Monitoring Forest Change with Remote Sensing

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Supported by the Landsat Science Team

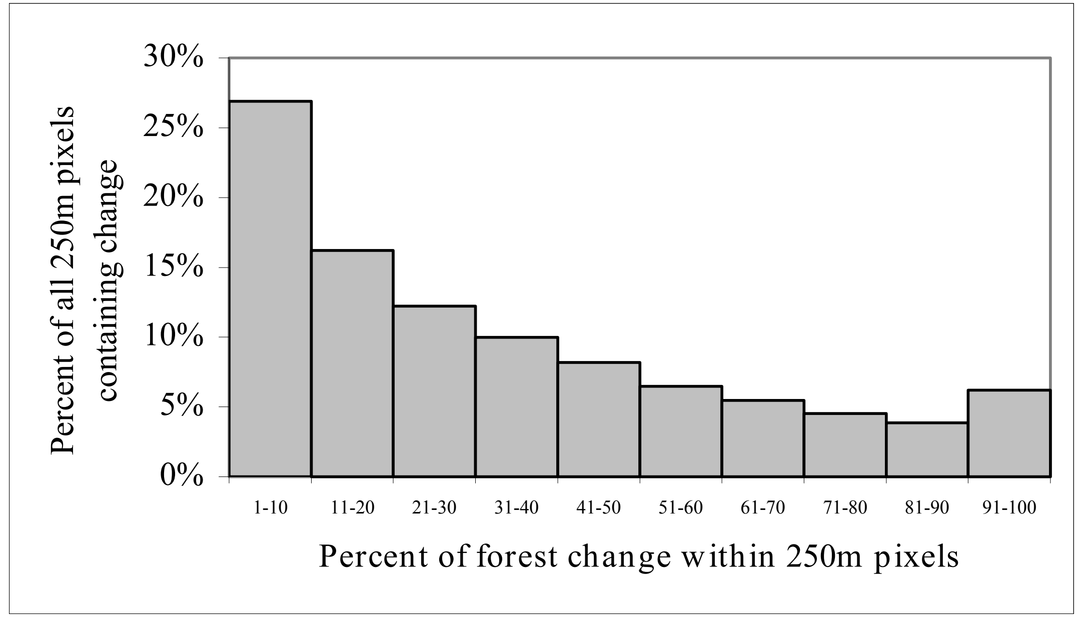
- Monitoring Forest Change over Large Areas with Landsat
- Monitoring Forest Succession (stand age) via spectral/temporal patterns in Landsat data
- Estimating tree size using multiresolution imagery

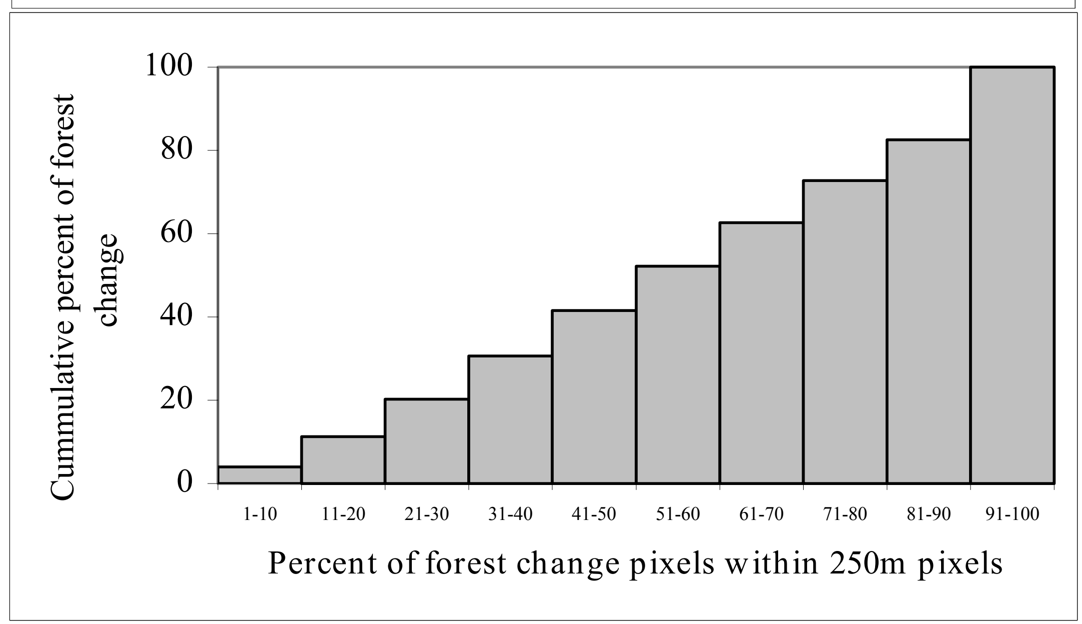
Regional to Continental Monitoring of Change in Temperate Conifer Forests

- We know less about the rates of forest change in the temperate zones of the world than in the tropics.
- Large area monitoring at high resolution is necessary in the temperate zone.
- New methods which are more automated and based on generalization are required.

250m

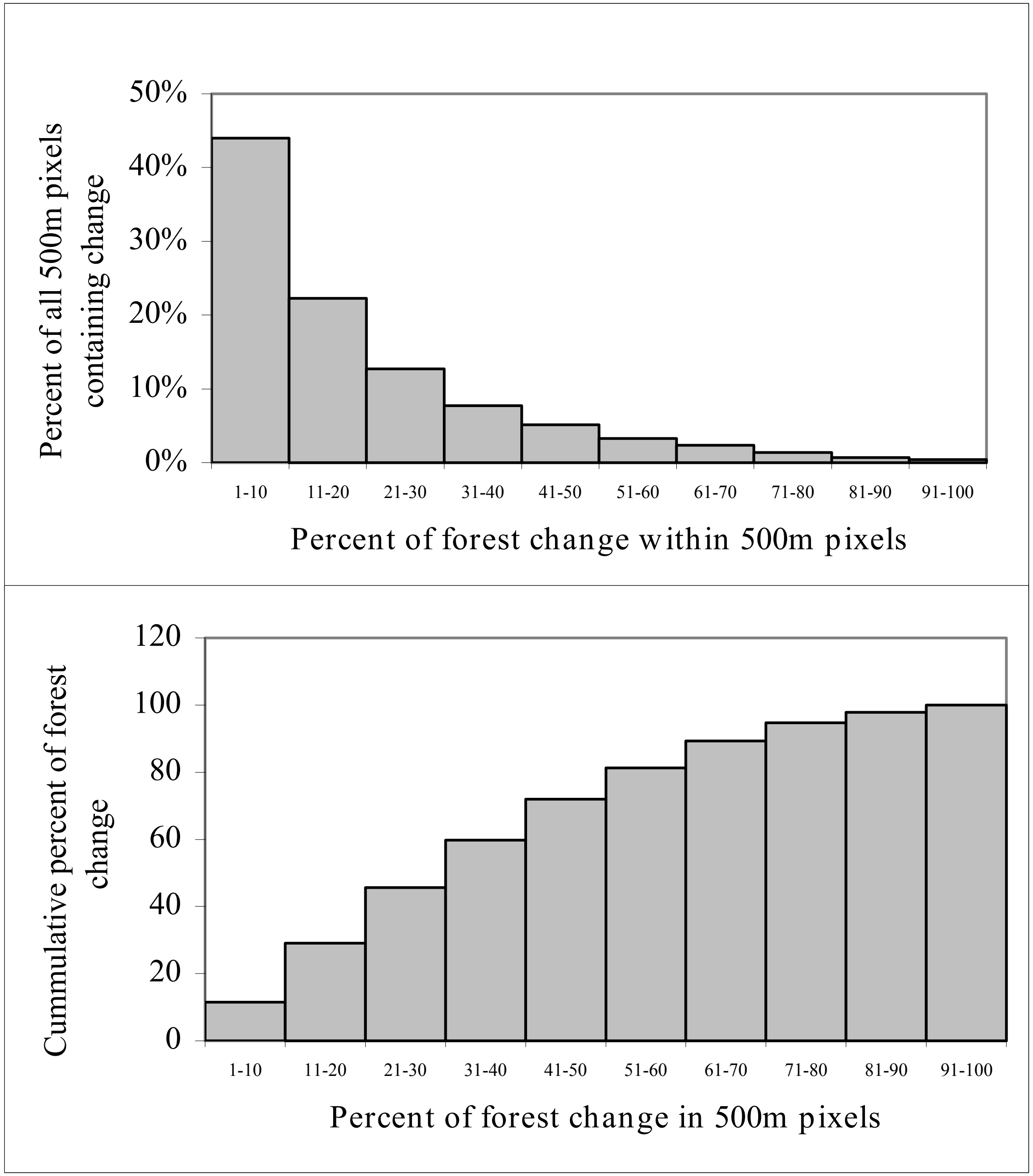
The top graph shows the proportion of forest change for each 250m pixel of the forest-change map (1991-1995). Most 250m pixels contain low percentages of forest change.The bottom graphs shows that approximately 50% of all forest change in the map occurs in 250m pixels containing less than 50% change.



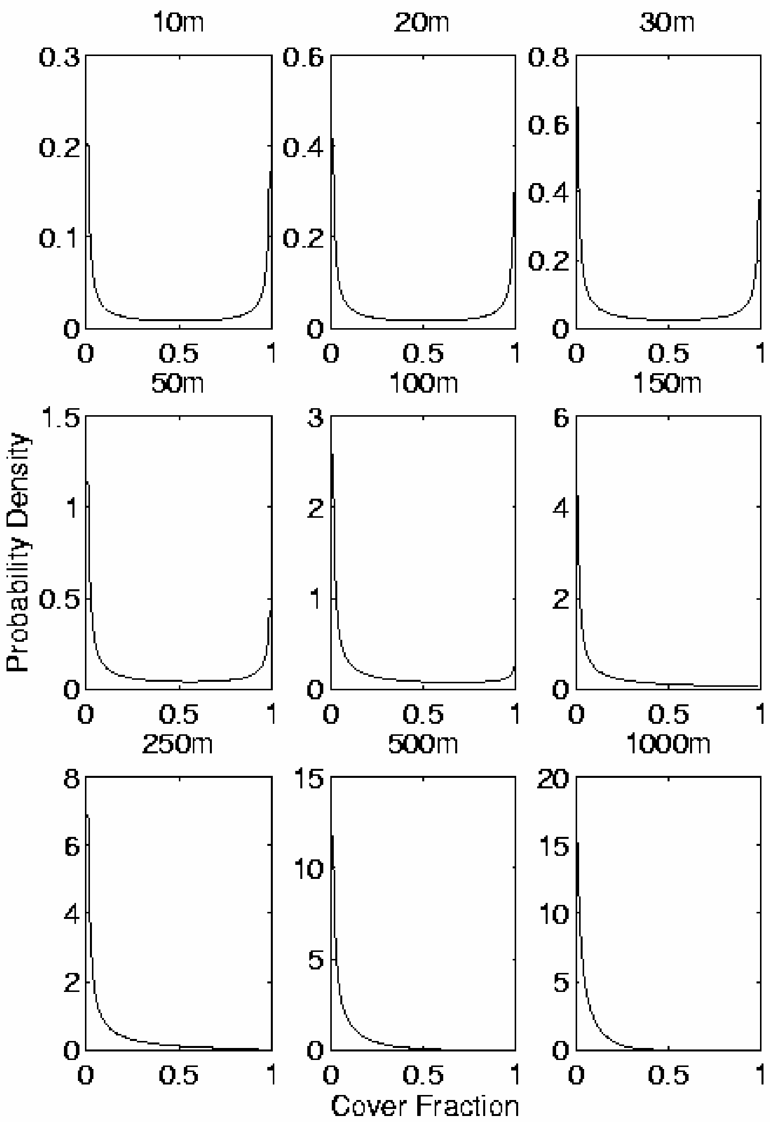


500m

The top graph shows the proportion of forest change for each 500m pixel of the forest change map. Most 500m pixels contain low percentages of forest change. The bottom graph shows that approximately 50% of all forest change in the map occurs in 500m pixels containing 30% or less of change.



The distribution of clearcut cover fraction as a function of resolution.



Levels of Generalization

Within Image: Trained on examples from within an image, a mapping process is applied to the rest of the image (the way most maps are made now).

Within Scene: Training from one time (or image) is used to train a mapping process applied to a different image of the same place (or scene).

Within Region: Examples from one geographic area are used to train a mapping process applied to neighboring scenes.

Levels of Generalization (cont.)

Across Regions: Training from one geographic region is applied to another.

Across Continents: Training from one continent is applied to another.

Across Sensor: Training from data acquired by one sensor is applied to data acquired from another.

