

On the Three-Dimensional Structure of Local Molecular Clouds

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ABSTRACT

We leverage the 1 pc spatial resolution of the [Leike et al. \(2020\)](#) 3D dust map to characterize the three-dimensional structure of nearby molecular clouds ($d \lesssim 400$ pc). We start by “skeletonizing” the clouds in 3D volume density space to determine their “spines,” which we project on the sky to constrain cloud distances with $\approx 1\%$ uncertainty. For each cloud, we determine an average radial volume density profile around its 3D spine and fit the profiles using Gaussian and Plummer functions. The radial volume density profiles are well-described by a two-component Gaussian function, consistent with clouds having broad, lower-density outer envelopes and narrow, higher-density inner layers. The ratio of the outer to inner envelope widths is $\approx 3 : 1$. We hypothesize that these two components may be tracing a transition between atomic and diffuse molecular gas or between the unstable and cold neutral medium. Plummer-like models can also provide a good fit, with molecular clouds exhibiting shallow power-law wings with density, n , falling off like n^{-2} at large radii. Using Bayesian model selection, we find that parameterizing the clouds’ profiles using a single Gaussian is disfavored. We compare our results with 2D dust extinction maps, finding that the 3D dust recovers the total cloud mass from integrated approaches with fidelity, deviating only at higher levels of extinction ($A_V \gtrsim 2 - 3$ mag). The 3D cloud structure described here will enable comparisons with synthetic clouds generated in simulations, offering unprecedented insight into the origins and fates of molecular clouds in the interstellar medium.

Keywords: molecular clouds, solar neighborhood, interstellar reddening, astronomy data visualization

1. INTRODUCTION

Much of our understanding of the structure and properties of molecular clouds is obtained via either two-dimensional (2D) observations of dust in emission or extinction (see [André et al. 2010](#); [Lombardi 2009](#); [Planck Collaboration et al. 2011](#)) or three-dimensional (3D) spectral-line observations of gas (see [Dame et al. 2001](#)), where the third dimension is not distance, but radial velocity. Until very recently, any insights into the true 3D spatial structure of molecular clouds were available only in numerical simulations, and were limited by the extent to which these simulations could

approximate the observed properties of real clouds. Even then, detailed comparisons between observations and simulations could, again, only be made either in 2D projected space, or via spectral line maps, where the correspondence of intensity features in *position-position-velocity* (p - p - v) space to “real” density features in *position-position-position* (p - p - p) space has been shown to be fraught with complications (Beaumont et al. 2013).

Interstellar dust reddens starlight, so by *simultaneously* modeling the distance and extinction to large numbers of stars, it is possible to infer a self-consistent 3D distribution of stars and dust that produces the observed distribution of stellar colors. Prior to the advent of *Gaia* (Gaia Collaboration et al. 2018) in 2018, accurate (e.g. astrometric) measurements of stars’ distances independent from measures of their colors were scarce, so transforming the 2D sky into a 3D physical picture of the distribution of stars and clouds that form them was extraordinarily challenging statistically. Several path-breaking 3D dust maps were created prior to *Gaia* (Marshall et al. 2006; Sale et al. 2014; Green et al. 2015), but *Gaia*’s astrometric constraints on stellar distances have allowed for significant gains in the spatial resolution of 3D dust maps. And the fidelity of 3D maps has improved even more as a variety of photometric catalogs, which offer billions of stellar color measurements needed to constrain extinction in fits, have been crossmatched with *Gaia*, (see e.g. Green et al. 2019; Lallement et al. 2019; Rezaei Kh. et al. 2018; Chen et al. 2019; Hottier et al. 2020; Leike & Enßlin 2019). Customization of the 3D dust mapping framework, where distance resolution can be enhanced at the expense of spatial resolution, has yielded highly accurate distance measurements for nearby molecular clouds, with typical distance uncertainties of $\approx 5\%$ (Zucker et al. 2019, 2020; Chen et al. 2020; Yan et al. 2019), a factor of five improvement over typical distance uncertainties in the pre-*Gaia* era.

While these new catalogs of molecular cloud distances have shown good agreement with maser distances (Zucker et al. 2020), revealed new Galactic-scale features (e.g. the *Radcliffe Wave*; Alves et al. 2020), and even mapped distance gradients *within* an individual molecular cloud (Zucker et al. 2019, 2018b), up until now, catalogs have not had the resolution to resolve the detailed 3D structure (e.g. thickness, orientation) of clouds on scales comparable to numerical simulations. Most existing approaches group batches of stars into pixels *on the sky*, and then fit stellar distance and extinction measurements in each pixel to obtain the distribution of dust along the line of sight. A 3D map can then be created by combining 1D line-of-sight information for all 2D sky pixels. However, the line-of-sight dust distributions suffer from a distortion effect, where the angular resolution on the sky is always superior to the distance resolution along the line of sight, resulting in dust clouds appearing to extend radially outward from the Sun in an unphysical manner.

Recently Leike et al. (2020) presented a new 3D dust map of the solar neighborhood out to a distance of ≈ 400 pc with a distance resolution of 1 pc. Leike et al. (2020) overcome the “fingers of god” effect by directly modeling the dust density in 3D x - y - z cartesian space. Their method combines metric Gaussian variational inference (Knollmüller & Enßlin 2019) with Gaussian Processes (e.g. Rasmussen & Williams 2006) in the context of information field theory (see Enßlin et al. 2009; Enßlin 2019; Arras et al. 2019; Enßlin & Frommert 2011). The integrated extinction for a star known to lie in a given 3D voxel with some uncertainty provides information on the integrated dust density along that given line of sight, acting as an “anchor” point that can constrain the smooth 3D distribution of dust. By inferring the spatial correlation of the dust on different scales, one can connect these anchor points, and infer the dust distribution at arbitrary points in space, including along lines of sight where no stars are observed. Specifically, Leike et al. (2020) model the dust as a log-normal Gaussian process, while *simultaneously* inferring the correlation kernel of the process, corresponding to the physical spatial correlation power spectrum of the dust. In this way, Leike et al. (2020) use information on the distance and extinction to 5 million stars in the vicinity of the Sun (obtained from the Starhorse algorithm; see Anders et al. 2019) to reconstruct the 3D spatial distribution of dust on a fixed cartesian grid with a spatial resolution of 1 pc. The Leike et al. (2020) results offer the first clear 3D spatial view of the local interstellar medium.¹

In this work, we utilize the high spatial resolution of the Leike et al. (2020) 3D dust map to analyze the 3D spatial structure and thicknesses of famous nearby star forming regions for the first time. Specifically, we extend two existing algorithms geared towards 2D data — **FilFinder** (Koch & Rosolowsky 2015) and **RadFil** (Zucker & Chen 2018) — into 3D. We apply the **FilFinder3D** algorithm to determine the topological skeletons of nearby clouds. We then use **RadFil3D** to determine their average radial volume density profiles, and characterize the shapes of these profiles via both Gaussian and Plummer fitting. We then validate our results by creating synthetic 2D dust extinction maps from

¹ The methodology is similar to that summarized in Rezaei Kh. et al. (2017, 2018) and implemented in Rezaei Kh. et al. (2020) to obtain a 3D cartesian view of the Orion A molecular cloud at a spatial resolution of approximately 10 pc. We will compare the Leike et al. (2020) results to the Rezaei Kh. et al. (2020) results in Orion A in §5.

the 3D density distributions, and comparing these maps to independent results (derived from the NICEST algorithm; Lombardi 2009; Lombardi et al. 2011) often used in star formation studies of nearby molecular clouds.

In §2, we present the datasets used in this work, including the Leike et al. (2020) dust map and the NICEST 2D extinction maps. In §3, we detail the methodology we use to derive the topological spines of the clouds, and to construct radial volume density profiles for each region. We also discuss the derivation of our 2D extinction maps. In §4, we present our results in the context of a custom 3D visualization environment, including the x - y - z - l - b - d values (the Heliocentric Galactic Cartesian coordinates, the Galactic coordinates, and the distance) for each point in the spine of every cloud, and their thicknesses derived from the radial profile fitting. We also compare the 2D dust extinction maps derived from the projected Leike et al. (2020) 3D dust distribution with NICEST 2D extinction maps, compute cloud masses from each method, and quantify the dynamic range in density that the Leike et al. (2020) dust map is able to probe. In §6, we discuss the implications of our results, including potential evidence of a phase transition in our radial density profiles. Finally, we conclude in §7.

2. DATA

2.1. Leike et al. (2020) 3D Dust Map

Leike et al. (2020) compute the 3D dust distribution on a cartesian grid centered on the Sun, extending $x = [-370$ pc, 370 pc], $y = [-370$ pc, 370 pc], and $z = [-270$ pc, 270 pc], where x , y , and z are the Heliocentric Galactic Cartesian coordinates. As such, the distance range of the map varies from $d = 370$ pc in the midplane, up to $d \approx 590$ pc at the corners of the grid. This distance range encompasses about a dozen well-studied nearby star-forming regions, and in this work we target the Chamaeleon, Ophiuchus, Orion B, Orion A, λ Orionis, Lupus, Taurus, Perseus, Musca, Pipe, and Cepheus molecular clouds for our radial profile analyses. We also provide the topological skeleton for one additional cloud — Corona Australis — but do not fit for its width, since it does not meet the density threshold required for inclusion in our study (see §3.1). We emphasize that three clouds — Orion A, Orion B, and λ Orionis — lie at the very edge of the Leike et al. (2020) grid, and the results for these clouds are subject to additional scrutiny, as discussed further in §4.

2.1.1. Converting to Gas Volume Density

The Leike et al. (2020) 3D dust map is provided in terms of the differential extinction, specifically the optical depth in the *Gaia* G-band, τ_G , per one parsec. Leike et al. (2020) generate twelve samples of their 3D dust map, and we adopt the mean of the samples in our main analysis. To ensure that uncertainties in the underlying dust reconstruction are not affecting our results, we will additionally repeat our radial profile analysis using all twelve realizations of the dust map, as discussed further in the Appendix.²

There are several steps needed to convert the data values of the mean map — referred to as the extinction density s_x in Leike et al. (2020) — to gas volume density. First, we use the relationship between $\frac{A_\lambda}{N_H}$ (the ratio of the extinction A at some wavelength λ over the hydrogen column density N_H) and inverse wavelength from Draine (2009, see Figure 1). Assuming a mean wavelength for the *Gaia* G-band of 673 nm ($\lambda^{-1} = 1.49 \mu\text{m}^{-1}$; Jordi et al. 2010), we obtain $\frac{A_G}{N_H} = 4 \times 10^{-22} \text{ cm}^2 \text{ mag}$ from Draine (2009).³ Given the known relationship between extinction A_G and optical depth ($A_G = 1.086 \times \tau_G$) we obtain $N_H = 2.71 \times 10^{21} \tau_G \text{ cm}^{-2}$. Finally, given that the Leike et al. (2020) map is provided in the form of $\frac{\tau_G}{1 \text{ pc}}$ (rather than the usual τ_G), we obtain $n_H = 880 \text{ cm}^{-3} \times s_x$. Thus, to convert the Leike et al. (2020) 3D dust map to volume density of hydrogen, we simply multiply the entire volume by a factor of 880. We emphasize that this volume density is the total volume density of hydrogen nuclei, independent of phase ($n = n_{\text{HI}} + 2n_{\text{H}_2}$) and is used to derive all results reported in §4. Volume density cubes for each cloud, with WCS information in a cartesian reference frame, are available on the Harvard Dataverse (see <https://doi.org/10.7910/DVN/IADP7W>).

2.1.2. Systematic Effects

While Leike et al. (2020) provide their results on a 1 pc grid, they argue that the functional resolution of the map is 2 pc, and only features which manifest at spatial scales greater than 2 pc should be considered reliable. Accordingly, for the main analysis, we exclude the inner 2 pc of each dust cloud’s radial volume density profile when inferring their structure, while reporting results including the inner 2 pc in the Appendix.

² For more details, see the public release of the Leike et al. (2020) map available on Zenodo (Leike et al. 2020). The mean dust map is available in the `mean_std.h5` file, while the twelve samples are available in `samples.h5`.

³ Draine (2009) is assuming an $R_V = 3.1$. Thus, variation in R_V could induce changes in our adopted conversion to gas volume density.

By performing tests on synthetic mock data, Leike & Enßlin (2019); Leike et al. (2020) also find that there are a small number of outliers in their 3D dust distribution, in which the differential dust extinction values in certain voxels is significantly larger than predicted, to a degree that cannot be captured by the reported uncertainties. While Leike & Enßlin (2019) and Leike et al. (2020) use different underlying stellar data for their statistical reconstruction, the methodology is similar, and we find the same high-differential-extinction outliers in the newer Leike et al. (2020) map. In this analysis, we will be averaging over many voxels and will find that our results are insensitive to these outliers.

We emphasize that the *3D volume densities reported here are likely lower limits*. We observe inhomogeneities in column density maps of nearby molecular clouds at spatial scales smaller than 2 pc, the effective spatial resolution of the Leike et al. (2020) 3D dust map (see e.g. Zari et al. 2016). Thus, much of the dense gas in these clouds is unresolved, not just due to the map’s spatial resolution, but due to the inability of the 3D dust mapping technique to probe high density gas, stemming from the lack of stellar data constraining the 3D dust reconstruction in this regime.

Finally, one additional consideration is the effect that YSOs have on the 3D dust reconstruction in Leike et al. (2020) and whether this would bias any 3D volume density estimates. The stellar catalog underpinning Leike et al. (2020) is based on the StarHorse algorithm, presented in Anders et al. (2019). Anders et al. (2019) does not employ any pre-main sequence models when determining stellar properties. Thus, as argued in Anders et al. (2019), any young stars detected with *Gaia* and included in the StarHorse sample will have poor fits, triggering a reliability flag. Since Leike et al. (2020) only use high-quality stellar data with no questionable reliability flags set, there should be very little contamination from YSOs in the 3D dust map.

2.2. 2D NICEST Extinction Maps

To validate our 3D cloud structure results (see §3) and quantify any “missing mass” in the 3D maps, we compute 2D maps of the K band extinction, A_K , using the NICEST algorithm (Lombardi 2009, A Near-Infrared Color Excess Method Tailored for Small-Scale Structures) for each cloud. Goodman et al. (2009) showed that dust extinction estimates based on the near-infrared color excess are relatively free from bias and provide more robust estimates of the column density, at higher dynamic range, than gas-based approaches. NICEST, and its predecessor NICER (Lombardi & Alves 2001), rely on the fact that the difference between the observed and intrinsic colors of a star (background to a cloud) provide information on the cloud’s extinction along the line of sight to that star. By measuring the unreddened colors of stars in a nearby, low extinction control field, it is possible to model the color excess on a star-by-star basis. Because there is a small dispersion in the intrinsic near-infrared colors of stars (and photometric errors), the technique requires averaging the extinction estimates for many individual stars in batches across the cloud, and pixel-by-pixel extinction estimates are computed as spatial averages via the adoption of a Gaussian smoothing kernel. Compared to NICER, NICEST removes contamination by foreground stars, which by their nature do not probe the cloud’s extinction, and better characterizes small-scale inhomogeneities (i.e. filaments) present in the dust.

Like Lombardi et al. (2011), to compute the extinction, we leverage the near-infrared J , H , and K band colors of millions of stars detected in 2MASS (Skrutskie et al. 2006) for each field. Using the 2MASS photometry, NICEST creates two sets of stellar samples: main sequence stars and YSOs, defined using their respective K -band magnitude distributions. In practice, given a star, the algorithm computes the intrinsic K -band magnitude (i.e. removes the extinction) and compares this with the K -band number counts of field stars (typically an exponential distribution) and YSOs (typically a Gaussian-like curve). This comparison is used to assign to each star a probability of being a YSO. The functionality to produce custom cloud-by-cloud NICEST extinction maps is available online (Lombardi & Alves 2001; Lombardi 2009)⁴ and we adopt the default map making and cluster parameters. The default option is to include all stars in the extinction calculation, including YSOs. To check that YSOs are not affecting our mass calculations, we compute two masses for Orion A both with and without including YSOs in the sample. We find that including the YSOs in the extinction calculation only increases the mass by 2%. Since Orion A contains the largest number of YSOs in the solar neighborhood, our decision to compute the extinction maps using all stars should have no effect on our results. The configuration files used to produce the NICEST maps are available online at the Harvard Dataverse; the NICEST maps for all clouds targeted in this study are likewise available online (see <https://doi.org/10.7910/DVN/WONVUH> for both).

3. METHODS

⁴ See <http://interstellarclouds.fisica.unimi.it/html/index.html>

3.1. *FilFinder 3D*

To determine the topological skeletons of nearby molecular clouds, we employ a modified 3D version of the *FilFinder* package from Koch & Rosolowsky (2015). *FilFinder* was originally developed in 2D to constrain the filamentary structure in H_2 column density maps obtained as part of the Herschel Gould Belt Survey (André et al. 2010). *FilFinder3D* uses similar morphological operations to the existing 2D version, but now employs the *skan* package for efficient operations on large morphological skeletons (Nunez-Iglesias et al. 2018). A full description of the 3D algorithm will be presented in Koch et al. (2021, in preparation).

To compute the skeletons, we start by defining the same density threshold for all clouds, equivalent to $n = 35 \text{ cm}^{-3}$, based on the volume density distribution computed in §2.1.⁵ Hierarchical structure finding algorithms for feature identification do exist for 3D volumes, the most common being dendrograms (Rosolowsky et al. 2008), which are frequently applied to spectral-line cubes of CO emission in *position-position-velocity* space (Rice et al. 2016). However, it is well known that dendrograms are not able to capture filamentary structure, with rarely any structures exceeding an aspect ratio of 2 : 1 (see Rice et al. 2016). Since we find that nearby star-forming regions are indeed filamentary, even at lower densities, we forgo dendrograms for this analysis and defer to future work. Before settling on a fixed threshold of $n = 35 \text{ cm}^{-3}$, we test a variety of thresholds, ranging from $20 - 50 \text{ cm}^{-3}$. Thresholds significantly higher than $n = 35 \text{ cm}^{-3}$ were too patchy to skeletonize, while thresholds significantly lower than $n = 35 \text{ cm}^{-3}$ meant that the peak radial densities were often offset from the main spine.⁶ Our choice of density threshold is validated in §4, since the spines defined in 3D tend to align very well with the spines of filaments seen in 2D dust emission from Planck (Planck Collaboration et al. 2011), and the radial density profiles peak near a radial distance of zero. Overall we find that all clouds are well-defined at $n = 35 \text{ cm}^{-3}$ and we can produce the most unbiased widths possible by not tweaking feature identification on a cloud-by-cloud basis.

After defining this initial $n = 35 \text{ cm}^{-3}$ threshold, we morphologically close the 3D mask by performing a dilation, followed by an erosion. This procedure removes small voids in the mask, rendering it suitable for skeletonization.⁷ We then skeletonize the 3D mask using the Medial Axis Transform, convert the skeleton to a graph, and run a longest path algorithm on the resulting skeleton to obtain the main trunk of each density feature. While we only use the spine computed from the longest path algorithm to derive the widths, we also preserve and report the full skeleton without pruning applied, in order to retain distance information on all branches. In this scheme, nearby molecular clouds can either be defined by a single, or multiple, trunks, depending on whether they are connected in density space above a threshold of $n = 35 \text{ cm}^{-3}$. Thus, this skeletonization process is performed between one and four times, depending on how many isolated 3D features there are after performing the initial thresholding. For clouds like Perseus, which manifest as a single feature in density space, we identify only a single spine. However, clouds like Taurus are actually composed of several distinct features in density space. The skeletonization and longest path algorithms are individually run on each isolated mask, to produce a set of trunks defining the cloud.⁸

Finally, we emphasize again that the *FilFinder* algorithm is designed to work on elongated, *filamentary* structures, with aspect ratios of at least 3 : 1. We find that the vast majority of our masks tend to be elongated with aspect ratios of at least 3 : 1, but there are a few sub-features in clouds which are better described as ellipsoids than filaments, some of which may be unresolved in the Leike et al. (2020) map. Ellipsoids do not dominate the set of density features, either across the sample, or within an individual cloud, so this has a negligible effect on the results. The volume density distributions (<https://doi.org/10.7910/DVN/IADP7W>), 3D masks (<https://doi.org/10.7910/DVN/NMRLP1>), and 3D spines (<https://doi.org/10.7910/DVN/YQYBRD>) are available online with full WCS information at the Harvard Dataverse. We refer interested readers there to explore our masking and skeletonization results on a cloud-by-cloud basis in more detail.

3.2. *RadFil 3D*

⁵ Corona Australis has no significant extended density features above a level of $n = 35 \text{ cm}^{-3}$, so we skeletonize it at a level of $n = 5 \text{ cm}^{-3}$ to provide distance information. It is included in Table 1 but not in Tables 2 and 3.

⁶ In previous analyses based on 2D dust emission maps (Zucker et al. 2018a), we implemented a “shift” option in the *RadFil* package to account for dense clumps offset from the main spine, since *FilFinder* does not take into the density range *inside* each mask when defining the spine. The “shift” option corrects for this by shifting each cut so that its peak density is centered at a radial distance of 0 pc. However, we forgo shifting in this work due to the small handful of noisy outliers at very high differential extinction, which would bias the density results at small radii.

⁷ More details on mathematical morphology, including the erosion, dilation, and closing of features in 2D or 3D space, can be found in the *scikit-image* documentation, which we use to perform these operations (van der Walt et al. 2014).

⁸ The two exceptions are the Musca filament and the Pipe nebula. We find that Musca is connected to the Chamaeleon cloud in 3D density space at a level of $n = 35 \text{ cm}^{-3}$. The same is true for the Pipe nebula, which is connected to Ophiuchus. Because these clouds have always been treated as individual entities in the literature, and obtaining widths for the Pipe nebula and Musca (as opposed to the Pipe-Ophiuchus, and Musca-Chamaeleon complexes) is beneficial for comparison with prior work, we mask out the Pipe nebula when obtaining widths for Ophiuchus, and the Musca cloud when obtaining widths for Chamaeleon (and vice versa). In reality, the complexes are connected by only very thin tendrils, so this procedure does not affect the morphology of the derived masks, or the resulting widths.

3.2.1. Building Profiles

To characterize the thicknesses of local clouds, we employ the radial profile builder **RadFil** (Zucker & Chen 2018). **RadFil** was designed in 2D to build radial column density profiles using filament spines determined by the **FilFinder** package (Zucker & Chen 2018; Koch & Rosolowsky 2015; Zucker et al. 2018a). **RadFil** builds profiles by taking radial cuts across the spine. The same logic for constructing a radial profile in 2D can easily be extended into 3D. We take the 3D skeleton returned by **FilFinder3D**, and fit a B-spline to obtain a smoothed continuous version of the spine and the first derivative along its length. Using functionality within the Python package **PyVista** (Sullivan & Kaszynski 2019), we generate a slice through the volume density cube at each point along the spine given the normal vector obtained from the first derivative. Then, for each point in the slice, we determine its radial distance from the spine point and its volume density via linear interpolation. On a slice by slice basis, we compute the median density in forty radial distance bins, spaced half a parsec apart, out to 20 pc. Given the full set of profiles, an average profile is obtained by computing the median volume density in each radial distance bin. Before taking the average, we remove the small minority of profiles in which the peak radial density is less than the density threshold used to define the mask ($n = 35 \text{ cm}^{-3}$). For clouds composed of multiple isolated density features, the average is taken using slices across all density features, to compute a representative width for each cloud.

This averaged radial profile is used to perform the Gaussian and Plummer fitting described in §3.2.2. Because of the 1 pc voxel size of the 3D dust map, and the fact that Leike et al. (2020) recommend that scales less than 2 pc are suspect, we remove the inner 2 pc of each averaged profile when fitting the profiles. However, in the Appendix, we report results for the full profile fits (including the inner 2 pc) and find that our choice to remove radial distances between 0 and 2 pc does not significantly affect our results.

