Using Space, Air, Marine, and Ground Assets for Disaster Response and Environmental Monitoring

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In collaboration EO-1, OASIS, OOI, Volcano, Flood, UAVSAR Sensorweb teams including: Goddard Space Flight Center, USGS/CVO/HVO, Washington State University, UCSD, Scripps, Rutgers, MIT, ASU, U. Arizona, MEVO/NMT, U. Iceland, Iceland Met. Office, HAII, U. Maryland, The Geophysical Institute of the National Polytechnic School of Ecuador (IGEPN), University of Florence, Dartmouth Flood Observatory, and the National Snow and Ice Data Center.

JPL Clearances: 10-2762, 11-0177, 11-0178, 11-2065, 11-2245, 12-0499, 12-1201, 12-1244, 12-2847
Intl Workshop on Planning & Scheduling for Space , Moffett Field, CA 2013.

Environmental Monitoring

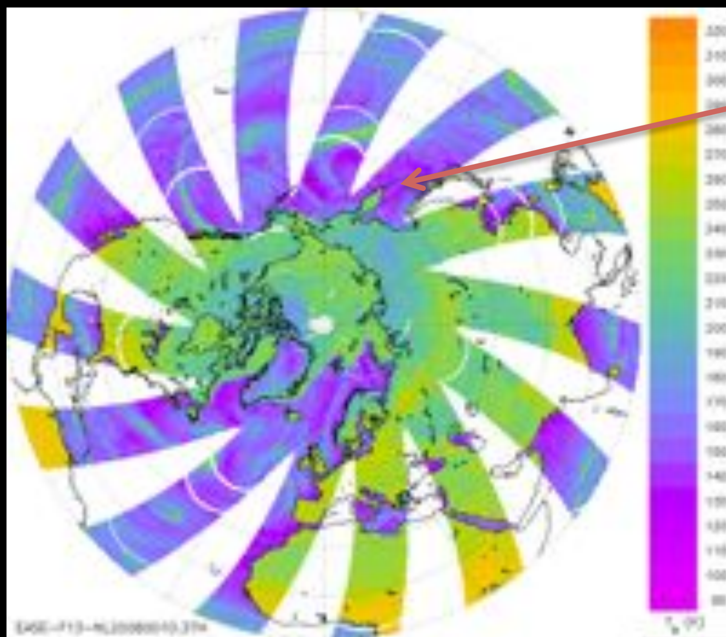
- Flooding is the most costly ($$ and humanitarian) natural disaster
  - 2011 Thailand Flooding: **600 deaths and $45.7 Billion USD damage** [World Bank 2011]
- Over two hundred million people live near volcanoes.
  - The Iceland volcanic eruption caused damages **1.9-3.3 billion USD** (EU Transport Commissioner Siim Kallas 27 April 2010) in air travel, tourism, and industrial disruption.

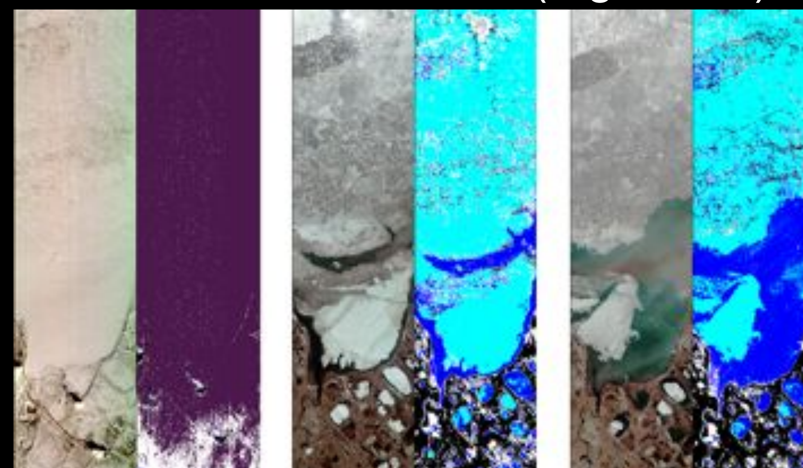
Adaptive Sensing and Sensorwebs

- Adaptive Sensing offers the potential to revolutionize environmental sensing
  - Sensing optimization based on model uncertainty
  - Event-driven selective sensing
  - Integrated hierarchical sensing
- These techniques utilize: Machine Learning, Automated Planning, and Multi-agent Systems
- My focus in this talk will be on sensorwebs that utilize remote sensing but the approaches and techniques apply to many platforms and modalities

Cryosphere Tracking

- Automatically determine areas of greatest change
- Automatically target with higher resolution limited swath sensors (e.g. EO-1)





SSMIS sensor on DMSP
1 days data ***25km/pixel resolution***

Hyperion Sensor on EO-1
Ice breakup at Prudhoe Bay
30m/pixel resolution

T. Doggett, R. Greeley et al, Arizona State University

MODIS Rapidfire [Justice et al.]

MODIS imagery courtesy NASA Earth Observatory

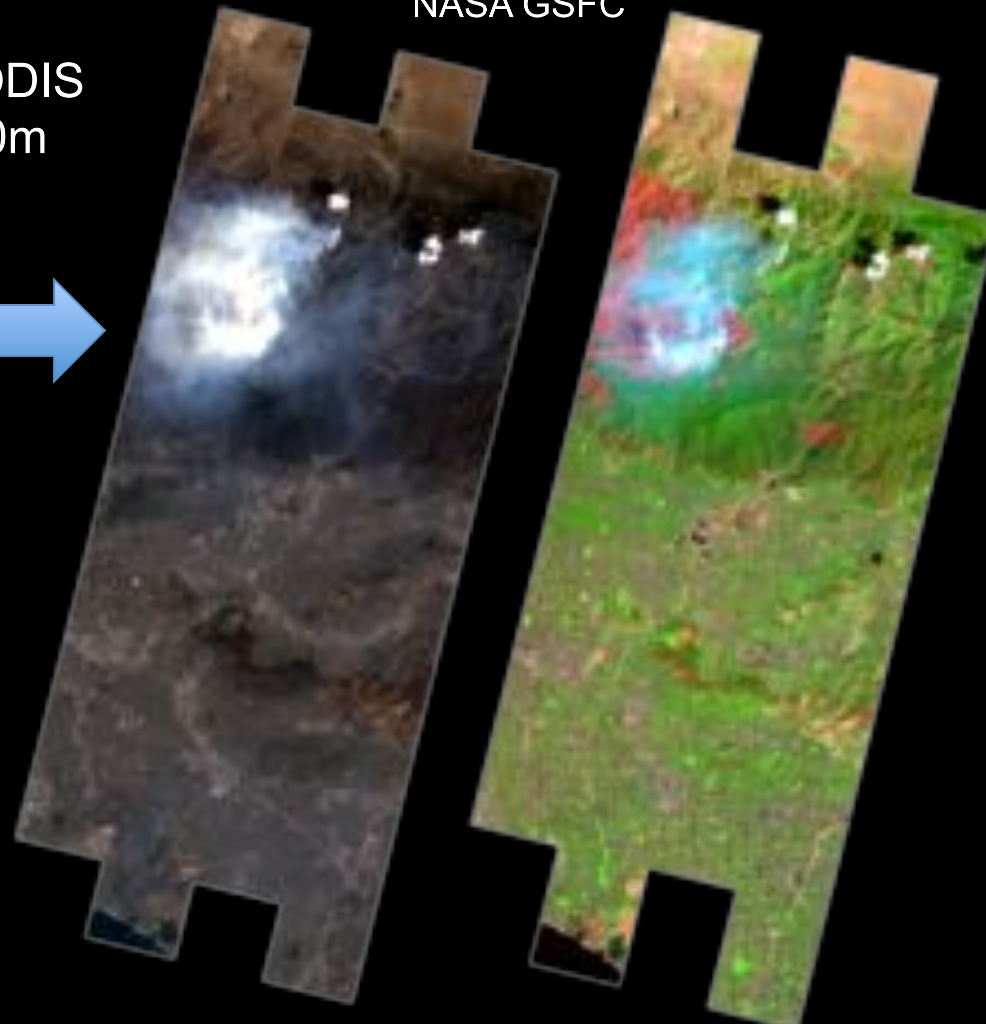
Wildfire

Visible and burn scar enhanced images from ALI instrument on EO-1 of Station Fire near Los Angeles 03 September 2009

Images courtesy EO-1 Mission NASA GSFC

MODIS 250m

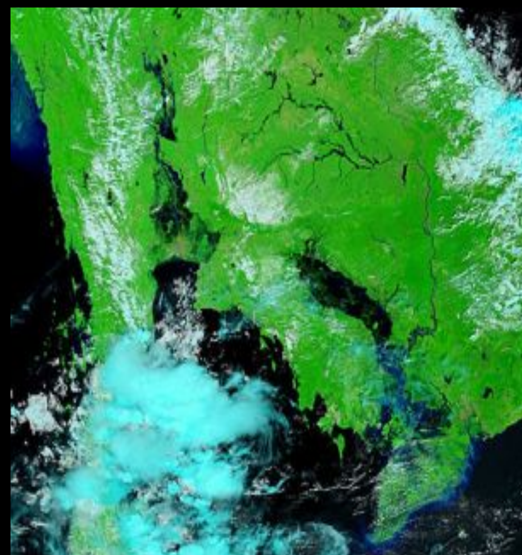
Station fire, La Canada, August 2009



EO-1/ALI: 30m resolution

Flooding

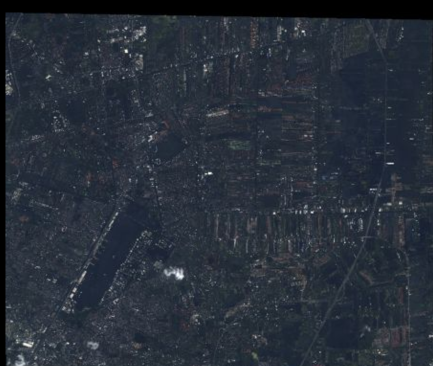
Dry



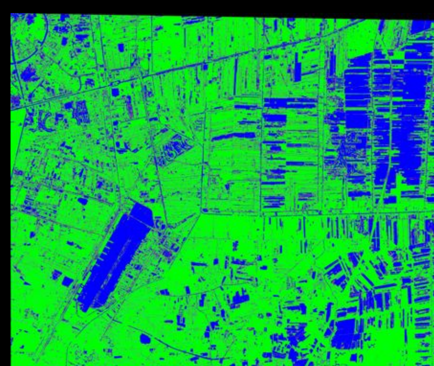
Flooded

MODIS, 250m resolution

Worldview-2,
2m resolution



Raw Image



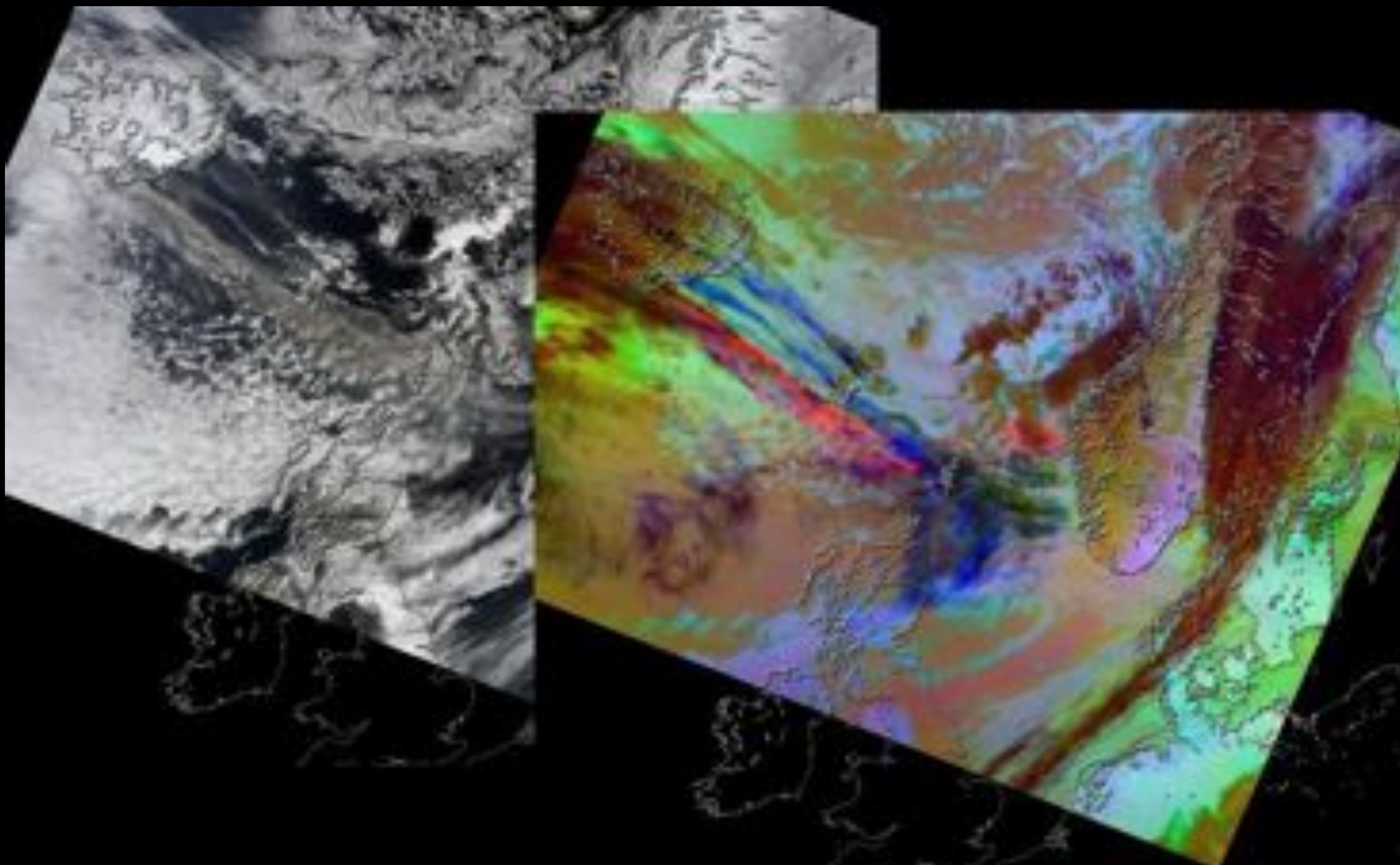
SVM Classified
Surface Water Extent

Volcano Monitoring

- Volcanoes can erupt with little warning, sometimes after 100s of years or dormancy

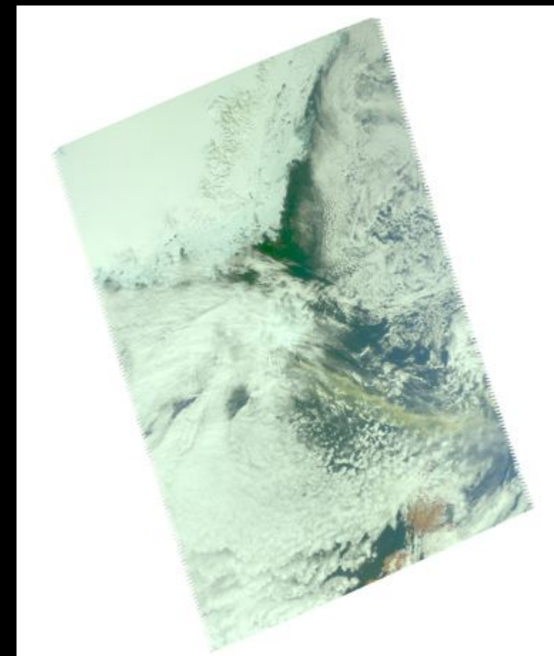
Chaiten volcano, Chile in a 2008 eruption
image courtesy USGS

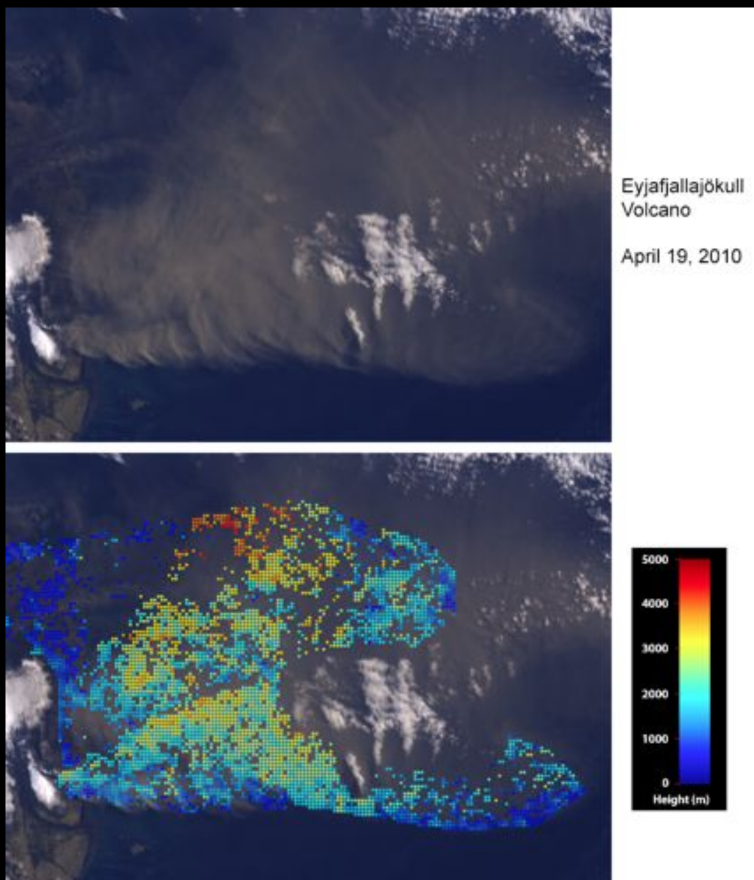
MODIS - Eyafallajökull



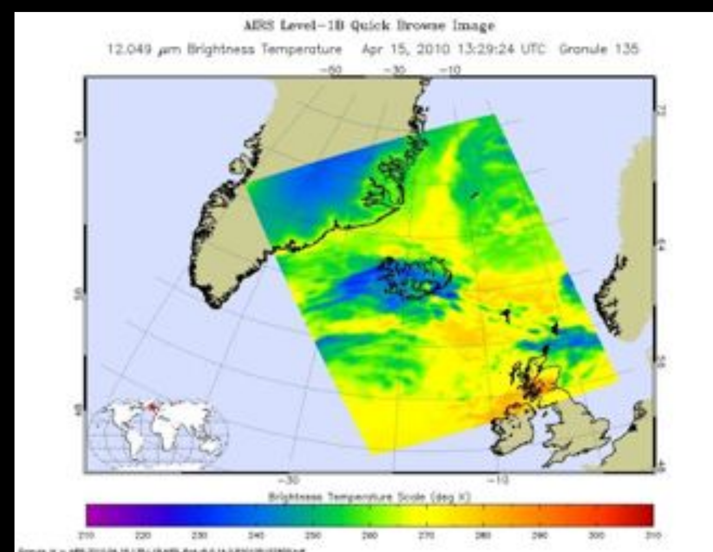
15 April 2010, MODIS, NASA/GSFC/JPL

MISR, AIRS





19 April 2010, MISR
NASA/GSFC/LaRC/JPL, MISR Team

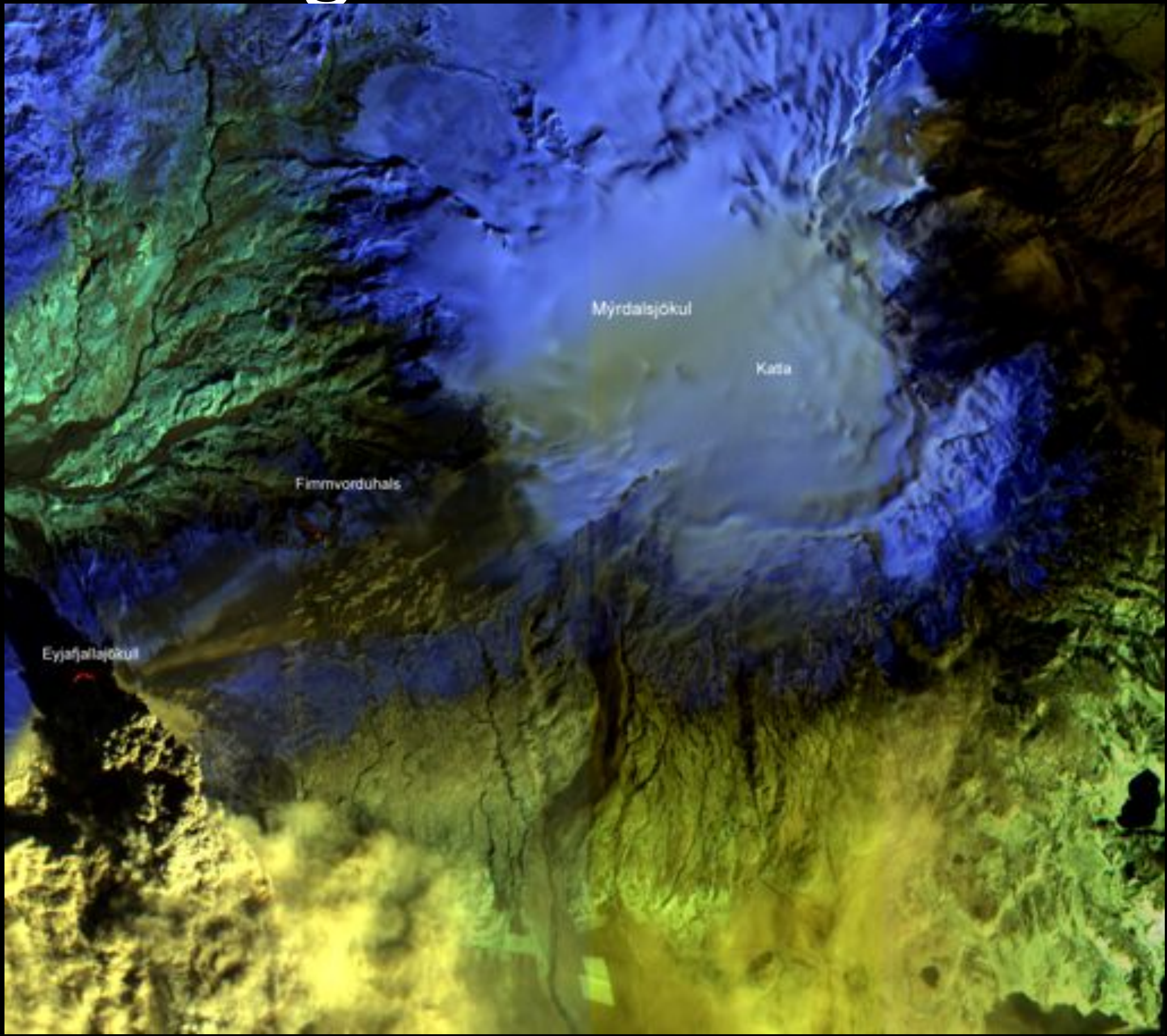


15 April 2010, AIRS - NASA/JPL

Space Monitoring and Sensorwebs

EO-1 ALI false color imagery of Eyafallajökull and Fimmvorduhals volcanoes acquired via Volcano Sensorweb.

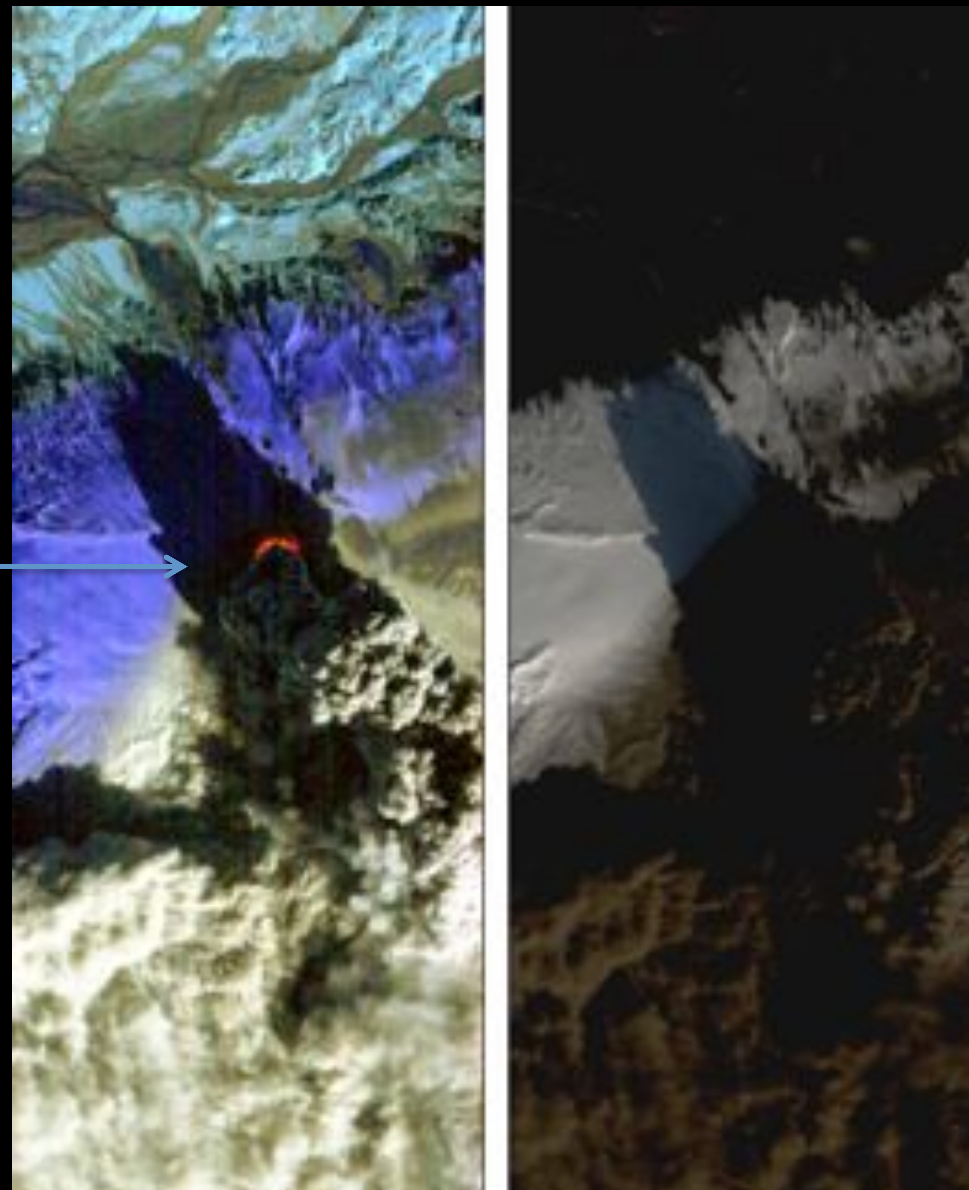
Image courtesy EO-1/ NASA GSFC Volcano Sensorweb JPL/A. Davies



Iceland Imagery

Eyafallajökull

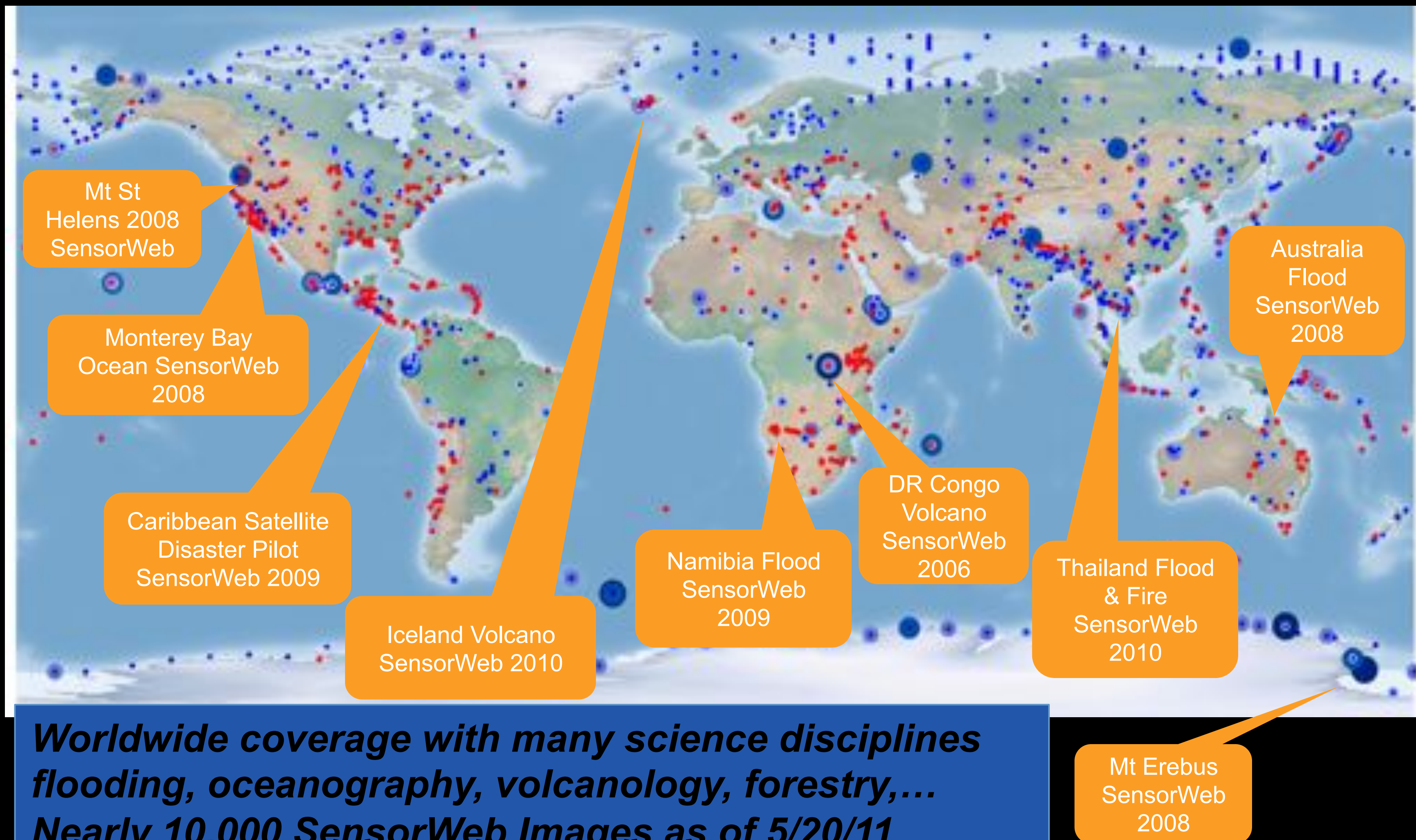
2 Giga Watt Thermal emission



Left – thermal false color
Right – True color

17 April 2010
Image credit: NASA/JPL/EO-1 Mission/ GSFC/Volcano Sensorweb/Ashley Davies

SensorWeb Imagery: EO-1

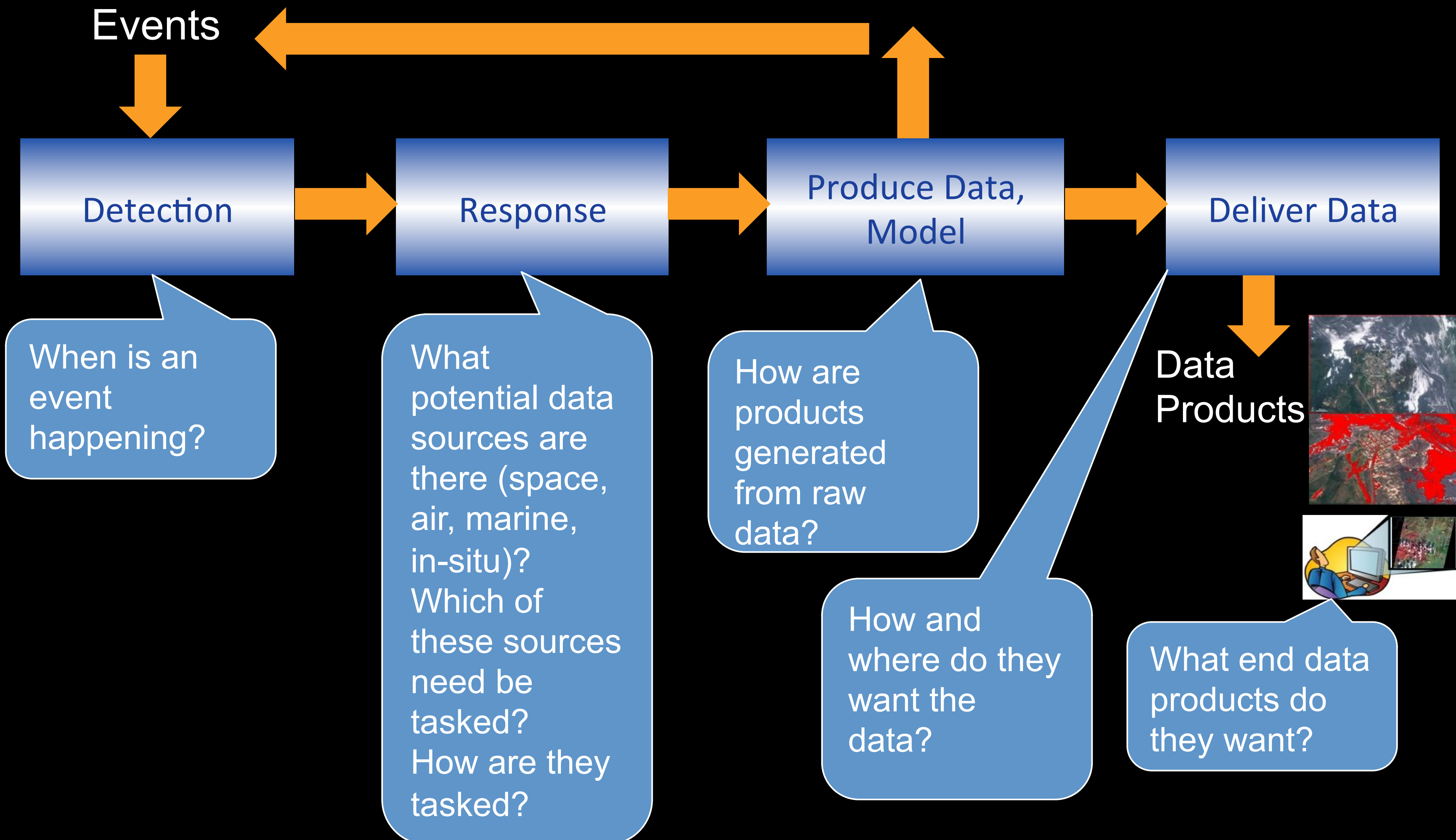


Worldwide coverage with many science disciplines flooding, oceanography, volcanology, forestry,…
Nearly 10,000 SensorWeb Images as of 5/20/11

