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**GALAXY EVOLUTION IN THE LAST 7 GYR
THROUGH OBSERVED STAR FORMATION
HISTORIES IN COSMOLOGICAL SIMULATIONS**

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Abstract

Large extragalactic campaigns, like the Sloan Digital Sky Survey, enriched our knowledge about multiple galaxy populations in the local Universe. However, several open questions regarding galaxy evolution still need to be answered. When do galaxies quench their star formation? Do quenched galaxies rejuvenate during their lifetime? What is the main channel for the gas supply for the rejuvenated galaxies?

A new opportunity to address these questions recently arrived. The Stellar Population at intermediate redshift Survey (StePS) is one of the eight surveys that will be carried out with WEAVE, the new wide-field spectroscopic facility for the 4.2m William Herschel Telescope in the Canary Islands. WEAVE-StePS aims to obtain high-resolution ($R \sim 5000$) spectra of galaxies in the redshift range $0.3 < z < 0.7$, thus providing reliable measurements of the absorption features in the stellar continuum for a large sample of galaxies. The excellent dataset that WEAVE-StePS promises to deliver will allow us to characterize with unprecedented accuracy the last 7 Gyr of galaxy evolution. However, models and observations still need to converge to a coherent description of the star formation history of massive galaxies.

Providing for the need for a more realistic comparison between theory and observations, in this manuscript I describe the creation of a synthetic spectroscopic dataset of ~ 750 massive galaxies from the TNG50 cosmological simulation tailored for WEAVE-StePS observations. I compare the star formation history of these galaxies, retrieved using a full spectral fitting analysis. This strategy will allow a proper comparison between observed star formation histories and those inferred from cosmological simulations, looking for possible systematics and observational biases.

Applying this framework, I find that the fractions of quiescent and green-valley systems increase toward lower redshift, consistent with ongoing quenching and the build-up of the red sequence; the green-valley fraction peaks at $z=0.5$ (11%), indicating an elevated incidence of transitioning galaxies. I introduce the simple diagnostic $\Delta\text{AGE} \equiv \text{AGE}_{\text{MW}} - \text{AGE}_{\text{LW}}$ to flag rejuvenation episodes and show that it robustly identifies recent star formation in otherwise quiescent systems. Rejuvenation signatures are stronger in integrated than in fiber-like spectra, suggesting that young populations preferentially reside outside galaxy centers.

I further extend the analysis to the local Universe to assess environmental effects, combining archival IFU data for Virgo and Fornax cluster galaxies with forward-modeled TNG100 analogs selected to match the host clusters' halo mass and virial radius. The main advantage of this approach is that, unlike observations that can only provide

a snapshot of the present-day universe, cosmological simulations offer comprehensive insights into the past of each galaxy, enabling a direct connection between present-day SFHs and assembly pathways. Overall, I find that infall time (e.g., when the galaxy enters the cluster) regulates the SFH timescale at low stellar mass, while mergers increasingly govern mass assembly at high stellar mass.

Together, these results deliver validated tools and benchmarks for interpreting forthcoming WEAVE–StePS spectra, and they sharpen constraints on the quenching and rejuvenation channels that shape the mass-assembly histories of massive galaxies.

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Introduction

Large extragalactic campaigns, like the Sloan Digital Sky Survey (SDSS; York et al., 2000), enriched our knowledge about the different galaxy populations in the nearby Universe (e.g., Strateva et al., 2001; Kauffmann et al., 2003; Blanton et al., 2003; Baldry et al., 2004; Gallazzi et al., 2005, 2006; Thomas et al., 2010; Goddard et al., 2017). These observations revealed a clear bimodality in the properties of local galaxies (i.e., morphology, color, spectral type, and star formation), with red, quiescent, early-type systems separating from blue, star-forming, late-type galaxies. As illustrated in Fig. 1, the same trend can be found if we look at the stellar velocity dispersion and luminosity-weighted ages of galaxies, separating them in bins of environmental density (Thomas et al., 2010). The bimodal age distribution is clear: a dominant, old red-sequence component (orange contours) and a secondary, rejuvenated component with light-weighted ages $\lesssim 2.5$ Gyr (cyan contours). The age- σ relation of the red sequence is essentially independent of environment, whereas the rejuvenated fraction increases toward lower densities (from $\sim 4\%$ at high density to $\sim 16\%$ at low density; $\sim 10\%$ overall). Another example of this bimodality appears in the color-magnitude diagram: galaxies in the *blue cloud* lie on a tight star-forming main sequence (a narrow $SFR-M_\star$ relation) (e.g., Brinchmann et al., 2004; Daddi et al., 2007; Whitaker et al., 2012; Rinaldi et al., 2025), whereas *red-sequence* galaxies are largely quenched and show no $M_\star-SFR$ correlation. These two populations are separated by transition galaxies, lying in the so-called *green valley* (Salim et al., 2007). This segregation of galaxies reflects the heterogeneity of physical processes affecting their evolution. Indeed, the comparison of galaxy properties at different redshifts show that they could experience transformations over cosmic time, mostly due to the cessation of star formation activity and rejuvenation events (Lilly et al., 2013; Vulcani et al., 2015; Mancini et al., 2019; Förster Schreiber & Wuyts, 2020; Pérez-González et al., 2023; Le Bail et al., 2024; Carnall et al., 2024).

Our ability to reconstruct the star formation histories (SFHs) of galaxies from their stellar populations is key to tracing their individual evolution and constraining their transformation. In this context, a common approach consists of *archaeologically* reconstructing the SFHs of local galaxies, analyzing key features in their spectra and the possible relation with other galaxy properties, e.g., stellar mass, kinematics, star formation activity, and environment. But, despite the large availability of high-resolution spectra of nearby galaxies, it is still extremely difficult to resolve their complex SFHs, due to the degeneracy between age and metallicity and the slow evolution of low-mass

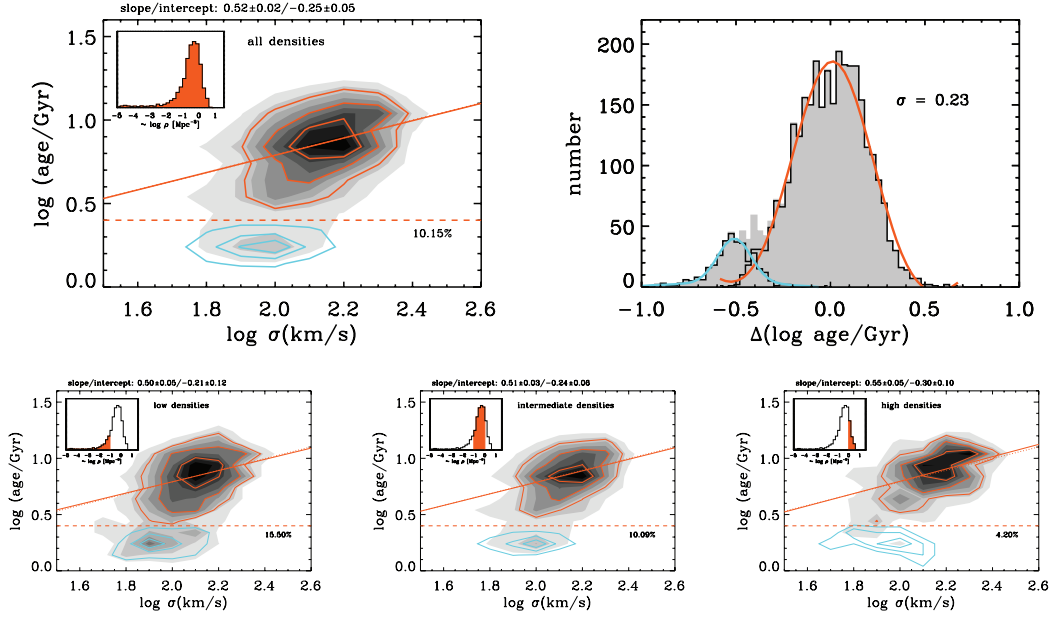


Figure 1. Stellar velocity dispersion versus luminosity-weighted age in bins of environmental density (the distributions of density for each bin are shown in the insets). Grey contours include all galaxies; orange contours mark the old red-sequence population; cyan contours show the rejuvenated objects with light-weighted ages < 2.5 Gyr, separated by the dashed line. The fraction of rejuvenated systems is indicated in each panel. Solid lines are linear fits to the red-sequence population in each density bin, while the dotted line is the fit for the full sample; the residual distribution and scatter are shown in the top-right panel. The age- σ relation for red-sequence galaxies is independent of environment, whereas the rejuvenated fraction increases toward lower densities. Adapted from Fig. 2 [Thomas et al. \(2010\)](#).

stars in evolved stellar populations (mass-weighted ages > 5 Gyr), typical of the majority of massive galaxies ($M_\star > 10^{10} M_\odot$; [Gallazzi et al., 2005](#); [Serra & Trager, 2007](#)).

The SFHs at early times can be better constrained at intermediate redshifts, when stellar populations were younger and galaxies contained more massive stars. Interestingly, the intermediate-redshift range ($0.3 \leq z \leq 0.7$) has remained largely underexplored by surveys of sufficient quality to apply the archaeological method. This gap limits our ability to reconstruct the evolutionary history of galaxies continuously over the ~ 8 Gyr (since $z \sim 1$). Until recently, only a handful of studies have derived ages and metallicities from high S/N spectra of intermediate redshift galaxies, with most focusing on quiescent cluster galaxies (e.g., [Kelson et al., 2000](#); [Sánchez-Blázquez et al., 2009](#); [Jørgensen & Chiboucas, 2013](#); [Ferré-Mateu et al., 2014](#); [Werle et al., 2022](#)), though see [Gallazzi et al. \(2014\)](#) for an analysis including both quiescent and star-forming field galaxies. Despite their limited sample sizes, typically ranging from a few dozen to about a hundred galaxies, these studies have underscored the value of tracing galaxy properties

across redshift and environment. To date, the Large Early Galaxy Astrophysics Census Survey (LEGA-C; [van der Wel et al., 2016](#)) is the best campaign suited to trace SFHs in individual galaxies at intermediate redshift ($0.6 < z < 1.0$), collecting approximately 3000 spectra with median signal-to-noise ratios $S/N \sim 20 \text{ \AA}^{-1}$ ([Straatman et al., 2018](#)). This effort will soon be complemented by the Stellar Population at intermediate redshift Survey (StePS; [Iovino et al., 2023a](#)), one of the eight surveys that will be carried out with the WHT Enhanced Area Velocity Explorer (WEAVE; [Jin et al., 2024](#)), the new wide-field spectroscopic facility for the 4.2-m William Herschel Telescope (WHT) in the Canary Islands. WEAVE-StePS aims to obtain relatively high-resolution ($R \sim 5000$) spectra with typical signal-to-noise ratios $S/N \sim 10 \text{ \AA}^{-1}$ for a sample of $\sim 25,000$ galaxies with magnitude $m_i \leq 20.5$ mag, the majority of which lie in the redshift range $0.3 < z < 0.7$ (for details, see [Iovino et al., 2023a](#)). Thus, the survey will provide reliable measurements of the emission lines and absorption features in the stellar continuum across a broad wavelength coverage ($3660 - 9590 \text{ \AA}$) for a large sample of galaxies in different environments.

The wide wavelength coverage that WEAVE-StePS promises to deliver includes numerous absorption and emission features that trace the stellar and ionized-gas components (see Fig. 2). The potential of StePS-like spectra for galaxy-evolution studies with spectral indices has been explored in detail by [Costantin et al. \(2019\)](#) and [Ditrani et al. \(2023\)](#). The spectra maps the rest-frame UV down to $\sim 2900 \text{ \AA}$ at $z \sim 0.3$ and to $\sim 2200 \text{ \AA}$ at $z \gtrsim 0.7$, providing sensitivity to hot, young stars that trace the most recent tail of galaxy star-formation histories. The high-quality WEAVE-StePS spectra will allow to infer robust stellar ages which, combined with LEGA-C and SDSS, will chart the buildup of stellar mass from $z \sim 1$ to today. The same diagnostics constrain star-formation decline timescales and quenching, reveal rejuvenation, and provide a census of genuinely old, passive systems. Furthermore, WEAVE-StePS will allow to measure stellar and gas-phase abundances to probe the mass-metallicity and fundamental metallicity relations—key indicators of gas cycling and exchange with the environment (e.g., [La Barbera et al., 2017](#); [Gallazzi et al., 2021](#); [Mannucci et al., 2010](#); [Maiolino & Mannucci, 2019](#)). The broad spectral range and $R \sim 5000$ resolution ($\text{FWHM} \sim 50 \text{ km s}^{-1}$) enable uniform AGN/LINER diagnostics and, via $[\text{O III}] \lambda 5007$ up to $z \sim 0.9$, kinematic decomposition of outflows into narrow ($\sim 100 \text{ km s}^{-1}$) and broad ($> 300 \text{ km s}^{-1}$) components ([Heckman & Best, 2014](#); [Rubin et al., 2012](#); [Harrison et al., 2018](#); [Woo et al., 2016](#)). As an additional effort, high-quality spectra ($S/N \sim 30 \text{ \AA}^{-1}$) for more than 3000 galaxies will be observed with the 4-metre Multi-Object Spectrograph Telescope (4MOST) facility mounted on the Visible and Infrared Survey Telescope for Astronomy (VISTA) as part of the 4MOST-StePS campaign ([Iovino et al., 2023b](#)), the complementary southern-sky counterpart to WEAVE-StePS.

These spectroscopic datasets are promising for advancing our understanding of galaxy evolution at intermediate redshifts. A powerful way to analyze integrated light spectra (and broad-band spectral energy distributions, SEDs) is to infer stellar population properties and thereby reconstruct SFHs. Foundational efforts trace back to [Morgan \(1956\)](#), [Wood \(1966\)](#), [Tinsley \(1968\)](#), [Faber \(1972\)](#), and [Spinrad \(1972\)](#) for a modern overview of the methodology, its applicability regimes, and the principal degeneracies

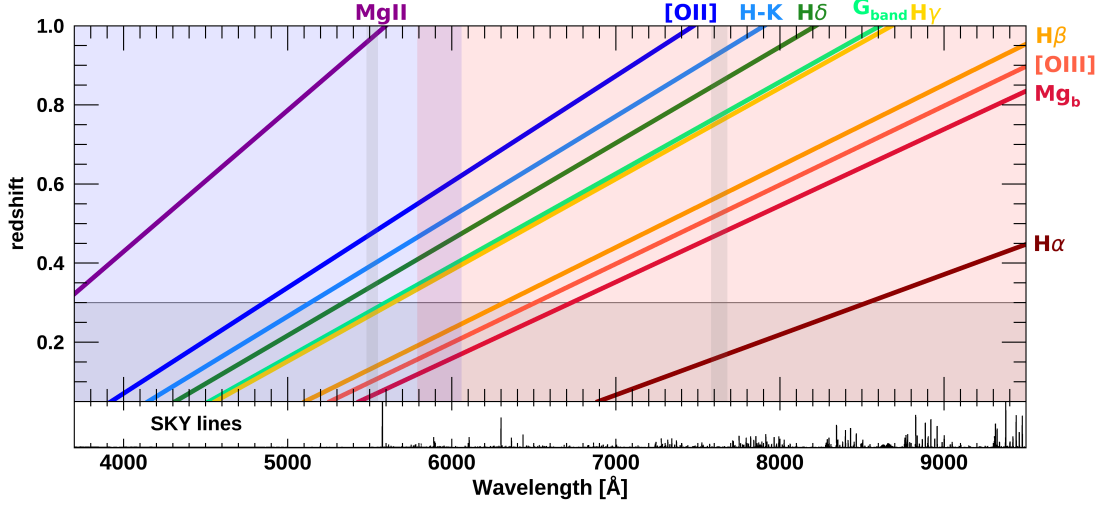
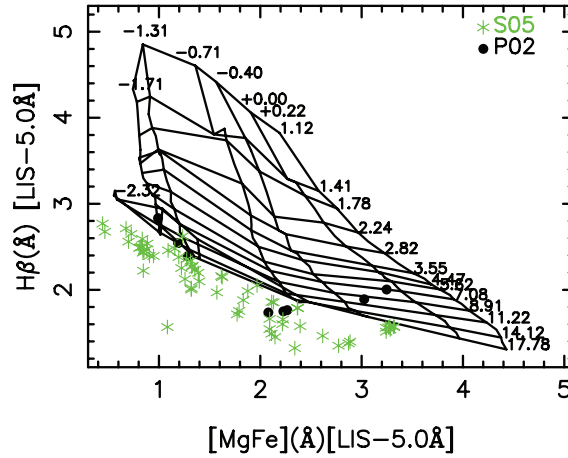


Figure 2. Visibility of key spectral indices versus redshift ($0.05 < z < 1.0$) within WEAVE’s low-resolution wavelength coverage. Blue/red shading marks the blue/red arms; violet shows the overlap. Narrow grey bands indicate CCD gaps where some features are unavailable. The empty region highlights the primary StePS target range ($z \gtrsim 0.3$). The bottom panel shows the OH sky spectrum. Adapted from Fig. 2 [Iovino et al. \(2023a\)](#).

(age–metallicity–dust–abundance, particularly acute at optical wavelengths), see [Conroy \(2013\)](#). A major step in the field came with the systematic use of optical Lick/IDS absorption-line indices ([Worthey et al., 1994](#); [Trager et al., 1998](#)). These indices represent a standard set of prominent metal- and hydrogen-line absorption features in stellar spectra, for which the equivalent widths are measured. The key idea is that different indices respond differently to variations in stellar population age and metallicity. By plotting metal-sensitive indices against hydrogen-line indices (for example, $[\text{MgFe}]$ versus $\text{H}\beta$) it becomes possible to disentangle the age–metallicity degeneracy and to estimate stellar population parameters. Such diagnostic diagrams (see Fig. 3) allow one to distinguish populations with different ages and chemical compositions. These indexes were later extended into the near-UV (e.g., [Fanelli et al., 1990](#)) and near-IR (e.g., [Conroy & van Dokkum, 2012](#)). However, using indices compresses a large amount of spectral information into a few measurements and can introduce sensitivities to spectral resolution, flux calibration, and the assumed abundance patterns.

The aforementioned caveats motivated full-spectral fitting, in which an observed spectrum is modeled as a linear combination of simple stellar population (SSP) templates spanning age, metallicity, and (where available) non-solar abundance ratios such as $[\alpha/\text{Fe}]$, optionally including kinematics and dust attenuation. This wavelength-by-wavelength approach takes advantage of the full information content of the spectrum, naturally propagates the spectral covariance, and is now widely adopted ([Koleva et al., 2008b](#); [Cappellari et al., 2011](#); [Ge et al., 2019](#); [Gonçalves et al., 2020](#)). Numerous public codes implement these ideas, including: *Starlight* ([Cid Fernandes et al., 2005](#));



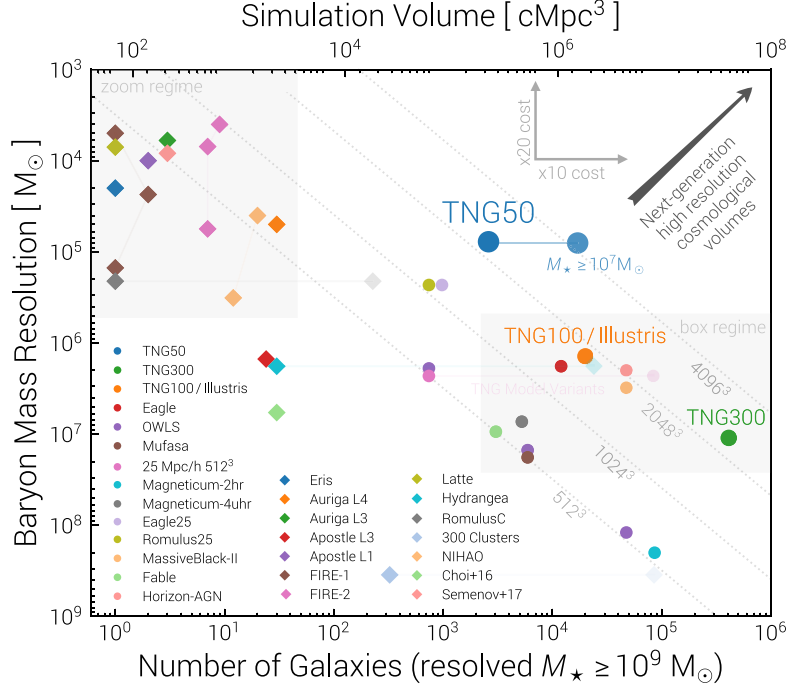


Figure 4. Comparison between recent cosmological hydrodynamical simulations. Adapted from Fig. 1 Nelson et al. (2019).

formation modeling. The most effective approach is to calibrate subgrid parameters to reproduce selected observable properties of galaxies. In this case, calibration parameters are not true predictions, but other properties can still reflect underlying physics if not dominated by subgrid assumptions. This method underlies major galaxy formation simulations such as ILLUSTRIS (Genel et al., 2014; Vogelsberger et al., 2014; Nelson et al., 2015), MAGNETICUM (Hirschmann et al., 2014), EAGLE (Crain et al., 2015; Schaye et al., 2015; McAlpine et al., 2016), ILLUSTRISTNG (Nelson et al., 2018; Pillepich et al., 2018a; Springel et al., 2018), and SIMBA (Davé et al., 2019).

In this work, I will focus on ILLUSTRISTNG, which is an improved successor to the original ILLUSTRIS simulation, featuring enhanced models of black hole feedback, stellar winds, and magnetic fields, allowing it to better match observed galaxy properties and large-scale gas distributions. The IllustrisTNG simulations adopt subgrid prescriptions for unresolved physical processes, in particular for stellar and AGN feedback. As with other simulation projects, the free parameters of these models were calibrated against a small number of key observables at $z = 0$, specifically the galaxy stellar mass function (GSMF) and the stellar size–mass relation (Pillepich et al., 2018a; Nelson et al., 2018; Springel et al., 2018). The stellar wind model was tuned to reproduce galaxy sizes, while AGN feedback was adjusted to suppress excessive star formation in massive halos and to regulate the baryon content of galaxy groups and clusters (Weinberger et al., 2017). These calibrations ensure that the simulations generate a broadly realistic galaxy

population.

IllustrisTNG reproduces a number of fundamental observational benchmarks:

- **Galaxy stellar mass function:** TNG matches the observed GSMF at $z = 0$ within ≈ 0.3 dex across the well-constrained stellar mass range (Pillepich et al., 2018a).
- **Galaxy sizes and morphologies:** the simulations reproduce the observed size–mass relation for both star-forming and quiescent galaxies at $z = 0$ and $z = 2$, a notable improvement over the original Illustris, which produced galaxies that were systematically too large (Genel et al., 2018; Rodriguez-Gomez et al., 2019a). However, the IllustrisTNG model has some difficulty with producing a strong morphology–colour relation (Rodriguez-Gomez et al., 2019a)
- **Star-formation histories:** IllustrisTNG broadly reproduces the observed evolution of the cosmic star-formation rate density (SFRD) across cosmic time. The overall shape of the SFRD history is consistent with observational estimates, with differences typically at the level of about a factor of two, comparable to current observational uncertainties (see e.g., Fig. 6 in Crain & van de Voort, 2023). In addition, Donnari et al. (2019) showed that IllustrisTNG reproduces the observed normalization, scatter, and redshift evolution of the galaxy star-forming main sequence, as well as the fraction of quenched galaxies out to $z \sim 2$.
- **Black hole–galaxy coevolution:** TNG reproduces the scaling relation between supermassive black hole (SMBH) mass and galaxy stellar mass, and demonstrates AGN-driven quenching in massive galaxies (Weinberger et al., 2018; Terrazas et al., 2020).
- **Gas content and circumgalactic medium (CGM):** the simulations predict substantial baryon fractions in the halos of $\sim 10^{12} M_{\odot}$ galaxies, regulated by AGN feedback, and provide a framework for interpreting observations of the CGM (Nelson et al., 2018; Truong et al., 2020).
- **Large-scale structure:** TNG reproduces galaxy clustering statistics and scaling relations connecting stellar mass, SFR, and halo properties, consistent with observational data (Springel et al., 2018; Nelson et al., 2019).

Overall, IllustrisTNG represents a substantial improvement over the original Illustris simulation, particularly in its treatment of feedback and its ability to reproduce both galaxy-internal properties and large-scale statistical observables. IllustrisTNG consists of three large cosmological volumes, TNG50, TNG100, and TNG300 of about 50, 100, and 300 Mpc on a side, respectively. In this manuscript, I will mostly focus on TNG50 (except in Chapter 3). While TNG100 features the same resolution and initial condition phases as Illustris, TNG50 extend the series to a better resolution. The TNG50 simulation is evolved using the moving-mesh code AREPO (Springel, 2010). The simulation follows the evolution of 2×2160^3 total initial resolution elements within a uniform periodic-boundary cube of 51.7 comoving Mpc per side. The spatial scale is

set by a gravitational softening of dark matter and stars of 0.575 comoving kpc until $z = 1$, and is then fixed to its physical value of 288 pc from $z = 1$ down to $z = 0$. For full details of the subgrid physics implemented in the simulation, I refer the reader to [Pillepich et al. \(2019\)](#) and [Nelson et al. \(2019\)](#).

Aim and Content of the Thesis

This work is driven by the need for a better understanding and characterization of complex physical processes involved in galaxy evolution, which are key ingredients of state-of-the-art cosmological simulations. Moreover, properly comparing the properties of observed and simulated galaxies is becoming crucial for both validating the physics implemented in the models and in designing the best observational strategies in extragalactic campaigns. In this context, a powerful tool for investigating the synergy between observations and theory is the so-called *forward modeling* of data (e.g., [Snyder et al., 2015](#); [Rodríguez-Gomez et al., 2019b](#); [Costantin et al., 2023](#); [Baes et al., 2024](#); [Euclid Collaboration Abdurro'uf et al., 2025](#)), which consists of generating and analyzing mock datasets from hydrodynamic simulations. The key to creating realistic mock observations from simulations is accounting for continuum and line emission; absorption and multiple anisotropic scattering by dust, electrons, and gas; dust heating with thermal and stochastic re-emission; and kinematic Doppler shifts, among other effects. The only proper way to address this is through three-dimensional radiative transfer calculations. However, solving the full 3D dust radiative transfer problem remains a significant challenge in computational astrophysics ([Steinacker et al., 2013](#)).

In recent years, the SKIRT radiative transfer code ([Camps & Baes, 2015, 2020](#)) has become increasingly popular, especially for post-processing IllustrisTNG simulations, where it has been used primarily to generate imaging datasets ([Rodríguez-Gomez et al., 2019a](#); [Costantin et al., 2023](#); [Baes et al., 2024](#)). However, the same strategy can be readily adapted to produce mock spectra or even full datacubes. These datasets are valuable not only for an apple-to-apple comparison between observations and simulations, but also offer the possibility for simulated-based inference of different pathways of galaxy evolution, which are only accessible following galaxies evolution across cosmic time.

In this thesis, I study the SFHs of massive galaxies in the redshift range $0.3 < z < 0.7$. In particular, my project addresses the following question: are galaxies at these redshifts truly quenched, or do they undergo rejuvenation episodes during their evolution? In this thesis, rejuvenation refers to a transition from a quiescent state, where the SFR is strongly suppressed, back to the star-formation main sequence, typically involving an increase in SFR by $\sim 2\text{--}4$ dex.

To answer this questions, I construct a benchmark framework to test upcoming WEAVE-StePS observations by creating and analyzing realistic mock datasets from the TNG50 cosmological simulation. The dataset, tailored to the WEAVE-StePS redshift range, enables a direct comparison between the SFHs of massive galaxies inferred from cosmological simulations and those derived from observations. This analysis serves as a crucial benchmark not only for the forthcoming WEAVE (and 4MOST) surveys, but also for other facilities, providing the community with realistic mock galaxies for

comparison against observed data.

The thesis is organised as follows:

Chapter 0 introduces a general forward-modelling methodology to generate realistic mock observations from the IllustisTNG simulation tailored to WEAVE-StePS. Starting from simulated galaxies, I perform three-dimensional radiative-transfer calculations to model dust absorption and scattering, then impose WEAVE observing conditions by adding PSF and instrumental noise for realism. The resulting mock data are analyzed with the same pipeline used for real galaxies (e.g., full spectral fitting with **pPXF**), ensuring consistency between simulated and observational data. The key assumptions and caveats of the full spectral analysis are also discussed.

Chapter 1 presents pipeline tests on a sample of nine galaxies at different redshifts and evolutionary stages. I assess currently available tools for deriving stellar population properties and SFHs from the mock spectra. The measured ages and metallicities of these galaxies are compared with the intrinsic values from TNG50 simulations. In addition, I investigate spatial variations by contrasting central and integrated galaxy properties.

Chapter 2 presents the analysis of the full WEAVE-StePS-like sample of ~ 750 massive galaxies from TNG50. I discuss the distribution of their main stellar population properties and explore their complex SFHs via full spectral fitting, quantifying possible systematic uncertainties.

Chapter 3 extends the methodology to MUSE observations in the local Universe. I construct mock datasets for galaxies in the Fornax cluster, enabling an assessment of the role of environment in shaping galaxy SFHs. First, I analyse publicly available archival ESO data, including ATLAS^{3D} for Virgo and Fornax3D for Fornax. I then identify Fornax-like clusters in TNG100 and adapt the algorithm to create MUSE-compatible mock datasets.

Then I summarize the conclusions of the thesis and outline directions for future research.

Throughout this work, I assume a [Planck Collaboration et al. \(2016\)](#) cosmology with $H_0 = 67.74 \text{ km s}^{-1} \text{ Mpc}^{-1}$, $\Omega_m = 0.3089$, and $\Omega_\Lambda = 0.6911$. Magnitudes are quoted in the AB system ([Oke & Gunn, 1983](#)), and all errors are reported as standard deviations unless stated otherwise.

Methodology Overview

In recent years, cosmological simulations have greatly advanced our understanding of galaxy formation and evolution. However, comparing simulation predictions directly with observational data is not straightforward. Real observations are affected by instrumental limitations such as noise, finite spatial sampling, and restricted spectral resolution. Moreover, simulations typically provide access to intrinsic quantities such as the full three-dimensional mass density distribution, whereas observations only capture the emitted light, projected onto the sky and integrated along the line of sight.

To establish a meaningful comparison between simulations and observations, one must adopt a forward-modelling approach. In this framework, simulated galaxies are processed through virtual instruments, accounting for physical effects such as dust attenuation and scattering, as well as observational effects such as instrumental resolution and noise. This ensures that the mock data are analysed in the same way as real observations, thereby providing a fair benchmark.

In this chapter, I present the methodology used to create such mock datasets, tailored to the WEAVE-StePS survey. I describe the radiative transfer calculations performed to model the effects of dust, the procedures adopted to mimic observational conditions (e.g., adding noise and imposing seeing effect), and the tests carried out to validate the final setup. This methodology forms the foundation for the analysis in the subsequent chapters.

The overall workflow is illustrated in Figure 0.1, and each step is discussed in detail in the subsequent sections. The main steps are the following.

- select galaxies from the IllustrisTNG simulations and extract the three-dimensional mass–density distributions of stars and gas;
- perform dust radiative-transfer modelling with **SKIRT**, assigning SPS spectra to stellar particles (primary source of emission) and adopting a physically motivated dust model;
- impose observing conditions by adding atmospheric seeing and instrumental effects (throughput, spectral resolution), and inject realistic noise;
- analyse the resulting mock data with the same pipeline used for real observations (e.g., full spectral fitting).

In the last step, the framework can accommodate any type of analysis (e.g., line-index studies, colour measurements, or kinematics). In this way, it provides a fundamental benchmark for the forthcoming WEAVE observations, offering the community realistic mock galaxies to compare with the first data releases and to explore optimal strategies for future surveys. This forward-modelling approach enables a direct, *apples-to-apples* comparison between simulated and observed data. Importantly, the same framework can be also readily adapted to different facilities and surveys.

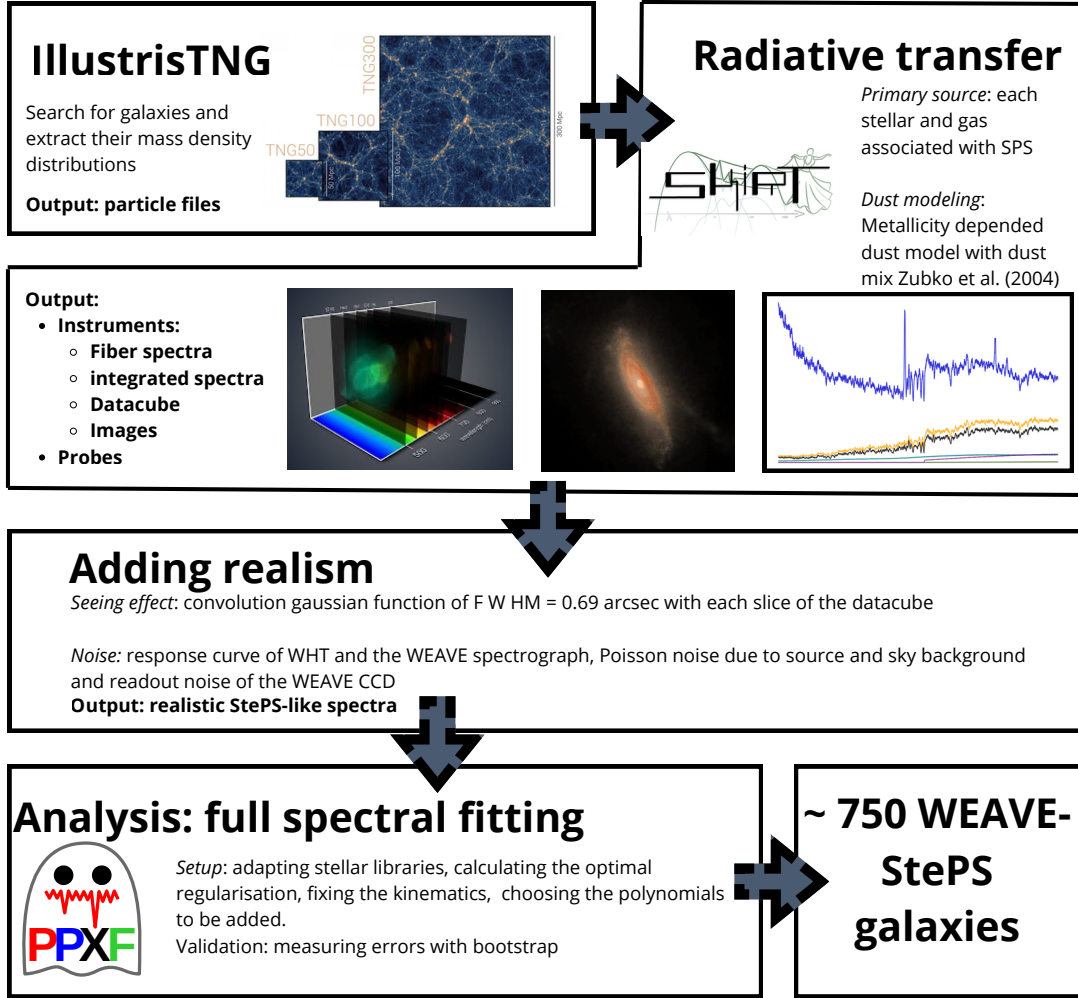


Figure 0.1. Overview of the mock dataset generation and analysis pipeline.

0.1 IllustrisTNG sample

The IllustrisTNG project is a suite of state-of-the-art cosmological galaxy-formation simulations (Nelson et al., 2019; Pillepich et al., 2019; Weinberger et al., 2017; Pillepich et al., 2018b). In the thesis, I make use of the TNG50 and TNG100 runs, corresponding to cosmological boxes of side length 50 Mpc and 100 Mpc, respectively.

To obtain the initial galaxy sample, I used the public API of the ILLUSTRITNG project. I have coded a Python script to automate the selection and downloading process. First, the script queries galaxies within a desired stellar-mass range using:

```
?mass_stars__gt={mass_min}&mass_stars__lt={mass_max}
```

The search is performed at a fixed redshift through an API call of the form:

`http://www.tng-project.org/api/TNG50-1/snapshots/z={redshift}/
subhalos/?mass_stars__gt={mass_min}&mass_stars__lt={mass_max}`

The server then returns a list of subhalos (galaxies) matching these criteria.

In a second step, the script iterates over this list of IDs and downloads the corresponding subhalos in `.hdf5` format. These files contain the relevant physical properties and particle data needed for further analysis and mock-data generation. I then automatically create summary files containing the necessary information for each particle type:

- **old stars** – stellar particles with ages greater than 10 Myr;
- **young stars** – stellar particles with ages younger than 10 Myr, representing sites of recent star formation;
- **star-forming gas** – gas particles with non-zero star-formation rates (`sfr_gas` > 0);
- **non-star-forming gas** – gas particles with `sfr_gas` = 0.0.

For every particle, I store its three-dimensional position, mass, metallicity, and velocity components. For stellar particles, I additionally record the age and star-formation rate, while for gas particles I keep the temperature. This dataset serves as the input for the SKIRT radiative-transfer simulations.

0.2 SKIRT

As mentioned at the beginning of this chapter, simulations and observations must be brought to a common ground in order to make meaningful comparisons and reliable predictions. The challenge is to translate the particle-based information from simulations, namely, positions, ages, and metallicities, into observable light-based quantities such as images, one-dimensional spectra, or three-dimensional datacubes. The simplest approach would be to assign a spectrum to each stellar particle, thereby producing mock observations. However, to properly account for scattering in the interstellar medium and the effects of dust attenuation, full three-dimensional radiative-transfer calculations are required. Dust attenuation plays a crucial role in shaping galaxy spectra, for instance by absorbing and scattering between one-third and one-half of the stellar light in typical spiral galaxies in the local Universe (Popescu & Tuffs, 2002; Viaene et al., 2016; Bianchi et al., 2018). It is therefore essential to account for these effects properly. In this section, I outline the strategy for constructing realistic mock datasets of galaxies, incorporating dust attenuation and scattering, starting from state-of-the-art cosmological simulations with use of the radiative-transfer code.

In order to produce a noiseless mock dataset, I retrieve the star and gas particles of each selected galaxy in IllustrisTNG and model the light distribution of the different stellar populations and star-forming regions, including the effects of dust on radiation. For this task, I employ the SKIRT¹ Monte Carlo radiative transfer code (v9.0; Camps &

¹SKIRT documentation: <http://www.skirt.ugent.be>.

Baes, 2020), which is a state-of-the-art to build mock datasets from different cosmological simulations (Costantin et al., 2023; Barrientos Acevedo et al., 2023; Baes et al., 2024; Nanni et al., 2024)).

My strategy is to model both the light distribution produced by stellar populations (old stars, as described in the previous section) and by star-forming regions (young stars), as well as the effects of dust on this radiation. For each galaxy and each snapshot, I extract the corresponding sets of subhalo star particles and gas cells, while stellar wind particles are ignored. The adopted field of view for each subhalo is set equal to the total (dark matter + stars + gas) half-mass radius of the corresponding galaxy. As a note of caution, several assumptions are required when post-processing numerical simulations (see Section 1.1.3.1). Another important parameter is the number of photon packets used to generate the SED. This can be evaluated by inspecting the probe (diagnostic) files produced by SKIRT (see Section 0.2.1.4). Similar strategies have been employed by Camps et al. (2016, 2018); Trayford et al. (2017); Rodriguez-Gomez et al. (2019b); Kapoor et al. (2021); Costantin et al. (2023). Unlike in these previous works, I adopt a metallicity-dependent dust-to-metal ratio instead of a constant value (see also Popping et al. 2022).

In this section, I describe the setup parameters (Section 0.2.1), including the primary sources of emission and the adopted dust model. I then discuss the output produced by SKIRT (Section 0.2.1.5), namely the mock datasets corresponding to different instruments, as well as the diagnostic probe files.

0.2.1 Setup parameters

In this section, I present a comparison of different setup choices and explain the parameters ultimately adopted. Throughout this thesis I make use of both the TNG50 (Chapters 1 and 2) and TNG100 (Chapter 3) simulations. Most of the tests presented here, such as library comparisons, resolution checks, and velocity component analyses, were performed with TNG100 to save computational time.

0.2.1.1 Primary source

For the primary source of emission, I assign to each star particle a SED that depends on its age and metallicity, which were extracted from the IllustrisTNG database. To account for the galaxy kinematics, I include the velocity components of each star particle. SKIRT offers a variety of stellar SED libraries that can be used to assign emission properties to stellar sources (see the box below).

Available stellar SED families in SKIRT

1. A black body SED family;
2. A Castelli–Kurucz SED family for stellar atmospheres;
3. A Bruzual–Charlot SED family for single stellar populations;
4. A Maraston SED family for single stellar populations;
5. A Starburst99 SED family for single stellar populations;
6. An FSPS SED family for single stellar populations;
7. A BPASS SED family for single stellar populations;
8. A user-provided SED family for single stellar populations;
9. A user-provided, indexed SED family;
10. A MAPPINGS III SED family for star-forming regions.

Each star particle older than 10 Myr is modeled with a simple stellar population (SSP) from the BPASS library (version 2.2.1; [Eldridge et al., 2017](#); [Stanway & Eldridge, 2018a](#)) and a [Chabrier \(2003\)](#) initial mass function with an upper mass limit of $300 M_{\odot}$ (the `bin-imf_chab300` model). Each star particle younger than 10 Myr is treated as an unresolved region of the interstellar medium (ISM) and is modeled with an SED from the MAPPINGS III library ([Groves et al., 2008](#)), which accounts both for the HII region and for the surrounding photodissociation region.

The choice of the BPASS library is motivated by the fact that it is the only option available in SKIRT that provides sufficiently high spectral resolution across the entire wavelength range of interest. This is particularly important when modelling detailed spectral features that are relevant for mock observations and subsequent analyses. Figure 0.2 shows a comparison between the spectra generated with BPASS and with the commonly used Bruzual–Charlot model, highlighting the differences in spectral resolution. Both spectra were interpolated to the same wavelength step ($1 \text{ \AA}$ per pixel, as expected after the WEAVE–StePS pipeline), but the BPASS model retains more detailed spectral-line information. The spectra are shown prior to adding the velocity component and were generated using 10^8 photon packets.

0.2.1.2 Dust modeling

IllustrisTNG does not include dust physics; therefore, I model the properties of dust in the ISM using the position, density, and metallicity of Voronoi gas cells defined through the built-in Voronoi dust grid ([Camps et al., 2013](#)). Following [Kapoor et al. \(2021\)](#), the dust component is assumed to be traced by either star-forming ($SFR > 0$) gas cells or cold gas cells (i.e., with temperature $T < 8000 \text{ K}$). The mass of the metals in the ISM is then converted into dust mass with a dust-to-metal ratio f_{dust} using the

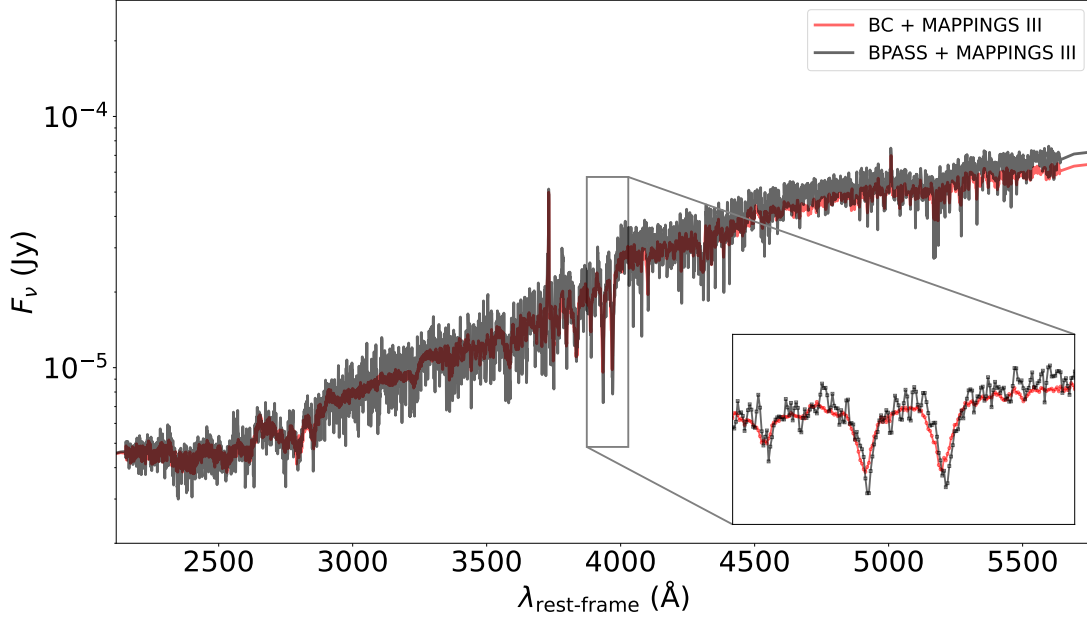


Figure 0.2. Comparison between spectra generated with the Bruzual–Charlot and BPASS libraries. The simulations were performed with 10^8 photon packets and no velocity component added. The inset shows a zoom on the Ca H+K doublet region.

relation described in Popping & Péroux (2022). To convert TNG50 metallicities to gas-phase metallicities, I assume that oxygen makes up 35% of the metal mass and hydrogen $\sim 74\%$ of the baryonic mass. These fractions follow the metal mixture used in IllustrisTNG (Torrey et al., 2019, see also the TNG forum discussion²). The dust mass density of cold and star-forming gas cells is then set to be $\rho_{\text{dust}} = f_{\text{dust}} Z_{\text{gas}} \rho_{\text{gas}}$, where Z_{gas} is the metallicity and ρ_{gas} is the density of the gas for cold and star-forming gas cells and zero for all the other gas cells.

The dust composition is modeled with the dust mix of Zubko et al. (2004), which includes non-composite silicates, graphite, and neutral and ionized polycyclic aromatic hydrocarbon dust grains. I allow dust grains to be stochastically heated and decoupled from local thermal equilibrium, also including dust self-absorption and re-emission.

0.2.1.3 Adding velocity component

To capture the full Doppler broadening in the SKIRT spectra, I included the three-dimensional velocities of both stellar and gas particles in the simulation setup. This step is not required when producing mock images, but is essential for generating realistic spectra, where line broadening plays a significant role. However, the raw TNG particle velocities also include the galaxy’s bulk motion (center of mass). For example, in the spectrum of galaxy ID = 5 at $z = 0.7$ in TNG100 (Fig. 0.3), including the velocity

²<https://www.tng-project.org/data/forum/topic/196/converting-given-metallicities-to-logoh12/>

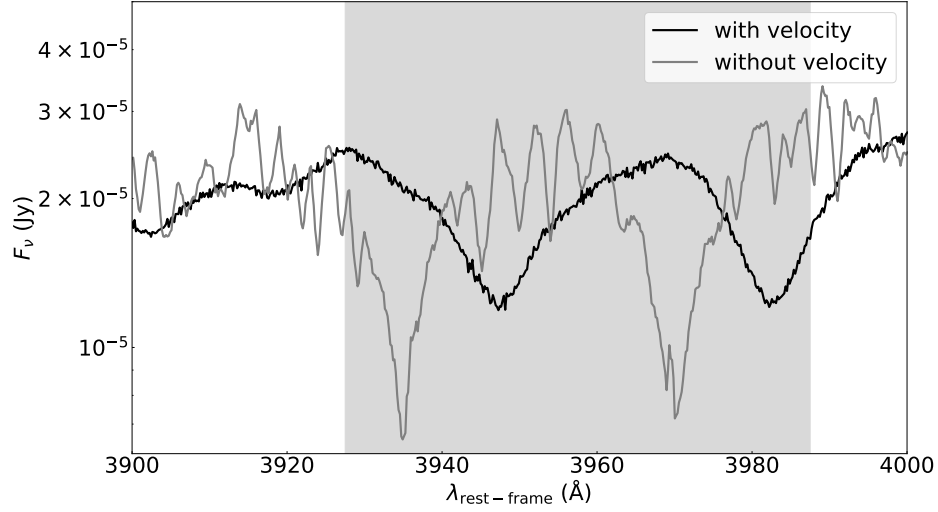


Figure 0.3. Synthetic spectrum of galaxy ID 5 (TNG100, $z = 0.7$) in the Ca H+K region, shown with (black) and without (grey) the inclusion of particle velocities in the SKIRT setup. Accounting for velocities both broadens the absorption lines and produces an overall wavelength shift.

component not only increases the line width (and thus decreases the effective resolution) but also produces an overall wavelength shift of the spectrum.

