

Inversion of CHASE H α spectral line during solar flares based on RADYN dataset via deep learning

Wenleyuan Xu¹ , Qi Hao^{1,2*} , Zhi Zheng^{1,2} , Jie Hong³ , Jiarui Hu^{1,4} , Ye Qiu⁵ ,
Chuan Li^{1,2,5} , Mingde Ding^{1,2} , Cheng Fang^{1,2}

¹School of Astronomy and Space Science, Nanjing University, Nanjing 210023, China

²Key Laboratory of Modern Astronomy and Astrophysics, Ministry of Education, Nanjing 210023, China

³Institute for Solar Physics, Department of Astronomy, Stockholm University, AlbaNova University Centre, Stockholm 106 91, Sweden

⁴Software Institute, Nanjing University, Nanjing 210023, China

⁵Institute of Science and Technology for Deep Space Exploration, Suzhou Campus, Nanjing University, Suzhou 215163, China

*Correspondence: haoqi@nju.edu.cn

Received: November 11, 2025; Accepted: December 24, 2025; Published Online: December 25, 2025; <https://doi.org/10.3724/ati2025087>; <https://cstr.cn/32083.14.ati2025087>

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Citation: Xu, W. L. Y., Hao, Q., Zheng, Z., et al. 2026. Inversion of CHASE H α spectral line during solar flares based on RADYN dataset via deep learning. *Astronomical Techniques and Instruments*, 3(3): 1–10. <https://doi.org/10.3724/ati2025087>.

Abstract: Solar flares are among the most intense forms of solar activity. Understanding the evolution of physical parameters in the solar atmosphere during flare events is key to studying their mechanisms and improving prediction capabilities, but directly measuring quantities such as electron number density, temperature, and plasma velocity remains challenging. Here, we introduce a novel, fully connected neural network, trained on synthetic data from the radiative hydrodynamics code simulations, to perform rapid inversion of physical parameters from H α spectral line profiles. The spectral data were processed to align with the observational resolution of the Chinese H α Solar Explorer satellite, enabling seamless application of the model to real-world observations. Results are highly consistent with simulations, achieving low errors under diverse flare conditions. We applied the developed model to analyze observations of a class X7.1 solar flare on October 1, 2024, revealing reasonable spatial and temporal evolution of key parameters throughout different flare phases. This work demonstrates the potential of deep learning techniques for fast and reliable spectral inversion, providing new tools for solar flare diagnostics based on H α data.

Keywords: Solar flare; Spectral inversion; Deep learning

1. INTRODUCTION

Solar flares are among the most intense forms of solar activity^[1], and are characterized by sudden, large-scale energy releases in localized regions of the solar atmosphere^[2], causing rapid heating and the emission of electromagnetic radiation spanning the entire electromagnetic spectrum. During solar flares, energy is deposited in the photosphere and chromosphere through mechanisms such as ion beam bombardment, thermal conduction, and magnetic reconnection. These processes induce significant physical changes, including electron number density, temperature, and plasma velocity, and the evolution of these parameters is closely linked to the onset and development of the flare. For example, rapid changes in plasma velocity

fields can trigger magnetic reconnection, which can then initiate a solar flare. Accurately measuring and inverting these physical parameters is therefore essential for understanding the mechanisms behind solar flare eruptions and improving flare prediction accuracy. However, directly measuring these parameters is technically challenging. Instead, such variations are often reflected in observed spectroscopic features. By analyzing strong spectral lines in visible, near-infrared, and ultraviolet spectra, we can infer what physical conditions are present. Spectral lines such as H, Ca II and Mg II reveal that the solar chromosphere, the atmospheric layer between the photosphere and the corona, is highly dynamic, finely structured, and complex^[3].

Complex inversion methods, based on physical models, often rely on intricate physical assumptions and approxi-

mations, resulting in high computational costs and limited practical application^[4,5]. Machine learning methods offer a promising alternative, enabling rapid and efficient inversion based on large-scale statistical data, independent of physical models. The application of deep learning techniques in solar flare research is emerging as a powerful approach, driven by advances in computational capabilities^[6–9]. Osborne et al.^[4] trained an Invertible Neural Network (INN) based on the results of simulations with the one-dimensional radiative hydrodynamics code, RADYN. The INN analyzes the input spectral lines, H α and Ca II 8542, and outputs physical parameters, such as the temperature and electron number density of the solar atmosphere. In validating the analysis of a class M1.1 solar flare, expected results were obtained. Chappell & Pereira^[5] used the results of a large number of 3D solar atmosphere simulations as a training set for a Convolutional Neural Network (CNN) called SunnyNet. SunnyNet computes three-dimensional nonlocal thermodynamic equilibrium radiative transfer in optically thick stellar atmospheres and can predict atomic populations in non-local thermodynamic equilibrium, as well as the temperature and electron number densities in solar flares, with reasonable accuracy. This CNN is nearly 100 000 times faster than conventional codes. Lee et al.^[10] inverted H α and Ca II spectra using Deep Neural Network (DNN) and avoided the gradient vanishing problem that DNNs suffer from, by using a jump-joining method. The final inversion results were accurate and took only 0.3 to 0.4 ms to calculate each spectral line, achieving a speed 250 times faster than conventional methods.

The Chinese H α Solar Explorer (CHASE) is China's

first solar exploration satellite, equipped with a solar space telescope that can make continuous 24-hour observations in a sun-synchronous orbit at an altitude of 517 km^[11–13]. The successful launch of CHASE has provided a wealth of high-resolution H α spectral data, enabling detailed studies of solar flares. During flares, the H α line provides crucial insights into the underlying physical processes.

In this study, we apply deep learning techniques innovatively to solar flare research. We construct an appropriate fully connected neural network model that can swiftly and accurately invert solar chromospheric parameters, including electron number density, temperature, and plasma velocity, using H α spectral data. We further validate the practical application of our model by analyzing real H α spectral data obtained by the CHASE satellite during solar flares. This work provides a solid scientific foundation for studying the physical mechanisms of solar flares and improving the accuracy of flare eruption predictions.

