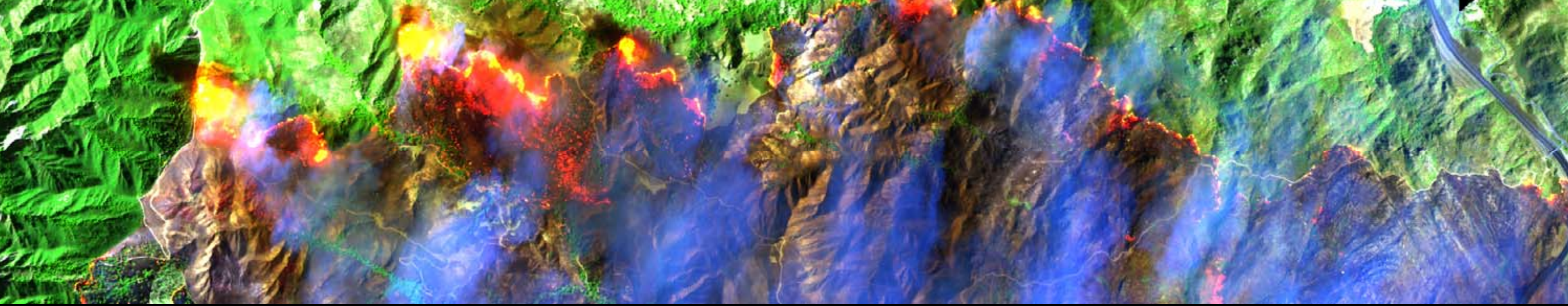


Remote Sensing of Fuel Type, Load, and Condition

Recent Research and Future Directions

Phil Dennison

University of Utah

Remote Sensing of Fuels

- Fuels are highly variable in space
- Remote sensing is well-suited to mapping this variability
- Surface fuels vs. canopy fuels
- Fuel properties that can be mapped using remote sensing:
  - Fuel type
  - Fuel load and structure
  - Fuel condition

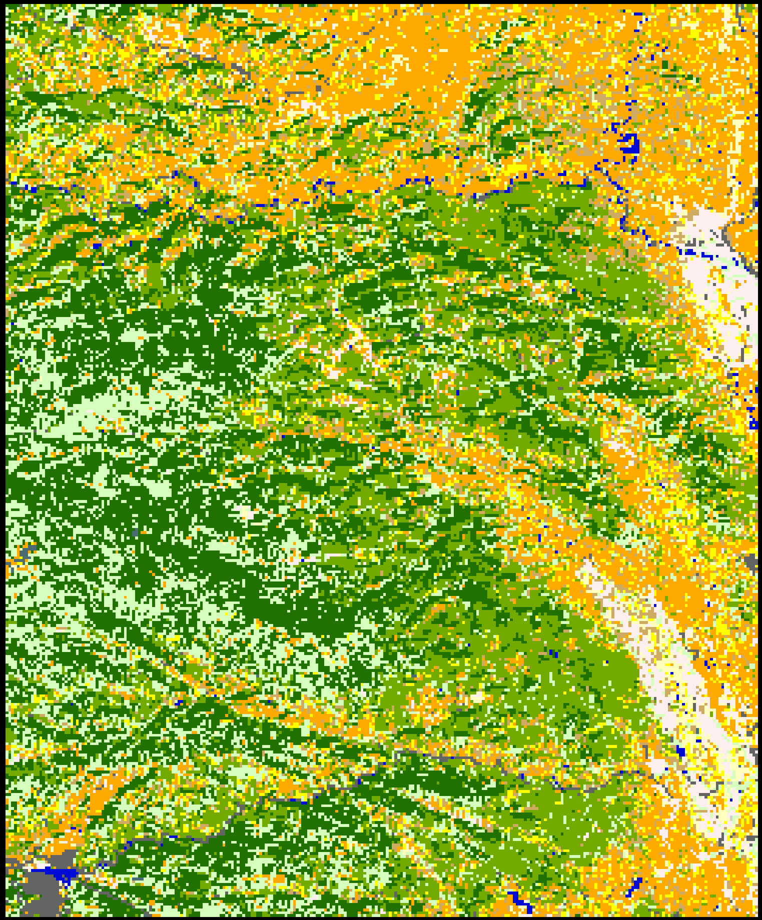
Fuel Type

Important parameters for fuels assessment and fire behavior modeling:

- Vegetation type or species maps (often intermediate step)
- Fuel models
  - Anderson (1982) → 13 models
  - Scott and Burgan (2005) → 40 dynamic fuel models

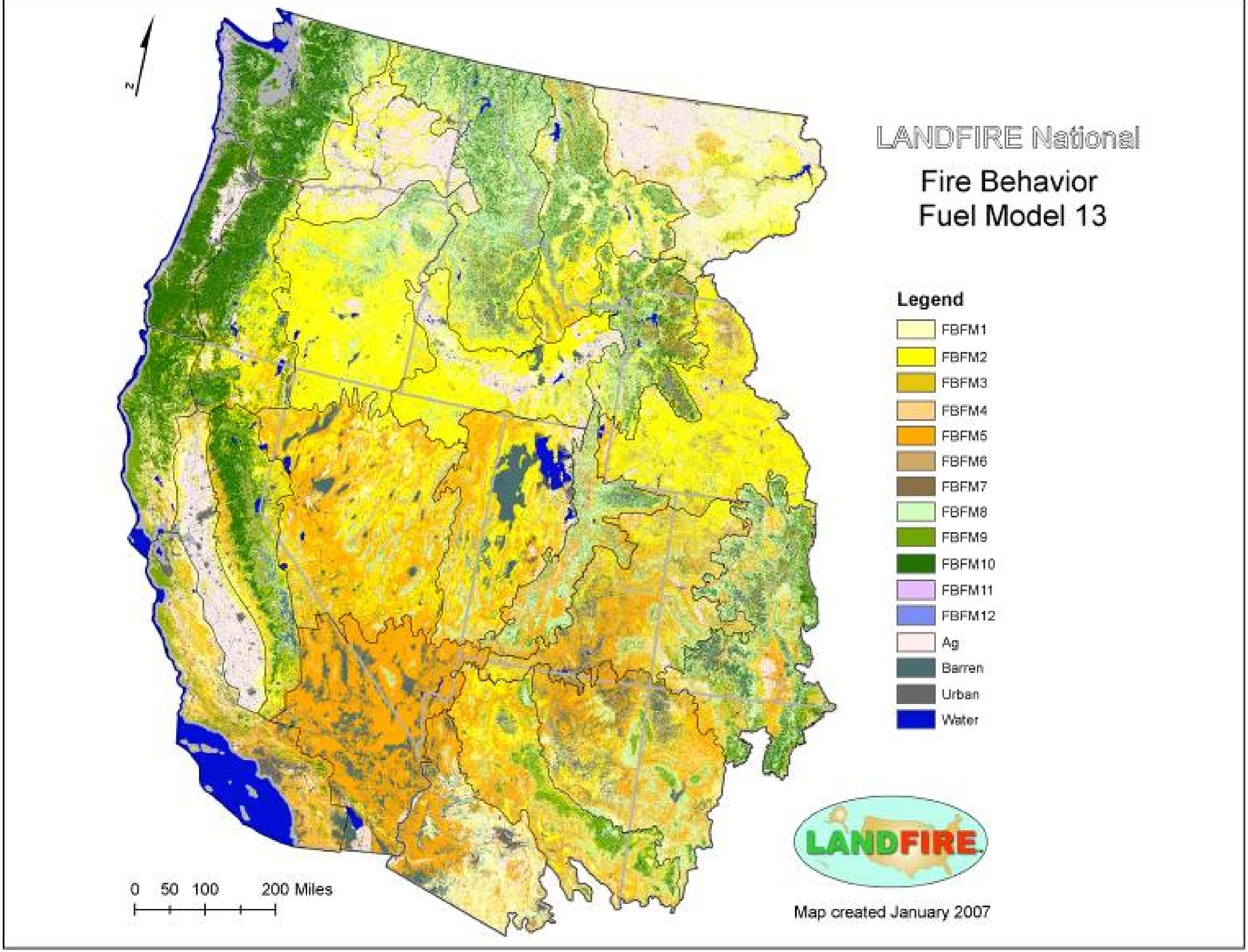
Mapping Fuel Type

- Moderate resolution multispectral data are sufficient for mapping vegetation for use in simpler fuel model classifications
- Hyperspectral data permit discrimination of more detailed fuel types