It is important to note that emission and absorption lines do not necessarily have the same velocity offset, since the light is emitted in physically distinct regions. In this model, emission lines are associated with H II regions, whereas stellar absorption features trace the broader stellar population, averaging over the full velocity dispersion of the disk or bulge. As a result, the centroids of emission lines can be systematically offset from the systemic velocity defined by absorption lines, as is also observed in real galaxy spectra.

0.2.1.4 Probes

The probes provide internal diagnostic information about the simulation process. They are designed to help verify both the physical validity and the numerical stability of the output.

In the SKIRT setup, I utilized three types of probes:

- **LaunchedPacketsProbe** records the number of photon packets launched per wavelength bin. This diagnostic is useful to verify whether a sufficient number of packets have been distributed across the spectrum. The results are written in plain text format and can be visualized using the Python toolkit for working with SKIRT (PTS)³.

³<https://skirt.ugent.be/pts9/namespaces.html>

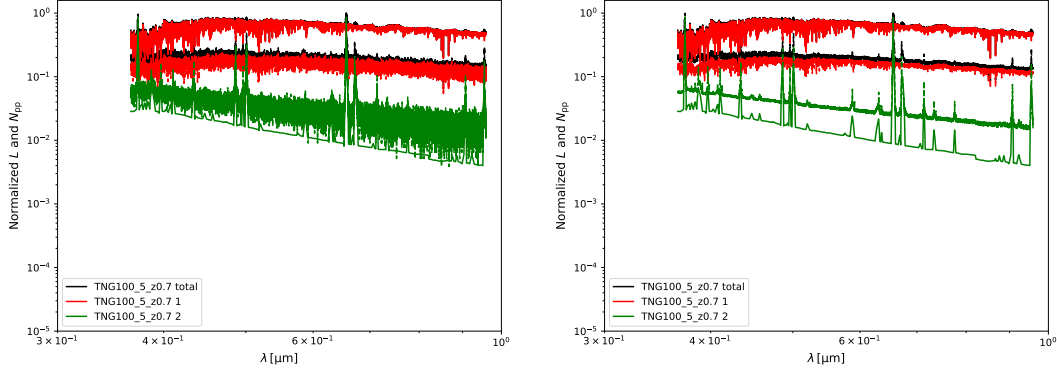


Figure 0.4. Comparison of SKIRT probe results for simulations run with 10^7 (left panel) and 10^9 (right panel) photon packets. The plots were created using the `plot_sources` command of the PTS and show the normalized luminosity (L , solid lines) and the number of photon packets (N_{pp} , dashed lines) as a function of wavelength for different emission components: total (black), stellar (red), and nebular (green). The higher photon-count simulation yields smoother continua and better-defined emission lines, particularly in low-luminosity regions.

- **LuminosityProbe** outputs the luminosities of the primary sources per wavelength bin. Combined with the information from the **LaunchedPacketsProbe**, this allows verification that the source luminosities are correctly sampled across the spectrum. Figure 0.4 compares the results from two simulations performed with 10^7 and 10^9 photon packets, respectively. These plots were created using the `plot_sources` command of the PTS. While both simulations recover the main spectral features, the 10^9 photon run produces much smoother continuum curves and more stable nebular emission lines, whereas the 10^7 photon run shows noticeable noise. For production runs, the final number of photon packets is chosen such that further increases no longer makes significant improvements in the results.
- **ConvergenceInfoProbe** serves as a sanity check to monitor the convergence behavior of the iterative dust temperature solver and the accuracy of the spatial dust grid. It produces a plain text log that records key metrics at each iteration step⁴. An example output is shown in the following box.

⁴https://skirt.ugent.be/skirt9/class_convergence_info_probe.html

Example Convergence Report

Spatial grid convergence information

----- Dust -----

Total mass

Input: 3.33138e+04 Msun

Gridded: 3.36473e+04 Msun (1.00 %)

Optical depth at 0.55 micron along full X-axis

Input: 1.23612e-05

Gridded: 1.27562e-05 (3.20 %)

Optical depth at 0.55 micron along full Y-axis

Input: 7.87348e-06

Gridded: 8.48081e-06 (7.71 %)

Optical depth at 0.55 micron along full Z-axis

Input: 7.18984e-06

Gridded: 7.03040e-06 (-2.22 %)

----- Cell statistics -----

Optical depth of cell diagonal at 0.55 micron

Largest: 0.00247173

Average: 9.86588e-05

90% < : 0.000247173

This report compares the input dust distribution with its discretized representation on the simulation grid. The dust mass is conserved to within 1%, and the optical depths along the three principal axes differ by less than 8%, which indicates good agreement. The cell statistics further show that all cells are extremely optically thin ($\tau \ll 1$), with the largest diagonal optical depth of only 0.0025. Here, the notation $90\% < : 0.000247$ indicates the 90th percentile of the cell optical depths. This ensures that photon packets traverse the medium with minimal numerical artifacts, confirming that the grid is well resolved and the simulation is numerically stable.

These diagnostic tools are especially valuable during the testing phase, allowing fine-tuning of parameters such as photon counts, wavelength resolution, and convergence thresholds. This ensures the internal consistency and reliability of the final mock observations.

0.2.1.5 Instruments

The main goal of the radiative transfer calculation is to produce a noiseless dataset, thereby simulating idealized astronomical observations. To achieve this, **SKIRT** provides a suite of virtual instruments that record the radiation from the simulated system. These instruments mimic the functionality of astronomical detectors and allow the user to generate a variety of outputs, such as SEDs, images, or data cubes. In total, **SKIRT** offers six types of instruments for recording the results of radiative transfer simulations:

1. A distant instrument that outputs the spatially integrated flux density as a SED;
2. A distant instrument that outputs surface brightness in each pixel as a data cube;
3. A distant instrument that outputs both the flux density (SED) and surface brightness (data cube);
4. An all-sky instrument for internal (embedded) observations;
5. A HEALPix-based all-sky instrument, suited for Planck-like observations;
6. A perspective instrument, primarily used for generating movies or visualizations.

In this work, I make use of the first three instrument types. Examples of instrument outputs below are shown for one WEAVE-StePS galaxy taken from the TNG50 simulation at redshift $z = 0.7$ (ID = 1722231).

- **SEDInstrument (Type 1):** This instrument is used to generate spatially integrated fiber spectra. In this work, I configure the instrument with a circular aperture of radius 0.65 arcsec, corresponding to a 1.3 arcsec fiber diameter as used in the WEAVE MOS setup.⁵

The final output includes not only the total spectrum but also its decomposition into several physical components, enabled by recording flux components in the **SKIRT** setup. These components represent the individual contributions to the total flux from both *primary* sources (e.g., stars, H II regions) and *secondary* sources (e.g., dust emission), each further separated into direct and scattered radiation (see Fig. 0.5). In addition, the output provides the corresponding flux in the absence of any attenuation, offering a transparent view of the system as if no intervening medium were present.

- **FrameInstrument (Type 2):** In addition to the spectroscopic dataset, I constructed a mock imaging dataset by convolving the **SKIRT** flux densities with the

⁵WEAVE instrument overview: <https://www.ing.iac.es/astronomy/instruments/weave/weaveinst.html>

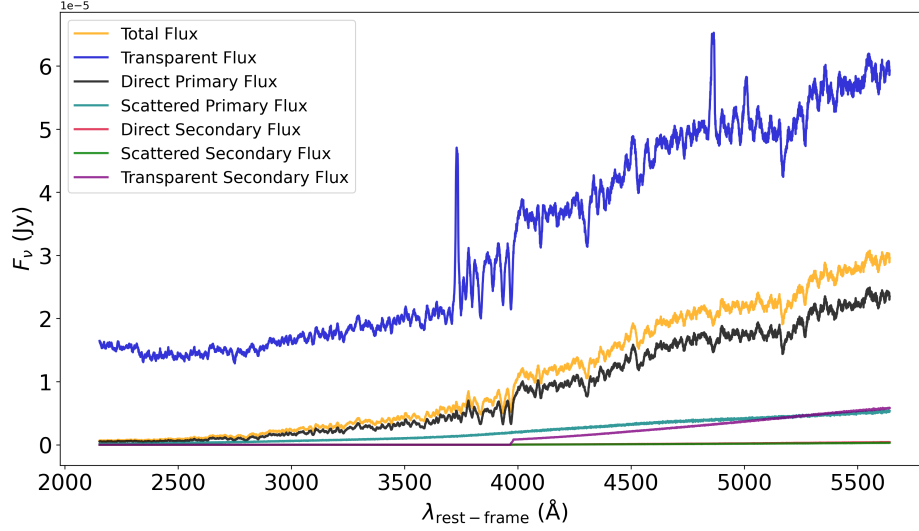


Figure 0.5. Spectral components of the fiber spectrum for galaxy ID 172231 ($z = 0.7$, TNG50). The decomposition shows the relative contributions from direct and scattered radiation of both primary and secondary emission sources, along with the transparent (unattenuated) flux.

response curves of multiple filters. To generate broadband images, I provided the corresponding filter transmission curves, obtained from the Spanish Virtual Observatory Filter Profile Service.⁶ Specifically, I generated Sloan Digital Sky Survey (SDSS; *ugriz*) images with a spatial resolution of $0.396 \text{ arcsec px}^{-1}$; Advanced Camera for Surveys (ACS) Wide Field Channel (WFC) images in filters F435W, F606W, and F814W with a resolution of $0.03 \text{ arcsec px}^{-1}$, and near-infrared filters F105W, F125W, and F160W with $0.06 \text{ arcsec px}^{-1}$; and Near-InfraRed Camera (NIRCam) images in filters F090W, F115W, F150W, F200W, F277W, F356W, and F444W with their native spatial resolutions of $0.031 \text{ arcsec px}^{-1}$ (short channel) and $0.063 \text{ arcsec px}^{-1}$ (long channel). Figure 0.6 shows an example of the resulting dataset for galaxy ID 172231 ($z = 0.7$) from TNG50.

- **FullInstrument (Type 3):**

This combined instrument is used to produce spectral data cubes together with the corresponding integrated spectra. I configure the data cube with a spatial resolution of $0.4 \text{ arcsec px}^{-1}$ in order to enable further post-processing, including the application of seeing effects (see Section 0.3).

For this instrument, I employ hybrid wavelength grids. In this configuration, low-resolution spectra covering a broad wavelength range are generated simultaneously with high-resolution sub-grids in the target ranges (WEAVE-StePS: Chapters 1–2; MUSE: Chapter 3). The extended, low-resolution spectra provide coverage across

⁶<https://svo2.cab.inta-csic.es/theory/fps/>

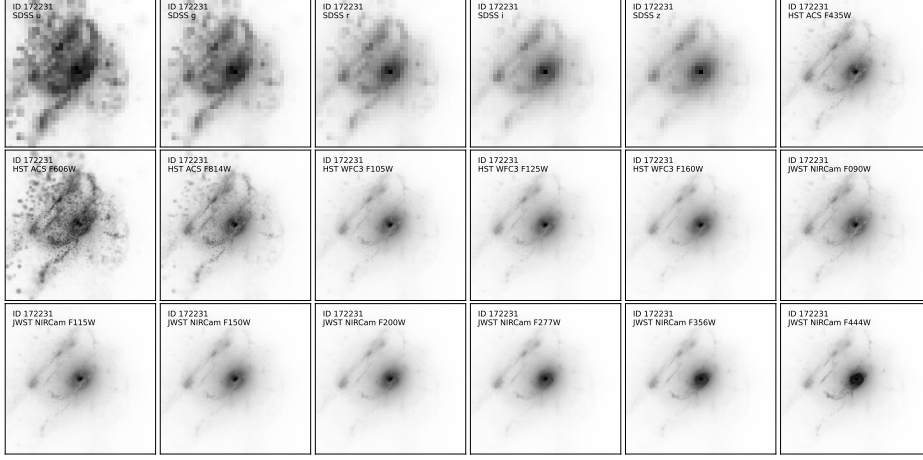


Figure 0.6. Example of the multi-wavelength imaging dataset for galaxy ID 172231 ($z = 0.7$, TNG50).

a wider wavelength range to support the construction of color-color diagrams (e.g., UVJ, Chapter 2) and to enable photometric analyses of different spectral regions, while the high-resolution sub-grids ensure accurate modeling in the specific observational windows of interest.

0.3 Observational realism

To reproduce realistic mock observations of IllustrisTNG galaxies, I emulate the WEAVE-StePS observing strategy by perturbing the simulated data cubes with seeing, noise, and instrumental spectral-resolution effects. To account for the impact of seeing, I convolve each monochromatic slice of the cube with a 2D Gaussian point-spread function (PSF) of $\text{FWHM} = 0.69$ arcsec, representative of typical WHT conditions (Wilson et al., 1999). I then extract a spectrum within a circular aperture, centered on the galaxy, with a diameter of 1.3 arcsec (see Fig. 0.7).

The PSF convolution conserves per-slice flux but redistributes it spatially; consequently, a fixed aperture captures less continuum and line flux, and line profiles appear broader because of PSF-induced mixing of velocities.

Finally, I follow the recipe described in Costantin et al. (2019) and Ditrani et al. (2023) and perturb each fiber spectrum accounting for the combined response curve of the WHT and that of the WEAVE spectrograph, Poisson contribution due to source and sky background, and readout noise of the WEAVE CCDs. In particular, the sky noise is computed assuming typical conditions of dark nights in La Palma (surface brightness $V \sim 22$ mag arcsec $^{-2}$; Benn & Ellison (1998)), while the read-out noise was assumed to be $\sim 2.5\text{e}^{-}\text{px}^{-1}$ (Dalton et al., 2016). Since StePS observing strategy consists of multiple but short exposures (~ 20 min), I neglect the contribution of thermal noise due to dark current ($< 0.1\text{e}^{-}\text{h}^{-1}$). Each source of noise is added in quadrature to estimate the total noise, which is used as the σ of a Gaussian distribution to perturb

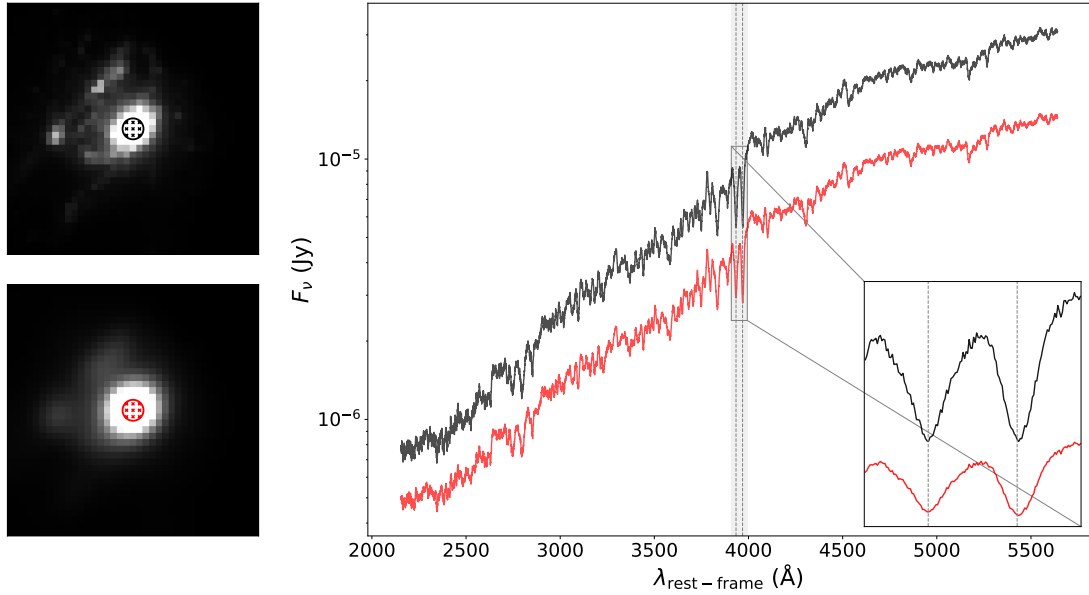


Figure 0.7. Fiber spectra extracted from the mock data cube of galaxy ID 172231 (TNG50, $z = 0.7$) before (black) and after (red) PSF convolution with $\text{FWHM} = 0.69$ arcsec. The left panels show the collapsed images (top: original; bottom: PSF-convolved) with the 1.3 arcsec aperture overlaid. The right panel shows the corresponding spectra with zoom on the Ca H+K doublet region.

each normalized spectrum. The final spectrum is shown in Fig. 0.8, corresponding to a signal-to-noise ratio of 10 in the observed I -band (7583.88–7783.88 Å).

To evaluate the quality of the extracted spectra, I measured the S/N in both the final (noisy) and the noiseless spectra using the `DER_SNR` algorithm⁷ (see Figure 0.8, bottom panel). This method estimates the S/N in a spectrum by calculating the median flux divided by the standard deviation of the high-frequency noise, making it robust against strong features and outliers. The results show that the target S/N was successfully achieved in the I -band, as intended.

0.4 Full-spectral fitting: pPXF

As noted at the beginning of this chapter, once the final spectra are produced one can analyse them exactly as real observations, enabling a true apples-to-apples comparison between mock datasets (outputs of cosmological simulations) and observations of analogous targets. The main focus of my PhD is the study of stellar populations, for which full-spectral fitting is a powerful approach (Koleva et al., 2008b; Cappellari et al., 2011; Ge et al., 2019; Gonçalves et al., 2020). In this section I describe the setup used for full-spectral fitting with the Penalized PiXel-Fitting method pPXF (Cappellari, 2017, 2023), which has been shown to deliver highly accurate results compared to other

⁷https://www.stecf.org/software/ASTROsoft/DER_SNR/der_snr.py

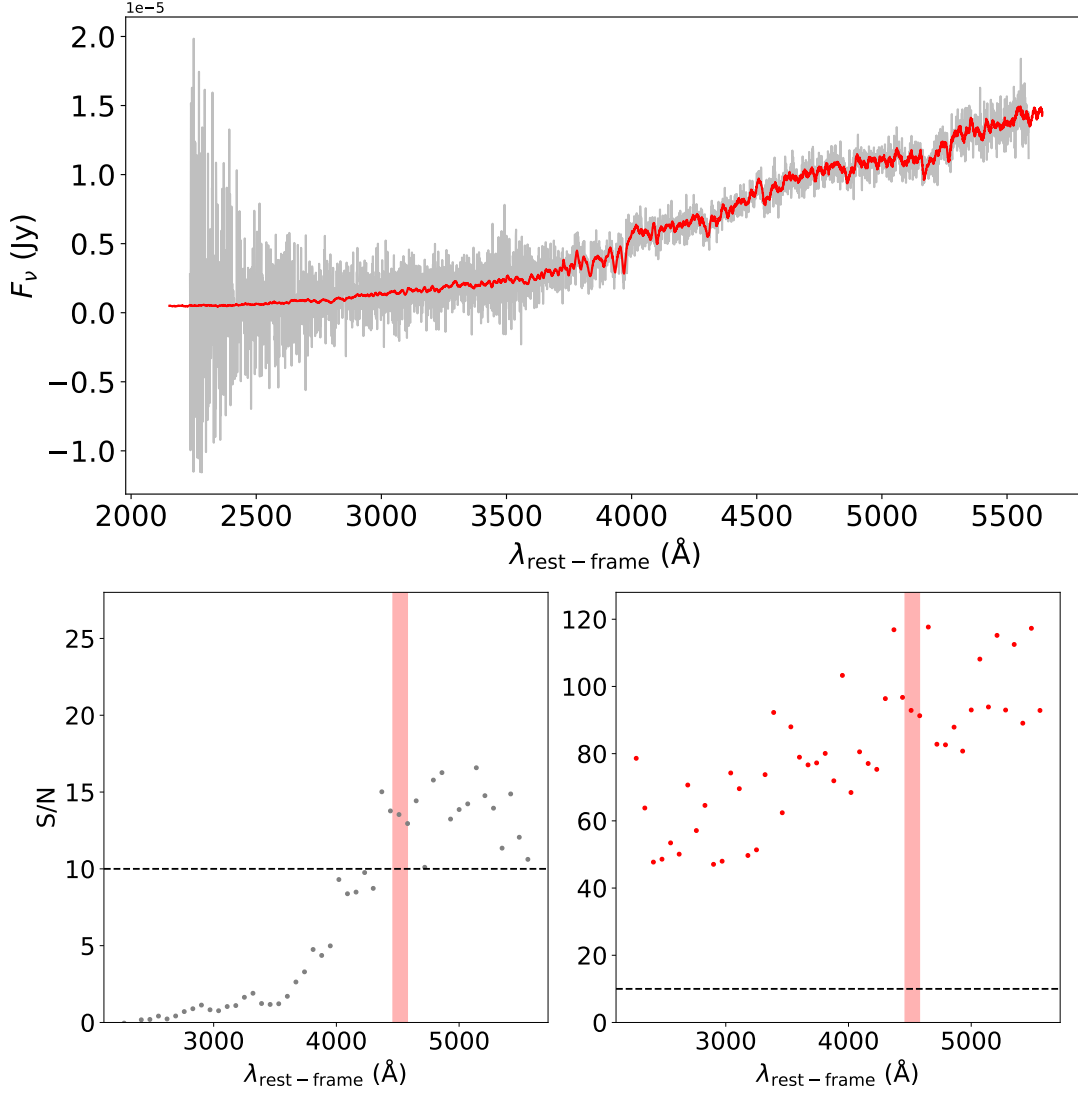


Figure 0.8. Final spectra with $S/N = 10$ and measured S/N in noisy (bottom left panel) and noiseless (bottom right panel) spectra. The red vertical band marks the rest-frame wavelength interval corresponding to the observed I -band filter.

codes (Woo et al., 2024). The method fits absorption-line spectra with a penalized maximum-likelihood scheme to recover stellar (and, when included, gas) kinematics and stellar population properties. I use pPXF version 9.1.1 which also allow the inclusion of broadband photometry, which can tighten constraints on age–metallicity–dust degeneracies (e.g., Cappellari, 2023).

The overall strategy is as follows. Spectra are shifted to the rest frame and rebinned logarithmically to a constant velocity scale (preserving flux). The stellar template library is convolved to match the instrumental line-spread function so that the template

resolution is not sharper than the data. When emission lines are present, they are fitted simultaneously with the stellar continuum. Multiplicative polynomials are used to absorb large-scale continuum-shape/calibration residuals; additive polynomials are avoided or kept low order to prevent biasing line depths.

For stellar population inference, **ppxf** regularization is employed to obtain smooth star-formation histories; the regularization strength is chosen following the standard **ppxf** prescription, i.e. increasing the χ^2 relative to the unregularized best fit by an amount consistent with the expected statistical fluctuation (of order $\sqrt{2 N_{\text{pix}}}$), ensuring an acceptable fit while discouraging unphysical, highly jagged solutions. Kinematic parameters are fitted prior to retrieval of the stellar population properties.

In the following, I detail the specific choices for the template library, regularization, measuring errors and preparing setup, and I summarize the tests used to select these parameters.

0.4.1 Setup SSP templates

The key ingredients for full-spectrum fitting are SSP spectra. Nowadays there are many such libraries available, and they have proven their efficiency in a wide range of applications. **ppxf** was designed to be independent of any specific set of stellar population models and has already been used with nearly all widely available ones. In **ppxf** version 9.1.1, stellar libraries must be provided in **.npz** format, and several libraries have already been adapted⁸. At the time of writing, the repository contains FSPS v3.2 SPS model templates by [Conroy et al. \(2009\)](#); [Conroy & Gunn \(2010\)](#), GALAXEV v2020 SPS model templates by [Bruzual & Charlot \(2003\)](#), E-MILES SPS model templates by [Vazdekis et al. \(2016\)](#), and XSL SPS model templates by [Verro et al. \(2022\)](#). Although these ready-to-use libraries have proven effective, they all assume a [Salpeter \(1955\)](#) IMF, whereas the mock spectra used here were generated with a [Chabrier \(2003\)](#) IMF. To ensure a consistent analysis, I therefore adapt the libraries accordingly. Below I describe a step-by-step procedure to convert existing libraries into the **ppxf**-ready format. I focus on one commonly used library (E-MILES) and on the library employed to create the mock SKIRT dataset (e.g., BPASS). To this end, I have coded a Python script that generates the required format from **.fits** files. To create the required **.npz** file, six parameters must be defined:

⁸The repository contains SSP templates ready for full-spectrum and SED fitting: https://github.com/micappe/ppxf_data

1. `templates[npixels, n_ages, n_metals]`: SPS spectra in units of $L_{\odot}/\text{\AA}$ (solar luminosities per Angstrom);
2. `lam[npixels]`: Wavelength array (in Angstroms), common to all spectra (can be non-uniform);
3. `fwhm[npixels]`: Vector or scalar (in Angstroms) representing the instrumental line-spread function at each wavelength;
4. `ages[n_ages]`: Ages corresponding to the second dimension of the SPS spectra (see first item); typically logarithmically spaced;
5. `metals[n_metals]`: Metallicity values corresponding to the third dimension of the SPS spectra (see first item);
6. `masses[n_ages, n_metals]`: Mass (in solar masses) of living stars plus remnants for each SPS model.

For the **E-MILES**, I first downloaded the models with Chabrier IMF and Padova isochrones from cloud storage⁹. After identifying the appropriate template files, I assigned the corresponding FWHM values across different wavelength ranges, as specified in the documentation (Vazdekis et al., 2016):

- FWHM = 3.0 Å (1680.2 – 3060.8 Å);
- FWHM = 5.0 Å (3060.8 – 3541.4 Å);
- FWHM = 2.51 Å (3541.4 – 8950.4 Å);
- $\sigma = 60 \text{ km s}^{-1}$ (8950.4 – 49999.4 Å).

For the stellar mass values, I used the *Photometric Predictions* tables available on the MILES website, specifically the `M(*+remn)` column, which includes the mass in living stars and stellar remnants.

To create the `.npz` file for the **BPASS** library, I first downloaded BPASSv2.2 (Stanway & Eldridge, 2018b) from the release page¹⁰. For 12 metallicities, I retrieved spectra of the single-star population templates (using `<opt> = 'sin'`) along with mass data from the *Spectral Energy Distributions* and *Surviving Stellar Masses* files. To convert metallicities from Z (the mass fraction of all elements heavier than He) to $[M/H]$ (the logarithmic metal abundance relative to the Sun) required by **ppxf**, adopting the BPASS solar metallicity $Z_{\odot} = 0.020$, I compute

$$[M/H] = \log_{10} \left(\frac{Z}{Z_{\odot}} \right).$$

⁹MILES website: <http://research.iac.es/proyecto/miles/pages/>

¹⁰BPASSv2.2 overview: <https://bpass.auckland.ac.nz/9.html>

The *Surviving Stellar Masses* file provides the total mass of the surviving stellar population as a function of age for a stellar population with an initial mass of $10^6 M_\odot$ formed in an instantaneous burst at $t = 0$. The sum of the mass in living stars and stellar remnants (i.e., white dwarfs, neutron stars, and black holes) was used as the total stellar mass. For the FWHM, I put a constant value of $1 \text{ \AA}$ over the full wavelength range. The BPASS templates are provided in solar luminosities per Angstrom and are normalized for a cluster of $10^6 M_\odot$ formed in a single instantaneous burst. Therefore, they are inherently mass-weighted.

Age and Metallicity Restrictions.

Old stellar populations exhibit very similar spectral features, making them difficult to distinguish from one another. As a result, when the full template grid is allowed, pPXF can assign excessive weight to the oldest SSPs, occasionally providing recovered ages that exceed the age of the Universe at the galaxy’s redshift. To enforce physical consistency, I impose a hard prior on the stellar age by truncating the template grid at the age of the Universe at the galaxy’s redshift ($t_U(z)$). Specifically, I keep only templates with ages

$$t \leq t_U(z),$$

so the effective maximum stellar age is $t_\star^{\max}(z) = t_U(z)$.

A similar edge effect appears in metallicity, especially with BPASS, whose grid includes very metal-poor SSPs, where fits can drift toward unphysically low values. I therefore restrict the metallicity range to

$$[M/H] > -1.5,$$

so it will not drift to the metal-poor end of the grid while remaining broad enough not to bias typical solutions. This is also fully consistent with observations as massive galaxies are known to have relatively high stellar metallicities (Gallazzi et al., 2005, 2006).

Weighting Effects in Stellar Population Fits.

In pPXF the recovered template weights depend on how the templates are normalized, and because stellar mass-to-light ratios vary steeply with age and metallicity, this choice changes the leverage on recent star formation. A mass-normalized fit (no bandpass normalization) provides coefficients that are mass fractions by construction, simple to interpret but tend to underemphasize very young components that dominate into light but contribute little mass. Alternatively, a light-normalized fit uses `norm_type='mean'` over a chosen `norm_range` (here, a V-band window) so that the coefficients are light fractions; I then convert these to mass fractions using the pre-normalization template fluxes stored in `sps.flux`, i.e. $m_j \propto w_j^L / F_j$ with a final renormalization to $\sum_j m_j = 1$. This reframes the result in mass without invoking an explicit (M/L) table, while retaining sensitivity to young, luminous populations.

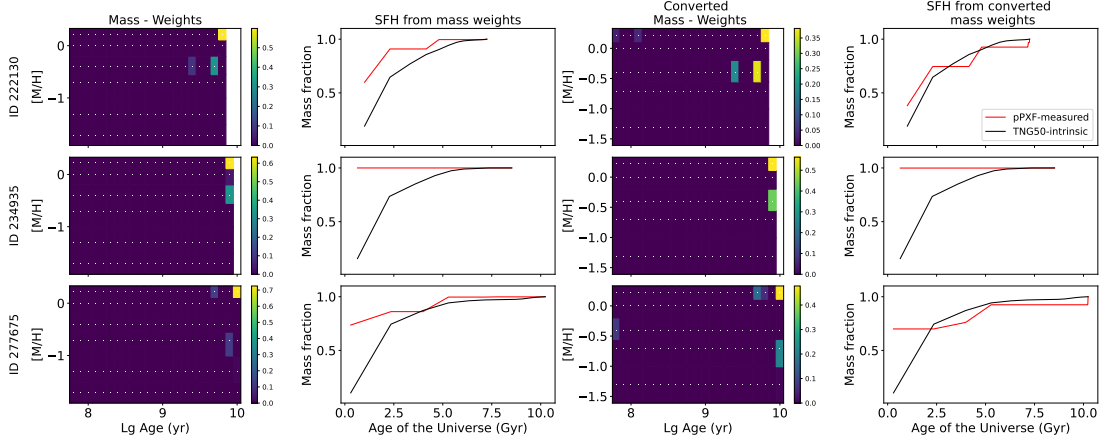


Figure 0.9. Comparison of the direct mass-weighted fits (left panels) and the corresponding reconstructed SFHs (second column), with mass weights converted from light-weighted fits (third column) and their reconstructed SFHs (right panels), shown for three example galaxies.

To isolate the impact of weighting, I compare the direct mass-normalized solution with the light-normalized solution converted to mass without applying regularization (smoothing the light weights is not equivalent to smoothing the mass weights). As shown in Fig. 0.9, both approaches give broadly consistent results, but the light→mass strategy resolves recent star-formation episodes more clearly (Fig. 0.9, columns 3–4). Therefore, for the main analysis I fit with light-normalized templates and convert the light fractions to mass using the pre-normalization fluxes.

0.4.2 Setup pPXF

Fixing the kinematics.

Simultaneously fitting stellar kinematics and stellar populations introduces degeneracies. Changes in the line-of-sight velocity dispersion can mimic metallicity-driven variations in the depth and width of absorption features, so the well-known σ –metallicity degeneracy (Laird & Levison, 1985; Koleva et al., 2008a) can bias the recovered mean metallicities if both parameters are solved for at the same time. To mitigate this, I adopt a two-step procedure. First, I run pPXF to measure the stellar and gas kinematics (velocity and velocity dispersion). Second, I rerun pPXF with those kinematic parameters held fixed so that the fit explores only the stellar population degrees of freedom. In practice, kinematics can be fixed either by setting `moments` to a negative value (fixing all parameters of a component) or by using the `fixed` keyword to pin selected parameters (e.g., only v or σ). In my setup, I include separate stellar and gas components and, in the second run, fix all of their kinematic parameters. I apply this two-step strategy both when determining the optimal regularization and in the final population fits. Similar two-step procedures are used in previous analyses, e.g., Sánchez-Blázquez et al. (2011);

Martín-Navarro et al. (2024).

Regularization.

Regularization in pPXF is used to enforce smoothness in the derived SFH by minimizing unphysical fluctuations between age or metallicity bins. Without regularization, the solution may overfit the noise in the spectrum, resulting in unrealistic and highly variable population weights. By introducing a controlled level of regularization, I obtain a more physically meaningful and stable representation of the underlying stellar population.

To test the impact of regularization, I performed a series of fits with fixed values of the regularization parameter (see Fig. 0.10 and Fig. 0.11). The comparison is illustrated using three galaxies at different redshifts, all belonging to the same main-progenitor branch. From TNG50, I derive each galaxy’s cumulative SFH by integrating the normalized, mass-weighted ages of star particles within the central 1.3 arcsec as a function of cosmic time (solid black line in Fig. 0.10). I also show the derived age-metallicity maps (Fig. 0.11) for three regularization values: 0, best, and 1000.

As expected, increasing the regularization produces smoother star-formation histories and age-metallicity distributions, and the solution approaches the simulated (ground-truth) SFH. Beyond a certain point, further increases in the regularization parameter have little effect, indicating that the solution has stabilized.

The final choice of regularization (highlighted in red in Fig. 0.10 and middle panels in Fig. 0.11) was determined automatically using a Python script. First, an unregularized pPXF fit (`regul` = 0) was performed. The noise spectrum was then rescaled so that the reduced chi-square $\chi^2/\text{DOF} \approx 1$. Following the approach described by Kacharov et al. (2018), the regularization strength was iteratively increased until the χ^2 value deviated from the unregularised value by $\Delta\chi^2 = \sqrt{2N}$, where N is the number of pixels used in the fit. A binary search between 0 and 1000 was used to efficiently converge on the optimal value. According to the pPXF documentation¹¹, the derived regularization corresponds to the maximum level still consistent with the data. The resulting SFH and age-metallicity maps thus represent the smoothest possible solution that remains compatible with the observed spectrum.

0.4.3 Bootstrap to estimate uncertainties

To properly evaluate the pPXF results, one needs reliable errors on the recovered mass-weighted distributions. There are three standard strategies. (i) *Monte Carlo perturbations*: add noise to the best-fit model (or directly to the data) using the error spectrum, refit N times, and take the dispersion of the derived quantities; this is widely used in stellar population work (Hogg et al., 2010; Pessa et al., 2023). (ii) *Bootstrap resampling*: resample residuals (or data) with replacement to build mock spectra and refit each realization; uncertainties are then the scatter of the refitted results (Wu, 1986). (iii) *Bayesian posterior sampling*: specify a likelihood and priors for the stellar population parameters/weights and sample the full posterior (e.g., with

¹¹<https://pypi.org/project/ppxf/>

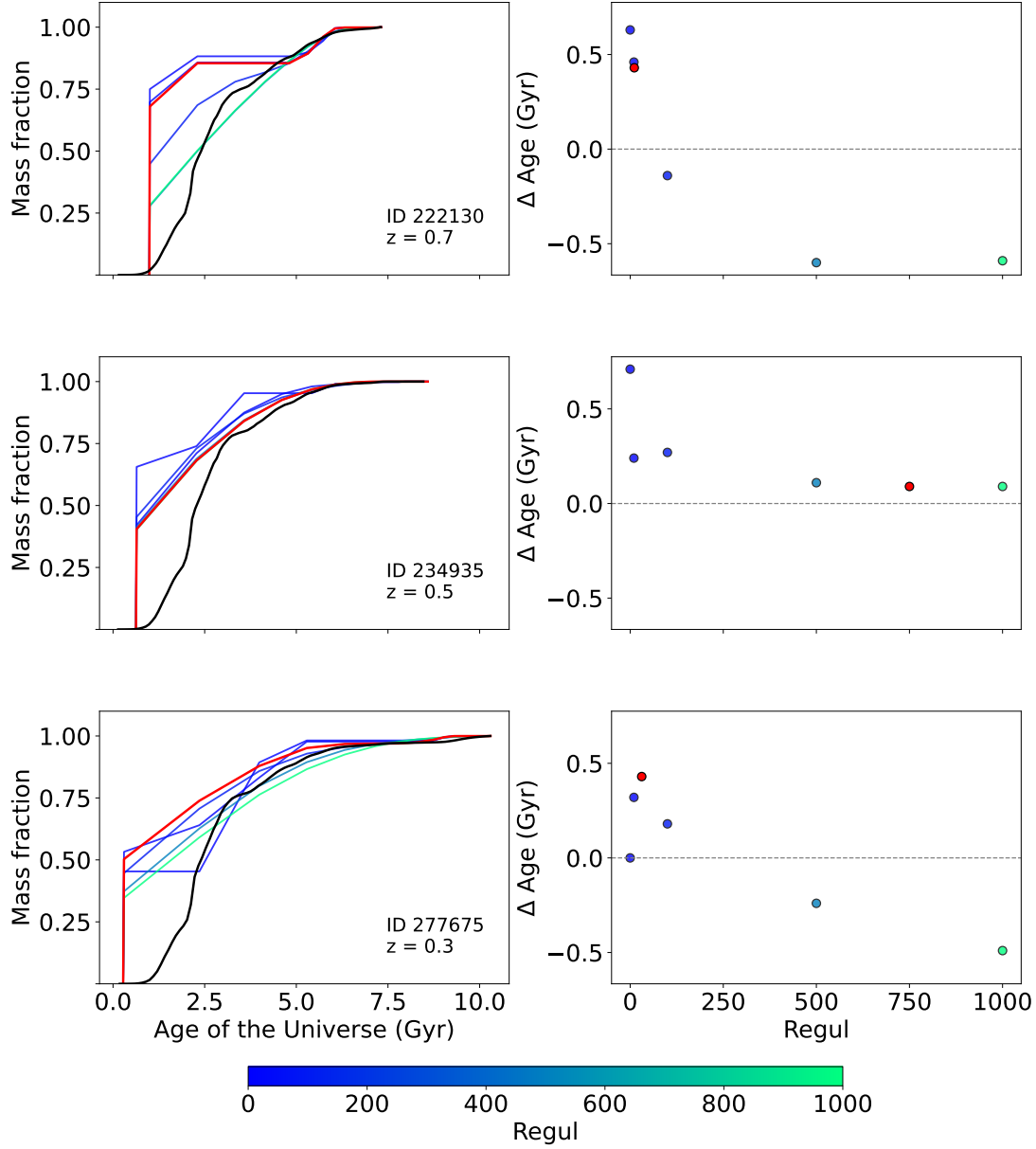


Figure 0.10. Left panels: cumulative SFHs for three galaxies at different redshifts, computed using pPXF with varying levels of regularization (indicated by color). The red line corresponds to the selected regularization value while the black one corresponds to the simulation. Right panels: difference between the recovered and true stellar population ages (ΔAge) as a function of the regularization strength, with each point color-coded to match the corresponding SFH on the left panel.

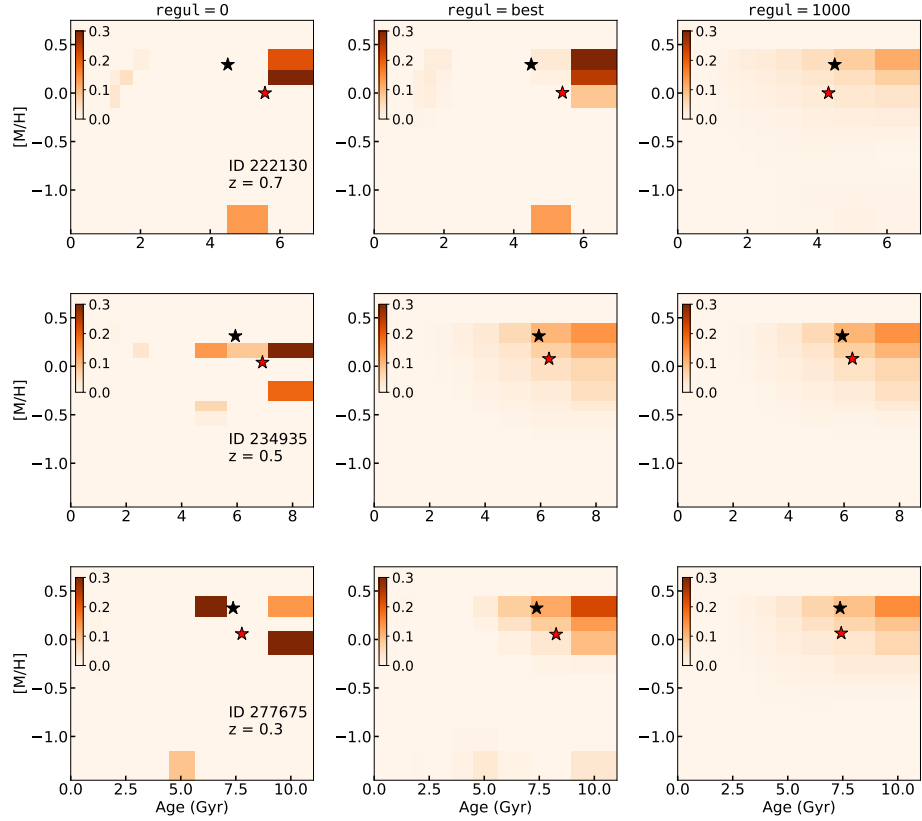


Figure 0.11. Age-metallicity maps of pPXF weights (color scale), which represent the mass fraction contributed by each SSP of a given age and metallicity. Results are shown for noiseless fiber spectra with three regularization values: **regul=0** (left panel), **regul=best** (middle panel), and **regul=1000** (right panel). The mass-weighted age and metallicity measured by pPXF are marked with a red star; the corresponding simulation values are shown with a black star.

affine-invariant Markov Chain Monte Carlo, MCMC); this method provides uncertainties and covariances but is computationally more demanding (Foreman-Mackey et al., 2013; Hogg & Foreman-Mackey, 2018).

In this work, I adopt a residual bootstrap. In particular, for each observed spectrum, I take the best-fitting regularized solution, compute the residuals, and generate 100 mock realizations by resampling those residuals (with replacement) and adding them back to the model. Each bootstrap spectrum is then refitted with the same setup but without regularization, so that the scatter reflects noise and model mismatch rather than the enforced smoothness of the prior. The dispersion of the resulting weights (and of any derived quantities) is adopted as the uncertainty estimate. The same strategy was adopted in Kacharov et al. (2018) and is consistent with the pPXF bootstrap example by Cappellari.¹²

¹²https://github.com/micappe/ppxf_examples/blob/main/ppxf_example_population_bootstrap.ipynb

Summary

This chapter presented a *general forward-modelling strategy* that puts simulations and observations to the same parameter space. The general workflow consists of selecting galaxies and extracting the needed particle/cell properties; translate intrinsic, particle-based quantities (positions, ages, metallicities) into observables via 3D radiative transfer; impose instrument and observing conditions (throughput, spectral resolution, PSF/seeing, noise); and analyse the resulting mock data with precisely the same pipeline used for real observations.

Within this framework I use **SKIRT**, a Monte Carlo radiative-transfer code that propagates photons through arbitrary 3D matter distributions. For each galaxy and snapshot I assemble stellar and gas components, define a field of view, and generate noiseless synthetic products (integrated spectra, IFU-like datacubes, images). I then pass these through an observation layer that applies the desired spatial PSF/seeing and realistic noise.

Alongside the data-production pipeline, I detailed the spectroscopic analysis choices that ensure physical and methodological consistency. I prepare SSP libraries in the **pPXF** `.npz` format and adopt an IMF consistent with the mocks. Because kinematics and stellar populations are degenerate, I determine stellar/gas kinematics in a first run and refit with kinematics fixed, both for regularization tuning and for the final fits. I evaluate the impact of regularization and weighting: unregularized tests clarify how smoothing shapes the SFH and age–metallicity maps, and light-normalized fits (converted to mass using the pre-normalization fluxes) improve sensitivity to recent star formation comparing to mass-normalized fits. Finally, uncertainties on mass-weight distributions and derived quantities are obtained via a residual bootstrap method.

In summary, this chapter presents a reusable strategy for transforming intrinsic simulation outputs into realistic, survey-ready data products. The same workflow is readily adaptable across facilities and surveys, enabling robust *apples-to-apples* comparisons and informed survey planning. In the chapters that follow, I apply this workflow configured to each instrument: **WEAVE**–**MOS** in Chapters 1–2 and **MUSE** in Chapter 3.

Code availability. The scripts used to generate the mock **WEAVE**–**StePS** observations (including downloading **TNG50** data and running **SKIRT** radiative-transfer code) are available at <https://github.com/AIkhsanova/skirt-run>.

1

Showcase of SFHs: nine StePS-like galaxies

The primary aim of this thesis is to analyse mock datasets and generate predictions for upcoming WEAVE-StePS observations. A full analysis of the sample and the step-by-step selection criteria are presented in Chapter 2, while to test the strategy described in Chapter 0 and to illustrate the expected data products, I select three main progenitor branches from the full mock WEAVE-StePS sample, as traced in the TNG50 merger trees. The galaxies are chosen such that, at $z = 0.7$, they occupy different position in the $SFR-M_*$ diagram (see Fig. 1.1). I then follow their evolution across cosmic time, verifying that each system remains on its selected main-progenitor branch. The physical properties of these three progenitors and their descendants (stellar mass, half-mass radius, and global SFR) are summarised in Table 1.1.

I separate galaxies into star-forming, green-valley, or quiescent following the criteria in [Croom et al. \(2021\)](#) and [Vaughan et al. \(2022\)](#). Galaxies are classified into these three categories, based on their deviation from the main sequence ($\Delta \log(SFR_{MS})$):

- **Star-Forming Galaxies (SF).** These galaxies are actively forming stars and remain on or near the main sequence:

$$\Delta \log(SFR_{MS}) > -0.6;$$

- **Green Valley Galaxies (GV).** These galaxies are transitioning from active star formation to a passive state, with a moderate star formation rate:

$$-1.6 < \Delta \log(SFR_{MS}) < -0.6;$$

- **Quenched Galaxies (Q).** These galaxies have little or no star formation and are typically red in color due to their older stellar populations:

$$\Delta \log(SFR_{MS}) < -1.6.$$

Galaxy ID 172231 is highly star forming at $z = 0.7$ and it slowly quenches, evolving into ID 218606 at $z = 0.5$ (SF) and into ID 251598 at $z = 0.3$ (GV). Galaxy ID 222130 (GV) evolves into ID 234935 at $z = 0.5$ (GV) and into ID 277675 at $z = 0.3$ (SF). Galaxy ID 212087 (Q) slowly rejuvenates, evolving into ID 253460 at $z = 0.5$ (GV) and into ID 298351 at $z = 0.3$ (SF). These three examples provide excellent test cases accounting for the variety of complex SFH and the many paths of galaxy evolution. For the test sample, it is worth noting that the descendants share the same SFH of their progenitors, since no major events happened in the evolution of the three example galaxies from $z = 0.7$ to 0.3.

