Numerical Calibration of the HCN–Star Formation Correlation

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ABSTRACT

HCN(1–0) emission traces dense gas and correlates very strongly with star formation rates (SFRs) on scales from small Milky Way clouds to whole galaxies. The observed correlation offers strong constraints on the efficiency of star formation in dense gas, but quantitative interpretation of this constraint requires a mapping from HCN emission to gas mass and density. In this paper we provide the required calibration by post-processing high-resolution simulations of dense, star-forming clouds to calculate their HCN emission ($L_{\text{HCN}}$) and to determine how that emission is related to the underlying gas density distribution and star formation efficiency. We find that HCN emission traces gas with a luminosity-weighted mean number density of $0.8 \times 10^4 \text{cm}^{-3}$ and that HCN luminosity is related to mass of dense gas of $> 6 \times 10^4 \text{cm}^{-3}$ with a conversion factor of $L_{\text{HCN}} = 14 M_\odot / (K \text{km s}^{-1} \text{pc}^2)$. We also measure a new empirical relationship between the star formation rate per global mean freefall time ($\epsilon_{\text{ff}}$) and the SFR–HCN relationship, $\text{SFR} / L_{\text{HCN}} = 5.73 \times 10^{-5} \epsilon_{\text{ff}}^{1.32} M_\odot \text{yr}^{-1} / (K \text{km s}^{-1} \text{pc}^2)$. The observed SFR–HCN correlation strongly constrains $\epsilon_{\text{ff}} \approx 1\%$ with a factor of at least 5 uncertainty. The scatter in $\epsilon_{\text{ff}}$ from cloud to cloud within the Milky Way is a factor of a few. We conclude that $L_{\text{HCN}}$ is an effective tracer of dense gas and that the IR–HCN correlation is a very strong diagnostic of the microphysics of star formation in dense gas.

Key words: galaxies: ISM – galaxies: star formation – ISM: molecules – radio lines: ISM – stars: formation

1 INTRODUCTION

The HCN(1–0) line is one of the brightest molecular lines produced in most star-forming galaxies, and it has a much higher critical density than the brighter lines of CO. It is thought to trace gas at number densities $n_H > 6 \times 10^4 \text{cm}^{-3}$ typically associated with active star formation. Consequently, HCN emission is of great interest and has been extensively studied over the past two decades both observationally (e.g., Gao & Solomon 2004a,b; Wu et al. 2005, 2010; García-Burillo et al. 2012; Kepley et al. 2014; Usero et al. 2015; Chen et al. 2015; Bigiel et al. 2015, 2016) and theoretically (e.g., Krumholz & Tan 2007; Krumholz & Thompson 2007; Narayanan et al. 2008; Hopkins et al. 2013; Leroy et al. 2014). HCN is a particularly useful tool because its high critical density means that HCN emission provides constraints on the volume density of the emitting gas, while lower critical density tracers such as CO are sensitive primarily to total mass, and offer little constraint on volumetric properties. Extragalactic observations of HCN provide one of the few methods available to study dense, star forming clumps in external galaxies, which we would otherwise not be able to resolve. Indeed, the opportunity offered by comparing Galactic and extragalactic HCN emission has motivated several studies of HCN emission in the Milky Way in order to provide a comparison sample for extragalactic surveys (e.g., Brouillet et al. 2005; Wu et al. 2005, 2010; Rosolowsky et al. 2011; Stephens et al. 2016).

The key result of HCN studies to date is that HCN(1–0) luminosities correlate very strongly with star formation rates (SFRs). This correlation is close to but not exactly linear, and extends over many order of magnitude in HCN luminosity and SFR. To the extent that HCN emission provides a direct measurement of the mass of gas at a particular density, this correlation can be used to constrain the local efficiency of star formation, $\epsilon_{\text{ff}}$, the fraction of gas converted into stars per freefall time (Krumholz & McKee 2005; Federrath & Klessen 2012). Values of $\epsilon_{\text{ff}}$ are theoretically significant because they directly relate to physical parameters of cloud structure and to the nature of star formation (Padoan & Nordlund 2002; Krumholz & McKee 2005; Hennebelle & Chabrier 2008; Federrath & Klessen 2012; Murray & Chang 2007).
Moreover, because $\epsilon_g$ is a scale-free quantity, it can be measured in objects of very different physical scales, enabling comparisons of star formation efficiency across scale.

