



A Parsec-scale Catalog of Molecular Clouds in the Solar Neighborhood Based on 3D Dust Mapping: Implications for the Mass–Size Relation

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Abstract

We dendrogram the Leike et al. 3D dust map, leveraging its ~ 1 pc spatial resolution to produce a uniform catalog of molecular clouds in the solar neighborhood. Using accurate distances, we measure the properties of 65 clouds in true 3D space, eliminating much of the uncertainty in mass, size, and density. Clouds in the catalog contain a total of $1.1 \times 10^5 M_\odot$, span distances of 116–440 pc, and include a dozen well-studied clouds in the literature. In addition to deriving cloud properties in 3D volume density space, we create 2D dust extinction maps from the 3D data by projecting the 3D clouds onto a 2D “Sky” view. We measure the properties of the 2D clouds separately from the 3D clouds. We compare the scaling relation between the masses and sizes of clouds following Larson. We find that our 2D projected mass–size relation, $M \propto r^{2.1}$, agrees with Larson’s Third Relation, but our 3D derived properties lead to a scaling relation of about one order larger: $M \propto r^{2.9}$. Validating predictions from theory and numerical simulations, our results indicate that the mass–size relation is sensitive to whether column or volume density is used to define clouds, since mass scales with area in 2D ($M \propto r^2$) and with volume in 3D ($M \propto r^3$). Our results imply a roughly constant column and volume density in 2D and 3D, respectively, for molecular clouds, as would be expected for clouds where the lower density, larger volume-filling gas dominates the cloud mass budget.

Unified Astronomy Thesaurus concepts: [Molecular clouds \(1072\)](#); [Solar neighborhood \(1509\)](#); [Star forming regions \(1565\)](#); [Scaling relations \(2031\)](#)

Supporting material: machine-readable tables, interactive figure

1. Introduction

Star formation takes place in molecular clouds, which are associated with the densest and coldest phase of the interstellar medium (ISM). Studying the properties of molecular clouds has thus long been the focus of star formation research, as the structure of these clouds has a direct impact on the location, number, size, and mass of newly formed stars (Rosolowsky et al. 2008).

Maps of the extinction or emission from dust trace out the ISM in “position–position” or “ p – p ” space, on the 2D plane of the sky (Lada et al. 2009; Lombardi 2009). Spectral-line observations of the ISM can add a third dimension, owing to the Doppler effect, which allows for conversion of wavelength or frequency to velocity. The resulting so-called “position–position–velocity” or “ p – p – v ” cubes can be analyzed as 2D maps (integrating over velocity) or as pseudo-3D maps, where velocity is treated as a nonspatial third dimension.

Catalogs of molecular clouds have previously been derived using both p – p and p – p – v data. Rice et al. (2016) use the dendrogram technique (Rosolowsky et al. 2008) to extract and analyze molecular clouds from the CO p – p – v survey of Dame et al. (2001), identifying over a thousand clouds across the full Galactic plane. Miville-Deschênes et al. (2016) apply a hierarchical cluster identification method to a Gaussian decomposition of Dame et al. (2001) and produce a catalog of 8107 clouds covering the entire Galactic plane. Using 2D

extinction maps derived from the NICEST color excess method (Lombardi 2009), Dobashi (2011) identifies over 7000 dark clouds in the Galactic plane using a fixed extinction threshold.

Numerical simulations show that projection effects intrinsic to p – p and p – p – v space impact the study of cloud structures (e.g., Ballesteros-Paredes & Mac Low 2002; Shetty et al. 2010). Investigating the overlap of clouds derived from simulated “position–position–position” (“ p – p – p ”) and p – p – v cubes, Beaumont et al. (2013) find that studying clouds in p – p – v space (rather than in true physical 3D space) can induce approximately 40% scatter in their masses, sizes, and velocity dispersions. Moreover, Beaumont et al. (2013) demonstrate that many p – p – v structures can be fictitious, especially in “crowded” regions. Thus, accurate estimates of cloud properties depend critically on studying clouds in p – p – p space, which requires knowledge of clouds’ distances.

In the past few years, distance estimates to molecular clouds have improved dramatically. Using so-called 3D dust mapping, Schlafly et al. (2014) produce one of the first uniform catalogs of accurate distances to nearby molecular clouds, with typical distance uncertainties of $\approx 10\%$. Specifically, Schlafly et al. (2014) use multiband photometry from Pan-STARRS1 (Chambers et al. 2019) to infer self-consistent distances and extinctions for a large number of stars across the solar neighborhood, the key ingredients necessary for constructing a 3D dust map (see also Green et al. 2015). The advent of the Gaia mission (Gaia Collaboration et al. 2016), and especially the results from its second and third data releases, Gaia DR2 and DR3 (Brown et al. 2018; Lindegren et al. 2021), has made it possible to construct ever-more-accurate 3D-dust-based distances to clouds, owing to stellar parallax measurements



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for millions of stars in the solar vicinity. Zucker et al. (2019) utilize the Gaia DR2 data release to produce an accurate catalog of distance estimates to molecular clouds, with uncertainties on the order of 5%–6% (see also Yan et al. 2019; Zucker et al. 2020).

Building on the accurate distances enabled in the Gaia era, there have only been two molecular cloud catalogs based on true three-dimensional p - p - p data obtained from 3D dust mapping, as presented in Chen et al. (2020) and Dharmawardena et al. (2023). Chen et al. (2020) obtain a catalog of 567 molecular clouds using the 3D dust map of Chen et al. (2018). However, the molecular clouds are typically resolved in distance on $\approx$ hundreds of parsecs scales, so key cloud properties, including the sizes of clouds, are still derived using 2D projections. Dharmawardena et al. (2023) also derive a catalog of molecular cloud properties toward sixteen complexes within 1–2 kpc from the Sun using their 3D dust mapping algorithm DUSTRIUM, which leverages stellar distance and extinction estimates from Fouesneau et al. (2022). Applying the *astrodendro* package (Robitaille et al. 2019) to 3D dust cutouts around each complex, Dharmawardena et al. (2023) obtain estimates of, e.g., the volume, mass, and density for each cloud and its myriad of substructure in p - p - p space (see also Dharmawardena et al. 2022).

However, one of the highest-resolution 3D dust maps over appreciable volumes of the solar neighborhood is the Leike et al. (2020) map, which traces the structure of the local ISM at ~ 1 pc distance resolution. Leveraging distance and extinction estimates from the StarHorse catalog (Anders et al. 2019), Leike et al. (2020) utilize a combination of Gaussian Processes and Information Field Theory to produce a highly resolved 3D dust map that charts molecular clouds out to a distance of $d \approx 400$ pc with distance uncertainties of lower than 1%. Such accurate distance uncertainties enable the extraction and characterization of molecular clouds in true 3D p - p - p space.

In this work, we dendrogram the Leike et al. (2020) 3D dust map and uniformly analyze the properties of resolved molecular clouds derived in p - p - p space. We produce a catalog of 65 distinct local molecular clouds, including a dozen well-studied clouds in the literature, and compare our results to extant literature derived primarily from p - p - v and p - p space. In Section 2 we present the Leike et al. (2020) data used to create the catalog. In Section 3 we present the dendrogram technique applied to the data to derive the properties of our molecular clouds in real 3D space. We then describe how we project our data into 2D space following Zucker et al. (2021), in order to measure the 2D properties of clouds. In Section 4 we summarize our cloud property results and characterize Larson’s mass–size relation in both 2D and 3D space. In Section 5 we hypothesize what could be driving differences between the 3D- and 2D-derived mass–size relations, and discuss our mass–size results in the context of existing literature, including a previous exploration of the mass–size relation using analytic theory and mathematical modeling (see Ballesteros-Paredes et al. 2012). Finally, we conclude in Section 6

2. Data

Leike et al. (2020) reconstruct the 3D dust distribution in a heliocentric Galactic cartesian reference frame out to a distance of ≈ 400 pc (-370 pc $< xy < 370$ pc, -270 pc $< z < 270$ pc). This distance range includes about a dozen well-studied star-

forming regions, including Taurus, Perseus, and Orion. We convert from the native units of the Leike et al. (2020) map (optical depth in the Gaia G band per 1 pc) to volume density of hydrogen nuclei (n_H) following Zucker et al. (2021) and Bialy et al. (2021). We derive all results in this work using the total volume density of hydrogen nuclei, including contributions from both atomic and molecular hydrogen gas.

3. Methods

3.1. Generating the 3D Dendrogram

After converting the 3D dust map of Leike et al. (2020) to total volume density of hydrogen nuclei, we segment the Leike et al. (2020) 3D dust map into a set of molecular cloud features and measure their properties using the dendrogram algorithm. To do so, we build upon the existing functionality for dendrogramming 3D p - p - v data in the *astrodendro* package. Abstractly, the dendrogram algorithm constructs a tree starting from the highest density point in N -dimensional density (volume density in this work) data, moving to the next largest value and connecting along isosurfaces of constant density. A leaf is defined to be a feature without any descendants. Each time a local maximum point is found (i.e., a leaf), the algorithm determines, based on neighboring maxima and the behavior of the contour levels between maxima, whether to join the pixel to an existing structure or to create a new structure. Once a local minimum point between the two structures is found, it is classified as a branch that connects the two structures. Iterations of this procedure will eventually either merge all values into a single tree or create multiple trees. Moreover, once the data are contoured with levels, the algorithm searches through every contour level, starting from the top, and records how many local maxima are above each contour level. When the surface around two local maxima merge together, that density level is recorded as a branch. If more than two local maxima merge together between two successive contour levels, the algorithm will continue to search with better tuned contour levels such that every merger includes up to two leaves. The dendrogram algorithm depends on three user-defined parameters set in the *astrodendro* package, $n_{\min}$, Δ_n , and $\#_{\text{voxels}}$:

1. $n_{\min}$: the minimum absolute volume density threshold for a structure to be included as part of the dendrogram.
2. Δ_n : how significant a leaf must be in order to be considered an independent entity. The significance is measured from the difference between its peak density and the density value at which it is being merged into the tree.
3. $\#_{\text{voxels}}$: the minimum number of voxels needed for a leaf to be considered an independent entity. If a leaf is about to be joined onto a branch or another leaf, the algorithm checks the leaf’s number of voxels. If the leaf’s number of voxels is lower than $\#_{\text{voxels}}$, the algorithm combines it with the branch or leaf it is being merged with, so that it is no longer considered a separate entity.