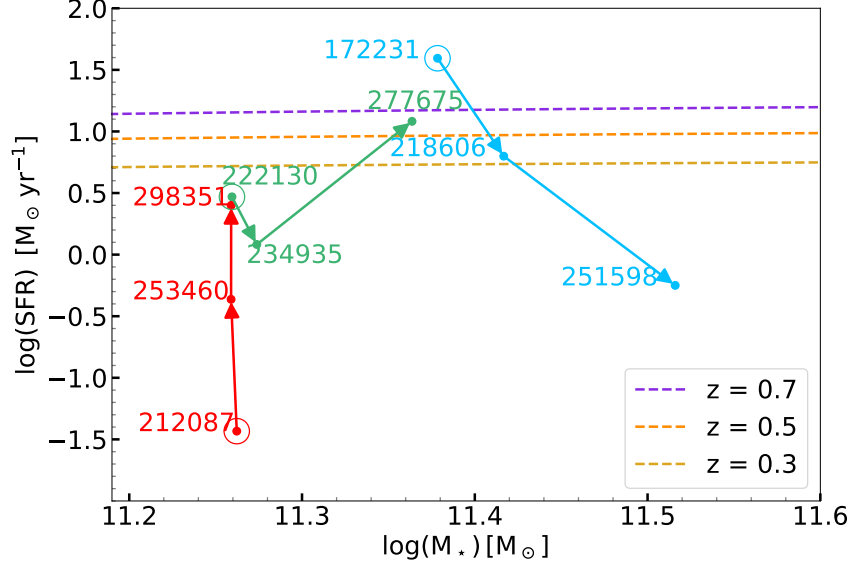


Figure 1.1. $SFR - M_*$ time evolution of the three example galaxies (bigger symbols), from redshift $z = 0.7$ to 0.3 . The galaxy ID follows the nomenclature as in TNG50. Galaxy ID 172231 (blue arrows) slowly quenches (ID 218606) until it reaches the red sequence (ID 251598). Galaxy ID 222130 (green arrows) stays in the green valley (ID 234935) and then moves to the blue cloud sequence (ID 277675). Galaxy ID 212087 (red arrows) slowly rejuvenates (ID 253460) and then moves to the green valley (ID 298351). Dashed lines mark the main sequence at $z=0.3$, 0.5 , and 0.7 as defined in [Koprowski et al. \(2024\)](#).

Table 1.1. Physical properties of three examples of galaxies and their descendants.

z	ID	Class	$\log(M_*/M_\odot)$	R_*	SFR
			[dex]	[kpc]	$[M_\odot \text{ yr}^{-1}]$
(1)	(2)	(3)	(4)	(5)	(6)
0.7	172231	SF	11.38	5.83	39.29
0.5	218606	SF	11.42	5.69	6.30
0.3	251598	Q	11.52	8.38	0.56
0.7	222130	GV	11.26	4.84	2.95
0.5	234935	GV	11.27	5.49	1.21
0.3	277675	SF	11.36	7.51	12.08
0.7	212087	Q	11.26	1.32	0.04
0.5	253460	GV	11.26	1.41	0.43
0.3	298351	SF	11.26	1.48	2.51

(1) Redshift. (2) Galaxy ID. (3) Class: SF = star forming, GV = green valley, Q = quiescent (see [Croom et al., 2021](#)). (4) Stellar mass within half-mass radius. (5) Half-mass stellar radius. (6) Global star formation rate.

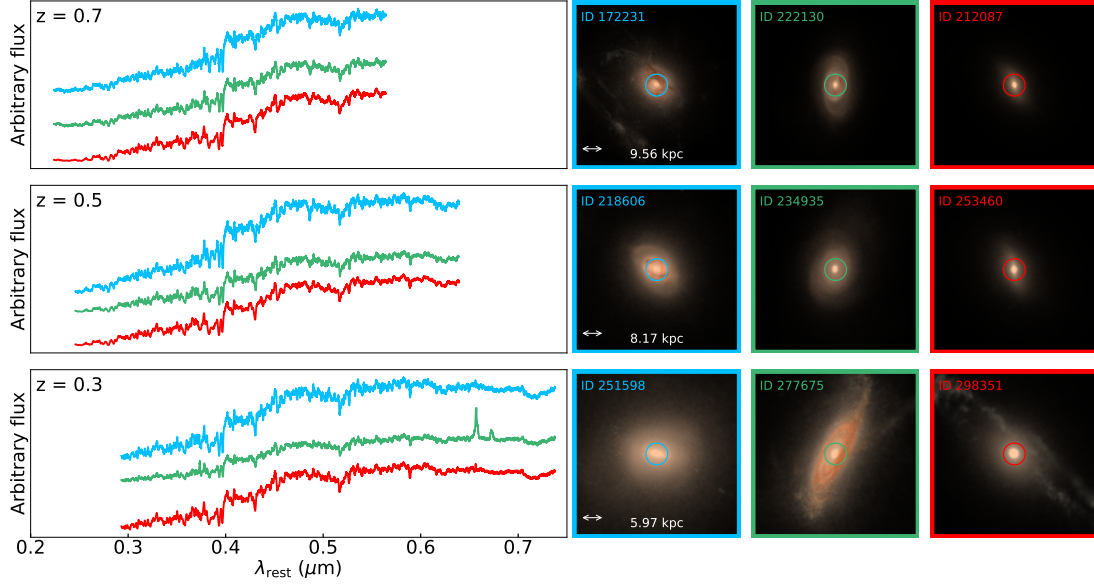


Figure 1.2. Rest-frame spectra (first column) and RGB images (second to fourth columns) for three example galaxies at redshift $z = 0.7$ (top row), $z = 0.5$ (middle row), and $z = 0.3$ (bottom row), respectively. The first column demonstrates fiber spectra extracted from the central 1.3 arcsec of each galaxy, with arbitrary offset applied in the flux (linear units). In each panel of the first column: green spectra are extracted from galaxy ID 222130, ID 234935, and ID 277675, respectively; blue spectra from galaxy ID 172231, ID 218606, and ID 251598, respectively; red spectra from galaxy ID 212087, ID 253460, and ID 298351, respectively. The fiber size and corresponding physical size are also shown.

Figure 1.2 shows the RGB images of the nine galaxies (right panels) and their fiber noiseless spectra (left panels) that I create following the procedure described in Chapter 0. For each set of galaxies, the different rest-frame wavelength covered depends on their redshift. In particular, spectra for galaxies at $z = 0.7$ reach the bluer part of the spectrum, covering absorption features such as Fe II 2402, BL2538, Fe II 2609, and Mg II. Regarding the emitting component, in galaxies at $z = 0.3$ one can also target the H α region, which provides the best proxy of star-forming regions. At all redshifts, the H β and [O III] 5007 emission lines are available.

1.1 Results and discussion

In this section, I describe the methodology to analyze mock observations of intermediate-redshift galaxies tailored for WEAVE-StePS (recently published in [Ikhsanova et al., 2025](#)). Firstly, I quantify possible biases in observing galaxies with limited spatial information, looking at their central and integrated properties. Then, I test pPXF full spectral fitting for deriving the stellar population properties of mock galaxies and

compare the measured age and metallicity of the nine example galaxies with the intrinsic values derived from TNG50. I then compare the timescale of star formation from the mix of different stellar populations both in simulations and observations. Finally, I discuss potential caveats in the procedure, both in the creation of the mocks (e.g., biases introduced by **SKIRT** in the assignment of ages, metallicities, and viewing angles) and in the spectral analysis with **pPXF** (e.g., the impact of using additional polynomials during the fitting).

Following the procedure described in Section 0.4, I fit both the integrated and StePS-like fiber spectra of each galaxy and determine stellar/gas kinematics which I later fix. From the second **pPXF** run, the mean stellar age, metallicity, and SFH of each galaxy are obtained (see Section 1.1.1 and 1.1.2). The results of the spectral fitting for the three progenitor galaxies (i.e., ID 172231, ID 212087, and ID 222130) are shown in Figure 1.3.

1.1.1 Mass-weighted age and metallicity

In this section I retrieve the mass-weighted age and metallicity of the example galaxies, comparing the observed values with the intrinsic ones obtained from the simulation. Furthermore, I compare how these quantities vary if I analyze the spectrum of the entire galaxy or just the central 1.3 arcsec.

I first compare the age and metallicity of the entire subhalo in TNG50 with the values obtained for the central aperture. The latter is done by selecting all the star particles within a circular aperture of 1.3 arcsec. I then weight the age and metallicity distribution of the star particles according to their mass.

In Table 1.2 (columns 4-5), it can be seen that the average difference in the mass-weighted age between the central region and the entire galaxy is usually small (average of ~ 0.4 Gyr), although the core is systematically older than the entire galaxy. This is consistent with the majority of star formation taking place in the disk while the bulge/nuclear region consists of a more mature stellar population, in agreement with an inside-out growth (e.g., [Nelson et al., 2021](#); [Costantin et al., 2021, 2022](#)). A similar trend is observed in the metallicity difference (Table 1.2, columns 8-9), with the central region being systematically but slightly more metal-rich than the entire galaxy (average of ~ 0.2 dex).

It is worth noticing that, using a fixed aperture, at $z = 0.7$ I am probing larger physical scales (9.56 kpc) compared to $z = 0.3$ (5.97 kpc). Thus, the contamination from the mixed bulge and disk populations are more significant at the highest redshifts (but also depending on the galaxy morphology). The average age difference between fiber and integrated stellar particles is 0.21 ± 0.12 Gyr at $z = 0.7$ and 0.61 ± 0.33 Gyr at $z = 0.3$.

As for real galaxies, I analyze each mock spectrum with **pPXF** and derive the non-parametric SFH of each galaxy, modeling both the stellar and gas components. The spectra were fitted with the BPASS library and the Chabrier IMF ([Chabrier, 2003](#)), consistent with the strategy outlined in Section 0.4. I consider models with stellar ages from 50 Myr to the age of the Universe at each considered redshift in 24, 23, and 22

Table 1.2. Mass-weighted ages and metallicities of the example galaxies.

z	ID	Class	age _{sim} ^{total} [Gyr]	age _{sim} ^{fiber} [Gyr]	age _{obs} ^{total} [Gyr]	age _{obs} ^{fiber} [Gyr]	[Z/H] _{sim} ^{total} [dex]	[Z/H] _{sim} ^{fiber} [dex]	[Z/H] _{obs} ^{total} [dex]	[Z/H] _{obs} ^{fiber} [dex]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)
0.7	172231	SF	3.29	3.39	3.8 ± 0.2	4.0 ± 0.2	0.08	0.26	-0.58 ± 0.04	-0.56 ± 0.04
0.5	218606	SF	4.23	4.28	4.8 ± 0.3	4.6 ± 0.3	0.09	0.29	-0.13 ± 0.02	-0.02 ± 0.02
0.3	251598	GV	5.87	6.31	6.3 ± 0.2	6.0 ± 0.3	0.09	0.31	-0.17 ± 0.03	0.06 ± 0.03
0.7	222130	GV	4.12	4.50	4.9 ± 0.2	4.7 ± 0.2	0.12	0.29	-0.06 ± 0.02	-0.08 ± 0.02
0.5	234935	GV	5.30	5.94	5.7 ± 0.2	6.0 ± 0.3	0.10	0.31	-0.08 ± 0.02	0.09 ± 0.02
0.3	277675	SF	6.31	7.38	8.4 ± 0.4	8.0 ± 0.4	0.08	0.32	-0.47 ± 0.05	0.02 ± 0.03
0.7	212087	Q	5.38	5.53	5.5 ± 0.1	5.6 ± 0.1	0.13	0.28	-0.08 ± 0.02	0.04 ± 0.01
0.5	253460	GV	6.67	6.84	6.9 ± 0.2	7.0 ± 0.2	0.13	0.29	-0.08 ± 0.01	0.04 ± 0.01
0.3	298351	SF	8.28	8.59	8.5 ± 0.5	8.5 ± 0.2	0.12	0.31	0.03 ± 0.04	0.08 ± 0.01

- (1) Redshift. (2) Galaxy ID. (3) Class: SF = star forming, GV = green valley, Q = quiescent.
(4) Mass-weighted age of the entire galaxy derived from TNG50.
(5) Mass-weighted age of the central 1.3 arcsec derived from TNG50.
(6) Mass-weighted age of the entire galaxy derived with **pPXF** from noiseless spectra.
(7) Mass-weighted age of the central 1.3 arcsec derived with **pPXF** from noiseless spectra.
(8) Mass-weighted metallicity of the entire galaxy derived from TNG50.
(9) Mass-weighted metallicity of the central 1.3 arcsec derived from TNG50.
(10) Mass-weighted metallicity of the entire galaxy derived with **pPXF** from noiseless spectra.
(11) Mass-weighted metallicity of the central 1.3 arcsec derived with **pPXF** from noiseless spectra.

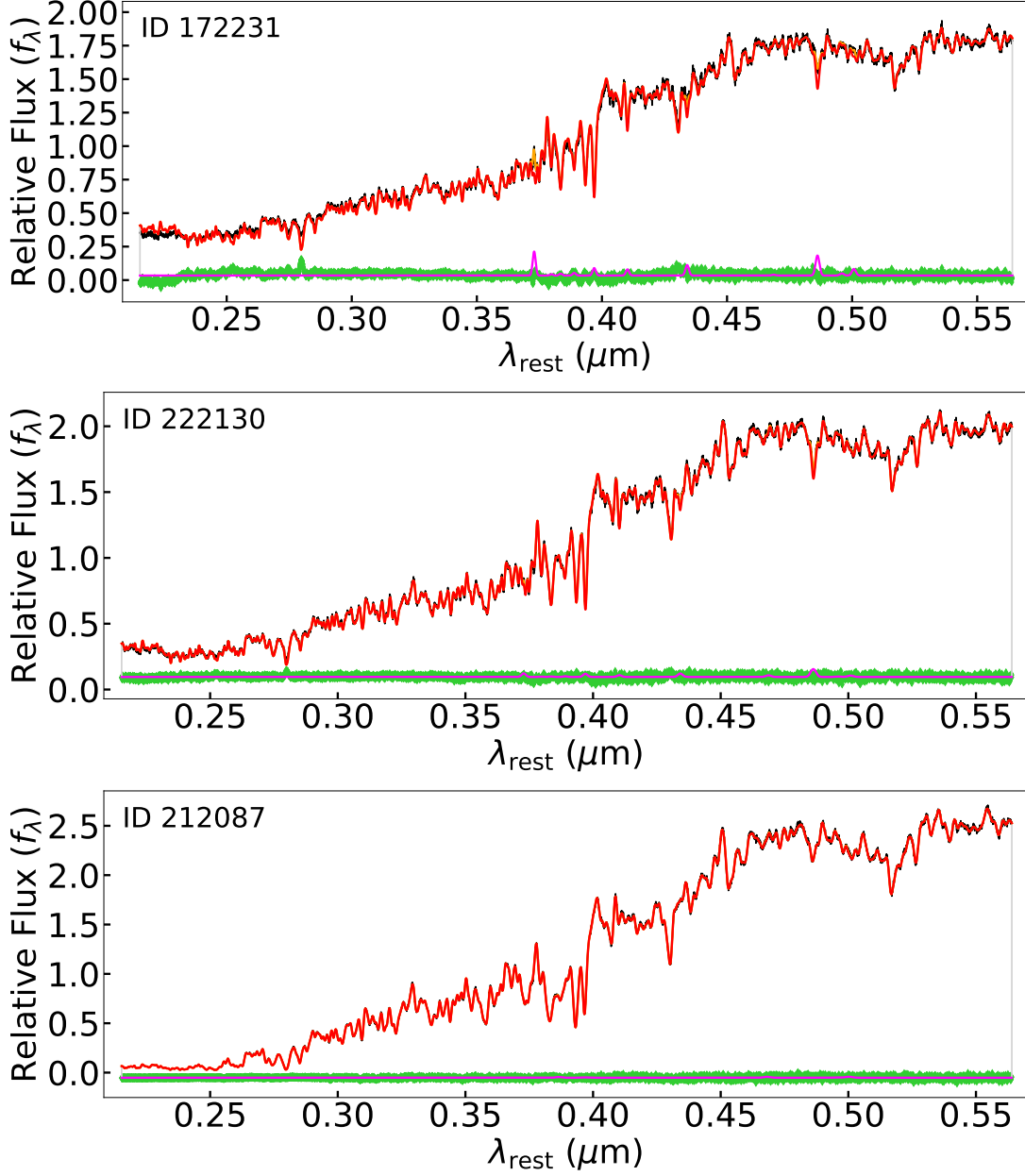


Figure 1.3. Example of full spectral fitting performed with pPXF for three galaxies at redshift $z = 0.7$. The rest-frame noiseless spectra (black solid lines) are plotted with the best-fitting model (orange lines). Each emission line is modelled with the same kinematic component. The best-fitting stellar spectrum alone and the gas emissions alone are shown with red and magenta solid lines, respectively. The residuals (green diamonds; arbitrarily offset) are calculated by subtracting the model from the observed spectrum.

bins at $z = 0.3, 0.5$, and 0.7 , respectively. I tested whether this last choice would not affect the results by repeating the analysis including stellar ages down to 1 Myr and found no systematics in the retrieved stellar population properties. For metallicities, I use the same setup as adopted in Cappellari (2023), adopting the BPASS v2.2.1 stellar population synthesis models, in 10 bins with $[Z/H] = [-1.3, -1, -0.8, -0.7, -0.5, -0.4, -0.3, 0, 0.2, 0.3]$ dex. It is worth noticing that the TNG50 star particles may have metallicities above the upper limit of the templates, as already discussed in Sarmiento et al. (2023).

In Figure 1.4, I compare the two-dimensional distribution of pPXF weights derived for the fiber noiseless spectra in the age-metallicity diagram with the distribution of ages and metallicities derived from the simulation. I find a good agreement in the mass-weighted ages of the nine example galaxies. For the fiber spectra, the values of age inferred from pPXF agree with the intrinsic ones, with an average difference of 0.2 ± 0.3 Gyr. I find a similar trend for the integrated spectra, with measured ages compatible with intrinsic ones (average difference of 0.6 ± 0.6 Gyr). Regarding metallicities, I find that measured values are systematically lower than the intrinsic ones, since one is unable to retrieve unrealistically high metallicities for some stellar particles in TNG50. The average difference between the retrieved and intrinsic metallicities is 0.3 ± 0.2 dex for both the fiber and integrated spectra.

Overall, the analysis suggests that there is a good agreement in the inference of mass-weighted ages, even if I tend to predict lower metallicities for the galaxies, as can also be seen in the marginalized age and metallicity distributions (Fig. 1.4). In next chapter, I aim at quantifying statistically these specific trends for the selected population, also considering the effect of different S/N in observations.

1.1.2 Star formation history

In this section, I examine the ability to recover the SFHs by comparing the characteristic timescales of stellar mass assembly. Specifically, I contrast the SFH derived from the mix of stellar populations in the simulations with that obtained from the pPXF analysis of the mock dataset.

Thanks to TNG50, I have full access to the variety of SFHs and stellar, gas, and dark matter properties of the sample galaxies. To bridge the gap between theoretical and observational descriptions of the SFH of galaxies, I analyze the noiseless spectra and compare the SFHs of the example galaxies retrieved from pPXF with those inferred from the simulation. To visualize the burstiness of the SFH, I compute the sum of the star formation rates (SFRs) of all progenitors at each snapshot, as shown in the first row of Figure 1.5. One can appreciate the complexity of the SFH of the three example galaxies, which are characterized by multiple episodes of intense star formation. In the second to fourth rows, I describe the SFH as the cumulative mass fraction over cosmic time. From TNG50 (Fig. 1.5, black lines), I derive the cumulative SFH of each galaxy by integrating across cosmic time the normalized mass-weighted age of each star particle either in the entire galaxy (dashed black line) or in the central 1.3 arcsec (solid black line). For the noiseless mock spectra (Fig. 1.5, red lines), I marginalize over

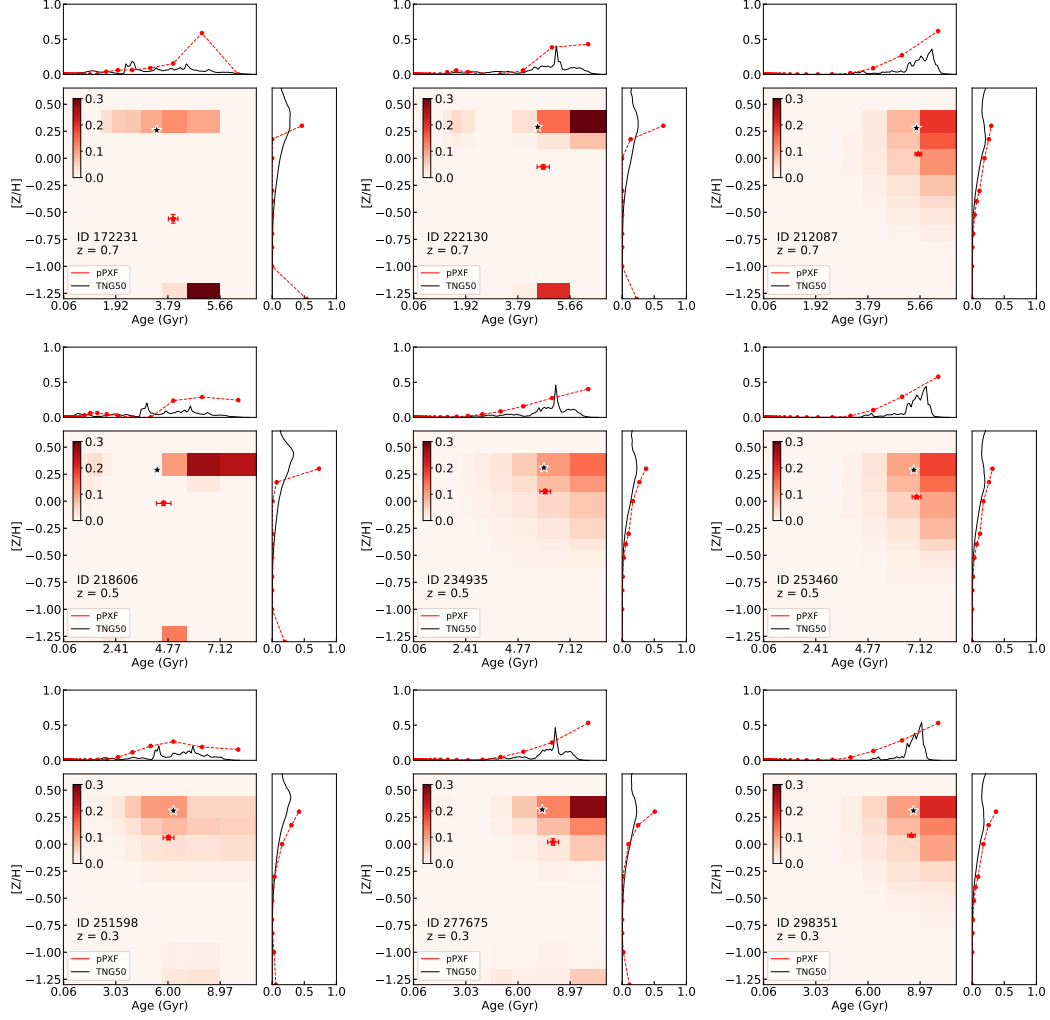


Figure 1.4. Distribution of the pPXF weights (red colors), indicating the mass fraction of each stellar population of given age and metallicity, derived from fiber noiseless spectra. The mass-weighted age and metallicity measured with pPXF is shown as a red star, while mass-weighted age and metallicity derived from the simulation is marked as a black star. Black lines represent the marginalized distribution of ages and metallicities derived from the simulation, while red curves show those inferred from pPXF. The progenitor galaxies at $z = 0.7$ are shown in the top row, while their descendants at $z = 0.5$ and $z = 0.3$ are shown in the middle and bottom rows, respectively.

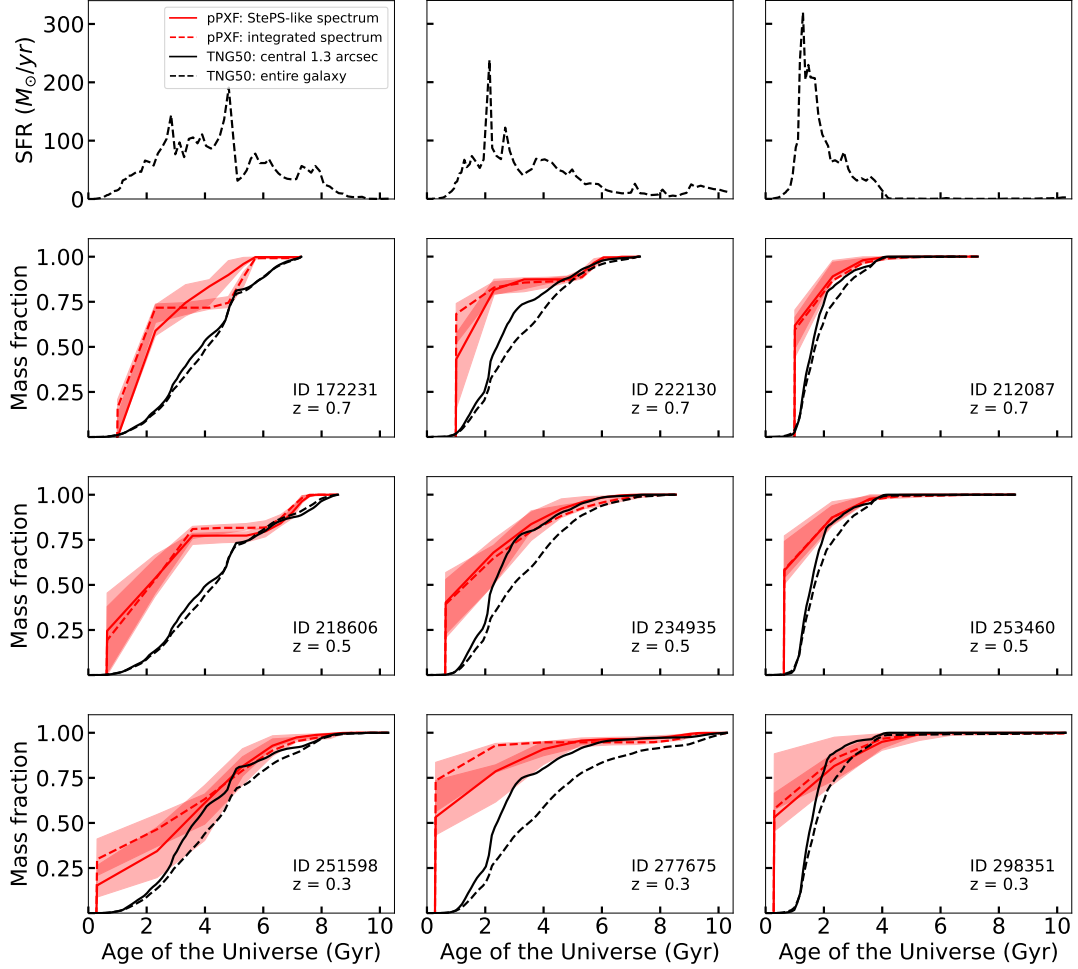


Figure 1.5. Examples of SFHs (first row) and cumulative SFHs of the target galaxies at redshift $z = 0.7$ (second row), $z = 0.5$ (third row), and $z = 0.3$ (fourth row). The SFHs are derived directly from the cosmological simulation and represent the sum of the integrated SFR s of all progenitors at each snapshot. The cumulative SFHs of each galaxy are retrieved by fitting with pPXF both the StePS-like fiber spectra (red solid line) and integrated noiseless spectra (red dashed line). The shaded red regions indicate the 16th–84th percentile range across 100 bootstrap realizations. For comparison, the cumulative SFHs derived directly from the cosmological simulation are shown both for the entire galaxy (black dashed line) and for the central 1.3 arcsec (black solid line).

Table 1.3. Timescale of mass assembly of the example galaxies derived from the central 1.3 arcsec.

z	ID	Class	t_{10}^{sim} [Gyr]	t_{50}^{sim} [Gyr]	t_{90}^{sim} [Gyr]	t_{10}^{obs} [Gyr]	t_{50}^{obs} [Gyr]	t_{90}^{obs} [Gyr]
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
0.7	172231	SF	2.00	3.86	6.13	1.22 ± 0.01	2.11 ± 0.01	4.8 ± 0.3
0.5	218606	SF	2.03	4.05	7.44	0.63 ± 0.02	2.1 ± 0.3	7.0 ± 0.1
0.3	251598	GV	1.94	3.63	6.56	0.29 ± 0.03	3.3 ± 0.9	6.1 ± 0.5
0.7	222130	GV	1.37	2.40	5.05	0.99 ± 0.01	1.24 ± 0.01	5.2 ± 0.4
0.5	234935	GV	1.32	2.28	4.60	0.63 ± 0.01	1.2 ± 0.1	4.4 ± 0.5
0.3	277675	SF	1.38	2.40	5.11	0.28 ± 0.01	0.30 ± 0.06	3.9 ± 0.9
0.7	212087	Q	1.15	1.60	2.83	0.99 ± 0.01	1.00 ± 0.01	2.4 ± 0.1
0.5	253460	GV	1.13	1.57	2.74	0.63 ± 0.01	0.64 ± 0.01	2.6 ± 0.4
0.3	298351	SF	1.17	1.57	2.45	0.28 ± 0.01	0.30 ± 0.01	3.4 ± 0.7

(1) Redshift. (2) Galaxy ID. (3) Class: SF = star forming, GV = green valley, Q = quiescent.
 (4)–(6) Time when the galaxy formed 10%, 50%, and 90% of its stellar mass, respectively, as derived from TNG50.
 (7)–(9) Time when the galaxy formed 10%, 50%, and 90% of its stellar mass, respectively, as derived with pPXF from noiseless spectra.

metallicity the age weights obtained from pPXF and integrate them across cosmic time. From the recovered cumulative SFHs, I derive t_{10} , t_{50} , and t_{90} as the time when the galaxy formed 10%, 50% and 90% of its stellar mass (Table 1.3).

The three progenitor galaxies (and their descendants) have very different SFHs: galaxy ID 212087 formed its stars over a short period of time ($z \sim 4.5$), when the Universe was only 1.3 Gyr old; ID 222130 had one prominent burst at $z \sim 3$ (age of the Universe of 2.1 Gyr) and a residual star formation during a few Gyr down to $z \sim 0.3$; ID 172231 shows a very bursty evolution with an extended period of intense bursts ($SFR > 100 M_{\odot} \text{ yr}^{-1}$ from $z = 2.3$ to $z = 1.3$; age of the Universe from 2.8 to 4.8 Gyr) and mild residual star formation during a few Gyr until it quenches at $z \sim 0.3$.

I find that if the galaxy forms at early cosmic times in a single burst, such as ID 212087, there is almost a perfect agreement between the intrinsic and inferred cumulative SFH (Fig. 1.5, third column). This could reflect the fact that galaxies forming in one single episode have simpler stellar populations (e.g., Pappalardo et al., 2021). In general, if the dominant burst is older than ~ 5 Gyr, the inferred stellar populations are massively old (see also Grèbol-Tomàs et al., 2023). The difference between intrinsic and measured cumulative SFH is higher for prolonged and very bursty SFHs (e.g., ID 172231). In all cases, I find that the percentage of mass formed in the first Gyr is greater than 25%, while the intrinsic values could be as low as 2-5%. Despite this systematic trend, which reflects the fact that one is not sensitive to the shape of the SFH, there is better agreement in the timescale when the galaxies formed almost the totality of its stellar mass, especially at the highest redshifts, reflecting the fact that one is very sensitive to the timescale of the main quenching event.

I find that the example galaxies and their descendants have similar t_{90} at all redshifts (average difference between intrinsic and mock of 0.4 ± 0.6 Gyr). However, galaxies can show different t_{10} and t_{50} , with inferred values being older than intrinsic ones (average difference of 0.8 ± 0.5 Gyr and 1.2 ± 0.5 Gyr). Again, this reflects the fact that one is overestimating the fraction of mass forming in the first phases of galaxy evolution, especially when they have complex SFHs. This trend is partially mitigated once comparing the assigned values during the radiative transfer modeling to the inferred ones (see Sect. 1.1.3.1). Finally, I calculate the symmetric mean absolute percentage error for all galaxies in bins of 1 Gyr (lookback time). I notice that there is an almost perfect agreement between the predicted and measured trends of SFH in a lookback time of 4 Gyr (average values $< 5\%$), except for galaxy ID 172231.

1.1.3 Systematic Effects and Caveats

In this section, I examine the main systematic effects and caveats that may influence both the construction of the mock observations and their subsequent analysis. These limitations are important to keep in mind when interpreting the results, as they can introduce biases in the derived stellar population properties and SFHs.

1.1.3.1 Assigned and intrinsic values.

Here I address the main systematic introduced in the radiative transfer modeling, which has to be kept in mind for a proper comparison between observations and simulations.

In Section 0.2.1, I model each star particle older than 10 Myr with a SSP from the BPASS library. However, once assigning the correspondent SSP within SKIRT, I am limited by the BPASS metallicity grid, which, in particular, does not reproduce the highest metallicities in TNG50.

In Figure 1.6 and 1.7, I show the same analysis described in Sec. 1.1.1 and 1.1.2 but considering also the assigned values together with the intrinsic ones. From Table 1.4, the difference between intrinsic and assigned values, i.e. the bias introduced by stellar population assignment, is 0.1 ± 0.2 Gyr for age and 0.14 ± 0.02 dex for metallicity. This bias partially explains the metallicity offset noted in Sec. 1.1.1. Regarding the SFH (Table 1.5), the intrinsic–assigned difference shows a clear bias in t_{10} (0.8 ± 0.4 Gyr), consistent with the discrepancy highlighted in Sec. 1.1.2. In contrast, for t_{50} (0.3 ± 1.2 Gyr) and t_{90} (0.2 ± 1.3 Gyr), the scatter dominates over any systematic bias.

In this case, the comparison between the assigned values and those retrieved with pPXF show a slightly better agreement in the mass-weighted ages, with an average difference of 0.1 ± 0.3 Gyr (see Table 1.4). Overall, the assigned SFHs are only slightly closer to the inferred ones, highlighting that part of the systematics are not due to the modeling of stellar spectra, especially in the last ~ 4 Gyr of galaxy evolution (see also Table 1.5).

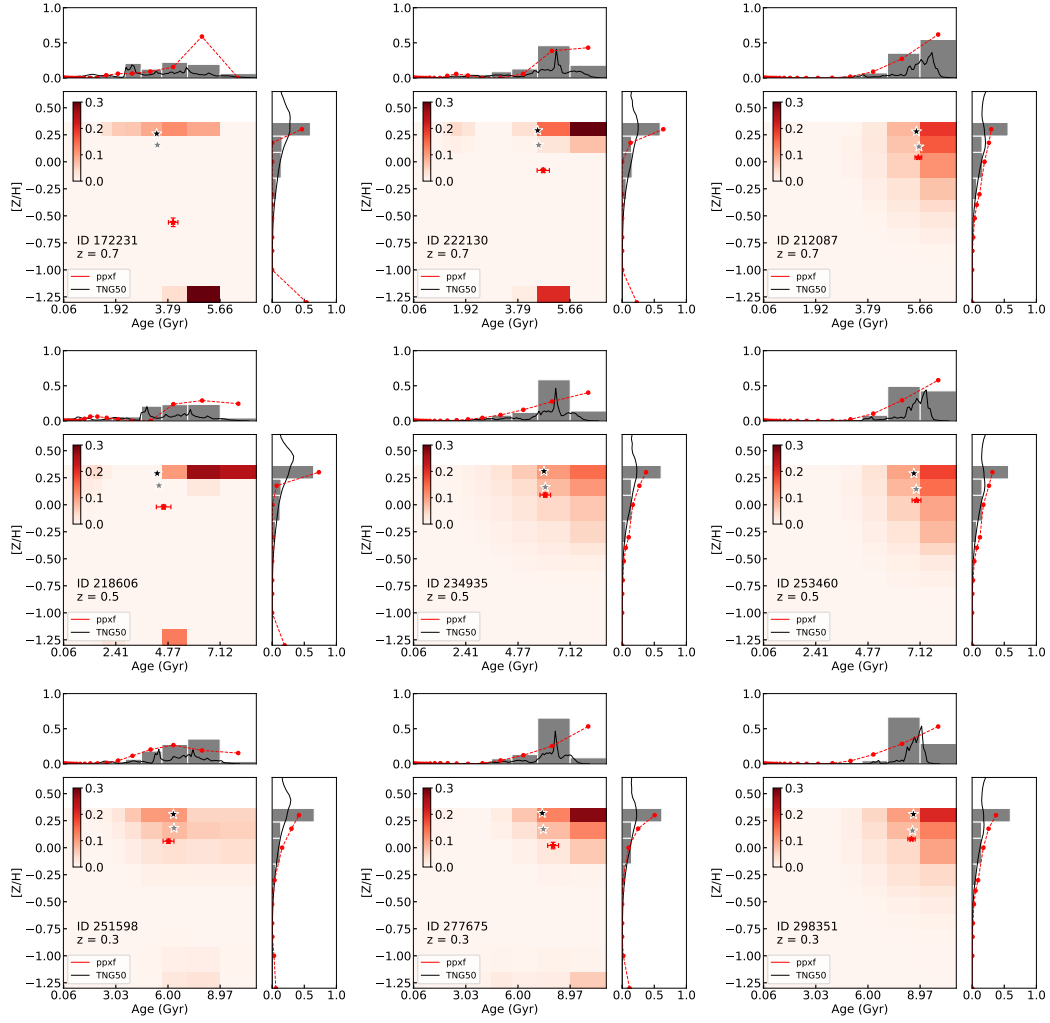


Figure 1.6. Same as Figure 1.4, but gray stars representing assigned values in SKIRT.

Table 1.4. Mass-weighted ages and metallicities of the central part of the example galaxies extended with assigned values.

z	ID	Class	age _{sim} [Gyr]	age _{sim} [Gyr]	age _{obs} [Gyr]	[Z/H] _{sim} [dex]	[Z/H] _{sim} [dex]	[Z/H] _{obs} [dex]
0.7	172231	SF	3.39	3.42	4.0 ± 0.2	0.26	0.15	−0.56 ± 0.04
0.5	218606	SF	4.28	4.36	4.6 ± 0.3	0.29	0.18	−0.02 ± 0.02
0.3	251598	GV	6.31	6.35	6.0 ± 0.3	0.31	0.18	0.06 ± 0.03
0.7	222130	GV	4.50	4.55	4.7 ± 0.2	0.29	0.15	−0.08 ± 0.02
0.5	234935	GV	5.94	6.02	6.0 ± 0.3	0.31	0.16	0.09 ± 0.02
0.3	277675	SF	7.38	7.46	8.0 ± 0.4	0.32	0.17	0.02 ± 0.03
0.7	212087	Q	5.53	5.67	5.6 ± 0.1	0.28	0.14	0.04 ± 0.01
0.5	253460	GV	6.84	6.99	7.0 ± 0.2	0.29	0.14	0.04 ± 0.01
0.3	298351	SF	8.59	8.57	8.5 ± 0.2	0.31	0.16	0.08 ± 0.01

- (1) Redshift. (2) Galaxy ID. (3) Class: SF = star forming, GV = green valley, Q = quiescent.
(4) Mass-weighted age of the central 1.3 arcsec derived from TNG50.
(5) Mass-weighted age of the central 1.3 arcsec assigned by SKIRT.
(6) Mass-weighted age of the central 1.3 arcsec derived with pPXF from noiseless spectra.
(7) Mass-weighted metallicity of the central 1.3 arcsec derived from TNG50.
(8) Mass-weighted metallicity of the central 1.3 arcsec assigned by SKIRT.
(9) Mass-weighted metallicity of the central 1.3 arcsec derived with pPXF from noiseless spectra.

Table 1.5. Same as Table 1.3 but extended with assigned values.

z	ID	Class	t_{10}^{sim} [Gyr]	t_{50}^{sim} [Gyr]	t_{90}^{sim} [Gyr]	t_{10}^{assigned} [Gyr]	t_{50}^{assigned} [Gyr]	t_{90}^{assigned} [Gyr]	t_{10}^{obs} [Gyr]	t_{50}^{obs} [Gyr]	t_{90}^{obs} [Gyr]
0.7	172231	SF	2.00	3.86	6.13	1.23	3.45	5.94	1.22 ± 0.01	2.11 ± 0.01	4.8 ± 0.3
0.5	218606	SF	2.03	4.05	7.44	1.02	3.52	7.28	0.63 ± 0.02	2.1 ± 0.3	7.0 ± 0.1
0.3	251598	GV	1.94	3.63	6.56	0.65	2.97	6.18	0.29 ± 0.03	3.3 ± 0.9	6.1 ± 0.5
0.7	222130	GV	1.37	2.40	5.05	1.00	1.89	4.76	0.99 ± 0.01	1.24 ± 0.01	5.2 ± 0.4
0.5	234935	GV	1.32	2.28	4.60	0.64	1.61	4.23	0.63 ± 0.01	1.2 ± 0.1	4.4 ± 0.5
0.3	277675	SF	1.38	2.40	5.11	0.30	1.57	4.51	0.28 ± 0.01	0.30 ± 0.06	3.9 ± 0.9
0.7	212087	Q	1.15	1.60	2.83	0.99	1.00	2.29	0.99 ± 0.01	1.00 ± 0.01	2.4 ± 0.1
0.5	253460	GV	1.13	1.57	2.74	0.63	0.81	2.20	0.63 ± 0.01	0.64 ± 0.01	2.6 ± 0.4
0.3	298351	SF	1.17	1.57	2.45	0.28	0.81	2.17	0.28 ± 0.01	0.30 ± 0.01	3.4 ± 0.7

(1) Redshift. (2) Galaxy ID. (3) Class: SF = star forming, GV = green valley, Q = quiescent.

(4)–(6) Time when the galaxy formed 10%, 50%, and 90% of its stellar mass, as derived from TNG50.

(7)–(9) Same, assigned during radiative transfer calculations.

(10)–(12) Same, derived with **PPIX** from noiseless spectra.

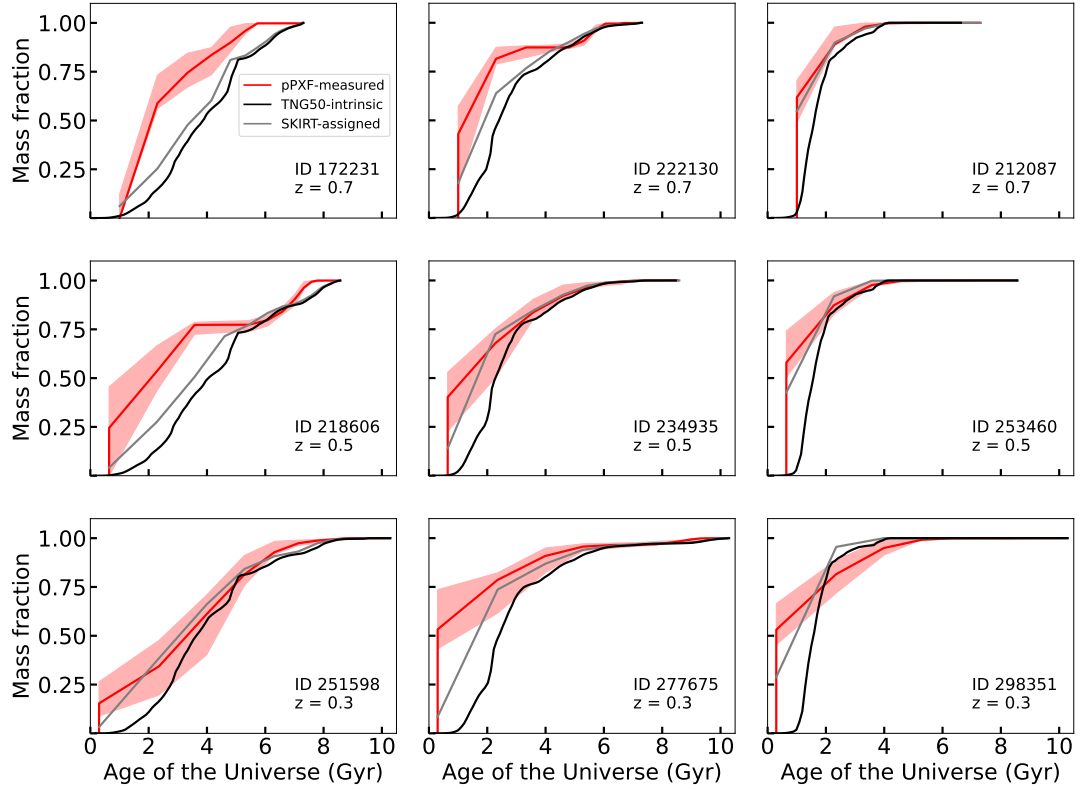


Figure 1.7. Same as Figure 1.5, but gray solid lines representing assigned values in radiative transfer modeling (i.e., SKIRT) for the fiber spectra.

1.1.3.2 Effect of different orientations on the inferred SFHs.

To investigate how the observer’s viewing angle affects the recovered SFHs, I followed the approach of Baes et al. (2024), adopting six different lines of sight defined by their inclination (i) and azimuthal angle (ϕ) within the simulation volume, as listed in the array below.

Config.	i [deg]	ϕ [deg]
<i>A</i>	0.0	0.0
<i>B</i>	30.5	−94.1
<i>C</i>	60.3	99.8
<i>D</i>	99.0	−19.7
<i>E</i>	109.8	−146.2
<i>F</i>	149.5	85.9

It is important to note that the inclination and azimuth angles used here do not refer to the galaxy’s intrinsic orientation (e.g., face-on or edge-on), but instead define the position of the observer within the simulation volume, while galaxies in TNG50 are randomly orientated.

In the following, I focused on the three galaxies at redshift $z = 0.7$. For each orientation, I extracted the integrated spectrum of the entire galaxy. This choice allows a clean comparison of SFHs across different inclinations, as it eliminates projection effects related to spatial coverage (which would otherwise affect fiber-based extractions). Since the entire galaxy is always considered, the intrinsic stellar population remains fixed. In Figure 1.8, I show the cumulative SFHs recovered via pPXF for all six orientations, along with the true simulation-based SFH (shown as a black dashed curve). Each orientation is color-coded based on inclination, and the corresponding synthetic image (created combining F435W, F606W, F814W HST filters) is shown alongside the SFH to illustrate morphological differences caused by the corresponding projection.

