Tracing the Intrinsic Shapes of Dwarf Galaxies Out to Four Effective Radii: Clues to Low-mass Stellar Halo Formation

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Abstract

Though smooth, extended spheroidal stellar outskirts have long been observed around nearby dwarf galaxies, it is unclear whether dwarfs generically host an extended stellar halo. We use imaging from the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP) to measure the shapes of dwarf galaxies out to four effective radii for a sample of 6758 dwarfs at 0.005 < z < 0.2 and 10^{7.9} < M_*/M_\odot < 10^{9.6}. We find that dwarfs are slightly triaxial, with ⟨B/A⟩ ≥ 0.75 (where the ellipsoid is characterized by three principal semiaxes constrained by C ≤ B ≤ A). At M_*> 10^{8.5} M_\odot, the galaxies grow from thick disk-like at one effective radius toward the spheroidal extreme at four effective radii. We also see that although blue dwarfs are, on average, characterized by thinner disks than red dwarfs, both blue and red dwarfs grow more spheroidal as a function of radius. This relation also holds true for a comparison between field and satellite dwarfs. This uniform trend toward relatively spheroidal shapes as a function of radius is consistent with an in situ formation mechanism for stellar outskirts around low-mass galaxies, in agreement with proposed models where star formation feedback produces round stellar outskirts around dwarfs.

Unified Astronomy Thesaurus concepts: Dwarf galaxies (416); Galaxy stellar halos (598); Galaxy structure (622); Observational astronomy (1145)

1. Introduction

The existence of a smooth stellar component in the outskirts of local dwarfs is a common but puzzling phenomenon (Lin & Faber 1983; Minniti & Zijlstra 1996; Grebel 1999; Minniti et al. 1999; Roychowdhury et al. 2013). Round stellar halos are a near-ubiquitous component of more massive galaxies; thought to be assembled largely through the accretion of satellite galaxies, the stars that populate these outskirts provide key insights into the galaxy’s assembly history (see, e.g., Bullock & Johnston 2005; Abadi et al. 2006). Due to a decreasing stellar-mass-to-halo-mass ratio, satellite accretion by dwarf centrals deposits fewer stars per unit halo mass than analogous events around more massive systems (Purcell et al. 2007; Brook et al. 2014). It is thus considered unlikely that minor mergers are able to fuel the formation of a stellar halo in dwarf galaxies.

Instead, it has been suggested that the stellar outskirts of dwarfs are an in situ structure. In the field, dwarf galaxies sit in shallow potential wells; their structure is therefore more sensitive to the details of star formation feedback than more massive galaxies. Supernova-driven winds (Hu 2019), cosmic-ray feedback (Dashyan & Dubois 2020), stellar winds, radiation pressure, and photoionization (Muratov et al. 2015; El-Badry et al. 2016) are all expected to more efficiently displace gas in dwarfs than in more massive hosts (both in moving gas to large radii and in removing it from the system entirely). In particular, hydrodynamical simulations have predicted that star formation feedback can induce significant size fluctuations in the stellar content of dwarf galaxies, driving the formation of a round stellar halo by inducing radial migration via potential fluctuations, as well as forming stars in outflowing and inflowing gas (Stinson et al. 2009; Maxwell et al. 2012; El-Badry et al. 2016).

Not all theories of dwarf stellar halo formation are purely in situ, however; Bekki (2008) suggested that round stellar outskirts around dwarfs may be formed as a product of dwarf–dwarf major mergers (a merger wherein the mass of the secondary is at most a factor of ∼3 less than that of the primary). Such major mergers are expected to occur for about 75% of galaxies in this stellar mass range but are expected to proceed far more often in the early universe; only 30% of these galaxies are expected to have undergone a major merger in the last 10 Gyr (Deason et al. 2014; Besla et al. 2018). Stellar outskirts formed in this manner would tend to be comprised of ancient stellar populations; using the surface brightness profile given by Bekki (2008) directly after the outskirts are formed and taking into account surface brightness dimming due to passive evolution (Conroy et al. 2009), in the major-merger scenario, we would not expect to detect an extended round stellar component around the majority of dwarfs.

