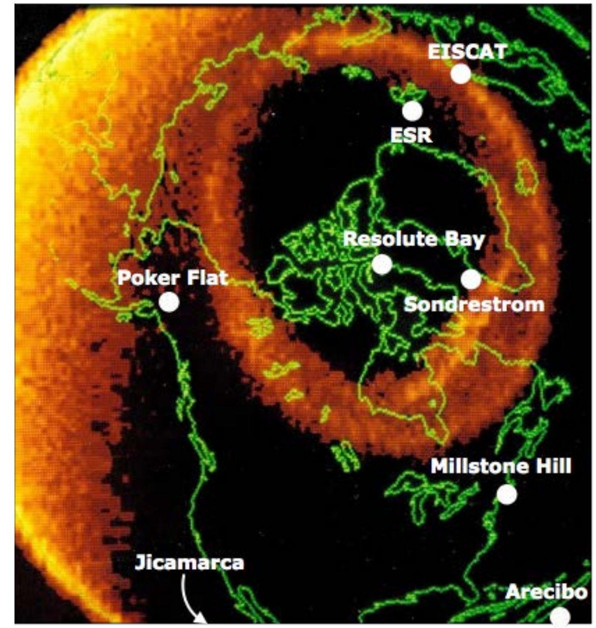
Sensor Network Examples

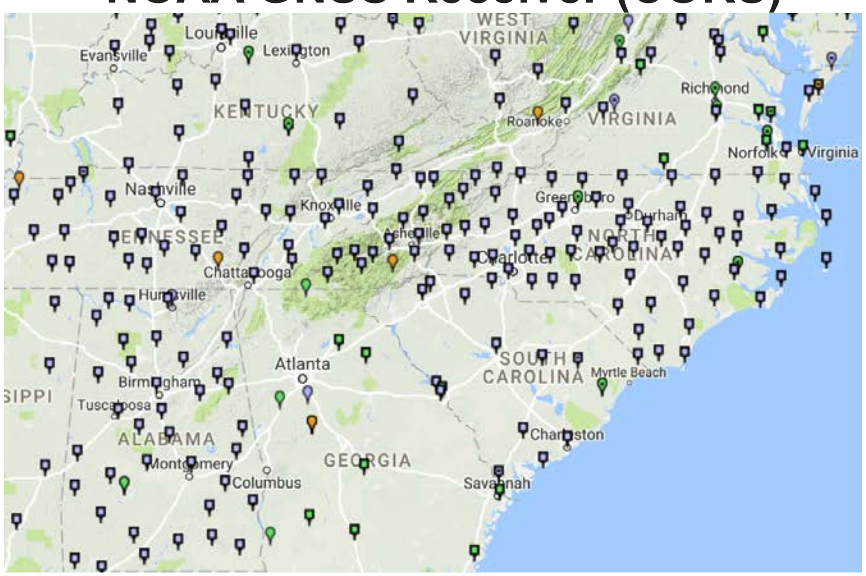
Space based sensor networks

Intermagnet

Incoherent Scatter Radars



NOAA GNSS Receiver (CORS)



Crowdsourcing and Citizen Science

Technology trends

Top500 Supercomputers, 1993

CM-5 Los Alamos
- 1024 processors
- 59.7 GFLOPS

[1 GFLOP = 10^9 floating point ops]

http://www.top500.org/timeline/

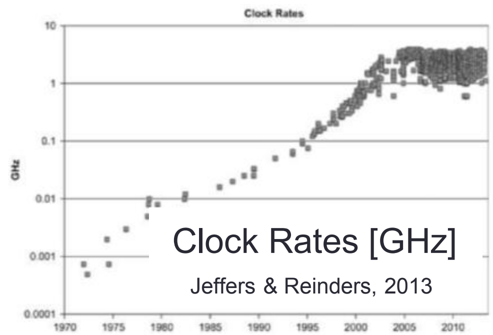
2013

iPhone 5S (A7 64 Bit)
76.8 GFLOPS (GPU@300MHz)

iPad3
38.4 GFLOPS (GPU@300MHz)

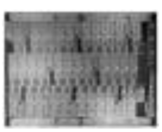
[Source: AnandTech.com]

Processor Trends

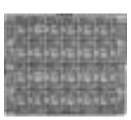


General-Purpose

60 Cores



48 Cores



2 - 16 Cores

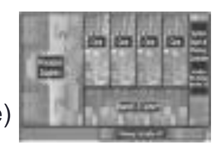
Special-Purpose

Thousands of Cores (GPUs)

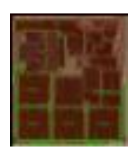
192 Cores (Networking)

Hybrids

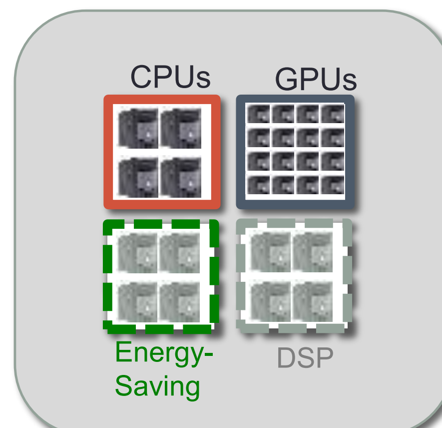
4 CPU + 16 GPU (Ivy Bridge)



2 CPU + 4 GPU (ARM A6X)



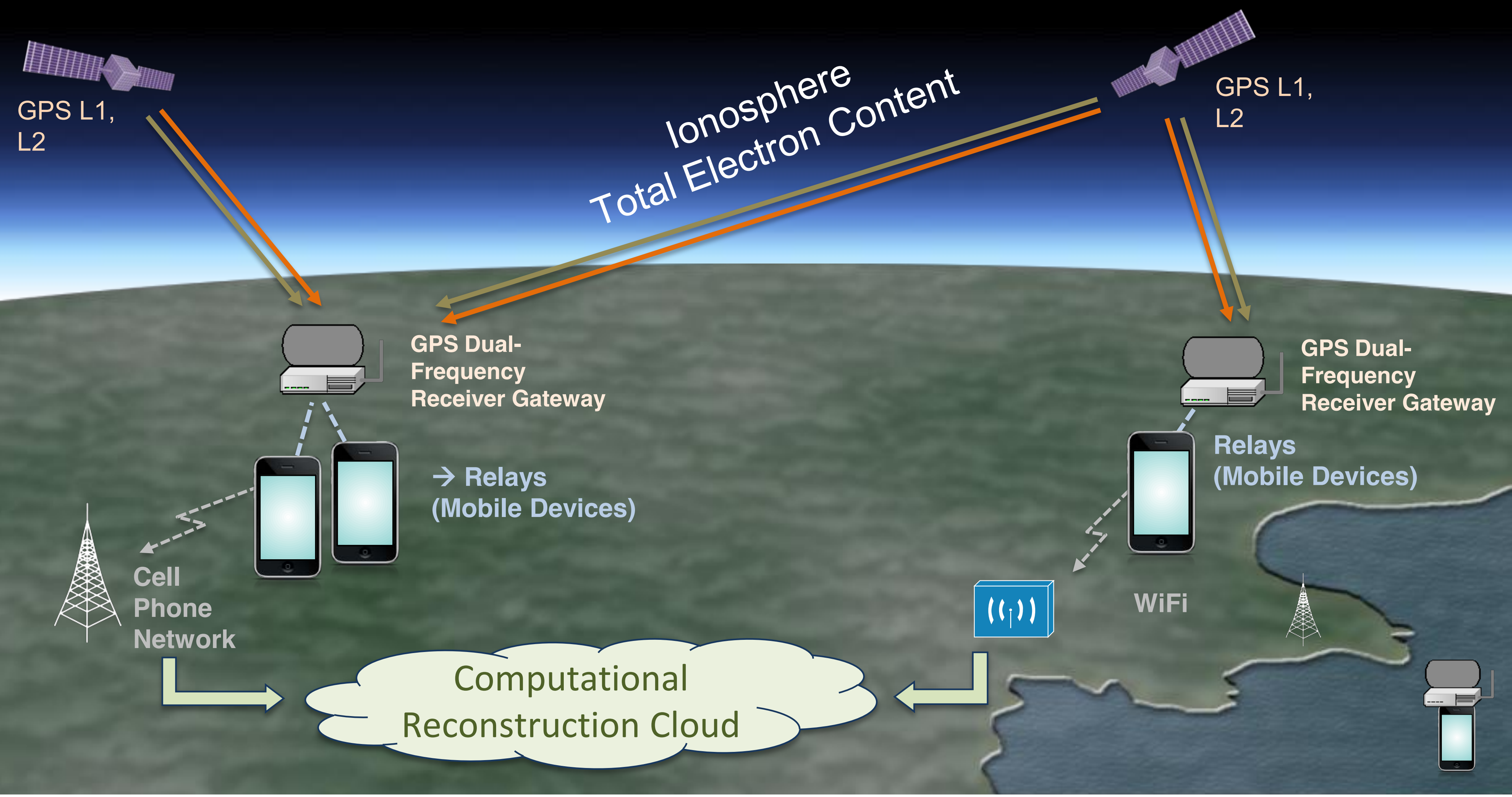
Mobile Processors



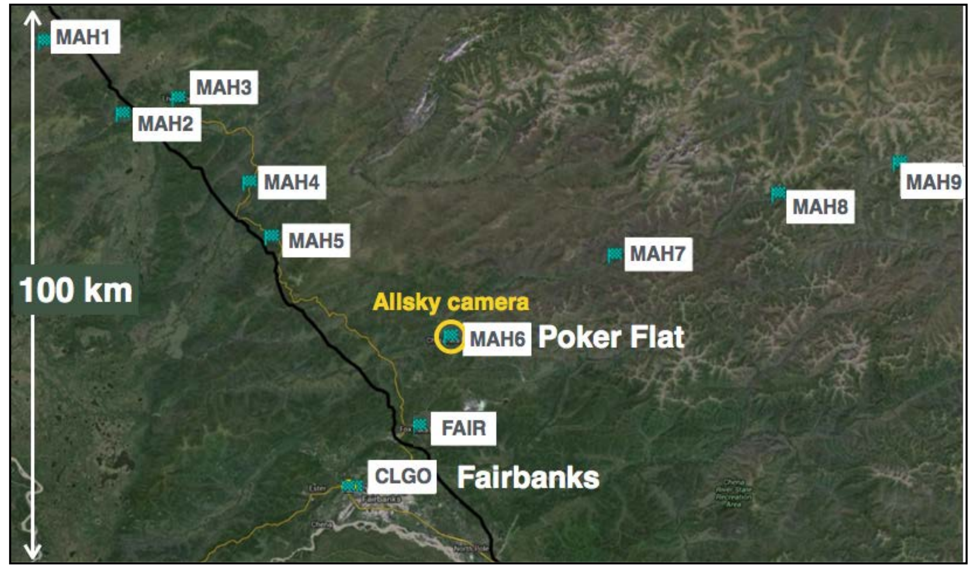
Mahali: Space Weather Monitoring Everywhere

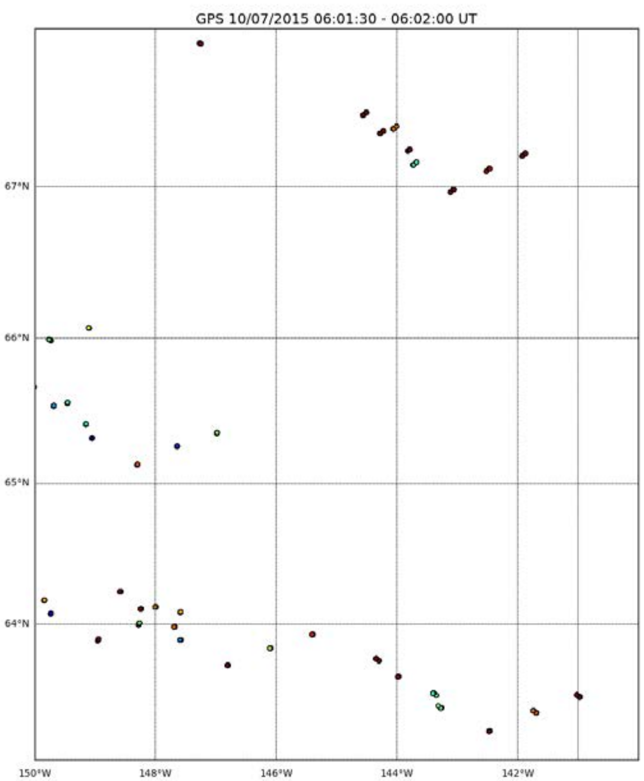
MIT: Victor Pankratius, Phil Erickson, Anthea Coster, Frank Lind

