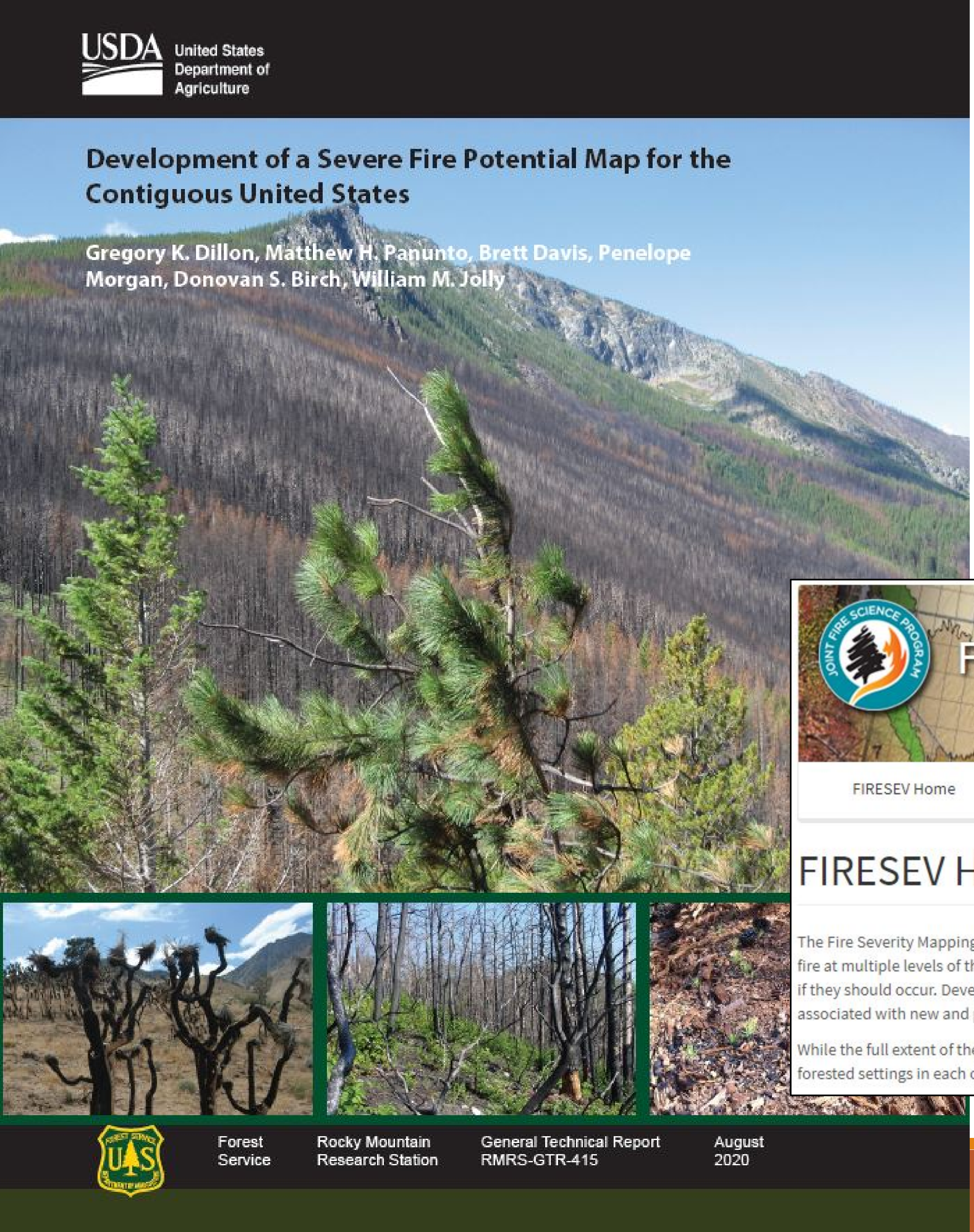
Where and when are high severity fires more likely to occur?

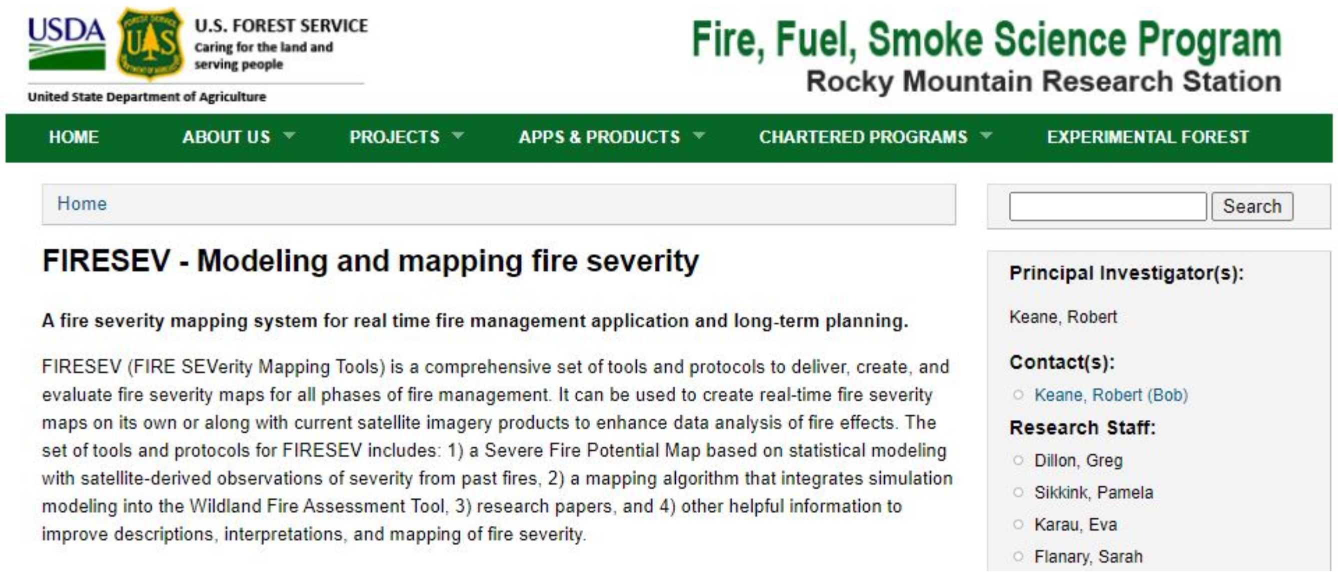
LANDFIRE Webinar | December 9, 2020

Greg Dillon
USDA Forest Service, Rocky Mountain Research Station, Fire Modeling Institute
Missoula, Montana

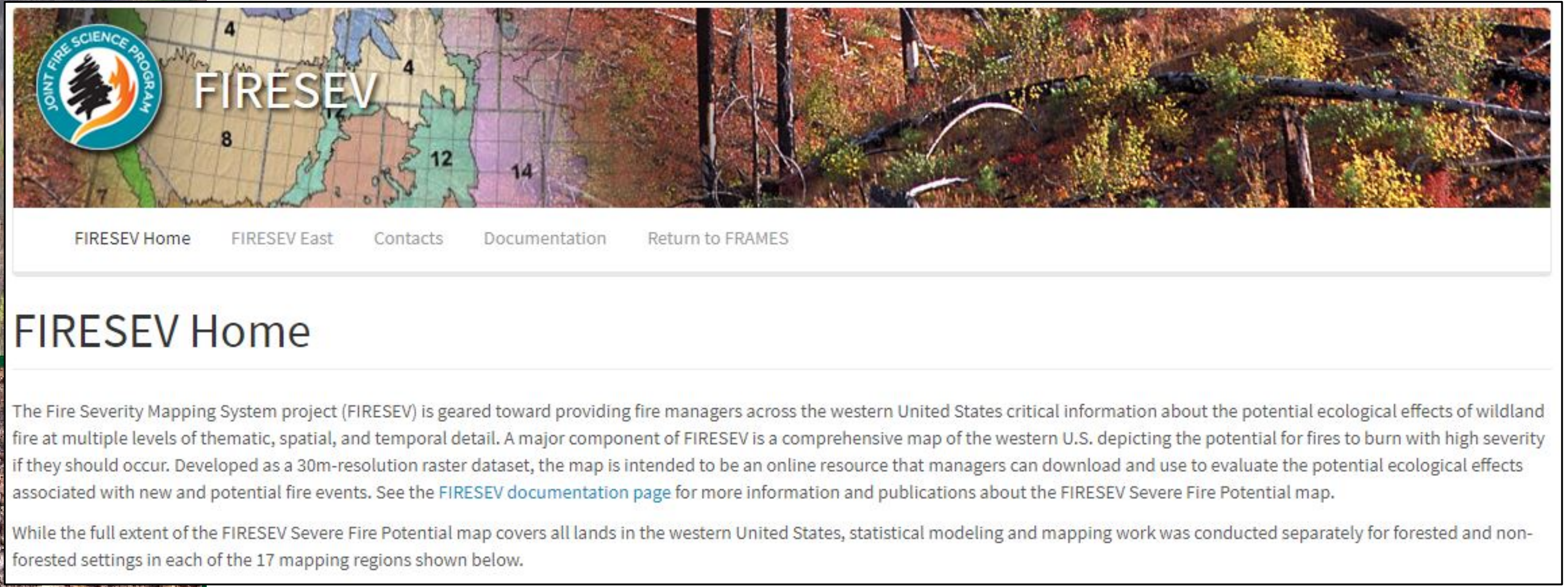
FOREST SERVICE U.S. DEPARTMENT OF AGRICULTURE

USDA





https://www.firelab.org/project/firesev-modeling-and-mapping-fire-severity



https://www.frames.gov/firesev/home

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

Photo: USGS and NPS

Burn severity… high severity… severe fire

Photo: USGS and NPS

Burn severity… high severity… severe fire

Burn severity… high severity… severe fire

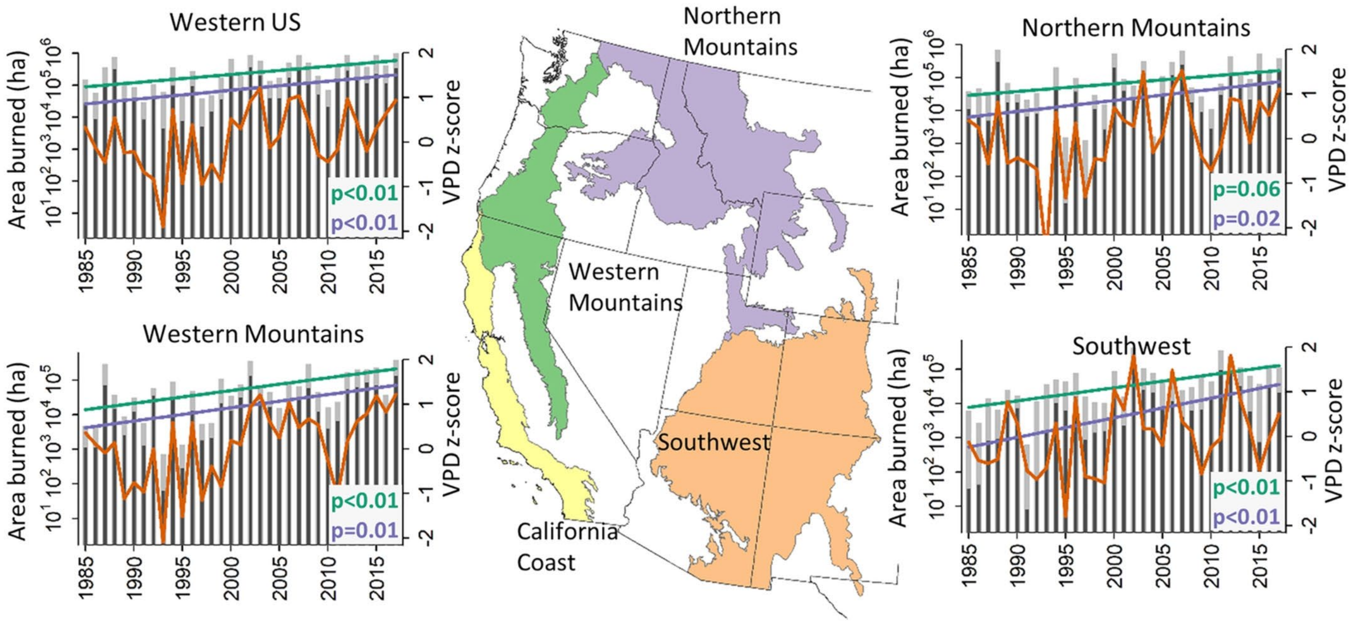
Why focus on high severity?

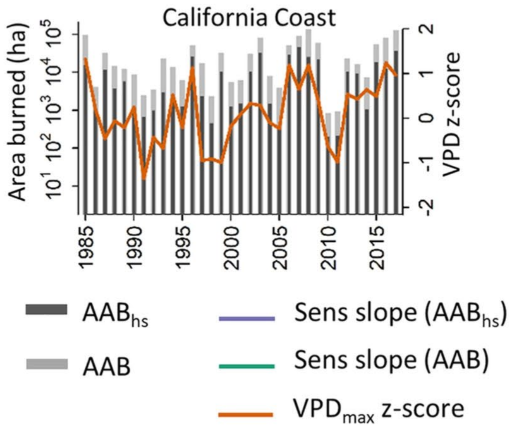
Geophysical Research Letters

Research Letter | Free Access

Warmer and Drier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017

S. A. Parks, J. T. Abatzoglou





Correlation (Pearson's *r*) between AAB$_{hs}$ and AAB and the three climate variables ($p \leq 0.01$ for all relationships; Table S3). Arrows indicate that the climate variable has experienced a statistically significant increase from 1985-2017 (Table S5).

	AAB$_{hs}$			AAB		
Ecoregion	**VPD$_{max}$**	**T$_{max}$**	**CWD**	**VPD$_{max}$**	**T$_{max}$**	**CWD**
California Coast	0.67 ↑	0.58	0.69	0.70	0.62	0.69
Western Mountains	0.74 ↑	0.70 ↑	0.71	0.73	0.67	0.70
Northern Mountains	0.90 ↑	0.89 ↑	0.88	0.89	0.90	0.86
Southwest	0.59	0.40	0.64 ↑	0.55	0.41	0.56
Western US	0.83 ↑	0.79 ↑	0.74	0.80	0.73	0.69

Why focus on high severity?

Geophysical Research Letters

Research Letter | Free Access

Warmer and Drier Fire Seasons Contribute to Increases in Area Burned at High Severity in Western US Forests From 1985 to 2017

S. A. Parks, J. T. Abatzoglou

LETTER • OPEN ACCESS

Fire-catalyzed vegetation shifts in ponderosa pine and Douglas-fir forests of the western United States

Kimberley T Davis[1], Philip E Higuera[1], Solomon Z Dobrowski[2], Sean A Parks[3], John T Abatzoglou[4], Monica T Rother[5] and Thomas T Veblen[6]

Published 13 October 2020 • © 2020 The Author(s). Published by IOP Publishing Ltd

Environmental Research Letters, Volume 15, Number 10

Wildfire-Driven Forest Conversion in Western North American Landscapes

Jonathan D Coop, Sean A Parks, Camille S Stevens-Rumann, Shelley D Crausbay, Philip E Higuera, Matthew D Hurteau, Alan Tepley, Ellen Whitman, Timothy Assal, Brandon M Collins, Kimberley T Davis, Solomon Dobrowski, Donald A Falk, Paula J Fornwalt, Peter Z Fulé, Brian J Harvey, Van R Kane, Caitlin E Littlefield, Ellis Q Margolis, Malcolm North, Marc-André Parisien, Susan Prichard, Kyle C Rodman

BioScience, Volume 70, Issue 8, August 2020, Pages 659–673, https://doi.org/10.1093/biosci/biaa061

Published: 01 July 2020

Size Isn't the Best Way to Talk About Fires

by *Crystal Kolden*

October 22, 2020

BAY NATURE

SCIENCE

4 Million Acres Have Burned In California. Why That's The Wrong Number To Focus On

October 7, 2020 · 4:06 PM ET

Heard on All Things Considered

npr

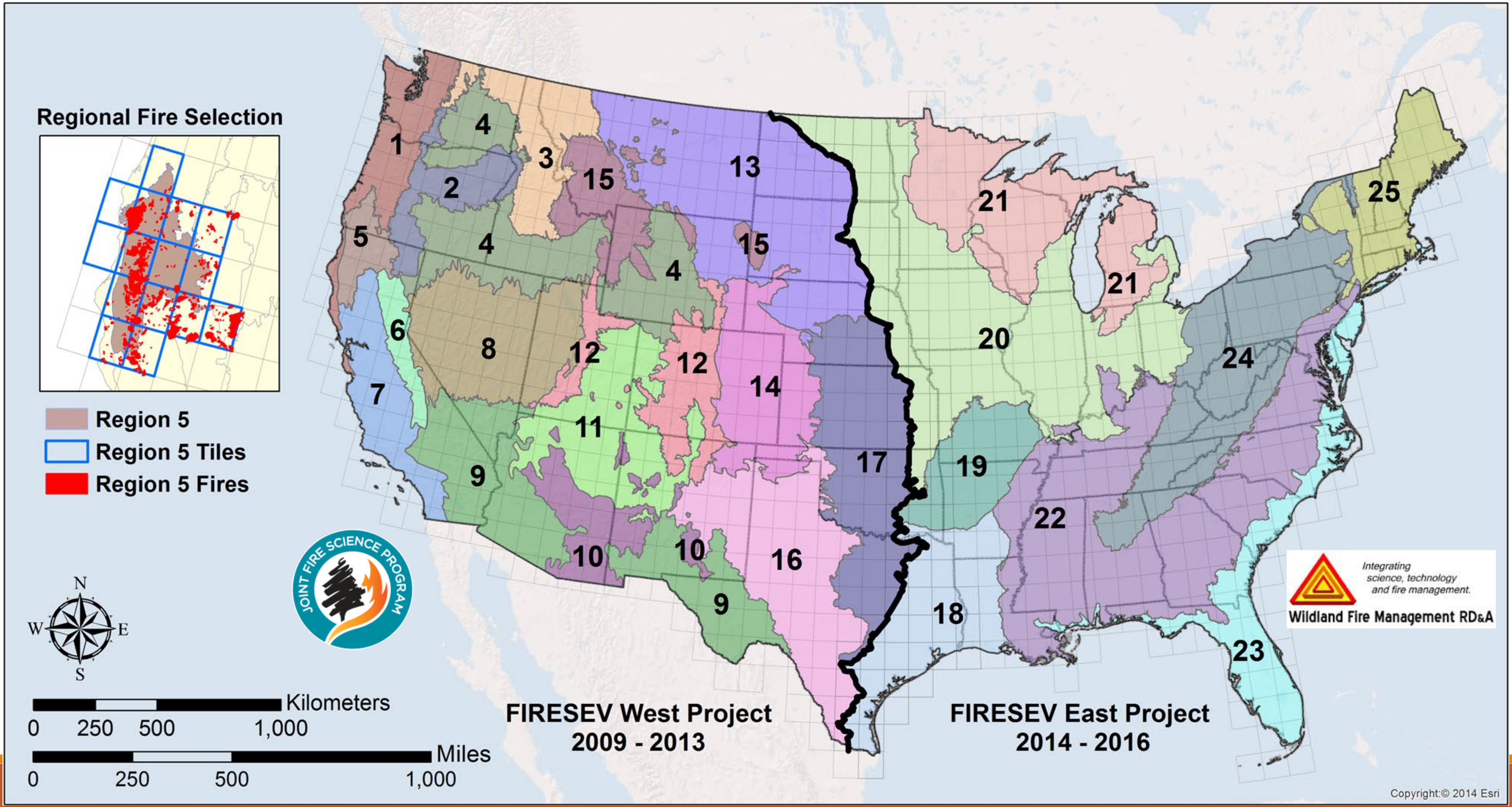
Objectives

1. Develop a comprehensive map of the potential for high burn severity for all areas in the contiguous United States using empirical observations and statistical modeling

2. Evaluate the quality of the map to provide managers with guidance on its interpretation and use

3. Contribute to our understanding of what factors drive the occurrence and patterns of high burn severity

Study Areas


Regional Fire Selection
Region 5
Region 5 Tiles
Region 5 Fires
1
2
3
4
5
6
7
8
9
10
11
12
13
14
15
16
17
18
19
20
21
22
23
24
25
N
S
E
W
Kilometers
0 250 500 1,000
Miles
0 250 500 1,000
JOINT FIRE SCIENCE PROGRAM
FIRESEV West Project
2009 - 2013
FIRESEV East Project
2014 - 2016
Integrating science, technology and fire management.
Wildland Fire Management RD&A
Copyright:© 2014 Esri

