Possibility of using exhaustive end-to-end simulations of supernovae as a database for Machine Learning

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Motivation

- This is not so much about how to apply machine learning on astronomical data
- But more about what data we should let the machines to learn from in the first place

Motivation

- So far most studies of massive star explosions (SNe) and their aftermaths (SNRs) have followed an object-by-object approach
- Furthermore, usually these works are limited to interpreting a certain specific observational aspect of a single object

Motivation

- But it is well known that every physical processes involved in each SN/SNR system are inter-connected in a complex network
- A fuller picture of progenitor-SN-SNR connection is unavailable
- Both of these are extremely important for understanding the physics and astrophysics of stellar evolution and its peripheries

Plan

iTHEMS RIKEN interdisciplinary Theoretical & Mathematical Sciences

RIKEN iTHEMS Working Group Proposal

Excerpts from Astro-AI WG proposal (PI: Uchiyama-san)

1. Working Group Title

Astro-AI: New Generation Astronomy Powered by Artificial Intelligence

2. Objective (less than 1000 words)

systematically perform spatial and spectral analysis of the clusters at different redshifts using machine learning methods to reveal their detailed evolution history.

5) Supernova explosions and their remnants exhibit an extremely rich diversity thanks to their different circumstellar environments, nature of progenitor stars and possibly explosion mechanisms. Linking progenitor stars with their final explosive events is of utmost importance in understanding the last stages of massive star evolution, but progress has been hindered by the complexity of the problem. Machine learning will help recognize patterns from lots of simulation results invoking a matrix of different initial conditions. Matching them with observational characteristics will reveal the key factors that dictate the diversity seen.

Plan

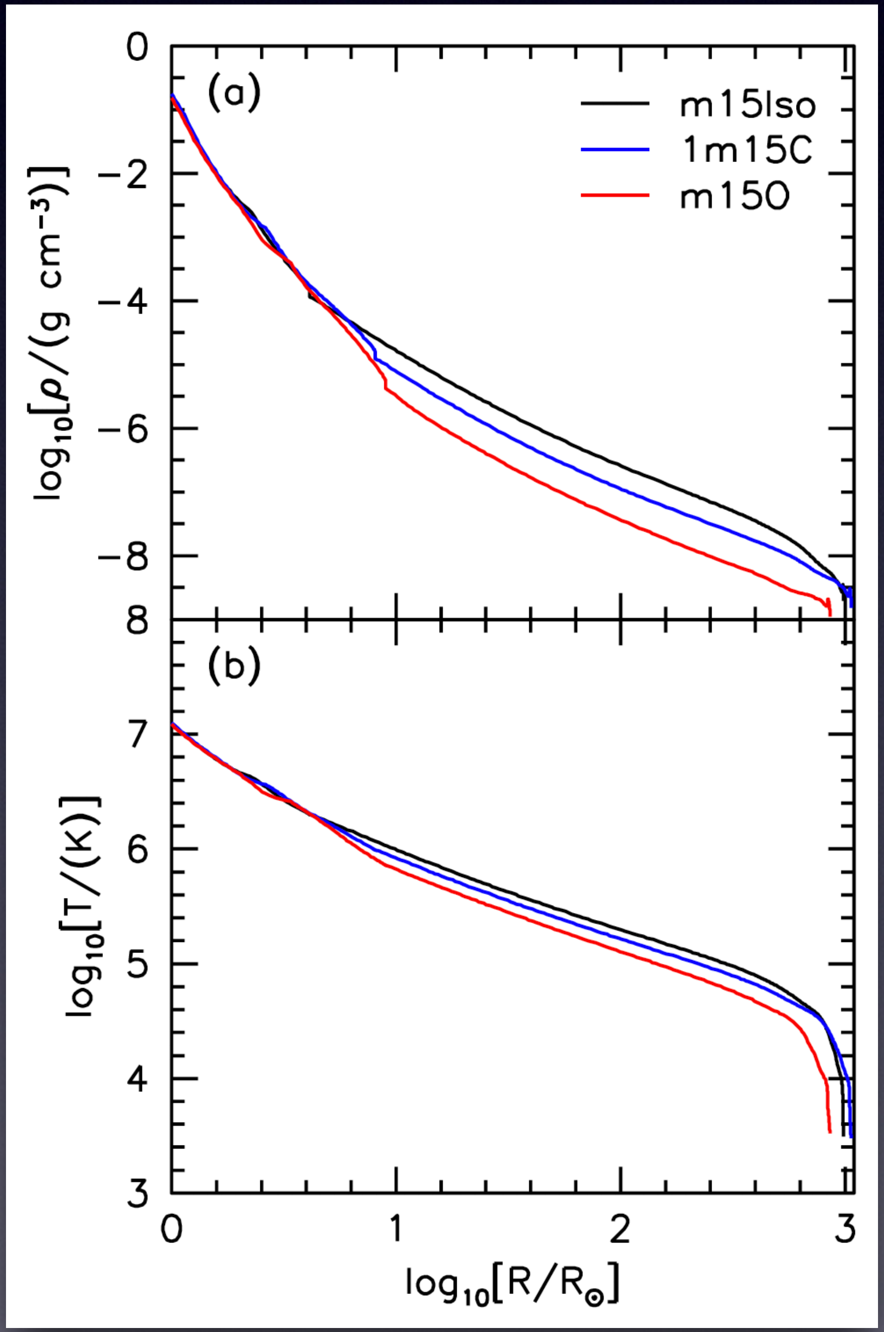
1. **Create the database**: perform exhaustive end-to-end simulations of SNe based on hydrodynamical models with extensive set of microphysics
2. **Identify key observable characteristics**: search for model-differentiating aspects from simulation data
3. **Learn the patterns**: establish links of the end results (obtainable from observations) with model initial conditions
4. **Application to astronomical data**: collect necessary information from multi-wavelength observations of many SNe/SNRs, feed them to the machine, and narrow down the "parameter space"
5. **Broadened understanding of SNe/SNRs as population(s)**

