REMOVING BIASES IN RESOLVED STELLAR MASS MAPS OF GALAXY DISKS THROUGH SUCCESSIVE BAYESIAN MARGINALIZATION

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ABSTRACT

Stellar masses of galaxies are frequently obtained by fitting stellar population synthesis models to galaxy photometry or spectra. The state of the art method resolves spatial structures within a galaxy to assess the total stellar mass content. In comparison to unresolved studies, resolved methods yield, on average, higher fractions of stellar mass for galaxies. In this work we improve the current method in order to mitigate a bias related to the resolved spatial distribution derived for the mass. The bias consists in an apparent filamentary mass distribution and a spatial coincidence between mass structures and dust lanes near spiral arms. The improved method is based on iterative Bayesian marginalization, through a new algorithm we have named Bayesian SPS models. We have applied BSP to M51 and to a pilot sample of 90 spiral galaxies from the Ohio State University Bright Spiral Galaxy Survey. By quantitatively comparing both methods, we find that the average fraction of stellar mass missed by unresolved studies is only half what previously thought. In contrast with the previous method, the output BSP mass maps bear a better resemblance to near-infrared images.

Key words: galaxies: fundamental parameters – galaxies: photometry – galaxies: spiral – galaxies: stellar content – methods: statistical

1. INTRODUCTION

How galaxies form and assemble their mass is a primordial question in modern astrophysics. Galaxy masses are crucial for their evolution and for the evolution of cosmic structures at all scales. The determination of the stellar mass content of galaxies can help constrain, e.g., the dark matter fraction, the specific star formation rate ($\Psi_*$, the star formation rate, $\Psi$, per unit stellar mass), the stellar mass function, and the universe’s stellar mass density and star formation history (SFH).

There are different methods to estimate the mass of a galaxy, e.g., dynamical or through gravitational lensing (see Courteau et al. 2014, for a review). Regarding the stellar mass component, the use of stellar population synthesis (SPS) models to estimate mass through the stellar mass-to-light ratio, $T_*$, has been frequently advocated (e.g., Bell & de Jong 2001; Bell et al. 2003). Notwithstanding their common degeneracies, SPS models can in general yield reliable mass estimates. One novel technique is the resolved stellar mass-map method (Zibetti et al. 2009, ZCR hereafter), which delivers a map of the stellar mass surface density by photometric means. Galaxy masses determined by treating the galaxies as point sources are often underestimated (and sometimes overestimated, see Roediger & Courteau 2015), thus the need to resolve structures (ZCR; Sorba & Sawicki 2015). Even more, if the stellar mass of each galaxy in a cluster is estimated separately, the total stellar mass fraction is lower than when a constant $T_*$ is assumed (Leauthaud et al. 2012).

The resolved stellar mass method is truly powerful, since it can solve not only for the mass, but for other physical parameters of the SPS models, based solely on photometry. Resolved maps of stellar mass are also important for studies aimed at understanding the dynamics of bars and/or spirals (since gravity is the main driver), and their secular evolution (e.g., Foyle et al. 2010; Martínez-García & González-Lópezlira 2013; Egusa et al. 2016). Additionally, they can be used to determine the baryonic contribution to rotation curves (e.g., Repetto et al. 2013, 2015; McGaugh et al. 2016). The method can also be extended to higher redshift studies (e.g., Lanyon-Foster et al. 2007; Wynts et al. 2012).

Despite their potential, the resulting mass maps may be biased in the sense that the stellar mass shows a filamentary structure and is concentrated in dust lanes. In this paper we aim to understand the origin of this shortcoming and improve the method to derive resolved stellar mass maps. We must also note that in this research we use SPS models that assume a constant metallicity along the SFH. Gallazzi & Bell (2009) studied the effects of using a variable metallicity SPS library and found no significant biases when estimating $T_*$. Nevertheless, Intò & Portinari (2013) indicated that the color-mass-to-light ratio relations (CMLR, see, e.g., McGaugh & Schombert 2014) resulting from an evolving metallicity along a coherent SFH within an individual galaxy are probably different from the CMLR established for the general galaxy population. Furthermore, biases in mass determinations from CMLR can be even more significant at high redshifts than for local studies (see, e.g., Mitchell et al. 2013). In this work we do not use CMLR to recover $T_*$; instead, we use a statistically robust Bayesian technique to infer the predicted $T_*$ via the comparison of observed colors with a comprehensive library of SPS models.

The paper is organized as follows. In Section 2, we describe the resolved stellar mass-map method in its present form and explain/investigate the source of the bias. We introduce a new method (based on the former) in Section 3. In Section 4, we...
apply the new method to the spiral galaxy M51 (NGC 5194); comparisons with other methods are also briefly described. In Section 5, we apply the new method to a pilot sample of spiral galaxies and discuss and analyze the results. The uncertainties in the stellar mass estimates are discussed in Section 6. Finally, we give our conclusions in Section 7.

2. RESOLVED MAPS OF STELLAR MASS

The ZCR method uses a Monte Carlo library of SPS models obtained from the 2007 version of Bruzual & Charlot (2003; CB07) models with the Chabrier (2003) stellar initial mass function (IMF). The library was built by adopting prior probability distributions for parameters such as the SFH, the dust attenuation (treated as in the two-component model of Charlot & Fall 2000), and a non-evolving metallicity. By randomly drawing the parameters from the prior distributions (see da Cunha et al. 2008), the resulting library consists of ≈5 × 10^4 templates (or models).

The ZCR fiducial method is based on surface brightness photometry at the g and i Sloan Digital Sky Survey (SDSS) optical bands, and one near-infrared (NIR) filter, such as J, H, or K. The method was extended to include the Spitzer Space Telescope Infrared Array Camera (IRAC) 3.6 μm band by Repetto et al. (2015). Other optical color combinations are possible, with the disadvantage of having more degeneracy in Τ_*, and thus more uncertain results (see, e.g., Bell & de Jong 2001; Repetto et al. 2015, their Figures 2 and 1, respectively). The templates from the SPS library are binned in colors (g − i) and (i − H), using a bin width of 0.05 magnitude (see Figure 1). The median mass-to-light ratio at the H band, Τ_H^B, is estimated for each bin. A look-up table can thus be constructed to compare with observed photometry on a pixel-by-pixel basis. The Τ_H^B is the effective mass-to-light ratio, i.e., refers to the light that reaches the observer, as opposed to the light that is emitted. The effective Τ_H^B may be affected by extinction (ZCR).

Earlier studies concerning pixel-by-pixel spatially resolved properties of galaxies can be found in Bothun (1986), Abraham et al. (1999), Conti et al. (2003), Eskridge et al. (2003), Kassin et al. (2003), Lanyon-Foster et al. (2007), and Welikala et al. (2008).

2.1. Application to M51. A Filamentary Mass Structure?

Here we present results obtained by applying the ZCR method to the spiral galaxy M51. We use g- and i-band imaging from the 12th data release (DR12) of the SDSS (Alam et al. 2015), as well as the K_s-band mosaic from Gonzalez & Graham (1996). The NIR images were obtained at Kitt Peak National Observatory, with the IR Imager (IRIM) camera on the 1.3 m telescope; the IRIM had a 256^2 NICMOS3 array with a 2'' pixel^-1 plate scale. The observations were performed during March 1994, in non-photometric conditions, and the exposures were resampled with sub-pixel accuracy before combining. The final K_s-band mosaic has 0.5 × 0.5 arcsec^2 pixels and a total exposure time of 22 minutes; it was photometrically calibrated with the Two Micron All Sky Survey (2MASS, Skrutskie et al. 2006). The SDSS frames were resampled to the resolution of the NIR data and registered with the K_s-band image. The registration was done with the IRAF (Tody 1993) tasks GEOMAP and REGISTRY. No point-spread function (PSF) match was done to the images, since the data have similar PSFs and the process can corrupt the noise properties (Zibetti et al. 2009). In Figure 2(a) (top-left panel), and 2(b) (top-right panel), we show the K_s-band and g-band final images, respectively. The foreground stars and background galaxies were removed and their pixels replaced with values from the background-subtracted “sky.” With the purpose of isolating the disk from the lower signal-to-noise ratio (S/N) background, the final mosaics were treated with the Adaptsmooth code of Zibetti (2009), as follows. A first run of Adaptsmooth was performed on the the K_s-band data (which have a lower S/N than the SDSS images), with the requirement of a minimum S/N per pixel of 20, a maximum smoothing radius of 10, and the assumption of background-dominated noise. In order to homogenize the lower limit of the S/N per pixel, the output smoothing K_s-band mask was then used as an input in subsequent runs of Adaptsmooth for the SDSS g and i bands.

