



# STEREO Science Highlight

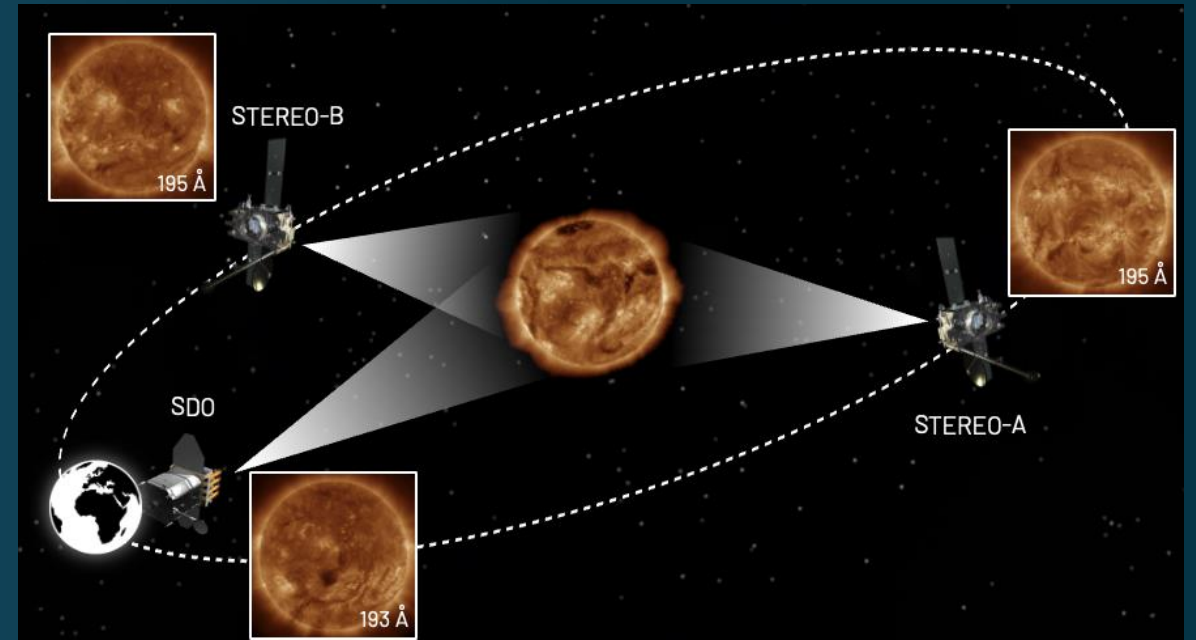
## SuNeRF: 3D Reconstruction of the Solar EUV Corona Using Neural Radiance Fields

Robert Jarolim, Benoit Tremblay, Andrés Muñoz-Jaramillo, Kyriaki-Margarita Bintsi, Anna Jungbluth, Miraflor Santos, Angelos Vourlidas, James P. Mason, Sairam Sundaresan, Cooper Downs, & Ronald M. Caplan, *ApJL* **961** L31, 2024, doi: [10.3847/2041-8213/ad12d2](https://doi.org/10.3847/2041-8213/ad12d2)



# Background

- The project aims to estimate the 3-dimensional Extreme UltraViolet (EUV) emission of the solar corona using a deep-learning approach
- Knowledge of the distribution of the EUV radiance is required to understand how the solar magnetic energy is distributed and released in both short range and solar cycle time scales.
- Current approaches to 3D reconstruction rely on observations over multiple days and thus are unsuited for understanding fast dynamics, which power solar flares and eruptive events
- The authors adapt a deep-learning algorithm from machine vision to simultaneous EUV observations from multiple viewpoints to create 3D coronal maps. The project was developed during the 8-week Frontiers Development Lab 2022 season.



