

The Robustness of Synthetic Observations in Producing Observed Core Properties: Predictions for the ToITEC Clouds to Cores Legacy Survey

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Abstract

We use hydrodynamical simulations of star-forming gas with stellar feedback and sink particles—proxies for young stellar objects (YSOs)—to produce and analyze synthetic 1.1 mm continuum observations at different distances (150–1000 pc) and ages (0.49–1.27 Myr). We characterize how the inferred core properties, including mass, size, and clustering with respect to diffuse natal gas structure, change with distance, cloud evolution, and the presence of YSOs. We find that atmospheric filtering and core segmentation treatments have distance-dependent impacts on the resulting core properties for d < 300 pc and 500 pc, respectively, which dominate over evolutionary differences. Concentrating on synthetic observations at further distances (650–1000 pc), we find a growing separation between the inferred sizes and masses of cores with and without YSOs in the simulations, which is not seen in recent observations of the Monoceros R2 (Mon R2) cloud at 860 pc. We find that the synthetic cores cluster in smaller groups, and that their mass densities are correlated with gas column density over a much narrower range, than those in the Mon R2 observations. Such differences limit the applicability of the evolutionary predictions we report here, but will motivate our future efforts to adapt our synthetic observation and analysis framework to next generation simulations, such as Star Formation in Gaseous Environments (STARFORGE). These predictions and systematic characterizations will help to guide the analysis of cores on the upcoming ToITEC Clouds to Cores Legacy Survey on the Large Millimeter Telescope Alfonso Serrano.

Unified Astronomy Thesaurus concepts: Star formation (1569); Molecular clouds (1072); Protostars (1302)

1. Introduction

Dense cores within giant molecular clouds (GMCs) are the birthplaces of stars (Bergin & Tafalla 2007; di Francesco et al. 2007; Ward-Thompson et al. 2007). These cores are part of a hierarchical structure of fragments within GMCs (Pokhrel et al. 2018) that form as a result of a variety of physical processes, including self-gravity (Heyer et al. 2009; Ballesteros-Paredes et al. 2011, 2012), magnetohydrodynamic turbulence (Mac Low & Klessen 2004; Hennebelle & Falgarone 2012), supersonic interstellar turbulence (e.g., Pudritz & Kevlahan 2013), and the ionization of molecular gas (Whitworth et al. 1994; Dale et al. 2009). The densest filamentary structures within clouds have been observed to host cores (André et al. 2010; Polychroni et al. 2013) of order 10^{4-5} cm⁻³ in density, 0.03–0.1 pc in size, and T < 12 K in temperature (di Francesco et al. 2007). Through gravitational instabilities, some prestellar cores may collapse to form protostars.

In the millimeter to submillimeter regime, thermal emission from cores is optically thin, which allows the flux density to trace the total dust mass, making them ideal targets of study for both ground-based and space-based submillimeter telescopes. Various surveys of nearby Gould Belt molecular clouds (d < 500 pc) have produced censuses of dense cores (e.g., Könyves et al. 2015; Marsh et al. 2016; Bresnahan et al. 2018; Benedettini et al. 2018; Ladjelate et al. 2020; Enoch et al. 2006, 2007, 2008). These surveys have also confirmed that the cores are predominantly found within relatively dense ~0.1 pc filamentary structures in clouds (André et al. 2010, 2014; Men'shchikov et al. 2010; Arzoumanian et al. 2011, 2019; Polychroni et al. 2013). These cores have been observed in varying stages of gravitational stability, from those that are gravitationally collapsing and forming young stellar objects (YSOs) to those that are pressureconfined but at too low masses to collapse further under selfgravity (Kirk et al. 2016, 2017; Friesen et al. 2017).

Overall, the mass distribution of cores (core mass function; CMF) has been shown to follow the same shape as the stellar initial mass function (IMF), shifted to $1-5 \times$ in mass in a variety of clouds (André et al. 2010; Könyves et al. 2015; Marsh et al. 2016; Bresnahan et al. 2018; Benedettini et al. 2018; Könyves et al. 2020; Sokol et al. 2019; Ladjelate et al. 2020). This similarity has been interpreted as evidence that the CMF sets the distribution of stellar masses (Offner et al. 2014). However, most core surveys remain incomplete at masses $< 1 M_{\odot}$, so it is difficult to determine whether the CMF turnover is similar to that of the IMF and likewise invariant with the environment (Offner et al. 2014; Guszejnov & Hopkins 2015). The incomplete sampling of the CMF at the low mass end is a result of the limited sensitivities and angular resolutions of previous measurements, which limited their ability to distinguish dense cores from larger natal gas structures, like filaments. Along with the sensitivity issue, the various Gould Belt surveys only observed clouds within 500 pc, which limited their view to only a narrow range of star-forming environments. Surveys of more distant and active star-forming clouds, including Cygnus-X (Cao et al. 2019) and Monoceros R2 (Mon R2; Sokol et al. 2019), give insights into more active star formation, but also suffer from low sensitivity and angular resolution.

In order to address these issues, the ToITEC Clouds to Cores Legacy Survey (C2C) will survey the cores in 10 clouds at a variety of ages and distances using the new ToITEC three-band submillimeter imaging polarimeter on the Large Millimeter Telescope Alfonso Serrano (LMT; Wilson et al. 2020). Under optimal performance conditions for the LMT and ToITEC, C2C plans to survey 88 deg² of nearby molecular clouds in 100 hr of observations, with the goal of reaching 0.24 mJy/beam rms at 1.1 mm in order to detect cores with 0.1 M_{\odot} at 4σ . The survey will observe thousands of spatially resolved cores at a uniform surface brightness, and therefore mass, from Ophiuchus (at 137 pc) to Cygnus-X (1400 pc), as a result of the high angular resolution (5" at 1.1 mm) and fast mapping speed (2–12 deg²/mJy²/hr). This will allow a complete characterization of the CMF down to < 0.3 M_{\odot} , and will place potent new constraints on the origin of the CMF, how it potentially varies with natal environmental conditions, and how or if it influences the stellar IMF.

Numerical simulations of core formation play a key role in interpreting observations, including understanding the potential relationship between the CMF and IMF, and the role of environmental processes in shaping cores (Lee et al. 2020). Previous works have predicted a range of relationships between the IMF and CMF, from no link between the two (Bonnell et al. 2001; Bate et al. 2003; Clark et al. 2007) to the IMF directly mapping from the core mass distribution (Padoan & Nordlund 2002; Hennebelle & Chabrier 2008, 2009; Oey 2011; Hopkins 2012; Guszejnov & Hopkins 2015). Simulations have shown that the CMF and resulting IMF are sensitive to a variety of physical and environmental processes. These include magnetic fields limiting fragmentation (Padoan et al. 2007; Commercon et al. 2011; Hennebelle et al. 2011; Myers et al. 2013); radiative feedback heating the surrounding material and thereby increasing the local Jeans mass (Bate 2009; Offner et al. 2009; Krumholz et al. 2011, 2016); kinematic feedback, such as outflows and winds, which reduce the star formation efficiency of dense cores (Krumholz et al. 2012; Cunningham et al. 2018; Guszejnov et al. 2020); and turbulence that decreases the local freefall time and prevents collapse (Robertson & Goldreich 2012; Murray et al. 2017). When comparing their results to observations, most of these simulations do not take into account the observational biases, such as atmospheric filtering, noise, and image segmentation algorithms, that affect the observation results. They also focus on snapshots in time, and rely on sink particles or an overdensity mass to define a core. Recent work by Smullen et al. (2020) has investigated the evolution of cores over time in magnetohydrodynamic simulations in order to explore how gas reservoirs evolve, and how core identification using a common structurefinding algorithm based on dendrograms may bias core properties. They found that, while the distributions of core properties and the CMF remained relatively stable in time, the boundaries of the individual cores fluctuated significantly. Although a variety of simulations have explored the environmental effects on the formation of cores, less attention has been devoted to using synthetic observations as tools for: (a) testing the robustness of simulations in reproducing observational core properties, along with the systematics of the observational and analytic reduction tools (data reduction pipelines and core identification analysis); and (b) determining how the above environmental effects influence the observed core properties.

Due to the extensive nature of C2C, the properties of the cores surveyed will be influenced by their environment and evolutionary status, as stellar feedback, the magnetic field, and gas accretion can all play roles in core formation and evolution (Kirk et al. 2013; Pokhrel et al. 2018). In order to compare cores at varying distances and ages, and to interpret the core properties, including mass, size, clustering, and star-forming yield, predictions of core properties are necessary in order to distinguish the underlying mechanisms. However, without a

detailed analysis and characterization of the robustness of both the simulations and the analysis tools, we will not be able to use synthetic observations or simulations to accurately interpret how core formation varies in different environments in the various molecular clouds in C2C.

In this paper, we test the reduction and the analysis tools that are currently planned to be used on C2C in terms of their ability to identify and characterize cores uniformly at various distances and ages. We will also probe the robustness of synthetic 1.1 mm emission maps of star-forming molecular gas regions from numerical radiative transfer simulations in reproducing the observed core properties. In Section 2, we describe the hydrodynamical radiative transfer simulations, the observational data, and the construction of the synthetic emission maps. In Section 3, we describe the core identification and property characterization algorithms. In Section 4, we assess the core properties and systematics found from the synthetic observations. In Section 5, we compare the synthetic observations to observations of the Mon R2 GMC in order to test the robustness of the simulation in reproducing the observed core properties. In Section 6, we explore the evolution of the observable core properties (mass, size, and clustering) by extracting and characterizing cores in three snapshots in time from one simulation. We conclude by summarizing our results in Section 7.