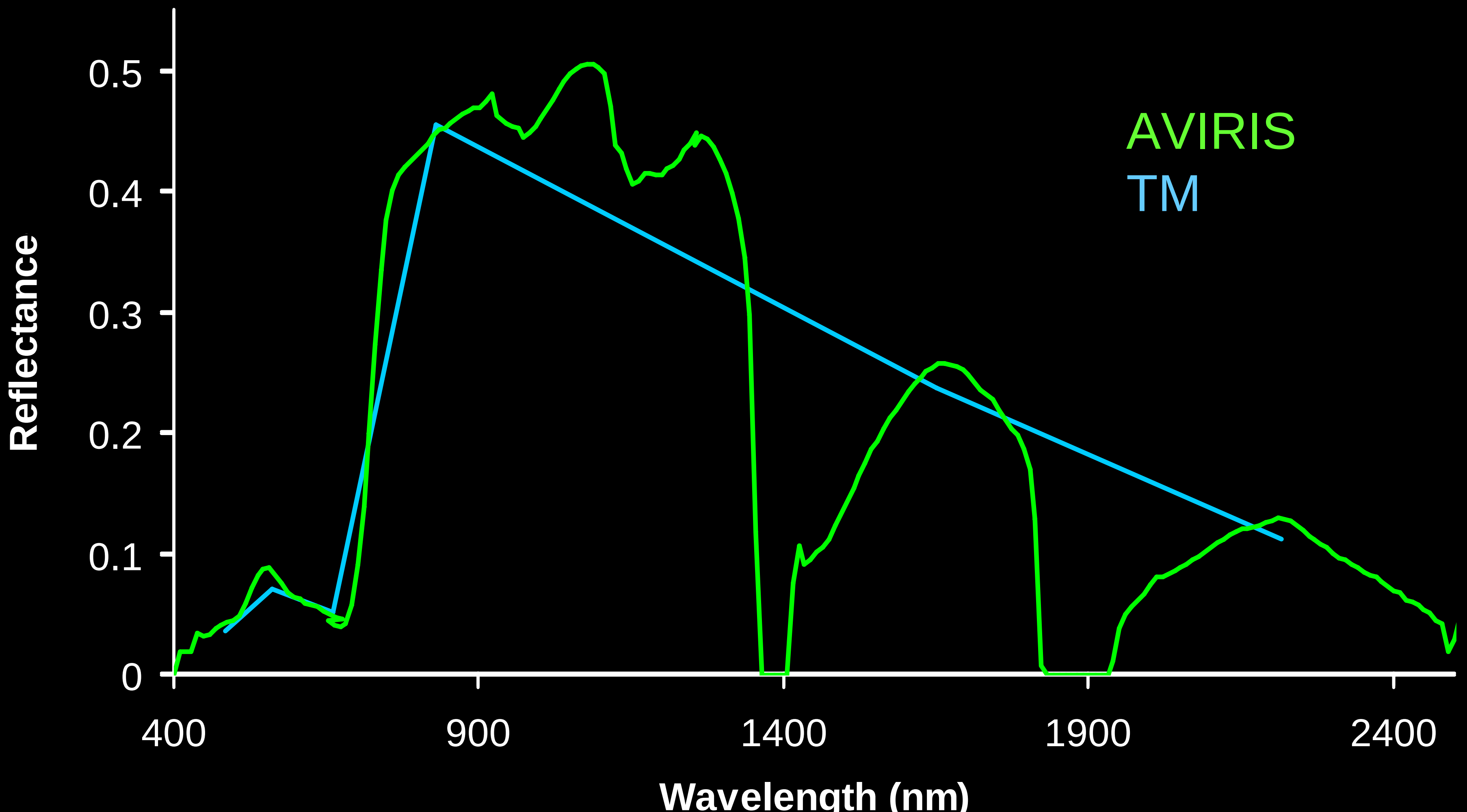


LANDFIRE™

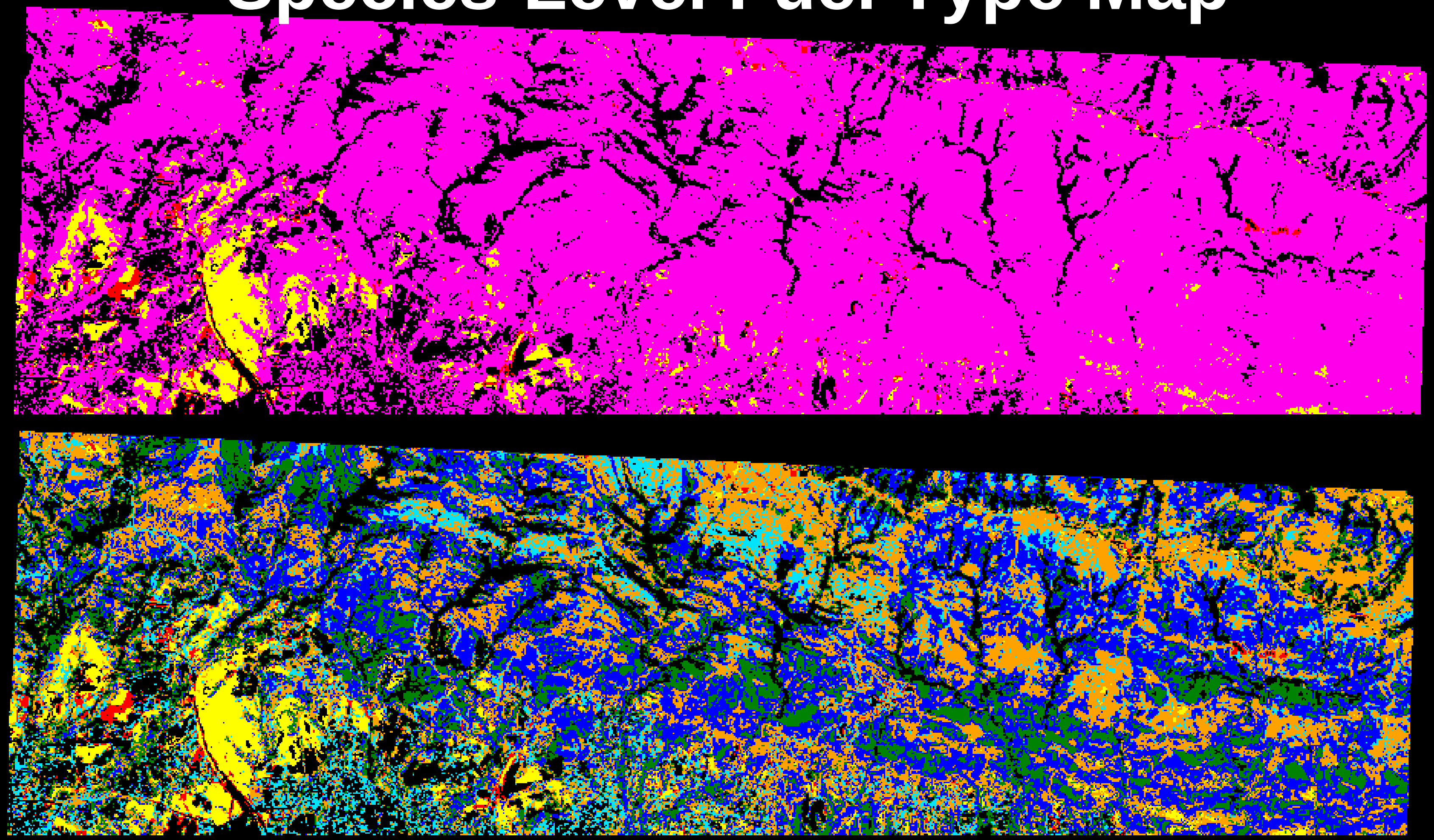
- National fuels mapping project supported by US Forest Service, USGS, and Nature Conservancy
- Surface fuel models mapped using four variables:
  - existing vegetation type
  - canopy cover
  - canopy height
  - environmental site potential
- Existing vegetation type and canopy cover/height are derived from Landsat data
- Fuel model classification rulesets were developed using expert review and refined through calibration workshops


LANDFIRE National
Fire Behavior
Fuel Model 13
Legend
FBFM1
FBFM2
FBFM3
FBFM4
FBFM5
FBFM6
FBFM7
FBFM8
FBFM9
FBFM10
FBFM11
FBFM12
Ag
Barren
Urban
Water
N
0 50 100 200 Miles
LANDFIRE
Map created January 2007