The dendrogram is most sensitive to changes in $n_{\min}$, as this value determines the minimum volume density value required to classify local maxima as meaningful. Setting a high $n_{\min}$ can lead to multiple isolated single-leaf trees, especially when dealing with 3D dust maps. To determine what values to adopt for these parameters, we created a set of different combinations

of values and compared the subsequent masses computed using these values to a benchmark sample of about a dozen well-studied clouds in p - p space from Lada et al. (2010) and p - p - p space from Zucker et al. (2021). We tailored the parameters to reproduce similar results to the bench-marked cloud samples. After testing multiple values for the parameters, we ultimately settled on a fixed threshold of: $n_{\min} = 25 \text{ cm}^{-3}$, $\Delta_n = 25 \text{ cm}^{-3}$, $\#_{\text{voxels}} = 150$ voxels. The result of this procedure is a hierarchy of cloud emission, where each structure in the dendrogram corresponds to a contiguous, resolved feature in 3D heliocentric Galactic cartesian xyz coordinates, bounded by a surface of constant volume density. In the next section, we filter the dendrogram to extract clouds and their properties.

3.1.1. Filtering 3D Features

After generating a hierarchy of cloud structure using the dendrogram approach, we need to convert the dendrogram tree into a meaningful set of molecular cloud features for analysis. In order to avoid both spurious features (with relatively low mass) and double counting of nested clouds (i.e., counting a branch and its leaves as separate structures), we introduce a filtering scheme.

Our filtering scheme is based on the adoption of a minimum cloud mass, $M_{\min}$, and cloud radius, $r_{\min}$, required for a feature to be included in the catalog. The mass is computed for all features as described in Section 3.1.2 below. We define $M_{\min} = 500 M_{\odot}$ and $r_{\min} = 2 \text{ pc}$. By using this definition, the algorithm only includes structures that correspond to trunks in the dendrogram that are above $M_{\min}$ and $r_{\min}$. All other structures are removed to avoid counting nested clouds, which by definition are not trunks.

Given that most dendrograms computed from 3D dust maps are composed of an ensemble of single structure trees, retaining only the trunk feature means retaining the structures defined by isosurfaces near $n_{\min} = 25 \text{ cm}^{-3}$. The filtered molecular cloud features extracted using this approach are highlighted and overlaid on the underlying Leike et al. (2020) 3D dust map in Figure 1. The implication of this filtering method is that we are removing most of the cloud hierarchy and limiting the extracted clouds to a narrow range in mean cloud density. In theory, we could achieve a similar catalog by thresholding the Leike et al. (2020) volume above a density of $n_{\min} = 25 \text{ cm}^{-3}$. However, we choose to dendrogram both to utilize the existing functionality of the *astrodendro* package (Robitaille et al. 2019) and to enable further follow-up studies of the full hierarchy.

In Figure 2, we show the full dendrogram and highlight the cloud features that survive filtering. The combined mass of the filtered-out structures is $3.7 \times 10^4 M_{\odot}$ and they are shown in black in Figure 2. The remaining, surviving clouds are color coded by the mean density, with the clouds possessing mean densities of between $n_{\text{average}} = 33\text{--}92 \text{ cm}^{-3}$. As we will discuss further in Section 5, the narrow range in density of extracted clouds will preordain the mass–size results we obtain in Section 4 due to the large filling factor of low-density gas near the chosen $n_{\min}$ (see, e.g., further discussion in Beaumont et al. 2012).

Finally, we also recognize that a relatively low volume density isosurface is defining the 3D cloud boundaries. However, it is not possible to define clouds using significantly higher volume density thresholds because the Leike et al. (2020) 3D dust map is not sensitive to the highest volume

density regions within molecular clouds due to the map’s reliance on optical stellar photometry and astrometry from Gaia (Brown et al. 2018). Despite not being sensitive to very high volume densities, Zucker et al. (2021) show that the Leike et al. (2020) is still recovering cloud properties based on 2D integrated approaches, as determined for a benchmark sample of well-studied clouds. Thus, the low isosurface levels defining cloud boundaries should not have a significant effect on our mass results.

3.1.2. Measuring Cloud Properties in 3D

To calculate the properties of clouds in p - p - p space, we again build on existing infrastructure for computing cloud properties in p - p and p - p - v space using the *astrodendro* package (Robitaille et al. 2019). In order to calculate cloud properties, we take as input the dendrogrammed cloud structure, where each cloud structure consists of a set of contiguous volume density voxels bounded by a surface of constant volume density. We first calculate physical properties for all structures and subsequently define the final cloud catalog through filtering as explained in Section 3.1.1. Our catalog includes the following properties for every cloud (see Table 1).⁴

1. V (pc^3): exact volume of the structure in p - p - p space.
2. r (pc): equivalent radius of the sphere occupying the same volume as the exact volume V
3. x , y , z (pc): central x , y , and z position of the cloud in heliocentric Galactic cartesian coordinates.
4. l ($^{\circ}$), b ($^{\circ}$), and d (pc): the cloud’s Galactic coordinates (longitude, latitude, and distance), computed from the mean x , y , and z position of the cloud in heliocentric Galactic cartesian coordinates.
5. M ($M_{\odot}$): the mass of the cloud, calculated as follows:

$$M = \sum dM_i = \sum 1.37 m_p \times n_i \times dV_i. \quad (1)$$

The total mass is the sum of the mass in each individual voxel dM_i , computed by multiplying the volume density in the i th voxel (n_i) by the mean molecular weight of hydrogen ($1.37 \times m_p$, correcting for the helium abundance) and its volume (1 pc^3).

6. n_{peak} (cm^{-3}): maximum volume density within the cloud.
7. A (pc^2): surface area of the cloud, calculated by assuming a spherical geometry with a radius of r and determining the cross-sectional area (πr^2).
8. Σ ($M_{\odot} \text{ pc}^{-2}$): the mass surface density of the cloud, given as the cloud’s mass divided by its surface area.
9. n_{average} (cm^{-3}): average volume density of the cloud.

3.2. 2D Methods

3.2.1. Converting 3D Dust Data into 2D Extinction Maps

Once a catalog of cloud features is defined and characterized in 3D, we create a 2D projected map of each 3D cloud following the methodology of Zucker et al. (2021; see their Section 3.3 for full details). Briefly, that work uses the *yt* package (Turk et al. 2011) to integrate 3D volume density cubes (containing the 3D cloud of interest) along the line of

⁴ We adapted and extended a version of the *astrodendro* package written by Dario Colombo and Ana-Duarte Cabral. The software is available here: <https://github.com/dendrograms/astrodendro/pull/147/files>.

