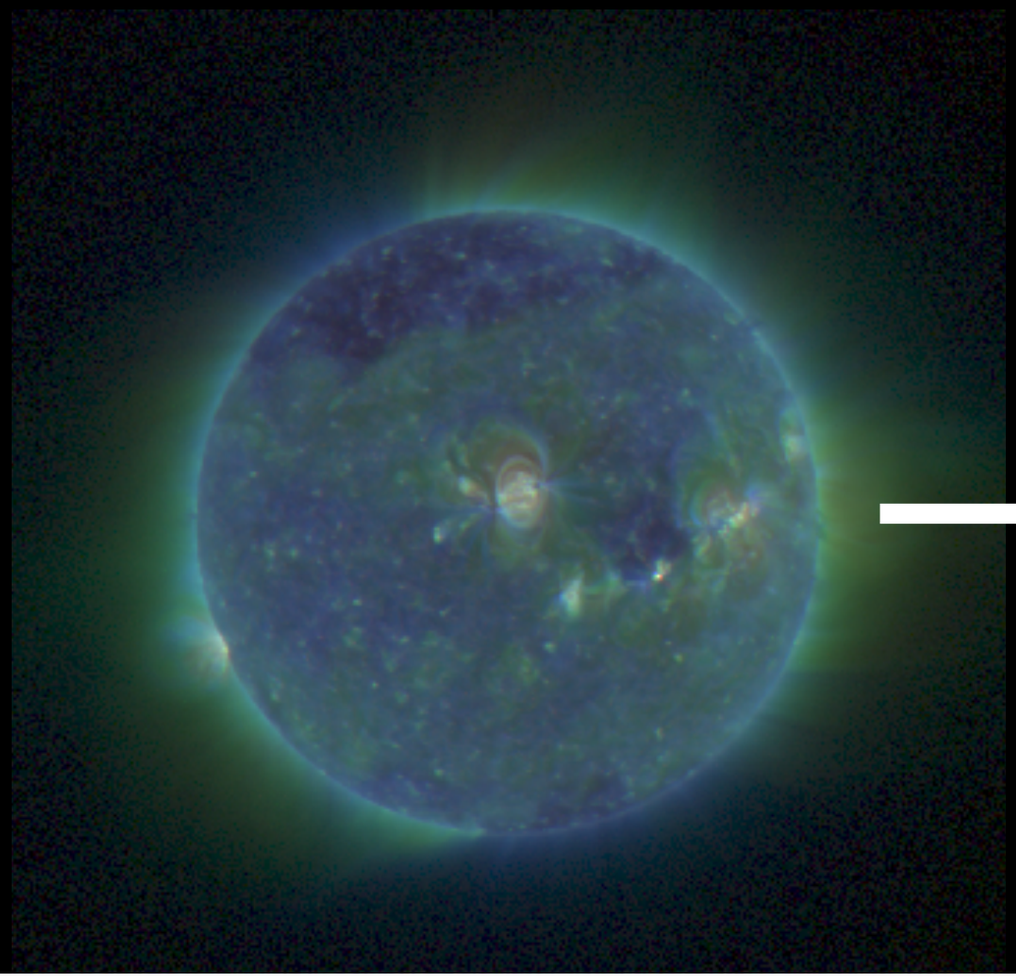
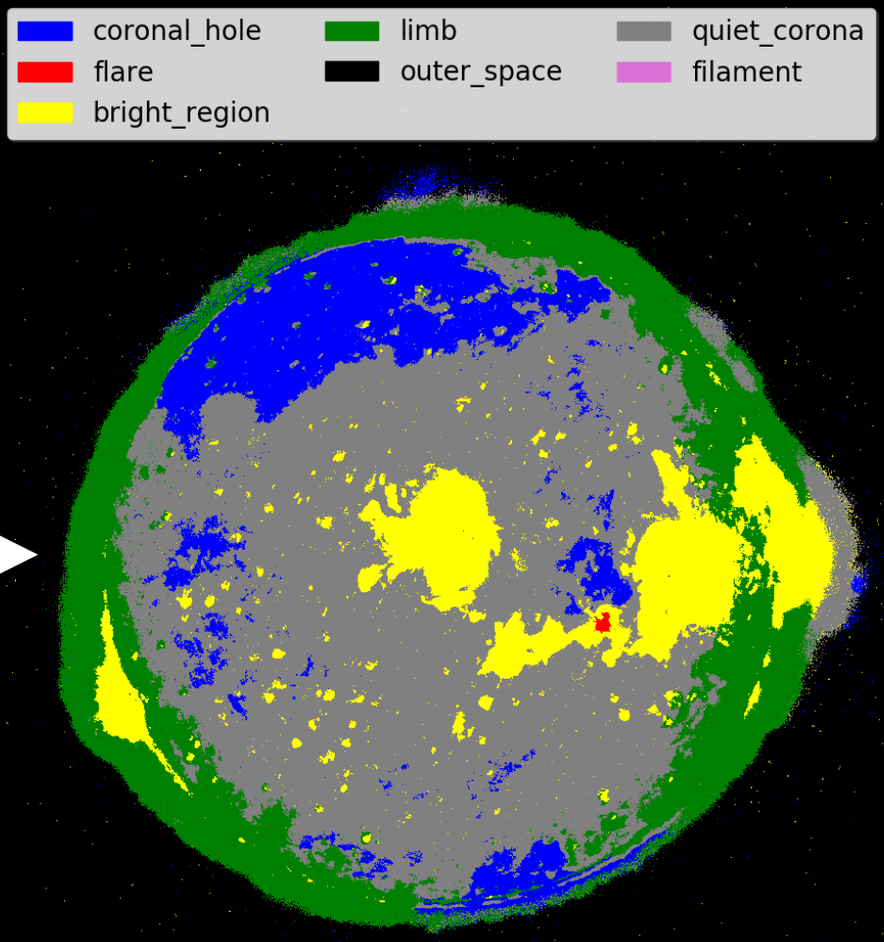
Solar Thematic Maps from SUVI

Marcus Hughes, Williams College, 2 August 2017

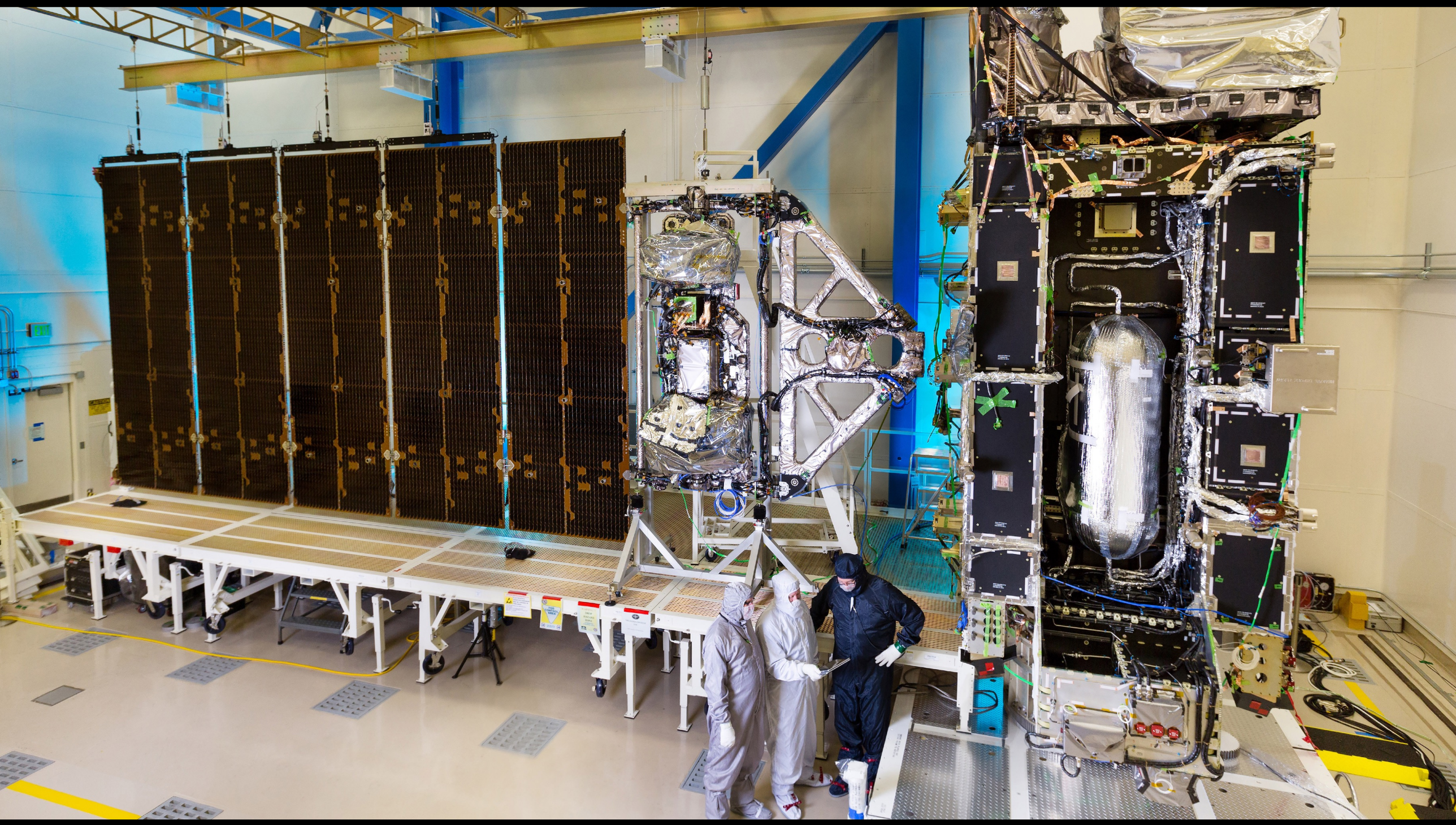
Mentors: Dan Seaton and Jon Darnel, CIRES



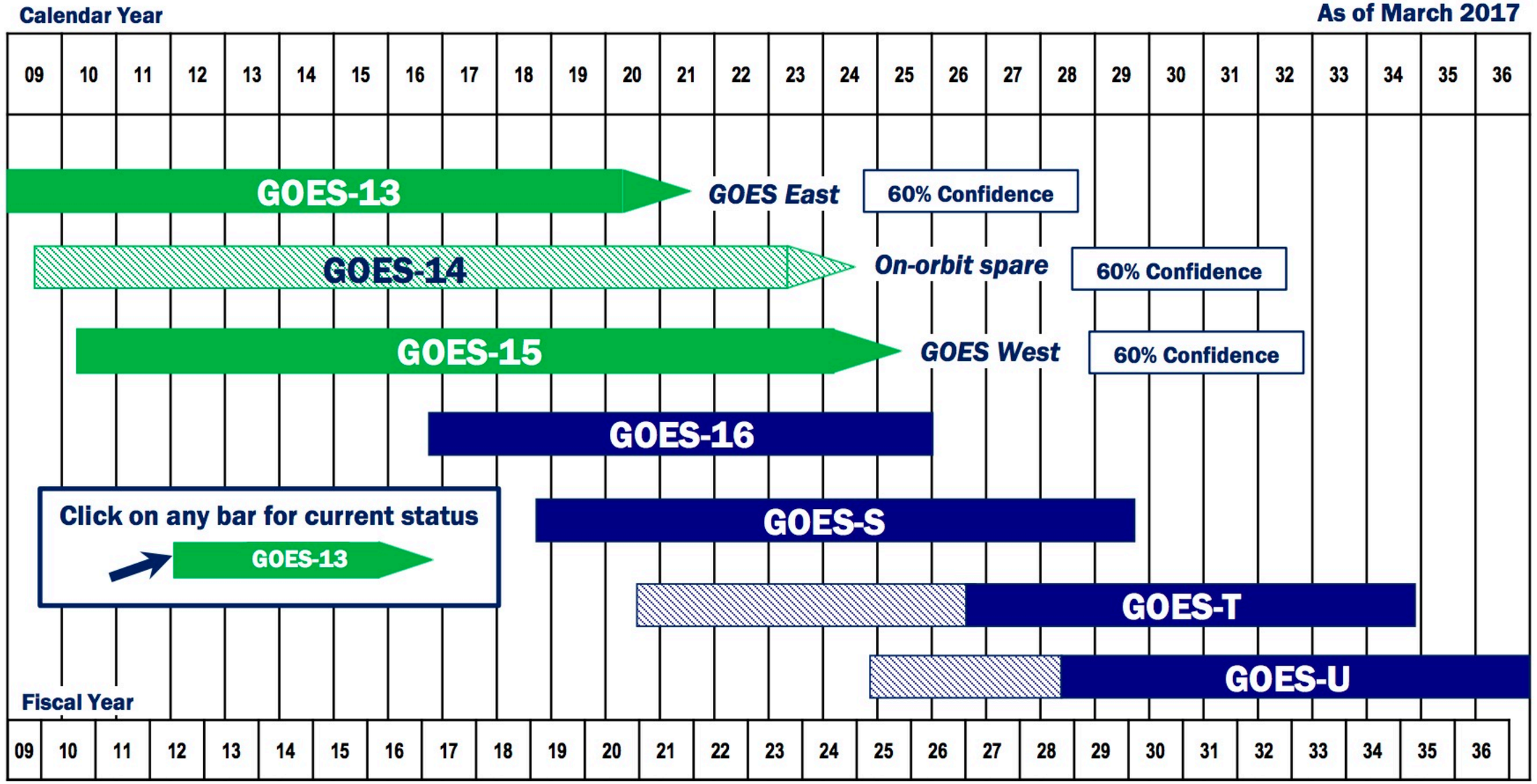


INTRODUCTION

SPACE WEATHER HAZARDS

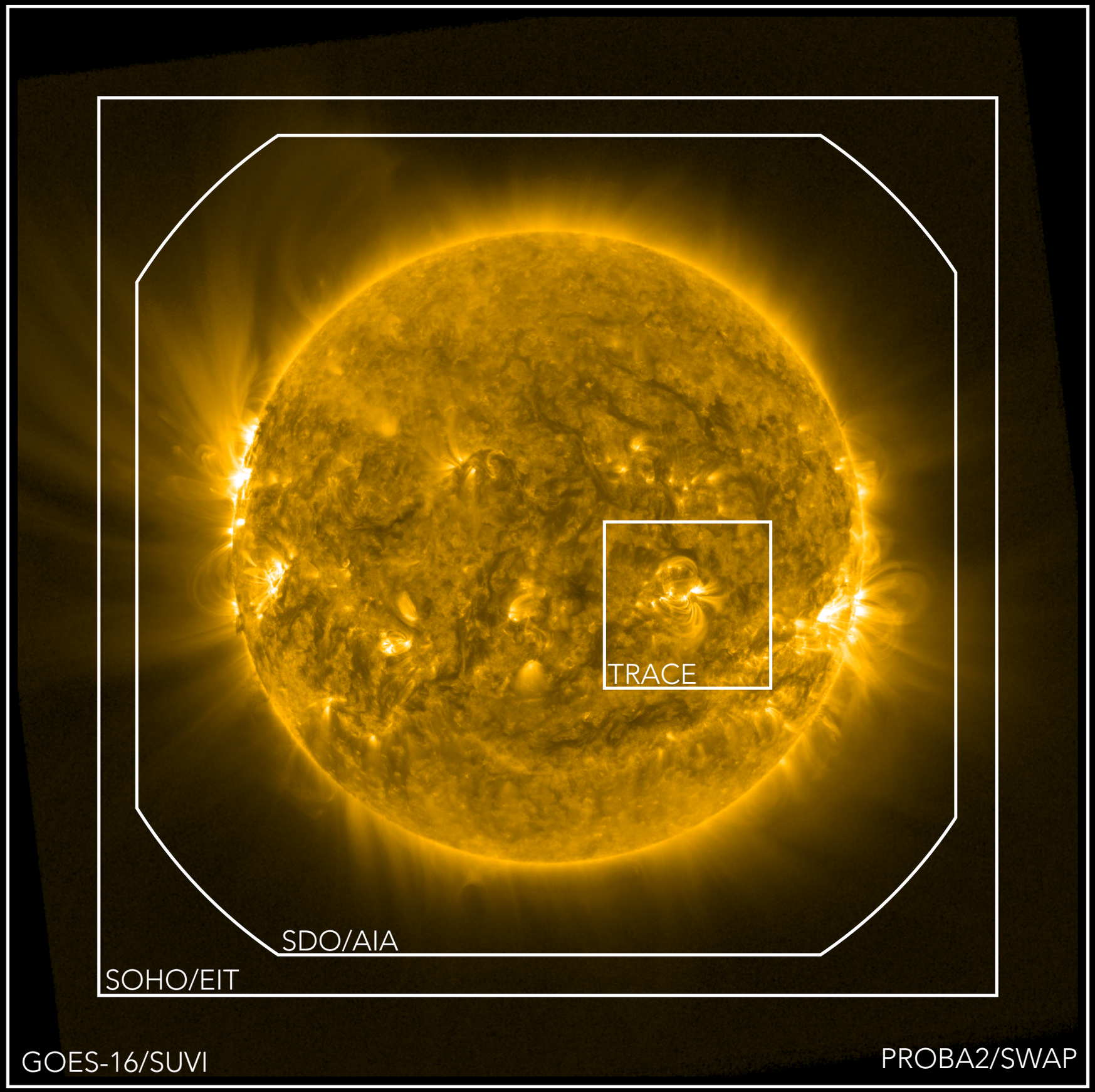


NOAA Geostationary Satellite Programs
Continuity of Weather Observations



Approved: _____
Assistant Administrator for Satellite and Information Services

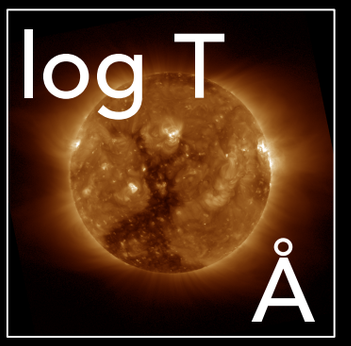
- In orbit, operational
- In orbit, storage
- Planned in-orbit Storage
- Planned Mission Life
- Reliability analysis-based extended weather observation life estimate (60% confidence) for satellites on orbit for a minimum of one year – Most recent analysis: March 2017

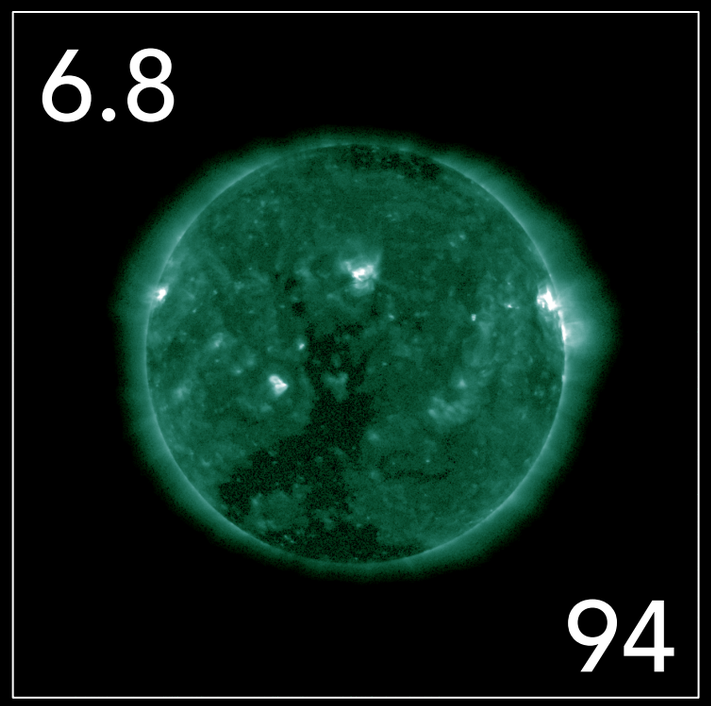


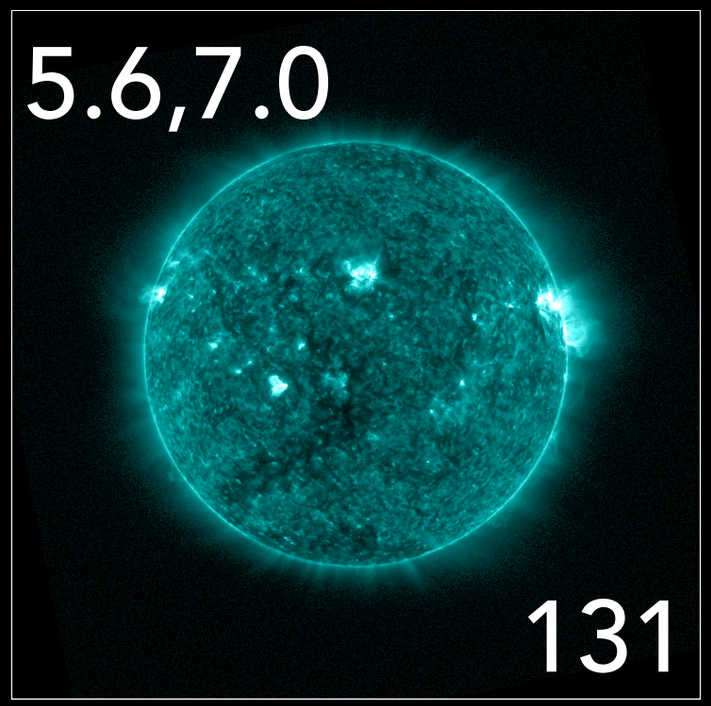
THEMATIC MAP GENERATION: MARCUS HUGHES, 4 JUNE 2017

