Getting ready for the LSST data - estimating the physical properties of $z < 2.5$ main sequence galaxies

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August 9, 2021

ABSTRACT

Aims. In this work we study how to employ the upcoming Legacy Survey of Space and Time (LSST) data, from the Vera C. Rubin Observatory, to constrain physical properties of normal, star forming galaxies (so-called, the main sequence galaxies). Since the majority of observed LSST objects will have no auxiliary data, we use simulated LSST data and existing real observations to test the reliability of estimations of the physical properties of galaxies, such as their star formation rate (SFR), stellar mass ($M_{\text{star}}$), and dust luminosity ($L_{\text{dust}}$). We focus on normal star-forming galaxies, as they form the majority of the galaxy population in the universe and therefore are more likely to be observed by the LSST.

Methods. We perform a simulation of LSST observations and uncertainties of 50,385 real galaxies within redshift range $0 < z < 2.5$. In order to achieve this goal, we used the unique multi-wavelength data from the Herschel Extragalactic Legacy Project (HELP) survey. Our analysis focus on two fields: ELAIS N1 and COSMOS. To obtain galaxy physical properties we fit their Spectral Energy Distributions (SEDs) using the Code Investigating GALaxy Emission (CIGALE). We simulate the LSST data by convolving the SEDs fitted by giving the full information about the star formation activity of galaxies from ultraviolet to far infrared to the ones obtained from the simulated LSST optical measurements only.

Results. We present the catalogue of simulated LSST observations for 23,291 main sequence galaxies in the ELAIS N1 field and 9,093 in the COSMOS field, available on the HELP virtual observatory. The stellar masses estimated based on the LSST measurements are in agreement with the full UV-FIR SED estimations, as they depend mainly on the UV and optical emission, well covered by LSST in the considered redshift range. Instead we obtain a clear overestimation of the dust related properties (SFR, $M_{\text{star}}$, and $L_{\text{dust}}$) estimated with LSST only, highly correlated with redshift. We investigate the cause of this overestimation and we conclude that it is related to an overestimation of the dust attenuation, both UV and NIR. We find that it is necessary to employ auxiliary rest-frame mid-infrared observations, simulated UV observations, or FUV attenuation (AFUV)-$M_{\text{star}}$ relation, to correct the overestimation. We also deliver the correction formula log$10\left(\text{SFR}_{\text{LSST}}/\text{SFR}_{\text{real}}\right) = 0.26 \cdot z^2 - 0.94 \cdot z + 0.87$, based on the 32,384 MS galaxies with Herschel detection.

1. Introduction

In the last 20 years, the study of the multi-wavelength emission of galaxies from X-rays to radio was found to be necessary to properly analyse the physical properties of galaxies. As the spectral energy distribution (SED) is the result of a complex interplay between several components: old and young stars, stellar remnants, interstellar medium, dust and supermassive black holes (Walcher et al. 2011, Conroy 2013), only the panchromatic view of galaxies can give the full information about their physical properties. For example, the emission from the hot interstellar medium, active galactic nuclei (AGN) or stellar remnant can be observed in the X-ray band (Fabbiano 2006), while the emission of the dust heated by the interstellar radiation can be observed in the mid- and far-infrared band (Silva et al. 1998, Noll et al. 2009, da Cunha et al. 2010, Hao et al. 2011, Calzetti et al. 2012, Schreiber et al. 2018, Leja et al. 2018). To fully comprehend the interactions between these parts, the simultaneous use of different spectral ranges is needed. As broad band photometry is much less expensive than spectroscopy, in terms of observation time, modelling the broad band SED of galaxies has become one of the most common methods to evaluate and constrain the physical properties. In this way, properties such as star formation rate (SFR) and stellar mass $M_{\text{star}}$, that are essential to have a complete understanding of galaxy formation and evolution, can be evaluated.

However, modelling the SED can be an intricate problem, as galaxies with very different properties can look similar over some wavelength range: i.e. a young dusty galaxy can imitate old dust-free galaxy, as both look red in the optical. This is particularly the case when considering restricted wavelength ranges rather than the full SED, that is rarely available. Therefore, estimating the physical properties with only a limited wavelength range is an important challenge for SED modelling.

In the literature (i.e. Kennicutt 1998, Le Floc’h et al. 2005, Schreiber et al. 2015, Whitaker et al. 2017) it has already been shown that the ultraviolet (UV) to infrared (IR) SED contains important information about the star formation activity of galaxies. For example, some knowledge on newborn stars can be directly inferred from the UV band, making it a very efficient tracer.
of the SFR. But, the region were these stars are created are highly obscured by dust, making them very difficult to observe. Dust, composed of carbonaceous and silicate grains, absorbs part of the UV emission and re-emits it in the IR band. For example, Fig. 10 of Buat et al. (2019) shows that the total SFR of a galaxy is a sum of the SFR obtained from UV/optical measurements and the SFR estimated from IR data. Therefore, considering the important role played by dust, the introduction of attenuation laws, that describe how dust obscures the light coming from the stars, is fundamental for the SED fitting process.

The attenuation law built by Calzetti et al. (1994) for nearby UV-bright starburst galaxies is by far the most commonly used in literature. However other laws such as the one proposed by Charlot & Fall (2000) and Lo Faro et al. (2017) are widely employed in the SED fitting codes. Malek et al. (2018) used a combination of UV and IR observations to find the best approach to fit SEDs of million of galaxies from the Herschel Extragalactic Legacy Project (HELP) across a wide redshift range (0 < z < 6) to obtain homogeneous estimates of the main physical properties. They found that, using three different attenuation laws, the estimation of stellar masses can change by a factor of 2 on average. Similar results were found, e.g., in a sample of Ultra Luminous IR Galaxies at z ∼ 2 by Lo Faro et al. (2017), for galaxies obtained from the semi-analytic galaxy formation model GALFORM by Mitchell et al. (2013), and by Burgarella et al. (2013) who combined UV to IR measurement up to z = 3.6 to calculate the redshift evolution of the total SFR and dust attenuation. They found that the attenuation increases up to z = 1.2 and then decreases at higher redshift. Also the ratio between UV and far IR (FIR) emission serves as an indicator of the dust attenuation in galaxies (Buat et al. 2005, Takeuchi et al. 2005). All these factors make the combined usage of UV and IR observations necessary to provide a better understanding of the star formation history (SFH), SFR and dust attenuation properties of the galaxies. In order to perform the SED fitting of galaxies, different methods and codes were developed, such as STARLIGHT (Cid Fernandes et al. 2005), VESPA (Tojeiro et al. 2007), Hyperz (Bolzonella et al. 2000), Le Phare (Arnouts et al. 1999, Ilbert et al. 2006), PEGASE.3 (Fioc & Rocca-Volmerange 2019), COSMOS2020 (Weaver et al. 2021) together with bayesian SED fitting codes such as GOSSIP (Franzetti et al. 2008), PROSPECTOR (Leja et al. 2017), CIGALE (Noll et al. 2009; Boquien et al. 2019), BayesSED (Han & Han 2014).

The main problem of the multi-wavelength fitting technique is the lack of high quality IR observations, both due to instrumental sensitivity and lower resolution of wide IR cameras or extremely expensive sub-millimeter observations, i.e. ALMA. On the contrary, a very large and high quality coverage of the optical part of the spectrum is usually available, both for wide field surveys and for narrow and deep field imaging, thanks to several ground and space telescopes. With the upcoming Legacy Survey of Space and Time (LSST, Ivezić et al. 2019) from the Vera C. Rubin Observatory, we will obtain even higher quality optical images in the ugrizy bands. The LSST survey will observe around 20 billion galaxies during 10 years of observations. Most of this galaxies will not have any counterpart in the available IR catalogues. Moreover, IR astronomy often suffers from blending issues, which makes precise matching between optical and IR sources even more difficult (Hurley et al. 2017, Pearson et al. 2018).

