Applications of Image Translation Methods Based on Deep Learning to Solar Data

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0

Introduction

0 Introduction

Sun and Space Weather Group in Kyung Hee University

We have applied deep learning (DL) to various types of solar and space weather data and tasks

Our goal:

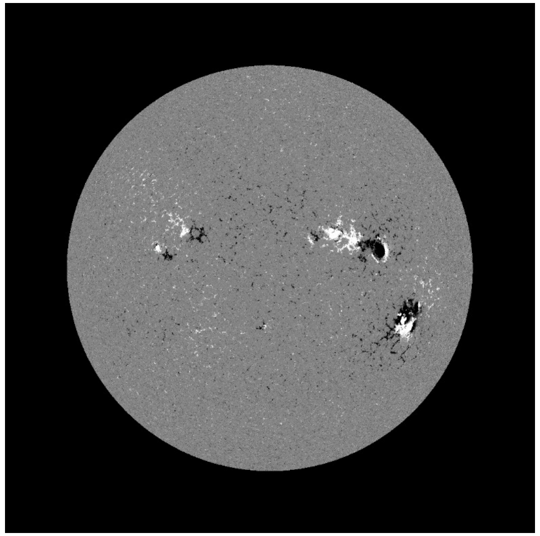
1) To improve space weather prediction models
2) To fill in observation blanks
3) To calibrate observational data such as denoising
4) To study whether DL-generated data are feasible for scientific data or not

Recently, we have applied image translation methods based on deep learning to various solar and space weather data.

0 Introduction

Why image translation?

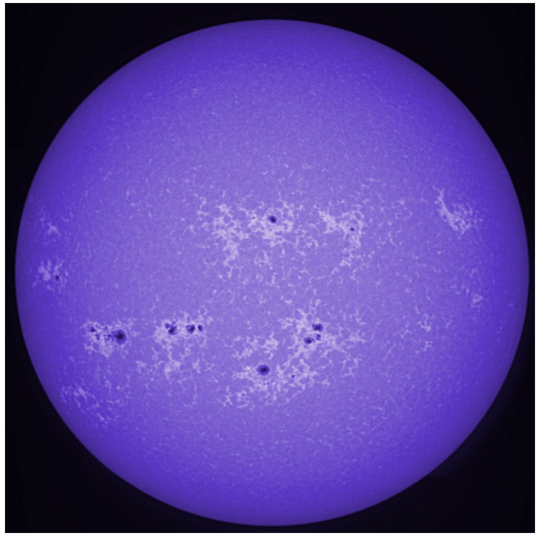
Magnetogram



EUV

H-alpha

Ca K



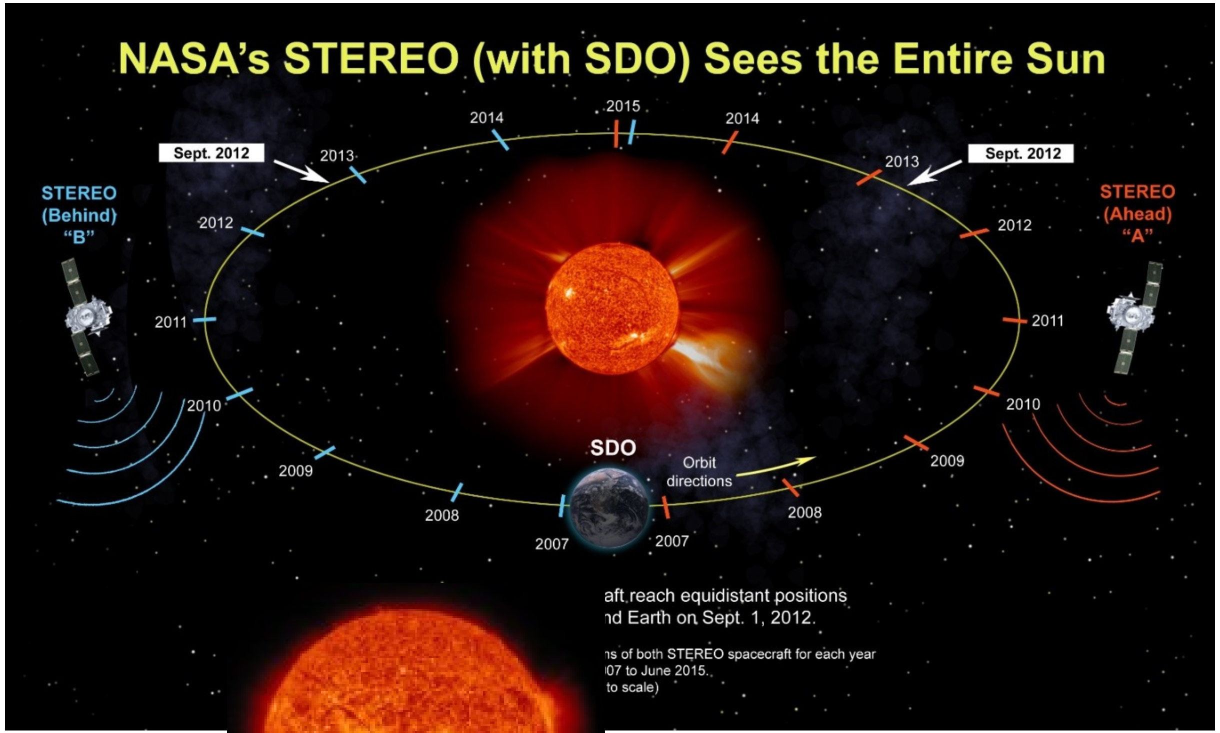
There are various types of multi-filter observations in solar and space weather, and many of them are observed **simultaneously.**
-> It is a **good condition for applying the image translation algorithms**.

1

Generation of Solar Far-side Magnetograms from STEREO/EUVI Images

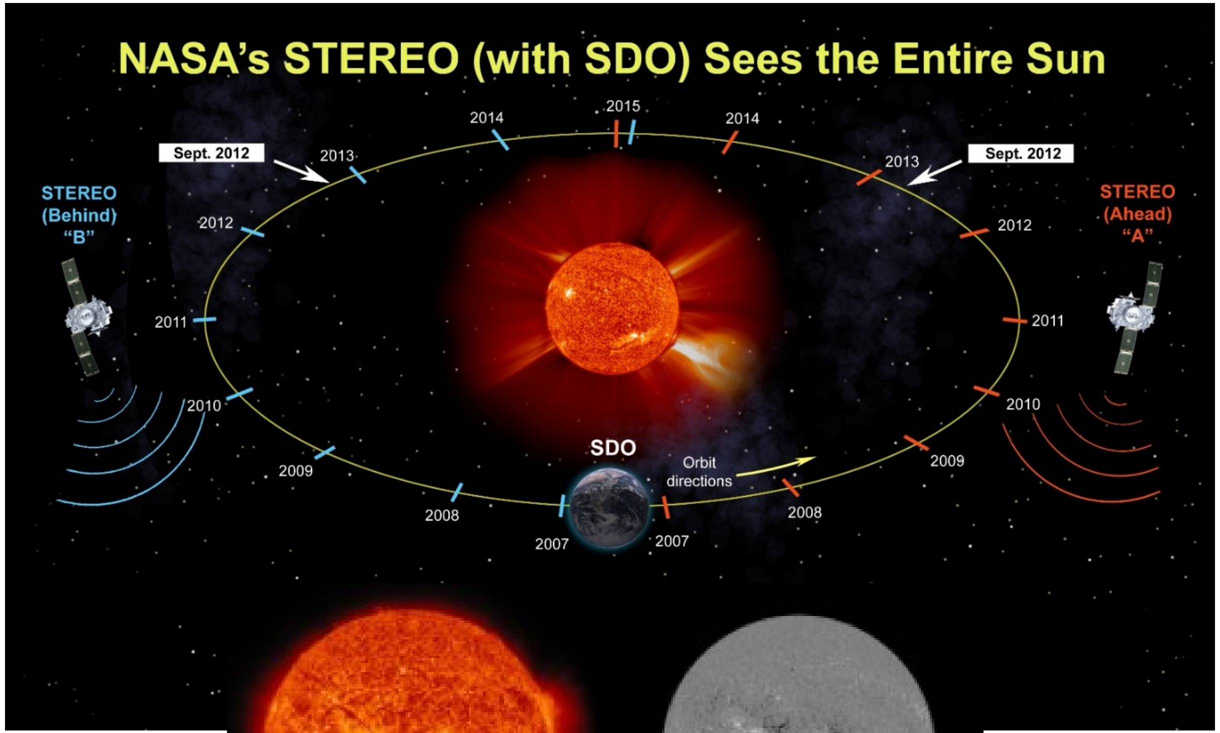
Kim, Park, Lee et al., 2019
Jeong et al., 2020
Park et al., 2021

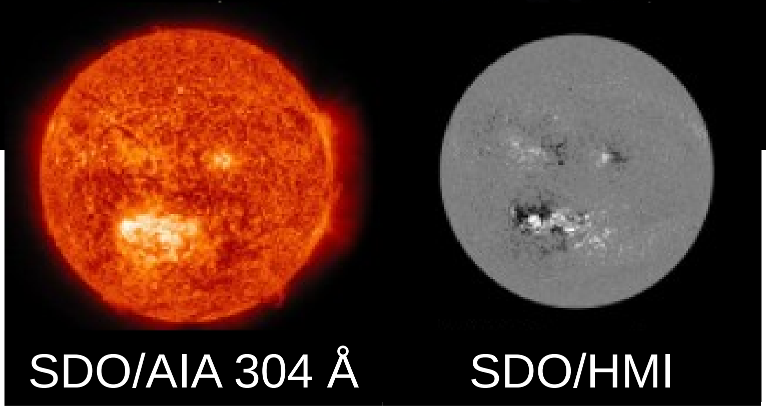
1 Generation of Solar Farside Magnetograms



Solar EUV images are being observed from the front and farside of the Sun

1 Generation of Solar Farside Magnetograms



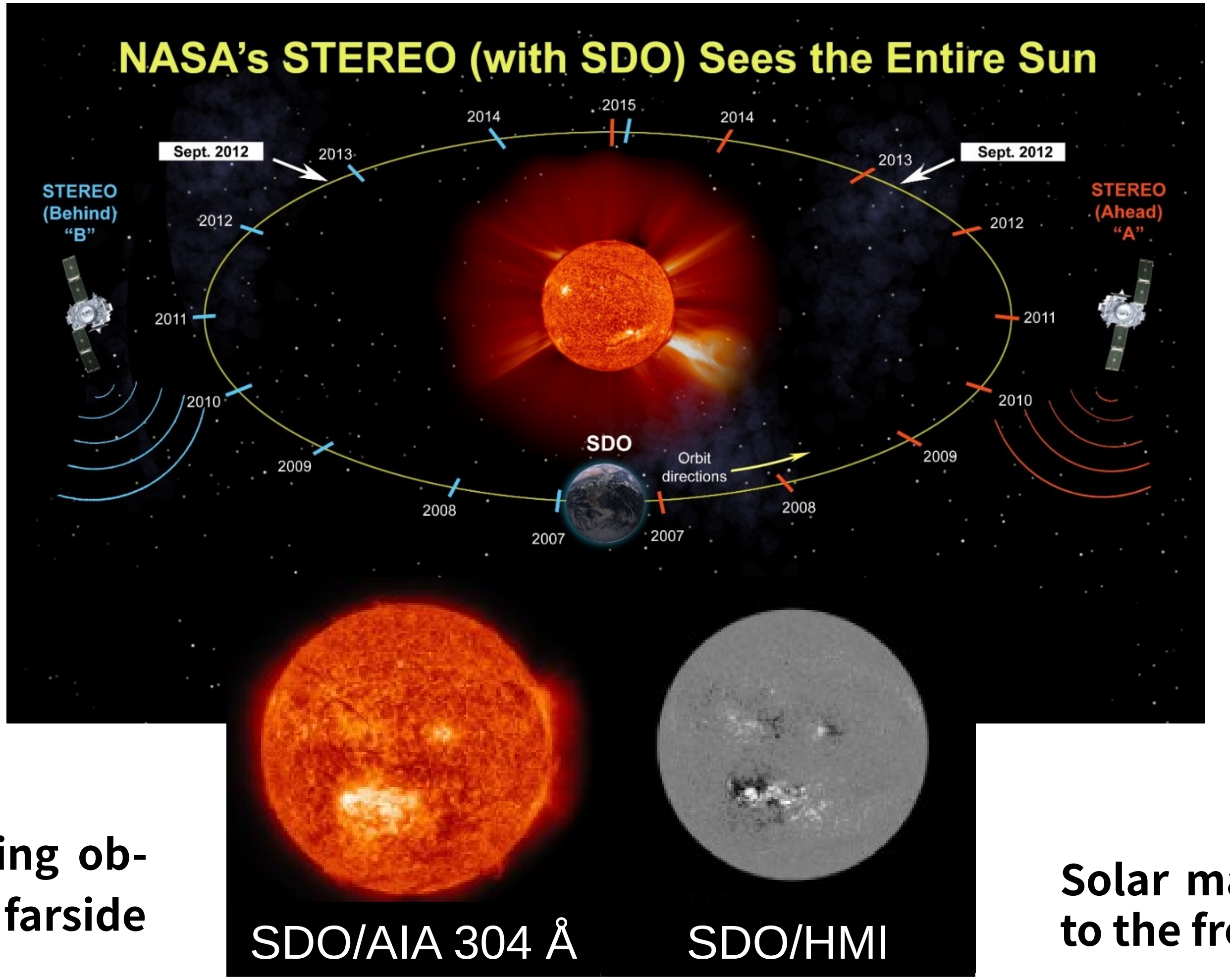


Solar EUV images are being observed from the front and farside of the Sun

Solar magnetograms are limited to the frontside solar disk

1 Generation of Solar Farside Magnetograms

STEREO B
EUVI 304 Å



SDO/AIA 304 Å
SDO/HMI

STEREO A
EUVI 304 Å

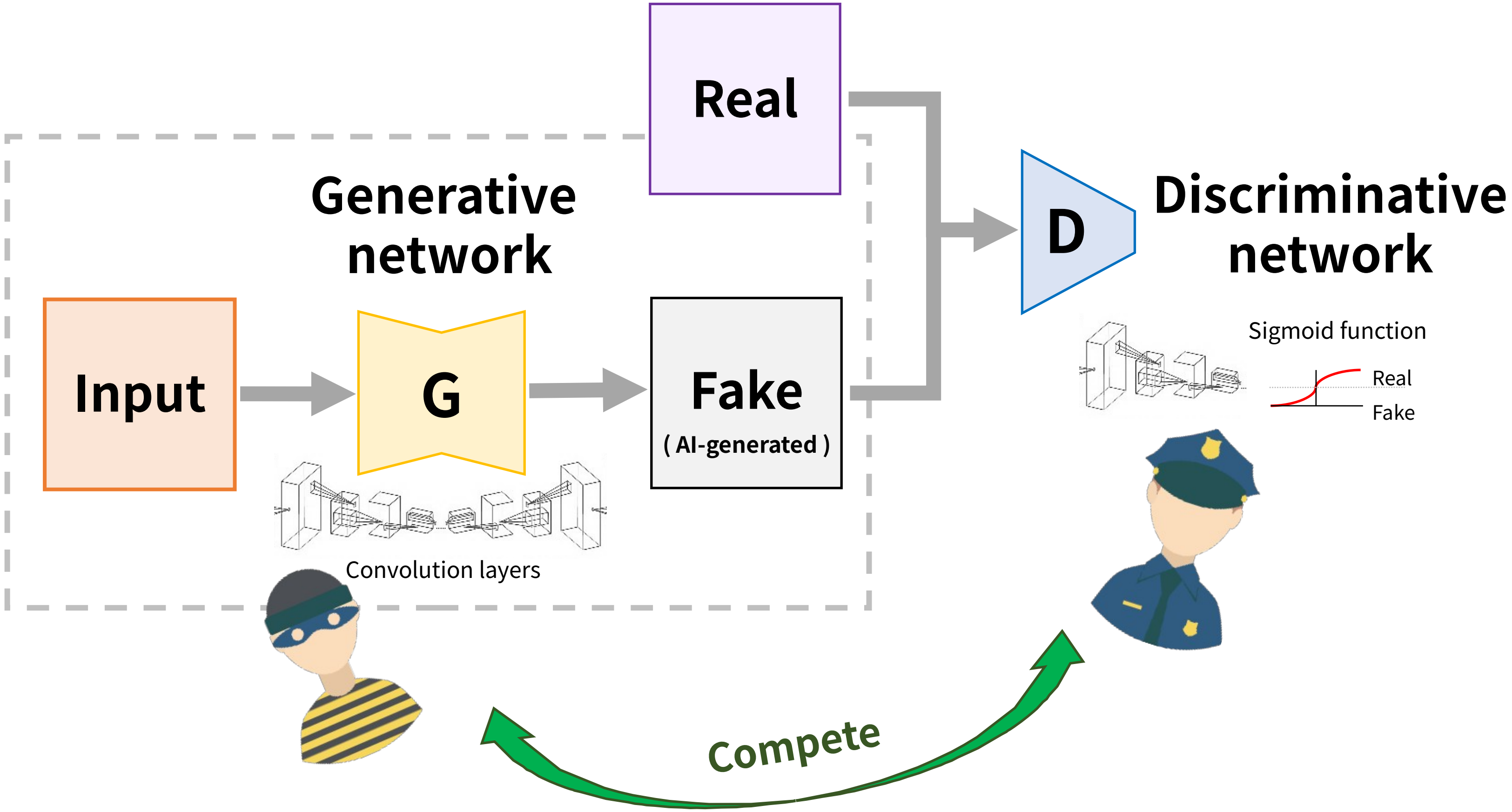
Solar EUV images are being observed from the front and farside of the Sun

Solar magnetograms are limited to the frontside solar disk

We design a model for the translation from solar EUV images to solar magnetograms

1 Generation of Solar Farside Magnetograms

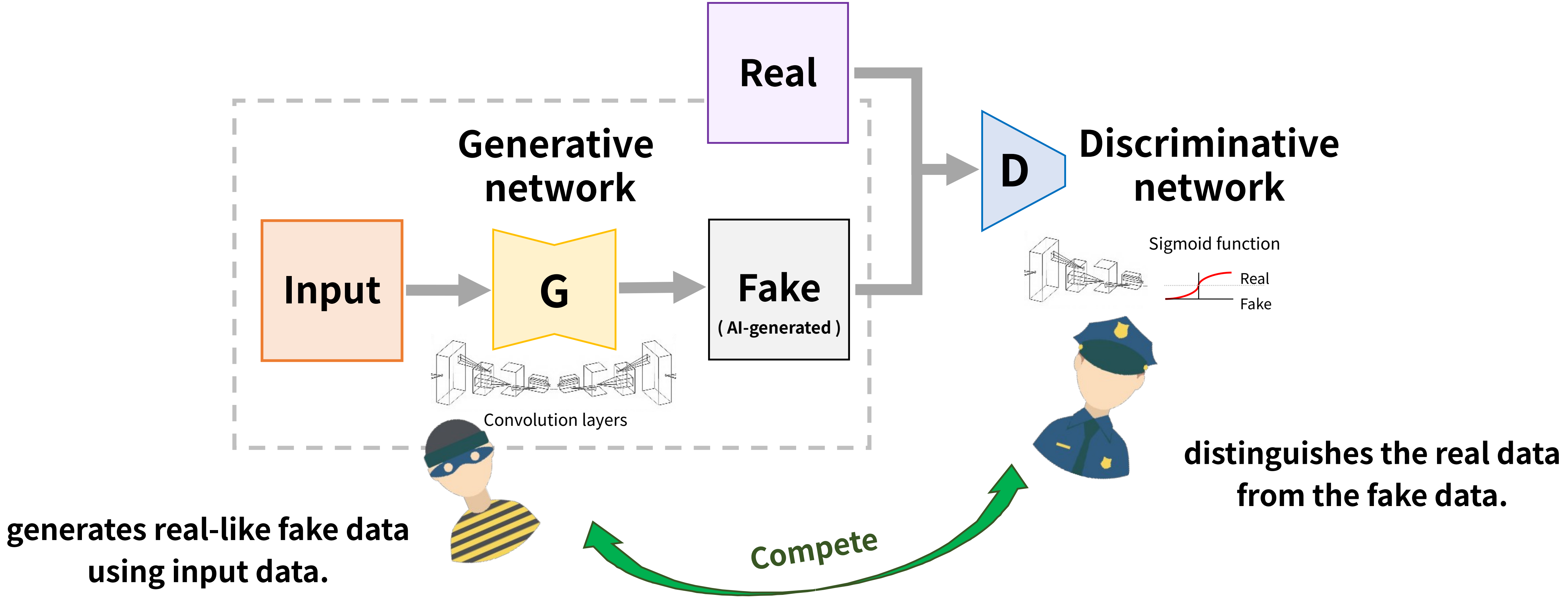
Generative Adversarial Network (GAN)



GAN is one of the popular deep learning methods in generation and translation tasks.

