Workflow-Driven Geoinformatics Applications and Training in the Big Data Era

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SDSC SAN DIEGO SUPERCOMPUTER CENTER

SAN DIEGO SUPERCOMPUTER CENTER at UC San Diego Providing Cyberinfrastructure for Research and Education

- Established as a national supercomputer resource center in 1985 by NSF
- A world leader in HPC, data-intensive computing, and scientific data management
- Current strategic focus on "Big Data", "versatile computing", and "life sciences applications"



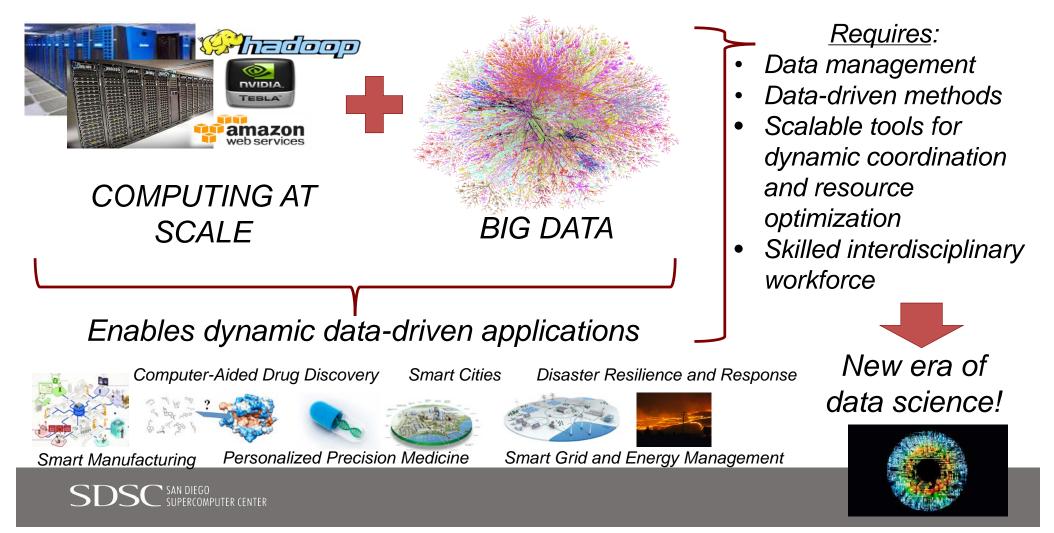


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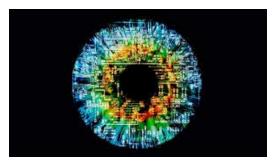
Recent Innovative Architectures

- Gordon: First Flash-based Supercomputer for Data-intensive Apps
- Comet: Serving the Long Tail of Science

Data Science Today is Both a Big Data and a Big Compute Discipline



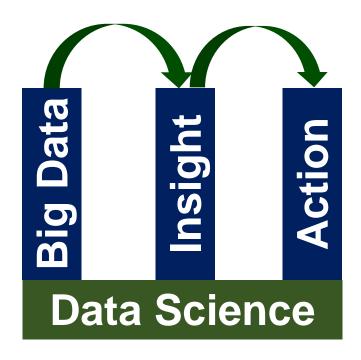
Needs and Trends for the New Era Data Science







