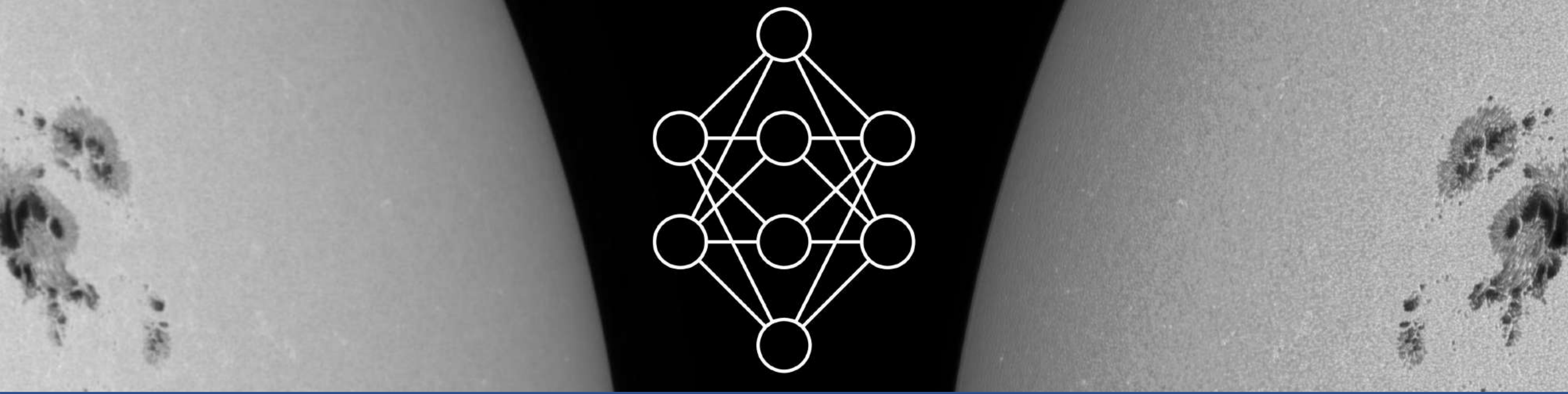
Solar image enhancement and quality assessment with deep learning

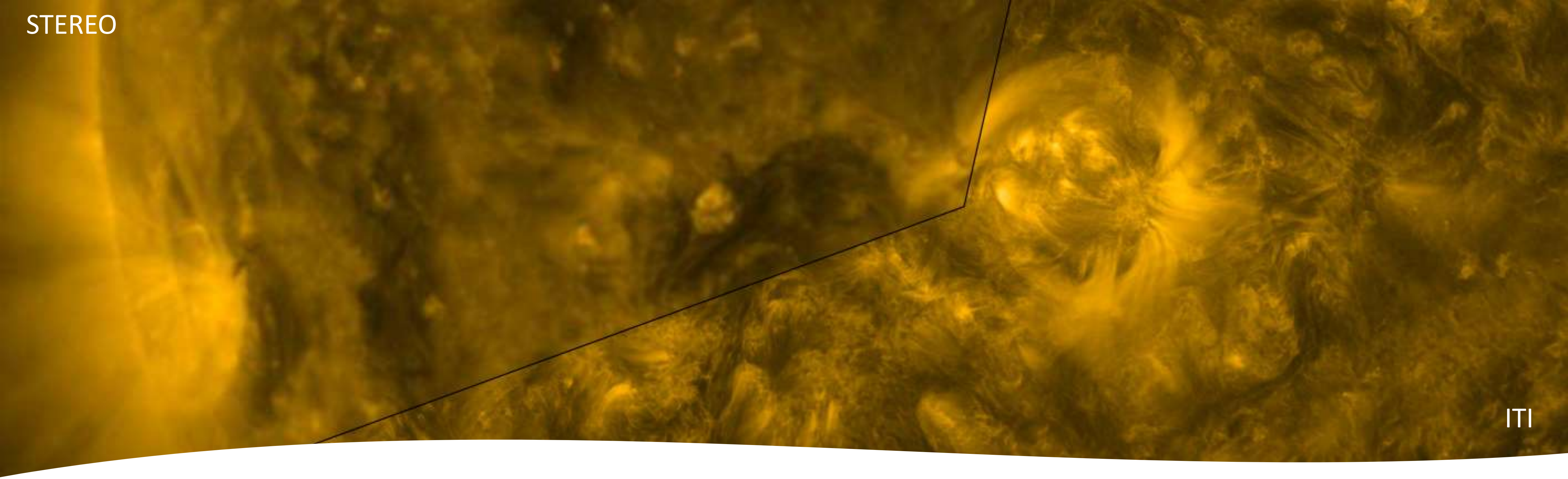


R. Jarolim[1], A. Veronig[1,2], W. Pötzi[2], T. Podladchikova[3]

[1]Institute of Physics, University of Graz, Austria (robert.jarolim@uni-graz.at)
[2]Kanzelhöhe Observatory for Solar and Environmental Research, University of Graz, Austria
[3]Skolkovo Institute for Science and Technology, Moscow, Russia

19-02-2021

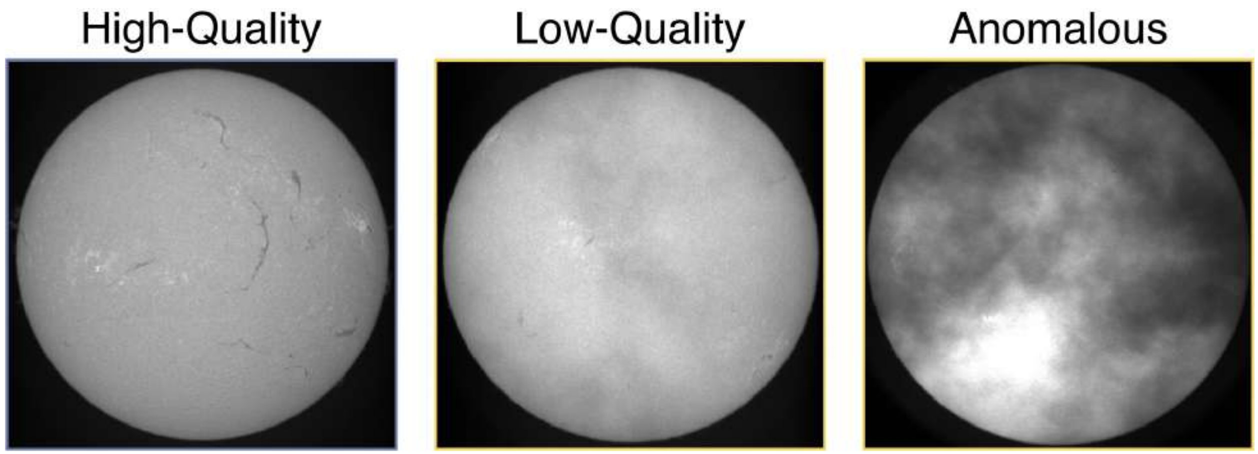
This research has received financial support from the European Union's Horizon 2020 research and innovation program under grant agreement No. 824135 (SOLARNET).



Outline

- Neural Networks
- Solar Image Quality Assessment
- Instrument-to-Instrument Translation
- SPRING related applications

SPRING – WP 8.3.3



(Example from KSO)

- Tasks:
  - T1: Image homogenization
  - T2: Image quality assessment
  - T3: Flare detection
- Provide reliable data series in real-time
- Create science-ready data sets and high-level data products

Artificial Intelligence – Neural Networks

- Generative adversarial networks (Goodfellow et al. 2014a)
  - Generator – generates realistic images
  - Discriminator – distinguishes real from generated images
  - Competitive training – networks improve iteratively
  - Model image distribution

