Revisiting the Local Star-Forming Galaxies Observed in the HETDEX Pilot Survey

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12 terms of the oxygen abundance, (-dominated by hydrogen and helium), but it is often expressed in (atoms heavier than helium) relative to the total mass of baryons $M_{\text{bar}}$ (Mannucci 2019). The metallicity $Z$ represents the mass of all metals (atoms heavier than helium) relative to the total mass of baryons (dominated by hydrogen and helium), but it is often expressed in terms of the oxygen abundance, $12 + \log (O/H) \equiv 12 + \log (N_O/N_H)$. (1)

where $N$ is the corresponding number density. Since most of the metals originate in stellar interiors, the metallicity is closely related to the integrated amount of star formation in a galaxy over time. Gas removal (e.g., outflows or stripping) and accretion of pristine gas also affect the metallicity. The metallicity of stellar populations can be determined from stellar photospheric absorption lines, using model spectra from stellar population synthesis (see Conroy 2013; Maiolino & Mannucci 2019). Conversely, the metallicity of the gaseous components of a galaxy is mainly determined from emission lines originating in the interstellar medium, using the electron-temperature method, recombination lines, or a photoionization model (see Peimbert et al. 2017; Maiolino & Mannucci 2019). These three methods for gas metallicity estimation usually give discrepant results each other (Tsamis et al. 2003; García-Rojas & Esteban 2007; Kewley & Ellison 2008; García-Rojas et al. 2009; Moustakas et al. 2010; López-Sánchez et al. 2012; García-Rojas et al. 2013; Peimbert et al. 2017; Toribio San Cipriano et al. 2017); the abundance difference can be as much as a factor of five between the electron-temperature and recombination lines methods (Tsamis et al. 2003), and as much as 0.6–0.7 dex between photoionization models and the other two (e.g., Kewley & Ellison 2008; Moustakas et al. 2010; López-Sánchez et al. 2012). Other than the three methods, the strong-line method is also used due to the weakness of the emission lines required to apply the electron-temperature or recombination lines methods (see Maiolino & Mannucci 2019). The strong-line method employs an empirically calibrated relation between the metallicity and the ratios of strong emission lines, and there exist diverse calibrations (see section 3.1).

When one tries to extract any information—e.g., metallicity—from the observational data using a parameterized model, one must perform parameter estimation. There are two distinct ways to do this: one is the frequentist approach (i.e., the classical approach), and the other is the Bayesian approach (see Wasserman 2004; Held & BovÄť 2013). The frequentist approach treats the true parameter(s) as unknown-but-fixed and the data as random. In contrast, the Bayesian approach treats the true parameter(s) as random and the data as fixed. Also, the frequentist approach uses the concept of confidence interval, while the Bayesian approach uses that of credible interval (see Held & BovÄť 2013). Bayesian parameter estimation is based on

1 INTRODUCTION

Galaxies evolve after their formation through diverse processes such as star formation, stellar explosions, galaxy mergers, gas removal and accretion, etc. These processes leave traces in various observable properties of the galaxies, one of which is metallicity (see Maiolino & Mannucci 2019). The metallicity $Z$ represents the mass of all metals (atoms heavier than helium) relative to the total mass of baryons (dominated by hydrogen and helium), but it is often expressed in terms of the oxygen abundance, $12 + \log (O/H) \equiv 12 + \log (N_O/N_H)$. (1)

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the posterior distribution, which is proportional to the product of the likelihood and the prior distribution according to Bayes’ theorem (see Sharma 2017). Many studies have adopted Bayesian parameter estimation because of its usefulness in inferring the information of interest from a given data set with the use of background knowledge (Sharma 2017). This method has some pitfalls, however. For instance, the posterior distribution can be much different from the likelihood due to the prior distribution, so reproducibility tests with mock data should be done after eliminating the effects of the prior distribution. The posterior distribution is usually obtained using sampling methods such as Markov-Chain Monte Carlo (MCMC, see Sharma 2017). Since the MCMC method samples the target distribution based on random movements over a model parameter space, its convergence must be monitored to assess how close the sampled distribution is to the target distribution (Hogg & Foreman-Mackey 2018); however, such convergence monitoring is often omitted in the literature.

Recently, Indahl et al. (2019) studied galactic gas metallicity using Bayesian parameter estimation. More specifically, they reported gas metallicities and star formation rates (SFRs) for 29 low-redshift \(z < 0.15\) galaxies, and they studied the distribution of those galaxies in mass-metallicity-SFR phase space. Their targets are extraordinary, because they were selected using emission lines only—without any photometric (continuum-flux) preselection—over a wide area of the sky \((\sim 169 \text{ arcmin}^2)\). In this way, they were able to explore for a new galaxy population that might have been missed in previous studies. Indahl et al. (2019) determined the metallicities and the nebular emission-line color excesses \(E(B - V)\) using the strong-line method. They followed the approach of Grasshorn Gebhardt et al. (2016), and they carried out parameter estimation by employing the Bayesian approach and the MCMC method. However, I noticed three points that can be improved. First, Indahl et al. (2019) adopted a relatively small uncertainty for the line-ratio calibration. This affects the uncertainties of the estimated model parameters, since Indahl et al. (2019) included the scatter of the line ratio for a given metallicity as an uncertainty term in the likelihood. Second, reproducibility test with mock data, which is not mentioned in Indahl et al. (2019), will help determine how reliable the obtained results are. This test is important, because it can be hard to recover the true metallicity from the observed line ratios due to the scatter in the line-ratio calibration. Third, monitoring the convergence of MCMC sampling, which is also not mentioned in Indahl et al. (2019), will enhance the statistical accuracy of the parameter estimates. As mentioned in the previous paragraph, convergence monitoring is essential for MCMC analyses, since it gives an estimate of the accuracy of the MCMC sampling results. Also, we cannot secure the convergence by simply repeating the iterations because of the recursive emergence of correlated samples, as I reported in Shinn (2019); hence again, convergence monitoring is important.

Improved data-analysis leads to improved results and consequently improved conclusions. Here I reanalyze the emission-line data of Indahl et al. (2019) following their analysis scheme but focusing on the three points mentioned above. Then I see how Indahl et al.’s results change and check which of Indahl et al.’s conclusions need to be reconsidered. I modeled the emission lines in the same way as Indahl et al. (2019), but I adopted a larger scatter of the line ratio calibration in order to match the strong-line calibration that Indahl et al. (2019) selected, i.e., that of Maiolino et al. (2008). I also performed several reproducibility tests with mock data, and I found that the metallicity is reproducible to within the 1-\(\sigma\) level. However, \(E(B - V)\) is poorly reproducible, and it can be overestimated by \(> 2-\sigma\); hence, the reddening-corrected SFRs of Indahl et al. (2019) are likely to be overestimated. I also monitored the convergence during the MCMC sampling, and I found that the metallicity values of Indahl et al. (2019) are systematically lower than mine, mostly by 2-\(\sigma\).

2 DATA ACQUISITION

Since I have reanalyzed the emission line data of Indahl et al. (2019), all the data I used are the line fluxes reported in Indahl et al. (2019). Here I briefly describe how Indahl et al. (2019) obtained the spectra and line fluxes, and the reader is referred to Indahl et al. (2019) and Adams et al. (2011) for more information.