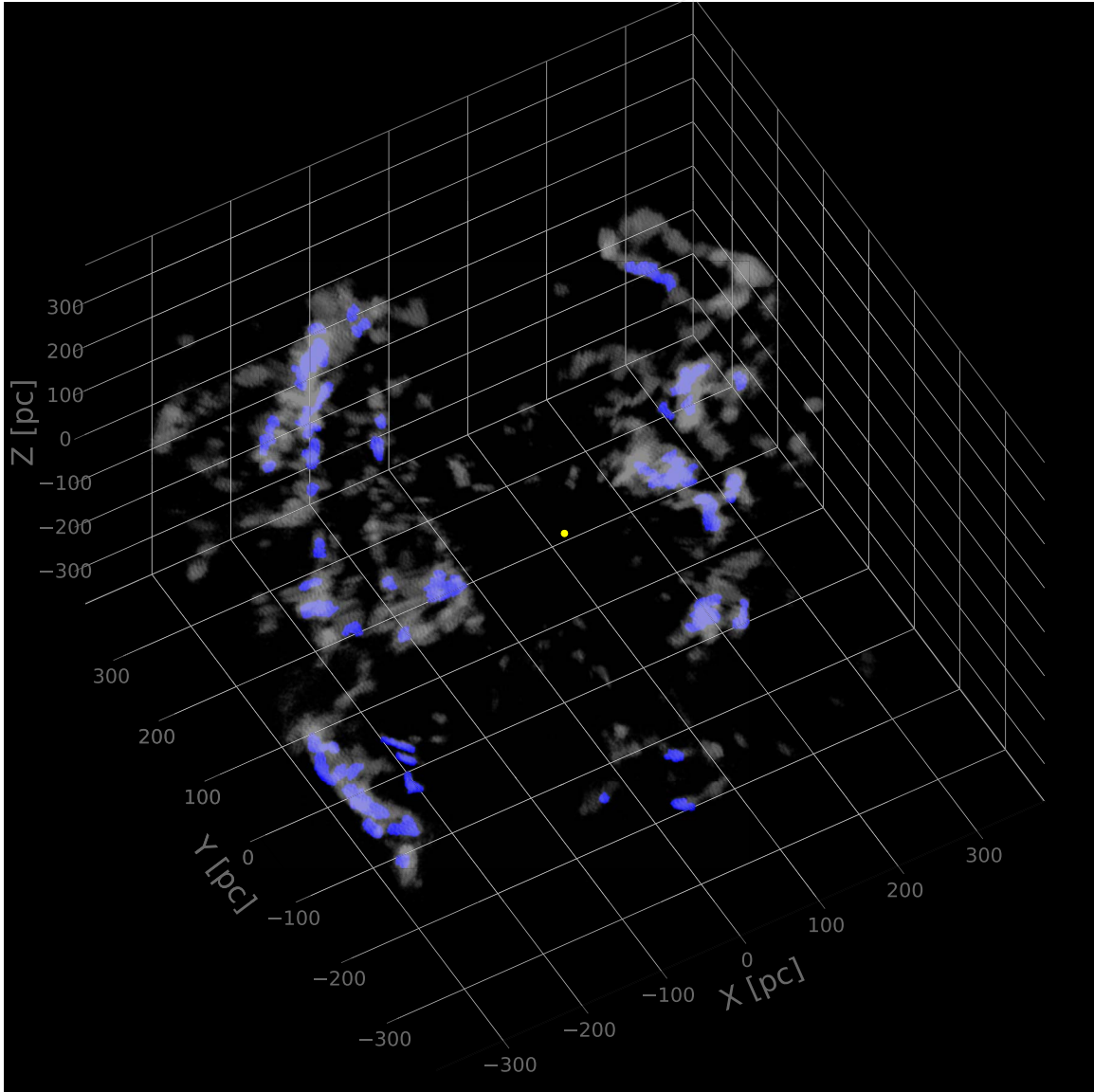


Figure 1. The 3D spatial map of the local ISM, showing all gas with density $n > 5 \text{ cm}^{-3}$ (gray) and clouds identified in this work (blue). The Sun is shown at center in yellow. An interactive version of this figure is available in the electronic edition and at https://faun.rc.fas.harvard.edu/czucker/Paper_Figures/3D_Cloud_Catalog_Cahlon_2023.html. The text to the right can be clicked to turn on/off these portions of the figure. In addition, the standard Plotly commands, i.e., zoom, pan, rotation, and reset, are available via the buttons in the top-right corner of the interactive figure. An interactive version of this figure is available.

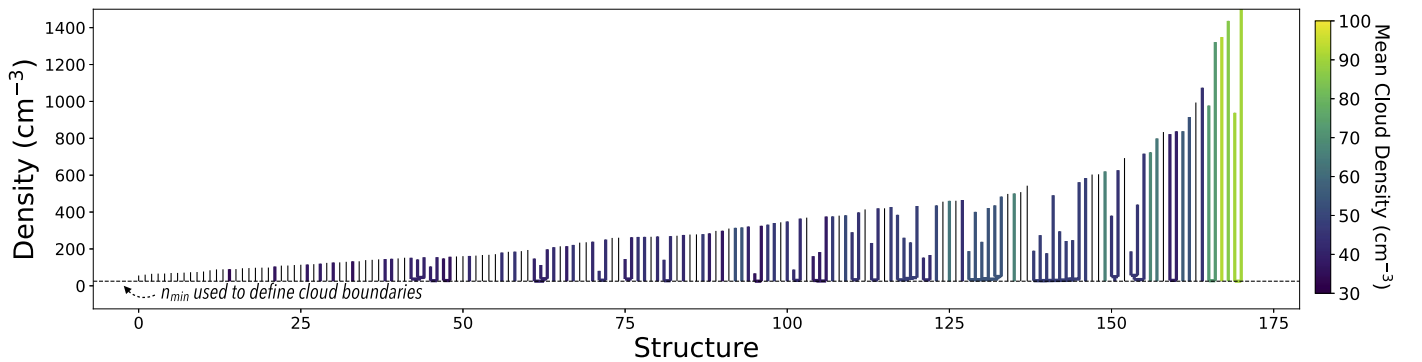


Figure 2. Dendrogram of the Leike et al. (2020) 3D dust map. Structures that survive the cloud filtering scheme summarized in Section 3.1.1 are color coded by their mean density (n_{average} in the context of Table 1), with filtered-out structures shown in black (totaling $3.7 \times 10^4 M_{\odot}$). A constant isosurface density of $n_{\text{min}} = 25 \text{ cm}^{-3}$ (dashed horizontal line) is used to define cloud boundaries and will preordain the narrow range of mean cloud volume densities ($33 \text{ cm}^{-3} \leq n_{\text{average}} \leq 92 \text{ cm}^{-3}$) seen in our sample.

Table 1
The 3D Cloud Catalog

Cloud	Complex	x (pc)	y (pc)	z (pc)	l (deg)	b (deg)	d (pc)	n_{average} (cm^{-3})	n_{peak} (cm^{-3})	M ($M_{\odot}$)	r (pc)	A (pc^2)	V (pc^3)	Σ ($M_{\odot} \text{pc}^{-2}$)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
0	...	-218	82	-157	159.2	-33.9	282	52	314	1352	5.8	106	826	12
1	Orion A ^a	-340	-236	-148	214.8	-19.8	440	38	120	774	5.4	90	647	8
2	Orion A ^a	-348	-184	-143	207.9	-20.0	419	45	221	1624	6.5	133	1163	12
3	Orion A ^a	-320	-204	-135	212.6	-19.6	403	44	1074	3996	8.9	247	2923	16
4	...	-288	-162	-116	209.4	-19.3	350	92	1349	2947	6.3	123	1029	23
5	...	-356	-158	-117	204.0	-16.8	406	53	915	590	4.4	61	359	9
6	Perseus	-257	97	-102	159.3	-20.4	294	40	154	6425	10.7	361	5159	17
7	Orion B ^a	-351	-172	-100	206.1	-14.4	404	45	716	10,878	12.3	472	7736	23
8	...	140	-147	-113	313.5	-29.1	232	47	427	590	4.6	66	406	8
9	Orion λ ^a	-363	-101	-108	195.6	-16.0	392	38	375	2019	7.4	173	1718	11
10	...	-280	-136	-102	206.0	-18.2	328	85	1436	1867	5.5	95	704	19
11	...	-277	-114	-101	202.4	-18.8	316	90	3505	2207	5.7	103	790	21
12	Orion λ ^a	-360	-76	-86	192.0	-13.2	378	39	838	1526	6.7	140	1248	10
13	...	142	-145	-84	314.6	-22.5	220	66	620	758	4.4	62	368	12
14	Orion λ ^a	-359	-129	-79	199.7	-11.7	390	39	146	1031	5.9	107	843	9
15	Orion λ ^a	-350	-94	-78	195.0	-12.2	371	72	1321	1335	5.2	85	594	15
16	...	-254	118	-76	155.0	-15.3	291	42	364	925	5.5	95	697	9
17	...	-61	-363	-69	260.4	-10.7	374	55	838	1649	6.1	117	953	14
18	...	-129	-310	-74	247.4	-12.4	344	66	500	595	4.1	52	289	11
19	...	-347	-140	-69	202.0	-10.6	381	36	325	626	5.1	82	560	7
20	Musca and Chamaeleon	88	-153	-48	300.0	-15.3	183	53	483	6162	9.6	291	3734	21
21	...	-212	-13	-43	183.8	-11.5	216	38	284	660	5.1	81	554	8
22	Taurus	-141	20	-37	171.6	-14.8	147	47	562	6352	10.1	320	4312	19
23	...	-41	-313	-41	262.4	-7.5	318	63	799	1244	5.3	89	632	14
24	...	191	111	-24	30.1	-6.3	223	43	209	548	4.6	66	411	8
25	...	281	101	-17	19.8	-3.4	299	37	126	761	5.4	91	657	8
26	...	-197	44	-15	167.3	-4.4	202	39	214	590	4.9	74	488	7
27	...	272	282	-12	46.0	-1.8	392	40	197	4501	9.5	285	3625	15
28	...	74	-171	-13	293.4	-4.0	187	41	275	639	4.9	75	495	8
29	...	215	120	-8	29.2	-2.0	247	36	104	718	5.3	89	639	8
30	...	96	-159	-7	301.1	-2.4	186	43	267	613	4.8	72	461	8
31	Lupus	193	-35	12	349.6	3.5	197	40	263	2267	7.6	180	1816	12
32	...	-245	112	8	155.3	1.9	269	44	348	896	5.4	90	645	9
33	Lupus	149	-59	16	338.5	5.9	161	44	398	4210	9.0	253	3029	16
34	Pipe and Ophiuchus	134	-5	29	357.8	12.3	138	47	432	8177	11.0	378	5529	21
35	...	228	114	21	26.5	4.7	256	35	157	2188	7.8	189	1969	11
36	...	201	77	21	21.1	5.6	217	33	90	601	5.2	84	586	7
37	...	-225	263	24	130.6	4.0	347	39	155	868	5.5	95	707	9
38	...	-205	283	24	125.9	4.0	350	42	162	633	4.9	74	485	8
39	...	-148	318	31	115.0	5.2	352	43	250	1043	5.7	101	772	10
40	...	-175	267	28	123.2	5.0	321	46	331	511	4.4	61	359	8
41	...	219	113	31	27.2	7.3	249	39	145	552	4.8	71	453	7
42	Ophiuchus	141	-24	38	350.0	15.1	148	43	180	1054	5.7	102	777	10
43	...	-199	207	39	133.9	7.9	290	44	420	1388	6.2	121	1009	11
44	...	-106	218	37	116.1	8.7	245	42	239	522	4.6	65	397	8
45	...	-164	271	39	121.2	7.1	319	47	584	621	4.6	67	420	9
46	Ophiuchus	107	18	39	9.9	19.9	116	46	376	640	4.7	70	443	9
47	...	-245	221	42	138.0	7.3	333	44	265	858	5.3	88	626	9
48	Ophiuchus	141	10	43	4.1	17.2	148	37	298	660	5.1	83	570	7
49	Lupus	138	-55	45	338.2	16.7	156	63	460	663	4.3	58	340	11
50	Lupus	168	-71	48	337.0	14.9	189	43	269	595	4.7	70	442	8
51	...	-223	166	48	143.3	9.9	282	44	185	609	4.7	69	439	8
52	...	-132	179	54	126.5	13.8	230	46	280	1589	6.4	129	1106	12
53	...	-144	275	56	117.7	10.4	315	42	434	1193	6.0	112	903	10
54	...	-195	208	64	133.2	12.6	293	46	340	964	5.4	93	675	10
55	...	-191	227	73	130.0	13.9	306	50	436	904	5.2	84	583	10
56	Cepheus	-78	320	80	103.7	13.8	339	53	316	854	5.0	77	515	11
57	Cepheus	-133	303	99	113.8	16.6	346	44	627	4535	9.2	267	3283	17
58	Cepheus	-69	318	89	102.3	15.4	338	68	724	988	4.8	73	469	13
59	Cepheus	-79	328	108	103.6	17.8	354	35	132	568	5.0	78	518	7
60	Cepheus	-143	293	116	116.0	19.6	346	44	265	1065	5.7	102	780	10
61	Cepheus	-128	320	126	111.8	20.2	367	50	382	1261	5.8	104	802	12

