Using Sensorwebs to Monitor Ecosystems – Integrating sensing, tracking, and modeling

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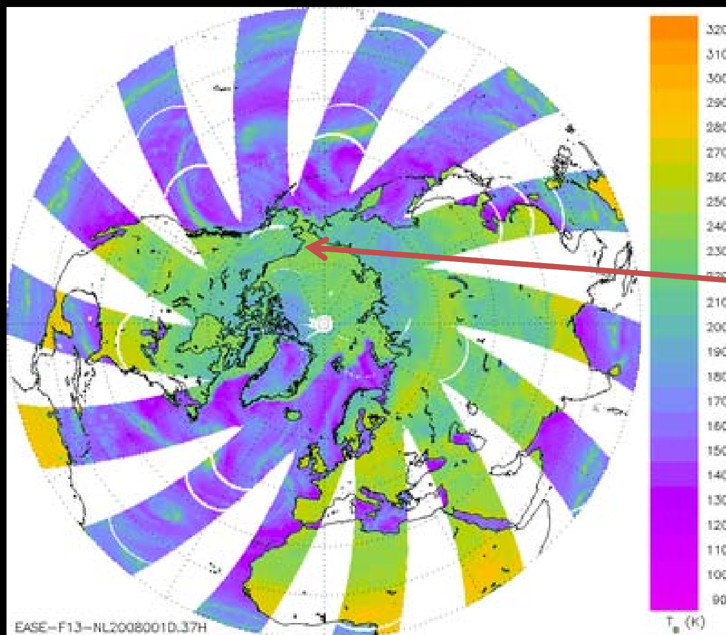
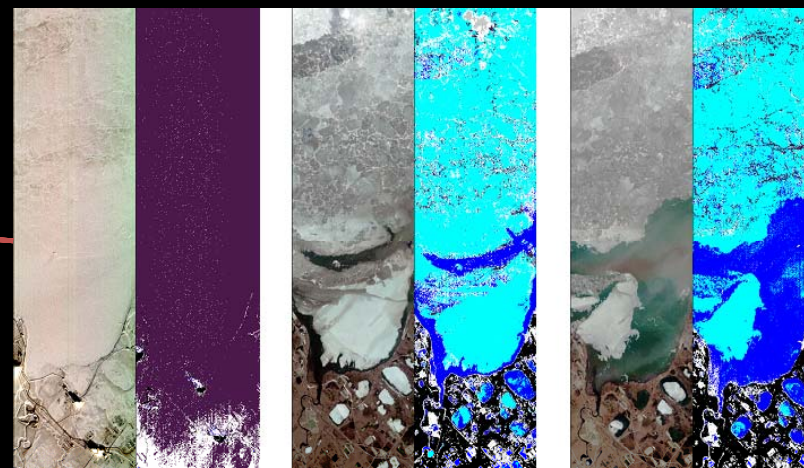
In collaboration EO-1, OASIS, OOI, Volcano, Flood, LIS, UAVSAR Sensorweb teams including:
Goddard Space Flight Center, USGS/CVO/HVO, Washington State University, UCSD, Scripps, Rutgers, MIT, ASU, U. Arizona, MEVO/NMT, U. Iceland, Iceland Met. Office

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 rely on 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





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

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

Wildfire

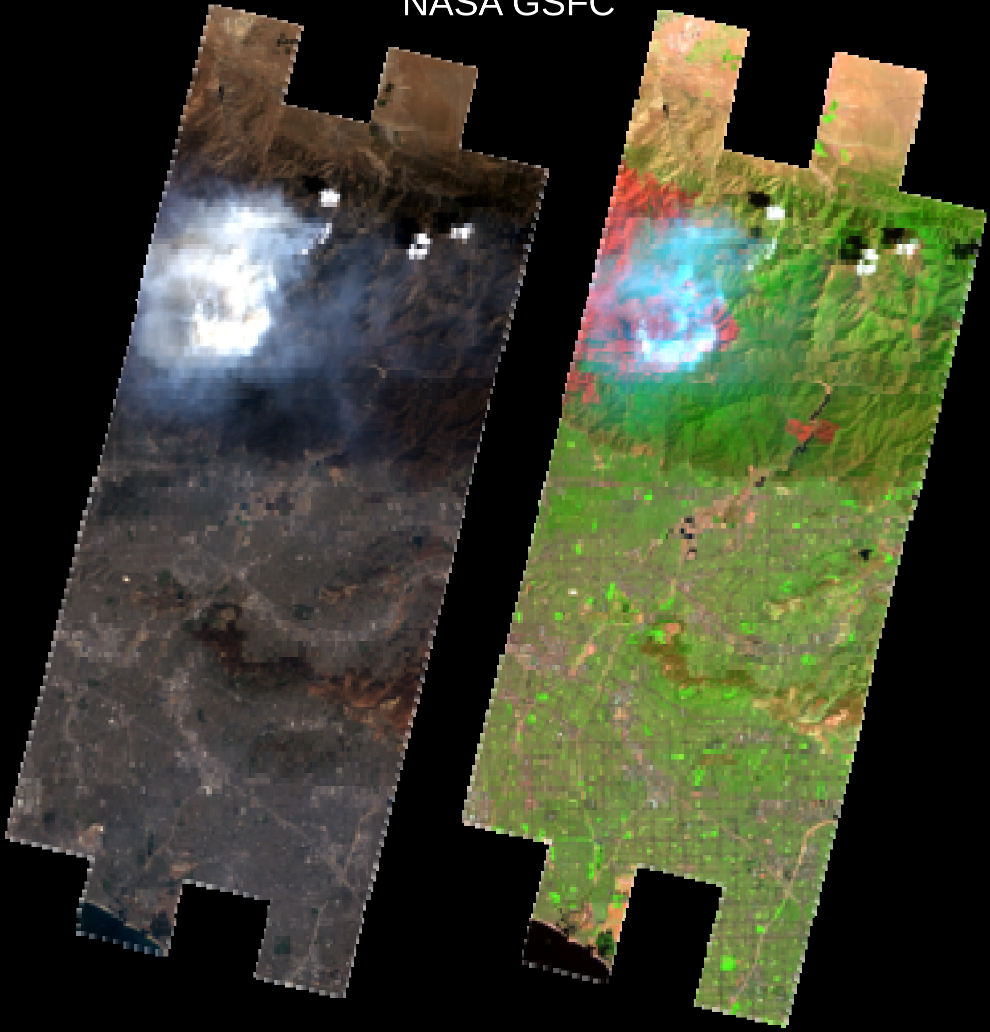
MODIS Rapidfire [Justice et al.]
1km / pixel resolution
Near real time
2003 SoCal Fires

NASA/MODIS Land Rapid Response

Station fire, La Canada, August 2009

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

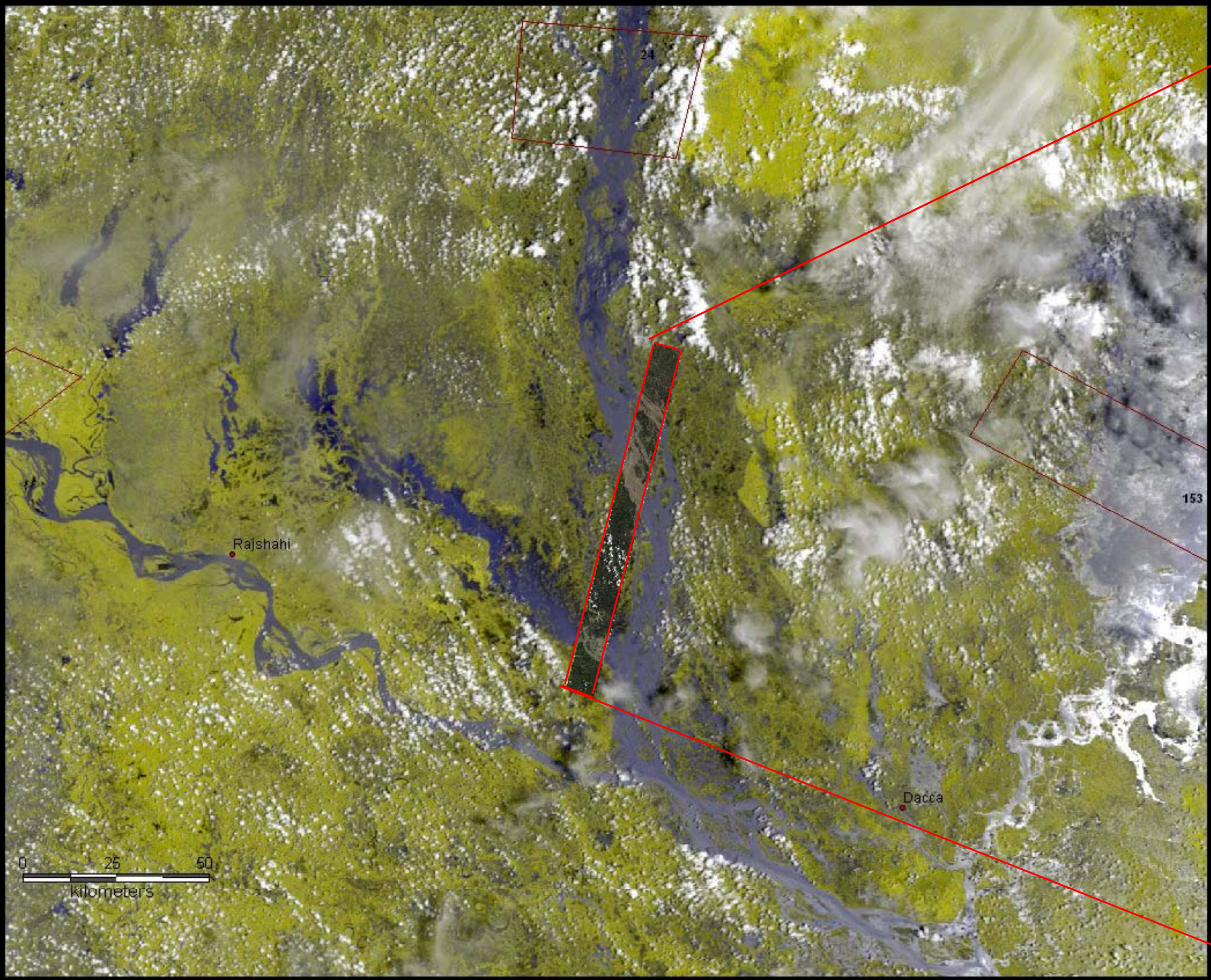
Images courtesy EO-1 Mission NASA GSFC



Flood alerts are then used to retask EO-1.

EO-1 Hyperion Image Brahmaputra Aug 6, 2003

MODIS Image Brahmaputra, India Aug 6, 2003



MODIS/NASA/GSFC, B. Brakenridge/DFO

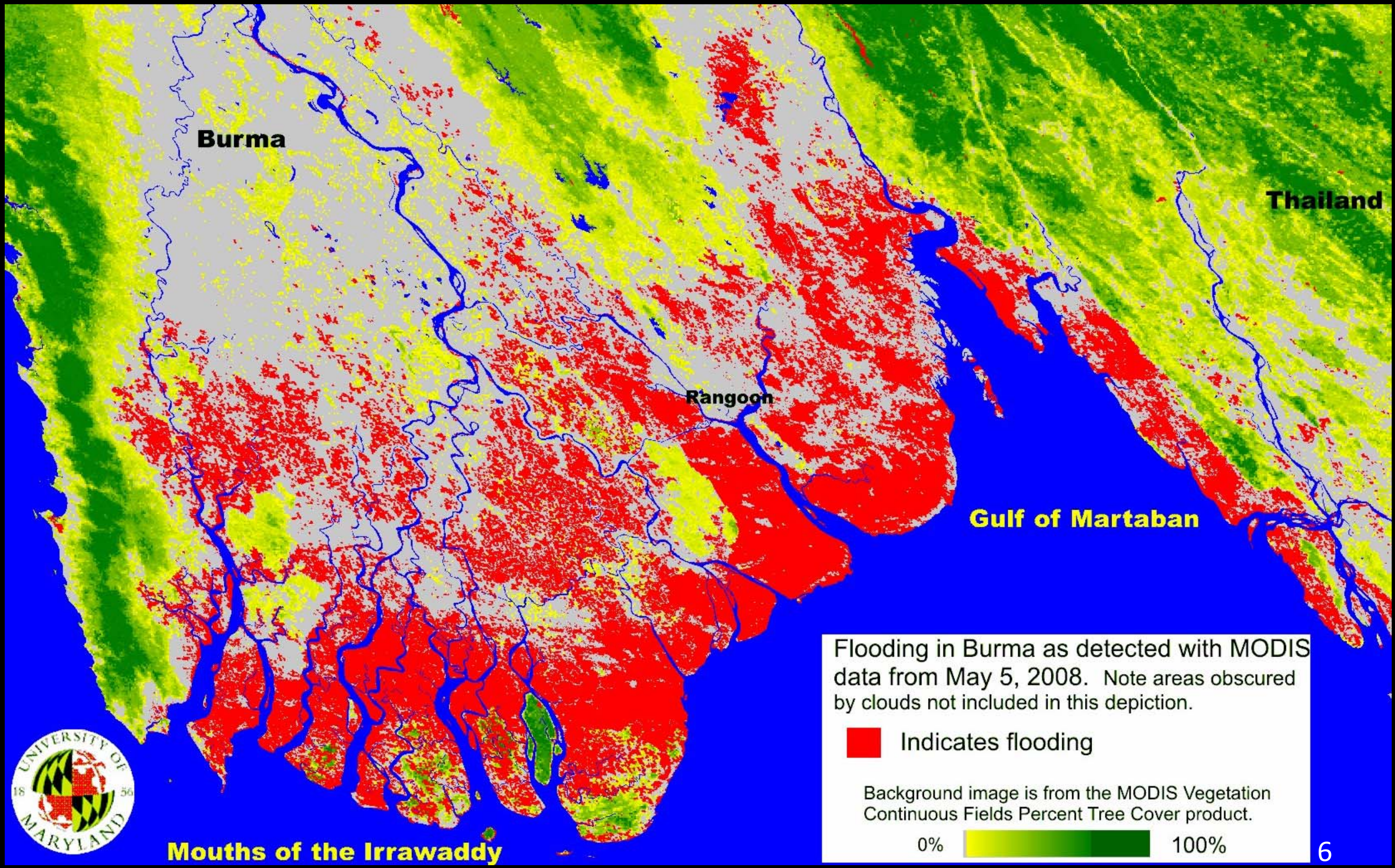
250M resolution

(10M ALI Pan band possible)

30M resolution

Flooding

- UMD Flood tracking - Myanmar using MODIS bands 1,2,5,7 (620-2155 nm)