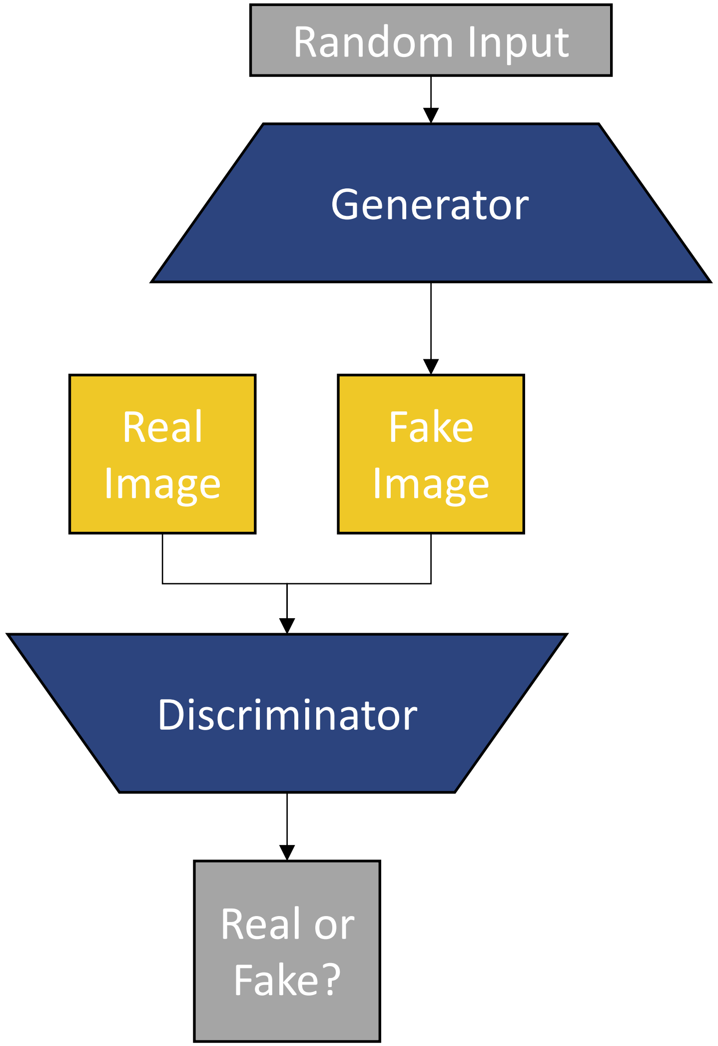
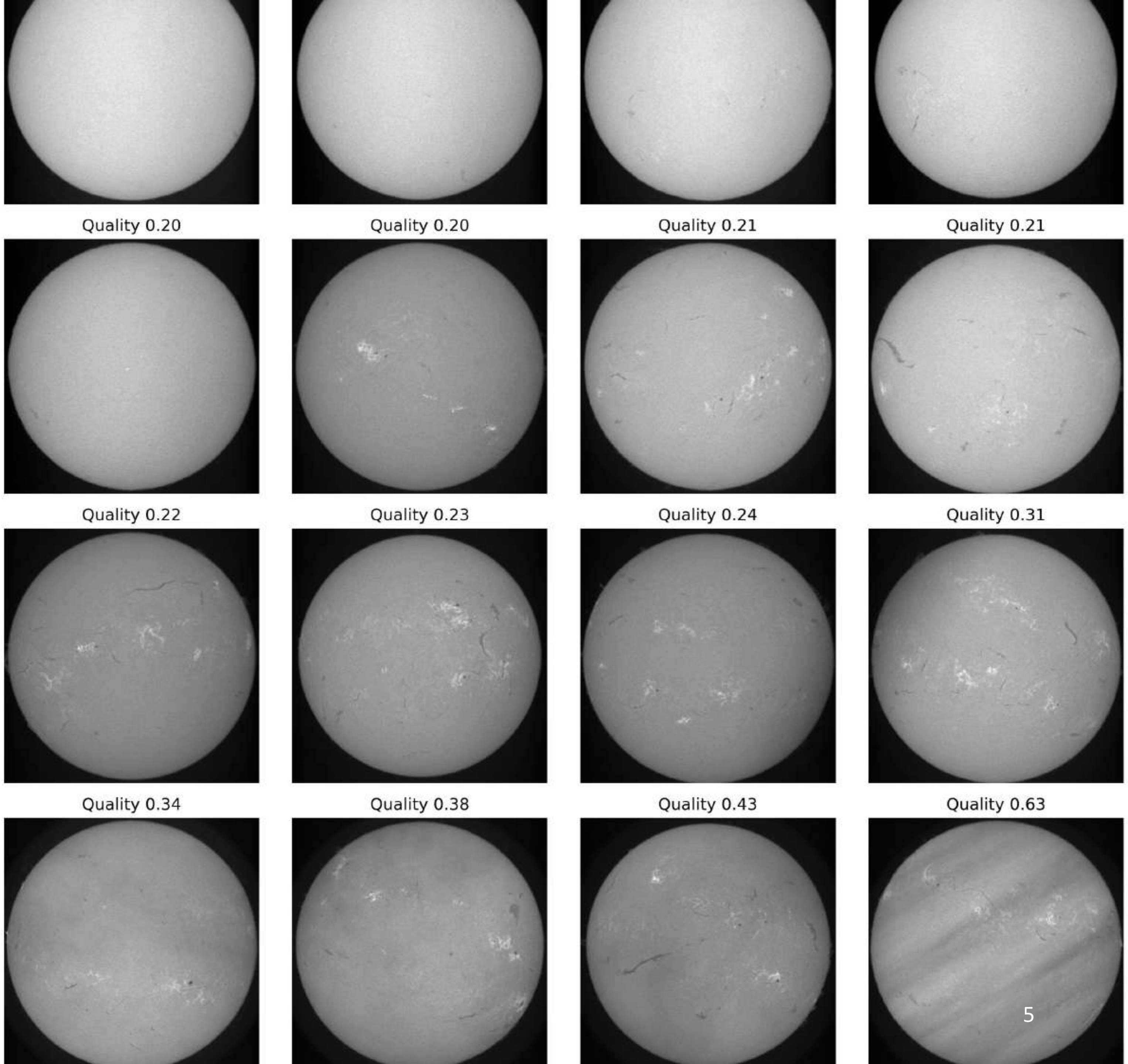
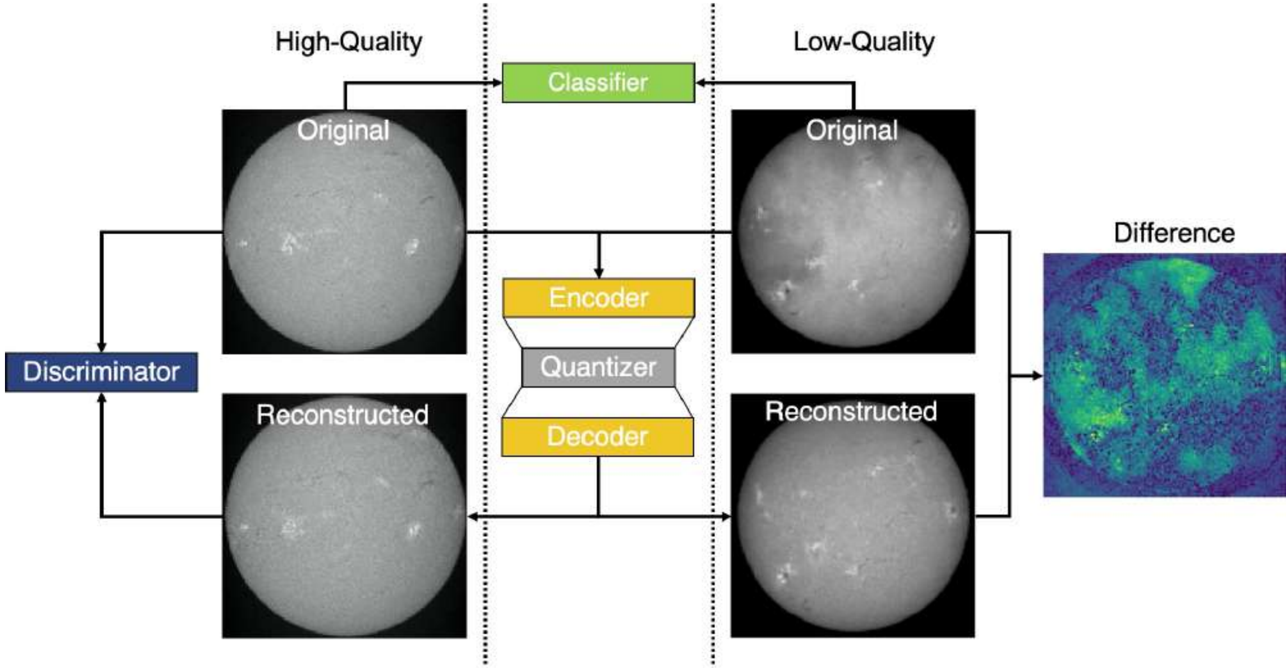


Image-quality assessment for full-disk solar observations with generative adversarial networks (Jarolim et al. 2020)



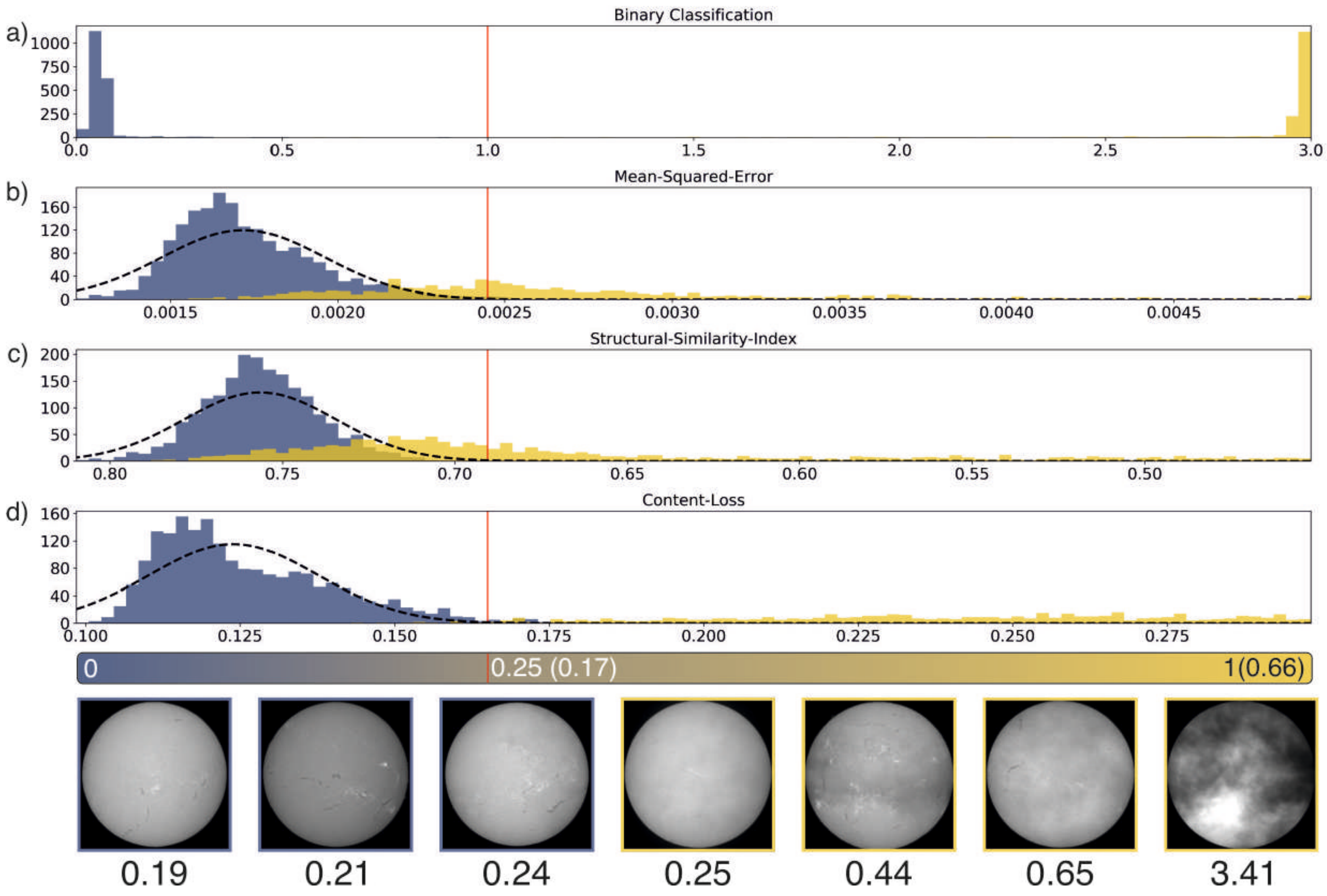
Method

- Learn high-quality characteristics
  - GAN models image distribution
  - Image compression
- Estimate deviation for low-quality features
  - Content loss from discriminator network
- Additional binary classification