2. Simulations, Observations, and Their Synthesis

Our goal is to produce synthetic millimeter-wave continuum observations from projected views of simulations of starforming molecular gas, for core extraction and analysis, as if they were observed in the real sky. Here we describe the simulations and the LMT and AzTEC 1.1 mm observations that we used to make our synthetic observations, followed by the process that we used to make them.

2.1. Radiative Transfer Simulations

We use hydrodynamic simulations produced using Orion, an adaptive mesh refinement (AMR) code that follows the equations of hydrodynamics, including self-gravity and gray flux-limited diffusion radiative transfer (RT; see Klein (1999) and Krumholz et al. (2004, 2007) for full details of the numerical methods employed). These simulations include star particles that follow a subgrid prescription of protostellar evolution, including radiative feedback due to accretion and nuclear processes (Offner et al. 2009), and that are meant to simulate low mass star formation in a turbulent molecular cloud.

We analyze two RT simulations with different domain sizes and resolutions (see Table 1). Both simulations adopt periodic boundary conditions. The larger simulation (RT1) has a domain size of 10 pc, a Mach number of 14, a base grid of 512^3 , 2 AMR levels of refinement, and a maximum resolution of 1030 au (previously also analyzed in Qian et al. 2015). The smaller simulation (RT2) has a domain size of 5 pc, a Mach number of 10.5, a base grid of 256^3 , 4 AMR levels of refinement, and a maximum resolution of 126 au. Both simulations have an initial gas temperature of 10 K.

The simulations are initialized by applying velocity perturbations of the form $P(k) \propto k^0$ to an initially uniform density field (Mac Low 1999), with input-normalized wavenumbers in the range $k \sim 1-2$. The perturbations are continued until a turbulent steady state is reached and the gas distribution follows $P(k) \propto k^{-2}$

Simulation Properties												
Model ^a	$M \over (10^4 M_{\odot})$	\mathcal{M}	L (pc)	Age (Myr)	<i>T_i</i> (K)	N^3	Δx_{min} (pc)	N _{sink}				
RT1	1.425	14	10	0.83	10	512 ³	0.005	169				
RT2.1	0.378	10.5	5	0.49	10	256^{3}	0.001	3				
RT2.2	0.364	10.5	5	0.92	10	256 ³	0.001	62				
RT2.3	0.327	10.5	5	1.27	10	256^{3}	0.001	120				

Table 1imulation Properties

Note.

^a Model name, gas mass, Mach number, domain length, analysis output time, initial gas temperature, base grid size, minimum cell size, and number of sink particles.

(at approximately two crossing times), at which time self-gravity is turned on within the simulation. Energy is continually injected to ensure the turbulence remains steady and does not decay as a result of shock dissipation. At each time step of the simulation, the radiative transfer equation in a gray flux-limited diffusion approximation is solved to determine the radiation energy density (Krumholz et al. 2007). The gravitational potential is also calculated from the Poisson equation (Klein 1999), and the radiation, including the radiation feedback from sink particles (forming stars), is updated (Offner et al. 2009).

Once self-gravity is turned on, collapse can commence. New AMR grids are added when the density in a collapsing region exceeds the critical Jeans density for a Jeans number of $N_J > 0.25$ (Truelove et al. 1997). If the critical Jeans density is exceeded at the maximum AMR level, a sink particle is inserted (Krumholz et al. 2004). When this occurs, the excess mass within the dense cells is transferred to the inserted sink particle. The sink particles interact with the gas through mass accretion within the nearest four cells and through gravitational attraction; however, all knowledge of the hydrodynamics within the cell is lost, and the gas will continue to collapse. In these calculations, each sink particle represents an individual star system; only wide binaries, i.e., those with initial separations $d \gtrsim 800$ au, are resolved.

2.2. Observational Data

We use the 1.1 mm continuum data from Sokol et al. (2019) for two purposes in this work. First, these data are the foundation of the synthetic observations providing actual realizations of atmospheric emission and other observational systematics once the Mon R2 emission has been removed (described below). Second, the core census of Mon R2 provides an important comparison set for the analyzed synthetic observations. The original observations were taken between 2014 November 27 and 2015 January 31 with AzTEC, a 144-element 1.1 mm bolometer array (Wilson et al. 2008; Austermann 2009), during the 32 m diameter early science configuration on the 50 m diameter LMT. 14 fields of Mon R2 were mapped, covering a region of 2 deg². Noise levels of \sim 7 mJy per beam rms are determined from the Scott et al. (2008) jackknifing technique (see Sokol et al. (2019) for a coverage map of the fields and a full description of the observations). The maps (of both the original observations and the synthetic observations) were reduced using the standard AzTEC C++ reduction pipeline described in Sokol et al. (2019) (macana; Scott et al. 2008). The final maps have an angular resolution of $\sim 12''$ FWHM, corresponding to 0.05 pc at the distance of Mon R2 (860 pc; derived from Gaia Collaboration et al. 2018; Pokhrel et al. 2020).

2.3. Synthetic Observations

We use one snapshot from RT1 and three snapshots from RT2 (see Table 1) to produce the synthetic observations. These snapshots correspond to different output times from the simulations once gravity has been turned on (t = 0). At the output time of RT1, 0.83 Myr, there are 169 sink particles. For the three RT2 snapshots —RT2.1 (0.49 Myr), RT2.2 (0.92 Myr), and RT2.3 (1.27 Myr)— there are 3, 62, and 120 sink particles, respectively. The sink particles are proxies for YSOs. Their locations indicate where the density has exceeded the Jeans number and collapse has occurred until the eventual star formation, i.e., they mark the locations of protostellar cores.

We convert the simulation gas to 1.1 mm continuum synthetic emission maps at the resolution of the Mon R2 AzTEC maps (1" per pixel) and a representative range of distances for the C2C clouds (150–1000 pc), while preserving the fluxes and physical scales of the simulations.

We first flatten the snapshot gas density cubes onto a fixed grid (RT1: 2048×2048 pixels; RT2.1–2.3: 4096×4096 pixels). The projected density of the resulting 2D map is given a world coordinate system, where the center pixel of the map corresponds to the center pixel from one field of the AzTEC data. We use Field 4, centered on R.A. (J2000): $06^{h}07^{m}59^{s}89$ and decl. (J2000): $-07^{\circ}00'04''$.1, to map our simulation. This field is large ($40' \times 40'$), with a noise level of 7 mJy/beam and a maximum peak flux of 109 mJy/beam, making it an ideal candidate for inserting the synthetic emission maps. The density maps are scaled to the resolution necessary for the synthetic observation to appear at a given distance in the sky. The simulations are then reprojected onto the same grid as Field 4, while preserving their fluxes and scales. The 3D Cartesian sink particle positions are similarly flattened and projected onto the same world coordinate grid.

As noted above, the simulations are 5 and 10 pc across, and Field 4 is larger (or further) than that at the Mon R2 distance. To address this, we exploit the periodic boundary conditions of the simulations and tile the projected density map in order to fill the whole field. We next apply a Gaussian kernel the same size as the LMT (32 m) and AzTEC natural beam (FWHM $\sim 8.5''$) to smooth the projected maps to the resolution of the AzTEC maps.

To determine the thermal dust emission at 1.1 mm (in Jy/ beam), we assume the dust and gas are thermally coupled (Offner et al. 2009), and the gas density is optically thin ($\tau \sim 0.005$ for RT1 and RT2). Therefore, we can apply the radiative transfer equation for an optically thin gas to convert the projected gas density (g cm⁻²) to the dust emission (Jy/ beam):

$$I_{\nu} = B_{\nu}(T_d)\tau_{\nu},\tag{1}$$



Figure 1. Prefiltered synthetic observation S/N map (left) and post-macana synthetic observation S/N map (right) for RT1_D860z.

where I_{ν} is the emission, $B_{\nu}(T_d)$ is the Planck function for a dust temperature T_d , and τ_{ν} is the optical depth of the simulated cloud. The dust temperature, T_d , is the temperature at each map pixel found from the radiation energy of the projected simulation. Since $\tau_{\nu} = \kappa_{\nu}\Sigma$, where $\Sigma = M/D^2$ is the mass surface density and κ_{ν} is the dust opacity, then the emission at 1.1 mm is

$$I_{1.1 \text{ mm}} = B_{1.1 \text{ mm}}(T_d) \kappa_{1.1 \text{ mm}} \left(\frac{M}{D^2}\right).$$
(2)

We assume a constant dust opacity of $0.0121 \text{cm}^2 \text{ g}^{-1}$ at 1.1 mm (model 4 opacities; Ossenkopf & Henning 1994), including a gas-to-dust ratio of 100. *M* is the gas mass and *D* is the distance corresponding to each model's distance. This converts the gas density from g cm⁻² to Jy cm⁻². In order to convert Jy cm⁻² to Jy/beam we multiply by the beam in cm²/beam.

The scaled and beam-smoothed synthetic emission map is then added to the timestream data for Field 4 and reduced with macana to produce a synthetic emission map with the effects of atmospheric filtering. However, in order to obtain a pure synthetic observation, the original AzTEC signal must be removed from the timestream. This is achieved through the following steps:

- 1. Reduce the original Field 4 timestream data to make a map of the Field 4 Mon R2 cores;
- 2. Negate the astronomical AzTEC emission (S/N > 2.5) in the Field 4 map to create an inverted map; and
- 3. Project the Field 4 map with the negated astronomical signal along with the synthetic emission from the simulation back into the timestream to produce a synthetic observation of the simulation.