3.2.2. Fitting Profiles

We fit three functions to the averaged radial volume density profile computed for each cloud in §3.2.1 — a single-component Gaussian, a two-component Gaussian, and a Plummer function. One important consideration is the modeling of the scatter in the averaged profile. In our case, the scatter in the volume density within a bin at fixed radial distance is not a true measurement error, but rather encompasses real physical variation in the radial density profile taken at different slices along the spine of a cloud. For this reason, we choose to model the scatter on the density as part of our fitting procedure, introducing it as an additional free parameter in all three of our models. We perform our inference in a Bayesian framework, adopting a simple Gaussian likelihood (see e.g. Hogg et al. 2010) and flat priors on all our parameters. None of our parameters are prior-dominated, so this choice of flat prior has no effect on our results. For computational expediency, we minimize the negative log-likelihood, in lieu of maximizing the likelihood. Our Gaussian log-likelihood is of the form:

$$\ln p(n|\theta, \sigma_n^2) = -\frac{1}{2} \sum_i \left[\frac{[n_i - n_{\theta,i}]^2}{\sigma_n^2} + \ln(2\pi\sigma_n^2) \right] \quad (1)$$

where n_i is the measured density in the i th radial distance bin, $n_{\theta,i}$ is the modeled density in the i th radial distance bin (defined by the free parameters θ), and σ_n^2 is the square of the scatter in the density across all bins that we also infer as part of our modeling.

For the single-component Gaussian fit, our model for the volume density of hydrogen nuclei n as a function of radial distance r is of the form:

$$n(r) = a \exp\left(\frac{-r^2}{2\sigma^2}\right) \quad (2)$$

Our free parameters θ are the amplitude (a) and standard deviation (σ). The mean of the Gaussian is fixed to zero. We adopt a flat prior between $0 - 80 \text{ cm}^{-3}$ for a , between $0 - 15 \text{ pc}$ for σ and between $0 - 100 \text{ cm}^{-3}$ for σ_n^2 .

To better model the significant tails of the distribution, we additionally fit a two-component Gaussian, again with the mean of each component fixed to zero:

$$n(r) = a_1 \exp\left(\frac{-r^2}{2\sigma_1^2}\right) + a_2 \exp\left(\frac{-r^2}{2\sigma_2^2}\right) \quad (3)$$

where the amplitudes (a_1, a_2) and their standard deviations (σ_1, σ_2) are the free parameters in the modeling. We adopt a flat prior between $20 - 80 \text{ cm}^{-3}$ for a_1 , between $0 - 6 \text{ pc}$ for σ_1 , between $2 - 20 \text{ cm}^{-3}$ for a_2 , between $6 - 25 \text{ pc}$ for

σ_2 , and between $0 - 100 \text{ cm}^{-3}$ for σ_n^2 . The offset in the prior range between a_1 and a_2 is adopted to avoid degeneracies in the modeling.

Finally, we fit a Plummer function, which we parameterize as:

$$n(r) = \frac{n_0}{[1 + (\frac{r}{R_{\text{flat}}})^2]^{\frac{p}{2}}} \quad (4)$$

where our free parameters are n_0 (peak profile height), R_{flat} (the flattening radius), and p (index of the density profile). Equation 4 is the same ubiquitous Plummer function applied to column density maps of smaller-scale filaments (widths a few tenths of a parsec, lengths a few parsecs; Arzoumanian et al. 2019; Panopoulou et al. 2017) from the Herschel Gould Belt Survey (André et al. 2010), except we have transformed the model from column density space back to volume density space (see Equation 1 of Arzoumanian et al. 2011). We adopt a flat prior between $20 - 170 \text{ cm}^{-3}$ for n_0 , between $0 - 15 \text{ pc}$ for R_{flat} , between $0 - 6$ for p , and between $0 - 100 \text{ cm}^{-3}$ for σ_n^2 .

We sample for all model parameters using the nested sampling code **dynesty** (Speagle 2020). We adopt the default parameters of the nested sampler, with a stopping criterion of $\text{dlogz} = 0.1$. We utilize the logarithm of the evidence $\ln(Z)$ extracted from the **dynesty** chains to compute a Bayes Factor for the purpose of model comparison, as discussed further in §4.

3.3. Creating 2D Dust Extinction Maps from 3D Dust Data

To compare the Leike et al. (2020) 3D dust map with traditional 2D approaches (see §2.2), we create projected 2D dust extinction maps from the 3D volume density distributions used in the construction of the radial profiles. To do so, we utilize the **FitsOffAxisProjection** functionality from the Python package **yt** (Turk et al. 2011). The **FITSOffAxisProjection** function integrates the volume density n along a line of sight \hat{l} , where \hat{l} is determined by the vector between the Sun and the median cartesian coordinates of the points in a cloud’s skeleton, $(x_{\text{cen}}, y_{\text{cen}}, z_{\text{cen}})$. The resulting projection corresponds to the total hydrogen column density distribution $N = N_{\text{HI}} + 2N_{\text{H}_2}$ (in cm^{-2}) as seen from the Sun. In order to compare with the NICEST maps of the K band extinction A_K (from §2.2), we convert from total hydrogen column density to A_K by assuming a constant conversion factor from Lada et al. (2009) of $\frac{N(\text{HI})+2N(\text{H}_2)}{A_K} = 1.67 \times 10^{22} \text{ cm}^{-2} \text{ mag}^{-1}$.

To assign sky coordinates to each projection, we convert from the skeleton’s central coordinates $(x_{\text{cen}}, y_{\text{cen}}, z_{\text{cen}})$ to sky coordinates $(l_{\text{cen}}, b_{\text{cen}}, d_{\text{cen}})$, where l_{cen} and b_{cen} become the central Galactic Longitude and Latitude of the projected image on the plane of the sky, and d_{cen} is the distance between the Sun and the central point of the cloud’s skeleton. The pixel scale of the image is computed by determining the angular size spanned by a 1 pc voxel (the voxel size of the original 3D dust grid) at the central distance of the cloud’s skeleton d_{cen} . These projected A_K maps are available for download at the Harvard Dataverse (see <https://doi.org/10.7910/DVN/GXXXKHD>).

3.4. Mass Calculation

To quantify the fraction of cloud mass being recovered with 3D dust mapping, we compute cloud masses using both traditional NICEST 2D dust extinction maps (from §2.2) and the projected A_K maps we derive from the 3D dust in §3.3. In both cases, we adopt a consistent threshold of $A_K = 0.1 \text{ mag}$. This threshold is the same used in previous literature to calculate cloud masses from the NICEST 2D dust extinction maps (see e.g. Lada et al. 2010).⁹ The masses are calculated inside the cloud boundaries by assuming the same mass surface density relation as Zari et al. (2016). This relation is equivalent to $\frac{\Sigma_{\text{gas}}}{A_K} = \mu m_p \beta_K = 183 M_{\odot} \text{ pc}^{-2} \text{ mag}^{-1}$, where $\mu = 1.37$ is the mean molecular weight, $m_p = 1.67 \times 10^{-24} \text{ g}$ is the mass of the proton, and β_K is the same gas-to-dust ratio that we adopt above, equivalent to $1.67 \times 10^{22} \text{ cm}^{-2} \text{ mag}^{-1}$. To ensure a fair comparison, the NICEST maps from §2.2 are convolved to the same resolution as the Leike et al. (2020) based extinction maps. In both cases, the same distance d_{cen} — the average distance to a cloud’s skeleton — is adopted.

4. RESULTS

4.1. Skeletonization

⁹ Like Lada et al. (2010), we also subtract a constant background of $A_K = 0.15 \text{ mag}$ from the Pipe nebula, due to its position close to the plane and towards the Galactic center. Furthermore, because the 2D dust extinction maps based on Leike et al. (2020) are computed using only dust local to the cloud, rather than integrated along the line of sight, we limit our comparison to latitudes $|b| > 5^\circ$. In reality, this latitude cut only masks out a small section of the Pipe and Lupus clouds.

Table 1. Skeletonization Results

Cloud	l	b	d_{min}	d_{med}	d_{max}	x_{min}	x_{max}	y_{min}	y_{max}	z_{min}	z_{max}	$N_{components}$	$l_{skeleton}$
	$^{\circ}$	$^{\circ}$	pc	pc	pc	pc	pc	pc	pc	pc	pc		pc
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
Chamaeleon	299.0	-15.9	173	183	190	69	99	-159	-148	-57	-35	1	68
Ophiuchus	355.4	17.0	115	136	150	104	144	-26	5	24	48	3	74
Lupus	341.7	5.1	155	165	198	139	196	-73	-28	4	47	3	80
Taurus	172.6	-15.6	131	148	168	-166	-122	6	44	-45	-26	3	79
Perseus	158.9	-20.2	279	295	301	-270	-236	95	100	-116	-81	1	57
Musca	301.0	-9.7	171	172	173	86	91	-146	-145	-36	-22	1	16
Pipe	2.1	4.1	147	152	163	146	163	-8	7	6	18	1	27
Cepheus	112.1	15.9	337	345	370	-133	-65	300	323	81	133	4	52
Corona Australis ^a	6.5	-24.6	136	161	179	132	162	-2	24	-77	-33	1	86
Orion A*	212.5	-19.6	391	405	445	-349	-315	-241	-177	-149	-118	3	52
Orion B*	205.5	-14.0	397	404	406	-362	-332	-190	-157	-114	-76	1	69
λ Orionis*	194.3	-14.6	375	386	397	-367	-356	-129	-73	-109	-73	3	62

NOTE—Properties of the 3D skeletons for local molecular clouds. (1) Name of the cloud. (2-3) Median Galactic longitude l and latitude b of the points defining the cloud’s skeleton. (4 - 6) Minimum, median, and maximum distance of the points defining the skeleton. (7-8) Minimum and maximum extent of the cloud’s skeleton in the Heliocentric Galactic cartesian x direction. (9-10) Minimum and maximum extent of the cloud’s skeleton in the Heliocentric Galactic cartesian y direction. (11-12) Minimum and maximum extent of the cloud’s skeleton in the Heliocentric Galactic cartesian z direction. (13) Number of skeletons per cloud, determined by the number of significant features above a density threshold of $n = 35 \text{ cm}^{-3}$. (14) Total length of the set of skeletons in (13), computed using only each skeleton’s main trunk via **FilFinder**’s longest path algorithm. At the [Harvard Dataverse](https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/gallery.html), we provide tables in FITS format with the (x, y, z, l, b, d) values of each point in the spine (for both the longest path skeleton summarized here, and the full, unpruned skeleton). We also provide a machine readable version of this table (see <https://doi.org/10.7910/DVN/CAVMAQ>). Interactive figures highlighting these skeletonization results are available at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/gallery.html.

^aCorona Australis is too diffuse to meet the minimum density threshold to be included in the width analysis for this study. We skeletonize the cloud at a much lower threshold ($n = 5 \text{ cm}^{-3}$) to provide distance information, but do not include it in subsequent analysis in Tables 2 and 3.

*Clouds below the horizontal line – Orion A, Orion B, and λ Orionis – should be treated with caution, as they lie at the very edge of the [Leike et al. \(2020\)](#) 3D dust grid and are subjected to additional biases. Part of Orion A, toward the Orion Nebula Cluster, is also devoid of dust in the [Leike et al. \(2020\)](#) 3D dust map despite being highly extinguished. See §5 for full details.

In Table 1 we summarize the properties of the skeletons, determined using **FilFinder3D**’s longest path algorithm, for all clouds in our sample. This includes the minimum, median, and maximum distance to each cloud’s skeleton, along with the extent of the cloud’s skeleton along the Heliocentric Galactic cartesian x , y , and z directions. We also include the number of skeletal components (skeletonized at a density threshold above $n = 35 \text{ cm}^{-3}$) and the total length of these components. The length is the total length of *denser* features (computed using only the skeleton returned by the longest path algorithm) so it does not include features branching off the main trunk. The properties of both the longest path skeletons, and the full unpruned skeletons, are available online in machine readable format on the [Harvard Dataverse](https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/gallery.html) (see <https://doi.org/10.7910/DVN/YQYBRD>). The skeletonization results for two clouds (Perseus and Chamaeleon) are shown in Figures 1 and 2, respectively. These figures are interactive in their online version; it is possible to manipulate the skeleton in 3D, or hover over any point in the 2D skeleton to obtain its plane-of-the-sky coordinates and distance. Comparable interactive figures for the rest of the clouds in the sample are available at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/gallery.html or in the online version of the published article.

We have separated Table 1 into two parts, representing “complete” (top rows) and “incomplete” (bottom rows) clouds. Incomplete clouds – Orion A, Orion B, and λ Orionis — are those which lie at the very edge of the [Leike et al.](#)

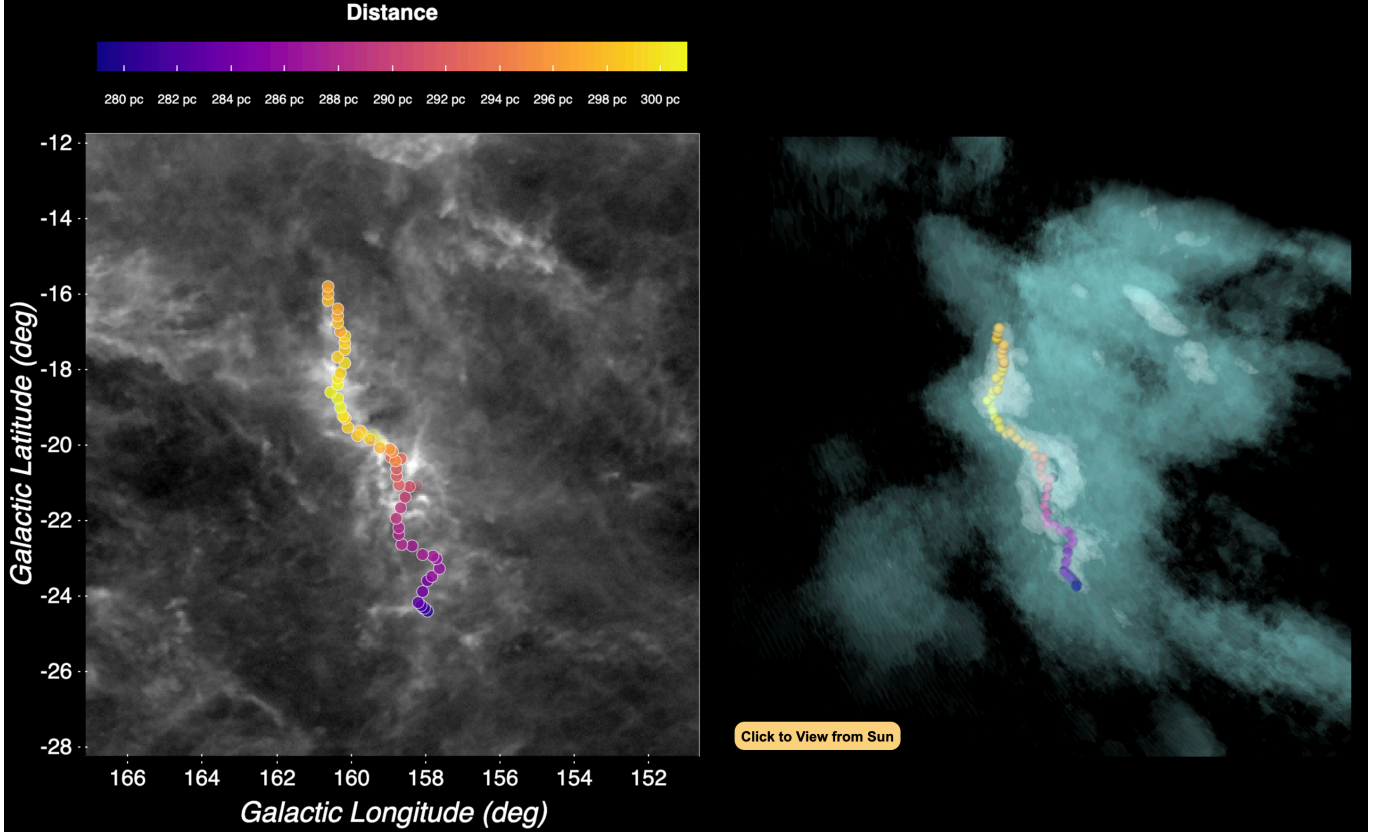


Figure 1. Skeletonization results for the Perseus Molecular Cloud shown in 2D (left panel) and 3D (right panel). In both panels, the scatter points (colored by distance over the range $d = 279 - 301$ pc) delineate the skeleton of the cloud, determined in 3D Cartesian space and projected back on the plane of the sky. In the 3D version of the figure we show the 3D volume density of the cloud n , where the cyan and white distributions indicate lower thresholds of $n = 4 \text{ cm}^{-3}$ and $n = 35 \text{ cm}^{-3}$ respectively. In the plane of the sky version, we show the Planck reddening map (Planck Collaboration et al. 2011). An interactive version of this figure is available at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/perseus_topology/perseus.html or in the online version of the published article. Comparable interactive figures for all clouds in the sample are available at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/gallery.html. In the online version, the cyan and white boundaries (toggleable on/off) correspond to the FWHM of the inner and outer envelopes of the cloud, derived from the two-component Gaussian fitting results in §4.

(2020) 3D dust map, which extends to 370 pc along the cartesian x and y directions. While these three clouds are still capable of being skeletonized, it is likely that some fraction of each cloud lies beyond the map boundary, which would bias the skeletons to be mildly closer in distance than they actually are. This incompleteness will be further validated in §4.4, where projected 2D extinction maps based on the Leike et al. (2020) 3D dust distribution indicate that Orion A, Orion B, and λ Orionis are the only three clouds in the sample whose masses are significantly discrepant from counterpart masses calculated out to “infinity” (that is, using the NICEST algorithm; Lombardi 2009). This discrepancy indicates that there is missing mass present beyond the boundaries of the map.

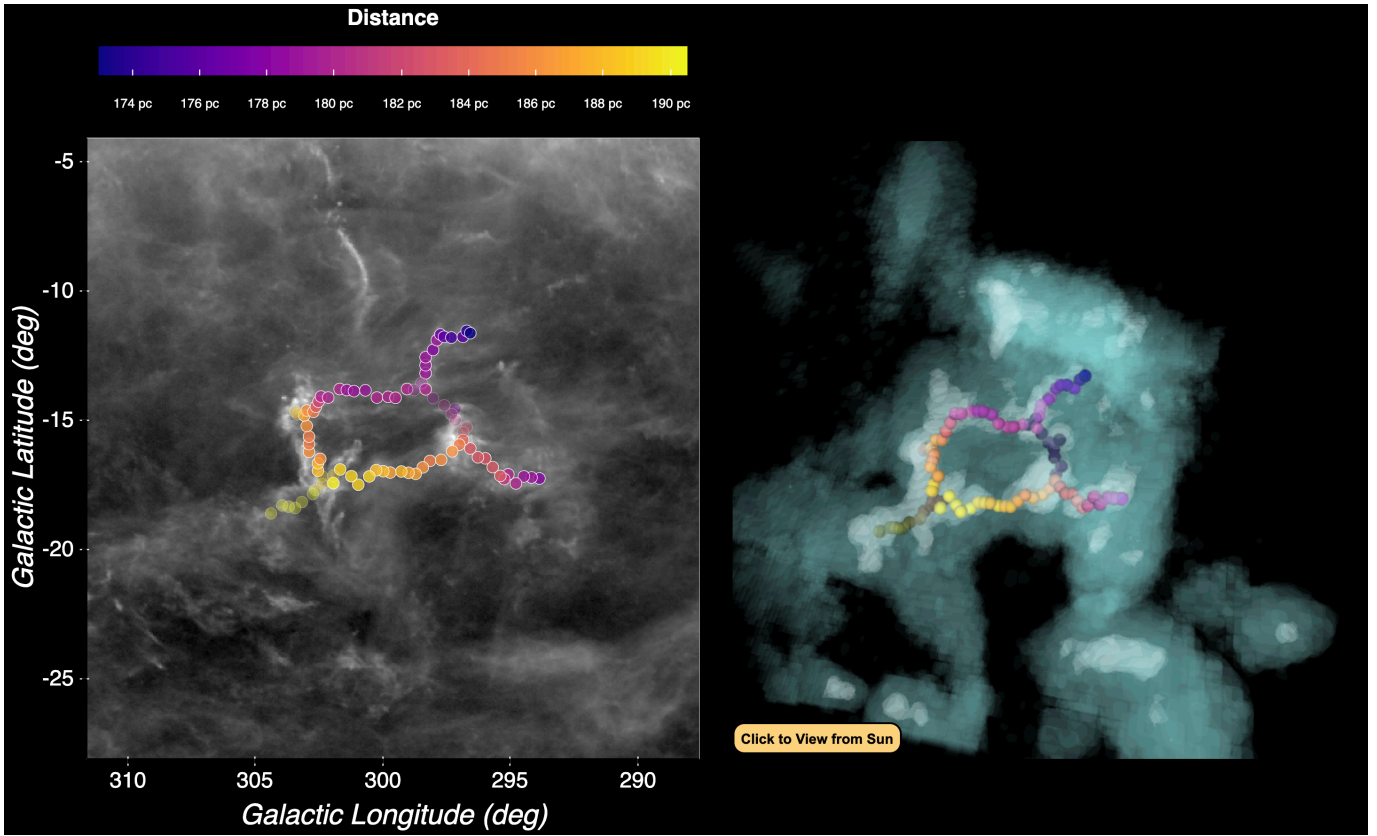


Figure 2. Same as in Figure 1 but for the Chamaeleon Molecular Cloud, with the spine (colored points) spanning a distance range of $d = 173 - 190$ pc. Opaque spine points constitute the skeleton's main spine, while semi-transparent points are part of the full, unpruned skeleton. An interactive version of this figure is available at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/chamaeleon_topology/chamaeleon.html or in the online version of the published article. Comparable interactive figures for all clouds in the sample are available at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Topologies/gallery.html.