BU: Joshua Semeter, Sebastijan Mrak, Michael Hirsch, John Swoboda, Greg Starr



Mahali Deployment

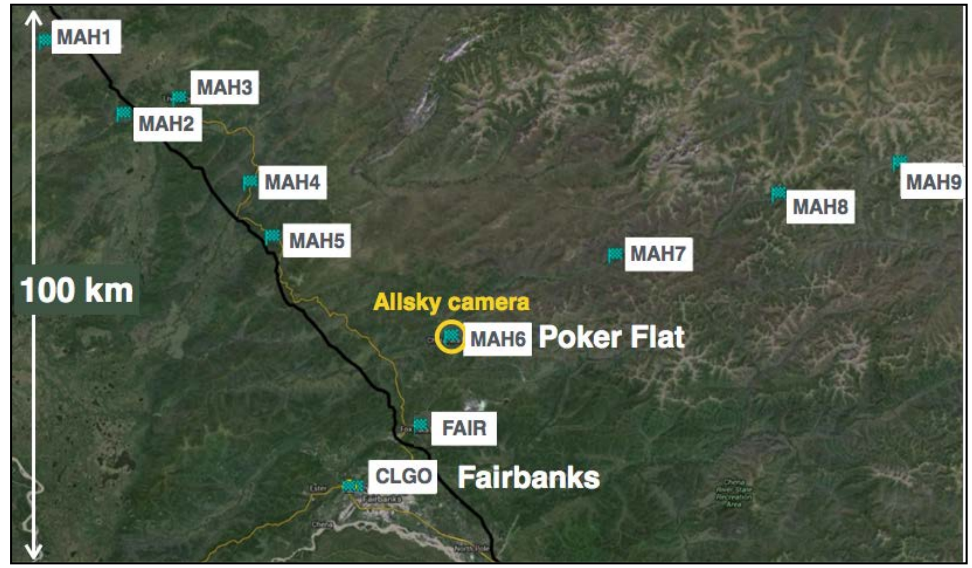


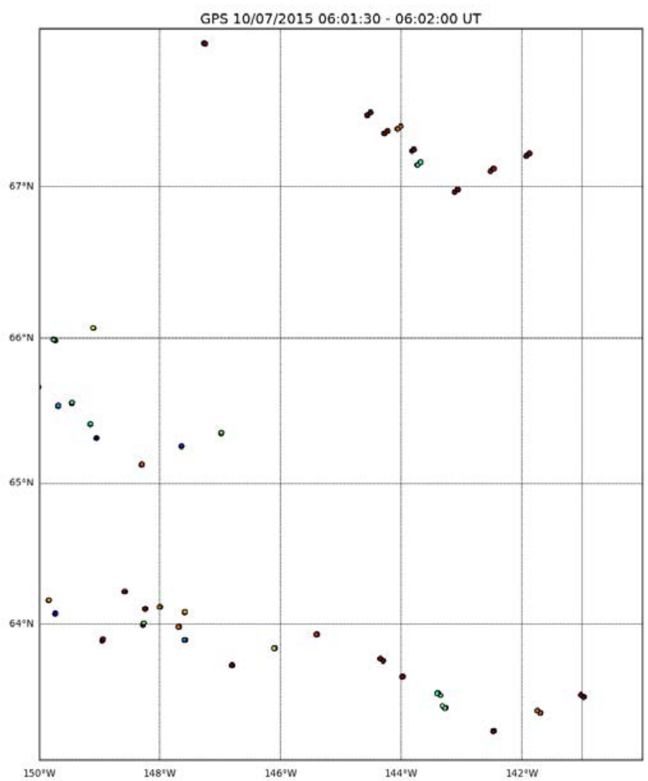


Features:

1. Relocatable / scalable
2. Autonomous
3. Data relayed to cloud
4. Data products produced in the cloud

Mahali Deployment





Features:

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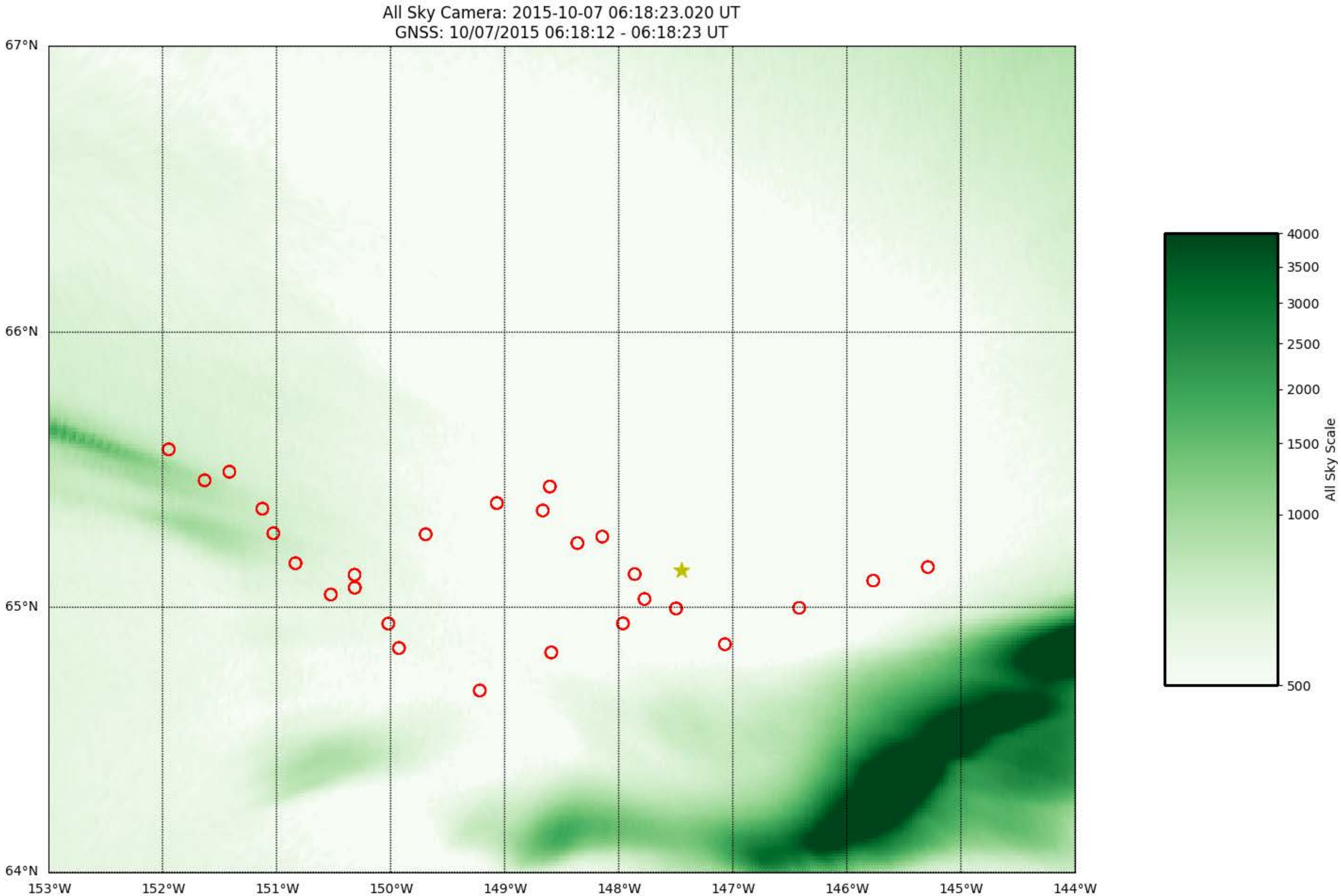
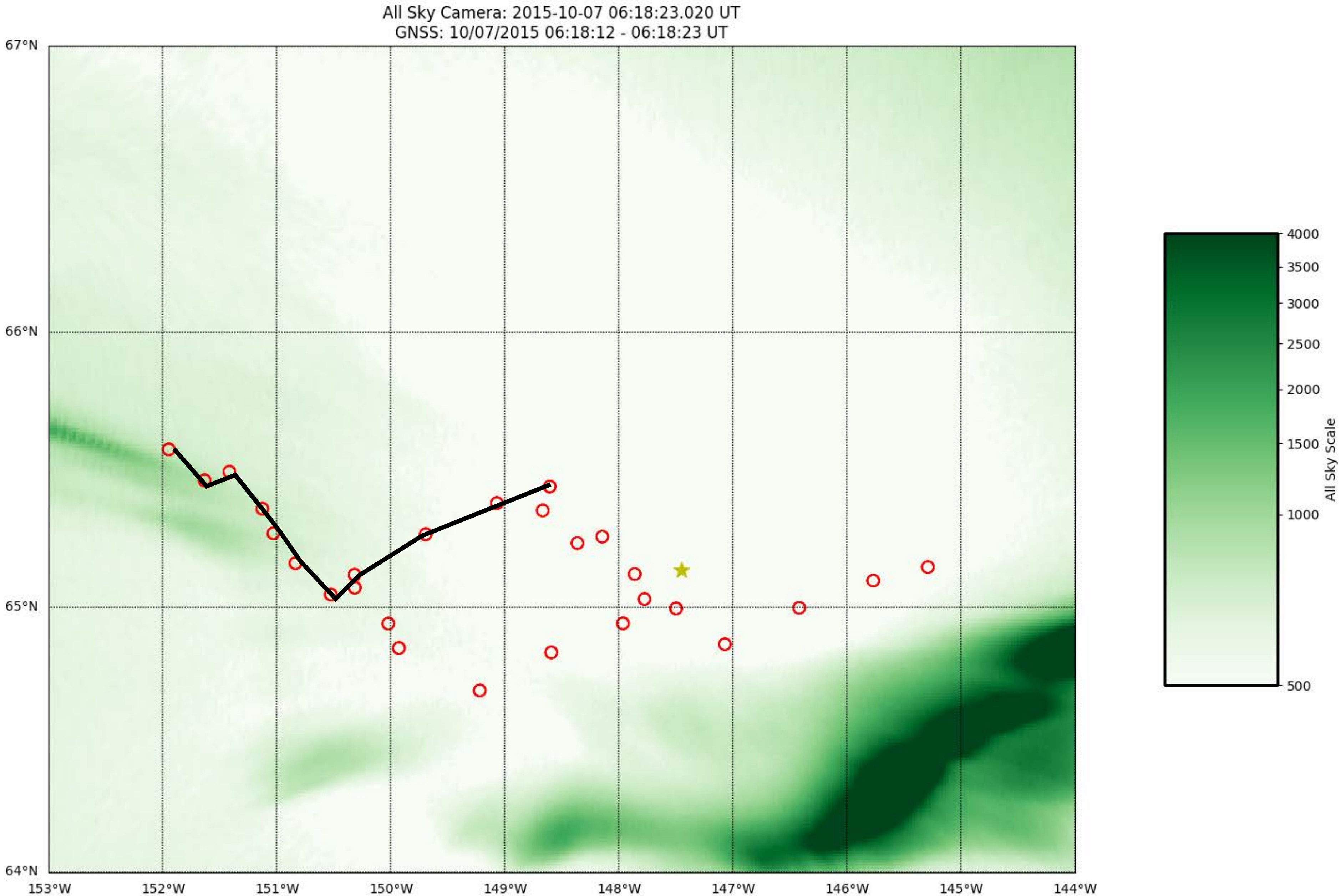
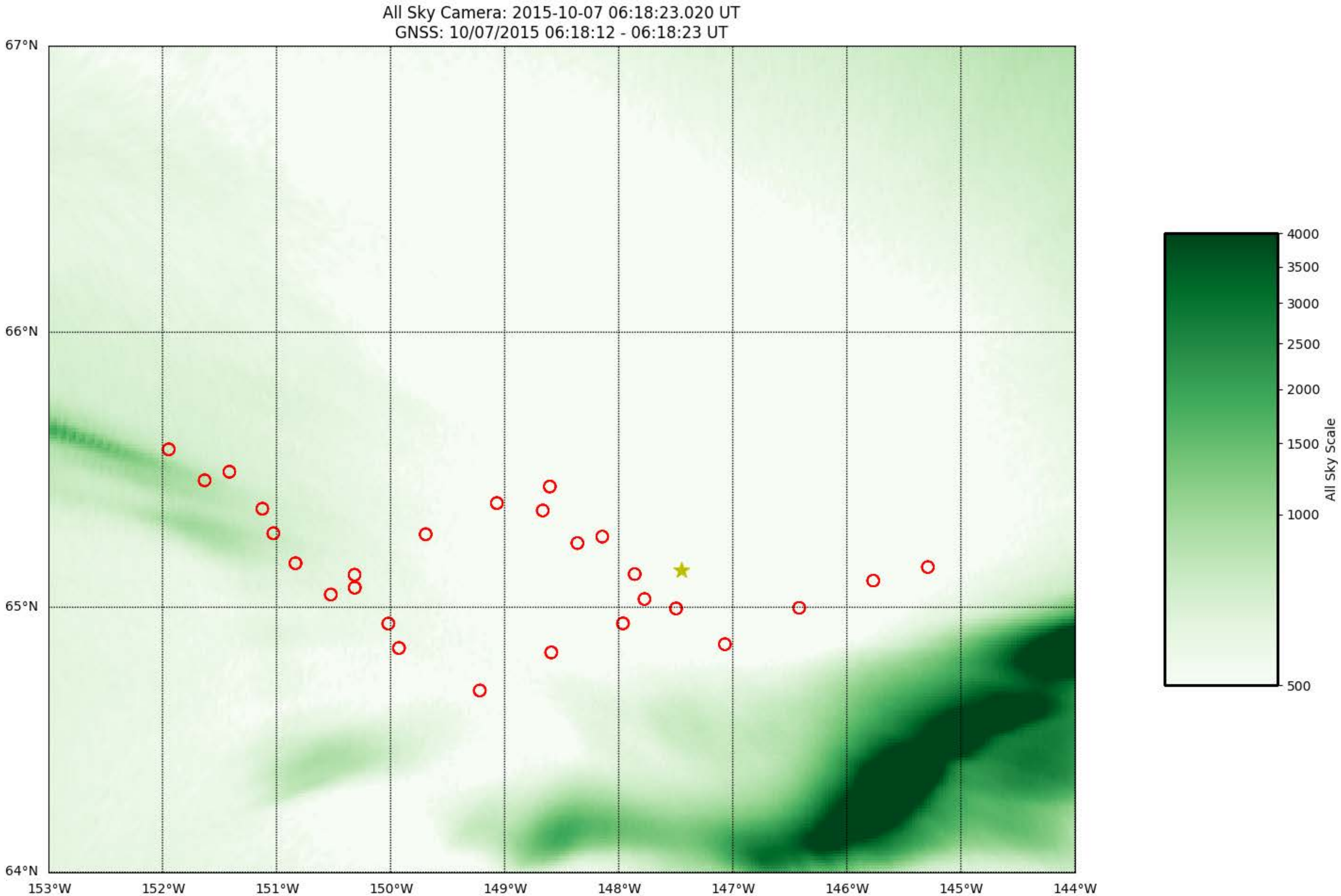


