An argument for temporal segmentation of the Landsat archive

Robert E. Kennedy[1], Warren B. Cohen[2],

Zhiqiang Yang[1], Peder Nelson[1], Eric Pfaff[1]

[1] Department of Forest Ecosystems and Society, Oregon State University
[2] USDA Forest Service Pacific Northwest Research Station

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Premise

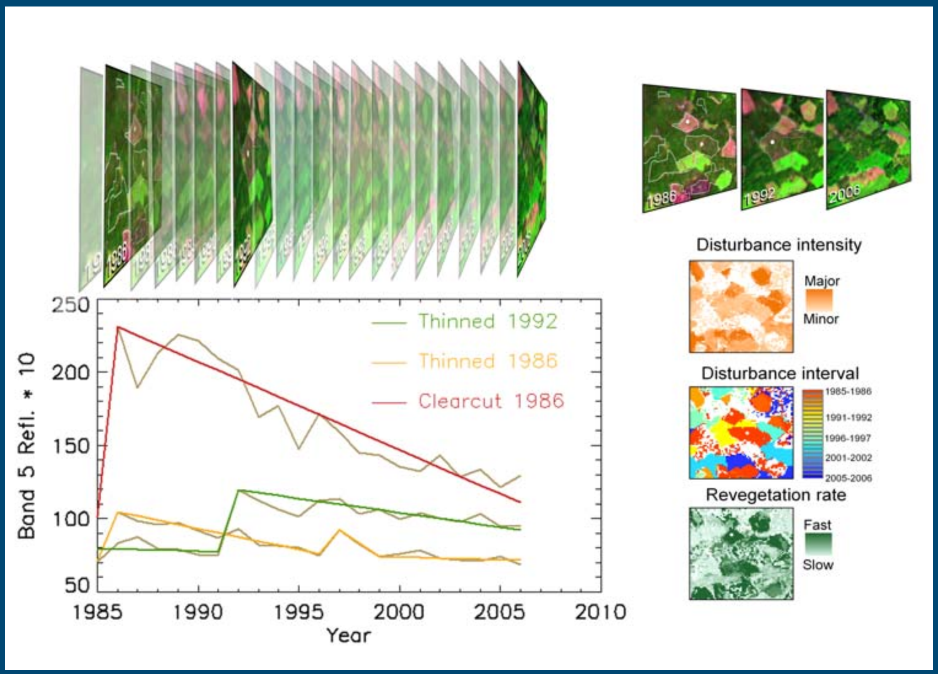
- History is strength
  - The Landsat archive begs for ***characterization of change***
  - Questions now on the table (vegetation-centric):
    - State change: urbanization, deforestation, land cover conversion
    - Condition change: drought effects, insects, loss of productivity, encroachment in novel ecosystems
  - ***Year-over-year change*** is Landsat's strength
- Consistency is crucial
  - Phenology, clouds, sun angle are noise in many research and application arenas
  - Labeling change over time requires a ***stable spectral space*** for every year in the archive

Consistency: How?

- Necessary but not sufficient
  - Georectification
  - Atmospheric correction
  - Cloud & shadow identification and masking
  - Mosaicking best-pixels
- Residual issues:
  - Sun-angle / BRDF
  - Seasonality / phenology
- Can they be modeled from first principles?
  - Yes? Maybe?
- Another approach: Temporal segmentation

LandTrendr: Landsat-based Detection of Trends in Disturbance and Recovery

- Goal: Segmentation to capture both <u>events</u> (abrupt) and <u>trends</u> (slow) in spectral trajectories of pixels



Prepare stack of yearly imagery

Statistically identify and fit segments with consistent trends

Segment rules

Temporal-smoothing

Maps of change

Spectrally stable stack

Evaluation

Any spectrally-based operation: Classification, modeling, etc.

Preparing stack: Pre-processing

- Geometric
  - Believe USGS
- Atmospheric
  - Current approach: COST, but any atmospheric correction base could be used
  - Relative normalization to a base is critical (MADCAL, Canty et al. approach)
- Cloud, shadow masking
  - Current approach: fairly dumb and labor intensive, but it works (uses cloud-free reference year and tasseled-cap differencing)
  - Any good approach could be used

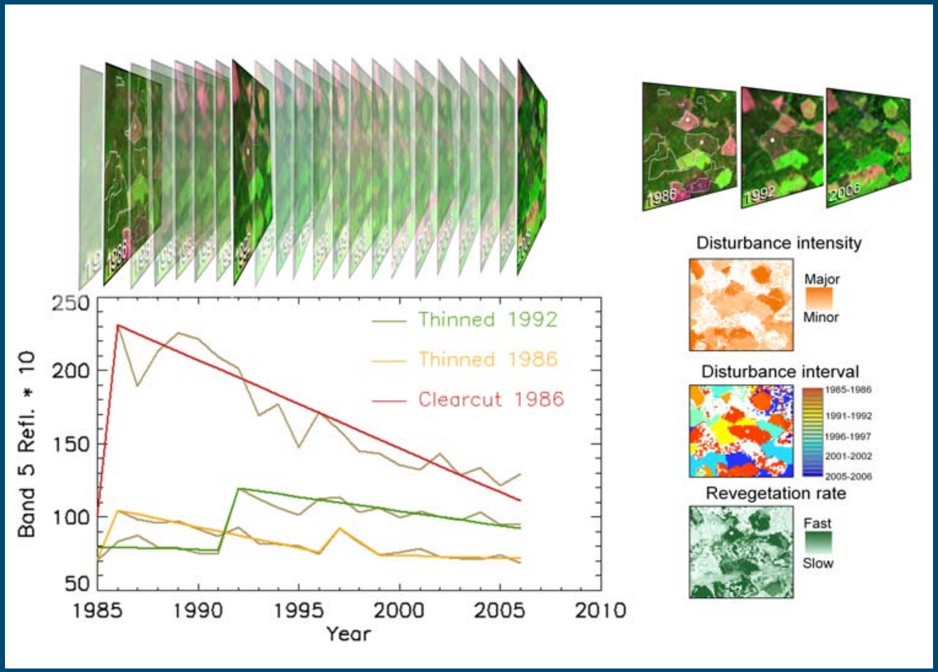
Preparing stacks: On-the-fly mosaicking

- Stacks constructed from any number of images per year
  - In Pacific Northwest, regularly using 30 to 60 images to create 22-24 years of usable image stacks
  - Images prioritized based on proximity to median julian data of whole stack
  - *Consistency of date (phenological state) trumps cloud-free imagery!*
    - "Give me three semi-cloudy images in July and August over one clean one in mid-September"
- SLC-off data?
  - Yes, give us as much as you want. We'll use every good pixel.

LandTrendr: Landsat-based Detection of Trends in Disturbance and Recovery

Prepare stack of yearly imagery

Statistically identify and fit segments with consistent trends



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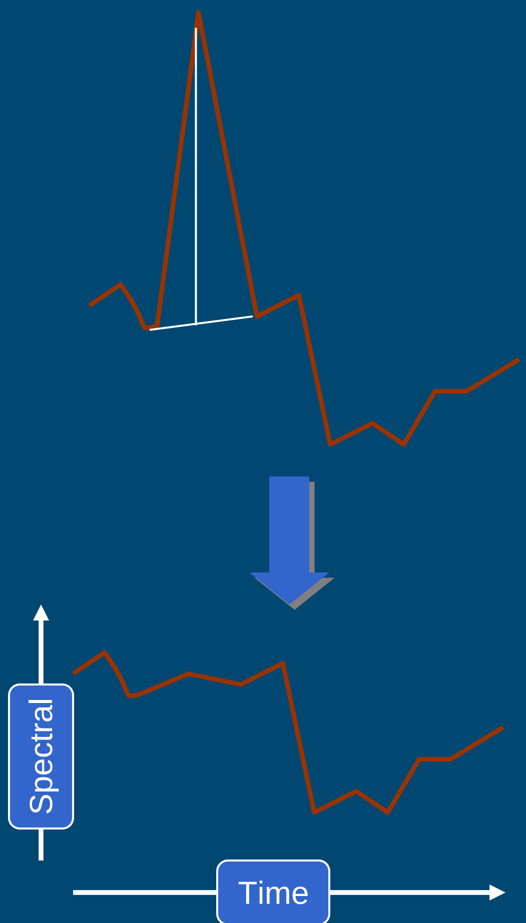
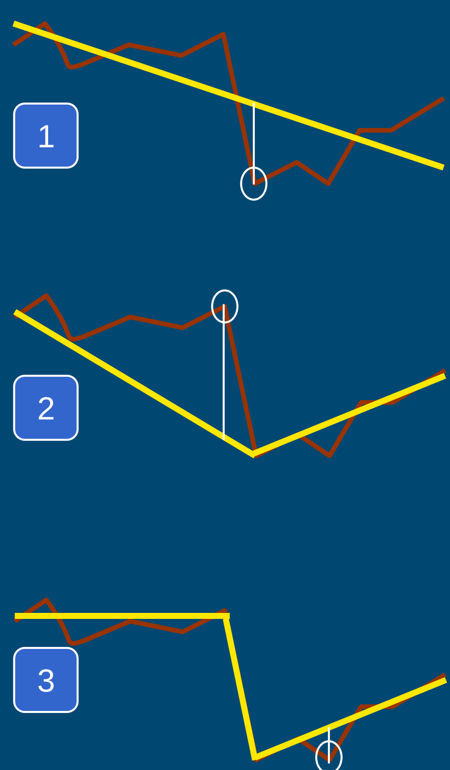
Any spectrally-based operation: Classification, modeling, etc.

Identifying segments: Vertices

Eliminate spikes

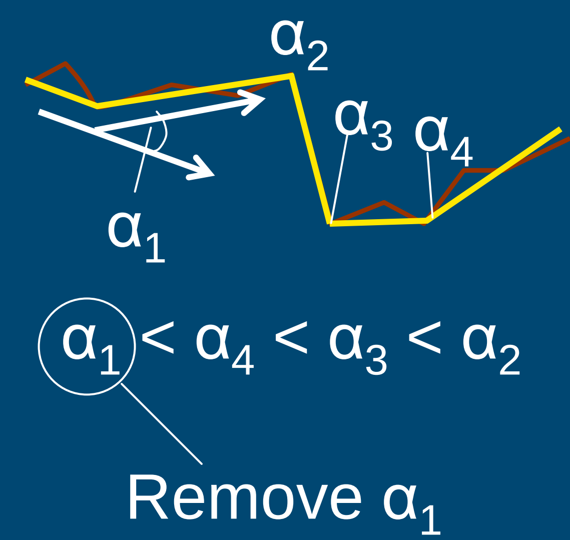


Identify potential vertices using regression deviation



Identify > *n*

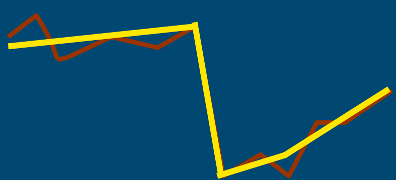
Re-sort and cull back to *n* based on angle



Result: Vertices defining maximum desired number of segments

Identifying segments: Iterative fitting

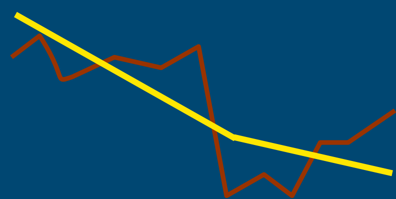
Identify best path through all vertices using combination of regression or vertex-to-vertex connection

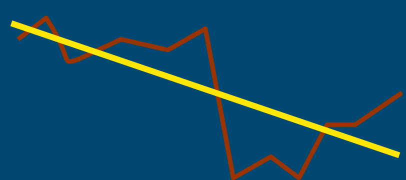


Notes:

1. Regression works from left to right
2. Initial regression may be "free"
3. If left-to-right not effective, a second pass using full floating vertices is used

Iteratively cull vertices using segment-wise MSE





Calculate *p* of *f*-statistic (accounts for degrees of freedom but not temporal autocorrelation)

Pick best model using either lowest *p*-val, or allow more complex models win if nearly as good

Results:

Vertices (x and y)

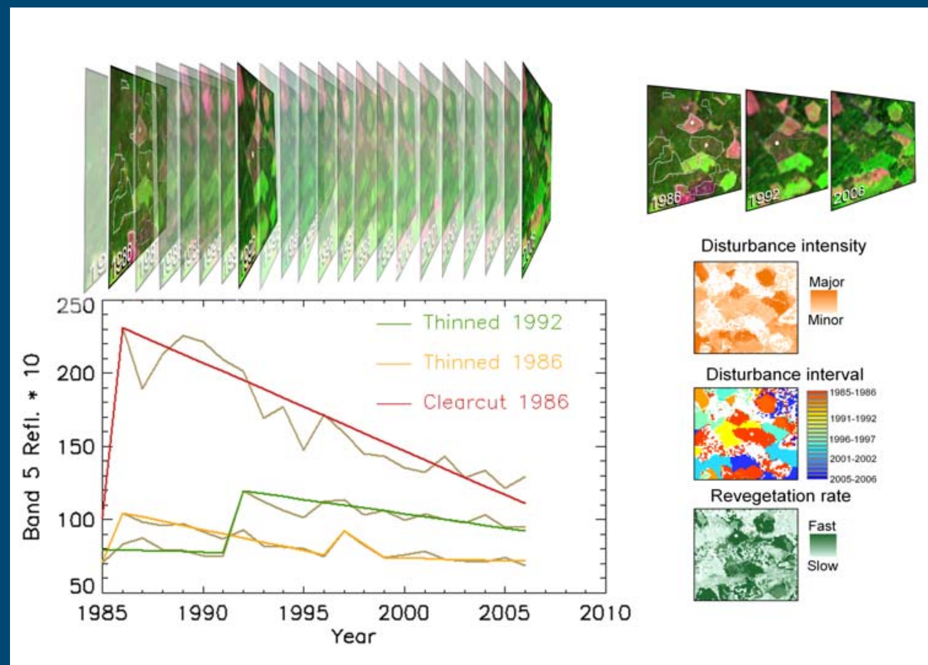
Fitted values of original index

Summary fitting statistics

Segment-based mapping

Prepare stack of yearly imagery

Statistically identify and fit segments with consistent trends



Any spectrally-based operation: Classification, modeling, etc.

Evaluation

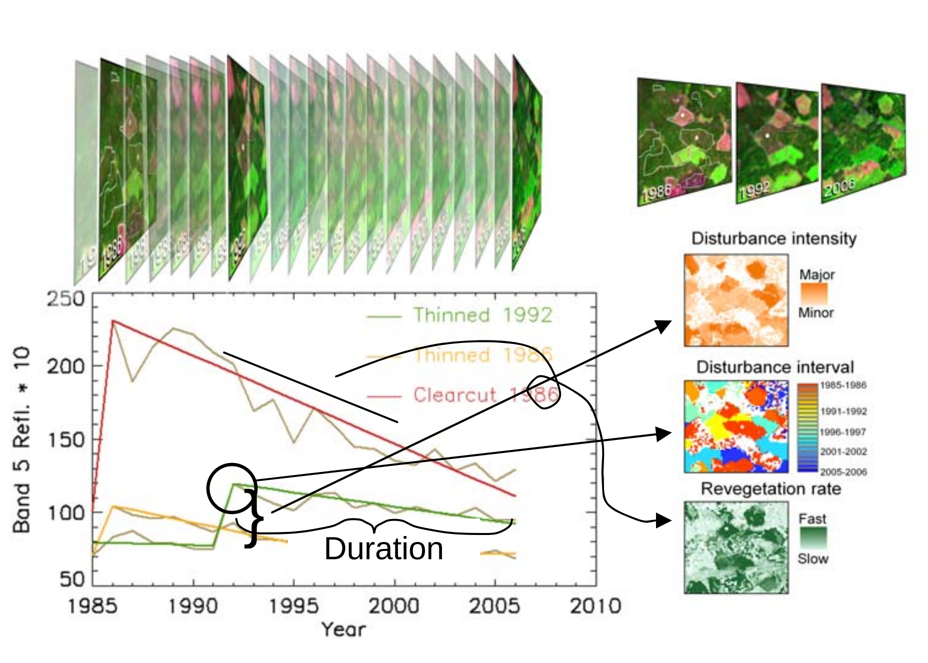
Segment rules

Temporal-smoothing

Maps of change

Spectrally stable stack

Segment rules



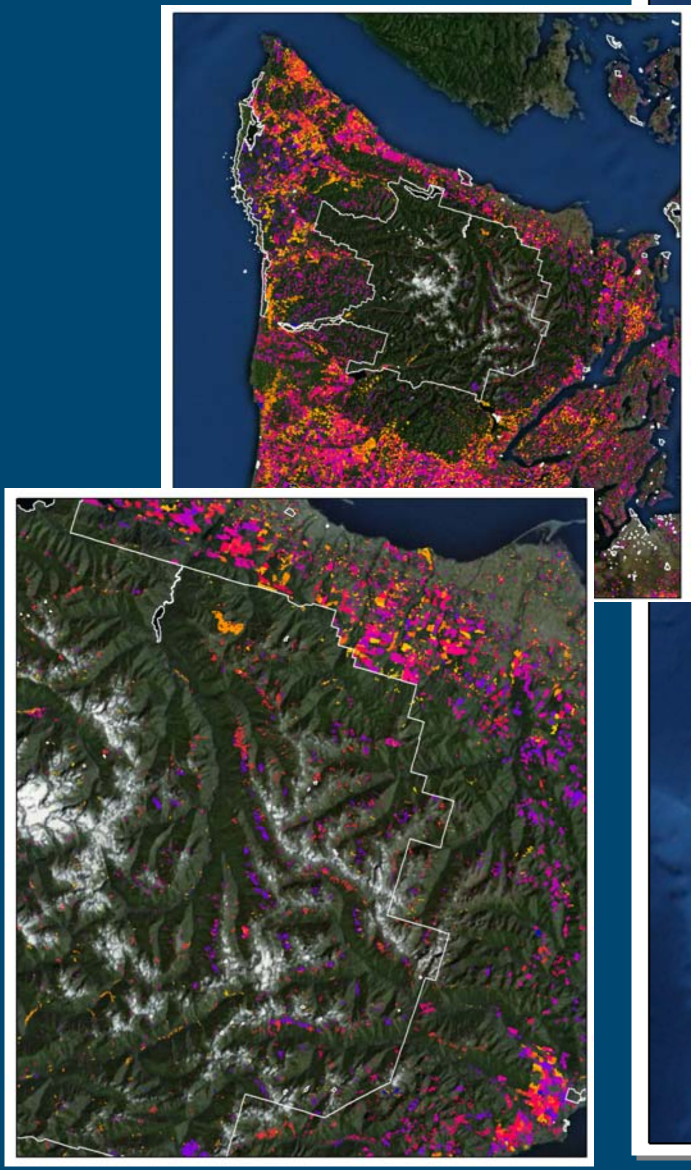
Mapping

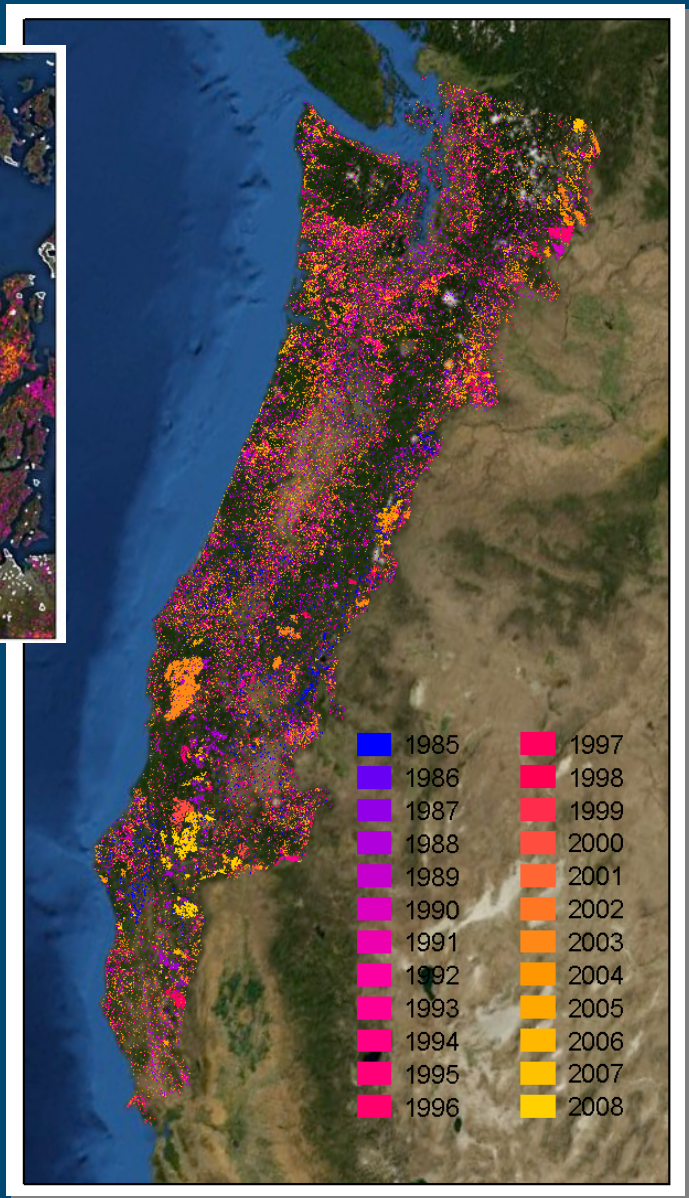
Segment-based: Onset, duration, slope, magnitude of single segments

