

Lessons Learned on Dynamic Data-Driven Wildfire Modeling in WIFIRE

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How do we Better Predict Wildfire Behavior?

Fire is Part of the Natural Ecology....

... but requires Monitoring, Prediction and Resilience

- Wildfires are critical for ecology, but volatile
- Fuel load is high due to fire suppression over the last century
- Drought, higher temperatures
- Better prevention, prediction and maintenance of wildfires is needed



Disaster management of (ongoing) wildfires heavily *relies on* understanding their **Direction** and **Rate of Spread (RoS)**.



What was lacking is...

a dynamic system integration of real-time sensor networks, satellite imagery, near-real time data management tools, wildfire simulation tools, and connectivity to emergency command centers

.... before, during and after a firestorm.



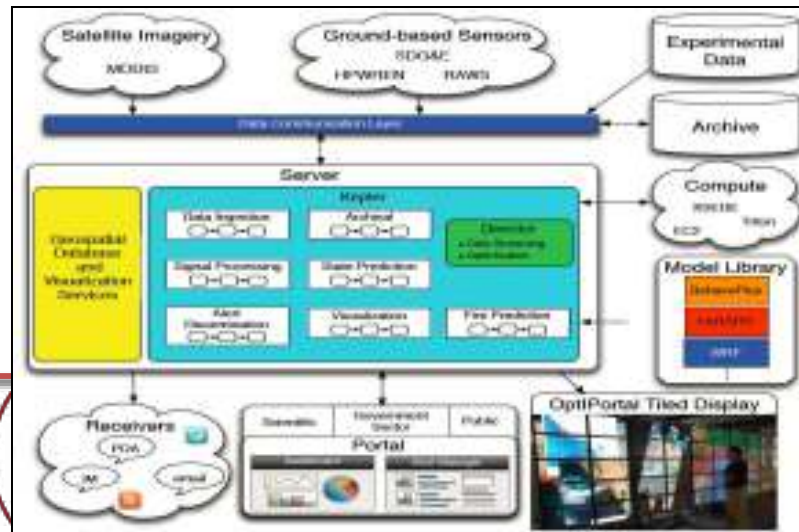
WIFIRE: A Scalable Data-Driven Monitoring, Dynamic Prediction and Resilience Cyberinfrastructure for Wildfires



Big Data

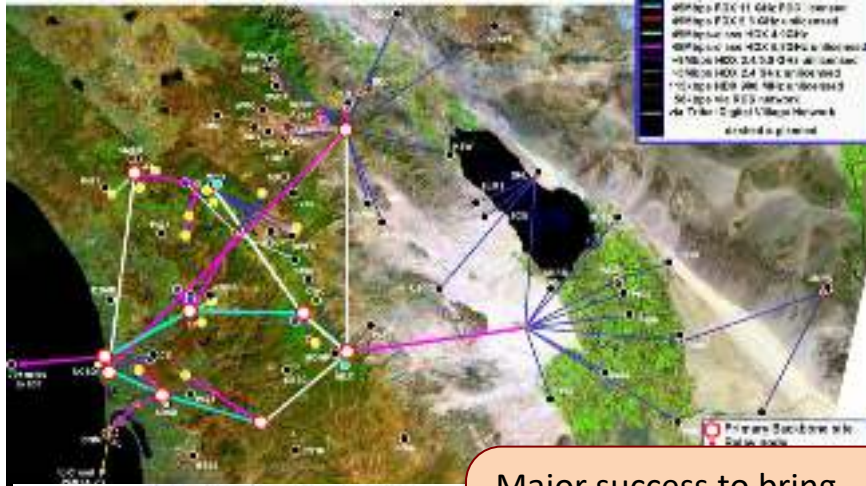


Monitoring
Visualization
Fire Modeling



High Performance Wireless Research and Education Network

FARSITE



Major success to bring internet to incident command in the field. Used in over 20 fires over time.



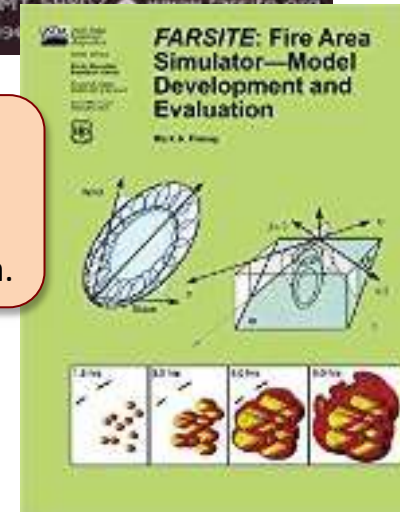
<http://hpwren.ucsd.edu/cameras>



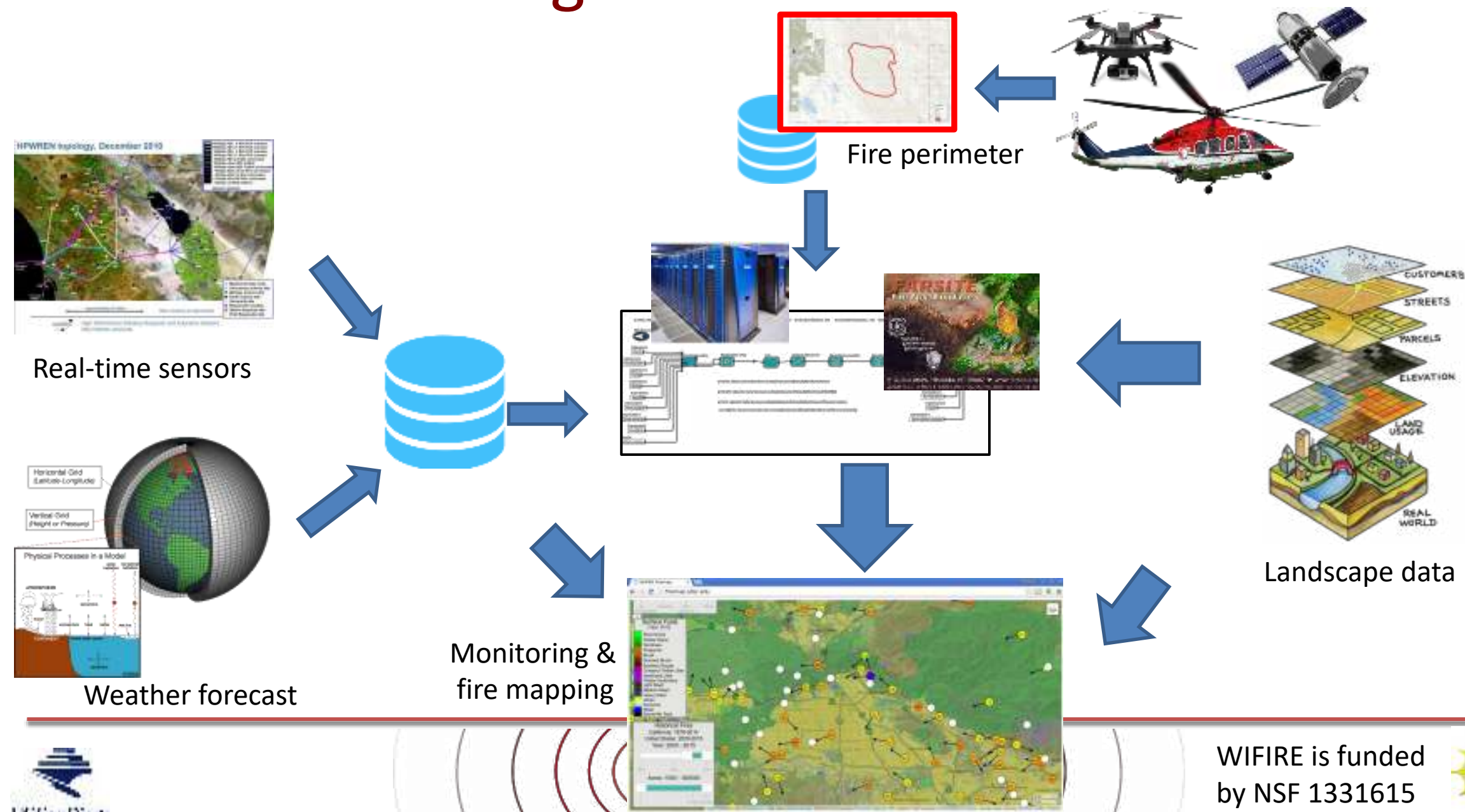
>160 Meteorological Sensors and Growing



Most popular operational fire behavior modeling system.



Fire Modeling Workflows in WIFIRE

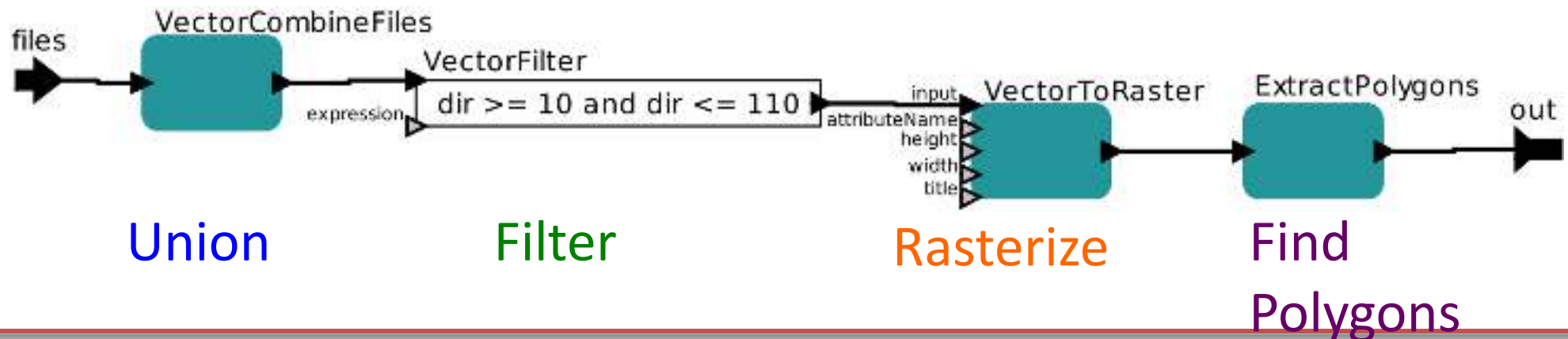


WIFIRE is funded
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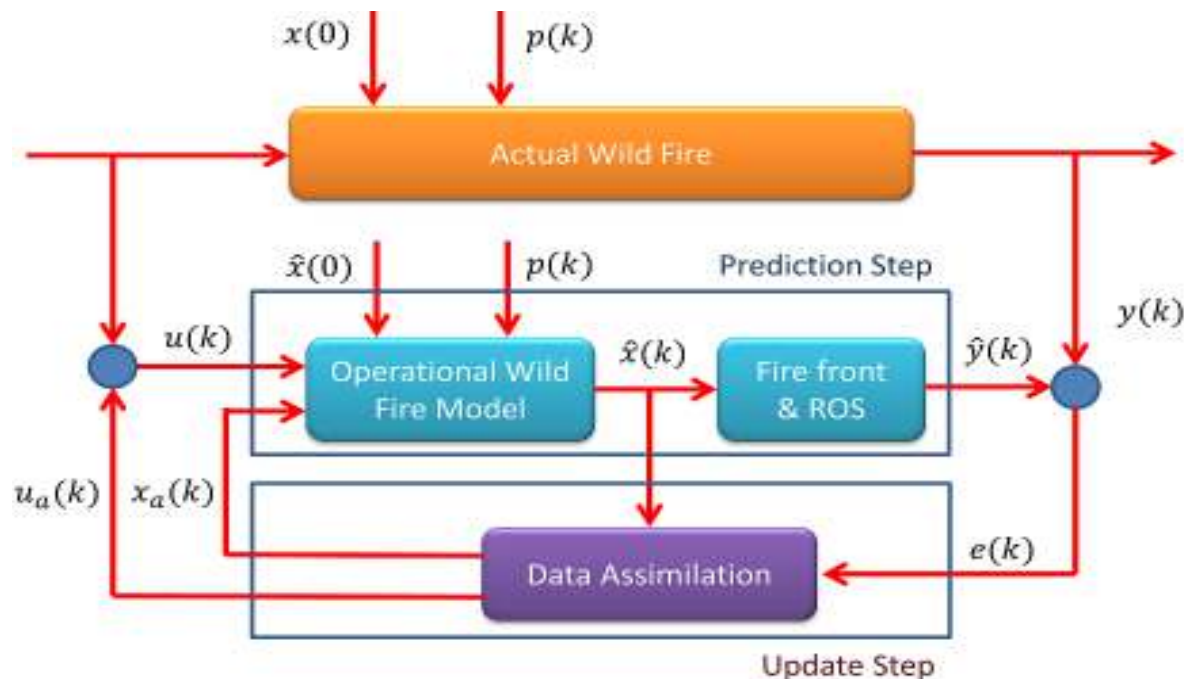
Many Integrated Workflows and Processing Tools