Overview

- Sensorweb
  - Networked set of sensors
  - Data from one sensor is used to reconfigure other parts of network
  - In space context – data from one or more instruments is used to retask another asset
  - Automated data processing (workflows) may also develop products and deliver to end users

Process flow:



Technologies:

Events

Detection → Response → Produce Data, Model → Deliver Data

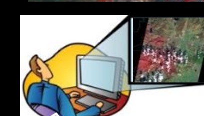
Workflows for data delivery

Workflows for automated data interpretation: spectral, support vector machine

Automated planning to task spacecraft (EO-1), marine assets, reconfigure in-situ sensors

Workflows for product generation – surface water extent, burn severity maps, volcano thermal output

Data Products



Dashboards and mashups for user display

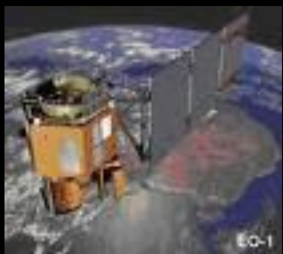
Agent-based architecture

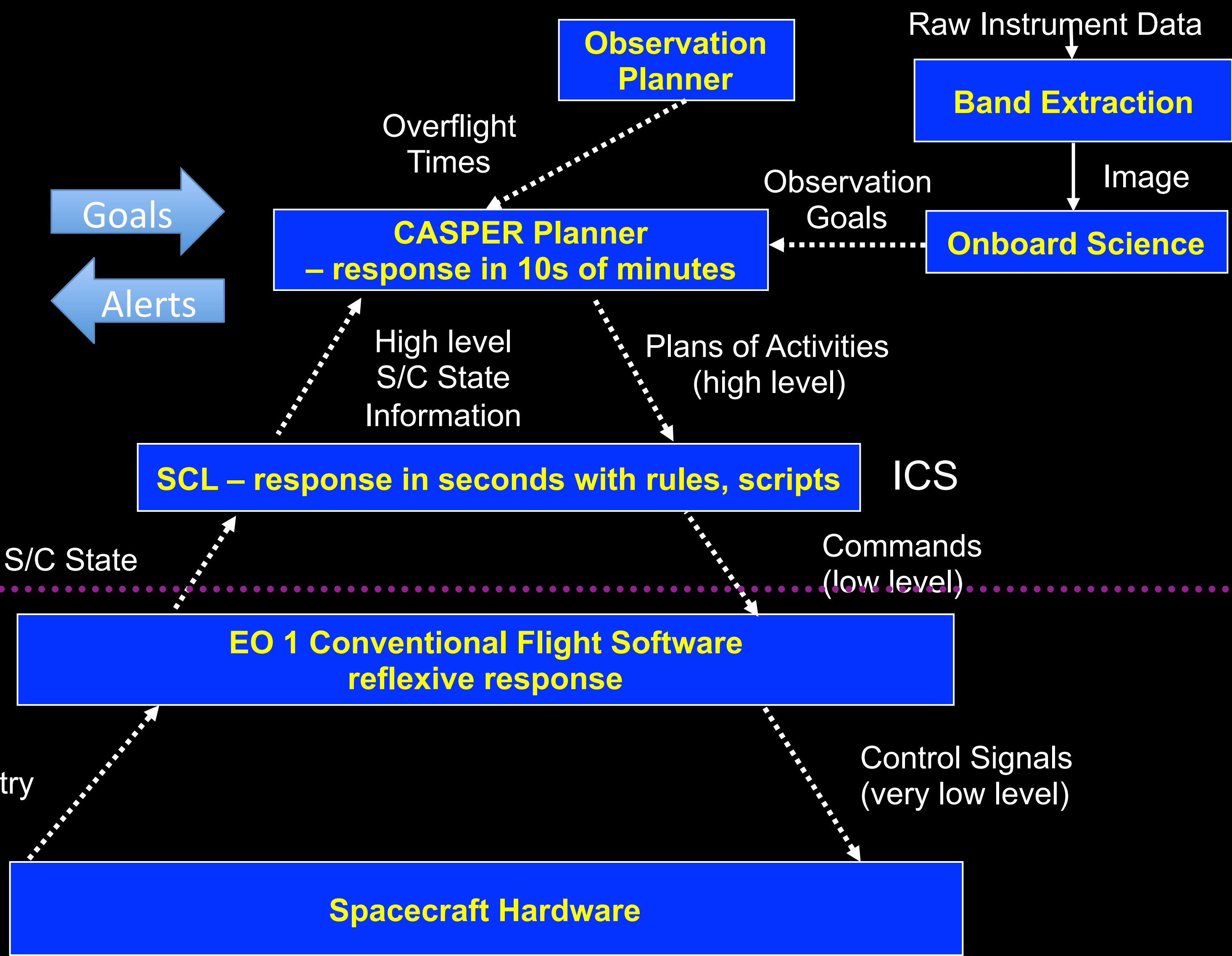
- System is comprised of a set of agents
- Agents are described by beliefs, desires, intentions (BDI)
- Agents communicate by sending beliefs, request for services, acknowledgements of services, …

Inside an Agent

- Agents have internal mechanisms to support goal-directed behavior, such as
    - A space asset might have a mission planner to determine if the spacecraft can satisfy requests for imaging (or if higher priority activities prevent, or if resources are not available, etc.)
    - An asset might have an execution system to achieve high level requests (such as imaging, or to reconfigure a ground network)

Inside an “agent” – Autonomous Sciencecraft





For further information see [Chien et al. 2005 JACIC]

Hierarchical Multi-agent Systems for Integrated, Intelligent, Space–Ground Volcano Monitoring

For further information see [Huang et al. 2010 JSTARS]

Integrated with multiple volcano observatories worldwide including: Iceland, Ecuador, Mount Erebus, Etna,…

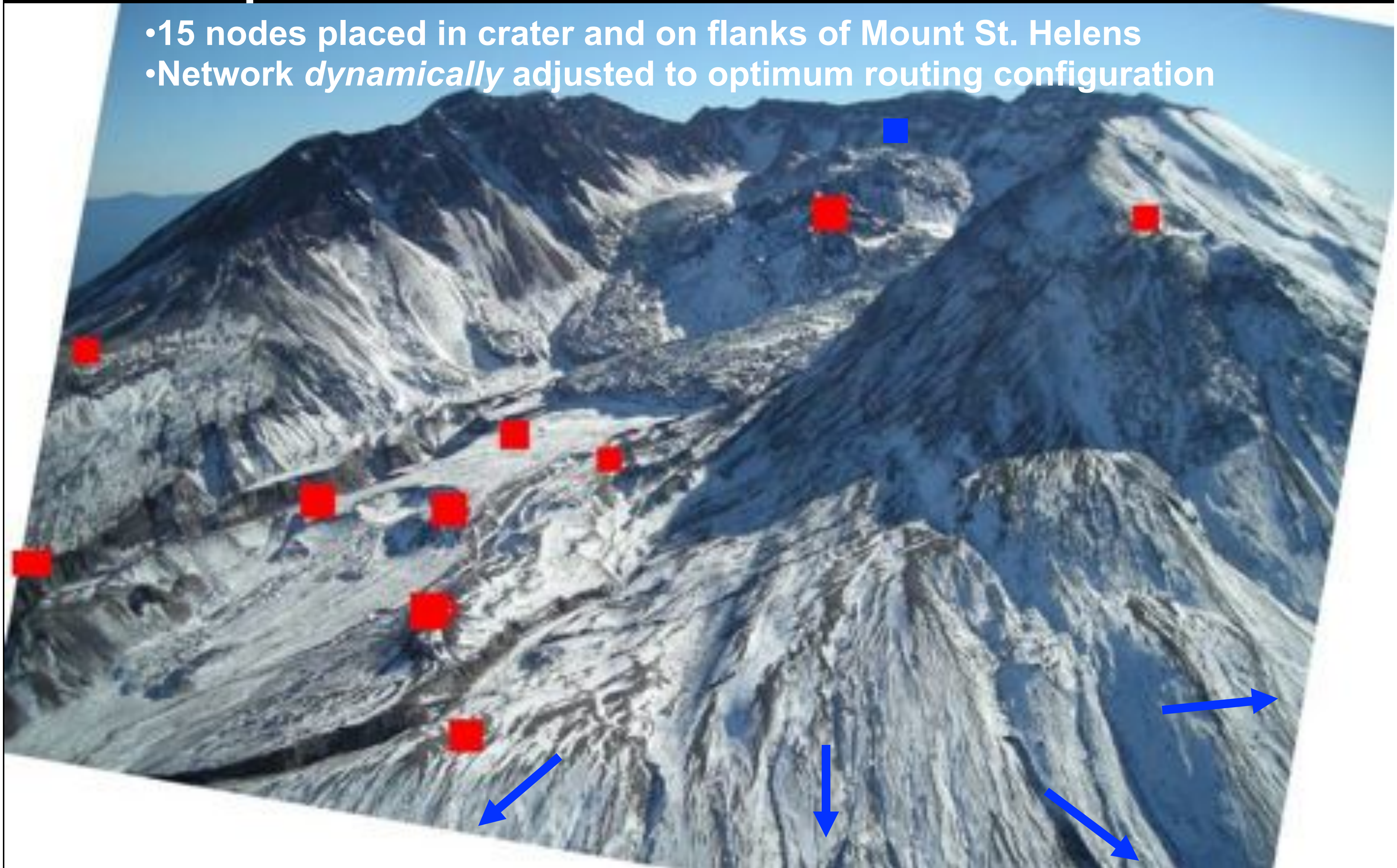
Spider Sensors Hardware (USGS)

- MEMS accelerometer (seismographic)
- Acoustic Sensor
- GPS sensor
- Lightning Sensor
- Radio

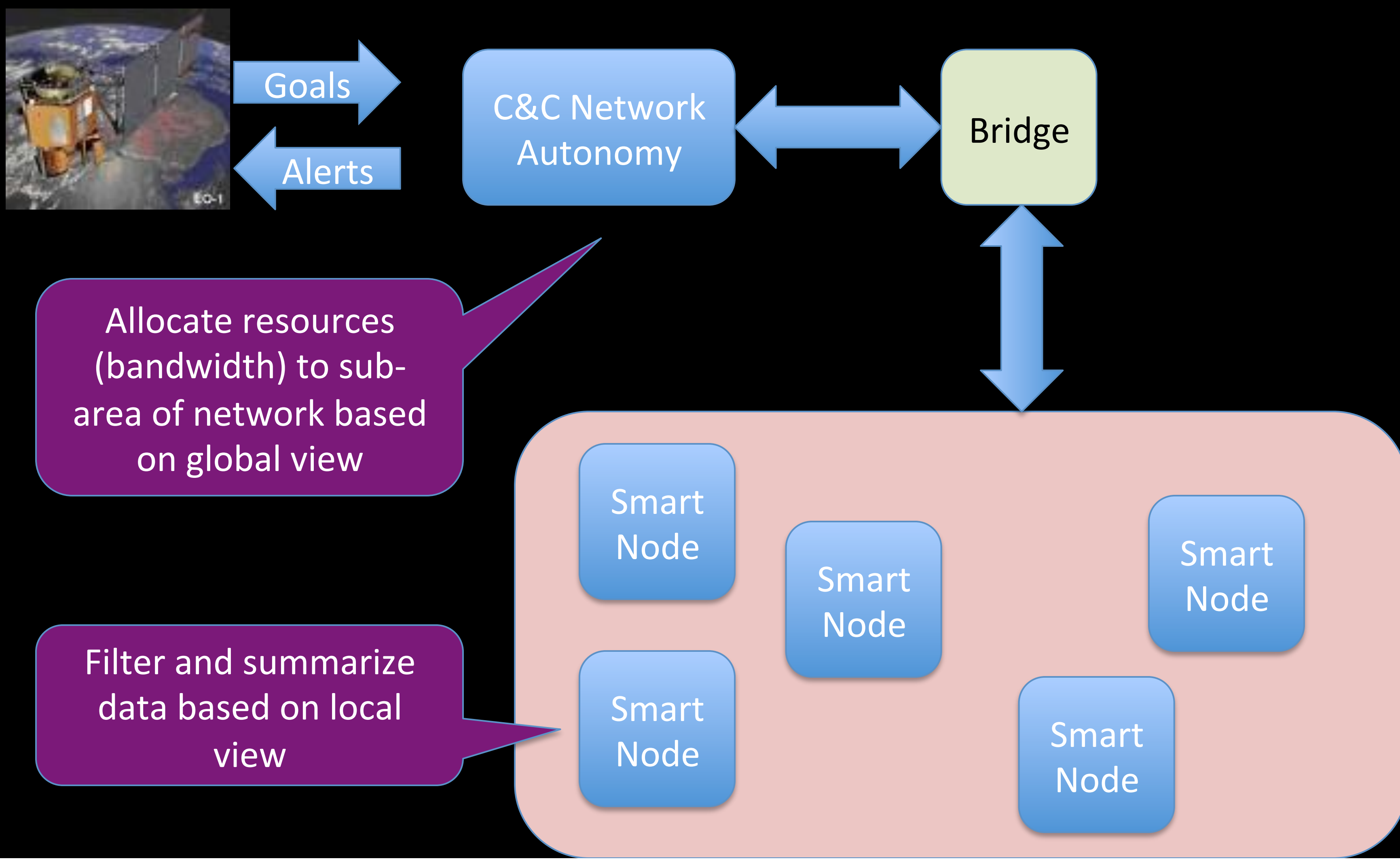
Spider Node on Mt St Helens

Spider Node on Mt St Helens

- **15 nodes placed in crater and on flanks of Mount St. Helens**
- **Network *dynamically* adjusted to optimum routing configuration**

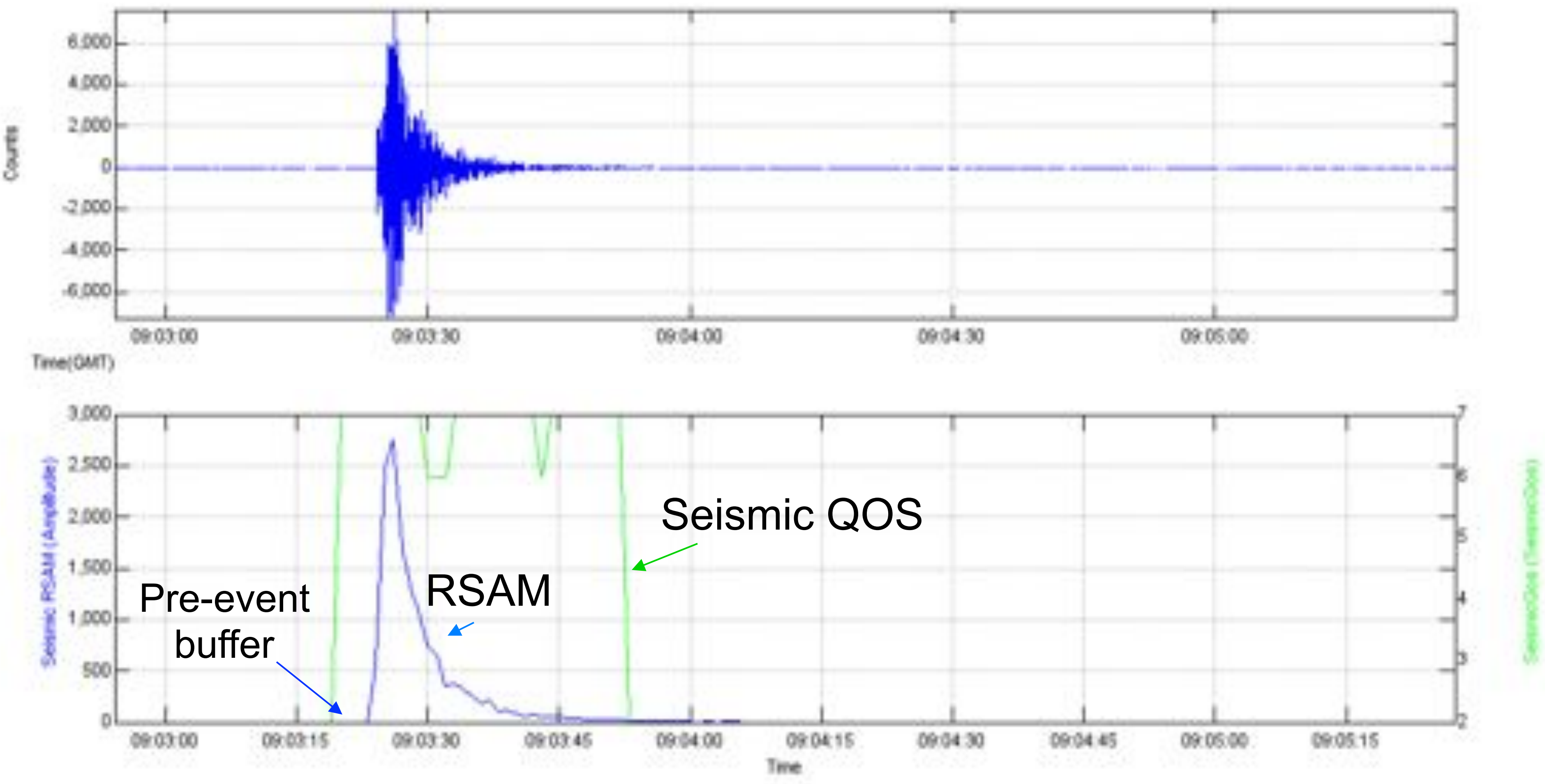


Mount Saint Helens "Agent"



Onboard Node Smart Software

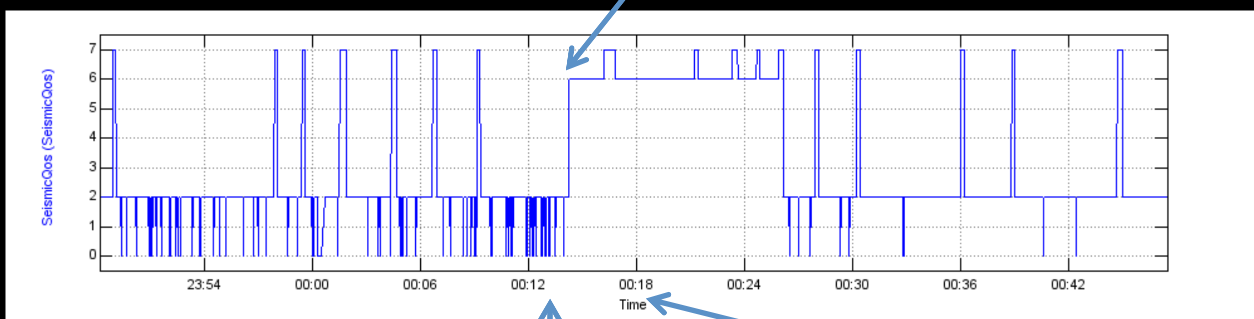
- Onboard node software can detect events to change operating modes to capture critical events
- Quality of Service Node software ensures highest priority data is tranferred
- Example from OASIS Node 05 showing waveform, in-situ RSAM and in-situ event triggered QOS prioritization

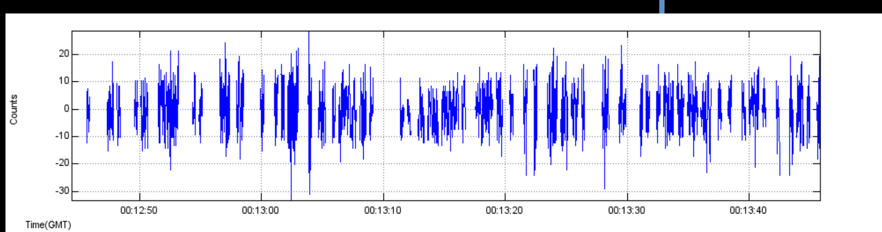


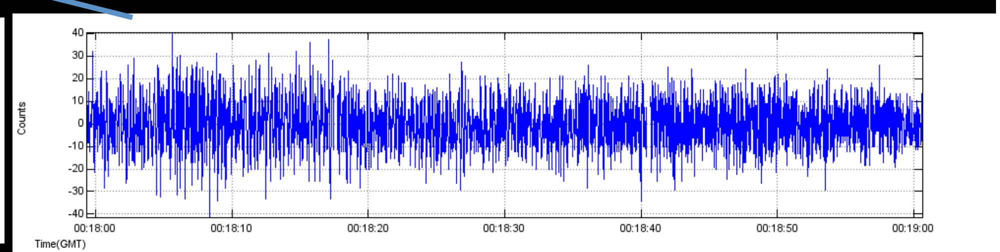
End-to-End ground and space cross-trigger

- Data autonomously delivered to Ground System and ingested into time-series DB.
- VAlarm detects new data and triggers autonomous ground response through C&C: heighten priority (QoS) of crater node (node 4) seismic data.

Thermal data detected / ground response





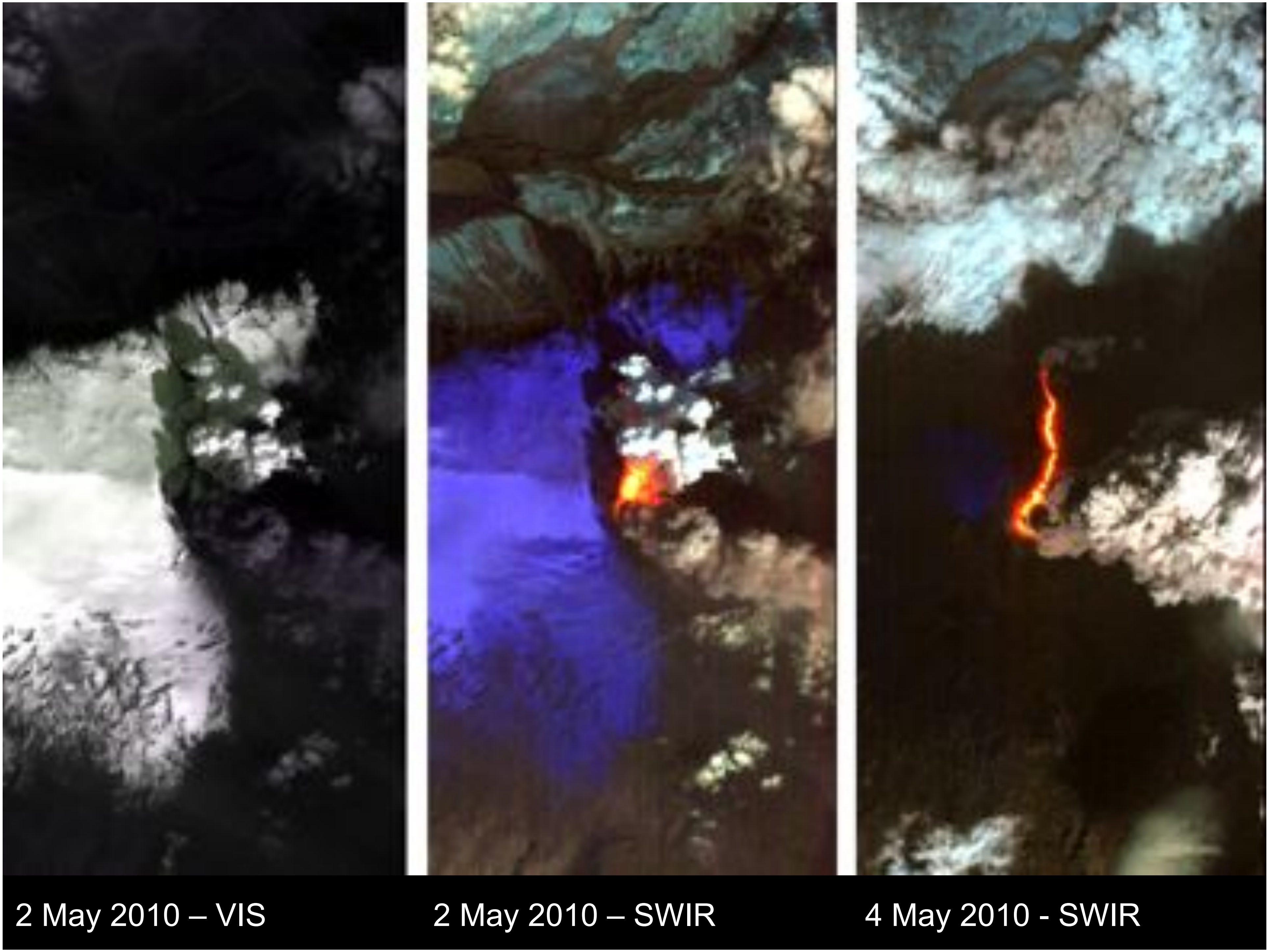


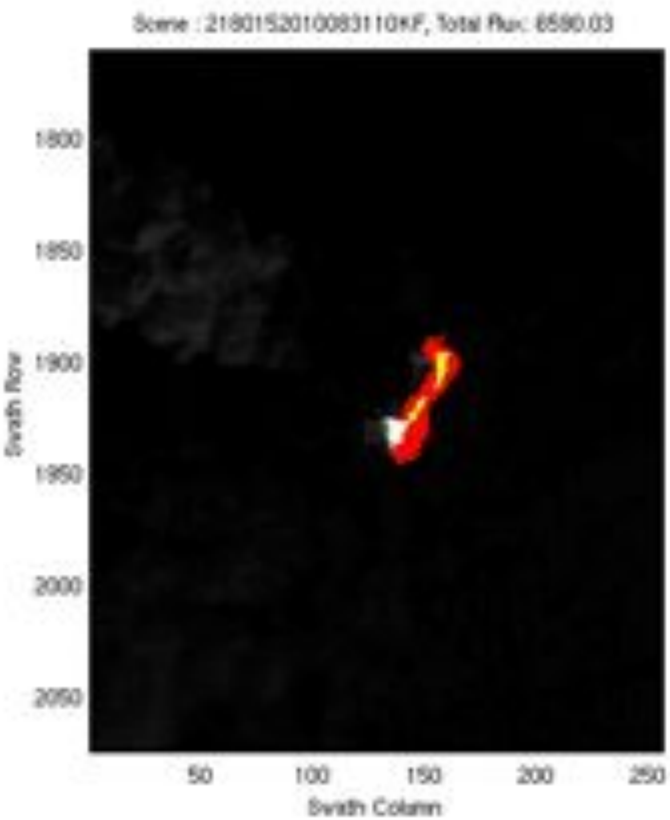
Data transmission loss at low QoS.

Increased QoS results in nearly continuous data, at node of interest.