The 29 target galaxies in Indahl et al. (2019) are from the pilot survey for the Hobby-Eberly Telescope Dark-Energy Experiment (HETDEX, Hill et al. 2008a; Hill & HETDEX Consortium 2016); hence, it is called the HETDEX Pilot Survey (HPS, Adams et al. 2011). The HETDEX is a blind spectroscopic survey for a 450 deg\(^2\) area (filling factor \(\sim 1/4.5\)) that is designed to provide a large sample of galaxies selected purely on the basis of their emission lines, without any photometric (continuum-flux) preselection. The HETDEX uses an integral-field-unit (IFU) spectrograph called VIRUS (Hill et al. 2018) on the McDonald Observatory 10 m Hobby-Eberly Telescope; VIRUS has \(\sim 35,000\) 1’’\(\times\)1’’ diameter fibers and covers \(3500 - 5500\) \(\AA\) with \(\sim 5.7\) \(\AA\) resolution. The HPS is a HETDEX-like survey, but with a much smaller survey area \((\sim 169 \text{ arcmin}^2)\), and it was carried out using the George and Cynthia Mitchell Spectrograph (GMS, previously known as VIRUS-P: Hill et al. 2008b) on the McDonald Observatory 2.7 m Harlan J. Smith Telescope. The GMS has 246 4’’\(\times\)2’’ diameter fibers, and it was configured to cover \(3500 - 5800\) \(\AA\) at \(\sim 5\) \(\AA\) resolution for the HPS (to be similar to the HETDEX).

Indahl et al. (2019) collected 29 low-redshift \(z < 0.15\) galaxies that have [O II] \(\lambda3727, \lambda3729\), [O III] \(\lambda5007, \lambda5537\), or H\(\beta\) lines from the HPS dataset. In order to ensure that their galaxy list contains line-flux information for at least these three emission lines, Indahl et al. (2019) performed follow-up observations with another IFU spectrograph called LRS2 (Chonis et al. 2016) on the McDonald Observatory 10 m Hobby-Eberly Telescope. The LRS2 has 280 fibers, each of which has a lenslet that covers a 0’’6 hexagonal field element, and it covers the wavelength range \(3700 - 10500\) \(\AA\) with a resolving power of \(\sim 1100 - 2000\). Indahl et al. (2019) measured the line fluxes using a model consisting of Gaussian line(s) plus a linear continuum. They tabulated a single summed flux for the line pair [O II] \(\lambda3726, 3729\) (reported as [O II] \(\lambda3727\)) and for the line pair [O III] \(\lambda4959, 5007\) (listed as [O III] \(\lambda5007\)).

3 ANALYSIS AND RESULTS

3.1 Line-Flux Model Test

Indahl et al. (2019) estimated metallicities from the ratios of emission lines using the strong-line method, following the approach of Grasshorn Gebhardt et al. (2016). The strong-line method is a technique invented for an easier-but-less-precise estimation of metallicity. The metallic emission lines used to determine the metallicity directly through the electron-temperature method or the recombination-line method are usually weaker than the Balmer lines by about a factor of \(10 - 10^4\) (Maiolino & Mannucci 2019). An alternative method was therefore developed to estimate the metallicity from strong emission lines, which can be detected more easily. Calibration of the strong lines has been done empirically using the electron-temperature method (e.g., Pettini & Pagel 2004; Pilyugin & Thuan 2005; Pilyugin et al. 2010; Pilyugin & Grebel 2016; Curti et al. 2017), a photoionization model (e.g., Zaritsky et al. 1994; McGaugh 1991;
Kewley & Dopita 2002; Kobulnicky & Kewley 2004; Tremonti et al. 2004; Nagao et al. 2011; Dopita et al. 2016), or both (e.g., Denicoló et al. 2002; Nagao et al. 2006; Maiolino et al. 2008). Indahl et al. (2019) adopted the calibration of Maiolino et al. (2008), which was done with local galaxies ($z \sim 0$) using both the electron-temperature method and a photoionization model. For the low-metallicity region $[12 + \log(O/H)] < 8.3$, Maiolino et al. (2008) used 259 galaxy samples from Nagao et al. (2006), for which metallicities were determined using the electron-temperature method. For the high-metallicity region $[12 + \log(O/H)] > 8.3$, they used 22,482 galaxies from the Sloan Digital Sky Survey (SDSS, York et al. 2000) DR4 (Adelman-McCarthy et al. 2006), and they determined the metallicities with the photoionization model of Kewley & Dopita (2002).

Indahl et al. (2019) modeled the emission-line flux using the strong-line calibration of Maiolino et al. (2008). They used the following three line ratios:

$$R_{23} = \frac{[O\ II] \lambda 3727 + [O\ III] \lambda 4959 + [O\ III] \lambda 5007}{H\beta},$$

$$O_{32} = \frac{[O\ III] \lambda 5007 + [O\ III] \lambda 4363}{H\beta},$$

$$N_2 = \frac{[N\ II] \lambda 6584}{H\alpha}.$$  

Using these three line ratios, I modeled the line fluxes with three parameters: the metallicity $[O\ II] \lambda 3727 + [O\ III] \lambda 4959 + [O\ III] \lambda 5007$, the intrinsic $[N\ II] \lambda 6584$ flux$^1$. I fixed the ratio of $[O\ III] \lambda 5007$ to $[O\ III] \lambda 4959$ at 2.98 (Storey & Zeippen 2000), as in Indahl et al. (2019). A given metallicity, $[O\ II] \lambda 3727 + [O\ III] \lambda 4959 + [O\ III] \lambda 5007$, determines the ratios $R_{23}, O_{32}, N_2$ and their uncertainties from the calibration function of Maiolino et al. (2008). Then, the intrinsic $[O\ III] \lambda 5007$ flux determines the fluxes of other emission lines in the equations (2) and (3). In a similar way, the intrinsic $[N\ II] \lambda 6584$ flux determines the flux of the other emission line in the equation (4), i.e., Hα. The corresponding uncertainties of the line fluxes are calculated from eqs. (2)-(4) using the error propagation.

To check whether the line-flux modeling was done appropriately, I compared the line ratios calculated from the modeled line fluxes directly to the calibration of Maiolino et al. (2008). Fig. 1 shows a comparison of the line ratios. The line ratios themselves clearly follow the calibration function of Maiolino et al. (2008) very well. Indahl et al. (2019) had adopted 10% of each ratio as the uncertainty for all three line ratios, but I found that it is small to mimic the spreads of the line ratios $O_{32}$ and $N_2$ (see Fig. 5 of Maiolino et al. 2008). Therefore, I adjusted the line-ratio uncertainty to cover most of the data points plotted in Maiolino et al. (2008) at the 3-$\sigma$ level. The values I adopted are as follows: $\Delta \log(O_{32}) = 0.2$, $\Delta \log(R_{23}) = 0.05$, and $\Delta \log(N_2) = 0.1$. In addition, I set the correlation between $([O\ II] \lambda 3727 + [O\ III] \lambda 4959 + [O\ III] \lambda 5007)$ and $R_{23}$—which is arbitrary—to be $-1$, since this makes the modeled uncertainty most similar to the data-point scatter in the calibration plot of Maiolino et al. (2008).

