RADYNVERSION: Learning to Invert a Solar Flare Atmosphere Using Invertible Neural Networks

John A. Armstrong
with: C. Osborne and L. Fletcher

University of Glasgow
Science & Technology Facilities Council
ScotDIST

University of Glasgow

Basics of Deep Learning

- **Machine learning the process of using statistical techniques to give computers the ability to learn how to perform a specific task *without* being explicitly programmed**
- **Deep neural networks are very good function approximators (Cybenko 1989, Lu et al. 2017)**
  - processes that can be expressed by well-defined functions can be learned by a deep neural network

Trained neural network

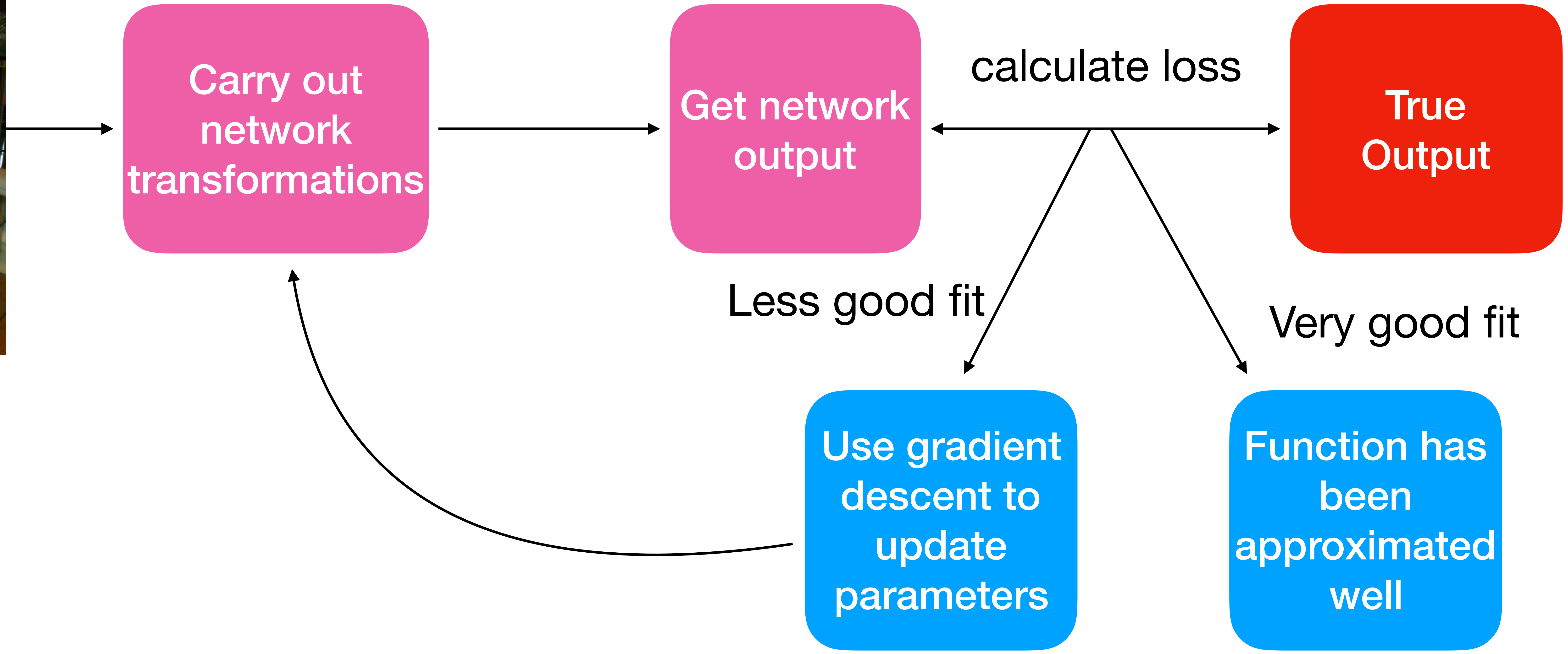
$$y \approx f(x; \underbrace{\{\theta_1, \ldots, \theta_n\}}_{\text{Learnable Parameters}})$$

