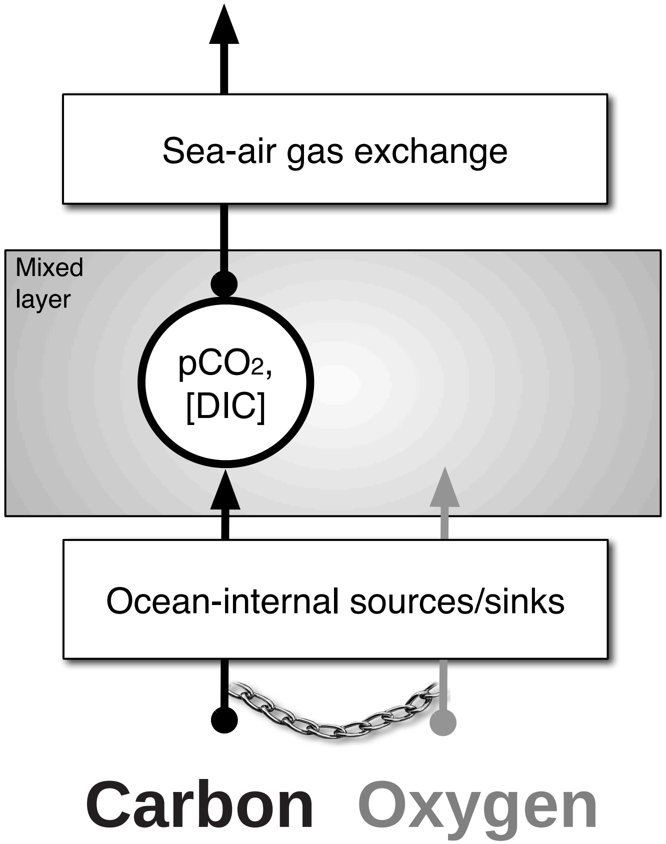
Carbon



Carbon


Sea-air gas exchange
Mixed
layer
pCO2,
[DIC]
Ocean-internal sources/sinks

Carbon



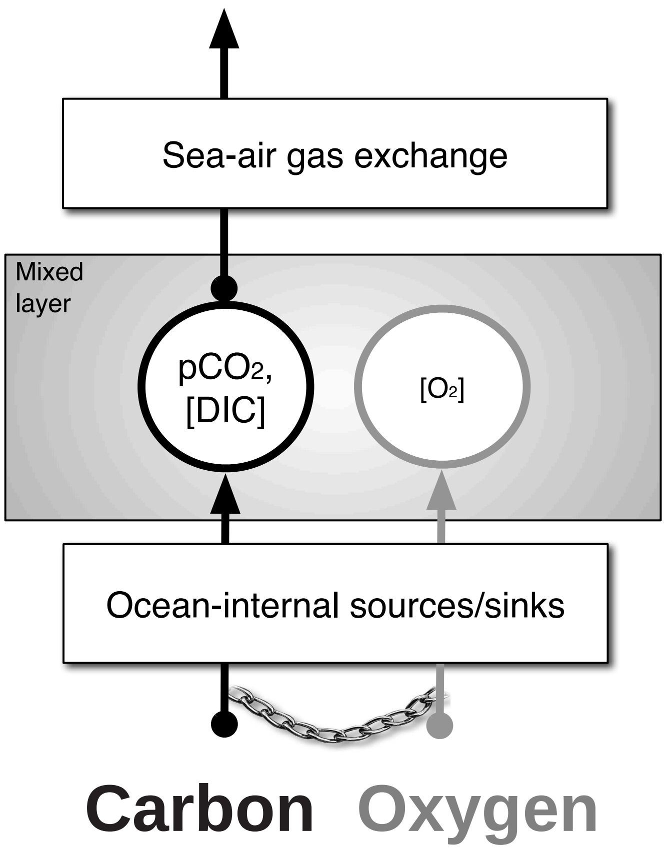
- **Biology:**

  Redfield stoichiometry

  $R_{\mathrm{O:C}} \approx -1.4$