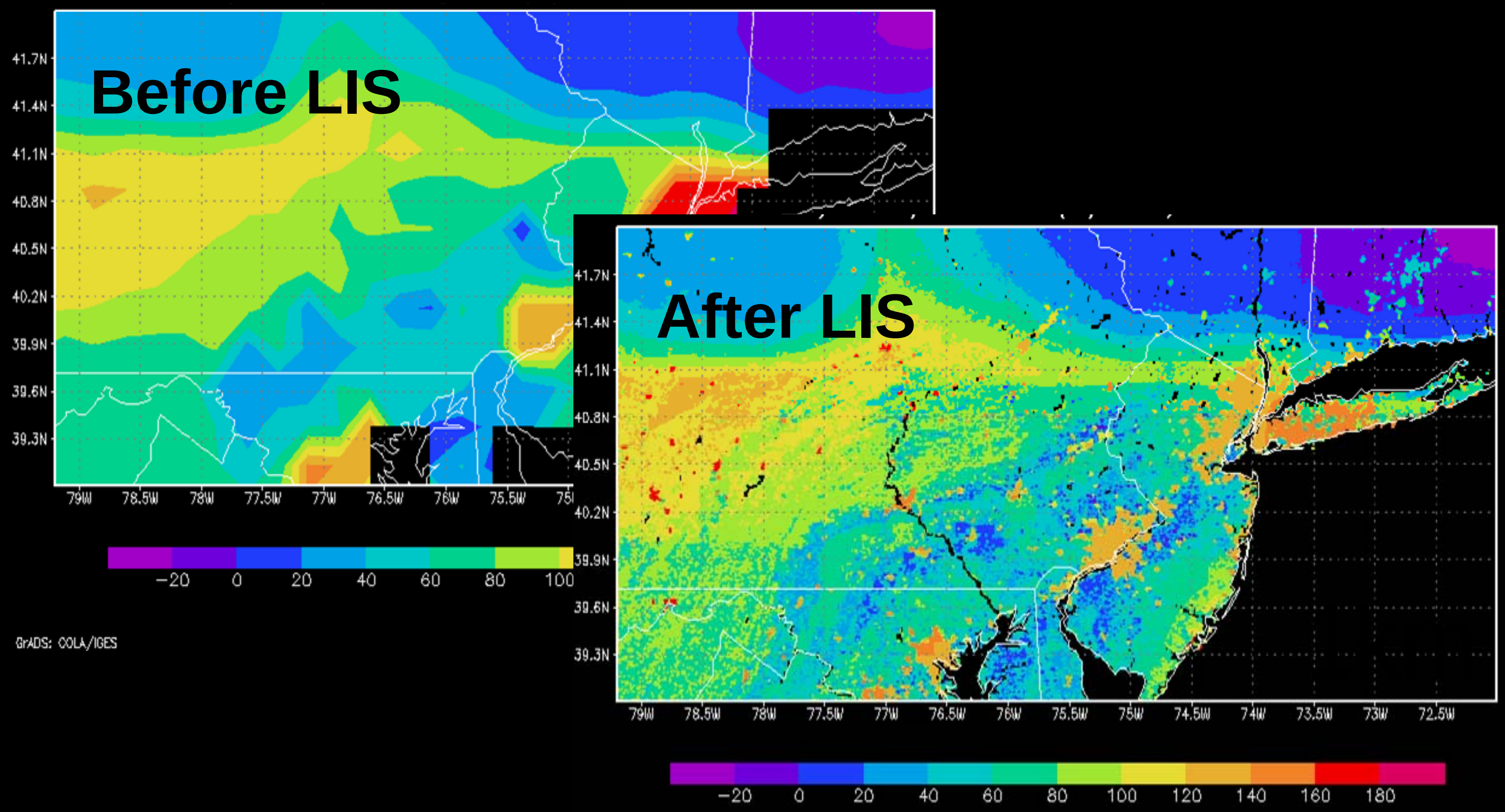


M. Carroll et al.
UMD

Land Information System?

A high-resolution land surface modeling and data assimilation system that supports land surface research activities and applications.

C. Peters-Lidard / NASA GSFC P. Houser, George Mason University



LIS Science and Data Flow

Inputs

Topography, Soils

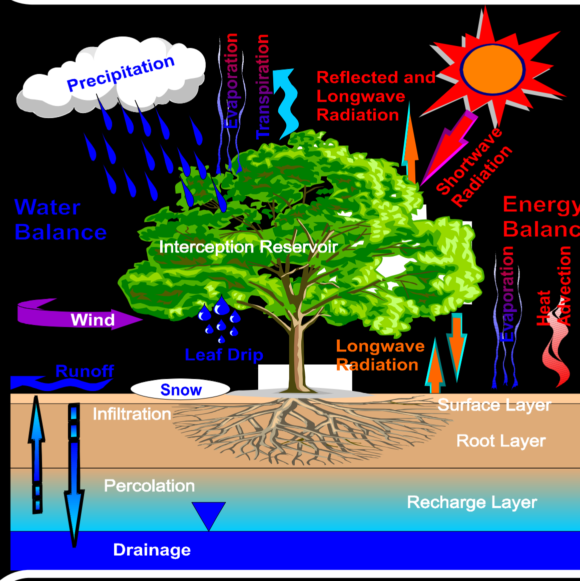
Land Cover, Vegetation Properties

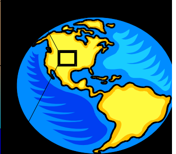
Meteorology

Snow Soil Moisture Temperature

Physics

Land Surface Models





Data Assimilation Modules

Outputs

Soil Moisture & Temperature

Evaporation

Runoff

Snowpack Properties

Applications

Weather/ Climate

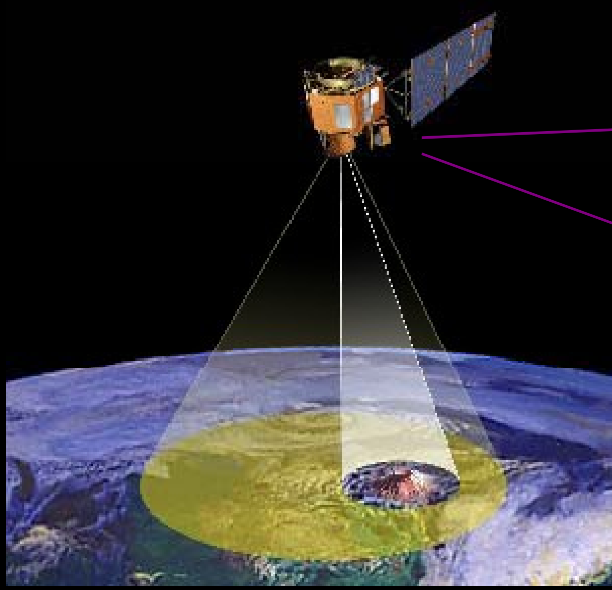
Water Resources

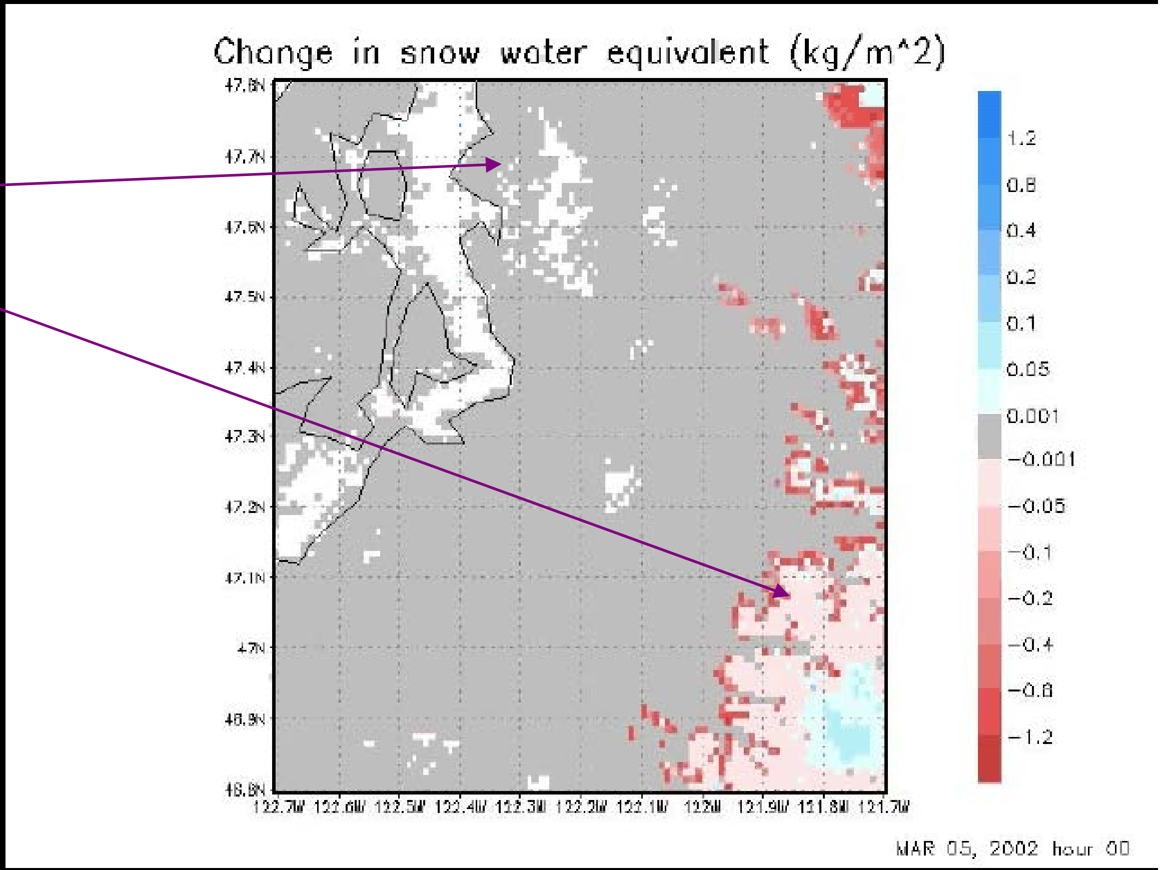
Homeland Security

Military Ops

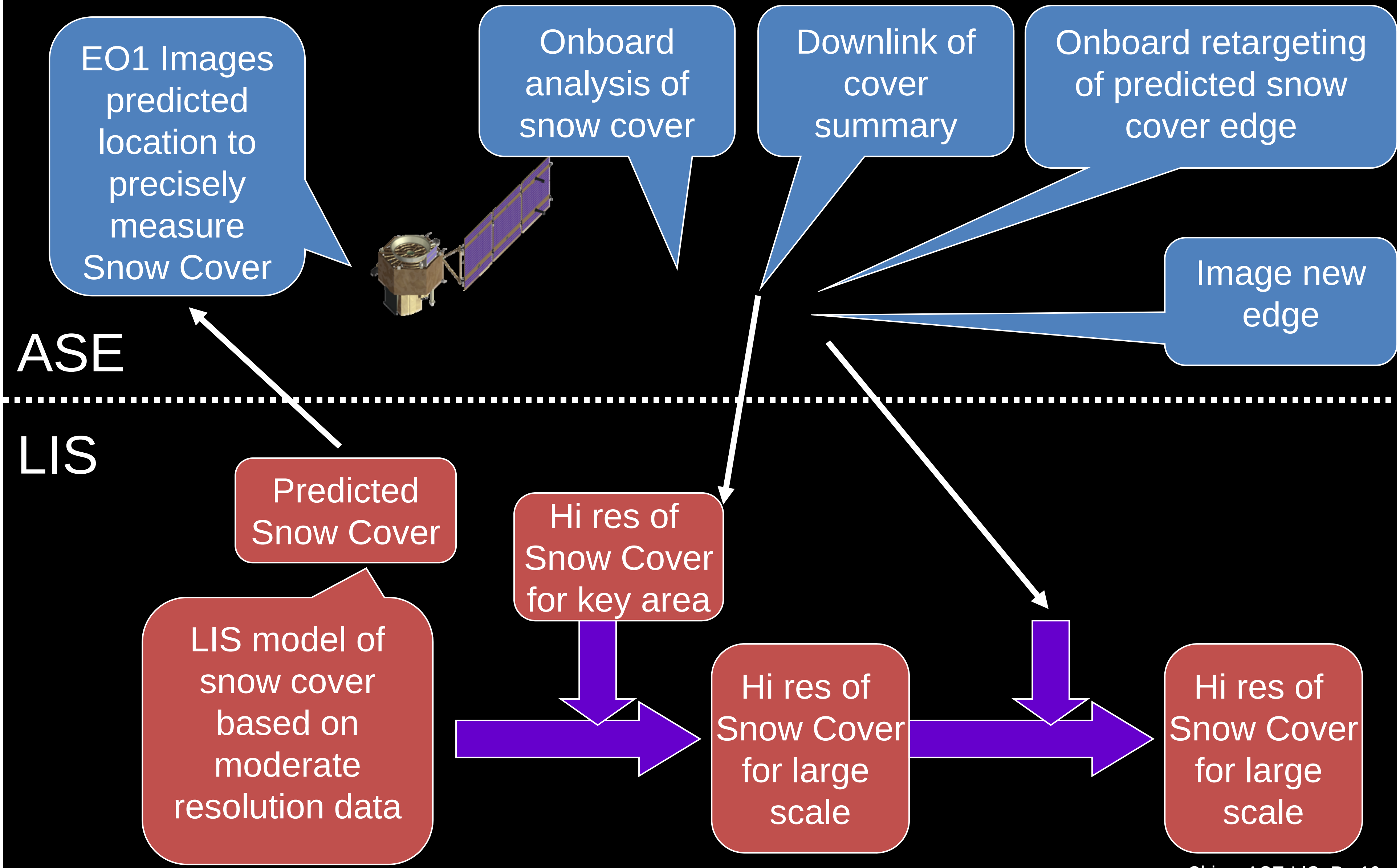
Natural Hazards

ASE + LIS




Change in snow water equivalent (kg/m^2)
47.8N
47.7N
47.6N
47.5N
47.4N
47.3N
47.2N
47.1N
47N
46.9N
46.8N
122.7W 122.6W 122.5W 122.4W 122.3W 122.2W 122.1W 122W 121.9W 121.8W 121.7W
1.2
0.8
0.4
0.2
0.1
0.05
0.001
-0.001
-0.05
-0.1
-0.2
-0.4
-0.8
-1.2
MAR 05, 2002 hour 00