Multispectral vs. Hyperspectral

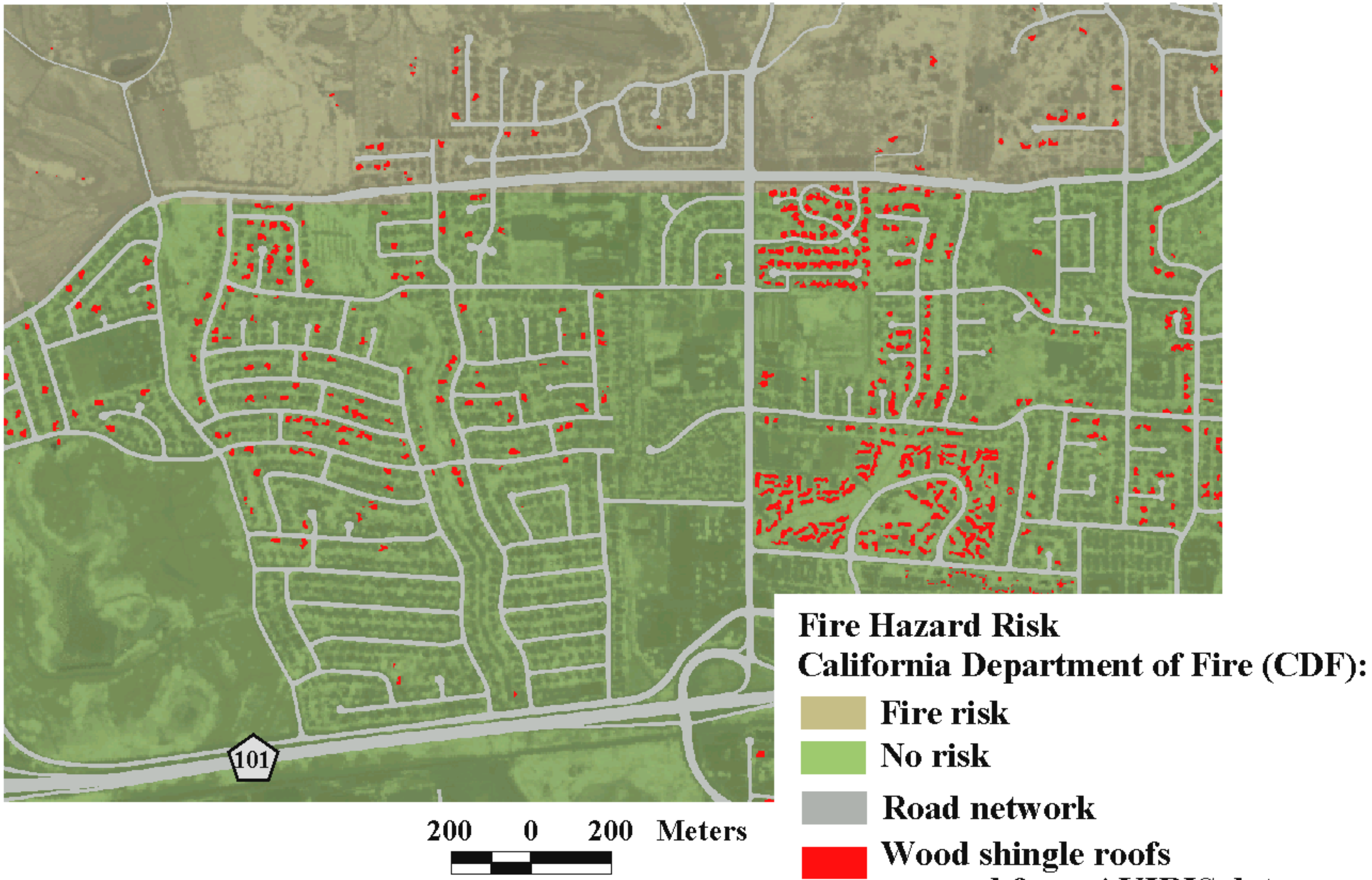


Santa Barbara Wildland-Urban Interface Species-Level Fuel Type Map



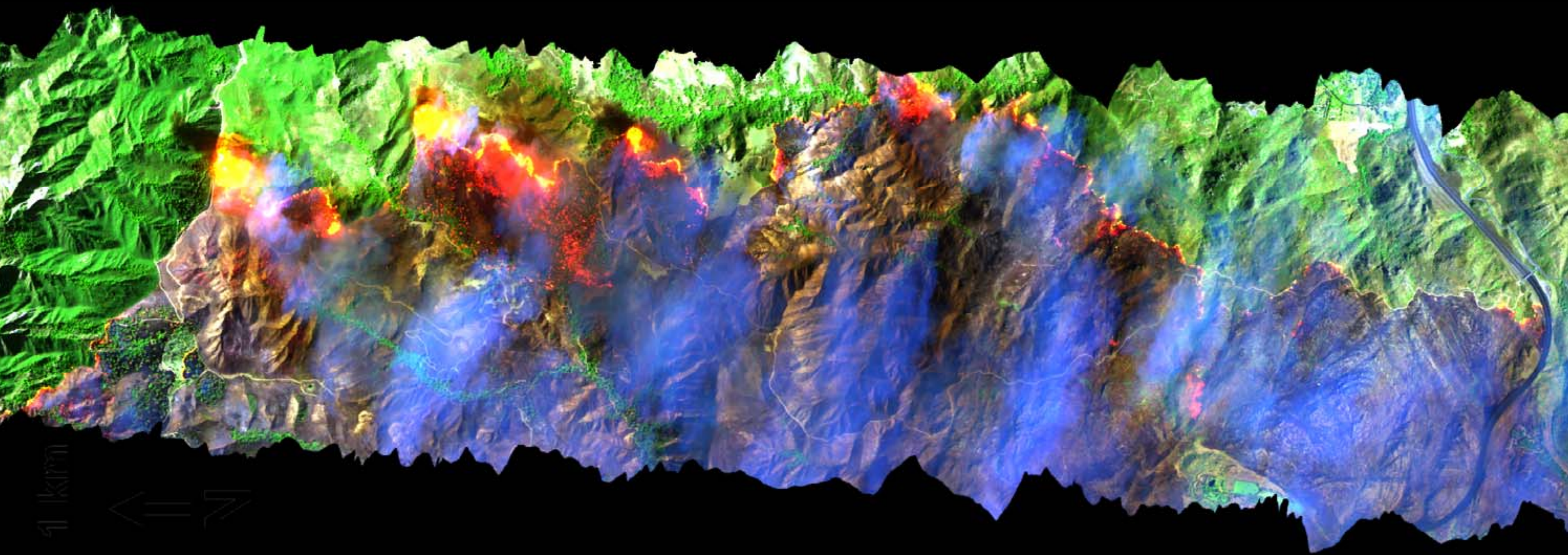
Dennison and Roberts, 2003

Urban Fuels: Hyperspectral Mapping of Wood Shake Roofs



Martin Herold

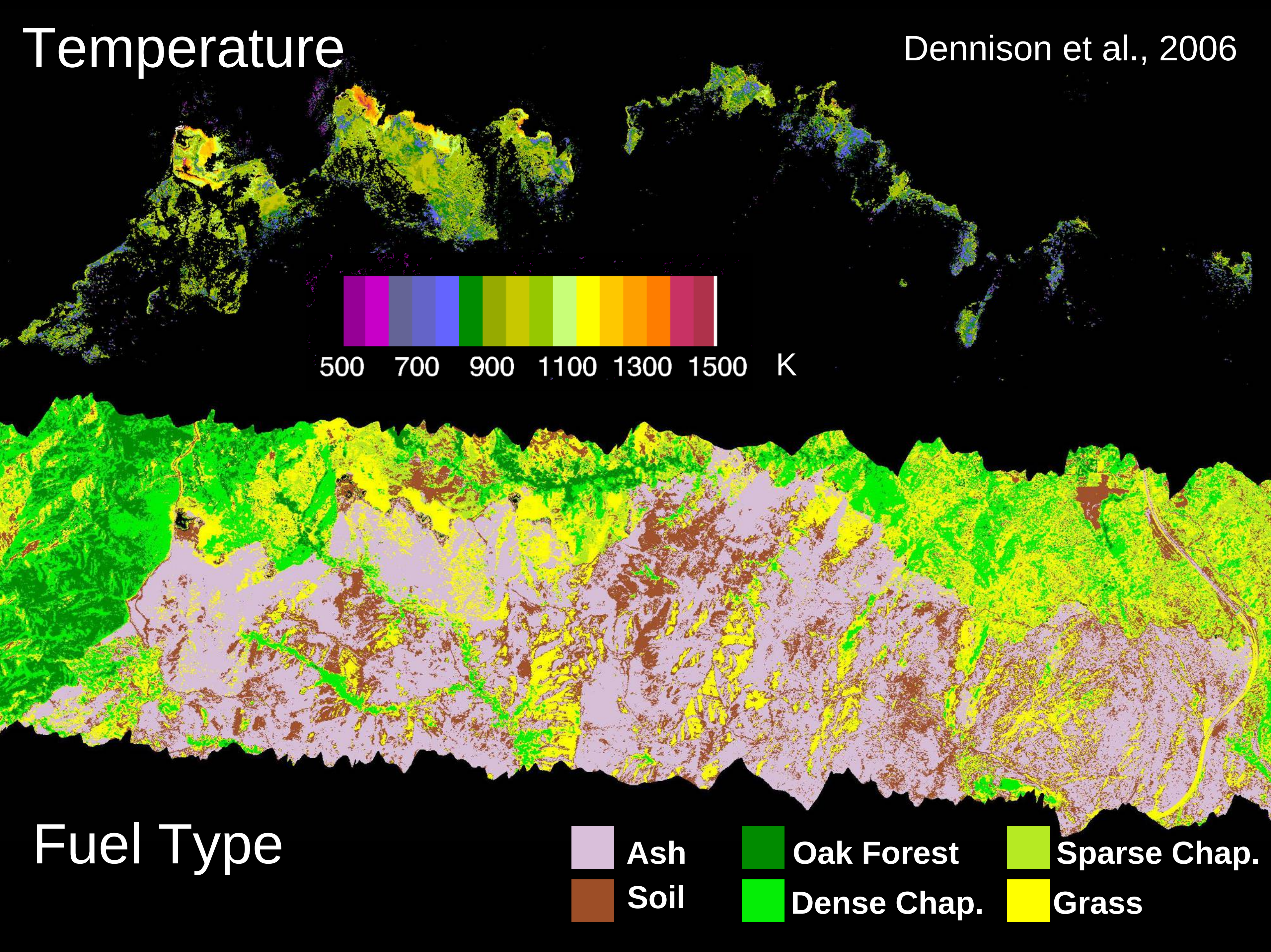
AVIRIS Image Acquired over 2003 Simi Fire



1682 nm 1107 nm 655 nm

← N

1 km



Temperature
Dennison et al., 2006
500 700 900 1100 1300 1500 K
Fuel Type
Ash
Soil
Oak Forest
Dense Chap.
Sparse Chap.
Grass

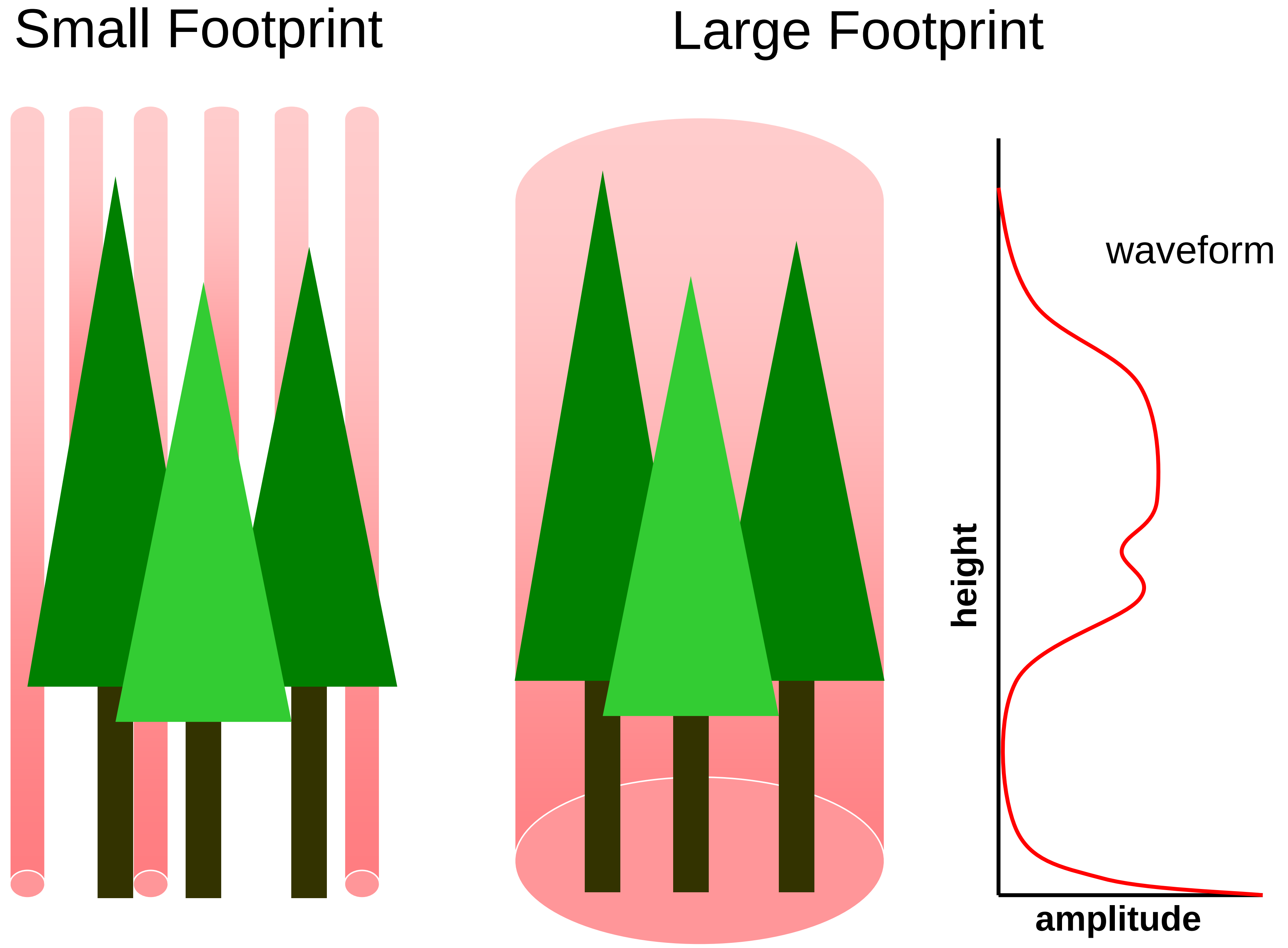
Fuel Load and Structure

Important parameters for fuels assessment and fire behavior modeling:

- Fuel load (surface fuels)
- Canopy bulk density
- Canopy height
- Canopy base height
- Canopy cover
- Ladder fuels

Remote Sensing of Fuel Load and Structure

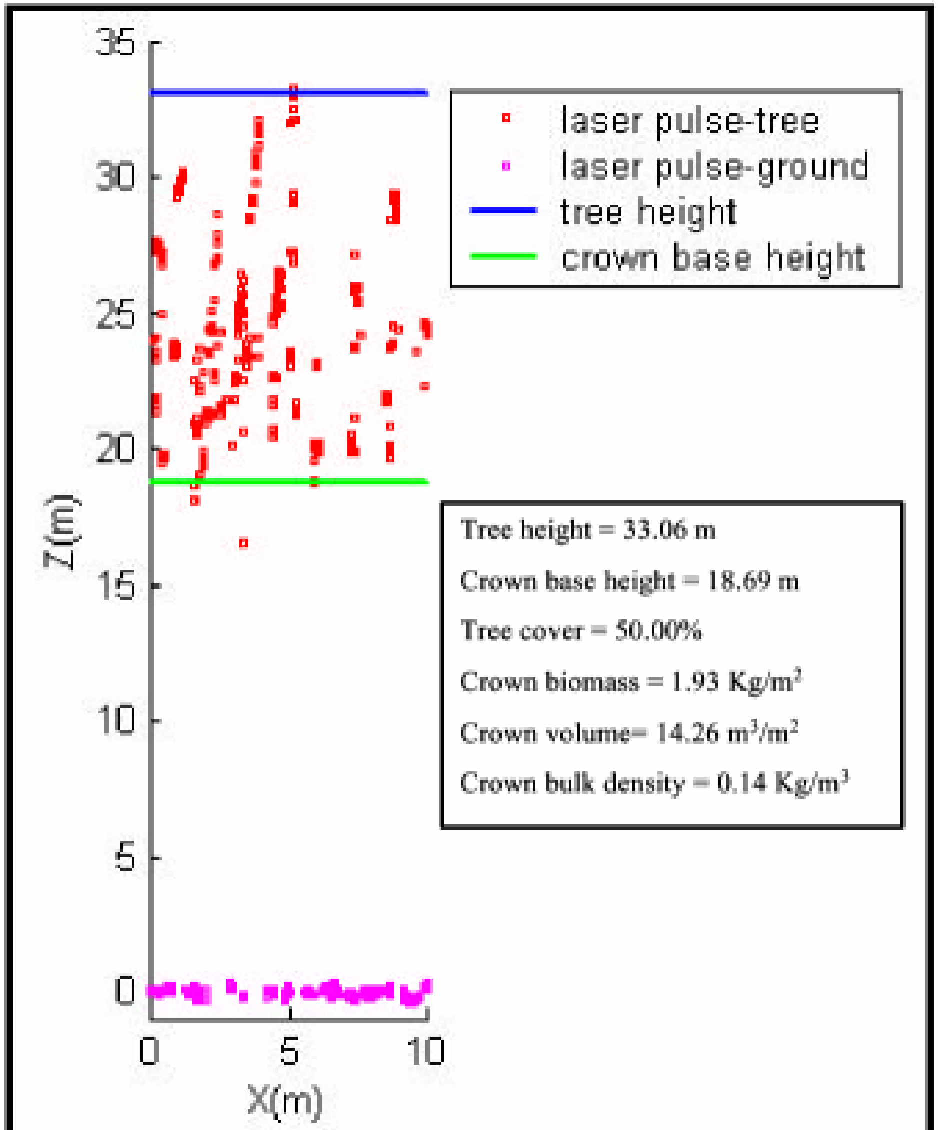
- Grass, shrub surface fuel loadings can be mapped using multispectral indices
- LANDFIRE uses Landsat data as one input into a predictive model for canopy bulk density and canopy base height
- Lidar can directly measure canopy height and canopy base height
- Models can be used to estimate canopy bulk density from lidar returns



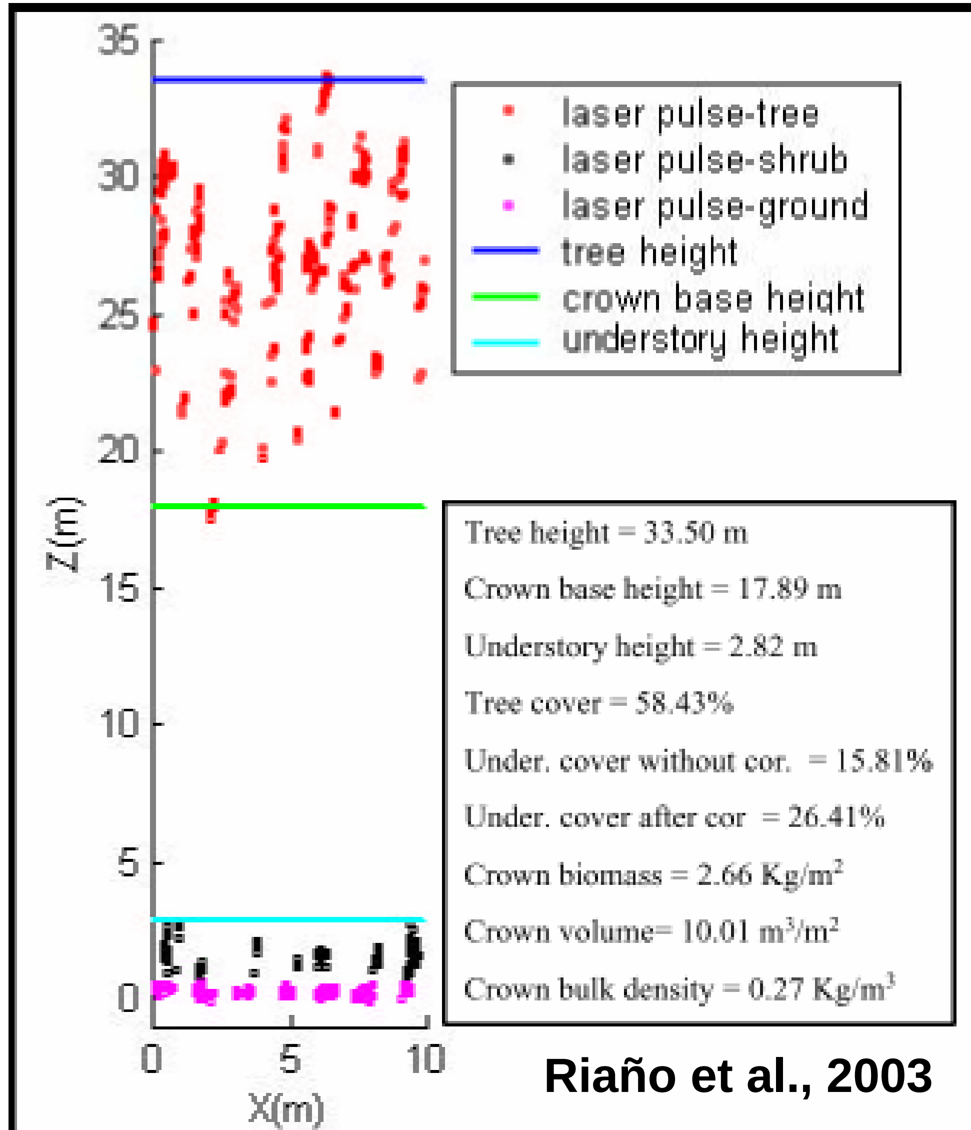
Small Footprint
Large Footprint
waveform
height
amplitude