Output

Input

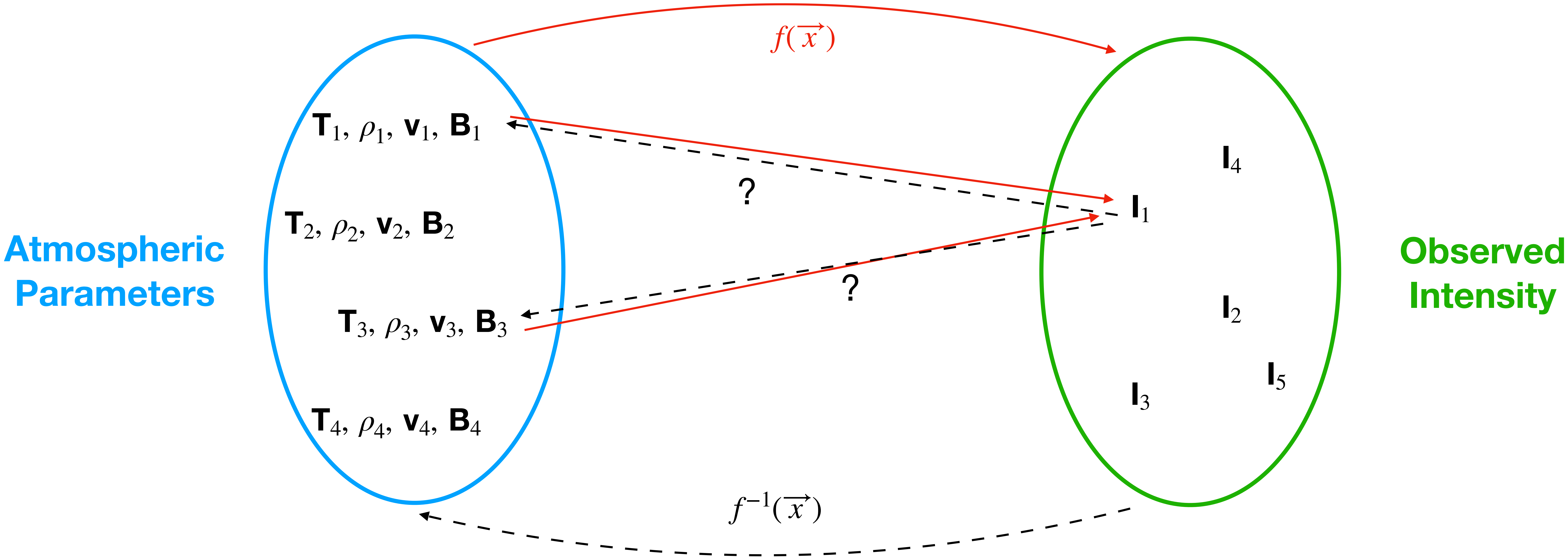
Basics of Deep Learning

- **The optimisation (training) takes place like a feedback loop similar to how the inversion process works**



The Problem with Inversions

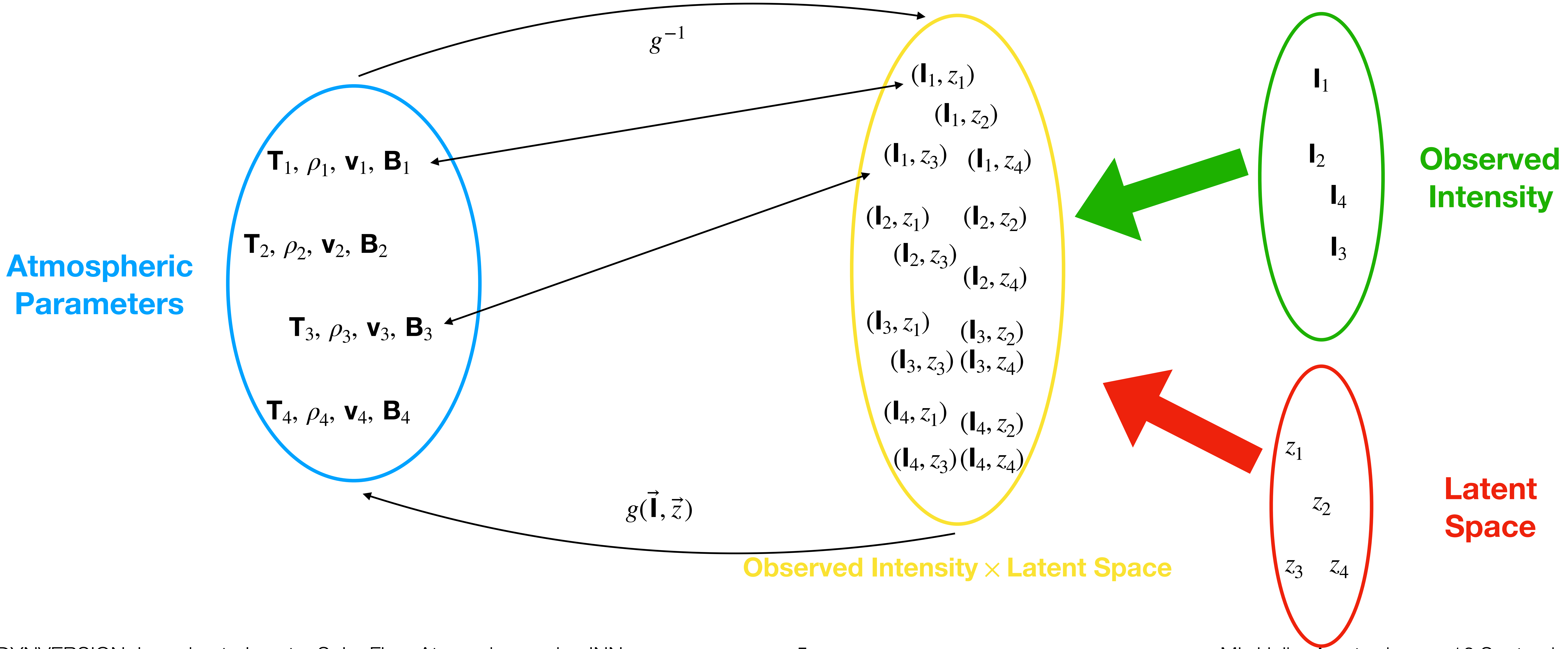
- **Inversions, however, are not well-defined functions**
  - there are many combinations of atmospheric parameters that can produce the same line profiles
  - there is information lost about the physics in the forward process