Change Mapping Methods
Need to do once:

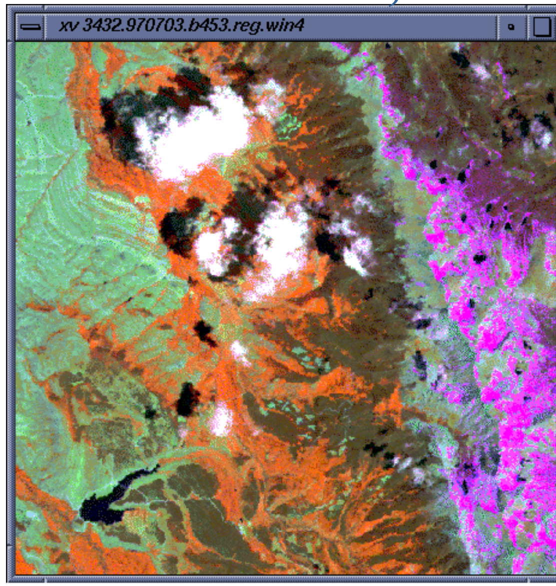
- Train a Fuzzy ARTMAP, Artificial Neural Network
  - A) Only two classes:
    - 1) “Forest” to “No Longer Forest”
    - 2) “Everything Else”
  - B) Training Sites
- Benefits of the Fuzzy ARTMAP algorithm
  - Algorithm modeled on the human brain
  - No assumptions regarding the distributional properties of the data
  - Many to one mapping

Change Mapping Methods
For each pair of Landsat Images:

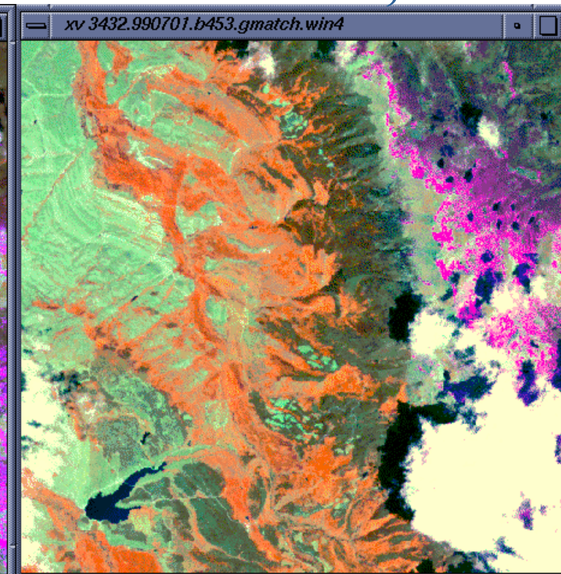
- Registration (Must be done well)
- Cloud and Cloud-shadows must be removed
- Atmospheric Correction (dark-object subtraction)
- Change Detection
  - Fuzzy ARTMAP which was previously trained
- Post Processing (per pixel results are noisy):
  - image segmentation
- Manual Editing (Create and use an image of the change in band 5 between the two dates)

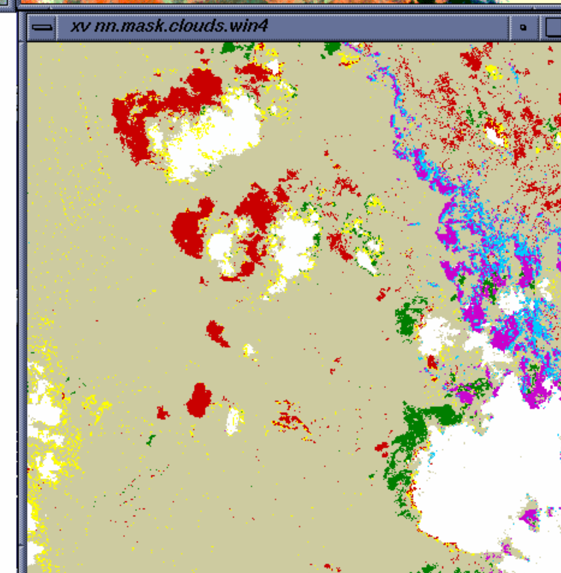
Cloud Screening with Landsat 7

Landsat 5, 1997



Landsat 7, 1999





Cloud Mask

<u>Legend for Cloud Mask</u>:

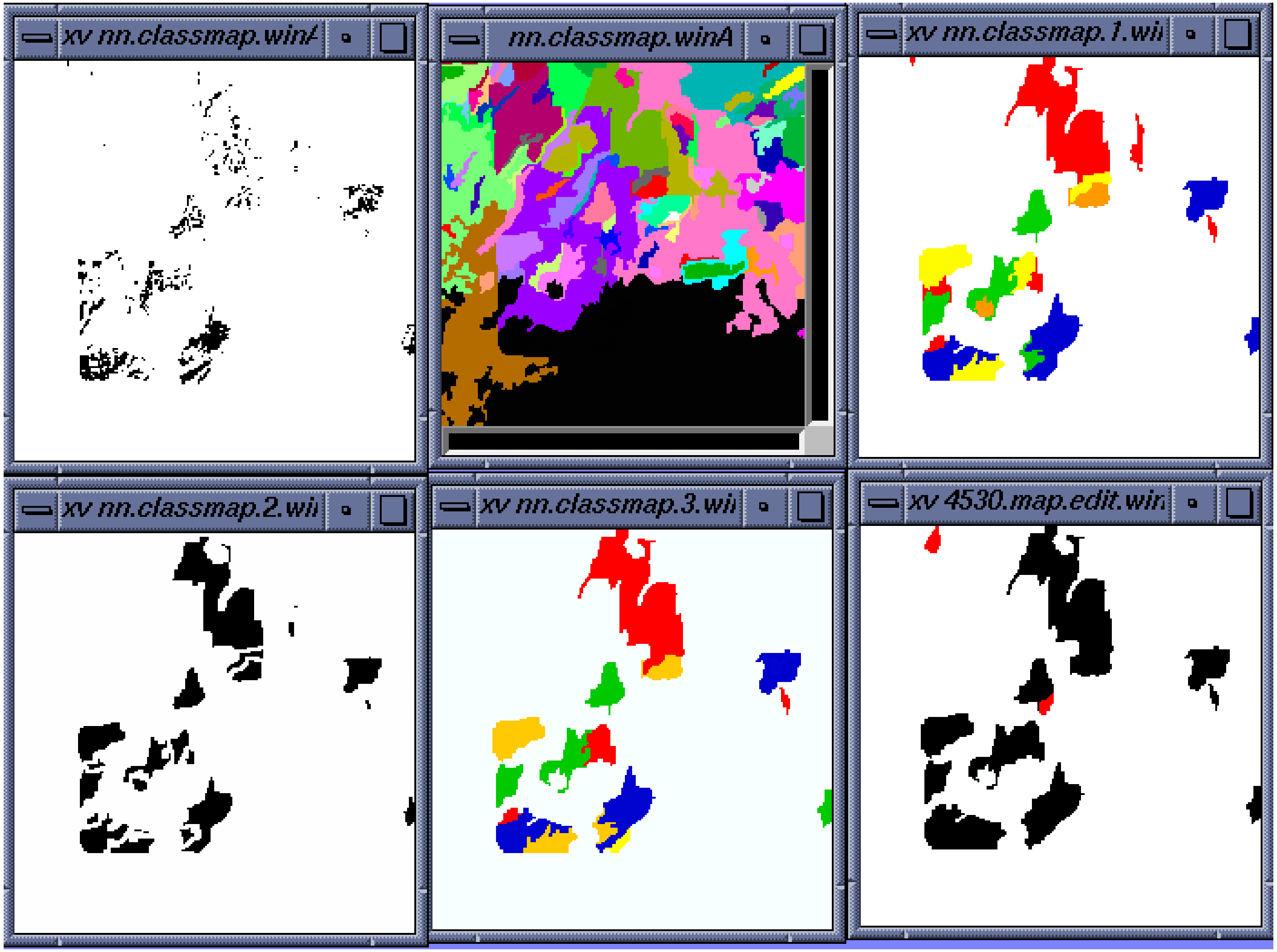
White = Clouds in either image

Red = Cloud shadow in ‘97

Green = Cloud shadow in ‘99

Purple, Blue = Snow

Area shown is 15km x 15km



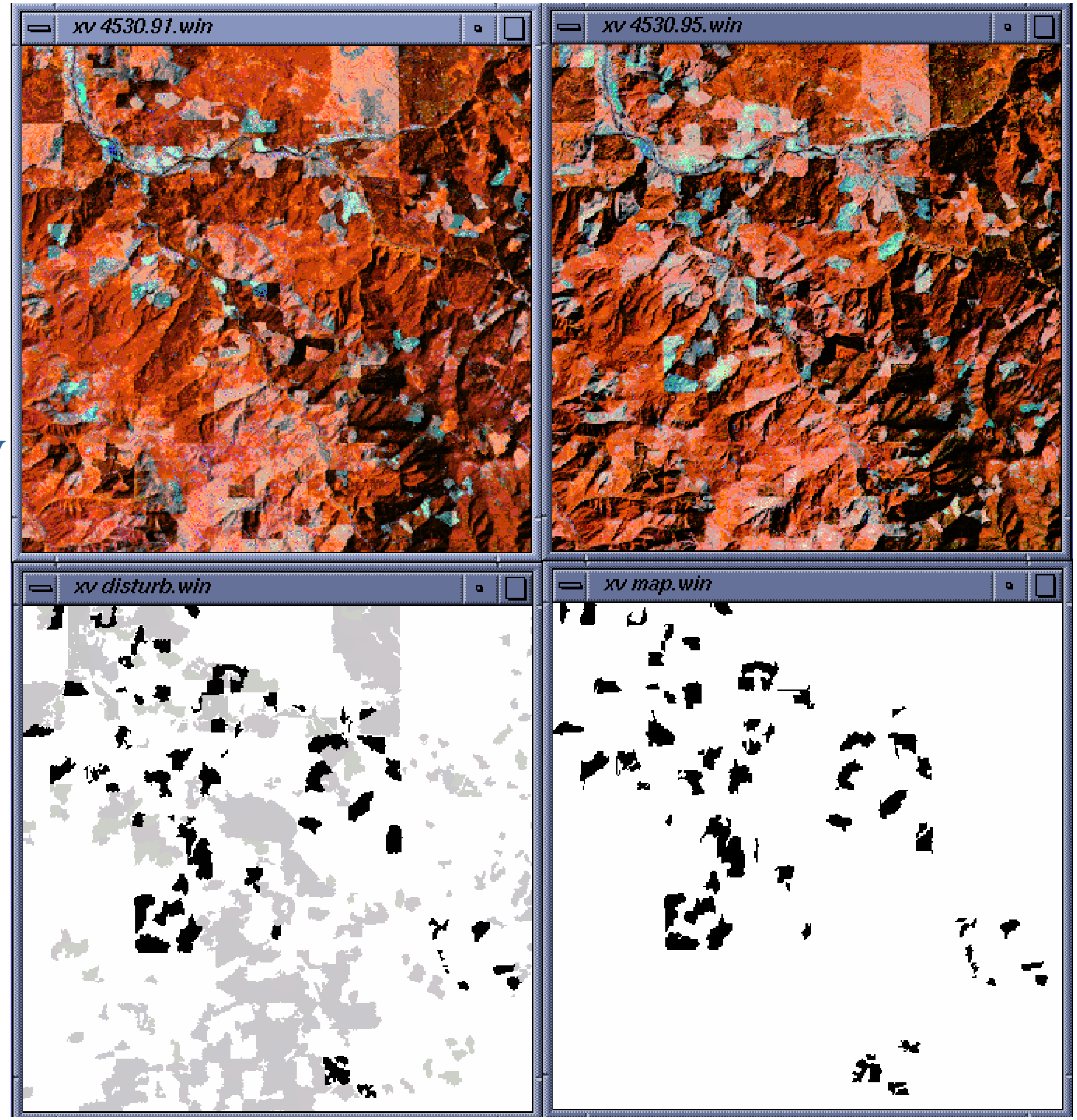
1. Per-pixel results   2. Segmentation results
3. Proportion of change in each polygon
4. Erosion of image 3.
5. Combination of images 2 and 4.
6. Edited map (black: original - red: edit)

Key Points of Mapping processes

- USDA FOREST SERVICE MAP:
  - 6 Landsat Scenes were used
  - 4 Time periods were covered
  - Maps for each time period and scene were done separately (i.e. 24 classifications)
  - Only areas of change greater than 2.5 hectares (clearcuts and fires) were mapped
- BOSTON UIVERSITY MAP:
  - We tried to match their results & used their images
  - We trained on one pair of images from 1992/1995
  - We applied the trained neural net to 6 pairs of images from 1991 to 1995

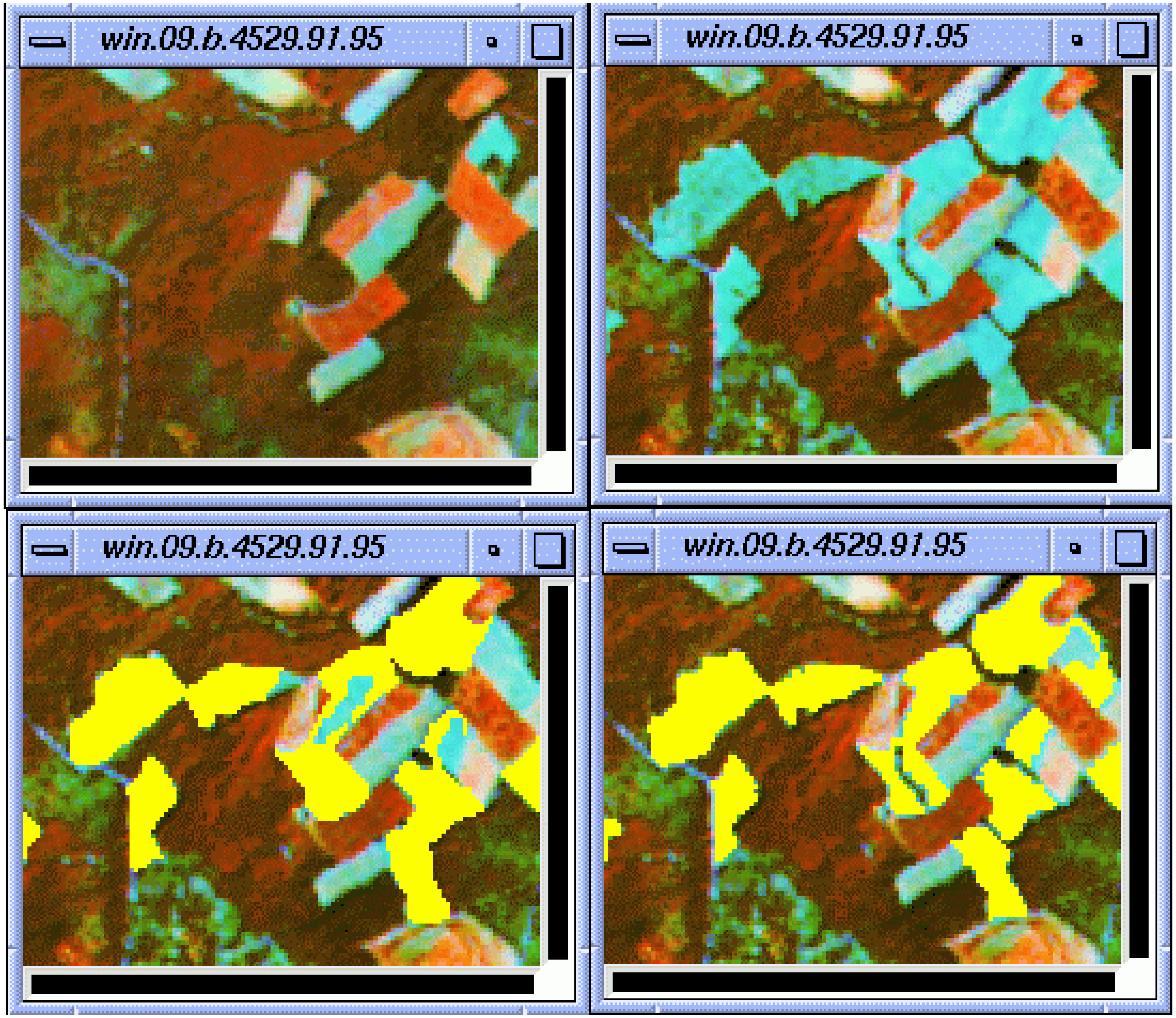
Forest change maps made with traditional and generalization methods are very similar.