**Credits:** NASA/FDL & the SPI3S FDL2022 team



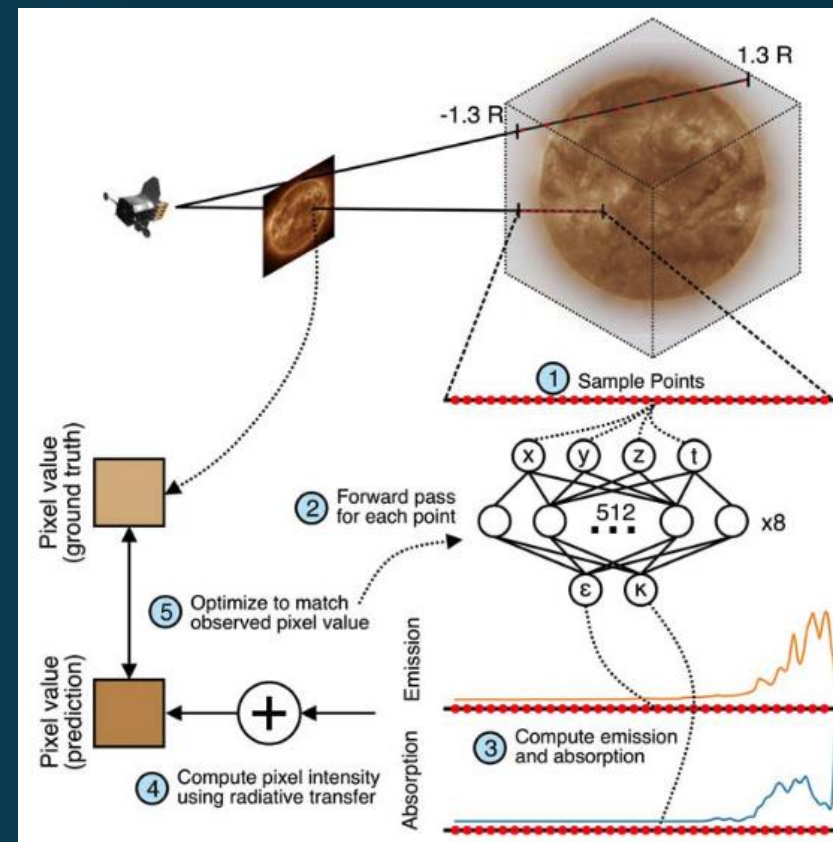
# Analysis

- The analysis uses STEREO/EUVI and SDO/AIA images in 171, 195/193 and 304 Å channels from Aug-Sep 2012
- The method leverages the Neutral Radiance Field (NeRF) deep-learning algorithm. NeRFs are used extensively to create 3D representations of every day objects from images captured from different angles. In this case, the authors modified the algorithm to account for the physics of the optically thin EUV emission and used rotation to increase the number of viewpoints for the training set. The new method is called SuNeRF
- Another novel ML algorithm was used to cross-calibrate the intensities across the EUVI and AIA channels.

The results were validated against

Synthetic EUV images estimated from 3D MHD simulations provided by Predictive Science Inc.

CHRONNOS (Coronal Hole RecOgnition Neural Network Over multi-Spectral-data) measurements of coronal hole boundaries.

