

J-PAS:

A Neural Network approach to single stellar population characterization

Helena Domínguez Sánchez

Instituto de Física de Cantabria

Thanks to:

P. Coelho
G. Bruzual
A. Hernán-Caballero
and J-PAS collaboration



MINISTERIO
DE CIENCIA, INNOVACIÓN
Y UNIVERSIDADES



Cofinanciado por
la Unión Europea



AGENCIA
ESTATAL DE
INVESTIGACIÓN



UC | Universidad
de Cantabria

ML4Astro – 02/09/2026 – Valletta

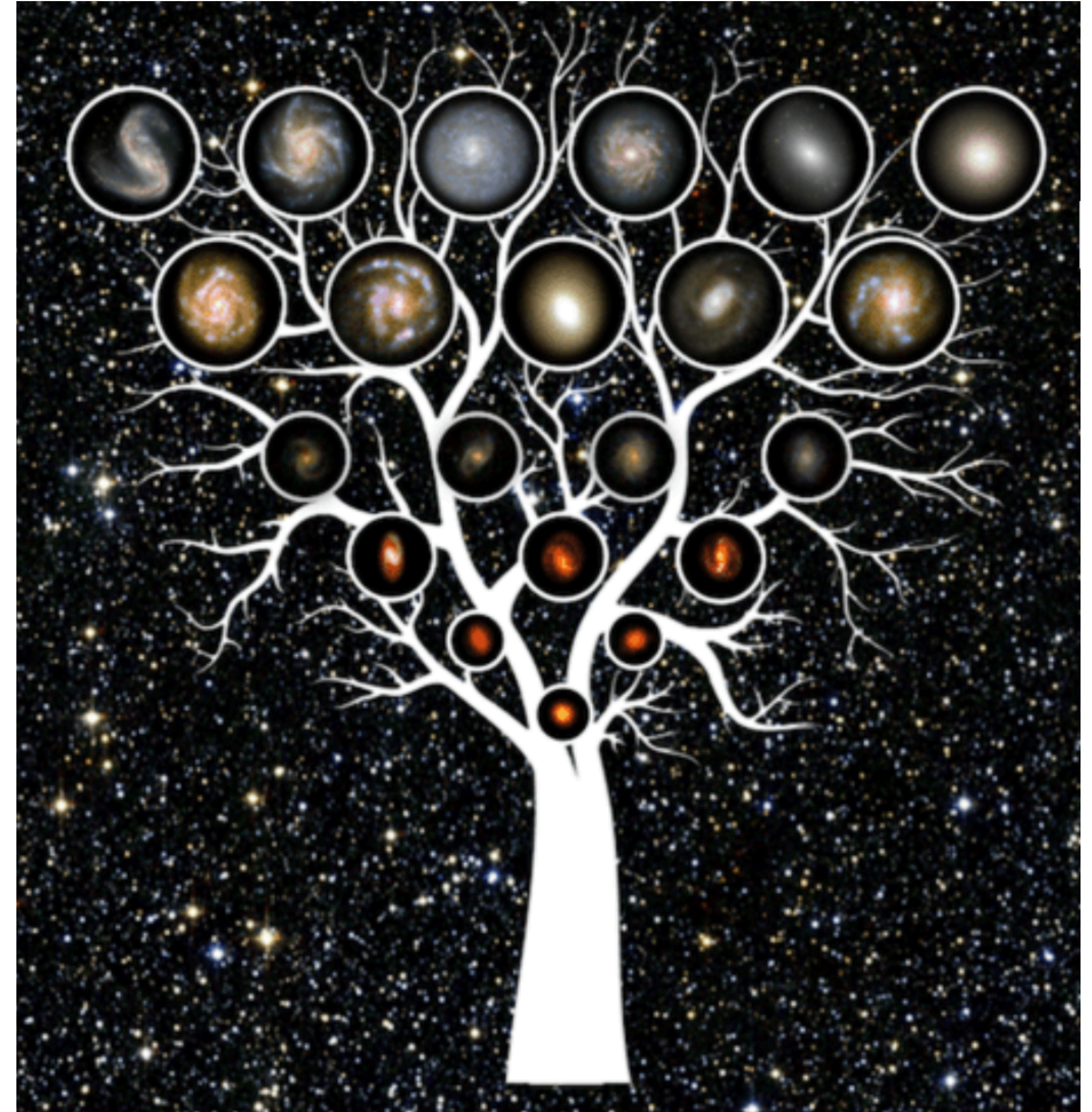


J-PAS

Javalambre Physics of the Accelerating
Universe Astrophysical Survey

Introduction

- **Stellar populations:** Intrinsic properties of the stars forming a galaxy (age, metallicity, dust extinction, etc.)
- **Fundamental for understanding galaxy evolution:** dependence on other galaxy properties (e.g., morphology, mass, gas fraction), environment and how they have changed across cosmic time.
- **Traditionally recovered through:**
 - Line indices
 - SED-fitting (photometry)
 - Full spectra fitting (spectra)
- **Neural networks** have proven extremely useful for many astronomical purposes:
 - Morphological classification (e.g. *Dieleman+15, Huertas-Company+15, Vega Ferrero+21, Domínguez-Sanchez+18,19,22,23, Walmsley+22, Bom+24, Huertas-Company&Lanusse+26*)
 - Redshift estimation (e.g., *Hayat+21, Treyer+26, Merz+26, Moran+26*)
 - Rather unexplored for stellar populations prediction (*Martínez-Solaache+21,22,23, Liew-Cain+21, Woo+24, Wang+24, Iglesias-Navarro+24, Galcerán+26*)



Based on Domínguez Sánchez et al. 2026



A&A, 705, A219 (2026)
<https://doi.org/10.1051/0004-6361/202556251>
© The Authors 2026

Astronomy
&
Astrophysics

J-PAS: A neural network approach to single stellar population characterisation

H. Domínguez Sánchez^{1,2,★}, P. Coelho⁴, G. Bruzual⁵, A. Hernán-Caballero^{2,3}, C. López Sanjuan^{2,3},
J. A. Fernandez-Ontiveros^{2,3}, L. A. Díaz-García⁶, L. Suelves⁷, A. Álvarez-Candal⁶, I. Breda⁶,
S. Gurung-López^{8,9}, V. Placco¹⁰, J. Vega-Ferrero², J. M. Vílchez⁶, R. Abramo¹¹, J. Alcaniz¹², N. Benítez⁶,
S. Bonoli¹³, S. Carneiro¹², J. Cenarro^{2,3}, D. Cristóbal-Hornillos², R. Dupke¹², A. Ederoclite^{2,3},
C. Hernández-Monteagudo^{14,15}, A. Marín-Franch^{2,3}, C. Mendes de Oliveira¹¹, M. Moles², L. Sodré Jr¹¹,
K. Taylor¹⁶, J. Varela², and H. Vázquez Ramío^{2,3}

- ¹ Instituto de Física de Cantabria, Av. de los Castros, 39005 Santander, Cantabria, Spain
² Centro de Estudios de Física del Cosmos de Aragón, Plaza de San Juan, 1, E-44001 Teruel, Spain
³ Unidad Asociada CEFCA-IAA, CEFCA, Unidad Asociada al CSIC por el IAA y el IFCA, Plaza San Juan 1, 44001 Teruel, Spain
⁴ Universidade de São Paulo, Instituto de Astronomia, Geofísica e Ciências Atmosféricas, Rua do Matão, 1226, 05508-090 São Paulo, SP, Brazil
⁵ Instituto de Radioastronomía y Astrofísica, Universidad Nacional Autónoma de México, Morelia, Michoacán 58089, Mexico
⁶ Instituto de Astrofísica de Andalucía (CSIC), PO Box 3004, 18080 Granada, Spain
⁷ Tartu Observatory, University of Tartu, Observatooriumi 1, Tõravere 61602, Estonia
⁸ Observatori Astronòmic de la Universitat de València, Ed. Instituts d'Investigació, Parc Científic. C/ Catedrático José Beltrán, n2, 46980 Paterna, Valencia, Spain
⁹ Departament d'Astronomia i Astrofísica, Universitat de València, 46100 Burjassot, Spain
¹⁰ NSF NOIRLab, Tucson, AZ 85719, USA
¹¹ Departamento de Astronomia, Instituto de Astronomia, Geofísica e Ciências Atmosféricas, Universidade de São Paulo, São Paulo, Brazil
¹² Observatório Nacional, Rua General José Cristino, 77, São Cristóvão, 20921-400 Rio de Janeiro, RJ, Brazil
¹³ Donostia International Physics Center (DIPC), Manuel Lardizabal Ibilbidea, 4, San Sebastián, Spain
¹⁴ Instituto de Astrofísica de Canarias, C/ Vía Láctea s/n, E-38205, La Laguna, Tenerife, Spain
¹⁵ Universidad de La Laguna, Avda Francisco Sánchez, E-38206 San Cristóbal de La Laguna, Tenerife, Spain
¹⁶ Instruments4, 4121 Pembury Place, La Canada Flintridge, CA 91011, USA

Received 4 July 2025 / Accepted 10 November 2025

ABSTRACT

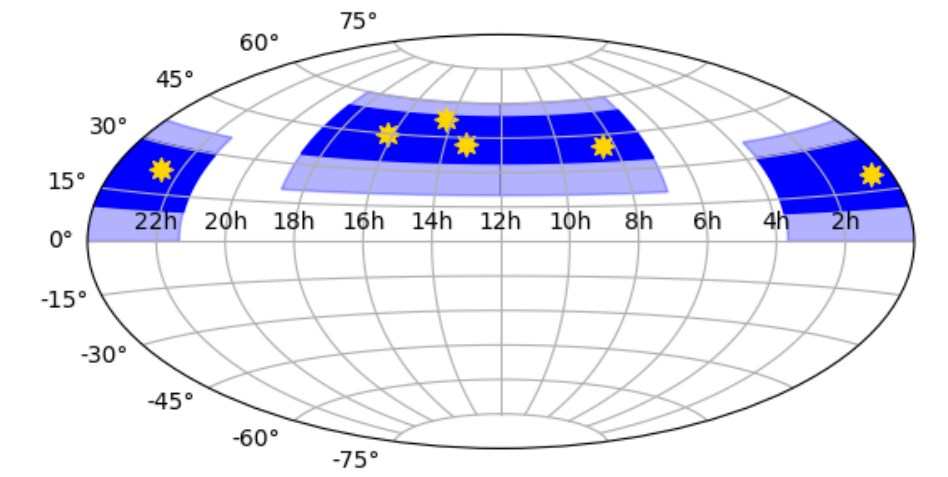
J-PAS (Javalambre Physics of the Accelerating Universe Astrophysical Survey) will present a groundbreaking photometric survey covering 8500 deg² of the visible sky from Javalambre, capturing data in 56 narrow-band filters. This survey promises to revolutionise galaxy evolution studies by observing ~10⁸ galaxies with low spectral resolution. A crucial aspect of this analysis involves predicting stellar population parameters from the observed galaxy photometry. In this study, we combined the exquisite J-PAS photometry with state-of-the-art single stellar population (SSP) libraries to accurately predict stellar age, metallicity, and dust attenuation with a neural network (NN) model. The NN was trained on synthetic J-PAS photometry from different SSP libraries (E-MILES, Charlot & Bruzual, and XSL) to enhance the robustness of our predictions against individual SSP model variations and limitations. To create mock samples with varying observed magnitudes, we added artificial noise in the form of random Gaussian variations within typical observational uncertainties in each band. Our results indicate that the NN was able to accurately estimate stellar parameters for SSP models without any evident degeneracies, surpassing a Bayesian SED-fitting method on the same test set. We obtained the median bias, scatter, and the percentage of outliers: $\mu = (0.01 \text{ dex}, 0.00 \text{ dex}, 0.00 \text{ mag})$, $\sigma_{\text{NMAD}} = (0.23 \text{ dex}, 0.29 \text{ dex}, 0.04 \text{ mag})$, $f_o = (17\%, 24\%, 1\%)$ at $i \sim 17 \text{ mag}$ for the age, metallicity and dust attenuation, respectively. The accuracy of the predictions is highly dependent on the signal-to-noise ratio (S/N) of the photometry, achieving robust predictions up to $i \sim 20 \text{ mag}$.

Key words. galaxies: fundamental parameters – galaxies: photometry – galaxies: stellar content

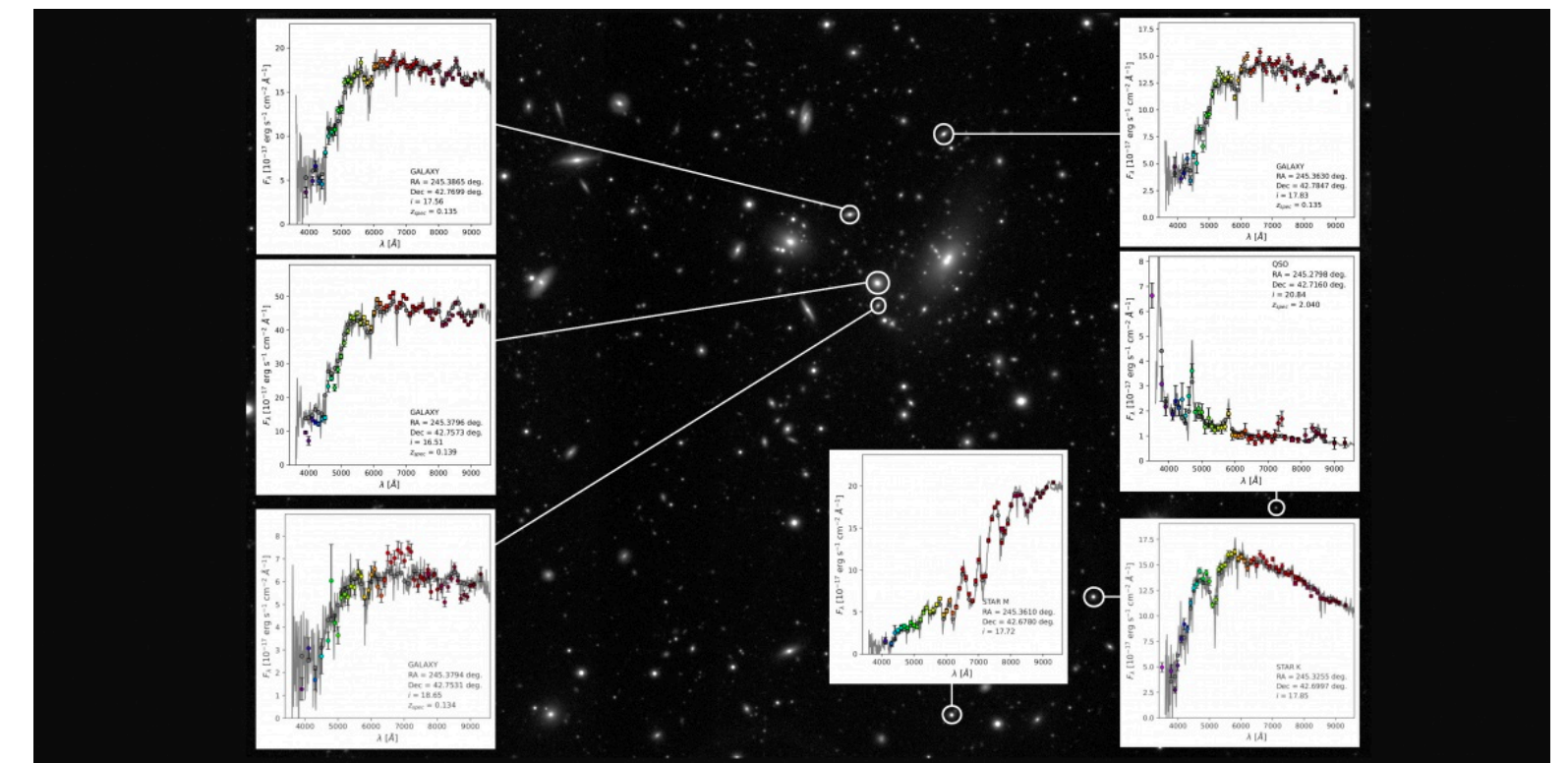
J-PAS survey

Benítez+2009, 2014

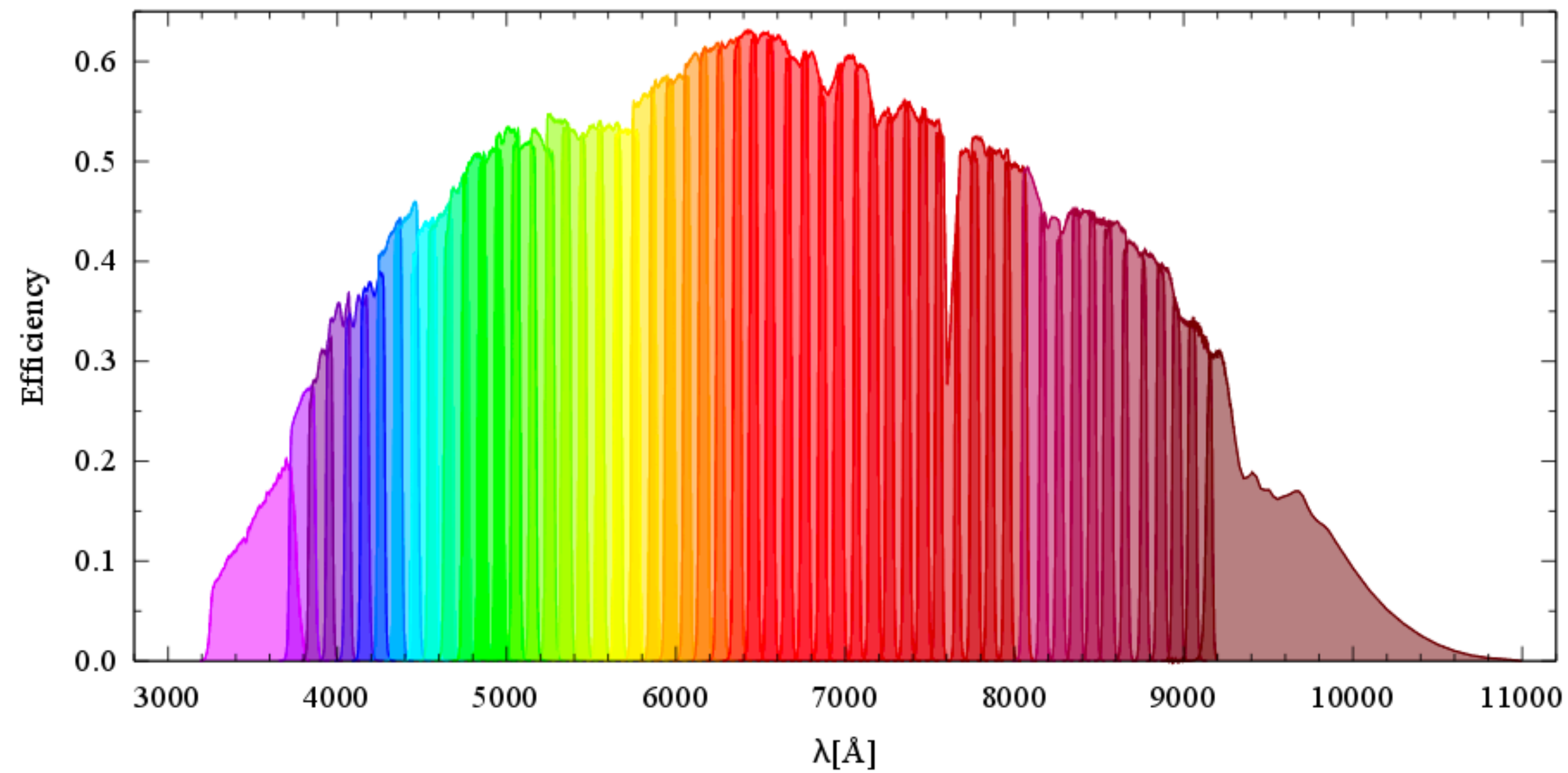
Javalambre Physics of the Accelerating Universe Astrophysical Survey



- Photometric survey with J-PCam (14 CCDs)
- 2.5 m telescope at Observatorio Astrofísico de Javalambre (Teruel)
- Large FoV (7 square degrees)
- Pixel scale = 0.226"/pixel
- **56 narrow-band filters** (pseudo-spectra)
- **8000 deg²** footprint (northern hemisphere)
- First light: 08/2023; 24 deg² observed
- 100s million galaxies ($\text{mag}_i < 22.5$)