Table 1
(Continued)

Cloud	Complex	x (pc) (3)	y (pc) (4)	z (pc) (5)	l (deg) (6)	b (deg) (7)	d (pc) (8)	n_{average} (cm^{-3}) (9)	n_{peak} (cm^{-3}) (10)	M ($M_{\odot}$) (11)	r (pc) (12)	A (pc^2) (13)	V (pc^3) (14)	Σ ($M_{\odot} \text{pc}^{-2}$) (15)
(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
62	...	−165	268	145	121.6	24.7	347	40	321	960	5.7	100	760	9
63	...	−179	265	150	124.0	25.2	353	43	465	705	5.0	78	519	9
64	...	−175	256	181	124.4	30.2	360	37	115	675	5.2	84	580	8

Notes. Properties of local molecular clouds derived in 3D p - p space. (1) Cloud Index; (2) association with well-studied nearby cloud complexes; (3)–(5) heliocentric Galactic cartesian coordinates x , y , z ; (6)–(7) central Galactic longitude l and latitude b ; (8) distance; (9) average volume density; (10) peak volume density; (11) mass; (12) radius; (13) surface area; (14) volume; (15) surface mass density. A FITS version of this table is available at doi:[10.7910/DVN/BFYD88](https://doi.org/10.7910/DVN/BFYD88).
^a The Orion Clouds lie at the very edge of the Leike et al. (2020) 3D dust grid, thus adding more uncertainty to their derived properties, and should be treated with caution.

(This table is available in machine-readable form.)

sight and produce 2D maps of the total hydrogen column density. For each cloud, we obtain a 3D volume density subregion suitable for projection by extracting a cutout of the Leike et al. (2020) 3D dust map using the minimum and maximum extent of the cloud boundaries along x , y , and z . Once we obtain the projected 2D column density maps, we convert from total hydrogen column density to visual extinction in the K band using a relation from Lada et al. (2009) of $\frac{N(\text{H I}) + 2N(\text{H}_2)}{A_K} = 1.67 \times 10^{22} \text{ cm}^{-2} \text{ mag}^{-1}$ to produce a map of K -band extinction, A_K . Converting to A_K allows us to compare to previous 2D cloud catalogs built on similar maps of integrated dust extinction from Lada et al. (2009).

To analyze the 2D maps, we extract clouds on the plane of the sky using the existing p - p dendrogramming functionality of the *astrodendro* package. In order to understand how 3D clouds map to 2D projected space we use Zucker et al. (2021) as a guide, who analyze the 3D cartesian space (x , y , z) and Galactic (l , b , d) coordinates of a sample of famous nearby clouds. Identifying the relevant plane-of-sky features from the 3D projected famous cloud data, we then use Lada et al. (2009) as a benchmark to determine the optimal $A_{K_{\min}}$, Δ_{A_K} , and $\#_{\text{pixels}}$ parameters (where $A_{K_{\min}}$, Δ_{A_K} , and $\#_{\text{pixels}}$ are the 2D analogs of the $n_{\min}$, Δ_n , and $\#_{\text{voxels}}$ 3D input parameters described in Section 3.1) for computing the dendrogram, with the goal of obtaining cloud sizes similar to those derived by Lada et al. (2009). With the intention of also having a single 2D structure representing each 3D cloud feature, we settle on $A_{K_{\min}} = 0.05 \text{ mag}$, $\Delta_{A_K} = 0.05 \text{ mag}$, and $\#_{\text{pixels}} = 300 \text{ pixels}$ as the dendrogram input parameters.

In Figure 3, we show an example of the 3D to 2D projection for a single feature in the catalog (the Perseus molecular cloud). We emphasize that due to the imperfect mapping from 3D to 2D space—stemming from the complex geometries of individual clouds (Zucker et al. 2021)—a few 3D features do not have a 2D counterpart, largely because they were subdivided into multiple components and failed to produce a cloud feature with the same mass and/or size minima adopted for the 3D catalog. Our goal in this work is not to measure the most accurate 2D-based properties of molecular clouds. Rather, we seek to understand how defining features in 3D versus 2D projected space (given the same underlying 3D data) affects cloud properties in aggregate.

Nevertheless, for clouds that have a 2D counterpart meeting these criteria (61/65 clouds, or $\approx 94\%$ of the 3D sample), the morphological matching between 3D and 2D cloud shapes is

clear. We show and discuss the correspondence between 3D and 2D further in Appendix B.

3.2.2. Calculating Properties for 2D Projected Structures

After creating the dendrogram based on the A_K maps, we filter the features in our 2D catalog by implementing the same minimum mass threshold ($M_{\min} = 500 M_{\odot}$) and radius threshold ($r_{\min} = 2 \text{ pc}$) as our 3D data. In 2D space we measure the following properties:

1. l ($^{\circ}$): central longitude of the cloud.
2. b ($^{\circ}$): central latitude of the cloud.
3. d (pc): the distance of the cloud.⁵
4. A (pc^2): exact surface area of the structure in p - p space.
5. M ($M_{\odot}$): mass of the cloud, derived using the following mass surface density relation from Zari et al. (2016) and the distance of the cloud originally detected in 3D:

$$\frac{\Sigma_{\text{gas}}}{A_K} = \mu m_p \beta_K = 183 M_{\odot} \text{ pc}^{-2} \text{ mag}^{-1}. \quad (2)$$

6. r (pc): radius calculated using the exact area of the structure in p - p space ($\sqrt{\frac{A}{\pi}}$) assuming a spherical geometry.
7. Σ ($M_{\odot} \text{ pc}^{-2}$): the mass surface density of the cloud, given as the cloud’s mass divided by its surface area.

4. Results

4.1. Summary of 3D and 2D Cloud Properties

In Table 1, we present a summary of the properties of molecular clouds derived in 3D space following Section 3.1.2. A machine-readable version of Table 1 and its associated *astrodendro* dendrogram file is available online at the Harvard Dataverse (doi:[10.7910/DVN/BFYD88](https://doi.org/10.7910/DVN/BFYD88)). The 3D catalog contains a total mass of $1.1 \times 10^5 M_{\odot}$ across the 65 cloud features identified in 3D volume density space, with an average cloud mass of $M = 1.7 \times 10^3 M_{\odot}$. The distance range of the clouds spans $d = 116$ – 440 pc . The typical average density of clouds in the 3D catalog is $n_{\text{average}} = 47 \text{ cm}^{-3}$, while the typical peak density is about an order of magnitude higher ($n_{\text{peak}} = 414 \text{ cm}^{-3}$). We find an average cloud volume of $V = 1220 \text{ pc}^3$ and an average equivalent radius assuming a spherical geometry of $r = 6 \text{ pc}$, though we emphasize that

⁵ Retrieved from the 3D cloud structure before projecting.

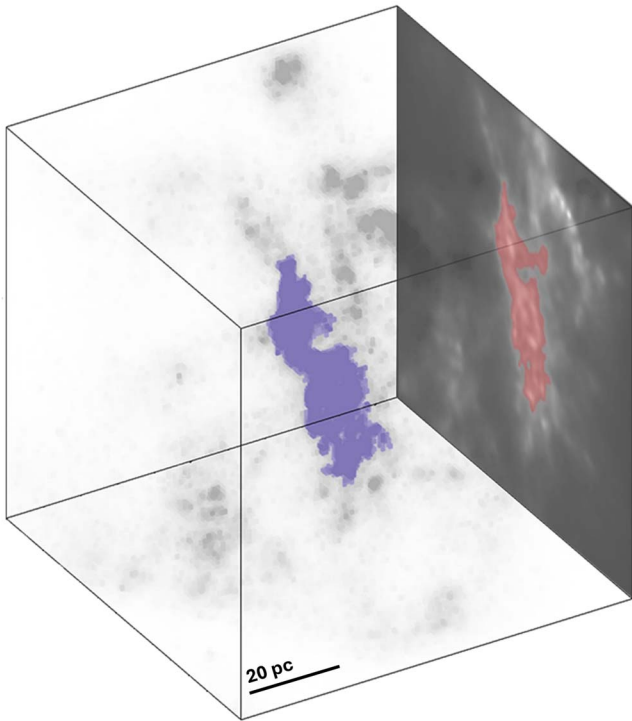


Figure 3. Comparison between the 3D and projected 2D dust data for the Perseus molecular cloud. The feature corresponding to the Perseus molecular cloud in 3D volume density space is shown in blue. The 3D dust has been projected onto the plane of the sky and shown via an A_K extinction map in the background, where the 2D feature corresponding to the Perseus molecular cloud is shown in red.

some of the clouds show more complex, extended geometries. While every 3D cloud feature is assigned a unique identifier, the catalog includes a number of well-studied clouds in the literature, including Perseus, Taurus, Lupus, Chamaeleon, Cepheus, and the Orion complex (Orion A, Orion B, and λ Orion) that have been denoted as such in a separate column in Table 1 to aid comparison with existing studies.