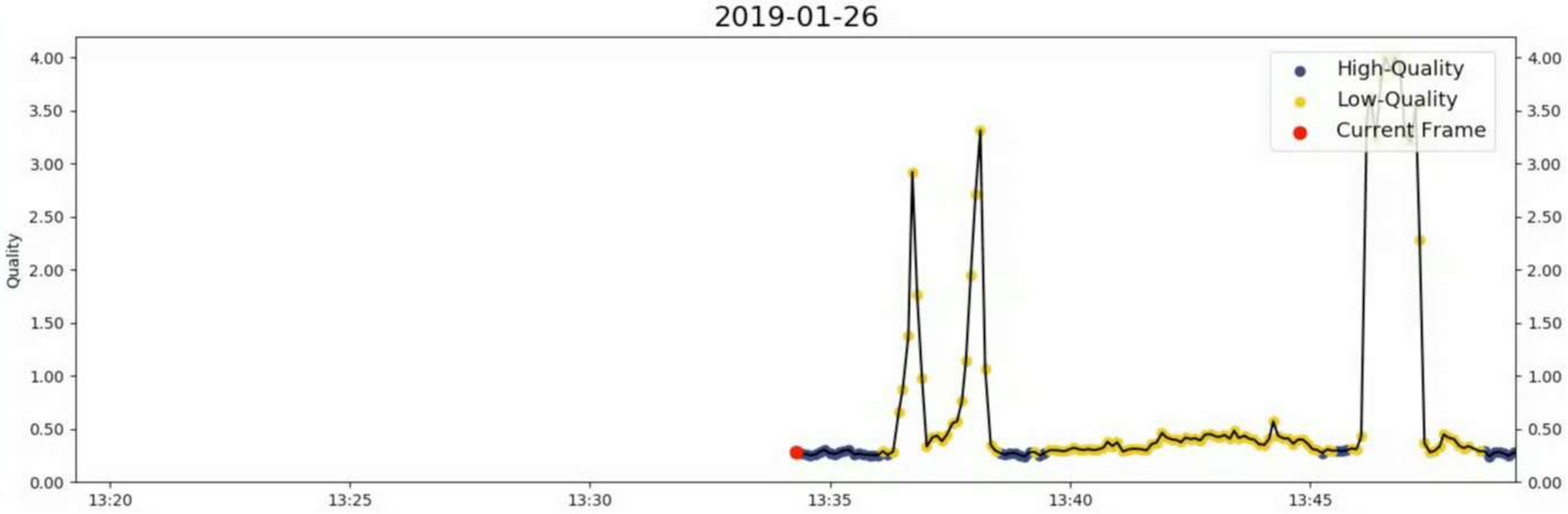
Results

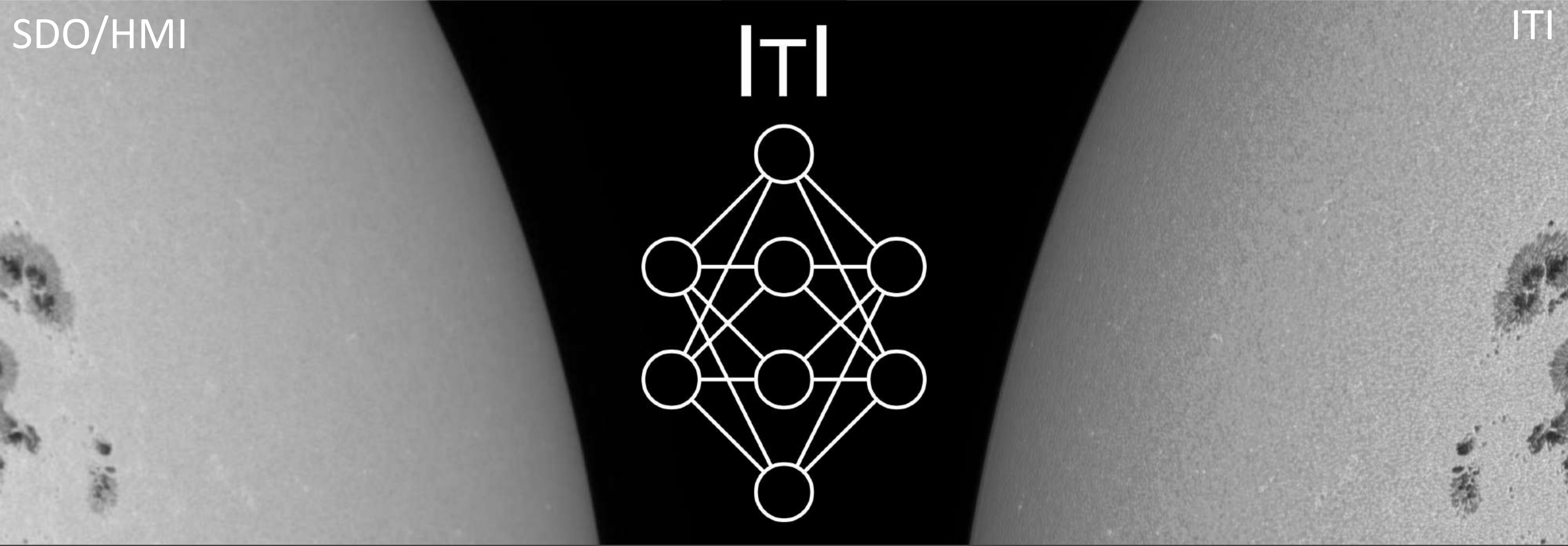
- Objective quality metric
  - Classification
  - Content loss
- Comparison to manual labels (3,300 samples)
  - Accuracy: 98.5 %
  - TSS: 0.97



Application

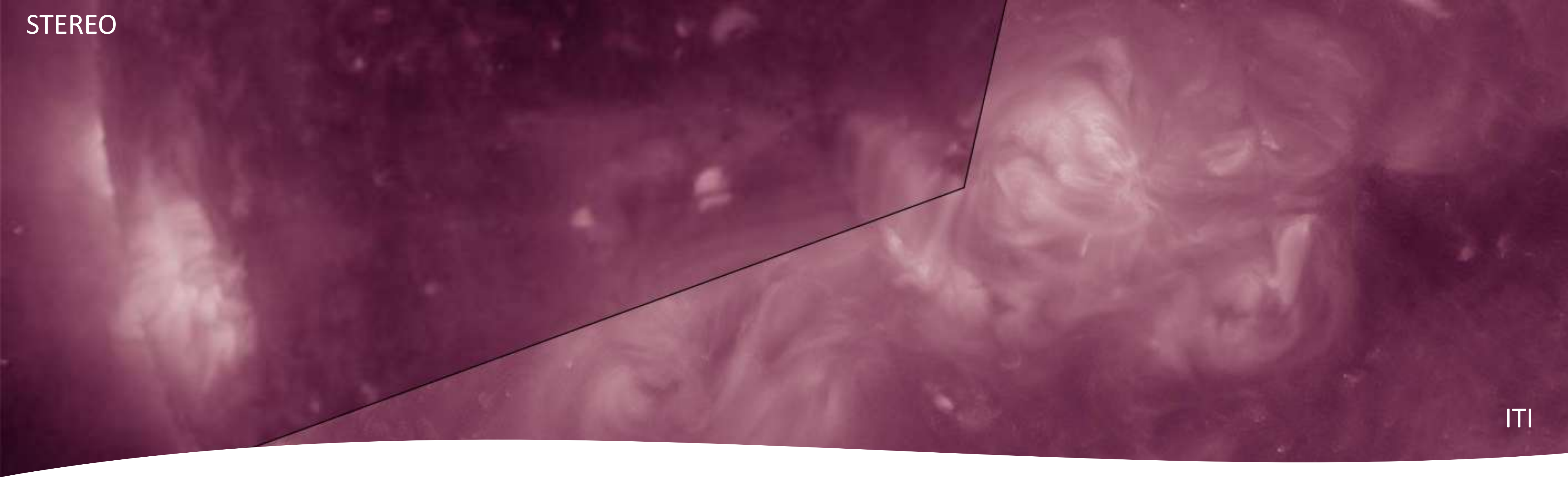
- Full observing day with varying observing conditions
- Clear observations can be identified between occulting clouds





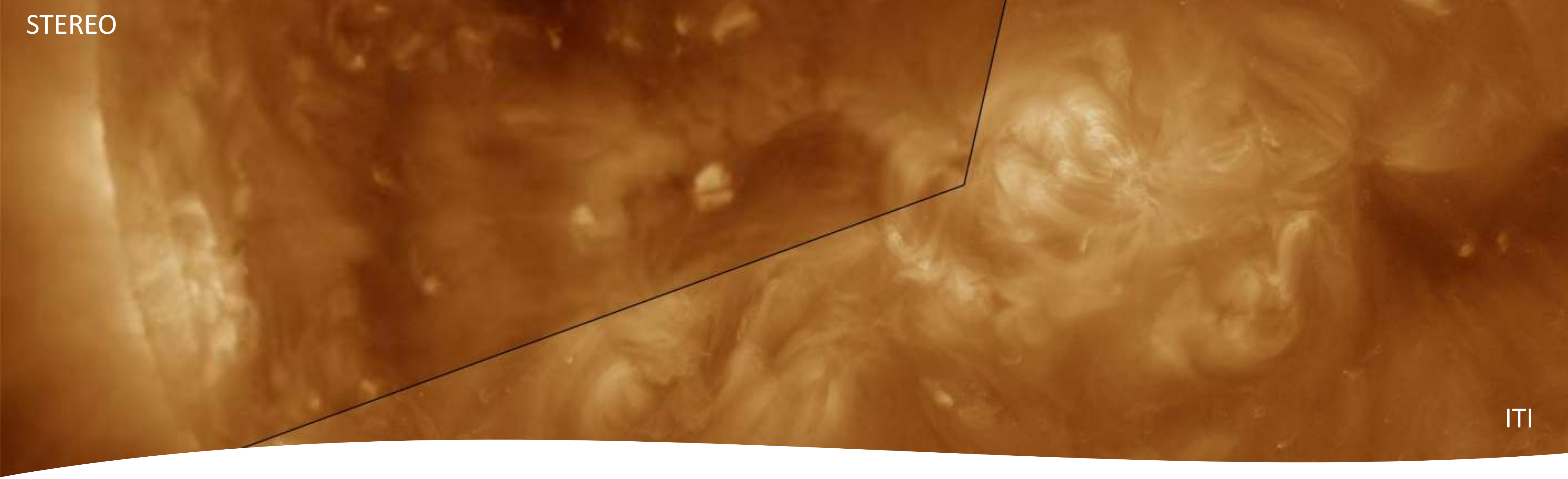
Instrument-to-Instrument translation:

image enhancement and time series restoration with deep learning (in preparation)



Motivation

- Rapid upgrade of solar observations
  - Different image quality
  - Instrumental characteristics
- Long-term studies / multi-instrument studies
- Calibration of different data sets (homogenization)
- Image enhancement beyond instrumental limitations