1991 1995



Traditional Generalization

Close-up of Traditional & Generalization forest change maps. Change polygons are in yellow.



Pacific Northwest Forest Change 1991-1995 Accuracy Assessments

Boston University Map

Truth

Map Label	Change	No Change	User's Accuracy
Change	137	9	93.8%
No Change	16	376	95.9%
Producer's Accuracy	89.5%	97.7%	95.4%

USDA Forest Service Map

Truth

Map Label	Change	No Change	User's Accuracy
Change	132	5	96.4%
No Change	21	380	94.8%
Producer's Accuracy	86.3%	98.7%	95.2%

Pacific Northwest Forest Change 1991-1995 Accuracy Assessments

- Overall accuracies similar to those of USDA Forest Service (1998)
- Commission errors include the effects of:
  - a) Misregistration
  - b) Inclusion of non-forest change in 'forest change' map (solvable)
- Omission errors due largely to poor polygon definition in post processing procedures (probably solvable)

Forest Change in the Rockies, Using Landsat 7

- Goal:Test the use of methods based on generalization to monitor forest change in the Rocky Mountain Region of Colorado

Forest Change in the Rockies, Using Landsat 7

- Approach: Train on one pair of images

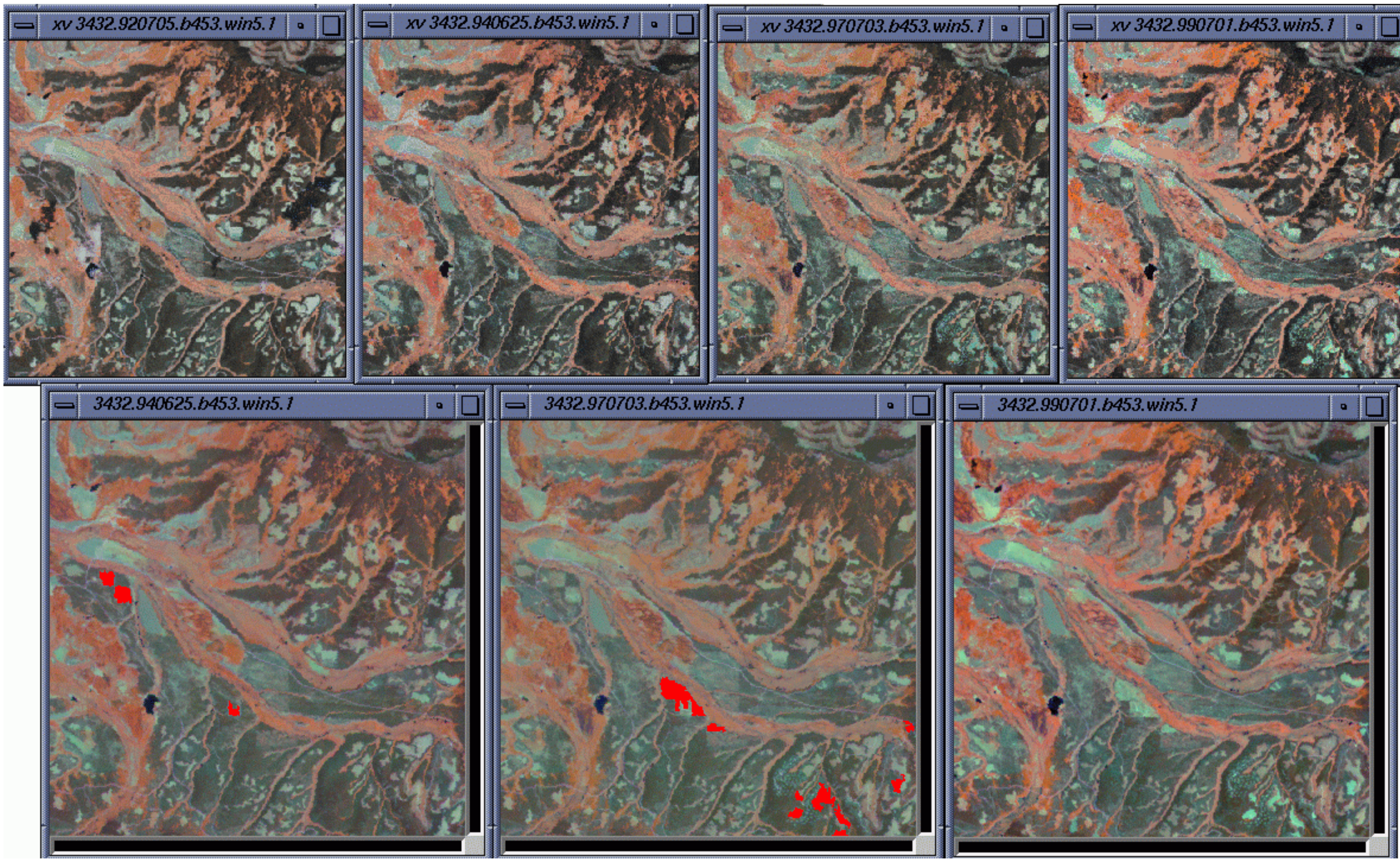
Path-Row	Year1	Year2
34-32	‘92 (Landsat 5)	‘94 (Landsat 5)

- Then apply to other image pairs:

Path-Row	Year1	Year2
34-32	‘92 (Landsat 5)	‘94 (Landsat 5)
34-32	‘94 (Landsat 5)	‘97 (Landsat 5)
34-32	‘97 (Landsat 5)	‘99 (Landsat 7)
34-33	‘97 (Landsat 5)	‘99 (Landsat 7)
34-34	‘97 (Landsat 5)	‘99 (Landsat 7)

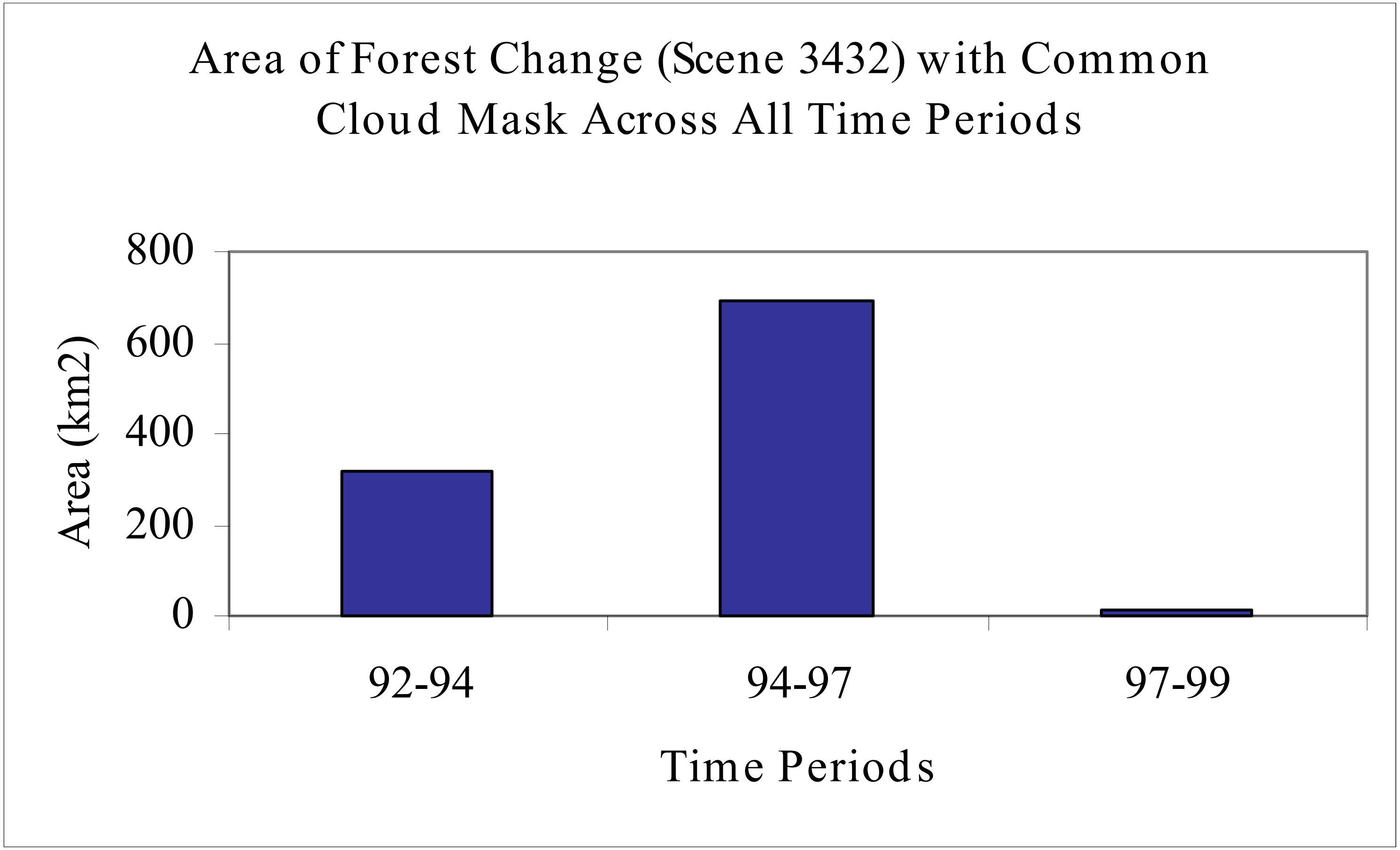
Forest to Non-Forest Change in the Rocky Mtns, CO.

1992 | 1994 | 1997 | 1999 Landsat 7



\`92 to \`94 | \`94 to \`97 | \`97 to \`99

(15km x 15km)



Area of Forest Change (Scene 3432) with Common Cloud Mask Across All Time Periods
800
600
400
200
0
Area (km2)
92-94
94-97
97-99
Time Periods

Forest Change in the Rockies, Using Landsat 7

- Accuracy Assessment:

Path-Row	Year1	Year2	Accuracy
34-32	'92 (Landsat 5)	'94 (Landsat 5)	95%
34-32	'94 (Landsat 5)	'97 (Landsat 5)	96%
34-32	'97 (Landsat 5)	'99 (Landsat 7)	97%
34-33	'97 (Landsat 5)	'99 (Landsat 7)	96%
34-34	'97 (Landsat 5)	'99 (Landsat 7)	100%

Forest Change in the Rockies, Using Landsat 7

- Results to date:
  - 1. There is a significant drop in forest clearing between 1997-1999 in the Rocky Mountain Region.
  - 2. We are having good success generalizing our neural nets, trained on two dates of Landsat 5 imagery for use on Landsat 5 -Landsat 7 combinations.

Why is Landsat 7 so Wonderful?

- Reduced Cost
- Improved image availability
  - Combination of increased archiving capacity and Long Term Acquisition Plan
- Improved Accessibility (couple of days)
- Improved image quality
- New Panchromatic band (15meter)
- Best ever calibration
- Can share images

Conclusions

- 1. Accuracies for methods based on generalization match conventional methods.
- 2. For monitoring forest change, generalization in time, within geographic regions and across Landsat sensors is possible.
- 3. The use of methods based on generalization allows for more efficient or frequent monitoring of large areas.

Conclusions

- 4. Lower image cost and increased availability of Landsat 7 data, combined with methods based on generalization, make it practical to begin regional to continental, and eventually global, monitoring of temperate forest change at high spatial resolutions.

Monitoring Succession in Temperate Conifer Forests with Remote Sensing: Implications for Terrestrial Carbon Budgets

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Cascade Ranges of Oregon

(Picture taken Summer 2000)

Landsat 7 ETM+ Imagery (22 Aug 1999)
(RGB=453)

An Example of Forest Succession

Why Is Forest Succession Important?

- **Sustainable Natural Resource Management**

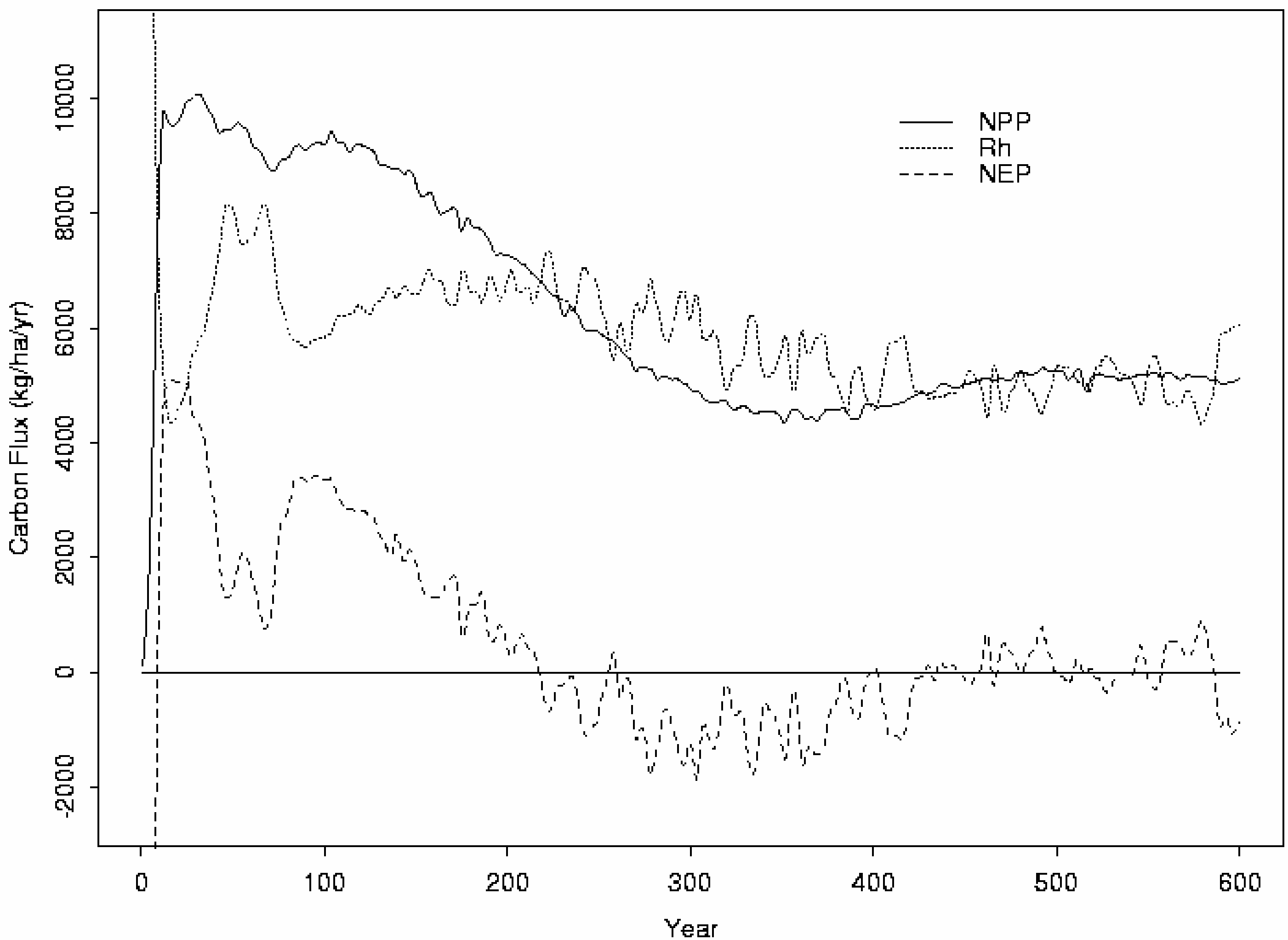
- **Biodiversity**

- **Preserve Soil and Water Resources**

- **Global Climate Change**

Forests cover 31% of Earth's land area. They dominate the dynamics of the terrestrial C cycle. Forests contain 86% of the world's above ground C and 73% of the C in the soil.