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6 Throughout this work NIR magnitudes are Vega; SDSS magnitudes are in the AB magnitude system.

7 IRAF is distributed by the National Optical Astronomy Observatories, which are operated by the Association of Universities for Research in Astronomy, Inc., under cooperative agreement with the National Science Foundation.
The SPS library was obtained from the Multi-wavelength Analysis of Galaxy Physical Properties package (MAGPHYS-CB07 library, hereafter) by da Cunha et al. (2008). The absolute magnitudes of the Sun were taken from Blanton & Roweis (2007). We assume a distance to M51 of $9.9 \pm 0.7$ Mpc (Tikhonov et al. 2009) and correct the models for Galactic extinction (Schlafly & Finkbeiner 2011).

The resulting mass map is presented in Figure 2(c) (bottom-left panel). For comparison purposes we show in Figure 3 the $i$-band image. The color range covered by the observed photometry of M51 is shown as a 2D histogram in Figure 4. In the left panel we show the observed colors of the pixels after applying the Adaptsmooth procedure as described earlier. The right panel shows the observed colors of the same pixels without using the Adaptsmooth procedure. From the comparison of these plots we appreciate the advantage of increasing the S/N in the outskirts of the disk, otherwise the uncertainties in the fits would be quite large. In these figures we also demarcate the color range covered by 99% and 68% of the total templates in the MAGPHYS-CB07 library with a blue and a red contour, respectively. Most of the observed colors fall within the span of the SPS library. The plots are illustrative and do not reflect the observational uncertainties of the data.

One striking thing to note about the mass map (Figure 2(c)) is that it does not present a smooth spiral arm structure. There is a well-defined two-arm spiral pattern, but many filamentary
structures are also observed. In addition, a visual comparison of the mass structure with the optical $g$ band indicates that, presumably, most of the structure is coincident with the dust lanes, as inferred from optical extinction. This can be seen more easily in Figure 2(d) (bottom-right panel), where we show the $(g-K_s)$ image. To test the similarities between the mass map and the $(g-K_s)$ image quantitatively, we use cross-correlation techniques. The Pearson correlation coefficient is defined as

$$r = \frac{\sum_i \sum_j (f_{ij} - \bar{f})(g_{ij} - \bar{g})}{\sqrt{\sum_i \sum_j (f_{ij} - \bar{f})^2} \sqrt{\sum_i \sum_j (g_{ij} - \bar{g})^2}},$$  \hspace{1cm} (1)

where $f_{ij}$ is the intensity of the $i$th, $j$th pixel in the first image, $g_{ij}$ is the intensity of the $i$th, $j$th pixel in the second image, $\bar{f}$ is the mean intensity of the first image, and $\bar{g}$ is the mean intensity of the second image. The cross-correlation function, $(f*g)(\theta)$, is then obtained by rotating the first image with respect to the second one, while fixing the center of rotation at the center of the object (the nuclei of M51 in this case). We obtain $r(\theta)$ from Equation (1) by varying $\theta$ from $-180^\circ$ to $180^\circ$ in increments of 1\degree; we assume that the angle $\theta$ increases counterclockwise. All of the M51 data were deprojected assuming an inclination angle of 20\degree, and a position angle of 172\degree (Leroy et al. 2008).

The result of the cross-correlation between the output mass-map of the ZCR method and the intensity ratio in the $(g-K_s)$ image is shown in Figure 5. By “intensity ratio,” we mean the ratio between the intensity in the $g$-band image and the intensity in the $K_s$-band image. We use this ratio instead of the $(g-K_s)$ color because the latter scales logarithmically and cannot be compared with the mass distribution, which scales linearly. Note that we actually take the intensity ratio in the minus $(g-K_s)$ image; this is done with the purpose of getting positive values of $r$ (when using Equation (1)). Error bars were estimated with bootstrap methods (Bhavsar 1990; Lepage & Billard 1992). We replace each pixel separately with a random value, drawn from a Gaussian probability distribution, and for each $\theta$ recalculate Equation (1). We repeat this process a total of 30 times and calculate $\sigma_r$, the standard deviation of the resulting distribution.

There is clearly a peak in the cross-correlation function near $\theta = 0^\circ$, indicating a similarity between the structures. For comparison, we also show the cross-correlation between the intensity in the $K_s$-band image and the intensity ratio in the $(g-K_s)$ image. The absolute maximum in this case occurs around $\theta = -157.5^\circ \pm 0.8$ and marks the angular offset between the spiral arms in the $K_s$-band and the dust lanes in the $(g-K_s)$ image. This means that if we rotate the spiral arms in the $K_s$-band by $15^\circ$, clockwise, they will match the spatial location of the dust lanes.

As is well known, disk galaxies, when studied at different wavelengths, often show significant differences (e.g., Block & Wainscoat 1991; Block et al. 1994). Even if at NIR wavelengths, young stars and clusters can contribute

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**Figure 4.** 2D histograms of the observed $(g-i)$ and $(i-K_s)$ colors of M51’s pixels. The areas inside the blue and red dashed lines contain 99% and 68%, respectively, of the templates in the MAGPHYS-CB07 SPS library corrected for Galactic extinction. Left: after applying the Adaptsmooth procedure as described in the text. The maximum of log(number) occurs near $(i-K_s) \sim 2.29$ and $(g-i) \sim 0.85$. Right: without applying the Adaptsmooth procedure.

**Figure 5.** Cross-correlation functions $r(\theta)$ (see the text). Solid line: between the mass structure resulting from the ZCR method and the intensity ratio in the $(g-K_s)$ image. The absolute maximum is at $\theta = 0^\circ$, indicating similarity. Dashed line: between the intensity in the $K_s$-band image and the intensity ratio in the $(g-K_s)$ extinction map. The maximum occurs at $\theta \sim -15^\circ$ (marked by the vertical dotted line), and corresponds to the angular lag between the dust lanes and the stellar arms. The total height of each error bar is $2\sigma_r$. 
20%–30% to the total radiation in spiral arm regions (e.g., Rix & Rieke 1993; Gonzalez & Graham 1996; Rhoads 1998; James & Seigar 1999; Patsis et al. 2001; Grosbøl et al. 2006; Grosbøl & Dottori 2008), most of the light in the disk comes from evolved giant stars, and most of the mass is concentrated in low-mass main-sequence stars. Hence, any structures present in resolved stellar mass maps should resemble the NIR surface brightness morphology to a significant degree. This is not the case of the stellar mass map shown in Figure 2(c) (bottom-left panel), where we see filamentary structures not present in the \( K_s \) light distribution, Figure 2(a) (top-left panel).

We perform three other different and independent tests and compare the resulting stellar mass maps as described below.

1. We do not use the NIR band and instead rely only on the optical SDSS colors, e.g., \((u - i)\) and \((g - i)\), and on the mass-to-light ratio estimated in the \( i \)-band, \( \Upsilon_i \).

2. We remove the binning of the models and use the full \( 5 \times 10^4 \) templates of the MAGPHYS-CB07 library in the computations.

