Resolved maps of Stellar Mass from iterative Bayesian marginalization of SPS models

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The Interplay Between Local and Global Processes in Galaxies

Cozumel, México, 11th-15th April, 2016

ABSTRACT

Stellar masses of galaxies are frequently obtained via SPS fitting to observed photometry, or galaxy spectra. "State of the art" methods resolve spatial structures within a galaxy to asses the total stellar mass content. Current methods commonly deliver biased resolved spatial structures. In this work we will introduce a new algorithm, based on Bayesian statistics, aimed to mitigate the bias. We apply this algorithm to M51 and show the results.

1 INTRODUCTION

There are different methods to derive the mass of a galaxy, e.g., dynamical or lensing mass estimates (see Courteau et al., 2014, for a review). Regarding the stellar mass component, the use of stellar population synthesis (SPS) models (e.g. Bruzual & Charlot, 2003), as a mean to translate stellar light into mass (through the stellar mass-to-light ratio), has been frequently advocated (e.g. Bell & de Jong, 2001; Bell et al., 2003). Notwithstanding their common degeneracies, SPS models can asses reliable mass estimates in general.

One novel technique is the *resolved stellar mass map method* (Zibetti, Charlot, & Rix, 2009, ZCR henceforth), which delivers a map of the stellar mass surface density by photometric means. In principle, the method is truly powerful, since it can resolve not only for the mass, but also for other physical parameters of the SPS models, based solely on photometry. On the other hand, galaxy masses determined by unresolved means (where galaxies are treated as point sources) are often underestimated (or even overestimated for some objects, Roediger & Courteau, 2015), thus the need for resolved structures (Zibetti, Charlot, & Rix, 2009; Sorba & Sawicki, 2015)

Despite its potential, which can also be extended to higher redshift studies, ZCR's method produces biased spatial structures which contradict what we know of the evolution of galaxies in general (Martínez-García et al., 2016). The bias consists in a filamentary morphology for the stellar mass surface density, and an apparent spatial coincidence between the dust lanes and massive structures (see figure 1). The bias is due to a limited mass-to-light ratio accuracy (~0.1-0.15 dex), and SPS models degeneracies (Martínez-García et al. 2016).