During the reduction with macana, the negated AzTEC signal will be added to the original timestream, canceling it out and leaving only the synthetic signal. However, removing the original emission in the timestream oversubtracts the signal, resulting in negative valleys at the locations of high S/N. To get around this oversubtraction, we must only add a fraction of the negated signal back into the timestream, such that the final map consists of just the simulated signal. For Field 4, we find that we must subtract 55% of the original emission to produce a clean noise-only map. See Appendix A for more details of how we determine this fractional amount. Figure 1 shows the prefiltered synthetic observation map and the final synthetic flux map after running it through macana for RT2.3_D860z. The synthetic emission macana runs are listed in Table 2.

3. Core Property Extraction

3.1. Core Identification

To identify the cores in the simulations, we create a pythonbased core identification and selection process (ImSeg⁴), following the method described in Sokol et al. (2019). This method of core identification will be used by C2C; therefore, we aim to test the robustness of this algorithm in detecting the same synthetic cores at various distances.

This method utilizes the python library photutils. Segmentation (p.Seg), a multi-thresholding algorithm for blob identification, which implements a watershed algorithm for separating blobs into individual components.

Before identifying the candidate cores, the signal map produced from macana is first masked on values with S/N < 2.5 and/or where the weight is less than 40% of the median nonzero weight values of the map. This masking restricts our core search to those areas with relatively uniform coverage depth. A noise map is also created from the signal and S/N map in order to give a threshold level for detection. The masked signal map is then run through the p.Seg multi-thresholding algorithm.

Each segment that is found with the p.Seg multi-thresholding algorithm is run through a modified p.Seg deblending process. This process utilizes the watershed algorithm to search for saddle points within each segment in order to separate an

⁴ http://github.com/sbetti22/ImSeg

Table 2macana Runs and ImSeg Results

Model	Distance (pc)	View	Resolution ^a (")	N _{cores}	N _{starred cores}	$f_{\rm sink}^{\rm b}$	f_{starred}^{c}
RT1_D860z	860	Z.	1.21	222	78	0.53	0.35
RT2.1_D150z	150	z	1.68	146 (146)	1 (1)	0.50 (0.50)	0.01 (0.01)
RT2.1_D300z	300	z	0.84	83 (165)	2 (2)	1.00 (1.00)	0.01 (0.01)
RT2.1_D450z	450	z	0.56	41 (206)	2 (2)	1.00 (0.50)	0.01 (0.05)
RT2.1_D650z	650	z	0.38	21 (198)	2 (4)	1.00 (0.80)	0.09 (0.02)
RT2.1_D860z	860	z	0.30	11 (178)	2 (5)	1.00 (0.38)	0.18 (0.03)
RT2.1_D1000z	1000	z	0.25	11 (246)	2 (10)	1.00 (0.56)	0.18 (0.04)
RT2.2_D150z	150	z	1.68	89 (89)	2 (2)	0.12 (0.14)	0.02 (0.02)
RT2.2_D300z	300	z	0.84	63 (110)	11 (19)	0.64 (0.49)	0.17 (0.17)
RT2.2_D450z	450	z	0.56	34 (144)	12 (33)	0.85 (0.48)	0.35 (0.23)
RT2.2_D650z	650	z	0.38	27 (211)	11 (60)	0.84 (0.38)	0.40 (0.28)
RT2.2_D860z	860	z	0.30	18 (258)	11 (90)	0.69 (0.38)	0.61 (0.35)
RT2.2_D1000z	1000	z	0.25	15 (280)	11 (114)	0.68 (0.30)	0.73 (0.41)
RT2.3_D150z	150	z	1.68	135 (135)	14 (14)	0.50 (0.50)	0.10 (0.10)
RT2.3_D300z	300	z	0.84	49 (105)	16 (24)	0.51 (0.27)	0.32 (0.22)
RT2.3_D450z	450	z	0.56	44 (123)	18 (37)	0.58 (0.28)	0.41 (0.30)
RT2.3_D650z	650	z	0.38	37 (191)	18 (61)	0.58 (0.21)	0.48 (0.32)
RT2.3_D860z	860	Z	0.30	24 (178)	13 (98)	0.42 (0.20)	0.55 (0.54)
RT2.3_D1000z	1000	z	0.25	21 (287)	13 (147)	0.41 (0.20)	0.62 (0.51)

Notes. For models RT2.1–2.3, the ImSeg results outside parentheses are the results for the cores in the same physical region as the 150 pc distance model field, which covers a $\sim 2.3 \times 2.3$ pc region, while the results in parentheses are the results for the cores in the whole field, including duplicates from tiling. ^a The resolution of 1 pixel before reprojecting.

^b The fraction of the number of sink particles with cores to the total number of sink particles in the field.

^c The fraction of the number of cores with sink particles to the total number of cores.

otherwise continuous emission region. The resulting output is a footprint map of the candidate dense gas cores. Properties, including the total footprint area, center position, total and peak flux, S/N, and half-peak power (HPP) information (position, total and peak flux, S/N, and area) are calculated for each candidate core. As in Sokol et al. (2019), all cores that fall within 8 arcseconds of the coverage edge are subsequently rejected in order to eliminate the majority of false detections.

In the macana reduction process, a jackknife technique is applied to the time stream data in order to characterize the noise. For each reduction, 15 fully filtered and spatially mapped noise realizations are produced. These noise realizations are passed through ImSeg and are used to estimate the false detection probability for each candidate core. To determine the final core candidates, we create 2D histograms of the total S/N and the ratio of the simulation-derived column density to the synthetic dust emission column density for both the noise realization false cores and the core candidates. The ratio of these two histograms is used to isolate the regions of the parameter space in which false detections dominate. Confidence intervals are calculated for the histogram ratio. If a core candidate lies within the 75% confidence interval, then it is considered a false detection. Cores that lie outside this confidence interval have a low probability of being considered false detections, and are considered to be core candidates.

3.2. Core Flux, Mass, and Size Measurements

Once the synthetic cores are identified, we measure their sizes, masses, and temperatures. As in Sokol et al. (2019), we

assume that the synthetic cores are spatially resolved and that the lower S/N cores are not detected across their full radial extents. Sokol et al. (2019) corrected the underestimation of total flux and core mass by modeling and characterizing the peak-to-total flux ratio relation, and then correcting for high ratios at low S/N. They tested their correction by constructing several Plummer-like models that span the expected ranges of the peak-to-total flux and total S/N of the prestellar cores. To confirm that our simulated cores have these same features, and that we can use the same correction, we model the peak-to-total flux ratio relation and find the same "iceberg" effect as seen by Sokol et al. (2019) (see their Figure 7) in all of the model runs. We then apply the same correction

$$F_{\rm corr} = F_{\rm peak} \left(\frac{F_{\rm peak}}{F_{\rm tot}} - \delta R \right)^{-1},\tag{3}$$

where F_{peak} is the observed peak flux, F_{tot} is the observed total flux, F_{corr} is the corrected total flux, and δR is the S/N-dependent flux correction term found to be

$$\delta R = 5.25 \times (S/N)^{-1.8}.$$
 (4)

The simulated core flux ratios are corrected for noise bias. We show fluxes before and after correction for RT1_D860z in Figure 2. We use this process to correct all of the total observed fluxes for all of the model runs.

We then calculate the mass of the cores from the corrected fluxes. At 1.1 mm, the mass is found to be



Figure 2. The peak-to-total flux ratio vs. the total S/N for all cores (bluestarless; gold-starred) in model run RT1_D860z. The left panel shows the uncorrected flux ratios with the "iceberg effect," where the lower S/N cores are not detected over their full extents. The right panel shows the corrected flux ratios, where the fluxes are not underestimated. The final beam profile is shown as the solid line, while the Plummer models are shown as dashed lines. The Plummer models have aspect ratios of 2, power-law indices of 2, and scale lengths of 2, 12, and 18 arcseconds (top to bottom), respectively.

$$M = 1.3 \times 10^{-5} \left(\frac{S_{1.1 \text{ mm}}}{1 \text{ Jy}} \right) \left(\exp\left(\frac{13 \text{ K}}{T_d}\right) - 1 \right) \\ \times \left(\frac{D}{1 \text{ pc}}\right)^2 \left(\frac{\kappa_{1.1 \text{ mm}}}{0.0121 \text{ cm}^2 \text{ g}^{-1}}\right)^{-1} M_{\odot},$$
(5)

where $S_{1.1 \text{ mm}}$ is the total flux density at 1.1 mm, T_d is the dust temperature, D is the distance, and $\kappa_{1.1 \text{ mm}}$ is the dust opacity at 1.1 mm. Following Sokol et al. (2019), we take the dust opacity to be 0.0121 cm² g⁻¹ at 1.1 mm. The dust opacity is found from the Ossenkopf & Henning (1994) model 4 opacities for icy dust grains at 1.1 mm, and assumes a gas-to-dust ratio of 100.

The core sizes are calculated following Sokol et al. (2019) and Könyves et al. (2015). The widths of the cores are found from the deconvolved FWHM size given by

$$size_{deconv} = \sqrt{FWHM^2 - HPBW^2}$$
, (6)

where the FWHM is the HPP diameter and the half-power beam width (HPBW) is the final AzTEC beam width (12"). As in Sokol et al. (2019), there is a bias toward smaller areas for cores with S/N < 5. We therefore use the correction found by Sokol et al. (2019) to calculate the unbiased HPP areas of the cores in order to determine the FWHM.

