A new estimator of resolved molecular gas in nearby galaxies

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ABSTRACT
A relationship between dust-reprocessed light from recent star formation and the amount of star-forming gas in a galaxy produces a correlation between WISE 12µm emission and CO line emission. Here we explore this correlation on kiloparsec scales with CO(1-0) maps from EDGE-CALIFA matched in resolution to WISE 12µm images. We find strong CO-12µm correlations within each galaxy (median Pearson r = 0.85) and we show that the scatter in the global CO-12µm correlation is largely driven by differences from galaxy to galaxy. The correlation is stronger than that between star formation rate and H2 surface densities over the same set of pixels (median r = 0.71). We explore multi-variable regression to predict Σ(H2) surface density using the WISE 12µm data combined with global and resolved galaxy properties, and provide the fit parameters for the best estimators. We find that Σ(H2) estimators that include Σ(12µm) are able to predict Σ(H2) with > 10% better accuracy than estimators that include resolved optical properties (Σ(SFR), Σ(M*), Aν and 12 + log O/H) instead of Σ(12µm). The best single-property estimator is log Σ(H2) = (0.49±0.01)+(0.71±0.01) log Σ(12µm), with an average predictive accuracy of 0.19 dex per pixel, and intrinsic scatter of 0.17 dex. This correlation can be used to efficiently estimate H2 surface densities down to at least 1 M⊙ pc−2 on small spatial scales within nearby galaxies. This correlation may prove useful to probe even lower gas densities with the better mid-infrared sensitivities expected from the James Webb Space Telescope.

Key words: galaxies: ISM – infrared: ISM – radio lines: ISM

1 INTRODUCTION

Stars form out of molecular hydrogen in cold, dense regions of the interstellar medium (ISM). Empirically this picture is supported by correlations between tracers of cold gas and the radiation output from young stars such as the Kennicutt-Schmidt (KS) law

Σ(SFR) = C Σ(gas)N,

where Σ(SFR) is the star formation rate (SFR) surface density (M⊙ kpc−2), Σ(gas) is the atomic (H I) + molecular (H2) gas surface density (M⊙ pc−2), and N is a power-law index of ≈ 1.4, or ≈ 1.0 if only H2 is included (Kennicutt 1989; Kennicutt et al. 2007; Bigiel et al. 2008; Leroy et al. 2008, 2013). Within the scatter of the KS law, there are systematic variations between galaxies and sub-regions within galaxies, suggesting that this law may not be universal (Shetty et al. 2013). For instance, below Σ(gas) ≳ 10 M⊙ pc−2 and Σ(SFR) ≲ 10−3 M⊙ yr−1 kpc−2, the stellar mass surface density Σ*, becomes important in regulating the star formation rate (Σ(SFR) ∝ [Σ0.5Σ(gas)],10) (Shi et al. 2011, 2018). Another example of a modification to the KS law is the Silk-Elmegreen law, which incorporates the orbital dynamical timescale Σ(SFR) ∝ t−1 dyn Σ(gas) (Elmegreen 1997, Silk 1997). On the galaxy-integrated (“global”) side, Gao & Solomon (2004) found a strong correlation between global measurements of HCN luminosity (a dense molecular gas tracer) and total infrared luminosity (a SFR tracer) ranging from normal spirals to ultraluminous infrared galaxies, again supporting a picture in which stars form in cold dense gas. The physical interpretation of these relationships requires an understanding of the limitations and mechanisms behind the tracers used to measure Σ(SFR) and Σ(gas) (e.g. Krumholz & Thompson 2007). One manifestation of the KS law is the correlation between 12µm luminosity, measured with the Wide-field In-
frared Survey Explorer (WISE; Wright et al. 2010), and CO luminosity measured by ground-based radio telescopes. The 12µm (also called W3) band spans mid-infrared (MIR) wavelengths of 8 to 16 µm. In nearby galaxies, 12µm emission traces SFR (e.g. Donoso et al. 2012; Jarrett et al. 2013; Salim et al. 2016; Cluver et al. 2017; Salim et al. 2018; Leroy et al. 2019), vibrational emission lines from polycyclic aromatic hydrocarbons (PAHs), and warm dust emission (Wright et al. 2010). Galaxy-integrated 12µm luminosity is strongly correlated with CO(1-0) and CO(2-1) luminosity in nearby galaxies (Jiang et al. 2015; Gao et al. 2019). Gao et al. (2019) find

\[
\log \left( \frac{L_{\text{CO}(1-0)}}{\text{K km s}^{-1} \text{ pc}^2} \right) = N \log \left( \frac{L_{12\mu m}}{L_\odot} \right) + \log C,
\]

(2)

with \(N = 0.98 \pm 0.02\) and \(\log C = -0.14 \pm 0.18\), and scatter of 0.20 dex. The correlation between 22µm luminosity and CO luminosity is weaker (0.3 dex scatter) than that between 12µm and CO (0.2 dex scatter), implying that 12µm luminosity is a better indicator of CO luminosity than 22µm (Gao et al. 2019). The scatter in the global 12µm CO fit is reduced to 0.16 dex when g - r colour and stellar mass are included as extra variables in the fit (Gao et al. 2019). Empirical relationships such as these are useful for predicting molecular gas masses in galaxies, since 12µm images are easier to obtain than CO luminosities. Other work has established that PAH emission is better correlated with cold rather than warm dust emission, and may be used as a molecular gas mass tracer in star-forming galaxies (Cortzen et al. 2019). Mid-infrared tracers of cold gas will be particularly useful upon the launch of the James Webb Space Telescope, which will observe the MIR sky with better resolution and sensitivity than WISE.

Optical extinction AV (e.g. using the Balmer decrement Hα/Hβ) has also been proposed as an H2 mass tracer in nearby galaxies (Güver & Özel 2009; Barrera-Ballesteros et al. 2016; Concas & Popesso 2019; Yesuf & Ho 2019; Barrera-Ballesteros et al. 2020). This method is convenient since spatially resolved extinction maps are available for large samples of galaxies thanks to optical integral-field spectroscopy surveys. However, unlike 12µm, extinction as measured by the Balmer decrement is only valid over a range that is limited by the signal-to-noise ratio of the Hβ emission line.

It is not yet known whether the correlation between 12 µm and CO holds at sub-galaxy scales, or how it compares with the resolved correlation between AV and H2. The WISE 12 µm beam full-width at half-maximum (FWHM) is 6.6 arcsec (Wright et al. 2010), which corresponds to \(\leq 1\) kpc resolution for galaxies closer than 31 Mpc. This resolution and distance range is well-matched to the Extragalactic Database for Galaxy Evolution survey (EDGE; Bolatto et al. 2017). EDGE is a survey of CO(1-0) in 126 nearby galaxies with 4.5 arcsec spatial resolution using the Combined Array for Research in Millimeter-wave Astronomy (CARMA). One of the main goals of EDGE was to allow studies of resolved molecular gas and optical integral-field spectroscopy data in a large sample of nearby galaxies.

In this study, we use the EDGE CO and WISE data to measure the 12µm and CO(1-0) correlation within individual galaxies. We find that the fit parameters vary significantly among galaxies. We perform multivariate linear regression using a combination of global galaxy measurements and quantities derived from spatially resolved optical spectroscopy from the Calar Alto Legacy Integral Field Area Survey (CALIFA; Sánchez et al. 2012; Walcher et al. 2014; Sánchez et al. 2016). This yields a set of linear functions with log(H2) as the independent variable which can be used as spatially resolved estimators of H2 surface density. These estimators can predict H2 surface density with an RMS accuracy of \(\approx 0.2\) dex for galaxies for which 12 µm data are available.