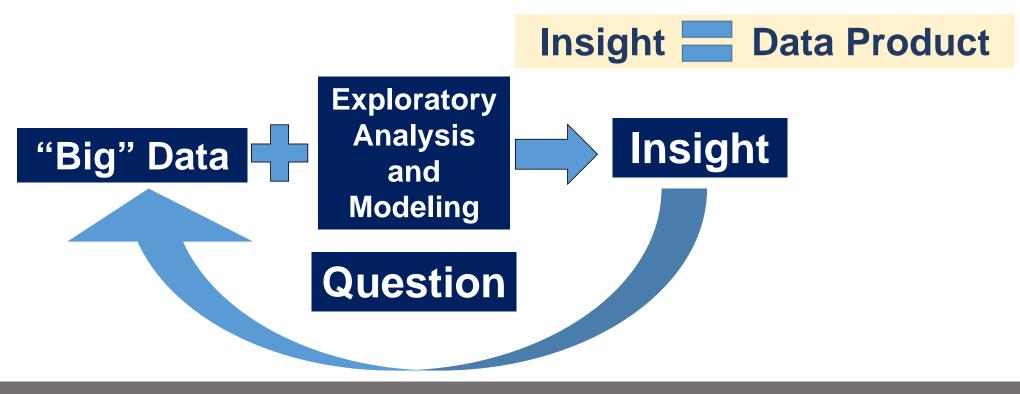
Ultimate Goal





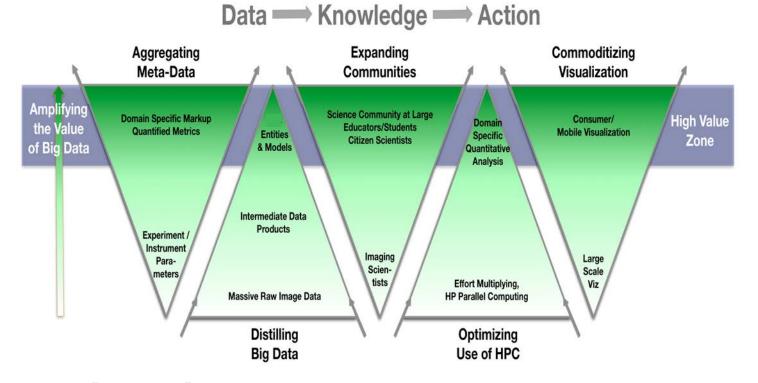


How does successful data science happen?



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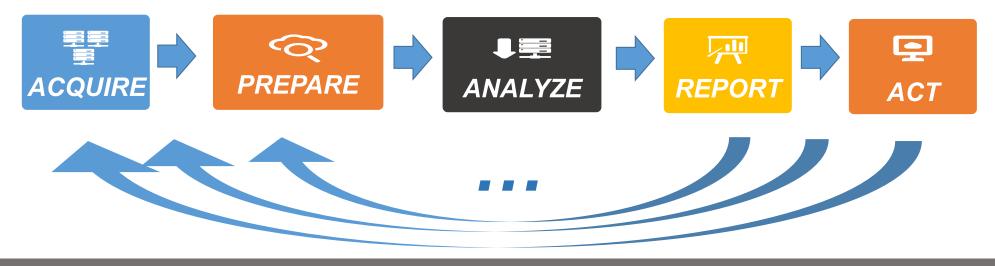
Insights amplify the value of data...



..., but there are many ways to get to insights.

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Approach: Focus on Process and Team Work