In Table 2 we present the corresponding catalog of 2D cloud properties derived from the projected 3D data following Section 3.2.2. A machine-readable version of Table 2 is likewise available online at the Harvard Dataverse (doi:10.7910/DVN/BFYD8). The 2D catalog contains a total mass of $2 \times 10^5 M_\odot$ across the 61 cloud features derived from the projection of the 3D cloud data. One of these 61 clouds, feature 7, is broken into two components, leading to a total of 62 clouds in Table 2. Moreover, in Table 2 we use the same cloud identifiers as Table 1, which specifies how each 2D cloud feature maps to its 3D counterpart. In the case of a cloud in Table 1 that has no corresponding cloud identifier in Table 2, the cloud was filtered for not meeting our minimum mass threshold of $500 M_\odot$. The typical radius of clouds in the 2D catalog is marginally larger than in the 3D catalog, averaging $r = 7$ pc, and the average cloud mass is about a factor of two higher, at $M = 3.2 \times 10^3 M_\odot$.

Considering the ensemble of clouds, the total mass of the entire 2D-derived catalog is approximately $\approx 1.9\times$ higher than the total mass of the 3D-derived catalog. The discrepancy suggests that projecting 3D gas density into 2D can alter the perceived shape of molecular clouds enough to bear significantly on their derived mass. This effect likely stems from the complications of projecting a nonspherical 3D cloud geometry

onto the plane of the sky, resulting in a different cloud boundary definition. However, diffuse emission in the vicinity of the cloud also likely plays a major role.

As a testament to the impact of diffuse intervening gas, recall that we create 2D dust maps by projecting 3D dust cutouts that were extracted using a bounding box corresponding to the minimum and maximum extents of the 3D cloud features in xyz space. Over the sample of 3D cutouts, we compute the ratio of the mass inside the 3D features to the mass outside the feature but within the bounding box used for 2D projections. We find that, over the full sample, there is $2\times$ as much mass outside the 3D dendrogrammed features as within them. Thus, if even half of this excess mass in the vicinity of each cloud is incorporated into the 2D cloud definitions, this contamination would be enough to account for the discrepancy in total mass between the 3D- and 2D-derived catalogs that we observe.

4.2. Fitting the Mass–Size Relation

We use the masses and sizes in Tables 1 and 2 to explore the mass–size relation, first proposed by Larson (1981). Larson (1981) concludes that the mass M contained within a cloud of radius r obeys a power law of the form:

$$M(r) = a \times \left(\frac{r}{\text{pc}} \right)^b. \quad (3)$$

Larson (1981) obtains the relation that $M(r) = 460 M_\odot \times \left(\frac{r}{\text{pc}} \right)^{1.9}$ or, more generally, that the mass of a cloud is proportional to its area, implying constant column density. This law of constant column density has come to be known as one of the fundamental properties of molecular cloud structure (McKee & Ostriker 2007). Recently, a similar relationship between the masses and lengths L of filaments ($M \propto L^2$) has also been found (Hacar et al. 2022) and attributed to turbulent fragmentation. With the goal of testing whether the dimensionality used to define clouds affects our results, we fit the mass–size relation in both 3D and 2D space. Fitting the relation in log–log space, we use a linear-least-squares fitter to obtain a , b and their associated uncertainties. For the 3D results, we obtain $\log M = 2.9 \times \log r (\pm 0.1) + 0.86 (\pm 0.3)$ such that:

$$M(r) = 7 M_\odot \times \left(\frac{r}{\text{pc}} \right)^{2.9}. \quad (4)$$

And for the 2D results, we obtain $\log M = 2.1 \times \log r (\pm 0.2) + 1.59 (\pm 0.4)$, such that:

$$M(r) = 39 M_\odot \times \left(\frac{r}{\text{pc}} \right)^{2.1}. \quad (5)$$

Moreover, we have included in the Appendix (see Appendix A) another version of the 2D catalog with a minimum extinction threshold when defining the dendrogram of $A_{K_{\min}} = 0.1$ mag. This test yielded fewer features, as expected, but maintained a similar mass–size relation of $M(r) = 83 M_\odot \times \left(\frac{r}{\text{pc}} \right)^{1.9}$, confirming that the scaling of the mass–size relation does not depend on the threshold used to define cloud boundaries. We also repeat both fits using only the subset of the clouds which are well studied in the literature (e.g., Perseus, Taurus, Lupus,

Table 2
The 2D Projected Catalog

Cloud	Complex	l	b	d	M	r	A	Σ
(1)	(2)	(deg)	(deg)	(pc)	($M_{\odot}$)	(pc)	(pc^2)	($M_{\odot} \text{pc}^{-2}$)
0	...	159.1	−33.8	282	1609	5.2	84	19
1	Orion A ^a	214.9	−19.6	440	1184	5.2	85	14
2	Orion A ^a	207.8	−20.0	419	2179	6.6	137	16
3	Orion A ^a	212.7	−19.5	403	6159	10.4	341	18
4	...	209.2	−19.3	350	2758	6.2	121	23
6	Perseus	159.0	−20.3	294	13,083	14.7	679	19
7 ₀	Orion B ^a	206.1	−13.9	404	20,143	18.0	1013	20
7 ₁	Orion B ^a	204.0	−16.6	404	595	3.7	43	14
8	...	313.5	−28.9	232	887	4.4	59	15
9	Orion λ^a	195.1	−16.0	392	2917	8.2	209	14
12	Orion λ^a	192.0	−13.3	378	3055	8.7	238	13
13	...	313.9	−22.4	220	508	3.3	34	15
14	Orion λ^a	199.7	−11.6	390	1537	5.6	98	16
15	Orion λ^a	194.8	−12.0	371	1436	5.1	81	18
16	...	154.9	−15.3	291	1507	5.5	95	16
17	...	260.2	−10.5	374	1458	5.5	96	15
18	...	247.5	−12.4	344	590	3.0	28	21
19	...	201.9	−10.4	381	1635	5.9	109	15
20	Musca and Chamaeleon	299.5	−14.7	183	10,500	14.6	668	16
21	...	183.5	−11.7	216	1267	5.7	102	12
22	Taurus	171.2	−14.2	147	16,652	17.3	936	18
23	...	262.8	−7.6	318	615	3.5	38	16
24	...	30.4	−6.0	223	618	3.8	46	13
25	...	20.1	−3.4	299	1576	6.3	124	13
26	...	167.0	−4.1	202	620	4.0	49	13
27	...	46.4	−1.5	392	10,262	14.1	625	16
28	...	293.4	−3.9	187	975	4.6	67	15
29	...	29.3	−1.8	247	1206	5.5	93	13
30	...	301.3	−2.3	186	721	4.0	49	15
31	Lupus	349.6	3.8	197	4179	9.5	285	15
32	...	155.3	1.9	269	1247	5.3	88	14
33	Lupus	338.3	6.1	161	8462	13.0	530	16
34	Pipe and Ophiuchus	0.0	13.7	138	30,146	22.0	1516	20
35	...	26.4	5.3	256	8225	12.1	463	18
36	...	21.4	5.3	217	1915	7.2	161	12
37	...	131.2	4.2	347	1792	6.4	130	14
38	...	126.0	4.0	350	876	4.5	62	14
39	...	115.0	5.1	352	1743	6.1	115	15
40	...	123.2	5.1	321	577	3.7	41	14
41	...	27.3	7.3	249	871	4.6	66	13
42	Ophiuchus	350.3	15.2	148	1454	5.5	95	15
43	...	133.7	7.9	290	1998	6.7	142	14
44	...	115.9	8.7	245	677	4.1	52	13
45	...	121.4	7.0	319	616	3.7	42	15
46	Ophiuchus	9.5	19.9	116	1018	4.8	73	14
47	...	137.9	7.5	333	1158	5.1	81	14
48	Ophiuchus	4.5	17.3	148	1172	5.4	92	13
49	Lupus	338.4	16.9	156	703	3.6	39	18
51	...	143.1	10.0	282	702	3.9	48	15
52	...	126.3	13.9	230	2273	6.8	144	16
53	...	117.4	10.8	315	1256	5.6	98	13
54	...	133.1	12.7	293	1224	5.2	85	14
55	...	129.8	14.0	306	1177	4.9	76	16
56	Cepheus	103.6	13.9	339	998	4.2	54	18
57	Cepheus	113.7	16.7	346	6944	10.6	353	20
58	Cepheus	102.2	15.4	338	1055	4.1	53	20
59	Cepheus	103.4	17.8	354	1019	5.2	85	12
60	Cepheus	116.0	19.7	346	1447	5.4	92	16
61	Cepheus	111.7	20.2	367	1556	5.5	94	17
62	...	121.4	24.8	347	1431	5.7	102	14
63	...	124.0	25.3	353	976	4.6	65	15
64	...	124.3	30.2	360	998	4.9	74	14

Notes. Properties of the 2D projected local molecular clouds. (1) Cloud index; (2) association with well-studied nearby cloud complexes; (3)–(4) central Galactic longitude l and latitude b ; (5) distance; (6) mass; (7) radius; (8) exact area; (9) surface mass density. A small fraction of the 3D clouds did not have a 2D counterpart that met our cloud definition, which accounts for the fact that there are 62 structures identified in 2D after projecting our 65 3D structures from Table 1 onto the plane of the sky. A FITS version of this table is available at doi:[10.7910/DVN/BFYD88](https://doi.org/10.7910/DVN/BFYD88). Projecting feature 7 from 3D into 2D with $A_{K_{\min}} = 0.05$ mag yields two components, 7₀ and 7₁. A version of this table with a higher minimum threshold for cloud boundary definition, $A_{K_{\min}} = 0.1$ mag, is available in the Appendix.