Fig. 1 shows the schematic of our workflow in this study. The RADYN data source and data preprocessing are described in Section 2, while the model selection and prediction are described in Section 3. Section 4 presents the model application on CHASE data, and our discussion and conclusions are given in Section 5.

2. DATASET ACQUISITION

2.1. The RADYN Flare Dataset

RADYN is a radiative hydrodynamics code devel-

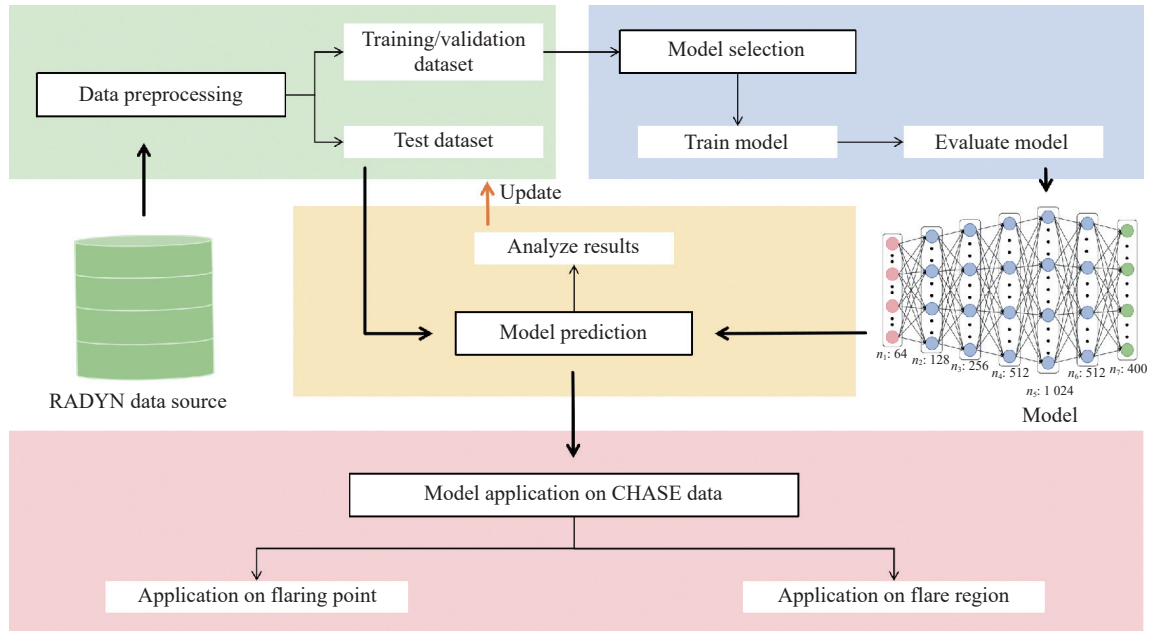


Fig. 1. Schematic diagram of the workflow. The arrows indicate the direction of flow. The process begins with synthetic flare data from the RADYN radiative hydrodynamics simulations, followed by pre-processing steps. These data are used to train three independent, fully connected neural networks to map H α spectral profiles to their corresponding vertical distributions of physical parameters. The models are then validated using synthetic test cases before being applied to real CHASE H α spectral observations.

oped by Carlsson & Stein, Carlsson & Stein^[14,15] to simulate acoustic shocks in the chromosphere. It has since been adapted to simulate flare responses in the chromosphere^[16,17]. RADYN uses an adaptive grid method to solve the radiative hydrodynamics equations for one-dimensional plane-parallel atmospheres, and optimizes data resolution by taking denser samples in regions with larger parameter gradients. This approach ensures that maximum information is retained within the same storage capacity, making it particularly effective for modeling the complex dynamics of solar flares.

The dataset used in our study was from the RADYN F-CHROMA database^[18]. The dataset comprises 79 flare models characterized by different spectral indices, cutoff energies, and total energy of the beam electrons that are injected at the flare loop top as an energy source. The energy flux of the beam electrons has a triangular shape as a function of time, with a 10 s increase and a 10 s decrease. Thus, a total energy of 1×10^{12} erg cm⁻² corresponds to a maximum energy flux of 1×10^{11} erg cm⁻²s⁻¹. Each flare model spans 50 s, and the data is recorded at 0.1 s intervals, yielding 39574 time slices. Each data entry includes one-dimensional H α spectroscopic data, as well as the corresponding height distributions of physical parameters such as electron number density, temperature, and plasma velocity. This comprehensive dataset is a valuable resource for analyzing solar flare dynamics, allowing us to explore the relationships between spectral variations and underlying physical processes in the chromosphere. Using multiple flare configurations and detailed, time-resolved data, we can robustly analyze flare-induced changes in the solar atmosphere, enhancing our understanding of flare mechanisms and their impact on solar activity.

2.2. Preprocessing of Spectra

To effectively apply our model to the real spectra obtained by the CHASE satellite, we pre-process the spectral data from the RADYN dataset. This involves applying a point spread function (PSF) convolution to the original spectroscopic data to simulate the resolution of the CHASE spectrograph. The selected wavelength range is $6562.82 \text{ \AA} \pm 1.5 \text{ \AA}$, which corresponds to 64 wavelength data points in the CHASE data. After applying the PSF, the RADYN data are interpolated to a coarser grid to match the CHASE observation features.

2.3. Preprocessing of Physical Parameters

We perform interpolation on the distribution data of physical parameters, such as electron number density, temperature, and plasma velocity. This creates smooth profiles suitable for neural network training and inversion. We select 400 equally spaced points within a height range of 0–2000 km. This process ensures that the physical parameter distributions are well-resolved and compatible with the spatial resolution required for subsequent model applications.

Fig. 2 shows an example of preprocessed RADYN simulation data derived from the impulsive phase, where panels A–D show the preprocessed spectrum, electron number density distribution, temperature distribution, and plasma velocity distribution, respectively.