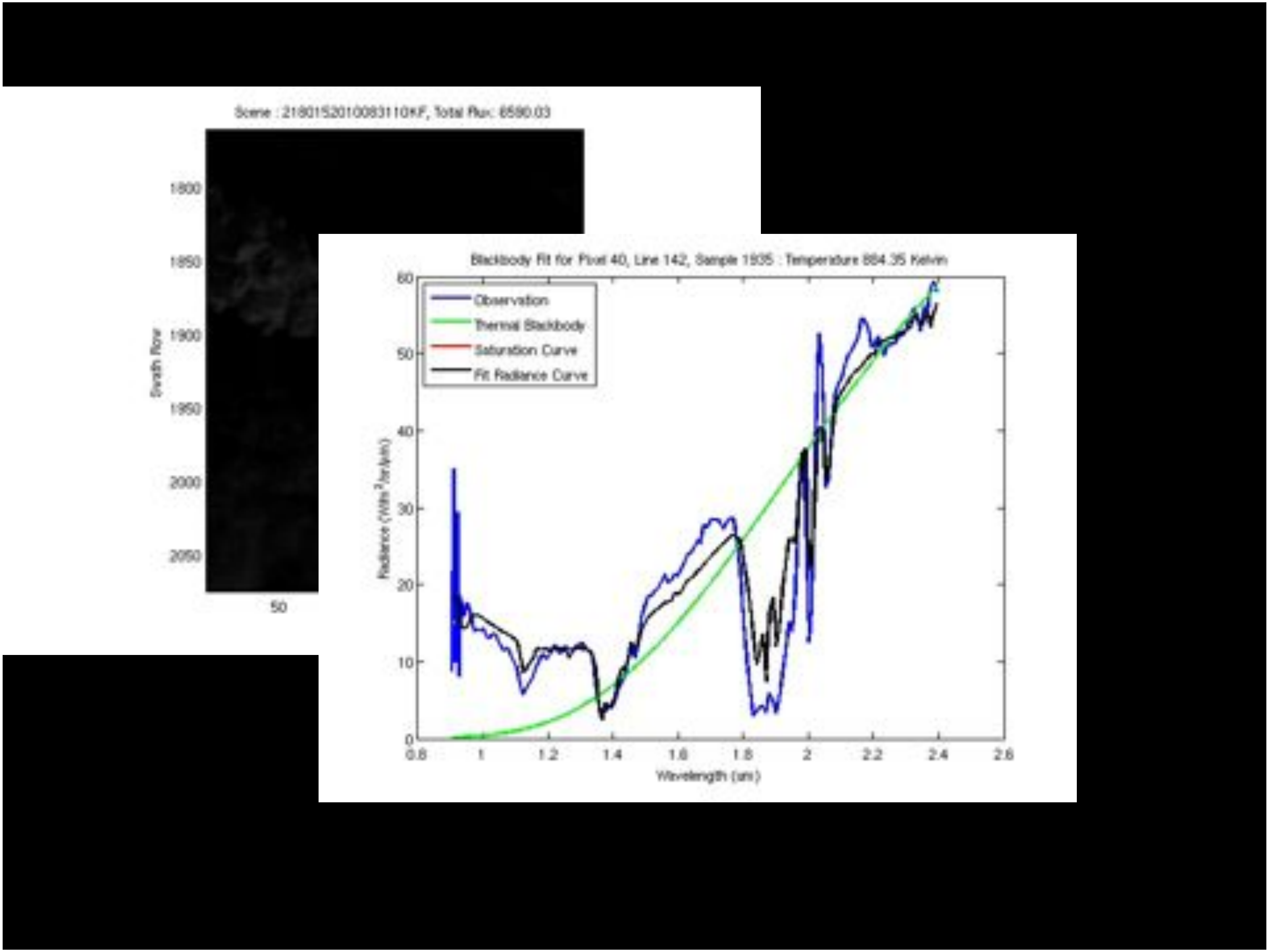
Automated Workflows for Automatic Data Interpretaton

For further information see [Davies et al. 2006 RSE, Davies et al. 2008 JVGR, Davies et al. 2013 JGRI]

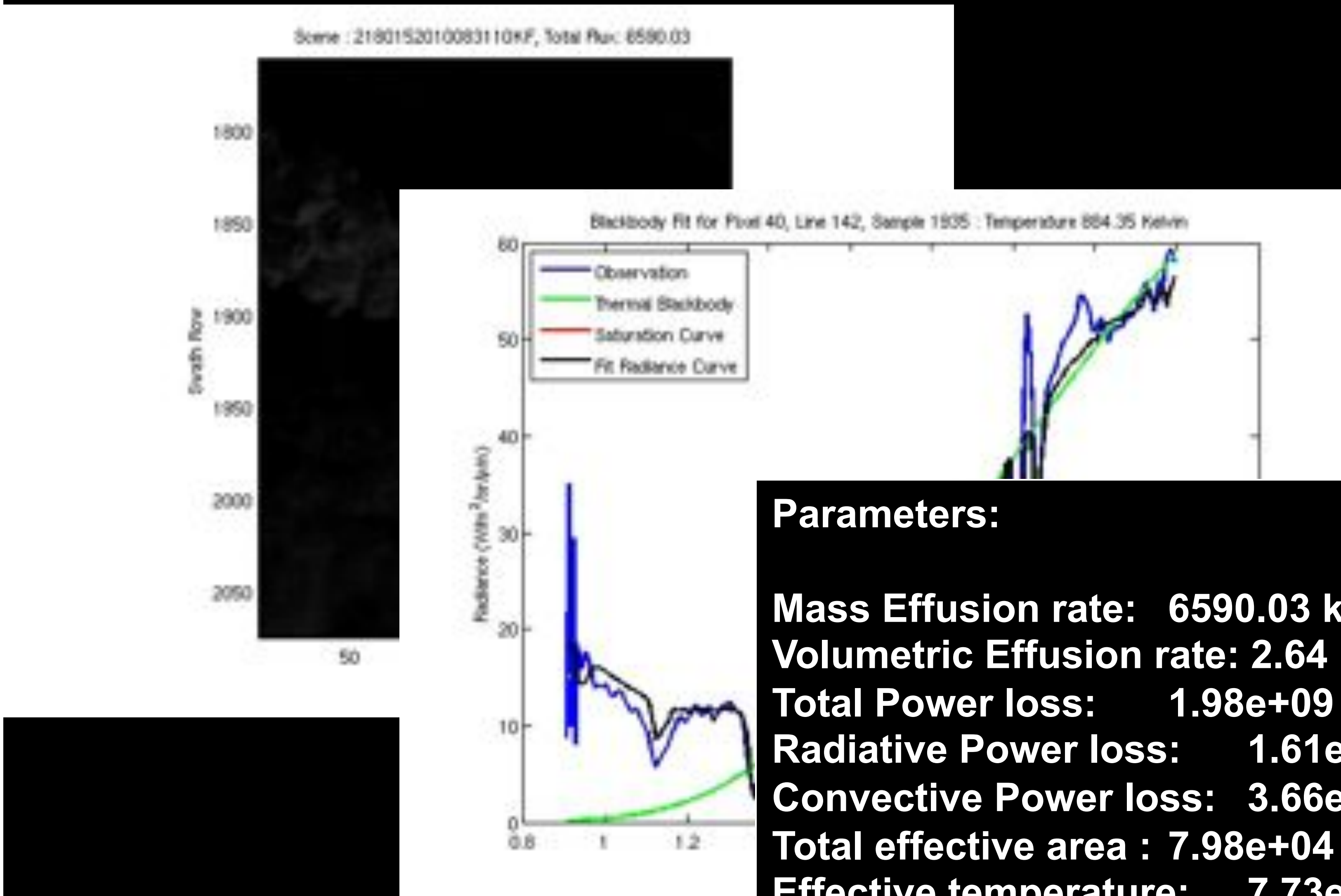

2 May 2010 – VIS
2 May 2010 – SWIR
4 May 2010 - SWIR



Scene : 2180152010083110KF, Total Flux: 6590.03
1800
1850
1900
1950
2000
2050
Swath Row
50
100
150
200
250
Swath Column

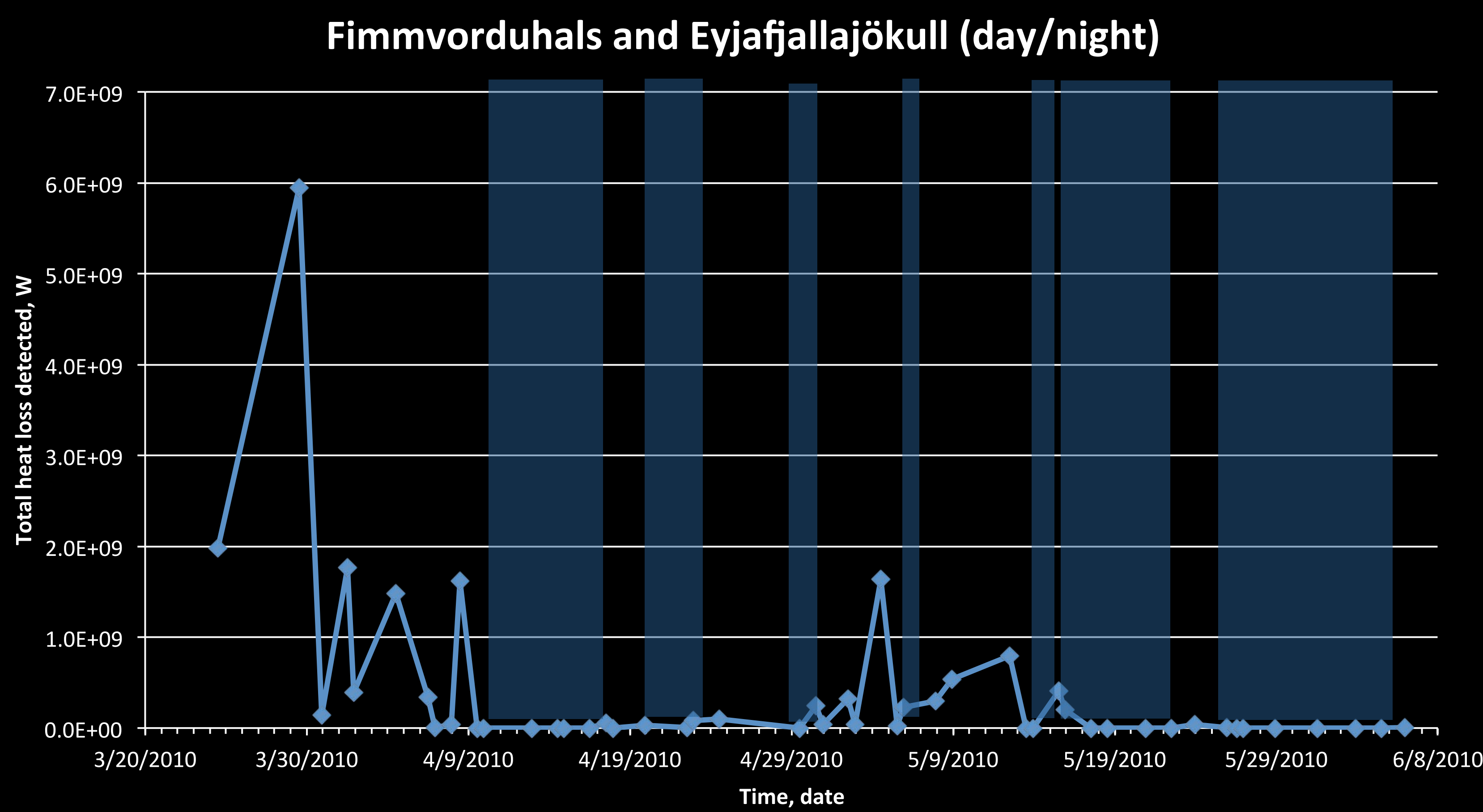


Scene : 2180152010083110KF, Total Flux: 6590.03
Swath Row
Blackbody Fit for Pixel 40, Line 142, Sample 1935 : Temperature 884.35 Kelvin
Observation
Thermal Blackbody
Saturation Curve
Fit Radiance Curve
Wavelength (um)



Parameters:

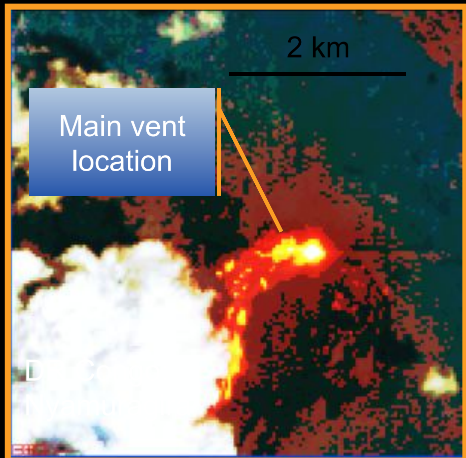
Mass Effusion rate: 6590.03 kg/s
Volumetric Effusion rate: 2.64 m^3/s
Total Power loss: 1.98e+09 W
Radiative Power loss: 1.61e+09 W
Convective Power loss: 3.66e+08 W
Total effective area : 7.98e+04 m^2
Effective temperature: 7.73e+02 K
Look Angle: 12.63 deg.
Range to Ground: 705.85 km



Thermal emission estimate is minimum value:

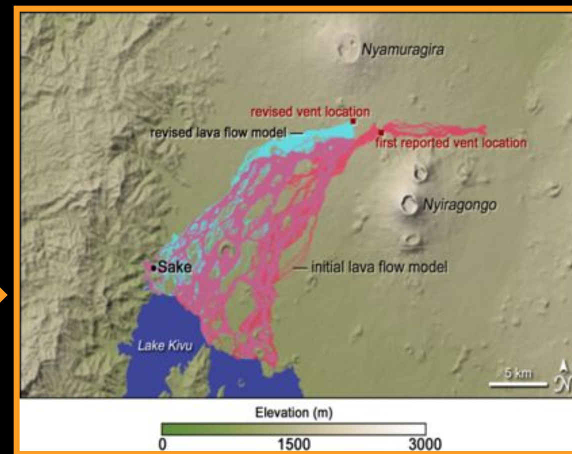
- estimates from short wavelength data
- thermal detections heavily impacted by cloud and/or plume…
  … and we would like to know by how much!

Volcano SensorWeb



EO-1 Hyperion SWIR image of destructive lava flows at Nyamuragira, DR Congo, 4 Dec 2006.

This vital data acquisition allowed pinpointing of the vent and enabled accurate modeling of likely lava flow direction.



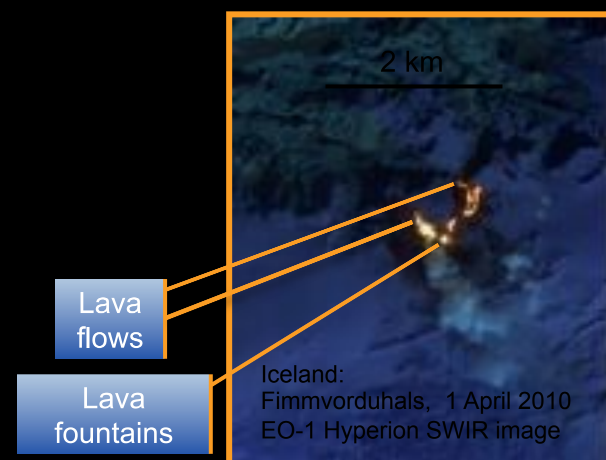
"This was a stunning demonstration of the capability of an autonomous system to obtain and provide vital information during a volcanic emergency."
- Gari Mayberry, Geoscience Advisor, USAid

Alert: Uses alerts from multiple sources (*in situ* sensors, MODIS, AFWA, VAAC, et al.)

Response: Alerts are used in a prioritized fashion to trigger follow up targeted satellite observations.

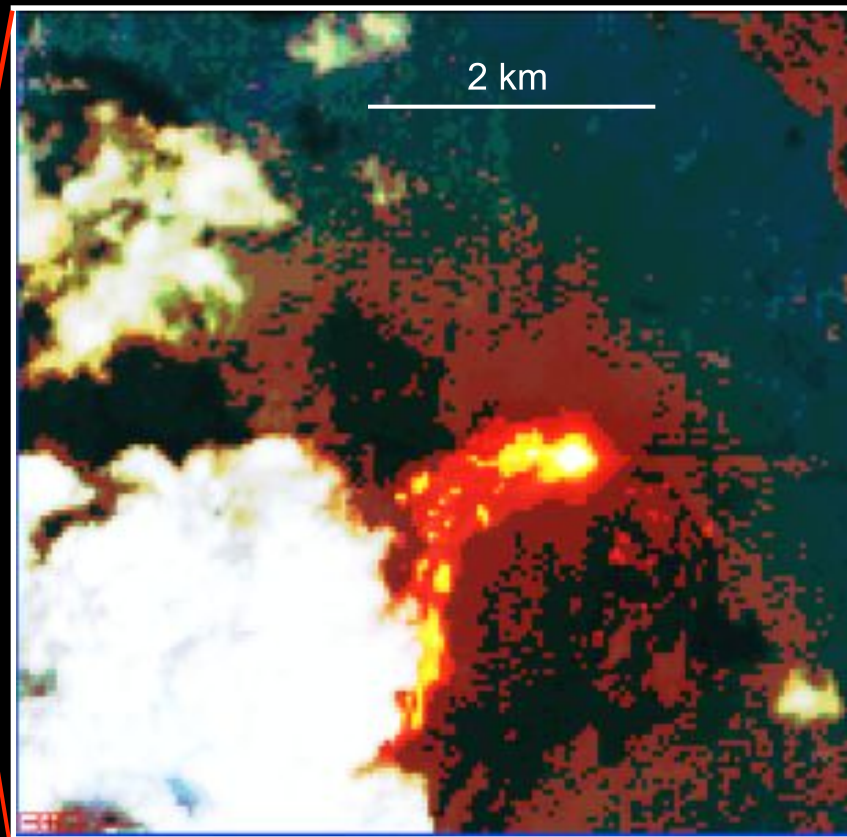
Product Generation & Delivery: Rapid data processing, thermal maps, modeling of eruption parameters, and posting to end users.

SensorWeb now includes in-situ sensor monitoring of Icelandic volcanoes:
http://en.vedur.is/earthquakes-and-volcanism

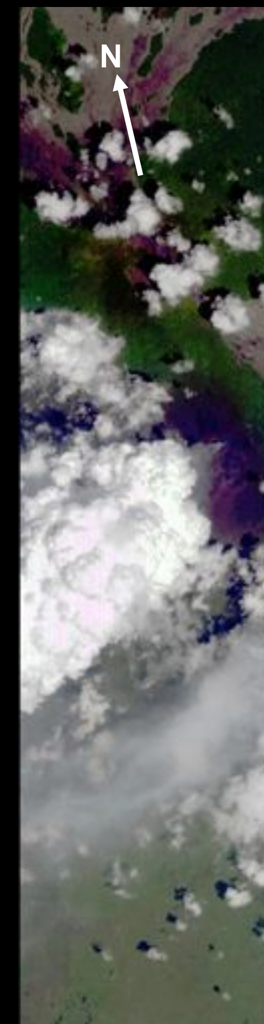


A. G. Davies / JPL

Hyperion VIS   Classifier output



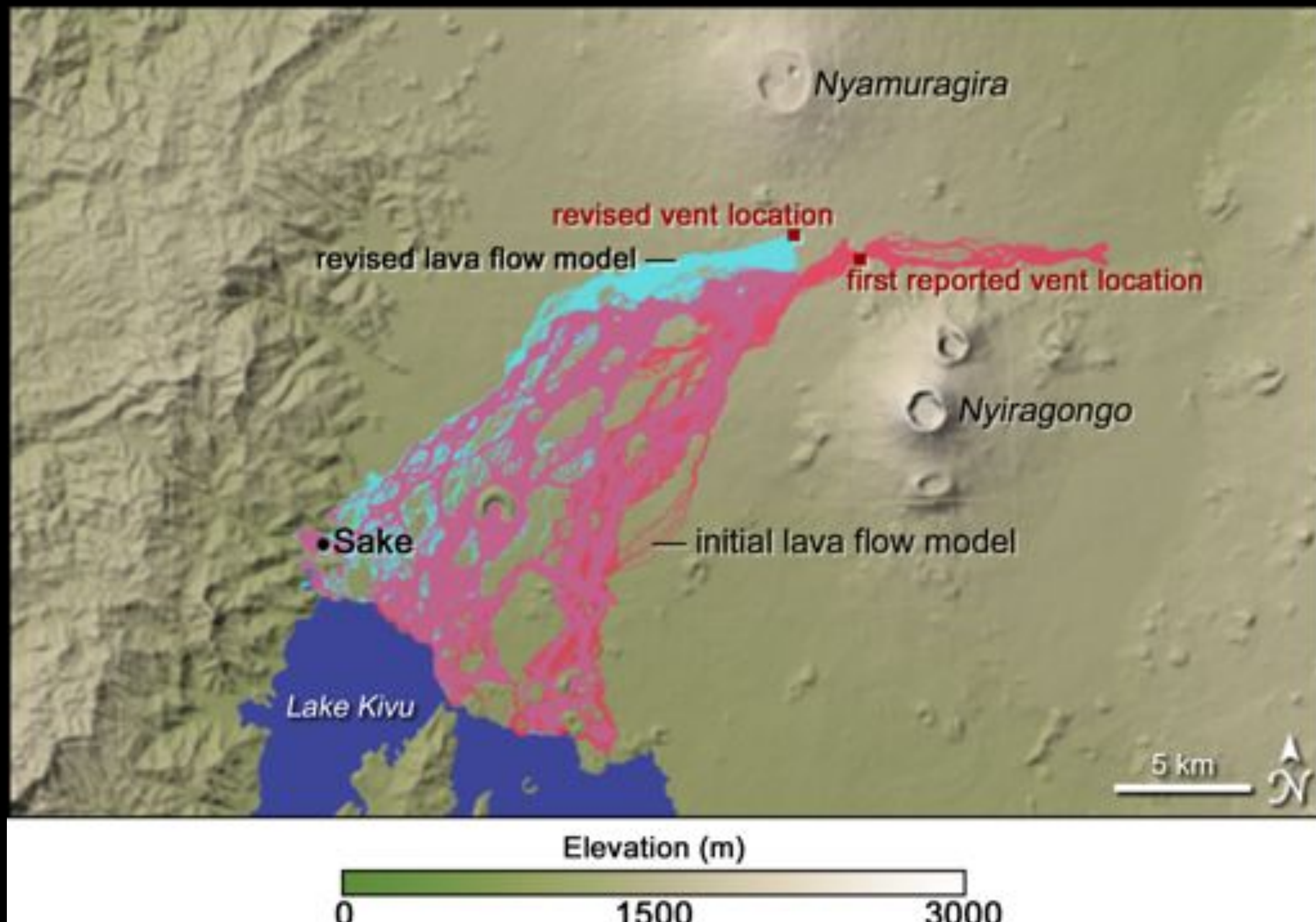
Hyperion SWIR image of active vent and flows



Nyamuragira
4 Dec 2006
07:59 UT

Davies, A. G. *et al., 2008, Proc. IEEE-AC*
Scott, M. (2008) *Earth Imag. J., 5, no 2, 26-29.*

Predicting lava flow emplacement



Modelling by Paolo Papale (INGV) *et al.*

Scott, M. (2008)

Machine Learning and Workflows for Automatic Data Interpretation

For further information see [Chien et al. 2011 IGARSS, Mclaren et al. 2012 SPIE, Chien et al 2012 i-SAIRAS, Chien et al 2013 JSTARS]

Flooding in Southeast Asia, Fall 2011

Dry: March 6, 2011
(MODIS)

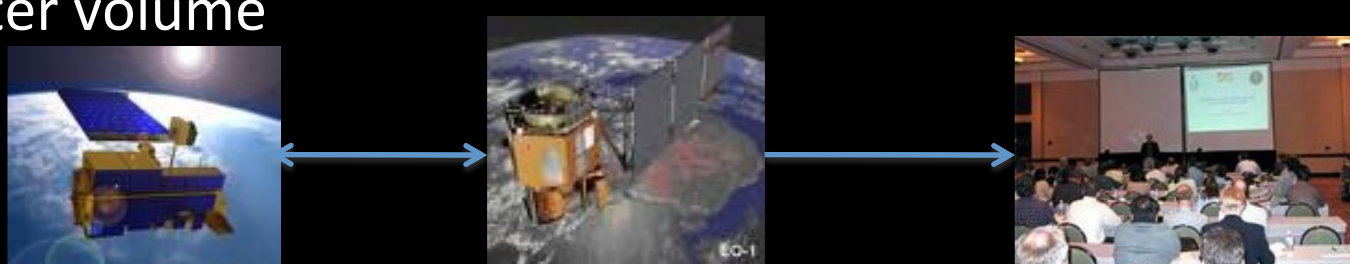
Flood: October 27, 2011
(MODIS)

2011 Thailand Flooding

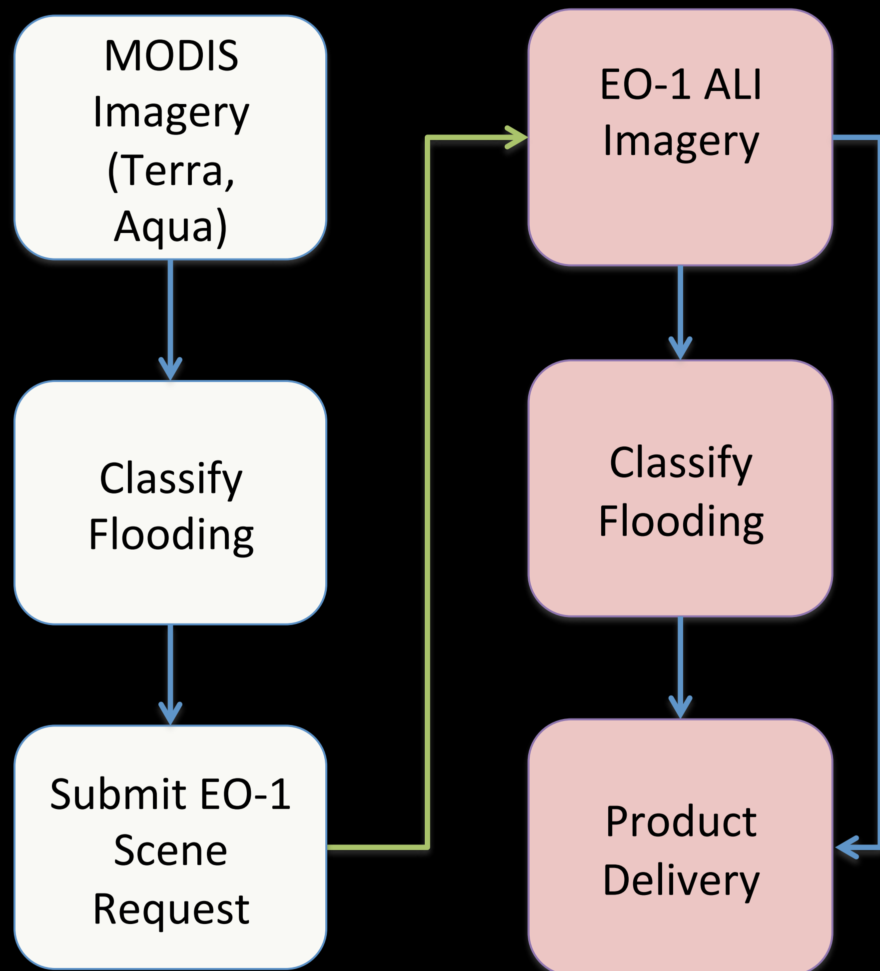
- Flooding in Thailand in late 2011: over 800 deaths, $45 Billion USD damage (according to World Bank), and over 13 million people affected as of January 2012
  - Threatened Bangkok and outlying areas
  - Disrupted industrial production and global supply chains

Thailand Flood Sensorweb (TFS): Overview

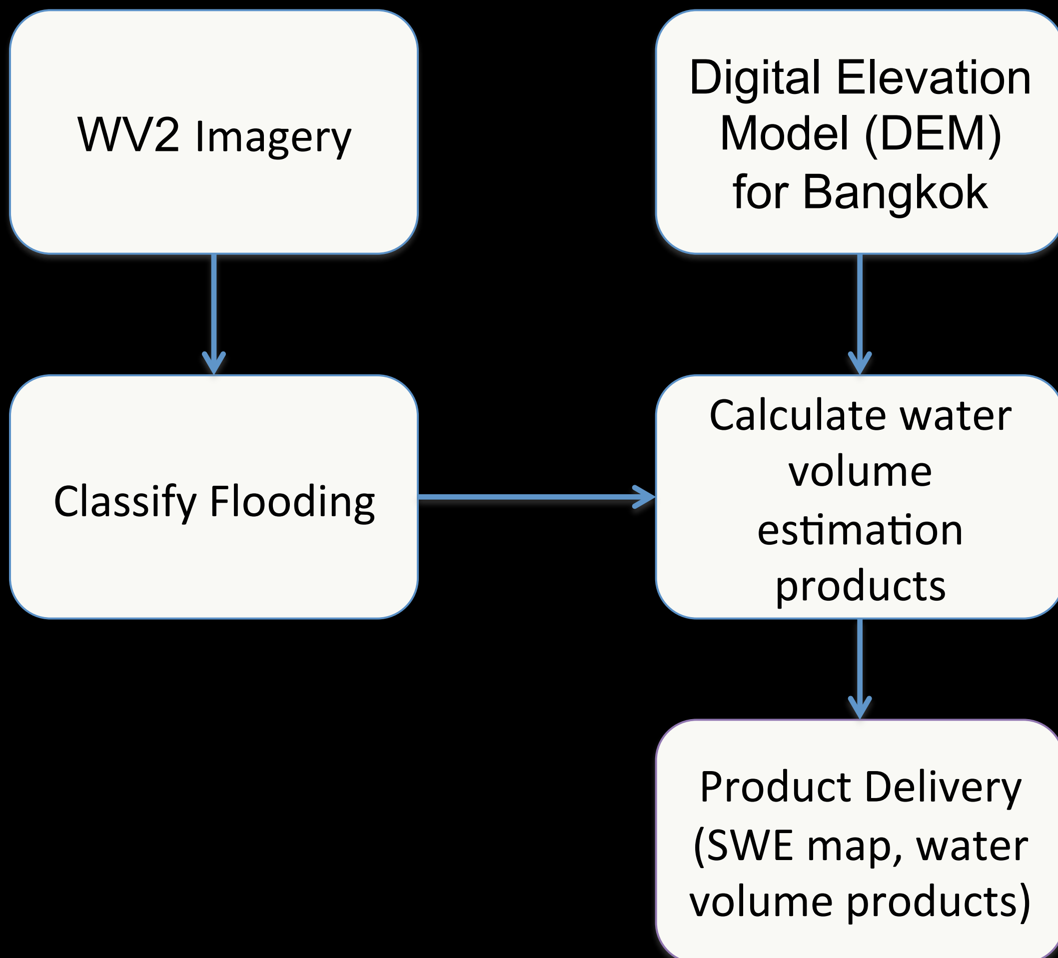
- Networked set of sensors (space), data from sensors used to reconfigure/task other parts of network
- In TFS, twice-daily Moderate Resolution Imaging Spectroradiometer (MODIS) imagery is classified, compared to a baseline, and used to request observations from EO-1
  - Automatically deliver data products for EO-1 Advanced Land Imager (ALI) images to end users
    - Thailand Hydro & Agro Informatics Institute (HAII)
- Manually retrieved WV-2, Ikonos-4, Geo-Eye, Landsat, Radarsat2 scenes can be automatically classified and combined with Digital Elevation Model (DEM) to estimate water volume



Automated TFS Operation



Workflow for WV2 water volume estimation



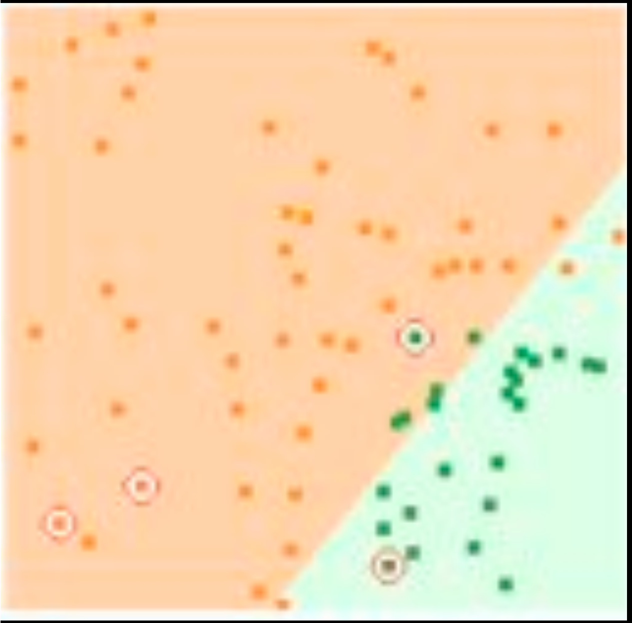
WV2 Flood Classification

Used Support Vector Machine (SVM) Technique: Finds a separating hyperplane between two labeled classes

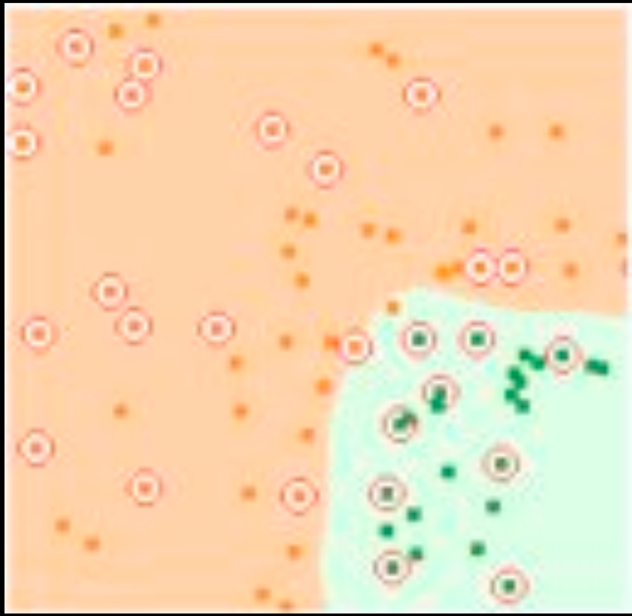
$$f(\mathbf{x}) = sign(\sum_{i=1}^{n} v_i \cdot k(\mathbf{x}, \mathbf{x}_i) + b)$$