Table 2. Radial Volume Density Fitting Results

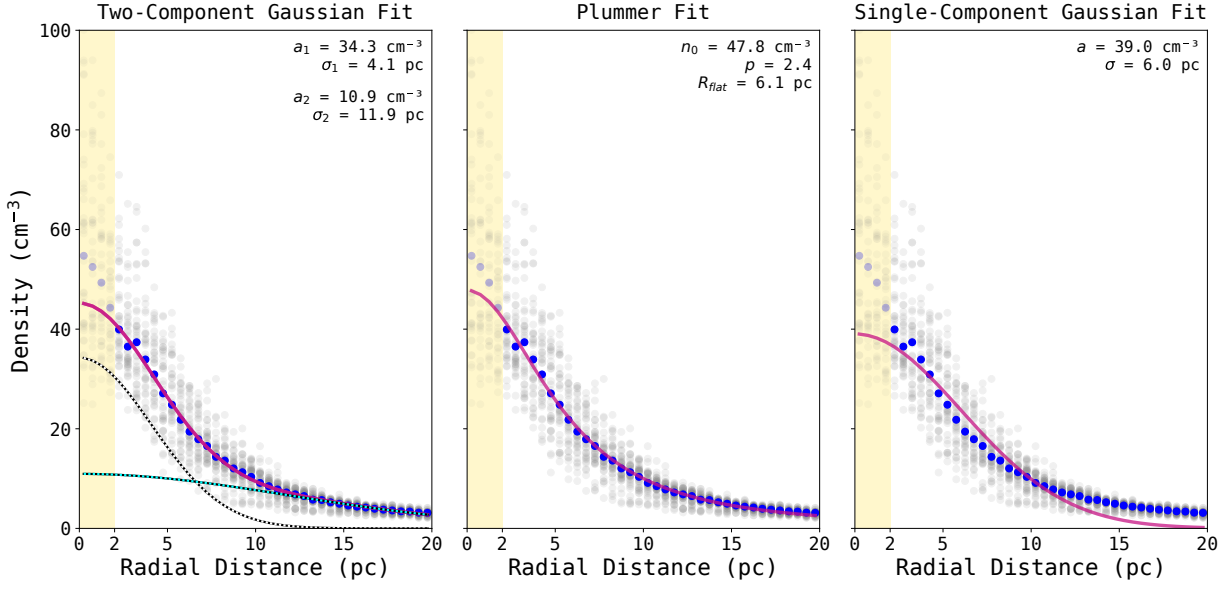
Cloud	Two-Component Gaussian					Plummer					Single Gaussian				
	σ_1	a_1	σ_2	a_2	$\sigma_{n,G2}^2$	$\frac{\sigma_2}{\sigma_1}$	$\ln Z_{G2}$	n_0	R_{flat}	p	$\sigma_{n,P}^2$	$\ln Z_P$	σ	a	$\sigma_{n,G1}^2$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Chamaeleon	$2.9^{+0.1}_{-0.1}$	$31.3^{+0.5}_{-0.6}$	$10.2^{+0.4}_{-0.3}$	$8.7^{+0.5}_{-0.5}$	$0.2^{+0.0}_{-0.0}$	3.5	-2.9	$47.8^{+1.5}_{-1.2}$	$3.1^{+0.1}_{-0.2}$	$1.8^{+0.1}_{-0.1}$	$0.1^{+0.0}_{-0.0}$	-1.5	$4.8^{+0.3}_{-0.3}$	$30.8^{+2.1}_{-2.0}$	$6.1^{+1.9}_{-1.3}$
Ophiuchus	$2.7^{+0.2}_{-0.2}$	$31.1^{+1.6}_{-1.5}$	$10.1^{+0.6}_{-0.5}$	$12.6^{+1.1}_{-1.1}$	$0.8^{+0.2}_{-0.2}$	3.8	-27.2	$56.0^{+3.5}_{-2.9}$	$2.3^{+0.2}_{-0.2}$	$1.4^{+0.0}_{-0.0}$	$0.3^{+0.1}_{-0.1}$	-11.9	$5.8^{+0.5}_{-0.4}$	$29.1^{+2.0}_{-2.0}$	$9.5^{+2.6}_{-2.0}$
Lupus	$2.6^{+0.3}_{-0.2}$	$30.6^{+1.8}_{-1.8}$	$8.1^{+0.6}_{-0.5}$	$15.5^{+1.9}_{-2.0}$	$0.9^{+0.3}_{-0.2}$	3.1	-29.2	$48.6^{+2.3}_{-1.9}$	$3.6^{+0.3}_{-0.3}$	$1.9^{+0.1}_{-0.1}$	$0.5^{+0.1}_{-0.1}$	-19.3	$5.2^{+0.3}_{-0.3}$	$32.7^{+1.8}_{-1.7}$	$6.2^{+1.7}_{-1.3}$
Taurus	$2.6^{+0.1}_{-0.1}$	$30.9^{+1.2}_{-1.1}$	$11.9^{+0.6}_{-0.5}$	$9.2^{+0.5}_{-0.5}$	$0.4^{+0.1}_{-0.1}$	4.6	-17.4	$72.8^{+22.7}_{-11.1}$	$1.2^{+0.3}_{-0.3}$	$1.2^{+0.0}_{-0.0}$	$0.4^{+0.1}_{-0.1}$	-17.3	$5.8^{+0.6}_{-0.6}$	$24.3^{+2.4}_{-2.2}$	$10.3^{+3.3}_{-2.3}$
Perseus	$4.1^{+0.1}_{-0.1}$	$34.3^{+0.9}_{-0.9}$	$11.9^{+0.8}_{-0.6}$	$10.9^{+1.0}_{-1.0}$	$0.3^{+0.1}_{-0.1}$	2.9	-15.0	$47.8^{+0.9}_{-0.9}$	$6.1^{+0.3}_{-0.3}$	$2.4^{+0.1}_{-0.1}$	$0.5^{+0.1}_{-0.1}$	-20.7	$6.0^{+0.2}_{-0.2}$	$39.0^{+1.6}_{-1.5}$	$6.9^{+2.1}_{-1.4}$
Musca ^a	$3.1^{+0.1}_{-0.1}$	$31.8^{+1.5}_{-1.5}$	$17.9^{+4.1}_{-3.0}$	$4.9^{+0.7}_{-0.6}$	$1.3^{+0.4}_{-0.3}$	5.8	-34.4	$48.3^{+8.4}_{-5.5}$	$2.5^{+0.6}_{-0.5}$	$1.6^{+0.2}_{-0.2}$	$2.4^{+0.7}_{-0.5}$	-44.5	$4.4^{+0.4}_{-0.4}$	$29.8^{+3.0}_{-2.9}$	$8.9^{+2.7}_{-2.0}$
Pipe	$4.1^{+0.4}_{-0.4}$	$25.5^{+2.7}_{-2.8}$	$9.7^{+2.5}_{-1.2}$	$9.0^{+3.3}_{-3.4}$	$1.5^{+0.5}_{-0.3}$	2.4	-36.7	$35.5^{+1.5}_{-1.4}$	$7.7^{+1.2}_{-1.0}$	$3.4^{+0.6}_{-0.5}$	$1.4^{+0.4}_{-0.3}$	-35.5	$5.7^{+0.2}_{-0.2}$	$30.6^{+1.2}_{-1.1}$	$3.5^{+1.1}_{-0.7}$
Cepheus	$2.5^{+0.1}_{-0.1}$	$46.6^{+1.7}_{-1.6}$	$10.9^{+0.7}_{-0.6}$	$10.1^{+0.7}_{-0.7}$	$0.7^{+0.2}_{-0.2}$	4.4	-26.4	$116.9^{+23.7}_{-17.5}$	$1.3^{+0.2}_{-0.2}$	$1.4^{+0.0}_{-0.0}$	$0.5^{+0.1}_{-0.1}$	-21.6	$4.3^{+0.4}_{-0.4}$	$39.1^{+3.9}_{-3.7}$	$14.3^{+4.2}_{-3.0}$
Orion A*	$2.9^{+0.1}_{-0.1}$	$52.4^{+1.8}_{-1.8}$	$8.4^{+1.0}_{-0.8}$	$8.8^{+1.9}_{-1.7}$	$1.3^{+0.4}_{-0.3}$	2.9	-35.0	$68.3^{+3.4}_{-3.0}$	$4.4^{+0.5}_{-0.4}$	$3.1^{+0.3}_{-0.3}$	$1.5^{+0.5}_{-0.3}$	-37.2	$3.7^{+0.1}_{-0.1}$	$53.1^{+2.5}_{-2.4}$	$5.8^{+1.8}_{-1.3}$
Orion B*	$4.9^{+0.1}_{-0.1}$	$39.2^{+1.1}_{-1.1}$	$14.6^{+1.9}_{-1.3}$	$9.0^{+1.3}_{-1.2}$	$0.3^{+0.1}_{-0.1}$	3.0	-13.6	$50.3^{+0.8}_{-0.8}$	$8.1^{+0.5}_{-0.4}$	$3.0^{+0.2}_{-0.2}$	$0.6^{+0.2}_{-0.1}$	-23.6	$6.5^{+0.2}_{-0.2}$	$43.8^{+1.4}_{-1.3}$	$5.9^{+1.8}_{-1.2}$
λ Orionis*	$3.7^{+0.1}_{-0.1}$	$27.2^{+0.5}_{-0.5}$	$12.8^{+0.5}_{-0.4}$	$9.3^{+0.4}_{-0.4}$	$0.1^{+0.0}_{-0.0}$	3.4	-0.7	$40.2^{+1.1}_{-1.0}$	$4.3^{+0.3}_{-0.2}$	$1.7^{+0.1}_{-0.1}$	$0.3^{+0.1}_{-0.1}$	-14.0	$6.3^{+0.3}_{-0.3}$	$29.1^{+1.6}_{-1.6}$	$7.2^{+2.0}_{-1.5}$

NOTE.—Cloud thickness results, obtained via radial volume density profile fitting of each cloud's 3D density distribution. (1) Name of the cloud. (2-6) Best-fit parameters for the two-component Gaussian fit, including the standard deviation and amplitude of the narrower Gaussian (σ_1 , a_1), the standard deviation and amplitude of the broader Gaussian (σ_2 , a_2), and the square of the modeled scatter in the density measurements ($\sigma_{n,G2}^2$). (7) Ratio of the outer to inner Gaussian standard deviations. (8) Logarithm of the evidence of the two-component Gaussian fit. (9-12) Best-fit parameters of the Plummer fit, including the peak amplitude n_0 , the flattening radius R_{flat} , the power index of the density profile p , and the square of the modeled scatter in the density measurements ($\sigma_{n,P}^2$). (13) Logarithm of the evidence of the Plummer fit. (14-16) Standard deviation σ , amplitude a , and the square of the modeled scatter in the density measurements ($\sigma_{n,G1}^2$) for the single component Gaussian fit. (17) Logarithm of the evidence of the single-component Gaussian fit. We report the single-component Gaussian results here for completeness only, as it is a poor fit to the data particularly at large radial distances. A machine readable version of this table is available at <https://doi.org/10.7910/DVN/QKYR3G>.

^a At small radial distances, Musca is largely unresolved in the [Leike et al. \(2020\)](#) map, and at large radial distances, its structure is consistent with being prior-dominated, so we urge caution when interpreting the results.

* Clouds below the horizontal line – Orion A, Orion B, and λ Orionis – should be treated with caution, as they lie at the very edge of the [Leike et al. \(2020\)](#) 3D dust grid and are subjected to additional biases. Part of Orion A, toward the Orion Nebula Cluster, is also devoid of dust in the [Leike et al. \(2020\)](#) 3D dust map despite being highly extinguished. See §5 for full details.

Perseus



Chamaeleon

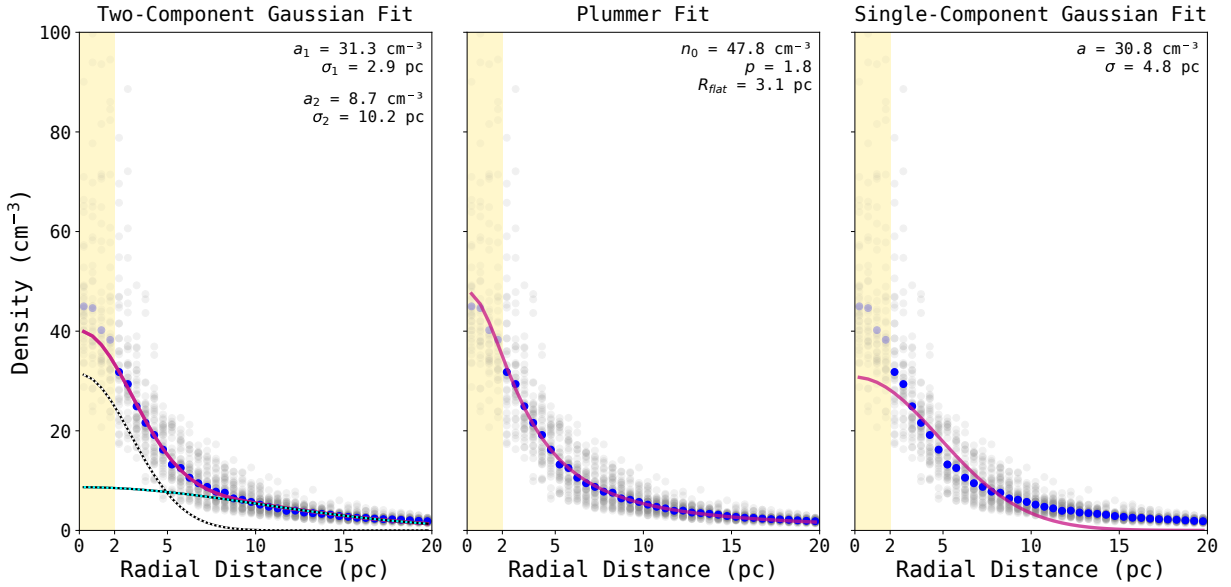


Figure 3. Radial volume density profile for the Perseus Molecular Cloud (top) and the Chamaeleon Molecular Cloud (bottom). Because the [Leike et al. \(2020\)](#) 3D dust map is more reliable at scales > 2 pc and is not capable of probing the highest gas densities, we exclude the inner 2 pc (coincident with the yellow bar) from the fit. In each panel the gray dots indicate the profiles for individual slices along the spine, while the blue dots indicate the median of all slices. We fit three functions to the averaged radial volume density profile, whose fits are shown in solid red: a two-component Gaussian function (left), a Plummer function (middle), and a single-component Gaussian function (right). In the left panel, we additionally overlay the decomposition of the two Gaussians via the dashed white and cyan lines, corresponding to the “inner” (black-white dotted) and “outer” (black-cyan dotted) components. Identical plots for the rest of the sample are available in the Appendix.

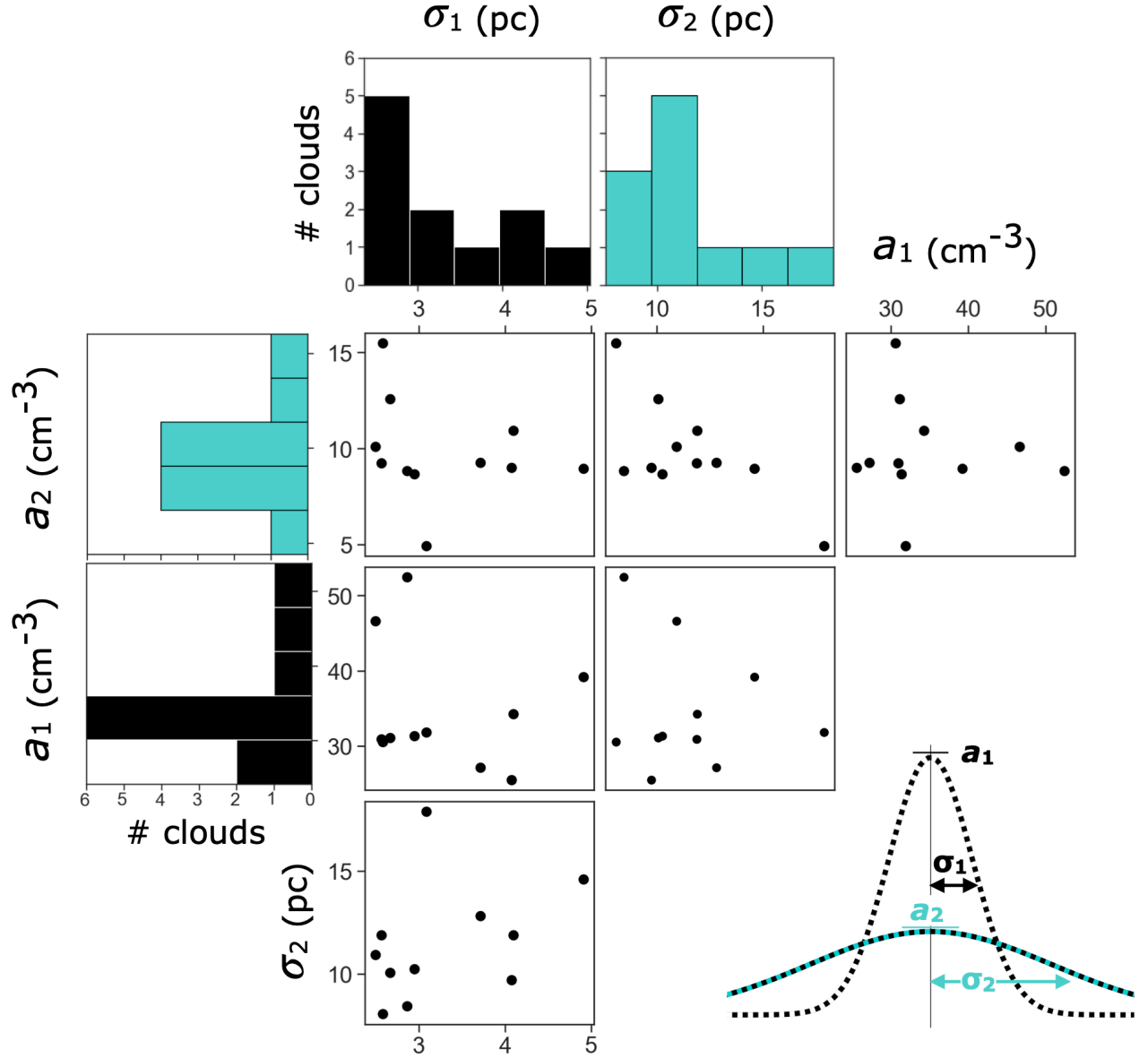


Figure 4. Summary of the radial volume density profile fitting results for the two-component Gaussian function, including the standard deviation σ_1 of the inner Gaussian, the standard deviation σ_2 of the outer Gaussian, the amplitude of the inner Gaussian a_1 , and the amplitude of the outer Gaussian a_2 . Each point represents a single local cloud in the sample.

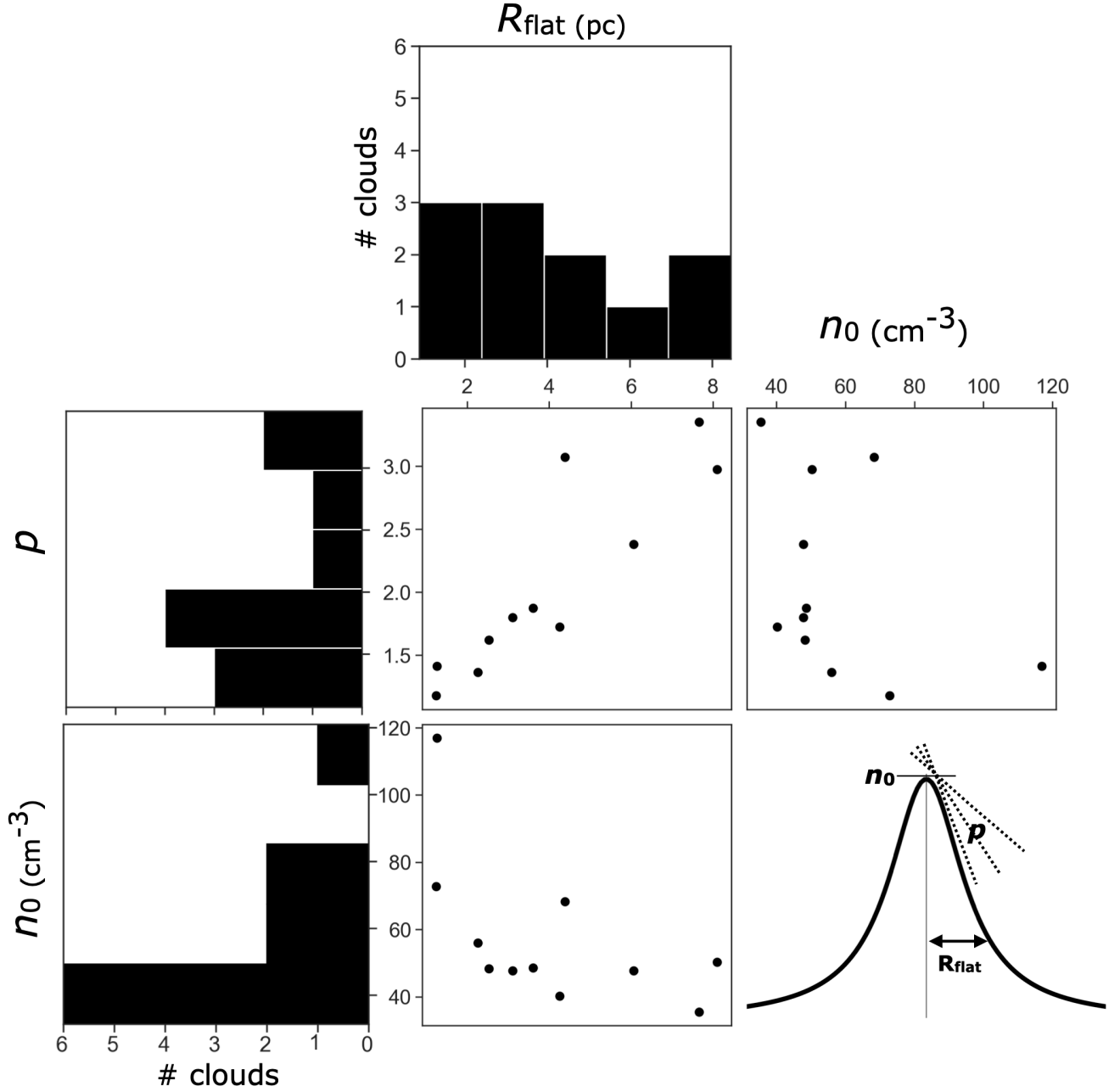


Figure 5. Summary of the radial volume density profile fitting results for the Plummer function, including the distribution of the flattening radius R_{flat} , the peak density n_0 , and the index of the density profile p . Each point represents a single local cloud in the sample. We observe a strong degeneracy in the Plummer modeling, particularly between the R_{flat} and p parameters.

4.2. Width Results

In Table 2, we summarize the results of our radial volume density fitting procedure. A machine readable version of Table 2 is available at the Harvard Dataverse (<https://doi.org/10.7910/DVN/QKYR3G>). For each cloud and fit (two-component Gaussian, Plummer, single-component Gaussian) we list the average and 1σ uncertainty on each parameter. In each case, we obtain a set of samples derived from the **dynesty** nested sampling procedure. The average value reported is the median (50th percentile) of the samples. The upper and lower bounds are the difference between the 50th and 84th percentiles of the samples, and the 16th and 50th percentiles of the samples, respectively. Cornerplots showing the marginalized posterior distributions for each cloud and type of fit are available online at the Harvard Dataverse (<https://doi.org/10.7910/DVN/YVQC7X>). The radial volume density profiles for two clouds — Perseus and Chamaeleon — are shown in Figure 3, and similar figures are available for the rest of the clouds in the Appendix. The data behind these figures, including both the median and full ensemble of radial profiles computed for each cloud, are available at the Harvard Dataverse (see <https://doi.org/10.7910/DVN/JBRWHB>).

We summarize the width results in Figure 4 and Figure 5. We exclude the single-component Gaussian from the summary due to its poor Bayes Factor relative to the two-component Gaussian and Plummer profiles (as justified in §4.2.1). Figure 4 shows a cornerplot of the best-fit results for the two-component Gaussian model parameters, while Figure 5 shows a cornerplot of the best-fit results for the Plummer model parameters. We find that for our two-component Gaussian results, inner widths σ_1 span 2.5 to 4.9 pc, with an average of ≈ 3.0 pc. The outer widths span 8 and 18 pc, with an average of ≈ 11 pc. We find a relatively tight spread in the ratio of the widths of the outer to inner envelopes ($\frac{\sigma_2}{\sigma_1}$), with an average value of 3.4 and a scatter of only 0.9. The amplitude a_1 of the inner Gaussian spans $n = 25 - 53 \text{ cm}^{-3}$, about three times as large as the amplitude a_2 of the outer Gaussian, which spans $n = 5$ to 15 cm^{-3} . The widths of our Plummer fits R_{flat} span 1.2 - 8.1 pc with a typical value of $R_{\text{flat}} = 3.6$ pc. The power-law indices p of the Plummer fit range from 1.2 and 3.4, with a median value of 1.8. The peak density parameter n_0 ranges from $35 - 117 \text{ cm}^{-3}$, with a median of 49 cm^{-3} . When the inner 2 pc of the profile is excluded, the Plummer fits often have a higher value of n_0 than measured, suggesting, as we will argue in §6, that much of the densest structure in the 3D dust map is unresolved.