3. THE DEEP LEARNING SPECTRAL INVERSION MODEL

3.1. Neural Network Architecture

We employ a Fully Connected Neural Network (FCNN) to determine the nonlinear mapping from H α spectral profiles to corresponding height-dependent physical parameters. The network architecture consists of an input layer, multiple hidden layers with nonlinear activation functions, and an output layer. Each layer is densely connected, meaning every neuron in one layer is connected to all neurons in the subsequent layer. This architecture is selected to balance model capacity and generalization performance, based on preliminary experiments. The layer widths are empirically chosen to progressively expand and contract the feature space, allowing the network to learn both low- and high-level representations from the spectral input.

The input to the model is a 64-dimensional vector representing the preprocessed H α spectral intensities, and the output is a 400-dimensional vector corresponding to the vertical distribution of a given physical quantity (i.e., electron number density, temperature, or plasma velocity). Three separate models with the same architecture are trained independently to invert each physical parameter. To enable the network to capture complex spectral-physical relationships while mitigating overfitting, we adopt a moderately deep architecture with PReLU activation functions^[19] and dropout regularization between layers. In addition, weight decay is applied during training to further constrain model complexity. The FCNN architecture is shown in Table 1.

3.2. Training Process

We use the PyTorch deep learning library^[20] to build and train our models. The models are trained using the AdamW optimizer^[21], which combines the benefits of momentum and adaptive learning rates, efficiently navigating the high-dimensional parameter space. To optimize model performance, we implement a learning rate decay mechanism to stabilize convergence. We set the initial learning rate to 0.001, with a decay of 0.7 after every 100 iterations. Mean Squared Error (MSE) is used as the loss function. The size of the training batch is set to 128.

The dataset is divided into a training set, a validation set, and a test set. The RADYN dataset consists of 79 events with four different values of total energy ($3 \times$

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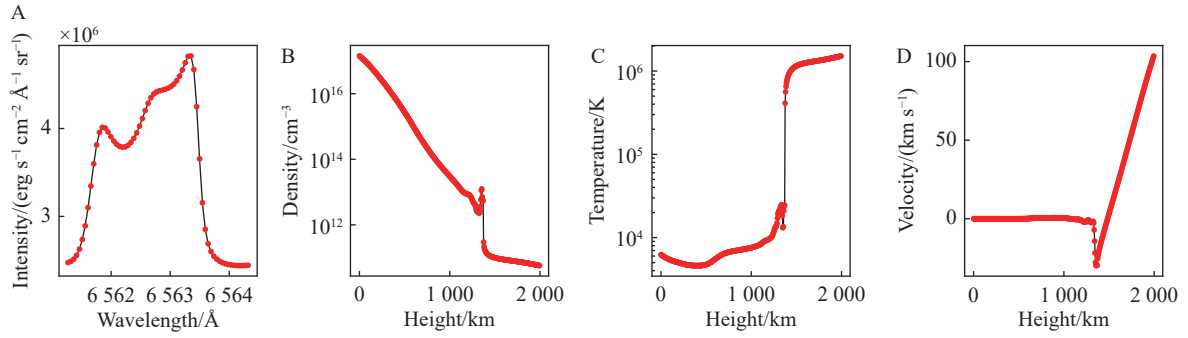


Fig. 2. An example of preprocessed RADYN simulation data. (A) Spectrum. (B) Electron number density distribution. (C) Temperature distribution. (D) Plasma velocity distribution. Red dots show interpolation points.

Table 1. The FCNN architecture used in this study

Layer/Operation	Shape of output
Input	64
Linear (64→128)	128
PReLU	128
Dropout (dropout_rate = 0.2)	128
Linear (128→256)	256
PReLU	256
Dropout (dropout_rate = 0.2)	256
Linear (256→512)	512
PReLU	512
Dropout (dropout_rate = 0.2)	512
Linear (512→1024)	1024
PReLU	1024
Dropout (dropout_rate = 0.2)	1024
Linear (1024→512)	512
PReLU	512
Dropout (dropout_rate = 0.2)	512
Linear (512→400)	400

10^{10} erg cm $^{-2}$, 1×10^{11} erg cm $^{-2}$, 3×10^{11} erg cm $^{-2}$, and 1×10^{12} erg cm $^{-2}$). For each value set, we ran-

domly select four events to form the test set, for a total of sixteen events (approximately 20% of the data). This ensures that the test events are completely separate for unbiased evaluation. The remaining events are then randomly split 7:1 between the training and validation sets, resulting in an approximate general distribution of 70% training data (27613 time slices), 10% validation data (3945 time slices), and 20% test data (8016 time slices). The models undergo 800 iterations on both the training and validation datasets. Throughout this process, training and validation losses steadily decline and ultimately converge, demonstrating effective model fitting to both datasets.

3.3. Performance Evaluation

The inversion performance of the models is systematically evaluated using comprehensive error metrics on the training, validation, and test sets. Table 2 presents a quantitative assessment of the electron number density, temperature, and plasma velocity inversion models, using Root Mean Square Error (RMSE) and symmetric Mean Absolute Percentage Error (sMAPE).

Table 2. RMSE and sMAPE evaluations of the electron number density, temperature, and plasma velocity inversion models

		Training set	Validation set	Test set
Electron number density	RMSE/cm $^{-3}$	3.81×10^{13}	3.83×10^{13}	5.47×10^{13}
	sMAPE	1.96%	2.02%	6.32%
Temperature	RMSE/K	2.05×10^4	2.06×10^4	3.03×10^4
	sMAPE	3.97%	4.11%	11.31%
Plasma velocity	RMSE/(km s $^{-1}$)	12.67	12.60	20.96
	sMAPE	9.52%	9.82%	18.47%

RMSE is a commonly used metric in regression analysis, which measures the standard deviation of prediction errors. It is sensitive to large deviations and provides an overall measure of model accuracy. It is given by the expression,

$$RMSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (\hat{y}_i - y_i)^2}, \quad (1)$$

where $\hat{y}_i$ and y_i are the predicted and true values at the

i -th grid point, and n is the total number of spatial points.