- **Transport+Mixing:**

  Common pathways



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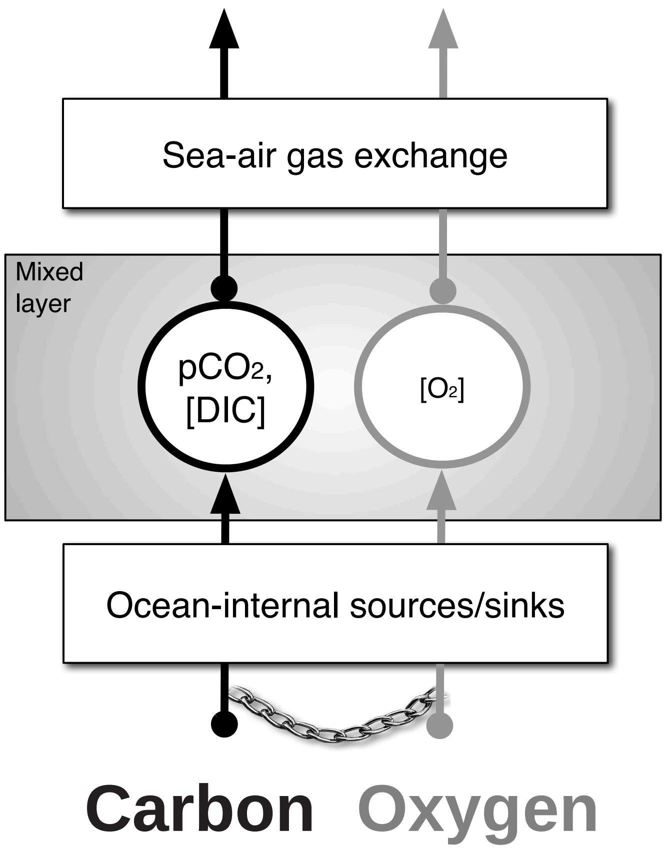

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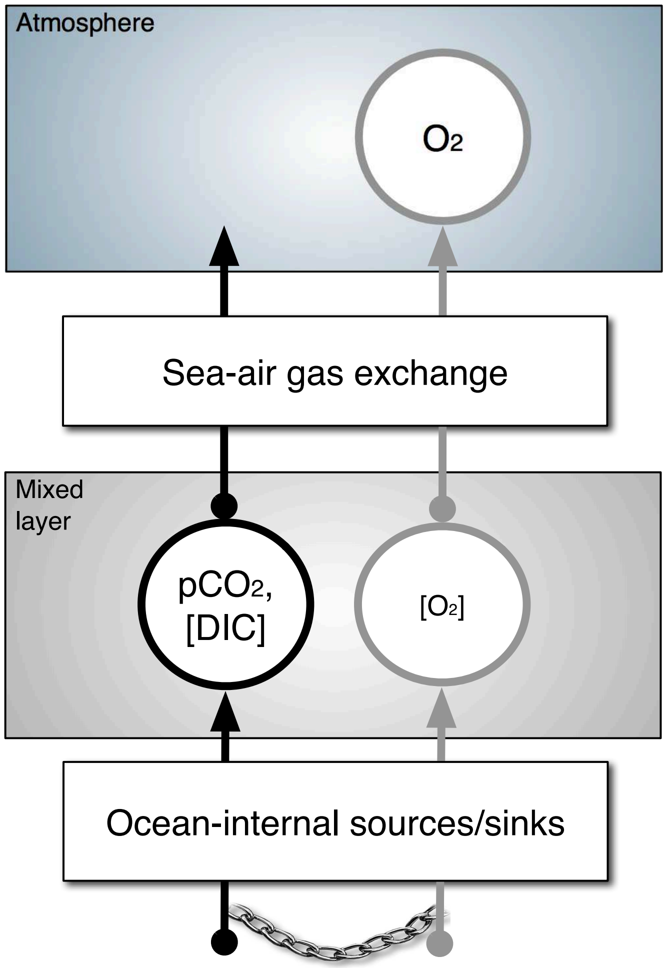