4.2.1. Model Comparison

In addition to the best-fit parameters, we evaluate the performance of the models in light of the data. From Bayes' Theorem the posterior probability of a model \mathcal{M} given the data \mathcal{D} is proportional to:

$$p(\mathcal{M}|\mathcal{D}) \propto p(\mathcal{D}|\mathcal{M})p(\mathcal{M}) \quad (5)$$

where $p(\mathcal{D}|\mathcal{M})$ is the likelihood of the data given the model and $p(\mathcal{M})$ is the prior probability of the model. To directly compare two models, \mathcal{M}_1 versus \mathcal{M}_2 , we are interested in the ratio of their posterior probabilities (or posterior odds), given as:

$$\frac{p(\mathcal{M}_1|\mathcal{D})}{p(\mathcal{M}_2|\mathcal{D})} = B_{12} \frac{p(\mathcal{M}_1)}{p(\mathcal{M}_2)} \quad (6)$$

with the Bayes Factor, B_{12} , equal to the ratio of the marginal likelihood (also known as the evidence \mathcal{Z}) of the two models:

$$B_{12} = \frac{p(\mathcal{D}|\mathcal{M}_1)}{p(\mathcal{D}|\mathcal{M}_2)} = \frac{\mathcal{Z}_1}{\mathcal{Z}_2} \quad (7)$$

Assuming equal prior odds ($\frac{p(\mathcal{M}_1)}{p(\mathcal{M}_2)} = 1$), the posterior odds is simply the Bayes Factor. The logarithm of the evidence $\ln(\mathcal{Z})$ is conveniently returned for each model fit by the nested sampling package **dynesty** and is summarized in Table 2. The logarithm of the Bayes Factor is then given as:

$$\ln(B_{12}) = \ln(\mathcal{Z}_1) - \ln(\mathcal{Z}_2) \quad (8)$$

Computing $\ln(B_{12})$ for the two-component Gaussian and Plummer Models, respectively, with regards to the single-component Gaussian model, we find that the two-component Gaussian has on average $\ln(B_{12}) = 44$ over the single-component Gaussian, whereas the Plummer model has on average $\ln(B_{12}) = 39$ over the single-component Gaussian. Based on the empirical “Jeffrey’s” scale for evaluating the relative strength of two models (Jeffreys 1939), $\ln(B_{12}) > 5$

represents decisive evidence in favor of a given model. Because the Bayes Factor has a built in penalty for model complexity, the decisive evidence in favor of the two-component Gaussian and Plummer models is not due to the increased parameterization of the fit. Based on these Bayes Factor calculation, we can conclude that the single-component Gaussian fit is heavily disfavored with respect to both the two-component and Plummer fits. When comparing $\ln(\mathcal{B}_{12})$ for the two-component Gaussian and Plummer models, we find that the Plummer is decisively favored for two clouds, while the two-component Gaussian is decisively favored for four clouds, with the remaining clouds only having moderate evidence in favor of either model. Ruling out the single-component Gaussian model, we will discuss the theoretical implications of both the two-component Gaussian and Plummer profiles in §6.

4.3. Potential Additional Sources of Fitting Uncertainty

While the formal uncertainties on all parameters are reported in Table 2, there are potential additional systematic effects, which we discuss here.

4.3.1. Degeneracy of the Plummer Profile

While the Bayes Factor indicates that the Plummer function is sometimes preferred over the two-component Gaussian function, there are clear caveats to using a Plummer fit that should not go unsaid. In particular, it is well-known — both from observations and simulations — that two parameters in the Plummer function — p and R_{flat} are *highly* degenerate. We see this trend clearly in Figure 5, where p and R_{flat} are strongly correlated. In particular, as R_{flat} increases so does the value of p . This covariance has also been shown in synthetic filaments on much smaller scales (lengths \approx a few parsecs, widths \approx a few tenths of a parsec) in AREPO simulations from Smith et al. (2014), where the Plummer function was fit to the radial *column* density distribution. We likewise see this in observations of the radial column density distributions of large-scale filaments (lengths \approx tens of parsecs, widths \approx 1 pc) (Zucker et al. 2018a), where p and R_{flat} show strong correlation. Accordingly, we urge caution when interpreting the Plummer profiles, as discussed in §6.2.

4.3.2. Intra-Cut Variation in the Radial Profiles

In producing the averaged radial profile for fitting, we are not explicitly taking into account the variation in the radial profiles along the spine of each cloud. To summarize the variation, we have chosen to model the variable σ_n^2 , which represents the scatter in the density profile values, capturing how much variation in the density we observe in a radial distance bin across all cuts. In general, for our better fitting models (Plummer and two-component Gaussian), we find that our fits prefer a small value for σ_n^2 , equivalent to a few particles per cubic centimeter in density n . This trend is also evident in Figures 1 and 2. We do see a large scatter from cut to cut at small radial distances ($r < 2$ pc), but these distances are excluded from the fit. For the remainder of the profile the scatter is significantly reduced, and is likely driving the low inferred value for σ_n^2 . From this, we conclude that while inter-cut variation in the radial volume density profile may have some modest effect on our inferred value for the inner width σ_1 of the two-component Gaussian, it likely has less effect on the outerwidth σ_2 of the two-component Gaussian or the R_{flat} of our Plummer fits.

4.3.3. Bias in Derived Widths as a Function of Cloud Distance

In order to confirm that we are probing intrinsic variation in the cloud widths, rather than the resolution of the underlying 3D dust map, it is necessary to verify that our derived cloud widths are *not* dependent on the distance of the cloud. If this dependence exists, we expect clouds at larger distances to have larger widths, due to degradation in the quality of *Gaia* parallax measurements underpinning the Leike et al. (2020) 3D dust map at larger distances. To examine this potential correlation, we plot all width parameters in Table 2 as a function of cloud distance, which we show in Appendix B and Figure B1. We find no correlation between cloud distance and cloud width for any width parameter, suggesting that our properties are being driven by the intrinsic widths of clouds, rather than by distance biases.

4.3.4. Including the Inner 2 pc of the Radial Profiles When Fitting

In §4, we report results where radial distances between 0 and 2 pc (closest to the spine) are excluded from the radial profiles, due to combination of the 3D dust map’s 1 pc voxel width and the caveat from Leike et al. (2020) that scales less than 2 pc are unreliable. To ensure that our choice to exclude the inner 2 pc does not significantly affect our

results, we refit the radial profiles using all radial distances between 0 and 20 pc, and those results are reported in Appendix D. Overall, we find that including the inner 2 pc has a modest effect on our results, changing the widths on average by $\lesssim 20\%$ across all models. However, the quality of the fit degrades, validating our choice to remove the inner 2 pc of each radial profile in our main analysis.

4.3.5. *Uncertainties in the Underlying 3D Dust Distribution*

All results reported in this section are derived from the mean 3D dust distribution reported in Leike et al. (2020). However, Leike et al. (2020) also report twelve different realizations of their dust distribution, which are used to derive the mean map. Since the different realizations reflect the underlying uncertainty in the 3D dust reconstruction, it is necessary to quantify the effect this uncertainty has on our results. Accordingly, in Appendix E, we implement a more sophisticated fitting procedure, which simultaneously takes into account all twelve realizations of the 3D dust map when computing the model parameters. We find that overall, the uncertainty in the 3D dust map does not dominate our results, particularly for the two-component Gaussian fit, with best-fit parameters again typically changing $\lesssim 20\%$ across all clouds and all model fits. See Appendix E for full details.

4.3.6. *Relationship Between 3D Dust Correlation Kernel and Profile Shapes*

Finally, to construct their 3D dust map, Leike et al. (2020) model the dust as a log-normal Gaussian process, while simultaneously inferring the correlation kernel of the process, corresponding to the physical spatial correlation power spectrum of the dust. This correlation kernel acts as a prior on the dust extinction density¹⁰. The adoption of a log-normal Gaussian process prior was primarily chosen for statistical reasons, to ensure that the dust density is always positive, and to allow the dust density to vary by orders of magnitude. While this kernel is inferred from the data, it is necessary to quantify the similarity between the shapes of the radial profiles and the shape of the inferred kernel. If the shapes of the kernel and the profiles differ, it is likely that the data in the vicinity of the cloud directly determines the profile shapes. However, if the shapes of the kernel and profiles look similar, it is possible that the kernel is being imprinted on the clouds' structure.

In Appendix C and Figure C1 therein we compare the structure of our radial profiles to the structure of the Leike et al. (2020) kernel inferred in the 3D dust map's reconstruction. We find that at radial distances between 0 and 10 pc, the cloud profiles deviate significantly from the kernel, indicating that their shapes are being driven by data local to the cloud. This deviation provides evidence that we are probing the *intrinsic* structure of the cloud at smaller radial distances. However, at large radii ($r > 10$ pc), the shapes of the kernel and the cloud profiles become increasingly similar, particularly for the Musca cloud. This similarity indicates that the cloud structure at lower densities may be driven by the prior on the dust extinction density. However, since the kernel is inferred using data inclusive of the cloud's structure (in addition to structure beyond each cloud of interest) the outer envelopes may still be physically meaningful. Accordingly, while we will discuss the physical significance of the profiles at lower densities in §6, we caution against overinterpretation of the tails of the radial volume density until the lower density outer envelopes can be better validated in future work.

4.4. *2D Extinction Maps and Masses*

In this section, we compare the cloud masses derived from 3D dust to those from traditional 2D dust approaches, with the goal of quantifying any discrepancies. In Figure 6, for the Perseus and Chamaeleon molecular clouds, we show a comparison between traditional 2D extinction maps (from the NICEST algorithm; Lombardi 2009, see §2.2) and 2D extinction maps derived by projecting 3D dust data (from Leike et al. 2020, see §3.3) on the plane of the sky. Both maps have been convolved to the same (lower) angular resolution of the projected 3D dust maps, given the average distance to the cloud shown in Table 1. In the same figures, we overlay for both NICEST (red) and 3D dust (blue) the $A_K = 0.1$ mag contours used to derive cloud masses in Table 3. As will become more clear in Figure 7, despite being morphologically very similar at the $A_K = 0.1$ mag level, the NICEST maps are able to probe a much larger dynamic range of extinction in comparison to the Leike et al. (2020) derived results. In particular, the NICEST maps show much more structure at the highest extinction levels, revealing clumps, cores, and filaments that are invisible in the Leike et al. (2020) projected version.

This lack of structure at high extinction is not surprising, given how the Leike et al. (2020) 3D dust map is produced. In order to probe highly extinguished regions (see Figure 6), any extinction-based dust mapping method must be able

¹⁰ The dust extinction density in the context of the Leike et al. (2020) is the optical depth in the Gaia G band per one parsec.

Table 3. Mass and Extinction Results

Cloud	Mass _{NICEST}	Mass _{Leike}	$\frac{\text{Mass}_{\text{NICEST}}}{\text{Mass}_{\text{Leike}}}$	Maximum $A_{K,\text{NICEST}}$	Maximum $A_{K,\text{Leike}}$
	M_{\odot}	M_{\odot}		mag	mag
(1)	(2)	(3)	(4)	(5)	(6)
Chamaeleon	4.9e+03	4.4e+03	1.1	1.19	0.29
Ophiuchus	9.4e+03	7.9e+03	1.2	1.99	0.31
Lupus	1.0e+04	8.9e+03	1.2	1.55	0.28
Taurus	1.6e+04	1.5e+04	1.0	0.90	0.38
Perseus	1.6e+04	1.3e+04	1.2	1.40	0.28
Musca	5.9e+02	4.9e+02	1.2	0.47	0.19
Pipe	8.5e+02	5.2e+02	1.6	1.29	0.23
Cepheus	1.2e+04	1.0e+04	1.2	1.15	0.33
Orion A*	3.2e+04	9.4e+03	3.4	1.48	0.34
Orion B*	2.9e+04	1.7e+04	1.7	1.34	0.33
λ Orionis*	1.2e+04	8.6e+02	13.7	1.36	0.22

NOTE—Summary of mass and extinction results for local molecular clouds. (1) Cloud Name (2) Mass derived from a traditional 2D extinction map computed using the NICEST algorithm from Lombardi (2009). (3) Mass derived for the cloud from the Leike et al. (2020) 3D dust map, which has been projected back on the plane of the sky. In both cases, the mass is computed above an $A_K = 0.1$ mag cloud boundary. (4) Ratio of the mass from columns (2) and (3). In (5) Maximum A_K inside the cloud boundary based on the NICEST algorithm. (6) Maximum A_K inside the cloud boundary for the 2D extinction map derived from the 3D dust data. We provide a machine readable version of this table at the [Harvard Dataverse](https://doi.org/10.7910/DVN/EIPHPR) (<https://doi.org/10.7910/DVN/EIPHPR>).

*Clouds below the horizontal line – Orion A, Orion B, and λ Orionis – should be treated with caution, as they lie at the very edge of the Leike et al. (2020) 3D dust grid and are subjected to additional biases. Part of Orion A, toward the Orion Nebula Cluster, is also devoid of dust in the Leike et al. (2020) 3D dust map despite being highly extinguished. See §5 for full details.

to see stars *through* dust. In contrast to NICEST, which relies only on near-infrared photometry, the Leike et al. (2020) analysis require *Gaia* optical photometry with relatively high signal-to-noise, which precludes stars behind dense regions from being included in the analysis. Another possible source of discrepancy between the Leike et al. (2020) projected 3D dust and traditional 2D dust maps might stem from the calibration of the likelihood function used to construct the Leike et al. (2020) 3D dust map. Specifically, the likelihood used in the construction of the Leike et al. (2020) 3D dust map is calibrated using stars in lines of sight with approximately zero extinction, which could introduce biases in regions of higher extinction.

This missing high extinction information in the Leike et al. (2020) 3D dust map is more apparent in Figure 7, which compares A_K PDFs for the inherently 2D NICEST technique (Lombardi 2009) and the 2D projection of the 3D maps (Leike et al. 2020), across the full cloud sample. The histograms are computed by stacking every pixel above an $A_K = 0.1$ mag for every cloud. The A_K PDF for the Leike et al. (2020) method shows more extinction than NICEST at low values ($A_K \approx 0.1$ mag), and much less (essentially no) extinction above an $A_K \approx 0.3$ mag. While the shapes of the two PDFs are \approx similar at the low extinction end ($A_K < 0.15$ mag), only the NICEST PDF shows a tail extending to high extinction ($A_K \approx 1.0$ mag). This high extinction tail manifesting in the NICEST maps is consistent with the maximum A_K we report on a cloud-by-cloud basis in Table 3. For the NICEST maps, the maximum A_K toward each cloud is $\approx 0.2 - 0.3$ mag, while for NICEST it is a factor of a few higher, with peak $A_K = 0.9 - 1.5$ mag inside each cloud boundary. So, these comparisons suggest that the Leike et al. (2020) map is a faithful representation of projected dust column density up to $A_K = 0.2 - 0.3$ mag, equivalent to $A_V = 2 - 3$ mag.

How does reduced sensitivity at high extinction affect masses derived from the Leike et al. (2020) map? Table 3 lists masses for clouds (above their $A_K = 0.1$ mag boundaries; see §3.4) computed using both methods and the *ratio* of

those masses. In general, the ratio is near unity because mass at high extinction makes up a small fraction of clouds’ total mass (see also e.g. [Lada et al. 2010](#)). In all cases, NICEST masses are larger, but not by a significant amount: the ratio of the NICEST mass to the 3D dust mass ranges from 1.0 to 1.6, with an average of 1.2, for the “complete clouds,” listed above the line in Table 3. Discrepancies are, as should be expected, significant for the “incomplete” clouds (below the line, Orion A, Orion B, and λ Orionis) which lie at the edge of the [Leike et al. \(2020\)](#) 3D dust map. While the mass ratio for Orion B is only modestly higher than the rest of the sample ($\frac{\text{Mass}_{\text{NICEST}}}{\text{Mass}_{\text{Leike}}} = 1.7$), the NICEST mass for Orion A is $3.4\times$ larger than its 3D dust derived mass, and for λ Orionis it is $13.7\times$ as large. This high ratio

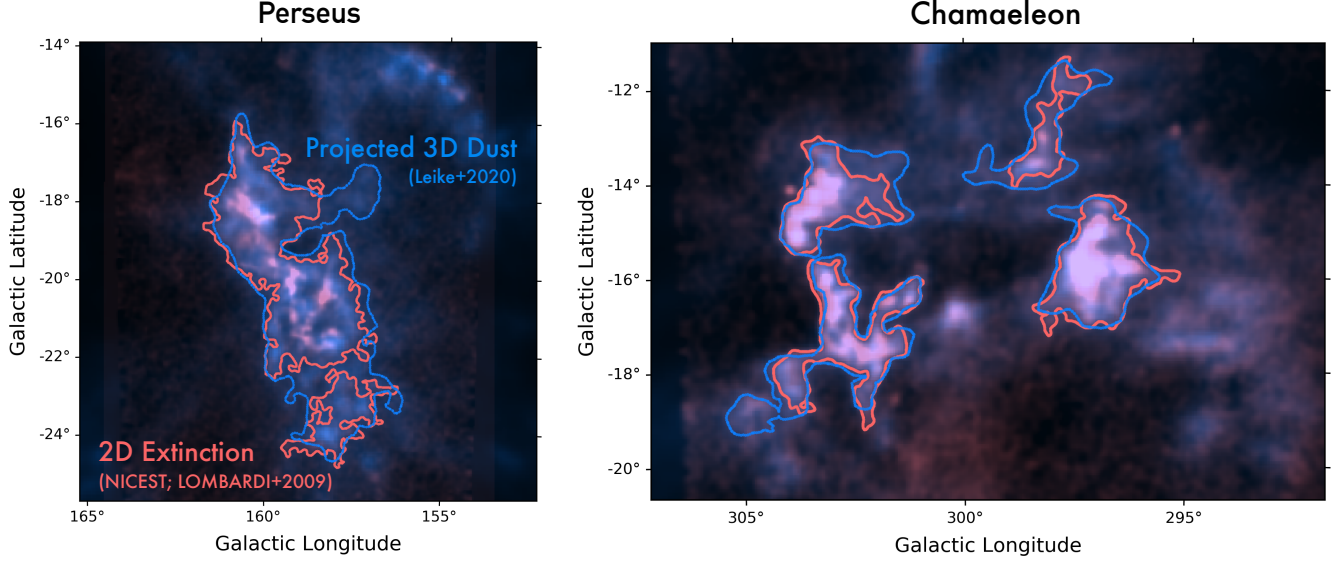


Figure 6. A comparison of the K band extinction (A_K) maps derived from the NICEST algorithm ([Lombardi 2009](#)) (red) and from the [Leike et al. \(2020\)](#) 3D dust map projected back on the plane of the sky (blue) for the Perseus Molecular Cloud (left) and Chamaeleon Molecular Cloud (right). The contours indicate the $A_K = 0.1$ mag cloud boundaries which are used to derive the clouds masses listed in Table 3.

5. CLOUD-BY-CLOUD EXPOSITION

In this section, we summarize the skeletonization and radial profile fitting results of §4 on a cloud-by-cloud basis, and in light of complementary results for each cloud from the literature. A gallery of 3D interactive figures for the full sample is available [here](#).

5.1. Chamaeleon

As shown in Figure 2 (interactive), we find that the skeleton of the Chamaeleon Molecular Cloud is located at distances between 173 and 190 pc, with a median distance of 183 pc. Curiously, and as apparent in Figure 2, we find that all the Chamaeleon clouds – Chamaeleon I, II, and III – are connected via a hub-like structure, with a void in the center. The Chamaeleon complex is also physically connected to the Musca dark cloud at a distance of 172 pc. Musca is also shown in the 3D dust map in Figure 2 but skeletonized separately in this work.

Based on two-component Gaussian fitting results, Chamaeleon has an inner envelope full-width half max (FWHM= 2.35σ) of 6.8 pc, and an outer envelope FWHM of 24 pc, with a ratio of the outer to inner width equal to 3.5.

5.2. Ophiuchus

As shown [online](#) (interactive), we find that the skeleton of Ophiuchus is located at distances between 115 and 150 pc. The median distance is 136 pc, which is also the distance of L1688, consistent with previous distance estimates

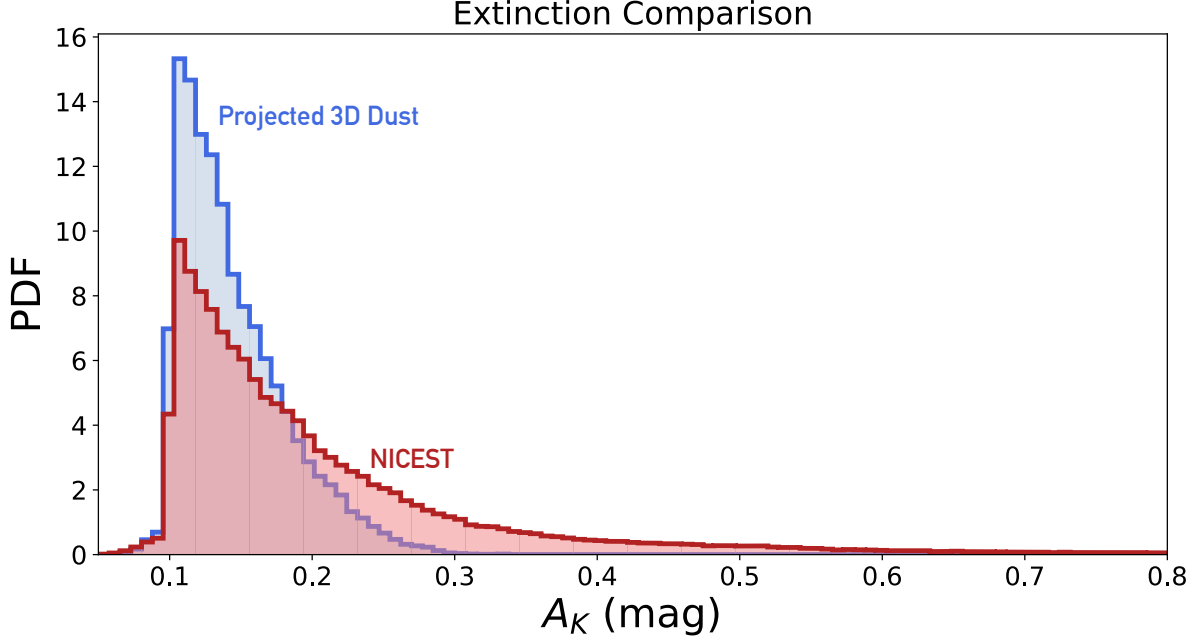


Figure 7. A comparison of the PDFs between the K band extinction (A_K) derived from the 2D NICEST algorithm (Lombardi 2009) (red) and from the Leike et al. (2020) 3D dust map projected back on the plane of the sky (blue). We only consider structure above the $A_K = 0.1$ mag threshold used to derive the cloud masses in Table 3. We extract the extinction distribution above this $A_K = 0.1$ mag boundary for each cloud, and then stack the per-cloud results to obtain a representative histogram for each method. The histograms are normalized such that their total area is equal to one. While similar at the $A_K \approx 0.1$ mag level, traditional 2D dust extinction maps show a larger dynamic range, with increased sensitivity at higher extinction ($A_K \gtrsim 0.2 - 0.3$ mag).

based on 3D dust mapping (from Zucker et al. 2019, 2020) and from VLBI parallax measurements of YSOs (from Ortiz-León et al. 2017). There is a 10 pc distance gradient across the B44 streamer, which extends from ρ Ophiuchus out to a distance of $d \approx 145$ pc. The farthest component is the “arc” of Ophiuchus, lying at $d \approx 150$ pc, while the nearest component is the Ophiuchus north complex, lying between $d \approx 115 - 125$ pc. The effect of feedback from OB stars (e.g. σ Sco, δ Sco) on the 3D distribution of dust, in particular the formation of the elongated streamers B44 and B45, will be discussed in detail in Alves et al. (2021, in prep.). While B44 appears as part of the main spine of Ophiuchus, B45 appears as a skeletal branch which is pruned prior to the width analysis. We find that the B45 streamer extends from B44, rather than from the core L1688 region. With a typical width of ≈ 1 pc we believe this is an artifact of B45 being only marginally resolved in the Leike et al. (2020) 3D dust, rather than a reflection of the true morphology of the B45 streamer.

Based on the two-component Gaussian fitting results, Ophiuchus has an inner envelope FWHM of 6.3 pc, and an outer envelope FWHM of 24 pc, with a ratio of the outer to inner width equal to 3.8.

