An Early-Warning Mapping Tool for Forecasting Fire Risk on DoD Lands in the Arid West

Legacy Resource Management Program Project 17-834

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Introduction

Conservation Science Partners (CSP) is a 501(c)(3) nonprofit collective established to meet the analytical and research needs of diverse stakeholders in conservation projects. We connect the best minds in conservation science to solve problems in a way that's comprehensive, flexible, and service-oriented.

Gage Cartographics has been providing geospatial services to clients since 2009. We provide services to federal, state and local government along with conservation organizations and private clients worldwide. We specialize in Data Visualization, Geospatial Analysis, Database Solutions, and Cartography.

Webinar Overview

1) **Impetus** for this project and **background** from previous related work
2) **Approach and methods** to modeling and mapping dynamic wildfire risk
3) **Introduction** to the interactive mapping tool
4) Example **use cases** of the tool
5) Next steps for **beta release** of the tool

The Need for this Tool

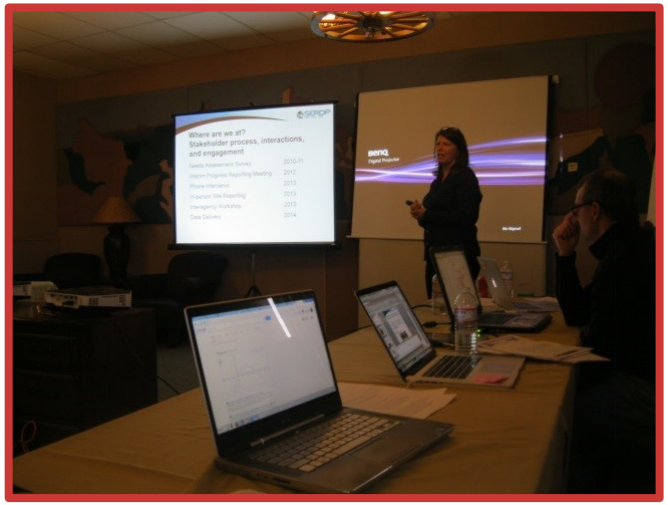
- Aridlands in the western US face **increasing threats due to the grass-fire cycle**, such as the realized or potential cascading effects on ecosystems and military mission-related activities
- Many installations rely on **coarse-scale weather data, static maps of fire risk, and/or time-intensive site inspections** to monitor wildfire risk across large landscapes
- From 2010-2015, we led SERDP project RC-1722, from which **a specific need emerged amongst managers in the Sonoran Desert to be able to predict fire risk in real time and at a landscape scale**

Impetus and Background

Table 9. Informational needs identified by stakeholders

Theme	Topic	Components
Non-native plant invasion	Distributions	Knowledge of where invasive plants occur Identification of potential suitable habitat
	Remote sensing-based solutions to invasive species mapping	Efficient mapping of invasive plant distributions, especially when true distribution is unknown
	Determination of potential impacts on native species	
Fire risk and threat	Fire and fine fuels characterization	Determination of: thresholds for fine fuel loads and fire spread potential; the fuels types that lead to increasing severity and intensity; susceptible dominant vegetation types; and the rates of recovery among different vegetation and terrain types
	Establishment of remote sensing-based solutions to capture fire patterns and fire risk	Need for data and maps on annual plant productivity and herbaceous biomass, fire connectivity, and fire risk
	Management plan facilitation	Context-based scenarios of fire outcomes and risk characterization translated into reports, software, and maps
	Decision support on DOD installations	Understanding where flammable herbaceous fuels are likely to develop in order to reduce the 'search space' and help guide decisions about operational activities
Communications and data sharing	Information exchange	Efficient information exchange that takes firewalls and other agency-specific limiting factors into consideration
	GIS solutions to managers	Acknowledgement of limitations in GIS experience, skills, and

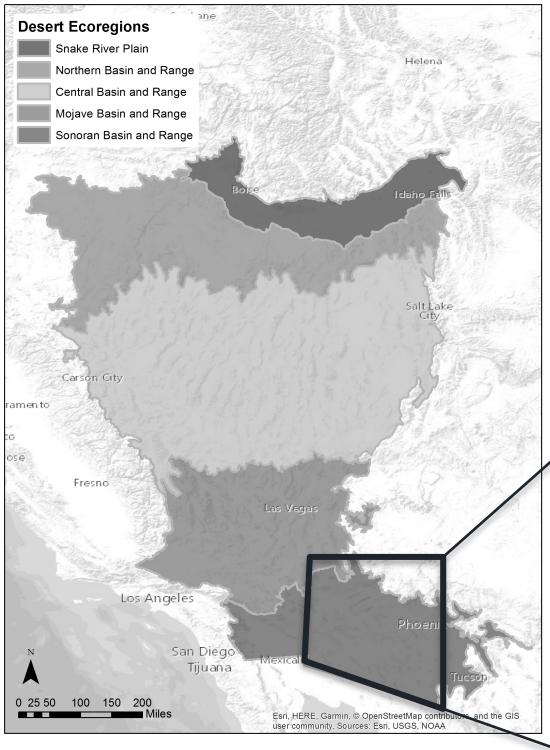
Source: SERDP Project RC-1722 Final Report