Create an Ecosystem that Enables Needs and Best Practices



- data-driven
- dynamic
- process-driven
- collaborative

- accountable
- reproducible
- interactive
- heterogeneous



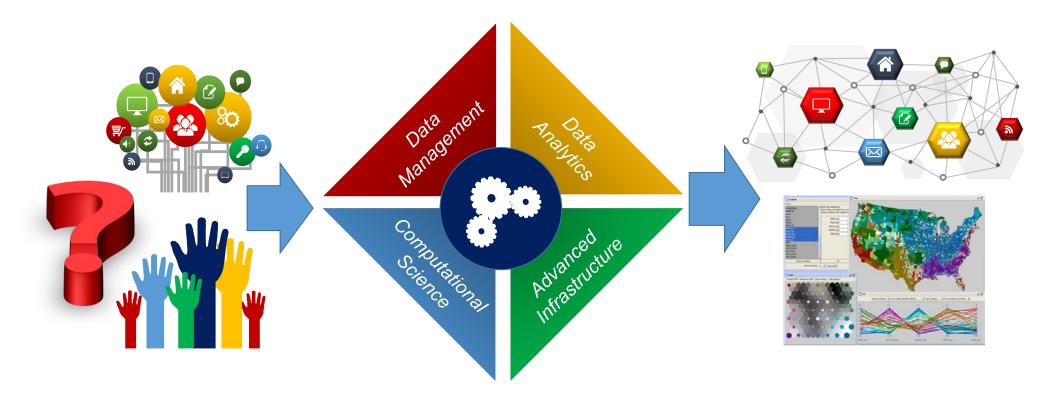




What would it such an ecosystem look like?







Creating a Collaborative Data Science Ecosystem on top of Advanced Infrastructure

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What are some challenges specific to atmospheric sciences?



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Geospatial Big Data

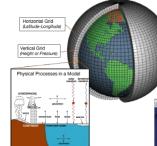
- Flood of new data sources and types
 - Needs new data management, storage and analysis methods
 - Too big for a single server, fast growing data volume
 - Requires special database structures that can handle data **variety**
 - Too continuous for analysis at a later time, with increasing streaming rate, i.e., **velocity**
 - Varying degrees of uncertainty in measurements, and other veracity issues
 - Provides opportunities for scientific understanding at different scales more than ever, i.e., potential high **value**





Drone imagery

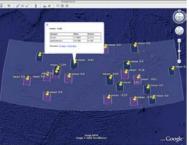
Real-time sensors



Weather forecast



Satellite imagery



Sea Surface Temperature Measurements





The 'scalability' bottleneck

- Resources needed for geospatial big data (e.g., satellite imagery) analysis exceed current capabilities, especially in an on-demand fashion
- Cloud computing is an attractive on-demand decentralized model
 - Need new scheduling capabilities
 - on-demand access to a shared configurable resources
 - programmable networks, servers, storage, applications, and services
 - Need ability to easily combine users environment and community tools together in a scalable way
 - Various tools with different computing scalability needs
 - Cost!!!





The 'sensor data' bottleneck

- Data streaming in at various rates
- "Big Data" by definition in its volume, variety, velocity and viscosity
 - Need to improve veracity and add value by providing provenance- and standards-aware on-the-fly archival capabilities
 - QA/QC and automate (real-time) analysis of streaming data before it is even archived.
 - Often low signal-to-noise ratio requiring new methods
- Need for integration of new streaming data technologies





The "workforce" bottleneck

- Geospatial data processing requires a lot of expertise
 - GIS, domain expertise, data engineering, scalable computing, machine learning, ...
- No open geospatially enabled big data science education platform
- Teach not just technical knowledge, but collaborative work culture and ethics