We also use sMAPE to complement RMSE, which is scale-dependent, defined as,

$$sMAPE = \frac{100\%}{n} \sum_{i=1}^n \frac{|\hat{y}_i - y_i|}{(|\hat{y}_i| + |y_i|)/2}. \quad (2)$$

sMAPE expresses errors as percentages, providing a scale-independent evaluation that is ideal for comparing variables with different units and magnitudes. Unlike traditional mean absolute percentage error, sMAPE robustly

handles near-zero values and treats over- and under-predictions symmetrically, making it ideal for physical parameter inversion.

Together, RMSE and sMAPE provide a balanced view of both absolute and relative model performance, offering a more comprehensive assessment of the inversion accuracy across different physical quantities.

For electron number density inversion, the model performs consistently on the training and validation sets and gives slightly degraded, but reasonable performance on

the test set. Similar patterns are observed for temperature and plasma velocity inversions, where test set errors are approximately 1.5 to 2.3 times higher than training/validation errors, reflecting the expected generalization gap.

Fig. 3 provides a detailed comparison of the simulated and inverted physical parameters, shows representative test cases from all four total energies in the test set, and further illustrates the inversion performance.

For electron number density distributions, the model shows excellent agreement with the simulated profiles

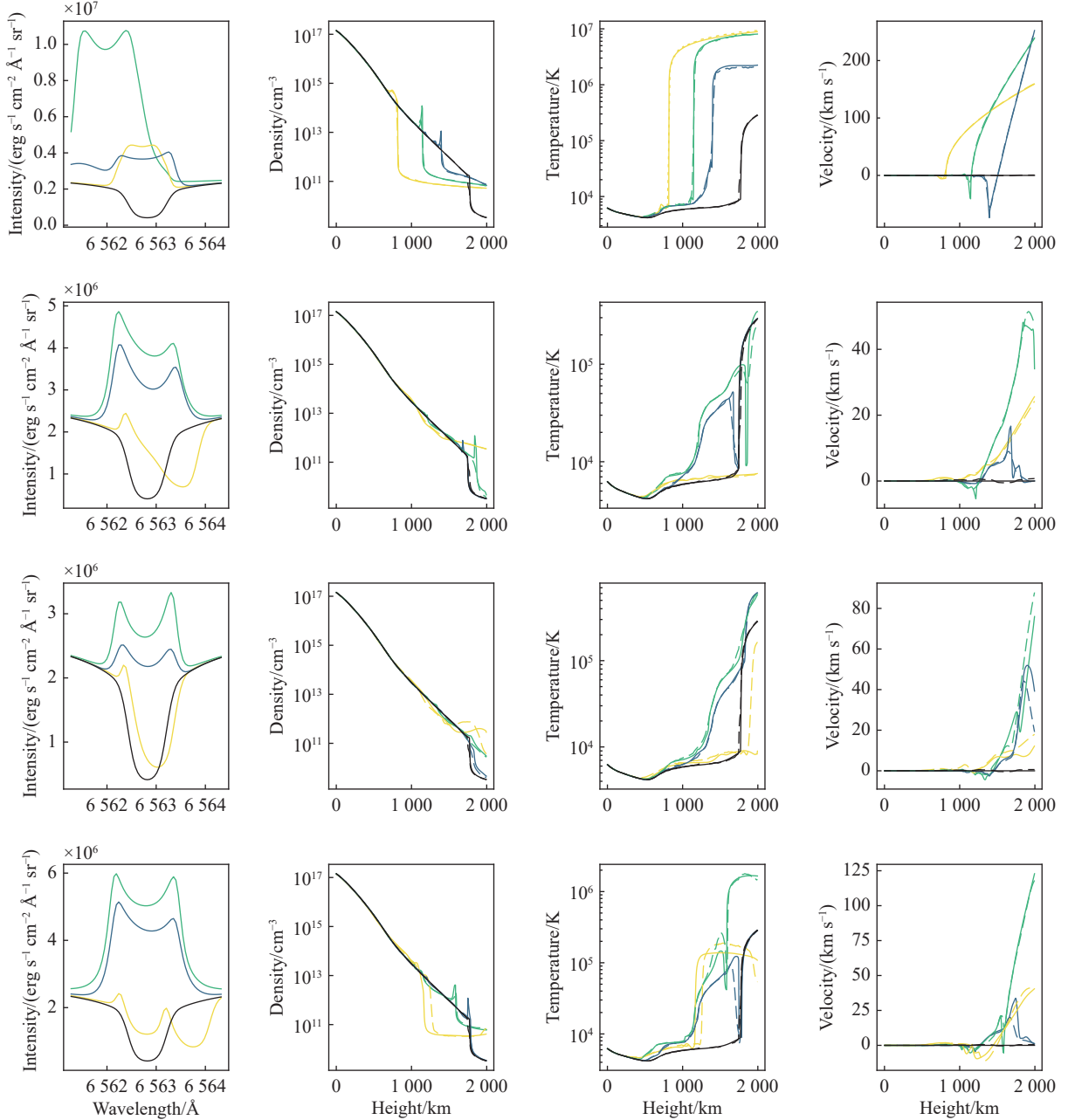


Fig. 3. Inversion test results using RADYN simulation data. The four rows, from top to bottom, show simulated flare events with total energies of 3×10^{10} erg cm $^{-2}$, 1×10^{11} erg cm $^{-2}$, 3×10^{11} erg cm $^{-2}$, and 1×10^{12} erg cm $^{-2}$. The four columns, from left to right, show spectra, electron number density distributions, temperature distributions, and plasma velocity distributions. Different colors indicate distinct evolutionary phases: background (black), rising phase (blue), impulsive phase (green), and decay phase (yellow). Solid lines show the height distribution of simulated physical parameters, and dashed lines show the height distribution of the inverted physical parameters.

across atmospheric layers, with minor discrepancies appearing at certain heights. The temperature inversion model performs particularly well, accurately reproducing the absolute values and height-dependent variations across all total energies and flare phases. Although plasma velocity profiles show slightly larger discrepancies compared with other parameters, consistent with the quantitative metrics in Table 2, the model nonetheless captures essential dynamic features and reproduces physically plausible velocity gradients throughout the atmosphere. This comprehensive visualization confirms that our inversion approach remains physically consistent across all parameters while handling the full range of total energies available in the RADYN dataset.