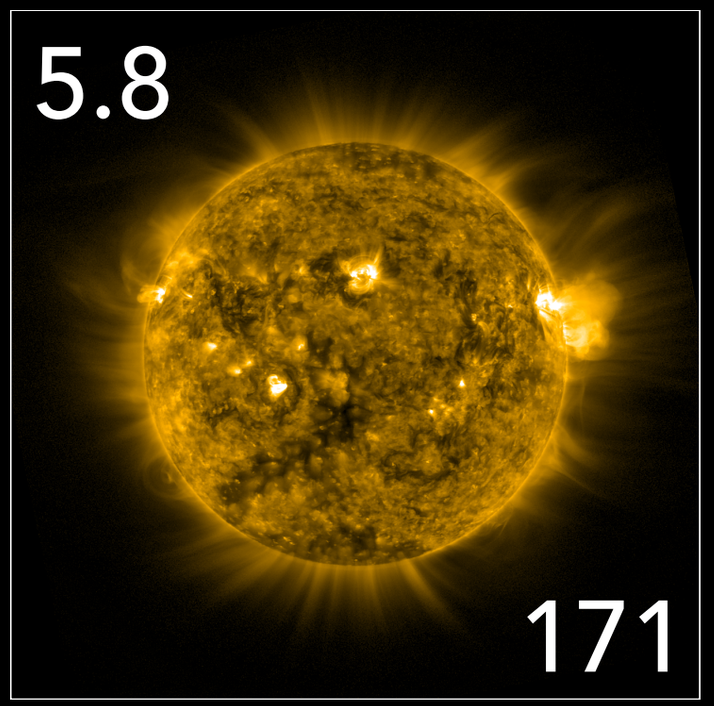
GOES-R/SUVI

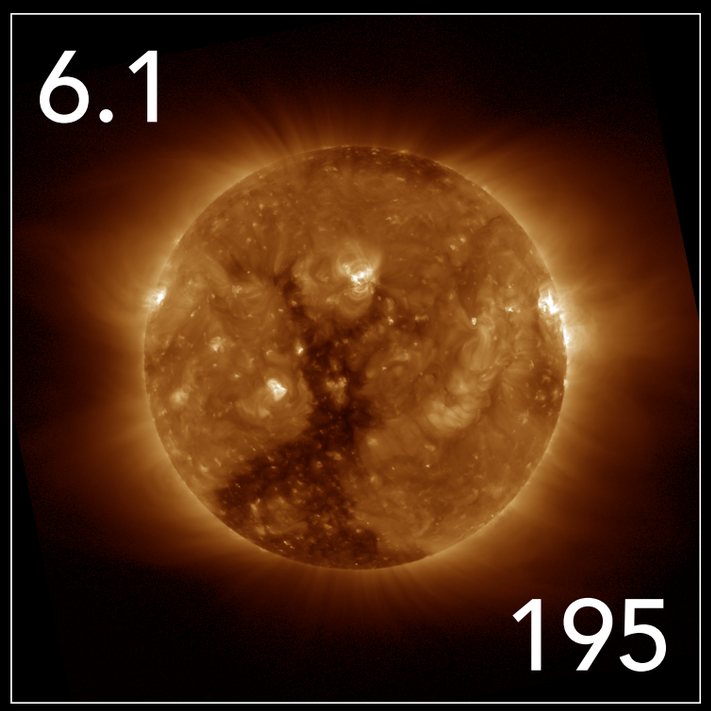
EUV PASSBANDS

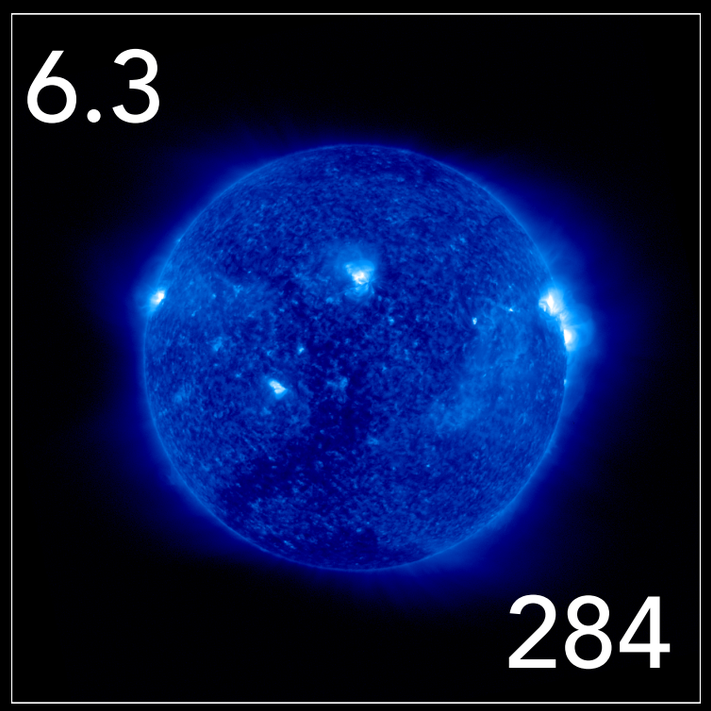


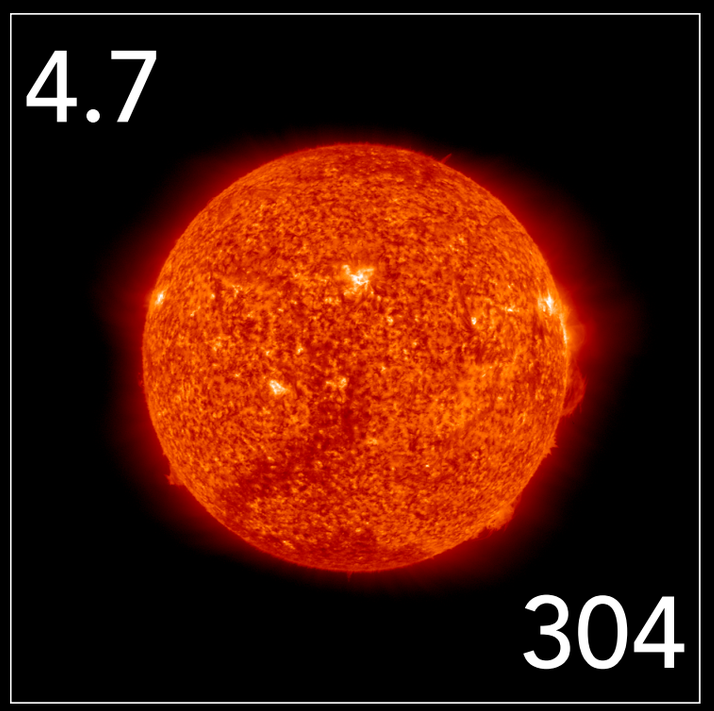




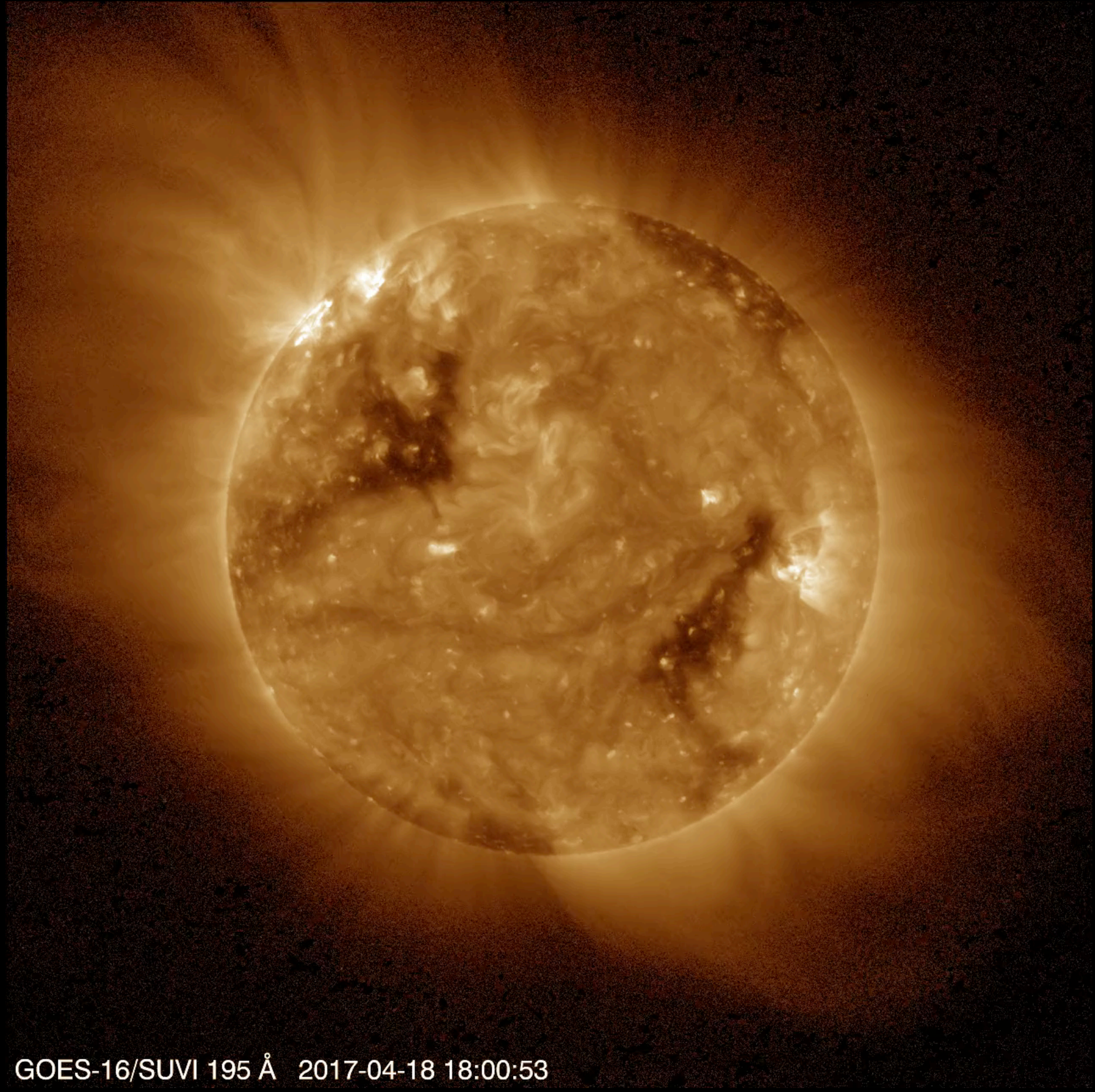








THEMATIC MAP GENERATION: MARCUS HUGHES, 2 AUGUST 2017


GOES-16/SUVI 195 Å 2017-04-18 18:00:53

Date: 18 Apr 2017
Time: 1804 U.T.
Forecaster: MARSHALL

N

+14

2651
40/10/1/1

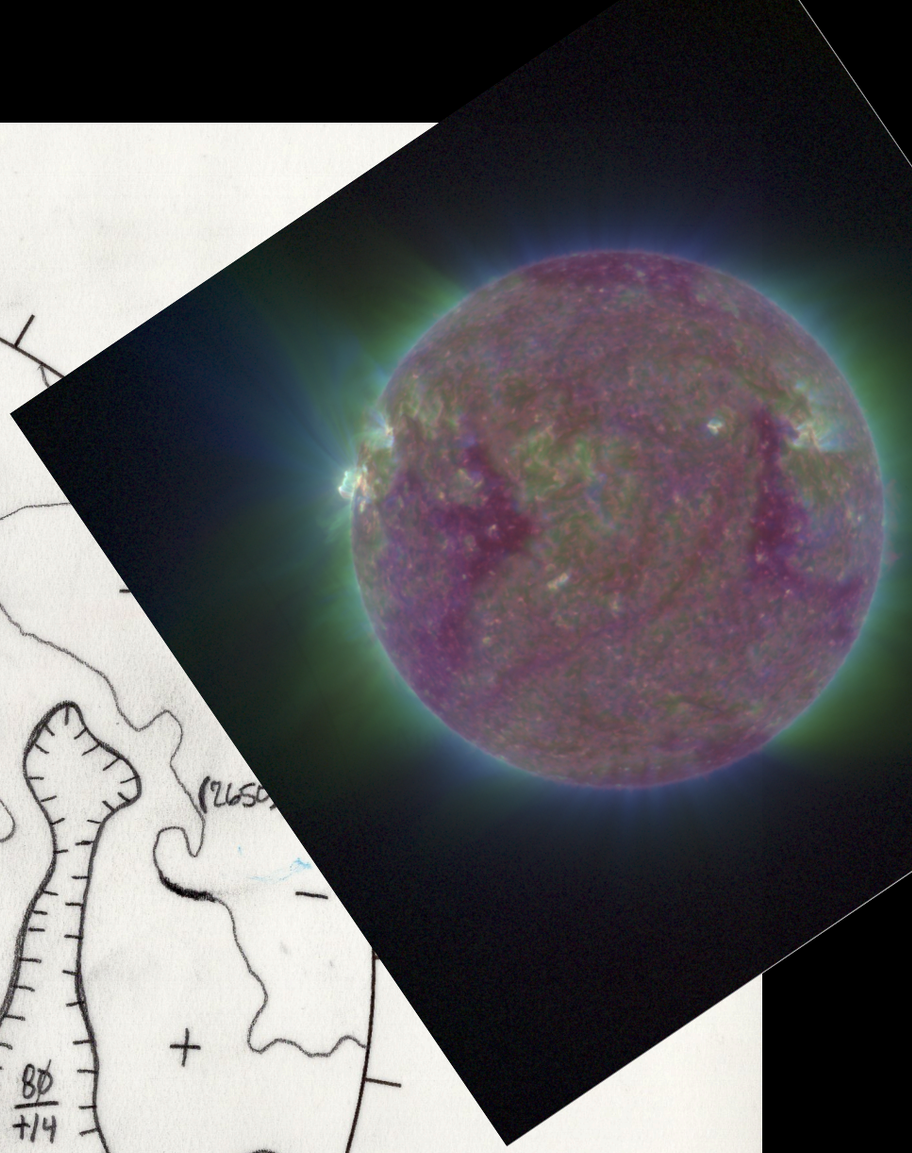
82
-13

80
+14

-14

53.7Φ E

S

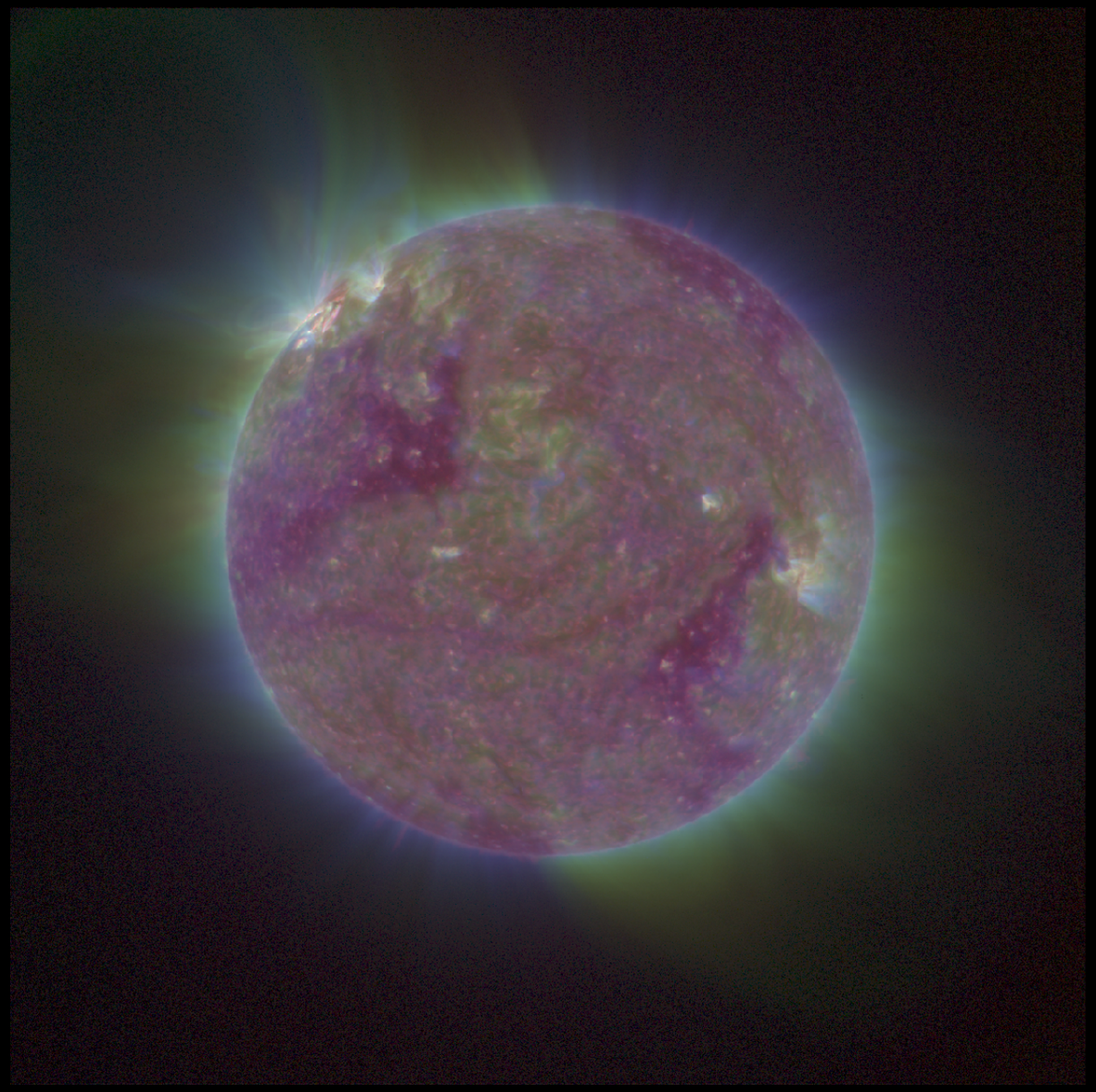


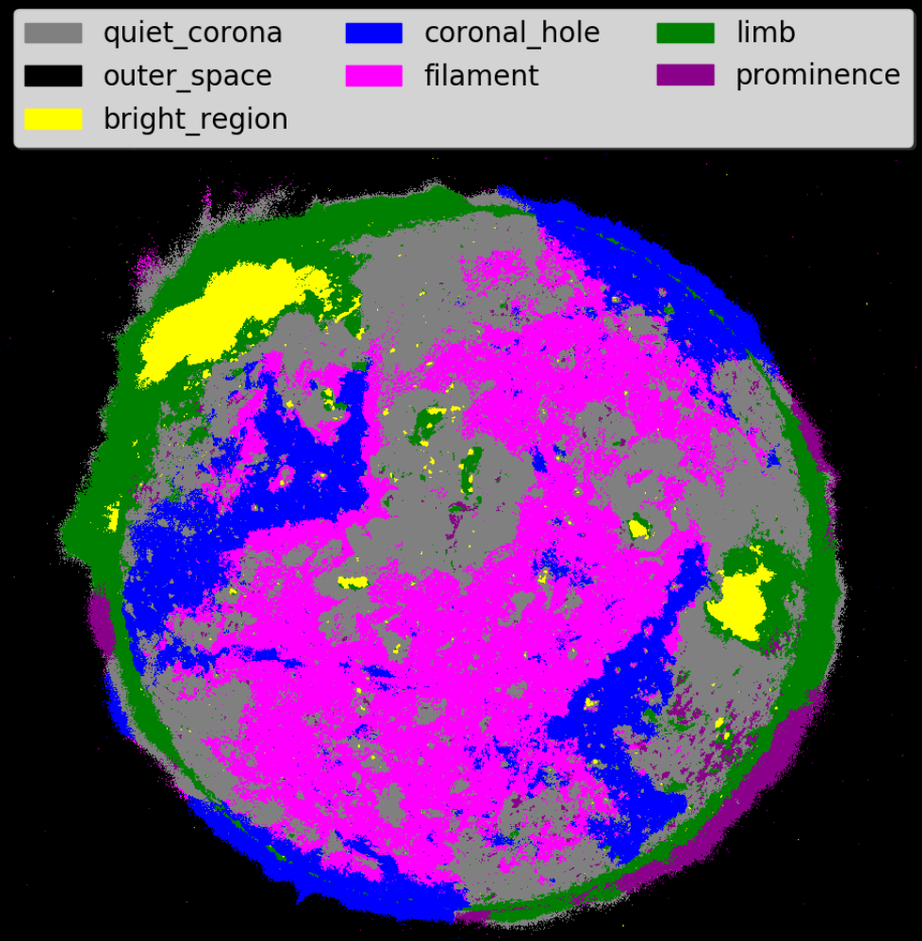
Returning
Carringtons:
5Φ.5 to 1Φ.8

Next Rgn. No. 2652
Next CH No. 83

L_t 143.7
B_t -5.3
P_t -25.7

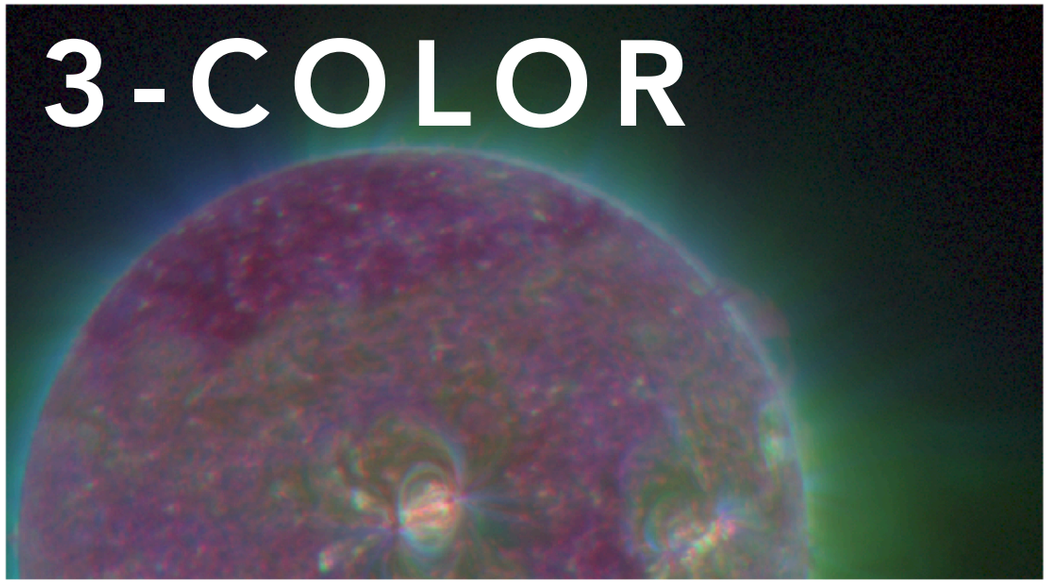
SWPC SOLAR SYNOPTIC ANALYSIS



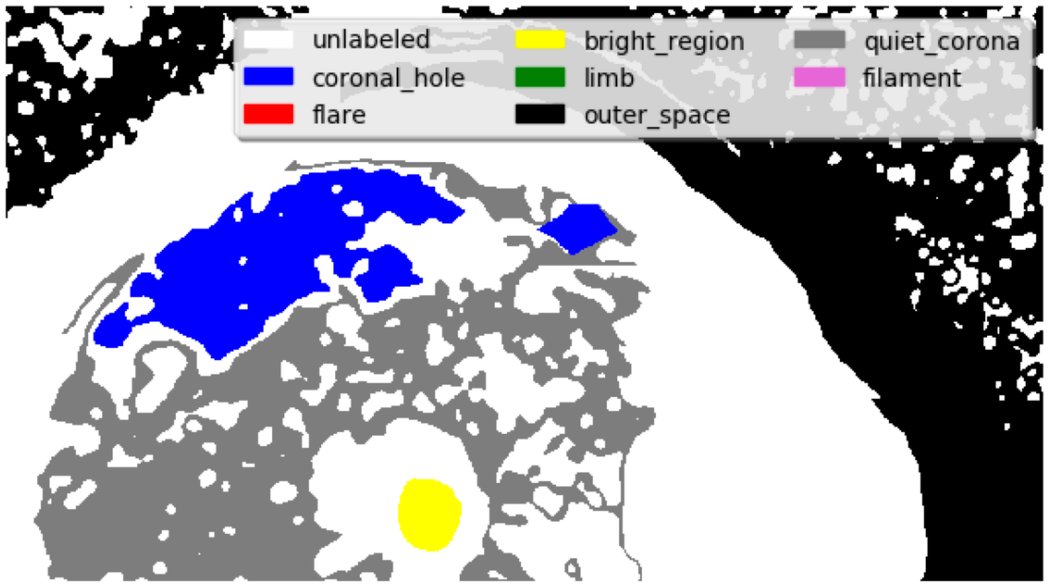

quiet_corona
coronal_hole
limb
outer_space
filament
prominence
bright_region

HOW IT WORKS

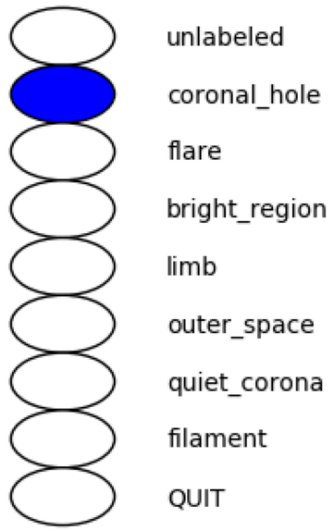
TRAINING:
LEARN FROM HUMANS



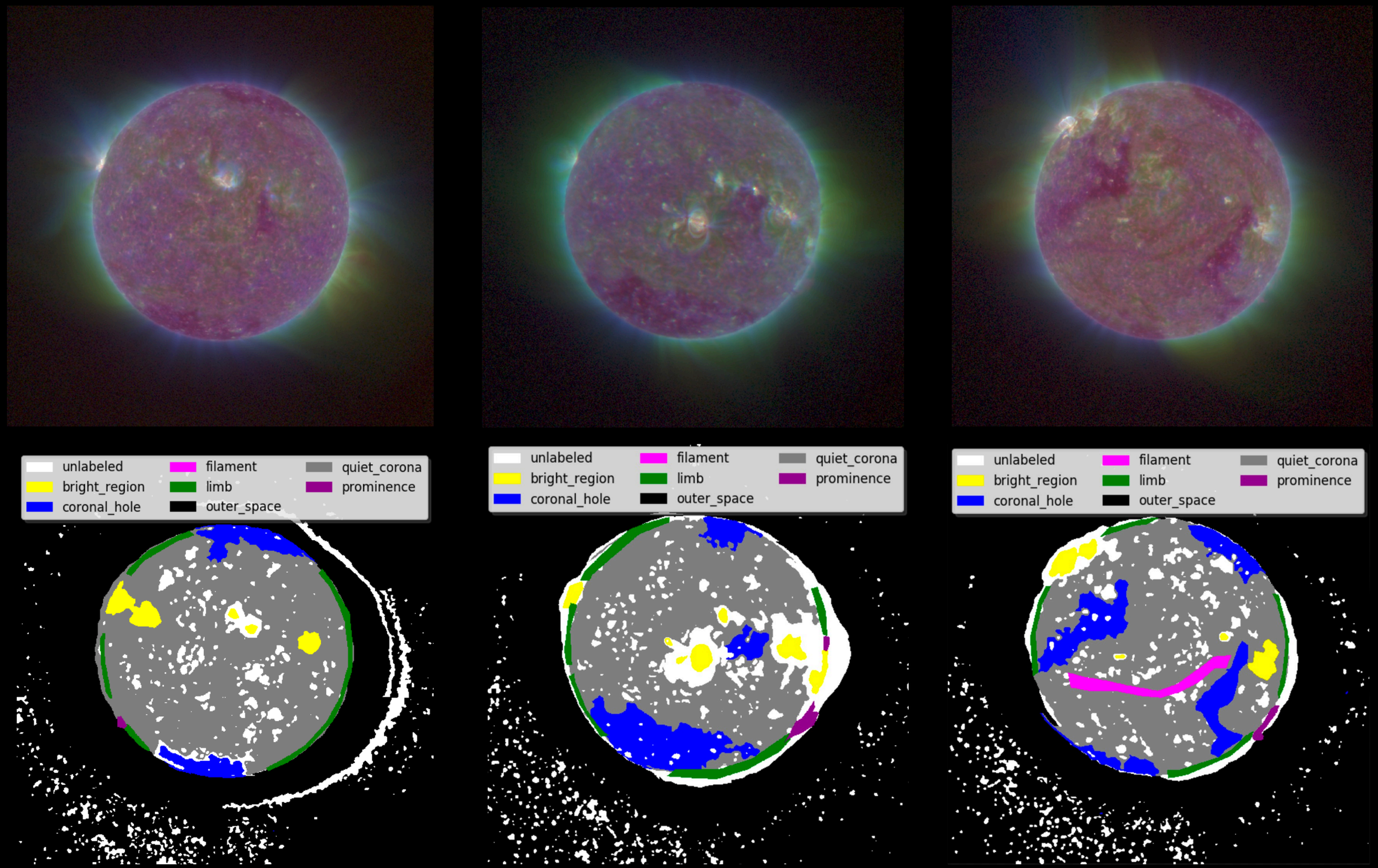
YOUR LABELS



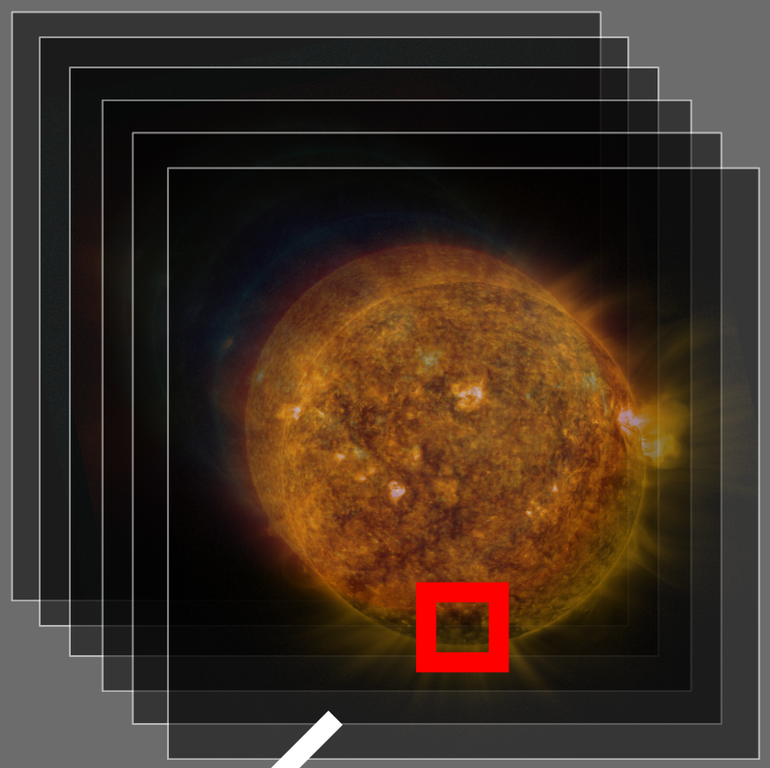
PICK A LABEL



TRAINING:
LEARN FROM HUMANS

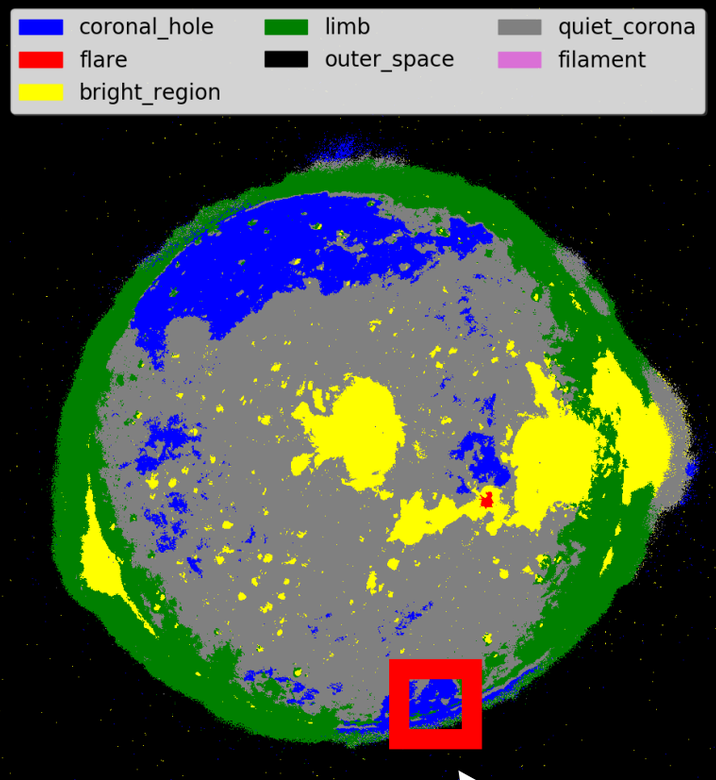


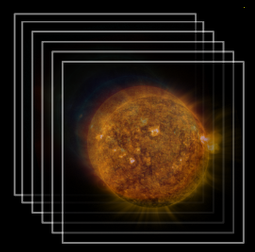
Training



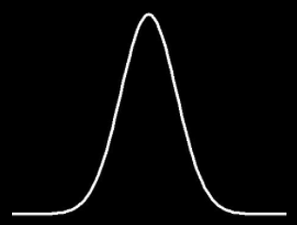
Coronal Hole

```
[ 0.0143274
  0.43174687
  0.39240143
  0.03449864
  4.47269058
  0.19410864]
```





Unlabeled image



Distribution for each theme

Calculate the probability of a pixel for each theme

Rigler et al., SPACE WEATHER, VOL. 10, S08009, 2012

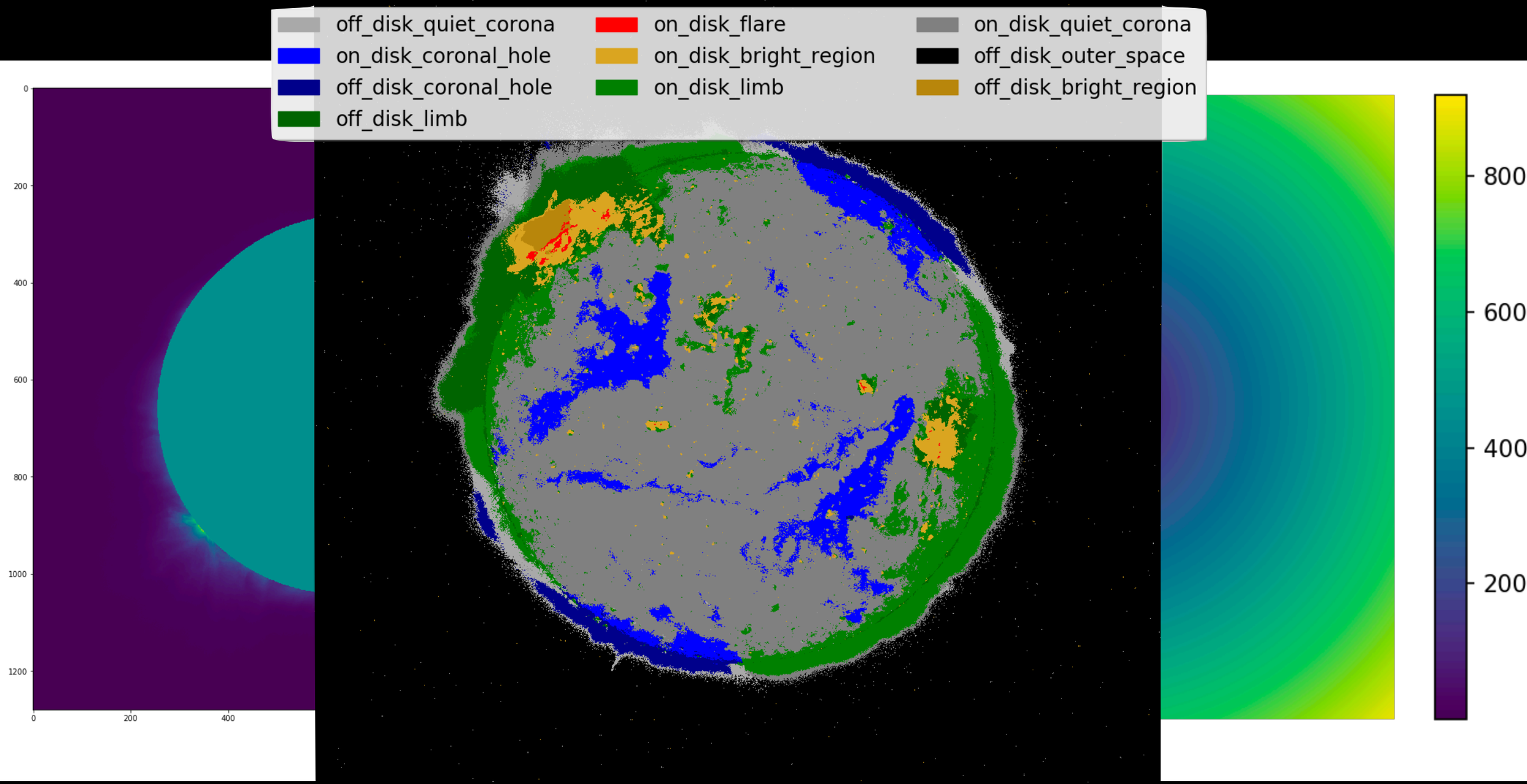
THE CHALLENGES

THE CHALLENGES

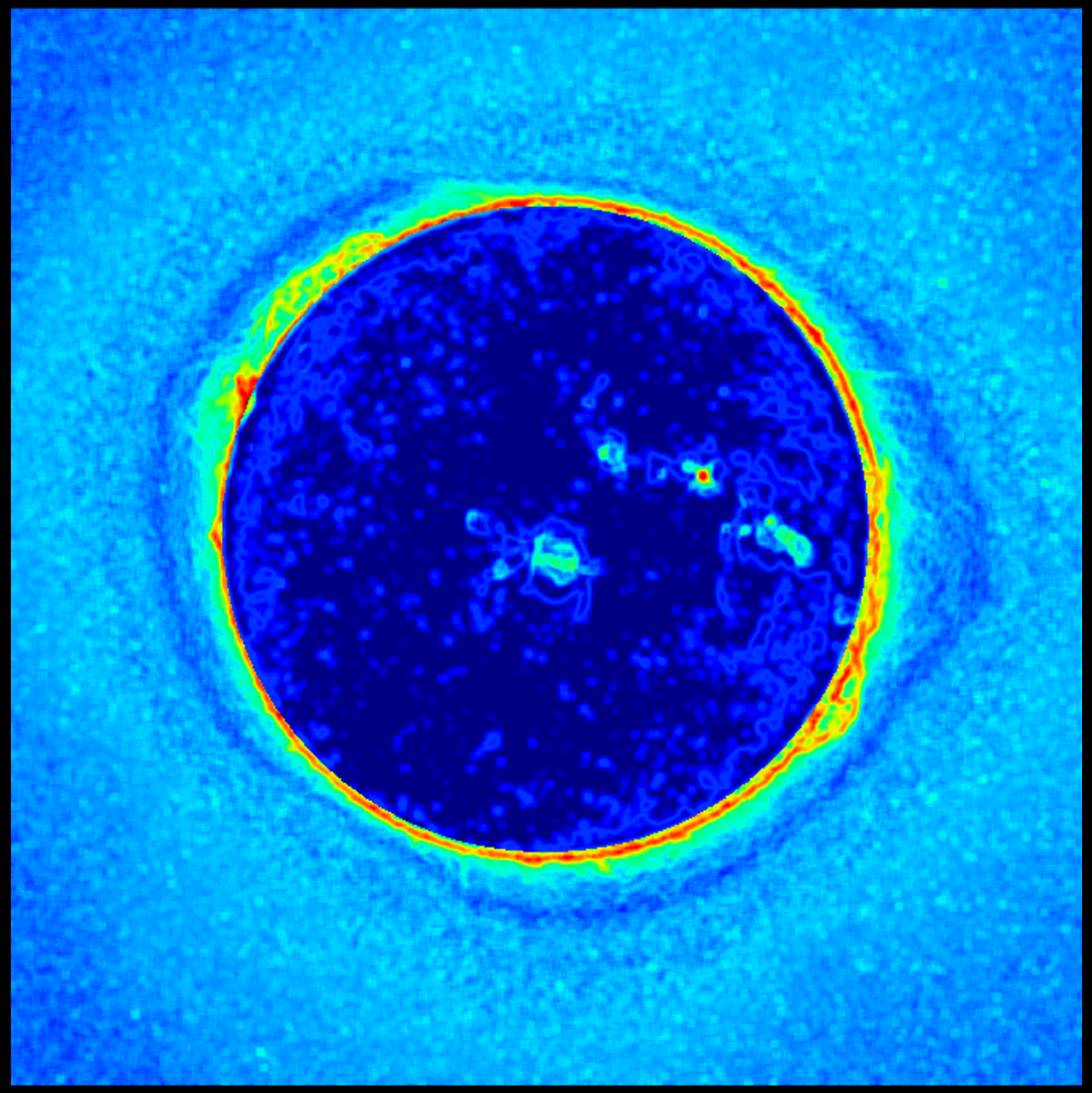
- There is data available that's not being used:
  - Location on the Sun
  - Spatial structure
  - Temporal similarity

- Not all themes are distinctly defined:
  - Bright regions have a multiple modes
  - Coronal holes and filaments can be difficult to distinguish