Interestingly, the shape of the recovered SFH depends strongly on the viewing angle only for galaxy 222130 (GV according to the classification). Some orientations give significantly younger cumulative profiles, suggesting that dust geometry, mixing of stellar populations in different morphological components, or the prominence of recent star formation along specific projections can substantially bias the interpretation. In contrast, for the quenched galaxy 212087, the SFHs are nearly identical across all inclinations, consistent with its passively evolving stellar population. The star-forming galaxy 172231 shows mild variation, but not as dramatic as the green valley case. To assess whether the redshift coverage impacts the retrieved results, I repeated the orientation-dependent analysis for a sample at redshift $z = 0.5$ (see Fig. 1.9). For the green valley galaxy with ID = 234935, the orientation appears to have a noticeable impact on the recovered SFH, particularly in the contribution of intermediate-age stellar populations. In contrast, for the star-forming galaxy (ID = 218606) and the other green valley (ID = 253460), the effect of orientation is much less pronounced, with the recovered SFHs remaining relatively consistent across different lines of sight. However, it is worth noting that although galaxy 253460 is classified as a GV galaxy, its position on the $SFR - M_\star$ diagram (Fig. 1.1) lies much lower, close to the quenched region, than that of the other

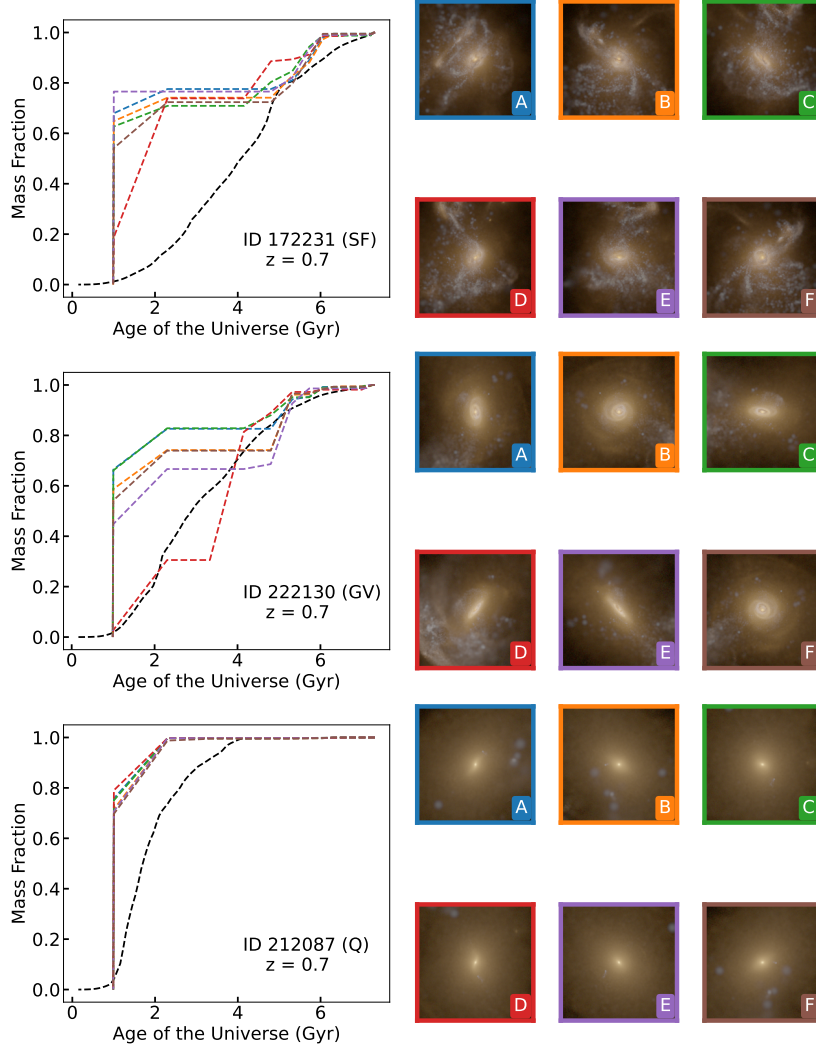


Figure 1.8. Effect of the viewing angle on the inferred SFHs for three $z = 0.7$ galaxies from TNG50. Each panel shows the recovered cumulative SFHs using integrated spectra from six different observed configurations, labeled A–F as defined in Sect. 1.1.3. The black dashed lines indicate the true SFH from the simulation. Right panels show synthetic HST-like images corresponding to each configuration.

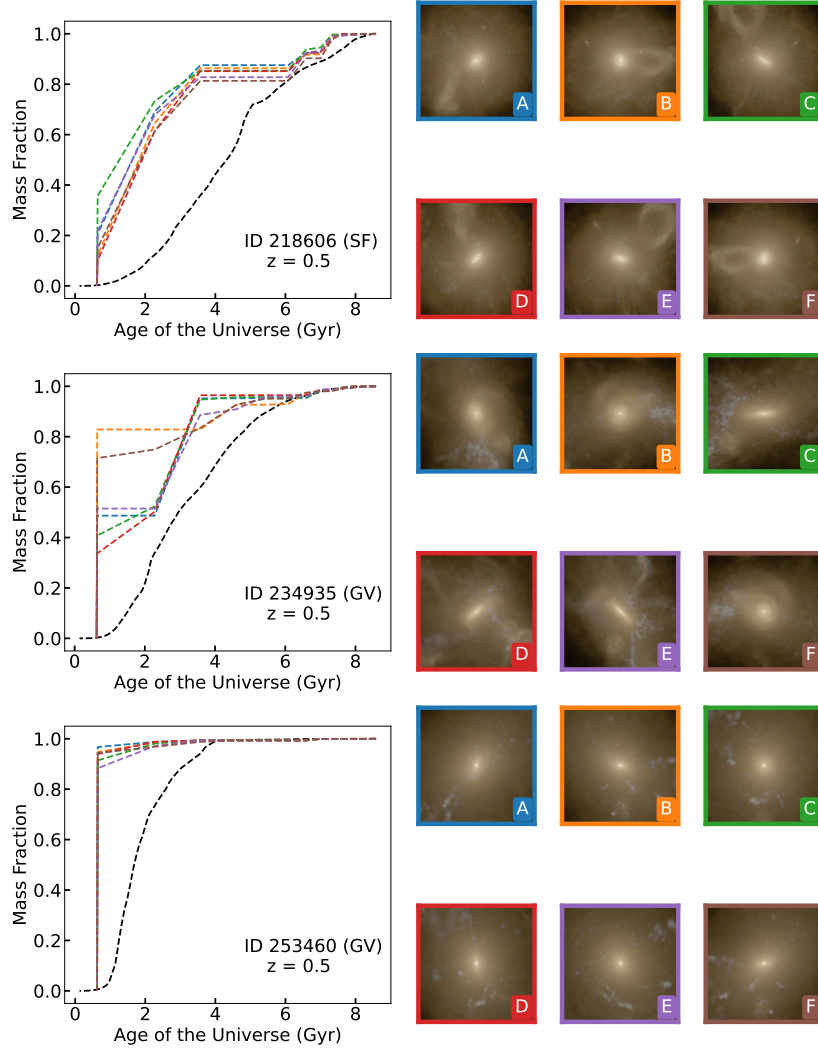


Figure 1.9. Same as Figure 1.8 but for $z = 0.5$.

GV galaxies.

These results imply that orientation effects can lead to systematic uncertainties in SFH recovery, especially for transitional systems, and that such effects should be accounted for when interpreting galaxy spectra.

1.1.3.3 Impact of polynomial degree on spectral fitting.

As demonstrated in the next chapter using the full galaxy sample, including additive or multiplicative polynomials in the `pPXF` fitting routine is essential for reliably recovering stellar population parameters. In particular, low-degree polynomials often help correct continuum mismatches, especially in the blue/UV range. To test whether this trend also holds for smaller subsamples, I applied different polynomial configurations to the 9 example galaxies. The results are summarized in Figures 1.10, 1.11, and 1.12. At $z = 0.7$, the three test cases show mixed behavior. For the star-forming galaxy 172231, additive polynomials provide a clear improvement in metallicity recovery, though at the expense of a slightly worse age estimate. A similar but weaker trend is observed for the green valley system 222130, where only a modest gain in $[Z/H]$ is achieved with additive polynomials, while multiplicative ones bring no benefit. By contrast, the quenched galaxy 212087 shows no noticeable sensitivity to polynomial choice. At $z = 0.5$, the overall impact is less pronounced. The star-forming system 218606 benefits moderately from additive polynomials, particularly in metallicity, while the two green valley galaxies (234935 and 253460) display essentially no differences across the tested setups. Finally, at $z = 0.3$, the results again vary. The quenched galaxy 251598 shows no improvement, whereas the green valley system 277675 behaves similarly to 222130, with a slight metallicity gain when additive polynomials are included. Surprisingly, even the star-forming galaxy 298351, whose spectrum contains strong UV and emission features, does not appear to benefit from polynomial corrections.

These results suggest that while polynomials are crucial in the large-sample analysis, their effect is not pronounced in the test sample. When improvements are present, they are almost exclusively associated with additive polynomials. Multiplicative polynomials rarely improve the fit and in many cases have no effect at all. The only exception is galaxy 172231, where both polynomial types improve $[Z/H]$, though additive still provides the best fit. This is consistent with expectations, as UV-sensitive star-forming galaxies are where continuum mismatches can be most problematic (see next chapter). However, even among other SF or emission-line galaxies (e.g., 298351), this pattern is not consistently observed.

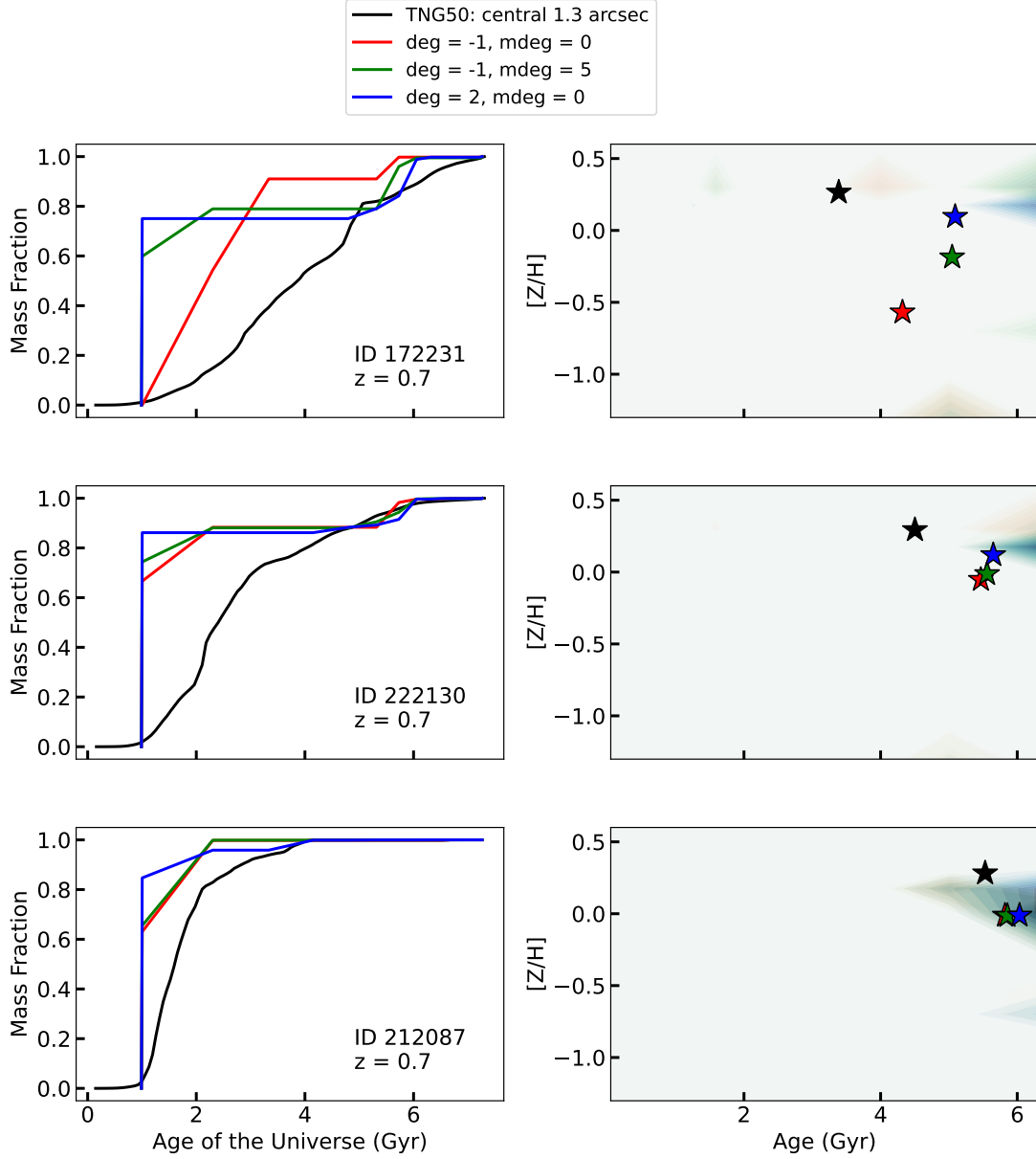


Figure 1.10. Effect of the polynomial degree on the inferred SFHs for three $z = 0.7$ TNG50 galaxies. For each galaxy, the left panel shows the cumulative SFHs recovered from the fiber spectra using three pPXF polynomial configurations: $(\text{degree}, \text{mdegree}) = (-1, 0)$, $(-1, 5)$, and $(2, 0)$. The curves are color-coded by these $(\text{degree}, \text{mdegree})$ combinations, while the black solid line shows the true SFH from the simulation. The right panels display the recovered mass-weighted ages and metallicities, with contours illustrating the distribution of pPXF weights.

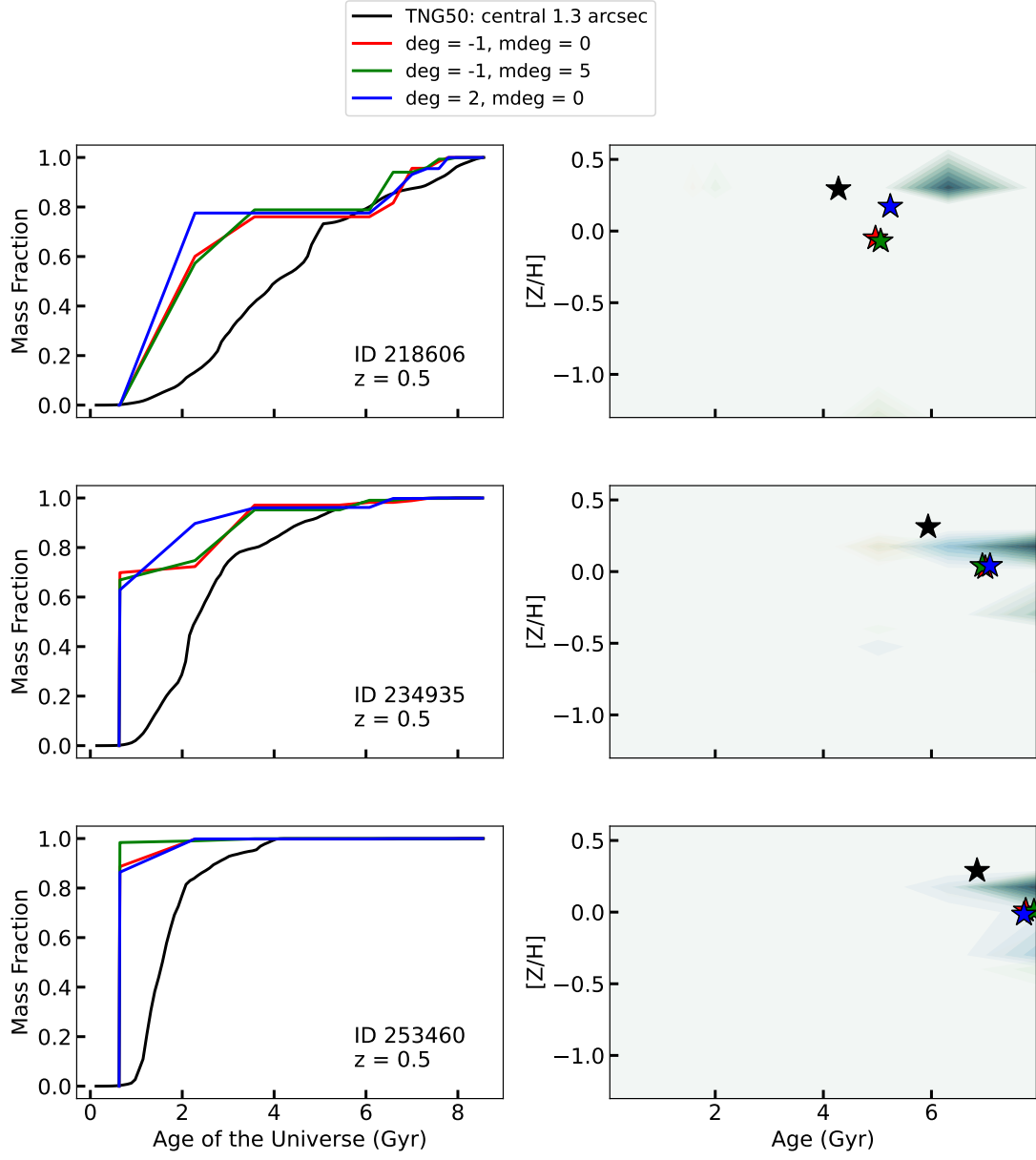


Figure 1.11. Same as 1.10 but for $z = 0.5$.

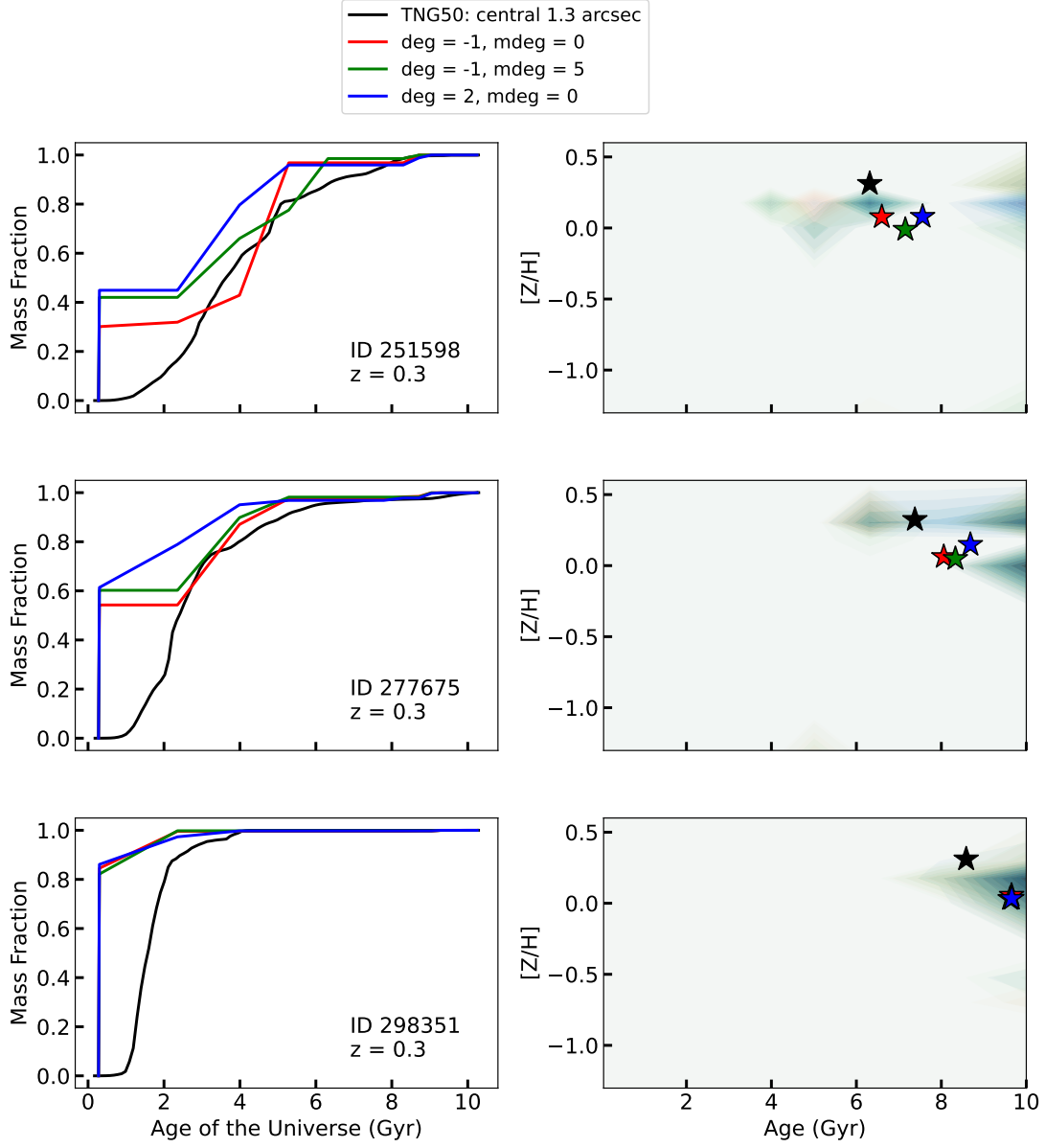


Figure 1.12. Same as 1.10 but for $z = 0.3$.

Summary

In this chapter, I analyzed three showcase galaxies at $z = 0.7$ and their descendants at $z = 0.5$ and $z = 0.3$, deriving their mass-weighted ages, metallicities, and SFHs.

By comparing the intrinsic stellar population properties to those inferred with **pPXF**, I found overall good agreement in recovering the cumulative SFHs of these galaxies. In particular, the method is sensitive to the timescale over which galaxies assemble the bulk of their stellar mass, with cumulative SFH estimates differing by less than $\sim 5\%$ over a lookback time of 4 Gyr (except for galaxy ID 172231). Across the three examples, selected for the diversity of their SFHs, the recovered ages are broadly consistent with the intrinsic ones, while metallicities tend to be systematically underestimated relative to the intrinsic TNG50 distributions. Part of this discrepancy arises from the procedure used to assign SSP templates in **SKIRT**, which particularly affects metallicities and t_{10} values. By contrast, the ability to reconstruct middle stages of the SFH (t_{50}) reflects limitations of the **pPXF** analysis itself, where **pPXF** tends to overestimate ages. I also showed that galaxy orientation has a measurable impact, especially for systems in transition, and that different polynomial setups in **pPXF** do not significantly change the results, likely because of the interplay with the geometry of the interstellar medium.

The analysis of the full galaxy sample, presented in the next chapter, will enable a statistical assessment of these systematics and clarify their impact across a broader population.

It is worth emphasizing that while this study adopts the WEAVE-StePS observational setup, the strategy can be adapted to mimic any spectroscopic facility. Moreover, the spectroscopic information can be combined with the imaging dataset, adding valuable information about the interplay between the mass build up and the morphological transformation of galaxies, and reducing the age-metallicity degeneracy that could increase the understanding of mass build-up in the early stages of galaxy evolution.

In conclusion, these mock observations can be used both for quantifying possible biases (and the correcting factors) in deriving the SFHs of galaxies and for properly comparing ages, metallicities, and star formation timescales of observed and simulated galaxies.

The SFHs of StePS-like galaxies

The main motivation of this chapter is to analyze the statistically significant sample of galaxies from the released mock catalog. Thus, providing predictions for intermediate redshift survey StePS-like together with investigating potential biases that may arise when analyzing real data. Specifically, I aim to explore how noise and the choice of different stellar libraries impact my results. Additionally, I will make predictions about the patterns one expect to observe in real data, such as the fraction of rejuvenated galaxies.

For the sample selection, I follow the WEAVE-StePS selection criteria as described in [Iovino et al. \(2023a\)](#), converting the magnitude limit to mass, and select TNG50 galaxies in three redshift snapshots (i.e., $z = [0.3, 0.5, 0.7]$), having $\log\left(\frac{M_*}{M_\odot}\right) > [10.28, 10.88, 11.23]$ and being brighter than $m_i = 20.5$ mag. The mass range was taken as a stellar mass completeness limit for blue galaxies (see Fig. 2.1). The sample consists of 764 galaxies, of which 562 are at $z = 0.3$, 155 at $z = 0.5$, and 47 at $z = 0.7$. In the sample, I allow for duplicates, meaning that the same galaxy could appear in different redshift snapshots. Table 2.1 summarizes the distribution of the main physical properties of this galaxies. Although at lower redshifts it is possible to observe less massive galaxies (due to lower mass limit), the SFR decreases, indicating a quenching process occurring in these massive galaxies.

The distributions of stellar mass and i -band magnitude are shown in Figure 2.2 (middle and right panels). It is evident that the samples differ significantly across redshifts. Therefore, when comparing galaxy properties at different redshifts, one must restrict the comparison to galaxies within the same stellar mass bin.

For each redshift, I followed the same procedure described in Sect. 0.4.2. That is, after adding noise to the spectra, I selected a stellar library, determined the appropriate regularization values, and then performed the analysis using `pPXF` with bootstrapping. To save computation time, in some cases I used fixed regularization values, which will be specified in the text where applicable.

The structure of this chapter is as follows: First, I describe the analysis procedure and present example applications, such as identifying rejuvenated galaxies or galaxies that have experienced a brief rejuvenation episode in the past before quenching. Then, I discuss possible systematics when analyzing noiseless spectra. Finally, I examine how the results change when using different stellar libraries and when noise is added, as well as the role that regularization plays in this context.

2.1 Main results

Unlike in the showcase galaxies, for the total sample a nonzero polynomial multiplicative degree was required to account for the strong UV part of the spectrum and I explicitly include young stellar templates. As I describe in Sect. 2.2, I adopt `mdegree` = 5

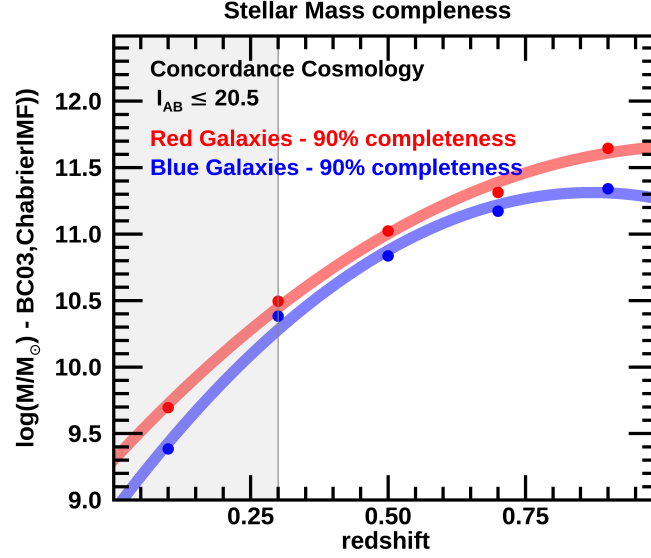


Figure 2.1. 90% colour-dependent completeness limit in stellar mass for blue and red galaxies as a function of redshift (blue and red lines). I used data and stellar masses (Chabrier IMF) from the UltraVISTA catalogue in the COSMOS field (McCracken et al., 2012; Ilbert et al., 2013), and the blue and red galaxies were defined using a simple colour-colour rest-frame NUV-R-J plot. The shaded area indicates the $z < 0.3$ redshift range. Adapted from Iovino et al. (2023a).

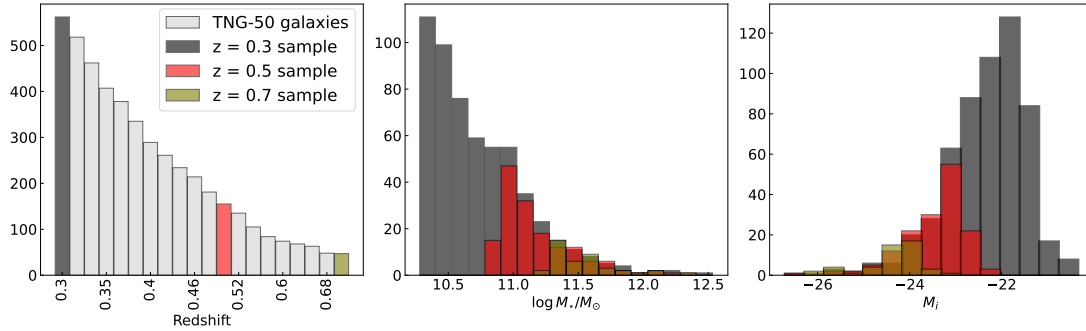


Figure 2.2. Left panel: Distribution of galaxies in TNG50 at $0.3 < z < 0.7$ satisfying the criteria of WEAVE-StePS. Galaxies at $z = [0.3, 0.5, 0.7]$ are shown in dark gray, red, and green, respectively. Middle panel: stellar mass distribution of the selected galaxies at different redshifts. Right panel: i -band AB magnitude of the selected galaxies at different redshifts.

Table 2.1. Physical properties of selected sample of galaxies.

z	Number of galaxies	$\log(M_{\text{total}})$ [$M_{\odot}$]	$\log(M_{\star})$ [$M_{\odot}$]	$R_{\star}$ [kpc]	SFR [$M_{\odot} \text{ yr}^{-1}$]
(1)	(2)	(3)	(4)	(5)	(6)
0.3	562	$11.91^{+0.47}_{-0.45}$	$10.65^{+0.43}_{-0.27}$	$4.66^{+3.17}_{-2.50}$	$3.82^{+4.95}_{-3.43}$
0.5	155	$12.39^{+0.40}_{-0.27}$	$11.08^{+0.41}_{-0.15}$	$5.54^{+3.41}_{-2.36}$	$8.75^{+11.23}_{-7.20}$
0.7	47	$12.8^{+0.42}_{-0.21}$	$11.47^{+0.22}_{-0.21}$	$5.83^{+3.34}_{-2.01}$	$17.06^{+27.25}_{-8.04}$

(1) Redshift. (2) Total number of galaxies in the sample. (3) Median total mass of the subhalos. (4) Median stellar mass of the subhalos. (5) Median 3D half-mass stellar radius. (6) Median star formation rate. Errors are quoted as 16th-84th percentile range.

to the final setup. The regularization value was calculated from the procedure described in Sect. 0.4.2.

To evaluate the ability to reconstruct the stellar population parameters, I compared the recovered values with those assigned by **SKIRT**. Both Fig. 2.3 and Table 2.2 confirm the results obtained for the showcase galaxies: ages are generally well recovered (typically within ~ 1 Gyr), while metallicities show a systematic offset. This offset can arise from several factors, including nebular continuum emission and the impact of dust attenuation on the broad spectral shape. As discussed in Section 2.2, using a low additive polynomial degree helps to correct large-scale continuum mismatches and therefore improves the recovery of stellar population parameters. This effect is most evident for metallicity: with `degree=2` the median bias drops from ~ 0.2 – 0.3 dex (for `mdgree=5`) to less than 0.1 dex. This improvement is illustrated by the 95% highest-density contour in the metallicity panel of Fig. 2.3. Despite this improvement, the use of additive polynomials is debated in the literature, since low-order additive terms can partially absorb real continuum features and potentially bias detailed stellar population diagnostics. Given these concerns, and because our analysis primarily focuses on star-formation histories rather than precise metallicity measurements, we adopt `mdgree=5` for the remainder of this work. This provides a more conservative and commonly used configuration, while still delivering reliable SFH reconstructions for our purposes.

Regarding the SFH parameters, the behaviour across the sample is consistent with the trends seen in the showcase galaxies. The early mass-assembly time t_{10} frequently saturates at the oldest template allowed by the model grid, whereas t_{50} tends to be underestimated (that is, the fits favor older ages to reach 50% mass). I find that the mass-assembly duration, defined as $\Delta t \equiv t_{90} - t_{10}$, is particularly well constrained. Across the three redshifts, Δt shows only a mild positive bias $\langle \text{recovered} - \text{assigned} \rangle \simeq 0.9, 0.3, 0.1$ Gyr (Table 2.2). The tightness of this relation likely arises because Δt is a differential age measure: several continuum and absolute age zero-point systematics partially cancel in the difference. As a result, Δt captures the duration of star formation (burstiness vs. extended histories) more robustly.

In Table 2.3 I report the median and scatter of the mass-weighted age and SF

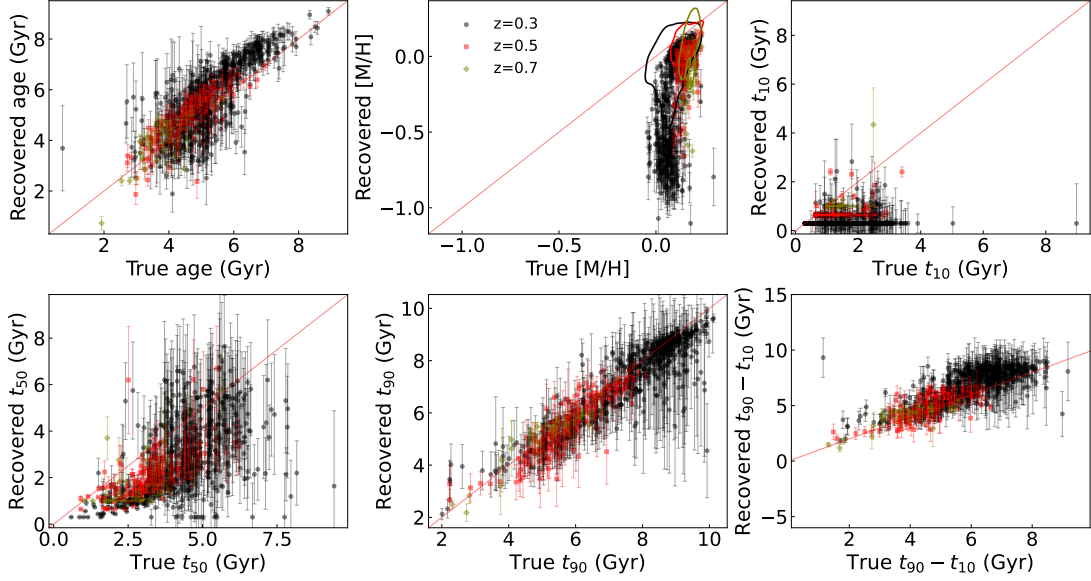


Figure 2.3. Six-panel comparison between recovered and assigned values for age, $[Z/H]$, t_{10} , t_{50} , t_{90} , and $t_{90} - t_{10}$ for the full sample. Scatter points (with 1σ uncertainties) correspond to the `mdegree` = 5 fits and are color-coded by redshift. In the metallicity panel, additionally shown a 95% highest-density contour derived from the `degree` = 2 fits, to illustrate how the low additive polynomial degree affects the metallicity recovery. The red diagonal line marks the one-to-one relation.

timescales for both the intrinsic (simulation) values and the quantities recovered with `pPXF`. In the intrinsic distributions, most timescales increase toward a lower redshift (from $z = 0.7$ to $z = 0.3$), consistent with an aging galaxy population (e.g., t_{90} : $6 \rightarrow 8$ Gyr; Δt : $3.7 \rightarrow 5$ Gyr). The recovered quantities show the same qualitative trend for age, t_{90} , and Δt , with a particularly strong growth at $z = 0.3$ ($\Delta t \approx 7$ Gyr). In contrast, t_{50} exhibits doesn't change from the $z \simeq 0.5$ to $z \simeq 0.3$, and t_{10} is biased low in all bins, likely because the fits push t_{10} toward the edge of the template grid and/or due to age–metallicity–dust degeneracies. The large t_{90} and Δt at $z = 0.3$ indicate older overall populations that nevertheless continue forming stars (i.e., extended SFHs), and may also reflect sample differences (inclusion of lower-mass, younger systems) and late-time rejuvenation episodes during this epoch.

It is important to evaluate why the apparent agreement in mass-weighted ages can coexist with sizable differences in t_{50} , where the bias is more than ~ 1 Gyr (see Table 2.2). In general, the two are not equivalent for asymmetric SFHs: the mass-weighted age traces a mean, while t_{50} is a median of the cumulative SFH. I therefore examine the age– t_{50} plane after converting t_{50} to lookback time, and compare the intrinsic, assigned, and recovered (`pPXF`) values (Fig. 2.4). For clarity, I analyze

$$\Delta \equiv t_{50}^{\text{LB}} - \langle \text{age} \rangle_{\text{MW}},$$

Table 2.2. Residual statistics vs. assigned values (recovered – assigned) for three redshifts.

z	Δ_{age} [Gyr]	$\Delta[\text{Z}/\text{H}]$ [dex]	Δt_{10} [Gyr]	Δt_{50} [Gyr]	Δt_{90} [Gyr]	$\Delta(t_{90} - t_{10})$ [Gyr]
(1)	(2)	(3)	(4)	(5)	(6)	(7)
0.3	0.4 ± 0.9	-0.3 ± 0.3	-1.2 ± 0.9	-1.4 ± 1.5	-0.4 ± 0.7	1 ± 1
0.5	0.3 ± 0.5	-0.2 ± 0.1	-0.6 ± 0.5	-1.1 ± 0.8	-0.3 ± 0.6	0.3 ± 0.8
0.7	0.2 ± 0.6	-0.3 ± 0.2	-0.2 ± 0.5	-1.1 ± 0.9	-0.1 ± 0.4	0.1 ± 0.6

(1) Redshift. (2) Bias and scatter of recovered stellar ages. (3) Bias and scatter of recovered metallicities. (4–6) Bias and scatter of characteristic formation times t_{10} , t_{50} , t_{90} . (7) Bias and scatter of the duration of star formation, $t_{90} - t_{10}$. Ages are in Gyr; metallicities in dex.

Table 2.3. Median intrinsic (simulation) and recovered (fiber/pPXF) quantities at each redshift for the central 1.3 arcsec.

z	Age [Gyr]		t_{10} [Gyr]		t_{50} [Gyr]		t_{90} [Gyr]		$\Delta t \equiv t_{90} - t_{10}$ [Gyr]	
	intrinsic sim	fiber obs	intrinsic sim	fiber obs	intrinsic sim	fiber obs	intrinsic sim	fiber obs	intrinsic sim	fiber obs
0.3	5 ± 1	6 ± 1	2.6 ± 0.8	0.30 ± 0.3	5 ± 1	2 ± 2	8 ± 2	8 ± 2	5 ± 1	7 ± 2
0.5	4.6 ± 0.8	5 ± 1	2.1 ± 0.5	0.6 ± 0.3	3.8 ± 0.9	2 ± 1	6 ± 1	6 ± 1	4.1 ± 0.9	5 ± 1
0.7	3.8 ± 0.7	4.1 ± 0.9	1.8 ± 0.5	1.0 ± 0.5	3.4 ± 0.8	1 ± 1	6 ± 1	5.5 ± 0.9	3.7 ± 0.9	4.4 ± 0.9

(1) Redshift. (2) Median mass-weighted age derived from TNG50.

(3) Median mass-weighted age derived with pPXF from noiseless spectra.

(4) Median time when 10% of the stellar mass has formed derived from TNG50.

(5) Median time when 10% of the stellar mass has formed derived with pPXF from noiseless spectra.

(6) Median time when 50% of the stellar mass has formed derived from TNG50.

(7) Median time when 50% of the stellar mass has formed derived with pPXF from noiseless spectra.

(8) Median time when 90% of the stellar mass has formed derived from TNG50.

(9) Median time when 90% of the stellar mass has formed derived with pPXF from noiseless spectra.

(8) Median time between 10% and 90% of the stellar mass being assembled derived from TNG50.

(9) Median time between 10% and 90% of the stellar mass being assembled derived with pPXF from noiseless spectra.

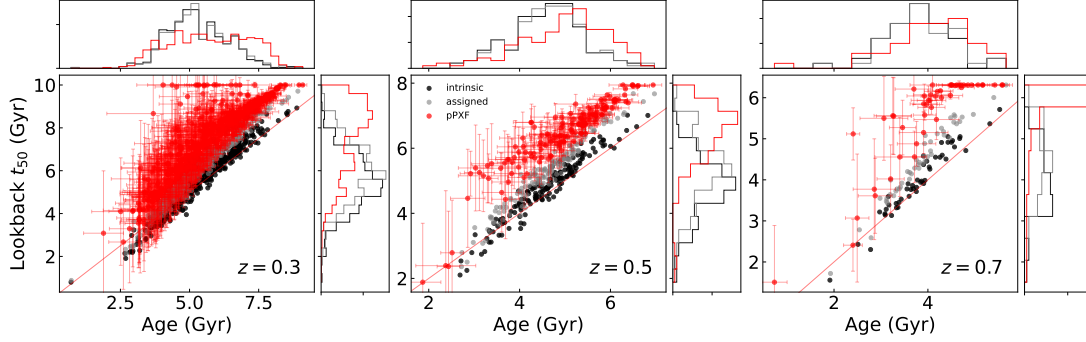


Figure 2.4. Age–lookback– t_{50} comparison for the full sample at three redshifts. Points show intrinsic (simulation), assigned (after SPS assignment), and recovered (pPXF) values. The diagonal marks $\Delta = 0$ (i.e., $t_{50}^{\text{LB}} = \langle \text{age} \rangle_{\text{MW}}$). The upward shift from intrinsic to assigned and recovered reflects increasing Δ , indicating earlier inferred assembly (larger lookback t_{50}) at fixed mass-weighted age.

where t_{50}^{LB} is the lookback time when 50% of the stellar mass is assembled and $\langle \text{age} \rangle_{\text{MW}}$ is the mass-weighted age. In the TNG intrinsic measurements that are free of methodological systematics, the offset is small, $\Delta = 0.2 \pm 0.3$ Gyr. After assigning SPS models to particles on a discrete grid, the offset increases to $\Delta = 0.7 \pm 0.4$ Gyr. The recovered values from pPXF show the largest shift, $\Delta = 1.7 \pm 0.7$ Gyr. Thus, the assignment step introduces a modest positive bias, and the complete spectral fitting further pushes t_{50}^{LB} to higher values at a fixed mass-weighted age, consistent with t_{50} being underestimated in age since formation.

I next examine the dependence of the recovered age, the assembly duration $\Delta t \equiv t_{90} - t_{10}$, and t_{50} on galaxy stellar mass and on its photometric proxies M_i and M_K (Fig. 2.5; top, middle, and bottom rows, respectively). Photometric values are taken from the TNG API (`stellarphotometrics_i`, `stellarphotometrics_k`), and stellar masses from `mass_stars`, converted to $M_\odot$ as $M_\star = \text{mass_stars} \times 10^{10}/h$ with $h = 0.6774$. The clearest trend appears for the star-formation timescale Δt : more massive galaxies exhibit shorter assembly durations (i.e., they form their stellar mass more rapidly). By contrast, the mass-weighted age and t_{50} show at most weak mass dependence within the current uncertainties. Consistent behavior is seen in the SFHs of Fig. 2.6 where lower-mass systems display more extended, gradual cumulative SFHs, especially at $z = 0.3$ (left panel).

Overall, my analysis shows that for noiseless spectra I recover ages and the star-formation timescale $\Delta t \equiv t_{90} - t_{10}$ reliably, but I observe a systematic offset in metallicity and a tendency to underestimate t_{50} —a bias that is already partly introduced by the SPS-assignment step. Galaxies at $z = 0.3$ exhibit more extended SFHs, consistent with late-time rejuvenation and/or a larger fraction of lower-mass systems, whose SFHs are typically more prolonged.

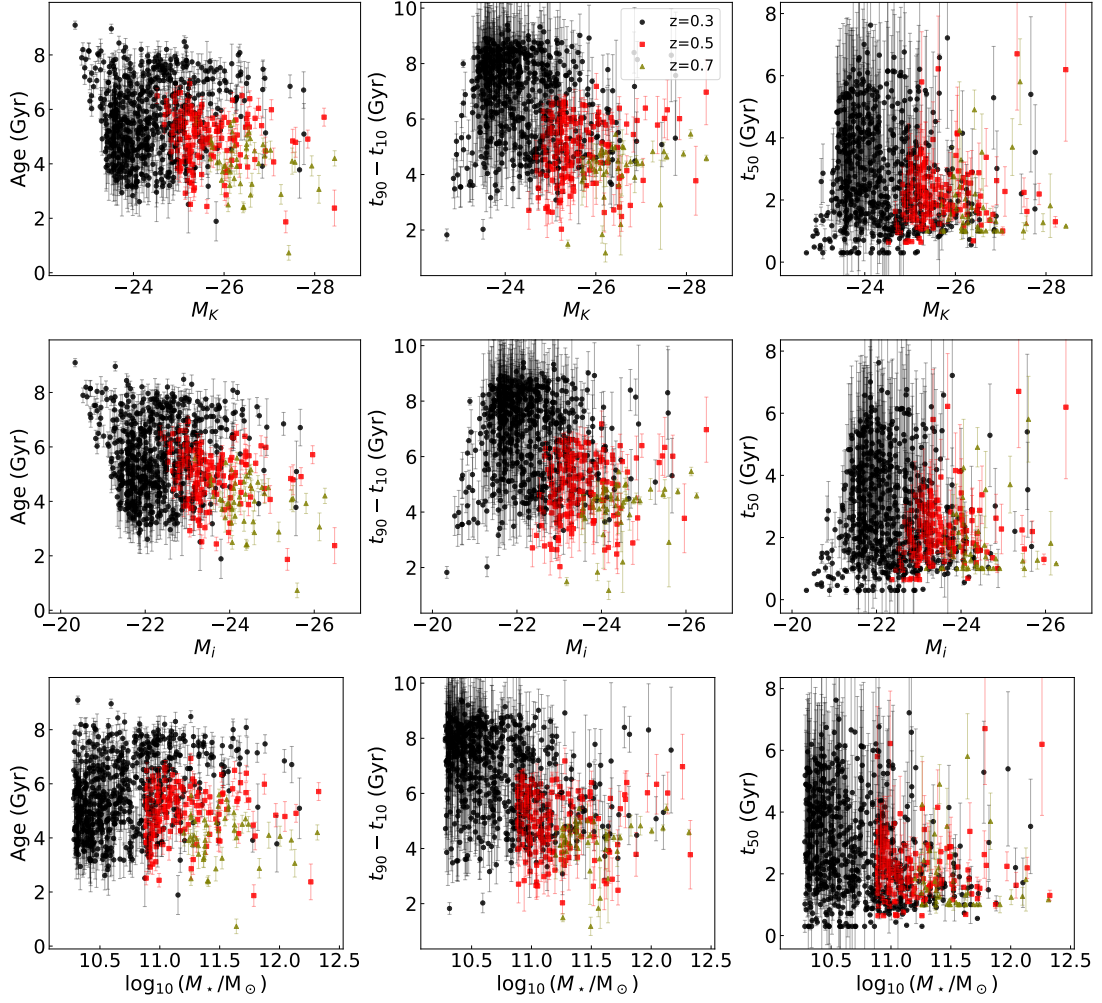


Figure 2.5. Recovered parameters versus photometric proxies and stellar mass. Top panels: M_K , middle panels: M_i , bottom panels: M_* . Points are color-coded by redshift; error bars show 1σ uncertainties. The strongest correlation is seen for the assembly duration $\Delta t \equiv t_{90} - t_{10}$, which decreases with increasing mass.

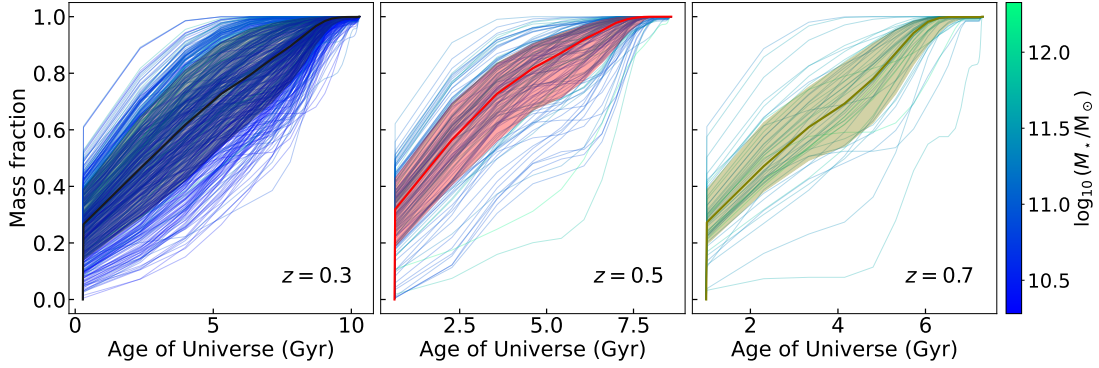


Figure 2.6. Cumulative SFHs for the three redshift bins, with individual galaxies color-coded by $\log_{10}(M_{\star}/M_{\odot})$. Median SFHs and 16–84th-percentile bands are overplotted.

2.1.1 Search for rejuvenating galaxies

One of the key open questions in galaxy evolution is characterizing the physical processes leading passive and quiescent galaxies to abruptly increase their star formation activity, globally or locally. The main physical mechanisms proposed for rejuvenation include gas accretion during gas-rich mergers and smooth cold gas accretion from the intergalactic medium (IGM). These channels can supply gas essential for the star formation process of a galaxy (e.g., Kaviraj et al., 2009; Fang et al., 2012; Dressler et al., 2013; Rowlands et al., 2018).

The search for rejuvenating galaxies remains challenging, primarily because there is no universally accepted, quantitative definition of rejuvenation. Generally, rejuvenation refers to a significant increase in star formation rate following a quiescent phase, but distinguishing this from typical star formation variability is nontrivial. However, estimates of the frequency of rejuvenation events vary significantly across cosmological simulations. For instance, the UniverseMachine model suggests that 40–70% of quiescent galaxies may undergo rejuvenation at some point (Behroozi et al., 2019), whereas in IllustrisTNG, this fraction is much lower, around 10% (Nelson et al., 2018). Similarly, the SIMBA simulations also report a low frequency of rejuvenation events and indicate that the frequency of rejuvenation is potentially dependent on both galaxy mass and redshift (Rodríguez Montero et al., 2019). This wide variation across models underscores the need for forward modeling to make meaningful comparisons with observational data and better constrain the physics of galaxy rejuvenation.

