

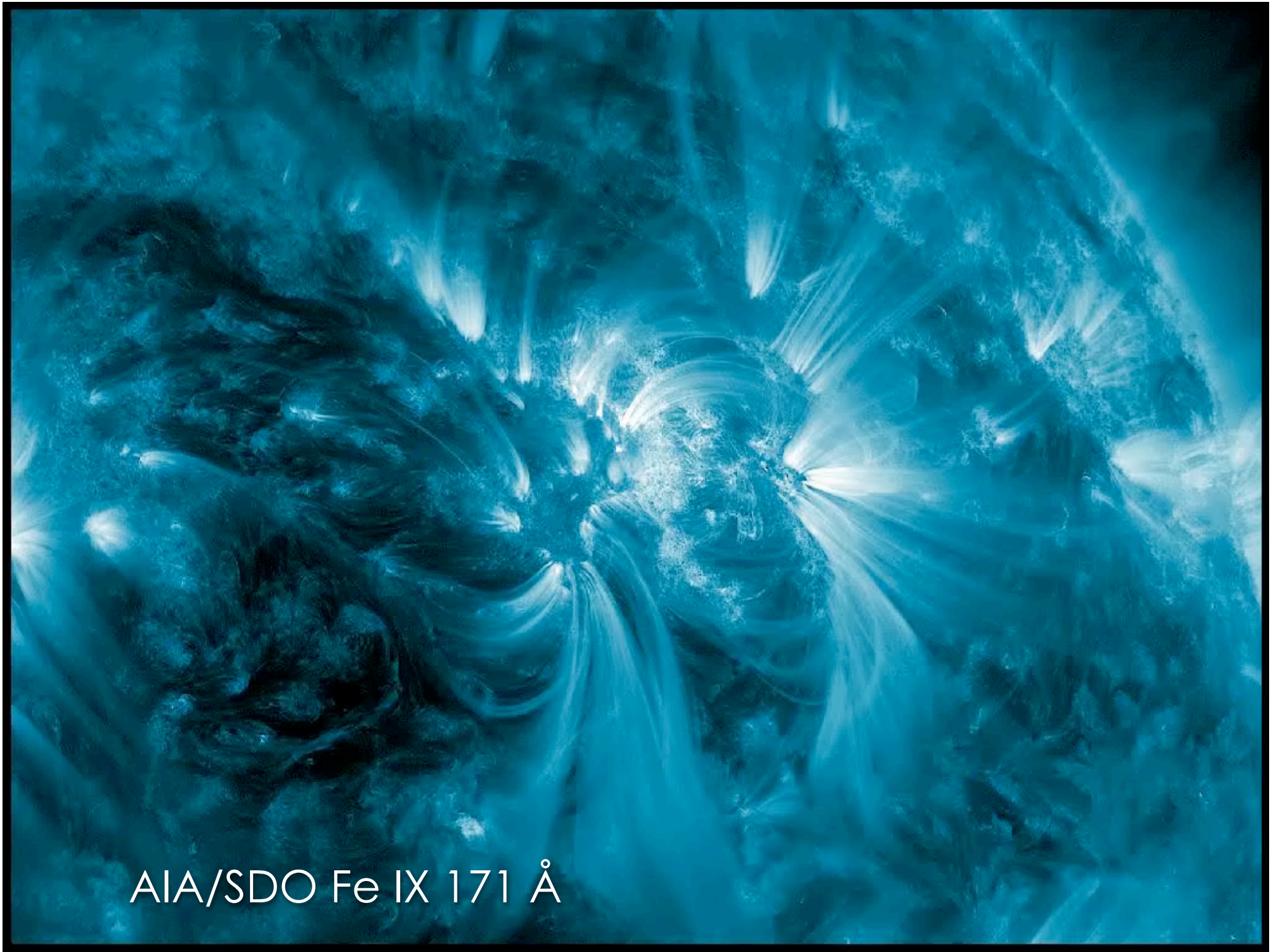
The Observation and Modeling of Active Region Emission: Constraints from Hinode

Harry Warren [Naval Research Laboratory] • Ignacio Ugarte-Urra [George Mason University]

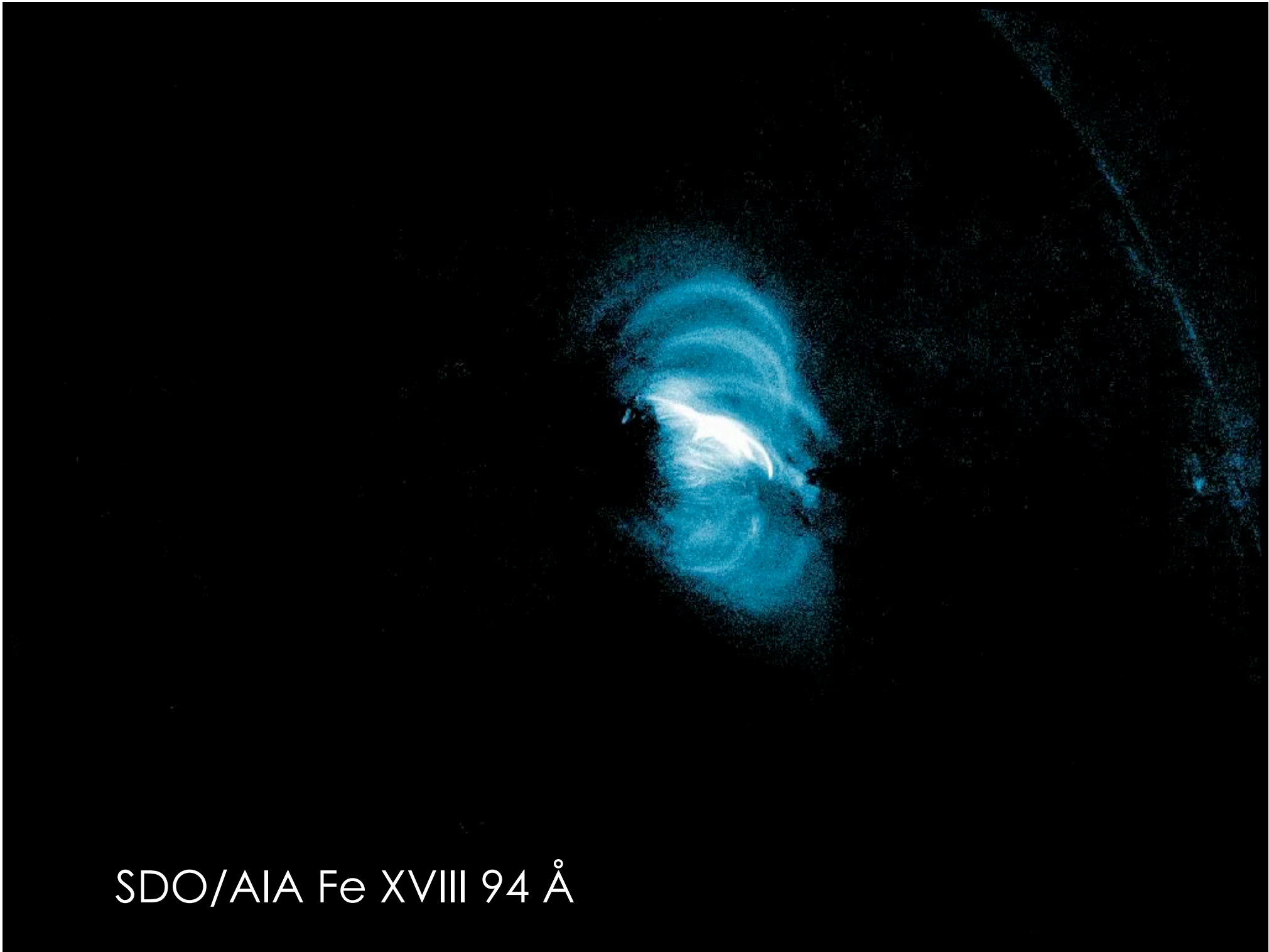
Hinode 7 • November 13, 2013 • Takayama, Japan

This Research is Sponsored by

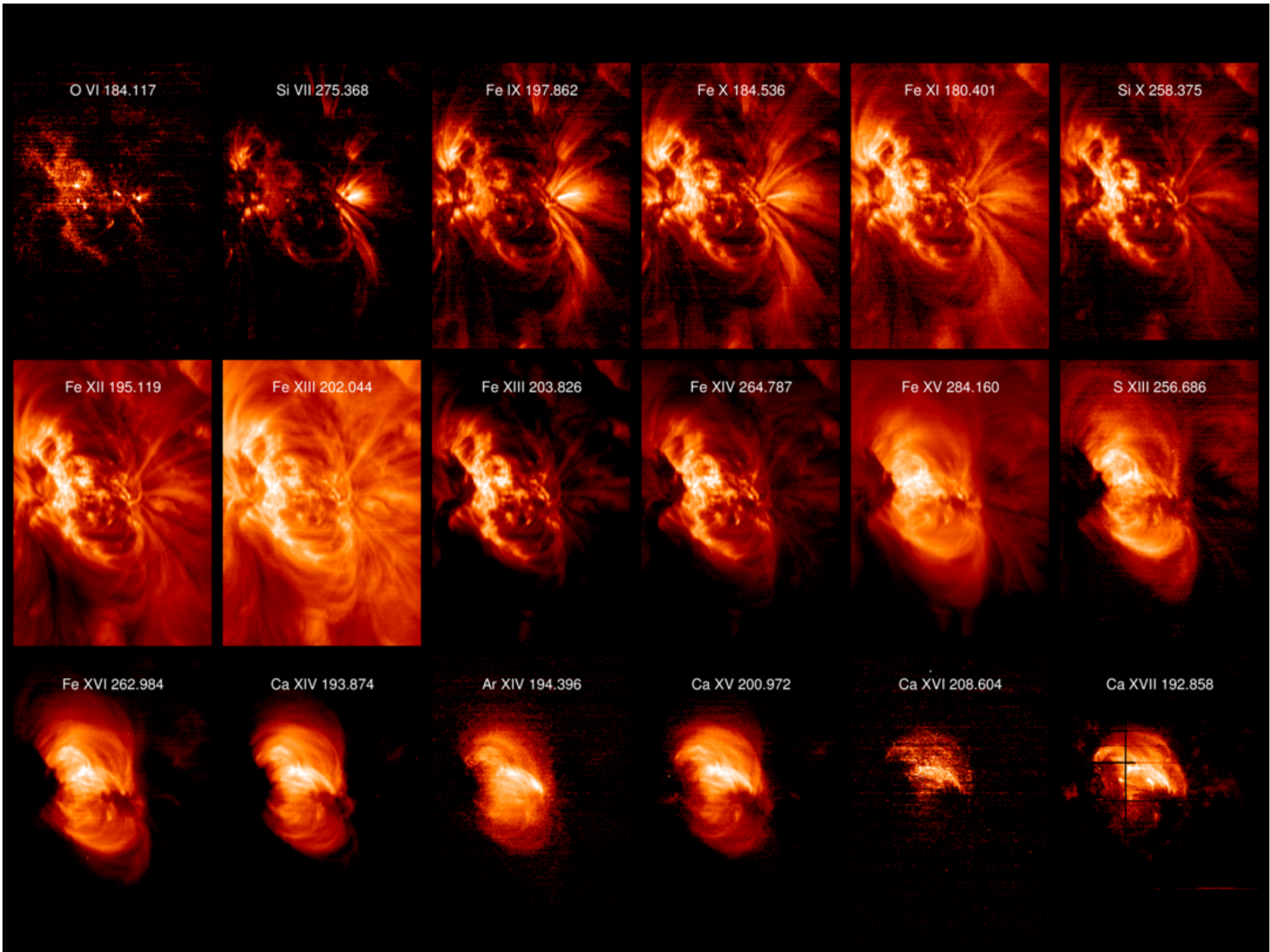


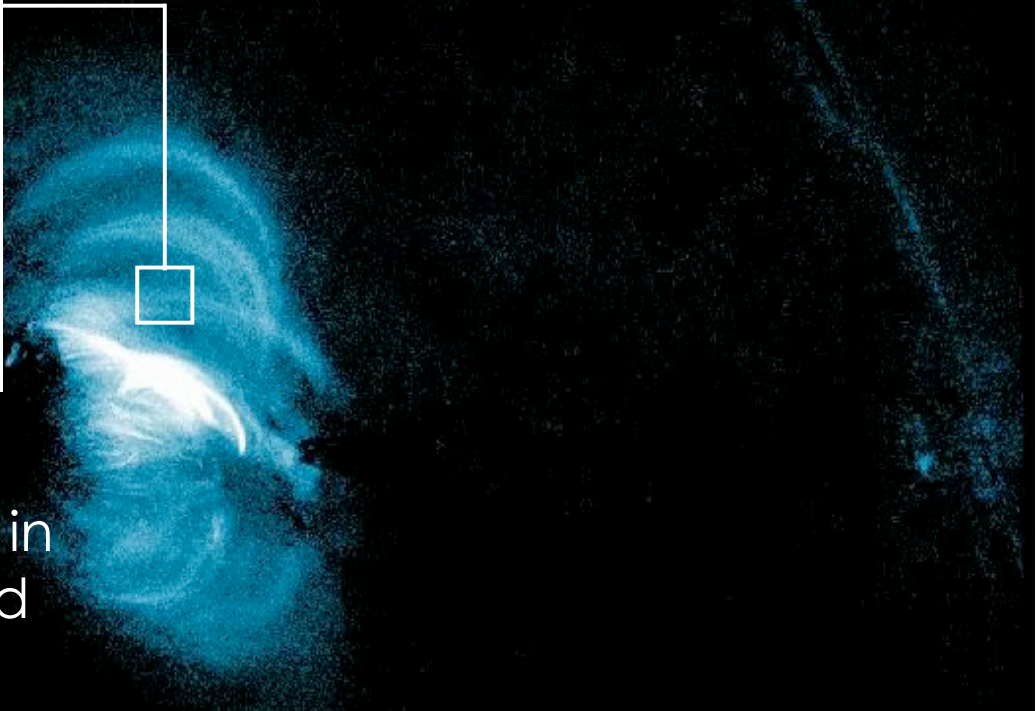
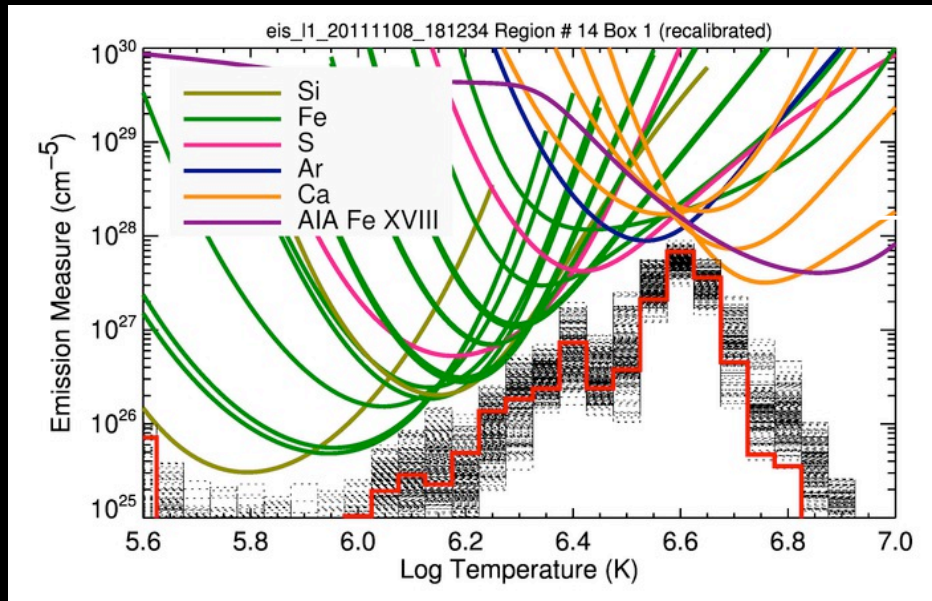


AIA/SDO Fe IX 171 Å



SDO/AIA Fe XVIII 94 Å





- Guennou et al. 2013 - uncertainty in the atomic data is underestimated
see poster S3 P25

1. *The application of sparse Bayesian inference to the DEM problem*

SDO/AIA Fe XVIII 94 Å

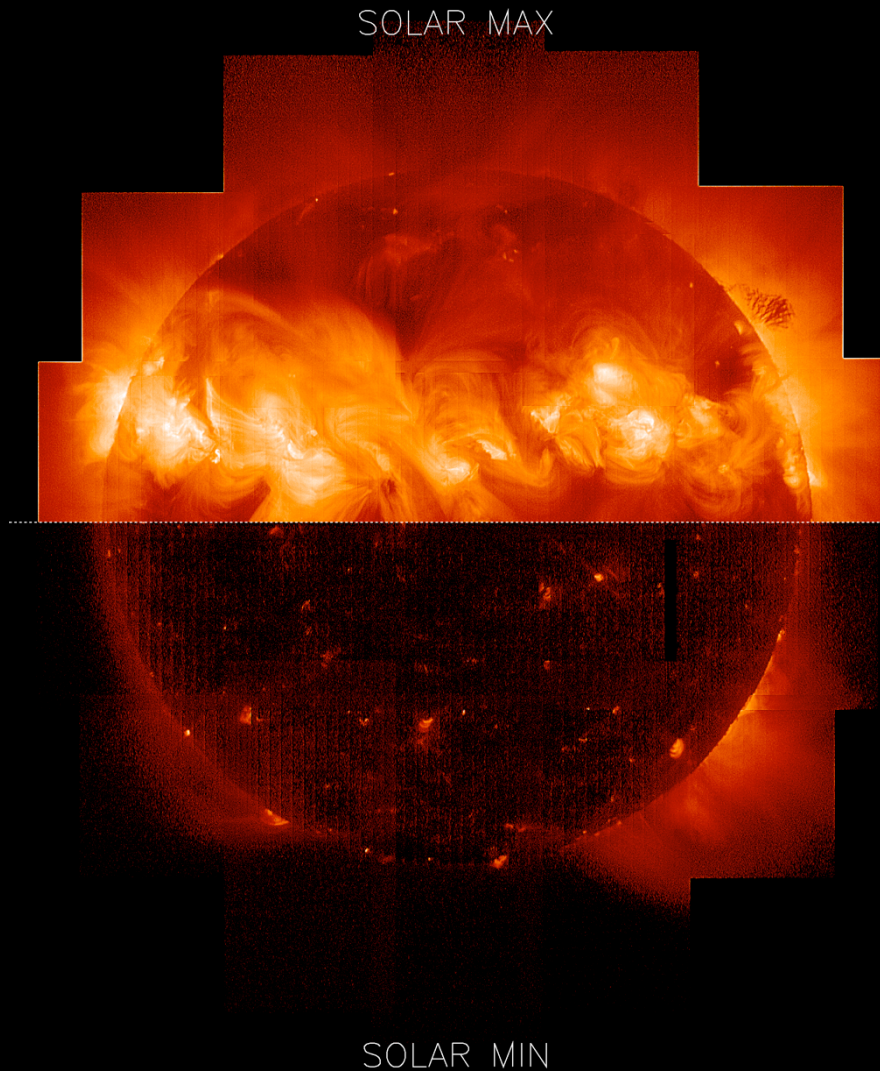
2. Active Region Modeling: Reproducing

- Temperature structure (DEM)
- Temporal variability
- Flux-luminosity relationship