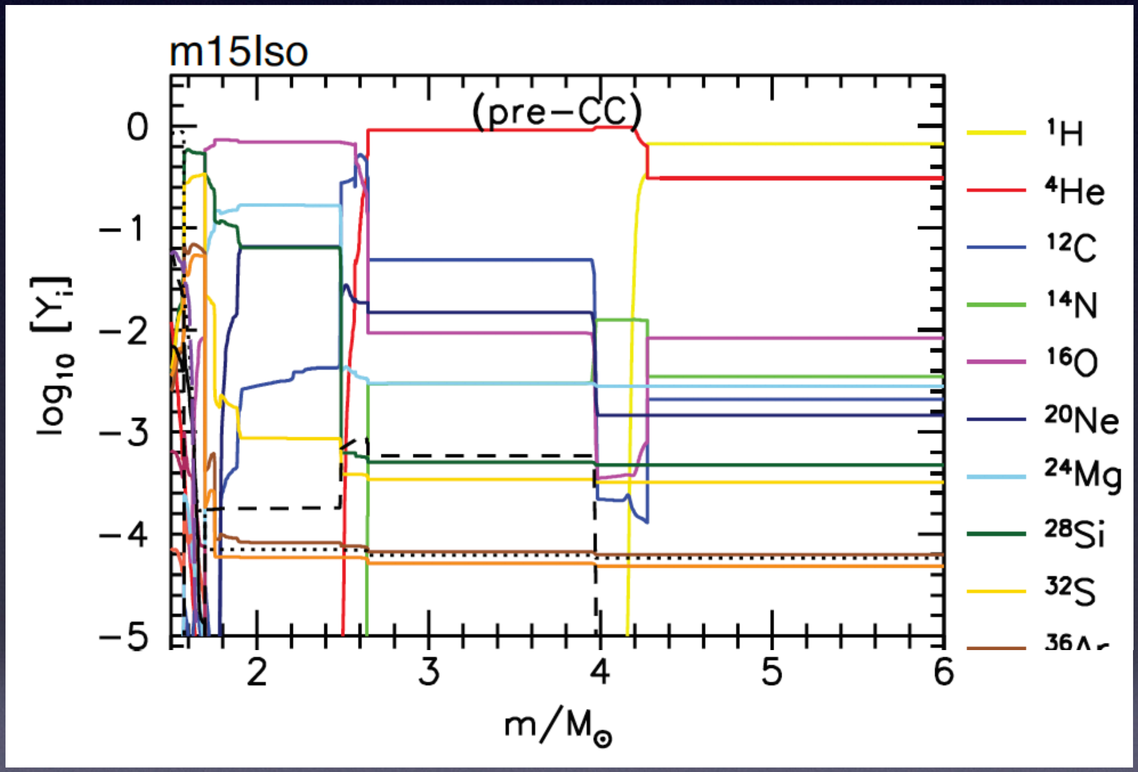
What has been done

- The CR-hydro-NEI code for young SNe to old SNR modeling (Lee et al.)
- A prototype end-to-end simulation platform (Patnaude, Lee et al. 2017) to follow:
  - stellar evolution and mass-loss history
  - core-collapse explosion and nucleosynthesis
  - evolution to supernova remnants, particle acceleration

Workflow and Components

- Stellar evolution (MESA)