Moreover, the dwarfs that have been found to host extended, smooth, intermediate-to-old-age stellar populations are nearby systems in the Local Volume (and mostly in the Local Group; see Aparicio & Tikhonov 2000; Aparicio et al. 2000; Zaritsky et al. 2000; Hidalgo et al. 2003; Demers et al. 2006; Bernard et al. 2007; Stinson et al. 2009; Strader et al. 2012; Nidever et al. 2019; Puchta et al. 2019). It remains unclear whether such a structure is a generic feature of dwarfs (pointing to an in situ origin) or a result of the influence of the more massive galaxies in the Local Group.

Understanding the intrinsic shape of dwarf galaxies is thus of interest in understanding the stellar assembly of these low-mass systems and constraining recipes for star formation feedback. However, it has historically been challenging to construct a sample of dwarfs with sufficient numbers whose imaging is...
deep enough to measure stable ellipticity profiles. Previous works have been confined to the Local Volume (Roychowdhury et al. 2013) or the most massive dwarfs \((M_* > 10^9 M_\odot)\); Padilla & Strauss 2008; van der Wel et al. 2014; Zhang et al. 2019). Moreover, there has not been an effort to measure the intrinsic shapes of dwarf outskirts, due largely to the aforementioned technical hurdles.

In this work, we combine the large sample of spectroscopically confirmed dwarfs observed by the Sloan Digital Sky Survey (SDSS) spectroscopic surveys (both legacy and BOSS surveys; Strauss et al. 2002; Dawson et al. 2013; Reid et al. 2016) and the Galaxy and Mass Assembly (GAMA) spectroscopic survey (Baldry et al. 2012) with the wide and deep imaging of the Hyper Suprime-Cam Subaru Strategic Program \(\text{(HSC-SSP; Aihara et al. 2018a, 2018b; Bosch et al. 2018; Kawanomoto et al. 2018; Komiyama et al. 2018; Miyazaki et al. 2018)}\) to quantify the 3D shape distribution of dwarf galaxies as a function of radius.

The wide area covered by the HSC-SSP, in conjunction with the surface brightness sensitivity and high resolution of its imaging, allows us to map stable ellipticity profiles of the dwarfs out to four times the half-light radius \((R = 4R_{\text{eff}}, \text{where } R_{\text{eff}} \text{ is defined by a single Sérsic fit, as described in Section 3})\) at 0.005 \(< z < 0.2 \text{ and } 7.0 < \log_{10}(M_*/M_\odot) < 9.6\). This allows us to construct a sufficiently large sample of dwarfs to infer the distribution of their intrinsic shapes from observations of their projected 2D shapes at fixed radius. In Section 2, we detail the sample selection and volume corrections implemented for the sample. We detail the methodology and validation of the 1D surface brightness profiles and 3D shape inference separately in Sections 3 and 4, respectively. We then examine the change in dwarf 3D shape as a function of radius and dwarf properties in Section 5 and consider the implications of the observed shape evolution to proposed dwarf stellar halo formation mechanisms in Section 6.

Throughout this paper, we adopt a standard flat \(\Lambda\)CDM model in which \(H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1}\) and \(\Omega_m = 0.3\).

2. Observations and Data Processing

2.1. HSC-SSP Imaging

As noted above, the HSC-SSP imaging boasts wide, deep, and high-resolution imaging, making it well suited for an exploration of the low surface brightness outskirts of low-mass galaxies. Upon completion, HSC-SSP will provide imaging with a median seeing of \(\sim 0.7\) arcsec in the \(i_{\text{HSC}}\) band in \(\sim 1400\) deg\(^2\) to a point-source depth of \(i_{\text{HSC}} \sim 28.5\) mag arcsec\(^{-2}\) for measurements around a known target (Huang et al. 2018a). We test the surface brightness limit of the HSC-SSP data in the vicinity of our sample in Appendix A and find that \(\mu_i = 28.5\) mag arcsec\(^{-2}\) is a conservative choice of limiting surface brightness. Indeed, with an empirical correction to the background, it has been shown that HSC-SSP reaches depths of \(\mu_i \sim 29.5\) mag arcsec\(^{-2}\). However, because we allow several parameters to drift during our surface brightness profile measurements, we adopt the fiducial surface brightness limit of \(\mu_i = 28.5\) mag arcsec\(^{-2}\).