Carbon **Oxygen**

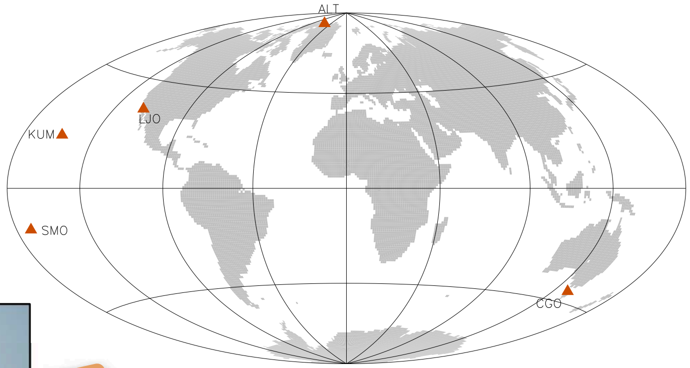
- **Biology:**

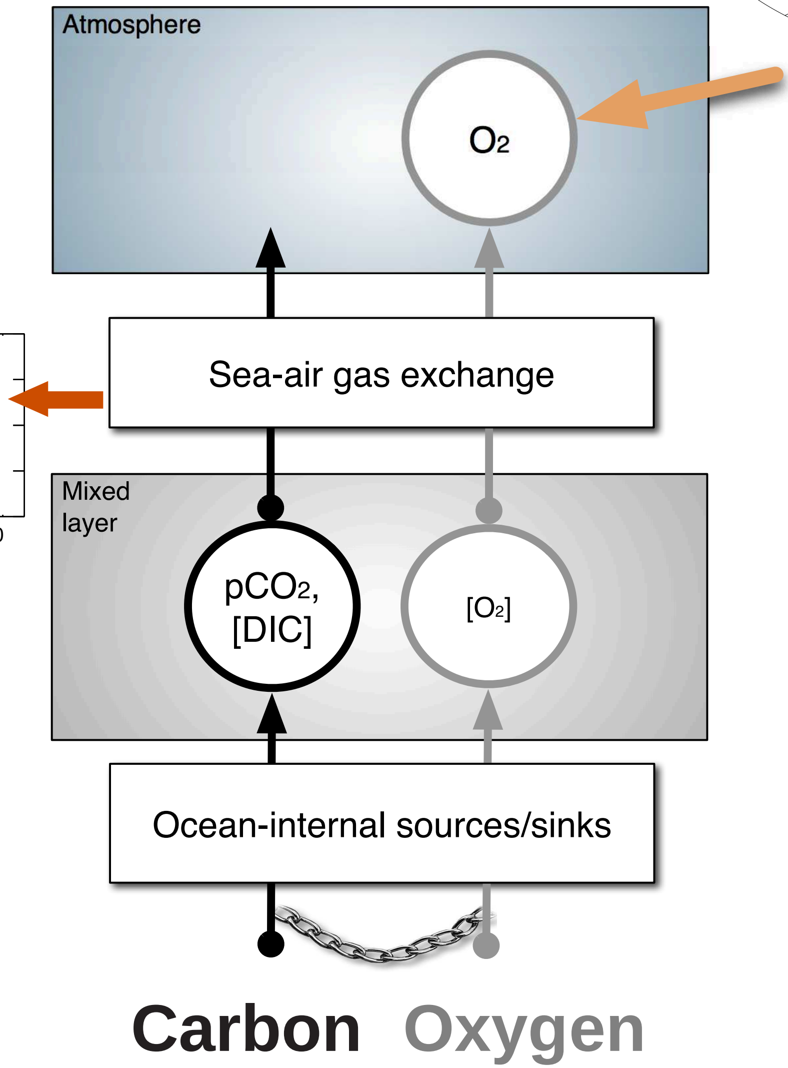
  Redfield stoichiometry

  $R_{\mathrm{O:C}} \approx -1.4$

- **Transport+Mixing:**

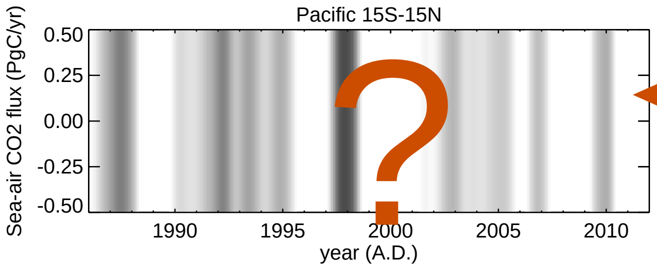