To identify rejuvenated galaxies, I first classify systems on the $\text{SFR}-M_{\star}$ plane, following the procedure described in Chapter 1. A galaxy is considered rejuvenated if it transitions from the quiescent region to the star-forming region at any time between $z = 0.7$ and $z = 0.3$ (a lookback interval of ≈ 3.5 Gyr). The $\text{SFR}-M_{\star}$ diagrams for the three redshift bins are shown in Fig. 2.7. In these plots, galaxies are colour-coded as star-forming (SF), green valley (GV), or quiescent (Q) according to the SFR thresholds, providing insight into the evolutionary pathways of galaxies and allowing to identify potential rejuvenation candidates across cosmic time. Table 2.4

Table 2.4. Population fractions by redshift.

Redshift (z)	Quiescent (Q)	Green Valley (GV)	Star-forming (SF)	Total
0.7	2 (4.3%)	3 (6.4%)	42 (89.4%)	47
0.5	12 (7.7%)	17 (11.0%)	126 (81.3%)	155
0.3	65 (11.6%)	57 (10.1%)	440 (78.3%)	562

(1) Redshift of the subsample. (2) Number (and percentage) of galaxies classified as quiescent. (3) Number (and percentage) of galaxies in the green valley. (4) Number (and percentage) of galaxies classified as star-forming. (5) Total number of galaxies in the redshift bin.

summarizes the distribution of different galaxy types across the three redshift bins. As the redshift decreases from $z = 0.7$ to $z = 0.3$, I observe an increasing fraction of quiescent and green-valley galaxies, consistent with ongoing quenching and the build-up of the red sequence over time. Notably, the green-valley fraction peaks at $z = 0.5$ (11%), suggesting an enhanced incidence of systems in transition between star-forming and quiescent phases at intermediate redshift.

I then examine the SFHs of two classes of rejuvenated systems: (i) galaxies identified as rejuvenated that remain in the SF population at $z = 0.3$, and (ii) galaxies that exhibit signatures of past rejuvenation events but are classified as quenched at $z = 0.3$.

2.1.1.1 Search for Rejuvenating Galaxies Among the Star-Forming Population

To identify rejuvenated galaxies in the simulation, I analyzed the evolutionary histories of galaxies classified as star-forming at $z = 0.3$. For each of these galaxies, I traced their main progenitor branch backward in time up to $z = 0.7$. The goal was to determine whether any of these star-forming galaxies had experienced a quiescent phase in the past, i.e., whether they were previously quenched and later resumed star formation, thereby qualifying as rejuvenated. An example of a SF path of the purely star-forming galaxy and a rejuvenated one is shown in Figure 2.8. The left panel illustrates a galaxy that remained star-forming throughout the redshift range, while the right panel shows a rejuvenated galaxy that had quenched progenitors between $z = 0.3$ and $z = 0.7$. Note that, occasional, small decreases in stellar mass along the main-progenitor branch (as seen for the left galaxy) are expected in IllustrisTNG and can arise from tidal stripping and/or SUBFIND re-identification/boundary effects, as well as bookkeeping of stellar-evolution mass loss (e.g., Lokas, 2020, see also the TNG forum discussions¹).

I then selected a control sample for the rejuvenated galaxies identified among the star-forming population. For each rejuvenated galaxy, I selected ten control galaxies from the star-forming population that had not undergone rejuvenation. Following the method of Li et al. (2023), control galaxies were chosen based on a unique, closest match in stellar mass within a tolerance of $\Delta \log(M_\star/M_\odot) \approx \pm 0.1$. Figure 2.9 shows the

¹<https://www.tng-project.org/data/forum/topic/211/mass-loss-due-to-stellar-evolution/>

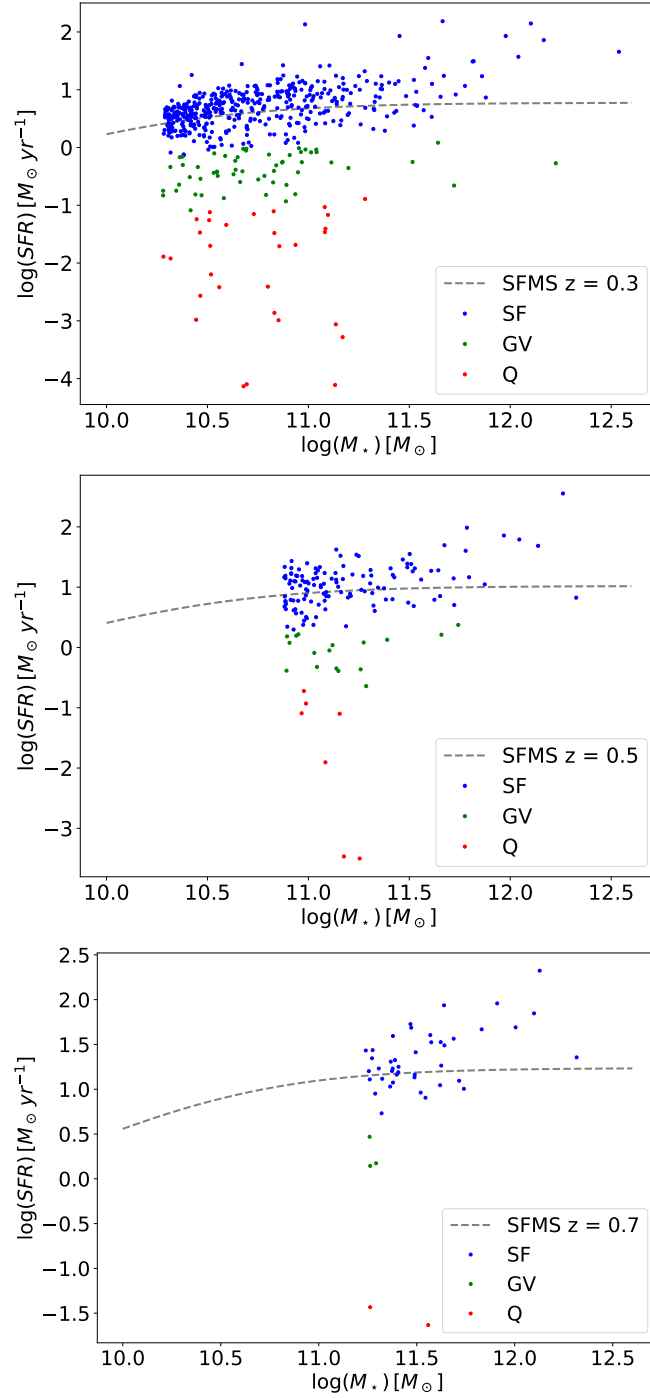


Figure 2.7. The SFR– M_* relation for galaxies in three redshift bins: $z = 0.3, 0.5$, and 0.7 . Galaxies are color-coded by type: star-forming (SF), green valley (GV), and quiescent (Q).

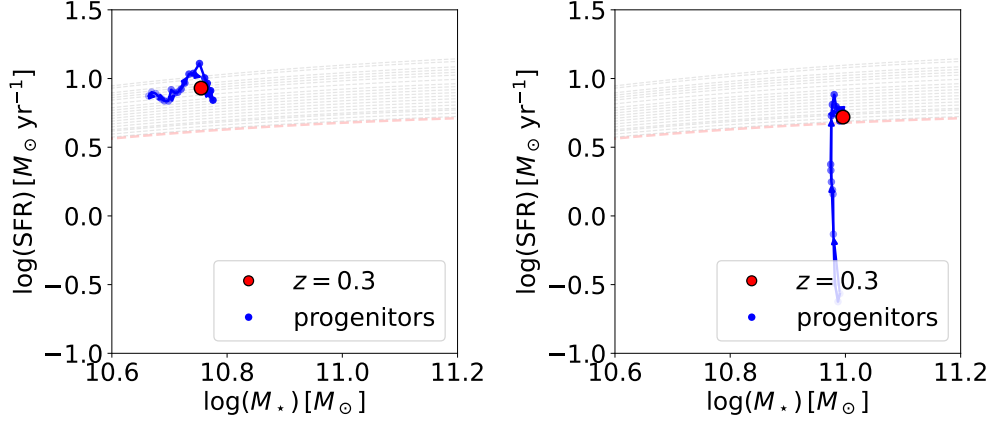


Figure 2.8. Examples of galaxy evolutionary tracks in the SFR– M_* plane from $z = 0.7$ to $z = 0.3$. Left panel: A purely star-forming galaxy with no quiescent progenitors. Right panel: A rejuvenated galaxy that experienced a quenched phase in the past and later resumed star formation. The dashed curves show the redshift-dependent star-forming main sequences.

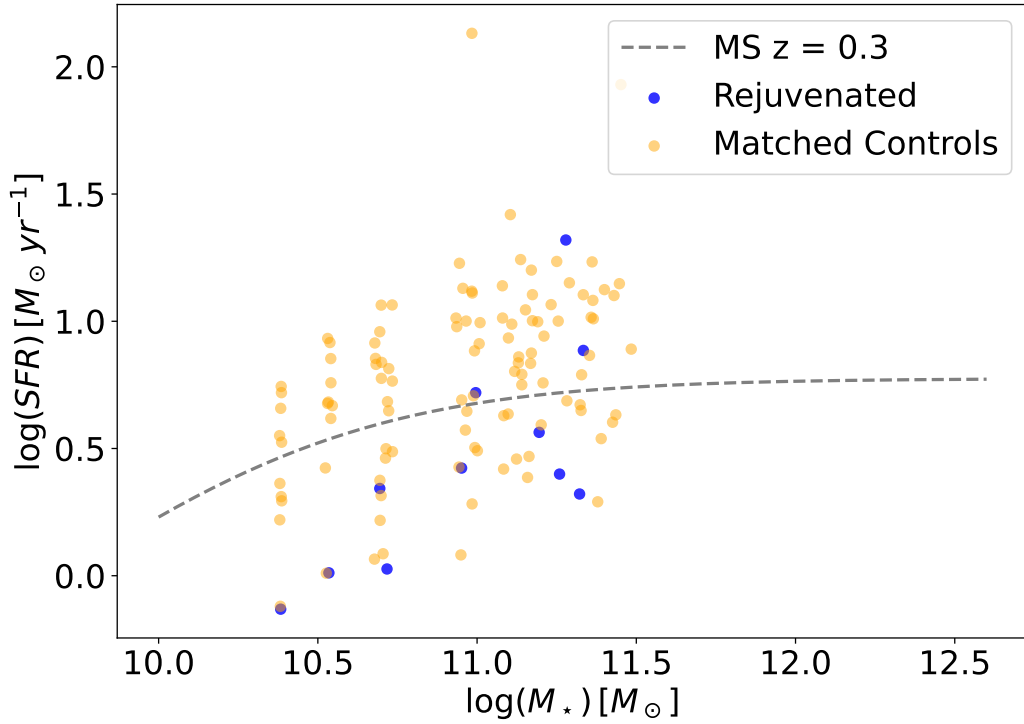


Figure 2.9. SFR versus stellar mass diagram for the 11 rejuvenated galaxies (blue) and their corresponding control sample of 110 non-rejuvenated star-forming galaxies (gold).

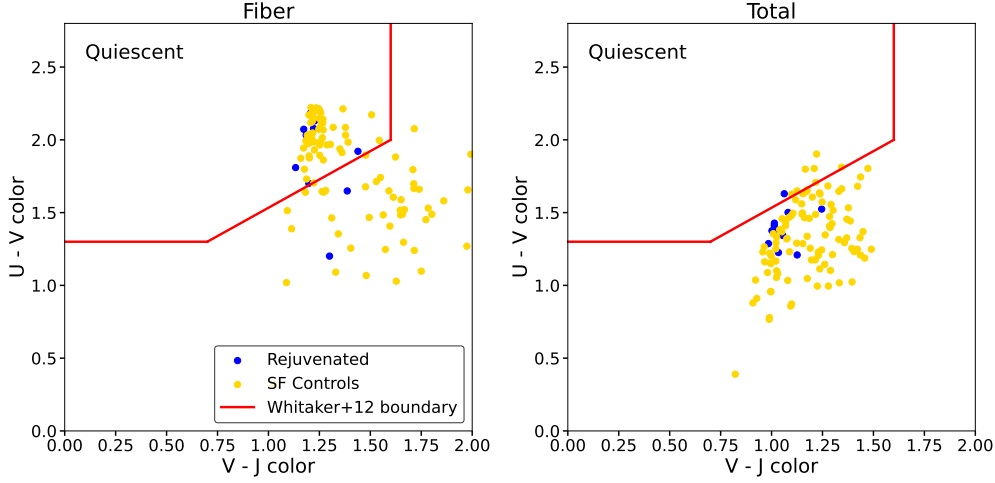


Figure 2.10. UVJ for fiber (left panel) and total (right panel) spectra for rejuvenated (blue) and control (gold) samples.

distribution of the rejuvenated and control galaxies in the $\text{SFR}-M_{\star}$ plane. Rejuvenated galaxies are shown in blue, while control galaxies are shown in gold.

It is worth noting that the properties of the sample in TNG50 refer to the integrated properties for each galaxy. However, the analysis is tailored for the observing strategy of WEAVE-StePS, thus limiting us to the central region of each galaxy, up to $\sim 1R_{\text{e}}$. This aperture mismatch may bias the interpretation and therefore should be quantified. To do so, I first tested for discrepancies in the color-based classification by measuring the commonly used UVJ colors from the low-resolution, wide-coverage grid spectra (see Sect. 0.2.1.5). As expected, almost all galaxies (both test and control) fall in the star-forming region when using integrated spectra, whereas most of the test sample and a substantial fraction of the control sample move to the quiescent region when using fiber spectra. This indicates that central apertures can miss rejuvenation and star-formation episodes occurring at larger radii because galaxy centers are typically older and more passive. Consequently, in what follows I analyze both fiber and integrated spectra.

I then used `pPXF` to measure the SFHs of all galaxies in the two groups, for both fiber and integrated spectra. Figure 2.11 shows the median SFH with shaded area corresponding to the 16th-84th percentile: the left panels show fiber spectra, the right panels integrated spectra; the top row shows the regularized solution and the bottom row the unregularized one. Including both regularization settings allows us to evaluate possible self-similarity biases introduced by regularization. In both apertures, rejuvenated galaxies (blue) assembled their stellar mass earlier than the purely star-forming control sample (gold), as expected given the intervening quiescent phase. The contrast is more visually pronounced in the regularized solutions. Quantitatively (Table 2.5), for fiber spectra comparing to control sample the rejuvenated sample has a shorter star-formation timescale, $t_{90} - t_{10}$, by ~ 2.0 Gyr (4.65 vs. 6.59 Gyr), and a smaller t_{50} by ~ 1.0 Gyr (1.19 vs. 2.13 Gyr). For integrated spectra the same pattern

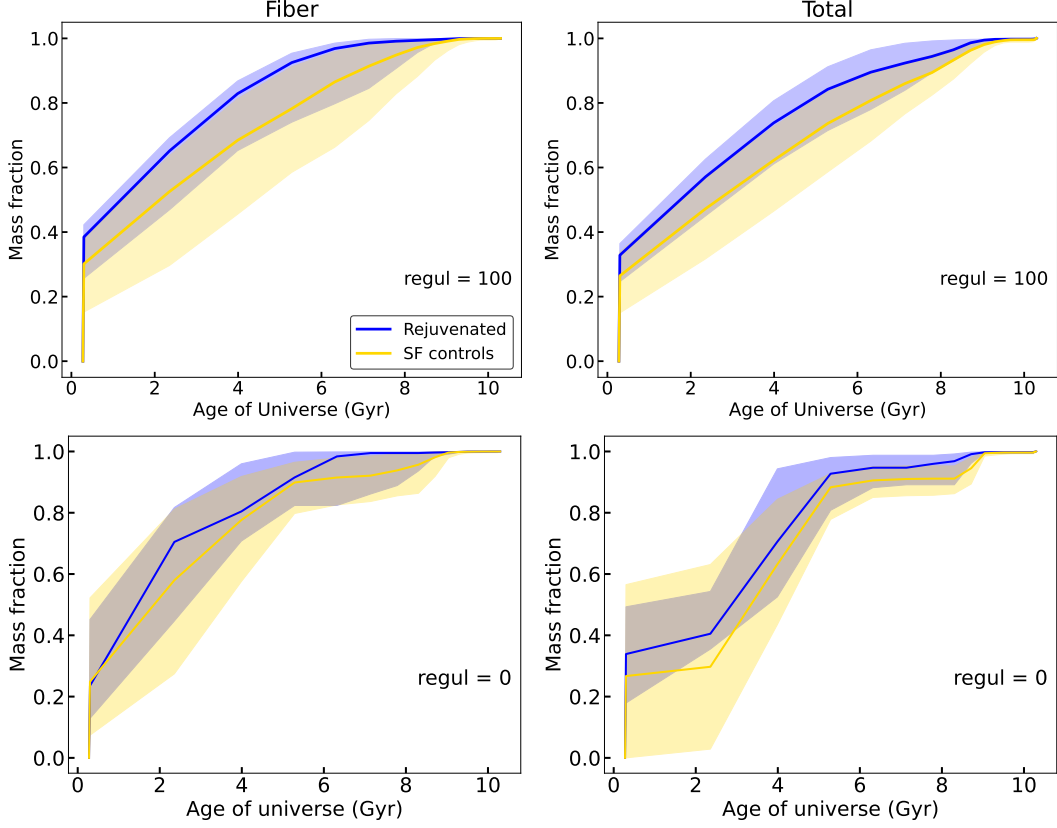


Figure 2.11. SFHs for fiber (left panels) and integrated (right panels) spectra for rejuvenated star-forming (blue) and purely star-forming (gold) samples. The top row shows the regularized solution, while the bottom row shows the non-regularized case. Shaded regions indicate the 16th–84th percentile range.

holds, with $t_{90} - t_{10}$ shorter by ~ 1.4 Gyr (6.16 vs. 7.54 Gyr) and t_{50} lower by ~ 0.9 Gyr (1.74 vs. 2.68 Gyr). Finally, the integrated spectra produce systematically younger ages than the fiber spectra (for both classes), consistent with the former that includes light from larger radii where younger populations are more prominent.

To further characterise the stellar populations, I introduce the quantity $\Delta\text{Age} \equiv \text{Age}_{\text{MW}} - \text{Age}_{\text{LW}}$, defined as the difference between the mass-weighted and light-weighted ages. This parameter is useful because the two age definitions respond differently to composite populations: Age_{MW} reflects the underlying mass-dominant (typically older) component, whereas Age_{LW} is strongly influenced by any young, luminous subpopulation. Therefore, a large positive ΔAge can indicate the coexistence of a younger stellar component with an older underlying population, i.e. potential rejuvenation. Figure 2.12 shows Age_{LW} versus ΔAge from the regularized solutions for fiber (left panel) and integrated (right panel) spectra. For fiber spectra, the two groups overlap in this plane, making them difficult to distinguish. In contrast, for integrated spectra ΔAge remains approximately constant at ~ 4 Gyr over the full range of Age_{LW} with small dispersion,

Table 2.5. Summary of stellar age and formation-timescale statistics for control and rejuvenated galaxy populations at $z = 0.3$ from pPXF (regularization `regul`=100). Each entry shows the median and the 16th–84th percentile range.

Aperture	Class	$t_{90} - t_{10}$ [Gyr]	t_{50} [Gyr]	$\langle \text{Age} \rangle_{\text{MW}}$ [Gyr]	$\langle \text{Age} \rangle_{\text{LW}}$ [Gyr]	ΔAge [Gyr]
Fibre	Control	$6.59^{+1.40}_{-1.76}$	$2.13^{+2.32}_{-0.87}$	$6.13^{+1.14}_{-1.67}$	$3.26^{+2.61}_{-2.32}$	$2.32^{+1.59}_{-1.05}$
Fibre	Rejuvenated	$4.65^{+2.69}_{-0.49}$	$1.19^{+1.46}_{-0.30}$	$7.45^{+0.32}_{-2.00}$	$4.82^{+2.03}_{-2.13}$	$1.55^{+1.81}_{-0.60}$
Integrated	Control	$7.54^{+0.67}_{-1.34}$	$2.68^{+1.66}_{-0.96}$	$5.57^{+0.81}_{-1.14}$	$1.30^{+1.20}_{-0.65}$	$3.73^{+0.97}_{-0.67}$
Integrated	Rejuvenated	$6.16^{+1.42}_{-1.31}$	$1.74^{+1.11}_{-0.37}$	$6.55^{+0.64}_{-1.22}$	$2.27^{+0.83}_{-0.83}$	$4.03^{+0.59}_{-0.38}$

(1) Aperture: Fibre = central, WEAVE-StePS-like spectra; Integrated = full-galaxy spectra.

(2) Class: Control = purely star-forming sample; Rejuvenated = systems with a recent secondary star-formation episode.

(3) Time between 10% and 90% of the stellar mass being assembled.

(4) Time when 50% of the stellar mass has formed. (5) Mass-weighted stellar age.

(6) Light-weighted stellar age. (7) Difference between mass- and light-weighted ages.

consistent with the values reported in Table 2.5.

In conclusion, rejuvenation signatures are more readily identified in the integrated spectra, probably because rejuvenated regions lie outside galaxy centers, while the fiber aperture tends to wash out these differences. The consistently elevated ΔAge recovered from the integrated spectra thus provides a practical diagnostic to select rejuvenated systems. In all cases, these differences are most reliably recovered with more physical, regularized solutions.

2.1.1.2 Search for Rejuvenated Galaxies Among Quenched

An alternative approach to identifying rejuvenation episodes is to study galaxies that are currently quenched and investigate their SFH. For example, [Rutkowski et al. \(2025\)](#) found that approximately 15% of massive, quiescent galaxies at redshifts $0.5 < z < 1.5$ exhibit signs of recent minor star formation activity. In their analysis, this recent activity contributes less than 10% to the total stellar mass and occurred within the past ~ 1 Gyr. These results suggest that a non-negligible fraction of quiescent galaxies may undergo brief episodes of star formation, potentially triggered by mechanisms such as gas accretion from the IGM or minor mergers.

My goal is to check whether traces of star formation in the past few Gyrs can be detected in the sample of quiescent galaxies, focusing on fiber spectra to maximize the outcome for the WEAVE-StePS survey. For this purpose, I divide the quiescent galaxies at $z = 0.3$ (Fig. 2.7) into three groups and compare their SFHs:

1. **Pure quiescent (gold colors)** — galaxies that remained in the quiescent region for the entire past ~ 3.5 Gyr (from $z = 0.7$ to $z = 0.3$);
2. **Recently quenched (red colors)** — galaxies that were star-forming at $z = 0.7$, but became quiescent at some point afterward;

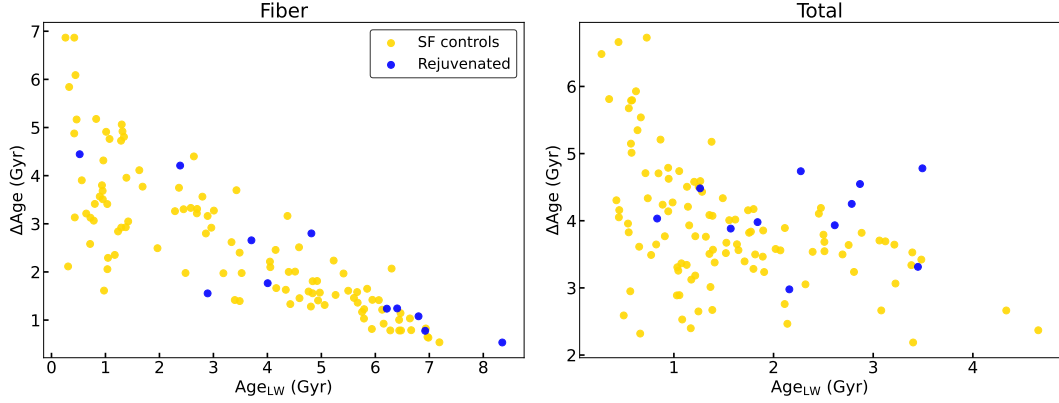


Figure 2.12. Comparison of Age_{LW} versus $\Delta\text{Age} \equiv \text{Age}_{\text{MW}} - \text{Age}_{\text{LW}}$ for fiber (left panel) and integrated (right panel) spectra. Rejuvenated and control galaxies are shown in blue and gold, respectively.

3. **Rejuvenated (blue colors)** — galaxies that temporarily moved into the star-forming region between $z = 0.7$ and $z = 0.3$, but later returned to the quiescent region in the $\text{SFR}-M_{\star}$ diagram.

From the UVJ diagram (Fig. 2.13), there is no mismatch in classification: all three samples fall in the quiescent region for both fiber and integrated spectra. Nevertheless, because it is unclear whether any rejuvenation signature would lie within the fiber aperture, I analyze both fiber and integrated spectra in what follows.

I present the SFH comparison in Fig. 2.14 for both fiber (left panels) and integrated (right panels) spectra. The derived SFHs show that recently quenched (red curves) and rejuvenated (blue curves) galaxies have very similar histories, both clearly distinct from the pure quiescent population (gold curves). The key statistics are summarized in Table 2.6. Relative to pure quiescents, recently quenched and rejuvenated systems have longer formation timescales (3.97 vs. 6.05 and 6.15 Gyr) and later half-mass assembly (0.76 vs. 1.98 and 1.74 Gyr), consistent with extended star formation, and are approximately 1 Gyr younger in $\langle\text{Age}\rangle_{\text{MW}}$ and 2 Gyr younger in $\langle\text{Age}\rangle_{\text{LW}}$. Apart from light-weighted ages, there are no strong differences between fiber and integrated results. $\langle\text{Age}\rangle_{\text{LW}}$ is typically ~ 0.5 – 0.7 Gyr younger in the integrated aperture, consistent with additional light from younger outskirts. They also show larger ΔAge , especially in the integrated aperture, where rejuvenated galaxies exceed pure quiescents by ~ 1.4 Gyr and recently quenched by ~ 0.6 Gyr.

I also note that rejuvenated galaxies tend to complete the final few percent ($< 5\%$) of their mass growth slightly later than recently quenched systems, consistent with my definition of rejuvenation as a recent (~ 4.5 Gyr) burst. In the integrated spectra, the ΔAge statistic (last column of Table 2.6) is ~ 0.5 Gyr larger for the rejuvenated class than for the recently quenched class, providing an additional indicator of rejuvenation; this contrast is less evident in the fiber aperture. A similar trend appears in the $\text{Age}_{\text{LW}}-\Delta\text{Age}$ plane (Fig. 2.15), where the rejuvenated sample preferentially occupies

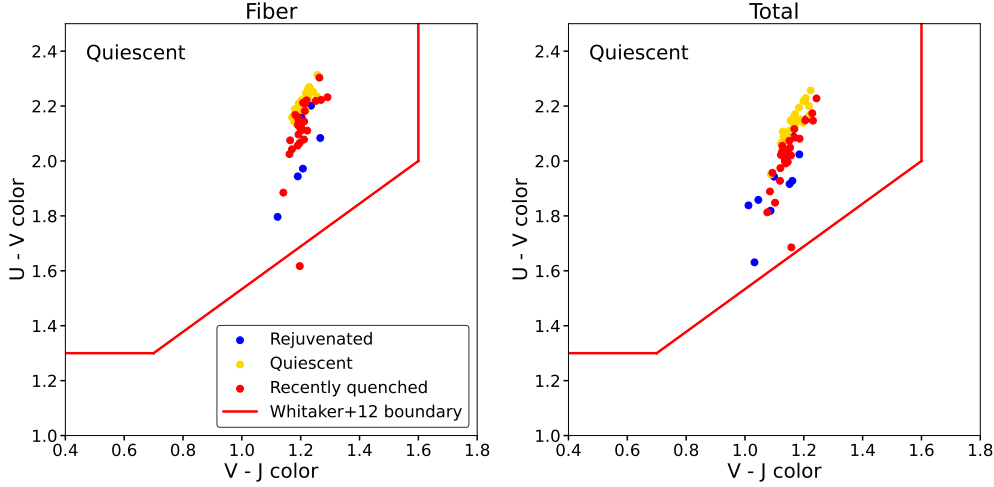


Figure 2.13. Same as Figure 2.10, but for the rejuvenated (blue), recently quenched (red), and pure quiescent (gold) samples.

the upper-left region, especially for integrated spectra.

All of this suggests that the analysis is sensitive enough to distinguish galaxies with recent star formation activity (both rejuvenated and recently quenched) from purely quiescent ones, even in fiber spectra, which is encouraging for investigating these processes within the WEAVE-StePS survey. At the same time, it remains challenging to clearly separate rejuvenated from recently quenched systems, especially with fiber data alone. The parameter ΔAge may offer some diagnostic power, but additional methods, such as spatially resolved datacube analysis or independent quenching indicators, are likely needed for a more robust classification.

2.2 Testing polynomial degrees in pPXF

As I mentioned at the beginning of this section, in the pPXF setup I ultimately adopt a multiplicative polynomial of degree $m = 5$ (`mdegree=5`). In the following, I justify this choice by comparing multiple setups. I focus on the redshift bin $z = 0.3$, which contains the largest number of galaxies in the total sample ($N > 500$).

Using the baseline configuration described in Sect. 0.4.2, i.e. without any multiplicative polynomials, I find that while the majority of the sample ($\approx 70\%$) is well recovered, a significant fraction ($\approx 30\%$) exhibits poor parameter recovery. To investigate this, I examine the star formation timescale $t_{90} - t_{10}$. The sample is divided into two groups on the basis of the recovery error of this parameter. Specifically, galaxies for which the recovered timescale is biased low by more than 2.5 Gyr,

$$(t_{90} - t_{10})_{\text{rec}} - (t_{90} - t_{10})_{\text{true}} < -2.5 \text{ Gyr},$$

are flagged as poorly recovered, and the rest are considered recovered.

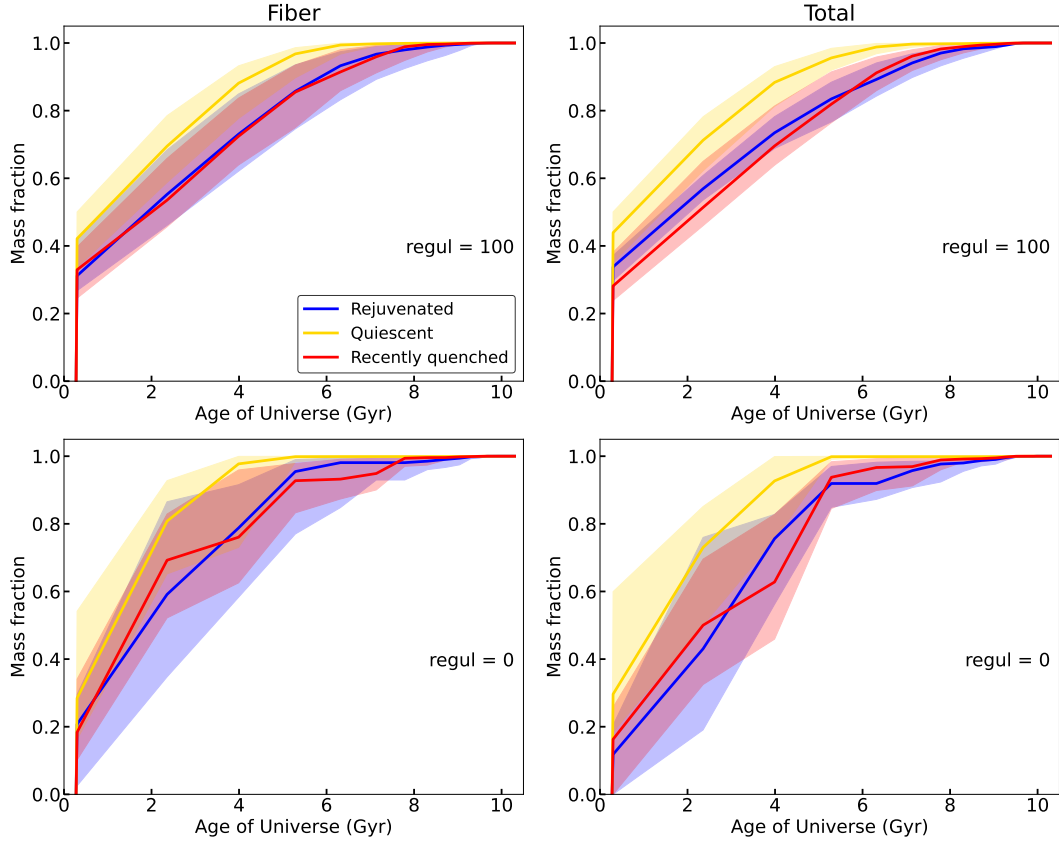


Figure 2.14. SFHs for fiber (left panels) and integrated (right panels) spectra for rejuvenated (blue), recently quenched (red), and pure quiescent (gold) samples. The top row shows the regularized solution, while the bottom row shows the non-regularized case.

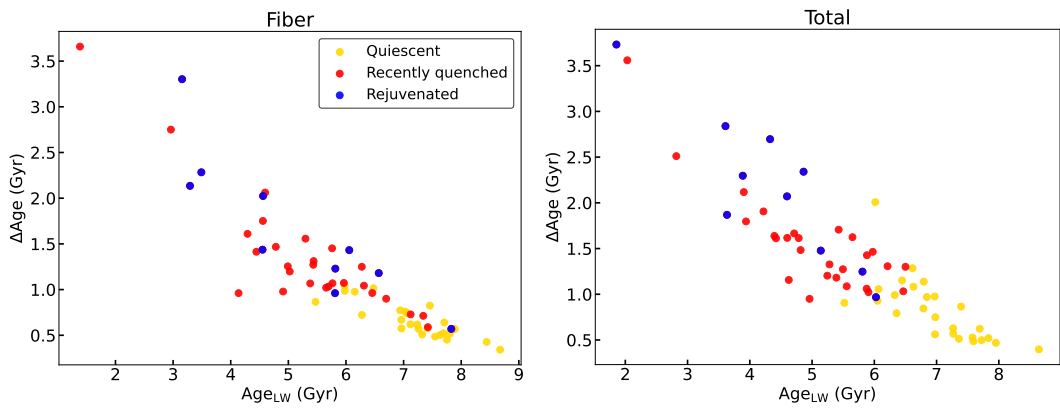


Figure 2.15. Same as Figure 2.12 but for rejuvenated (blue), recently quenched (red) and pure quenched (gold) samples.

Table 2.6. Same as Table 2.5, but for but for quenched galaxies (at $z = 0.3$).

Aperture	Class	$t_{90} - t_{10}$ [Gyr]	t_{50} [Gyr]	$\langle \text{Age} \rangle_{\text{MW}}$ [Gyr]	$\langle \text{Age} \rangle_{\text{LW}}$ [Gyr]	ΔAge [Gyr]
Fiber	Pure quiescent	$3.97^{+1.06}_{-0.63}$	$0.89^{+0.75}_{-0.59}$	$7.83^{+0.49}_{-0.70}$	$7.25^{+0.50}_{-0.97}$	$0.62^{+0.25}_{-0.12}$
Fiber	Recently quenched	$5.61^{+1.07}_{-1.08}$	$2.00^{+0.75}_{-0.92}$	$6.70^{+0.84}_{-0.82}$	$5.43^{+1.05}_{-1.18}$	$1.25^{+0.78}_{-0.29}$
Fiber	Rejuvenated	$5.57^{+1.44}_{-1.14}$	$1.89^{+0.86}_{-0.95}$	$6.68^{+0.96}_{-0.81}$	$5.19^{+1.16}_{-1.81}$	$1.43^{+0.78}_{-0.38}$
Integrated	Pure quiescent	$3.97^{+0.79}_{-0.61}$	$0.76^{+0.67}_{-0.46}$	$7.88^{+0.38}_{-0.56}$	$6.97^{+0.72}_{-0.64}$	$0.82^{+0.26}_{-0.31}$
Integrated	Recently quenched	$6.05^{+0.63}_{-1.01}$	$1.98^{+0.74}_{-0.72}$	$6.57^{+0.65}_{-0.69}$	$4.86^{+1.02}_{-0.96}$	$1.61^{+0.69}_{-0.47}$
Integrated	Rejuvenated	$6.15^{+0.71}_{-0.87}$	$1.74^{+0.31}_{-0.29}$	$6.64^{+0.40}_{-0.79}$	$4.46^{+1.05}_{-0.84}$	$2.18^{+0.59}_{-0.83}$

(1) Aperture: Fiber = central, WEAVE–StePS–like spectra; Integrated = full-galaxy spectra.

(2) Class: Pure quiescent = no recent star formation; Recently quenched = star formation ceased recently; Rejuvenated = recent secondary star-formation episode.

(3) Time between 10% and 90% of the stellar mass being assembled.

(4) Time when 50% of the stellar mass has formed.

(5) Mass-weighted stellar age. (6) Light-weighted stellar age.

(7) Difference between mass- and light-weighted ages.

Figure 2.16 illustrates the two groups using density contours. Galaxies with accurate recovery (“Group 1”, blue) are contrasted with those with poor recovery (“Group 2”, orange), defined by the timescale criterion above. Systems with large discrepancies in their star-formation timescales also tend to show poorer recovery of stellar ages. The left column shows the SF timescale $t_{90} - t_{10}$, stellar age, and $[M/H]$; the right panels show the recovered t_{10} , t_{50} , and t_{90} versus their true values. The same population that fails the SF timescale criterion exhibits significant deviations in t_{90} , whereas t_{50} is largely unaffected. The metallicity distribution likewise separates the two groups: well-recovered galaxies span a broad range with a tail toward lower metallicities, while the poorly recovered group is narrowly concentrated at the low-metallicity end, suggesting that the recovery of metallicity is also impacted when the overall fit quality degrades.

To investigate the possible cause of the poor parameter recovery, I stacked the spectra within each group by taking the mean flux at each wavelength. The resulting mean spectra for the two groups are shown in Figure 2.17. From this figure, it is evident that the spectra corresponding to Group 2 (orange) exhibit strong emission features, which are largely absent in Group 1 (blue). This suggests that the presence of strong emission lines may be contributing to the failure of parameter recovery.

Another possible explanation is the influence of dust. To assess this, I examined two random galaxies from the sample, one of which is from Group 1 (ID = 11 at $z = 0.3$) and another from Group 2 (ID = 191599 at $z = 0.3$). The individual spectral components generated during the simulation process (see Sect. 0.2.1.5) are shown in Figure 2.18. These components demonstrate that in the case of the star-forming galaxy (ID = 191599), the inclusion of the dust (i.e., going from the transparent to the total flux) causes a significant change of the spectrum. In contrast, for galaxy ID = 11, the transparent and total spectra are nearly identical, indicating that the presence of the medium does not affect the observed spectrum. This difference may contribute to the

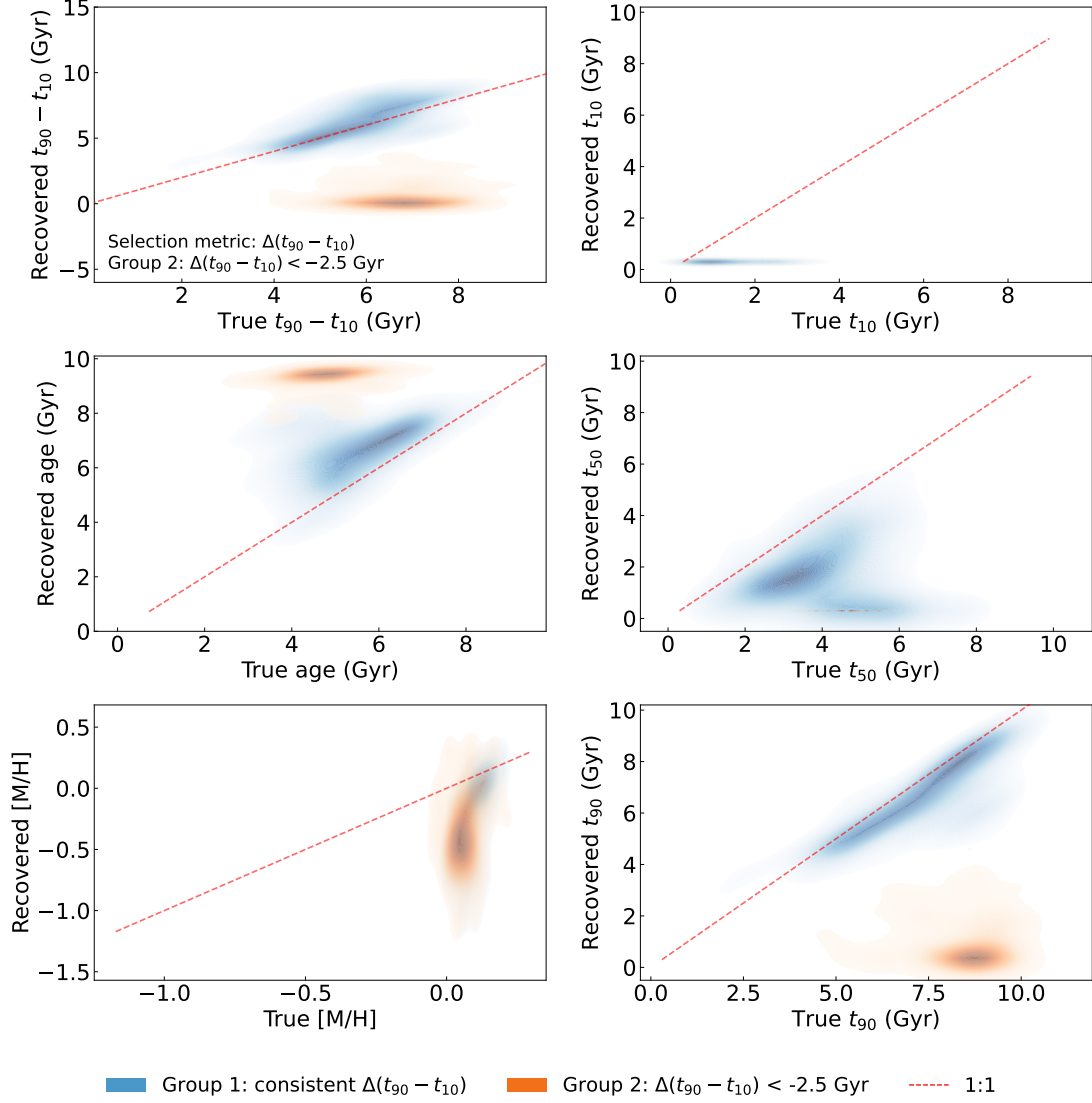


Figure 2.16. Recovered vs. true (assigned) values at $z = 0.3$ for noiseless spectra. Blue contours (Group 1) show well-recovered galaxies; orange contours (Group 2) mark galaxies with poor recovery, defined by $(t_{90} - t_{10})_{\text{rec}} - (t_{90} - t_{10})_{\text{true}} < -2.5$ Gyr. Left panels: $t_{90} - t_{10}$, age, and $[M/H]$. Right panels: t_{10} , t_{50} , t_{90} . The dashed red line indicates the one-to-one relation.

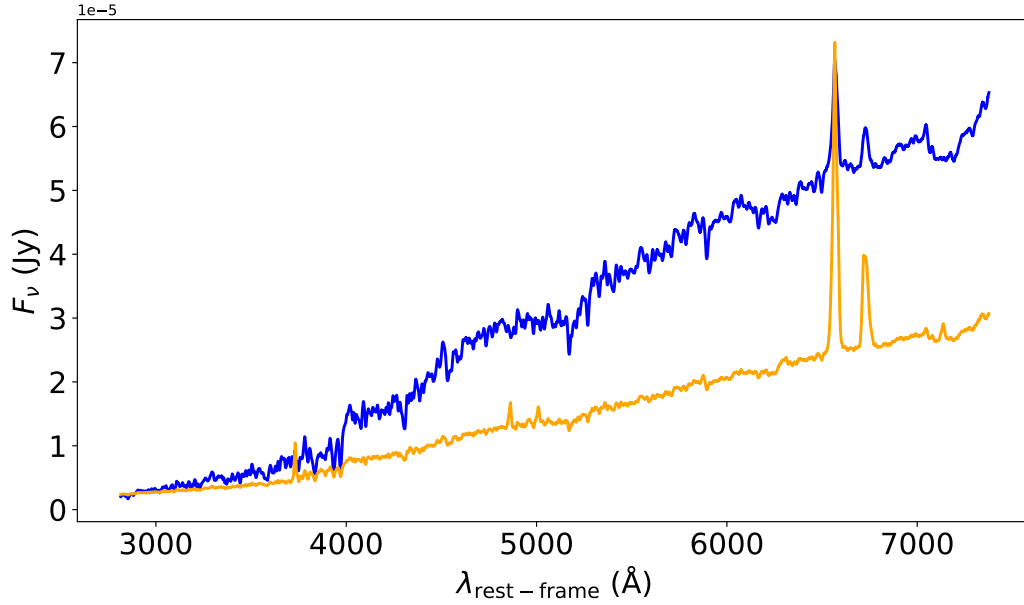


Figure 2.17. Mean stacked spectra for the two groups. Blue represents the well-recovered group (Group 1), and orange represents the poorly recovered group (Group 2).

poor recovery performance for the first galaxy.

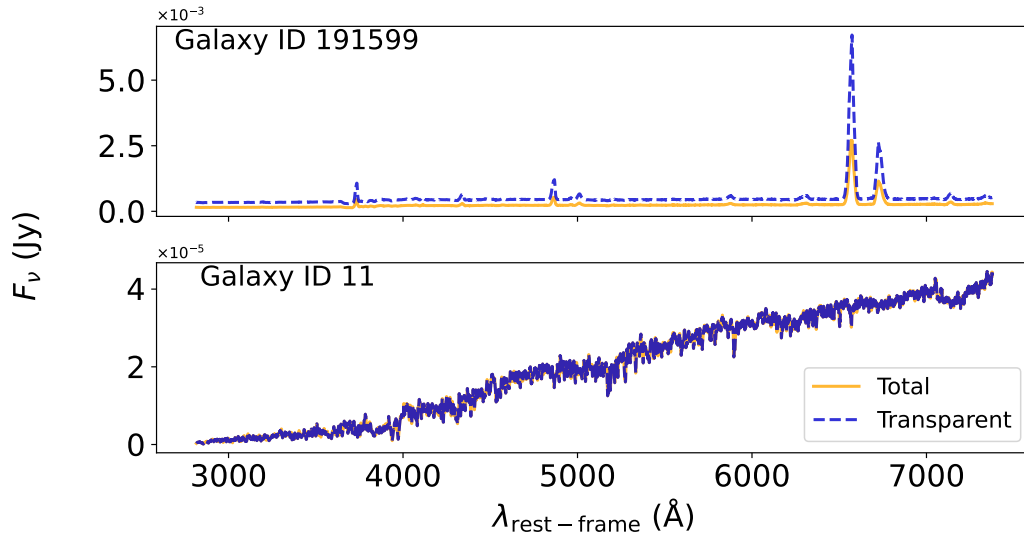


Figure 2.18. Comparison of spectral components for the non-recovered galaxy (ID = 191599, upper panel) and for the well-recovered galaxy (ID = 11, bottom panel) at $z = 0.3$. Each panel shows the total flux (orange) and the corresponding transparent flux (blue dashed), which represents the spectrum in the absence of any attenuation.

Furthermore, I noticed an excess of flux in the bluer part of the poorly retrieved spectra, which could also be due to the nebular continuum contribution. In my case, I modeled the nebular continuum and emission using the MAPPINGS III library as part of the radiative transfer modeling (see Chapter 0). However, when running the full spectral fitting routine, `pPXF` accounts only for the stellar continuum and discrete emission lines, while the nebular continuum is not included in the fitting process. In the following, I provide a detailed description of this possible systematic in the context of the analysis.