Sequence-based: Pattern of progression of individual segments

Slice-based: Snapshots of year-over-year change

Segment-based mapping: Onset

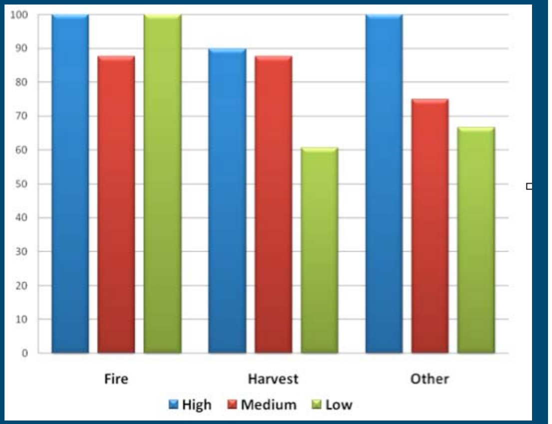




Project: Region 6 Effectiveness Monitoring Program for the Northwest Forest Plan (NWFP)

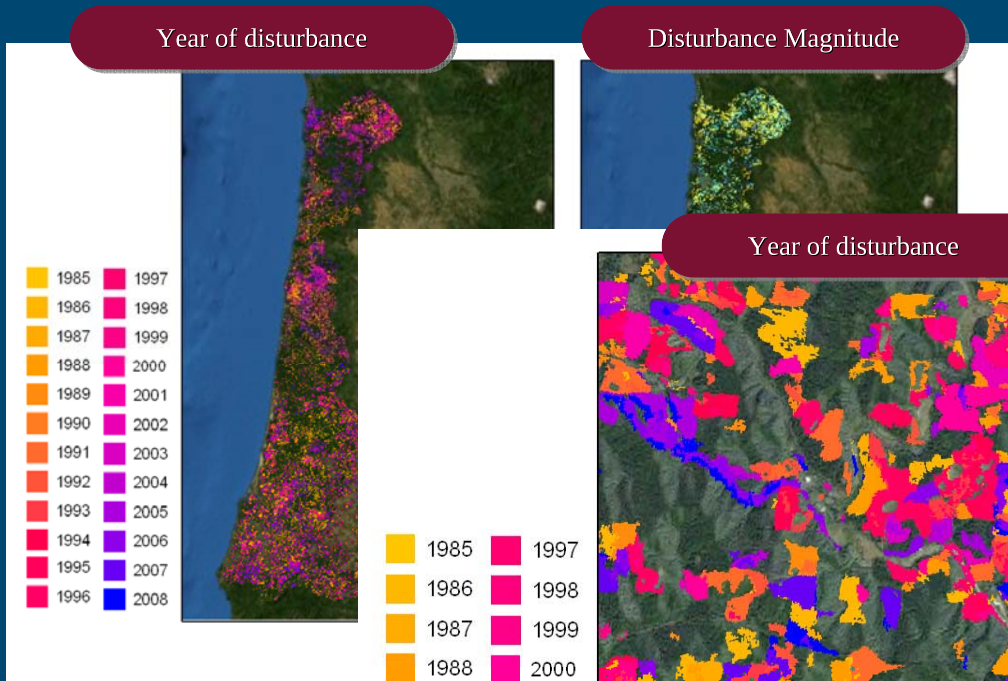
Data: > 500 individual Landsat scenes

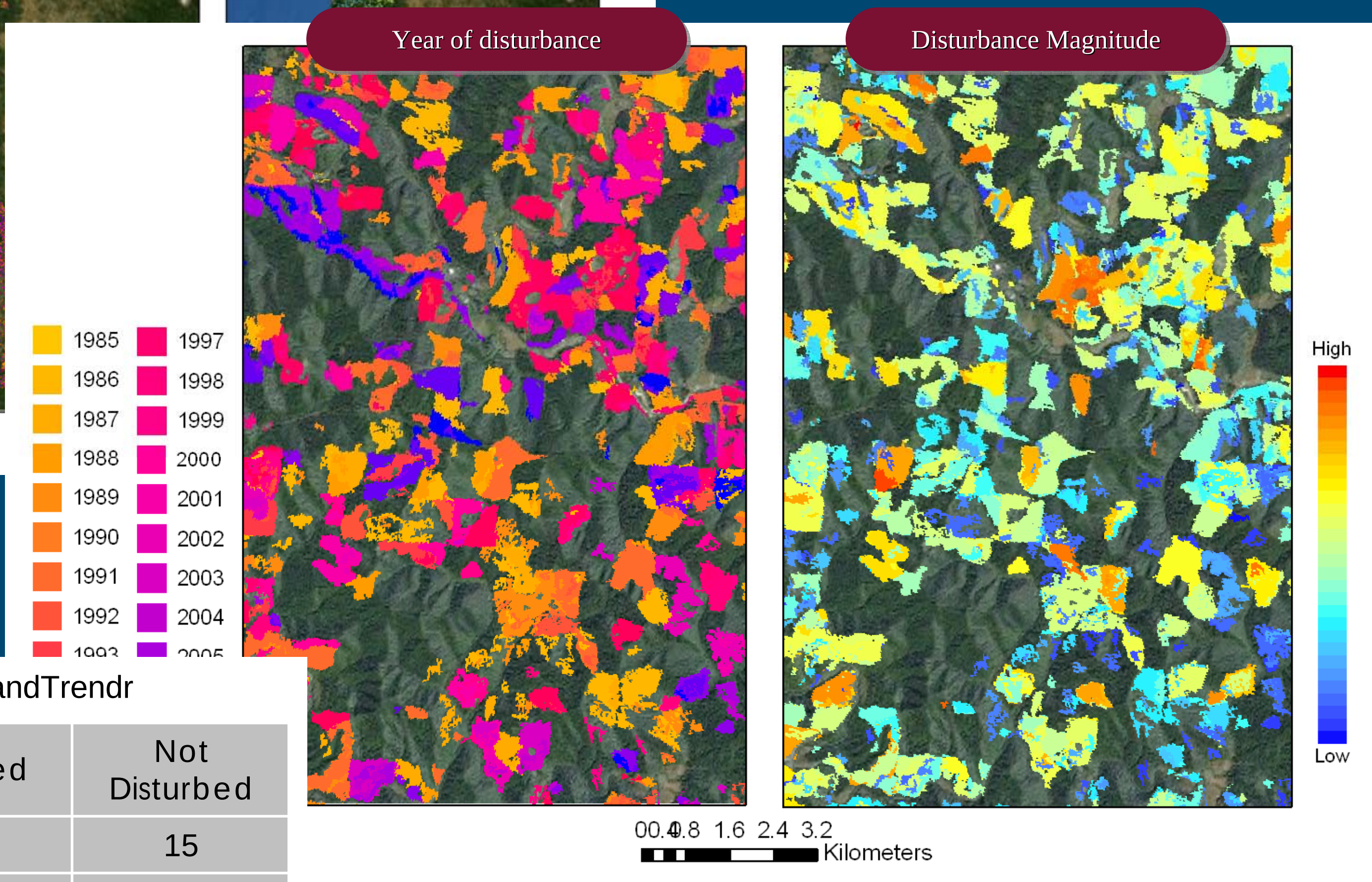
TimeSync Interpretation ongoing



Segment-based: Onset and Magnitude

Project: Quantify trends in harvest within Coastal Coho ecologically-significant unit

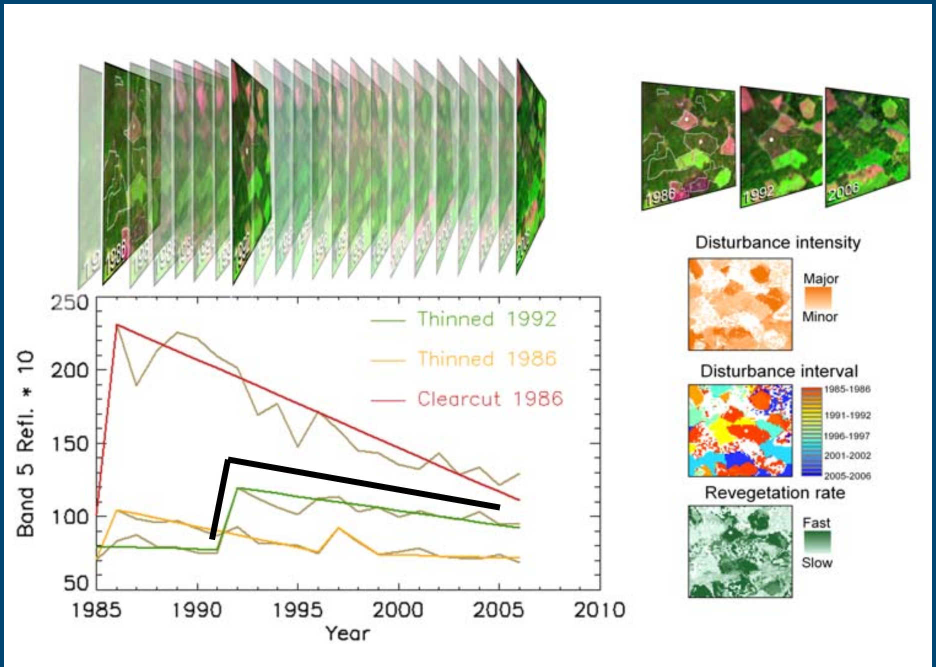




LandTrendr

TimeSync	Disturbed	Not Disturbed
Disturbed	89	15
Not Disturbed	13	157

Sequence-based mapping



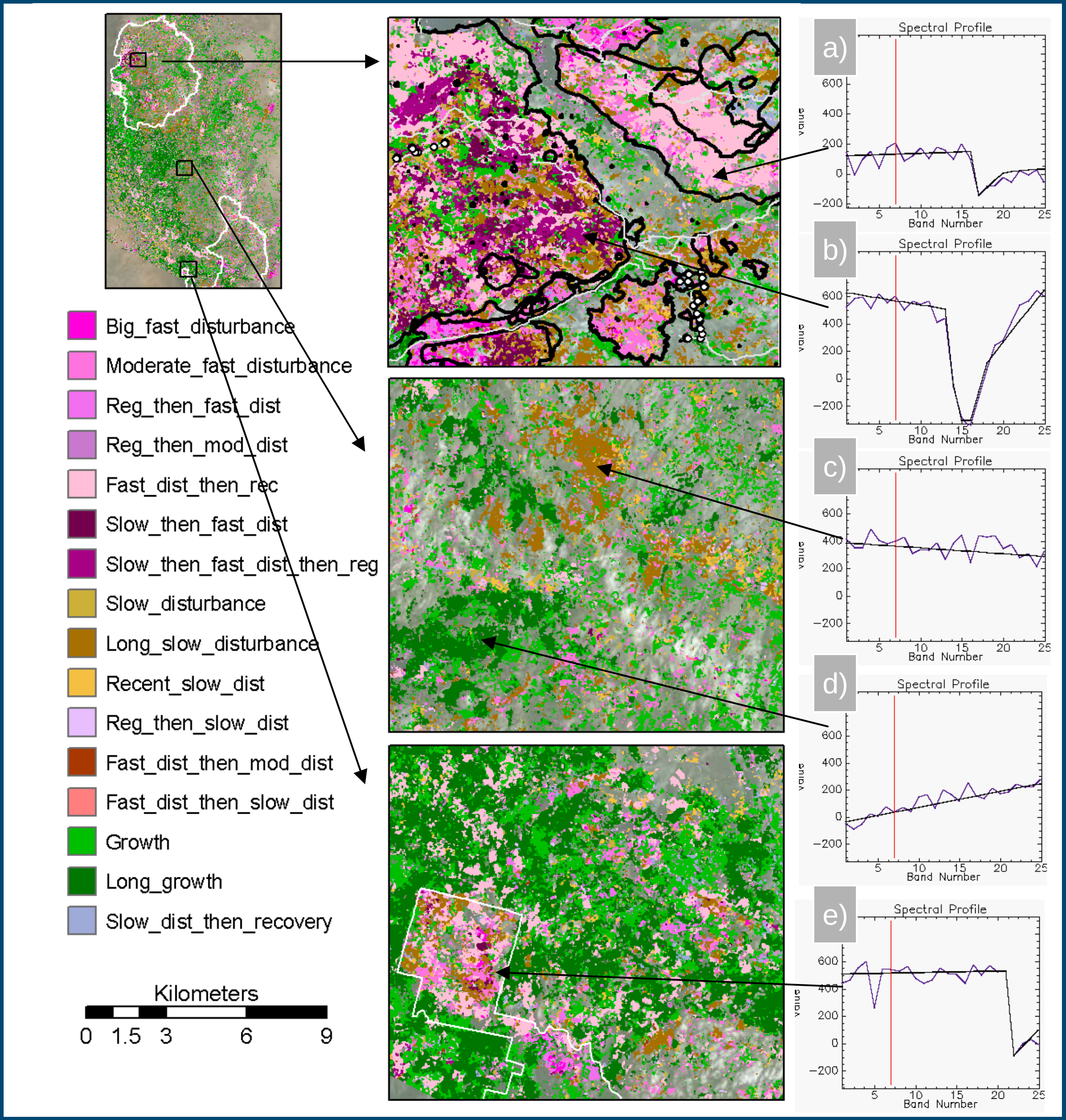
Mapping

Segment-based: Onset, duration, slope, magnitude of single segments

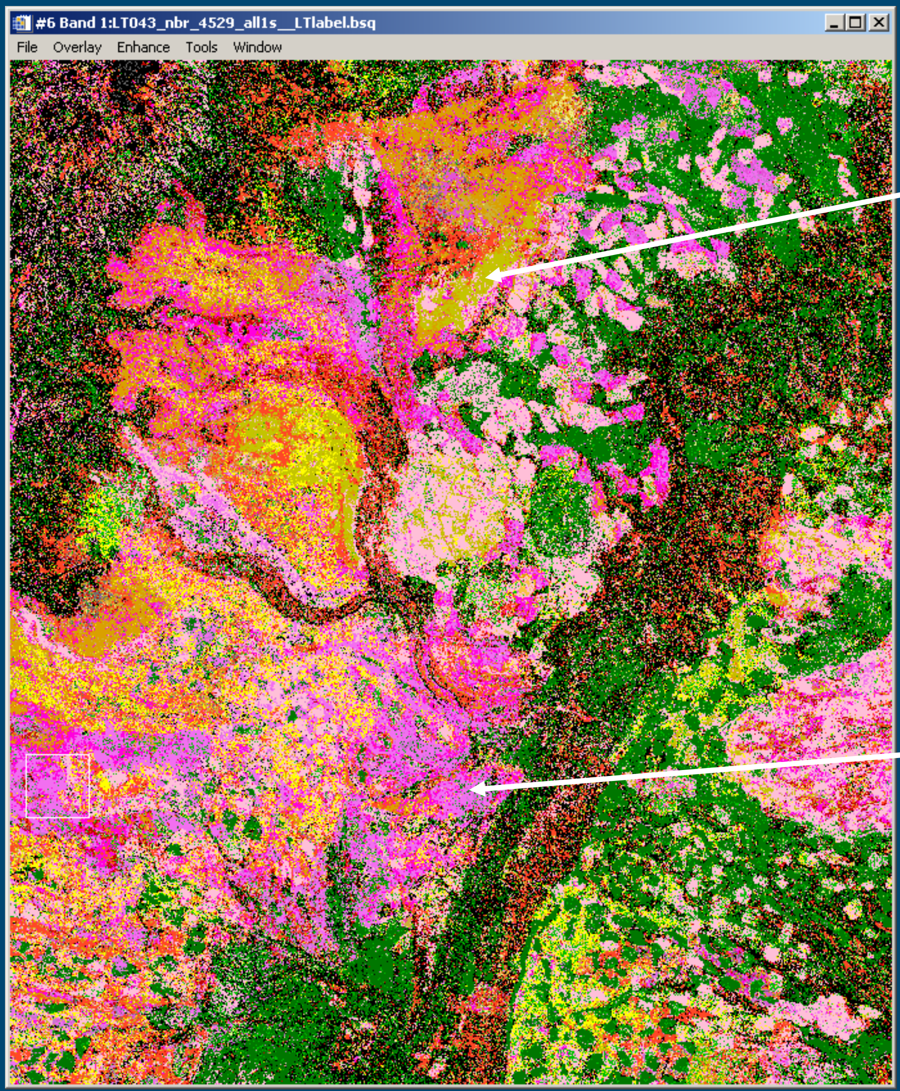
Sequence-based: Pattern of progression of individual segments

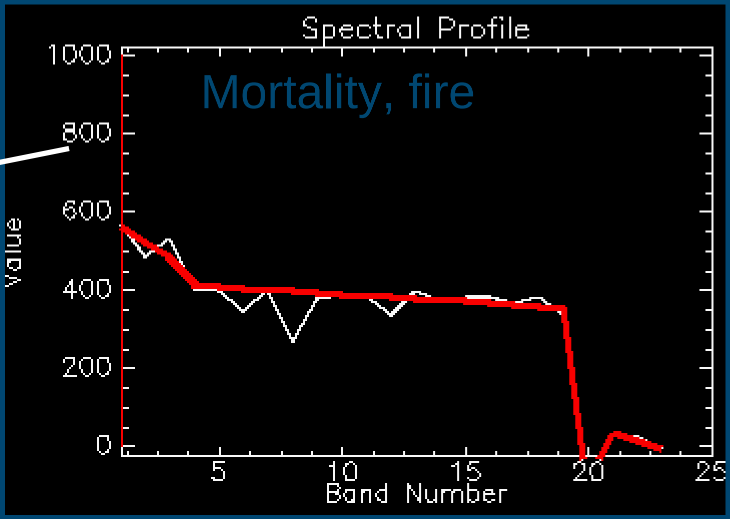
Slice-based: Snapshots of year-over-year change

