Data Mining and Knowledge Discovery of Land Cover and Terrestrial Ecosystem Processes from Global Remote Sensing Data

Mark Friedl Department of Geography & Environment, Boston University friedl@bu.edu

Carla Brodley Department of Computer Science, Tufts University brodley@cs.tufts.edu

Surajit Ray Department of Mathematics and Statistics, Boston University sray@math.bu.edu



Support from NASA (NASA TEP, LCLUC, MODIS, and IDU)

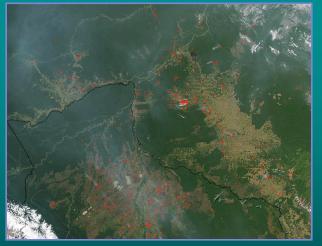
## **Context: Global Change Studies**

- Global Observation Systems
  - EOS/GEOSS, remote sensing, in-situ, sensor webs....
  - Large, heterogeneous, complex data sets
    - High dimensional: multi-spectral, multi-temporal, multi-resolution...
    - Significant analysis problems: noise, missing data...
- Dynamics in Earth System
  - Characterized by high complexity, variability at multiple scales
    - Climate change vs variability
    - Ecosystem response (species composition, phenology, & population dynamics)
    - Human activities

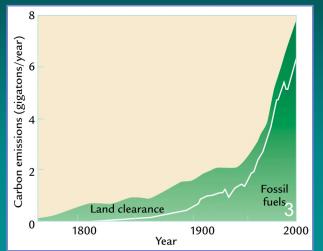
## Why Does this Matter?

# Monitoring and quantification of human impacts

- Land conversion and land use by humans represent the largest single mechanism of environmental change
- Carbon storage/release
- Biodiversity
- Ecosystem Services
  - Land resources & food security
  - Hydrology and water resources
- Etc.....



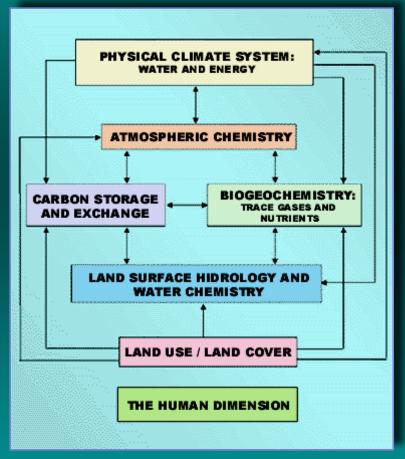




#### Global Land System

 Modeling Perspective

 Global ecosystems and land surface provides key boundary condition to global weather and climate system



(credit: NASA LBA)

### Ecosystem Response to Climate Change

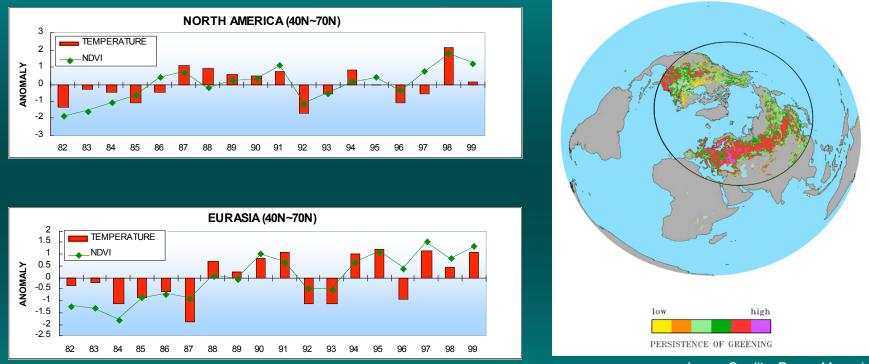


Image Credits: Ranga Myneni

Growing evidence that ecosystems are responding to changing climate at a variety of space-time scales (Myneni et al, *Nature*, 1997; Nemani et al, *Science*, 2003; others...)