Stand Scale Carbon Fluxes With Forest Succession



Mapping Forest Age or Tree Size has proven difficult

Substitute Space for Time

To characterize succession using stands at varying succession stages from different locations at a single time.

Empirical analysis

Supervised and unsupervised classification, regression analysis.

What have we learned?

- Reflectance from near-infrared and mid-infrared bands are important in monitoring forest succession.
- Simple linear approaches using one or more spectral indices generally do not work well in monitoring forest succession with optical imagery.

Approach Taken: Follow forest development through time

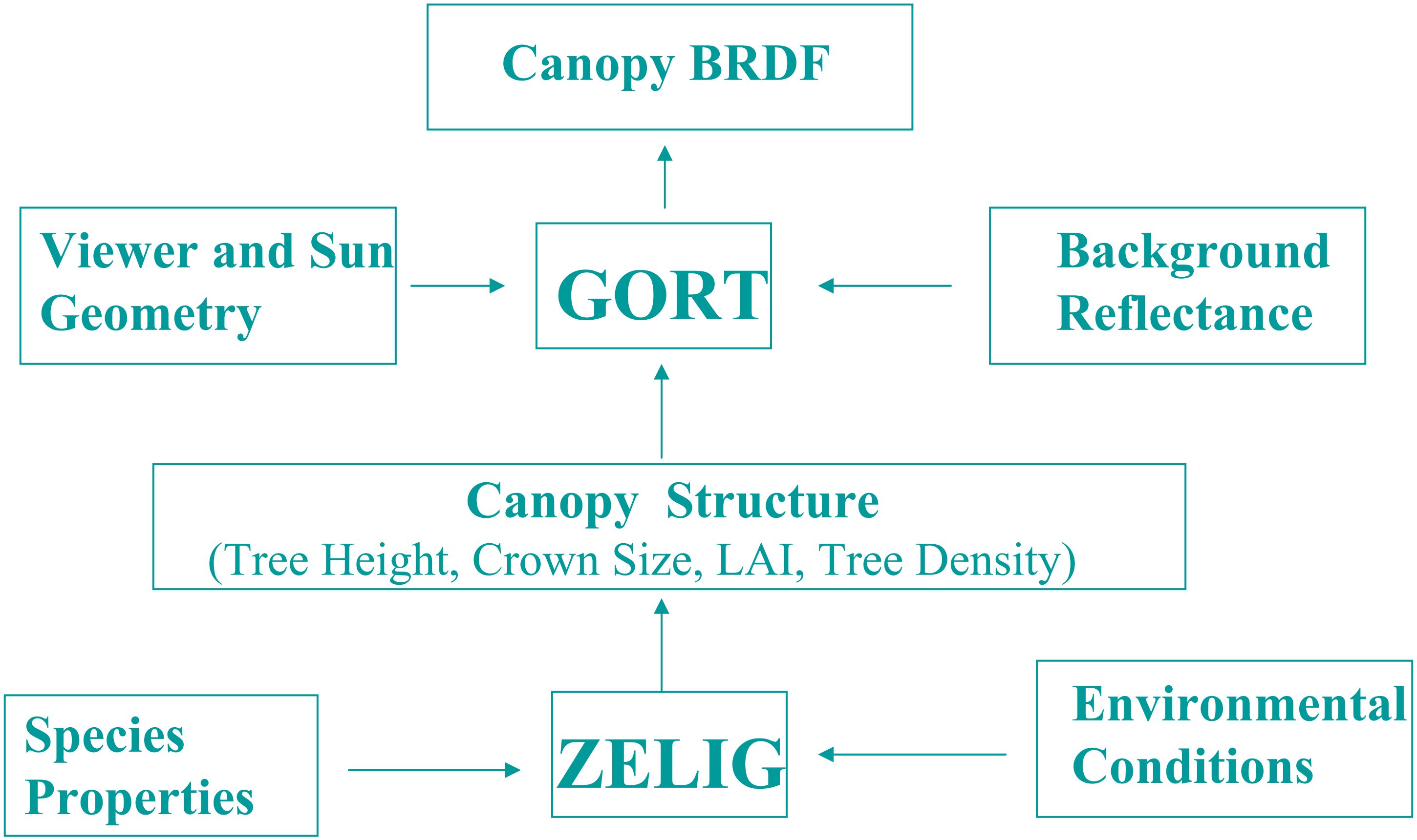
Method Used: Modeling

Merged two very different kinds of models: an ecological model of forest succession and a forest canopy reflectance model.

Objectives

- to improve our understanding of the manifestation of forest succession in optical imagery
- to provide a theoretical basis for improved monitoring forest succession
- to develop methods more easily transferred to new locations

Spectral-Temporal Modeling Platform



GORT

(Geometric Optical Radiative Transfer)

Model Objective: Photon transport through plant Canopies

Model Input:

Canopy Structure

- Tree Size
- Tree Density
- Leaf Area
- Canopy Height
- Crown Shape

Background Reflectance

Sun and Viewer Geometry

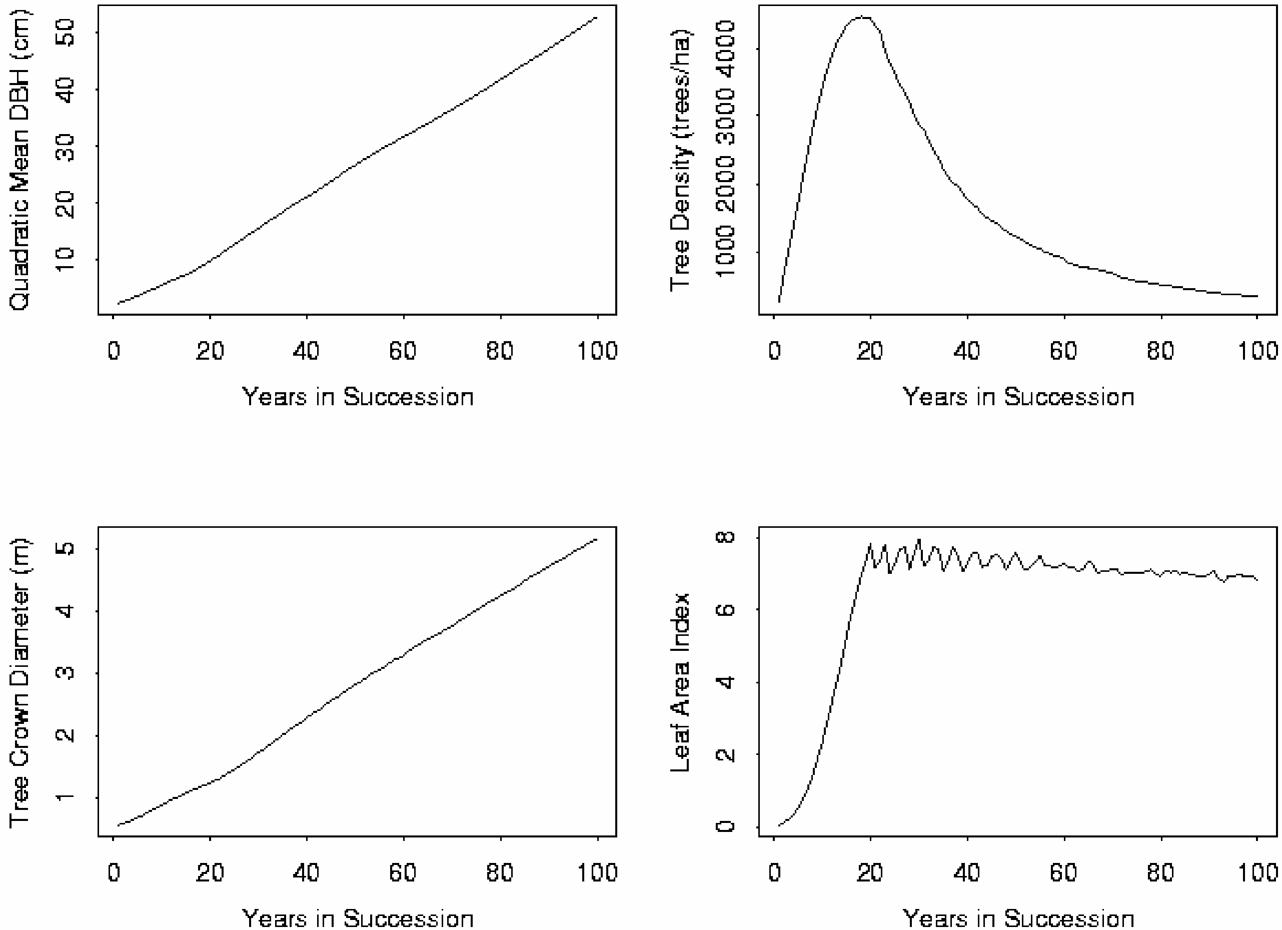
Model Output: Canopy BRDF, Scene Component Proportions and Signatures

Model Advantages:

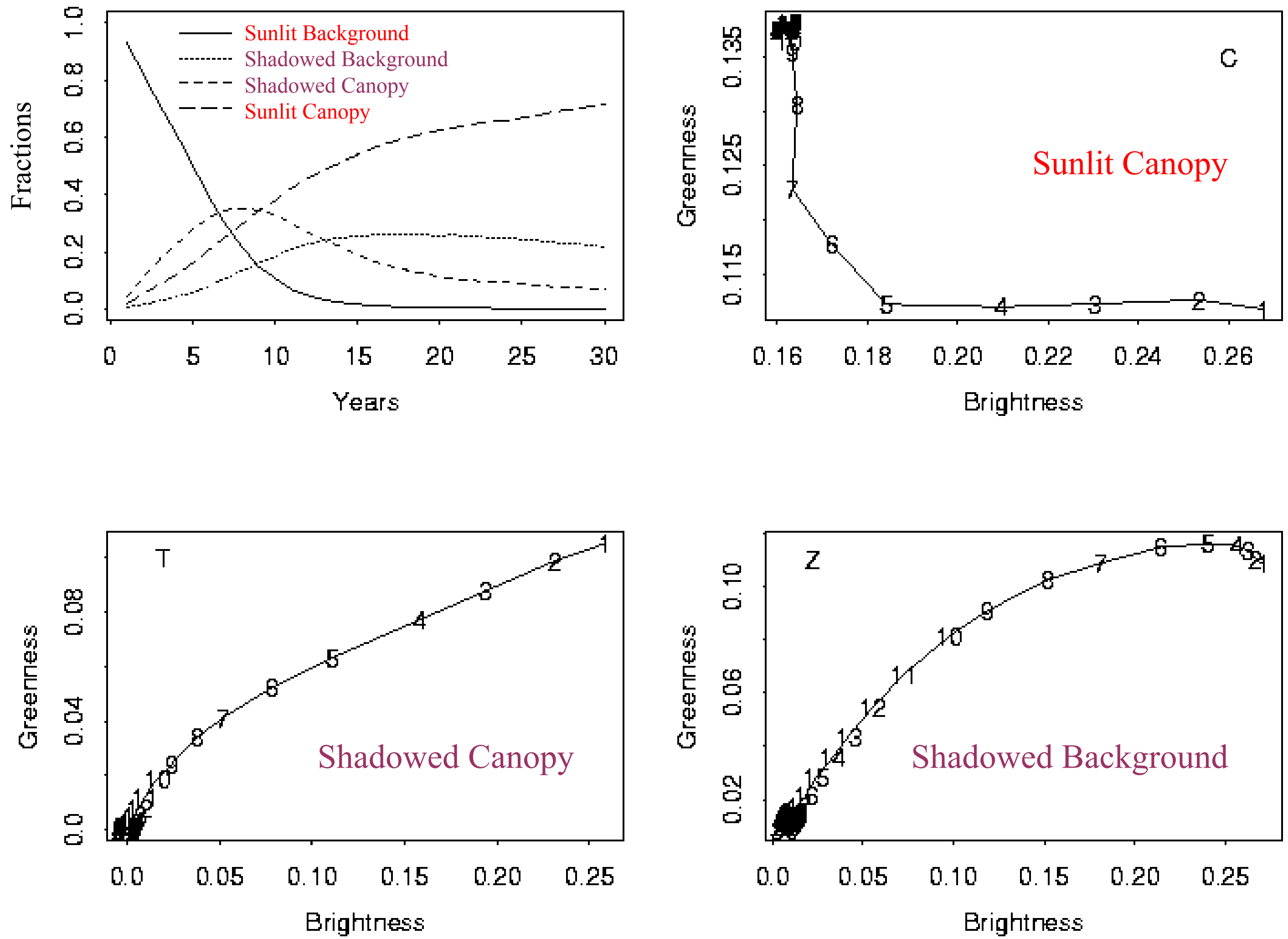
Integrates the strengths from both the GO and the RT approaches, and is capable of handling the spatial heterogeneity of forest canopies.

Li, X., Strahler, A. H. and Woodcock, C. E. 1995. A Hybrid Geometric Optical-Radiative Transfer approach for Modeling Albedo and directional Reflectance of Discontinuous Canopiies. IEEE Trans. Geosci. Rem. Sens. 33:466-480.