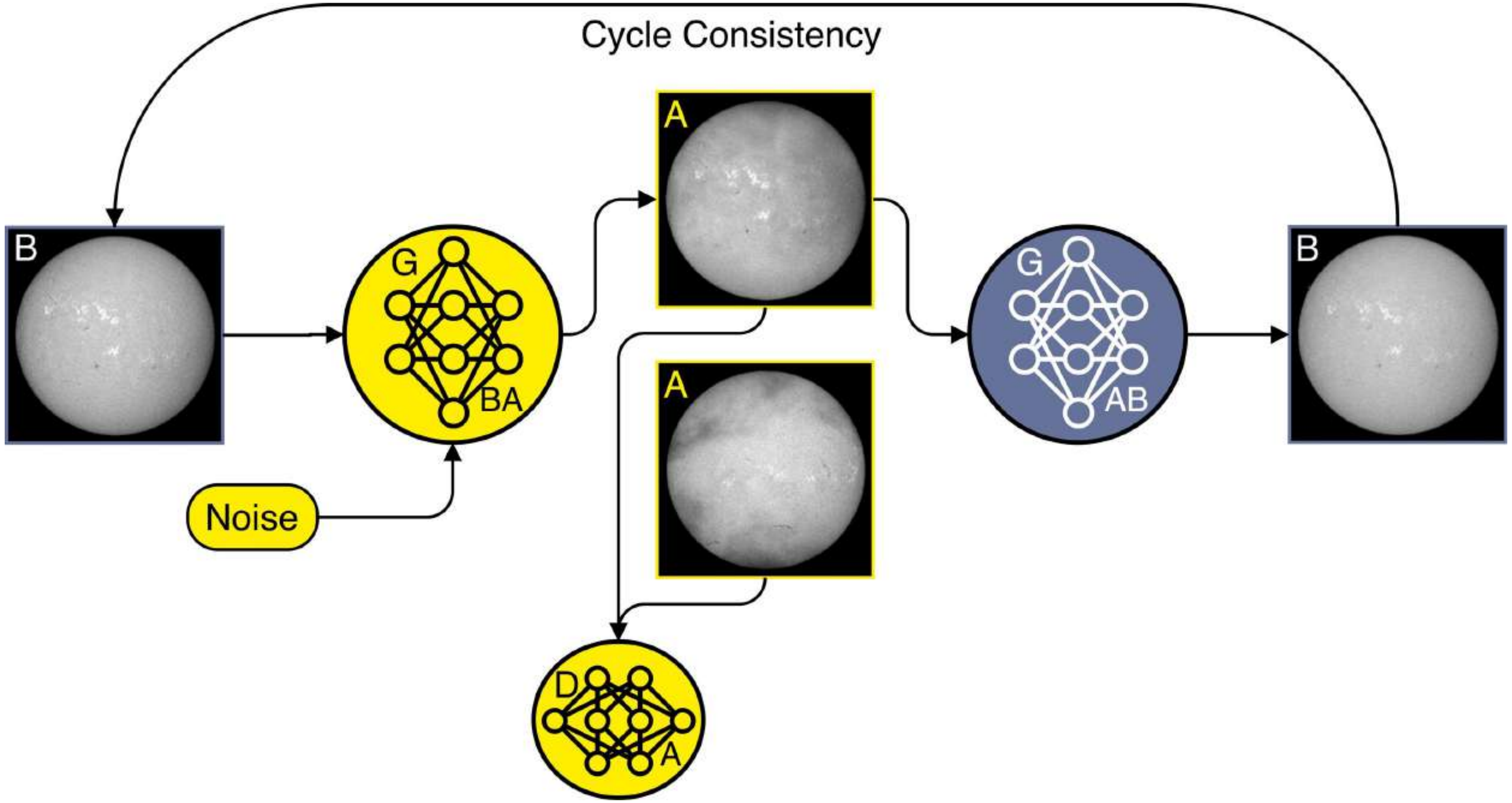


Motivation

- General Framework
- Informed image enhancement
  - Use most recent observations as reference
- Data driven approach
  - Avoid artificial assumptions
  - No data alignment required
  - Cover all quality degrading effects

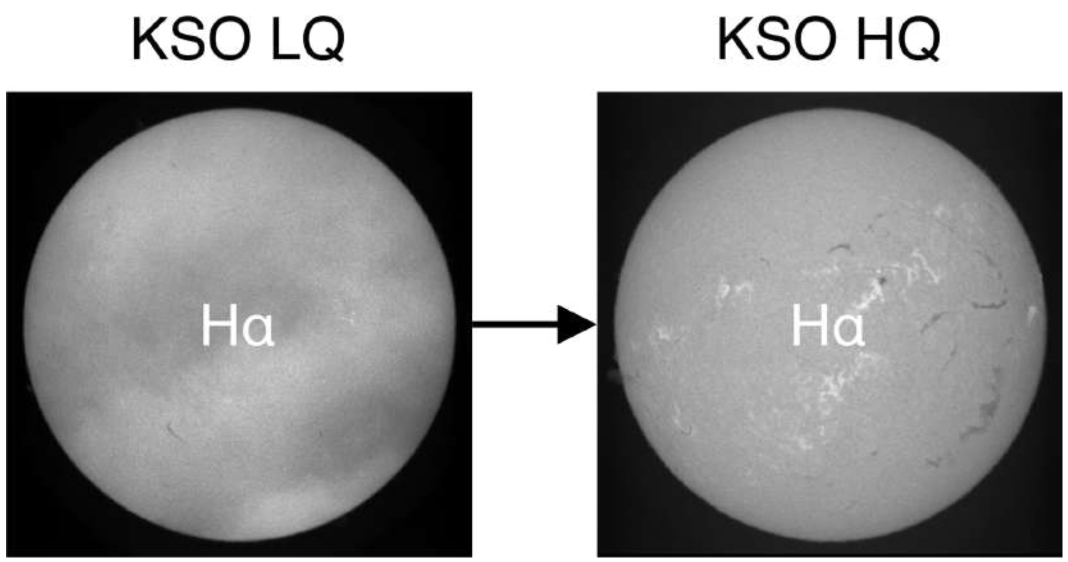
ITI Method

- Unpaired image-to-image translation with cycle consistency (Zhu et. al, 2018)
- Cycle B-A-B
  - Generate realistic low-quality images (B-A)
  - Reconstruct the original high-quality image (A-B)
  - Add noise for one-to-many mapping
- Discriminator A enforces generation of low-quality images
- Optimization of Perception-Distortion (Blau et al., 2018)



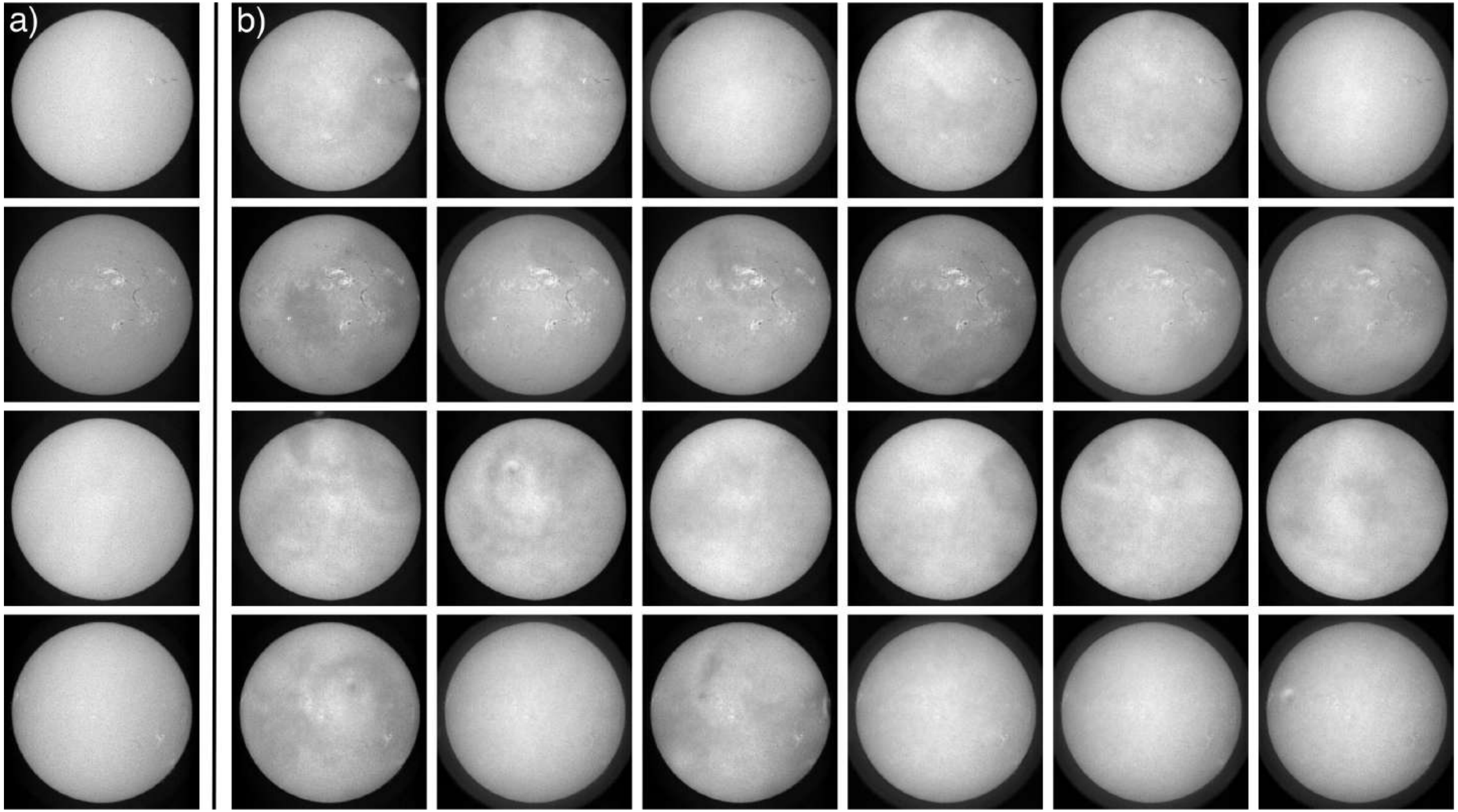
Mitigation of atmospheric effects

- Reduce dropout for automated methods
- More reliable detection algorithm(s)
- Homogeneous observation series