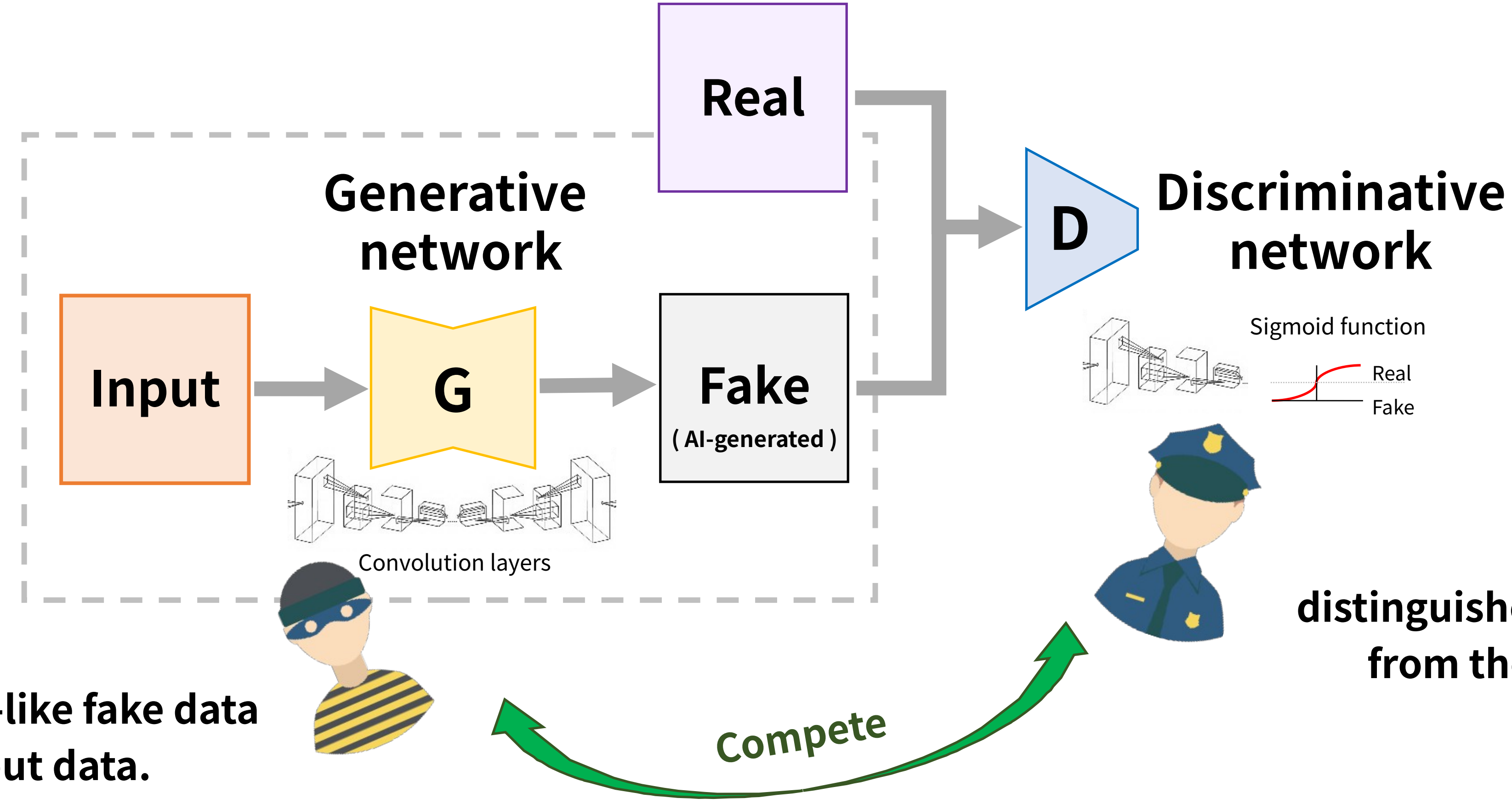
1 Generation of Solar Farside Magnetograms

Generative Adversarial Network (GAN)



1 Generation of Solar Farside Magnetograms

Generative Adversarial Network (GAN)



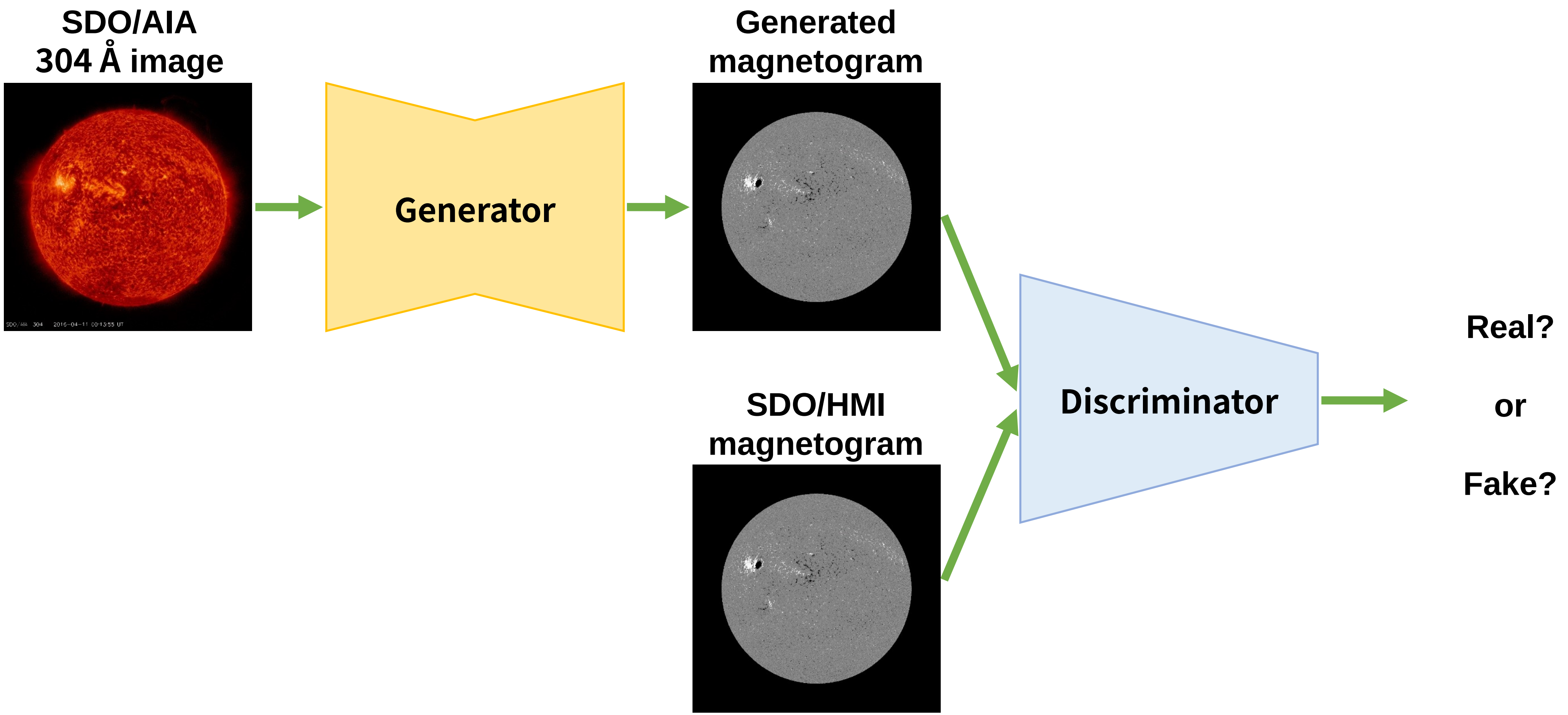
generates real-like fake data using input data.

distinguishes the real data from the fake data.

We train the Generator and the Discriminator, this process looks like a competition between the two networks.

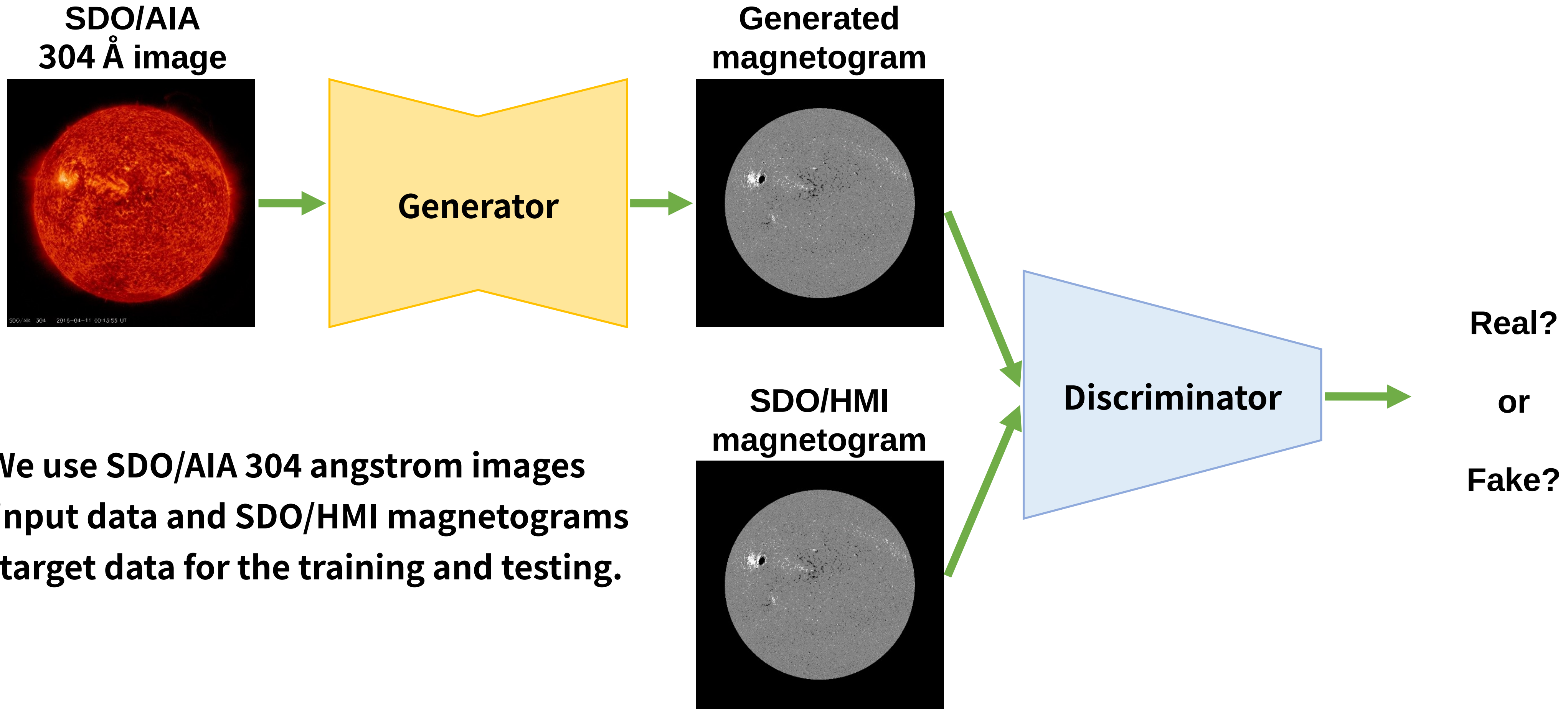
1 Generation of Solar Farside Magnetograms

Structure of our model for the translation from solar EUV images to solar magnetograms



1 Generation of Solar Farside Magnetograms

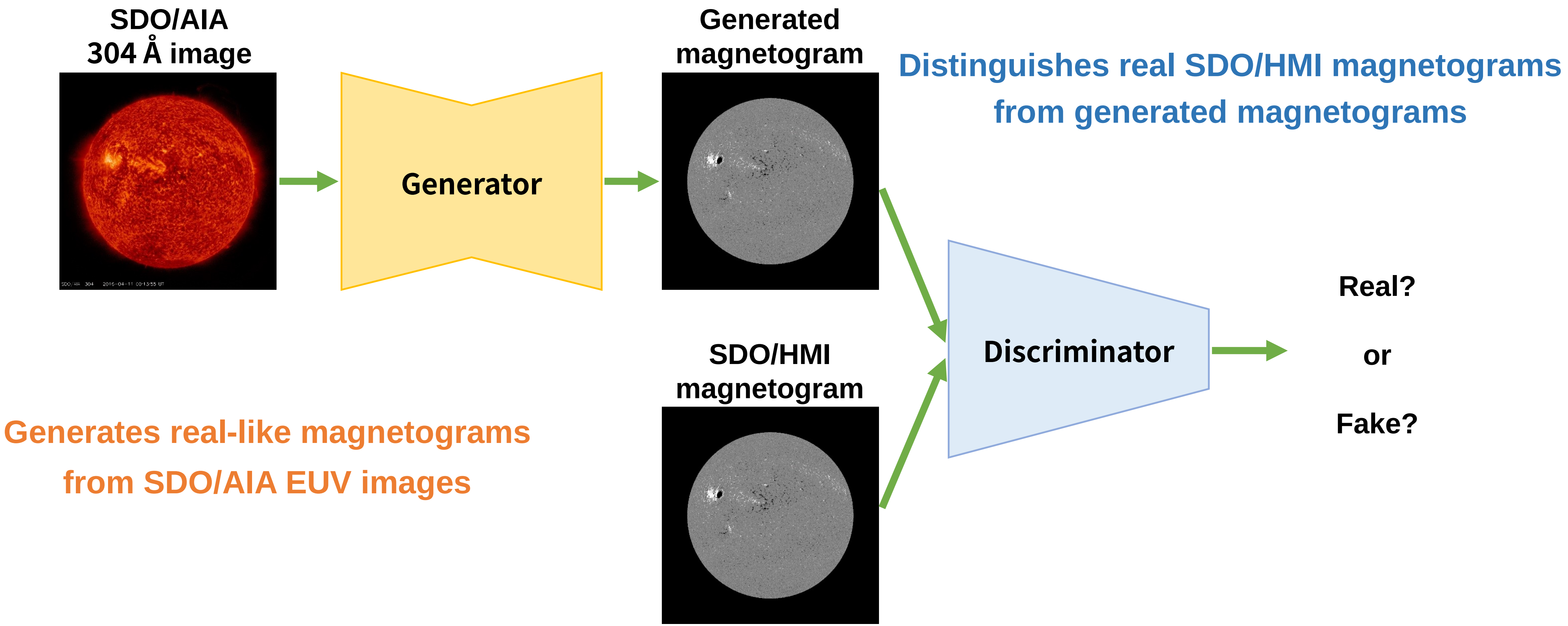
Structure of our model for the translation from solar EUV images to solar magnetograms



We use SDO/AIA 304 angstrom images
as input data and SDO/HMI magnetograms
as target data for the training and testing.

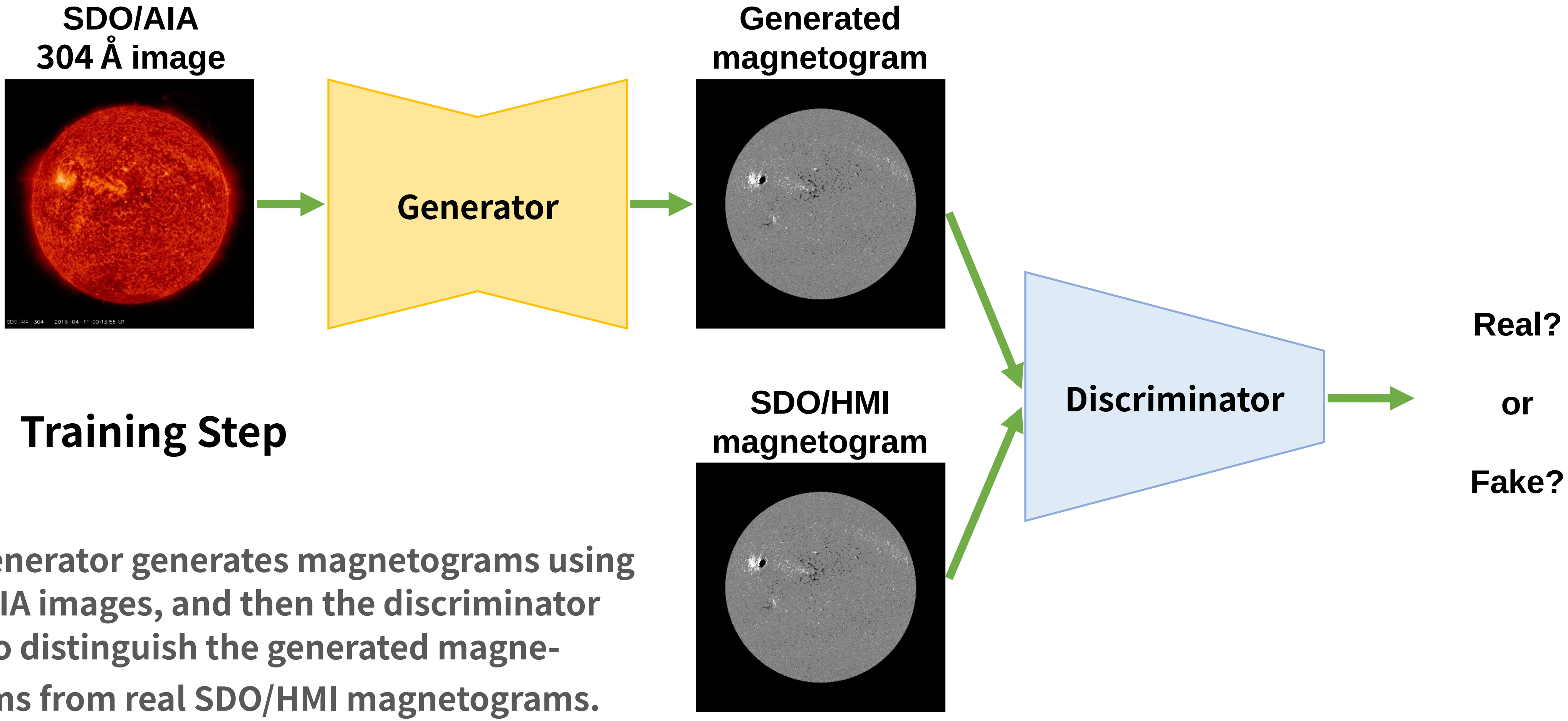
1 Generation of Solar Farside Magnetograms

Structure of our model for the translation from solar EUV images to solar magnetograms



1 Generation of Solar Farside Magnetograms

Structure of our model for the translation from solar EUV images to solar magnetograms

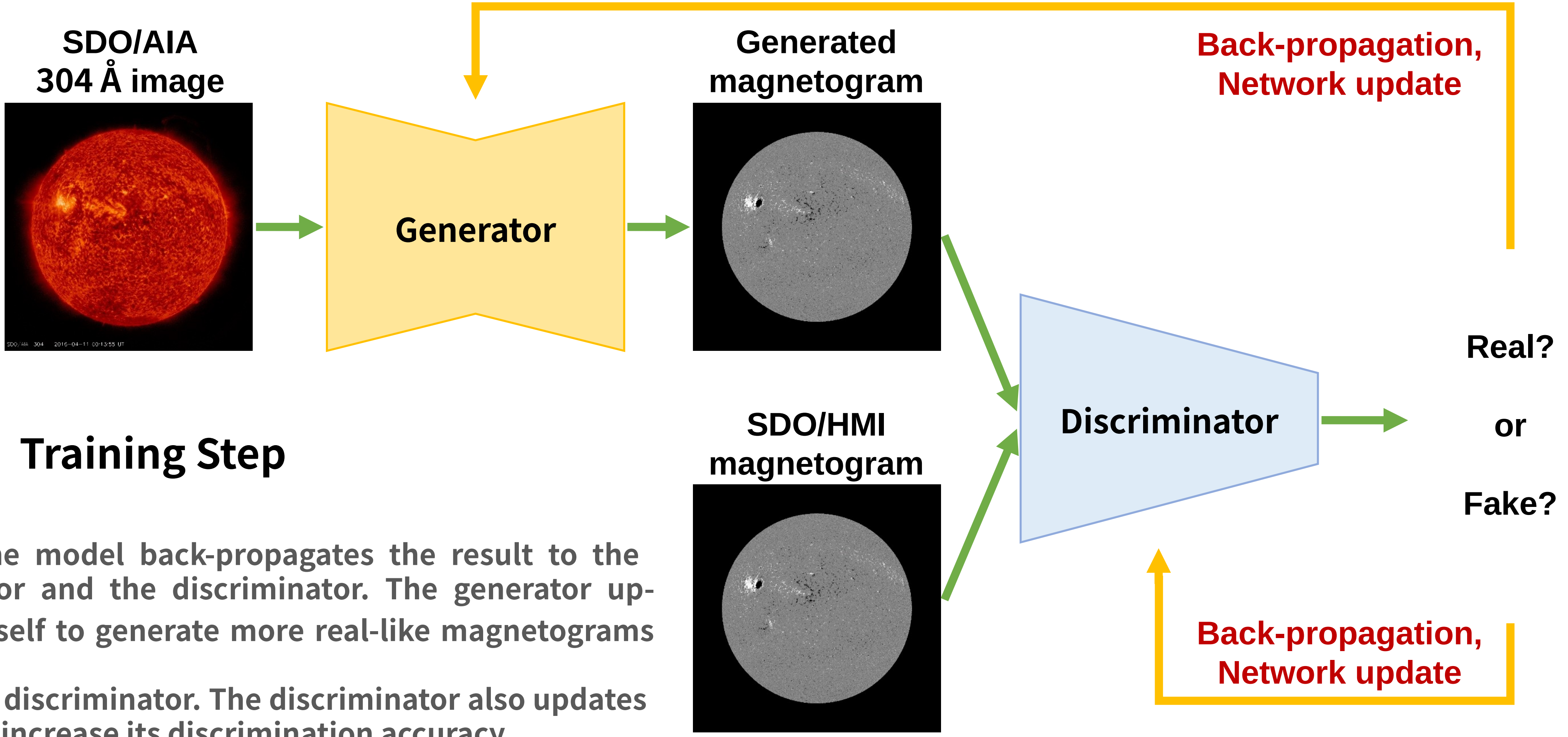


Training Step

The generator generates magnetograms using SDO/AIA images, and then the discriminator tries to distinguish the generated magnetograms from real SDO/HMI magnetograms.