Linear kernel
fast (simply dot product)
inflexible
C (error penalty)

Gaussian (RBF) kernel
slow
flexible
C (error penalty)
γ (Gaussian width)



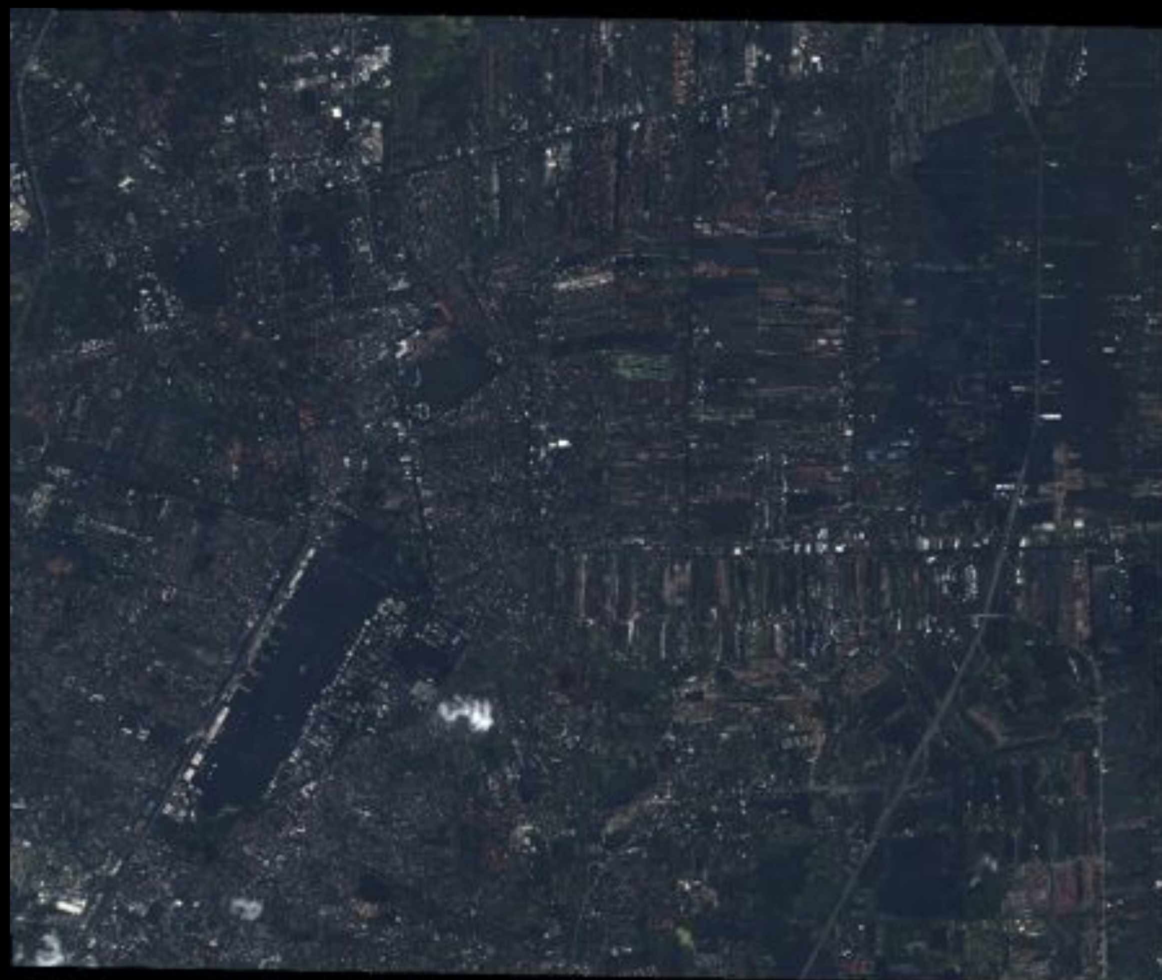
More than two classes can be separated recursively



WV2 Flood Classification

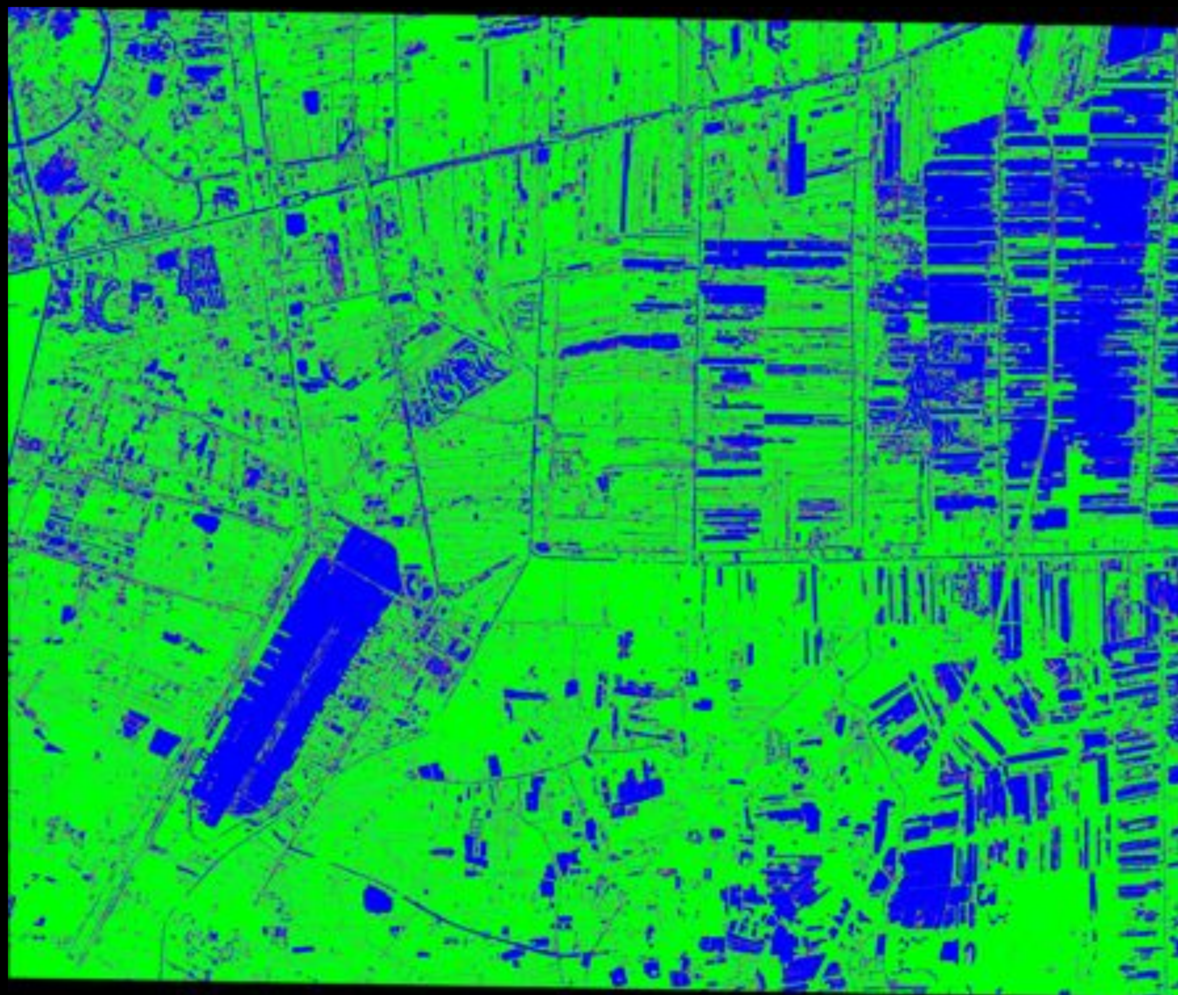
- Hand-labeled subset of WV2 scenes
- Training, validation, and kernel selection using PixelLearn tool created by Machine Learning and Instrument Autonomy (MLIA) Group at JPL
- 5th degree polynomial kernel, cost factor C = 1.0
  - Feature sets using 8 MS bands or 28 band ratios gave plausible results
  - Experimented with classes for clouds and urban areas, but settled on land/water/border
    - Found more classes difficult to generalize to multiple scenes
  - Runtime for classification w/in PixelLearn tool: ~5 minutes
- Other SVM kernels in experiment
  - Linear: Often performed well for training scene, but failed to generalize to multiple scenes
  - Radial Basis Function (RBF): Inconsistent results, sometimes better, sometimes worse than Polynomial

WV2 SVM Classification



Reflectance of WV2 scene of Bangkok w/ flooded Don Muang Airport, acquired 11.3.2011

WV2 SVM Classification



Surface water extent (blue) from SVM classifier using 5th degree polynomial kernel on 8 WV2 bands

WV2 SVM Classification

Class	Unlabeled	Border	Water	Land	Unlabeled	Border	Water	Land
Unlabeled	0	13156222	20395227	45959337	0.0%	16.5%	25.7%	57.8%
Border	0	223	0	0	0.0%	100.0%	0.0%	0.0%
Water	0	0	6847	338	0.0%	0.0%	95.3%	4.7%
Land	0	0	0	1044	0.0%	0.0%	0.0%	100.0%

Confusion matrix for 5th degree polynomial SVM for 8 features, run on hold-out scene acquired November 3, 2011. Overall classification accuracy: 96.0%.

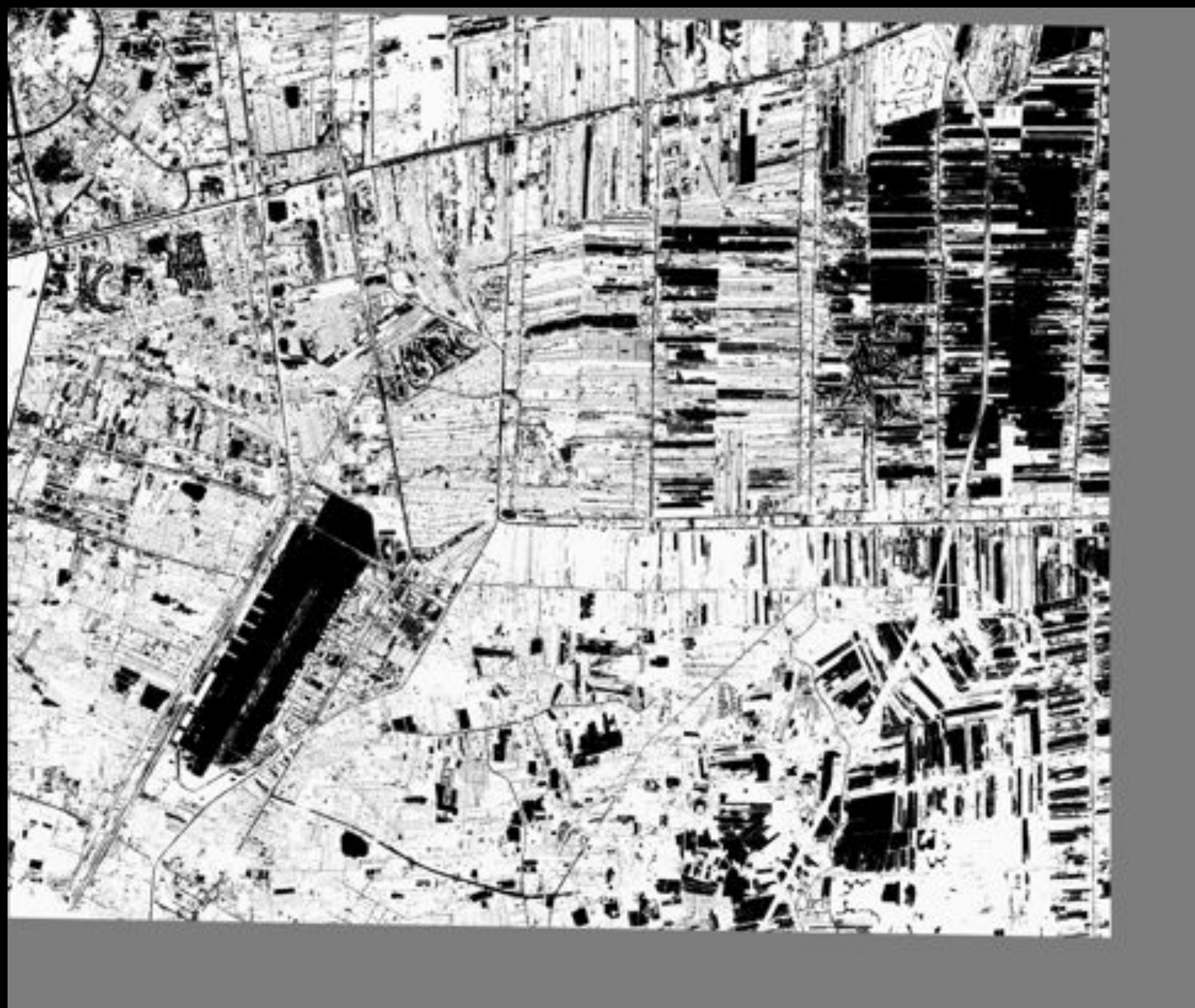
Class	Unlabeled	Border	Water	Land	Unlabeled	Border	Water	Land
Unlabeled	0	25639043	12807455	22806048	0.0%	41.9%	20.9%	37.2%
Border	0	349	0	0	0.0%	100.0%	0.0%	0.0%
Water	0	0	2206	287	0.0%	0.0%	88.5%	11.5%
Land	0	0	3	3110	0.0%	0.0%	0.1%	99.9%

Confusion matrix for 5th degree polynomial SVM for 8 features, run for hold-out scene acquired November 8, 2011. Overall classification accuracy = 95.1%.

WV2 Thresholding

- Used ratio of WorldView-2's NIR1 (831 nm) / Green (546 nm) bands
  - Bands selected because of their similarity to the bands used in prior work for ALI instrument [Ip et al. 2006, Chien et al. 2011]
  - Tested different nir1/g thresholds from 0.6 - 1.0
    - Marking areas with g/nir1 threshold < 0.8 as water yielded results comparable to SVM

Water Volume Estimation

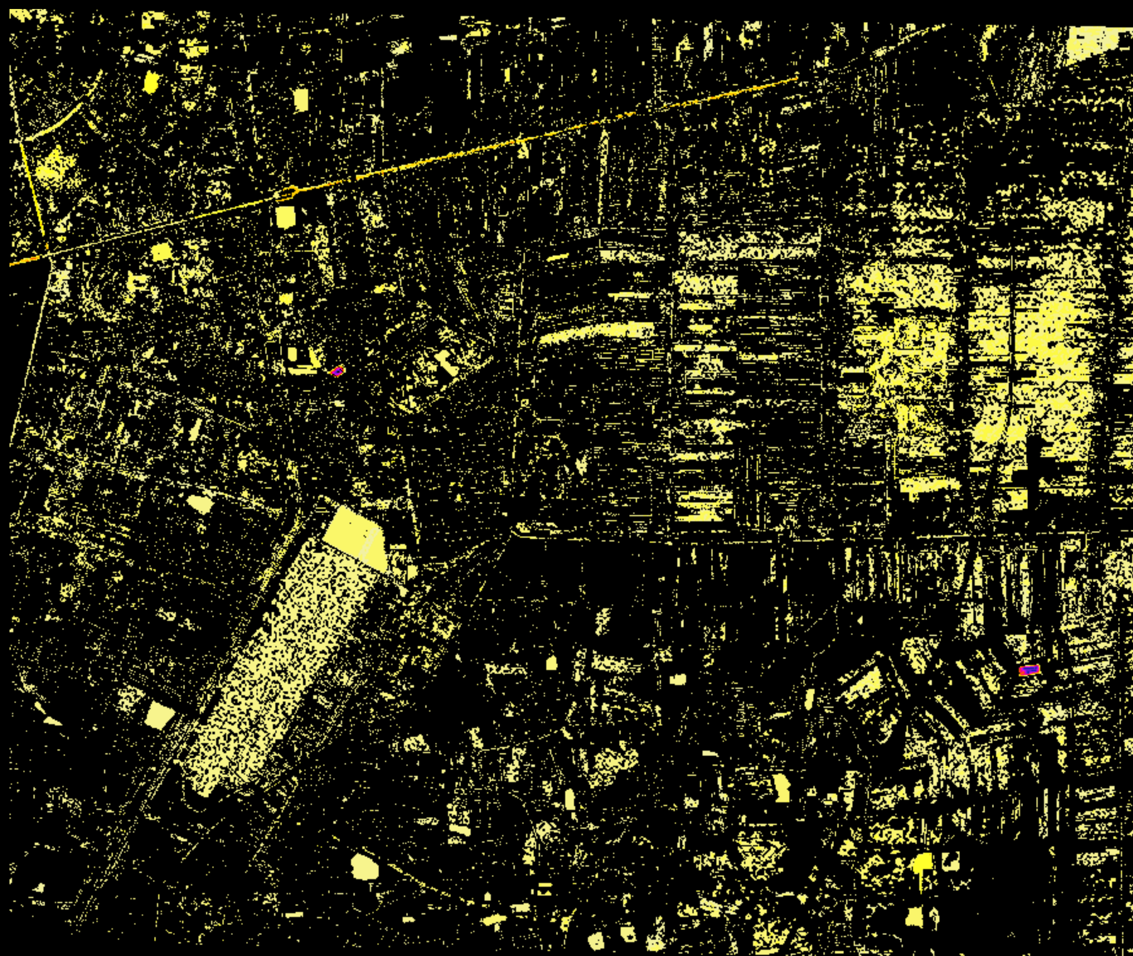


Surface water extent (black) from thresholding WV2 green, NIR1 bands

Water Volume Estimation

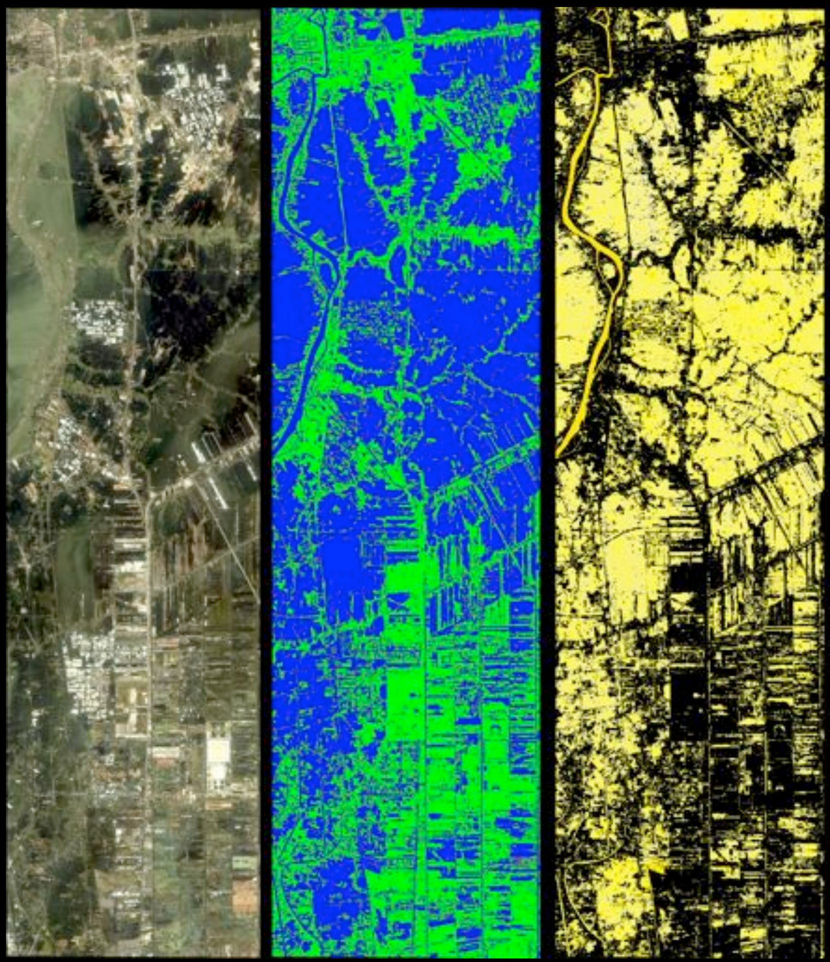
- Goal: Estimate depth of water in flooded areas and total volume of flood-water remaining
- Inputs
  - Surface water extent map classified from MODIS, ALI, WV2, or RADARSAT2 GeoTIFFs
  - DEM acquired from HAII (Resolution: 5 meters horizontal, 1 m vertical)
- Algorithm Outline
  - Identify land, water, and no-data pixels in classification results
    - No-data includes clouds, borders
  - Identify all unique, 8-connected water bodies in the image
  - Find pixels that constitute boundary around each unique water body
  - For each water body, estimate mean height of boundary pixels using a DEM, and set this as water body elevation
  - For each water pixel, set water depth to max(0, water_body_elevation – pixel_elevation)
- Output: water depth map (GeoTIFF), water volume statistics

Water Volume Estimation



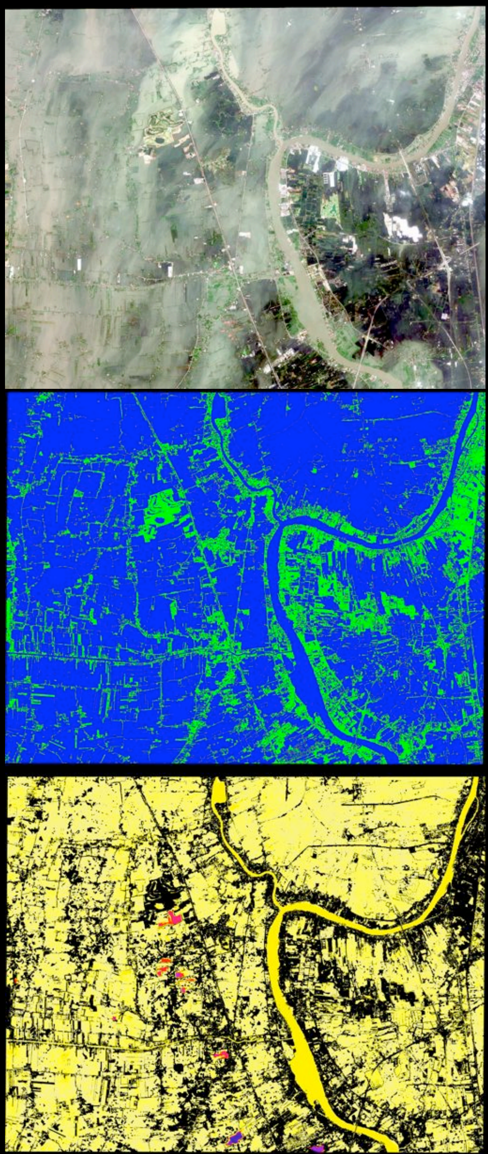
Resulting water depth map calculated using SVM-classified surface water extent map and DEM. Total water volume calculated: ~27,872,000 m^3; average flooded pixel depth: 0.64 m.

Ikonos-4, Geo-Eye



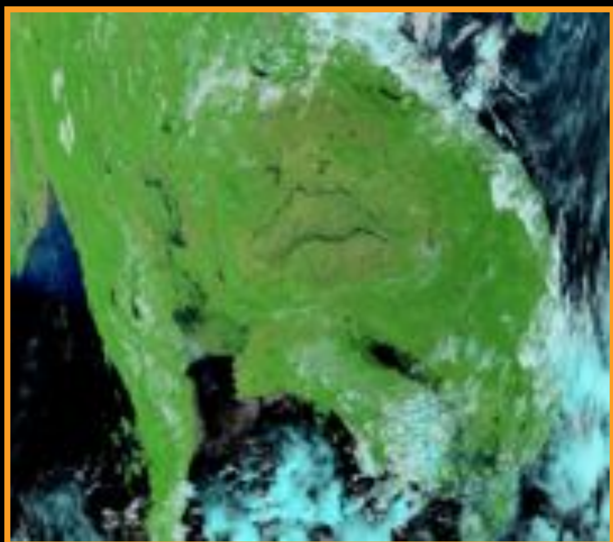
Ikonos RGB, SWE, depth

Geo-Eye
RGB
SWE
depth



Thailand Flood SensorWeb

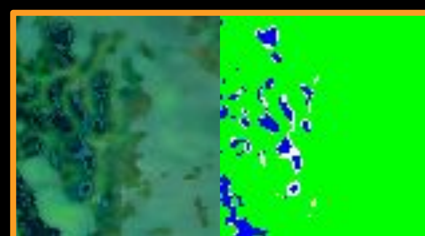
- **Detect:** Pull 2x daily RAPIDFire subsetted MODIS data, support Vector Machine Learning (SVM) & band ratio methods of classifying gauging reaches against baseline dry scores
- **Respond:** Earth Observing 1 autonomously responds to acquire more detailed imagery
- **Product Generation & Delivery:** Data and flood products electronically delivered to Thailand Hydro Agro Informatics Institute (http://www.haii.or.th)



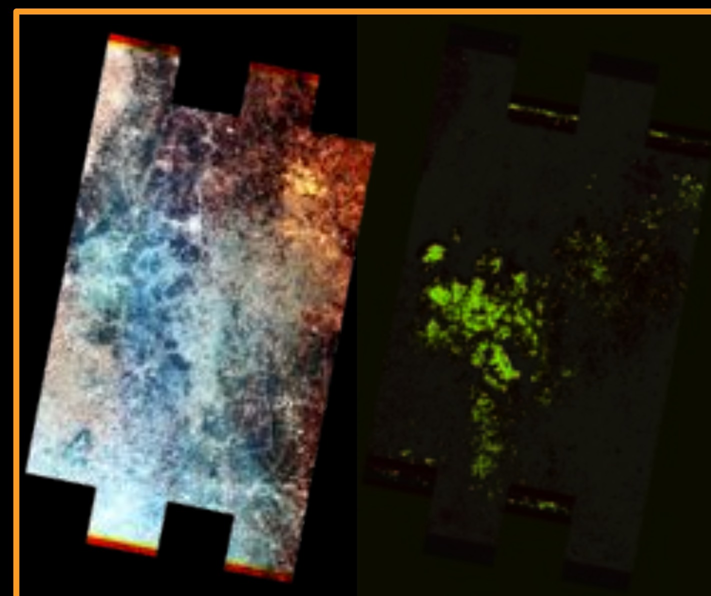
MODIS 28 Nov 2010 Imagery of Thailand Flooding (band 7-2-1)
Est. damage over $1.67B USD
[Thailand MCOT, CNN], Oct–Nov 2010

"The Thailand Flood SensorWeb provides a unique capability to detection, monitoring, response, and mitigation of flooding in Thailand"
Dr. Royol Chitadron, Director, HAII Thailand

S. Chien / JPL



Detect:
(L) MODIS imagery of Bang Pla Ma from 20 Jan 2011
(R) Classified surface water extent from MODIS image



Respond → Generate → Deliver
(L) ALI imagery of Bang Pla Ma from 21 Jan 2011
(R) Classified surface water extent from ALI image

Thailand Flood Sensorweb in Operations

	2010: 6/2010-5/2011	2011: 6/2011-5/2012	2012: 6/2012-12/2012	Total per Instrument
MODIS (est.)	300	730	420	1450
EO-1/ALI	11	34	10	55
Worldview-2	0	55	32	87
IKONOS	0	5	5	10
Geo-Eye-1	0	3	3	6
Landsat-7/ETM	0	6	20	26
				Pointable:
Total per Year	11	103	70	184

Inside the Technology: Machine Learning for automated Image Interpretation

For further information see [Mclaren et al. 2012 SPIE]

Volcano Plume Measurement

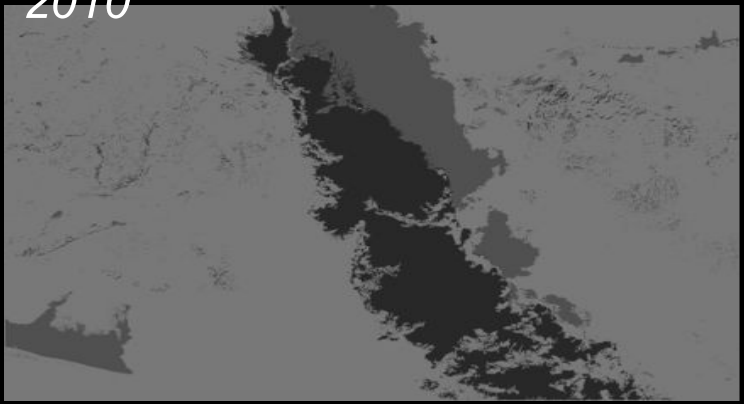
MODIS, Acquired 15 April 2010

- Plume measurements, including height, volume, density, lateral extent, and ejection velocity, are critical to volcano monitoring because of the direct impact of volcanic ash on transportation, agriculture, and human health
- Plume height measurement:
  - Provides data on eruption strength and mechanisms
  - Allows estimation of volumetric eruption rate and volume of ash ejected into the atmosphere

Automatic Height Estimation Concept

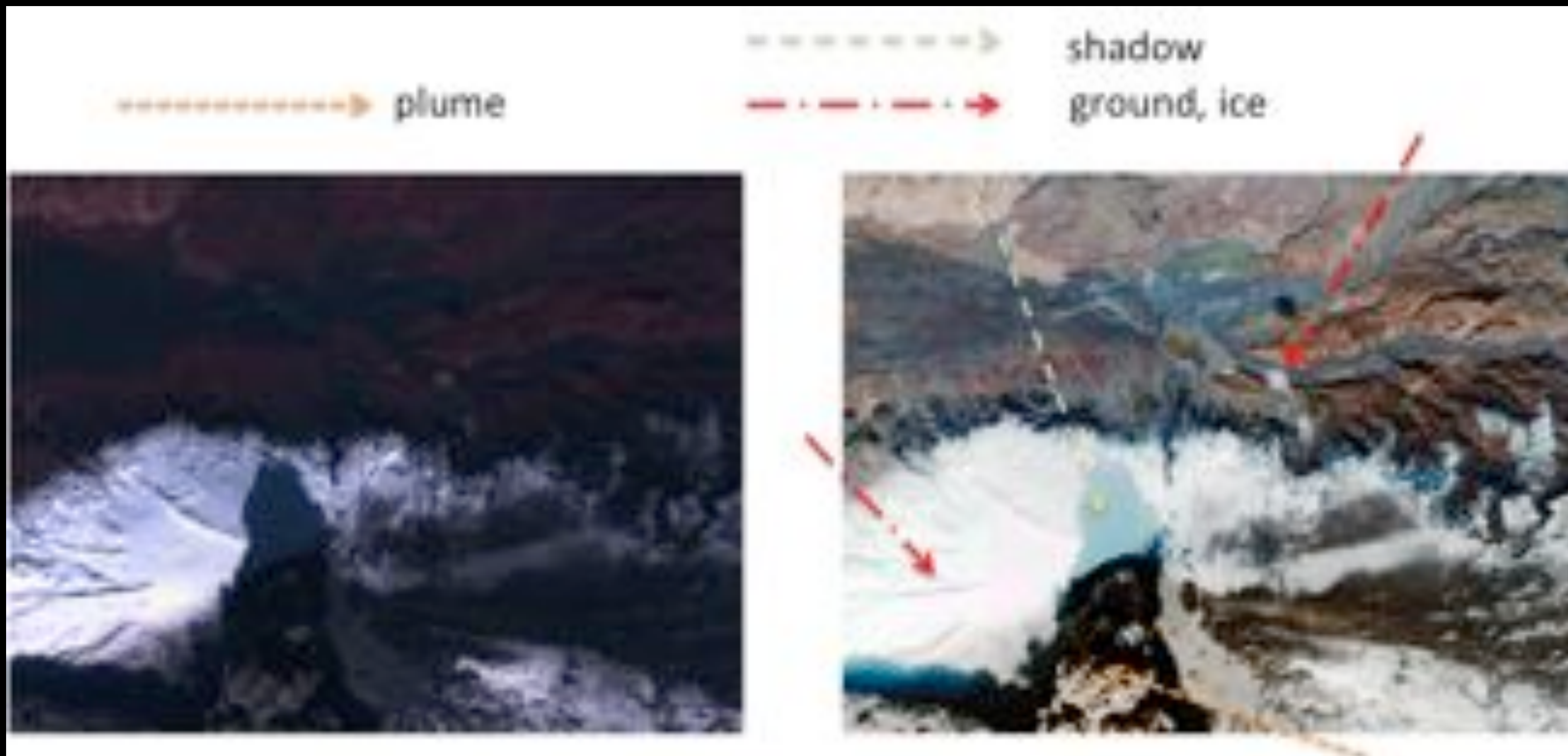
- Explored feasibility of automatically classifying and mapping ash plumes and shadows in WorldView-2 imagery
- Calculated lower bound plume height estimate using classification, solar geometry, spacecraft geometry, and digital elevation information
- Applied method to two sets of WorldView-2 images of the Eyjafjallajökull eruption of 2010 and compared the automatically-derived estimates to externally-derived estimates of plume height