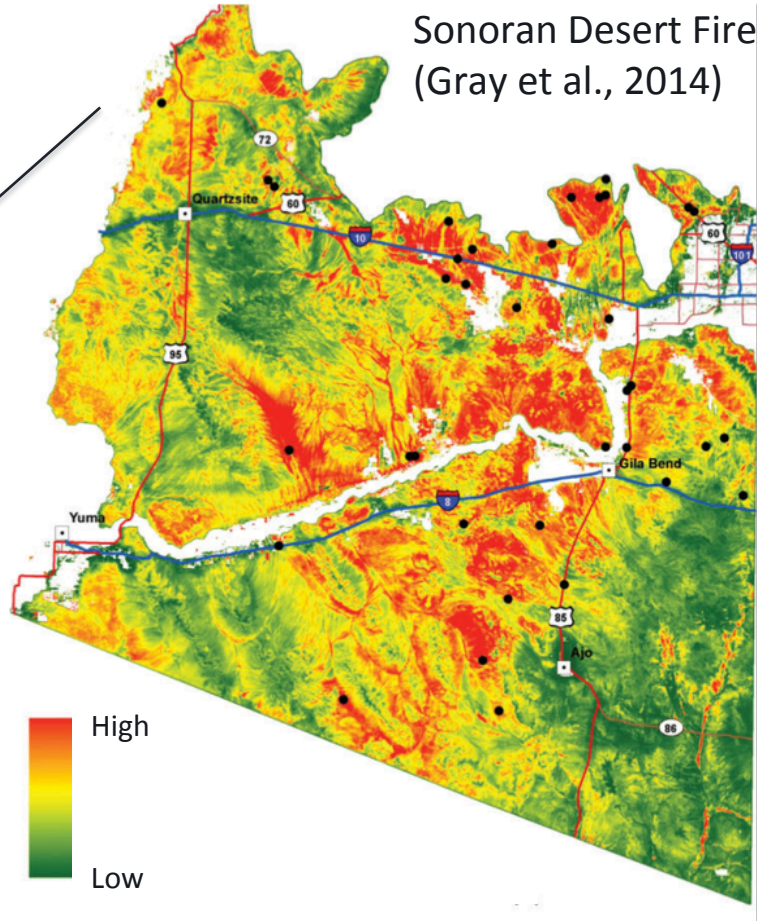


SERDP Project RC-1722 'Managers Meeting', 2013

Impetus and Background

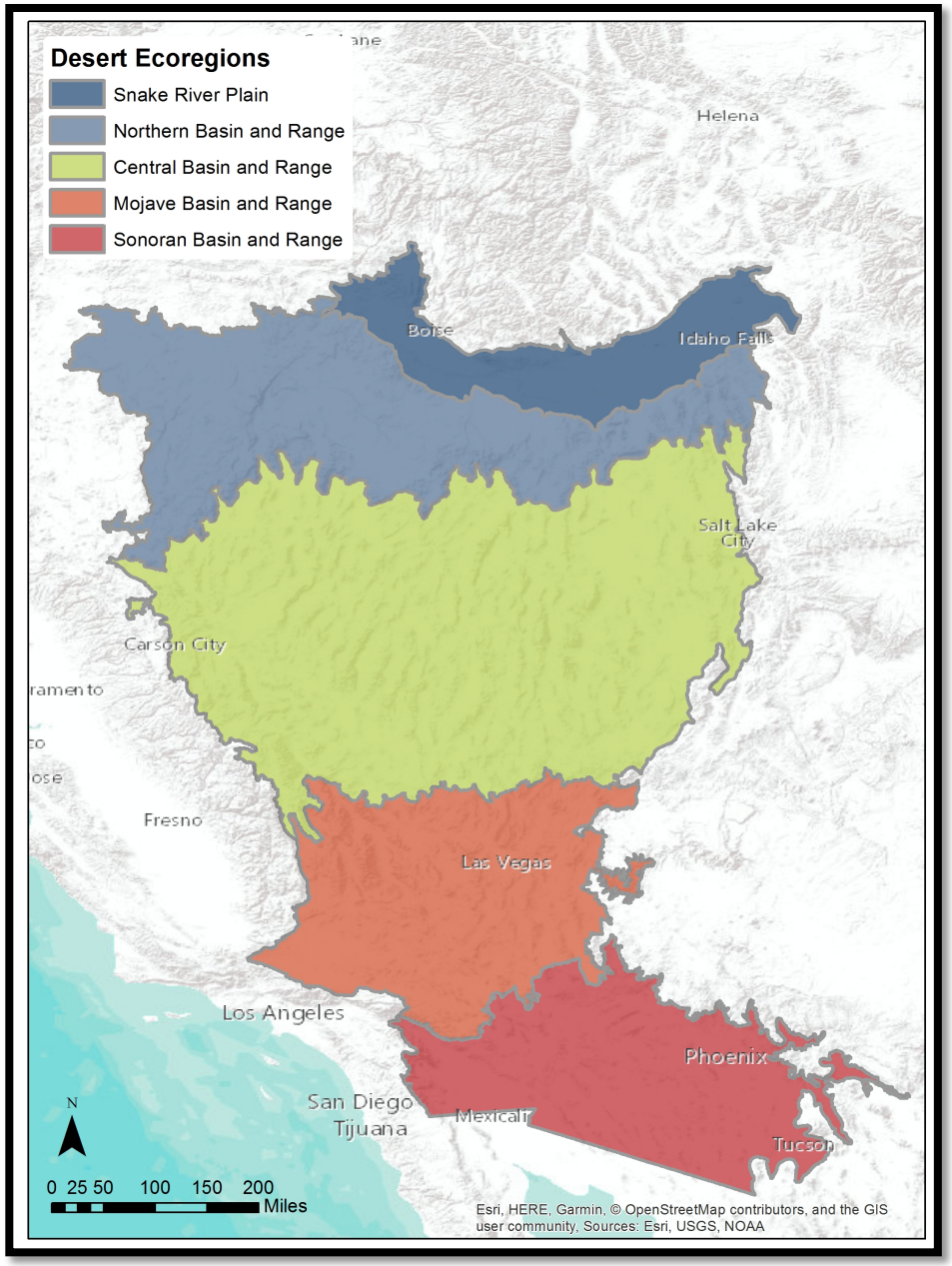
- Efforts from SERDP Project RC-1722 resulted in annual maps of fire risk
- Stakeholders expressed future need for dynamically updated and interactive 'early-warning indicators' of fire risk