1 Generation of Solar Farside Magnetograms

Structure of our model for the translation from solar EUV images to solar magnetograms



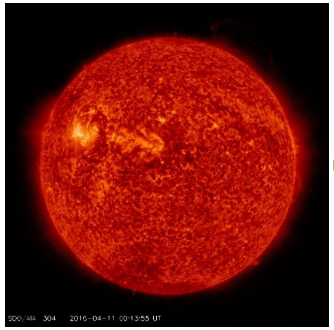
Training Step

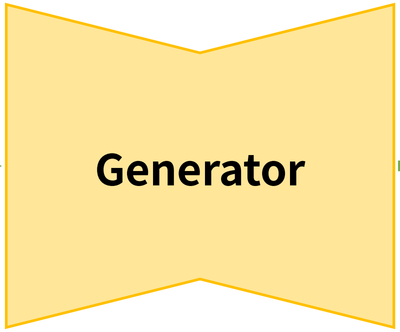
Then the model back-propagates the result to the generator and the discriminator. The generator updates itself to generate more real-like magnetograms to
fool the discriminator. The discriminator also updates itself to increase its discrimination accuracy.

1 Generation of Solar Farside Magnetograms

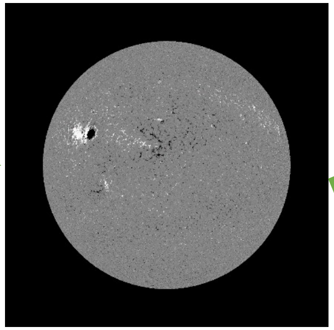
Structure of our model for the translation from solar EUV images to solar magnetograms

SDO/AIA 304 Å image

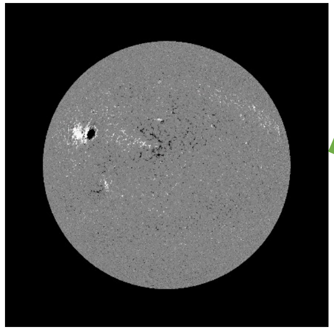




Generated magnetogram



SDO/HMI magnetogram



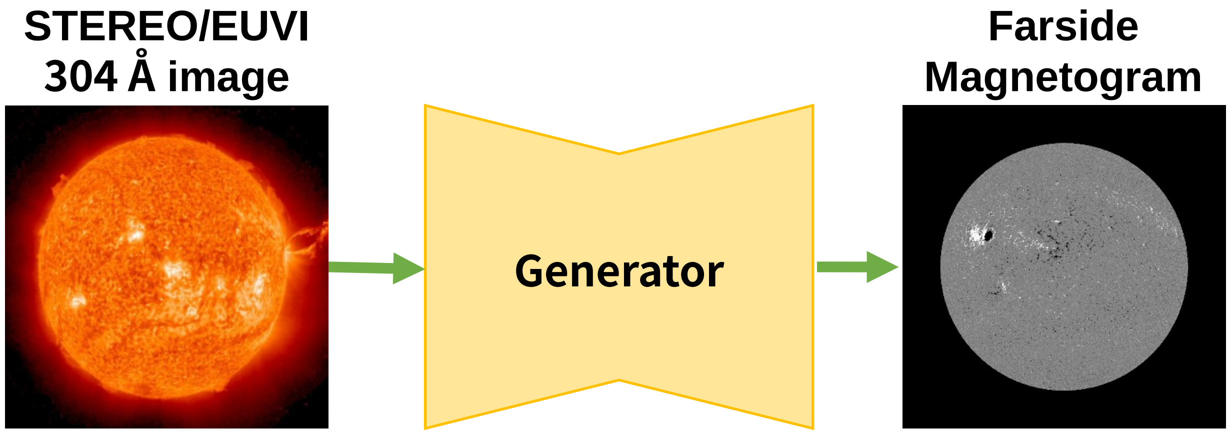
Comparison by model performance score

Evaluation Step

We use only the generator network. The generator produces magnetograms using SDO/AIA images, and then we compare the generated magnetograms with SDO/HMI magnetograms to estimate the model performances.

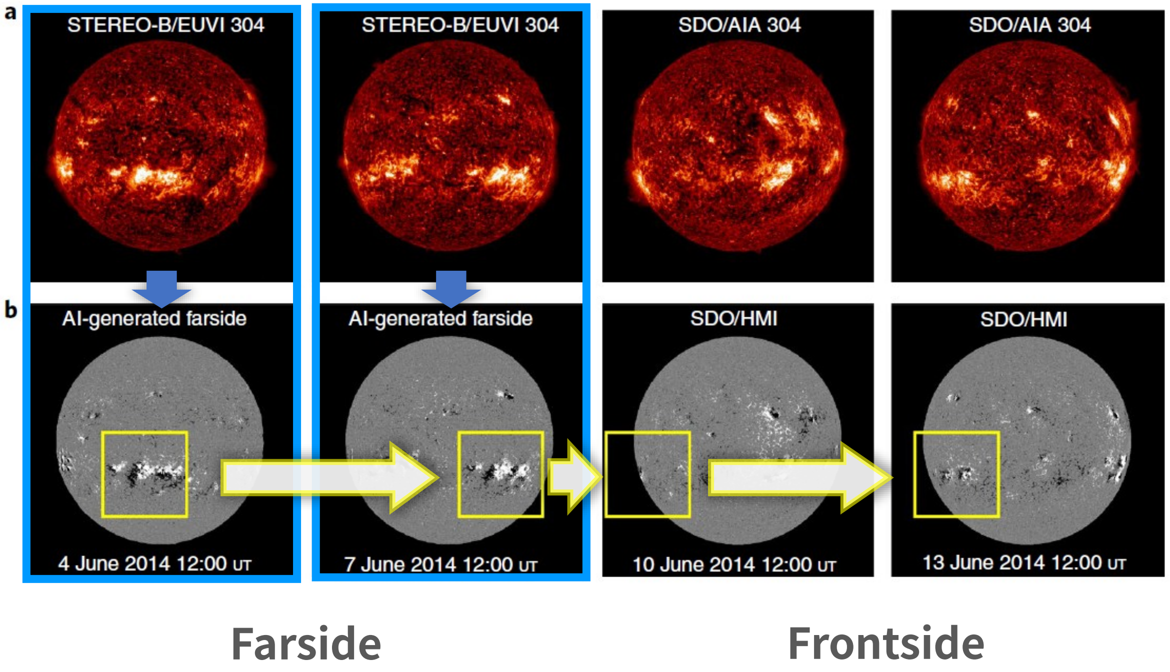
1 Generation of Solar Farside Magnetograms

Structure of our model for the translation from solar EUV images to solar magnetograms

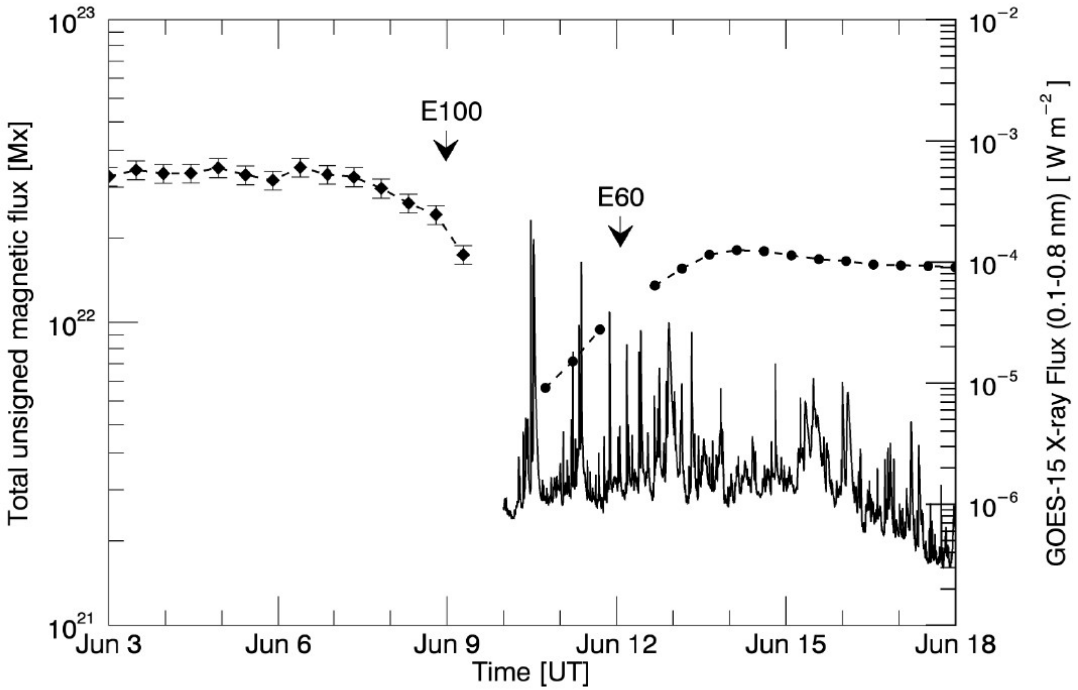


Generation Step

1 Generation of Solar Farside Magnetograms



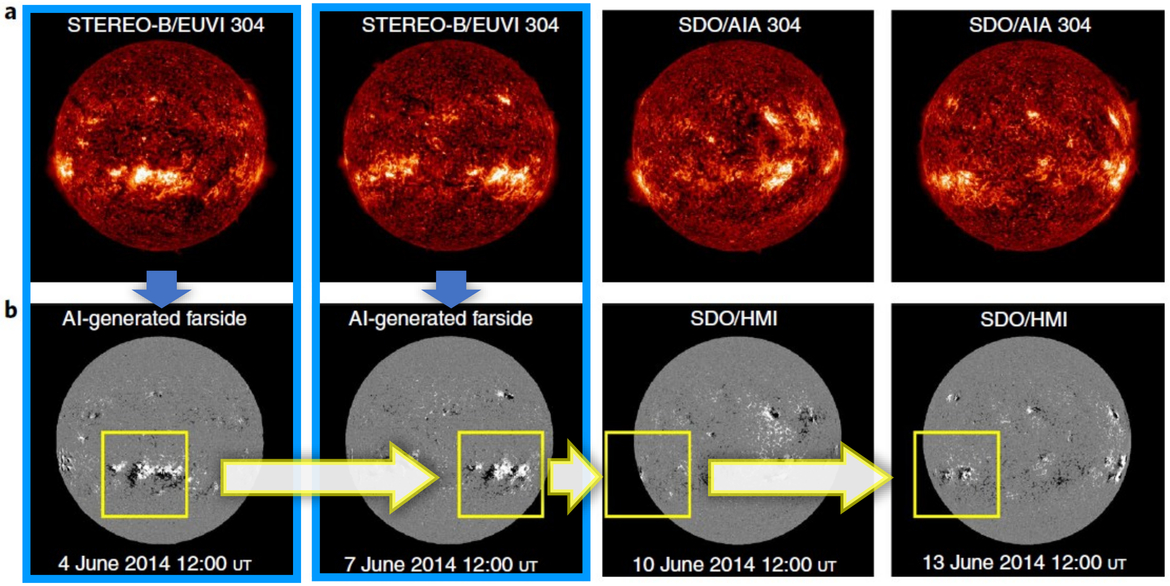
Time Series Images from farside to frontside



A temporal evolution of total unsigned magnetic flux of the NOAA AR 12087 from June 3 to 19 2014

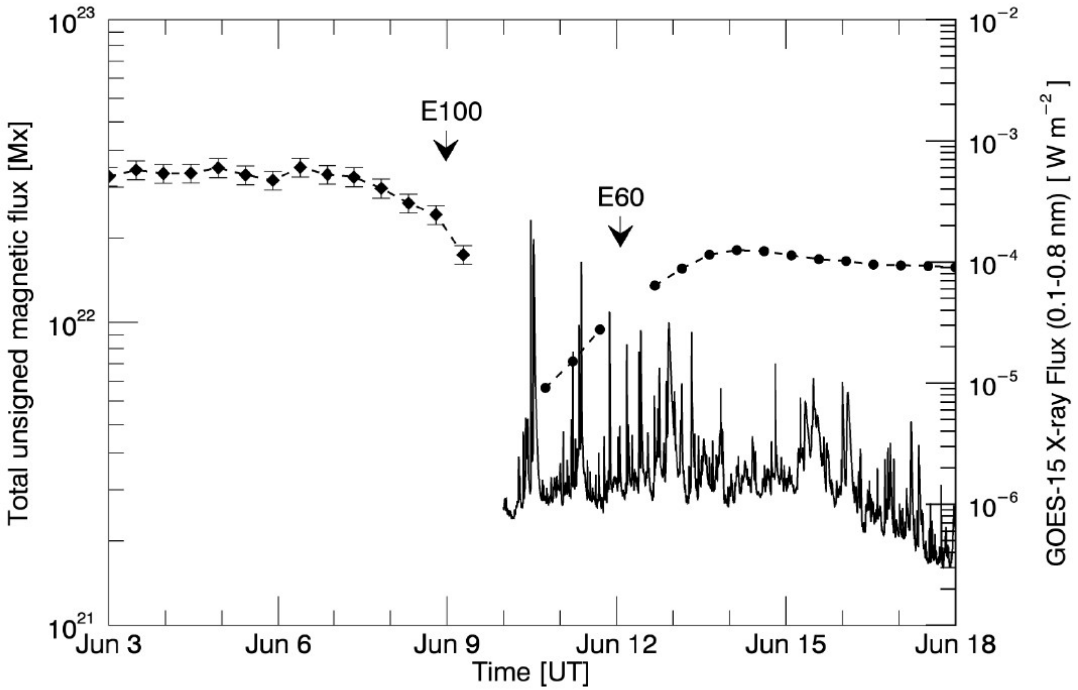
Kim, Park, Lee et al. (2019) suggest a deep learning model for generating solar farside magnetograms from STEREO/EUVI observations. The result shows that we could monitor the temporal evolution of magnetic fields from the solar far side to the solar front side using DL-generated data.

1 Generation of Solar Farside Magnetograms



Farside Frontside

Time Series Images from farside to frontside



A temporal evolution of total unsigned magnetic flux of the NOAA AR 12087 from June 3 to 19 2014

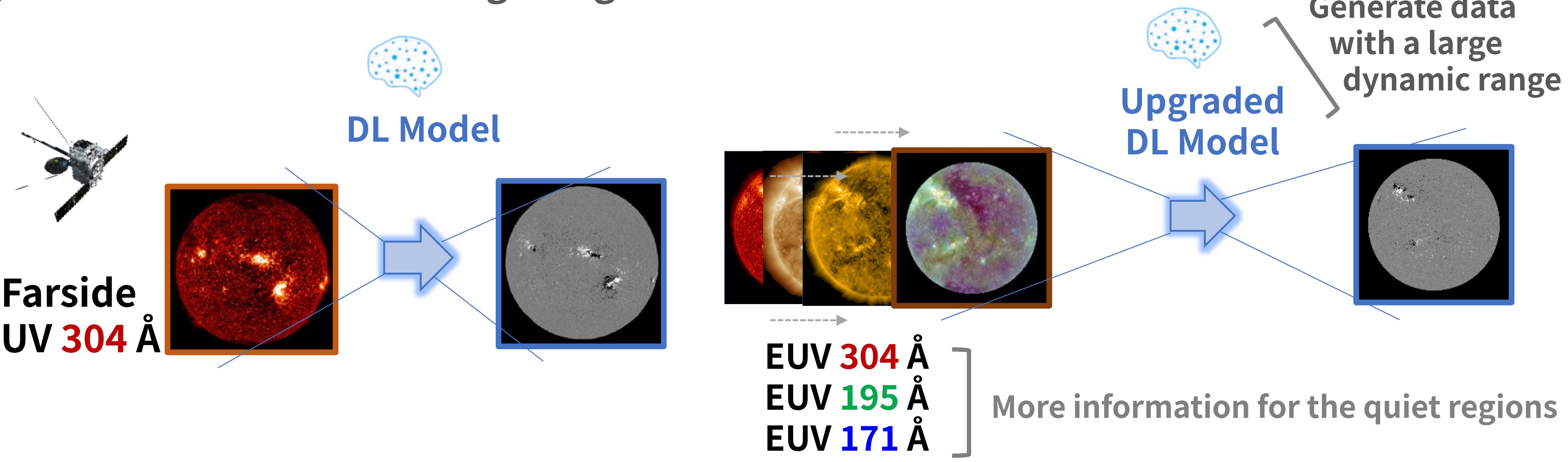
However, this study is limited to the maximum magnetic field strength of 100 G and shows low correlations in solar quiet regions.