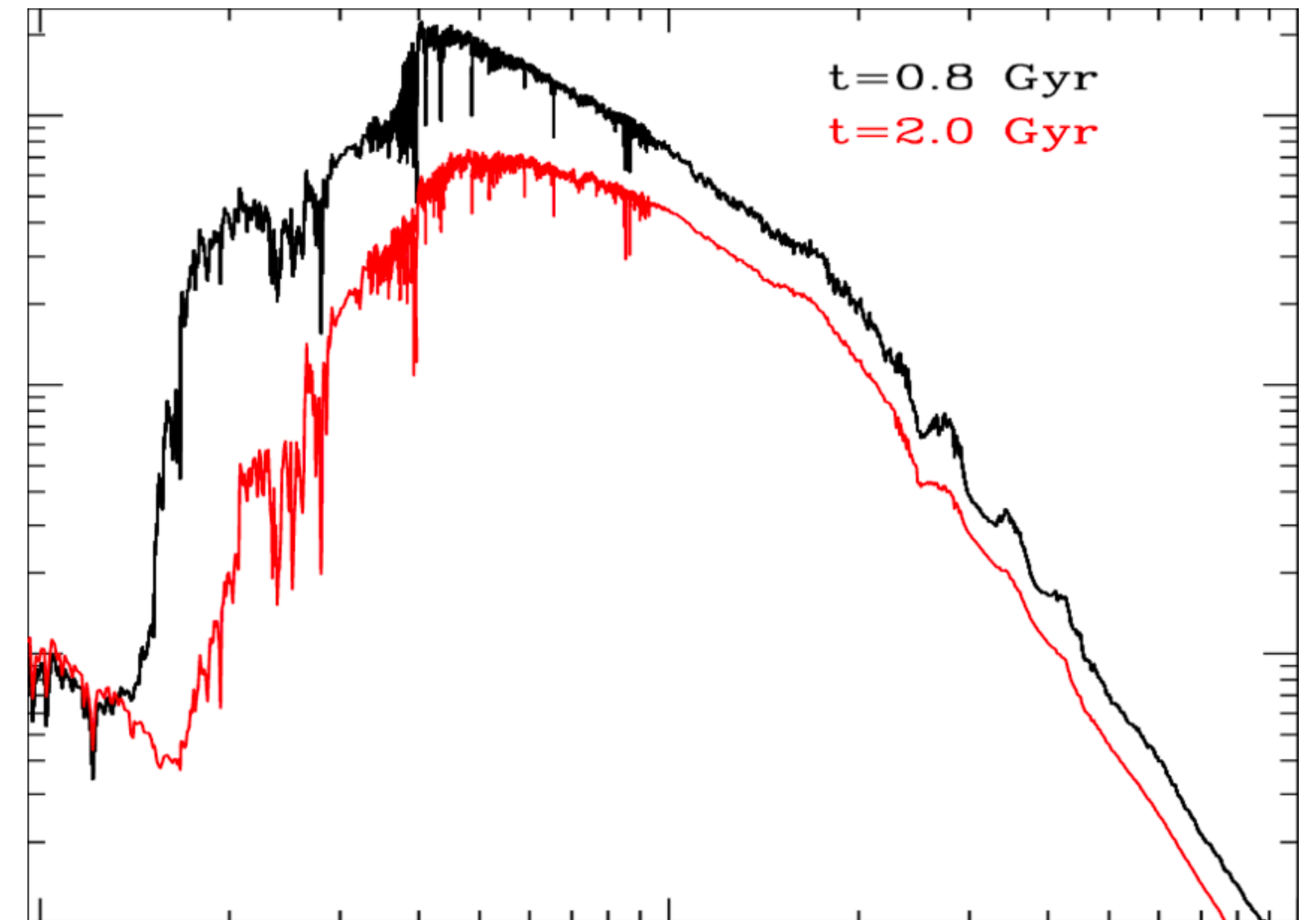


Synthetic photometry



J-PAS filter system (56 bands)

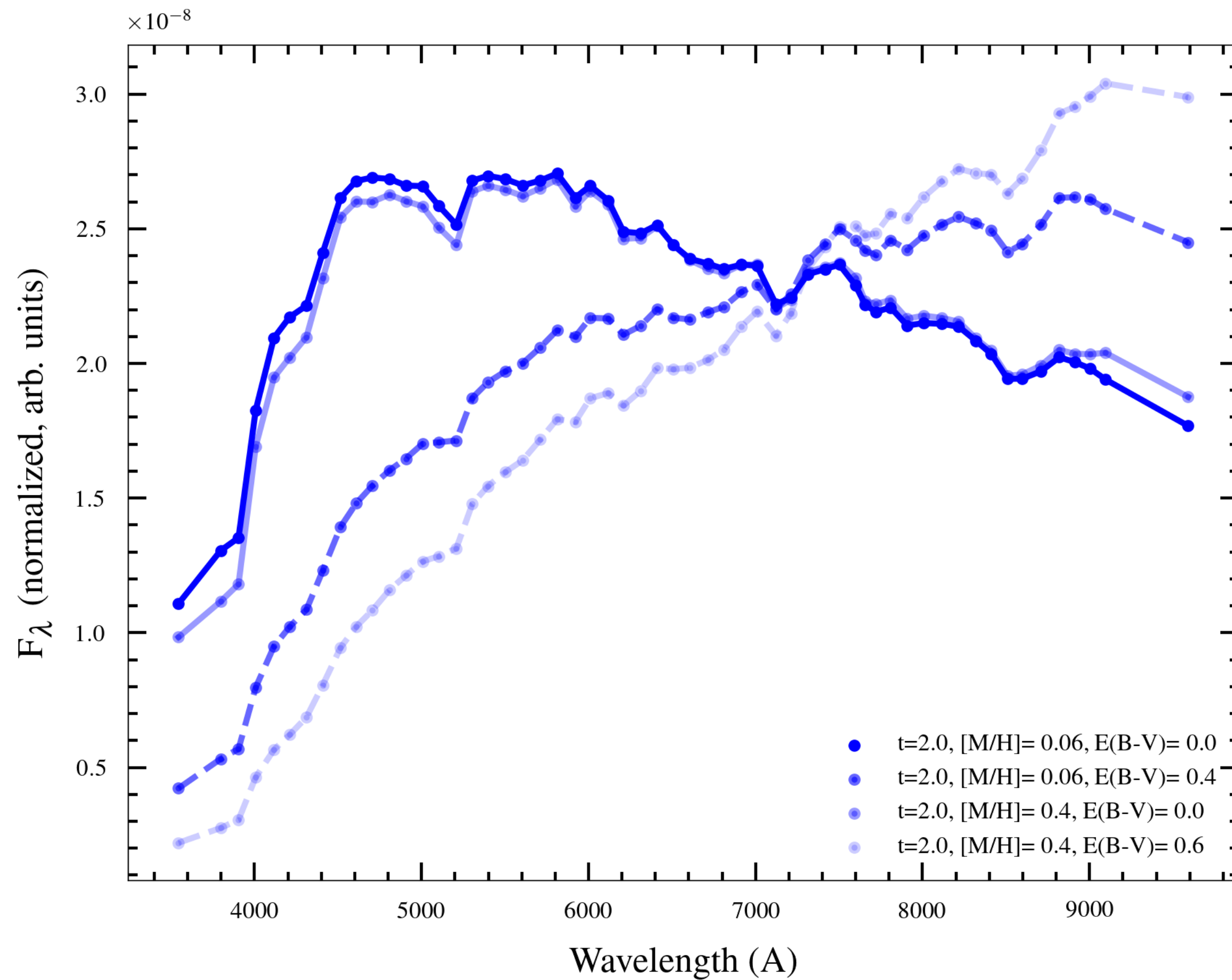
+



Single Stellar Population templates (SSP)

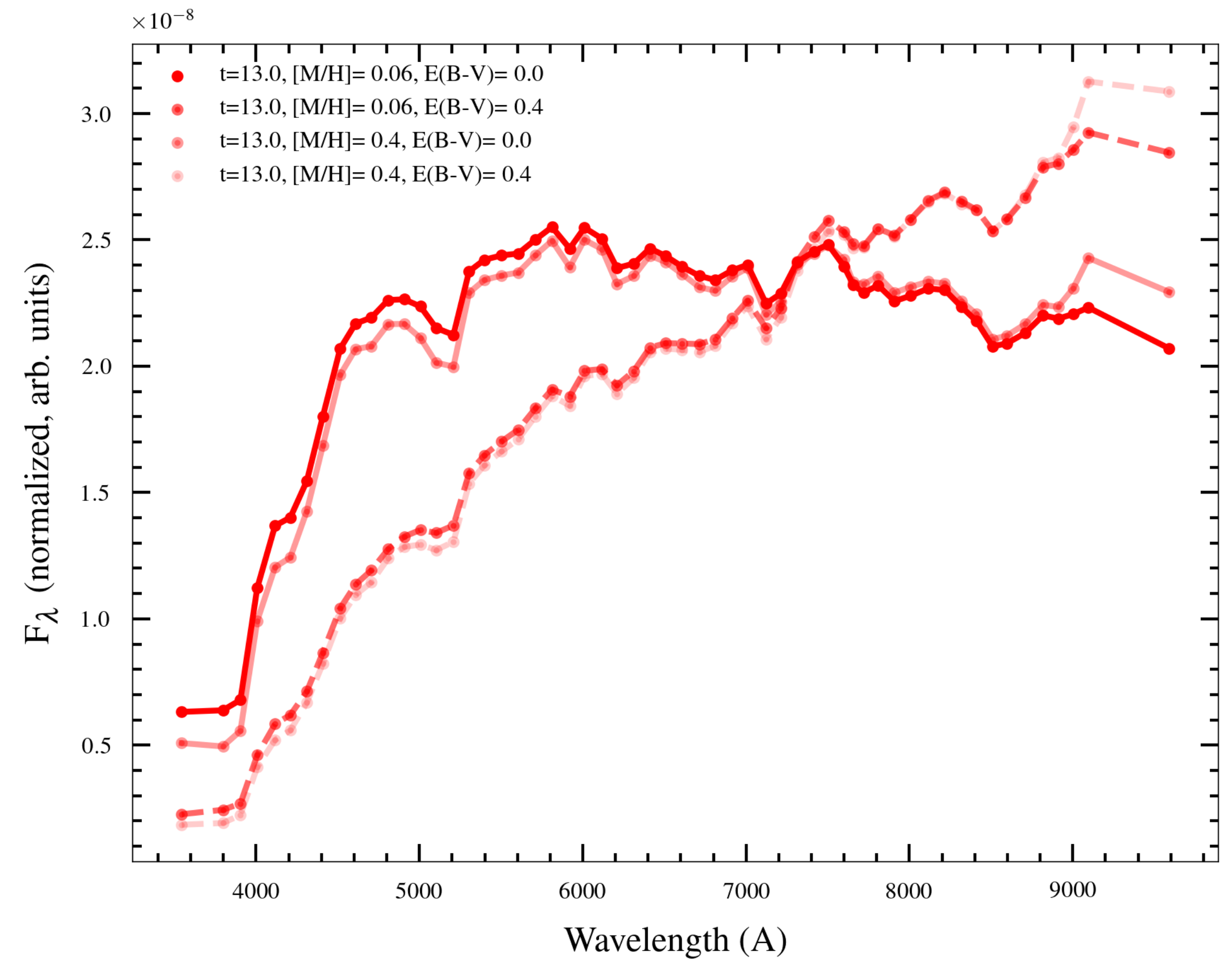
Synthetic photometry

Young galaxy (2 Gyr)



Very subtle differences in the SEDs

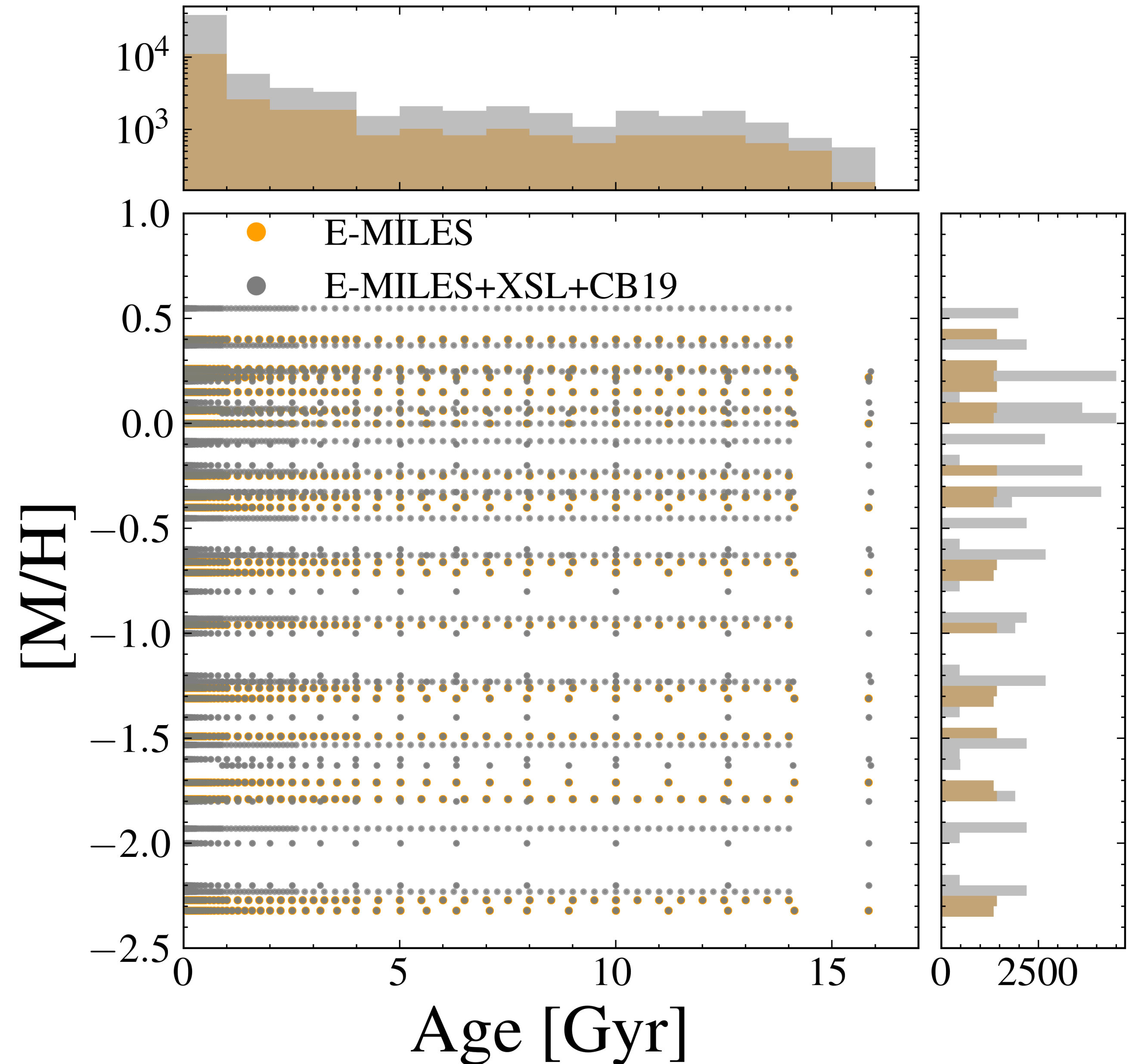
Old galaxy (13 Gyr)



eMiles

Vazdekis+2016

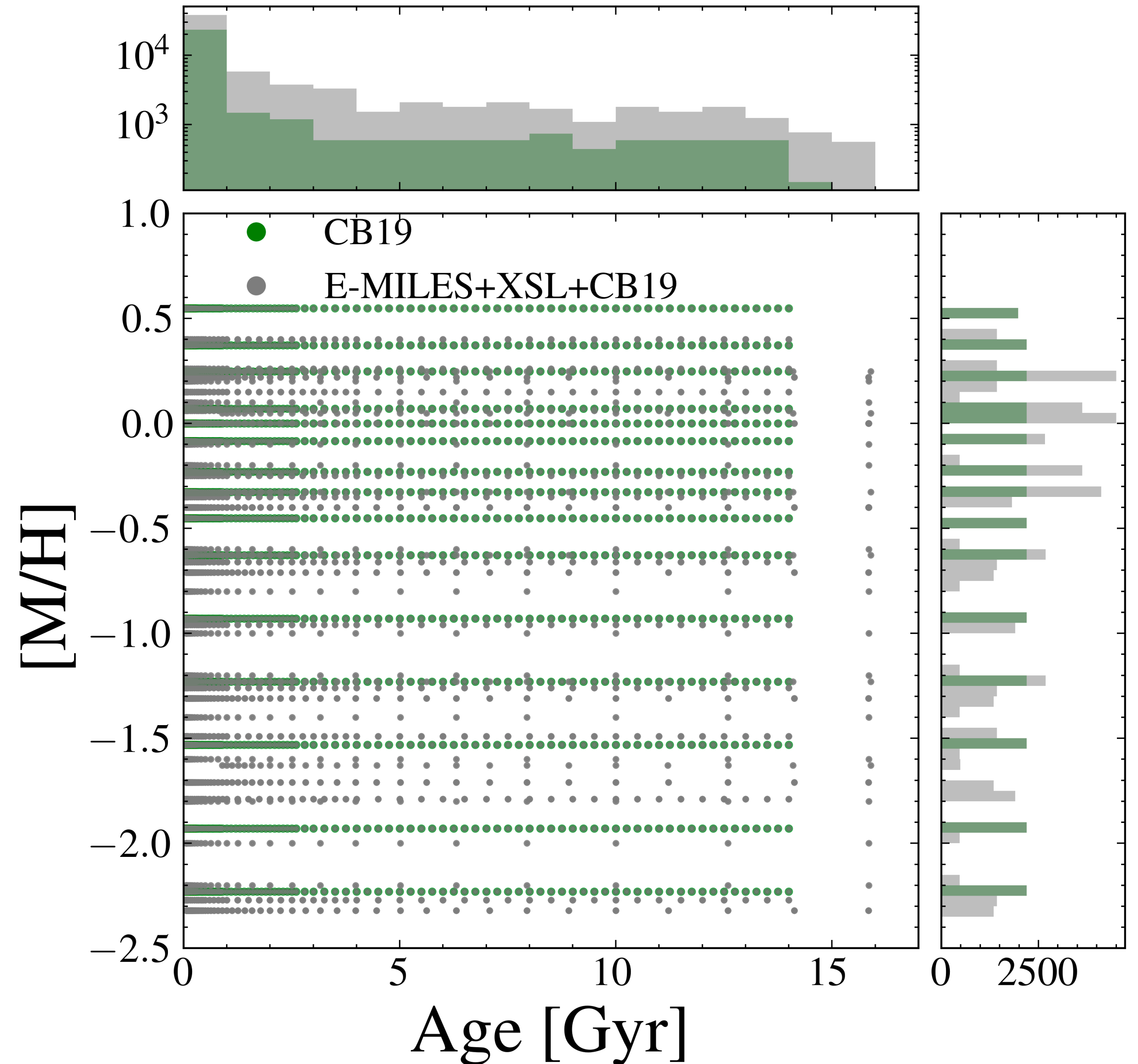
- 26,622 SSP
- WI coverage: 168nm–5micron
- **Stellar fluxes from literature**
- isochrones: Padova+2000 and BaSTI
- **IMF:** Chabrier+2003, Kroupa+2001, Unimodal (1.3)



CB19

Plat+2019

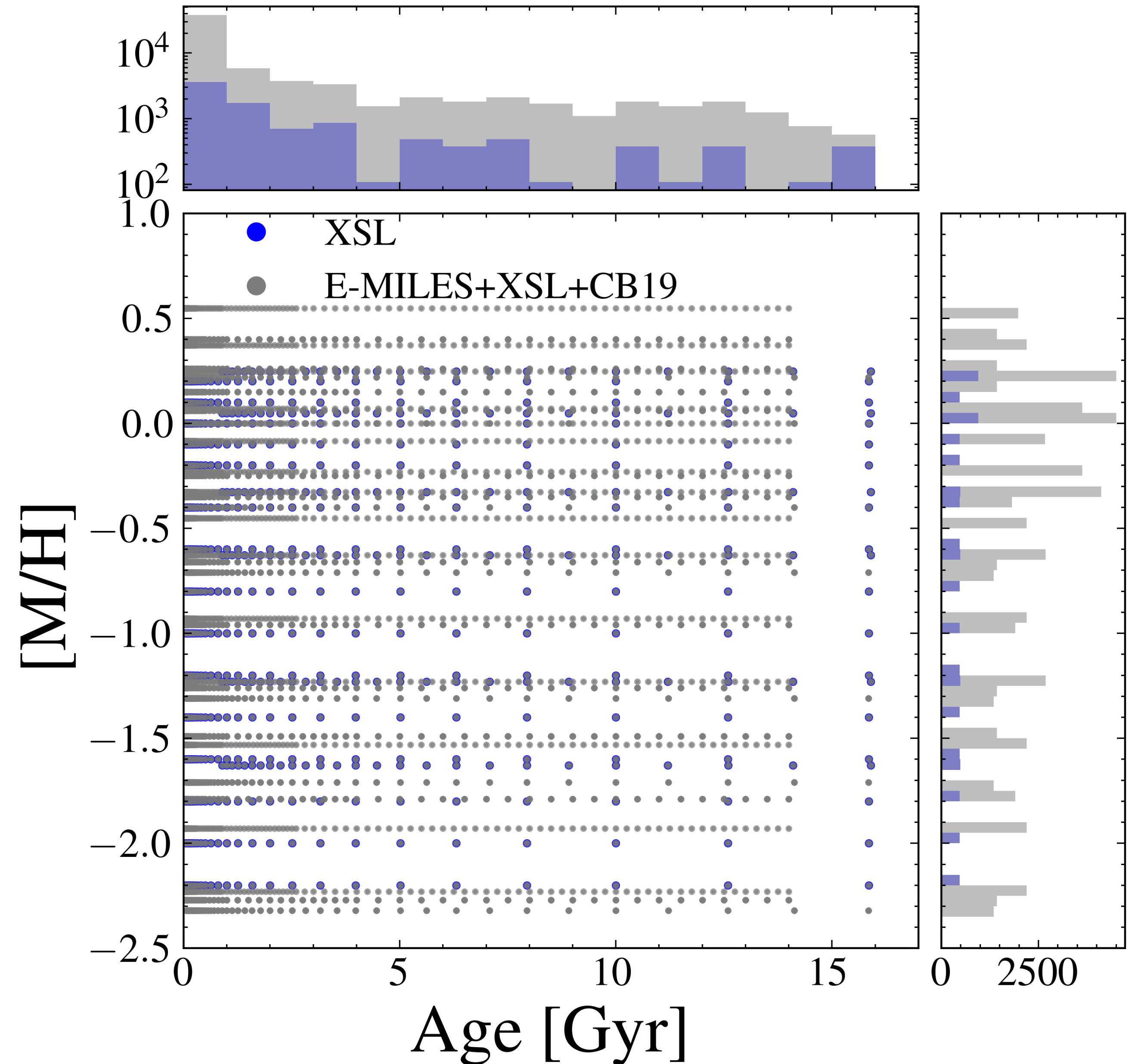
- 32,780 SSP
- WI coverage: 5A–8micron
- Stellar fluxes from literature
- isochrones: PARSEC
- IMF: Chabrier+2003
- **Carefully modelling of UV and young systems**