^a The Orion Clouds lie at the very edge of the Leike et al. (2020) 3D dust grid, thus adding more uncertainty to their derived properties, and should be treated with caution.

(This table is available in machine-readable form.)

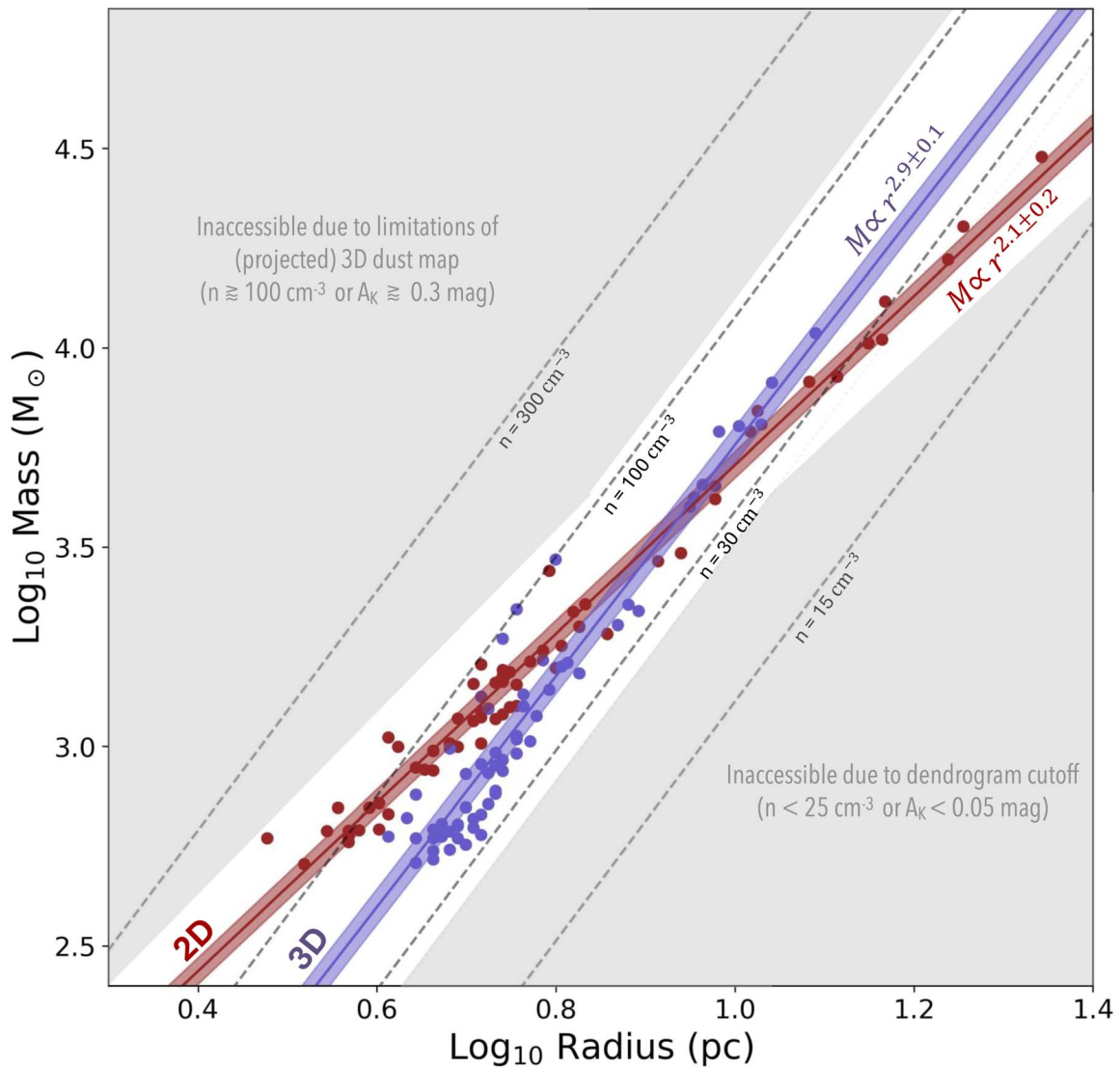


Figure 4. Comparison of the mass–size relation derived from our 3D catalog (blue points) and 2D catalog (red points) of molecular cloud properties. In 3D, $M \propto r^{2.9}$, while in 2D, $M \propto r^{2.1}$. We demarcate the 95% confidence interval with the thin semitransparent band around each best-fit line. We include four lines of constant volume density ($n = 15, 30, 100, 300 \text{ cm}^{-3}$) in dashed semitransparent black lines. The gray triangles represent the inaccessible volume and column densities, either due to the minimum volume and extinction thresholds required for inclusion in the 3D and 2D dendrograms ($n < 25 \text{ cm}^{-3}$ and $A_K < 0.05 \text{ mag}$) or the inability of the 3D dust map to probe higher densities due to the map’s reliance on optical stellar photometry ($n \gtrsim 100 \text{ cm}^{-3}$ or $A_K \gtrsim 0.2\text{--}0.3 \text{ mag}$).

Chamaeleon, Cepheus, and the Orion complex), finding that the results agree with the full catalog fits within our reported uncertainties.

In Figure 4, we plot mass versus size for our 3D and 2D catalogs with the best fits overlaid and four lines of constant volume density ($n = 15, 30, 100, \text{ and } 300 \text{ cm}^{-3}$), assuming purely spherical geometries. Figure 4 shows that the clouds in the 3D catalog lay between $n = 30 \text{ cm}^{-3}$ and $n = 100 \text{ cm}^{-3}$ lines of constant volume density, which we will argue in Section 5 is a consequence of our dendrogramming procedure and the narrow volume density range probed by the Leike et al. (2020) 3D dust map.

5. Discussion

Here, we compare our results for the 3D and 2D mass–size relation with extant results from the literature. We base our comparison on the work of Lada & Dame (2020), which analyzes both dust-based cloud catalogs and CO-based cloud

catalogs to investigate the nature of the mass–size relation in the Milky Way. Specifically, we consider the original cloud sample of Larson (1981), alongside more recent cloud catalogs reanalyzed in Lada & Dame (2020), including: the Rice et al. (2016) catalog based on a dendrogram decomposition of the Dame et al. (2001) ^{12}CO survey; the Miville-Deschênes et al. (2016) catalog based on a hierarchical clustering algorithm applied to Gaussian fits of the same Dame et al. (2001) ^{12}CO survey; and the Chen et al. (2020) catalog based on the 3D dust map of Chen et al. (2018). We also include a comparison to Dharmawardena et al. (2023), which is the only other study to extract cloud properties in p – p – p space. For consistency, we compare to the Dharmawardena et al. (2023) primary trunks only catalog (see Table 2 in their work).

In Figure 5, we plot our mass–size results in context. Following Lada & Dame (2020), the catalogs from Miville-Deschênes et al. (2016), Rice et al. (2016), and Chen et al. (2020) are all consistent with $b = 2$ ($M \sim r^2$), implying constant

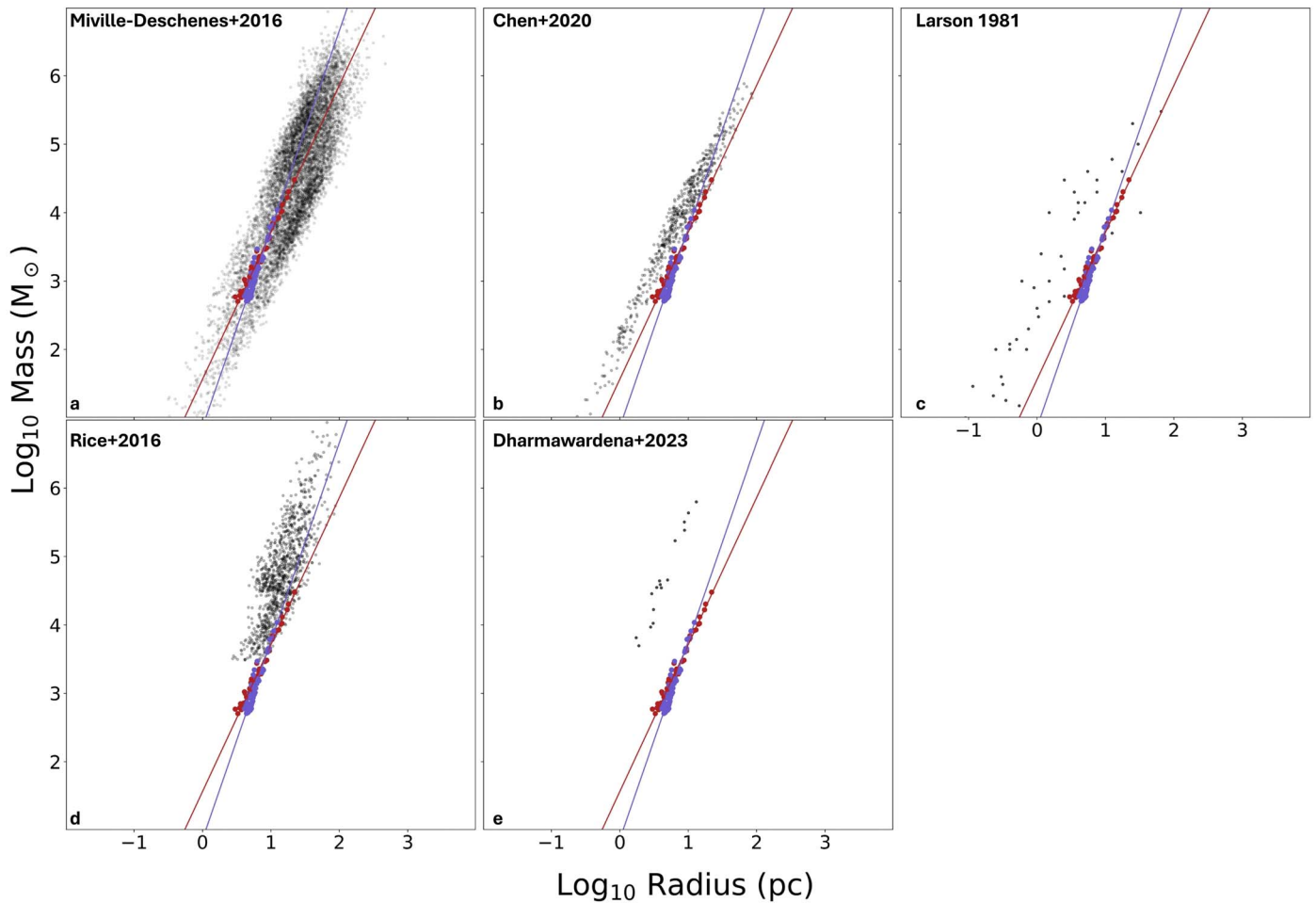


Figure 5. The 3D and 2D mass–size relations for the 3D dust (blue) and projected 2D dust (red) cloud catalogs, in comparison to five catalogs from the literature, including (a) Miville-Deschênes et al. (2016), (b) Chen et al. (2020), (c) Larson (1981), (d) Rice et al. (2016), and (e) Dharmawardena et al. (2023).