### 2 DATA AND DATA PROCESSING

#### 2.1 Sample selection

The sample is selected from the EDGE survey (Bolatto et al. 2017, hereafter B17). The typical angular resolution of EDGE CO maps is 4.5 arcsec, and the typical H2 surface density sensitivity before deprojecting galaxy inclination is 11 M⊙ pc\(^{-2}\) (B17). Every EDGE galaxy has optical integral field unit (IFU) data from CALIFA, allowing joint studies of the content and kinematics of cold gas (H2), ionized gas, and stellar populations, all with \(\sim\)kpc spatial resolution. We selected 95 galaxies that were classified as CO(1-0) detections in the EDGE survey. We then selected those galaxies with inclinations less than 75 degrees, leaving 83 galaxies. Inclination angles were derived from CO rotation curves where available (B17), and otherwise were taken from the HyperLEDA database (Makarov et al. 2014). Redshifts z (from CALIFA emission lines) and luminosity distances DL were taken from B17. A flat ΛCDM cosmology was assumed (\(h = 0.7\), \(Ω_m = 0.27\), \(Ω_\Lambda = 0.73\)).

#### 2.2 WISE 12µm surface density maps

We downloaded 2 degree by 2 degree cutouts (pixel size 1.375 arcsec) of WISE 12µm (W3) flux \(F_{12\mu m}\) and uncertainty for each galaxy from the NASA/IPAC Infrared Science Archive. The background for each galaxy was estimated using the IDL package Software for Source Extraction (SExtractor; Bertin & Arnouts 1996), with default parameters and with the corresponding W3 uncertainty map as input. The estimated background was subtracted from each cutout. The background-subtracted images were reprojected with 6 arcsec pixels to avoid over-sampling the 6.6 arcsec beam. These maps were originally in units such that a W3 magnitude of 18.0 corresponds to \(F_{12\mu m} = 1.0\), or

\[
F_{12\mu m} = 10^{-0.4(m_{W3}) - 18}.
\]

(3)

We converted the maps in their original units to flux density in Jy, given by

\[
S_{12\mu m} = 31.674 \text{ Jy} \times 10^{-0.4(m_{W3})}
\]

(4)

\[
= \frac{31.674}{10^{0.4}} F_{12\mu m}
\]

(5)

\[
= 1.998 \times 10^{-6} F_{12\mu m}.
\]

(6)

where the isophotal flux density 31.674 Jy for the W3 band is from Table 1 of Jarrett et al. (2011). Luminosity in units
of $L_\odot$ is given by

$$L_{12\mu m} = 4\pi D_L^2 \Delta v S_{12\mu m}$$

(7)

$$= 7.042 F_{12\mu m} \left( \frac{D_L}{\text{Mpc}} \right)^2 L_\odot$$

(8)

where $\Delta v = 1.1327 \times 10^{13}$ Hz is the bandwidth of the 12\(\mu\)m band (Jarrett et al. 2011), and $D_L$ is the luminosity distance. Luminosities were then converted into surface densities $\Sigma(12\mu m)$ ($L_\odot$pc$^{-2}$) by

$$\Sigma(12\mu m) = 7.042 F_{12\mu m} \left( \frac{D_L}{\text{Mpc}} \right) \cos i \frac{\lambda_{\text{pix}}}{\xi_{\text{pix}}}$$

(9)

where $i$ is the galaxy inclination, and $\lambda_{\text{pix}}$ is the pixel area in pc$^2$.

The uncertainty in each pixel of the rebinned surface density maps is the quadrature sum of the instrumental uncertainty and the 4.5 per cent uncertainty in the zero-point magnitude (Appendix A). Maps for an example galaxy are shown in Figure 1.

### 2.3 $\text{H}_2$ surface density maps at WISE W3 resolution

The original CO(1-0) datacubes were downloaded from the EDGE website, converted from their native units of K km s$^{-1}$ to Jy beam$^{-1}$ km s$^{-1}$, and then smoothed to a Gaussian beam with FWHM = 6.6 arcsec using the Common Astronomy Software Applications (CASA; McMullin et al. 2007) task imsmooth to match the WISE resolution. The cubes have a velocity resolution of 20 km s$^{-1}$, and span 44 channels (880 km s$^{-1}$). Two methods were used to obtain CO integrated intensity (moment-0) maps $S_{\text{CO}} \Delta v$:

**Method 1:** an iterative masking technique for improving SNR, described in Sun et al. (2018), shown in Figure 1, and

**Method 2:** integrating the flux along the inner 34 channels (680 km s$^{-1}$ total). In this “simple” method, the first 5 and last 5 channels were used to compute the root-mean-square (RMS) noise at each pixel. Method 1 is used for all results in this work, while Method 2 is used as a cross-check and to estimate upper limits for non-detected pixels.

In Method 1 (described in Sun et al. 2018) a mask is generated for the datacube to improve the signal-to-noise of the resulting moment-0 map. A “core mask” is generated by requiring SNR of 3.5 over 2 consecutive channels (channel width of 20 km s$^{-1}$), and a “wing mask” is generated by requiring SNR of 2.0 over 2 consecutive channels. The core mask is dilated within the wing mask to generate a “signal mask” which defines detections. Any detected regions that span an area less than the area of the beam are masked. The signal mask is then extended spectrally by ±1 channels. Method 2 gives a map with lower signal-to-noise, but is useful for computing upper-limits for pixels which are masked in Method 1, and for cross-checking results.

The moment-0 maps were then rebinned with 6 arcsec pixels, and the units were converted to integrated intensity per pixel

$$\frac{S_{\text{CO}} \Delta v}{\text{Jy km s}^{-1}\text{pixel}^{-1}} = \frac{S_{\text{CO}} \Delta v}{\text{Jy beam}^{-1}\text{km s}^{-1}} \frac{4\pi^2 \text{pix}^2 \ln 2}{\text{FWHM}^2}$$

(10)

where the beam FWHM = 6.6 arcsec, and the pixel size $\theta_{\text{pix}}$ = 6 arcsec.

The total noise variance in each pixel is the sum in quadrature of the instrumental noise which we assume to be the same for both moment-0 map versions, and calibration uncertainty which depends on the moment-0 method (Appendix B). Instrumental noise maps were computed by measuring the RMS in the first five and final five channels at each pixel (Method 2 above). The instrumental noise maps were rebinned (added in quadrature, then square root) into

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**Figure 1.** Selected maps for an example galaxy. Top row (left to right): Sloan Digital Sky Survey (SDSS; Blanton et al. 2017) gri thumbnail; WISE 12\(\mu\)m surface density ($L_\odot$pc$^{-2}$); H$_2$ mass surface density ($M_\odot$pc$^{-2}$) at 6.6 arcsec resolution and assuming $\alpha_{\text{CO}} = 3.2$ $M_\odot$ (K km s$^{-1}$pc$^2$)$^{-1}$; BPT diagram for each pixel constructed from the processed CALIFA data (Section 2.4). The pixel size is 6 arcsec. Bottom row: signal-to-noise ratio (SNR) of the 12\(\mu\)m and H$_2$ surface density maps, and the metallicity-dependent $\alpha_{\text{CO}}$ values in units of $M_\odot$ (K km s$^{-1}$pc$^2$)$^{-1}$ (Equation 17).
6 arcsec pixels. To obtain the total noise for each moment-0 map, a calibration uncertainty of 5 per cent of the rebinned moment-0 map (both versions described above) was added in quadrature with the instrumental uncertainty. The sensitivity of the CO data is worse than that of WISE W3, and so upper limits are calculated with the second moment-0 map-making method. All pixels detected at less than 3σ in CO were assigned a 3σ upper limit of 5 times the total noise at each pixel. This comes from the fact that if one assumes Gaussian noise, then for a signal-to-noise threshold of 3 there is a 99% probability of detecting flux below $(3 + 2.054)\sigma = 5\sigma$, where $\sigma$ is the RMS noise.