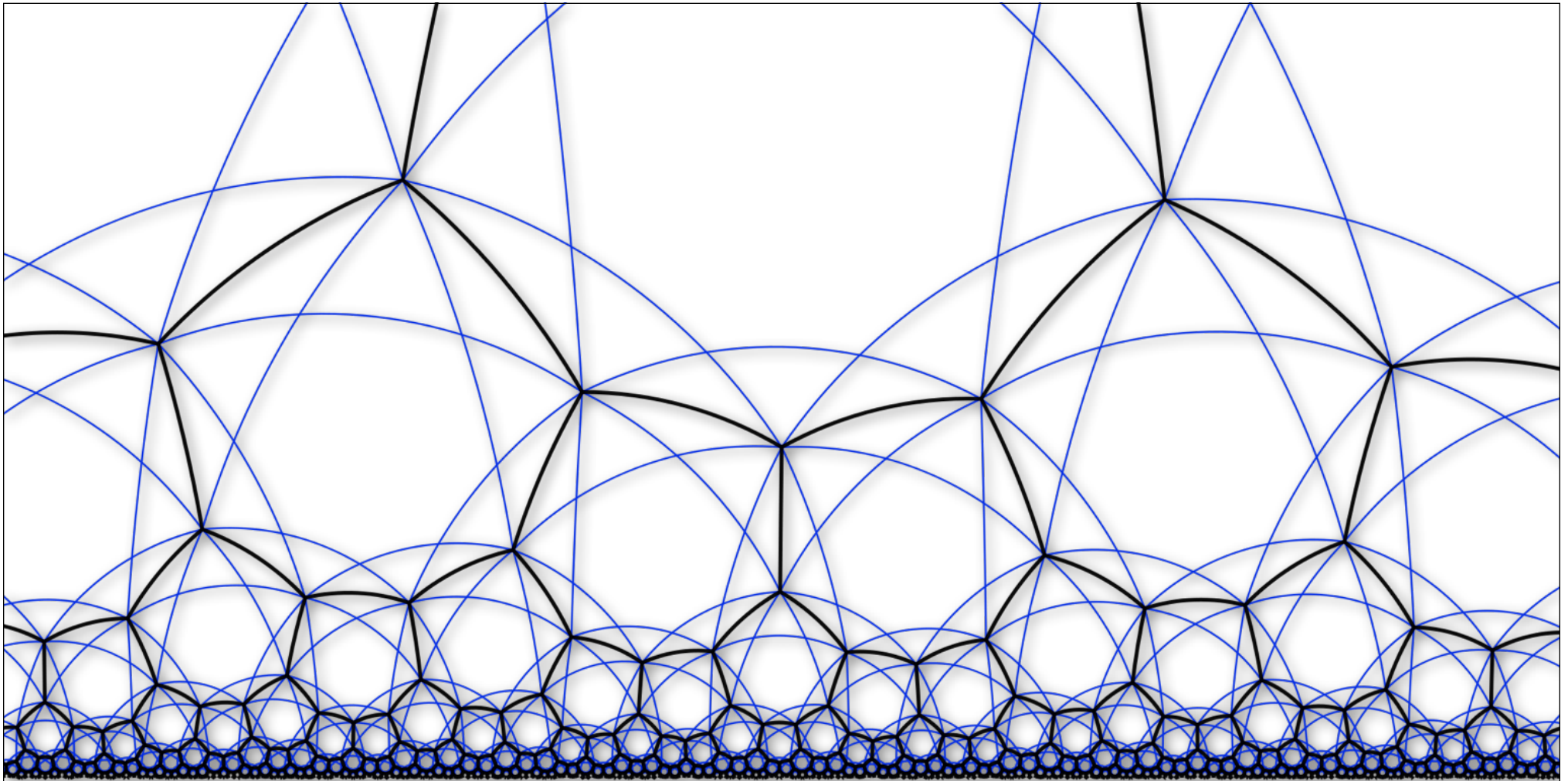
SDO/HMI

A grayscale image of the Sun's surface from the Solar Dynamics Observatory (SDO) using the Helioseismic and Magnetic Imager (HMI). The image shows a large active region in the center-right, characterized by a cluster of dark sunspots and a bright, irregularly shaped emission region. The background is filled with smaller sunspots and magnetic field structures. The right edge of the image is curved, representing the limb of the Sun.

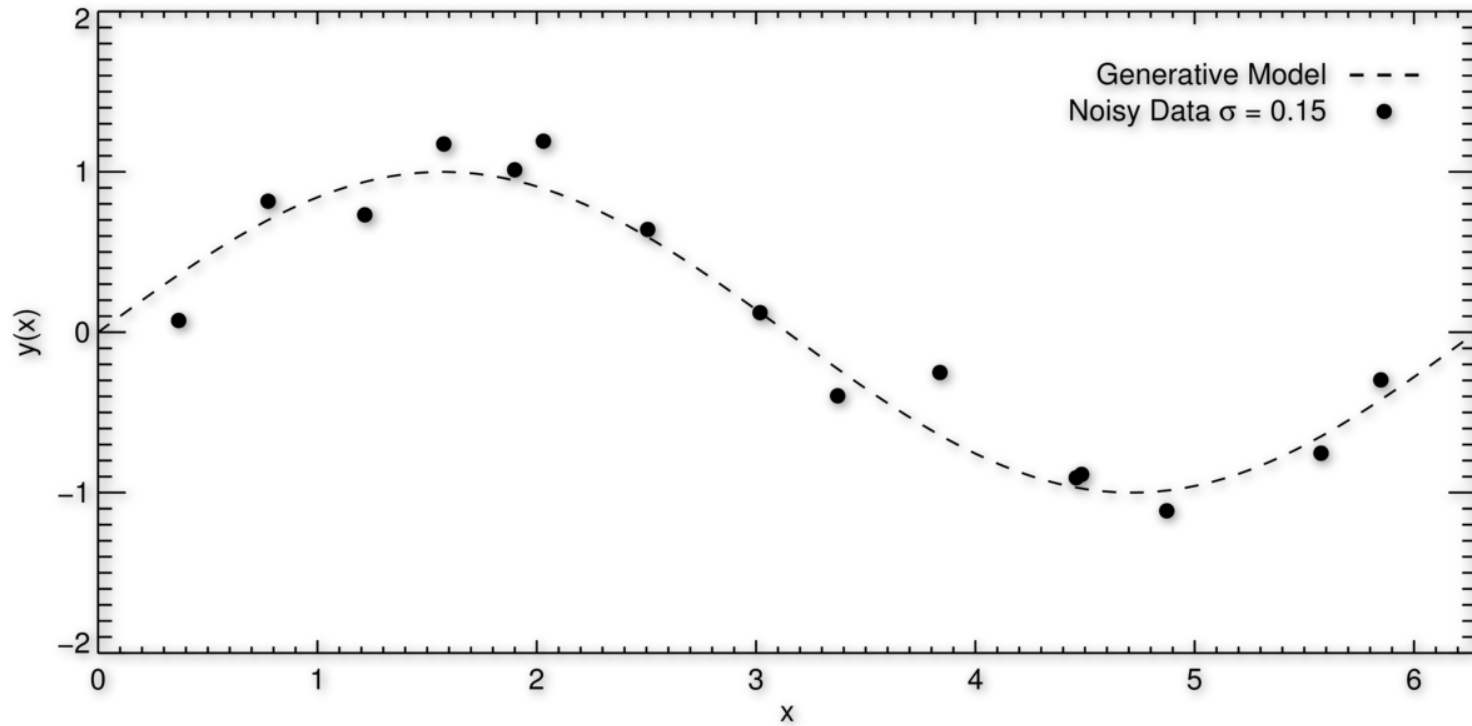
3. HOP 130, Atomic Physics, and the EIS Calibration



EIS Fe XV 284.16 Å



*Sparse Bayesian Inference and the
Temperature Structure of the Solar Corona*

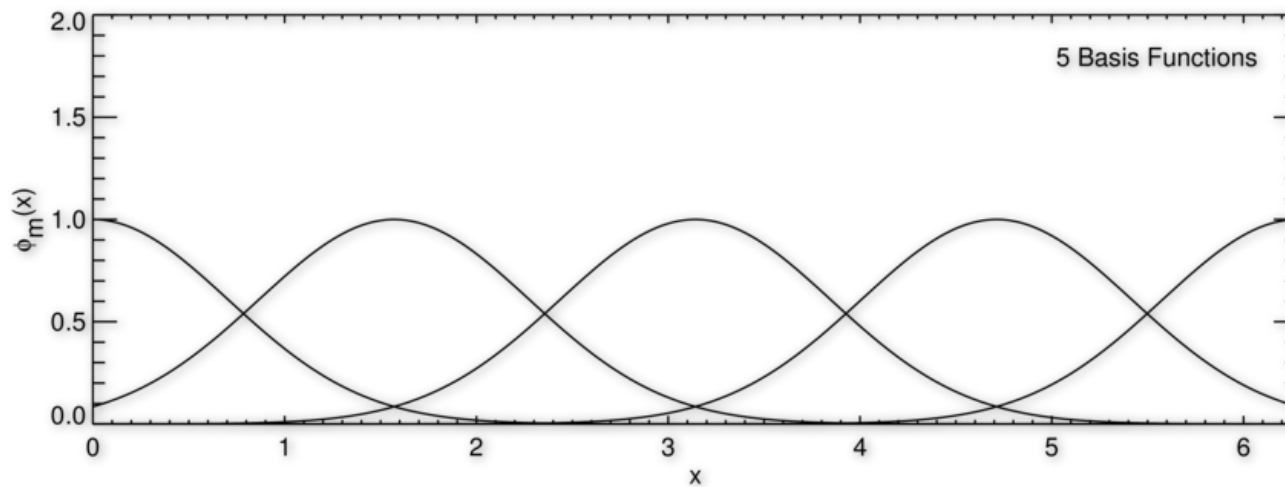
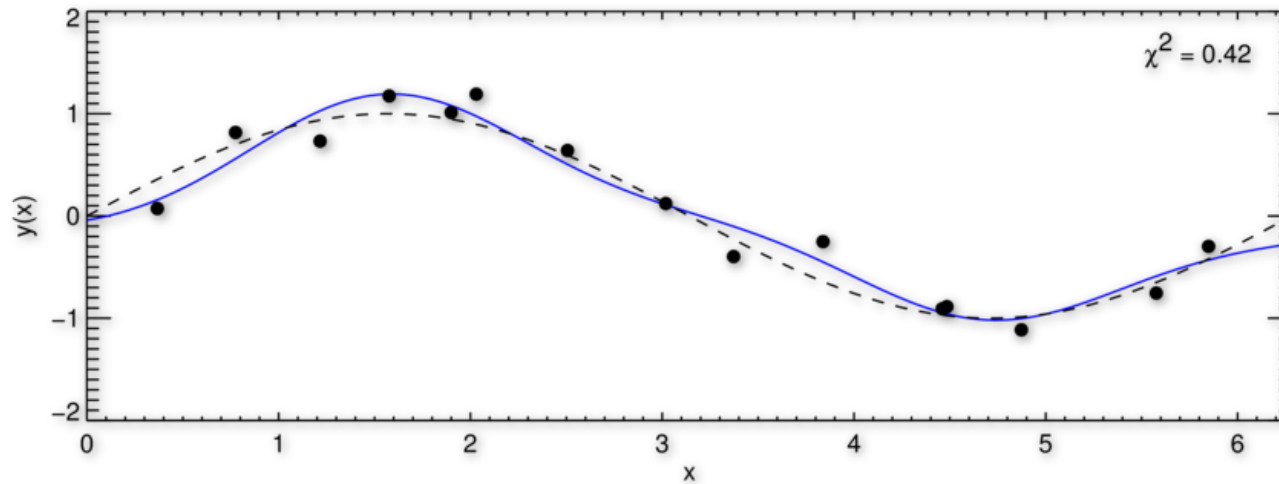


$$y(x) = \sum_{m=1}^M w_m \phi_m(x)$$

$$\phi_m(x) = \exp \left[-\frac{(x - x_m)^2}{r^2} \right]$$

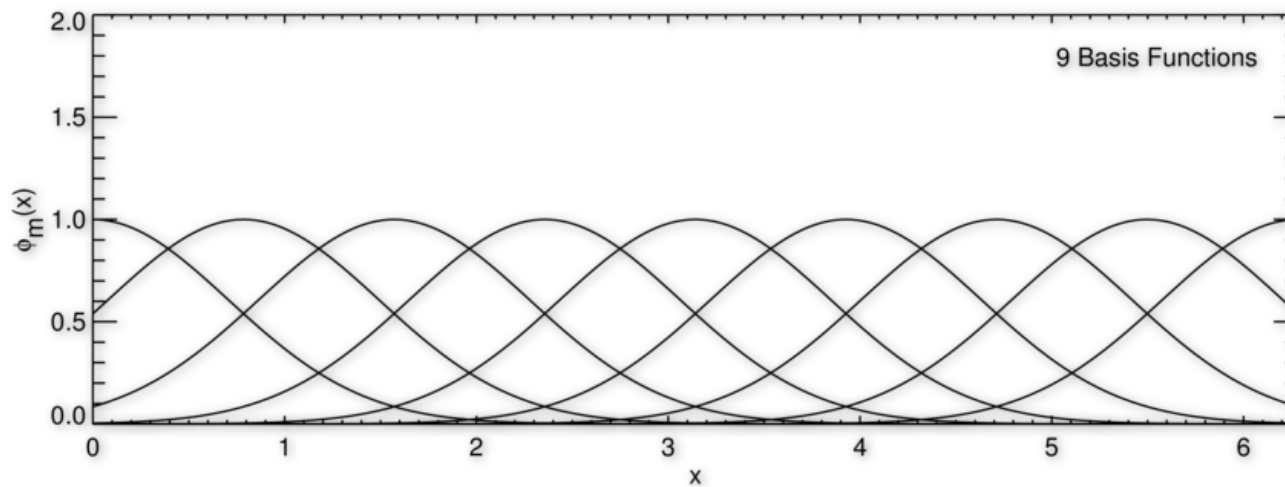
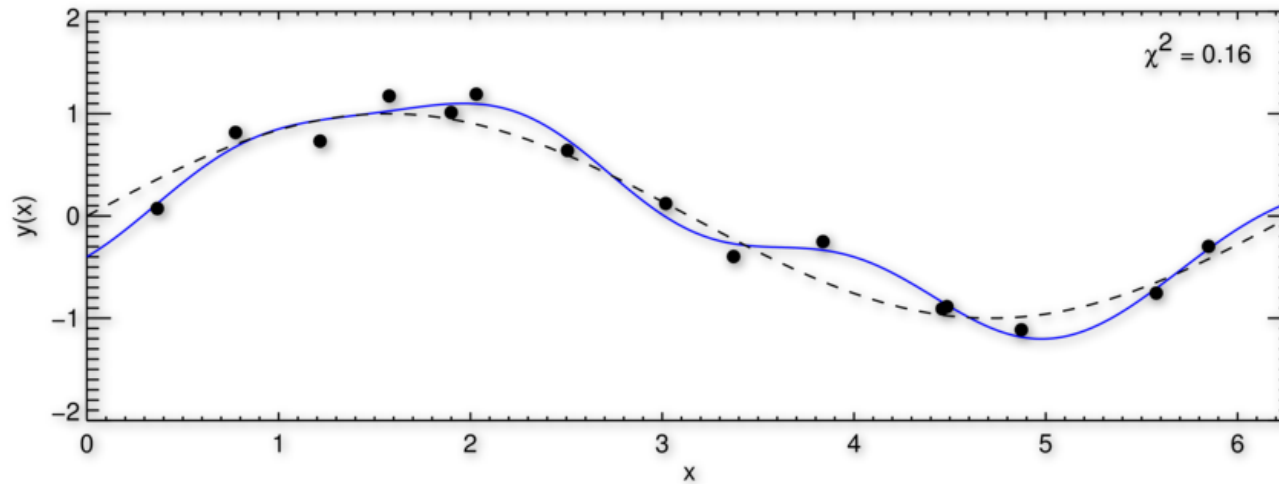
Least Squares Solution

$$\mathbf{w} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$$



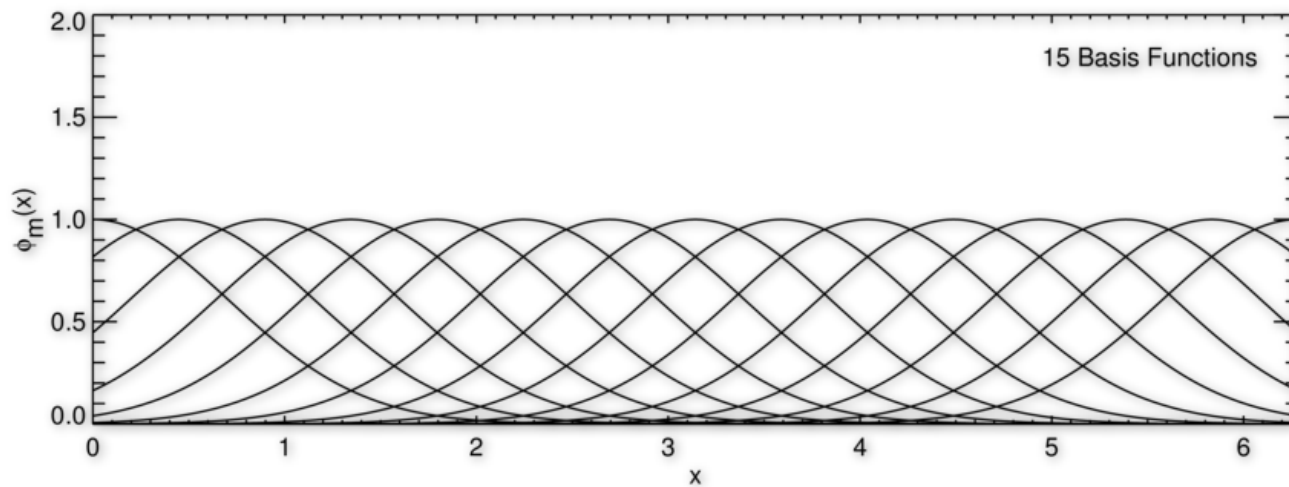
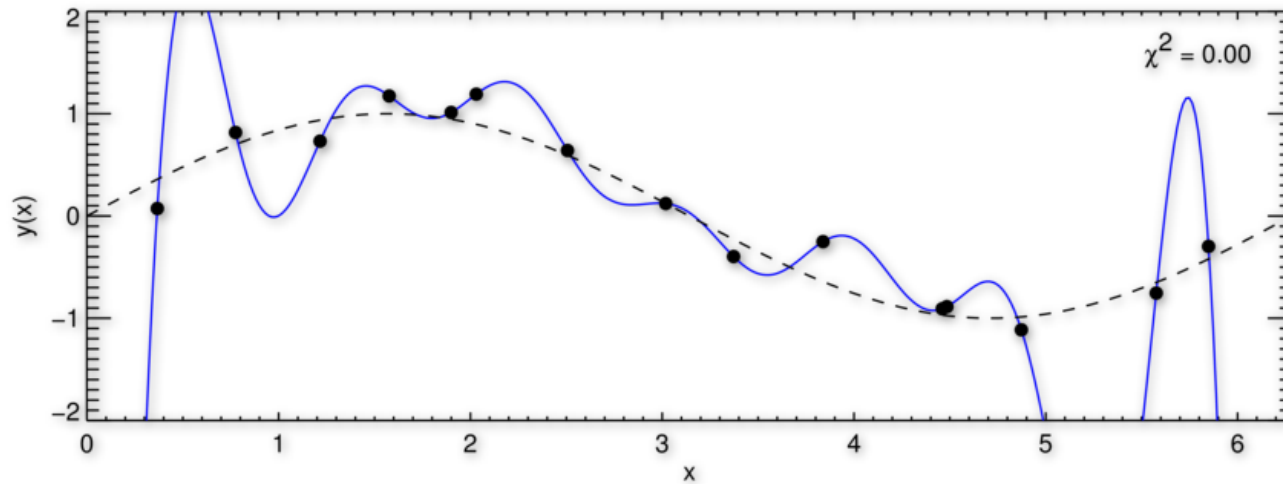
Least Squares Solution

$$\mathbf{w} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$$



Least Squares Solution

$$\mathbf{w} = (\Phi^T \Phi)^{-1} \Phi^T \mathbf{y}$$



A “SuperSet” of Least Squares: Bayesian Inference

Bayes’ Theorem

$$P(\mathcal{M} | \mathcal{D}) = \frac{\overset{\text{likelihood}}{P(\mathcal{D} | \mathcal{M})} \overset{\text{prior}}{P(\mathcal{M})}}{\underset{\text{evidence}}{P(\mathcal{D})}}$$