- Components for modeling and data tools
- Understanding of geo data formats
- Transparent interaction with data and computing resources
- Open source and extensible



Closing the Loop using Big Data

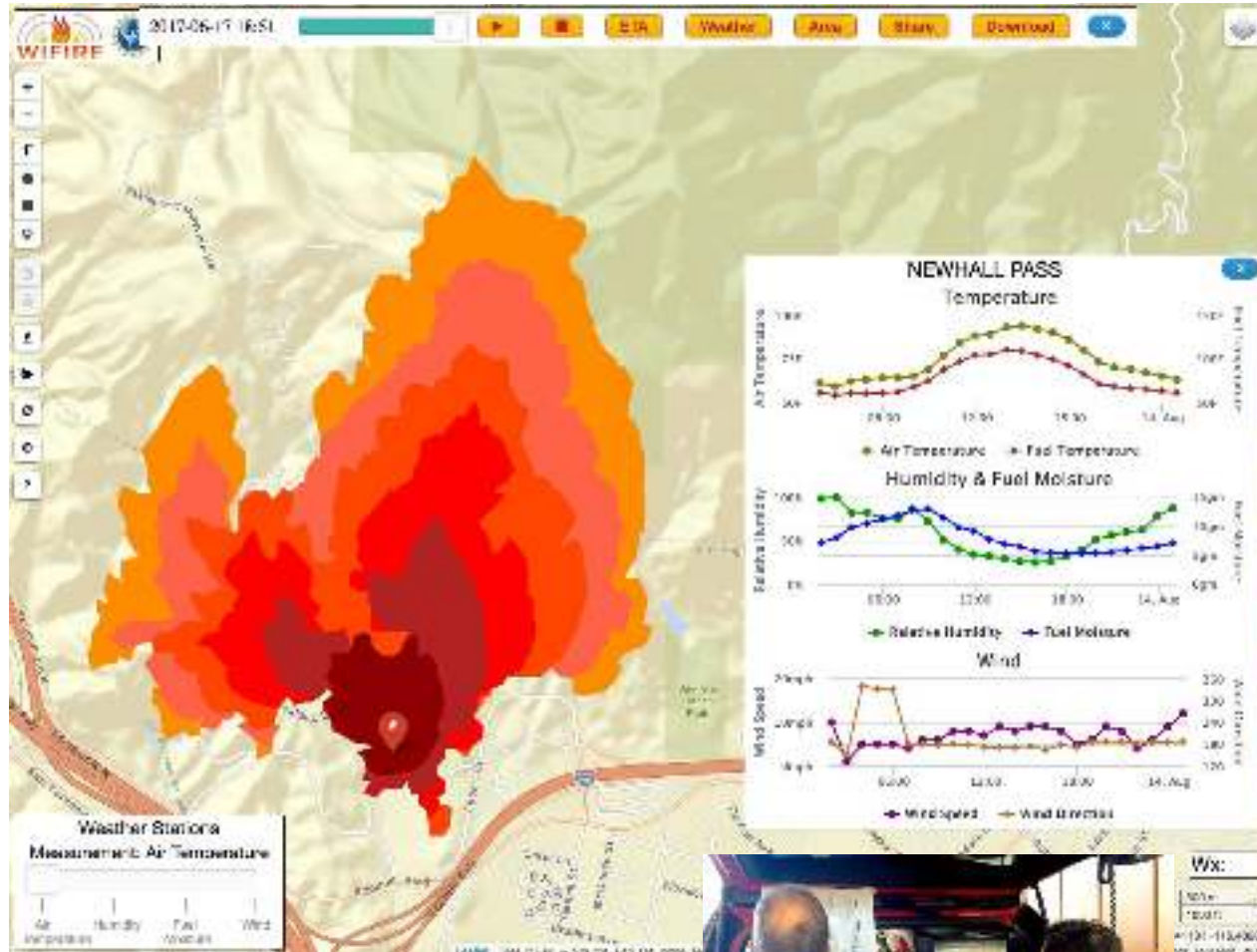
-- Wildfire Behavior Modeling and Data Assimilation --



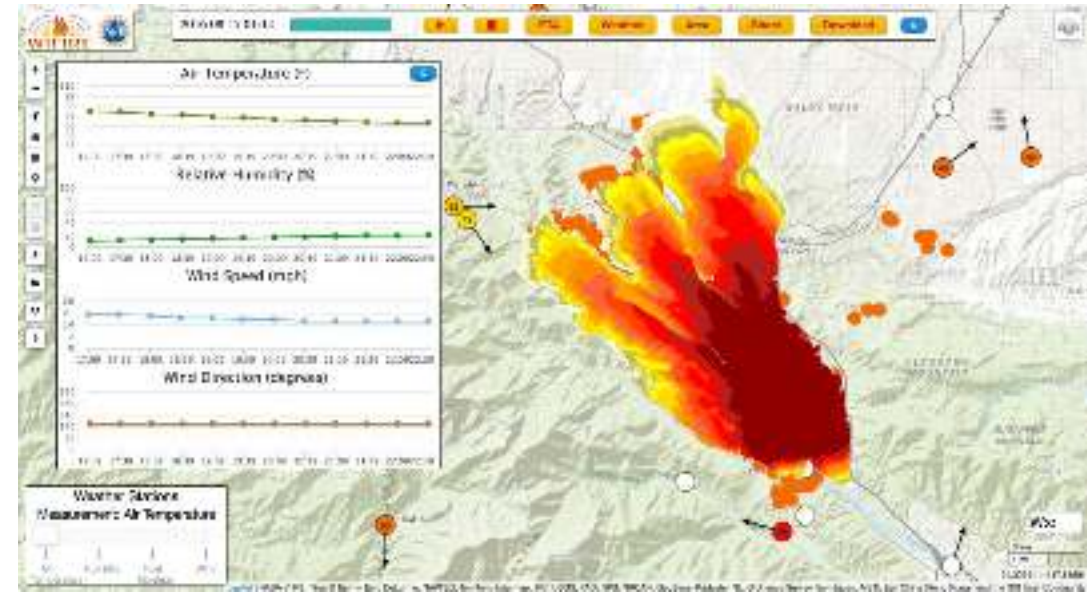
Conceptual Data Assimilation Workflow with Prediction and Update Steps using Sensor Data

- Computational costs for existing models too high for real-time analysis
- *a priori* -> *a posteriori*
 - Parameter estimation to make adjustments to the (input) parameters
 - State estimation to adjust the simulated fire front location with an a posteriori update/measurement of the actual fire front location

Data-Driven Fire Progression Prediction Over Three Hours



August 2016 – Blue Cut Fire

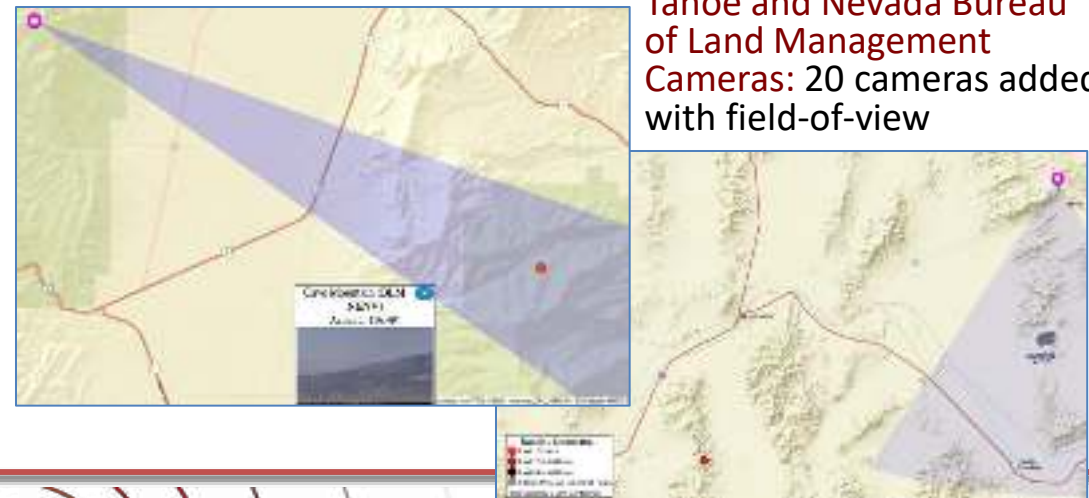


Collaboration with LA and SD Fire Departments

<http://firemap.sdsc.edu>



Tahoe and Nevada Bureau of Land Management Cameras: 20 cameras added with field-of-view



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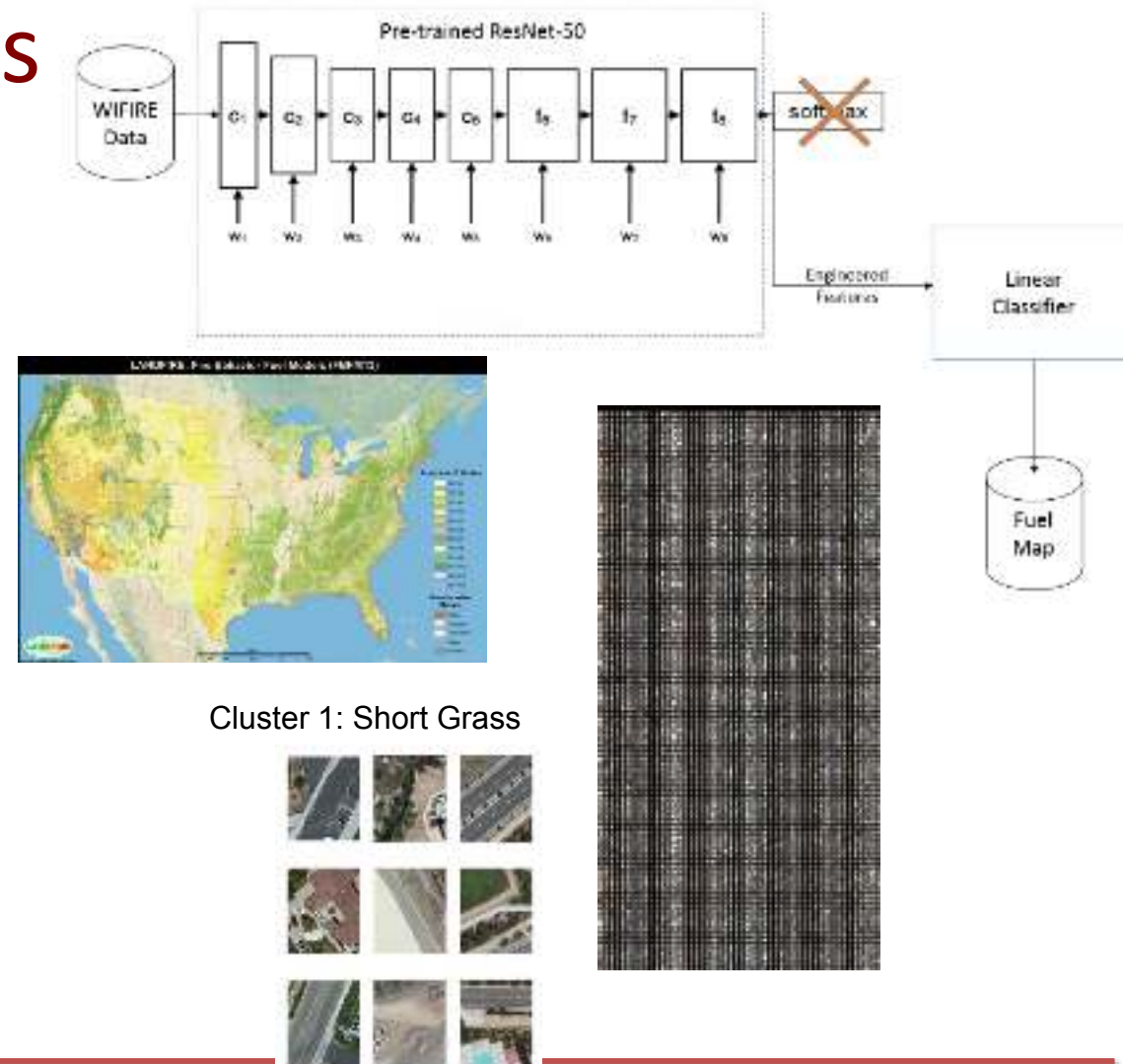


