Quantifying Variability and Persistence in Remotely Sensed Chlorophyll Time Series Data

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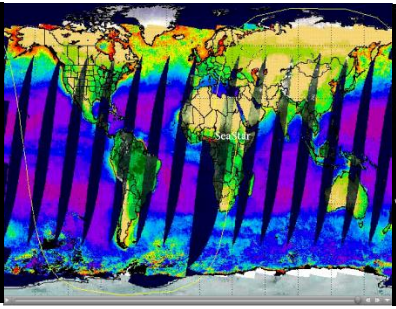
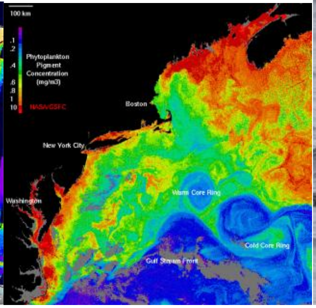
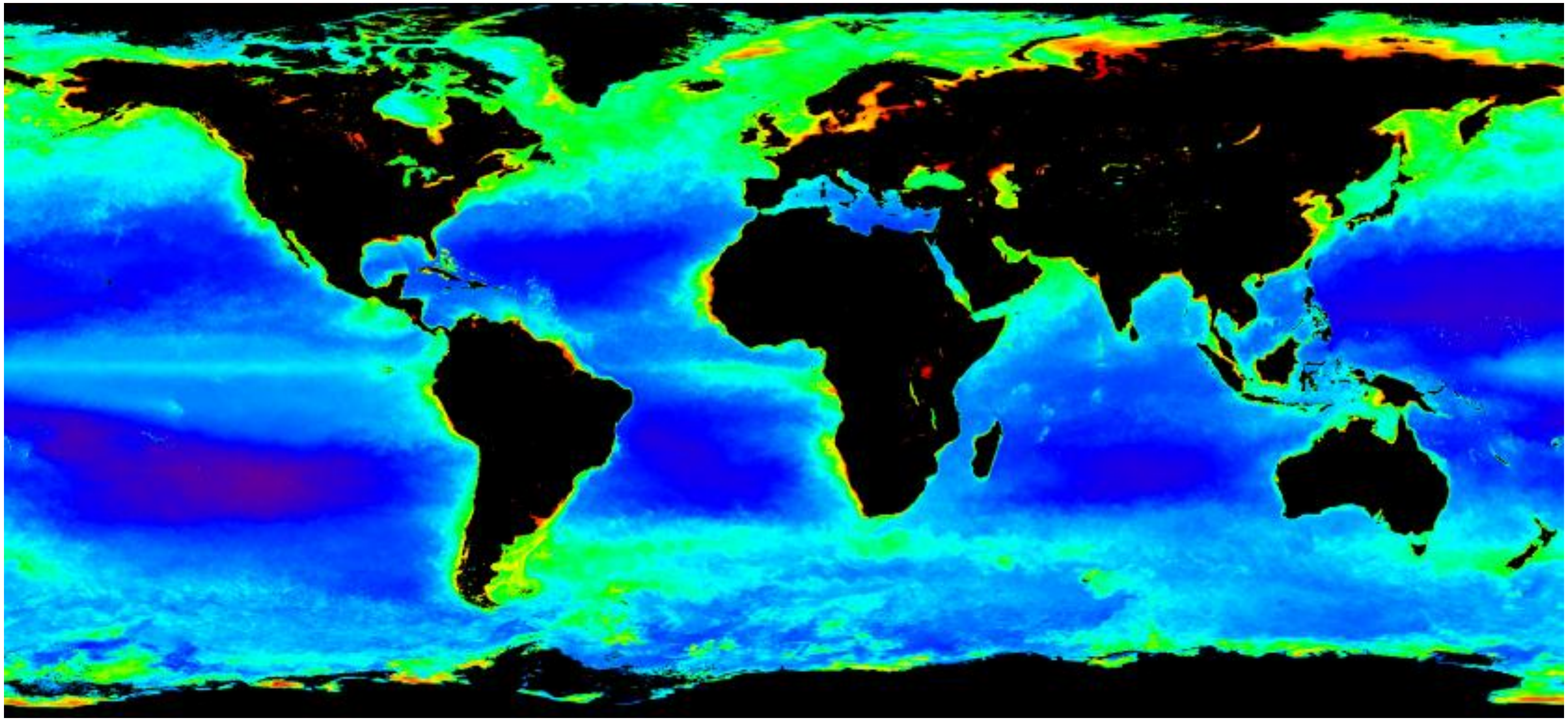




Background:

➢ **Satellite remote sensing has provided unprecedented insight into global patterns of primary production**

➢ **Yet its utility to understand and predict the distribution of mid- to upper trophic-level predators remains equivocal**



Problems:

➢ **Extrapolating to secondary or tertiary productivity often provides mixed results (Worm et al. 2005 Science; Suryan et al. 2006 DSRII; Gremillet et al. 2008 JAE, and MANY OTHERS)**

1. **Does not reflect chlorophyll maximum**
2. **Advection of surface waters**
3. **Variation in grazing rates**
4. **Time lags in the response of consumers to primary production**
5. **Predators do not consume phytoplankton directly**

Nur et al. 2011 Ecol Appl. Where the wild things are: Predicting hotspots of seabird aggregations in the California Current System
"Overall, bathymetric variables were often important predictive variables, whereas oceanographic variables derived from remotely sensed data were generally less important."

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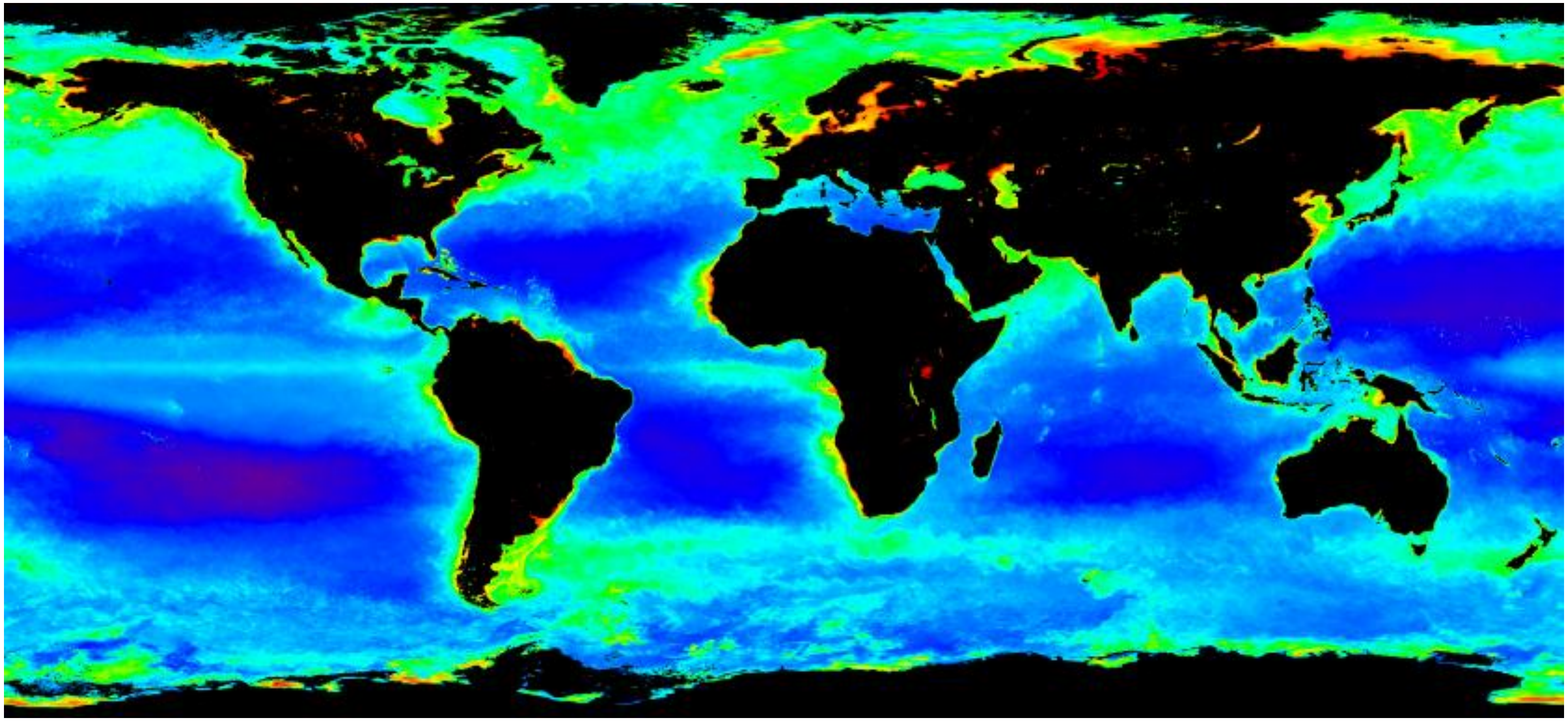
Possible Solutions?

