Improving Fuel Characterization and Maps useful for Emissions and Smoke Modeling

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JOINT FIRE SCIENCE PROGRAM FIRESCIENCE.GOV Research Supporting Sound Decisions

University of Maryland 1856 · Michigan Tech Research Institute · University of Washington · Forest Service U.S. Department of Agriculture




Motivation & Outline

Fuels are the foundation of what comprises smoke from wildland fire.

There is very large variability and uncertainty in forest fuel loadings, and this variability is poorly described in existing datasets.

Background

- Emissions modeling
- Fuel variability & emissions uncertainty

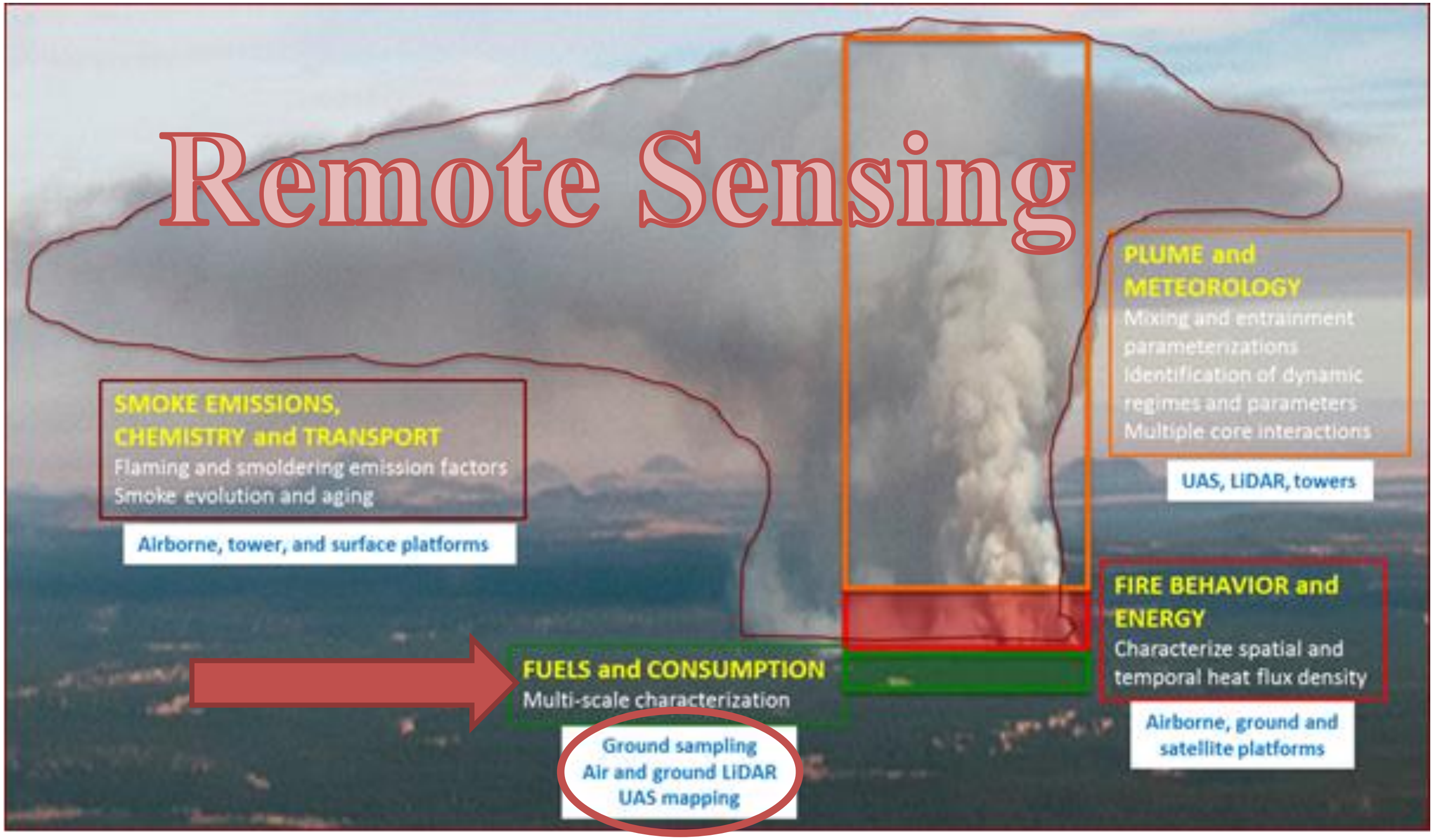
Database development

- Wildland fuel loading data
- Distributions & sensitivity analysis

Applications

- Spatial Emissions Modeling

Characterizing Smoke



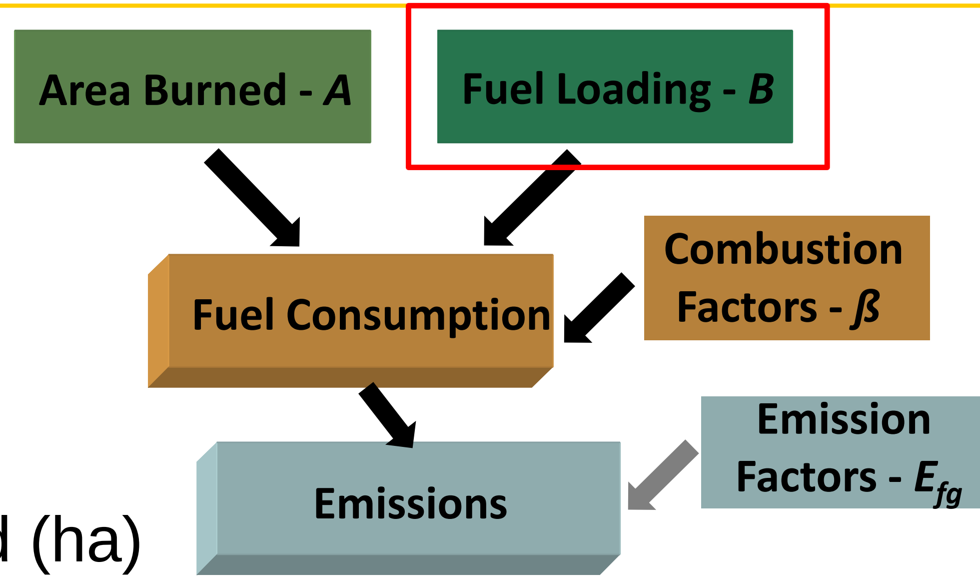
The FASMEE concept is to measure and characterize smoke and the precursor attributes of fuels and fire behavior in order to fully model smoke from a wildland fire.

https://www.fasmee.net/

Emissions Modeling

Total Emissions:

$$E_t = A \cdot \beta \cdot B \cdot E_{fg}$$



E_t is the total Emissions

A is the total Area burned (ha)

β is the fraction of biomass/fuel consumed during fire

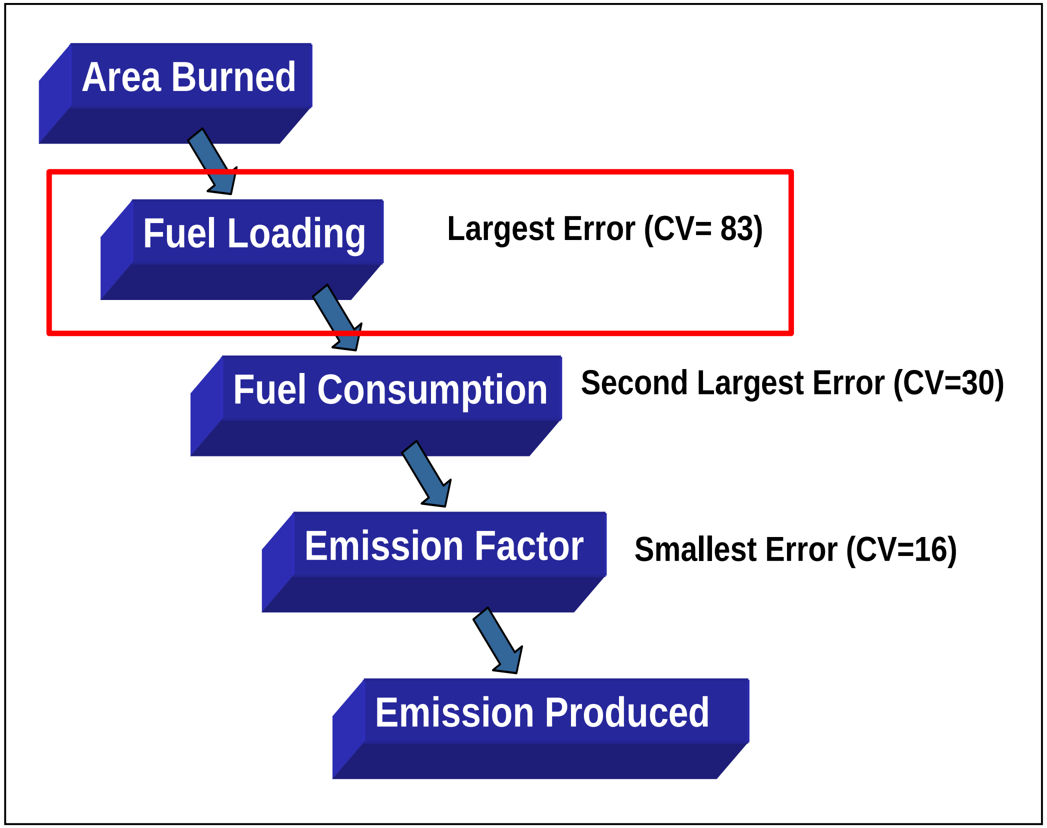
B is the fuel loading (Mg/ha)

E_{fg} is the Emission Factor for each gas species (g gas/kg fuel) [e.g. CO_2, CO, CH_4, NMHC]

Emissions Modeling

- Fuel loading and the proportion of the fuel that is combusted (consumption) have highest uncertainty.

- Errors stated here are from Peterson, J. L. 1987
- Similar conclusions were found by Larkin et al. in the SEMIP project



Peterson, J.L., Analysis and reduction of the errors of predicting prescribed burn emissions, Thesis, University of Washington, Seattle, 1987.