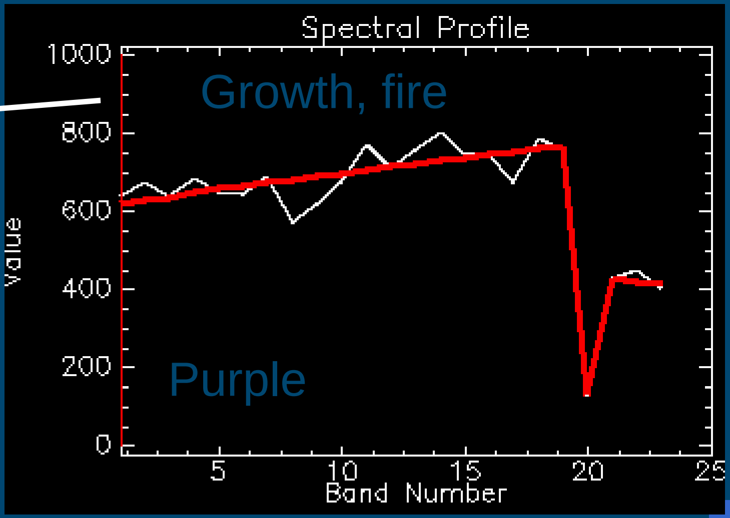
Sequence-based labels



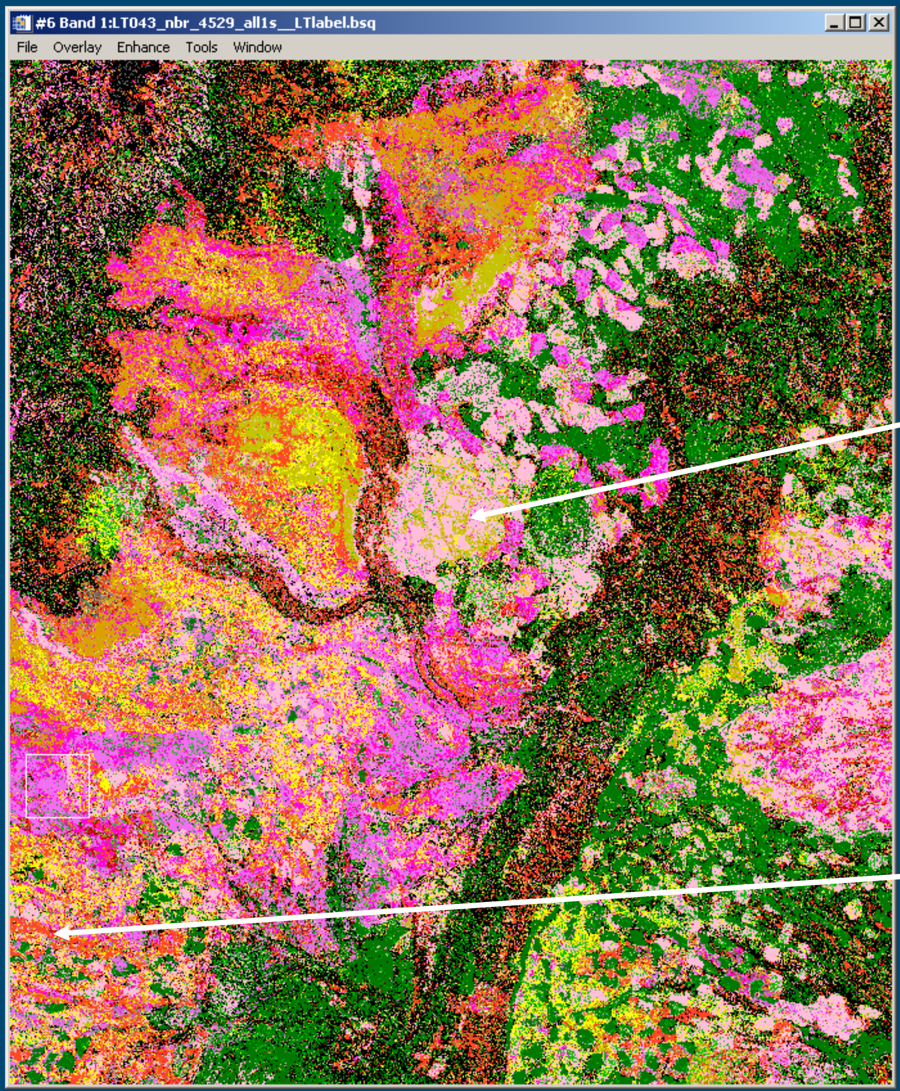
Pre-fire, fire

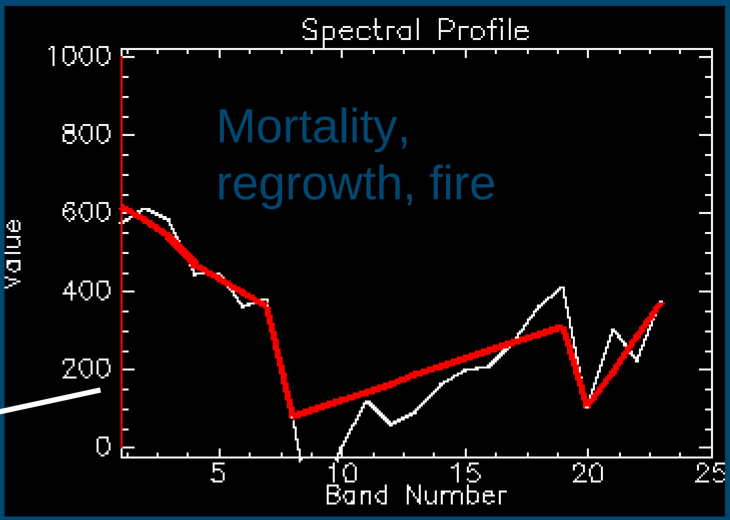


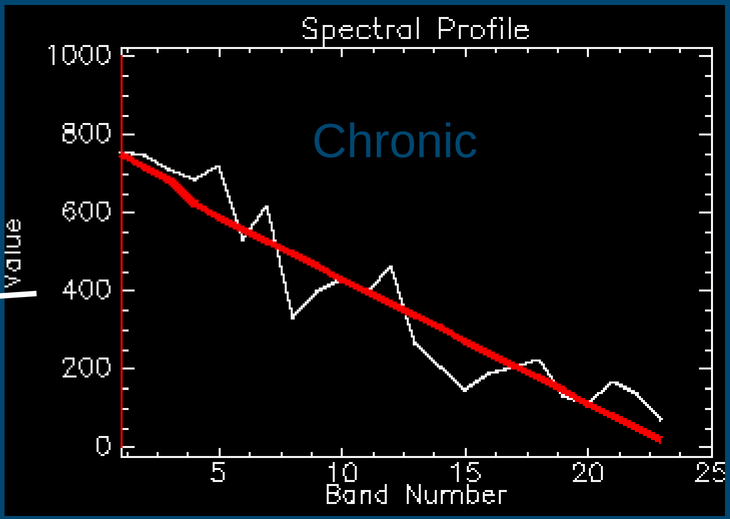




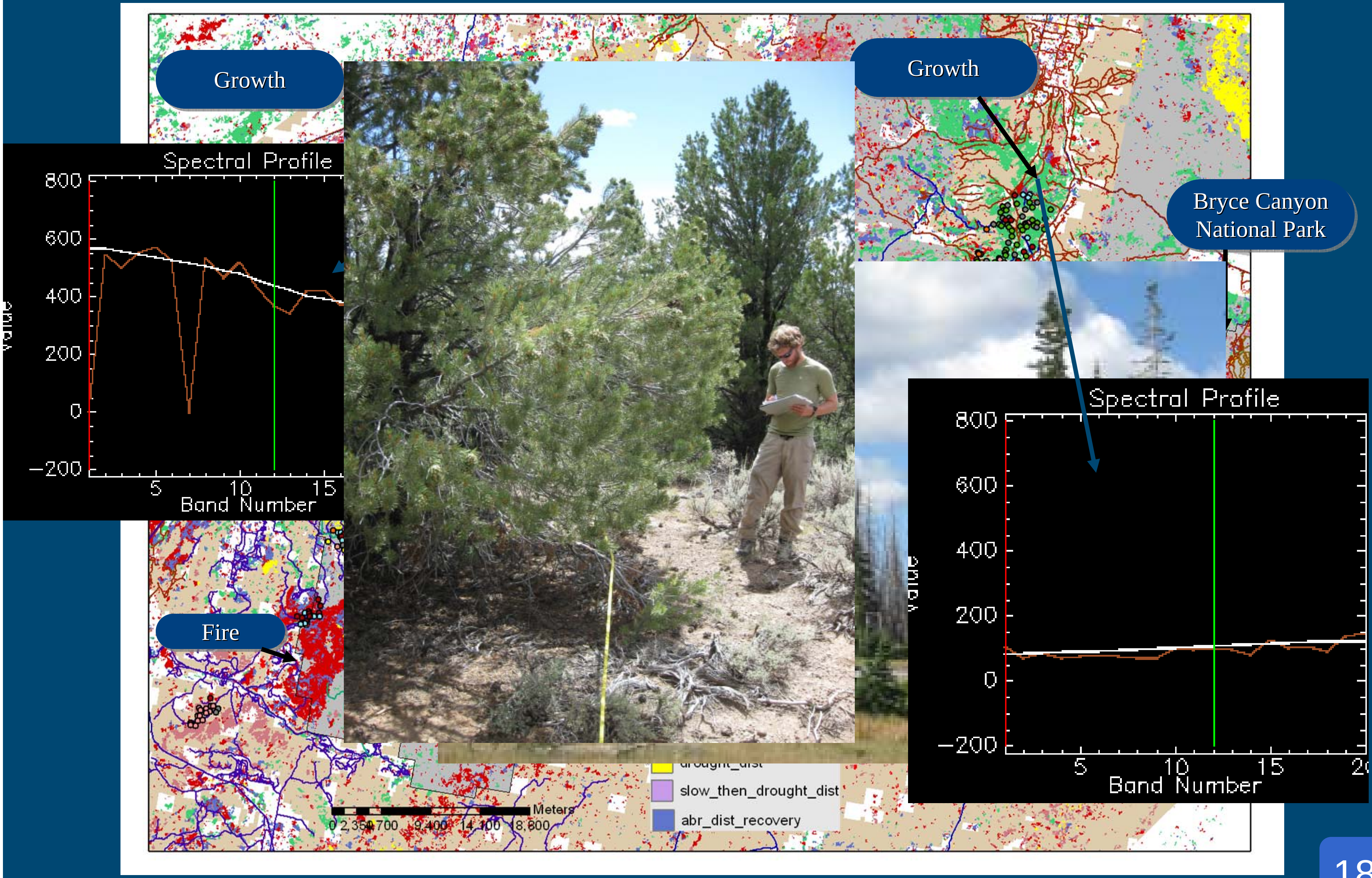
Pre-fire, fire



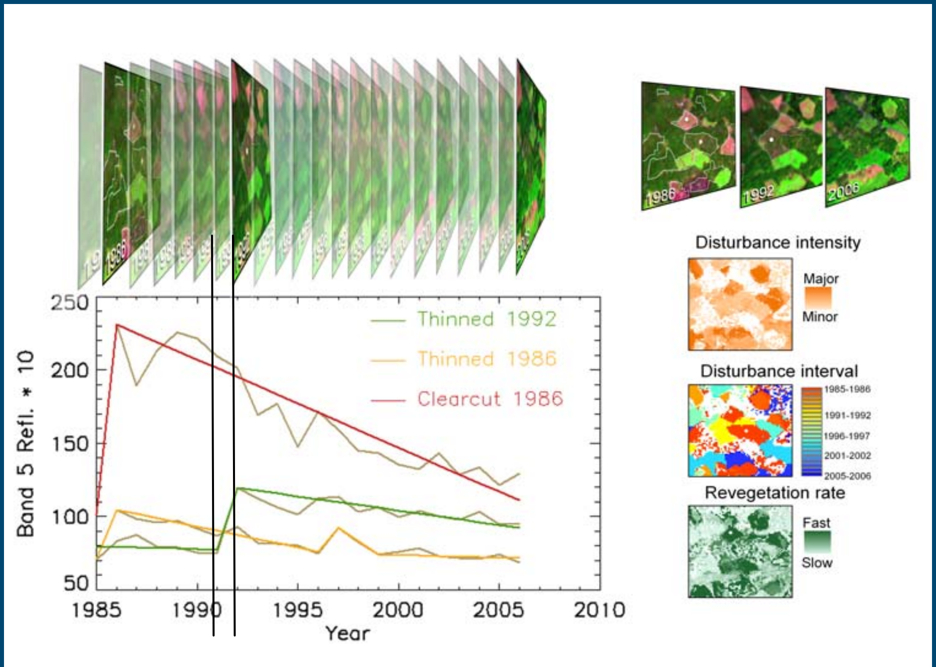




Landscape dynamics: Temporal signals



Slice-based mapping



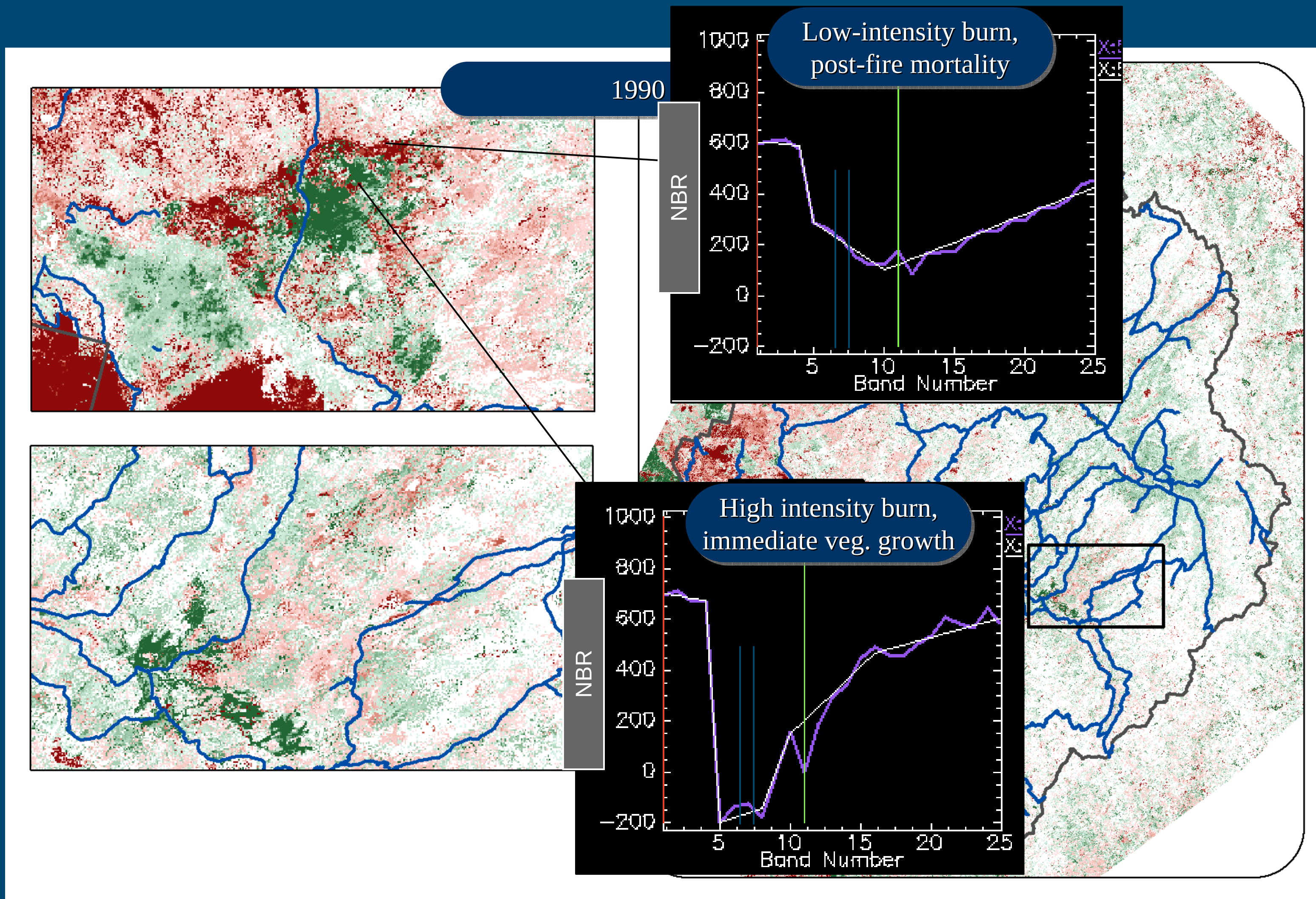
Mapping

Segment-based: Onset, duration, slope, magnitude of single segments

Sequence-based: Pattern of progression of individual segments

Slice-based: Snapshots of year-over-year change

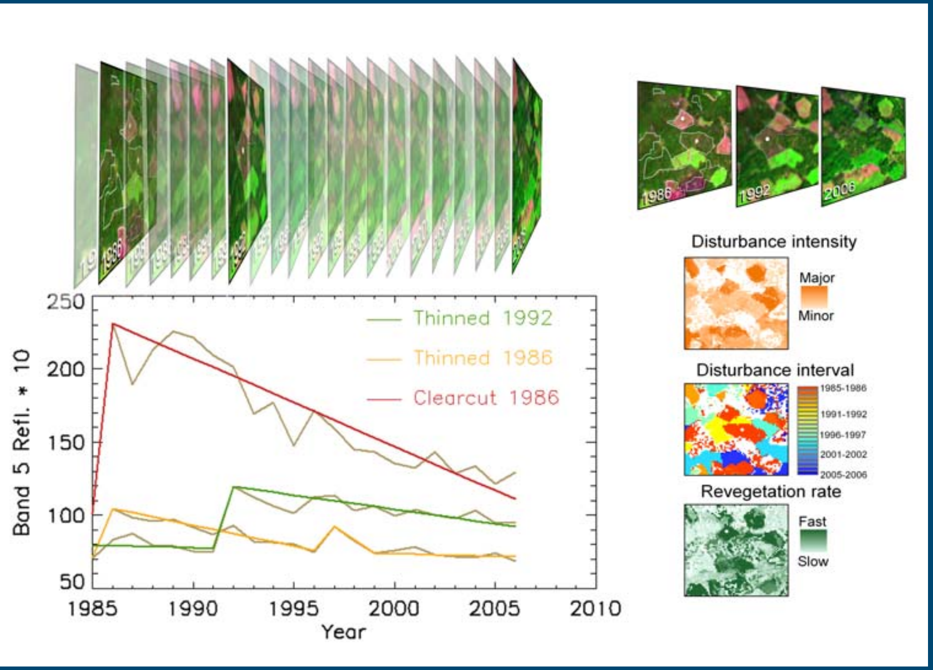
Slice-based mapping: Disturbance & growth



Temporal smoothing

Prepare stack of yearly imagery

Statistically identify and fit segments with consistent trends



Segment rules

Temporal-smoothing

Maps of change

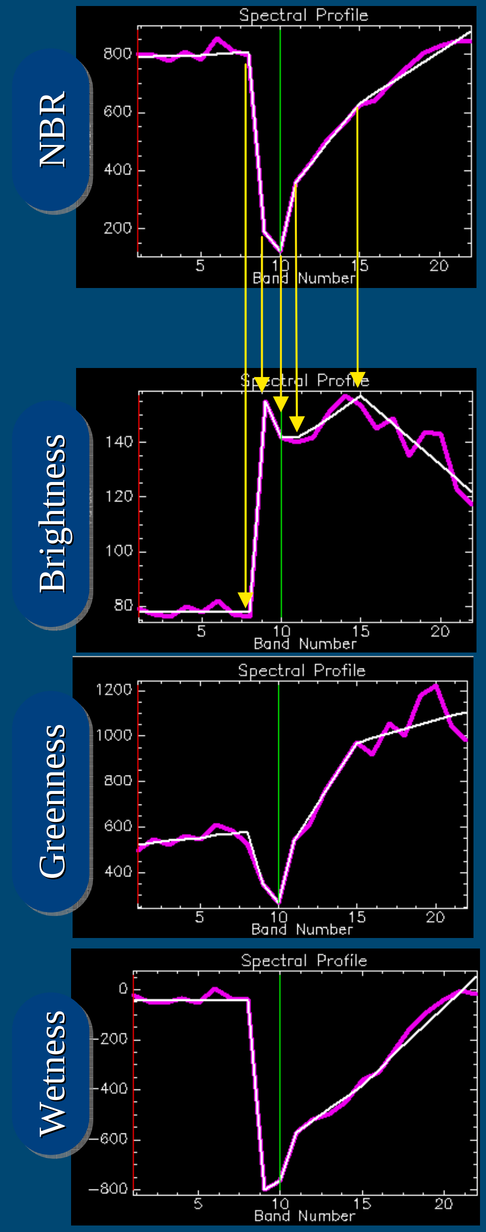
Spectrally stable stack

Any spectrally-based operation: Classification, modeling, etc.