➢ Change scale (temporal or spatial) of remote sensing data.

➢ Measure "persistence." Investigators note the importance of persistence (e.g., Palacios et al. 2006 DSR II, Sigler et al. 2012 DSR II).



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Not all areas of high chl a concentration are equally productive from a food web perspective

Objectives:

- **Identify areas of elevated productivity that reflect enhanced trophic transfer and food web development and are persistent in space and time**

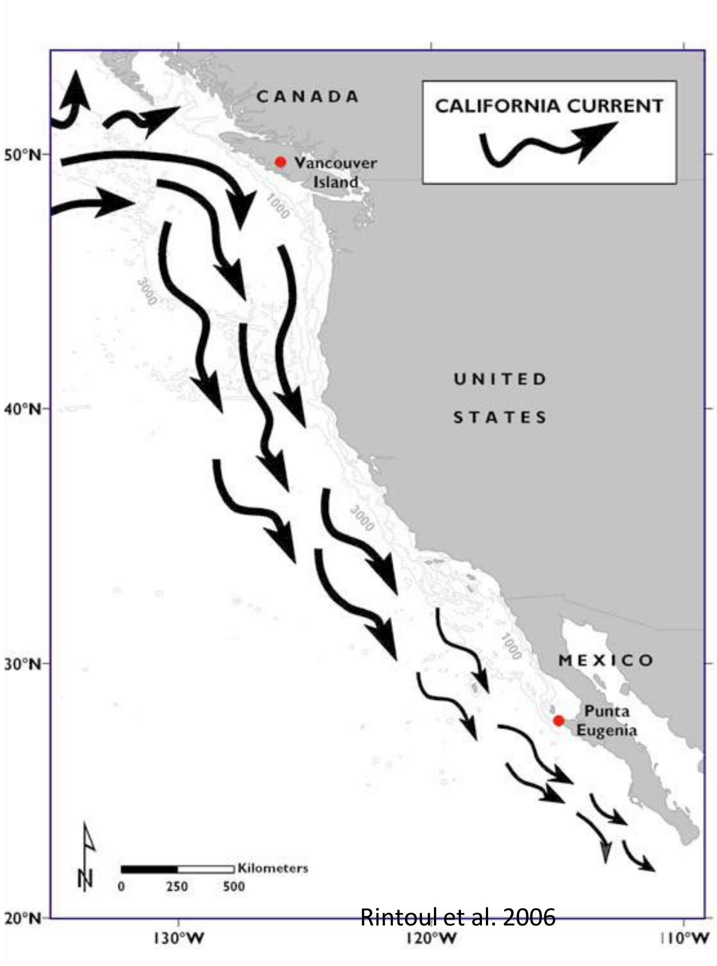
- **Derive a spatially and temporally explicit chl *a* variability and persistence metric to expand the use of chl *a* data in predicting areas of elevated consumer abundance – i.e., enhanced trophic transfer of energy**

- **Test whether it is a better predictor of marine consumer distribution than more typically used mean chl *a***

Suryan et al. 2012 Mar. Ecol. Prog. Ser. 451:213-225

Methods – Remote Sensing Data

- **9 yrs (1998-2006) of Level 3 SeaWiFS data for the California Current System (CCS)**
- **9x9 km (n=29,504 pixels) , monthly (n=108 months per pixel) resolution**

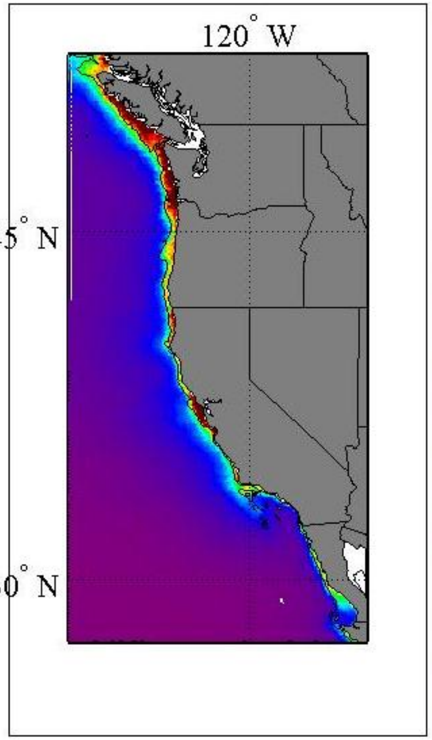


Rintoul et al. 2006

Methods – Remote Sensing Data

- **3 step process**

1. **Log transform and standardize data in each pixel using a z-score**



$$\frac{X - \mu}{\sigma}$$

$\mu = 0$ **and** $\sigma = 1$

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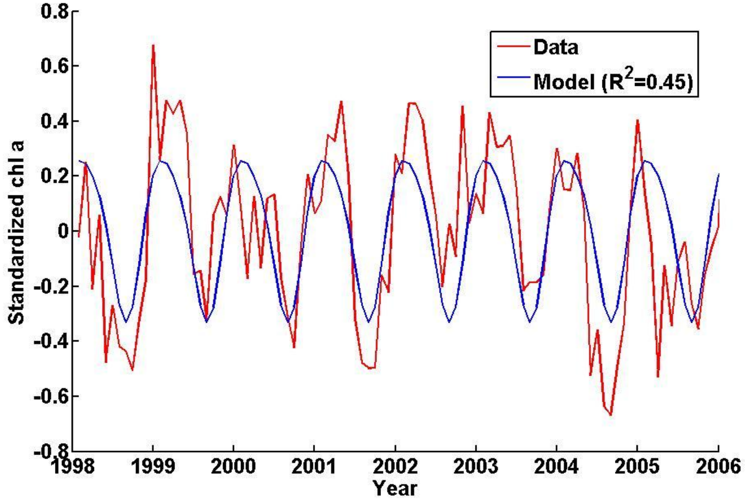
Methods – Remote Sensing Data

➢ **3 step process**

1. Log transform and standardize data in each pixel using a z-score

2. Spatial mean among pixels for each month, then create an CCS-scale model including seasonal cycles (6 and 12 month) and linear trend



$$\text{chl } a = \beta_0 + \beta_1 \sin(2\pi f_1 t) + \beta_2 \cos(2\pi f_1 t) + \beta_3 \sin(2\pi f_2 t) + \beta_4 \cos(2\pi f_2 t) + \beta_5 t$$