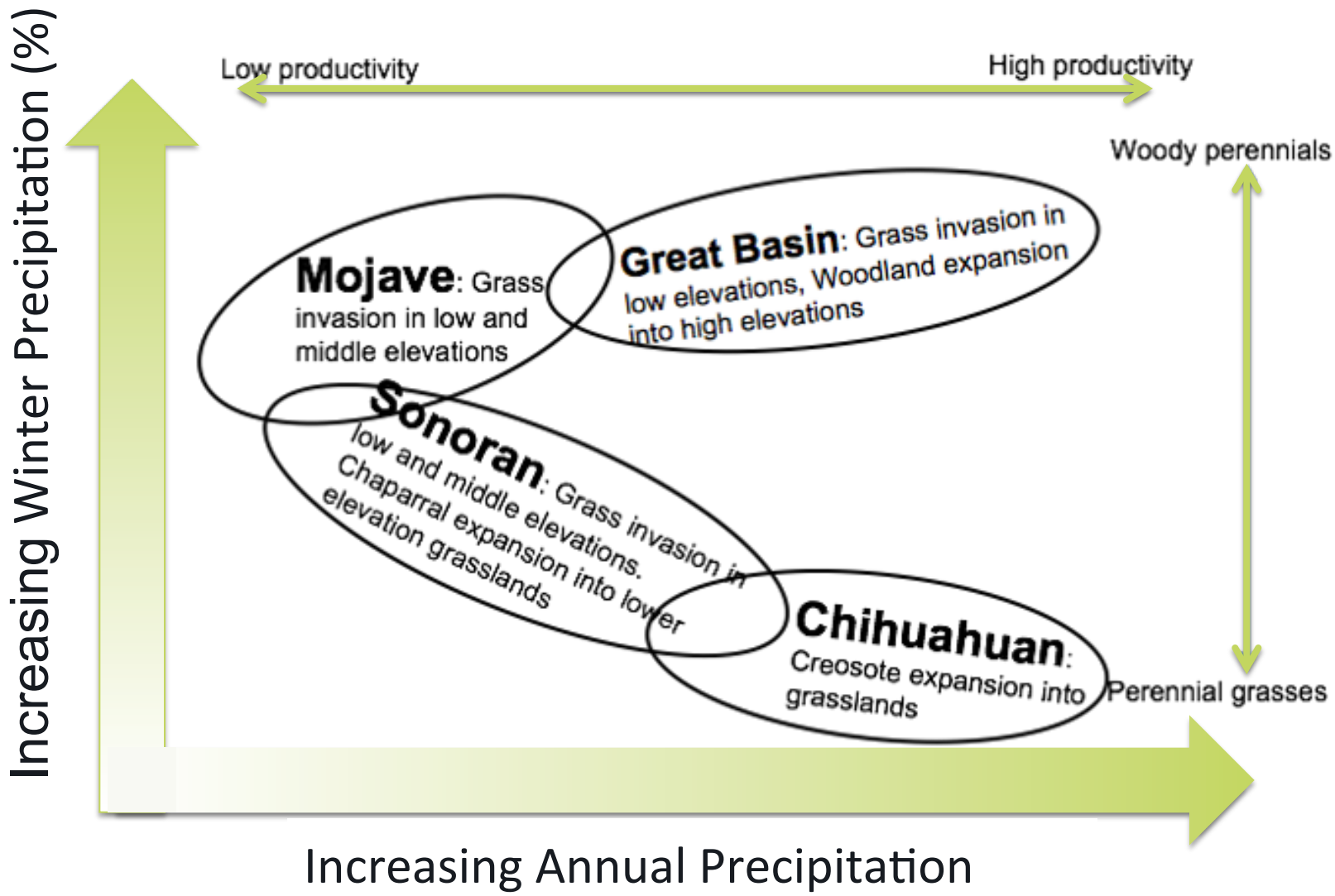


Sonoran Desert Fire Risk in 2005 (Gray et al., 2014)

Impetus and Background



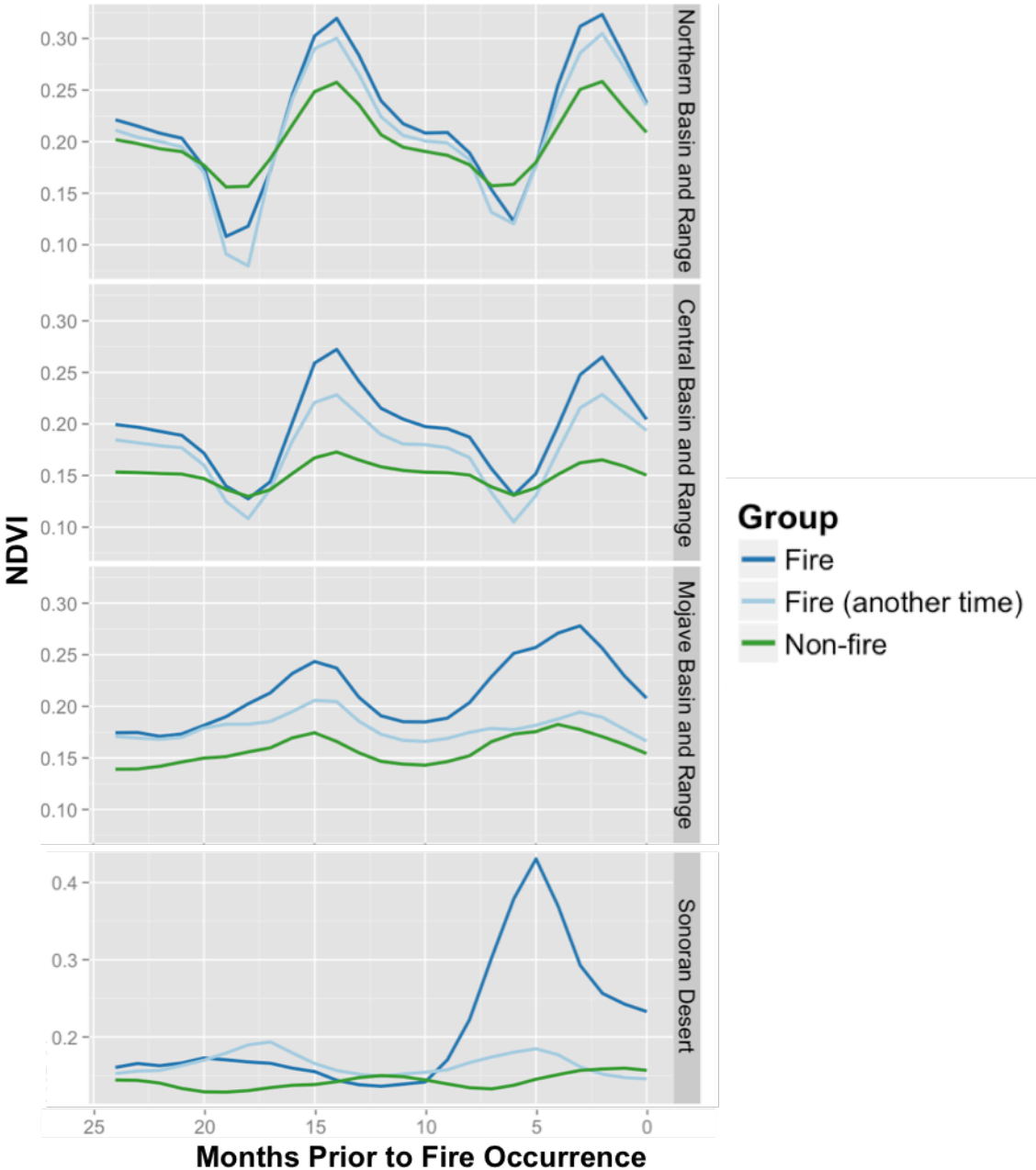
Impetus and Background



Adapted from Brooks and Chambers, 2011

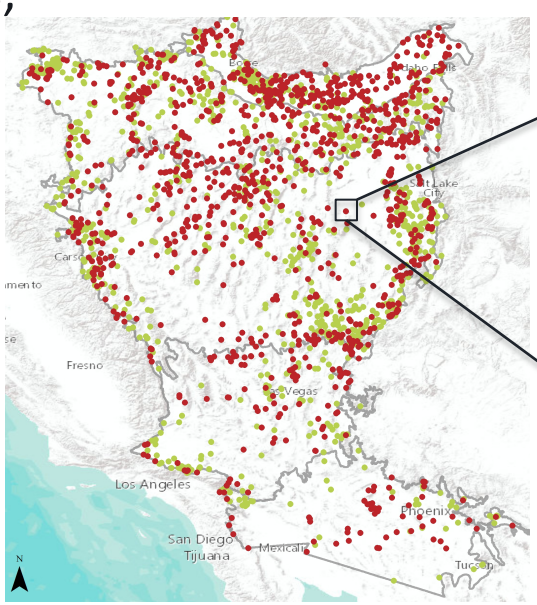
Impetus and Background

- Preliminary analyses of **remotely sensed** early-warning indicators of fire risk
- Signal in antecedent Normalized Difference Vegetation Index (NDVI) **across all desert ecoregions**
- Fuel indicators can be coupled with **other, high-frequency weather indicators**