Mrak et al., JGRA, in review



Mrak et al., JGRA, in review



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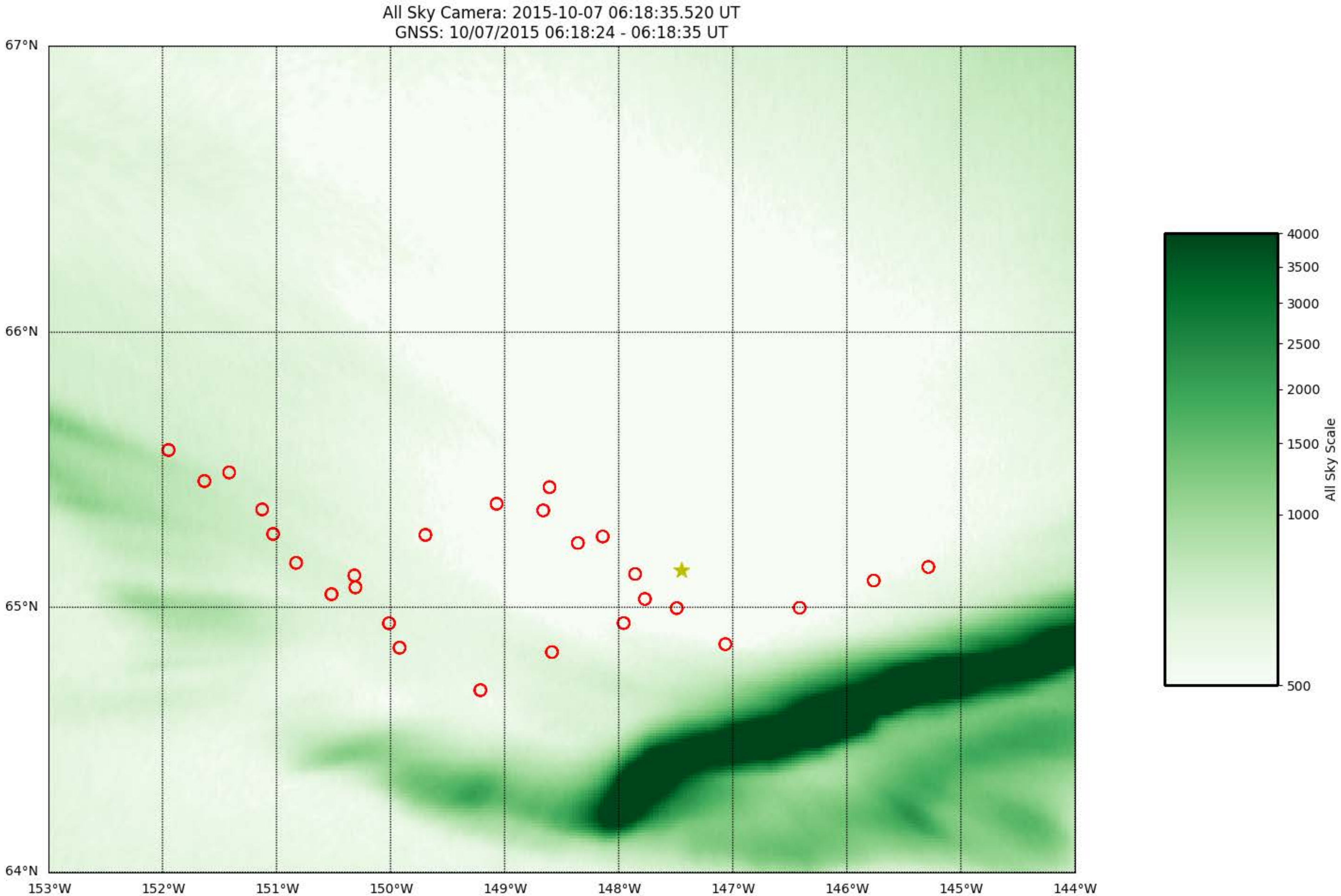