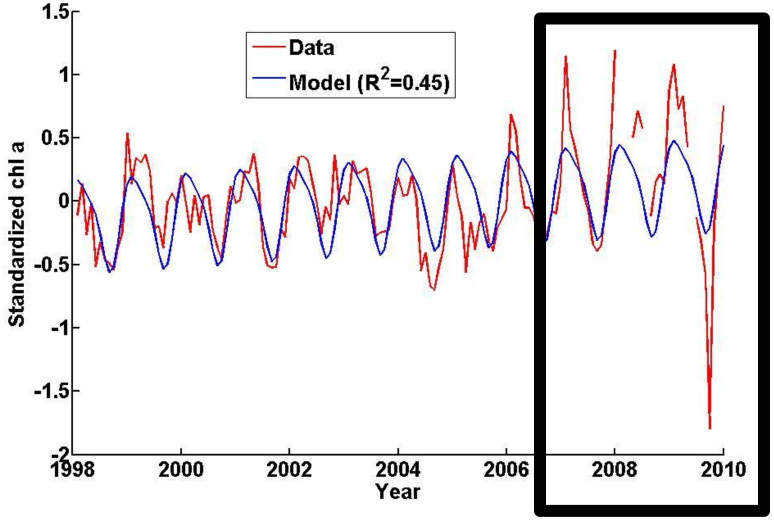
* $R^2 = 0.45$, $F = 16.614$, $P < 0.001$ *

Methods – Remote Sensing Data

➢ **3 step process**

1. **Log transform and standardize data in each pixel using a z-score**

2. **Spatial mean among pixels for each month, then create an CCS-scale model including seasonal cycles (6 and 12 month) and linear trend**



$$\text{chl } a = \beta_0 + \beta_1\sin(2\pi f_1 t) + \beta_2\cos(2\pi f_1 t) + \beta_3\sin(2\pi f_2 t) + \beta_4\cos(2\pi f_2 t) + \beta_5 t$$

*** $R^2 = 0.45$, $F = 16.614$, $P < 0.001$ ***

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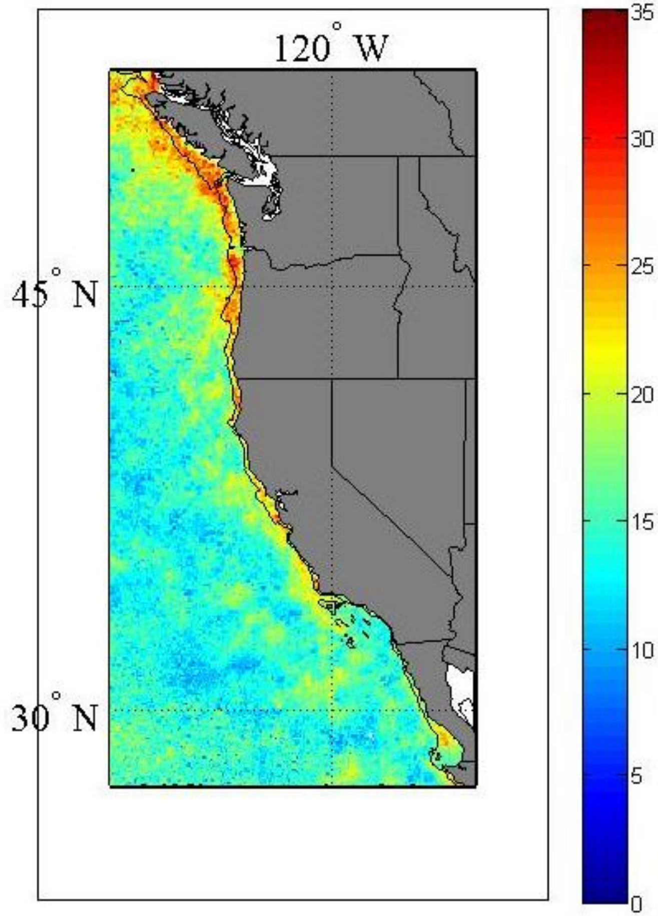
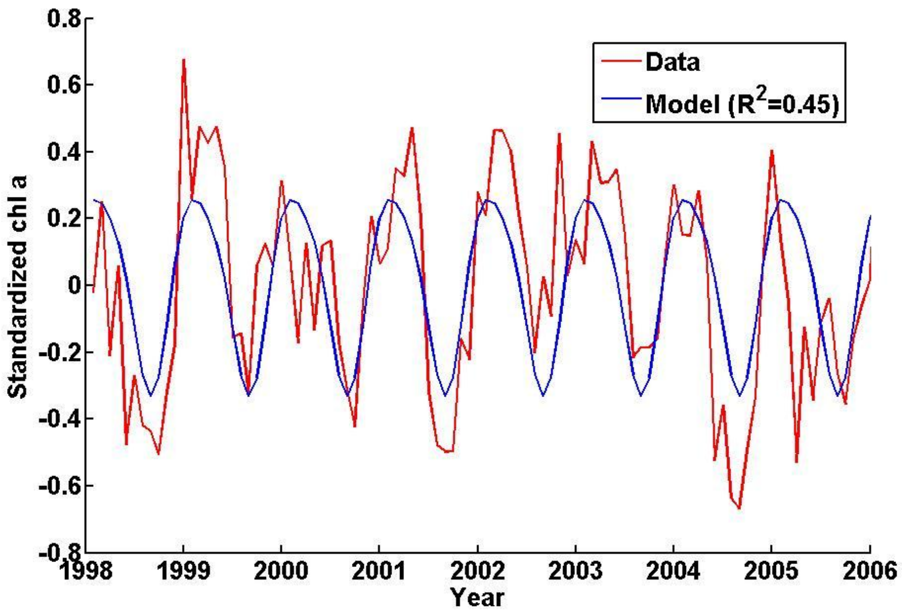
Methods – Remote Sensing Data

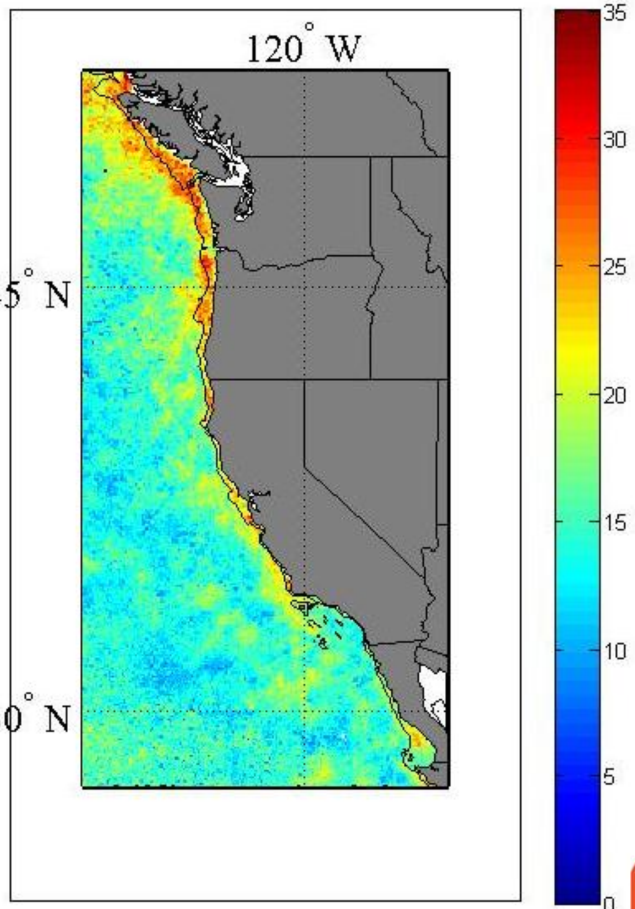
- **3 step process**

1. Log transform and standardize data in each pixel using a z-score
2. Spatial mean among pixels for each month, then create an CCS-scale model including seasonal cycle and linear trend
3. Calculated the proportion of months (from Step 1) each pixel had a positive anomaly of ≥ 1 SD above the CCS-wide model (from Step 2)