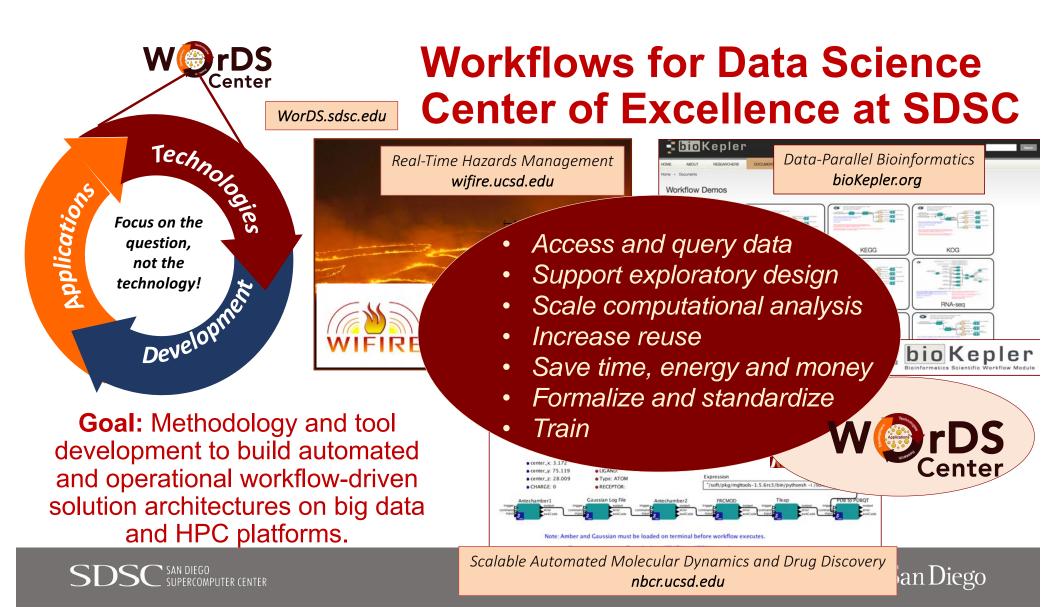




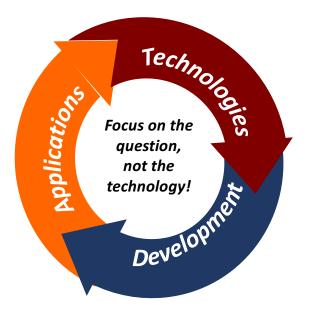
Using workflows to get there...





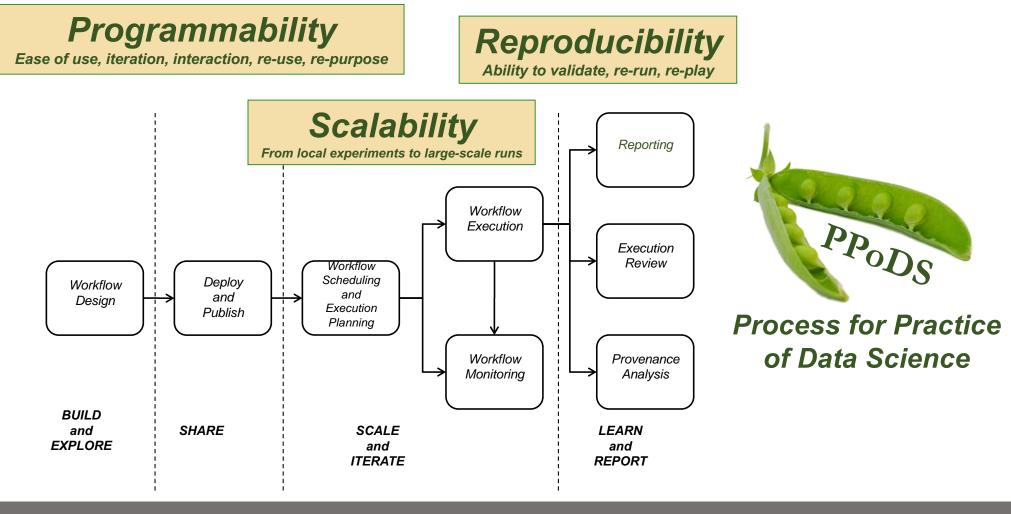


How can I get smart people to collaborate and communicate to analyze data and computing to generate insight and solve a question?