Sparse Bayesian Inference: The Relevance Vector Machine [RVM]

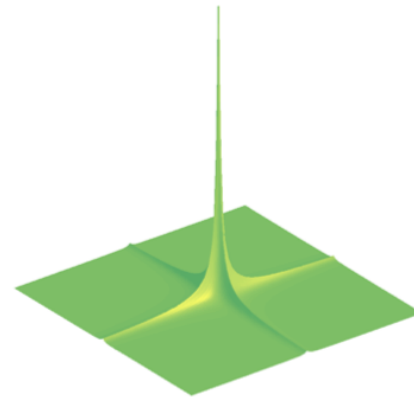
Michael Tipping, Microsoft Research
Journal of Machine Learning Research (2001)

$$P(\mathcal{M} | \mathcal{D}) = \frac{P(\mathcal{D} | \mathcal{M})P(\mathcal{M})}{P(\mathcal{D})}$$

“hierarchical prior”

$$p(\mathbf{w} | \alpha) = \prod_{m=1}^M \sqrt{\frac{\alpha_m}{2\pi}} \exp \left[-\frac{1}{2} \alpha_m w_m^2 \right]$$

$$p(w_m) =$$



Student-t distribution

After much gnashing of teeth a Quasi-Analytic Solution

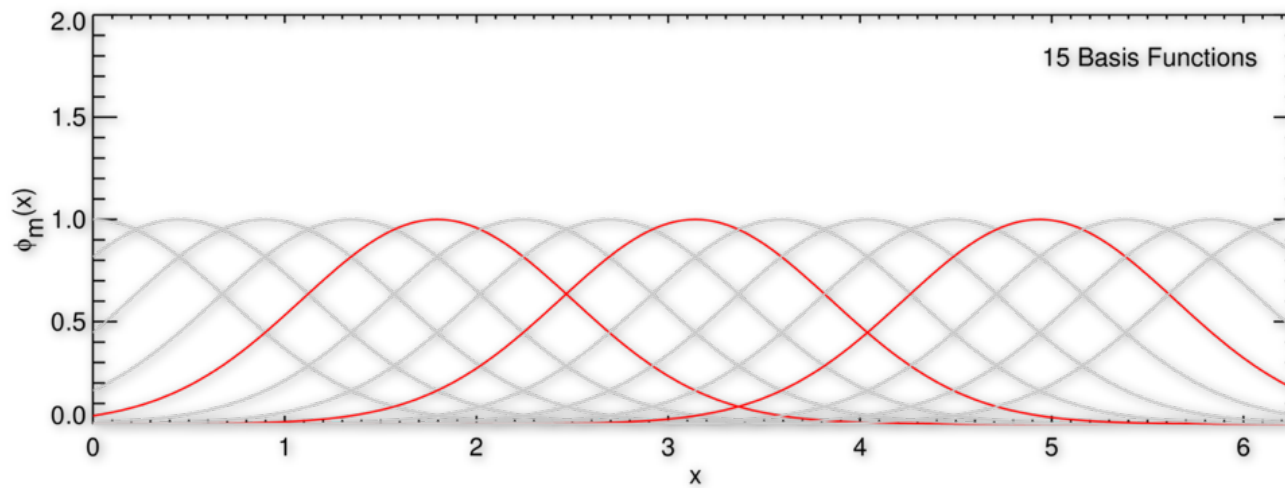
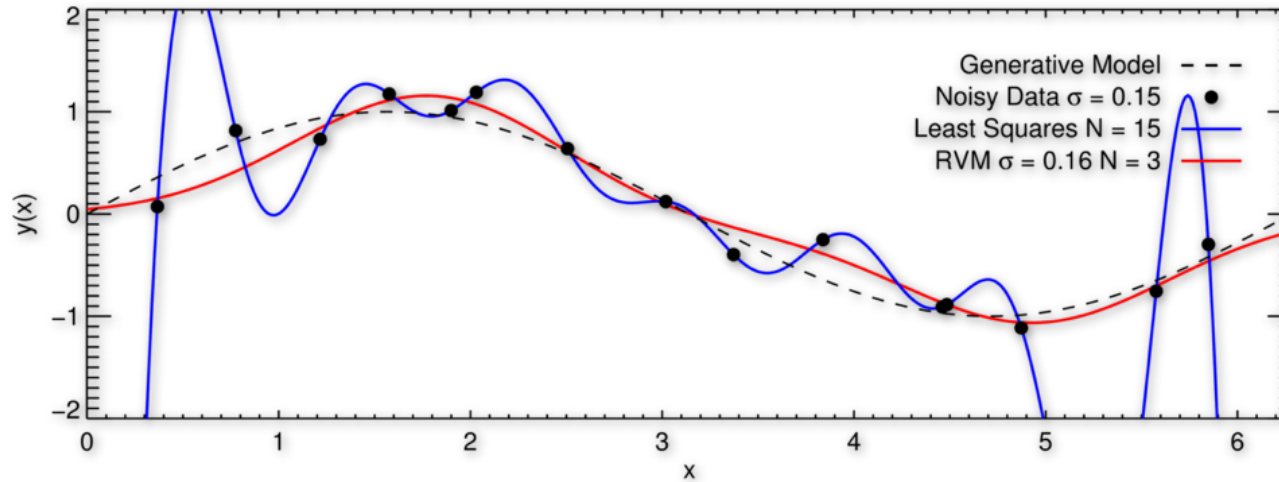
$$\mathbf{w} = \sigma^{-2} (\sigma^{-2} \Phi^T \Phi + \mathbf{A})^{-1} \Phi^T \mathbf{y} = \sigma^{-2} \Sigma \Phi^T \mathbf{y}$$

solve by iteration

$$\alpha_i^{new} = \frac{1 - \alpha_i \Sigma_{ii}}{w_i^2}$$

$$\sigma^{new} = \frac{\|\mathbf{y} - \Phi \mathbf{w}\|}{\sqrt{N - c}}$$

RVM vs Least Squares Magic!



Positivity: A Fly in the Ointment!

Positivity is not built in. How do we do the DEM problem?

$$I_n = \int \epsilon_n(T) \xi(T) dT$$

$$\xi(T) = \sum_{m=1}^M w_m \phi_m(T)$$

a simple solution

$$\xi(T) = \sum_{m=1}^M 10^{w_m} \phi_m(T) > 0$$

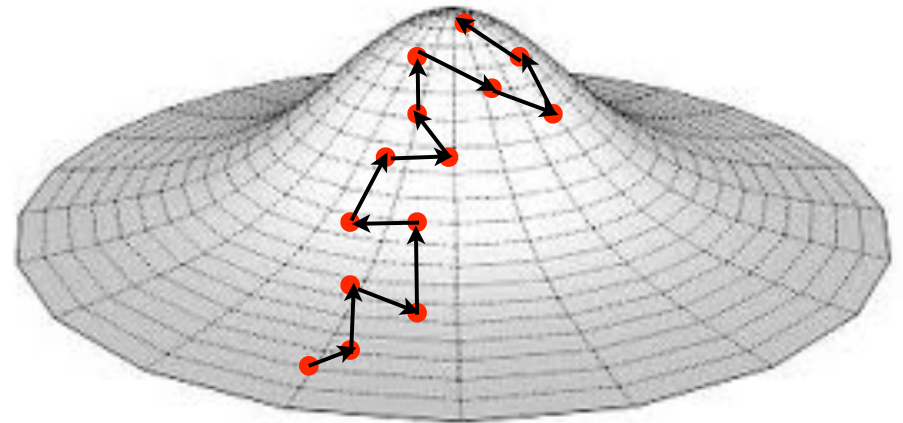
but this breaks Tipping's iterative scheme

Exploring the Posterior: Markov Chain Monte Carlo and Metropolis-Hastings

we need to *explore* the posterior



move to where the posterior is
highest,
but not always



The Metropolis-Hastings Algorithm

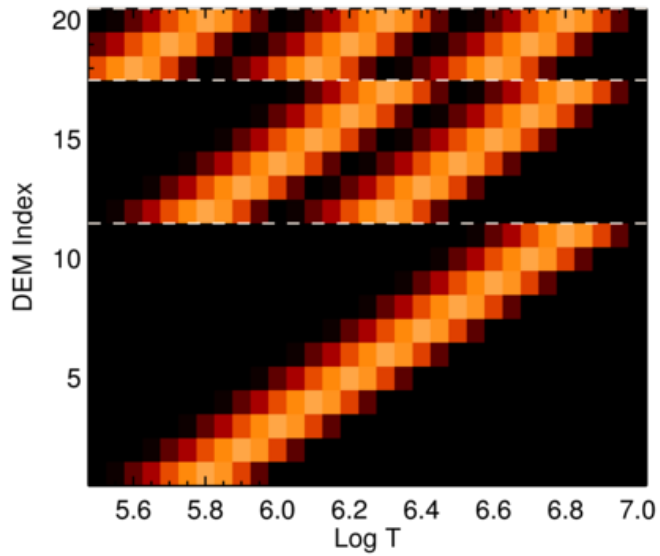
consider $\mathbf{w} \rightarrow \mathbf{w}'$

accept if: $P(D | \mathbf{w}') > P(D | \mathbf{w})$

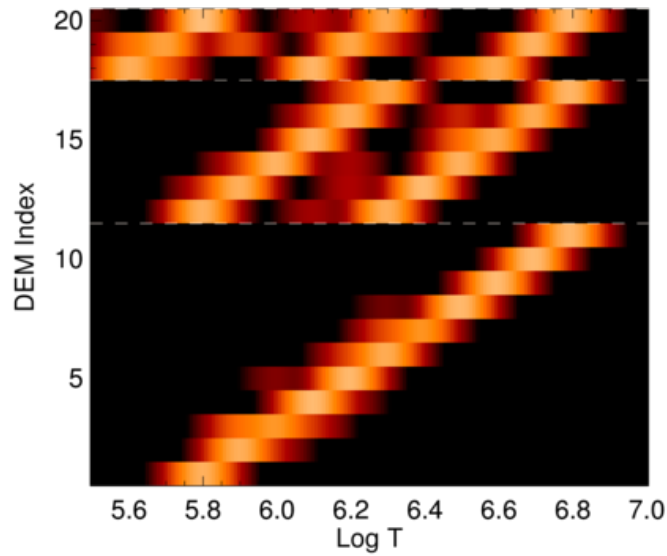
or if: $u < P(D | \mathbf{w}') / P(D | \mathbf{w})$ $u \in [0, 1]$

The DEM “Library”

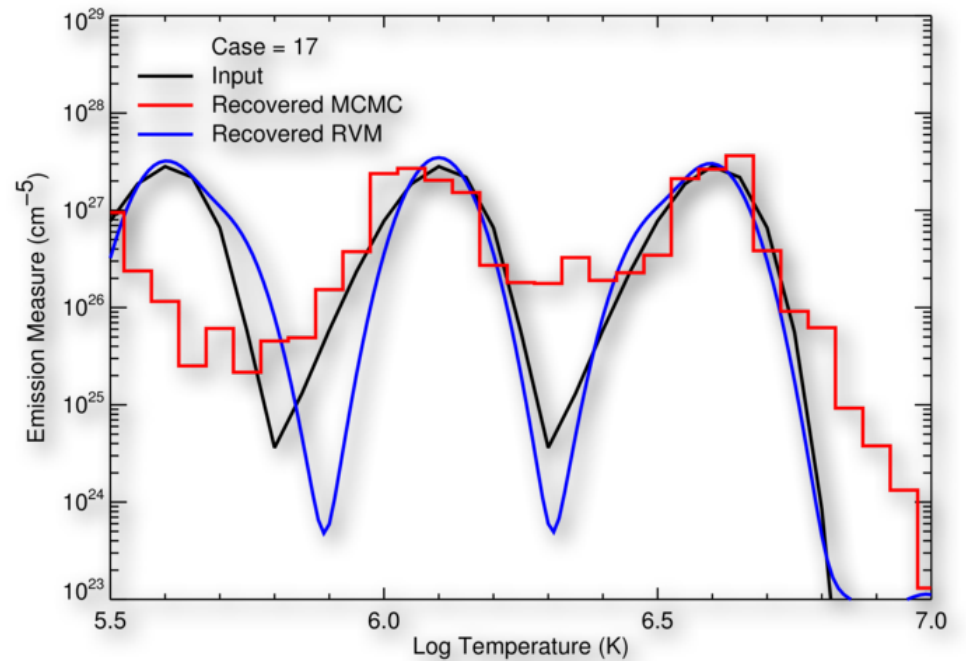
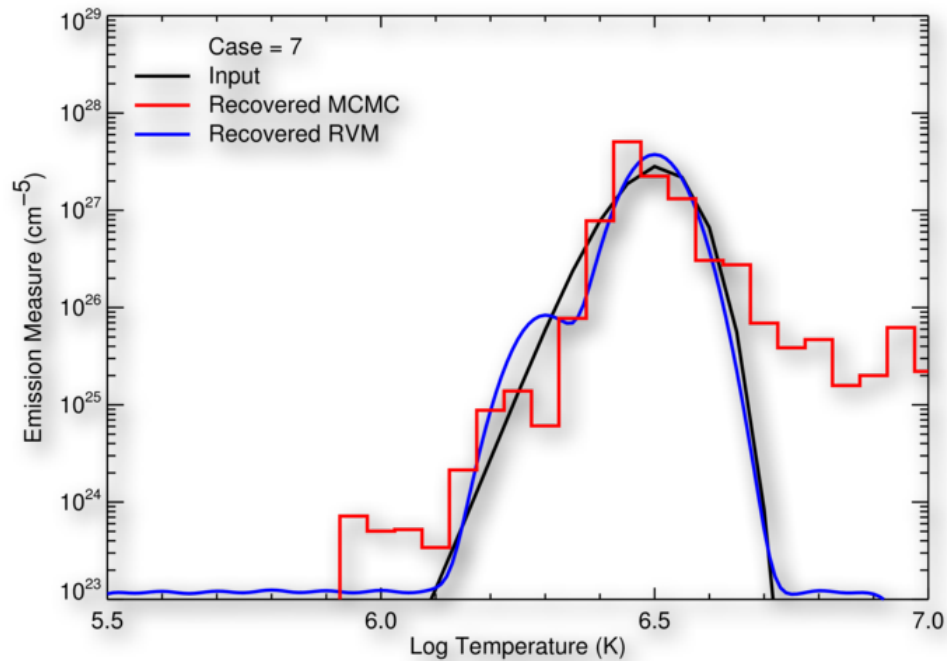
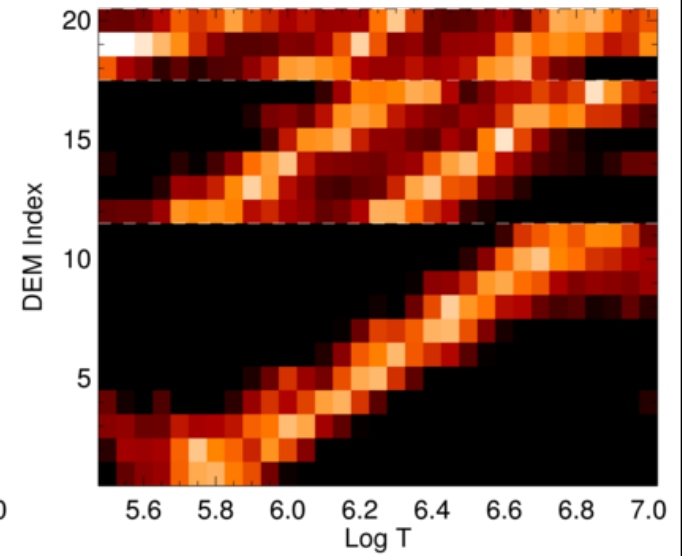
Input