Observations of $\epsilon_g$ based on direct measurements of individual clouds in the Milky Way or nearby galaxies have for the most part indicated uniformly low values of $\epsilon_g \approx 1\%$ (Krumholz et al. 2012; Evans et al. 2014; Vutisalchavakul et al. 2016; Heyer et al. 2016; Leroy et al. 2017b), though there are a few exceptions (Murray 2011; Lee et al. 2016). Some authors have also proposed that there are a few exceptions (Murray 2011; Lee et al. 2016; Heyer et al. 2016; Leroy et al. 2017b), though (Krumholz et al. 2012; Evans et al. 2014; Vutisalchavakul et al. 2016; Heyer et al. 2016; Leroy et al. 2017b), though there are a few exceptions (Murray 2011; Lee et al. 2016).

In contrast, other models predict small values of $\epsilon_g$ that has come closest to attempting such a calculation is GTBJR which includes self-gravity and driven hydrodynamic turbulence. GTBJR adds magnetic fields, and GTBJR includes protostellar jet and radiation feedback as well (following the implementation described by Federrath et al. 2014, 2017). Each simulation has an initial virial ratio $\alpha_{vir} = 1.0$; those with magnetic fields have a plasma beta of $\beta = 0.33$ (corresponding to an Alfvén Mach number $M_A = 2.0$). Simulations including turbulence have velocity dispersion of $\sigma_v = 1 \text{ km s}^{-1}$ and an rms Mach number of $M = 5$, resulting from a sound speed of $c_s = 0.2 \text{ km s}^{-1}$ at temperature $T = 10 \text{ K}$. Simulations with a magnetic field initially have a uniform field of $B = 10 \mu \text{G}$ which is subsequently compressed, tangled and twisted by the turbulence. These properties are summarised in Columns 3 – 7 of Table 1.

We measure the star formation rate (SFR) in the simulations through the sink particle method developed by Federrath et al. (2010b), which is enhanced by applying a jet feedback module (Federrath et al. 2014). The simulation’s SFRs span an order of magnitude, which gives us an advantageous calibration set which can be compared to observations to see which simulations match the observed SFR–HCN relation.

2.2 Modeling HCN Emission

We use the code DESPOTIC (Krumholz 2014) to calculate the HCN luminosity of every cell in the simulations. DESPOTIC solves the equations of statistical equilibrium for the HCN level populations, including non-local thermodynamic equilibrium (LTE) effects. It treats optical depth effects using an escape probability formalism, and for the purposes of this paper we estimate the escape probabilities
One is required to choose an approximation for $dv/dr$ because the LVG approximation is one-dimensional, and thus there is some ambiguity in how to apply it to our three-dimensional simulations. The line luminosity escaping to an observer is most directly connected to the gradient in the line of sight velocity, while the radiative trapping factor that enters into the level populations is sensitive to the average of the velocity gradient over all directions, which is more closely related to $\nabla \cdot \mathbf{v}$. 

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1. http://home.strw.leidenuniv.nl/~moldata/
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**Table 1. Key simulation parameters**

| Simulation | Turbulence | $\sigma_r$ (km s$^{-1}$) | $M$ | $B$ ($\mu$G) | $\beta$ | $M_{\text{H}_2}$ | Jet+Radiation Feedback | $N_{\text{HCN}}^0$ | SFR(M$_\odot$ yr$^{-1}$) | $\epsilon_L$ | $L_{\text{HCN}}$ (K km s$^{-1}$ pc$^2$) |
|------------|------------|-----------------|-----|-------------|------|----------------|-----------------------|------------|-------------------|------|-------------------|
| G          | None       | 0               | 0   | 0           | $\infty$ | $\infty$ | No                    | 1024$^3$   | 1.6x10$^{-4}$     | 0.47 | 4.6               |
| GT         | Mix        | 1.0             | 5.0 | 0           | $\infty$ | $\infty$ | No                    | 1024$^3$   | 8.3x10$^{-5}$     | 0.25 | 17                |
| GTB        | Mix        | 1.0             | 5.0 | 10          | 0.33   | 2.0      | No                    | 1024$^3$   | 2.8x10$^{-5}$     | 0.083| 14                |
| GTBJR      | Mix        | 1.0             | 5.0 | 10          | 0.33   | 2.0      | Yes                   | 2048$^3$   | 1.0x10$^{-5}$     | 0.031| 13                |