3.2 Reproducibility Tests with Mock Data

To estimate the metallicity from the observed line fluxes using the line-flux model presented in section 3.1, Indahl et al. (2019) took account of dust reddening using the Calzetti attenuation curve (Calzetti et al. 2000) by adding one more parameter, $E(B - V)$, the nebular emission-line color excess. They corrected the reddening in this way, because the HPS does not cover Hα (see section 2) and hence they were unable to use the line ratio between Hα and Hβ for the reddening correction. Indahl et al. (2019) then used the Bayesian approach and sampled the posterior distribution using the MCMC method. Their log-likelihood expression has the form below:

$$\ln L \sim -\frac{1}{2} \sum \frac{(x_{\text{obs},l} - x_{\text{mod},l})^2}{\sigma^2_{\text{obs},l} + \sigma^2_{\text{mod},l}}.$$

Here $l$ means the different emission lines over which the fraction is summed; $x$ and $\sigma$ are the line flux and its uncertainty; and the subscripts ‘obs’ and ‘mod’ mean the corresponding values from the observations and the model, respectively. This likelihood includes the uncertainty in the model line flux ($\sigma_{\text{mod},l}$), which can be large, since the scatter in the line ratios for a given metallicity is large (see Maiolino et al. 2008). This can make it difficult to recover the true model values. In this section, I test with mock data how well the likelihood is able to recover the model input values. For this test, I first took flat priors to see the effects of likelihood only. The prior ranges are as follows: $[O\ II] \lambda 3727 + [O\ III] \lambda 4959 + [O\ III] \lambda 5007$ (6.5, 10.0); $E(B - V)$, (0, 0.79); the intrinsic $[O\ III] \lambda 5007$ flux, (0, $10^{-8}$) erg s$^{-1}$ cm$^{-2}$; and the intrinsic $[N\ II] \lambda 6584$ flux, (0, $10^{-8}$) erg s$^{-1}$ cm$^{-2}$. The metallicity range is the same with the one of Indahl et al. (2019), which is a little wider than the calibration range of Maiolino et al. (2008), (7.0, 9.3). The $E(B - V)$ range is based on the prior used by Indahl et al. (2019): a Gaussian prior with $\sigma = 0.165$ centered at 0.295. Indahl et al. (2019) obtained these two values from local SDSS star-forming galaxies. For the flat prior for $E(B - V)$, I set the maximum to be the Gaussian mean $+ 3 \times$ Gaussian sigma. For the intrinsic line fluxes, I used a sufficiently large range.

First, I created mock data with four model input values: $[O\ II] \lambda 3727 + [O\ III] \lambda 4959 + [O\ III] \lambda 5007$, the intrinsic $[O\ III] \lambda 5007$ flux, and the intrinsic $[N\ II] \lambda 6584$ flux. To set the line-flux uncertainty for the mock data, I referred to the signal-to-noise ratio (S/N) distribution for the observational data tabulated in Indahl et al. (2019). Fig. 2 shows the S/N distribution of all the observed emission lines. The S/N ratio can be as high as $\sim 100$, but it is mostly $\leq 10$. Thus, I started the test with mock data having S/N = 100, excluding the model uncertainty from the likelihood. Second, I carried out MCMC sampling of the posterior distribution, employing the affine-invariant ensemble sampler called emcee (Foreman-Mackey et al. 2013, 2019). I used the stretch move (Goodman & Weare 2010) with the stretch scale parameter $a = 2$. For MCMC initialization I used the mode of the posterior distribution (see Hogg & Foreman-Mackey 2018; Shinn 2019). To find it, I employed a global optimization method called differential evolution (Storn & Price 1997). I repeated the optimization process 32 times and used the 32 results for the MCMC initialization; hence, the number of walkers for the MCMC sampling is also 32.

Fig. 3 shows the posterior distribution for the mock data with S/N $= 100$, where the model uncertainty is excluded from the likelihood. This figure shows that the model input values are well reproduced, and the model parameters all have positive correlations with each other. The tight positive correlations among $E(B - V)$, the intrinsic $[O\ III] \lambda 5007$$^2$, and the intrinsic $[N\ II] \lambda 6584$$^3$ are reasonable.

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1 Indahl et al. (2019) used the intrinsic Hα flux as a free parameter instead of the intrinsic $[N\ II] \lambda 6584$ flux.

2 The word ‘flux’ is dropped from ‘the intrinsic $[O\ III] \lambda 5007$ flux’ for simplicity from here on.

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because a higher \(E(B-V)\) requires higher line fluxes for a fixed metallicity. In the upper-right corner of Fig. 3, I plot the evolution of the integrated autocorrelation time \(\tau_{\text{int}}\) to monitor the convergence of the MCMC sampling. MCMC sampling has only \(N/\tau_{\text{int}}\) independent samples, where \(N\) is the total sample length (Sharma 2017), because the samples from dynamic Monte Carlo methods are usually correlated (Sokal 2013). The number \(N/\tau_{\text{int}}\) is called the effective sample size (ESS), and I also plot two ESS lines as convergence checks in the upper-right panel in Fig. 3. The ESS lines are equal to \(N/\tau_{\text{int}}\) multiplied by the number of walkers (i.e., 32), since I calculated \(\tau_{\text{int}}\) from the mean of the ensemble walkers (i.e., \(X_t = \frac{1}{N} \sum_{i=1}^{N} x_i\)), as in Goodman & Weare (2010). I used the following definition of \(\tau_{\text{int}}\):

\[
\tau_{\text{int}} = \sum_{t=-\infty}^{\infty} \rho_{xx}(t), \quad \text{where} \quad \rho_{xx}(t) = \frac{\mathbb{E}[(x_t - \bar{x})(x_{t+t} - \bar{x})]}{\mathbb{E}[(x_t - \bar{x})^2]}. \tag{6}
\]

Here \(\rho_{xx}\) is the autocorrelation function for the sequence \(\{x_t\}\), \(t\) is the time difference—or distance—between two points in the sequence \(\{x_t\}\). \(\bar{x}\) is the mean of sequence \(\{x_t\}\), and \(\mathbb{E} \{ \cdot \} \) means the expectation value. I calculated \(\tau_{\text{int}}\) with a routine in the \texttt{emcee} package, using an “automatic windowing” size of 5 (see Sokal 2013). I considered the sampling to be sufficiently converged when the values of \(\tau_{\text{int}}\) for all of the parameters cross the ESS = 2000 line (Fig. 3). This value of ESS is larger than the number 1665 that is required to determine the 0.025 quantile to within 0.0075 with probability 0.95, which corresponds to about a 10% error in the 0.025 quantile for light-tailed (normal) or moderate-tailed (student’s \(t_{\text{std}}\)) distributions (Raftery & Lewis 1992). After achieving convergence, I checked to determine whether there exist any unexplored local extrema by increasing the stretch-scale parameter by a factor of five (i.e., \(a = 10\)) in the MCMC sampler, as in Shinn (2019). I obtained nil for this check and it is the same for all the following tests shown in this section.

Next, I reduced the S/N of the mock data to 10, which is a bit higher than the most probable S/N of the observed line fluxes (Fig. 2), and examined how the posterior distribution changes. Fig. 4 shows the results. As the marginal distributions show, all the parameters are overestimated, but they recover the input model values around the 1-\(\sigma\) level. Obviously, the lowered S/N of 10 causes the overestimation (compare Fig. 3 and 4). In other words, the higher \(\sigma_{\text{obs}}\) in eq. (5) deforms the likelihood and consequently the posterior. Note that the uncertainty of the model line flux \(\sigma_{\text{mod}}\) is not included in the likelihood [eq. (5)] under this test. The \(E(B-V)\) and the intrinsic [O III] \(\lambda5007\) pair, as well as the \(E(B-V)\) and the intrinsic [N II] \(\lambda6584\) pair, start to show narrow and curved covariances (Fig. 4).