The CO(1-0) luminosity and noise maps (in units of K km s$^{-1}$ pc$^2$) were computed via (Bolatto et al. 2013)

$$L_{\text{CO}(1-0)} = \frac{2453 L_{\text{CO}} (\text{K} \text{ km s}^{-1} \text{ pc}^2)}{1 + z},$$

(11)

where $z$ is the redshift. The luminosity maps were converted to H$_2$-mass surface density $\Sigma(H_2)$ using a CO-to-H$_2$ conversion factor $\alpha_{\text{CO}}$

$$\Sigma(H_2) = \frac{\alpha_{\text{CO}} L_{\text{CO}} \cos i}{A_{\text{pix}}},$$

(12)

where $i$ is the galaxy inclination angle, and $A_{\text{pix}}$ is the pixel area in pc$^2$. In normal star-forming regions a CO-to-H$_2$ conversion factor of $\alpha_{\text{CO}} = 3.2\ M_\odot(K\ \text{km}\ \text{s}^{-1}\ \text{pc}^2)^{-1}$ (multiply by 1.36 to include helium) is often assumed (Bolatto et al. 2013). We consider both a constant $\alpha_{\text{CO}}$ and a spatially-varying metallicity-dependent $\alpha_{\text{CO}}$ (Section 2.5).

### 2.4 Maps of stellar population and ionized gas properties

In the third data release (DR3) of the CALIFA survey there are 667 galaxies observed out to at least two effective radii with $\leq 2.5$ arcsec angular resolution over wavelength ranges 3700-7500 Å (Sánchez et al. 2012, 2016). The observations were carried out in either a medium spectral resolution mode ("V''100," $R = 1700$, 3700–4200 Å, 484 galaxies) or a low spectral resolution mode ("V''500," $R = 850$, 3750–7500 Å, 646 galaxies). Cubes using data from both V''100 and V''500 were made by degrading the spectral resolution of the V''100 cube to that of V''500 and averaging the spectra where their wavelength coverage overlaps, and using only V''200 or V''500 for the remaining wavelength bins between 3700-7140 Å (Sánchez et al. 2016). Combined V''200 + V''500 datacubes and V''500 datacubes were downloaded from https://califaserv.caha.es/CALIFA_WEB/public_html/?q=content/califa-3rd-data-release. Of the 95 EDGE galaxies detected in CO, combined V''200 + V''500 datacubes are available for 87 galaxies. V''500 datacubes were used for the remaining 8 galaxies. We refer to this sample of 8 + 87 galaxies as "Sample A" (Table 1).

The native pixel size of a CALIFA cube is 1 arcsec. The spaxels were stacked into 6 arcsec spaxels to be compared with the WISE and EDGE CO data. Spectral fitting was performed on the stacked spectra using the Penalized Pixel-Fitting (pPXF) Python package (Cappellari 2017) to obtain 2D maps of emission and absorption line fluxes, equivalent widths, and velocity dispersions, as well as stellar population properties such as stellar mass and light-weighted stellar age. A Kroupa initial mass function (IMF) was assumed (Kroupa & Weidner 2003).

Line fluxes were corrected for extinction using the Balmer decrement. Stellar mass was measured from the datacubes after subtracting a dust attenuation curve using the method of Li et al. (2020). The unattenuated H$_\alpha$ emission line flux $F_{\text{H}\alpha}$ is related to the observed (attenuated) flux according to

$$F_{\text{H}\alpha} = F_{\text{H}\alpha, \text{obs}} (10^{0.4 A_V})$$

(13)

where the extinction is given by

$$A_V = 5.86 \log \left( \frac{F_{\text{H}\alpha, \text{obs}}}{2.80 F_{\text{H}\beta, \text{obs}}} \right).$$

(14)

and $F_{\text{H}\alpha, \text{obs}}$ and $F_{\text{H}\beta, \text{obs}}$ are the observed (attenuated) line fluxes. The star formation rate (SFR) surface density is given by

$$\Sigma(\text{SFR}) = \frac{C_{\text{SFR, H}_\alpha} L_{\text{H}_\alpha}}{A_{\text{pix}}}$$

(15)

where the H$_\alpha$ luminosity-to-SFR calibration factor $C_{\text{SFR, H}_\alpha} = 5.3 \times 10^{-42} M_\odot\ yr^{-1}\ cm^{-2}$ (Hao et al. 2011; Murphy et al. 2011; Kennicutt & Evans 2012), $d$ is the luminosity distance in cm, and $A_{\text{pix}}$ is the pixel area in kpc$^2$.

The mechanism of gas ionization at each pixel was classified as either star formation (SF), low-ionization emission region (LIER), Seyfert (Sy) or a combination of star formation (FSF, LI+FSF) by a combination of star formation and AGN ("composite") on a Baldwin, Phillips, and Terlevich (BPT) diagram (Baldwin et al. 1981). It is important to identify non-star-forming regions, especially when estimating SFR from H$_\alpha$ flux. BPT classification (Figure 1) was done in the [O ii] vs. [N ii] plane using three standard demarcation curves in this space: Eq. 5 of Kewley et al. (2001), Eq. 1 of Kauffmann et al. (2003), and Eq. 3 of Cid Fernandes et al. (2010) (see Figure 7 of Husemann et al. 2013).

### 2.5 CO-to-H$_2$ conversion factor

The CO-to-H$_2$ conversion factor decreases slightly with metallicity (Wilson 1995; Genzel et al. 2012). This is because at lower metallicities there is less CO present and therefore lower CO luminosity, but not necessarily less H$_2$ present as would be suggested by applying a constant $\alpha_{\text{CO}}$. A metallicity-dependent $\alpha_{\text{CO}}$ equation (Genzel et al. 2012) was calculated at each star-forming pixel (Figure 1)

$$\log \left( \frac{\alpha_{\text{CO}}}{M_\odot(K\ \text{km}\ \text{s}^{-1}\ \text{pc}^2)^{-1}} \right) = a + b (\log(\text{O/H})),$$

(17)

where $a = 12 \pm 2$, and $b = -1.30 \pm 0.25$. Gas-phase metallicity $12 + \log(\text{O/H})$ was computed for the star-forming pixels using

$$12 + \log(\text{O/H}) = p + q \log \left( \frac{[\text{N} \text{ ii}]}{[\text{H} \alpha]} \right),$$

(18)

where $p = 9.12 \pm 0.05$, and $q = 0.73 \pm 0.10$ (Denicoló et al. 2002). The uncertainties in $a$, $b$, $p$, and $q$ were not used in this analysis.

The metallicity-dependent $\alpha_{\text{CO}} = \alpha_{\text{CO}}(Z)$ (Eq. 17) is our
Previous work has shown a strong correlation between the resolution of the EDGE CO maps to WISE (Jiang et al. 2015; Gao et al. 2019). To determine if this correlation is strong within galaxies, the correlation is strong. To assess the impacts of these effects, three α scenarios are considered:

(i) α = 3.2, using all pixels (star-forming or not);
(ii) α = 3.2, only using star-forming pixels; and
(iii) a metallicity-dependent α = α(CO(Z)) (Eq. 17).