Larkin, N.K.; et. al., "PHASE 1 of the Smoke and Emissions Model Intercomparison Project (SEMIP): Creation of SEMIP and evaluation of current models" (2012).JFSP Research Project Reports. Paper 42. http://digitalcommons.unl.edu/jfspresearch/42

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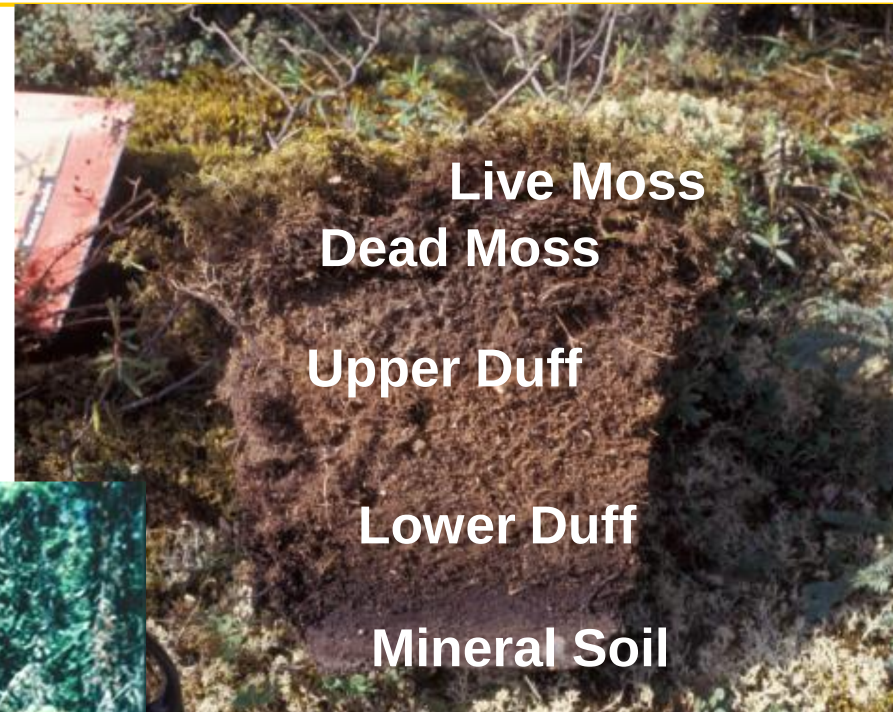
Improving Fuel Loading Data for Emissions and Smoke Models

- Improving methods for characterizing & mapping fuels
  - Add to our expanding database of fuels - use database to target under-sampled types.
  - Advancing measurement methodologies with remote sensing
    - LiDAR-measured
    - Structure from motion 3-D modeling
    - Multi-sensor mapping and monitoring for change
  - Improve and validate maps (a part of this project)
- Quantifying consumption & emissions with thermal IR Fire Radiative Energy (FRE)
  - This method is reliable and independent of fuel-loading
    - more energy = more fuel consumption
  - Satellite-based methodology is operationally used in Europe
  - HOWEVER: Fuels and fuel loads are still important to know
    - Emission factors depend on type of material burning
    - Flaming vs. smoldering is not well studied
    - Needed for understanding variability and uncertainty (this study)

Variability of Fuels

- Forest/vegetation type
- Duff depth
- Conifer vs. deciduous
- Forest structure & density
- Ground fuel amount, condition, configuration



Boreal black spruce sites, for example, have varying amounts of duff.

Variability of Fuels

Southeast conifer sites can have sparse or dense understory shrubs and surface woody material.

Fuel Characteristic Classification System

FCCS Fuelbed Strata

Strata		Categories
CANOPY		Trees, snags, and ladder fuels
SHRUBS		Primary and secondary shrub layers
HERBACEOUS		Primary and secondary herb layers
DOWNED WOOD		Sound wood, rotten wood, stumps, and piles
LITTER-LICHEN-MOSS		Litter, lichen and moss layers
GROUND FUELS		Duff, basal accumulations and squirrel middens

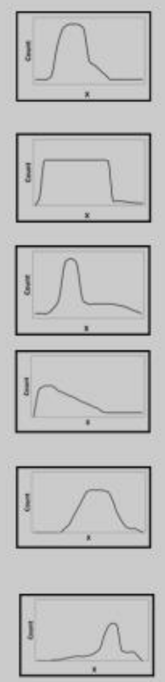
https://www.fs.fed.us/pnw/fera/fft/fccsmodule.shtml

Improving Fuel Loading Database (JFSP Project)

- Primary Task: Utilize the existing, extensive data on fuels and fuel loadings across the US to describe a distribution of fuel loadings for all fuelbeds and strata.
- Note that not all fuelbeds contain all strata.

Stratum	Category
Canopy	Trees, snags, ladder fuels
Shrubs	Primary and secondary layers
Nonwoody vegetation	Primary and secondary layers
Woody fuels	Sound wood, rotten wood, stumps, and woody fuel accumulations
Litter-lichen-moss	Litter, lichen, and moss layers
Ground fuels	Duff, basal accumulations, and squirrel middens

Fuel Loading



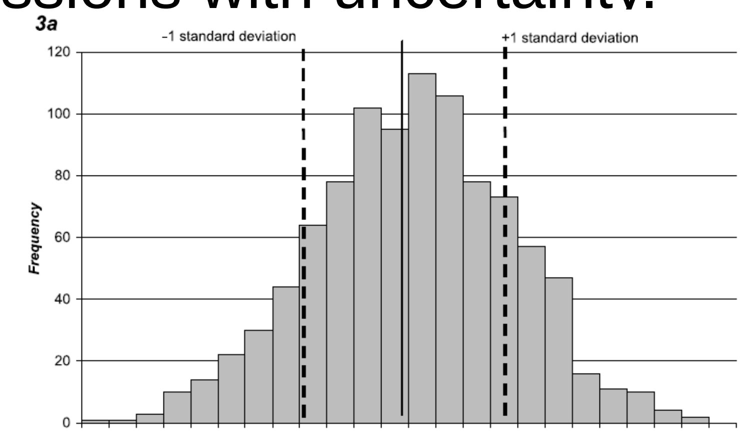
Emissions Modeling with Uncertainty

French, N.H.F., P. Goovaerts and E.S. Kasischke (2004). *Uncertainty in estimating carbon emissions from boreal forest fires. Journal of Geophysical Research 109: D14S08 doi: 10.1029/2003JD003635.*

Monte Carlo simulation:

- Use a stratified random sampling of probability distributions for each input parameter;
- Each combination of sampled values is combined to retrieve the corresponding simulated emission value.
- Result is an estimate of emissions with uncertainty.

Implementation of the Monte Carlo simulation requires information regarding the characteristics of the probability distributions (shape, spread) of each fuelbed and strata.



Predicted E_{CO2}

Fuel Loadings Database

- Data Sources:
  - FIA plot data
  - LANDFIRE reference database
  - Natural fuels photo series
  - Continuous Vegetation Survey Plots (USFS)
  - Source data for FOFEM development (courtesy of Bob Keane)
  - Source data for Fuel Loading Model development (courtesy of D. Lutes)
  - FCCS fuelbed development references
- Data compilation and QA/QC
  - Translation to metric (Mg/ha)
  - Preservation of source
  - Geolocation of samples where possible

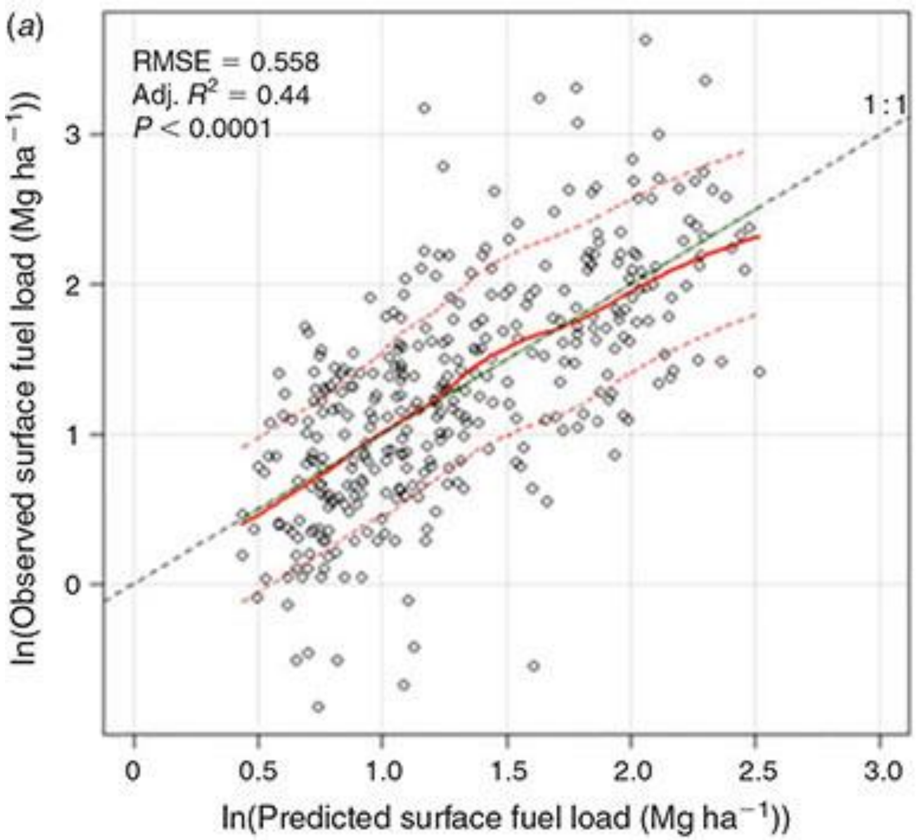
Currently "complete" but considered a "work in progress"

Fuel Loadings Database Fields

Variable name	Definition
LFEVTGroupID	Existing Vegetation Group ID
LFEVTGroup	Existing Vegetation Group Name
sourceID	Source reference ID
source	Source reference
studyPointID	Study point ID
plotname	Plot name
state	State
inventoryYear	Inventory year
veg_notes	Vegetation type notes
us_loading	Understory tree crown loading
ms_loading	Midstory tree crown loading
os_loading	Overstory tree crown loading
tree_crown_loading	Total tree crown loading
tree_loading	Aboveground tree biomass, including boles
snag_loading	Snag loading
shrub_loading	Shrub loading
herb_loading	Herb loading
1hr_loading:	1hr downed wood loading
10hr_loading	10hr downed wood loading
100hr_loading	100hr downed wood loading

Variable name	Definition
fwd_loading	Fine downed wood loading (1-100hr total)
1KhrS_loading	1000hr sound downed wood loading
1KhrR_loading	1000hr rotten downed wood loading
1Khr_loading	1000hr total downed wood loading
10KhrS_loading	10,000hr sound downed wood loading
10KhrR_loading	10,000hr rotten downed wood loading
10Khr_loading	10,000hr total downed wood loading
GT10KhrS_loading	>10,000hr sound downed wood loading
GT10KhrR_loading	>10,000hr rotten downed wood loading
GT10Khr_loading	>10,000hr total downed wood loading
cwd_sound_loading	Coarse sound downed wood loading (>= 1000hr)
cwd_rotten_loading	Coarse rotten downed wood loading (>= 1000hr)
cwd_loading	Coarse total downed wood loading (>= 1000hr)
moss_loading	Moss loading
lichen_loading	Ground lichen loading
litter_depth	Litter depth
litter_loading	Litter loading
duff_depth	Duff depth
duff_loading	Duff loading