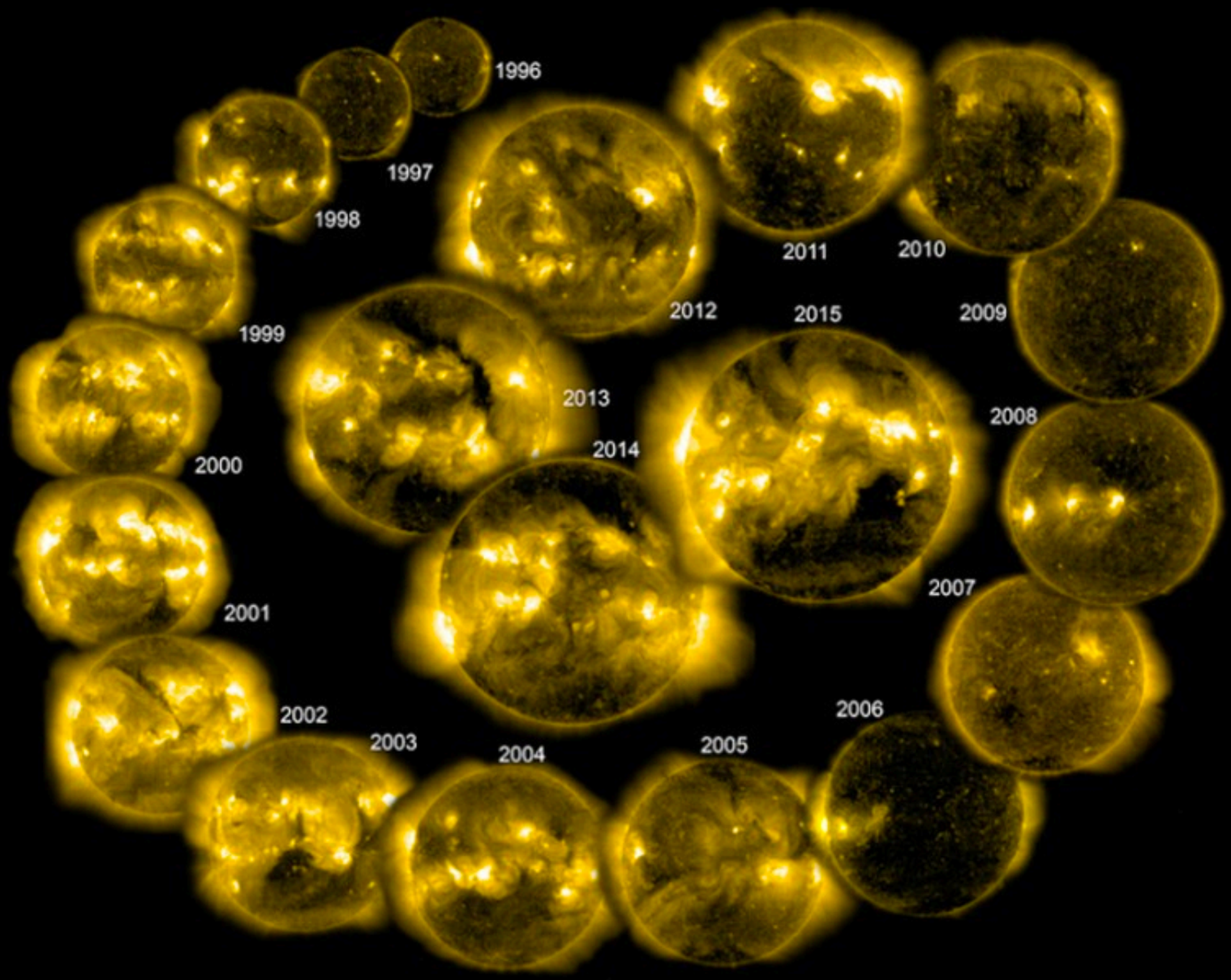
LOCATION ON THE SUN



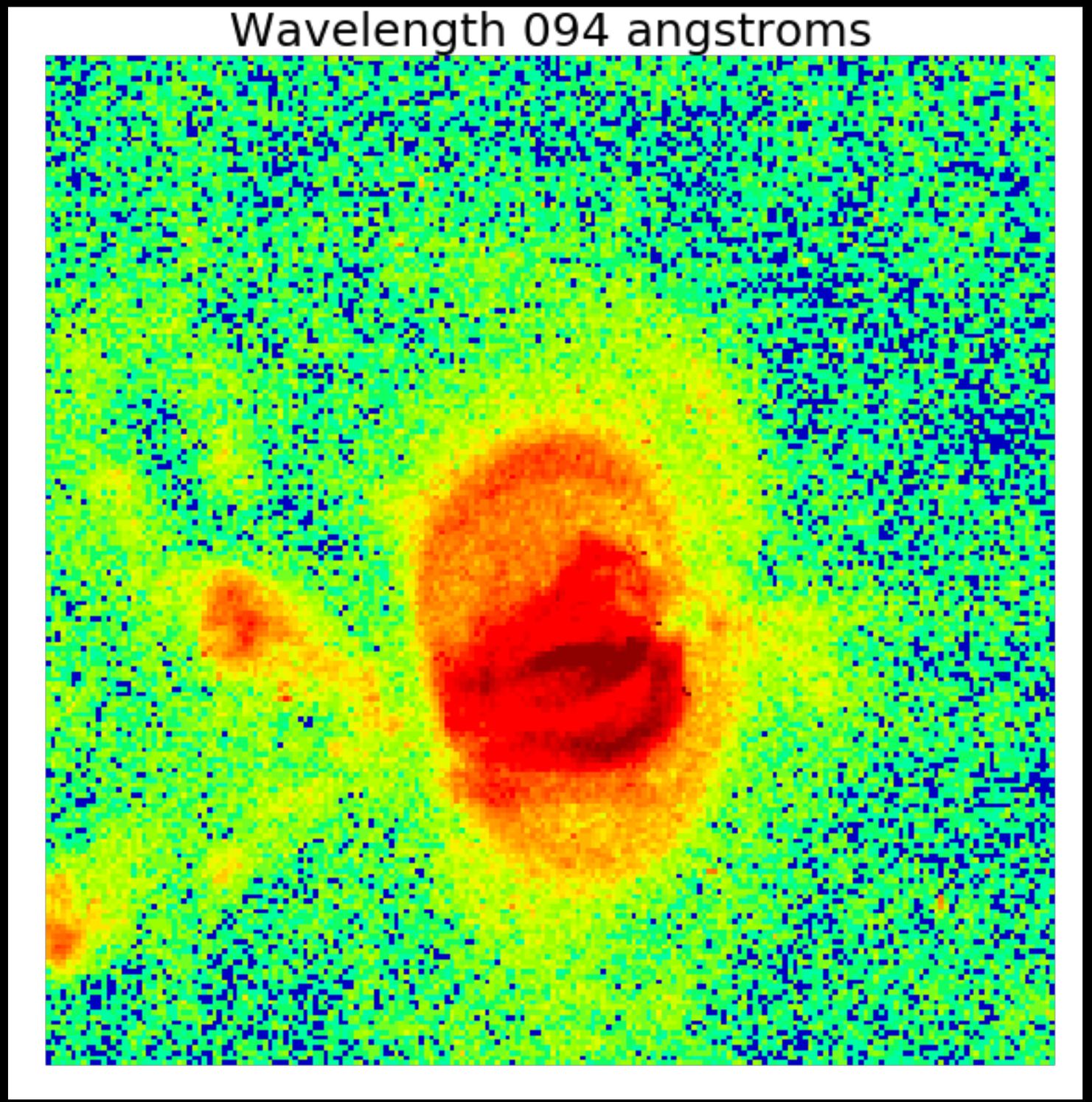
SPATIAL STRUCTURE



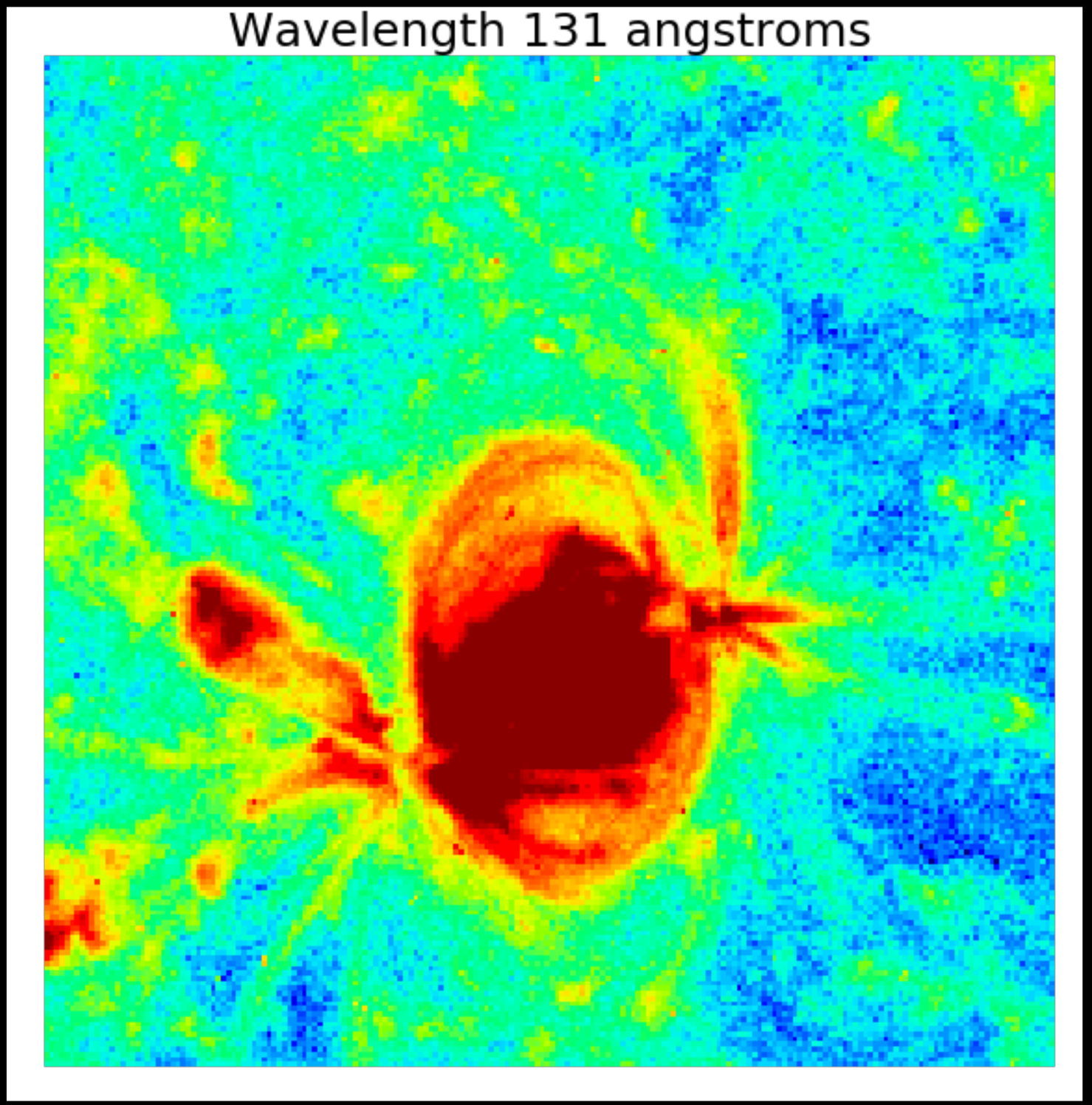
TEMPORAL SIMILARITY



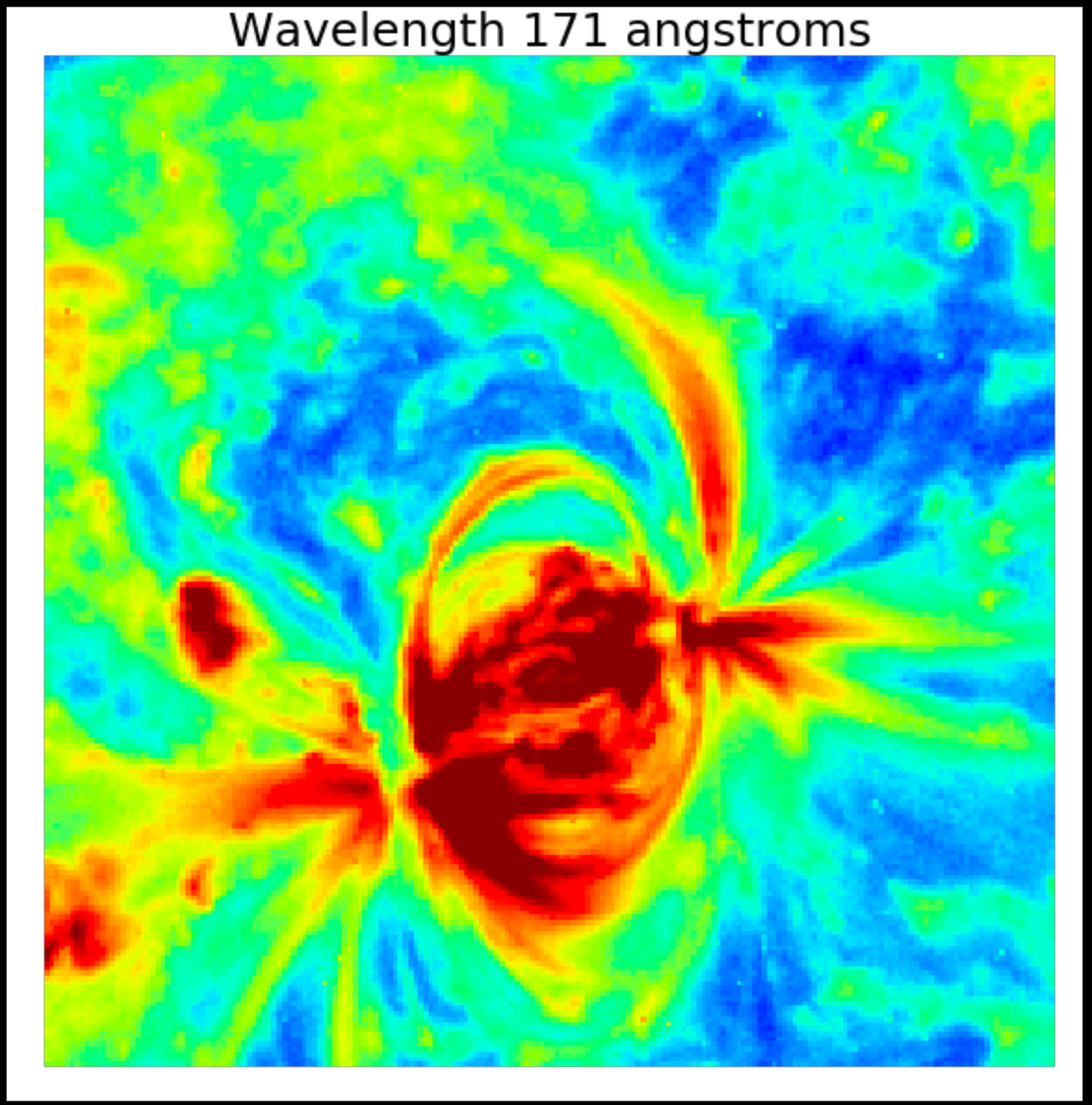
BRIGHT REGIONS HAVE MULTIPLE MODES



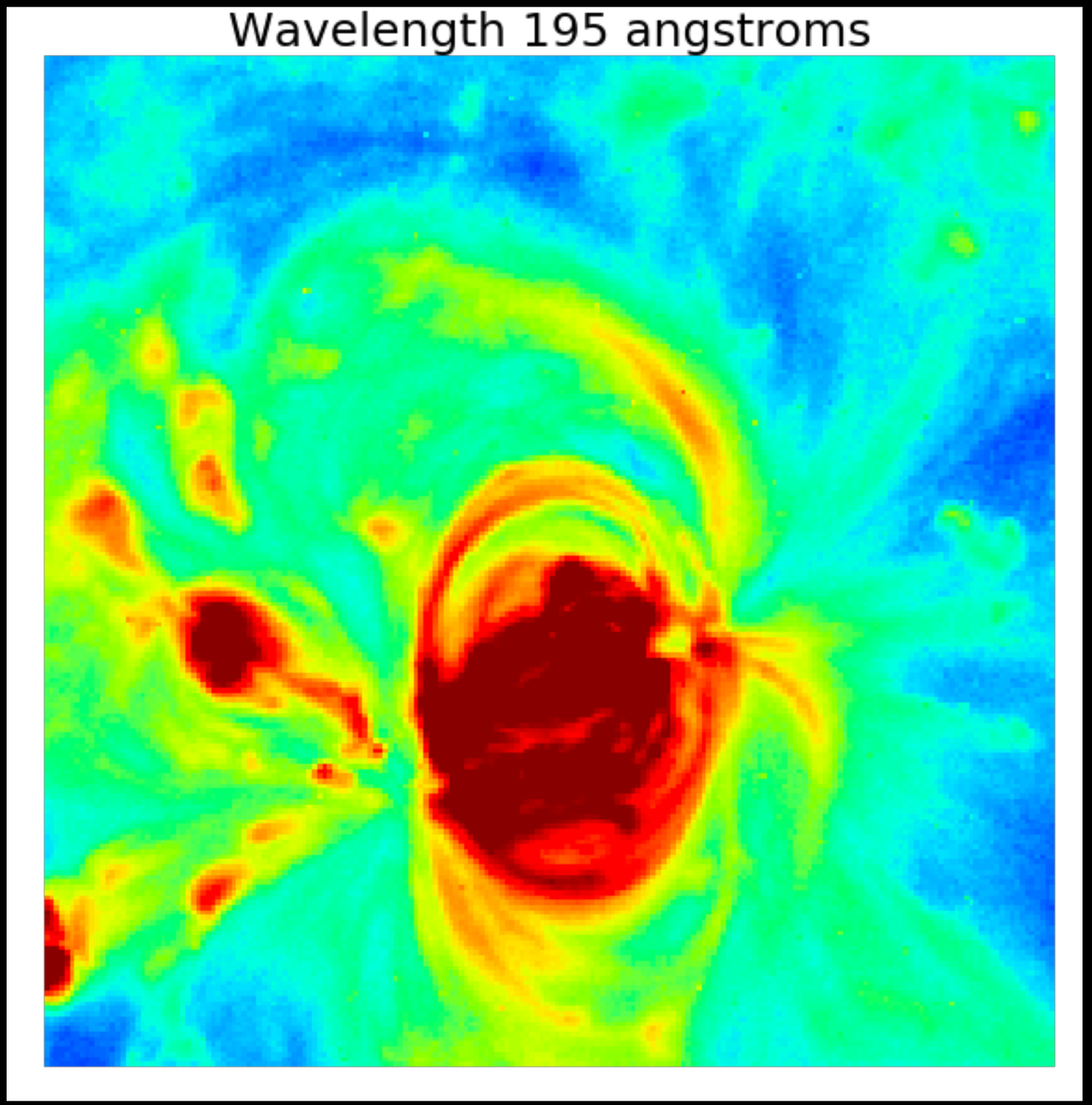
BRIGHT REGIONS HAVE MULTIPLE MODES



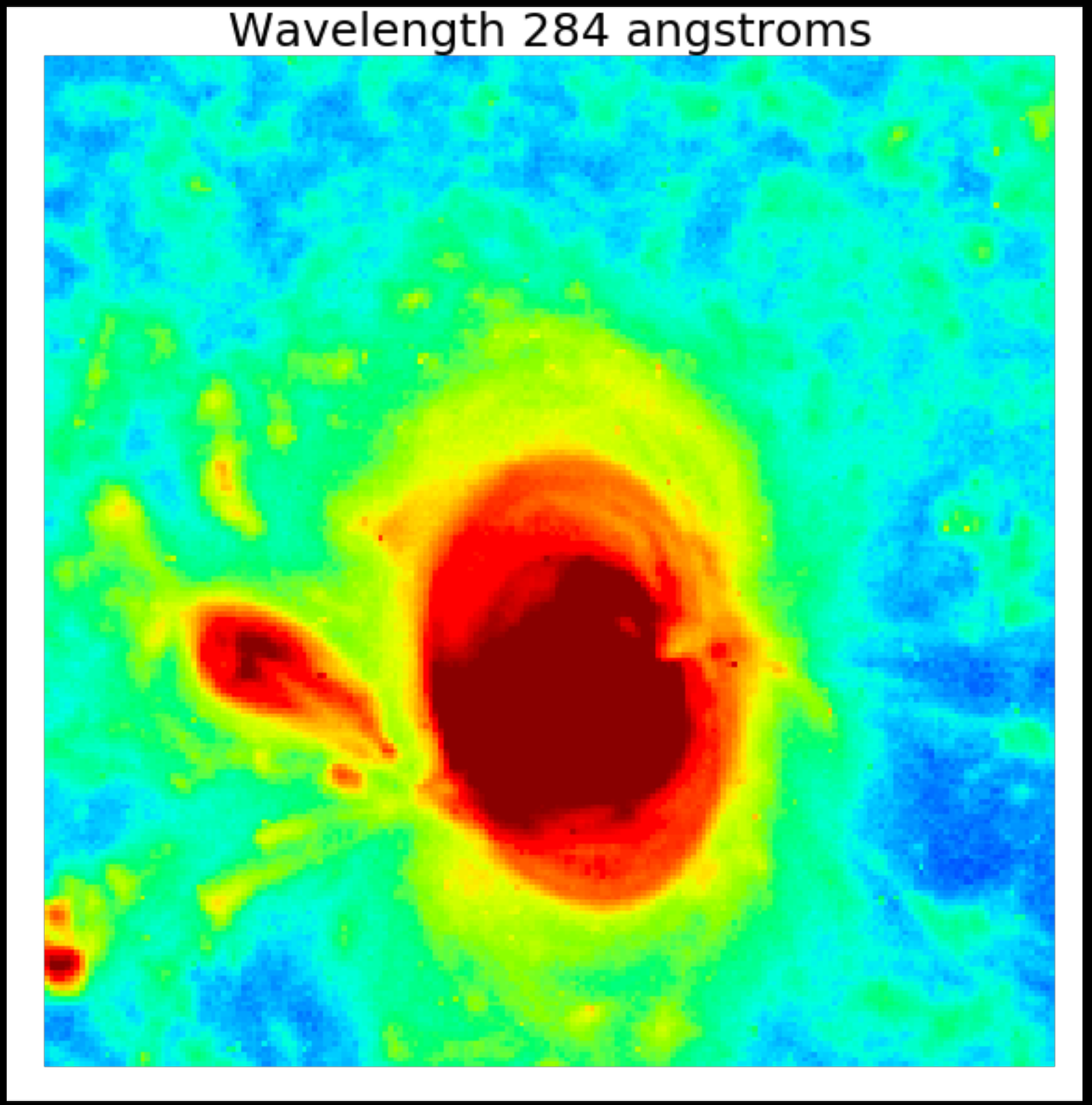
BRIGHT REGIONS HAVE MULTIPLE MODES



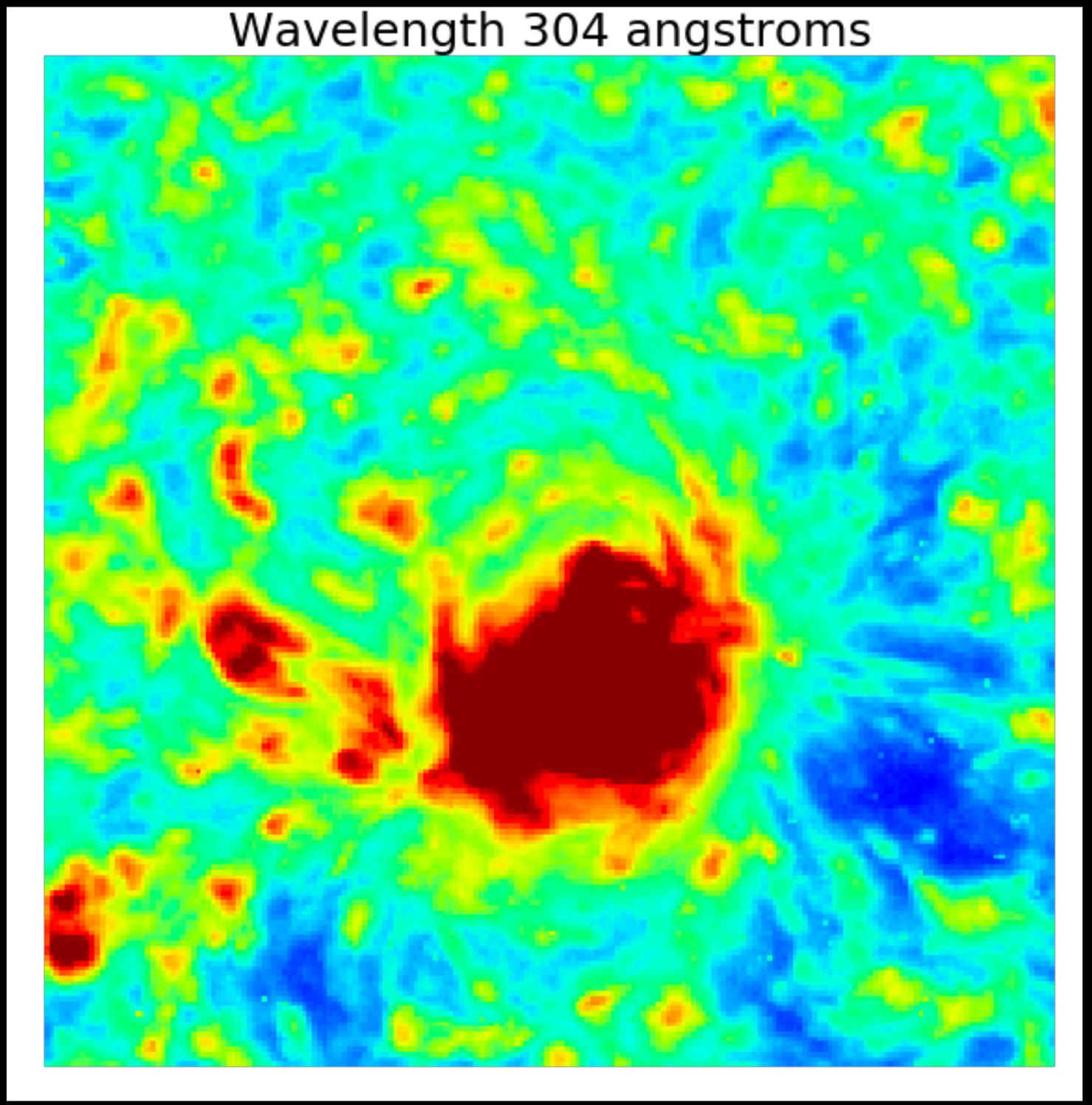