The impact of only considering star-forming pixels on the total number of pixels and galaxies (Table 1) varies depending on how many pixels per galaxy are required. For example, starting from the 95 galaxies in Sample A (Table 1), if we require at least 4 CO-detected pixels per galaxy, our sample will consist of 83 galaxies and 2059 pixels (Sample B).

If we require at least 4 CO-detected star-forming pixels per galaxy (e.g. to apply a metallicity-dependent α), we would have to remove 43% of the pixels and 22% of the galaxies from the sample, and would be left with 1168 pixels and 64 galaxies (Sample C). In the analysis that follows, we use Sample C exclusively except for comparison with Sample B in Section 3.1.

3 ANALYSIS AND RESULTS

3.1 The degree of correlation between Σ(12μm) and Σ(H2)

The relationship between 12μm and CO emission resembles the Kennicutt-Schmidt relation, which also shows variation from galaxy to galaxy (Shetty et al. 2013). We model the relationship between log Σ(12μm) and log Σ(H2) with a power-law

\[ \log \Sigma(12\mu m) = N \log \Sigma(H_2) + \log C. \]  

To determine whether the 12μm-CO relation is universal or not, we performed linear fits of log Σ(12μm) against log Σ(H2) for each galaxy with at least 4 CO-detected star-forming pixels (Sample C in Table 1; middle panel of Figure 2). A metallicity-dependent α was used in Figure 2. These fits were performed using LinMix, a Bayesian linear regression code which incorporates uncertainties in both x and y (Kelly 2007). We repeated the fits for each αCO (Sec. 2.5) and with log Σ(12μm) on the x-axis instead.

For a given galaxy, the best-fit parameters do not vary much depending on the αCO assumed, provided there are enough pixels to perform the fit even after excluding non-starforming pixels. However, we find significant differences in the slope and intercept from galaxy to galaxy, indicating a non-universal resolved relation. The galaxy-to-galaxy variation in best-fit parameters persists for all three αCO scenarios. The galaxy-to-galaxy variation can be seen in the distribution of slopes and intercepts assuming a metallicity-dependent αCO for example (Figure 4). The best-fit intercepts span a range of ± 1 dex (−1 to 0.5, median −0.11), and the slopes range from 0.4 to 1.2, with a median of 0.72. To quantify the significance of the galaxy-to-galaxy variation in best-fit parameters, residuals in the parameters relative to the mean parameters were computed. For example,
if the measurement of the slope for galaxy $i$ is $N_i \pm \sigma_{N_i}$, the residual relative to the average slope over all galaxies $\bar{N}$ is $(N_i - \bar{N})/\sigma_{N_i}$. Similarly, if the measurement of the intercept for galaxy $i$ is $\log C_i \pm \sigma_{\log C_i}$, the residual relative to the average intercept over all galaxies $\bar{C}$ is $(\log C_i - \log \bar{C})/\sigma_{\log C_i}$. The residual histograms (Figure 4) show that most of the slopes $N_i$ are within $\pm 1.5\sigma_{N_i}$ of $\bar{N}$, but the intercepts show more significant deviations (many beyond $3\sigma_{\log C_i}$).

To establish how well-fit all pixels are to a single model, linear fits were done on all CO-detected pixels from all 83 galaxies in Sample B (Table 1) using LinMix (black crosses in Figure 5). The fits were done separately for luminosities ($\log L_{12\mu m}$, $\log L_{CO}$; left column of Figure 5) and surface densities ($\log \Sigma_{12\mu m}$, $\log \Sigma(H_2)$; right column of Figure 5). The fits were done separately with CO/H$_2$ or 12µm on the x-axis (top and bottom rows of Figure 5, respectively). In all cases there are strong correlations (correlation coefficients of $\approx 0.90$), and good fits (total scatter about the fit $\sigma_{\text{fit}} \approx 0.19$ dex). By comparing the total scatter $\sigma_{\text{tot}}$ and intrinsic scatter $\sigma_{\text{int}}$ (Appendix C), it is clear that most of the scatter is intrinsic rather than due to measurement uncertainties.

Similarly, to establish how well-fit all global values are to a single model, linear fits were done on the galaxy-integrated values for all 83 galaxies in Sample B (Table 1) using LinMix (green diamonds in Figure 5). The fits were done separately for luminosities ($\log L_{12\mu m}$, $\log L_{CO}$; left column of Figure 5) and surface densities ($\log \Sigma_{12\mu m}$, $\log \Sigma(H_2)$; right column of Figure 5). The fits were done separately with CO/H$_2$ or 12µm on the x-axis (top and bottom rows of Figure 5, respectively). The results show good fits overall (correlation coefficients of $\approx 0.90$, scatter about the fit $\sigma_{\text{fit}} \approx 0.20$ dex). The global values do indeed follow uniform trend (with the exception of one outlier), and the global fits with molecular gas on the x-axis show steeper slopes and smaller y-intercepts than the pixel fits (Figure 5). The global fits with 12µm on
the x-axis show shallower slopes and larger y-intercepts than the pixel fits.

3.3 Spatially resolved estimator of $\Sigma(H_2)$

To develop an estimator of $\log \Sigma(H_2)$ from $\log \Sigma(12\mu m)$ and other galaxy properties, we performed linear regression on all of the star-forming pixels from all galaxies combined. Global properties (from UV, optical, and infrared measurements) and resolved optical properties were included (Table 2). The model is

$$\tilde{y} = \theta_0 + \sum_i \theta_i x_i,$$

where each entry of $\tilde{y}$ is $\log \Sigma(H_2)$ for each pixel of each galaxy (using the metallicity-dependent $\alpha_{CO}$, Eq. 17), the $\theta$ are the fit parameters, and the sum is over $i$ properties (a combination of pixel properties or global properties). We used ridge regression, implemented in the Scikit-Learn Python package (Pedregosa et al. 2012), which is the same as ordinary least squares regression except it includes a penalty term. The best value of $\delta$ is determined by cross-validation using RidgeCV. In ridge regression it is important to standardize the data prior to fitting (subtract the sample mean and divide by the standard deviation for all global properties and pixel properties) so that the penalty term is not affected by different units or spreads of the properties. The standardized version of Equation 20 is

$$y - \text{mean}(y) = \sum_i \hat{\theta}_i \left( x_i - \text{mean}(x_i) \right).$$

Note that it is not necessary to divide $y - \text{mean}(y)$ by $\text{std}(y)$ because it does not impact the regularization term. After performing ridge regression on the standardized data (which provides $\hat{\theta}_i$), the best-fit coefficients in the original units are given by

$$\theta_i = \frac{\hat{\theta}_i}{\text{std}(x_i)}.$$

The intercept $\theta_0$ is given by

$$\theta_0 = \text{mean}(y) - \sum_i \hat{\theta}_i \left( \frac{\text{mean}(x_i)}{\text{std}(x_i)} \right).$$