WorldView-2, acquired May 11, 2010



Classification: plume = black, shadow = gray, background = light

WorldView-2 Data



WorldView-2 Image of Eyjafjallajökull eruption, acquired April 17, 2010

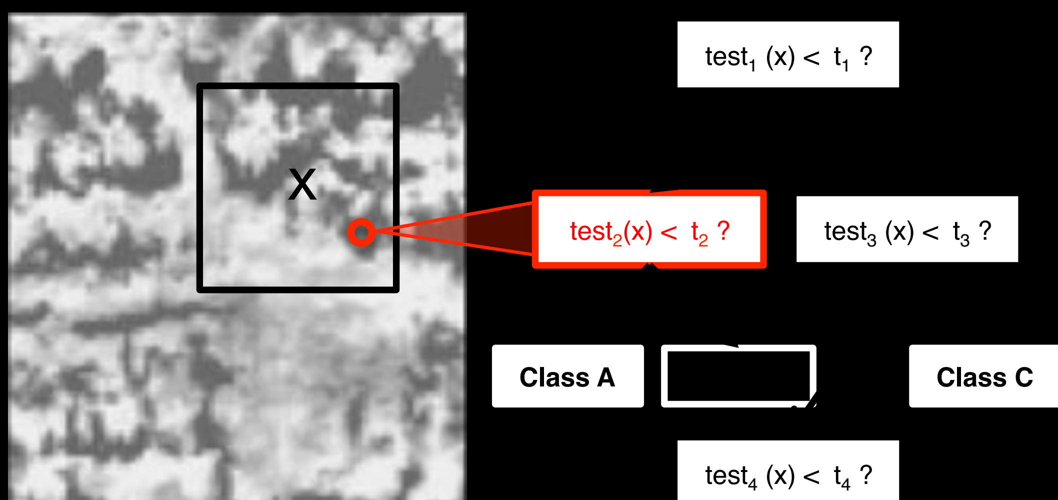
Histogram-equalized image

Machine Learning Approach

- Manual labels
  - Plume, shadow, background (land/ice/water/other) classes
- Input features: 28 ratios of WV-2 multispectral bands
- Trained *random decision forest* on one labeled image, classified five remaining images
- Assigned a probabilistic surface classification to each pixel incorporating cues learned from:
  - Multispectral intensity
  - Local texture
  - Local pixel statistics
  - Other image data

TextureCam

- TextureCam: framework and library of image processing and classification techniques intended for integration into a "smart" instrument
- Uses training data to construct a *random forest* pixel classification system, combining result of multiple independent decision tree classifiers
- Each decision tree is a hierarchical sequence of tests applied to local image values in the neighborhood of the classified pixel. Tests consider numerical attributes such as:
    - Absolute intensity of a nearby location, relative to the target pixel
    - Difference in intensity between two nearby locations
    - Absolute difference in intensity between two nearby locations

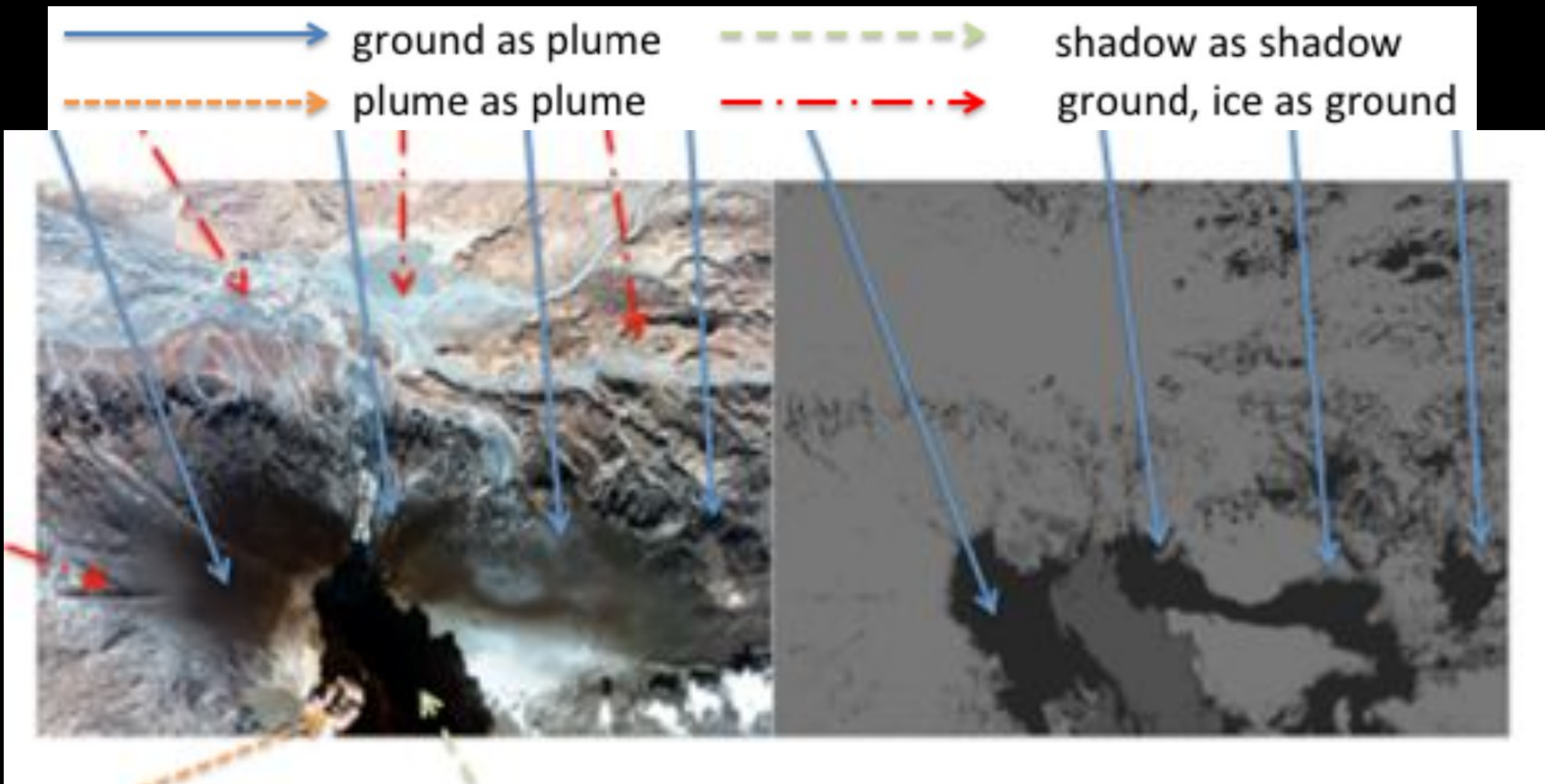


Classification Output

Probability Maps:
White = higher probability

Integrated classification map:
black = plume, grey = shadow, light = land

Challenges

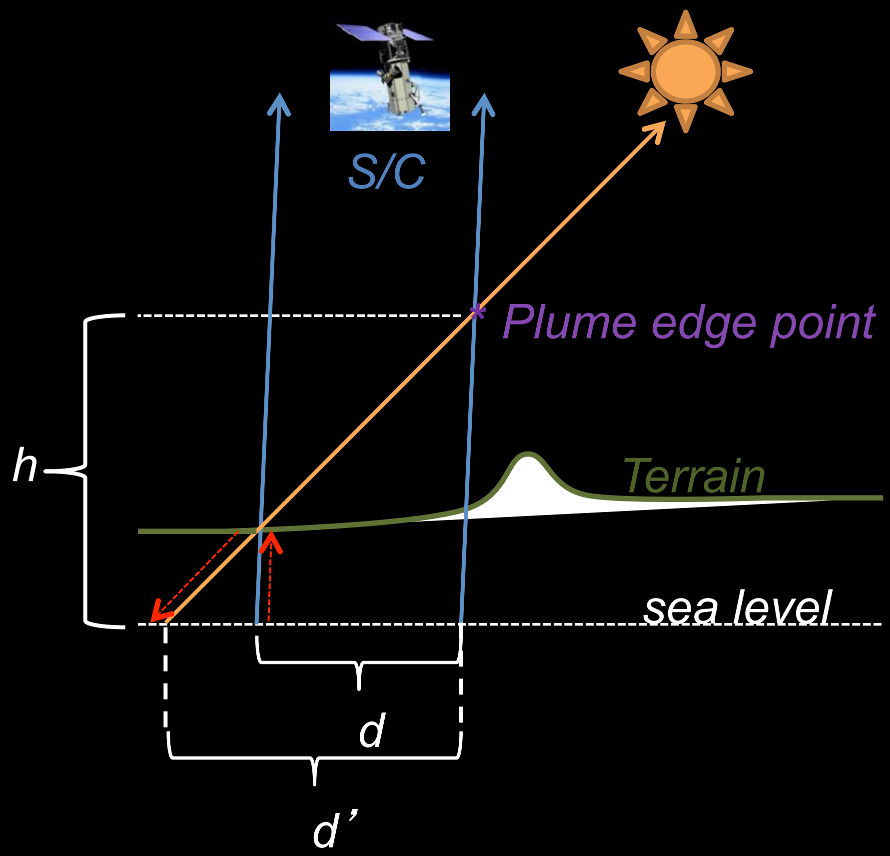


Histogram-equalized WV2 image, acquired May 17, 2011

Classification map: black = plume, grey = shadow, light = land

Height Estimation

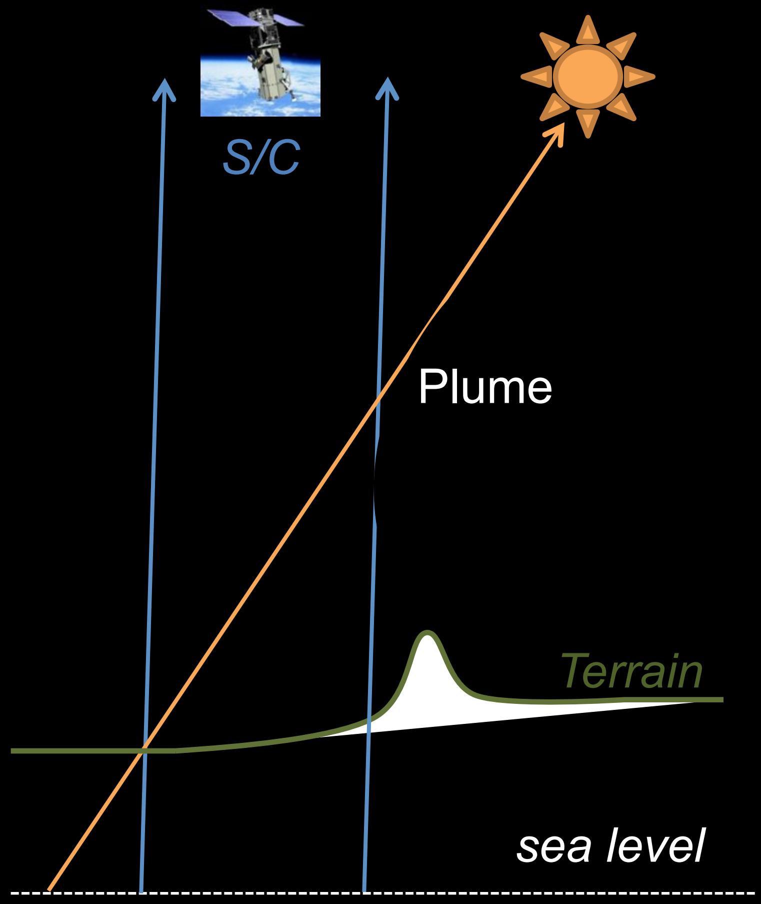
- Estimate plume height from shadows
- Followed calculations derived in A. J. Prata and I. F. Grant, "Determination of mass loadings and plume heights of volcanic ash clouds from satellite data"
- Rotated classification maps so sun rays are coming from –Y axis (bottom of the image)
- Collected shadow line segments which have a neighboring plume region in sunward direction
- Corrected shadow lengths for:
  - Sun and spacecraft azimuth, elevation
  - Ground elevation at shadow edge
    - ASTER GDEM2 DEM
    - 30m horiz. spacing, 1m vert.



d *: Initial shadow length*
d' *: Shadow length after projecting up to DEM & down along sun vector*
h *: Plume point height*

Height Estimation

- Method underestimates plume height– highest part of the plume is not necessarily casting the shadow seen in the image
  - Shadow not necessarily cast from plume edge seen by spacecraft
- Select and report largest measurements
  - Height estimates for long shadow rays traced from large regions of classified plume



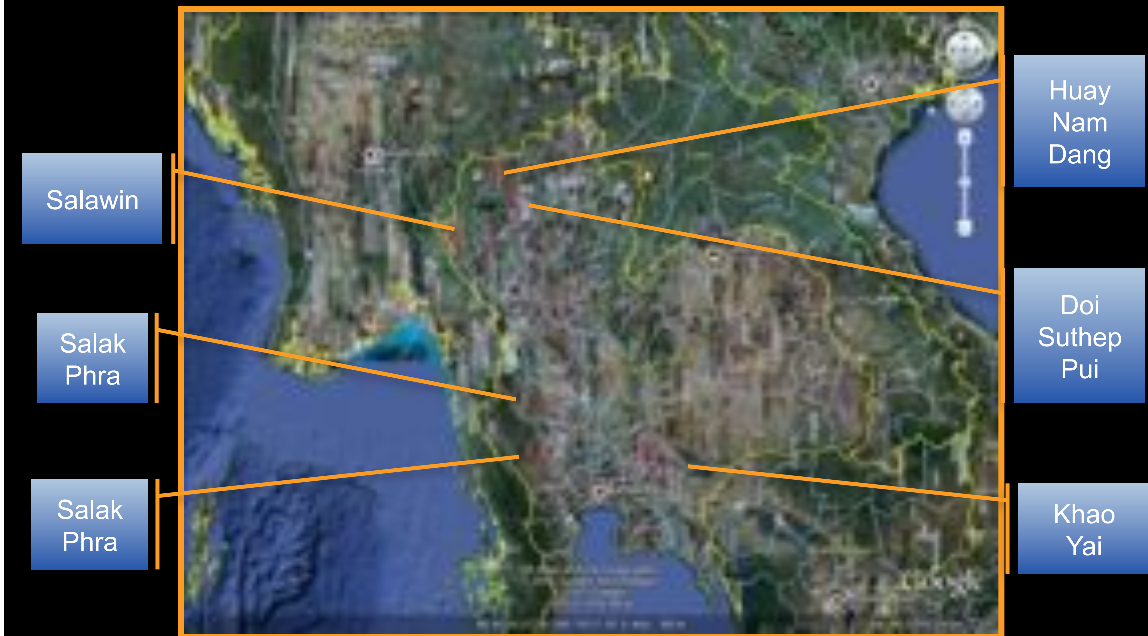
Height Estimation Results

- For each image, compute mean, std deviation of top quartile of height estimates, and keep estimates w/in 2 stds of the mean
- Observed estimates from Þ. Arason, G.N. Petersen and H. Björnsson, "Observations of the altitude of the volcanic plume during the eruption of Eyjafjallajökull, April-May 2010"

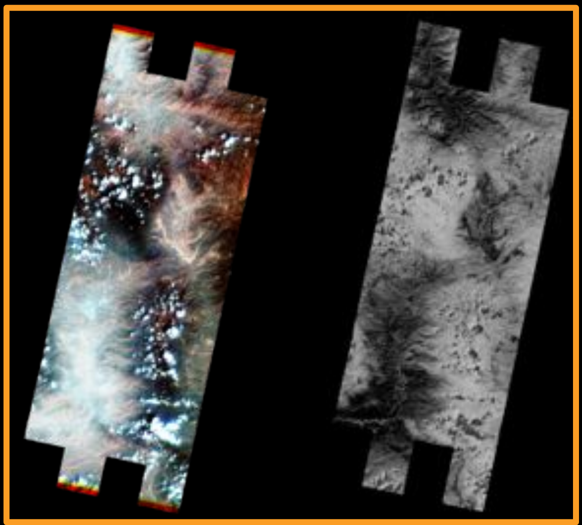
Image Date	Plume height estimate (in km above sea level)				
	WorldView-2 Shadow-based Estimates			Observed Estimates from Arason et al. 2011	
	# samples	Best estimate (mean, km)	20^{th} - 80^{th} %-ile Range (km)	Visual Estimate	Radar Estimate
17 Apr 2010	290	2.66	2.52-2.97	2.3-5.5km	4.8-8.5km
17 Apr 2010	199	3.57	3.51-3.64		
17 Apr 2010	585	3.06	2.94-3.15		
17 Apr 2010	8	4.35	4.35-4.36		
11 May 2010	12	3.02	3.02-3.03	3.8-4.4 km, mean=4.3km	3.6-4.9 km, mean = 4.3km
11 May 2010	154	4.58	4.47-4.67		

Other Sensorweb Applications

Thailand Fire Sensorweb



Color image (L) & Normalized Burn Ratio (R) product of Huay Nam Dang acquired 4 March 2011 in response to active fire alert



Detect: Uses FIRMS MODIS-based fire detection system to monitor National Heritage Areas and Wildlife Sanctuaries

Respond: Alerts are used in a prioritized fashion to trigger follow-up targeted satellite observations by EO-1.

Product Generation & Delivery: Imagery & burn severity products electronically delivered to National Park, Wildlife and Plant Conservation Department of Thailand (NPWPCD; http://www.dnp.go.th)

"We are currently using the system to monitor fire activity in six critical areas of Thailand."

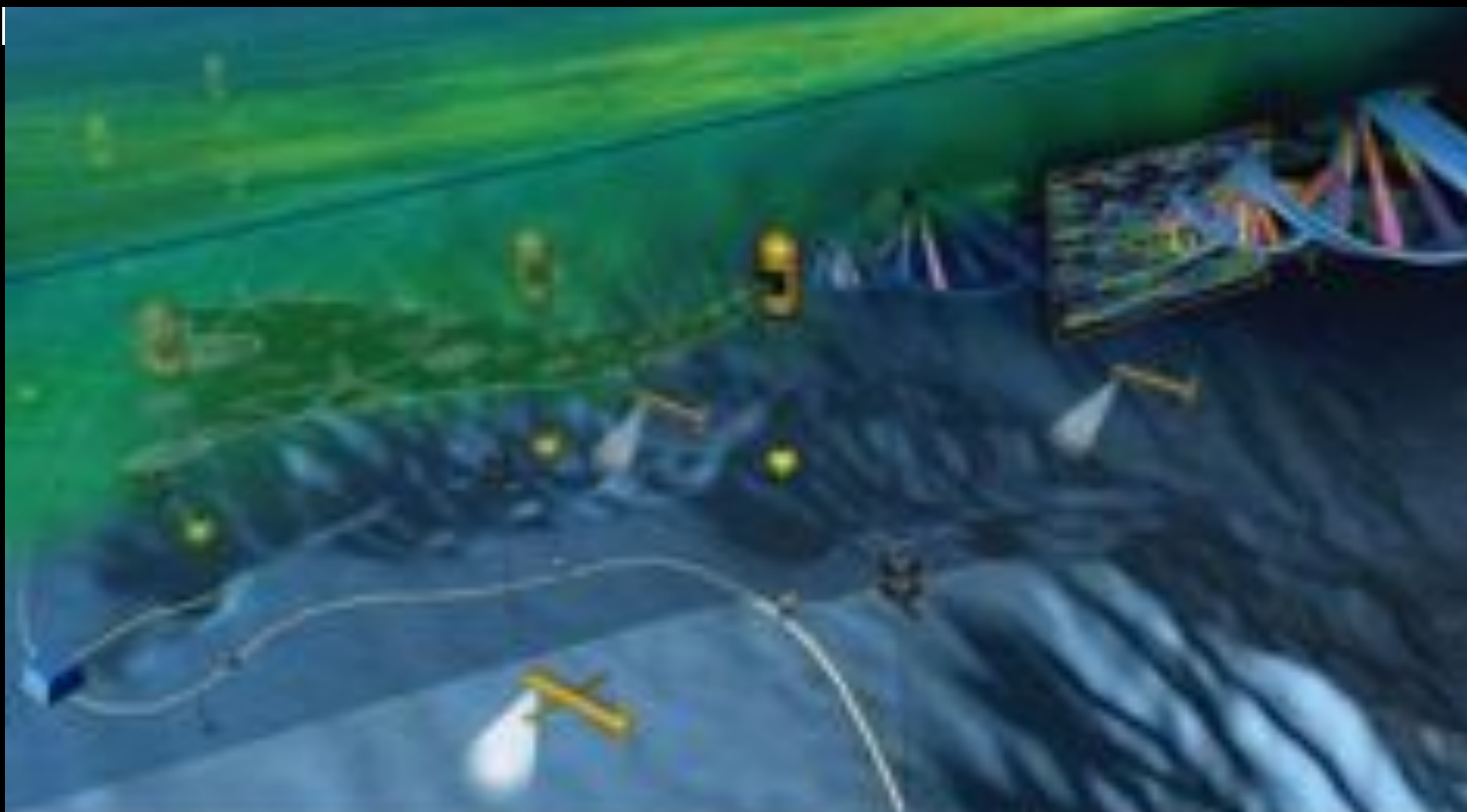
– Director General, National Park, Wildlife & Plant Conservation Department of Thailand

S. Chien / JPL

Ocean Sensorwebs

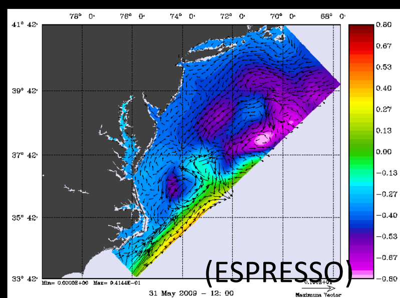
For further information see [Schofield et al. 2010 EOS, Wang et al. 2012 CR, Thompson et al. 2010 ICRA, Dahl et al. 2011 IROS]

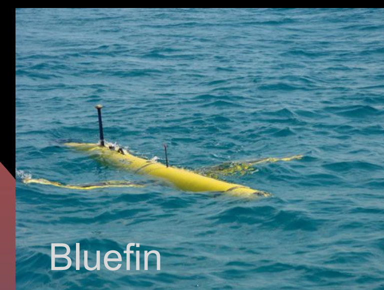
Ocean Observatories Initiative



The Ocean Observatories Initiative

Ocean Models





multimodal

model-driven

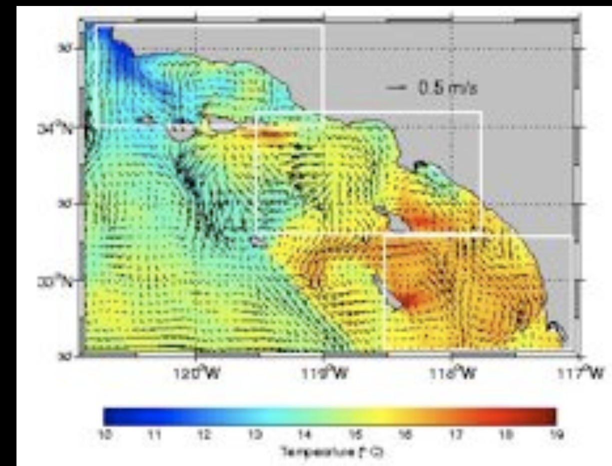
coodinated

CODAR

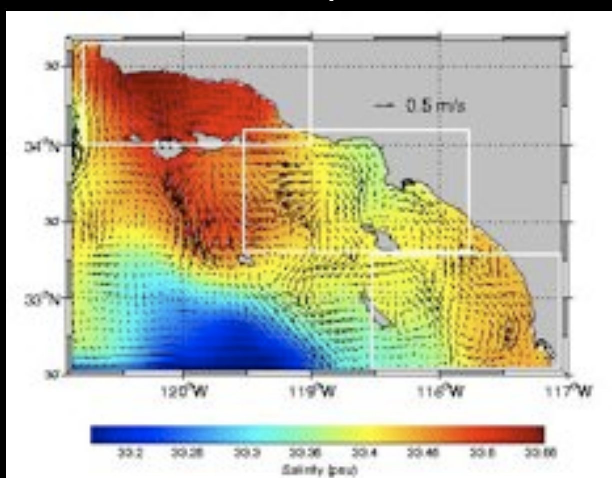
ROMS ocean model

- 4DVar assimilation and forecast
- Up to 1km horizontal resolution
- Variable depth resolution

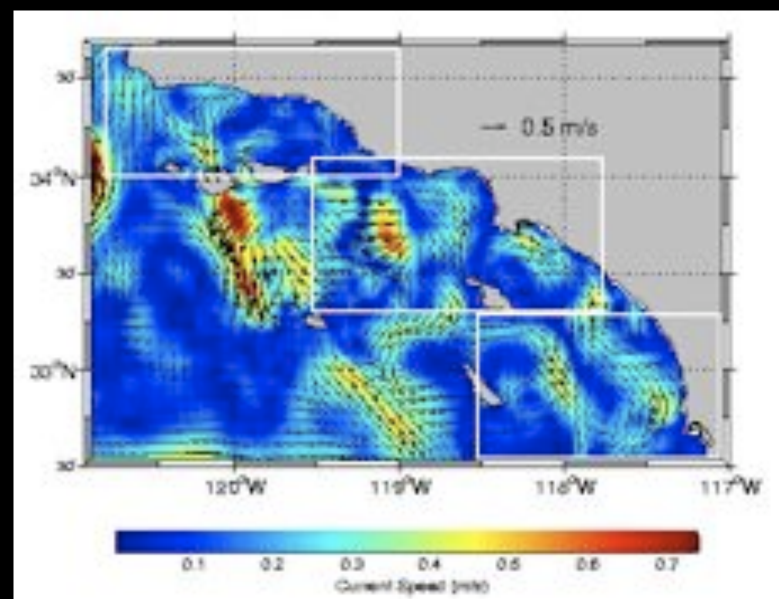
Temperature



Salinity

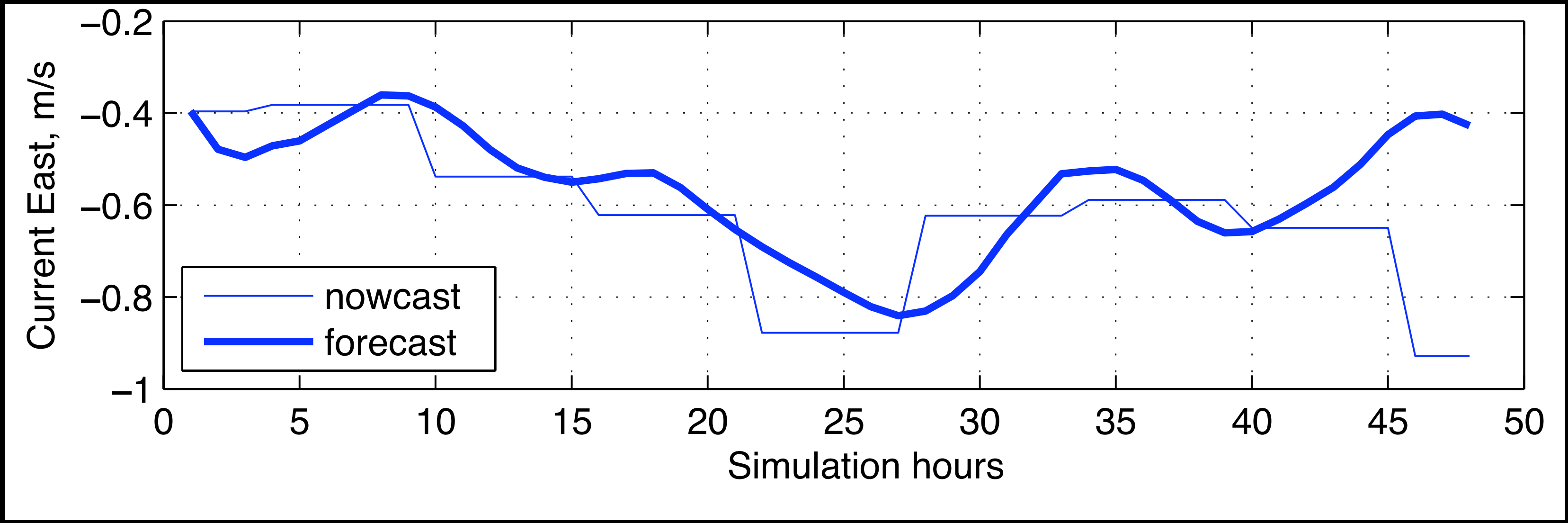


Currents



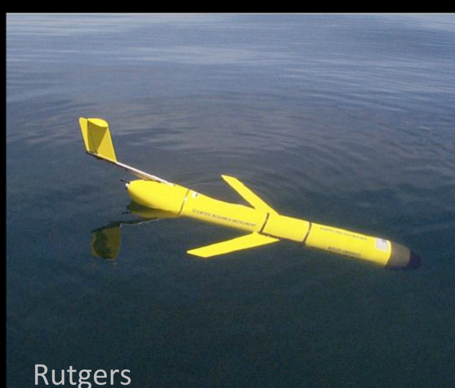
ROMS ocean model

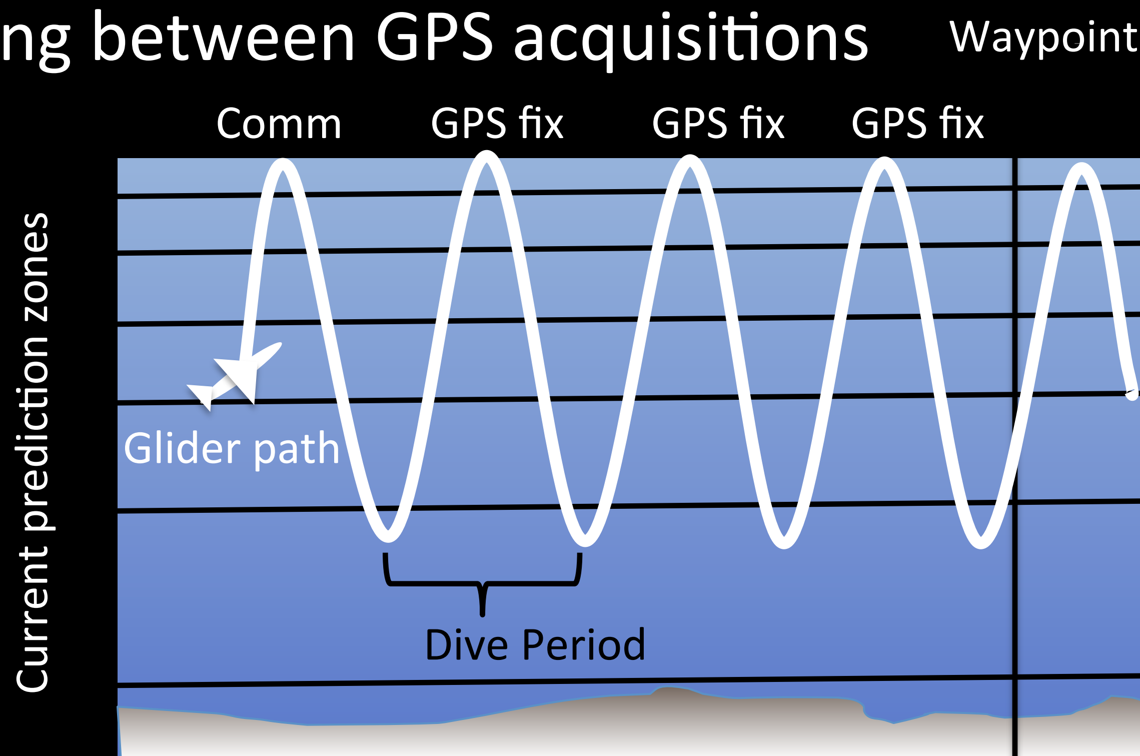
- 48-hour lookahead
- 6-hour re-assimilation and "nowcast"