BRIGHT REGIONS HAVE MULTIPLE MODES



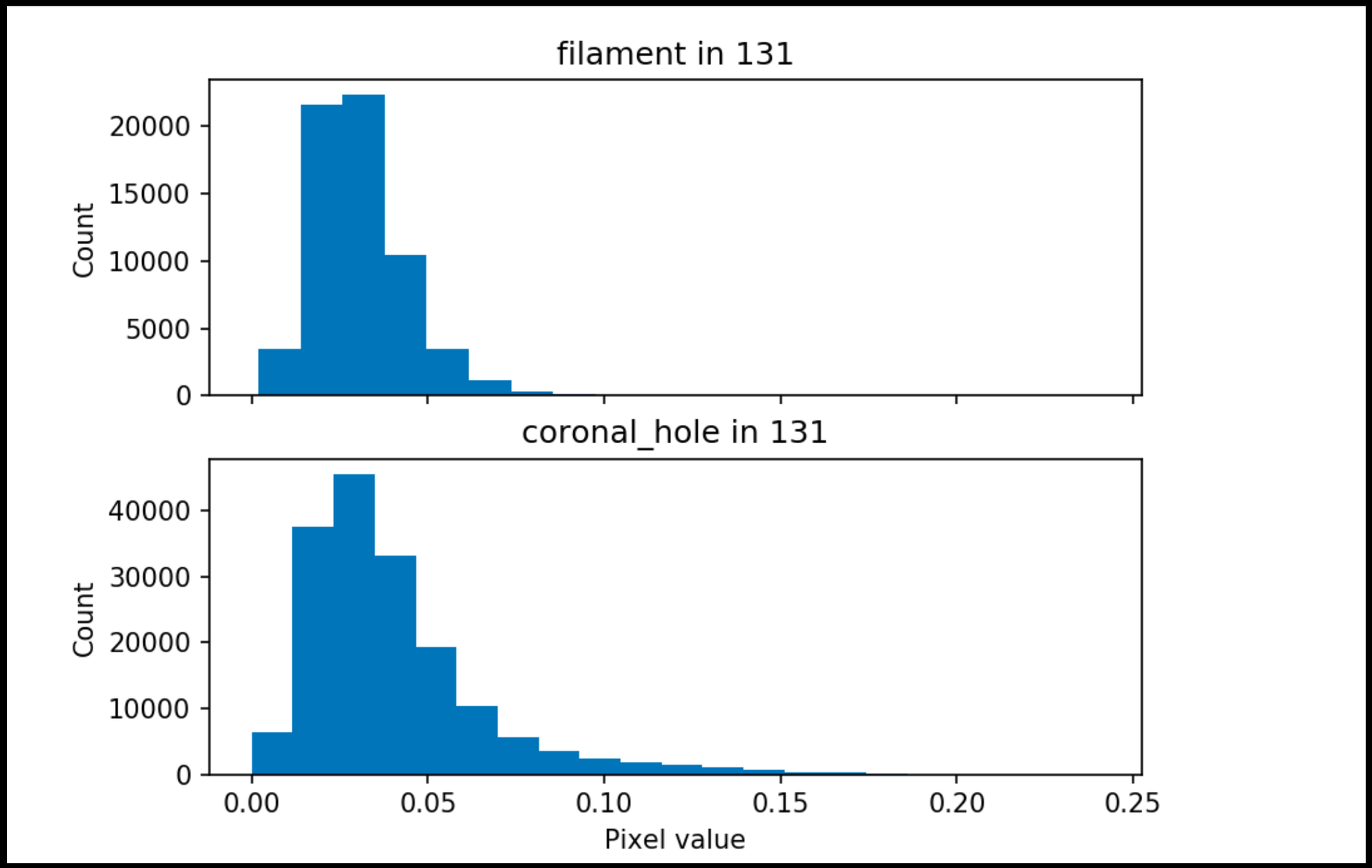
BRIGHT REGIONS HAVE MULTIPLE MODES



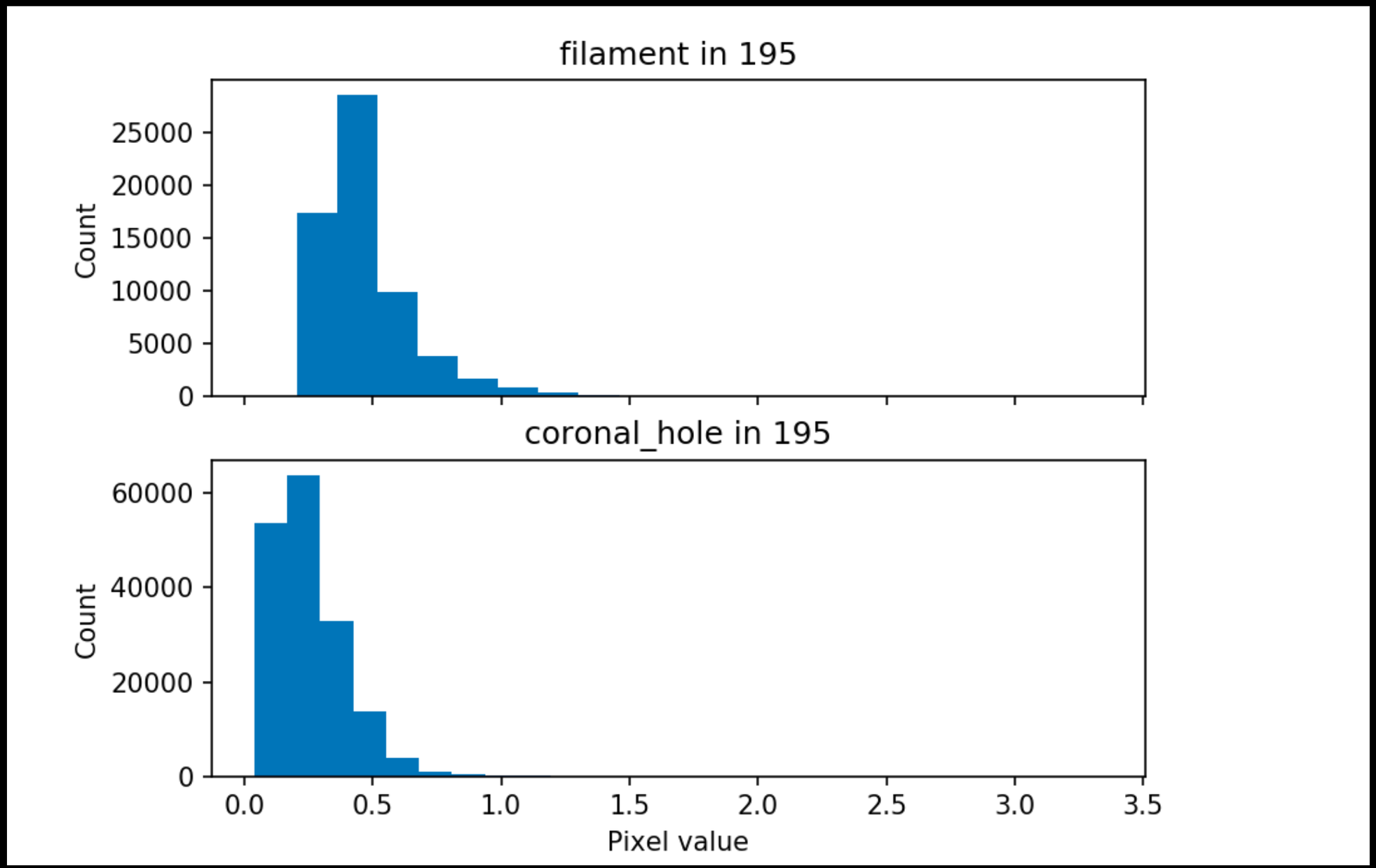
BRIGHT REGIONS HAVE MULTIPLE MODES

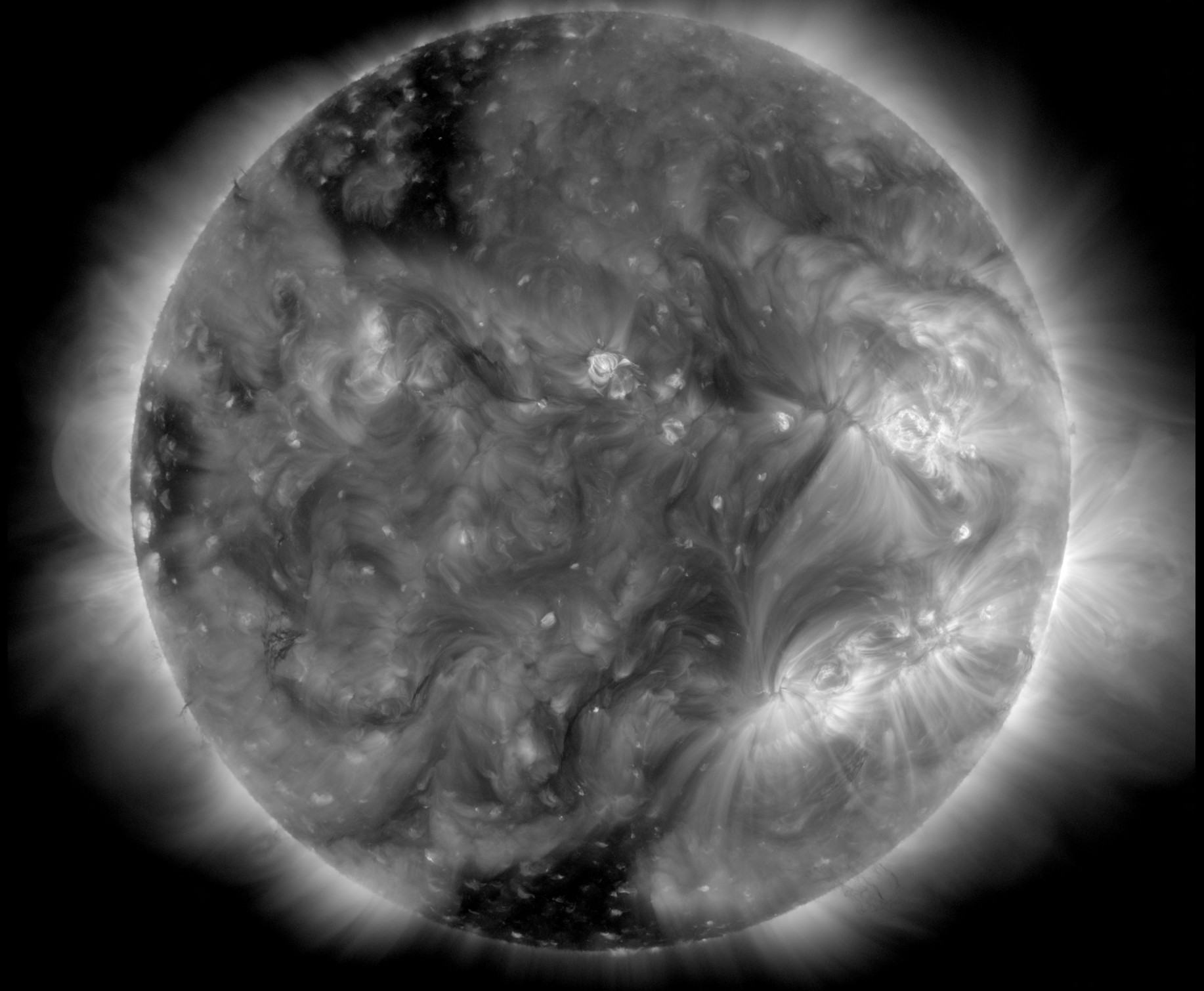


CORONAL HOLES AND FILAMENTS ARE DIFFICULT TO DISTINGUISH



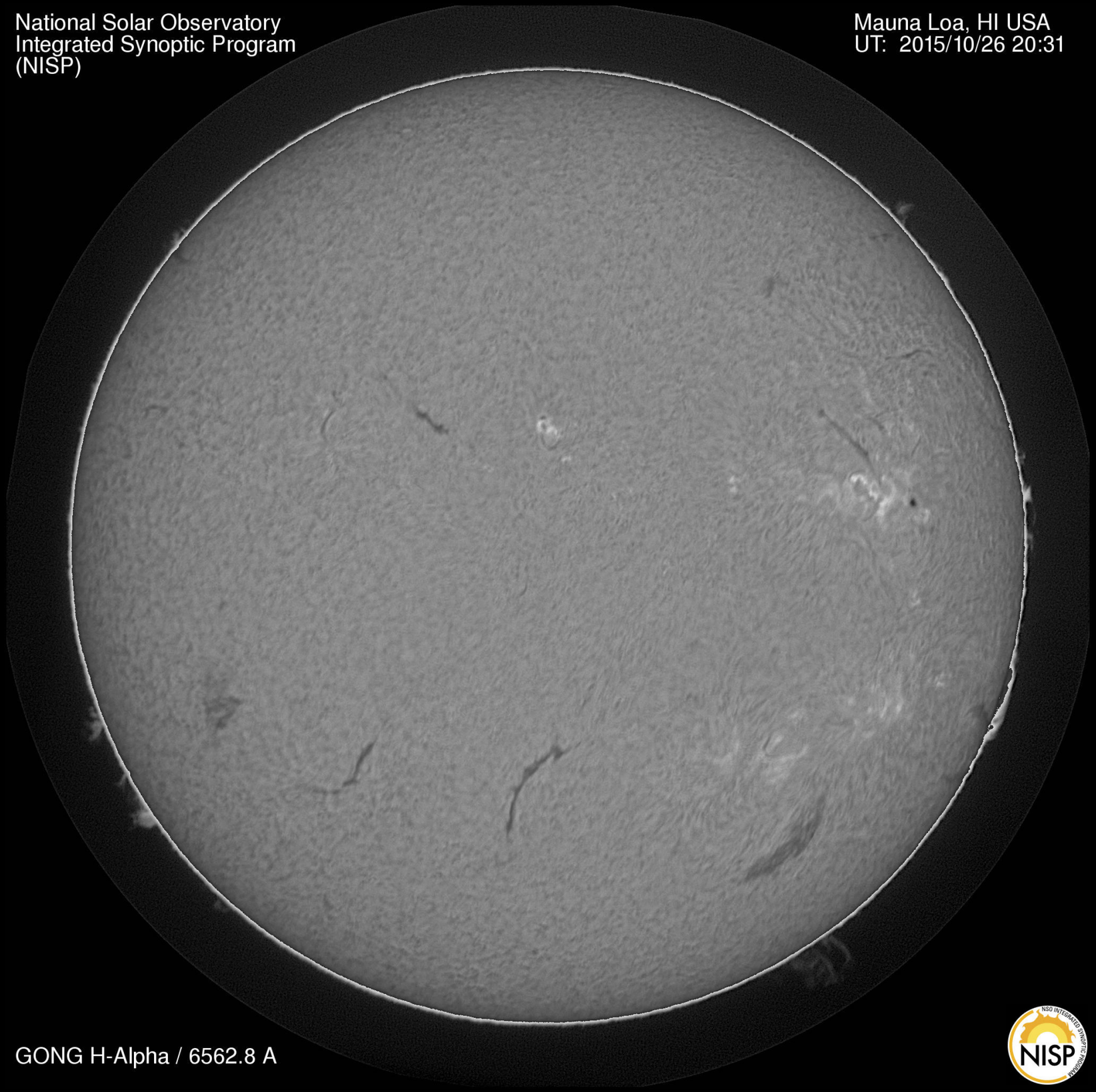
CORONAL HOLES AND FILAMENTS ARE DIFFICULT TO DISTINGUISH



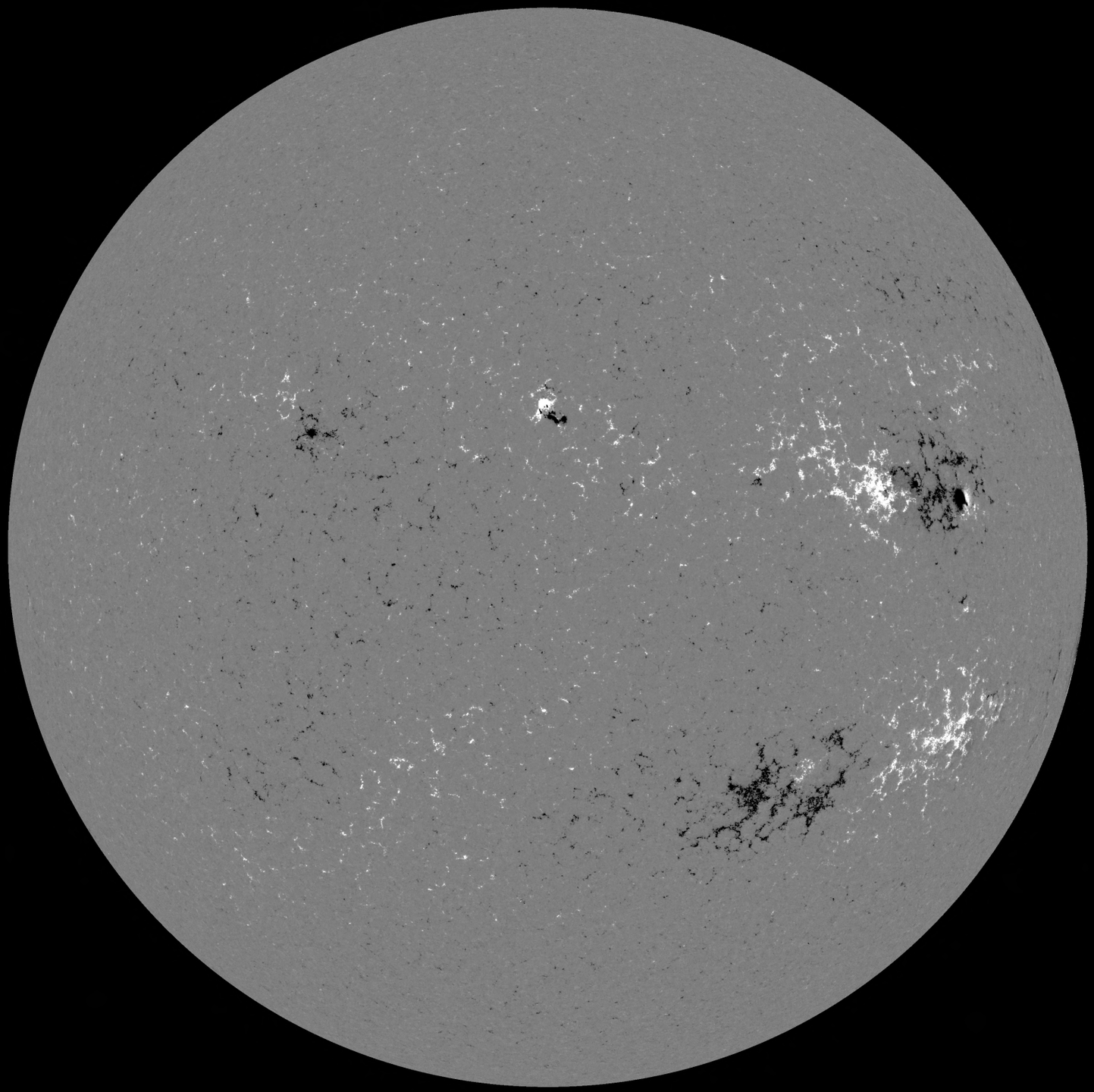


National Solar Observatory
Integrated Synoptic Program
(NISP)