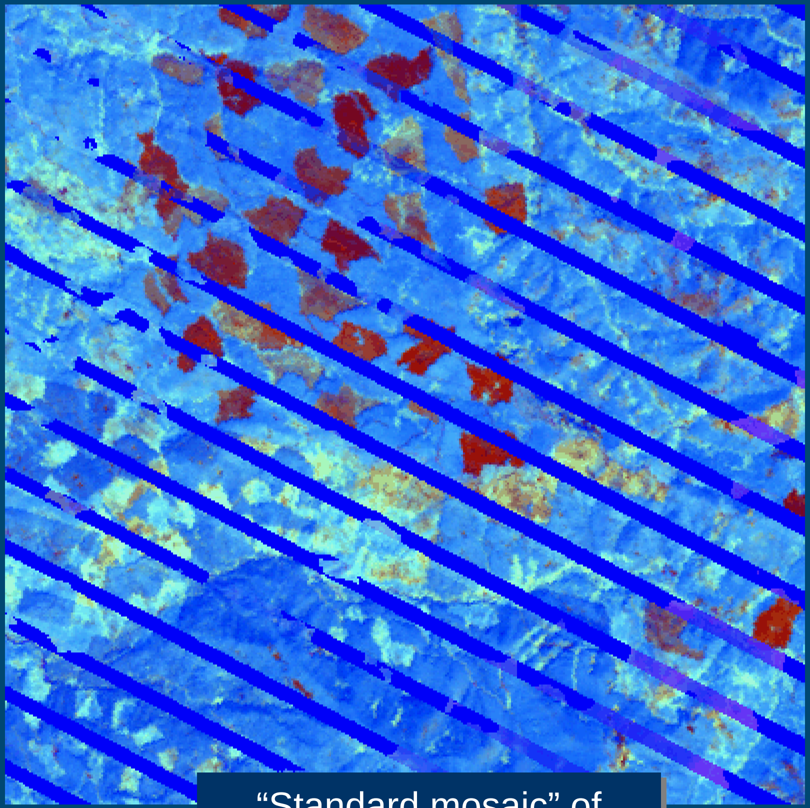
Evaluation

LandTrendr: Temporal fitting

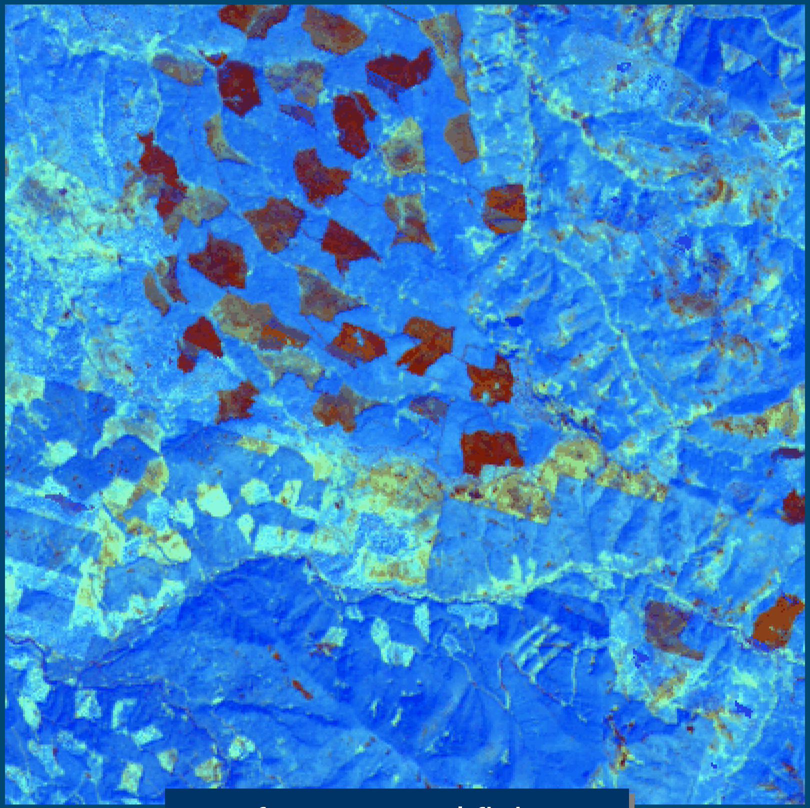
- Use segmentation of one band to identify "vertices" in time series
- Smooth between vertices in other bands
- Result: "Pseudo-images" with year-to-year noise removed, but actual change retained



Temporally-fit imagery

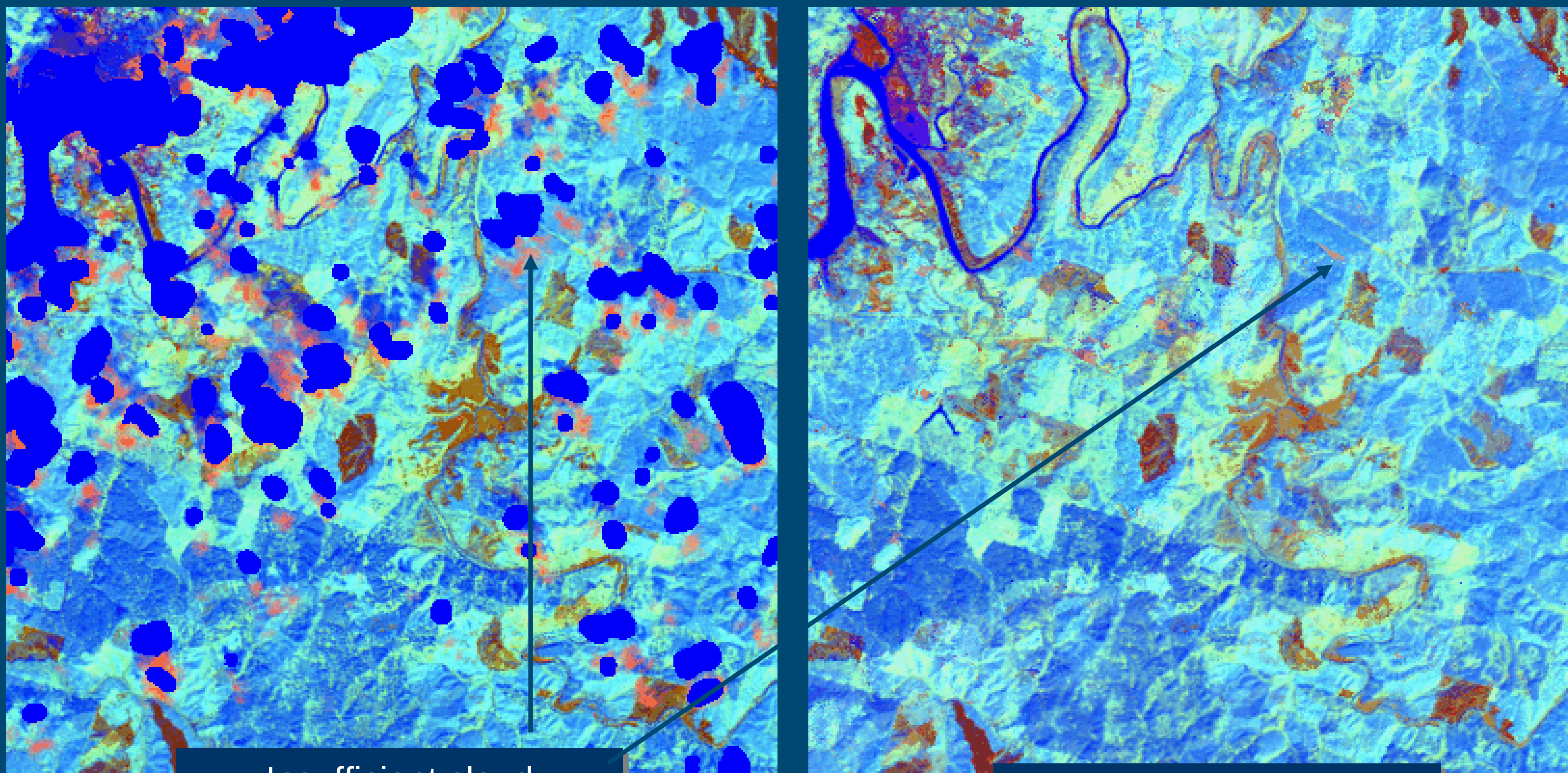


"Standard mosaic" of images within one year



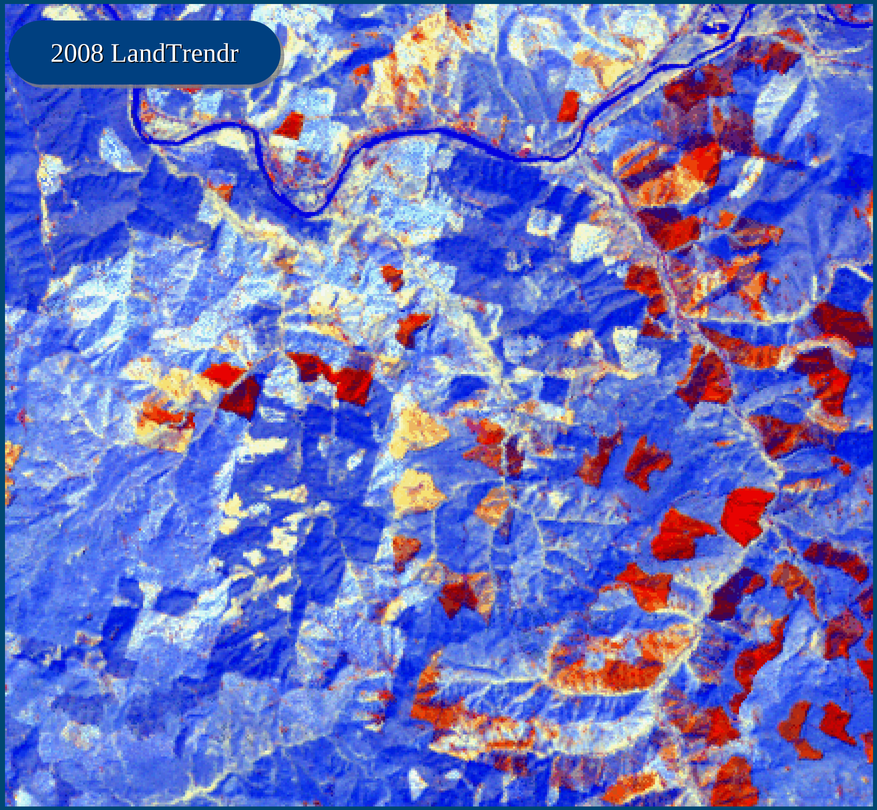
After temporal fitting

Temporal fitting

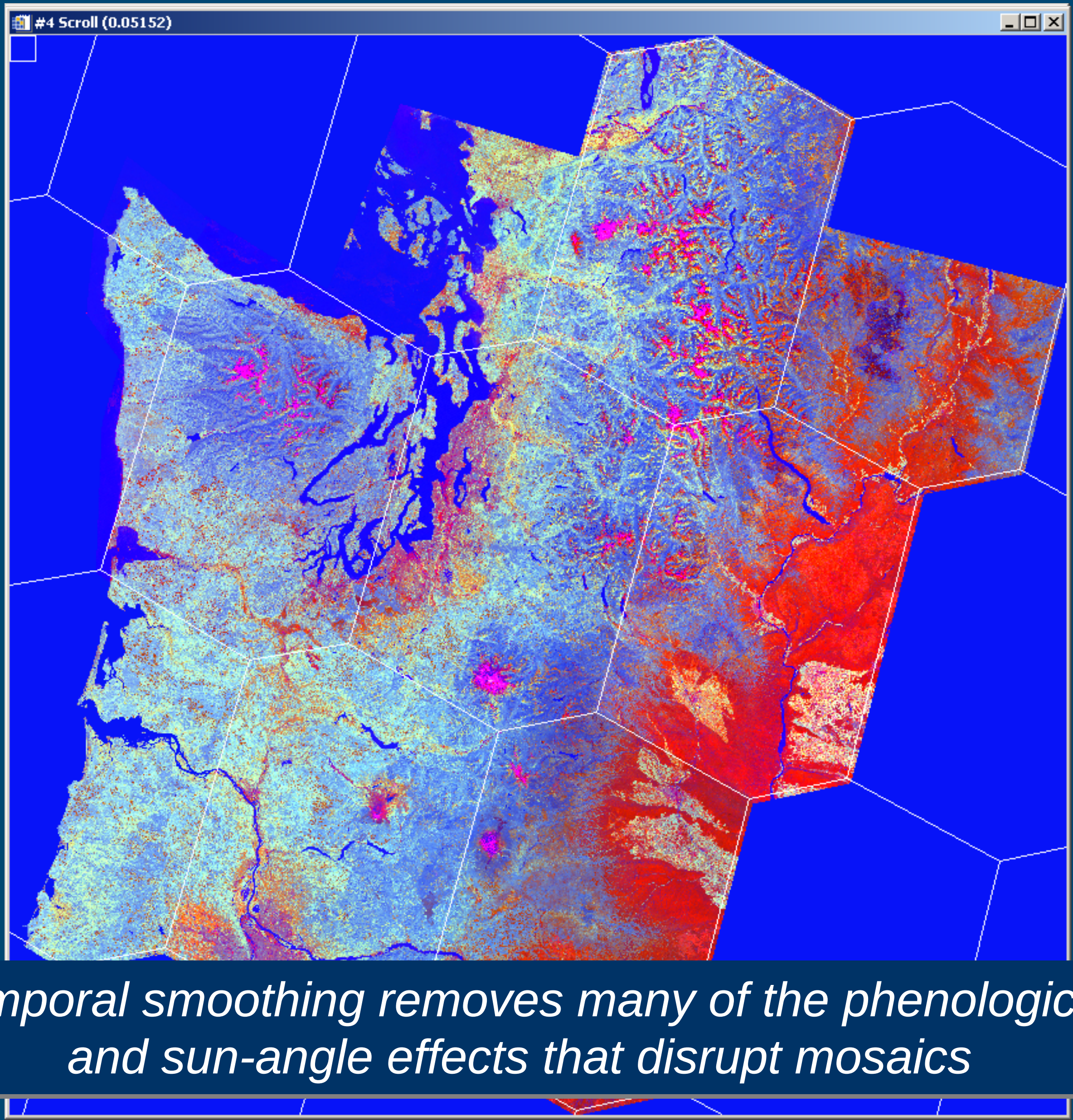


Cloud screening (especially cirrus clouds) is critical!

LandTrendr: Temporal fitting



Bonus: Mosaicking

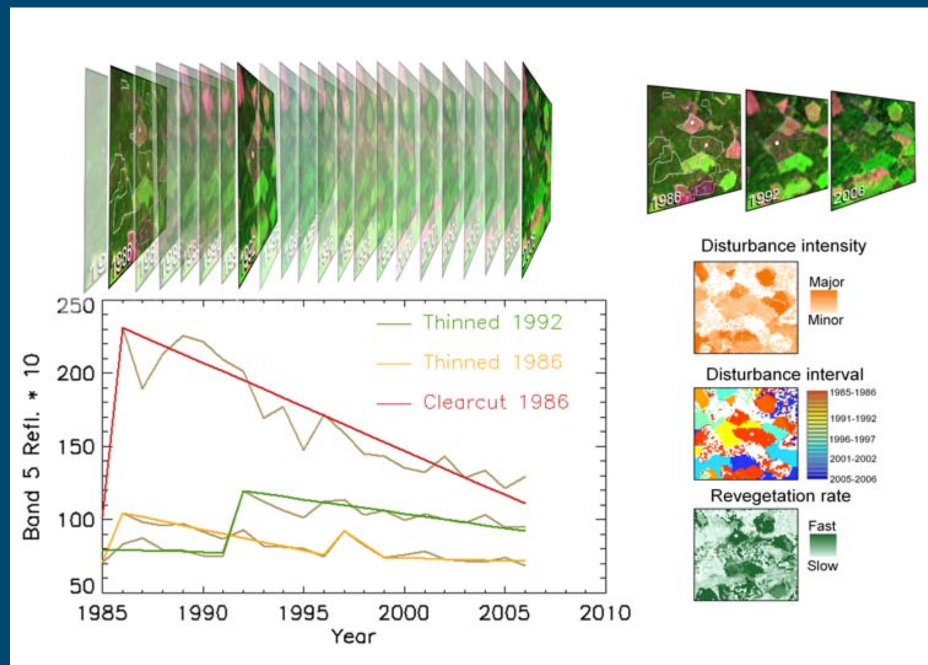


Temporal smoothing removes many of the phenological and sun-angle effects that disrupt mosaics

Temporal smoothing

Prepare stack of yearly imagery

Statistically identify and fit segments with consistent trends



Any spectrally-based operation: Classification, modeling, etc.