  Common pathways

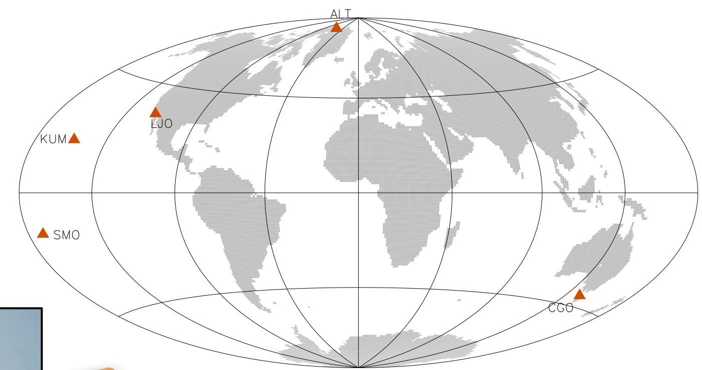


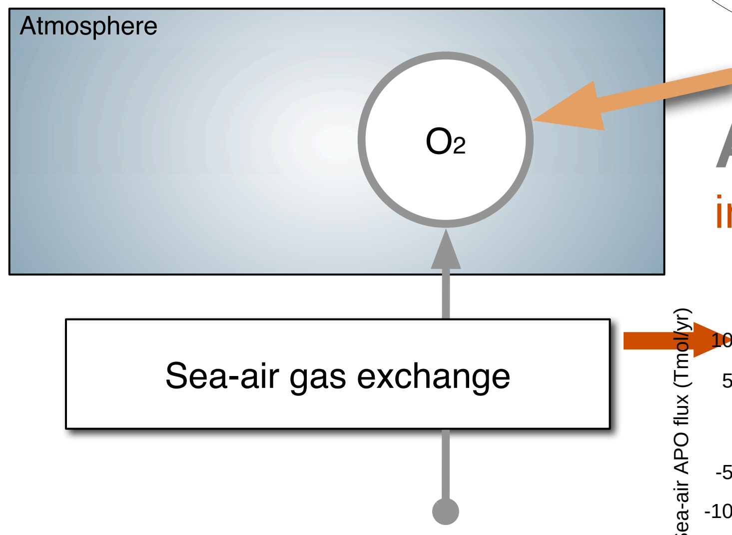


CO_2 **flux**

inferred from O_2/N_2

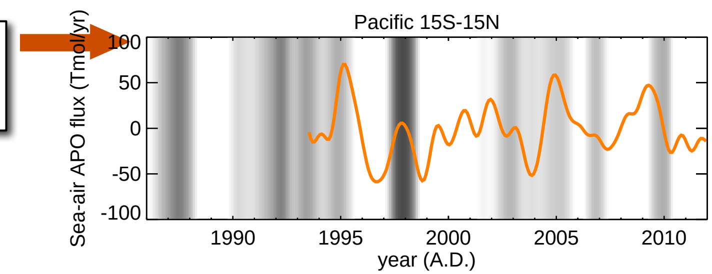




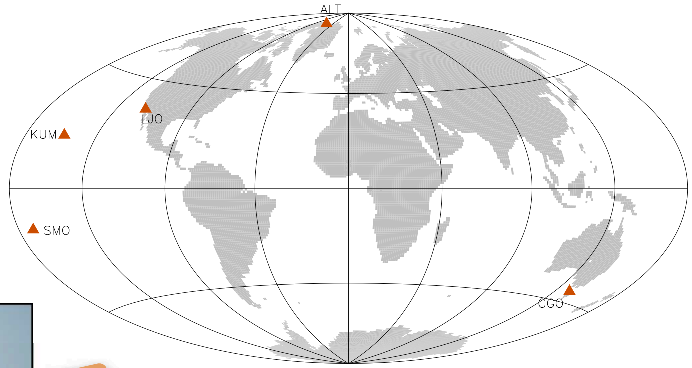