surface (column) density across molecular clouds. While some of the clouds in these catalogs may have originally been identified using 3D p – p – v data (Miville-Deschênes et al. 2016; Rice et al. 2016) or even 3D p – p – p data (Chen et al. 2020), the masses and/or sizes of these clouds have all been measured in 2D by projecting the 3D data onto the plane of the sky (Miville-Deschênes et al. 2016; Rice et al. 2016; Chen et al. 2020).

By measuring the masses and sizes of fully resolved molecular clouds *directly* in 3D volume density space, we find a larger power-law slope of approximately three, or $b = 2.9$. This discrepancy suggests that the power-law slope is directly dependent on the number of dimensions used to measure mass and area, with the power-law slope consistent with $b = 2$ when measuring cloud properties in column density space and $b = 3$ when measuring cloud properties in volume density space. We directly test this hypothesis by projecting the 3D volume density data into 2D, redefining the cloud boundaries in column density space and remeasuring their masses and areas. We find that despite stemming from the same underlying 3D dust data, the projected results are consistent with a shallower power-law slope of $b = 2.1$.

While Dharmawardena et al. (2023) argue that their p – p – p -based mass–size results are consistent with Larson’s $b = 1.9$ relationship, Figure 4 suggests that the Dharmawardena et al. (2023) results may be closer to $b = 3$, albeit with an order of magnitude higher cloud masses. We attribute the difference in

3D-derived cloud masses to the existence of more extended cloud substructure along the line of sight in Dharmawardena et al. (2023), which is not observed in Leike et al. (2020). This claim is supported by Figure 6, which shows that the Taurus molecular cloud—one of the 16 cloud complexes in the Dharmawardena et al. (2023) sample—spans distances of $d = 93$ – 342 pc, about a factor of 5 more extended than we find in this work ($d = 127$ – 170 pc; based on Leike et al. 2020).

The higher power-law slope for the 3D catalogs observationally validates previous predictions for the scaling of the mass–size relation based on a combination of extant 2D observational results, numerical simulations, and analytic theory. For example, Shetty et al. (2010) measure masses and sizes of clouds in both volume and column density space based on hydrodynamical simulations, finding $b = 3.03 \pm 0.02$ in 3D and $b = 1.95 \pm 0.03$ in 2D. Likewise, Ballesteros-Paredes et al. (2012) argue that the mass–size relation depends on cloud boundary definition, with column density definitions yielding a power-law slope $b = 2$ and volume density definitions yielding $b = 3$. The Ballesteros-Paredes et al. (2012) argument stems from the fact that for clouds with similar boundary definitions, the filling factor of dense structures is small, while the filling factor of fluffier structures used to define the cloud boundaries is high, implying that mass should scale with the area in 2D and with volume in 3D (see also, e.g., Ballesteros-Paredes & Mac Low 2002; Ballesteros-Paredes et al. 2019). When clouds are

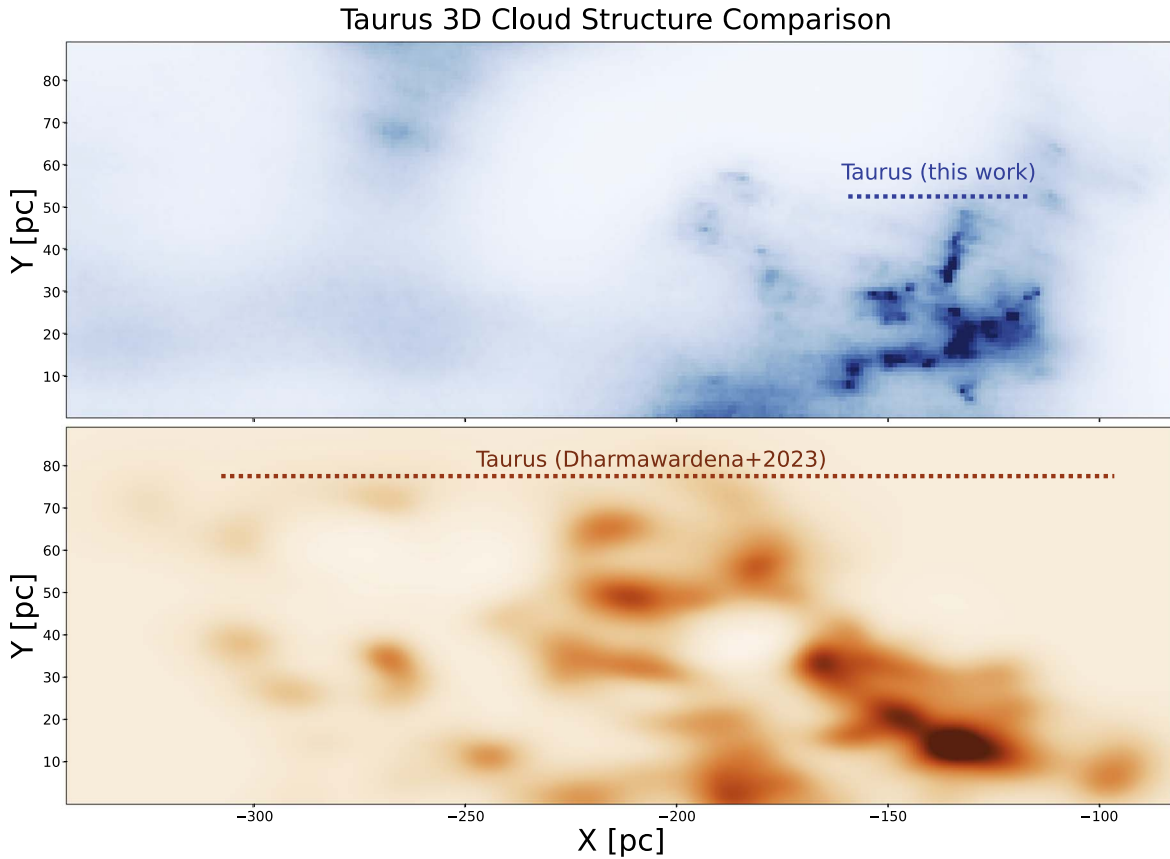


Figure 6. A bird’s eye comparison between the Taurus molecular cloud complex as analyzed in Dharmawardena et al. (2023; orange) and in this work (blue), based on the 3D dust map from Leike et al. (2020). Both 3D dust cutouts have been integrated over the same range in z . Dharmawardena et al. (2023) find roughly an order of magnitude higher cloud masses across their sample of 16 local clouds compared to this work, likely due to the presence of cloud substructure at farther distances along the line of sight, which is largely not detected in Leike et al. (2020).

defined as isocontours or isosurfaces above a particular threshold, the average column or volume density of the cloud is similar to the adopted threshold because a large fraction of pixels or voxels in the cloud lie close to the threshold value.

As an observational counterpart to the investigations of Shetty et al. (2010) and Ballesteros-Paredes et al. (2012), Beaumont et al. (2012) examine the mass–size relationship in terms of the column density probability distribution function (PDF) and its possible variation within and between clouds. Leveraging 2D dust extinction maps from Lombardi et al. (2010), Beaumont et al. (2012) find that for structures defined with a constant extinction threshold, the mean of the column density PDF within each structure varies less than the region-to-region dispersion in area, naturally yielding $M \propto A \propto r^2$.

In our work, the thresholds used to define cloud boundaries lie close to the minimum volume density ($n_{\min}$) or extinction ($A_{K_{\min}}$) threshold required for a feature to be included in the dendrogram and are roughly constant across the sample. As seen in Figure 4, on the lower mass end, the clouds all lie above the $n = 25 \text{ cm}^{-3}$ line of constant volume density and $N = 8 \times 10^{20} \text{ cm}^{-2}$ line of constant column density, which is predetermined by the minimum volume density ($n_{\min} = 25 \text{ cm}^{-3}$) and extinction threshold ($A_{K_{\min}} = 0.05 \text{ mag}$) required for inclusion in the 3D and 2D catalogs, respectively. On the higher mass end, the clouds lie below $n \approx 100 \text{ cm}^{-3}$ and $N \approx 4 \times 10^{21} \text{ cm}^{-2}$, which is also predetermined by the fact that the Leike et al. (2020) 3D dust map is not sensitive to the densest, most extinguished regions in molecular clouds ($A_K \gtrsim 0.3 \text{ mag}$) due to their reliance

on optical photometry (see, e.g., the discussion in Section 4.4 of Zucker et al. 2021). Thus, following Beaumont et al. (2012), Ballesteros-Paredes et al. (2019), and Shetty et al. (2010), mass should scale with area in 2D and volume in 3D given the narrow range of column and volume density probed, which we validate here for the first time using the same underlying observational data.