Evaluation

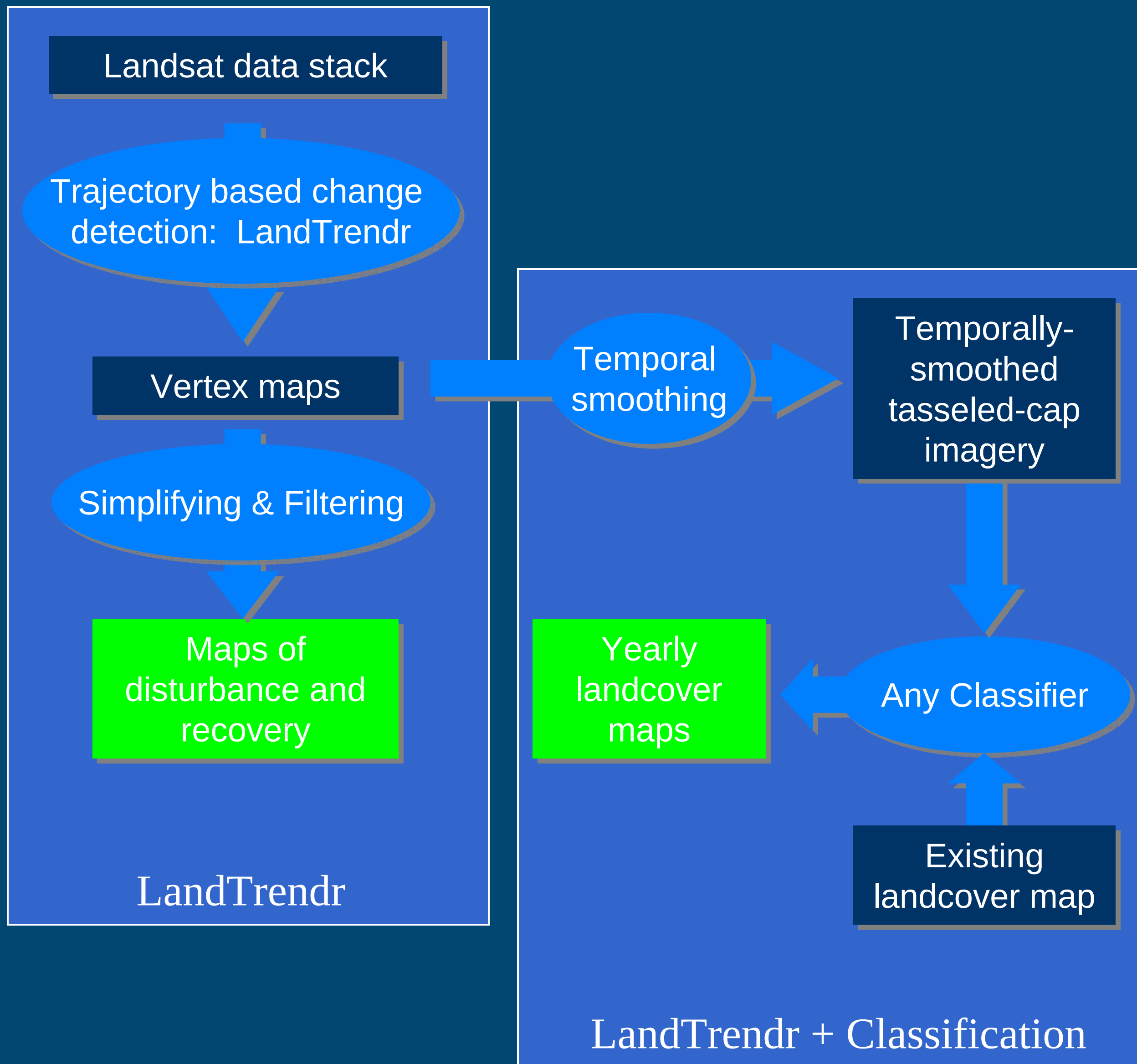
Segment rules

Temporal-smoothing

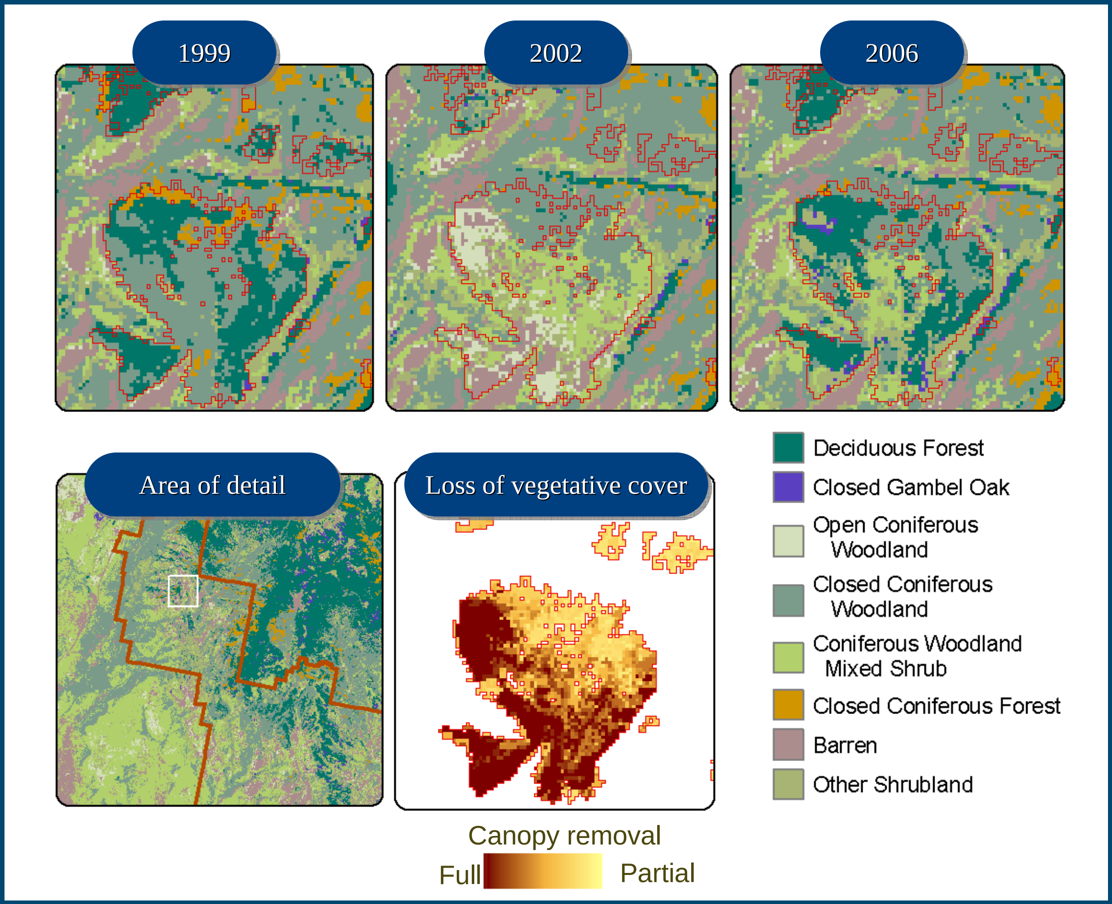
Maps of change

Spectrally stable stack

LandTrendr + Classification



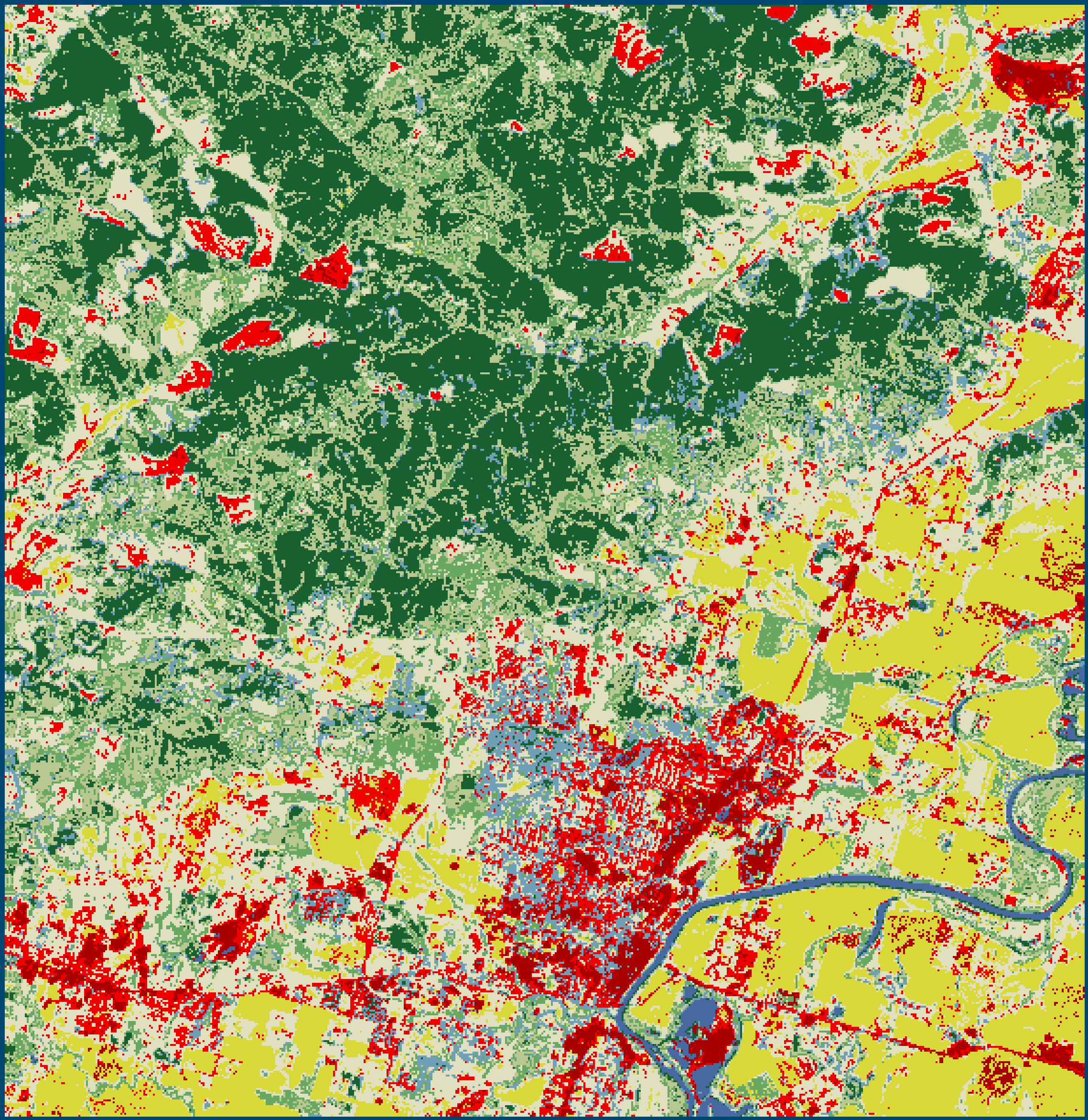
Yearly classification: Fire effects



Track fire effects using class labels familiar to users

Example: Application to NLCD mapping

1984
1986
1987
1988
1989
1991
1992
1993
1994
1995
1996
1997
1998
1999
2000
2001
2002
2003



2008
2007
2006
2005
2004

Summary: Opportunities

- Segmentation of spectral trajectory allows for a variety of temporal descriptors
  - “Standard” disturbance year, magnitude
  - Subtle trends
  - Sequences of segments
  - Slice-based snapshots
- It also allows for construction of clean pseudo-images that users from which users can derive their own products
  - Mosaics
  - Yearly-classifications

Summary: Challenges

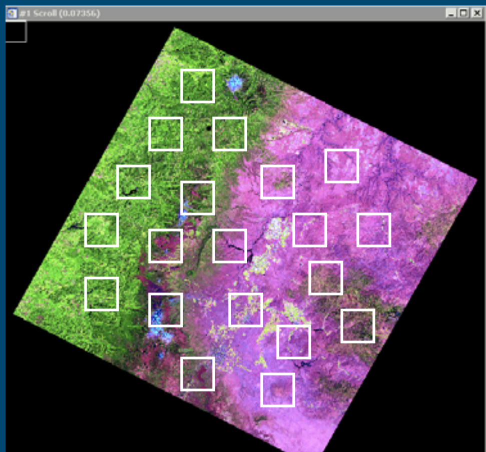
- Cloud-screening is critical
- Dense image stacks are necessary
- Year-to-year variation may be informative (rather than noise) for some applications
- Highly dependent on change detection using single spectral index
  - If we miss it, the index doesn't detect it, or we mess it up in some other way, it affects all products downstream
- Not tested in some highly-dynamic systems
- Computationally and operationally demanding
- Likely will require use of different spectral indices, parameter sets for non-woody systems

Thank you

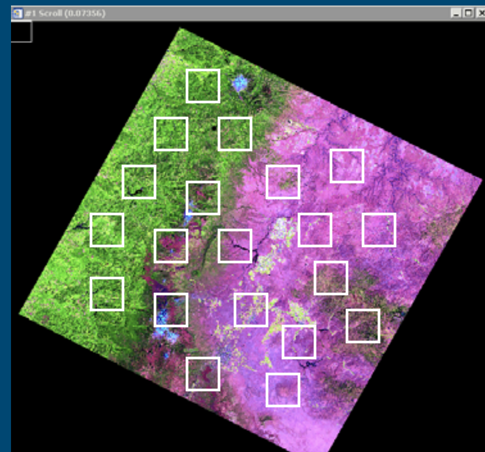
Funding:
NASA New Investigator Program
NASA Terrestrial Ecology Program
USDA Forest Service
National Park Service
National Marine Fisheries Service

Extras

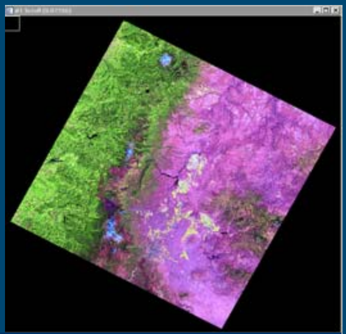
MADCAL Example



COST-Corrected Radiometric Reference



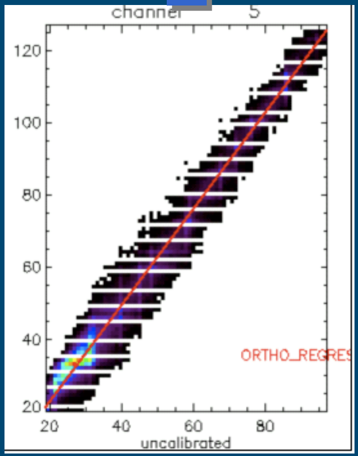
Target image



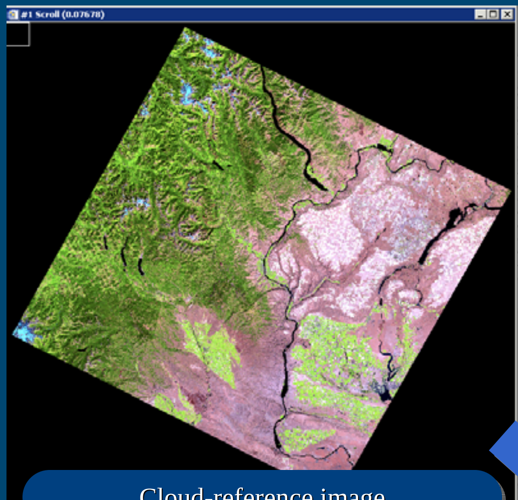
Apply to target image to create normalized image

Multivariate Alteration Detection (MAD) Calibraiton (CAL) to identify “no-change” pixels