As a third test, I included the model uncertainties \((\sigma_{\text{mod}})\) into the likelihood [eq. (5)], and Fig. 5 shows the results. The prominent changes in the posterior distribution are that the three model parameters—\(E(B-V)\), the intrinsic [O III] \(\lambda5007\), and the intrinsic [N II] \(\lambda6584\)—suffer severely from overestimation. The input values of the mock data fall well below the medians of the posterior parameter distributions at the 2-\(\sigma\) level or more. This drastic overestimation for the three parameters is due to the inclusion of the model uncertainties, which stem from the uncertainty of the strong-line calibration (see Fig. 1), into the likelihood [eq. (5)]. However, note that the posterior distribution of the metallicity recovers the input value of the mock data well at the 1-\(\sigma\) level, although it is still an overestimate.

As a final test, I replaced the flat prior for \(E(B-V)\) with the one used by Indahl et al. (2019): a Gaussian prior with \(\sigma = 0.165\) centered at 0.295. Fig. 6 shows the results. As the marginal distributions show, the overall trend is still the same as in the previous test (Fig. 5). The three parameters—\(E(B-V)\), the intrinsic [O III] \(\lambda5007\), and the intrinsic [N II] \(\lambda6584\)—are still overestimated at the 2-\(\sigma\) level or more, while the metallicity is well recovered within the 1-\(\sigma\) level. I tested two more cases by setting \(12 + \log(O/H) = 7.0\) (Fig. 7) and \(12 + \log(O/H) = 9.0\) (Fig. 8) as the input values for the mock data, but the overestimation trends remained. For comparison, I also ran an additional test with a higher input value of \(E(B-V)\) = 0.3 (near the mode of the prior distribution), but the overestimation trends still remained, except that the overestimates of the three parameters are reduced to 1-\(\sigma\). In the case of the input \(E(B-V) = 0.5\), all four parameters were well recovered within 1-\(\sigma\).

From all the test results shown in this section, I draw the following two conclusions: First, the metallicity can be recovered to within the 1-\(\sigma\) level by the method of Indahl et al. (2019). Second, the remaining three parameters—\(E(B-V)\), the intrinsic [O III] \(\lambda5007\),...
and the intrinsic $[\text{N II}] \, \lambda 6584$—can be overestimated by as much as 2-$\sigma$ or more by the method of Indahl et al. (2019).

### 3.3 Reanalysis of the Data of Indahl et al.

I reanalyzed the line fluxes observed by Indahl et al. (2019) as done above for the mock data. One exception was that I reduced the metallicity prior range from (6.5, 10.0) to (7.0, 9.3) to make it equal to the metallicity calibration range of Maiolino et al. (2008). I initialized the MCMC sampler at the mode of the posterior distribution, and I sampled that distribution until the MCMC samples converged sufficiently—i.e., $\tau_{\text{int}}$ for each of the parameters crossed the line $\text{ESS} = 2000$. Then I checked to determine whether there are any unexplored local extrema by increasing the stretch scale parameter by a factor of five ($\alpha = 10$), and I obtained nil for all the analyzed galaxies. Here I only analyze 27 [O II]-selected galaxies and ignore the two [O III]-selected galaxies (see Table 3 and 4 of Indahl et al. 2019); hence, only the ratios $R23$ and $O32$ were used. There are two reasons for this. First, Indahl et al. (2019) did not provide the $H\alpha$ absorption values, so I could not correct the observed $H\alpha$ line flux, which is needed to use the ratio $N2$ [eq.(6)]. Second, for the [O III]-selected galaxies, Indahl et al. (2019) did not tabulate the model parameter values estimated by using the ratios $R23$ and $O32$ only (excluding $N2$), so I could not compare my model parameter values to theirs. As a result, only three parameters—$12 + \log (\text{O/H})$, $E(B-V)$, and the intrinsic $[\text{O III}] \, \lambda 5007$—were used for the modeling; I did not need the intrinsic $[\text{N II}] \, \lambda 6584$ parameter since the [O II]-selected galaxies do not have the $H\alpha$ and $[\text{N II}] \, \lambda 6584$ flux data.

Fig. 9 shows the posterior distributions obtained from the MCMC sampling results, and Table 1 lists the parameter values determined from the marginal posterior distributions. I show only the HPS035 result here in Fig. 9, but the complete results for 27 galaxies are available in the online supplementary data. Overall, the posterior distributions show covariance shapes similar to those obtained for the mock data whose input metallicity is 8.0 (Fig. 6) and 9.0 (Fig. 8). This is reasonable considering that all the metallicity estimates fall between $\sim 8.5$ and $\sim 9.0$ (Table 1). Three cases (HPS067, HPS235, and HPS237) have a bit different covariance shapes from the rest, and it seems that the low S/Ns of [O II] and [O III] emission lines cause it; these three targets have the three lowest S/Ns in [O II] and [O III] fluxes (Table 3 of Indahl et al. 2019).

Here I note that I had to run the MCMC sampler for each galaxy on a step-by-step basis to secure convergence by monitoring the evolution of $\tau_{\text{int}}$. In other words, I had to run the sampler using...
Figure 3. Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) from a mock-data test. The ten panels in the lower left corner are the corner plot of the Markov-Chain Monte Carlo (MCMC) sampling results. It shows the correlations among the model parameters and their marginal distributions. Two names ‘intrinsic [O III] $\lambda$5007’ and ‘intrinsic [N II] $\lambda$6584’ indicate the corresponding line fluxes in units of $10^{-16}$ erg s$^{-1}$ cm$^{-2}$. The red solid lines are the input values used to generate the mock data. The vertical dashed lines indicate the median, 1-$\sigma$ (68 %), and 2-$\sigma$ (95 %) credible intervals. The panel in the upper right corner shows the evolution of $\tau_{\text{int}}$. For convergence diagnosis, I also plot two straight lines, which correspond to effective sample sizes (ESSs) of 1000 and 2000, respectively. The title at the top of the figure indicates the following: SNR### (signal-to-noise ratio of the mock data), metal08 [metallicity $12 + \log (O/H) = 8.0$], mderrN (model uncertainty excluded), EBVpriorF [flat prior for $E(B-V)$], and BurnIn#### (burn-in iterations excluded before plotting).

multiple short iterations, because $\tau_{\text{int}}$ soars abruptly at some point due to the emergence of correlated samples; I reported this phenomenon previously in Shinn (2019). When $\tau_{\text{int}}$ soars abruptly at a certain run, I truncated that part and reran the sampler again at the end of the remaining sample. When I ran the MCMC sampler mindlessly for a long iteration instead, $\tau_{\text{int}}$ usually continued to increase, and hence the ESS did not increase. Fig. 10 shows a single long-iteration example for the target HPS035 (compare it to Fig. 9). At the end of the iteration (iteration $\sim 10,000$), $\tau_{\text{int}}$ for $E(B-V)$ and for the intrinsic [O III] $\lambda$5007 abruptly increase, making the corresponding ESSs fall below 1000. The statistical accuracy of the posterior distributions for these two parameters at the end of the iteration is therefore no better than at the start of the iteration, say at iteration = 100. In other words, the posterior distribution from the 32 $\times$ 20,000 samples has the statistical accuracy as poor as the one from the 32 $\times$ 100 samples (Fig. 10); the number 32 is the number of walkers used for the MCMC sampling (see section 3.2). Note that the median and 1-$\sigma$ intervals of the marginal distributions are similar between the
Figure 4. Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) from another mock-data test. The setting for this test is the same as for Fig. 3, except that I changed the signal-to-noise ratio of the mock data from 100 to 10 (and hence changed the title to SNR010). The figure description is otherwise the same as for Fig. 3.