**Notes.** Column 1: simulation name. Columns 2–4: the type of turbulence driving, turbulent velocity dispersion, and turbulent rms sonic Mach number. Columns 5–7: magnetic field strength, the ratio of thermal to magnetic pressure (plasma $\beta$), and the Alfvén Mach number. Column 8: whether jet/outflow feedback and radiation was included or not. Column 9: maximum grid resolution. Columns 10–11: absolute SFR and the SFR per mean global freefall time. Column 12: the total HCN luminosity at SFE of 5%. Simulations are listed in order of increasing physical complexity.

**Table 2. Key Parameters of HCN(1–0) Emission Models**

| Model Name | $X_{\text{HCN}}$ $\equiv n_{\text{HCN}}/m_H$ | $T$ (K) | $dv/dr$ |
|------------|---------------------------------------------|--------|---------|
| Standard   | $1.0 \times 10^{-8}$                      | 10     | $\nabla \cdot \mathbf{v}$ |
| LOS        | $1.0 \times 10^{-8}$                      | 10     | Line-of-Sight $\nabla \cdot \mathbf{v}$ |
| Low HCN    | $3.3 \times 10^{-9}$                      | 10     | $\nabla \cdot \mathbf{v}$ |
| High HCN   | $3.0 \times 10^{-8}$                      | 10     | $\nabla \cdot \mathbf{v}$ |
| High Temp  | $1.0 \times 10^{-8}$                      | 20     | $\nabla \cdot \mathbf{v}$ |
| Varied Temp| $1.0 \times 10^{-8}$                      | Varied| $\nabla \cdot \mathbf{v}$ |

**Notes.** Column 1: model name. Column 2: HCN abundance $X_{\text{HCN}} = n_{\text{HCN}}/m_H$. Column 3: gas temperature; see main text for details of the Varied Temp run. Column 4: method used to approximate $dv/dr$ in the LVG optical depth (see main text): velocity divergence $\nabla \cdot \mathbf{v}$ or an $x$-axis line-of-sight velocity.

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3 RESULTS

3.1 What Density Range Does HCN Emission Trace?

Figure 1 shows the distribution of HCN luminosity (bottom panel) in comparison to density (top panel) and velocity gradient (middle panel) for the Standard model in a slice through the GTBJR simulation at a star formation efficiency, SFE = M\text{stars}/(M\text{stars} + M\text{gas}), of 5%. We can observe a clear correlation between the density distribution and HCN luminosity. That is, regions of denser gas (shown in red) correspond to regions of high \( L_{\text{HCN}} \) and likewise regions of low density (shown in blue) correspond to regions of low \( L_{\text{HCN}} \). However, this correlation is predominantly in high-density regions. In low-density regions, the HCN luminosity drops much faster than the density, resulting in a considerably larger dynamic range of \( L_{\text{HCN}} \) than density. This supports the idea of HCN as a dense gas tracer.

In Figure 2, we plot the probability distribution functions (PDFs) for total mass and HCN luminosity with respect to density in each simulation at the time when the SFE is 5%. The mass PDFs are well-approximated by log-normal distributions, as expected (Padoan & Nordlund 2002; Hennebelle & Chabrier 2008; Federrath & Klessen 2012). The exception is the Gravity only simulation (G, top panel), in which we observe an extended power-law tail at high density. This abnormality can be attributed to a large \( \epsilon_{\text{ff}} \) of 0.47, as the power-law tails arise as a result of strong gravitational collapse (Klessen 2000; Federrath & Klessen 2013).