3. We use a new Monte Carlo SPS (optical-NIR) library taken from the Synthetic Spectral Atlas of Galaxies (SSAG; Magris et al. 2015). SSAG\(^9\) assumes random SFHs according to the Chen et al. (2012) prescription, which includes a burst and a truncation event. Dust is treated as in Charlot & Fall (2000), and metallicty is distributed between 0.02 \( Z_\odot \) and 2.5 \( Z_\odot \), with 95% galaxy templates having \( Z > 0.2 Z_\odot \). The adopted IMF is Chabrier. The library consists of \( 6.7 \times 10^4 \) templates (SSAG-BC03 library henceforth). The range in these models of the effective mass-to-light ratio in the \( K_s \) band, \( \Upsilon_{K_s} \), as determined by a \((g - i)\) versus \((i - K_s)\) color–color diagram, is shown in Figure 6, left panel. For comparison purposes we show the same diagram for the BC03 version of the MAGPHYS library (MAGPHYS-BC03) in the right panel. The MAGPHYS library extends to redder colors due to the different probability distribution functions used to model the optical depth in the \( V \) band, \( \tau_V \) (see Figure 7).

The filamentary structure and the spatial coincidence between mass and dust lanes prevail in all the tests. A similar result is obtained for other spiral galaxies as well and was

\(^9\) http://www.astro.ljmu.ac.uk/~asticabr/SSAG.html

### 2.2. The Level of Accuracy in Mass-to-light Ratio Estimates

Gallazzi & Bell (2009) thoroughly discuss the \( \Upsilon_i \) accuracy that can be achieved by comparing colors with predictions from

![Figure 6](image-url)

**Figure 6.** Left: decimal logarithm of the effective mass-to-light ratio at the \( K_s \)-band, \( \Upsilon_{K_s} \), derived from the \((g - i)\) vs. \((i - K_s)\) color–color diagram. The data are taken from the SSAG-BC03 Monte Carlo SPS library (Magris et al. 2015), corrected for Galactic extinction toward M51. SDSS \( g \) and \( i \) magnitudes are in the AB magnitude system, \( K_s \) magnitudes are Vega. The blue (red) dashed contour delimits 99% (68%) of the observed colors for M51 (see Figure 4, left panel). Right: analogous to the left panel, but for the MAGPHYS-BC03 Monte Carlo SPS library.

![Figure 7](image-url)

**Figure 7.** Probability distribution functions of the \( V \)-band optical depth of the dust seen by young stars, \( \tau_V \), used by the SSAG-BC03 (solid line) and the MAGPHYS (dashed line) Monte Carlo SPS libraries, respectively.
a large library of SFHs. Typical accuracies are on the order of 0.1–0.15 dex. A similar result is deduced by other authors (e.g., Bell & de Jong 2001; ZCR; Taylor et al. 2011). This level of accuracy is barely improved with spectroscopic data (Gallazzi & Bell 2009).

To better understand the impact of a limited $Y_e$ accuracy on the resolved mass maps of galaxies, we build a sample of mock galaxies drawn from the MAGPHYS-CB07 Monte Carlo SPS library. Each of the $\approx 5 \times 10^4$ templates is used as an individual object in our mock catalog. In order to simulate the photometric error, we add to each of the $g$, $i$, and $K_s$-band magnitudes in our mock galaxies a random noise component with a Gaussian distribution having $\sigma_{\text{mag}} = 0.02$ mag ($\approx 2\%$ intensity variation). We then try to fit the noisy $(g - i)$ and $(i - K_s)$ values of each simulated object with the noise-free $(g - i)$ and $(i - K_s)$ colors, via $\chi^2$ minimization. Afterwards, we compute

$$\Delta \log [Y_e^k] = \log [Y_e^k]\text{fit} - \log [Y_e^k]\text{true},$$

i.e., the ratio between the fitted $Y_e^k$ and the true value. The results of this test are shown in Figure 8\textsuperscript{10}, where we get a dispersion (standard deviation) $\sigma(\Delta \log [Y_e^k]) \sim 0.16$ dex, as expected. We carry out the same exercise for different $\sigma_{\text{mag}}$ values and obtain $\sigma(\Delta \log [Y_e^k])$ for each one. The results are shown in Figure 9, upper panel. There is a nearly linear decrease of $\sigma(\Delta \log [Y_e^k])$ with diminishing $\sigma_{\text{mag}}$ down to $0.005$. For lower values of $\sigma_{\text{mag}}$, the shape of the $\Delta \log [Y_e^k]$ distribution abruptly begins to change, from nearly Gaussian with kurtosis $\sim 3$, going through Laplace distributions, and finally tending to a Dirac delta function with kurtosis $\rightarrow \infty$. This effect can be appreciated in the lower panel of Figure 9, where we plot the excess kurtosis\textsuperscript{11} of $\Delta \log [Y_e^k]$ versus $\sigma_{\text{mag}}$.

As $\sigma_{\text{mag}}$ tends to zero, the dispersion, $\sigma(\Delta \log [Y_e^k])$, also tends to zero. A (hypothetical) value of $\sigma(\Delta \log [Y_e^k]) = 0$ would indicate that our adjusted values are equal to the true values (the noise-free models). We can infer that it is not feasible to get accurate $Y_e$ values unless the intrinsic errors of the observations are diminished to zero, i.e., $\sigma_{\text{mag}} \rightarrow 0$. Typical photometric calibration errors are on the order of $1\%$–$2\%$ for the SDSS (Padmanabhan et al. 2008) and other photometric surveys. Additionally, the degeneracies between the different SPS model parameters (e.g., age–metallicity–reddening) will prevail even when $\sigma_{\text{mag}} \rightarrow 0$.

Taking all of this into account, we can conclude that the features in resolved mass maps, acquired from a simple $\chi^2$ minimization, will be discrepant from the structures of NIR surface brightness maps, owing to a limited $Y_e$ accuracy. In this manner, the fit we can obtain for some observed colors will result in a $Y_e$ value near the statistical mode of similar colors in the SPS library (see also the discussion in Taylor et al. 2011), and within 0.1–0.15 dex of the true value. Even for the same SPS library, the “recovered” $Y_e$ will depend on the colors used in the fit.

3. BAYESIAN INFERENCE AIMED AT AN OBJECT

In this section we introduce the Bayesian successive priors (BSP) algorithm, aimed at an individual object, in order to solve for the mass map avoiding the bias in the spatial structure. The idea is to use the previous information regarding

\textsuperscript{10} Gallazzi & Bell (2009) obtained a similar plot in spite of neglecting dust corrections, which indicates that dust is not a decisive factor for $Y_e$ accuracy.

\textsuperscript{11} Excess kurtosis is measured with respect to the kurtosis of any univariate normal distribution, which equals three. Therefore, excess kurtosis equals kurtosis minus three.
the stellar surface mass density as deduced from the NIR bands. The massive older population of a galaxy is mainly traced in the NIR bands, specially the K band (Rix & Rieke 1993). Having established this, we can adopt the NIR surface brightness distribution as a Bayesian prior in order to infer the “true” stellar surface mass density. In this work, we will use the term “prior” in reference to the prior probability distribution function. The Bayesian prior is then directed to a particular galaxy and not to the entire galaxy population.

3.1. Bayes’ Theorem

Bayesian probability posits that the best outcome of any event is found by calculating the probabilities of the various hypotheses involved, using the rules of probability theory (e.g., Loredo 1992, 1995).

The ZCR approach uses a method similar to a Bayesian maximum-likelihood estimate by including a uniform (or flat) prior in the fits to the observed colors, regardless of the SPS library. In this work, a significant improvement is made in the calculation of the stellar mass maps by introducing a Bayesian method with an informative non-uniform prior. Applications of Bayesian inference with non-uniform priors have been used in, e.g., Benítez (2000) for cosmological redshift estimates, Rovilos et al. (2014) for AGN sources analysis, and Schönrich & Bergemann (2014) for the determination of stellar parameters.

In our case, Bayes’ theorem for the most probable stellar mass-to-light ratio $\Theta_1$ is given by

$$P(\Theta_1|C) = \frac{P(C|\Theta_1)P(\Theta_1)}{P(C)},$$

where $P(\Theta_1|C)$ is the posterior probability, i.e., the probability of having $\Theta_1$ for a certain stellar population if colors C are observed. $P(C|\Theta_1)$ is the likelihood function (or the probability of observing colors C given the set of parameters $\Theta_1$):

$$P(C|\Theta_1) \propto \frac{1}{\sqrt{2\pi}} \exp\left(-\frac{\chi^2}{2}\right),$$

$$\chi^2 = \sum_{i=1}^{N_{\text{colors}}} \left(\frac{C_{n_{\text{obs}}} - C_{n_{\text{template}}}}{\sigma_{\text{col}}}\right)^2,$$

where $C_{n_{\text{obs}}}$ is the observed $n_{\text{th}}$ color with $\sigma_{\text{col}}$ photometric error and $C_{n_{\text{template}}}$ is the color from a certain template in our SPS library. In our case, $N_{\text{colors}} = 2$, for instance, $(g - i)$ and $(i - K_s)$, hence $n = 1, 2$.