Our goal was to identify a combination of properties such that the linear fit of $\log \Sigma(H_2)$ vs. these properties (including $\log \Sigma(12\mu m)$) was able to reliably predict $\log \Sigma(H_2)$. The $\log \Sigma(H_2)$-predicting ability of the fit to a given parameter combination was quantified by performing fits with one galaxy excluded, and then measuring the mean-square (MS) error of the prediction for the excluded galaxy (the “testing error”)

$$\text{MS error} = \frac{1}{N_{\text{pix}}} \sum_{y_{\text{true}}} (y_{\text{true}} - y_{\text{pred}})^2,$$

where $N_{\text{pix}}$ is the number of pixels for this galaxy, $y_{\text{true}}$ is the true value of $\log \Sigma(H_2)$ in each pixel, and $y_{\text{pred}}$ is the predicted value at that pixel using the fit. The RMS error
Figure 4. Best-fit slope $N$ (top) and intercept $\log C$ (bottom) of fits to individual pixel measurements of $\log \Sigma(12\mu m)$ ($y$-axis) versus $\log \Sigma(H_2)$ ($x$-axis). Each point is for one galaxy. A metallicity-dependent $\alpha_{CO}$ was used, so only star-forming pixels were used in the fits. At least 4 CO-detected star-forming pixels per galaxy were required (Sample C, Table 1). Left: The horizontal lines show the inverse-variance weighted means (dotted), un-weighted means (solid), and medians (dashed). Right: Histograms of the residuals for each galaxy relative to the weighted mean, divided by the uncertainty for each galaxy. The vertical lines indicate ±1 times the standard deviation of each distribution.

over all test galaxies

$$\text{RMS error} = \sqrt{\frac{1}{N_{\text{galaxies}} \sum_{\text{galaxy}} \text{MS error}_{\text{galaxy}}}}$$

was used to decide on a best parameter combination.

To identify the best possible combination of parameters we did the fit separately for all possible combinations. At least one resolved property was required in each combination. We did not want to exclude the possibility of parameters other than $12\mu m$ being better predictors of $H_2$, so we included all combinations even if $12\mu m$ was excluded. To avoid overfitting, we excluded galaxies if the number of CO-detected star-forming pixels minus the number of galaxy properties in the estimator was less than 4 (so there are at least 3 degrees of freedom per galaxy after doing the fit), and only considered models with less than 6 independent variables. We used the metallicity-dependent $\alpha_{CO}$, so the sample used for these fits was Sample C (Table 1); however, depending on the number of galaxy properties used and the number of CO-detected star-forming pixels, the sample is smaller for some estimators. We require a minimum of 15 galaxies for each estimator.

After this selection procedure, the following steps were performed for each combination of galaxy properties:

(i) Generate all possible sets of pixels such that each set has the pixels from one galaxy left out.
(ii) For each set of pixels:

(a) Compute mean($\bar{\mathbf{x}}_i$) and std($\sigma_{\bar{\mathbf{x}}_i}$) of the resolved and global properties $\mathbf{x}_i$. Use these to standardize the data.
Figure 5. Measurements of 12μm and H₂ (or CO) using all individual pixels from all galaxies in the sample (black crosses), and the galaxy-integrated values (red regions). The fits (Sec. 3.2) were done separately for the pixel measurements (blue regions) and the global measurements (red regions). Best-fit parameters assuming a power-law model (Eq. 19), and the total $\sigma_{tot}$ and intrinsic $\sigma_{int}$ scatter (Appendix C) about the fits are indicated. Since the relationships may be viewed from either the physical perspective where H₂ (or CO) belongs on the x-axis (the top row), or the “practical” perspective where H₂ is the quantity one wants to determine (bottom row), both are shown here. The left and right columns show the fits to luminosities and surface densities respectively. H₂ surface densities were calculated using a metallicity-dependent $a_{CO}$ (Equation 17). For completeness, a version of these plots with a constant $a_{CO}$ and non-starforming pixels is shown in Appendix D.

(b) Perform the multi-parameter fit on the standardized data, which yields $\hat{\theta}_j$ (Eq. 21).

(c) Compute the un-standardized coefficients $\theta_i$ (Eq. 22) and zero-point $\hat{\theta}_0$ (Eq. 23).

(d) Use these $\theta_i$, $\hat{\theta}_i$ to predict $\hat{y}$ of the excluded galaxy (Eq. 20).

(e) Tabulate the mean squared-error (Eq. 24).

(iii) Compute the mean squared-error (Eq. 24) from all of the MS errors. This indicates the ability of this multi-parameter fit to predict new $\hat{y}$. The RMS error for each estimator is shown in Figure 6.

In practical applications outside of this work, not all of the global properties and pixel properties will be available. For this reason, we provide several $\log \Sigma(H_2)$ estimators which can be used depending on which data are available. To highlight the relative importance of resolved optical proper-
ties vs. 12 µm, the best-performing estimators based on the following galaxy properties are compared:

(i) all global properties + IFU properties + 12 µm (Table 3),
(ii) all global properties + 12 µm but no IFU properties (Table 4),
(iii) all global properties + IFU properties but no 12 µm (Table 5).

The performance of the estimators was ranked based on their RMS error of predicted log Σ(H2) (Figure 6). The reported estimators are those with the lowest RMS error at a given number of galaxy properties (those corresponding to the stars and squares in Figure 6). We estimated the uncertainty on the coefficients in each estimator by perturbing the 12 µm and H2 data points randomly according to their uncertainties, redoing the fits 1000 times, and measuring the standard deviation of the parameter distributions.

The lack of points below the green curve in Figure 6 indicates that there is little to be gained by adding IFU data to the estimators with resolved 12 µm (little to no drop in RMS error). The RMS error of the estimator with only resolved AV for example (black circle, upper left) performs significantly worse than the fit with only 12 µm (green square, lower left). Estimators with resolved 12 µm but no IFU data perform better than those with IFU data but no resolved 12 µm. There is also no improvement in predictive accuracy of the estimators using global properties + resolved 12 µm + no IFU data beyond a two-parameter fit (Σ(12 µm) and ΣUV). The best H2 estimators all contain log Σ(12 µm), which indicates that this variable is indeed the most important for predicting H2.

For the fits in the opposite direction, log Σ(H2) was found to be the most important for predicting 12 µm. The best estimators for 1-5 galaxy properties show that if log Σ(H2) is already included, there is essentially no improvement in predictive accuracy (little to no drop in RMS error) when resolved optical IFU data are included.

We compared how well these multi-parameter estimators perform relative to the one-parameter estimator from the bottom right panel of Figure 5:

\[ \log \Sigma(H_2) = 0.49 + 0.72 \log \Sigma(12 \mu m). \]  

Note that this fit, obtained via Bayesian linear regression (Sec. 3.2) is consistent with the result from ridge regression (first row of Table 3). To compare the performance of each estimator with the fit above, predicted log Σ(H2) for each pixel was computed from the one-parameter fit, and the RMS error (square root of Eq. 24) was computed for each galaxy (Figure 7). Most points lie below the 1:1 relation in Figure 7, indicating that the multi-parameter fits have lower RMS error per pixel than the single-parameter fit.