The temperature of each core is found from temperature maps derived from the simulated radiation energy density smoothed to the Herschel beam at $500 \,\mu\text{m}$ (36") at each model's distance. We take the average temperature within the footprint of each core as the temperature. As the Herschel beam and pixel scale is larger than the AzTEC maps, the synthetic temperature maps may be biased due to blending and the large beam causing the temperatures to be overestimated. Since this same effect will occur for C2C, as Herschel temperature maps will be used for the analysis, this provides a good test for temperature robustness.

4. Core Property Systematic Effects Assessment

With synthetic observations, we can probe how measurements of identical molecular gas structures are impacted by observational and analytical algorithm biases. Here we describe



Figure 3. RT2.3 overlaid with the sizes of the simulation at different distances (black boxes). At these different distances, different amounts of the simulation fit into the Field 4 area.



Figure 4. Median recovered sizes, masses, and temperatures as a function of distance for starless and starred cores. For all panels, the red squares are RT2.1, the green circles are RT2.2, and the purple diamonds are RT2.3. The cores show a size and mass increase at large distances, which is indicative of oversegmentation and overfiltering at closer distances.

two systematic biases identified by placing the simulations at a range of heliocentric distances.

Using the three RT2 snapshots, we look at how varying the distance and age of the cloud affects the core properties. This



Figure 5. Footprint map at 1000 pc (grays) overlaid with the 150 pc contours (reds) for RT2.2. False core detections are indicated by light gray/pink, while core candidates are shown as dark gray/red. The dark red outline is the coverage edge for the 150 pc map. The oversegmentation and overfiltering at 150 pc is shown by the increased number and narrower areas of the segments compared to the cores at 1000 pc.

will help to place constraints on the CMFs and core sizes from clouds at various distances and ages that are planned to be observed in C2C. The three RT2 outputs are placed at 150, 300, 450, 650, 860, and 1000 pc in order to cover the full range of distances of C2C. 860 pc is specifically chosen as a direct point of comparison with the cores from Mon R2 presented in Sokol et al. (2019). In Figure 3, the black boxes indicate the extent of the tiled prefiltered synthetic observations seen at each distance. RT2.3 is tiled and shown underneath the black boxes for visualization purposes.

At 150 pc, only the center 2.3 pc of the synthetic emission map fits within the Field 4 coverage; therefore, when comparing the cores at all distances, we only look at cores within the center 2.3 pc of each model to make a fair comparison. This region will be called the "center," while the whole Field 4 coverage will be called "total." The center core candidates found for each model run are summarized in Table 2, with the total core candidates being shown in parentheses. On average, for all of the synthetic emission model runs, we recover cores subtending 65% of the sink particles within the center and $\sim 60\%$ of all sink particles.

We find that the median recovered masses, sizes, and temperatures for the synthetic cores vary with distance for the three RT2 synthetic observations, as shown in Figure 4 (red is RT2.1, green is RT2.2, and purple is RT2.3). From 150 to 1000 pc, the mass increases by 1.4 dex, the size increases by 0.64 dex, and

the temperature decreases by $37 \pm 6\%$. At D > 450 pc, these physical properties level off, varying only by ~0.2 dex. Though there is slight temperature dependency with distance, the order of magnitude discrepancy in mass cannot be fully explained by this. If the temperature was the only cause of the mass discrepancy, the temperature would have to vary by ~1 dex in the opposite sign to our result, with the core temperatures being around 6 K at 150 pc and 60 K at 1000 pc. As this is not the case, the discrepancy in mass and size is not due to the variation in temperature.

This significant increase in core mass and size with distance is problematic, as these properties should be intrinsic quantities, and not dependent on distance. Though we could be probing substructures within the cores themselves, we clearly need to identify and extract similar gas structures across all distances to ensure their fair comparison. We consider two likely causes of the observed discrepancies here: (1) atmospheric filtering in our data reduction process, and (2) oversegmentation during the core identification and extraction analysis. The former is likely to shrink the extent of the diffuse emission for clouds at closer distances. The latter occurs when resolved substructures within cores are considered distinct objects at close distances, yet are blended together at further distances.

We present an example comparison in Figure 5, where the red/pink contours show the footprint map for the segments at 150 pc overlaid on gray footprint maps of the segments at 1000 pc. The pink and light gray contours are false core



Figure 6. Top: the total flux and total area of the synthetic observations and Mon R2 AzTEC cores. Bottom: the percentage of flux and area recovered as a function of distance. The synthetic observations are shown as black squares, and the red squares mark the "Herschel-like" 36'' 1.1 mm prefiltered map within the center 2.3×2.3 pc region. The gray circles are the AzTEC Mon R2 total flux and the area within each field mapped by AzTEC, while the black circle is Field 4 (Sokol et al. 2019). The red circles are the Herschel total flux and the area within each field, and the dark red circle is Field 4. The solid black and red lines follow the D^{-2} dependence for flux and area, while the dashed black lines show the deviation from this dependence. The uncertainties in flux and area are insignificant for all maps.

detections, while the red and dark gray contours are core detections. The most obvious difference is that there are several smaller segments at 150 pc for every segment that is found at 1000 pc. Using the ratio of core counts in Table 2, there are ~ 6 times as many cores at 150 pc compared to 1000 pc, though of course there are other minor differences in the cores found at each distance. This segmentation discrepancy results in the



Figure 7. Column density vs. temperature for the cores from the RT1_D860z synthetic observation (magenta diamonds) and the AzTEC Mon R2 observations (gray contours). In order to conduct a fair comparison between the synthetic and real observations, we required a sample of cores that lie in the same types of environments. Therefore, we only selected observed cores with column densities N(H $_2$) > 10²² cm⁻² (which is the fifth percentile of the synthetic column density value, marked by the black dashed line).

closer distance extraction providing many more segments overall, and with commensurately smaller typical masses and sizes. The apparent "cores" in the 150 pc synthetic observation have an average size of 0.025 pc (5100 au) and a mass of $0.25 M_{\odot}$, similar to the protostellar "envelopes" found *within* cores by millimeter-wave interferometers (Pokhrel et al. 2018). Regardless of their origin, extracting only the smallest resolvable structures will not yield a consistent set of structure properties across our distance range.

The combined red 150 pc footprint is also distinctly narrower than the footprint at 1000 pc, due to the strong negative halos surrounding the positive flux, a classic sign of atmospheric filtering affecting the detectable astrophysical signal. If overfiltering was not an issue, the total amount of flux and the emission area within the same physical area should scale inversely with the distance squared. However, as shown in Figure 6, there is a substantial loss of flux and area at relatively close distances. At 150 pc, only 1.3×10^{-3} of the total original flux is recovered, compared to $\sim 3 \times 10^{-3}$ being recovered at larger distances, a factor of 2.3 greater. The total emission footprint area (with pixels greater than the median noise, \sim 7 mJy) is similarly discrepant, with only 0.03 of the total original area recovered at 150 pc compared to 0.1 of the total area recovered at 650-1000 pc (the uncertainties for both flux and area are insignificant here), a factor of 3.3 greater. This small reduction of the region-wide mean flux density within the identified emission footprint, by a factor of 0.7, despite a net increase in the total flux detected, masks complex flux-filtering behavior. Ultimately, the median mass surface densities of the cores increased by a factor of 2.3 over our distance range. This is the opposite sign of the change in mean flux density, but consistent with the increase in total flux within the fixed field of view of the center region (the median core temperature difference also impacts the mass-to-flux conversion).

In summary, the mass and size discrepancies of cores at close distances are a direct result of both overfiltering and oversegmentation. Care should be taken in C2C when comparing cores at various distances, and future work will need to address these issues, as the smaller ToITEC beam may exacerbate the issues at the closest distances. With that stated, it is expected that the ToITEC data will not suffer as much filtering damage, because of its larger array footprint and massive increase in



Figure 8. RT1_D860z synthetic core observations compared to Mon R2 AzTEC Field 4 cores with similar column densities. (a) RT1_D860z synthetic CMF (x/ square) and AzTEC Mon R2 CMF (histograms). The incomplete CMF is shown by the squares/dark histogram, while the result after correcting for completeness is shown by x/the hatched histogram. Error bars are shown in the corrected CMFs if they have >20% completeness. A Chabrier (2003) IMF with a mass scale factor of 3 is shown as the black line. (b) RT1_D860z synthetic (blue circles/gold stars) and AzTEC Mon R2 Field 4 (blue/gold contours) corrected mass vs. corrected deconvolved FWHM size. The cores with YSOs for the synthetic observation and the AzTEC data are shown as gold stars and contours, while the starless cores are shown as blue circles and contours. The black line is the Bonnor–Ebert stability line for the median core temperature (T=16 K; Könyves et al. 2015). The cores above this line are gravitationally unbound.

sampling density over AzTEC in terms of both space (35 times more detectors at 1.1 mm) and time (a higher sampling frequency). Furthermore, ToITEC's simultaneous observations at 3 mm wavelengths may enable additional advances in atmospheric filtering that are less destructive to the astronomical signal. For this work, however, we will only use synthetic observations at D > 500 pc for the remainder of the analysis, so that the effects of these biases are negligible.

5. Comparison to AzTEC Mon R2 Observations

To analyze how well the simulations can reproduce the observed core properties within molecular clouds, we compare our synthetic cores to the observed cores in Mon R2 (Sokol et al. 2019). We use the RT1 simulation, as it is approximately the same size as Field 4 (10 pc simulation versus the \sim 12 pc AzTEC Mon R2 field), and therefore the simulation fills the whole field with little duplication from tiling. At this distance and scale, sink particles are proxies for YSOs. The core candidates found for model run RT1_D860z are summarized in the first row of Table 2. All cores where a sink particle falls within the core footprint are considered to be starred, while all other cores are considered to be starless. We find 222 core candidates, with 35% of them considered to be starred. However, only $\sim 53\%$ of all sink particles are located within the footprint of a core. The sink particles that are not within core footprints are in areas of low S/N emission, and are thus not detected in the synthetic observation.