Some Machine Learning Case Studies

- Smoke and fire perimeter detection based on imagery
- Prediction of Santa Ana and fire conditions specific to location
- Prediction of fuel build up based on fire and weather history
- NLP for understanding local conditions based on radio communications
- Deep learning on multi-spectra imagery for high resolution fuel maps
- Classification project to generate more accurate fuel maps (using Planet Labs satellite data)

Classification project to generate more accurate fuel maps

- Accurate and up-to-date fuel maps are critical for modeling wildfire rate of speed and potential burn areas.
- Challenge:
 - USGS Landfire provides the best available fuel maps every two years.
 - The WIFIRE system is limited by these potentially 2-year old inputs. Fuel maps created at a higher temporal frequency is desired.
- Approach:
 - Using high-resolution satellite imagery and deep learning methods, produce surface fuel maps of San Diego County and other regions in Southern California.
 - Use LandFire fuel maps as the target variable, the objective is create a classification model that will provide fuel maps at greater frequency with a measure of uncertainty.

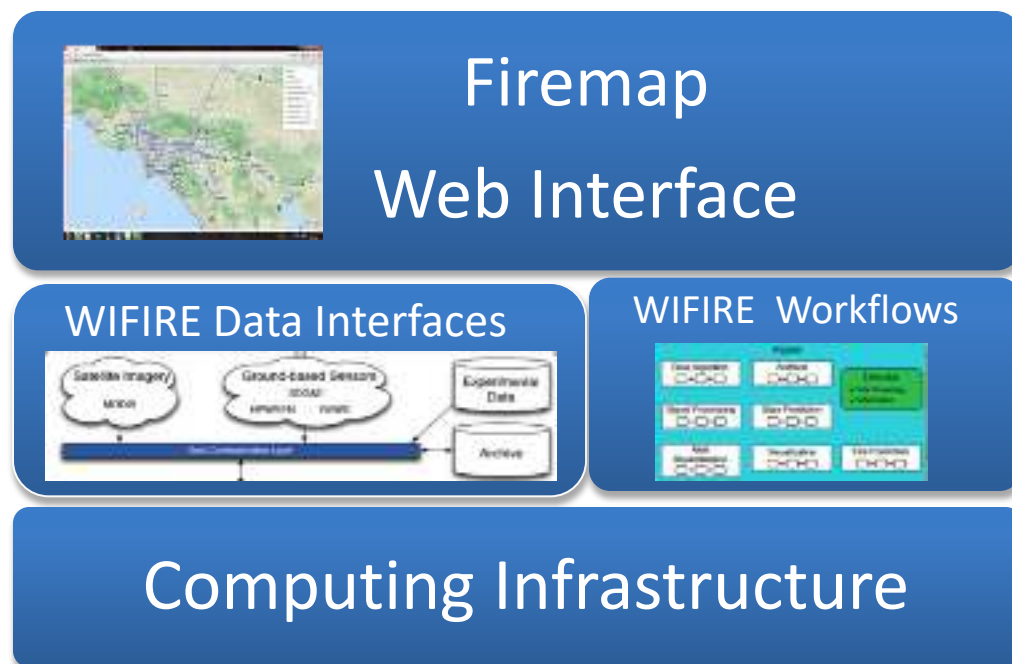




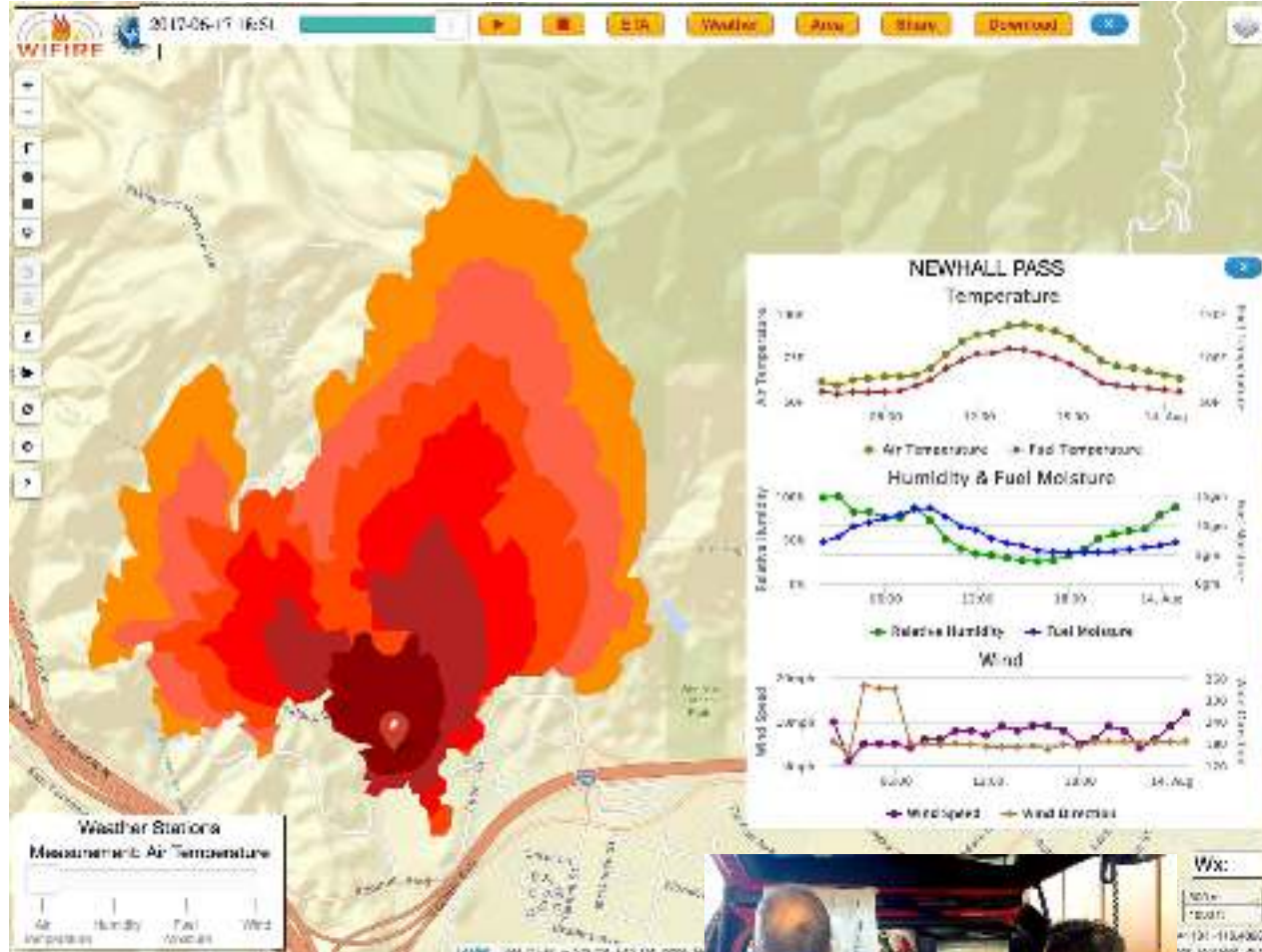
Firemap Tool

<http://firemap.sdsc.edu>

- A web-based GIS environment:
 - access information related to fire behavior
 - analyze what-if scenarios
 - model real-time fire behavior
 - generate reports
- Powered by WIFIRE