Study Areas

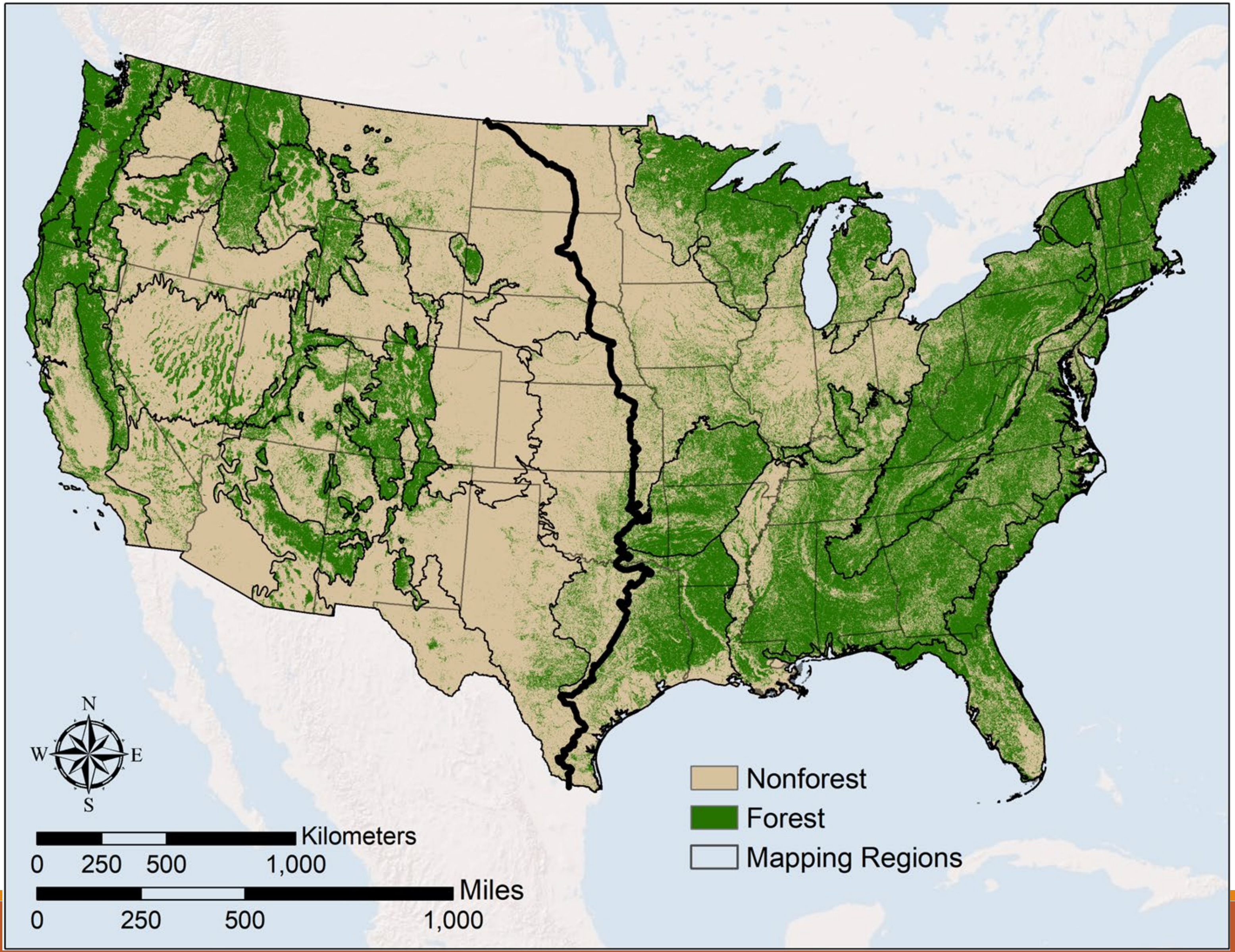
<u>Forest and Nonforest</u>

Current Conditions

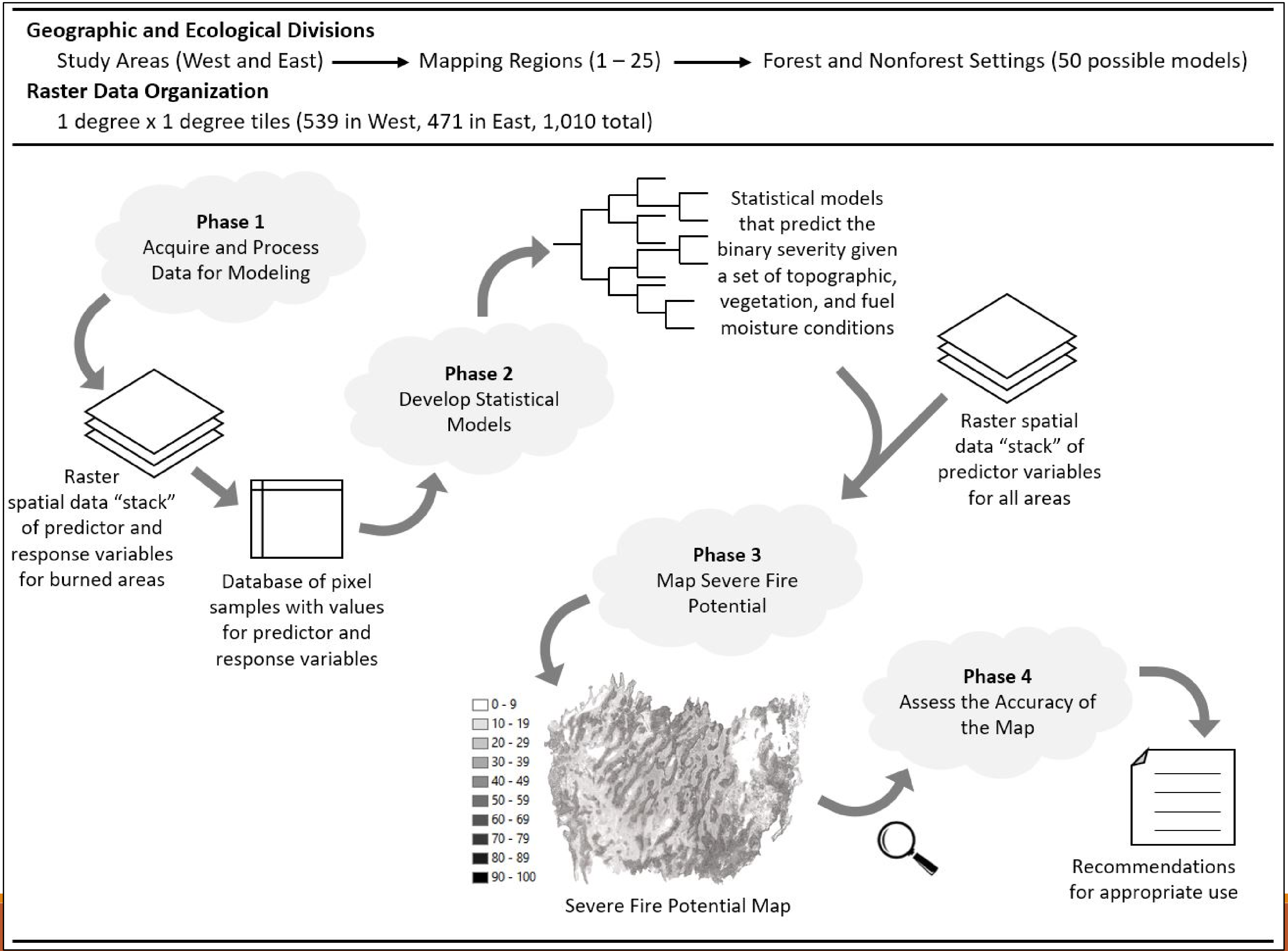
- LANDFIRE Existing Vegetation Cover (EVC)

Prefire

- LANDFIRE Environmental Site Potential (ESP)
- Landsat Time Series Stacks – Vegetation Change Tracker
- LANDFIRE EVC

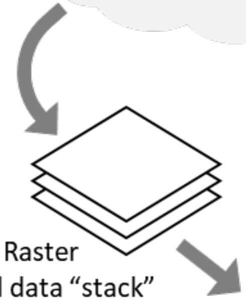


Methods

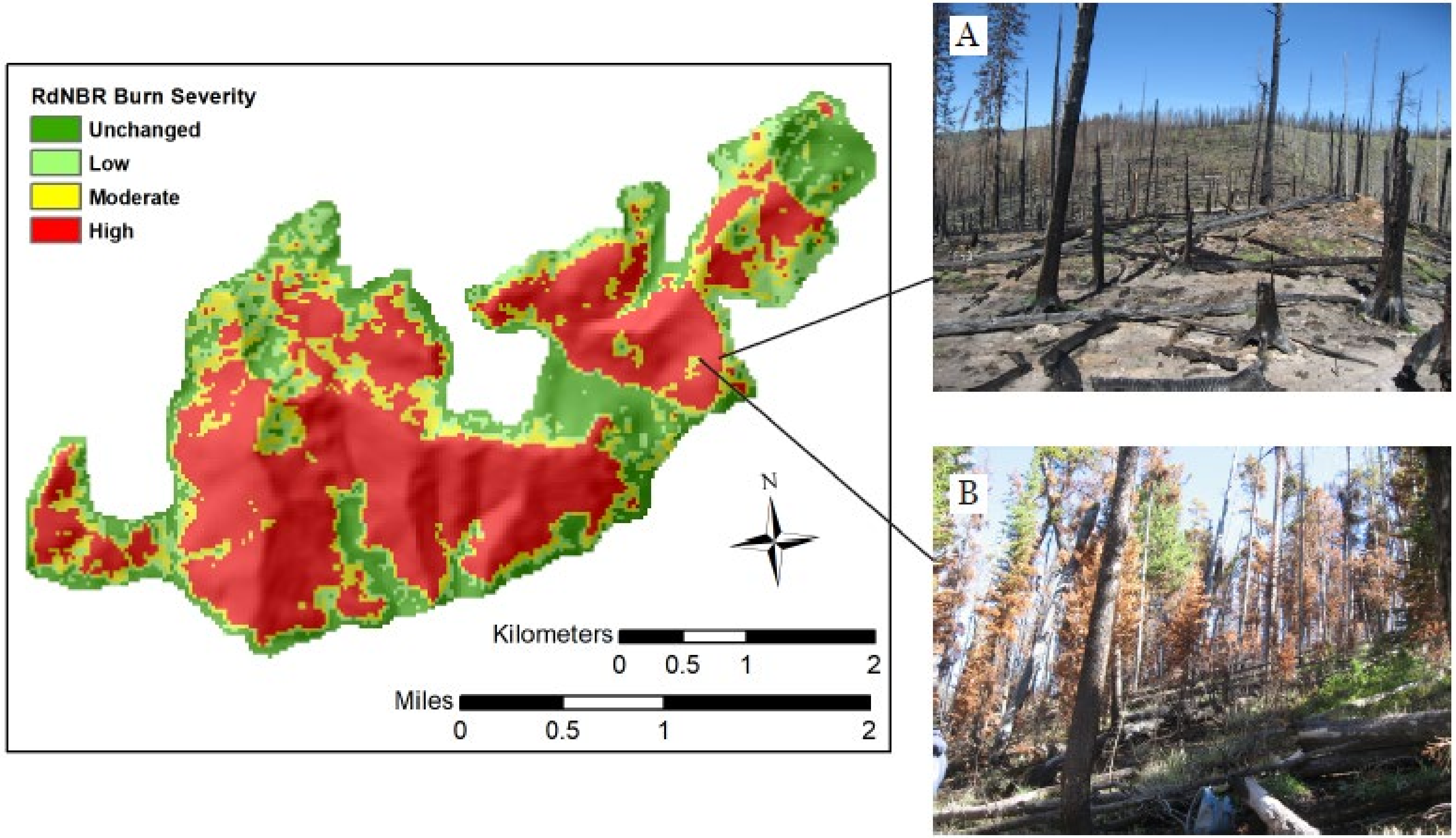

Geographic and Ecological Divisions
Study Areas (West and East)
Mapping Regions (1 – 25)
Forest and Nonforest Settings (50 possible models)
Raster Data Organization
1 degree x 1 degree tiles (539 in West, 471 in East, 1,010 total)
Phase 1
Acquire and Process Data for Modeling
Raster spatial data "stack" of predictor and response variables for burned areas
Database of pixel samples with values for predictor and response variables
Phase 2
Develop Statistical Models
Statistical models that predict the binary severity given a set of topographic, vegetation, and fuel moisture conditions
Raster spatial data "stack" of predictor variables for all areas
Phase 3
Map Severe Fire Potential
0 - 9
10 - 19
20 - 29
30 - 39
40 - 49
50 - 59
60 - 69
70 - 79
80 - 89
90 - 100
Severe Fire Potential Map
Phase 4
Assess the Accuracy of the Map
Recommendations for appropriate use

Methods

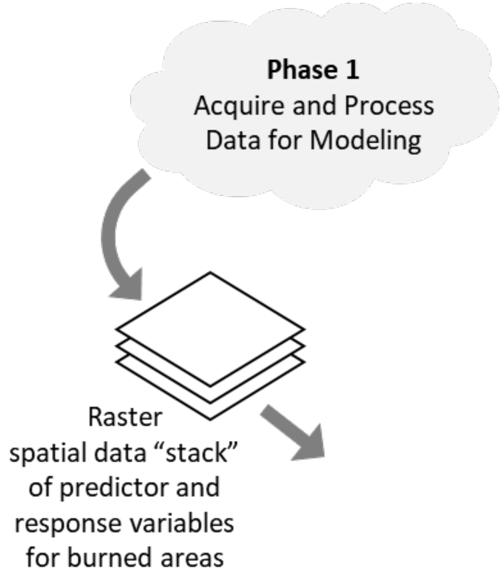
Phase 1
Acquire and Process Data for Modeling

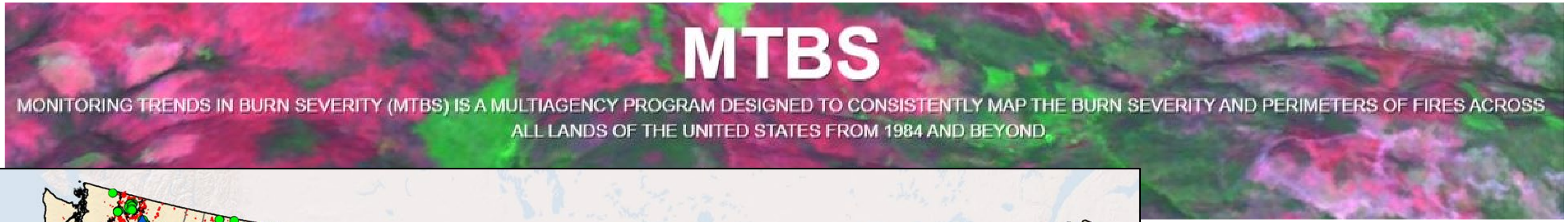


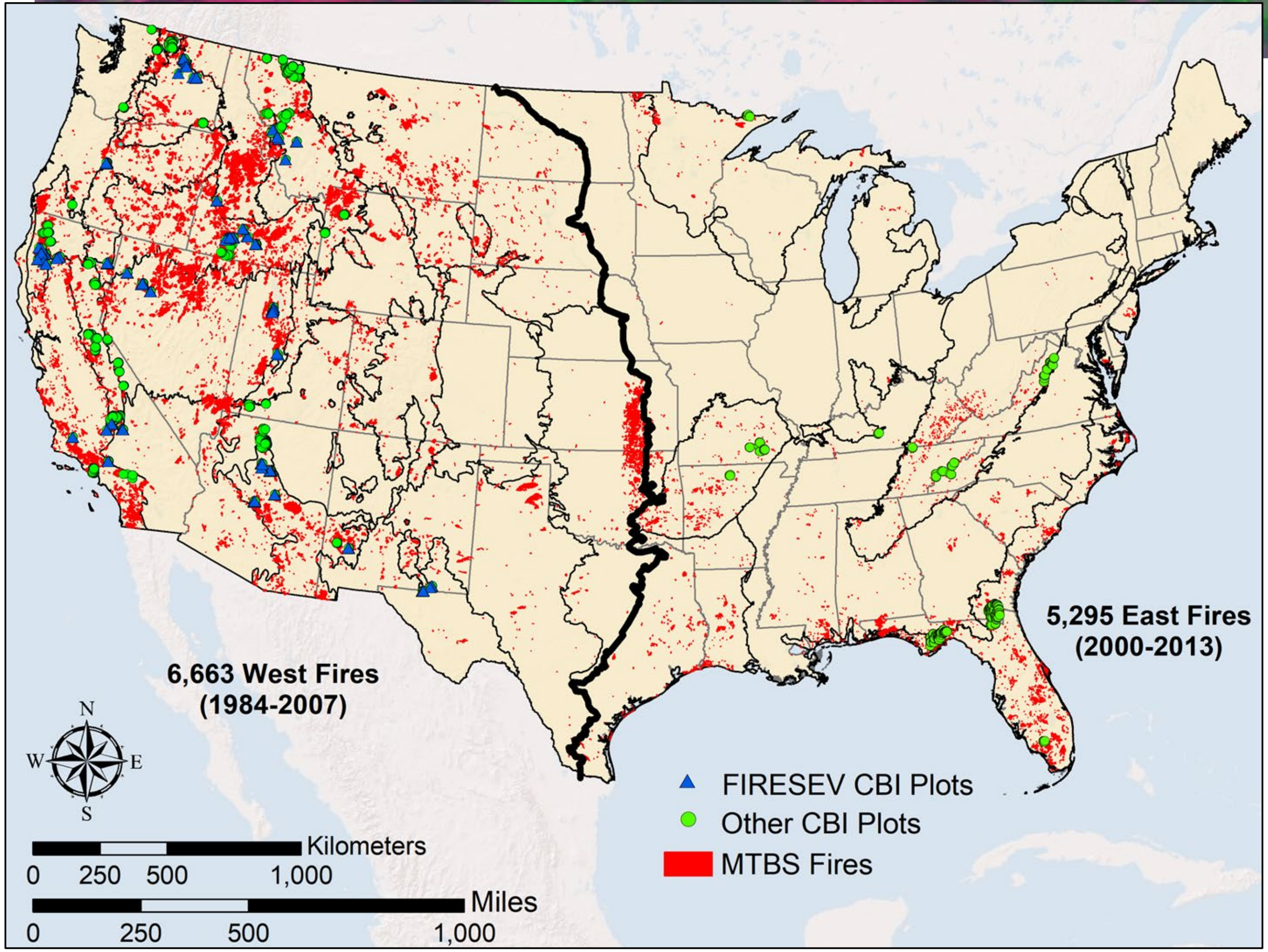
Raster spatial data "stack" of predictor and response variables for burned areas



Methods







Satellite-derived severity metrics

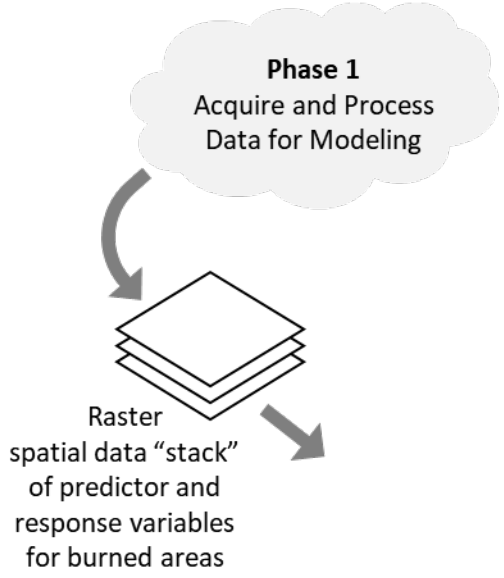
- West – RdNBR
- East – dNBR and prefire NBR

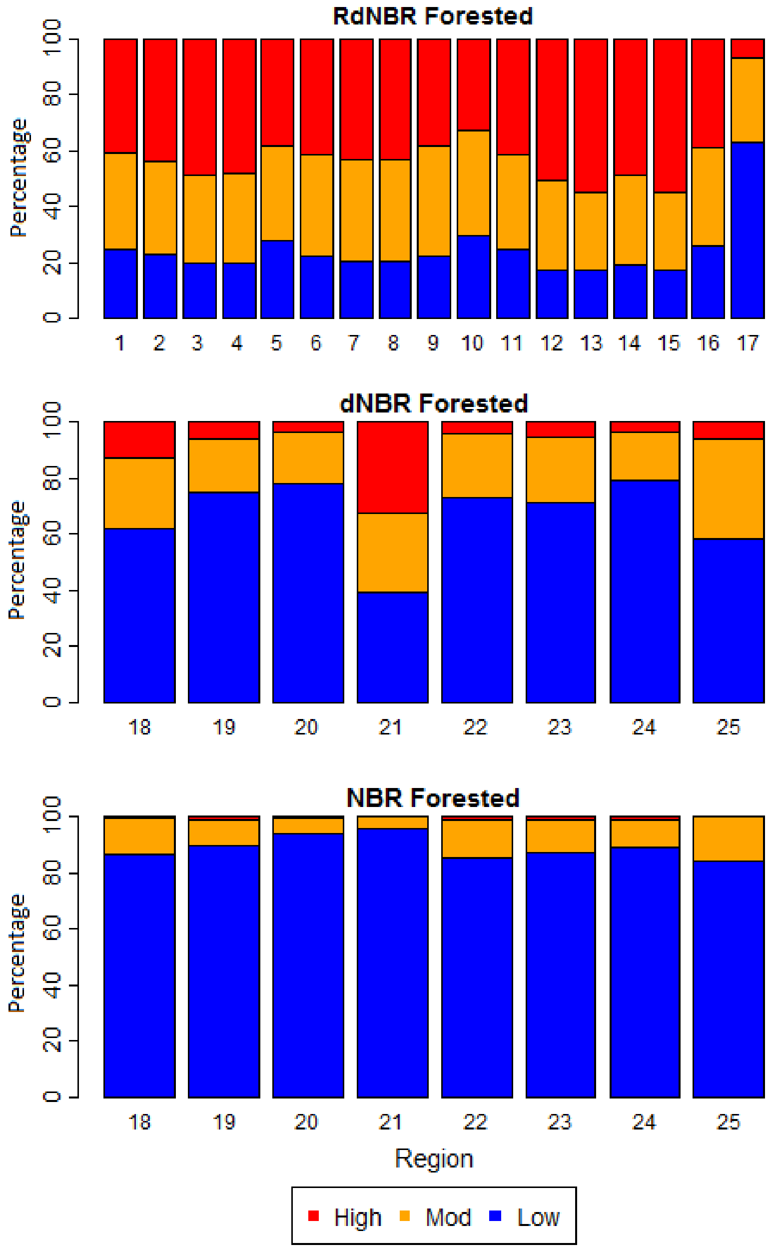
> 12,000 fires

> 3600 field plots

Firesev CBI plots: https://doi.org/10.2737/RDS-2013-0017 | Compiled CBI plots for CONUS: https://doi.org/10.5066/P91BH1BZ