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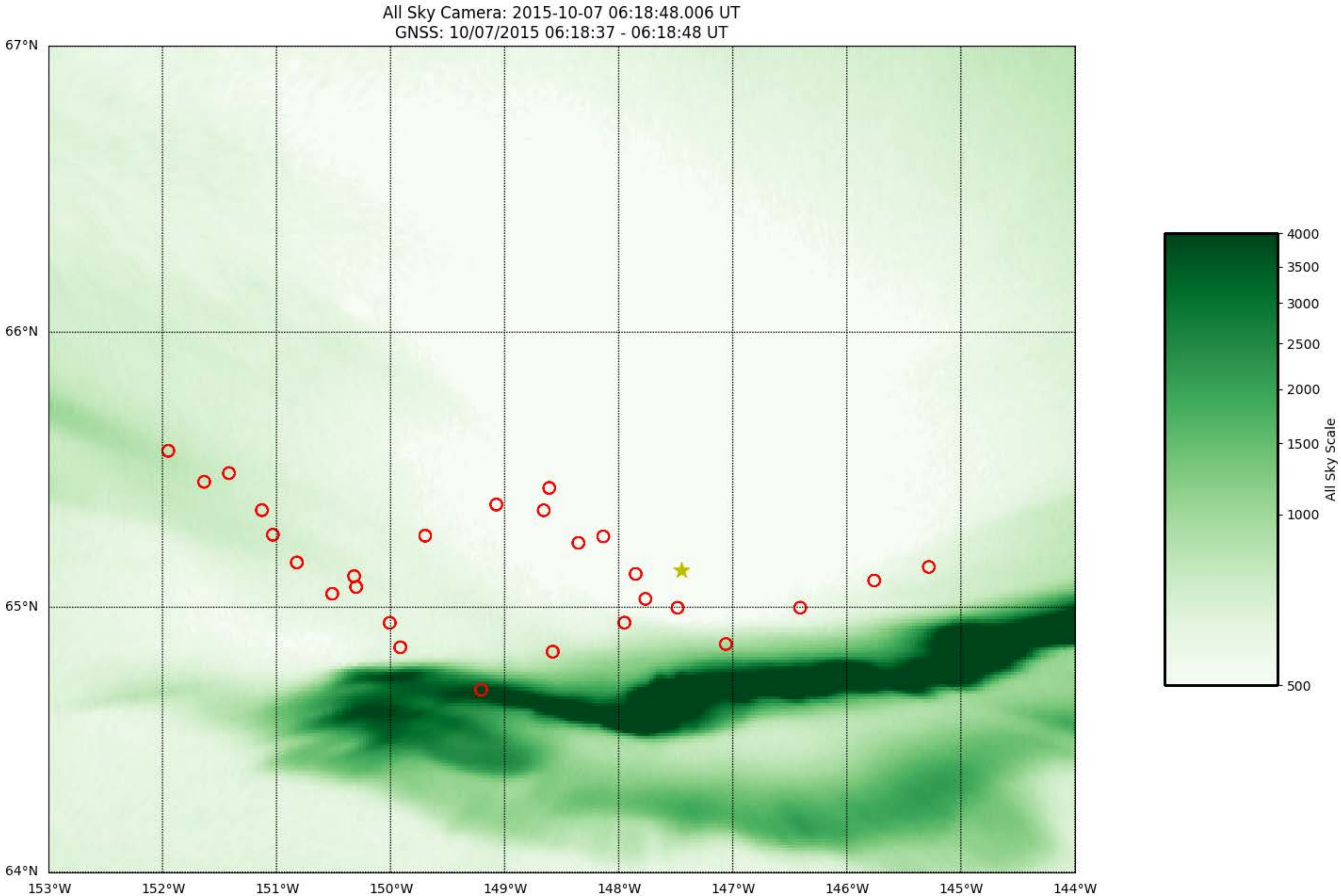
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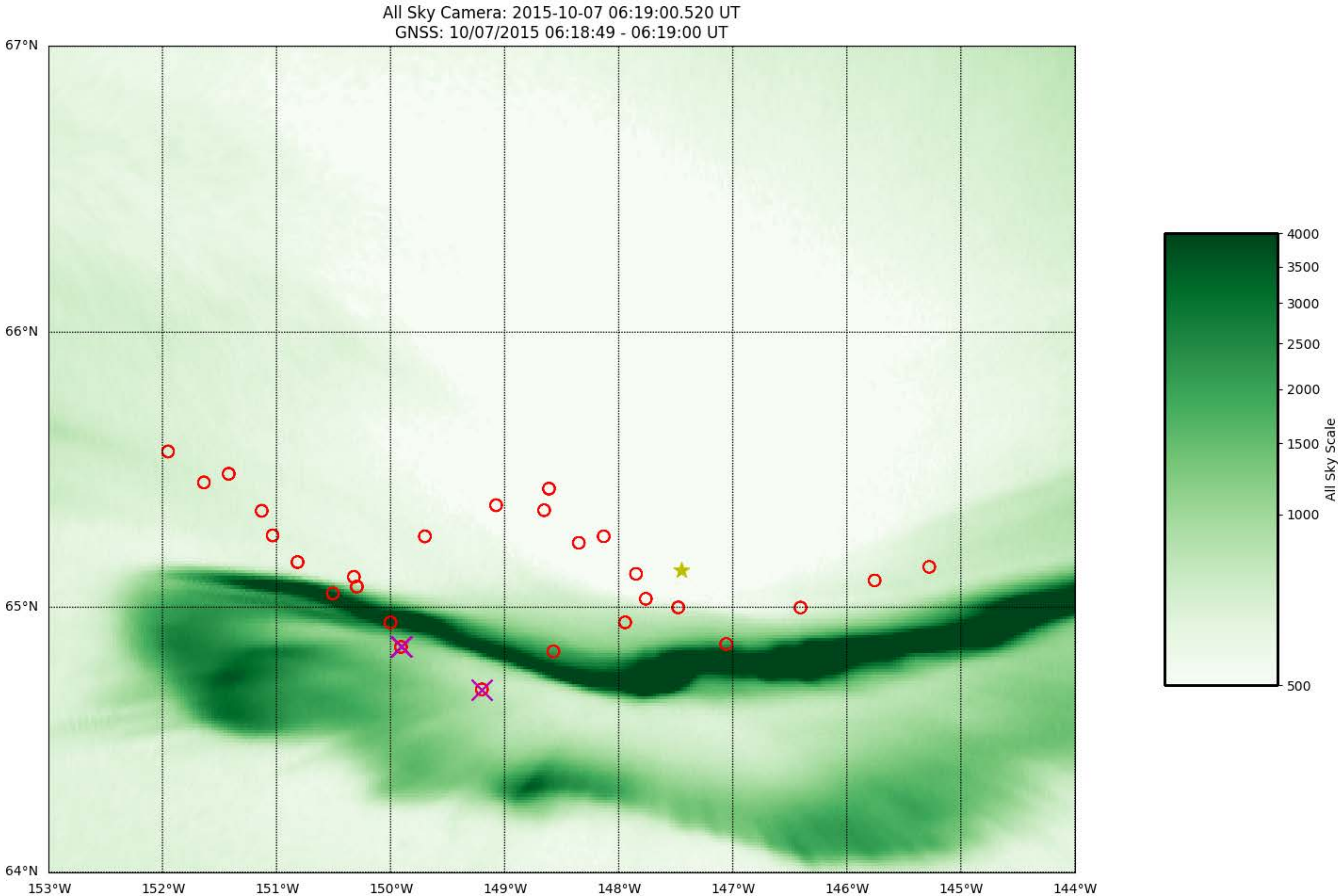
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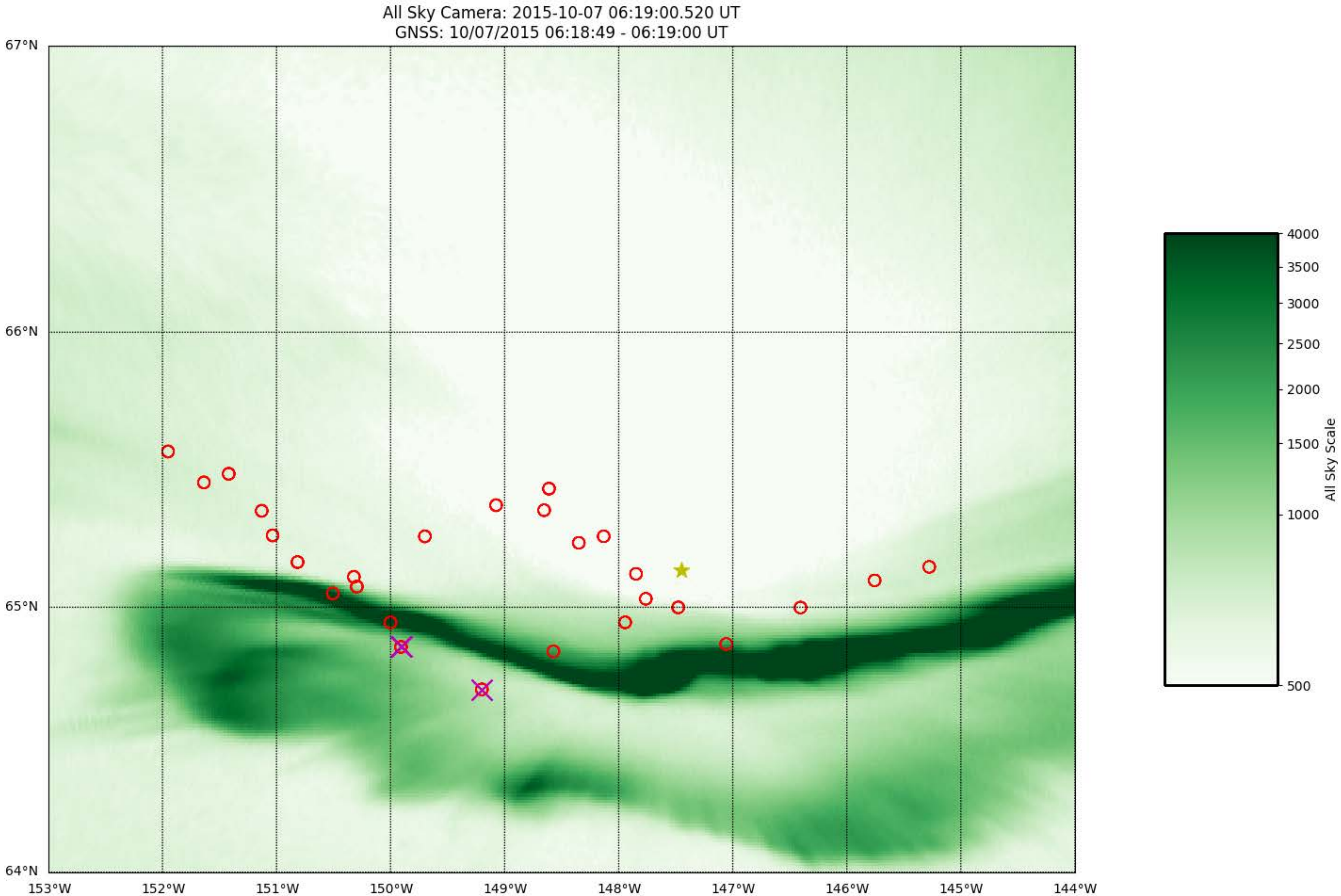
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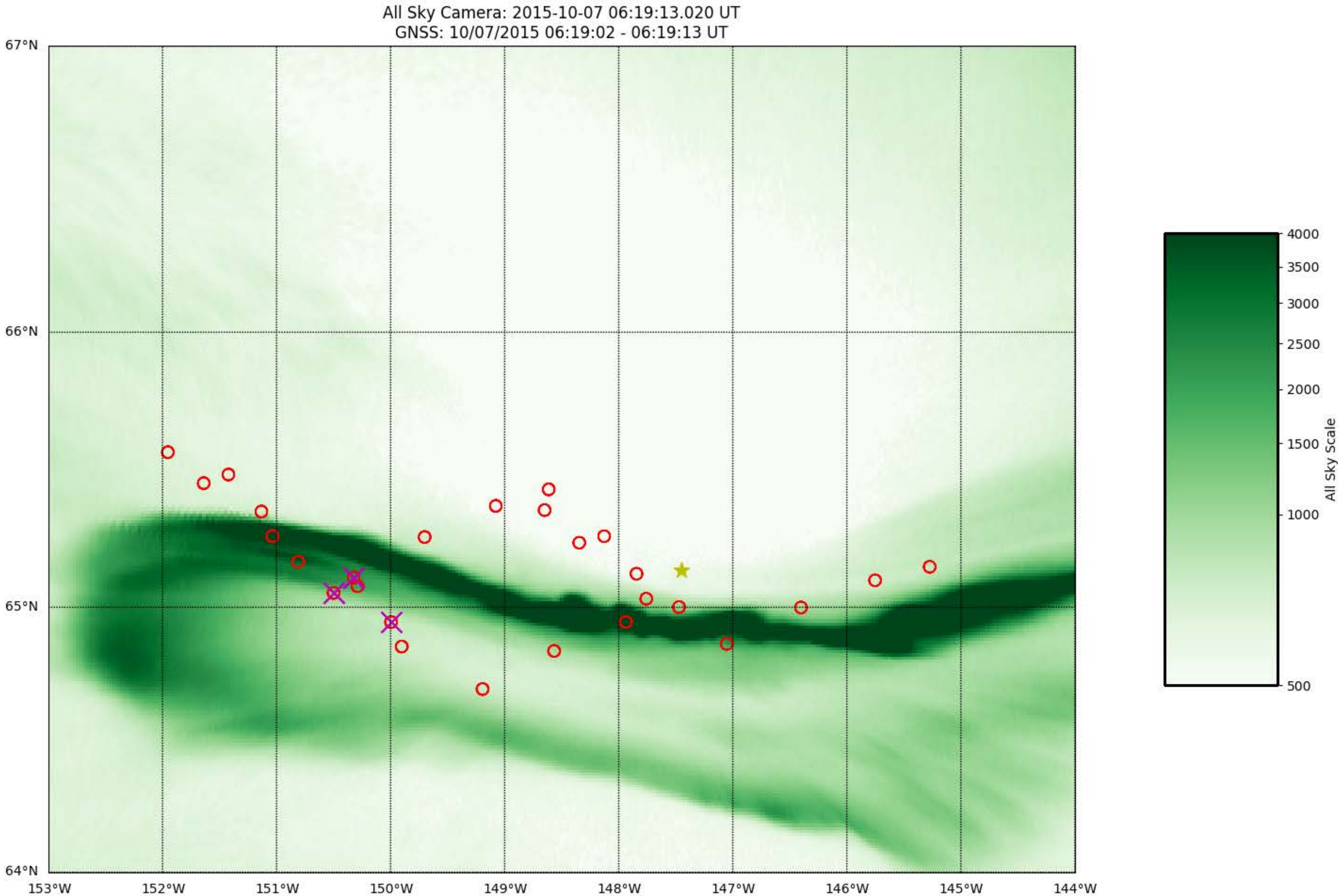

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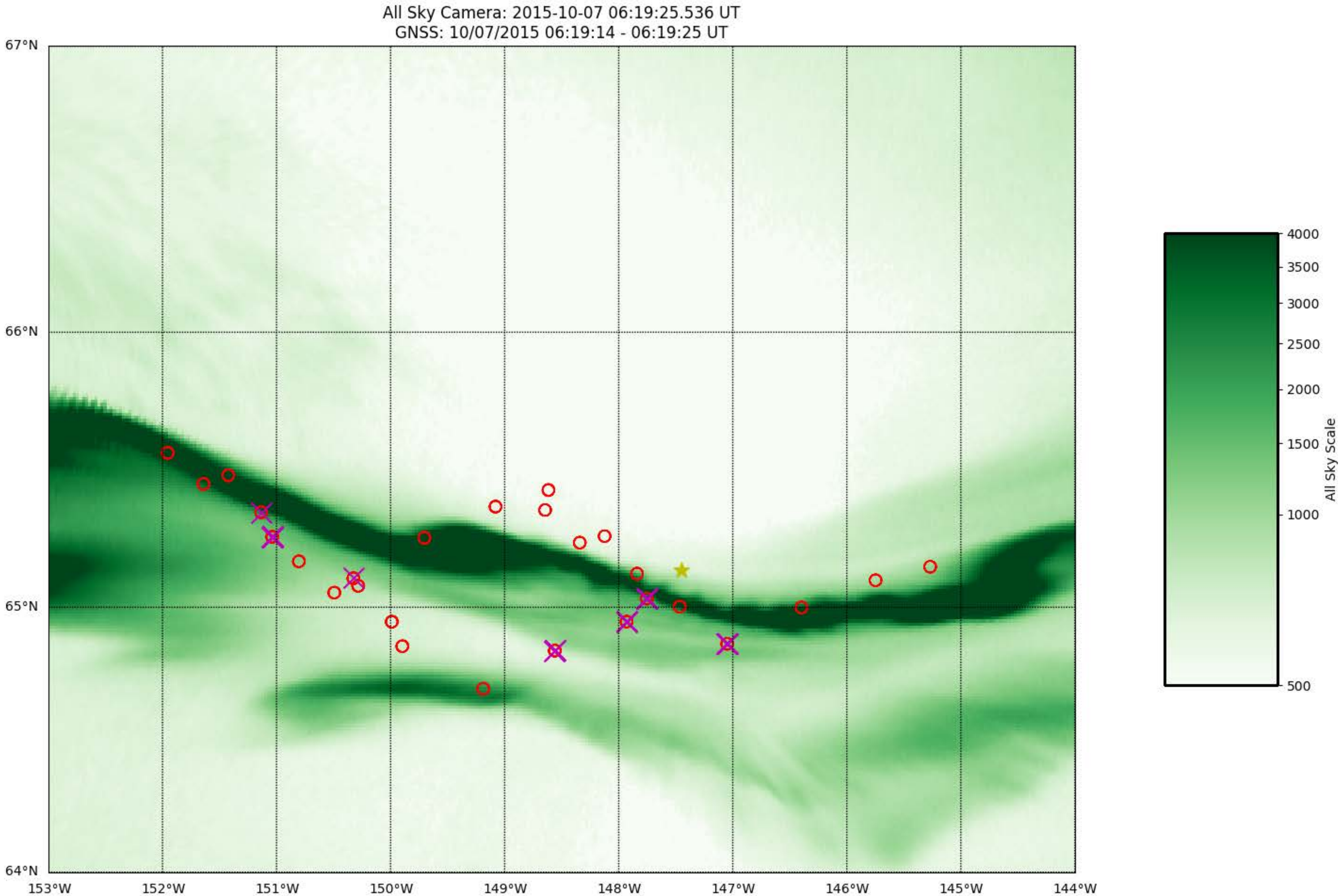
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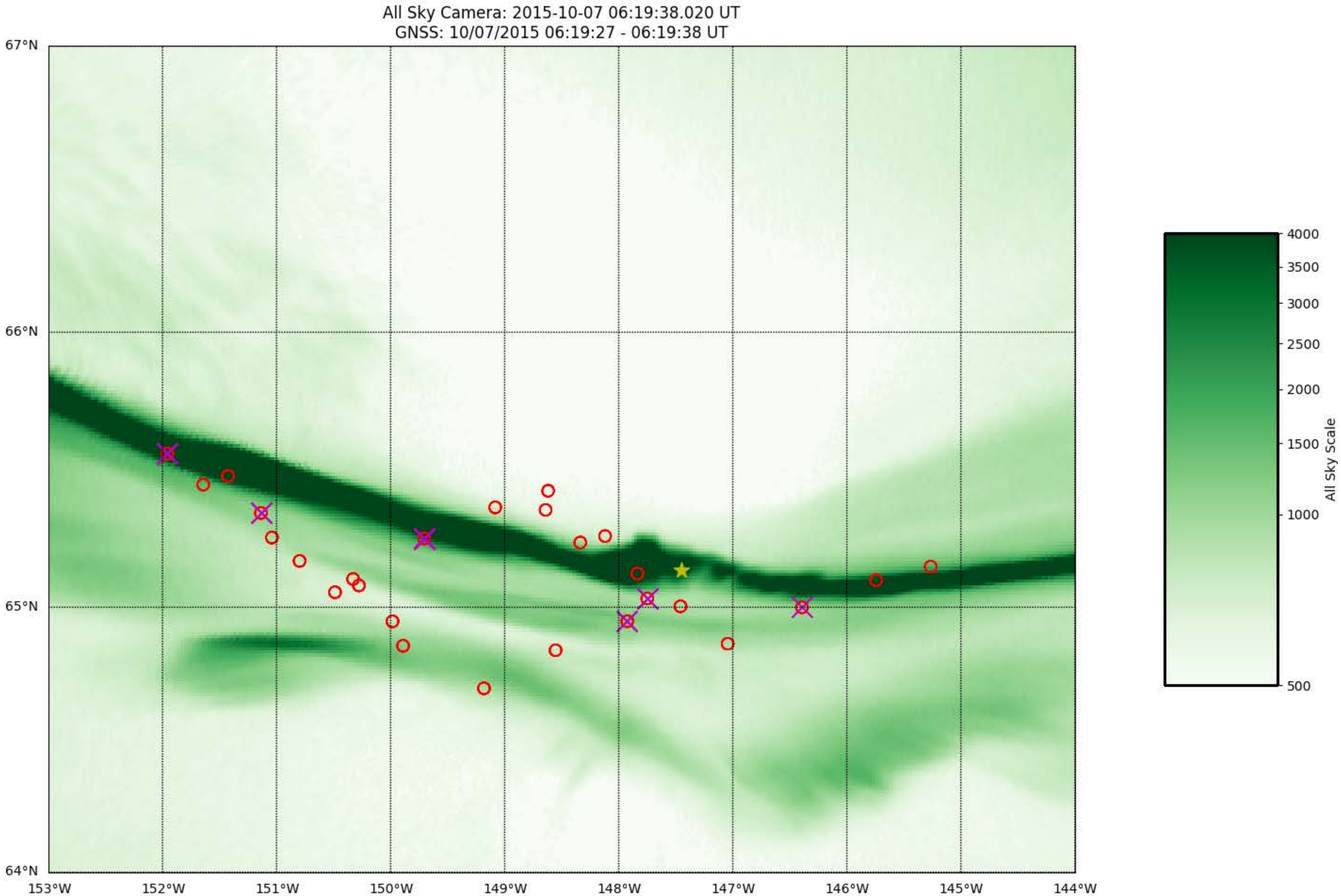