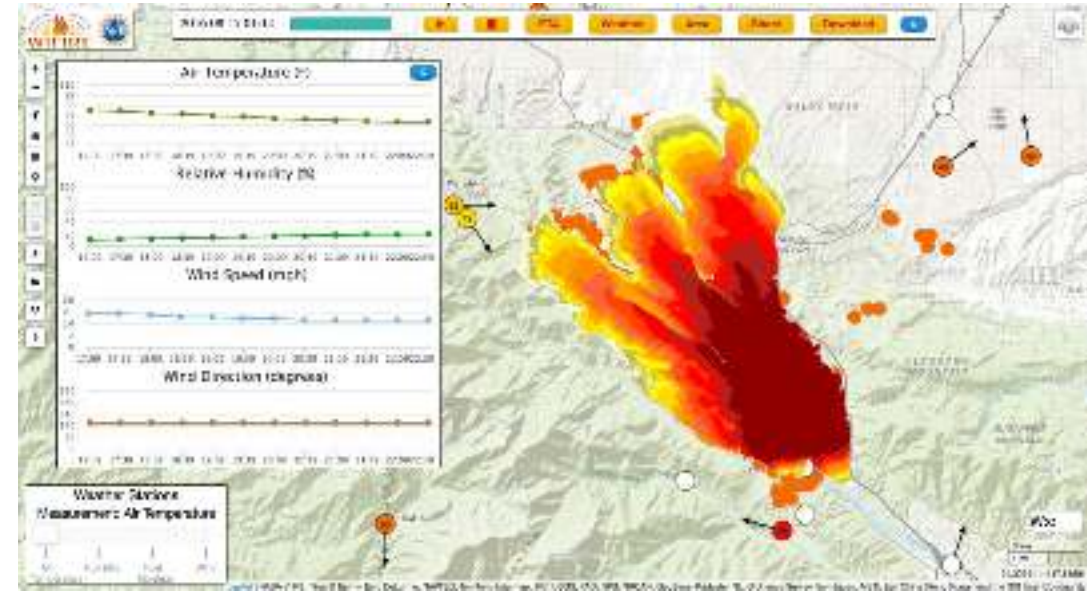


Data-Driven Fire Progression Prediction Over Three Hours

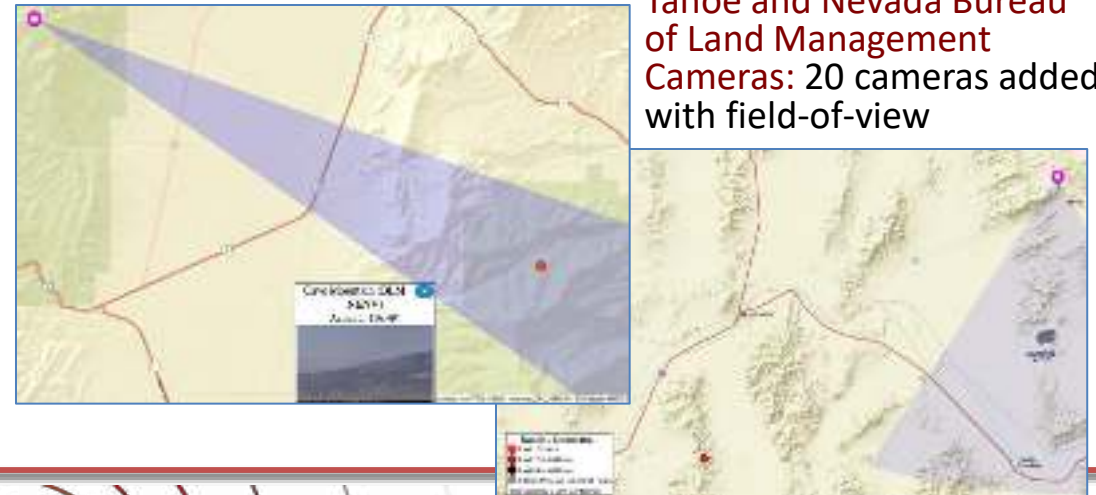


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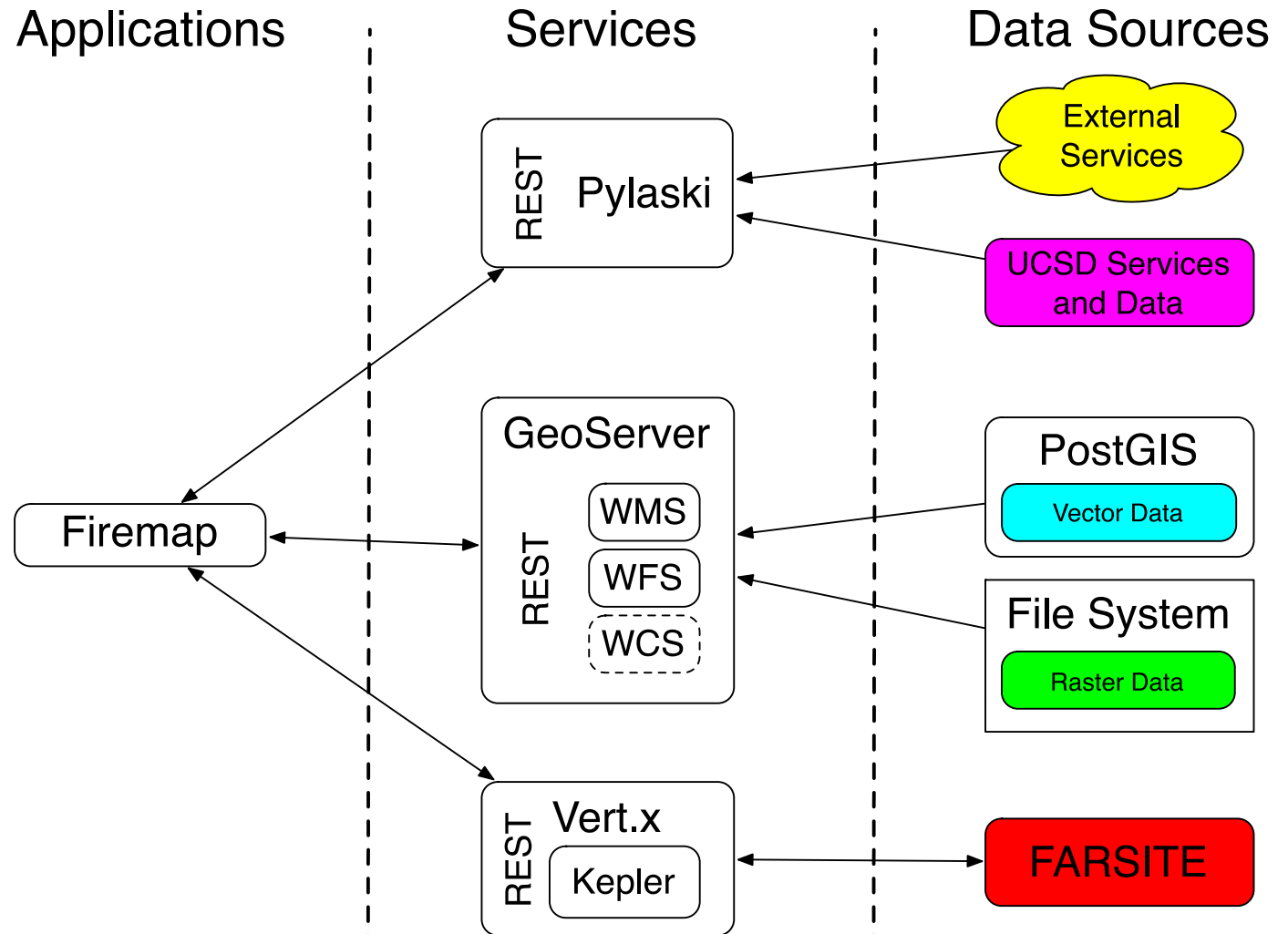


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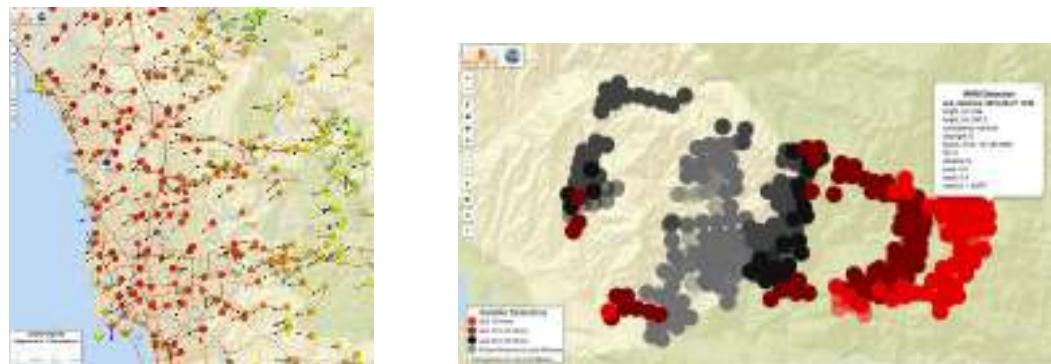


Firemap Overview

Architecture

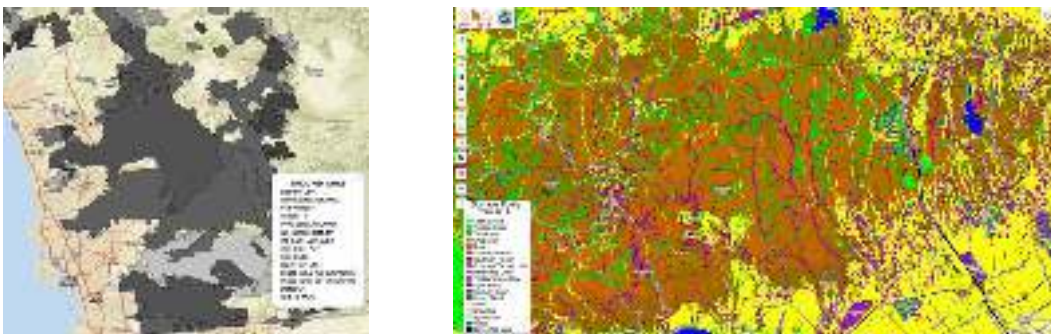


Firemap Layers



(a)

(b)

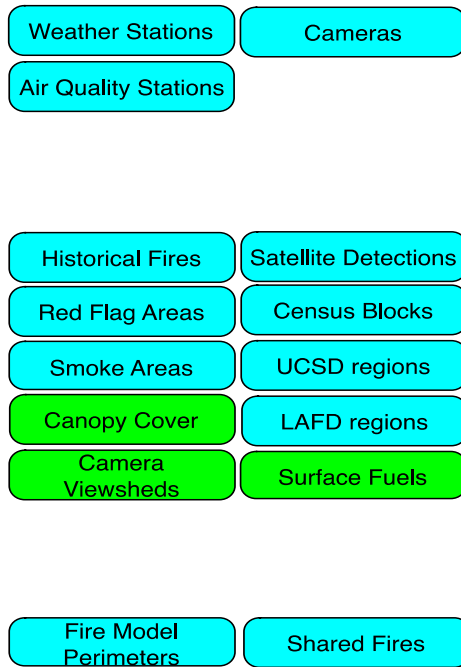


(c)

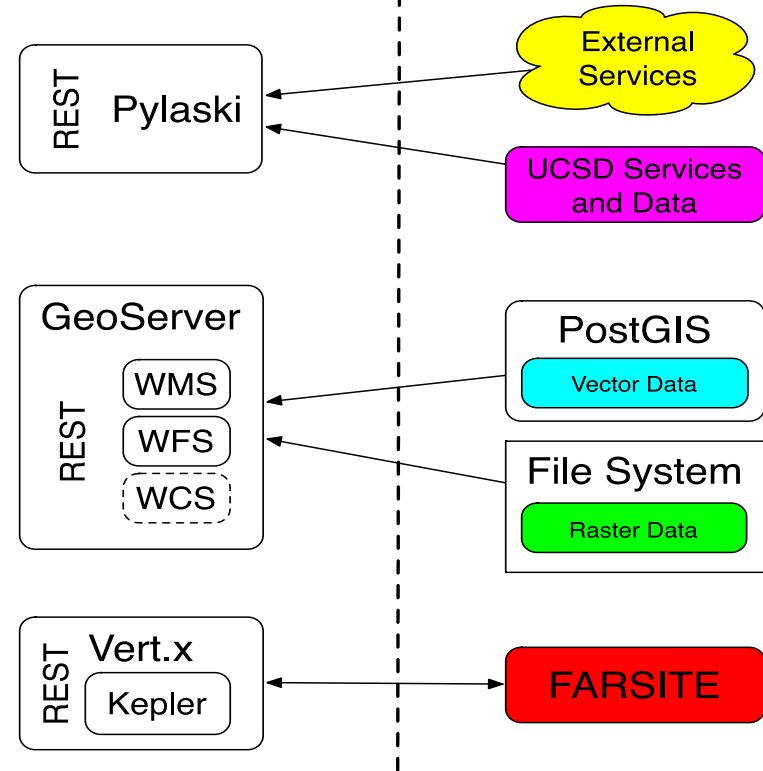
(d)

Figure 2: Firemap layers: (a) Weather Stations Layer showing MesoWest stations in San Diego County during Santa Ana conditions on 26 September, 2016; (b) VIIRS Layer showing 7 days of thermal detections of the Rey Fire, north of Santa Barbara, CA, during 14-21 August, 2016; (c) Historical Fires layer showing wildfires in San Diego County during 1970-2015; and (d) Surface Fuels Layer showing the vegetation fuels for the canyons northwest of Los Angeles in 2014.