1 Generation of Solar Farside Magnetograms

AISFM* Ver 1.0

AISFM Ver 2.0

* AI-generated Solar Farside Magnetogram

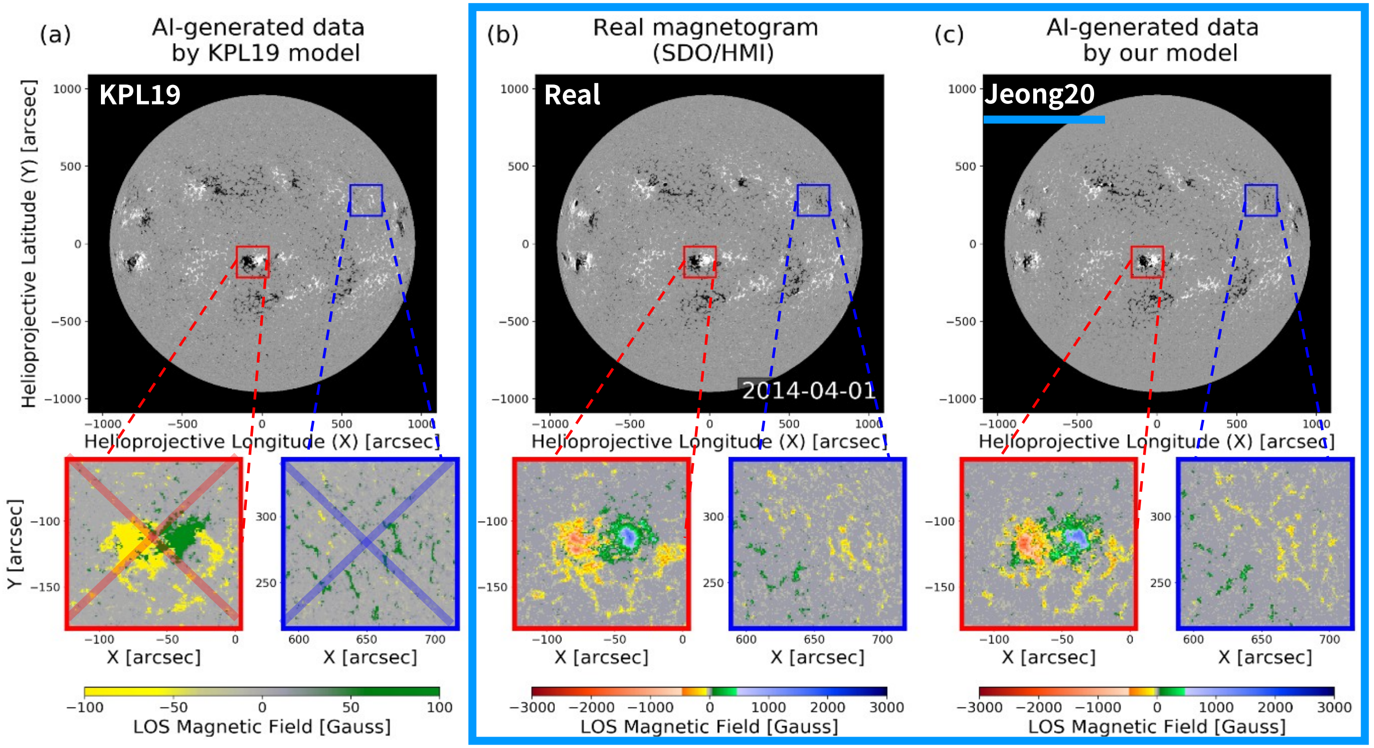


Jeong et al. (2020) upgrade the model with 3,000 Gauss dynamic range to generate more realistic magnetic fluxes, and with multi-channel input to improve the generation of quiet regions.

1 Generation of Solar Farside Magnetograms

AISFM* Ver 1.0

AISFM Ver 2.0



Three Objective Measures of Comparison between SDO/HMI Magnetograms and AI-generated Ones for Full Disk, ARs, and QRs

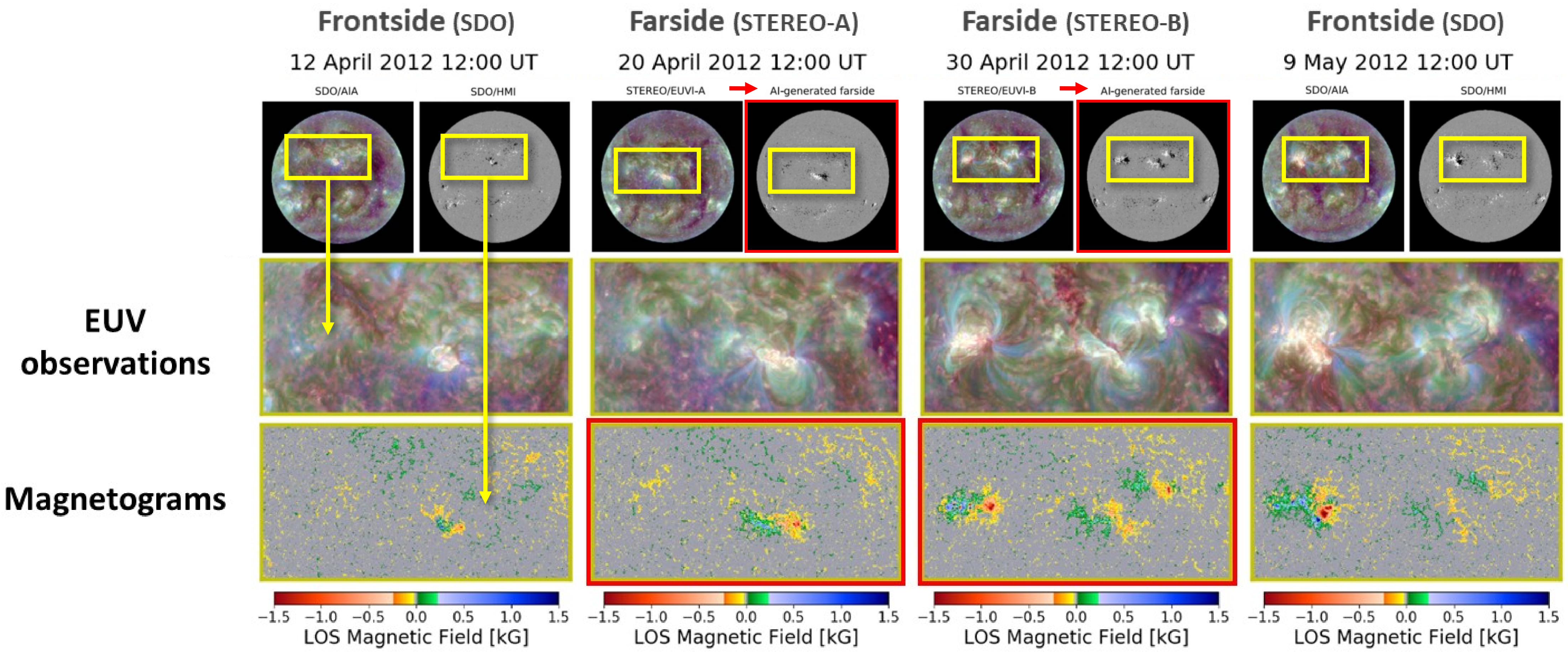
	Full Disk		AR		QR	
	825 images		1,033 patches		825 patches	
	(1,024 × 1,024 pixels)		(128 × 128 pixels)		(128 × 128 pixels)	
	Ours	KPL19	Ours	KPL19	Ours	KPL19
Total unsigned magnetic flux CC	0.99	0.97	0.95	0.95	0.98	0.74
Net magnetic flux CC	0.86	⋯	0.93	⋯	0.97	⋯
Mean pixel-to-pixel CC (8 × 8 binning)	0.81	0.77	0.79	0.66	0.62	0.21

The model (AISFM Ver 2.0) generates both the active and quiet regions more realistically than the previous model (A-ISFM Ver 1.0) and shows better results in quantitative comparisons.

1 Generation of Solar Farside Magnetograms

A series of full-disk EUV images and magnetograms

yellow boxes show the tracking of solar active regions over a solar rotation



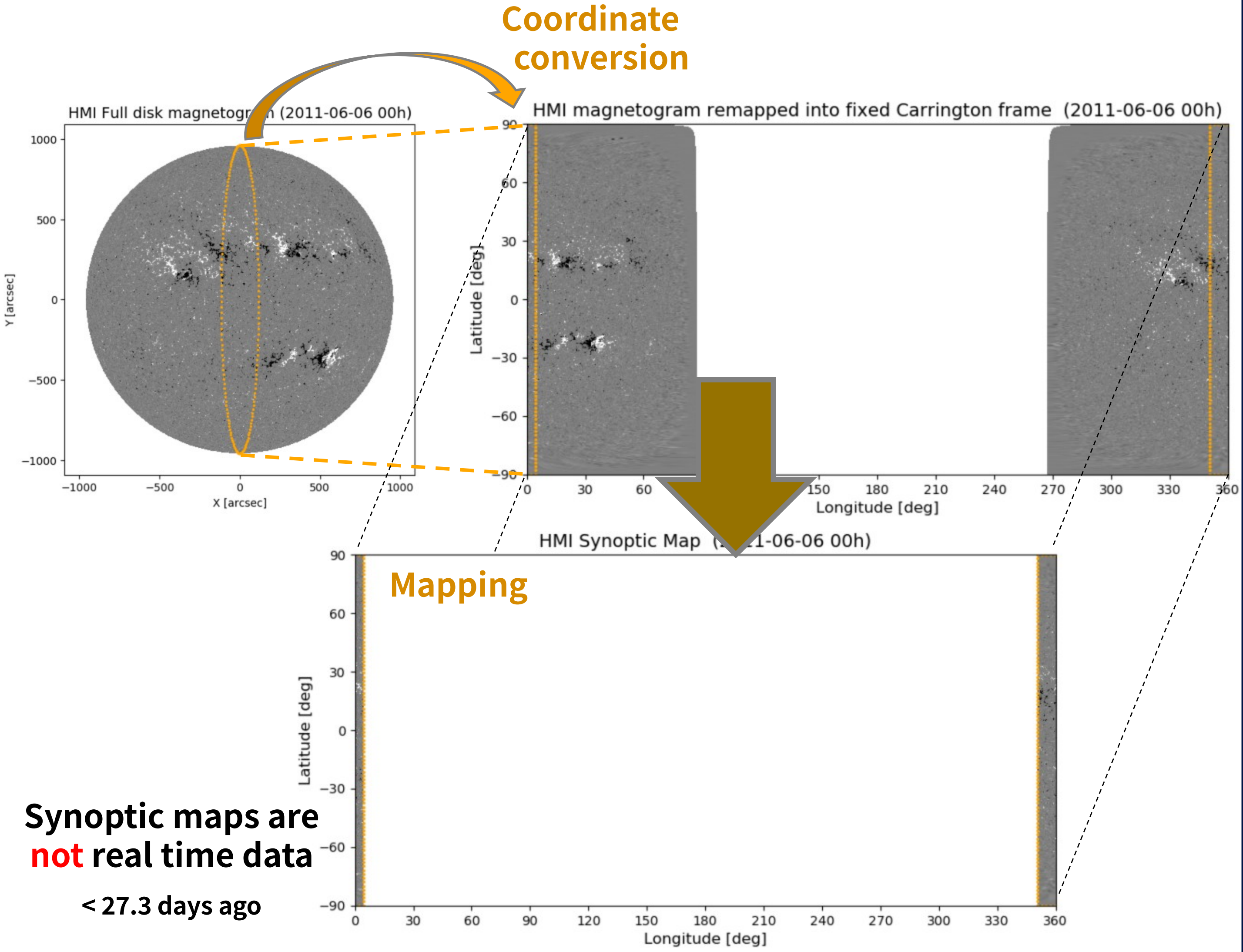
The model generates solar active regions with more realistic magnetic field strengths.

1 Generation of Solar Farside Magnetograms

Conventional Synoptic Map

Conventional magnetic field synoptic maps have been constructed by merging frontside magnetograms over a 27 day solar rotation period because there is no magnetogram in solar farside.

The conventional synoptic maps are **not based on real-time** ones.

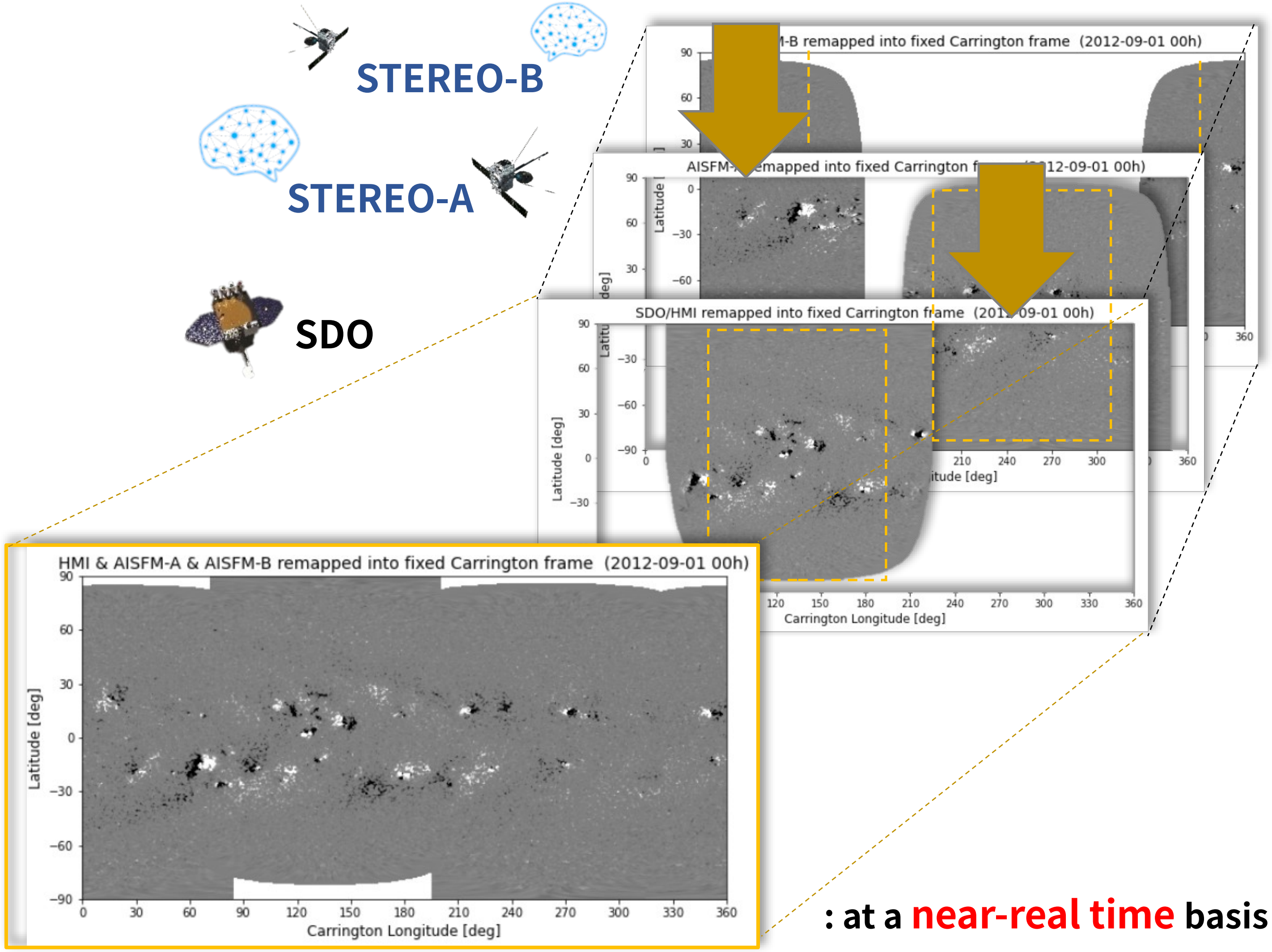


1 Generation of Solar Farside Magnetograms

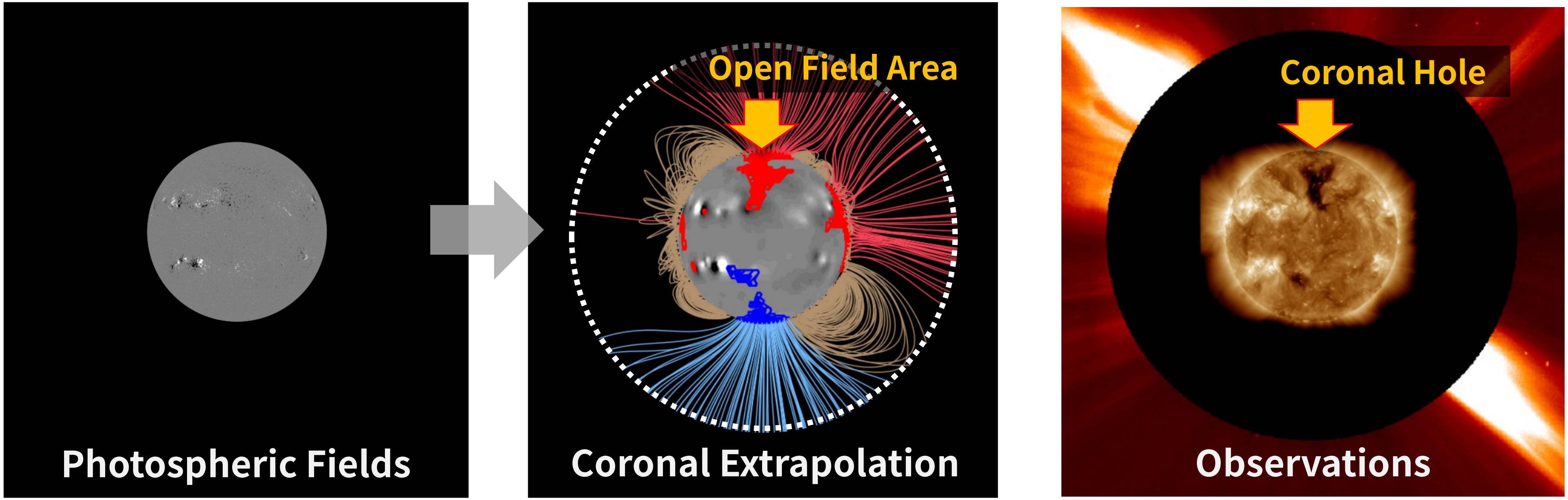
HMI & AI Synchronic Map

We construct AI synchronic global magnetic field maps by merging the farside magnetograms and SDO/HMI magnetograms.

These AI synchronic maps can cover mostly real-time global solar photospheric fields.



1 Generation of Solar Farside Magnetograms

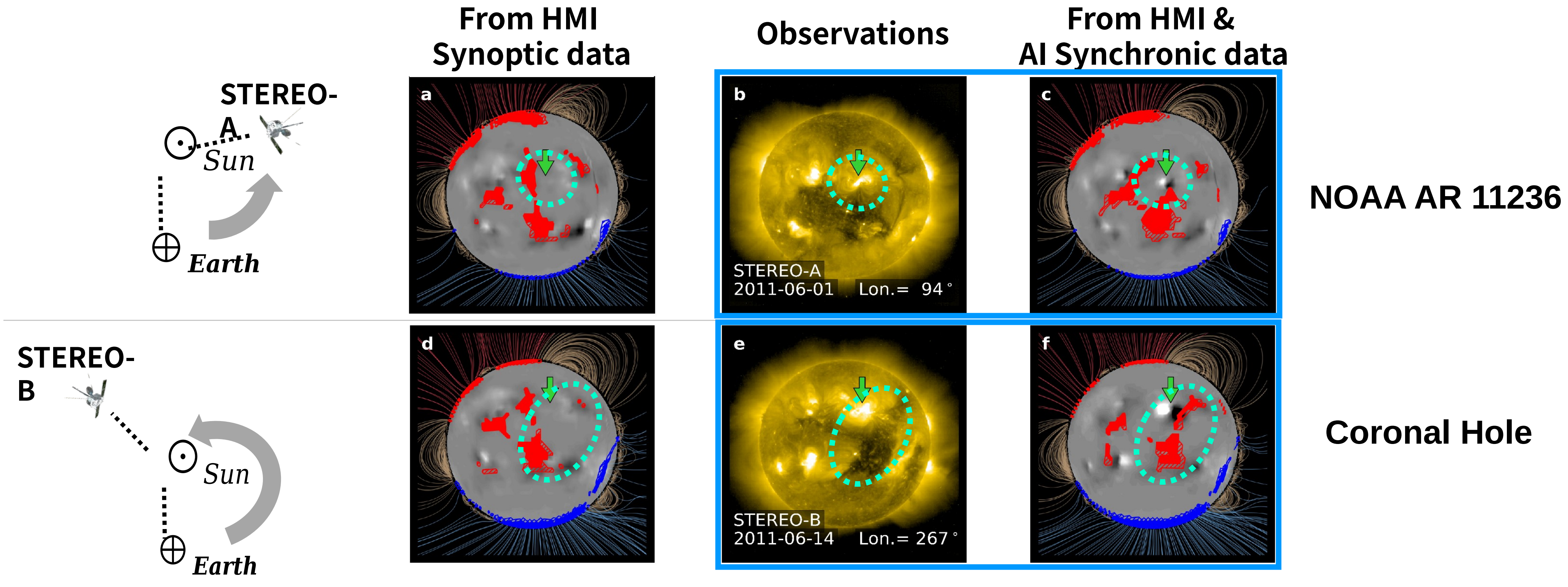


We extrapolate the global coronal magnetic field from the AI synchronic maps using Potential Field Source Surface (PFSS) model, then compare the results with coronal observations.