5.3. *Lupus*

As shown online (interactive), the skeleton of the Lupus molecular cloud lies between 155 and 198 pc, with a median distance of 165 pc. On a region-by-region basis, we find Lupus 9 to be the farthest cloud in the complex, at a distance of ≈ 197 pc. Lupus 3-8 are all connected within the same complex in 3D space (at the level of our thresholding algorithm, $n = 35 \text{ cm}^{-3}$) at a distance of ≈ 163 pc. Lupus 1 lies the closest in distance, at ≈ 155 pc, though the Lupus 1 line of sight suffers from confusion. By confusion, we mean that there is evidence of multiple components along the line of sight, in that there is a component immediately to the south of Lupus 1 (appearing to connect to Lupus 1 on the plane of the sky) but which lies at a much farther distance of 190 pc. Our distances to Lupus 1, 3, 4, 5, and 6 are broadly consistent with those from Galli et al. (2020b), whose distances range from 150 – 160 pc based on *Gaia* DR2 astrometry towards young stars associated with the complex. Curiously, we find no prominent feature at higher gas

densities ($n > 35 \text{ cm}^{-3}$) associated with Lupus 2. However, [Galli et al. \(2020b\)](#) place Lupus 2 at a distance of 158 pc, suggesting it is indeed associated with the Lupus 1, 3, 4, 5, and 6 regions.

Based on the two-component Gaussian fitting results, Lupus has an inner envelope FWHM of 6.1 pc, and an outer envelope FWHM of 19 pc, with a ratio of the outer to inner width equal to 3.1.

5.4. *Taurus*

As shown [online](#) (interactive), the skeleton of the Taurus Molecular Cloud extends between 131 and 168 pc. When viewed top down, it is evident that Taurus is comprised of dust in two different layers, separated on average by about 10-15 pc. This layering is consistent with several previous studies, which find evidence of significant depth effects (see e.g. [Galli et al. 2018, 2019](#); [Zucker et al. 2019](#)) over this same distance range. The furthest component of Taurus, at a distance of 168 pc, is an elongated component of the cloud extending out from L1538 towards $(l, b) = (177.5^\circ, -8.5^\circ)$.

Based on the two-component Gaussian fitting results, Taurus has an inner envelope FWHM of 6.1 pc, and an outer envelope FWHM of 28 pc, with a ratio of the outer to inner width equal to 4.6.

5.5. *Perseus*

As shown in Figure 1 (interactive), the skeleton of the Perseus Molecular Cloud extends between 279 to 301 pc. It exhibits a prominent ≈ 20 pc distance gradient. This distance gradient is very similar to that found independently in [Zucker et al. \(2018b\)](#), which also used 3D dust mapping to obtain distances to star-forming regions across Perseus, finding them to be located between 279 and 302 pc. This gradient is also broadly consistent with the VLBI parallax results towards young stars in Perseus from [Ortiz-León et al. \(2018\)](#), though [Ortiz-León et al. \(2018\)](#) find IC348 to be at a distance of 320 pc, about 20 pc farther away than we find either in this work or in [Zucker et al. \(2018b\)](#). Upon further examination of the distribution of the 3D dust and young stars in this region, we find that neither the [Zucker et al. \(2018b\)](#) nor [Ortiz-León et al. \(2018\)](#) distance to IC348 is inaccurate. Rather, it appears that the IC348 stellar cluster has actually migrated beyond the distance of the dust cloud from which it formed, which results in the discrepancy between the dust- and star-based approaches. This migration is consistent with the estimated age of IC348 of $\approx 2 - 6$ Myr ([Muench et al. 2007](#)). No such discrepancy is found for the younger NGC1333 cluster. When considering solely the 3D dust distribution, neglecting information from YSOs, no component of Perseus lies beyond 300 pc.

Based on the two-component Gaussian fitting results, Perseus has an inner envelope FWHM of 9.6 pc and an outer envelope FWHM of 28 pc, with a ratio of the outer to inner width equal to 2.9.

5.6. *Musca*

As shown [online](#) (interactive), the Musca dark cloud is located between distance of 171 and 173 pc. We find no evidence that Musca is a sheet viewed edge-on, but rather is a true filament in 3D space (c.f. [Tritsis & Tassis 2018](#)). It is physically connected to the Chamaeleon Molecular Cloud complex at a level of $n = 35 \text{ cm}^{-3}$ but is skeletonized separately in this work to obtain an independent width.

Based on the two-component Gaussian fitting results, Musca has an inner envelope FWHM of 7.3 pc, and an outer envelope FWHM of 42 pc, with a ratio of the outer to inner width equal to 5.8. Musca is a clear outlier in the distribution of its outer Gaussian profile, which is significantly larger and more extended than the rest of the sample. At large radial distances, the shape of Musca's radial profile shows the highest correspondence to that of the underlying kernel inferred during the reconstruction of the [Leike et al. \(2020\)](#) 3D dust map (see §4.3.6 and Appendix C), indicating that this highly extended envelope is likely prior-dominated. In addition to the outer envelope being prior-dominated, we also believe that the inner envelope of Musca – manifesting as an infrared dark cloud – is unresolved in our map, as 2D dust results targeting the infrared dark component of the cloud find widths as small as a few tenths of a parsec ([Cox et al. 2016](#)). As a result, we urge extreme caution when interpreting these width results.

5.7. *Pipe*

As shown [online](#) (interactive), the Pipe dark cloud is located between a distance of 147 and 163 pc, with a 15 pc distance gradient. The stem of the Pipe nebula, near B59, is located at a distance of 150 pc, and the bowl, extending down to latitudes of $b = 2.4^\circ$, lies as far as 163 pc. About halfway down the stem, a thin tendril of gas connects the Pipe nebula with the Ophiuchus cloud complex, meeting an extension of Ophiuchus that reaches beyond the B44 streamer. However, the Pipe nebula is skeletonized separately from Ophiuchus in this work, in order to obtain an

independent width. The distance to B59 in the stem of the Pipe nebula is smaller than, but still consistent with, independent *Gaia* parallax measurements of YSOs in the complex (163 pc, from Dzib et al. 2018).

Based on the two-component Gaussian fitting results, the Pipe nebula has an inner envelope FWHM of 9.6 pc and an outer envelope FWHM of 23 pc, with a ratio of the outer to inner width equal to 2.4. This ratio of the outer to inner width is the smallest of all clouds in the sample.

5.8. *Cepheus*

As shown [online](#) (interactive), the skeleton of the Cepheus molecular cloud is located between distances of 337 and 370 pc, with a median distance of 345 pc. Our skeletonization only includes the northern section of Cepheus, as the southern section (closer to the Galactic plane) actually lies at distances > 900 pc (Grenier et al. 1989; Zucker et al. 2019). The median skeleton distance is in excellent agreement with the average Cepheus “near” distance of 352 pc, based on an independent 3D dust mapping pipeline from Zucker et al. (2019). Our Cepheus skeletonization includes four isolated density features at a level above our chosen threshold ($n = 35 \text{ cm}^{-3}$), the highest of any cloud in the sample. These features include the sub-regions L1148/L1552/L1155 ($d = 338$ pc), L1172 ($d = 340$ pc), L1228 ($d = 368$ pc), L1241 ($d = 349$ pc), and L1247/L1251 ($d = 340$ pc).

Based on the two-component Gaussian fitting results, Cepheus has an inner envelope FWHM of 5.9 pc, and an outer envelope FWHM of 26 pc, with a ratio of the outer to inner width equal to 4.4.

5.9. *Corona Australis*

As shown [online](#) (interactive), the skeleton of the Corona Australis cloud is located between distances of 136 and 179 pc, with a median distance of 161 pc. Corona Australis is one of the fluffiest local clouds in the Leike et al. (2020) map and has no significant extended features above a density threshold of $n = 35 \text{ cm}^{-3}$ so it is skeletonized at a much lower level ($n = 5 \text{ cm}^{-3}$) to provide distance information. We find that the Corona Australis cloud exhibits a prominent distance gradient, with the head of the cloud about 20-30 pc closer than the tail. The most extinguished part of Corona Australis, which manifests as a dark cloud at optical wavelengths, lies at a distance of $d = 144$ pc, which is in good agreement with the results of Galli et al. (2020a) (149 pc), and Zucker et al. (2019) (151 pc). The reason we determine a higher overall median spine distance is due to the existence of Corona Australis’ diffuse tail, which extends as far as 179 pc at a latitude of $b = -26^\circ$.

5.10. *Orion A*

As shown [online](#) (interactive), we determine that the skeleton of the Orion A cloud spans distances of 391 to 445 pc, with a median distance of 405 pc. The 3D dust distribution towards Orion A is peculiar, due to the fact that there is a large piece of the cloud missing towards the Orion Nebula Cluster — the densest part of the entire complex. This lack of dust is *not physical*, and represents the inability of the Leike et al. (2020) to fully probe high gas densities. As a result, the head (toward the Orion Nebula Cluster) and tail of Orion A (toward L1647) appear not to connect as they should in 3D space. Analysis of Orion’s YSO distribution (Großschedl et al. 2018) and other high resolution 3D dust maps of Orion A (Rezaei Kh. et al. 2020) clearly show that the head and tail *are* physically connected. The missing ONC region could explain in part the significant discrepancy between the cloud mass derived from 2D dust extinction versus from the projected 3D dust distribution (see §4.4).

In general, we find good agreement with previous studies towards regions probed by the dust map, as well as a similar *range* of distances. For example, Großschedl et al. (2018) find that the bulk of the Orion A cloud lies between distances of $d \approx 380 - 460$ pc, which is not inconsistent with our spread of 391 – 445 pc. However, there is no visible connection between the farthest point in Orion A (L1647-S at a distance of 445 pc) and the main Orion A cloud consisting of L1641, while this connection *does* appear in other approaches (Großschedl et al. 2018; Rezaei Kh. et al. 2020). This lack of connection at the tail could be physical, or it could be indicative of another missing mass situation, like toward the Orion Nebula Cluster. In addition to mass missing *within* the grid, it is also possible that there is mass missing *beyond* the grid, since Orion A lies at the boundary of the Leike et al. (2020) dust mass. Thus, our skeletonization and width analysis results for Orion A should be treated with more caution than for other “complete” clouds. The most likely effect of Orion A lying at the edge of the grid is that we will slightly underestimate the distance to the complex.

Based on the two-component Gaussian fitting results, we find that Orion A has an inner envelope FWHM of 6.8 pc and an outer envelope FWHM of 20 pc, with a ratio of the outer to inner width equal to 2.9.

5.11. *Orion B*

As shown [online](#) (interactive), we determine that the skeleton of the Orion B cloud spans distances of 397 to 406 pc, with a median distance of 404 pc. Our median distance is consistent with [Kounkel et al. \(2018\)](#), which leverages *Gaia* DR2 parallax measurements toward young stars in the complex to obtain a distance of 407 ± 4 pc. Unlike Orion A, we find no evidence of a strong distance gradient, and also find that Orion B consists of a single density feature with a length of 69 pc. However, since Orion B again lies at the very edge of the [Leike et al. \(2020\)](#) dust map, it is possible that parts of Orion B could still be missing, which would bias our distance estimates lower compared to a cloud that lies well within the map boundaries. Thus, like our skeletonization and width analysis results for Orion A, we caution that our results for Orion B should be treated with more caution than for other “complete” clouds.

Based on the two-component Gaussian fitting results, Orion B has an inner envelope FWHM equal of 11.4 pc and an outer envelope FWHM of 34 pc, with a ratio of the outer to inner width equal to 3.0.

5.12. λ Orionis

Finally, as shown [online](#) (interactive), we determine that the skeleton of the λ Orionis cloud spans distances of 375 to 397 pc, with a median distance of 386 pc. A clear ring-like morphology is observed in 2D dust extinction maps, which [Dolan & Mathieu \(2002\)](#) argue formed from ejected material driven by a supernovae blast at the center of the ring about 1 Myr ago.

We observe the same ring-like morphology in 3D. However, the skeletonization, and resulting widths, should be considered with extreme caution, as the skeleton lies only a few parsecs from the boundary of the [Leike et al. \(2020\)](#) 3D dust map, so the skeletonization is likely to underestimate the cloud’s distance. There is clearly mass missing in the λ Orionis region, given that the mass for the cloud based on 2D dust maps (from NICEST) is a factor of fourteen higher than what we calculate using just the 3D dust volume local to the cloud (see §4.4 and Table 3). Consistent with this missing mass scenario, average distances to the λ Orionis region tend to be higher in other studies (e.g. 402 pc from [Zucker et al. 2020](#)). The average distance to λ Orionis from [Zucker et al. \(2020\)](#) is also consistent with independent distances of young stars, for which [Kounkel et al. \(2018\)](#) obtain $d = 404$ pc.

Based on the two-component Gaussian fitting results, λ Orionis has an inner envelope FWHM of 8.7 pc and an outer envelope FWHM equal of 30 pc, with a ratio of the outer to inner width equal to 3.4. Despite only measuring the cloud width using voxels in front of λ Orionis (due to the [Leike et al. \(2020\)](#) grid ending directly beyond the spine), these results are consistent with results for the “complete” clouds.

6. DISCUSSION

In Section 4, we have shown that the radial volume density profiles measured in 3D for local molecular clouds are well-described by two functions: a two-component Gaussian function and a Plummer function. A single-component Gaussian is universally a poor fit to the data. We have also shown that the [Leike et al. \(2020\)](#) technique is capturing a majority of the cloud mass for all “complete” clouds in the sample, deviating from 2D integrated dust extinction measurements (from the NICEST methodology; [Lombardi 2009](#); [Lombardi et al. 2011](#)) only at higher extinction ($A_K \gtrsim 0.3$ mag). In this section, we discuss the potential implications of our results, and provide an initial comparison of the 2D and 3D shapes of the radial profiles for a subset of the sample, as a basis for future work.

6.1. Two-Component Gaussian — Probing a Phase Transition?

In terms of the two-component Gaussian model, one possible explanation for the shape of the radial density profiles is that we are probing gas in different phases, where the transition between the outer and inner Gaussian profiles represents a shift in temperature, density, and/or chemical composition of the gas. In the density range consistent with our radial profiles, possible transitions include a chemical transition between atomic and molecular hydrogen (the HI-to-H₂ transition), or a thermal transition between the unstable neutral medium (UNM) and cold neutral medium (CNM), driven by the temperature dependence of the atomic cooling curve. While the data are suggestive, we do not yet have enough detailed evidence to prove the link between the shape of the radial volume density profiles and a phase transition. Thus, in what follows, we only seek to present a plausibility argument.

6.1.1. Chemical Transition Between Atomic and Molecular Gas

The first explanation for the bimodality in the radial profiles is that the broader, lower amplitude “outer” Gaussian probes the shape of the atomic HI gas envelope, while the narrower higher amplitude “inner” Gaussian probes the molecular phase. If so, the noticeable break in volume density coincident with the start of the inner Gaussian would

represent a chemical transition of the gas, delineating the radial distance in 3D space at which point molecular hydrogen becomes self-shielded. Models suggest that the transition to self-shielding — at which point molecular hydrogen can persist — can be either sharp or gradual, depending on the strength of the UV radiation field relative to the gas density. However, once a critical column density of H_2 has been produced, the fraction of hydrogen in molecular form should rise rapidly (Bialy & Sternberg 2016; Sternberg et al. 2014; Krumholz et al. 2008). If this transition is occurring in local molecular clouds — as predicted by analytic theory — it might explain why we find the two-component Gaussian model to be so strongly favored over a single-component Gaussian model.

We have known for a few decades that HI envelopes around molecular clouds are common (see e.g. Moriarty-Schieven et al. 1997; Williams & Maddalena 1996; Williams et al. 1995). These HI envelopes are significantly extended with respect to the molecular gas and may be either the remnants of atomic clouds which condensed to form GMCs, or photodissociated gas on the outskirts of the molecular cloud. More likely, the atomic envelope arises from a combination of both phenomena. In addition to being observed in solar neighborhood clouds (e.g. in Perseus and Taurus; see Stanimirovic et al. 2014; Pascucci et al. 2015; Lee et al. 2015) and toward the inner galaxy (Beuther et al. 2020; Bialy et al. 2017), atomic envelopes have also been observed at much lower resolution in the nearby Large Magellanic Cloud (Fukui et al. 2009). Recent numerical simulations characterizing the properties of highly resolved synthetic molecular clouds (e.g. Duarte-Cabral & Dobbs 2016; Seifried et al. 2017) also note the presence of large extended HI envelopes.

We find that the typical amplitudes of the outer Gaussian profiles are consistent with the typical densities of the atomic envelopes seen in observations, mainly via HI emission on the plane of the sky. In this study, the peak densities of the outer envelopes — characterized by the amplitude parameter a_2 — span $n = 5 - 15 \text{ cm}^{-3}$, with an average amplitude of $n = 9 \text{ cm}^{-3}$, falling off to only a few particles per cubic centimeter at large radii. This range is consistent with HI densities inferred for atomic envelopes around molecular clouds in both observations and simulations. Looking at a sample of 123 HI envelopes in the Large Magellanic Cloud, Fukui et al. (2009) derive a typical envelope density of 10 cm^{-3} , calculated by dividing each cloud’s HI column density by its approximate size on the plane of the sky.¹¹ Using GALFA HI and IRAS data, Bialy et al. (2015) also calculate the atomic hydrogen volume density towards the Perseus molecular cloud, finding that the atomic densities vary between $n = 2 - 11 \text{ cm}^{-3}$. This range of densities is similar to the range of densities captured by the outer Gaussian in the radial volume density profile we measure for Perseus, spanning $n = 12 \text{ cm}^{-3}$ toward the spine, down to $n \approx 2 \text{ cm}^{-3}$ toward the outskirts of the cloud.

In terms of the inner Gaussian, we find typical peak densities — parameterized by a_1 — to lie between $n \approx 25 - 52 \text{ cm}^{-3}$. While the amplitude for the averaged profile is of this order, a significant fraction of cuts show peak densities with $n = 100 \text{ cm}^{-3}$, with some extending as high as $n = 200 \text{ cm}^{-3}$. While these average volume densities are not high enough to be observationally probed by CO-bright molecular gas manifesting at $n \gtrsim 200 \text{ cm}^{-3}$ (see e.g. Busch et al. 2019), they are consistent with densities of so-called “CO-dark” gas, a phase associated with warmer, more diffuse molecular hydrogen which is not detectable in CO or HI. While invisible in both CO and HI, γ ray observations — capable of tracing a cloud’s gas mass independent of its chemical state — show that diffuse molecular gas surrounds all nearby CO-detected molecular clouds targeted in this study. This CO-dark phase effectively acts as an observational bridge between clouds’ extended atomic envelopes and their embedded CO-bright cores (Grenier et al. 2005), and would mark the true chemical transition between atomic and molecular gas. Tang et al. (2016) use [CII] emission to trace CO-dark diffuse molecular gas in the Galactic plane, finding that this gas manifests at a range of densities (from $n \approx 60 - 1000 \text{ cm}^{-3}$), with an average density of $n \approx 200 \text{ cm}^{-3}$.¹² The average density from Tang et al. (2016) is a factor of a few larger than our average peak density a_1 , but the lower estimates from Tang et al. (2016) remain consistent with our results. Also consistent with these observations, analysis of the CO-dark diffuse molecular gas for synthetic clouds from the SILCC-Zoom project (Seifried et al. 2019) find number densities between $10 - 1000 \text{ cm}^{-3}$, with an average density of CO-dark gas on the order of 100 cm^{-3} — only a factor of two higher than what we estimate here for the inner Gaussian. Given that the volume densities derived from the 3D dust data — particularly for the inner Gaussian component — should be lower limits (see also §2.1.2), our results are generally in agreement with literature estimates for CO-dark molecular gas from both observations and simulations.

¹¹ We note, however, that the HI-to-H₂ transition strongly depends on the dust-to-gas ratio, and the Large Magellanic Cloud has lower metallicity than Milky Way (Van der Swaelmen et al. 2013), so any direct comparison between the two systems should be treated with caution.

¹² While [CII] emission is commonly used as a tracer of CO dark gas, we note that a recent study by Hall et al. (2020) towards the local Perseus Molecular Cloud concludes that a [CII] envelope can also arise from the CNM phase, without a need to invoke CO-dark molecular gas.

Finally, there is a straightforward test to disprove this HI-to-H₂ transition hypothesis, involving a comparison between the radial extent of CO emission projected on the plane of the sky and radial extent of the inner Gaussian component derived here. The detection of CO emission significantly beyond the boundaries of the inner Gaussian profile would be in direct contradiction to the proposed origin, since no molecular gas should lie beyond the inner Gaussian. To test this scenario, we build CO radial profiles for a subset of the clouds in the sample, as described in detailed in Appendix F. We find that the CO profiles shows widths equal to or marginally smaller than that of the inner Gaussian profiles, consistent with the scenario that the inner Gaussian profiles could be tracing CO dark gas.

6.1.2. Thermal Transition Between Unstable and Cold Neutral Medium

While a diffuse molecular gas component offers one explanation for the shape of the inner Gaussian profile, no H₂ component necessarily needs to be invoked to explain the clouds' density structure. It is well established that the atomic neutral medium consists of two thermally stable states at significantly different densities and temperatures — the warm neutral medium (WNM) at $n \approx 0.2 - 0.9 \text{ cm}^{-3}$ and the cold neutral medium (CNM) at $n \approx 7 - 70 \text{ cm}^{-3}$ (Field et al. 1969; Wolfire et al. 2003; Murray et al. 2018b). This two-phase structure is a natural consequence of the density and temperature dependence of the cooling curve at play in the diffuse interstellar medium. While the peak densities we find for the inner Gaussian ($a_1 = 25 - 52 \text{ cm}^{-3}$) are consistent with lower-density estimates of CO-dark diffuse molecular gas, they are also in strong agreement with the densities of the CNM. However, the peak densities of the outer envelopes are much larger than expected for the WNM. In traditional two-phase models, HI at intermediate temperatures should be expected to quickly evolve into one of the stable phases. However, ample evidence has recently suggested that a significant fraction of Galactic HI lies in the thermally unstable phase, driven by dynamical processes in the interstellar medium (e.g. turbulence; c.f. Heiles & Troland 2003; Roy et al. 2013; Murray et al. 2018b). Thus, if the inner envelope is probing the CNM, then the outer envelopes (with peak densities $a_2 = 5 - 15 \text{ cm}^{-3}$) may probe the thermally unstable HI lying at densities between the WNM and CNM with $n \approx 1 - 10 \text{ cm}^{-3}$. The transition observed in the two-component Gaussian profiles would then be driven not by a change in the chemical state of the gas, but by a change in the thermal phase of the atomic neutral medium.

Consistent with this scenario, Murray et al. (2018b) analyzed HI spectra toward 57 lines of sight taken from the 21-SPONGE survey to infer the fraction of HI mass in the thermally unstable regime, finding that 20% is in the UNM phase, as opposed to 28% in the CNM phase (with the remaining mass in the WNM phase). Murray et al. (2018b) further find no significant difference in the UNM fraction as a function of latitude, with both high ($|b| > 10^\circ$) and low latitude lines of sight showing similar mass distributions. Given its ubiquity, both from Murray et al. (2018a) and complementary studies (Roy et al. 2013; Heiles & Troland 2003), the UNM-to-CNM transition represents a viable alternative to the HI-to-H₂ transition for explaining the two-component Gaussian shape of the radial profiles. We note, however, that while the Murray et al. (2018b) lines of sight span a wide range in latitudes, none of them intersect the clouds targeted in this work.