### 3.4 Dependence of the 12 µm-H2 relationship on physical scale

To establish whether the correlation between global surface densities (12 µm vs H2) arises from a local correlation between pixel-based surface densities, we computed residuals of the individual pixel measurements from the resolved pixel fit (bottom right panel of Figure 5) with varying surface areas (Figure 8). For each galaxy, contiguous regions of 1, 4, 7 or 9 pixels were used to compute surface densities (the four columns of Figure 8). The contiguous pixels were required to be CO-detected and star-forming, as a metallicity-dependent aCO was used. Each pixel was used in exactly one surface density calculation for each resolution, so all of the

| Label | Units | Reference | Description |
|-------|-------|-----------|-------------|
| 12 + log O/H glob | dex | B17 | [O iii]/[N ii]-based gas-phase metallicity |
| log ΣSFR glob | M⊙ yr⁻¹ kpc⁻² | B17 | Star formation rate surface density (5.3 × 10⁻⁴² L(Hα)/2πr₅₀²) |
| log Σglob | M⊙ kpc⁻² | B17 | Stellar mass surface density assuming a Kroupa IMF |
| log cos i | B17 | | Inclination i is either from CO kinematics, Hα kinematics, or LEDA |
| log ΣUV | 10²⁵ erg s⁻¹ kpc⁻² | C15 | Near-UV surface density |
| log ΣFUV | 10²⁵ erg s⁻¹ kpc⁻² | C15 | Far-UV surface density |
| log ΣIR | 10²⁵ erg s⁻¹ kpc⁻² | C15 | Total-IR (8-1000 µm) surface density |
| log Σν | 10²⁵ erg s⁻¹ kpc⁻² | C15 | WISE W4 (22 µm) surface density |
| u/r | mag | B17 | Colour from CALIFA synthetic photometry (SDSS filters applied to extinction-corrected spectra) |
| b/a | | C15 | Minor-to-major axis ratio from CALIFA synthetic photometry |
| (B/T)g | | C15 | Bulge-to-total ratio from g-band photometry |
| ng | | C15 | Sérsic index from g-band photometry |
| log σbulge | km s⁻¹ | G19 | Bulge velocity dispersion (5 arcsec aperture) |
| AV glob | mag | C15 | Extinction measured from the Balmer decrement |

| Label | Units | Reference | Description |
|-------|-------|-----------|-------------|
| 12 + log O/H pix | dex | Eq. 18 | [O iii]/[N ii]-based gas-phase metallicity |
| log ΣSFR pix | M⊙ yr⁻¹ kpc⁻² | Eq. 15 | Star formation rate surface density |
| log Σpix | M⊙ kpc⁻² | Sec. 2.4 | Stellar mass surface density, assuming a Kroupa IMF |
| AV pix | mag | Eq. 14 | Extinction measured from the Balmer decrement |
black circles are independent. We found that the scatter diminished as the pixel size approached the whole galaxy size. The total scatter about the individual pixel fit declines as pixel area increases, indicating that the global correlation emerges from the local one.

### 3.5 Testing the estimators for biases

To determine whether the best-fit relations are biased with respect to any global or resolved properties (Table 2), we performed the following tests for the best-performing H$_2$ estimators with 1, 2, and 3 parameters from Table 3.

For resolved properties, we plotted the residual in predicted vs. true log $\Sigma$(H$_2$) for each pixel versus resolved properties. We computed the Pearson-$r$ between the residuals and the resolved quantities. No significant correlations were found for any of the resolved properties. This indicates that the performance of the estimators is not biased with respect to resolved properties.

For global properties, we plotted the RMS error (Equation 25) for each galaxy versus global properties for that galaxy. We computed the Pearson-$r$ between the RMS error and global quantities. No significant correlations were found for any of the global properties. This indicates that the performance of the estimators is not biased with respect to global properties.

### 4 DISCUSSION AND CONCLUSIONS

Our findings show that significant power-law correlations between 12 $\mu$m and CO surface densities at kiloparsec scales are responsible for the observed correlation between global (galaxy-wide) measurements (Jiang et al. 2015; Gao et al. 2019). The median correlation coefficient between log $\Sigma$(12$\mu$m) and log $\Sigma$(H$_2$) is $\sim$0.86 (per galaxy). Linear fits for each galaxy yield a range of intercepts spanning $\sim$1 dex ($-1.0 \pm 0.01$) and a range in slopes (0.4 to 1.2, median 0.72). The 12$\mu$m and CO luminosities computed over the CO-detected area of each galaxy in the sample are well-fit by a single power law, with a larger slope and smaller y-intercept than the fit to all individual-pixel luminosities in the sample. Linear regression on all possible combinations of resolved properties and global properties (Table 2) yielded
several equations which can be used to estimate $\Sigma(H_2)$ (assuming a metallicity-dependent $\alpha_{CO}$) in individual pixels. A catalog of all resolved and global properties for each pixel in the analysis is provided in machine-readable format (Table 6). The estimators were ranked according to the average accuracy with which they can predict $\Sigma(H_2)$ in a given pixel (RMS error, Eq. 25). The best-performing estimators (Tables 3, 4, 5) with 1-5 independent variables are provided, and there is only marginal improvement in prediction error beyond 2 independent variables. Out of all possible parameter combinations considered, the best-performing estimators include resolved $\Sigma(12\mu m)$, indicating that $12\mu m$ emission is likely physically linked to $H_2$ at resolved scales.

Figure 6. RMS error (Eq. 25) of all estimators. Estimators with smaller RMS errors have better predictive accuracy. The RMS error decreases only slightly as the number of independent variables increases for the fits with resolved $12\mu m$ but no IFU data. The fits with resolved $12\mu m$ but no IFU data have lower RMS errors than those with IFU data. The lack of points below the green curve indicates that there is little to be gained by adding IFU data to the estimators with resolved $12\mu m$. The RMS error of the estimator with only resolved $A_V$ for example (black circle, upper left) performs significantly worse than the fit with only $12\mu m$ (green square, lower left).

Figure 7. Galaxy-by-galaxy RMS error (Eq. 25) computed from the specified multi-parameter fits with 2 galaxy properties, versus the RMS error computed from the one parameter surface density fit (Figure 5). The green squares and blue stars correspond to the green square and blue star in Figure 6 at $n = 2$ respectively. The RMS of the y-values of the green squares here gives the RMS error at $n = 2$ in Figure 6, and likewise for the blue stars (Equation 25).
Figure 8. Variation of the scatter in the $\Sigma(H_2)$-$\Sigma(12\mu m)$ relationship with the area over which surface densities are calculated. Top: black points are surface densities computed over area $A$ indicated at the top (36 arcsec$^2$ is one 6 arcsec pixel). Red circles are the sum of all pixels for each galaxy in the sample, and are the same in all panels in which that galaxy appears. The $H_2$ surface densities are computed with a metallicity-dependent $\alpha_{CO}$. For each galaxy, all contiguous CO-detected, star-forming pixels with area $A$ were used. Each pixel was used exactly once in each panel from left to right. The number of galaxies decreases from left to right because some galaxies do not have any contiguous pixels which form the specified area. The fit to individual pixels is the same in all panels. Bottom: residuals in 12 $\mu$m surface density, relative to the resolved pixel fit (black line) from the bottom right panel of Figure 5. The total scatter $\sigma_{\text{tot}}$ about the resolved fit decreases as the surface area approaches the total galaxy area, suggesting that the global correlation (red circles) emerges from the resolved correlation (black circles).
Table 6. Selected rows and columns of the catalog of resolved measurements for each pixel considered in the analysis. A full version with more columns and rows is available in machine-readable format. The luminosities corresponding to the surface densities in columns 9-12 are provided in the full catalog.