Orthoregression of target vs. reference

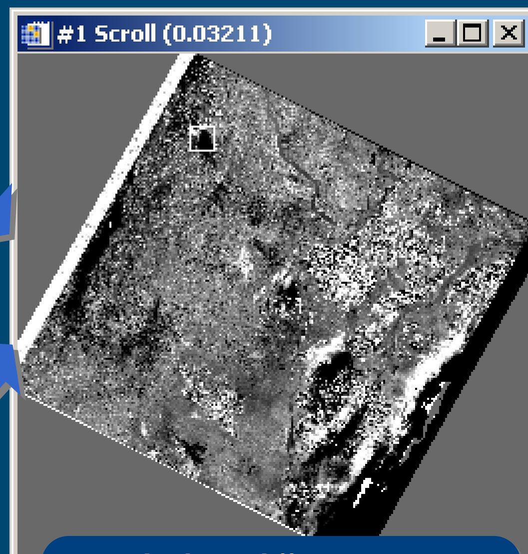


Cloud-masking: Example



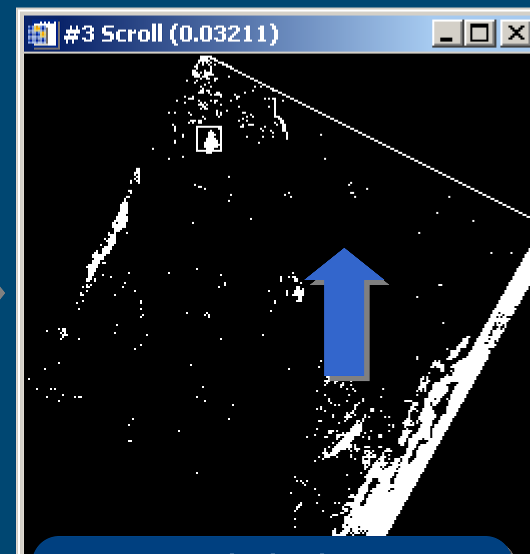
Cloud-reference image

Target image



Cloudscore difference image

Use Thermal and SWIR bands



Cloudmask

Spatial buffering included in mask

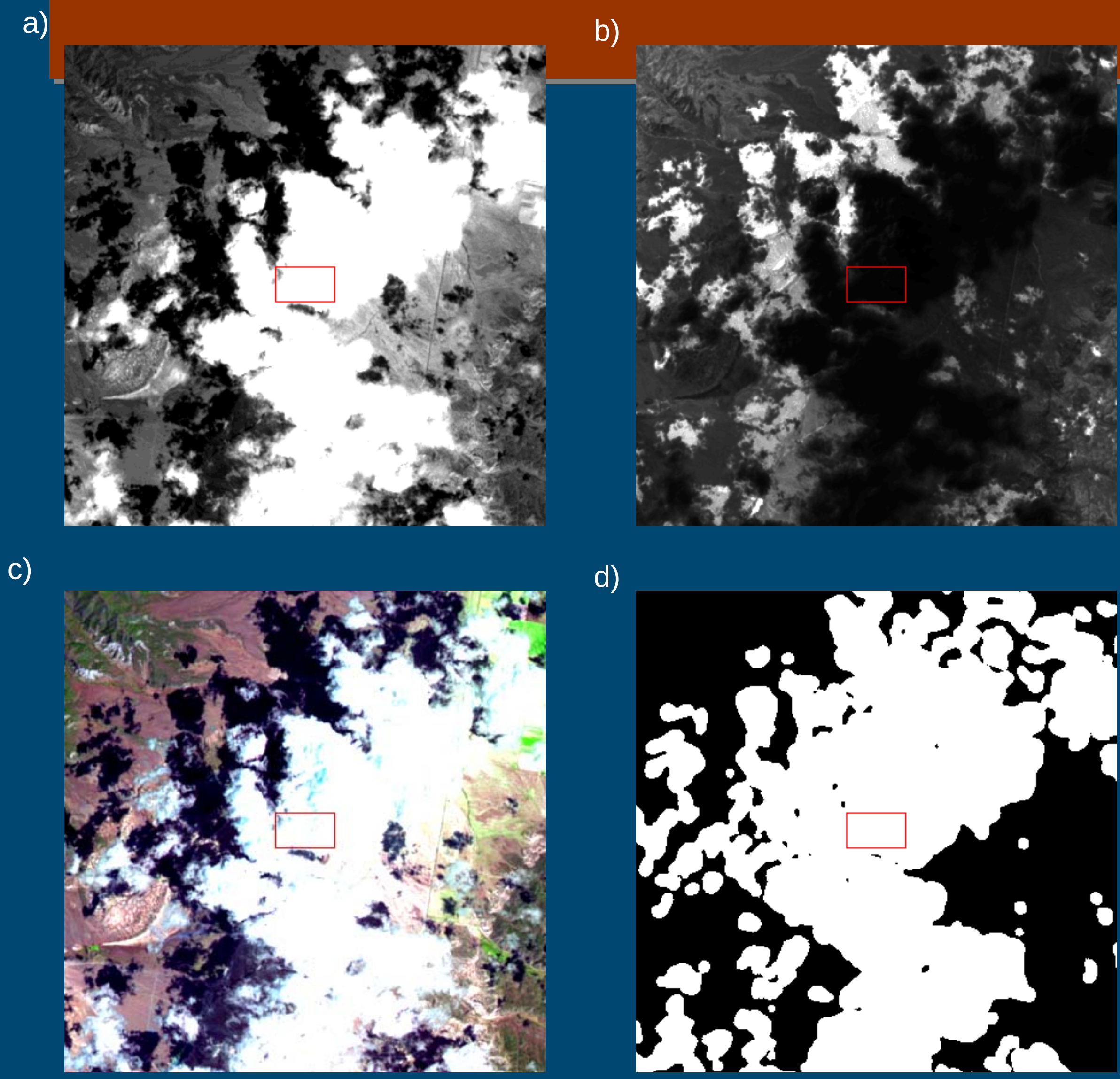
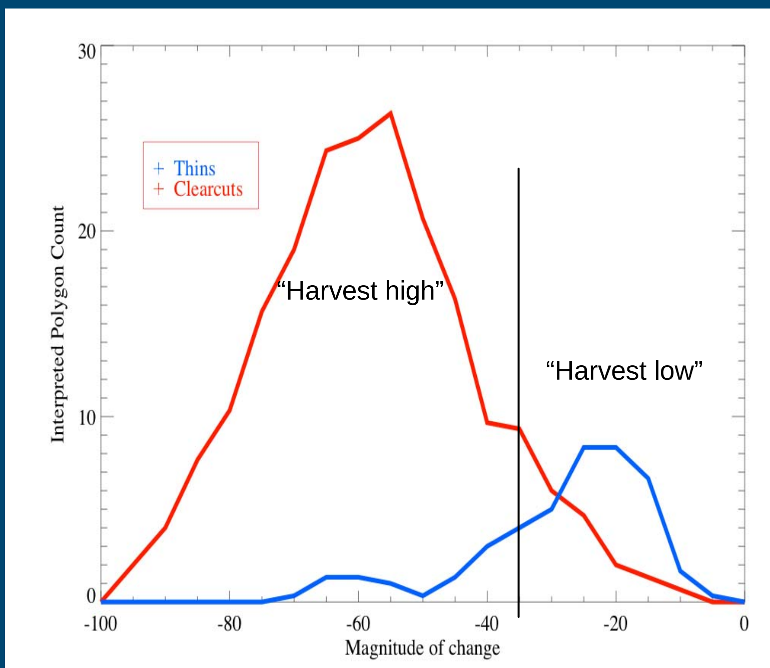


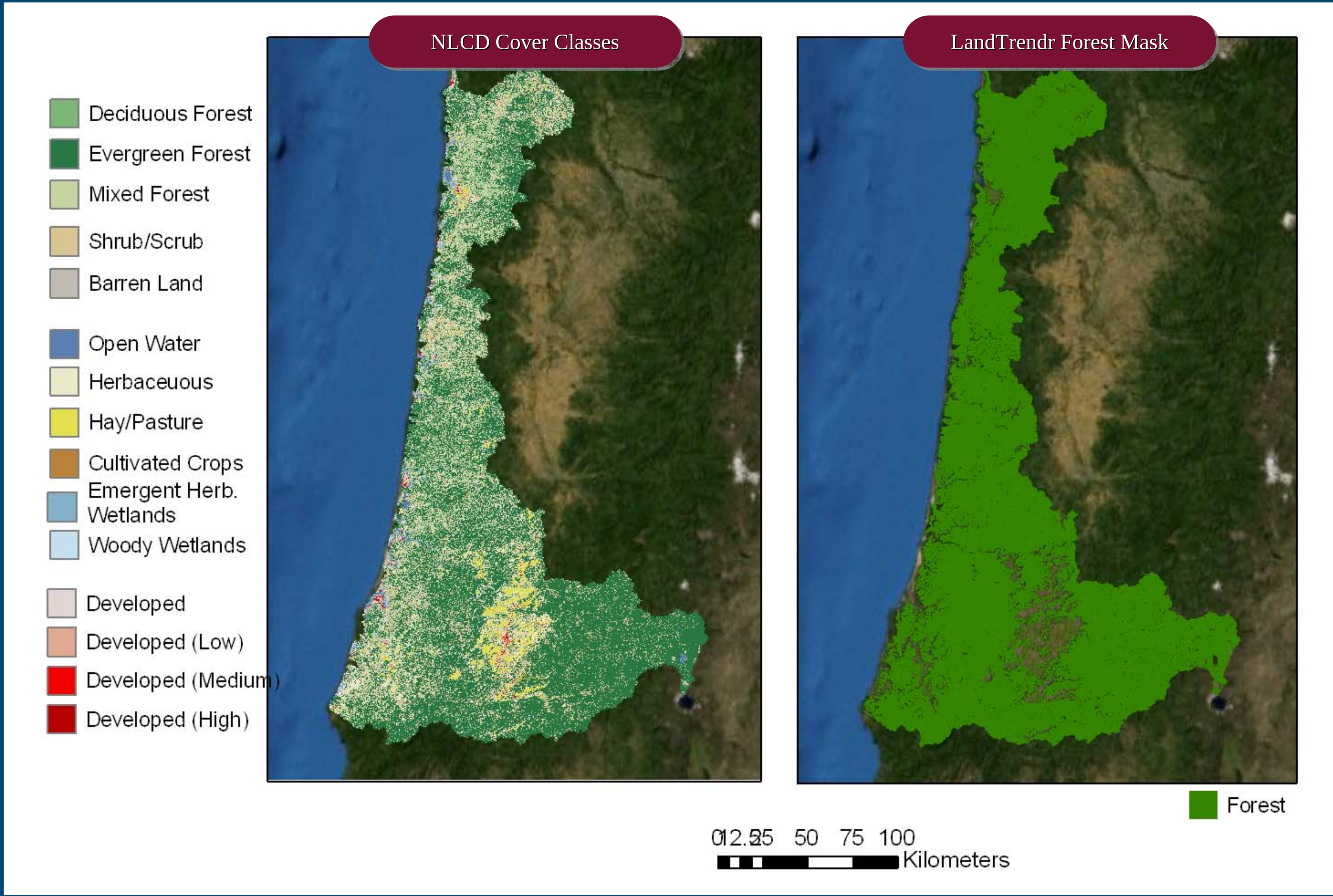
Figure 7. The cloud-masking process. For each image, a cloud score (a) and a cloud shadow score (b) image is produced. Part (c) shows the original image using a false-color 5,4,3 composite. For each image in (a) and (b), the analyst identifies a threshold below which cloud or cloud shadow is present, which is fed to a masking algorithm that combines the two into a mask (d).

Simplifying Magnitude Estimates

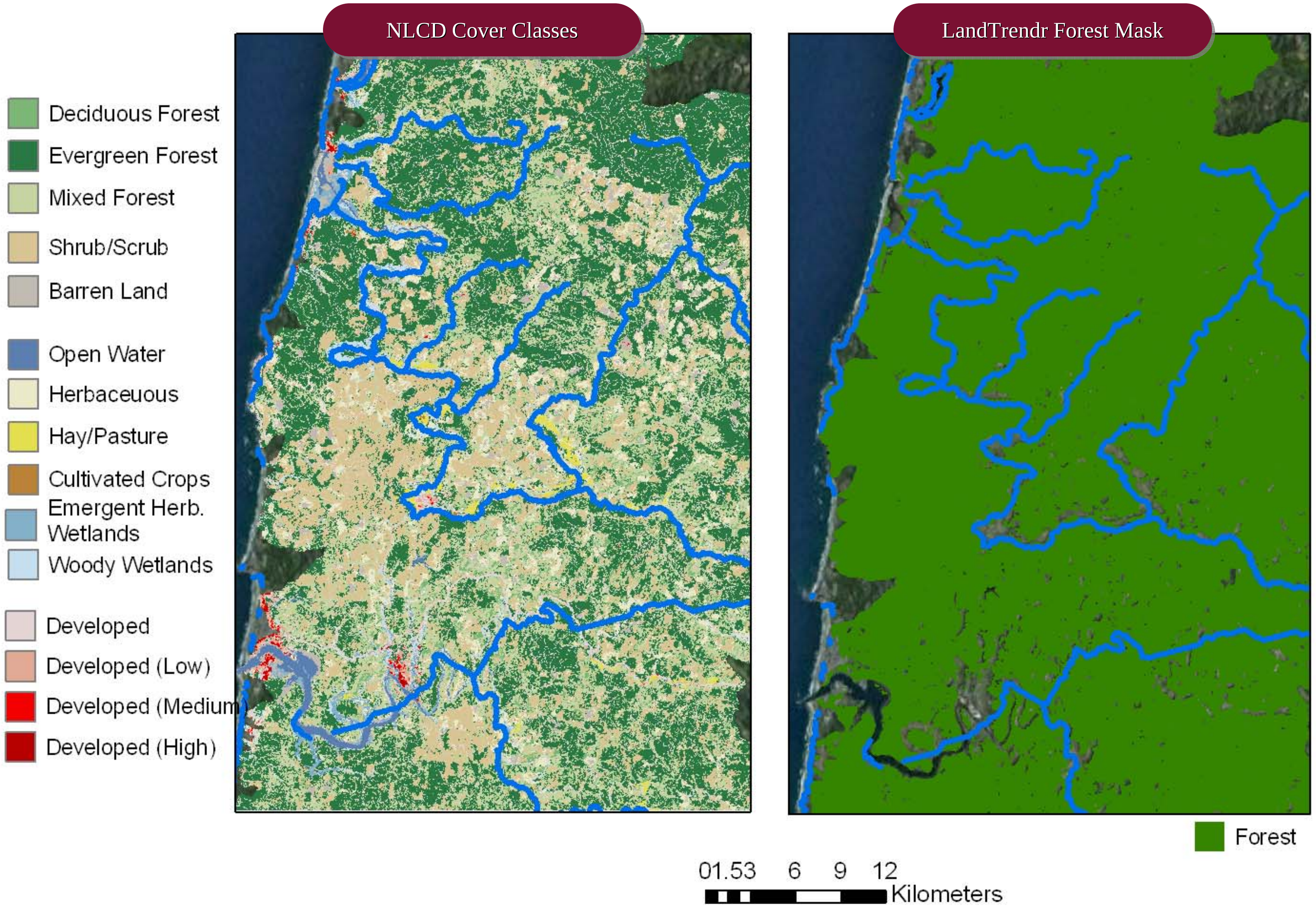
- Interpret Clearcut” vs. “Thinning” at 300 recent cuts, using airphoto interpretation
- Relate to magnitude of change estimates