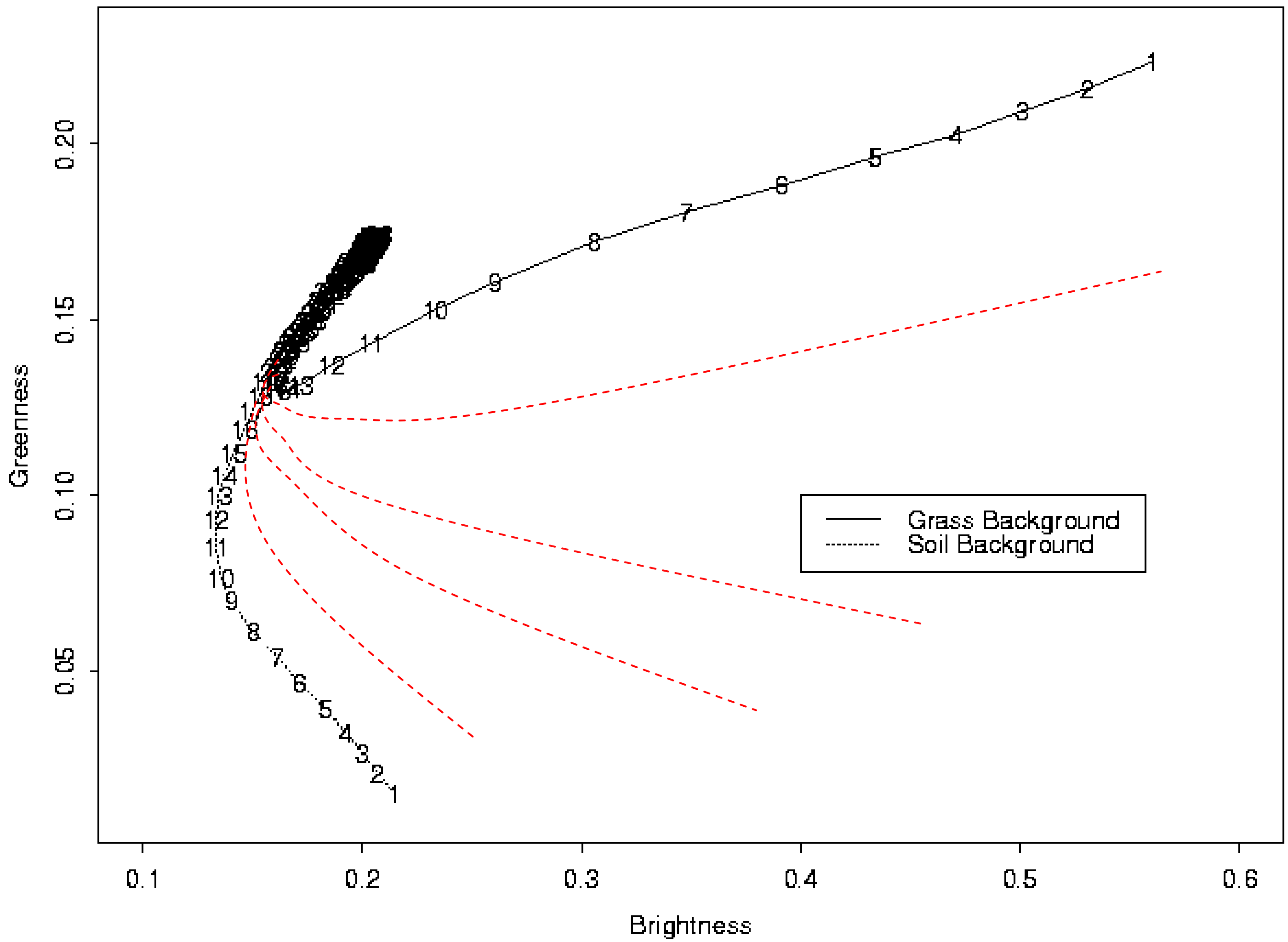
Results from ZELIG for a Douglas Fir/Hemlock Stand



Scene Component Fractions and Signatures

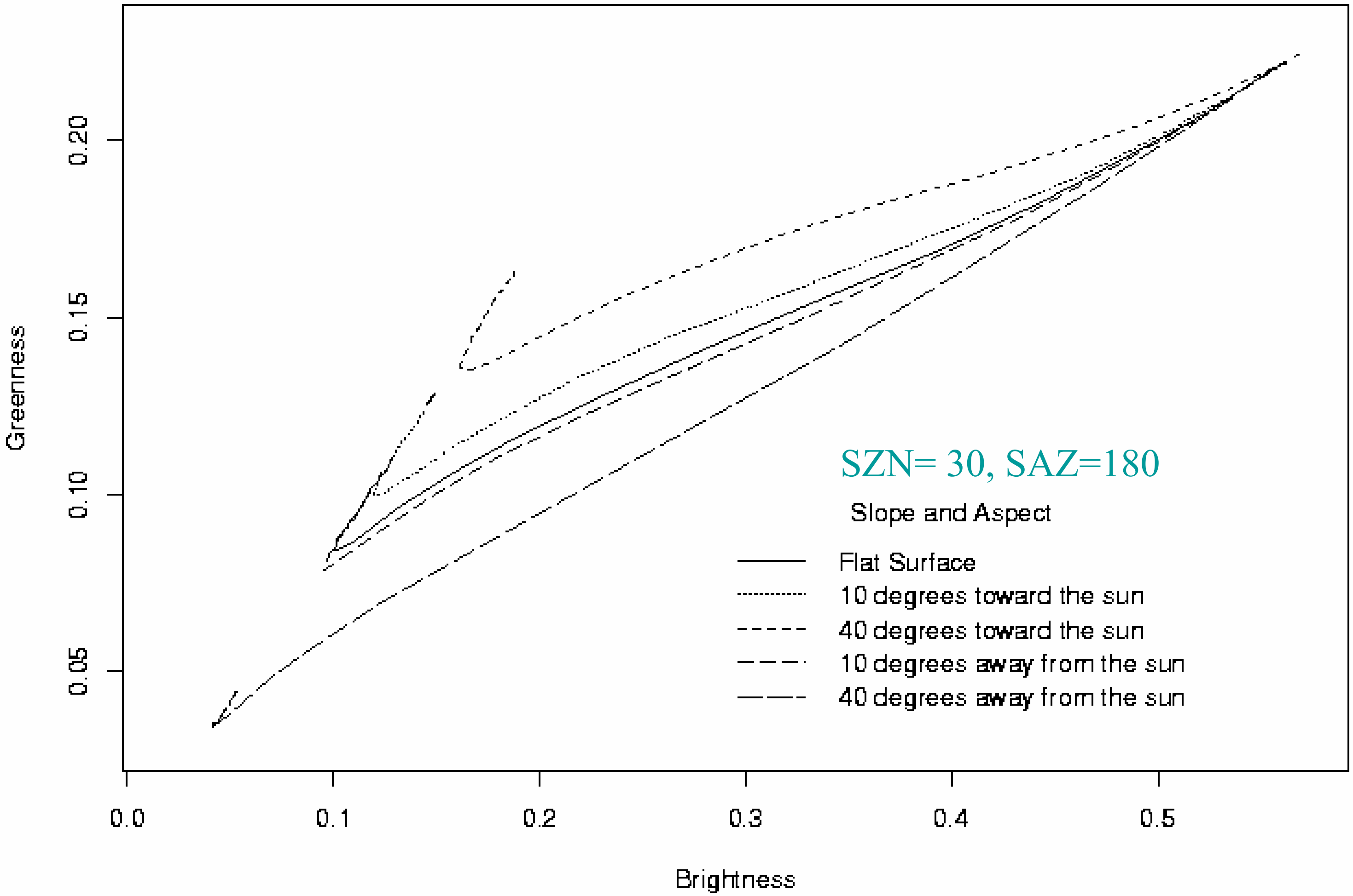


Succession Trajectories of a Natural Douglas Fir/Hemlock Forest



Location:H.J. Andrews
Nadir View
Sun Zen: 30 º
Sun Azi: Due South
Bands: ~ Landsat TM

Topography on Succession Trajectories



Schaaf et al. 1994. Topographic effects on bidirectional and hemispherical reflectance calculated with a Geometric-Optical model. IEEE Trans. Geosci. Rem. Sen. 32(6):1186-1193.

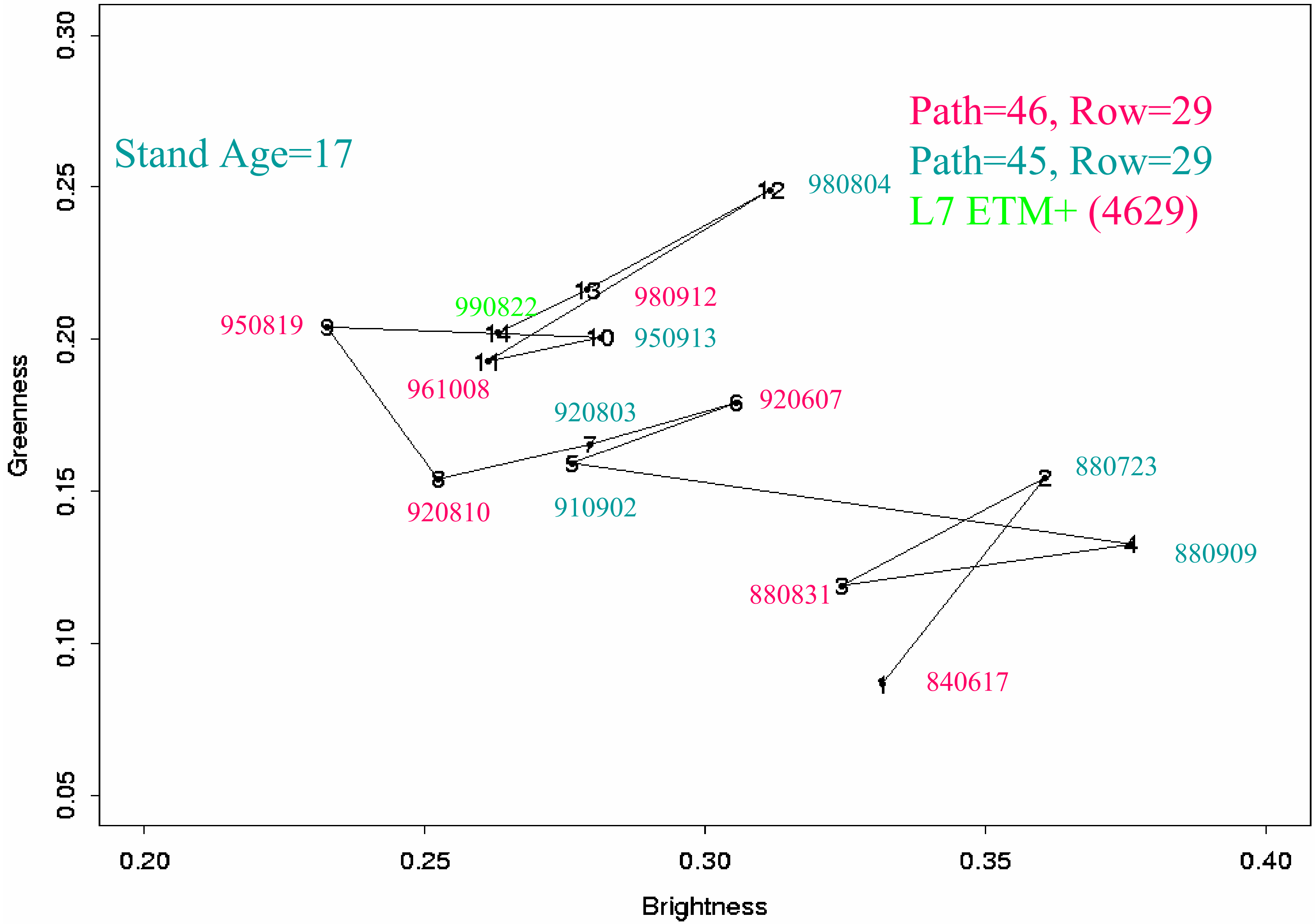
Validation Efforts

1. Collected sivilcultural histories for stands at different successional stages in the HJA

2. Compiled fourteen Landsat TM and ETM+ images from 1984-1999.

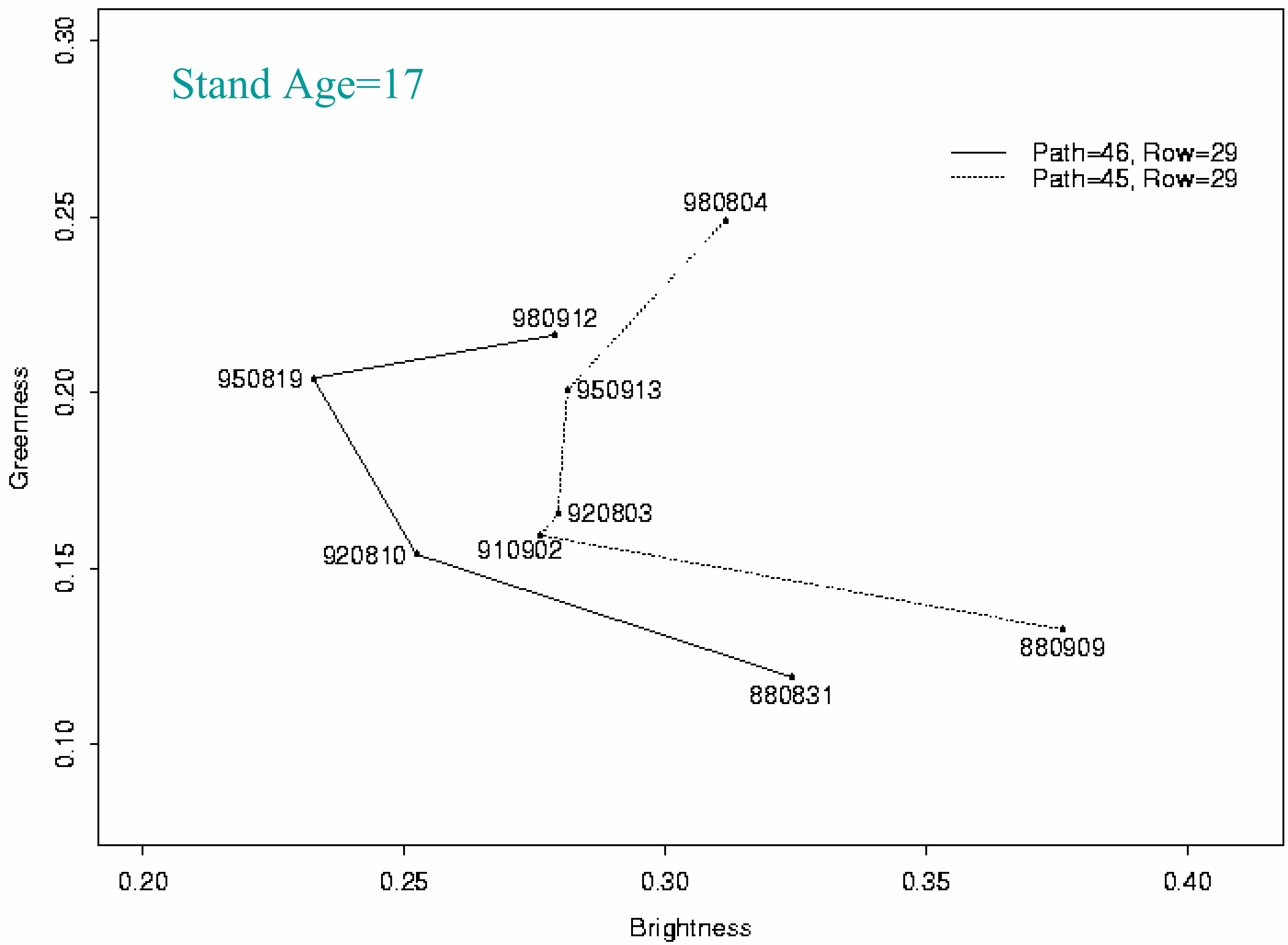
3. Analyzed stand spectral histories to see if real stands exhibit the properties of the simulated trajectories