The LSST will be the largest (8.4 meters of primary mirror) wide field ground telescope designed to obtain repeated images covering the sky visible from Cerro Pachón in Chile. The survey will observe around 30 000 deg² of the southern sky, covering the wavelength range 320-1 050 nm. It will reach, at the end of the 10 years survey, a magnitude depth ∼ 27.5 in r band and similar in the other bands. Considering the depth of forthcoming observations, it is expected that LSST will unveil a significant number of faint galaxies that have remained undetected in current wide area surveys. These potentially large datasets will raise multifold questions such as: how can we use only LSST optical observations to obtain estimates of the main physical properties of galaxies? How realistic and reliable would they be? In this paper we investigate the aforementioned topics by performing a simulation of LSST observations of main-sequence (hereafter MS) galaxies which form a nearly linear relation (in log-log space) between their stellar mass and SFR (Noeske et al. 2007, Elbaz et al. 2010, Rodighiero et al. 2011, Speagle et al. 2014, Schreiber et al. 2015, Whitaker et al. 2015, Pearson et al. 2018). Main sequence galaxies constitute the dominant population in deep fields such as COSMOS and ELAIS N1 that can reach very faint optical magnitudes (∼ 29-30 mag). LSST is expected to expand, among others, the observed MS population of galaxies to other fields which are not currently covered by deep field surveys. For this reason, we decided to focus on the MS galaxies.

The paper is organised as follows. In Section 2 we describe the data and the HELP project. In Section 3 we present the sample selection, outliers and starburst, and the methodology used for this work. In Section 4 we discuss the simulated LSST magnitude and errors. The same Section, together with Section 5 and 6, presents the results. Our conclusions are presented in Section 7. Throughout this paper we use WMAP7 cosmology (Komatsu et al. 2011); Ωm = 0.272, ΩΛ = 0.728, H0 = 70.4 km s⁻¹ Mpc⁻¹.

2. Data

The HELP collaboration provides extremely valuable multi-wavelength data over the HerMES (Oliver et al. 2012) and the H-ATLAS survey fields (Eales et al. 2010) and other relevant Herschel fields. The total area of HELP is 1 269.1 deg² (Oliver et al. in prep, Shirley et al. 2019). Herschel was equipped with two imaging instruments, the Photodetector Array Camera and Spectrometer (PACS; Poglitsch et al. 2010), that observed the FIR at 100 and 160 µm, and the Spectral and Photometric Imaging Receiver (SPIRE; Griffin et al. 2010) that covered 250, 350, and 500 µm wavelength ranges.

Surveys that combine a wide range of wavelengths have particular identification issues due to the different spatial resolution of the sources in different bands. To correct this issue HELP builds a master list catalogue of objects as complete as possible for each field and uses the NIR sources of this catalogue as prior information to deblend the Herschel maps. Detailed description can be found in Shirley et al. (2019). The tool developed to obtain the photometry of Herschel sources, XID+ (Hurley et al. 2017), is a probabilistic de-blending algorithm which extracts source flux densities from photometry maps that suffer from source confusion. It uses Bayesian inference to explore the posterior probability distribution and provide probability density function (PDFs) for all prior sources, and thus flux and uncertainties can be estimates. A detailed description can be found in Hurley et al. (2017). The whole procedure is described in Note-book and stored in a GitHub repository\footnote{https://github.com/H-E-L-P/dmu_products}.

In the following paper, we use two HELP fields, due to the wealth of multi-wavelength data available within their wide field
coverage: the European Large Area ISO Survey North 1, here- 
after ELAIS N1 (Oliver et al. 2000) and COSMOS field (Laigle
et al. 2016). Besides data from two PACS and three SPIRE maps,
we used available sets of photometric data at shorter wave-
lengths for both fields (listed in Table 1 and described below in Sec-
tions 2.1 and 2.2). Based on true galaxy observations from that
fields we evaluate the ‘LSST-like’ observations used for further
analysis.

2.1. ELAIS N1 field
According to the HELP strategy, all sources detected in any of
the Spitzer IRAC bands were used as a prior for XID+ to obtain
FIR fluxes. XID+ was run on the Spitzer MIPS 24 µm and
Herschel PACS and SPIRE maps. The flux level at which the aver-
age posterior probability distribution of the source flux becomes
Gaussian is 20 mJy for MIPS, 12.5 and 17.5 mJy for 100 µm and
160 µm PACS bands respectively, and 4 mJy for all three (250,
350 and 500µm) SPIRE bands (see for more details Hurley et al.
2017; indicating that the information from data dominates over
the prior). In the de-blending procedure, the priors used for com-
puting the fluxes satisfied two criteria: they must have an IRAC 1
band detection and they must have been detected in either the op-
tical or near IR (NIR) wavelengths to eliminate artefacts. More
information about the catalogue can be found in Malek et al.
(2018), Shirley et al. (in prep.) and on the main webpage of the
HELP project 2.

In addition to FIR bands, the catalogue is built on a position
cross match of all the public survey data available in the optical
and mid IR (MIR) range. This comprises observation from
Isaac Newton Telescope/Wide Field Camera (INT/WFC) sur-
voy (González-Solares et al. 2011), the Subaru Telescope/Hyper
Suprime-Cam Strategic Program Catalogues (HSC-SSP; Ai-
hara et al. 2018), the Panoramic Survey Telescope and Rapid
Response System (Pan-STARRS; Chambers et al. 2016), the
UK Infrared Telescope Deep Sky Survey – Deep Extragalac-
tic Survey (UKIDSS–DXS) (Swinbank 2013; Lawrence et al.
2007), the Spitzer Extragalactic Representative Volume Survey
(SERV; Mauduit et al. 2012), and the Spitzer Wide InfraRed
Extragalactic survey (SWIRE; Lonsdale et al. 2003; Stauffer et al.
2005). We show the list of filters for ELAIS N1 in Table 1. The
whole matching procedure is described in Shirley et al. (2019).

2.2. COSMOS field
For the COSMOS field, the XID+ analysis was perfomed on
Spitzer and Herschel maps for all the sources with fluxes greater
than 1 µJy in any of the IRAC bands from the COSMOS2015
catalogue (Laigle et al. 2016). The fluxes obtained follow the cri-
terion of goodness defined in XID+ and corresponds to a Gauss-
ian posterior distribution of the estimated flux.

Starting with this multi-wavelength catalogue, COS-
MOS2015 (Laigle et al. 2016), ancillary photometry is added
with a position cross match with other public survey contain-
ing, optical, optical and MIR observations. This comprises, other
than the one already mentioned for ELAIS N1, the WIRCam
Deep Survey (WIRDS, WIRCam bands J, H, Ks), the VLT Sur-
vey Telescope (VST; Arnaboldi et al. 1998), the Victor Blanco
4-m Telescope, the Visible and Infrared Survey Telescope for A-
stronomy (VISTA; Emerson et al. 2006, Dalton et al. 2006)
and UKIDSS-LAS (WFCAM bands J, H, K) catalogues. The
merging strategy is the same as for ELAIS N1 and is described
in detail in Shirley et al. 2019). The list of filters used for COS-
MOS survey is shown in Table 1.

Detailed description of both fields (the area, mean depths
in different filters, all raw files and ancillary data and many
others) can be found on the http://hedam.lam.fr/HELP/
dataproduts/dmu31/dmu31_Field_overviews/ webpage.

2.3. Total sample
As part of the HELP database, both fields catalogues include
photometric redshifts generated using a template fitting method,
biased on a Bayesian combination approach, described in Duncan
et al. (2018). They investigated the performance of three pho-
tometric redshift template sets as a function of redshift, radio
luminosity and infrared/X-ray properties, over the NOAO Deep
Wide Field Survey Bootes and COSMOS fields. The three tem-
plate sets used are: (1) default EZY reduced galaxy set (Bram-
mer et al. 2008), (2) “XMM COSMOS” templates (Salvato et al.
2009), and (3) atlas of Galaxy SEDs (Brown et al. 2014).