The simulations generally best represent the conditions found in denser "clump" regions within nearby molecular clouds (e.g., the center of Mon R2). Thus we must attempt to prune the observed cores to those that are found in similar environments to the simulation. We select observed cores with local diffuse gas column densities $N(H_2) > 10^{22}$ cm⁻² (the fifth percentile of the simulated column density value), as shown in Figure 7. All cores with N(H₂) > 10^{22} cm⁻² are relatively dense, but span a wide range of temperatures and fill the same parameter space as the synthetic cores. Only observed cores above this column density will be used in order to conduct a fair comparison of the properties of the two sets.

In order to determine the extent to which we can accurately compare synthetic cores, and therefore the robustness of the simulations in predicting core properties and environmental effects, we first look at the CMFs for the synthetic cores (×/square) and the AzTEC Mon R2 observations (histograms) in Figure 8(a). As the synthetic observations are created using the same spatially filtered maps and reduction process, we use the same differential core detection completeness characterizations and corrections as in Sokol et al. (2019). In that work, the authors inserted nine false cores per mass bin into the timestream data, reduced the modified data with macana, and ran a full core extraction analysis in order to determine the differential completeness as a function of the corrected core flux (see their Figure 6). Since we use their data for our synthetic observations, we also adopt their completeness trend in order to correct for the incomplete core number counts at the low mass end of our synthetic CMF.

We find that the CMF shape derived from the synthetic emission cores is the same as that in Sokol et al. (2019), with and without the completeness corrections. The mass-complete values in Figure 8(a) are shown by ×/the light gray hatched histogram, while the mass-incomplete observed values are shown by the gray squares/gray hatched histogram. The number counts between the starless and the starred synthetic cores vary, with 175 starless synthetic cores and 83 starred synthetic cores. We cannot rule out a turnover at the low mass end near $3 M_{\odot}$, similar to a Chabrier IMF with a mass shift of $3 \times$ (black line).

Figure 8(b) shows the masses and sizes of the synthetic cores, separated into starless (blue unfilled circles) and starred (yellow filled stars) cores, overlaid onto the parameter space occupied by the Mon R2 cores (with the prestellar cores being displayed as yellow contours, and the starless cores as blue contours). The median synthetic core size is 0.073 pc, while the median Mon R2 core size is 0.083 pc. We see a clear trend of small cores (cores with sizes <0.05 pc) primarily containing sink particles not seen in the observations. In RT1_D860z, separated at the median size (0.073 pc), $51 \pm 7\%$ of cores <0.073 pc. This substantial difference among the core sizes is not observed in the Mon R2 cores, where $33 \pm 5\%$ of cores with sizes <0.083 pc contain YSOs compared to $23 \pm 7\%$ for the larger sizes. This discrepancy appears for two reasons. First,



Figure 9. The RT1_D860z synthetic observation (magenta) and AzTEC/ Herschel Mon R2 (gray contour) core gas correlation for n = 4, 6, 11, and the 18 nearest neighbors. At high gas and core surface densities, the cores are clustered within small, dense regions, while at lower surface densities, the cores are in a more diffuse medium. As *n* increases, the amount of synthetic clustering in the dense regions decreases.

an inspection of the raw simulation data (see Appendix C) shows that these sources are mainly older objects, which have bright, massive disks and very little surrounding envelope. Hydrodynamic simulations, which neglect magnetic fields, commonly produce large disks (Zhao et al. 2020), which are much more massive than expected compared to the observations (e.g., Williams et al. 2019; Tobin et al. 2020). On the observational side, the region of the parameter space for smaller low mass cores, $M \leq 0.5 M_{\odot}$, has a completeness of < 5%, so we expect more starless and protostellar objects to reside in this region than are actually detected.

In order to gauge how the environment may affect the cores found in our synthetic observations, we examine how the cores are clustered relative to the column density of their surrounding diffuse gas. Following Sokol et al. (2019), surface density is calculated by finding the nearest neighbor distances (d_n) from each core, given as $(n-1)/(\pi(d_n)^2)$. This is multiplied by the mean mass of the *n* cores selected to get the core mass density.



Figure 10. The RT1_D860z synthetic observation (magenta) and AzTEC/ Herschel Mon R2 (black) gas surface density ranges from Figure 9, normalized to the n = 4 range. As *n* increases, the range in the synthetic gas surface densities decreases at a faster rate than the observations.

Using our Herschel-like synthetic column density map, we find the average column density over the same area that was used to calculate the core mass density. We measure the gas surface and core surface densities for n = 4, 6, 11, and 18 nearest neighbors to look at clustering at different size scales, similar to Gutermuth et al. (2008), Sokol et al. (2019), and Pokhrel et al. (2020).

As shown in Figure 9, RT1 (pink diamonds) tends to span a smaller range of gas densities than the Mon R2 observations, and that range decreases as more neighbors (n) are included. This effect is largely confined to the high column density end, while the the minimum gas densities remain relatively constant. This indicates that more diffuse gas (lower column density) is enclosed as the smoothing size scale increases, and the enclosed area also increases in order to contain more nearest neighbors. Figure 10 shows that when we compare the range of gas densities subtended, we see much stronger dilution for a given n compared to the Mon R2 observations. The synthetic gas densities shrink by 59% by n = 18, while the Mon R2 cores only shrink by 27% over the same range in *n* value selection. We also find that the average gas surface density in the synthetic observations shifts by a greater extent as more neighbors are included, from $212 M_{\odot}$ pc⁻² to $148 M_{\odot}$ pc⁻², while the Mon R2 observations shift from $210 M_{\odot} \text{ pc}^{-2}$ to $171 M_{\odot} \text{ pc}^{-2}$. This shrinking and shifting is predominantly a signature of the smaller N core groupings in the simulation than are in Mon R2, a systematic difference between the two data sets.

Overall, while the simulation can accurately reproduce the observed Mon R2 CMF for cores in a similar range of column densities, the environments that form these cores differ from the observations. While some cores form in areas of low column densities, the majority of the low mass cores preferentially form in small but overly dense regions. The discrepancies in the clustering characteristics between the observations and the synthetic results demonstrates the limiting nature of the simulations used here for the purpose of disentangling the environmental effects on core properties. Future work will employ next generation simulations, such as those from the Star Formation in Gaseous Environments (STARFORGE) project (Grudić et al. 2021), that simulate entire molecular clouds over a much wider dynamic range of spatial scales and gas column densities, and that incorporate more stellar feedback effects. Parallel improvements in the simulation suite used and the observations from C2C should facilitate much more



Figure 11. The corrected mass vs. corrected deconvolved FWHM size for RT2.1 (left), RT2.2 (center), and RT2.3 (right), at 650 (top), 860 (middle), and 1000 pc (bottom), within the center 5 pc of each model. The darker filled stars correspond to the starred cores, while the lighter unfilled circles are the starless cores. The large star or circle is the median value for the starred or starless cores, respectively. The black line is the BE stability line for the median core temperature (≈ 15 K for all panels; Könyves et al. 2015). By 1.27 Myr, there is a split in size between the starred and starless cores.

comprehensive analysis of the environmental impacts on core properties.

6. Core Property Evolution from Multiple Simulation Snapshots in Time

In order to analyze the cores from C2C across various environments and ages, we first need to characterize the systematic effects in the data reduction and analysis process; determine the extent to which the simulations can reproduce the observations; and, if the simulations are robust, start to probe how age will affect the observed core properties.

Understanding both the systematics in the data reduction techniques and the reliability of the simulations is essential for explaining and interpreting observations. Therefore, we focus our analysis on both these angles, with the goal of characterizing the potential issues that may arise in the C2C results and interpretation. We will show the differences between the synthetic cores as compared to the observed core properties, highlighting the potential issues of our understanding of star formation within simulations.

6.1. Mass and Size

We first characterize how the inferred masses and sizes (and therefore the CMF) will vary with both distance and age, two of the most prominent dependent variables for the C2C sample. Overall, the starless core properties are independent of age, with little variation in average mass, size, and temperature with time (Figure 11). However, as the cloud ages, starred cores appear above the distribution of starless cores, suggesting that the cores grow in mass before undergoing collapse. Over time, the starred cores collapse and shrink, on average, from a median mass of $12 M_{\odot}$ -2 M_{\odot} and a size of 0.98 pc-0.04 pc. This represents the depletion of the envelope as the protostar accretes.

In Figure 11, we show the mass-size relation for 650, 860, and 1000 pc at all ages, with the starred cores shown as stars, and the starless cores shown as circles. The black line is the approximate numerically modeled Bonnor-Ebert (BE) stability criterion line (Könyves et al. 2015). The critical BE mass is the largest mass that an isothermal sphere in a pressurized medium can have while maintaining hydrostatic equilibrium (Bonnor 1956). A core is considered self-gravitating and bound if its mass is above the approximate numerically modeled critical thermal BE mass, $M_{\text{BE,crit}} = 2.4R_{\text{BE}}c_s^2/G$. R_{BE} is the BE radius, c_s is the isothermal sound speed, and G is the gravitational constant (Könyves et al. 2015). This critical mass does not take into account nonthermal turbulent motions; these can be considered by substituting the total velocity dispersion for the sound speed. However, André et al. (2007) and Pokhrel et al. (2018) show that nonthermal motions are insignificant for low mass cores, and produce unphysical formation efficiencies when treated as an effective pressure. Therefore, we only consider the thermal BE mass. Cores with a BE mass ratio $\alpha_{\rm BE} = M_{\rm BE,crit}/M_{\rm obs} \leqslant 2$ are considered self-gravitating, and will eventually collapse and form protostars (generally these are cores above $M_{\rm BE,crit}$, while cores with $\alpha_{\rm BE} > 2$ do not have enough mass at that moment to remain bound). Though they



Figure 12. The CMFs for RT2.1 (left), RT2.2 (center), and RT2.3 (right), at 650 (top), 860 (middle), and 1000 pc (bottom), within the center 5 pc of each model.

may be pressure-confined, they may eventually dissipate if more mass is not accreted.