Underwater gliders

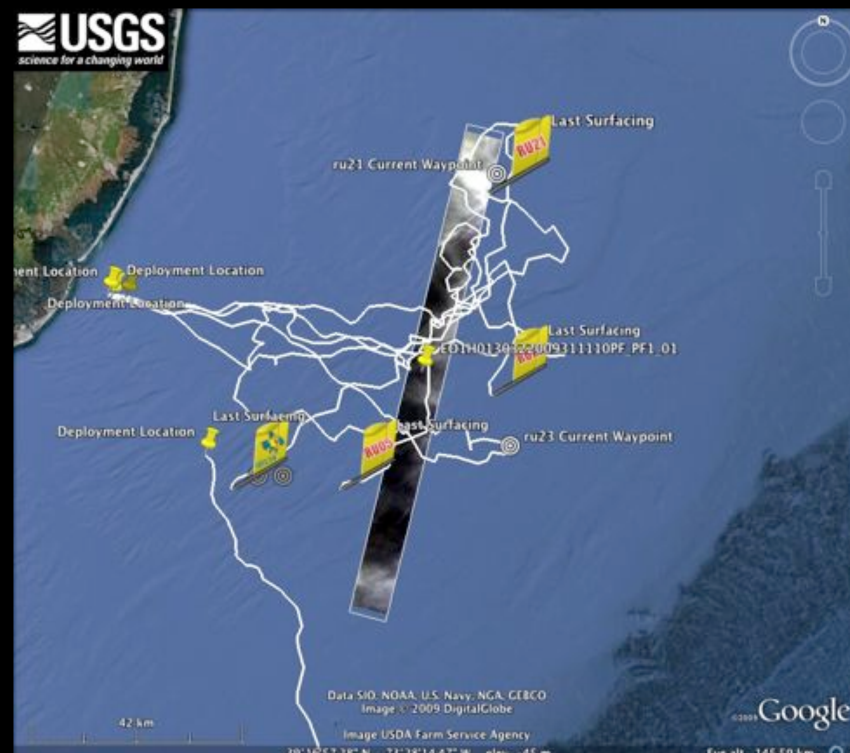
- Long duration missions, Low cost platform
- Limited propulsion (~0.3mps)
- Dead reckoning between GPS acquisitions





Glider goals must be *spatiotemporal*

- Asset coordination
- Coincident measurements
- Moving or transient targets
- **Objective:** find best grid waypoints between high-level spatiotemporal goals



Rugters gliders coordinating around a Hyperion / EO-1 overpass

Path planning challenges

- **STRONG** current [Soulignac et al 2008, Zhang et al 2008]
- **DYNAMIC** current [Soulignac et al 2009, Smith et al 2009]
- **SPATIOTEMPORAL** goals
- **UNCERTAIN** current predictions [Wolf et al 2010]

Path planning challenges

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- **SPATIOTEMPORAL** goals
- **UNCERTAIN** current predictions [Wolf et al 2010]

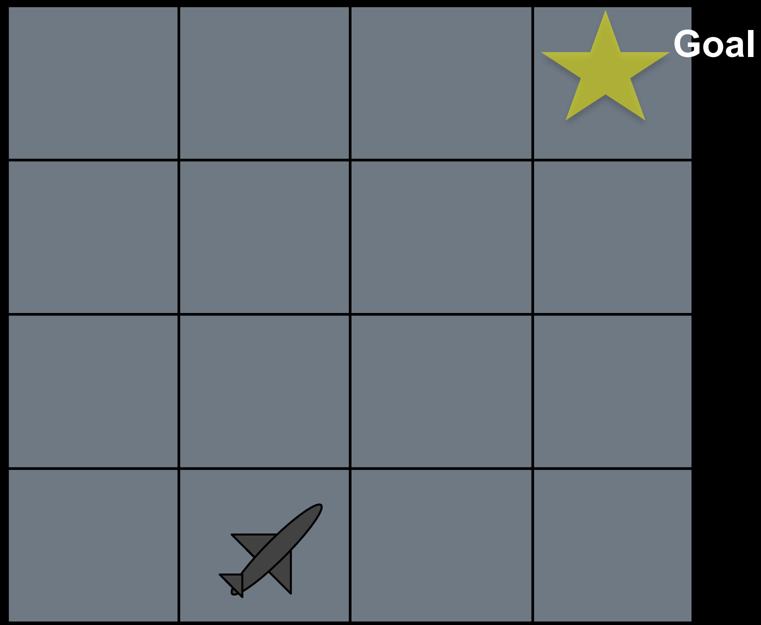
This work

SPATIOTEMPORAL planning in **STRONG, DYNAMIC** currents

Test **UNCERTAINTY** in simulation

“Earliest arrival” wavefront planning

- Find path to arrive at goal location as soon as possible
- Expand from start to goal
  - Travel in up to 8 directions
  - Record:
    - Time of arrival
    - Ancestor in best path
- Path then validated for consistency with state/resource planner ASPEN/CASPER



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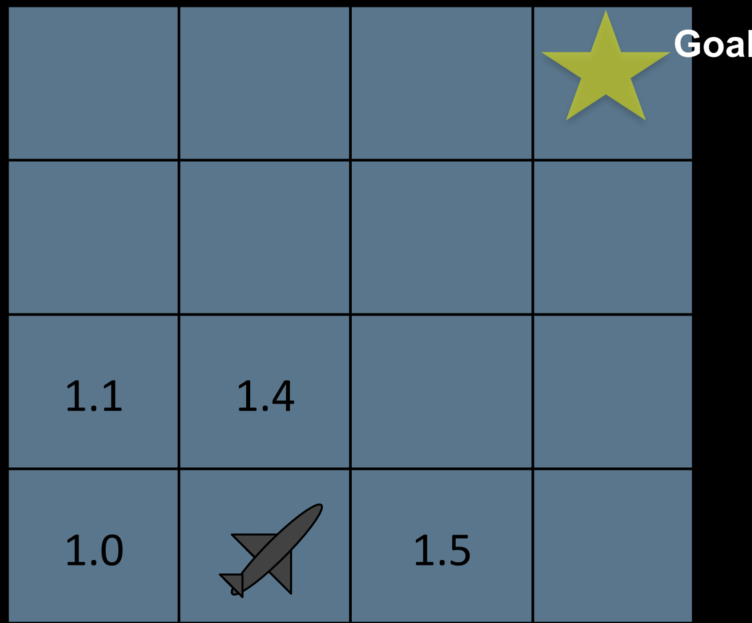

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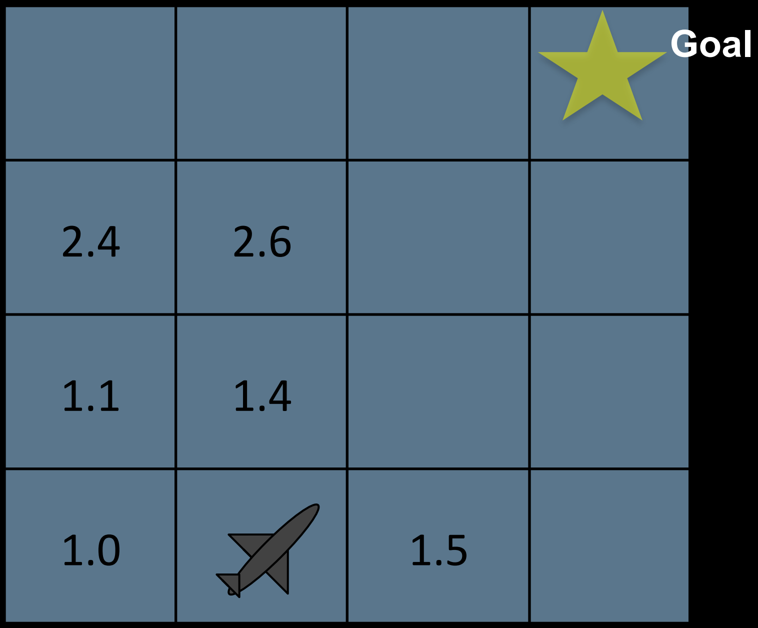

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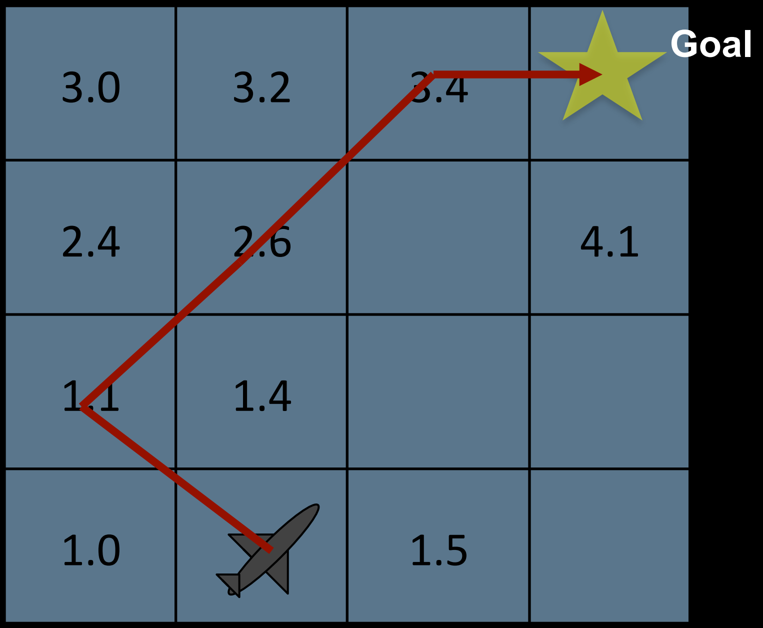
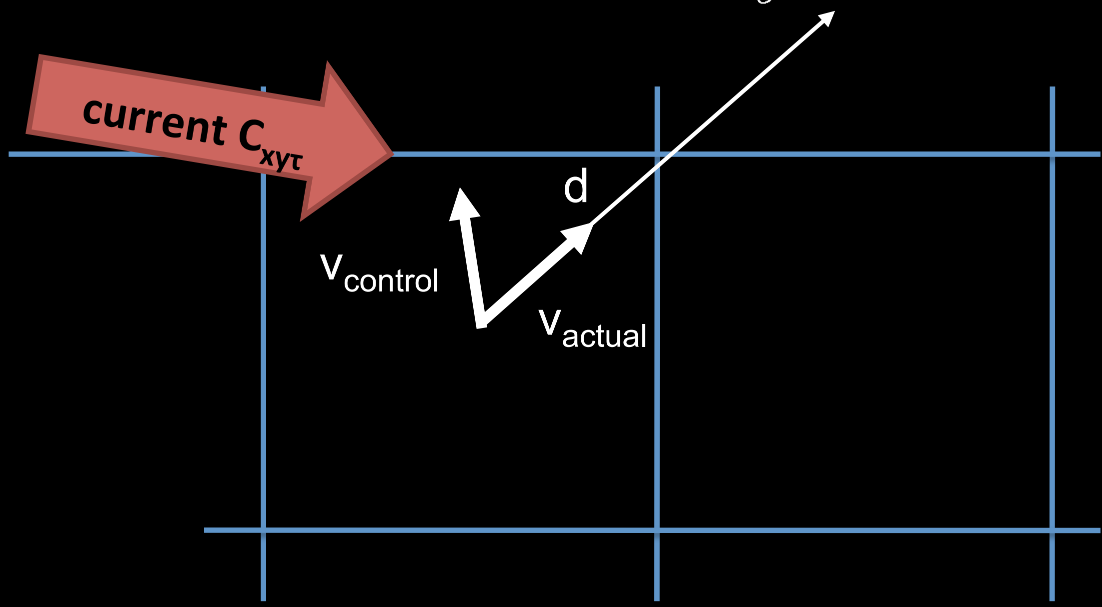


Calculation of motion time required

- Treat currents as constant over short timescales
- Glider velocity is sum of current and control velocities
- Travel time between grid squares:

$$v_{actual} = v_{control} + C_{xy\tau} = \lambda d$$



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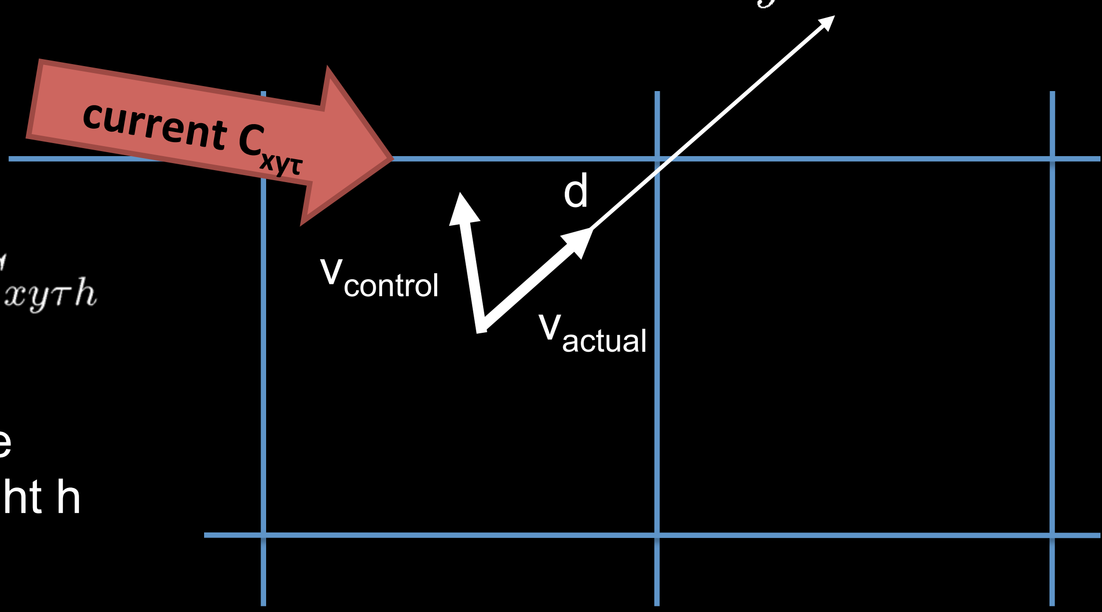
- Glider velocity is sum of current and control velocities
- Travel time between grid squares:

$$v_{actual} = v_{control} + C_{xy\tau} = \lambda d$$

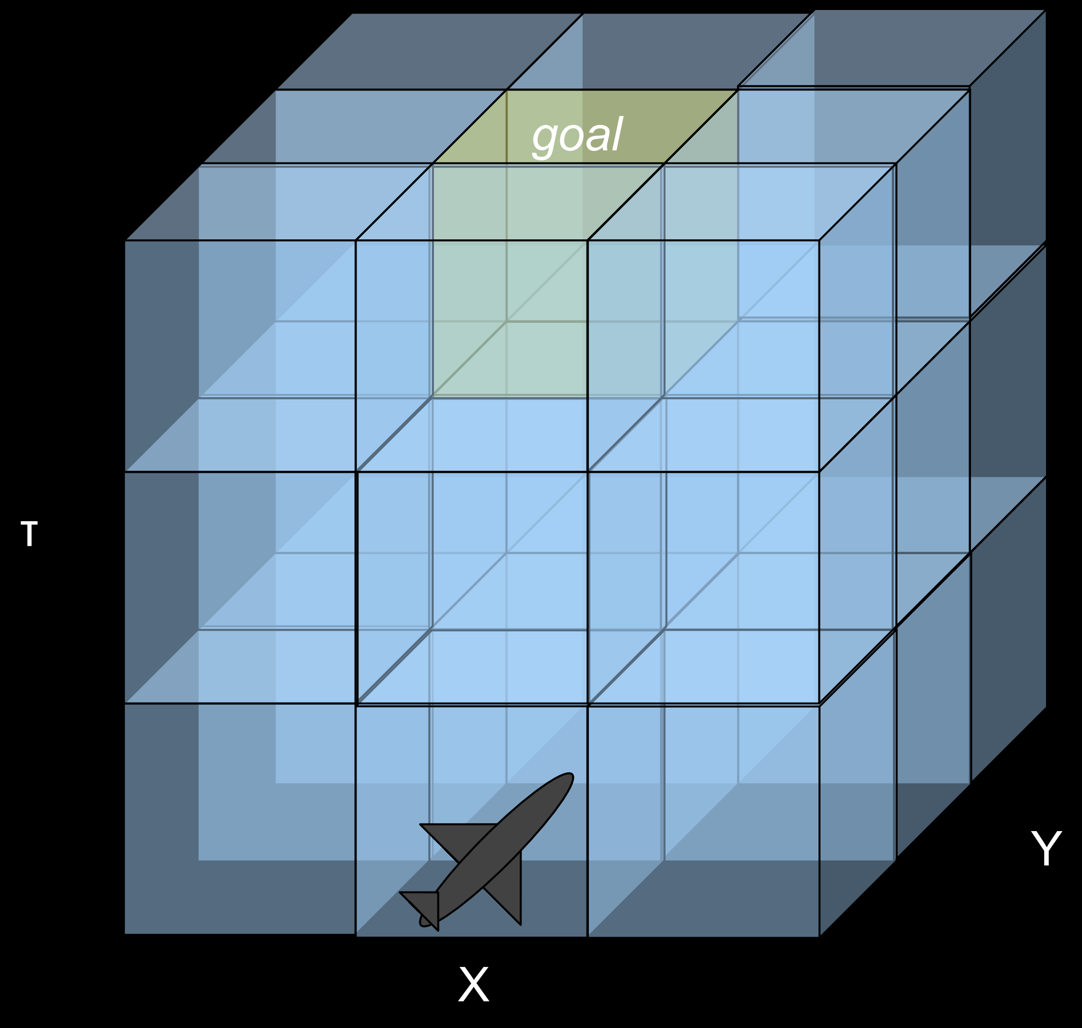
current prediction

$$C_{xy\tau} = \frac{1}{\sum_h f(h)} \sum_h f(h) C_{xy\tau h}$$

portion of dive period at height h

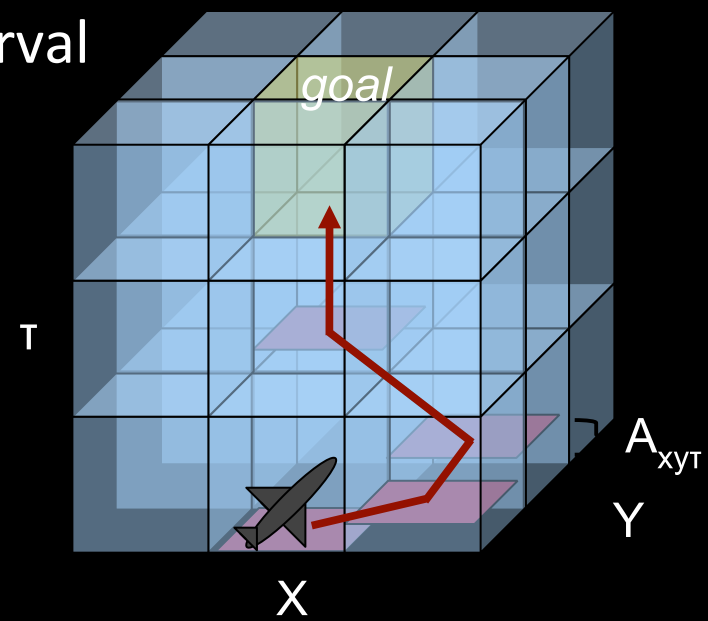


Spatiotemporal goals



“Earliest valid arrival” criterion

- Find path with earliest arrival that can still hold position until goal time
- Expand each grid square on the frontier
  - Travel in up to 8 directions, or…
  - Hold position to next time interval



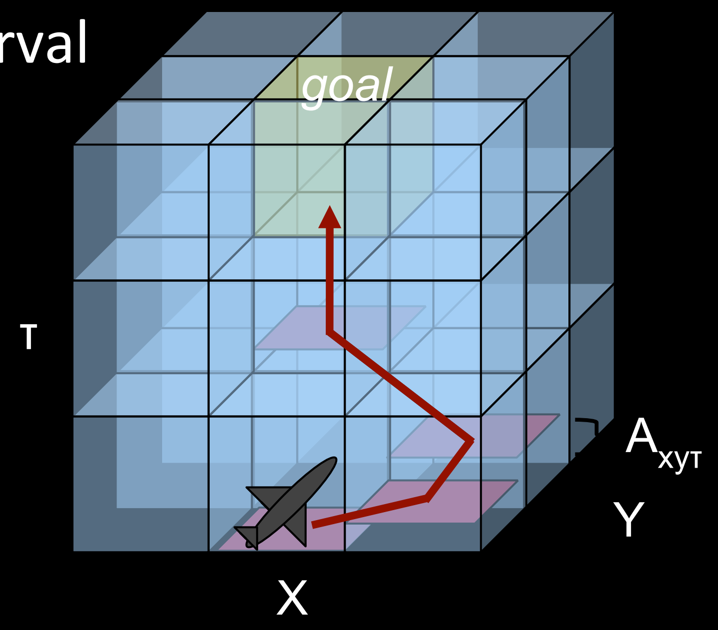
"Earliest valid arrival" criterion

- Find path with earliest arrival that can still hold position until goal time
- Expand each grid square on the frontier
  - Travel in up to 8 directions, or…
  - Hold position to next time interval

Some nice properties

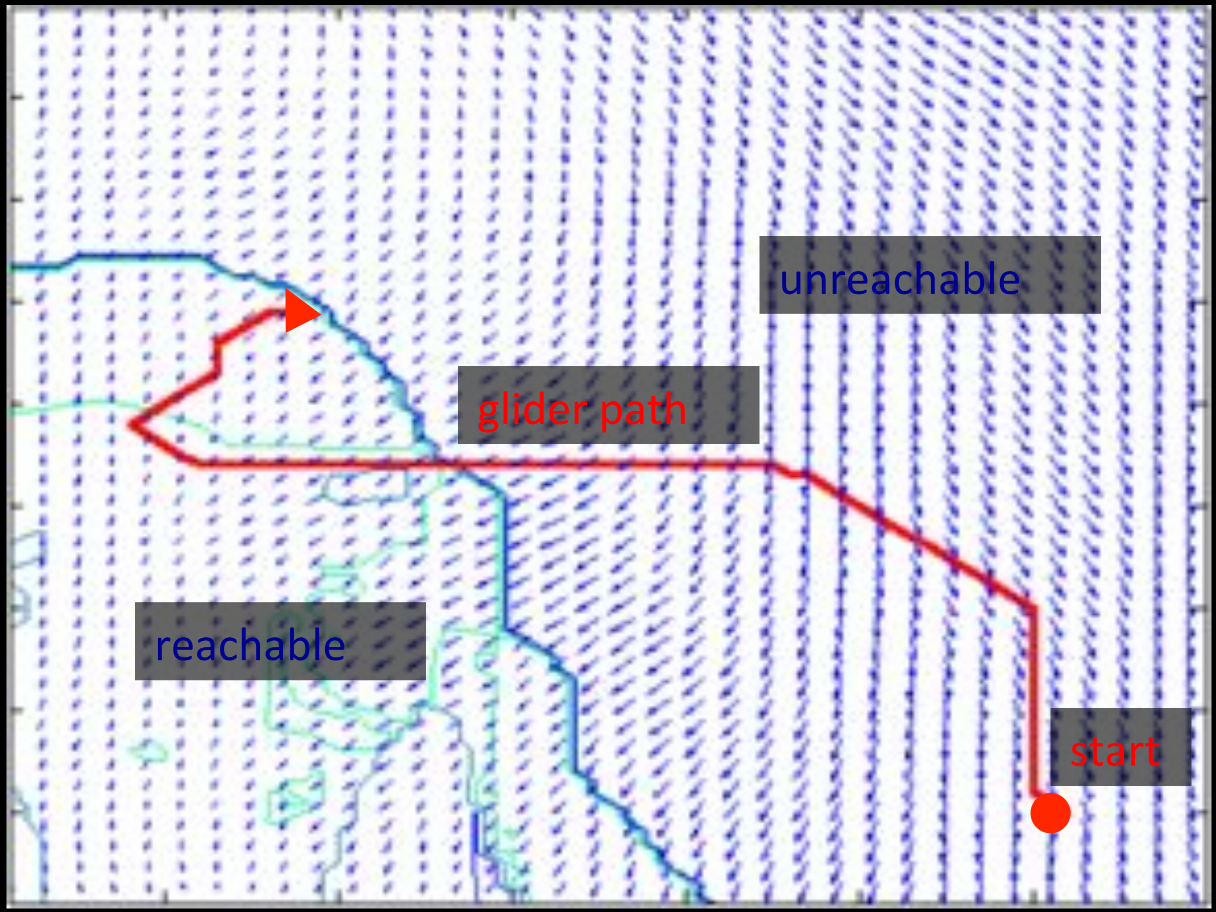
Globally optimal solution up to discretization error

Fast (runs in seconds)