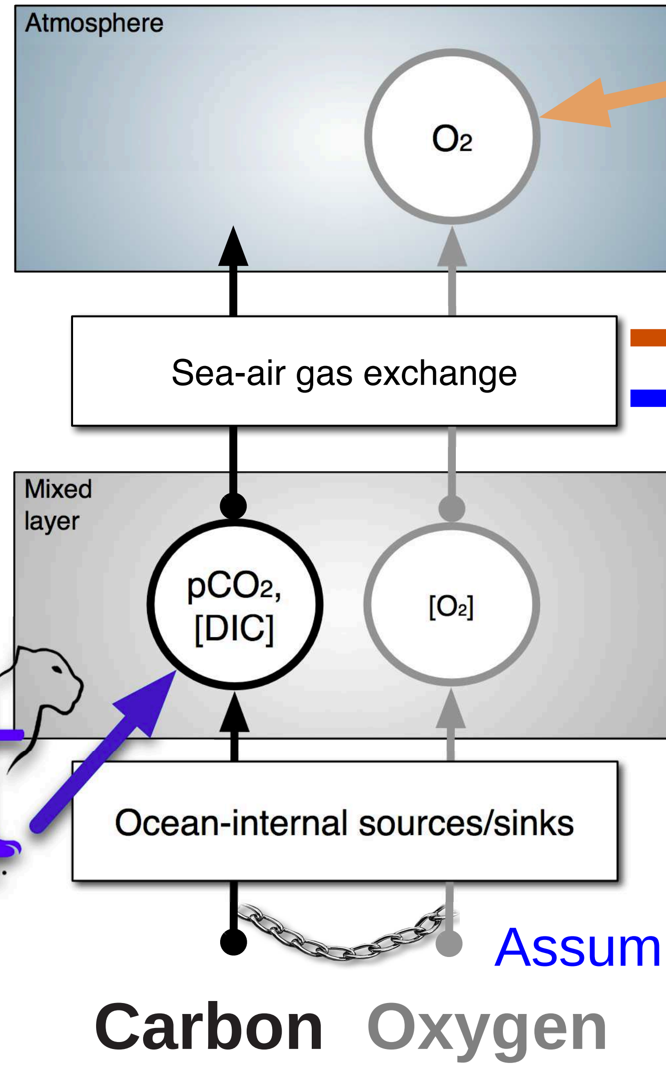
APO flux

inferred from APO inversion



Carbon **Oxygen**

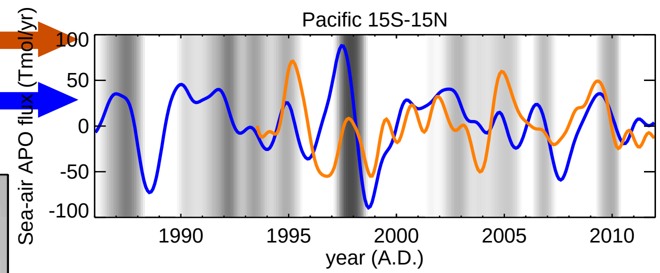




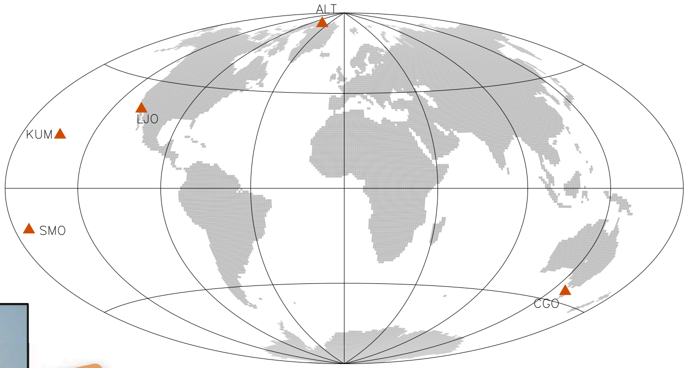
APO flux

inferred from APO inversion

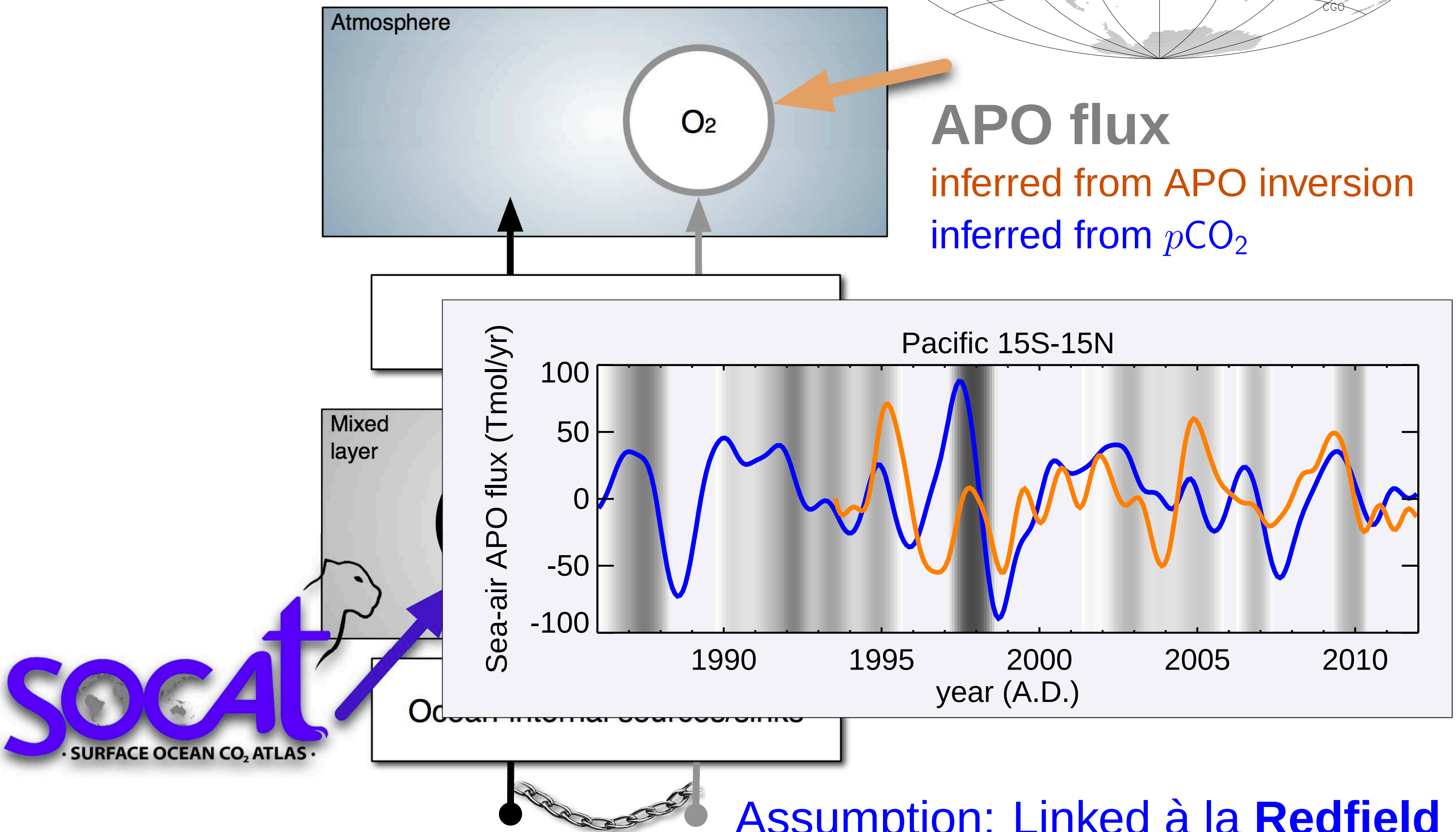