Frequency of Chlorophyll Peaks Index (FCPI)





Spatially Explicit Integration of "Variability" and "Anomaly Persistence"

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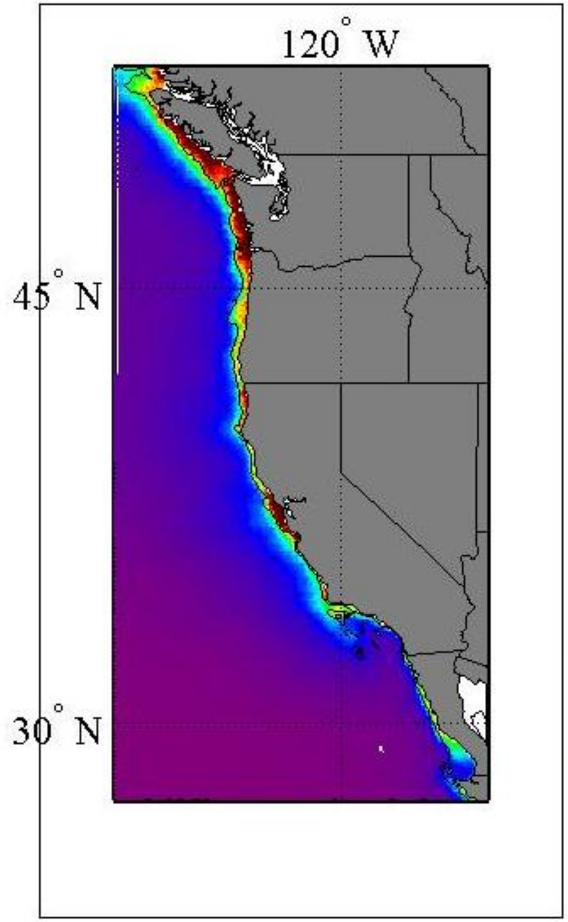
Methods – Data Processing

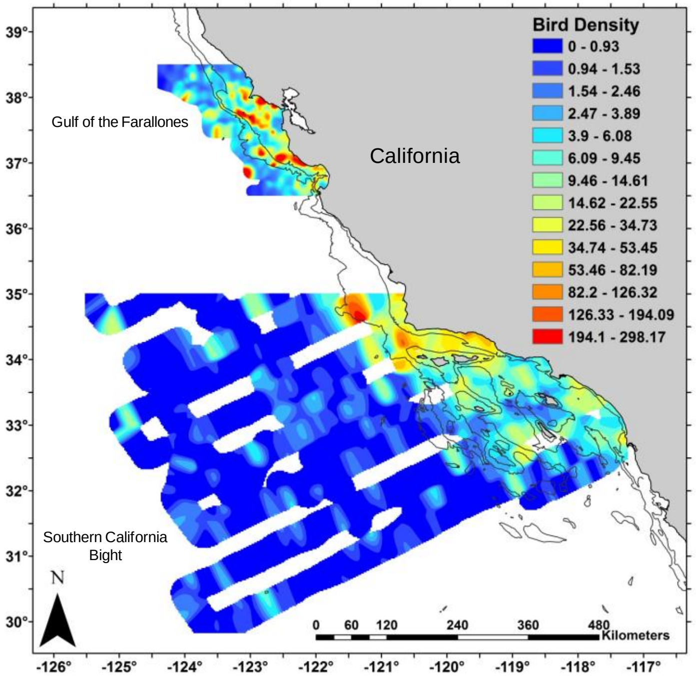
➢ **Mean climatology – 1 step process:**

1. **Arithmetic mean for each pixel**



Methods – Seabird Surveys

- Strip transects conducted 1996-2006 during May-June off Central CA and March-April and July-August off Southern CA
- Calculated total bird density per 0.9 km^2 bins
- Interpolated bird density as percent utilization distributions
- Seabird density chiefly reflects the abundance of four species: common murre, Cassin's auklet, sooty shearwater, and phalaropes

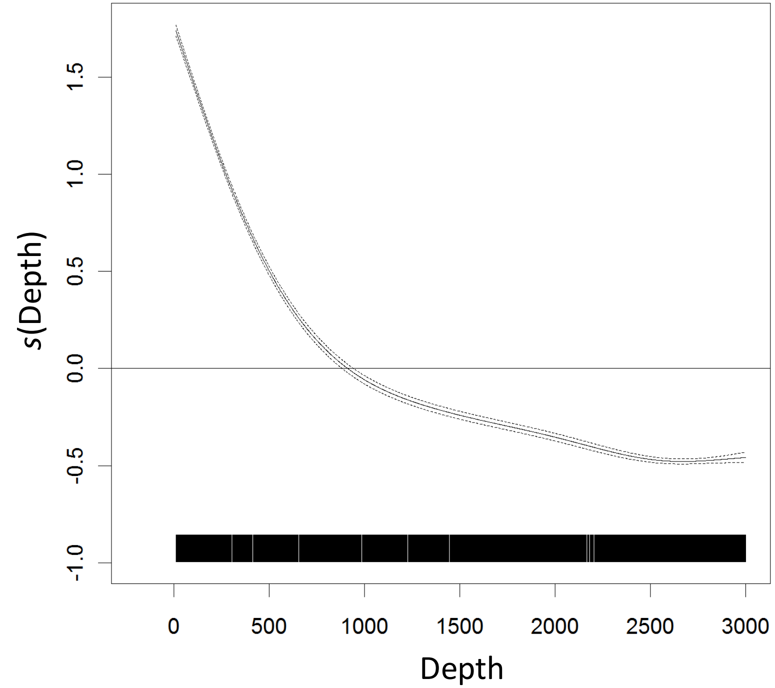


Results

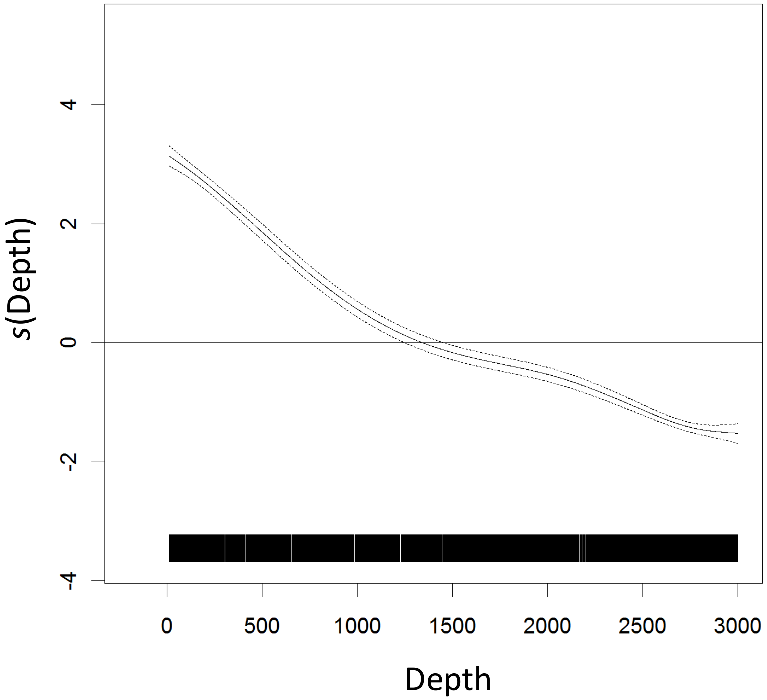
- **GAM of bathymetry vs. chl *a* and FCPI**