LiDAR-derived Fuel Load
Example from RxCADRE

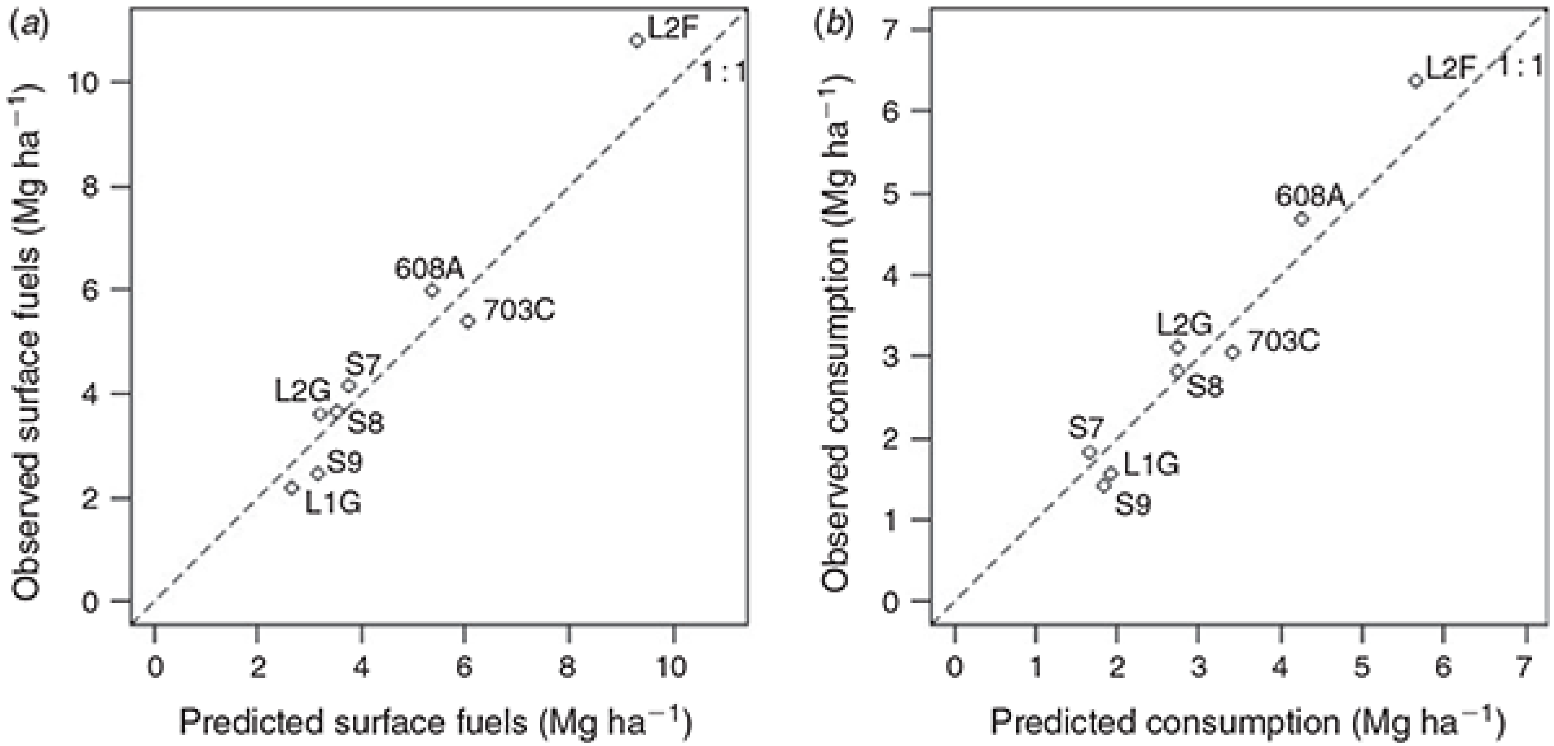


- Airborne discrete-return LiDAR-measured surface fuel loads in Longleaf pine and shrub-dominated sites.
- Multiple linear regression model predicting pre-fire surface fuel load (ln-transformed) from nine airborne lidar metrics.

From: Hudak et al. 2016. IJWF Special Issue Vol 25(1).

LiDAR-derived Fuel Load
Example from RxCADRE

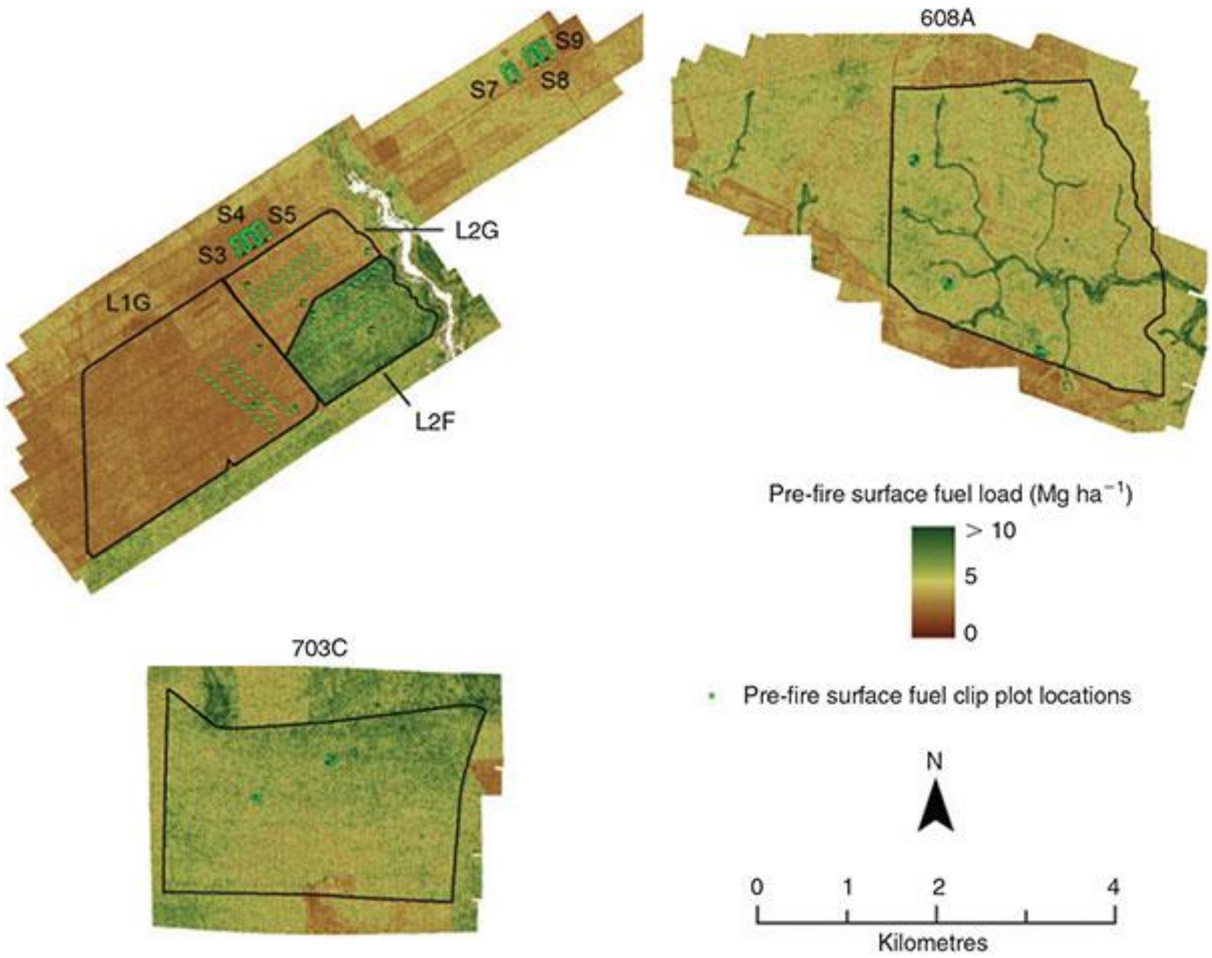
Plot-level fuel loads and surface fuel consumption predicted from LiDAR-derived model compared to observations.



From: Hudak et al. 2016. IJWF Special Issue Vol 25(1).

LiDAR-derived Fuel Load
Example from RxCADRE

Pre-fire surface fuels mapped across the extent of the 2011 and 2012 LiDAR collections based on field-derived predictive models.



From: Hudak et al. 2016. IJWF Special Issue Vol 25(1).

LiDAR-predicted Canopy Fuels

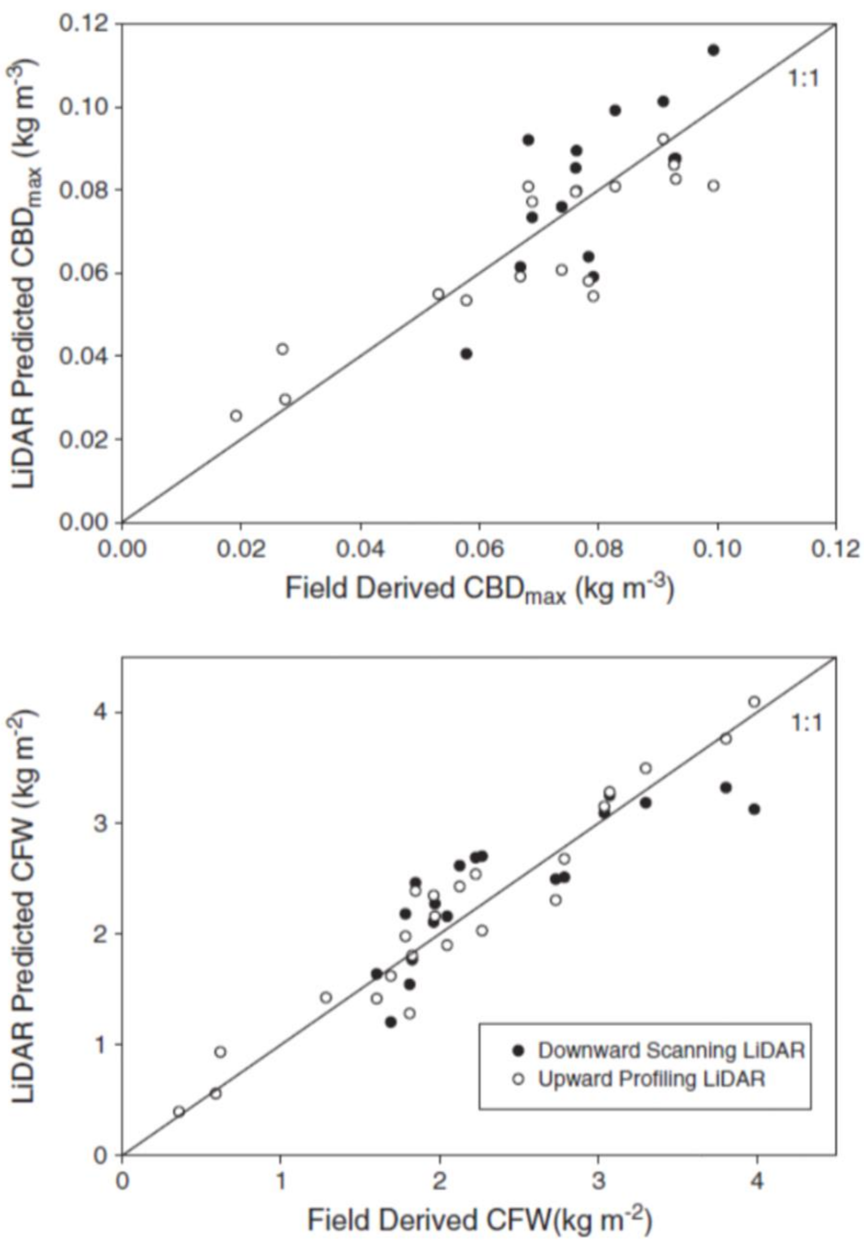


Fig. 5. Predicted values of CBD_{max} and CFW from equations for upward profiling LiDAR (open symbols) and downward scanning LiDAR systems (closed symbols) in Table 3 plotted against biometric estimates of CBD_{max} and CFW from field plots.