Spectral Trajectory For A Successfully Regenerated Stand

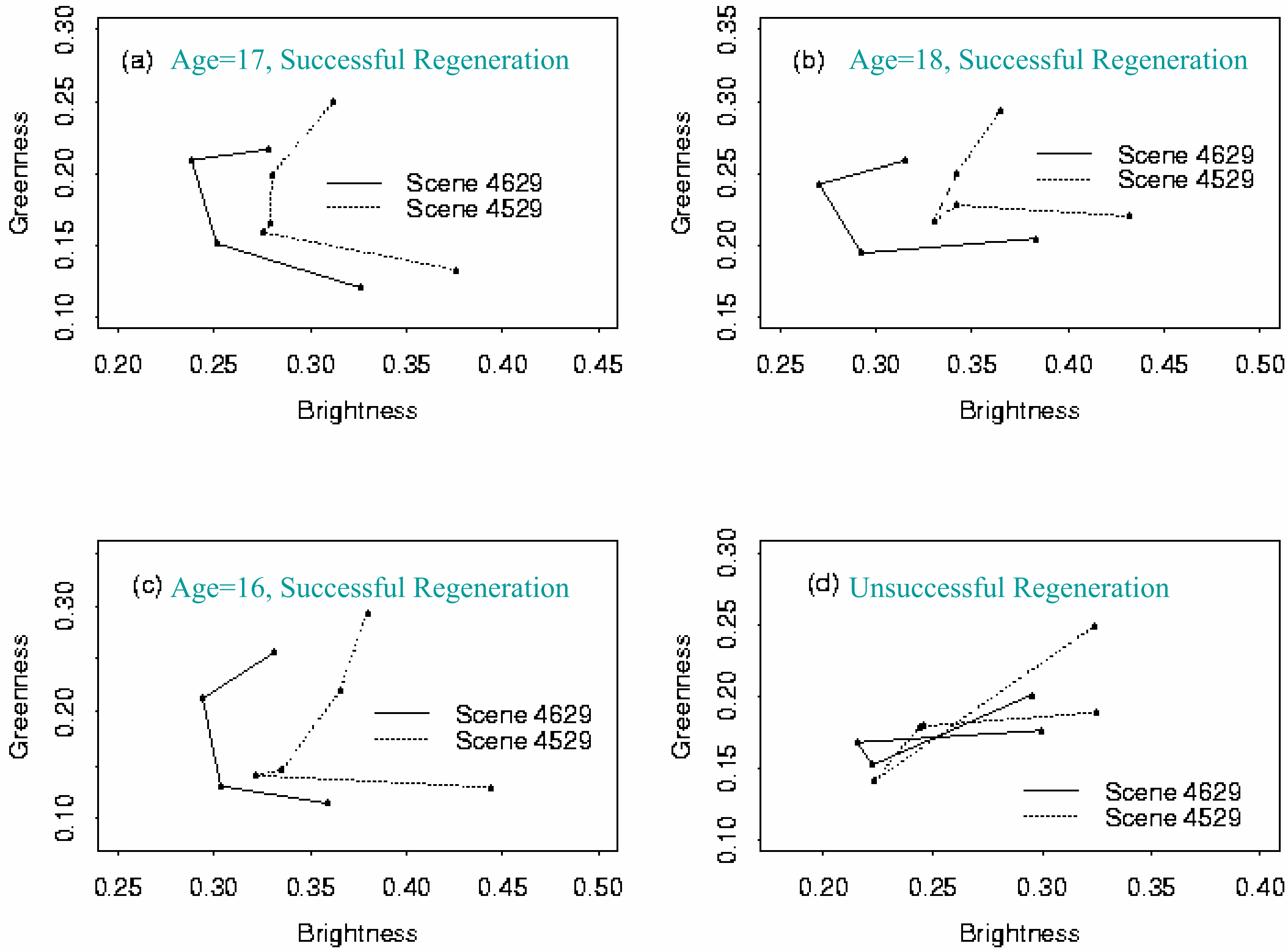


Song et al. 2001. Classification and change detection using Landsat data: When and how to correct for atmospheric effects? Remote Sensing of Environment. 75:230-244.

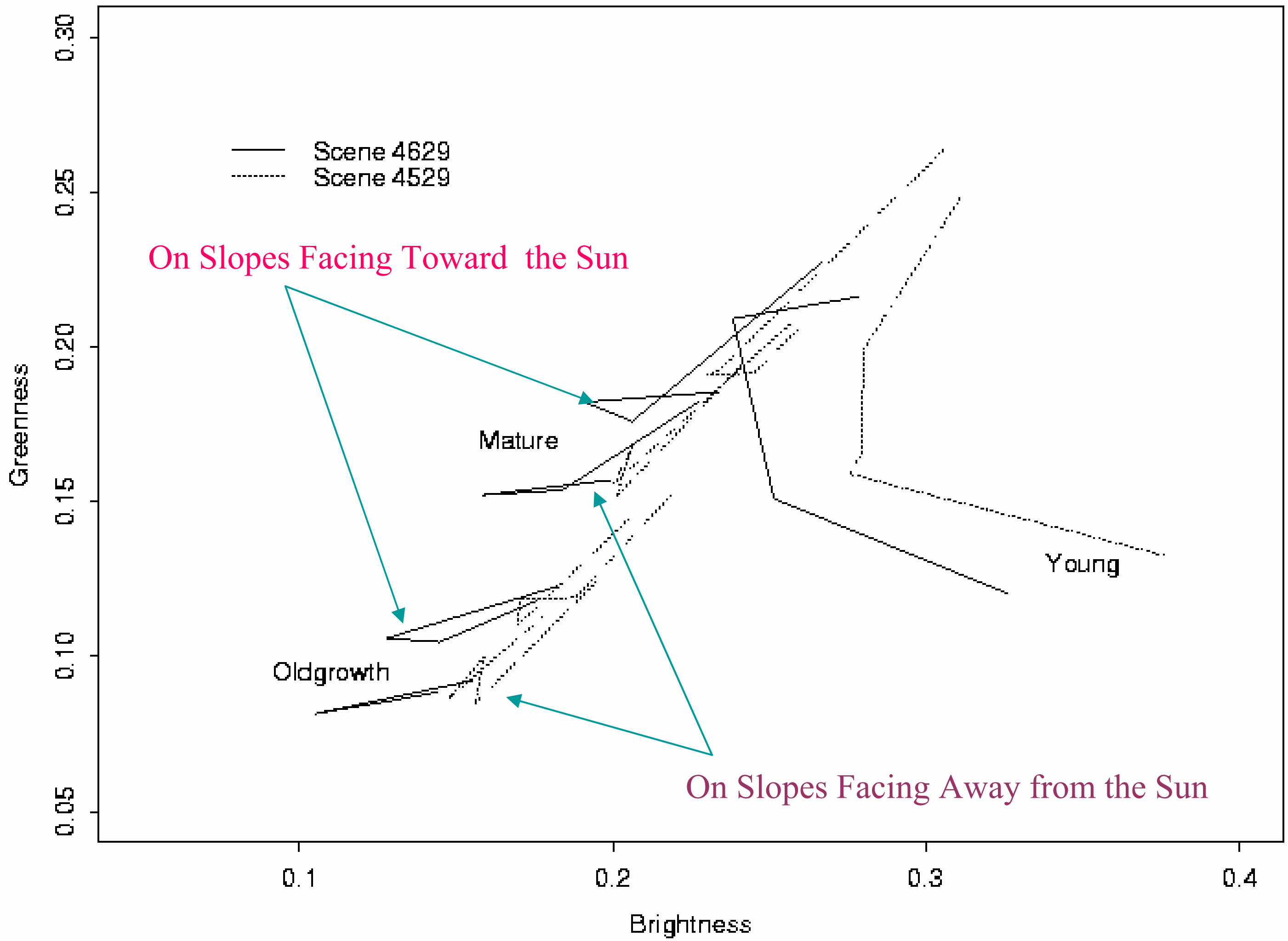
Trajectories After Limiting Dates and Separation of Scenes



More Examples of Succession Trajectories

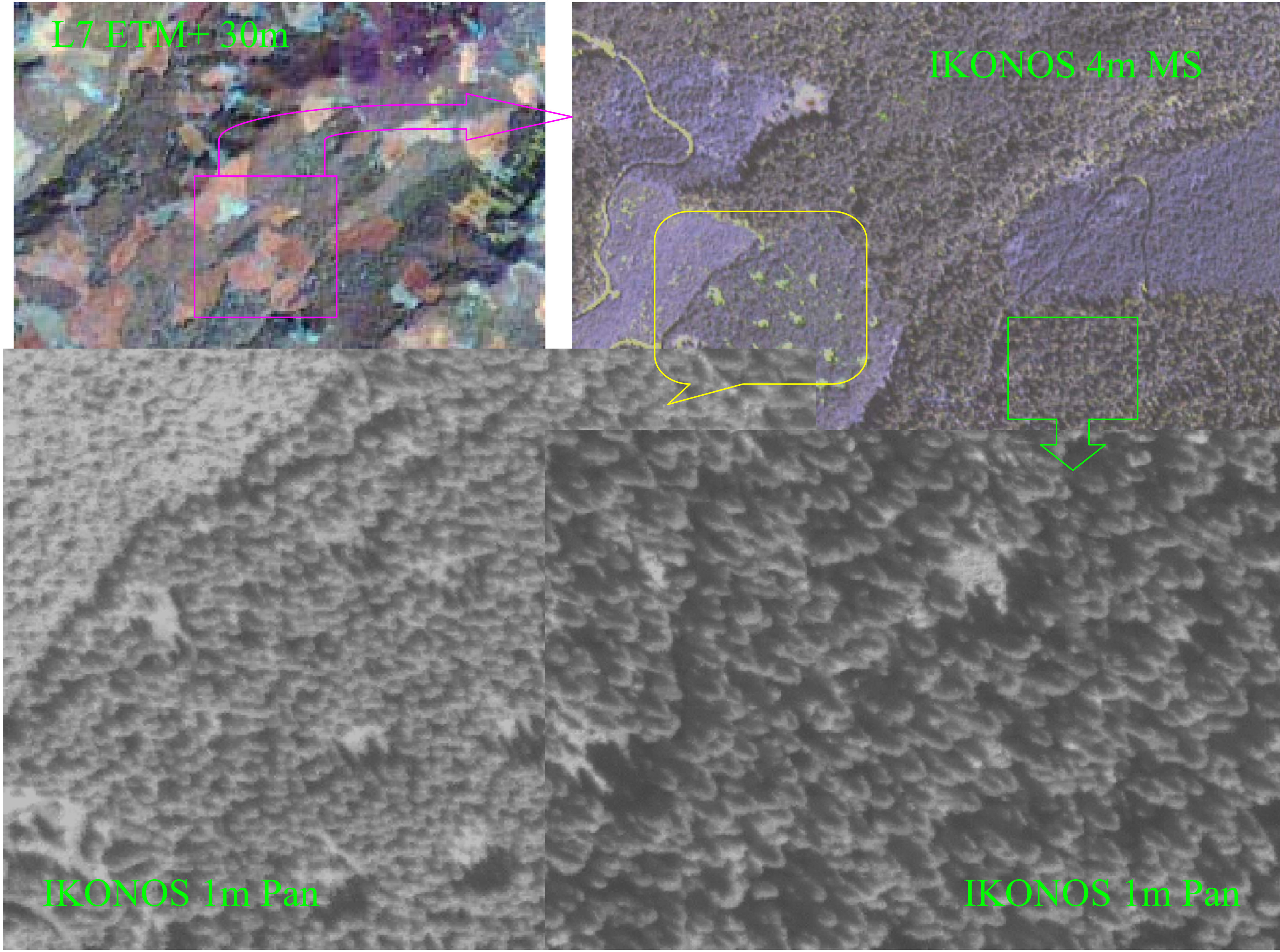


Spectral Trajectories for Young, Mature and Oldgrowth Stands



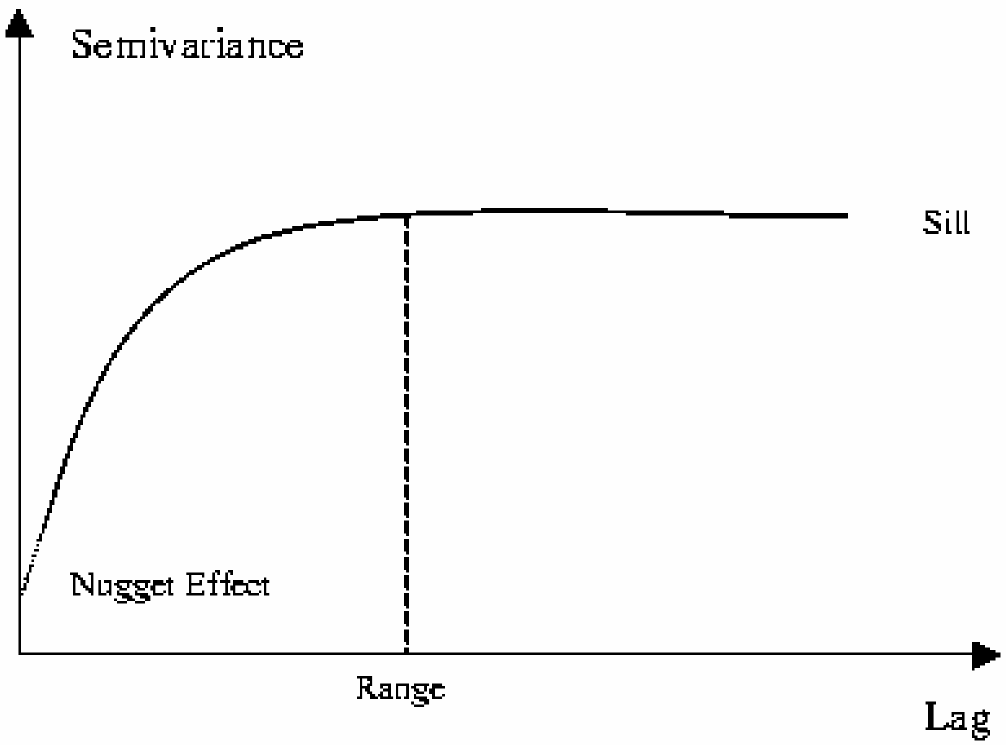
Conclusions for Spectral/Temporal Analysis