4. APPLICATION TO CHASE SPECTRAL OBSERVATIONS

4.1. Single Pixel Inversion

We have applied our models to real observational data, analyzing CHASE H α spectra, to assess model performance in real-world scenarios. For analysis, we select a typical X7.1-class solar flare that occurred in active region 13842 on October 1, 2024. The flare started at approximately 21:58 UT, peaked at 22:20 UT, gradually decayed, and ended at approximately 22:29 UT. Fig. 4 shows the evolution of the flare, including the pre-flare background, rising phase, impulsive phase, and decay phase.

The spectra of the pixel exhibiting maximum brightness during the impulsive phase were extracted across all

evolutionary phases and input into the inversion models to infer the corresponding distributions of physical parameters, i.e., electron number density, temperature, and plasma velocity. Considering the heights at which the H α spectral lines form, we display the inverted distributions in a height range of 750–1500 km. The inversion results are shown in Fig. 5. During the flare peak, the upper chromosphere is heated to the coronal temperature, and there appears to be a noteworthy chromospheric condensation region near 1400 km.

4.2. Flare Region Inversion

Although our model is based on one-dimensional RADYN simulation data, the spatial resolution of the CHASE spectral observations allows us to apply the model to the entire flare region without considering interactions between adjacent points. To this end, we have developed applications that reconstruct physical information from the flare region.

The October 1, 2024, event data is used again for this example. We extract CHASE spectral data of the flare, covering the entire flare region and its different evolutionary phases. These spectra are then input into models that invert the distributions of electron number density, temperature, and plasma velocity at various heights. Four slices are selected for display at heights of 750, 1000, 1250, and 1500 km. Fig. 6 shows the height distribution characteristics of the inverted physical parameters in the solar atmosphere within the flare region. The output parameters of our models reflect the physical changes in the different layers of the solar atmosphere during the solar flare.

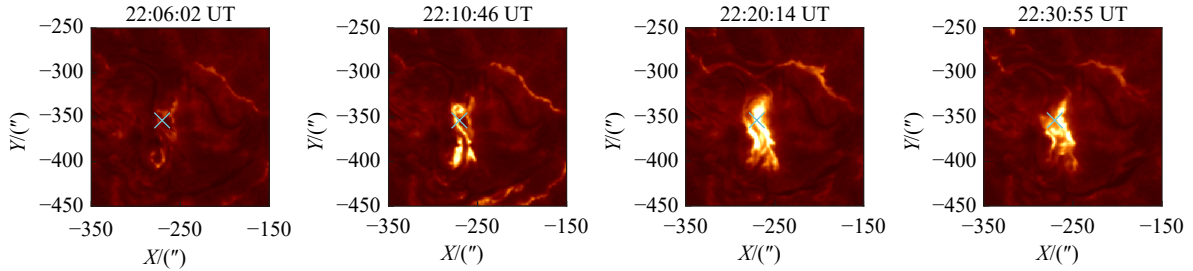


Fig. 4. Images of the class X7.1 solar flare event occurring on October 1, 2024. The four panels correspond to the background, rising phase, impulsive phase, and decay phase. Cyan crosses mark the point of maximum brightness during the impulsive phase.

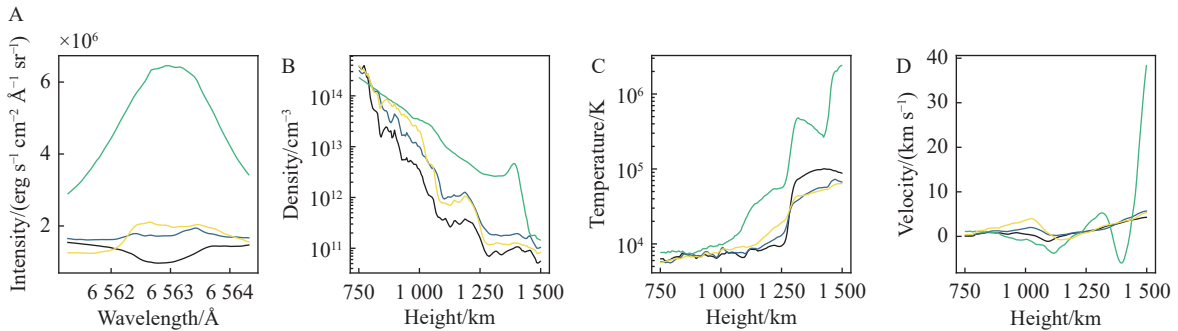


Fig. 5. Inversion results for the point of maximum brightness during the impulsive phase using CHASE observational data. (A) Spectra. (B) Electron number density distributions. (C) Temperature distributions. (D) Plasma velocity distributions. Different colors indicate distinct evolutionary phases: background (black), rising phase (blue), impulsive phase (green), and decay phase (yellow).