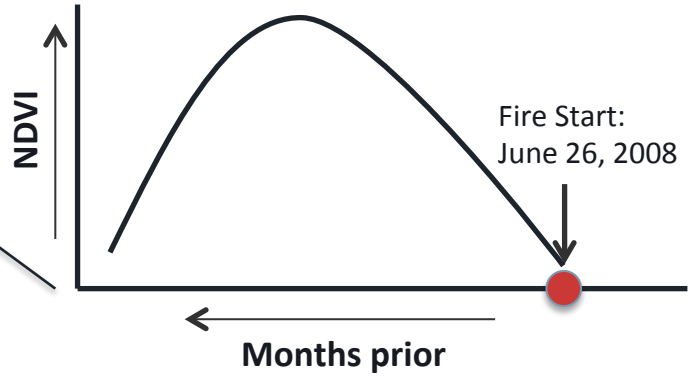


Methodological steps (Following Gray et al. 2018, *Earth Systems Science Data*)

1) Identify an empirically-based threshold of 'large wildfire' (300 acres) in desert ecoregions;
2) Sample historical small wildfires from the FPA Fire Occurrence Dataset (Short, 2017) and historical large wildfires from the MODIS Burned Area Dataset (Roy et al 2008);
3) Relate response data (i.e., small or large fire) to static *and* dynamic spatial predictors;



E.g., for a sample that burned on June 26, 2008, dynamic fuel and weather predictors are drawn from the weeks and months prior to this date



Methodological steps, continued

4) Use a Machine Learning technique (i.e., Random Forests; see Cutler et al. 2018) to train statistical models and **predict the conditional probability of large wildfire (i.e., Fire Risk)**;
5) Leverage continually updated, 'wall-to-wall' datasets of predictors to create spatial predictions (i.e., raster maps) across all desert ecoregions

Operational Definition of Fire Risk for this Tool

Fire Risk

The probability that an area on the landscape will burn in a large wildfire (i.e., >300 acres), *conditional* on an ignition event or fire spreading to that area.

Static *and* Dynamic Predictors

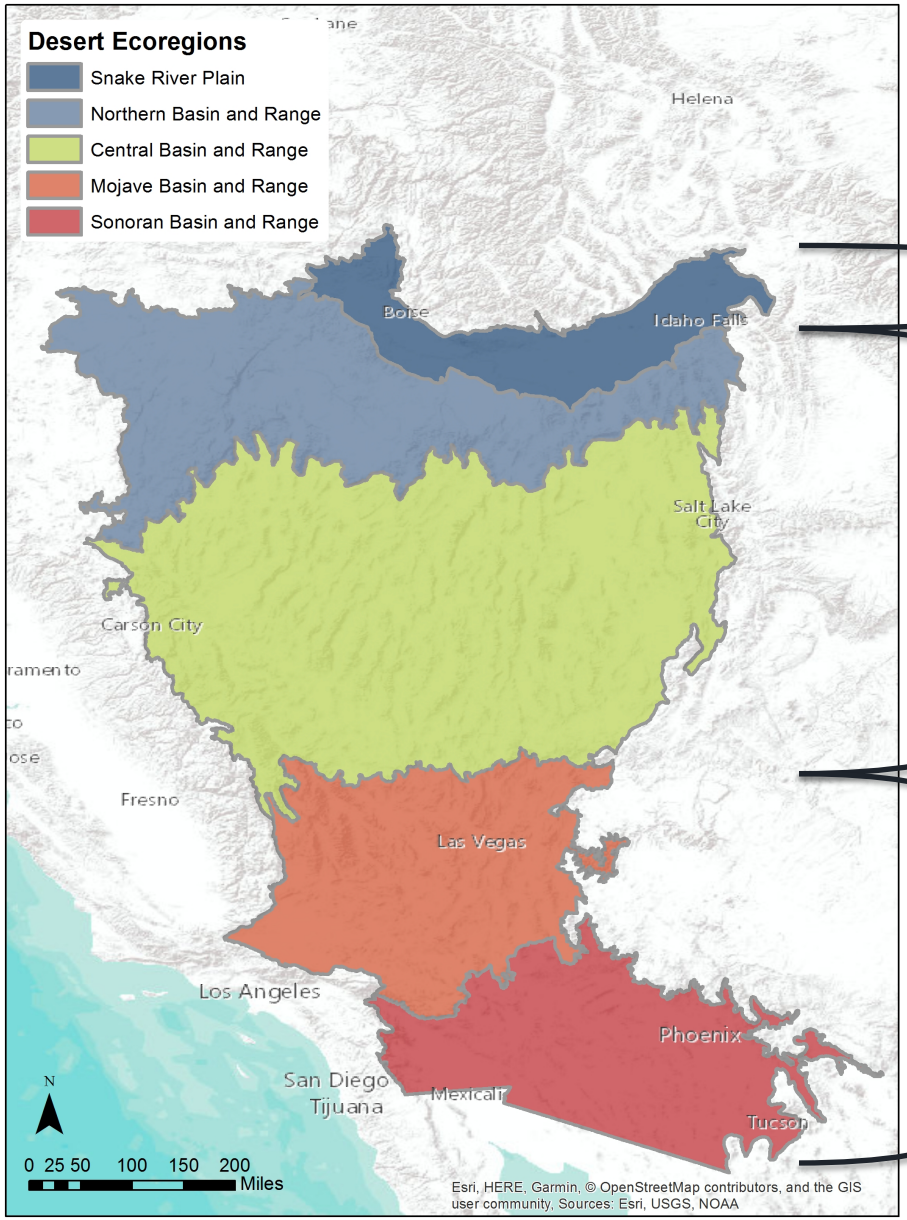
* = Static, * = Dynamic

Predictor Set	Source	Resolution
Climate variables		
Annual precipitation, Temperature seasonality (CV), Precipitation of the warmest month, Mean temperature of the wettest month, Mean temperature of the warmest month *	PRISM[1]	800 m
Long-term fuel and topography variables		
EVI[2] profile in the years preceding fire year *	MODIS	250 m
Elevation, Slope, Aspect, Topographic Roughness *	USGS	30 m
Near-term fuel variables		
EVI profile in the months preceding fire *	MODIS	250 m
Near-term weather variables		
100- and 1000-hr fuel moisture, Burning Index, Precipitation, Temperature, Relative Humidity, Specific Humidity, Potential Evapotranspiration, Solar Radiation, Wind Speed, Wind Direction *	GridMet[3]	4 km