For this work, we use the internal HSC-SSP S18A data release, which covers the same area as the second public data release of Aihara et al. (2019) and is processed with a very similar data reduction pipeline. Though there are some minor differences between the data reduction pipelines used for S18A and PDR2, these changes do not affect the parts of the pipeline discussed in this work. We require only coverage in the \(i_{\text{HSC}}\) band, resulting in an area of \(\sim 796\) deg\(^2\) with a point-source depth of \(i = 26.2 \pm 0.4\). The \(i_{\text{HSC}}\) band is the best choice to study the overall shape of the stellar distribution for two main reasons. First, the \(i_{\text{HSC}}\) band has the best seeing out of the five HSC bands. Second, it is less sensitive to dust extinction and star-forming regions relative to the bluer \(g_{\text{HSC}}\) and \(r_{\text{HSC}}\) bands and deeper than the redder \(z_{\text{HSC}}\) and \(y_{\text{HSC}}\) bands.

2.2. Initial Sample Selection

All dwarfs in the present sample have been spectroscopically observed by either the SDSS or GAMA spectroscopic surveys. We limit our sample to dwarfs at \(0.005 < z < 0.2\); the redshift distribution of the sample peaks at \(z \lesssim 0.05\), as shown in the bottom panel of Figure 1. Due to the intrinsic faintness of low-mass galaxies, the majority of our sample is at \(z \lesssim 0.1\).

This selection yields a sample of 11,338 dwarfs. In 3128 cases, there is a bright star (or related imaging artifact) within 5\(\text{r}_{\text{eff}}\) of the target galaxy; because our goal is to measure ellipticity profiles out to the outskirts of the dwarfs, we remove these galaxies from the final sample. An additional 548 galaxies are too close to neighbors to measure a reliable surface brightness profile or are coincident with an imaging artifact.

We adopt stellar masses measured by the SDSS and GAMA teams. The stellar masses measured by the GAMA team use a Chabrier initial mass function (Chabrier 2003) by Taylor et al. (2011). The stellar masses measured by the SDSS team are derived using the Conroy et al. (2009) flexible stellar population synthesis (FSPS) models with a Kroupa initial mass function (Kroupa 2001). In Kudo-Fong et al. (2020), we found that, for galaxies with both SDSS and GAMA spectroscopy, the SDSS stellar masses are higher than the GAMA stellar masses by a median of 0.08 dex and a median absolute deviation of 0.35 dex. We therefore reduce the masses derived from SDSS observations by 0.08 dex; it is, however, important to note that due to the width of our mass bins, including or excluding this shift does not impact this work.

2.3. Volume Corrections

Our sample is drawn from the SDSS and GAMA spectroscopic surveys, both of which comprise several subsets with different magnitude limits. The sample is composed of observations from the SDSS Legacy Survey \((r_{\text{petro}} < 17.77; \text{ Strauss et al. 2002})\), the low-redshift component of SDSS \(\text{BOSS } (r_{\text{petro}} < 19.6; \text{ Dawson et al. 2013})\), and the GAMA second public release \((r_{\text{petro}} < 19.4 \text{ or } 19.0, \text{ depending on the region}; \text{ see Liske et al. 2015})\). To convert this sample from magnitude-limited to volume-limited, we adopt the classical \(1/V_{\text{max}}\) correction to simulate a volume-limited sample.

As all of the galaxies in our sample are low mass, none have maximum observable redshifts for which the observed-frame \(r\) band lies outside of the wavelength range of the (SDSS or GAMA) optical spectrograph. We are thus able to compute the maximum redshift at which the observed \(r_{\text{SDSS}}\) Petrosian magnitude lies within the spectroscopic selection, \(z_{\text{max}}\), directly from the spectra using the public filter response curves.
transmission curve has evolved by less than 0.01 mag (Doi et al. 2010). We therefore use the fiducial SDSS transmission curve for all galaxies.

We remove galaxies for which $z \geq z_{\text{max}} + 0.005$ or $z_{\text{max}} \leq 0.005$ (recall that our minimum redshift cut is $z = 0.005$), as these conditions suggest that there is a problem with the catalog photometry or spectroscopy. From inspection, these are largely comprised of cases where a large galaxy has been erroneously divided into several “low-mass galaxies” during image segmentation (i.e., shredding; see Blanton et al. 2011). These cuts produce a final sample of 6758 galaxies.