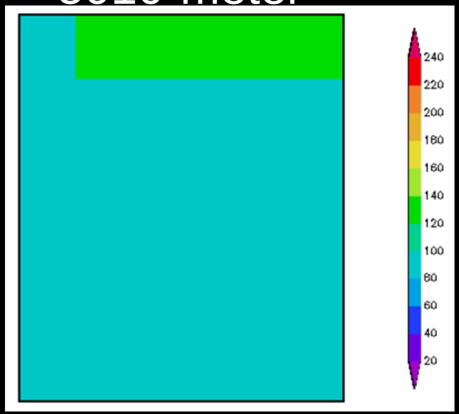
ASE + LIS Track Environment



Projected increase in capabilities

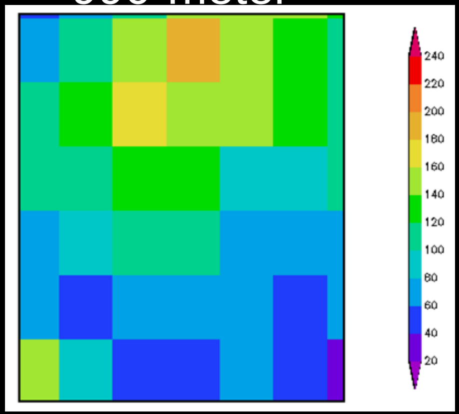
SWE OSSE Data For $6km^2$ Frasier Area

5010-meter



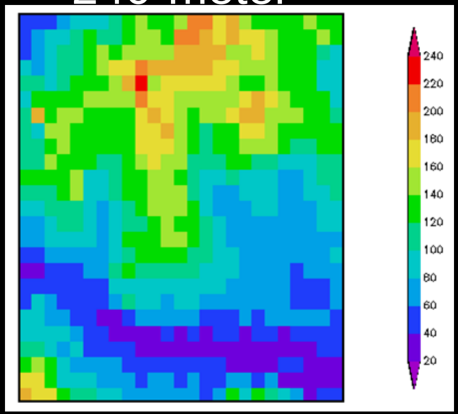
Microwave-Scale

990-meter

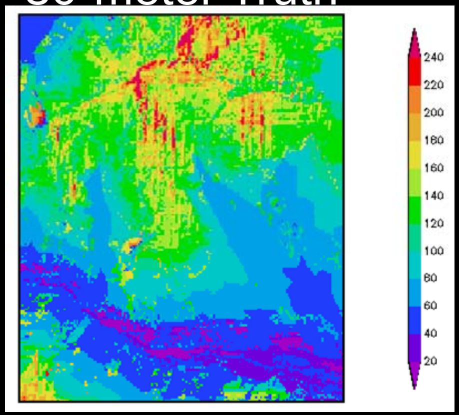


MODIS-Scale

240-meter



30-meter Truth



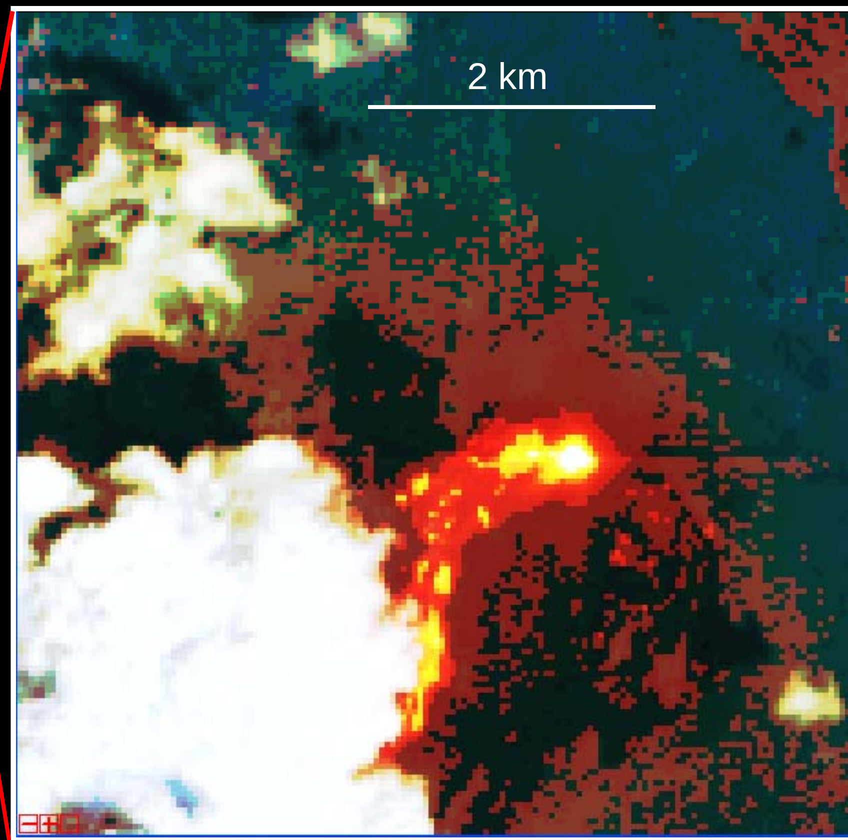
Process-Scale

Now → **With ASE + LIS**

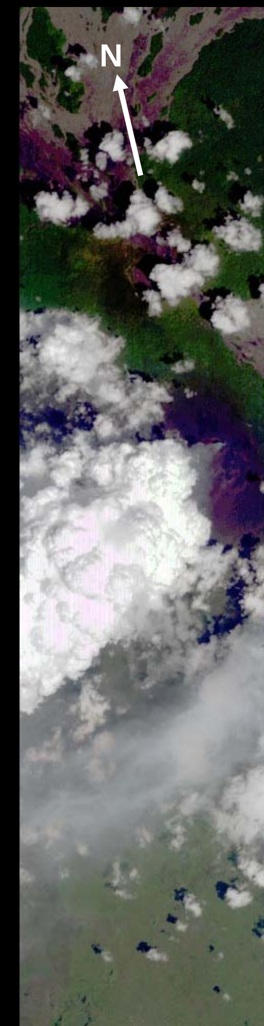
Volcano Monitoring

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

Chaiten volcano, Chile in a 2008 eruption
image courtesy USGS



Hyperion SWIR image of active vent and flows

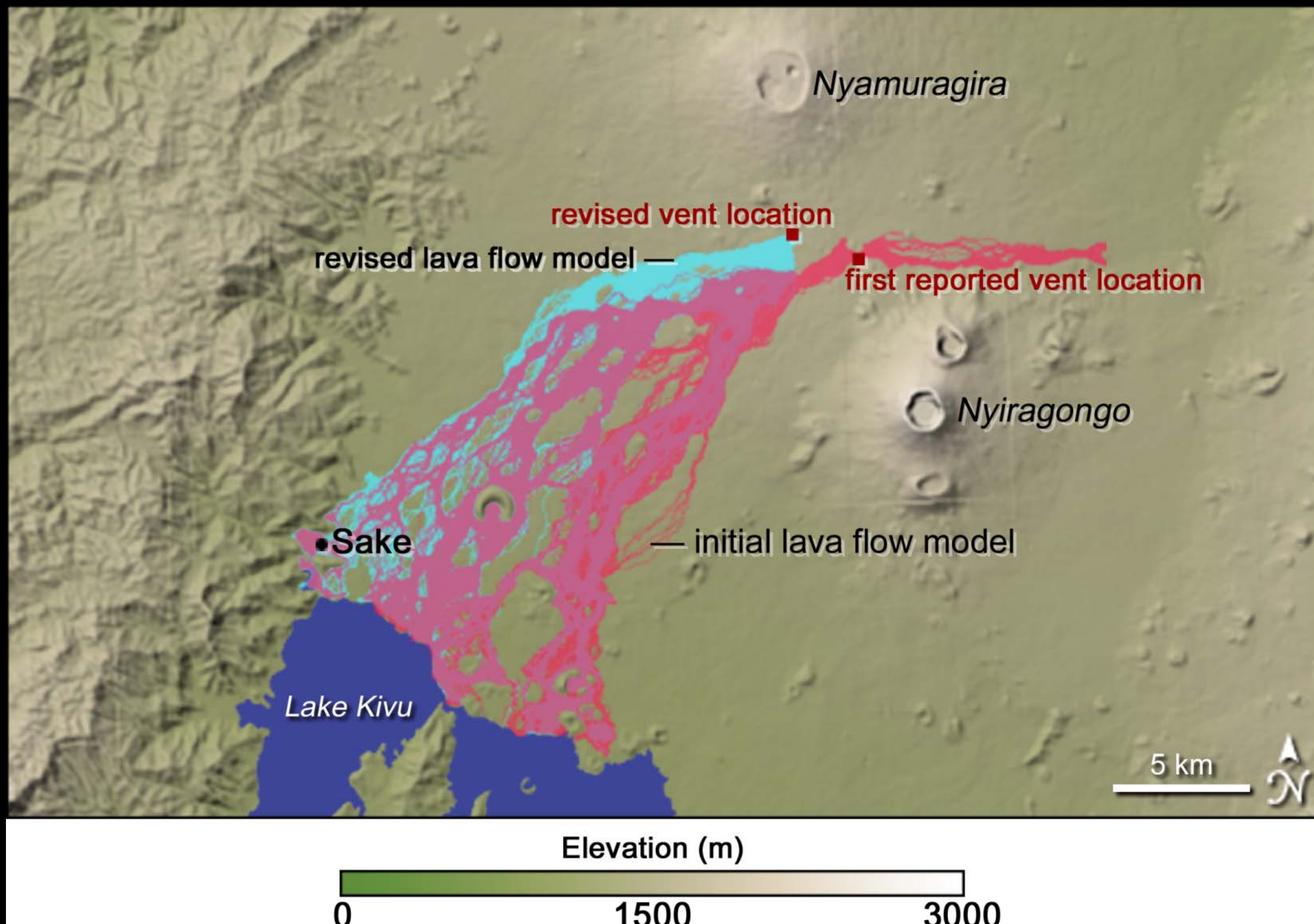


Hyperion VIS   Classifier output

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.*

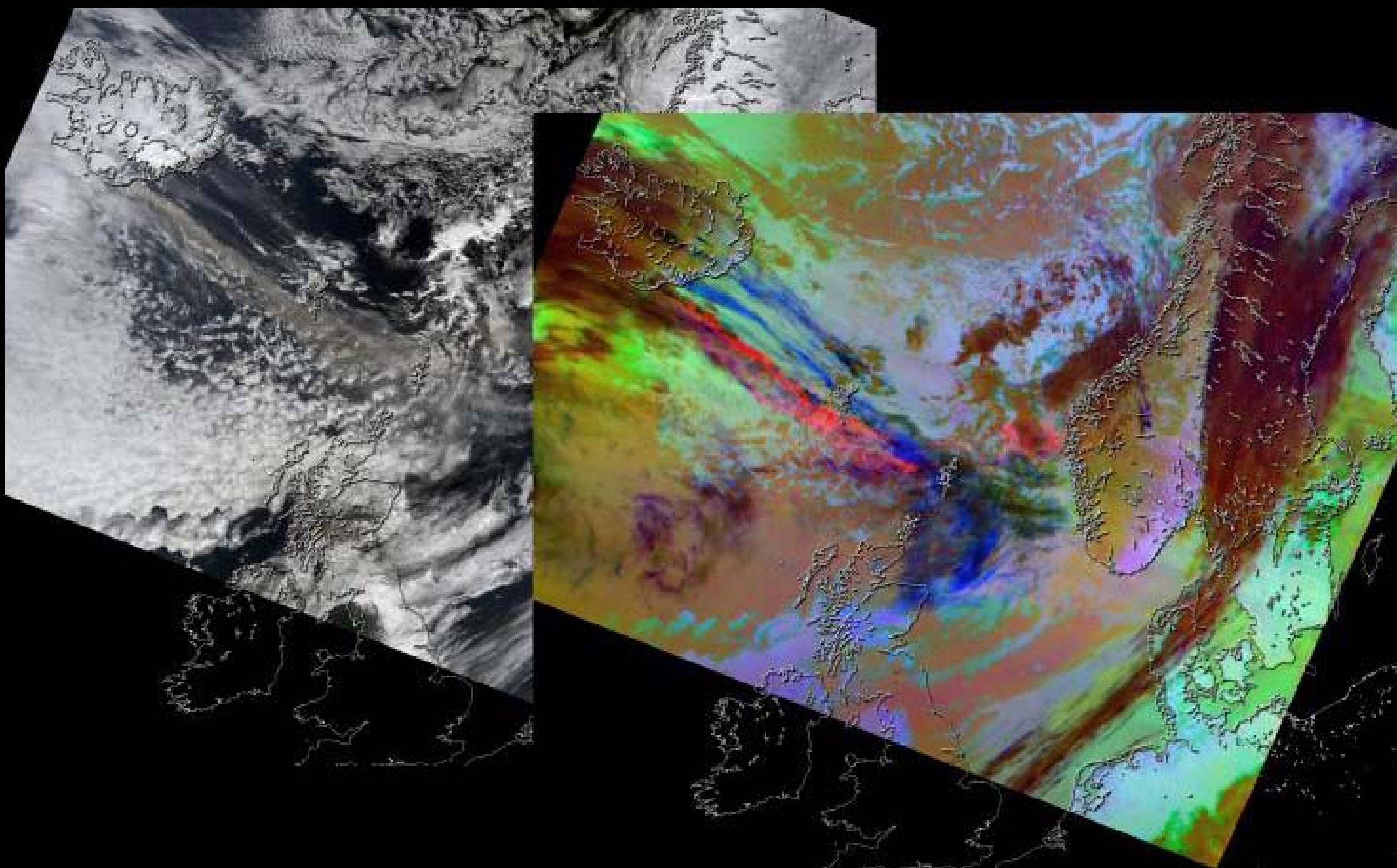
Predicting lava flow emplacement



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

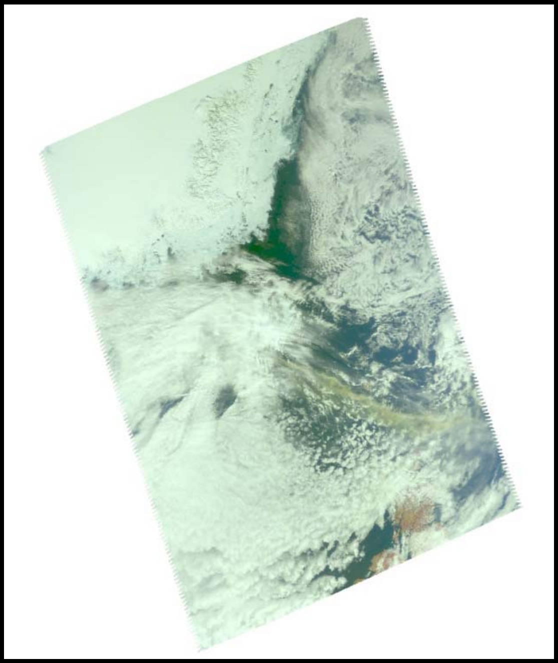
Scott, M. (2008)