XSL

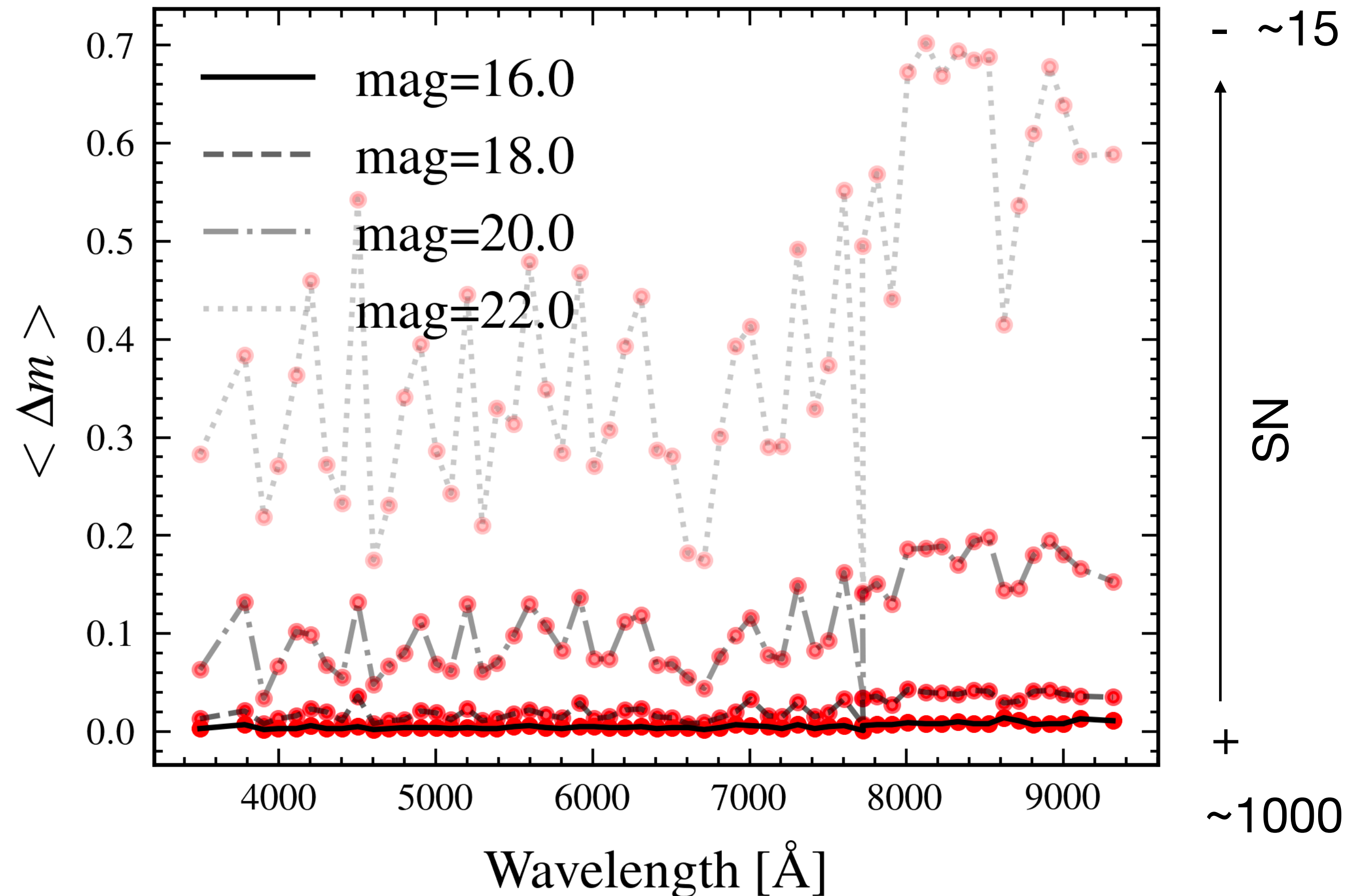
Verro+2022

- 9,936 SSP
- WI coverage: 350-2480nm
- Stellar fluxes: X-Shooter Library DR3
- isochrones: PARSEC and Padova+2000
- IMF: Salpeter and Kroupa
- **broad wavelength coverage** with an homogeneous stellar library, careful modelling of the **RGB and AGB** fluxes



Making SSP templates noisy: Gaussian variations

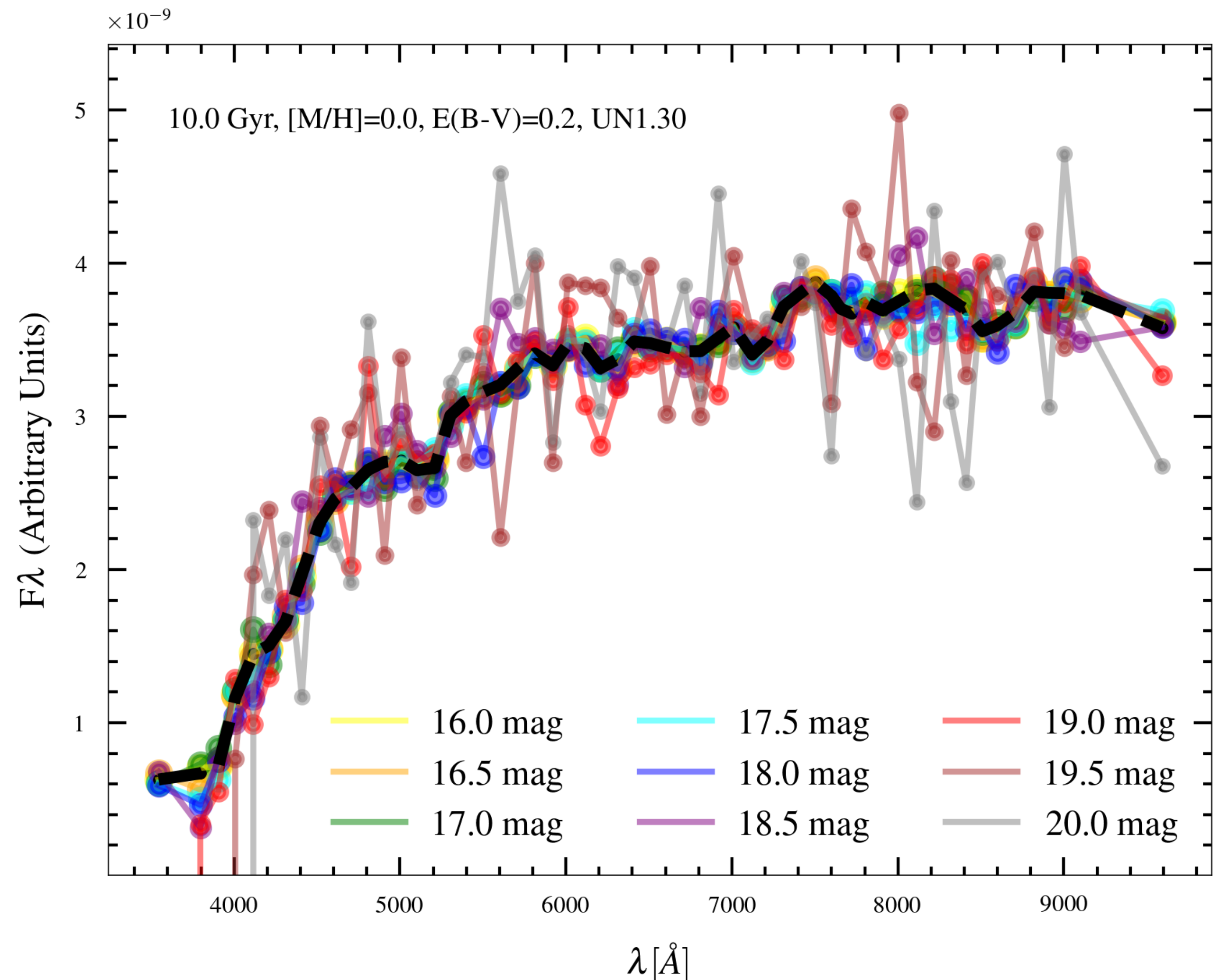
- Applied gaussian variations to the flux assuming typical errors of mini-JPAS* in each band at different magnitude bins.
- Fixed the magnitude in the i-SDSS band and computed the magnitude in the other bands from galaxy SED.
- Applied gaussian variations corresponding to the magnitude in each band.
- $SN = 1.08 / \text{mag_err}$



*J-PAS pathfinder, 1 deg² (Bonoli+2021)

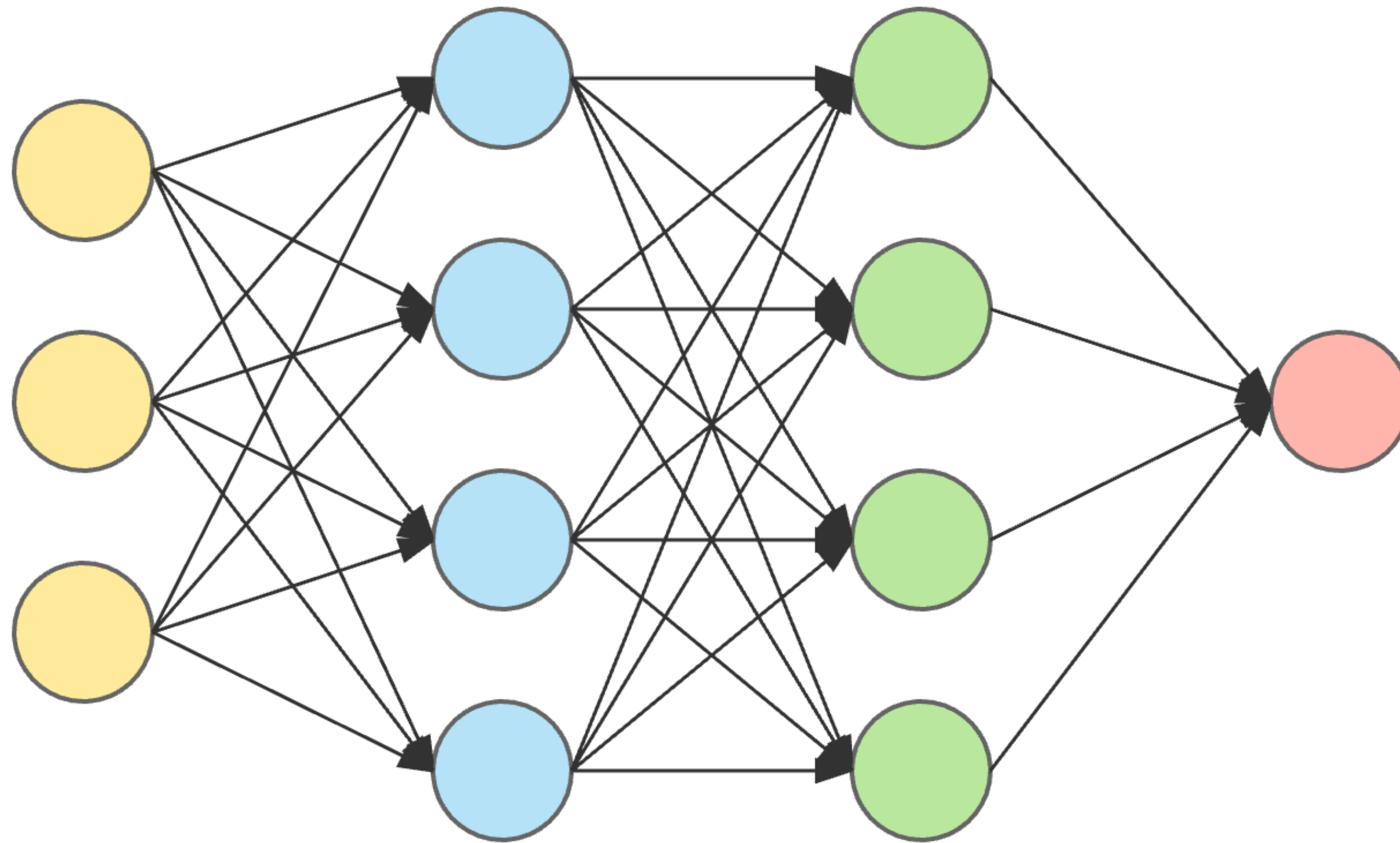
Making SSP templates noisy: Gaussian variations

- Applied gaussian variations to the flux assuming typical errors of mini-JPAS* in each band at different magnitude bins.
- Fixed the magnitude in the i-SDSS band and computed the magnitude in the other bands from galaxy SED.
- Applied gaussian variations corresponding to the magnitude in each band.
- $\text{SN} = 1.08 / \text{mag_err}$



*J-PAS pathfinder, 1 deg² (Bonoli+2021)

Neural Networks

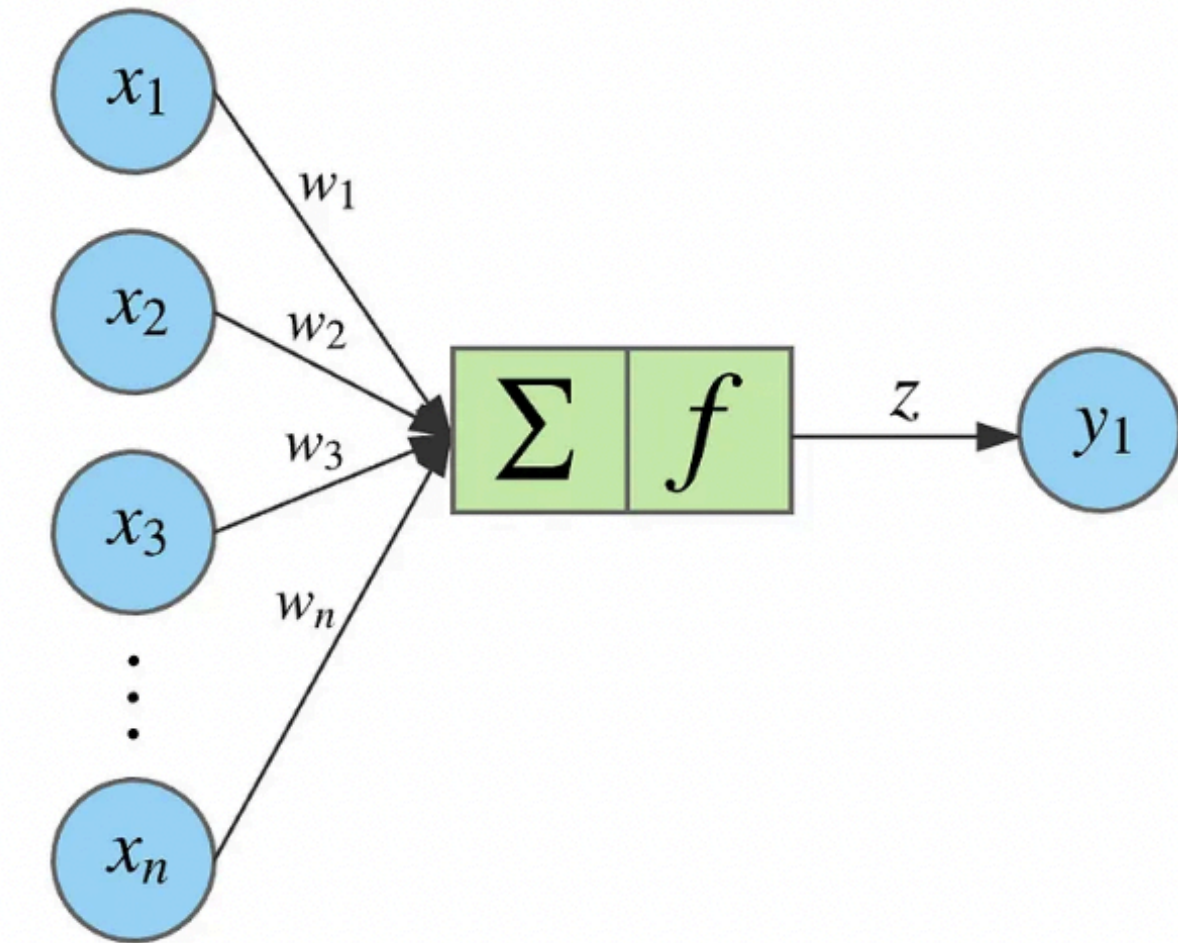


input layer

hidden layer 1

hidden layer 2

output layer



$$z = f(b + x \cdot w) = f \left(b + \sum_{i=1}^n x_i w_i \right)$$

$$x \in d_{1 \times n}, w \in d_{n \times 1}, b \in d_{1 \times 1}, z \in d_{1 \times 1}$$

Loss function

$$\text{MSE} = \frac{1}{N} \sum_{i=1}^N (y_i - \hat{y}_i)^2$$

Neural Network architecture

- **Architecture #1:** 1 hidden layer with 128 neurons + 6 hidden layer with 300 neurons + 1 dense layer (497 925 FP)
- **Architecture #2:** 1 hidden layer with 128 neurons + 3 hidden layer with 256 neurons + dense layer (172 289 FP)
- **Input:**
 - Data: Photometry (dims=56)
 - Tried flux, magnitude
 - tried different normalisation: max, min, median, ...
 - Labels: age, [M/H], E(B-V)
 - tried wi/wo normalization, log(age), age < 0.5 Gyr ...
 - Combined different SP libraries (eMILES + CB19 + XSL)
- **Output**
 - 3 dimensions (all variables in the same NN model)
 - 1 dimension (x3 independent NN models)

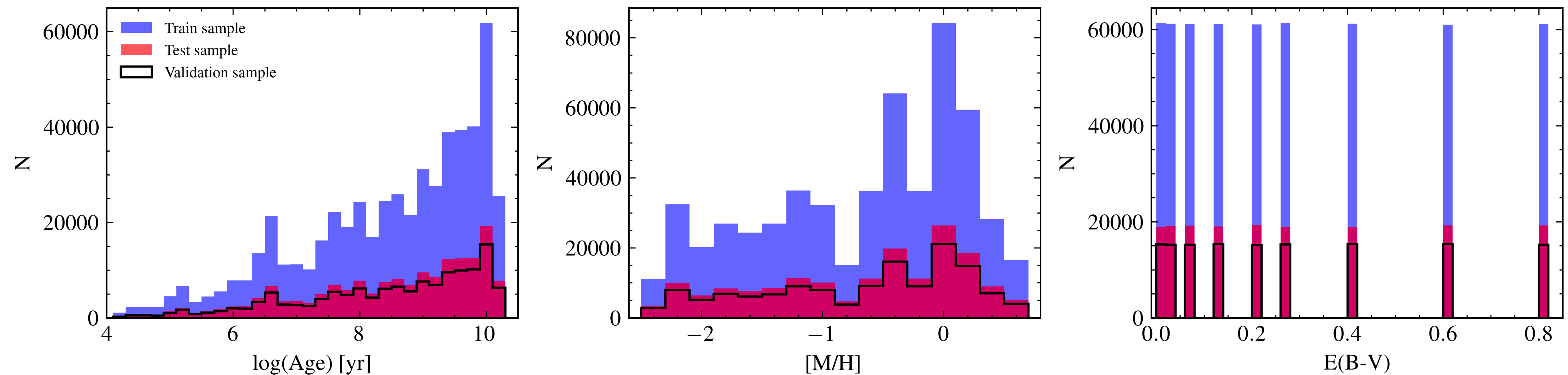
Neural Network architecture

- **Architecture #1:** 1 hidden layer with 128 neurons + 6 hidden layer with 300 neurons + 1 dense layer (497 925 FP)
- **Architecture #2:** 1 hidden layer with 128 neurons + 3 hidden layer with 256 neurons + dense layer (172 289 FP)
- **Input:**
 - Data: Photometry (dims=56)
 - Tried [flux](#), magnitude
 - tried different normalisation: max, min, [median](#), ...
 - Labels: age, [M/H], E(B-V)
 - tried wi/wo [normalization](#), [log\(age\)](#), age < 0.5 Gyr ...
 - Combined different SP libraries ([eMILES](#) + [CB19](#) + [XSL](#))
- **Output**
 - 3 dimensions (all variables in the same NN model)
 - 1 dimension (x3 independent NN models)