## IDU Challenge

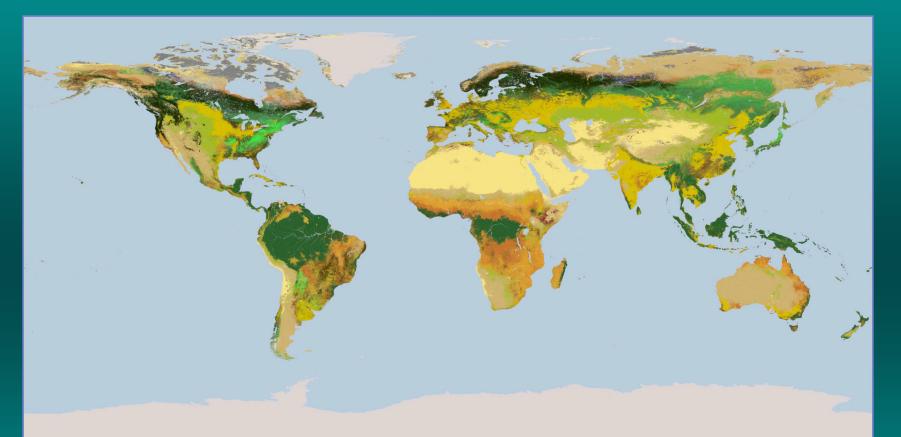
...Better tools for processing, analyzing, detecting change, and understanding patterns and process from large scale Earth science data sets......

- Machine learning, data mining, statistical tools are not the answer, but they can be part of the solution.
- Danger: Fishing expeditions
- *Require*: Earth scientists to better understand tools, data modelers to better understand problem domains.

#### **Overview of Talk**

- Three Problem Domains/Applications
  - Supervised classification of global land cover
    - Map global land cover from remote sensing
  - Unsupervised deomposition of space-time variance in remote sensing time series
    - Search, mine, discover patterns related to data artifacts and patterns in coupled climate-ecosystem dynamics
  - Use of functional models, clustering & mixture models
    - Reduce dimensionality & understand class structure in data.

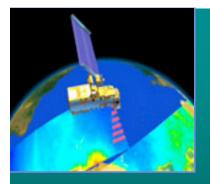
#### Supervised MODIS Land Cover Classification



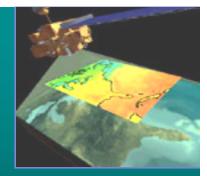
- 0 Water
- 1 Evergreen Needleleaf Forest
- 2 Evergreen Broadleaf Forest
- 3 Deciduous Needleleaf Forest
- 4 Deciduous Broadleaf Forest
- 5 Mixed Forests

- 6 Closed Shrublands
- 7 Open Shrublands
- 8 Woody Savannas
- 📕 9 Savannas
- 10 Grasslands
- 11 Permanent Wetlands

- 12 Croplands 13 Urban and Built-Up
- 14 Cropland/Natural Veg. Mosaic
- 15 Snow and Ice
- 16 Barren or Sparsely Vegetated
- 17 Tundra

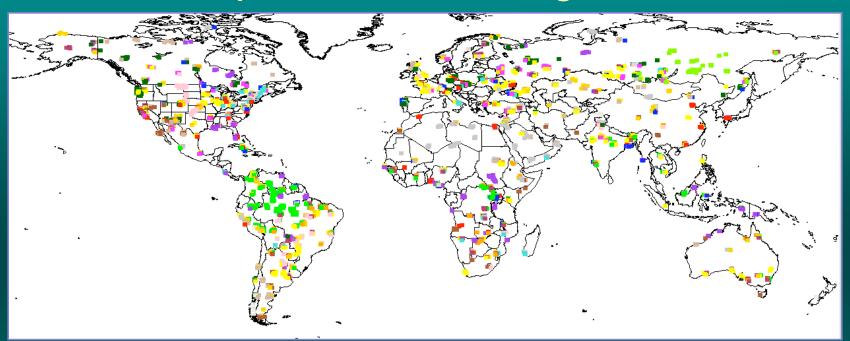


## MODIS



- Moderate Resolution Imaging Spectroradiometer
- Onboard EOS Terra (10:30 AM descending); and EOS-Aqua (1:30 PM ascending) local solar equatorial crossing
- Sun synchronous, near polar orbit; 705.3 km
  - 36 spectral bands, VNIR, SWIR, TIR (0.4–14 μm)
  - Spatial resolution 500-m; scan angle: +/-55°; 2330 km swath
  - 2-day global repeat, 1-day or less poleward of  $30^{\circ}$
  - Onboard calibration; Band-to-band registration, etc.
- Ingest: global, 500-m, 9-bands, 8-day intervals for one year
  - ~2.8 x10<sup>11</sup> input elements to produce a map with ~175x10<sup>6</sup> cells