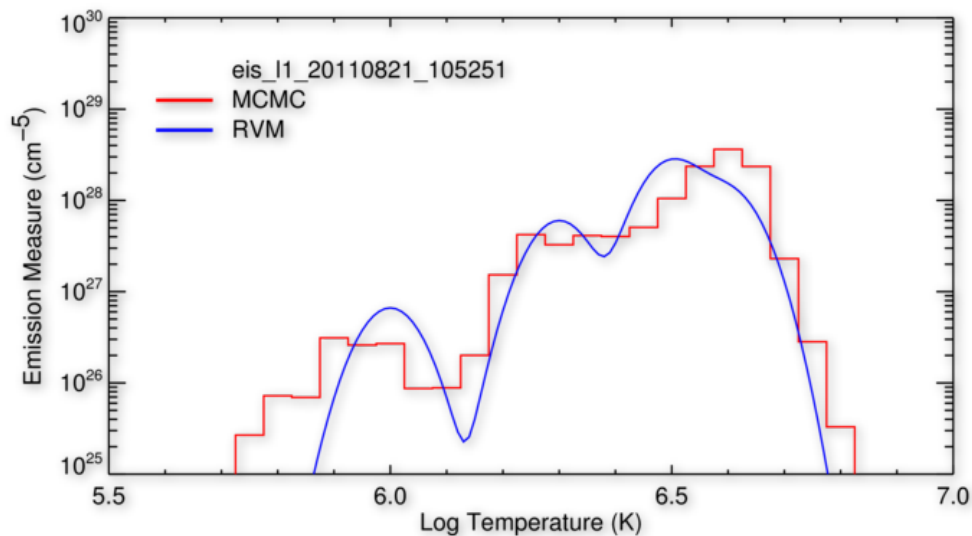
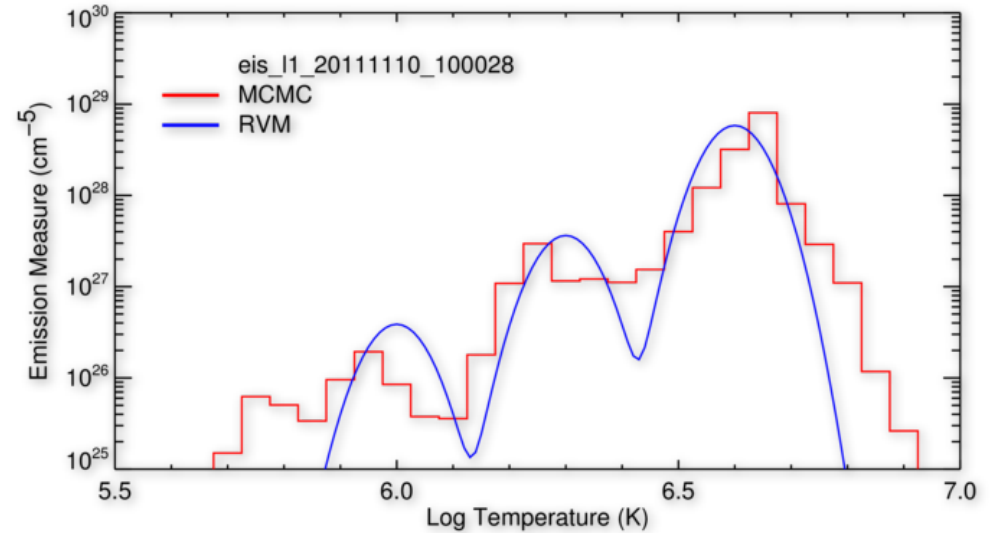
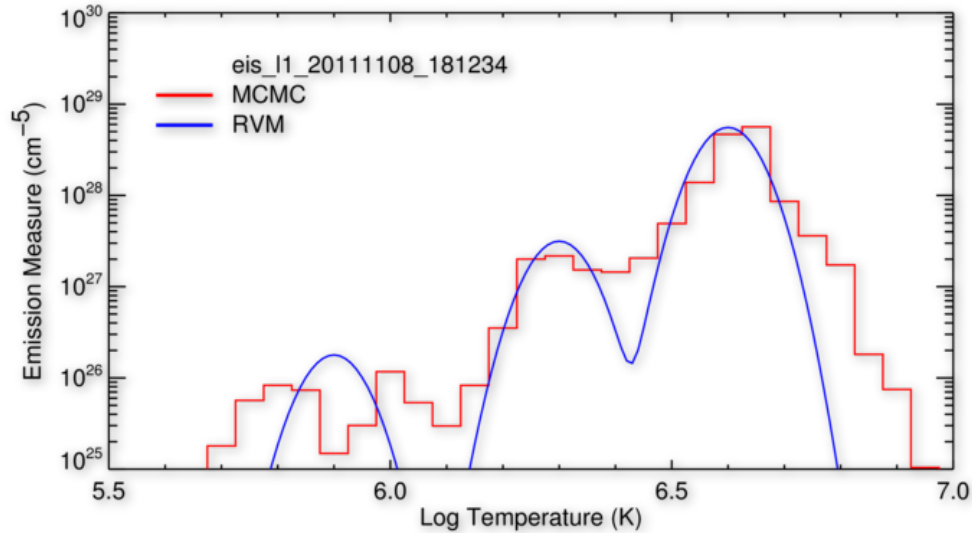
RVM



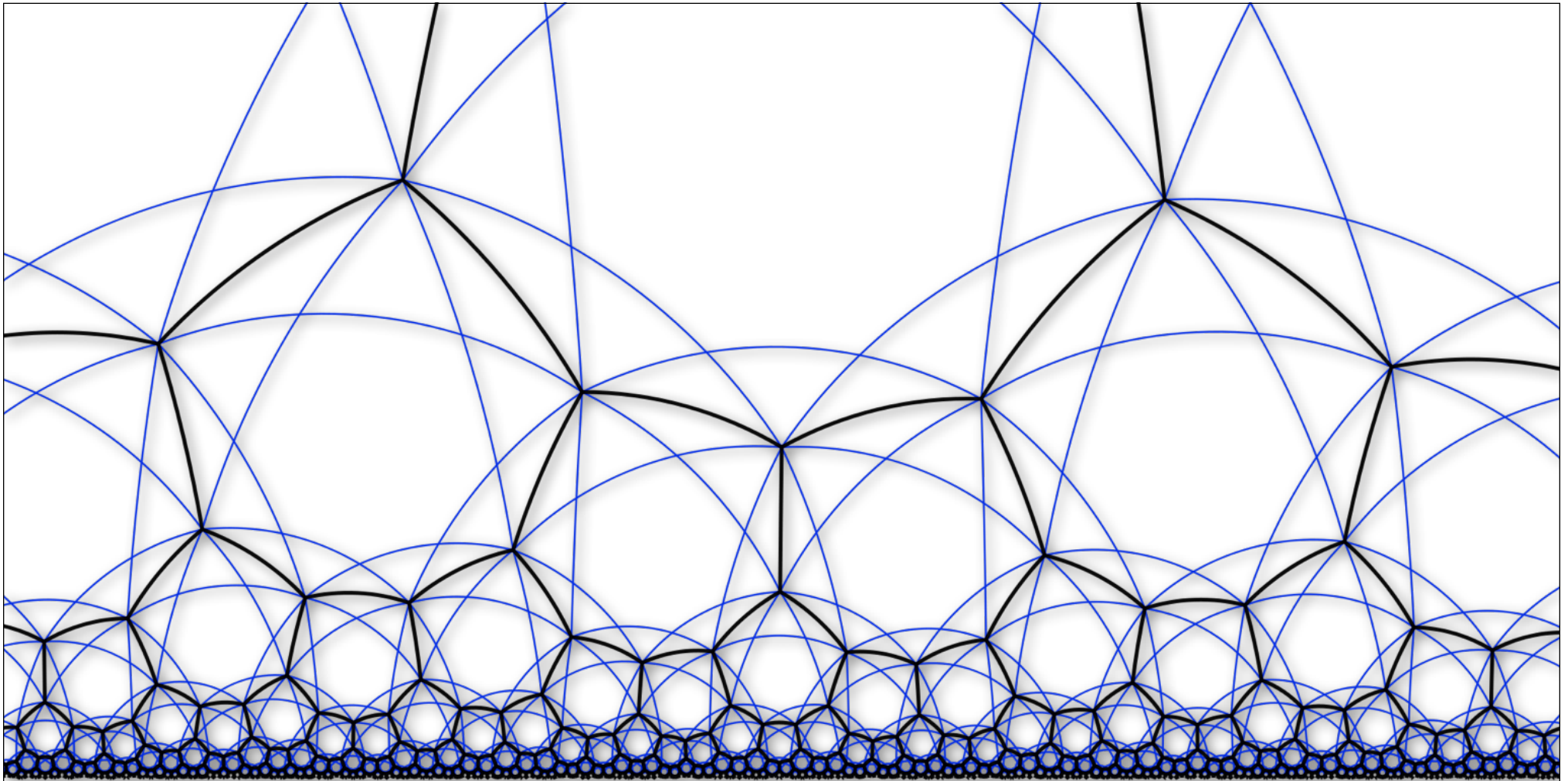
MCMC Kashyap & Drake 1998



Application to Observations



- Similar to previous results
- Slow! For speed see Hannah & Kontar (2012)
- Doesn't address errors in atomic data
- BUT, we know how to balance uncertainty and complexity



Modeling Solar Active Regions

19-Jun-10 01:57:44

12-Feb-11 15:32:13

21-Jun-10 01:46:37

25-Jul-11 09:36:09

31-Jan-11 11:25:19

HMI [4.08e+21]

HMI [4.22e+21]

HMI [4.72e+21]

HMI [5.68e+21]

HMI [7.50e+21]

21-Jan-11 14:10:50

02-Jul-11 03:38:08

23-Jul-10 15:03:07

29-Sep-10 23:51:36

19-Apr-11 13:32:20

HMI [1.02e+22]

HMI [1.09e+22]

HMI [1.12e+22]

HMI [1.16e+22]

HMI [1.35e+22]

11-Apr-11 12:00:42

21-Aug-11 12:25:42

15-Apr-11 01:17:19

08-Nov-11 19:14:27

10-Nov-11 11:33:19

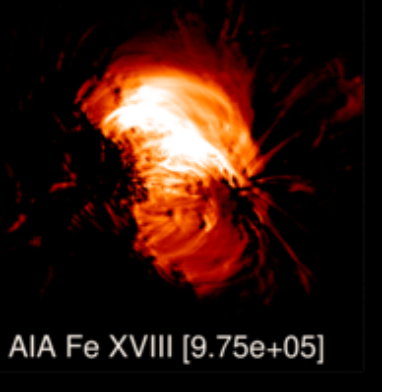
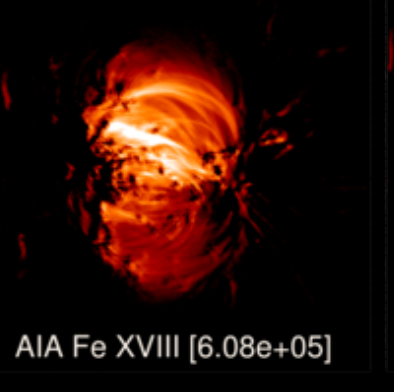
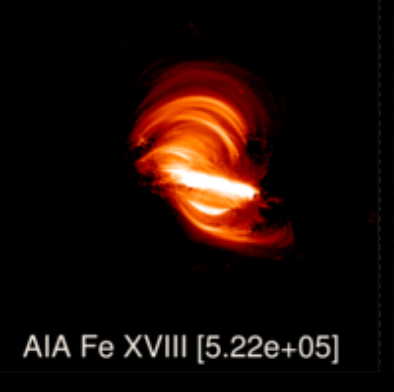
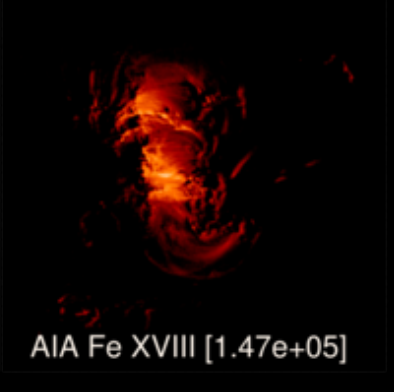
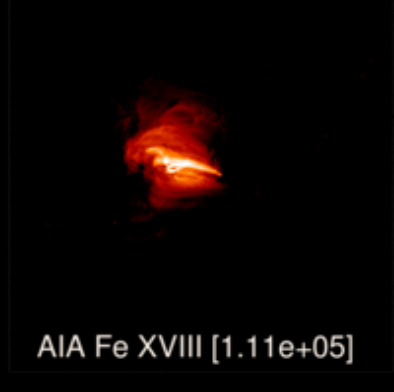
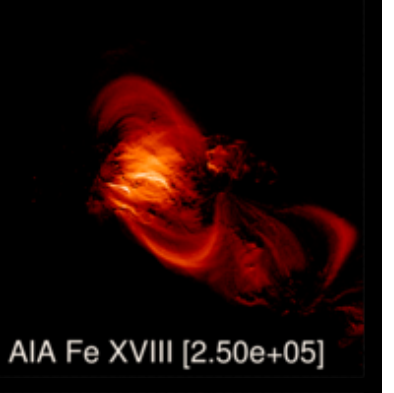
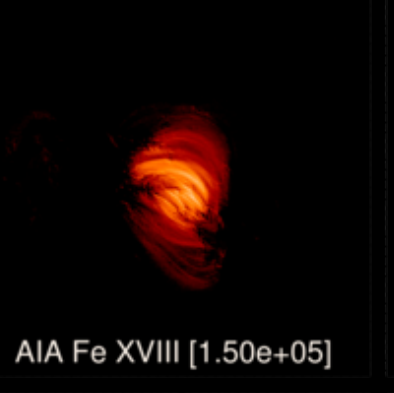
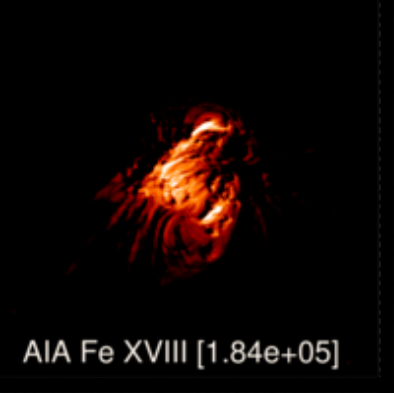
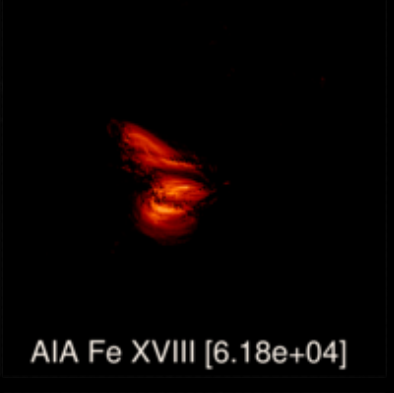
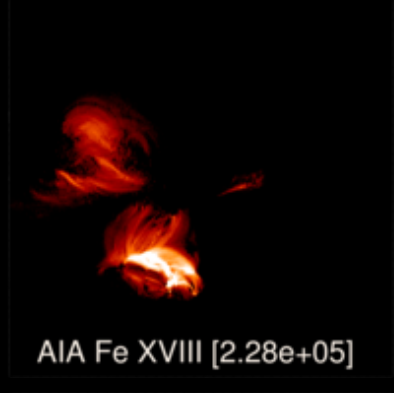
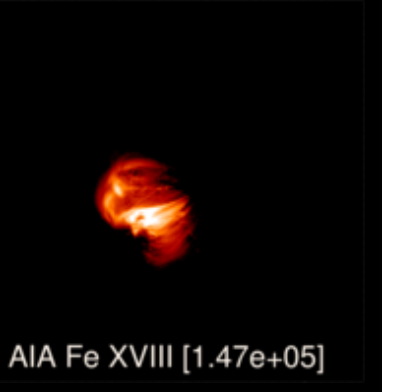
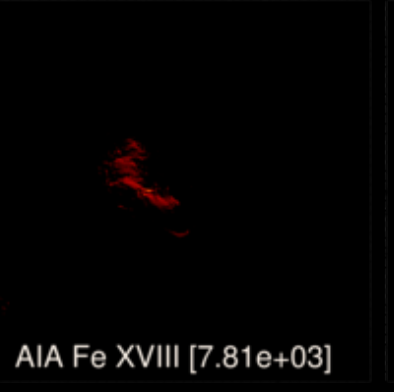
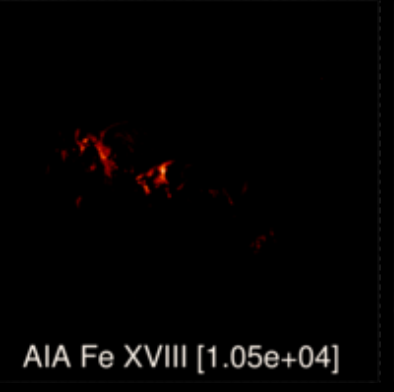
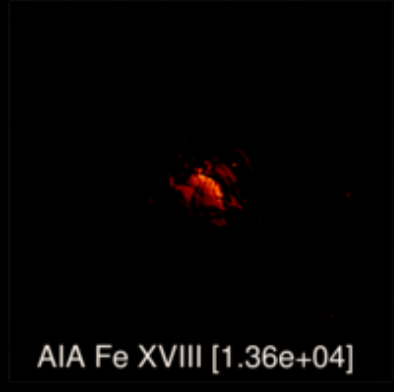
HMI [1.37e+22]

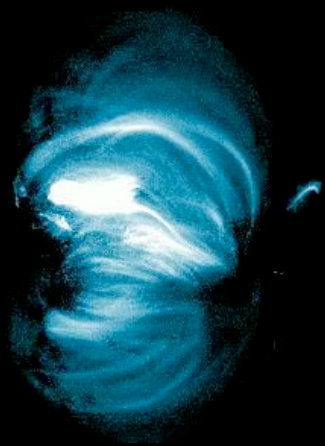
HMI [1.57e+22]

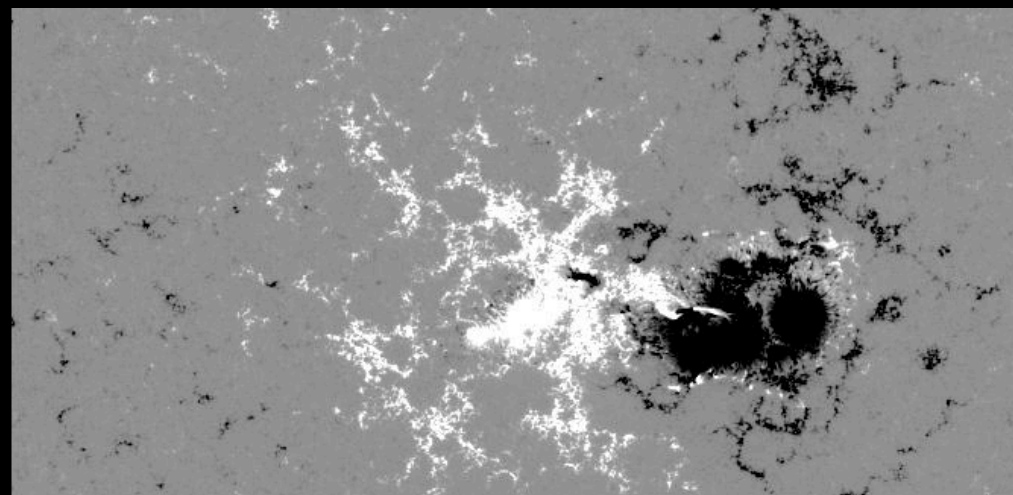
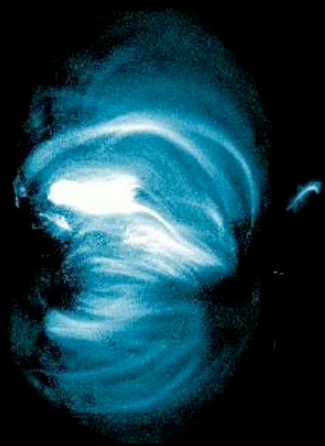
HMI [1.78e+22]