[1] PRISM = Precipitation-elevation Regressions on Independent Slopes Model (Daly et al., 1994)

[2] EVI = Enhanced Vegetation Index, an index of fuel availability that is derived from 16-day composites of MODIS imagery.

[3] GridMet = Gridded Surface Meteorological Data (Abatzoglou, 2013). Values were taken for the week preceding fire occurrence.

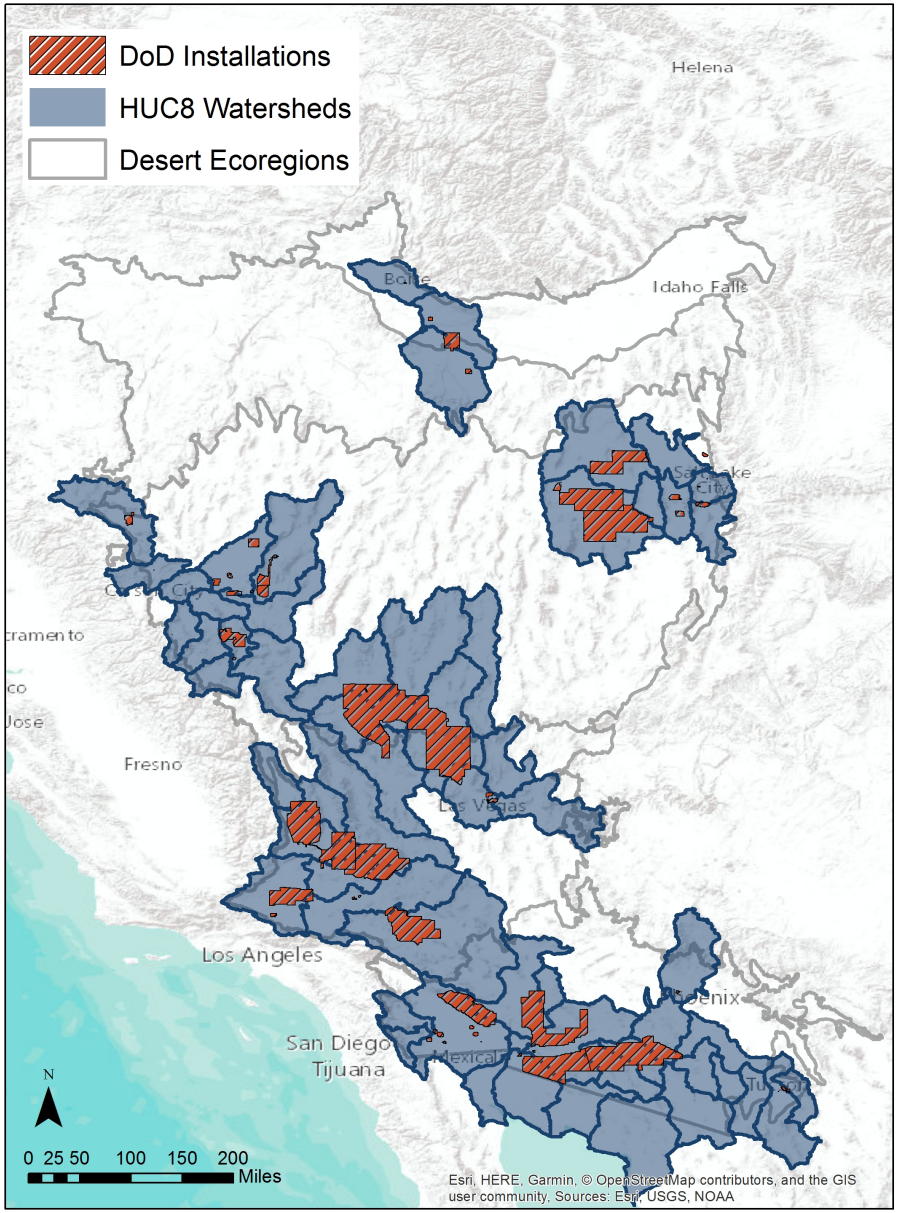


The Modeled Extent

Model 1: Snake River Plain

Model 2: Northern and Central Basin and Range

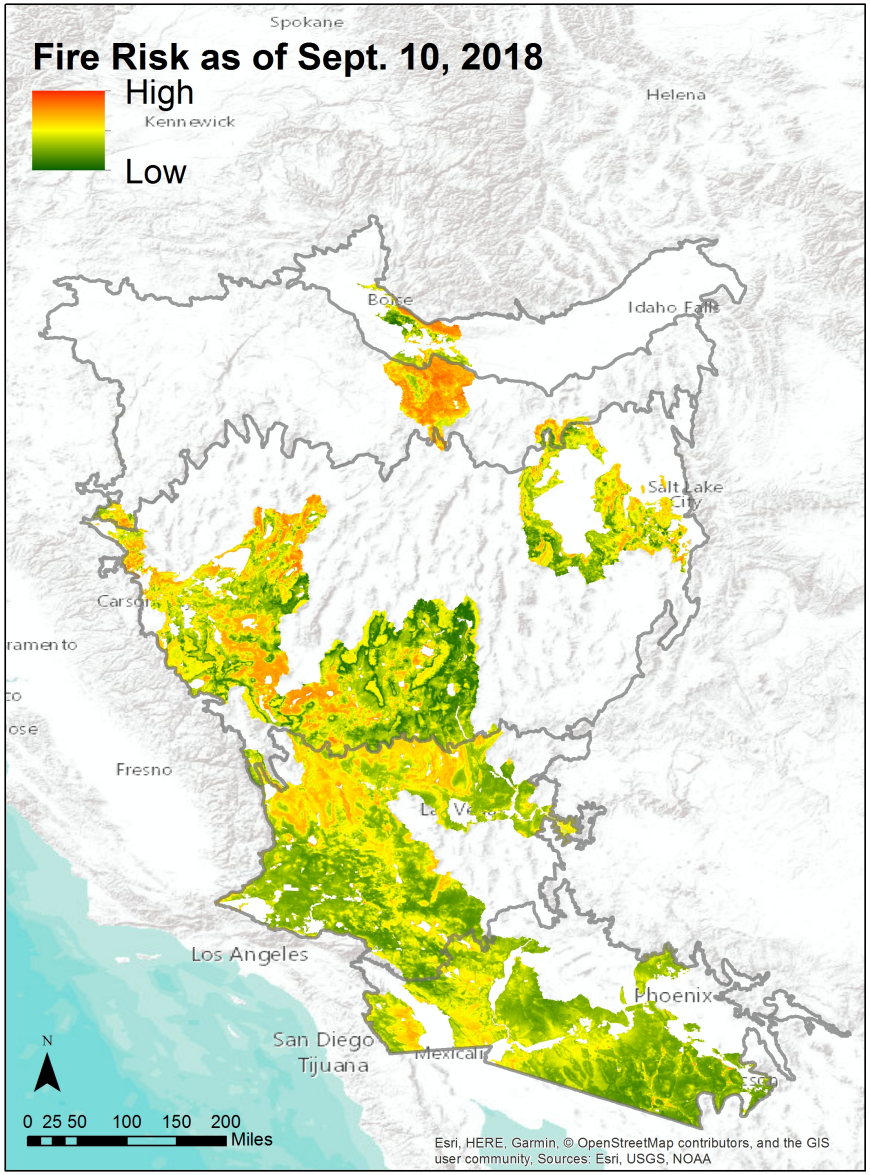
Model 3: Mojave and Sonoran Basin and Range