- Promising results in the literature for quantifying canopy fuels
- Relevant to boreal forests due to the prevalence of crown fires

From: N.S. Skowronski et al. (2011) Remote Sensing of Environment 115 pp 703–714

Sample Loadings Table (sorted by source)

LFEVTGroupCd_FINAL	LFEVTGroup	sourceID	source	studyPointID	plotname	state	1hr_loading: Mg/ha	10hr_load	100hr_load	1KhrS_load	1KhrR_load	litter_depth: cm	litter_load	duff_depth: cm	duff_loading: Mg/ha
639	Spruce-Fir Forest and Woodl	1	Barney et al. 1981	4		AK						5.46	0.04	5.82	0.16
756	Birch-Aspen Forest	1	Barney et al. 1981			AK									
758	Black Spruce Forest and Woc	1	Barney et al. 1981	2		AK (upland)						7.09	0.07	9.6	0.25
610	Conifer-Oak Forest and Woo	4	Van Wagtendonk	15		CA	0.65	0.92	0.67	0	0	1.35	3.38	3.23	27.37
610	Conifer-Oak Forest and Woo	4	Van Wagtendonk	20		CA	0.69	0.74	0.92	0	0	1.7	5.85	2.79	48.32
614	Douglas-fir Forest and Wooc	4	Van Wagtendonk	14		CA	3.7	4.73	1.52	0.38	0	0.33	3.07	4.39	60.57
620	Juniper Woodland and Savar	4	Van Wagtendonk	29		CA	0.38	1.1	0.78	0	0	0.1	0.78	1.27	22.83
621	Limber Pine Woodland	4	Van Wagtendonk	21		CA	1.5	2.15	4.55	4.93	0	0.71	7.44	6.96	159.94
622	Lodgepole Pine Forest and V	4	Van Wagtendonk	22		CA	0.83	1.41	1.75	0.38	0	0.43	4.17	3.53	57.88
626	California Mixed Evergreen I	4	Van Wagtendonk	17		CA	1.3	4.03	7.57	10.44	0	0.38	4.52	8.66	140.81
626	California Mixed Evergreen I	4	Van Wagtendonk	18		CA	2.44	2.82	1.39	3.18	0	0.2	2.69	4.88	83.6
626	California Mixed Evergreen I	4	Van Wagtendonk	19		CA	0.25	1.95	0.74	0	0	1.12	3.76	5.38	89.58
626	California Mixed Evergreen I	4	Van Wagtendonk	27		CA	1.43	1.77	3.9	0.85	0.09	2.11	7.41	5.97	87.11
626	California Mixed Evergreen I	4	Van Wagtendonk	30		CA	0.9	1.61	0.87	0	0	0.25	1.28	1.8	25.58
626	California Mixed Evergreen I	4	Van Wagtendonk	31		CA	2.89	3.7	1.95	1.75	0.02	0.15	1.28	6.45	79.68
627	Mountain Hemlock Forest ar	4	Van Wagtendonk	23		CA	2.17	2.49	1.84	1.81	0	0.36	4.3	6.05	108.75
630	Pinyon-Juniper Woodland	4	Van Wagtendonk	26		CA	2.17	1.12	0	0	0	0.48	5.67	3.25	78.76
631	Ponderosa Pine Forest, Woo	4	Van Wagtendonk	24		CA	0.13	2.15	2.6	4.28	0.78	1.88	5.62	7.87	113.01
631	Ponderosa Pine Forest, Woo	4	Van Wagtendonk	28		CA	0.18	1.08	0.27	0.22	0	0.66	3.52	3.66	65.83
633	Red Fir Forest and Woodlanc	4	Van Wagtendonk	25		CA	5.26	6.83	5.06	1.39	1.39	0.15	1.55	4.88	87.92
640	Subalpine Woodland and Pa	4	Van Wagtendonk	16		CA	1.86	1.39	0	0	0	0.18	1.77	1.6	36.47
640	Subalpine Woodland and Pa	4	Van Wagtendonk	32		CA	0.99	1.01	0.85	1.23	1.3	0.48	2.69	4.93	91.15

LFEVTGroupCd_FINAL	LFEVTGroup	sourceID	source	studyPointID	plotname	state	1hr_loading: M
639	Spruce-Fir Forest and Woodl	1	Barney et al. 1981	4		AK	
756	Birch-Aspen Forest	1	Barney et al. 1981			AK	
758	Black Spruce Forest and Woc	1	Barney et al. 1981	2		AK (upland)	
758	Black Spruce Forest and Woc	1	Barney et al. 1981	3		AK (lowland)	

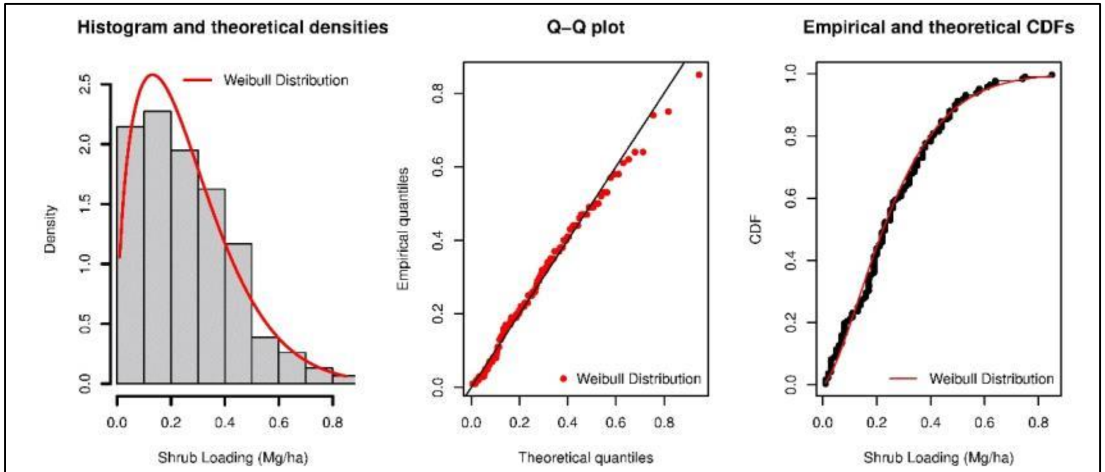
Distribution fitting

Explore distribution fitting options

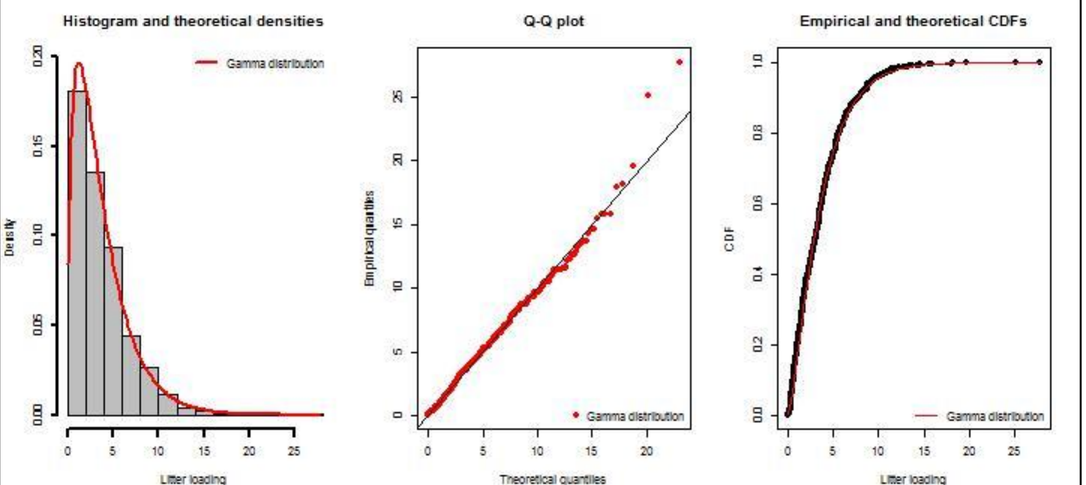
Candidate distributions:

- normal
- lognormal
- gamma
- weibull

weibull



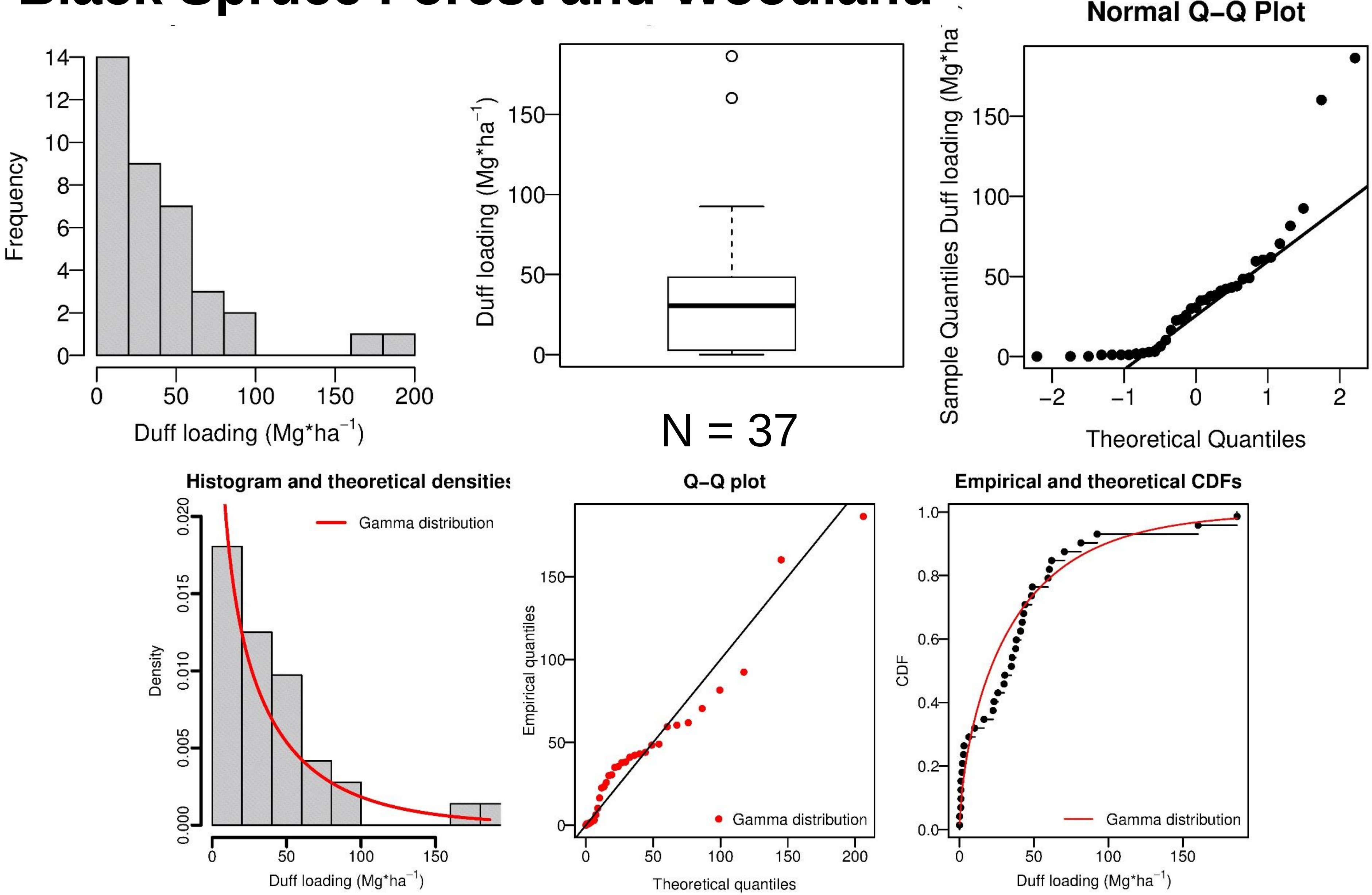
Weibull distribution fit to shrub loading (>0 Mg/ha) for Western Hemlock Forest vegetation type



Gamma distribution fit to litter loading (>0 tons/acre) for the US Eastern floodplain vegetation type

gamma

Black Spruce Forest and Woodland



Gamma distribution fit to Duff loading (Mg*ha^{-1}) for the Black Spruce Forest and Woodland vegetation type

Using the Database Sensitivity Analysis

Sensitivity Analysis

Local and global **sensitivity analysis** ranks fuels categories for their contribution to variability in emissions predictions

Data gap identification

Cross-reference important fuels categories with data gaps found in Task 1a

Prioritize resources for data acquisition

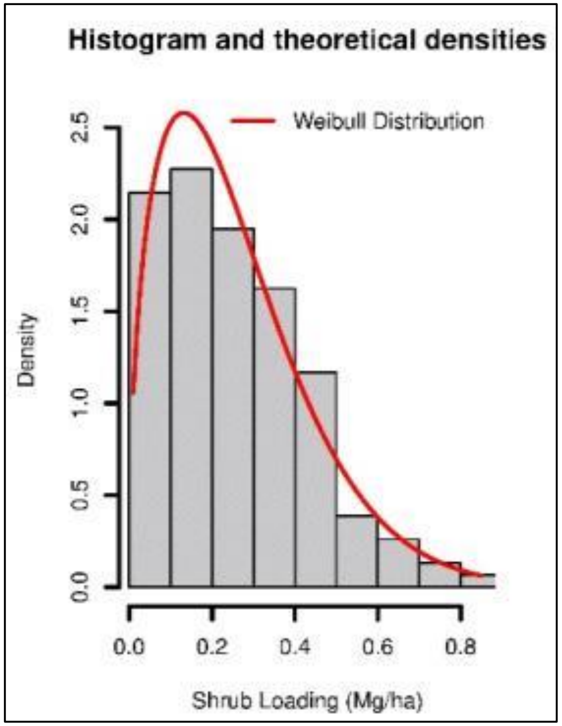
Emissions model predictions

Draw randomly from empirical joint distributions of important fuels categories, predict emissions for each

