Super-resolution of MDI Solar Magnetograms: Performance Metrics and Error Estimation

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1. Summary

Aim: Develop an approach to convert and upscale line-of-sight magnetic field data to a reference survey in order to understand long-term variability of the magnetic field on time-scales larger than the lifespan of a single instrument.

a Data Pre-Processing

1. Standardize the Sun's orientation and distance from the detector such that the solar radius is constant over time
2. Register & shift individual 128" x 128" patches (see in set regions, **Figure 1**) to account for orbital differences.

b Neural Network Architecture

We use an Encoder-Decoder architecture based on HighRes-Net (see, **github.com/ElementAI/HighRes-net**). The trained Neural Network (NN) output is shown in **Figure 2**.

c Loss Functions & Metrics

To train our supervised NN, we include a range of terms alongside MSE (mean-squared-error) loss, and evaluate on additional performance metrics.

1. Loss Functions

Histogram: The magnetic field distribution is non-Gaussian; by implementing a *differentiable* histogram, we better preserve the observed distribution of magnetic field.

Structural Similarity Metric (SSIM): Measure the perceived similarity between images.

Gradients: Preserve the gradients of the magnetic field.

2. Performance Metrics

Information Entropy: To understand the informational content of the output over all spatial scales, and to diagnose hallucination in the NN.

d Error Estimation

We use a Bayesian framework as in Kendall & Gal (2017) that decomposes uncertainty in to two components: ***epistemic*** (ignorance of the true data generating process), and ***aleatoric*** (the inherent noise). In practice, we implement this by adding Monte Carlo (MC) dropout in each convolutional layer, and track both the mean and variance of the magnetic field values.

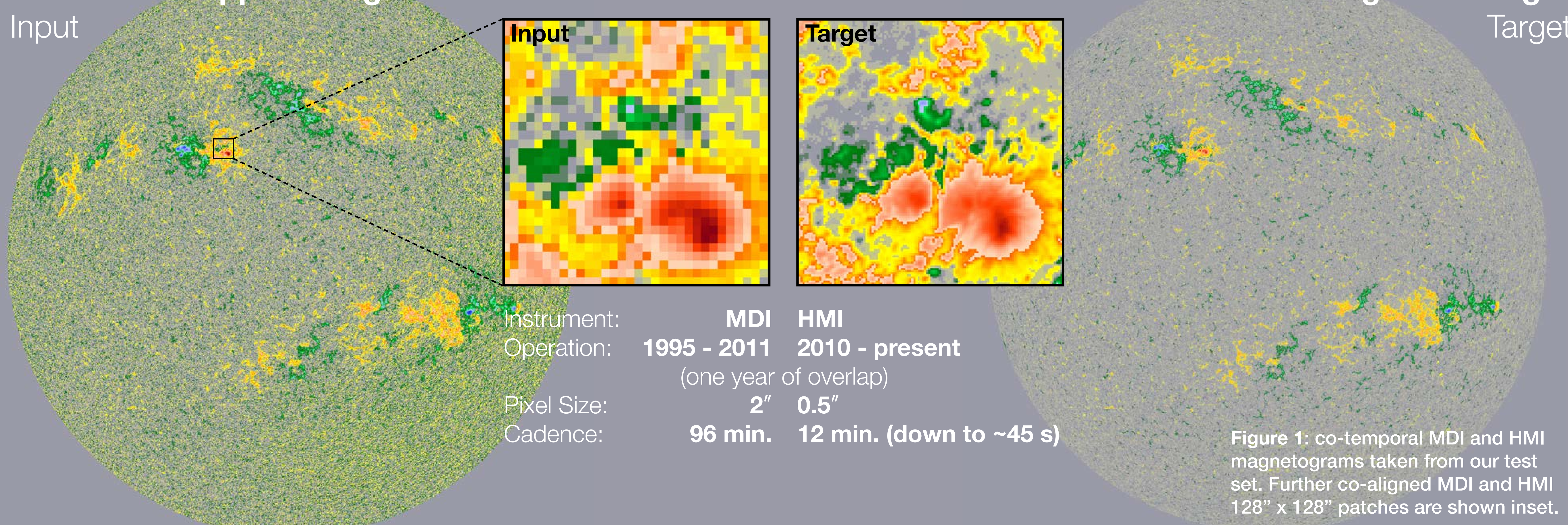
e Conclusions & Future Work

- To our knowledge, this is the first application of Bayesian Neural Networks to a super-resolution problem.
- Earlier versions of this work were published in workshops at NeurIPS 2019 (Gitiaux *et al* 2019, arxiv: **1911.01486**; Jungbluth *et al* 2019, arxiv: **1911.01490**).
- **Shortly we will provide test users with the super-resolution output to understand the suitability for various science tasks.**

2. Data Overview

Michelson Doppler Imager
Input

Helioseismic & Magnetic Imager
Target



Instrument:	MDI	HMI
Operation:	1995 - 2011	2010 - present
	(one year of overlap)	
Pixel Size:	2″	0.5″
Cadence:	96 min.	12 min. (down to ~45 s)

Figure 1: co-temporal MDI and HMI magnetograms taken from our test set. Further co-aligned MDI and HMI 128" x 128" patches are shown inset.