From here on, I compare my metallicity estimates, $12 + \log(O/H)$, with those of Indahl et al. (2019). I skip the comparisons for $E(B-V)$ and for the intrinsic [O III] $\lambda 5007$, since their values are not reliable because of overestimation (see section 3.2). In Fig. 11, I compare the metallicity estimates from this work with those from Indahl et al. (2019). Their median values are systematically lower than mine by 0.18 dex. The uncertainties are more-or-less similar to each other, except for the three targets that have much larger lower-credible-limits (HPS067, HPS235, and HPS237). These targets have the three lowest S/Ns of [O II] and [O III] fluxes (Table 3 of Indahl et al. 2019) as mentioned above. This low S/Ns may be related to the uncertainty differences for these three targets between this work and Indahl et al. (2019).

Fig. 12 shows how much the metallicity estimates from this work deviate from those of Indahl et al. (2019). The left panel of Fig. 12 shows that all of my estimates are larger than theirs. The right panels of Fig. 12 show histograms of the difference between the lower credible limits from this work and the medians from Indahl et al. (2019).
**Figure 5.** Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) from another mock-data test. The setting for this test is the same as for Fig. 4, except that I have included the model uncertainty (hence the title mderrY). The figure description is otherwise the same as for Fig. 3.

(2019). These histograms show that there is an overall 2-σ difference between the metallicities from this work and from Indahl et al. (2019).

Fig. 13 compares the two metallicity distributions. Their shapes are similar, but my estimates are shifted to higher values, as expected from the systematically larger values of my estimates shown in Fig. 11. The medians of the distributions are 8.94 for this work and 8.76 for Indahl et al. (2019).

Fig. 14 compares the mass-metallicity plot obtained in this work with that from Indahl et al. (2019). The mass estimates are from Indahl et al. (2019), which were derived from spectral-energy-distribution fitting with MCSED (Bowman et al. 2020). My metallicity estimates are a bit higher than those of Indahl et al. (2019), although the 1-σ uncertainties overlap each other somewhat. The general trend of the almost-flat mass-metallicity relation is common to both estimates.

### 4 DISCUSSION

The gas metallicities, 12 + log (O/H), I have newly determined are systematically higher than those of Indahl et al. (2019), overall by about 0.18 dex, as shown in Fig. 11. This trend is also shown in Figs. 13 and 14. Excluding three galaxies that have large lower-credible-limits (HPS067, HPS235, and HPS237) in the estimates from Indahl et al. (2019), my 1-σ uncertainty estimates are comparable to or smaller than those of Indahl et al. (2019) (Fig. 11). These differences in estimates are probably due to the two factors that differ between Indahl
Figure 6. Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) from another mock-data test. The setting for this test is the same as for Fig. 5, except that I adopted a Gaussian prior for $E(B-V)$ (hence the title EBVpriorG). The figure description is otherwise the same as for Fig. 3.

et al. (2019) and this work—the uncertainties in the strong-line calibration (see section 3.1) and the convergence monitoring of MCMC sampling—but it is hard to pinpoint the dominant one. The three targets (HPS067, HPS235, and HPS237) have the three lowest S/Ns of [O II] and [O III] fluxes (Table 3 of Indahl et al. 2019), but it is not clear whether this is the cause of the big differences in the uncertainty estimates between this work and Indahl et al. (2019). This big difference may be caused by a combination of the low S/Ns of the oxygen line fluxes and the different two factors in metallicity estimation mentioned above.

The 0.18 dex difference in metallicity, $12 + \log(O/H)$, mentioned above may seem insignificant, but I note that the median metallicities of Indahl et al. (2019) are smaller than mine by as much as 2-$\sigma$ in general (Fig. 12). What is more important is the degree of convergence of the MCMC sampling. I have shown that if one carries out MCMC sampling without monitoring the convergence, the ESS at the end of iteration can be as small as the one near the iteration start (compare Fig. 10 to Fig. 9). This means that the statistical accuracy of the MCMC sampling at the end of the iteration can be as poor as the one near the start of the MCMC sampling. Therefore, it is improper to compare simply my results, which achieved ESS > 2000, to Indahl et al.’s by assuming that both have the same statistical accuracy.

Indahl et al. (2019) compared their mass-metallicity relation to those of other galaxy populations, such as SDSS star-forming galaxies, and to some other extreme star-forming galaxies, like green-pea galaxies (Cardamone et al. 2009), blueberry galaxies (Yang et al. 2017), and blue compact dwarfs (Sargent & Searle 1970; Kunth & Östlin 2000). They estimated the metallicities of these reference
mock_SNR010_metal07_mderrY_EBVpriorG_BurnIn0500

Figure 7. Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) from another mock-data test. The setting for this test is the same as for Fig. 6, except that I changed the metallicity from 8 to 7 (hence the title metal07). The figure description is otherwise the same as for Fig. 3.

galaxies, using their own strong-line method from the line fluxes in the literature: SDSS star-forming galaxies (median $z \sim 0.078$, Andrews & Martini 2013), green pea galaxies ($0.1 \lesssim z \lesssim 0.4$, Hawley 2012), blueberry galaxies ($z \lesssim 0.05$, Yang et al. 2017), and blue compact dwarfs ($0.2 \lesssim z \lesssim 0.5$, Lian et al. 2016). Since (1) Indahl et al. (2019) used the same method to estimate the metallicities of both the target galaxies and the reference galaxies and (2) there is a systematic difference in metallicity between my estimates and those of Indahl et al. (2019) (Fig. 11), the relative difference in metallicity between the target galaxies of Indahl et al. (2019) and the reference galaxies would probably be the same, even if the metallicities of all the galaxies are estimated according to my procedure. Therefore, the conclusion of Indahl et al. (2019) concerning the relative positions of the galaxies in the mass-metallicity plane would remain intact.

For example, the [O II]-selected galaxies from Indahl et al. (2019), the SDSS star-forming galaxies, and the blue compact dwarfs would follow similar mass-metallicity relations, while the green-pea galaxies and blueberry galaxies would occupy a lower-metallicity region. Here I mention that using more recent and accurate calibration of Curti et al. (2017) in metallicity estimation would not make much difference in the mass-metallicity plot, because it returns a lower metallicity overall than the calibration of Maiolino et al. (2008) as Indahl et al. (2019) showed in their Fig. 10. Additionally, I note that the location accuracy of a certain galaxy population in the mass-metallicity plane can be enhanced if the metallicity is estimated following my procedure, because I obtained much smaller credible limits for a few galaxies than did Indahl et al. (2019) (see Fig. 11).