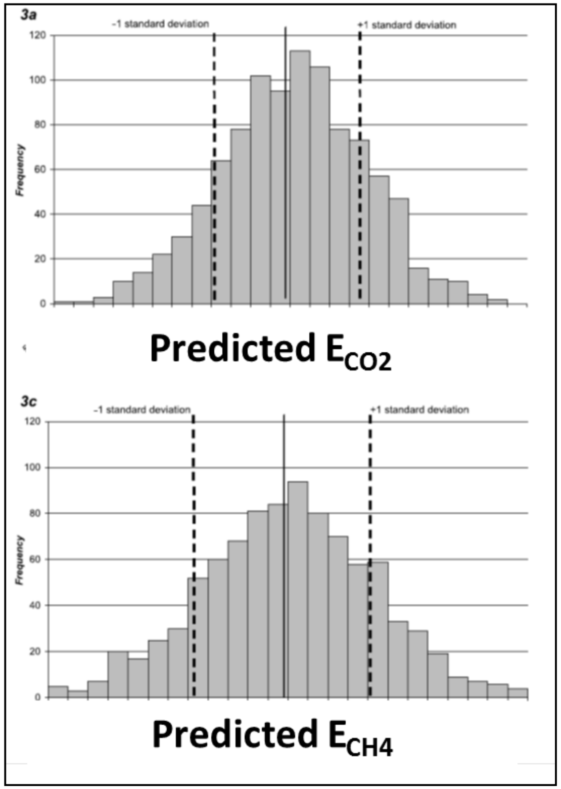
Produce expected distributions and prediction intervals for emissions estimates

Using the Database Emissions Modeling

Sample loading values from fit distributions → Estimate emissions for sample values → Calculate distribution of emissions



As in French et al. 2004



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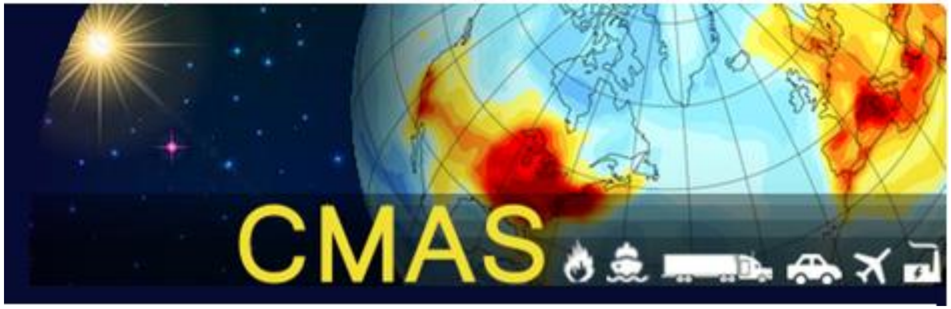
Applications

- **Smoke and Air-quality Models**

draw from probability distributions of mapped fuels rather than single-average values.

Community Multiscale Air-quality System (CMAS)



- **Global Climate Models**

enable coupled models* to incorporate spatial variation in fuels when projecting uncertainty in GHG emissions.

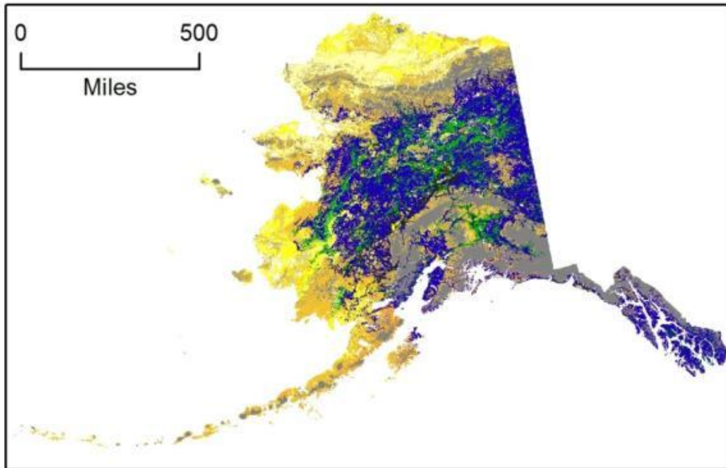
(*e.g., GCMs + land-surface models + smoke dispersion models)

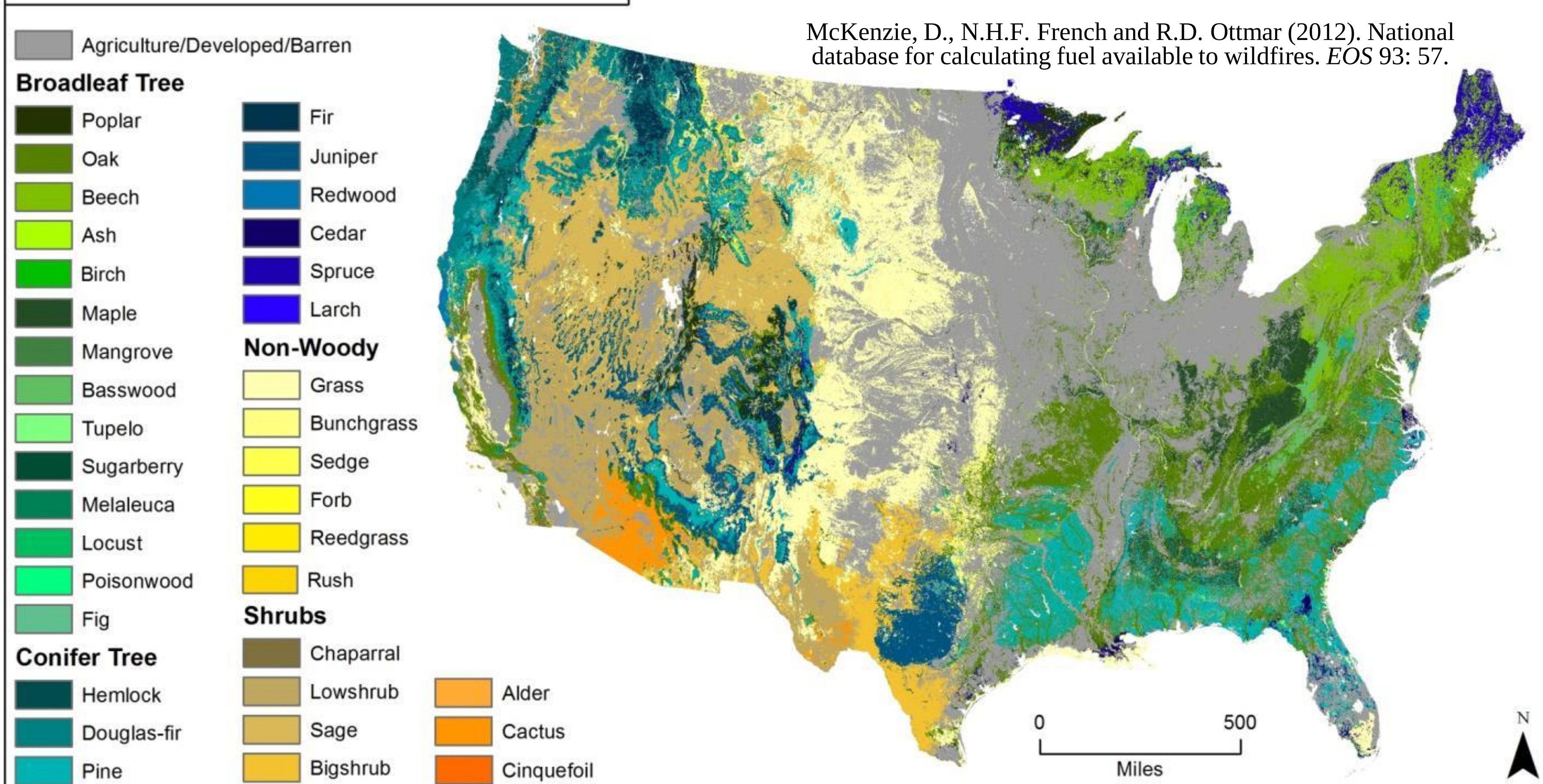
Note: this methodology can be extended, in theory, to coarse-scale GCMs

Fuel Characteristic Classification System Standard Fuelbeds

1-km resolution

McKenzie, D., N.H.F. French and R.D. Ottmar (2012). National database for calculating fuel available to wildfires. *EOS* 93: 57.





Spatial Emissions Modeling

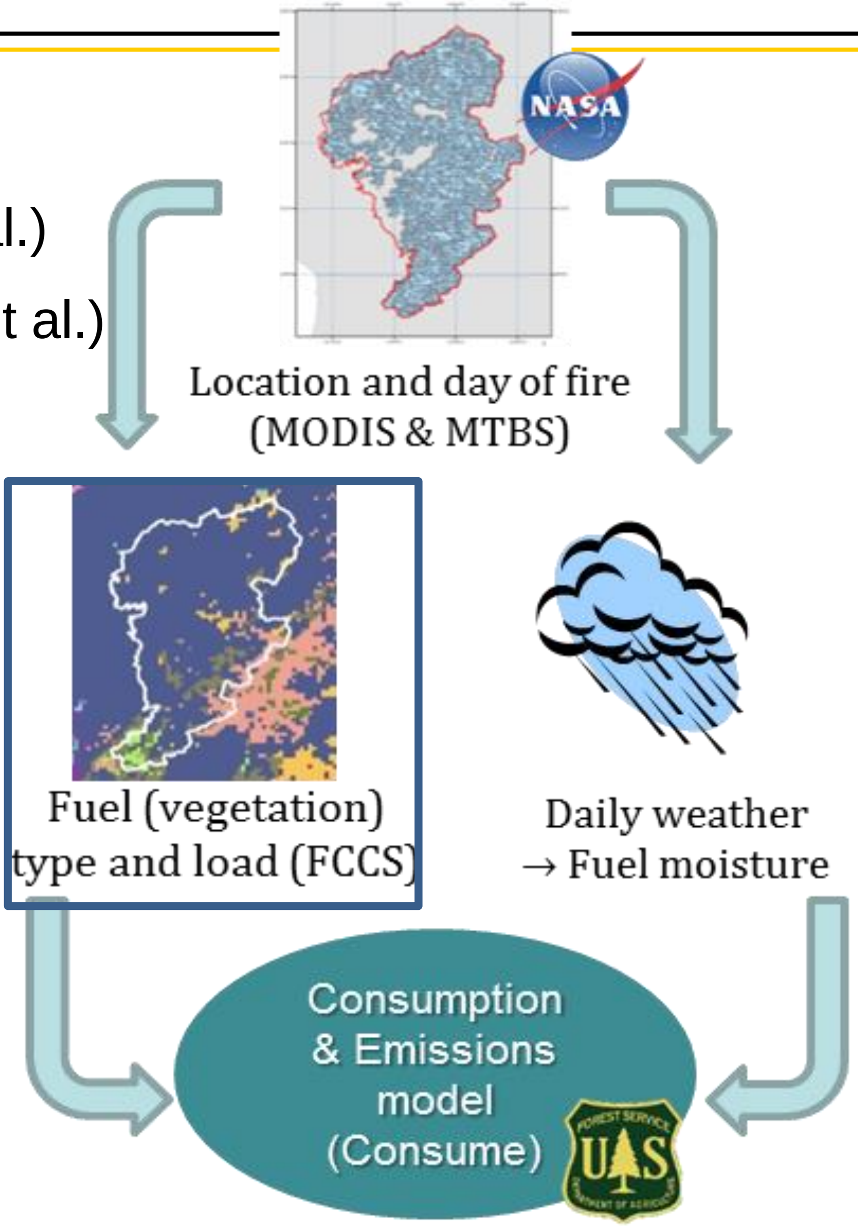
FCCS-based

- WFEIS/Consume (French et al.)
- BlueSky Framework (Larkin et al.)