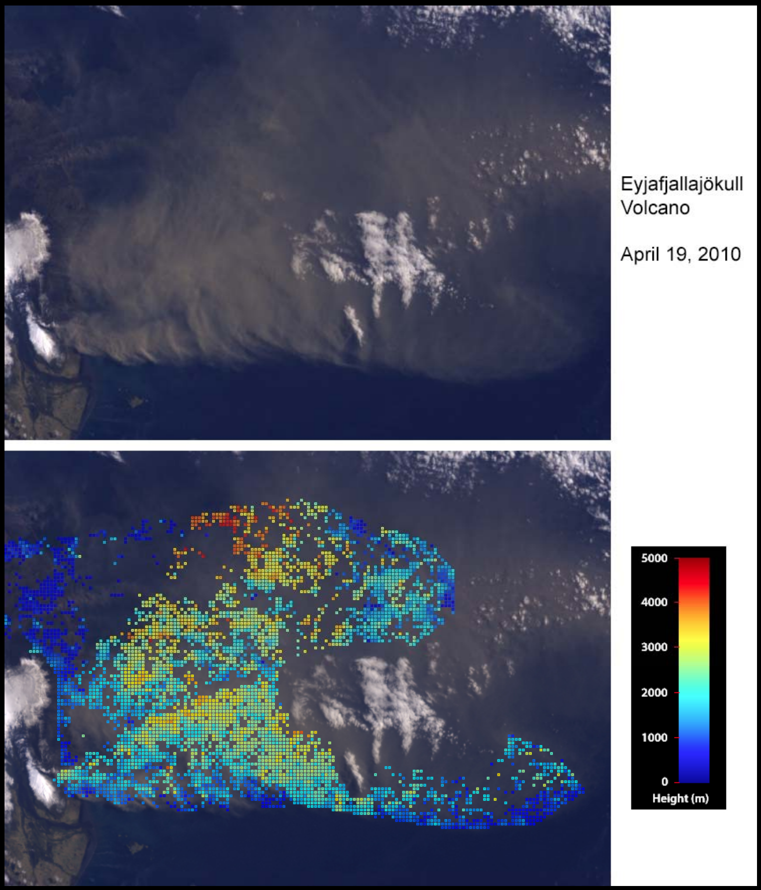
MODIS - Eyafallajökull



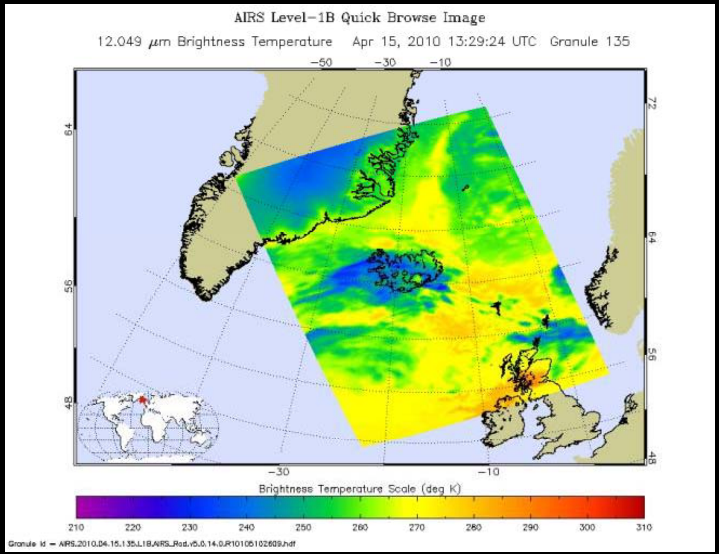
15 April 2010, MODIS, NASA/GSFC/JPL

MISR, AIRS





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

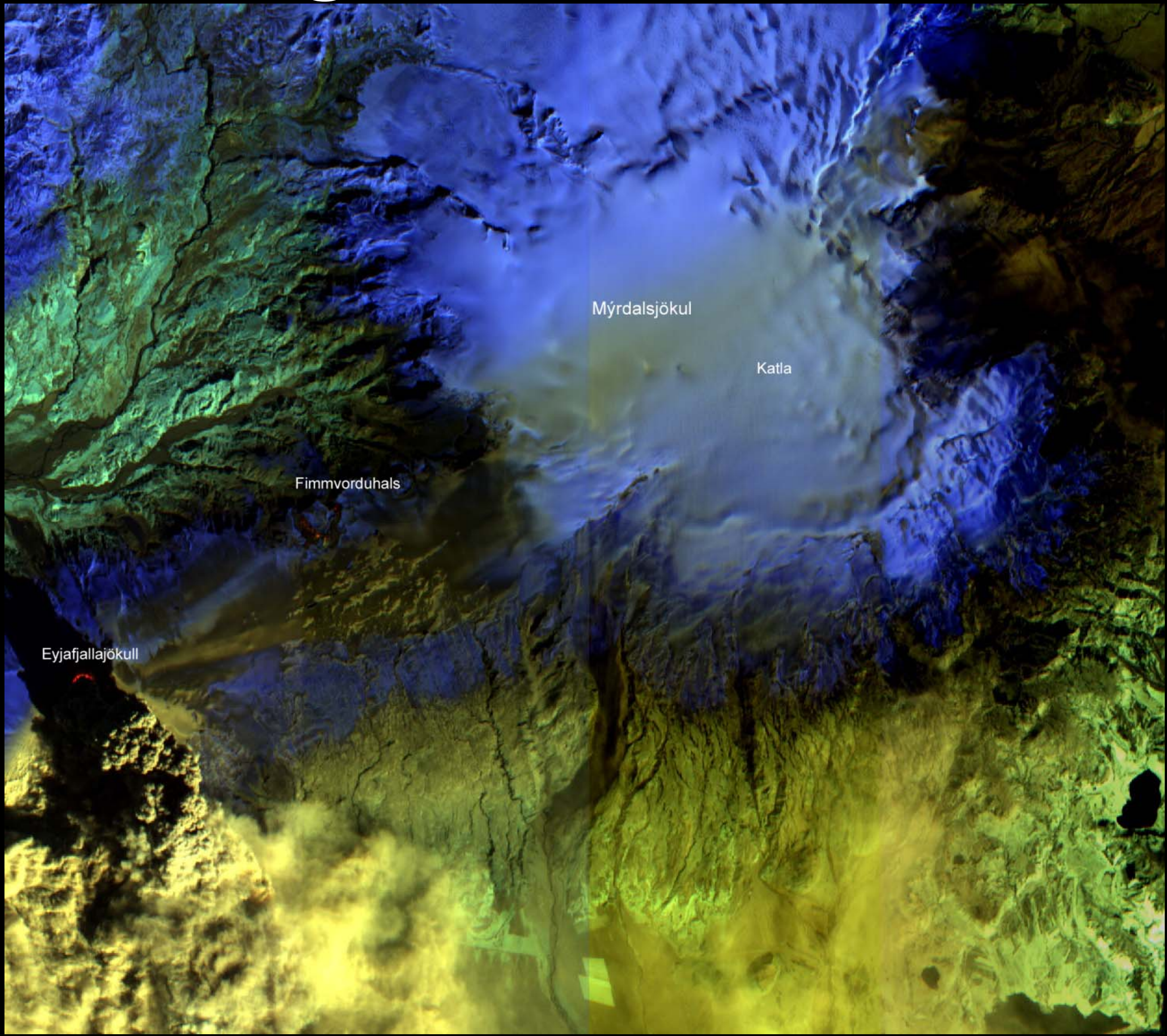


15 April 2010, AIRS - NASA/JPL

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



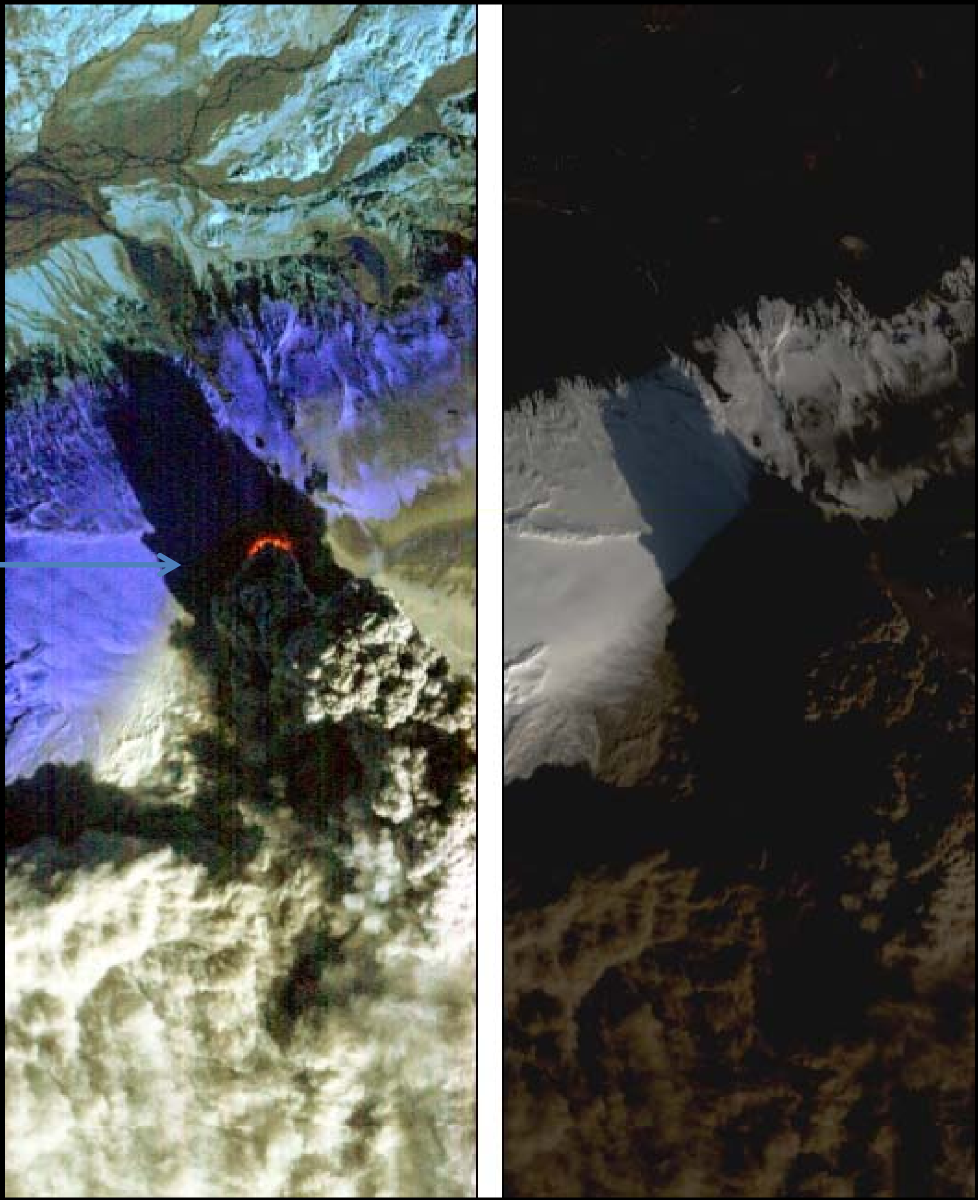
Iceland Imagery

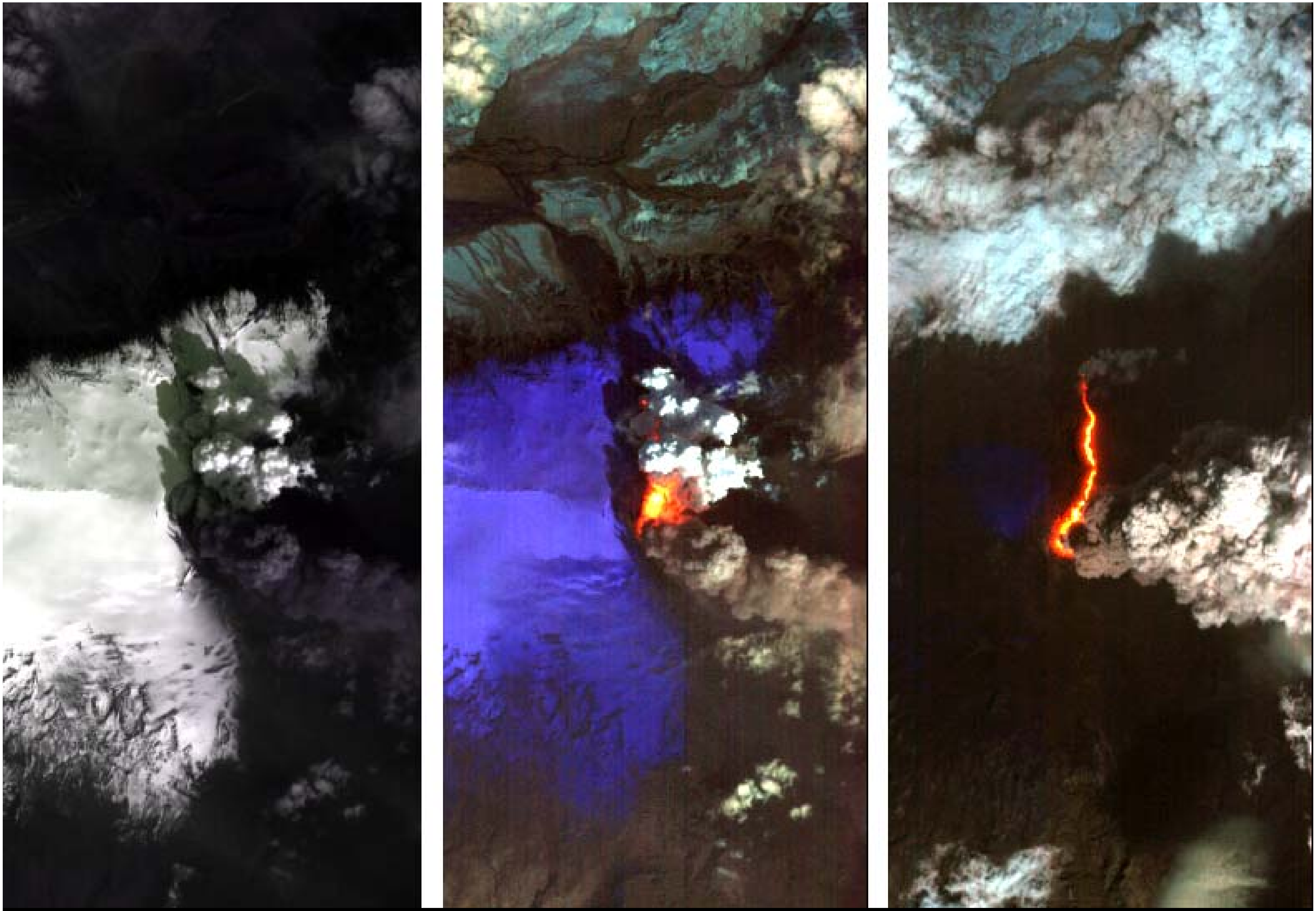
Eyafallajökull

2 Giga Watt Thermal emission

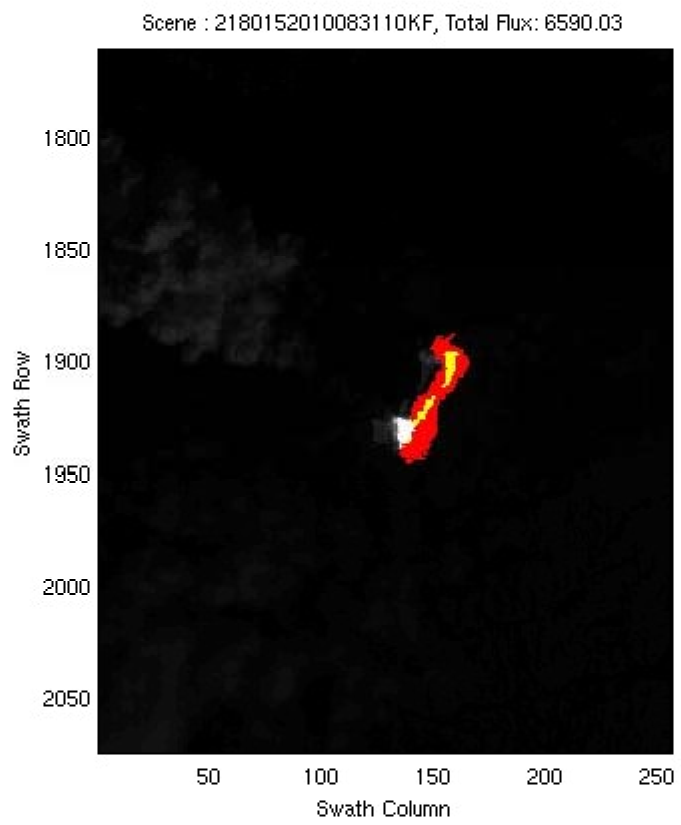
Left – thermal false color
Right – True color

