

# Lecture 2: Using the ocean color time series to address climate change

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## Outline

- I. A brief tutorial on detection and attribution
- II. Detection studies using ocean color
- III. Detection time studies using climate model simulations

## I. A brief tutorial on detection and attribution

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## Detection and attribution

- Our strategy for detecting the impact of global warming on ocean biogeochemistry is to combine modeling and observations in the framework of *detection and attribution*
- *Detection and attribution* is a set of statistical methods that have been developed to study climate change [Hasselmann, 1979, 1997; Hegerl and North, 1997], and have been extensively applied to studies of atmospheric variability and, to a lesser extent, oceanic variability [e.g., Santer et al., 1995; Barnett et al., 2001]

## Detection

- “*Detection* has been defined as the process of demonstrating that an observed change is significantly different (in a statistical sense) from natural internal climate variability, by which we mean the chaotic variation of the climate system that occurs in the absence of anomalous external natural or anthropogenic forcing (Mitchell et al. 2001).” (Hegerl et al., 2006)

## Detection problem

Purpose: to determine the origin of an **observed change** in a climate variable of interest (e.g. temperature, precipitation). The following model can be fitted:

$$\Psi(\mathbf{x}, t) = \Psi_n(\mathbf{x}, t) + \alpha_s \Psi_s(\mathbf{x}, t)$$

- $\Psi(\mathbf{x}, t)$  represents the available measurements at station (or grid cell)  $\mathbf{x}$  and time  $t$
- $\Psi_n(\mathbf{x}, t)$  represents the natural climate variability at station (or grid cell)  $\mathbf{x}$  and time  $t$  (diurnal, seasonal, and interannual)
- $\Psi_s(\mathbf{x}, t)$  represents the climate change signal or “fingerprint” at station (or grid cell)  $\mathbf{x}$  and time  $t$
- $\alpha_s$  is the magnitude of the change and, which is estimated by fitting the regression model above. If it is significantly different from zero, the hypothesis of no detectable climate change is rejected.

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## Detection elements

In order to undertake a detection study, three main elements are required:

- (i) An observational data base,
- (ii) a firm estimate of natural processes in order to establish the patterns and magnitude of background variability, and
- (iii) an estimate of the signatures associated with climate change.

The first element is purely based on observations, the second element is usually determined by a combination of modeling and observations, while the third element ultimately requires a fully coupled earth system model.

## Attribution

- “*Attribution* of anthropogenic climate change is generally understood to require a demonstration that the detected change is consistent with simulated change driven by a combination of external forcings, including anthropogenic changes in the composition of the atmosphere and internal variability, and not consistent with alternative explanations of recent climate change that exclude important forcings [see Houghton et al. (2001) for a more thorough discussion]. This implies that all important forcing mechanisms, natural (e.g., changes in solar radiation and volcanism) and anthropogenic, should be considered in a full attribution study.” (Hegerl et al., 2006)

## II. Detection studies using ocean color

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### A first step towards detection: linear regression

Model expressing a linear trend (ordinary least squares or OLS):

$$y_t = \mu + \omega t + \varepsilon_t$$

$y_t$  is the variable of interest (e.g. chl concentration),

$\mu$  is the intercept,

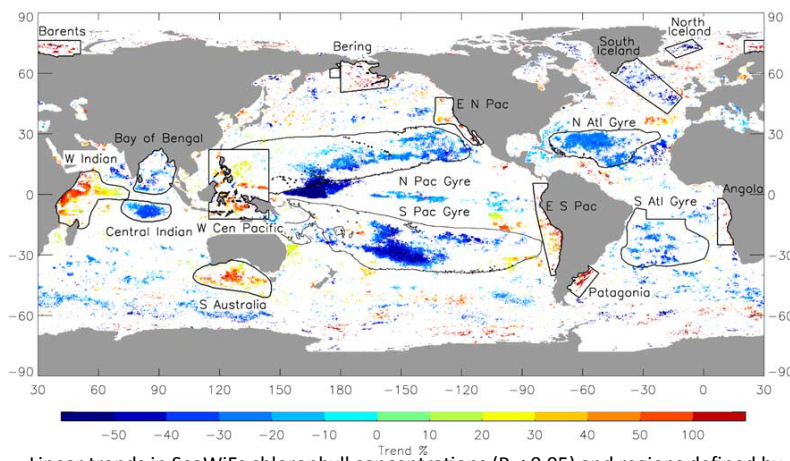
$\omega$  is the magnitude of the trend,

$t$  is the time (e.g. months),

$\varepsilon_t$  is the random errors assumed **independent** and identically distributed i.i.d  $N(0, \sigma_N^2)$ .