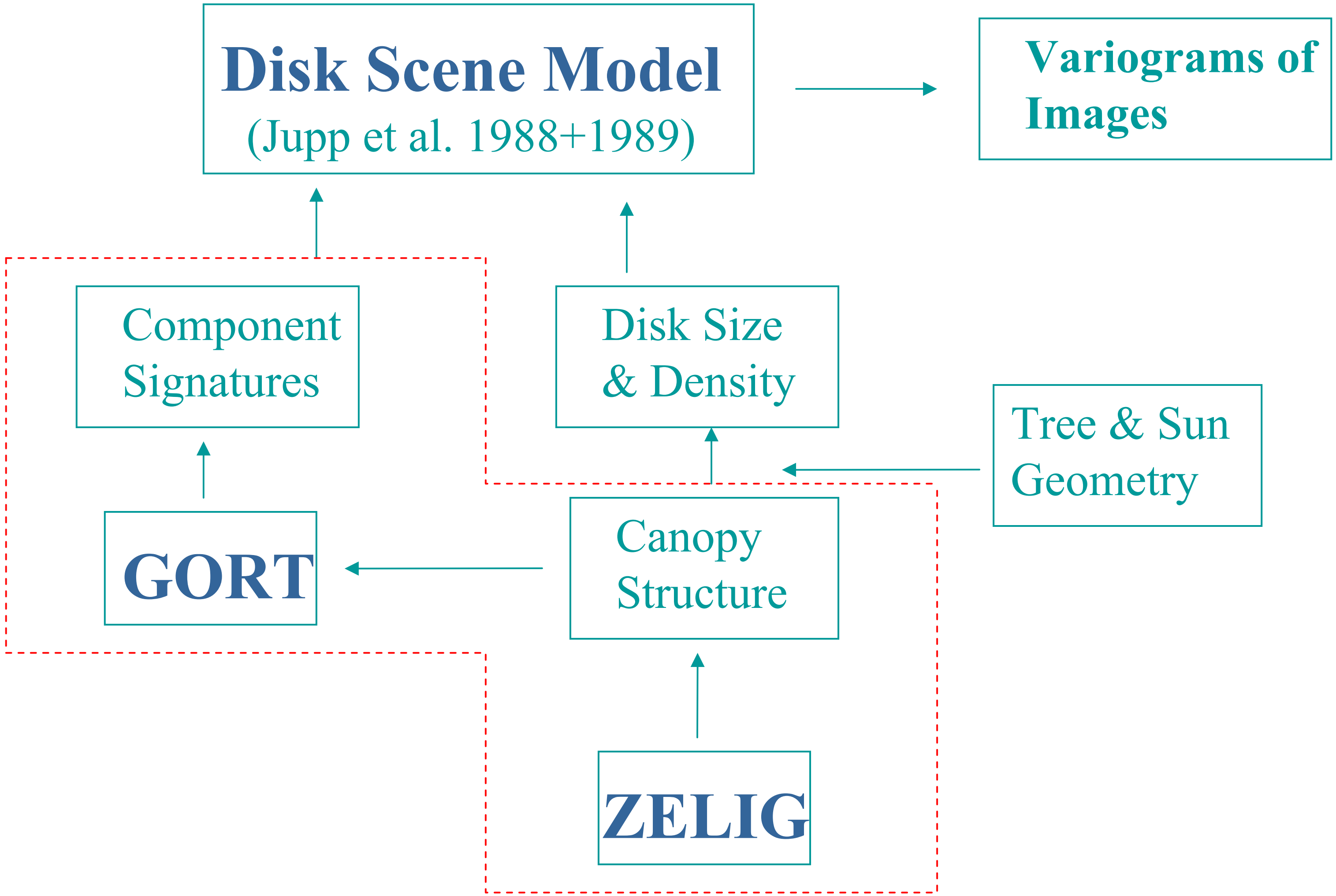
- GORT-ZELIG simulation reveals that the temporal trajectories of forest succession in spectral space are highly nonlinear, including both the rate and the direction of changes.
- Background conditions strongly influence canopy reflectance during early years of succession.
- Modeling results provide a theoretical basis for developing new approaches to monitor forest succession using multitemporal images.
- Multitemporal Landsat TM images show the modeled patterns of spectral/temporal trajectories associated with succession for young stands, but these results are very sensitive to noise from sun and look angles, phenology and topographic effects.
- Empirical observations indicate a strong effect in older stands due to changes in the composition of the canopy, the effects of which are not currently included in the model.


L7 ETM+ 30m
IKONOS 4m MS
IKONOS 1m Pan
IKONOS 1m Pan

Spatial Analysis of Forest Succession in Optical Imagery

$$V_f(h) = \frac{1}{2} E\{[f(x) - f(x+h)]^2\}$$





Jupp, D.L.B., A.H. Strahler and C.E. Woodcock, 1988,1989. Autocorrelation and Regularization in Digital Images. IEEE Trans. Geo. Rem. Sen. 26(4):463-473 and 27(3):247-258.

Punctual Variogram of Disk Scene Model:

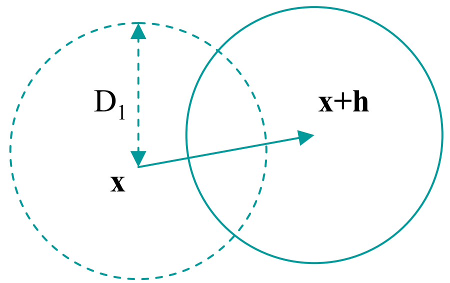
$$\boldsymbol{V_f(h)} = \frac{1}{2}\boldsymbol{E}\{[\boldsymbol{f(x)} - \boldsymbol{f(x+h)}]^2\} = \sigma^2 - \boldsymbol{Cov_f(h)}$$

Where:

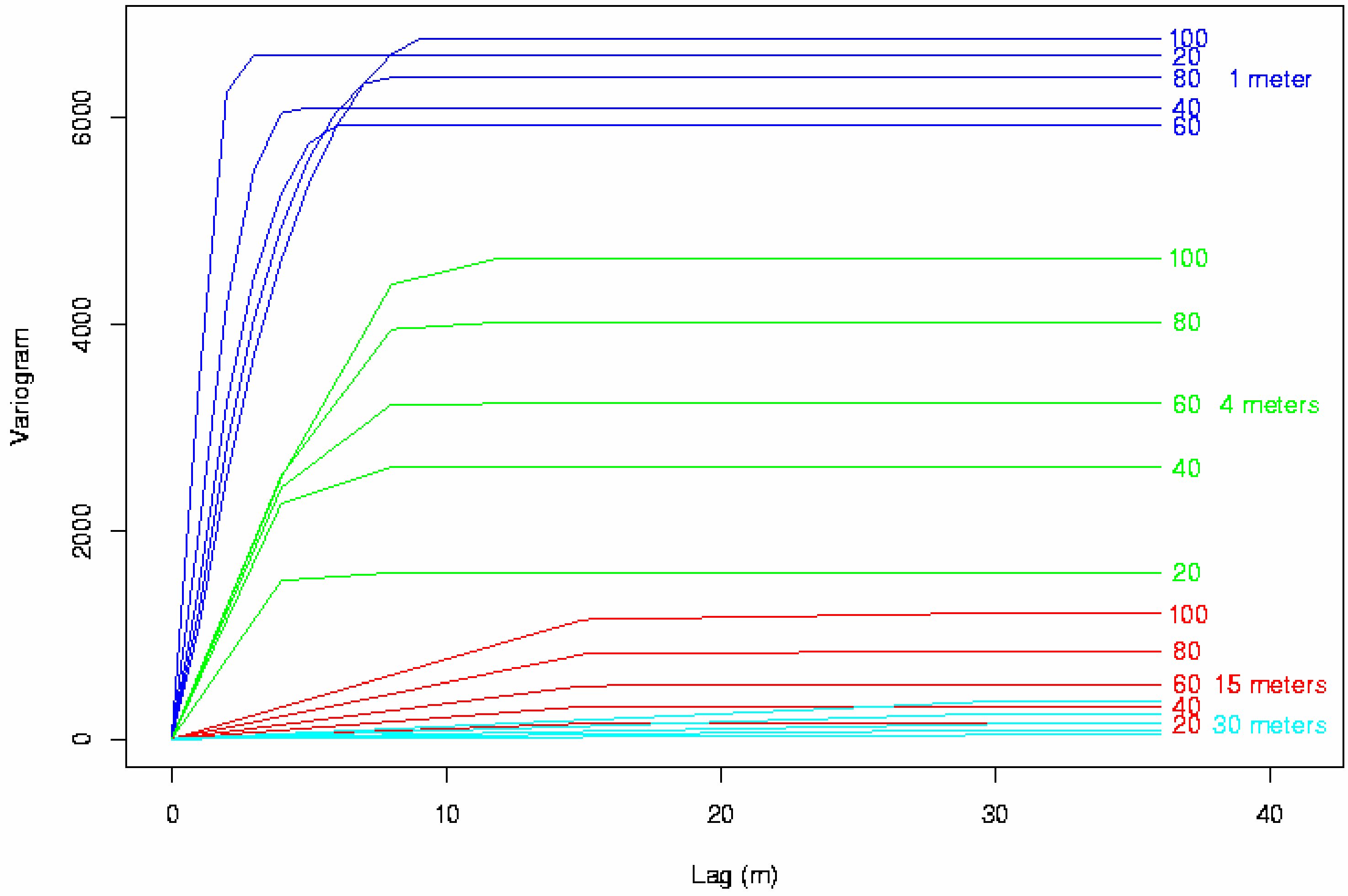
$$\sigma^2 = (g_D - g_B)^2 Q_1 (1 - Q_1)$$

$$Cov_f(h) = (g_D - g_B)^2 Q_1{}^2 (e^{\lambda A T(s)} - 1)$$

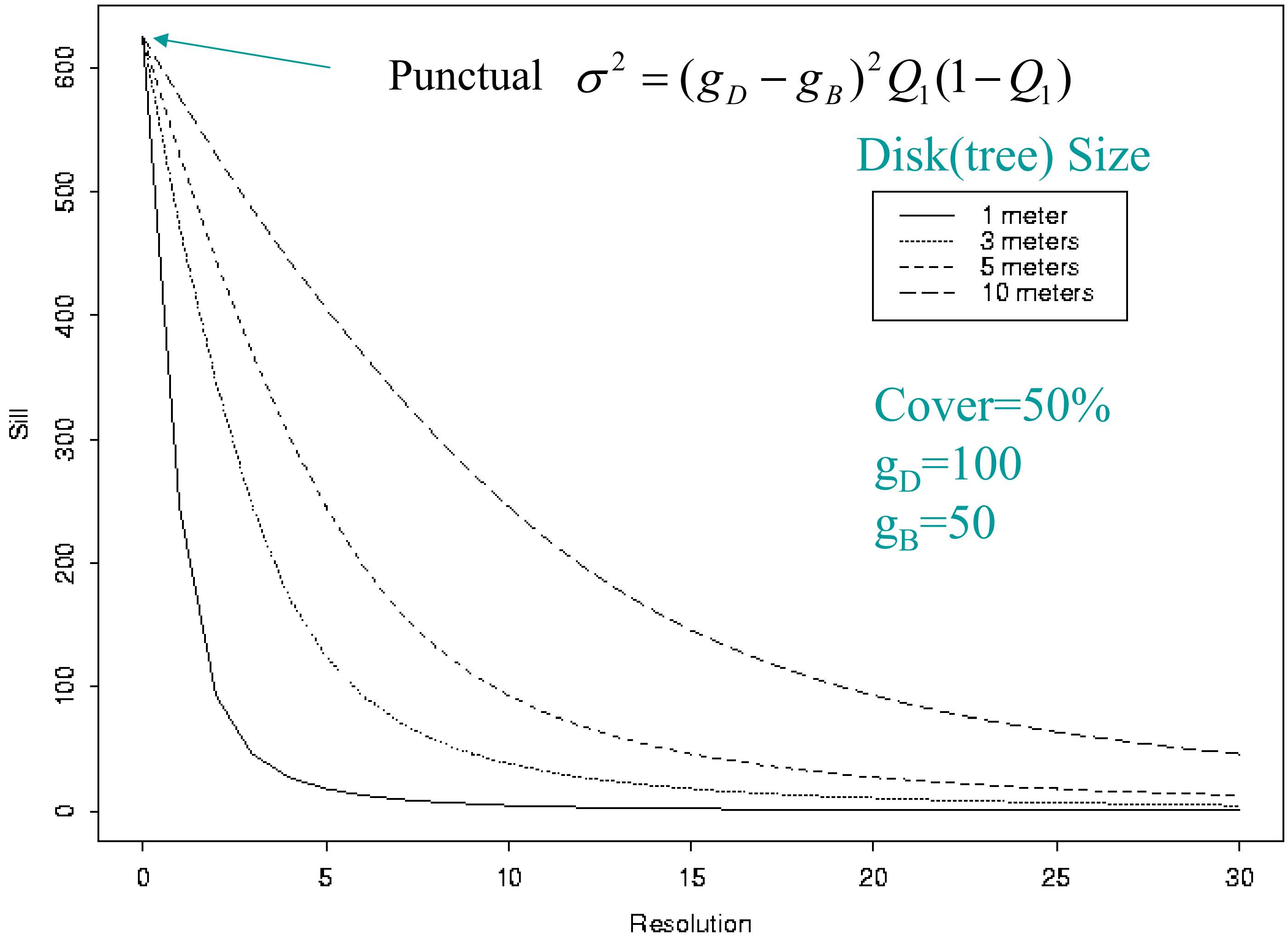
g_D = Disk Color
g_B = Background Color
Q_1 = Background Fraction
λ = Stem Density
$s = h/D_1$
T(s)=Overlap Function