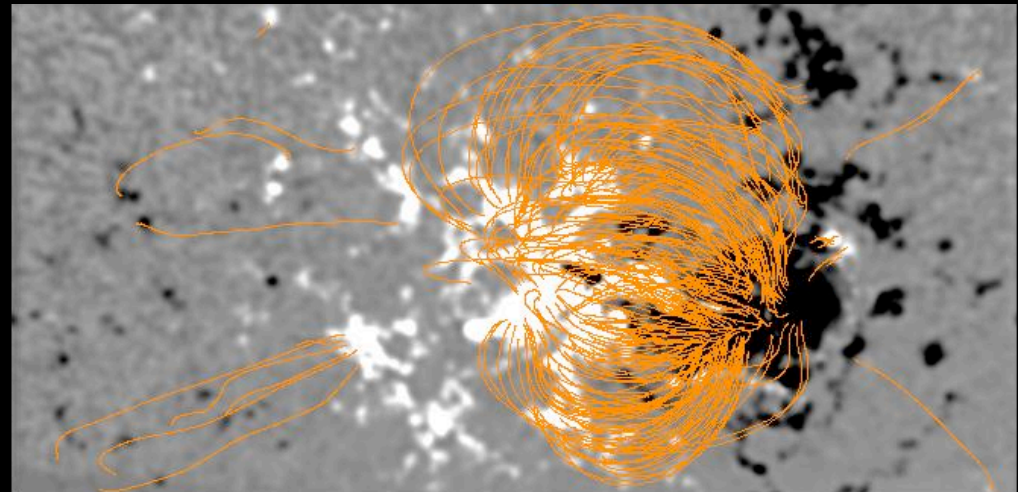
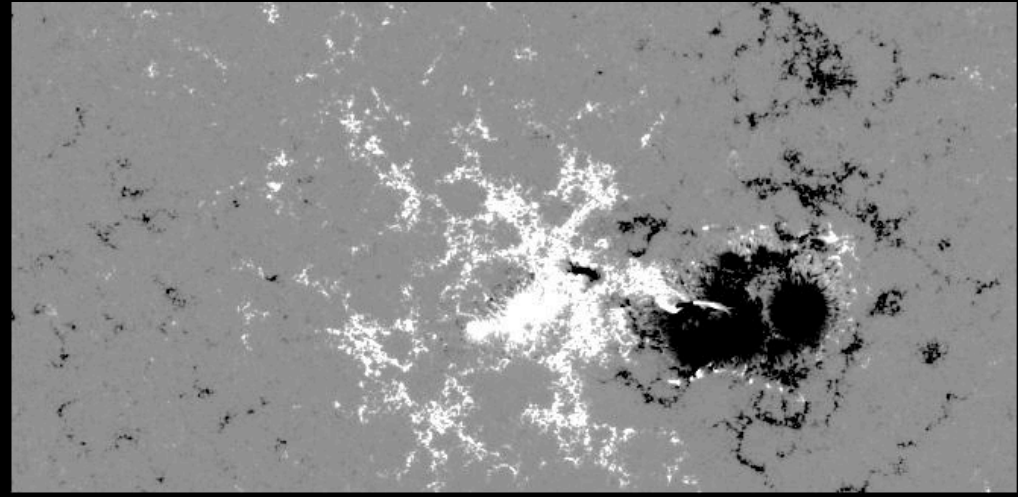
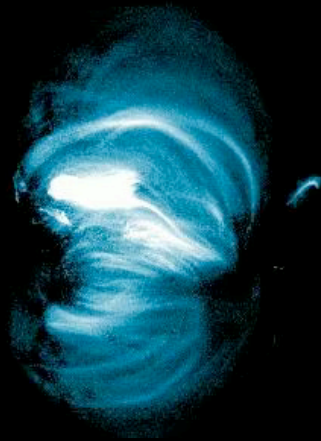
HMI [2.60e+22]

HMI [2.73e+22]

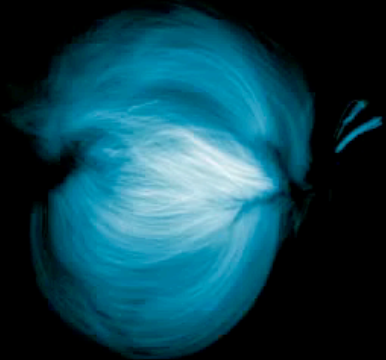
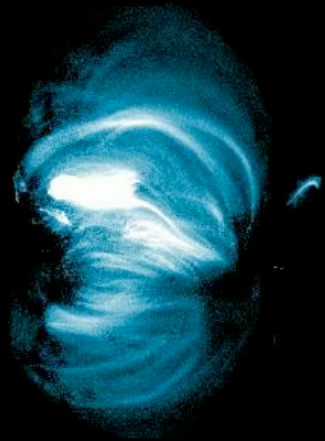




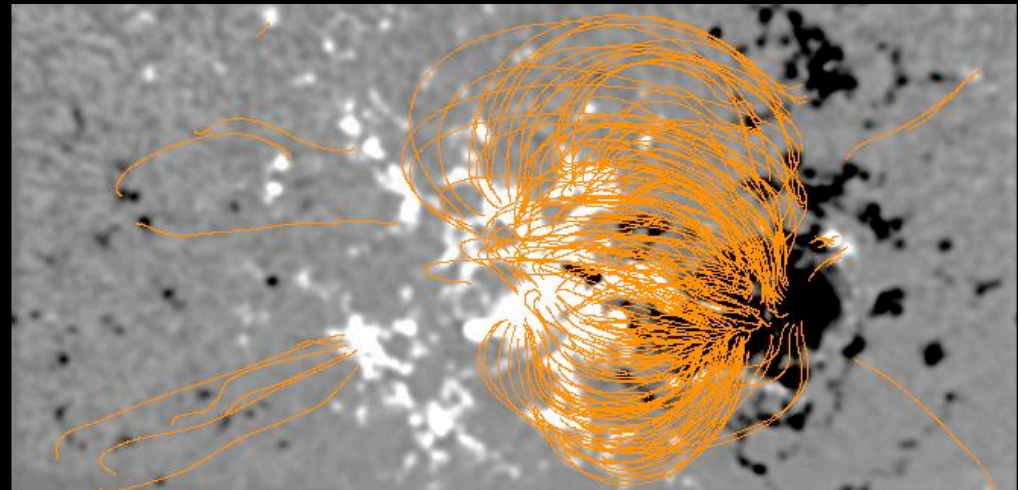
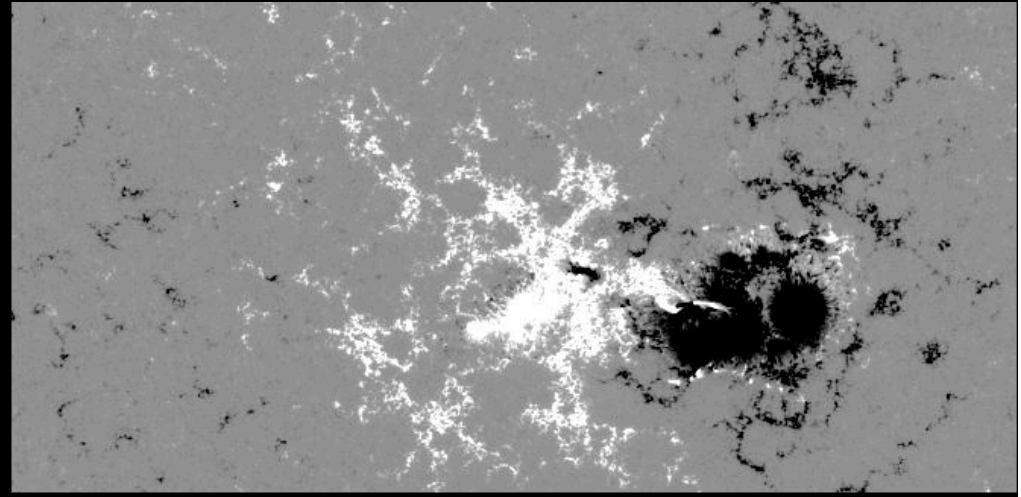




NLFF:Wiegelmann et al. (2012)



EBTELv2: Cargill et al. (2012)



NLFF:Wiegelmann et al. (2012)

Steady

$$\epsilon_E = \epsilon_0 \left(\frac{\bar{B}}{\bar{B}_0} \right)^\alpha \left(\frac{L_0}{L} \right)^\beta$$

$$\alpha = \beta = 1$$

Schrijver et al., 2004; Lundquist et al., 2008; Warren & Winebarger 2006, 2007; Winebarger et al., 2008, 2011;

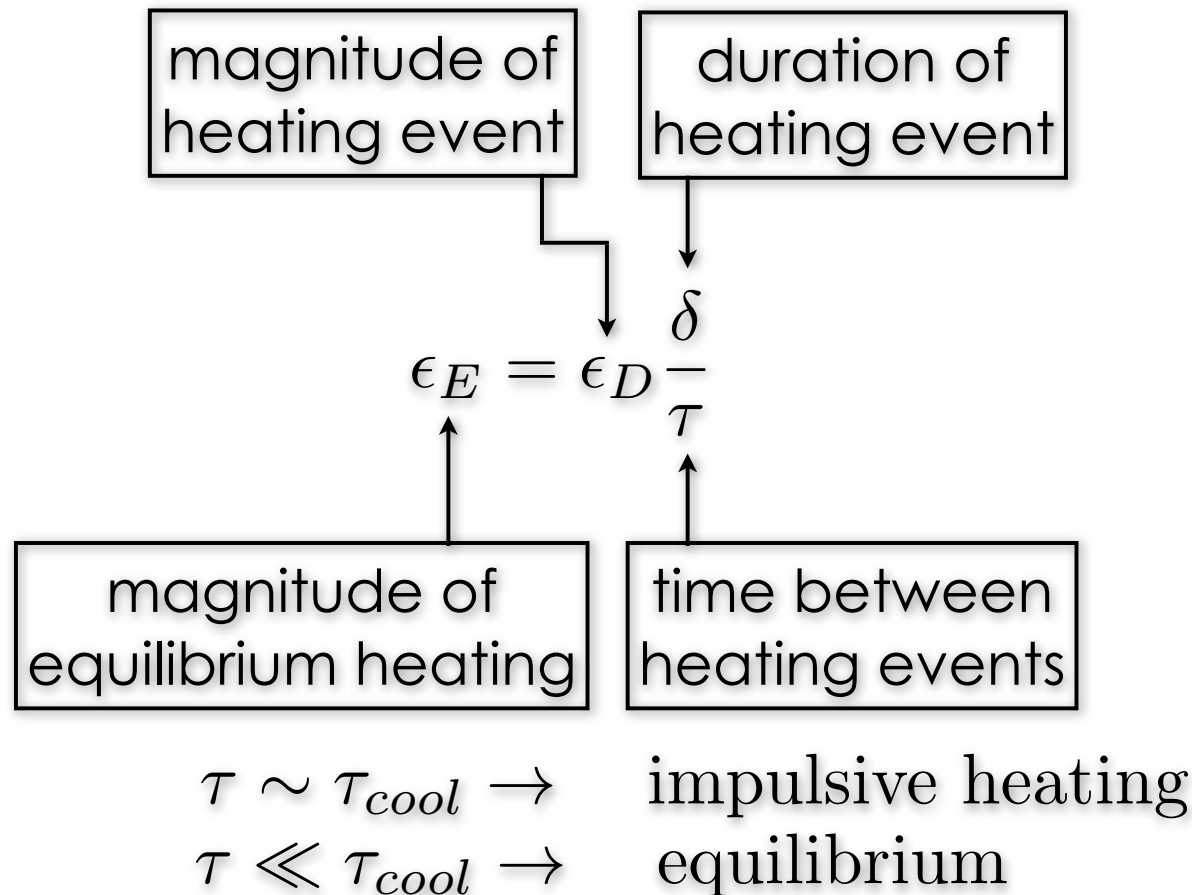
Steady

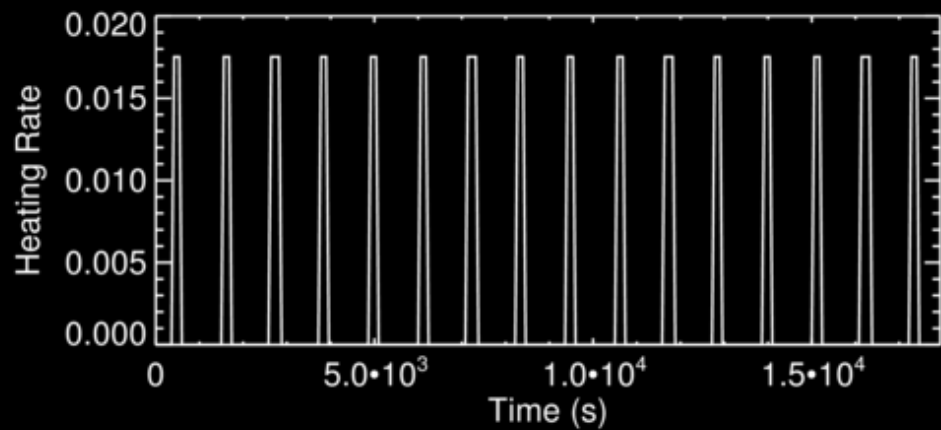
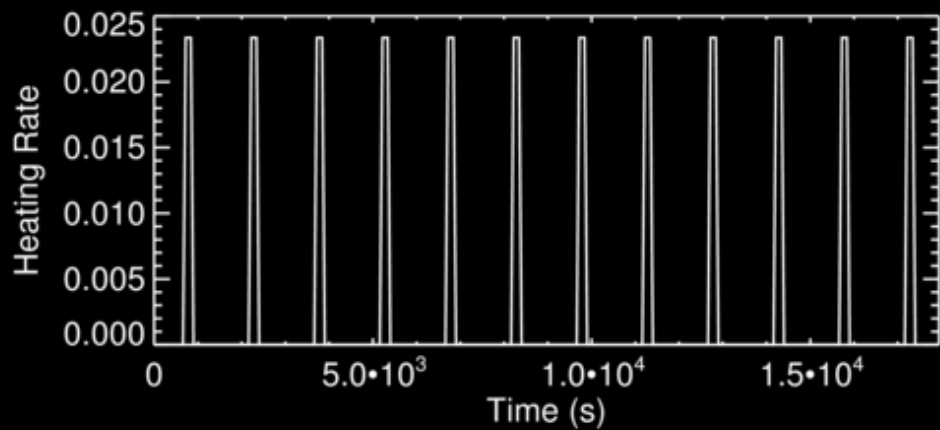
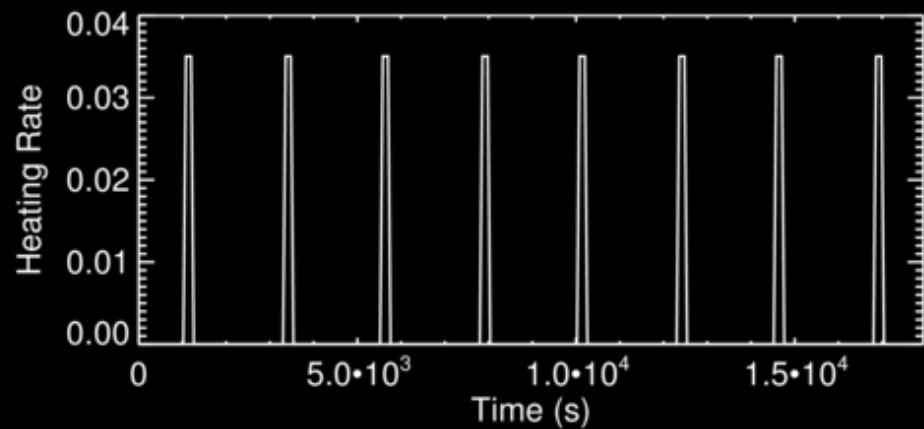
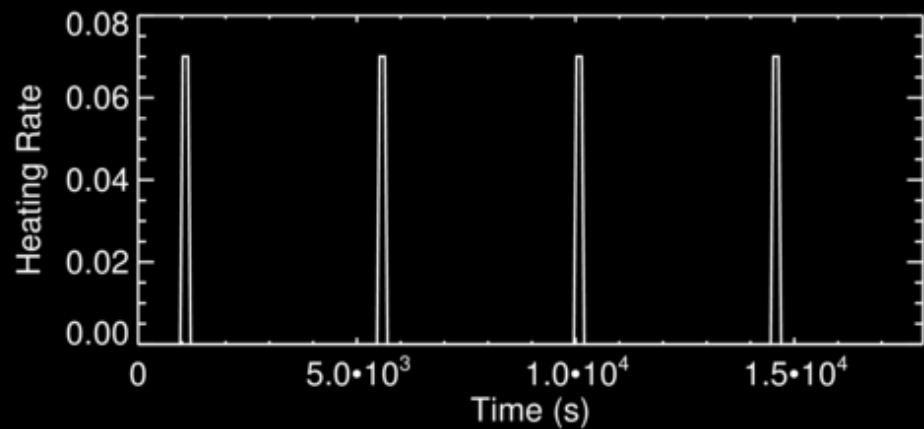
$$\epsilon_E = \epsilon_0 \left(\frac{\bar{B}}{\bar{B}_0} \right)^\alpha \left(\frac{L_0}{L} \right)^\beta$$

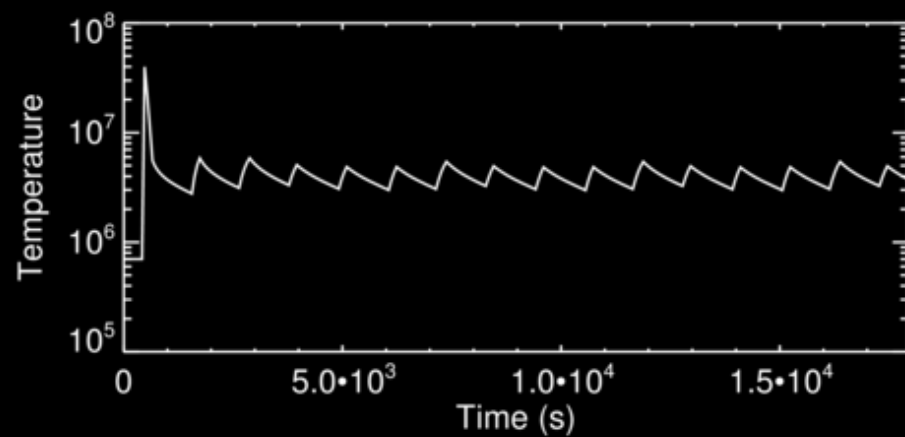
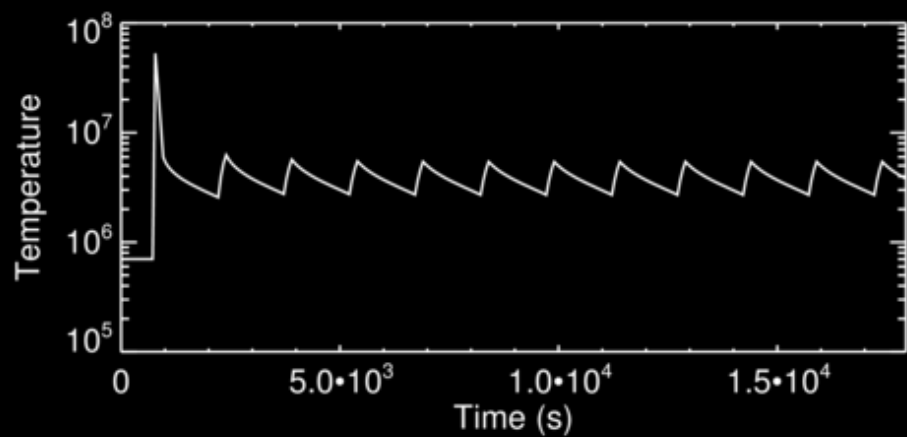
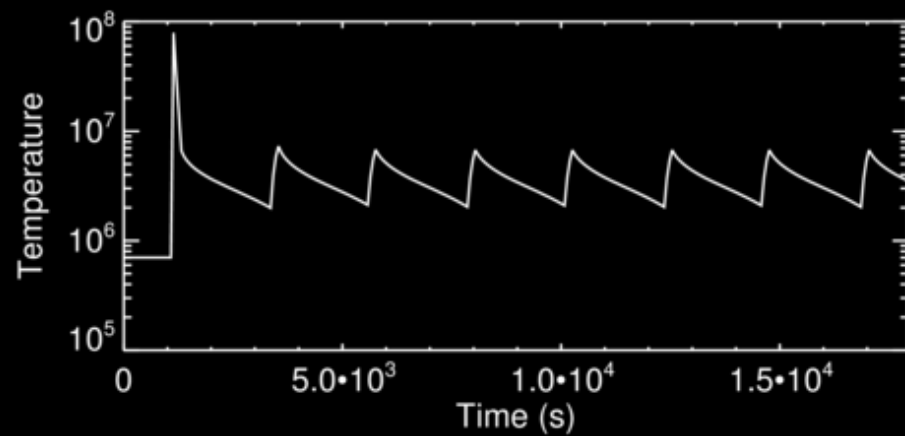
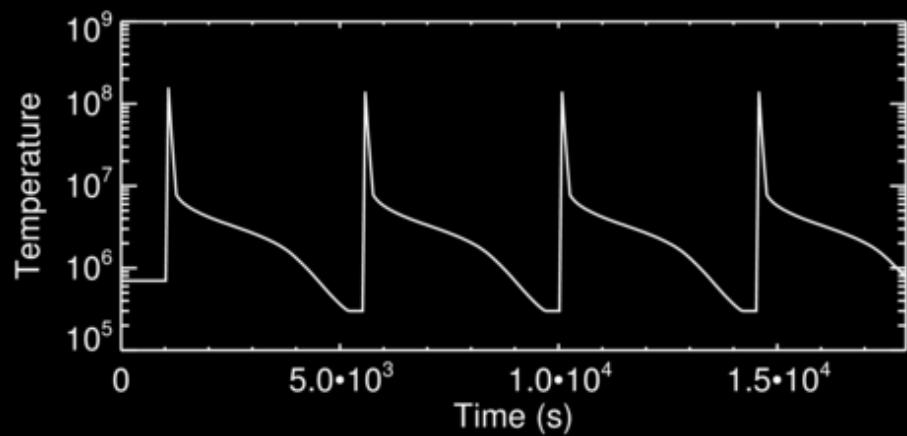
$$\alpha = \beta = 1$$