Other functional forms (e.g., exponential) were tried by Henson et al. (2010), but fit did not improve significantly.

### Trends in ocean chlorophyll SeaWiFs data From 1998-2003

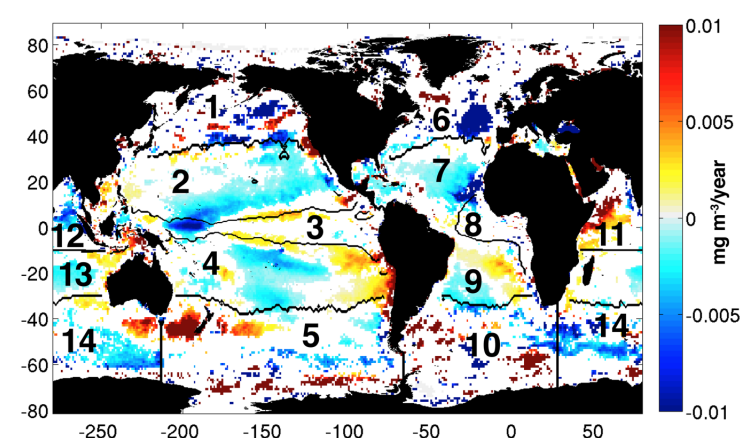


Linear trends in SeaWiFs chlorophyll concentrations ( $P < 0.05$ ) and regions defined by coherent distribution of 25-km grid points. White means not significant. Use annual mean data

Figure from Gregg et al. (2005)

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### Trends in ocean chlorophyll SeaWiFs data From 1997-2007

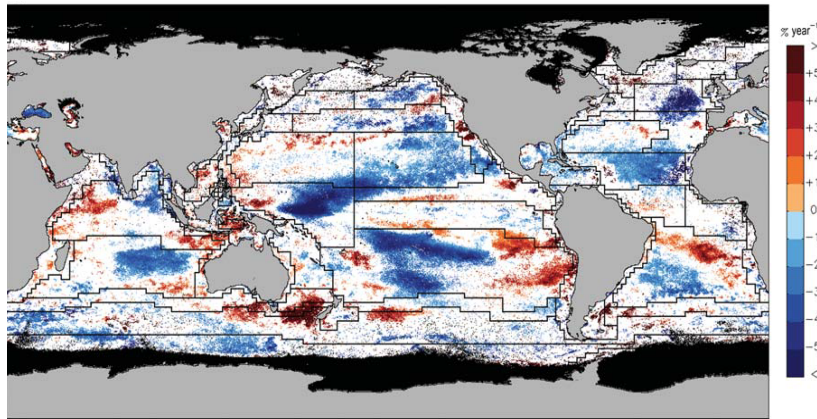


Linear trends in SeaWiFs chlorophyll concentrations ( $P < 0.05$ ). White means not significant.

Figure from Henson et al. (2010)

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## Trends in ocean chlorophyll SeaWiFs data From 1997-2007



Linear trends in SeaWiFs chlorophyll concentrations ( $P < 0.05$ ). White means not significant. Use monthly data.

Figure from Vantrepotte and Mélin (2009)

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## Autocorrelation (red noise) problem

- Autocorrelation is the correlation of a process with itself and indicates the strength of the 'memory' of the process.
- In the presence of autocorrelation the assumption that the errors are independent is not respected. Thus, we need to take autocorrelation into account to figure out whether there are statistically significant trends.

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## Trend detection in presence of autocorrelation (red noise)

Model expressing a linear trend and first-order autocorrelation:

$$y_t = \mu + \omega t + N_t$$

$y_t$  is the variable of interest (e.g. chl concentration),

$\mu$  is the intercept,

$\omega$  is the magnitude of the trend,

$t$  is the time (e.g. months).

$$N_t = \phi_1 N_{t-1} + \varepsilon_t$$

$N_t$  is the noise,

$\phi$  is the first-order autocorrelation,

$\varepsilon_t$  is the random errors i.i.d.  $N(0, \sigma_N^2)$ .