Methods



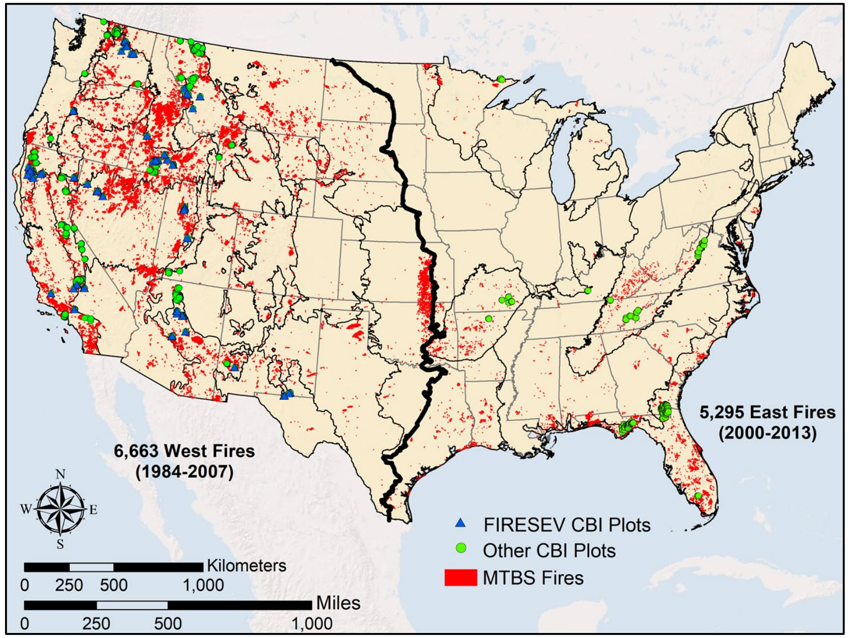


Convert to binary severity

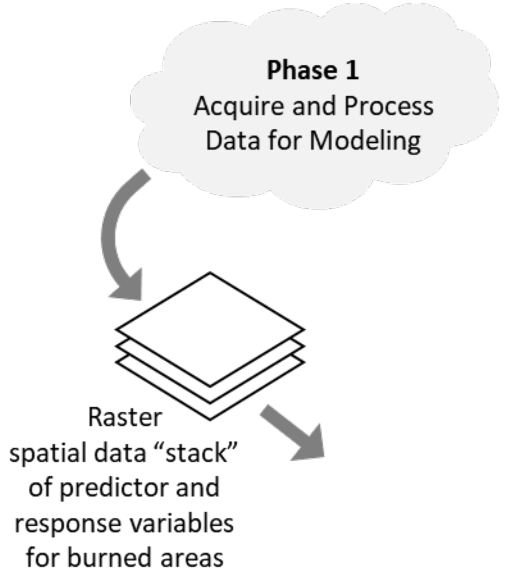
- West – High
- East – High + Moderate

Draw a 1% sample of burned pixels

- > 2 million sample points



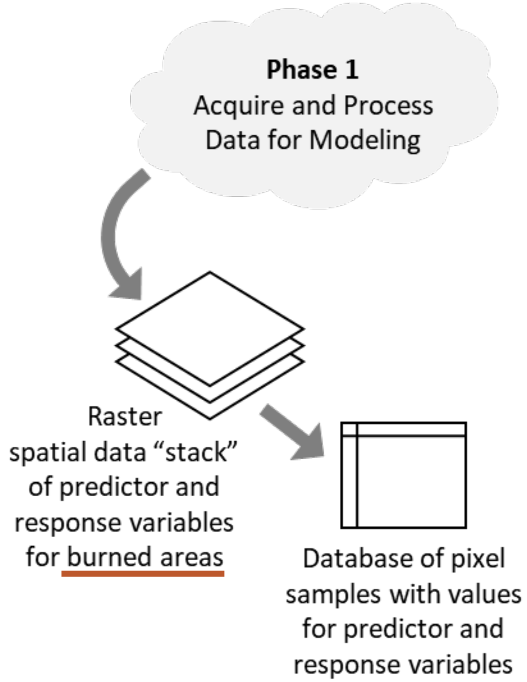
Methods



	Burn Severity Data	Topographic Data	Vegetation Data	Fuel Moisture Data
Acquire	**West:** RdNBR[1] from MTBS[2] for 1984 to 2007 **East:** dNBR[3] or NBR[4] from MTBS for 2000 to 2013 **CONUS:** Field CBI[5] Data	**CONUS:** National Elevation Dataset (NED) 3 arc second (~30m) Digital Elevation Model (DEM). Acquired in 2009 (West) and 2014 (East)	**West:** pre-fire Landsat scenes from MTBS **East:** pre-fire MODIS[7] NDVI[8] images	**CONUS:** Daily 4-km gridded weather data for 1980 to 2010 (West) and 1980 to 2013 (East)
Process	**West:** Calculate thresholds to classify severity from statistical relationship between RdNBR and CBI. **East:** Calculate thresholds to classify severity from statistical distribution of MTBS thematic classifications.	**West:** Calculate potential solar radiation with SOLPET6[6] model **East:** Calculate relative potential solar radiation with ArcGIS Area Solar Radiation tool **CONUS:** Calculate 11 topographic indices from NED DEM	**West:** Calculate NDVI from 30m Landsat scenes **East:** Select pre-fire 250m MODIS NDVI with highest quality	**CONUS:** Calculate sea-level potential temperature and subsequently 1000-hour fuel moisture for every grid cell, every day in the time series. Calculate the lowest site-specific fuel moisture percentile for each fire in the study, within a 10-day window of each fire's start date .
Data Product	**West:** 30m binary severity raster for burned areas. Classified to high severity vs. other. **East:** 30m binary severity raster for burned areas. Classified to high or moderate ("higher") severity vs. other.	**West:** 6 30m solar radiation rasters for all lands. **East:** 1 30m solar radiation raster for all lands. **CONUS:** Elevation and 11 30m topographic index rasters for all lands.	**West:** 30m pre-fire NDVI raster for burned areas. **East:** 250m pre-fire NDVI raster for burned areas.	**CONUS:** Database of minimum 1000-hour fuel moisture percentiles at the time of each fire in the study.

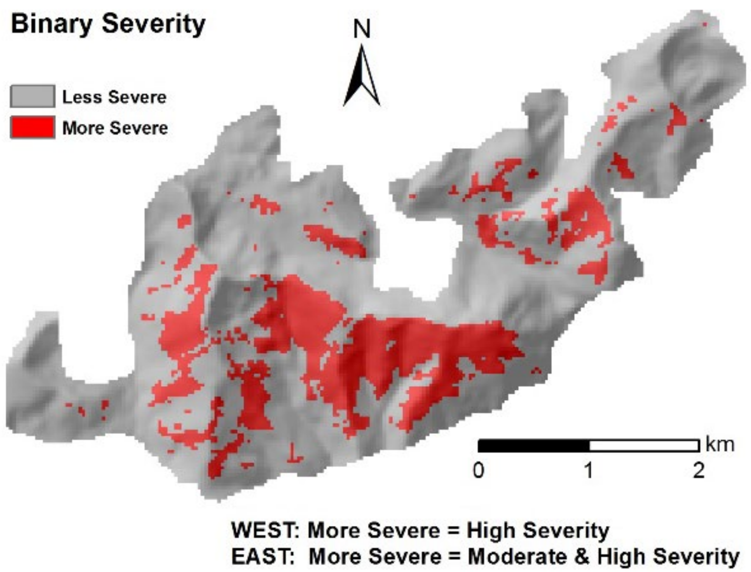
[1] RdNBR = Relative Differenced Normalized Burn Ratio, [2] MTBS = Monitoring Trends in Burn Severity, [3] dNBR = Differenced Normalized Burn Ratio, [4] NBR = Normalized Burn Ratio, [5] CBI = Composite Burn Index, [6] SOLPET6 = Flint and Childs (1987) solar radiation model, [7] MODIS = Moderate Resolution Imaging Spectroradiometer, [8] NDVI = Normalized Differenced Vegetation Index

Methods



Response Variable

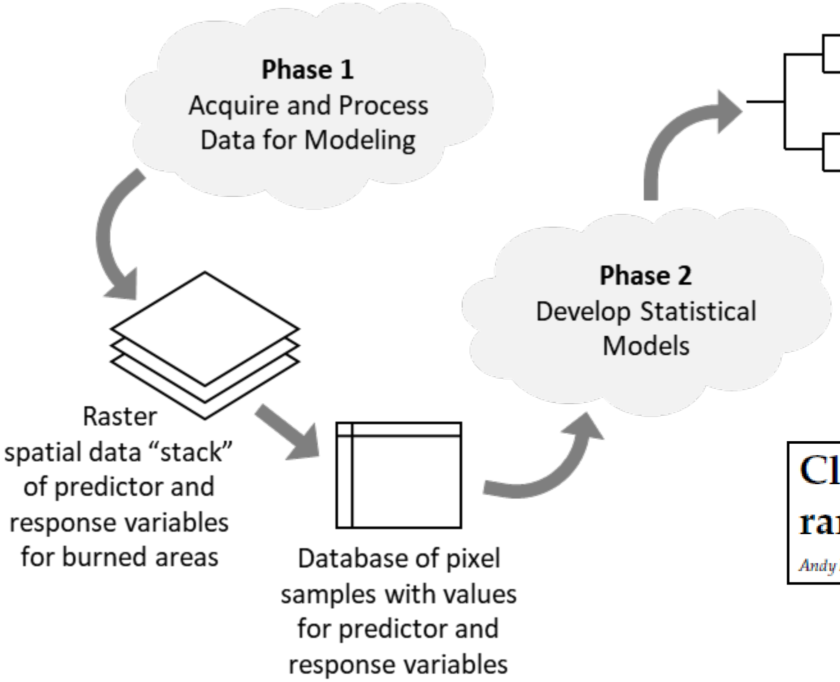
- Binary severity

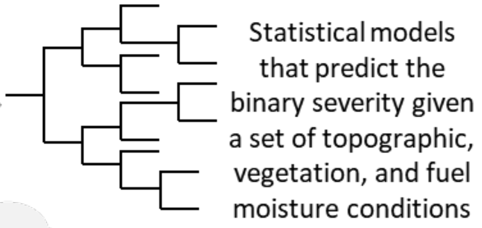


Predictor Variables

- Topography
  - 30m elevation
  - 11 topographic indices
  - Solar radiation
- Vegetation
  - NDVI
- Fuel Moisture
  - 1000-hour fuel moisture percentiles, inverted

Methods

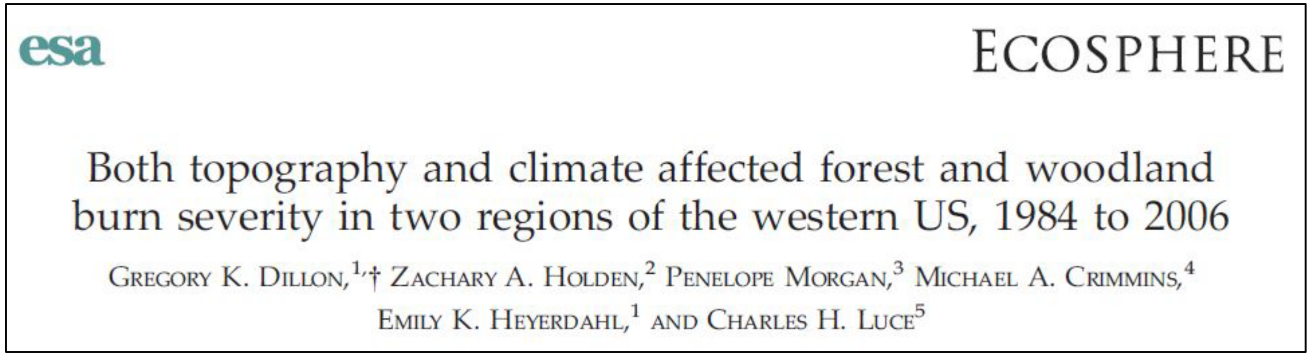




- Random Forest, implemented in R
- 1500 classification trees
- Select optimal model with lowest classification error
- Outputs
  - Model performance
  - Variable importance
  - RF model object for predictions


Classification and Regression by randomForest

Andy Liaw and Matthew Wiener

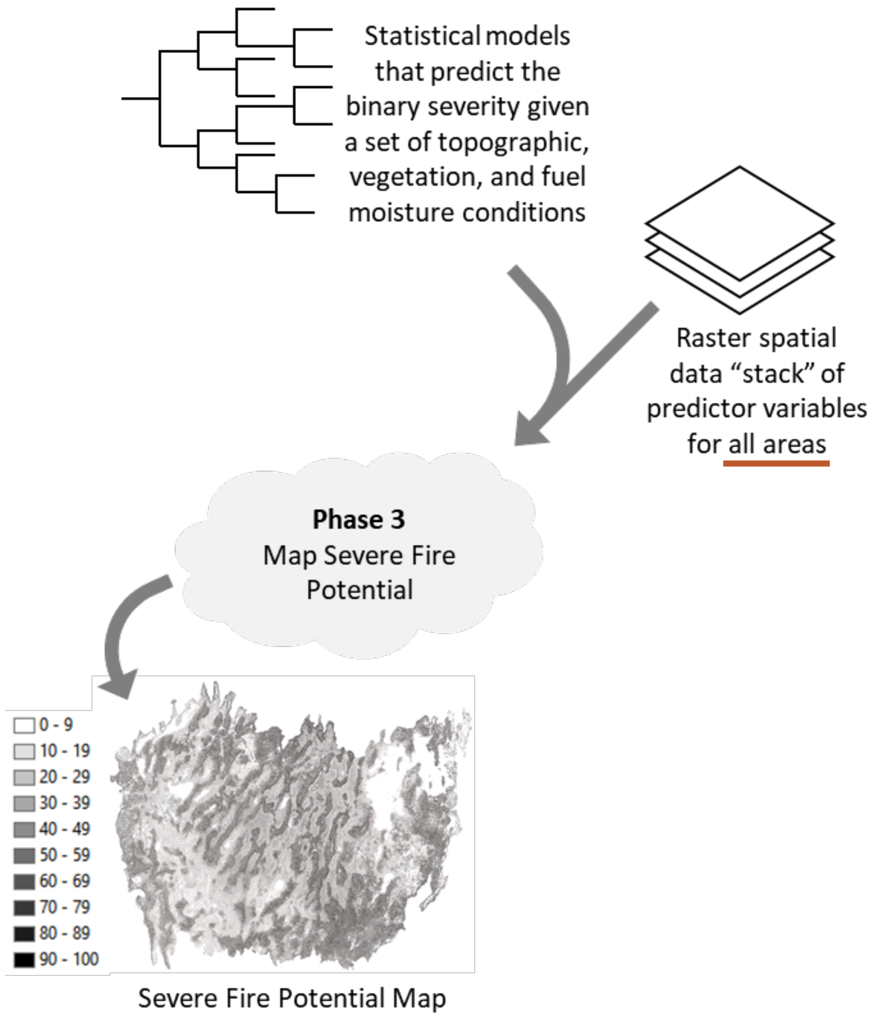

esa ECOSPHERE

Both topography and climate affected forest and woodland burn severity in two regions of the western US, 1984 to 2006

Gregory K. Dillon,[1,†] Zachary A. Holden,[2] Penelope Morgan,[3] Michael A. Crimmins,[4] Emily K. Heyerdahl,[1] and Charles H. Luce[5]

https://doi.org/10.1890/ES11-00271.1

Methods

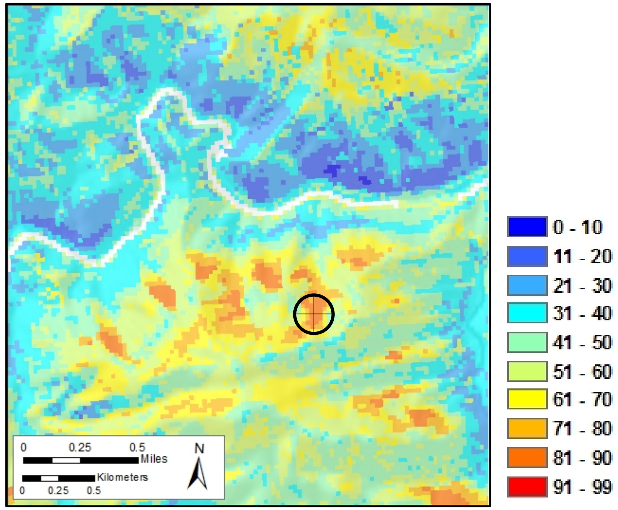


Predictor Variables

- Must be spatially comprehensive
- Represent the landscape for which you want predictions
- Topography – static
- Vegetation – used NDVI from MODIS
  - West – 2011
  - East – 2014
- Fuel moisture – use constant values at common fire weather thresholds (80th, 90th, 97th percentile)

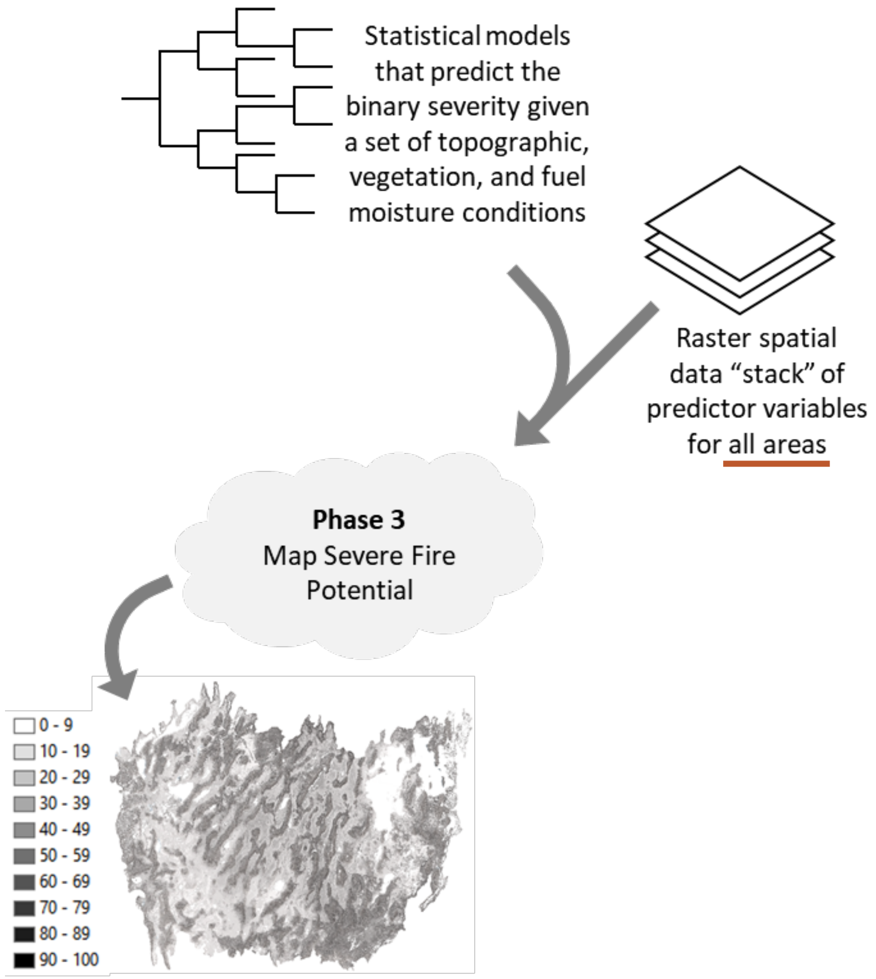
Predictions

- Every 30m pixel classified by each tree
- 1500 predictions of binary severity



Example:
1,245 yes
255 no
} 1,245 / 1,500 = 83%

Methods



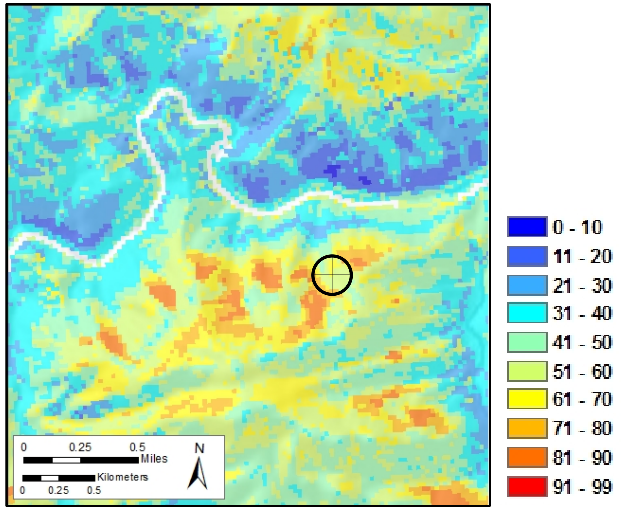
Severe Fire Potential Map

Predictor Variables

- Must be spatially comprehensive
- Represent the landscape for which you want predictions
- Topography – static
- Vegetation – used NDVI from MODIS
  - West – 2011
  - East – 2014
- Fuel moisture – use constant values at common fire weather thresholds (80th, 90th, 97th percentile)

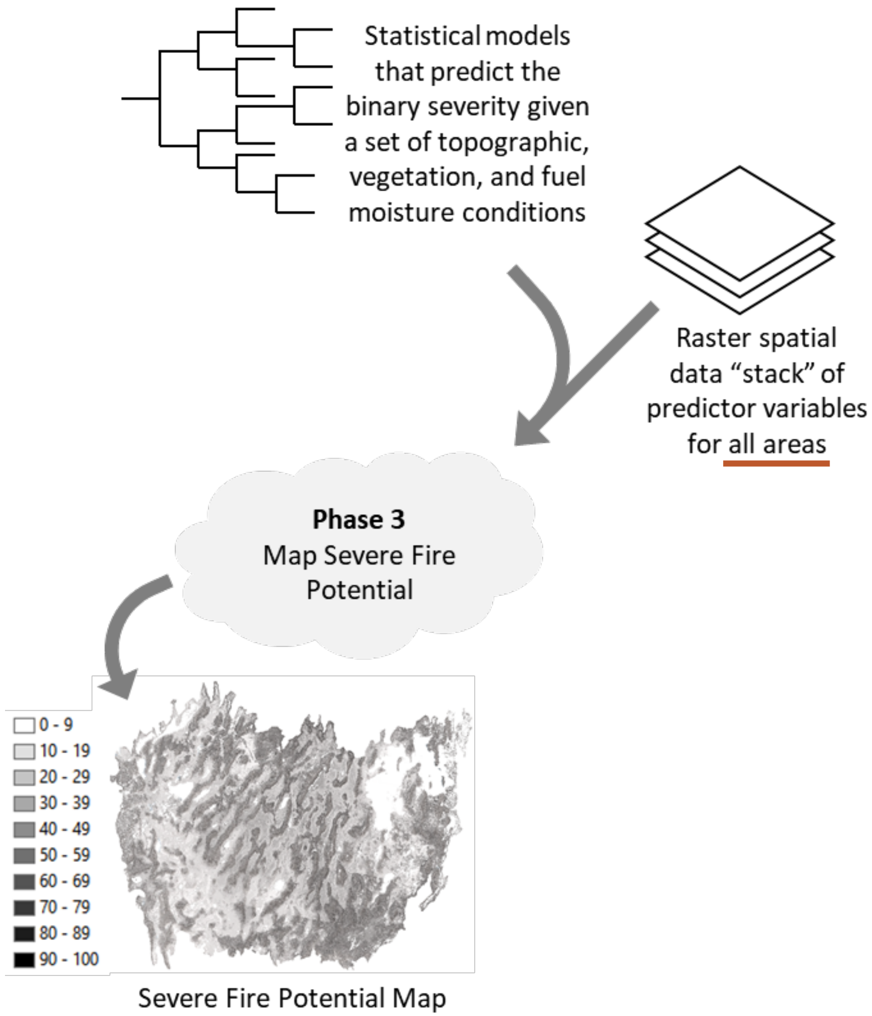
Predictions

- Every 30m pixel classified by each tree
- 1500 predictions of binary severity



Example:
840 yes
660 no
} 840 / 1,500 = 56%

Methods

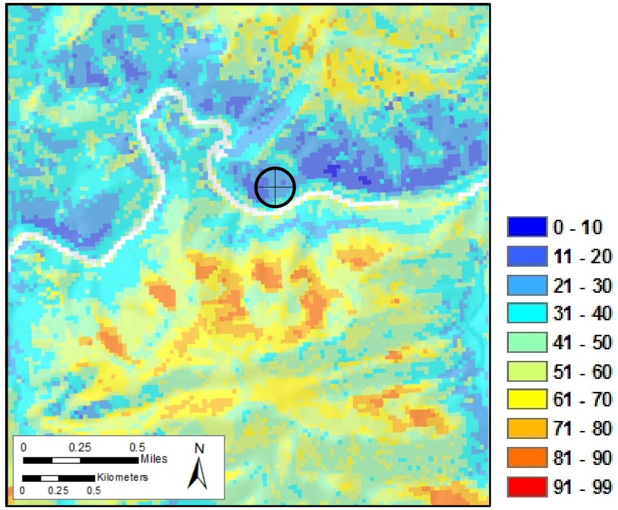


Predictor Variables

- Must be spatially comprehensive
- Represent the landscape for which you want predictions
- Topography – static
- Vegetation – used NDVI from MODIS
  - West – 2011
  - East – 2014
- Fuel moisture – use constant values at common fire weather thresholds (80^{th}, 90^{th}, 97^{th} percentile)

