

Extending the Cosmic Distance Ladder to High Redshifts with Gamma-Ray Bursts

Tamador Aldowma
Soebur Razzaque, Saeeda Sajjad, Adrita Khan, Maria
Dainotti, and Ankur Gosh

HEASA 2026 (29 Sep – 02 Oct)





Outline

- **Brief Introduction**
- **The LADDER Framework**
- **GRB Calibration and Extension to High Redshift**
- **Updated Datasets**
- **Redshift Estimation through Correlation Inversion**
- **Preliminary Results**
- **Summary**

Introduction

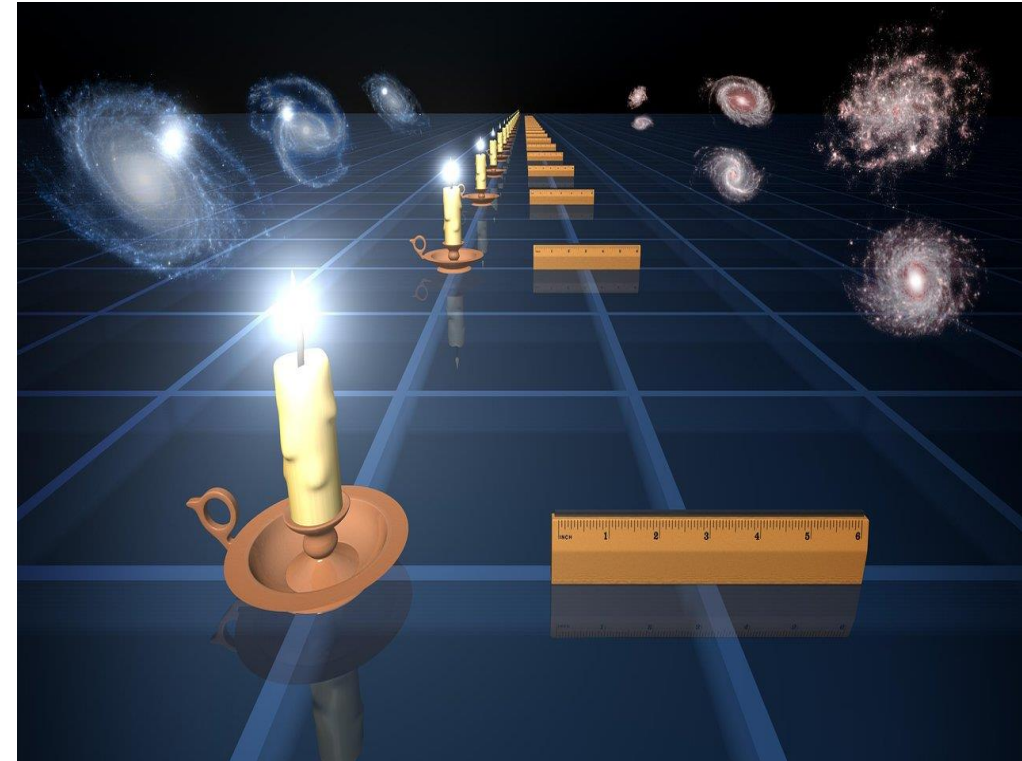
Type Ia supernovae (SNe Ia) act as standardizable candles to measure cosmic distances.

Their **Hubble diagram** shows how distance changes with redshift. (Scolnic et al., 2022).

GRBs reach higher redshifts, potentially extending this diagram into the early Universe (Cucchiara et al., 2011; Liang et al., 2008).

The circularity problem:

Calibrating GRB energy and luminosity correlations, such as **Amati** and **Yonetoku**, requires luminosity distances. If these distances are calculated using an assumed cosmology, subsequently using the calibrated correlations to constrain cosmology introduces circularity (Liang et al., 2008).



Credit: NASA/JPL-Caltech



Introduction

Addressing the GRB Circularity Problem

- **SNe interpolation:** Calibrate GRBs using SNe Ia distances (Liang et al., 2008).
- **Gaussian processes:** Reconstruct SNe distances to calibrate Amati (Liang et al., 2022).
- **Joint fitting:** Fit GRB correlations and cosmology simultaneously (Cao, Dainotti & Ratra, 2022; Aldowma, Razzaque, Martinelli et al., 2026).
- **Cosmic chronometers:** Calibrate the Dainotti relation using chronometers and Gaussian processes (Favale et al., 2024).

Another approach, introduced by Shah et al. (2024), uses deep learning to reconstruct the supernova distance–redshift relation

Learning **A**lgorithm for **D**eep **D**istance **E**stimation and **R**econstruction

LADDER

From SNe to GRBs

The central idea of the LADDER approach (Shah et al., 2024) is to:

- Reconstruct the apparent-magnitude–redshift relation directly from the observed SNe Ia Hubble diagram.
- Transfer this information to GRBs with measured redshifts **within the SNe calibration range**.
- Calibrate GRB correlations and apply them to higher-redshift GRBs to extend the Hubble diagram.

How LADDER addresses circularity

1. Train a neural network to reconstruct $m(z)$ **and its uncertainty**, without assuming a specific cosmological model.
2. Calibrate GRB correlations using the reconstructed $m(z)$, avoiding distances calculated from a preselected cosmology.

$$z \rightarrow [m_{LADDER}(z), \sigma_{LADDER}(z)]$$

$$\mu(z) = m(z) - M_B ,$$

$$\mu(z) = 5 \log_{10} \left(\frac{d_L}{\text{Mpc}} \right) + 25,$$

$$m(z) = M_B + 5 \log_{10} \left(\frac{\mathbf{d_L(z)}}{\text{Mpc}} \right) + 25.$$

$\mathbf{d_L(z)}$: never enters the LADDER pipeline as a quantity to be calculated from an assumed cosmology.

LADDER uses a recurrent neural-network architecture based on Long Short-Term Memory (**LSTM**) units to learn the statistical relation between redshift and apparent magnitude.

$$\text{SNe Ia data} \longrightarrow P(m \mid z) \longrightarrow m_{\text{LADDER}}(z)$$

No **GRB** data are required to train the SNe reconstruction itself.

To calibrate GRB using Amati relation

$$2 \log_{10} \left(\frac{d_L}{\text{Mpc}} \right) = \frac{2}{5} (m - M_B - 25).$$

$$\log_{10} E_{iso} = \log_{10} \left[\frac{S_{bol}}{1+z} \right] + 2 \log_{10} d_L + \log_{10} 4(\pi).$$

$$d_L(z) = d_L(z; H_0, \Omega_m, \Omega_\Lambda, \dots),$$

The Amati relation can consequently be rearranged into:

$$y' = a' + bx$$

$$x = \log_{10} \left[\frac{E_p(1+z)}{300 \text{ keV}} \right],$$

$$y' = \log_{10} \left[\frac{S_{bol}}{1+z} \right] + \frac{2}{5} \mathbf{m_{LADDER}(z)}$$

$$a' = a + 2 \left(\frac{M_B}{5} + 5 \right) - \log_{10} [4\pi(\text{Mpc} \rightarrow \text{cm})^2]$$