To validate our directly computed $z_{\text{max}}$ values, we compare the distribution of stellar masses in our sample, as weighted by $1/V_{\text{max}}$, to published stellar mass functions (SMFs) in the literature. We report the SMF normalized over our sample mass range, that is, $\phi(\log_{10}(M_{*}/M_\odot)) \equiv C_0 \, dN/d(\log_{10}(M_{*}/M_\odot))$, where $C_0$ is a constant defined such that $\int_{9.6}^{10} \phi(x) \, dx = 1$.

The top panel of Figure 1 shows this normalized SMF of each magnitude-limited subset in our sample as dashed curves. The distribution over the full sample is shown by the solid blue line, while the original unweighted stellar mass distribution of the sample is shown by the filled gray histogram. The double Schechter fit of Wright et al. (2017; from GAMA) is shown by the solid black line, and the Schechter fit of Panter et al. (2007; from SDSS) is shown by the dashed black line. In both cases, the parametric fits are normalized over the stellar mass range of our sample.

Our $1/V_{\text{max}}$-corrected stellar mass distribution is in good agreement with the results of Wright et al. (2017) and somewhat steeper than the mass function of Panter et al. (2007). This is expected, as Wright et al. (2017) included significantly more galaxies at the stellar mass range of the present sample; the agreement between our normalized SMF and that of Wright et al. (2017) indicates that the $1/V_{\text{max}}$ weights we implement are well behaved.

3. 1D Surface Brightness Profile Measurement

With a volume-corrected sample in hand, we now turn to the main objective of this work. The measurement of a 3D shape distribution requires both careful measurements of the projected 1D surface brightness profiles and a framework with which the 3D shape distribution may be inferred from these projected profiles.

We first address our adopted 1D profile measurement scheme. To establish a reasonable initial guess for the centroid position, mean ellipticity, and position angle (PA) of the source, we first fit each galaxy with a single Sérsic profile. We also use the Sérsic profile fit to measure an effective radius ($R_{\text{eff}}$) for each source. We then extract a 1D ellipticity profile from each galaxy by allowing the isophotal shape to vary with radius.

3.1. Single Sérsic Fits

Though a single Sérsic model is not flexible enough to fully describe the structure of dwarf galaxies, it provides a stable and robust model to extract basic flux-weighted structural parameters.

The PA, ellipticity, and centroid from this single Sérsic fit are used to initialize the nonparametric surface brightness profile measurement at $R_{\text{eff}}$. Because dwarf galaxies are often characterized by irregular, off-center star-forming regions...
(Binney & Tremaine 2008), an inflexible and monotonically decreasing model is necessary to establish a reliable galaxy centroid. We additionally adopt the Sérsic-derived effective radius as $R_{\text{eff}}$ throughout the paper. In Figure 2, we show the distribution over Sérsic index (top) and effective radius (bottom) for our sample. The dwarfs tend to be well described by an exponential ($n = 1$) profile with a median [25th, 75th percentile] Sérsic index of 0.94 [0.79, 1.1]. Their effective radii are typically a few kpc, with a median [25th, 75th percentile] value of 2.5 kpc [1.6, 3.7 kpc], though we note that there is a strong relationship between stellar mass and effective radius.

### 3.2. Nonparametric Surface Brightness Profiles

Though a single Sérsic fit provides a reasonable initial guess for their surface brightness profiles, dwarf galaxies are rich in substructure and not well described by a single Sérsic profile. Single Sérsic profiles are also unable to trace changes in ellipticity as a function of radius, by definition.

In order to better describe the complex structure of low-mass galaxies and test whether ellipticity changes as a function of radius, we adopt a more flexible nonparametric method to measure the 1D surface brightness profiles of the galaxies in our sample. We use the method introduced by Huang et al. (2018a), which is based on the IRAF Ellipse algorithm (Jedrzejewski 1987) and allows ellipticity $\epsilon$, central position $(x_c, y_c)$, and PA to vary as a function of semimajor axis $a$. The exceptional depth of the HSC-SSP imaging allows us to fit profiles with these parameters free without the fit becoming unstable. To further safeguard against an unstable fit, if the centroid shifts by more than $0.5R_{\text{eff}}$ at $r = R_{\text{shift}}$, we disregard the surface brightness profile at $r > R_{\text{shift}}$.