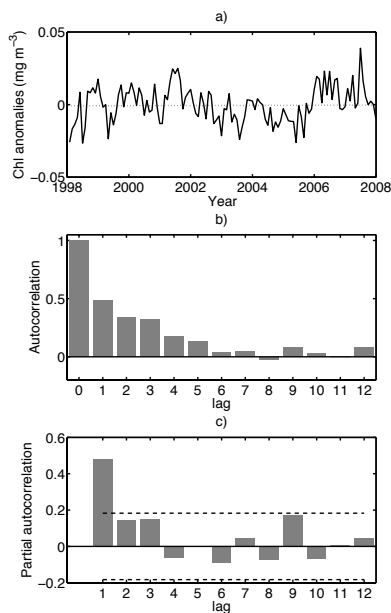
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## Trend detection with autocorrelation

- The parameters can be estimated using generalized least squares (GLS) regression as opposed to the usual ordinary least squares (OLS) regression.

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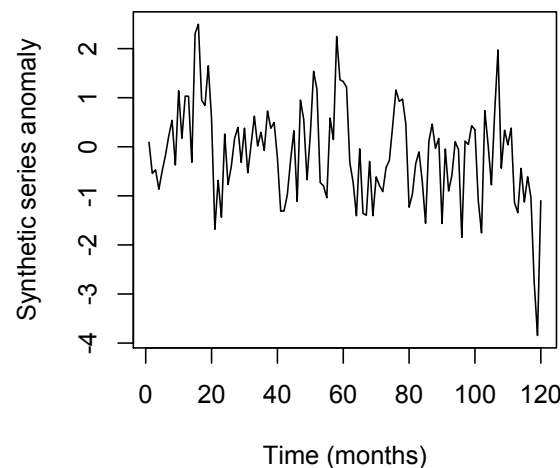
## GLS trend in global chlorophyll concentration

Trend estimate:  
0.1% per year (p-value = 0.5)

Beaulieu et al., 2012, in prep. 26

## Effect of autocorrelation

- If not accounted for, autocorrelation can be falsely interpreted as a trend

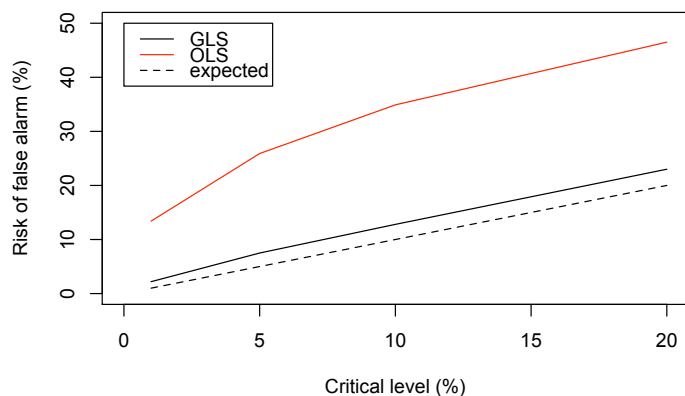


- Note here that with a first-order autocorrelation of 0.5, the decorrelation time is 3 months. It takes 3 months of data before the noise forgets its current state.

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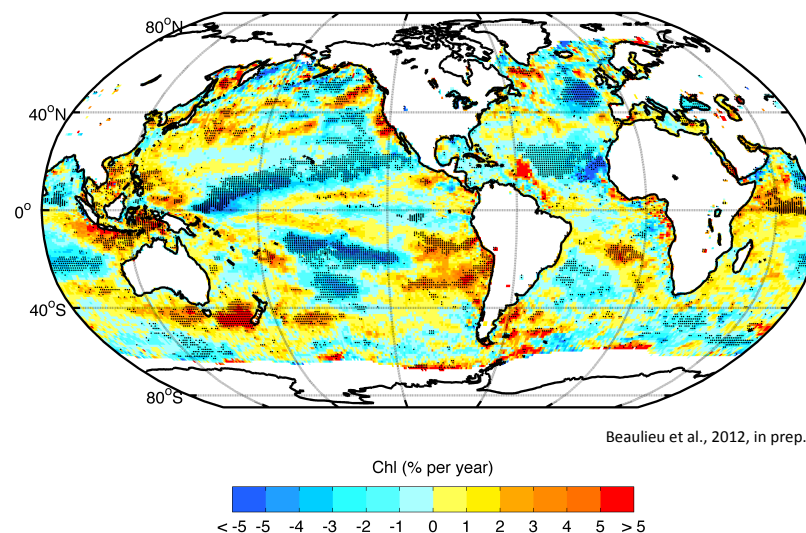
## GLS vs OLS

- Simulation on 1000 synthetic time series with a first-order autocorrelation of 0.5.  $N_t = 0.5N_{t-1} + \varepsilon_t$
- If the usual 5% critical level (95% confidence level) is used, the risk of false detection using OLS is increased by 20%.
- This increase depends on the autocorrelation value.