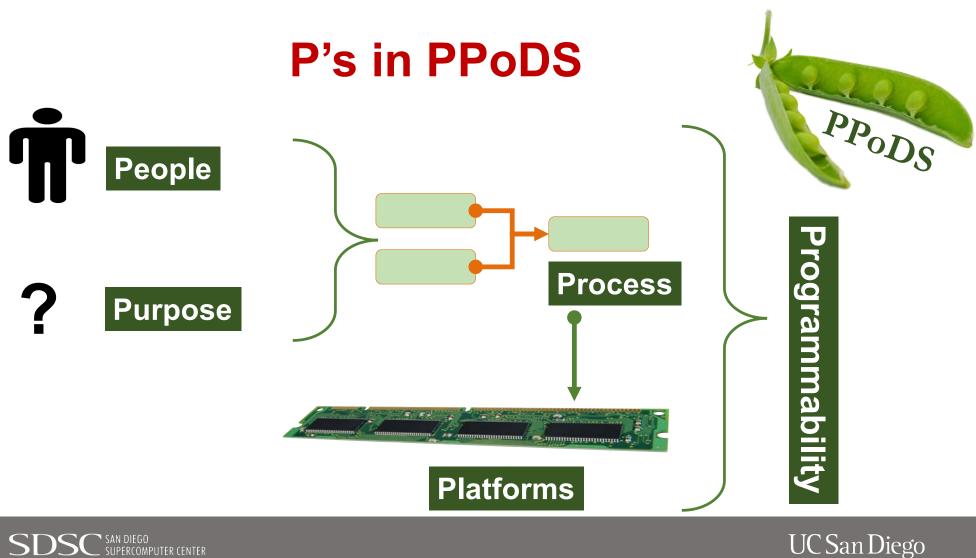








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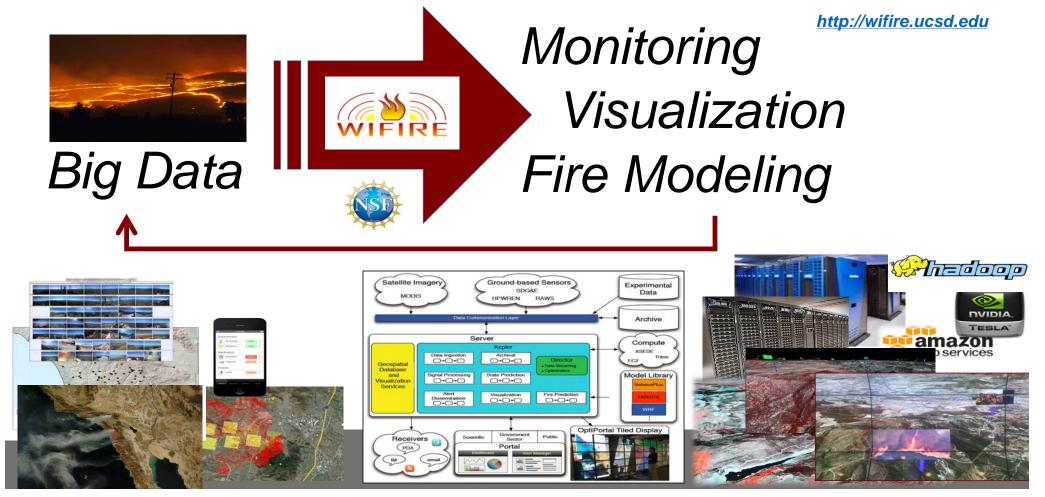


Example: Using geospatial big data for wildfire predictions



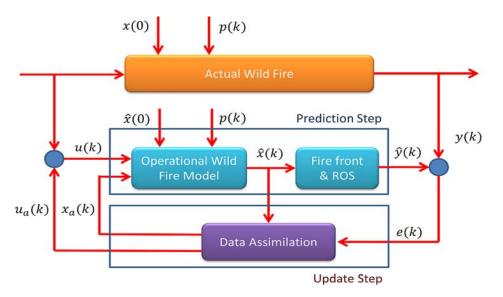


WIFIRE: A Scalable Data-Driven Monitoring, Dynamic Prediction and Resilience Cyberinfrastructure for Wildfires