GRB Calibration and Extension to High Redshift

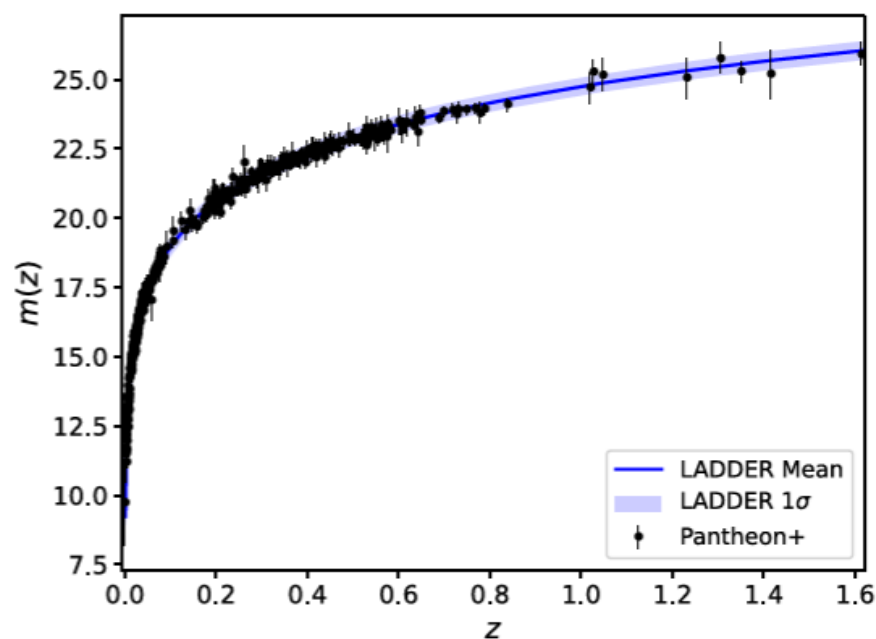
The calibration problem transformed into

$$z, E_p, S_{bol} + m_{LADDER}(z) \rightarrow x, y' \rightarrow a', b, \sigma_{int}$$

then fit via Reichart (2001)

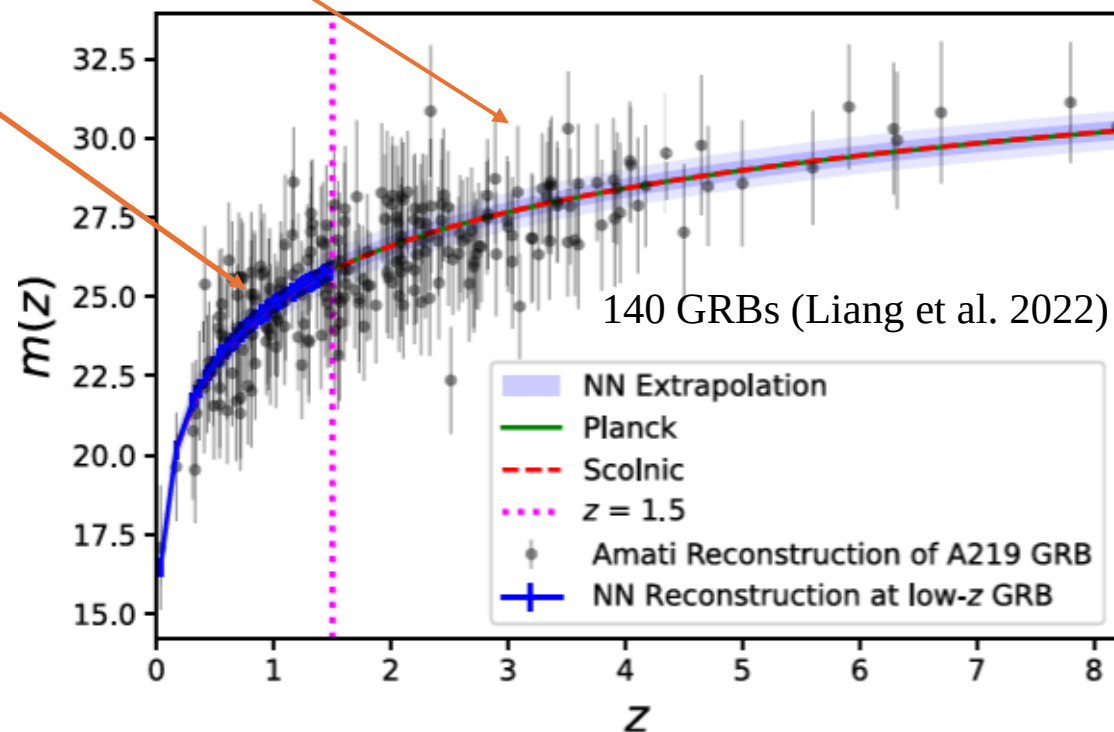
$$a' + b = \log_{10} \left[\frac{S_{bol}}{1+z} \right] + \frac{2}{5} m_{LADDER}(z)$$

$$m_{GRB} = \frac{5}{2} \left\{ a' + bx - \log_{10} \left[\frac{S_{bol}}{1+z} \right] \right\}$$



Pantheon+ vs LADDER

Pantheon SNe Ia (Scolnic et al. 2018)



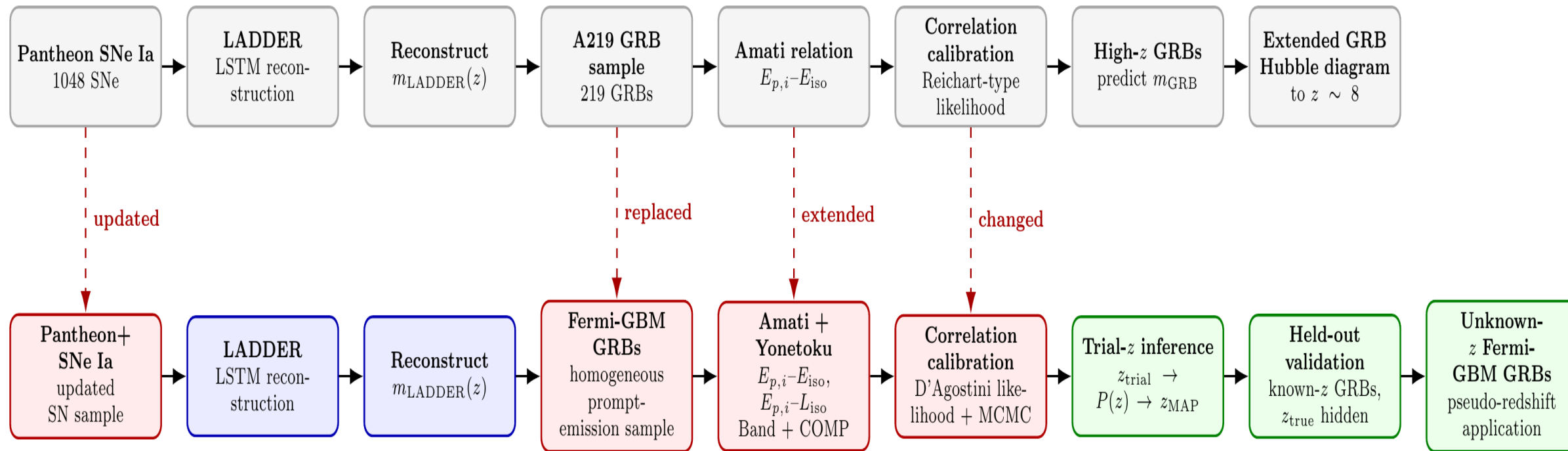
140 GRBs (Liang et al. 2022)

LADDER calibrated GRB dataset compared to other methods

Shah et al., 2024



Updated Datasets





Redshift Estimation through Correlation Inversion

1. Recalculate the GRB quantities at each trial redshift $\longrightarrow z_{trial} \in [z_{min}, z_{max}]$

$$E_{ip}(z) = E_p(1+z), \quad q(z) = \begin{cases} \log_{10} \left[\frac{S_{bol}(z)}{1+z} \right], & \text{Amati} \\ \log_{10} P_{bol}(z), & \text{Yonetoku} \end{cases}$$

2. Predict the magnitude using each calibration-posterior draw

$$m_{GRB_j}(z) = 2.5 [a_j + b_j x(z) - q(z)]$$

3. Compare the prediction with LADDER

$$\mathcal{L}_j(z) = \frac{1}{\sqrt{2\pi V_j(z)}} \exp \left[-\frac{(m_{GRB,j}(z) - m_{LADDER}(z))^2}{2V_j} \right], \quad V_j = \sigma_{GRB}^2 + \sigma_{LADDER}^2.$$