The total sample includes 39 329 objects for the ELAIS N1
survey and 14 864 for COSMOS, with FIR detections in at least
two photometric bands with signal-to-noise ratio (S/N)>3. This
cut is performed to remove objects with unreliable photometry
and thus improve the quality of the SED fitting process. We
keep in mind that by employing the aforementioned selection
we are restricting our analysis to only a subsample of galaxies
that LSST will observe, that are objects bright in the FIR. Then,
as we will show in the next Section, we have selected only the
so-called MS galaxies observed in the spectral range from UV
to FIR, as these are the most common type of galaxies observed.
The considered bands are u, g, r, i, z, N921, y, J, H, K, Spitzer
IRAC 3.6, 4.5, 5.8 and 8.0 µm, Spitzer MIPS 24 µm and five
passes from Herschel, two from PACS (100 and 160 µm) and
three from SPIRE (250, 350 and 500 µm), across the ELAIS N1
and COSMOS fields.

3. Methodology: SED fitting, starbursts and outliers
detection
3.1. SED fitting with CIGALE
The SED fitting is performed with the Code Investigating
GALaxy Emission3 (CIGALE) tool. For a detailed description
of the code we refer to Boquien et al. (2019), here we will
give just a brief summary. CIGALE is a Bayesian SED fitting
code that combines modelled stellar spectra with dust attenua-
tion and emission. CIGALE preserves the energy balance con-
considering both the energy emitted by massive stars, partially
absorbed by dust grains and then re-emitted in the MIR and FIR.
The quality of the fit is expressed by the best χ2 (and a reduced
best χ2 defined as χ2 = χ2/(N − 1), with N the number of data
points). The minimum value of χ2 correlates to the best model
selected from the grid of all possible computed models from the
input parameters. The physical properties and their uncertainties
are estimated as the likelihood-weighted means and standard de-
viations.

To obtain the starting MS sample of galaxies with the cor-
correct physical properties necessary to compare with those ob-
tained with LSST only, we run CIGALE on the ELAIS N1 and
COSMOS samples with the physical modules and parameters re-
ported in Table 2. We did not use the AGN module (see App. B

2 http://hedam.lam.fr/HELP/

3 https://cigale.lam.fr
and Sec. 3.5). As shown in Malek et al. (2018), this set of parameters corresponds to the one that best fits a large sample of IR detected galaxies in the 23 HELP fields, for the redshift range 0 < z < 6. We use a SFH modelled as delayed exponential function with an additional exponential burst to select and remove starburst galaxies from our sample in order to only retain MS galaxies. We perform the SED fitting by employing the modified version of Chariot & Fall (2000) attenuation law, as already employed in Malek et al. (2018) for a large sample of multi-wavelength HELP data. We use the Draine et al. (2014) dust emission module. A detailed description of each module can be found in Boquien et al. (2019) and Malek et al. (2018).

To improve the quality of our selection, from the full sample we only select objects with redshift lower than 2.5. Our cut in redshift is not related with the LSST redshift range, as the photometric redshifts for LSST will be applied and calibrated over the range 0 < z < 4 for galaxies to z ∼27.5 (LSST Science Collaboration et al. 2009). The z < 2.5 is related to the redshift distribution in the ELAIS N1 and COSMOS fields used in this analysis, and also it restricts us to high quality data and so maximize the accuracy of the estimation of physical properties. Moreover, we removed all the objects recognized as possible stars by GAIA (flag GAIA >0 in the database). In this way we remove 2921 objects (7.5% of the sample) from ELAIS N1 and 887 (6% of the sample) from the COSMOS catalogue.

From now on, we will refer to the remaining 36 408 and 13 977 galaxies from the ELAIS N1 and COSMOS fields respectively, as the real sample.

### 3.2. Starburst galaxies selection

Galaxies can be classified according to their different properties: morphology, colour, environment, mass etc. One of the properties often used in the literature is the rate of which stars are forming out of gas, the SFR. That leads to define three different types of galaxies: passive, normal/MS, and starburst (SB). The boundaries dividing these classifications are not precisely defined, as different authors use different methods to distinguish starbursts from MS galaxies (i.e. Rodighiero et al. 2011, Speagle et al. 2014, Elbaz et al. 2018, Donevski et al. 2020). A universally accepted method does not exist. Nevertheless, there is agreement that the three groups differ in regard to their evolution and physical properties, like SFH, dust and gas content, and others (Silverman et al. 2018, Elbaz et al. 2018).

Most galaxies observed with LSST will be composed of active IR galaxies, but the majority of them are likely to be normal, MS–like, or passive galaxies. For example, the current estimate on SB galaxies contributing to the full star-formation population is about 5% (Schreiber et al. 2016, Béthermin et al. 2017). However, this contribution increases if we isolate brighter IR galaxies only (e.g. Miettinen et al. 2017).

To interpret possible bias for the physical parameter estimation we have to ensure that the selection effects do not produce artificial trends in the analysis. To quantify the accuracy of the physical properties estimates of LSST galaxies we decide to focus on MS objects only, as we can select a large number of those galaxies from the HELP data to obtain a statistically important sample of real and simulated galaxies. The method we used to separate MS galaxies is described in detail in Rodighiero et al. (2011). We divided our sample in four redshift bins (Table 3), as the definition of starbursts changes with redshift. In fact, it was shown by Schreiber et al. (2015) that the average SFR of star forming galaxies, in the same ranges of masses, increases with redshift. In this work starbursts are defined according to their specific SFR distribution (SFR/Mₜot, hereafter sSFR). Figure 1 shows that the sSFR follows a Gaussian distribution. We follow the same definition of starbursts as Rodighiero et al. (2011), i.e objects with sSFR that lie above sSFR +3σ, where sSFR is the Gaussian mean of the sSFR distribution. The right panel in Fig. 1 shows the selected starbursts and the MS galaxies.

To further test the reliability of the SB selection we compare our distribution and the position of starbursts with the one found in Béthermin et al. (2017) (hereafter: B17), a catalogue of simulated galaxies. The B17 is built on IR/sub-mm data and it is one of few models that are able to simultaneously match the total IR number counts and the evolution of sSFR. It simulates 2 deg² field including physical clustering from dark matter simulation, and is thus perfectly suitable for the comparison purpose. Figure 2 shows the comparison between SB distribution derived in this paper and the sample of simulated SBs from B17 (cyan distribution). The simulated SB sample extends to sSFR values lower than the sSFR range obtained from our analysis. The discrepancy can be explained by the use of two different selection methods in our work and in B17. On the one hand, B17 randomly draw the SFR of each source using a continuous log-normal distribution (in agreement with the observational results, e.g. Rodighiero et al. 2011) and then used the Schreiber et al. (2015) definition of the MS to select the galaxies, with an addi-
Table 2. Input parameter of the code CIGALE.

| Parameters | Values |
|------------|--------|
| **Star formation history:** | |
| e-folding time of the main stellar population model (Myr) | 1000, 2000, 3000, 5000, 7000 |
| e-folding time of the late starburst population model (Myr) | 5000 |
| Mass fraction of the late burst population | 0.001, 0.01, 0.03, 0.1, 0.3 |
| Age (Myr) | 1000, 2000, 3000, 4000, 5000, 6500, 10000 |
| Age of the late burst (Myr) | 10, 40, 70 |
| **Delayed star formation history** | |
| e-folding time of the main stellar population model (Myr) | 1000, 2000, 3000, 4000, 5000, 6500, 8000 |
| Age (Myr) | 500, 1000, 3000, 4000, 5000, 6000, 7000, 8000, 9000, 10000, 12000 |
| Mass fraction of the late burst population | 0.0 |