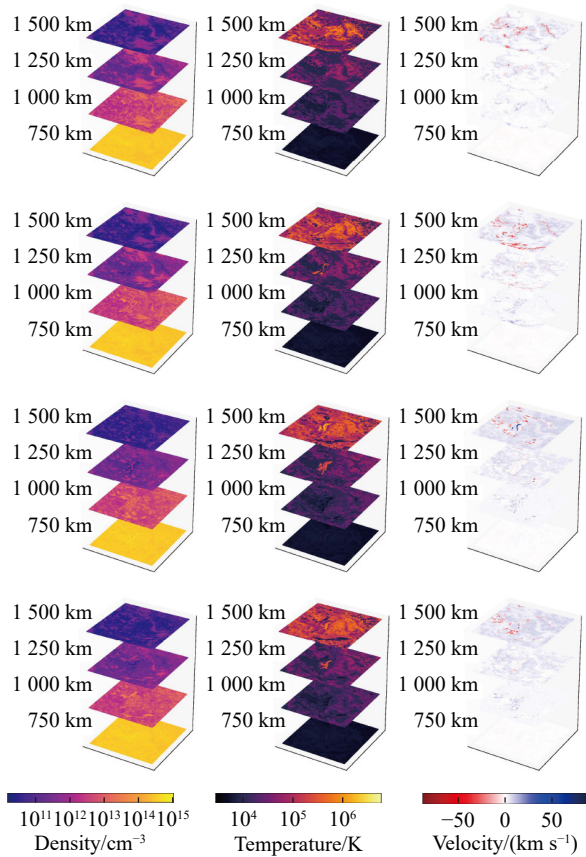


Fig. 6. Height distribution characteristics of inverted physical parameters in the solar atmosphere within the flare region. The four rows, from top to bottom, correspond to the background, rising phase, impulsive phase, and decay phase, while the three columns, from left to right, represent electron number density, temperature, and plasma velocity.

These three-dimensional representations provide a visual understanding of these phenomena and aid in understanding flare mechanisms.

5. SUMMARY

We have introduced a deep learning framework to invert physical parameters from H α spectral profiles. This framework is based on simulated flare data from RADYN and observations from the CHASE satellite. Training three separate FCNNs enables us to invert electron number density, temperature, and plasma velocity from spectra with high accuracy. Our models perform well with synthetic test data, accurately capturing the magnitude and structure of height-dependent profiles under various flare conditions. Of the three parameters, electron number density inversion shows the most consistent performance, while plasma velocity, though slightly noisier, still reproduces general trends. These results suggest that the models can learn nonlinear relationships between spectral features and physical quantities under non-local thermodynamic equilibrium (NLTE) conditions.

Applying the models to CHASE observations of an X-class flare demonstrates their effectiveness in real-

world scenarios. The inverted parameters show consistent variation across flare phases and provide a plausible picture of the solar atmospheric response. This highlights the potential of combining simulation-based training with deep learning to bridge the gap between physical models and observational data.

It is important to note that our method uses an FCNN, in which results are significantly influenced by the training data, specifically the outputs from the RADYN simulations. If scenarios are encountered that are not represented in the RADYN simulation data (e.g., observational spectra that are not included in the synthetic dataset), the model may fail to accurately reproduce the distribution of physical parameters. Therefore, flares with anomalous spectral profiles may require more sophisticated models for analysis. One example is the INN model proposed by Osborne et al.^[4], which incorporates additional spectral information and combines RADYN simulations with H α and Ca II spectra to improve parameter inference. We can improve the model by including additional spectral lines and expanding the training dataset.

Some errors were observed in the inversion results for certain time slices during the rising or decay phases of a flare. For example, discrepancies were observed between the temperature and density in the inversion results for a fixed spectral line intensity. This requires examining the observational characteristics of multiple spectral lines or incorporating additional physical constraints to eliminate such anomalies. Because our model is based on RADYN flare simulations with a vertical viewing angle, it would be best applicable to flare ribbon regions near the disk center. This method is unreliable for other regions, such as flare loops, and for other events occurring over the flare ribbon, such as filament eruptions. Caution should be exercised when applying the model to flare ribbons near the solar limb, because it does not account for any center-to-limb variations of the spectral lines. Additionally, the spatial alignment of the spectral data must be carefully considered, because neglecting this can result in misplaced inverted results and consequently generate inaccuracies. When interpreting the inversion results, it is important to note that there is a degeneracy between temperature and electron density which our current model has not managed to impose a physical constraint on.

In future work, we can explore architectures that incorporate physical constraints, such as an equation of state, to better couple density and temperature to prevent non-physical combinations where these quantities vary independently. Such constraints would enable the model to learn more consistent thermodynamic relationships, to improve the robustness of the inversion results under diverse observational conditions.

ACKNOWLEDGEMENTS

CHASE mission was supported by the China National Space Administration (CNSA). This work was sup-

ported by National Natural Science Foundation of China (12173019, 12333009, and 12127901), as well as CNSA project D050101, the Fundamental Research Funds for the Central Universities KG202506, and the Young Data Scientist Program of the China National Astronomical Data Center, as well as the AI & AI for Science Project of Nanjing University. Jie Hong is funded by the European Union through the European Research Council (ERC) under the Horizon Europe program (MAGHEAT, 101088184). The Institute for Solar Physics is supported by a grant for research infrastructures of national importance from the Swedish Research Council (2021-00169).

AI DISCLOSURE STATEMENT

Deepseek was employed for language and grammar checks within the article. The authors carefully reviewed, edited, and revised the Deepseek-generated texts to their own preferences, assuming ultimate responsibility for the content of the publication.

AUTHOR CONTRIBUTIONS

Qi Hao conceived the ideas and supervised the project. Wenleyuan Xu implemented the study and wrote the initial draft. Zhi Zheng and Jiarui Hu improved the model. Jie Hong supervised the spectral inversion. Ye Qiu processed the CHASE spectral data. Chuan Li, Mingde Ding, and Cheng Fang initiated the study and joined the discussions. All authors read and approved the final manuscript.

DECLARATION OF INTERESTS

Cheng Fang is a member of the steer committee for Astronomical Techniques and Instruments, and Mingde Ding is an editorial board member for Astronomical Techniques and Instruments. They were not involved in the editorial review or the decision to publish this article. The authors declare no competing interests.

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SUPPLEMENTARY MATERIAL: INVERSION RESULTS FOR M-CLASS AND C-CLASS FLARES

To further assess the generalization performance of our proposed method across a range of flare magnitudes, we applied the models to M-class and C-class flares. We strictly adhered to the same processing and inversion workflow used for the X7.1-class flare, as described in Section 4. This consistent approach ensures that the results pre-

sented here are directly comparable to those detailed in the main text, demonstrating the robust performance of the model across various real-world scenarios.