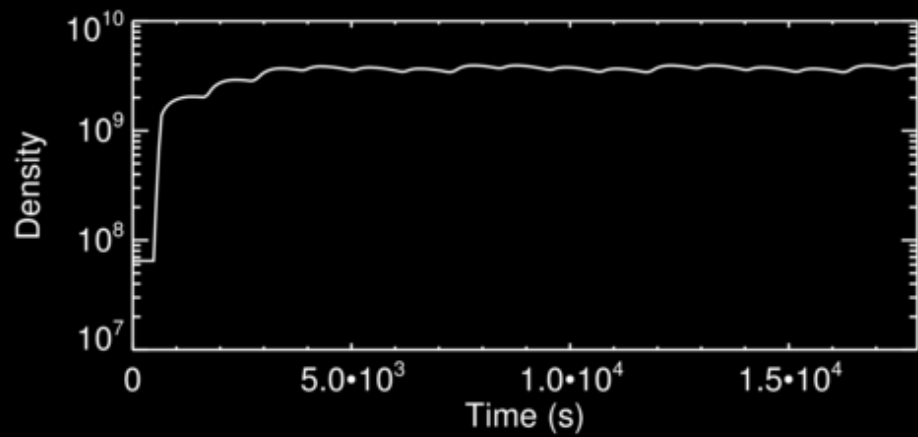
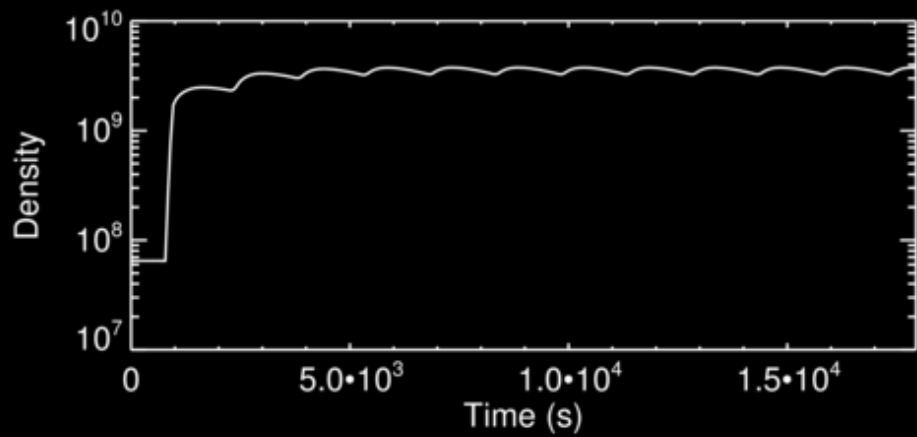
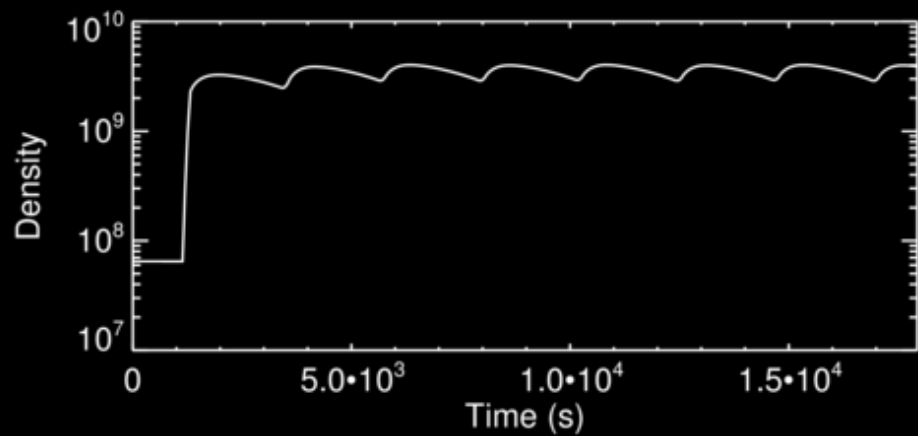
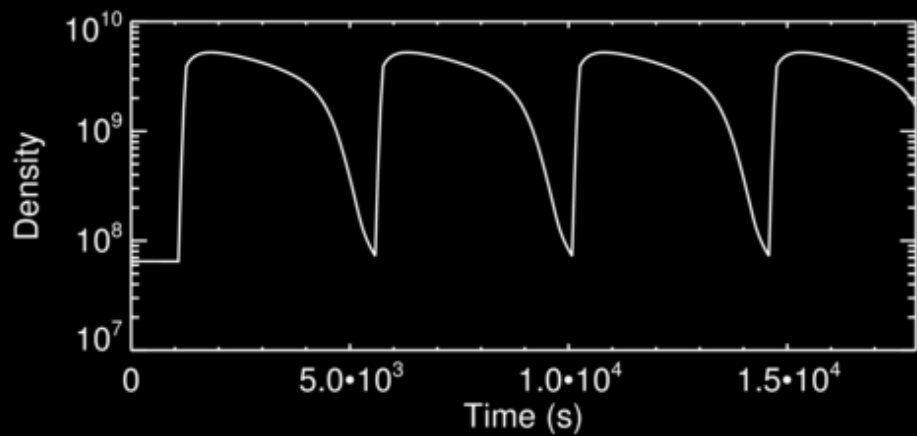
Schrijver et al., 2004; Lundquist et al., 2008; Warren & Winebarger 2006, 2007; Winebarger et al., 2008, 2011;

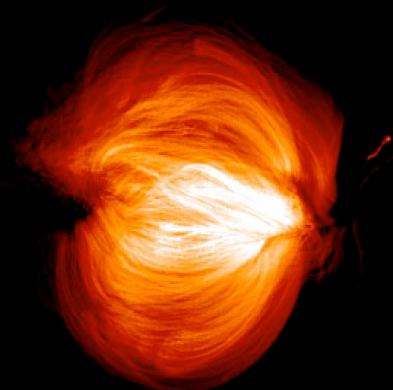
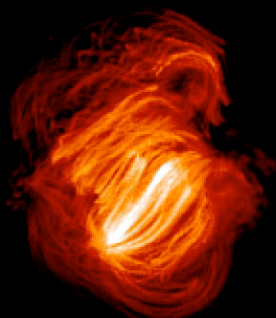
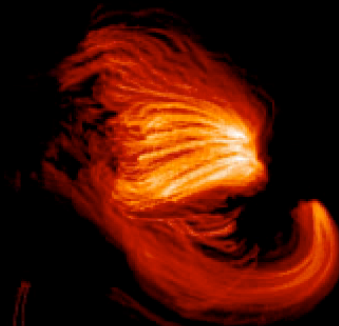
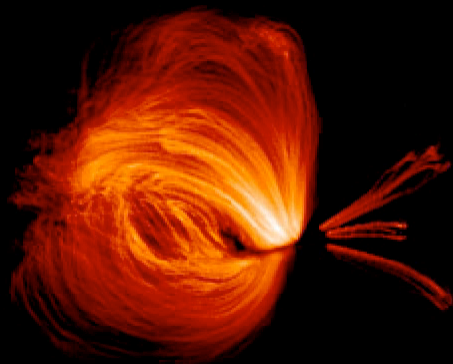
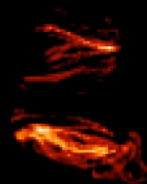
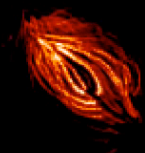
Impulsive



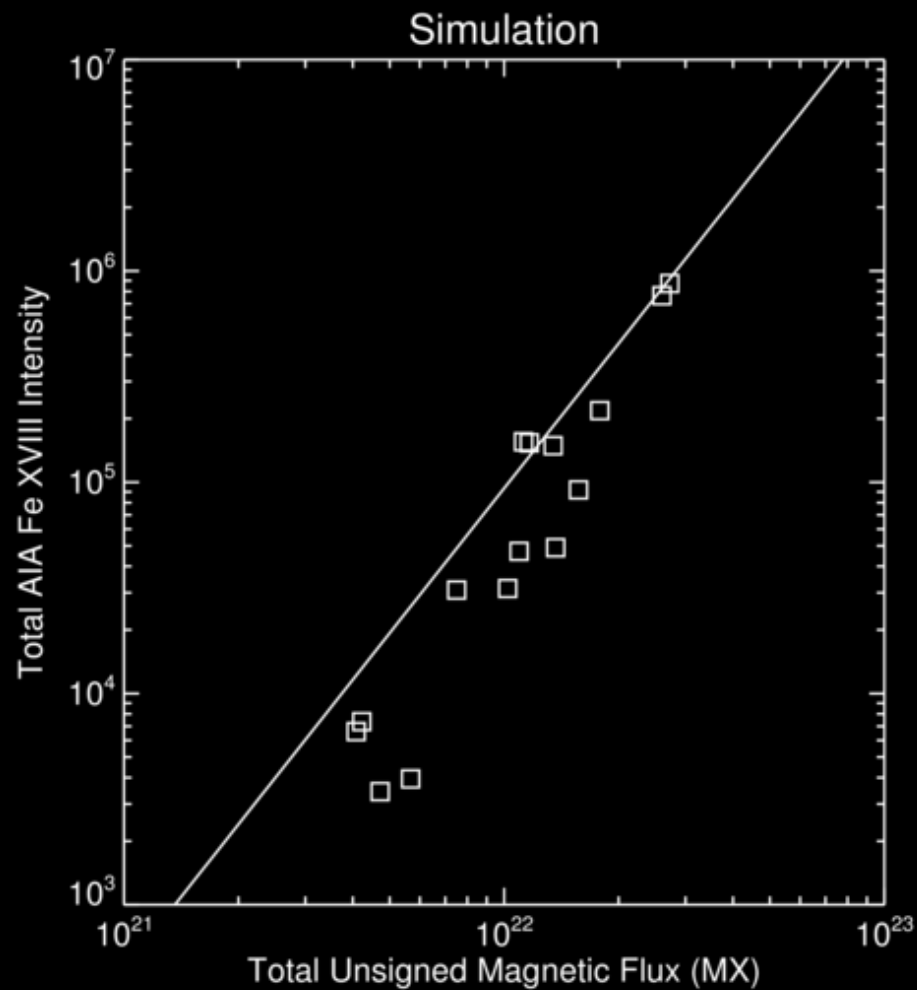
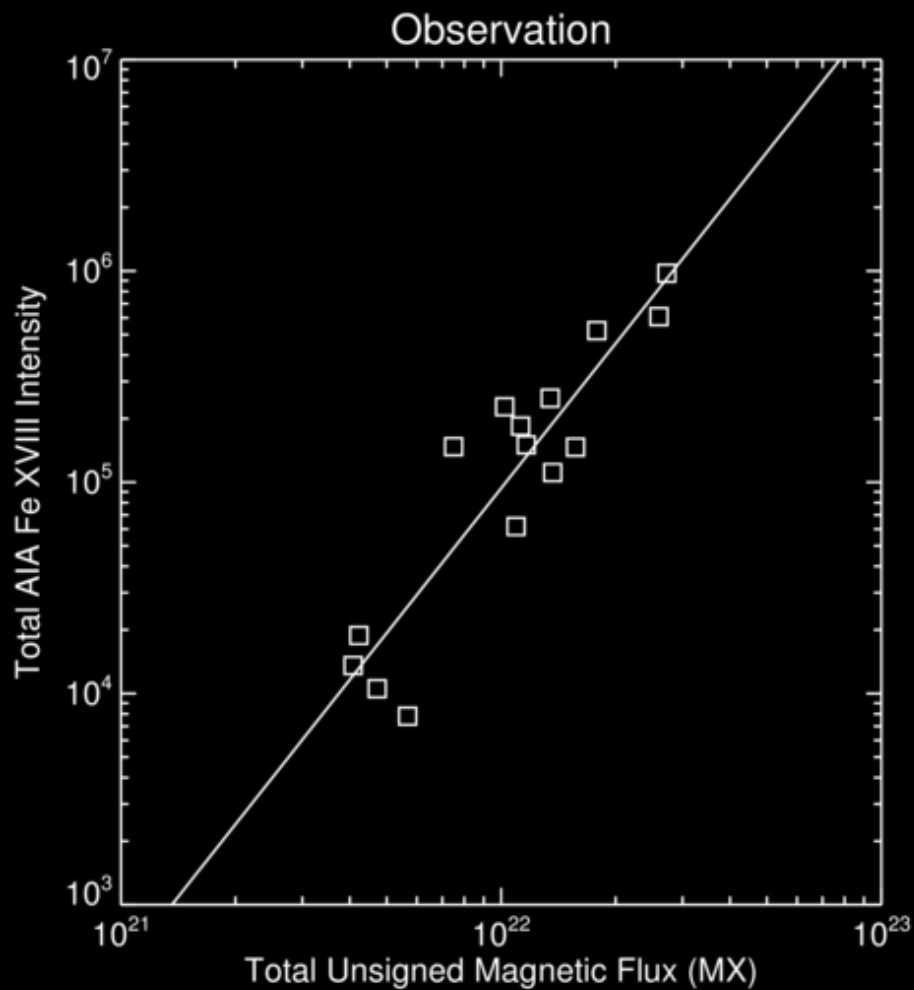








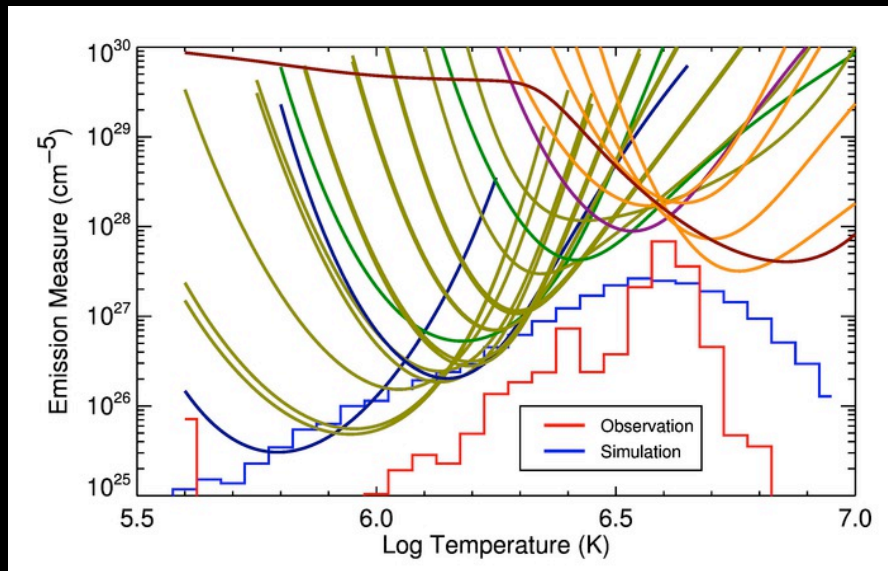
The Flux-Luminosity Relationship



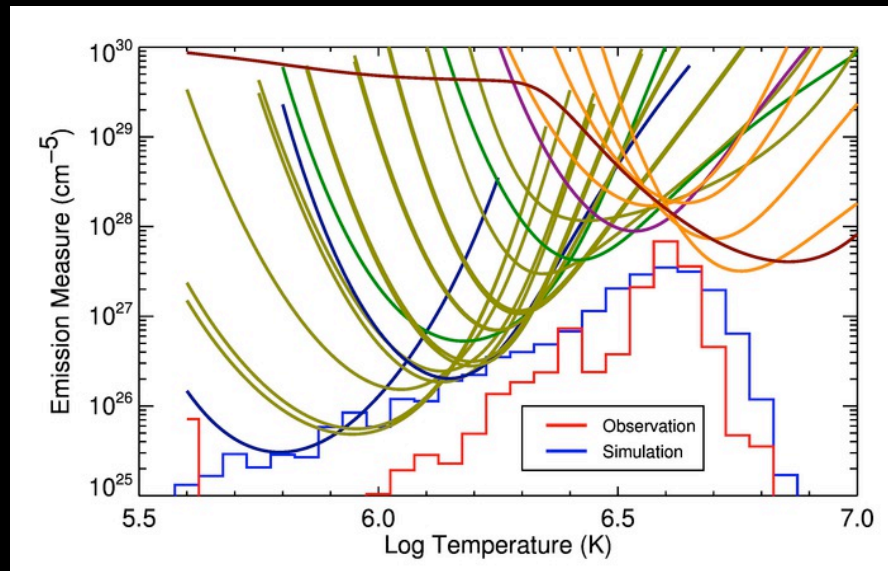
Reproduced for all heating scenarios. B/L works!