The separation between the median sizes of the starred and starless cores, as shown in Figure 11, increases with age, changing from an average separation of 0.016 ± 0.001 pc to 0.044 ± 0.002 pc. For RT2.2 and RT2.3, the majority of the starred cores have sizes less than the median size of the cores, with 60%–80% of the small cores containing YSOs. The number of starred cores less than the overall median size also increases as a function of age, though there is a slight turnover at 860 and 1000 pc for RT2.1. Due to the low number counts of starred cores that lie within the center region at all distances in RT2.1, there is no statistically significant separation of starred and starless cores. However, between RT2.2 and RT2.3, there is a $16 \pm 3\%$ increase in the number of starred cores with sizes smaller than the median.

In order to derive the synthetic core temperatures, we follow a similar approach to the approach that will be used by C2C, as described in Section 3. However, the large 36" beam (ranging from a physical size of 0.11 pc at 650 pc away to 0.17 pc at 1000 pc away) will resolve different size scale temperature estimates, depending on distance.

If we assume the median temperature of the cores at each age and distance (\sim 15 K), we find that the hotter cores are generally starred, gravitationally bound, and less extended compared to the starless cores, which are large (and thus less dense), gravitationally unbound, and colder. We also see a clear separation between the peak-to-total flux ratio (the "peakiness" of the core) of the starred (diamonds) and starless (squares) cores. The starred cores, which all generally fall on or above the BE line for all distances and ages, are smaller and less massive, but have higher S/N and are more concentrated ("peaky") compared to the starless cores. As discussed in Section 5, this is because many of the older protostars are embedded in massive disks and have little remaining envelope. The fraction of the starless cores above the BE line varies with evolutionary time and observational resolution, as early times show better agreement with the observed starless cores.

6.2. Core Mass Function

We find that the average mass over time decreases for the starred cores, while remaining constant for the starless cores, resulting in CMFs with increased low mass bins. This initial bias toward higher masses has been found in other molecular cloud simulations (Smullen et al. 2020), and can be fit with a high mass slope $dN/dM \propto M^{-2}$, as seen in Guszejnov & Hopkins (2015). However, from 0.49 Myr to 0.92 Myr, the high mass slope decreases to $dN/dM \propto M^{-1.3}$, consistent with a Chabrier IMF, though shifted by a factor of 2.5-3.5. The number of starred cores also increases significantly; within the original 5 pc box, the starred cores increase from 2-3 to ~ 30 . From 0.92 Myr to 1.27 Myr, the starred core counts remain fairly stable and span a wide range of masses $(1-30 M_{\odot})$. However, we do not produce cores in the low mass regime $(<1 M_{\odot})$, as the radiative feedback in the simulation and the lower resolution of turbulence can inhibit small-scale fragmentation (Offner et al. 2009; Urban et al. 2010; Krumholz et al. 2011; Bate 2012; Padoan et al. 2020). The starless core tallies, while initially high due to a lack of sink particles in the simulation, remain fairly constant between the two later time steps, both in mass and number counts.

Overall, the CMFs from 0.92 to 1.27 Myr remain nearly constant between the two snapshots. This consistency is seen in other simulations, such as those by Smullen et al. (2020) and Cunningham et al. (2018). The relative consistency of the masses of the starless cores has also been observed (e.g., André et al. 2014). However, Smullen et al. (2020) also found significant variation over time in the properties of individual simulated isolated starless cores, even while the total CMF



Figure 13. Left: the core gas correlation for RT2.1 (left/squares), RT2.2 (center/circles), and RT2.3 (right/diamonds) at 860 pc for n = 4 (top/small scales) and n = 11 (bottom/large scales). The black line corresponds to the best power-law fit from Sokol et al. (2019) with a power-law index of 1.99. The white markers indicate the starless cores, while the colored markers indicate the starred cores. Right: the gas surface density range as a function of the number of nearest neighbors (*n*) for each model shown in the left panel. As *n* increases, the gas surface density range decreases for all ages, indicating that clustering occurs only on the smallest scales.

shape remained invariant. Much of the core variation was due to the changing core definition, since the core identification method (dendrograms) was overly sensitive to small changes in the core's underlying physical structure. This leads to the concern that some algorithms, especially when used to identify cores in clustered regions, may not be robust.

The reproductions of the combined starred and starless CMFs, in both Figures 8 and 12, is a good indication that the simulations are able to reproduce cores at similar masses and ages. The consistency of the CMFs over this time range gives a good indication that the core identification and data reduction algorithms are able to identify the same cores with the same masses and sizes, confirming that systematic biases will not be a significant variable to untangle when analyzing the C2C core properties for most of the target clouds. Only Perseus and Ophiuchus are closer than 400 pc in the C2C sample, and thus are likely to need special consideration for biases.

6.3. Core Gas Correlation

We look at the core gas correlation at varying distances and ages to explore the effect of clustering and core formation over time within the simulations. We find that the synthetic data overlap at all distances, with very little variation in gas and core surface densities. Therefore, in Figure 13, we show the core gas correlation at 860 pc for all three ages as a representative sample. The left panel of Figure 13 shows the core gas correlation at small (n = 4) and larger scales (n = 11), overlaid with the power-law fit (index of 1.99) from Sokol et al. (2019), while the right panel shows the range of gas densities at various size scalings (number of nearest neighbors) at each age. Overall, the synthetic data loci parallel and often overlap the power-law fit at all ages and smoothing scales. The range in gas densities decreases with increasing distance, shifting toward low gas densities.

The range of gas surface densities that host the cores increases with age, and shows higher gas column densities for the same core densities, indicating that the gas has had time to accumulate due to the influence of gravity. At younger ages, the gas is highly diffuse for all size scales, indicating very few high gas density regions within the cloud. Over time, the gas accumulates and collapses into small, high column density "clumps" that form several cores at most, while the gas remains relatively uniform at large scales. This seeming inability to sustain larger molecular gas clumps may be a result of the driven turbulence and periodic boundary conditions of the simulation, which preclude large-scale gravitational collapse and prevent large clumps from forming.

The simulated core gas correlation falls along the same slope as found by Sokol et al. (2019), with a power-law index of 1.99 ± 0.03 . Sokol et al. (2019) found that this slope, which follows the model of thermal fragmentation (Myers 2009), indicates that the primordial gas distribution will be depleted quickly at high column densities, due to the high mass efficiency of the cores formed in that environment. The extent to which our synthetic cores extend in this core gas density space is more limited than in the observations, but the extent does grow toward the higher core densities as the simulation evolves with time, and this is especially noticeable in the small n nearest neighbor measurements. When we separate the starred and starless cores (Figure 14), they are both well represented across the entire density range subtended, in agreement with the Mon R2 observations. The main discrepancy appears to be the penchant for small number groupings in the simulations, which results in the representation of the higher density regions being extremely sensitive to n selection, as seen in both the core density and nearest neighbor distance measurements (Figures 14(a) and (b)), unlike the observations of Sokol et al. (2019). Along with this discrepancy, we also find no variation in mass with gas density (Figure 14(c)), which is inconsistent with the observations. However, this disagreement is only seen at the low and high gas density ranges; in the former, it is a result of noise-induced false detections, and in the latter, it is due to temperature variations not being taken into account in the observations.

6.4. Summary

We have explored the robustness of synthetic observations with the same noise properties, filtering effects, and core identification algorithms as real observations—in reproducing observed cores, in order to assess their feasibility for disentangling the environmental effects, ages, and distances of the core properties that will be observed by C2C. We have found substantial overfiltering and oversegmentation at close cloud distances (D < 300 pc and 500 pc, respectively) in the synthetic observations based on AzTEC on the 32 m LMT. The smaller ToITEC beam on the 50 m LMT may exacerbate the oversegmentation issue, while the larger field of view of the ToITEC arrays should reduce the impact of overfiltering at core scales when observing the nearest C2C target clouds. For further distances, however, at which these effects are less significant, we have been able to investigate



Figure 14. (a) The core gas correlation; (b) the smoothing size scales; and (c) the smoothed mass for RT2.3 at 860 pc for n = 4 (top panels/small scales) and n = 11 (bottom panels/large scales). The black line in (a) corresponds to the best power-law fit from Sokol et al. (2019) with a power-law index of 1.99. The yellow stars are the measurements centered on the starred cores, while the open blue circles are the measurements centered on the starless cores. The starless cores are generally found to be more isolated, while the starred cores are more clustered at large n.

observable evolutionary changes in the core properties. We find that the synthetic observations are able to reproduce the observed CMFs and produce cores with an efficiency that is consistent with the middle portion of the gas column density range of the Mon R2 AzTEC survey's field of view. However, the clump formation in the simulation does not advance far enough to reach the high gas column density and strong intermediate scale core clustering that is observed in Mon R2. Similarly, the simulations exhibit the increasing separation over time of the core masses and sizes of the starred and starless cores, while no such distinction is observed in Mon R2.