**Single stellar population** Bruzual & Charlot (2003)

| Parameters | Values |
|------------|--------|
| Initial mass function | Chabrier (2003) |
| Metallicities (solar metallicity) | 0.02 |
| Age of the separation between the young and the old star population (Myr) | 10 |

**Dust attenuation law** Charlot & Fall (2000)

| Parameters | Values |
|------------|--------|
| \( A_V \) in the Birth Clouds | 0, 0.05, 0.1, 0.3, 0.8, 1.2, 1.7, 2.3, 2.8, 3.3, 3.8, 4.0, 4.2 |
| Power law slopes of the attenuation in the birth clouds | −0.7 |
| BC to ISM factor (\( A_V \) ISM / \( A_V \) BC) | 0.5, 0.8 |
| slope ISM | −0.7 |

**Dust emission:** Draine et al. (2014)

| Parameters | Values |
|------------|--------|
| Mass fraction of PAH | 1.12, 2.5, 3.19 |
| Minimum radiation field (\( U_{\text{min}} \)) | 5.0, 10.0, 25.0 |
| Power law slope \( dU/dM (U^{\alpha}) \) | 2.0, 2.8 |
| Fraction illuminated from \( U_{\text{min}} \) to \( U_{\text{max}} \) (\( \gamma \)) | 0.02 |

**Dale et al. (2014)**

| Parameters | Values |
|------------|--------|
| AGN fraction | 0 |
| Powerlaw slope \( dU/dM (U^{\alpha}) \) | 2.0 |

The SFH with two or more stellar populations is suitable to fit active galaxies, with moderate or high SFR. For this reason we analyse the remaining objects without SBs employing the delayed SFH in the SED fitting, which is more suitable for normal MS galaxies (Ciesla et al. 2016). For the simplicity of the analysis, after removing SB galaxies, we replace delayed SFH with additional burst by simple delayed SFH. All the parameters used for the SED fitting are listed in Tab. 2. We performed again the SED fitting to obtain real physical properties of the sample of real MS galaxies. Those values were next used to simulate the LSST observations (see Section 4.1).

To ensure of the purity of the MS sample we additionally removed possible passive galaxies. As for the starburst evaluation, many different methods were employed in the literature to select red passive galaxies, i.e. UVJ and NUVrK colour diagram analysis (Williams et al. 2009, Arnouts et al. 2013), division based on sSFR (Vulcani et al. 2015, Salim et al. 2016, Salim et al. 2018), division based on \( U_{\text{min}} \).
or unsupervised machine learning (Siudek et al. 2018). We decide to follow Salim et al. (2018) method by removing all objects with \( \log_{10}(sSFR[\text{yr}^{-1}]) < -11 \). In this way we remove 340 (1\%) and 63 (0.5\%) galaxies from ELAIS N1 and COSMOS field respectively. The almost negligible number of passive galaxies in the HELP sample is related to our initial sample selection, which required at least two Herschel measurements with S/N>3.

3.4. AGN contribution

Taking advantage of IRAC detection for all galaxies included in our analysis we used MIR detections to find how numerous is the AGN population in our sample. We employed two different selection criteria, based on MIR photometry (IRAC bands) analysis, explained in detail in Stern et al. (2005) and Donley et al. (2012). Fig. B.1 shows the IRAC colour-colour selection using Donley et al. (2012) (upper panels) and Stern et al. (2005) (lower panels) methods. Using both criteria, we find a negligible number of AGN, in comparison to the final sample (1.56\% and 5.16\% for Donley et al. 2012 and Stern et al. 2005 criterion, respectively, see Table 4 for detailed information for both fields). The redshift distribution of selected AGNs is shown in Fig. B.2. For consistency with the cuts made previously we removed AGNs from our sample. We decide to use a conservative approach, and we removed all 2 603 possible AGNs found with the Stern et al. (2005) method, as this selection includes all the AGNs detected with the Donley et al. (2012) approach.

3.5. Outlier selection

Due to the large and unknown number of galaxy’s free parameters, a simple \( \chi^2 \) selection cannot assure us to remove the majority of the outliers from our sample. In order to eliminate possible outliers and to assure the high quality of the SED fitting, along with a \( \chi^2 \) selection, we use an estimation of physical properties \( L_{\text{dust}} \) and \( M_{\text{star}} \) (See appendix A). A similar procedure was used by Malek et al. (2018) for HELP ELAIS N1 field. Based on that criteria we removed 2 117 galaxies from ELAIS N1, and 640 from COSMOS field, 5.81\% and 4.75\%, respectively.

3.6. Final sample

To obtain the final sample of normal star-forming galaxies, we removed possible starbursts (Sec. 3.2), passive galaxies (Sec. 3.3), and possible AGNs (Sec. 3.4). We also did additional cleaning using outlier selection (Sec. 3.5) to remove all galaxies with possible wrong photometry, or wrong matches between UV-optical and FIR measurements. At the end of the process we remain with 31 936 objects for ELAIS N1 (87\% of the total sample) and 11 716 galaxies for COSMOS (84\% of the total number). Furthermore, in order to validate the photometric redshift estimates used for this objects, we perform a comparison with spectroscopic redshift estimates, available for \( \sim 5000 \) galaxies in ELAIS N1 and COSMOS fields. Following Duncan et al. (2018) definition of critical outlier (\( \frac{|\Delta z|}{1+z_s} > 0.2 \)), we find the fraction of outlier in our sample at the level of 4\%, in agreement with what found in previous works (Ilbert et al. 2009, Hildebrandt et al. 2010, Duncan et al. 2018). The final redshift distributions of both samples are shown in Fig. 3.

4. LSST physical properties estimation

In the following section we discuss the LSST data and uncertainties from simulations and the estimation of the physical properties of the galaxies obtained by performing the SED fitting of: i) the fiducial input parameters plus LSST data only; ii) the fiducial input parameters plus LSST data coupled with other observations.

4.1. LSST simulated data and uncertainties estimation

LSST data simulation has been a popular topic in the last years, considering the upcoming start of the survey (Ivezić et al. 2019). In this work we derive an 'LSST-like catalogue' from the best fit
of the observational data, described in Sect. 2. In this way, we are able to quantify the difference between the estimation of the physical properties based on the LSST measurements only and the UV-to-FIR wavelength of the real, observed objects. Considering the depth reached with 10 years worth of survey data, it is very likely that LSST will observe objects not visible with the current ground survey telescopes, and this work will be a starting point to learn how to treat those objects with SED fitting methods.

We simulate the observed fluxes in the six LSST bands (ugrizy, of which the filter response curve is provided by the LSST developers team, Ivezić et al. 2019). To obtain LSST fluxes we run CIGALE by fitting the photometric measurements and providing to the code the LSST filter response curves. We use a CIGALE module (called fluxes) specifically designed to estimate the fluxes in the defined filters. We compute LSST fluxes from the best-fit model of each object. We include in our sample all the galaxies that will be detected in all bands at the depth of the 10 year survey: \( u < 26.1, g < 27.4, r < 27.5, i < 26.8, z < 26.1, y < 24.9 \). In this way we discard 8 645 objects (23% of the total sample) from ELAIS N1 and 2 623 (19% of the total sample) from COSMOS.

To incorporate an LSST-like observational uncertainty into our catalogue, we must take into account random phenomena that could occur during a real observation, such as change in the sky seeing, number of visits etc. The predicted magnitude errors, that we convert in flux errors following the conversion provided in the LSST manual (Ivezić et al. 2019), depend on the galaxy’s magnitude, the sky seeing, and the total survey exposure time in a given filter. We use the LSST simulation software package CatSim 4 to calculate magnitude errors. The aforementioned error evaluation is based on Eq. 5 of Ivezić et al. (2019), and takes into account variations in the photometry due to hardware and observational components (e.g. detector, darksky, atmosphere). The random error evaluated is then divided by the square root of the number of visits during the survey. The LSST manual provides mean values for all these components.