In the three other simulations, we observe the general trend that the HCN luminosity distribution is always centered around a greater average density and is less broadly distributed than the mass PDF. The luminosity PDF peaks in the range \( 2 \times 10^{-20} - 4 \times 10^{-20} \text{ g cm}^{-3} \), which corresponds to a number density of \( 0.8 \times 10^{4} - 1.7 \times 10^{4} \text{ cm}^{-3} \). This is a factor of ~5 less than what is assumed in studies such as Gao & Solomon (2004b), and at the low end of the range suggested in other observational studies (Usero et al. 2015). However, mass is distributed with a mean density of \( \sim 8 \times 10^{-21} \text{ g cm}^{-3} \) (\( \sim 3.4 \times 10^{3} \text{ cm}^{-3} \)), so we still find that HCN emission traces gas at densities 2.5 – 5 times greater than the mean density in the simulations.

In Table 3 we present the conversion factor between \( L_{\text{HCN}} \) and mass, \( \alpha_{\text{HCN}} \), for each simulation with each emission model. We compare the conversion for gas above the mean density for the luminosity distribution in our simulations (\( n_{\text{H}} \approx 1.0 \times 10^{4} \text{ cm}^{-3} \)) and above the critical density \( n_{\text{H}} \approx 6.0 \times 10^{4} \text{ cm}^{-3} \) (Gao & Solomon 2004a; Leroy et al. 2017a). We find \( \alpha_{\text{HCN}} = 14 \pm 6 \text{ M}_{\odot}/(\text{K km s}^{-1} \text{ pc}^{2}) \), where we quote the mean for the Standard emission model plus or minus the standard deviation of each model for each simulation (excluding G, with \( n_{\text{H}} = 1.0 \times 10^{4} \text{ cm}^{-3} \)). \( \alpha_{\text{HCN}} \) is thought to range between \( 3 - 30 \text{ M}_{\odot}/(\text{K km s}^{-1} \text{ pc}^{2}) \) based on various estimates of observed values (Gao & Solomon 2004a; Wu et al. 2005; Krumholz & Tan 2007; Shimajiri et al. 2017). This is typically supported by our results irrespective of the threshold density, albeit weighted towards larger values (with exception to the G simulation, which is not very realistic anyway). \( \alpha_{\text{HCN}} \) calculated with our mean density threshold is very similar to observed averages (Wu et al. 2005; Krumholz & Tan 2007) of \( \sim 10 \text{ M}_{\odot}/(\text{K km s}^{-1} \text{ pc}^{2}) \), and is a factor of
Figure 2. PDFs of the density distributions with respect to cloud mass (in blue) and HCN luminosity (Standard model, in green) for each of our simulations (at SFE of 5\%): Gravity only (G, top panel), Gravity + Turbulence (GT, second panel), Gravity + Turbulence & Magnetic Fields (GTB, third panel) and Gravity + Turbulence & Magnetic & Jet Feedback & Radiation (GTBJR, bottom panel).

Figure 3. Ratio of SFR/\(L_{\text{HCN}}\) versus \(\epsilon_{\text{ff}}\) for all simulations at star formation efficiencies of 1 – 5\%, as indicated in the legend, using our Standard HCN emission model. The solid line is a linear least-squares fit to the simulation results, using the parameters shown in Table 4.

1.5 – 2 less than when calculated with the critical density threshold of HCN(1–0) emission. This suggests that previous overestimates of densities traced by HCN emission \((n_H \gtrsim 6 \times 10^4 \text{ cm}^{-3})\) do not accurately reflect the true conversion between mass and luminosity for dense gas, as well as giving underestimates of \(t_{\text{ff}}\) and similar values. Our findings are also consistent with other suggestions in the literature that a significant portion of the total HCN emission comes from gas with densities up to a factor of \(\sim 10\) below the critical density (e.g. Shirley 2015; Shimajiri et al. 2017).