4. Average over calibration uncertainty to obtain the redshift posterior

$$p(z | GRB, LADDER) \propto \pi(z) \frac{1}{N_{draw}} \sum_{j=1}^{N_{draw}} \mathcal{L}_j(z)$$



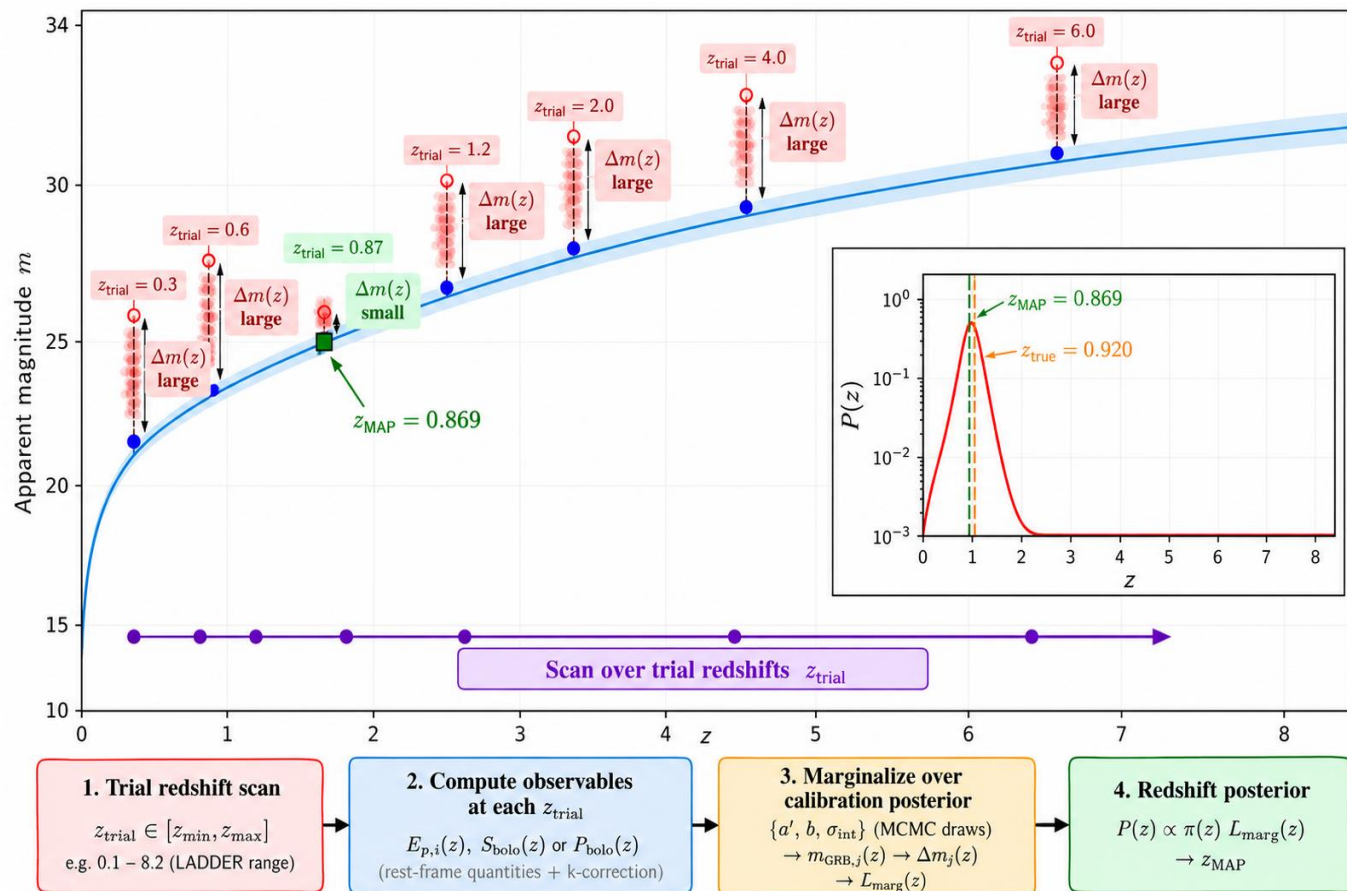
Redshift Estimation through Correlation Inversion

Marginalize over calibration uncertainty

- Evaluate the likelihood for each MCMC draw of the correlation parameters (a' , b , σ_{int}).
- Average these likelihoods to obtain the redshift posterior:

$$p(z | \text{GRB}, \text{LADDER}) \propto \pi(z) \underbrace{\frac{1}{N_{\text{draw}}} \sum_{j=1}^{N_{\text{draw}}} \mathcal{L}_j(z)}_{\text{average over calibration uncertainty}}$$

average over calibration uncertainty





Preliminary results: Validation

Sample: Fermi-GBM

- For each model, we repeated the train–validation split 20 times with different random seeds.

1

Calibration GRBs	124
Held-out validation GRBs	33

2

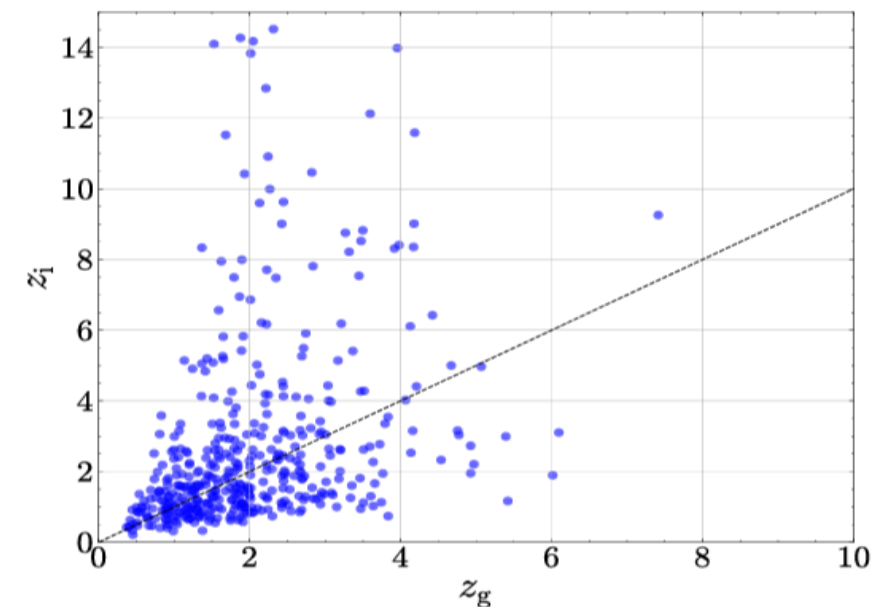
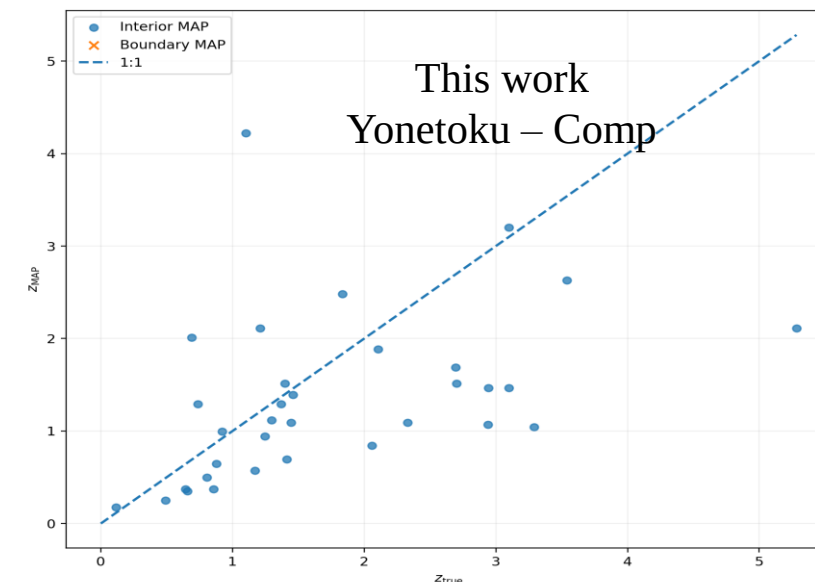
Parameter	a'	b	σ_{int}
Median and 68% CI	$4.0800^{+0.0734}_{-0.0739}$	$1.3149^{+0.1514}_{-0.1517}$	$0.6702^{+0.0493}_{-0.0438}$