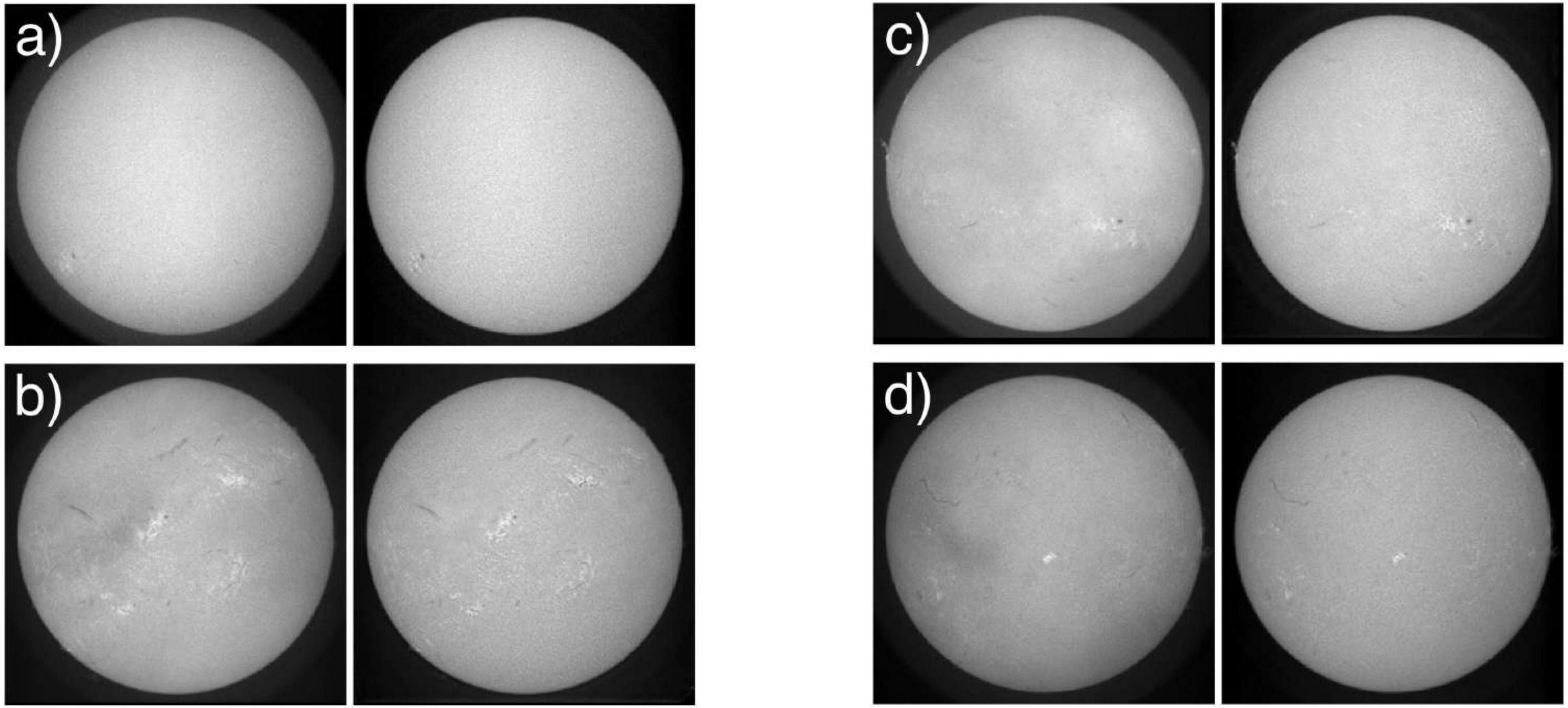


KSO low-to-high quality

- Multiple low-quality images (b) from a single high-quality image (a)
- Degradation independent of solar features
- Diverse synthetic low-quality images allow the reconstruction of real observations

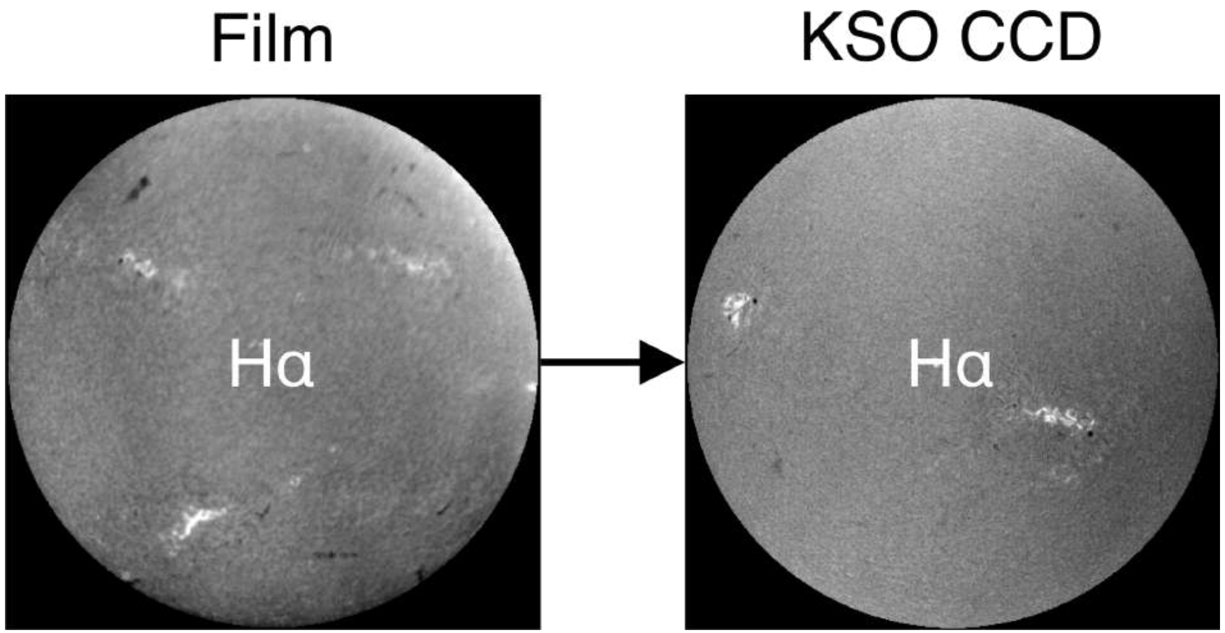


KSO low-to-high quality



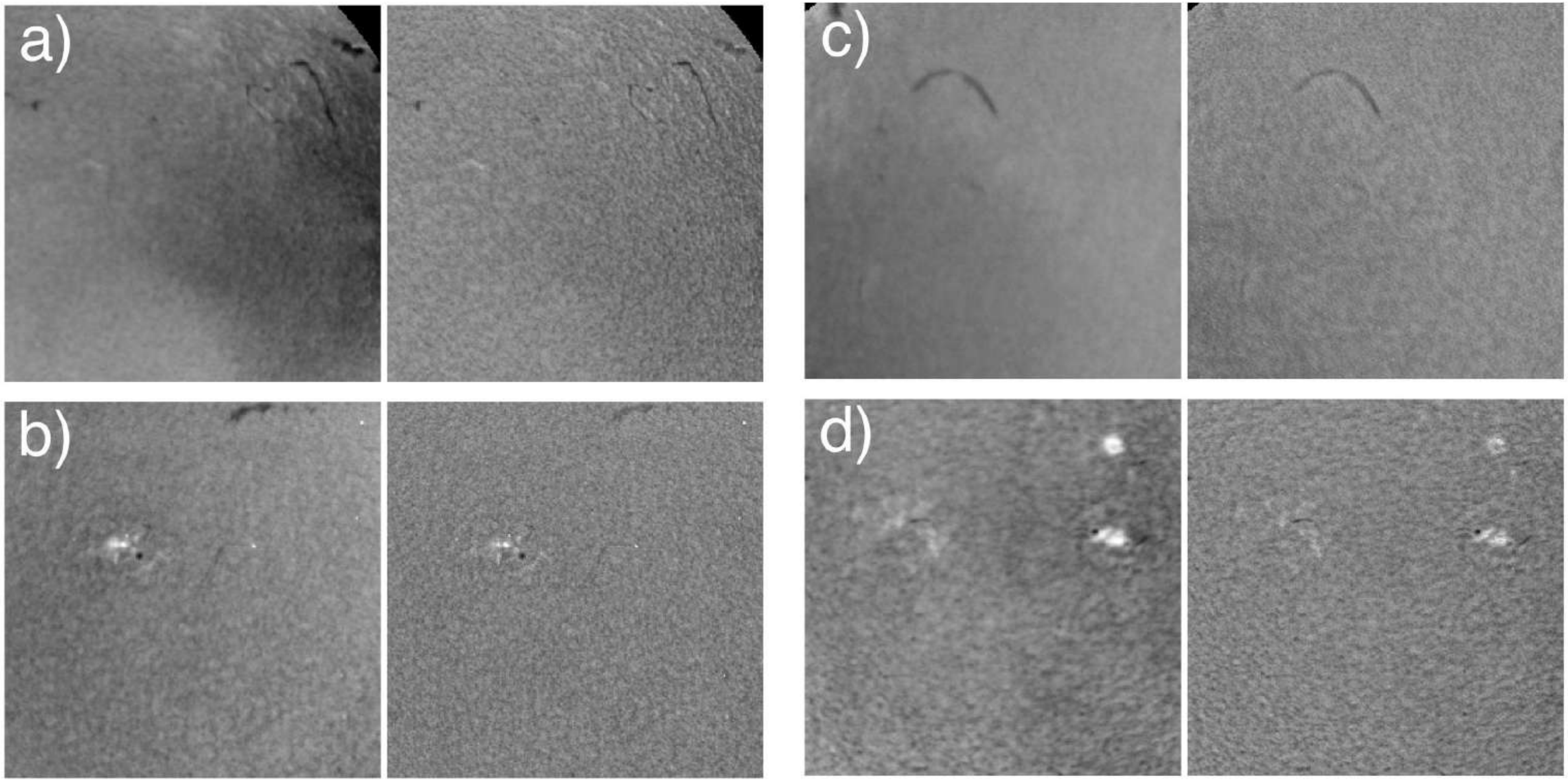
Restoring data sets

- Recovering old data sets
- Hα observations
  - Scanned photographic film (1973 - 2000)
  - Recent KSO observations (2010 - now)
- Data preparation
  - Limb-darkening corrected
  - Contrast normalized
  - Resize to 512 x 512 pixels