3.2 Star Formation – HCN Luminosity Ratio

Figure 3 shows the ratio of SFR/\(L_{\text{HCN}}\) versus \(\epsilon_{\text{ff}}\) for the Standard HCN emission model in each of our simulations. To characterise the level of fluctuations in SFR/\(L_{\text{HCN}}\) over time we show this relationship measured at SFEs of 1\% (yellow diamonds), 2\% (green squares), 3\% (cyan pentagons), 4\% (red triangles) and 5\% (purple circles); in this calculation we use the time-averaged star formation rate (since all observational tracers of star formation are also time-averaged), but we use the instantaneous HCN luminosity for each simulation snapshot. We see that SFR/\(L_{\text{HCN}}\) varies by less than a factor of two over this range in SFE, and thus is quite stable. Moreover, there is a very clear relationship between the value of SFR/\(L_{\text{HCN}}\) and \(\epsilon_{\text{ff}}\), which is well-fit by

\[
\frac{\text{SFR}}{L_{\text{HCN}}} = 5.73 \times 10^{-5} \epsilon_{\text{ff}}^{-1.32} \text{M}_\odot \text{yr}^{-1} / (\text{K km s}^{-1} \text{pc}^2) \quad (1)
\]

We show the fit line in Figure 3.

We can repeat this procedure for all our other HCN emission models, fitting functions of the form

\[
\frac{\text{SFR}}{L_{\text{HCN}}} = \left( \frac{\text{SFR}}{L_{\text{HCN}}} \right)_{0.01} \left( \frac{\epsilon_{\text{ff}}}{0.01} \right)^p \quad (2)
\]

In all cases we find fits comparable in quality to that shown in Figure 3, with best fit parameters as shown in Table 4.
Table 3. $\alpha$$_{\text{HCN}}$ for each emission model and simulation

| Simulation | Threshold Density (cm$^{-3}$) | Standard | LOS | Low HCN | High HCN | High Temp | Varied Temp |
|-----------|-------------------------------|----------|-----|--------|---------|----------|------------|
| G         | $1.0 \times 10^6$             | 63       | 48  | 83     | 53      | 37       | 41         |
|           | $6.0 \times 10^7$             | 120      | 73  | 130    | 110     | 55       | 58         |
| GT        | $1.0 \times 10^6$             | 12       | 13  | 23     | 7.8     | 8.9      | 12         |
|           | $6.0 \times 10^7$             | 19       | 21  | 25     | 16      | 11       | 13         |
| GTB       | $1.0 \times 10^6$             | 16       | 17  | 29     | 10      | 11       | 15         |
|           | $6.0 \times 10^7$             | 31       | 32  | 28     | 28      | 17       | 19         |
| GTBJR     | $1.0 \times 10^6$             | 15       | 15  | 28     | 9.5     | 11       | 14         |
|           | $6.0 \times 10^7$             | 25       | 25  | 23     | 23      | 14       | 16         |

Notes. Column 1: simulation name. Column 2: Minimum density for which $\alpha$$_{\text{HCN}}$ is measured. Columns 3–8: $\alpha$$_{\text{HCN}}$ of each model in M$_\odot$/(K km s$^{-1}$ pc$^2$).

Table 4. Fit Parameters for SFR$/L_{\text{HCN}}$ versus $\epsilon_f$

| Model       | (SFR$/L_{\text{HCN},0.01}$ (M$_\odot$ yr$^{-1}$/(K km s$^{-1}$ pc$^2$)) | $p$ | $\epsilon_f$Bigiel (%) |
|-------------|---------------------------------------------------------------|-----|---------------------|
| Standard    | $1.31 \times 10^{-7}$                                       | 1.32 | 0.951              |
| LOS         | $1.36 \times 10^{-7}$                                       | 1.31 | 0.978              |
| Low HCN     | $3.07 \times 10^{-7}$                                       | 1.28 | 1.85               |
| High HCN    | $6.02 \times 10^{-8}$                                       | 1.37 | 0.540              |
| High Temp   | $1.02 \times 10^{-7}$                                       | 1.31 | 0.785              |
| Varied Temp | $1.69 \times 10^{-7}$                                       | 1.23 | 1.17               |

Notes. Column 1: model name. Column 2: constant for equation 2. Column 3: exponent in equation 2. Column 4: $\epsilon_f$ predicted for the SFR–$L_{\text{HCN}}$ correlation in Bigiel et al. (2016) (see Section 4 and Figure 4).