$P(\Theta_1)$ represents the previous knowledge that we may have about the likely value of the $\Theta_1$ parameter and

$$P(C) = \sum_{j=1}^{N_{\text{templates}}} P(C|\Theta_1)P(\Theta_1),$$

is a normalization constant, also called the Bayesian evidence (Savage & Oliver 2007). $N_{\text{templates}}$ stands for the number of templates in our SPS library.

3.2. The BSP Algorithm

3.2.1. The Prior Probability Distribution Function

In order to apply the BSP algorithm, we have chosen a prior probability distribution function, $P(\Theta_1)$, of the form

$$P(\Theta_1) = \exp\left(-\frac{1}{2} \left(\frac{\Theta_1 - \Theta_1^*}{\sigma_{\Theta_1}}\right)^2\right),$$

where

$$\sigma_{\Theta_1} = \left[\ln(10)\right] \sigma_{\text{mag}} Y_{\text{prior}}.$$

Here, $\sigma_{\text{mag}}$ is the photometric error for a certain passband, which is related to $\sigma_{\text{col}}$ in Equation (5) through $\sqrt{2} \sigma_{\text{mag}} = \sigma_{\text{col}}$.

Each template in the SPS library corresponds to a single $\Theta_1$. Using Equation (7) and Bayes’ theorem (Equation (3)), we can effectively marginalize the templates from our SPS library, as we will demonstrate in the following sections.

3.2.2. Description of the BSP Algorithm

The BSP algorithm consists of three iterations that are described below. The algorithm is intended to work with an SPS library and surface photometry in several/variables bands. In the following we assume that these are the optical g and i bands, and the NIR $K_s$ filter. For the library, we use SSAG-BC03 (although the algorithm is designed to work independently of the choice of SPS library). The mass-to-light ratio is taken in the $K_s$ band, $\Theta_1^{K_s}$. Other waveband combinations will be discussed later. The algorithm is applied on a pixel-by-pixel basis, although in each iteration all pixels are addressed before moving to the next iteration.

1. In the first iteration, we use a uniform prior, i.e., $P(\Theta_1) = \text{constant}$, and apply Equation (3). We then calculate the absolute maximum (which should be near the median) of the posterior probability distribution function $P(C|\Theta_1)$ and the 16th and 84th percentiles to account for the corresponding error map. We estimate the percentiles by progressively integrating the area under the posterior probability curve until we accumulate an area of 0.16 and 0.84 (being the total area equal to 1), for the 16th and 84th percentiles, respectively.

Up to this point the method provides a maximum-likelihood estimate and is similar to the ZCR algorithm, with the only difference being that the templates are not binned in our case. We call the unbinned version of the ZCR algorithm ZCRt from now on. We then use the results of this step for two purposes. First, we identify all of the pixels for which the difference (absolute value) between their observed color and the fitted template in the SPS library is smaller than $3\sigma_{\text{col}}$, i.e.,

$$|\Delta C_n| = |C_{n_{\text{obs}}} - C_{n_{\text{template}}}| < 3\sigma_{\text{col}},$$

for $n = 1, 2$. The pixels that do not fulfill the $3\sigma_{\text{col}}$ condition are isolated and flagged. This step guarantees that we keep only pixels that can be described by our SPS

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12 These values are equivalent to $-1\sigma$ and $1\sigma$, respectively, in a normal distribution.

13 These include elements recording emission from AGN activity.
library. Next, we take the resulting $Y_{s}^{K}$ values for all the kept pixels and calculate the statistical median.\textsuperscript{14}

2. In the second iteration, this median value of $Y_{s}^{K}$, from iteration number 1, is used as a constant parameter in Equation (7), i.e.,

$$Y_{s}^{\text{prior}} = \text{constant}$$

(10) for all pixels in the disk.\textsuperscript{15} The prior, $P(T_{s})$, is not uniform in this case and adopts the functional form of Equation (7). Now we compute the maximum in $P(T_{s}^{K}|C)$, and the respective 16th and 84th percentiles. Similarly to iteration number 1, we identify all of the pixels where the difference between the observed colors and the fitted library templates is smaller than $\alpha \sigma_{p}$, i.e.,

$$|\Delta C_{n}| < \alpha \sigma_{p},$$

(11) for $n = 1, 2$. The value of $\sigma_{p}$ is determined from the resulting $\Delta C_{n}$ (no absolute value) pixel distribution by calculating its 16th and 84th percentiles, $P_{16}$ and $P_{84}$, respectively, and then using

$$\sigma_{p} = (P_{84} - P_{16})/2,$$

(12) for each color. After some tests (see Appendix A), we found that $\alpha = 1.0$ is an adequate value that allows us to isolate the pixels that deviate significantly from $\Delta C_{n} \sim 0$. In a hypothetical case, having $\Delta C_{n} = 0$ would indicate that our observed colors match perfectly the fitted library templates. The $|\Delta C_{n}| < \alpha \sigma_{p}$ pixels will be the “backbone” of our mass map and represent the locations in the disk where the $K_s$ band is a reliable tracer of the stellar mass surface density, considering the $Y_{s}^{\text{prior}} = \text{constant}$ condition. The $|\Delta C_{n}| > \alpha \sigma_{p}$ pixels belong mainly to luminous red stars in the asymptotic giant branch, red supergiants, low-surface brightness regions in the outskirts of the disk, and high-extinction regions where $Y_{s}^{K}$ does not have the constant (median) value we assumed earlier. We then need to provide a new $T_{s}^{K}$ value for these $|\Delta C_{n}| > \alpha \sigma_{p}$ pixels. For this purpose we use the information from the “backbone” pixels. We interpolate the stellar mass surface density to fill the places where we need a new $T_{s}^{K}$ value. The interpolation is done in the $0^\circ$, $45^\circ$, $90^\circ$, and $135^\circ$ directions and then an average is taken. After the interpolation, we visually inspect the resulting maps to determine whether a minor smoothing is needed. The smoothing is only applied to the $|\Delta C_{n}| > \alpha \sigma_{p}$ pixels and is performed by replacing each pixel value with the average of the neighboring pixels. There are other interpolation techniques that could be used (see, e.g., Gumus & Sen 2013), but for the present work we will apply the above-mentioned procedure to all objects. Having established this, the new $T_{s}^{K}$ values are estimated as the ratio of the interpolated mass map and the observed $K_s$ photometry.

3. The third and last iteration is intended to deal only with the $|\Delta C_{n}| > \alpha \sigma_{p}$ pixels, identified in iteration number 2. For each pixel, we use the $T_{s}^{K}$ value also estimated in iteration number 2 to represent $Y_{s}^{\text{prior}}$ in Equation (7) and calculate the absolute maximum of the posterior probability distribution in Equation (3). Before this, we may also update the uncertainty in $Y_{s}$, in Equation (7); such uncertainty now reads

$$\sigma_{Y_{s}} = \sqrt{\left(\frac{\ln(10)}{2.5}\sigma_{\text{mag}} Y_{s}^{\text{prior}}\right)^{2} + \beta^{2}},$$

(13) where $\beta$ accounts for the propagation of uncertainties arising from the previous iteration (e.g., the mass surface density interpolation from neighboring pixels). Using bootstrap methods we have estimated that $\beta \approx 0.6\%$.

From the resulting $T_{s}^{K}$ map we then obtain the stellar mass surface density to complete our mass map.

As an optional last step, the flagged pixels from iteration number 1 that belong to the inner disk can be interpolated in mass with the information about the surrounding pixels provided by all three iterations. For the external disk pixels, the interpolation is more uncertain.