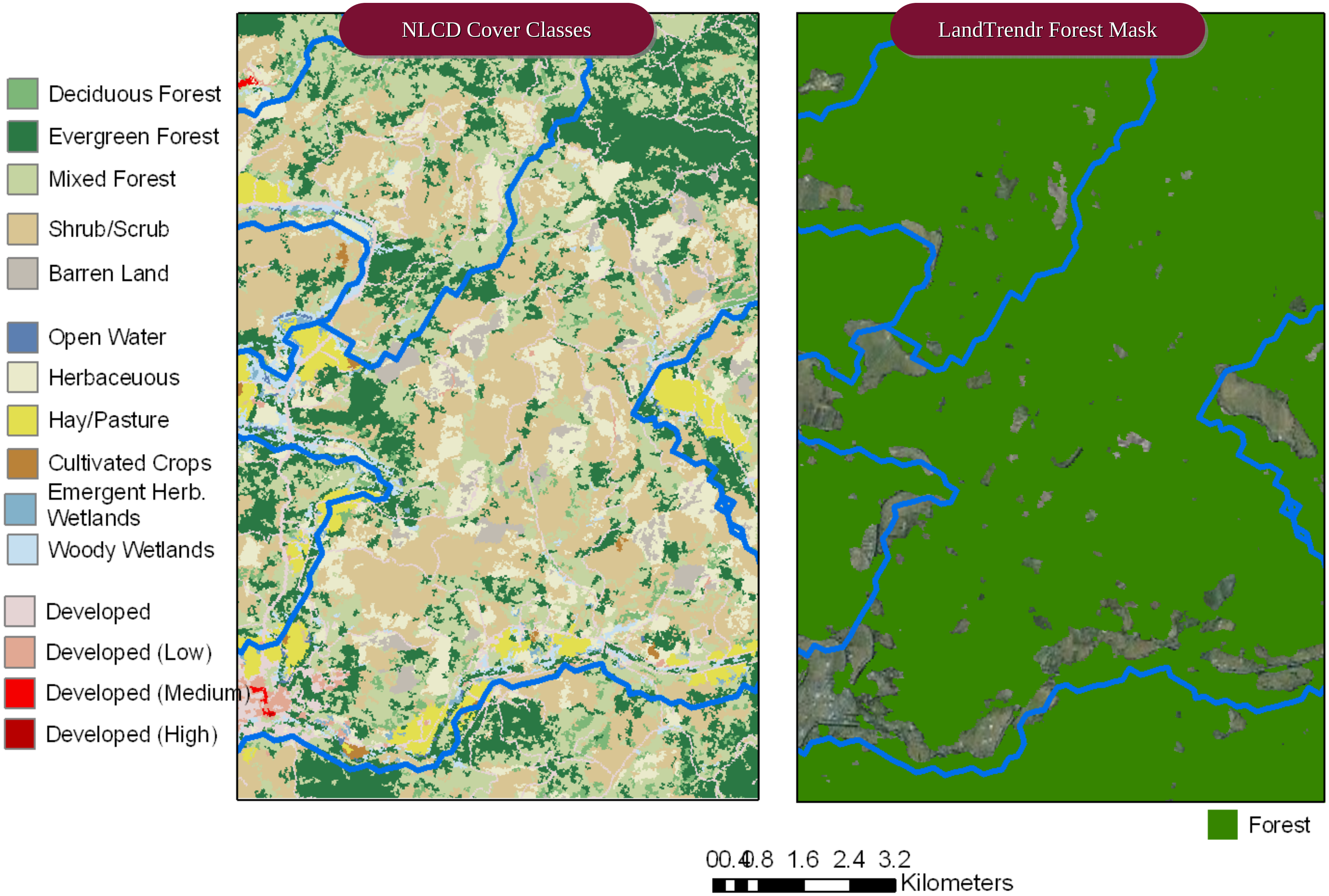
Geospatial data: Forest Mask



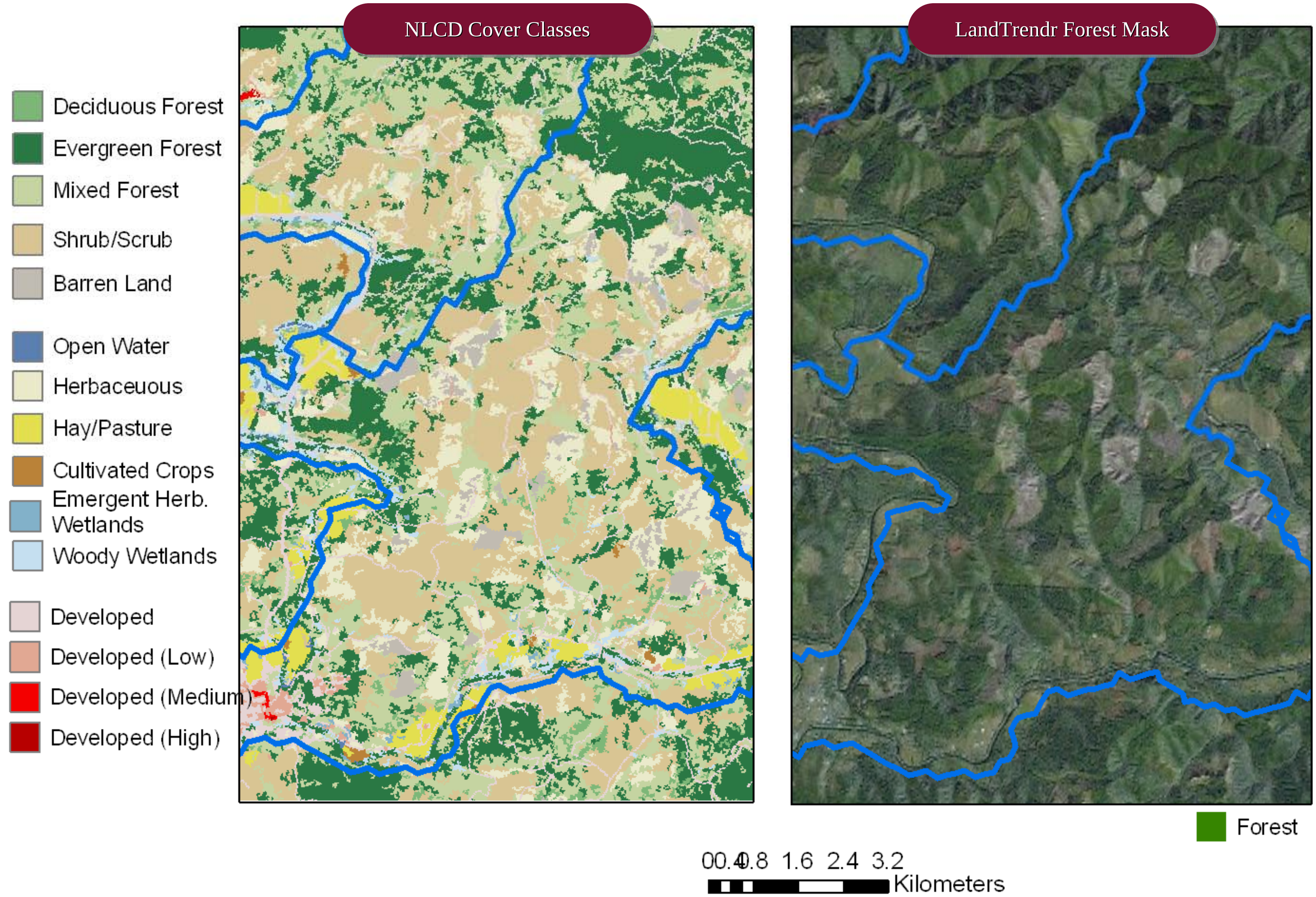
Geospatial data: Forest Mask



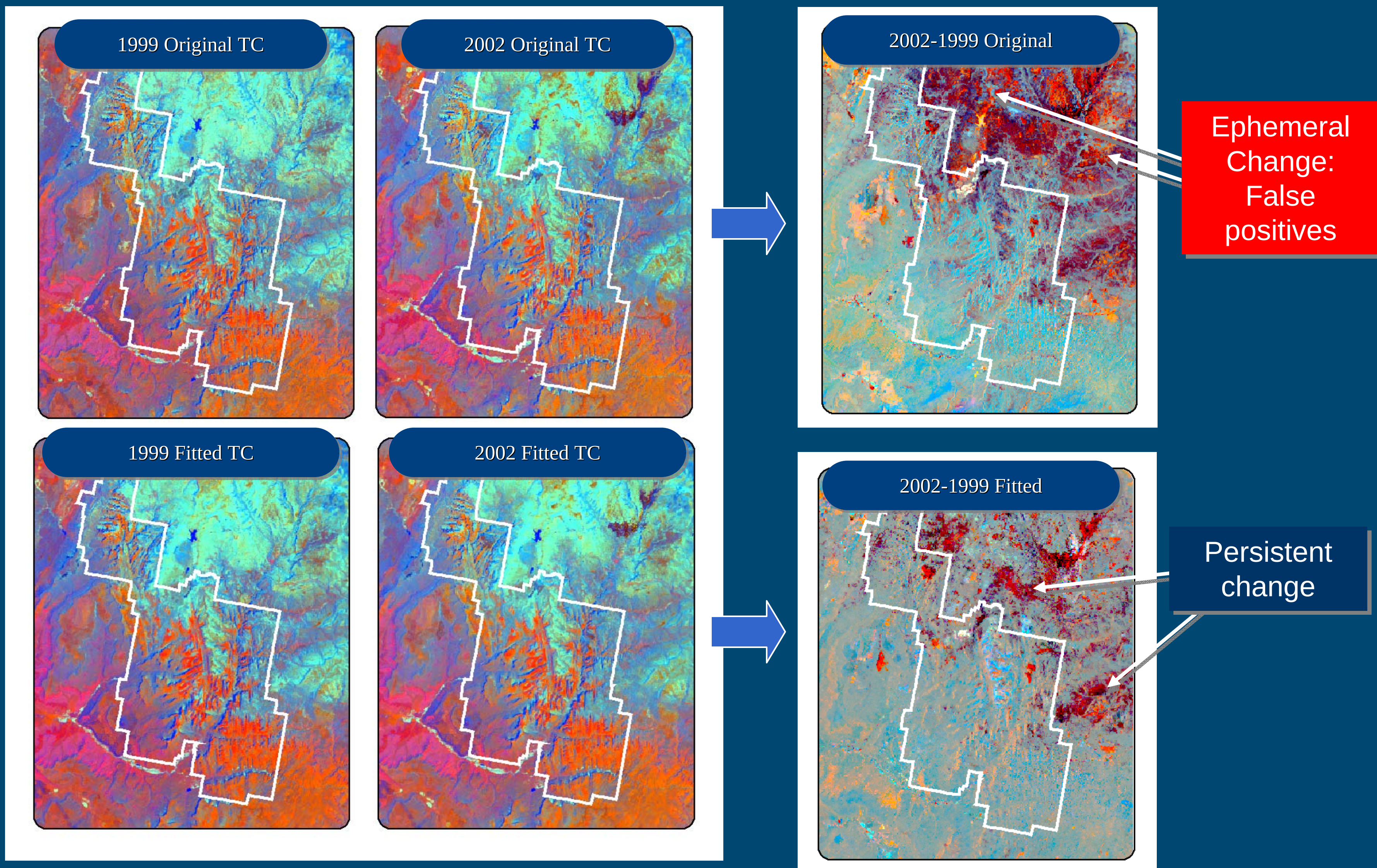
Geospatial data: Forest Mask

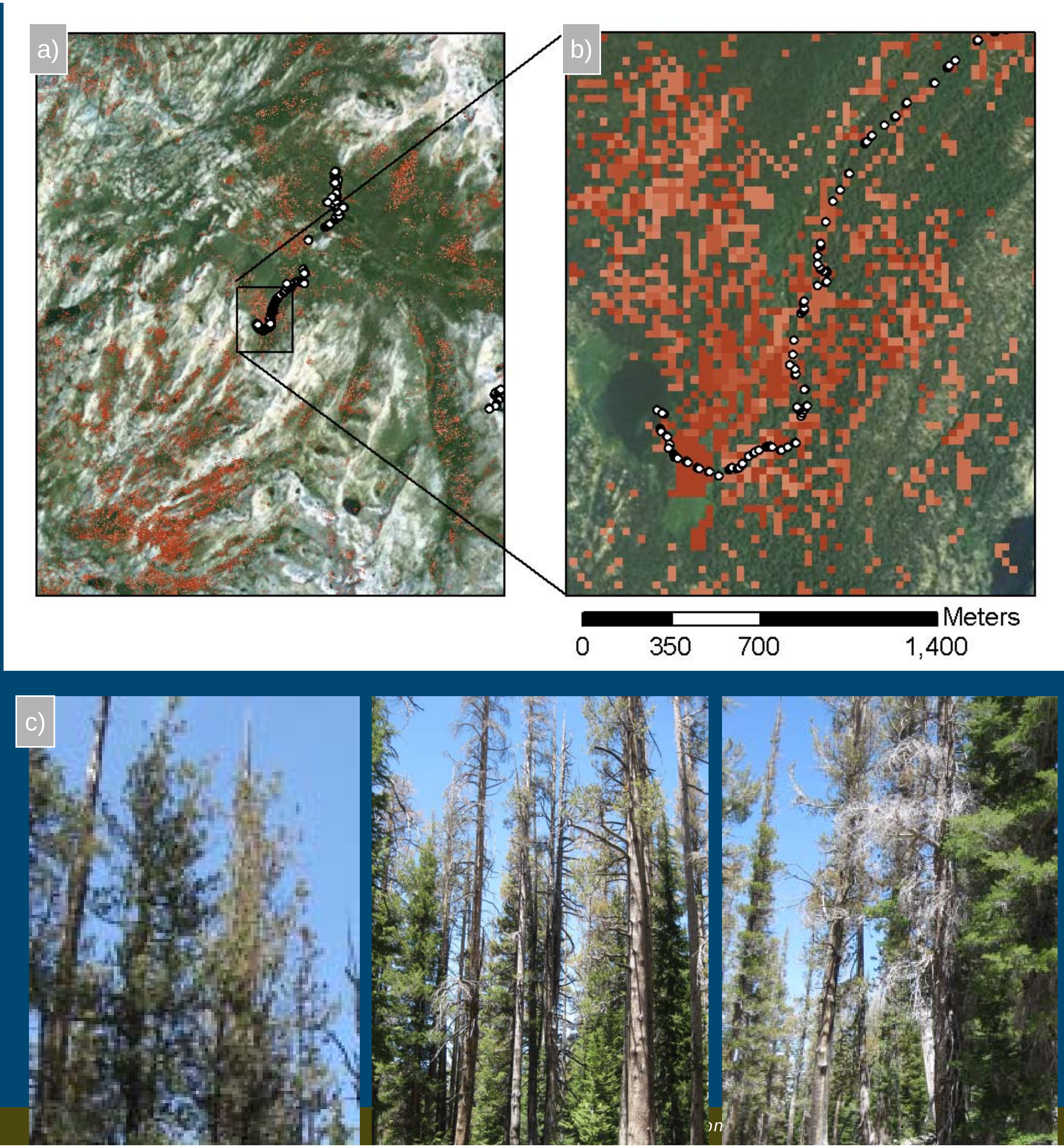


Geospatial data: Forest Mask

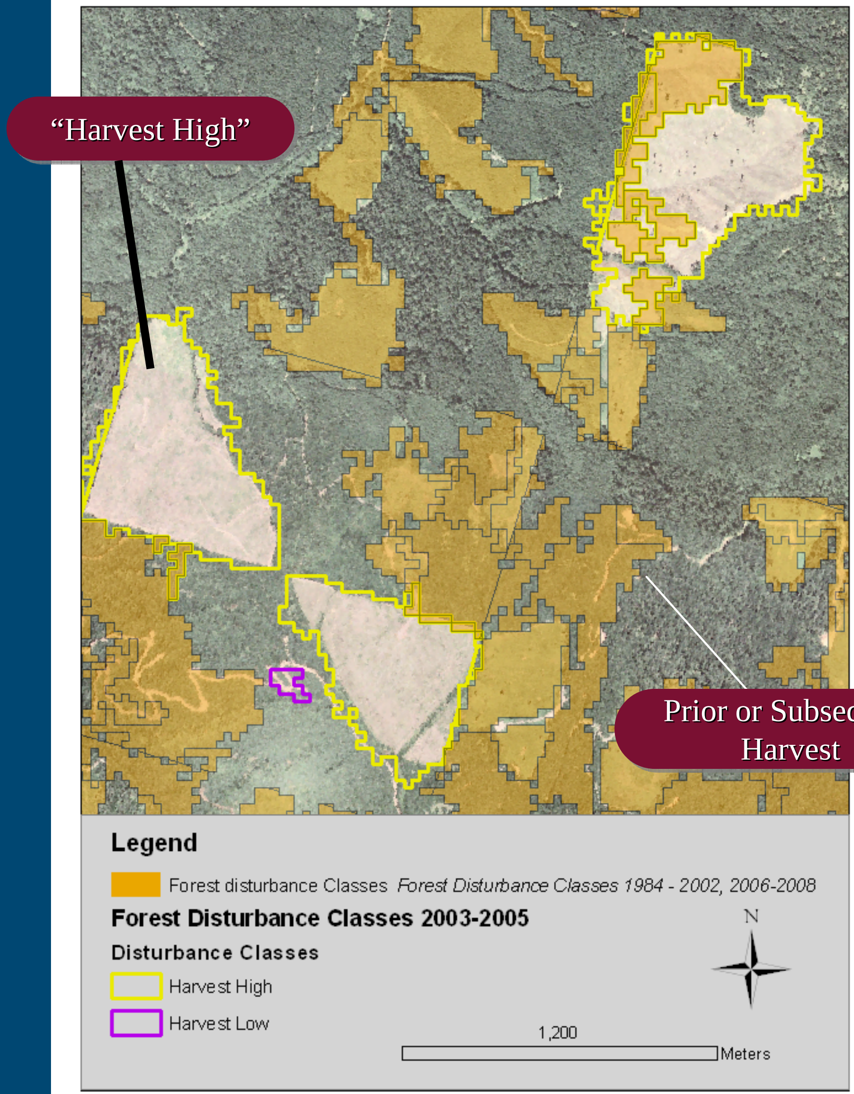


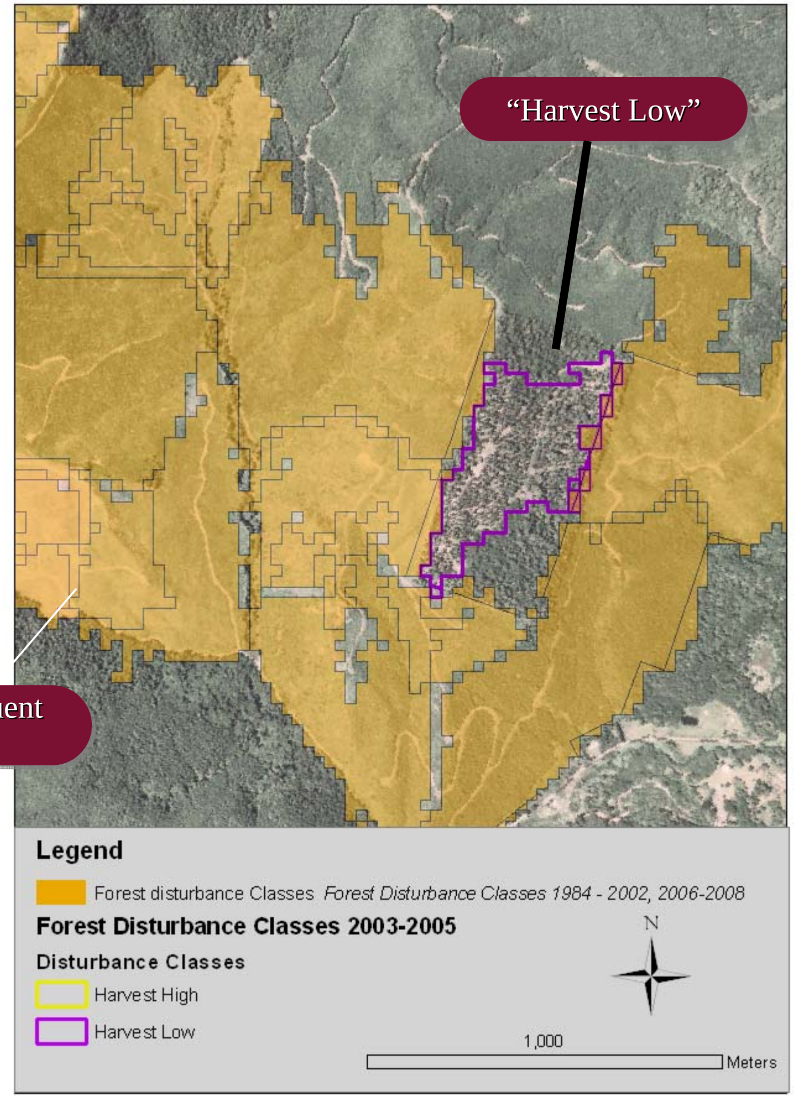
Examples of false positives: Zion NP



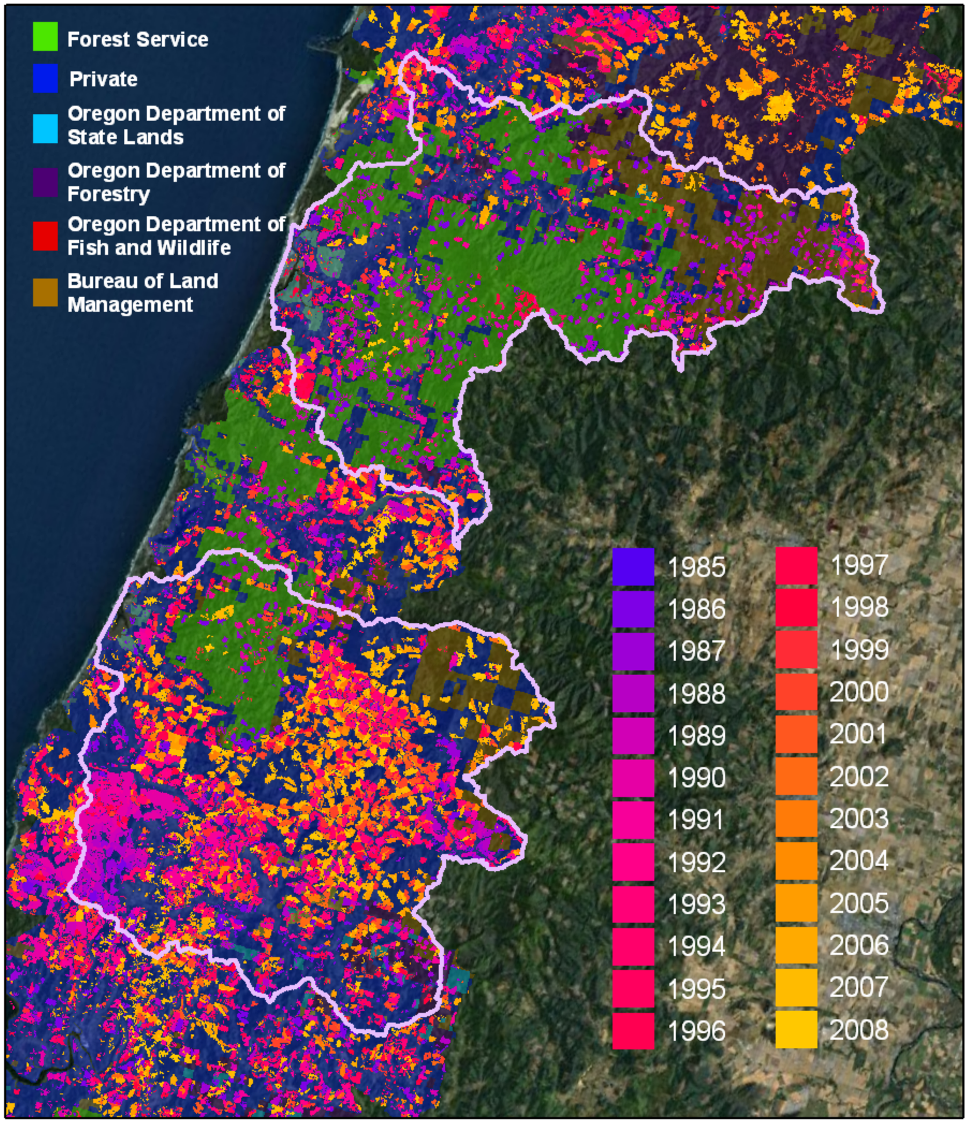

a)
b)
Meters
0
350
700
1,400
c)

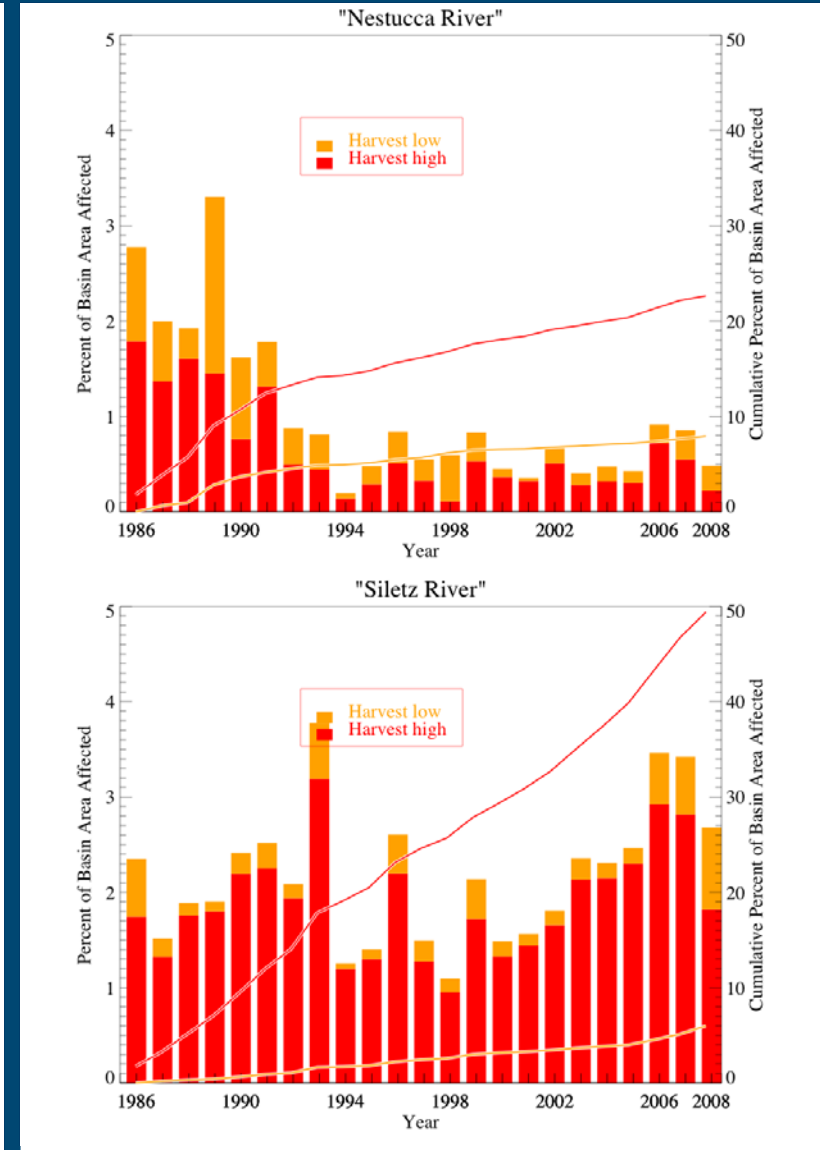
Segment-based mapping: Patches by magnitude