Small Footprint Lidar Vertical Cross-sections

No Understory

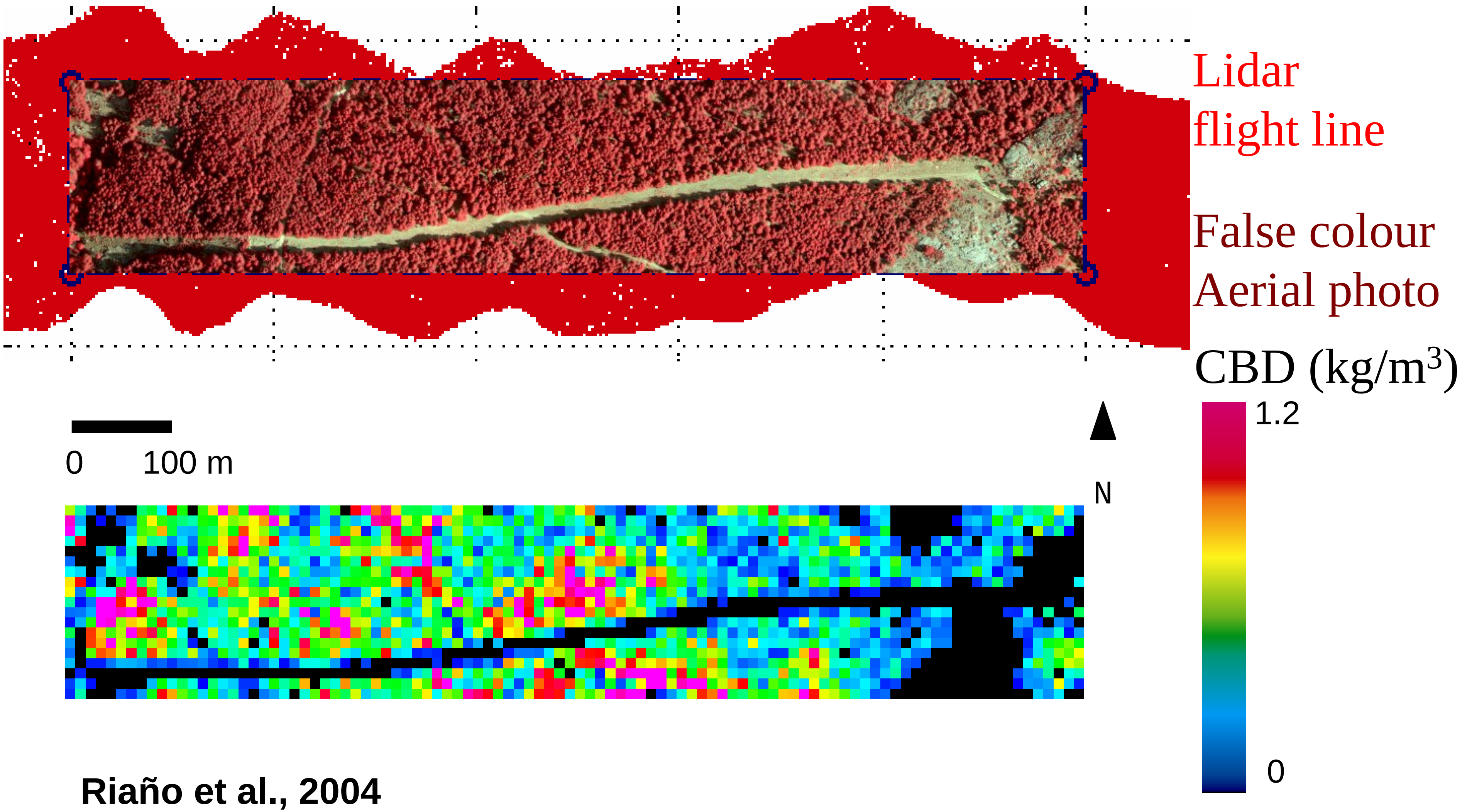


Understory



Riaño et al., 2003

Canopy Bulk Density Mapping Using Clustering



Riaño et al., 2004

Fuel Load and Structure Estimation Using Canopy Complexity

- Small footprint lidar was used to create digital canopy model (DCM)
- Canopy complexity measures calculated from DCM
  - Rumple index (Parker et al., 2004) = ratio of DCM area to ground surface area
  - Standard deviation of DCM height

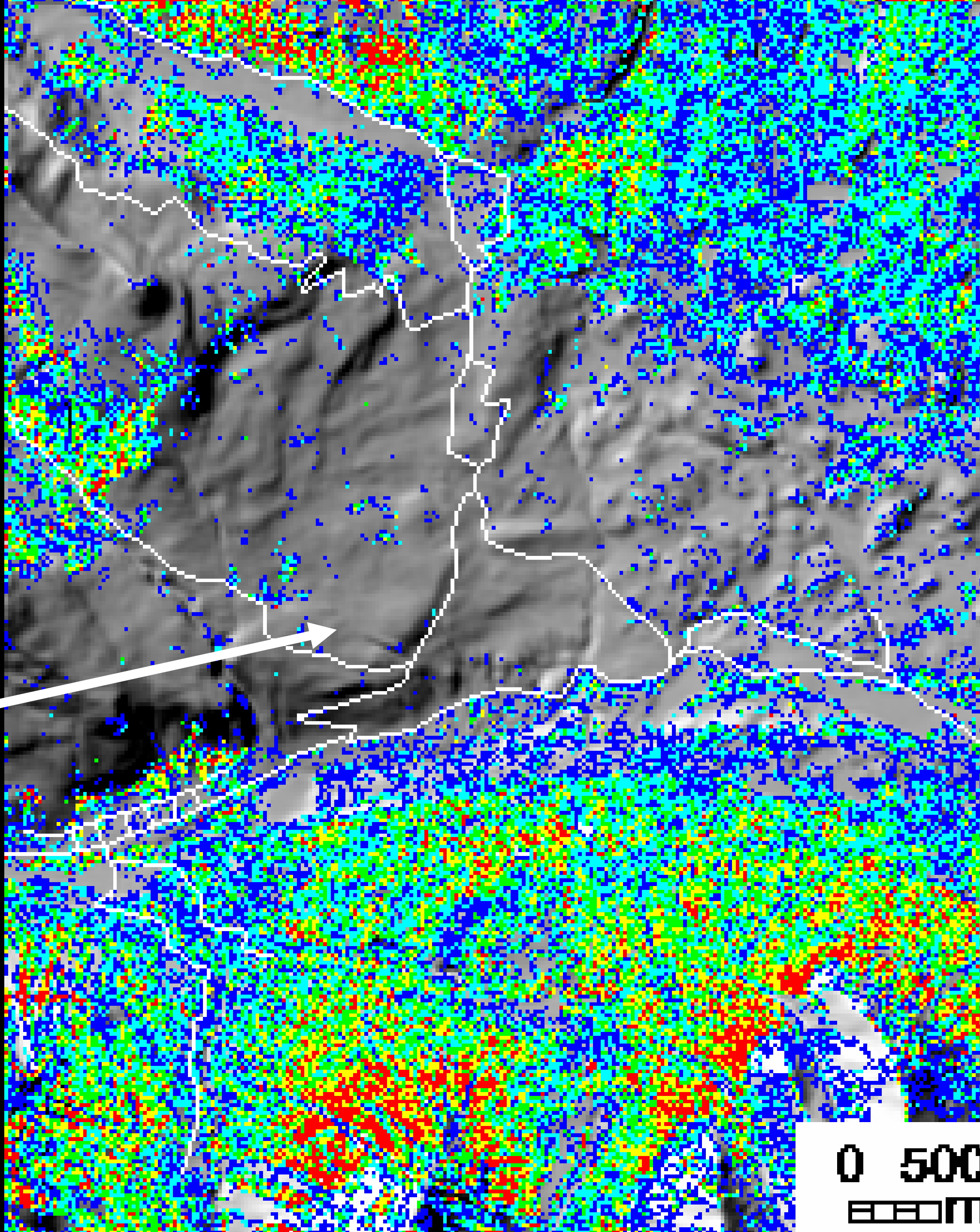
Parameter	**Linear Model**	**Adjusted r^2**
Available Canopy Fuel (Mg/ha)	8.071*MEAN -6.95*RUMPLE + 8.441	0.851
Canopy Bulk Density (kg/m^3)	0.062*MEAN -0.063*RUMPLE + 0.099	0.745

Kerry Halligan and Dar Roberts

Available Canopy Fuel

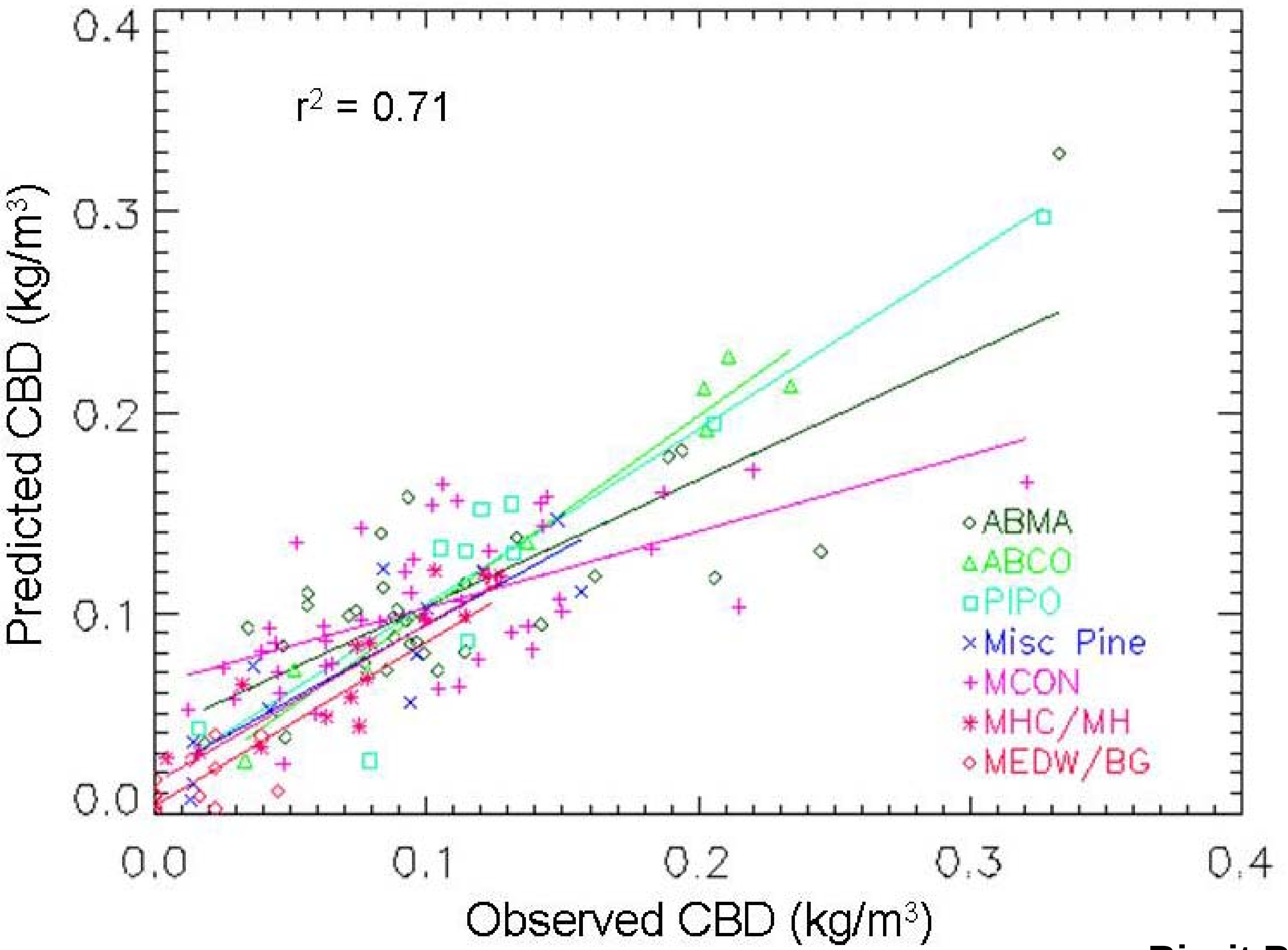
- 10-20 Mg/ha
- 20-30 Mg/ha
- 30-40 Mg/ha
- 40-50 Mg/ha
- > 50 Mg/ha