We find that adding more iterations does not lead to any further improvement in the mass maps. The flowchart of the BSP algorithm is shown in Figure 10.

For the BSP algorithm to work properly, the requirement of NIR data with high S/N is essential; otherwise, any noisy and patchy features will be transferred to the mass map. A minimum S/N of $\sim 10$–20 in the outskirts of the disk is necessary. This level can be achieved with techniques as the one used by the Adaptsmooth code, or alternatively with Voronoi two-dimensional binning (Cappellari & Copin 2003).

In this investigation we have adopted only two colors, $(g - i)$ and $(i - K_s)$, and thus $N_{\text{colors}} = 2$. The benefits of using the $g$ and $i$ SDSS data together with one NIR band are an excellent spatial resolution per element (pixel) and extensive spatial coverage (of the entire object). Nevertheless, the BSP algorithm can also be applied using $N_{\text{colors}} > 2$, with the only requirement of the inclusion of one NIR band as described earlier. In a future publication we will explore the use of the algorithm to fit optical IFU observations, for instance, the Calar Alto Legacy Integral Field Area survey (CALIFA, Sánchez et al. 2012) and the Mapping Nearby Galaxies at Apache Point Observatory survey (MaNGA, Bundy et al. 2015).

4. APPLICATION OF BSP TO M51

We apply the BSP algorithm to M51 employing the same data described in Section 2.1. We calculate $\sigma_{\text{mag}}$ on a pixel-by-pixel basis assuming that

$$\sigma_{\text{mag}} \approx \sqrt{\sigma_{\text{flux}}^{2} + \sigma_{\text{calib}}^{2}},$$

(14) where $\sigma_{\text{flux}}$ is the random error in the flux per pixel, which we assume to be dominated by the uncertainty in the background (see also Mentuch Cooper et al. 2012), and $\sigma_{\text{calib}}$ is the calibration uncertainty, or zero-point error, for which we assume $\sigma_{\text{calib}} \sim 0.01$ mag for the SDSS images and $\sigma_{\text{calib}} \sim 0.03$ mag for the $K_s$ image (Jarrett et al. 2003). We compute $\sigma_{\text{flux}}$ in mag using $\sigma_{\text{flux}} = 1.085736 \times \sigma_{\text{flux}}$, where $\sigma_{\text{flux}}$ is the standard deviation in the background (in a sky-subtracted image). We compute $\sigma_{\text{back}}$ by sampling the background statistics in different boxes near the edges of the images. To account for the use of the Adaptsmooth procedure we divide $\sigma_{\text{back}}$ by $\sqrt{n_{\text{pix}}}$, where $n_{\text{pix}}$ is the number

\textsuperscript{14} The number separating the lower and higher value halves of $Y_{s}^{K}$.

\textsuperscript{15} A refinement of the method could be achieved by separating the bulge from the disk of the corresponding galaxy and treating them as objects with different median $Y_{s}^{K}$ (Portinari et al. 2004).
of pixels used to increase the S/N of the corresponding pixel by Adaptsmooth.

Without taking into account correlation between bands, we compute \( \alpha_{\text{col}} \) by summing in quadrature the \( \alpha_{\text{mag}} \) values of each band involved in the color determination.

In Figures 11 and 12, we show the results of adopting the SSAG-BC03 and MAGPHYS-CB07 libraries, respectively. In both figures, the top-left panels (a) show the mask obtained after iteration number 1. White regions represent the pixels where the observed colors are within 3\( \sigma \) of at least one SPS-library template (see Figures 4 or 6). In the respective top-right panels (b), we show the masks obtained after iteration number 2. For these masks, the gray regions represent the pixels where the color difference (absolute value) between the models and the observations, \( |\Delta C_{\text{col}}| \), is greater than \( \alpha \sigma_{\text{col}} \), with \( \alpha = 1 \) (see Section 3.2 and Appendix A), assuming a constant \( \gamma_{\text{prior}}^{*} \). These regions will be interpolated in mass with the information of neighboring pixels. We can also appreciate that the SSAG-BC03 library does a better job at modeling the outskirts of the disk than the MAGPHYS-CB07 library. To investigate the cause of this behavior we obtain a mass map using MAGPHYS-BC03. We obtain very similar masks to those from the SSAG-BC03 library (Figure 11, top panels). With this in mind, most of the differences between BC03 and CB07 mass maps in our results are mainly due to the distinct treatments of the TP-AGB stage. To a lesser extent, we also note an improvement when SSAG-BC03 is used instead of MAGPHYS-BC03. We attribute this to the fact that SSAG covers a wider range of possible SFHs.

In the bottom-left panels (c) of Figures 11 and 12, we show the resulting stellar mass surface density map after iteration number 3. The filamentary structure is no longer present and the maps show greater resemblance to the features in NIR bands, as expected. Finally, the bottom-right panels (d) of both figures show the “residuals”; these are the result of subtracting the final output (iteration 3) mass map using BSP, from a mass map that assumes a constant \( \gamma_{\text{ext}}^{*} \) (the median \( \gamma_{\text{ext}} \) after iteration number 1). The dark (white) regions represent positive (negative) mass differences, i.e., where \( \gamma_{\text{ext}} \) has been overestimated (underestimated). For example, the \( \gamma_{\text{ext}} \) may be overestimated when young luminous red stars are mixed with older populations, and underestimated due to extinction in the NIR bands. This is different from the “outshining bias” (Maraston et al. 2010; Sorba & Sawicki 2015), where the light from young stars eclipses the old population and the amount of stellar mass is underestimated. In our case we overestimate the mass (using a constant \( \gamma_{\text{ext}}^{*} \)) because we are assuming, mistakenly but for convenience, that all the light comes from old stars.

### 4.1. Isolating the Old Massive Disk

We now discuss in more detail the positive mass differences in the residuals. In Figure 13 we plot a 2D histogram of the colors of the pixels for which the mass difference is \( > 2 \times 10^{4} M_{\odot} \). This cut in the mass was chosen in order to isolate most of the positive residuals near the spiral arms. We have excluded the pixels from the bulge region. We note that most points gather in a group with a maximum near \((i - K_{s}) \sim 2.4 \) and \((g - i) \sim 0.4 \). Their \((g - i) \) color is relatively blue when compared with all the colors observed (delimited by the blue dashed contour). We also note a cluster of points with redder colors, near \((i - K_{s}) \sim 2.5 \) and \((g - i) \sim 1.3 \). These pixels mainly correspond to point sources outside the spiral arms.

In Figure 14 we show the marginalized probability distributions (see Appendix B) for the \( r \)-band light-weighted age and for \( \gamma_{\text{ext}}^{*} \), obtained for M51 using the MAGPHYS-CB07 library. The dash–dotted green line corresponds to the previously described “positive mass differences” in the residuals, while the blue solid line refers to the whole disk, both results after BSP. Interestingly, the excess mass regions are younger (age \( \sim 1 \) Gyr) and have a lower \( \gamma_{\text{ext}}^{*} \) (by 30\%) than most of the pixels in the disk. Together with the bluer \((g - i) \) color, the above characteristics indicate that these regions contain relatively young stars that mix with the old stellar population in star forming regions. These were effectively isolated by BSP!

The red dashed line in Figure 14 shows the probability distributions for the whole disk after applying the ZCR'
approach. The light-weighted age yields a larger fraction of younger pixels with $ZCR'$. As expected from our previous assumptions, the values of $\Gamma^K_s$ are more narrowly confined with BSP, around $\Gamma^K_s = 0.2450 \pm 0.0242$. This value is dominated by red giant branch stars.

Regarding the output SSAG-BC03 estimates of $\Gamma^K_s$ for the whole disk, we recover a median $\Gamma^K_s = 0.4232$ after BSP iteration number 1. After iteration number 3 the mean value for the entire disk is $\Gamma^K_s = 0.4247 \pm 0.0386$. For the $|\Delta C_o| < \alpha \sigma_P$ pixels we have $\Gamma^K_s = 0.4231 \pm 0.0034$, while for the $|\Delta C_o| > \alpha \sigma_P$ pixels we obtain $\Gamma^K_s = 0.4264 \pm 0.0556$, both results after BSP.