Cannot be modelled with traditional deep learning*

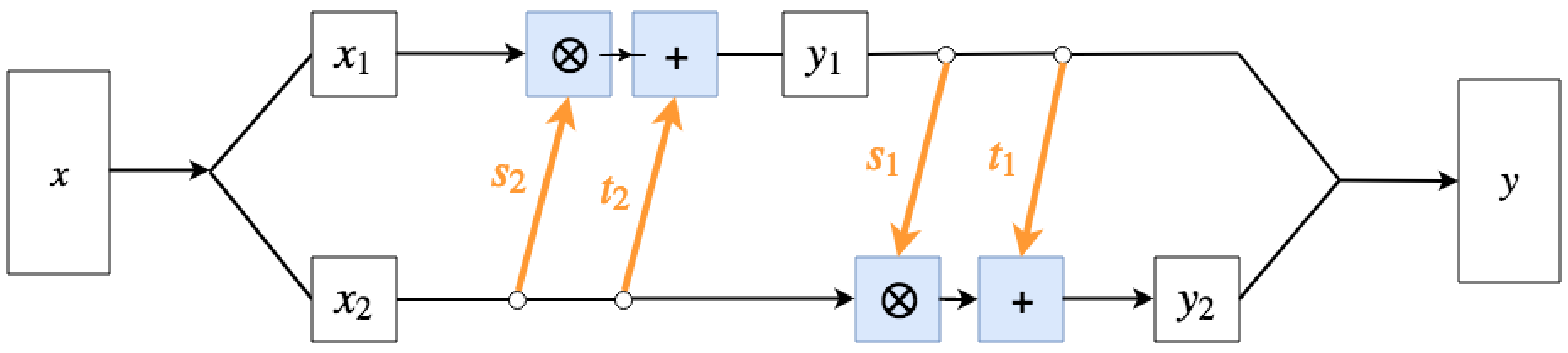
Fixing the Problem

- **How do we formulate the inverse process in such a way as to make it well-defined?**
  - Introduce a latent space, z, which contains the information lost in the forward process



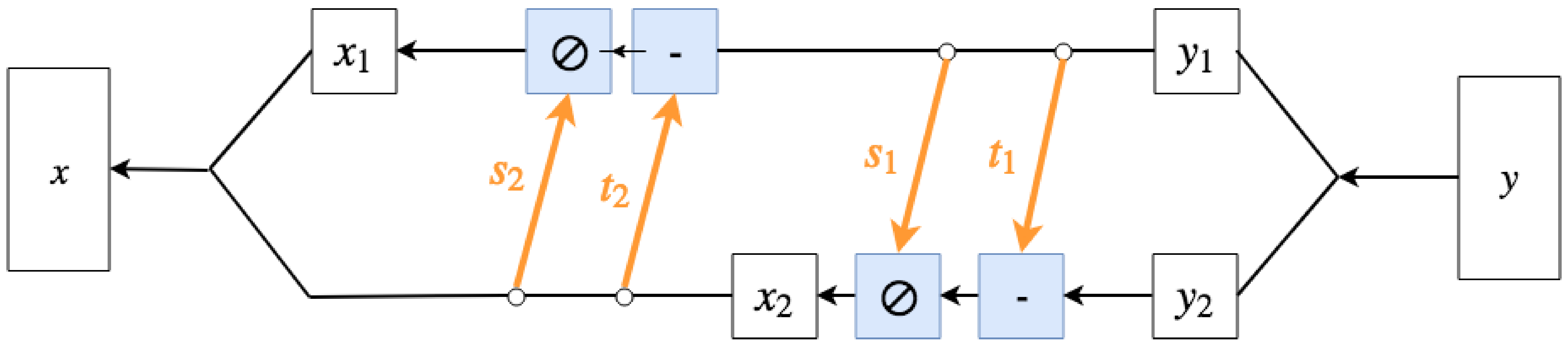
Invertible Neural Networks (INNs)

- The layers we stack in INNs are known as affine-coupling blocks:



$$y_1 = x_1 \otimes \exp\left(s_2\left(x_2\right)\right) + t_2\left(x_2\right)$$

$$y_2 = x_2 \otimes \exp\left(s_1\left(y_1\right)\right) + t_1\left(y_1\right)$$

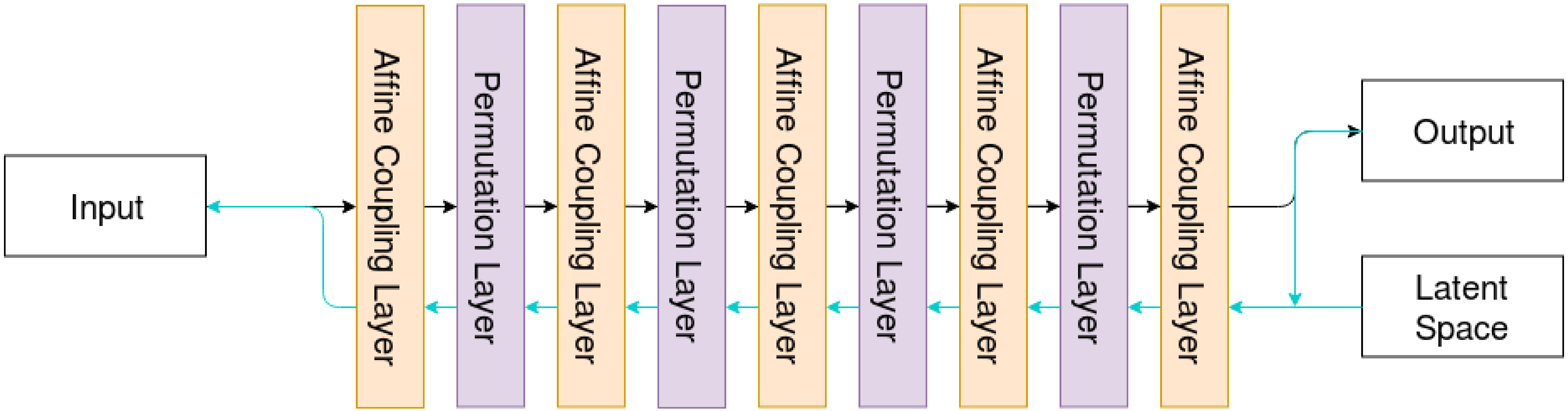


$$x_2 = \left(y_2 - t_1\left(y_1\right)\right) \oslash \exp\left(s_1\left(y_1\right)\right)$$

$$x_1 = \left(y_1 - t_2\left(x_2\right)\right) \oslash \exp\left(s_2\left(x_2\right)\right)$$

See Dinh+ 2014, 2017 & Ardizzone+ 2018 for more details

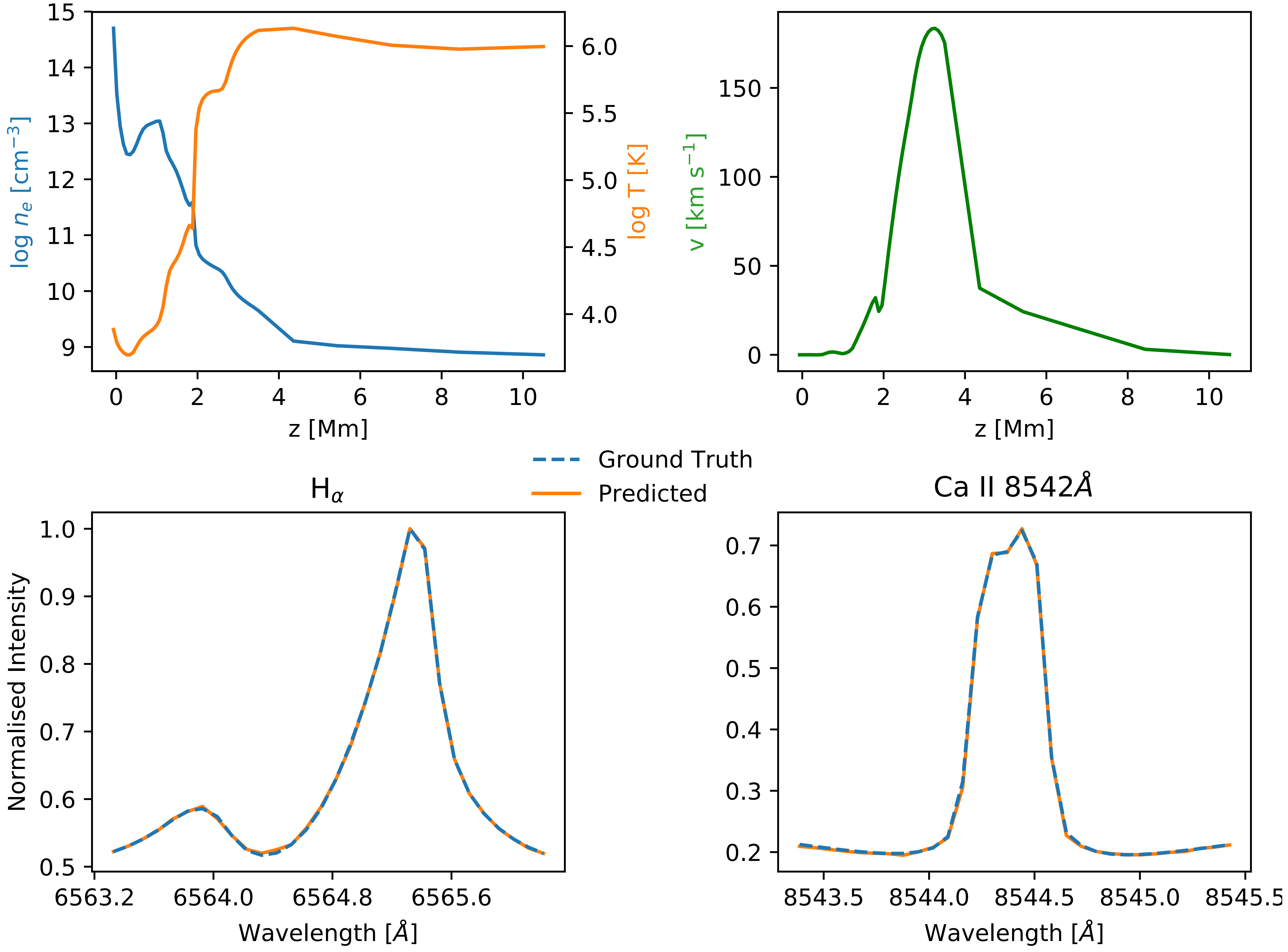
Invertible Neural Networks (INNs)