Open field lines, which are computed by the PFSS model, arriving at the source surface are associated with coronal holes.

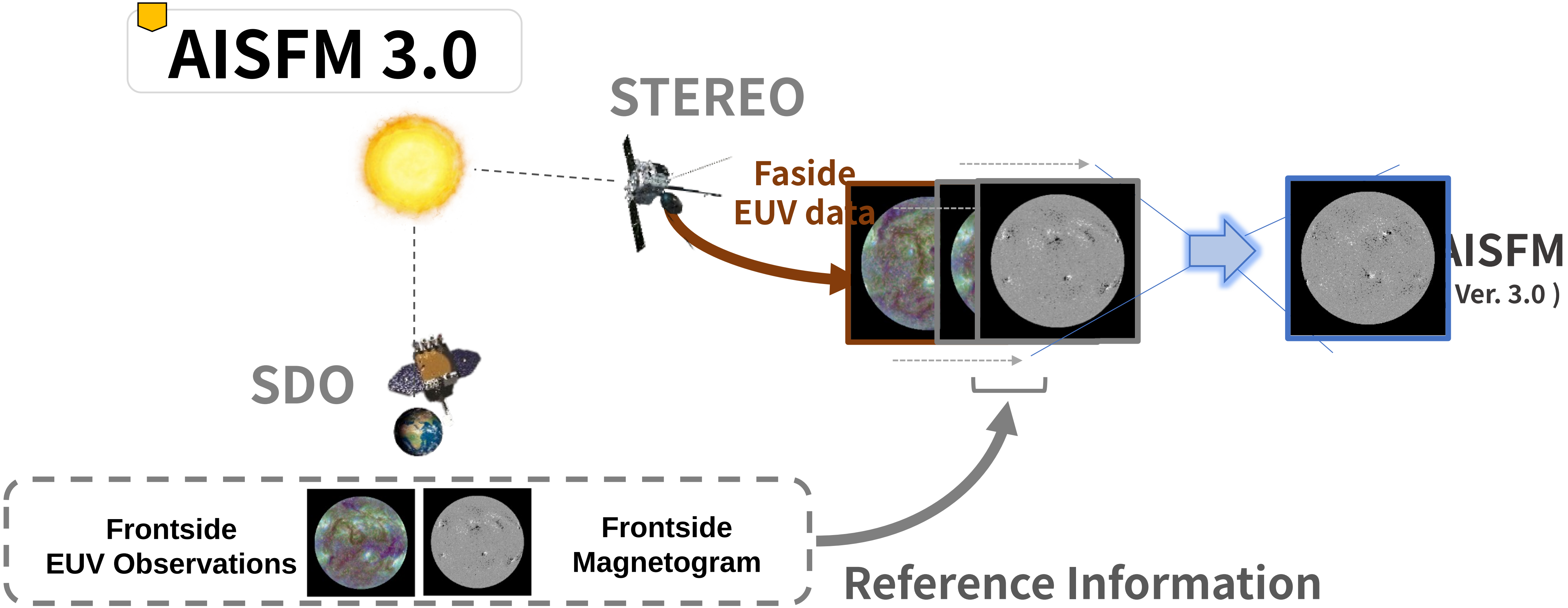
1 Generation of Solar Farside Magnetograms

Comparison between farside solar EUV observations and results of PFSS extrapolations



The extrapolation results using AI synchronic data well represent the appearance of the active region and the coronal hole,
and the results agree with the observations.

1 Generation of Solar Farside Magnetograms



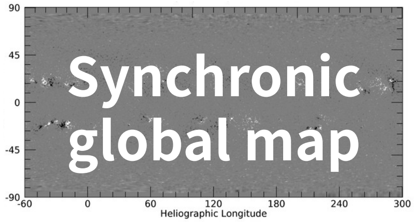
We are trying to improve our model by providing solar frontside data to the model as reference information.

1 Generation of Solar Farside Magnetograms

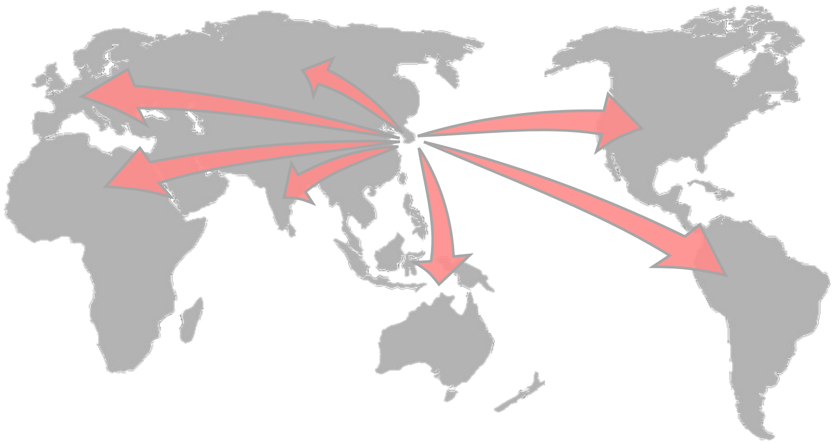
Public release of solar farside magnetograms soon

-A: 2011.01 ~ 2019.12 (~ 47 GB)

-B: 2011.01 ~ 2014.09 (~ 21 GB)



2011.01 ~ 2019.12 (~ 26 GB)



We are going to release the solar farside magnetograms and AI synchronic maps through Korean Data Center (KDC) for SDO in Korean Astronomy and Space Science Institute (KASI).

KDC for SDO in KASI

2

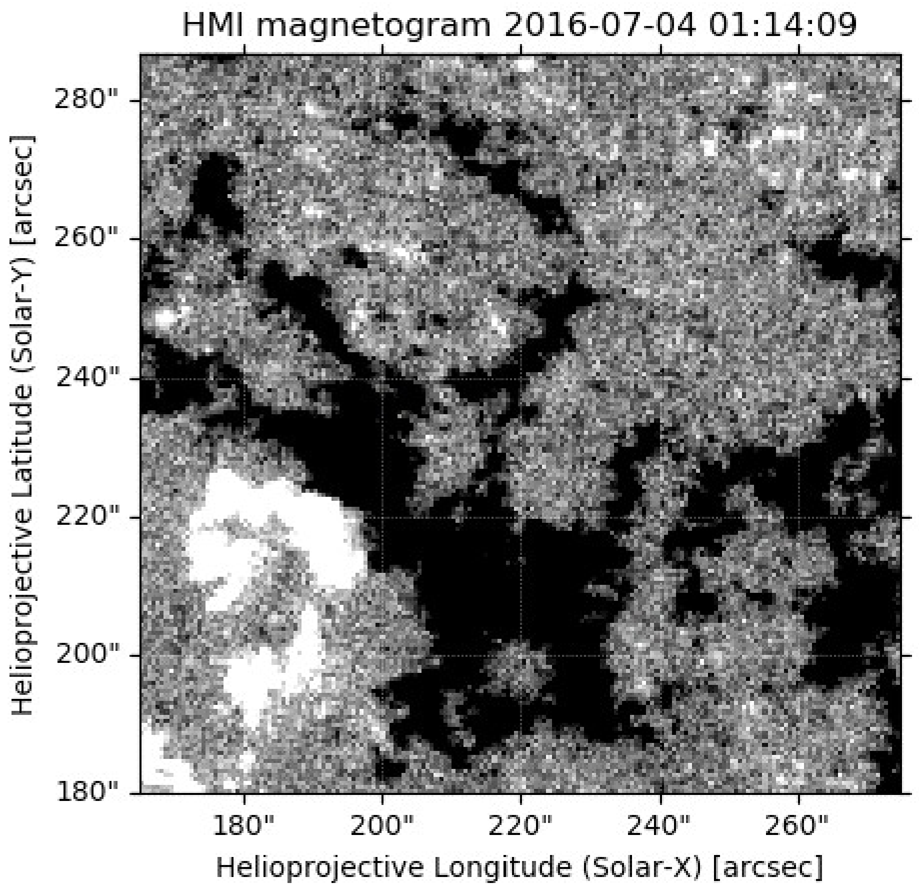
De-noising SDO/HMI Magnetograms

Park et al., 2020

2 Denoising SDO/HMI Magnetogram

Liu+ (2012) reported that

"An upper bound to the random noise for the 1" resolution HMI 45-second magnetograms is 10.2 G, and 6.3 G for the 720-second magnetograms."



2 Denoising SDO/HMI Magnetogram

- Several studies investigated weak solar magnetic field structures such as solar intra-network and small bi-poles by integrating magnetic field observations to increase the signal-to-noise ratio (Wang et al. 1995; Schrijver et al. 1997; Chae et al. 2001).
- Several studies tried to reduce the noise level of solar magnetograms by several types of computing algorithms (DeForest 2017; DiasBaso et al. 2019).
- In this study, we apply two deep learning methods to denoising SDO/HMI magnetograms.

2 Denoising SDO/HMI Magnetogram

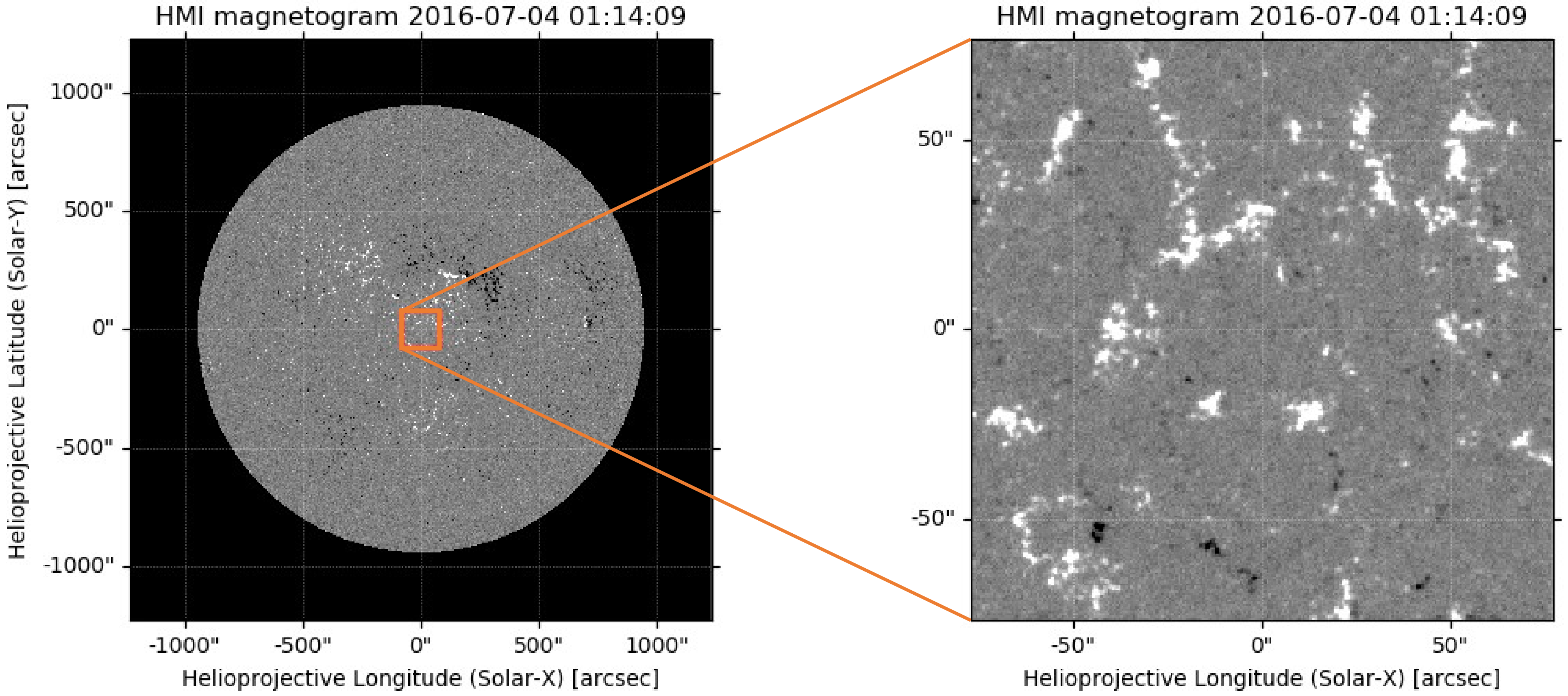
We design a deep learning model that translates from original magnetograms to corresponding de-noised magnetograms.

-> We need pairs of the original magnetograms and the denoised magnetograms to train the model.

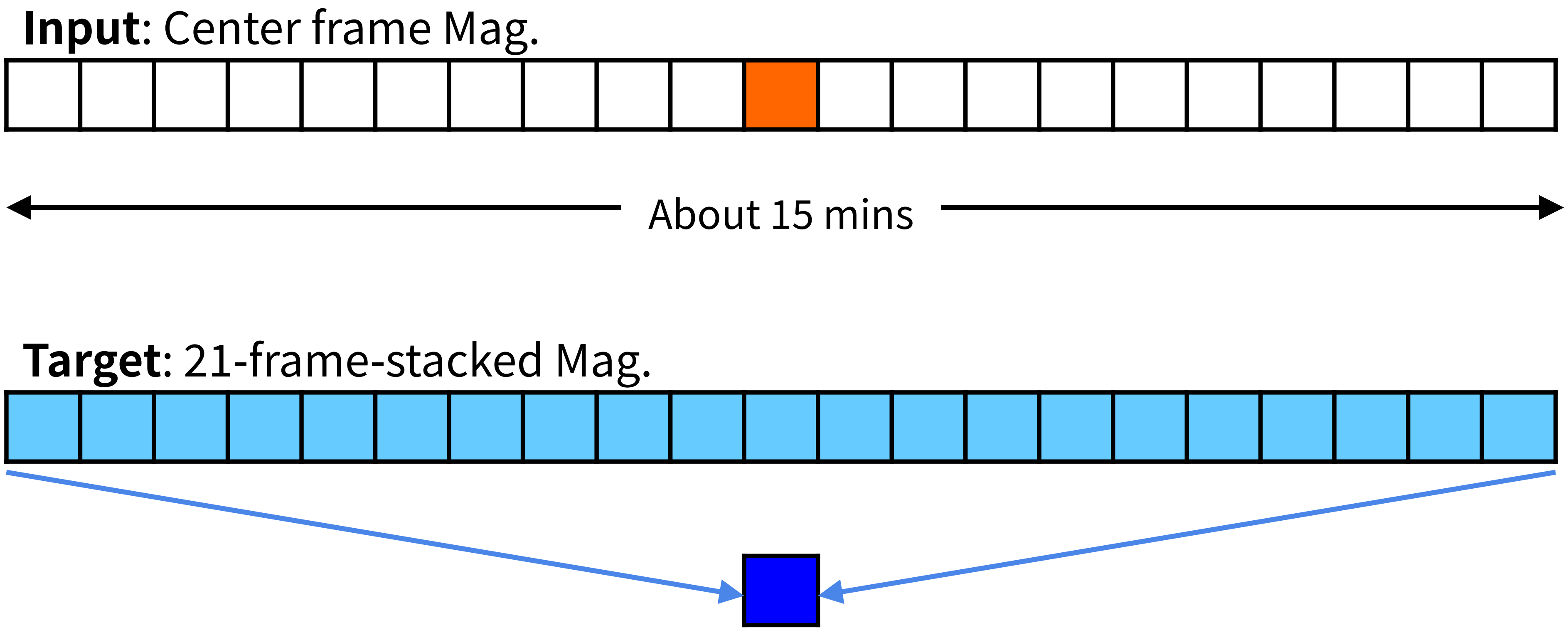
2 Denoising SDO/HMI Magnetogram

Crop patches from full disk HMI 45-second magnetogram

patch size: 256 x 256 (± 76.8 arcsec)



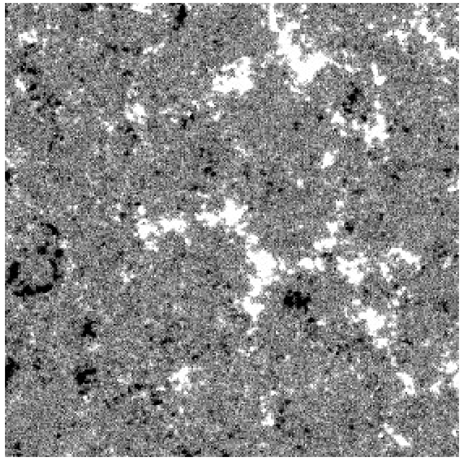
2 Denoising SDO/HMI Magnetogram



We integrate 21 magnetogram patches that include 10 frames before and 10 frames after the input magnetogram patch considering solar rotation. A stacked magnetogram has approximately 15 minutes of exposure time.

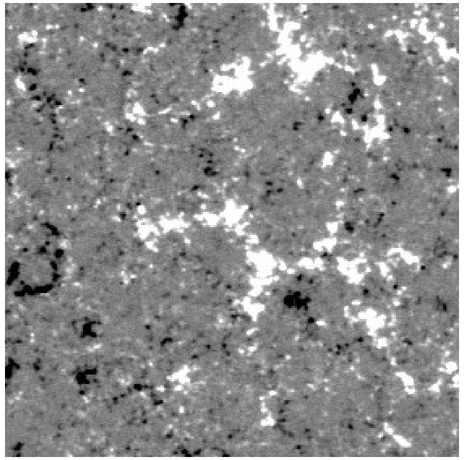
Denoising SDO/HMI Magnetogram

Original HMI
(Input)



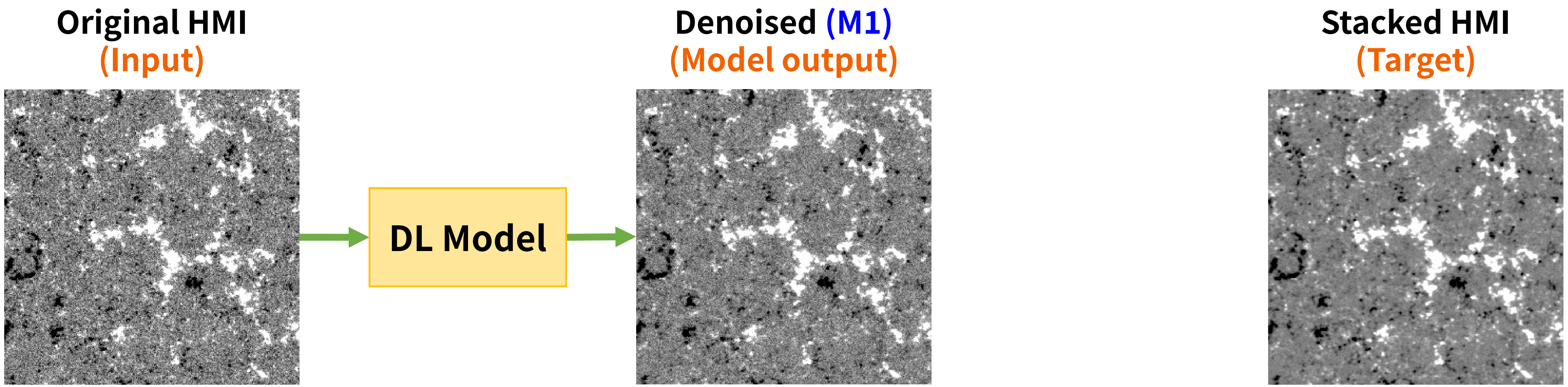
DL Model

Stacked HMI
(Target)



We prepare the pairs of the original magnetograms and the stacked magnetograms.