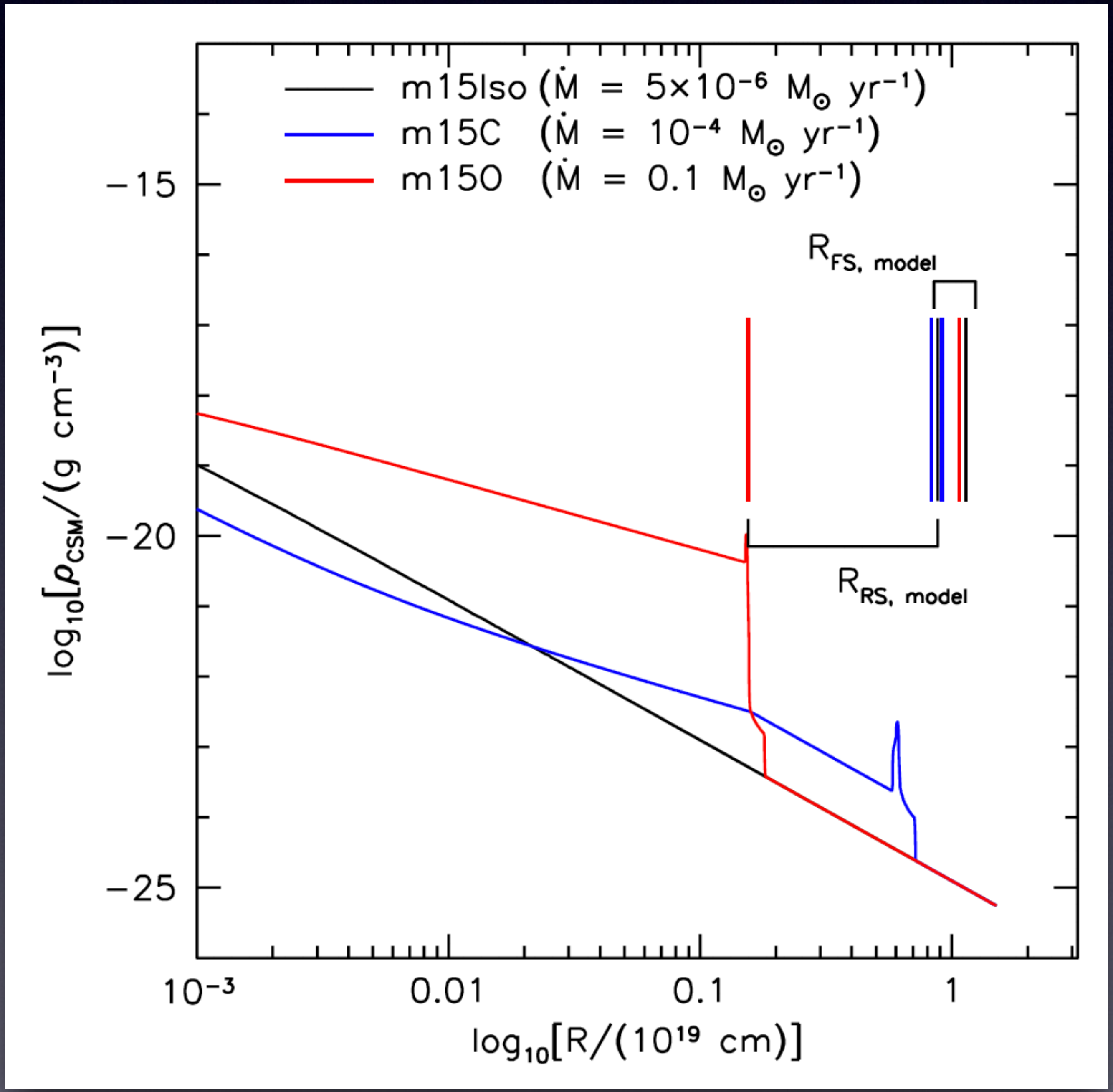




Pre-CC interior chemical structure

Workflow and Components

- Mass loss history (MESA and VH-1)



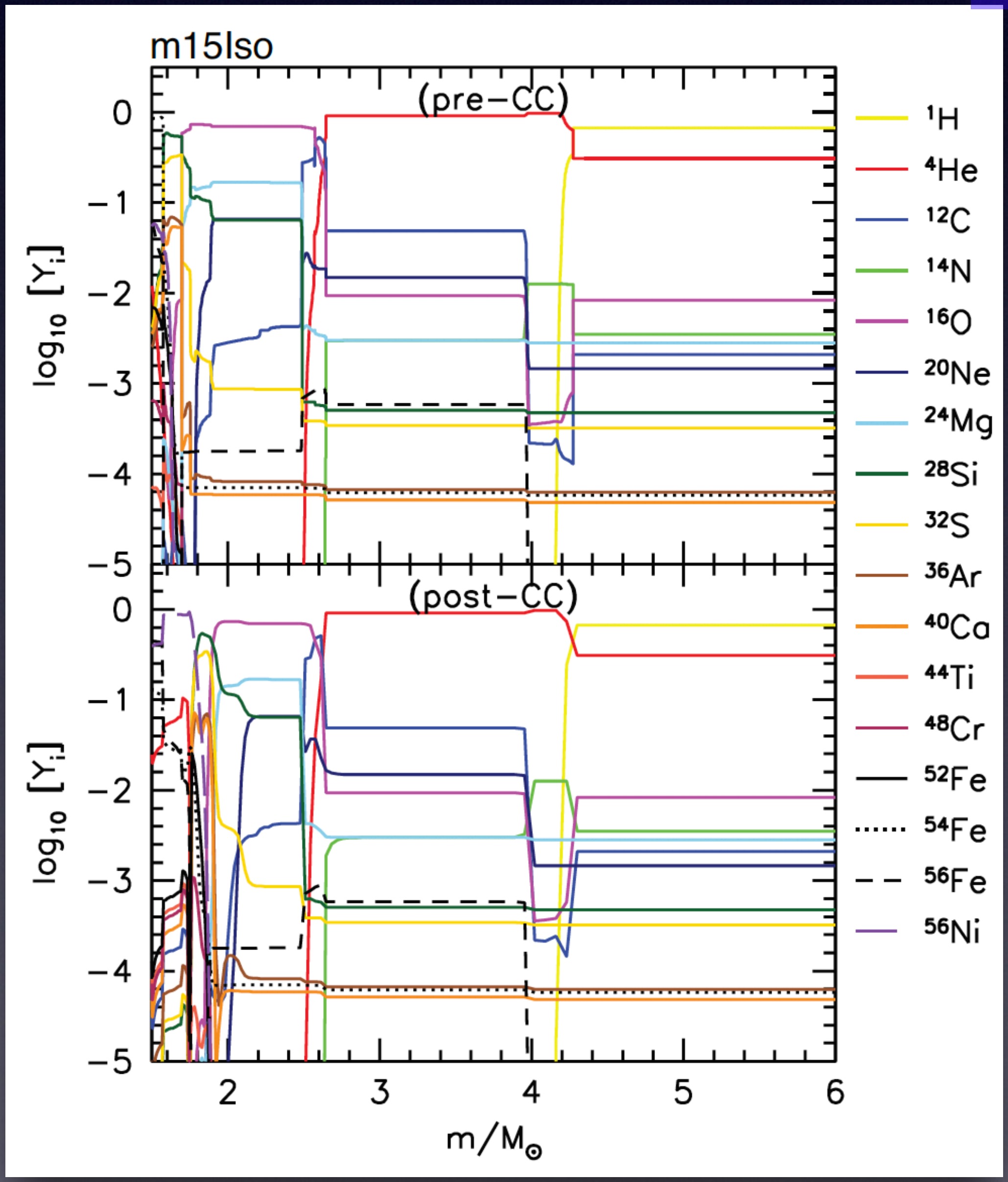
Various circumstellar environment (CSM) for different progenitor stars