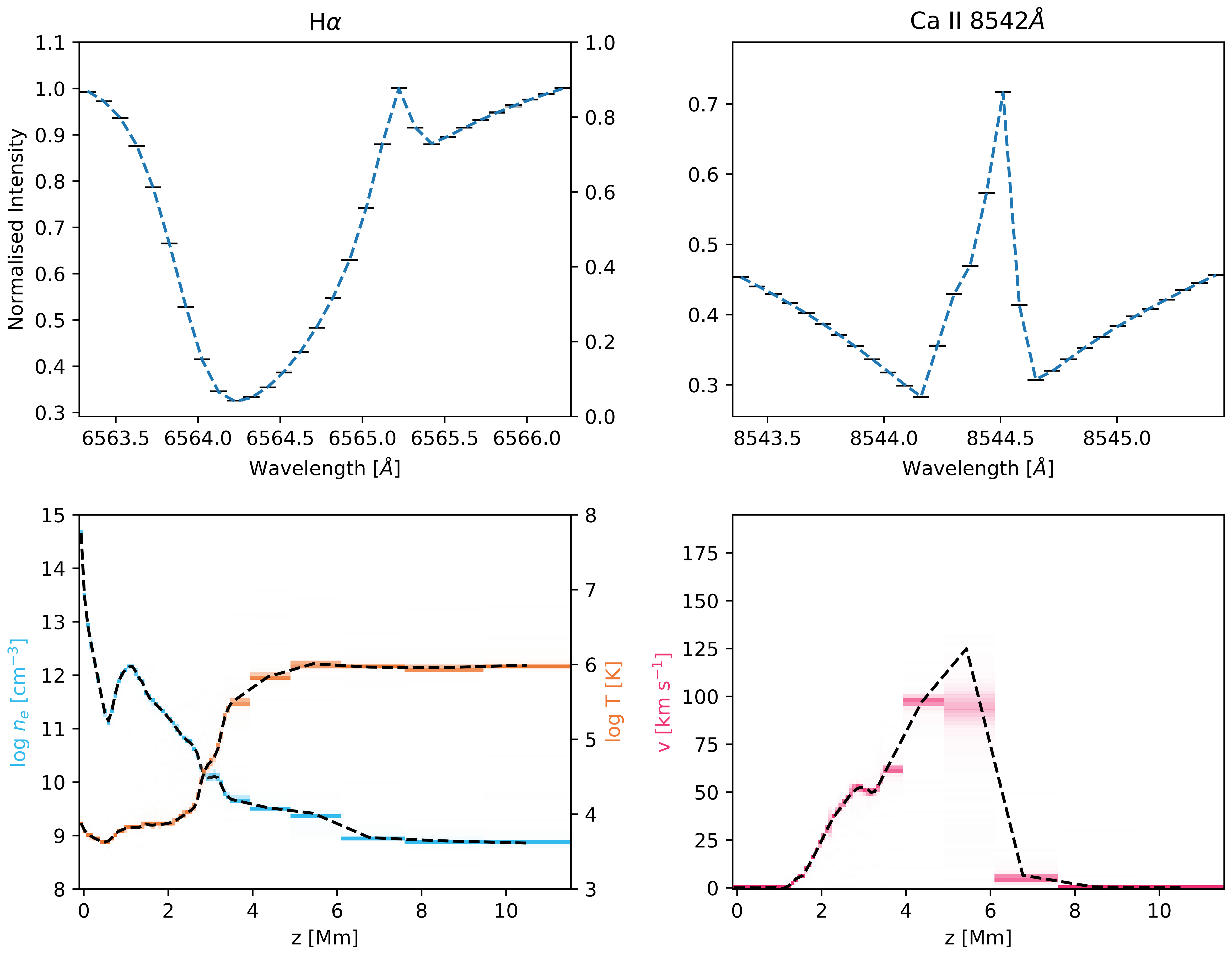
Training Data

- **We use the F-CHROMA RADYN grid for training data**
  - available here: https://star.pst.qub.ac.uk/wiki/doku.php/public/solarmodels/start
- **Each simulation has 500 timesteps**
- **All electron beams, range of cutoff energies: 10—25keV, range of spectral index: 3—8 and range of total energy deposited**
- **We extract Hα and Ca II λ8542 line profiles as well as temperature, velocity and density profiles from each timestep of each simulation**
- **This gives us >40000 pairs of spectral lines to learn our inversions from**
- **Each pair of lines has corresponding atmospheric parameters**
- **Using any less than 2 lines doesn't work**

Validation Data



Forward Model Test



Inversion Test

Inversion of Real Data

- **M1.1 flare SOL20140906T17:09 NOAA AR12157**
- **Observed by SST/CRISP in Hα and Ca II λ8542**
- **Wavelength sampling: 15 points for Hα, 25 for Ca II**