As a note of caution, the implementation of MAPPINGS in `SKIRT` has been linked to known issues in previous post-processing studies of cosmological hydrodynamical simulations. These studies reported significant discrepancies between synthetic and observed galaxies in the UV and MIR regimes, specifically, an underestimation of UV attenuation and an overestimation of MIR emission (Baes et al., 2019; Trčka et al., 2020, 2022; Kapoor et al., 2021; Camps et al., 2022). The MAPPINGS III templates used to model young stellar populations were identified as at least partially responsible for these mismatches. To address this, Kapoor et al. (2023) has started to develop a new library of emission templates (`TODDLERS`) designed for use with `SKIRT`. This updated library aims to improve the treatment of young stellar populations and their nebular environments, particularly enhancing predictions in the UV while leaving the optical largely unaffected. A detailed analysis of its impact, however, is beyond the scope of this work.

To better quantify and minimize the impact of these systematics, I tested different `pPXF` setups. As mentioned earlier, poor recovery performance is probably caused by the distortions in the continuum shape due to nebular continuum. In this case, introducing additive polynomials of various degrees may help to correct this mismatch. Indeed, by including both additive and multiplicative polynomials (`degree = 4`, `mdegree = 4`), I observed an immediate improvement in successful recovery accuracy, with the recovery rate increasing from approximately 70% to 90%.

I then explore multiple setups to recover the optical combination of multiplicative and additive polynomials for the strategy. In general, additive polynomials can help with different issues such as template mismatch, AGN contamination, or sky subtraction errors, while multiplicative polynomials are better suited for correcting spectral flux calibration uncertainties or reddening effects (Cappellari, 2023). To specifically address potential template mismatch introduced by nebular emission, I first tested different degrees of additive polynomials on individual galaxies.

I found that using additive polynomials of `degree 1` or `2` allows for accurate recovery of stellar ages, at least in individual galaxies. For example, for the galaxy with ID = 10 ($age_{\text{true}} = 4.24$ Gyr), I tested various degrees of additive polynomials in `pPXF` and obtained the following results. Using no polynomial (`degree = -1`) resulted in a recovered age of 9.11 Gyr; `degree = 1` produced 4.24 Gyr; `degree = 2` gave 4.10 Gyr; `degree = 3` resulted in 5.32 Gyr; and `degree = 4` produced 5.79 Gyr.

Extending this approach to the full sample, the best overall performance was consistently obtained with an additive polynomial `degree` of 2. Increasing the degree of additive polynomials beyond this value led to a significant drop in accuracy, likely

because of artificial changes in the depth of absorption features introduced by high-order polynomials.

Since the use of additive polynomials could alter the strengths of absorption lines (Fahrion et al., 2022; Grasser et al., 2024), I also tested configurations without additive terms (`degree` = -1). When `mdegree` is fixed to 2 and the same constraints are applied as for the showcase sample (e.g., restriction on ages and metallicities, Chapter 1) $\sim 22.4\%$ of galaxies are still poorly recovered. However, constraining only metallicity (e.g., allowing young stellar templates) reduces failures to $\sim 4.3\%$. This underscores that allowing young templates is critical when no additive polynomials are used. However, I retained a constraint on low-metallicity components, since freeing both young and metal-poor templates led to strong degeneracies and poor recovery of metallicity values. Therefore, when multiplicative polynomials are used it became necessary to include templates representing young stellar populations to increase the successful recovered fraction. Notably, similarly good results were obtained in the configuration with a small additive term (`degree` = 2, `mdegree` = -1), which already delivered satisfactory recovery despite also constraining both young stellar populations and low-metallicity templates.

I then tested different `mdegree` (with `degree` fixed to -1) to find the maximum successful recovery rate. I found that when `mdegree` increases from 0 to 12, the fraction of poorly recovered galaxies falls below 1 % at `mdegree` = 5, then increases steadily again at higher orders. Thus, the optimal configuration is `mdegree` = 5, with only $\sim 0.6\%$ failures. Surprisingly, even this 'best' non-additive setup underperforms (`degree` = 2, `mdegree` = -1) contrary to the usual assumption that any additive polynomial necessarily biases stellar population fits. This suggests that a small additive correction may help to account for systematic errors without significantly distorting line features and is very helpful in accounting for distortion caused by the nebular continuum. However, this benefit comes at the cost of data-specific tuning that may not be generalized for real data (e.g., when adding noise).

I include here a comparison of the spectral fits with a zoom-in on the H_δ line region (Fig. 2.19) for three different `pPXF` setups: no additive or multiplicative polynomials (left panels), additive `degree` = 2 (center panels), and multiplicative `mdegree` = 5 (right panels). The figure shows results for five galaxies, four of which were originally not retrieved (the last row includes a control galaxy that is always successfully retrieved). For galaxy ID = 10, both setups with `degree` = 2 and `mdegree` = 5 enable successful parameter retrieval. In contrast, for ID = 226460, only the multiplicative degree setup works, while for ID = 408456, only the additive degree setup leads to retrieval. Interestingly, although the number of non-retrieved galaxies is the same for the setups with `degree` = 2, `mdegree` = 0 and `degree` = -1, `mdegree` = 5 (3 out of 513 galaxies), they overlap only partially (one galaxy with ID = 191599). In general, introducing low-order polynomials that account for continuum-shaped mismatches significantly improves retrieval robustness even when the visual fit to the H_δ line is not noticeably better (for example, in case of ID = 191599). This suggests that accounting for the nebular continuum helps the model capture the broadband shape needed for stable parameter inference.

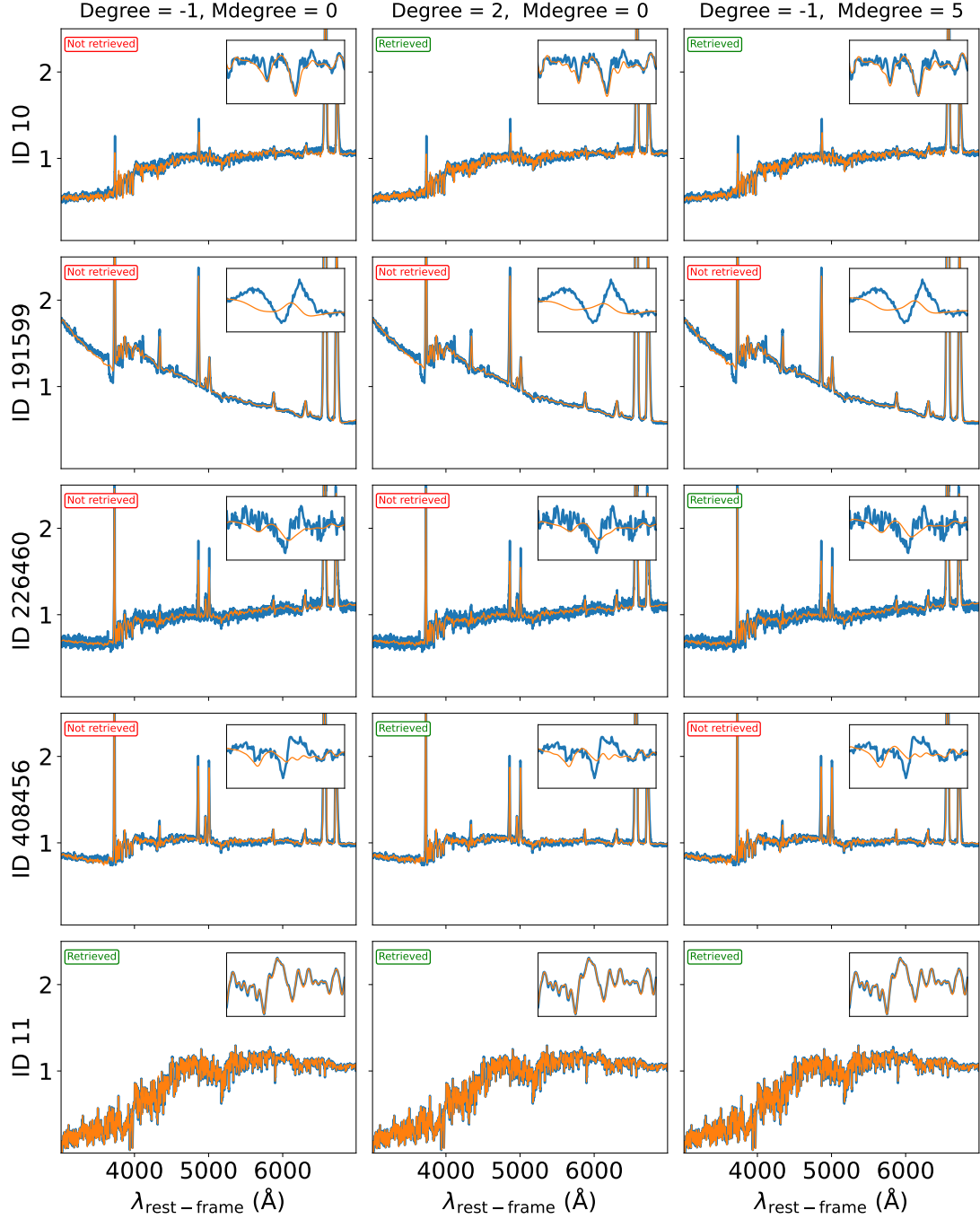


Figure 2.19. Comparison of spectral fits for five galaxies across three `ppxf` setups, with a zoom-in on the H_δ line region. Left panels: no polynomials, Middle panels: additive `degree` = 2, Right panels: multiplicative `mdegree` = 5. Green and red labels indicate whether parameters were retrieved or not, respectively.

Building on the result that galaxies parameters are not retrieved without low-order continuum polynomialism, most likely because the nebular continuum biases the fit, I test whether parameter recovery degrades with increasing Balmer emission strength. For this purpose, I plot the offsets between the assigned and retrieved age values, $t_{90} - t_{10}$, t_{50} , and $[M/H]$ as a function of the Balmer-line flux measured by **pPXF**. Here the Balmer-line fluxes refer to the integrated emission-line strengths returned by **pPXF**, expressed in the same units as the input spectra. Since the spectra were continuum-normalized, these values are relative (arbitrary units) rather than absolute physical fluxes. Results are presented for three setups: no polynomials (Fig. 2.20, left panels), additive polynomials with **degree** = 2 (middle panels) and multiplicative polynomials with **mdegree** = 5 (right panels). All fits are based on regularized solutions, using the recipe described in Sect. 0.4.2. The results clearly improve when polynomials are included (Fig. 2.20, middle and right panels). I find that the most accurate recovery of stellar population parameters is achieved using additive polynomials with **degree** = 2. Increasing the degree beyond this distorts the continuum shape, making the results unreliable. A comparable improvement in age recovery is observed using multiplicative polynomials with **mdegree** = 5; however, in this case, the metallicity estimates remain poorly constrained (Fig. 2.20, bottom row).

Final setup

With the resulting parameter distributions for the no-additive configuration (**mdegree** = 5), significant improvements are evident in the recovery of age, metallicity, and t_{50} versus t_{90} . In the following sections, I will show how this setup performs on mock spectra mimicking real observations, once noise is taken into account. Further comparisons may be possible using fitting codes that include nebular continuum modeling, such as BAGPIPES [Carnall et al. \(2018b\)](#), PROSPECTOR [Johnson et al. \(2021\)](#), or FADO [Gomes & Papaderos \(2017\)](#).

2.3 Library Dependence

When modeling a galaxy spectrum in order to infer its physical properties, a number of assumptions must be made about the stellar populations and the interstellar medium. These include how and when the stars formed, the distribution of stellar masses at birth (IMF), the stellar evolutionary tracks and isochrones, the spectral libraries, and the amount and type of dust that attenuates and re-emits the radiation. In other words, spectral fitting relies on a physical model that connects the observed spectrum to the underlying stellar populations. Figure 2.21 reproduces a summary diagram from the review by [Conroy \(2013\)](#), which illustrates the key ingredients of stellar population synthesis modeling.

Therefore, my motivation for testing different stellar population libraries is to mimic the conditions of real observations, where, unlike in simulations, the true underlying physical model of the stellar populations is not known. In practice, this means that when analysing real spectra, the assumptions built into the models (IMF, isochrones, spectral

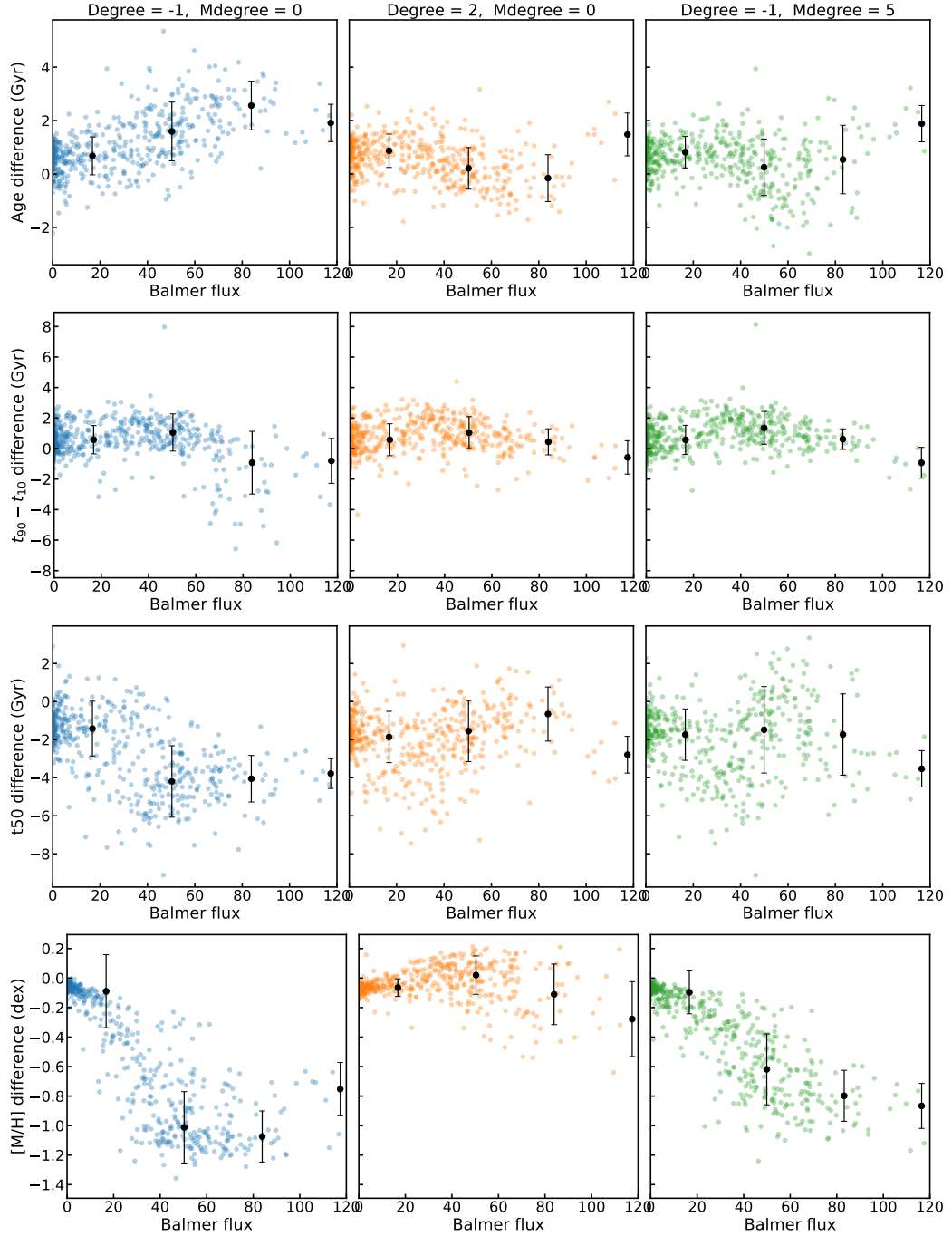


Figure 2.20. Differences between assigned and retrieved parameters as a function of Balmer emission line flux (arbitrary units). Left panels: no polynomials. Middle panels: additive $\text{degree} = 2$. Right panels: multiplicative $\text{mdegree} = 5$. Parameters shown (top to bottom): age, $t_{90} - t_{10}$, t_{50} , and metallicity $[M/H]$.

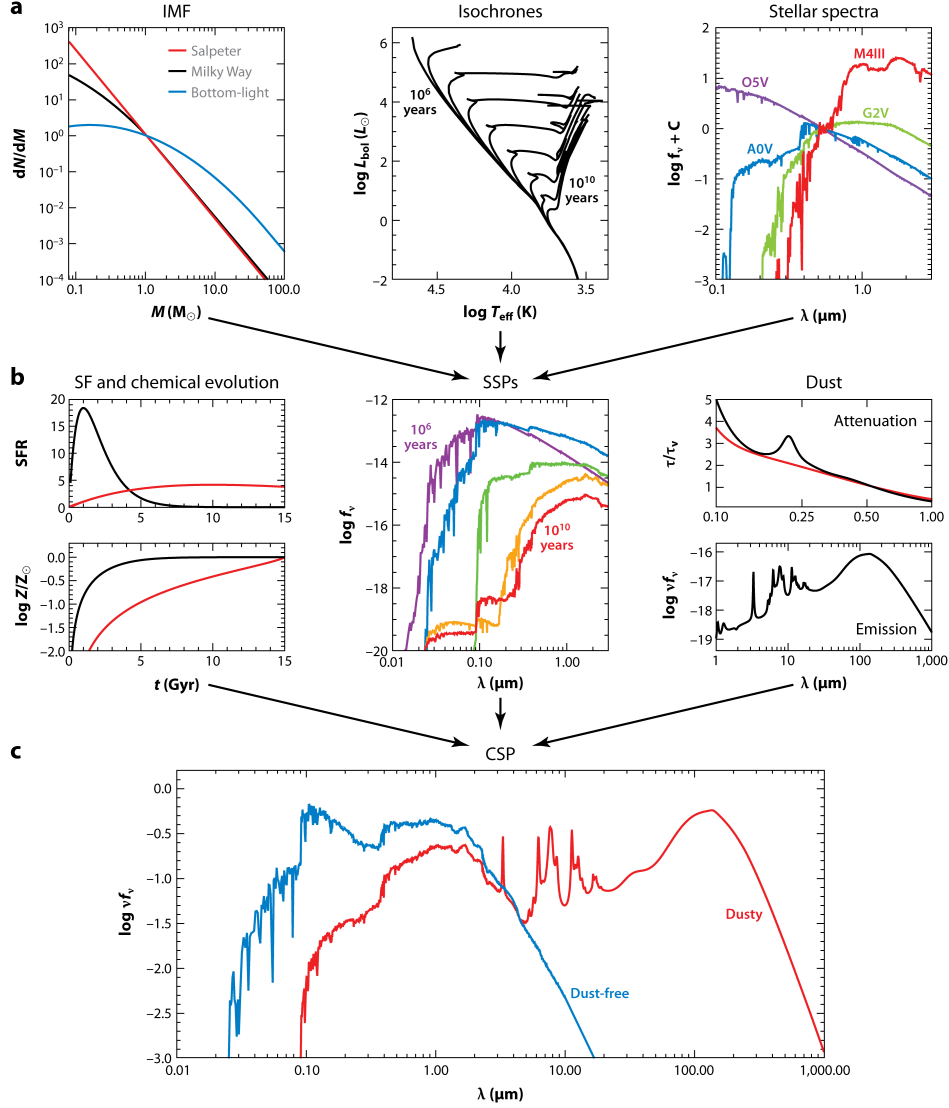


Figure 2.21. Schematic illustration of the main ingredients that enter stellar population synthesis modeling, adapted from [Conroy \(2013\)](#). The construction of a model spectrum involves assumptions about the IMF, stellar evolutionary tracks/isochrones, stellar spectral libraries, dust attenuation and emission, as well as additional components such as nebular emission and kinematics.

Table 2.7. Summary of the stellar population synthesis libraries used.

Library	Min log(Age)	Max [M/H]	IMF
	yr	[dex]	
(1)	(2)	(3)	(4)
EMILES1	7.8	0.22	Salpeter
EMILES2	7.8	0.22	Chabrier
BPASS	6.0	0.30	Chabrier
GALAXEV v2020	6.0	0.46	Salpeter
FSPS v3.2	6.0	0.25	Salpeter

(1) Library name; (2) Minimum logarithmic stellar age (in years); (3) Maximum metallicity [M/H]; (4) Adopted IMF.

libraries, etc.) may not perfectly match the actual properties of the observed systems. To quantify the biases that can result from such mismatches, I compare the performance of multiple libraries in recovering stellar age and SFH parameters: t_{10} , t_{50} and t_{90} . For this test, I use noiseless spectra and a **pPXF** configuration with `mdegree=5` and a fixed regularization of 100, ensuring a fair comparison across libraries. The libraries are listed in Table 2.7: **EMILES1**, **GALAXEV**, and **FSPS** are already implemented in **pPXF**, while **BPASS** and **EMILES2** were adapted as described in Chapter 0. The mean relative offsets between the retrieved and true (assigned) values, defined as $(\text{param} - \text{param}_{\text{true}})/\text{param}_{\text{true}}$, are shown in Fig. 2.22. As expected, **BPASS**, which was also used to generate the synthetic spectra, delivers the most accurate recovery. **GALAXEV** also performs comparatively well, likely owing to its broader metallicity coverage (see the third column of Table 2.7).

Overall, spectral fitting at redshift $z = 0.7$ outperforms that at $z = 0.3$ and $z = 0.5$, which may be due to a smaller number of fitting templates or a reduced sample size at higher redshifts. Ages are generally well recovered, though larger positive offsets are seen for libraries such as **EMILES2** and **FSPS**; the mean relative age offset across libraries is $+0.19$ at $z = 0.7$, $+0.28$ at $z = 0.5$, and $+0.38$ at $z = 0.3$. In contrast, **BPASS**, which was also used to generate the mock spectra, consistently provides the most accurate recovery across all parameters and redshifts (e.g., age offsets -0.07 , $+0.07$, $+0.07$ at $z = 0.7, 0.5, 0.3$, respectively), while **GALAXEV** performs second best, likely due to its broader metallicity coverage. The most noticeable discrepancy arises in the recovery of t_{10} . Across all redshifts, t_{10} is systematically biased toward earlier times, with mean offsets of -0.29 at $z = 0.7$, -0.40 at $z = 0.5$, and -0.73 at $z = 0.3$. This behaviour is likely a consequence of **pPXF**'s tendency to favour bursty SFHs, which pushes t_{10} to the oldest age allowed by the templates, limited by the age of the Universe at the corresponding redshift (see Sect. 0.4.2). The later formation timescales, t_{50} and t_{90} , show milder but systematic trends for non-**BPASS** libraries. The mean offset in t_{50} is -0.42 at $z = 0.7$, -0.59 at $z = 0.5$, and -0.66 at $z = 0.3$; for t_{90} it is -0.19 , -0.25 , and -0.30 at the same redshifts. In each case, **BPASS** remains closest to zero (e.g., $t_{50} \approx -0.07, -0.37, -0.33$ and $t_{90} \approx +0.01, -0.03, -0.05$ at $z = 0.7, 0.5, 0.3$), underscoring its consistency across diagnostics.

Among the SFH timescales, t_{50} exhibits the largest fractional offsets across libraries:

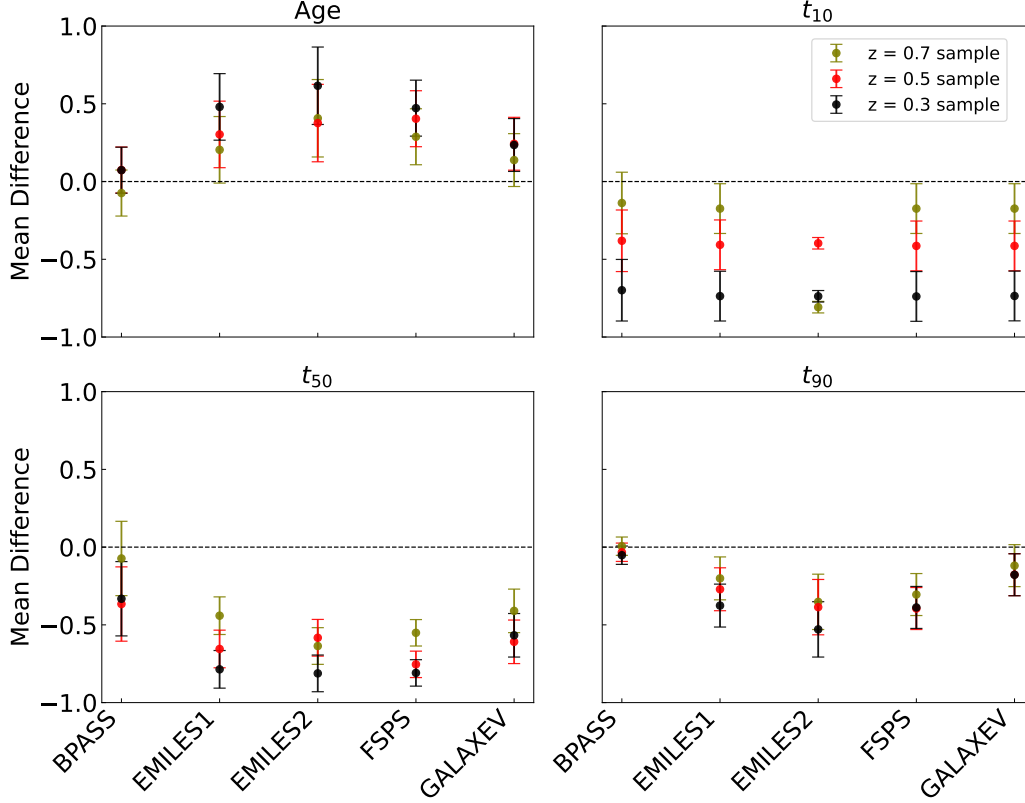


Figure 2.22. Comparison of parameter recovery accuracy across different stellar population synthesis libraries for three redshift bins. The input spectra were generated using BPASS, and the fitting was performed with pPXF using $m_{\text{degree}} = 5$ and regularization = 100.

the mean difference relative to BPASS reaches ≈ 0.56 at $z = 0.7$ (EMILES2 vs. BPASS; -0.636 vs. -0.073), ≈ 0.39 at $z = 0.5$ (FSPS vs. BPASS; -0.754 vs. -0.366), and ≈ 0.48 at $z = 0.3$ (EMILES2 vs. BPASS; -0.812 vs. -0.332). In absolute units, these differences correspond to nearly 1.6 Gyr at $z = 0.7$, 1.4 Gyr at $z = 0.5$, and 2.1 Gyr at $z = 0.3$ between BPASS and EMILES2. In practical terms, using different stellar population libraries can degrade the recovered t_{50} by up to $\sim 50\%$ (or up to 2 Gyr) relative to the true value. This result highlights the level of systematic uncertainty that must be kept in mind when interpreting results from real data.

2.4 The role of S/N

Up to this point, I analyzed noiseless spectra, but real observations are affected by Poisson noise from the sky background, CCD read-out noise, and instrumental effects such as wavelength-dependent sensitivity curves and detector response. Therefore, the main objective of this section is to assess how adding noise to mock data affects the

ability to recover stellar population properties.

For this purpose, I generated noisy versions of the mock dataset with S/N values of 10, 20, and 30, where $S/N = 10$ corresponds to the minimum signal-to-noise expected for WEAVE–StePS observations (Iovino et al., 2023a). These noisy datasets were created following the same procedure described in Section 0.3. To focus on this particular matter, I analyzed the subsample of galaxies at $z = 0.3$, which contains the larger number of galaxies among the different datasets. By doing so, I provide enough statistics to understand the role of S/N in the analysis and avoid comparing different conditions in terms of wavelength coverage and timescales of galaxy evolution. I also fix the regularization value to 100 as mentioned at the introduction of this chapter.

The first step was to examine whether the trends observed in the noiseless spectra regarding the use of `degree` and `mdegree` are also present when I account for different S/N. To this end, I compared the distributions of the retrieved stellar age and metallicity across different polynomial setups. I start the analysis with the highest $S/N = 30$. As shown in Figure 2.23, the age recovery remains relatively consistent in all configurations: no polynomials, additive polynomials, and multiplicative polynomials. However, metallicity estimates improve when polynomials are used. Notably, even without any polynomials, I no longer observe the ‘cloud’ of incorrectly recovered star-forming galaxies that was evident in the noiseless case (Fig. 2.16). This improvement in the non-polynomial setup might be due to the high noise level in the UV region, which likely diminishes the contribution of the nebular continuum.

The same analysis was carried out for $S/N = 20$ (Fig. 2.24) and $S/N = 10$ (Fig. 2.25). In both cases, the same patterns were observed as for $S/N = 30$: adding polynomials no longer significantly affects age recovery. Furthermore, at the lowest $S/N = 10$, additive polynomials also do not improve the recovery of metallicity.

In conclusion, as shown in Fig. 2.26, comparing recovery fractions across the three setups for both noiseless spectra and spectra with added noise ($S/N = 10, 20, 30$) indicates that, although polynomials were essential for accurate recovery in the noiseless case, at lower S/N their inclusion can degrade performance: the additive `degree` configuration (green points) and the multiplicative `mdegree` configuration (orange points) give higher non-recovered fractions than the no-polynomial setup (blue points) for the spectra with added noise. At the same time, while polynomials can still help to improve the metallicity recovery in some cases, `degree=2` becomes ineffective for metallicity recovery at low S/N. Taken together, these results suggest that polynomials can be avoided for low-S/N samples, where the nebular continuum probably has a reduced impact due to the higher noise in the blue part of the spectrum (see Sect. 0.3).

2.4.1 Effect of regularization

One important observation is that, at lower S/N, the retrieved ages become very similar across different galaxies (see Fig. 2.25 for an example). This behavior is likely driven by the use of strong regularization. Although I fixed the regularization to 100 in the previous tests, which can already be considered high, when computing the optimal regularization parameter as described in Sect. 0.4.2, the value for low-S/N spectra often

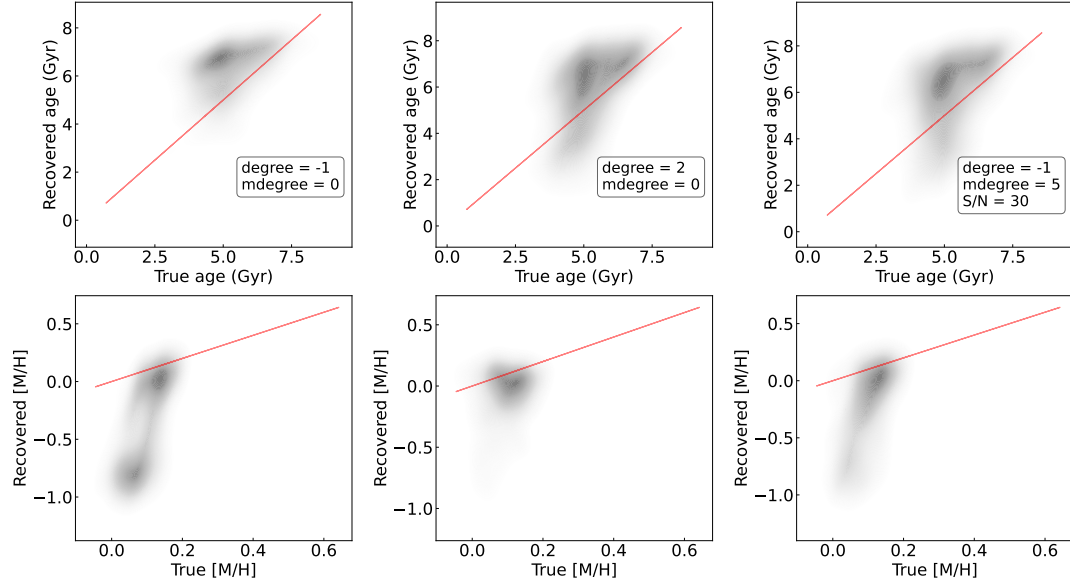


Figure 2.23. Recovered parameter distributions for $S/N = 30$: no polynomials (left panels), degree = 2 (middle panels), and mdegree = 5 (right panels).

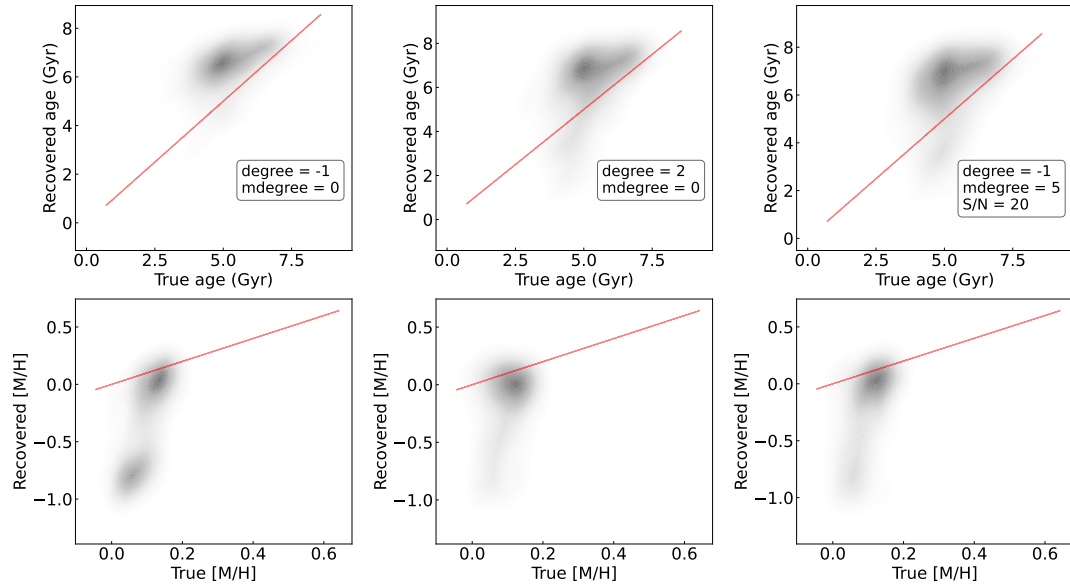


Figure 2.24. Same as Figure 2.23, but for $S/N = 20$.

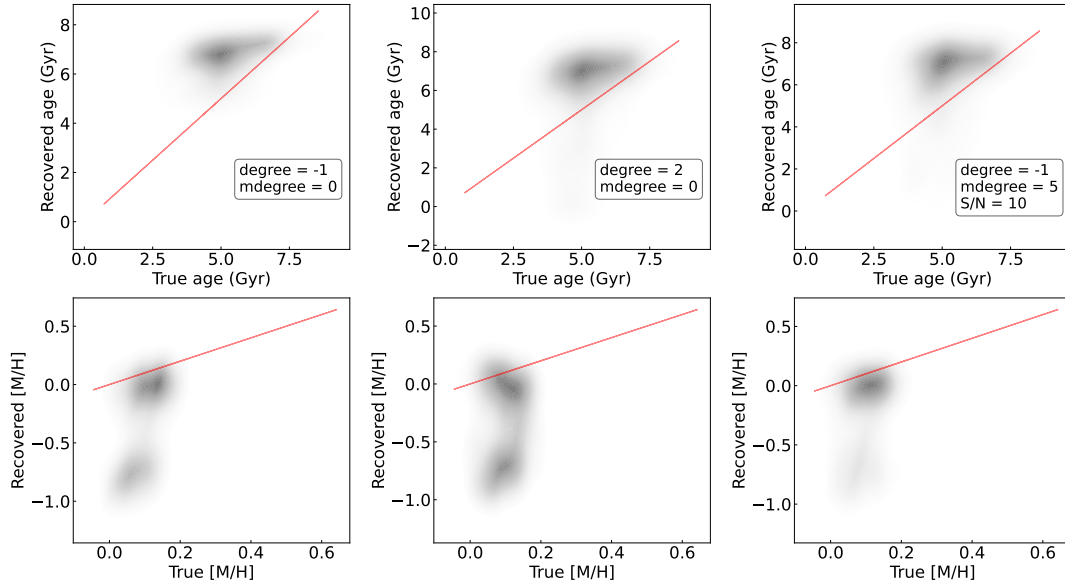


Figure 2.25. Same as Figure 2.23, but for $S/N = 10$.

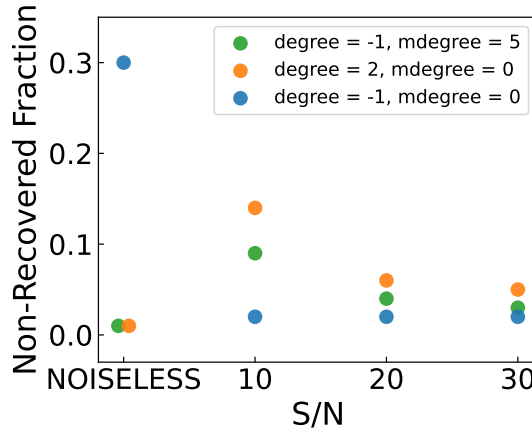


Figure 2.26. Non-recovered fraction for noiseless and noisy datasets ($S/N = 10, 20, 30$) across three polynomial setups: no polynomials (blue), `degree = 2, mdegree = 0` (orange), and `degree = -1, mdegree = 5` (green).

reaches the upper bound of the binary search (i.e. `regul = 1000`). This tendency naturally suppresses variations between galaxies and pushes solutions toward overly smooth star-formation histories, making ages appear more alike. I note here that, while in the main science analysis I use the optimally computed regularization value for each galaxy individually, a fixed value was adopted in the exploratory tests, where computing the optimal `regul` for every galaxy would have been computationally expensive.

To study the effect of regularization, I take the results from the previous test with fixed `regul=100` and compare them to the non-regularized case (see Fig. 2.27). When

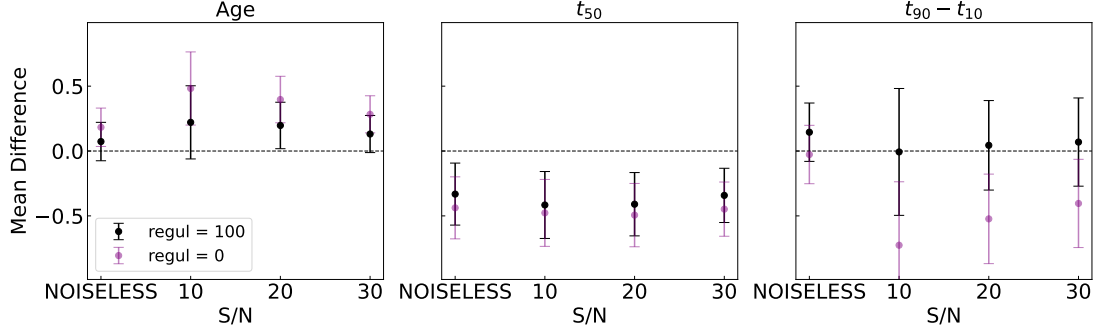


Figure 2.27. Difference in retrieving the parameters for regularized (black) and non-regularized (purple) solutions for $z = 0.3$.

regularization is applied, the results show little variation across S/N levels and lie systematically closer to the true values (black dots), indicating improved accuracy. In contrast, the non-regularized solutions (purple dots) exhibit a clear improvement with increasing S/N, yet they remain farther from the truth than the regularized case at all S/N. Thus, regularization enhances both robustness (stability with S/N) and accuracy, with the benefit being most noticeable at low S/N.

Examining the two-dimensional distributions of recovered vs. true age and $t_{90} - t_{10}$, I find that improved median recovery is accompanied by a degeneracy toward similar solutions. Figure 2.28 shows how the solutions change when moving from the non-regularized case `regul` = 0 (purple) to the regularized case with `regul` = 100 (black), for both S/N = 10 (left panels) and noiseless spectra (right panels) in the $z = 0.3$ sample. For the spectra with noise added, the regularized solutions cluster tightly across galaxies, indicating that regularization promotes convergence toward a common solution. A similar (though weaker) convergence is visible even without regularization, implying that noise alone can drive solutions toward similarity; however, the regularized solutions lie systematically closer to the true values. By contrast, in the noiseless case (right), this trend largely disappears and regularization has little to no impact on the results.

Overall, regularization improves both the accuracy and consistency of parameter retrieval, particularly under low S/N conditions, by stabilizing the solutions and reducing their sensitivity to noise. This makes the use of regularization essential for analyzing spectra with added noise.

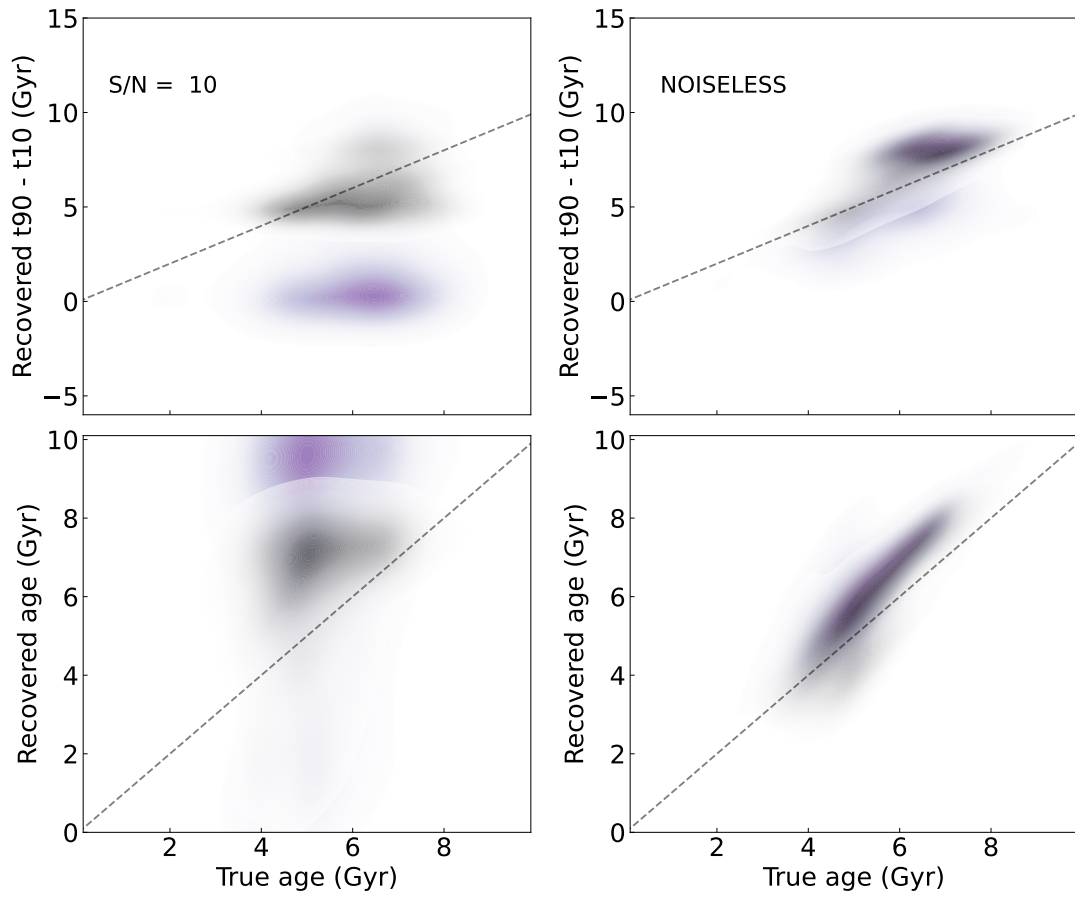


Figure 2.28. Recovered vs True value values for regularized (black) and non-regularized (purple) solution for $S/N = 10$ (left panel) and noiseless spectra (right panel).

Summary

In this chapter, I have investigated the performance of full spectral fitting across a variety of setups and galaxy types, with particular attention to spectral quality, the treatment of the continuum, and the ability to recover the SFHs for StePS-like mock dataset.

First, I analyzed the stellar populations of the full mock sample. I show that relative to the SKIRT-assigned reference, mass-weighted ages are generally well recovered, whereas metallicities are systematically underestimated. Early assembly metrics are biased: t_{10} is often pushed to the youngest allowed templates and t_{50} tends to be underestimated. By contrast, the assembly duration $\Delta t \equiv t_{90} - t_{10}$ is robust, showing only a mild positive bias. Median trends with redshift are reproduced for age, t_{90} , and Δt —with more extended SFHs in the lowest-redshift bin—while t_{50} evolves weakly and t_{10} remains biased. A comparison of $\langle \text{age} \rangle_{\text{MW}}$ with the lookback t_{50} indicates that additional offset is introduced by both the SPS-assignment step and the full spectral fitting. Finally, Δt anti-correlates with stellar mass (more massive galaxies assemble faster), whereas mass-weighted age and t_{50} show at most weak mass dependence; accordingly, lower-mass systems display more extended cumulative SFHs.

Secondly, I explored the SFHs of two classes of rejuvenated galaxies: those in the star-forming population and those in the quiescent population. In both cases, I observe substantial differences between fiber-like (StePS) and integrated spectra. Rejuvenation features are more clearly visible in the integrated spectra, likely because rejuvenated stellar populations tend to be located outside the galaxy centers and thus missed in fiber observations. The main difficulty remains the short duration of the rejuvenation phase, which limits its detectability. However, the parameter $\Delta \text{AGE} = \text{AGE}_{\text{MW}} - \text{AGE}_{\text{LW}}$ proves to be a promising diagnostic for identifying recent star formation in otherwise quiescent systems.

I then demonstrate that the use of polynomials is necessary to account for continuum shape variations, caused probably by dust attenuation or nebular continuum, especially in high-S/N. The best results for noise-free spectra are achieved with a multiplicative polynomial degree of `mdegree` = 5. However, in the presence of noise, the inclusion of polynomials can degrade the quality of the fit. These results suggest that polynomial correction may be safely avoided for low-S/N spectra, where the contribution of nebular continuum is likely diminished due to high noise in the blue part of the spectrum.

Additionally, I find that regularization becomes essential for low-S/N spectra. It significantly improves the robustness of the recovered SFHs, although at the cost of increased degeneracy and a tendency toward smoother, more similar solutions between different spectra.

Overall, this work highlights the strong potential of mock datasets not only for benchmarking existing methods but also for making physical predictions that can inform and guide upcoming spectroscopic observations.

Data availability. The mock datasets generated and used in this thesis are publicly available at <https://doi.org/10.5281/zenodo.15862207>.

The role of the environment in shaping the Star Formation Histories in galaxies

Building on my work within the WEAVE-StePS collaboration, where I developed mock observations based on the TNG50 simulation and worked extensively with large datasets and statistical tools, I have been able to apply these skills to other instruments and facilities. The mock datasets and strategies I designed are highly adaptable and transferable across various observational frameworks, including upcoming surveys such as 4MOST and multiwavelength data from facilities like HST, JWST, and Euclid. In particular, during my research stay at European Southern Observatory (ESO, Germany) under the Scientific Visitor Program, I was working on constructing mock observations for a project aimed at evaluating the impact of environment on the SFHs of galaxies, with a focus on two nearby, well-studied clusters, Virgo and Fornax. The main properties of these two clusters are summarized in Table 3.1.

It is well known that the environment has an influence on the global galaxy properties (Thomas et al., 2005; McDermid et al., 2015; Coccato et al., 2022). It is also known that galaxy properties, particularly stellar mass, correlate with SFH and star formation timescale (Thomas et al., 2005; McDermid et al., 2015). It has already been established that the quenching fraction is strongly dependent on the environment density in the local Universe (Gómez et al., 2003; Hou et al., 2014), intermediate redshift (De Lucia et al., 2004; Just et al., 2019) and at $z > 1$ (Muzzin et al., 2012; van der Burg et al., 2020). But we are still missing the detailed information on SFH, e.g., when exactly galaxies quenched their star formation, and how much this process is affected by different environments (i.e., different clusters). In this sense, Virgo and Fornax are ideal laboratories, sampling different evolutionary stages: from massive and unrelaxed (Virgo) to lower mass and more virialised (Fornax). Therefore, the main goal of this chapter is to assess the role of environment in shaping galaxy SFHs and to compare these results with simulations.

I analyze publicly available data from the ESO archive taken as part of the ATLAS^{3D} (Cappellari et al., 2011) and Fornax3D surveys (Sarzi et al., 2018). ATLAS^{3D} is a survey carried out with the SAURON integral-field spectrograph (WHT) that carefully examined the structure, kinematics, gas content, and stellar populations of 260 early-type galaxies (ETGs, mostly in the Virgo cluster). SFHs for these galaxies are already available (McDermid et al., 2015). Fornax3D observed with the use of the MUSE spectrograph (VLT) 31 members of the Fornax cluster with $m_B < 15$ mag within the virial radius of the cluster.