Our estimation for $\Gamma^K_s$, derived with MAGPHYS-CB07 and SSAG-BC03, are consistent (within 3.0$\sigma$) with the result derived by Just et al. (2015) for the solar cylinder from star counts ($\Gamma^K_s = 0.34$) and with the average found by Martinsson et al. (2013) for a sample of 30 disk galaxies ($\Gamma^K_s = 0.31$).

4.2. Integrated Mass Estimates

With respect to the total resolved mass, defined as

$$M^{\text{resolved}}_s = \sum_j \sum_i M_{sij},$$

(15)

where $M_{sij}$ is the stellar mass of the $i$th, $j$th pixel, we find the following results. Using the MAGPHYS-CB07 library we obtain for M51 a total stellar mass of $M^{\text{resolved}}_s = 3.84 \times 10^{10} M_\odot$ with ZCR' and $M^{\text{resolved}}_s = 3.22 \times 10^{10} M_\odot$ with BSP. The SSAG-BC03 library, meanwhile, leads to $M^{\text{resolved}}_s = 6.43 \times 10^{10} M_\odot$ with ZCR' and $M^{\text{resolved}}_s = 5.56 \times 10^{10} M_\odot$ with BSP. The discrepancy between the SSAG-BC03 and MAGPHYS-CB07 mass estimates is mainly due to the different treatments of the TP-AGB phase (Bruzual 2007). In Figure 15, we show the azimuthally averaged surface mass

![Figure 11. Application of the BSP algorithm to the spiral galaxy M51. The Monte Carlo SPS library used is SSAG-BC03. Top left: resulting mask after iteration number 1. White regions have observed colors within 3$\sigma$ of at least one template in the library. Top right: resulting mask after iteration number 2. Gray regions represent pixels where the assumption of a constant $\Gamma^K_s$ for the whole disk is not fulfilled by the observed colors. Bottom left: resulting mass map after iteration number 3. Bottom right: residuals after subtracting the mass map obtained at the end of the BSP algorithm (iteration 3), from a mass map that assumes a constant $\Gamma^K_s$ (the median after iteration 1). Dark (white) regions represent positive (negative) mass differences.](image-url)
density versus radius for M51 obtained with SSAG-BC03. For most of the disk, the BSP method yields smaller mass estimates than ZCR', resulting in a ~10% decrease in the total mass. To complement the analysis, we show the $\Upsilon_*$ maps obtained with the ZCR' method and the BSP algorithm in Figures 16(a) and (b) (top-left and top-right panels), respectively. Figures 16(c) and (d) (bottom-left and bottom-right panels) present the $\Upsilon_*$ maps from ZCR' and BSP, respectively. Figure 17 shows the azimuthally averaged $\Upsilon_*$ for the $g$, $i$, and $K_s$ bands as a function of radius. As expected, the $K_s$ profile is virtually constant, while the $g$ and $i$ profiles show variations with radius, with lower values at the outskirts of the disk as a result of a lower surface brightness and bluer colors (de Jong 1996; Bell & de Jong 2001).

In Figure 18, we show the azimuthally averaged stellar metallicity, $Z/Z_\odot$; similar results are obtained for both BSP and ZCR'. In this figure we also plot the metallicity abundance gradients for M51 from Moustakas et al. (2010). From ancillary data, Moustakas et al. (2010) estimated radial oxygen abundance gradients for 75 galaxies in the Spitzer Infrared Nearby Galaxies Survey (SINGS, Kennicutt et al. 2003), using both the Kobulnicky & Kewley (2004; KK04) and the Pilyugin & Thuan (2005; PT05) calibrations. We transform Moustakas et al. (2010) oxygen abundance gradients in units of $12 + \log(O/H)$ to units of $Z/Z_\odot$, adopting (e.g., Martínez-García et al. 2009)

$$\log(Z/Z_\odot) \simeq 3.12 + \log(O/H).$$

The stellar metallicity we recover with SSAG-BC03 falls between the two curves of Moustakas et al. (2010). Mentuch Cooper et al. (2012) obtained a similar result for the Whirlpool galaxy from optical and infrared photometry.

### 4.3. Other Filter Combinations

In this section we discuss the application of the BSP algorithm with other filter combinations. Using only optical filters, e.g., the $(g-i)$ color and $\Upsilon_*$, the method is not able to recover a spatial structure consistent with the one obtained with optical-NIR combinations. This is due to the fact that the information of the prior spatial structure is missing as it can only be provided by the NIR bands. The $\Upsilon_*$ cannot be assumed to be constant through the entire disk (see Figure 17); besides, dust lanes can still be noticed near spiral arms, even at the redder optical wavelengths (see Figure 3).
is more degenerate at 8 band. We used the colors $m_{\text{band16}}$, the BSP result indicates that the issues we encounter when trying to fit the $u$-band SDSS data with our methods are mainly due to their low S/N. This shortcoming can be remedied with deeper data. We should also note that $m_s$ is more degenerate at shorter wavelengths.

We also applied the BSP algorithm including the Spitzer-IRAC 3.6 μm band. We used the colors $(g-i)$ and $(i-K_s)$ and the $m_{3.6 \mu m}$. We computed pixel-by-pixel $\sigma_{\text{mag}}$ errors as in Section 4, assuming $\sigma_{\text{calib}} \sim 0.01$ mag for the SDSS images and $\sigma_{\text{calib}} \sim 0.03$ mag for the 3.6 μm band (Reach et al. 2005). We corrected for Galactic extinction as in Schlafly & Finkbeiner (2011) and Chapman et al. (2009). The results with the MAGPHYS-BC03 library are shown in Figure 19. We note that the residuals, i.e., the difference between a mass map that assumes a constant $m_{3.6 \mu m}$ and the output mass map from BSP (Figure 19(d), bottom-right panel) are significantly different from the ones obtained when using the $K_s$ band (see Figures 11(d) and 12(d), bottom-right panels). We attribute this to polycyclic aromatic hydrocarbons and continuum dust emission at 3.6 μm. To corroborate this, we compare our result to the one derived through the Independent Component Analysis (ICA) method of Meidt et al. (2012, 2014). This method separates the stellar emission from the dust emission; Querejeta et al. (2015) applied it to the Spitzer Survey of Stellar Structure in Galaxies (S’G, Sheth et al. 2010). We compare quantitatively the residuals from BSP with the non-stellar (dust) component from ICA for M51 by following the same cross-correlation procedure as in Section 2.1 (Equation (1)). The results of this test are shown in Figure 20. We find that there is a strong spatial correlation between the ICA dust component and the BSP residuals, indicated by the sharp peak at $\theta = 0$ in Figure 20. We also compare the BSP residuals to the stellar component obtained by ICA and find no spatial correlation at $\theta = 0$. Although our adopted SPS library does not include the emission from dust in the 3.6 μm band. The BSP algorithm was able to isolate much of it, together with that of red luminous young stars.

A discussion of the differences between ICA and BSP would require further analysis and comparisons using a larger sample of galaxies. This goes beyond the scope of the present work and will be investigated in a future publication.

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16 In principle, the emission from dust could be included because it is predicted by MAGPHYS. Nevertheless, the number of templates increases from $5 \times 10^3$ to $\sim 6.67 \times 10^3$ and CPU time would be $\sim 1 \times 10^3$ times larger.
Figure 16. $\gamma_g$ maps for M51 with the SSAG-BC03 library. Top left: $\gamma_g^i$, obtained with ZCR$'$ method. Top right: $\gamma_g^i$ with BSP algorithm. Bottom left: $\gamma_{Ks}^i$, ZCR$'$ method. Bottom right: $\gamma_{Ks}^i$, BSP algorithm. Darker pixels indicate higher $\gamma_g$.

Figure 17. Azimuthally averaged $\gamma$, as a function of radius, $R$ (kpc). Solid lines: BSP; dashed lines: ZCR$'$. Dark blue: $g$ band; green: $i$ band; dark red: $K_s$ band. Results are for deprojected maps of M51 with the SSAG-BC03 library.