To mimic the real conditions we add to the average value of each component provided in the LSST manual, a value randomly

### Table 4. Number of AGN selected based on the MIR features for ELAIS N1 and COSMOS field. The last column shows the total number (and percentage) of AGNs in the full sample.

| Method          | ELAIS N1       | COSMOS         | Total sample |
|-----------------|----------------|----------------|--------------|
| Stern et al. (2005) | 1 269 (3.48%) | 1 334 (9.50%)  | 2 603 (5.16%) |
| Donley et al. (2012) | 497 (1.36%)   | 291 (2.08%)    | 788 (1.56%)   |

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4 https://www.lsst.org/scientists/simulations/catsim
chosen from a Gaussian distribution centred on the provided mean value, having standard deviation the 10% of the mean. In this process, we vary the number of visits and sky seeing. The assumed standard conditions for these components are 0.8 arcsec for the seeing, and a uniform progression that assumes a total of 56, 80, 184, 184, 160 and 160 visits in filters $ugrizy$, respectively.

At the end, to further mimic a possible divergence of the `real’ observed flux from the simulated value evaluated from the best-fit SED, we again add to the latter a value randomly chosen from a Gaussian distribution centred on 0, having standard deviation the flux error calculated before. Figure 4 shows the magnitude errors as a function of the simulated observed magnitude for our sample of galaxies. We only select objects that would be observed in all six bands according to our simulation. As a result, we reach the LSST magnitude limit only for the r band. The final catalogue contains simulated LSST fluxes and uncertainties for 23,291 galaxies in the ELAIS N1 field and 9,093 in the COSMOS field. The catalogues, together with the photometric redshifts and HELP IDs, are available on the HELP virtual observatory.

4.2. Fiducial parameters and LSST data only

To estimate the main physical properties of the LSST sample, we run CIGALE on simulated LSST observations and uncertainties employing the same modules and parameters used for the HELP MS sample (Table 2, with delayed SFH). Figure 5 shows two example SEDs of the same galaxy at redshift 0.92, obtained with the UV-FIR and LSST photometric only data set, respectively. For this specific case, we found an agreement between estimated stellar masses ($M_{\text{star, real}} = 6.05 \times 10^{10} \pm 5.62 \times 10^{9} M_{\odot}$, $M_{\text{star, LSST}} = 5.59 \times 10^{10} \pm 1.80 \times 10^{10} M_{\odot}$). Instead, the SFR, calculated for the LSST-like photometric data only is highly overestimated (by a factor of six) with respect to the real value obtained by employing the UV-FIR data set ($\text{SFR}_{\text{real}} = 11.9 \pm 2.16 M_{\odot} \text{yr}^{-1}$ and $\text{SFR}_{\text{LSST}} = 67.4 \pm 45.9 M_{\odot} \text{yr}^{-1}$). We can also notice that the residuals for LSST are very small (but never null), as we can easily find a model that almost perfectly fits just 6 observation

\footnote{https://www.herschel-vos.phys.susx.ac.uk}

in the optical part. However, the IR part of the SED, and so the dust emission module, is completely unconstrained (in our work we used the same dust emission module, Draine et al. (2014), as it was used for the original HELP data with the same grid of parameters).

The relation between SFR and $M_{\text{star}}$ in the four redshift bins is shown in Fig. 6. In this Figure, we compare the MS relation obtained for the LSST-like sample with the one obtained from the full UV-FIR SED fitting. We show the MS from Speagle et al. (2014) as a reference for the reader. We notice that at low redshift the LSST estimation fails to probe low SFR objects, and this leads to a clear division between the respective MS relations, which however overlap at higher redshifts. In Appendix D we discuss the scatter between our sample and the MS law. Figure 7 shows this overestimation as a function of redshift, separately for ELAIS N1 and COSMOS (left upper panel). We also plot in the same figure the ratio between the LSST-derived stellar mass, $L_{\text{star}}$, and $M_{\text{dust}}$ and the ones from the full UV-IR SED fitting. We obtain an overestimation of the dust related properties (SFR, $L_{\text{dust}}$, $M_{\text{dust}}$) while the values of $M_{\text{star}}$ are comparable. The overestimation of the SFR is strongly dependent on the redshift. The ratio between the stellar masses is evenly distributed around zero, leading to comparable results between the two runs, as stellar masses mostly rely on optical data. This results stands both for ELAIS N1 and COSMOS fields and shows that there is no dependence on the field.

The aforementioned results can be explained if we consider how the physical properties are evaluated by the Bayesian method. This is basically done through the likelihood estimation. Each model in the grid of models built from the starting input parameters will have an associated likelihood taken as $\exp(-\chi^2/2)$, that is used as weight to estimate the physical parameters (the likelihood-weighted mean of the physical parameters attributed to each model) and the related uncertainty (see Sec. 4.3 of Boquien et al. 2019). Fitting just LSST optical observations results in having high likelihood values even for templates that do not reflect the real physical properties of the modelled galaxy. As
To check if the complex set of parameter used for Draine et al. (2014) model is responsible for the overestimation of the SFR, we run the whole analysis adopting Dale et al. (2014) model. Dust emission in this model is parametrised by a single parameter $\alpha$ defined as $dM/dU = U^{\alpha}$, where $M$ is the dust mass heated by a radiation field at intensity $U$. We used the parameter $\alpha = 2$ as better describe the stellar emission from MS galaxies. The module allows also to add an optional AGN component, that we set to 0 for this test. Comparing the LSST physical properties with the real one using the Dale et al. (2014) module we obtain the same overestimation of the SFR and $\nu_{50}$ as those obtained with Draine et al. (2014) dust emission. We were not able to compare dust masses as it is not an output parameter of the Dale et al. (2014) module. As we found no improvement by employing a simpler model, we decided to keep the results obtained with Draine et al. (2014) for the homogeneity with the results published by HELP project (Małek et al. 2018, Shirley et al., in prep.).

4.3. Fiducial parameters, LSST and ancillary data

A different approach to correct the overestimation consists in applying the SED procedure on the LSST data together with other available observations in different bands (e.g., MIR Spitzer bands, FIR Herschel Spire bands). Figure 9 shows the results for SFR ratios obtained by adding IRAC MIR and SPIRE FIR observations. We expect that by adding the rest-frame NIR part of the SED will better constrain the attenuation of the old stellar population, while the MID and FIR mainly constrains the dust emission from the star-forming regions and the missing SFR, hidden by dust. The left upper panel of Fig. 9 shows that, just adding MR observations, the overestimation of the SFR is fully corrected independently of the considered redshift range.

We could also expect that the combined use of UV and LSST data will correct the overestimation of the SFR at low redshift. We test this hypothesis by adding the UV observations from GALEX and performing the SED fitting. We perform a 1.5 arcsec crossmatch with the HELP catalogue and we identify ~3 000 galaxies having a GALEX counterpart. Figure 9 (left bottom panel) shows the comparison of the SFR estimation for LSST-like and UV–FIR data set of those 3 000 galaxies. We conclude from this plot, that by adding GALEX observations we obtain in general slightly lower overestimation but still consistent with previous results, meaning that the observed UV fluxes are not enough to completely correct the differences. Furthermore for $0.5 < z < 1.5$ we obtain a slight underestimation of the parameters. Nevertheless, we stress that this result can be biased due to the low number of GALEX counterparts of the LSST-like catalogue, and the low quality of GALEX observations for higher redshift sources. To confirm this statement, we simulate GALEX NUV and FUV observations for the whole sample (from now we refer to it as GALEX$_{sim}$), again using the CIGALE module $\text{fluxes}_s$, and employ it together with LSST to estimate the physical properties. We decide to cut objects with $z > 1.5$ as, after this limit, both NUV and FUV GALEX bands are probing emissions below the Lyman break. Fig. C.1 shows the comparison of the SFR evaluated in this way and the one evaluated using LSST observation only. We find a clear correction of the overestimation, highlighting the great impact that UV observations have on the SFR estimation. We confirm that the overestimation is partially due to the lack of the direct tracer of the young stellar population. Unfortunately, as there are no new UV missions planned in the near future, we do not expect to have available a UV cover-
Fig. 6. The main sequence (SFR vs. $M_{\star}$) relation for the ELAIS N1 and COSMOS fields in four redshift bins. In blue is represented LSST-like sample, while in black the real sample. The solid black line represent the MS by Speagle et al. 2014, while the dashed lines mark the loci 2 times above and below the MS. This plot shows a clear SFR overestimation obtained using LSST bands only, that tends to disappear moving to higher redshift ranges.