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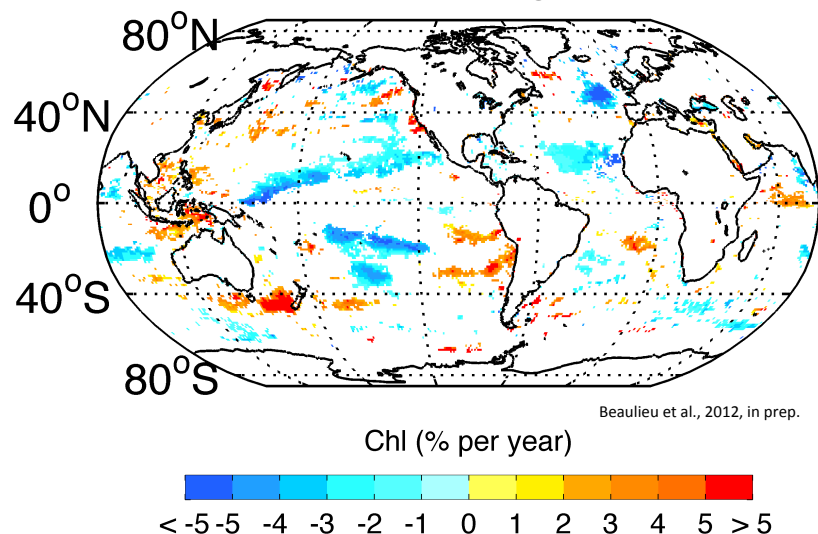
## GLS trends in SeaWiFs chlorophyll concentration



Beaulieu et al., 2012, in prep.

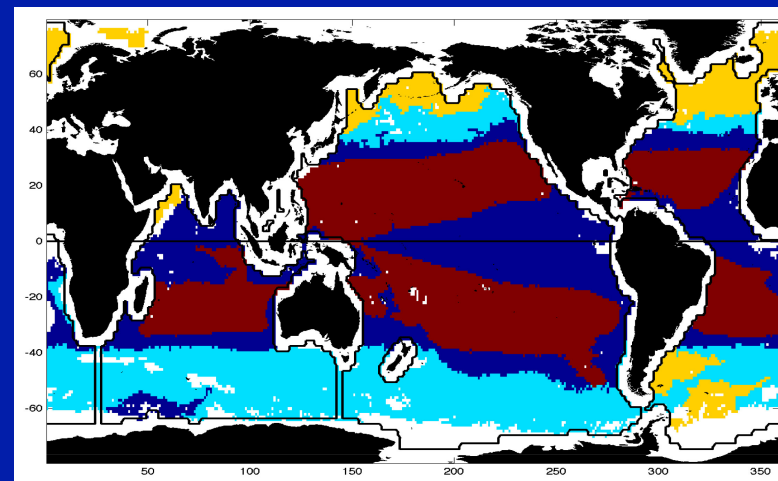
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# GLS trends in SeaWiFS chlorophyll concentration (white indicates non-significant)



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# Biomes based on clustering of SeaWiFS chl and carbon