Our results indicate that the changes in how we apply the LVG method (as explored in the LOS model) produce only $\sim$10% shifts in the predicted relationship between SFR$/L_{\text{HCN}}$ and $\epsilon_f$. Changes in the gas temperature within the plausible range of $\sim$ 10 – 20 K produce shifts at the $\sim$30% level at most. The parameter to which the results are most sensitive is the HCN abundance, where factor of 3 changes in the assumed value induce factor of $\sim$2 changes in the normalisation of the IR–HCN correlation. While the dependence is sublinear (as expected, since the changes are partially cancelled by optical depth effects), the uncertainty in HCN abundance still clearly dominates the overall uncertainty.

4 IMPLICATIONS FOR THE INTERPRETATION OF OBSERVATIONS

While our simulations span a considerable range in $\epsilon_f$ and thus SFR$/L_{\text{HCN}}$, observed systems do not – Bigiel et al. (2016) find that $L_{\text{IR}}/L_{\text{HCN}} \approx 900$ L$_\odot$/(K km s$^{-1}$ pc$^2$) well approximates the IR–HCN correlation observed on all scales. This suggests that the observed SFR$/L_{\text{HCN}}$ provides a strong constraint on $\epsilon_f$ and thus on the physics that governs star formation. Since most observational studies of the SFR–$L_{\text{HCN}}$ correlation use infrared luminosity as their SFR tracer, in order to exploit this constraint we must translate our simulated SFRs to infrared luminosities. For this purpose we adopt a conversion (Kennicutt & Evans 2012)

$$SFR/L_{\text{IR}} = 1.5 \times 10^{-10} M_\odot \text{yr}^{-1}/L_\odot.$$  

Using this conversion together with equation 1, we can immediately translate the observed relation $L_{\text{IR}}/L_{\text{HCN}} \approx 900$ L$_\odot$/(K km s$^{-1}$ pc$^2$) into a measurement of $\epsilon_f$. For our standard emission model, the observed IR–HCN ratio corresponds to $\epsilon_f \approx 0.95%$. For the other emission models (Table 4) inferred $\epsilon_f$ values fall in the range 0.5% – 1.9%. Thus our results imply $\epsilon_f \approx 1\%$ with roughly a factor of 2 uncertainty.

In addition to interpreting the average IR–HCN relation in terms of $\epsilon_f$, our calibration allows us to do so on a source-by-source basis. In Figure 4 we overplot curves of constant $\epsilon_f$ for our standard model with observations of massive, dense...
gas clumps in the Milky Way from Wu et al. (2010) and Stephens et al. (2016); we also show our raw simulation results and the average relationship for comparison.

There are two immediate and obvious points to take from Figure 4. The first is that, of our simulations, only the one with the lowest value of $\epsilon_f$ (simulation GTBJR) falls near the locus of observed points. Clearly simulations where star formation proceeds at high efficiency are strongly inconsistent with the observed IR–HCN relation. The second point is that the observed systems show relatively little scatter. With the exception of a single outlier with exceptionally low HCN luminosity, the entire sample of Milky Way objects tends to fall between the $\epsilon_f = 0.1\%$ and $5\%$ lines (with only two outliers), and the vast majority falls in the range $\epsilon_f = 0.5\% - 2\%$. This small scatter is consistent with the findings of most other studies that have used different methods to estimate $\epsilon_f$ on cloud scales (e.g., Krumholz et al. 2012; Federrath 2013; Evans et al. 2014; Salim et al. 2015; Vutisalchavakul et al. 2016; Heyer et al. 2016; Leroy et al. 2017b), but is substantially smaller than the range reported in Murray (2011) or Lee et al. (2016). Indeed, the substantial population of objects with $\epsilon_f > 10\%$ reported in Lee et al. appears to be absent in the massive clump sample. This is significant because one possible explanation for the discrepancy, proposed by Lee et al., is that other methods have focused on smaller star-forming clouds nearby and as a result have missed a class of highly-efficient star-formers at larger distances. The failure of these sources to turn up in the HCN clump samples, which are targeted on massive star-forming regions, casts doubt on this explanation.