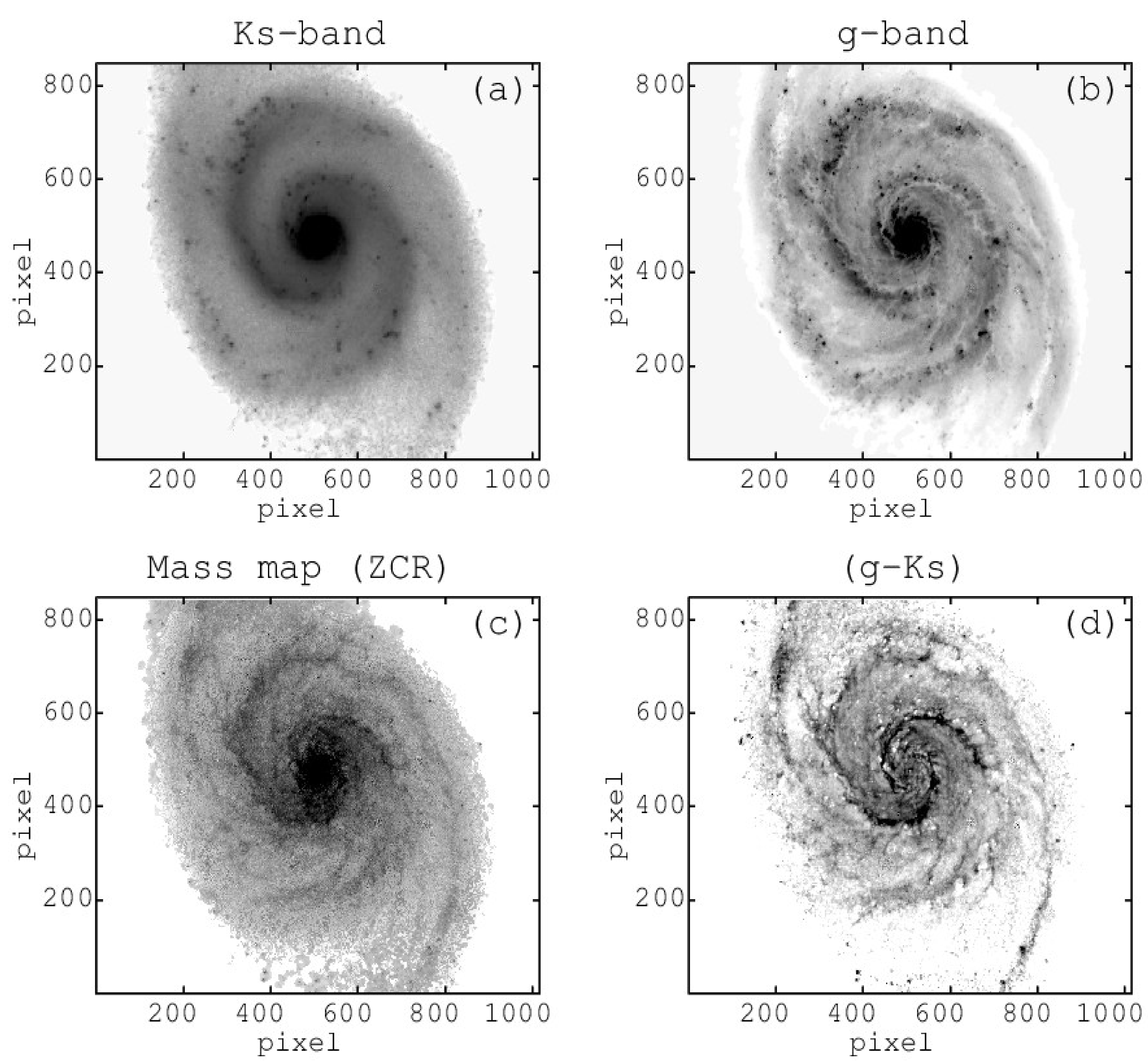

Fig 1.-
- Panel a: *Ks*-band mosaic of M51. Display is in logarithmic scale.
- Panel b: *g*-band (SDSS) mosaic of M51.
- Panel c: M51's stellar mass map based on $(g - i)$ & $(i - Ks)$ colors, and *Ks* mass-to-light-ratio, by using the Zibetti, Charlot, & Rix (2009, ZCR) method.
- Panel d: Dust lanes traced with the $(g - Ks)$ color. Notice the resemblance between the structure and the "stellar mass" map produced by ZCR (panel c).

2 THE BAYESIAN SUCCESSIVE PRIORS (BSP) ALGORITHM

The Bayesian successive priors (BSP) algorithm is intended to correct the bias in ZCR's method. The idea is to use the prior information regarding the stellar surface mass density as deduced from the NIR bands. The massive older population of a galaxy is mainly traced by the NIR bands, specially the *K*-band (Rix & Rieke 1993).

The BSP algorithm consists of three iterations, which are described in what follows. The algorithm is intended to work with surface photometry, and a Montecarlo SPS library in three bands. The algorithm is applied on a pixel-by-pixel basis.

1. In the first iteration we use a uniform prior probability distribution. Then we identify all the pixels where the difference between the observed colors and the SPS library colors is less than 3-σ (figure 2, panel a). This guarantees that each pixel can be described by at least one template in our SPS library. Next we use the posterior NIR mass-to-light ratio from all pixels and calculate the statistical median.

2. In the second iteration, the median NIR mass-to-light ratio from iteration number 1 is used as a constant parameter for the entire disk, together with a Gaussian prior probability distribution. Similarly to iteration number 1, we identify all the pixels where the difference between the observed colors and the SPS library colors is less than 1-σ (figure 2, panel b). These pixels will be the "backbone" of our mass map. The rest of the pixels belong mainly to relatively young luminous red stars, low surface brightness regions in the outskirts of the disk, and high extinction regions. For these pixels we used the information from the "backbone" pixels to interpolate the stellar mass surface density, and obtain new NIR mass-to-light ratios.

3. The third and last iteration is intended to deal only with the interpolated regions from iteration number 2. We apply a Gaussian prior probability distribution in Bayes' theorem, taking into account the new NIR mass-to-light ratios. We then obtain a free-bias stellar mass surface density map (figure 2, panel c).