chl *a* (or FCPI) ~ *s*(depth) + *s*(slope) + *te*(latitude, longitude)

chl *a*



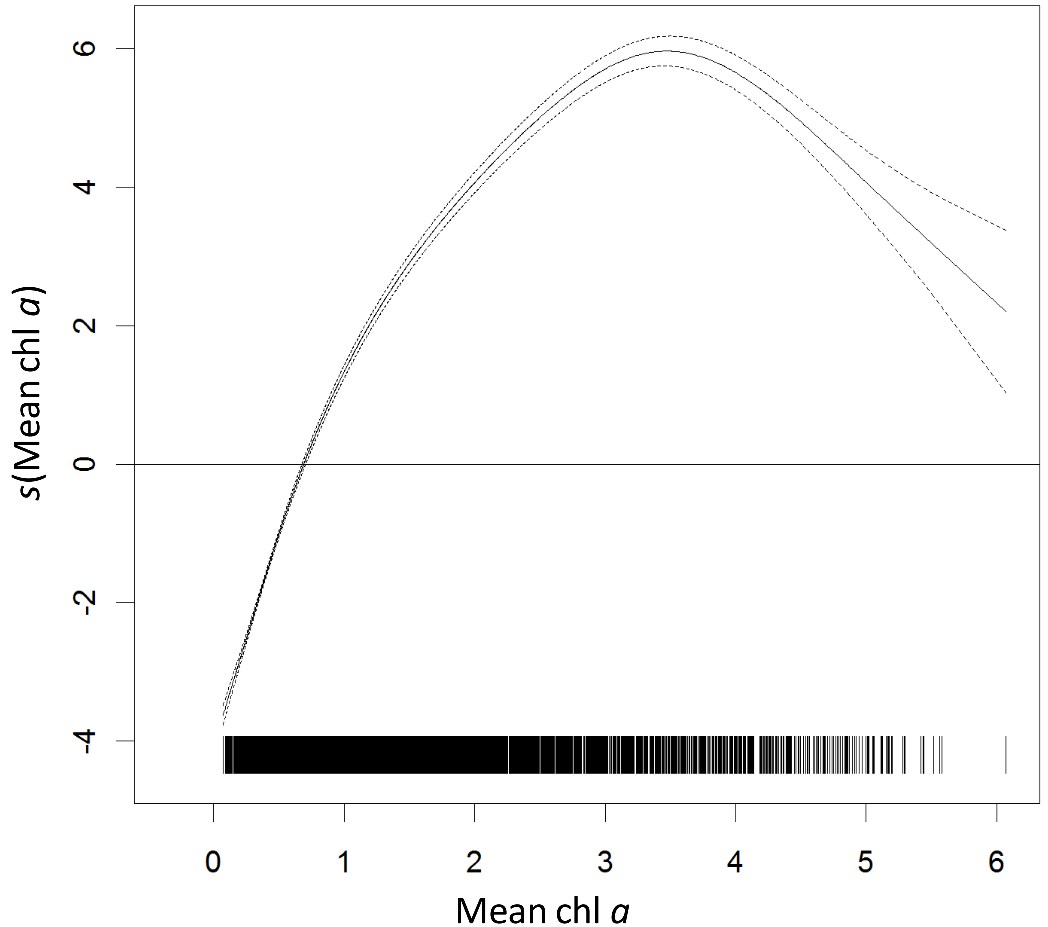
FCPI



Results

- **GAM of chl *a* vs. FCPI**

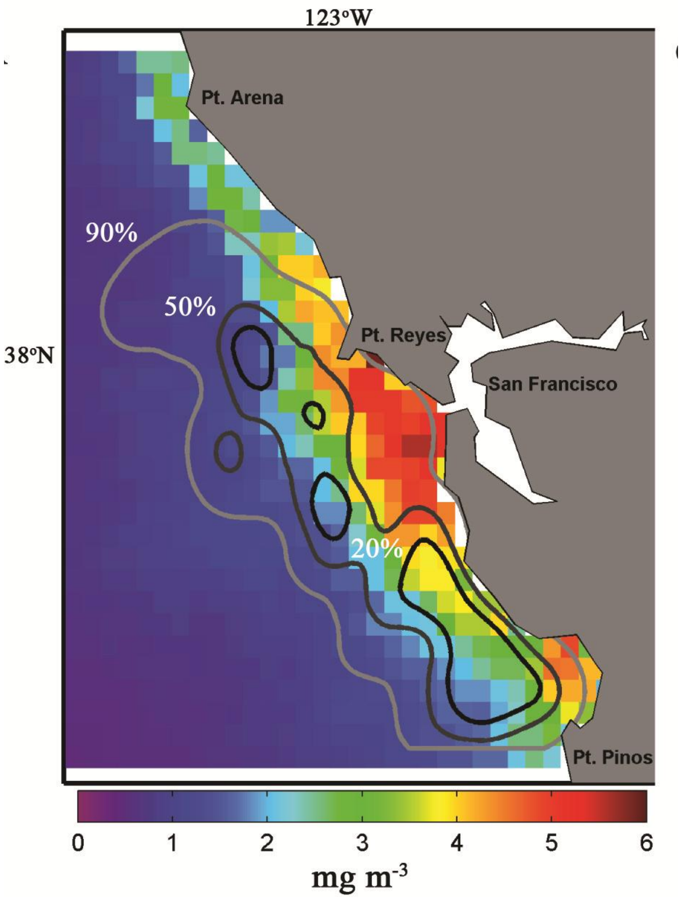
  FCPI ~ *s*(chl *a*)

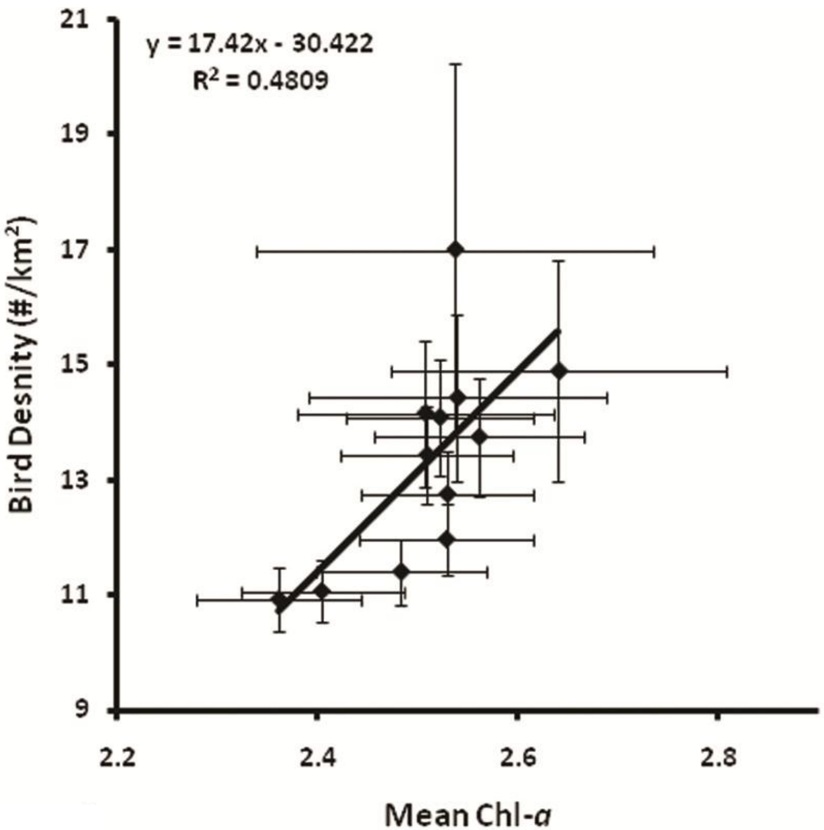


Results

- Chl *a* all months for Central CCS and bird density polygons
- R^2 = 0.48 between mean chl *a* and seabird densities