As shown in section 3.2, the $E(B - V)$ values estimated from...
this work and Indahl et al. (2019) are not reliable, because they are overestimated (see Figs. 6-8). Indahl et al. (2019) used the estimated $E(B - V)$ to correct the $[\text{O II}]$ line fluxes, and this consequently affects the SFR estimates. A typical value of the $E(B - V)$ obtained both in this work and in Indahl et al. (2019) is about $0.40 \pm 0.15$. If $E(B - V)$ is overestimated by about 2-$\sigma$, as shown in Figs. 6-8, the true $E(B - V)$ would be around $0.4 - 0.15 \times 2 = 0.1$. I calculated the overestimation factor for the $[\text{O II}]$ line using the Calzetti attenuation curve (Calzetti et al. 2000), and found it to be $8.65/1.72 \sim 5.05 \sim 0.70$ dex. This means that the SFR estimates of Indahl et al. (2019) can be overestimated by a factor of five, and thus some of their conclusions regarding the SFR need to be reconsidered.

First, Indahl et al. (2019) found that the SFR distribution of their target galaxies was similar to those of the SDSS star-forming galaxies (Andrews & Martini 2013). With our analysis, the SFR distribution of Indahl et al.’s galaxies turns out to be lower than that of the SDSS star-forming galaxies. The difference may be smaller because the SFR of the SDSS star-forming galaxies is the total galactic SFR, instead of being calculated only from the light within the fiber as in Indahl et al. (2019).

Second, Indahl et al. (2019) found that their $[\text{O II}]$-selected galaxies reside between the green-pea galaxies (Hawley 2012) and the SDSS star-forming main-sequence galaxies (Duarte Puertas et al. 2017) along the SFR axis in the mass-SFR plane, implying that their blind spectroscopic survey fills in a galaxy population that SDSS missed. Since the SFRs of the green-pea galaxies and of Indahl et al.’s $[\text{O II}]$-selected galaxies were determined using the overestimated $E(B - V)$ from Indahl et al. (2019), the SFRs of these galaxies should be lower...
**Figure 9.** Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) for HPS035. The complete figure set of 27 galaxies is available in the online supplementary data. The six panels in the lower left corner are the corner plot of the Markov-Chain Monte Carlo (MCMC) sampling results, which shows the correlations among the model parameters and their marginal distributions. The name ‘intrinsic [O III] $\lambda$5007’ indicates the corresponding line flux in units of $10^{-16}$ erg s$^{-1}$ cm$^{-2}$. The vertical dashed lines indicate the median, 1-$\sigma$ (68 %), and 2-$\sigma$ (95 %) credible intervals. The panel in the upper right corner shows the evolution of $\tau_{\text{int}}$. For convergence diagnosis, I also plot two straight lines corresponding to the effective sample sizes (ESSs) of 1000 and 2000, respectively. The title at the top of the figure indicates the following: HPS### (HPS ID), line3 (number of data points used for the analysis), mderrY (model uncertainty included), EBVpriorG [Gaussian prior for $E(B-V)$], and BurnIn#### (burn-in iterations excluded before plotting).

than the values presented in Indahl et al. (2019). Therefore, the SFRs of the [O II]-selected galaxies are not likely to exceed the values of the star-forming main-sequence galaxies, which undermines their conclusion about filling in a missed galaxy population. However, Indahl et al. (2019) have only 27 [O II]-selected galaxies. Considering the 680-times-larger survey volume and the lower line-flux limit of the HETDEX than of the HPS (Indahl et al. 2019), it is premature to conclude that such a missed galaxy population would not be discovered from the forthcoming HETDEX survey.

As shown in section 3.2, the model parameter $E(B-V)$ does not recover the input value well. Therefore, $E(B-V)$ should be determined another way in order to correct the reddening properly. Since the HETDEX does not cover H$\alpha$, one simple way would be to use the Balmer decrement between H$\beta$ and H$\gamma$. I have verified that when $E(B-V)$ is correctly and independently estimated, the other three model parameters—$12 + \log(O/H)$, the intrinsic [O III] $\lambda$5007, and the intrinsic [N II] $\lambda$6584—recover the input values to within the 1-$\sigma$ level (Fig. 15). In Fig. 15, I have adopted a narrow Gaussian...
prior for $E(B-V)$ that is centered at the input value (i.e., 0.1) with $\sigma = 0.02$ in order to mimic the independently determined $E(B-V)$. I also checked how many targets would show a detectable Hγ line in the HETDEX survey. The HETDEX survey has a sensitivity of $\sim 3.5 \times 10^{-17}$ erg s$^{-1}$ cm$^{-2}$ in a baseline 20 min observation (Hill & HETDEX Consortium 2016). Assuming $E(B-V) = 0.3$ (close to the mean of the prior), Calzetti’s attenuation curve (Calzetti et al. 2000), and Case B recombination of Balmer lines (flux ratio of Hγ to Hβ $\sim 0.47$, Osterbrock & Ferland 2005), I found that the reddened Hβ flux of $\sim 1 \times 10^{-16}$ erg s$^{-1}$ cm$^{-2}$ corresponds to the reddened Hγ flux similar to the HETDEX sensitivity. If I apply this Hβ cutoff value to the galaxies observed in Indahl et al. (2019), 20 out of 29 galaxies would show a detectable Hγ line in the HETDEX survey. Not to lose the rest 1/3 of the targets, the attenuation correction should be done using Hα and Hβ lines instead, which consequently demands the follow-up observations. Another way to avoid the $E(B-V)$ overestimation is to use another strong-line calibration that shows much less scatter of line ratios for a given metallicity. However, comparable scatters are seen in other more recent calibrations that use the electron-temperature method (e.g., Pilyugin & Grebel 2016; Curti et al. 2017). Thus, this way does not seem to alleviate the $E(B-V)$ overestimation problem.
I have reanalyzed the local (z < 0.15) star-forming galaxies of Indahl et al. (2019) and have newly determined the gas metallicities, 12 + log (O/H). Indahl et al.’s target galaxies are from the HPS, which is a pilot survey for the more extensive, IFU-based, blind spectroscopic survey HETDEX. The HPS covers 3500 – 5800 Å at ∼ 5 Å resolution. Indahl et al. (2019) collected the line-emitting galaxies from this survey and measured the line fluxes of [O II] λ3727, Hβ, [O III] λ5007, etc. They estimated the gas metallicities of the galaxies using the strong-line method, which employs the flux ratios of strong (i.e., easy to observe) emission lines, employing the Bayesian approach and MCMC sampling. However, I noticed three points that can be improved in their analysis: (1) they had adopted a relatively small uncertainty for the line-ratio calibration; (2) they had not presented reproducibility tests with mock data; and (3) they had not mentioned the convergence of the MCMC sampling, which is important for ensuring the statistical accuracy of the MCMC samples. Here I reanalyzed the 27 [O II]-selected galaxies from Indahl et al. (2019), following their analysis scheme but carefully dealing with the three points mentioned above. I adopted a higher uncertainty for the line-ratio calibration to mimic properly that of the calibration Indahl et al. (2019) had adopted (Maiolino et al. 2008), and I secured ESS > 2000 for all the MCMC samples to achieve enough convergence. From reproducibility tests with mock data, I found that the parameter-estimation method of Indahl et al. (2019) can overestimate E(B − V), the intrinsic [O III] λ5007, and the intrinsic [N II] λ6584 by as much as 2-σ or more, although it can recover the metallicity to within 1-σ. Therefore, among the four model parameters only the metallicity estimates are reliable. When reanalyzing the HPS data, I excluded two [O III]-selected galaxies (see Indahl et al. 2019) because of the difficulty in one-to-one comparison between this work and Indahl et al.’s. Therefore, I only used the ratios R23 [eq. (2)] and O32 [eq. (3)], and hence needed three model parameters: 12 + log (O/H), E(B − V), and the intrinsic [O III] λ5007 (see section 3.3).