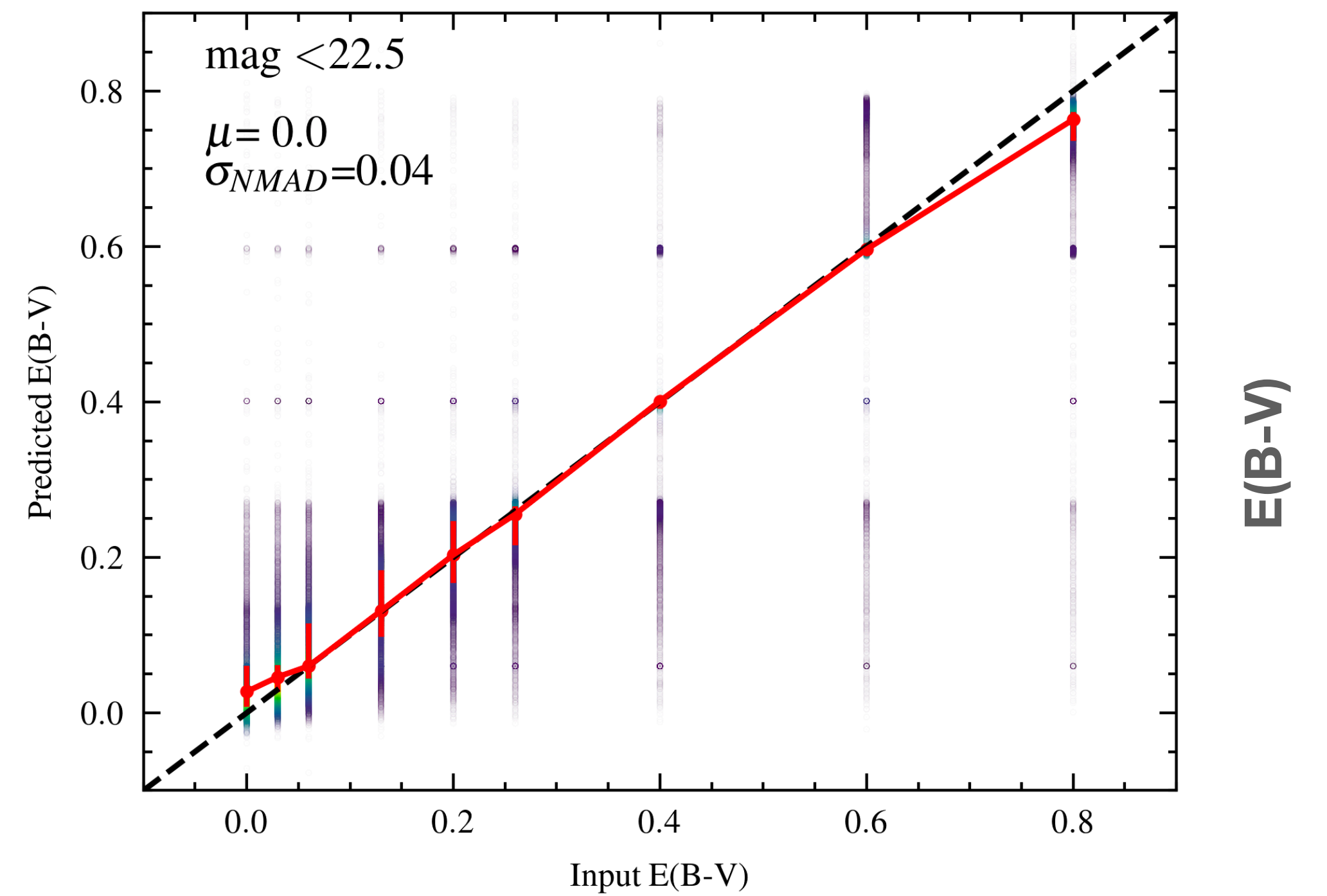
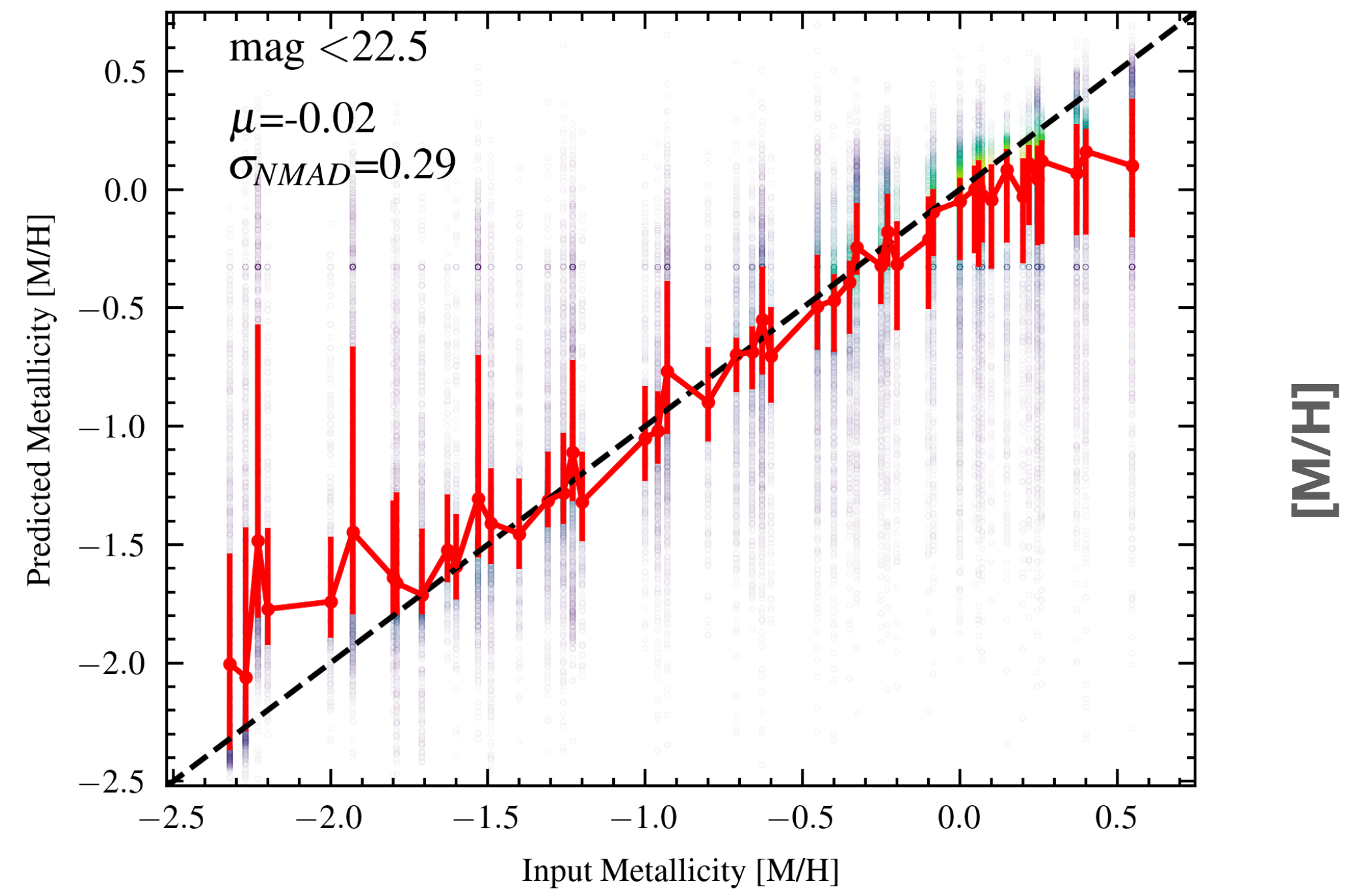
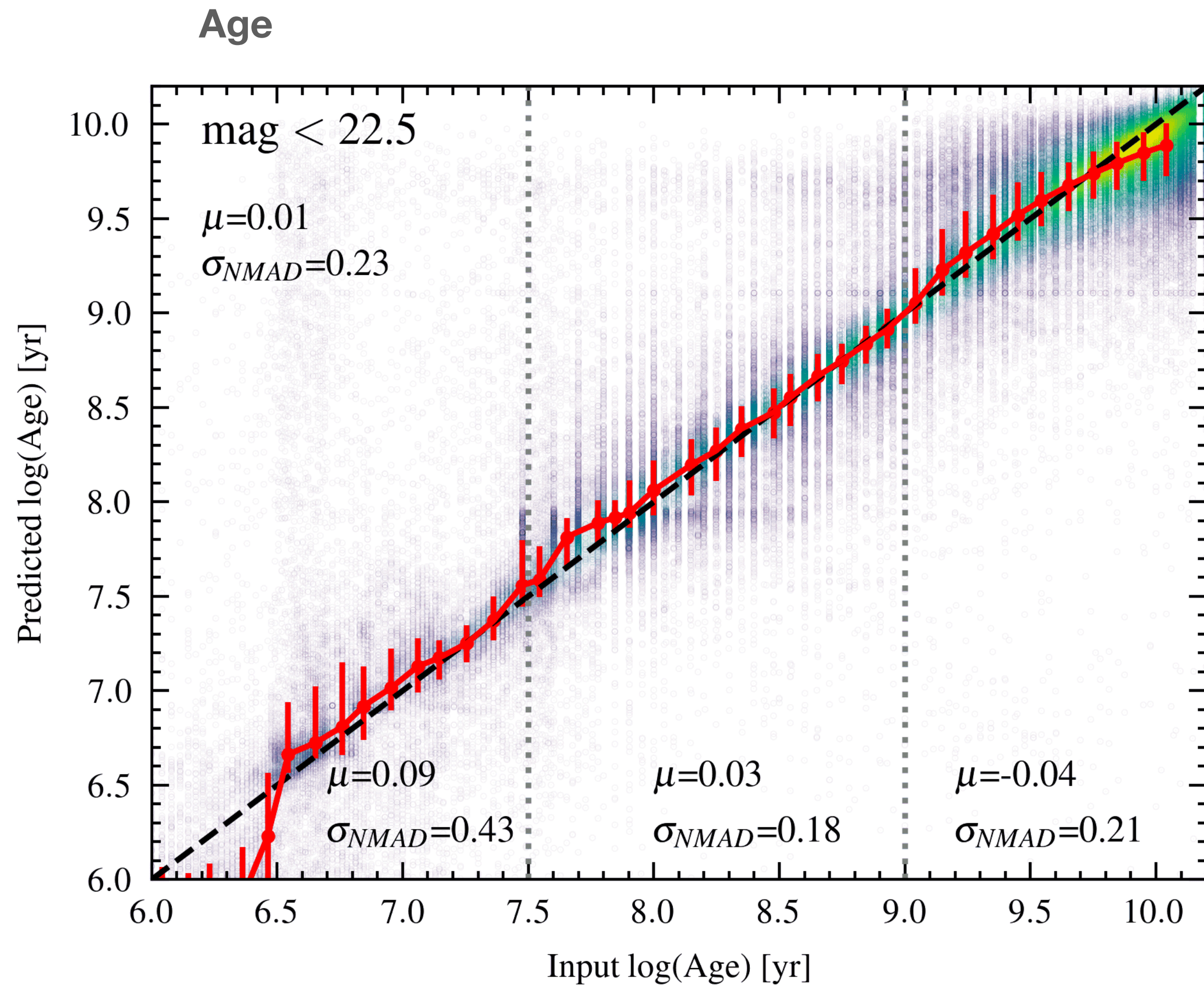
Train/Validation/Test samples

- Applied dust attenuation $E(B-V)$ using *Cardelli+1989* with $R=3.1$
- Original templates x 13 mag_bins (16, 16.5, 17., ..., 22.0 mag)
- Combined different SSP libraries: eMILES + CB19 + XSL
- Train/Validation/Test = 64/16/20% randomly selected

SSP model	N	N_{mock}
E-MILES	26 622	346 086
BC19	29 700	386 100
XSL	9936	129168

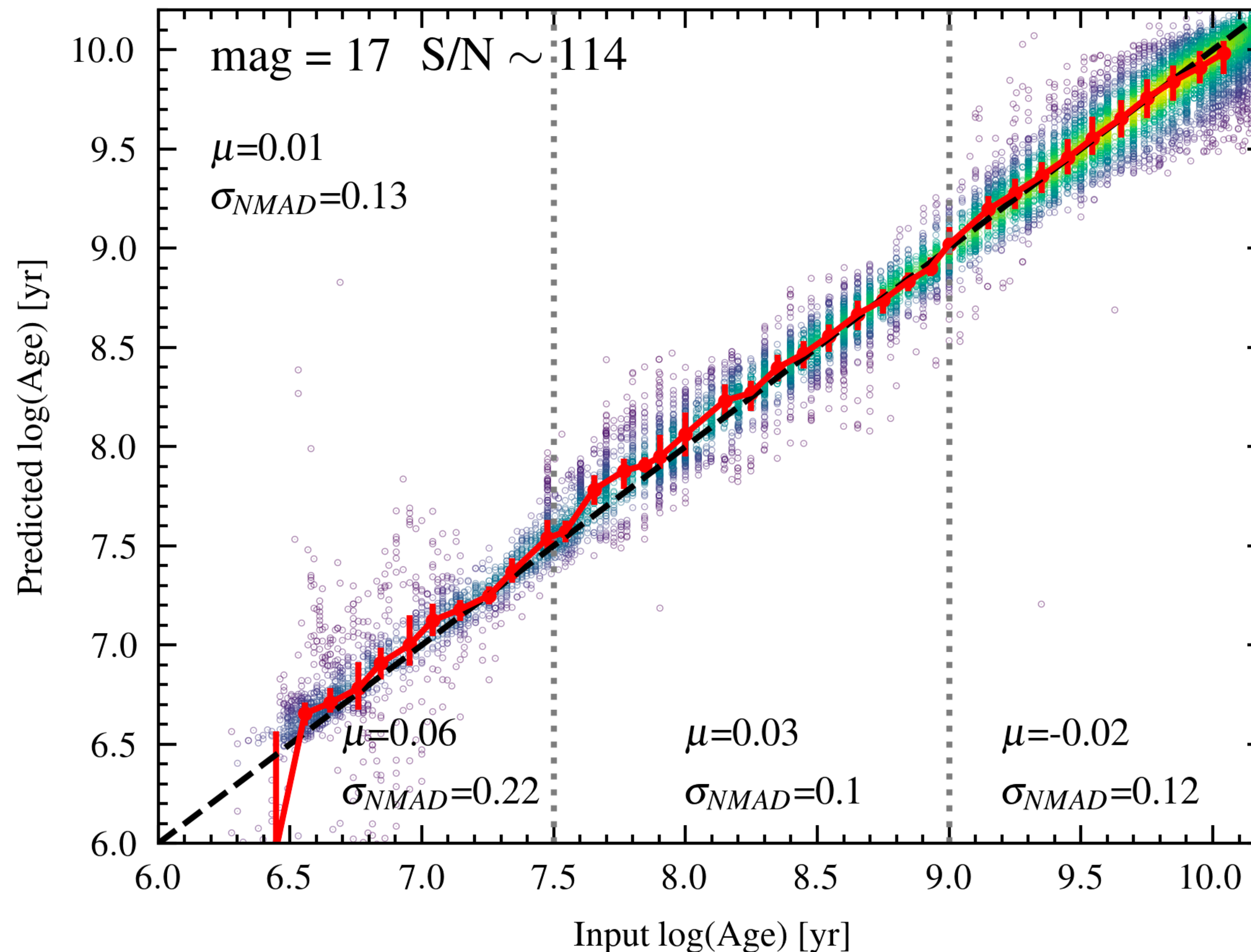


Results



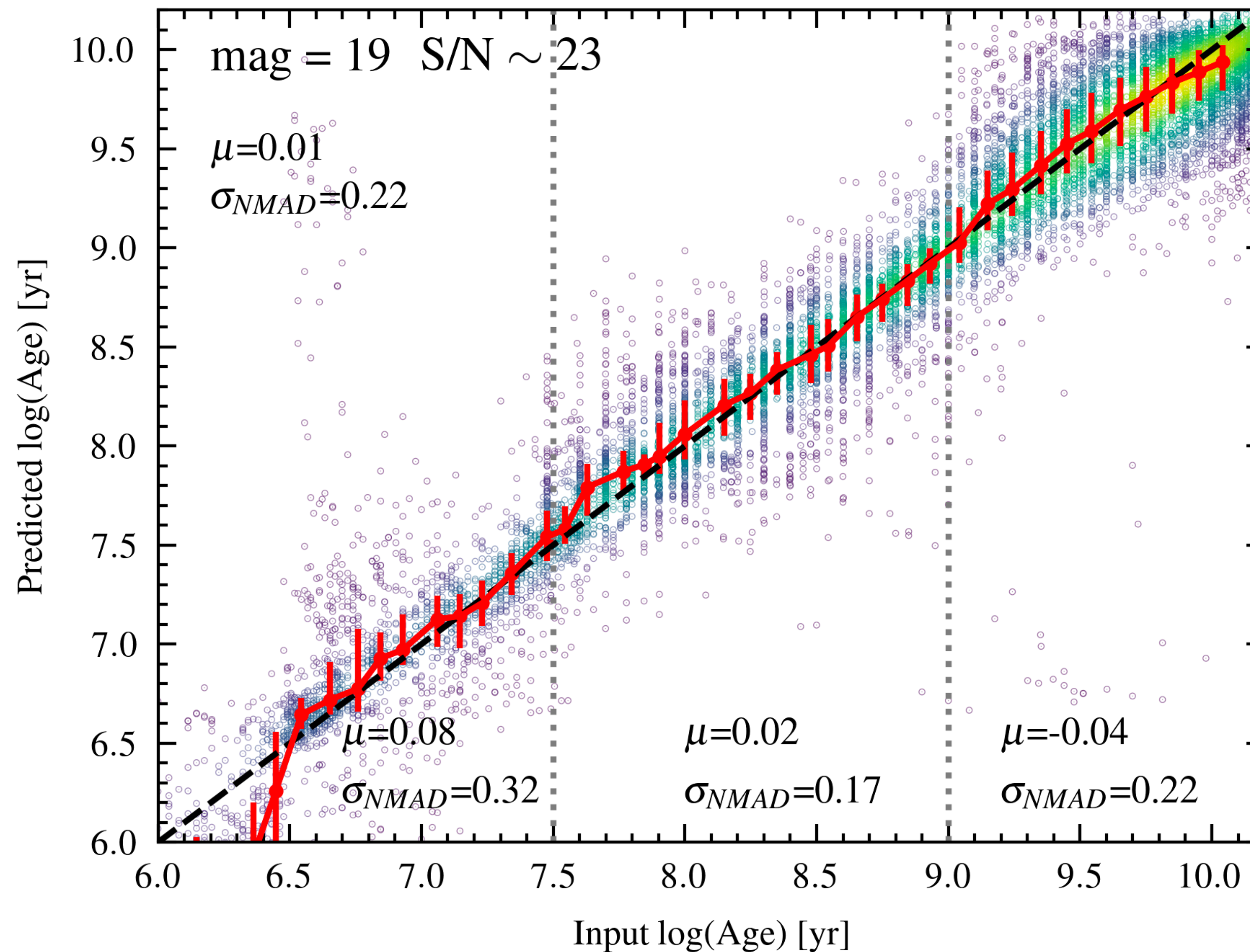
Dependence with magnitude

- Clear dependence with observed magnitude (SN)
- Bias and scatter increase
- Flattening of ages at fainter magnitudes



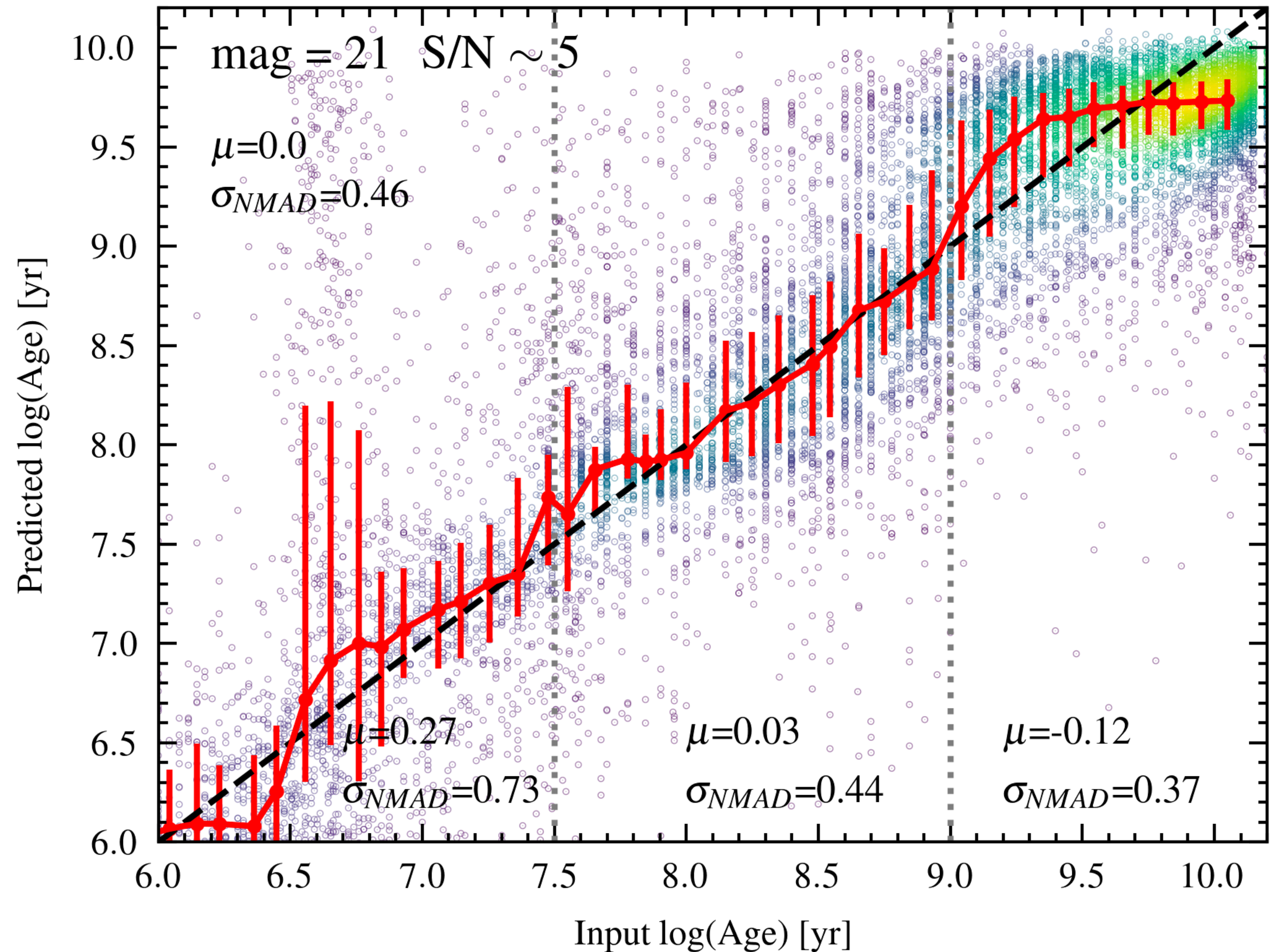
Dependence with magnitude

- Clear dependence with observed magnitude (SN)
- Bias and scatter increase
- Flattening of ages at fainter magnitudes