S.1. M-class Flare Event

For the M-class example, the M9.0-class solar flare

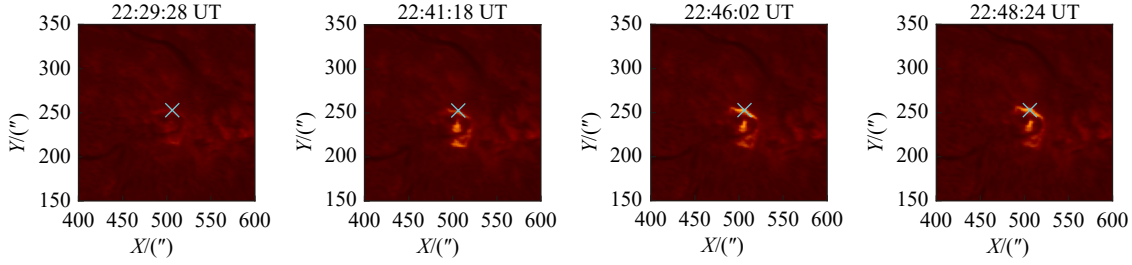


Fig. S1. Images of the class M9.0 solar flare event occurring on January 10, 2025. The four panels correspond to the background, rising phase, impulsive phase, and decay phase. Cyan crosses mark the point of maximum brightness during the impulsive phase.

Similarly to the process in Section 4.1, the spectra at the marked pixel in the different evolutionary phases are input into the inversion models. The models then infer the distributions of the corresponding physical parameters, i.e. electron number density, temperature, and plasma velocity. The inversion results are shown in Fig. S2. The thermodynamic evolution of the chromosphere is well-captured, showing heating patterns and velocity fields consistent with the impulsive nature of the flare.

Using the same process detailed in Section 4.2, we apply the model to the entire flare region. We extracted

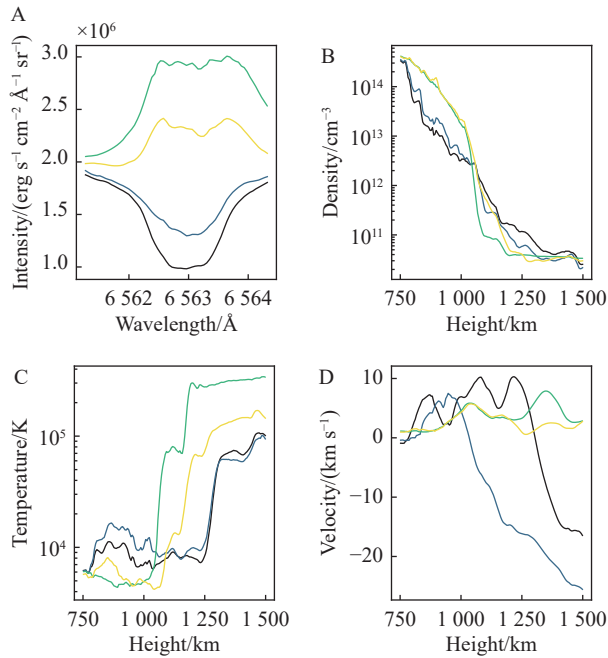


Fig. S2. Inversion results for the point of maximum brightness during the impulsive phase using CHASE observational data. (A) Spectra. (B) Electron number density distributions. (C) Temperature distributions. (D) Plasma velocity distributions. Different colors indicate distinct evolutionary phases: background (black), rising phase (blue), impulsive phase (green), and decay phase (yellow).

that occurred in active region 13947 on January 10, 2025, was selected. The flare started at approximately 22:29 UT, peaked at 22:46 UT, and ended at approximately 22:53 UT. Fig. S1 shows the evolution of the flare, including the pre-flare background, rising phase, impulsive phase, and decay phase.

CHASE spectral data of the flare, covering the entire flare region and its different evolutionary phases. Fig. S3 shows the height distribution characteristics of the inverted physical parameters in the solar atmosphere

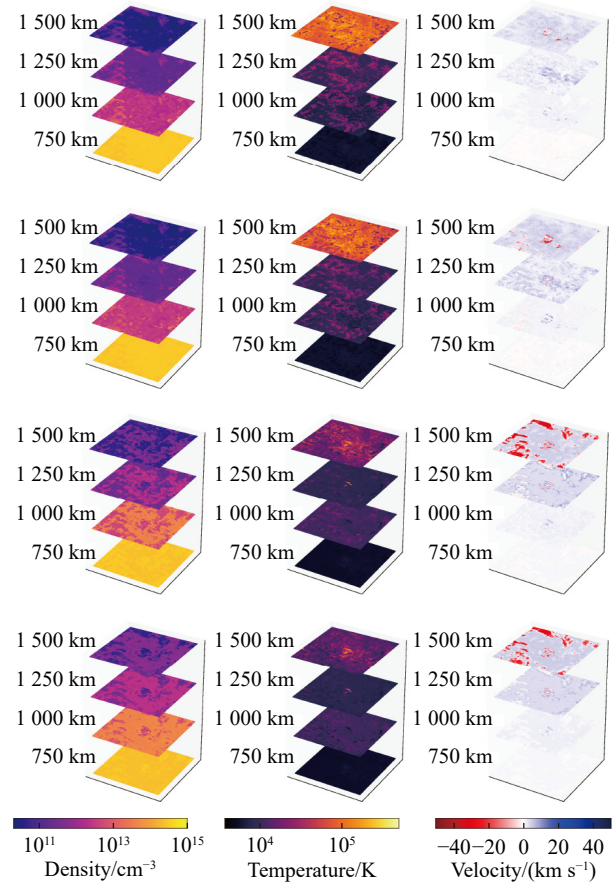


Fig. S3. Height distribution characteristics of inverted physical parameters in the solar atmosphere within the flare region. The four rows, from top to bottom, correspond to the background, rising phase, impulsive phase, and decay phase, while the three columns, from left to right, show electron number density, temperature, and plasma velocity.

within the flare region.