Others:

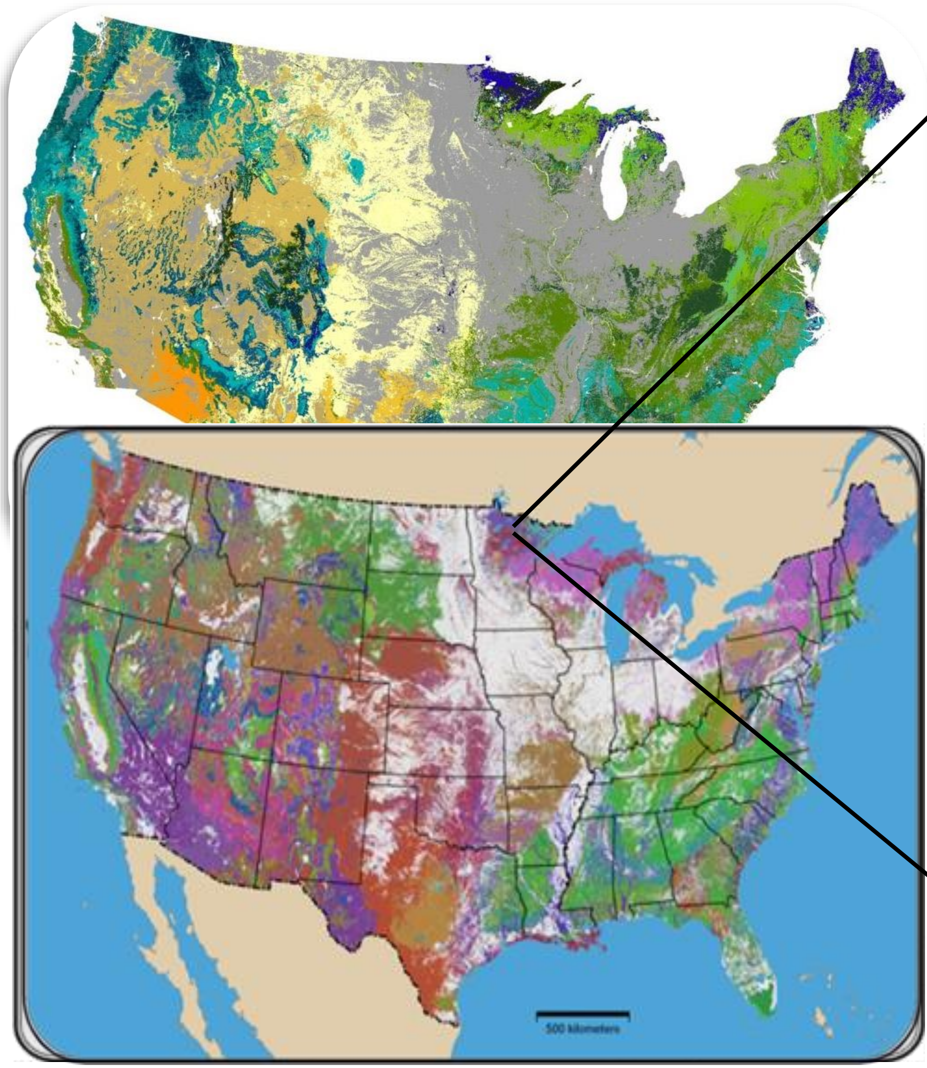
- CanFIRE (de Groot et al.)
- GFED (van der Werf et al.)
- FINN (Wiednmyer et al.)

Improvements needed →

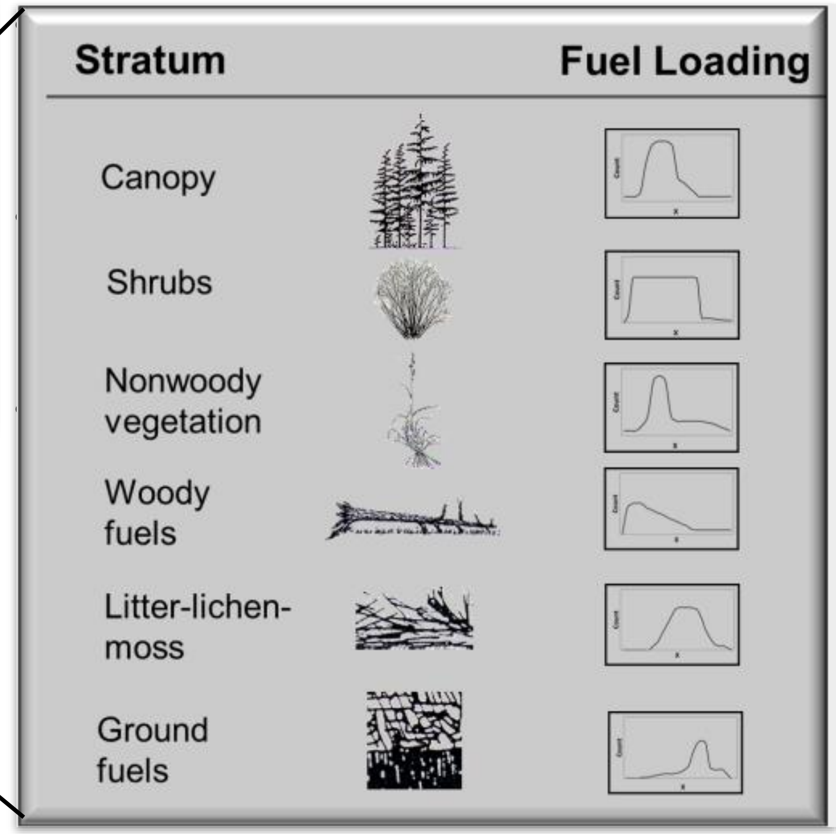


French, N.H.F., D. McKenzie, T. Erickson, B. Koziol, M. Billmire, K.A. Endsley, N.K.Y. Scheinerman, L. Jenkins, M.E. Miller, R. Ottmar and S. Prichard (2014). "Modeling regional-scale fire emissions with the Wildland Fire Emissions Information System". Earth Interactions 18: 1-26 doi: 10.1175/EI-D-14-0002.1.

Spatial Emissions Modeling



Fuelbed Map



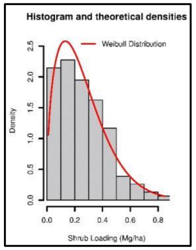
includes fuel loadings by type

http://www.fs.fed.us/pnw/fera/fccs/index.shtml

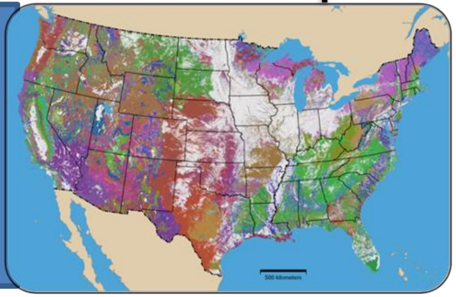
McKenzie, D., N.H.F. French and R.D. Ottmar (2012). National database for calculating fuel available to wildfires. *EOS* 93: 57.

Spatial Emissions Modeling

Select out loadings for each strata & fuelbed using quasi-random sequence of selections informed by stand age and fuelbed structure



Stand age (disturbance map)



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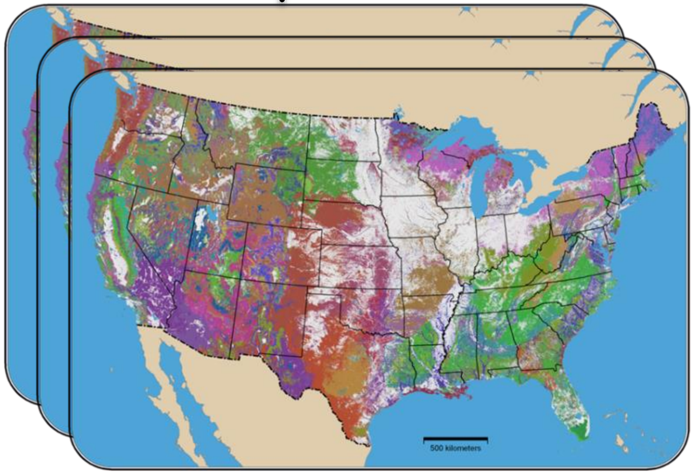
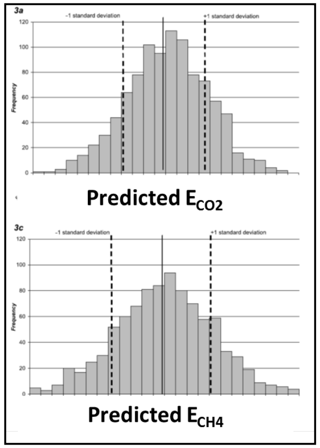
Fuel moisture scenarios

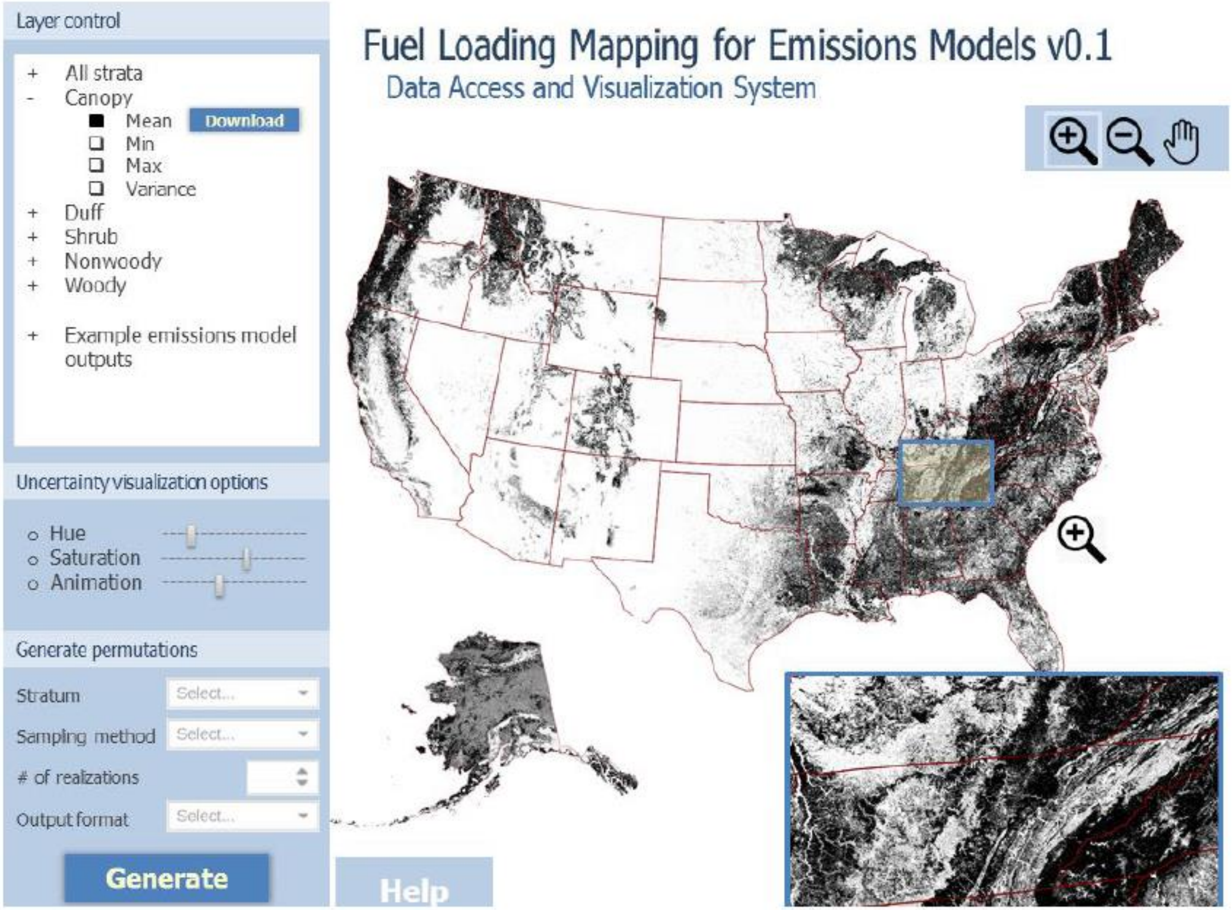
Fuels emissions product:
A set of emissions for each strata and each 1-km cell determined from the new map's loadings distributions for appropriate site age.