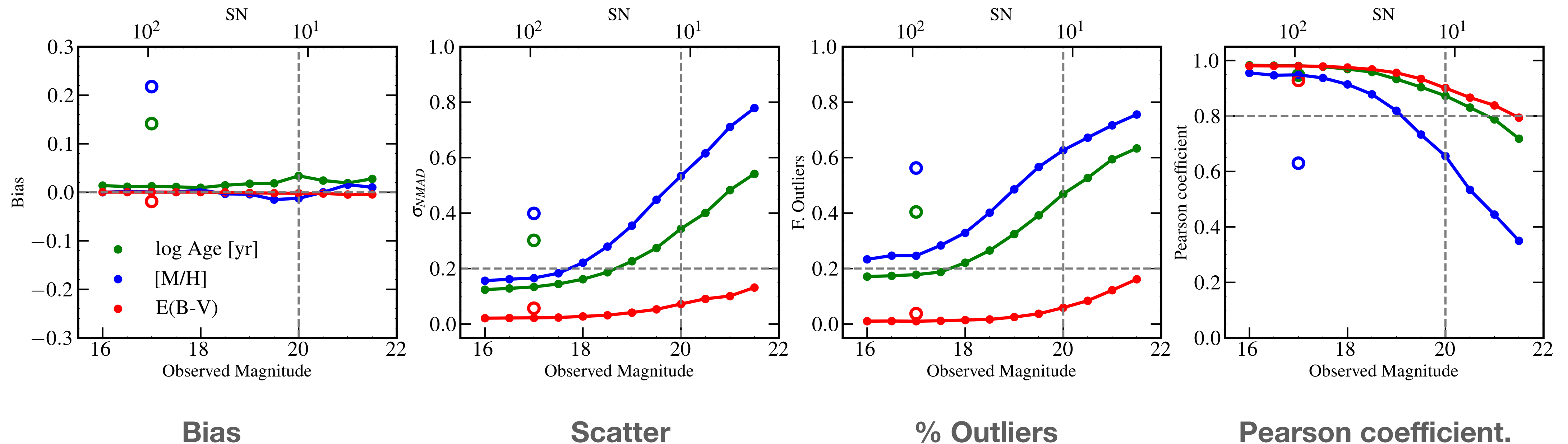
Dependence with magnitude

- Clear dependence with observed magnitude (SN)
- Bias and scatter increase
- Flattening of ages at fainter magnitudes



Dependence with magnitude

- Dependence with SN for all properties: NN is learning from real signal (no overfitting)
- Reliable results up to $\text{mag}_i < 20$
- $[M/H]$ largest scatter and outliers
- $E(B-V)$ very well constrained, even at faint magnitudes



Comparison with SED-fitting

- SED-fitting with CIGALE using the same input data as the NN
- Test on CB19 library only (other libraries not implemented in CIGALE)
- SFH $\sim$ SSP ($\tau = 1$ Myr), fine grid of age, metallicity and dust attenuation

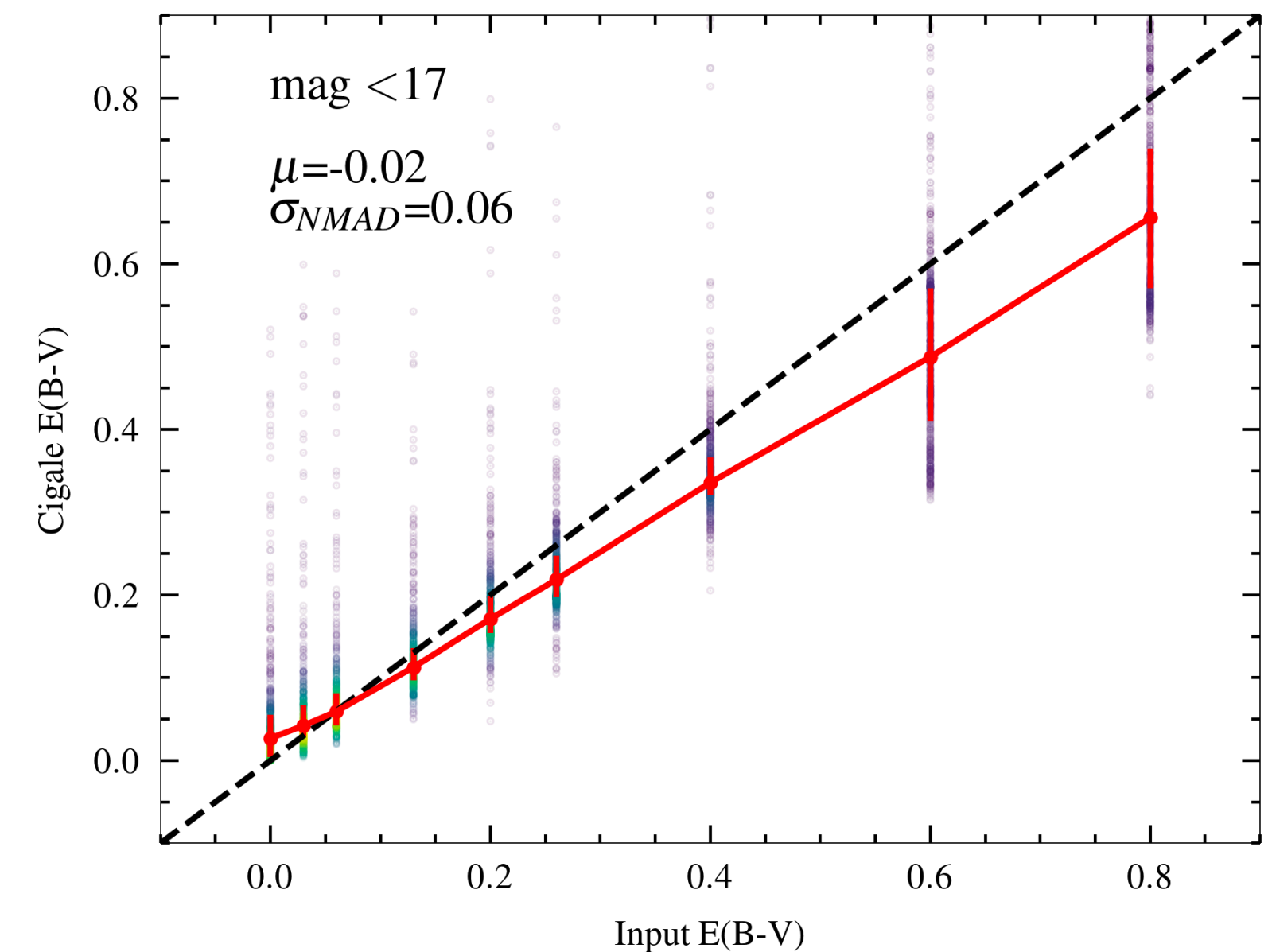
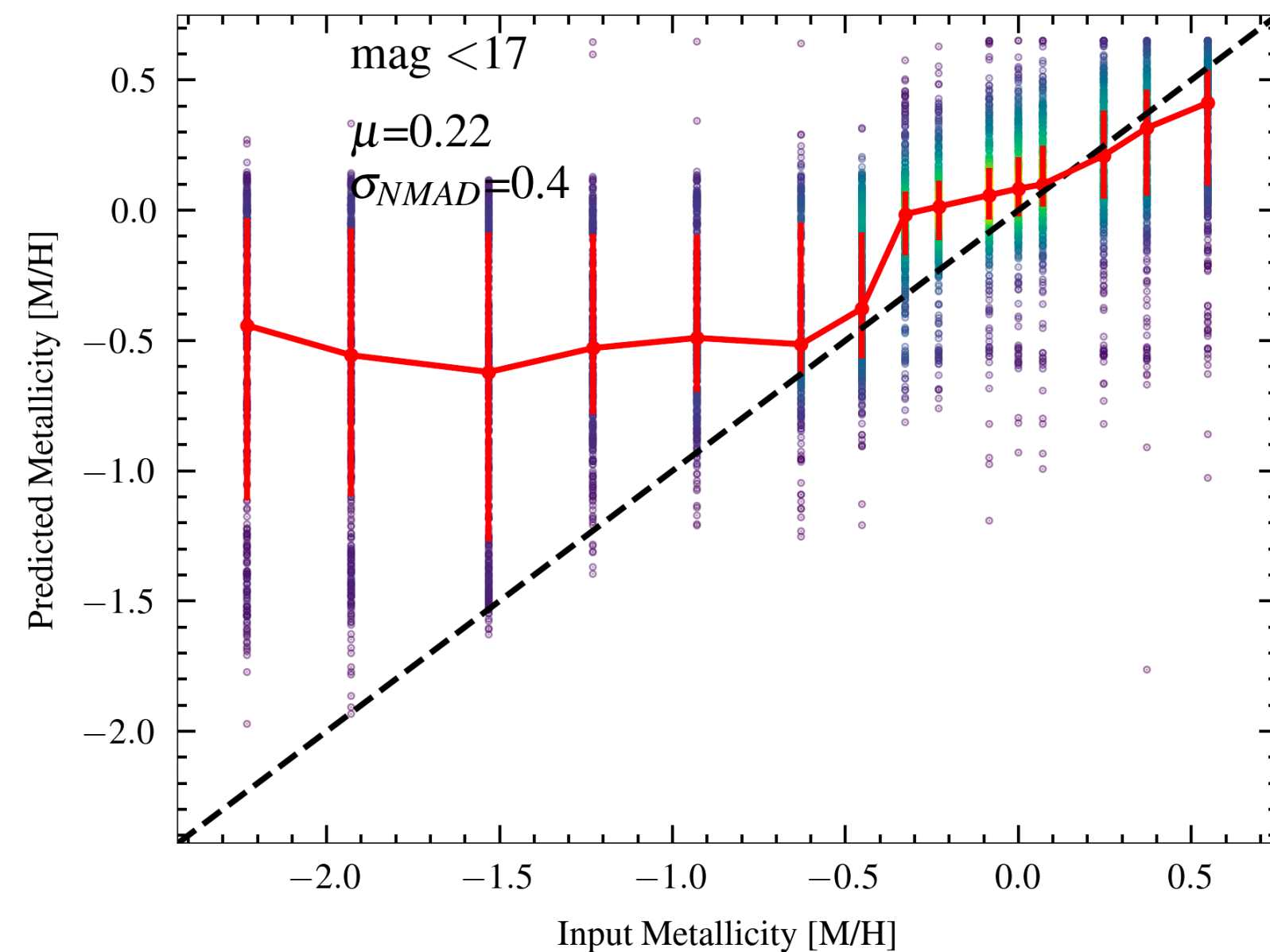
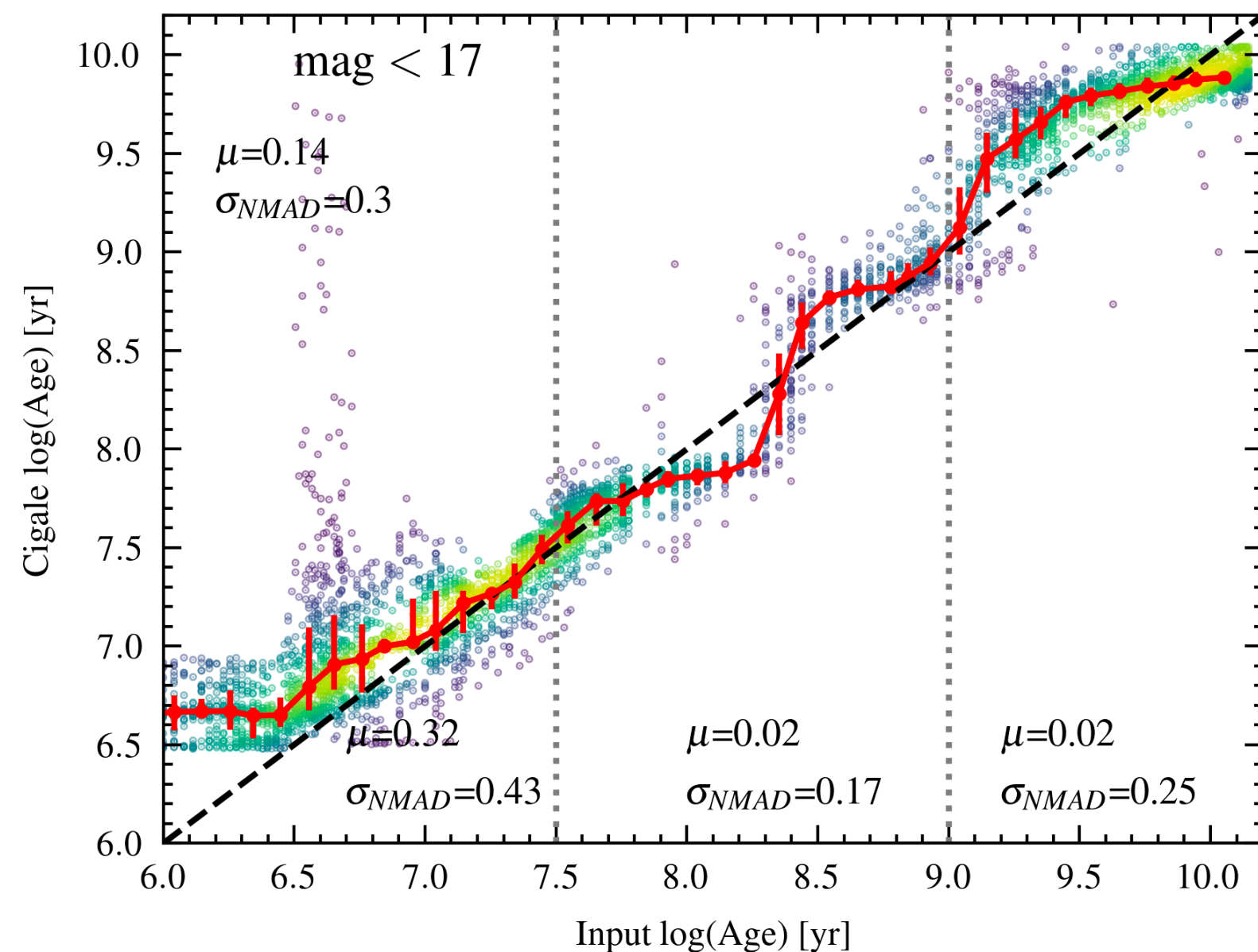
Table 2. Parameter space covered by the CB19 models used in the SED-fitting procedure with CIGALE.

Parameter	Possible values
Metallicity [Z]	0.0001, 0.0002, 0.0005, 0.001, 0.002, 0.004, 0.006, 0.008, 0.01, 0.014, 0.017, 0.02, 0.03, 0.04, 0.06
Age [Myr]	1, 3, 5, 8, 10, 20, 30, 40, 50, 80, 100, 500, 800, 1000, 2000, 3000, 4000, 5000, 6000, 7000, 8000, 9000, 10 000, 11 000
E(B-V) _{lines}	0.0, 0.1, 0.2, 0.3, 0.4, 0.5, 0.6, 0.7, 0.8, 0.9, 1.0, 1.3, 1.5, 1.9, 2.2

Notes. We used all the possible metallicity values in CIGALE.

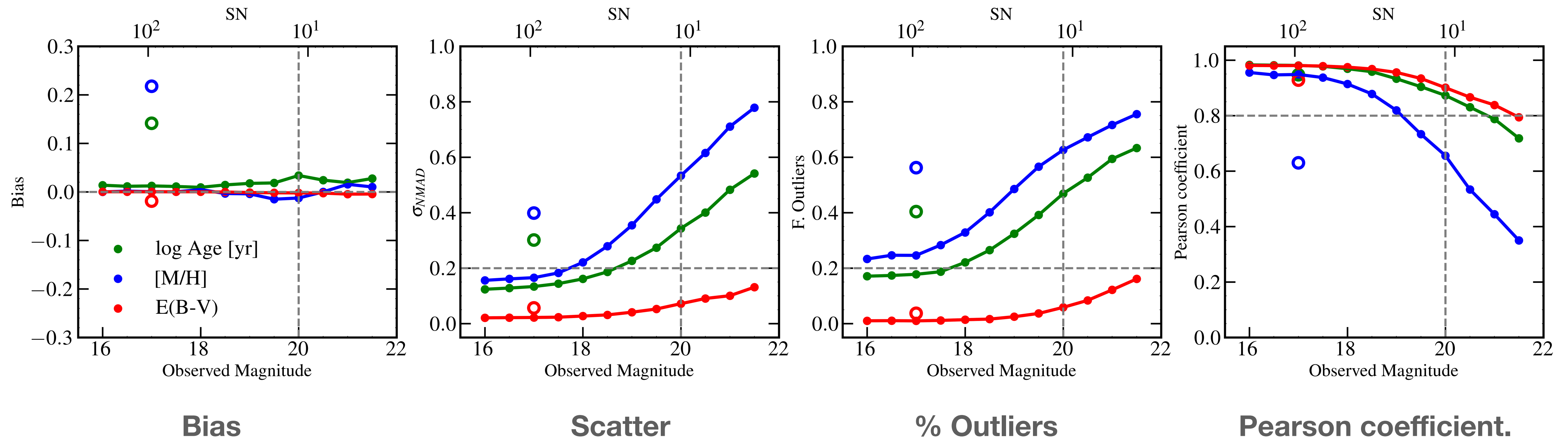
Comparison with SED-fitting

- SED-fitting with CIGALE using the same input data as the NN
- Test on CB19 library only (other libraries not implemented in CIGALE)
- SFH $\sim$ SSP ($\tau = 1\text{Myr}$), fine grid of age, metallicity and dust attenuation

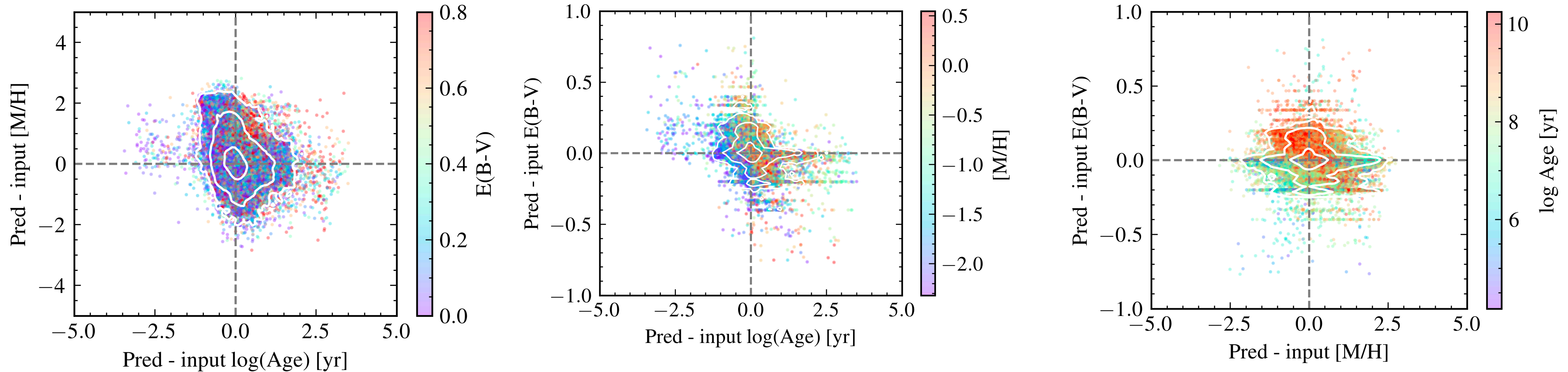


Comparison with SED-fitting

- Results are shown as empty circles for $\text{mag}_i \sim 17$
- NN results outperform SED-fitting for all quantities and metrics