Closing the Loop using Big Data

-- Wildfire Behavior Modeling and Data Assimilation --



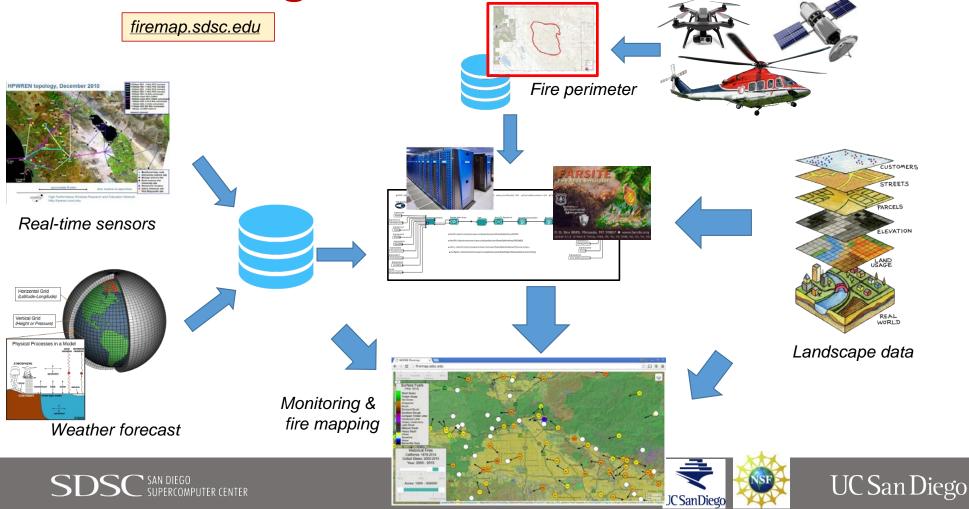
Conceptual Data Assimilation Workflow with Prediction and Update Steps using Sensor Data

- 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

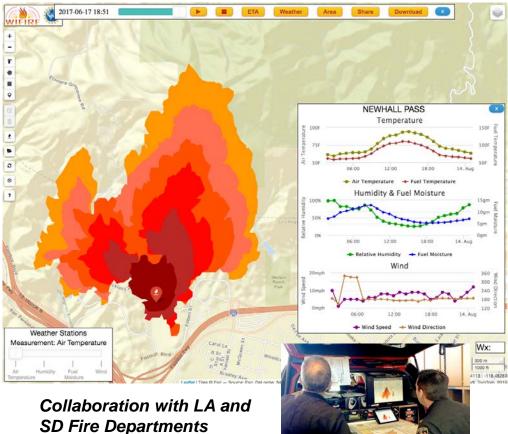




Fire Modeling Workflows in WIFIRE

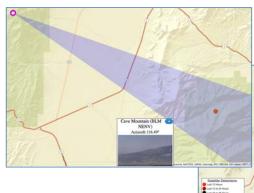


Data-Driven Fire Progression Prediction Over Three Hours



12/39 14/9 14/9 15/9 20/9 25/9 21/9 21/9 22/922/9 Relative Humidity 00 12/39 14/9 14/9 15/9 20/9 25/9 21/9 22/922/9 Wind Speed (mph) 12/39 14/9 14/9 15/9 20/9 25/9 21/9 22/922/9 Wind Direction (degrees)

August 2016 – Blue Cut Fire



2016-08-17 01:14

Air Temperature (F

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



UC San Diego



http://firemap.sdsc.edu

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)