#### Supervised: Training Data



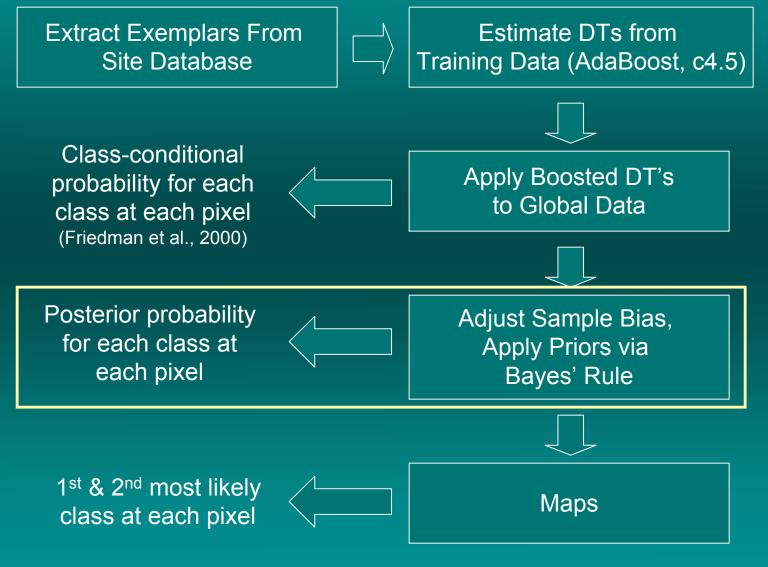
~2000 Sites derived from hi-res imagery & spanning all major regions & ecosystems, but sampling based on "opportunistic" criteria



#### **Technical Challenges**

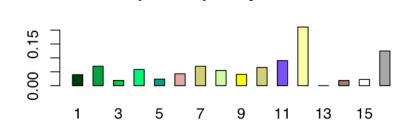
- Algorithms cannot compensate for inadequate features
  - Use of spatially varying priors
- Unbalanced, misrepresentative representative training data
  - Bias correction via global priors
- Each of these "corrections" reduce accuracy of predictions relative to training data, but improve quality of final maps!
- (Year-to-year classification variability vs real change?
  - Heuristic for updating labels based on estimated posterior probs)

#### MODIS Land Cover Processing Chain

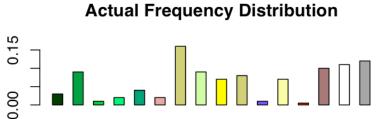


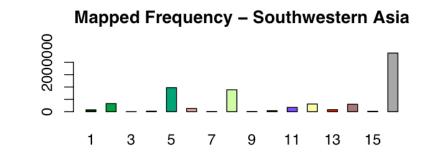
Friedl and Brodley, 1997; Friedl et al, 1999, 2002, 2008; McIver and Friedl, 2001, 2002