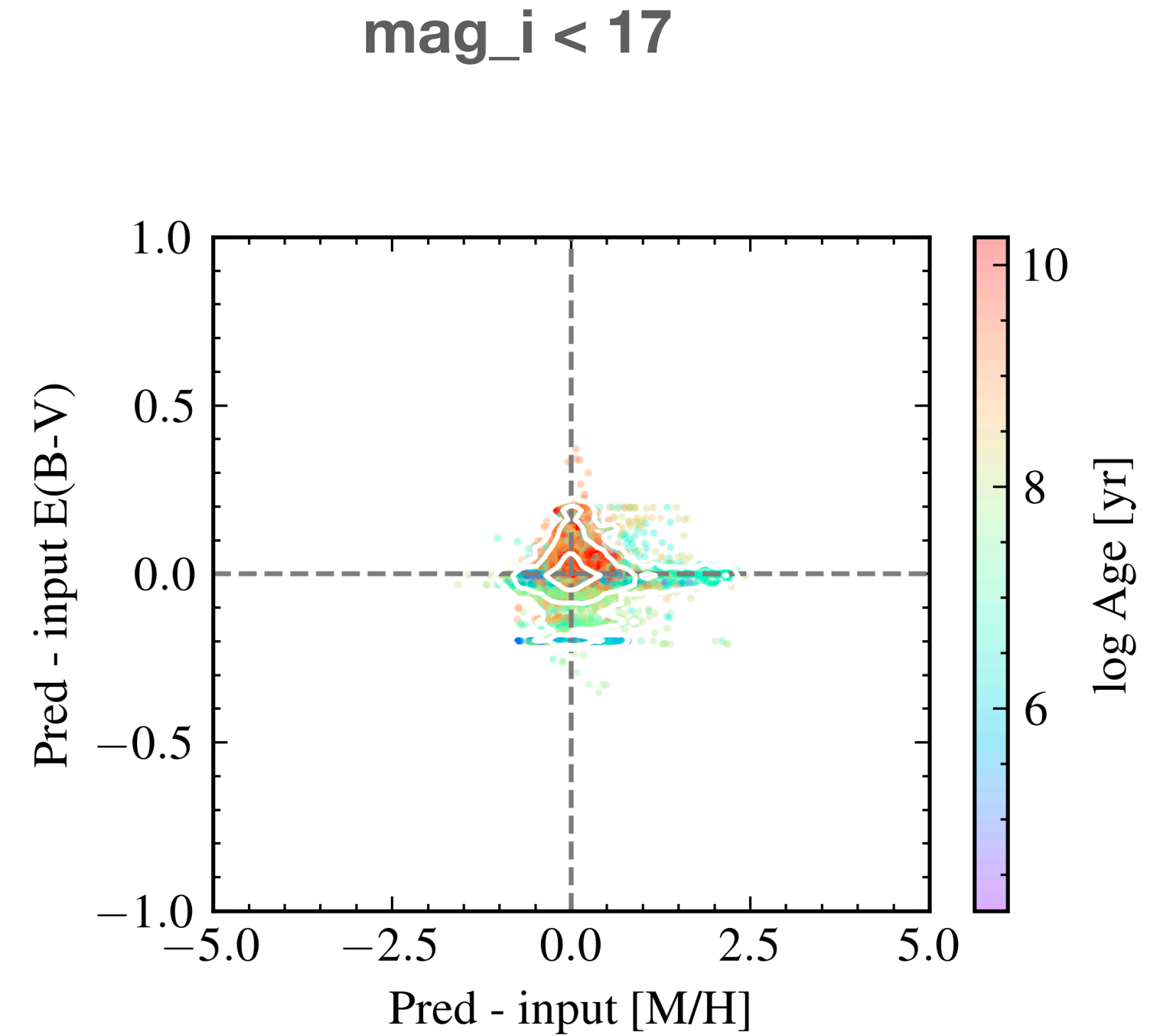
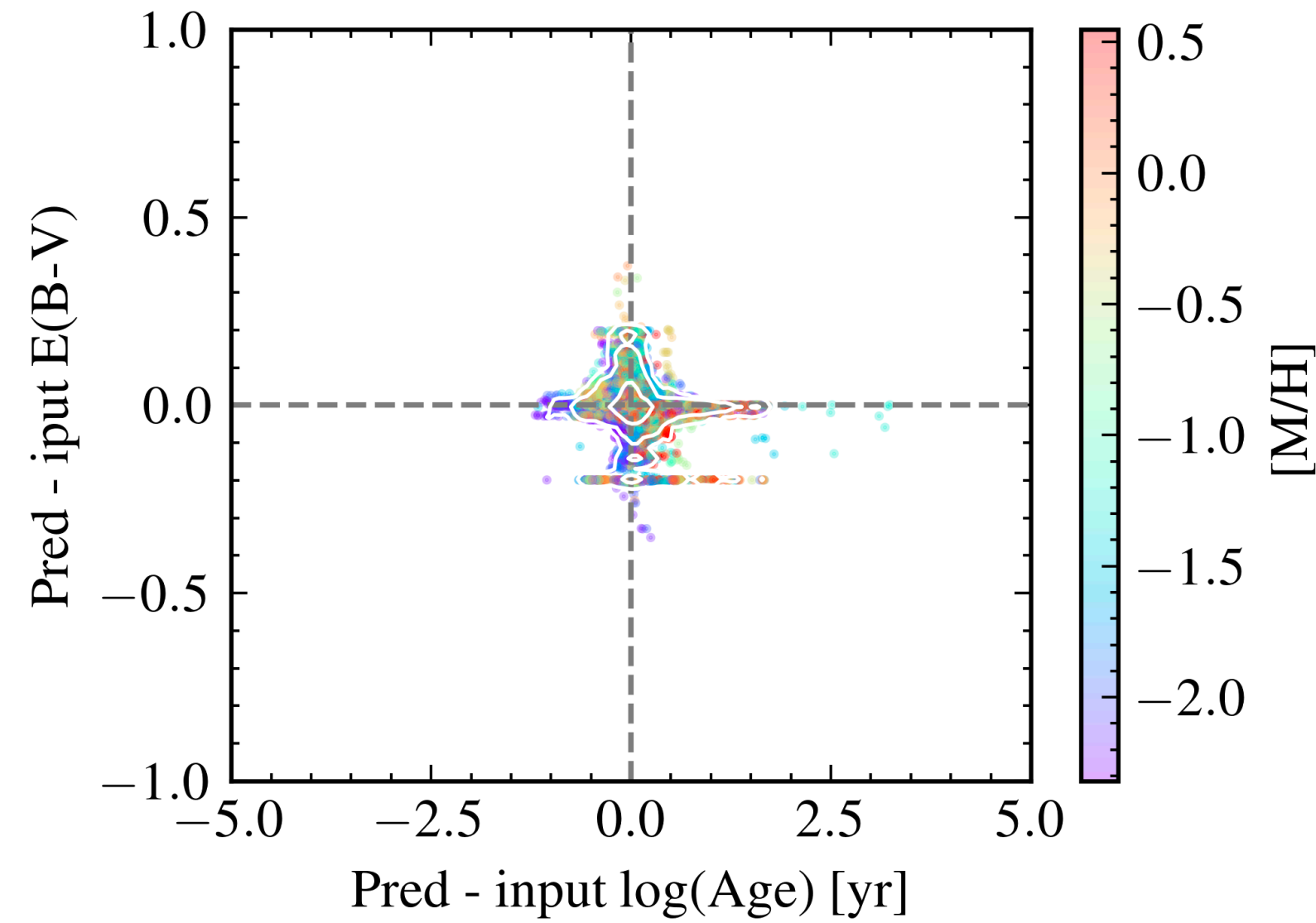
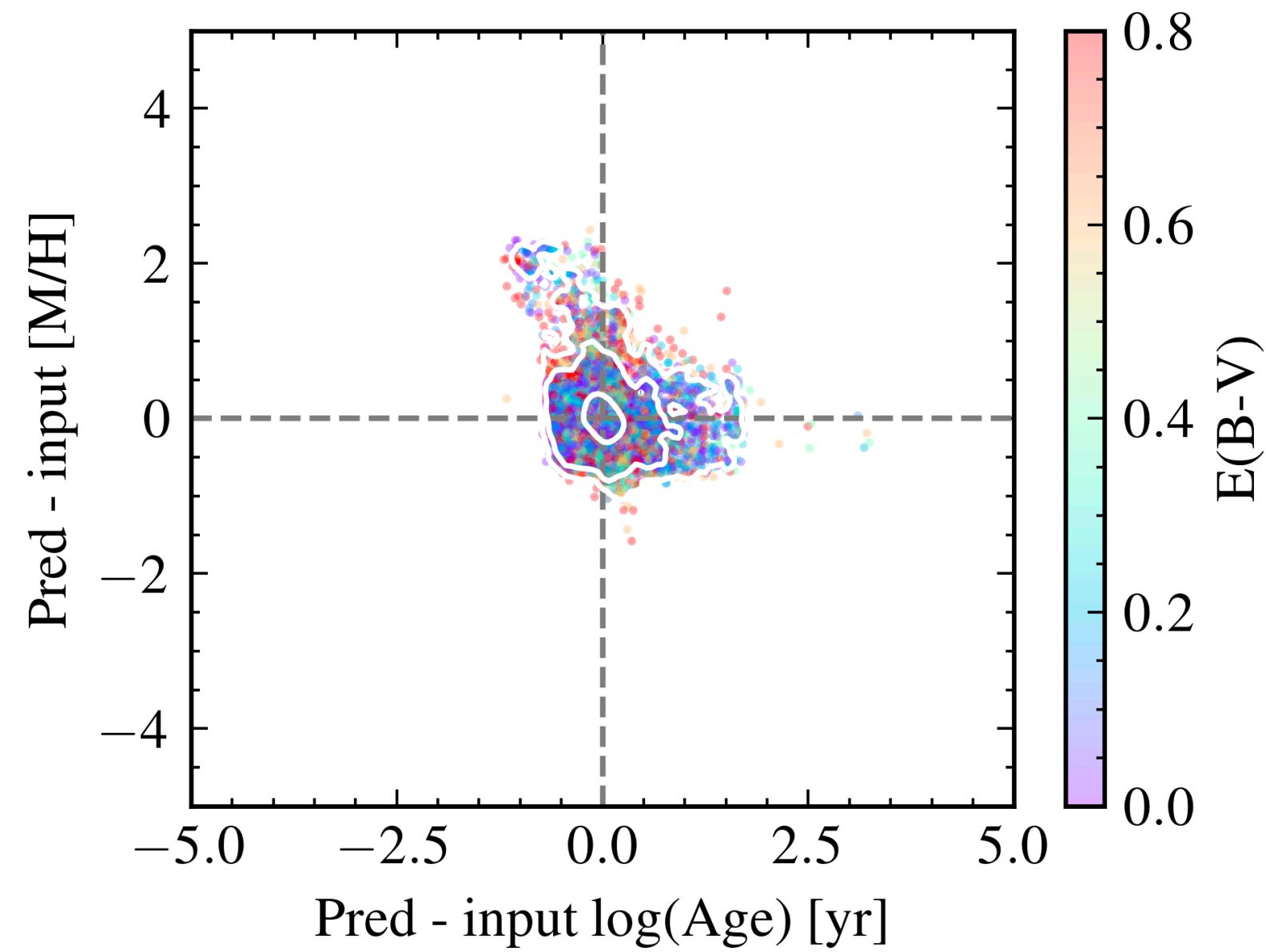


Degeneracies



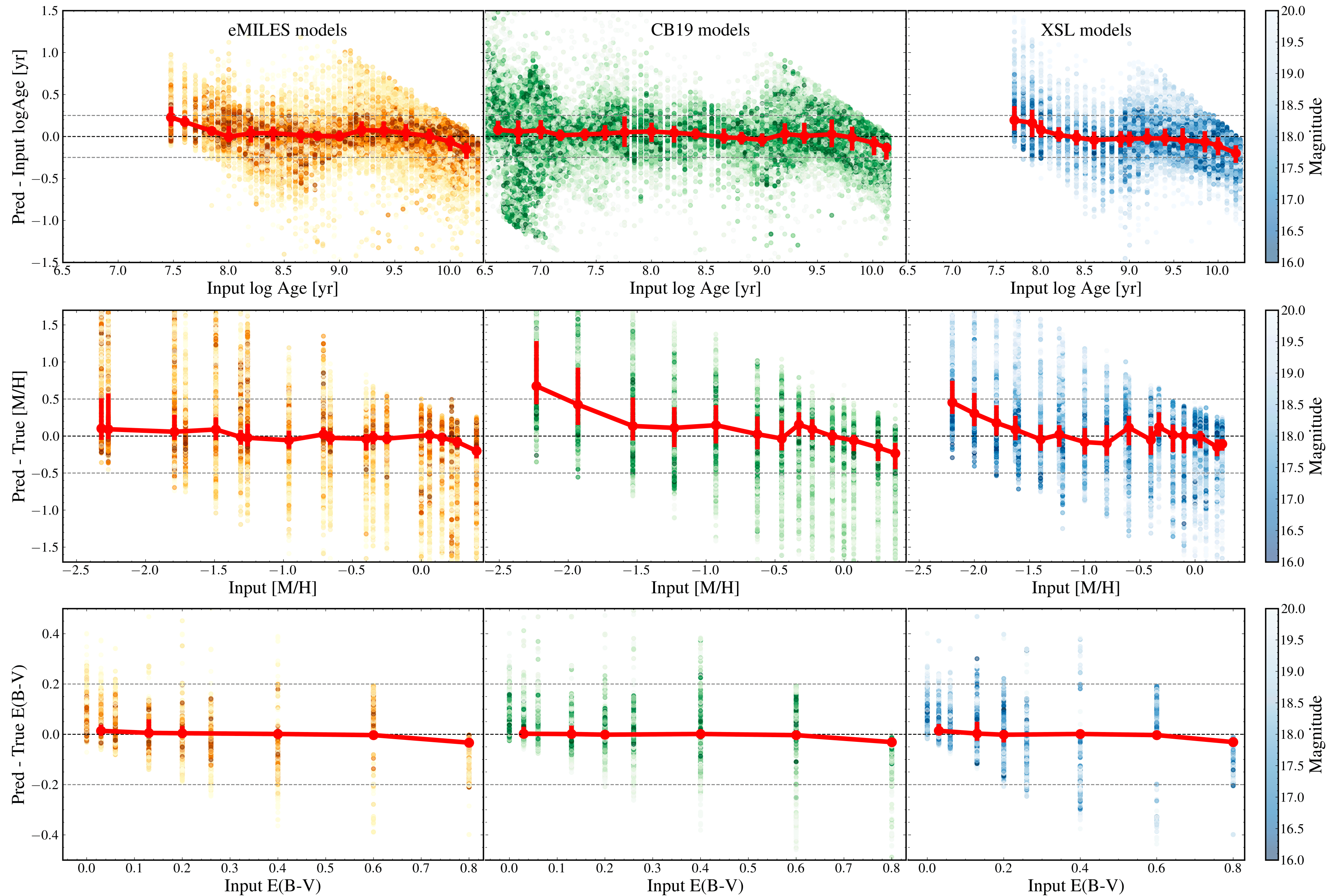
- Age, $[M/H]$ and $E(B-V)$ derived independently (in contrast to SED-fitting)
- **No evident degeneracies**, most outliers outside 3σ region (white contours)
- Weak trend with age residuals and $[M/H]$ (especially for $\text{mag}_i > 17$)

Degeneracies



- Age, $[M/H]$ and $E(B-V)$ derived independently (in contrast to SED-fitting)
- **No evident degeneracies**, most outliers outside 3σ region (white contours)
- Weak trend with age residuals and $[M/H]$ (especially for $\text{mag}_i > 17$)

Dependence on SP library

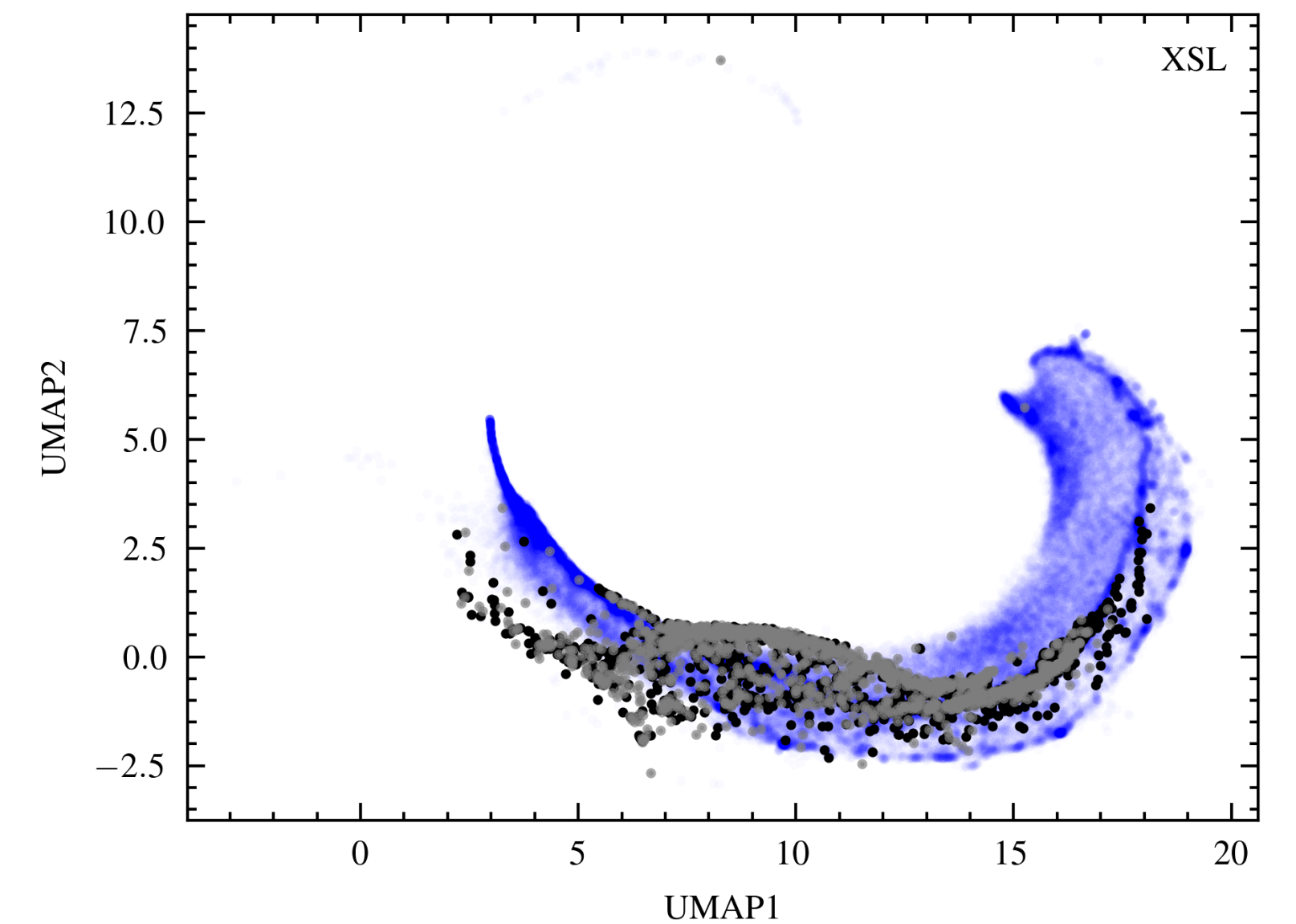
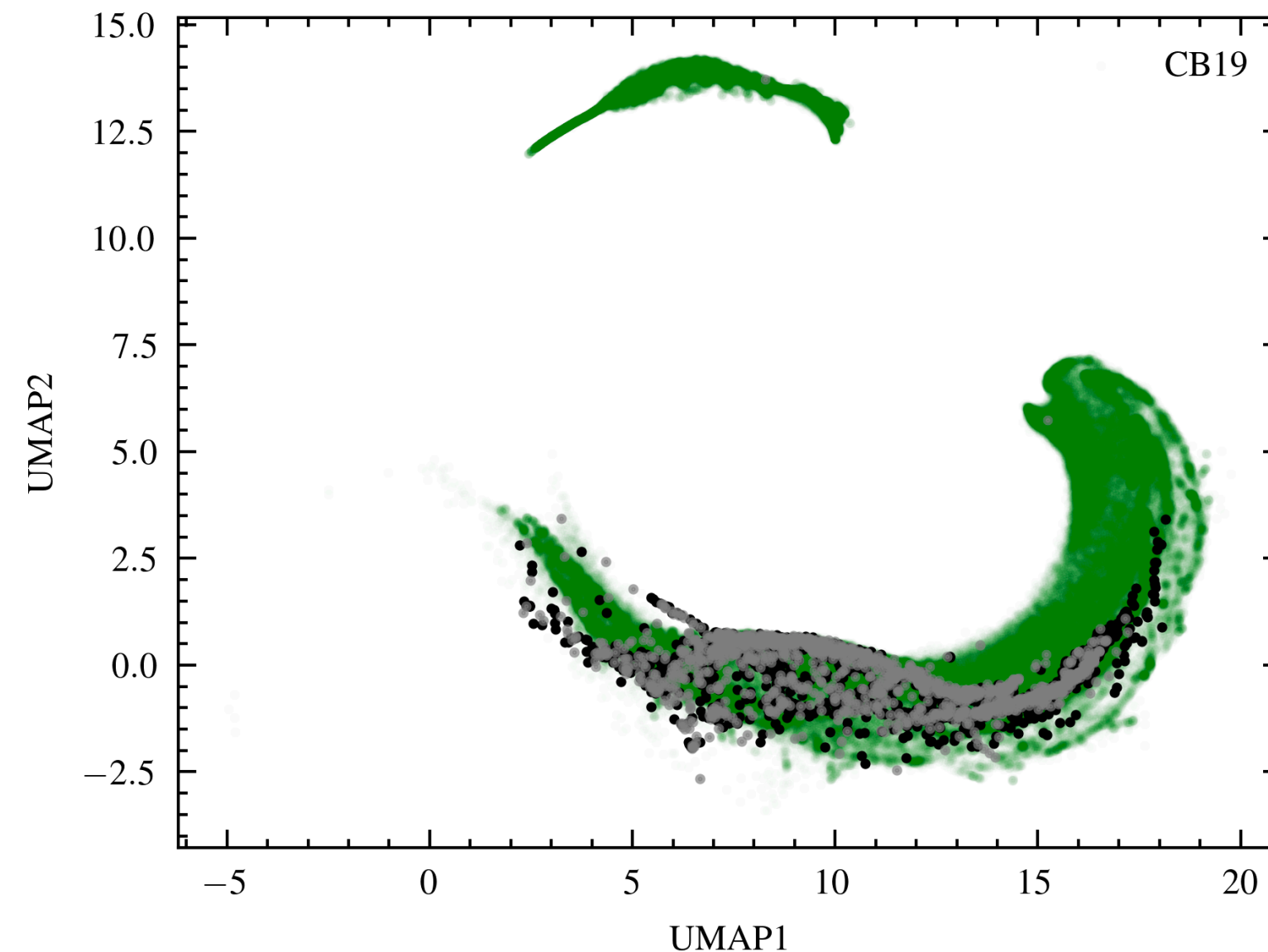
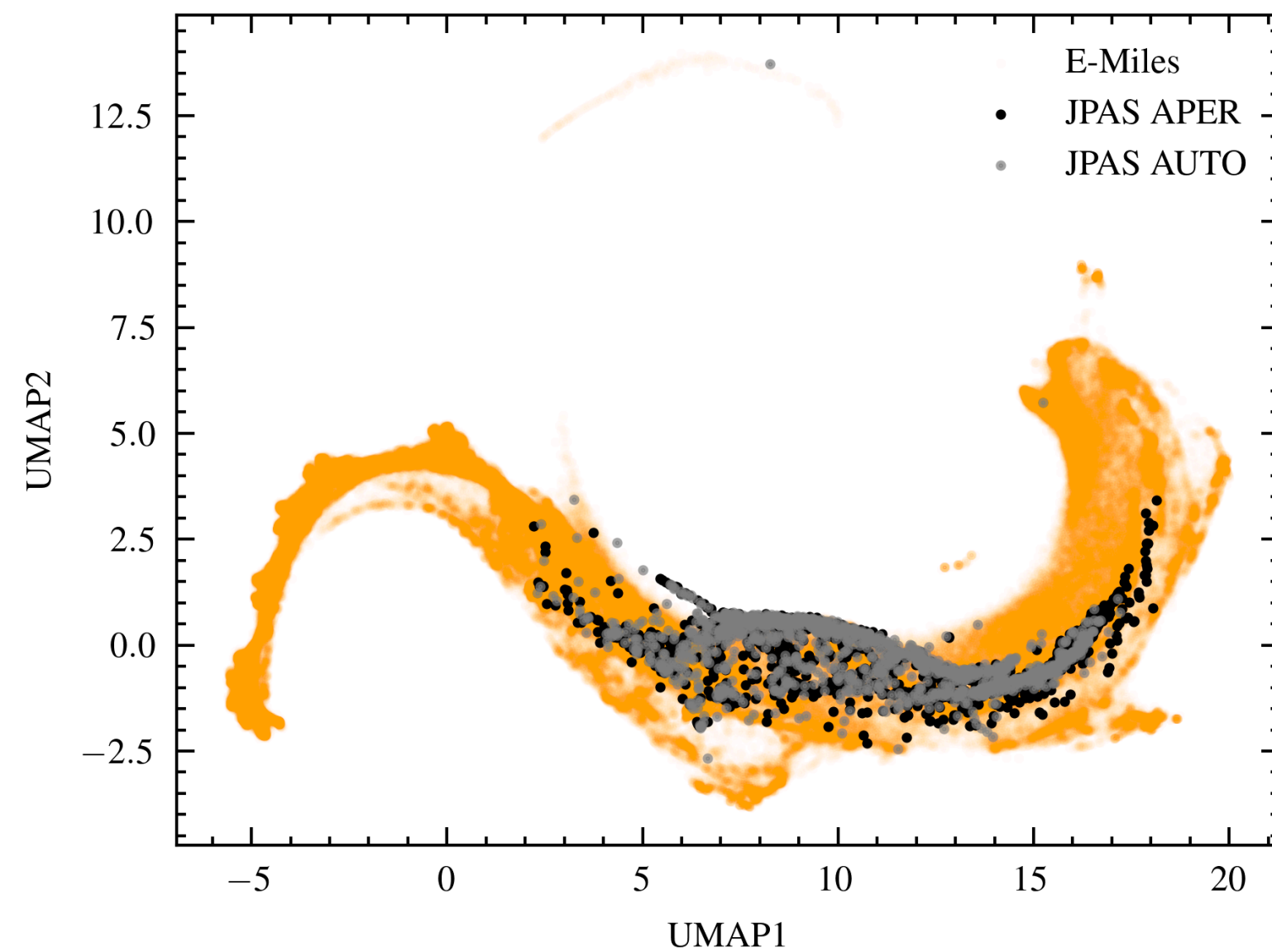