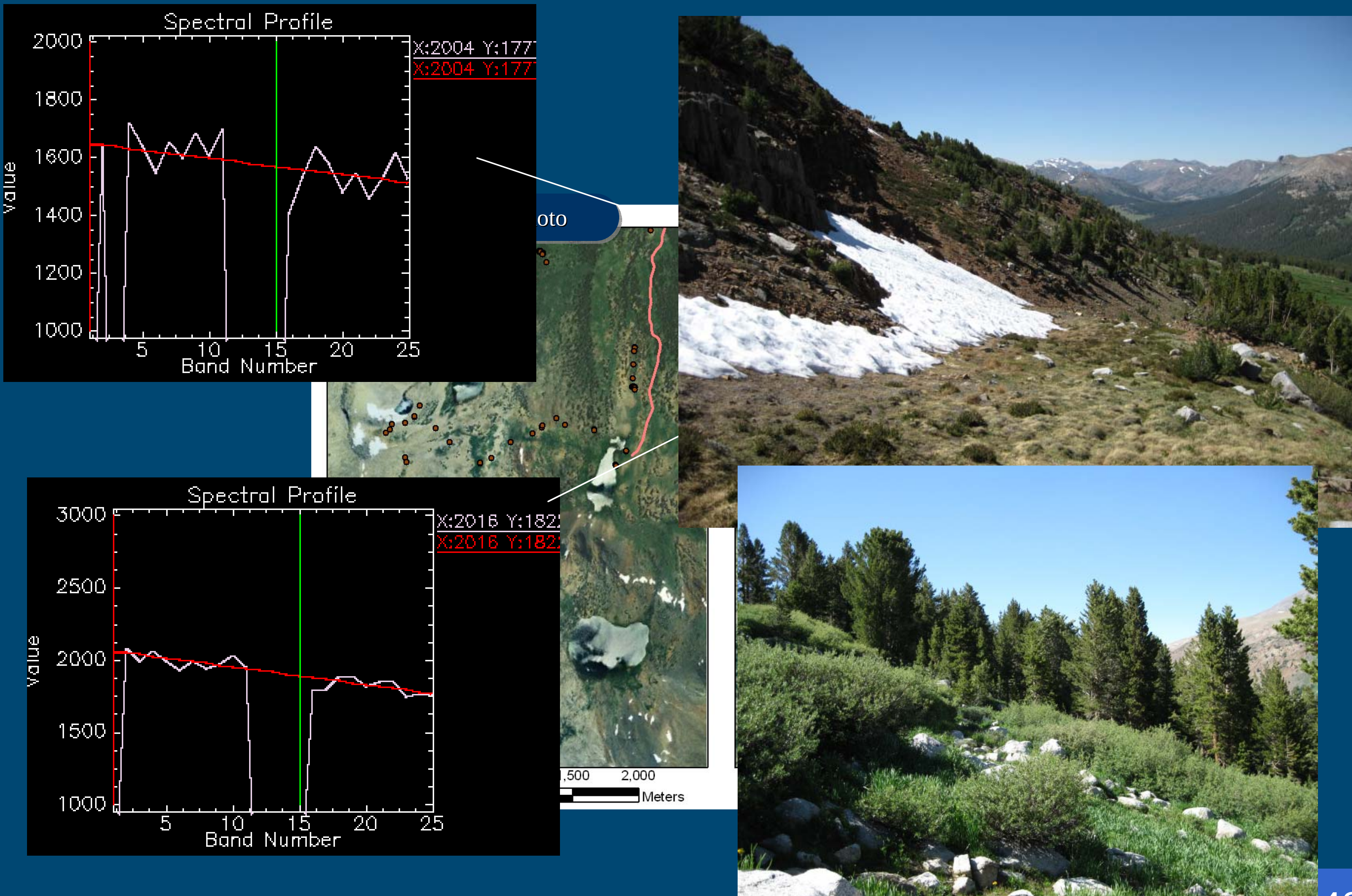


Contrasting temporal patterns

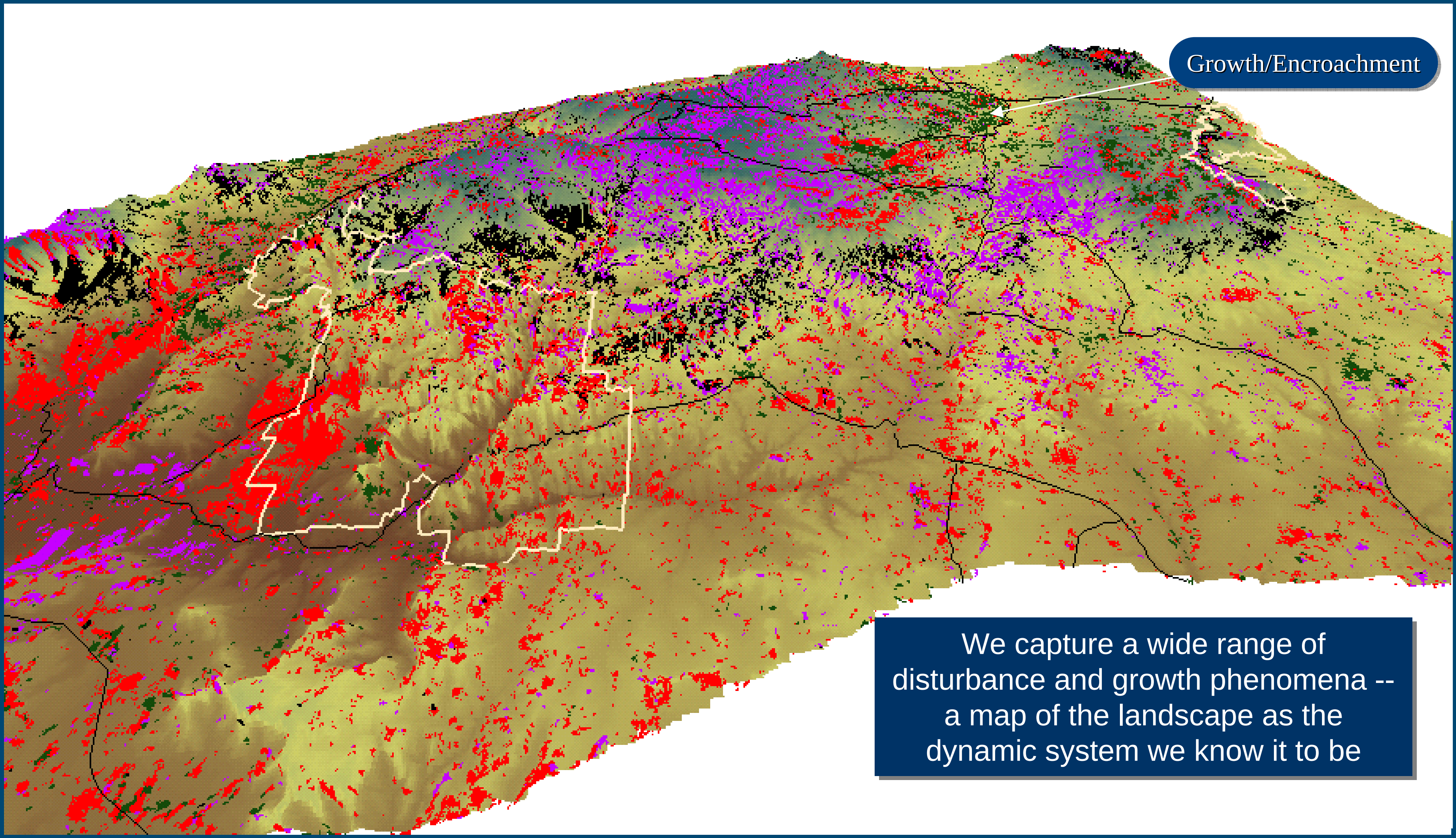




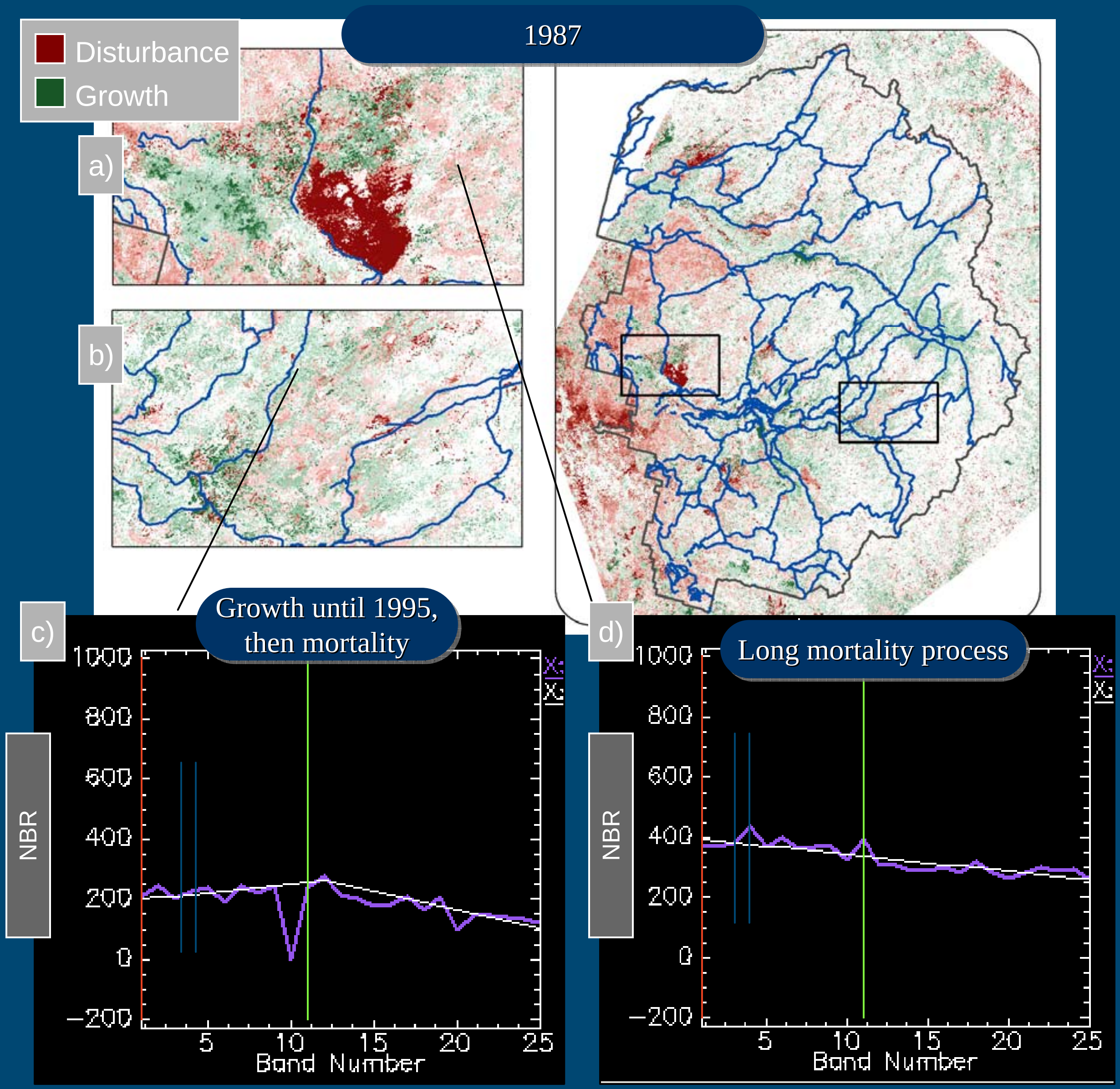
Encroachment at treeline: Yosemite



Landscape dynamics on the Colorado Plateau

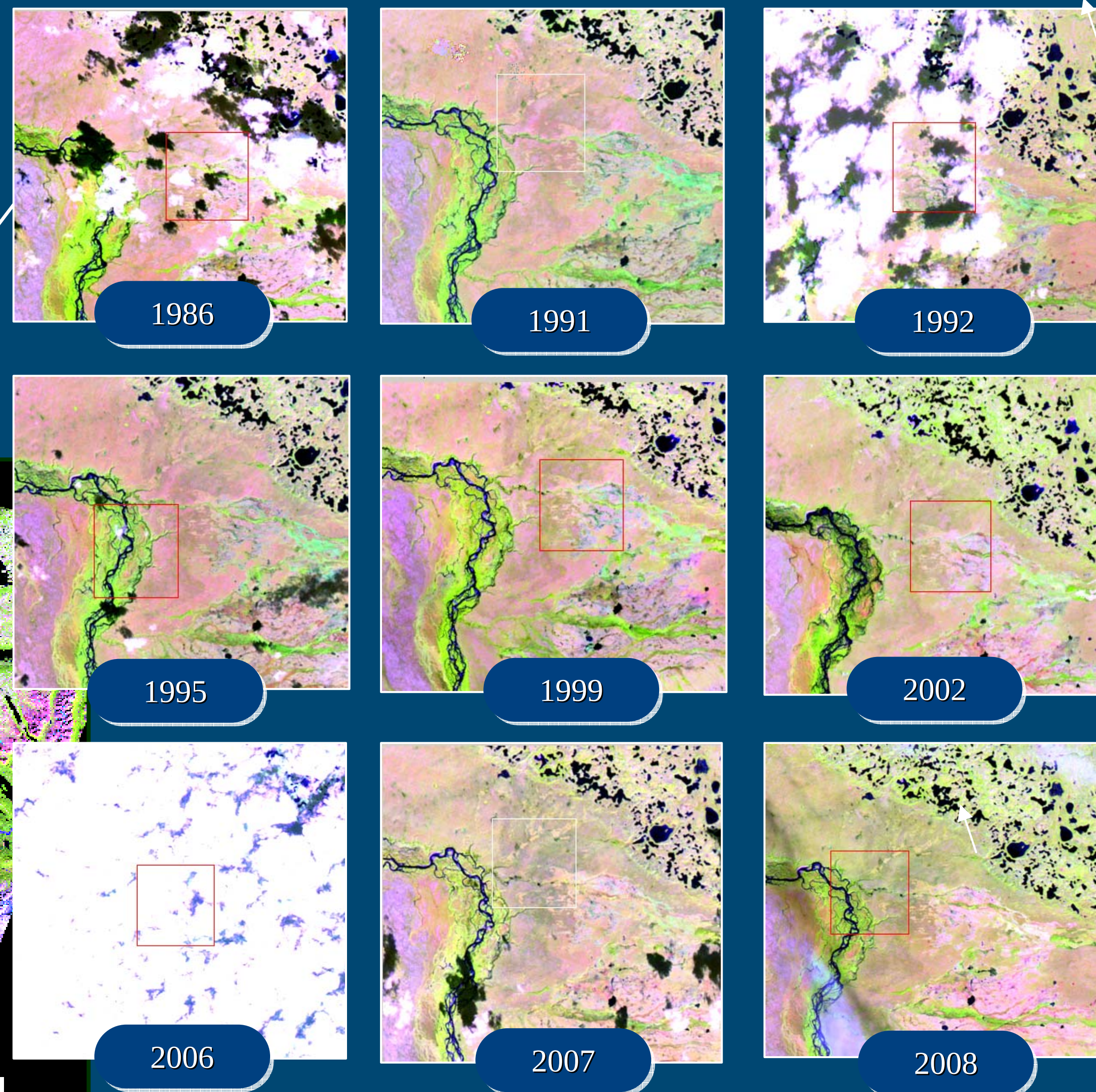


Slice-based mapping: Disturbance & growth



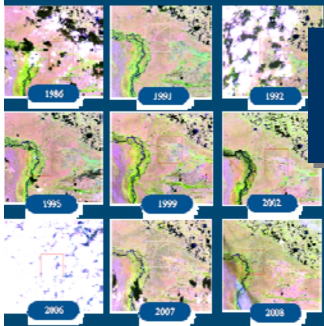
Growth/encroachment: Katmai NP

Much of this landscape is dominated by boreal tundra, including lichen for caribou browse. A key concern is ingrowth of shrubs (dwarf birch, etc.) overtopping and eventually replacing the lichen

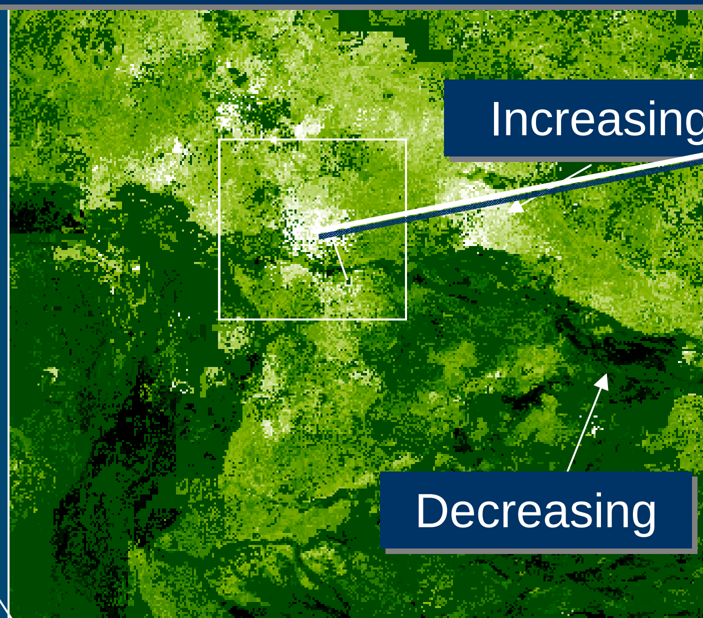


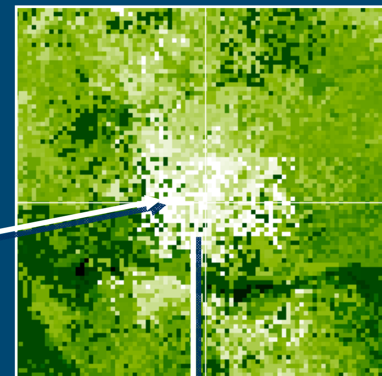
Western Katmai NP
(Landsat path 72/ row 19)

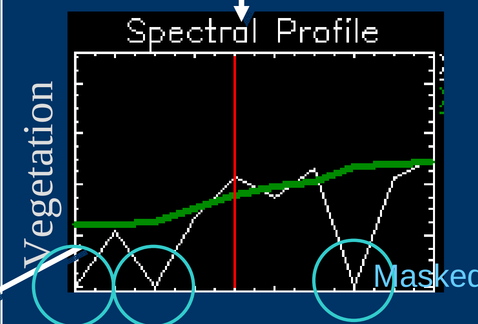
An example from Alaska



Landscape patterns of increasing and decreasing vegetation







An example of fitted vegetation indices. White line shows original values, green line the fitted value. Clouds are shown as inverted spikes, and are ignored during fitting. Overall increases in vegetation are captured here despite occasional cloudy years.

Yearly classification: Fire effects