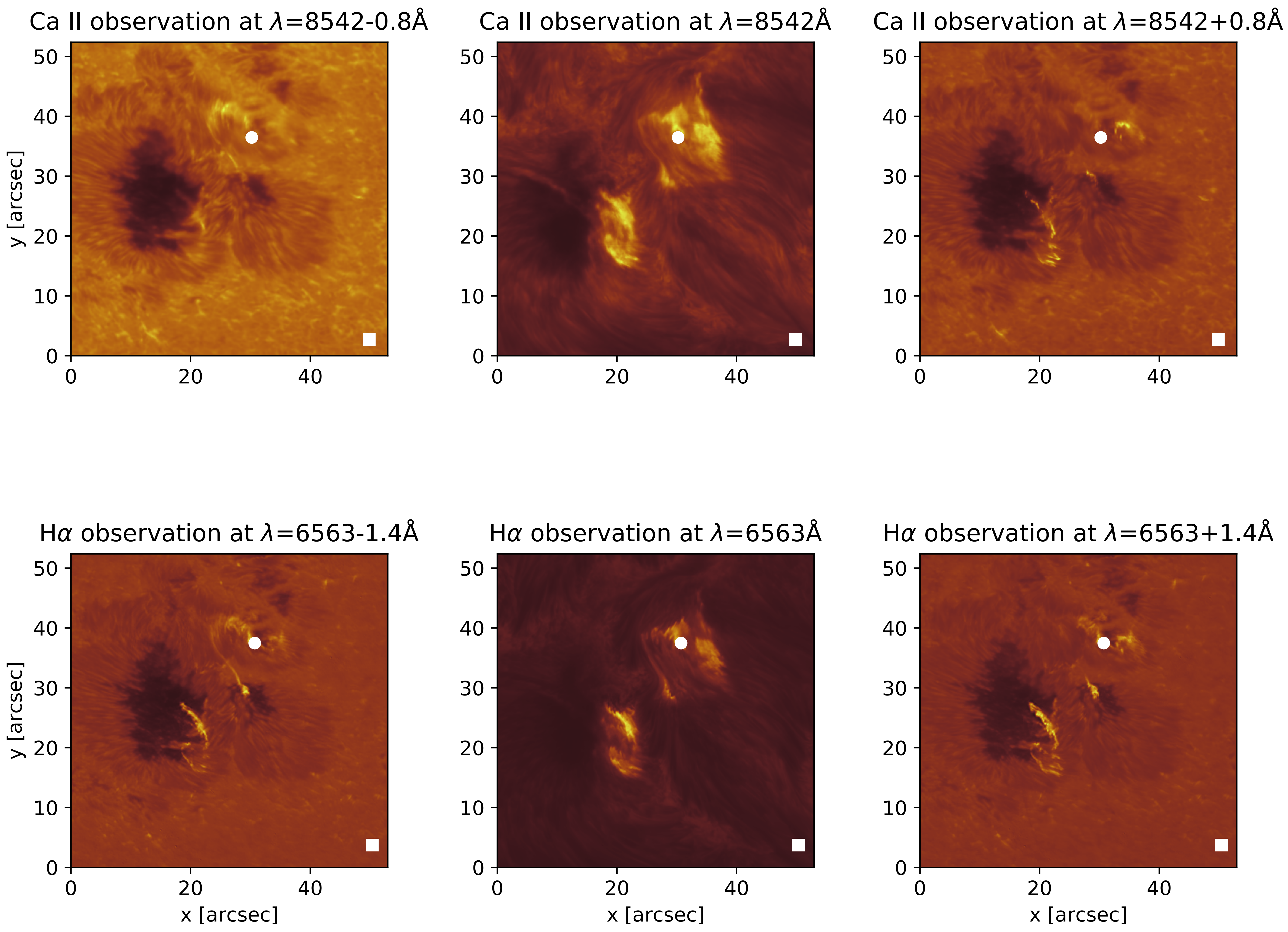
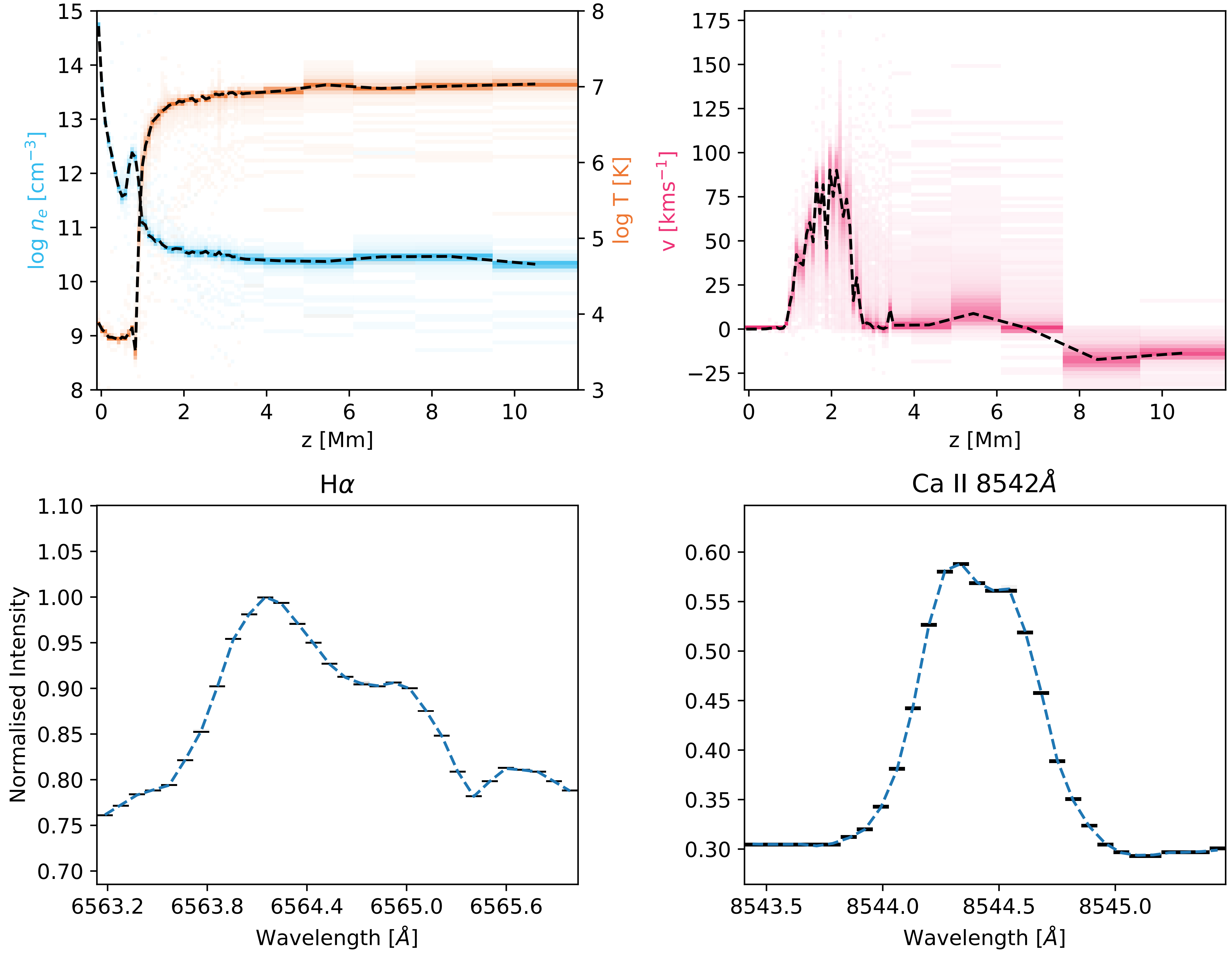