Storm Creek Fire scar



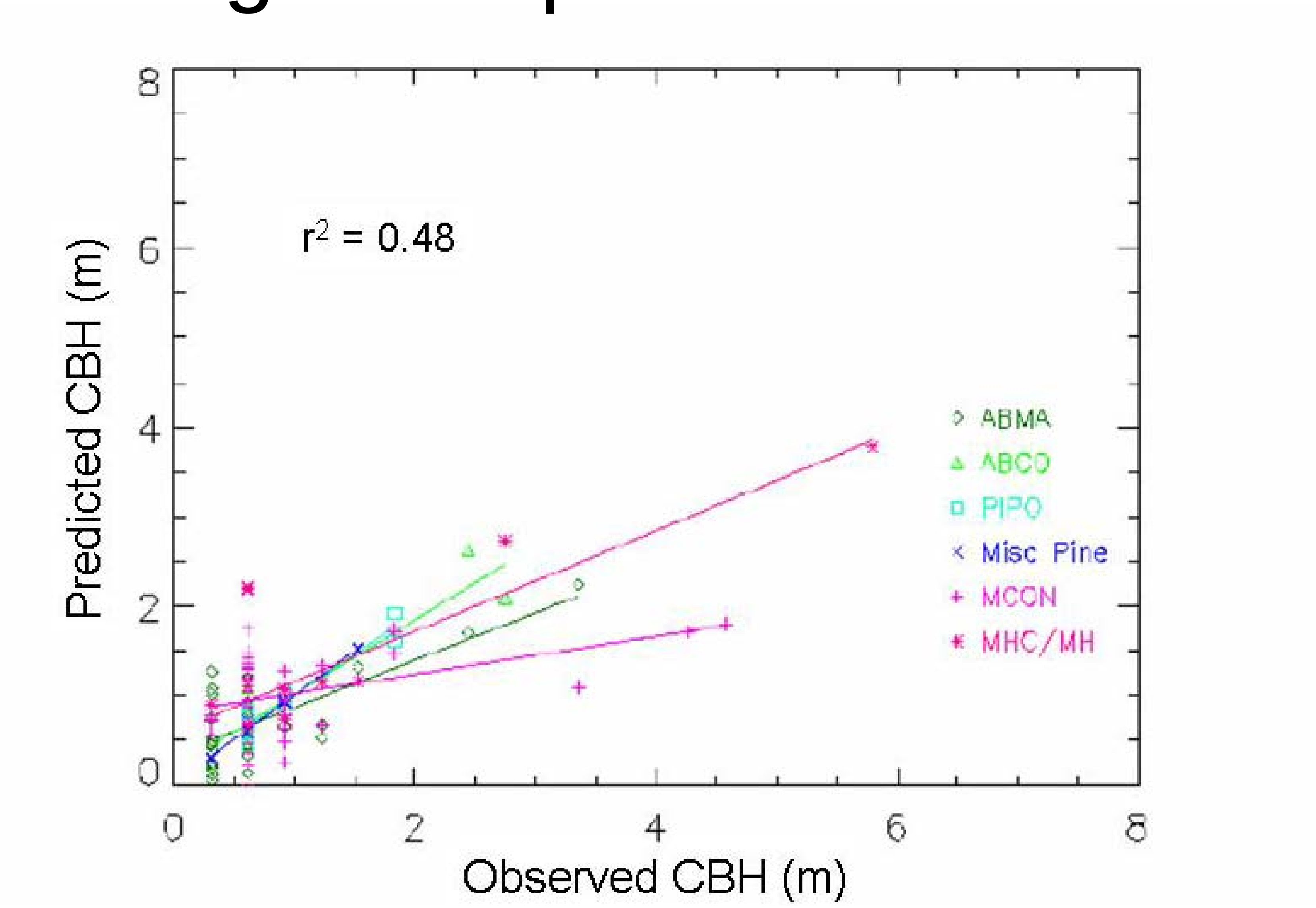
Kerry Halligan and Dar Roberts

Large Footprint Lidar: LVIS



Birgit Peterson

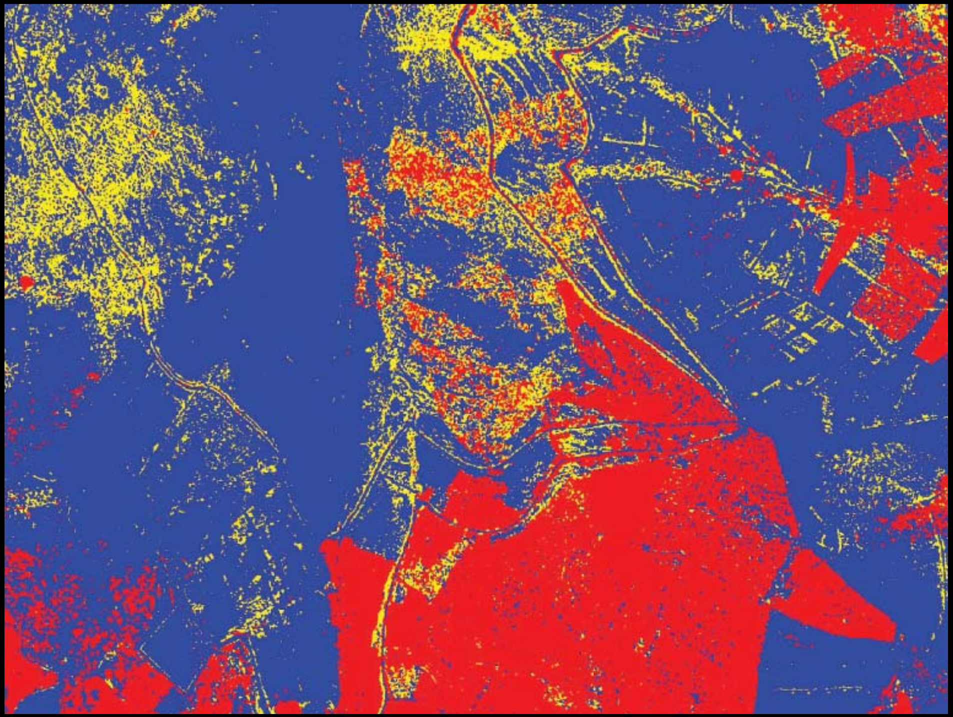
Large Footprint Lidar: LVIS

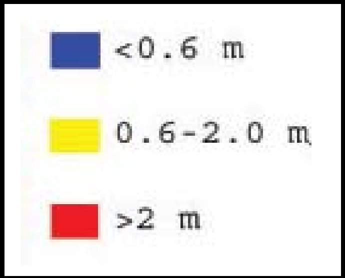


Birgit Peterson

Shrub Canopy Height

- Lidar has limited abilities for retrieving fuel properties from shrubs and grasses
- Riaño et al. (2007) demonstrated small footprint lidar estimation of shrub height using aerial orthoimages to separate shrub returns from ground returns





Riaño et al., 2007

Fuel Condition

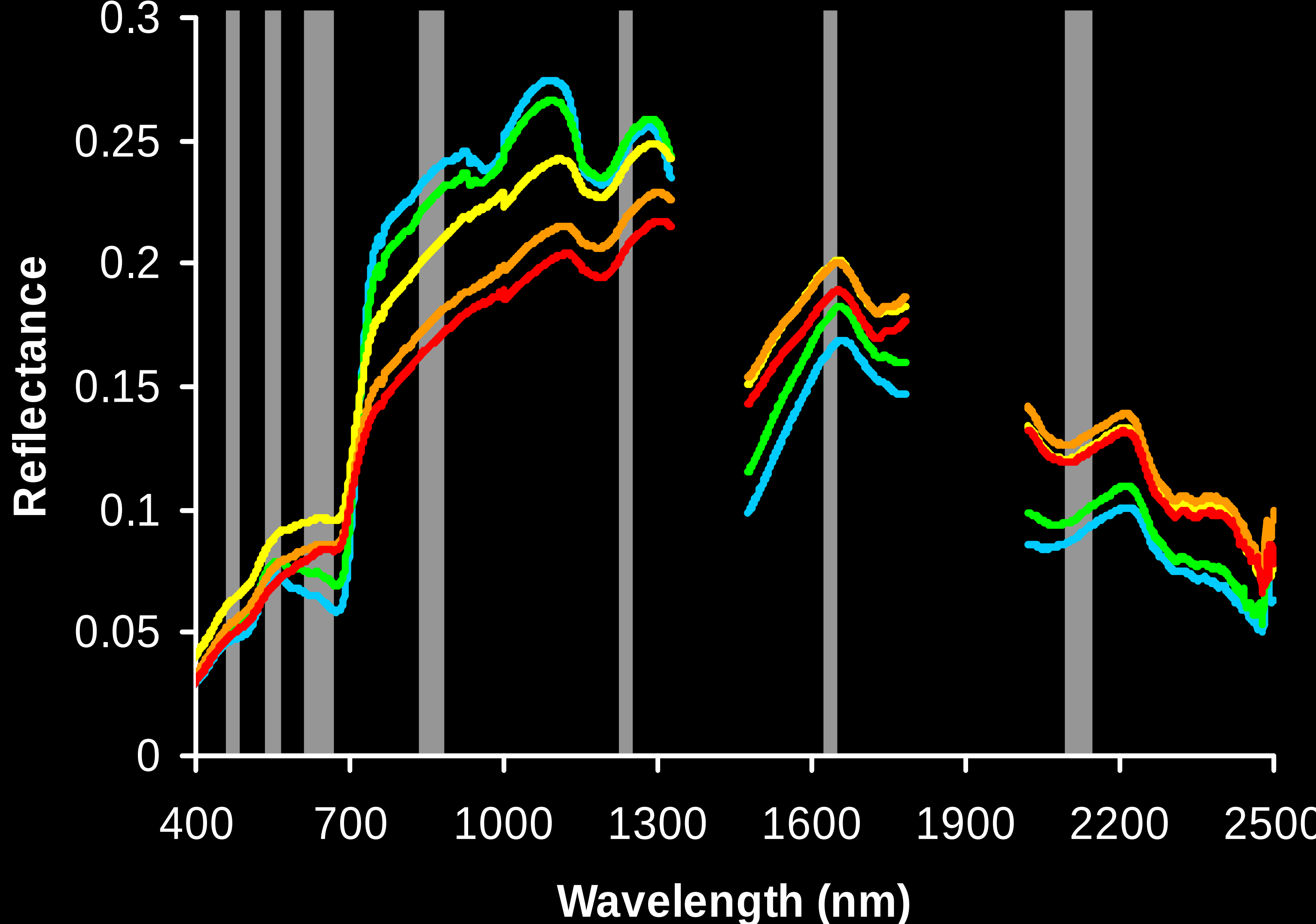
Important parameters for fuels monitoring and fire behavior modeling:

- Phenology and senescence
- Fuel moisture (live fuels)
- Fractions of live and dead fuels