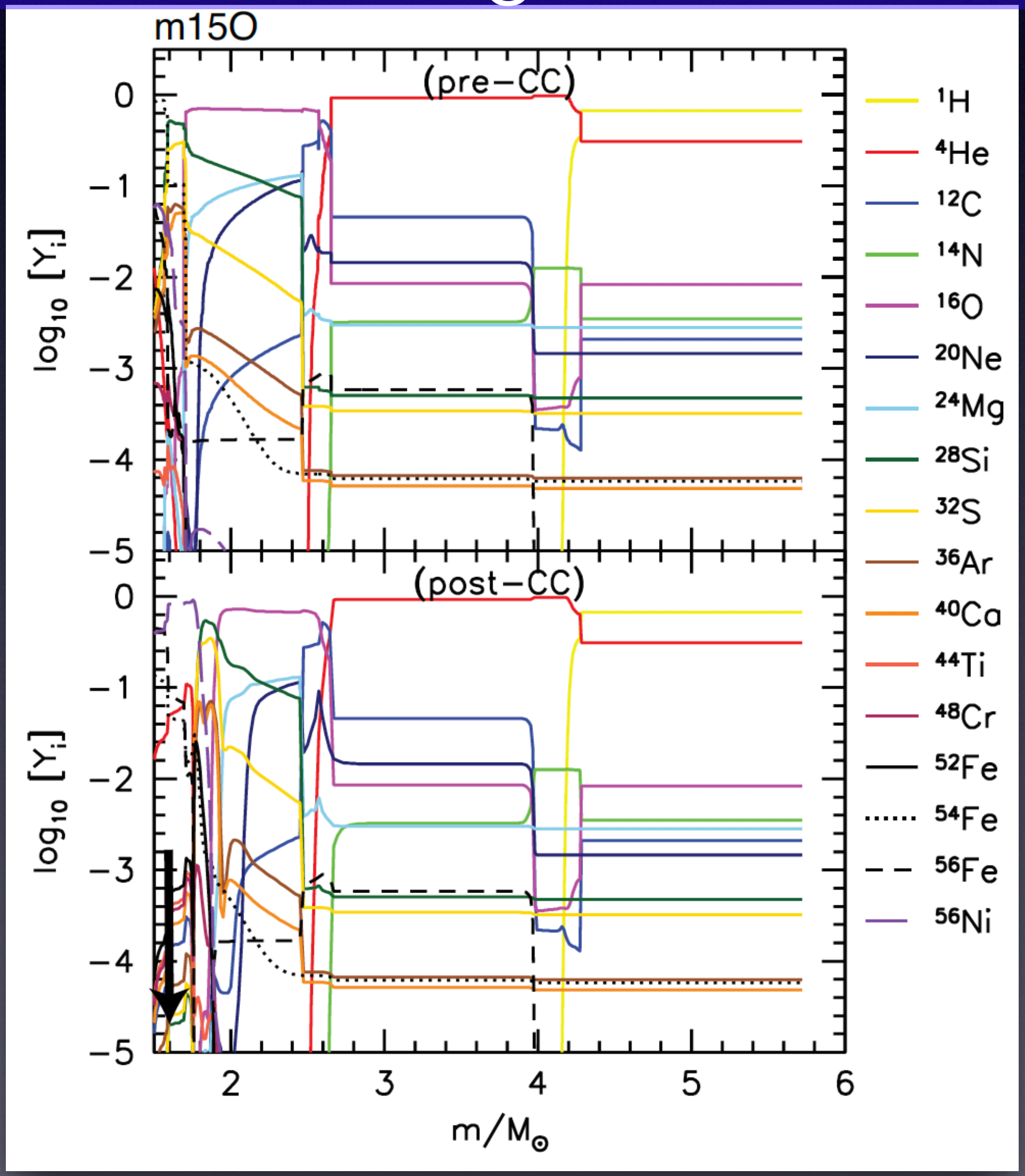
Equally important as progenitor interior nature

Workflow and Components

- CCSN and Nucleosynthesis (SNeC)