KSO Film-to-CCD

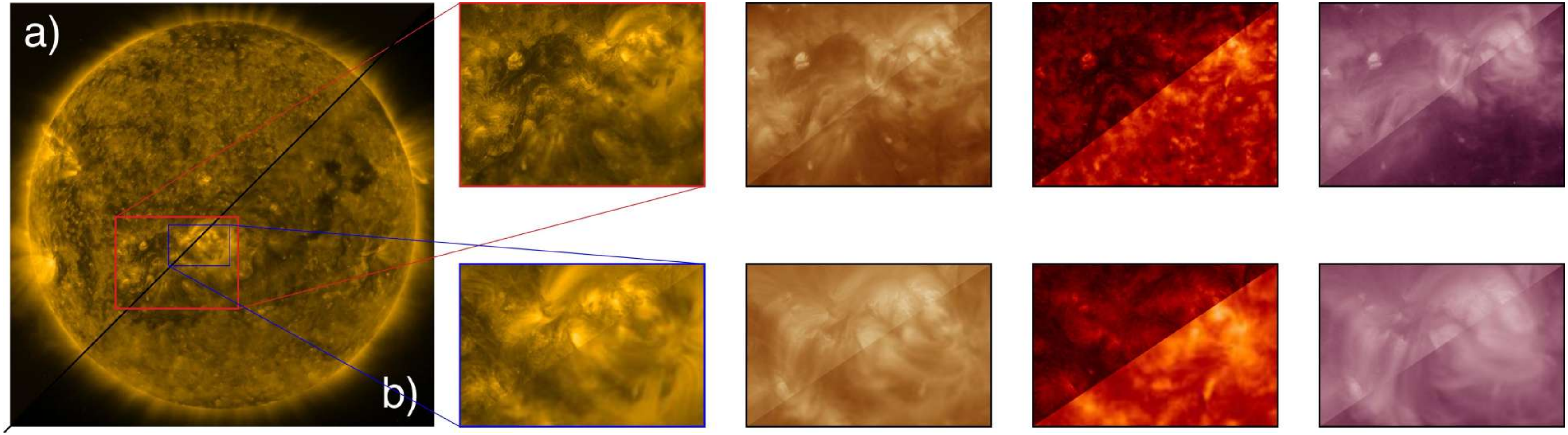
- Correction of illumination
- Mitigation of atmospheric effects
- Corrected saturation
- Deconvolution and contrast adjustment



STEREO-to-SDO

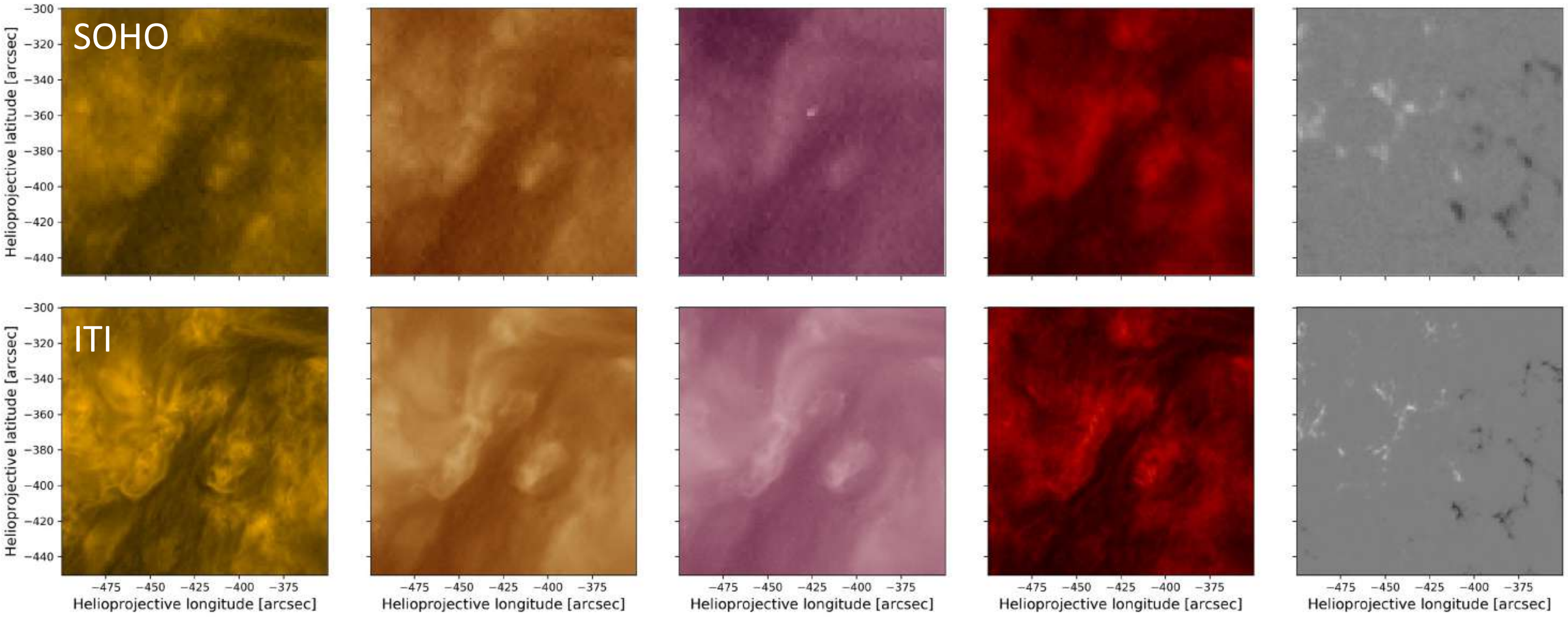
a) ITI enhanced

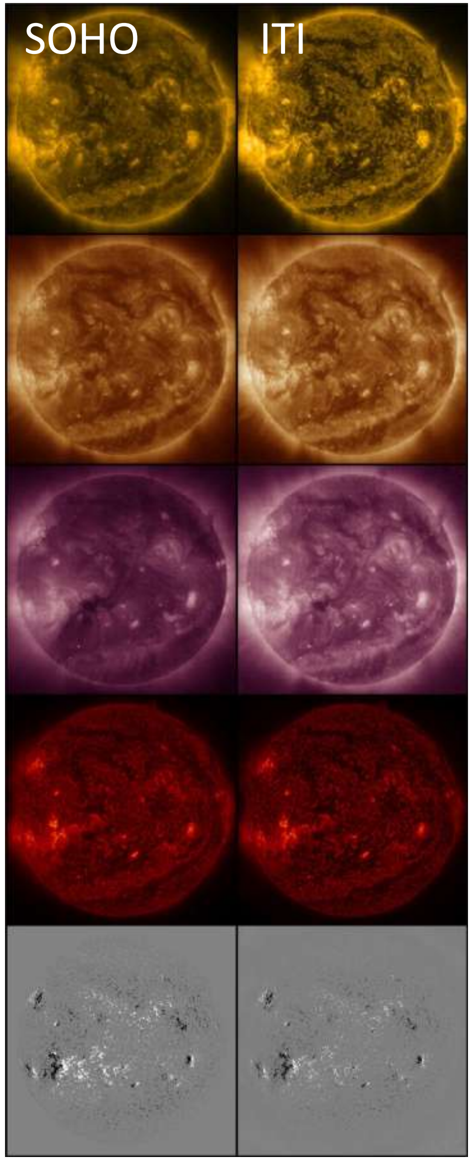
b) Original STEREO



SOHO-to-SDO

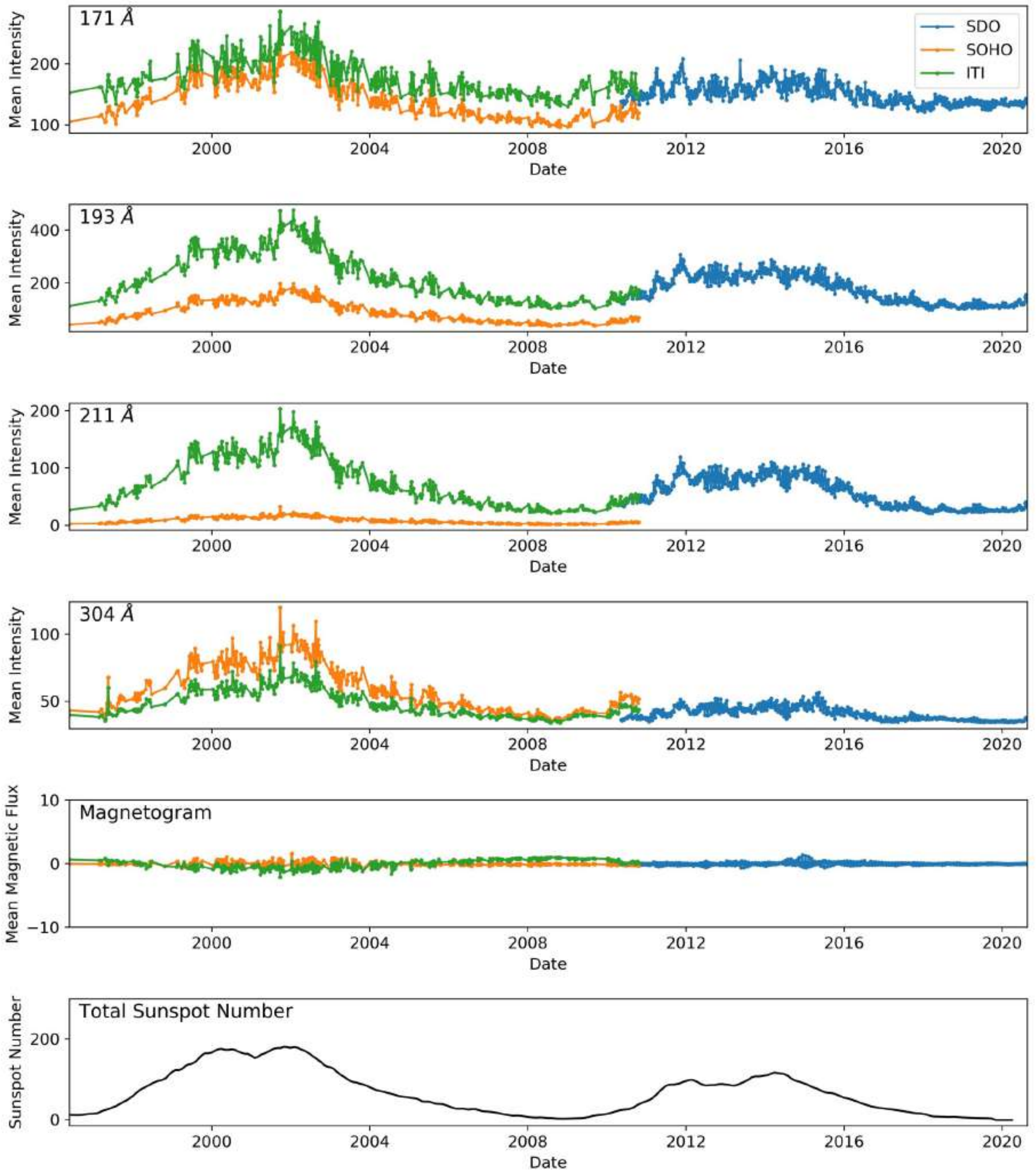
- Calibration of intensity (global; right)
- Enhancement of details (local; bottom)