3

Normalized error	Median bias	NMAD	RMSE_z
$e = \frac{z_{\text{MAP}} - z_{\text{true}}}{1 + z_{\text{true}}}$	$\text{median}(e)$	1.4826 median ($ e - \text{median}(e) $)	$\sqrt{\text{mean}[(z_{\text{MAP}} - z_{\text{true}})^2]}$

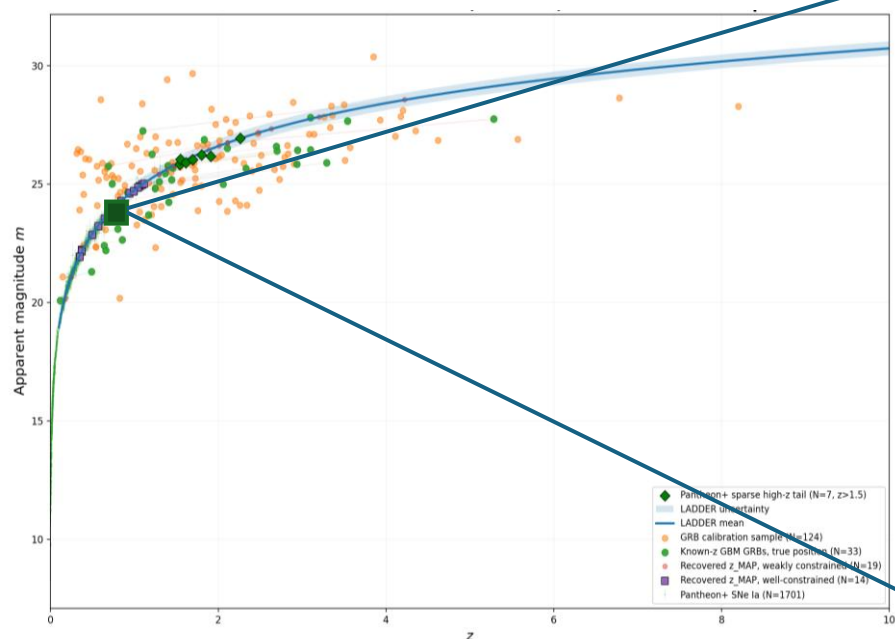
4

Well-constrained	Narrow, informative redshift posterior
Weakly constrained	Broad or prior-sensitive redshift posterior