Can follow through shock breakout

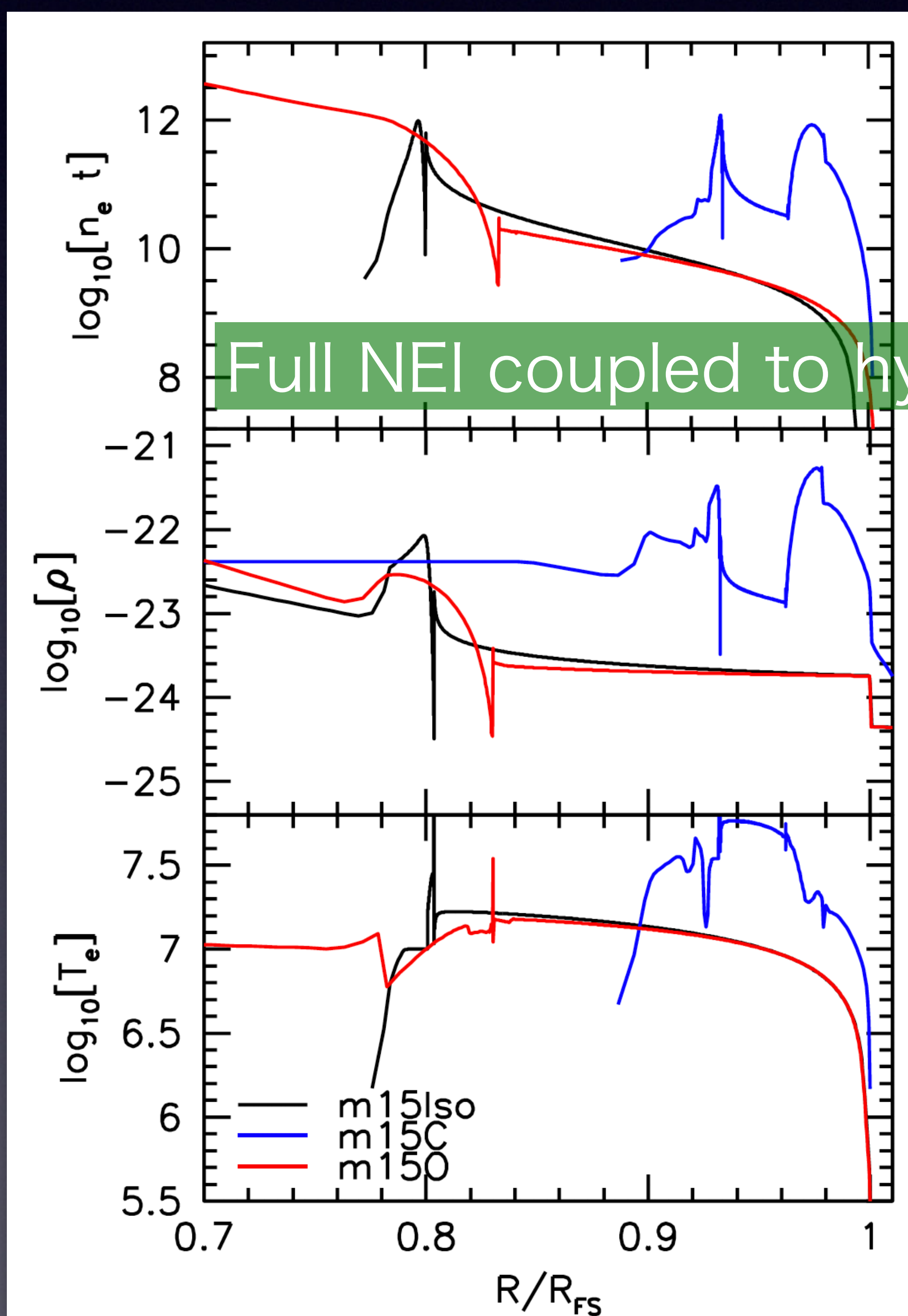




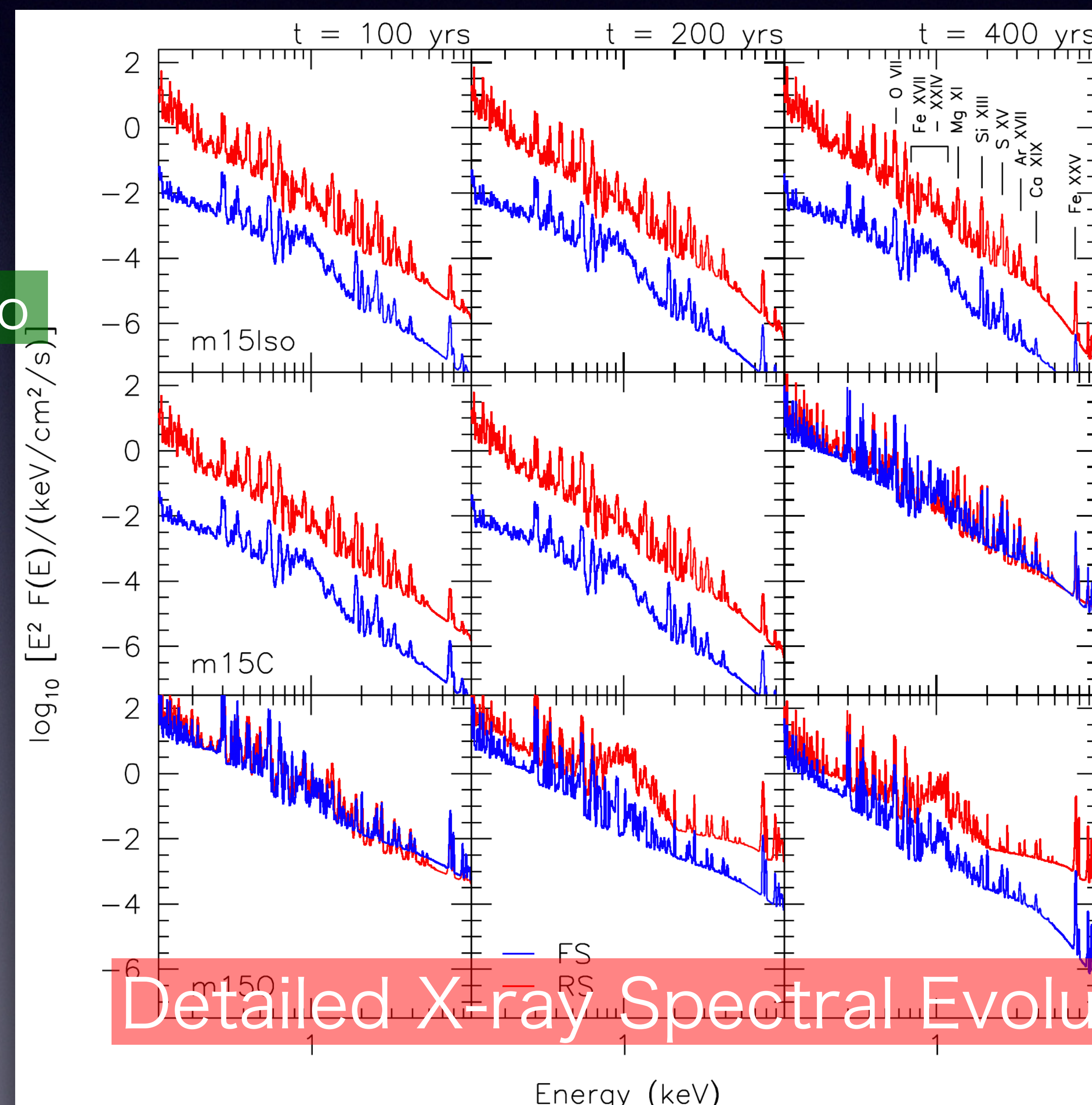
Workflow and Components

- SNR evolution (CR-hydro)