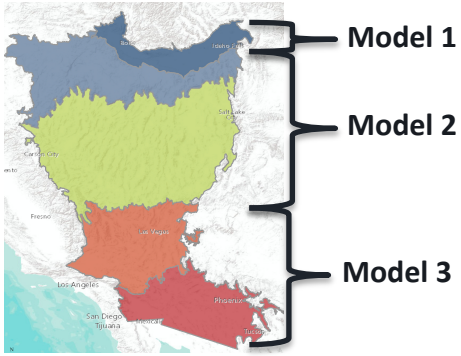


The Mapped Extent

- HUC8 watersheds that intersect DoD installations
- Masked all waterbodies (including dry lake beds), agriculture and urban areas
- Clipped to desert ecoregion boundaries

Model Results





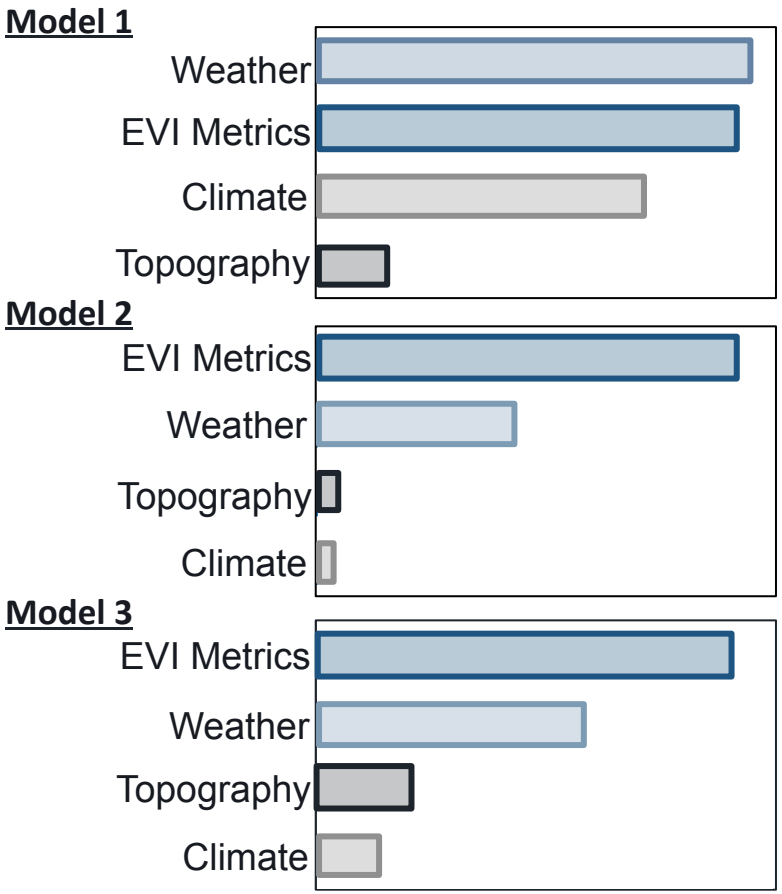
Model Accuracy against a Testing Dataset

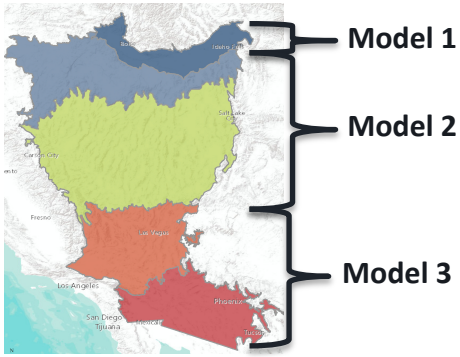
		Reference		Accuracy
Model 1 Prediction		Small	Large	
	Small	26	11 (FN)	
	Large	3 (FP)	21	0.77
Model 2 Prediction				
	Small	134	34 (FN)	
	Large	41 (FP)	119	0.77
Model 3 Prediction				
	Small	59	6 (FN)	
	Large	7 (FP)	64	0.90

FN = False Negative
FP = False Positive

Model Results

Predictor Variable Importance





Predictor Set

Climate variables

Annual precipitation, Temperature seasonality (CV), Precipitation of the warmest month, Mean temperature of the wettest month, Mean temperature of the warmest month