My metallicity determinations, 12 + log (O/H), are systematically higher than those of Indahl et al. (2019) by 0.18 dex (Fig. 11). Although this factor may seem insignificant, the median metallicities of Indahl et al. (2019) deviate from my estimates by as much as 2-σ overall (Fig. 12). The more important issue, however, concerns the convergence of the MCMC sampling. Indahl et al. (2019) did not mention the convergence, so one cannot know whether or not their estimates have appropriate statistical accuracy. I have shown that the statistical accuracy of the MCMC sampling can be as poor as the one near the iteration start if one runs the MCMC sampling without monitoring the convergence (see Fig. 10 and its counterpart Fig. 9). However, the conclusion of Indahl et al. (2019) about the relative position of their [O II]-selected galaxies to other star-forming galaxy populations in the mass-metallicity plane would remain intact, because (1) Indahl et al. (2019) used the same method to estimate the metallicity for all the galaxies under comparison and (2) there is a systematic difference between my estimates and those of Indahl et al. (2019) (Fig. 11).

Considering the E(B − V) overestimation, we need to rethink Indahl et al.’s two conclusions about the SFR, because they corrected the reddening using E(B − V), which can overestimate the SFR by as much as a factor of five (see section 4). First, Indahl et al.’s galaxies probably have a ‘lower’ SFR distribution than the SDSS star-forming galaxies (Andrews & Martini 2013), instead of a similar SFR distribution to the SDSS one as Indahl et al. (2019) described. Second, Indahl et al. (2019) found that their [O II]-selected galaxies reside between

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**Figure 11.** Comparison between the metallicity estimates from this work and from Indahl et al. (2019). The black dashed and red dotted lines are the 1:1 correspondence and 0.18 dex shifted lines, respectively. The three blue circles are the targets reported to have larger lower-credible-limits in Indahl et al. (2019): HPS067, HPS235, and HPS237.

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**5 CONCLUSION**

I have reanalyzed the local (z < 0.15) star-forming galaxies of Indahl et al. (2019) and have newly determined the gas metallicities, 12 + log (O/H). Indahl et al.’s target galaxies are from the HPS, which is a pilot survey for the more extensive, IFU-based, blind spectroscopic survey HETDEX. The HPS covers 3500 – 5800 Å at ∼ 5 Å resolution. Indahl et al. (2019) collected the line-emitting galaxies from this survey and measured the line fluxes of [O II] λ3727, Hβ, [O III] λ5007, etc. They estimated the gas metallicities of the galaxies using the strong-line method, which employs the flux ratios of strong (i.e., easy to observe) emission lines, employing the Bayesian approach and MCMC sampling. However, I noticed three points that can be improved in their analysis: (1) they had adopted a relatively small uncertainty for the line-ratio calibration; (2) they had not presented reproducibility tests with mock data; and (3) they had not mentioned the convergence of the MCMC sampling, which is important for ensuring the statistical accuracy of the MCMC samples. Here I reanalyzed the 27 [O II]-selected galaxies from Indahl et al. (2019), following their analysis scheme but carefully dealing with the three points mentioned above. I adopted a higher uncertainty for the line-ratio calibration to mimic properly that of the calibration Indahl et al. (2019) had adopted (Maiolino et al. 2008), and I secured ESS > 2000 for all the MCMC samples to achieve enough convergence. From reproducibility tests with mock data, I found that the parameter-estimation method of Indahl et al. (2019) can overestimate E(B − V), the intrinsic [O III] λ5007, and the intrinsic [N II] λ6584 by as much as 2-σ or more, although it can recover the metallicity to within 1-σ. Therefore, among the four model parameters only the metallicity estimates are reliable. When reanalyzing the HPS data, I excluded two [O III]-selected galaxies (see Indahl et al. 2019) because of the difficulty in one-to-one comparison between this work and Indahl et al.’s. Therefore, I only used the ratios R23 [eq. (2)] and O32 [eq. (3)], and hence needed three model parameters: 12 + log (O/H), E(B − V), and the intrinsic [O III] λ5007 (see section 3.3).

My metallicity determinations, 12 + log (O/H), are systematically higher than those of Indahl et al. (2019) by 0.18 dex (Fig. 11). Although this factor may seem insignificant, the median metallicities of Indahl et al. (2019) deviate from my estimates by as much as 2-σ overall (Fig. 12). The more important issue, however, concerns the convergence of the MCMC sampling. Indahl et al. (2019) did not mention the convergence, so one cannot know whether or not their estimates have appropriate statistical accuracy. I have shown that the statistical accuracy of the MCMC sampling can be as poor as the one near the iteration start if one runs the MCMC sampling without monitoring the convergence (see Fig. 10 and its counterpart Fig. 9). However, the conclusion of Indahl et al. (2019) about the relative position of their [O II]-selected galaxies to other star-forming galaxy populations in the mass-metallicity plane would remain intact, because (1) Indahl et al. (2019) used the same method to estimate the metallicity for all the galaxies under comparison and (2) there is a systematic difference between my estimates and those of Indahl et al. (2019) (Fig. 11).

Considering the E(B − V) overestimation, we need to rethink Indahl et al.’s two conclusions about the SFR, because they corrected the reddening using E(B − V), which can overestimate the SFR by as much as a factor of five (see section 4). First, Indahl et al.’s galaxies probably have a ‘lower’ SFR distribution than the SDSS star-forming galaxies (Andrews & Martini 2013), instead of a similar SFR distribution to the SDSS one as Indahl et al. (2019) described. Second, Indahl et al. (2019) found that their [O II]-selected galaxies reside between
Figure 12. Deviations between the metallicity estimates from this work and from Indahl et al. (2019). The dotted line in the left panel is the median metallicity estimated by Indahl et al. (2019), which is taken as the zero point for the present analysis. The circles with error bars in the left panel represent the metallicity distributions estimated in this work. The error bars are 1-σ (68 %), 2-σ (95 %), and 3-σ (99 %) credible intervals, respectively. The three right panels show how much the estimates from this work deviate from those of Indahl et al. (2019). Each histogram shows the 1-σ, 2-σ, or 3-σ lower credible limit from this work minus the median values from Indahl et al. (2019). Again, the dotted lines in the right panels represent the median metallicity estimated by Indahl et al. (2019), which is taken as the zero point for the present analysis. The data point for HPS235 falls outside the frame in both the middle and bottom panels, because the 2-σ and 3-σ lower credible limit for HPS235 are much smaller than those for the other galaxies.
Figure 13. Comparison of the metallicity distributions. The gray histograms are the median metallicity values from this work, and the white histograms are those from Indahl et al. (2019). The medians of the distributions are given in the legend.

