Outline:

Introduction: Predicting wildfire risk
Measuring Canopy Water Content
Operational CWC Model
Estimating Fuel Moisture Content
Early fire detection; false positive reduction
Fuel Moisture Content

• Equivalent water thickness

\[ \text{EWT} \left( \frac{g}{cm^2} \right) = \frac{W_f - W_d}{A} \]

W_f = Fresh weigh
W_d = Dry weigh
A = Leaf Area

• Dry matter

\[ \text{DM} \left( \frac{g}{cm^2} \right) = \frac{W_d}{A} \]

• Fuel moisture content

\[ \text{FMC (\%)} = \frac{(W_f - W_d)}{W_d} \times 100 \equiv \frac{\text{EWT}}{\text{DM}} \]

Inv_RTM can predict FMC by predicting EWT and Dry matter.
Can Fuel Moisture be Estimated from Spectral Measurements?

Numerous correlations between biochemicals and spectral indexes

\[ C = f(\rho(\lambda_1), \ldots, \rho(\lambda_n)) \]

Water
CSI (Canopy Structure Index), GVMI (Global Vegetation Moisture Index), RDI (Relative Depth Index), mNDWI (Modified Normalized Difference Water Index), NDWI (Normalized Difference Water Index), SRWI (Simple Ratio Water Index), WBI (Water Band Index), etc.

Plant Dry Matter: Cellulose, Lignin, Nitrogen
CAI (Cellulose Absorption Index),
NDLI (Normalized Difference Lignin Index),
NDNI (Normalized Difference Nitrogen Index), etc.
PROSPECT: A Physically Based Leaf Radiative Transfer Model

PROSPECT: A Model of Leaf Optical Properties Spectra

S. Jacquemoud and F. Baret
INRA, Station de Bioclimatologie, Montfavet, France
PROSPECT Accounts for Most of the Reflectance from Leaves

- pigments
- water
- structure
- dry matter

Total reflectance

Model: Baret & Fourty, 1997
Jacquemoud et al. 2000

Validation: Ceccato et al. 2001; Bacour et al. 2002


Physically Based Approach to Estimating Plant Biochemicals: Coupling RT Models: Prospect + Sail

18 Years of Vegetation Characterization

Modeling CWC Using ANN Trained with PROSPECT - SAILH

1. RTM

\[
\text{EWT, LAI, DM, N, C}_{ab}, \text{ LIDF, Soil} \rightarrow \text{Prospect-SailH} \rightarrow \text{Canopy reflectance}
\]

2. Training ANN

\[
\text{CWC} = \text{EWT} \times \text{LAI}
\]

3. Estimation

\[
\text{MODIS reflectance} \rightarrow \text{CWC}
\]
Canopy Scale Validation

Trained and Validated from independent samples generated from PROSPECT-SAILH model

Rano et al., 2006
Field Validation of EWT & LAI

Stronghold oak woodland

Tombstone, AZ

San Pedro River riparian zone

Tombstone, Arizona SMEX Experiment

Cheng et al., 2007

Curry Farms

Walnut Gulch watershed

NDVI

SIWSI

0 10 20 30 40

Kilometers

0 10 20 30 40

Kilometers

y = 7.9019x + 88.181

r² = 0.90

y = 1684.6x + 3.4998

r² = 0.87

Canopy EWT (um)

AVIRIS EWT (um)

AVIRIS EWT (um)

Cover

<20%

20-40%

>40%

Agriculture

Native species

<20% 20-40% >40%
MODELING of Regional Scales with MODIS

- ANN trained with PROSPECT-SAILH to generate EWT*LAI
- ANN run on MODIS MOD09A1
- Validation with AVIRIS EWT

AVIRIS - MODIS NDWI

Walnut Gulch, AZ

\[ R^2 = 0.82 \]
Schema for Implementing MODIS CWC algorithm

MODIS reflectance → Trained ANN → CWC → Calibration Sites AVIRIS data → ACORN → Calibrated_CWC

MODIS Land Cover Type → Calibrated CWC from MODIS


12 months USA CWC → Eco-regions Layer (Bailey et al., 1995)

Trombetti et al. 2008
Data trained separately for each Bailey Ecoregion for the U.S.
Monthly MODIS CWC for Continental U.S. in 2005

January  
February  
March    
April    
May      
June     
July     
August   
September 
October  
November 
December 