Predictions

- Every 30m pixel classified by each tree
- 1500 predictions of binary severity



Example:
330 yes
1,170 no } 330 / 1,500 = 22%

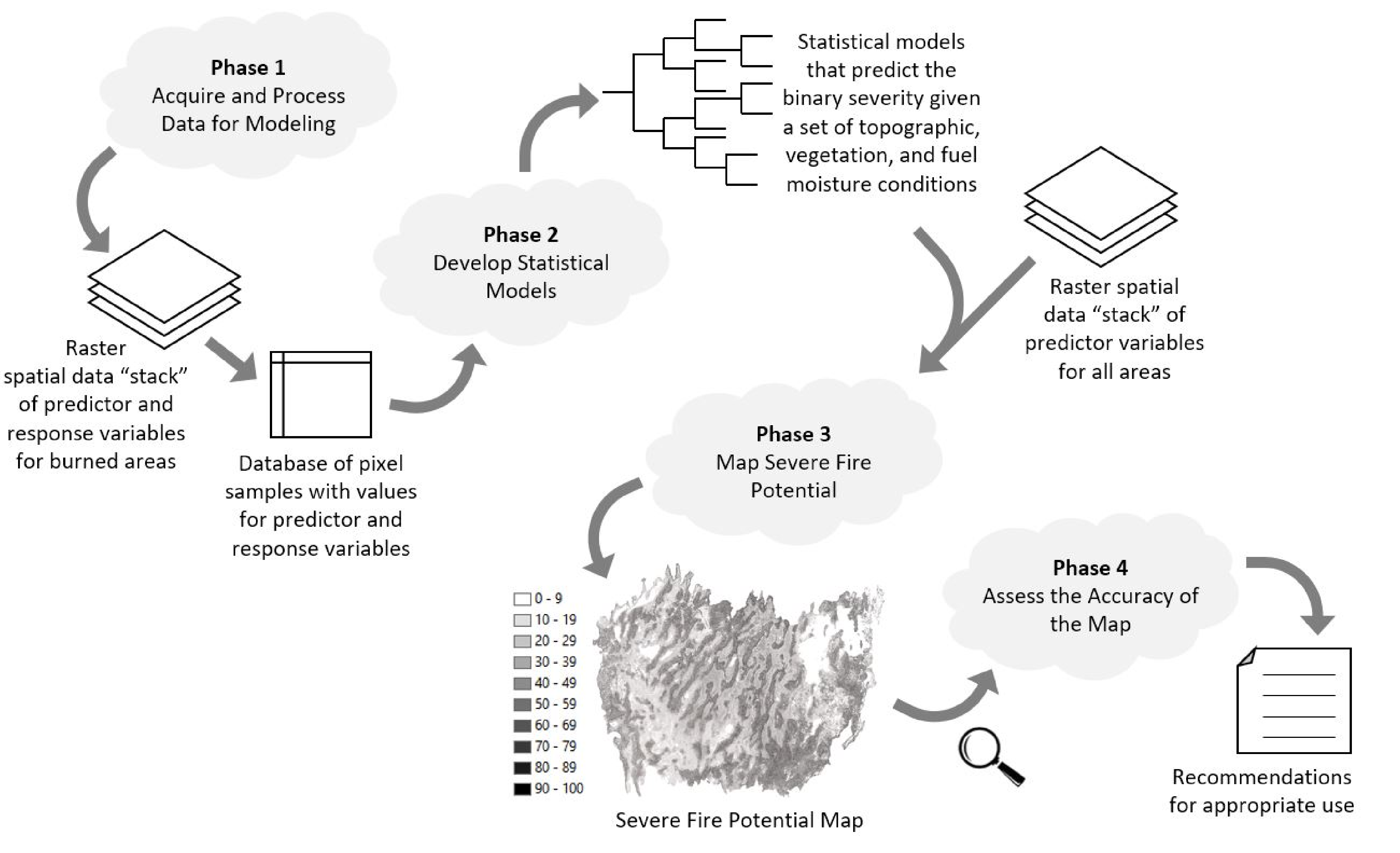
Methods

Geographic and Ecological Divisions

Study Areas (West and East) → Mapping Regions (1 – 25) → Forest and Nonforest Settings (50 possible models)

Raster Data Organization

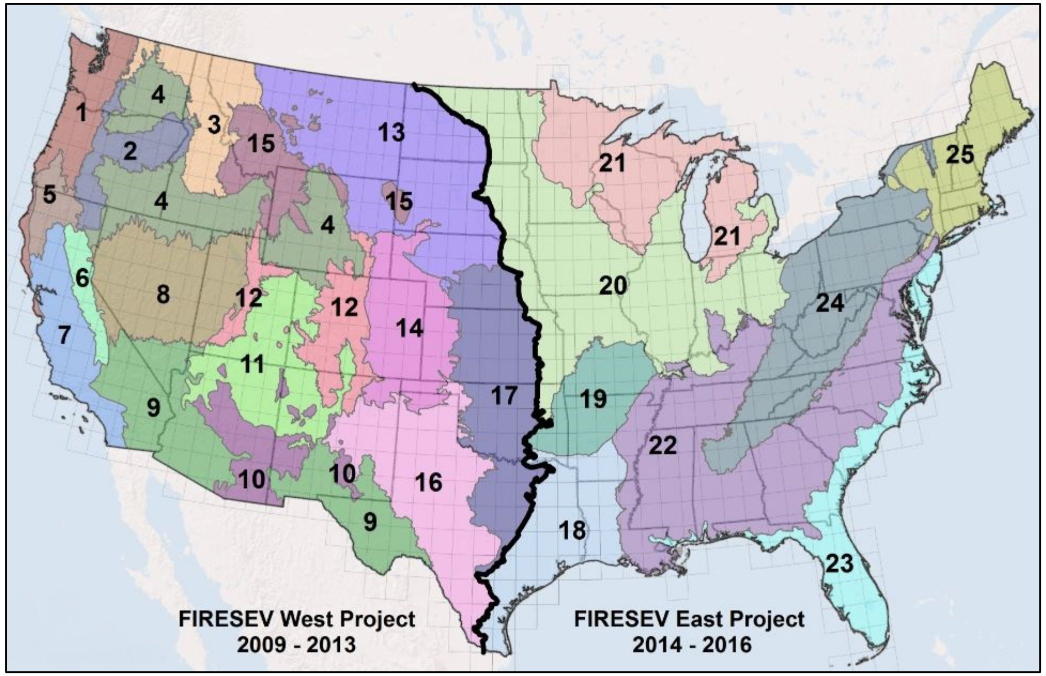
1 degree x 1 degree tiles (539 in West, 471 in East, 1,010 total)



Results

Random Forest Model Performance

- PCC = Percent Correctly Classified
- AUC = Area Under receiver operating characteristic Curve



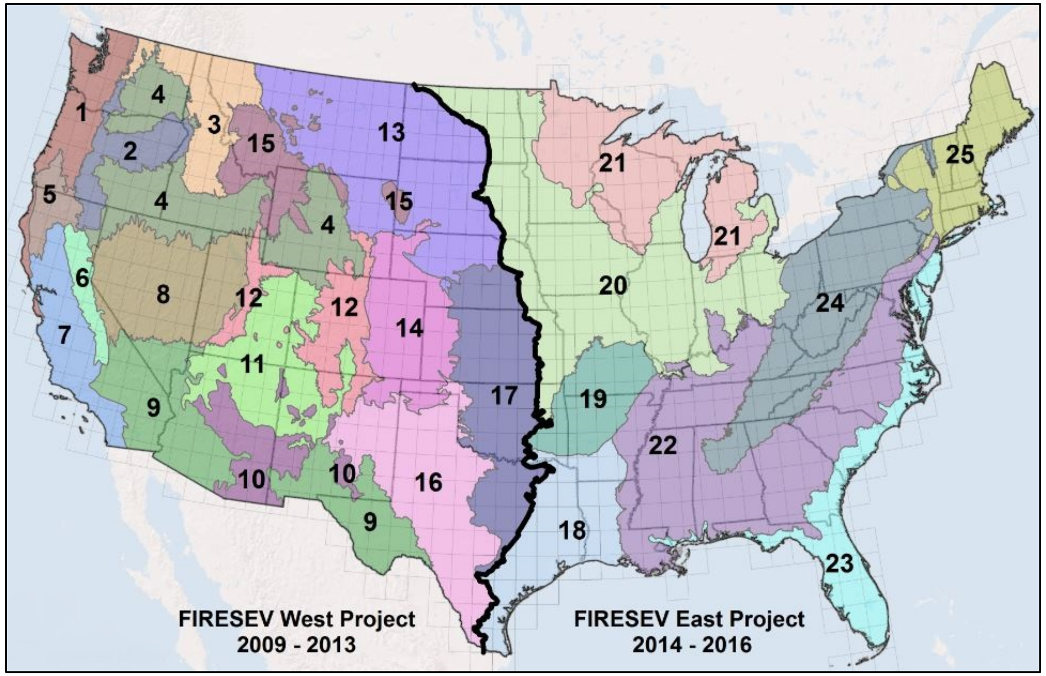
Forest

			Number of predictors		Random Forest model performance	
Region	MTBS fires [a]	Sample points	Full model	Optimal model	PCC [b]	AUC [c]
1	467	73,087	13	9	0.71	0.78
2	830	58,321	12	6	0.72	0.80
3	988	100,000	12	10	0.65	0.71
4	2,465	100,000	12	8	0.68	0.75
5	383	50,301	12	9	0.70	0.77
6	543	39,094	13	5	0.74	0.82
7	1,069	73,253	13	4	0.72	0.80
8	1,611	39,566	14	7	0.71	0.79
9	1,216	39,750	14	6	0.73	0.80
10	789	41,282	13	6	0.77	0.85
11	817	65,235	13	9	0.75	0.83
12	592	37,024	13	9	0.72	0.79
13	690	54,970	12	9	0.72	0.79
14	348	12,872	13	9	0.73	0.80
15	860	100,000	12	8	0.66	0.72
16	467	8,368	12	5	0.74	0.82
17	305	2,779	13	9	0.83	0.91
18	609	17,162	13	5	0.84	0.91
19	482	12,479	13	4	0.77	0.84
20	717	8,941	13	5	0.75	0.82
21	197	9,417	12	5	0.87	0.93
22	2,246	64,733	12	5	0.80	0.88
23	2,938	66,527	11	5	0.80	0.88
24	539	7,642	12	6	0.75	0.83
25	7	122	12	4	0.70	0.73

Results

Random Forest Model Performance

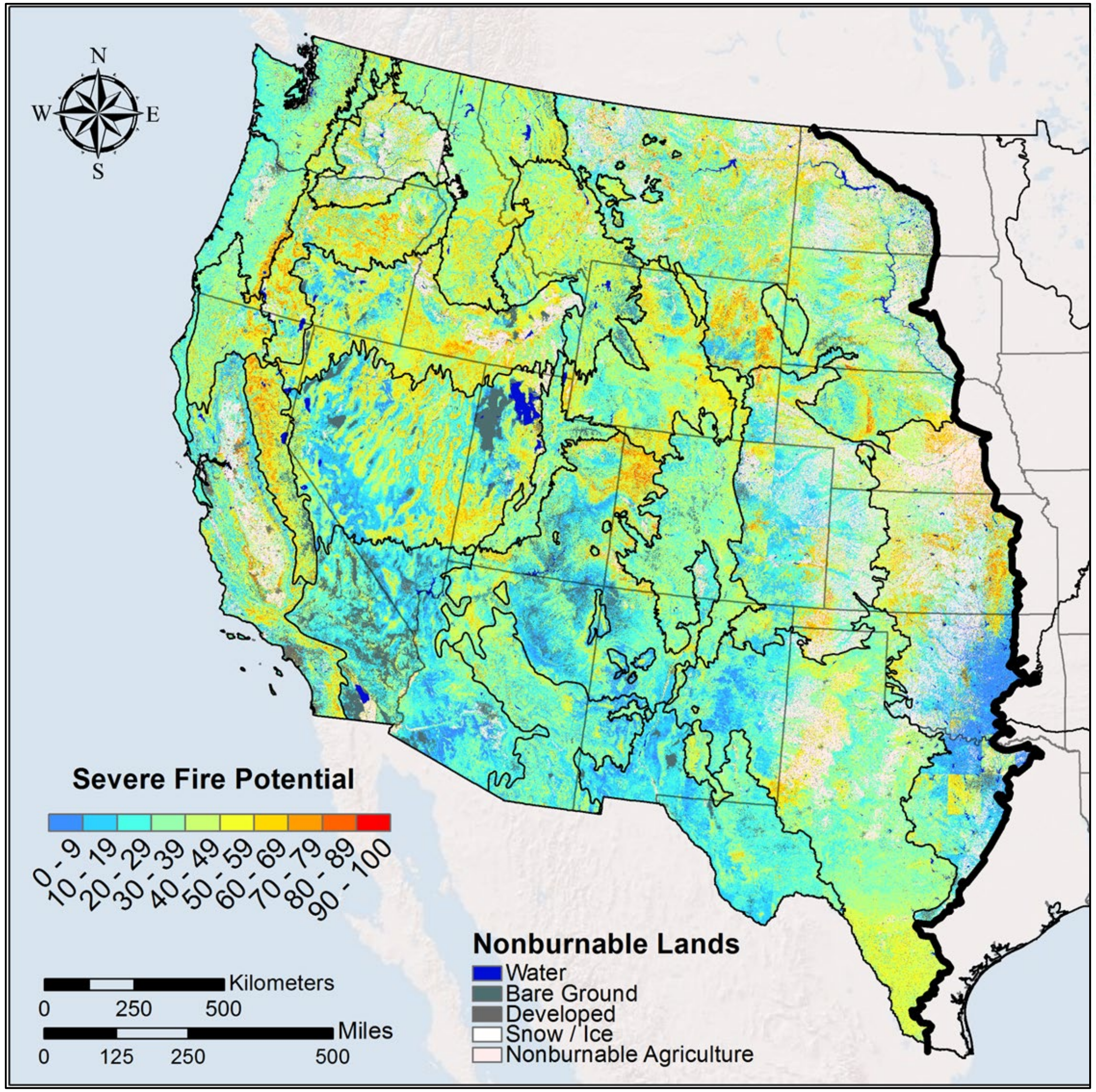
- PCC = Percent Correctly Classified
- AUC = Area Under receiver operating characteristic Curve



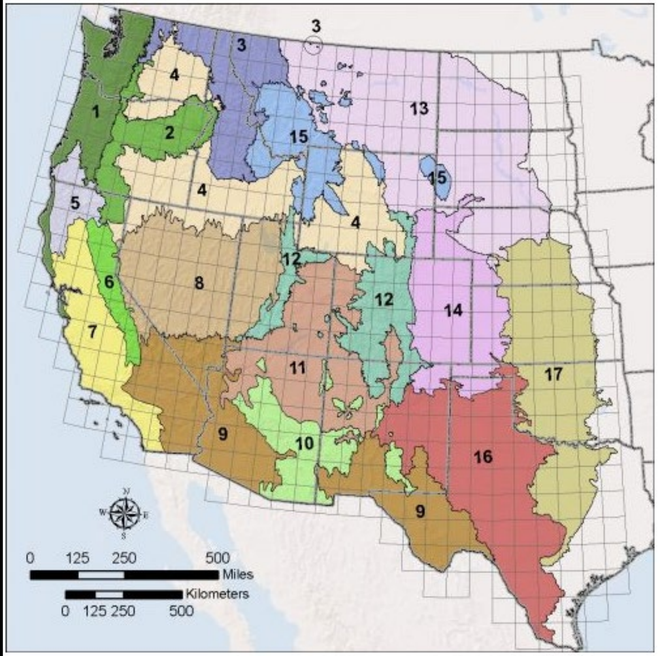
Nonforest

Region	MTBS fires [a]	Sample points	Number of predictors: Full model	Number of predictors: Optimal model	Random Forest model performance: PCC [b]	Random Forest model performance: AUC [c]
1	467	27,749	13	9	0.74	0.82
2	830	100,000	12	7	0.75	0.83
3	988	100,000	13	9	0.76	0.85
4	2,465	100,000	13	7	0.70	0.78
5	383	15,598	12	9	0.72	0.79
6	543	35,289	13	9	0.73	0.81
7	1,069	100,000	14	9	0.74	0.82
8	1,611	100,000	14	7	0.69	0.76
9	1,216	100,000	13	9	0.74	0.82
10	789	34,112	13	9	0.76	0.83
11	817	54,758	13	9	0.77	0.85
12	592	78,222	13	9	0.76	0.83
13	690	93,560	13	4	0.74	0.82
14	348	23,447	13	5	0.79	0.87
15	860	100,000	12	9	0.77	0.85
16	467	27,979	12	9	0.78	0.86
17	305	2,743	13	6	0.82	0.90
18	609	5,049	11	5	0.83	0.90
19	482	1,307	12	4	0.77	0.84
20	717	13,543	13	7	0.84	0.91
21	197	1,652	11	6	0.85	0.93
22	2,246	64,733	11	5	0.80	0.88
23	2,938	3,859	11	4	0.80	0.89
24	539	262	12	7	0.69	0.72
25	7	0	NA	NA	NA	NA