  (Bootstrap and Monte Carlo analyses, 5000 repetitions)

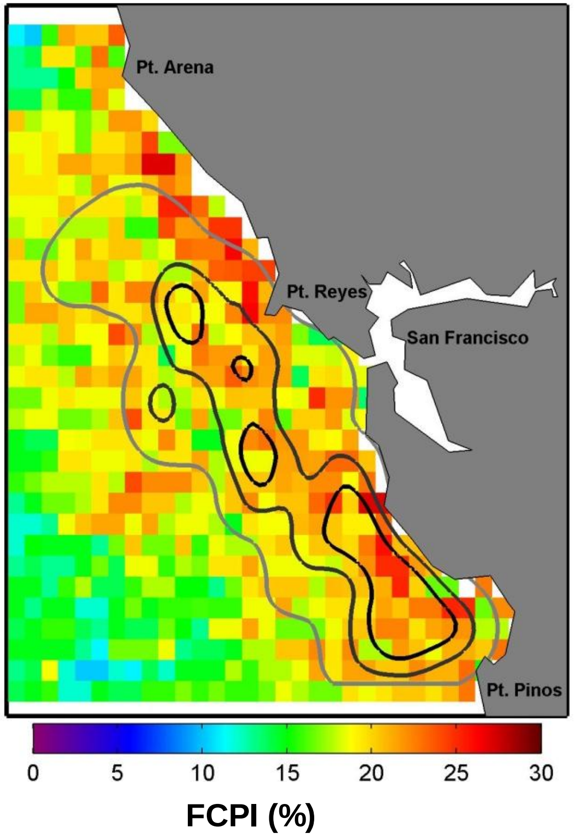


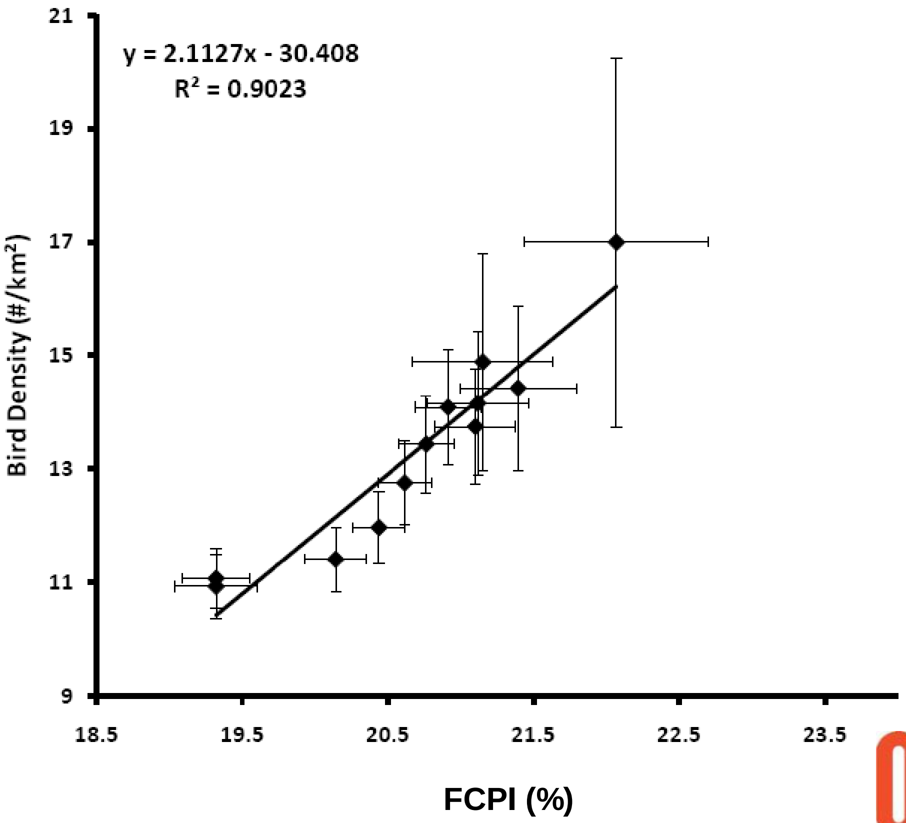


Results

- **FCPI for Central CCS and bird density polygons**
- **R^2 = 0.90 between FCPI and seabird densities**

(Bootstrap and Monte Carlo analyses, 5000 repetitions)





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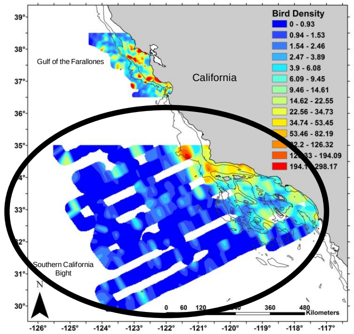
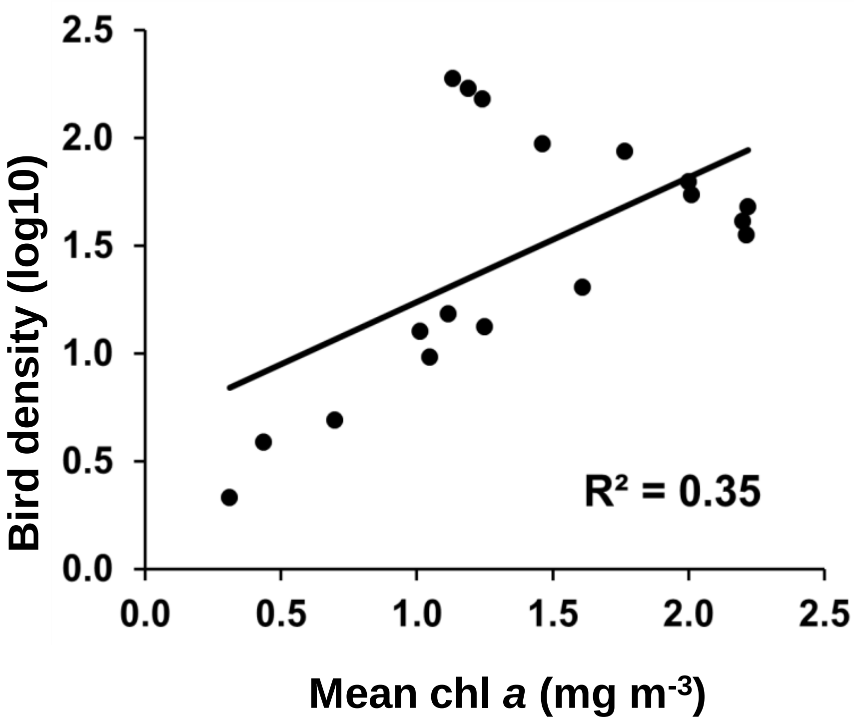
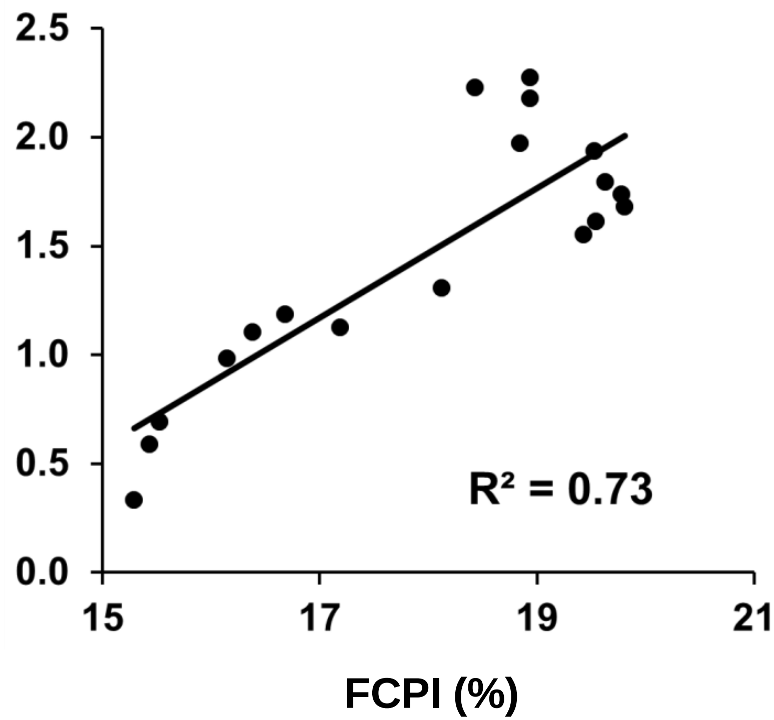
Results
Bird Density vs. Chl *a* mean and FCPI
Southern CA - Spring