However, observations can only give a present-day view of the Universe, whereas cosmological simulations can give us the whole information concerning the merger history, quenching, and rejuvenating processes of each galaxy. This helps us to recover the physical processes or conditions that led to a specific SFH. For this, it is essential

Table 3.1. Key properties of the Virgo and Fornax clusters.

Property	Virgo	Fornax
Distance, D [Mpc]	~ 16.5 (Mei et al., 2007)	~ 20 (Blakeslee et al., 2009a)
Total mass, M_{200} [$M_{\odot}$]	$(6.3 \pm 0.9) \times 10^{14}$ (Kashibadze et al., 2020)	$\sim (7 \pm 2) \times 10^{13}$ (Drinkwater et al., 2001)
Virial radius, R_{vir} [Mpc]	$\simeq 1.7$ (Kashibadze et al., 2020)	$\simeq 0.7$ (Drinkwater et al., 2001)
Velocity dispersion, σ_v [km s^{-1}]	638 ± 35 (Kashibadze et al., 2020)	374 ± 26 (Drinkwater et al., 2001)
ICM temperature, kT [keV]	~ 2.3 (Urban et al., 2011)	~ 1.3 (Murakami et al., 2011)
ICM / X-ray morphology	Irregular, multi-component; cold fronts and sloshing (Simionescu et al., 2010)	More compact and asymmetric; cool (~ 1 keV) features (Murakami et al., 2011)
Gas in member galaxies (HI/CO)	Strong HI deficiency in spirals; frequent ram-pressure tails; truncated star-forming disks (Haynes & Giovanelli, 1986; Chung et al., 2009)	Rapid HI removal in dwarfs; numerous HI tails/offsets; evidence for pre-processing in groups (Serra et al., 2023; Kleiner et al., 2021, 2023)
Dynamical state	Less virialised; pronounced substructure and ongoing accretion (Binggeli et al., 1987, 1993)	More relaxed core overall, with signatures of recent infall (Drinkwater et al., 2001; Scharf et al., 2005)
Dominant environmental mechanisms	ICM-driven and rapid: ram-pressure stripping (e.g., Boselli & Gavazzi, 2006; Boselli et al., 2022; Chung et al., 2009) (dominant across a broad mass/radius range); plus harassment/s-trangulation	Mixed: tides, pre-processing, and starvation dominate population-averaged quenching (e.g., Drinkwater et al., 2001; Kleiner et al., 2023); RPS strong but selective in the core and for low-mass satellites on fast orbits (Serra et al., 2023)

to provide an apple-to-apple comparison between observations and simulations. To properly compare observational IFU data with cosmological simulations, I made use of TNG100-1 (Marinacci et al., 2018; Nelson et al., 2018) of the IllustrisTNG project since it has both reliable stellar mass limit $\sim 1.4 \times 10^6 M_{\odot}$ and there is a sufficient number of clusters which are comparable to the mass of the Virgo cluster ($\sim 10^{14} M_{\odot}$) and Fornax cluster ($7 \times 10^{13} M_{\odot}$).

This chapter is structured as follows. I begin by deriving the SFHs of galaxies in the Fornax cluster to complete the available observational dataset and then compare them to the SFHs of galaxies in the Virgo cluster. Next, I describe the selection criteria used to identify analogous clusters in the TNG100 simulation and explain how the post-processing differs from the approach presented in Chapter 0. I then derive the SFHs for galaxies in the selected simulated clusters. Finally, I investigate which of the simulated clusters host galaxies with SFHs consistent with those observed in Virgo and Fornax.

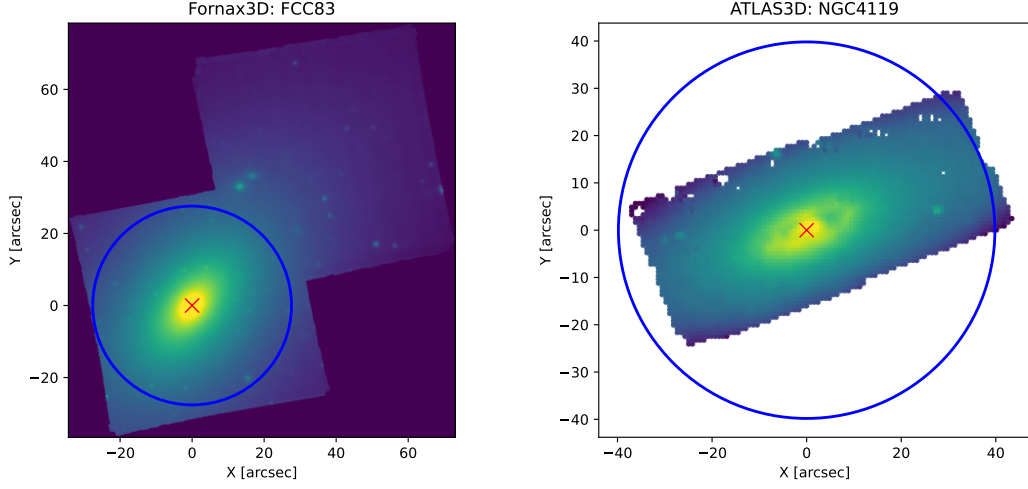


Figure 3.1. Normalised flux maps for FCC 83 (Fornax3D, MUSE) and NGC 4119 (ATLAS^{3D}, SAURON). Blue circles indicate the adopted R_e extraction regions.

3.1 Observed SFH

As a first task, I derive the 1D spectra for both the Fornax and Virgo member galaxies. It is worth to mention, that although both surveys contain the datacubes, I chose to use one-dimensional (1D) spectra for the comparison because of the high computational cost of generating matched simulations. The analysis starts with spectra extracted within one effective radius of each galaxy in the cluster (R_e), with the option to extend to $0.5 R_e$ and $0.25 R_e$. To derive the 1D spectra for the galaxies from the Fornax cluster, I identified galaxy centers using the IRAF task `imexam`. The R_e values were taken from Table 1 of Sarzi et al. (2018). For the Virgo sample, R_e values were taken from Table 3 of Cappellari et al. (2011). The center of each SAURON map corresponds to the coordinates (0, 0), which mark the center of the galaxy¹. While the MUSE field of view ($\approx 1' \times 1'$) allows probing the outskirts of the galaxies in the Fornax cluster, the ATLAS^{3D} sample targeting the Virgo cluster was observed with SAURON integral-field spectroscopy, which has a smaller field of view ($\approx 33'' \times 41''$). As a result, when comparing SFHs within $1 R_e$ (following McDermid et al., 2015), the “integrated R_e ” in ATLAS^{3D} does not always encompass the full physical extent of R_e . An example of the spatial extraction regions is shown in Fig. 3.1 for FCC 83 (Fornax3D, MUSE) and NGC 4119 (ATLAS^{3D}, SAURON).

Secondly, to compare results between the two clusters, I divide the galaxies into stellar mass bins. As a mass proxy, I adopt the absolute K -band magnitude M_K . For the Virgo sample, M_K values are taken directly from Table 3 of Cappellari et al. (2011). For the Fornax sample, I compute M_K as follows. The absolute K -band magnitude is calculated from the apparent K -band magnitude K_T (2MASS keyword `k_m_ext`) at the

¹<https://groups.physics.ox.ac.uk/atlas3d/>

adopted distance D , corrected for foreground Galactic extinction:

$$M_K = K_T - 5 \log_{10} D - 25 - \frac{A_B}{11.8}, \quad (3.1)$$

where A_B is the extinction in the B -band, and I adopt $A_B/A_K = 11.8$ following the ATLAS^{3D} methodology detailed in Cappellari et al. (2011).

The procedure is:

1. K_T is obtained from the 2MASS Extended Source Catalog².
2. The distance modulus ($m - M$) is taken from Blakeslee et al. (2009b) when available; for galaxies not in their list, I adopt $D = 19.3$ Mpc from Jordán et al. (2007a) for the Fornax cluster.
3. A_B is obtained from NASA/IPAC Extragalactic Database, NED (Landolt B -band, Schlegel et al. 1998), consistent with the ATLAS^{3D} analysis.

To be consistent in comparison of ETGs, for the Fornax sample, I converted the cataloged morphological classes to the numerical types de Vaucouleurs T using the CDS mapping³. In this system, ellipticals have $T \approx -5$, S0 span $T \sim -3$ to 0, and spirals increase from Sa ($T=1$), Sb ($T=3$), Sc ($T=5$), etc. The parameters described above are detailed in Table 3.2 for Virgo and 3.3 for Fornax cluster members.

Table 3.2. General properties of Virgo galaxies: effective radius R_e (arcsec), absolute K -band magnitude M_K (mag), and morphological type T .

Galaxy	R_e (arcsec)	M_K (mag)	T (—)
NGC 4119	39.81	-22.60	-1.3
NGC 4179	19.95	-23.18	-1.9
NGC 4262	12.59	-22.60	-2.7
NGC 4267	38.02	-23.18	-2.7
NGC 4324	19.95	-22.61	-0.9
NGC 4339	30.20	-22.49	-4.7
NGC 4340	37.15	-23.01	-1.2
NGC 4342	6.61	-22.07	-3.4
NGC 4350	16.98	-23.13	-1.8
NGC 4371	29.51	-23.45	-1.3
NGC 4374	52.48	-25.12	-4.3
NGC 4377	13.49	-22.43	-2.6
NGC 4379	18.62	-22.24	-2.8
NGC 4382	66.07	-25.13	-1.3

²<https://irsa.ipac.caltech.edu/cgi-bin/Gator/nph-scan?submit=Select&projshort=2MASS>

³https://cdsarc.u-strasbg.fr/viz-bin/getCatFile_Redirect/?-plus=-%2b&VII/155/./mtypes.tex

Table 3.2 – continued.

Galaxy	R_e (arcsec)	M_K (mag)	T (—)
NGC 4387	15.85	-22.13	-4.9
NGC 4406	93.33	-25.04	-4.8
NGC 4417	17.78	-22.86	-1.9
NGC 4425	23.99	-22.09	-0.6
NGC 4429	41.69	-24.32	-1.1
NGC 4435	30.90	-23.83	-2.1
NGC 4442	27.54	-23.63	-1.9
NGC 4452	19.95	-21.88	-2.0
NGC 4458	23.44	-21.76	-4.8
NGC 4459	36.31	-23.89	-1.4
NGC 4461	25.12	-23.08	-0.8
NGC 4472	95.50	-25.78	-4.8
NGC 4473	26.92	-23.77	-4.7
NGC 4474	19.95	-22.28	-2.0
NGC 4476	15.85	-21.78	-3.0
NGC 4477	38.90	-23.75	-1.9
NGC 4478	15.85	-22.80	-4.8
NGC 4483	17.38	-21.84	-1.3
NGC 4486	81.28	-25.38	-4.3
NGC 4486A	8.71	-21.82	-5.0
NGC 4489	26.30	-21.59	-4.8
NGC 4503	28.18	-23.22	-1.8
NGC 4526	44.67	-24.62	-1.9
NGC 4528	14.13	-22.05	-2.0
NGC 4550	15.49	-22.27	-2.1
NGC 4551	16.60	-22.18	-4.9
NGC 4552	33.88	-24.29	-4.6
NGC 4564	20.42	-23.08	-4.8
NGC 4570	19.95	-23.48	-2.0
NGC 4578	32.36	-22.66	-2.0
NGC 4596	38.90	-23.63	-0.9
NGC 4608	26.30	-22.94	-1.9
NGC 4612	25.12	-22.55	-2.0
NGC 4621	42.66	-24.14	-4.8
NGC 4623	20.42	-21.74	-1.5
NGC 4624	43.65	-23.67	-0.6
NGC 4638	16.60	-23.01	-2.7
NGC 4643	23.99	-23.69	-0.6
NGC 4649	66.07	-25.46	-4.6
NGC 4660	12.30	-22.69	-4.7

Table 3.2 – continued.

Galaxy	R_e (arcsec)	M_K (mag)	T (—)
NGC 4694	29.51	-22.15	-2.0
NGC 4710	30.20	-23.53	-0.9
NGC 4733	33.11	-21.80	-3.8
NGC 4754	31.62	-23.64	-2.5

Table 3.3. Same as Table 3.2, but for the Fornax cluster members.

Galaxy	R_e (arcsec)	M_K (mag)	T (—)
FCC 113	15.00	—	6
FCC 119	17.40	—	-4
FCC 143	9.60	-20.84	-5
FCC 147	25.20	-23.30	-5
FCC 148	15.00	-21.90	-4
FCC 153	11.40	-22.44	-4
FCC 161	23.40	-23.19	-5
FCC 167	37.20	-24.77	0
FCC 170	13.80	-23.29	-4
FCC 176	25.80	-20.70	1
FCC 177	15.00	-21.94	-4
FCC 179	30.00	-23.37	1
FCC 182	11.40	-19.86	-4
FCC 184	49.80	-24.01	-4
FCC 190	16.20	-21.50	-4
FCC 193	19.80	-23.00	-4
FCC 219	24.60	-24.71	-5
FCC 249	9.60	-21.92	-5
FCC 255	13.80	-21.07	-4
FCC 263	20.40	-20.25	4
FCC 276	32.40	-23.32	-5
FCC 277	9.60	—	-5
FCC 285	28.80	—	7
FCC 290	30.00	-22.40	5
FCC 301	10.20	-20.88	-5
FCC 306	30.00	—	8
FCC 308	3.60	-20.66	7
FCC 310	25.80	-21.54	-4
FCC 312	30.00	-22.29	6
FCC 83	27.60	-22.64	-5
FCC 90	12.00	-19.62	-5

This homogenized set of structural, photometric, and morphological parameters forms the basis for the analysis of the SFHs.

3.1.1 pPXF setup

For the pPXF setup, I followed a procedure similar to that described in Chapter 0, with the following minor adjustments:

1. The EMILES library was employed for the analysis;
2. Masks were applied to noisier or contaminated spectral regions;
3. Initial guesses were provided for the line-of-sight velocity V and velocity dispersion σ ;
4. The degree of the multiplicative polynomial used in the fit was chosen individually for each galaxy.

It is worth noting that I used the full spectral range available in each dataset to maximize the available spectral information. Consequently, the fitted wavelength ranges differ between the Fornax and Virgo samples because of the different instruments: for Fornax the available observed range is 4599.77 Å to 9351.02 Å, whereas for Virgo it is 4825.4 Å to 5301.5 Å.

Regarding the masking, there was no need to apply it to the Virgo spectra, i.e. the full wavelength range was fitted. In contrast, two practical masks were tested for the Fornax sample, and the preferred option was selected on a galaxy-by-galaxy basis:

1. **Mask 1:** retain $\lambda < 7000$ Å;
2. **Mask 2:** retain $\lambda < 7000$ Å or $8500 \leq \lambda \leq 8754$ Å.

As an example, Fig. 3.2 compares the non-regularized full-spectral-range fit (Mask 0) with alternative mask choices and shows the retrieved age-metallicity distribution and SFH for the galaxy FCC 308. In this case, I ultimately adopted Mask 2.

Regarding polynomial terms, as discussed in the previous chapter, I do not include additive polynomials because they can distort absorption-line strengths (see, for example [Fahrion et al., 2022](#); [Grasser et al., 2024](#)). Instead, I explore multiplicative polynomials. Figure 3.3 compares three setups: (1) no polynomials, (2) `mdegree` = 2, and (3) `mdegree` = 10; with insets zooming into the $H\beta + [O\text{ III}]$ and Ca II triplet regions for the FCC182 galaxy in the Fornax cluster. For this particular galaxy, the second option (`mdegree` = 2) was adopted. Because parts of the spectrum are masked, very high polynomial degrees can drive the fit to unphysical shapes in the remaining unmasked regions (see the bottom panels). This tendency becomes even worse when high regularization is applied (Figure 3.3, right panel). Figure 3.4 shows the fit of the same galaxy with the best regularization calculated (`mdegree` = 2 and `regul` = 15).

After these explorative tests, I decided to adopt the following configuration for the SFH analysis. For the Fornax sample, the multiplicative polynomial degree is chosen per galaxy in the range `mdegree` = 2–5. On the other hand, for the Virgo sample,

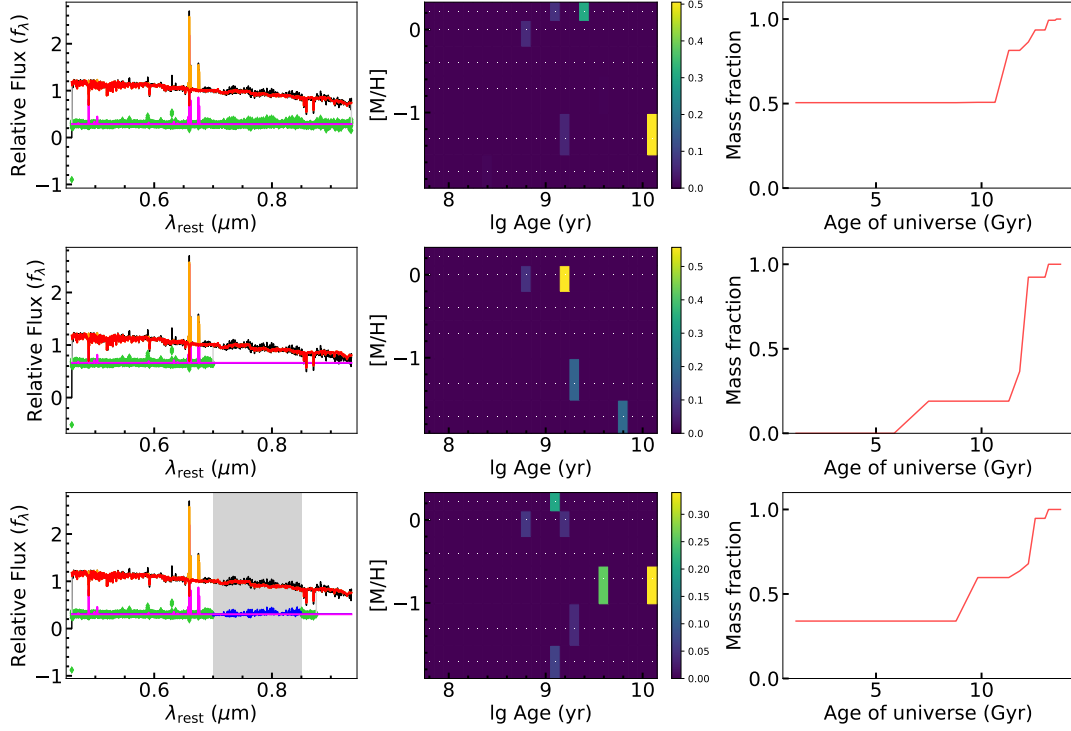


Figure 3.2. pPXF results without regularization for galaxy FCC 308. Rows, top to bottom, correspond to different mask choices (0, 1, 2). Columns, left to right: (1) observed spectrum with the pPXF model; (2) age-metallicity distribution; (3) cumulative star-formation history (integrated stellar mass fraction) as a function of cosmic time.

given its narrower wavelength coverage, I decided to employ a fixed value of `mdegree` = 3. The best regularization is calculated for each galaxy, while initial guesses for the line-of-sight velocity and velocity dispersion (σ) are set individually for each spectrum and then refined in each pPXF run. With this configuration in place, I now turn to a comparison of the SFHs between the two clusters.

3.1.2 The SFH of galaxies in the Fornax and Virgo clusters

In this section, I will discuss the SFH of galaxies in the Fornax and Virgo clusters, focusing on ETGs. This constraint allows a more fair comparison between the two clusters, since galaxies studied in the ATLAS^{3D} survey were selected to be only early-type ones. Therefore, I restrict the analysis to systems with de Vaucouleurs morphological type $T \leq 0$. In Figure 3.5, I present the center $1 R_e$ SFHs for the galaxies in the Fornax and Virgo clusters, color-coded by mass-weighted age, t_{90} (the time required to assemble 90% of the stellar mass under the hypothesis that stars are born in situ, and not acquired), total metallicity $[M/H]$, and absolute K -band magnitude M_K . As a first results, the comparison between galaxies in the two clusters reveals a larger fraction of

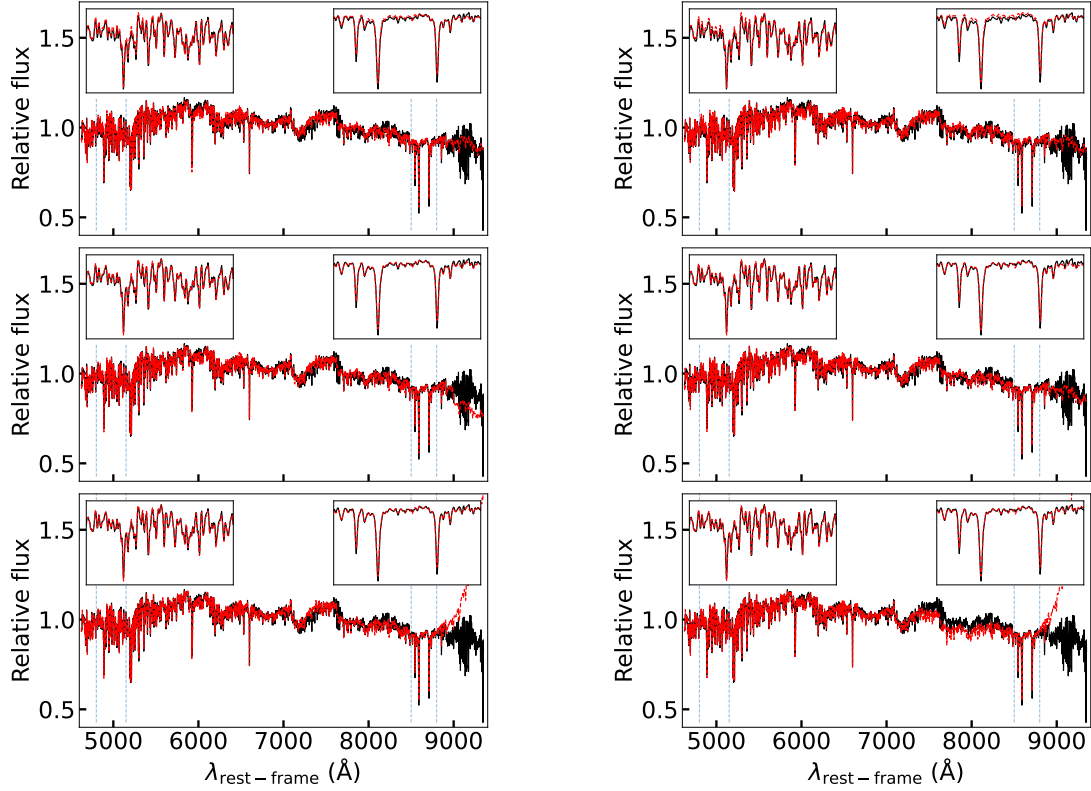


Figure 3.3. pPXF fits for FCC 182 without regularization (`regul` = 0; left panel) and with strong regularization (`regul` = 1000; right panel). Top to bottom: (1) no additive/multiplicative polynomials; (2) `mdegree` = 2; (3) `mdegree` = 10. Solid black line = observed spectrum; dashed red line = best fit. Insets zoom into 4800–5350 Å ($H\beta$ + [O III]) and 8500–8800 Å (Ca II triplet).

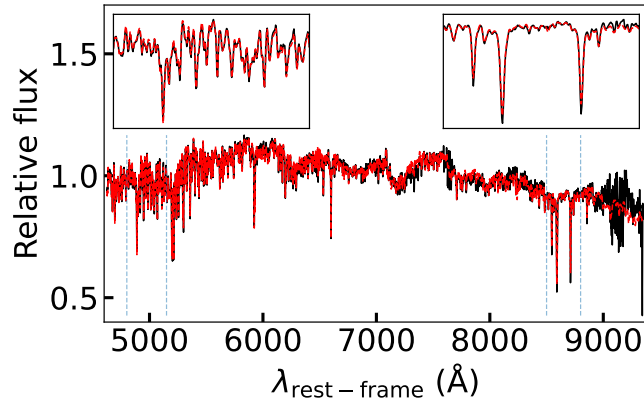


Figure 3.4. pPXF fit for FCC 182 at the best regularization value (`regul` = 15).

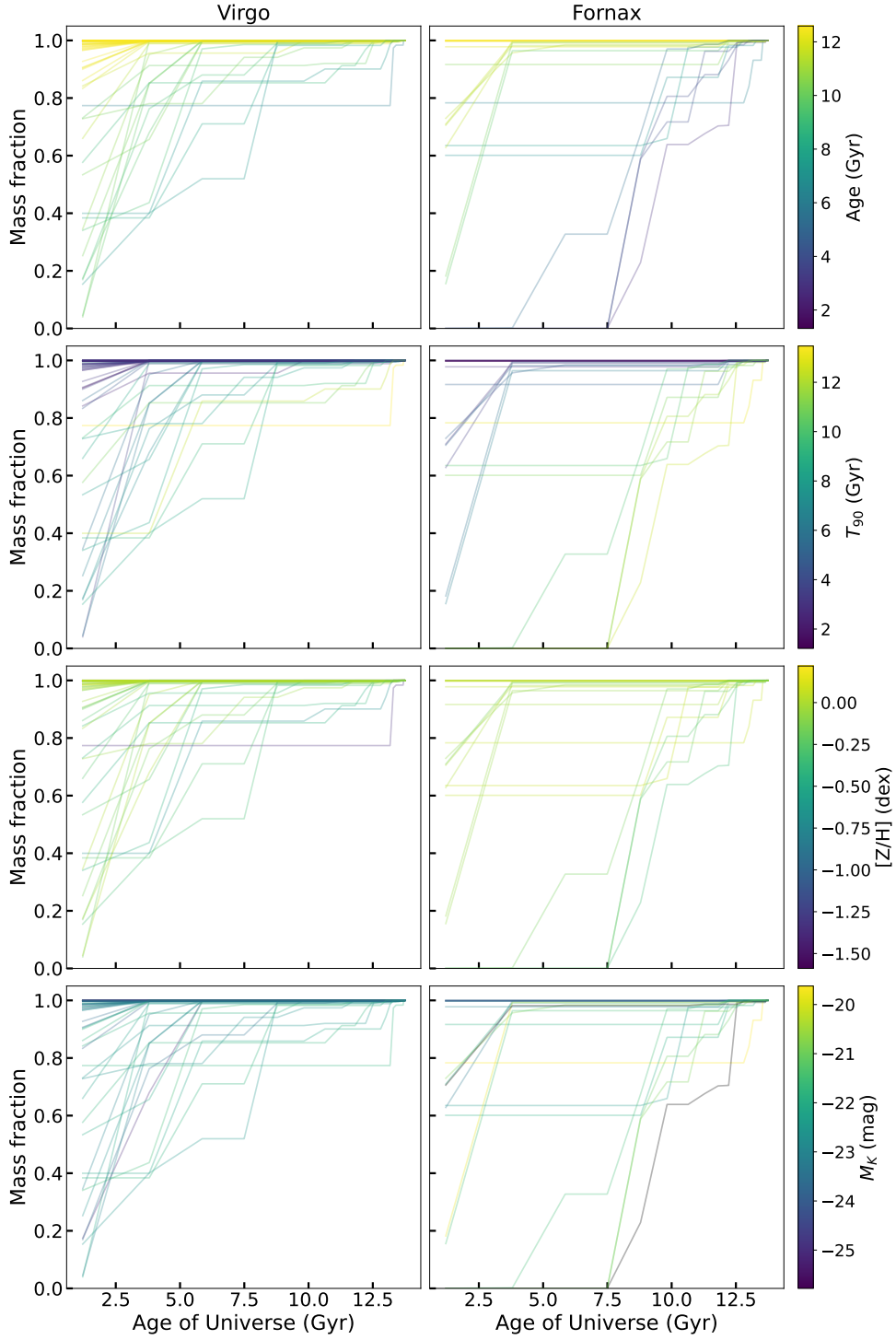


Figure 3.5. pPXF-derived SFHs for Virgo (left panels; ATLAS^{3D} early types) and Fornax (right panels; early types). The four rows are color-coded by (1) mass-weighted age, (2) t_{90} (time to assemble 90% of the stellar mass), (3) total metallicity $[M/H]$, and (4) absolute K -band magnitude M_K .

galaxies with extended SFHs in the Fornax cluster. As expected, galaxies with short formation timescales (low t_{90}) exhibit older mass-weighted ages, higher metallicities, and brighter M_K (i.e., higher stellar mass), consistent with massive systems forming earlier and enriching more rapidly.

Comparing clusters only via colour-coded SFHs is hard to interpret. Instead, in Fig. 3.6 I compare the K -band absolute magnitude M_K to mass-weighted age for Virgo (red) and Fornax (blue). For this comparison I use the best values of regularization as mentioned before. Several trends are apparent:

- **Downsizing:** brighter (more negative) M_K correlates with larger age. Massive ETGs assembled earlier than less massive ones.
- **Luminosity–function mismatch:** the top histograms show that Virgo contains comparatively more faint ETGs and fewer bright ones, while Fornax covers a brighter range. A fair like-for-like comparison is therefore limited to the overlap (middle M_K bins).
- **Different mass distributions:** the mismatch implies that the stellar mass distributions differ between the two samples.
- **Systematic offset:** at fixed M_K (within the overlapping bins) Virgo ETGs tend to have older age than Fornax ETGs by ~ 0.5 – 2 Gyr. In the brightest bin this offset reverses, which could reflect small-number statistics, morphology mix, or different environment properties at the time of galaxy formation.
- **Slope difference:** the Virgo relation is flatter, i.e. age depends less strongly on M_K in Virgo than in Fornax.

In order to quantify the mismatch in the magnitude distribution between Virgo and Fornax, I compare the distributions of M_K for ETGs using a smoothed kernel-density estimate (KDE) and the two-sample Kolmogorov–Smirnov (KS) test (Fig. 3.7). Over the full M_K range the KS test gives $p\text{-value} = 0.03$, so at the 5% level I reject the null hypothesis that the two samples are drawn from the same parent distribution.

Because the extremes of M_K are sparsely populated and cluster coverage differs in the tails, I define a common range where both samples have robust support as the intersection of their central percentiles (q):

$$[r_{\min}, r_{\max}] = \left[\max(q_{1\%}^{\text{Vir}}, q_{1\%}^{\text{For}}), \min(q_{99\%}^{\text{Vir}}, q_{99\%}^{\text{For}}) \right],$$

Repeating the KS test within this common range gives $p\text{-value} = 0.91$. This high p -value does not prove the distributions are identical; it means that I cannot reject the null at conventional levels when the comparison is restricted to the part of M_K where both clusters are well represented. Accordingly, all cross-cluster SFH comparisons are performed only within the common M_K range $[-24.71, -21.74]$.

Next, in Fig. 3.8 the cumulative SFHs (mass fraction vs. cosmic time) of ETGs in Virgo (left panel) and Fornax (right panel) are shown for a calculated regularization.

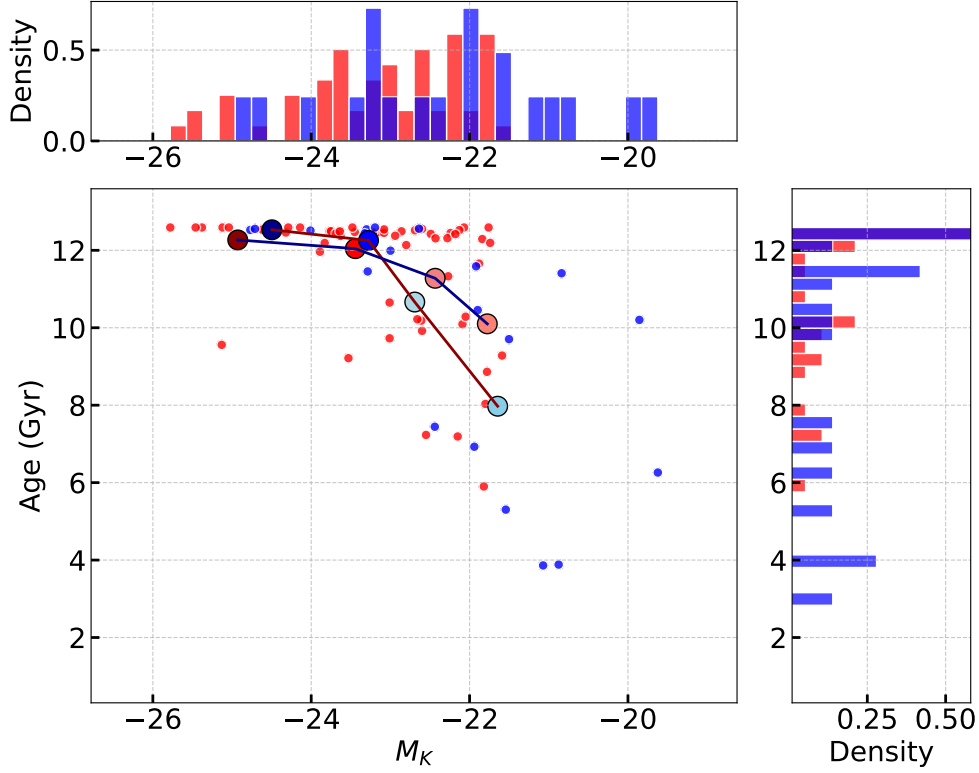


Figure 3.6. Virgo (red) and Fornax (blue) ETGs: M_K vs. age with medians and marginal histograms.

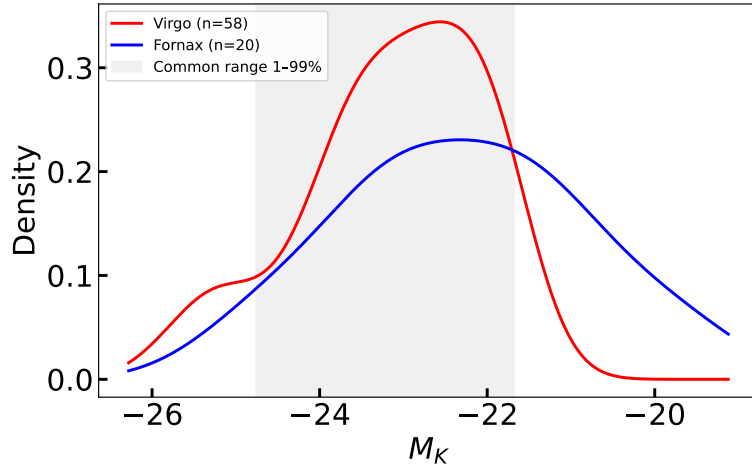


Figure 3.7. KDEs of the M_K distribution for Virgo (red) and Fornax (blue). The shaded vertical band marks the common range defined by the intersection of the 1st–99th percentiles of each cluster.

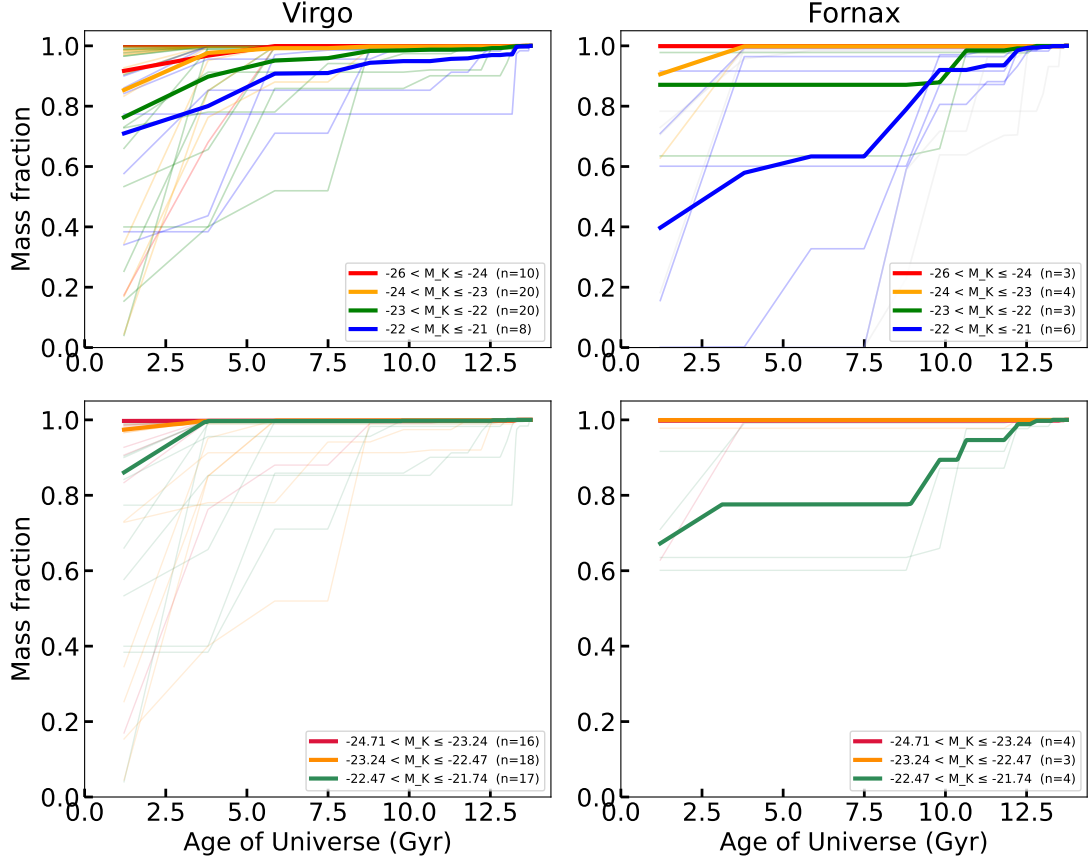


Figure 3.8. Cumulative SFHs of Virgo (left panels) and Fornax (right panels) ETGs for calculated regul values. Top panels: full M_K range with fixed bins (shown in the legend). Bottom panels: restricted to the common M_K range $[-24.71, -21.74]$ with equal-count bins. Faint curves are individual galaxies; thick curves are per-bin medians; legends report bin bounds and n .

The top row uses the full M_K range with fixed-width binning, whereas the bottom row restricts to the range common to all samples and rebins M_K into equal-count bins. The edges of the bin are reported in each legend and the sample sizes per bin (n) are indicated.

From the analysis, I can highlight two main results. First, the full-range comparison is dominated by the luminosity–function mismatch (Virgo contains a bin of brighter galaxies absent or poorly populated in Fornax), reinforcing the need to restrict to the common range. Second, within the common range the Virgo median curves lie systematically above the Fornax ones at intermediate look-back times (~ 3 – 8 Gyr), indicating that ETGs in Virgo assembled a larger fraction of their stellar mass earlier, whereas ETGs in Fornax exhibit more extended SFHs. This is consistent with the Age–vs– M_K offset reported above. This trend is even more evident for fixed regularization values (regul = 100), as shown in Fig. 3.9. The SFH of galaxies in the Virgo cluster show

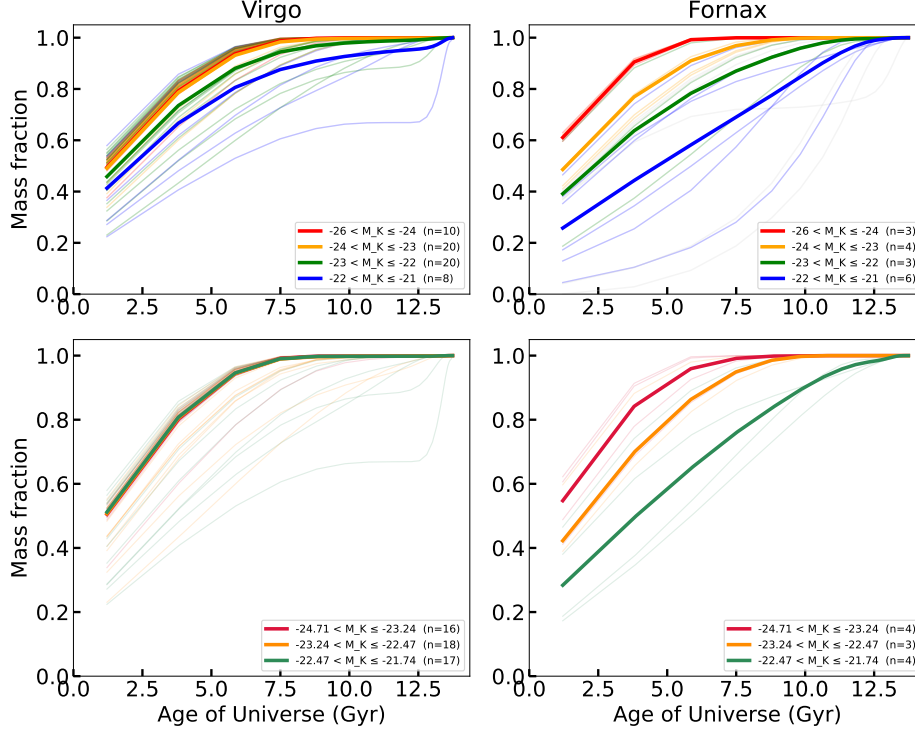


Figure 3.9. Same as 3.8, but for fixed regularization `regul` = 100.

consistent assembly timescales, almost indistinguishable among different magnitude bins. On the other end, the galaxies in the Fornax cluster show a correlation between luminosity and the extent (duration) of their SFHs. Note that the scatter is visibly larger and medians are noisier in Fornax due to the smaller number of galaxies. These results point to enhanced environmental quenching in Virgo, likely due to a denser ICM, leading galaxies to shut down star formation sooner.

As a final step, I check the positions of galaxies relative to their projected distances from the centers of the Virgo and Fornax clusters. I adopt J2000 equatorial coordinates from the NED. The adopted centers are: Virgo at $(\alpha, \delta) = (187.697167^\circ, +12.338972^\circ)$ and Fornax at $(\alpha, \delta) = (54.620833^\circ, -35.450278^\circ)$, where the Fornax center is taken as the NGC 1399 group. Following [Kashibadze et al. \(2020\)](#), I adopt for Virgo a virial radius of $R_{\text{vir}} = 6^\circ$ (1.7 Mpc). For the Fornax cluster, I take $R_{\text{vir}} \approx 0.7$ Mpc ([Drinkwater et al., 2001](#)).

In Fig. 3.10, I show the projected positions of galaxies in the Virgo (left panel) and Fornax (right panel) clusters in equatorial (J2000) coordinates. The points are color-coded by the absolute K -band magnitude M_K . The upper panel uses the full M_K range available for each cluster; the lower panel restricts to the common M_K interval (with the same bin edges as in Fig. 3.8). For each bin I reported in Table 3.4 the mean projected angular separation μ from the cluster center and its 1σ scatter (also converted to Mpc), together with the number of galaxies N .

Table 3.4. Mean clustercentric distances as a function of M_K .

Sample	M_K bin (mag)	$\mu \pm 1\sigma$ (deg)	$\mu \pm 1\sigma$ (Mpc)	N
(1)	(2)	(3)	(4)	(5)
<i>All M_K ranges</i>				
Virgo	[−26, −24]	2.66 ± 1.89	0.76 ± 0.54	10
	[−24, −23]	4.01 ± 3.35	1.14 ± 0.95	20
	[−23, −22]	3.32 ± 2.07	0.94 ± 0.59	20
	[−22, −21]	2.55 ± 2.28	0.72 ± 0.65	8
Fornax	[−26, −24]	0.37 ± 0.24	0.14 ± 0.09	3
	[−24, −23]	0.60 ± 0.17	0.22 ± 0.06	4
	[−23, −22]	1.10 ± 0.67	0.40 ± 0.24	3
	[−22, −21]	1.28 ± 0.76	0.47 ± 0.28	6
<i>Common M_K range</i>				
Virgo	[−24.71, −23.24]	3.72 ± 3.06	1.05 ± 0.87	16
	[−23.24, −22.47]	4.07 ± 2.76	1.15 ± 0.78	18
	[−22.47, −21.74]	2.16 ± 1.75	0.61 ± 0.50	16
Fornax	[−24.71, −23.24]	0.56 ± 0.22	0.20 ± 0.08	4
	[−23.24, −22.47]	0.87 ± 0.74	0.32 ± 0.27	3
	[−22.47, −21.74]	1.19 ± 0.65	0.43 ± 0.24	4

(1) Sample (Virgo or Fornax early-type galaxies). (2) Absolute K -band magnitude bin.

(3) Mean projected clustercentric distance and its dispersion, in degrees.

(4) Same as (3) in physical units (Mpc).

(5) Number of galaxies in the corresponding M_K bin.

Distances are projected separations from the adopted cluster centres.

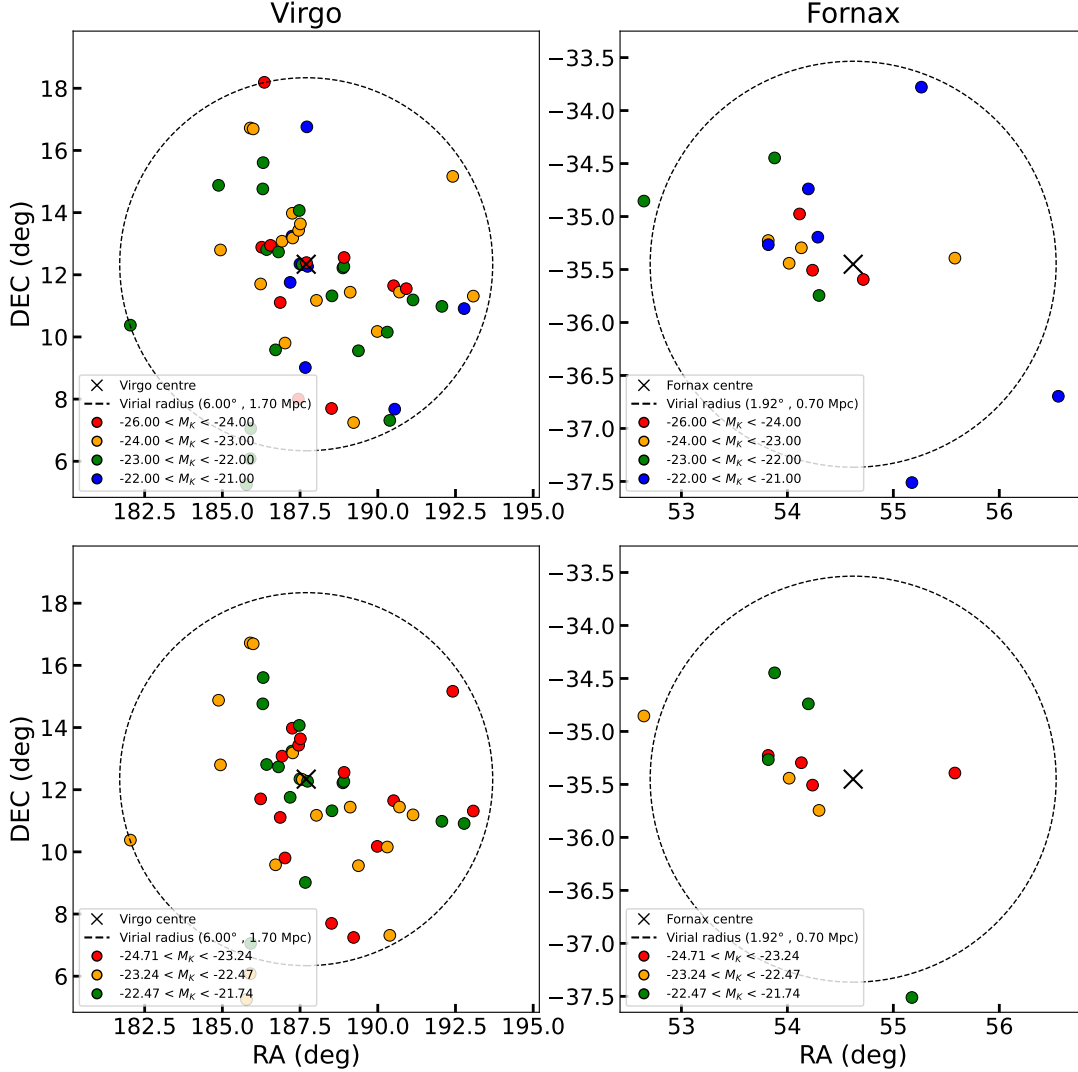


Figure 3.10. Projected positions of galaxies in the Virgo (left panel) and Fornax (right panel) clusters in equatorial (J2000) coordinates, colour-coded by absolute K -band magnitude M_K using the same bins as Fig. 3.8. The upper panels use the full M_K range of each sample; the lower panels restrict to the common M_K interval. Crosses mark the adopted cluster centres from NED, dashed circles indicate the virial radii.