Results



FIRESEV Home FIRESEV East Contacts Documentation Return to FRAMES

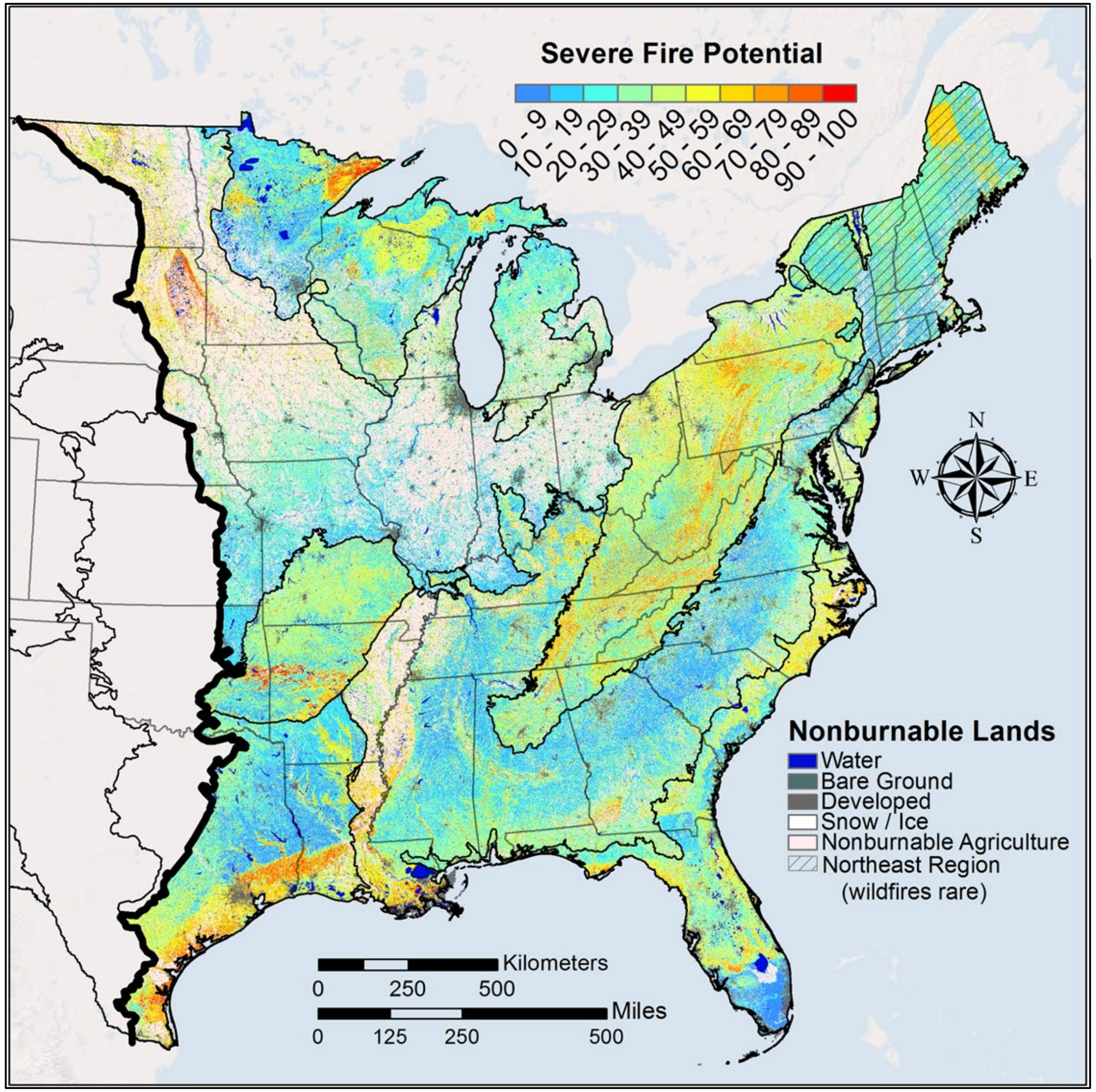


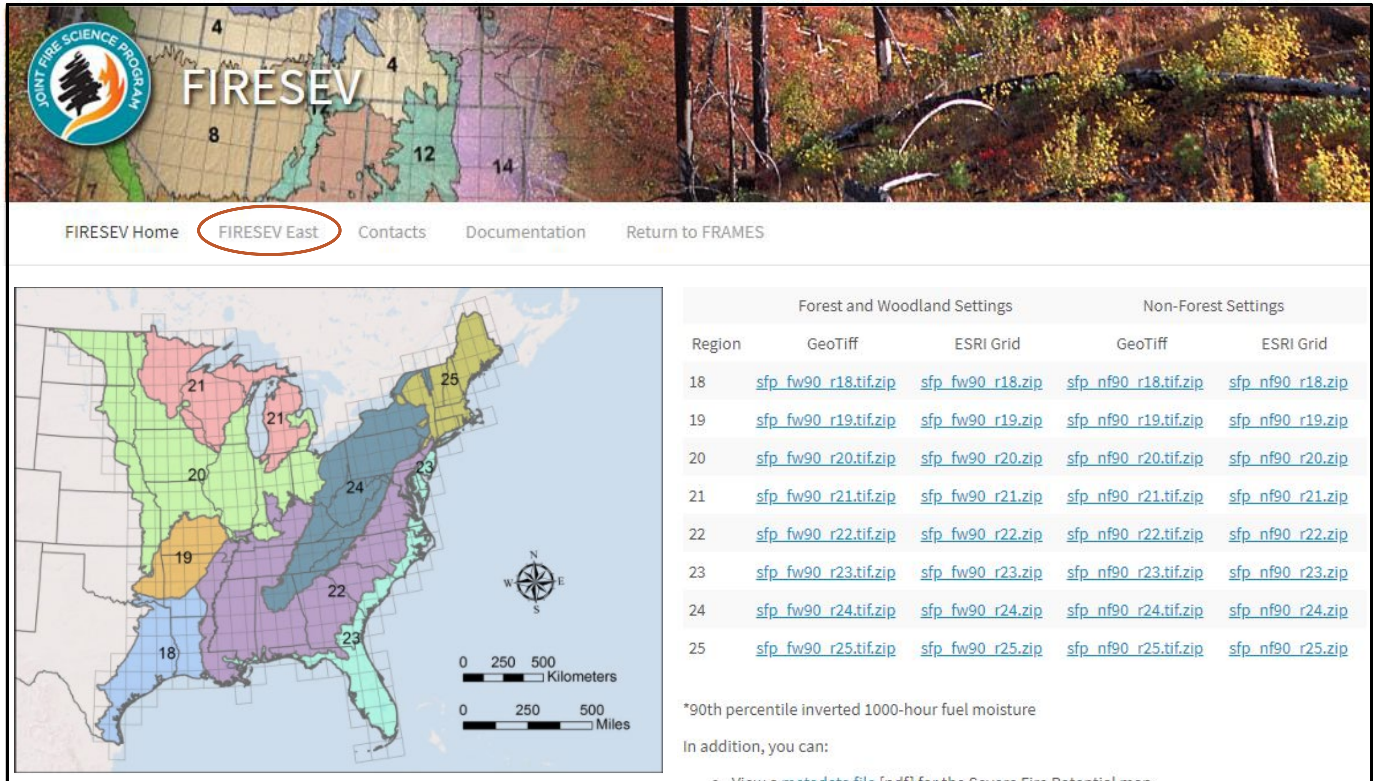
	Forest and Woodland Settings		Non-Forest Settings	
Region	GeoTiff	ESRI Grid	GeoTiff	ESRI Grid
1	sfp_fw90_r1.tif.zip	sfp_fw90_r1.zip	sfp_nf90_r1.tif.zip	sfp_nf90_r1.zip
2	sfp_fw90_r2.tif.zip	sfp_fw90_r2.zip	sfp_nf90_r2.tif.zip	sfp_nf90_r2.zip
3	sfp_fw90_r3.tif.zip	sfp_fw90_r3.zip	sfp_nf90_r3.tif.zip	sfp_nf90_r3.zip
4	sfp_fw90_r4.tif.zip	sfp_fw90_r4.zip	sfp_nf90_r4.tif.zip	sfp_nf90_r4.zip
5	sfp_fw90_r5.tif.zip	sfp_fw90_r5.zip	sfp_nf90_r5.tif.zip	sfp_nf90_r5.zip
6	sfp_fw90_r6.tif.zip	sfp_fw90_r6.zip	sfp_nf90_r6.tif.zip	sfp_nf90_r6.zip
7	sfp_fw90_r7.tif.zip	sfp_fw90_r7.zip	sfp_nf90_r7.tif.zip	sfp_nf90_r7.zip
8	sfp_fw90_r8.tif.zip	sfp_fw90_r8.zip	sfp_nf90_r8.tif.zip	sfp_nf90_r8.zip
9	sfp_fw90_r9.tif.zip	sfp_fw90_r9.zip	sfp_nf90_r9.tif.zip	sfp_nf90_r9.zip
10	sfp_fw90_r10.tif.zip	sfp_fw90_r10.zip	sfp_nf90_r10.tif.zip	sfp_nf90_r10.zip
11	sfp_fw90_r11.tif.zip	sfp_fw90_r11.zip	sfp_nf90_r11.tif.zip	sfp_nf90_r11.zip
12	sfp_fw90_r12.tif.zip	sfp_fw90_r12.zip	sfp_nf90_r12.tif.zip	sfp_nf90_r12.zip
13	sfp_fw90_r13.tif.zip	sfp_fw90_r13.zip	sfp_nf90_r13.tif.zip	sfp_nf90_r13.zip
14	sfp_fw90_r14.tif.zip	sfp_fw90_r14.zip	sfp_nf90_r14.tif.zip	sfp_nf90_r14.zip
15	sfp_fw90_r15.tif.zip	sfp_fw90_r15.zip	sfp_nf90_r15.tif.zip	sfp_nf90_r15.zip
16	sfp_fw90_r16.tif.zip	sfp_fw90_r16.zip	sfp_nf90_r16.tif.zip	sfp_nf90_r16.zip
17	sfp_fw90_r17.tif.zip	sfp_fw90_r17.zip	sfp_nf90_r17.tif.zip	sfp_nf90_r17.zip

*90th percentile inverted 1000-hour fuel moisture

https://www.frames.gov/firesev/home

Results





	Forest and Woodland Settings		Non-Forest Settings	
Region	GeoTiff	ESRI Grid	GeoTiff	ESRI Grid
18	sfp fw90 r18.tif.zip	sfp fw90 r18.zip	sfp nf90 r18.tif.zip	sfp nf90 r18.zip
19	sfp fw90 r19.tif.zip	sfp fw90 r19.zip	sfp nf90 r19.tif.zip	sfp nf90 r19.zip
20	sfp fw90 r20.tif.zip	sfp fw90 r20.zip	sfp nf90 r20.tif.zip	sfp nf90 r20.zip
21	sfp fw90 r21.tif.zip	sfp fw90 r21.zip	sfp nf90 r21.tif.zip	sfp nf90 r21.zip
22	sfp fw90 r22.tif.zip	sfp fw90 r22.zip	sfp nf90 r22.tif.zip	sfp nf90 r22.zip
23	sfp fw90 r23.tif.zip	sfp fw90 r23.zip	sfp nf90 r23.tif.zip	sfp nf90 r23.zip
24	sfp fw90 r24.tif.zip	sfp fw90 r24.zip	sfp nf90 r24.tif.zip	sfp nf90 r24.zip
25	sfp fw90 r25.tif.zip	sfp fw90 r25.zip	sfp nf90 r25.tif.zip	sfp nf90 r25.zip

*90th percentile inverted 1000-hour fuel moisture

In addition, you can:

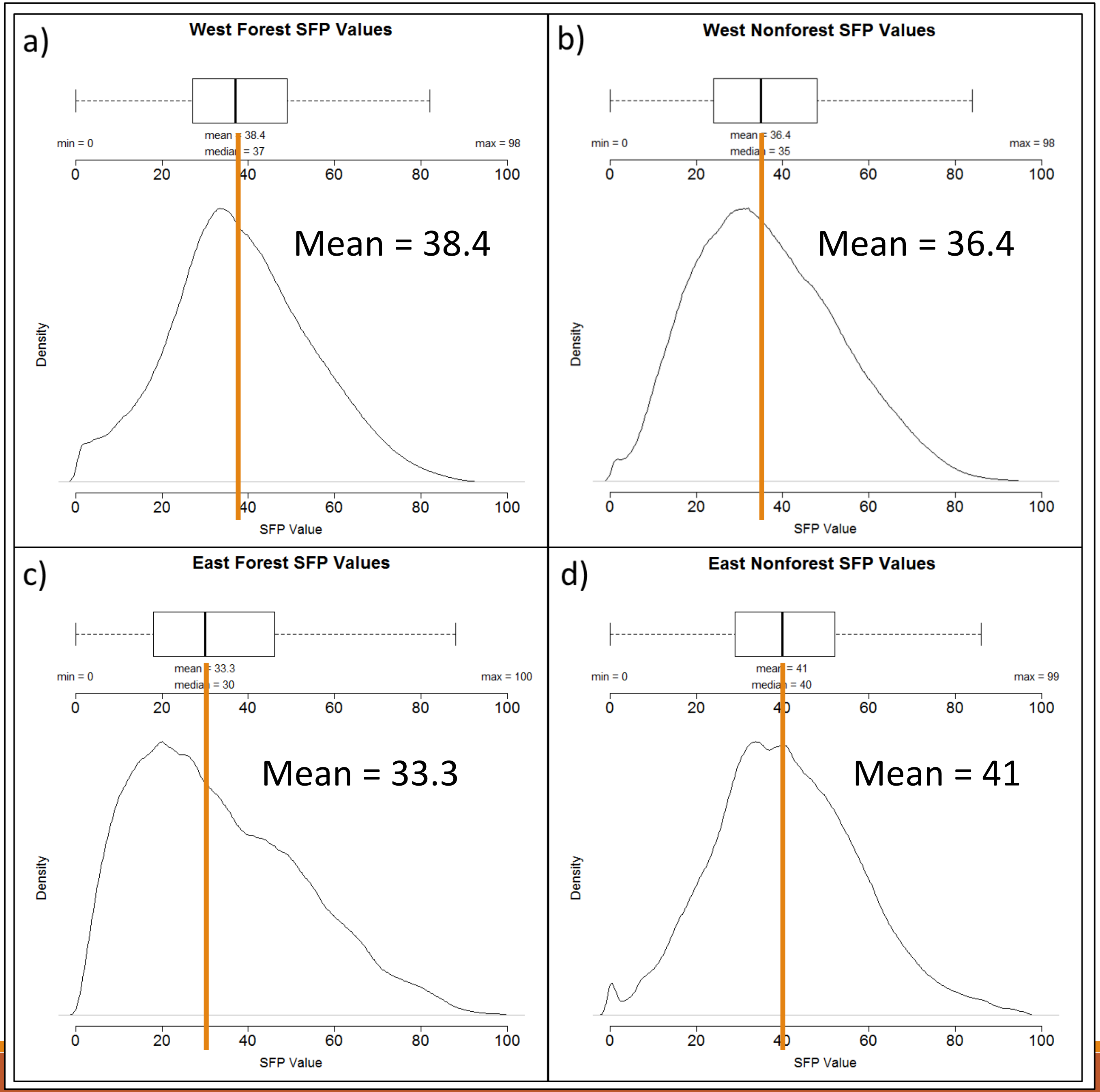
- View a metadata file [pdf] for the Severe Fire Potential map.
- Browse a graphic (JPG file or PDF file) of the Severe Fire Potential map at its full extent, with forest and non-forest combined.
- View model performance results for the Random Forest statistical models used to generate the Severe Fire Potential map for forest and woodland settings or non-forest settings.

https://www.frames.gov/firesev/east

Results

Distribution of SFP values

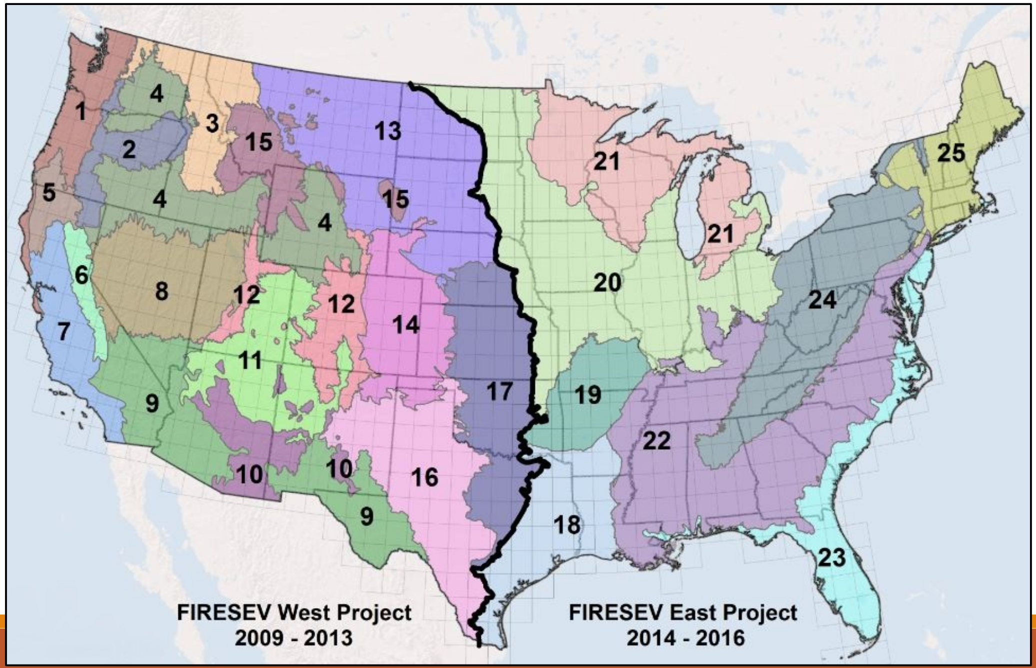
- Mostly below 50
- Values above 80 are rare



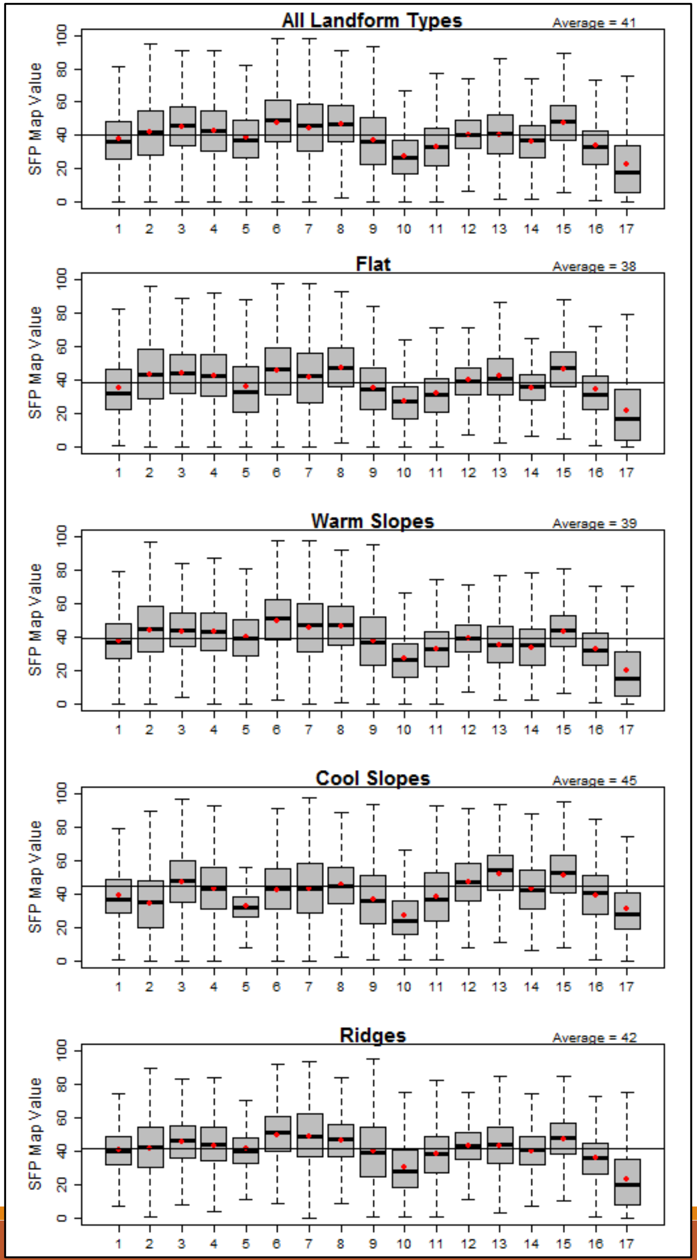
Results

Patterns in SFP predictions – West

- Average SFP values are highest on cool slopes



Forest

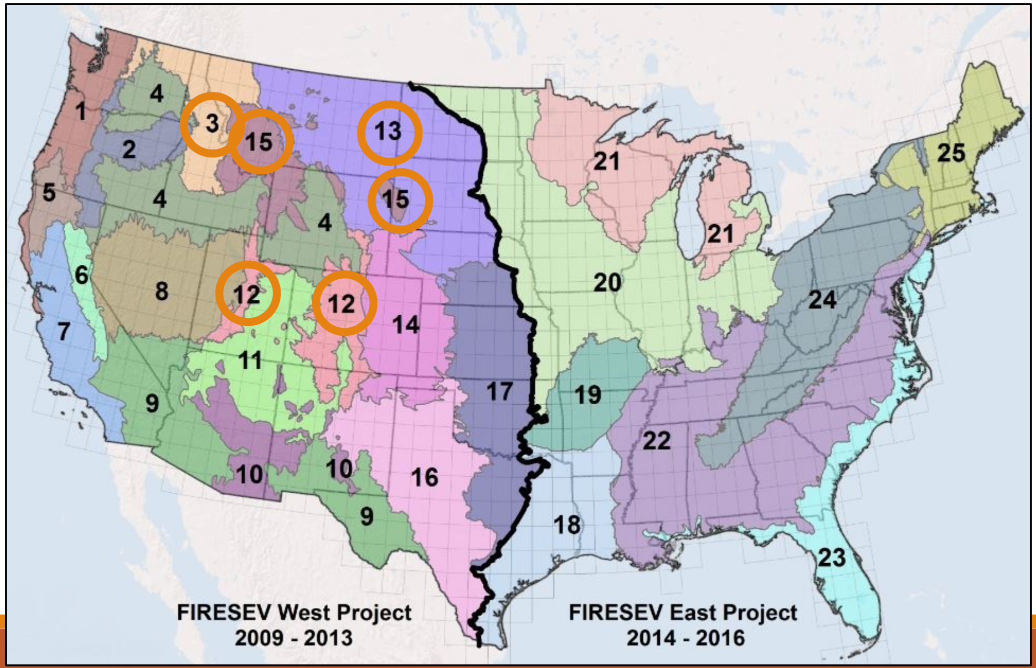


Average
41
38
39
45
42

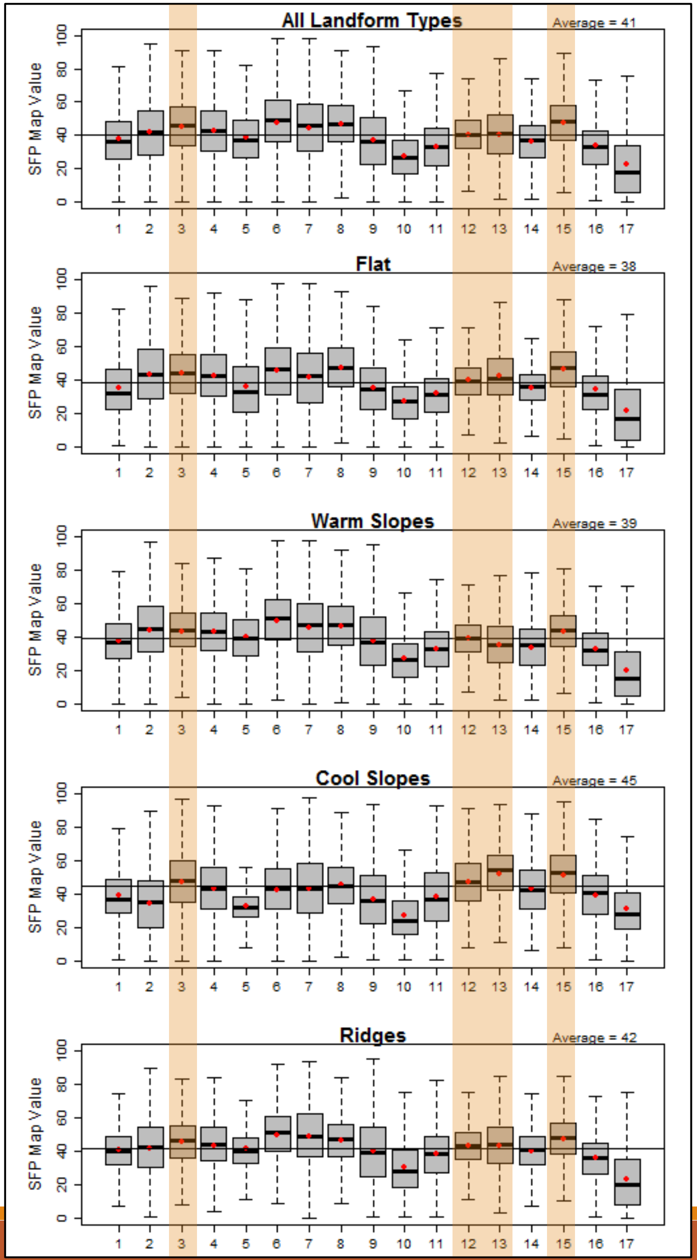
Results

Patterns in SFP predictions – West

- Average SFP values are highest on cool slopes
- Influenced by Middle and Northern Rockies