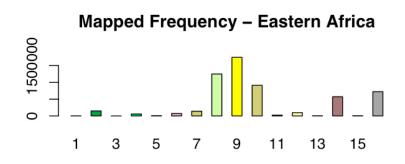
### Sample Bias and Spatial Priors

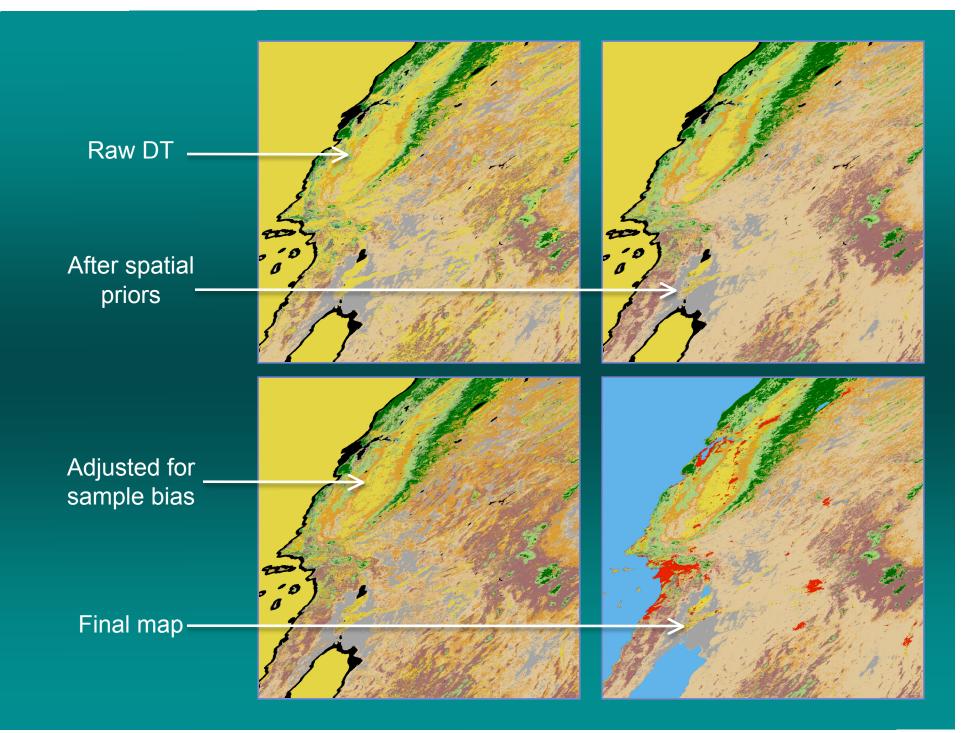


**Sample Frequency Distribution** 









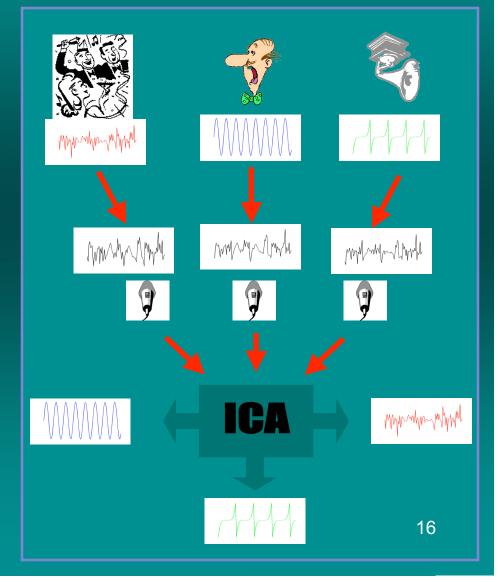
#### Unsupervised Analysis of Gridded Time Series

A. Independent Component Analysis (ICA)

- Non-linear decomposition of temporal variance
- Feature extraction from NDVI time series
- B. Principal/Canonical Correlation Analysis (PCA/CCA)
  - Joint (linear) variability of global vegetation and precipitation
  - Analysis of NH drought and SST patterns

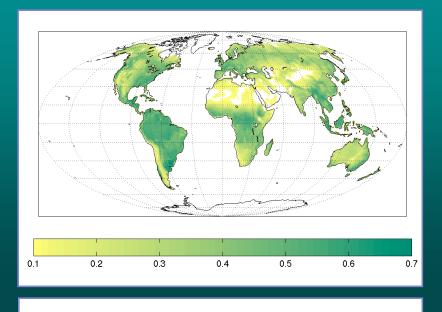
#### Independent Component Analysis of Time Series NDVI

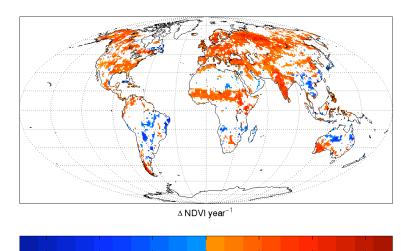
- Independent signals are convoluted and recorded by a sensor (e.g. microphones, satellite instrument)
- ICA separates the signal mixtures into the original source signals
- Independent, not just uncorrelated
- Blind Source Separation no a priori knowledge about the sources
- Looking for hidden sources of variance in time series



#### FASIR-NDVI

- Fourier Adjusted
   Solar zenith angle corrected
   Interpolated
   Reconstructed
   Normalized Difference Vegetation
- NOAA (7,9,11,14)-AVHRR
- Monthly 1982-1998
- 1x1 degree spatial resolution