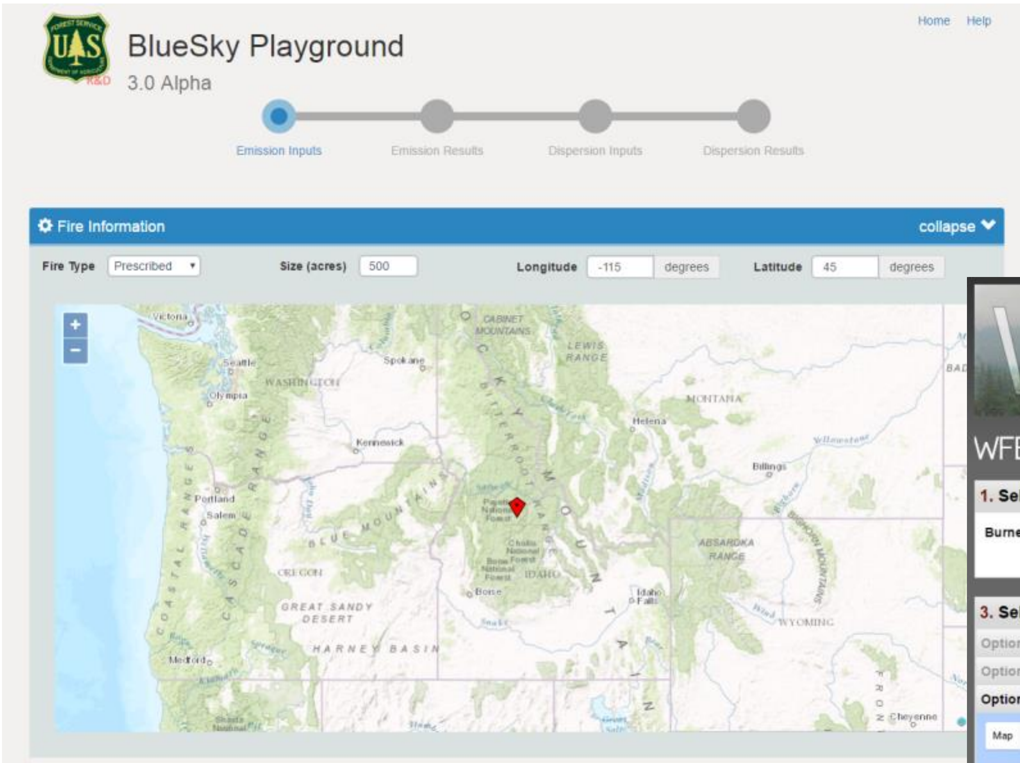
Data access and visualization

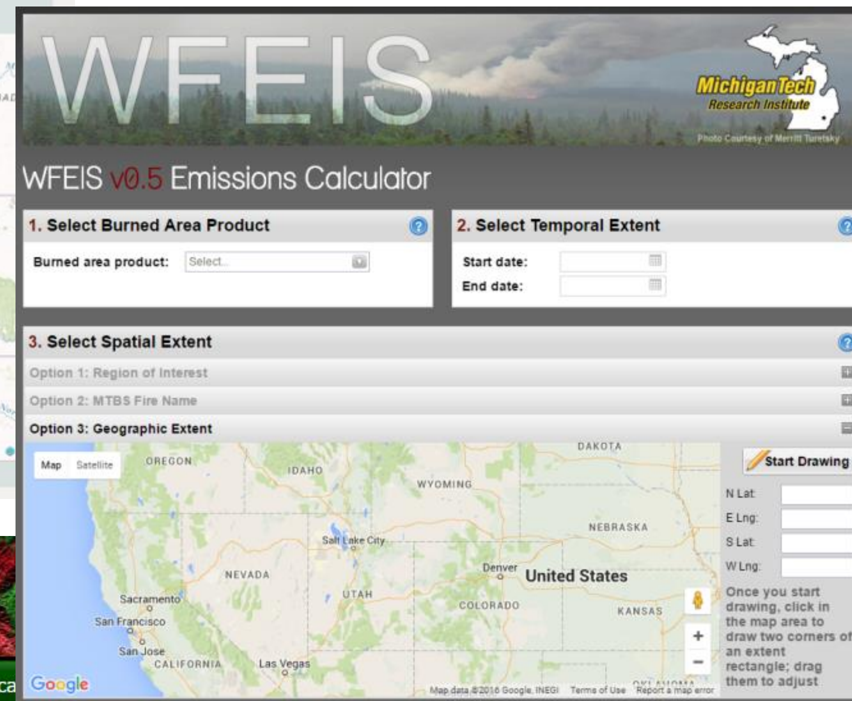
Web-based application for visualizing fuel loading distributions by region and fuel category



Applications

Emissions estimation





Wildland Fire Emissions Information System

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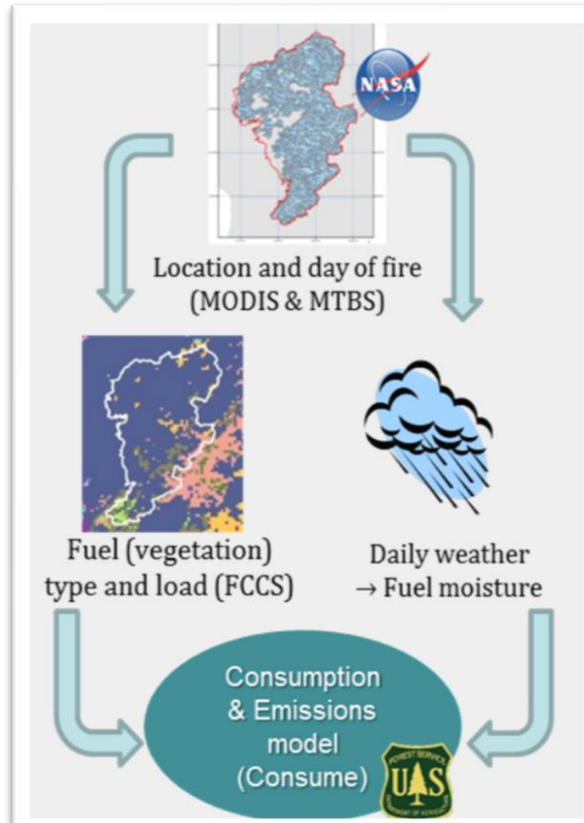
What is WFEIS?

The Wildland Fire Emissions Information System (WFEIS) is a web-based tool that provides users a simple interface for computing wildland fire emissions across CONUS and Alaska at landscape to regional scales (1-km spatial resolution). WFEIS integrates burned area maps along with corresponding fuel loading data layers and fuel consumption models to compute wildland and cropland fire fuel consumption and emissions for user-specified locations and date ranges. The system currently allows for calculation of emissions from fires within the United States (excluding Hawaii and territories) from 1984 through 2013 depending on the selected burned area product.

The WFEIS website allows for two approaches for making fuel consumption and emissions estimates:

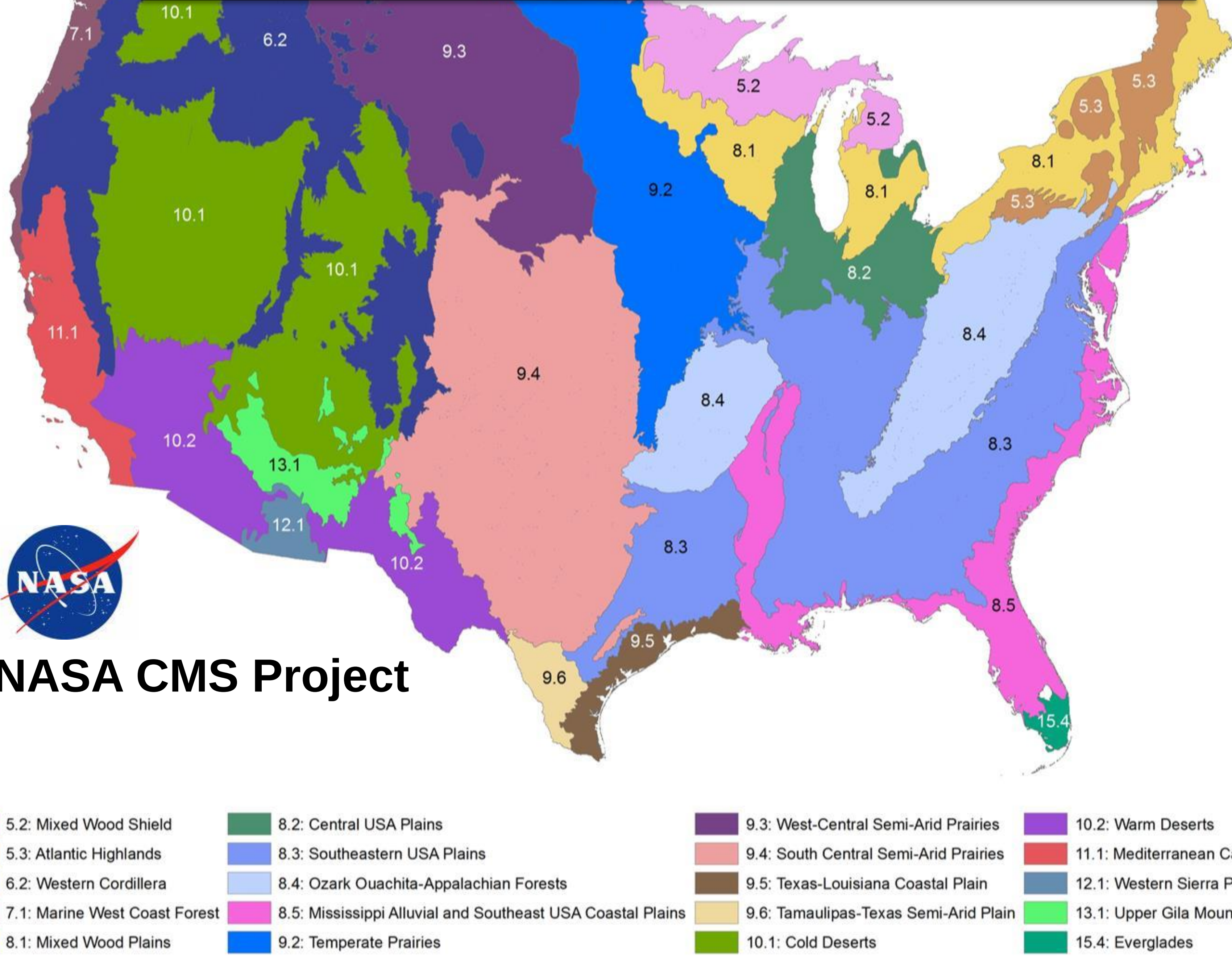
- First, there is an **Emissions Calculator** that provides a graphical user interface for constructing queries.
- Second, the WFEIS website responds to queries submitted via **properly encoded URL requests** (i.e. it implements a RESTful Web API). Examples of valid WFEIS URLs, accessed via the emissions calculator within the KML and text report output formats, can be modified by users and resubmitted to the WFEIS system.