Forest | Average



41

38

39

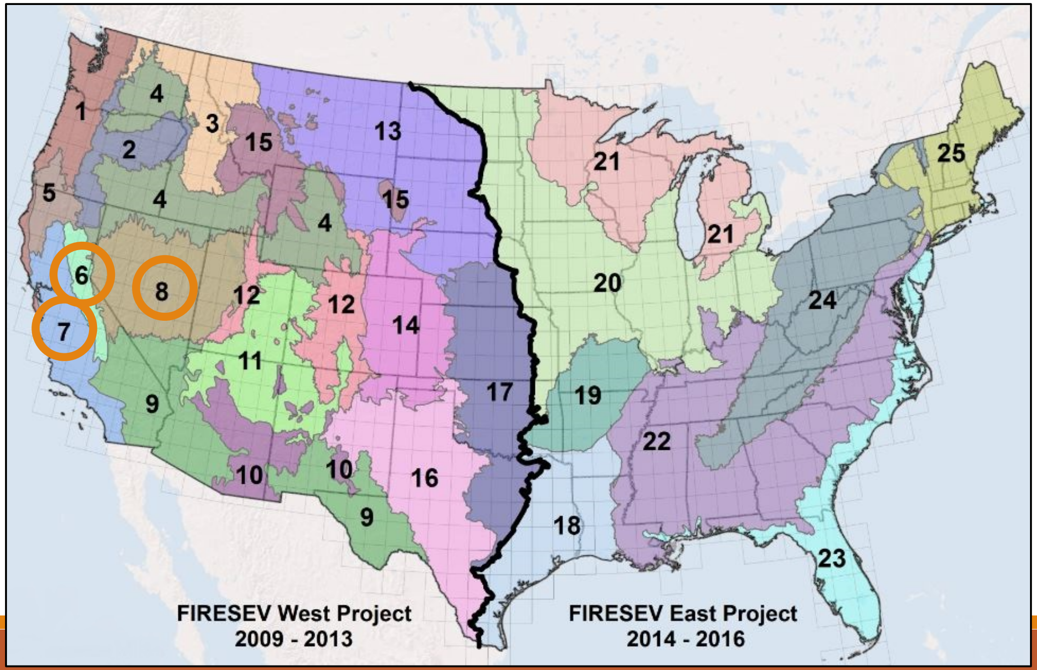
45

42

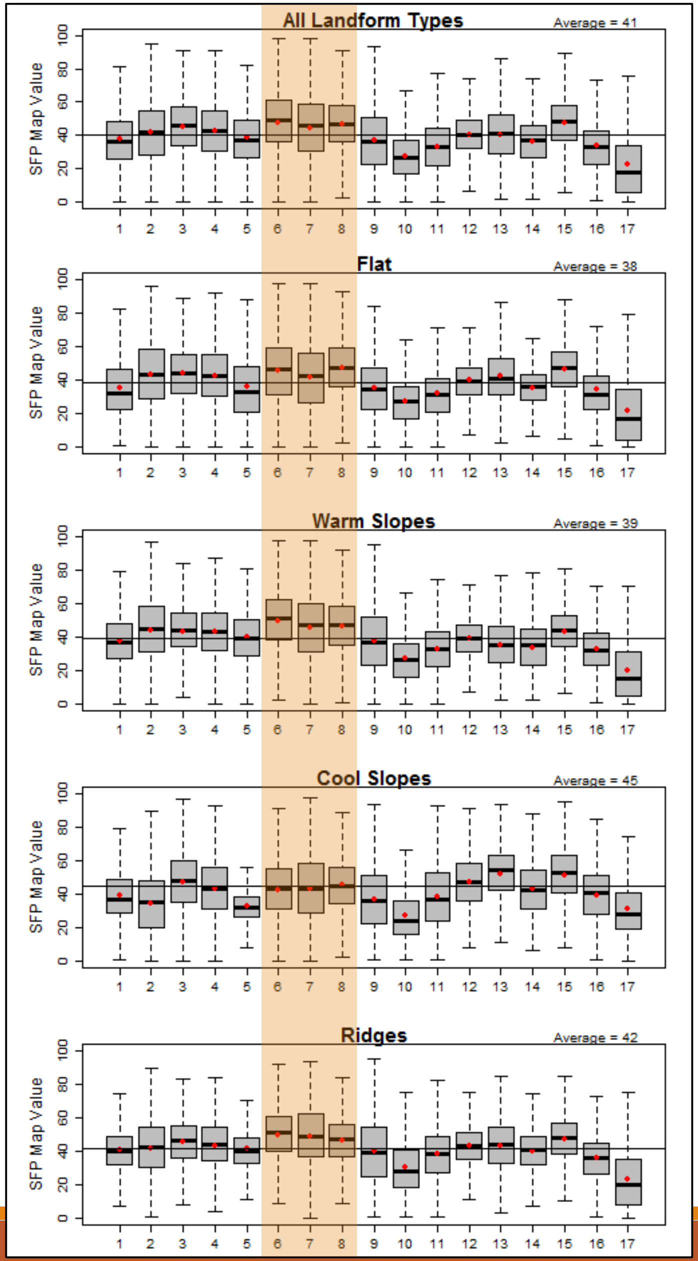
Results

Patterns in SFP predictions – West

- Average SFP values are highest on cool slopes
- Influenced by Middle and Northern Rockies
- Exception: S California, Sierras, and Great Basin



Forest

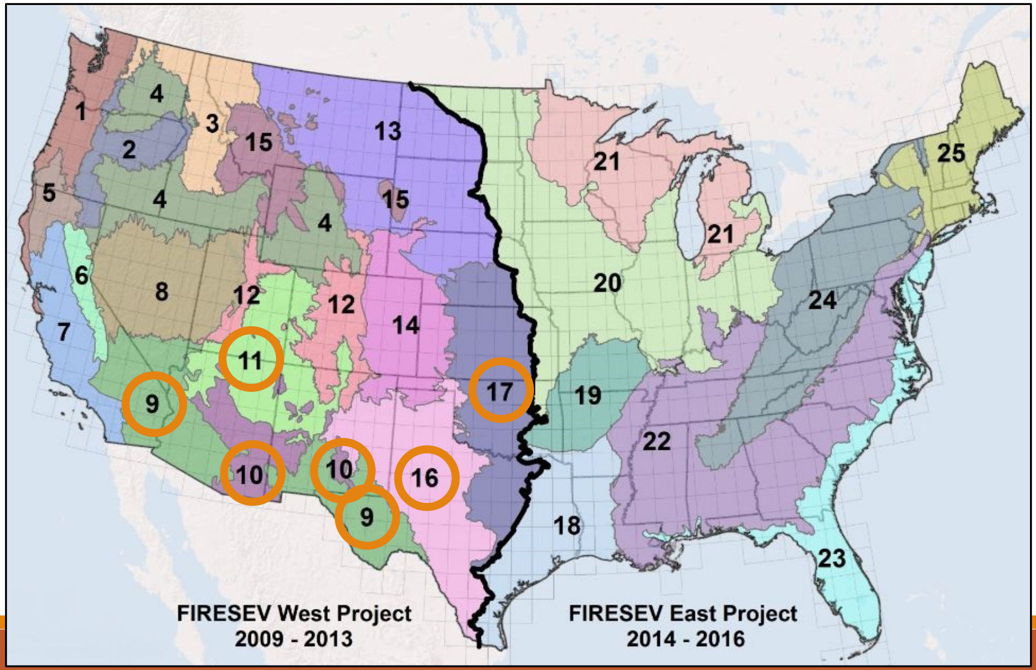


Average
41
38
39
45
42

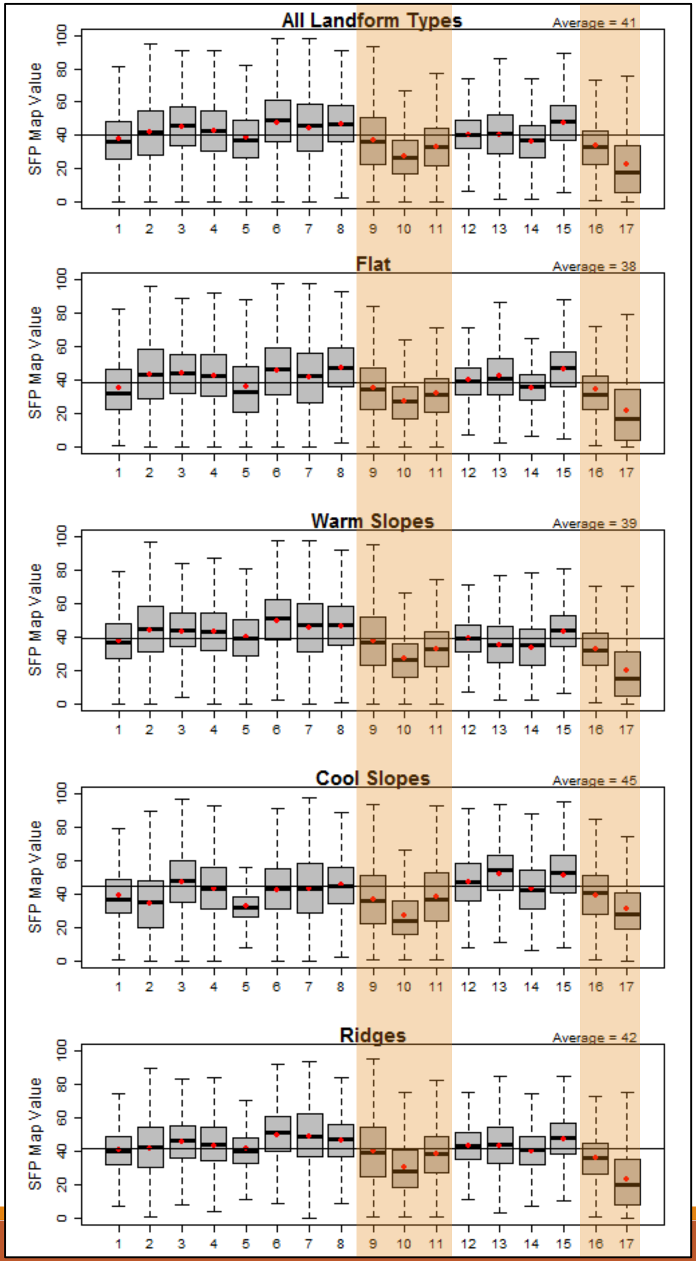
Results

Patterns in SFP predictions – West

- Average SFP values are highest on cool slopes
- Influenced by Middle and Northern Rockies
- Exception: S Calif, Sierras, and Great Basin
- SW and Southern Plains consistently lower



Forest | Average



41

38

39

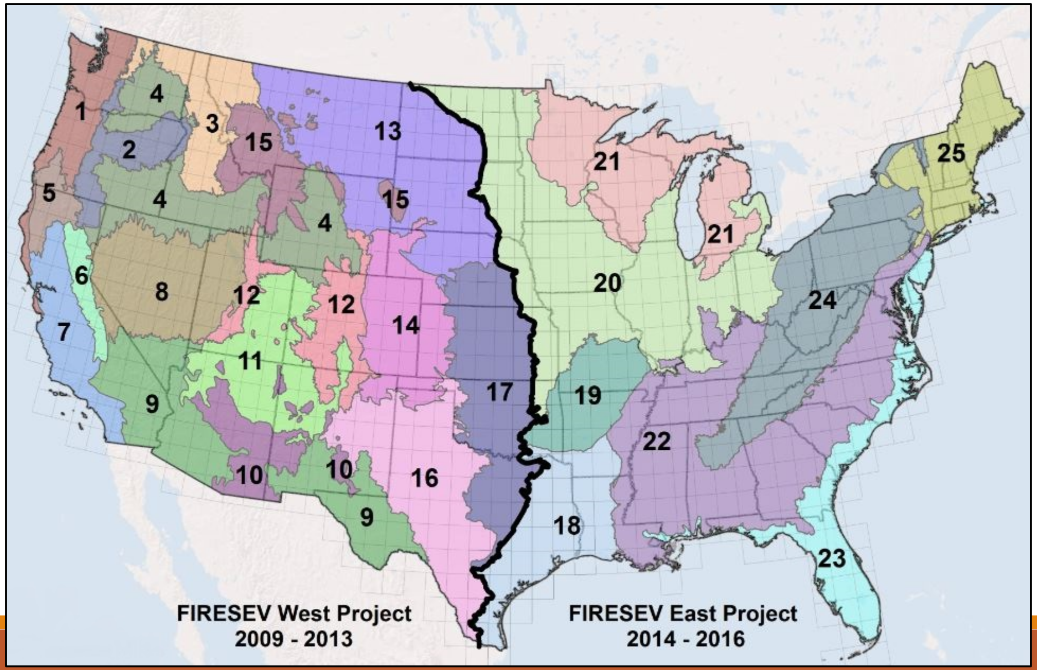
45

42

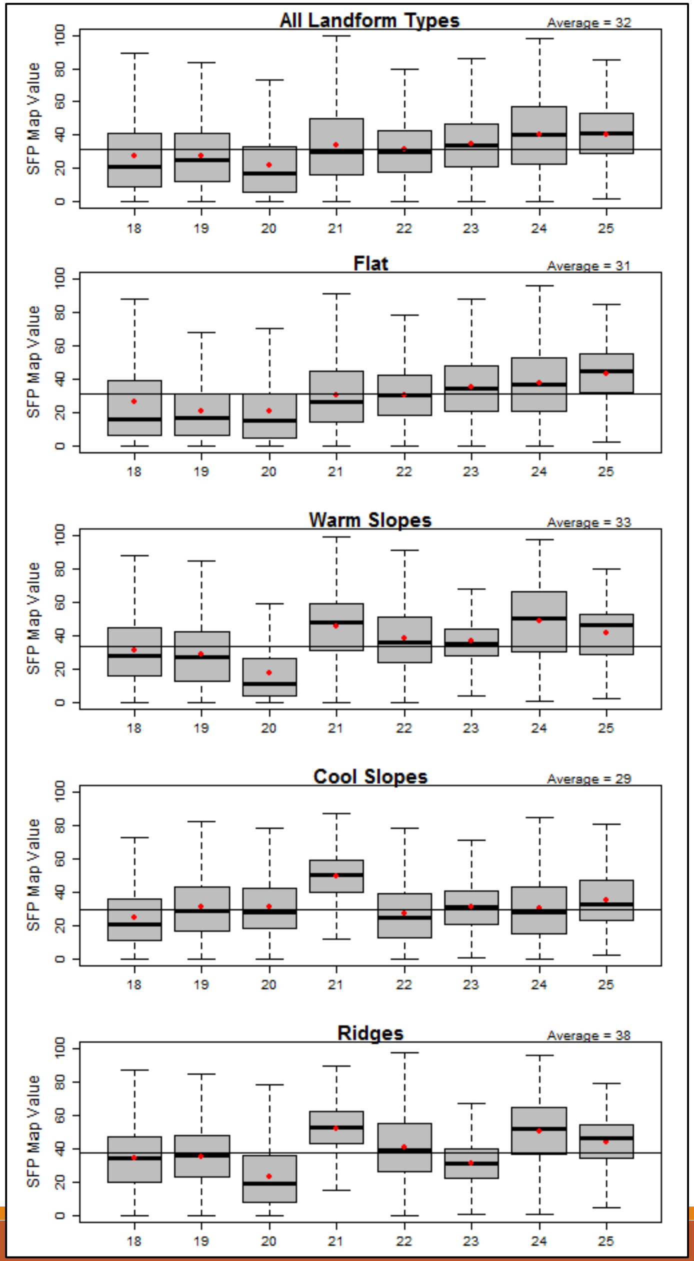
Results

Patterns in SFP predictions – East

- Average SFP values are highest on ridges



Forest

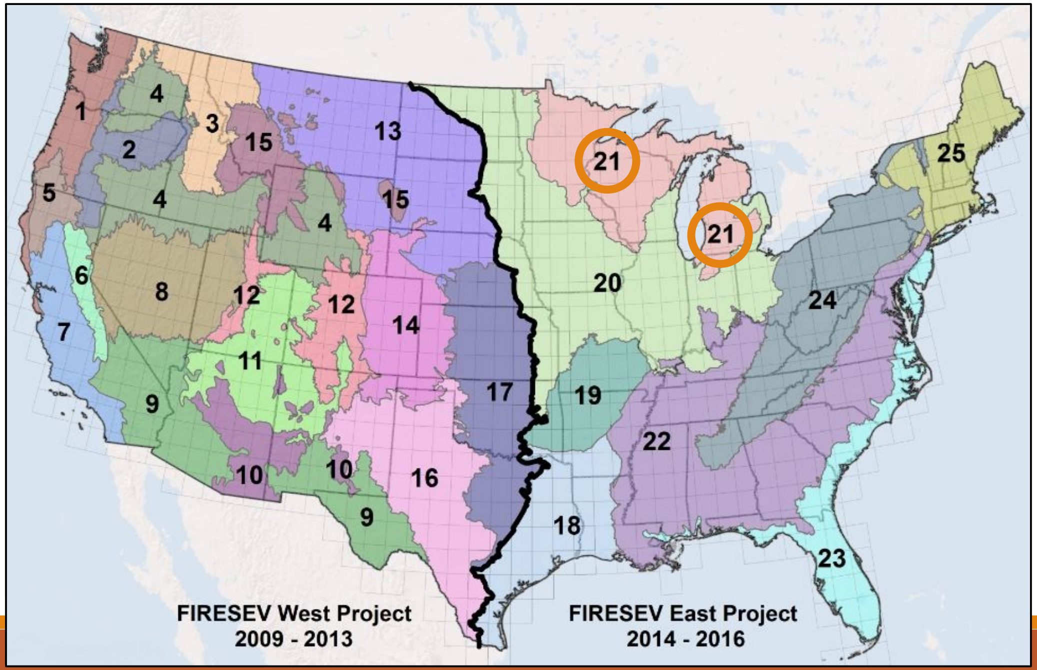


Average
32
31
33
29
38

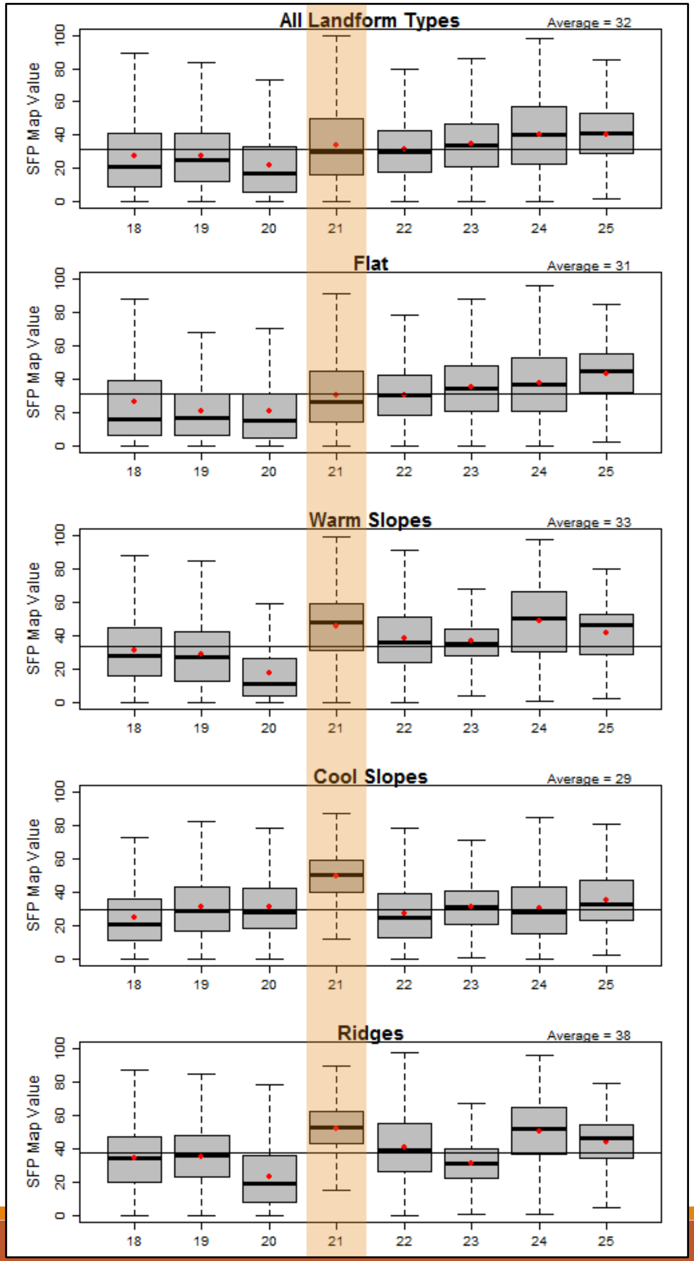
Results

Patterns in SFP predictions – East

- Average SFP values are highest on ridges
- Great Lakes higher on all slopes and ridges