inferred from $p\mathrm{CO}_2$



Assumption: Linked à la **Redfield**

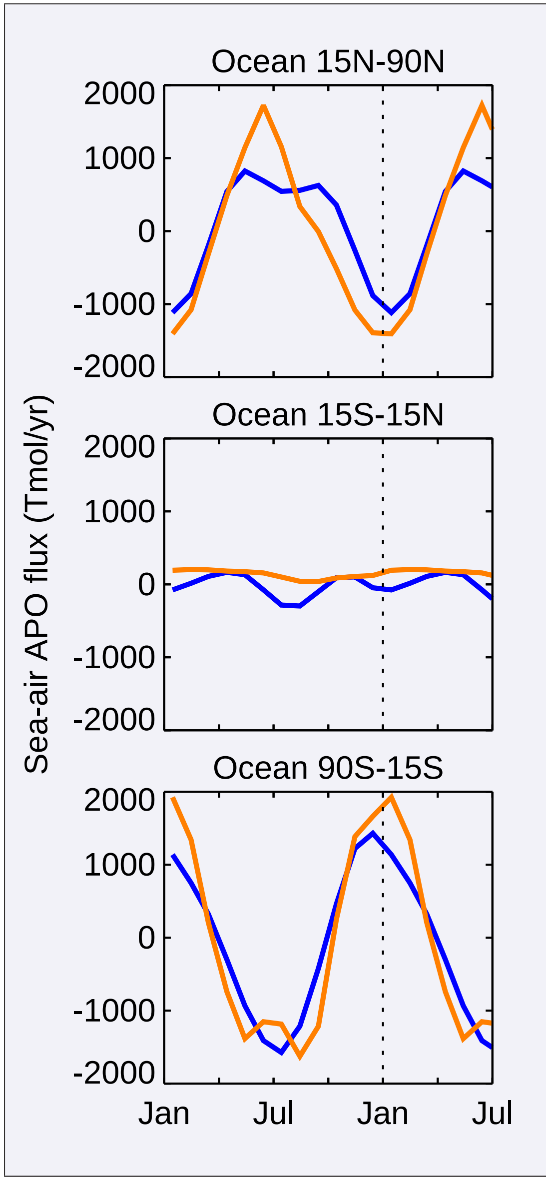


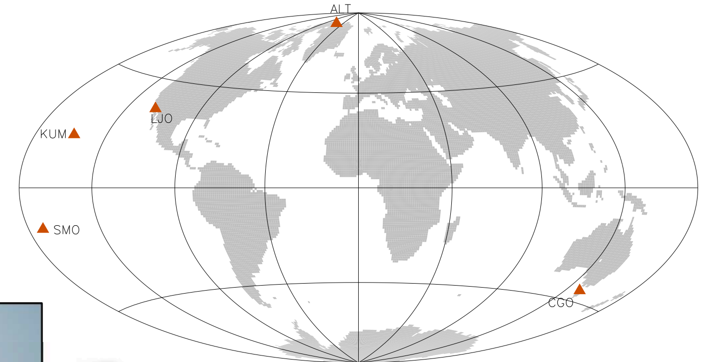
APO flux
inferred from APO inversion
inferred from $p\mathrm{CO_2}$