Long-term fuel and topography variables

EVI profile in the years preceding fire year

Elevation, Slope, Aspect, Topographic Roughness

Near-term fuel variables

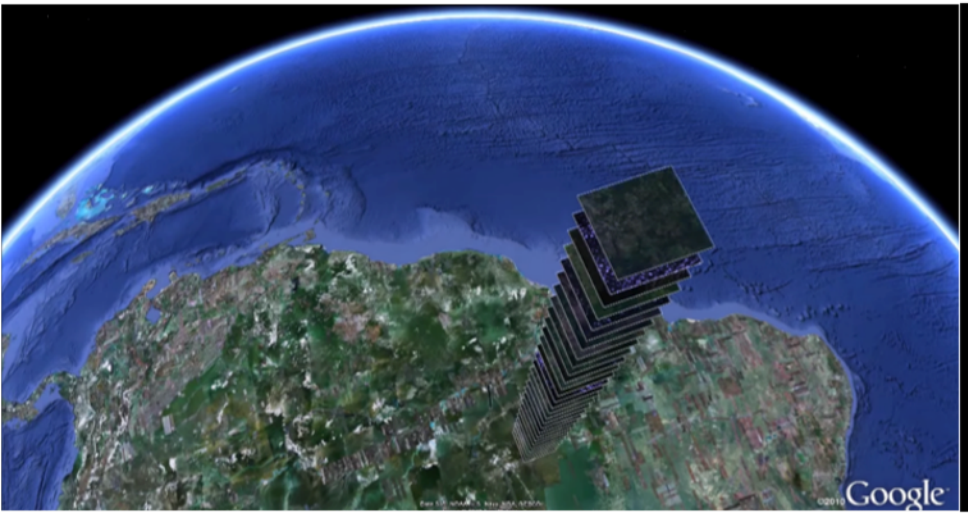
EVI profile in the months preceding fire

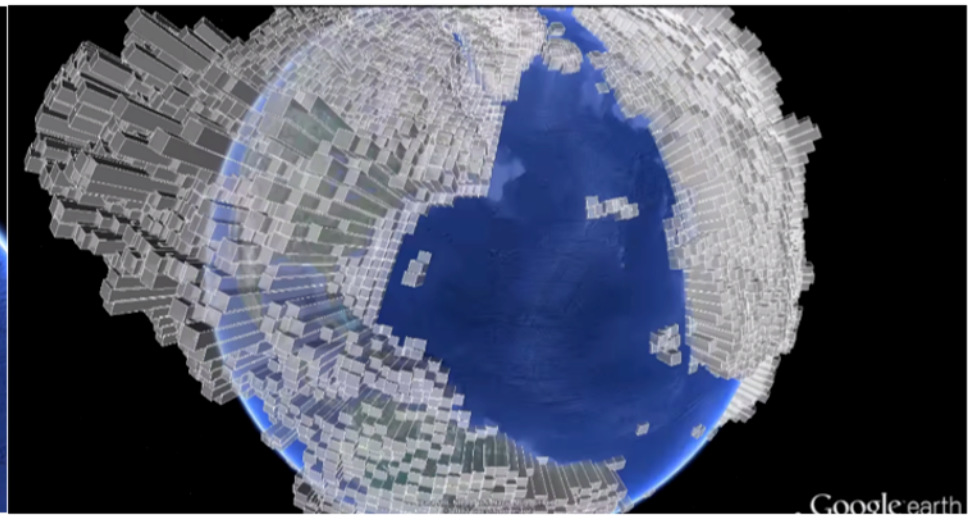
Near-term weather variables

100- and 1000-hr fuel moisture, Burning Index, Precipitation, Temperature, Relative Humidity, Specific Humidity, Potential Evapotranspiration, Solar Radiation, Wind Speed, Wind Direction

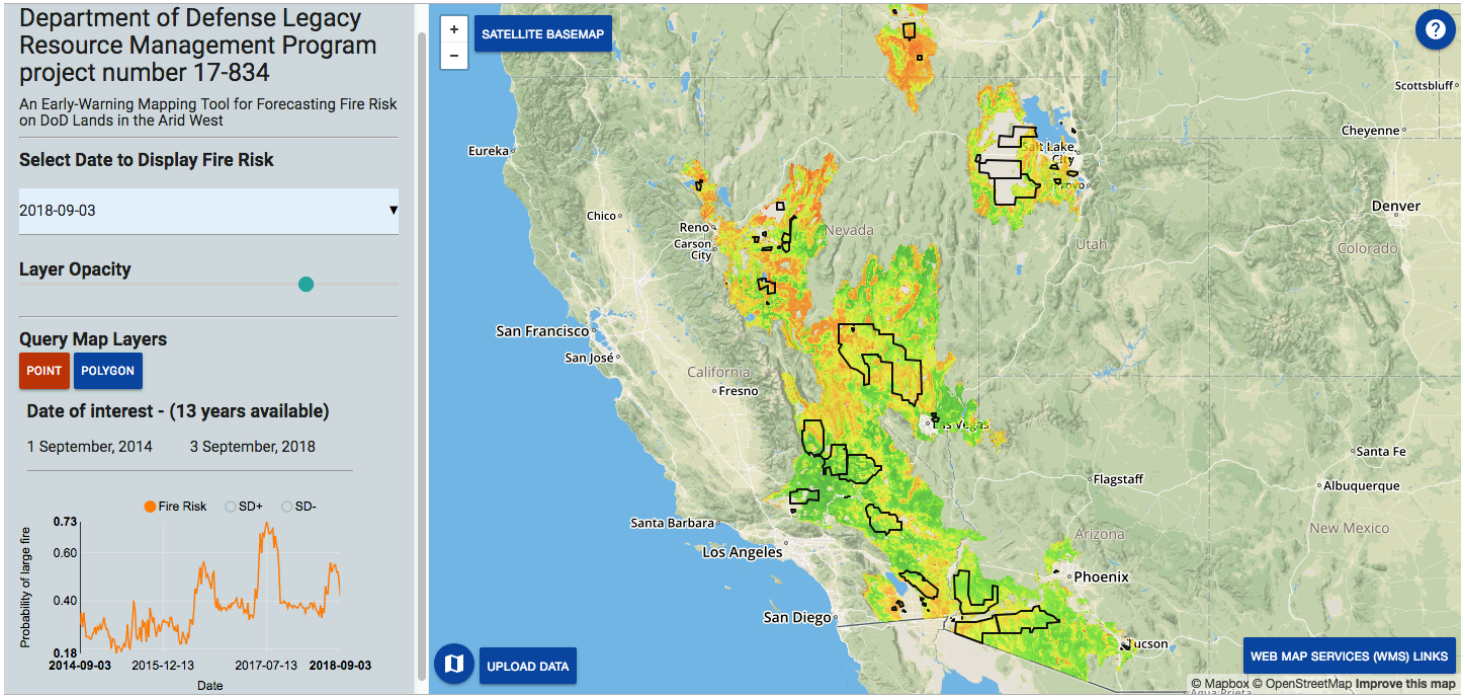
Continually Updated Maps of Fire Risk

- Created with Google Earth Engine (Gorelick et al. 2017)
- 688 (and counting) maps from 2005 to the present week
- Maps pushed weekly to the Interactive Mapping Tool