- [M/H] overestimated for CB19 and XSL, no bias for eMILES
- No age bias fro CB19
- Related to the training sample: youngest models come from CB19, lowest [M/H] from eMILES

J-PAS DR1 galaxies: UMAP projections

- J-PAS DR1 (*Vazqu  z-Rami   et al. in prep*)
- $\text{Spec}z < 0.1$ & $|\text{zphot-zspec}| < 0.005$
- $\text{mag}_i < 20$ mag = **1478 galaxies**
- APER_COR_3_0_FLUX as input for NN

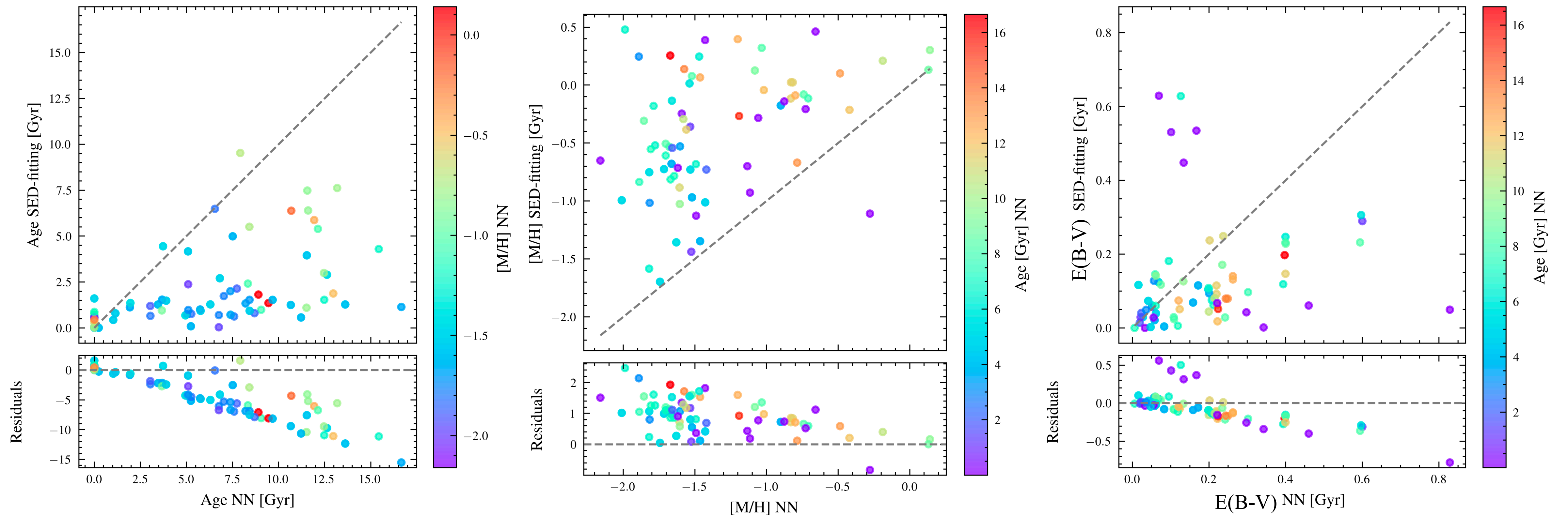
Some regions of the 2D UMAP not well covered by one SSP library, but yes when combined together



J-PAS DR1 galaxies: NN estimates

- Comparison with MUFFIT SED-fitting, 2 burst CSP, CB17 models, Chabrier IMF (*Díaz-García et al in prep*)
- Significant disagreement (CSP, emission lines...)

- $z_{\text{spec}} < 0.03$
- $\text{FLAGS_MASK} = 2$
- **90 galaxies**



Caveats and Future work

- **Redshift:** Models trained at $z=0$ only. Need to assess the impact of z variations. Probably need to train several NN.
- **SSP:** Training with SSP, predictions for CSP have significant biases (Appendix in DS+26).
- **Emission lines** not included in SSP models: mask emission lines, emulate flux contribution?
- Not optimized for **missing data** (~30% of J-PAS sources)

Conclusions

- NN estimates are **accurate but highly dependent on S/N**
- NN estimates on CB19 test sample **outperform** those obtained with **SED-fitting**
- Age, [M/H] and E(B-V) **derived independently**, thus **mitigating** typical **degeneracies**
- **Better results when combining different SSP libraries and IMF**: kind of data augmentation
- No clear dependence on the performance with SSP library
- Significant differences when compared to SED-fitting with CSP

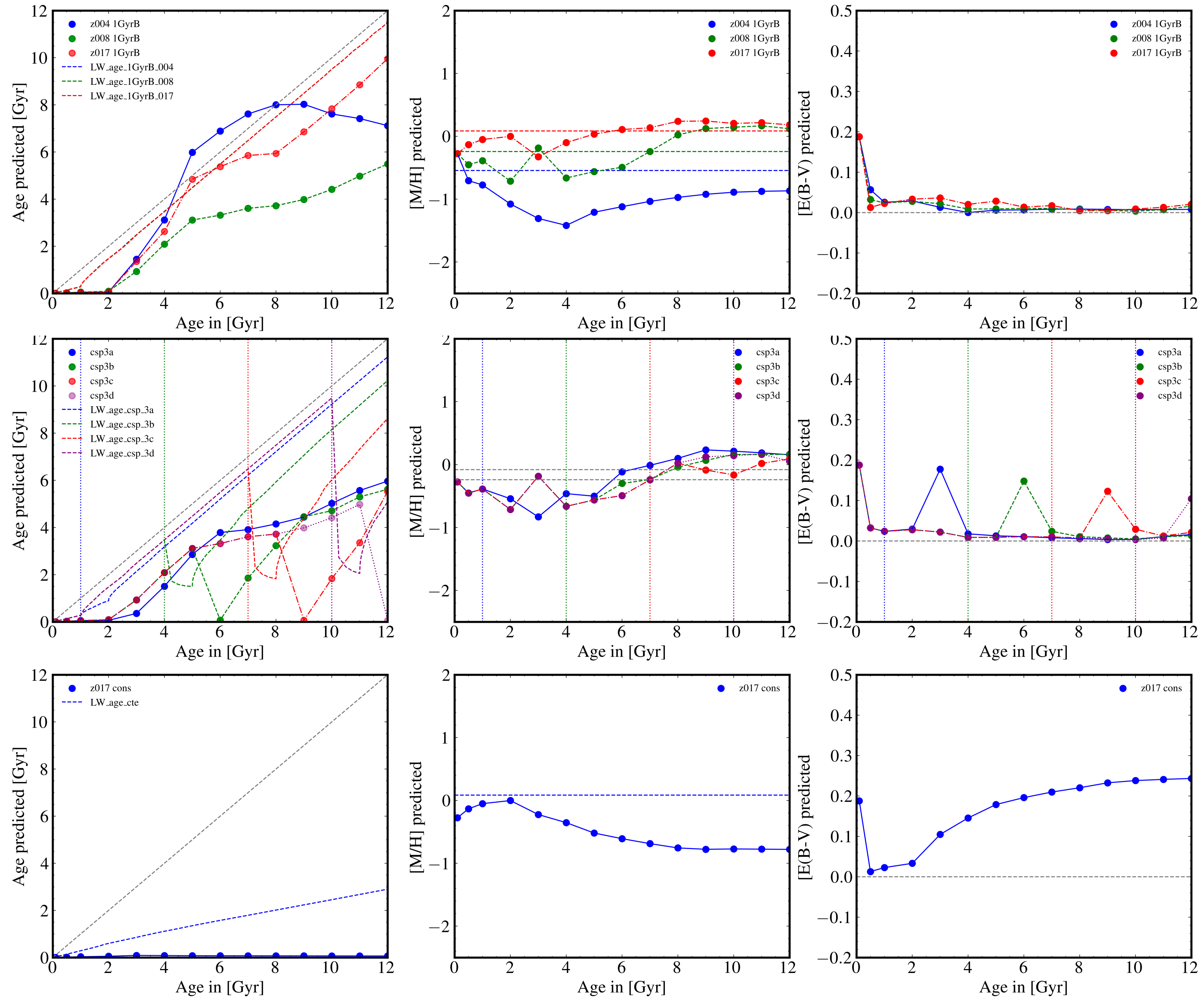
Conclusions

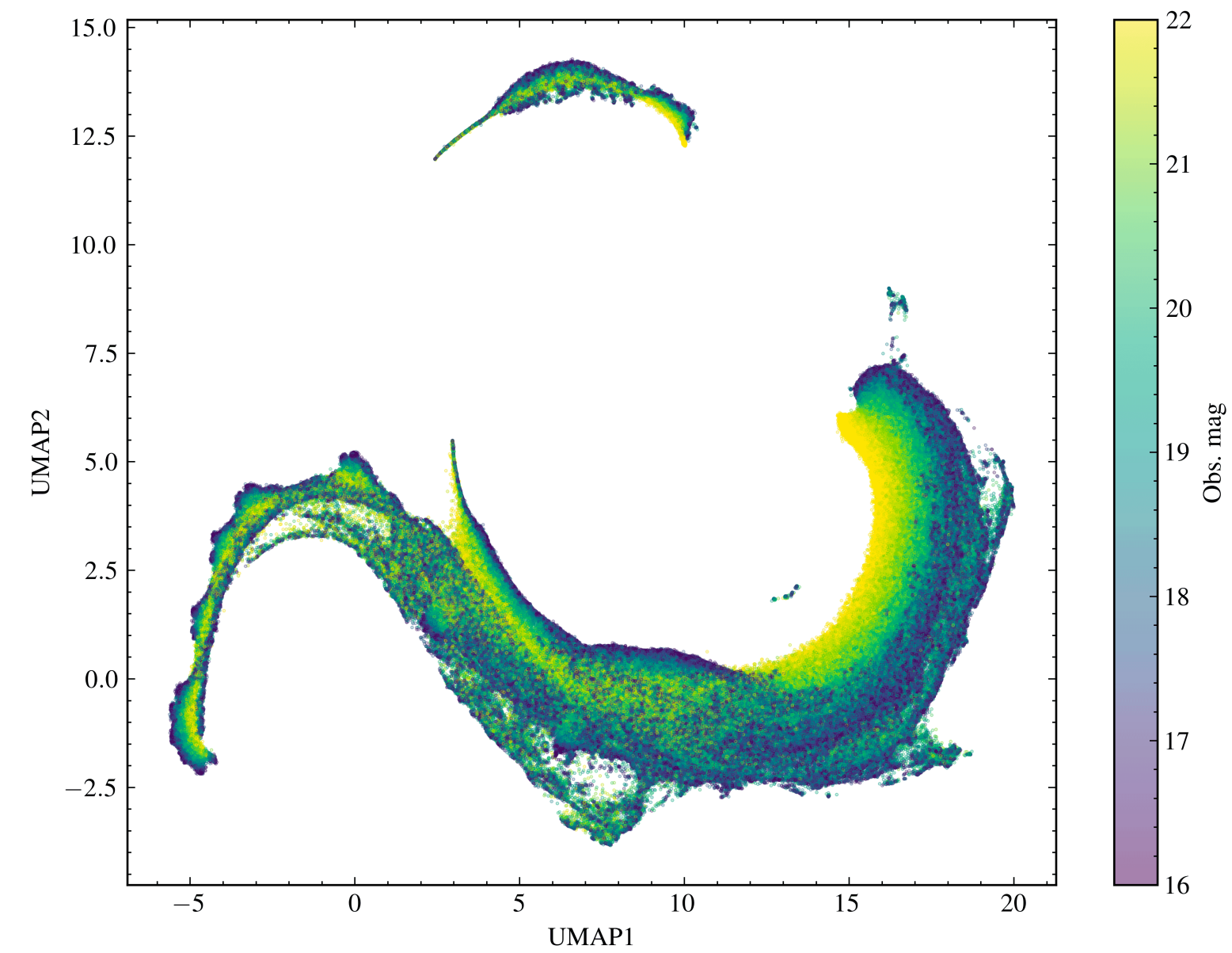
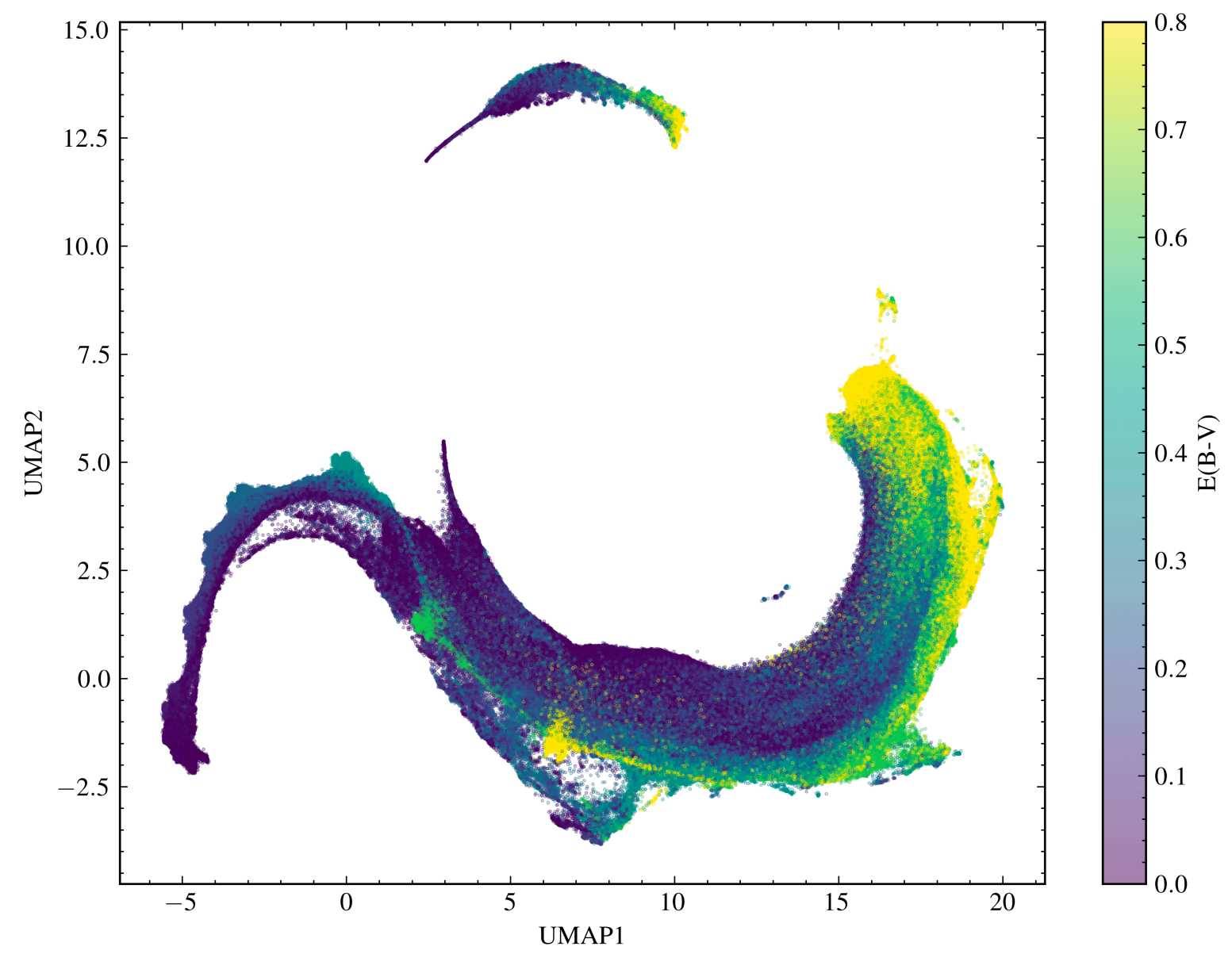
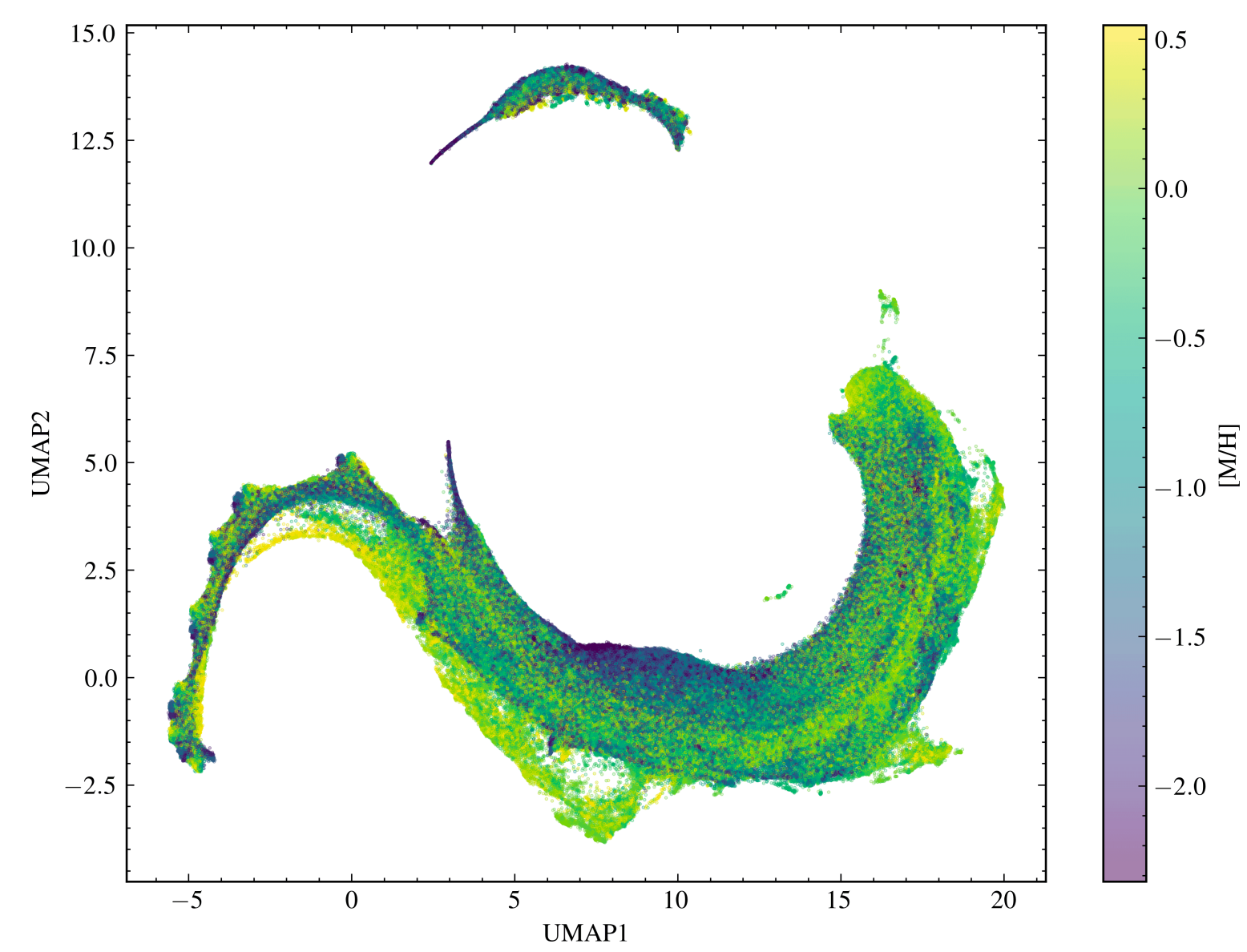
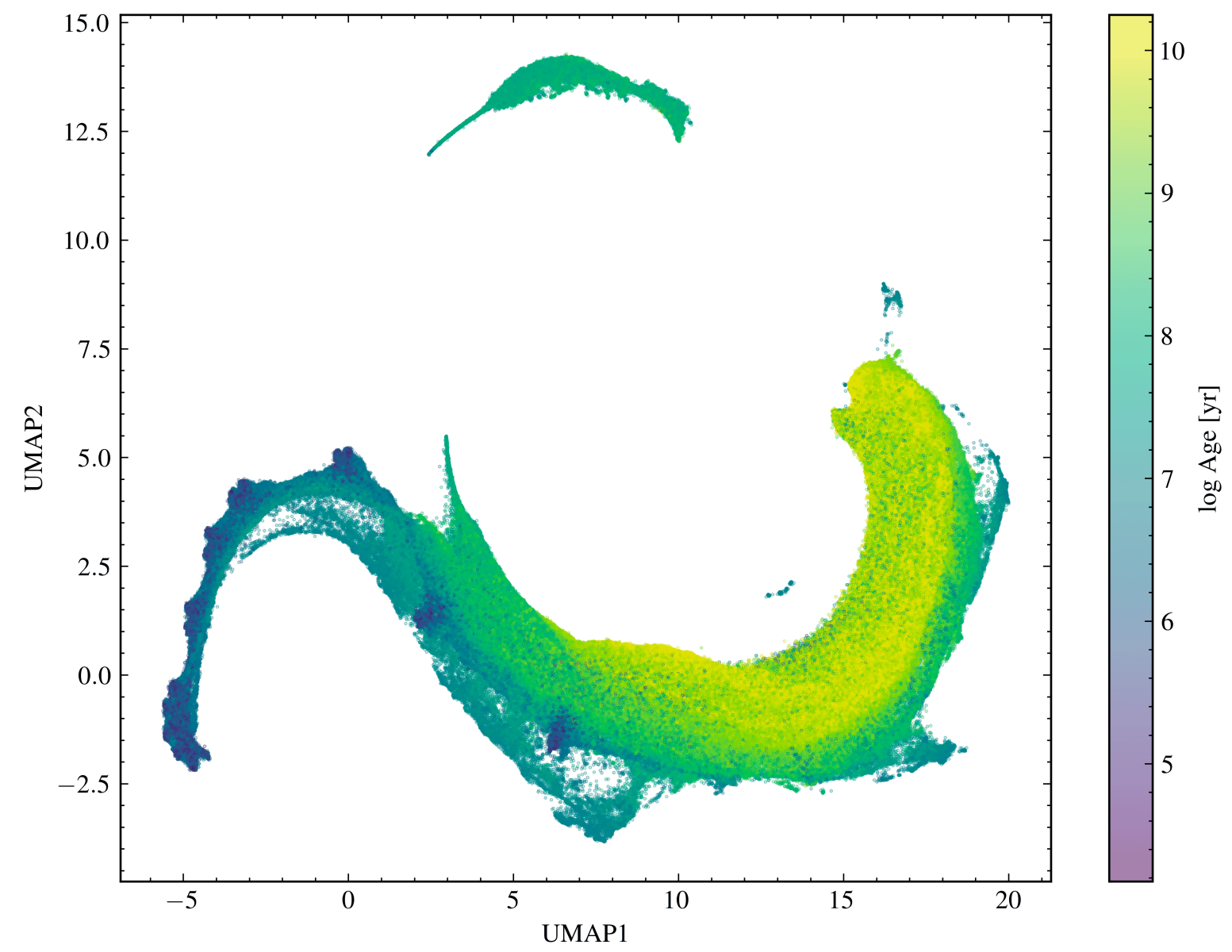
- NN estimates are **accurate but highly dependent on S/N**
- NN estimates on CB19 test sample **outperform** those obtained with **SED-fitting**
- Age, [M/H] and E(B-V) **derived independently**, thus **mitigating** typical **degeneracies**
- **Better results when combining different SSP libraries and IMF**: kind of data augmentation
- No clear dependence on the performance with SSP library
- Significant differences when compared to SED-fitting with CSP