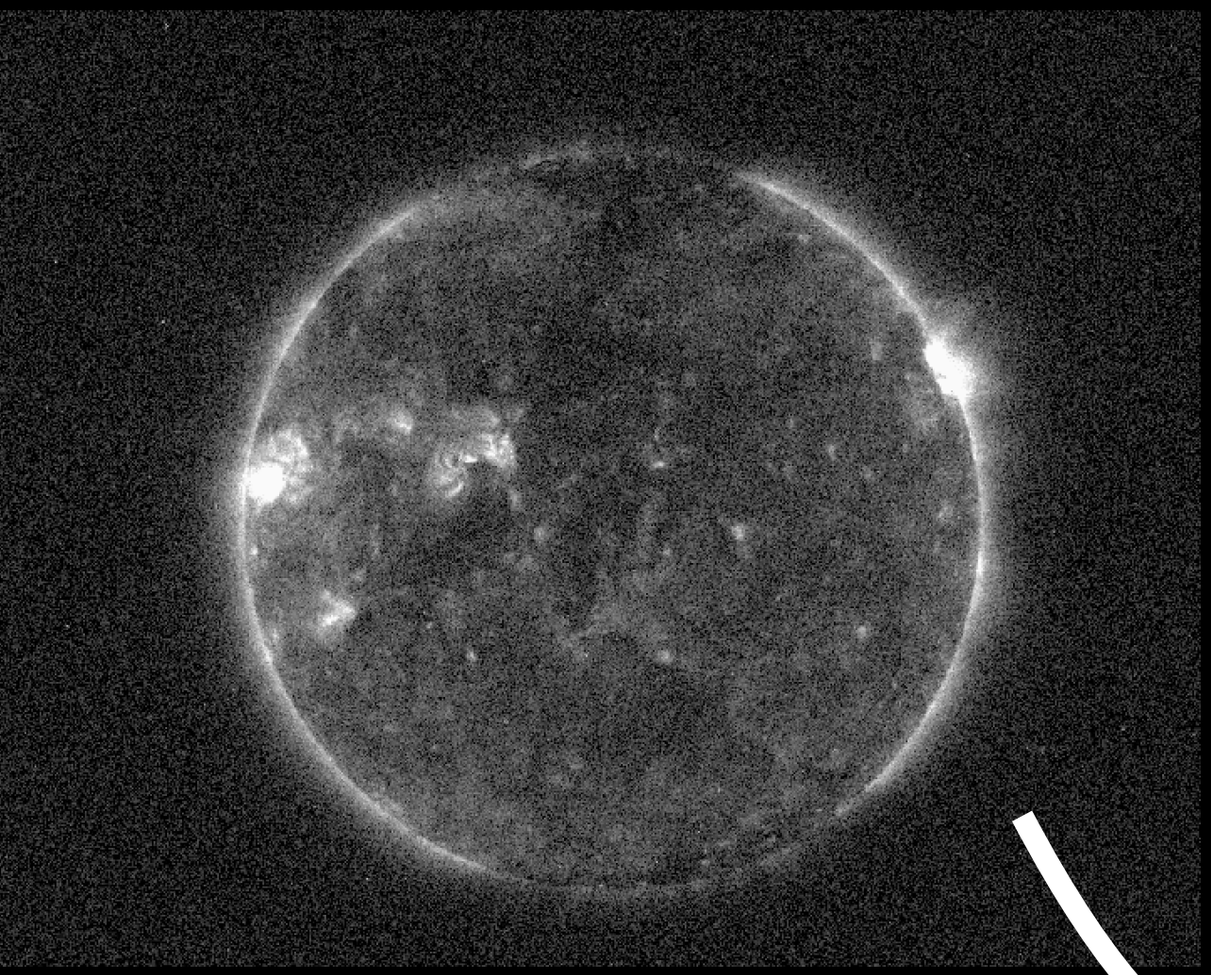
Mauna Loa, HI USA
UT: 2015/10/26 20:31

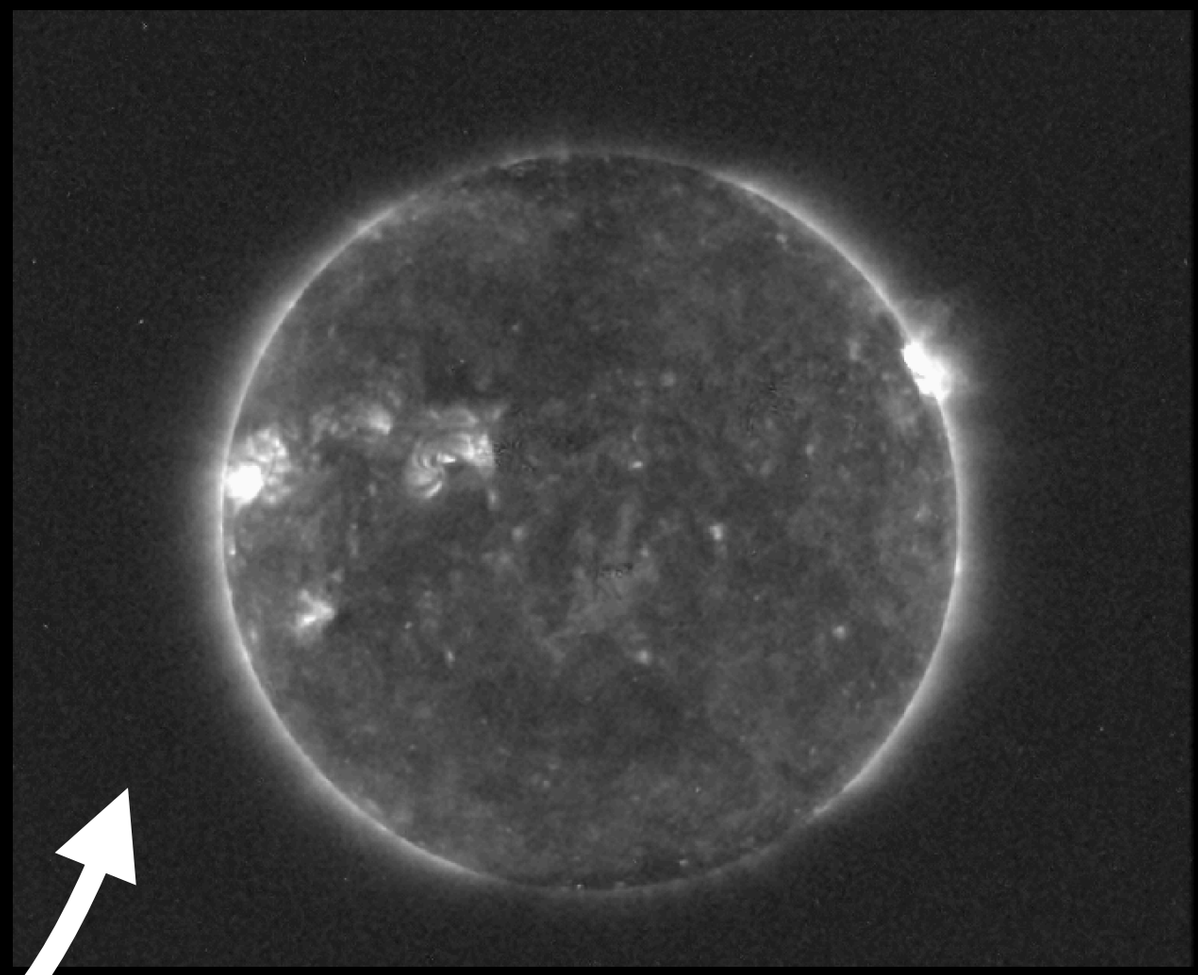


GONG H-Alpha / 6562.8 A



NOISE GATING



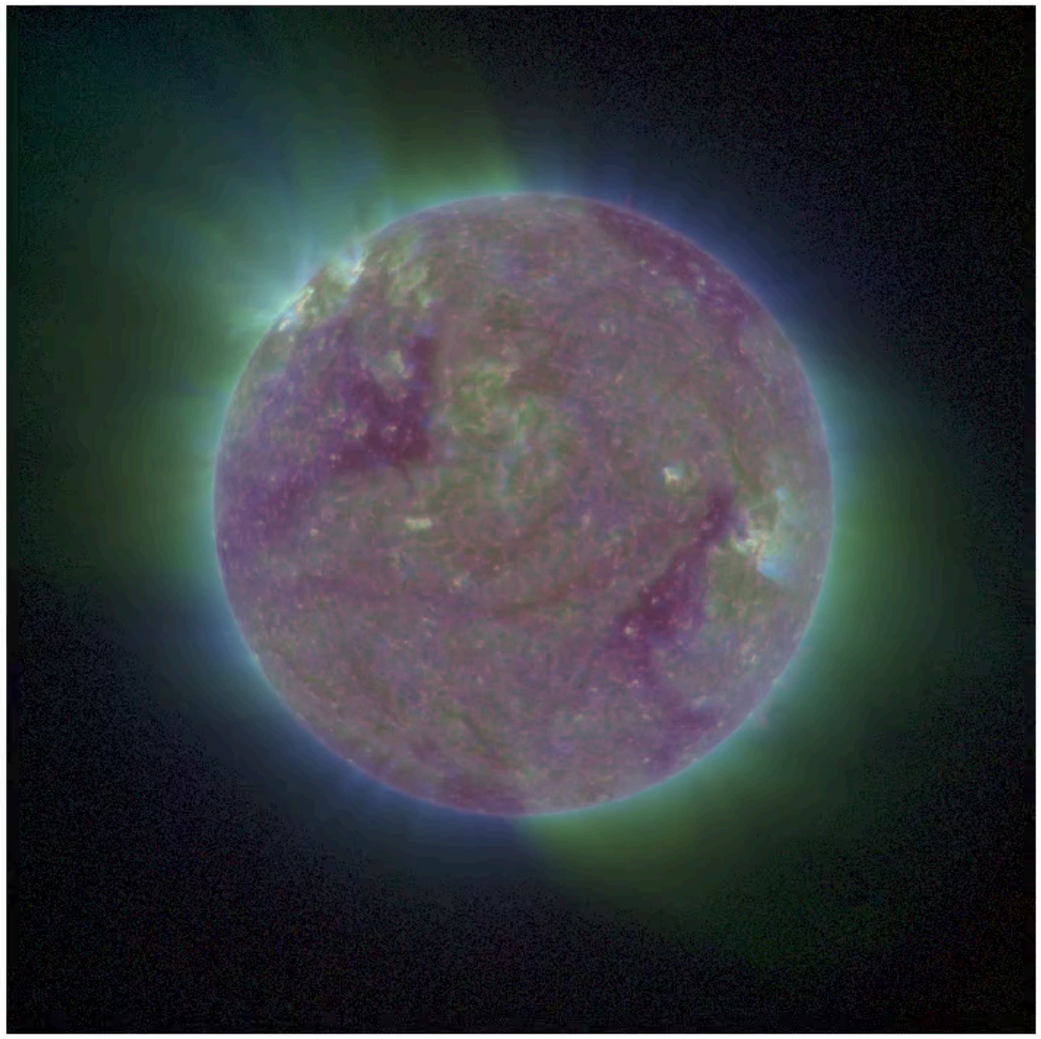


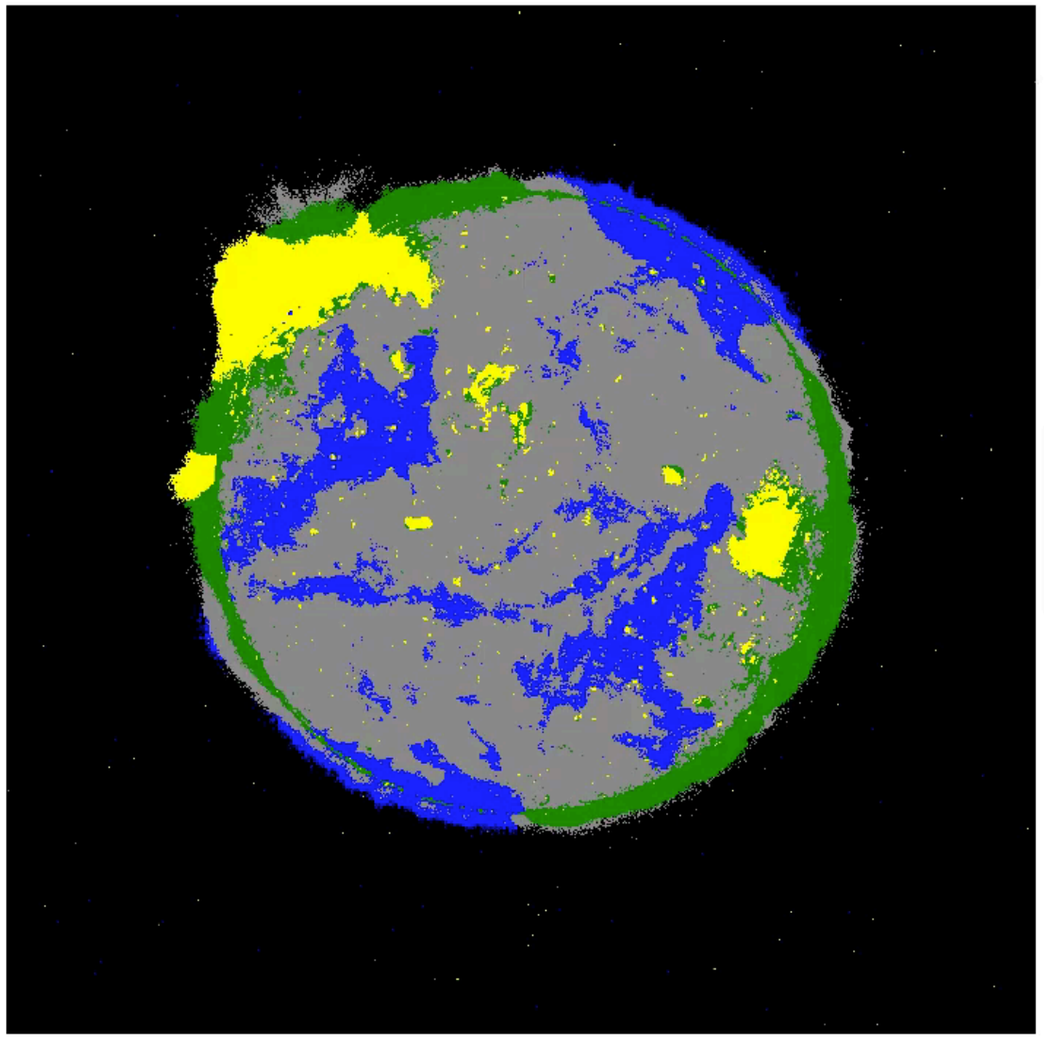
C. E. DeForest 2017 *ApJ* **838** 155

RESULTS

CONSISTENT OVER SHORT TIME SCALES

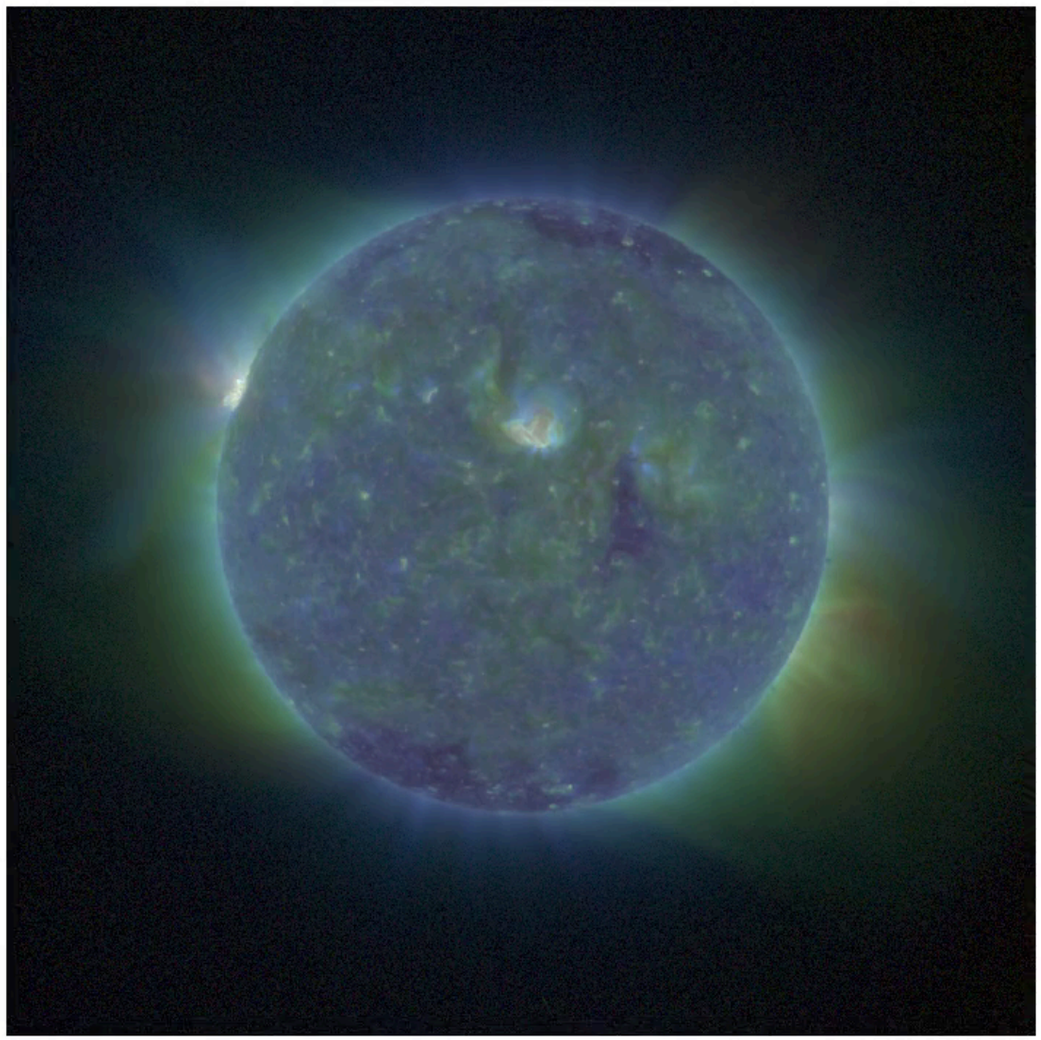
20170418 180246

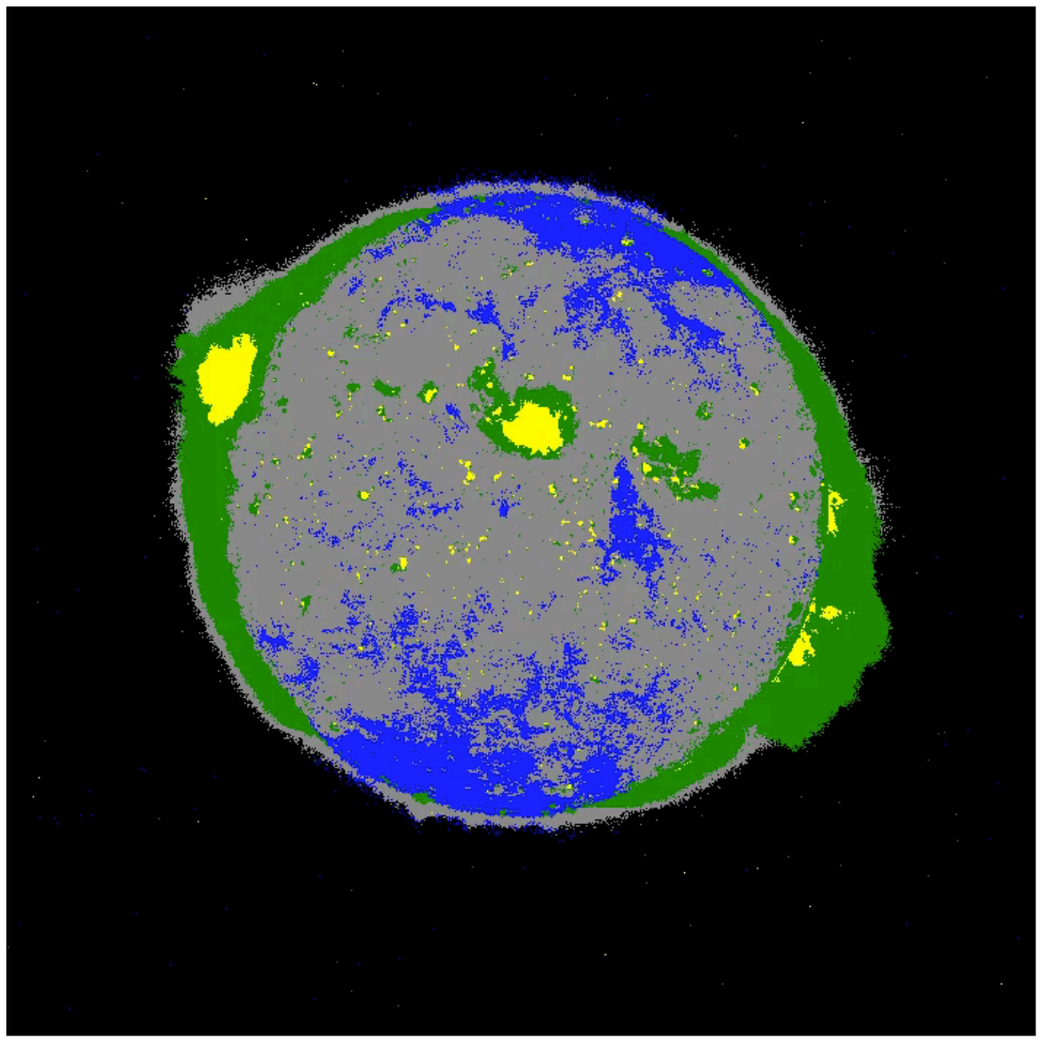




AND LONG!