To generate reliable surface brightness profiles, we must first mask out galaxies that are near the target. To do so, we use the method introduced in Kado-Fong et al. (2020, Appendix B) to detect and mask background sources by detecting sources at spatial frequencies that are high relative to the smooth light of the target outskirts. This approach allows us to remove background galaxies that are at small projected distances from the target galaxy, where they are most likely to contaminate measurements of the galaxy outskirts. We also apply a $3\sigma$ clipping to the pixel values along each isophote to reduce the impact from other objects. Huang et al. (2018a) and F. Ardila et al. (2020, in preparation) showed that this method works well even for massive galaxies with extended stellar halos. We also adopt a moderately large multiplicative step size of $(a_{n+1} - a_n)/a_n = 0.2$ to help stabilize the ellipticity measurement in the outskirts of the galaxy. In Figure 3, we show example 1D profiles that span the stellar mass and redshift range of our sample. The left panel of each pair shows the isophote at $1-4R_{\text{eff}}$ plotted over the $i$-HSC–band image. The $gri$HSC composite red, green, and blue (RGB) image is also shown by the inset panel. The right panels show the 1D surface brightness profile for each example. The examples decrease in stellar mass from top to bottom and increase in redshift from left to right. In addition, we show the overall distribution of surface brightness at $1-4R_{\text{eff}}$ for our 1D profile fits in the top panel of Figure 4 and the surface brightness versus ellipticity in the bottom panel. Though we use effective radii (and multiples thereof) in this work, we have also verified that using fixed physical radii does not change our results.

At $4R_{\text{eff}}$, the farthest extent to which we measure ellipticity profiles, the median surface brightness is $\langle \mu_i \rangle = 26.8$ mag arcsec$^{-2}$, significantly brighter than our surface brightness limit. Seven percent of galaxies have a surface brightness of $>28.5$ mag arcsec$^{-2}$ at $4R_{\text{eff}}$. We do not remove them from the sample, as their inclusion or exclusion from this analysis does not have a statistically significant impact on the overall ellipticity distribution of the overall sample or subsamples considered in this work. To ensure that we are able to reach this nominal surface brightness limit, we examine the residual sky background near our dwarf sample in Appendix A and find that the sky is slightly uniformly undersubtracted near our dwarfs, corresponding to a surface brightness difference of $\Delta\mu_i \lesssim 0.02$ mag arcsec$^{-2}$ at $\mu_i = 28.5$ mag arcsec$^{-2}$. We thus confirm that the profiles are well recovered down to our nominal surface brightness limit, and that the residual sky does not affect the shape measurements made in the outskirts of the galaxies.

#### 3.2.1. The Impact of the PSF

In many situations, it is important to correct for the effects of the point-spread function (PSF) in order to probe the outskirts of galaxies (see, e.g., Trujillo & Fliri 2016). In this work, we expect that the effect of the PSF does not significantly affect our results for the following reasons.

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7 We allow the centroid to drift in order to accommodate the presence of off-center star-forming regions that may dominate the light near the center of the galaxy. At the radii we consider for this work, the ellipticity distribution does not change significantly when the centroid is held constant or left free.
First, due to the high resolution of the HSC imaging, the region of interest for our sample \((r > R_{\text{eff}})\) is not strongly affected by the smearing effect of the finite seeing (the median seeing is \(i_{\text{HSC}} \sim 0.6\); Aihara et al. 2019), even at the high-redshift end of our sample. To visually demonstrate the size of the PSF with respect to the scale of the profile measurements, in Figure 3, we plot the profile of the PSF in gray. Second, it is important to note that because the cores of dwarfs are intrinsically fainter than those of their more massive analogs, the effect of scattered light is smaller for a intrinsically fainter than those of their more massive analogs, which was derived via optical tracing of the redshift end of our sample. To visually demonstrate the size of the extended HSC PSF can account for up to 40% of the flux in the stacked profile of galaxies at \(10^{9.2} < M_*/M_\odot < 10^{10.9}\) in HSC-SSP. At \(r \lesssim 20\) kpc, with the bulk of the sample sitting at \(z < 0.1\), however, the PSF has a much less significant effect.

In particular, Figure 9 in Wang et al. (2019) shows that the impact of the PSF, which depends on both the central surface brightness and concentration of the galaxy, should be small for our sample, which is populated by dwarf galaxies with low central surface brightnesses (relative to massive galaxies) and exponential profiles. For a dwarf with an exponential profile and a central surface brightness of \(\mu_c \sim 20\) mag arcsec\(^{-2}\), the extended wings of the HSC PSF appear at around a scale of \(2''\)
and a surface brightness of 27 mag arcsec$^{-2}$. At scales comparable to 4$R_{\text{eff}}$, this effect will be even smaller. We thus do not expect that the PSF will affect the results presented in this work.