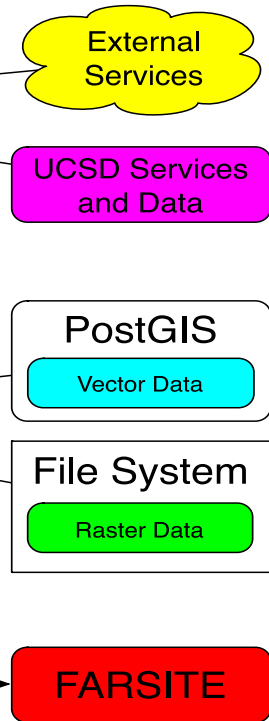
Map Layers



Services



Data Sources



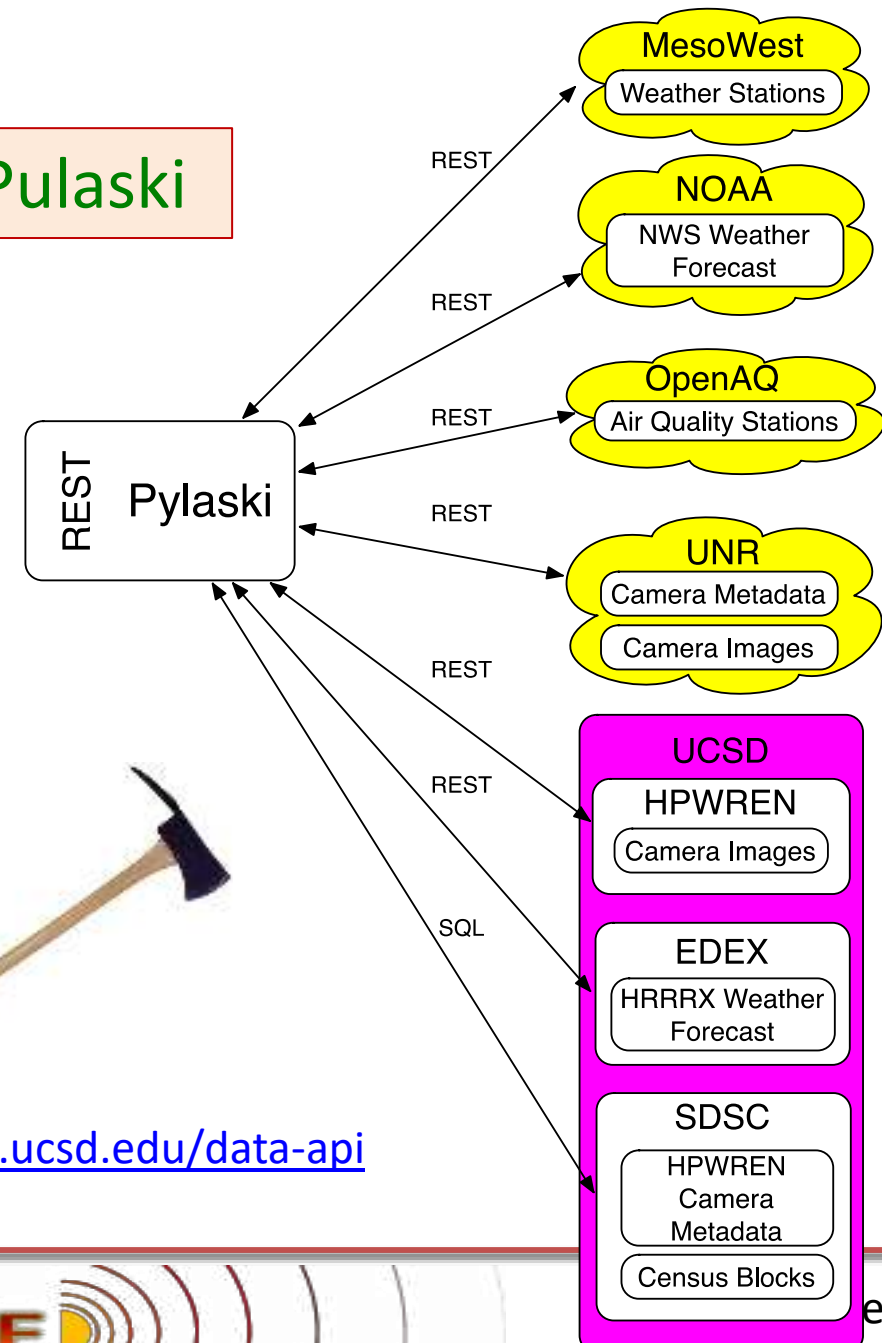
Pylaski

Pylaski = Python + Pulaski

- Uniform access to different data sources and types
 - e.g., OpenAQ (<http://openaq.org>) provides particulate matter, NO₂, SO₂, ozone, etc.
- Spatial and temporal queries
 - Closest to or within bounding box
 - Latest or within timespan
- Results are GeoJSON



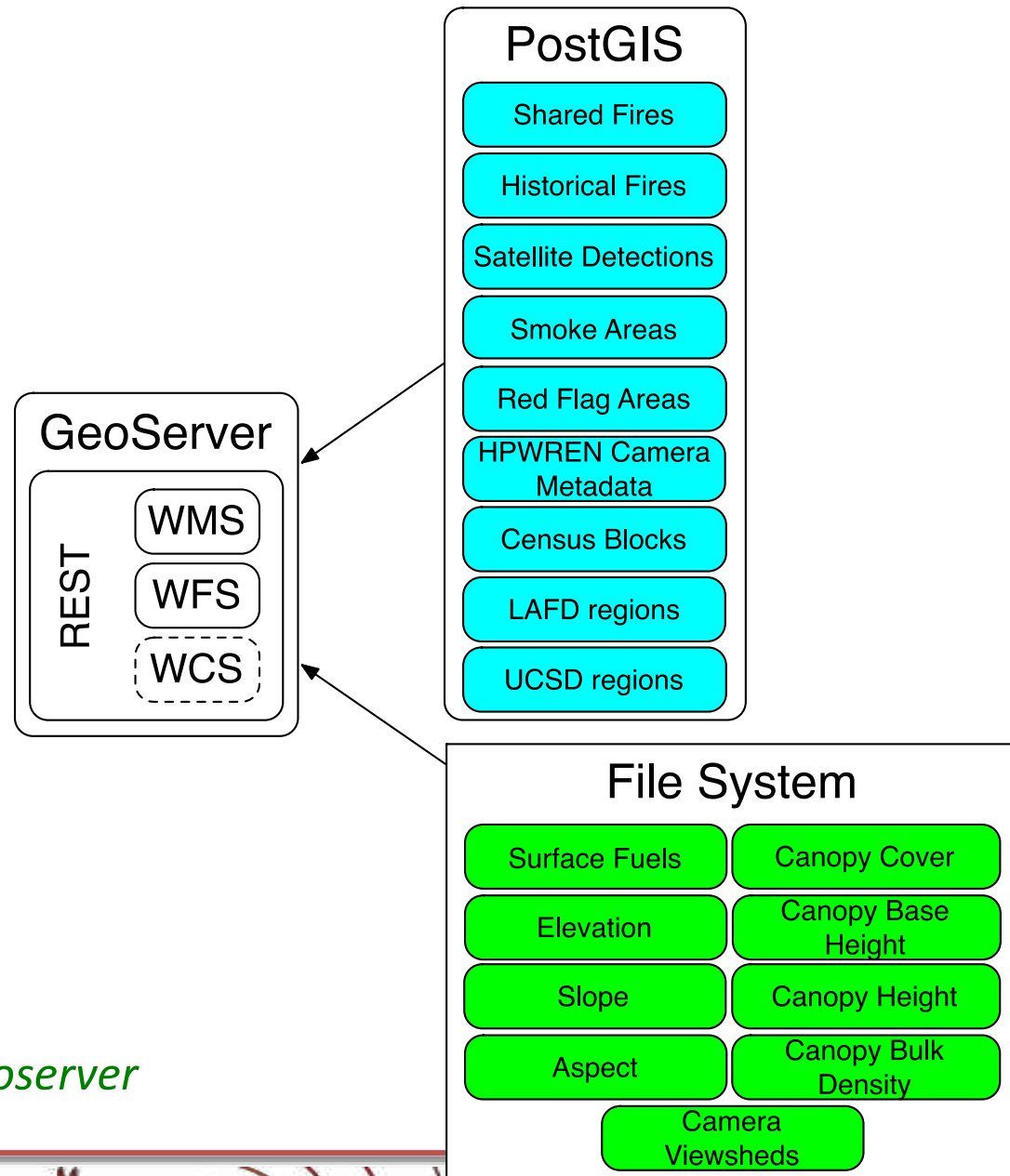
<https://wifire.ucsd.edu/data-api>



GeoServer

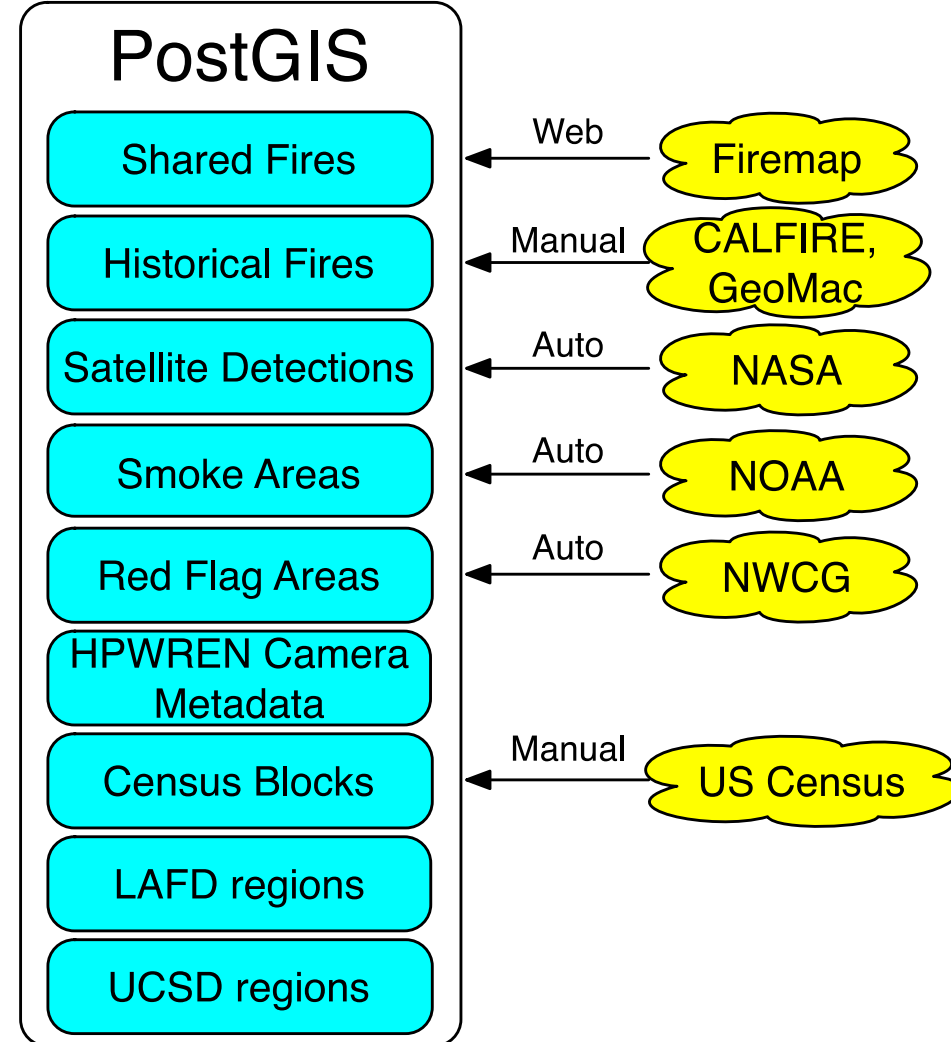
- REST access to GIS datasets
- WMS for image layers
 - Styling specifies color, opacity, etc.
- WFS for GeoJSON
- WCS for array data