| Pixel ID | Galaxy | BPT | $12 + \log O/H_{\mathrm{pix}}$ | $\alpha_{\mathrm{CO}}$ | $\log \Sigma_{\mathrm{CO}, \mathrm{pix}}$ | $\log \Sigma_{\mathrm{H_2}, \mathrm{pix}}$ | $A_V_{\mathrm{pix}}$ | $\log \Sigma_{\mathrm{H_2}}$ (Simple) | $\log \Sigma_{\mathrm{H_2}}$ (Sun) | $\log \Sigma_{\mathrm{H_2}}$ (Sun, $\alpha_{\mathrm{CO}}$(Z)) | $\log \Sigma_{12\mu m}$ |
|----------|--------|-----|-----------------|-----------------|------------------|-----------------|-------------|----------------|----------------|----------------|----------------|
| 1464     | NGC5980 Comp. | – | 2.49 | – | – | 1.27 ± 0.06 | 1.24 ± 0.05 | – | 1.09 ± 0.02 |
| 1465     | NGC5980 Comp. | – | 3.13 | – | – | 1.68 ± 0.05 | 1.70 ± 0.03 | – | 1.21 ± 0.02 |
| 1466     | NGC5980 SF | 8.83 | 2.44 | 2.48 | –1.61 ± 0.03 | 1.08 | 1.06 ± 0.11 | 1.13 ± 0.06 | 1.01 ± 0.06 | 1.03 ± 0.02 |
| 1467     | NGC5980 SF | 8.84 | 2.40 | 1.60 | –2.10 ± 0.02 | 1.02 | < 1.09 | 0.65 ± 0.07 | 0.52 ± 0.07 | 0.65 ± 0.02 |
| 1468     | NGC5980 Comp. | – | 0.73 | – | – | < 1.12 | – | – | 0.17 ± 0.02 |
| 1469     | NGC5980 SF | 8.84 | 2.39 | –1.04 | –3.77 ± 0.03 | –3.02 | < 1.24 | – | – | –0.29 ± 0.04 |
| 24622    | NGC4047 SF | 8.80 | 2.70 | 2.30 | –1.51 ± 0.03 | 1.26 | 1.58 ± 0.09 | 1.61 ± 0.04 | 1.54 ± 0.04 | 1.17 ± 0.02 |
| 24623    | NGC4047 SF | 8.76 | 2.97 | 2.65 | –1.30 ± 0.02 | 1.21 | 1.78 ± 0.05 | 1.87 ± 0.03 | 1.83 ± 0.03 | 1.35 ± 0.02 |
| 24624    | NGC4047 SF | 8.71 | 3.45 | 2.72 | –1.20 ± 0.02 | 1.08 | 1.88 ± 0.05 | 1.90 ± 0.03 | 1.93 ± 0.03 | 1.41 ± 0.02 |
| 24625    | NGC4047 SF | 8.76 | 3.02 | 2.46 | –1.40 ± 0.02 | 1.11 | 1.81 ± 0.07 | 1.81 ± 0.03 | 1.78 ± 0.03 | 1.36 ± 0.02 |
| 24626    | NGC4047 SF | 8.83 | 2.47 | 2.13 | –1.65 ± 0.02 | 1.09 | 1.47 ± 0.13 | 1.55 ± 0.04 | 1.43 ± 0.04 | 1.20 ± 0.02 |
| 24627    | NGC4047 SF | 8.85 | 2.32 | 2.04 | –1.82 ± 0.03 | 1.28 | < 1.63 | 1.20 ± 0.08 | 1.06 ± 0.08 | 0.96 ± 0.02 |
| 24628    | NGC4047 Comp. | – | 1.41 | – | – | < 1.63 | – | – | 0.63 ± 0.02 |
| 24629    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24630    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24631    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24632    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24633    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24634    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24635    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24636    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |
| 24637    | NGC4047 SF | 8.80 | 2.64 | 1.08 | –3.01 ± 0.09 | 0.50 | < 1.65 | – | – | 0.26 ± 0.03 |

(3) BPT classification (Section 2.4): starforming (“SF”), composite (“Comp.”), low-ionization emission region (“LIER”), or Seyfert (“Sy”).
(5) Metallicity-dependent $\alpha_{\mathrm{CO}}$ (Eq. 17) in units of $M_{\odot}$(K km s$^{-1}$ pc$^{-2}$)$^{-1}$.
(6) Resolved stellar mass surface density (Sec. 2.4) in units of $M_{\odot}$ pc$^{-2}$.
(7) Resolved SFR surface density (Equation 15) in units of $M_{\odot}$ yr$^{-1}$ pc$^{-2}$.
(8) Resolved extinction derived from the Balmer decrement, in units of mag (Equation 14).
(9) H$_2$ surface density ($M_{\odot}$ pc$^{-2}$) based on the “Simple” moment-0 map (Method 2, Section 2.3). Method 1 is better at improving the SNR in each pixel, so detects more pixels than Method 2. A constant $\alpha_{\mathrm{CO}}$ is assumed, and 98% confidence 3$\sigma$ upper limits are shown for non-detections.
(10) H$_2$ surface density ($M_{\odot}$ pc$^{-2}$) from the moment-0 map made using the Sun et al. (2018) method (Method 1), assuming a constant $\alpha_{\mathrm{CO}} = 3.2$.
(11) Same as (10) but assuming a metallicity-dependent $\alpha_{\mathrm{CO}}$ and only using star-forming pixels.
(12) Resolved 12$\mu$m surface density in units of $L_{\odot}$ pc$^{-2}$.
4.1 Comparisons to previous work

Previous work on the 12µm-CO relationship has been primarily focused on the total 12µm luminosity and the total CO luminosity for each galaxy (Jiang et al. 2015; Gao et al. 2019). Our fit of the global 12µm luminosity versus global CO luminosity yields a slope of 0.91 ± 0.04 and intercept of 0.77 ± 0.36. Our slope agrees well with Gao et al. (2019) who find 0.91 ± 0.04, but our intercept is significantly lower than their value of 0.77 ± 0.36. Our global CO luminosities are consistent with those reported in B17, which are believed to be accurate estimates of the true total CO luminosities. However, we find that our global 12µm luminosities (the sum over the CO-detected area) are systematically lower than the true total 12µm luminosities as measured by the method in Gao et al. (2019). The amount of discrepancy is consistent with the offset in intercept found between this work and Gao et al. (2019). This comparison indicates that 12µm emission tends to be more spatially extended than CO emission, so by restricting the area to the CO-emitting area, some 12µm emission is missed, leading to a smaller intercept. The fact that this does not affect the slope indicates that the fraction of 12µm emission that is excluded by only considering the CO-detected area, is roughly uniform across the sample.

When estimating the total CO luminosity in a galaxy, we recommend using the Gao et al. (2019) estimators. This is because they take the total 12 µm luminosity as input, whereas our estimators require the 12 µm luminosity over the CO-detected area. Although our total CO luminosities agree with the total CO luminosities presented in B17, there is the possibility that these interferometric measurements underestimate the true total CO luminosities. Without measuring the true total CO luminosities (e.g. with a suitable single-dish telescope) we cannot be certain whether the offset from Gao et al. (2019) is solely due to reduced 12µm luminosity.

Our results can be compared to recent work using optical extinction as an estimator of H2 surface density (Güver & Özel 2009; Barrera-Ballesteros et al. 2016; Concas & Popesso 2019; Yesuf & Ho 2019; Barrera-Ballesteros et al. 2020). We show that resolved 12µm surface density is better than optical extinction at predicting H2 surface density by a factor of 0.1 dex per pixel (Figure 6). Additionally, a 12µm estimator does not suffer from a limited dynamic range like AV traced by the Balmer decrement, which is invalid at large extinctions, and where the SNR of the Hα and Hβ lines are low. In the recent analysis of EDGE galaxies Barrera-Ballesteros et al. (2020) limit their analysis to AV < 3 due to the SNR of the Hβ line. Additionally, the correlation between resolved \( \Sigma(12\mu m) \) and \( \Sigma(H_2) \) is stronger than that between AV and \( \Sigma(H_2) \).