Lots of microphysics



Full NEI coupled to hydro

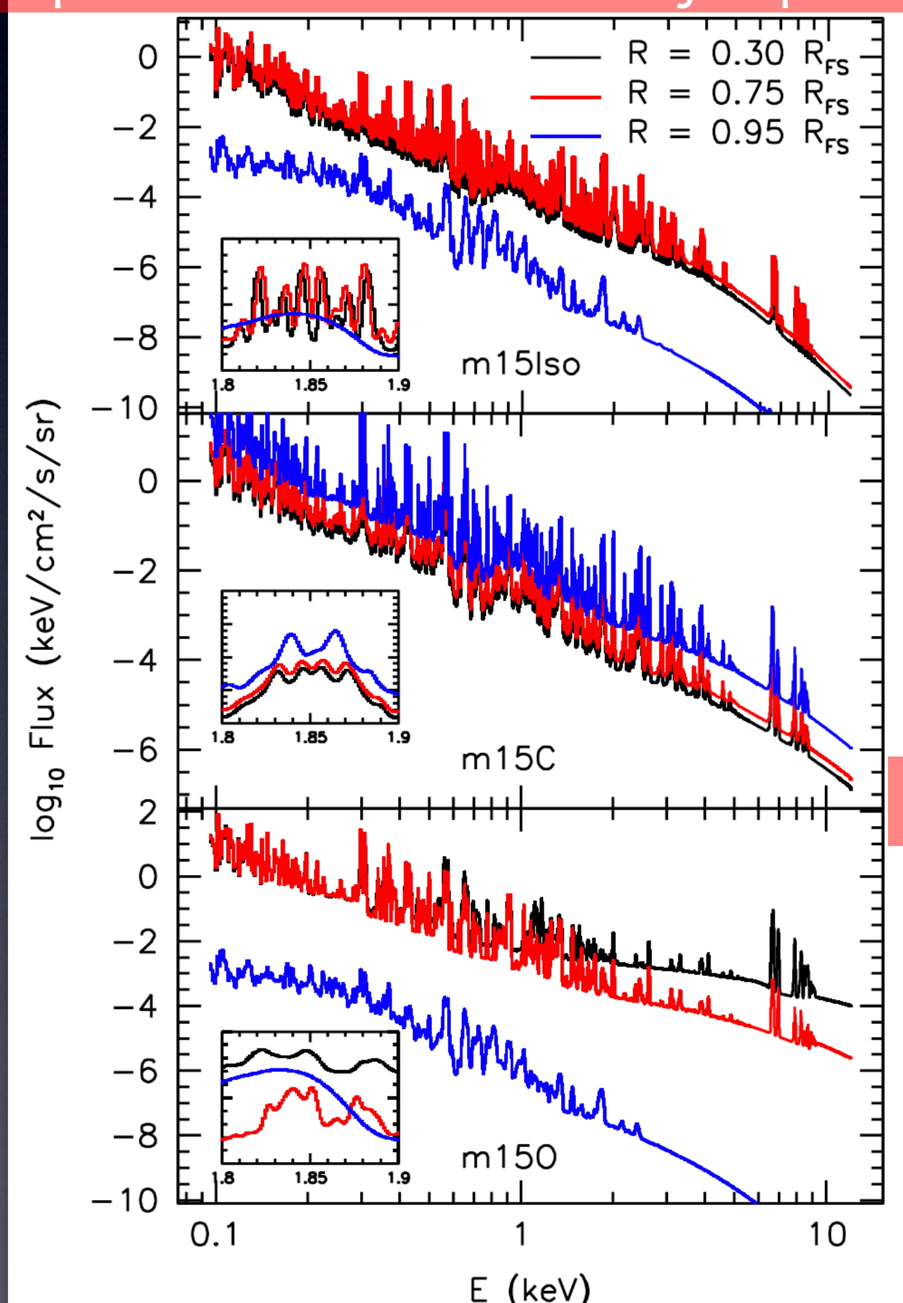


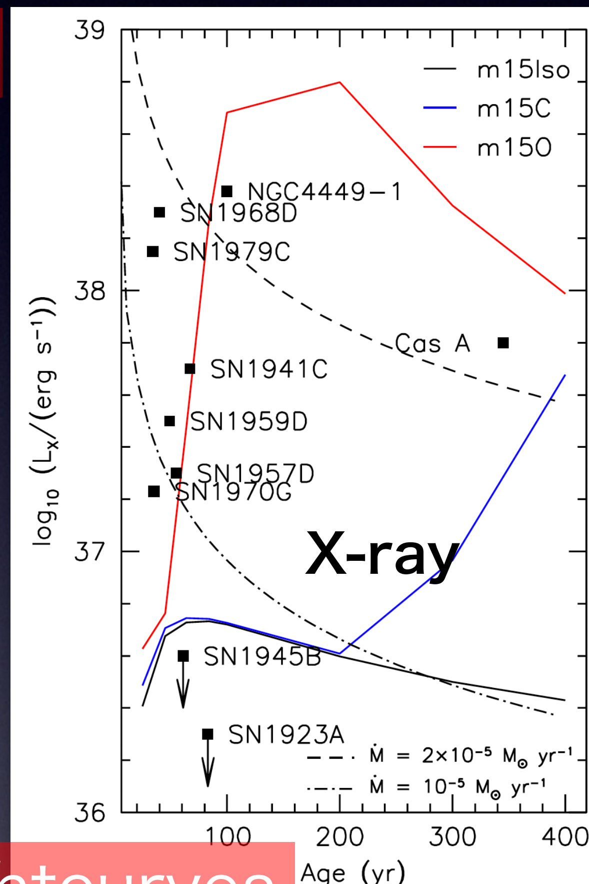
Detailed X-ray Spectral Evolution

Workflow and Components

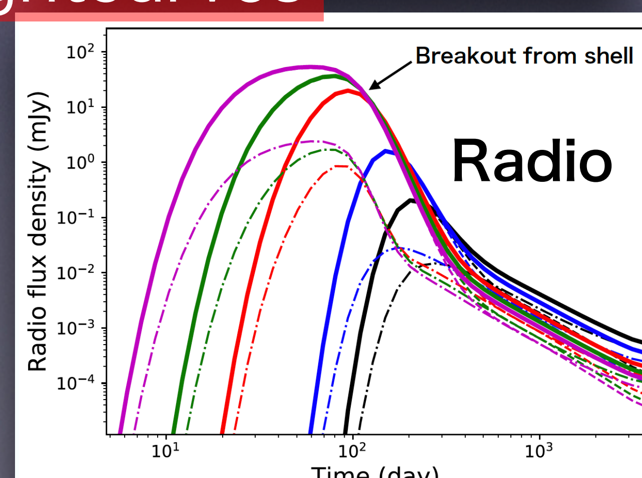
- Large variety of end products

Space-resolved X-ray Spectra

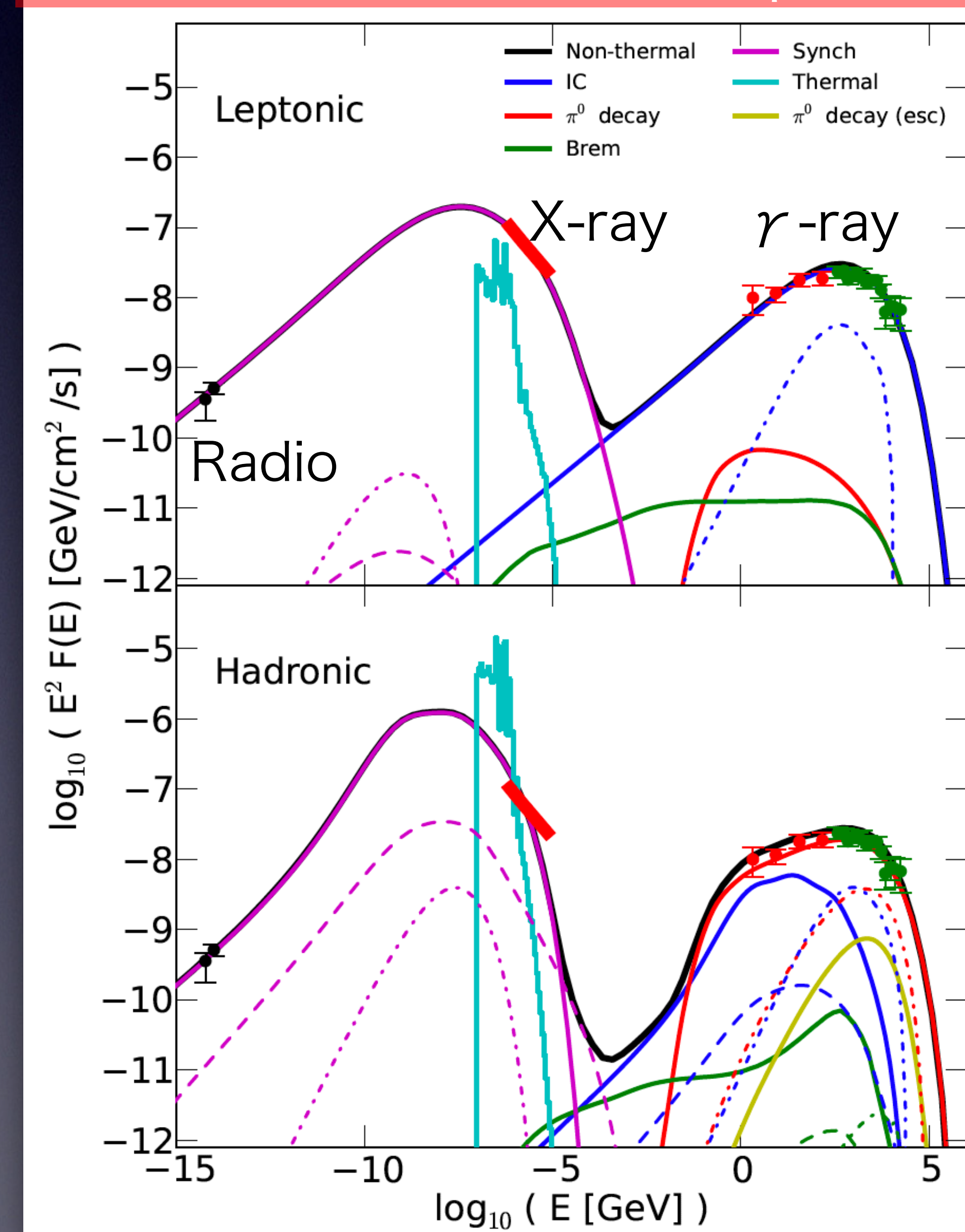




Lightcurves