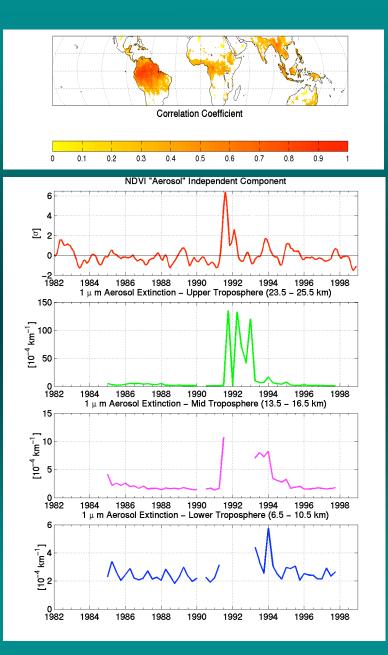




### "Aerosols" IC

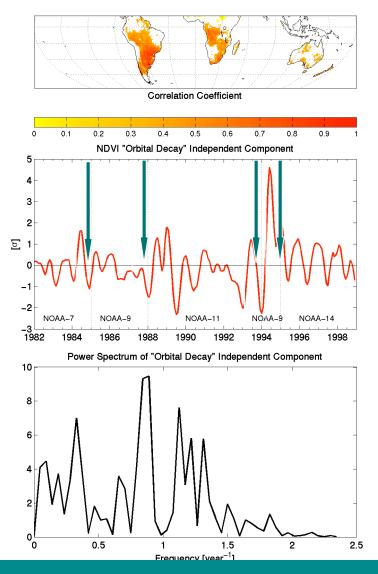
- Residual aerosol signal in tropics
- Co-variation with Stratospheric Aerosol and Gas Experiment (SAGE) II data 1985-1998
- Not revealed via linear methods like PCA

Lotsch et al., IEEE TGARS, 2003



## "Orbital Drift" IC

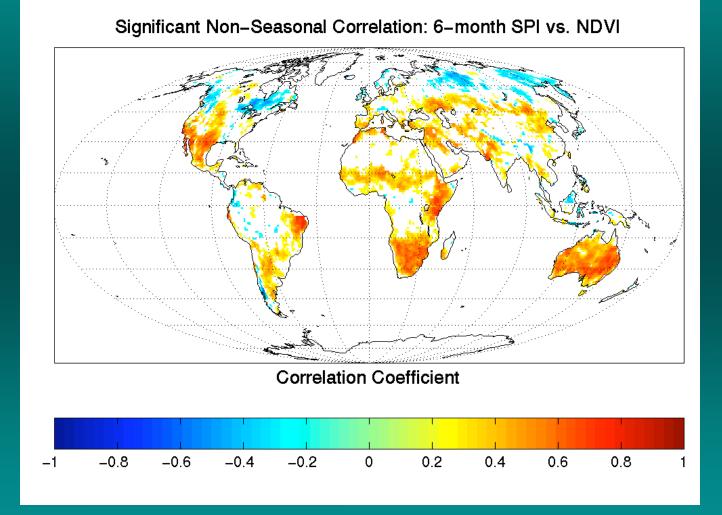
- Discontinuities coincide with AVHRR sensor changes
- Reflect changes in sensor view geometry & orbital drift
- Limited to southern latitudes



Lotsch et al., IEEE TGARS, 2003

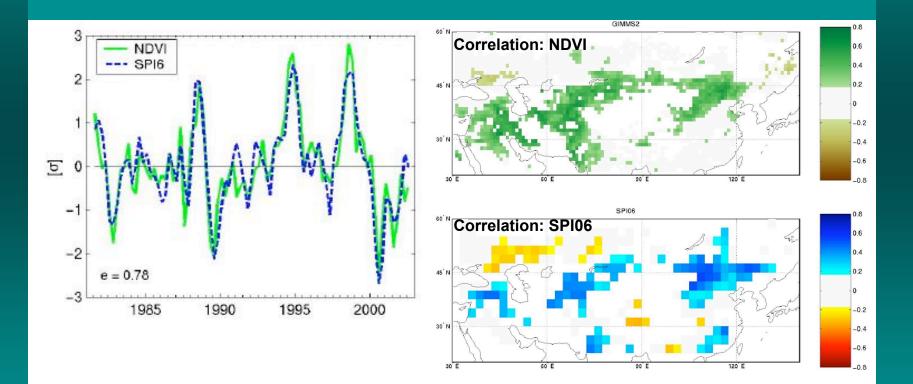
### Joint Variability in Climate & Vegetation