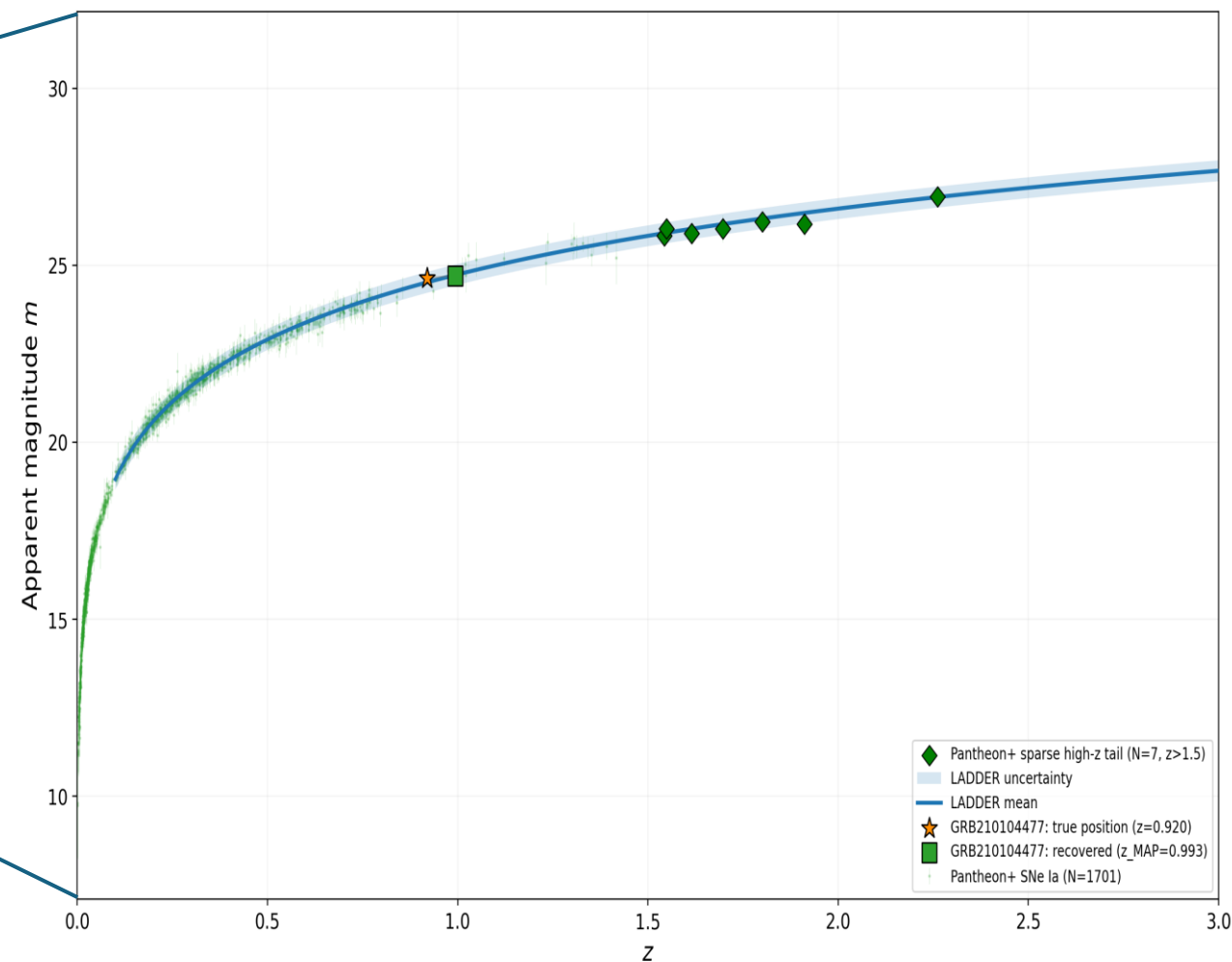




Preliminary results: Yonetoku relation - Band Model

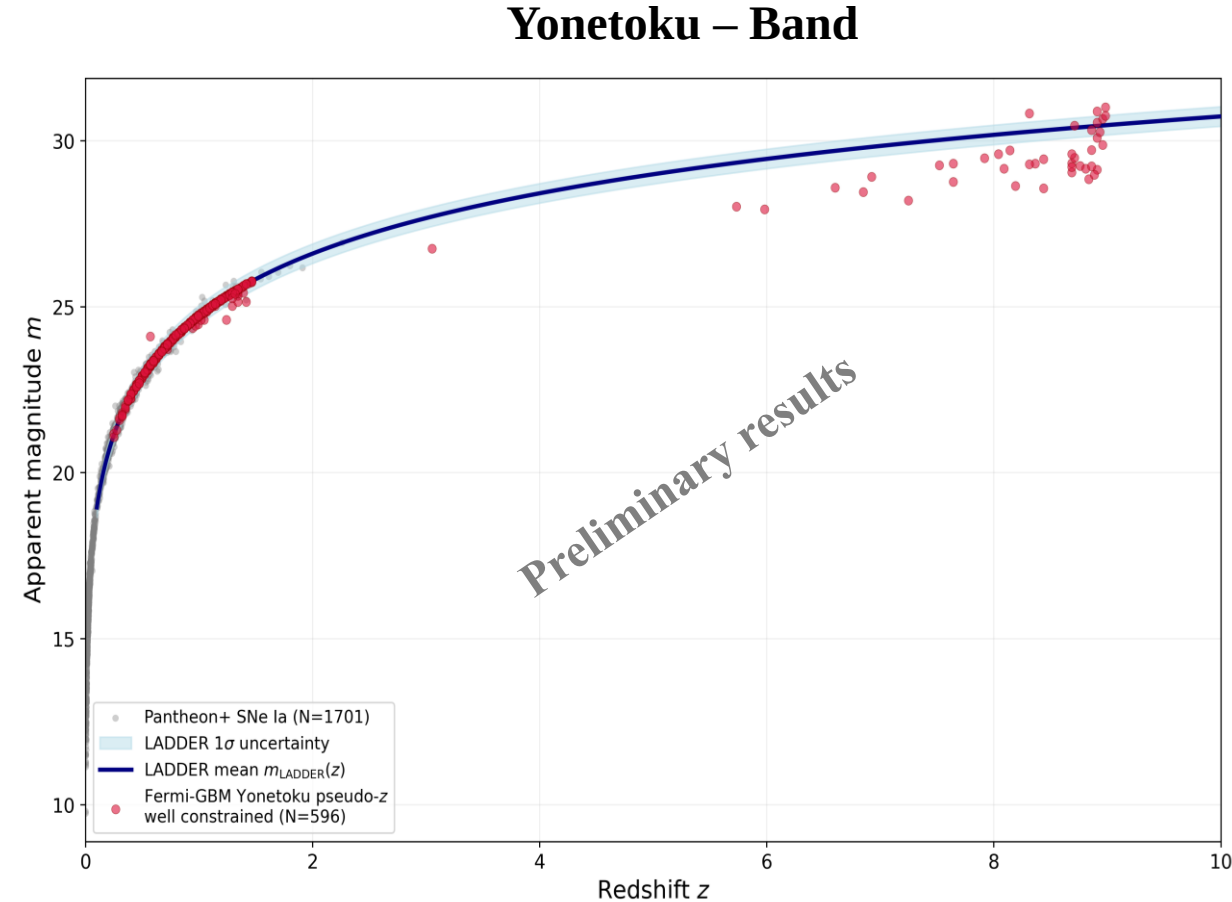


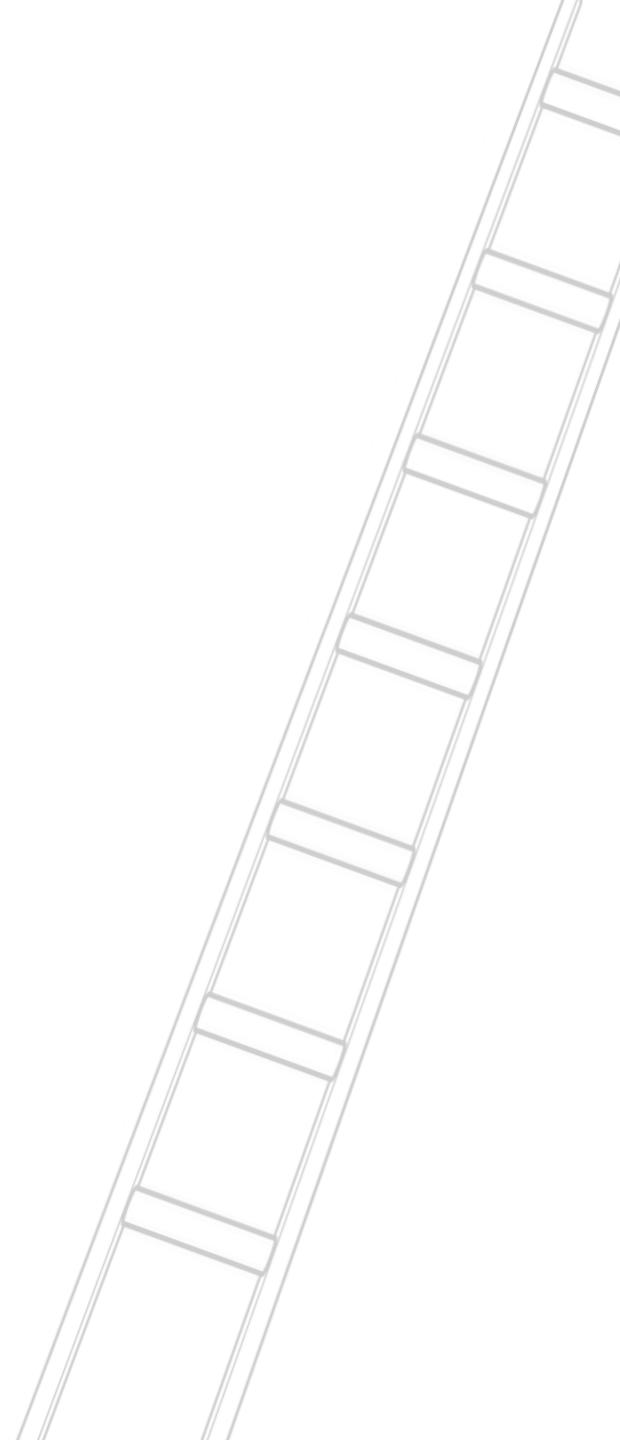
This work
Yonetoku – Band

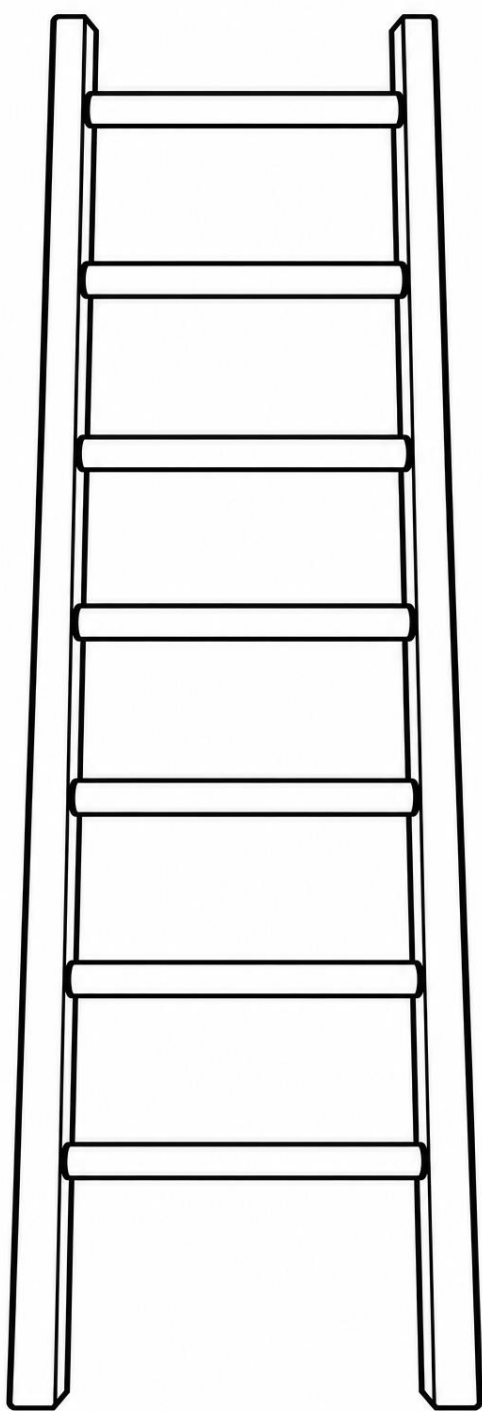


Summary

- Following validation, apply the method to the full Fermi-GBM sample that meets our selection criteria.
- Preliminary validation results favour **Yonetoku** for redshift estimation.
- **Amati** provides weaker redshift constraints in our analysis.
- **Next steps:** Retrain LADDER using alternative SNe Ia datasets (**DES5Y, JLA, and the MASTER**) sample and assess the impact on calibration and redshift estimates.