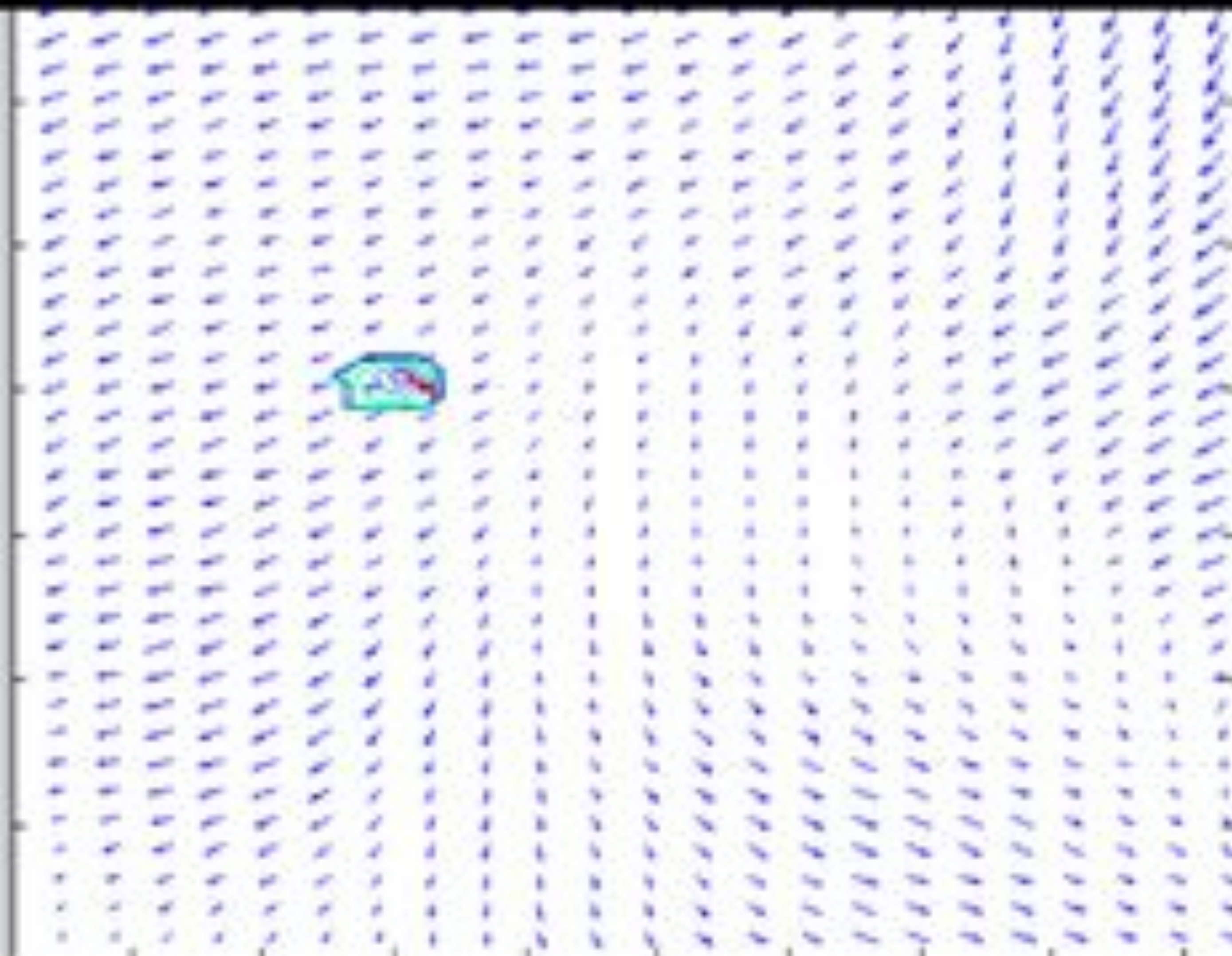
Reachable volumes

reachability isocontours

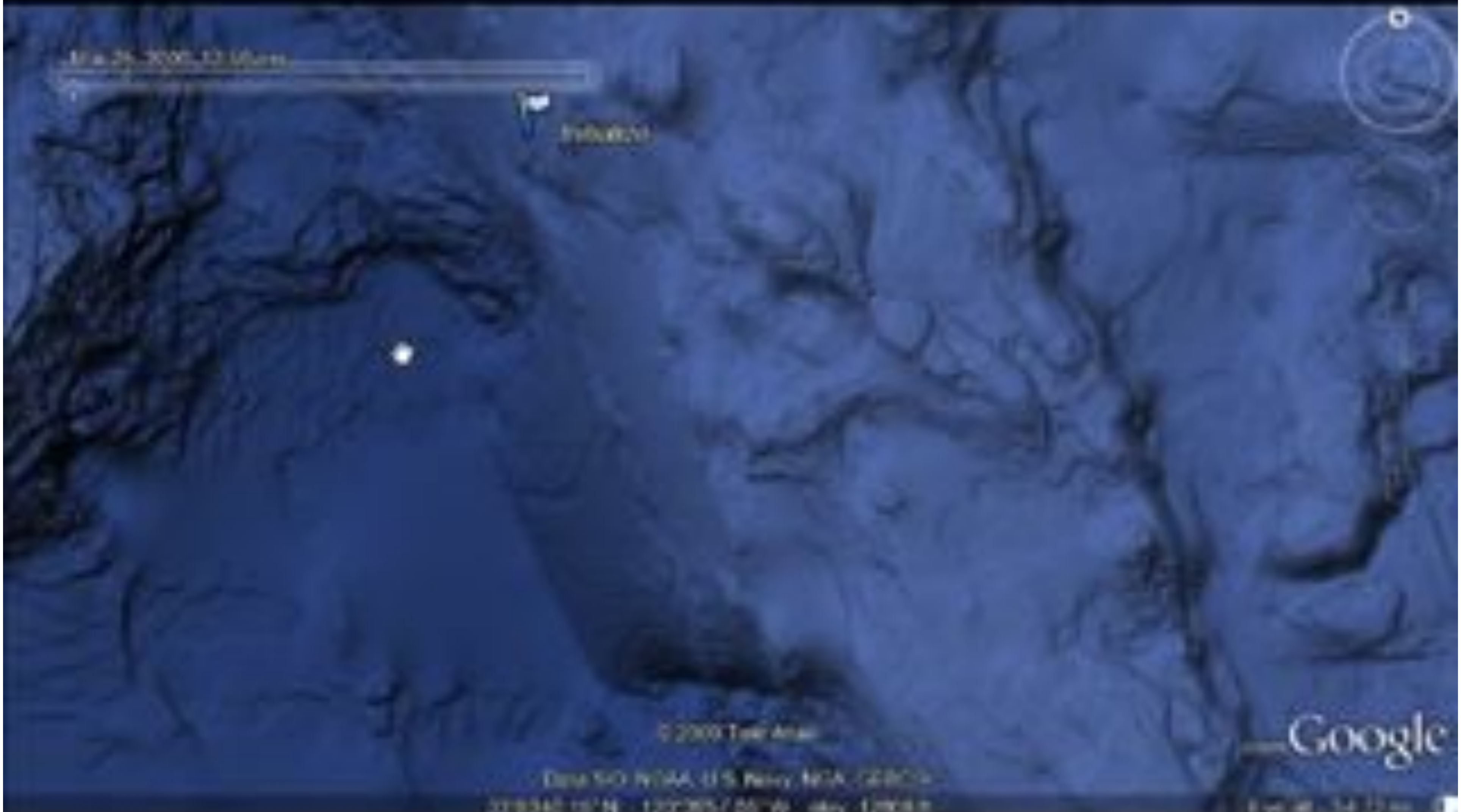


Reachable volumes

Current-Sensitive Path

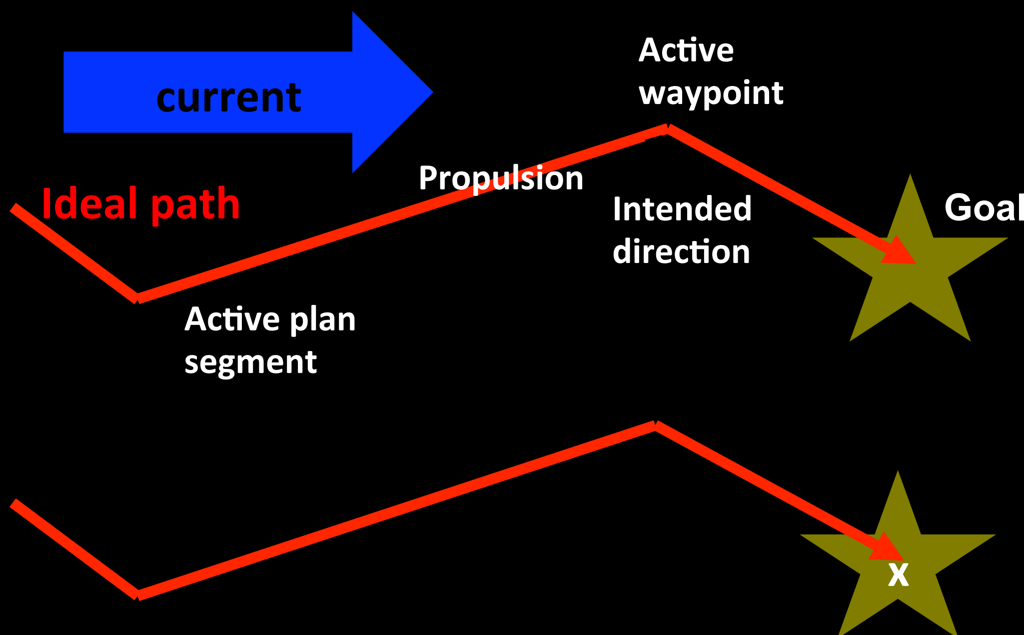


Visualizing Reachable Volumes



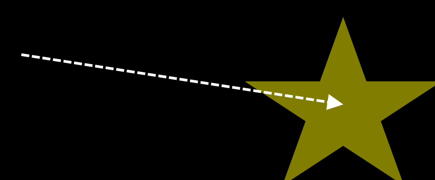
Control strategies to track the path

Current-sensitive control

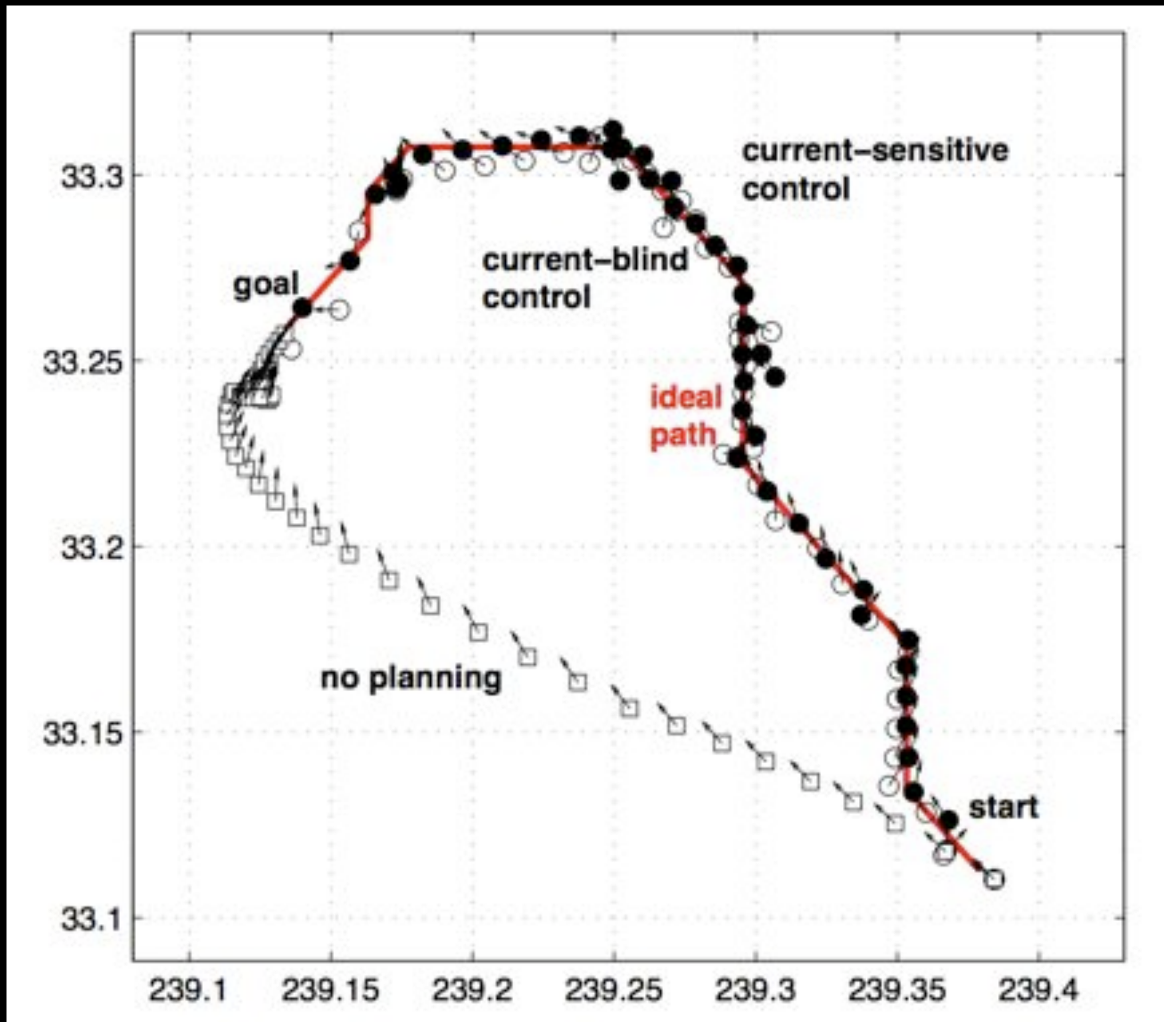


Current-blind control

Ignore current-sensitive path altogether

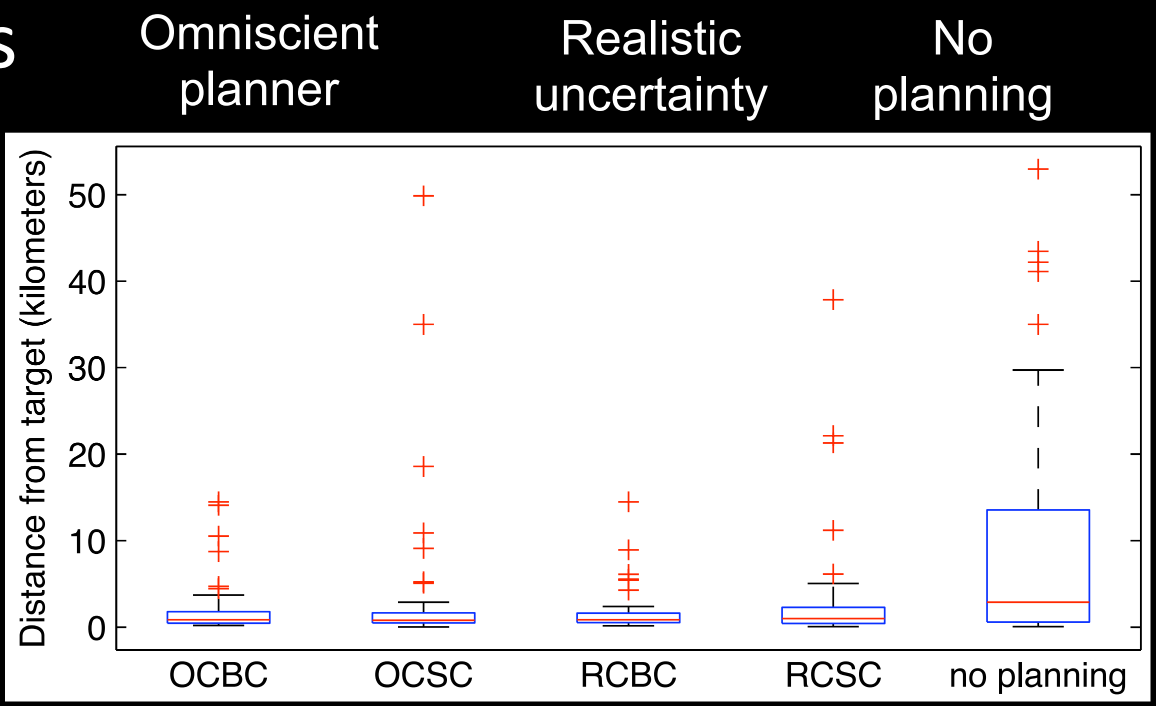


Control strategies to track the path



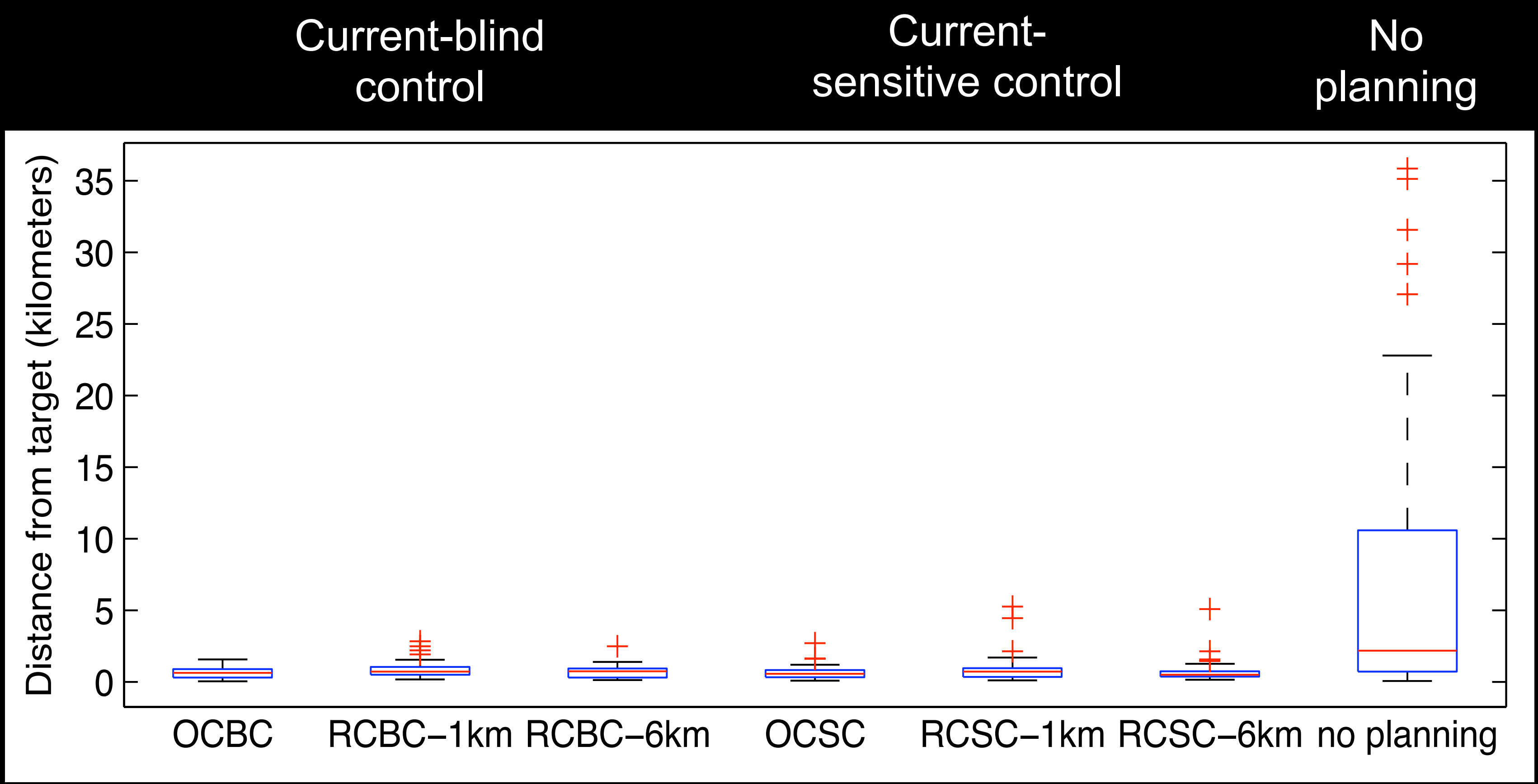
Experimental results with ROMS data

- 48-hour lookahead
- Random initialization and goal locations, times

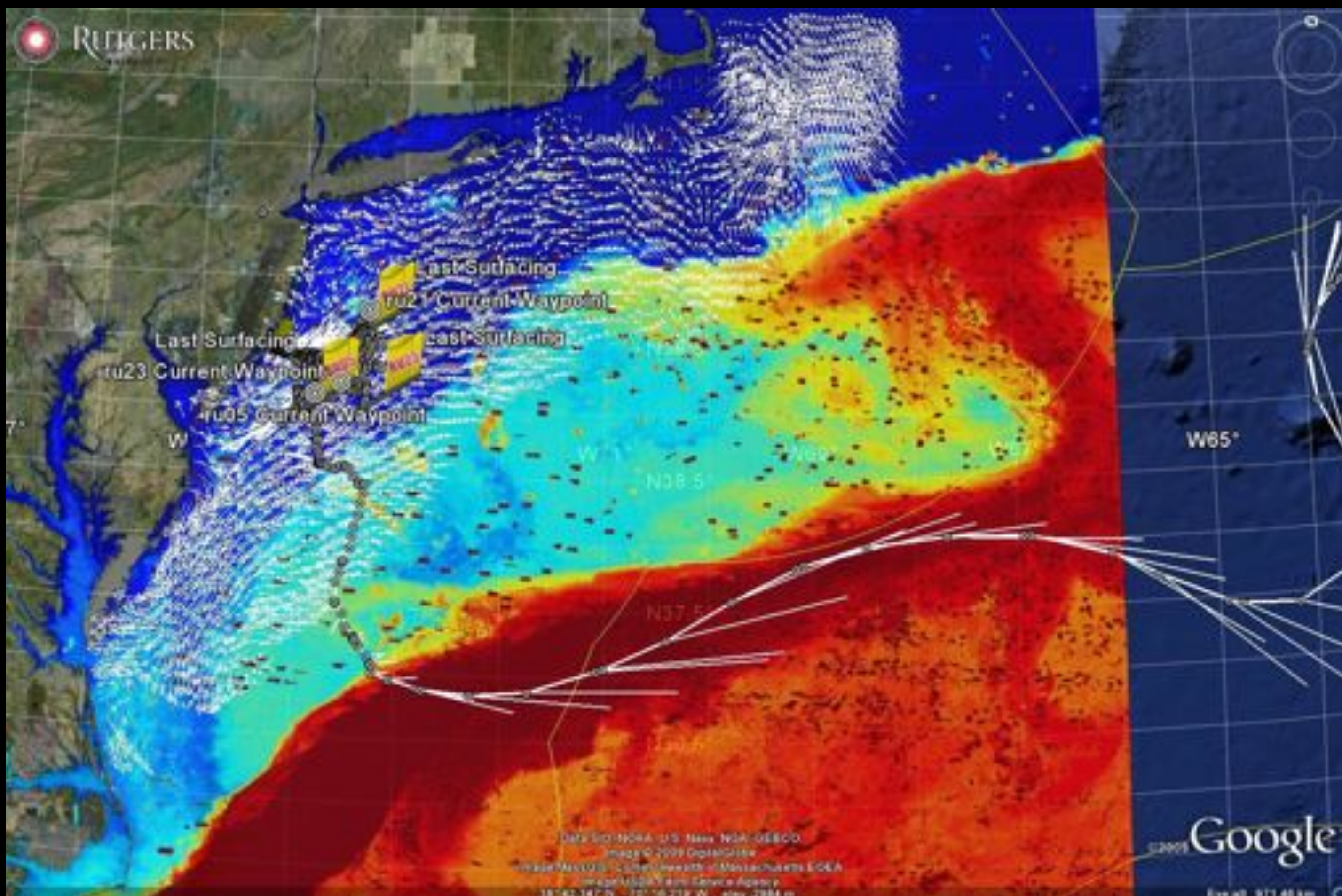


Experimental results with ROMS data

- Considered different spatial resolutions for planner

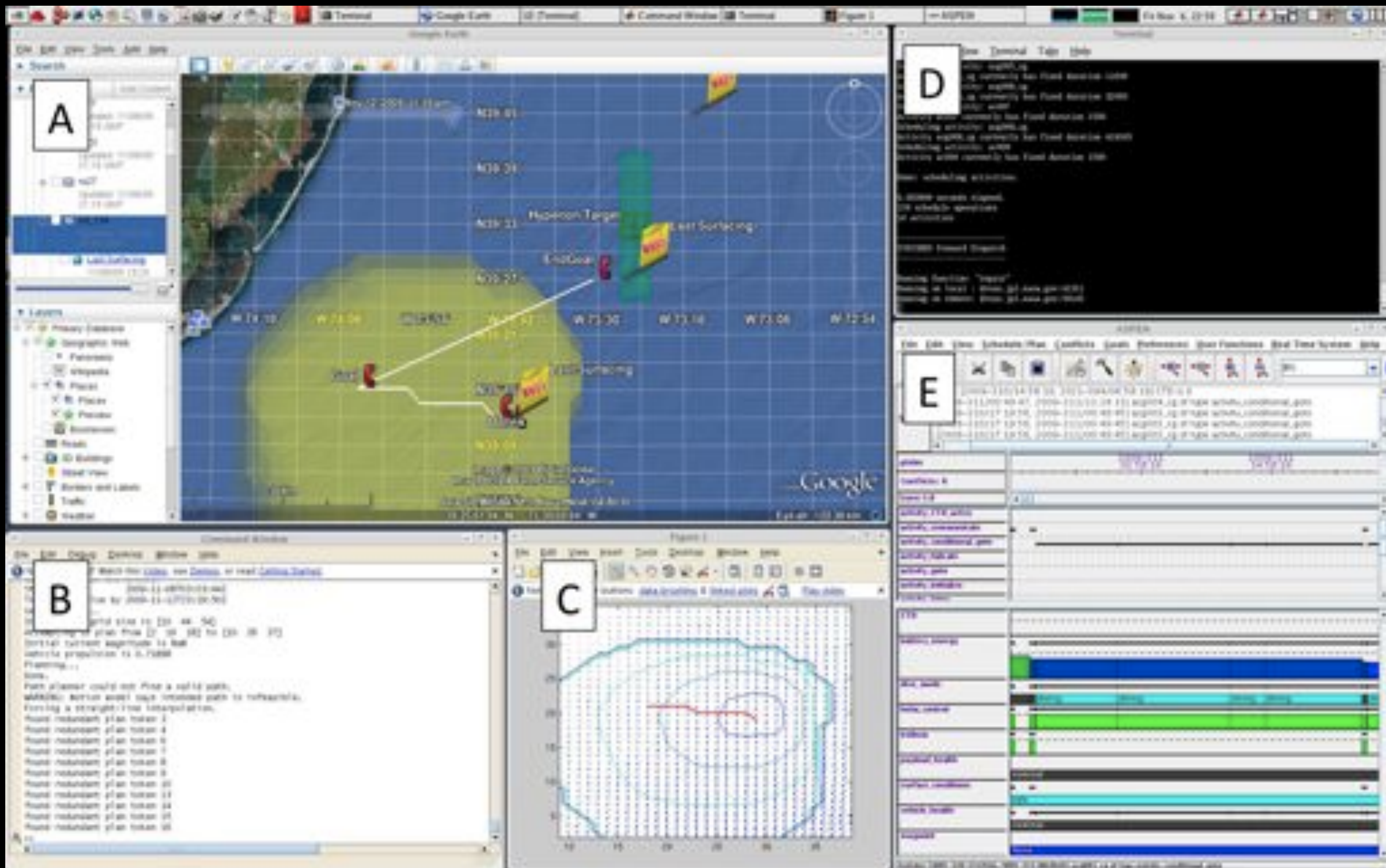


Caviat:
The OSSE NorEaster, (Nov 10-13 2009)



OSSE Glider Fleet

MAB 2009 Deployment



Key: (A) Waypoints are adjusted in a visual map interface. The white line shows glider ru23 traveling toward the coast; if extra time is available it will perform a "runout" activity, traveling toward the footprint of tomorrow's satellite overpass (green rectangle). Yellow polygons show areas reachable by the glider by the end of the forecast period. (B) The cartographic planning terminal provides utilities for rough manipulation of the plan. It draws on real-time glider position information from Rutgers University and five OpenDAP ocean simulation models. Its current-sensitive path planner computes optimal trajectories through the time-varying currents; these are visible in the vector-field animation (C). Finally, ASPEN command terminal and GUI appears in windows (D) and (E). Here ASPEN shows a timeline view of the ru23 plan, tracking resources and state.

Reachability envelopes!

Conclusions

- Adaptive sensing is revolutionizing environmental monitoring – cryosphere, flooding, volcanology:
  - Adaptive sensing integrated with modeling
  - Machine learning for data interpretation
  - Automated Planning/Execution for asset autonomy
  - Multi-agent systems for coordination

Integrating Aerial Assets
UAVSAR

Aerial Assets

- Complementary to Space Assets
- Can Loiter
- Generally lesser spatial coverage
- Must pay per deployment cost

Algorithm	Applications	Notes
Soil moisture	Agriculture, Water resource management	Currently requires sparse vegetation; generalization of algorithms to variable/dense vegetation future work.
Surface water extent	Flood mitigation	Extensions to varied topography, rough waters, and smooth land are future work.
Repeat-pass disturbance	General	Requires expert/interpreter and prior imagery onboard.
Snow/ice vs land SVM classification	Transportation, Freeze-thaw monitoring	Vegetation can complicate classification.
Amplitude Correlation	Sea transportation, Glacial movement monitoring	Strong transportation application. Glacial studies would desire higher fidelity (sub-pixel motion, per pixel).

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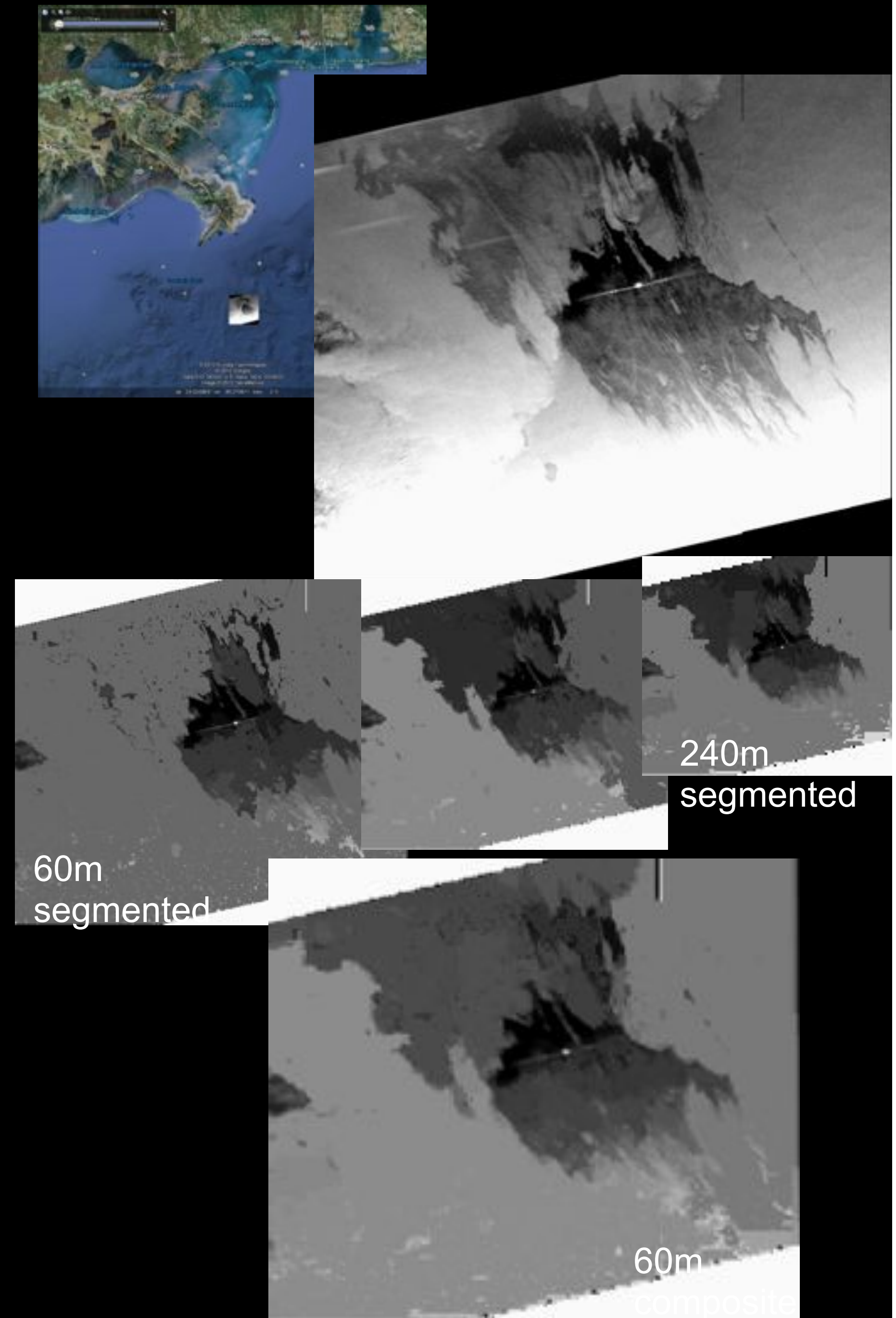
Oil / Amplitude Segmentation

- Flood fill on each pixel, with merging
- Felzenszwalb / Graph based segmentation
  - Results in areas of similarity that can be measured in expanse and average intensity
  - Geolocated features/events
  - Minimum spanning forest of 4-neigborhood graph over pixel magnitude metric
  - Run time complexity: nearly linear with image size
- Segmentation of original image at different multi-looked resolutions yields different results
- Composite of several resolutions to capture various scale features
  - Float32 multilook data: 2.5 MB
  - Multilook browse: 400kB
  - Segmented Composite Browse: 32kB, ~ 80x reduction in data volume

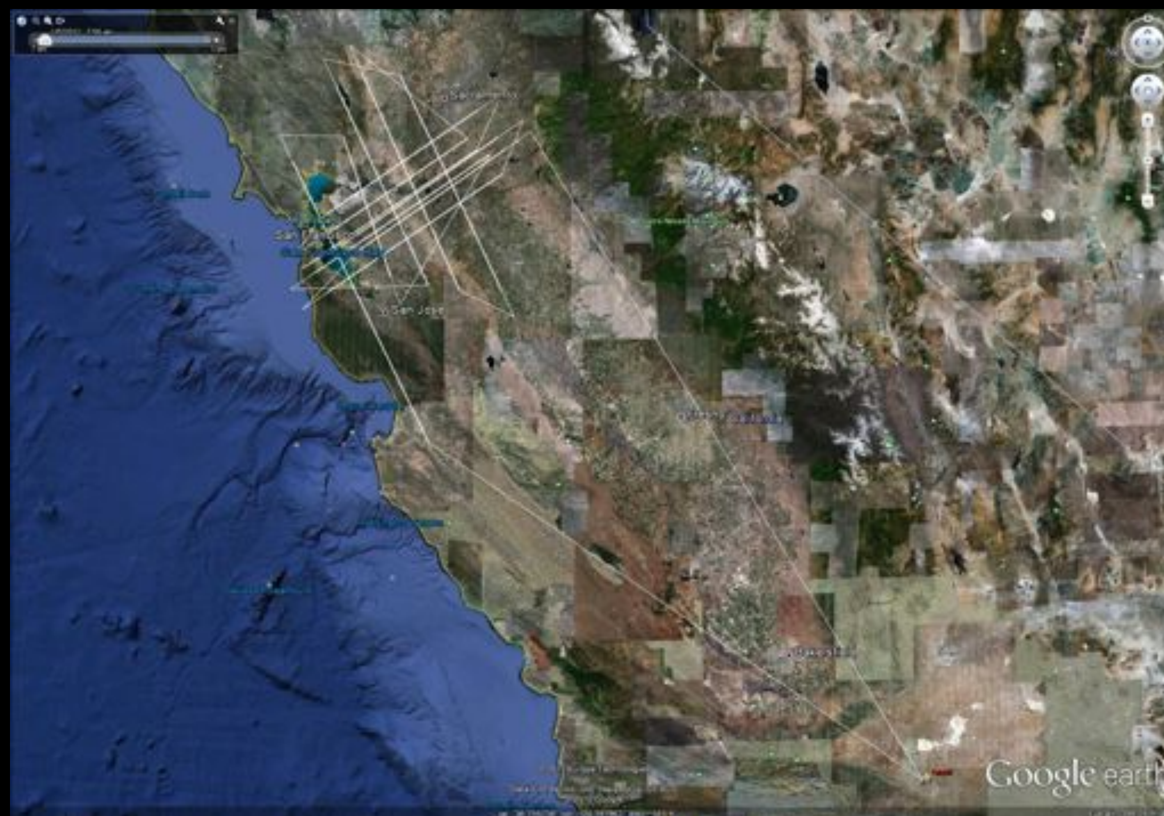


Autonomy Demo

- OBP single HH channel
  - Amplitude segmentation / “oil slick” algorithm processes geolocated backscatter images.
  - Detected features broadcast to local network
    - OGC Sensor Alert Service (SAS) packets
- CASPER has baseline plan of flight loaded
  - Monitors GPS data to update plan in real time
  - Receives SAS packets as Points of Interest (POI)
    - POI are checked against baseline to see if they are already covered by the remainder of planned flight
    - Non-covered POI result in a replan
  - CASPER replans respecting
    - Flight Plan constraints (using specialized UAVSAR flight planner) with deadlines, minimizing flight time
    - Onboard Resources