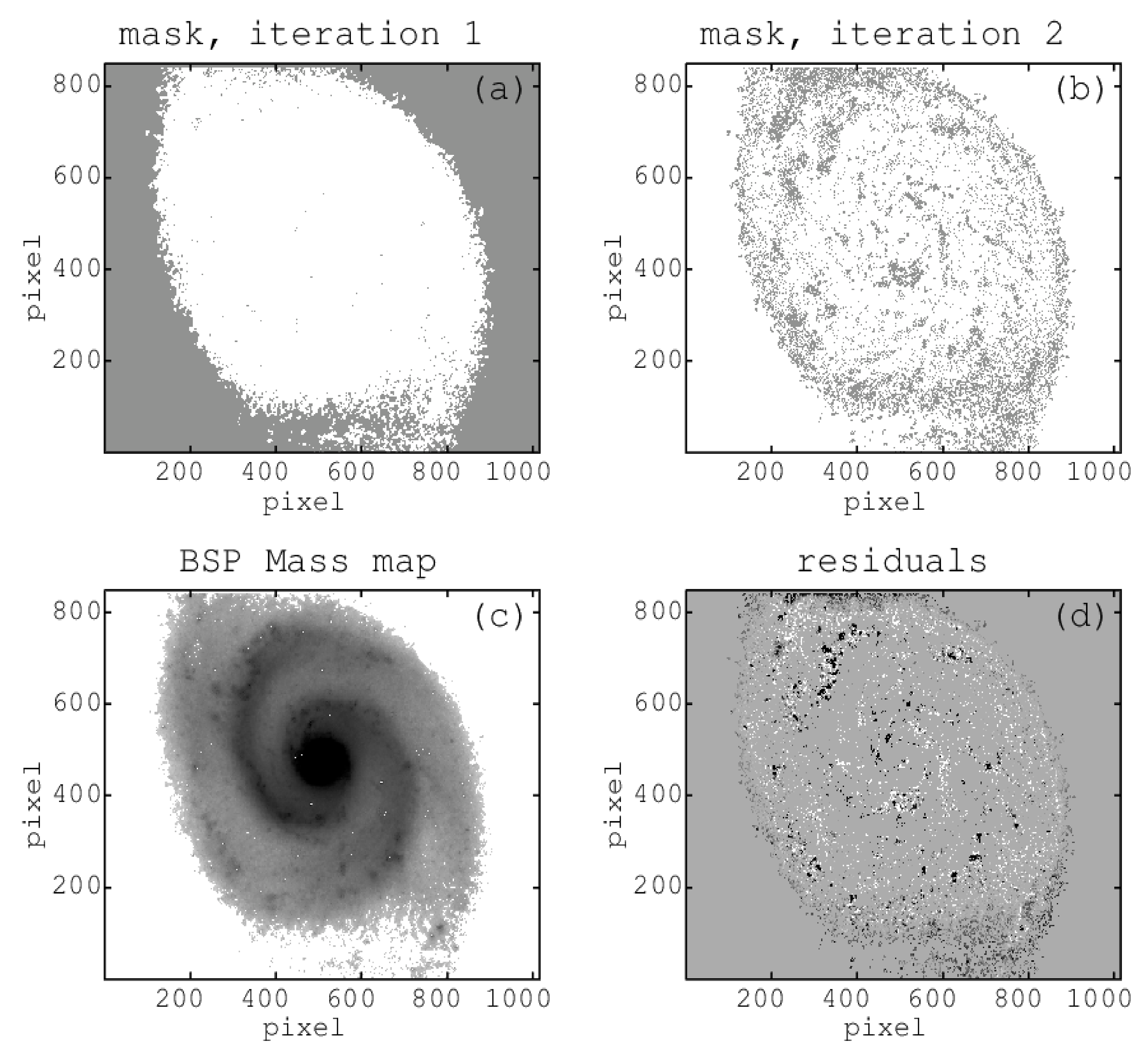

Fig 2.- Panel d: Residuals after subtracting a mass map that assumes a constant *Ks* mass-to-light ratio, and the resulting mass map obtained from the BSP algorithm. Dark regions represent positive mass differences, and white regions negative differences.

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