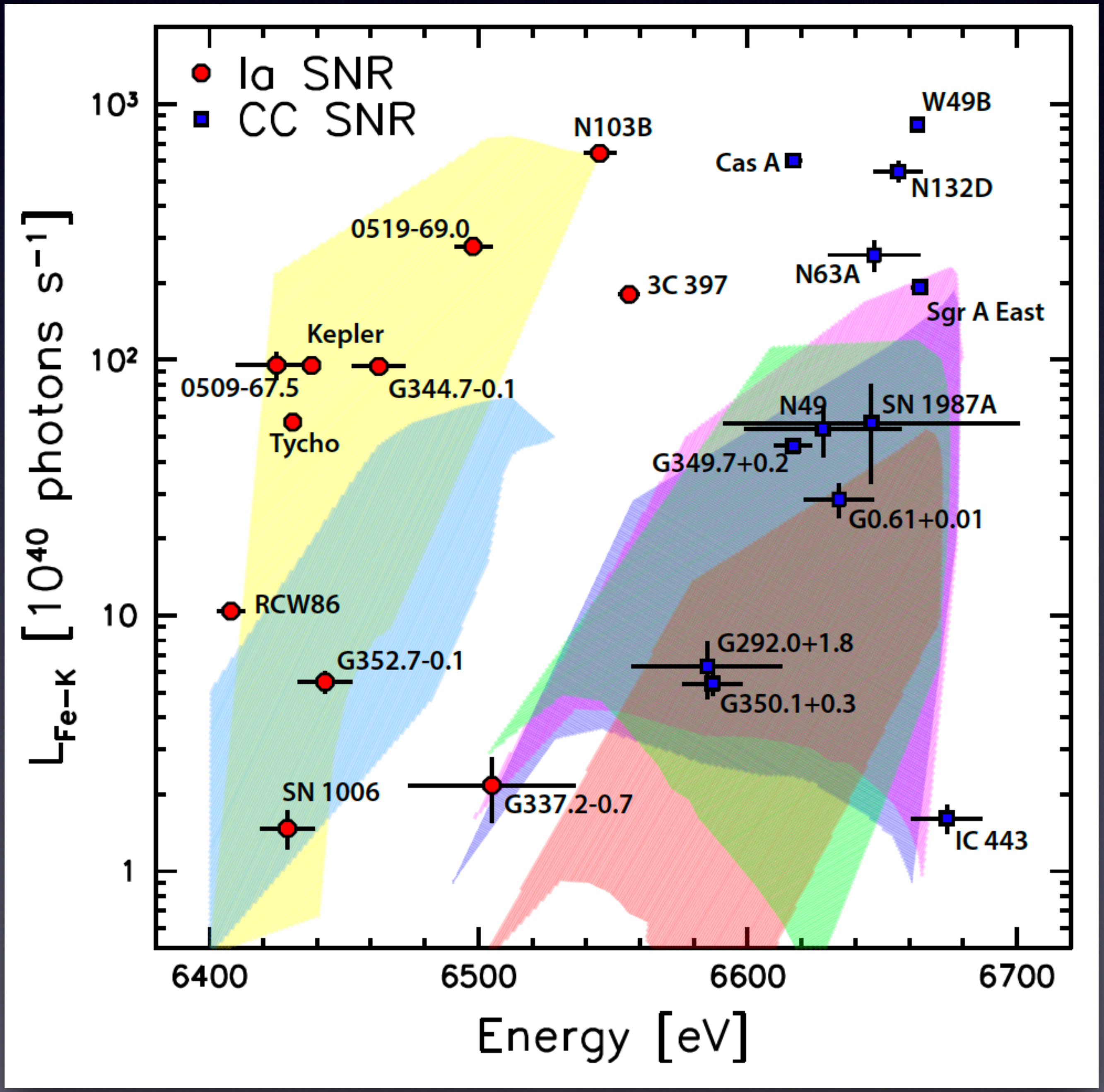


Non-thermal broadband spectrum



Workflow and Components

- Search for key and easily identified features to learn from



e.g., Fe-K line

Yamaguchi-san (Suzaku)
Patnaude, Lee et al 2015
H. M-R., Lee et al (in prep)

Advantages

- ☑ These end-to-end simulations are computationally light
    - One can always dream about creating a database from 3-D simulations with microphysics
- ☑ They have a well-established track record of successful models for well-known objects
- ☑ They are some of the most self-consistent models available in this field, covering both non-thermal and thermal physics and their observational consequences
- ☑ Same strategy should also work for Type-Ia models