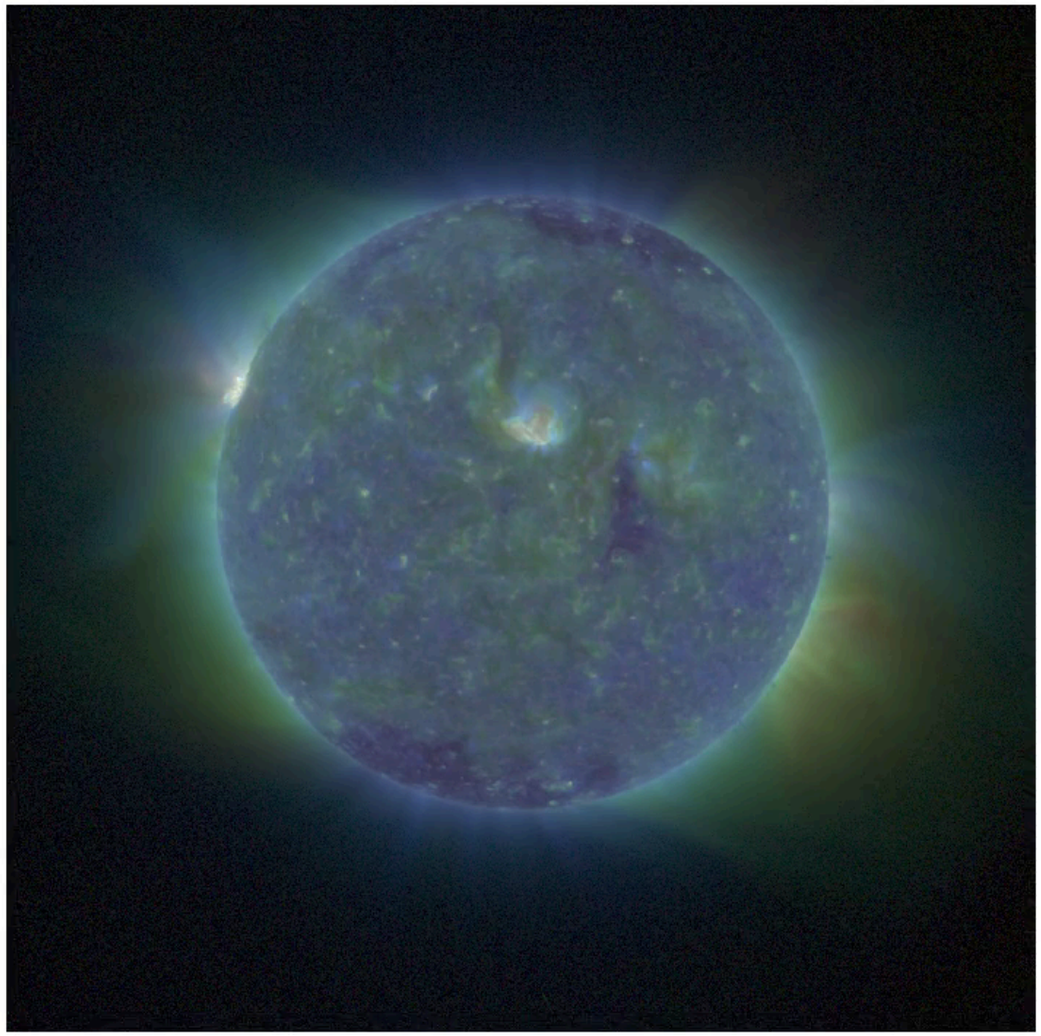
2017-06-01 10:24

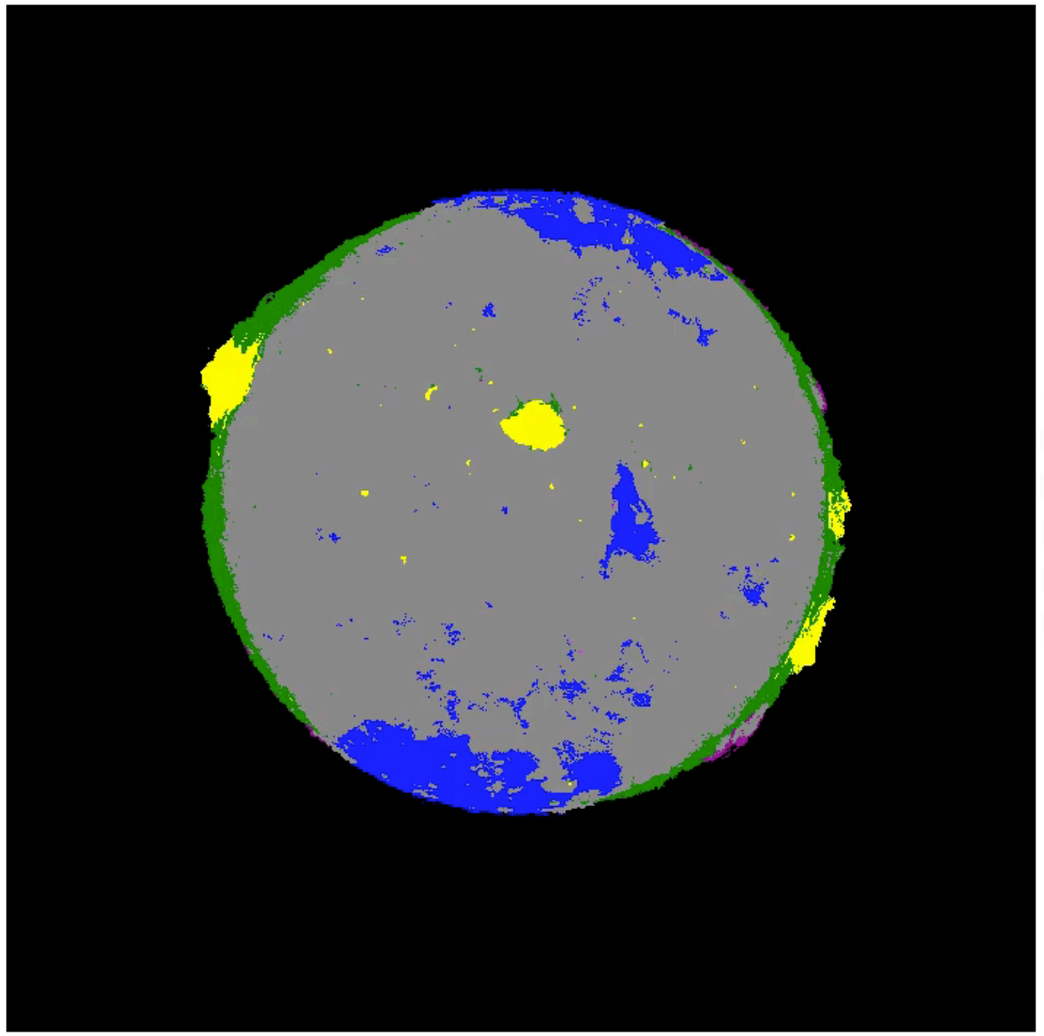




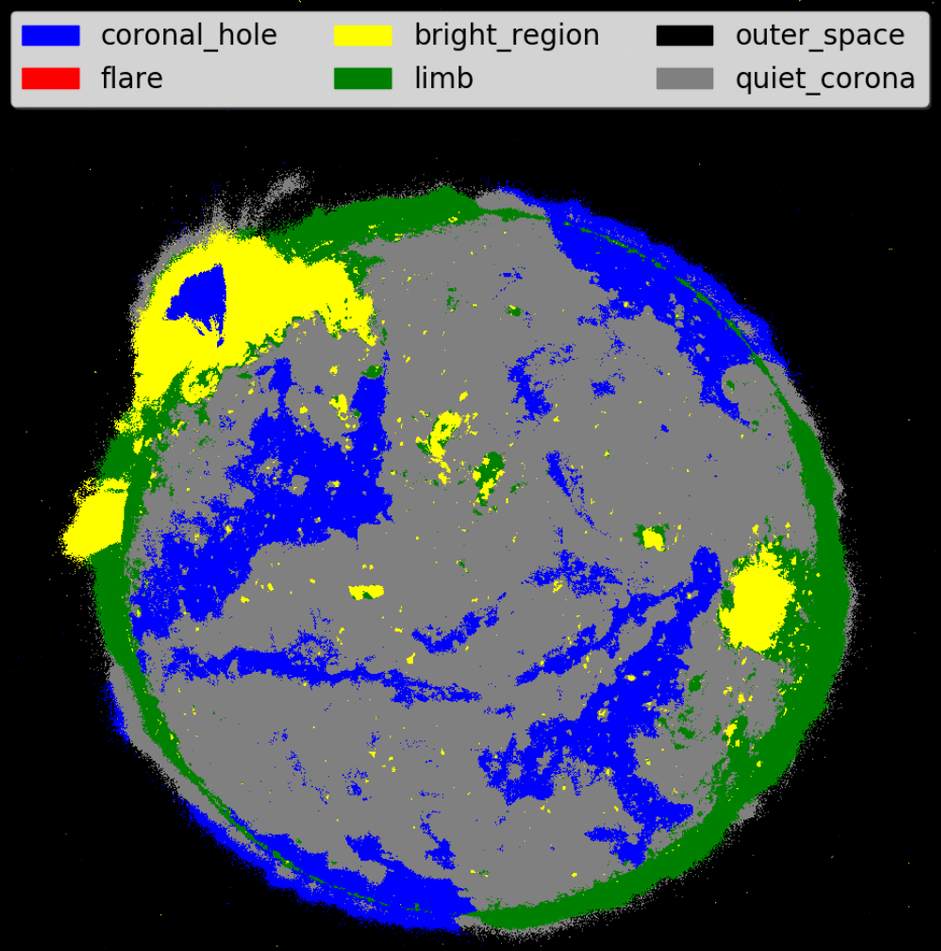
NEURAL NETWORKS

2017-06-01 10:24

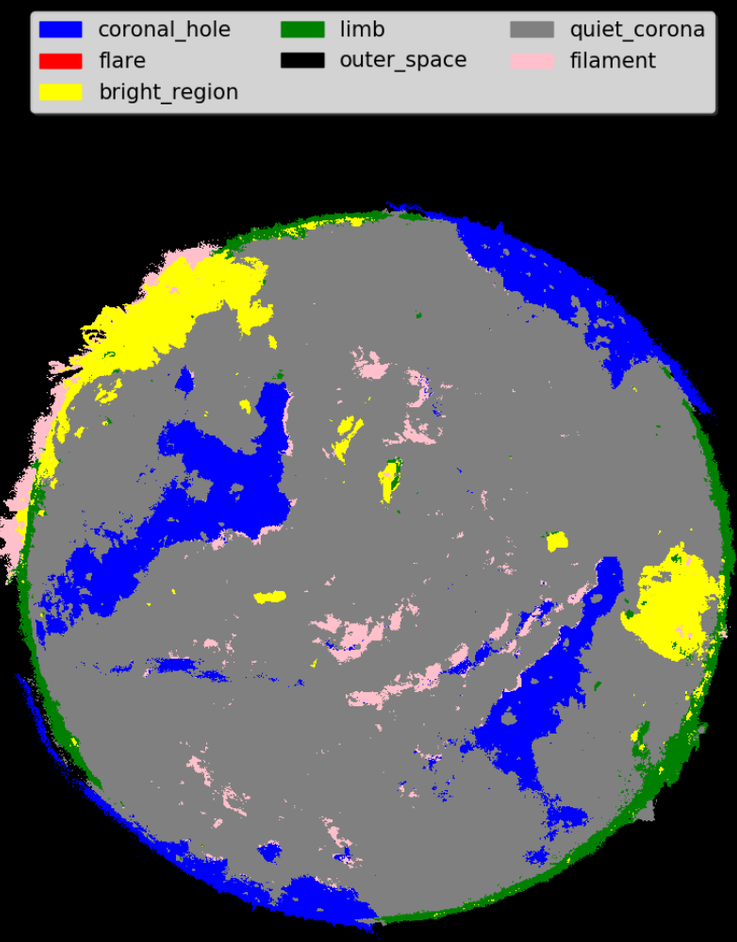




COMPARISON



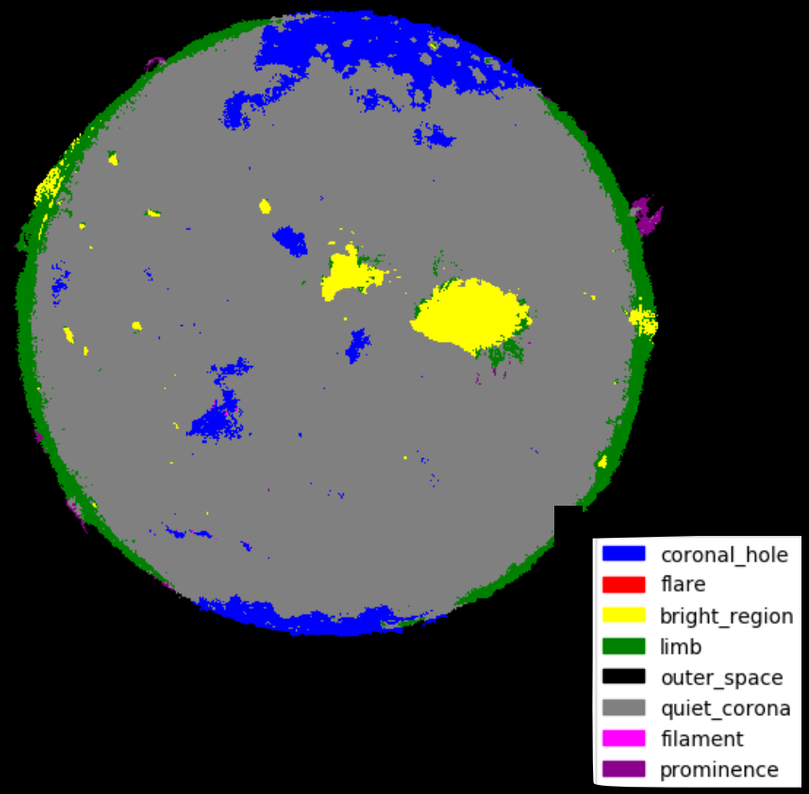
BAYESIAN

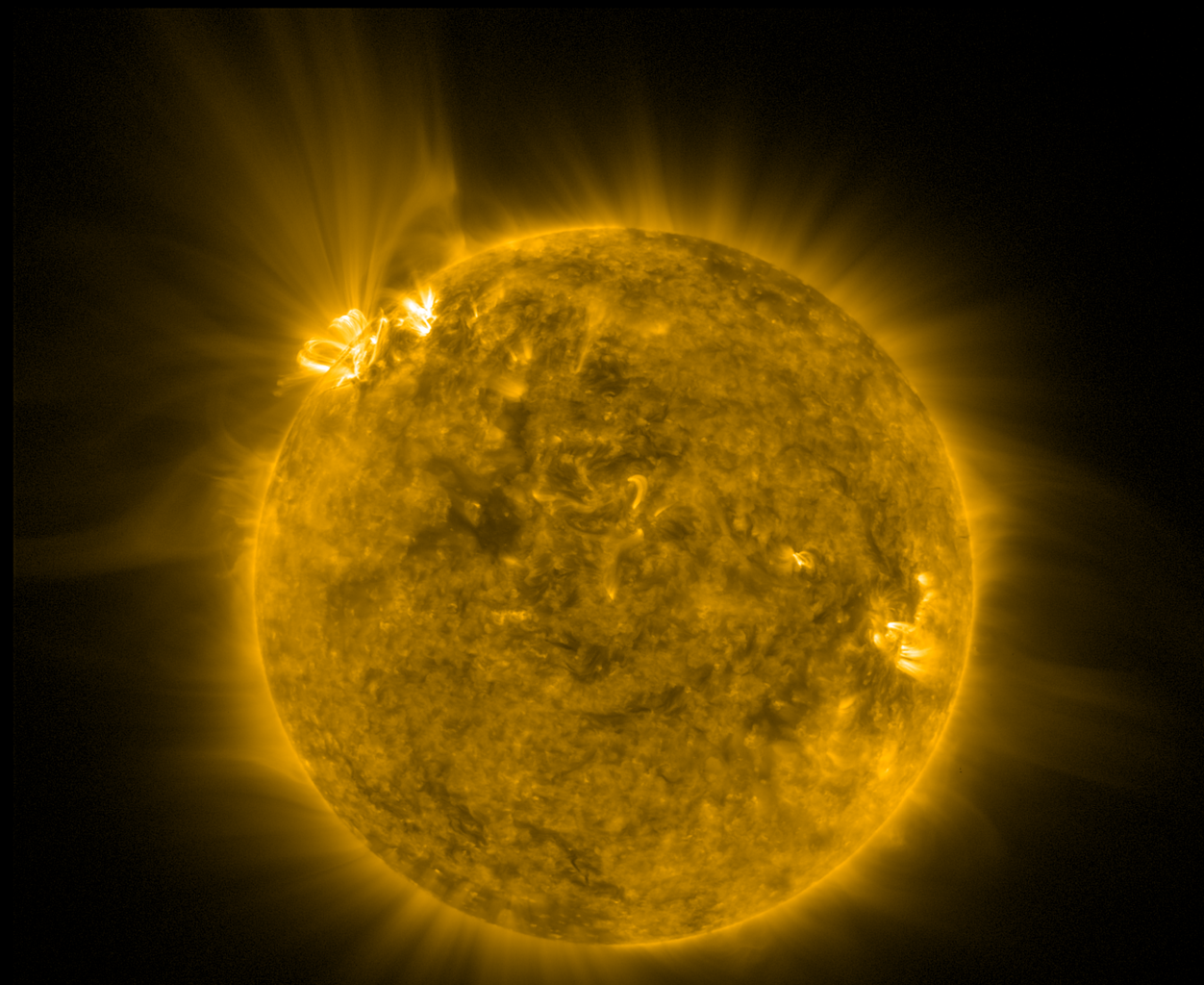


NEURAL

FUTURE STEPS

- Create larger training database
- Try convolutional neural network
- Incorporate magnetograms and H-alpha to distinguish between filaments & coronal holes
- Explore ensemble approach to classification





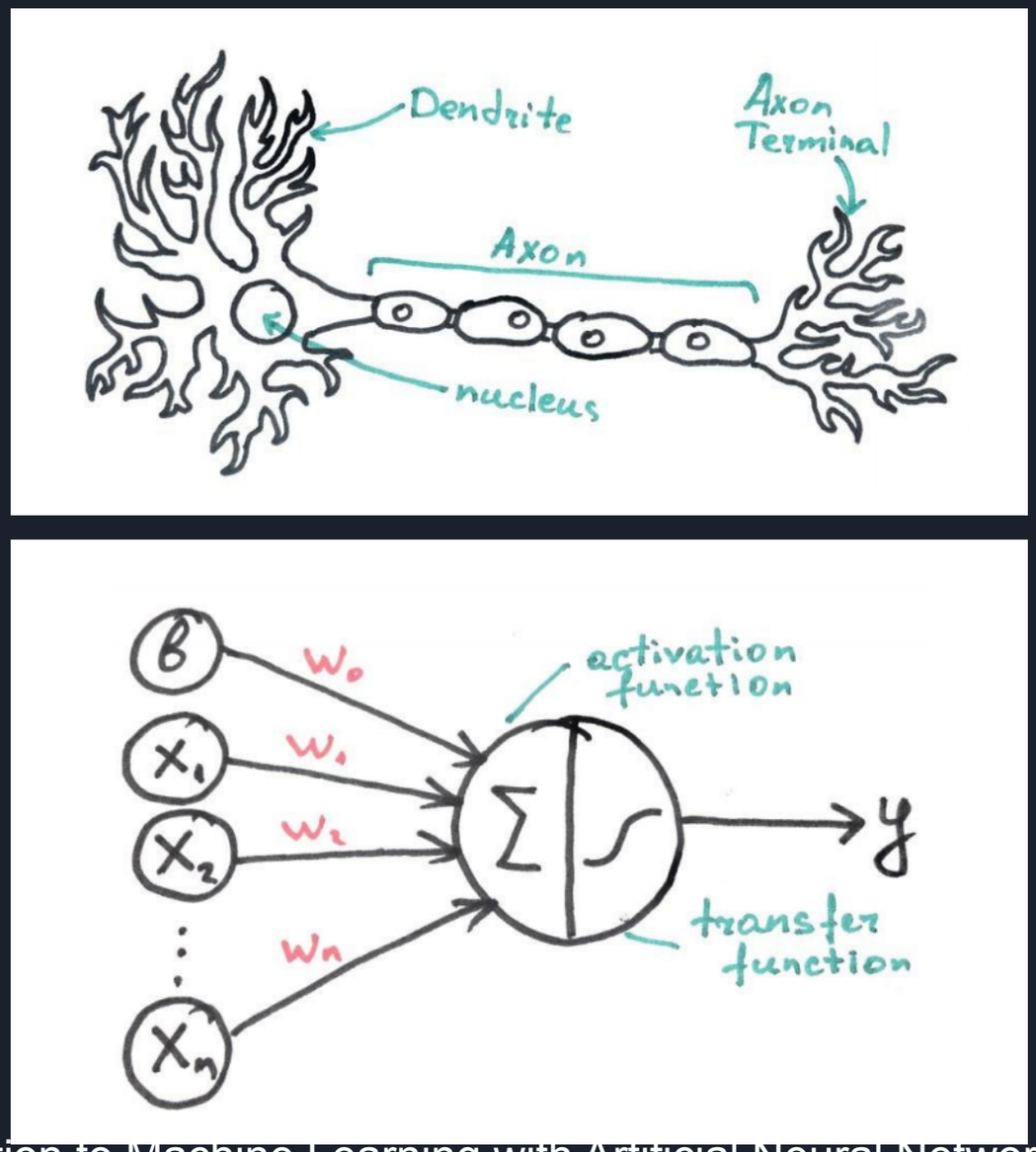
QUESTIONS?

Please don’t try this at home.

GOES-16 and SUVI data are still in a preliminary state and may contain errors. SUVI data should not be used operationally and the user assumes all responsibility for use of the data.