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

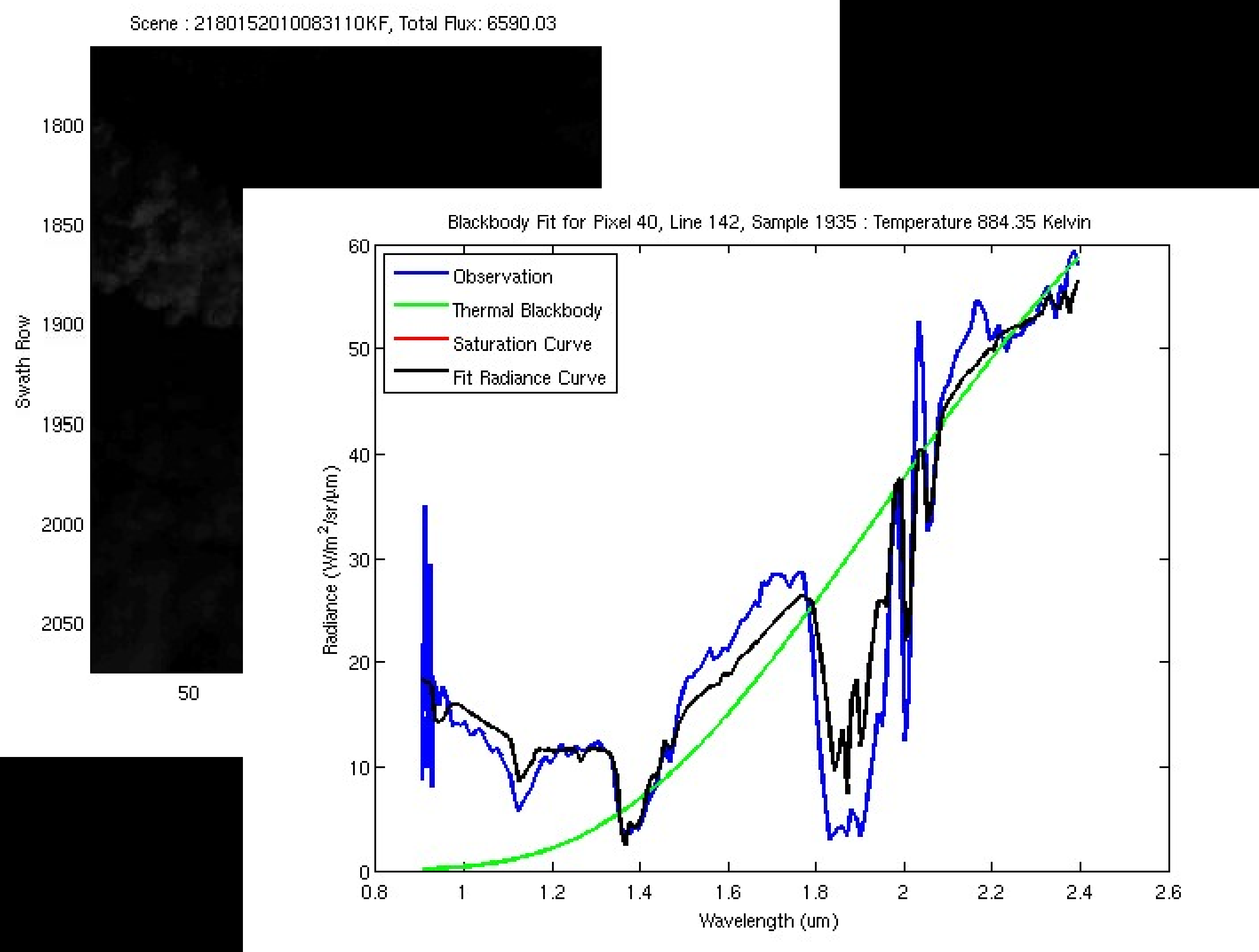


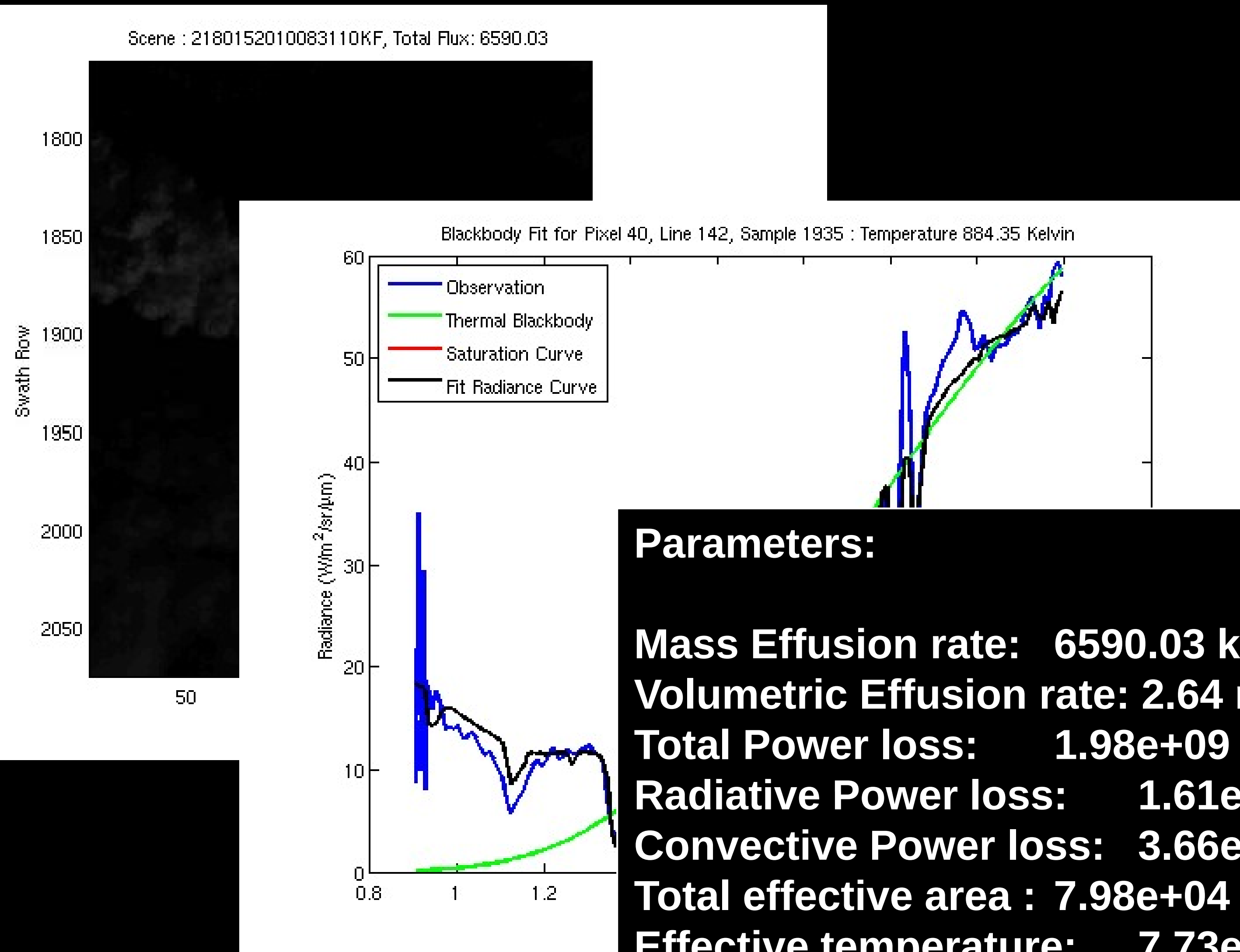


2 May 2010 – VIS 2 May 2010 – SWIR 4 May 2010 - SWIR



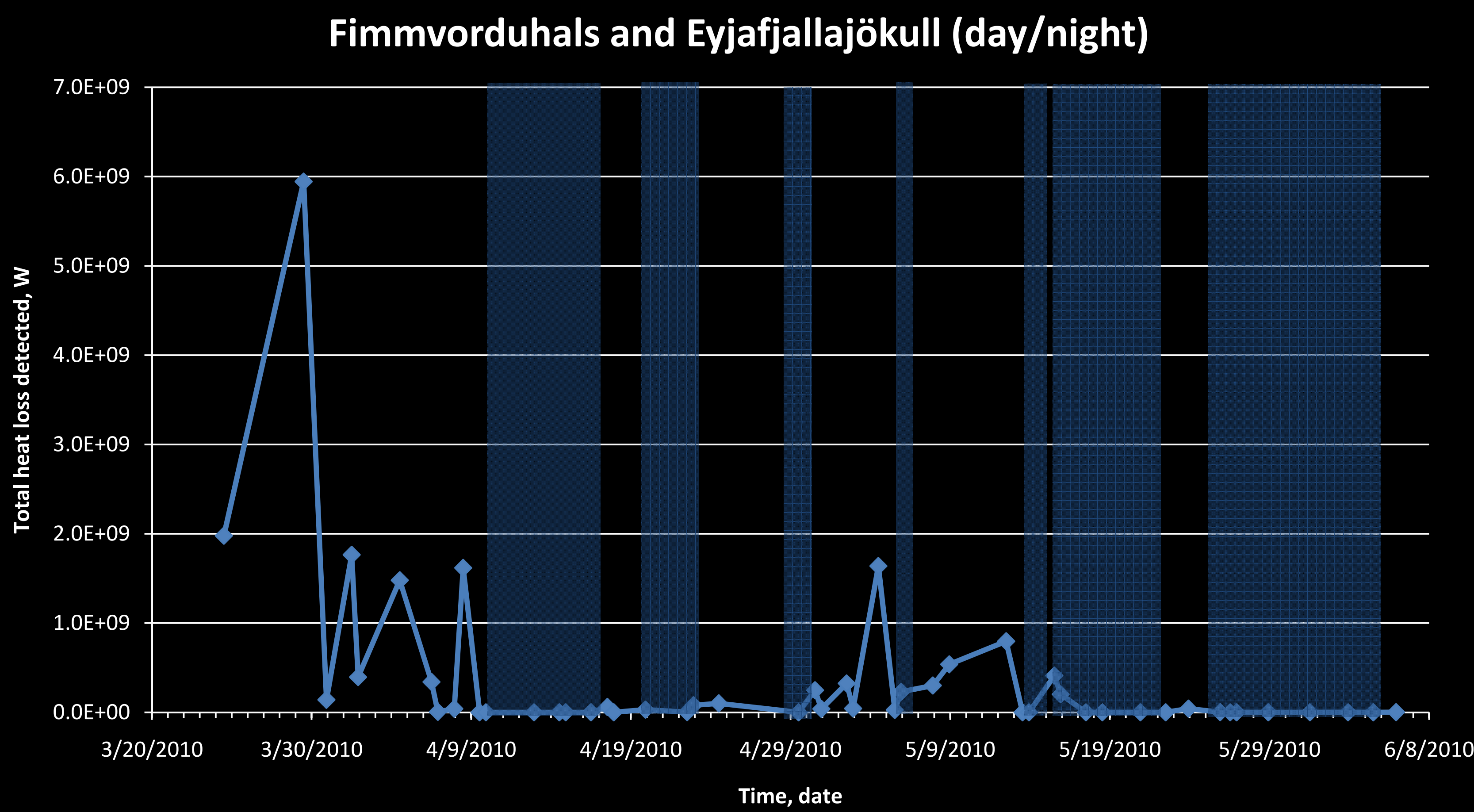
Scene : 2180152010083110KF, Total Flux: 6590.03
1800
1850
1900
1950
2000
2050
Swath Row
50
100
150
200
250
Swath Column


Scene : 2180152010083110KF, Total Flux: 6590.03
Swath Row
1800
1850
1900
1950
2000
2050
50
Blackbody Fit for Pixel 40, Line 142, Sample 1935 : Temperature 884.35 Kelvin
Observation
Thermal Blackbody
Saturation Curve
Fit Radiance Curve
Radiance (W/m2/sr/µm)
0
10
20
30
40
50
60
0.8
1
1.2
1.4
1.6
1.8
2
2.2
2.4
2.6
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



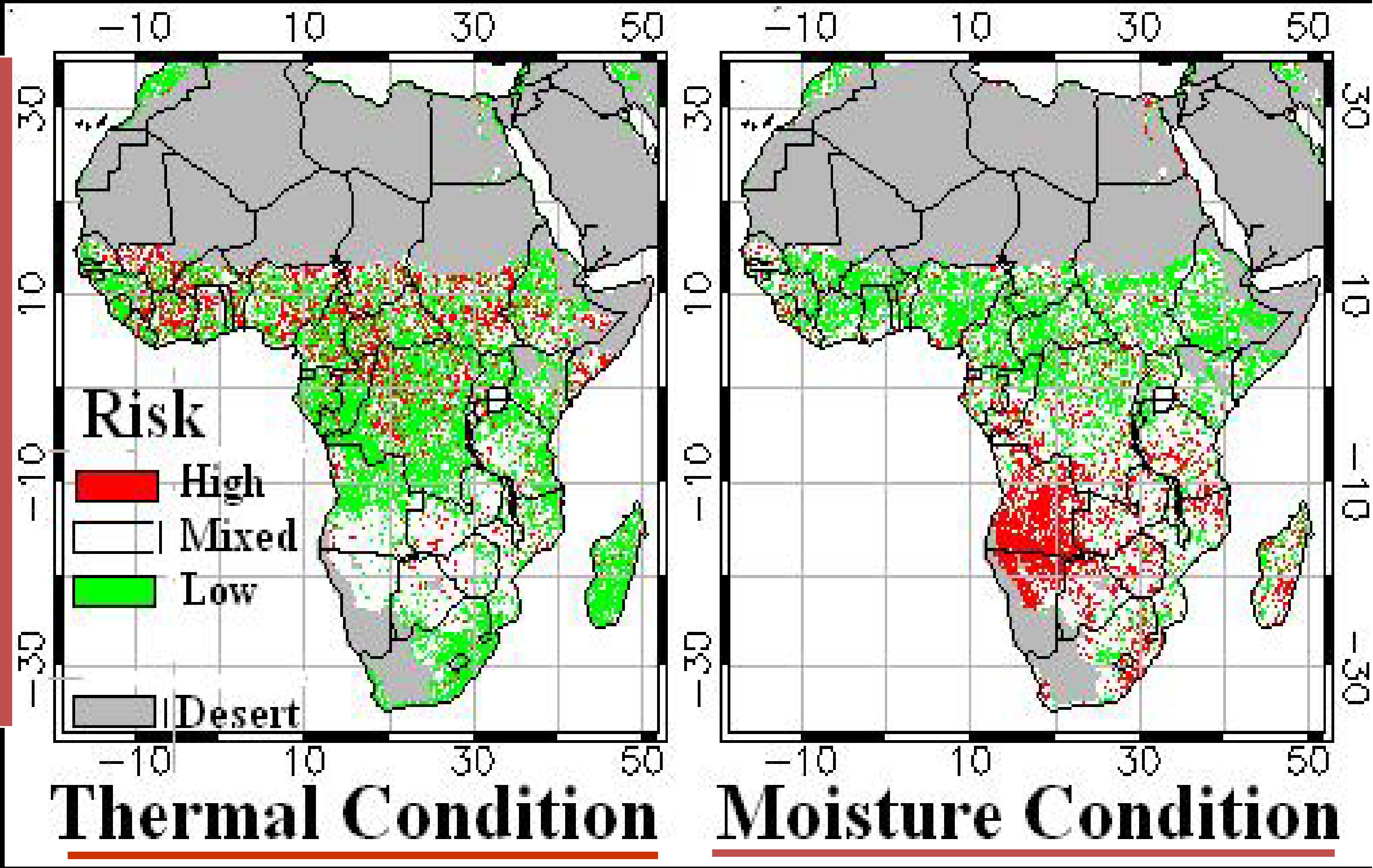
Thermal emission estimate is minimum value:

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

Disease Vector Estimation

Strategy: WEATHER PROXY AUGUST 26, 2008

Malaria risk map identifies priority areas and additional resources needed to fight epidemics effectively