Mapping Tool



Key Features and Functionalities of the Tool

- **View** any of the 688 maps of fire risk from 2005 to the present week
- **Query and graph** the mean and standard deviation of predicted fire risk over a continuous 4-year time period
- **Upload** custom shapefiles (points and polygons) to view over fire risk maps
- **Add Web Mapping Service (WMS)** layers of fire risk to a stand-alone GIS application (e.g., ArcGIS)

Example Use Case 1 : Mitigation of wildfire risk around critical wildlife habitat

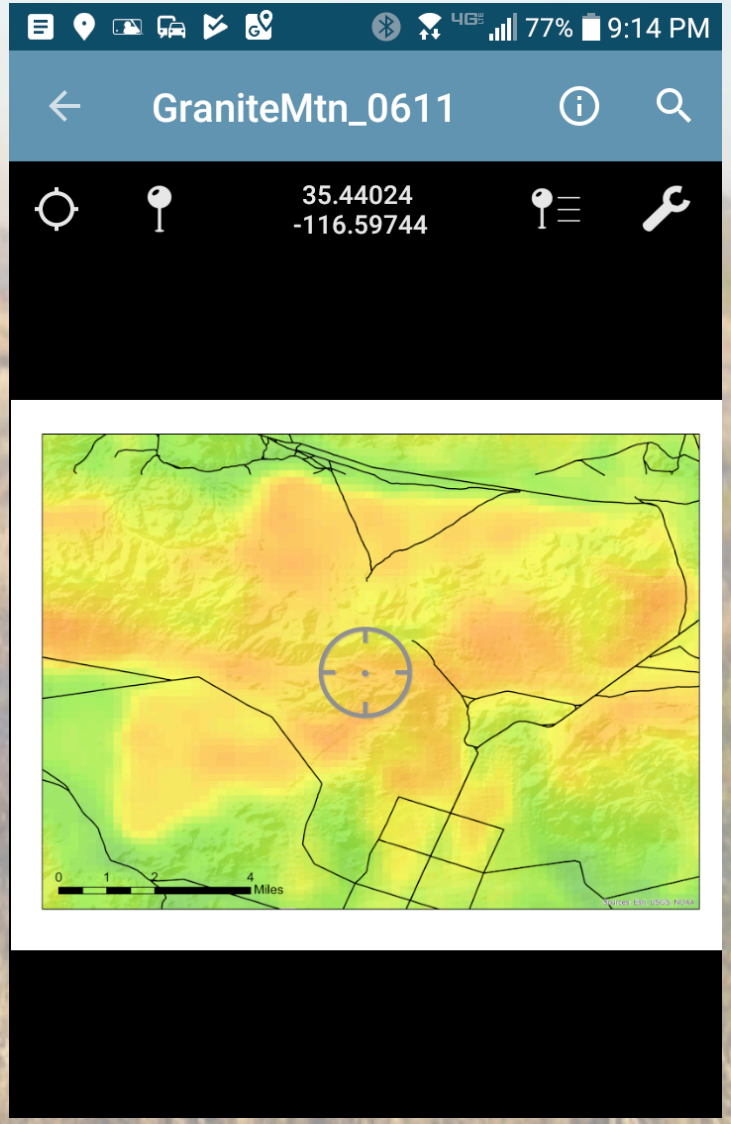
- Approximately 30,000 acres of Mojave desert tortoise critical habitat are on Naval Air Weapons Station China Lake
- A USFWS Biological Opinion requires fire management measures at China Lake to meet desert tortoise conservation, such as putting a buffer or halting operations around targets to lessen the probability of fire (Karen Howe, personal communication)
- Download shapefiles of final or proposed critical habitat from the ECOS Environmental Conservation Online System at https://ecos.fws.gov/ecp/report/table/critical-habitat.html

Example Use Case 2 : Near-term monitoring of active fires

- Time-sensitive and mission-critical decisions may be based on active fires within or around installation boundaries
- Monitor the last 24 hours, 48 hours, or 7 days of active fire detections in relation to current fire risk and installation boundaries
- Download near real-time active fire data from the Fire Information for Resource Management System (FIRMS) at https://firms.modaps.eosdis.nasa.gov/active_fire/#firms-shapefile

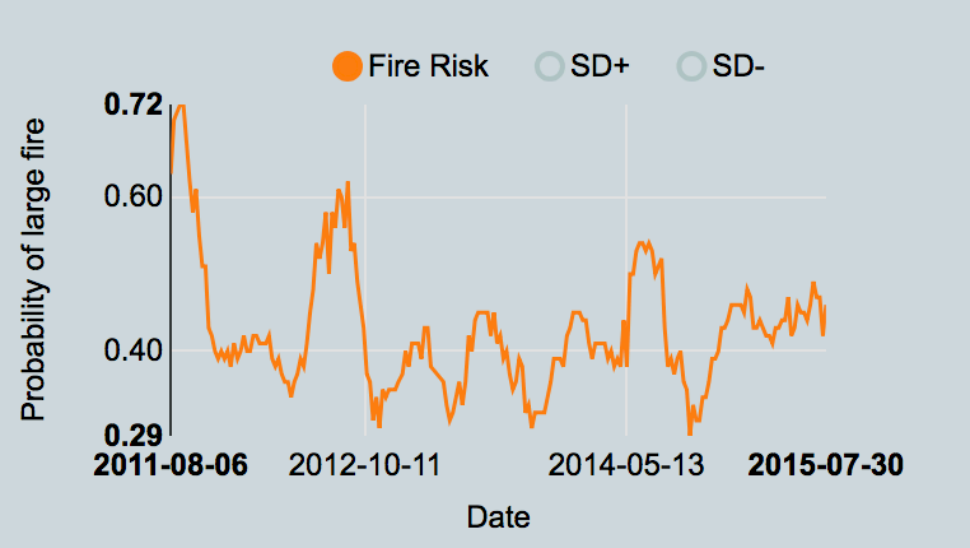
Example Use Case 3 : Integration with GIS

- Site-inspections may be necessary to determine where fuel loads are especially hazardous
- Mobile, GPS-enabled maps of fire risk can reduce the 'search space' in the field
- Create georeferenced PDF maps in ArcMAP and import to Avenza Maps for field-ready maps



Example Use Case 4 : Long-term monitoring and planning

- Time-series graphs lend insight into the timing and magnitude in means and extremes of fire risk over specified time periods
- Restoration and treatment units may be used to mitigate fire risk at targeted areas on the landscape
- Upload custom areas of interest to evaluate fire risk within completed treatments, or to inform planned treatments



Next Steps

- Beta release of the tool is scheduled for October 1, 2018
- Currently working with DoD on secure access to the tool for DoD and federal partners
- Please contact me anytime with questions or feedback at miranda@csp-inc.org

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