<https://firemap.sdsc.edu:8443/geoserver>



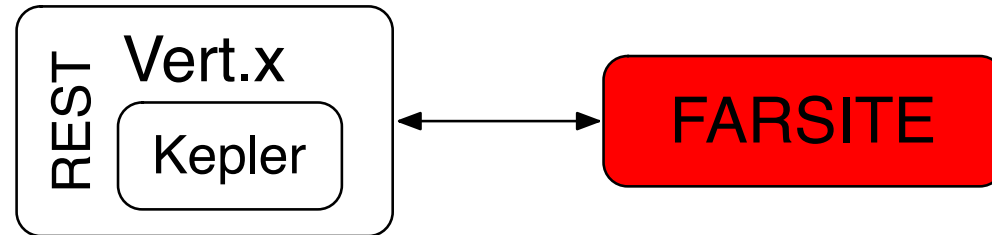
PostGIS

- Storage for vector GIS data
- Several datasets ingested every hour

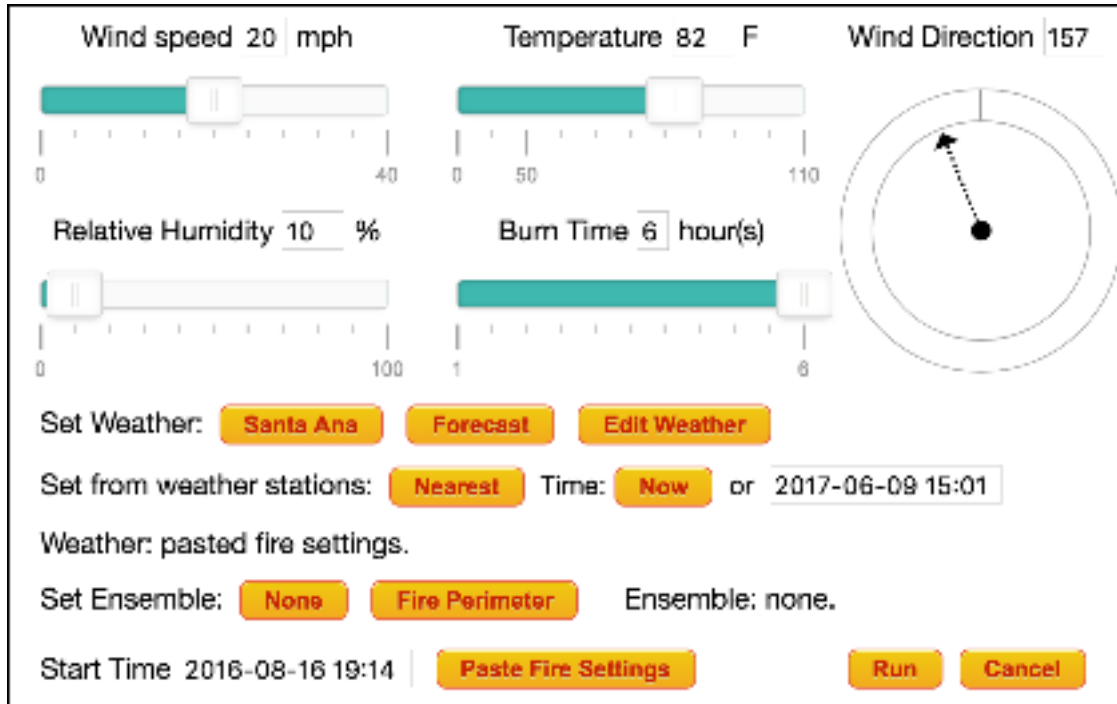


Kepler WebView

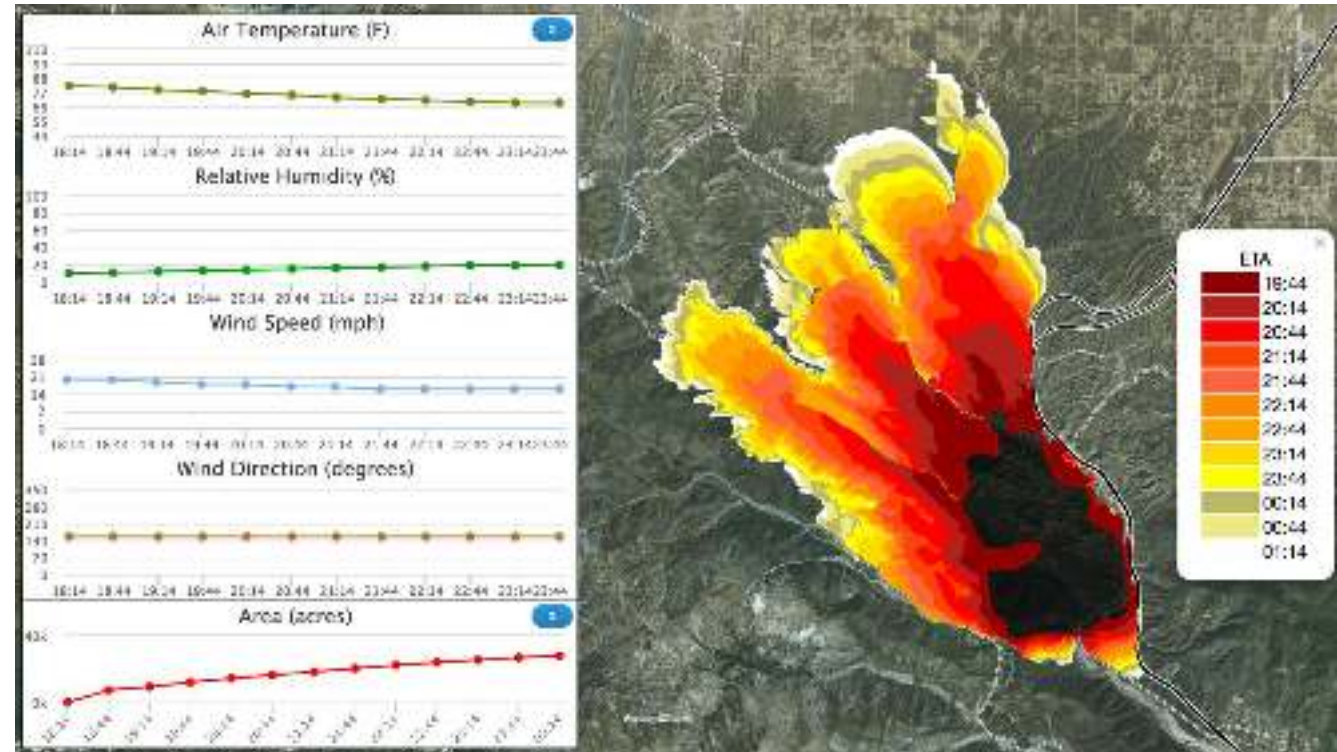
- REST service to run Kepler workflows
- FARSITE workflow
 - Inputs: ignition, weather, wind, landscape
 - Outputs: perimeters



Firemap Predictive Modeling

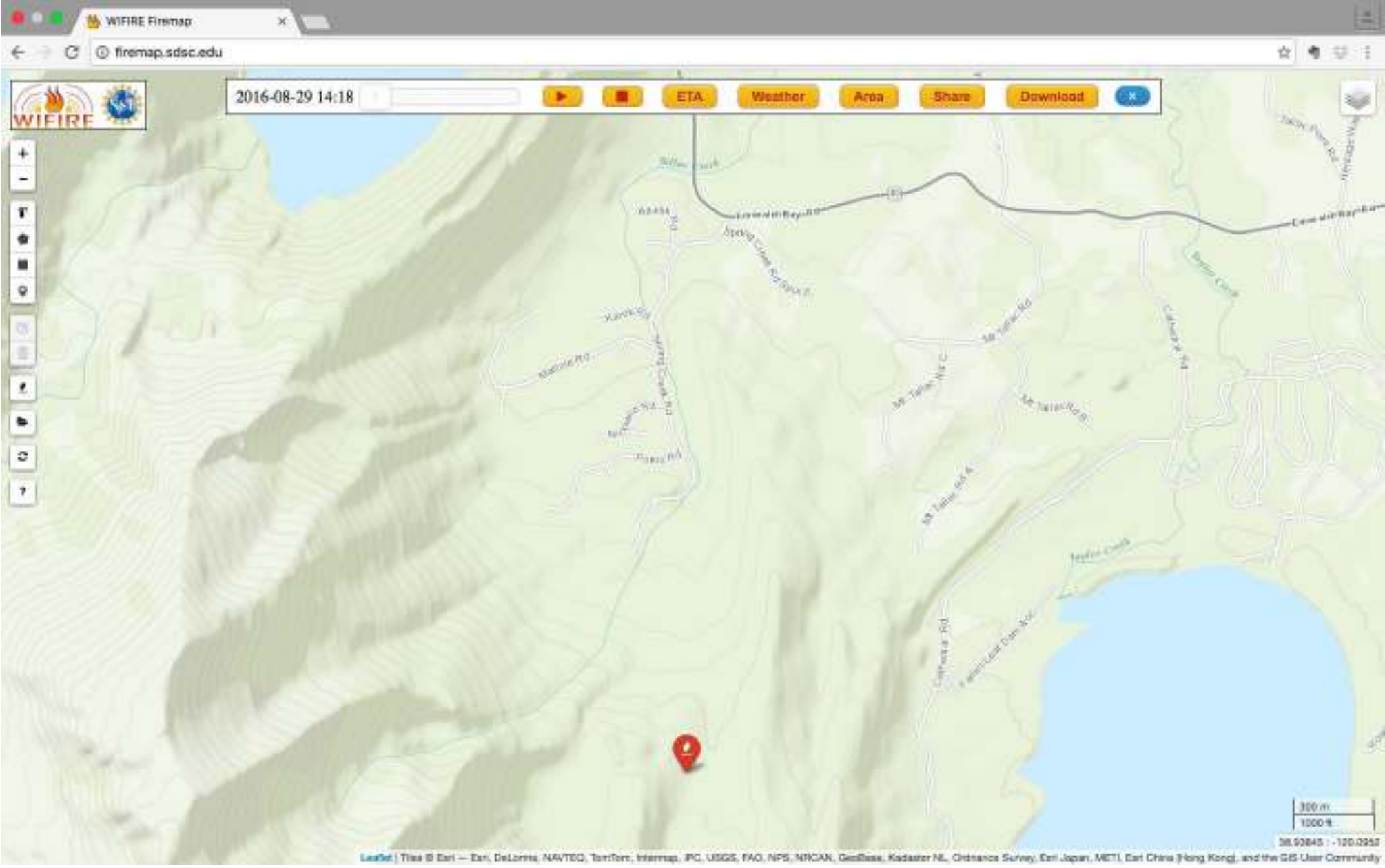


(a)



(b)

Figure 3: Firemap predictive modeling: (a) the configuration dialog specifying the simulation time, and weather conditions; (b) predicted fire spread for the Blue Cut Fire showing the weather conditions, fire perimeters, area, and arrival times.



Leaflet | Data © Esri - Esri, DeLorme, NAVTEQ, TomTom, Intermap, iPC, USGS, FAO, NPS, NRCAN, GeoBC, Kadaster NL, Ordnance Survey, Esri Japan, METI, Esri China (Hong Kong), and the GIS User Community

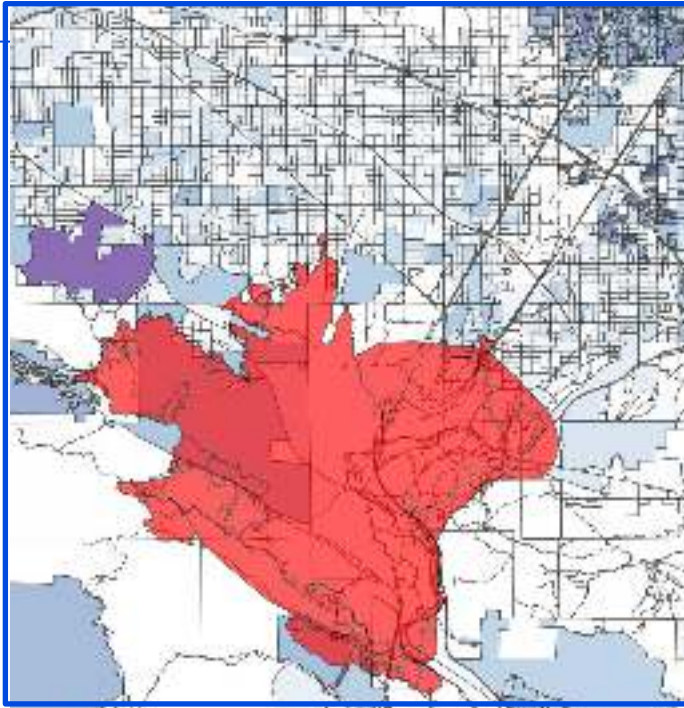


WIFIRE is funded by NSF 1331615



Some Related Experimental Features

- 2016 Blue Cut Fire in San Bernardino County
- 105 homes and 213 other buildings destroyed*
- Population estimates from US Census Bureau



Population
Density Near
Wildfires

3D Terrain
with
Photos and
Perimeters

- Terrain imagery from 2009 and 2012
- Fire perimeters from the San Diego May 2014 fires
- Images were collected via Twitter
 - Captioned with tweet tag on top