4.2 Why is \( \Sigma(12\mu m) \) a better predictor of \( \Sigma(H_2) \) than \( \Sigma_{SFR} \)?

Over the same set of pixels (star forming and CO detected), the correlation between log \( \Sigma(12\mu m) \) and log \( \Sigma(H_2) \) per galaxy (left panel, Figure 3) is better than the correlation between log \( \Sigma_{SFR} \) and log \( \Sigma(H_2) \) (right panel, Figure 3). Another manifestation of this is how our estimators of H2 from 12µm consistently perform better at predicting \( \Sigma(H_2) \) than estimators with \( \Sigma_{SFR} \) instead of 12µm, even over the same set of pixels. A potential explanation for the better correlation with 12µm is that the 12µm band includes dust emission and PAH emission, both of which trace the ISM content more directly than the SFR. This is one reason why 12µm is less preferred as an SFR indicator than say, FIR luminosity from cold dust that is heated by stellar FUV radiation. In contrast, Hα emission traces the SFR rather than the ISM content. It is unclear whether the stronger connection between 12µm emission and H2 is due to PAH emission or warm dust emission, but higher-redshift work (Cortzen et al. 2019) specifically on the PAH-CO relationship hints that PAH emission may be the dominant factor.

4.3 Applications

We present resolved \( \Sigma_{H_2} \) estimators which can be used for two key applications:

(i) generating large samples of resolved \( \Sigma(H_2) \) in the nearby Universe e.g. to study the resolved Kennicutt-Schmidt law, and

(ii) predicting \( \Sigma(H_2) \) and integration times for telescope observing proposals (e.g. ALMA).

Although the CO-detected pixels in our sample only extend down to \( \Sigma(H_2) \sim 1 M_\odot \text{pc}^{-2} \), our predictions for \( \Sigma(H_2) \) below this are consistent with the upper limits in our data. Thus we advise caution when applying the estimator to 12µm surface densities below about \( 1 L_\odot \text{pc}^{-2} \). Since WISE was an all-sky survey, in principle these estimators could be applied over the entire sky. In the future, using the MIR data with higher resolution and better sensitivity from the James Webb Space Telescope instead of WISE 12µm, and ALMA CO data instead of CARMA CO data, one could produce an H2 surface density estimator which reaches even lower gas surface densities.

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DATA AVAILABILITY

The data underlying this article are available in the article and its online supplementary material.

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APPENDIX A: DERIVATION OF WISE W3 UNCERTAINTY

The total uncertainty in each 6 arcsec pixel is the instrumental uncertainty added in quadrature with the zero-point uncertainty

\[ \sigma_{\text{tot}} = \sqrt{\sigma_{\text{inst}}^2 + \sigma_{\text{ZP}}^2} \]  

where the factor of 5 correction was estimated from Figure 3 of http://wise2.ipac.caltech.edu/docs/release/allsky/expsup/sec2_3f.html (since our 6 arcsec pixels are effectively apertures with radius of 5.4 arcsec). The zero-point uncertainty is given by

\[ \sigma_{\text{ZP}} = \frac{2.5 \times 10^{-14}}{F_{\text{z}} \text{mag}} \]

where the factor of 5 correction was estimated from Figure 3 of http://wise2.ipac.caltech.edu/docs/release/allsky/expsup/sec2_3f.html (since our 6 arcsec pixels are effectively apertures with radius of 3.175 = 5.1 pixels). The instrumental noise variance in each larger pixel is

\[ \sigma_{\text{inst, final}} = \sum_{\text{subpixels}} \sigma_{\text{inst, natv}}^2 \]

APPENDIX B: DERIVATION OF CO UNCERTAINTY

A noise map \( N(x, y) \) (in Jy beam\(^{-1}\) km s\(^{-1}\)) is calculated by adding a 5% calibration uncertainty in quadrature with the

MNRAS 000, 1–17 (2020)
instrumental uncertainty

\[ \frac{N(x, y)}{\text{Jy beam}^{-1} \text{ km s}^{-1}} = \left( [0.05 M_0(x, y)]^2 + \sigma(x, y)^2 \frac{N_{\text{pix, beam}}}{f_{\text{bin}}} \right)^{1/2}, \]

where \( M_0(x, y) \) is the moment-0 map (Jy beam\(^{-1}\) km s\(^{-1}\)) with 6 arcsec pixels, the factor of 0.05 is a 5% calibration uncertainty, \( N_{\text{pix, beam}} \) is the number of pixels per beam in the raw image (prior to any rebinning), \( f_{\text{bin}} \) is the binning factor (the number of original pixels in the rebinned pixels, \( f_{\text{bin}} = 36 \)), and

\[ \frac{\sigma(x, y)}{\text{Jy beam}^{-1} \text{ km s}^{-1}} = \left( \frac{\Delta v_{\text{chan}}}{\text{km s}^{-1}} \sqrt{N_{\text{chan}}(x, y)} \frac{\sigma_{\text{chan}}}{\text{Jy beam}^{-1}} \right). \]

where \( \Delta v_{\text{chan}} = 20 \text{ km s}^{-1} \) is the velocity width of the channels in the cube, \( N_{\text{chan}}(x, y) \) is the number of channels used to calculate the moment-0 map (which varies with position), and \( \sigma_{\text{chan}} \) is the RMS per channel. When calculating upper limits, \( N_{\text{chan}}(x, y) = 34 \) for all pixels. In a CO cube, \( \sigma_{\text{chan}} \) is calculated by measuring the RMS of all pixels within a 7 arcsec radius circular aperture in the center of the field in the first 3-5 channels, and again in the last 3-5 channels. \( \sigma_{\text{chan}} \) is taken to be the average of these two RMSes. Finally, we convert the noise maps into units of luminosity using Equation 11.

**APPENDIX C: DEFINITION OF SCATTER ABOUT A FIT**

The total scatter about a fit \( \sigma_{\text{tot}} \) is

\[ \sigma_{\text{tot}} = \sqrt{\frac{1}{N - m} \sum_i (y_i - \hat{y}_i)^2}, \]

where \( N \) is the number of data points, \( m \) is the number of fit parameters, \( y_i \) is \( i \)’th independent variable, and \( \hat{y}_i \) is the estimate of \( y_i \) from the fit. \( \sigma_{\text{tot}} \) can be directly computed from the fit. The total scatter can also be written as the sum in quadrature of random scatter due to measurement uncertainties, and the remaining “intrinsic” scatter \( \sigma_{\text{int}} \)

\[ \sigma_{\text{tot}} = \sqrt{\frac{1}{N} \sum_i \sigma_i^2 + \sigma_{\text{int}}^2}, \]

where \( \sigma_i \) is the measurement error on \( y_i \). The intrinsic scatter can be computed using

\[ \sigma_{\text{int}} = \sqrt{\sigma_{\text{tot}}^2 - \frac{1}{N} \sum_i \sigma_i^2}. \]

**APPENDIX D: CONSTANT \( \alpha_{\text{CO}} \) VERSION OF THE 12\( \mu \)m-CO RELATIONSHIP**

For completeness, Figure D1 shows the relationships and fits as Figure 5 except assuming a constant CO-to-H\(_2\) conversion factor \( \alpha_{\text{CO}} = 3.2 \frac{M_0(K \text{ km s}^{-1} \text{ pc}^2)^{-1}}{M_{\odot}(\text{K km s}^{-1})^{-1}} \), and including all CO-detected pixels (not just star-forming). The changes from Figure 5 are slight overall, and are the largest in the lower left panel (however the uncertainties are also larger in that panel).

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Figure D1. Same as Figure 5 except H$_2$ surface densities were calculated using $\alpha_{\text{CO}} = 3.2 M_\odot (\text{K km s}^{-1} \text{pc}^2)^{-1}$, and non-starforming pixels were included.