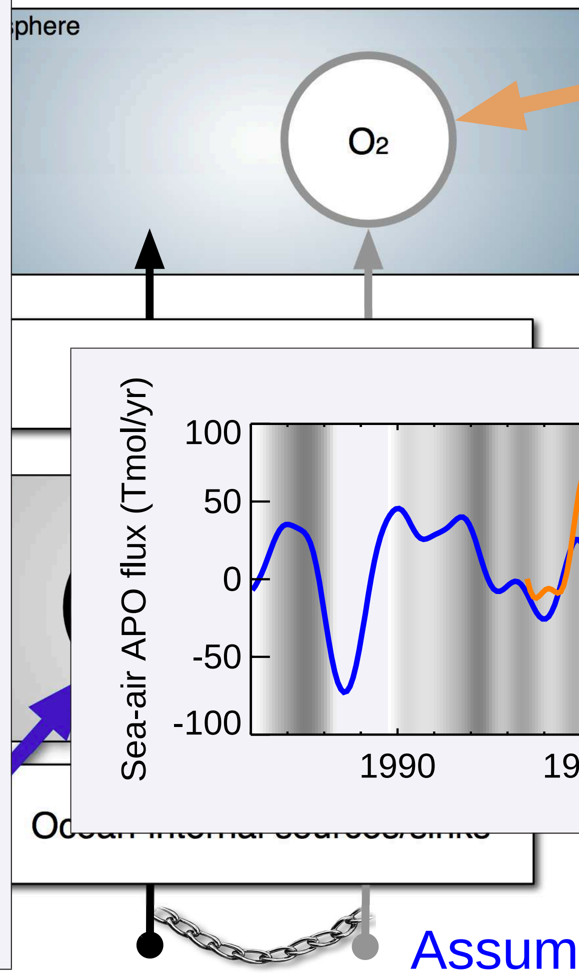


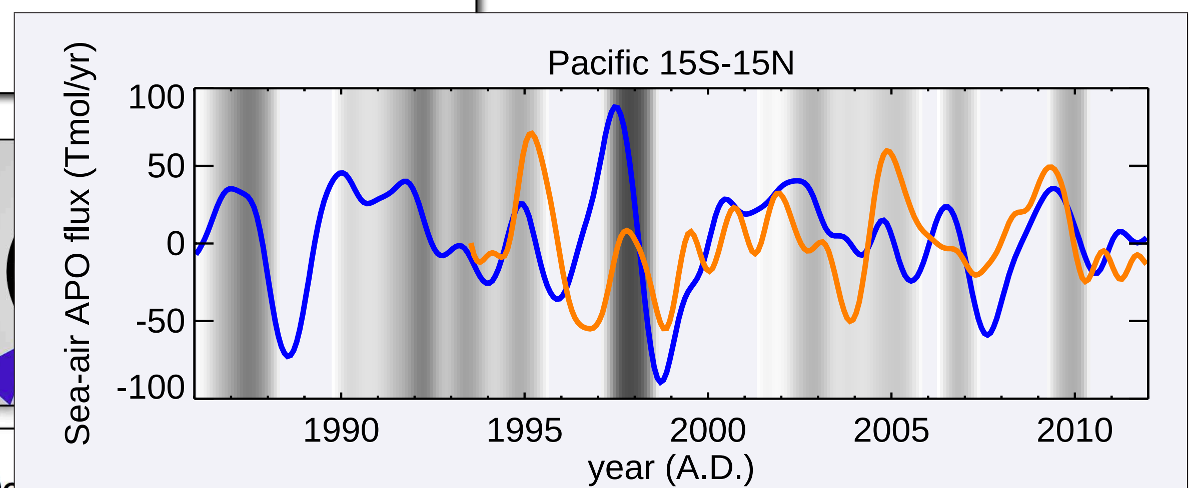
Assumption: Linked à la **Redfield**

Carbon Oxygen









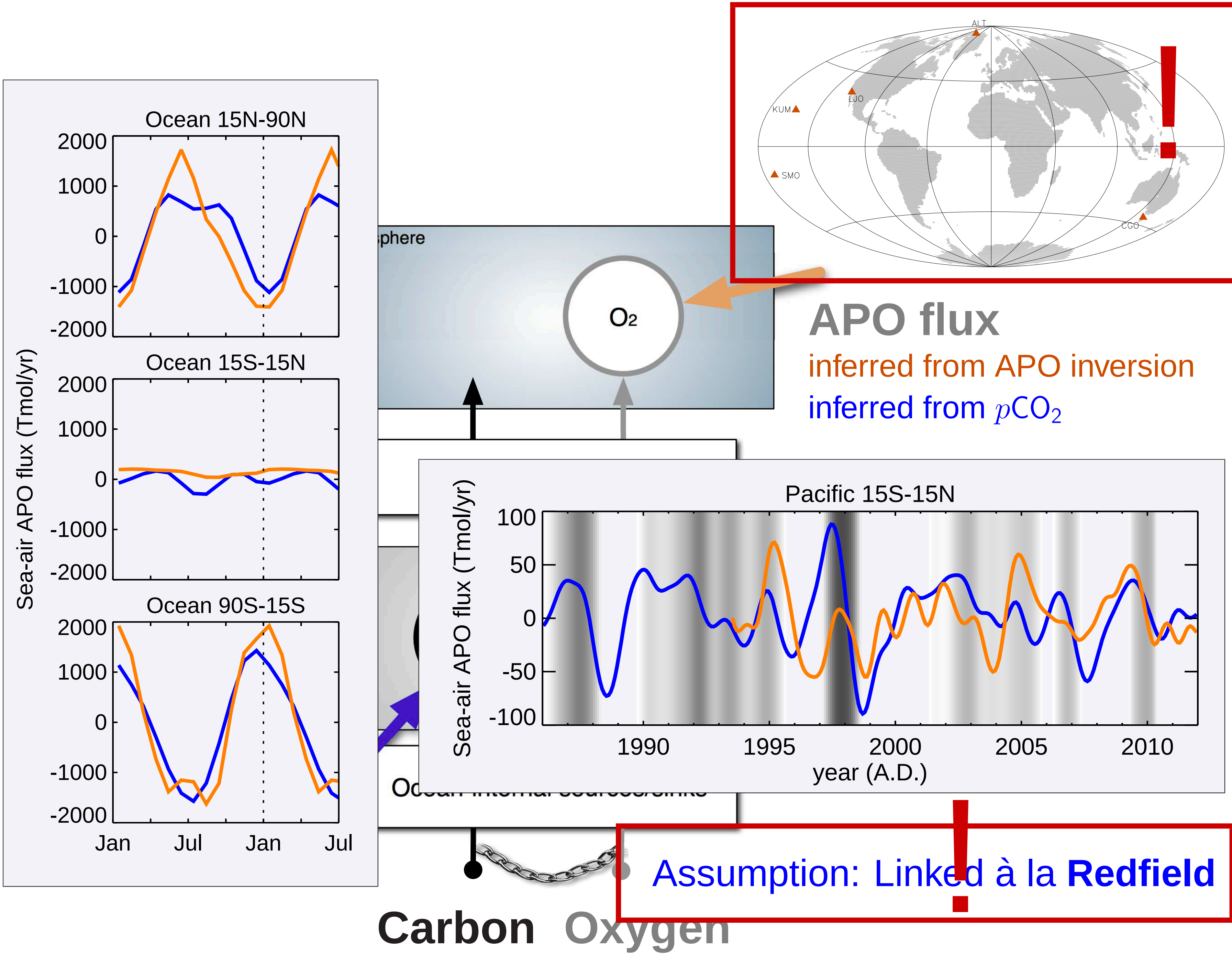
APO flux

inferred from APO inversion

inferred from $p\mathrm{CO_2}$

Assumption: Linked à la **Redfield**

Carbon **Oxygen**


Ocean 15N-90N
Ocean 15S-15N
Ocean 90S-15S
Sea-air APO flux (Tmol/yr)
2000
1000
0
-1000
-2000
Jan
Jul
Jan
Jul
...phere
O2
Oc... internal sources/sinks
ALT
LJO
KUM
SMO
CGO
!
APO flux
inferred from APO inversion
inferred from $p\mathrm{CO}_2$
Pacific 15S-15N
Sea-air APO flux (Tmol/yr)
100
50
0
-50
-100
1990
1995
2000
2005
2010
year (A.D.)
!
Assumption: Linked à la **Redfield**
Carbon
Oxygen

Conclusions

Aim:

Quantify variability of ocean biogeochemistry

from data

Conclusions

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Quantify variability of ocean biogeochemistry
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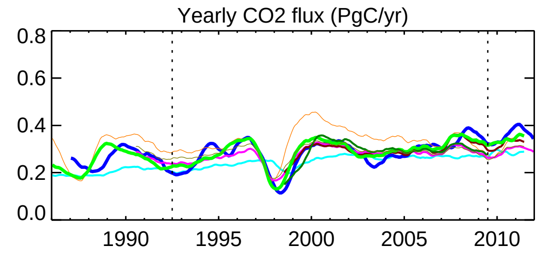
pCO$_2$ constraint & mapping methods:

- Well-constrained seasonality
- IAV constrained e.g. in Eq. Pac.