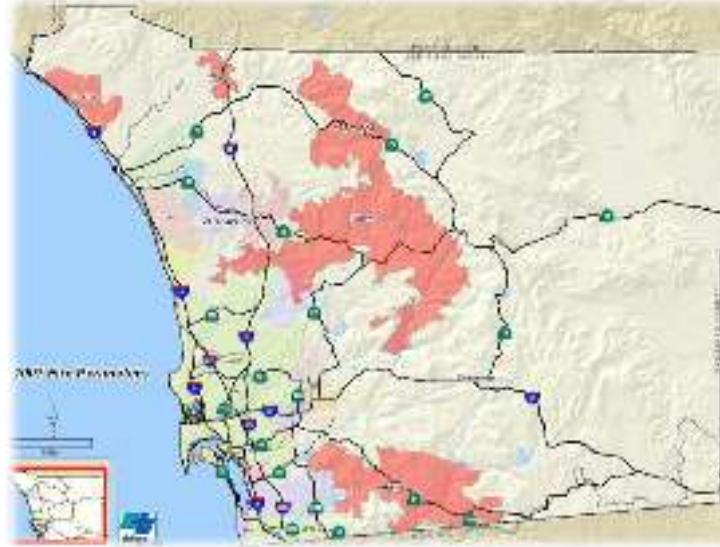


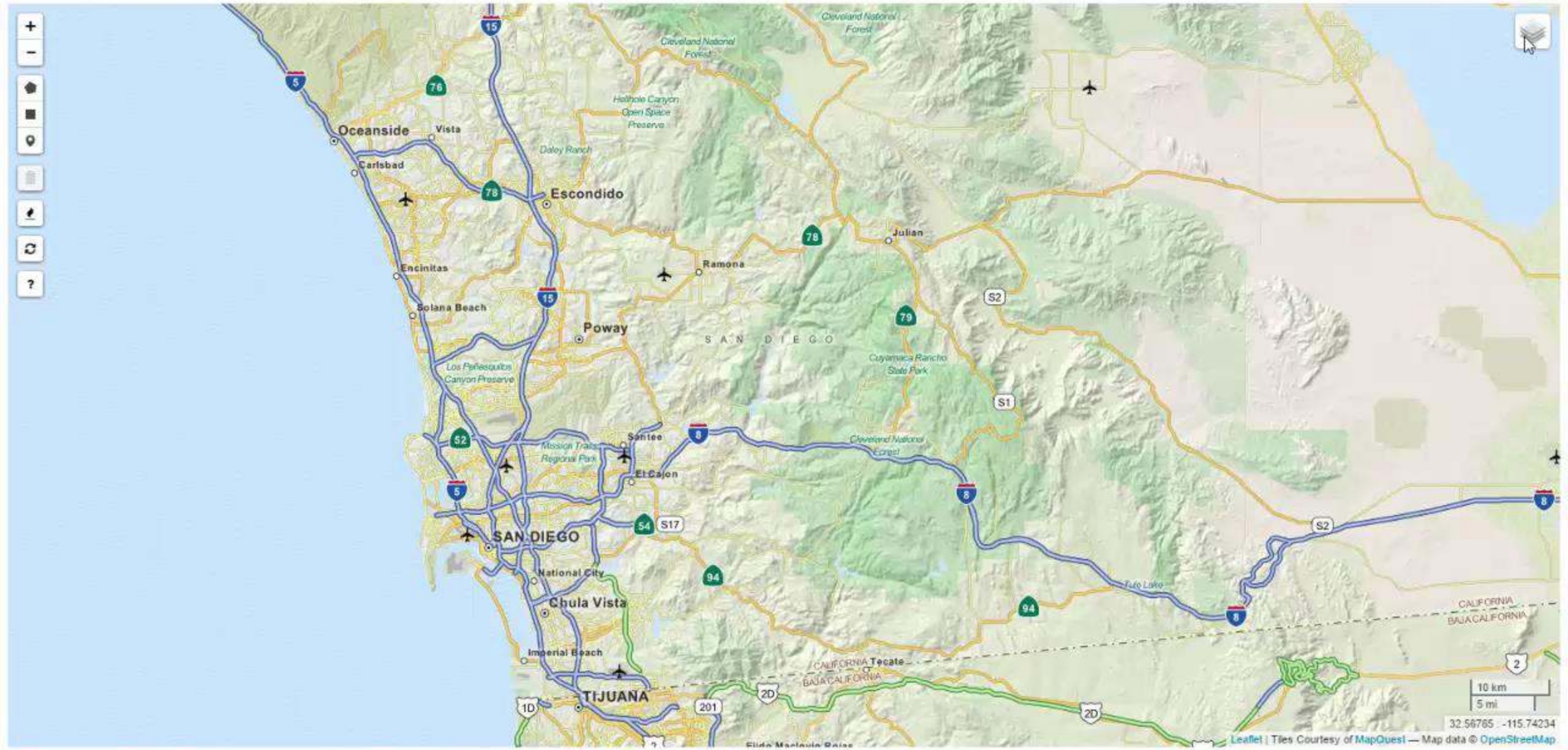
*<http://www.latimes.com/local/lanow/la-me-ln-blue-cut-fire-20160819-snap-story.html>



Crowd-Sourced Fire Perimeter Calculation

- Photos of fire locations from Twitter and Instagram
- Custom app allows recording additional data such as phone's location and orientation, focal length, etc.
- Improve camera location and orientation calculation through terrain map matching
- Image processing for fire/smoke localization within photos
- Goal: map of fire perimeter over time

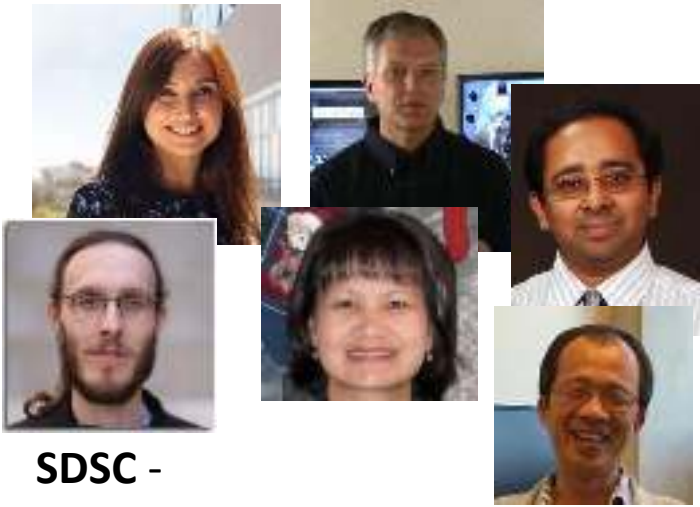




Some Lessons Learned

- User interface needs to be simple and not overloaded
- New fuel maps are vital to future success of fire modeling
- Data assimilation is needed to capture dynamics of fire
- Operationalization has production and support sustainability challenges unlike research sustainability
- On-demand large computing needs workflow automation
- Social media data is potentially useful, but not reliable

WIFIRE Team: It takes a village!



SDSC -
Cyberinfrastructure,
Workflows,
Data engineering,
Machine Learning,
Information
Visualization,
HPWREN

UCSD MAE - Data assimilation



Calit2/QI-
Cyberinfrastructure, GIS,
Advanced Visualization,
Machine Learning,
Urban Sustainability,
HPWREN



SIO - HPWREN



UMD - Fire modeling

- PhD level researchers
- Professional software developers
- 24 undergraduate students
 - UC San Diego
 - UC Merced
 - MURPA University
 - University of Queensland
- 1 high school student
- 4 MSc and 5 MAS students
- 2 PhD students (UMD)
- 1 postdoctoral researcher

<http://wifire.ucsd.edu>



Questions?

CONTACT

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UC San Diego and various industry partners.



Social Science Data

Example Data

- Microblogs
- News articles/blogs/comments
- Political/geographic organization structures
- Biographies
- Social Media Data (e.g., Instagram)
- Message networks (e.g., emails)
- Legal documents
- Economic surveys
- Demographic data

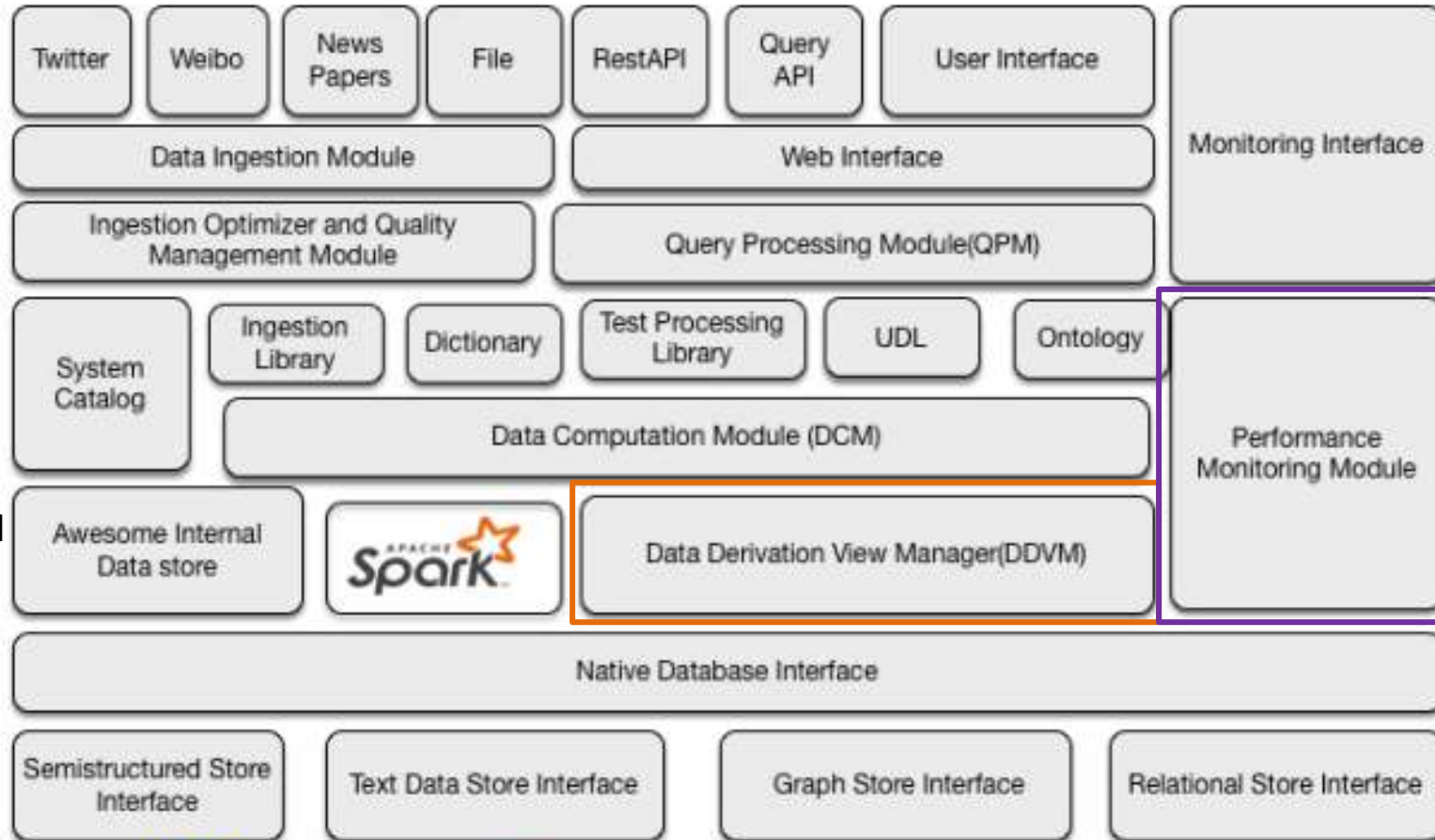


Example Analyses

- Political Science: Can we **detect situations** where the Chinese news media is trying to suppress information about local protests while people on social media are actively discussing it? Can we detect them in near-real time?
- Sociology: Can we **construct a statistical model** to detect and predict political unrest by observing user behavior and actions on social media? Can we trace how political movements form by watching important players in a situation?
- Social Medicine: Can we **identify individuals and communities** who are at high-risk for HIV/AIDS? Can we use a combination of social media and transmission networks to make informed medical intervention (e.g., proactive vaccination)?
- Social Media Analytics: Can we **develop a prediction model** for identifying potential violence by watching social media? Can we identify and correlate disparate events that may lead to such violence?
- Computational Jurisprudence: Does the government **ever provide compensation** for cases against it? Are there **any networks** of judges and lawyers who never penalize the government?