5. Testing different input parameters in CIGALE

As discussed in section 3.1, the set of parameters employed for the analysis presented so far corresponds to the best one to fit the large sample of objects in the area of $\sim 1300$ deg$^2$ of the HELP field. However, we also investigate how much the results obtained by only fitting the LSST simulated data are dependent on the CIGALE input parameters. In particular, we tested possible variations of the derived galaxy physical quantities as a function of the input radiation field, PAH fraction and dust attenuation law. For testing how the variations in the dust attenuation laws change our results, we re-fitted the UV to IR photometry and we re-derived the LSST simulated data that were later re-fitted by adopting a different attenuation law.

5.1. Dust emission and mass

Dust continuum emission is only determined by the energy balance and therefore it only depends on the amount of absorbed radiation. As a consequence, the total dust emission is not affected by the parameter $U_{\text{min}}$, but it is only sensitive to the total absorbed radiation. On the contrary, we find that $M_{\text{dust}}$ is not constrained by using the LSST data only, and its estimate is largely impacted by $U_{\text{min}}$ parameter employed. Indeed, by changing $U_{\text{min}}$ the amount of radiation that irradiates the dust is modified, but the amount of dust emission is unaltered. As a consequence, larger input values of $U_{\text{min}}$ translate in lower $M_{\text{dust}}$ and vice versa. Large values of the $U_{\text{min}}$ ($U_{\text{min}}=25$) parameter yield an underestimation of $M_{\text{dust}}$. As a consequence, since the shape of dust emission is completely unconstrained us-

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Fig. 7. Ratios between different physical properties obtained from the fitting of the simulated LSST data only and from the UV-FIR SED (e.g. \( SFR_{\text{ratio}} = \frac{SFR_{\text{LSST}}}{SFR_{\text{UV-FIR}}} \)), as a function of the redshift for the ELAIS N1 and COSMOS fields. The properties obtained from the UV-FIR SED fitting are considered as the true values. From the upper left panel moving clockwise we show: SFR, \( M_{\text{star}} \), \( L_{\text{dust}} \), and \( M_{\text{dust}} \) comparisons. The dashed lines represent polynomial fits performed on the samples. The points are the median values in each redshift bin, with median absolute deviation as errors. A Ratio equal to zero corresponds to a perfect agreement between estimations obtained based on the LSST-like sample and the real values. The distributions calculated for ELAIS N1 and COSMOS are comparable within the errors. The SFR is systematically overestimated, especially for the lowest redshift range. The stellar masses are instead comparable. At high redshift the stellar mass ratio diverges from zero, mostly because the optical bands are shifted to the NUV range.

Fig. 8. LSST coverage of an example SED at different redshifts, indicated in the panel.

When using only the LSST coverage, the Bayesian method cannot evaluate the \( U_{\text{min}} \) parameter and assigns to all galaxies an average value among all the input parameters considered. This results in having dust mass estimates strongly dependent on the input parameters employed. When the dust emission is constrained using SPIRE observations, the \( U_{\text{min}} \) parameter is well evaluated by the Bayesian method, and so the dust mass.

The use of different attenuation laws also changes the estimates of dust emission and mass, since the radiation absorbed and the re-emitted by dust grains is modified. By using either the Calzetti et al. (2000) and Charlot & Fall (2000) attenuation laws, we obtain an overestimation of the dust luminosity over the entire redshift range. The trends between the dust luminosity ratios and the redshift are however different. As far as the dust mass is concerned, by adopting Calzetti et al. (2000) we obtain a constant slight overestimation of the dust mass, centred around 0.3 dex across the whole redshift range, while by using Charlot & Fall (2000) the mass of dust is overestimated for local galaxies and underestimated for redshift greater than \( \sim 1 \).

5.2. Dust attenuation laws and the star formation history

We find the SFR to be unaffected by the PAH fraction and by the input radiation field (\( U_{\text{min}} \) and \( \alpha \) parameters) since the aforementioned input quantities only shape dust emission. The SFR is instead influenced by our choice of the attenuation law. When the Calzetti et al. (2000) modified attenuation law is employed, we obtain the results shown in Fig. 10. The results using Calzetti et al. (2000) attenuation curve are in good agreement with the
ones obtained with the Charlot & Fall (2000) prescription at low redshift but change in shape going to higher \( z \). The overestimation with the Calzetti et al. (2000) curve is more constant along the redshift range, while it decreases faster when using the Charlot & Fall 2000 prescription.

Furthermore, we check also the dependence of SFR estimates on the SFH module used. Performing the entire process using a delayed plus additional burst SFH we obtain an even higher overestimation when estimated using just LSST observations, that again decreases going to higher redshift.

We also inspect changes in the SFR difference while using the best values, instead of Bayesian one, for the LSST-like sample. We find a consistency between the SFR from the best fit and the one estimated from the UV-FIR fit, finding \( \log_{10}(SFR_{LSST, \text{best}}/SFR_{UV-FIR}) \) very well distributed around zero with a scatter of 0.05 dex. This result, that shows a good agreement between the best templates of the two runs, is understandable as the fluxes used for the LSST-like run were calculated based on the best template of the UV-FIR run. We confirm that the differences found must be sought in the Bayesian analysis, that tends to overestimate the attenuation when employed on LSST data only. Unfortunately, being estimated directly from the SED that best fits our data, the best-fit value has several drawbacks that make it not suitable for this type of analysis. For example it ignores the degeneracies one can encounter, as models with equally good fits can have very different properties. Moreover, the best fit in itself does not provide information on the uncertainties.

6. Application of the \( A_{FUV} - M_{\text{star}} \) relation to correct the SFR overestimation

Previous results shows major miscalculations of the SFR while using the LSST data only. Due to the lack of information in the
UV and MIR part of the spectrum, the SED fitting results in an overestimation of the attenuation, that leads to the general overestimation of the SFR. At the same time, as it is probed mainly from the optical emission of the galaxy, the $M_{\text{star}}$ seems to be well estimated using only LSST data. Taking into account that the $M_{\text{star}}$ is the result of the previous star formation activity of the galaxy, which is responsible for producing the dust, it could be used as a promising tracer of the dust content.

During past years, several works have explored possible relations between $M_{\text{star}}$ and dust attenuation (Xu et al. 2007, Martin et al. 2007, Buat et al. 2009, Bogdanoska & Burgarella 2020). Most of them suggest a possible linear relation between $A_{\text{FUV}}$ and $\log_{10}(M_{\text{star}})$ over a large mass range ($9 \leq \log_{10}(M_{\text{star}}) \leq 12$). According to the literature this relation is highly dependent on redshift.