K-means clustering on st.dev. of carbon and mean chl

# Trends in satellite data averaged by biomes

Region	Trend mg m <sup>-3</sup> year <sup>-1</sup> (% per year)	Autocorrelation (decorrelation time in months)
Global	0.00049 (0.11)	0.52 (3.2)
High latitude North Atlantic	-0.00555 (-1.31)**	0.16 (1.4)
Equatorial Atlantic	-0.00052 (-0.18)	0.61 (4.1)
Oligotrophic North Atlantic	-0.00127 (-0.95)	0.59 (3.9)
Southern Ocean Atlantic	0.00078 (0.26)	0.39 (2.3)
Oligotrophic South Atlantic	-0.00028 (-0.29)	0.52 (3.2)
High latitude North Pacific	-0.00138 (-0.34)	0.37 (2.2)
Equatorial Pacific	0.00054 (0.30)	0.87 (14.4)
Oligotrophic North Pacific	-0.00030 (-0.34)	0.84 (11.5)
Southern Ocean Pacific	0.00108 (0.65)*	0.47 (2.8)
Oligotrophic South Pacific	0.00020 (0.23)	0.80 (9.0)
Arabian Sea	0.00257 (1.45)	0.73 (6.4)
Bay of Bengal	-0.00076 (-0.50)	0.59 (3.9)
Southern Ocean Indian	-0.00044 (-0.21)	0.59 (3.9)
Oligotrophic Indian	-0.00029 (-0.32)	0.80 (9.0)

\* 95% CL, \*\* 99% CL

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# III. Detection time studies using climate model simulations

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## How can we estimate how long it will take before detecting trends?

The number of years necessary to detect a trend depends on the magnitude of the trend and the variability in the data. If we fix a confidence level of 95% and a probability of detection of 0.9, the number of years necessary can be estimated by (Tiao et al., 1990; Weatherhead et al., 1998):

$$n^* \approx \left[ \frac{3.3\sigma_N}{|\omega_0|} \sqrt{\frac{1+\phi_1}{1-\phi_1}} \right]^{2/3}$$

$n^*$  is the number of years necessary to detect a trend

$\omega_0$  is the magnitude of the trend

$\sigma_N$  is the standard deviation

$\phi_1$  is the first-order autocorrelation

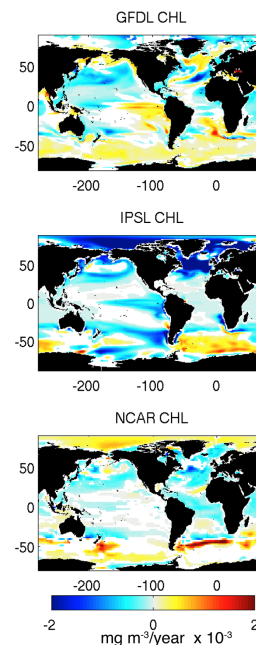
Trends having a small magnitude take more time to detect.

Trends having a large standard deviation and autocorrelation also take longer to detect.

By using magnitude predicted by ocean biogeochemical models and the variability in satellite data, we can estimate how long we may need in order to detect trends.

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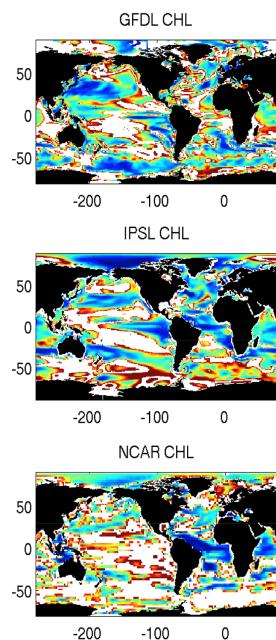
## Trends predicted by three ocean biogeochemical models



Linear trends in chlorophyll concentration projections from 3 ocean biogeochemical models for the period 2001-2100 under IPCC A2 global warming scenario (95% confidence level).

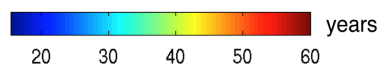
Henson et al., 2010

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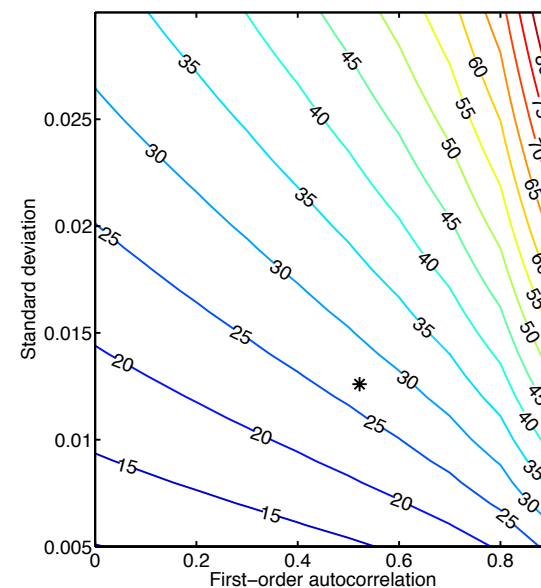
## How long will it take?