(GIMMS-NDVI vs Standardized Precipitation Index 7/1981-3/2003)



#### **Canonical Correlation** Example: Eurasia (CF1)



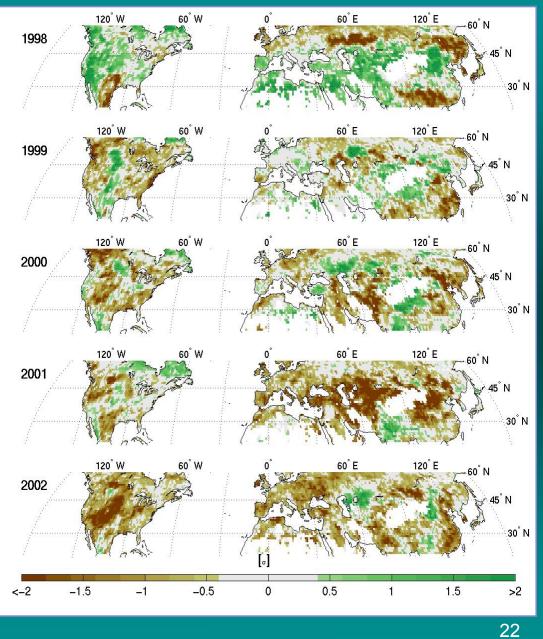


Lotsch et al, Geophysical Research Letters, 2003

1998 –2002 Northern Hemisphere Mid-Latitude Browning

June-August standardized anomalies in NDVI relative to 1981-2002 mean

Motivated by Hoerling and Kumar 2003, Perfect Ocean for Drought, *Science* 



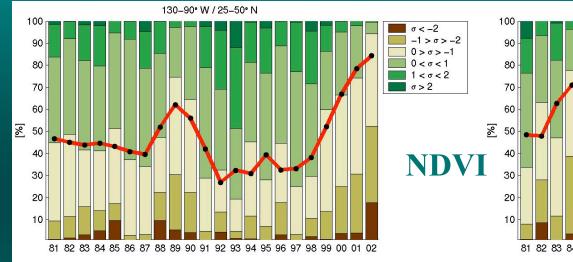
Lotsch et al. (2005) Geoph. Res. Letters

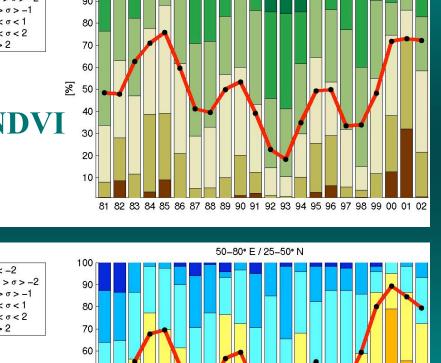
#### NDVI and SPI Anomalies May-September 1981-2002