Recently, Bogdanoska & Burgarella (2020), hereafter BB20, modelled a single parameter linear function, assuming a non-zero constant dust attenuation for low mass galaxies (Eq. 6, in BB20). They used a sample of galaxies based on the selection criteria which requires the IR Excess (IR) calculated directly from the IR-to-UV ratio or by SED fitting. This selection can introduce a bias in the local Universe and above redshift 2–3, due to the IR detection (at high redshift only the very dusty and massive galaxies are detected, while in the local universe the IR detected galaxies are rather rare). BB20 found that the $A_{\text{FUV}} - M_{\text{star}}$ relation cannot be described with a simple linear function, and they conclude their work with a new relation between $A_{\text{FUV}}$ and $M_{\text{star}}$ in function of redshift. In this section we will try to use the $A_{\text{FUV}} - M_{\text{star}}$ relation provided by BB20 to estimate the $A_{\text{FUV}}$ (from now on we will refer to it as $A_{\text{FUV \, BB20}}$) of the LSST sample. The procedure is as follows: (1) from the LSST data we estimate the $M_{\text{star}}$, (2) using Eqs. 5 and 6 from BB20 we calculate the $A_{\text{FUV \, BB20}}$, and finally (3) we use $A_{\text{FUV \, BB20}}$ as a prior of the new LSST CIGALE run.

Fig. 11 shows the $A_{\text{FUV \, BB20}}$ in comparison to the $A_{\text{FUV}}$ obtained from the full UV-FIR SED fitting, in function of $M_{\text{star}}$. We find that the estimates $A_{\text{FUV \, BB20}}$ are substantially lower than those obtained with the SED fitting process. The difference between $A_{\text{FUV \, BB20}}$ and $A_{\text{FUV \, UV-FIR}}$ is shown in Fig. 12 (green line). We can notice that the underestimation is accentuated for low redshift objects. As expected, employing the $A_{\text{FUV \, BB20}}$ as prior in the SED fitting process, along with LSST observations, result in a underestimation of the SFR, as shown in Fig. 13, where the ratios between the true SFR and the one derived by different methods are shown. We suspect that the reason for the substantial difference between the two estimates of $A_{\text{FUV}}$ can be traced back to the choice of the sample, as the sample used in BB20 is more general, while in our case we focus on IR bright galaxies, to ensure the highest quality of the UV-FIR SED fitting process. It is clear from this results that we cannot employ directly Bogdanoska & Burgarella (2020) relation to correct the SFR overestimation for our sample.

We decided to incorporate the general idea presented in Bogdanoska & Burgarella (2020) and to make use of a $A_{\text{FUV}} - M_{\text{star}}$ relation in order to correct the SFR for an LSST sample of data. We build, albeit simplified, a relation that represents our sample of IR bright main sequence galaxies by following a procedure similar to Bogdanoska & Burgarella (2020). For this purpose, we fit the $A_{\text{FUV}}$ estimated from the UV-FIR SED fitting as a function of the $\log_{10}(M_{\text{star}})$. We used four redshift bins (0-0.5, 0.5-1.0, 1.0-1.5, 1.5-2.5) to include the redshift dependence of the $A_{\text{FUV}} - M_{\text{star}}$ relation. Linear, power law and exponential functions were tested to obtain the best fit, but we found a negligible difference between them. To be as consistent as possible with the results obtained in the previous works, we decided to use the linear function, in the form:

$$A_{\text{FUV-Lsst}} = a \cdot \log_{10}(M_{\text{star-Lsst}}) + b.$$  \hspace{1cm} (2)

From the fitting process, we obtain $a$ and $b$ coefficients, for each redshift bin. Table 5 shows all coefficients together with uncertainties.

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Table 5. Obtained $a$ and $b$ coefficients from fitting Eq. 2, in the four redshift bins.

| Redshift | $a$       | $b$       |
|----------|-----------|-----------|
| 0-0.5    | 0.41 ± 0.02 | −1.39 ± 0.21 |
| 0.5-1    | 0.44 ± 0.03 | −0.49 ± 0.30 |
| 1-1.5    | 0.72 ± 0.03 | −3.42 ± 0.34 |
| 1.5-2.5  | 0.83 ± 0.04 | −5.19 ± 0.39 |

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The IR Excess is defined as $\text{IRX} = \log(L_{\text{IR}}/L_{\text{UV}})$, where the $L_{\text{IR}}$ stands for total integrated luminosity in the IR, and the $L_{\text{UV}}$ is the UV luminosity derived from flux measured with a filter, such as, for e.g. GALEX or estimated via SED process.
The SFR ratio, defined as in Fig. 7, in function of redshift.

Fig. 12. The difference between $A_{FUV}$ estimated from $A_{FUV} - M_{dust}$ relations: Bogdanoska & Burgarella 2020 (green) and Eq. 2 with coefficients reported in Table 5 (blue), and $A_{FUV}$ estimated from the UV-FIR SED fitting, in function of redshift.

Blue line in Fig. 12 shows the difference between the $A_{FUV}$–$M_{dust}$ relation calculated with our four linear relations and the one estimated from the UV-FIR SED fitting, as a function of redshift. We can see that our relation better reproduce the $A_{FUV}$ derived from the fitting of the full SED than Bogdanoska & Burgarella (2020) relation. By employing the $A_{FUV}$–$M_{dust}$ as a prior in the SED fitting, along with LSST observations, we obtain the blue relation shown in Fig. 13. This figure shows that the SFR overestimation is fully corrected while applying $A_{FUV}$–$M_{dust}$ prior. This result also proves that, knowing the $A_{FUV} - M_{dust}$ relation for a given sample of galaxies, it is possible to estimate SFR without the IR counterpart. This requires prior knowledge of the sample, which is often not available. We are aware that the relation constructed in this work may be applicable only to our sample, or at most to IR-bright normal, star forming galaxies, but further generalization of our results is outside the scope of this paper. However, considering the extreme usefulness of this relationship for future surveys as LSST, we are planning to extend our analysis to a more general sample of galaxies in the next work.

7. Conclusions

We perform a reliability check of physical properties estimation of MS galaxies by employing simulated LSST observations. For this purpose we select respectively 50 135 and 15 754 objects from ELAIS N1 and COSMOS fields of the Herschel Extra-galactic Legacy Project (HELP), in order to build the starting set of data to simulate observed LSST fluxes and to obtain reliable estimates of the physical properties of galaxies.

An important part of our analysis is the sample selection. We selected only galaxies from so called main sequence by removing all possible SBs from the sample using the same method as Rodighiero et al. (2011), and passive galaxies using the method described in Salim et al. (2018). Furthermore we removed also galaxies that contain AGN according to Stern et al. (2005) selection. We also cleaned the sample from all nonypical galaxies by implementing additional quality criteria on physical properties following Malek et al. (2018): from our analysis we removed all galaxies for which the $L_{dust}$ and $M_{dust}$ estimated from the full SED fitting (from UV to FIR) are different from the ones obtained from only the optical or only the infrared part of the spectrum. At the end of the sample selection, we selected in total 43 652 galaxies, 86% of the total sample.

We used such a sample of MS galaxies as a prior for the calculation of the corresponding LSST fluxes in the $ugrizy$ bands. We used the LSST simulation software package CatSim, in order to simulate the uncertainties on the photometric measurements, we took into account the possible effects due to the hardware and observational components (e.g. detector, dark sky, atmosphere). We then estimated the main physical properties of galaxies by performing the SED fitting of the simulated LSST data by employing the same sets of modules and parameters as for the originally used HELP galaxies (Shirley et al. in prep., Shirley et al. 2019).

We found that $M_{dust}$ is well estimated by the LSST-like data set. At the same time SFR, $L_{dust}$ are overestimated using the LSST–like sample only, while $M_{dust}$ is completely unconstrained and dependent on the input parameters employed. The overestimation of the SFR is redshift dependent, and clearly decreases with redshift, disappearing around redshift ~1. We found the relation which can correct the overestimation for the SFR parameter: $log_{10}(SFR_{ratio}) = 0.26 - 0.94 \cdot z + 0.87$.