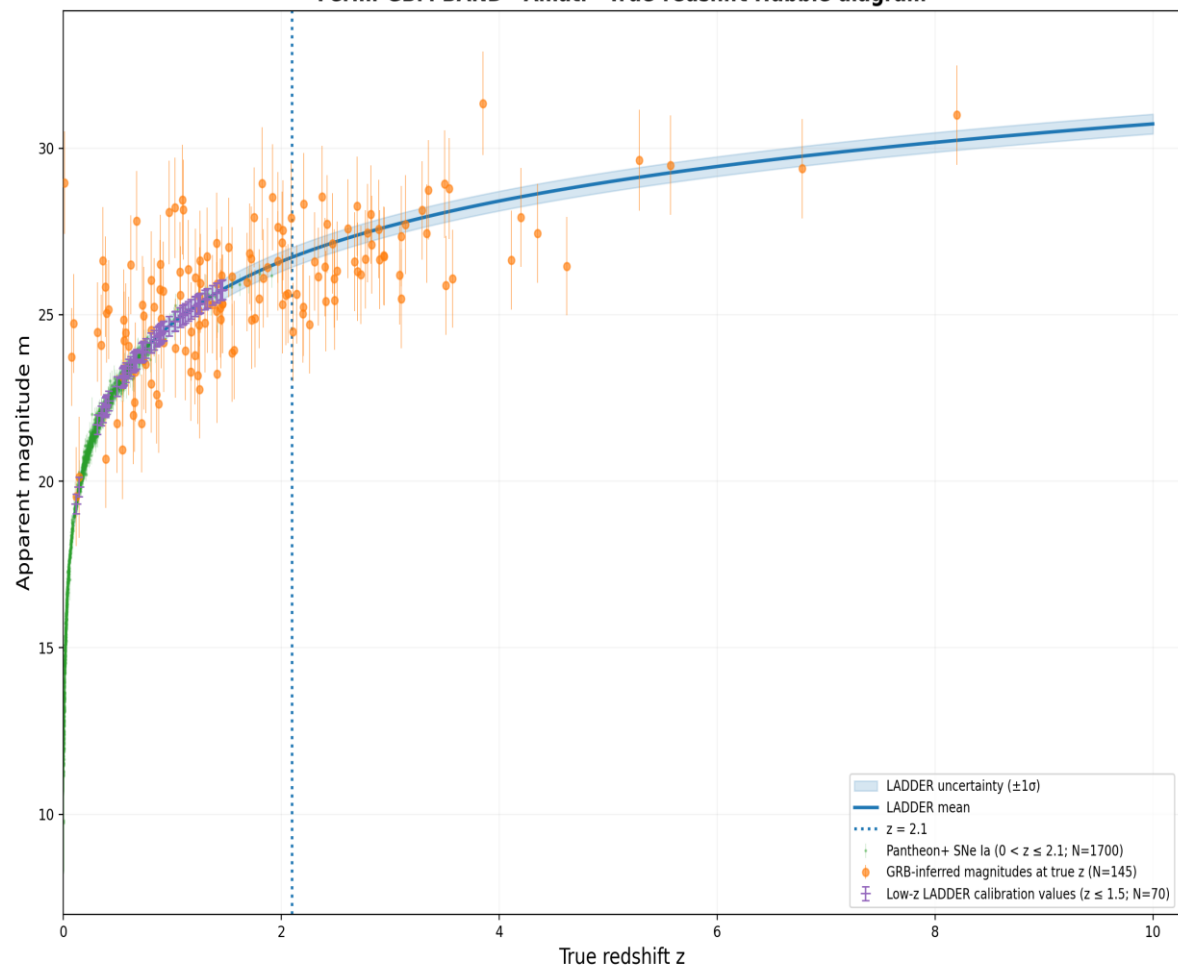
Backup Slides



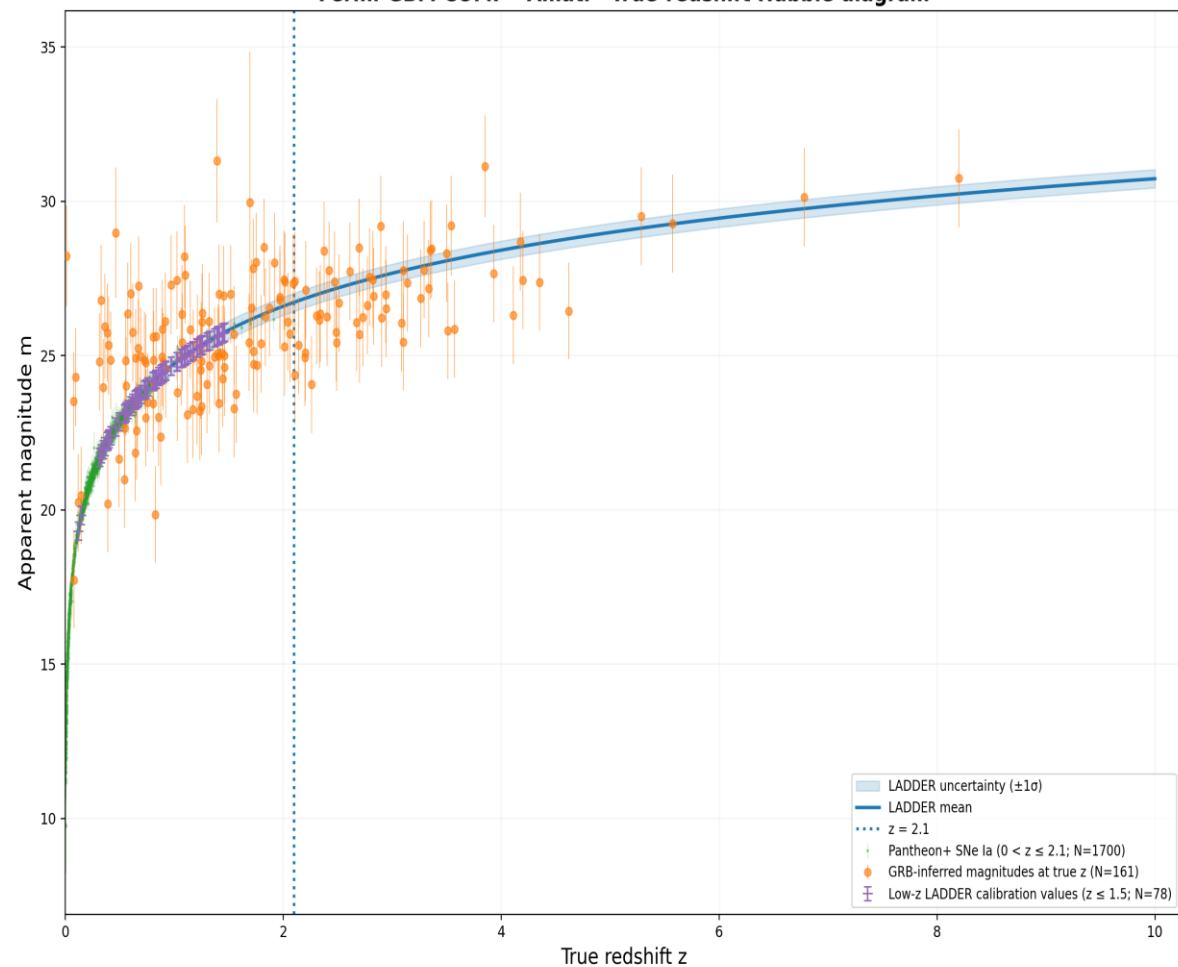
Backup

Preliminary results: Amati Relation - Band & Comp model

Fermi-GBM BAND · Amati · True-redshift Hubble diagram



Fermi-GBM COMP · Amati · True-redshift Hubble diagram