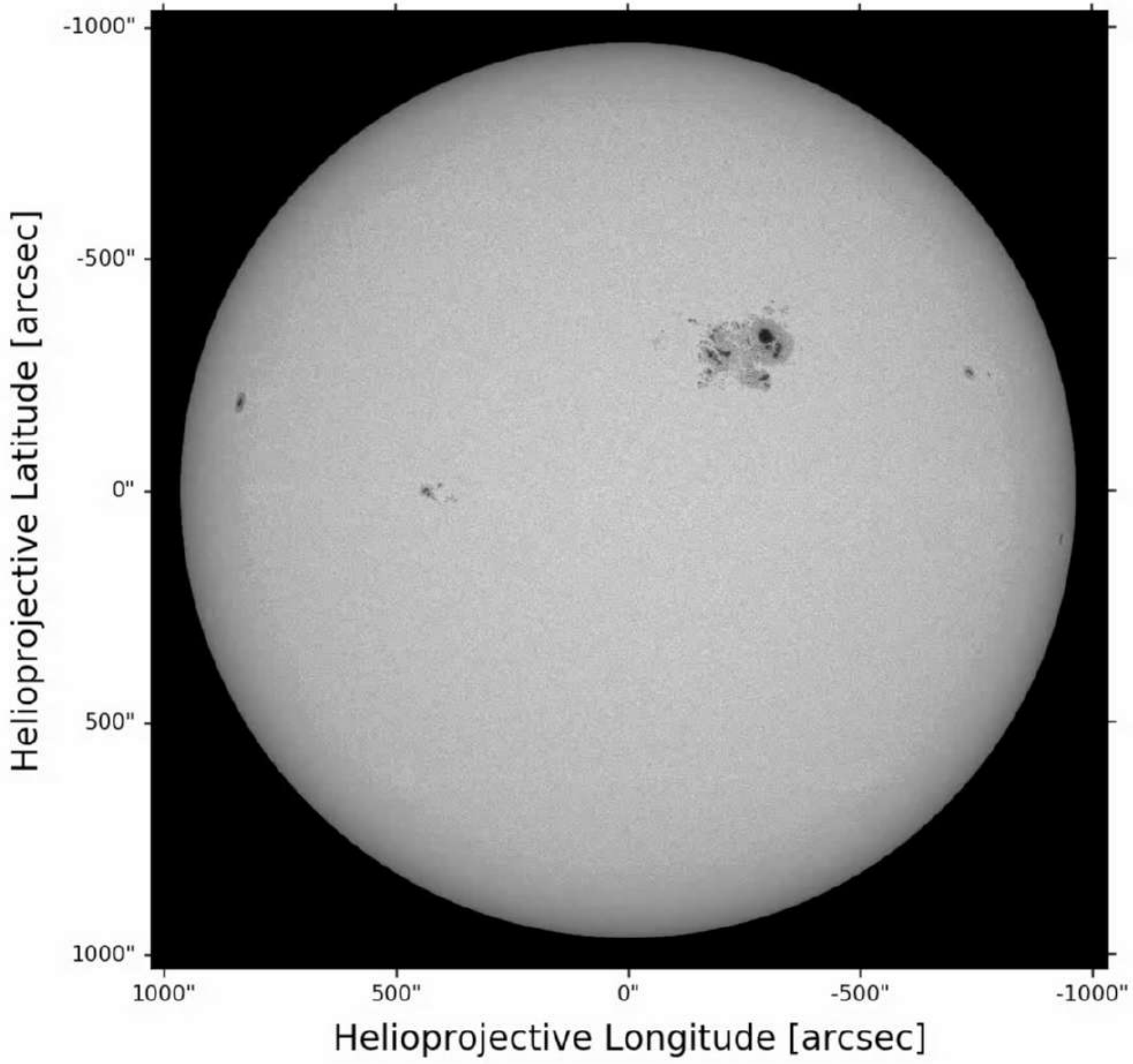
SOHO-to-SDO

- Photometric calibration of each channel
- Total magnetic flux close to zero

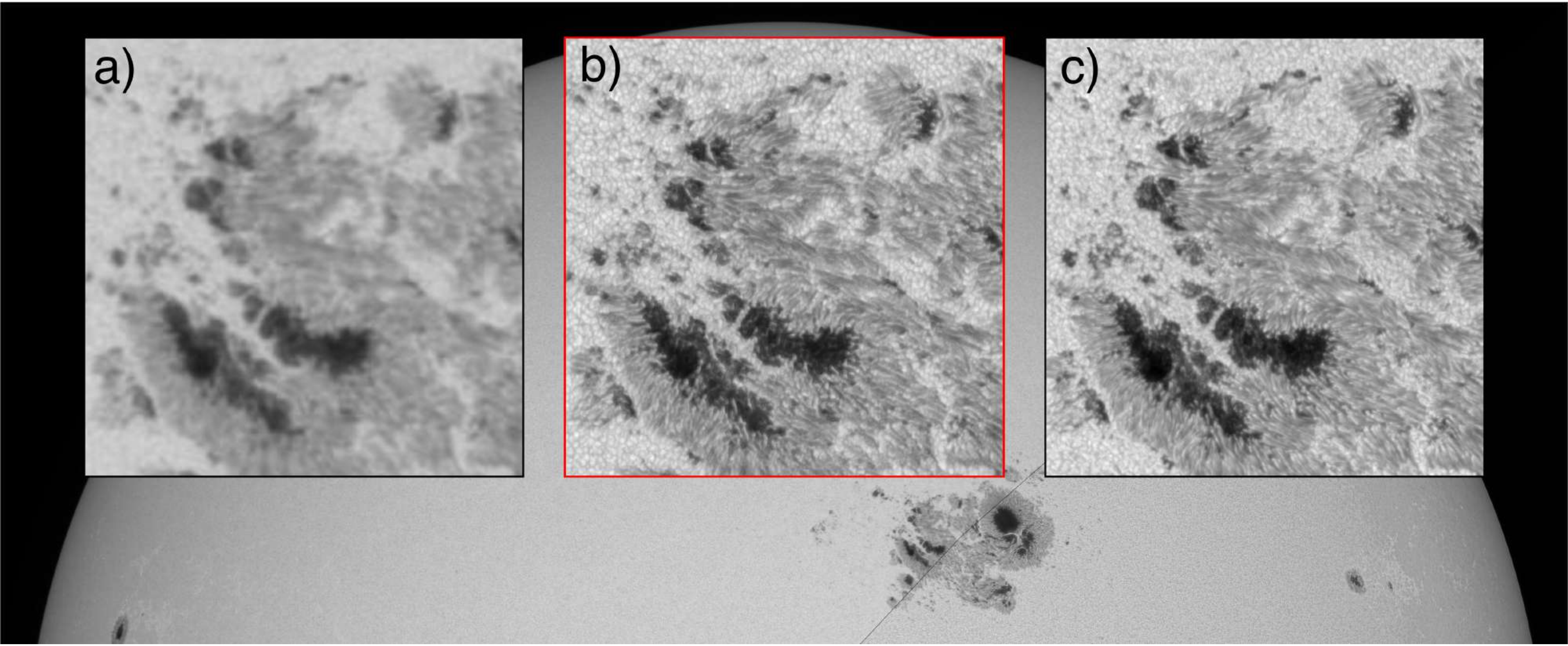


HMI-to-Hinode

- Different field-of-view
  - Hinode: 218 x 109 arcsec
  - SDO/HMI: full-disc
- Full-disc observations with 0.15 arcsec pixels resolution (16k x 16k)
- Provides:
  - context information
  - additional data set
  - extended time windows
- Similar application for SPRING and EST