Figure 18. Azimuthally averaged stellar metallicity, $Z/Z_\odot$. Blue solid line: BSP; red dashed line: ZCR$'$. Results are for deprojected maps of M51 with the SSAG-BC03 library. For comparison we show the metallicity abundance gradients of Moustakas et al. (2010), using the KK04 (black dashed line) and PT05 (black dotted line) calibrations.
5. PILOT TEST WITH OTHER GALAXIES

In order to better understand the differences between using the BSP algorithm of Section 3.2 and adopting the ZCR\textsuperscript{′} method (i.e., a maximum-likelihood estimate) to obtain resolved maps of stellar mass, we analyzed 90 objects with $H$-band imaging from the Ohio State University Bright Spiral Galaxy Survey (OSUBSGS, Eskridge et al. 2002). The main statistical results from this sample should hold for other surveys, such as SINGS and S\textsuperscript{4}G. Our sample comprises all objects in the OSUBSGS for which SDSS $g$ and $i$ data are available (see Table 1). A bar chart of the Hubble types of our OSUBSGS sample is shown in Figure 21. We subtracted the $H$-band data “sky offset” (see also Kassin et al. 2006) with either a constant or a plane, depending on the object, and then calibrated the resulting frames with 2MASS. We took optical $g$- and $i$-band frames from the eighth release (DR8) of SDSS (Aihara et al. 2011) and mosaicked them with the SWarp software (Bertin 2010). SDSS mosaics were registered and resampled to the (lower resolution) $H$-band data with the aid of foreground stars. All foreground stars and background objects were then removed and replaced with random values from the background. The Adaptsmooth code was then used to increase the $S/N$ at the outskirts of the disk, while maintaining the relatively higher $S/N$ for the inner disk pixels. We adopt a minimum $S/N$ per pixel of 10 and a maximum smoothing radius of 10.

Together with the OSUBSGS sample, we also analyzed M51b (companion of M51, aka NGC 5195) using the same data presented in Section 4.

5.1. Mass-map Results

We adopt the SSAG-BC03 SPS library for all mass estimates for this sample. For simplicity we assume that $\sigma_{\text{mag}} \sim 0.02$ mag for every band and pixel. The shortcoming of using a constant $\sigma_{\text{mag}}$ (and consequently a constant $\sigma_{\text{col}}$) for every band and pixel is that some of the fitted values could give slightly ($\sim 0.3\%$ for individual pixels) different results when compared to the case where individual errors are computed for every pixel. The reason for this is the use of Equation (4) together with Equation (5). In our case, we adopt two colors, hence Equation (4) can be seen as the product of two Gaussian functions (one for each color). In the case where $\sigma_{\text{col}}$ differs for

Figure 19. Application of BSP algorithm to M51 with $(g - i)$, $(i - 3.6 \mu m)$, $\Upsilon_3^{1.6 \mu m}$, and the MAGPHYS-BC03 SPS library. Panels organized as in Figures 11 and 12.
Thus, potential biases are introduced when the same $\Upsilon_*$ is used for a sample of galaxies with different Hubble types.

The total resolved stellar masses, $M_{k\text{resolved}}$ (Equation (15)), obtained, respectively, with the BSP algorithm, $M_{k\text{BSP}}$, and with the ZCR' approach, $M_{k\text{ZCR'}}$, are given in Table 1. In Figure 24 we display the behavior of the ratio $M_{k\text{BSP}}/M_{k\text{ZCR'}}$ versus $M_{k\text{BSP}}$. From these data we find that BSP mass estimates are on average $\approx 10\%$ lower than those derived from ZCR', similarly to the M51 result. We also investigate possible trends of the ratio $M_{k\text{BSP}}/M_{k\text{ZCR'}}$ with Hubble type; with the ratio of major to minor galaxy axes $a/b$; with star formation rate, $\Psi$; and with V-band optical depth, $\tau_V$. We find no strong or moderate correlations with these parameters, except for the star formation rate, having $r_{\psi} = -0.061$ for Hubble type, $r_{\psi} = -0.297$ for galaxy axial ratio (excluding the edge-on object NGC 7814), and $r_{\tau_V} = 0.082$ for the median $\tau_V$ for the entire disk, obtained via BSP. We computed the star formation rate averaged over the last 10$^9$ yr from the parameters of the fitted templates as

$$\langle \psi \rangle = \frac{\int_{t_{\text{last}}}^{t} \Psi(t') dt'}{t_{\text{last}}},$$  

(17)

where time $t$ corresponds to the current $\psi$ and $t_{\text{last}} = 10^8$ yr.

We calculate $\langle \psi \rangle$ on a pixel-by-pixel basis and then sum over all pixels (in the same way as the resolved mass estimate). We also estimate the specific star formation rate averaged over the last 10$^9$ yr:

$$\langle \psi \rangle_S = \frac{\int_{t_{\text{last}}}^{t} \Psi(t') dt'}{t_{\text{last}}} \approx \langle \psi \rangle M_{k\text{res}}^{-1},$$  

(18)

where $M_k$ is the current stellar mass. In this manner we obtain the resolved $\langle \psi \rangle$ and $\langle \psi \rangle_S$ for the corresponding object. In Figure 25 we show the ratio $M_{k\text{BSP}}/M_{k\text{ZCR'}}$ versus the resolved $\langle \psi \rangle_S$ for the whole disk. The correlation coefficient is $r_{\psi} = -0.335$ indicating a weak inverse correlation. In the case of the resolved $\langle \psi \rangle$ we obtain a correlation coefficient of $r_{\psi} = -0.240$. These results suggest that the bias in the resolved mass values $M_{k\text{ZCR'}}$, when compared to $M_{k\text{BSP}}$, is weakly related to the star formation rate over the disk.

For completeness, we show in Figure 26 the resolved galaxy “main sequence” of star formation (see, e.g., Daddi et al. 2007; Elbaz et al. 2007; Noeske et al. 2007; Salim et al. 2007), i.e., the relationship between resolved $\langle \psi \rangle$ and $M_{k\text{resolved}}$. We find that this correlation is stronger with BSP ($r_{\psi} = 0.853$) when compared to ZCR’ ($r_{\psi} = 0.797$).

5.2. Comparison with Unresolved Mass Estimates

We also obtain for each object an unresolved mass estimate, $M_{k\text{unresolved}}$. To this end, we fit the global $(g - i)$ and $(i - H)$ colors of the object to all templates and get the optimum one via Equation (4). Global magnitudes are calculated by summing the intensities of all the pixels:

$$m_{\text{glob}} = -2.5 \log_{10} \sum_j \sum_i f_{ij} + zp,$$

(19)