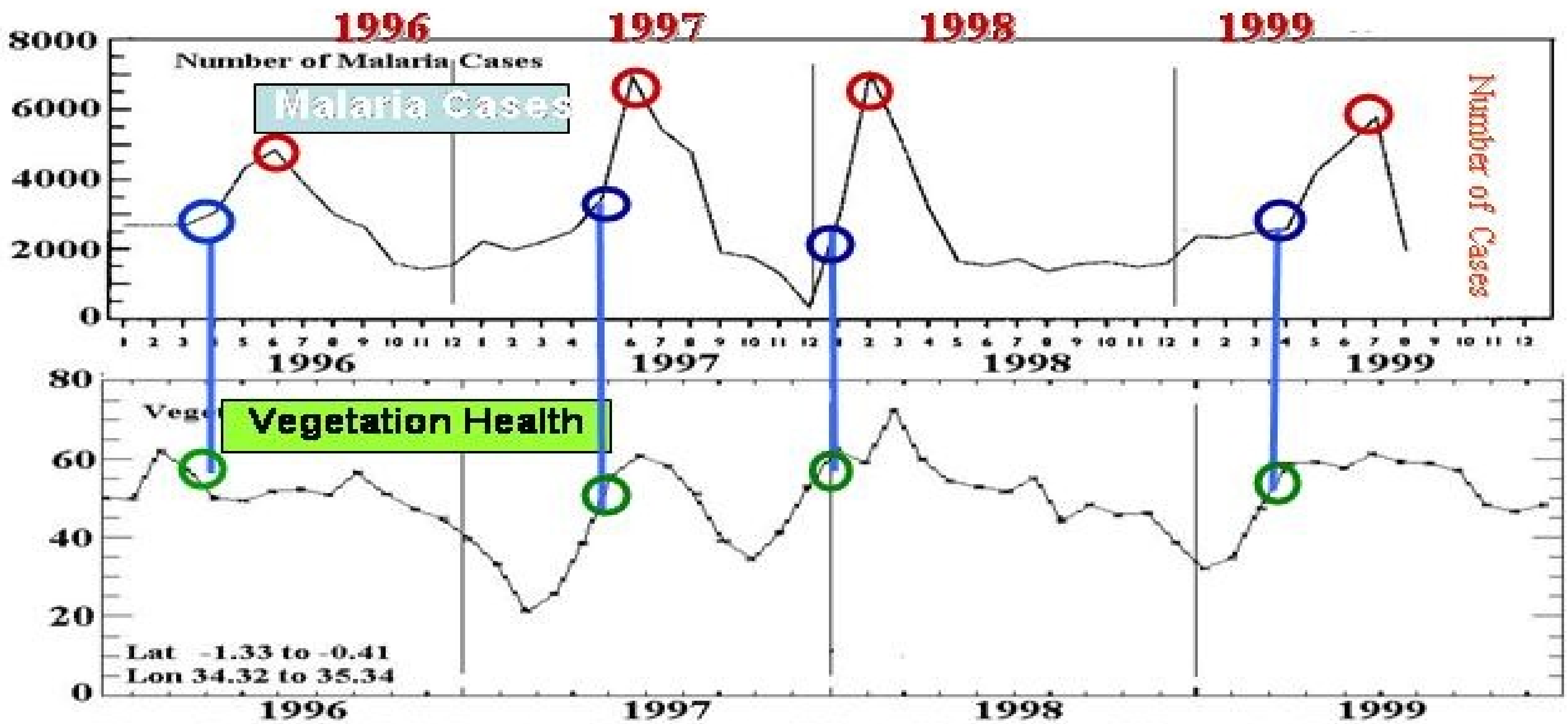


INTENSIVE MALARIA

F. Kogan/NOAA/NESDIS

Disease Estimation

Predicting Malaria in KENYA

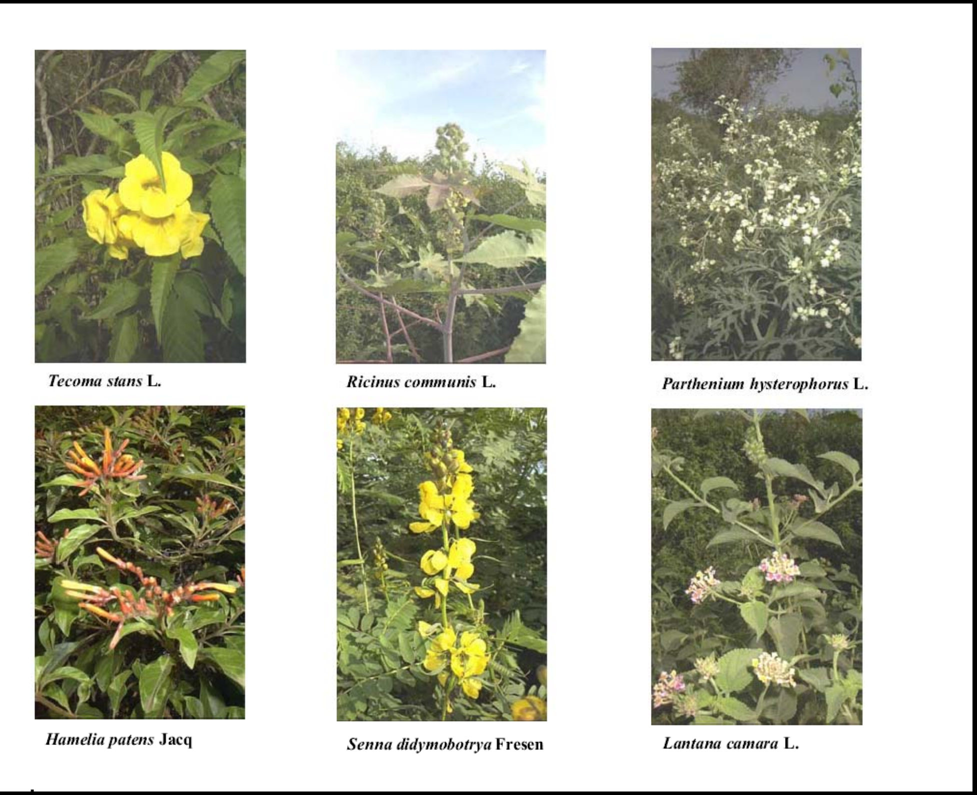


Number of Malaria Cases in Kisii District Hospital, Western Kenya and AVHRR-based Vegetation Health Index (VHI)

VH provides up to 4 months advance malaria warning

Heritage (Ground)

- Disease risk estimation via species identification



Preferred plants for Anopheles (in order of preference

- ❑ *T.stans ,S.didymobotrya*
- ❑ *R.communis*
- ❑ *H.patens*
- ❑ *Taraxacum officinale*
- ❑ *Hieracium pratense*

Least preferred plants

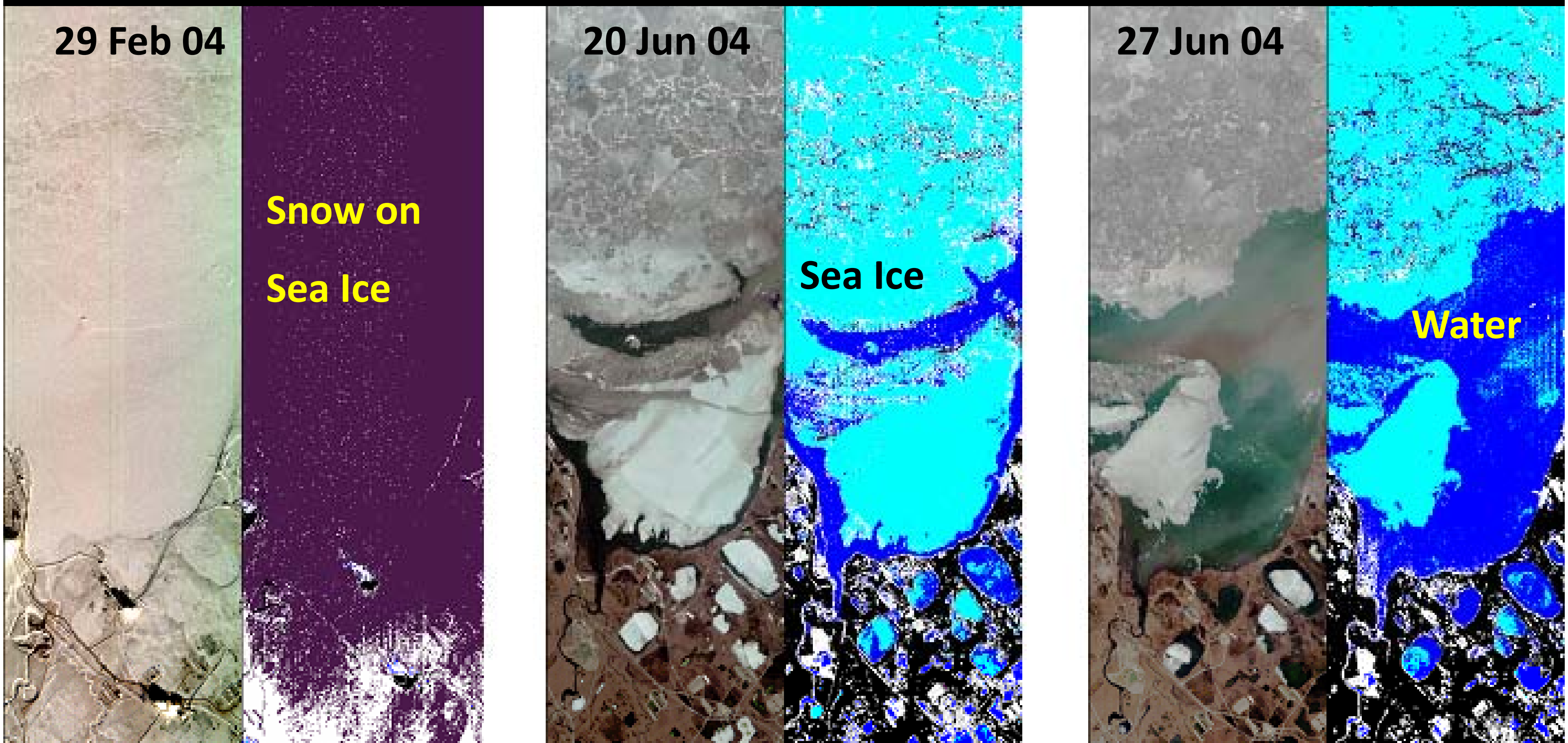
- ❑ *L. camara*
- ❑ *Viola sororia*

Advanced computation for Environmental Monitoring

- Machine learning for automatic classification and interpretation of imagery
- Automated planning & scheduling for asset autonomy
  - Enabled $1M US in operations savings for EO-1 [Chien et al. 2005 JACIC], co-winner NASA Software of the Year 2005
  - Enabled 40% increase in observations [Chien et al. 2010 ICAPS] (Best applied paper award)
- Multi-agent systems for coordination of multiple assets

Cryosphere Classifier

Deadhorse (Prudhoe Bay), Alaska



- Snow
- Water
- Ice
- Land
- Unclassified

Wavelengths used in classifier:
0.43, 0.56, 0.66, 0.86 and 1.65 μm

Arizona State University
Planetary Geology Group

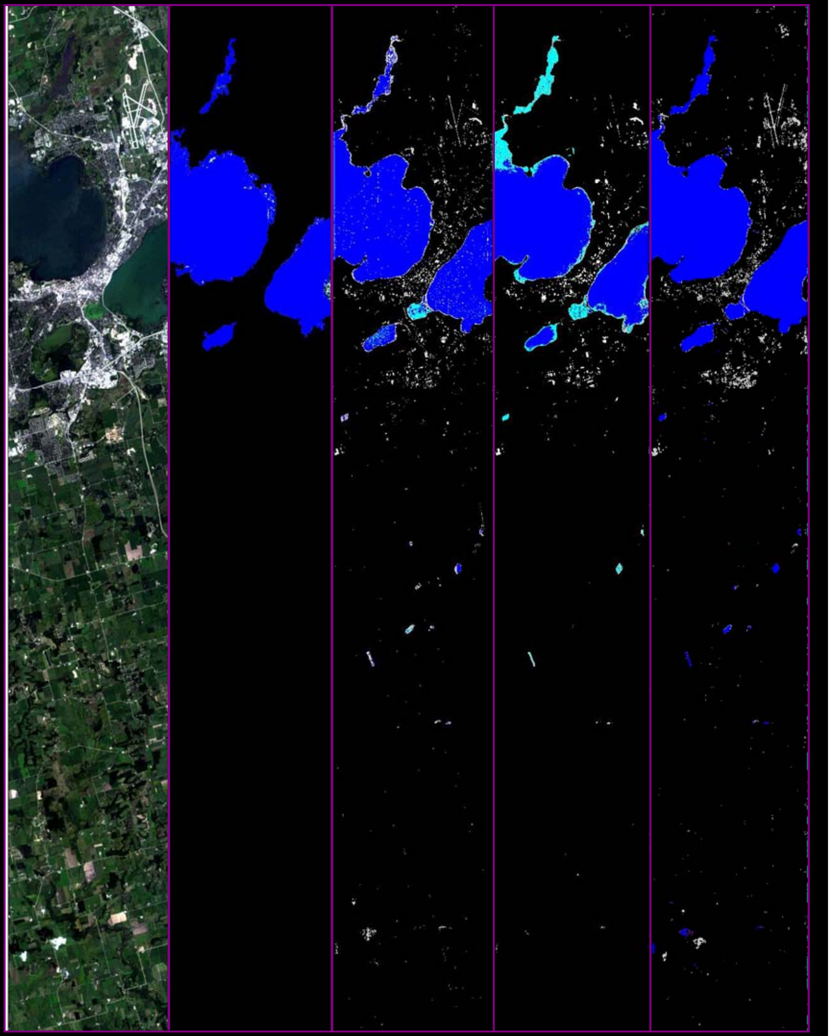
Land, Ice, Water, Snow Detection

- Primary Purpose
  - Identify areas of land cover (land, ice, water, snow) in a scene
- Three algorithms:
  - Scientist manually derived
  - Automatic best ratio
  - Support Vector Machine (SVM)

Classifier	Expert Derived	Automated Ratio	SVM
cloud	45.7%	43.7%	58.5%
ice	60.1%	34.3%	80.4%
land	93.6%	94.7%	94.0%
snow	63.5%	90.4%	71.6%
water	84.2%	74.3%	89.1%
unclassified	45.7%		

R. Castano et al. KDD 2005

Lake Mendota, Wisconsin



Visible Image | Expert Labeled | Expert Derived | Automated Ratio | SVM

SAR Classification – Open Water

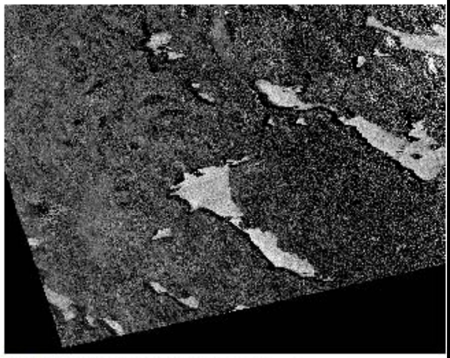


Figure 23: Auto4a.Howlnd.34702.09054.011.090805.L090HHHH.CX.01.dielec.sab.grd
http://ai.jpl.nasa.gov/public/home/jdoubled/uavsar/asf/Howlnd.34702.09054.011.090805.L090.CX.01/soilmoist/Auto4a.Howlnd.34702.09054.

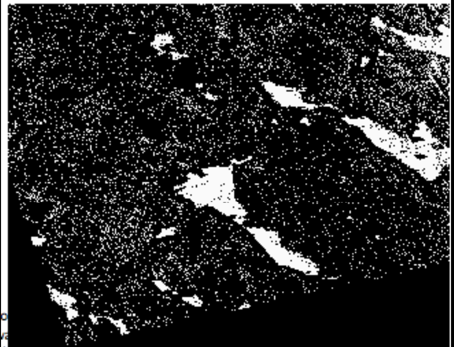
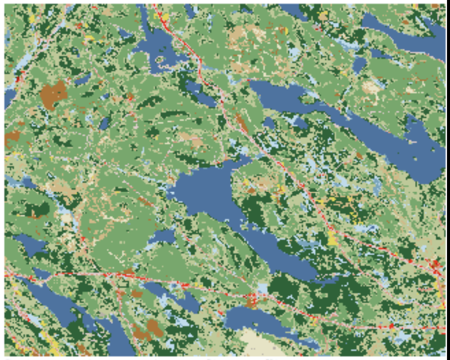


Figure 24: Auto4a.Howlnd.34702.09054.011.090805.L090HHHH.CX.01.waterdiel.grd
http://ai.jpl.nasa.gov/public/home/jdoubled/uavsar/asf/Howlnd.34702.09054.011.090805.L090.CX.01/water/Auto4a.Howlnd.34702.09054.011



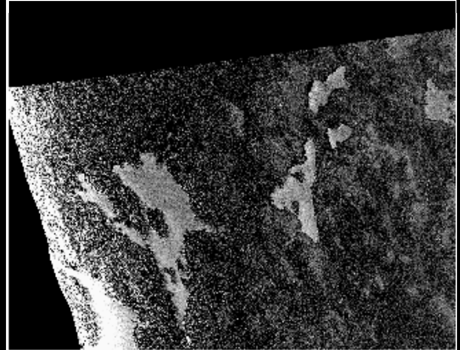


Figure 26: Auto4a.Howlnd.16701.09056.008.090807.L090HHHH.CX.01.dielec.sab.grd
http://ai.jpl.nasa.gov/public/home/jdoubled/uavsar/asf/Howlnd.16701.09056.008.090807.L090.CX.01/soilmoist/Auto4a.Howlnd.16701.09056.0

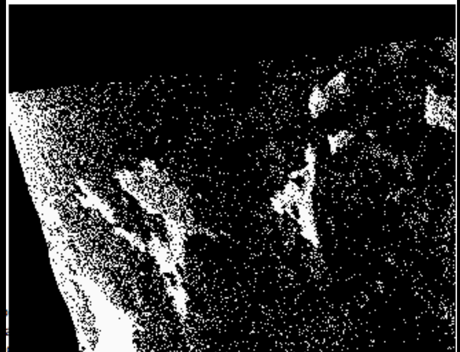


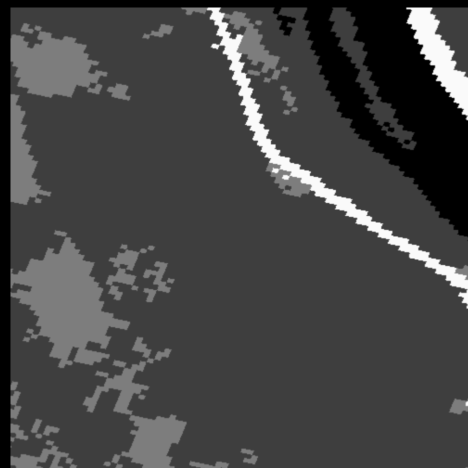
Figure 27: Auto4a.Howlnd.16701.09056.008.090807.L090HHHH.CX.01.waterdiel.grd
http://ai.jpl.nasa.gov/public/home/jdoubled/uavsar/asf/Howlnd-16701-09056-008-090807-L090-CX-01/water/Auto4a.Howlnd-16701-09056-008-