Remote Sensing of Fuel Condition

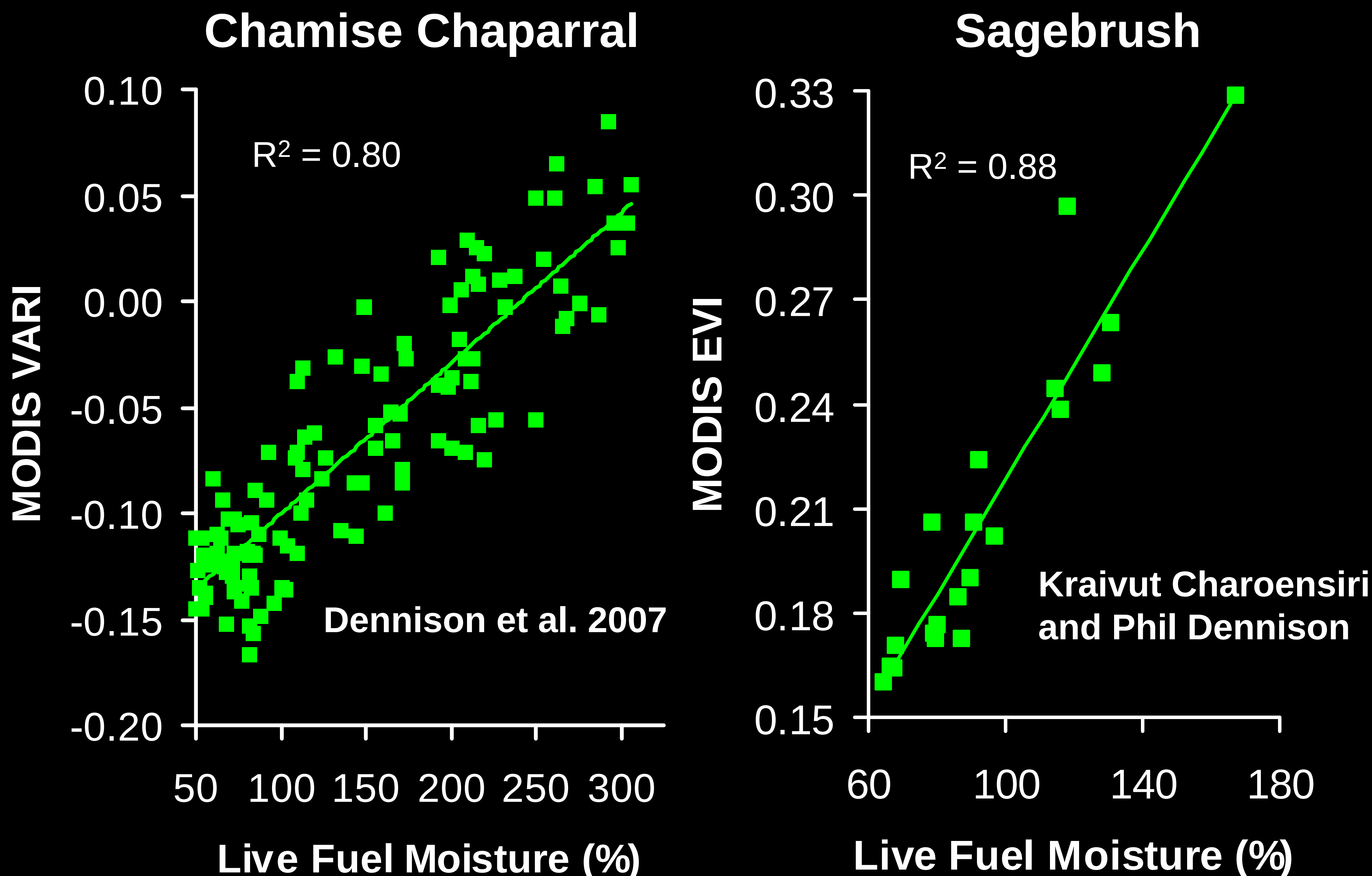
- Fuel condition can be assessed using multispectral, hyperspectral and radar remote sensing
  - Phenology and senescence can be assessed using time series of vegetation indices
  - Live fuel moisture is correlated with direct and indirect measures of canopy water content
    - Water absorption indices
    - Chlorophyll absorption indices
  - Fractions of live and dead fuels can be measured using spectral mixture analysis (green vegetation fraction vs. non-photosynthetic vegetation fraction)
  - Soil moisture is correlated with radar backscatter