where $f_{ij}$ is the intensity of the $i$th, $j$th pixel at a certain band and $zp$ is the appropriate zero-point. The same number of pixels is used in all mass estimates for the same object.
| Name        | RC3 Type      | T-type | Dist (Mpc) | $T_{\text{eff}}$ | $M_*^{\text{SSP}}$ ($M_\odot$) | $M_*^{\text{ZRC}}$ ($M_\odot$) | $M_*^{\text{unresolved}}$ ($M_\odot$) |
|-------------|---------------|--------|------------|------------------|---------------------------------|---------------------------------|------------------------------------------|
| M51         | SA(s)bc pec   | 4.0    | 9.9$^a$ ± 0.7 | 0.42 ($K_s$) | 5.56 × 10$^{10}$ | 6.43 × 10$^{10}$ | (9.02 ± 3.00) × 10$^{10}$ |
| M51b        | I0 pec        | 90.0   | 9.9$^a$ ± 0.7 | 0.97 ($K_s$) | 2.96 × 10$^{10}$ | 4.66 × 10$^{10}$ | (3.26 ± 0.22) × 10$^{10}$ |
| NGC 155     | SAB(s)bc      | 4.0    | 22.6 ± 1.6  | 0.58             | 4.52 × 10$^{10}$ | 4.92 × 10$^{10}$ | (3.96 ± 0.85) × 10$^{10}$ |
| NGC 428     | SAB(m)        | 9.0    | 15.9 ± 1.1  | 0.40             | 3.71 × 10$^{9}$  | 4.28 × 10$^{9}$  | (3.80 ± 0.61) × 10$^{9}$  |
| NGC 488     | SA(rs)b       | 3.0    | 30.4 ± 2.1  | 1.04             | 2.61 × 10$^{11}$ | 2.60 × 10$^{11}$ | (3.19 ± 0.87) × 10$^{11}$ |
We compare in Figure 27 $M^\text{resolved}_* \sim M^\text{unresolved}_*$ with $M^\text{resolved}_*$. The results for ZCR' are shown in the left panel, and those for BSP are presented on the right. On average we find that for our sample of galaxies, unresolved values underestimate masses by \(-20\%\) compared to ZCR', but only by \(\sim 10\%\) relative to BSP. We also find, however, that for a fraction of the objects (15\% when comparing to ZCR' and 25\% vis-a-vis BSP) the unresolved mass estimates are actually larger than those determined from resolved studies. The estimate we can get for an unresolved mass depends on how each pixel contributes to the global colors. Pixels that contain relatively young star forming regions will lead to global bluer colors, and consequently a lower global $\Sigma_*$ (see Figures 1 or 6). On the other hand, pixels that contain extinction regions due to dust will lead to global redder colors and therefore a higher global $\Sigma_*$. In spite of these possible effects the error bars for $\log(M^\text{unresolved}_*/M^\text{resolved}_*) > 0$ (see Figure 27) are within the $\log(M^\text{unresolved}_*/M^\text{resolved}_*) \sim 0$ value.

We find no correlation of $M^\text{unresolved}_*/M^\text{resolved}_*$ with Hubble type ($r = 0.07$ for BSP and $r = 0.024$ for ZCR’), global $(g - i)$ color ($r = 0.057$ for BSP, $r = -0.025$ for ZCR’), or median $\sigma_*$ ($r = 0.055$ for BSP, $r = 0.116$ for ZCR’). The correlation test was also negative for galaxy inclination (see Figure 28), with $r = 0.114$ for BSP and $r = -0.090$ for ZCR’. When comparing the resolved $\langle \psi \rangle_\Sigma$ for each object with the ratio $M^\text{unresolved}_*/M^\text{resolved}_*$, we find a weak positive correlation ($r = 0.262$) for BSP and no correlation ($r = 0.118$) for ZCR’. In Figure 29 we show the ratio $M^\text{unresolved}_*/M^\text{resolved}_*$ versus resolved $\langle \psi \rangle$. The correlation coefficients are $r = 0.336$ for BSP (right panel) and $r = 0.212$ for ZCR’ (left panel) indicating a weak correlation in our case test.

6. UNCERTAINTIES IN THE STELLAR MASS ESTIMATES

All of the stellar mass estimates given in Table 1 are for the SSAG-BC03 library; if, instead, the MAGPHYS-CB07 library is used, the masses will be smaller (\(\sim 50\%\)), due to the different
We also have quantified that using only a constant $\Upsilon_b$ (i.e., skipping iteration number 3) yields masses per pixel $\sim 1\%$ higher on average, and up to $\sim 30\%$ larger in localized regions.

6.1. Dependence on Disk Inclination

Stellar mass is an intrinsic property of galaxies, independent of inclination to the line of sight. Stellar mass determinations from broadband colors, however, are independent of inclination only as surface brightness at different wavelengths is independent of it. Mallier et al. (2009) studied the effects of inclination on mass estimates by comparing a statistically significant sample of edge-on ($a/b \geq 3.33$) and face-on ($a/b \leq 1.18$) SDSS galaxies. They find no statistical difference for masses derived from $K$-band photometry by Bell et al. (2003) but, on the other hand, point out the very important corrections with inclination that are necessary for the $B$ band (Driver et al. 2007).

We remind the reader that all of our calculations are based on the effective $\Upsilon_b$. Extinction effects may introduce biases with inclination. In subsequent publications we will address this issue in more detail.

7. CONCLUSIONS

We have demonstrated quantitatively that resolved maps of stellar mass obtained by the maximum-likelihood estimate (as in ZCR) yield biased spatial structures. The bias consists in a filamentary morphology and a spatial coincidence between dust lanes and purported stellar mass surface density. The bias is due to a limited $\Upsilon_b$ accuracy ($\sim 0.1$–$0.15$ dex) arising from uncertainties inherent to observations and to degeneracies between templates of similar colors in the SPS libraries. Similar observed colors will yield the mode $\Upsilon_b$. Here, we have succeeded in mitigating the bias with the BSP algorithm we have developed. We have applied the new algorithm to M51 and a pilot sample of 90 spirals. BSP effectively identifies and isolates the old stellar population, and the output mass maps bear more resemblance to NIR structures.

The results also indicate that total resolved mass estimates obtained by adding up the pixel-by-pixel contributions are on average $\sim 10\%$ lower with BSP than with the ZCR approach. Hence, unresolved stellar mass estimates for our pilot sample underestimate the mass by $\sim 20\%$ when compared to the resolved ZCR results, but only by $\sim 10\%$ vis-à-vis BSP.

The fact that the same SPS libraries can produce, or not, filamentary structures where the mass is supposedly organized in ZCR yields biased spatial structures. The bias consists in a filamentary morphology and a spatial coincidence between dust lanes and purported stellar mass surface density. The bias is due to a limited $\Upsilon_b$ accuracy ($\sim 0.1$–$0.15$ dex) arising from uncertainties inherent to observations and to degeneracies between templates of similar colors in the SPS libraries. Similar observed colors will yield the mode $\Upsilon_b$. Here, we have succeeded in mitigating the bias with the BSP algorithm we have developed. We have applied the new algorithm to M51 and a pilot sample of 90 spirals. BSP effectively identifies and isolates the old stellar population, and the output mass maps bear more resemblance to NIR structures.

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Figure 22. Resolved maps of stellar mass. Columns 1 and 3: ZCR; columns 2 and 4: BSP. From left to right, in pairs: NGC 157, NGC 1042, NGC 4254, NGC 4051, NGC 4548, NGC 7606, NGC 7814, and M51b.
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APPENDIX A
DETERMINATION OF THE $\alpha$ PARAMETER FOR BSP

The last step of iteration number 2 is to identify the pixels that satisfy the condition $|\Delta C_n| < \alpha \sigma_{\alpha}$. From the definition of

$$\Delta C_n = C_n^{\text{obs}} - C_n^{\text{template}},$$

we have

$$\Delta C_1 = (g - i)^{\text{obs}} - (g - i)^{\text{template}}$$

and

$$\Delta C_2 = (i - K_s)^{\text{obs}} - (i - K_s)^{\text{template}}$$

for the $(g - i)$ and $(i - K_s)$ colors, respectively. The value of $\sigma_{\alpha}$ is computed from Equation (12). In Figure 30 we show a plot of $\Delta C_1$ versus $\Delta C_2$ for the case of the MAGPHYS-CB07 SPS library, before applying the $|\Delta C_n| < \alpha \sigma_{\alpha}$ condition to the pixels of M51 (see Section 4). From these $\Delta C_n$ distributions we obtain $\sigma_{\alpha} = 0.02376$ and $\sigma_{\alpha} = 0.0272$ for the $(g - i)$ and $(i - K_s)$ colors, respectively. The purpose of applying the $|\Delta C_n| < \alpha \sigma_{\alpha}$ condition is to isolate the pixels that deviate significantly from the value $\Delta C_n \sim 0$. In Figure 31 we show a plot of the skewness (a measure of the degree of asymmetry) of
where \( n_{\text{pix}} \) is the number of pixels in our set with standard deviation \( \sigma_G \). We then convolve the resulting histogram of the pixel population with a Gaussian function having a standard deviation \( \sigma_{G_{\text{conv}}} = \lambda_{G} / h_{G} \). In the convolution, the Gaussian kernel extends to \( 3\sigma_{G_{\text{conv}}} \). When building the histogram of the pixel population, all pixels have the same weight.

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