3. Neural Net. Output

Super-resolution MDI
Neural Network Output

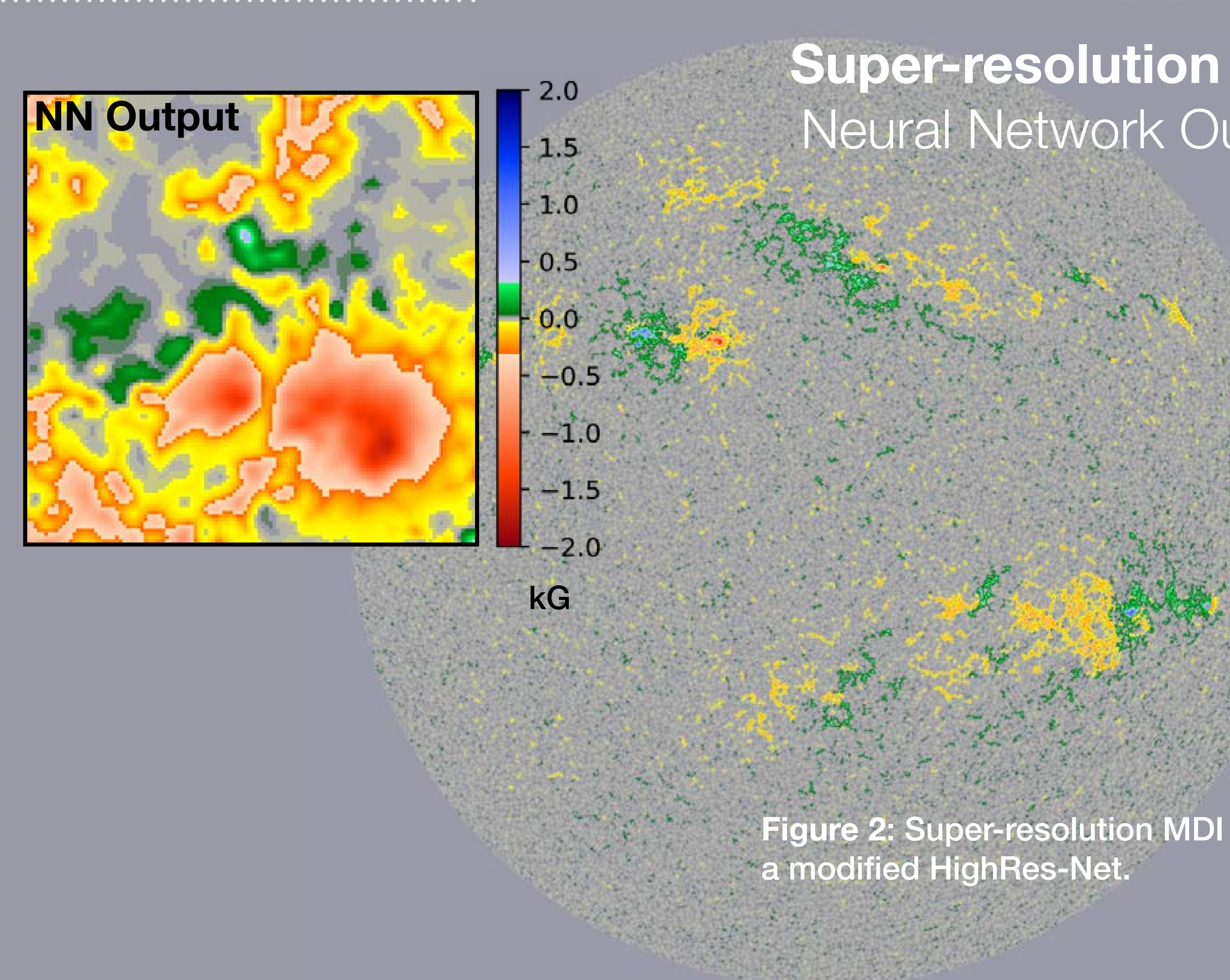


Figure 2: Super-resolution MDI using a modified HighRes-Net.

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