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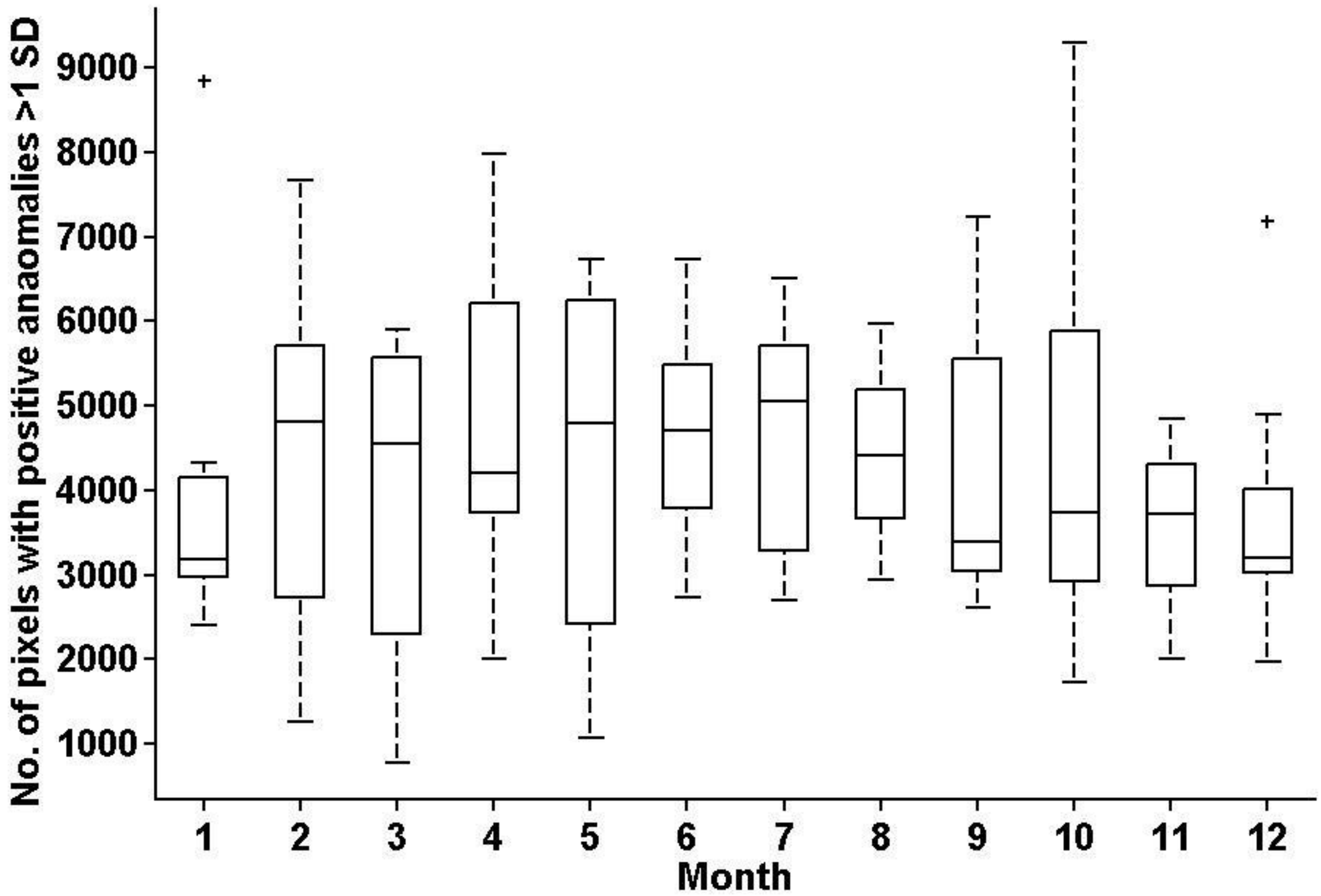
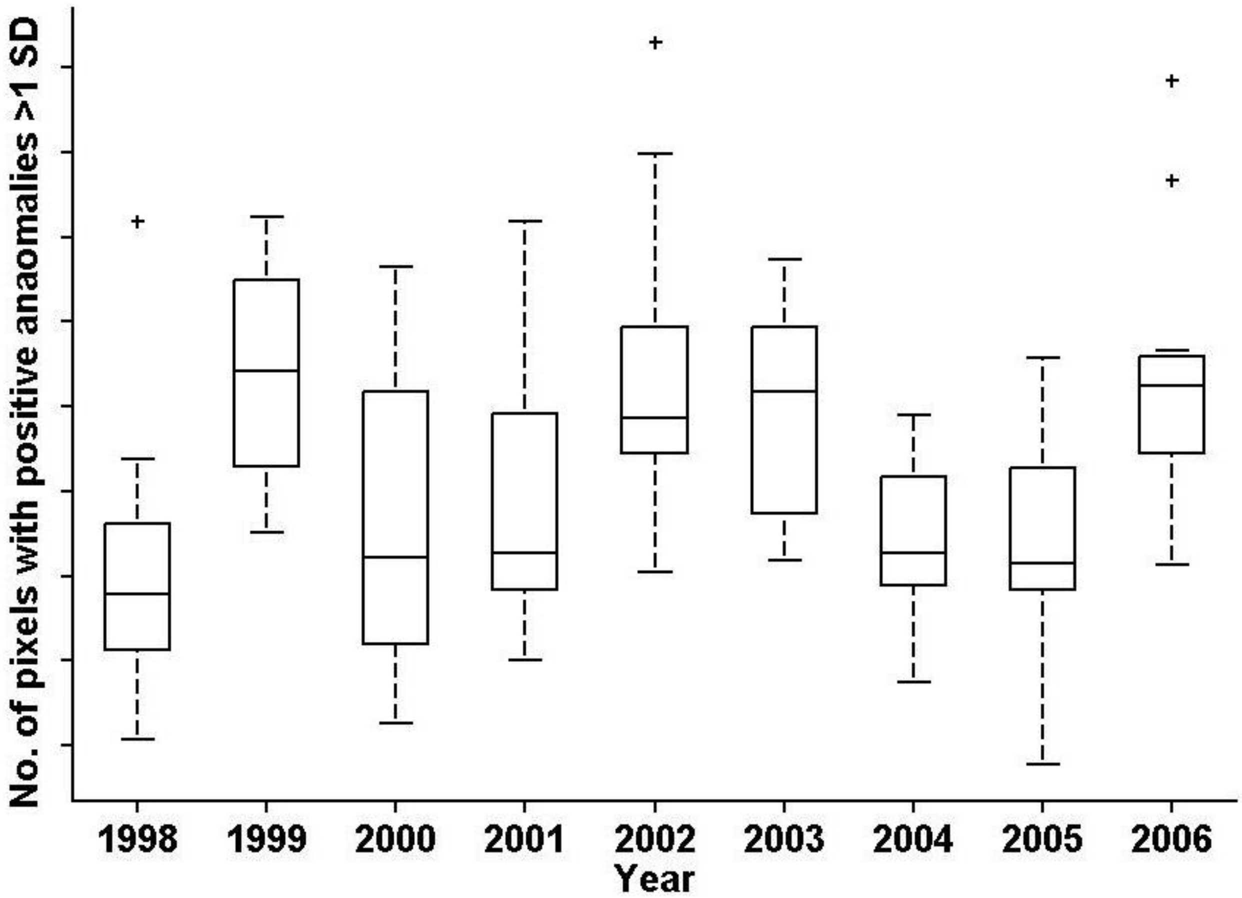
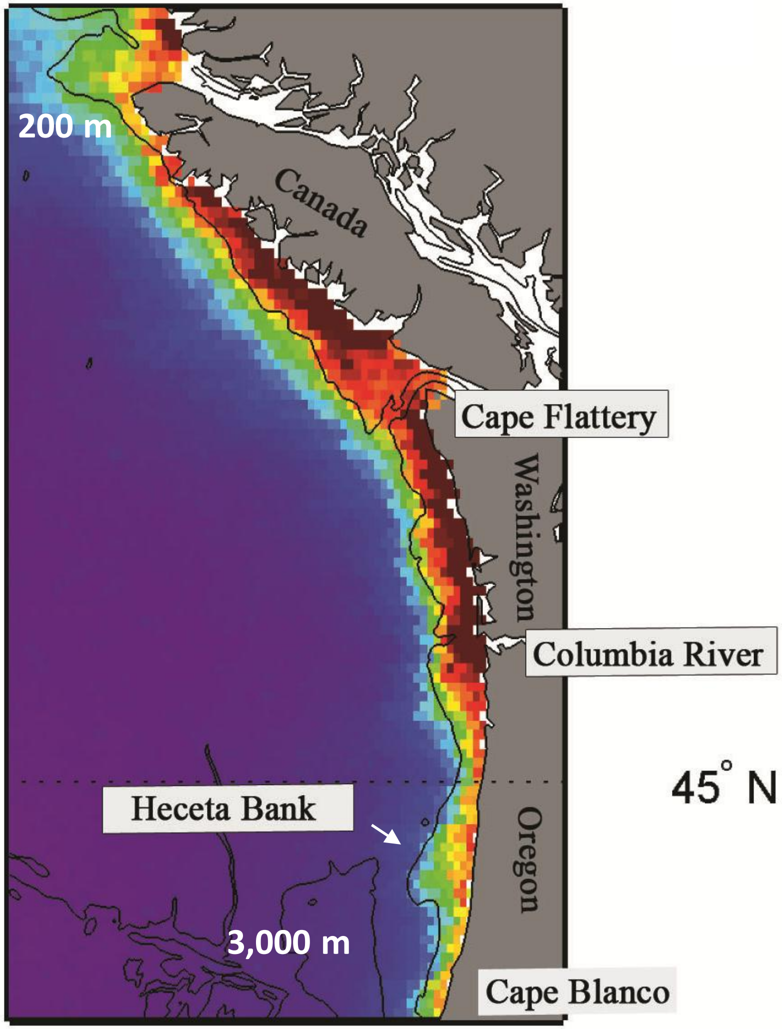
Results
Seasonal Variability in FCPI