These discrepancies between the observations and the simulations limit the power of using synthetic observations to predict how observed core properties should behave when they are exposed to various environmental factors. Next generation simulations, such as STARFORGE (e.g., Grudić et al. 2021), are better able to capture the physics from cloud to core size scales, and thus they may address some of the apparent discrepancies reported here. Similarly, future work on the observation side is needed to address the filtering and segmentation issues that plagued our analysis of nearby synthetic clouds. An observation simulator for TolTEC and LMT is under active development (Z. Ma, private communication), which will include end-to-end treatments of the telescope, the optical and electronics system, and the model atmosphere, and which will provide an extremely useful test platform for future iterations of C2C data treatment and core analysis.

7. Conclusions

In this paper, we have begun to explore the robustness of synthetic observations in accurately predicting molecular cloud core properties for C2C on the 50 m diameter LMT. As this survey aims to map clouds at different ages and within different environments, assessing the feasibility of using synthetic observations to predict how environmental factors affect the core properties and their evolution is essential.

We produced synthetic 1.1 mm continuum emission observations by inserting snapshots of hydrodynamical radiative transfer simulations of star-forming regions into AzTEC/LMT-32 m observations of the Mon R2 cloud. We used a pythonbased image segmentation algorithm to find core candidates in the synthetic observations and to calculate various core properties, including mass, size, and temperature. We explored a variety of simulation outputs at different ages and varying distances in order to probe the full range of clouds that will be surveyed by C2C. We found the following:

- 1. Overfiltering and oversegmentation of cores occurs at distances less than 300 pc and 500 pc, respectively, under the current data treatment and analysis path developed for C2C. The higher resolution and better sampling that ToITEC will provide may improve or exacerbate these issues. Regardless, caution should be taken when analyzing cores from nearer distances because of these effects.
- 2. The core masses, sizes, and CMFs found from the synthetic observation of the RT1 simulation at 860 pc are consistent with the same observed core properties for the cores in Mon R2 found by Sokol et al. (2019). However, we find a separation in size between the starred and starless cores that is not seen in the Mon R2 observations, where the majority of synthetic cores with sizes <0.073 pc contain sink particles/YSOs ($51 \pm 7\%$) compared to only $23 \pm 4\%$ of the cores with sizes >0.073 pc. We expect that this discrepancy is caused by both the overly massive disks in the simulations, which appear as bright, compact emissions, and the observational incompleteness for small core masses.
- 3. In sampling several ages of the RT2 simulations for the synthetic observations, we explore the ranges of core mass, size, and clustering that are potentially observable. We find that the starred cores decrease in mass and size, while the starless cores remain invariant over time. In the simulations, the synthetic starred cores move down the

BE stability line with age, as they accrete their envelope, separating from the starless cores.

4. The simulated cores cluster where the gas is densest, but the groupings are universally small *N*, exhibiting notable density reductions for modest increases in smoothing scale. The character of their clustering with respect to gas density is only consistent with the Mon R2 observations within a narrow gas column density range. The Mon R2 observations exhibit core clustering that is correlated with gas structure at a wide range of gas column densities and smoothing scales. These results suggest that while the synthetic observations can reproduce the CMFs, the discrepancies between some of the simulations and observations of Mon R2 are nonetheless substantial, and will require amelioration in order to improve confidence in the predictions that we derive from the simulations.

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Facilities: LMT(AzTEC), Herschel(SPIRE).

Software: Astropy (Astropy Collaboration et al. 2018), Photutils (Bradley et al. 2020), Matplotlib (Hunter 2007), NumPy (Harris et al. 2020).

Appendix A Removing the AzTEC Signal

In order to insert the simulations into the AzTEC 1.1 mm continuum maps, the original signal must be removed, such that all of the astronomical signal in the final synthetic observation is from the original simulation. We find that a straight subtraction oversubtracts the original signal, leaving negative halos surrounding the observed signal. To address this, we determine the fraction of the original signal that should be subtracted (the oversubtraction fraction, f_{sub}), before inserting the simulation into the AzTEC 1.1 mm continuum maps. We create negated AzTEC signal maps multiplied by various values of f_{sub} that are added to the time



Figure 15. The effect of f_{sub} on the negating signal in the Field 4 map. Top: the resulting S/N background map for Field 4, with different factors of f_{sub} (0, 1, 0.5, 0.55, 0.6) applied post-macana. Middle: 2D histograms comparing the S/N of the original map to the background maps, with various factors of f_{sub} applied. The dashed line is unity. Bottom: histograms of the S/N in the background maps (red) compared to the S/N of the original map (gray). When the significant signal is removed from the map, the background S/N is $-4 \leq S/N \leq 4$. When oversubtraction occurs, negative halos produce significant negative S/N values, and when undersubtraction occurs, the positive signal produces a significant positive S/N. At $f_{sub} = 0.55$, the optimal amount of signal is subtracted, diminishing the negative halos and the strong positive signal.



Figure 16. The effect of S/N on the oversubtraction fraction for three fields in Mon R2: Field 1, Field 4, and Field 9. Oversubtraction increases with the increase of the signal in the field; therefore, the oversubtraction fraction required to remove all of the signal from the field also increases.

stream and run through macana. The goal is to create a map of well-behaved noise without a strong correlated signal (or antisignal). Figure 15 shows how the oversubtraction of the signal in Field 4 changes for different f_{sub} values. When all of the original signal is subtracted, the background-only map is significantly oversubtracted, resulting in negative S/N values for all original S/ N > 2.5. However, when the original signal is halved ($f_{sub} \sim 0.5$), the amount of oversubtraction is much less severe, with every pixel having |S/N| < 5.

To quantify f_{sub} , we find a linear relationship between f_{sub} and the average S/N of pixels with S/N values greater than the pivot S/N. The pivot S/N is found by:

- 1. Selecting all of the bins that have a background-only S/ N ${\sim}0;$
- 2. Determining the bins in that selection with counts greater than the median number of counts in the whole histogram;
- 3. Finding S/N_{thresh} : the original S/N value that corresponds to the rightmost bin with counts greater than the median number of counts in the whole histogram; and
- 4. Calculating the average S/N in each map with $S/N > N_{thresh}$.

This average S/N is the S/N of all of the pixels for which the original S/N was large enough to be affected by the oversubtraction. With this relationship, we can then find f_{sub} where the average S/N of those affected pixels will be zero, and create a blank canvas on which to add the synthetic emission map. As shown in Figure 16, for the three fields that we tested—Field 01 (relatively empty), Field 4, and Field 09 (relatively strong emission)—we found a range of f_{sub} from 0.55 (Field 01) to 0.8 (Field 09), indicating that fields with more emission have a higher f_{sub} .

Appendix B Image Segmentation

At submillimeter wavelengths, the thermal emission from the cores is optically thin, allowing the full flux density to be measured. However, how these cores are identified is still an issue that must be resolved before the core properties can be measured. Beyond searching by eye, several clump-finding algorithms exist, which search for bright peaks (ClumpFind; Williams et al. 1994), ascend gradients until reaching a peak (FellWalker; Berry 2015), or use hierarchical branches to find a

range of clumps (dendrograms; Rosolowsky et al. 2008). Each of these methods have biases and work in different ways. However, none take into account the noise properties and maps that are produced by the data reduction pipeline from AzTEC and eventually ToITEC.

macana, the AzTEC C++ Data Reduction Pipeline, produces a coadded signal, weight, S/N, and point-spread function (PSF) maps. In order to characterize the noise in each scan of the time stream data, noise realization maps are produced through a jackknifing technique. These produce a good estimation of the noise variance in each scan, and can give a false detection rate when finding clumps. In order to utilize the noise realization maps to the fullest extent and obtain an accurate core census, Sokol et al. (2019) used a core identification algorithm similar to ClumpFind for both the signal maps and the noise realization maps to identify the real and false cores. This algorithm was written in IDL and uses the IDL watershed algorithm to search for continuous emission. With the upcoming C2C, this algorithm has been updated, converted into a working python-based library (named ImSeg⁵), and documented so that it can be used by the C2C community.

ImSeg is a core detection and characterization utility that uses the photutils package photutils.Segmentation to detect and deblend clumps and cores in both observational data and simulations. After detecting core candidates, ImSeg measures the characteristics of each core, including R.A./ decl., total and peak flux, area, FWHM semimajor/minor axes, and mass. All core candidates are then put through a "goodness" test, using the noise realization maps, to determine the final core catalog and CMF.

ImSeg is currently set up for 350, 450, 850, and 1100 μ m wavelength observations, and it has been successfully applied to James Clerk Maxwell Telescope Submillimetre Common-User Bolometer Array 2 (SCUBA-2) 450 and 850 μ m data, as well as to LMT AzTEC 1100 μ m data.