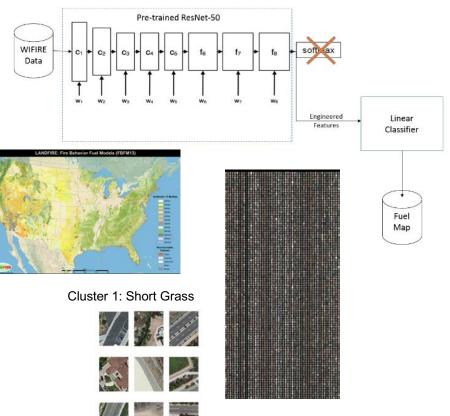


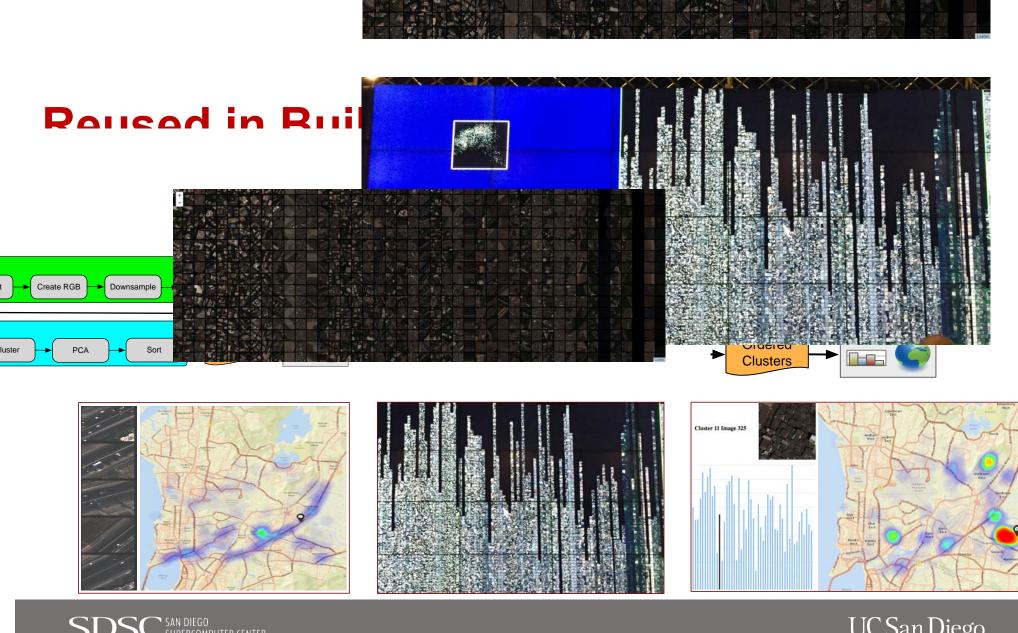


Classification project to generate more accurate fuel maps

- 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.

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Summary

- Geospatial big data has all the typical big data challenges
- Lessons learned from other disciplines to deal with these challenges should be applied
- Workflows can be used both for managing scalable coordination and training students and workforce
- Dynamic data-driven integration of machine learning, data assimilation and modeling is of potential use to many geo applications





WIFIRE Team: It takes a village!



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

Adv Mac Urb HPN

UCSD MAE - Data assimilation





Calit2/QI-

Cyberinfrastructure, GIS, Advanced Visualization, Machine Learning, Urban Sustainability, HPWREN

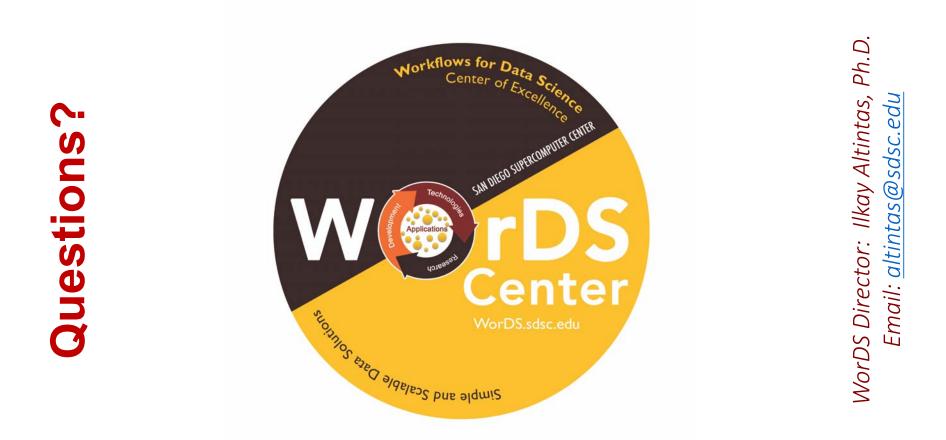


UMD - Fire modeling

SIO - HPWREN

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





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