Results
Annual Variability in FCPI

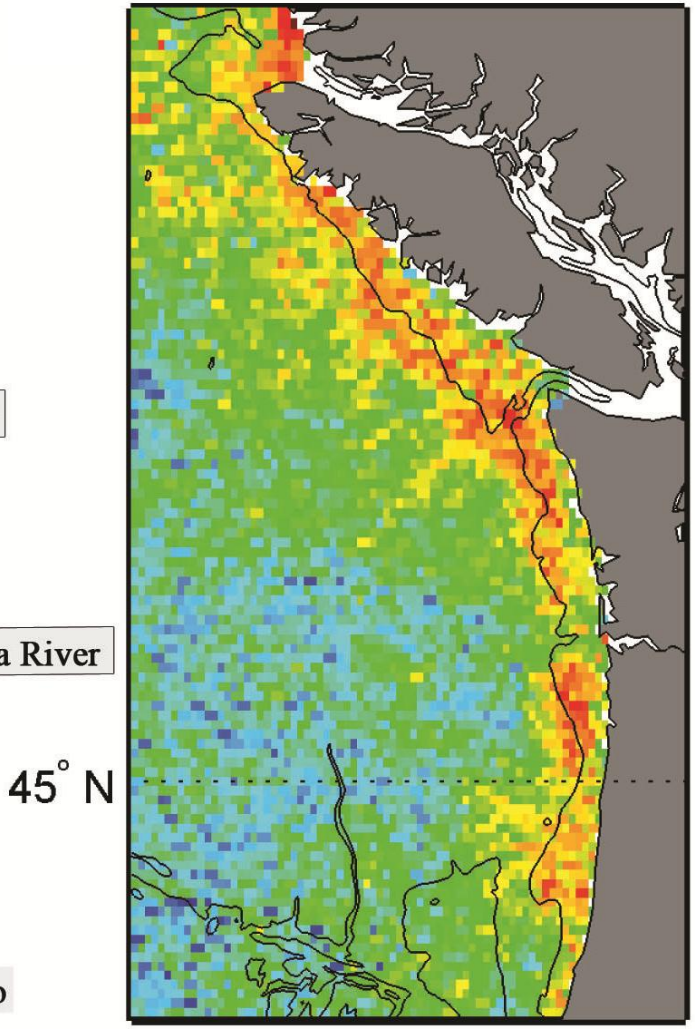


Chl *a*



200 m
Canada
Cape Flattery
Washington
Columbia River
Heceta Bank
3,000 m
Oregon
Cape Blanco

FCPI



45° N

Conclusions:

- Satellite-derived FCPI is an equal or better predictor of predator distribution than chl *a* mean concentration for offshore species

- FCPI appears to identify areas of enrichment, retention, aggregation (e.g., Bakun 1996) – regions of enhanced food web productivity and energy transfer to upper trophic levels

- FCPI metric highlighted some known hotspots in the CSS that were indistinguishable from background levels using mean chl *a*

- Potential widespread application for identifying important pelagic habitats and linking remotely-sensed chl *a* to consumer distribution and in marine spatial planning

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