The main result of this analysis is that Fornax exhibits a clear luminosity–radius segregation: brighter galaxies are, on average, more centrally concentrated (the mean projected separation μ increases from $\sim 0.37^\circ$ to $\sim 1.28^\circ$ in the full range, and from $\sim 0.56^\circ$ to $\sim 1.19^\circ$ in the common range). By contrast, Virgo shows no monotonic trend across the same M_K bins (means spanning $\sim 2.5^\circ$ – 4.1° in the full range). It is worth to mention that all radii quoted are projected (2D) separations on the sky, not true 3D clustercentric distances, so the line-of-sight mixing can place galaxies at large physical

radii at small μ if they lie near the line of sight. This biases μ downward, especially for the more numerous, less luminous systems, and can therefore make faint galaxies appear closer to the centre than they really are.

Summarizing, I compared the pPXF-derived SFHs of ETGs in the Virgo and Fornax clusters. Virgo is the more massive system, with $R_{\text{vir}} \simeq 1.7$ Mpc and $M_{200} = (6.3 \pm 0.9) \times 10^{14} M_{\odot}$ (Kashibadze et al., 2020), whereas Fornax is less massive, $M_{200} \sim 9 \times 10^{13} M_{\odot}$ with $R_{\text{vir}} \simeq 0.7$ Mpc (Drinkwater et al., 2001). Multiple lines of evidence indicate that Fornax is dynamically more evolved/relaxed in its core (Jordán et al., 2007b), while Virgo is more irregular and turbulent (Ferguson & Sandage, 1988). As emphasized by Romero-Gómez et al. (2024), the dynamical state implies different dominant environmental mechanisms: in Fornax, tidal effects can be comparatively important for gas removal (e.g., Serra et al., 2023), whereas in Virgo the denser intracluster medium (ICM) and higher encounter rates enhance rapid processes such as ram-pressure stripping, harassment, and strangulation.

In this context, our measurements show a higher fraction of Fornax ETGs with extended SFHs, while Virgo ETGs tend to have shorter formation timescales (low t_{90}), older mass-weighted ages and brighter M_K . A natural interpretation is that quenching in Virgo proceeds more rapidly, consistent with its deeper potential and denser ICM, whereas Fornax ETGs experience more gradual, possibly tidally aided, gas depletion and pre-processing, which causes longer SFHs. I also note a mild radial/luminosity trend in Fornax where lower-luminosity galaxies preferentially appear at larger distances whereas no comparable trend is evident in Virgo, plausibly due to projection effects.

Future work should confront these observational trends with cosmological hydrodynamical simulations by comparison with SFHs and luminosity functions of forward-modeled data. In particular, tracking the mass-assembly and quenching histories of ETG analogs, and forward-modeling our selection and pPXF systematics, will allow us to discriminate between rapid ICM-driven quenching and slower, tide-dominated pathways.

3.2 MAH from TNG100

A key quantity for galaxy evolution is the MAH, which combines growth from in-situ star formation and ex-situ accretion through mergers. However, observationally we can only access the present-day stellar population. Indded, different techniques allow us to retrieve SFH, i.e. when the stars formed, but contains no direct information about when any ex-situ stars were added to the galaxy. For example, a star formed 10 Gyr ago in a satellite and accreted 3 Gyr ago will contribute to the observed SFH at 10 Gyr lookback time, while the merger time remains unconstrained.

On the other hand, simulations provide both: (i) the stellar MAH, by tracking stellar mass of the main progenitor across snapshots, and (ii) the intrinsic SFH, by converting the snapshot star-formation rates. To compare fairly with an observed cumulative SFH, I must forward-model the simulation into the observational plane. Thus, substantial effort is needed to post-process the stellar mass distribution with radiative transfer to generate mock spectra, apply the appropriate instrumental and observational effects, and then recover the SFH using the same strategy as for real data (i.e., pPXF).

In this section, I describe the strategy used to identify Fornax analogs in the simulation and present the corresponding analysis based on the simulation output. In the following section, I outline how the radiative-transfer pipeline differs from that used for the WEAVE-StePS mock catalog, and I analyze the resulting mock spectra using the same pPXF-based workflow in order to derive SFHs that can be directly compared with the observations.

3.2.1 TNG100 Fornax-like clusters

To study how environment shapes the SFHs of galaxies, I adopt the ILLUSTRISTNG TNG100 simulation. While TNG50-1 offers the highest mass resolution ($\simeq 8.5 \times 10^4 M_\odot$), being ideal for studying in detail the structure of galaxies, the small volume ($\simeq 51.7$ cMpc on a side) undersamples the high-mass end of the halo mass function and thus the number of independent cluster-scale environments. TNG100 trades some resolution for volume: its target baryonic mass is $\simeq 1.4 \times 10^6 M_\odot$ and the box side is $\simeq 110.7$ cMpc. This volume is ideal because it affords a substantially larger cluster sample while still maintaining sufficient resolution for the SFH analysis.

To identify Fornax-like clusters in ILLUSTRISTNG, I used the public JupyterLab environment⁴, which provides access to the full ILLUSTRISTNG data set hosted at the Max Planck Computing and Data Facility (MPCDF, Germany). First, I queried the group catalog with the Python interface (`il.groupcat.loadHalos`). Following Galán-de Anta et al. (2022), I selected halos in TNG100-1 at $z = 0$ that satisfy both a size and a mass criterion around Fornax:

$$\begin{aligned} R_{\text{Fornax}} - 0.2 < R_{200c}/\text{Mpc} < R_{\text{Fornax}} + 0.2, & \quad R_{\text{Fornax}} = 0.7 \text{ Mpc} \\ \log_{10} M_{\text{Fornax}} - 0.5 < \log_{10} M_{200c} < \log_{10} M_{\text{Fornax}} + 0.5, & \quad M_{\text{Fornax}} = 7 \times 10^{13} M_\odot. \end{aligned}$$

This search gives 59 Fornax-like clusters. For visualization, I used the TNG on-the-fly viewer to plot stellar surface density⁵ and show two examples in Fig. 3.11.

Next, I identified individual galaxies (i.e., subhalos in TNG100) using the Python group catalog; in the arrays returned by `il.groupcat.loadSubhalos`, the array index equals the subhalo ID at that snapshot. For example:

```
subhalos = groupcat.loadSubhalos(basePath, 99,
                                fields=['SubhaloMass', 'SubhaloPos',
                                        'SubhaloGrNr', 'SubhaloStellarPhotometrics'])
```

```
subhalos['SubhaloMass'][259332]
```

returns the total bound mass of the subhalo with ID 259332 (see also the matching API record⁶). IDs are zero-based and valid within a given snapshot; they are distinct from the parent Group IDs.

⁴<https://www.tng-project.org/data/lab/>

⁵<https://www.tng-project.org/data/groupcat/>

⁶<https://www.tng-project.org/api/TNG100-1/snapshots/99/subhalos/259332/>

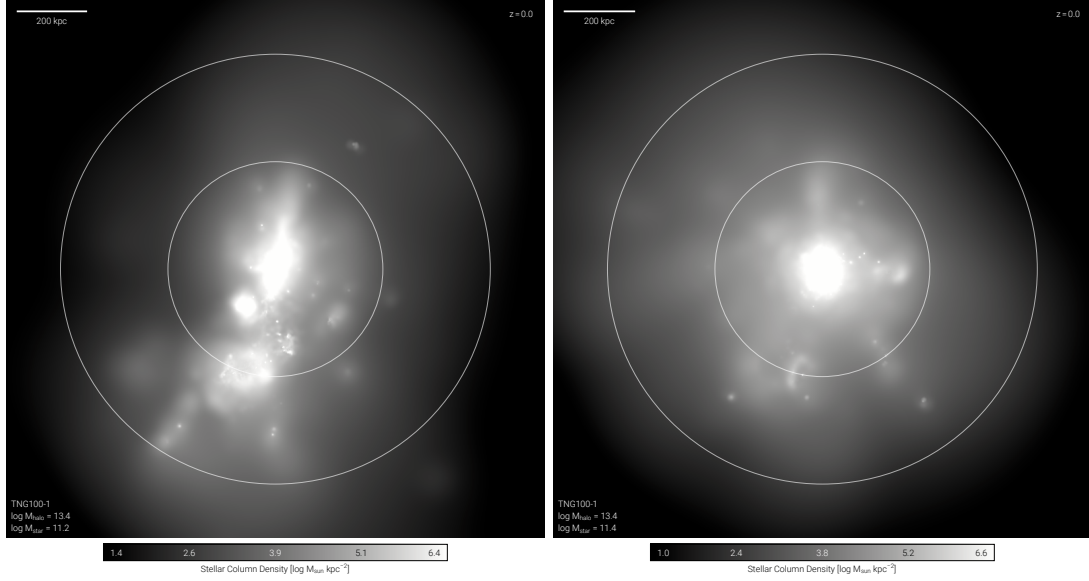


Figure 3.11. Fornax-like clusters at $z = 0$ in TNG100-1 with group IDs 59 (left panel) and 82 (right panel). The two circles mark R_{vir} and $0.5 R_{\text{vir}}$.

To select ETGs, I cross-matched TNG subhalos with the *Galaxy Morphologies (Deep Learning)* catalog (Huertas-Company et al., 2019; Varma et al., 2022) by subhalo ID and kept systems labelled as early type (using the $p > 0.5$ probability threshold). Finally, I restricted the sample to bright members within the cluster virial region by requiring $M_K < -19.5$ mag and projected cluster-centric distance $R < R_{\text{vir}}$. Absolute magnitudes are taken from the TNG100 stellar photometry (SubhaloStellarPhotometrics; K band), and membership is defined relative to the cluster center from the group catalog. This selection led to a sample of $N = 471$ galaxies residing in 59 Fornax-like groups (clusters) selected from TNG100-1. I finally require `SubhaloFlag`= 1, so that only bona fide galaxies appear in the final sample. Thus, the final sample consists of 422 galaxies.

For each galaxy, I follow the SubLink main-progenitor branch and compute its stellar MAH as $\psi(t) \equiv M_\star(t)/M_{\star,0}$ as a function of cosmic time, where $M_{\star,0}$ is the stellar mass at $z = 0$. Galaxies are then grouped by their present-day stellar mass into the bins shown in Fig. 3.12: three bins for satellite galaxies,

$$\log M_\star < 10.5, \quad 10.5 \leq \log M_\star < 11, \quad \log M_\star \geq 11,$$

followed by a separate bin containing the central galaxy of each cluster (bottom row). Within each bin, one curve represents the cluster-averaged MAH of the member galaxies in that cluster, and the shaded region indicates the within-cluster 1σ scatter among those members. Figure 3.12 reveals substantial diversity in MAHs across clusters: galaxies of the same stellar mass can experience markedly different assembly histories depending on their host environment, likely reflecting variations in preprocessing, infall times, and the mass-assembly history of the cluster itself. The most massive systems, corresponding

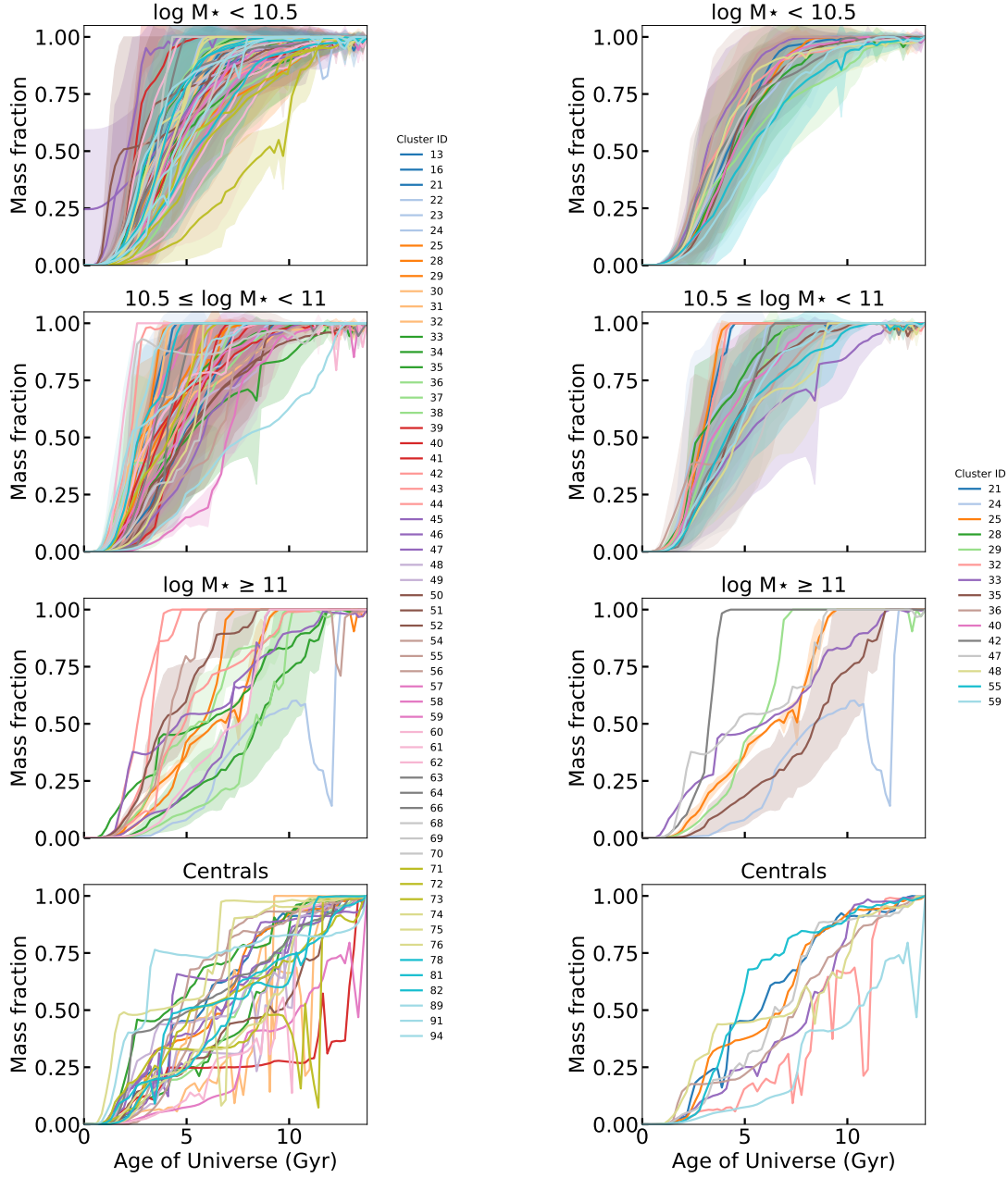


Figure 3.12. Cluster-averaged stellar MAHs of Fornax-like clusters. Each panel shows the mean MAH of the member galaxies in a given cluster, normalised by their present-day stellar mass, $M_\star(t)/M_{\star,0}$ (solid), together with the 1σ within-cluster scatter (shaded). Left panels: all 59 clusters in the sample ($N = 422$ galaxies after the `SubhaloFlag=1` cut). Right panels: only the 15 clusters hosting at least 10 bright ETGs. The top three rows show satellites split into three stellar-mass bins, while the bottom row shows the MAHs of the central galaxies of the same clusters.

to the central galaxies (bottom panels), show the most extended late-time growth, consistent with continued stellar-mass build-up through predominantly dry mergers at low redshift (e.g. [De Lucia & Blaizot, 2007](#); [Rodriguez-Gomez et al., 2016](#); [Lidman et al., 2013](#)).

To connect the MAHs with the environment, I also plot the same figures color-coded by the median infall time t_{infall} of the galaxies contributing to each cluster/ mass-bin curve (Fig. 3.13), where gray indicates centrals for which infall time is undefined. I define t_{infall} as the first snapshot s at which the galaxy’s progenitor belongs to the same FoF group as the cluster’s central galaxy main-progenitor,

$$t_{\text{infall}} \equiv \min\{t(s) : \text{SubhaloGrNr}_{\text{gal}}(s) = \text{SubhaloGrNr}_{\text{host}}(s)\}.$$

A clear trend emerges at low masses: smaller t_{infall} (more recent accretion) correlates with a rapidly saturating MAH, while this trend is weak or absent at higher masses (third row), consistent with massive galaxies assembling most of their stellar mass before entering the cluster.

Because the MAHs include both in-situ star formation and ex-situ accretion, they are not directly comparable to observed cumulative SFHs. To isolate the impact of mergers, I compare the main-progenitor brunch (MPB) MAH to an “archaeological” variant that, at each snapshot, sums the stellar mass over all progenitors in the merger tree (thereby counting ex-situ mass before coalescence). Figure 3.14 shows this comparison for clusters with at least 10 ETGs. In the massive bins (third and fourth rows), the all-progenitor curves (middle column) shift to earlier times relative to the MPB curves (left column), indicating that stars present at $z = 0$ are predominantly old and that the last ~ 5 Gyr of growth was driven largely by dry mergers rather than in-situ star formation. At low masses, the shift is minimal, consistent with mergers playing a minor role and mass assembly effectively halting after infall leading to quench. This qualitative behavior mirrors the dependence on t_{infall} , reinforcing the interpretation provided before. Finally, the right panels of Fig. 3.14 show the difference

$$\Delta\psi(t) \equiv \psi_{\text{all}}(t) - \psi_{\text{MPB}}(t) = \frac{\sum_{\text{prog}} M_{\star}(t) - M_{\star,\text{MPB}}(t)}{M_{\star,0}},$$

which measures, at each time, how much stellar mass resides in all progenitors relative to the main galaxy, normalized by the $z = 0$ stellar mass $M_{\star,0}$. When major mergers occur and ex-situ mass is incorporated into the MPB, $\Delta\psi(t)$ decreases toward zero. For massive galaxies (third and fourth rows), $\Delta\psi(t)$ shows pronounced dips around ages of ~ 5 –11 Gyr, pointing to a substantial merger activity over that interval. The overall amplitude of $\Delta\psi$ also increases with mass, highlighting the growing role of mergers. In some massive cases, the MPB curve exhibits apparent late-time mass decreases (e.g., due to tidal stripping or problems with subhalo identification in the simulations), which is also reflected in the difference. A related caveat is that the sum of all-progenitors traces surviving stellar mass and does not explicitly account for stellar mass loss. A more direct comparison to the observed cumulative SFHs would help to bring together the simulations and observations.

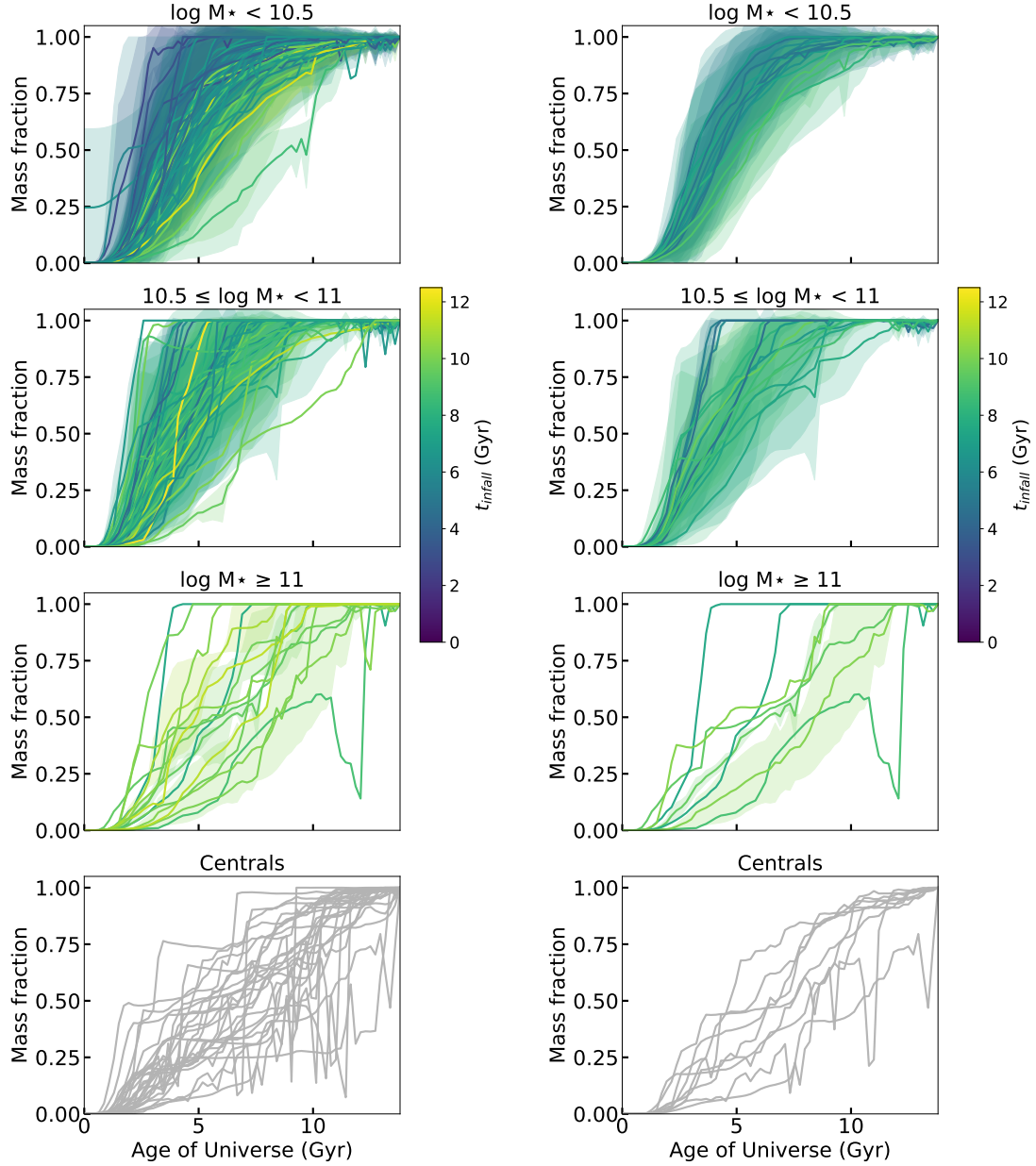


Figure 3.13. Same as Fig. 3.12, color-coded by the median t_{infall} (age of the Universe at infall) of the galaxies contributing to each cluster/ mass-bin curve; grey indicates centrals.

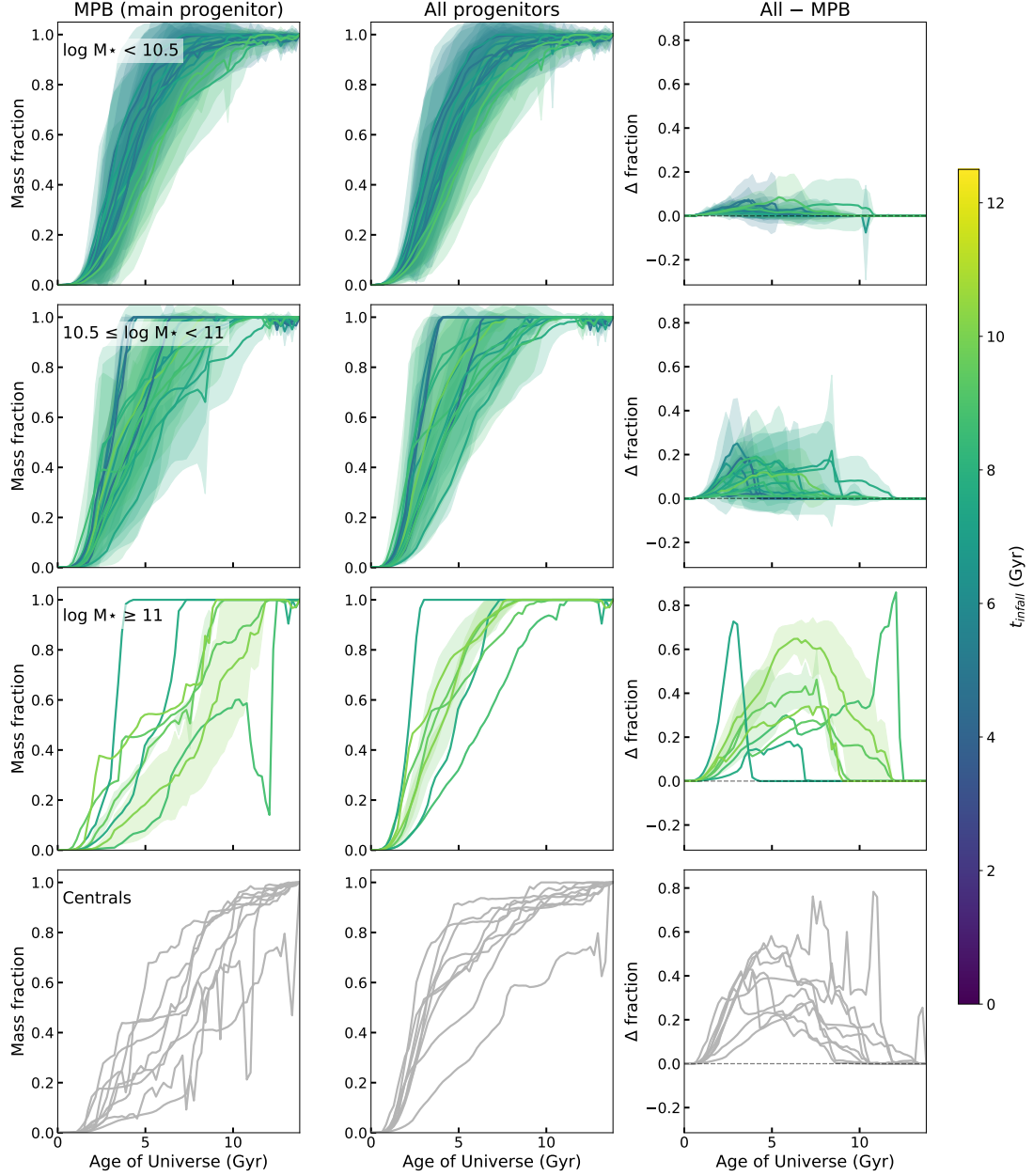


Figure 3.14. Cluster-averaged stellar mass assembly, color-coded by the median t_{infall} . left panels: MPB MAHs; Middle panels: “archaeological” MAHs summing stellar mass over all progenitors at each snapshot; Right panels: the difference between middle and left panels $\psi(t)$.

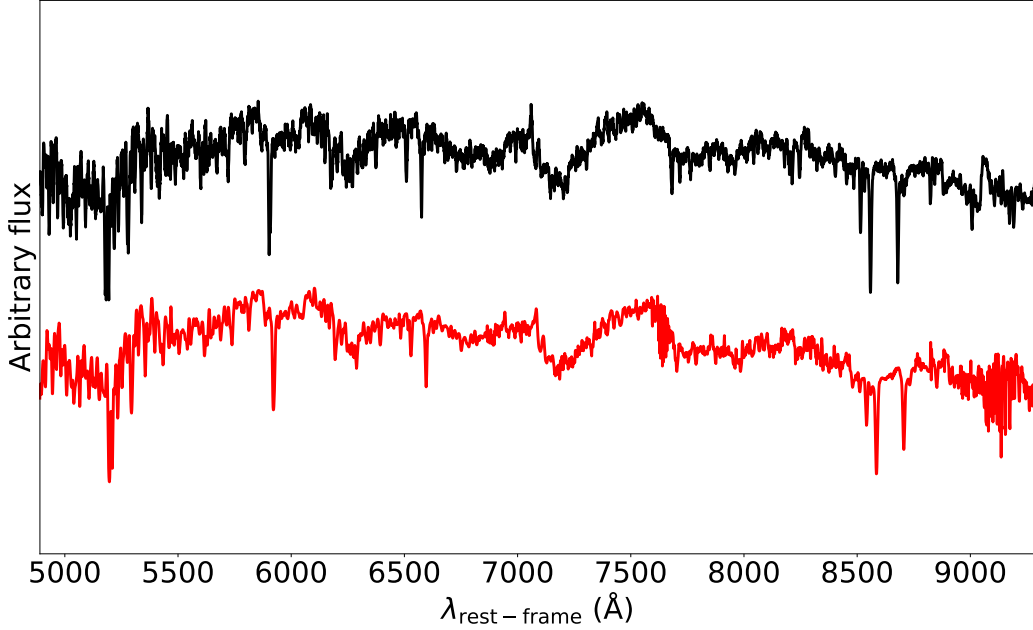


Figure 3.15. Comparison of the $1 R_e$ aperture spectra for a representative Fornax galaxy: MUSE (red) versus simulation (black).

3.3 SFH of Mock galaxies in the TNG100 clusters

While the simulation outputs discussed in the previous section already provide valuable insight into the intrinsic MAHs and SFHs of Fornax analogs, a proper comparison with observations requires placing the simulations into the observational plane. This involves post-processing the simulations with radiative transfer to generate realistic mock spectra that reproduce the effects of dust and noise. A detailed guide to generating mock observations with **SKIRT** is provided in Chapter 0. In this section, I will briefly summarize the key steps and main differences, which are mostly relevant to create mock galaxies of the Fornax clusters using TNG100.

As a first step, since the Fornax cluster is located at a distance of 20 Mpc ($z = 0.005$), all **SKIRT** runs are performed at $z = 0$. Unlike the WEAVE–StePS mock sample, which adopted a flat-Universe model at a given redshift, here I use the dedicated $z = 0$ configuration. At $z = 0$, **SKIRT** requires an explicit distance; for Fornax-like clusters I adopt $D \simeq 19.95$ Mpc to the central galaxy NGC 1399 (Tonry et al., 2001). As a second step, concerning the stellar population modeling, I used the Bruzual–Charlot library. Finally, considering that our sample consists of ETGs at $z = 0$, which are predominantly quiescent and gas-poor, I decide to not consider any dust component (if there is no gas) in our modeling.

As output, I generate three observables: (i) broad-band imaging using the same filter set as StePS (JWST; HST/WFC3 and ACS; SDSS), (ii) circular-aperture (“fiber”) spectra within $0.5 R_e$, $0.75 R_e$, $1 R_e$, and $2 R_e$, and (iii) integrated spectra.

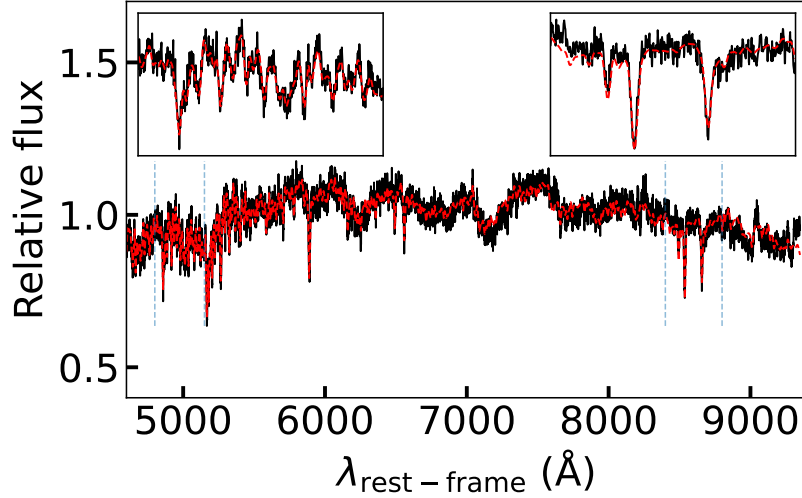


Figure 3.16. pPXF fit for ID = 140737 ($\text{cluster}_{id} = 21$) with $\text{regul} = 100$.

For the fiber spectra I employ a nested logarithmic wavelength grid, with a coarse grid to cover a wide spectral range at low resolution, and a fine grid to obtain high-resolution Fornax-like spectra. For each instrument, I extract six line-of-sight orientations (see Section 1.1.3). As a final remark, since the observational dataset consists of extremely high S/N spectra, I do not add noise to the simulated spectra at this stage and instead analyze noiseless spectra.

As an example of the outputs, I show in Fig. 3.15 a comparison between the simulated and observed spectra for a galaxy in the Fornax cluster.

3.3.1 Main results

As detailed above, I analyze only Fornax-like clusters that host at least ≥ 10 bright ETG (15 clusters in total). pPXF fits are performed with a fixed multiplicative polynomial of $\text{mdegree} = 3$, without additional masks and with a fixed regularization $\text{regul} = 100$. As an example, I show in Fig. 3.16 the best fit for the galaxy 140737.

The absolute K -band magnitude (M_K) of each simulated galaxy was derived directly from its low resolution fiber spectral energy distribution. The observed-frame spectra were integrated through the 2MASS K_s transmission curve using the `speclite` package. The synthetic apparent magnitude K_T was obtained in the Vega system, consistent with the definition of 2MASS photometry. Following the procedure adopted in the ATLAS^{3D} survey (Cappellari et al., 2011), the absolute magnitude was then computed as

$$M_K = K_T - 5 \log_{10} D - 25 - \frac{A_B}{11.8}, \quad (3.2)$$

where D is the adopted distance in Mpc and A_B is the Galactic extinction in the B -band. For the simulated galaxies, no Milky Way foreground extinction is present, and thus $A_B = 0$. This ensures that the model magnitudes are defined in the same Vega-based

system as the ATLAS^{3D} observational dataset.

After running pPXF for mock galaxies, I compute the cumulative SFH of each galaxy, the fraction of stellar mass formed as a function of cosmic time. I then average these curves by cluster within three stellar-mass bins. In the middle panel of Fig. 3.17, the clusters are color-coded by the median t_{infall} of their member galaxies. The same qualitative trends seen in the simulations are recovered: in the low-mass bins, earlier infall (smaller t_{infall}) correlates with a faster, earlier assembly (shorter cSFH), whereas later infall produces more extended cSFHs. In the most massive bins this dependence weakens, plausibly because the central galaxies continue to grow through (largely dry) mergers and occasional rejuvenation, which dilutes a simple t_{infall} -SFH relation.

To compare with real data, I repeat the analysis in M_K bins chosen to track the mass bins and overplot the observed the ETGs in the real Fornax cluster (see right panel of Fig. 3.17). The faintest bin shows extended cSFHs consistent with later infall, while the most massive bin exhibits a more shorter cSFH in the Fornax cluster than in the mock Fornax-like stacks, consistent with a growth dominated by accretion of already old satellites. Overall, the mock-to-data comparison supports the picture in which t_{infall} regulates the SFH timescale at low mass, whereas a merger-driven assembly has a stronger effect in the high-mass regime.

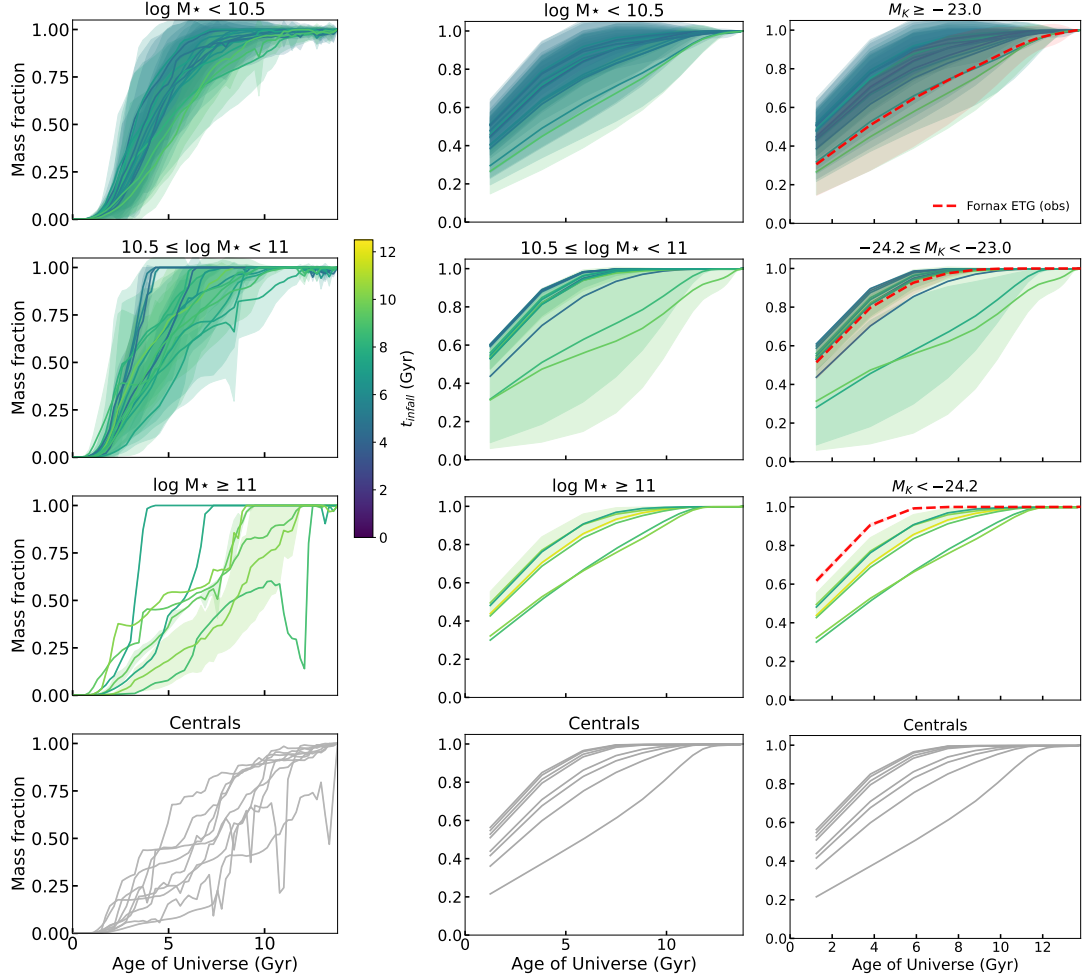


Figure 3.17. Left panels: simulation MAHs using the sum over all progenitors, color-coded by median t_{infall} . Middle panels: pPXF-based cumulative SFHs in $z = 0$ stellar-mass bins (same color-coding). Right panels: the same cSFHs in M_K bins; the Fornax ETG sample (Type ≤ 0) is overplotted as a red dashed mean with a red 1σ band. All pPXF fits use a fixed regularization `regul` = 100.

Summary

In this chapter, I analyze the stellar population properties and SFHs of ETGs in the Fornax cluster and compare them with those in the more massive, less virialised (more irregular) Virgo cluster. I then extend the analysis using Fornax analogues in the TNG100 simulation, which provides additional insight into cluster assembly (e.g., typical infall times as a function of stellar mass).

Although Virgo is dynamically younger and more turbulent, its ETGs are, on average, older and formed on shorter timescales. These patterns are consistent with environmental quenching: Virgo’s deeper potential well and denser intracluster medium (ICM) favour rapid, ICM-driven mechanisms (ram-pressure stripping, harassment, strangulation), whereas Fornax’s more relaxed core permits more gradual, tide-aided gas depletion and pre-processing, which gives longer SFHs.

To isolate the role of environment, I identify 59 Fornax-like clusters in TNG100 and perform a full forward analysis for the 15 richest systems (≥ 10 ETGs), applying the same pPXF-based pipeline as for the real data. From MAHs along the MPB, earlier infall times (t_{infall}) correlate with more rapidly saturating stellar-mass growth at low masses; this correlation weakens at high masses, where most galaxies have a later t_{infall} and all stars are in place before cluster entry. Considering all progenitors, massive galaxies assemble earlier than their MPBs alone would imply, indicating that the last ~ 5 Gyr of growth was dominated by dry mergers of already old satellites. At low masses, mergers play a minor role and assembly largely stops after infall and quenching.

After creating mock spectra and comparing them with the observations, I find that in the lowest-mass bin the observed ETGs display extended cSFHs consistent with later t_{infall} . In the highest-mass bin, Fornax galaxies exhibit shorter cSFHs than the Fornax-like TNG stacks, consistent with growth dominated by the accretion of already old satellites rather than in-situ star formation. Overall, the comparison supports a scenario in which t_{infall} regulates the SFH timescale at low mass, while merger-driven assembly becomes increasingly important at high mass.

Outlook This work can be extended by (i) applying the same forward modelling to Virgo, (ii) exploring trends at different apertures, e.g., as a function of effective radius R_e , and (iii) incorporating realistic noise and instrumental systematics for more direct mock–data comparisons. Beyond the current samples, the methodology can be applied to public surveys such as SDSS (York et al., 2000) and MAGIC (Epinat et al., 2024), which provide environmental information from the local to intermediate-redshift Universe. Finally, the new TNG-CLUSTER⁷ suite offers a broader cluster population with which to test these conclusions.

⁷<https://www.tng-project.org/data/cluster/>

Summary and conclusions

Understanding how massive galaxies assemble their stellar mass and cease forming stars is a central goal of galaxy–evolution studies. Therefore, in this thesis, I addressed this question by focusing on the crucial but underexplored redshift range $0.3 \leq z \leq 0.7$, where stellar populations are younger and their SFHs are more constrained. A great opportunity to explore this in observations will soon arrive with the high-quality spectroscopic data from the upcoming WEAVE–StePS survey.

In parallel, modern cosmological hydrodynamical simulations have become a powerful, complementary avenue for studying galaxy evolution. While observations provide snapshots of different galaxies at different redshifts and infer trends statistically, simulations follow the time evolution of individual systems within a self-consistent physical framework. For this reason, in my thesis I studied galaxies in modern IllustrisTNG simulations and generated realistic mock observations tailored to the upcoming WEAVE–StePS dataset. To enable robust, like-for-like comparisons, I explicitly accounted for observational selection, aperture and instrumental effects, dust attenuation, and measurement systematics.

Therefore, the main goal of this thesis was to study the SFHs of massive galaxies at $0.3 < z < 0.7$ and to provide predictions for intermediate redshift survey data. To address this, I built a forward-modeling framework that places simulations and observations in the same parameter space. Realistic mock data based on TNG50 are generated with SKIRT, tailored to the WEAVE–StePS redshift range, and passed through an observational layer converting to fiber spectra and accounting for seeing and noise effects, and analyzed with the same pPXF pipeline used for real spectra. The resulting benchmark enables robust apples-to-apples comparisons and is easily reusable by forthcoming surveys. This mock dataset is now publicly available for the StePS community to use in comparative analyses against upcoming observations.

Methodologically, I find good agreement in recovering cumulative SFHs and stellar population properties. For the showcase systems examined in detail in Chapter 1, the recovered cumulative mass–assembly tracks match the intrinsic ones to within $\sim 5\%$ over the last ~ 4 Gyr. The recovered SFH shows a measurable viewing–angle dependence, with the impact most pronounced in galaxies undergoing transition. For this systems, stellar metallicities are systematically underestimated, in part due to the template–assignment procedure used to build the mocks. Recovery of intermediate assembly timescales (e.g., t_{50}) is also limited, as pPXF tends to underestimate this value, shifting t_{50} toward earlier times. The same patterns are seen in the analysis of the entire

sample of ~ 750 galaxies presented in Chapter 2. Mass-weighted ages, t_{90} , and the star-formation timescale $\Delta t \equiv t_{90} - t_{10}$ are generally well recovered, while metallicities remain systematically underestimated. I also show that polynomial treatment and regularization depend on data quality: multiplicative polynomials help at high S/N to account for continuum shape mismatches, while at low S/N they can degrade the overall results; conversely, regularization becomes essential at low S/N, improving robustness at the cost of smoother solutions.

Furthermore, I showed that across the sample, the fractions of quiescent and green-valley galaxies increase toward lower redshift, consistent with ongoing quenching and the build-up of the red sequence; notably, the green-valley fraction peaks at $z = 0.5$ (11%), indicating a higher incidence of systems in transition. Analysis reveals that rejuvenation signatures are clearer in integrated spectra than in fiber-like spectra, consistent with rejuvenated populations residing outside galaxy centers. Although the short duty cycle hampers detection, the suggested diagnostic $\Delta \text{AGE} \equiv \text{AGE}_{\text{MW}} - \text{AGE}_{\text{LW}}$ appears to be a useful indicator of recent star formation in otherwise quiescent systems. Future work should test how the choice of normalization band used to define AGE_{LW} influences sensitivity to rejuvenation. Taken together, these results suggest that a non-negligible fraction of massive galaxies at $0.3 < z < 0.7$ may not be strictly passive and that robust tests for rejuvenation will benefit from larger apertures and joint spectroscopic imaging constraints.

Finally, I applied this framework to quantify how the environment shapes galaxy evolution. The environment clearly affects global galaxy properties, but its imprint on SFHs remains uncertain. Using simulations to study environmental effects is especially powerful because they provide temporal continuity: unlike observations that target different galaxies at different redshifts, simulations track the same systems through their full merger and infall histories. In this work, I first analyze ETG stellar populations and SFHs in Fornax versus the more massive, less virialised Virgo, and extend to Fornax analogues in TNG100. Virgo ETGs are, on average, older and assembled on shorter timescales, consistent with rapid, ICM-driven quenching in a deeper potential, whereas Fornax shows more gradual, preprocessed SFHs. In TNG100, earlier infall correlates with faster mass saturation at low mass; at high mass, most stars form before infall and late growth is dominated by dry mergers of old satellites, while low-mass systems largely cease assembling after infall. Mock data comparisons reveals that low-mass ETGs exhibit extended SFHs (later t_{infall}), and high-mass Fornax ETGs appear shorter than TNG stacks, consistent with merger-dominated growth. Overall, t_{infall} regulates the SFH timescale at low mass, while mergers increasingly govern assembly at high mass. The next step is to apply the same forward-modelling pipeline used for Fornax-like clusters to Virgo-like clusters in the TNG100 simulations, enabling a direct Virgo–Fornax comparison and extending our understanding of how different environments affect SFHs.

This thesis is well timed: the MOS mode of WEAVE is in its commissioning phase, and the first data of the survey will be collected in the next months. The framework developed here provides a practical benchmark for WEAVE–StePS and other facilities, clarifying where SFH inferences are reliable and where systematics dominate. This thesis includes one published paper (Ikhsanova et al., 2025) describing

the algorithm for creating the mock dataset and the analysis of the showcase galaxies, and one manuscript in preparation presenting the full-sample analysis described in Chapter 2. Future extensions include scaling to larger samples for statistical assessments, combining spatially resolved spectroscopy with imaging to further break age–metallicity degeneracies, and extending the environmental baseline beyond rich clusters to groups. StePS promises to characterize the stellar populations of a large galaxy sample at intermediate redshift ($0.3 < z < 0.7$) with high precision, echoing the extraordinary success that SDSS achieved in the local Universe. In this survey, galaxies will be observed across diverse environments, enabling a quantitative assessment of environmental effects at higher redshift. As WEAVE–StePS observations are now being delivered, I will apply this pipeline to measure SFHs across environments, quantify the incidence of rejuvenation, and link trends to cluster-centric radius, local density, and inferred infall times using TNG analogues as a control. Another powerful avenue is to use the public mock dataset to train and validate machine learning models for SFH inference, delivering fast, scalable predictors anchored to physically motivated forward models.

All in all, I developed a forward–modeling framework that unifies simulations and observations and used it to study SFHs in two regimes: StePS–like galaxies at intermediate redshift and early–type galaxies in two nearby clusters. I find that rejuvenation is non-negligible and more evident in integrated apertures, and that environment shapes SFHs in local clusters, primarily via earlier infall time at low mass and merger-driven growth at high mass. This framework not only provides prediction on stellar population properties but is ready-to-use for any scientific analysis, and the algorithm is easily adaptable for other instruments and facilities. Therefore, these results provide a practical benchmark for interpreting WEAVE–StePS and related surveys.

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