Thanks for your attention!

helenad@ifca.es

Backup plots





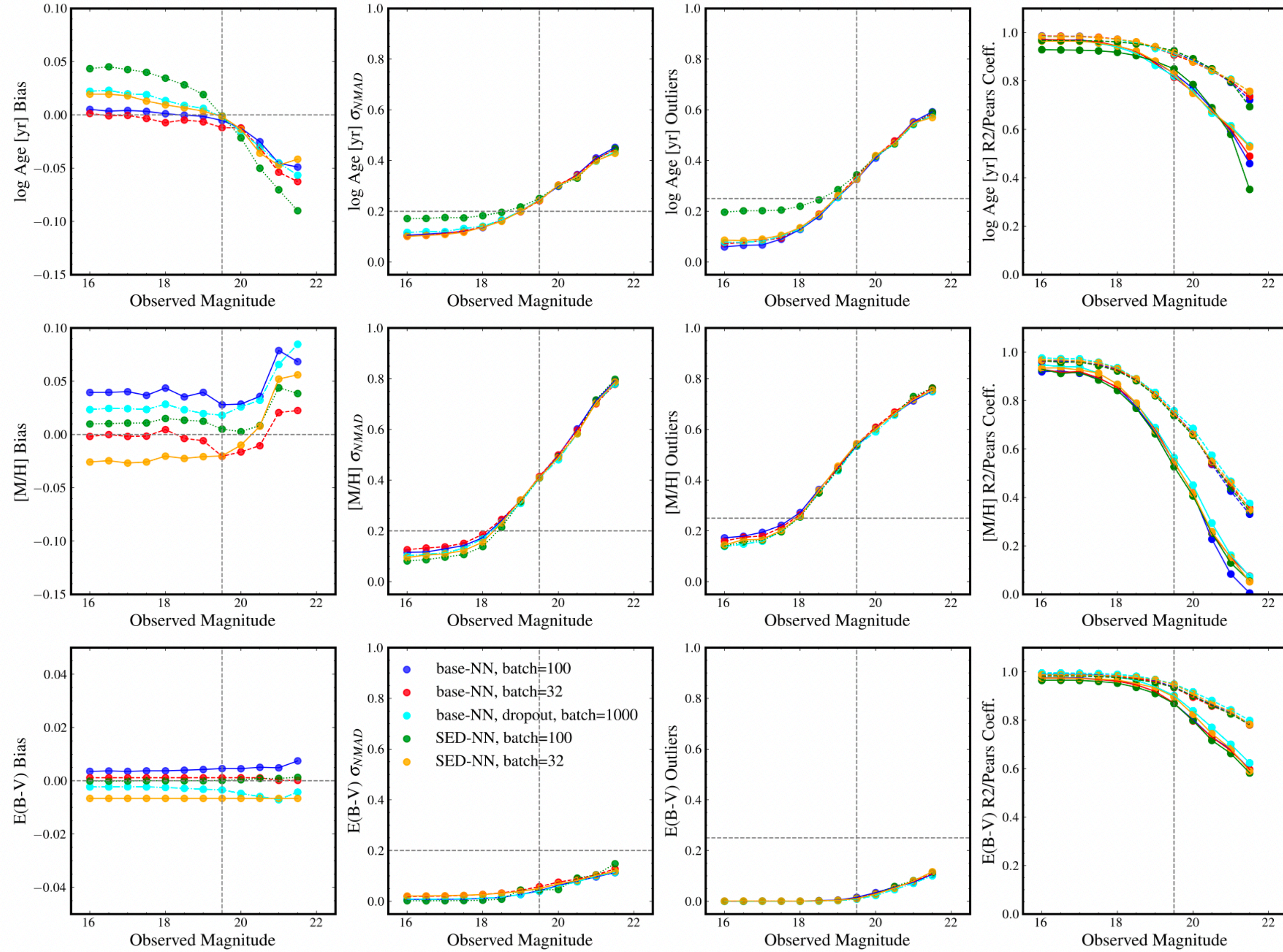


Fig. A.1. Comparison of the metrics (bias, scatter, fraction of outliers and Pearson (dashed line) and R2 (thick line) coefficients (from left to right) for different parameters (age, metallicity, and E(B-V) (top to bottom) as a function of galaxy *i*-band magnitude, obtained for different training strategies, as stated in the legend (details in Sect. 3).

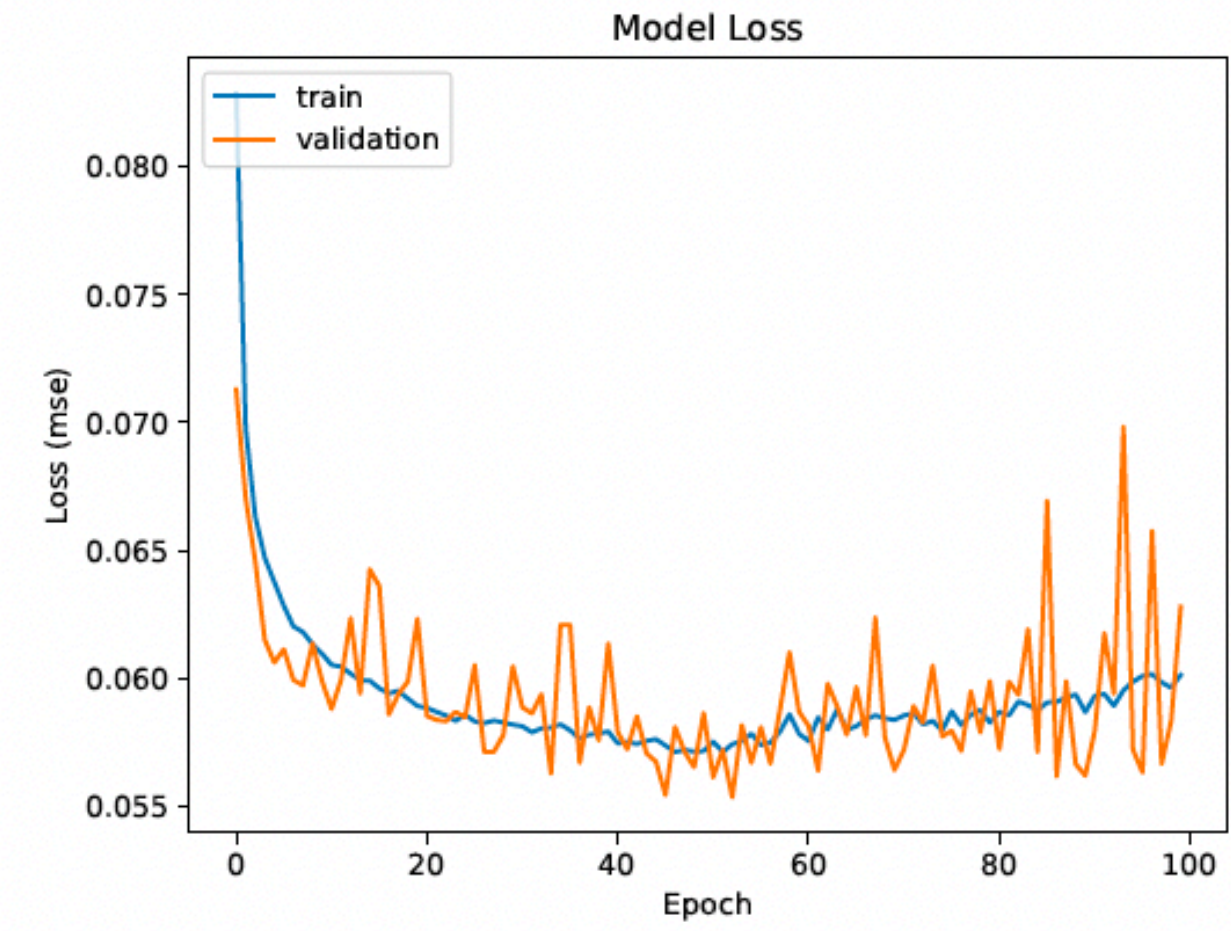
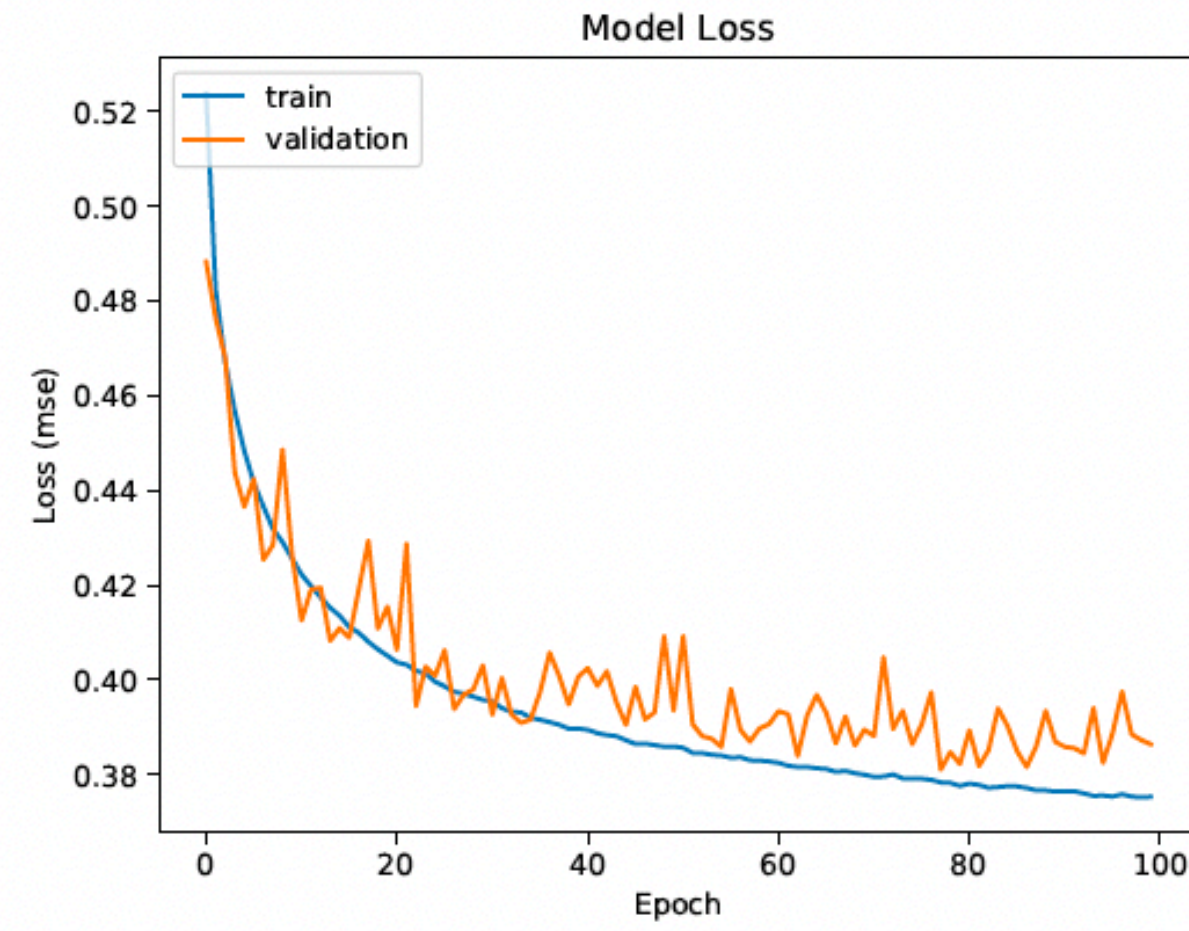
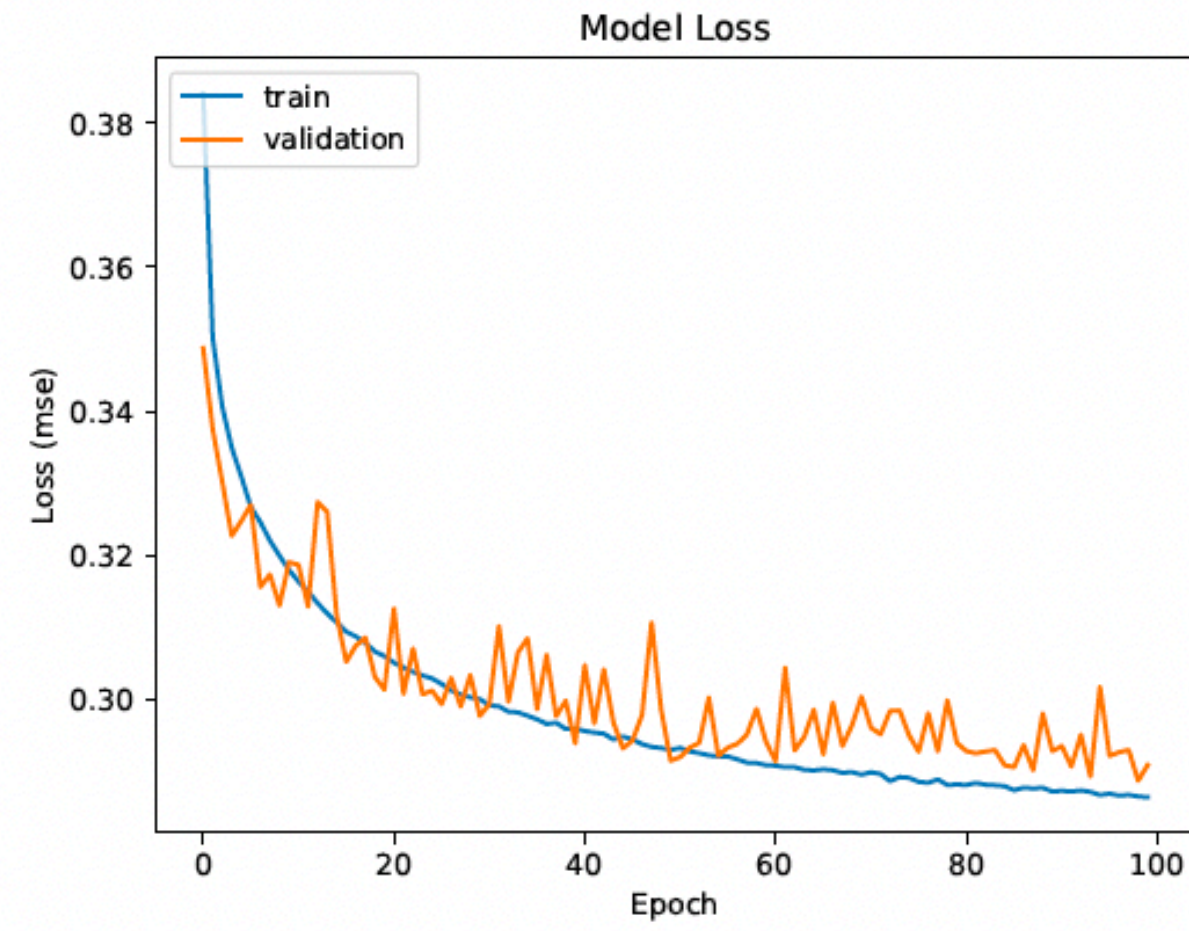


Fig. B.1. Loss curves (loss function as a function of training epoch) for the train (blue) and validation (orange) samples for the age (left), metallicity (middle), and dust attenuation (right) NN models.