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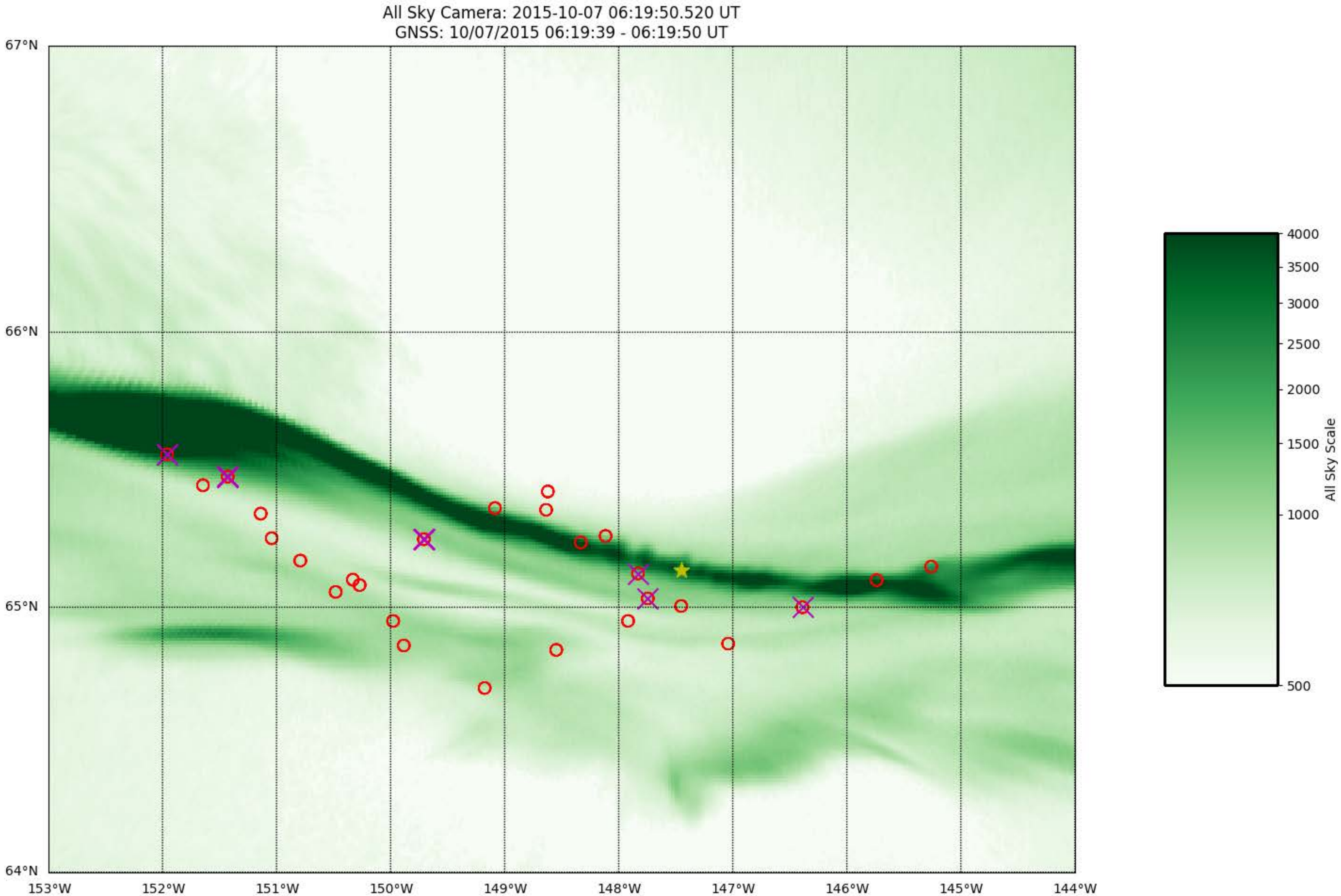
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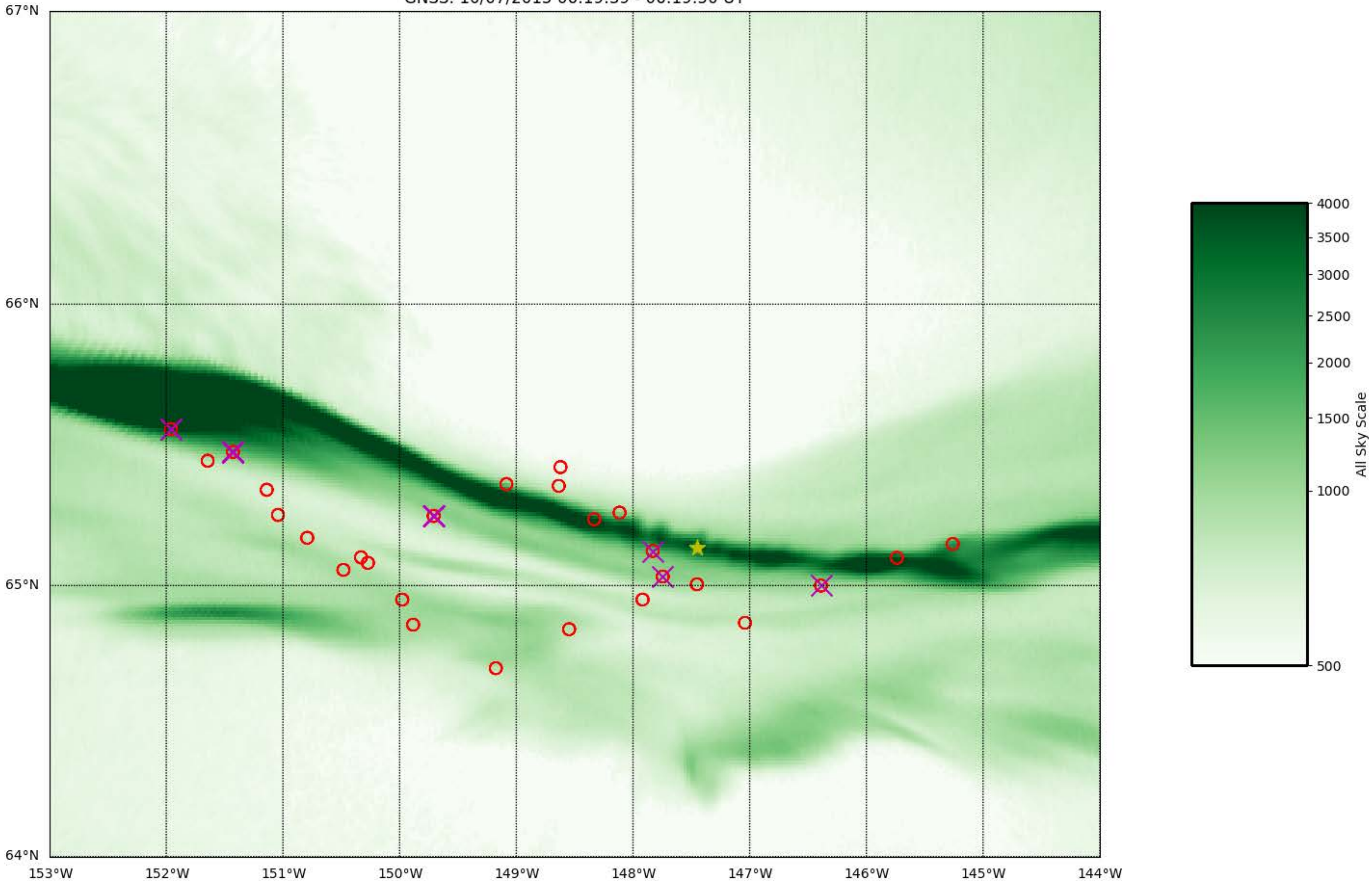