large active region

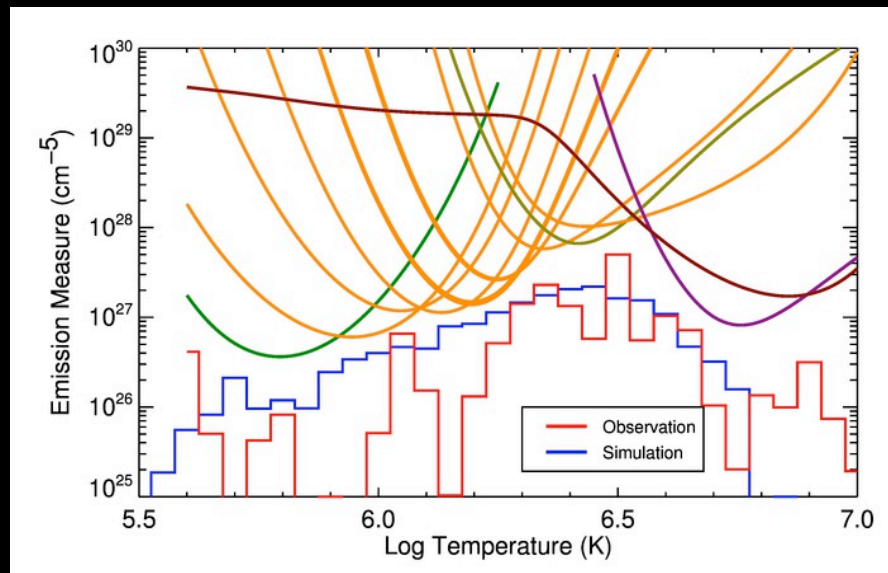
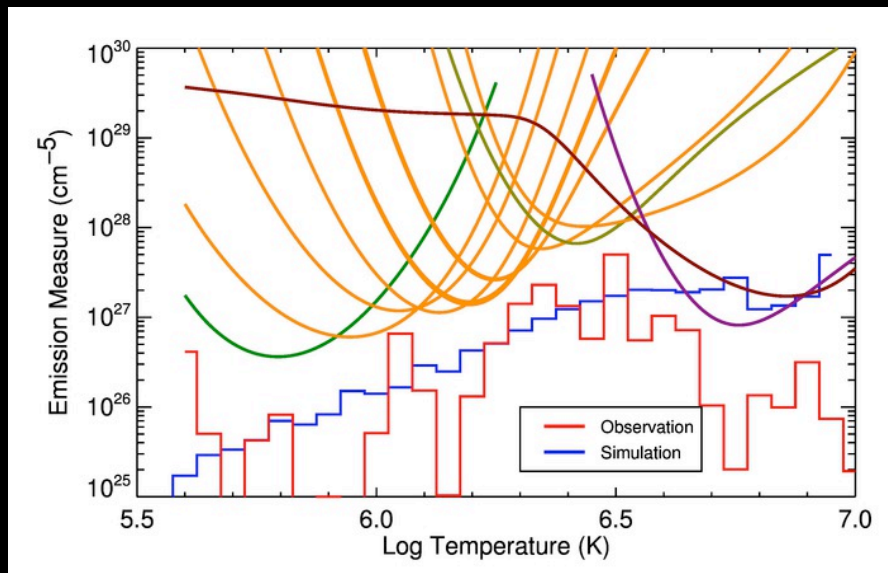
low frequency heating



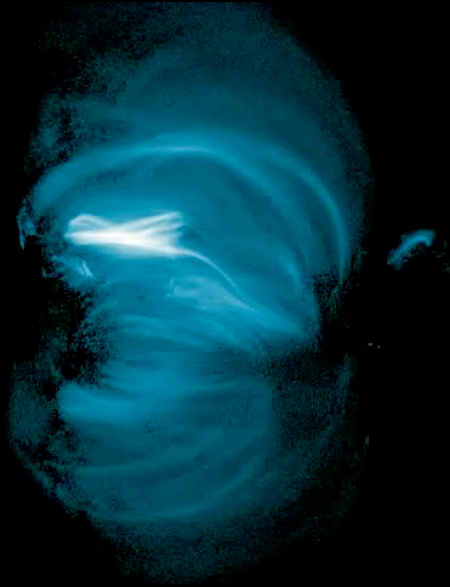
high frequency heating



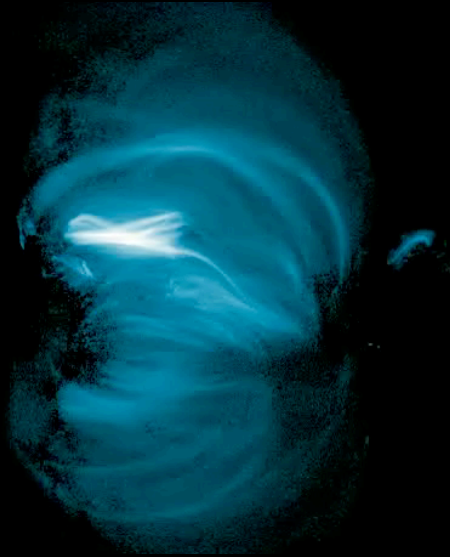
small active region



2011/11/08 14:00:23 UT



2011/11/08 14:00:23 UT



NO EVENT

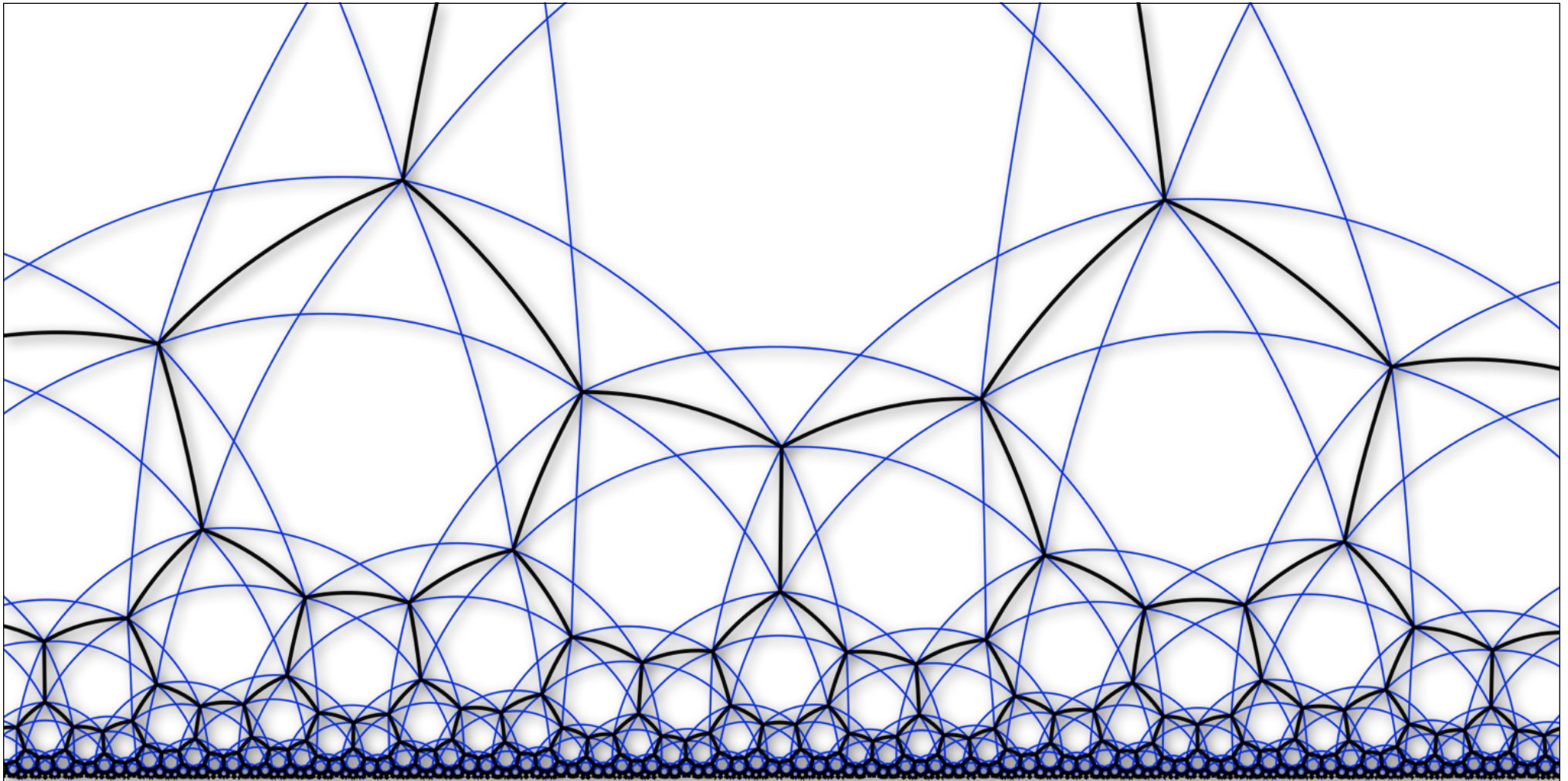


EVENT

START



END



The EIS Calibration

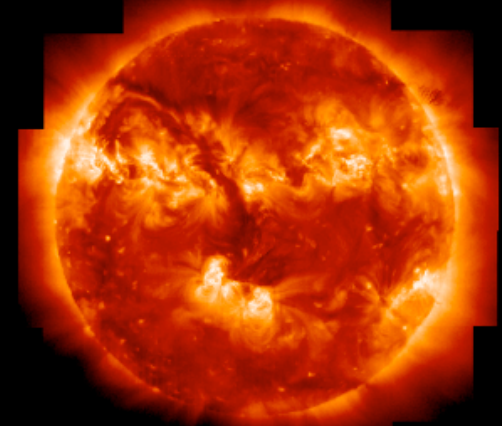
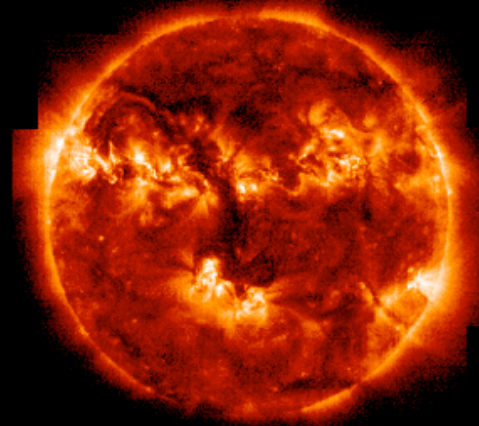
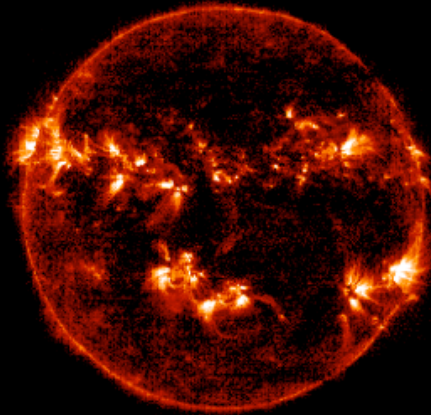
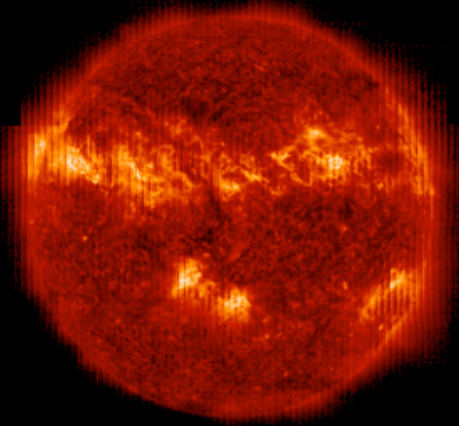
Example HOP 130 EIS Data

He II 256.317 Å

Si VII 275.368 Å

Fe XI 180.401 Å

Fe XII 195.119 Å

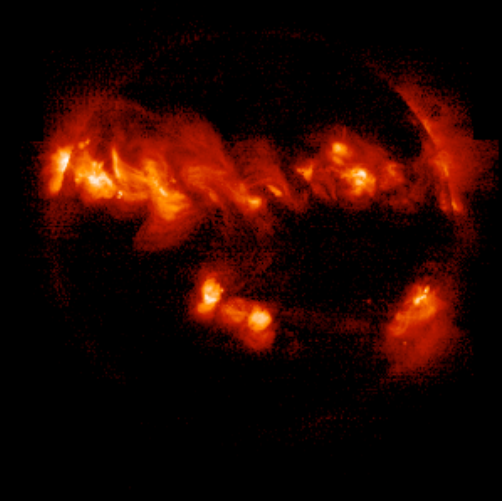
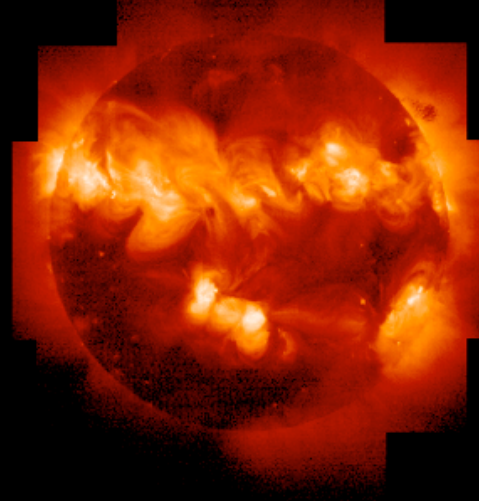
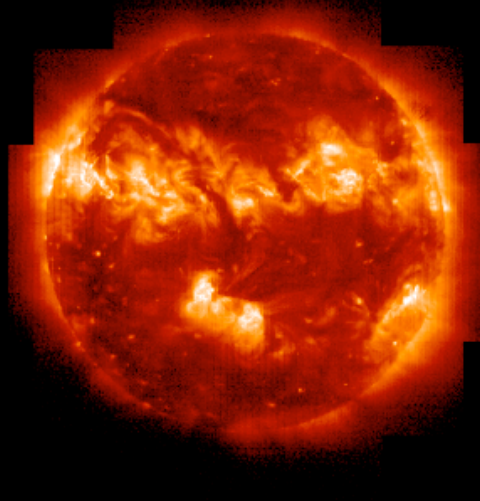
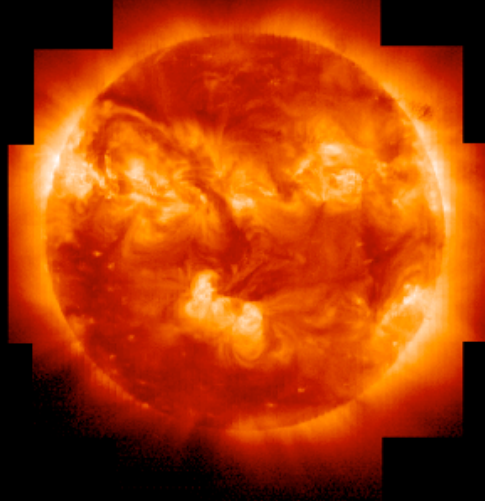


Fe XIII 202.044 Å

Fe XIII 203.826 Å

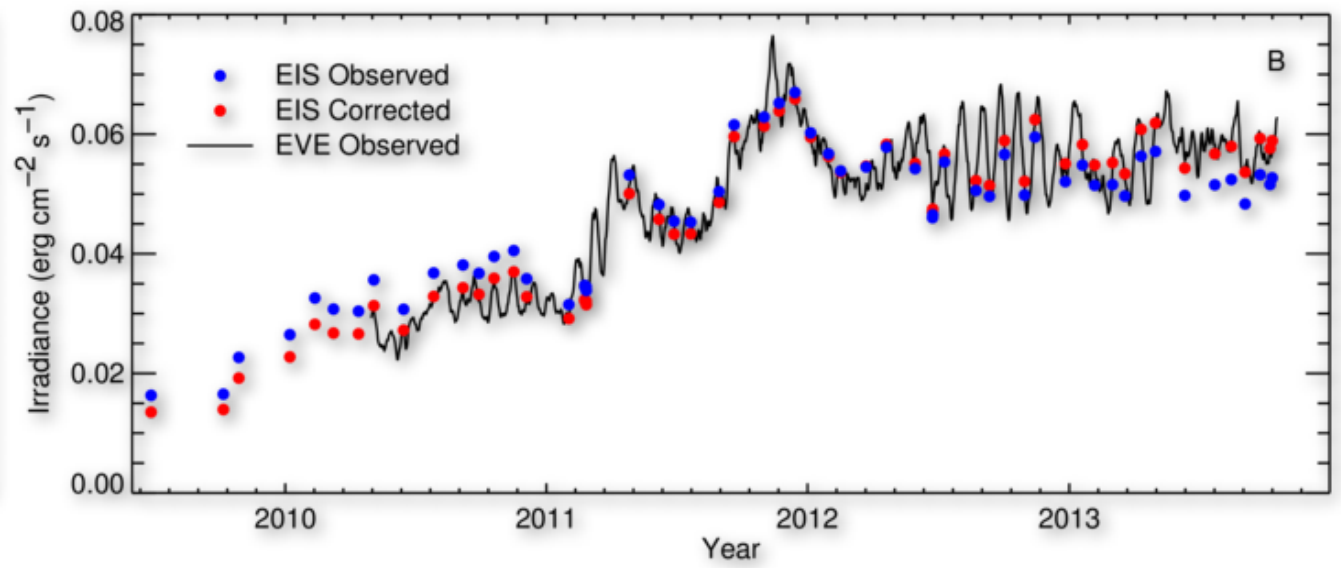
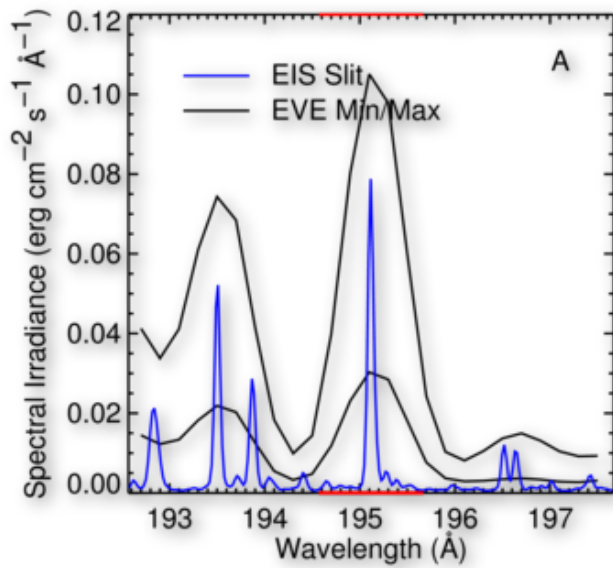
Fe XV 284.160 Å