Forest

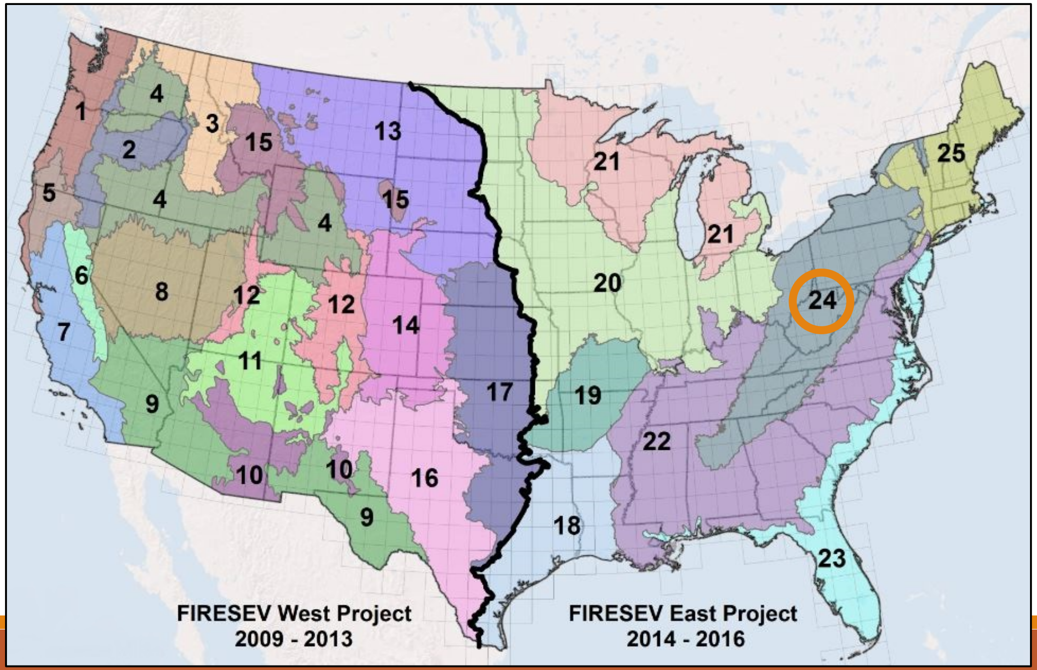


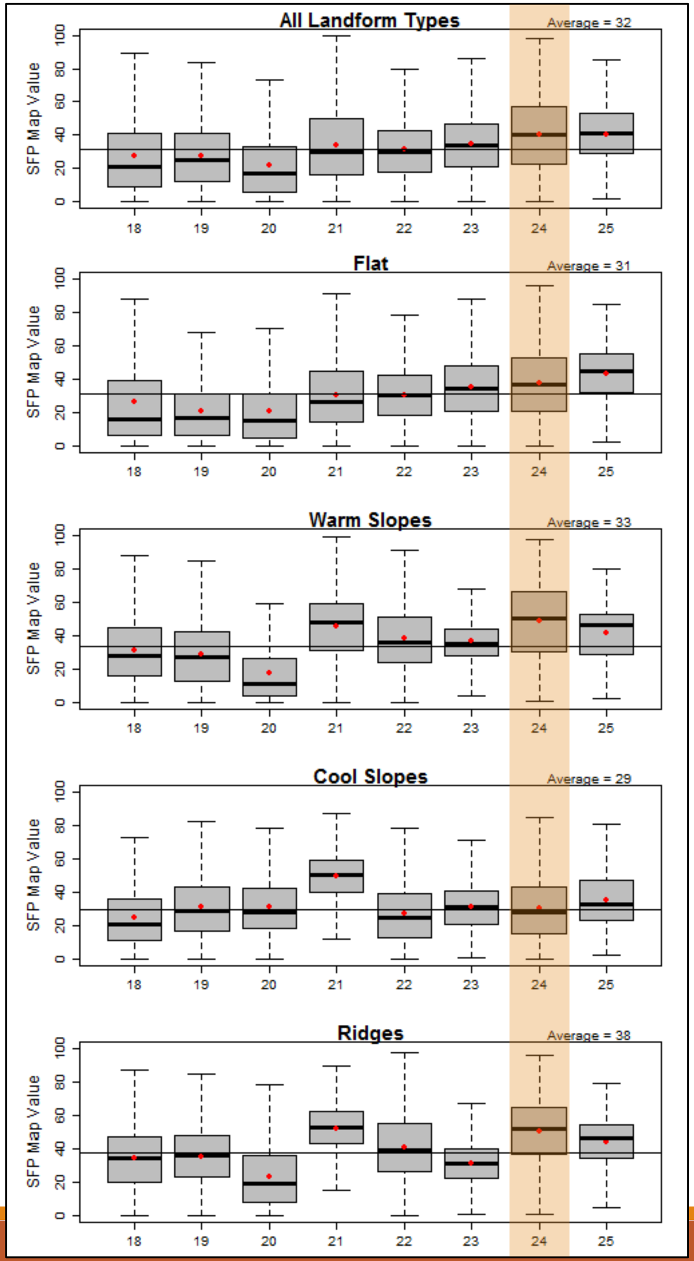
Average
32
31
33
29
38

Results

Patterns in SFP predictions – East

- Average SFP values are highest on ridges
- Great Lakes higher on all slopes and ridges
- SFP in Appalachians high on warm slopes and ridges

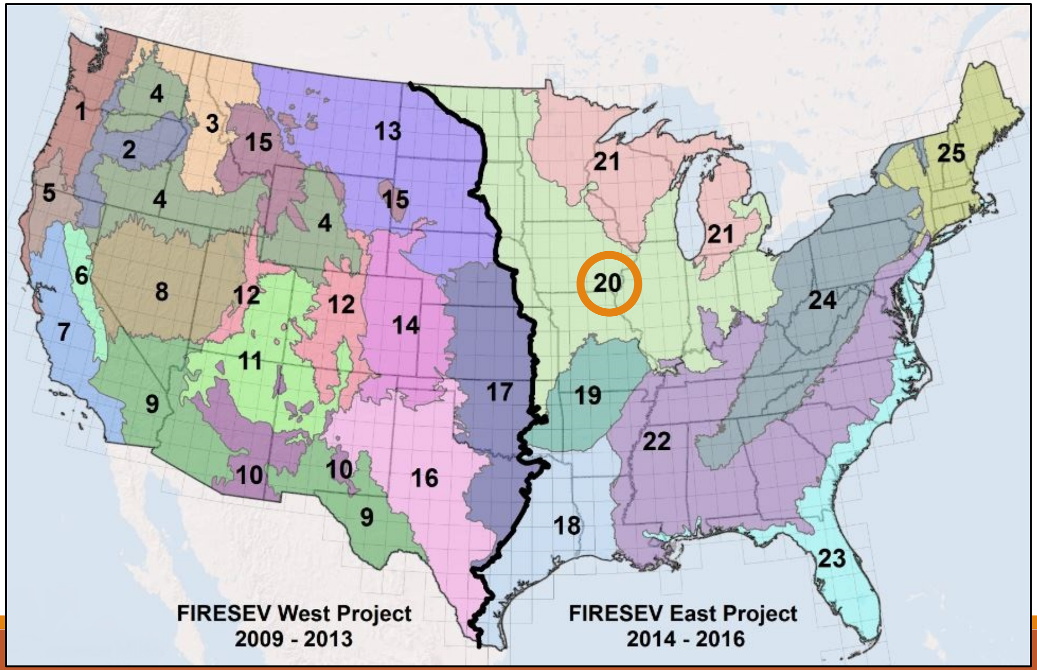


Forest	Average
	
	32
	31
	33
	29
	38

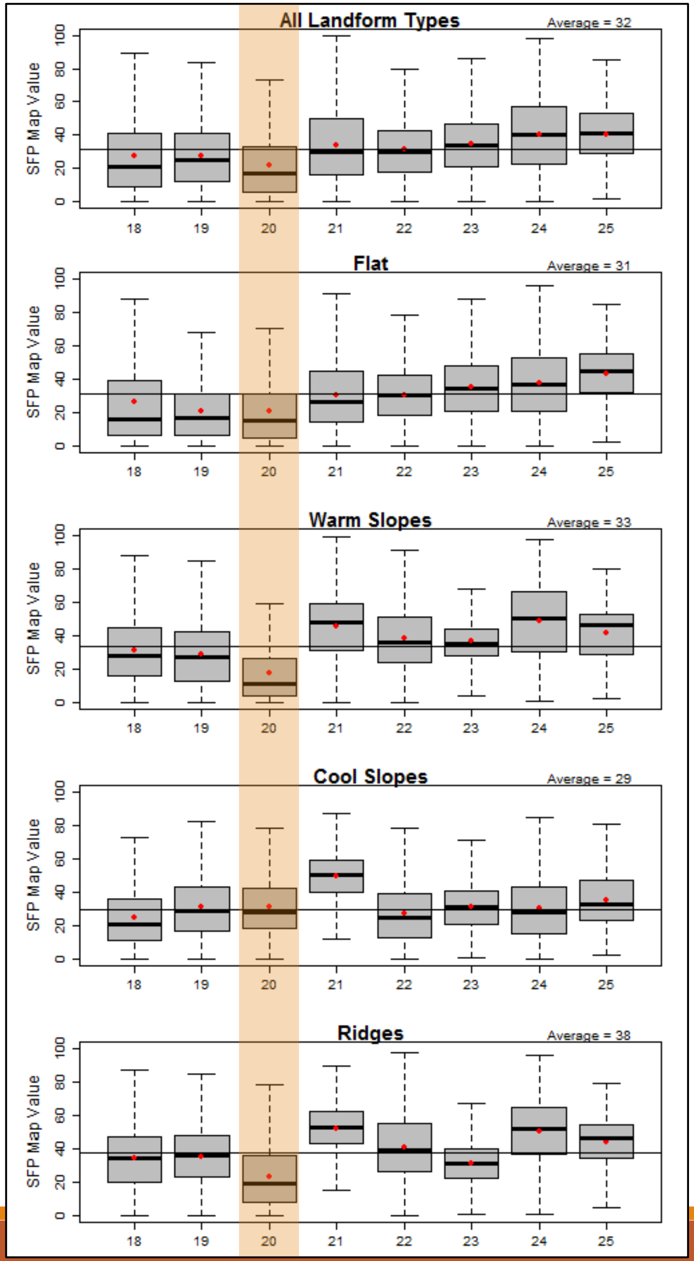
Results

Patterns in SFP predictions – East

- Average SFP values are highest on ridges
- Great Lakes higher on all slopes and ridges
- SFP in Appalachians high on warm slopes and ridges
- Central and Eastern Plains consistently low



Forest

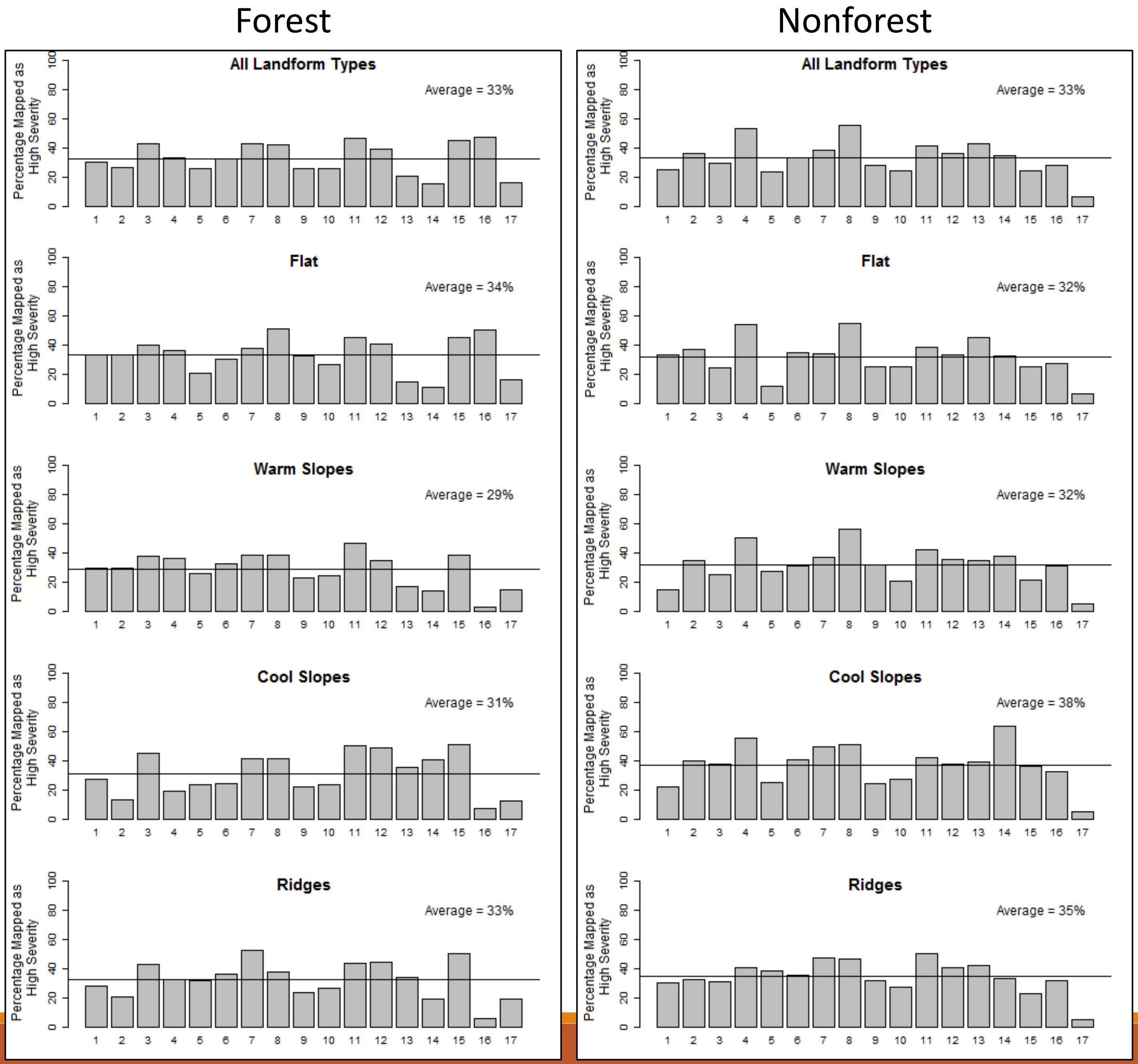


Average
32
31
33
29
38

Results

Patterns in MTBS data

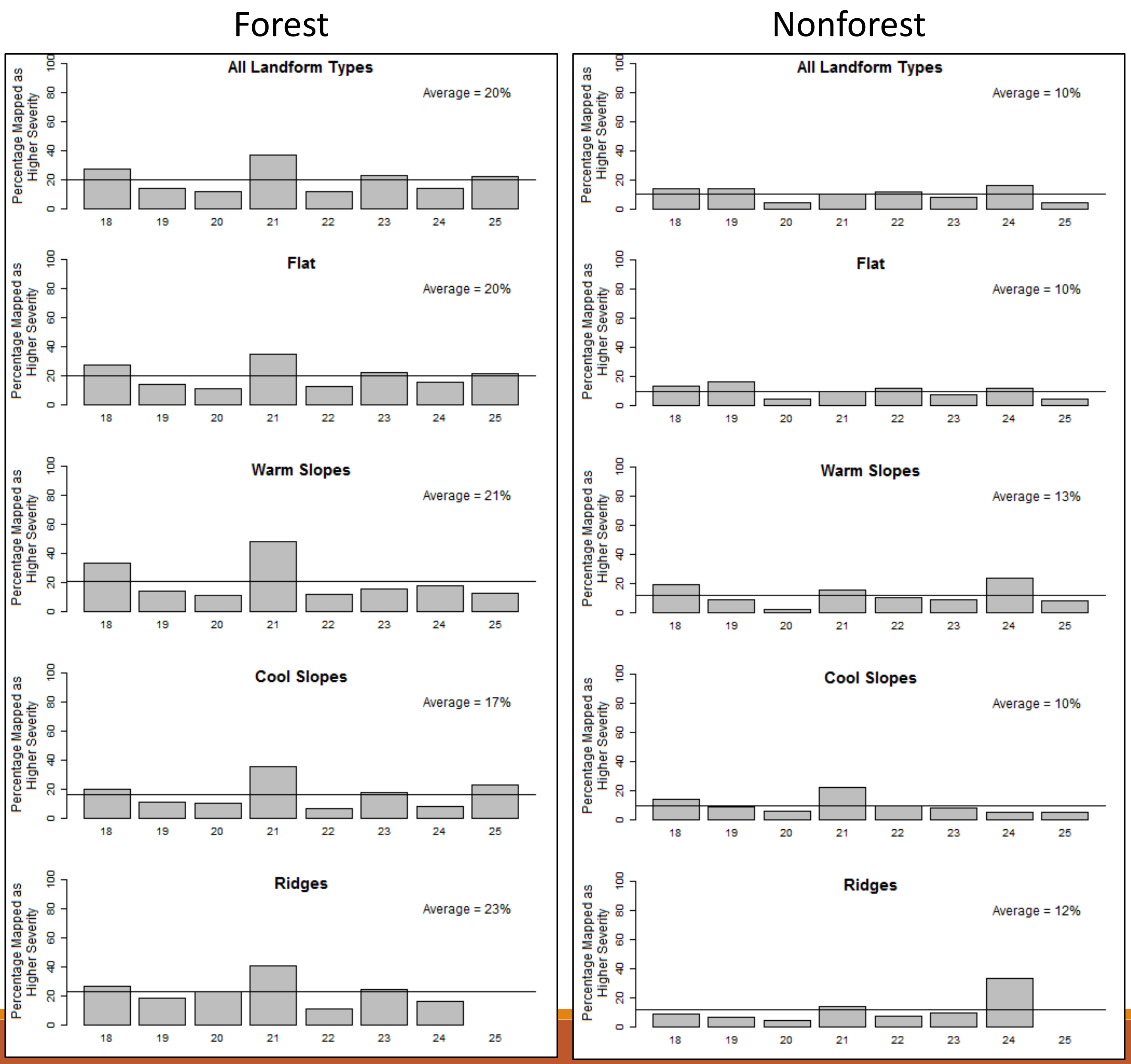
- Average percent high severity in the west
  - Forest: 33%
  - Nonforest: 33%



Results

Patterns in MTBS data

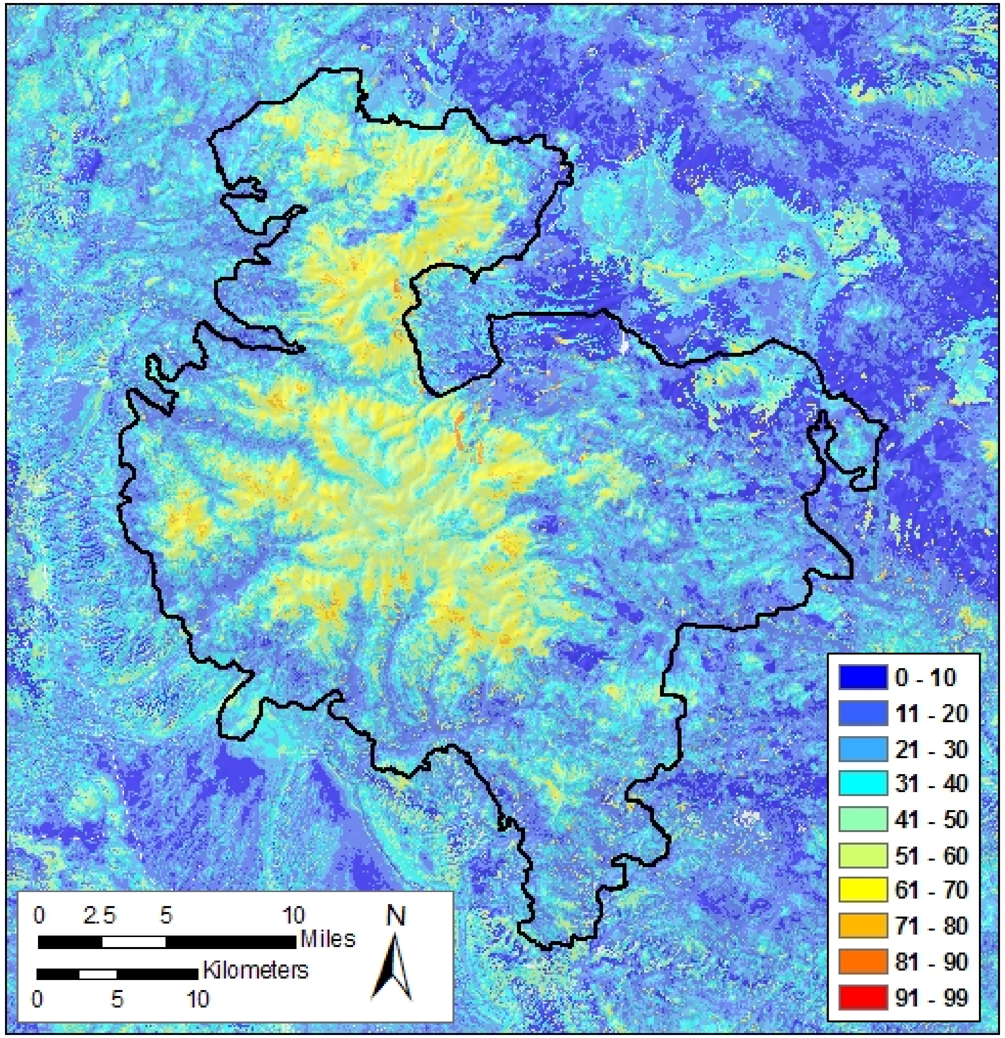
- Average percent high severity in the west
  - Forest: 33%
  - Nonforest: 33%
- Average percent higher severity in the east
  - Forest: 20%
  - Nonforest: 10%