Nevertheless, to broadly verify the consistency of our results with those of Murray et al. (2018b), we can compare for each cloud the relative amount of mass contained in the outer and inner envelope. If our results are consistent with Murray et al. (2018b), we would expect the ratio of the outer and inner envelope masses to be $\frac{M_2}{M_1} = \frac{M_{\text{UNM}}}{M_{\text{CNM}}} = \frac{20\%_{\text{UNM}}}{28\%_{\text{CNM}}} = 0.71$. We compute this ratio in two ways. First, we compute the mass of the inner envelope, M_1 , and outer envelope M_2 by taking the definite integral of the Gaussian density profiles (shown via the black-white dotted and cyan-black dotted curves in e.g. Figure 1) over the volume, assuming a cylindrical geometry:

$$M_1 = 2\pi l \mu m_p \int_{-\infty}^{+\infty} a_1 e^{\frac{-r^2}{2\sigma_1^2}} r dr$$

$$M_2 = 2\pi l \mu m_p \int_{-\infty}^{+\infty} a_2 e^{\frac{-r^2}{2\sigma_2^2}} r dr$$

where the parameters a_1 , σ_1 , a_2 , σ_2 are the same as those reported in Table 2, $\mu = 1.37$ is the mean molecular weight, corrected for the helium abundance, m_p is the mass of a proton, and l is the length of the cloud reported in Table 1. Computing M_1 and M_2 numerically and taking the ratio across the sample we obtain a median ratio for $\frac{M_2}{M_1} = 2.9$, with a spread of 1.3, which is higher than the predicted Murray et al. (2018b) results of 0.72. Given that we are likely underestimating the densities in potentially CNM-associated regions, one possible explanation is that while the typical extents of the inner and outer components could be correct, their amplitudes, particularly for the

inner Gaussian, may not be. Thus, a second, more extreme way to test this is to assume that the inner envelope is entirely composed of CNM, and UNM only exists beyond the edge of the inner envelope. To compute this, we create cylindrical representations of the inner and outer envelopes, where the width of each 3D cylinder is equivalent to the FWHM derived from the σ_1 and σ_2 values reported in Table 2 (FWHM = $2.355 \times \sigma$). These cylinders are toggle-able on and off in the [gallery of interactive cloud figures](#). The cylinders define a mask in 3D volume density space over which the masses are computed:

$$M_{\text{cylinder}_{\text{inner}}} = \sum_i \mu m_p \times n_{i,\text{inner}} dV$$

$$M_{\text{cylinder}_{\text{outer}}} = \sum_i \mu m_p \times n_{i,\text{outer}} dV$$

Here, dV is the volume element of an individual voxel i in the 3D volume density map, equal to 1 pc^3 . The $\sum_i n_{i,\text{inner}}$ and $\sum_i n_{i,\text{outer}}$ terms represent the sum over the set of voxels (in gas density space n) which lie within the 3D inner and outer cylindrical regions, respectively. *Under the assumption that no UNM lies within the bounds of the inner envelope*, the resulting mass ratio would be:

$$\frac{M_2}{M_1} = \frac{M_{\text{cylinder}_{\text{outer}}} - M_{\text{cylinder}_{\text{inner}}}}{M_{\text{cylinder}_{\text{inner}}}}$$

As expected, we calculate a lower value of $\frac{M_2}{M_1}$, with a median of 2.1 and a spread of 1.0. In reality the true mass ratio is likely somewhere between the two examples given here, and additional follow-up work will be needed to rule out the possibility of a UNM-to-CNM transition.

6.1.3. Constant Ratio Between Outer and Inner Cloud Envelopes

Regardless of whether the transition between the outer and inner envelopes is due to a a) chemical transition between HI and H₂ gas b) a thermal transition between the UNM and the CNM; or neither, we find that the **ratio between the widths of the outer and inner envelopes across the sample is roughly 3.4**, with a relatively small scatter of ≈ 1 . This ratio could be physically significant, with the potential to constrain the formation timescale of H₂, or the rate at which gas flows between different thermal phases of the diffuse interstellar medium (e.g. between the UNM and CNM). More targeted analytic modeling (e.g. in the style of [Sternberg et al. 2014](#); [Bialy & Sternberg 2016](#); [Krumholz et al. 2009](#)), further contextualization with CO and HI spectral-line maps, and comparisons to simulations that track HI, H₂ and CO formation and destruction in a time-dependent chemical network (e.g. the Cloud Factory Simulations; [Smith et al. 2020](#)) should shed more light on this behavior.

6.2. An Isothermal Self-Gravitating Cylinder?

For the past ten years, Plummer models (originally describing the stellar surface density of globular clusters; [Plummer 1911](#)) have often been used to characterize the radial profiles of filaments extracted from H₂ column density maps as part of the Herschel Gould Belt Survey ([André et al. 2010](#)). These studies ([Arzoumanian et al. 2011, 2019](#); [Palmeirim et al. 2013](#); [Cox et al. 2016](#)) adopt an idealized Plummer-like analytic model for the (column) density profile of a cylindrical filament, featuring a denser, flat inner portion and an outer portion that falls off like a power-law at larger radii:

$$n(r) = \frac{n_0}{\left[1 + (r/R_{\text{flat}})^2\right]^{p/2}} \longrightarrow \Sigma(r) = A_p \frac{N_0}{\left[1 + (r/R_{\text{flat}})^2\right]^{\frac{p-1}{2}}}, \quad (9)$$

where $n(r)$ describes the volume density profile adopted throughout this work, and $\Sigma(r)$ is the corresponding column density profile employed in the literature, with N_0 the peak column density, R_{flat} the flattening radius, p the index of the density profile, and A_p is a constant factor that accounts for the filament's inclination angle to the plane of the sky. In column density studies, the inclination of the filament to the plane of the sky is assumed to be zero, which is not the case in our volume density analysis. Following the formalism outlined in [Ostriker \(1964\)](#) and Equation 9, the density structure of an isothermal, self-gravitating gaseous cylinder in hydrostatic equilibrium corresponds to a special case with a power-law index $p = 4$ or $n \propto r^{-4}$ at large radii ($r \gg R_{\text{flat}}$). Analyzing the *Herschel* column density distribution of filaments, various works ([Arzoumanian et al. 2011, 2019](#); [Palmeirim et al. 2013](#); [Cox et al. 2016](#)) have found that these filaments are inconsistent with the $p = 4$ scenario, instead preferring much shallower power-law indices ($p = 1.5 - 2.5$).

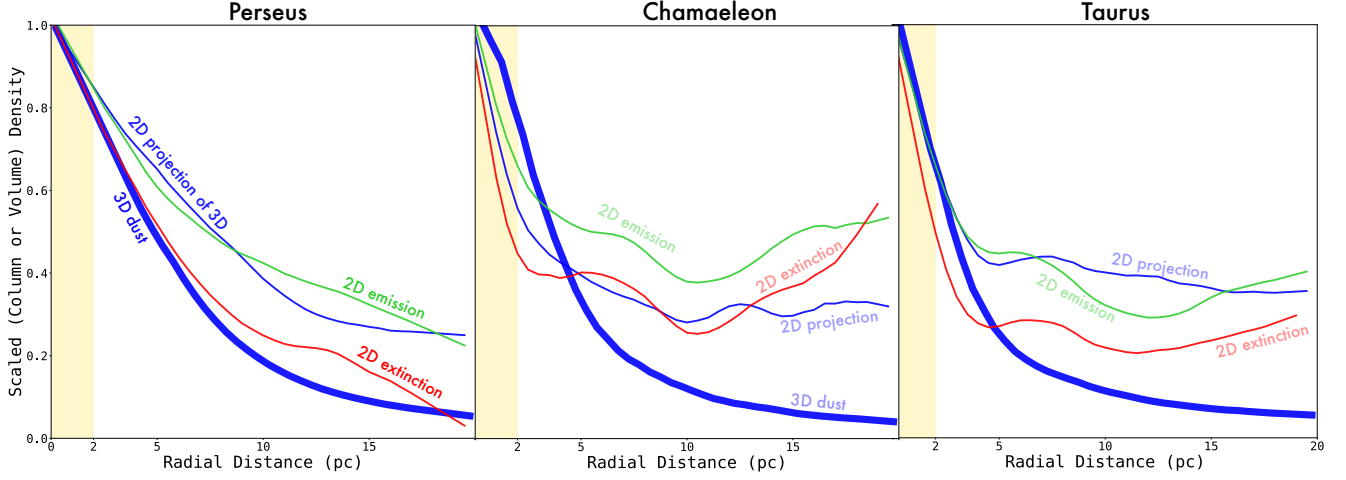


Figure 8. Comparison between 2D radial column density profiles and 3D radial volume density profiles for the Perseus (left), Chamaeleon (middle) and Taurus (right) molecular clouds. The **thick blue lines** show **3D volume density** derived from the Leike et al. (2020) 3D dust map. The **thin blue lines** show **2D column density** profiles derived by **projecting** the Leike et al. (2020) 3D dust map on to the plane of the sky (§3.3). The **red lines** show **2D column density** from the NICEST map (Lombardi 2009). The **green lines** show profiles derived from **2D dust emission** maps (Schlegel et al. 1998). All maps have been scaled to a peak value of 1.0, to facilitate a comparison of the shapes of the volume and column density profiles. While the 2D and 3D results largely agree at radial distances < 5 pc, significant deviations are observed at larger radial distances, particularly for the Chamaeleon and Taurus clouds.

The *Herschel* filaments analyzed in previous work lie *within* the local molecular clouds we analyze here, persisting at much higher column densities ($N_{\text{H}_2} > 10^{22} \text{ cm}^{-2}$), and on much smaller scales (widths \approx a few tenths of a parsec, lengths \approx a few parsecs). As such, they are unresolved in the Leike et al. (2020) 3D dust maps we analyze. Nevertheless, the same formalism can be applied to the much larger molecular clouds these dense filaments inhabit, since the analytic models are scale-free, and we have shown here that local molecular clouds are well-described as cylindrical filaments, even at lower densities ($n < 100 \text{ cm}^{-3}$), where their aspect ratios are often in excess of 3 : 1 (see lengths and widths in Tables 1 and 2). Thus, while we target a very different regime – about two orders of magnitude lower in density, and an order of magnitude larger spatial scale – the comparison to the classical $p = 4$ Ostriker (1964) model for an isothermal, self-gravitating filament in hydrostatic equilibrium, is still relevant.

We find that the local, large-scale, molecular clouds studied here have shallower radial density profiles, with typical power-law indices p between 1.5 – 2.5, than would an isothermal self-gravitating cylinder in hydrostatic equilibrium. This shallower power-law, while inconsistent with isothermal self-gravitating filaments in the absence of a magnetic field, could be consistent with some models of magnetized filaments (Fiege & Pudritz 2000). Previous studies of the structure of the magnetic field in solar neighborhood clouds find a strong coupling between the gas column density and the magnetic field orientation, which is consistent with the idea that magnetic fields play an important role in structuring the interstellar medium in and around local molecular clouds (see e.g. Soler 2019).

However, given that the parameters of the Plummer profile are *highly* degenerate (see discussion in §4.2), and driven by behavior at the tail of the distribution (at very low densities), we are hesitant to assign any physical significance to the shape of the Plummer profile, other than broadly noting the inconsistency with the Ostriker (1964) result. Similar to the two-component Gaussian results, future comparison with numerical simulations should allow for more robust interpretation of the physical significance, if any, of the shape of the Plummer profiles.

6.3. Comparison between 3D Volume Density and 2D Column Density Radial Profiles

The ultimate goal of this work is to lay the foundation for a robust characterization and interpretation of the structure of molecular clouds. To do so will require the contextualization of these newly presented 3D results with extant 2D approaches. Traditionally, there have been three ways of measuring the column density structure

of molecular clouds: near-infrared extinction mapping (e.g. the NICEST method, §2.2; Lombardi 2009), thermal dust emission mapping in the far-infrared (e.g. the SFD or Planck dust maps; Schlegel et al. 1998; Planck Collaboration et al. 2016), and spectral-line mapping of CO isotopologues. A systematic analysis of and comparison to the 2D radial profiles of molecular clouds is beyond the scope of this work. So, as a precursor to a more expansive study, we offer in Figure 8 an initial comparison of our 3D radial volume density profile results with traditional 2D column density results for three clouds in the sample (Perseus, Chamaeleon, and Taurus). We compare the 3D radial profiles with three measurements of the 2D radial profile: one obtained from near-infrared extinction using the NICEST maps (see §2.2), one obtained from far-infrared dust emission maps (Schlegel et al. 1998), and one obtained by projecting the 3D dust map from Leike et al. (2020) on to the plane of the sky, using the same column density maps from §3.3. Each curve has been smoothed with a kernel roughly equal to 2 pc (the effective spatial resolution of the Leike et al. (2020) dust map), to alleviate noise in the profiles at large radial distances and facilitate comparison between the different tracers.¹³ We largely defer comparison to the 2D structure of clouds obtained from velocity-integrated spectral-line maps to future work, given the need for careful accounting of opacity effects and the presence of CO dark gas. In order to facilitate a comparison of the *shapes* of the profiles, we scale the radial volume density profile and the three radial column density profiles to a peak value of one.

In contrast to the 3D radial profiles, the 2D radial profiles show a much larger variation in structure both within and between clouds. In general, we find good agreement between 2D and 3D results at small radial distances ($r < 5$ pc), particularly for the Perseus and Taurus clouds. However, at radial distances > 5 pc, we observe a flattening of the 2D radial profiles that does not manifest in 3D. *These larger radial distances are beyond the $A_K = 0.1$ mag boundary used to validate the 3D-dust-based cloud masses in §4.4.* We observe flattening at large radii even in the projected dust map from Leike et al. (2020) (thin blue trace), which makes use of the same data as the 3D radial profile (thick blue trace), but simply integrates along the line of sight. The flattening seen (only) in 2D suggests two underlying causes. First, diffuse dust unassociated with (but potentially in the same general vicinity of) the cloud could be contaminating the inferred radial profiles at large radial distances. Second, projection effects intrinsic to the cloud itself (e.g. due to the cloud’s orientation with respect to the observer) could be driving this variation. In either or both scenarios, discrepancy between 2D and 3D cloud structure will have profound implications for interpreting the shapes of the column density PDFs of molecular clouds (c.f. Alves et al. 2017; Chen et al. 2019). These deviations also underline the difficulty of validating the atomic outer envelopes of clouds and the tails of the Plummer profiles (§6.2) using traditional 2D dust maps. Disentangling these effects will require careful calibration of 2D dust extinction and emission maps; careful supplementation of the 2D dust information with opacity-corrected spectral line maps of CO, HI, and [CII], and contextualization of both types of data in light of synthetic observations of local cloud analogs.

7. CONCLUSION

The rise of *Gaia* has transformed our understanding not just of the 3D distribution of stars, but also of the 3D distribution of dust that reddens their colors. The recent release of the Leike et al. (2020) 3D dust map, which provides 1 pc spatial resolution out to a distance of several hundred parsecs, offers an unprecedented opportunity to measure and describe the shape and internal structure of local molecular clouds on scales previously obtainable only in simulations. Converting from differential dust extinction in the *Gaia* G-band to volume density using a wavelength-dependent extinction curve, we characterize the shapes and thicknesses of famous local clouds in 3D gas density space for the first time. Local clouds appear filamentary, even at gas densities $n < 100 \text{ cm}^{-3}$. Thus, we start by extending the **FilFinder** algorithm – originally applied to 2D maps of dust emission (Koch & Rosolowsky 2015) – into 3D, to determine the skeletons of nearby clouds, equivalent to a one-voxel-wide representation of their 3D structure. We then extend the **RadFil** algorithm (Zucker & Chen 2018) to measure the radial volume density profiles with respect to the cloud spines. Our results are as follows:

- By projecting each cloud’s skeleton – determined in 3D (x, y, z) cartesian space — back to sky coordinates (l, b, d) , we constrain the distances to famous local molecular clouds. The 1 pc uncertainty on the distances allows for complete characterization of distance gradients and the presence of multiple components.

¹³ In all three cases, the radial profiles are obtained identically to our 3D results presented in §3.2.1, except the threshold for mask (and thus skeleton) creation was defined in 2D column density space as opposed to 3D volume density space. All 2D maps are convolved to the same resolution. The difference in “zero point” emission and extinction levels in traditional 2D approaches precludes the application of an identical column density threshold for all three column density maps. To avoid biases in our analysis, we define thresholds using the total area of the cloud masks, rather than absolute column density. That is, we adopt the same $A_K = 0.1$ mag threshold (converted to N_H) used in the §3.4 NICEST results to define the optimal mask, and set the thresholds for the 2D dust emission (Schlegel et al. 1998) and projected Leike et al. (2020) 2D results so they occupy approximately the same area. By doing so, all masks are defined using a narrow range in column density, spanning $N = 1 - 3 \times 10^{21} \text{ cm}^{-2}$. A tutorial for how to build 2D radial column density profiles with the **RadFil** package is available on Zenodo (Zucker & Chen 2018).

- We model each cloud’s radial volume density profile with three functions: a two-component Gaussian, a single-component Gaussian, and a Plummer-like function. Comparing the relative quality of models, we find that a single-component Gaussian function is universally disfavored, with significantly worse odds compared with the two-component Gaussian and Plummer models.
- For the two-component Gaussian model, we find widths σ_2 of the “outer” Gaussian between 8 – 18 pc, with amplitudes between $n = 5 - 15 \text{ cm}^{-3}$. For the “inner” Gaussian, we find widths σ_1 of 2.5 – 4.9 pc, with amplitudes between $n = 25 - 52 \text{ cm}^{-3}$. The typical ratio of the outer to inner widths is 3.4 : 1, with relatively small scatter (< 1). We hypothesize that the boundary might represent a chemical transition between HI and H₂ gas in local clouds, with the inner regions probing warm, diffuse molecular gas, and the outer regions tracing the extended atomic envelopes. Another plausible scenario includes a thermal transition between the unstable neutral medium (UNM) and the cold neutral medium (CNM). Future comparison with numerical simulations (e.g. [Smith et al. 2020](#)) will be needed to verify these hypotheses.
- We produce synthetic 2D dust extinction maps (A_K) by projecting the [Leike et al. \(2020\)](#) 3D dust distribution on the plane of the sky. We compare the 2D extinction maps derived from 3D dust with traditional integrated 2D dust extinction maps (from the NICEST algorithm; [Lombardi 2009](#)). Computing cloud masses, we determine that the [Leike et al. \(2020\)](#) map is recovering a majority of each cloud’s mass. However, the 3D dust is insensitive to structure above $A_K = 0.3 \text{ mag}$ ($A_V = 3 \text{ mag}$)
- All data underpinning this work are publicly available online at the Harvard Dataverse (https://dataverse.harvard.edu/dataverse/3D_cloud_structure/). An online gallery of interactive figures illustrating our cloud results is also available online [here](#).

Ultimately, these results are only the beginning of what is possible through the combination of *Gaia* astrometry, large photometric surveys, innovative computational and statistical techniques, and exploratory 3D data visualization. The quality of the [Leike et al. \(2020\)](#) 3D dust map, and of similar maps extending out many more kiloparsecs ([Green et al. 2019](#); [Zucker et al. 2020](#)), relies on accurate measurements of the distance and integrated extinction to individual stars. Not only will future *Gaia* data releases produce increasingly better estimates of stellar distance, but upcoming photometric surveys like LSST will allow for improved constraints on the integrated extinction. Future 3D dust maps, built on much larger catalogs of stellar properties (e.g. the *brutus* algorithm; [Speagle et al. 2021](#), in prep.) should allow for improved models of the 3D dust distribution, probing not only clouds at larger distances, but also with improved sensitivity to higher densities within molecular clouds.

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APPENDIX

A. RADIAL PROFILES FOR FULL CLOUD SAMPLE

In Figure 3, we present the radial density profiles for two clouds in the sample — Perseus and Chamaeleon. In Figures A1, A2, and A3, we show the same radial density profiles for the remaining nine clouds.

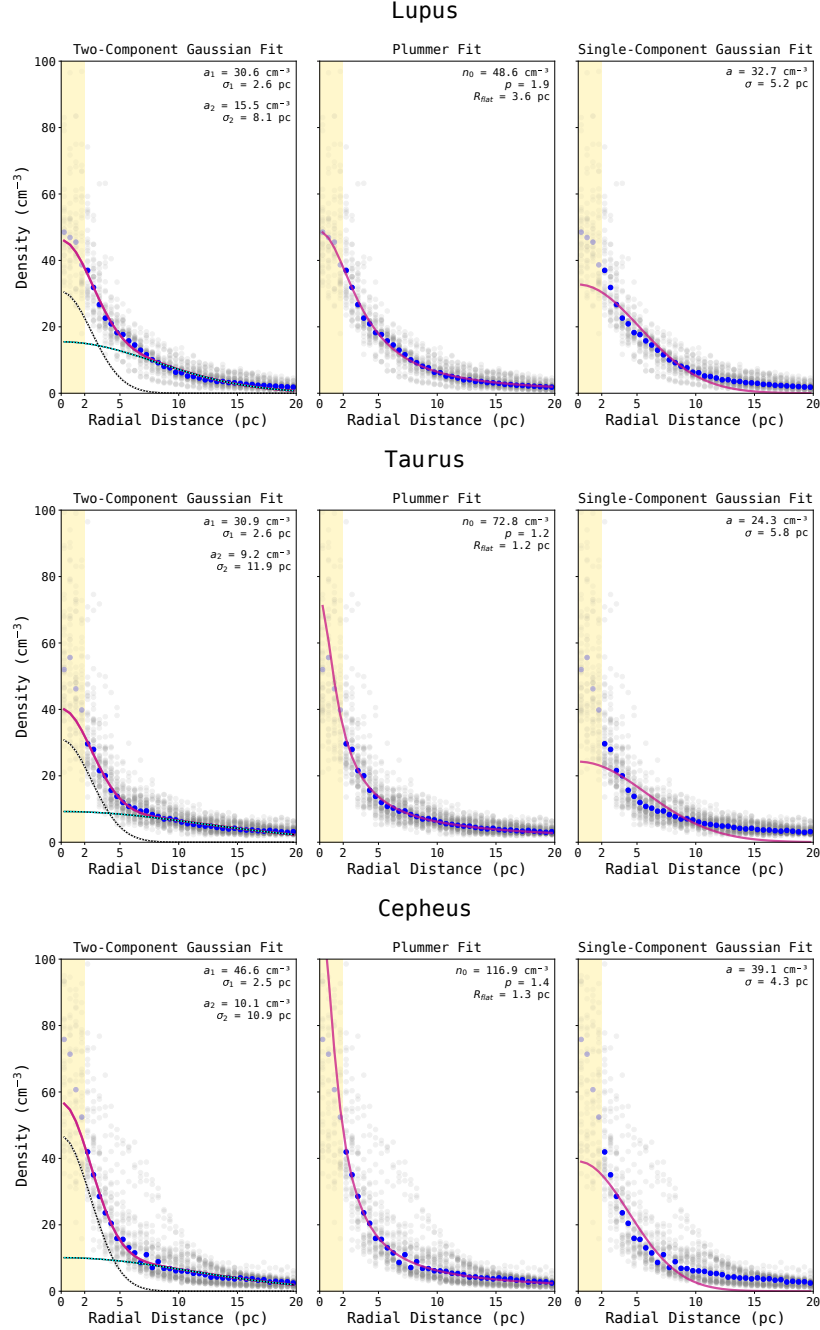


Figure A1. Same as in Figure 3 except for the Lupus molecular cloud (top), the Taurus molecular cloud (middle), and the Cepheus molecular cloud (bottom)

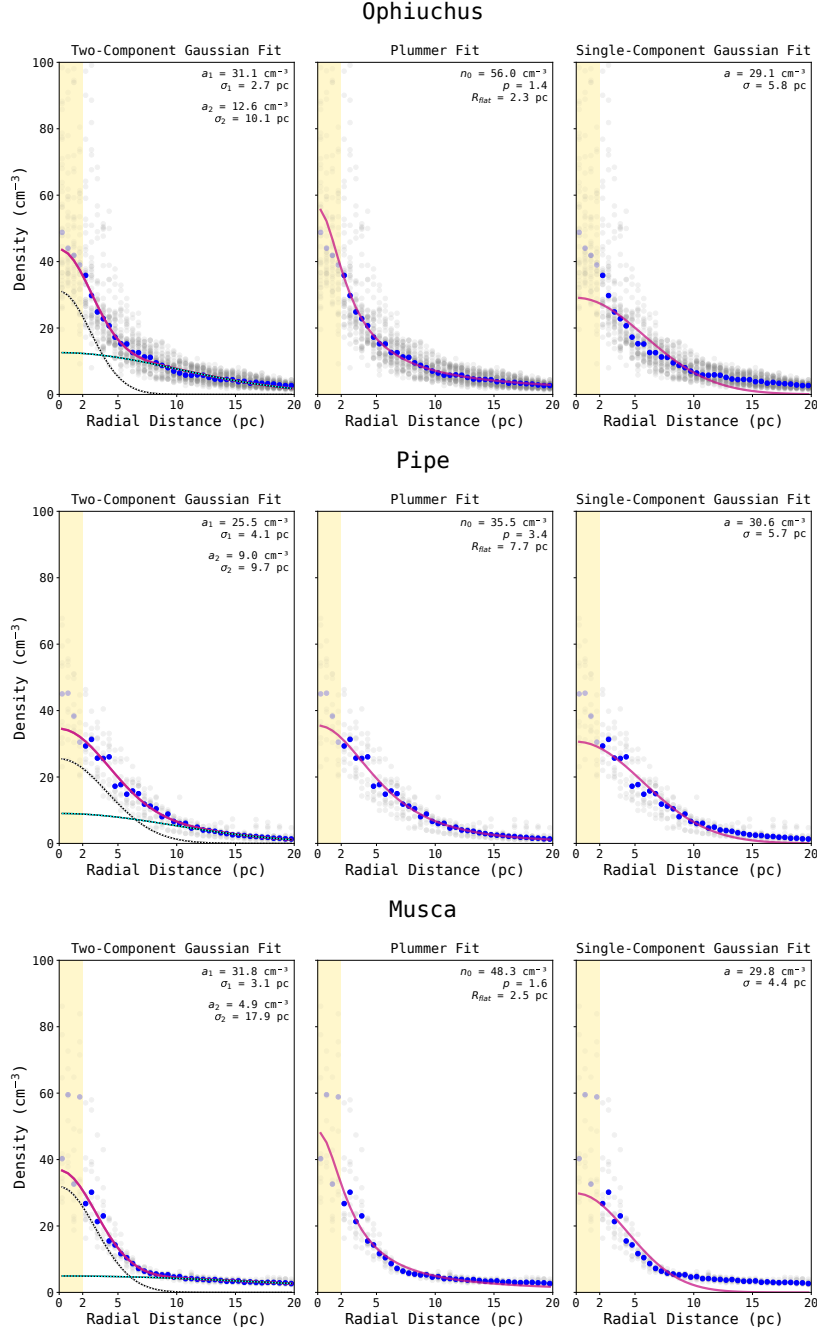


Figure A2. Same as in Figure 3 except for the Ophiuchus molecular cloud (top), the Pipe nebula (middle), and the Musca dark cloud (bottom)

B. CLOUD WIDTHS AS A FUNCTION OF DISTANCE

To determine whether the distance of the cloud influences the widths we derive, we plot the four width parameters fitted for in this study (σ_1 and σ_2 from the two-component Gaussian function, R_{flat} from the Plummer function, and σ from the single-component Gaussian) as a function of distance. The results are shown in Figure B1. If distance was influencing the cloud widths, we would expect the cloud widths to increase as a function of distance. As we show in Figure B1, we find no such correlation, indicating that the cloud distance is not strongly biasing our results.