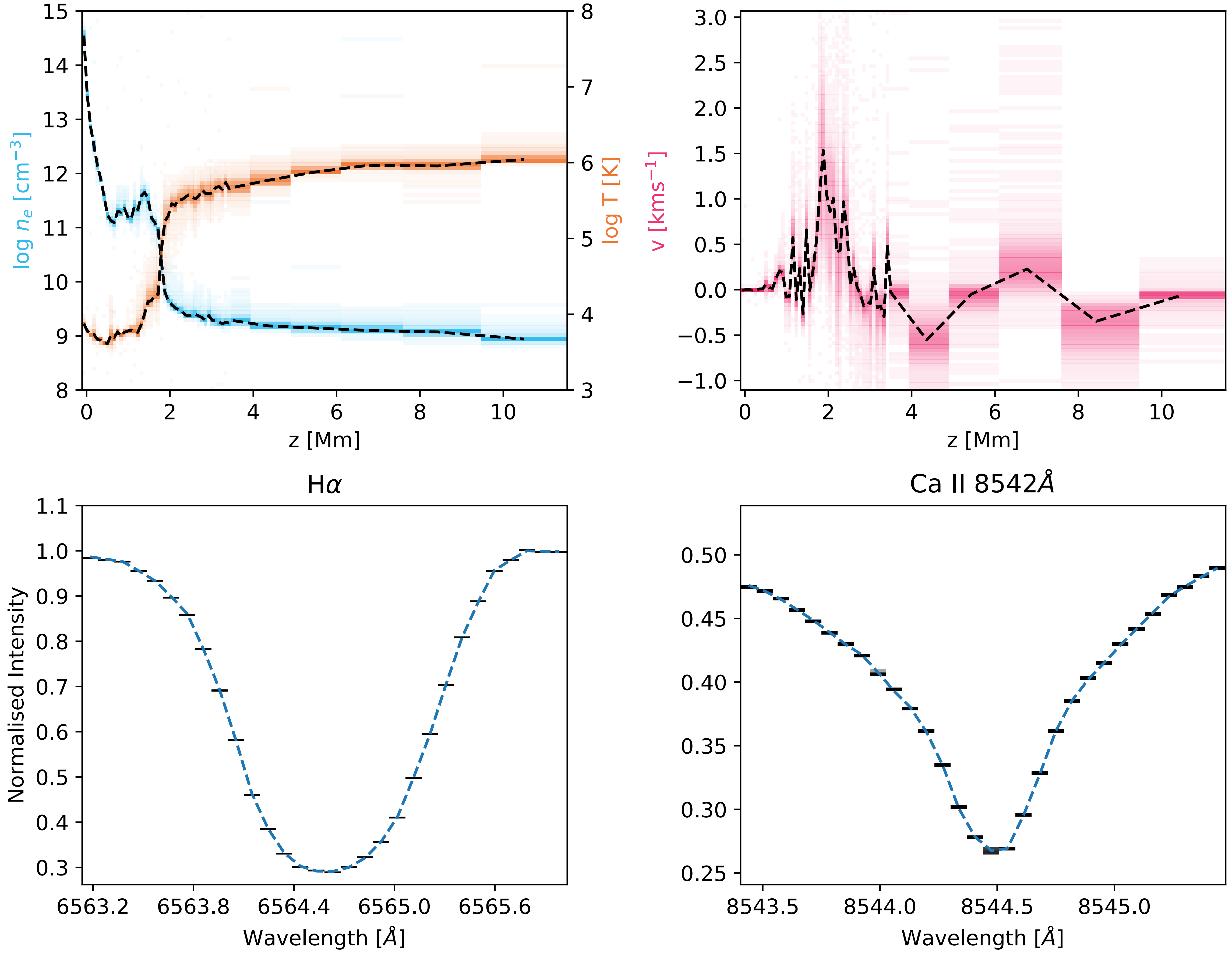