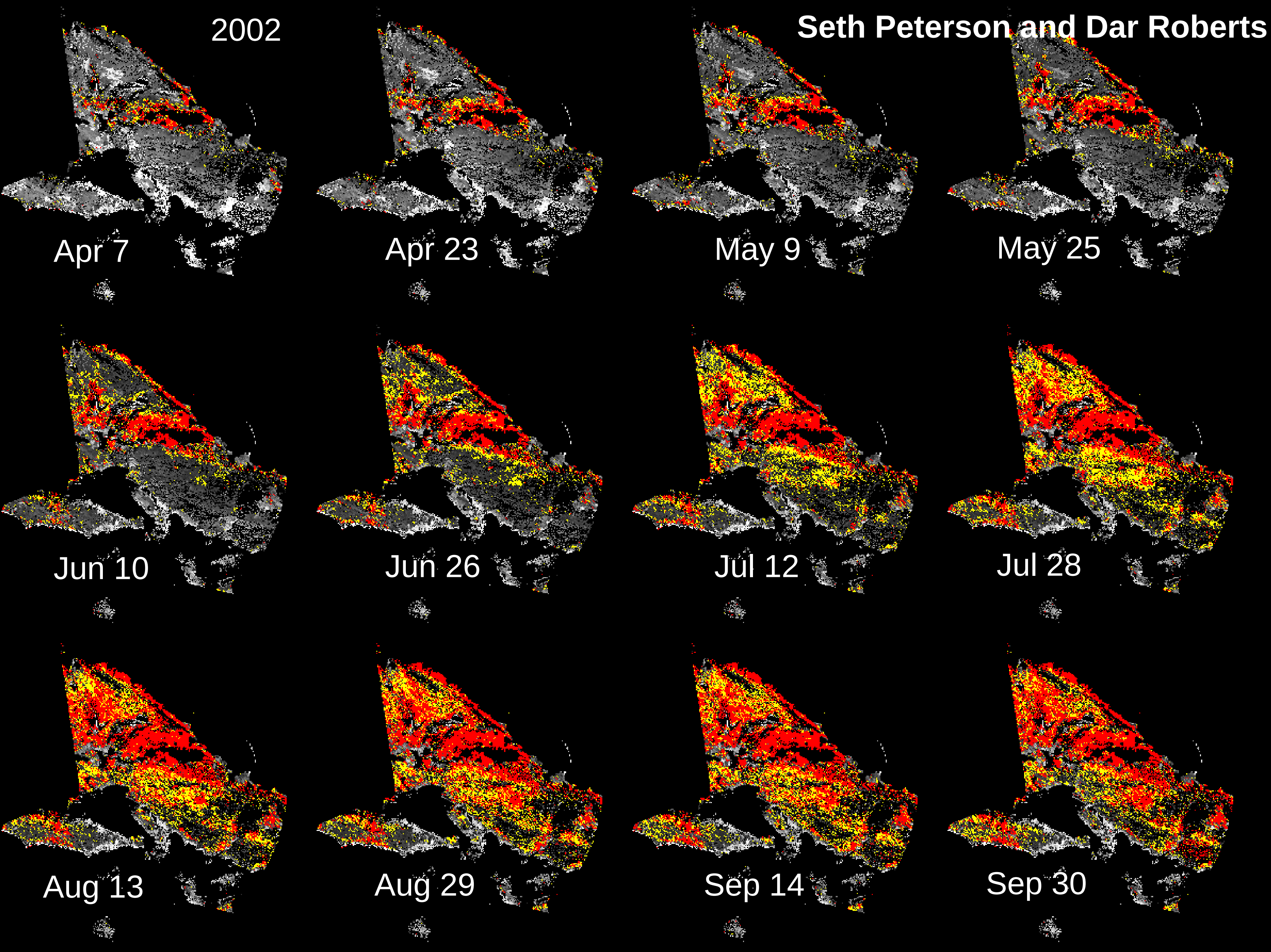
Vegetation Spectral Changes



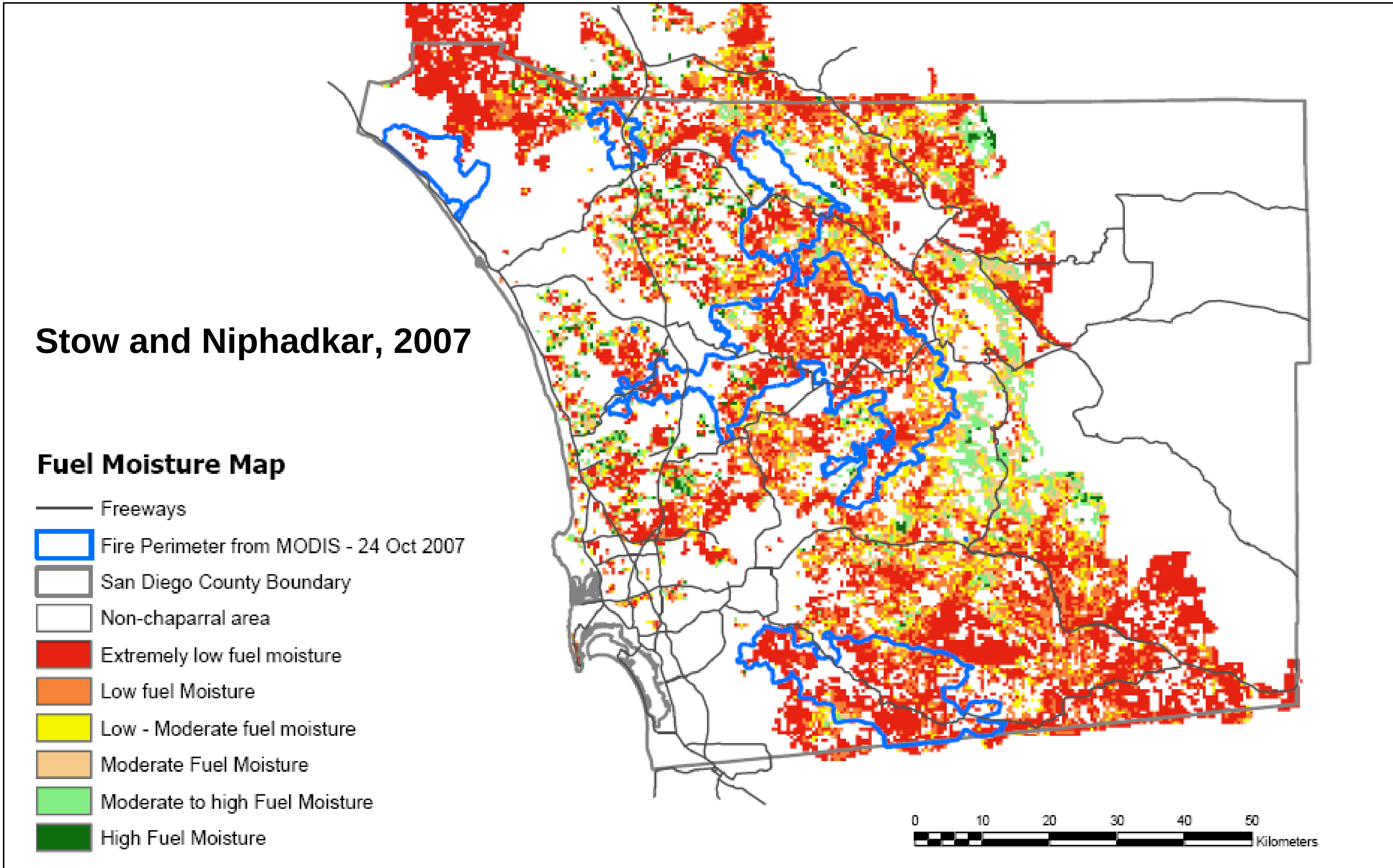
Dennison and Charoensiri

MODIS Index Correlations with LFM



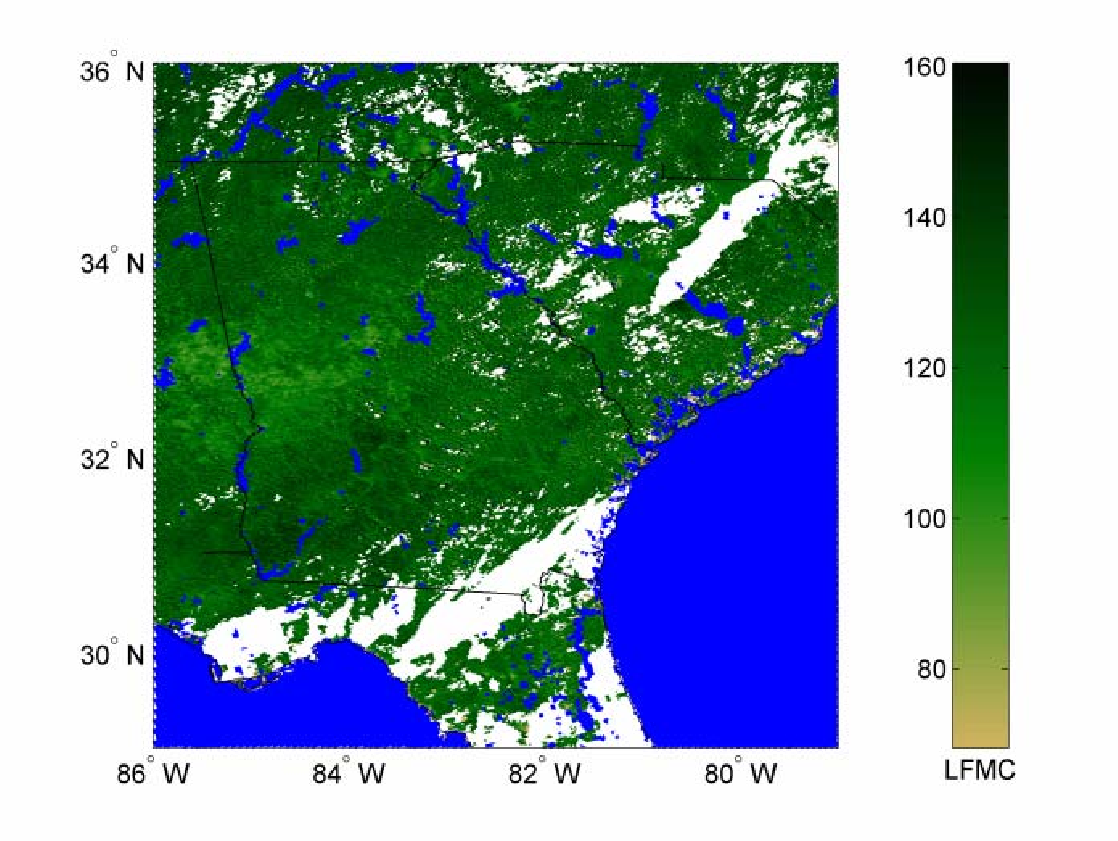

2002
Seth Peterson and Dar Roberts
Apr 7
Apr 23
May 9
May 25
Jun 10
Jun 26
Jul 12
Jul 28
Aug 13
Aug 29
Sep 14
Sep 30

Satellite-derived Map of Chaparral Live Fuel Moisture
San Diego County - 8-15 October 2007



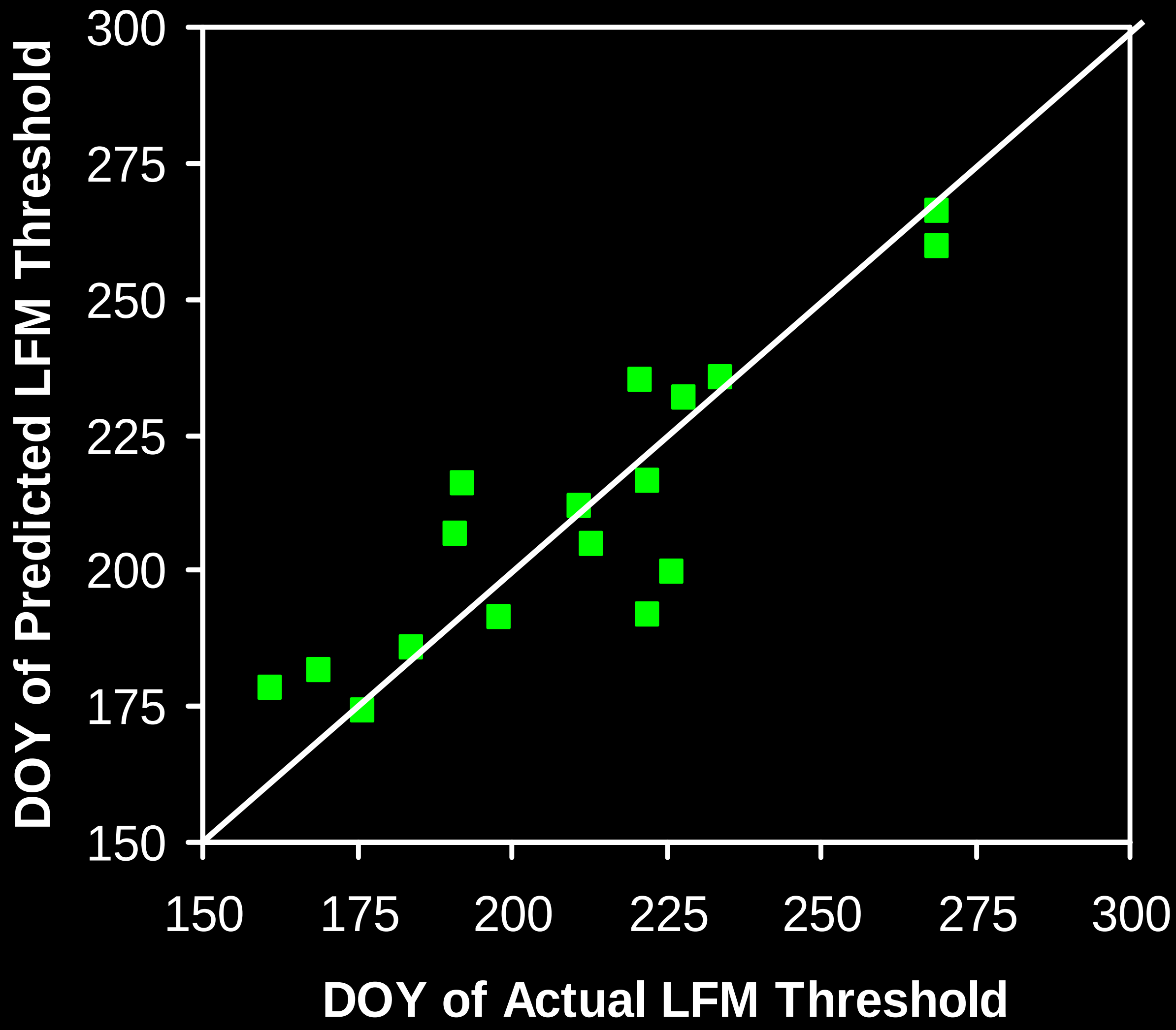
Eastern Forest Live Fuel Moisture

- MODIS band response to LFM simulated using PROSPECT leaf model
- An inversion model calibrated using ground data can be used to map live fuel moisture



Hao and Qu, 2007

Chaparral LFM Prediction

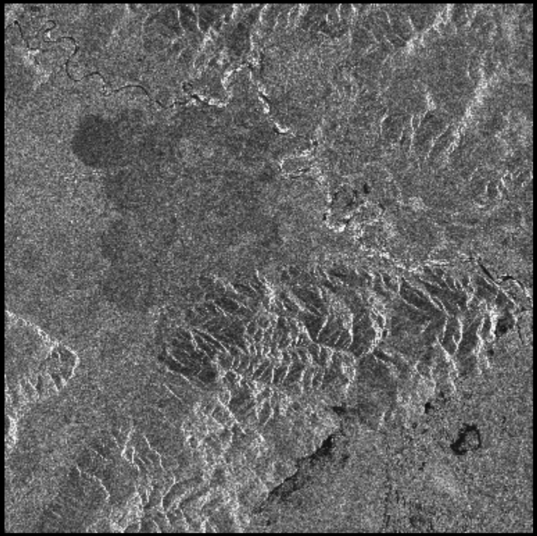


Dennison et al. 2008

SAR Monitoring of Soil Moisture

- Backscatter increases with increased soil moisture
- Scattering by vegetation canopies reduces the magnitude of the backscatter signal
- Works best in fire scars and low canopy cover
- Backscatter is well correlated with the “Drought Code” portion of the Canadian Forest Fire Danger Rating System