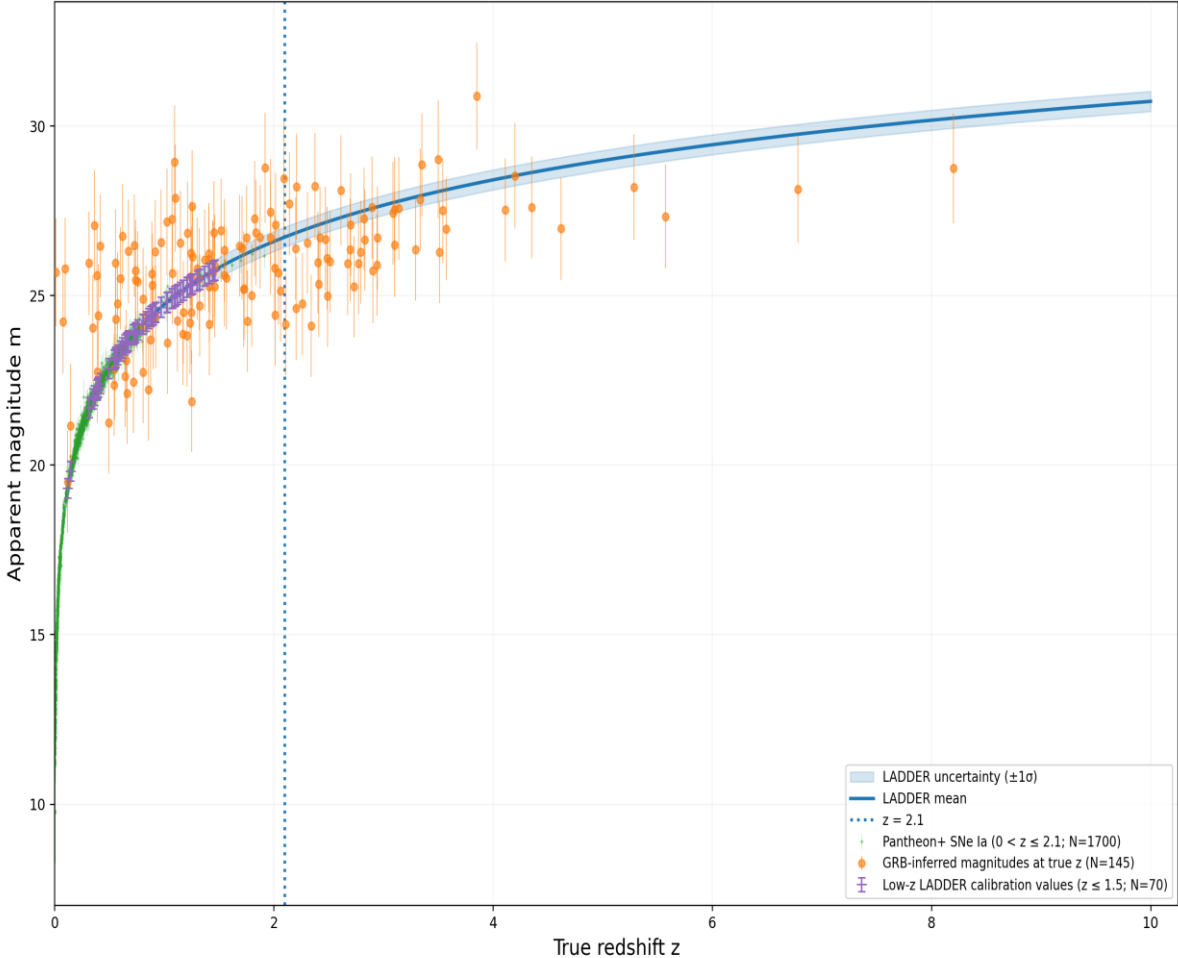




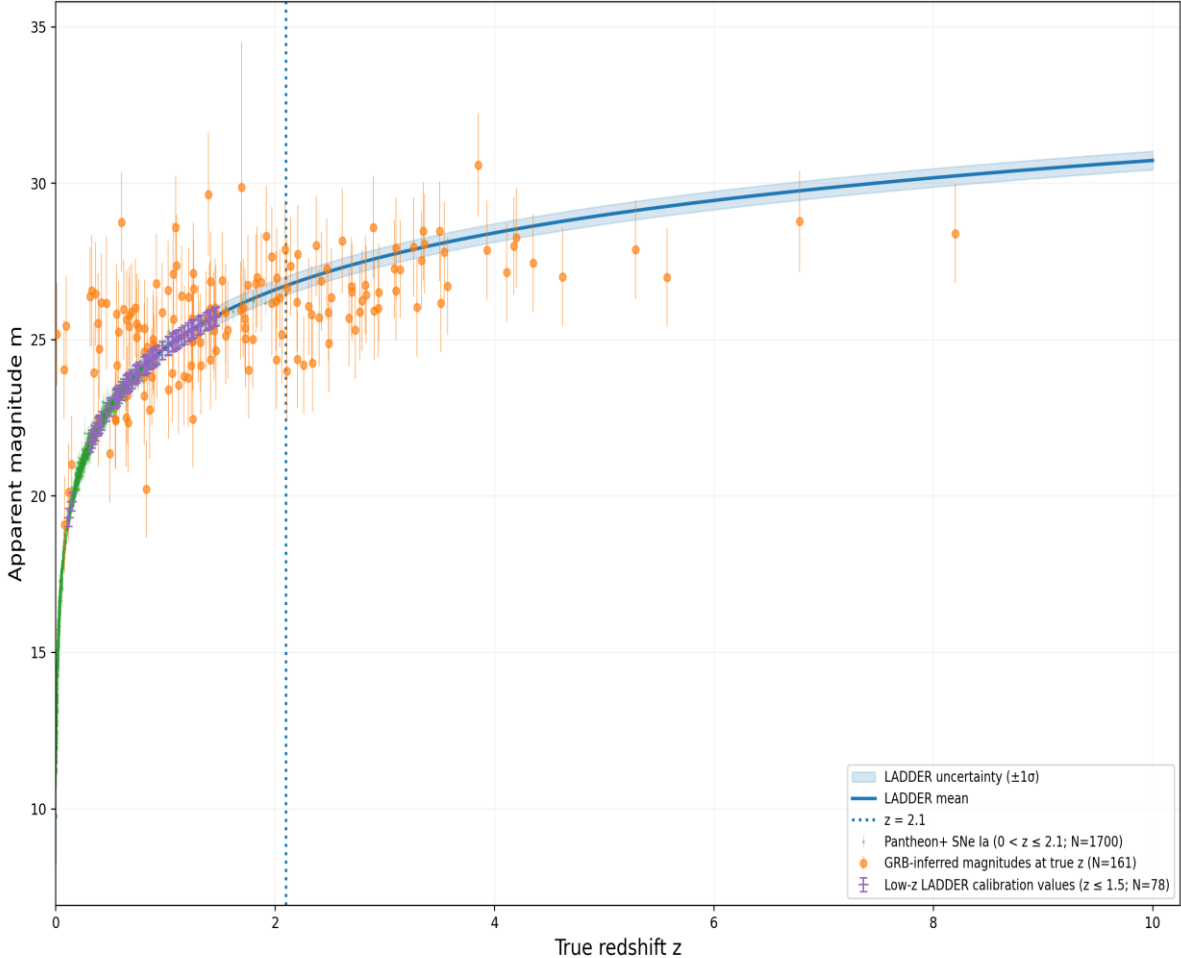
Backup

Preliminary results: Yonetoku Relation - Band & Comp model

Fermi-GBM BAND · Yonetoku · True-redshift Hubble diagram



Fermi-GBM COMP · Yonetoku · True-redshift Hubble diagram