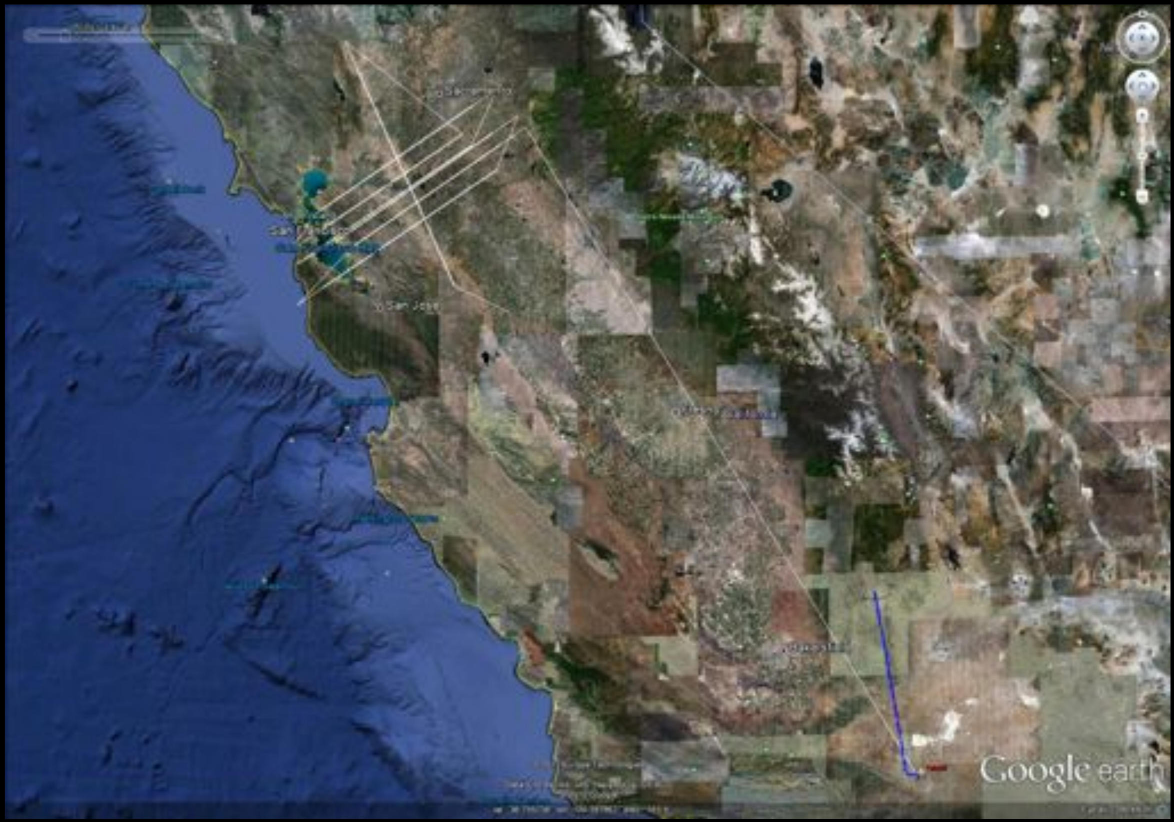
Flight Demonstration 1/2012

- Base line flight plan:
  - fp340v01

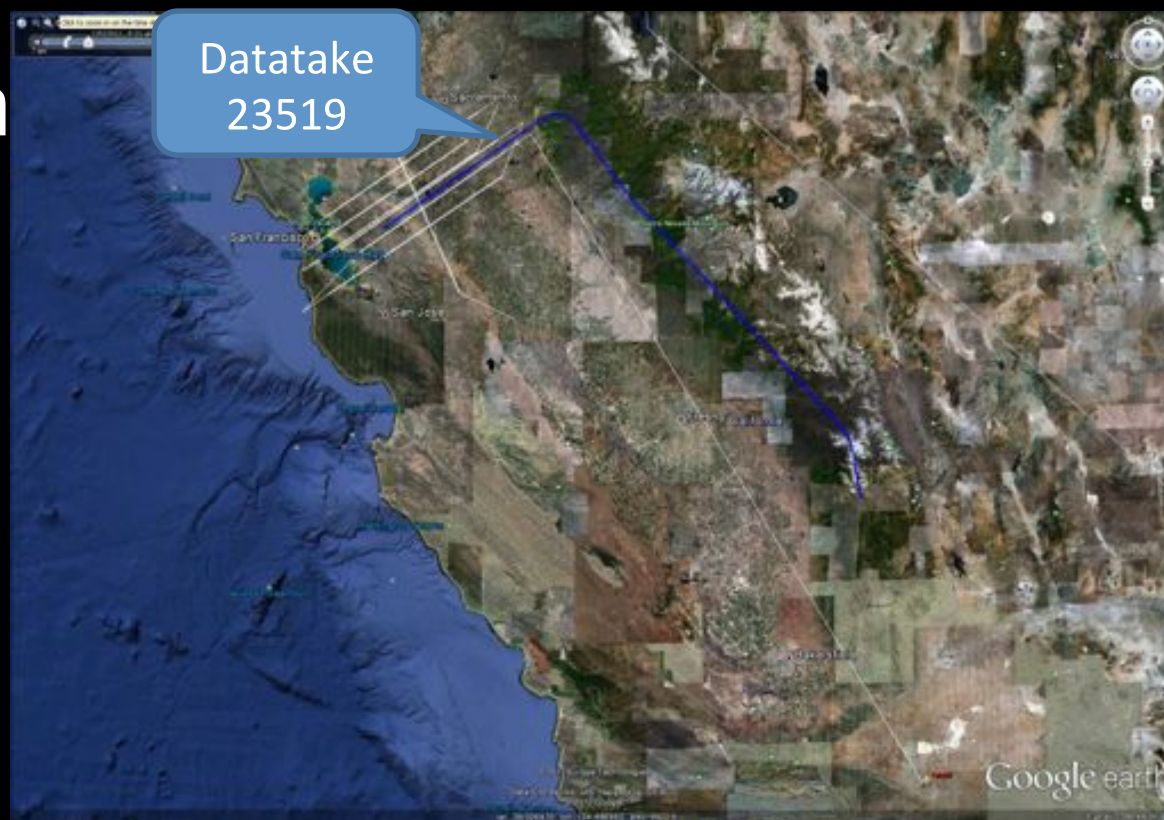


End-to-End Demo

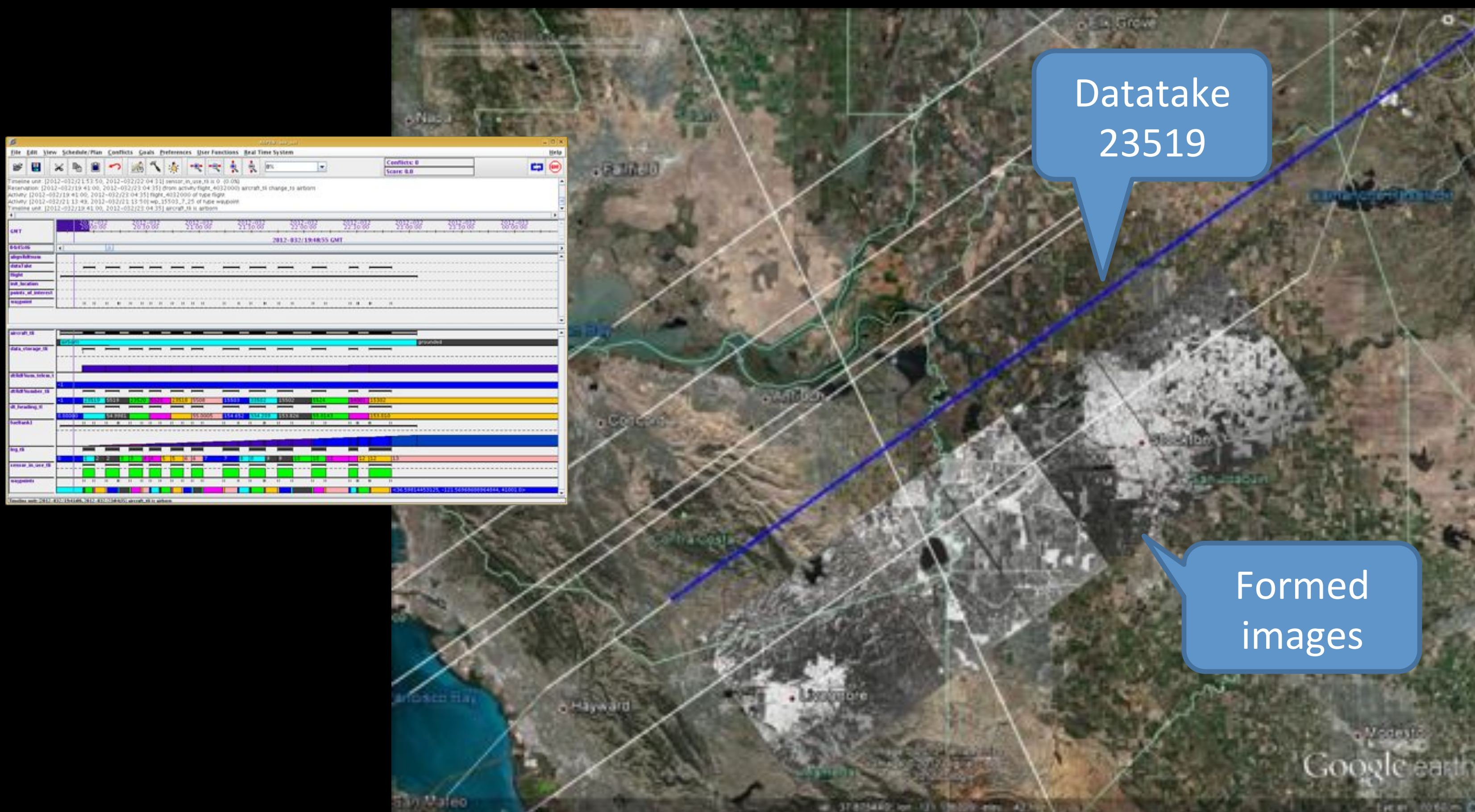
- Actual aircraft path in blue
- First half of planned flight



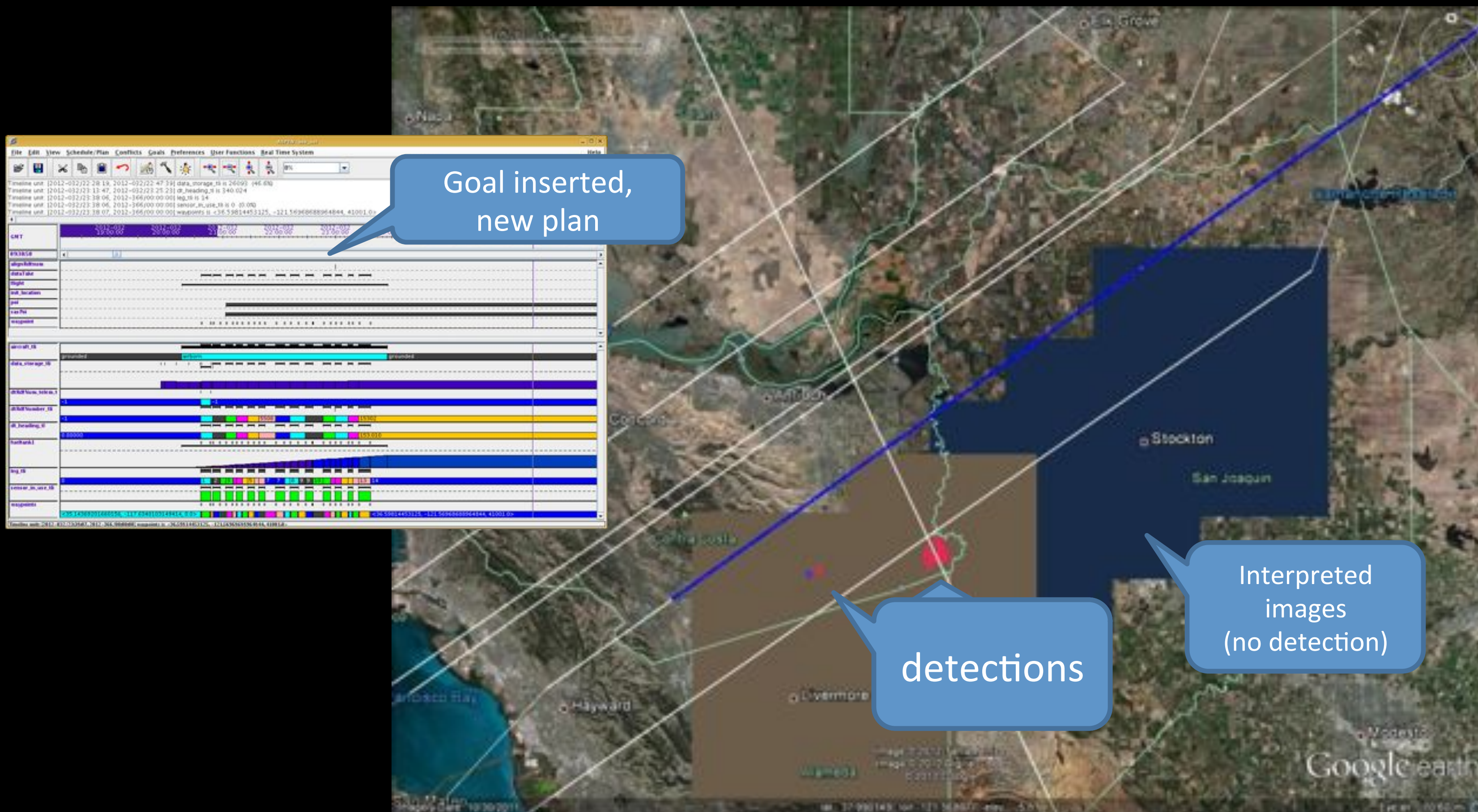
- First data acquisition begins



Images acquired

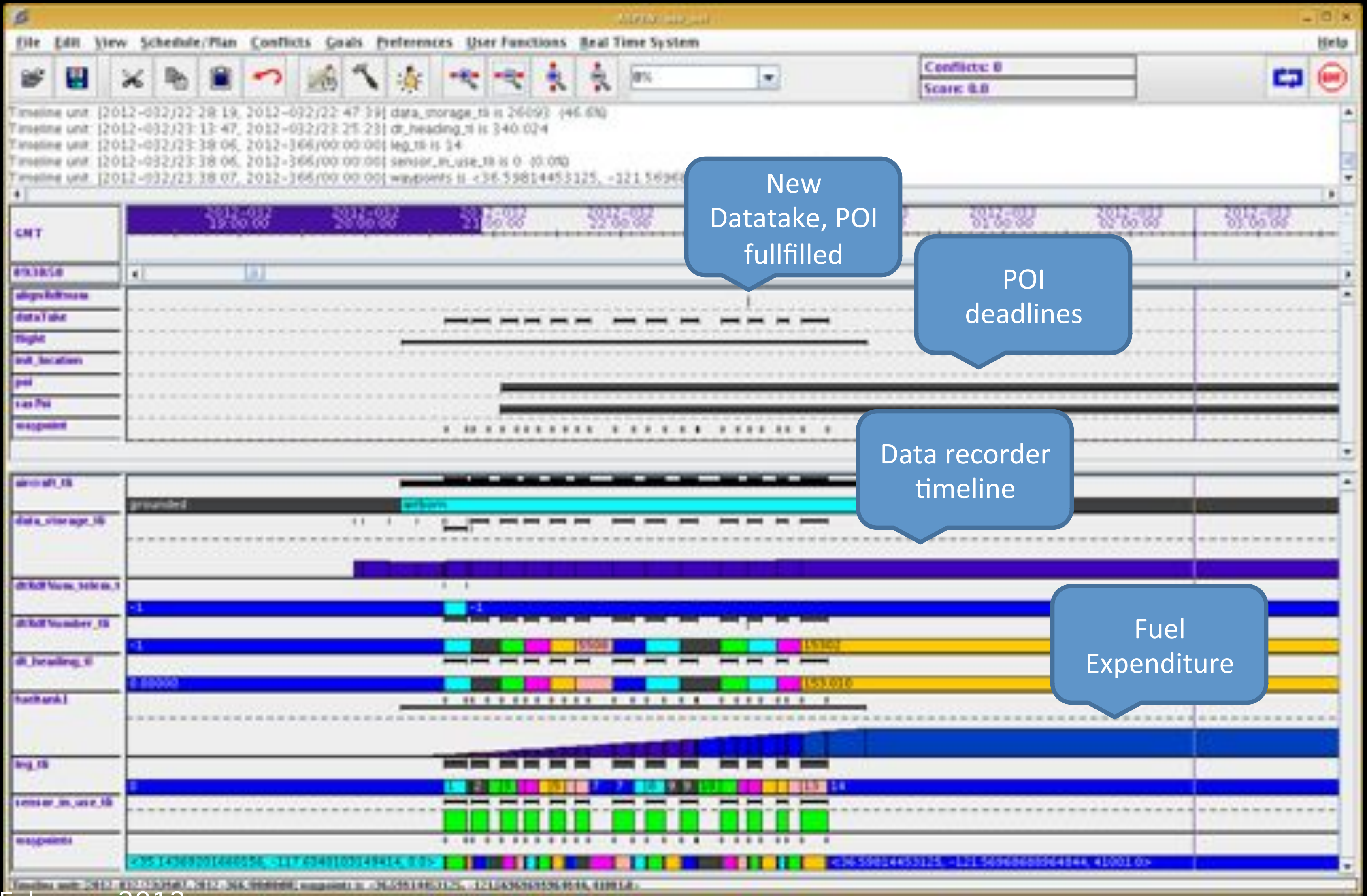


Images processed and alerts generated



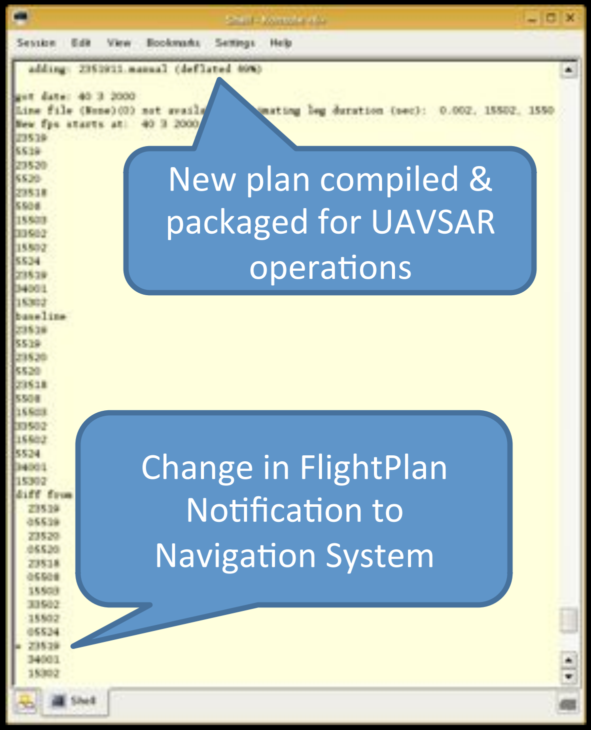
February 2012

CASPER Replanning

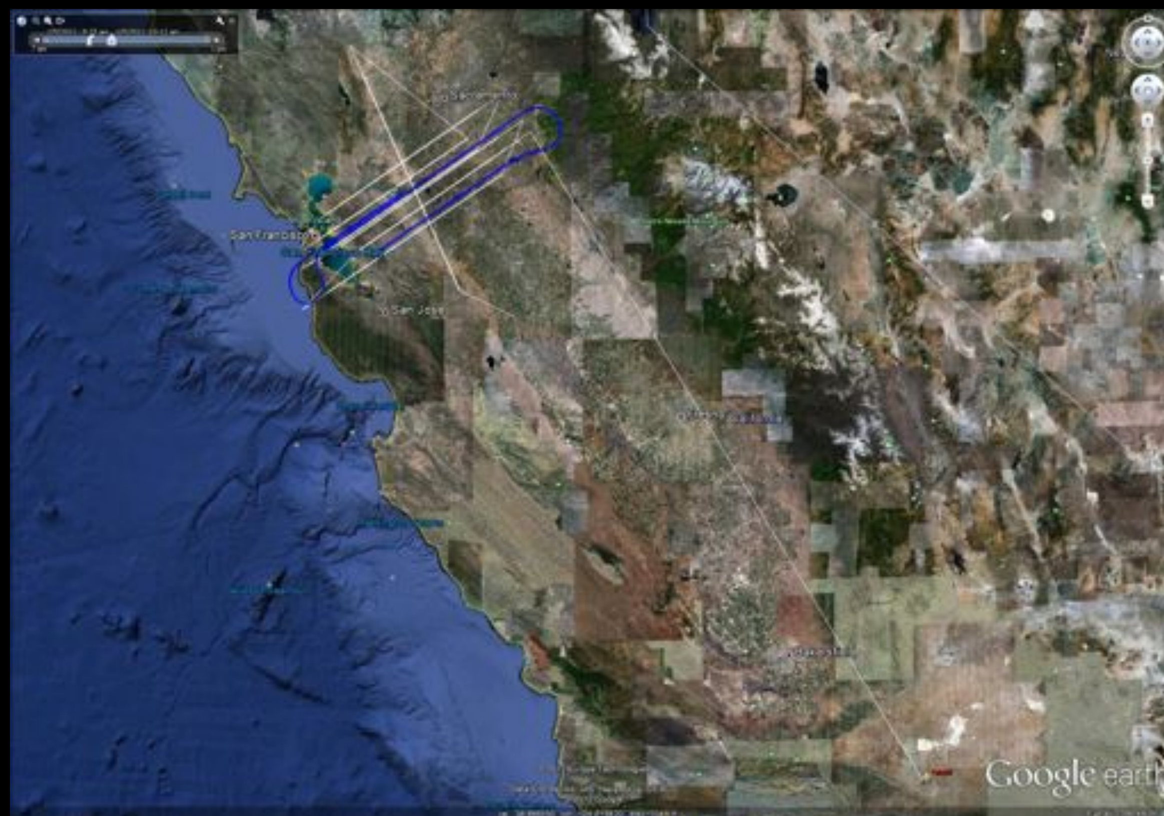


Replan result – flight plan delta to ROW

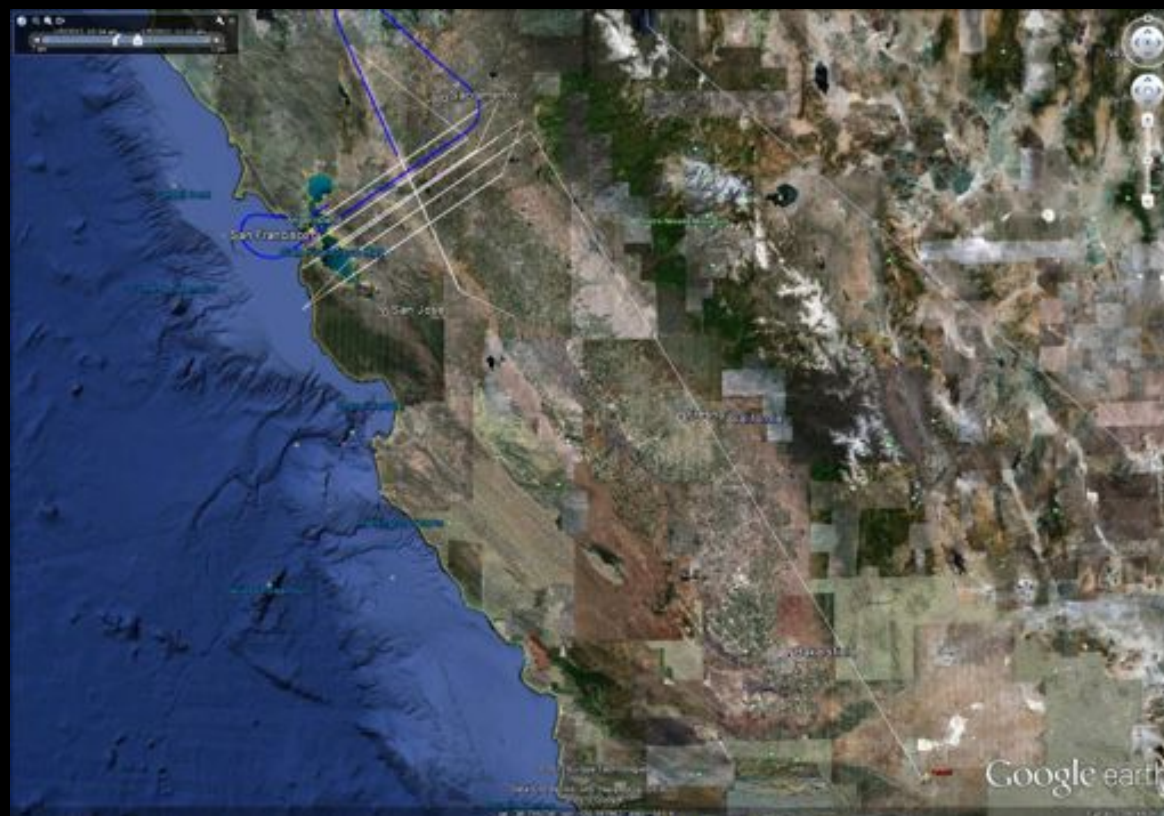
- CASPER continuously monitors GPS stream for progress through current flightplan
- POI are added to schedule as optional goals
  - Casper will insert new datatakes into plan sequence
    - at least cost (Fuel) to fullfill goals
    - provided sufficient remaining fuel and datastorage
    - Datatake is from a precompiled library of datapaths



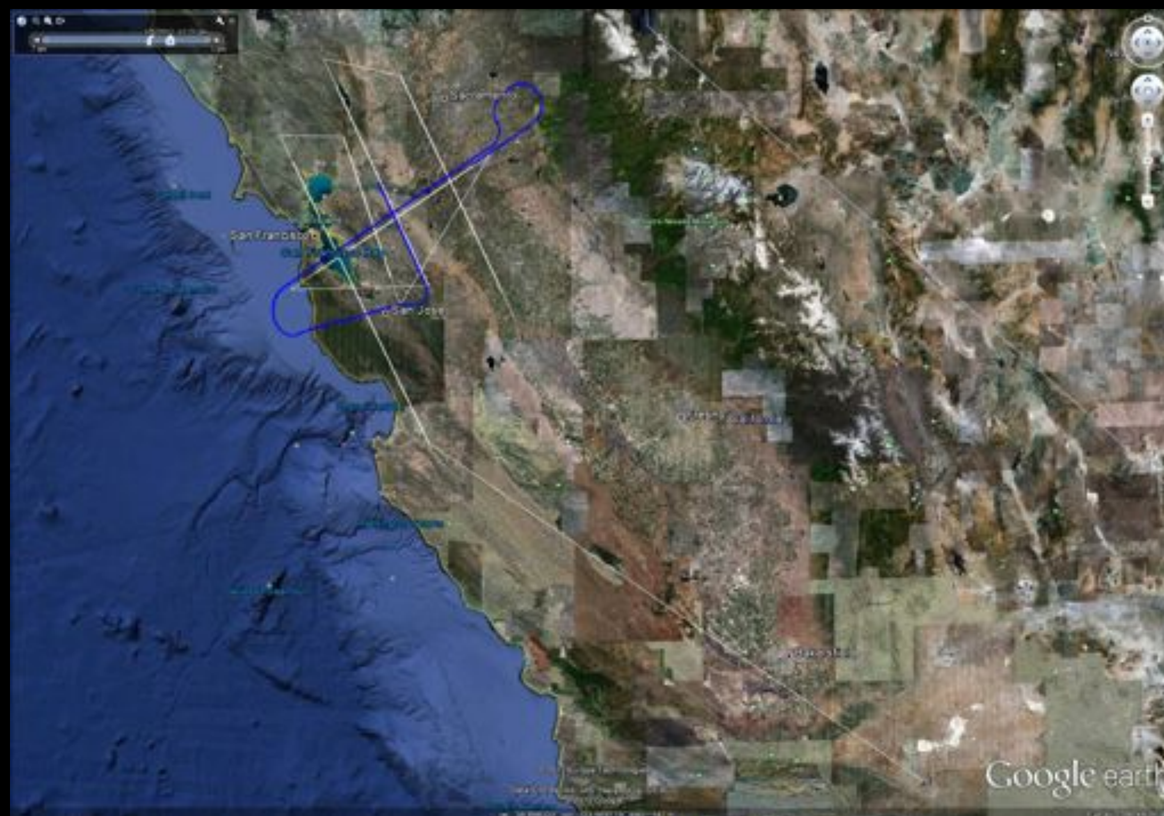
Flight continues



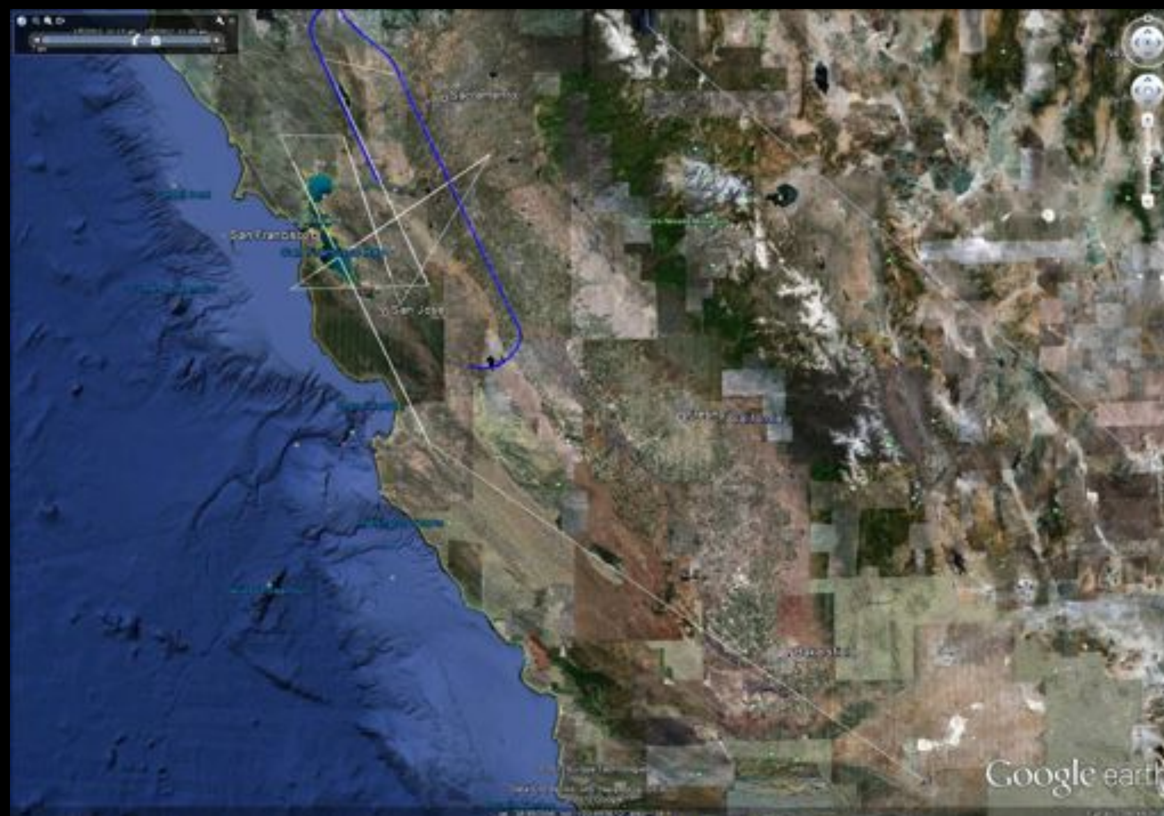
Subsequent data is collected, processed, and further alternative re-plans from baseline are generated



... but only one will be selected for execution (cost and logistics).



Single replan selected – 23519 (repeat of first) at third to last datatake.



Pilots confirm airspace and flight plan change with FAA

February 2012

...Diversion from original flight plan...

...resume original flight...

February 2012