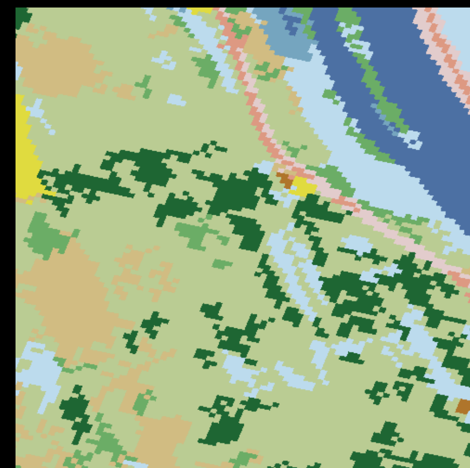
SVM SAR Classification:

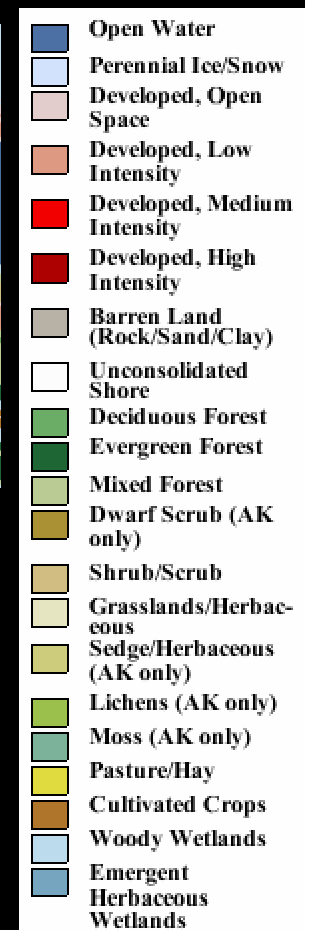
Howlnd_34701_09056_009_090807_L090HHVV_CX_01.grd.Auto0a

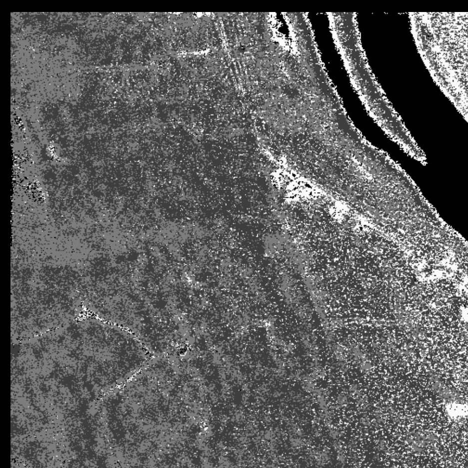
progress: 100000 / 250000 0.4
Accuracy: 57735 / 100000 (57.73)
progress: 200000 / 250000 0.8
Accuracy: 50717 / 100000 (50.72)
progress: 300000 / 250000 1.2
=== Testing class 2000 vs 1000
=== Testing class 5000 vs 2000
=== Testing class 5000 vs 1000
=== Testing class 5000 vs 3000
=== Testing class 3000 vs 2000
=== Testing class 3000 vs 1000
Accuracy: 27623 / 50000 (55.25)

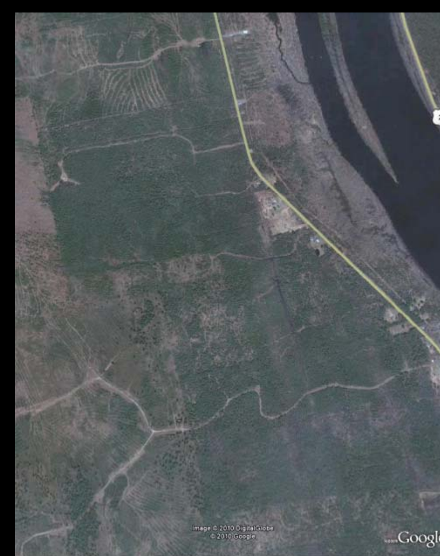
Class	Result count	Truth count	R / (T+1)
2000 high veg	109554	190794	0.5741
4000 med veg	0	0	
5000 urban	25591	8884	2.880
3000 low-no	94518	28943	3.26554
1000 wa ter	20337	21379	0.9512











Overview

- Sensorweb
  - Networked set of sensors
  - Data from one sensor is used to refigure 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

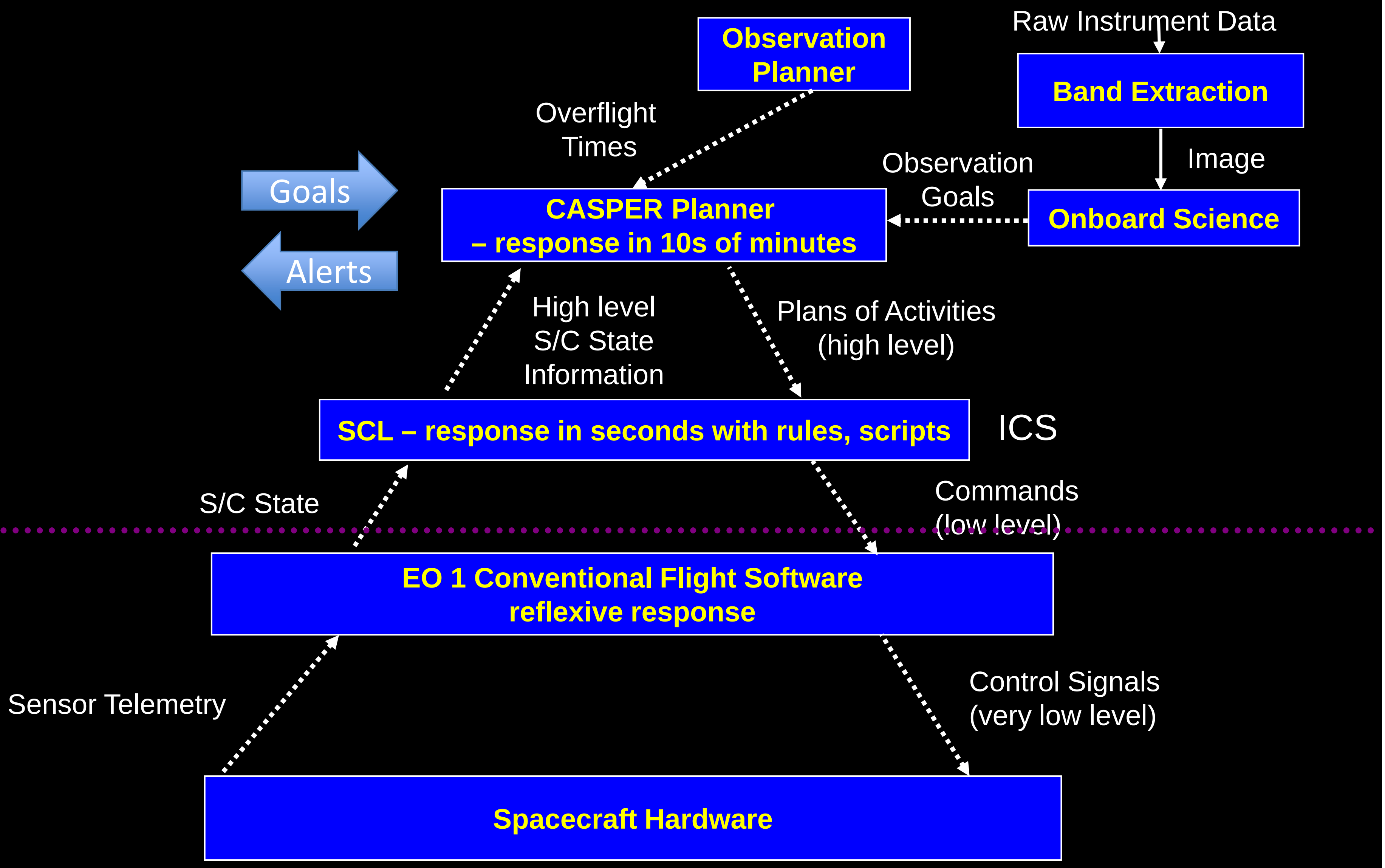
Agent-based architecture

- 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" - ASE



Mount Saint Helens In-situ Network

- Collaboration between
  - Washington State University (node SW, node networking, node quality of service SW)
  - US Geological Survey, Cascade Volcano Observatory (HW design and fabrication, volcano experts)
  - JPL (autonomy, C&C, space component, volcanology)

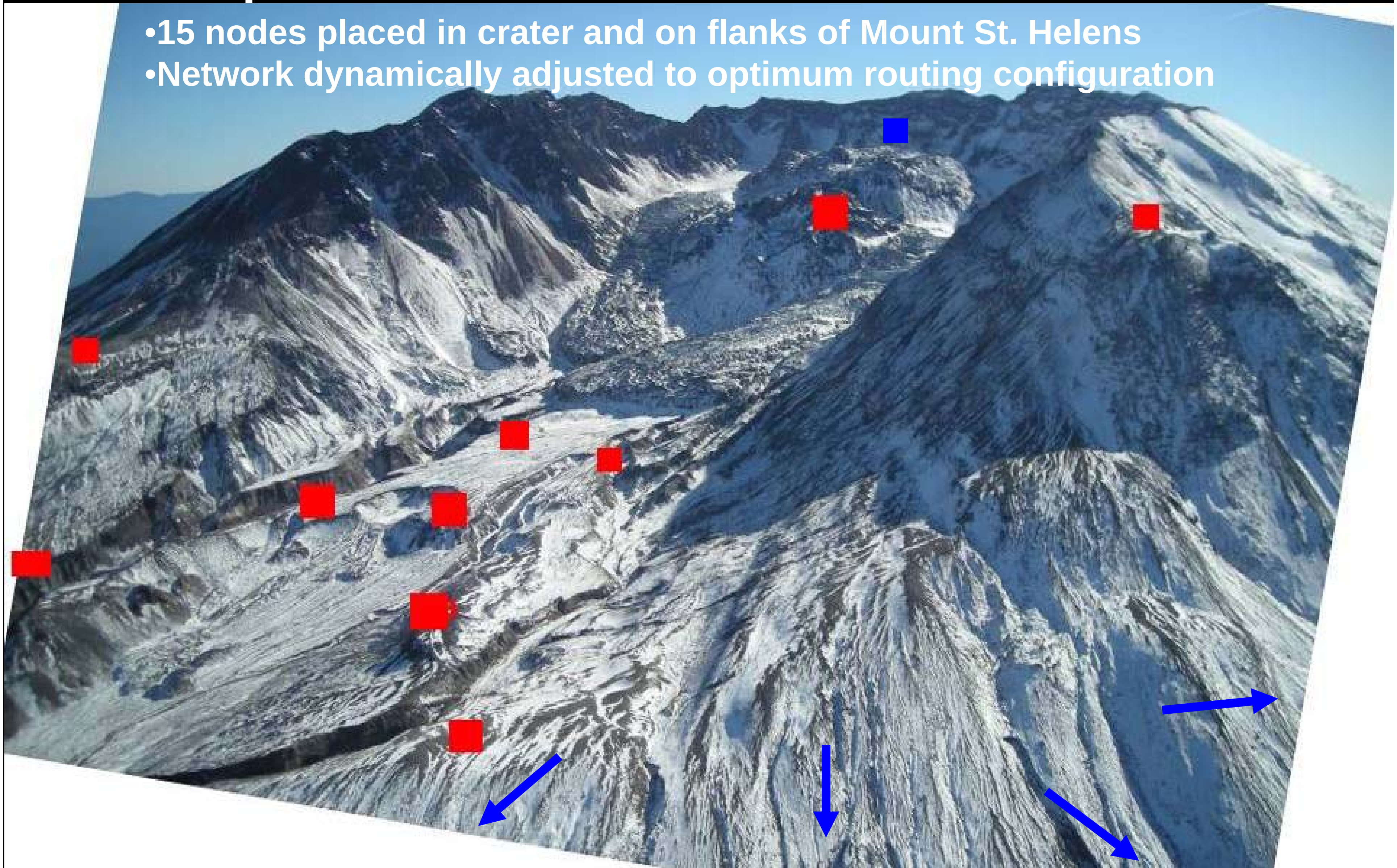
Spider Sensors Hardware (USGS)