We check which photometric data can be combined with the LSST data to remove the overestimation. In our analysis we used not simulated but real, sometimes uncompleted data, to fully mimic the auxiliary data for the LSST one, since we do not expect to have better UV or FIR data soon. We found that the most efficient way to correct the overestimation of the SFR is by adding mid-IR observations (IRAC data), while $M_{dust}$ is corrected by adding the far-IR bands (SPIRE data). The addition of UV observations from GALEX does not correct the differences. Our findings suggest that the main problem of the pure LSST-like sample in the Local Universe will be the inability to mimic the real attenuation for the old and young stellar populations.

By testing the input parameters of CIGALE, we found that the SFR overestimation is preserved using different attenuation laws commonly employed in the literature (e.g. Calzetti et al. 2000, Charlot & Fall 2000), but its trend as a function of the redshift changes. The estimate of $M_{dust}$ is instead found to be dependent on both the input radiation field ($U_{min}$) and attenuation law and is unconstrained if LSST data only are employed for the SED fitting.

In Section 6 we show that another efficient way to correct the SFR is by exploiting, if available, a prior knowledge of $A_{FUV}$. 
We stress that the further analysis of the $A_{FUV} - M_{*}$ relation can be useful for future surveys and help to properly estimate main physical parameters of galaxies without IR observations.

As future work, we plan to extend this test to different SED fitting methods andHELP fields, to check the systematics of our results.

Acknowledgements. We would like to thank William Pearson for his help in understanding our object’s behaviour in the SFR-$M_{\text{star}}$ diagram. GR, KM, AN, MH and AP acknowledges support from the National Science Centre (UMO-2018/30/E/ST9/00082, UMO-2018/30/M/ST9/00757 and UMO-2020/36/E/ST9/00777). Authors are grateful for the support from Polish Ministry of Science and Higher Education through a grant DIF/RK/2018/12. We also thank the anonymous referee who has helped clarify and improve various aspects of this article.

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We would like to thank William Pearson for his help in understanding our object’s behaviour in the SFR-M* diagram. GR, KM, AN, MH and AP acknowledges support from the National Science Centre (UMO-2018/30/E/ST9/00082, UMO-2018/30/M/ST9/00757 and UMO-2020/36/E/ST9/00777). Authors are grateful for the support from Polish Ministry of Science and Higher Education through a grant DIF/RK/2018/12. We also thank the anonymous referee who has helped clarify and improve various aspects of this article.
Appendix A: Outlier selection

To implement additional quality criteria based on physical properties of the sample, we run CIGALE two more times: (1) for optical data only, to estimate the stellar mass based on the optical measurements only (from now $M_{\text{star,OPT}}$), and (2) for FIR data only, to calculate the dust luminosity (hereafter $L_{\text{dust,IR}}$). In Fig. A.1 we compare the physical properties obtained by employing this method with the one from full wavelength, UV-FIR, fits ($M_{\text{star,all}}$ and $L_{\text{dust,all}}$, respectively).

As shown in Malek et al. (2018), the inconsistency between estimated $L_{\text{dust}}$ values might be induced by energy balance issues of heavily dust-obscured galaxies or lensed objects. We have also removed galaxies with inconsistent $M_{\text{star}}$ estimation, mostly due to problems with optical and IR catalogues matching. Figure A.1 shows two example SEDs for objects considered as outliers. Based on these criteria we remove 1,642 ELAIS N1 sources (4.5% of the total sample), and 460 COSMOS sources (3.2% of the total sample) with inconsistent estimates of $L_{\text{dust}}$. The $M_{\text{star}}$ inconsistency removed 475 (1.5% of the total sample), and 214 (1.5% of the total sample) galaxies for ELAIS N1 and the COSMOS field respectively.

Appendix B: AGN selection

The AGN selection in ELAIS N1 and COSMOS fields. We used two different selection criteria, based on the MIR features (IRAC bands) analysis: Stern et al. (2005) and Donley et al. (2012). Figure B.1 shows the IRAC colour-colour selection using Donley et al. (2012) (upper panels) and Stern et al. (2005) (lower panels) methods. The redshift distribution of selected AGNs is shown in Fig. B.2.

Appendix C: GALEX data simulation

Star-forming galaxies follow a relatively tight, almost linear relation between SFR and $M_{\text{star}}$ known as MS. One of the most noticeable feature is that the MS relation at any given redshift shows a rather small scatter of $\sigma_{\text{MS}}$ that can vary from ~0.2 to ~0.4 dex (Whitaker et al. 2012, Speagle et al. 2014, Pearson et al. 2018). Here we discuss the scatter of our sample from the MS, given that an high scatter could lead to an incorrect estimate of the physical parameters. Figure D.1 shows the scatter of our objects from two reference main sequence laws (Speagle et al. 2014, Whitaker et al. 2017) and we compare the results

Appendix D: Scatter of the MS

Fig. A.1. Outlier selection. Comparison between $L_{\text{dust,IR}}$ and $L_{\text{dust,all}}$ (upper panel), and $M_{\text{star,OPT}}$ and $M_{\text{star,all}}$ (bottom panel). The $L_{\text{dust}}$ inconsistent objects are represented as magenta stars, while full blue stars correspond to the $M_{\text{star}}$ outliers. Gray circles represent objects with consistent estimate of the $L_{\text{dust}}$ and $M_{\text{star}}$ parameters. Inside each panel we present an example SED of the respective black star highlighted outliers.

Based on that analysis we eliminate galaxies that show $L_{\text{dust}}$ and/or $M_{\text{star}}$ inconsistency with the ones estimated from the full SED fitting. Outliers are selected based on the distance from the 1:1 relation:

- criterion 1: $L_{\text{dust}}$ inconsistent (within 2$\sigma$ level) with the $L_{\text{dust,IR}}$
- criterion 2: $M_{\text{star}}$ inconsistent (within 3$\sigma$ level) with the $M_{\text{star,OPT}}$

Fig. C.1. SFR ratio, defined as in Fig. 7, estimated with LSST data only (red) and LSST plus simulated GALEX observations ($GALEX_{\text{star}}$, in blue). Differently from the result shown in 9, in this case we are able to correct the overestimation, underlining the impact that high quality UV observations would have on the SFR estimate, when available for the entire sample.

Fig. D.1 shows the scatter of our objects from two reference main sequence laws (Speagle et al. 2014, Whitaker et al. 2017) and we compare the results
with the MS intrinsic scatter in the literature (Speagle et al. 2014, Pearson et al. 2018). We can notice that the scatter found in our sample is in agreement with those found previously in literature, within the error bars. This is valid also for the lowest redshift bin where the scatter appears to be the largest. Therefore, we are confident that we are working with MS objects and that the input parameters are adequate to provide us with reliable physical properties for the purposes of this analysis. The origin of this scatter can be traced back to different enhancements or decrements events of star formation that could occur during the galaxy life-time. In fact, large scale gas inflow/outflow events can trigger gas compaction/depletion phenomena, that can lead to an enhancement/decrement of the SFR of the galaxy (Tacchella et al. 2016).

Fig. B.1. IRAC colour-colour diagrams for ELAIS N1 (left column) and COSMOS (right column) fields. The AGN (magenta points) are selected following the criteria described in Donley et al. 2012 (upper row black line) and Stern et al. 2005 (lower row black line).

Fig. B.2. AGN redshifts distribution for the full sample of ELAIS N1 + COSMOS fields.

Fig. D.1. Intrinsic scatter of our objects around exemplar MS, in comparison with the results found in previous works. Red and green points represent the scatter of our objects from Speagle et al. (2014) and Whitaker et al. (2017) MS respectively, blue points represent the results found in Pearson et al. (2018), while grey stars, triangles and diamonds represent the results presented in Speagle et al. (2014).