6. Conclusions

Using the Leike et al. (2020) 3D dust map with a distance resolution of 1 pc, we extend the dendrogram technique to *position–position–position* space to extract and measure the properties of clouds in 3D physical space, including their 3D positions, masses, sizes, and volume densities. To compare with extant results, we also create synthetic 2D dust extinction maps from the 3D dust distributions and derive similar properties for the same clouds defined on the plane of the sky. Given the masses and sizes of clouds obtained in 2D and 3D space, we fit the mass–size relation following Larson (1981). Consistent with predictions from extant observational studies and numerical simulations (see, e.g., Beaumont et al. 2012; Ballesteros-Paredes et al. 2019), we find that our 2D projected mass–size relation, $M \propto r^{2.1}$, agrees with the original Larson (1981) results ($M \propto r^2$), where mass scales according to the cloud’s area. However, we obtain a steeper power-law slope for the 3D results, $M \propto r^{2.9}$, where the mass scales according to the cloud’s volume. This difference in scaling is a natural

consequence of the roughly constant thresholds used to define cloud boundaries, in combination with the fact that the PDFs of column and volume density do not systematically scale with structure size. Future work connecting these high-resolution 3D cloud results to complementary tracers of a cloud’s CO kinematics should enable further constraints not only on Larson’s other relations (see also, e.g., Kainulainen et al. 2021 for insight into the Kennicutt–Schmidt relation) but also on the physical conditions of star formation within molecular clouds.

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Software: Astropy (Astropy Collaboration et al. 2013, 2018, 2022), glue (Beaumont et al. 2015), Astrodendro (Robitaille et al. 2019).

Appendix A Dependence of 2D Catalog Properties on Minimum Extinction Threshold

To confirm that the 2D mass–size relation is robust to the choice of boundary definition, we repeat the cloud extraction procedure described in Section 3.2.2 but use a higher minimum extinction threshold of $A_{K_{\min}} = 0.1$ mag (in comparison to $A_{K_{\min}} = 0.05$ mag, whose results are described in Section 4). As expected, this higher extinction threshold version yields fewer features and also divides several of the clouds into multiple components, which can be seen in Table 3.⁶ Nevertheless, the catalog maintains a similar mass–size relation of $\log M = 1.9 \times \log r(\pm 0.2) + 1.92(\pm 0.4)$, such that $M(r) = 83 M_{\odot} \times \left(\frac{r}{\text{pc}}\right)^{1.9}$, confirming that the scaling of the mass–size relation does not depend on the threshold used to define cloud boundaries.

⁶ If a single 3D feature is broken up into multiple 2D features, the same distance is assigned for each 2D feature.

Table 3
The 2D Catalog Properties with $A_{K_{\min}} = 0.1$ mag

Cloud	Component ID	Complex	l	b	d	M	r	A	Σ
(1)	(2)	(3)	(deg)	(deg)	(pc)	($M_{\odot}$)	(pc)	(pc^2)	($M_{\odot} \text{pc}^{-2}$)
2	0	Orion A ^a	207.8	−20.0	419	2179	6.6	137	16
4	0	...	209.2	−19.3	350	1879	4.4	61	31
4	1	...	209.4	−19.4	350	1559	4.0	49	32
4	2	...	209.4	−19.4	350	1458	3.8	46	32
4	3	...	209.4	−19.4	350	1356	3.7	43	32
4	4	...	209.5	−19.5	350	1043	3.2	31	34
6	0	Perseus	159.1	−20.4	294	8638	10.5	347	25
7	0	Orion B ^a	206.2	−14.3	404	13,038	12.6	498	26
7	1	Orion B ^a	203.9	−11.8	404	595	2.9	26	23
11	0	...	192.0	−13.3	378	2868	8.5	225	13
11	1	...	191.9	−14.1	378	1480	5.9	110	14
11	2	...	192.0	−11.7	378	849	4.4	60	14
13	0	...	199.7	−11.6	390	1537	5.6	98	16
15	0	Orion λ ^a	155.2	−14.7	291	503	2.6	21	24
16	0	...	260.2	−10.5	374	1458	5.5	96	15
18	0	...	297.0	−15.8	183	1124	3.5	38	30
20	0	Musca and Chamaeleon	171.2	−15.1	147	7596	9.4	278	27
25	0	...	46.3	−1.5	392	9037	13.3	554	16
28	0	...	301.3	−2.3	186	721	4.0	49	15
31	0	Lupus	338.3	6.1	161	8462	13.0	530	16
32	0	...	358.4	17.5	138	14,493	12.9	523	28
32	1	...	354.4	16.3	138	4437	6.1	116	38
32	2	...	357.0	19.3	138	1574	3.8	44	36
33	0	Lupus	26.4	5.3	256	8225	12.1	463	18
44	0	...	9.5	19.9	116	1018	4.8	73	14
47	0	...	338.4	16.9	156	703	3.6	39	18
50	0	Lupus	126.3	13.9	230	2273	6.8	144	16
53	0	...	129.8	14.0	306	1177	4.9	76	16
54	0	...	103.6	13.9	339	998	4.2	54	18
55	0	...	113.6	16.7	346	4582	7.5	175	26
56	0	Cepheus	102.2	15.4	338	677	2.8	24	28
59	0	Cepheus	111.6	20.1	367	657	2.8	25	26
60	0	Cepheus	124.0	25.3	347	943	4.5	63	15
61	0	Cepheus	124.0	25.3	353	976	4.6	65	15

Notes. Properties of the 2D projected local molecular clouds. (1) Cloud index; (2) component ID (3); association with well-studied nearby cloud complexes (4)–(5); central Galactic longitude l and latitude b ; (6) distance; (7) mass; (8) radius; (9) exact area; (10) surface mass density. A FITS version of this table is available at doi:[10.7910/DVN/BFYDG8](https://doi.org/10.7910/DVN/BFYDG8).

^a The Orion Clouds lie at the very edge of the Leike et al. (2020) 3D dust grid, thus adding more uncertainty to their derived properties, and should be treated with caution.

(This table is available in machine-readable form.)

Appendix B

Morphological Matching between 3D Projected and 2D Cloud Features

After projecting the 3D data onto the plane of the sky to derive the 2D cloud features, we compare the morphological agreement

between each 3D projected feature and its corresponding 2D cloud counterpart. As seen in Figure 7 for a subset of the sample, overall we find good morphological agreement between the 3D and 2D clouds. The remainder of the morphological maps can be accessed at doi:[10.7910/DVN/BFYDG8](https://doi.org/10.7910/DVN/BFYDG8).

3D 2D Maps Comparison

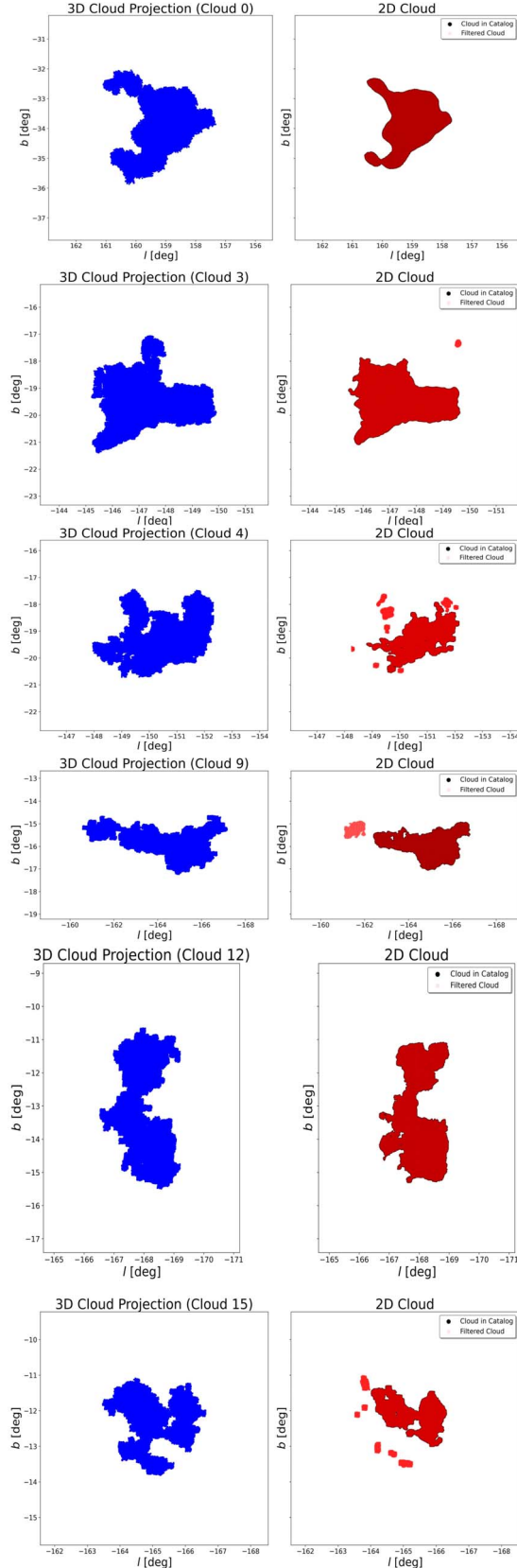


Figure 7. Morphological matching between 3D projected and 2D cloud features for a subset of six clouds in the catalog (Clouds 0, 3, 4, 9, 12, and 15). The semitransparent red on the 2D cloud panels denote 2D projected cloud components that are filtered out from the catalog, since they did not meet our minimum mass or radius requirements.

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