Fe XVI 262.984 Å

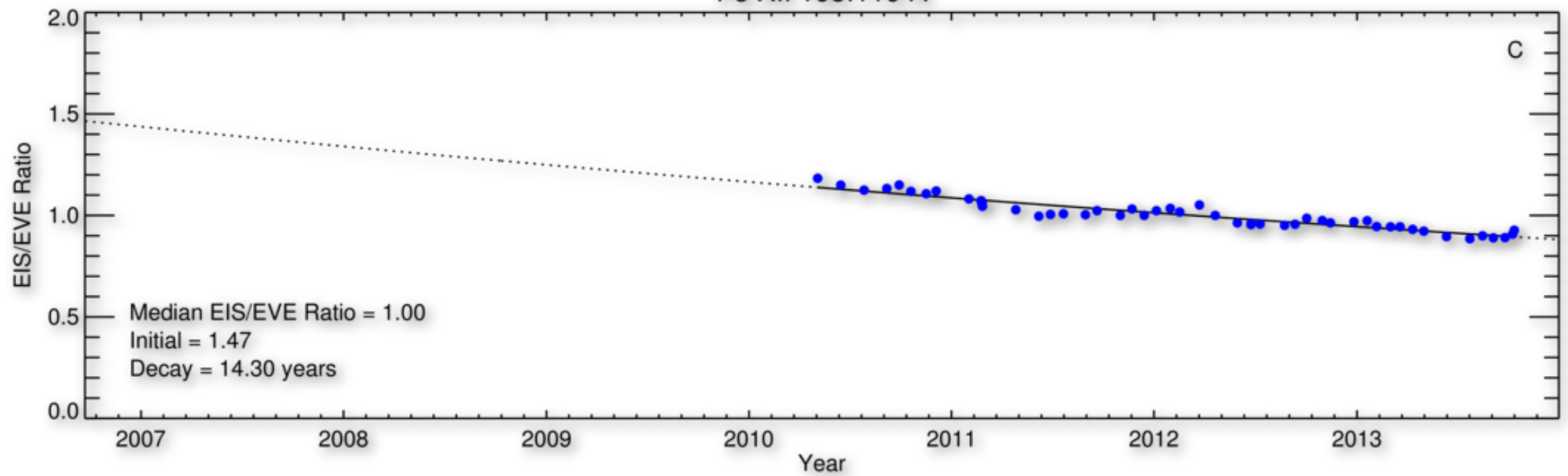


2011/11/22 10:40:20 — 14:09:14
EIS/Hinode

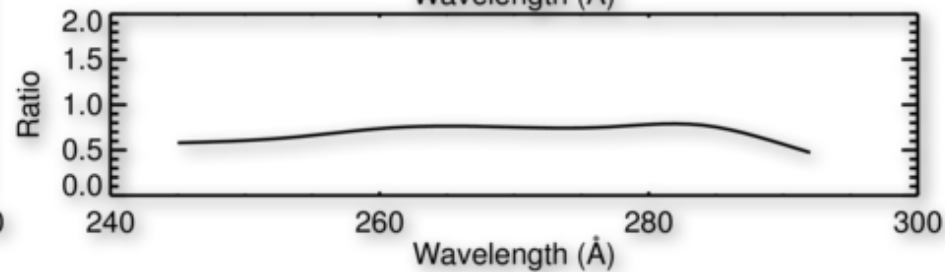
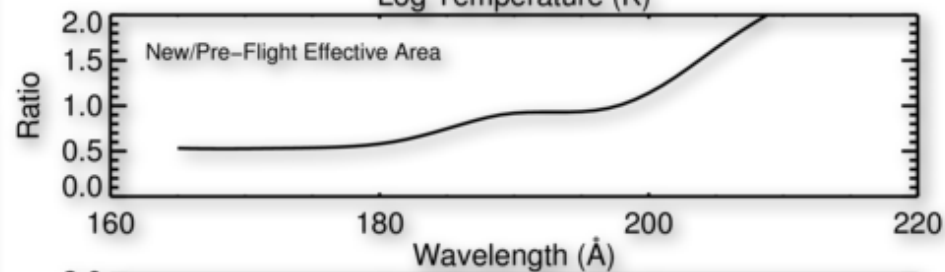
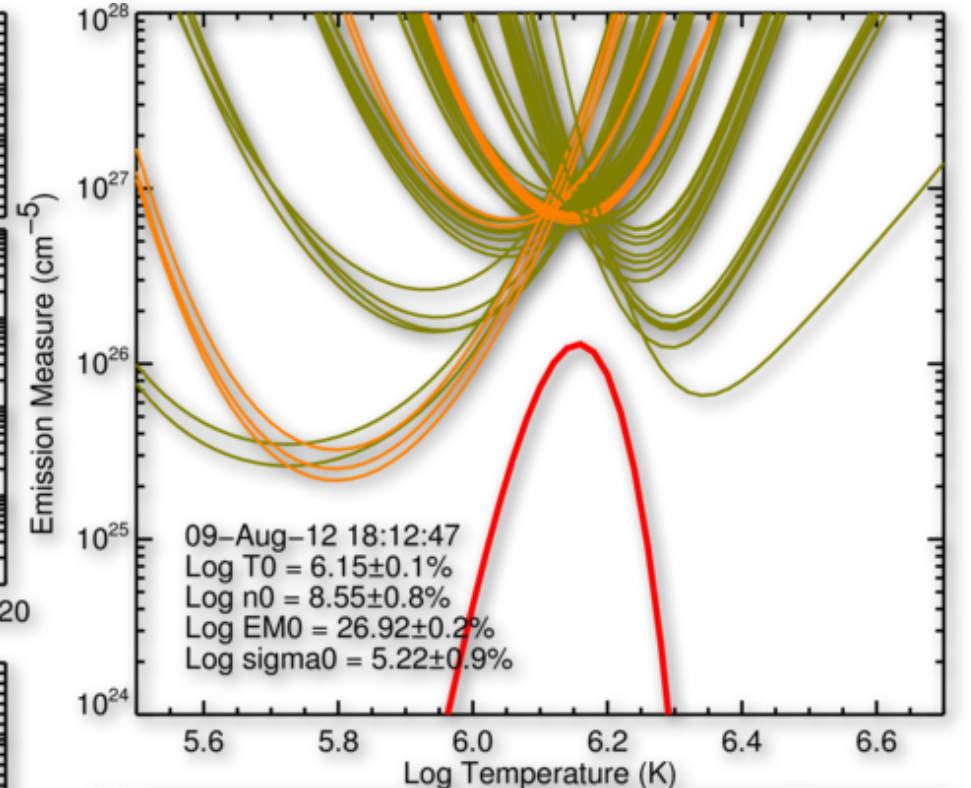
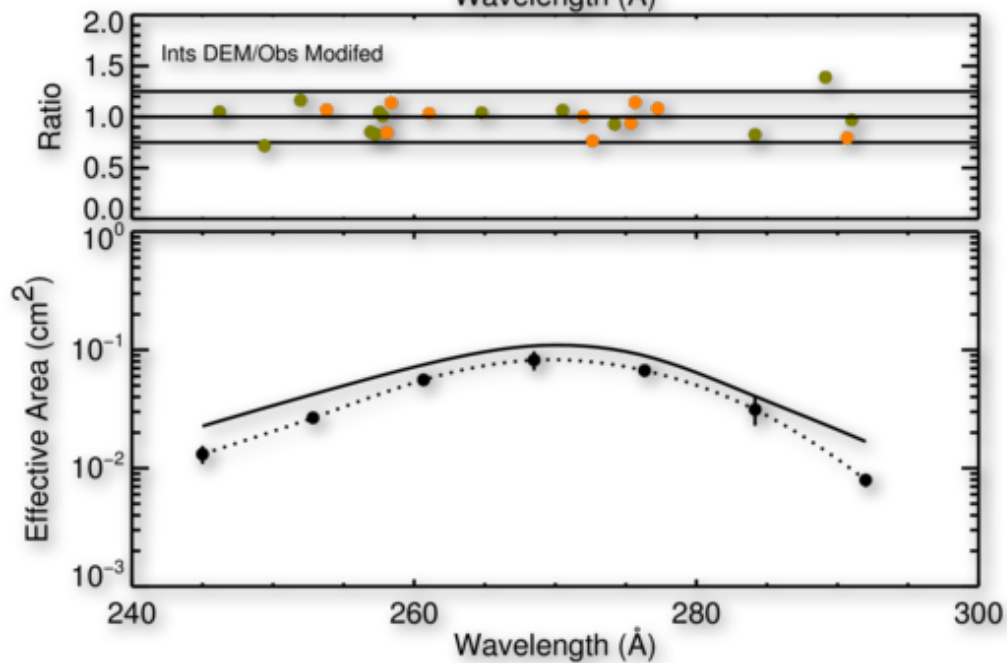
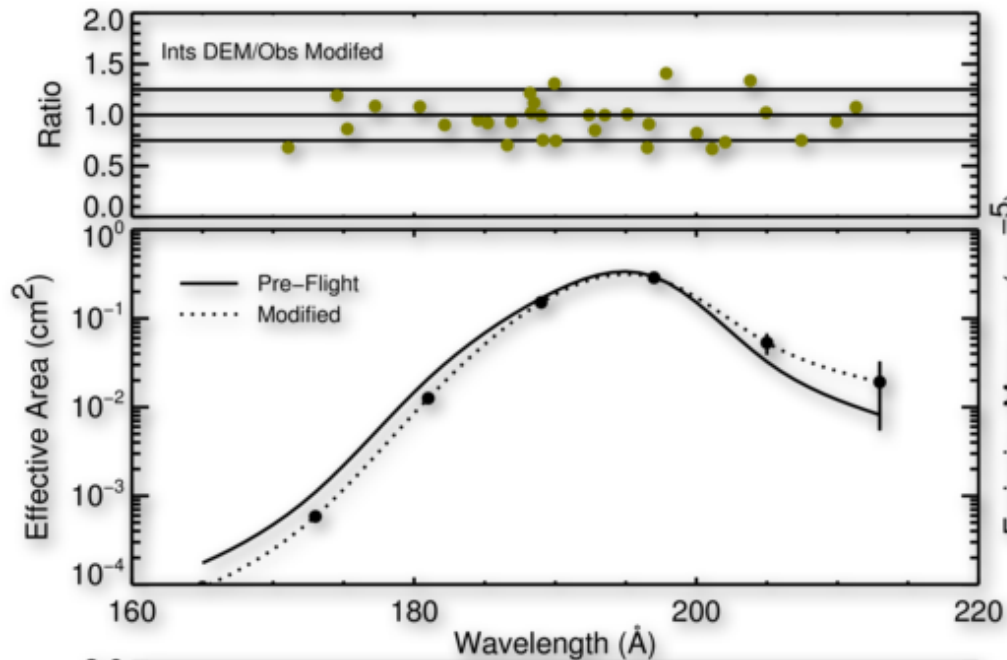
EIS and EVE Irradiance Data



Fe XII 195.119 Å

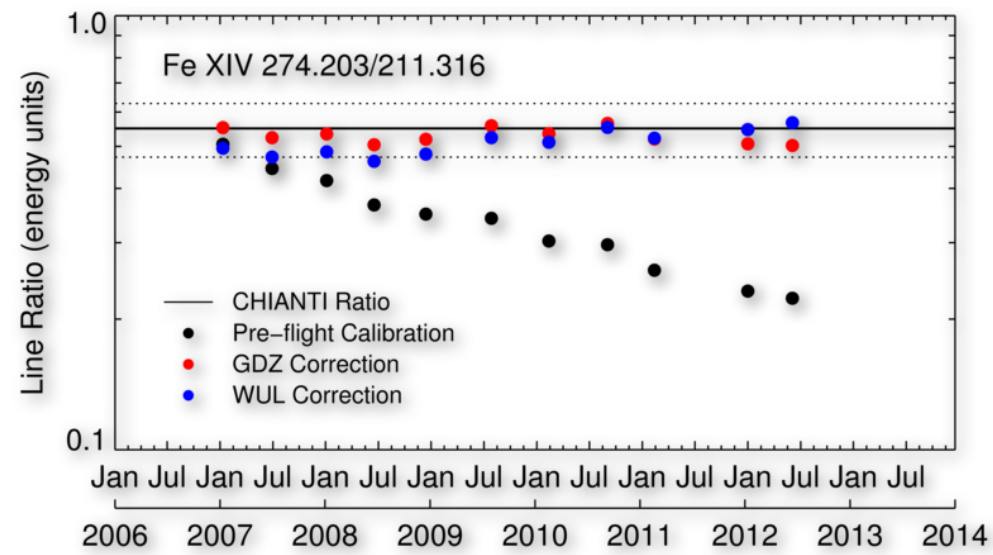


Inferring the EIS Effective Areas

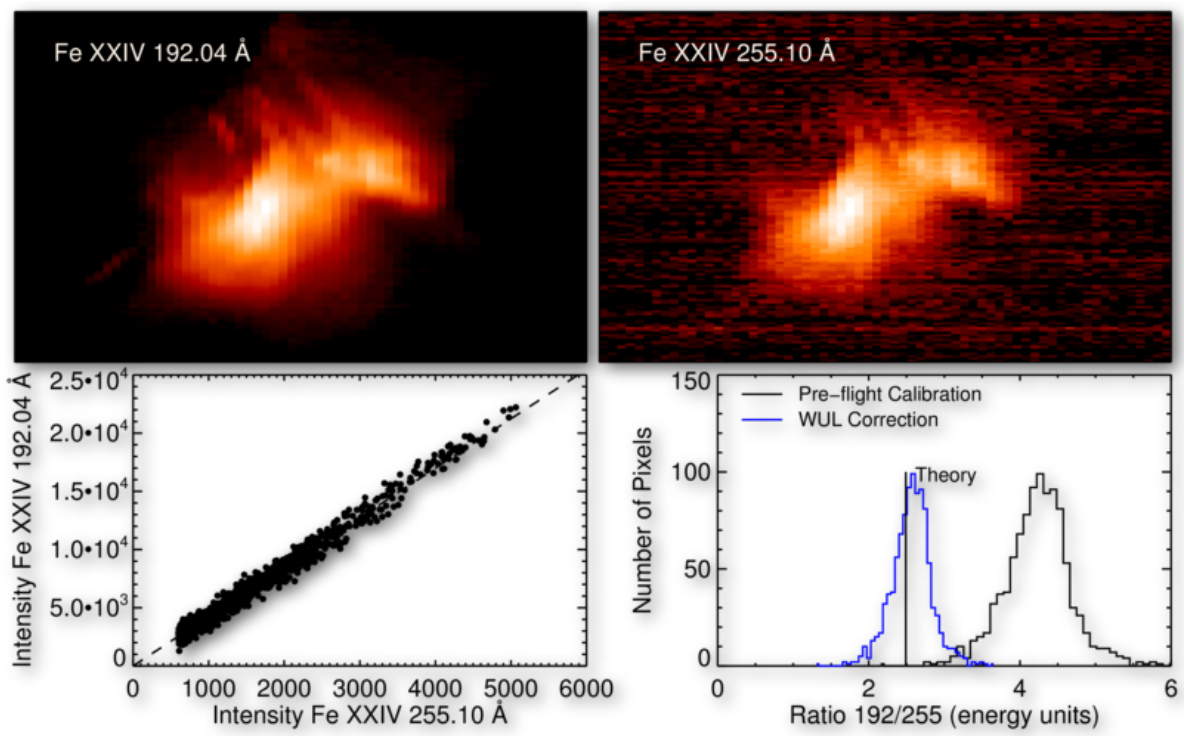


Checking the Revised Effective Areas

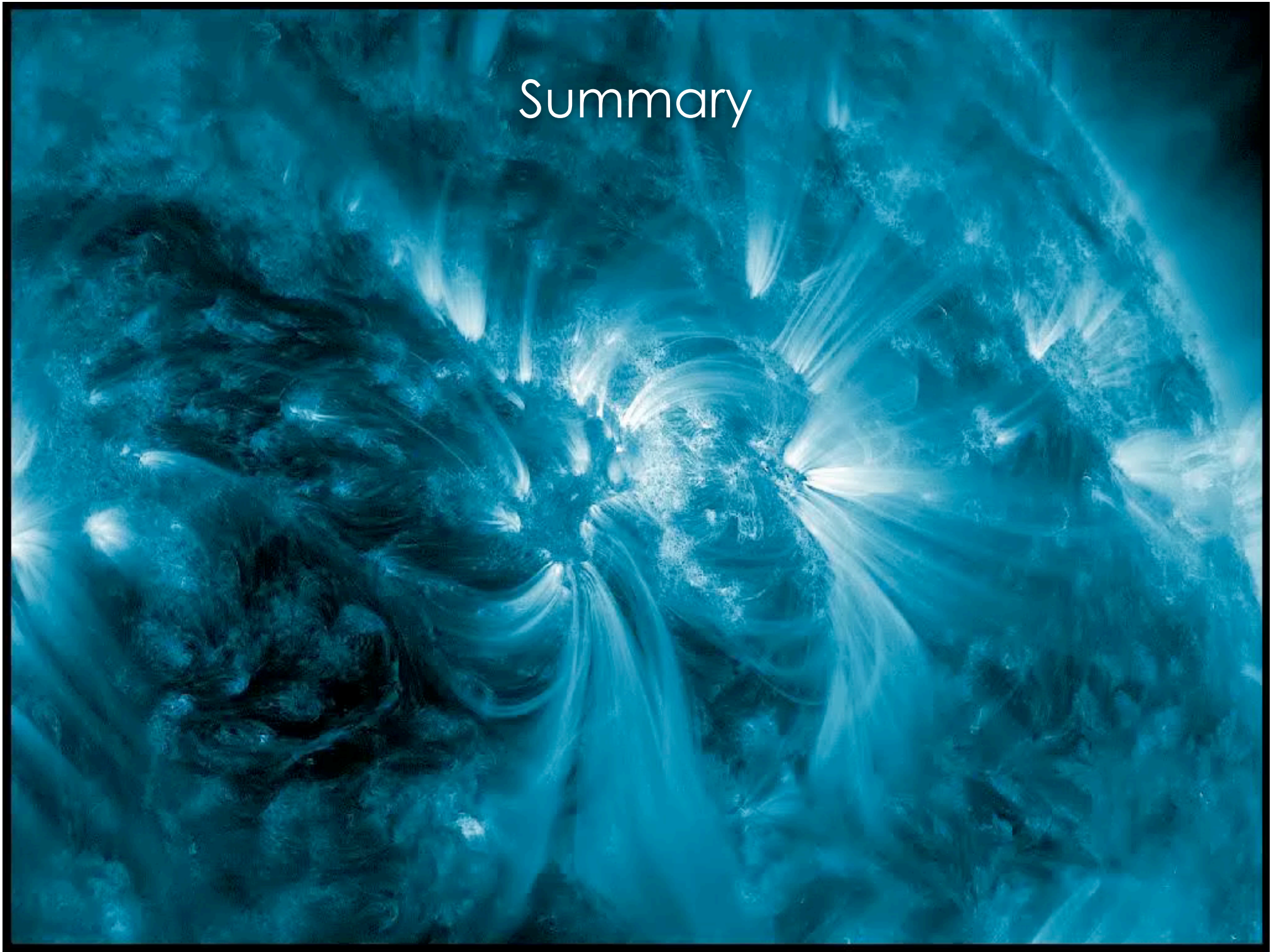
Fe XIV Ratio



Fe XXIV Ratio



Summary



Summary

- EIS Calibration
 - see the EIS wiki and routines in ssw
 - see Del Zanna A&A (2013), Warren et al. astro-ph (2013)

Summary

- EIS Calibration
 - see the EIS wiki and routines in ssw
 - see Del Zanna A&A (2013), Warren et al. astro-ph (2013)
- Active Region Modeling
 - Work in progress
 - Need to reproduce DEM, flux-luminosity, variability
 - High frequency heating is “winning” . . . ?

Summary

- EIS Calibration
 - see the EIS wiki and routines in ssw
 - see Del Zanna A&A (2013), Warren et al. astro-ph (2013)
- Active Region Modeling
 - Work in progress
 - Need to reproduce DEM, flux-luminosity, variability
 - High frequency heating is “winning” . . . ?
- Sparse Bayesian Inference
 - Promising!
 - Errors in the atomic data need to be addressed
 - Not magic! - Still limitations to DEM (e.g., Testa et al 2012)