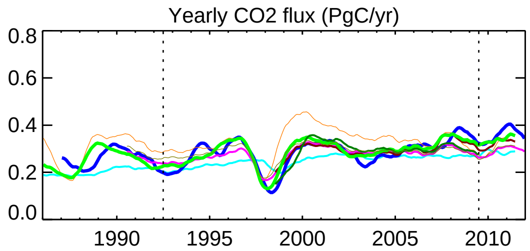
SOCOM
SURFACE OCEAN pCO$_2$ MAPPING INTERCOMPARISON

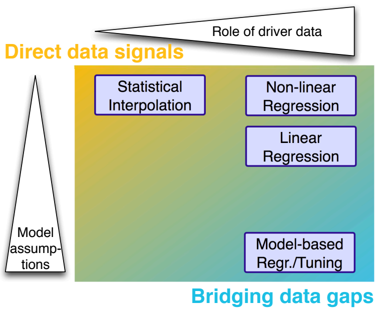
Conclusions

Aim:
Quantify variability of ocean biogeochemistry
from data

$p\mathrm{CO_2}$ constraint & mapping methods:

- Well-constrained seasonality
- IAV constrained e.g. in Eq. Pac.





Interpolation: Can *fit any IAV signals* in the data

Regression: Can *bridge* temporal data gaps

Robustness check through complementary methods

Conclusions

Aim:

Quantify variability of ocean biogeochemistry
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- Well-constrained seasonality
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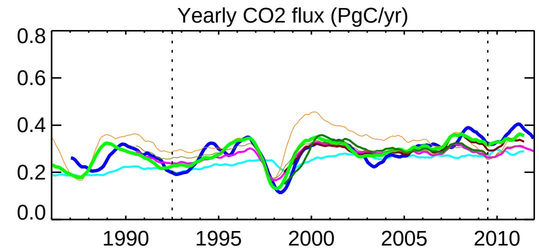
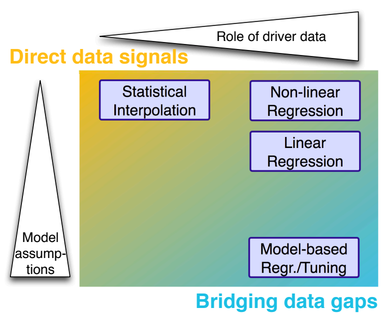


SOCOM
SURFACE OCEAN pCO$_2$ MAPPING INTERCOMPARISON



Interpolation: Can *fit any IAV signals* in the data

Regression: Can *bridge* temporal data gaps

Robustness check through complementary methods

Multiple constraints:

- surface-ocean pCO$_2$
- atmospheric CO$_2$
- atmospheric O$_2$/N$_2$

combined through mixed-layer scheme

Jena
CarboScope