Results

SFP Map Validation

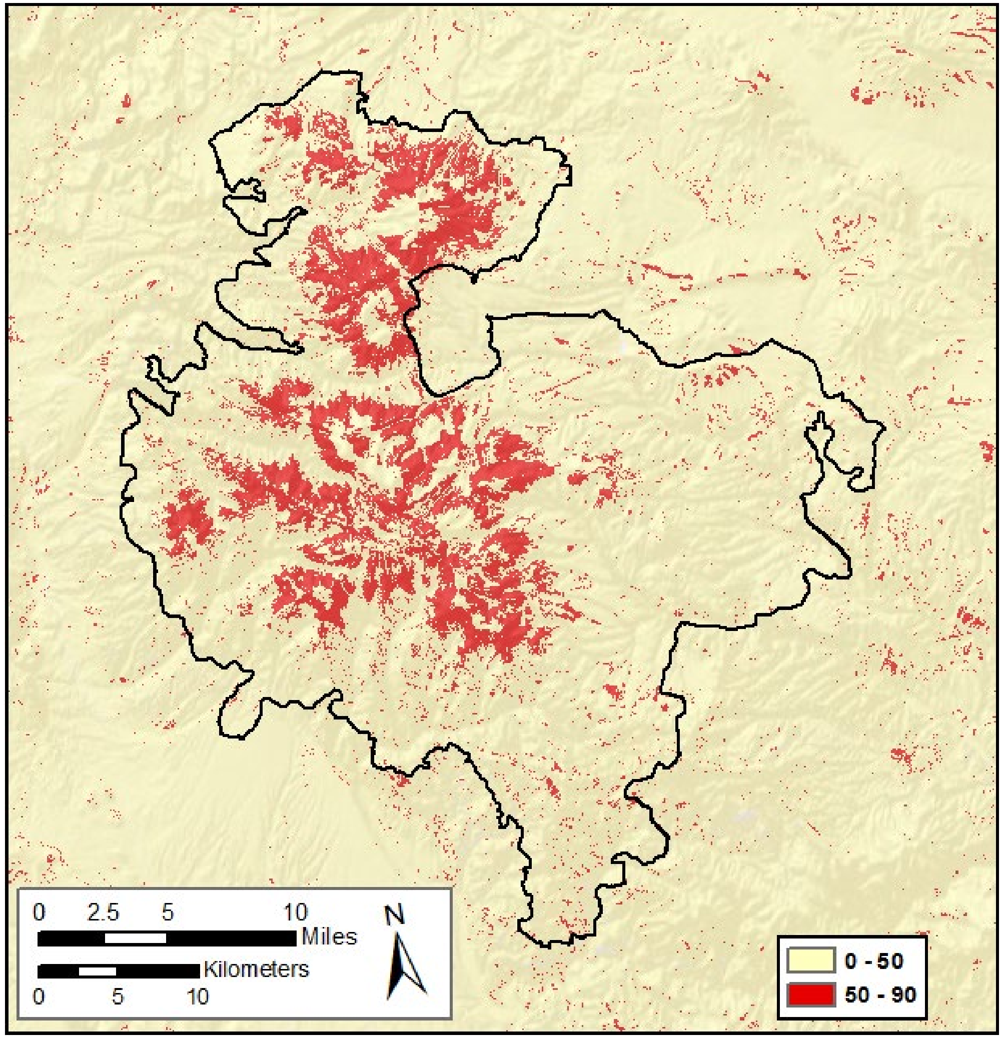
- Evaluate the predictive ability of the map
  - How often are our predictions “right”?
- Use a 10% subset of sample pixels withheld for validation
- Only used fires between 85th and 95th percentile of 1000-hour fuel moisture index
- Reclassify SFP to binary, testing a range of breakpoints (25 – 75)



Results

SFP Map Validation

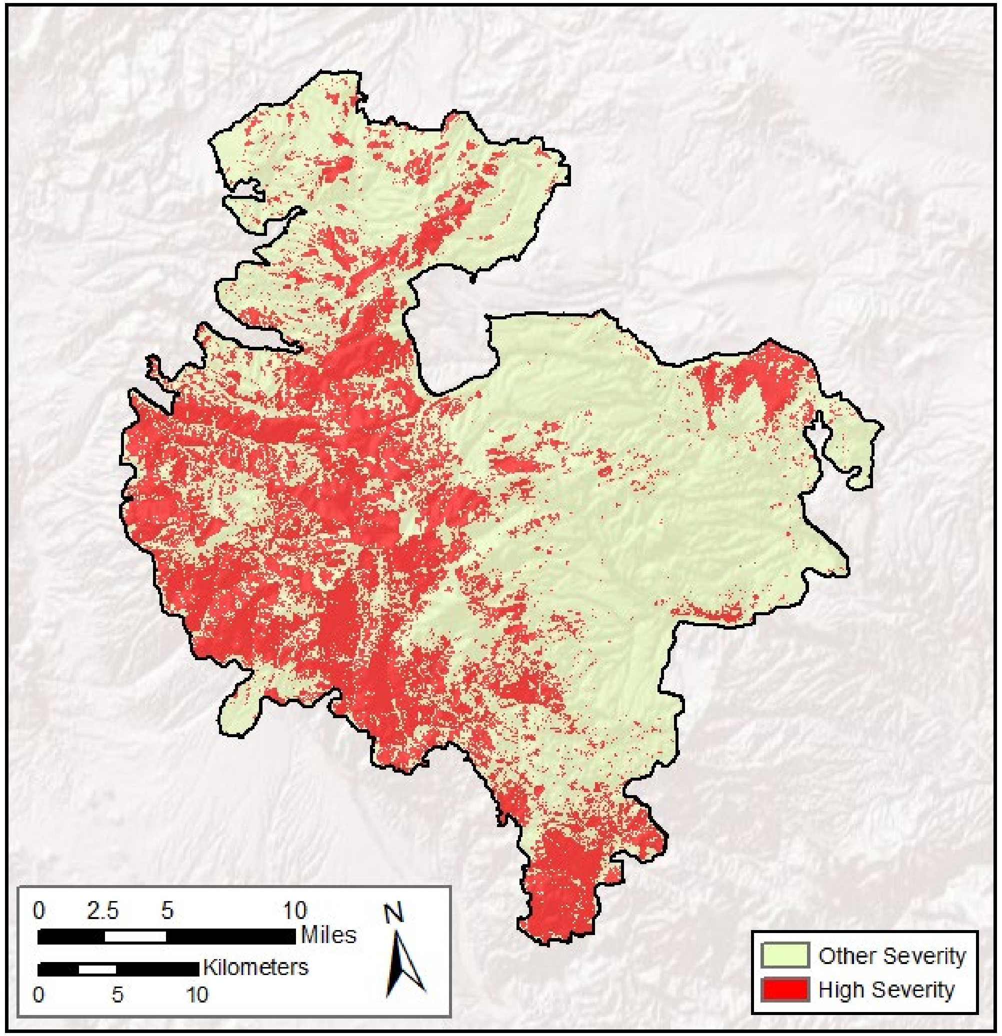
- Evaluate the predictive ability of the map
  - How often are our predictions "right"?
- Use a 10% subset of sample pixels withheld for validation
- Only used fires between 85th and 95th percentile of 1000-hour fuel moisture index
- Reclassify SFP to binary, testing a range of breakpoints (25 – 75)



Results

SFP Map Validation

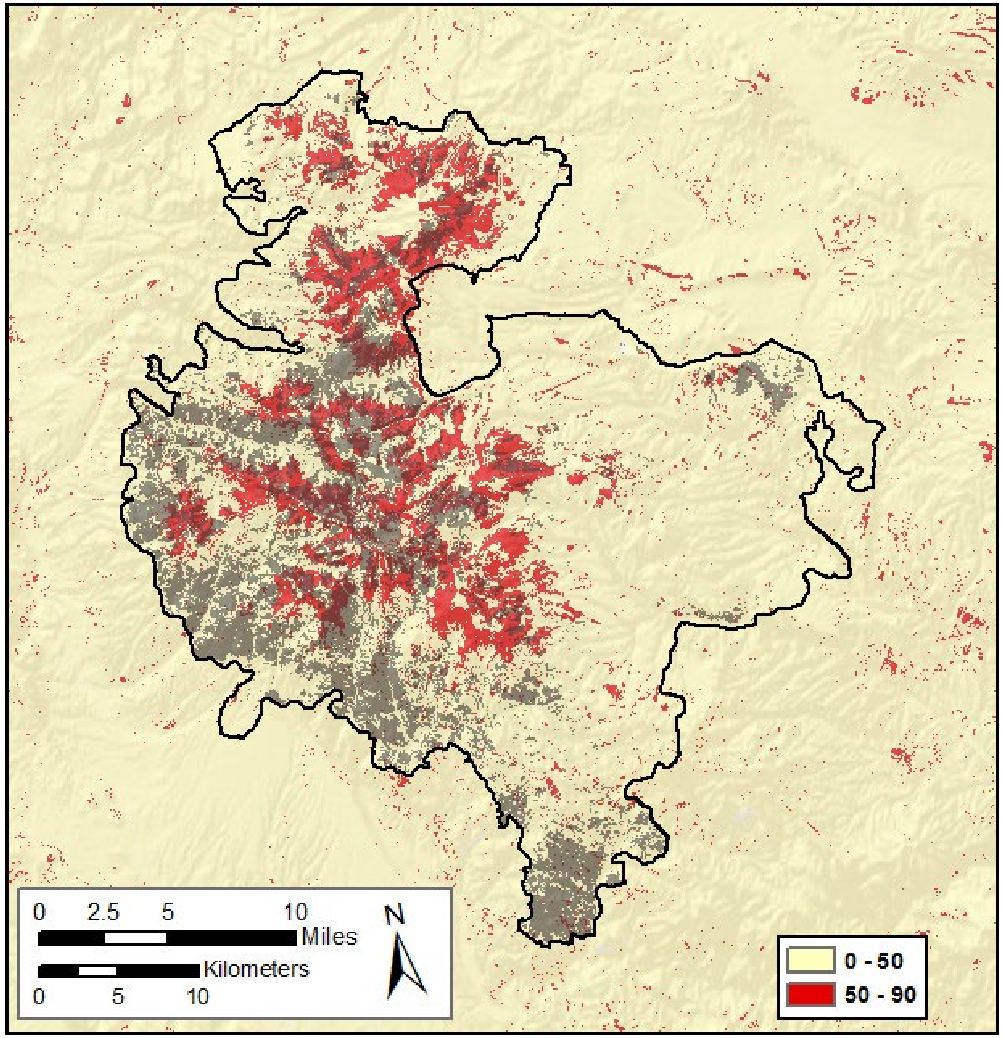
- Evaluate the predictive ability of the map
  - How often are our predictions "right"?
- Use a 10% subset of sample pixels withheld for validation
- Only used fires between 85th and 95th percentile of 1000-hour fuel moisture index
- Reclassify SFP to binary, testing a range of breakpoints (25 – 75)
- Compare to binary severity from MTBS



Results

SFP Map Validation

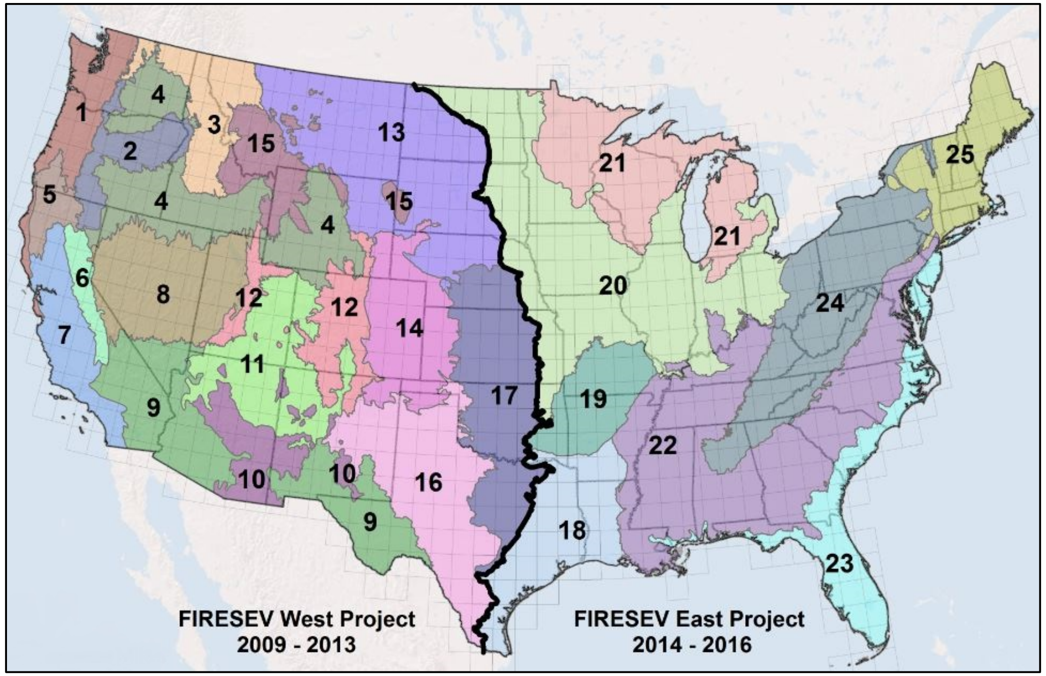
- Evaluate the predictive ability of the map
  - How often are our predictions “right”?
- Use a 10% subset of sample pixels withheld for validation
- Only used fires between 85th and 95th percentile of 1000-hour fuel moisture index
- Reclassify SFP to binary, testing a range of breakpoints (25 – 75)
- Compare to binary severity from MTBS



Results

SFP Map Validation

- Best SFP breakpoints mostly under 50
- AUC values mostly under 0.7
- PCC values mostly 50-70%



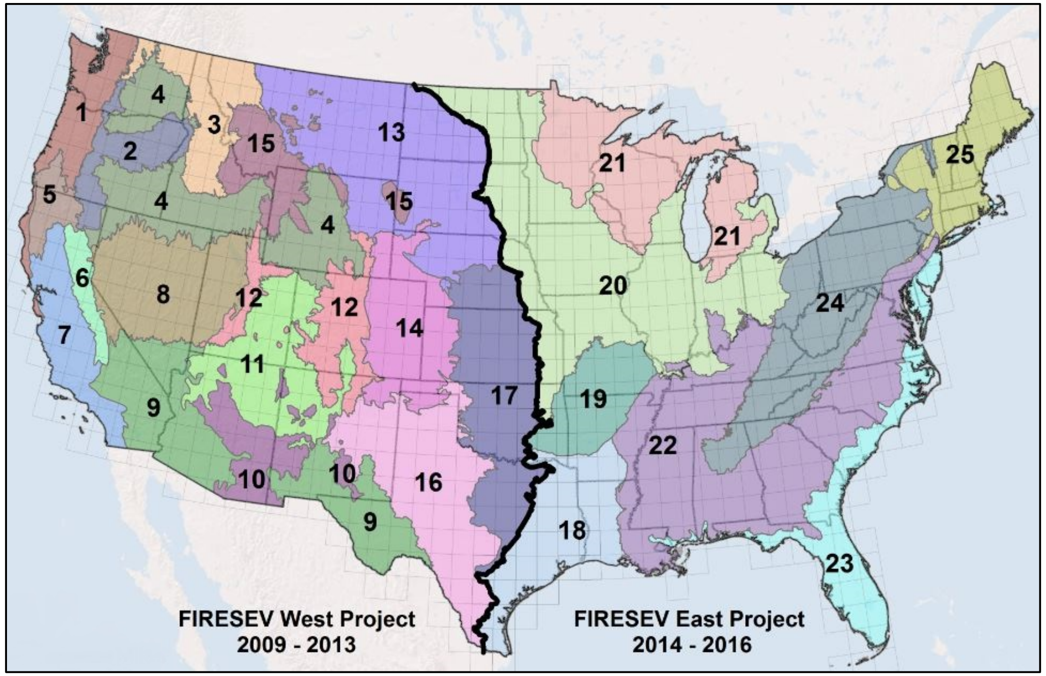
Forest

Region	Fires	Samples	Best SFP breakpoint	Results for best breakpoint AUC [a]	PCC [b]
1	125	2,250	40	0.58	0.61
2	119	1,959	45	0.61	0.60
3	277	6,052	40	0.54	0.51
4	243	3,990	50	0.58	0.60
5	98	1,539	40	0.64	0.63
6	82	1,243	35	0.59	0.59
7	161	1,834	45	0.61	0.60
8	126	916	35	0.55	0.52
9	93	1,061	30	0.61	0.60
10	66	981	25	0.55	0.55
11	87	1,035	35	0.68	0.67
12	54	625	25	0.54	0.46
13	57	1,150	50	0.58	0.59
14	6	144	25	0.53	0.50
15	184	3,151	50	0.58	0.59
16	13	301	25	0.50	0.47
17	2	4	NA	NA	NA
18	105	279	55	0.74	0.86
19	127	328	35	0.62	0.66
20	83	197	35	0.50	0.62
21	36	401	40	0.71	0.75
22	413	1,352	25	0.61	0.56
23	490	1,549	35	0.64	0.63
24	47	83	50	0.63	0.64
25	0	0	NA	NA	NA
Average	124	1,297	38	0.60	0.60

Results

SFP Map Validation

- Best SFP breakpoints mostly under 50
- AUC values mostly under 0.7
- PCC values mostly 50-70%



Nonforest

Region	Fires	Samples	Best SFP breakpoint	Results for best breakpoint AUC[a]	PCC[b]
1	97	959	45	0.60	0.60
2	244	3,986	50	0.58	0.60
3	312	4,947	35	0.60	0.56
4	771	18,593	50	0.60	0.61
5	68	436	45	0.64	0.62
6	106	934	35	0.60	0.52
7	258	2,989	40	0.62	0.62
8	473	9,110	50	0.57	0.57
9	323	4,867	35	0.63	0.62
10	127	1,044	40	0.65	0.67
11	116	1,215	45	0.68	0.67
12	129	1,528	45	0.59	0.55
13	148	1,871	45	0.58	0.59
14	28	274	50	0.58	0.58
15	205	3,403	40	0.61	0.60
16	38	226	25	0.61	0.49
17	7	15	NA	NA	NA
18	45	161	45	0.52	0.44
19	13	23	NA	NA	NA
20	115	431	35	0.50	0.75
21	24	71	40	0.79	0.76
22	48	65	55	0.60	0.63
23	73	149	25	0.72	0.70
24	4	5	NA	NA	NA
25	0	0	NA	NA	NA
Average	151	2,292	42	0.61	0.61

Results

Variable Importance – Forest

West

1. Elevation (avg rank 1.6)
2. NDVI (avg rank 2.1)
3. Fuel moisture (avg rank 2.6)

East

1. Fuel moisture (avg rank 2.1)
2. NDVI (avg rank 2.5)
3. Elevation (avg rank 3.0)

	Region																								
	West																	East							
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Vegetation																									
NDVI	2	2	2	3	1	2	3	3	1	2	3	2	2	3	2	1	1	2	3	2	3	2	2	2	4
Fuel moisture																									
FM1000	3	3	4	4	2	3	2	2	3	1	1	3	3	1	3	3	3	1	1	1	1	1	1	3	8
Topography																									
DEM	1	1	1	1	4	1	1	1	2	3	2	1	1	2	1	2	2	3	2	3	2	3	4	4	3
SLOPE	4	4	3	2	5	…	…	5	5	4	4	7	9	…	4	…	8	…	…	…	…	…	…	5	…
RAD[b]	8	…	9	5	8	…	…	6	…	…	7	5	6	7	6	…	5	4	…	4	4	4	3	1	…
GSPET[c]	6	—	—	—	—	5	—	4	4	…	6	4	—	5	—	—	4								
HLI	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—
TPI150	…	…	7	9	6	…	…	…	…	…	…	…	…	…	…	…	…	5	4	5	…	…	…	6	…
TPI2000	5	5	5	6	3	4	4	7	6	5	5	8	4	4	5	4	6	…	…	…	—	…	—	…	…
HSP	…	…	8	…	…	…	…	…	…	…	…	…	8	8	…	…	…	…	…	…	…	…	…	…	…
DISS3	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	5	…	…	…	1
DISS27	7	…	6	7	7	…	…	…	…	…	8	6	5	6	7	…	9	…	…	…	…	…	…	…	…
ERR3	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	—	—	…	—	—	—	—
ERR15	—	—	—	—	—	—	…	…	…	—	—	—	—	—	—	—	—	…	…	…	…	5	5	…	2
ERR27	9	6	10	8	9	…	…	…	…	6	9	9	7	9	8	5	7	3	2	3	2	3	4	4	3

Results

Variable Importance – Nonforest

West

1. NDVI (avg rank 1.2)
2. Elevation (avg rank 2.2)
3. Fuel moisture (avg rank 3.0)

East

1. Fuel moisture (avg rank 1.2)
2. NDVI (avg rank 2.4)
3. Elevation (avg rank 3.0)

	Region																								
	West																	East							
Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25
Vegetation																									
NDVI	1	1	1	1	2	2	2	1	1	1	1	1	1	1	1	1	1	2	3	2	1	2	4	3	
Fuel moisture																									
FM1000	2	3	3	5	3	3	3	4	3	2	3	3	3	3	2	3	3	1	1	1	2	1	1	…	
Topography																									
DEM	3	4	2	3	1	1	1	2	2	3	2	2	2	2	3	2	2	4	2	3	3	3	2	4	
SLOPE	5	6	6	6	6	7	6	6	9	7	6	9	…	…	8	8	…	…	…	5	…	…	…	6	
RAD[b]	—	2	7	4	5	6	5	5	5	4	4	6	…	…	7	4	5	3	…	4	4	4	3	2	
GSRAD[c]	4	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—								
APET[c]	6	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—								
GSPET[c]	—	—	5	2	—	4	4	3	4	5	5	4	—	5	—	—	4								
HLI	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	—	
TPI150	…	…	…	…	8	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	
TPI2000	7	5	4	7	4	5	7	7	6	6	7	5	4	4	4	6	6	…	4	7	…	…	…	…	
HSP	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	—	…	…	…	…	—	7	
DISS3	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	…	—	…	…	…	
DISS27	8	…	8	…	7	8	9	…	8	8	9	7	…	…	6	7	…	…	…	…	6	…	…	1	
ERR3	…	…	…	…	…	…	…	…	…	…	…	…	…	…	9	9	…	…	…	…	…	…	…	5	
ERR15	—	—	—	—	—	—	…	…	—	—	—	—	…	—	—	—	—	—	—	…	5	—	—	—	
ERR27	9	7	9	…	9	9	8	…	7	9	8	8	…	…	5	5	…	5	…	6	—	5	…	…	

Key Findings

1. Burn severity is a complex phenomenon. Evaluating it across different ecosystems requires flexibility and adaptability. Data are noisy.
2. Availability of burn severity data is patchy… affects ability to model everywhere.
3. Vegetation, topography, and site-specific fuel moisture affect severity.
    a. Topographic variables may be surrogates for vegetation distribution
    b. Fires can burn hotter where there is more fuel… especially in the West
    c. Fuel moisture is most important in the East… severity is climate-limited

Key Findings

4. Independent validation is important with this type of modeling and mapping.
5. High burn severity occurs on a relatively small portion of burned area.
   a. About 1/3 of burned area in the West, much less in the East
   b. Proportion of high severity generally stable over time (Dillon et al. 2011)
   c. Area burned with high severity is increasing (Parks and Abatzoglou 2020)
6. Data from our work has contributed to ongoing studies of severity
   a. Next Generation Fire Severity Mapping – Sean Parks and others

Management Implications

1. Best use of SFP map is for long-term assessments and strategic planning.
2. The strength of the SFP map is in generalized patterns in potential severity, rather than how a specific pixel is mapped.
3. The SFP index represents the likelihood of high severity (or moderate and high in the East) but says nothing about the likelihood of low severity fire.
4. The SFP map could provide a starting point to inform where fuels treatments could help to moderate severe fire potential, but it is not detailed enough to guide specific placement of treatments.

Photo: Greg Dillon

Thank You

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