☐ no data

CWC (mm)

2.6

0
MODIS CWC for Forest, Shrub and Grassland Types in Relation to Weather (Temperature, Precipitation) Parameters

Canopy Water Content - US - Year 2005

- Shrublands
- Forest
- Grassland
- Temperature
- Rainfall

Rainfall (mm) - Temperature (°C)

CWC (mm)
Relationship of CWC to Weather Parameters in Different Ecoregions

Hot Continental Division

CWC (mm)

Rainfall (mm) - Temperature (C)

Jan  Feb  Mar  Apr  May  Jun  Jul  Aug  Sept  Oct  Nov  Dec

Shrublands  Forest  Grassland  Temperature  Rainfall
Difference between El Niño years and 6 year average CWC

Difference between La Niña years and 6 year average CWC

Difference between El Niño and La Niña years and average CWC in years since 2000
Regional-San Diego Wildfires September 2007: CWC

Deviation from mean CWC (%)

-80 to -60
-60 to -40
-40 to -20
-20 to 0
0 to 20
20 to 40
40 to 60
60 to 80
>80

Low
High

no data

State of California boundary

Trabucco et al. unpublished
San Diego wildfires (local)

Deviation from mean CWC (%)

-80
-80 to -60
-60 to -40
-40 to -20
-20 to 0
0 to 20
20 to 40
40 to 60
60 to 80
>80

2007 wildfire perimeters
Fuel Moisture Content

- **Equivalent water thickness**

  \[
  \text{EWT} \left( \frac{\text{g}}{\text{cm}^2} \right) = \frac{W_f - W_d}{A}
  \]

  \(W_f=\text{Fresh weigh}\)
  \(W_d=\text{Dry weigh}\)
  \(A=\text{Leaf Area}\)

- **Dry matter**

  \[
  \text{DM} \left( \frac{\text{g}}{\text{cm}^2} \right) = \frac{W_d}{A}
  \]

- **Fuel moisture content**

  \[
  \text{FMC (\%)} = \frac{(W_f - W_d)}{W_d} \times 100 \equiv \frac{\text{EWT}}{\text{DM}}
  \]

Inv_RTM can predict FMC by predicting EWT and Dry matter
**Estimation of FMC**

**Inversion on fresh leaves**

\[ y = 0.9552x + 13.655 \]

\[ R^2 = 0.3635 \]

**Inversion on dry leaves**

\[ y = 1.3651x - 71.181 \]

\[ R^2 = 0.8978 \]

\[ \text{FMC} \% = \frac{\text{Inv-PROSPECT EWT}}{\text{Inv-PROSPECT Dry matter}} \]
• Inv_RTM can predict FMC:
  Both EWT and Dry matter can be predicted
• BUT dry matter must be estimated from dry vegetation, thus, measured in dry season

Emilio Chuvieco et al., JGR-Atm 2004
Comparison of CWC to FMC (USFS Data)

Some are Good Fits and Others Poor: Likely Issues:

1) Representativeness of FMC to MODIS pixel area
2) Differences in data collection, processing or other problems
3) Characterization of vegetation type in relation to MODIS pixel
4) Suitability of ecotype calibration of the CWC algorithm to the specific site
Operational Awareness: Need for near-real time fire detection capability:

Combine Estimates of CWC and FMC with Early Detection of Wildfire Events:

Reduce False Alarms in Early Fire Detection Predictions
Increase Understanding of Fire Risk Following Detection of Event
New Early Fire Detection Algorithm:  
Experiments with MODIS and GOES data

• July 15 – Aug 14, 2006 (every 15-20 minutes)
• Brightness Temperatures Bands:
  \[ T_{\text{band } 4} (4 \, \mu\text{m}) \text{ and } T_{\text{band } 12} (12 \, \mu\text{m}) \]  
  \[ (\Delta T = T_4 - T_{12}) \]

Koltunov and Ustin 2007 and unpublished data
Fire Detection Example 1

Quail Fire: Brush fire near Gorman, CA reported @12:34 Aug 13, 2006

\[ \Delta T = T(4\mu m) - T(12\mu m) \]

GOES-10 images from 12:00
DDM first detection – in 11:30-image

11:15  11:30  11:45  12:00

not detected  detected by DDM

<1°C warmer than it should be
Thank you for your attention!
Questions?