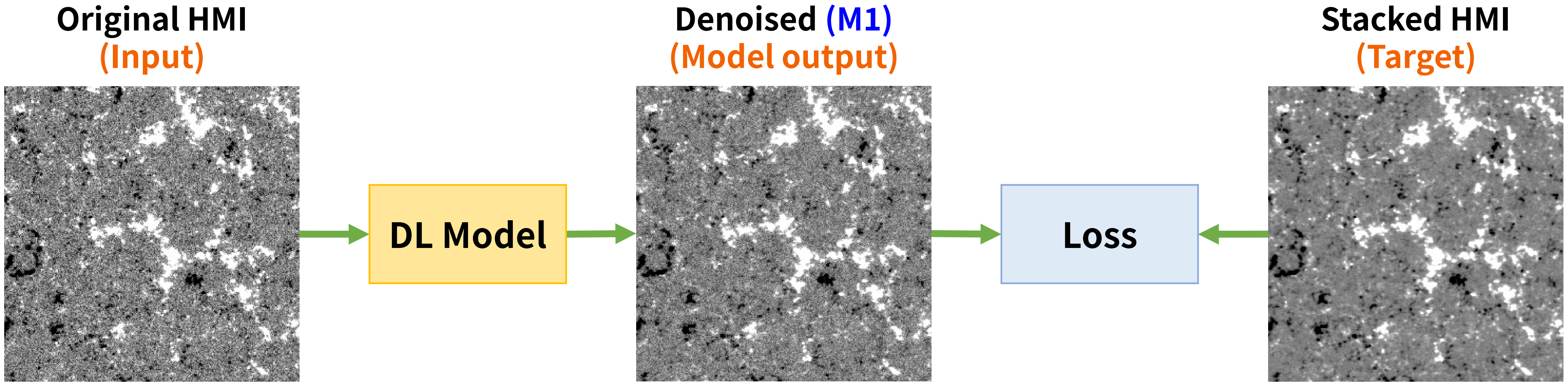
2 Denoising SDO/HMI Magnetogram



We prepare the pairs of the original magnetograms and the stacked magnetograms.
The model

1) generates the denoised magnetograms using the original magnetograms,

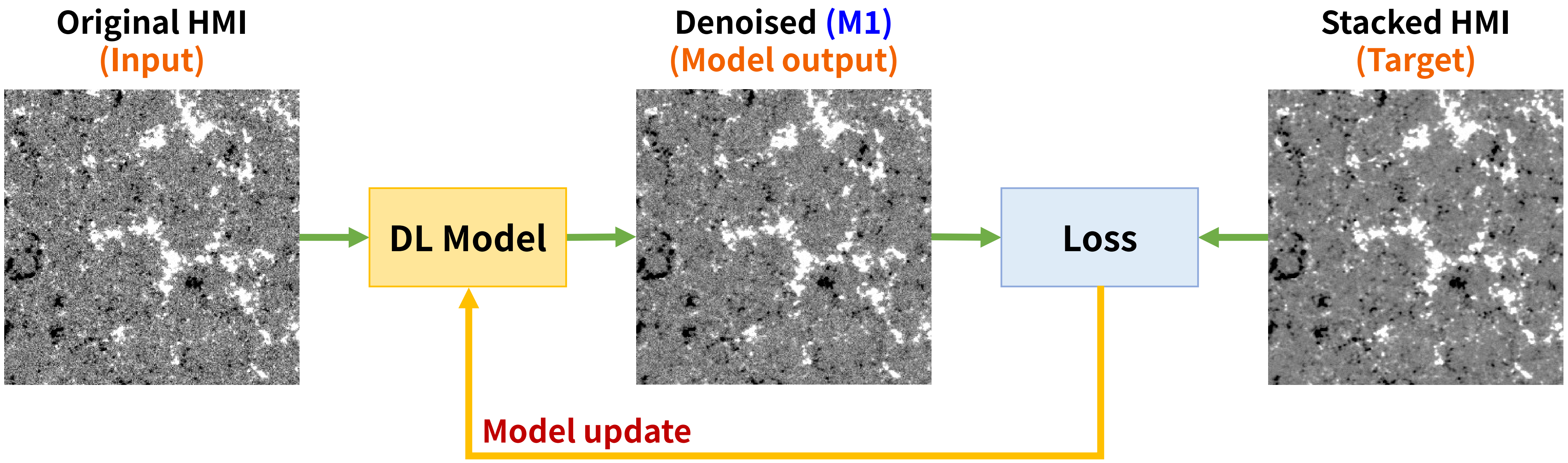
2 Denoising SDO/HMI Magnetogram



We prepare the pairs of the original magnetograms and the stacked magnetograms.
The model

1) **generates the denoised magnetograms using the original magnetograms,**
2) **calculates the difference between the denoised and the stacked magnetograms,**

2 Denoising SDO/HMI Magnetogram

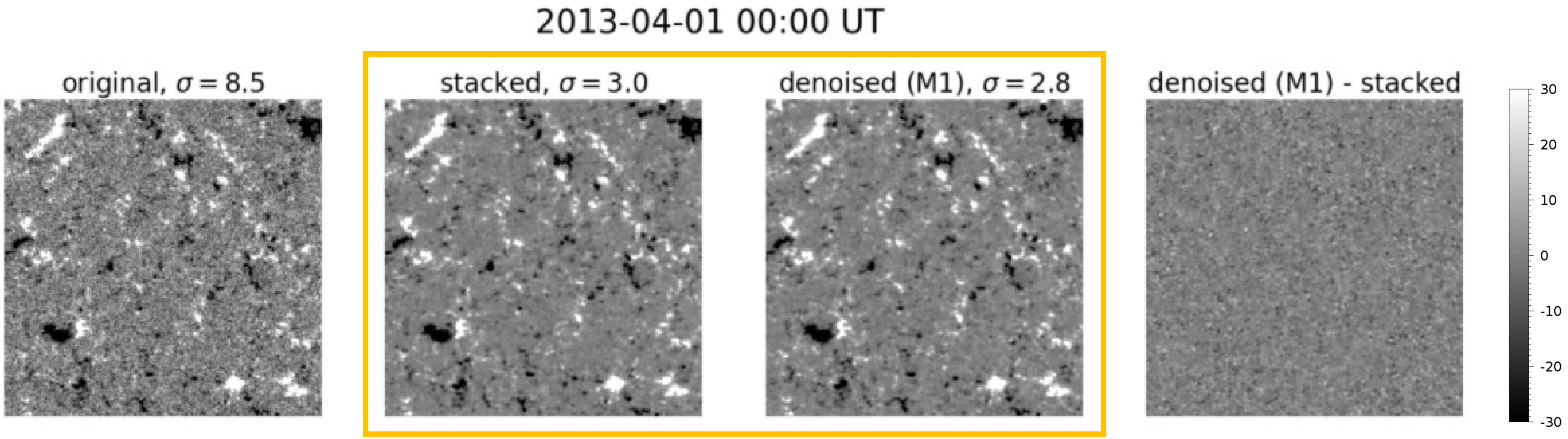


We prepare the pairs of the original magnetograms and the stacked magnetograms.
The model
1) generates the denoised magnetograms using the original magnetograms,
2) calculates the difference between the denoised and the stacked magnetograms,
3) back-propagates the difference, and updates itself to minimize the difference.

2

Denoising SDO/HMI Magnetogram

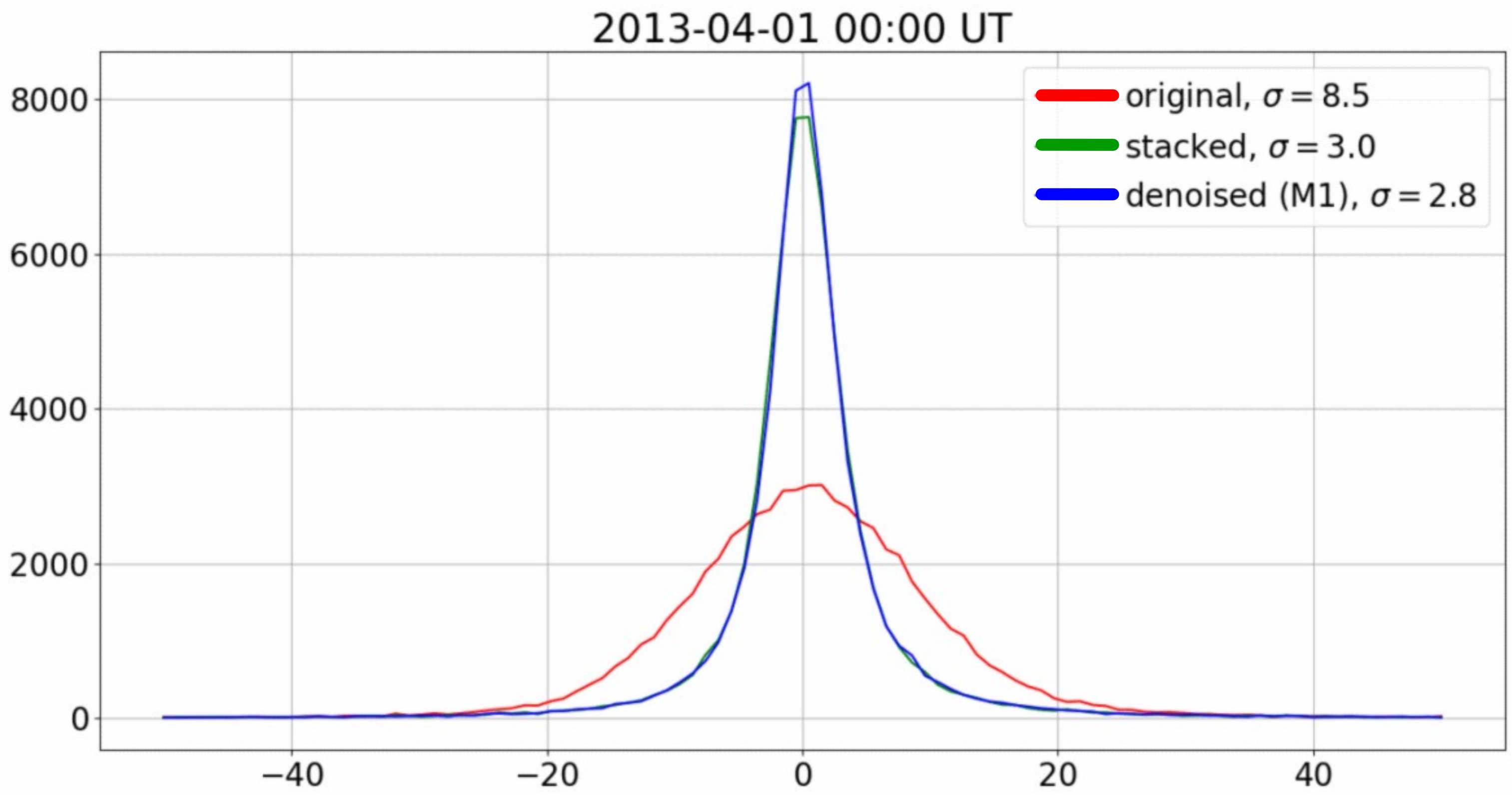
Comparisons between the original, stacked, and denoised magnetograms



The denoised magnetograms by our model are consistent with the stacked ones.

2 Denoising SDO/HMI Magnetogram

Histograms of magnetic flux densities from the original, stacked, and denoised magnetograms



The histograms of the denoised magnetograms are similar to those of the stacked ones, and their noise levels are almost same.

2 Denoising SDO/HMI Magnetogram

- **Our model based on image translation method successfully reduce the noise level of SDO/HMI magnetograms.**

- **This method can be applied only when we have pairs of the original magnetograms (input) and the denoised magnetograms (target).**

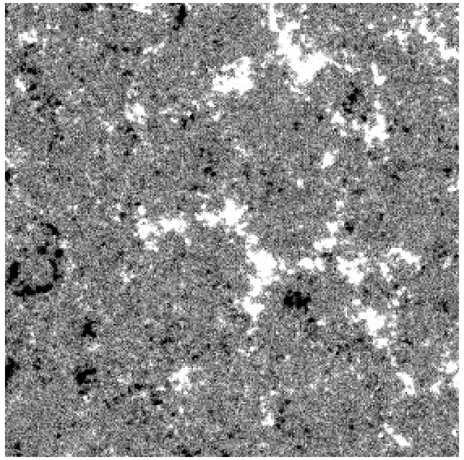
- **The quality of the model outputs can be affected by the condition of the target data, such as the number of frames for the stacked magnetograms.**

2 Denoising SDO/HMI Magnetogram

- Our model based on image translation method successfully reduce the noise level of SDO/HMI magnetograms.
- This method can be applied only when we have pairs of the original magnetograms (input) and the denoised magnetograms (target).
- The quality of the model outputs can be affected by the condition of the target data, such as the number of frames for the stacked magnetograms.
- We design an additional model (M2) based on AutoEncoder method that can train without target magnetograms.

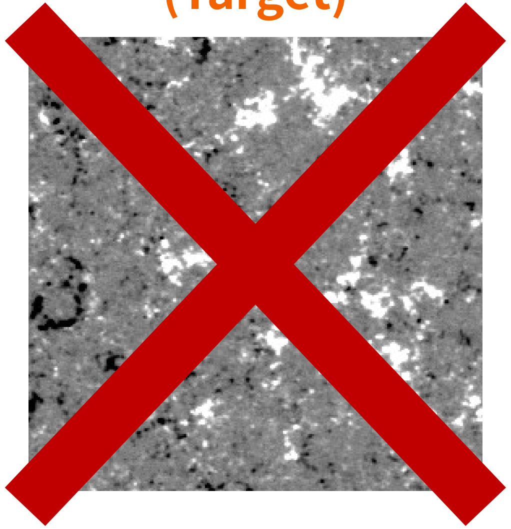
2 Denoising SDO/HMI Magnetogram

Original HMI
(Target)



DL Model

Stacked HMI
(Target)

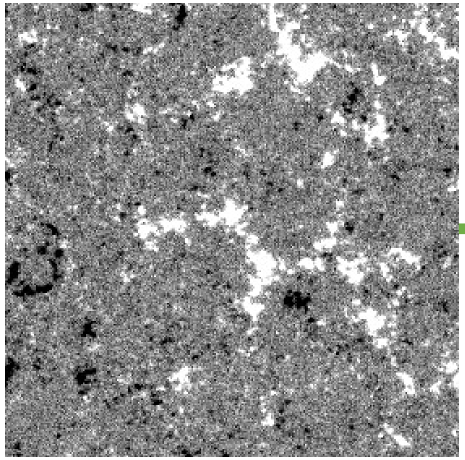


The dataset is the same as the previous study, but we will not use the stacked magnetograms.

2 Denoising SDO/HMI Magnetogram

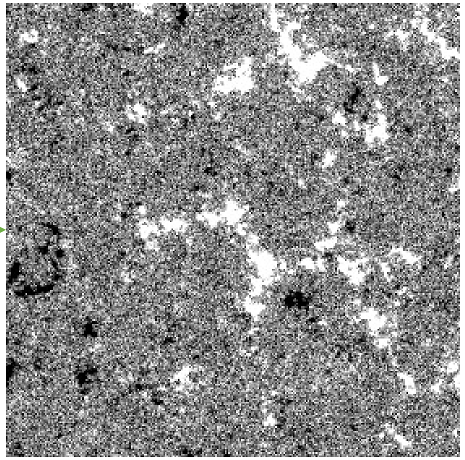
Training Step

Original HMI (Target)



Add Noise

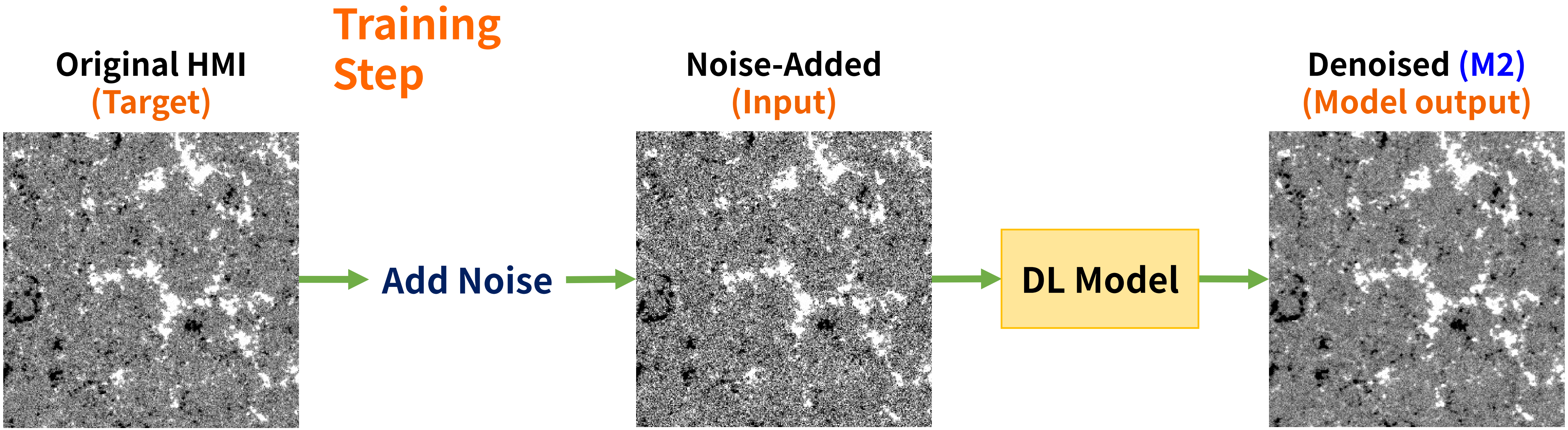
Noise-Added (Input)



DL Model

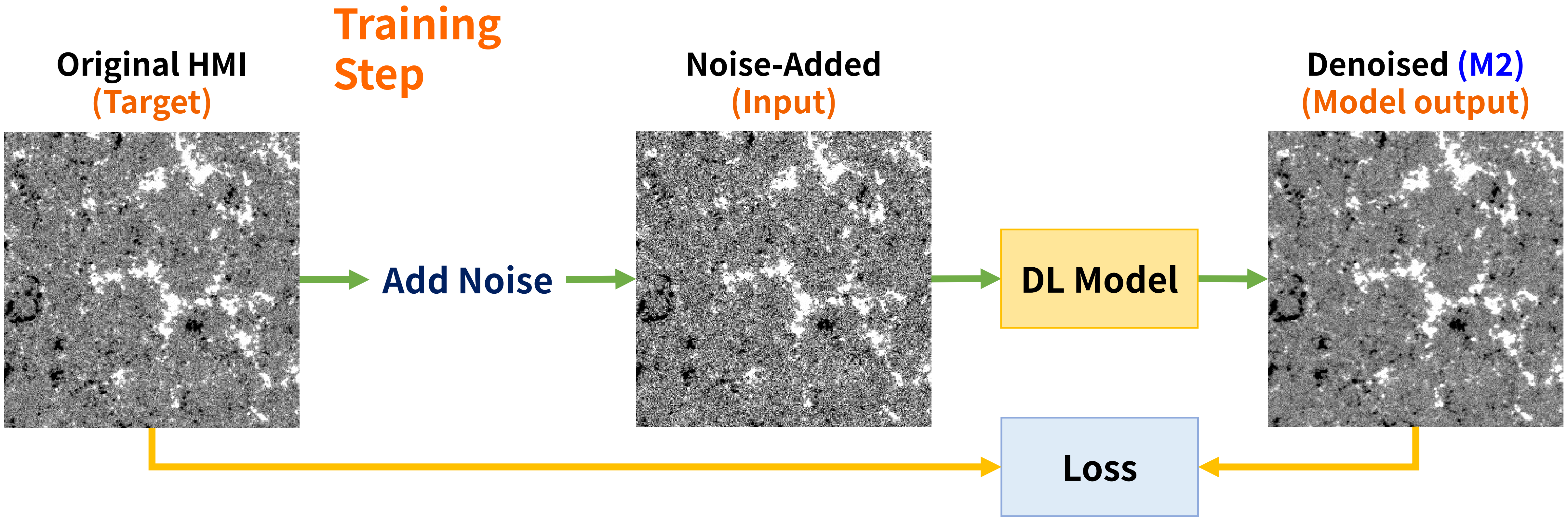
We prepare the original magnetograms and add random Gaussian noise to the magnetograms. The noise distributions are similar to those of the original ones.