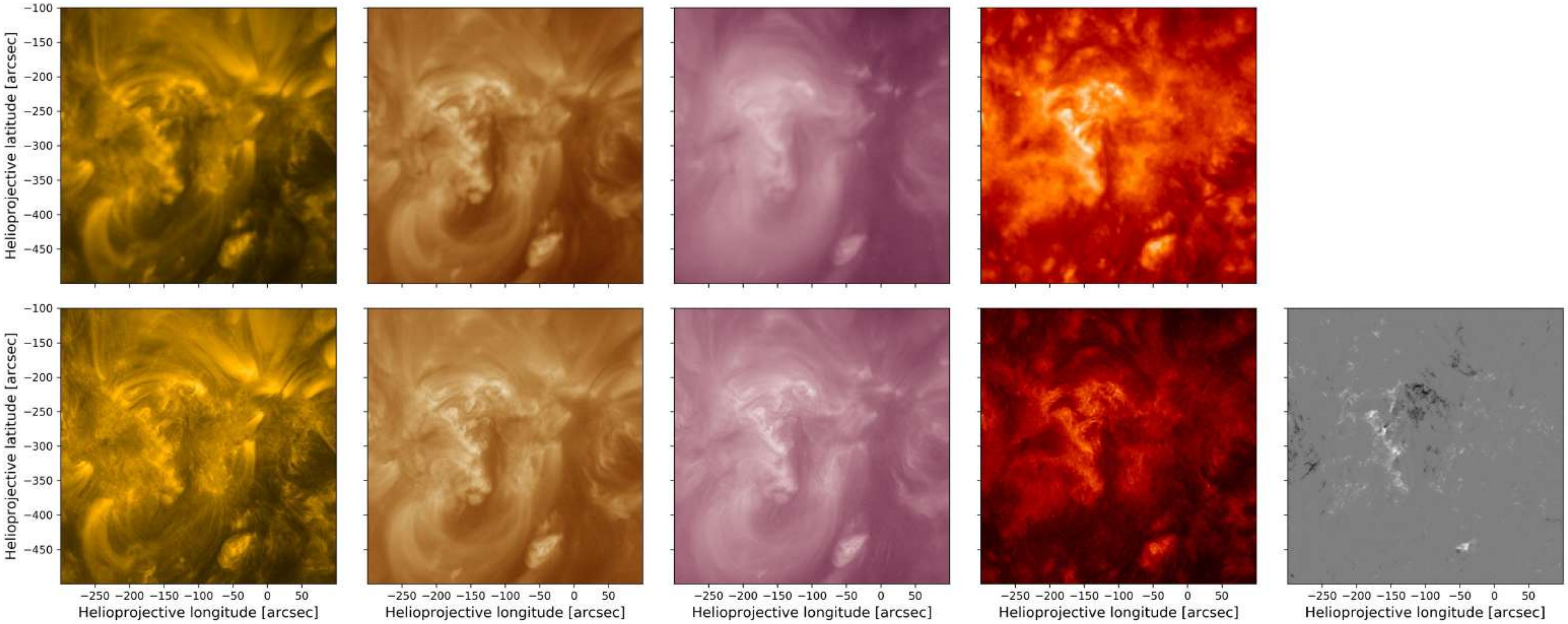


HMI-to-Hinode - comparison



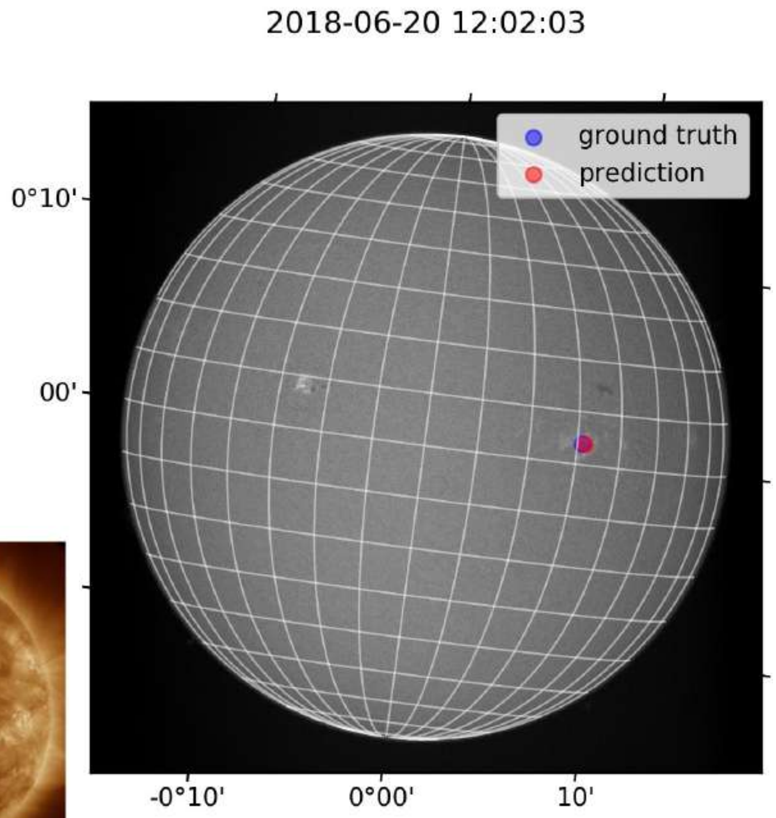
STEREO-to-SDO – far-side magnetogram

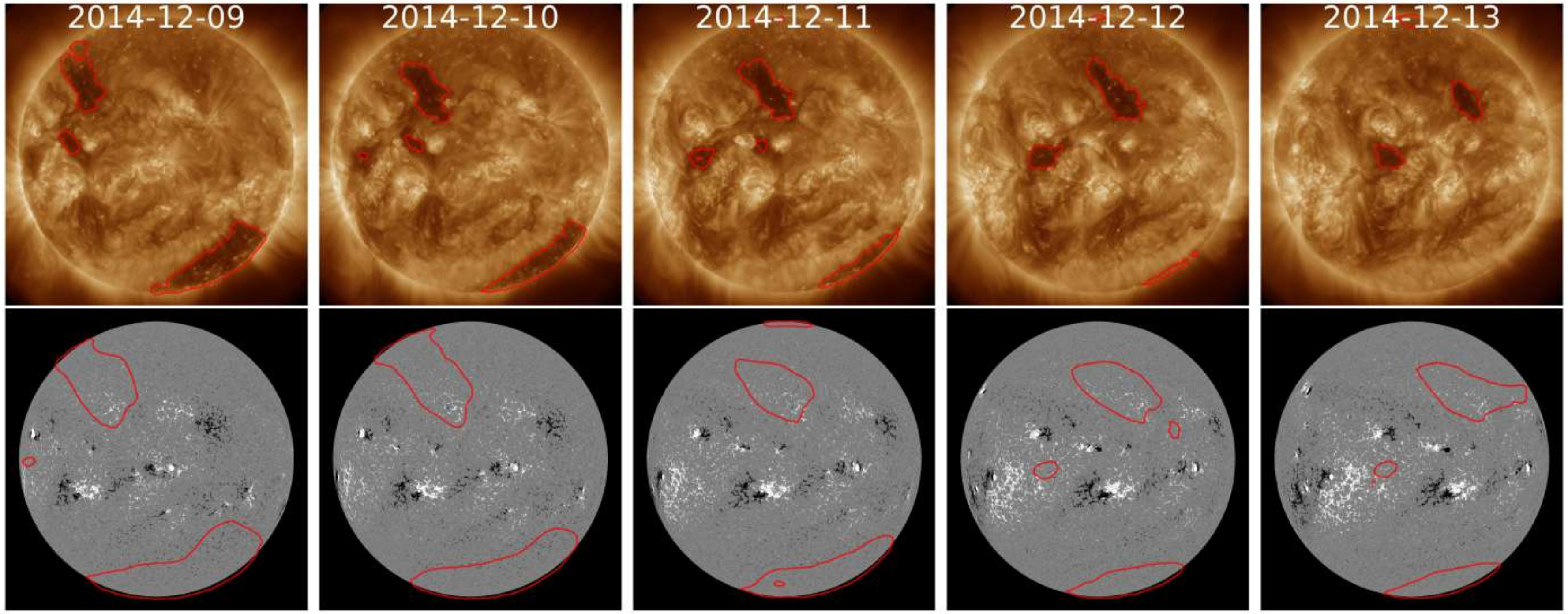
- Use proxy information to estimate missing channels

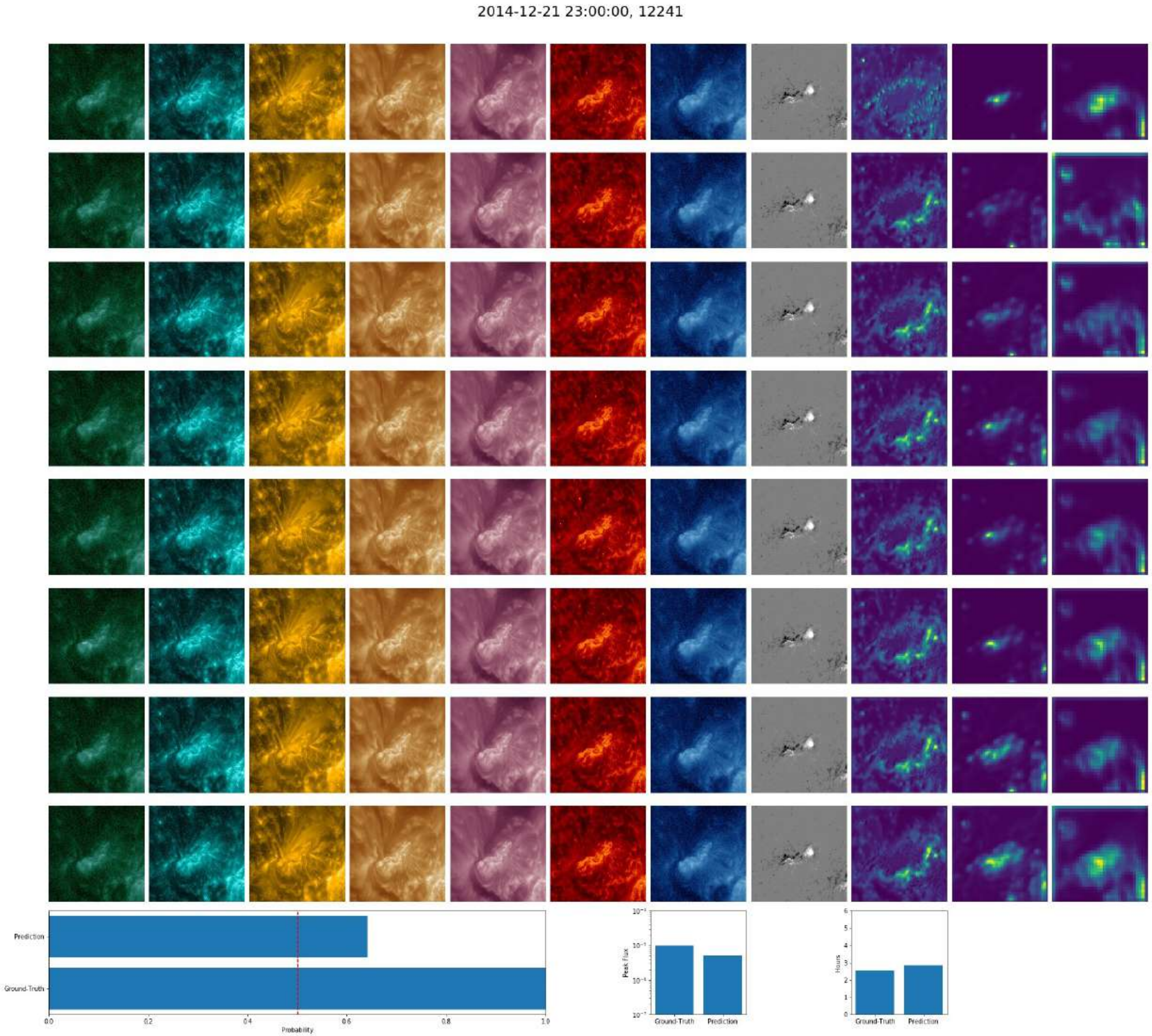


Upcoming AI applications

- Flare detection (ongoing; GONG + KSO)
- Coronal hole detection (submission next week)
- Filament detection (collaboration with AIP)
- Interpretable solar flare prediction (ongoing)






2014-12-21 23:00:00, 12241
Prediction
Ground-Truth
0.0
0.2
0.4
0.6
0.8
1.0
Probability
Peak Flux
Ground-Truth
Prediction
Hours
0
1
2
3
4
5
6
Ground-Truth
Prediction

Conclusion

- Solar image quality assessment
  - Objective quality metric
  - High accuracy in identifying low-quality observations
  - Application to multi-site observations, high-resolution observations, detection of solar transient events
- Instrument-to-Instrument
  - Data set homogenization
  - Image enhancement
  - No temporal or spatial overlap required
  - Wide range of applications (e.g., more instruments, image stacking, magnetograms)

Thank you!

SOLARNET

Integrating High Resolution Solar Physics

This research has received financial support from the European Union’s Horizon 2020 research and innovation program under grant agreement No. 824135 (SOLARNET).

References

- Zhu, J. Y., Park, T., Isola, P., & Efros, A. A. (2017). Unpaired image-to-image translation using cycle-consistent adversarial networks. In *Proceedings of the IEEE international conference on computer vision* (pp. 2223-2232).
- Blau, Y., & Michaeli, T. (2018). The perception-distortion tradeoff. In *Proceedings of the IEEE Conference on Computer Vision and Pattern Recognition* (pp. 6228-6237).
- Jarolim, R., Veronig, A. M., Pötzi, W., & Podladchikova, T. (2020). Image-quality assessment for full-disk solar observations with generative adversarial networks. *Astronomy & Astrophysics*, *643*, A72.
- Goodfellow, I., Pouget-Abadie, J., Mirza, M., Xu, B., Warde-Farley, D., Ozair, S., Courville, A. and Bengio, Y., 2014. Generative adversarial nets. In *Advances in neural information processing systems* (pp. 2672-2680).