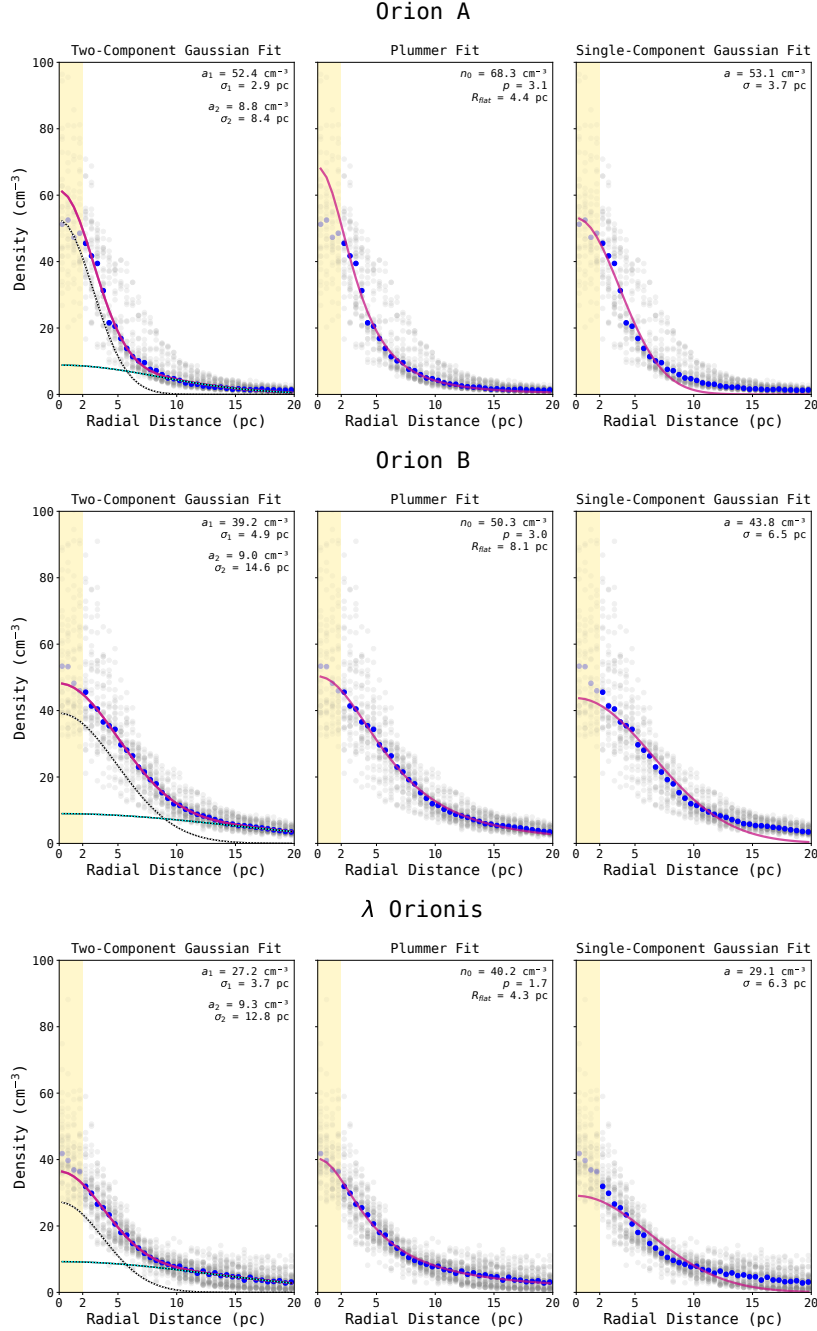


Figure A3. Same as in Figure 3 except for the Orion A molecular cloud (top), the Orion B molecular cloud (middle), and the λ Orionis molecular cloud (bottom). These clouds are at the edge of the Leike et al. (2020) 3D dust grid, so the results should be treated with more caution than our “complete” cloud sample.

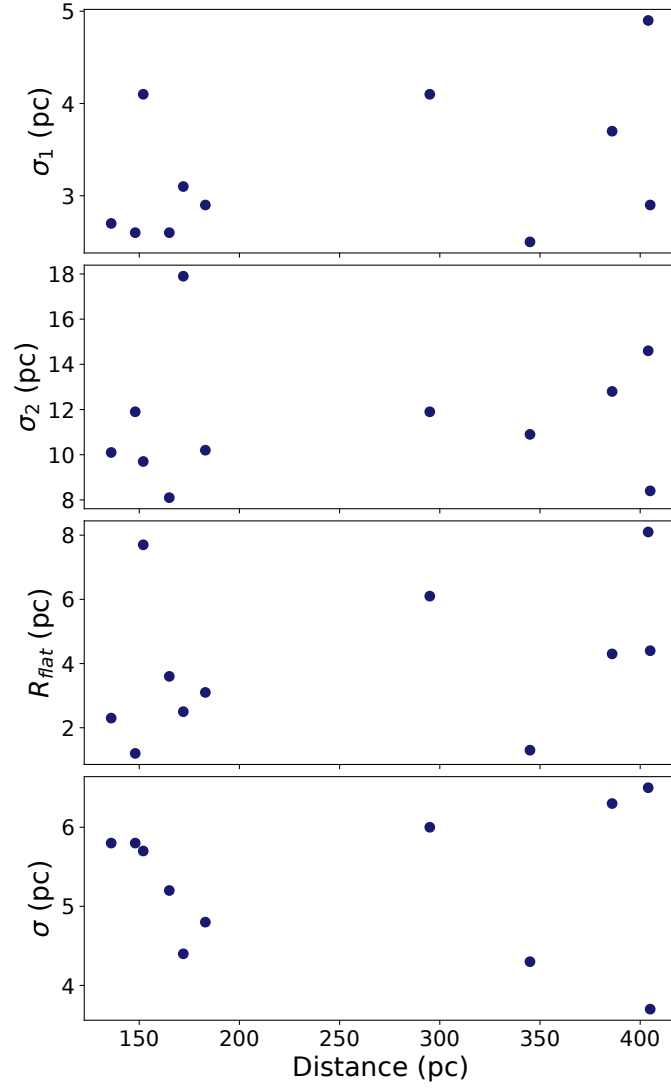


Figure B1. The derived width parameters as a function of cloud distance, with the “inner” width σ_1 of the two-component Gaussian fit, the “outer” width σ_2 of the two-component Gaussian fit, the flattening radius R_{flat} of the Plummer fit, and the standard deviation σ of the single-component Gaussian fit shown from top to bottom.

C. COMPARISON BETWEEN 3D DUST CORRELATION KERNEL AND MEASURED PROFILES

In this section, we compare the shape of the correlation kernel of the [Leike et al. \(2020\)](#) 3D dust reconstruction with the shape of our cloud profiles. Our goal is to determine the extent to which our cloud profiles are driven by data local to the cloud, versus the prior on the dust extinction density. [Leike et al. \(2020\)](#) assume the prior on the dust extinction density s_x to be positive and spatially correlated, enforced via a log-normal Gaussian process prior of the form:

$$s_x = \rho_0 \exp(\tau_x) \\ \tau \sim \mathcal{G}(\tau|0, T)$$

where ρ_0 is the prior median extinction density and T is the correlation kernel of the Gaussian Process τ_x . The ρ_0 term is a hyperparameter of the model, and is set to $\rho_0 = \frac{1}{1000 \text{ pc}^{-1}}$. The correlation kernel T is inferred during their reconstruction. To parallelize the reconstruction, [Leike et al. \(2020\)](#) split the local volume into eight octants, with the correlation kernel inferred on an octant by octant basis. We take samples of the correlation kernel inferred for the octant in which each cloud resides, which is equivalent to obtaining samples of the two-point correlation matrix of the logarithmic dust density. The two-point correlation matrix directly indicates how the density at one point is correlated with another point in 3D space.

To facilitate a comparison between the two-point correlation matrix and our profiles, we compute the correlation of each measured profile $C_p(r)$. Before doing so, we convert the radial profiles as a function of gas density $n(r)$, utilized throughout this study, back to the native units of the [Leike et al. \(2020\)](#) 3D dust map, by dividing each profile by a factor of 880 (see §2) to obtain $s_x(r)$. Since the two-point correlation matrix describes the logarithmic dust density, rather than the dust density, we further transform $s_x(r)$ into logarithmic density space, hereafter $p(r)$:

$$p(r) = \log(s_x(r) \times 1000) \quad (\text{C1})$$

where the factor of 1000 accounts for the scaling of the hyperparameter ρ_0 . To calculate the correlation of the profile $C_p(r)$, we compute:

$$C_p(r) = p(r) \times p(0) \quad (\text{C2})$$

where $p(0)$ is the logarithmic density of the radial profile in Equation C1 at a radial distance of 0 pc. Given the overdensity of the dust at $r = 0$ pc, this comparison describes how much of the dust at larger radial distances can be explained by the correlation kernel of the dust map. In Figure C1 we plot T versus $C_p(r)$ for each cloud, where T constitutes samples of two-point correlation matrix inferred in the cloud’s octant, and $C_p(r)$ is the correlation of the profile we construct in §3.2.1. We normalize both T and $C_p(r)$ to a peak value of 1.0.

We observe that the shape of $C_p(r)$ and T are qualitatively different between radial distances of 2 and 10 pc, indicating that the “inner” widths of our two-component Gaussian results are driven by data local to the cloud, rather than the kernel used in the 3D dust’s reconstruction. However, for radial distances > 10 pc, we see the slopes of $C_p(r)$ and T become increasingly similar, particularly for the Musca, Taurus, Ophiuchus, and Orion A clouds. The similarity between the shape of $C_p(r)$ and T at larger radial distances could indicate that the kernel is driving the structure of clouds at lower densities. However, since the kernel is inferred using data inclusive of the cloud’s structure (in addition to structure beyond each cloud of interest) the outer envelopes could still be physically meaningful. More validation in future work will be needed to fully verify the relationship, if any, between the outer envelopes we observe in our radial profiles and the atomic gas envelopes of local molecular clouds, as discussed in §6.

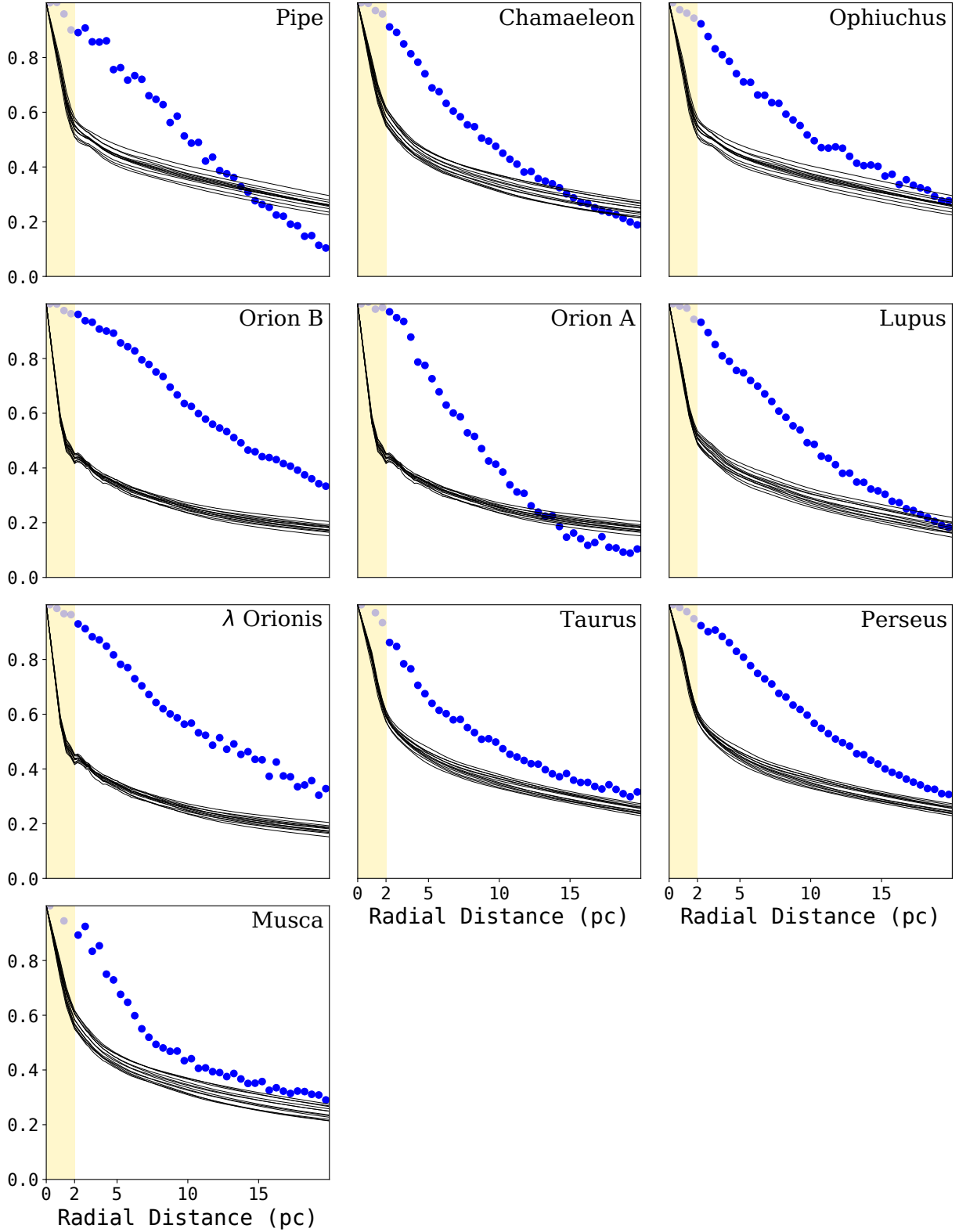


Figure C1. Comparison between samples of the two-point correlation function derived from the [Leike et al. \(2020\)](#) 3D dust kernel (black lines) and the derived correlation of each cloud’s radial profile obtained in this work (blue points). Both the 3D dust map’s correlation kernel and correlation of the cloud radial profiles have been scaled to a peak value of one. At smaller radial distances, our measured profiles deviate significantly from the underlying correlation kernel used to derive the map, indicating that the inner widths we obtain for the clouds are robust. However, at larger radial distances, the shape of the kernel and profiles become similar, indicating the dust at larger radial distances may be prior-dominated. However, since the prior is inferred using real cloud structure, the outer envelopes could still be physically meaningful. See Appendix C for full details.

D. RADIAL PROFILE FITTING RESULTS FOR THE FULL PROFILE

In §4, we discuss the width results where the inner profiles (radial distances < 2 pc) are excluded from the fit, due to the [Leike et al. \(2020\)](#) map’s 1 pc grid and its caveat that features less than 2 pc in size should be treated with caution. For completeness, in Table D1, we report the results of the full profile fits, including radial distance bins between 0 and 20 pc.

In general, we find that including the inner 2 pc of each radial profile in the fit has a modest effect on the model parameters. When including the inner 2 pc for the two-component Gaussian-fit (in comparison to the results from §4), the inner width σ_1 changes on average by 15%, while the outer width typically differs by 17%. For the single-component Gaussian, σ differs on average by 20%. We see the largest difference in the Plummer model, with R_{flat} changing by 28% on average. Overall, however, the quality of all model fits decreases when including the inner 2 pc, which is why we report the results excluding the inner 2 pc, over the full profile results, in the main text. The decline in the quality of the fit, as determined using the same procedure outlined in §4.2.1, is consistent with our understanding that the [Leike et al. \(2020\)](#) dust map is unreliable at scales < 2 pc, and is also less accurate at reconstructing the highest gas densities, which are closest to the spine. Thus, it is not surprising that the fit improves when only higher fidelity measurements, farther from the spine, are included.

Table D1. Radial Volume Density Fitting (Full Profile)

Cloud	Two-Component Gaussian						Plummer					Single Gaussian				
	σ_1	a_1	σ_2	a_2	$\sigma_{n,G2}^2$	$\frac{\sigma_2}{\sigma_1}$	$\ln Z_{G2}$	n_0	R_{flat}	p	$\sigma_{n,P}^2$	$\ln Z_P$	σ	a	$\sigma_{n,G1}^2$	$\ln Z_{G1}$
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Chamaeleon	$2.6^{+0.1}_{-0.1}$	$34.5^{+0.7}_{-0.7}$	$9.4^{+0.5}_{-0.4}$	$10.2^{+0.7}_{-0.7}$	$0.4^{+0.1}_{-0.1}$	3.6	-19.7	$46.1^{+0.3}_{-0.3}$	$3.4^{+0.1}_{-0.1}$	$1.9^{+0.1}_{-0.1}$	$0.3^{+0.1}_{-0.1}$	-10.8	$3.8^{+0.2}_{-0.2}$	$41.1^{+1.6}_{-1.6}$	$10.0^{+2.8}_{-2.0}$	-73.1
Ophiuchus	$2.4^{+0.1}_{-0.1}$	$33.1^{+0.9}_{-1.0}$	$9.6^{+0.5}_{-0.5}$	$13.6^{+1.0}_{-0.9}$	$0.9^{+0.3}_{-0.2}$	3.9	-33.8	$48.1^{+0.5}_{-0.5}$	$2.9^{+0.1}_{-0.1}$	$1.5^{+0.0}_{-0.0}$	$0.5^{+0.1}_{-0.1}$	-22.6	$4.3^{+0.3}_{-0.3}$	$40.6^{+2.2}_{-2.0}$	$16.9^{+4.9}_{-3.5}$	-82.3
Lupus	$2.3^{+0.1}_{-0.1}$	$31.4^{+1.3}_{-1.3}$	$7.7^{+0.4}_{-0.3}$	$17.1^{+1.3}_{-1.4}$	$1.0^{+0.3}_{-0.2}$	3.3	-34.3	$49.0^{+0.5}_{-0.5}$	$3.6^{+0.2}_{-0.1}$	$1.9^{+0.1}_{-0.1}$	$0.5^{+0.2}_{-0.1}$	-24.6	$4.2^{+0.2}_{-0.2}$	$42.9^{+1.8}_{-1.7}$	$12.1^{+3.4}_{-2.5}$	-76.6
Taurus	$2.0^{+0.1}_{-0.1}$	$43.1^{+1.0}_{-1.1}$	$10.4^{+0.8}_{-0.7}$	$11.2^{+0.9}_{-0.9}$	$1.8^{+0.5}_{-0.3}$	5.2	-45.3	$56.8^{+1.0}_{-1.0}$	$1.9^{+0.1}_{-0.1}$	$1.4^{+0.1}_{-0.1}$	$1.8^{+0.5}_{-0.4}$	-46.0	$3.1^{+0.3}_{-0.2}$	$48.2^{+3.2}_{-3.0}$	$24.4^{+7.1}_{-5.0}$	-89.3
Perseus	$3.3^{+0.2}_{-0.2}$	$35.0^{+1.9}_{-1.9}$	$9.7^{+0.8}_{-0.6}$	$16.5^{+2.0}_{-2.0}$	$1.8^{+0.5}_{-0.4}$	3.0	-45.0	$52.5^{+0.6}_{-0.6}$	$4.8^{+0.3}_{-0.3}$	$2.0^{+0.1}_{-0.1}$	$1.1^{+0.3}_{-0.2}$	-37.3	$5.2^{+0.2}_{-0.2}$	$46.8^{+1.5}_{-1.5}$	$13.6^{+3.7}_{-2.8}$	-79.0
Musca ^a	$2.6^{+0.3}_{-0.2}$	$42.8^{+3.1}_{-3.5}$	$14.7^{+6.1}_{-4.9}$	$6.1^{+2.6}_{-1.7}$	$23.6^{+6.8}_{-4.5}$	5.7	-89.0	$49.9^{+3.2}_{-3.3}$	$3.9^{+1.6}_{-1.0}$	$2.6^{+1.4}_{-0.7}$	$26.2^{+7.5}_{-5.4}$	-91.4	$3.2^{+0.3}_{-0.3}$	$46.7^{+3.3}_{-3.3}$	$33.6^{+10.0}_{-6.7}$	-95.7
Pipe	$2.6^{+0.3}_{-0.2}$	$24.4^{+2.4}_{-1.8}$	$7.6^{+0.6}_{-0.4}$	$18.1^{+1.4}_{-2.8}$	$4.0^{+1.1}_{-0.9}$	2.9	-58.3	$42.0^{+1.2}_{-1.2}$	$4.8^{+0.7}_{-0.6}$	$2.2^{+0.4}_{-0.3}$	$3.8^{+1.1}_{-0.8}$	-57.2	$4.9^{+0.2}_{-0.2}$	$37.4^{+1.4}_{-1.4}$	$10.4^{+2.9}_{-2.2}$	-73.6
Cepheus	$2.0^{+0.1}_{-0.1}$	$60.6^{+1.3}_{-1.3}$	$9.1^{+0.7}_{-0.6}$	$13.5^{+1.2}_{-1.1}$	$2.1^{+0.6}_{-0.4}$	4.6	-48.2	$77.9^{+0.8}_{-0.7}$	$2.1^{+0.1}_{-0.1}$	$1.6^{+0.0}_{-0.0}$	$0.8^{+0.2}_{-0.2}$	-32.9	$2.8^{+0.2}_{-0.2}$	$67.9^{+3.1}_{-3.1}$	$28.3^{+8.2}_{-5.9}$	-92.3
Orion A*	$3.3^{+0.1}_{-0.1}$	$48.6^{+1.4}_{-2.0}$	$11.2^{+3.9}_{-2.2}$	$5.0^{+2.0}_{-1.5}$	$2.4^{+0.7}_{-0.5}$	3.4	-48.6	$54.2^{+1.0}_{-1.0}$	$7.0^{+0.7}_{-0.7}$	$4.8^{+0.7}_{-0.7}$	$3.3^{+0.9}_{-0.7}$	-54.3	$3.7^{+0.1}_{-0.1}$	$52.4^{+1.1}_{-1.1}$	$5.4^{+1.7}_{-1.1}$	-62.8
Orion B*	$4.5^{+0.2}_{-0.2}$	$38.1^{+2.1}_{-2.3}$	$12.0^{+1.6}_{-1.1}$	$12.6^{+2.4}_{-2.3}$	$1.2^{+0.3}_{-0.2}$	2.7	-36.5	$51.6^{+0.5}_{-0.5}$	$7.5^{+0.4}_{-0.4}$	$2.8^{+0.2}_{-0.2}$	$1.0^{+0.3}_{-0.2}$	-34.7	$6.0^{+0.2}_{-0.2}$	$47.8^{+1.2}_{-1.1}$	$8.7^{+2.4}_{-1.7}$	-70.5
λ Orionis*	$3.3^{+0.1}_{-0.1}$	$28.9^{+0.8}_{-0.8}$	$11.6^{+0.7}_{-0.6}$	$10.9^{+0.8}_{-0.8}$	$0.5^{+0.2}_{-0.1}$	3.5	-23.7	$41.0^{+0.4}_{-0.4}$	$4.1^{+0.2}_{-0.2}$	$1.7^{+0.1}_{-0.1}$	$0.4^{+0.1}_{-0.1}$	-17.5	$5.2^{+0.3}_{-0.3}$	$35.9^{+1.5}_{-1.5}$	$11.1^{+3.2}_{-2.2}$	-74.6