S.2. C-class Flare Event

To evaluate performance on a weaker event, we selected a C7.0-class solar flare that occurred in active

region 14100 on May 31, 2025. The flare started at approximately 07:22 UT, peaked at 07:27 UT, and ended at approximately 07:30 UT. Fig. S4 shows the evolution of the flare, including the pre-flare background, rising phase, impulsive phase, and decay phase.

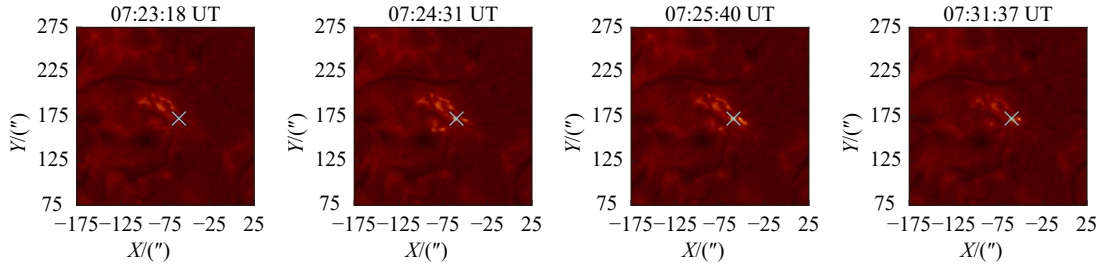


Fig. S4. Images of the class C7.0 solar flare event occurring on May 31, 2025. The four panels correspond to the background, rising phase, impulsive phase, and decay phase. Cyan crosses mark the point of maximum brightness during the impulsive phase.

The spectra from this event were processed using the same inversion pipeline. The inversion results for the single pixel are shown in Fig. S5. Even for this less energetic event, the models effectively infer the distributions of physical parameters, revealing the characteristic chromospheric response to the flare energy deposition.

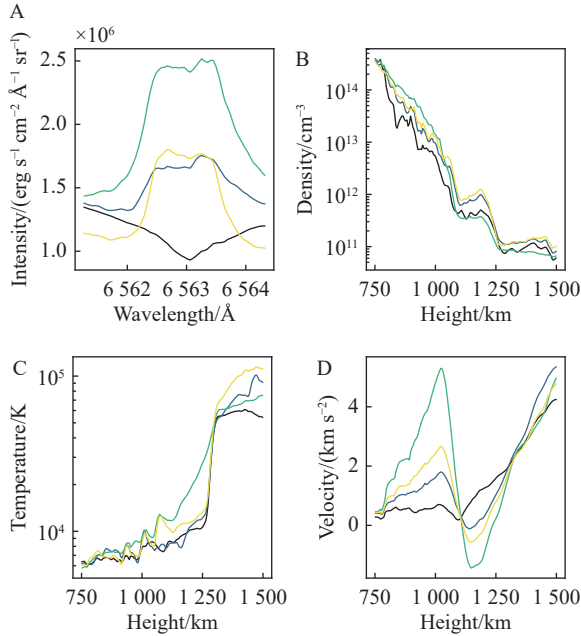


Fig. S5. Inversion results for the point of maximum brightness during the impulsive phase using CHASE observational data. (A) Spectra. (B) Electron number density distributions. (C) Temperature distributions. (D) Plasma velocity distributions. Different colors indicate distinct evolutionary phases: background (black), rising phase (blue), impulsive phase (green), and decay phase (yellow).

Finally, a region-wide inversion is performed to reconstruct the spatial parameters. Fig. S6 shows the height distribution characteristics of the inverted physical parameters. These output parameters reflect the physical changes in the different layers of the solar atmosphere during this C-class event.

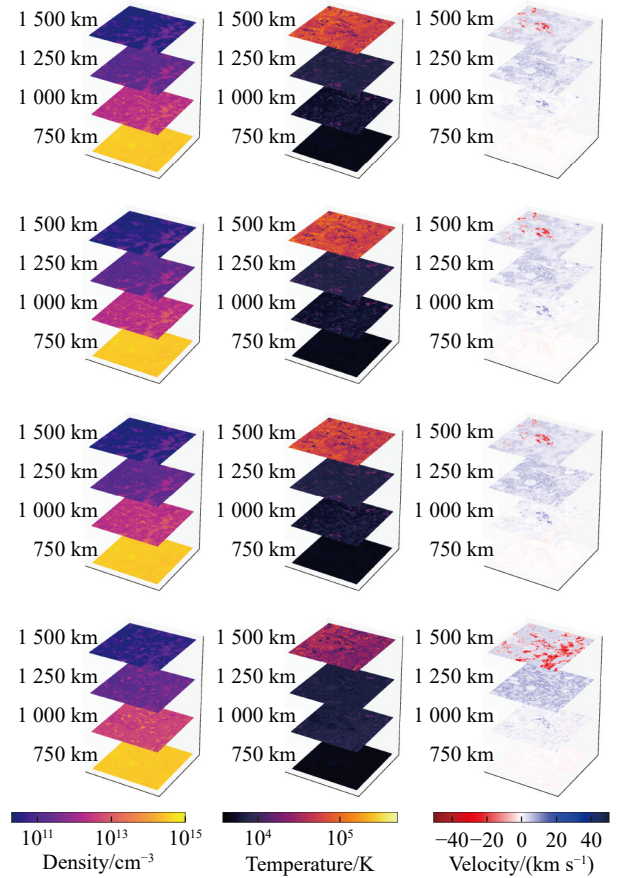


Fig. S6. Height distribution characteristics of inverted physical parameters in the solar atmosphere within the flare region. The four rows, from top to bottom, correspond to the background, rising phase, impulsive phase, and decay phase, while the three columns, from left to right, show electron number density, temperature, and plasma velocity.