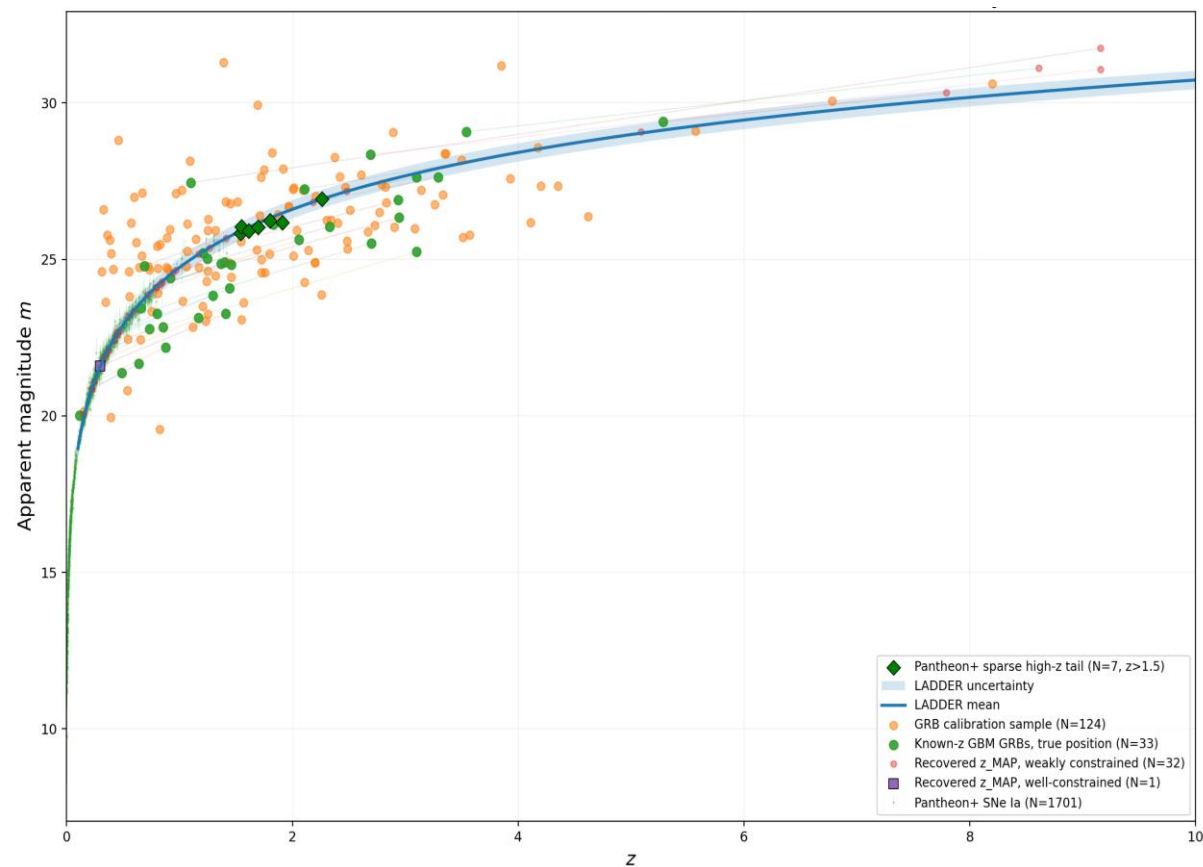
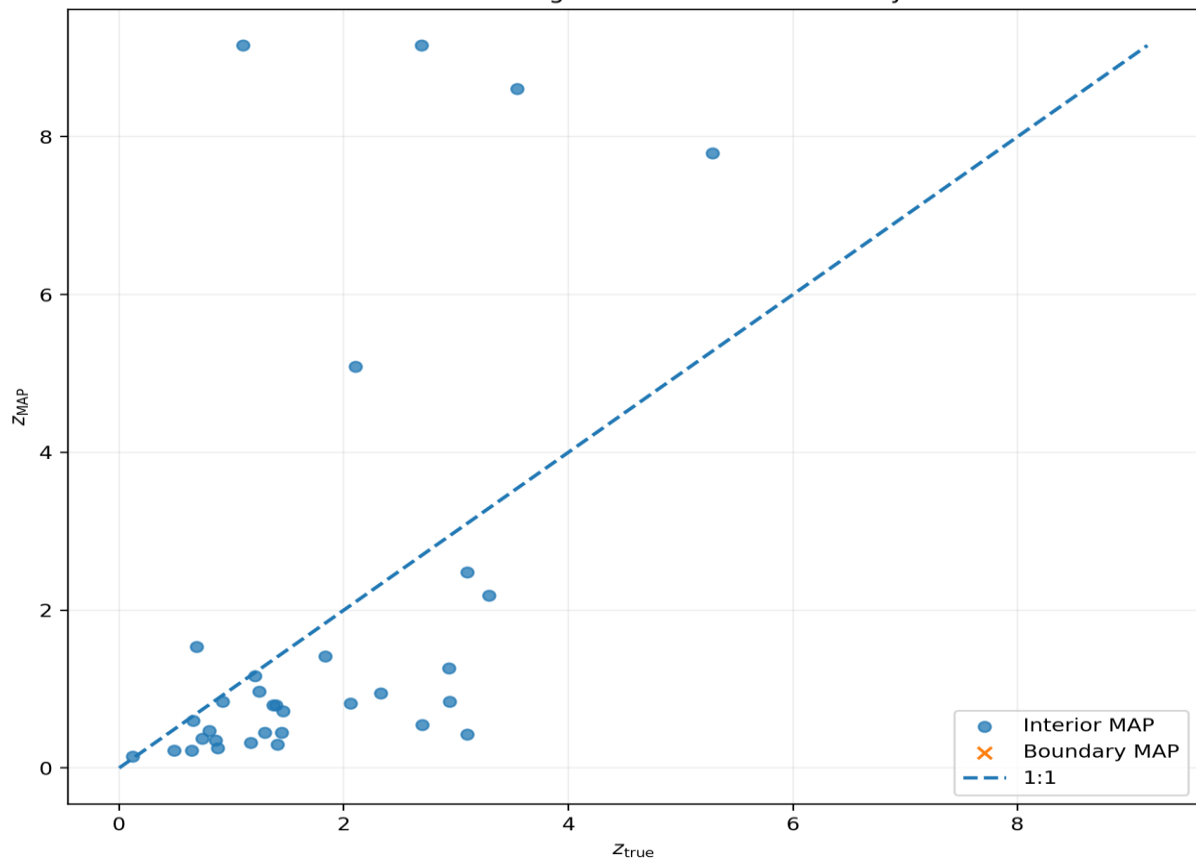




Backup

Preliminary results: Amati Relation - Band model

Amati — leakage-aware known-z recovery





Backup

Corner Plot: Yonetoku relation – Band