Figure: Observations in both wavelengths just after the flare onset. The circular point is a point on the flare ribbon.
The square point is a point off the flare ribbon.

Single-pixel Inversions



Inversion of circular point

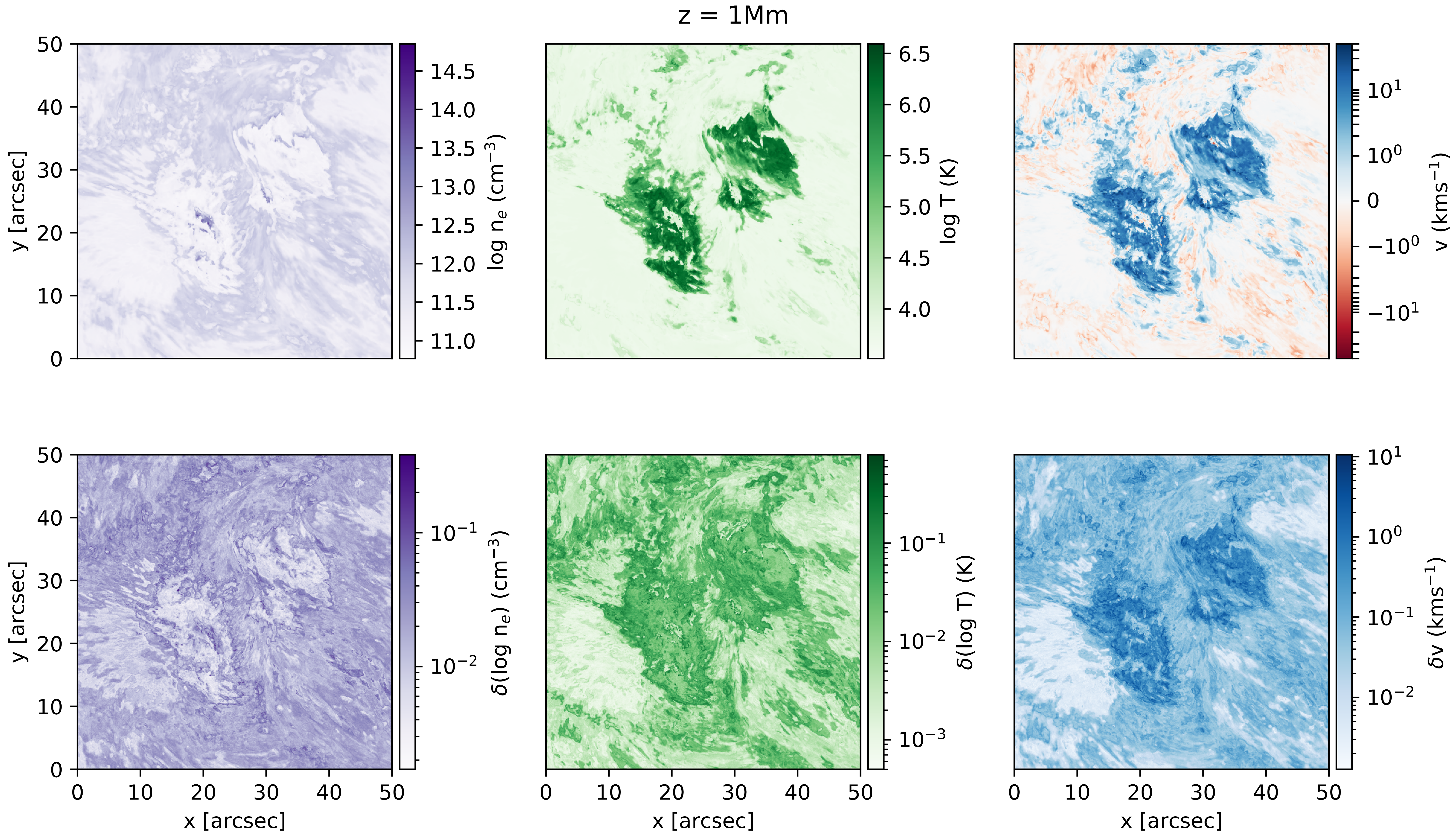


Inversion of square point

See Osborne, Armstrong & Fletcher, 2019

Whole Image Inversions

- Can do a whole image inversion in ~30 minutes (50 nodes in each of the three atmospheric parameters, for ~100s of inversions on 1k x 1k FOV)
- Includes errors by calculating standard error on median solution
- ~1.5TB of inverted data (largest inversion ever done?)
- Figure shows whole image inversions at heights where Ca II core forms in flares according to Kerr+ 2016



Armstrong, Osborne and Fletcher (in prep.)