Figure 14. Comparisons in the mass-metallicity plot. The red circles are the metallicity estimates from this work, and the gray circles are from Indahl et al. (2019). The mass estimates are from Indahl et al. (2019), which were derived from spectral-energy-distribution fitting with MCSED (Bowman et al. 2020).
the green-pea galaxies (a kind of extreme star-forming galaxies) and the SDSS star-forming main-sequence galaxies along the SFR axis in the mass-SFR plane. In actuality, this is probably not the case, because the SFRs of Indahl et al.’s galaxies and of the green-pea galaxies have been overestimated. That is, Indahl et al.’s galaxies are likely to overlap with the main-sequence galaxies. This undermines Indahl et al.’s conclusion that their blind spectroscopic survey fills in a galaxy population that has been missed in photometric surveys with continuum-flux preselection, like the SDSS. However, it is premature to conclude that the forthcoming HETDEX would not discover hitherto-unknown galaxy populations, considering that the HETDEX will have a much larger survey volume and lower line-flux limit than the HPS. To avoid the $E(B-V)$ overestimation, I checked whether the independent determination of $E(B-V)$ from H$\beta$ and H$\gamma$ lines is a viable option. I found that once $E(B-V)$ is independently determined, the other three model parameters—$12 + \log(O/H)$, the intrinsic $[O\,\text{III}]\,\lambda5007$, and the intrinsic $[N\,\text{II}]\,\lambda6584$—recovery the input values well (Fig. 15). I also found that $\sim2/3$ of the galaxies observed in Indahl et al. (2019) would show a detectable H$\gamma$ line in the HETDEX survey, although another follow-up observation would be required not to lose the rest $1/3$ of the galaxies (for the independent $E(B-V)$ determination using H$\alpha$ and H$\beta$ lines).

**Figure 15.** Posterior distribution and evolution of the integrated autocorrelation times ($\tau_{\text{int}}$) from another mock-data test. The setting for this test is the same as for Fig. 6, except that I have adopted a narrower Gaussian prior for $E(B-V)$ that is centered at the input value (0.1) with $\sigma = 0.02$ in order to mimic an independently determined $E(B-V)$. The figure description is otherwise the same as for Fig. 3.
| HPS ID  | 12+log(O/H) | \(E(B-V)\) | intrinsic [O III] \(\lambda 5007\) flux (10\(^{-16}\) erg s\(^{-1}\) cm\(^{-2}\)) |
|--------|-------------|-------------|--------------------------------------|
| HPS035 | 8.94\(^{+0.12}_{-0.08}\) | 0.42\(^{+0.15}_{-0.14}\) | 163.70\(^{+130.55}_{-12.66}\) |
| HPS044 | 8.84\(^{+0.14}_{-0.12}\) | 0.39\(^{+0.14}_{-0.14}\) | 11.28\(^{+10.16}_{-10.16}\) |
| HPS065 | 9.06\(^{+0.16}_{-0.09}\) | 0.37\(^{+0.13}_{-0.13}\) | 23.00\(^{+21.96}_{-11.08}\) |
| HPS067 | 9.12\(^{+0.13}_{-0.12}\) | 0.40\(^{+0.14}_{-0.14}\) | 3.76\(^{+3.90}_{-2.38}\) |
| HPS105 | 8.77\(^{+0.12}_{-0.13}\) | 0.40\(^{+0.14}_{-0.14}\) | 23.27\(^{+20.94}_{-14.07}\) |
| HPS118 | 8.99\(^{+0.13}_{-0.12}\) | 0.38\(^{+0.14}_{-0.14}\) | 5.94\(^{+2.97}_{-2.97}\) |
| HPS119 | 8.86\(^{+0.12}_{-0.09}\) | 0.39\(^{+0.14}_{-0.14}\) | 51.48\(^{+23.36}_{-23.36}\) |
| HPS125 | 8.93\(^{+0.12}_{-0.09}\) | 0.42\(^{+0.14}_{-0.14}\) | 63.15\(^{+58.07}_{-58.07}\) |
| HPS129 | 8.73\(^{+0.14}_{-0.12}\) | 0.42\(^{+0.14}_{-0.14}\) | 32.95\(^{+29.49}_{-29.49}\) |
| HPS138 | 8.93\(^{+0.08}_{-0.09}\) | 0.37\(^{+0.13}_{-0.13}\) | 20.30\(^{+19.79}_{-19.79}\) |
| HPS158 | 8.90\(^{+0.13}_{-0.10}\) | 0.38\(^{+0.14}_{-0.14}\) | 8.25\(^{+3.99}_{-3.99}\) |
| HPS219 | 8.90\(^{+0.13}_{-0.10}\) | 0.37\(^{+0.13}_{-0.13}\) | 24.42\(^{+22.86}_{-14.64}\) |
| HPS225 | 8.90\(^{+0.14}_{-0.14}\) | 0.39\(^{+0.14}_{-0.14}\) | 11.93\(^{+5.16}_{-5.16}\) |
| HPS235 | 8.90\(^{+0.16}_{-0.17}\) | 0.39\(^{+0.14}_{-0.14}\) | 5.23\(^{+2.86}_{-2.86}\) |
| HPS237 | 9.01\(^{+0.14}_{-0.13}\) | 0.39\(^{+0.14}_{-0.14}\) | 5.15\(^{+6.61}_{-6.61}\) |
| HPS260 | 8.89\(^{+0.12}_{-0.13}\) | 0.39\(^{+0.14}_{-0.14}\) | 4.63\(^{+2.99}_{-2.99}\) |
| HPS278 | 8.70\(^{+0.10}_{-0.10}\) | 0.40\(^{+0.14}_{-0.14}\) | 58.89\(^{+34.23}_{-28.53}\) |
| HPS300 | 8.99\(^{+0.12}_{-0.09}\) | 0.40\(^{+0.14}_{-0.14}\) | 6.97\(^{+6.39}_{-5.39}\) |
| HPS303 | 8.77\(^{+0.14}_{-0.12}\) | 0.43\(^{+0.13}_{-0.13}\) | 16.47\(^{+15.83}_{-8.09}\) |
| HPS326 | 8.94\(^{+0.09}_{-0.13}\) | 0.38\(^{+0.14}_{-0.14}\) | 13.34\(^{+11.94}_{-9.48}\) |
| HPS363 | 9.04\(^{+0.13}_{-0.12}\) | 0.37\(^{+0.13}_{-0.13}\) | 5.45\(^{+2.99}_{-2.99}\) |
| HPS375 | 8.97\(^{+0.08}_{-0.13}\) | 0.39\(^{+0.14}_{-0.14}\) | 71.38\(^{+59.99}_{-31.19}\) |
| HPS386 | 8.95\(^{+0.11}_{-0.13}\) | 0.39\(^{+0.14}_{-0.14}\) | 26.84\(^{+12.01}_{-12.01}\) |
| HPS413 | 9.01\(^{+0.06}_{-0.10}\) | 0.37\(^{+0.13}_{-0.13}\) | 22.74\(^{+20.10}_{-10.51}\) |
| HPS438 | 8.90\(^{+0.09}_{-0.13}\) | 0.38\(^{+0.14}_{-0.14}\) | 4.61\(^{+2.91}_{-2.91}\) |
| HPS449 | 8.84\(^{+0.09}_{-0.13}\) | 0.40\(^{+0.14}_{-0.14}\) | 18.67\(^{+16.87}_{-9.84}\) |
| HPS458 | 9.07\(^{+0.11}_{-0.10}\) | 0.36\(^{+0.14}_{-0.14}\) | 10.29\(^{+4.78}_{-4.78}\) |

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DATA AVAILABILITY

All the MCMC sampling results can be downloaded from https://data.kasi.re.kr/vo/Stat_Reanal/ with a plotting script.
This paper has been typeset from a \TeX/\LaTeX\ file prepared by the author.