WFEIS is built entirely from open-source software components. Data can be requested and delivered in multiple spatial and non-spatial formats including text reports, CSV, ESRI Shapefiles, KML documents, GeoTIFF images, and netCDF files.



wfeis.mtri.org

Regional-scale Estimates of Emissions for the US

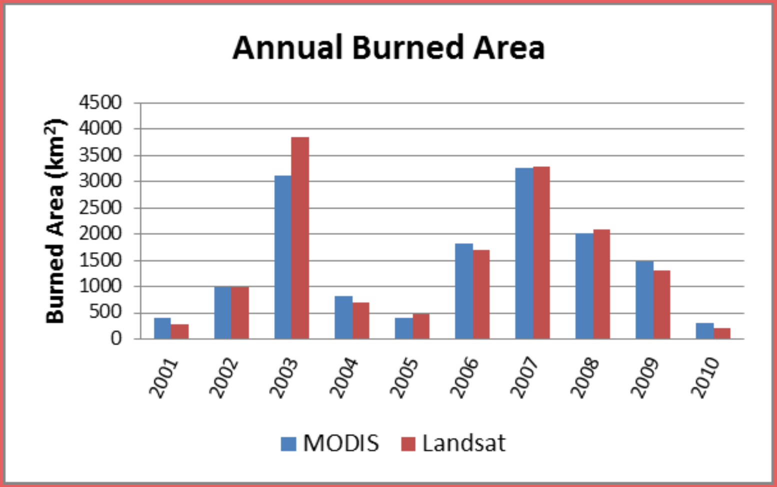


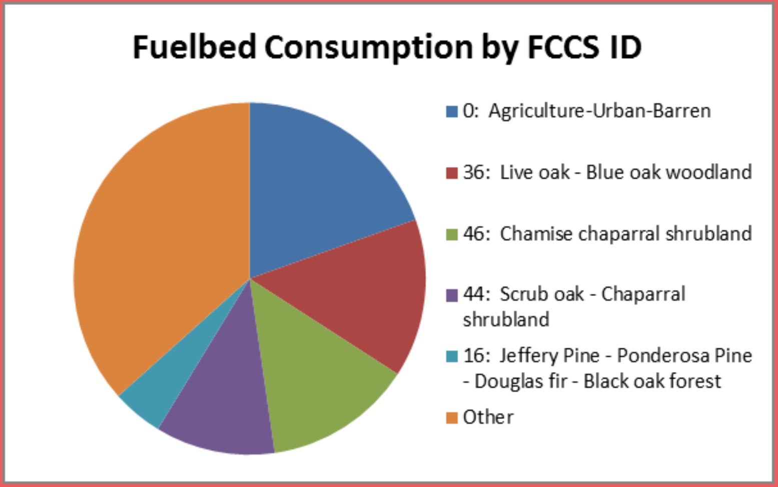
NASA CMS Project

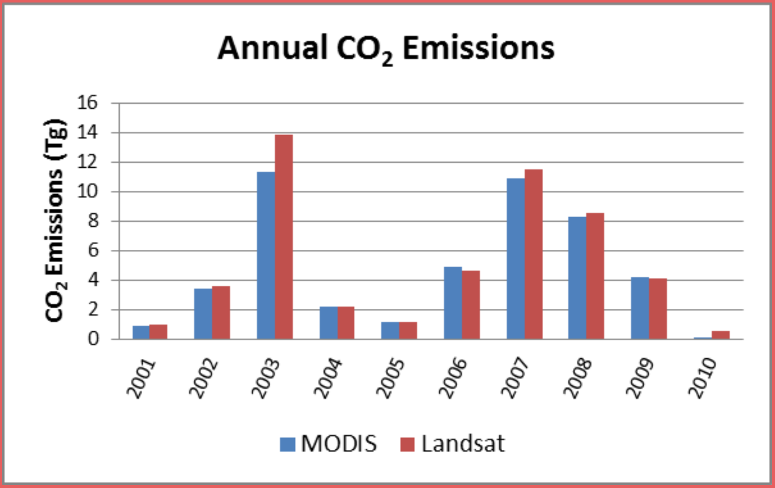
Region 11 – Mediterranean California

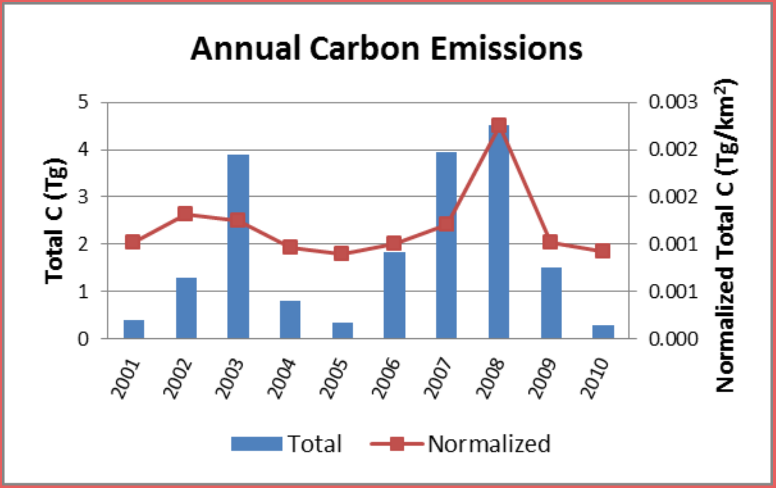
This is the only ecoregion in the continental US with a Mediterranean climate – summers are hot and dry, and winters are mild. Droughts are common, with precipitation averaging from 200-1,000 mm per year. With irrigation, these features create a prime environment for high value agriculture. Native vegetation is dominated by shrubs, with patchy areas of grasslands and forests of evergreen and deciduous trees.

11.1 Mediterranean California

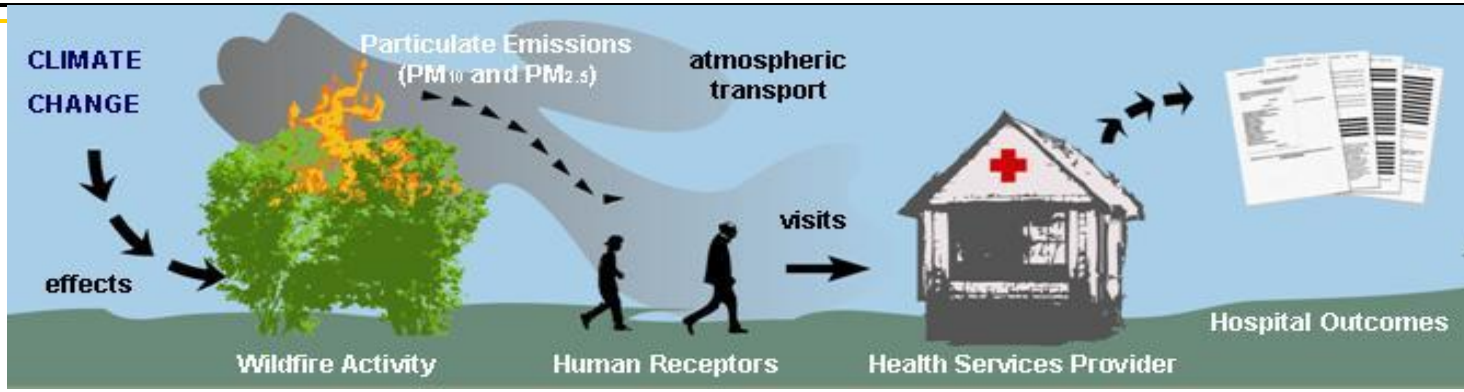


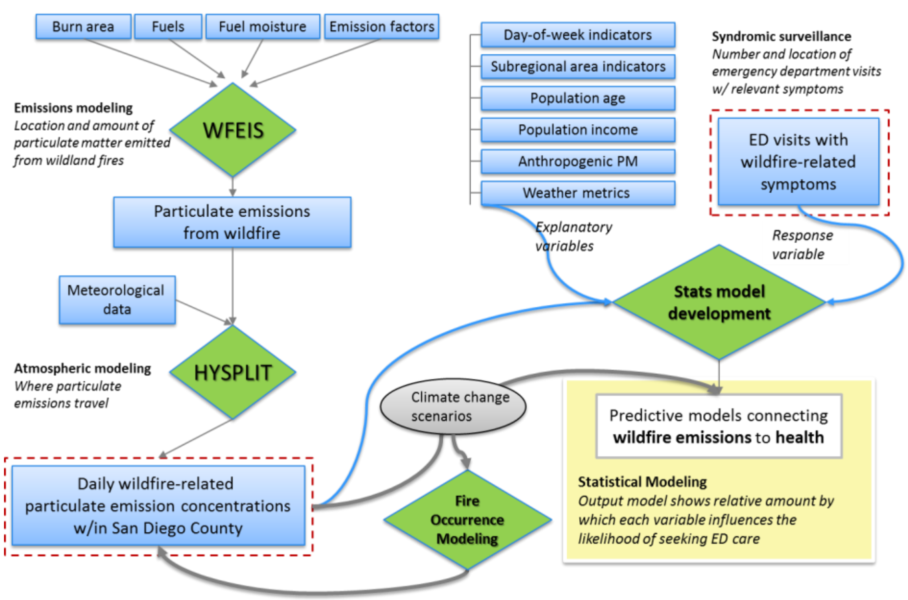






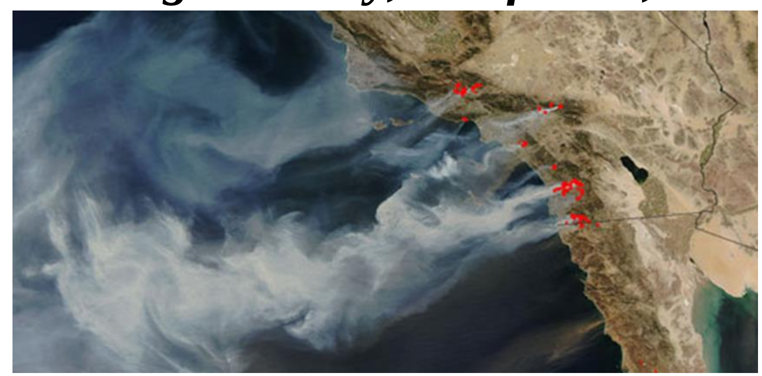
Fire & Health





Approach: Coupled statistical and process-based model system

San Diego County, California, 2007



Result: Maximum estimated effect on the odds of seeking ED care from *wildland fire* $PM_{<10}$ is **41%** change for San Diego County model and **72%** change for the Subregional model.


Thank-You
Nancy French at the 1990 Bettles Fire
May of 1991

EXTRA SLIDES

Fuels vs. Biomass

Fuels information includes more than just amount of or density of vegetative material (loading)

- Fuel structure is very important to fire behavior and fire effects, including consumption.
- Fuel composition can determine flammability and other factors relevant to emissions
  - combustion type (flaming vs. smoldering) and
  - types of emissions (e.g. combustion efficiency; smoke chemistry).

Fuels vs. Biomass

- A "Fuelbed" is defined by the vegetation and other materials, including all components important to combustion
  - Organic forest floor material and amount is very important in some ecosystems.
  - Shrubs are important in other types.
- Biomass measures often include only aboveground live components (evolved from silviculture methods)

  - Trees boles are often not a major component of fire emissions, as they often don't burn.
  - Woody debris and forest floor dominate emissions for some types.
  - Crown fires are common only in some forest types.