Before identifying the cores, the flux map is first masked on values with S/N < 2.5 and/or where the weight was less than 40% of the median nonzero weight values of the map. This masking ensures that only a significant signal is identified. A noise map is also created from the signal and S/N maps in order to give a threshold level for detection. The masked signal map is then run through the photutils.Segmentation detect sources() algorithm, which detects blobs with values greater than the noise at each pixel. For a blob to be identified, it must have a minimum number of 8 connected pixels (npixels; pixels touching along edges or at corners). This parameter is tuneable; however, we choose a value of npixels that corresponds to blobs slightly smaller than 0.05 pc. As 0.05 pc is the average core size, we include cores by choosing a slightly smaller npixel, while excluding potential noise peaks or hot pixels. However, as this method only determines the connected pixels, overlapping blobs will be identified as one component. Therefore, we utilize the photutils. Segmentation deblend_sources() multi-thresholding and watershed algorithm to separate the individual cores. This method requires two parameters: nlevels and contrast. nlevels refers to the number of multi-thresholding levels, while contrast is the fraction of the total flux that a peak must have to be its own blob. The number of levels is used for every source; this

⁵ http://github.com/sbetti22/ImSeg



Figure 17. Footprint matching between ImSeg (red) and the IDL watershed (white; Sokol et al. 2019) on top of the 1.1 mm AzTEC emission maps for the Mon R2 region (top), the GGD 12 15 region (bottom left), and the GGD 17 region (bottom right). These main areas of the molecular cloud are shown in order, to give a range of core densities.

means that 2σ sources are separated by the same number of levels as a 10σ source. This poses a problem, as either oversegmenting (where the nlevels is too high) or undersegmenting (where the nlevels is too low) can occur. To get around this issue, we make several changes to the deblen-d_sources() function. Before running the function, we create a noise-based contour image of our signal map, with steps 1σ in size. The contour image is found by scaling the masked signal map by the median noise value of the masked pixels, before the fractional values are truncated to yield the noise-based contour image. This image is stored as a greyscale byte image.

The deblend_sources() function is then changed to use this noise-based contour map to find the number of multithresholding levels to use for each blob and their corresponding data values. Each blob is then segmented with a different number of levels, based on the contour image; however, the step size between the thresholding levels for each blob is always 1σ .

After each core is deblended, the properties of each core are then determined. For each core, photutils.Segmentation source_properties calculates several properties. We utilize the central R.A. and decl., the peak S/N and signal, the area in pixels squared, and the flux values within each core. With these various properties, we find and calculate the central R.A. and decl., the peak S/N, the peak signal, the total S/N, the total signal, the area in degrees squared, the HPP area, and the HPP central R.A. and decl., then determine if the core is too close to the edge of the map. Additionally, we calculate the temperature of each core and the number of YSOs within the footprint of each core.

The final core candidates are selected using a "goodness" test, based on the whether the core passes three tests: the minimum S/N threshold, the "good" score minimum threshold, and the minimum column density ratio threshold.

The column density from the emission map is calculated as:

$$N(\mathrm{H}_2) = \frac{S_{\nu}}{B_{\nu}(T)\kappa_{\nu}\,\mu_{\mathrm{H}_2}m_H\Omega_B},\tag{B1}$$

where S_{ν} is the total signal from each core in Jy; $B_{\nu}(T)$ is the Planck function at the temperature of each core in K; κ_{ν} is the dust opacity; $\mu_{\rm H_2}$ is the mean molecular weight, which we take to be 2.8 (Kauffmann et al. 2008); and Ω_B is the beam area. We assume a constant dust opacity interpolated for various wavelengths, taken from model 5 in Ossenkopf & Henning (1994) for thin ice



Figure 18. Histograms of the corrected deconvolved FWHM sizes for all of the cores within each field and all combined, found with ImSeg (black) and the IDL watershed (gray hatch; Sokol et al. 2019).

mantles. For 350, 450, 850, and 1100 μ m, we assume 0.101, 0.0674, 0.0114, and 0.0121 cm² g⁻¹, respectively. We also assume a gas-to-dust ratio of 100.

As shown by Sokol et al. (2019), the false cores from noise realization maps are poor matches with the diffuse gas from an inputted column density map, while the high S/N core candidates correlate well (their column density ratio is approximately unity). Therefore, by finding cores that occupy the same S/N–column density ratio parameter space as the false noise realization cores, we can separate the false detections from the cores.

To do this, we create a 2D histogram of the S/N–column density ratio for both the noise realization false cores and the core candidates. The ratio of these two histograms is found in order to determine the parameter space in which false detections are likely to occur. Confidence intervals are calculated for the histogram ratio. If a core candidate lies within the "good" score minimum confidence interval, then it is considered a false detection. The cores that lie outside this confidence interval have a low probability of being considered a false detection. The final census of core candidates is selected from the cores that lie outside this "good" score confidence interval, have an S/N above the minimum threshold, and have a column density ratio greater than the provided threshold. If no noise realizations are provided, only the final two criteria are used to create the final catalog.

B.1. Comparison to the IDL Implementation in Sokol et al. (2019)

ImSeg is based on a similar implementation outlined in Sokol et al. (2019) that is written in IDL, using the IDL watershed. In order to gauge the effectiveness and reliability of ImSeg, we compare the two methods in order to see if we can produce the same results.

We use 1.1 mm Mon R2 GMC data taken with AzTEC on the LMT from 2014 November 27–2015 January 31. 14 fields were observed, covering an area of 2 deg², and they were reduced with macana. We then applied ImSeg to the reduced maps in order to identify the cores within the cloud. We used the Herschel 500 μ m-derived column density and temperature maps from Pokhrel et al. (2016). These cores were then compared to the original core catalog and footprints found in Sokol et al. (2019) using IDL. In Figure 17, we show a comparison between the IDL method and ImSeg for the main clusters within Mon R2. Red shows the footprint found with ImSeg, while white shows the footprint found with the IDL watershed. By visually inspecting both the dense cluster and the more isolated cores, we see that ImSeg reproduces the same footprints as the IDL watershed.

We then look at the core properties for all fields specifically area, size, and mass—to see how the two methods compare. Figure 18 shows the deconvolved FWHM size of all



Figure 19. The peak-to-total flux vs. the total S/N for the cores found with ImSeg (left) and the IDL watershed (right; Sokol et al. 2019). The top panels show the uncorrected flux ratio, while the bottom panels show the flux ratio corrected for the noise bias. The black dashed lines are the three Plummer-like models with a power-law index of 2 and scale lengths of 2, 12, and 18 arcseconds (top to bottom), respectively; the black solid line is the final beam profile; and the black dotted line is the composite core profile.



Figure 20. Mass vs. deconvolved FWHM size for the cores found with ImSeg (left and center) and the IDL watershed (right; Sokol et al. 2019). The left panel shows the cores found with ImSeg where the mass was calculated using the average temperature of the core found in Herschel. The center panel shows the cores found with ImSeg where the mass was calculated assuming 12 K, the temperature assumed in Sokol et al. (2019). The right panel shows the cores found with the IDL watershed from Sokol et al. (2019). The black lines in all of the panels mark the BE line for cores with T = 12 K. The black squares represent the started cores, while the gray circles are the starteds cores.



Figure 21. The mass-corrected CMFs found with ImSeg (left and center) and the IDL watershed (right; Sokol et al. 2019). The panels are as in Figure 20. Masses less than 3 M_{\odot} have incomplete sampling.

of the cores found with ImSeg that passed the threshold cuts. Overall, we found 306 cores with ImSeg and 246 ± 9 matches $(83 \pm 3\%)$ in the original 295-core IDL catalog. Therefore, ~ 50 IDL cores were not found with ImSeg, and ~ 60 ImSeg cores were not found with IDL. The majority of the nonmatches occurred for cores with predominantly small or large areas. This is either due to ImSeg or the IDL watershed not breaking up a core candidate into multiple candidates, instead giving candidates with larger overall areas or small-area candidates not passing either the watershed algorithm or the threshold cuts.

Finally, we reproduce the diagnostics from Sokol et al. (2019) in order to make sure that the core properties are similar. As shown in Figures 7 and 8 of Sokol et al. (2019), the 1.1 mm AzTEC Mon R2 survey is shallow, so the cores are spatially resolved, and the lower S/N cores are not fully detected. Sokol et al. (2019) corrected the underestimation of the total flux and core mass by modeling and characterizing the peak-to-total flux ratio relation, and then correcting for high ratios at low S/N. They tested their correction by constructing several Plummer-like models that range the peak-to-total flux and total S/N parameter space, as they fit the radial profile of the prestellar cores. We applied these same models and corrections to confirm that ImSeg gives the same noise bias and that the same corrections can be used to correct the underestimation of the flux (Figure 19).

We then apply the flux correction to correct the core mass in order to look at the mass versus size relation (Figure 20) and the CMF (Figure 21). As we use a Herschel temperature map to derive the temperatures of the cores, the masses will be different from the masses found by Sokol et al. (2019), who assumed T = 12 K for all cores. We therefore recalculate the masses, assuming this temperature, to confirm the reproducibility of these diagnostics. Figures 19–21 visually confirm that ImSeg reproduces the same properties as the IDL watershed.

Appendix C Disks within Synthetic Starred Cores

The starred synthetic cores are generally less massive and smaller than the starless cores. This is due to the addition of



Figure 22. Representative samples of the different types of simulated starred cores overlaid by their synthetic observed core boundaries (the white contours): (a) a disk with an extended halo; (b) a disk with a compact halo; (c) a disk with streamers; and (d) a diffuse emission.

bright, massive disks within the simulation. When these are smoothed and run through the macana pipeline, they appear as "peaky" small cores encompassing a sink particle. These massive older disks are a common occurrence in HD simulations (e.g., Zhao et al. 2020), and help to account for the discrepancy between the observations and the synthetic cores as described in Section 5.

By inspecting the original simulation, we find four main types of starred cores: (a) those with a disk surrounded by an extended halo; (b) those with a disk surrounded by a compact halo; (c) a disk with streamers; and (d) only a diffuse emission, where the disk is not visible (but a sink particle is still located within the core boundary). We illustrate these four types with a representative sample in Figure 22.

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