2 Denoising SDO/HMI Magnetogram



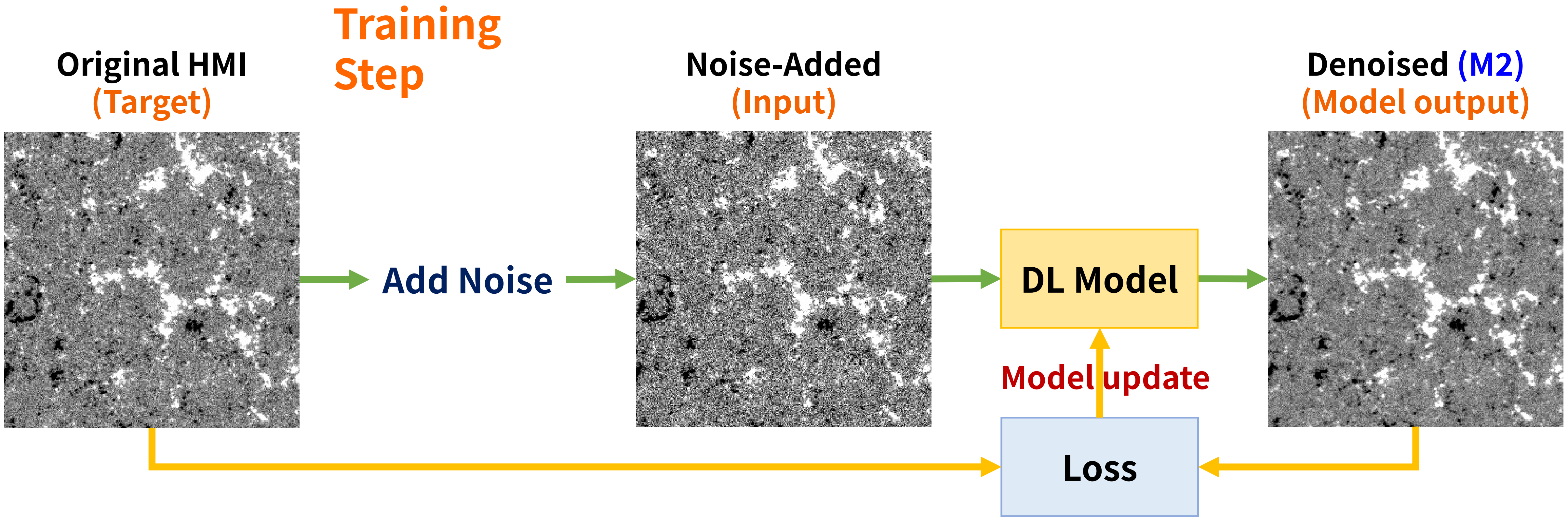
We prepare the original magnetograms and add random Gaussian noise to the magnetograms.
The model
1) generates the denoised magnetograms using the noise-added magnetograms,

2 Denoising SDO/HMI Magnetogram



We prepare the original magnetograms and add random Gaussian noise to the magnetograms.
The model
1) generates the denoised magnetograms using the noise-added magnetograms,
2) calculates the difference between the denoised and the original magnetograms,

2 Denoising SDO/HMI Magnetogram

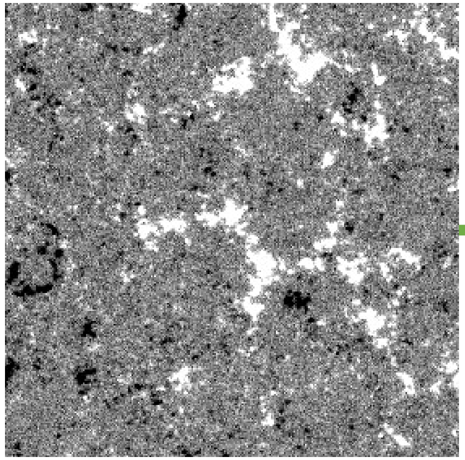


We prepare the original magnetograms and add random Gaussian noise to the magnetograms.
The model

1) generates the denoised magnetograms using the noise-added magnetograms,
2) calculates the difference between the denoised and the original magnetograms,
3) back-propagates the difference, and updates itself to minimize the difference.

2 Denoising SDO/HMI Magnetogram

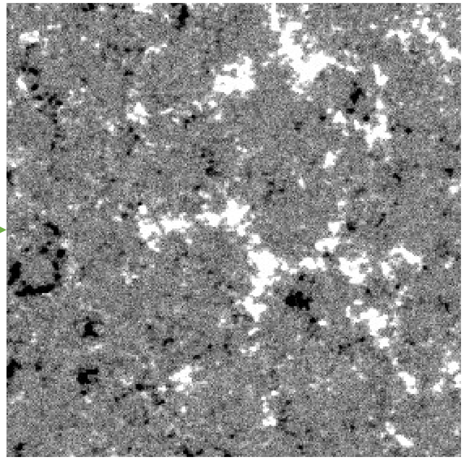
Original HMI
(Input)



Generation Step

DL Model

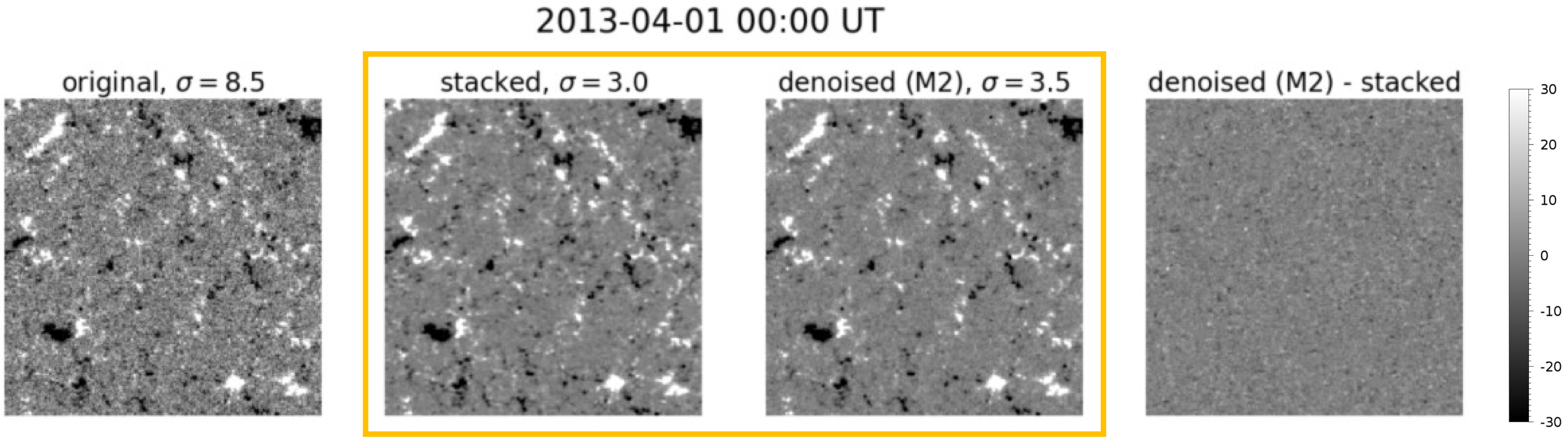
Denoised (M2)
(Model output)



The model generates the denoised magnetograms using the original magnetograms.

2 Denoising SDO/HMI Magnetogram

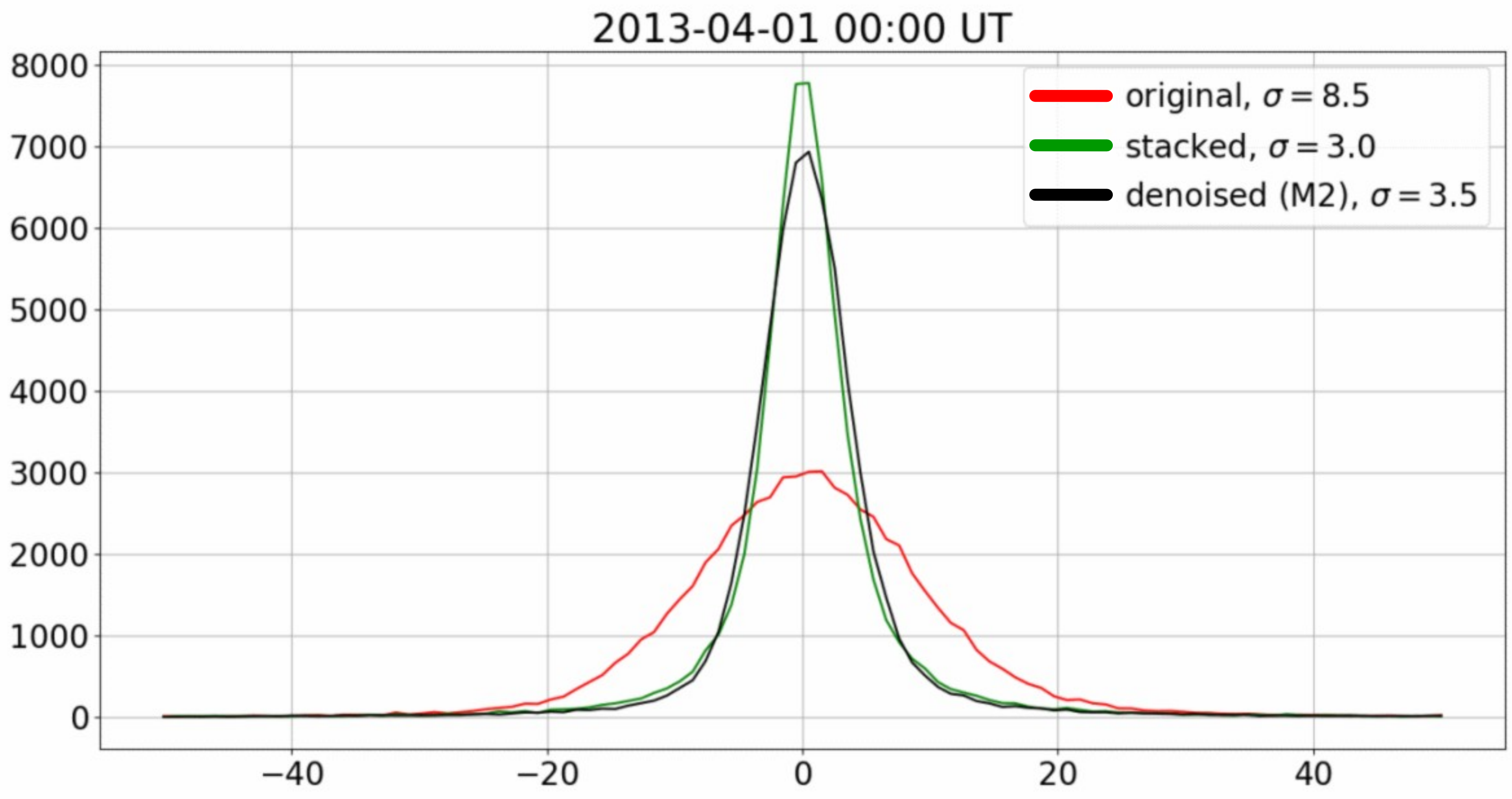
Comparisons between the original, stacked, and denoised magnetograms



The denoised magnetograms by our AutoEncoder model are consistent with the stacked ones

2 Denoising SDO/HMI Magnetogram

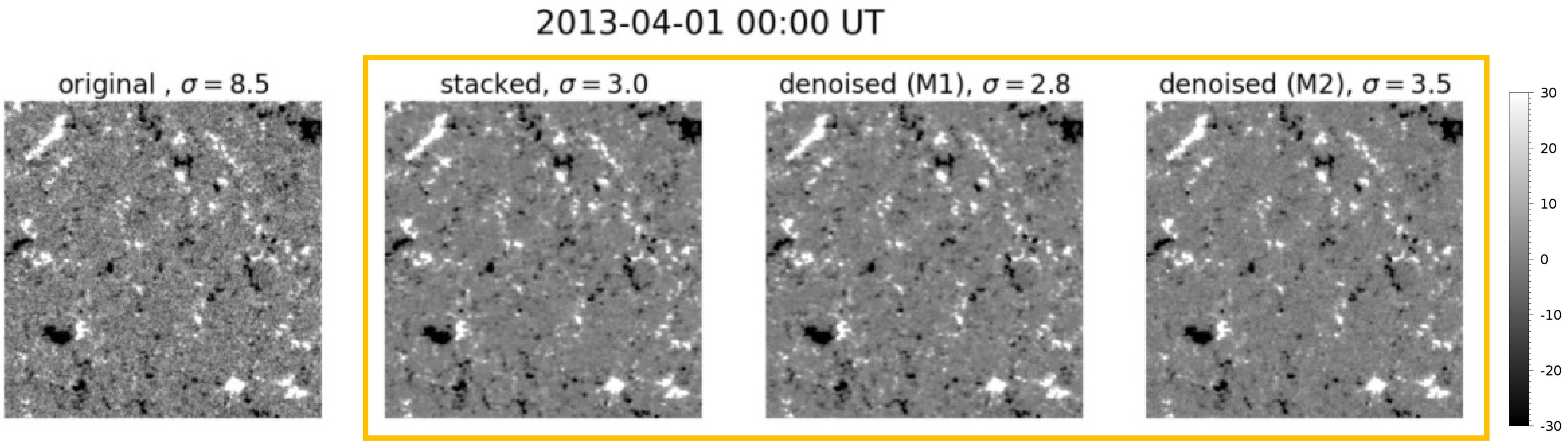
Histograms of magnetic flux densities from the original, stacked, and denoised magnetograms



The histograms of the denoised magnetograms are similar to those of the stacked ones

2 Denoising SDO/HMI Magnetogram

Comparisons between original, stacked, and denoised magnetograms by two models

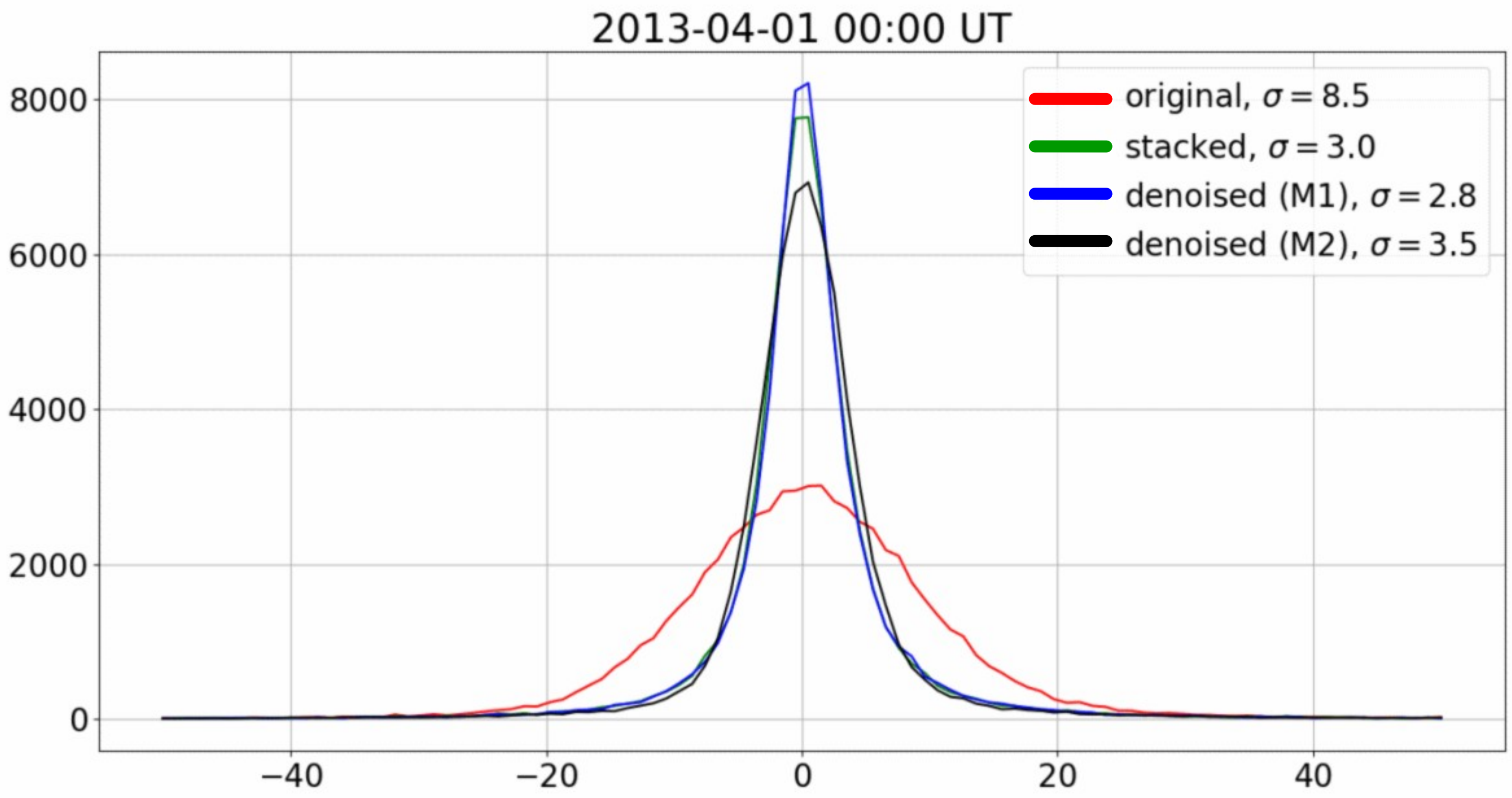


The denoised magnetograms by two models are consistent with each other.

M1: Image translation model, M2: AutoEncoder model

2 Denoising SDO/HMI Magnetogram

Histograms of magnetic flux densities from the original, stacked, and denoised magnetograms by two models



M1: Image translation model

M2: AutoEncoder model

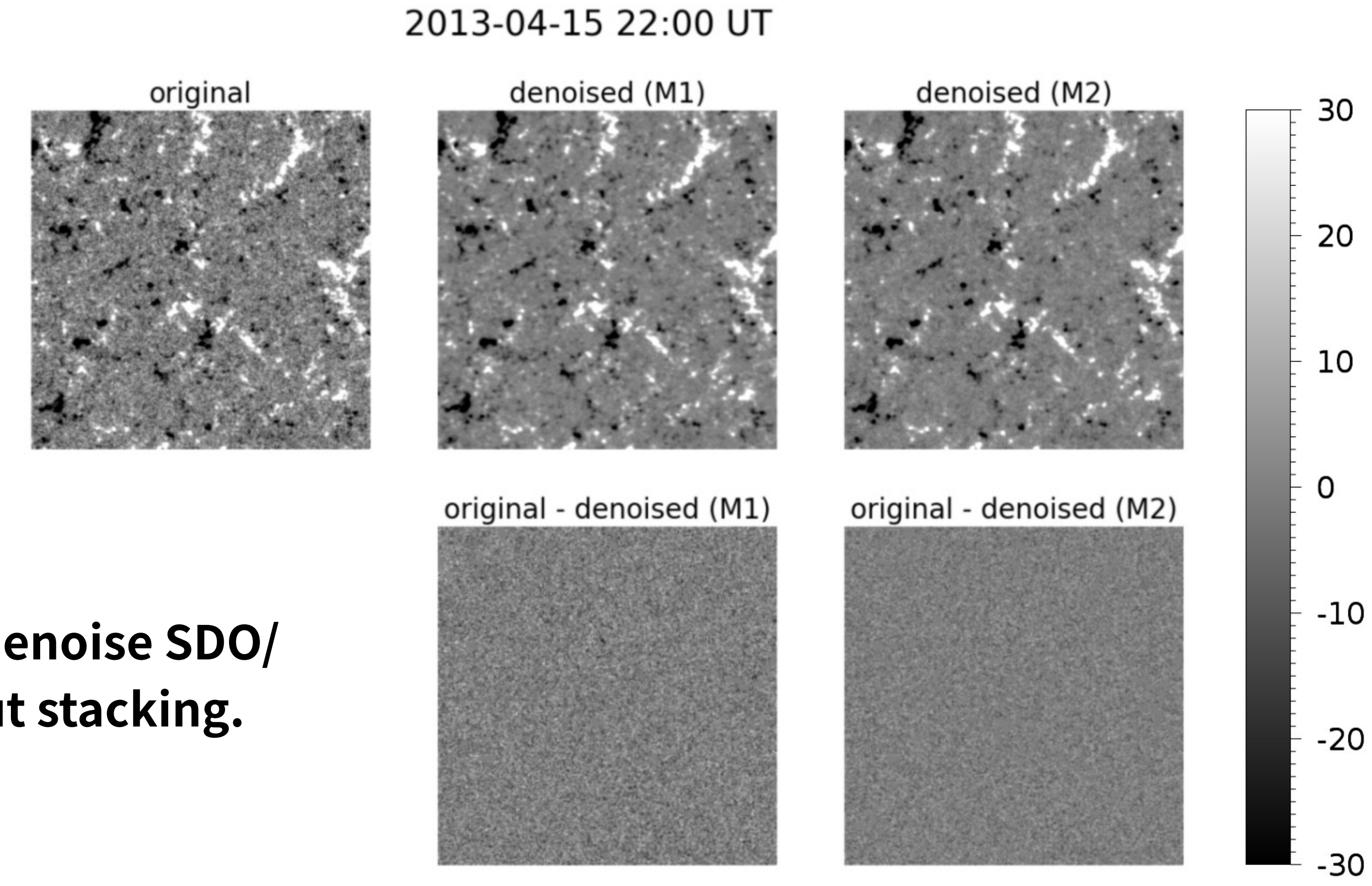
The denoised magnetograms by the two models are similar to each other