27 July 1992
Low Fire Danger
DC = 231

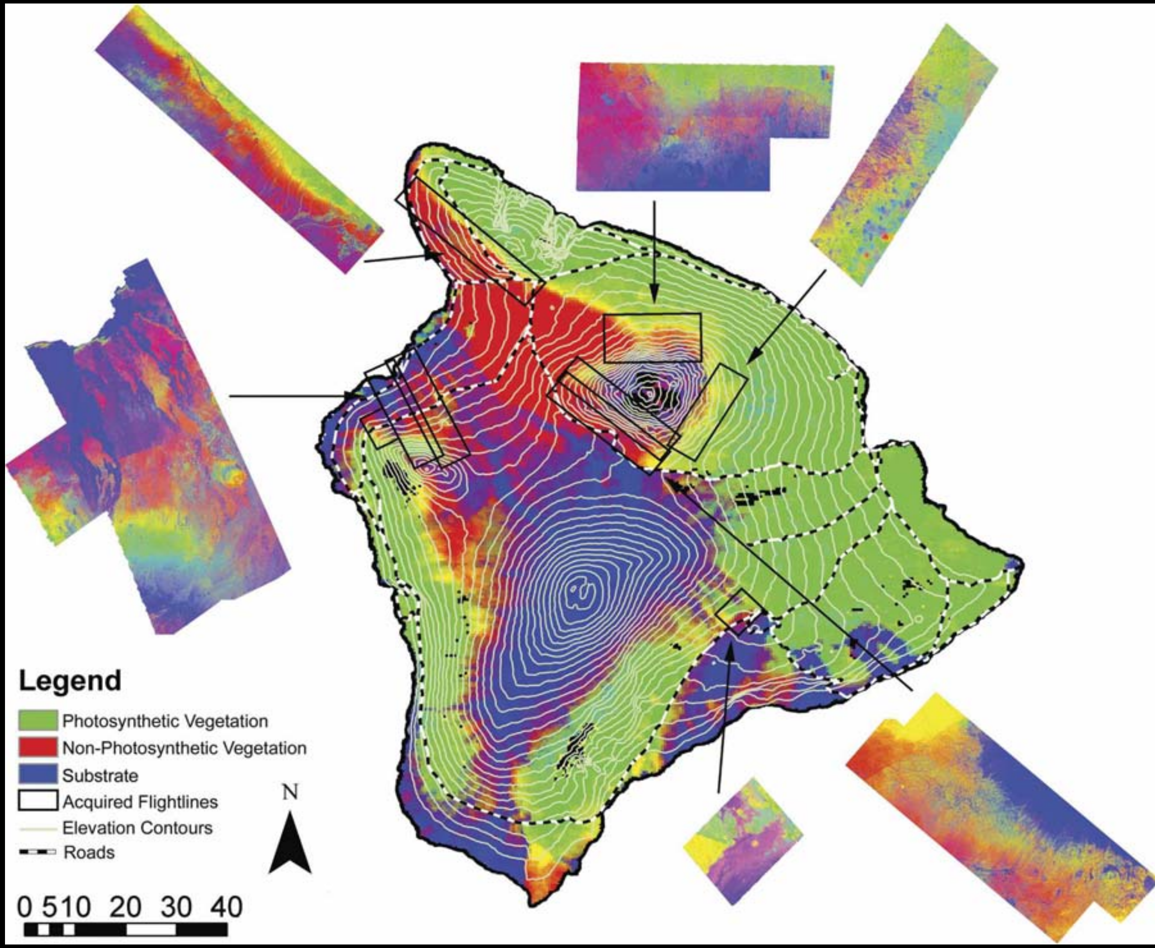


26 August 1994
Extreme Fire Danger
DC = 616

Laura Bourgeau-Chavez

SMA Fractions for Fuel Condition Monitoring

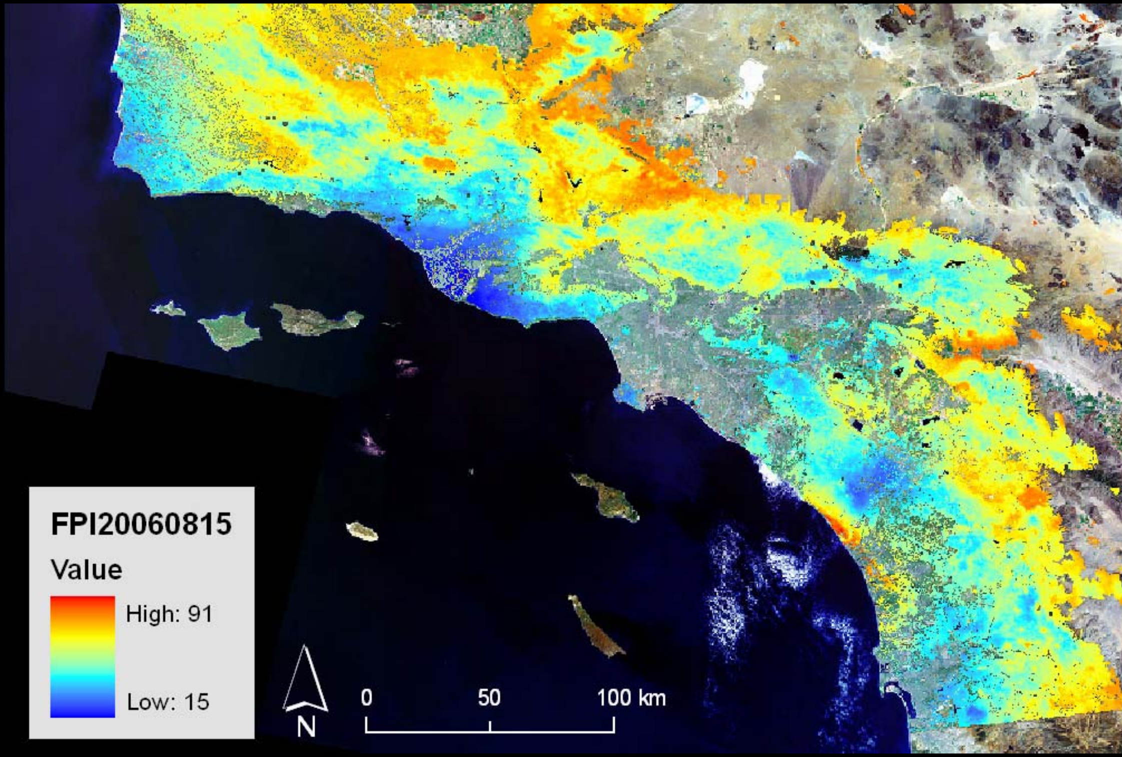
- Fractions of green vegetation and non-photosynthetic vegetation can be used to assess grass fuel condition
- Elmore et al., 2005 used SMA fractions calculated from AVIRIS and MODIS data to monitor seasonal changes in grassland fuels



Elmore et al., 2005

Fire Potential Index for MODIS

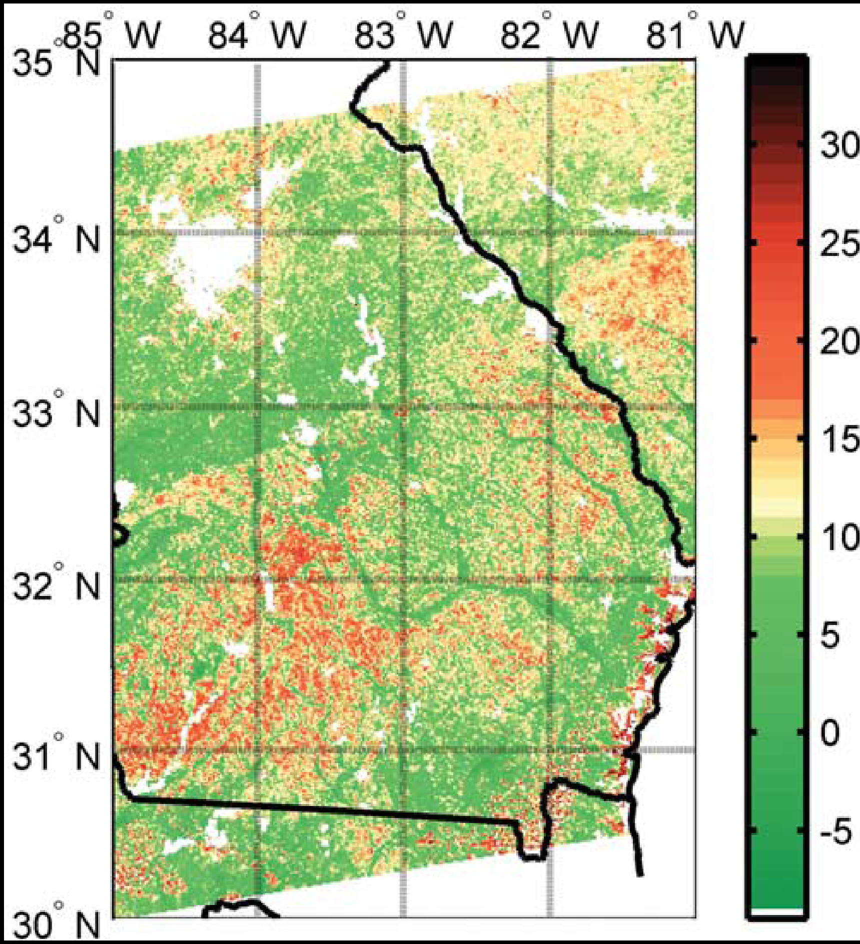
- MODIS indices more closely related to live fuel moisture can be used to improve the Fire Potential Index
- A new FPI developed for Southern California uses VARI-based relative greenness, dead fuel moisture, moisture of extinction, and live-to-dead ratio



Schneider et al., 2008

Fire Danger Monitoring Based on Energy of Pre-ignition

- Pre-ignition energy is the energy required to bring fuel from its ambient temperature to ignition temperature
- Live fuel moisture and land surface temperature measured from MODIS data can be used to approximate pre-ignition energy



Fire Susceptibility Index values

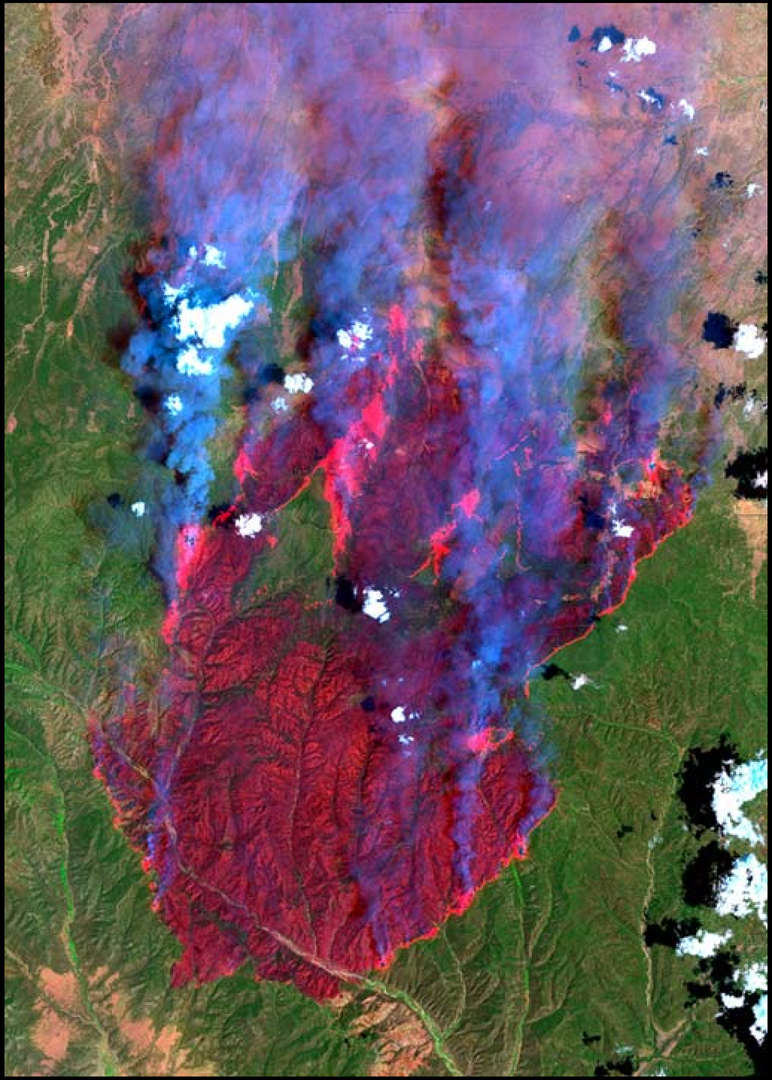
Dasgupta et al., 2006

Future Research Directions

1. Increased exploitation of lidar data, hyperspectral data, and data fusion
2. Movement towards mapping continuous fuel properties rather than discrete fuel models
3. More complex models of fire danger and fuel condition
   – Example: Non-photosynthetic vegetation fraction + soil water balance
4. Mapping disturbance and climate change impacts on fuels
   – Fire, bark beetle outbreaks, invasive species, drought

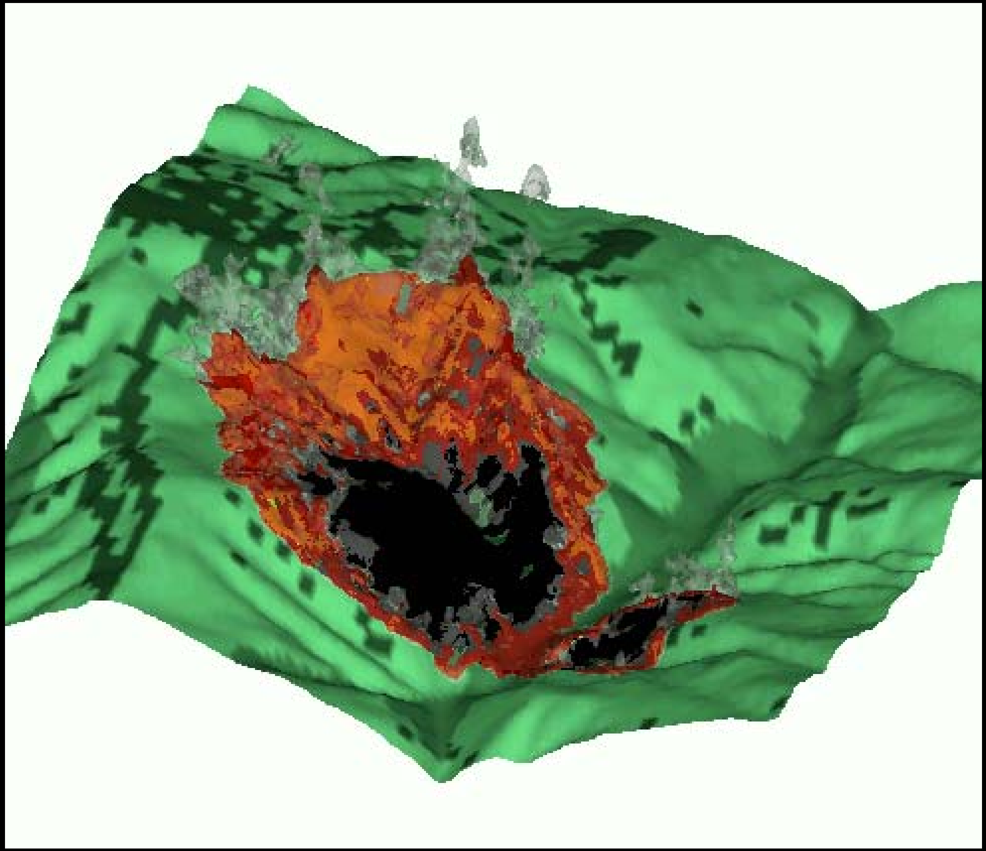
Issues Facing Future Research: Limited Data Availability

- Recent research using hyperspectral and lidar data can't be applied to large areas
- Data availability is also an issue for applications using multispectral data



Issues Facing Future Research: Fuel Properties as Inputs for Fire Models

- Current operational fire spread models don't make good use of most remote sensing products
- Can remote sensing products drive future fire models?



Rod Linn

Issues Facing Future Research: Spatial Scale

- What scales are appropriate for research on remote measurement of fuel properties?



Acknowledgements

- **Laura Bourgeau-Chavez**, Michican Tech Research Institute
- **Kerry Halligan**, Sanborn
- **Martin Herold**, Friedrich Schiller University
- **Birgit Peterson**, USGS
- **John Qu**, George Mason University
- **David Riaño**, University of California Davis
- **Dar Roberts**, University of California Santa Barbara
- **Seth Peterson**, University of California Santa Barbara
- **Doug Stow**, San Diego State University
- **Zhiliang Zhu**, Forest Service