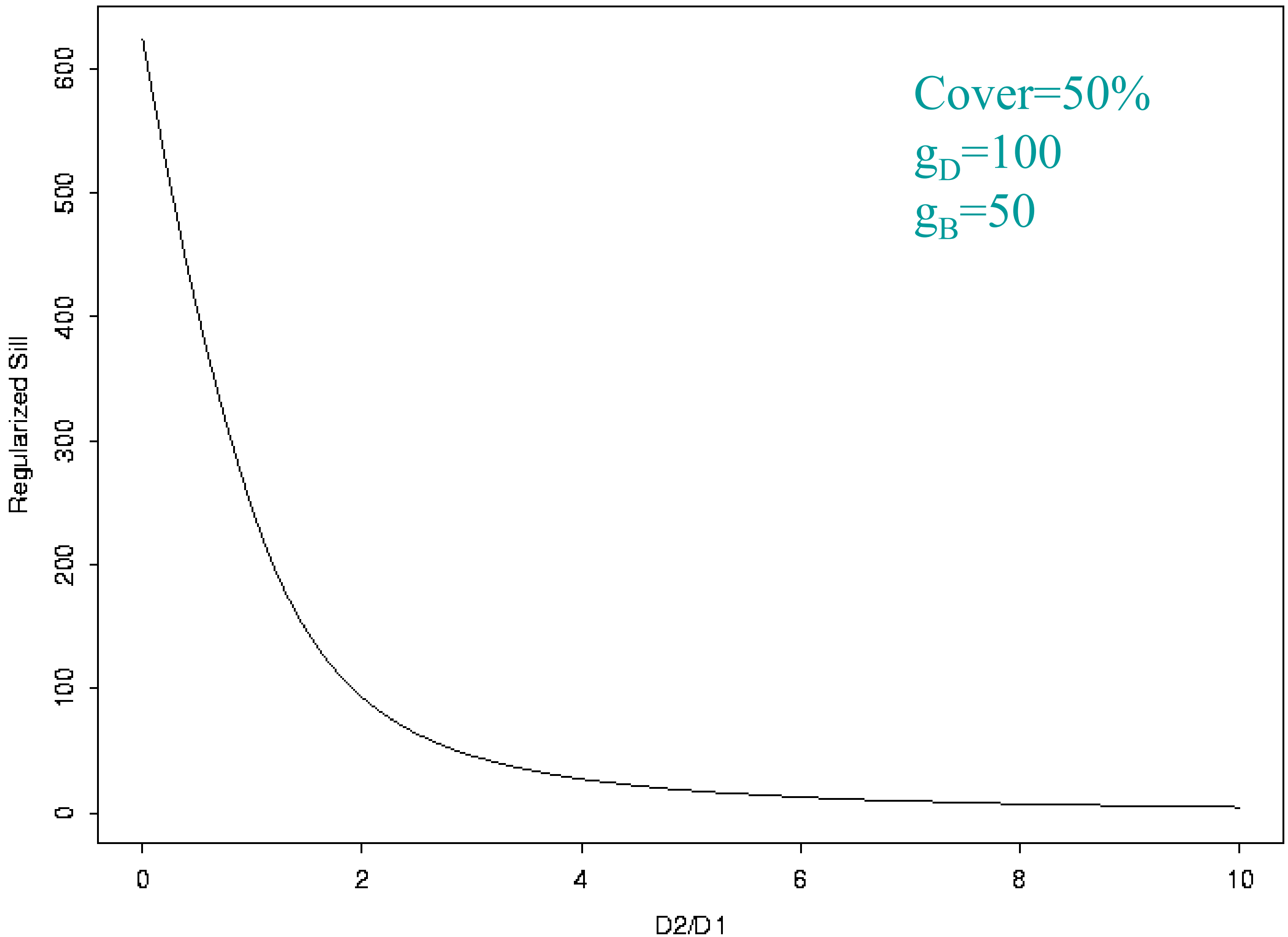
Variograms of a Forest in Succession



Effects of Disk(tree) Size on Sills with Regularization

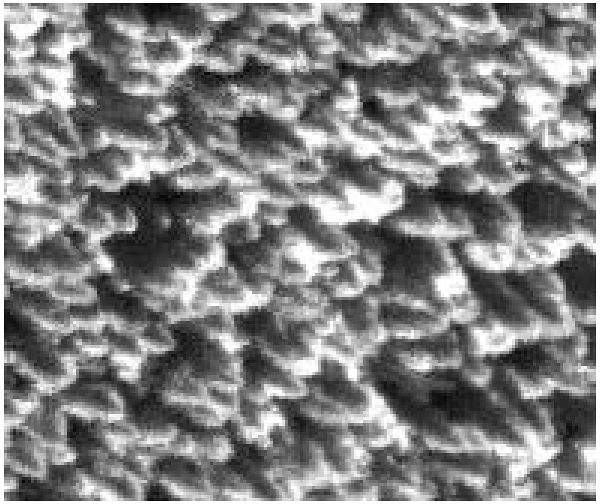


Effects of EFOV and Disk(tree) Size on Regularized Sill

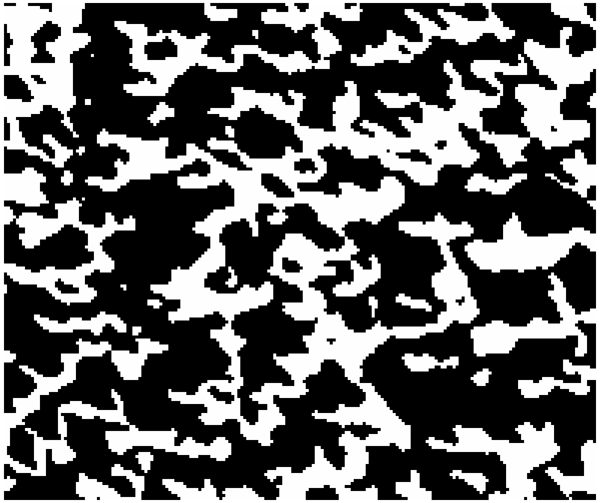


D2=EFOV, D1=Disk(tree) Size

Validation of Spatial Properties with IKONOS Imagery

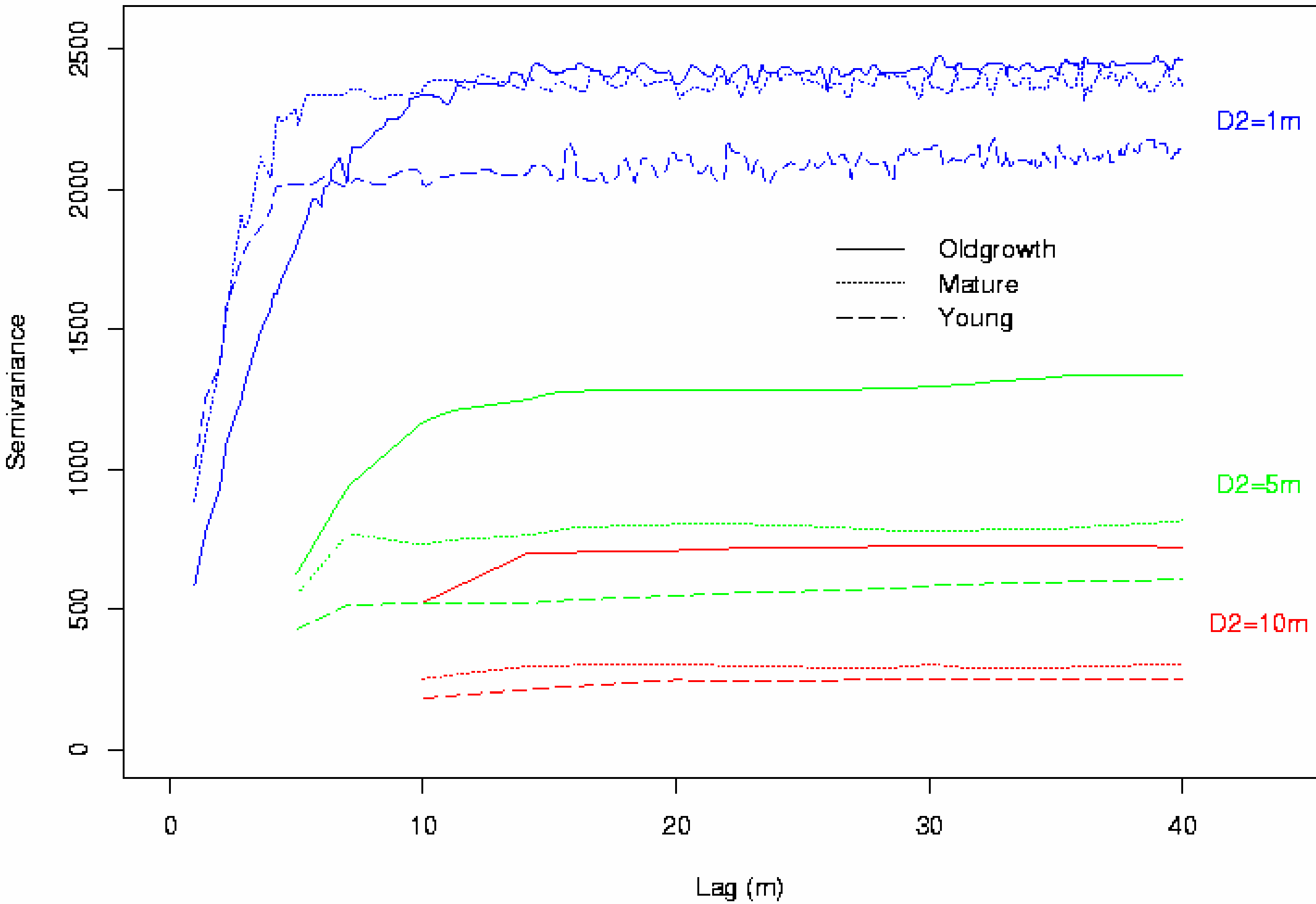


One meter Pan Image from IKONOS for an Oldgrowth

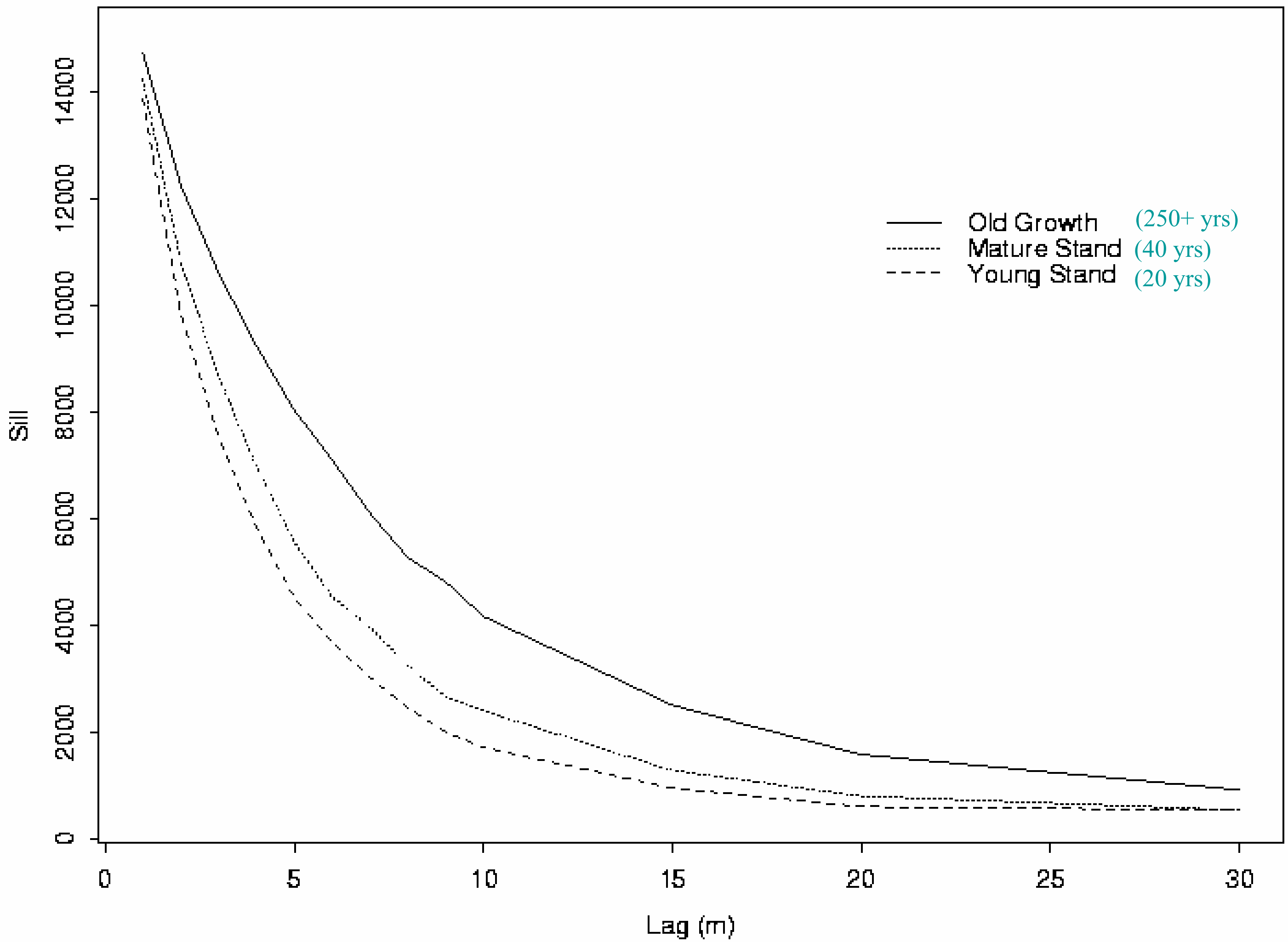


Two Component Equivalent Sunlit Canopy & “Background”

Observed Variograms with Regularization



Sills of Observed Variograms with Regularization



Conclusions for Spatial Analysis

- Spatial properties of remotely sensed imagery are the combined effects of object size, cover and the pixel size.
- Spatial properties of multiresolution imagery are diagnostic of tree size.
- This study provides the theoretical basis to map tree size using multiresolution imagery.
- Tests using IKONOS imagery show the modeled spatial patterns with tree size as regularization.

Overall Conclusions

Monitoring forest change over large areas using methods based on generalization appear to be feasible.

Multitemporal Landsat TM images show the modeled patterns of spectral/temporal trajectories associated with succession and indicate the potential for using multitemporal imagery to map stand age (as long as you control carefully effects from the atmosphere, sun and look angles and phenology) .

Observed spatial patterns in IKONOS imagery show the modeled effects of changes in pixel and tree size, indicating the potential for mapping tree size from multiresolution imagery.