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

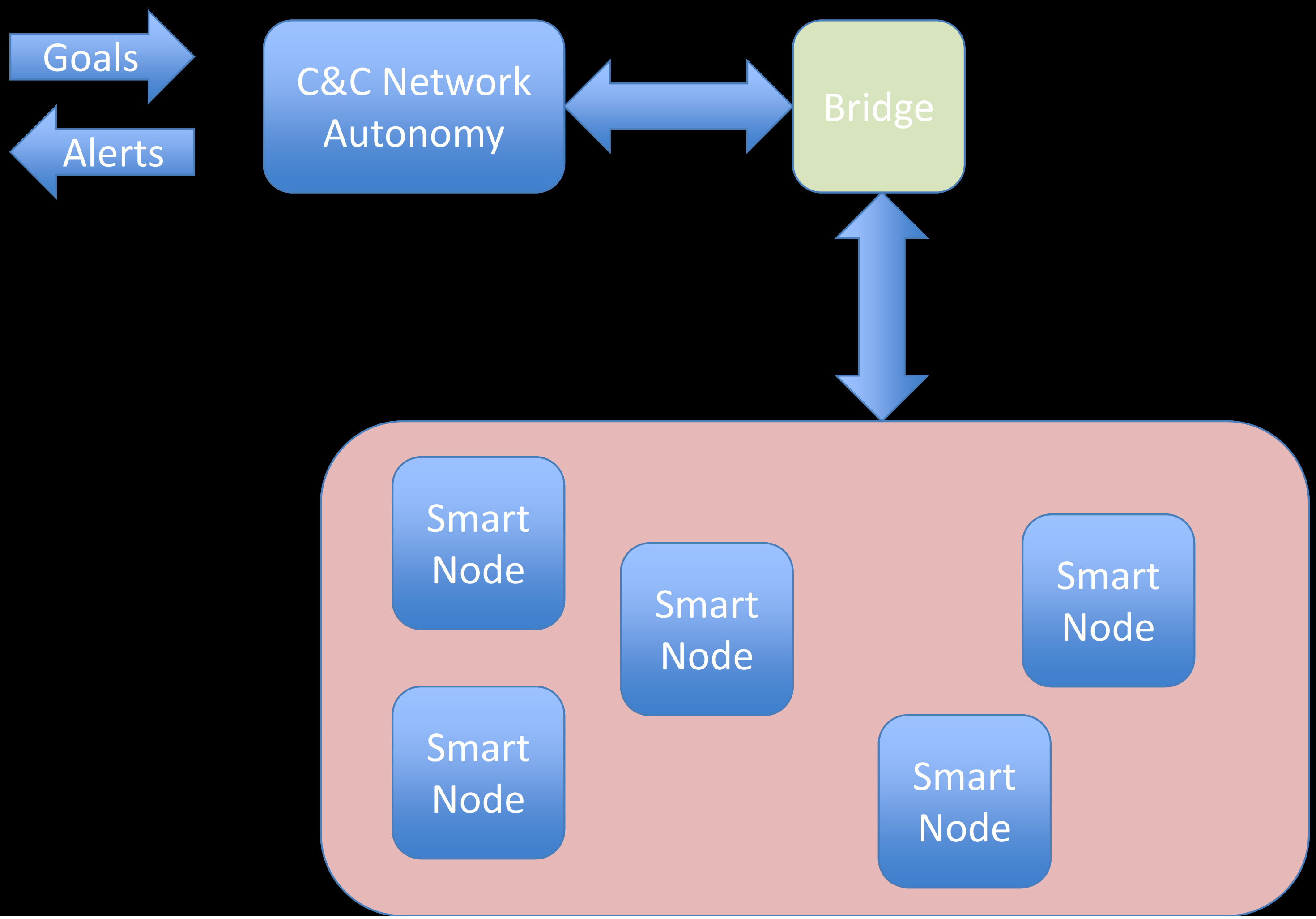
Spider Node on Mt St Helens

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**

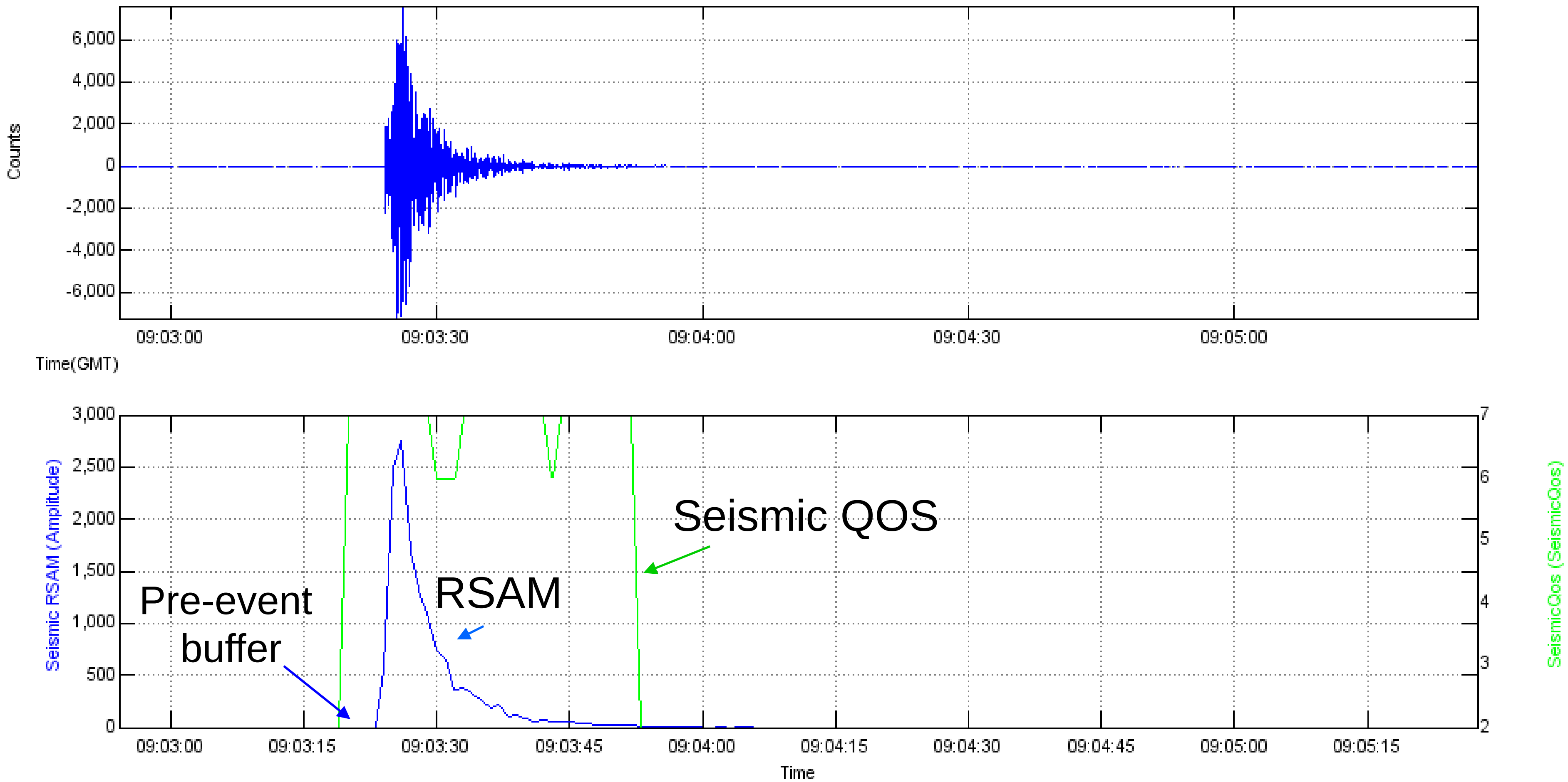


Mount Saint Helens "Agent"



Onboard Node Smart Software

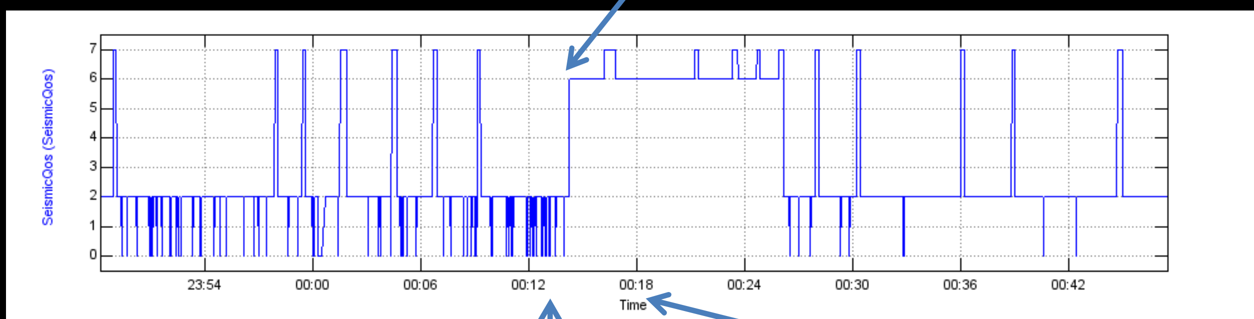
- **Onboard node software can detect events to change operating modes to capture critical events**
- **Quality of Service Node software ensures highest priority data is tranferred**
- **Example from OASIS Node 05 showing waveform, in-situ RSAM and in-situ event triggered QOS prioritization**

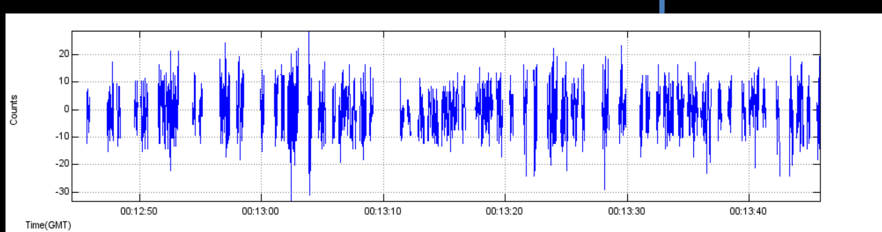


(…continued) Results of Space Trigger End-to-End Test

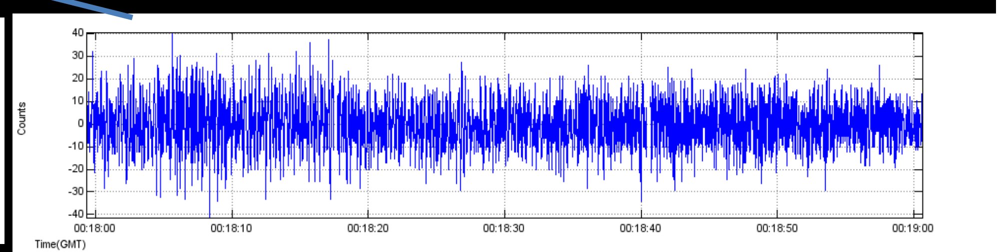
Data autonomously delivered to Ground System and ingested into time-series DB. VAlarm detects new data and triggers autonomous ground response through C&C: heighten priority (QoS) of crater node (node 4) seismic data.

Thermal data detected / ground response





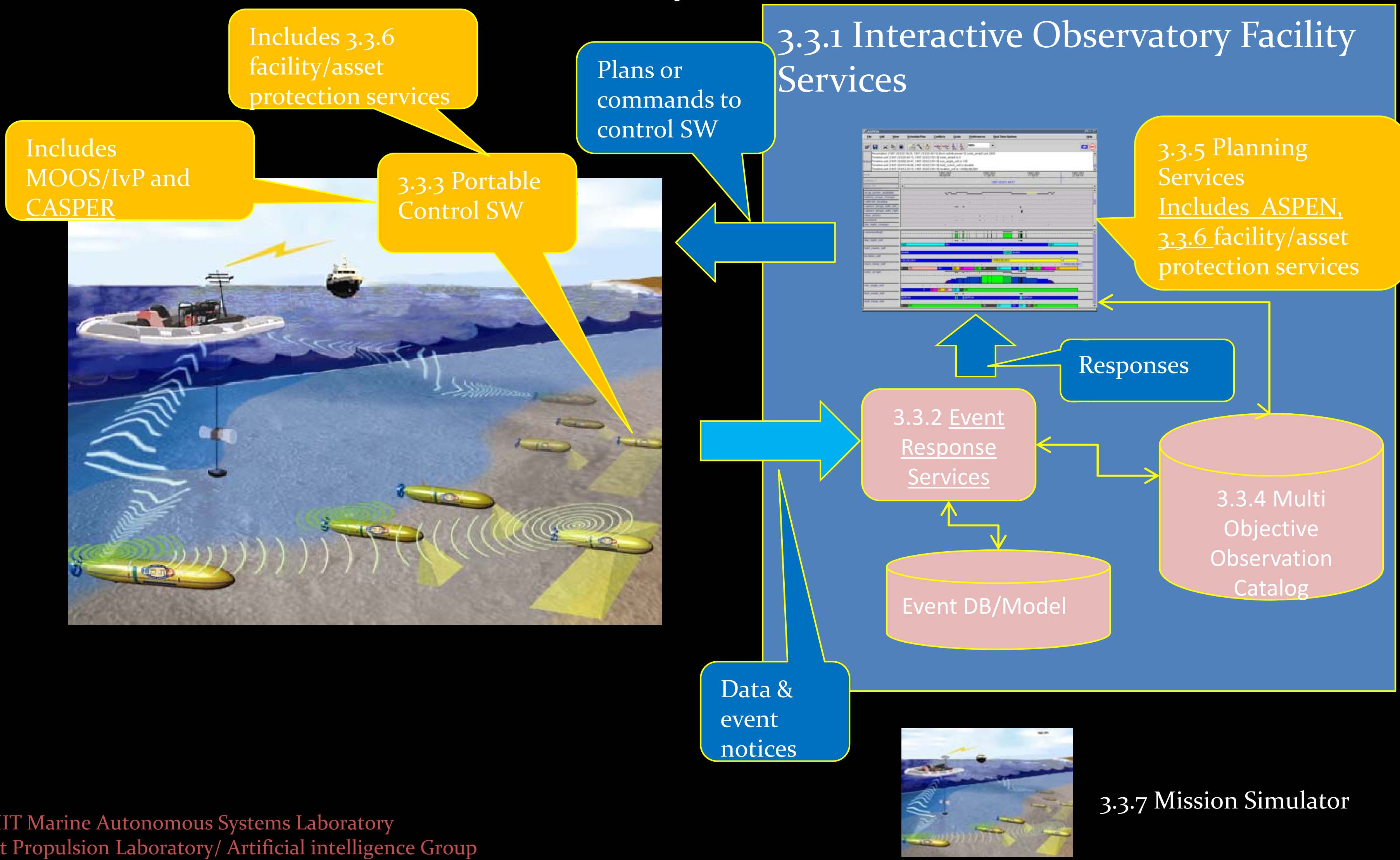
Data transmission loss at low QoS.



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

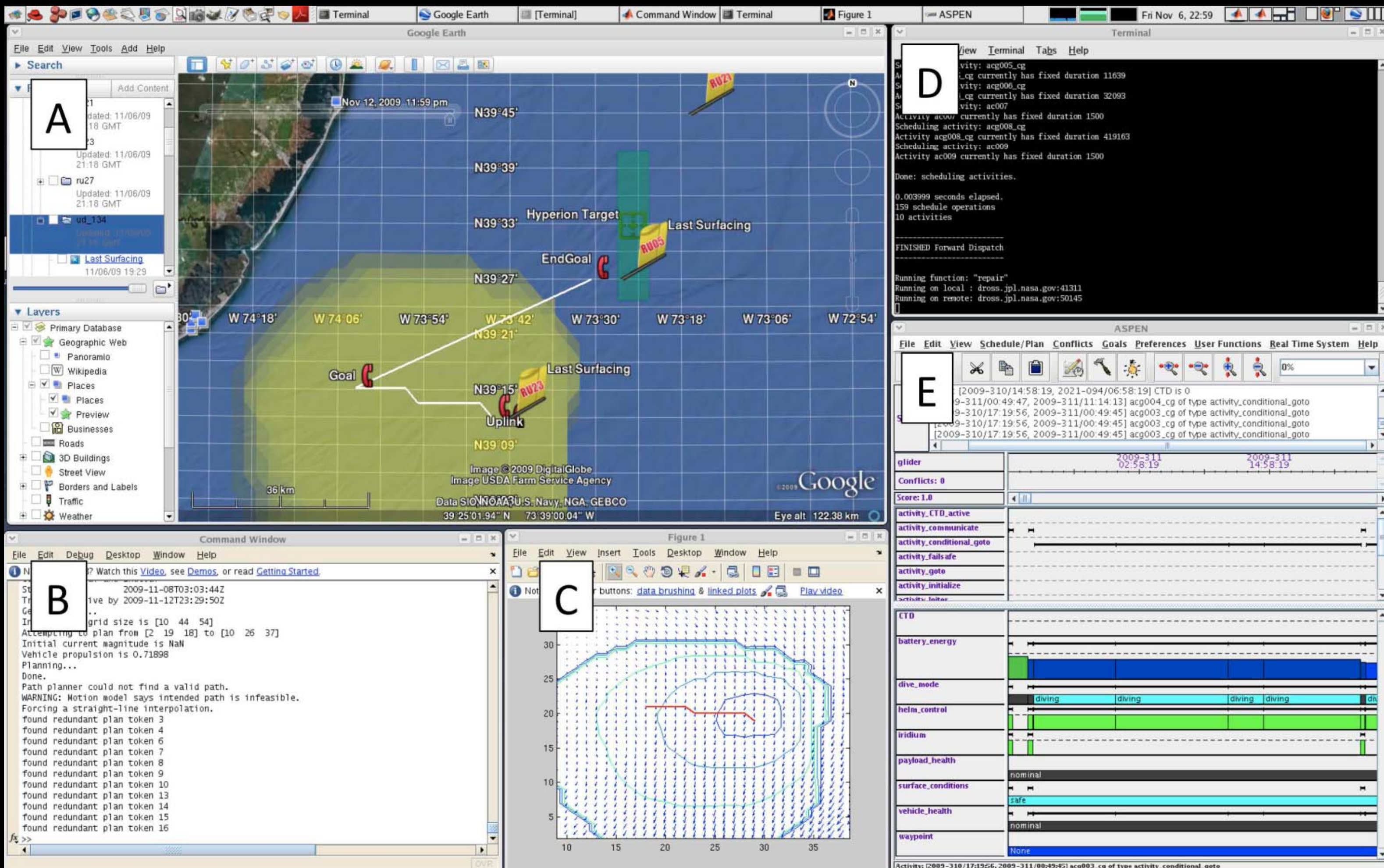
Undersea - Planning & Prosecution

NSF/OOI



MIT Marine Autonomous Systems Laboratory
Jet Propulsion Laboratory/ Artificial intelligence Group

NJ 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.

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