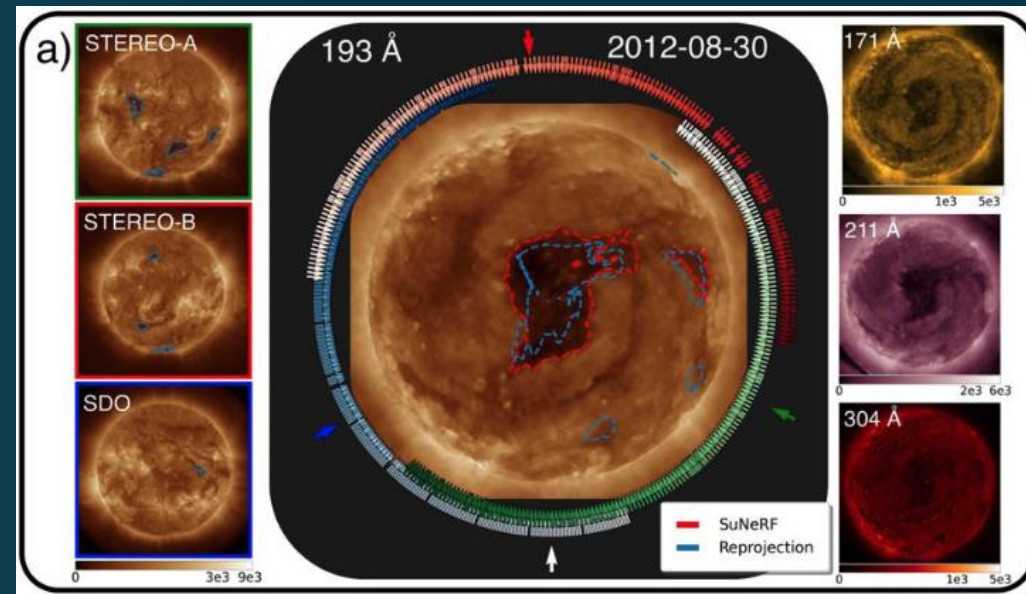


**Above:** Overview of the 3D reconstruction method: (1) For each pixel in the input sequence points within 1.3 Rs are sampled along the ray path. The endpoints of the rays passing through the Sun are fixed to the solar surface. (2) The sampled points are passed through the neural network, which outputs the emission  $\epsilon$  and absorption  $\kappa$  coefficient per point. (3) the emission and absorption along each ray and then the total intensity (4) are computed. (5) The predicted intensity value is compared to the actual pixel value, which serves as a loss function for our model training. Each update step optimizes a set of 32,768 rays. The spatiotemporal representation of the solar corona is obtained by iteratively fitting all pixel values. Credit: Jarolim et al 2024



# Findings

- The validation with the MHD model (ground truth) demonstrated that the SuNeRF method greatly improves the coronal intensity representation against the current standard (spherical rejections of synchronic maps) shown by several metrics (structure similarity index, mean absolute error).
- The reconstructed images can provide unique (unobserved) views of the solar corona, including the solar poles (see image)
- The method is uniquely capable of providing height estimates for features off the solar limb across the whole volume
- The method can capture dynamics, including eruptions (image next slide), including temperature changes manifested as changes in absorption and emission. This is impossible with all other current 3D reconstructions method without detailed case-by-case analysis



**Above:** Global reconstruction of the solar EUV corona on 2012 August 30 00:00:00 (UT). (a) Complete image of the solar south pole as reconstructed from STEREO/EUVI and SDO/AIA observations (left). Reconstructions in 171, 211, and 304 Å are shown on the right. The image at the center shows the reconstruction in 193 Å, where the polar coronal hole is best visible. Coronal hole boundaries detected using CHRONNOS are indicated as contour lines. Blue lines refer to spherical reprojections from the ecliptic perspective, and red lines are obtained from the SuNeRF reconstruction. The arrows indicate the positions of individual observations used for training, and the color coding refers to the temporal distribution of each instrument (green: STEREO-A; red: STEREO-B; blue: SDO). Adapted from Jarolim et al 2024.





# Impacts

The paper demonstrates that meaningful representations of physical systems (the solar corona, in this case), are possible when deep-learning algorithms are combined with physical constraints and carefully curated data sets.

Further improvements on the SuNeRF algorithms will enable better understanding of the interplay between local magnetic field changes and global coronal connectivity. This in turn, will allow scientists to understand how the Sun stores and explosively releases magnetic energy.

- The paper is a great example of the cross-pollination of ideas from the private industry (image reconstruction for education) can benefit basic research and vice versa. For example, the SuNeRF approach could be used in autonomous systems to navigate through cloudy, foggy and generally partially obscured environments



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# Publication Information

- Publication information

*SuNeRF: 3D Reconstruction of the Solar EUV Corona Using Neural Radiance Fields*, Robert Jarolim<sup>1</sup>, Benoit Tremblay<sup>2</sup>, Andrés Muñoz-Jaramillo<sup>3</sup>, Kyriaki-Margarita Bintsi<sup>4</sup>, Anna Jungbluth,<sup>5</sup> Mirafior Santos<sup>6</sup>, Angelos Vourlidis<sup>7</sup>, James P. Mason<sup>7</sup>, Sairam Sundaresan<sup>8</sup>, Cooper Downs<sup>9</sup>, & Ronald M. Caplan<sup>9</sup>, *ApJL* **961** L31, 2024, doi: [10.3847/2041-8213/ad12d2](https://doi.org/10.3847/2041-8213/ad12d2)

*Instrument-To-Instrument translation: Instrumental advances drive restoration of solar observation series via deep learning*, Robert Jarolim<sup>1</sup>, Astrid M. Veronig<sup>1, 10</sup>, Werner Pötzi<sup>10</sup>, & Tatiana Podladchikova<sup>11</sup>, Submitted to Nature Communications, <https://arxiv.org/abs/2401.08057>

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