Number of years necessary to detect trends predicted for 2001-2100 under IPCC A2 global warming scenario (95% confidence level, 90% probability of detection)



Henson et al., 2010

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## How long will it take?

Number of years necessary to detect trends predicted for 2001-2100 under IPCC A2 global warming scenario (95% confidence level, 90% probability of detection)

Beaulieu et al., 2012, in prep.

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## Trend detection in presence of autocorrelation and an intervention

Model expressing a linear trend with an intervention:

$$y_t = \mu + \omega t + \delta I_t + N_t \quad I_t = \begin{cases} 0, & t < T_0 \\ 1, & t \geq T_0 \end{cases} \quad \tau = (T_0 - 1) / T$$

$y_t$  is the variable of interest (e.g. chlorophyll concentration),

$\mu$  is the intercept,

$\omega$  is the magnitude of the trend,

$t$  is the time (e.g. months),

$\delta$  is the intervention effect,

$T_0$  is the time of the intervention,

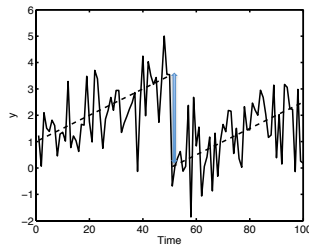
$\tau$  is the fraction of data before the intervention.

$$N_t = \phi_1 N_{t-1} + \varepsilon_t$$

$N_t$  is the noise,

$\phi$  is the first-order autocorrelation,

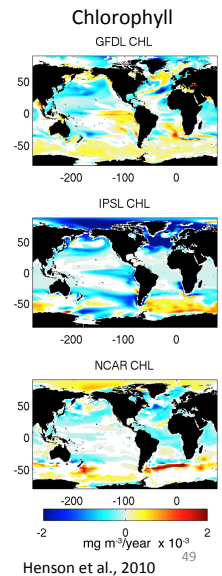
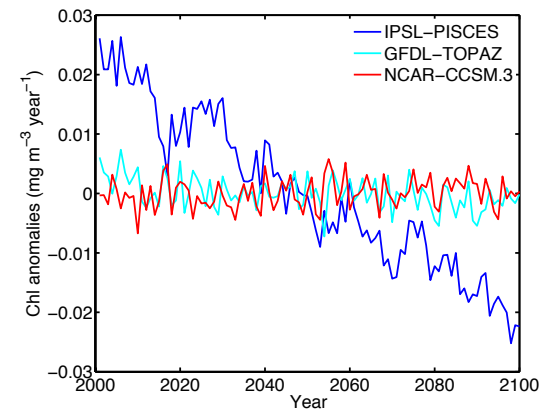
$\varepsilon_t$  is the random errors i.i.d  $N(0, \sigma_N^2)$ .



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## Trends predicted by three ocean biogeochemical models

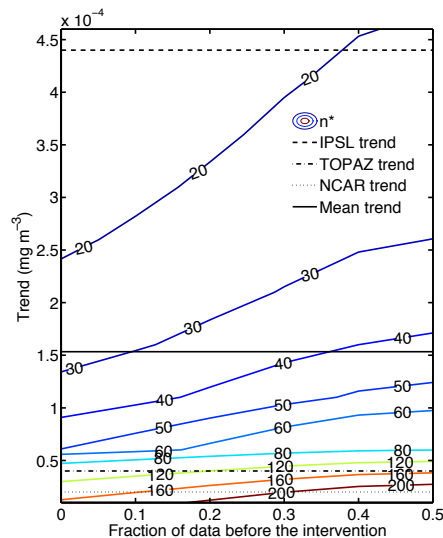
Linear trends in chlorophyll concentration projections from 3 ocean biogeochemical models for the period 2001-2100 under IPCC A2 global warming scenario (95% confidence level).



Henson et al., 2010

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## How long it will take without instrument overlap?



We could need an additional 13-16 years of observations to detect the multi-model average trend, depending on the timing of the discontinuity.

Beaulieu et al., 2012, in prep.

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## Concluding remarks

- We are not yet able to detect trends in ocean chlorophyll satellite data except in the high latitude North Atlantic.
- It will take a few more decades of observations to have very high probabilities to detect trends.
- A change of instrument without overlap would highly affect our ability to detect trends.
- Currently, our measurement records are too short to detect trends, so our best guess for when we can detect trends comes from models.

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# The End