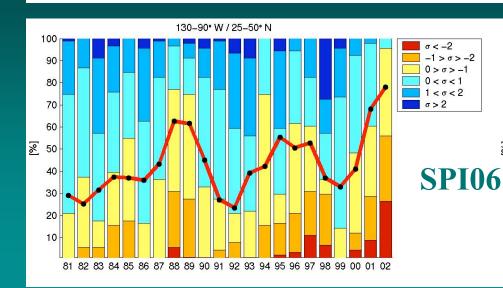
#### North America 130°-90°W

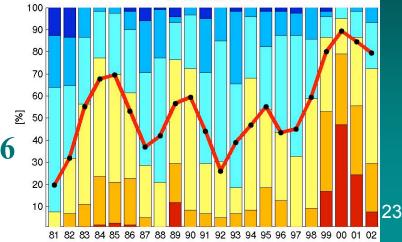
#### CSW Asia $50^{\circ}-80^{\circ}W$

50-80° E / 25-50° N

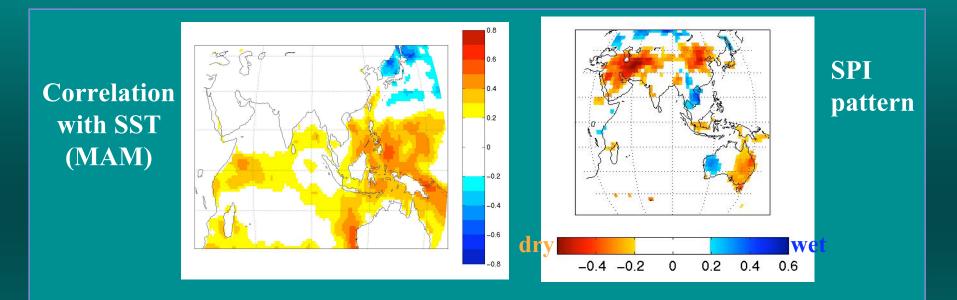




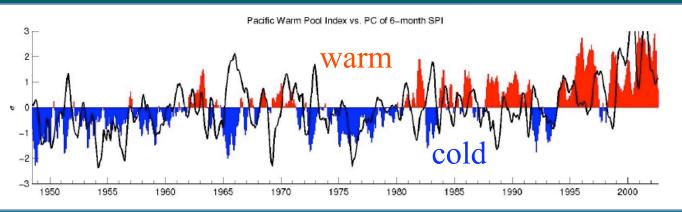




#### Ocean-Drought Teleconnections e.g., Eurasia & Australasia 1948-2002

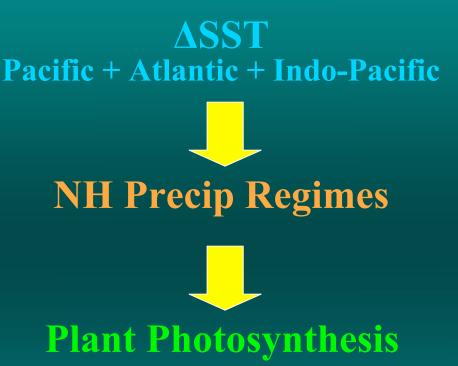


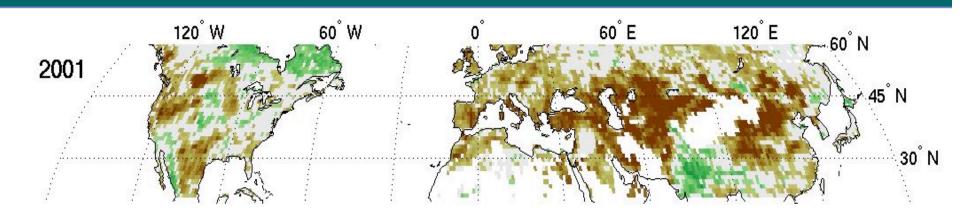




#### Conclusion

Unprecedented reduction of plant photosynthetic activity linked to synchronous patterns of sea surface temperature fluctuations and extensive patterns of drought in the Northern Hemisphere midlatitudes during 1998-2002





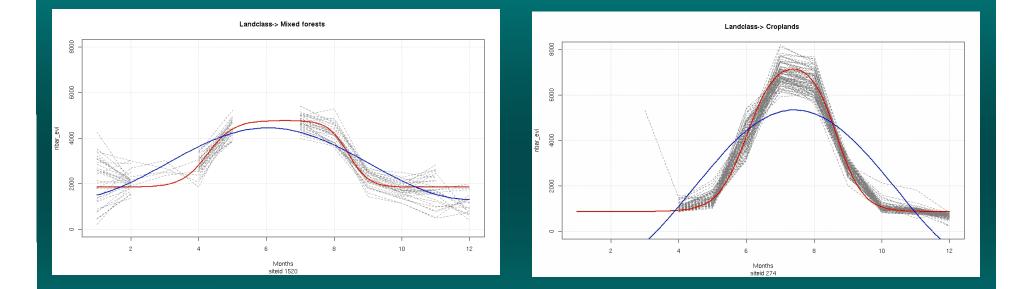
### **Ongoing Work**

- Functional Data Analysis & Modal Clustering
  - Basic Question: How to best characterize temporal patterns and reduce feature dimensionality?
  - Functional Model Double Logistic:

$$Y(x) = a_1 + (a_2 - a_1) \left( \frac{1}{1 + \exp(-a_3(x - a_4))} + \frac{1}{1 + \exp(a_5(x - a_6))} - 1 \right)$$