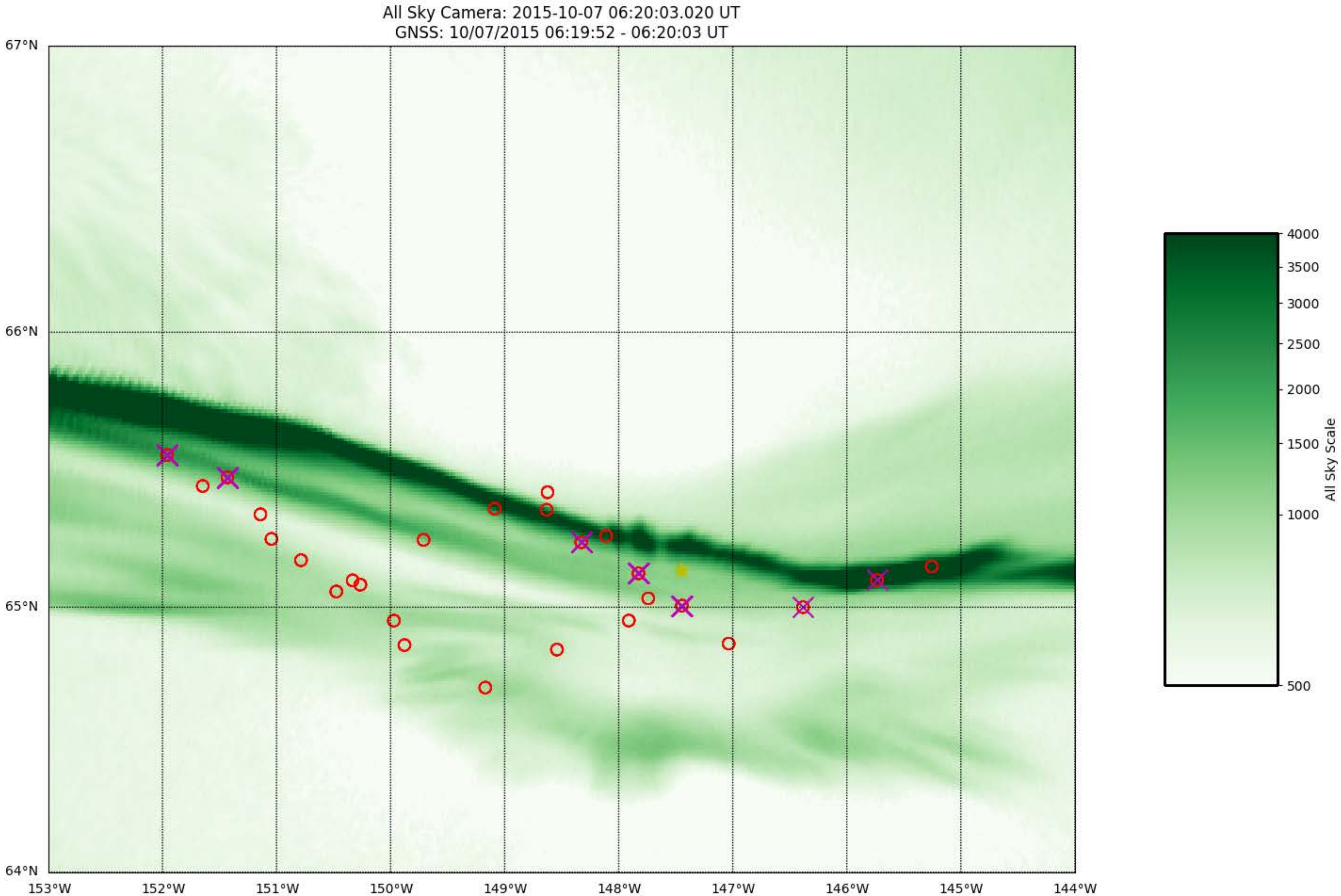

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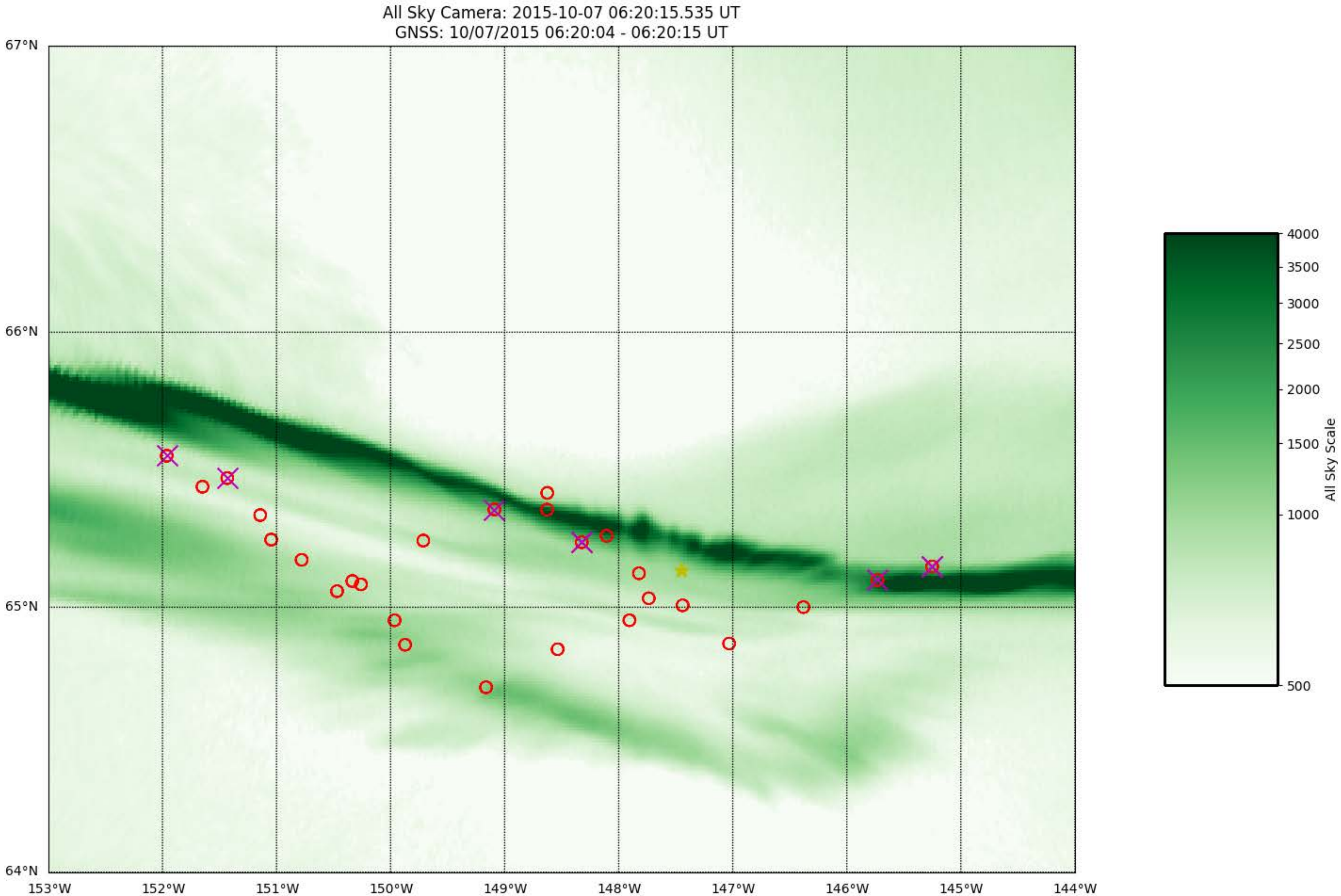

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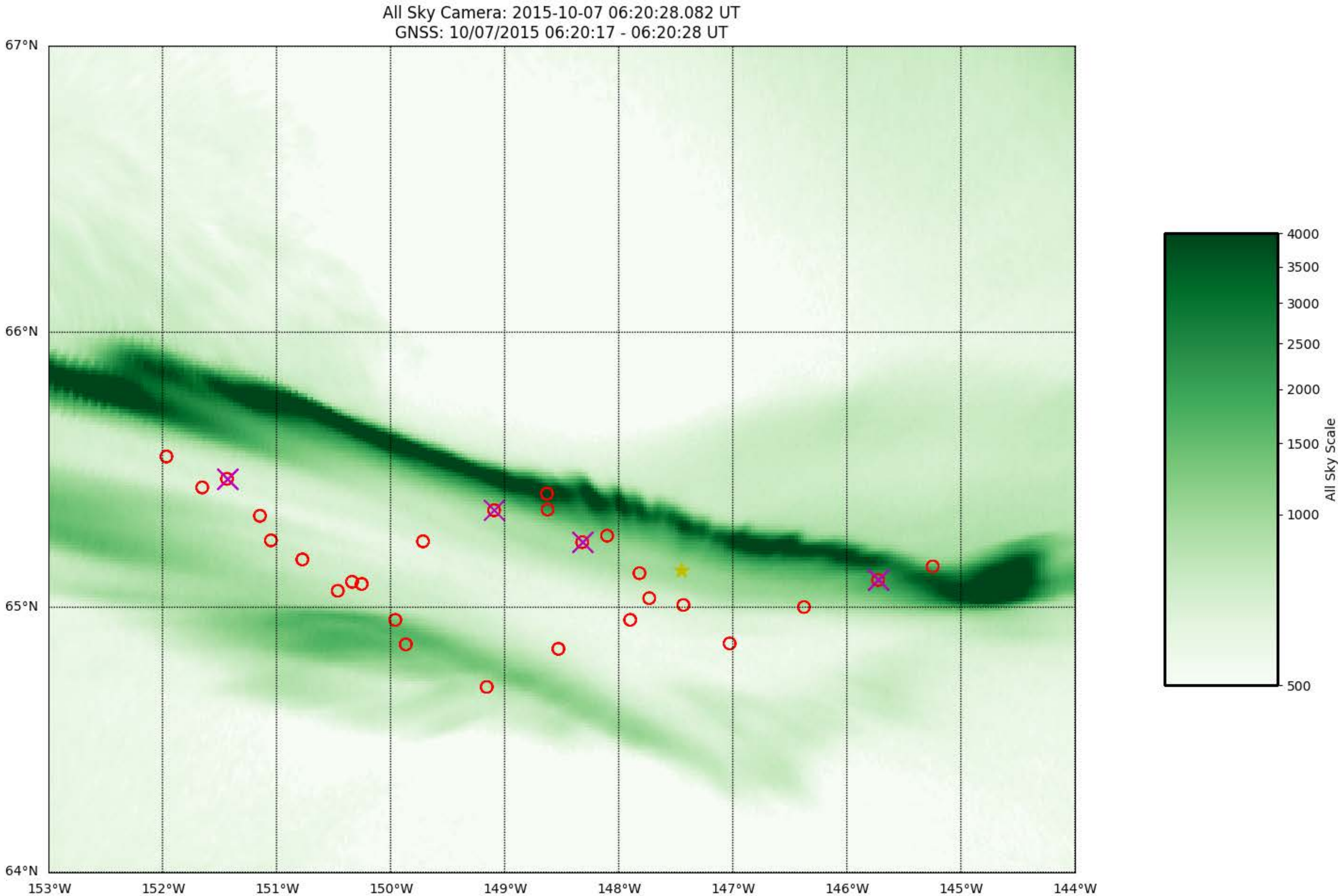
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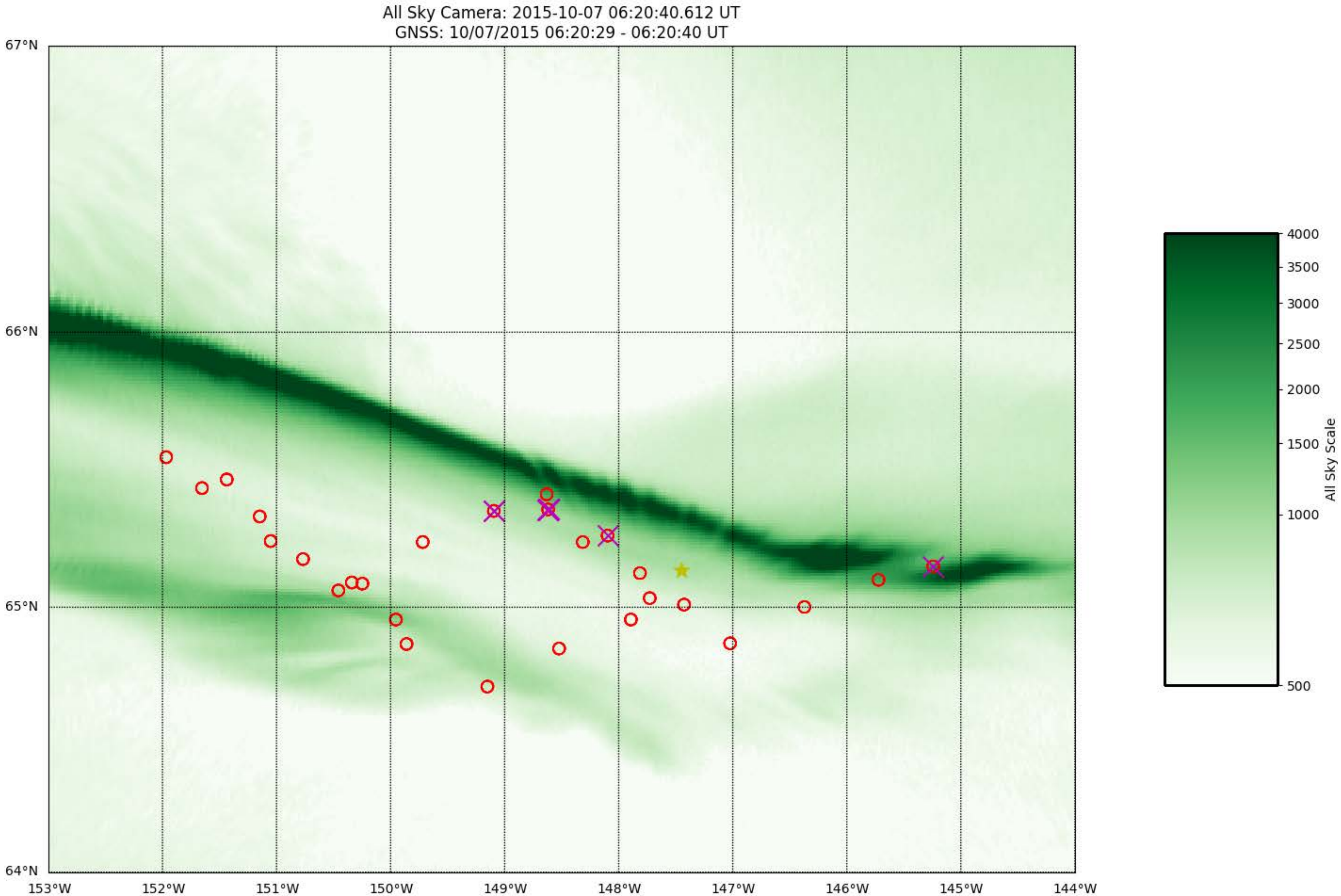