NOTE—Radial density profile fitting results for local clouds, computed over radial distances between 0 and 20 pc. Unlike Table 2, we do not exclude the inner 2 pc from the fit. (1) Name of the cloud. (2 - 6) Best-fit parameters for the two-component Gaussian fit, including the standard deviation and amplitude of the narrower Gaussian (σ_1, a_1), the standard deviation and amplitude of the broader Gaussian (σ_2, a_2), and the square of the modeled scatter in the density measurements ($\sigma_{n,G2}^2$). (7) Ratio of the outer to inner Gaussian standard deviations. (8) Logarithm of the evidence of the two-component Gaussian fit. (9-12) Best-fit parameters of the Plummer fit, including the peak amplitude n_0 , the flattening radius R_{flat} , the power index of the density profile p , and the square of the modeled scatter in the density measurements ($\sigma_{n,P}^2$). (13) Logarithm of the evidence of the Plummer fit. (14-16) Standard deviation σ , amplitude a , and the square of the modeled scatter in the density measurements ($\sigma_{n,G1}^2$) for the single component Gaussian fit. (17) Logarithm of the evidence of the single-component Gaussian fit. We report the single-component Gaussian results here for completeness only, as it is a poor fit to the data particularly at large radial distances. A machine readable version of this table is available at <https://doi.org/10.7910/DVN/V8NGLX>.

^a At small radial distances, Musca is largely unresolved in the Leike et al. (2020) map, and at large radial distances, its structure is consistent with being prior-dominated, so we urge caution when interpreting the results.

* Clouds below the horizontal line — Orion A, Orion B, and λ Orionis — should be treated with caution, as they lie at the very edge of the Leike et al. (2020) 3D dust grid and are subjected to additional biases. Part of Orion A, toward the Orion Nebula Cluster, is also devoid of dust in the Leike et al. (2020) 3D dust map despite being highly extinguished. See §5 for full details.

E. RADIAL PROFILE FITTING RESULTS USING SAMPLES OF THE 3D DUST MAP

In deriving their 3D dust map, [Leike et al. \(2020\)](#) generate twelve posterior samples, or realizations, of the extinction density, and the 3D dust map derived from the mean of these posterior samples is used in the fitting results reported in §4. However, because the uncertainty in the underlying 3D dust reconstruction is not accounted for when characterizing the radial profiles, it is necessary to quantify how much our results change when different realizations of the 3D dust distribution are used, rather than just the mean. To do so, we create a new likelihood function, building on the formalism described in §3.2.2. Recall that when fitting 3D dust determined by the mean of the samples, we adopt a Gaussian log-likelihood that takes the following form:

$$\mathcal{L}_{\text{mean}} = \ln p(n|\theta, \sigma_n^2) = -\frac{1}{2} \sum_i \left[\frac{(n_i - n_{\theta,i})^2}{\sigma_n^2} + \ln(2\pi\sigma_n^2) \right] \quad (\text{E1})$$

where n_i is the measured profile in the i th radial distance bin characterized by the mean 3D dust map, $n_{\theta,i}$ is the model density profile in the i th distance bin (for the single Gaussian, two-component Gaussian, or Plummer fit), θ constitutes the parameters characterizing the model density profile for each fit (e.g. σ , a for the single Gaussian fit), and σ_n^2 is the square of the scatter in the density (across all bins) that we infer as part of our modeling.

Our new likelihood function, taking into account all twelve realizations of the 3D dust map, is of the form:

$$\mathcal{L}_{\text{samples}} = \ln[\exp(\mathcal{L}_{\text{sample}_1}) + \exp(\mathcal{L}_{\text{sample}_2}) + \dots + \exp(\mathcal{L}_{\text{sample}_{12}})] - \ln(12) \quad (\text{E2})$$

where $\mathcal{L}_{\text{sample}_1}$ is calculated equivalently to $\mathcal{L}_{\text{mean}}$, except the measured radial density profile n is derived from the 1st sample of the 3D dust map. There are twelve samples, so we compute the radial profile for each, assuming the same filament spine as determined for the mean dust map. We exclude the inner 2 pc of the radial profiles when fitting, as we do for the results reported in Table 2. Each of the twelve samples is a possible reality with a probability of $\frac{1}{12}$, and therefore the combined probability is their average. Thus, the total log-likelihood is the average of the individual likelihoods derived from each realization. We sample for the best-fit model parameters for all three functions (single-component Gaussian, two-component Gaussian, Plummer) for all clouds, using the same priors and the same `dynesty` nested sampling framework we employ in §3.2.2. Our results are summarized in Table E1.

Overall, we find that that uncertainty in the profile fitting derived from the uncertainty in the 3D dust map has only a modest effect on our results. For the two-component Gaussian, the typical percent difference between the sample-based inference and the mean-based inference is 2% for σ_2 , 10% for σ_1 , 21% for a_2 and 11% for a_1 . For the Plummer fit, p changes by an average of 8%, n_0 by 17%, and R_{flat} by 22%. However, we do note that for three clouds — Pipe, λ Orionis, and Musca, the R_{flat} parameter changes more drastically, increasing by a factor of two when using the 3D dust samples rather than the mean. This larger change could be tied to the degeneracy in the Plummer modeling described in §4.3, which provides another reason not to overinterpret the Plummer models, as we caution in §6.2. The two-component Gaussian fit is much more robust, and the sample-based fitting results reported in Table E1 do not affect any physical interpretation of the profile shapes described in §6.

Table E1. Radial Volume Density Fitting (Computed using All Realizations of 3D Dust Map)

Cloud	Two-Component Gaussian						Plummer						Single Gaussian			
	σ_1	a_1	σ_2	a_2	$\sigma_{n,G2}^2$	$\frac{\sigma_2}{\sigma_1}$	$\ln Z_{G2}$	n_0	R_{flat}	p	$\sigma_{n,P}^2$	$\ln Z_P$	σ	a	$\sigma_{n,G1}^2$	$\ln Z_{G1}$
	pc	cm ⁻³	pc	cm ⁻³	cm ⁻³			cm ⁻³	pc		cm ⁻³		pc	cm ⁻³	cm ⁻³	
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)
Chamaeleon	2.8 ^{+0.1} _{-0.1}	29.2 ^{+0.7} _{-0.6}	10.4 ^{+0.4} _{-0.3}	8.0 ^{+0.4} _{-0.4}	0.1 ^{+0.0} _{-0.0}	3.7	-4.1	46.9 ^{+1.7} _{-1.9}	2.6 ^{+0.2} _{-0.1}	1.7 ^{+0.1} _{-0.0}	0.1 ^{+0.0} _{-0.0}	0.3	4.7 ^{+0.4} _{-0.4}	28.3 ^{+3.7} _{-2.3}	4.8 ^{+1.6} _{-1.1}	-55.7
Ophiuchus	2.7 ^{+0.1} _{-0.1}	34.0 ^{+1.2} _{-1.5}	10.9 ^{+0.5} _{-0.5}	10.3 ^{+0.6} _{-0.6}	0.4 ^{+0.1} _{-0.1}	4.1	-19.7	56.6 ^{+2.7} _{-2.5}	2.3 ^{+0.2} _{-0.1}	1.4 ^{+0.0} _{-0.0}	0.2 ^{+0.1} _{-0.0}	-8.2	5.2 ^{+0.5} _{-0.4}	28.7 ^{+2.3} _{-2.3}	7.9 ^{+2.4} _{-1.8}	-63.0
Lupus	3.5 ^{+0.2} _{-1.4}	27.6 ^{+14.6} _{-1.4}	10.0 ^{+1.3} _{-1.4}	9.4 ^{+4.0} _{-1.8}	0.4 ^{+0.1} _{-0.1}	2.9	-19.5	42.3 ^{+11.7} _{-3.8}	3.5 ^{+1.3} _{-0.9}	1.8 ^{+0.2} _{-0.2}	0.3 ^{+0.1} _{-0.1}	-13.3	5.4 ^{+0.3} _{-0.2}	29.5 ^{+1.4} _{-1.5}	4.2 ^{+1.2} _{-1.0}	-54.0
Taurus	2.3 ^{+0.1} _{-0.1}	36.2 ^{+1.2} _{-1.5}	11.5 ^{+0.6} _{-0.4}	8.7 ^{+0.3} _{-0.4}	0.2 ^{+0.1} _{-0.0}	5.0	-9.7	54.4 ^{+7.2} _{-4.7}	1.6 ^{+0.2} _{-0.2}	1.3 ^{+0.0} _{-0.0}	0.2 ^{+0.1} _{-0.0}	-10.2	5.2 ^{+0.7} _{-0.7}	24.0 ^{+4.1} _{-2.8}	7.9 ^{+2.4} _{-1.8}	-63.0
Perseus	3.7 ^{+0.1} _{-0.1}	26.3 ^{+0.9} _{-0.9}	11.4 ^{+0.7} _{-0.6}	11.5 ^{+1.0} _{-1.0}	0.4 ^{+0.1} _{-0.1}	3.1	-20.3	40.8 ^{+1.0} _{-0.9}	4.7 ^{+0.3} _{-0.3}	1.8 ^{+0.1} _{-0.1}	0.3 ^{+0.1} _{-0.1}	-17.5	6.4 ^{+0.4} _{-0.6}	31.1 ^{+3.2} _{-1.7}	6.1 ^{+1.9} _{-1.4}	-59.3
Musca ^a	2.9 ^{+0.1} _{-0.1}	36.1 ^{+0.8} _{-0.8}	20.9 ^{+2.7} _{-2.9}	3.3 ^{+0.3} _{-0.2}	0.4 ^{+0.1} _{-0.1}	7.1	-17.1	145.3 ^{+16.9} _{-22.9}	1.0 ^{+0.2} _{-0.1}	1.6 ^{+0.0} _{-0.0}	0.5 ^{+0.2} _{-0.1}	-24.3	3.6 ^{+0.2} _{-0.2}	34.5 ^{+2.7} _{-2.5}	5.2 ^{+1.6} _{-1.1}	-56.9
Pipe	2.9 ^{+0.4} _{-0.2}	29.5 ^{+8.4} _{-9.3}	9.9 ^{+0.8} _{-0.7}	8.3 ^{+1.3} _{-1.1}	0.5 ^{+0.2} _{-0.1}	3.4	-21.8	49.5 ^{+3.4} _{-3.1}	2.6 ^{+0.3} _{-0.2}	1.8 ^{+0.1} _{-0.1}	0.3 ^{+0.1} _{-0.1}	-16.0	6.6 ^{+0.2} _{-0.2}	21.8 ^{+0.8} _{-0.8}	2.3 ^{+0.7} _{-0.5}	-44.9
Cepheus	2.8 ^{+0.1} _{-0.6}	41.6 ^{+8.7} _{-1.4}	10.9 ^{+1.4} _{-1.6}	6.7 ^{+1.9} _{-0.9}	0.6 ^{+0.2} _{-0.1}	3.9	-25.1	159.1 ^{+8.0} _{-12.6}	1.0 ^{+0.1} _{-0.0}	1.6 ^{+0.0} _{-0.0}	0.2 ^{+0.1} _{-0.0}	-6.5	3.9 ^{+0.2} _{-0.2}	38.9 ^{+2.7} _{-2.8}	6.5 ^{+2.1} _{-1.4}	-61.0
Orion A*	3.1 ^{+0.2} _{-0.6}	48.0 ^{+19.7} _{-14.4}	8.7 ^{+3.3} _{-1.0}	7.0 ^{+2.3} _{-3.5}	0.4 ^{+0.1} _{-0.1}	2.8	-18.9	80.1 ^{+3.4} _{-34.0}	4.2 ^{+0.6} _{-0.3}	3.3 ^{+0.4} _{-0.4}	0.4 ^{+0.1} _{-0.1}	-17.7	3.9 ^{+0.1} _{-0.1}	46.9 ^{+1.5} _{-1.3}	2.1 ^{+0.6} _{-0.5}	-43.4
Orion B*	3.8 ^{+0.1} _{-0.1}	35.5 ^{+1.1} _{-1.2}	11.1 ^{+0.8} _{-0.7}	11.7 ^{+1.3} _{-1.3}	0.6 ^{+0.2} _{-0.1}	2.9	-25.3	50.8 ^{+1.1} _{-1.1}	5.4 ^{+0.3} _{-0.3}	2.3 ^{+0.1} _{-0.1}	0.5 ^{+0.2} _{-0.1}	-24.4	6.0 ^{+0.2} _{-0.2}	39.9 ^{+1.5} _{-1.4}	5.0 ^{+1.6} _{-1.2}	-57.0
λ Orionis*	3.8 ^{+0.1} _{-0.1}	30.3 ^{+0.6} _{-0.7}	13.9 ^{+1.6} _{-1.2}	5.9 ^{+0.7} _{-0.6}	0.3 ^{+0.1} _{-0.1}	3.7	-14.3	85.1 ^{+22.9} _{-11.7}	1.2 ^{+0.2} _{-0.3}	1.3 ^{+0.0} _{-0.0}	0.2 ^{+0.1} _{-0.0}	-8.7	5.7 ^{+0.4} _{-0.3}	28.0 ^{+2.7} _{-6.0}	3.5 ^{+1.1} _{-0.8}	-50.5

NOTE—Radial density profile fitting results for local clouds, computed using the likelihood function shown in Equation E2 and described in Appendix E. The likelihood in Equation E2 utilizes all realizations of the 3D dust map distribution from Leike et al. (2020), rather than just the mean distribution, allowing us to quantify the effect of the underlying uncertainty in the 3D dust reconstruction on our results. (1) Name of the cloud. (2 - 6) Best-fit parameters for the two-component Gaussian fit, including the standard deviation and amplitude of the narrower Gaussian (σ_1 , a_1), the standard deviation and amplitude of the broader Gaussian (σ_2 , a_2), and the square of the modeled scatter in the density measurements ($\sigma_{n,G2}^2$). (7) Ratio of the outer to inner Gaussian standard deviations. (8) Logarithm of the evidence of the two-component Gaussian fit. (9-12) Best-fit parameters of the Plummer fit, including the peak amplitude n_0 , the flattening radius R_{flat} , the power index of the density profile p , and the square of the modeled scatter in the density measurements ($\sigma_{n,P}^2$). (13) Logarithm of the evidence of the Plummer fit. (14-16) Standard deviation σ , amplitude a , and the square of the modeled scatter in the density measurements ($\sigma_{n,G1}^2$) for the single component Gaussian fit. (17) Logarithm of the evidence of the single-component Gaussian fit. We report the single-component Gaussian results here for completeness only, as it is a poor fit to the data particularly at large radial distances. A machine readable version of this table is available at <https://doi.org/10.7910/DVN/94OKZD>.

^a At small radial distances, Musca is largely unresolved in the Leike et al. (2020) map, and at large radial distances, its structure is consistent with being prior-dominated, so we urge caution when interpreting the results.

* Clouds below the horizontal line — Orion A, Orion B, and λ Orionis — should be treated with caution, as they lie at the very edge of the Leike et al. (2020) 3D dust grid and are subjected to additional biases. Part of Orion A, toward the Orion Nebula Cluster, is also devoid of dust in the Leike et al. (2020) 3D dust map despite being highly extinguished. See §5 for full details.

F. COMPARISON TO CO RADIAL PROFILES

We build radial profiles of the CO emission in order to test the HI-to-H₂ transition hypothesis presented in §6.1.1. Specifically, if CO emission is detected significantly beyond the boundaries of the inner Gaussian profile, the two component Gaussian would not represent a phase transition between atomic and molecular gas, disproving the hypothesis discussed in §6.1.1. For this test, we leverage data from the 1.2 m CfA CO survey (Dame et al. 2001), selecting all clouds which have broad enough CO coverage to probe potential emission at large radial distances (seven of eleven clouds in the sample). For each cloud, we produce integrated intensity maps of the ¹²CO emission over the velocity range of -15 to 15 km s⁻¹. We then smooth each map to the resolution of the Leike et al. (2020) data at the distance of the cloud (see Table 1) and define 2D masks by thresholding the integrated intensity maps at a level of 10 K km s⁻¹. We then follow the procedure for building radial profiles in 2D space, as presented in Zucker & Chen (2018), which involves skeletonizing the mask and taking cuts across the spine. We employ the “shift” option to account for CO emission offset from the main spine, ensuring the emission peaks at a radial distance of zero.

The results are presented in Figure F1. In the top left hand corner of Figure F1 we show an example of what the 2D skeletonization of the CO integrated intensity masks looks like for a single cloud in the sample — the Perseus Molecular Cloud. In the subsequent panels of Figure F1, we show normalized CO integrated intensity profiles (blue) alongside the normalized density profiles (black) for the inner Gaussian component based on the 3D dust mapping. Both profiles have been scaled to a peak value of one for comparison purposes. We find no extended CO emission beyond the bounds of the inner Gaussian, with most CO profiles showing smaller widths. The one exception is the Taurus Molecular Cloud, whose CO profile is almost identical to the 3D dust profile out to a radial distance of 5 pc, but also shows a secondary peak at larger radial distances. We find that the secondary peak is entirely due to projection effects, stemming from the two components of Taurus (separated by about 10 - 15 pc along the line of sight) which project to similar areas on the plane of the sky. Thus, we are unable to disprove the HI-to-H₂ transition hypothesis given the results of the CO radial profile analysis.

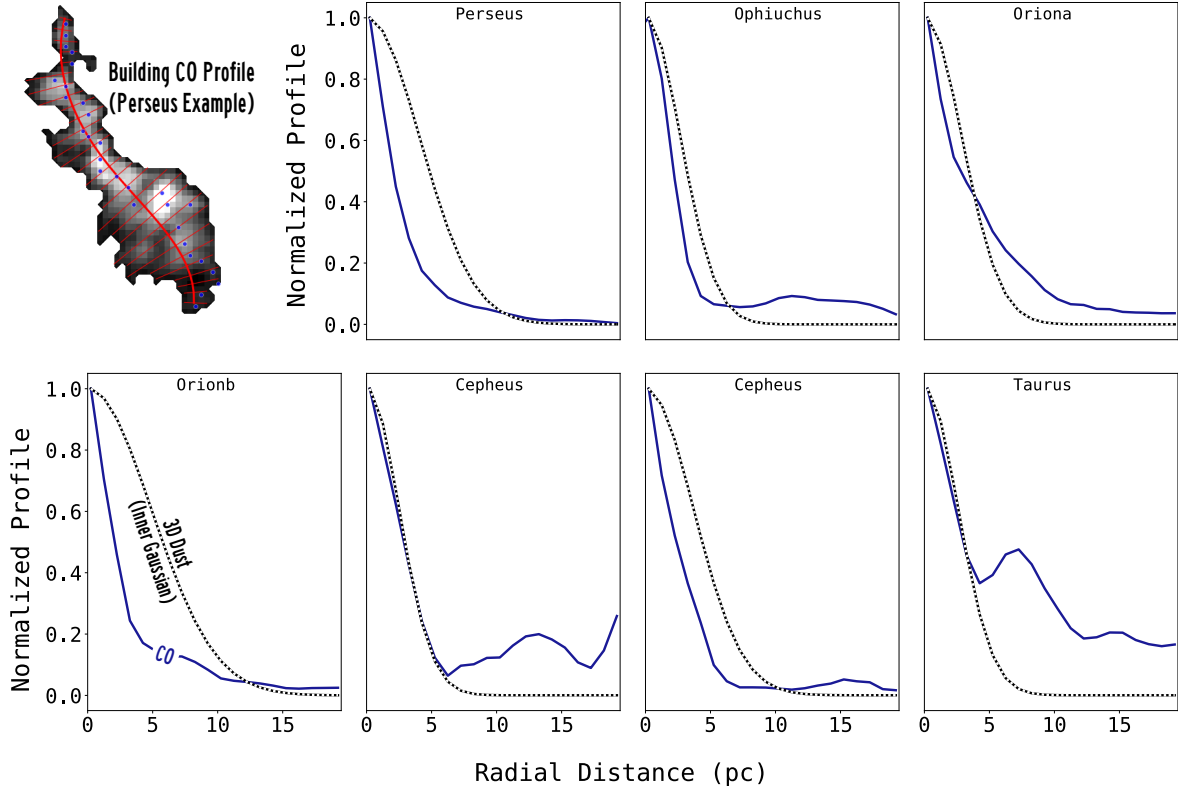


Figure F1. Comparison to CO radial profiles for seven clouds in the sample. The top left hand panel shows a schematic for building 2D radial profiles from the ^{12}CO integrated intensity maps for an example cloud (the Perseus Molecular Cloud), including the spine (thick red line), the distribution of integrated CO emission inside the filament mask (background grayscale), the perpendicular cuts across the spine (thin red lines) and the shifted peak integrated emission inside the filament mask (blue points). Note that the radial profiles are measured well beyond the boundaries of the mask, and the mask extent is only used for defining the spine and the optional shifting procedure. The remaining panels show normalized CO integrated intensity radial profiles (navy blues curves) alongside the inner component of the 3D dust derived profiles (black dotted curves) for the two-component Gaussian fits presented in the main text. Both components have been normalized to a peak value of one. We find no significant CO emission beyond the boundary of the 3D-dust-derived inner Gaussian profile, finding no direct evidence against the HI-to- H_2 transition scenario presented in §6.1.1