AWESOME Polystore Architecture

(Analytical Workbench for Exploration of Social Media)



Simple statistical data structures

JSON, XML (after conversion) streaming data feeds



VSM over Relational

Property graphs

Relational Data

All data objects are temporal and may have annotations

WIFIRE is funded by NSF 1331615



A Public Health Example (UCLA-led)

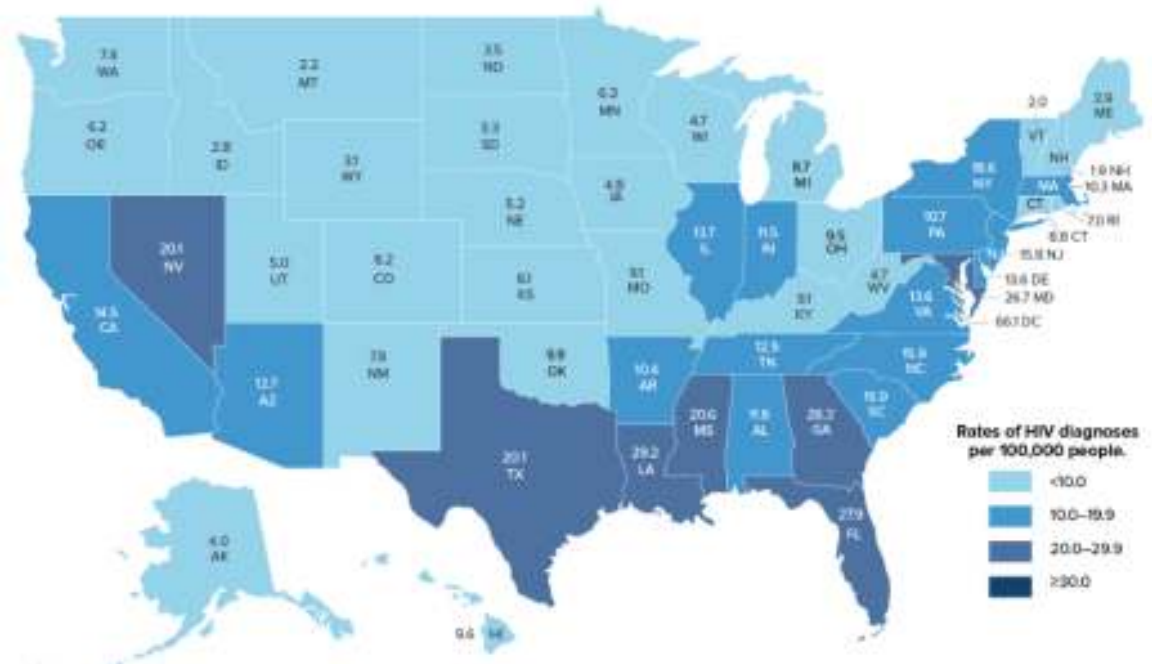
- CDC reports are usually delayed by 2+ years
- We need current, continual estimates of HIV counts and rates
 - Deploy resources according to urgency
 - Mobile clinics
 - Determine new relevant events
 - Burst in meth use activity
 - Determine efficacy of measures
 - Clean need exchange programs

Can we use Social Media more timely estimates?

Numbers and rates of diagnoses of HIV infection during 2010–2014 and preliminary numbers for 2015 are based on data from all 50 states, the District of Columbia, and 6 U.S. dependent areas (American Samoa, Guam, the Northern Mariana Islands, Puerto Rico, the Republic of Palau, and the U.S. Virgin Islands).

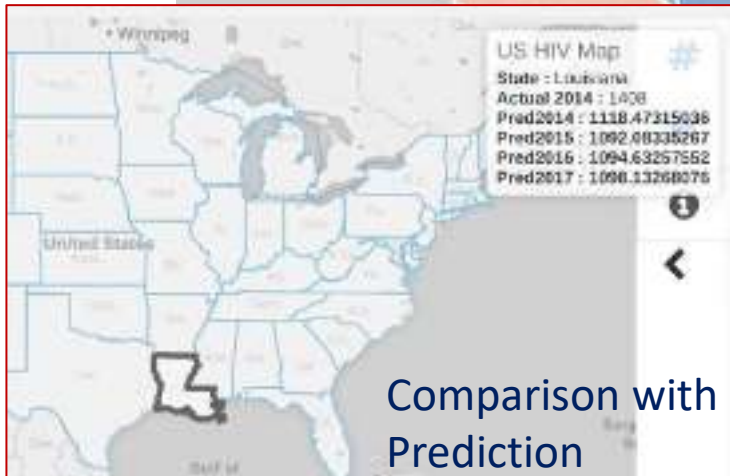
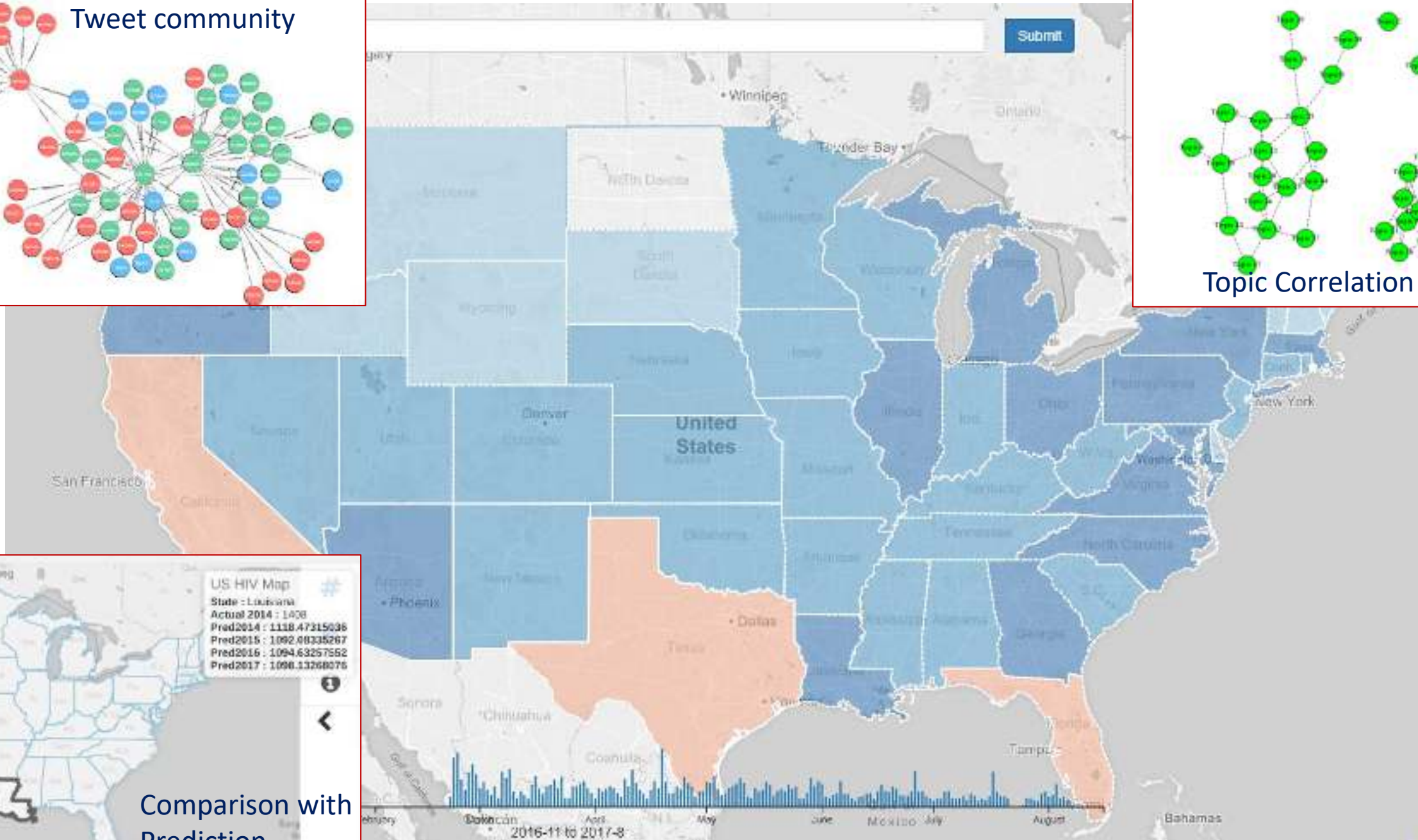
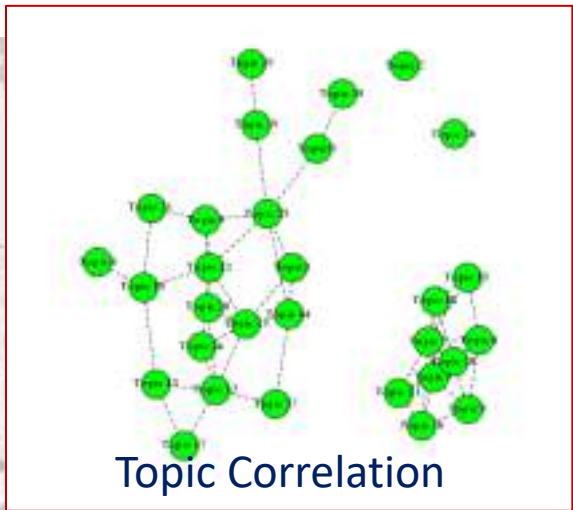
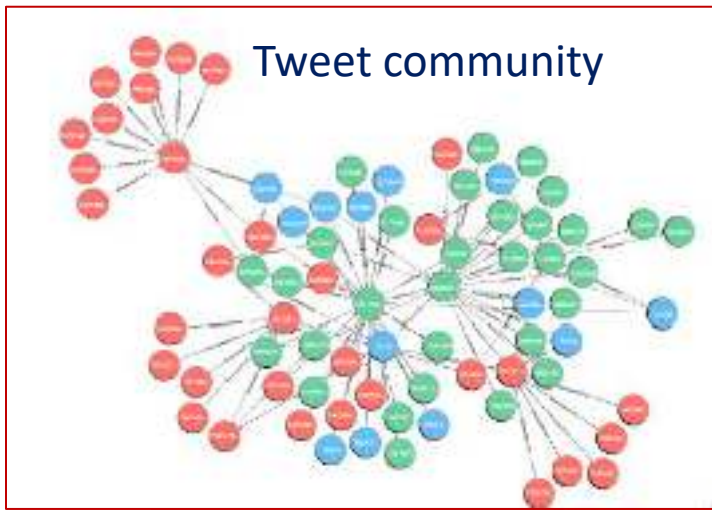


Rates of HIV Diagnoses Among Adults and Adolescents in the US in 2015, by State



Data Sources and Derived Data

- Current sources
 - Twitter – real-time JSON data (seed keywords from HIV experts)
 - Has geocodes, text content and topic markers (hashtags)
 - Prior statistics from CDC – mostly tables
 - Geocoded locations of interest
- Derived data
 - What are the user communities and what are they talking about?
 - Derive communities (graphs of closely communicating users) and perform theme extraction with topic model like techniques
 - Is there a shift in topics like “social stigma” after a policy has been implemented?
 - Perform time-series analysis based on drifts in topics created from the above



Please direct all questions on AWESOME to:
Amarnath Gupta (a1gupta@ucsd.edu)