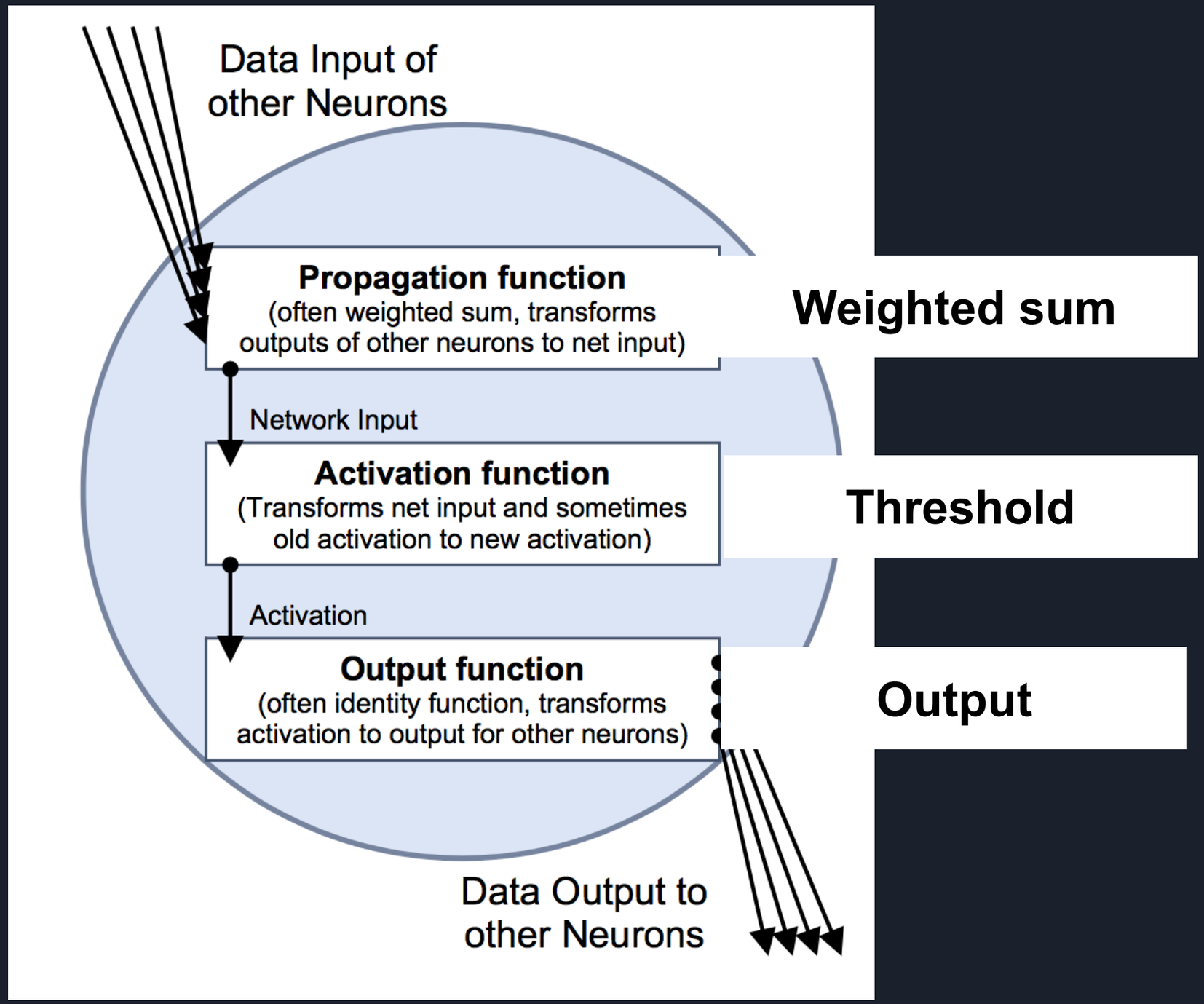
EXTRA SLIDES

What is an artificial neural network?

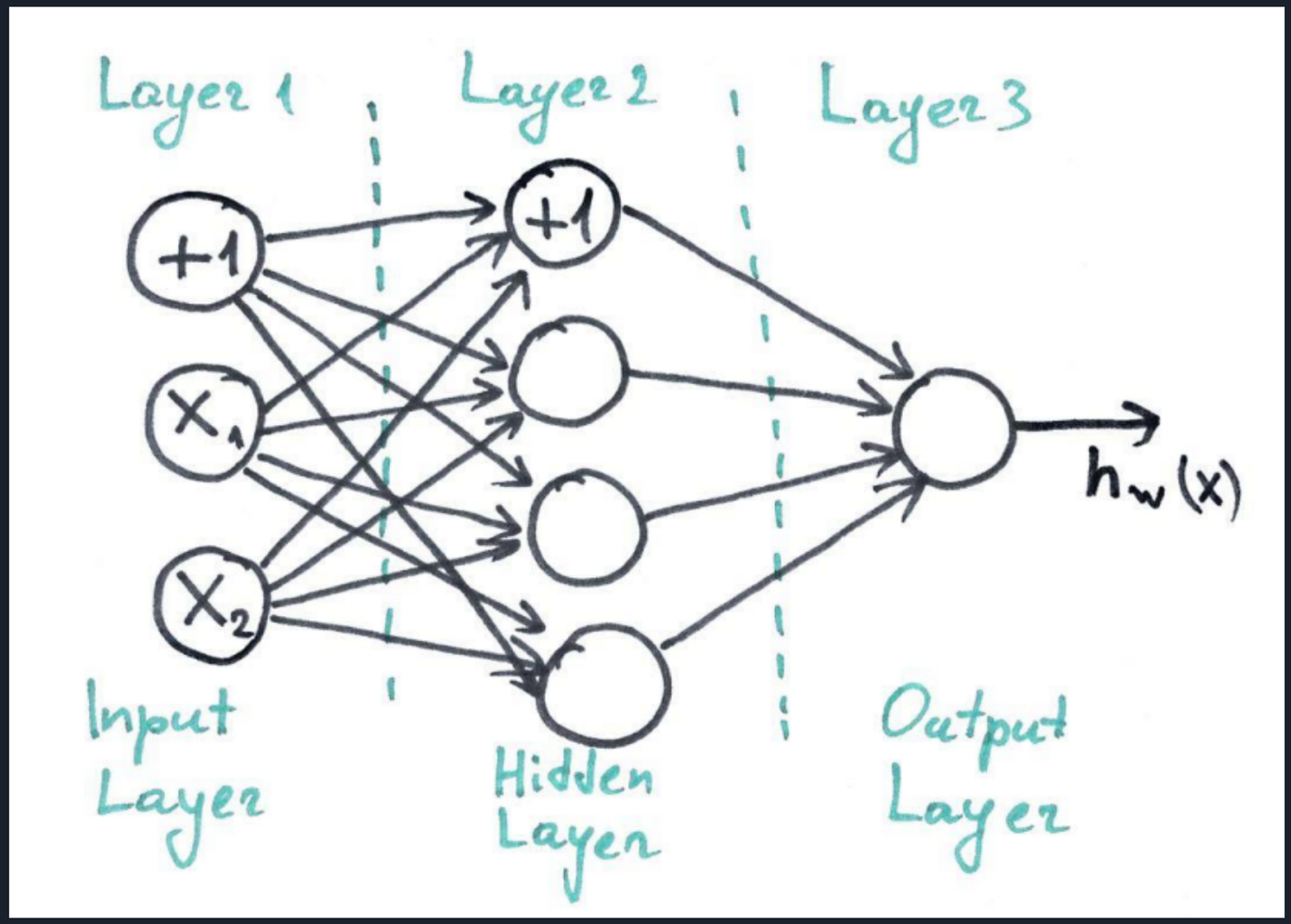


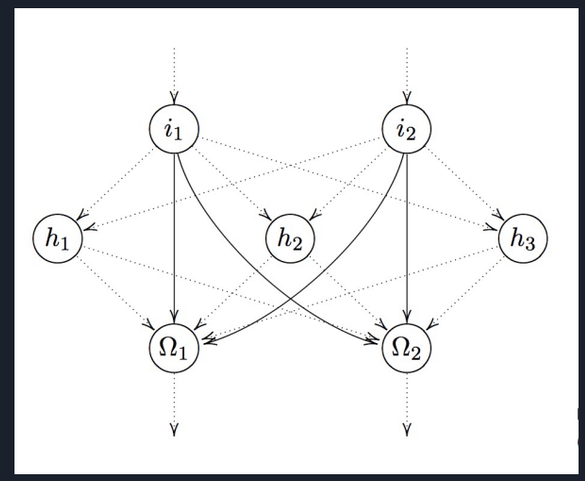
Human

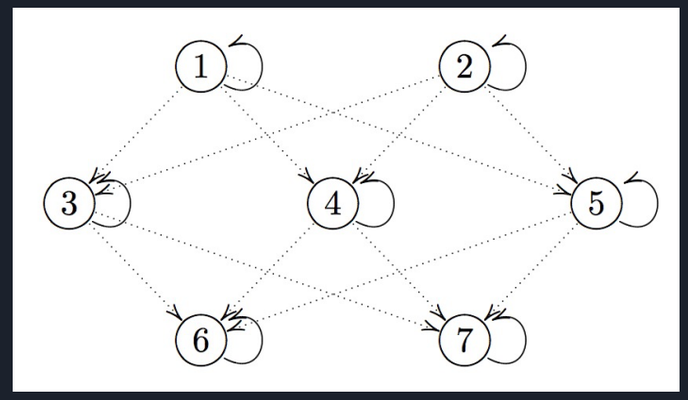
Artificial model


Data Input of other Neurons
Propagation function
(often weighted sum, transforms outputs of other neurons to net input)
Network Input
Activation function
(Transforms net input and sometimes old activation to new activation)
Activation
Output function
(often identity function, transforms activation to output for other neurons)
Data Output to other Neurons
Weighted sum
Threshold
Output

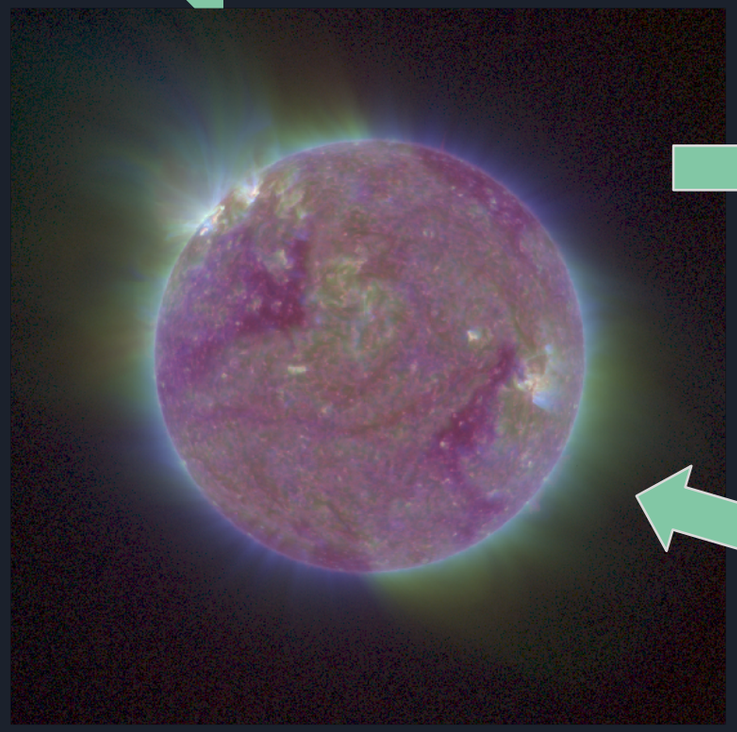
What is an artificial neural network?



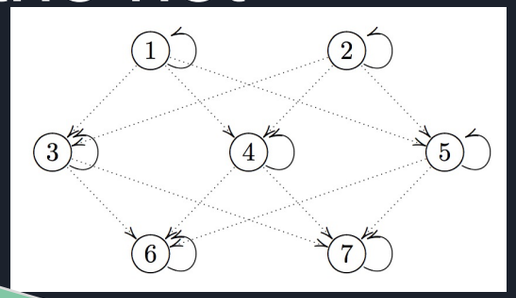


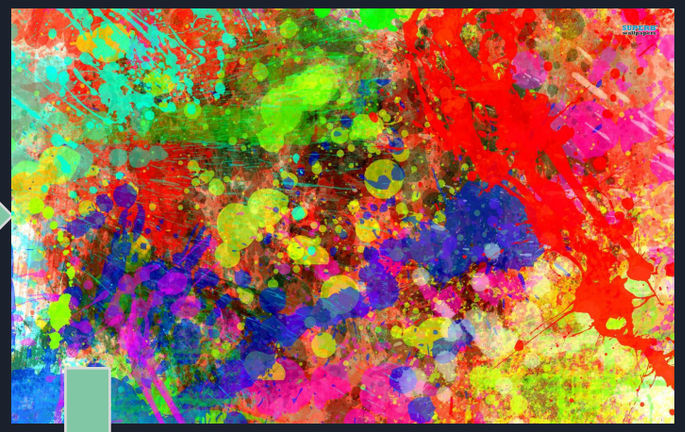


It’s all in the weights!
Backpropagation

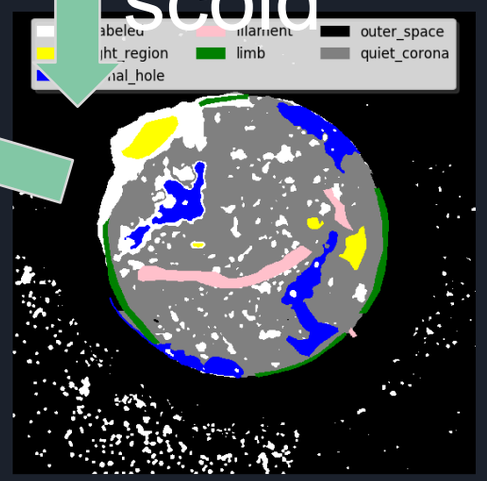


Run it through the net

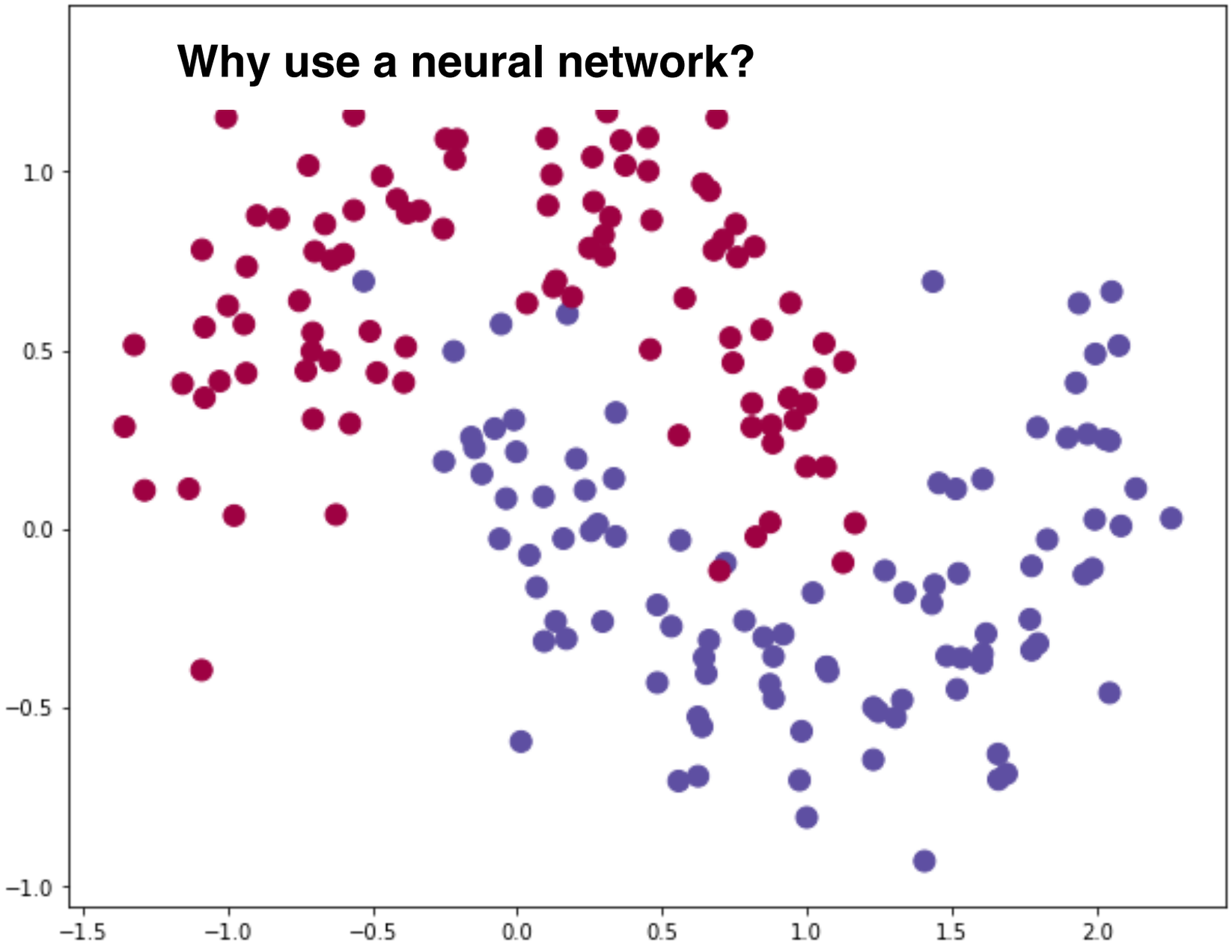


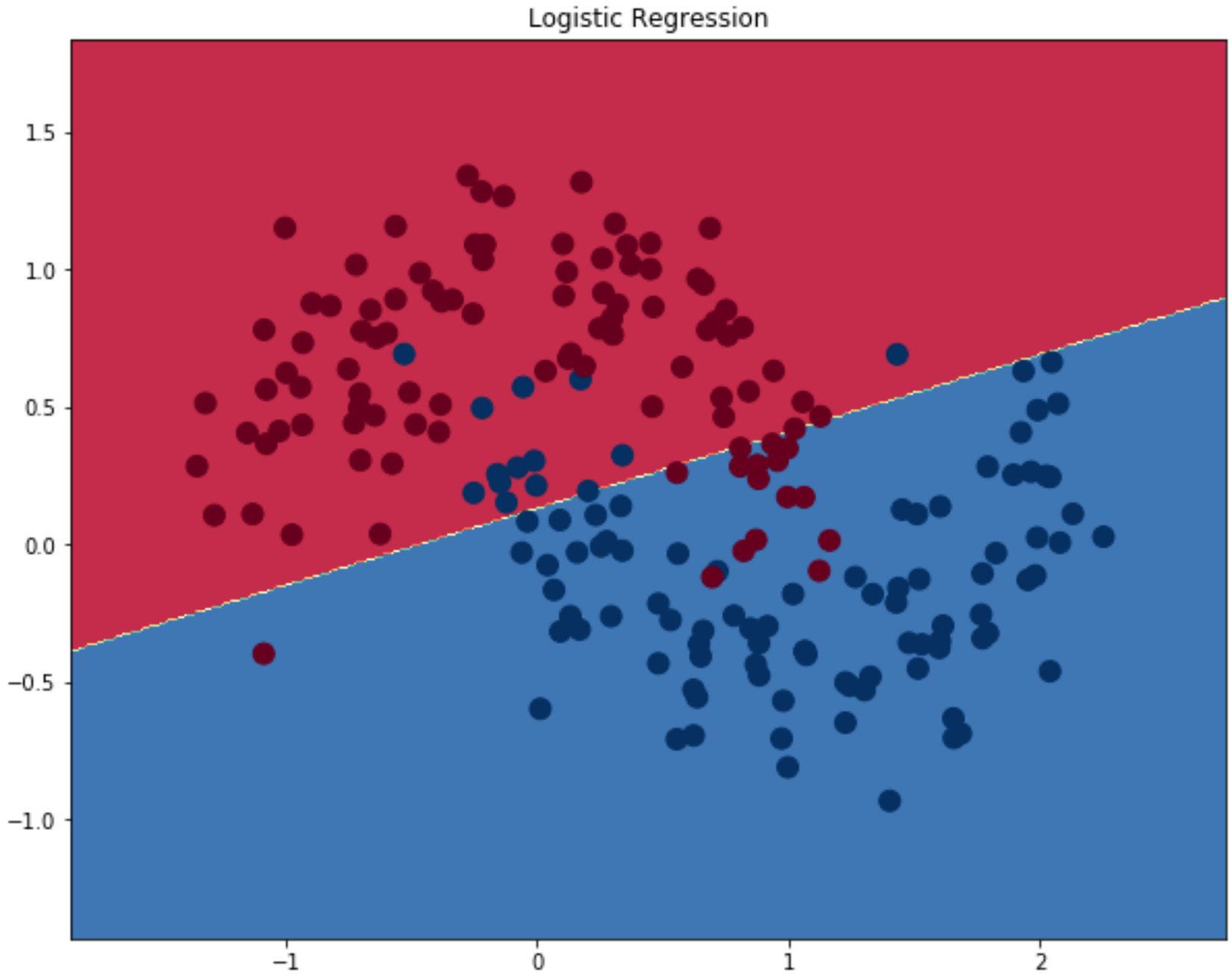


Estimate error and scold



Adjust weights and repeat


Why use a neural network?
1.0
0.5
0.0
−0.5
−1.0
−1.5
−1.0
−0.5
0.0
0.5
1.0
1.5
2.0


Logistic Regression
1.5
1.0
0.5
0.0
−0.5
−1.0
−1
0
1
2


Decision Boundary for hidden layer size 3
1.5
1.0
0.5
0.0
−0.5
−1.0
−1
0
1
2

Guidelines

1. Understand and specify the problem in terms of inputs and required outputs
2. Take the simplest form of network you think might be able to solve your problem
3. **Train** until the network produces the right outputs for each input in its training data
4. Make sure that the network works on its **training data** and test its generalization by checking its performance on **new testing data**
5. If the network doesn't perform well enough, go back to stage 3 and try harder
6. If the network still doesn't perform well enough, go back to stage 2 and try harder
7. If the network still doesn't perform well enough, go back to stage 1 and try harder
8. Problem solved – or not

Kevin Swingler lecture: http://www.cs.stir.ac.uk/courses/ITNP4B/lectures/kms/2-Perceptrons.pdf

Toolkits

1. Theanos
2. TensorFlow
3. Keras
4. From scratch!
5. Many more