On the other hand, unless the factor of few variation in $\epsilon_f$ apparent in Figure 4 is entirely due to variations in gas temperature or HCN abundances, there is clearly some region-to-region variation in $\epsilon_f$. Variations at the factor of few level that we find have in fact been predicted to exist as a result of variations in the Mach numbers, virial parameters, magnetic field strengths, and solenoidal-to-compressive turbulence ratios of molecular clouds (e.g., Kaufmann et al. 2013; Schneider et al. 2013; Federrath 2013; Federrath et al. 2016; Jin et al. 2017; Kainulainen & Federrath 2017; Körtgen et al. 2017).

5 SUMMARY AND CONCLUSIONS

We post-process a series of high-resolution hydrodynamical simulations of star cluster formation to predict their luminosities in the HCN(1–0) line, and to determine the relationship between HCN luminosity, gas density distribution, and star formation rate. The simulations include a range of physical processes and thus probe a range of modes of star formation, from relatively slow star formation inhibited by strong magnetic fields, turbulence, jets and radiation, to rapid star formation in near free-fall collapse. We find that, nearly independent of the overall star formation rate, HCN emission traces gas with a luminosity-weighted mean density of $0.8 - 1.7 \times 10^7$ cm$^{-3}$, and that the conversion between HCN luminosity and mass of gas above $10^3$ cm$^{-3}$ is $s_{\text{HCN}} = 14 M_\odot/(K \text{cm}^3 \text{s}^{-1} \text{pc}^2)$. This value is uncertain at the factor of $\sim 2$ level, mainly due to uncertainties in the total HCN abundance. This indeed justifies the perception that HCN(1–0) transitions trace dense gas regions associated with star formation.

We also find that the ratio of star formation rate to HCN emission is strongly correlated with the star formation rate per free-fall time $\epsilon_f$, as $\text{SFR}/L_{\text{HCN}} = 5.73 \times 10^{-3} \epsilon_f 1.32 M_\odot \text{yr}^{-1}/(K \text{km s}^{-1} \text{pc}^2)$. Expressed in the more usual terms of the IR–HCN correlation, we find $L_{\text{IR}}/L_{\text{HCN}} = 875(\epsilon_f/0.01)^{1.32} L_\odot/(K \text{km s}^{-1} \text{pc}^2)$. Our relation indicates that the observed IR–HCN relation corresponds to a mean star formation rate per free-fall time $\epsilon_f = 0.95\%$, which is highly supportive of typically observed values of $\epsilon_f \sim 1\%$ for similar studies. Of our simulations, only the one with the lowest $\epsilon_f$ and the slowest mode of star formation approaches the observed IR–HCN correlation, while those with more rapid modes of star formation all predict far to little HCN luminosity per unit star formation.

We further find that, in a large sample of massive molecular clumps in the Milky Way, the clump-to-clump scatter in $\epsilon_f$ is only a factor of a few, with more than 99% of values falling in the range $\epsilon_f = 0.1\% - 5\%$. This result is consistent with findings based on other techniques that $\epsilon_f$ varies little from cloud to cloud within the Milky Way. Conversely, we fail to find evidence to support published claims that there is a population of massive star-forming regions with $\epsilon_f > 10\%$.

We conclude that HCN(1–0) transitions are indeed an effective tracer of dense, star-forming gas and that the IR–HCN relation provides a strong constraint on models of star formation that is independent of other methods for determining $\epsilon_f$. We suggest that future simulations of star formation check their results against this constraint, and to facilitate such comparisons we provide an implementation of our code to compute HCN luminosities from simulations at http://bitbucket.org/aonus/hcn.

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