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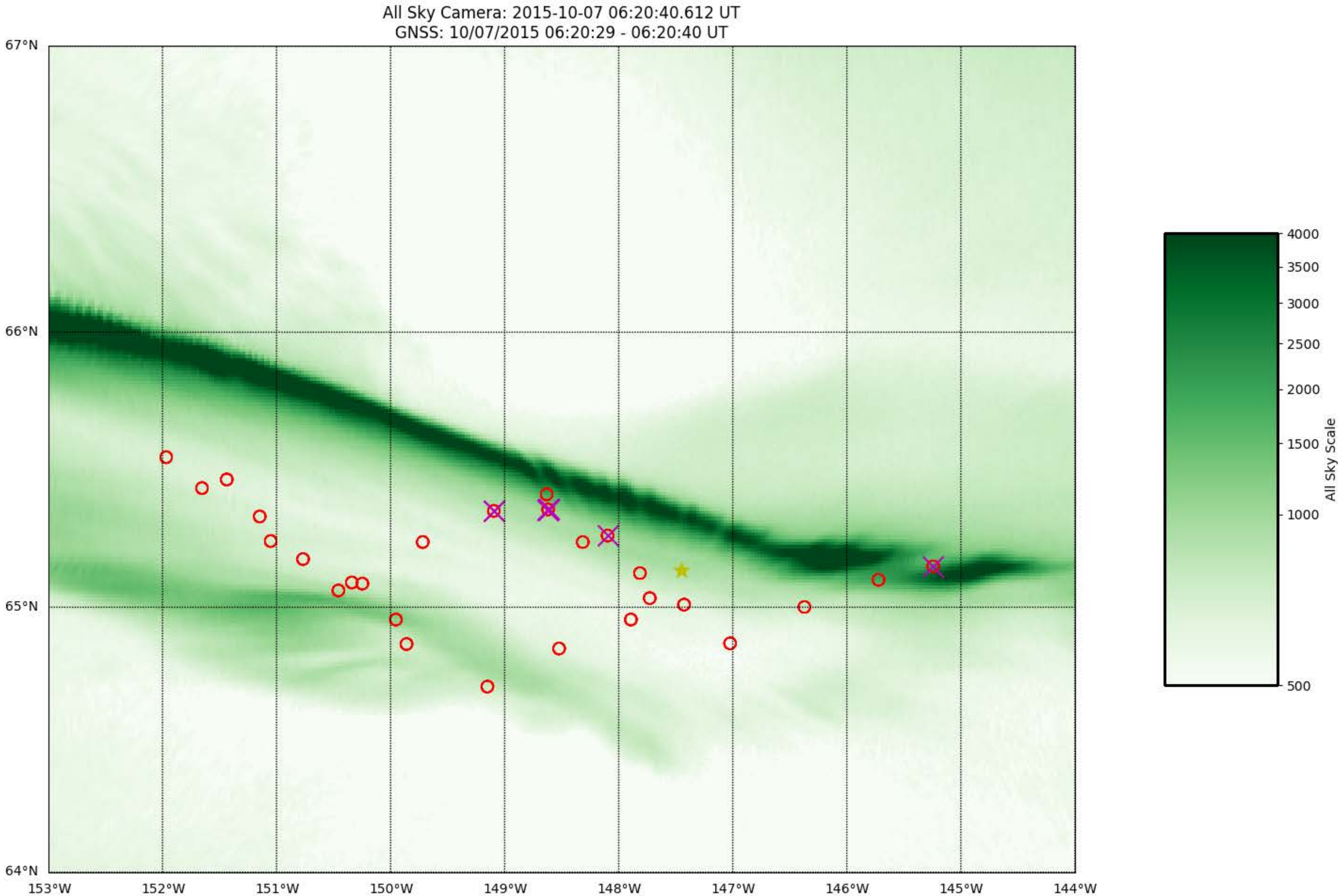
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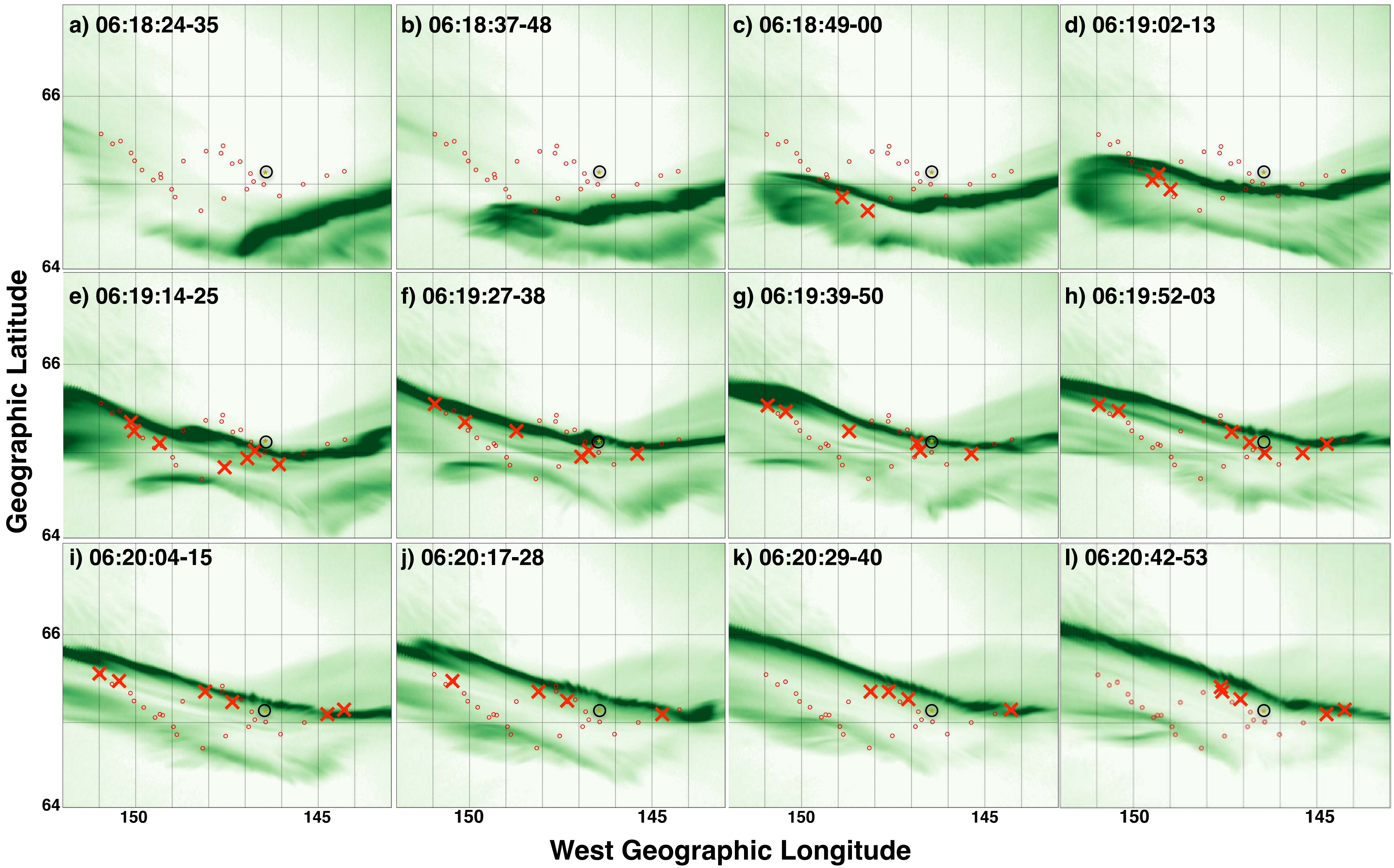

a) 06:18:24-35
b) 06:18:37-48
c) 06:18:49-00
d) 06:19:02-13
e) 06:19:14-25
f) 06:19:27-38
g) 06:19:39-50
h) 06:19:52-03
i) 06:20:04-15
j) 06:20:17-28
k) 06:20:29-40
l) 06:20:42-53
Geographic Latitude
66
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West Geographic Longitude

Logical extension

- Billions of GNSS measurements provided by crowd sourced network
- Many intersecting lines of site, possibility of 3D tomographic reconstructions of the ionosphere at unprecedented resolution.
- A “modest” scenario:
  - 1 million provides, each seeing 10 satellites = 10 million TEC samples / second
  - Discretize the ionosphere: 1^o Lat x 1^o Lon + 50 altitudes = 3 million pixels
  - **30 trillion element, time-varying, projection matrix !**
- Direct pixel-based reconstruction (very) far from feasible!

$$\widehat{ionosphere} = \Sigma_m A^T \left(A \Sigma_m A^T + \Sigma_e \right)^{-1} (measurements)$$

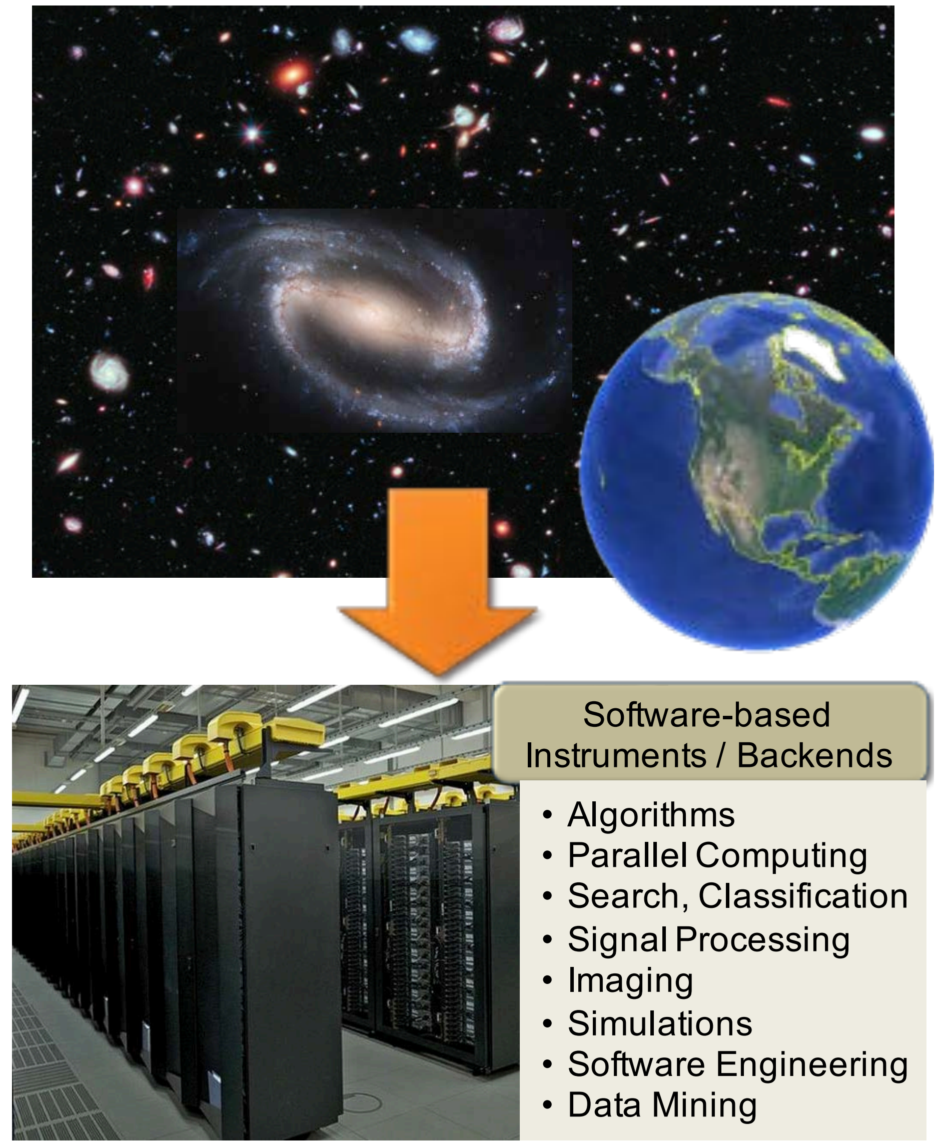
- Based on current theory, how many feasible solutions are there?
- Can a human-machine collaboration discover the right answer?

Data – all the time – everywhere on earth and in space

- Scalable machine assistance is needed to help humans in the discovery process

- Overcome human cognitive limits through algorithmic support

  - The scientific discovery process becomes a search process across multidimensional data sets. Scientific question answering by matching theory variants to empirical data sets.



Computer Aided Discovery

Challenge

"Pragmatics" — Discovery and Insight Generation

- What does feature X imply?
- How does it fit into the theoretical context?
- Does it contradict or confirm established models?