2 Denoising SDO/HMI Magnetogram

Application of our models to 21 frames of original SDO/HMI magneotgrams

M1: Image translation model

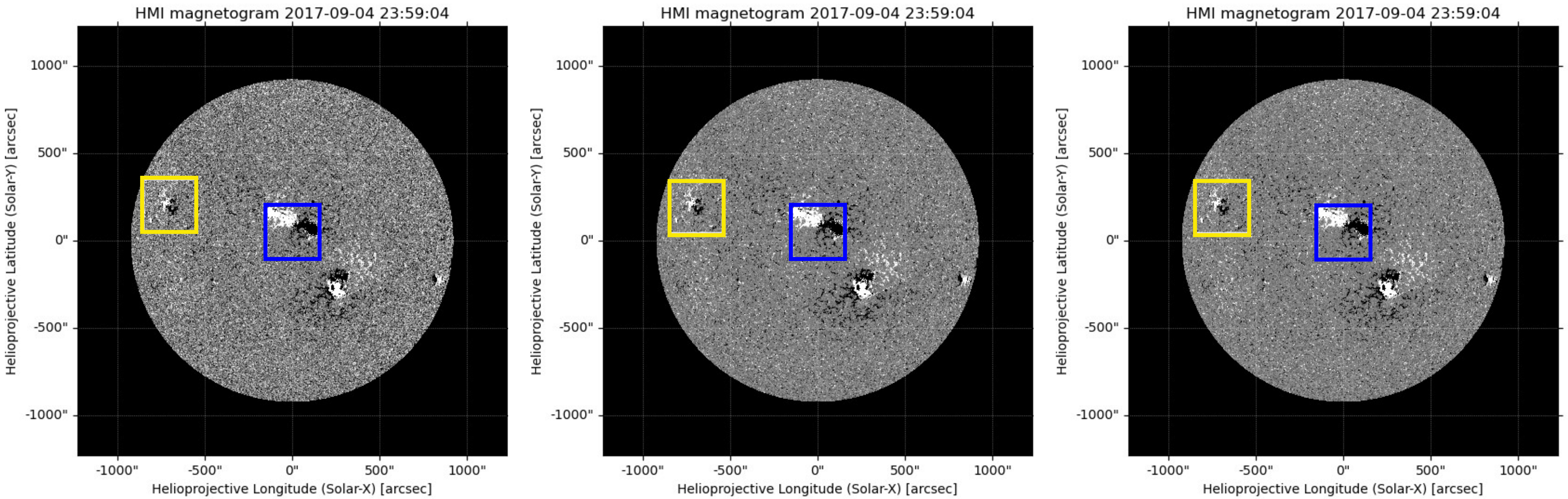
M2: AutoEncoder model



After the training, we can denoise SDO/HMI magnetograms without stacking.

2 Denoising SDO/HMI Magnetogram

Application of our model to a full-disk SDO/HMI magnetogram



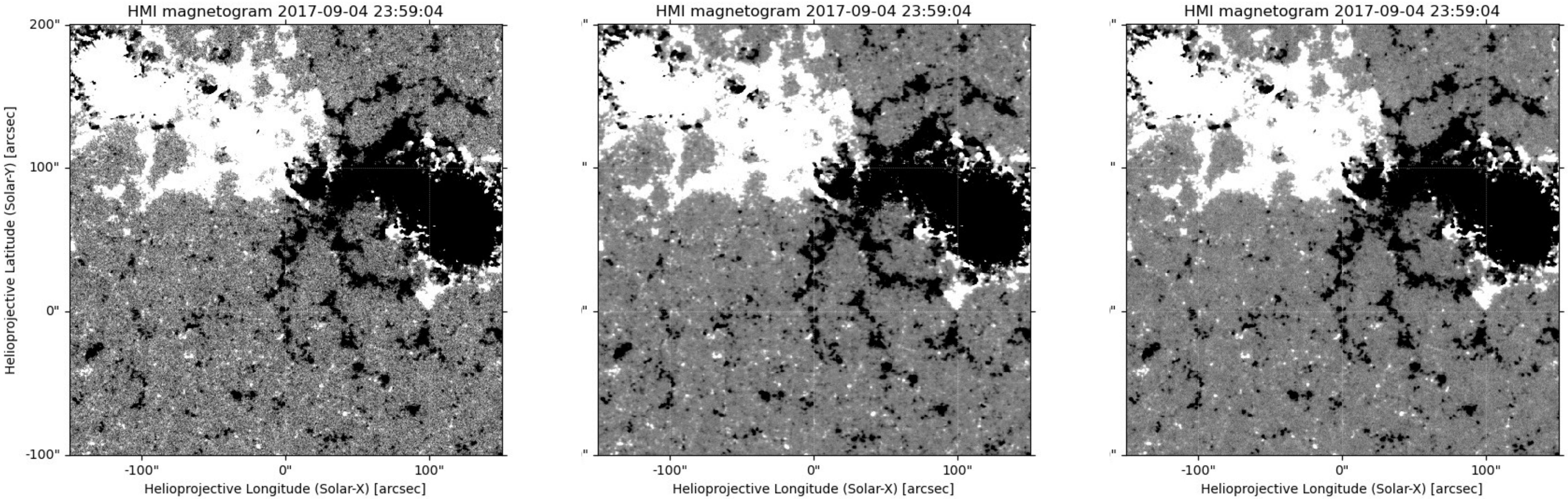
Original

Denoised (M1: Image Translation)

Denoised (M2: AutoEncoder)

2 Denoising SDO/HMI Magnetogram

Application of our model to a full-disk SDO/HMI magnetogram: center of disk



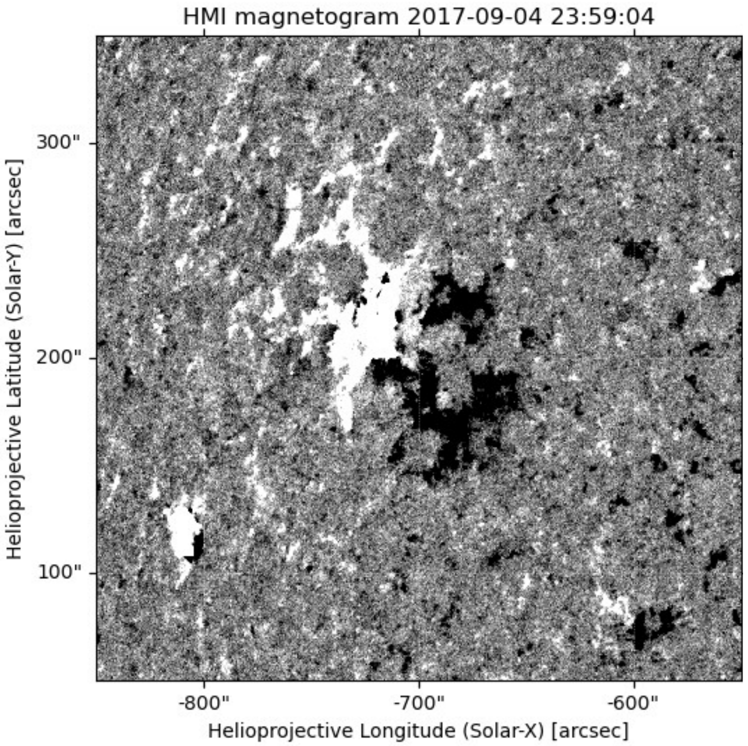
Original, noise level: 9.1 G

Denoised, noise level: 3.4 G (M1: Image Translation)

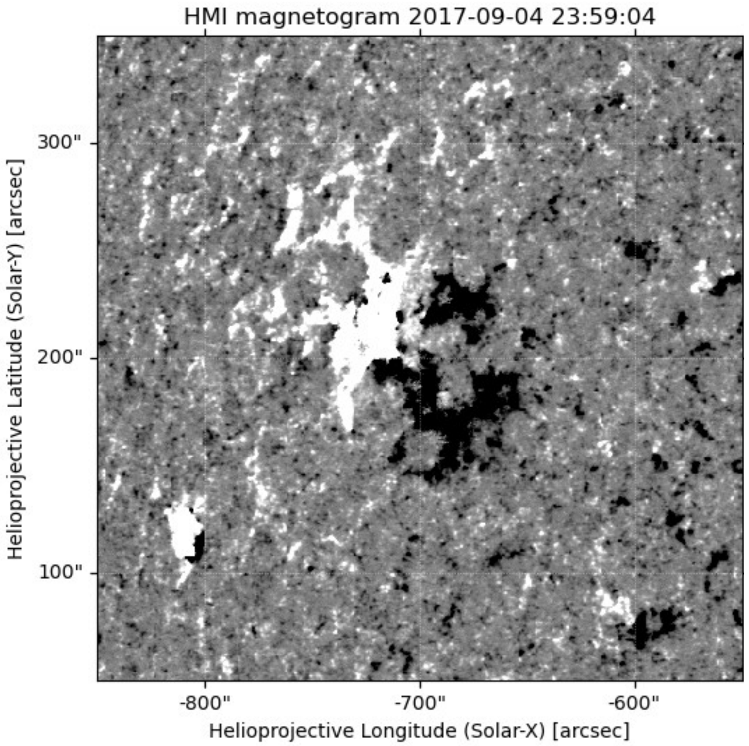
Denoised, noise level: 3.9 G (M2: AutoEncoder)

2 Denoising SDO/HMI Magnetogram

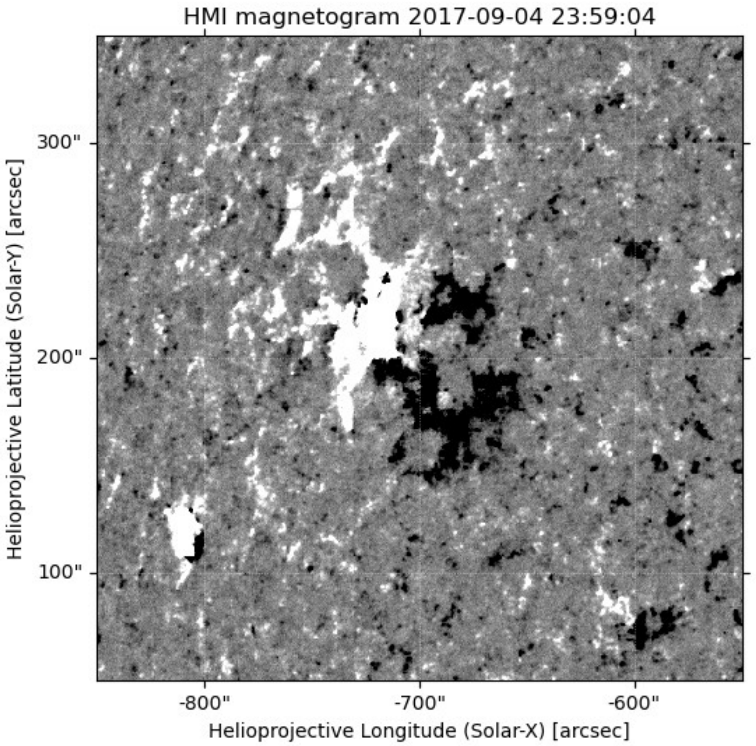
Application of our model to a full-disk SDO/HMI magnetogram: near the limb



Original, noise level: 10.7 G



Denoised, noise level: 4.5 G (M1: Image Translation)



Denoised, noise level: 4.9 G (M2: AutoEncoder)

2 Denoising SDO/HMI Magnetogram

- The image-translation method can be applied to denoising solar and space weather data if we can build many target noise-reduced data.

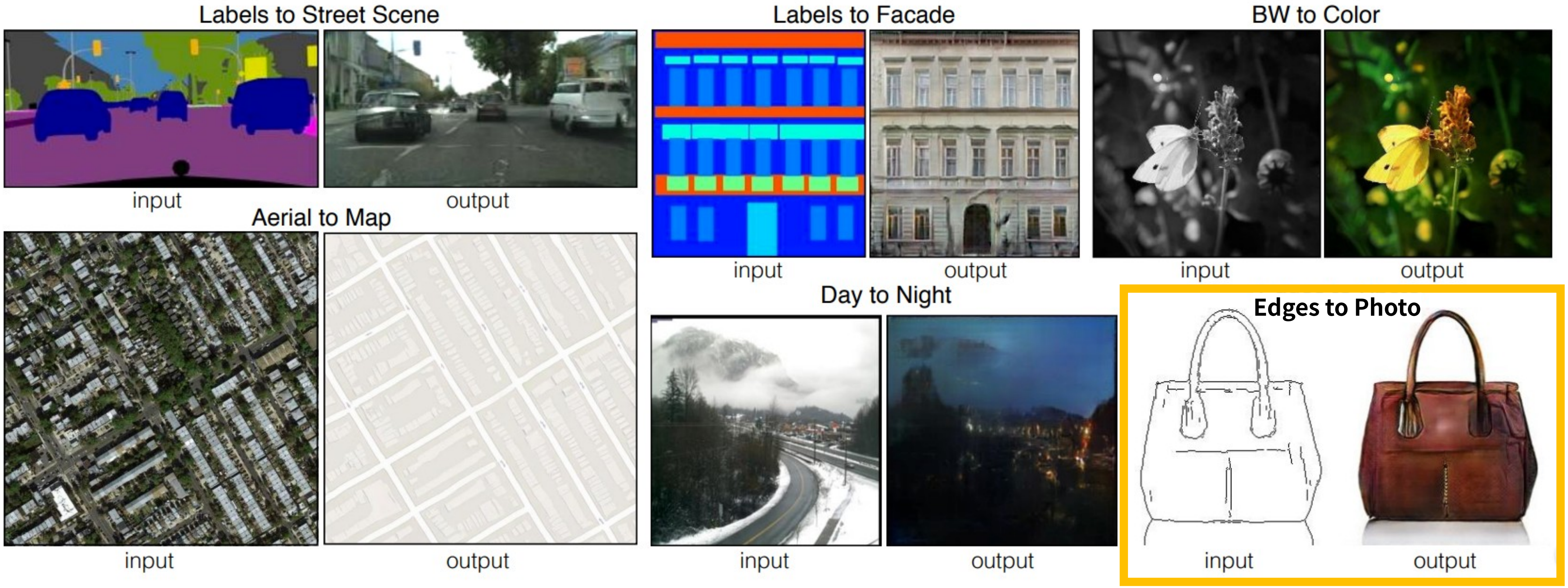
- If it is difficult to build the denoised target data, the AutoEncoder method can be applied to denoising solar and space weather data as an alternative.

3

Generation of Modern Satellite Images from Galileo sunspot drawings in 1612

Lee et al., 2021

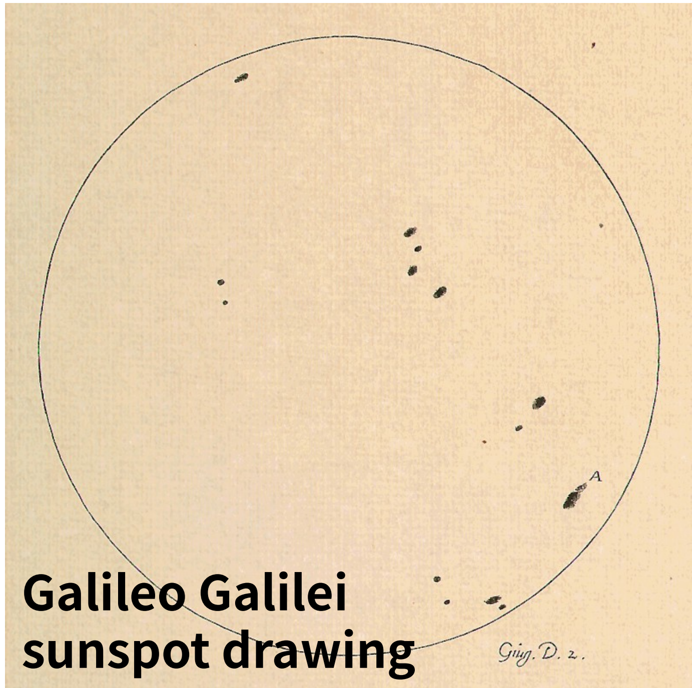
3 Generation of Satellite Image from Galileo Sunspot



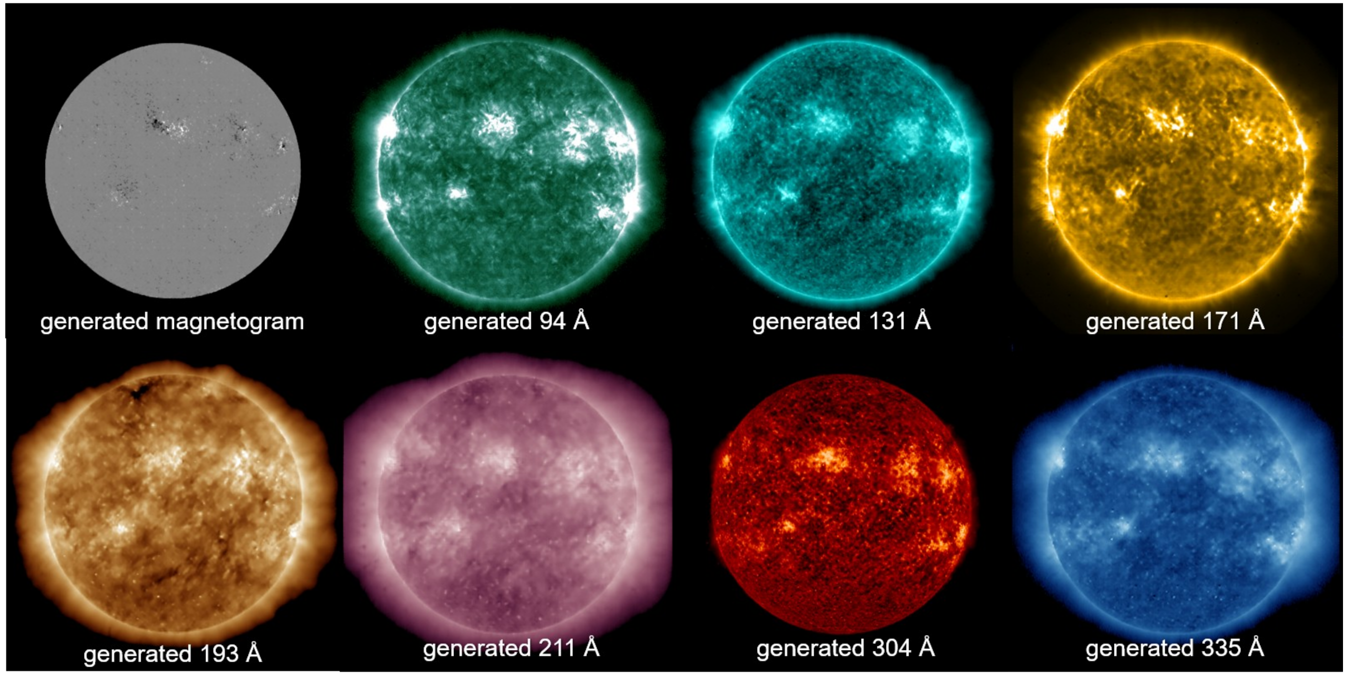
Isola et al. 2017

We have similar data to this example, that is sunspot drawings.

3 Generation of Satellite Image from Galileo Sunspot



http://galileo.rice.edu/sci/observations/sunspot_drawings.html



poster session

Title: Generation of Modern Satellite Data from Galileo Sunspot Drawings by Deep Learning

Author: Harim Lee

THANK YOU

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UNIVERSITY