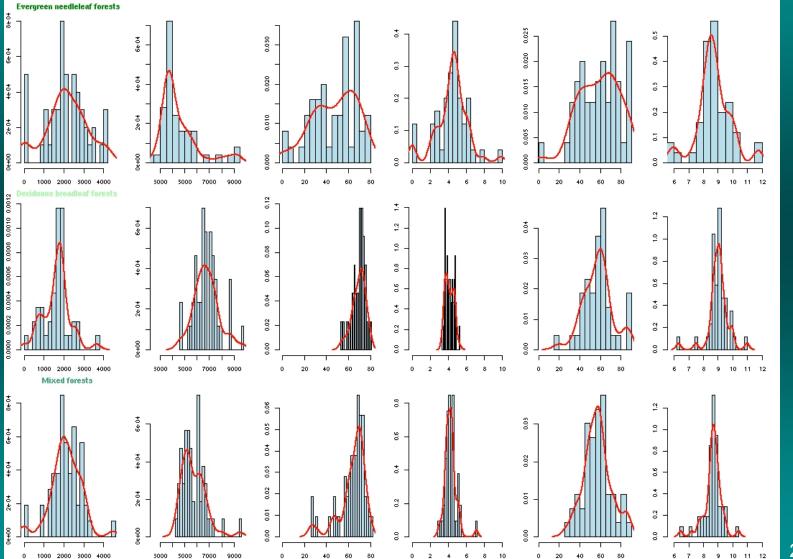
- captures timing, magnitude & form of temporal variation ( $a_1$  = min;  $a_2$  = max,  $a_3$  = angle of inflection 1;  $a_4$  = time of inflection 1  $a_5$  = angle of inflection 2;  $a_6$  = time of inflection 2)

### Sample Double Logisitic Fits



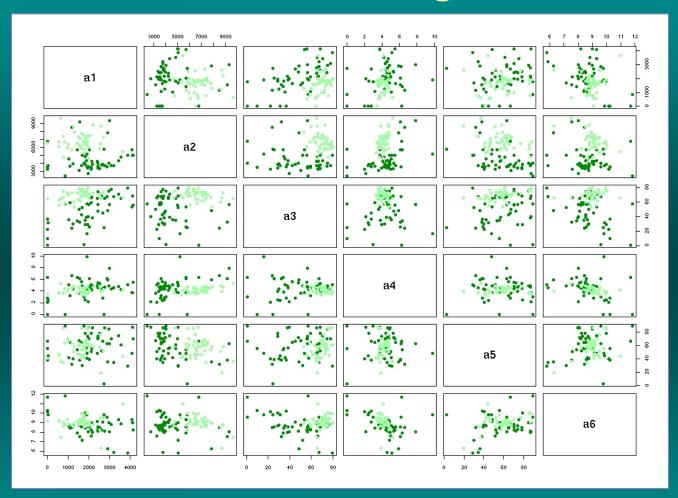
Blue: symmetric (Fourier-based) model; Red: double logistic Note fit, missing values

#### **Distribution of Coefficients Across Classes**



28

#### Clustering



Next step: compare clustering of original data w/coefs from functional model using modal clustering to deal with non-normal distributions

Ray, S. and Lindsay, B. G. (2008). Model selection in high dimensions: a quadratic-risk-based approach. *J. Roy. Statist. Soc. Ser. B*, 70(1):95–118. Ray, S. and Mallick, B. (2006). Functional clustering by Bayesian wavelet methods., *J. Roy. Statist. Soc.* Ser. B, 68(2):305–332.

## Conclusions: Technical

#### • Supervised Learning

- It's not just the learning algorithm.....
- Data and biases associated with training data are what count
  - Unbalanced training data
  - Feature selection
  - Active Sampling or identifying redundant training data
  - How to stabilize classification results across years
- Unsupervised
  - Linear vs non-linear methods; Gaussian vs non-Gaussian
  - Danger of fishing expeditions
    - Analyses need to be hypothesis driven
  - Toolkit feels less mature, esp for very large data sets.
    - Clustering, PCA, CCA, etc. (may reflect my ignorance)
    - Dimensionality, feature selection key challenges.

### **Conclusions: General**

- Data mining in Earth Sciences is hard
  - Looking for causal relations, not just patterns
  - Need teams to prevent natural scientists from doing naïve analysis and computational scientists from doing naïve science
  - NASA should be supporting this interests in missions and measurements in support of science
- Need to foster community
  - Funding?
  - Publishing:
    - Where to publish this work?
    - Is it technical or is it science?
  - Where to present? What meetings?