"Semantics" — Data Exploration, Analysis, Mining

"This is feature X"

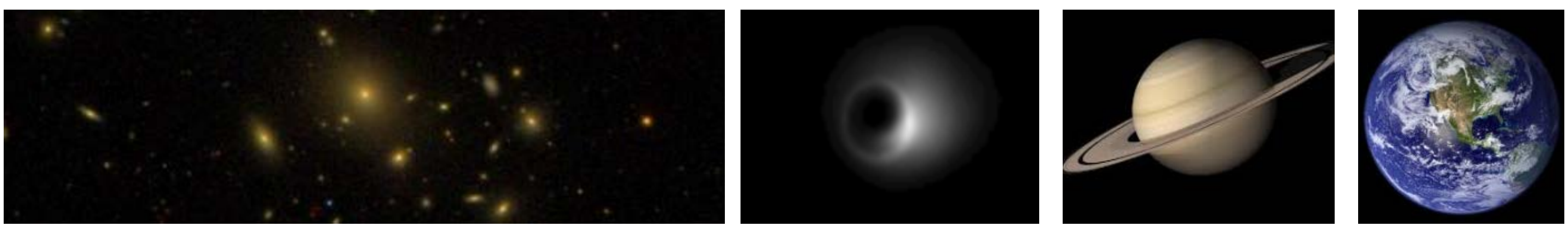
"Syntax" — Data

Numbers correctly encode actual measurements

Signals

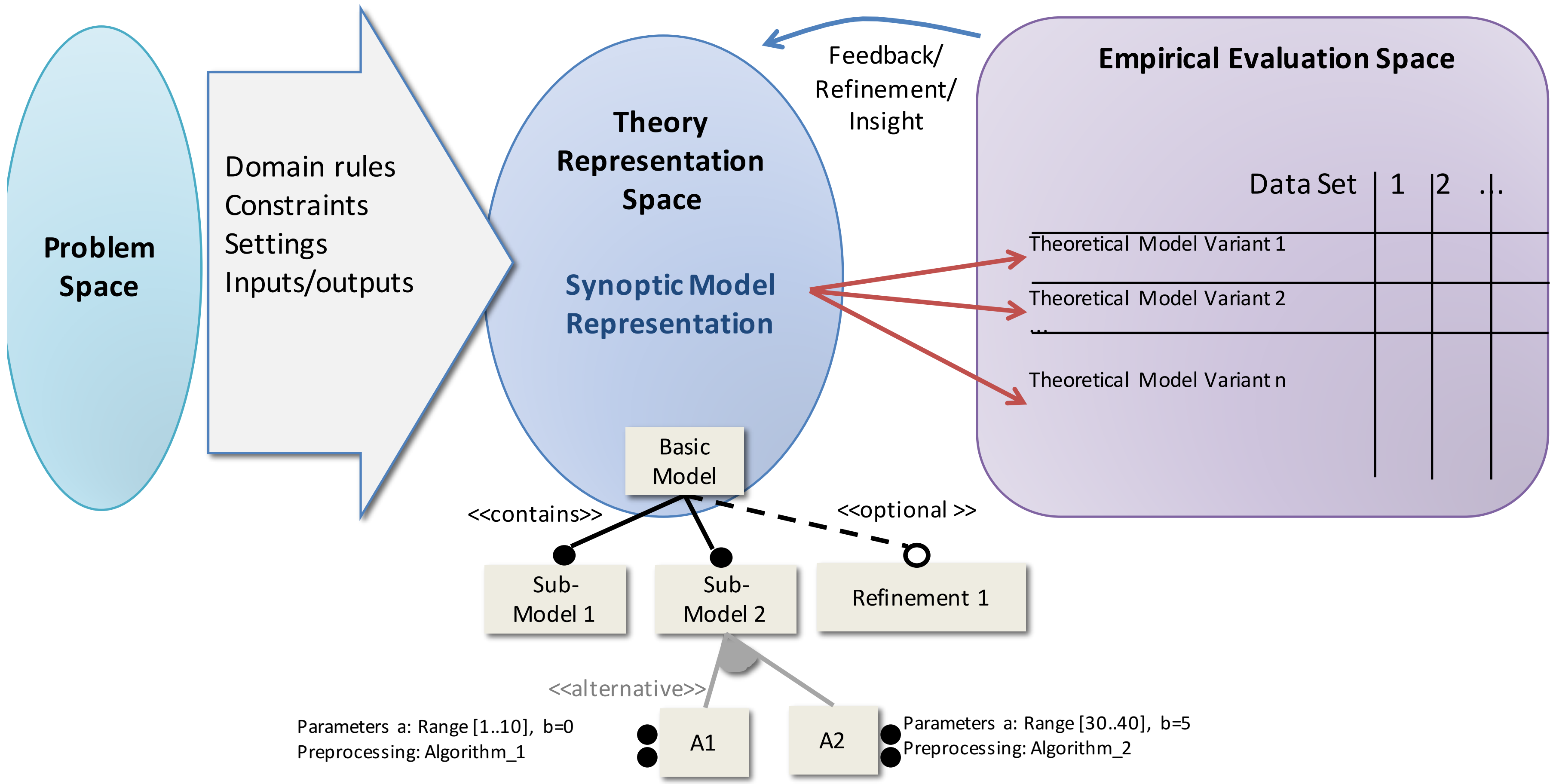
Semiotic Layers

Real-World Phenomena

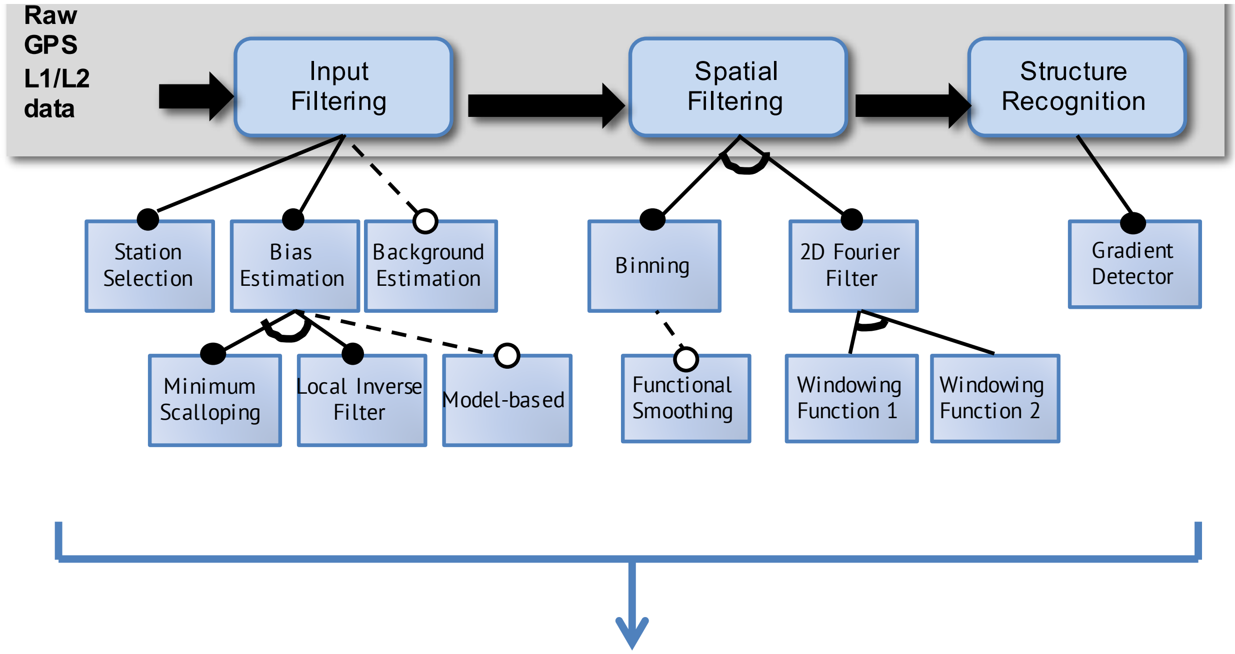


ACI, PI Pankratius
1442997

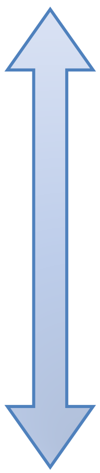
Model Representations



TEC Imaging Workflow

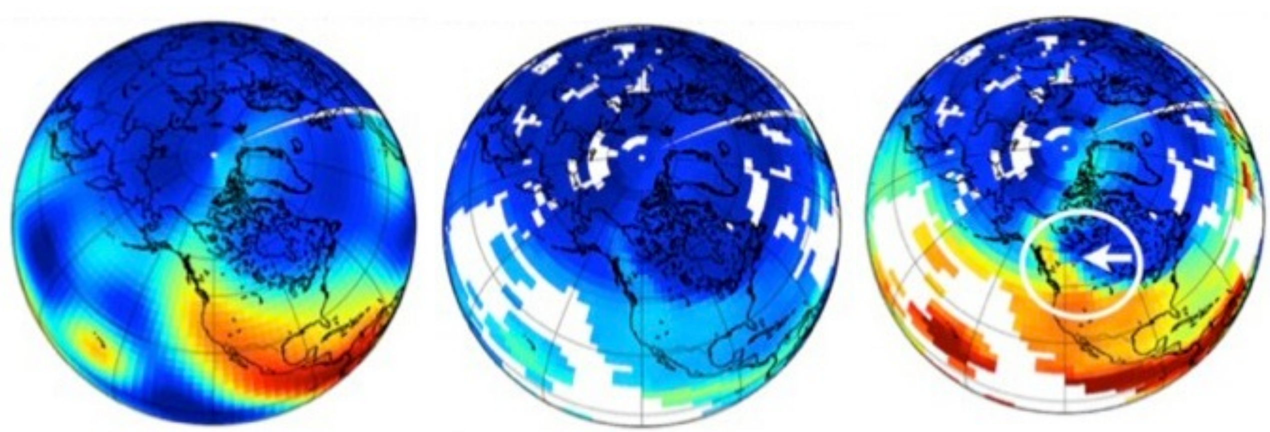


Empirical Data



Theory

Variants of ionospheric feature models



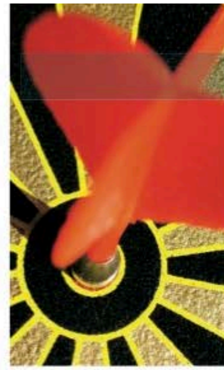
[V.Pankratius et al., IEEE Intelligent Systems, 2016]

References

- **Computer-Aided Discovery: Towards Scientific Insight Generation with Machine Support.**
  Victor Pankratius, Justin Li, Michael Gowanlock, David M. Blair, Cody Rude, Tom Herring, Frank Lind, Philip J. Erickson, Colin Lonsdale, IEEE Intelligent Systems 31(4), July/August 2016
  http://doi.ieeecomputersociety.org/10.1109/MIS.2016.60

- **Computer Aided Detection of Transient Inflation Events at Alaska Volcanoes using GPS Measurements from 2005-2015**
  Justin Li, Cody Rude, David Blair, Michael Gowanlock, Thomas Herring, Victor Pankratius, Journal of Volcanology and Geothermal Research 327, Nov 2016
  http://dx.doi.org/10.1016/j.jvolgeores.2016.10.003

- **Improving Spacecraft Site Selection Through Computer-Aided Discovery And Data Fusion.**
  David Blair, Michael Gowanlock, Justin Li, Cody Rude, Tom Herring, Victor Pankratius, 47th Lunar and Planetary Science Conference (LPSC), 2016
  http://www.hou.usra.edu/meetings/lpsc2016/pdf/1987.pdf



EXPERT OPINION
Editor: Daniel Zeng, University of Arizona and Chinese Academy of Sciences, zengdaniel@gmail.com

Computer-Aided Discovery: Toward Scientific Insight Generation with Machine Support

Victor Pankratius, Justin Li, Michael Gowanlock, David M. Blair, Cody Rude, Tom Herring, Frank Lind, Philip J. Erickson, and Colin Lonsdale, *Massachusetts Institute of Technology*

Recent technical advances have enabled growing data volumes in astronomy and geoscience.[1] Scientists are now challenged to create insights from a deluge of data.[2] We are in the midst of a fundamental change, transitioning swiftly from an era in which data was scarce to an era in which data exceeds our ability to extract meaning from it, and the scientific community is facing an *analysis wall*.

Planetary and space-based sensor networks are generating continuous streams of data to monitor our environment, characterize diverse phenomena, and, in many cases, predict natural hazards. Computer science and intelligent systems are now called to action to develop a new breed of systems to extract insight from large datasets and different types of datasets (such as optical, radar, and GPS time series). Furthermore, data fusion from different instruments is gaining importance in making new discoveries of natural phenomena and ruling out false positives, especially because making the right connections can often be nonintuitive for humans.

Looking at information processing from the semiotics point of view, there are several layers. As Figure 1 shows, digitized sensor signals become data that represents the starting point for more complex analyses. The syntax layer essentially provides syntactically valid data—that is, numbers that codify actual valid measurements. The next layer on top typically aims to introduce semantics (for example, "this data represents feature X") by employing data exploration, analysis, and mining techniques. However, this alone is not enough to advance scientific progress, and scientists need support for pragmatics: What does it imply that a certain feature has been identified? What does a finding mean, and how does it fit into the big theoretical picture? Does it contradict or confirm previously established models and findings? How can the researcher test concepts and ideas effectively? Many of the implementation tasks that result from such questions are currently left to the individual researcher, who must artfully deduce the tools and workflows that lead to adequate answers.

Why Scientists Need Machine Support for Discovery Search

We can view the scientific discovery process essentially as a search process. This search space is defined not only by the large and diverse scientific datasets themselves, but also by the choices humans can make in the workflow processing that data (for example, choosing the parameters, order, or which algorithm, method, or filter to use in a certain stage of a processing pipeline). The workflow is assumed to be a sequence of processing steps that has the expressive power of a Turing machine.

As our case studies show, the choices made in the configuration of the processing workflow can drastically affect our ability to make discoveries. For example, if a set of processing steps highlights large-scale phenomena in a data product, discoveries of previously unknown small-scale phenomena will be suppressed. In addition, some natural phenomena might be rare or counter-intuitive in nature, so humans require machine assistance in configuring a potentially large parameter space to create data processing and discovery workflows.

The value of discovery automation also arises because of the sheer size of datasets on the order

FINI