### 3.3. Profile Measurement Validation

In order to test the validity of our inferred size and ellipticity profiles, we perform several mock galaxy injection tests. In particular, we first confirm that we can recover the ellipticity of Sérsic profiles injected at low surface brightness without significant bias. Then, we compare our nonparametric measurements of ellipticity at 1$R_{\text{eff}}$ to both the parametric measurements of our Sérsic fits to the HSC data and published ellipticity measurements from SDSS imaging to verify that there is no systematic shift between the parametric and nonparametric measurements.

#### 3.3.1. Recovery of Injected Sérsics

First, we inject mock galaxies composed of a single Sérsic profile, the parameters of which (effective surface brightness, effective radius, and intrinsic axis ratios) are drawn from a known distribution, into the HSC coadds. The surface brightness of the mock galaxies is set to cover the same range as the real galaxies, and the Sérsic index is fixed at $n = 1$ (exponential) for all galaxies. The positions of the mock galaxies are selected to be empty locations where there are no detections in any of the five HSC bands, but no other constraints are made on the galaxy placement. These mock galaxies should therefore be affected by imaging artifacts, background galaxies, and residual astrophysical foreground (e.g., galactic cirrus) in the same way as the real galaxies in our sample.

Figure 5 shows the injected and recovered distributions of the galaxy structural parameters. We find that the properties of the injected galaxies in this simple test are well recovered: at 4$R_{\text{eff}}$, for 75% of cases, the ellipticity of the mock galaxy is recovered to better than $|\epsilon_{\text{truth}} - \epsilon_{\text{obs}}| \leq 0.065$. Crucially, decreasing surface brightness does not significantly bias our ellipticity measurement. In Figure 4, we show the surface brightness distribution of the real galaxy 1D profiles measured at 1–4$R_{\text{eff}}$. The lower envelope of the projected axis ratio distribution clearly increases with increasing radius (and therefore decreasing surface brightness). We do not find such a trend for the injected disk population, which samples $b/a$ uniformly, over the same range in surface brightness.

While we do not test for the impact of asymmetric features that are not captured by a single Sérsic model, this test verifies that the ellipticity profile is well recovered in HSC imaging conditions across a range of different injected distributions.

#### 3.3.2. Comparison to Parametric $b/a$ Measurements

In order to capture the often irregular and asymmetric structure of dwarf galaxies, our nonparametric profile fits allow many parameters to vary as a function of semimajor axis. Thus, it is important to compare our nonparametric measurements of ellipticity to measurements of the same quantity using a more rigid model.

In the left panel of Figure 6, we show the distribution over the observed axis ratio, $q = b/a = 1 - \epsilon$, as measured from the nonparametric ellipticity profiles at $R_{\text{eff}}$ (filled teal histogram), Sérsic fits to the HSC-SSP imaging (open green histogram), and exponential fits to SDSS imaging of the same galaxies. We find that our nonparametric measurements are in good agreement with both the Sérsic profile fits ($\sigma_{\Delta q} = 0.07$) and the SDSS exponential profile fits ($\sigma_{\Delta q} = 0.101$). The increase in scatter with respect to the SDSS measurements is not unexpected, as the SDSS imaging is significantly shallower and fit with a less flexible model (i.e., where the Sérsic index is fixed to $n = 1$). The lack of bias as a function of projected axis ratio, however, is a good indication that our nonparametric measurements obtain reasonable results despite their flexibility.

### 4. 3D Shape Inference

Let us assume that the 3D shapes of each galaxy in our sample (or subsample) are drawn from a single distribution over the intrinsic axis ratios $B/A$ and $C/A$, given by $P(\alpha)$, where $\alpha$ is some set of parameters that describes the distribution of $B/A$ and $C/A$. The projected axis ratio, $q$, for any given ellipsoid is determined solely by the observer’s viewing angle, ($\theta$, $\phi$). That is to say, the projected axis ratio $q$ can be written as $q = \mathcal{F}(B/A, C/A, \theta, \phi)$.

The analytic expression for $\mathcal{F}$ was presented by Simonneau et al. (1998) and is reproduced below. First, $(ab)^2$ and $(a^2 + b^2)^2$
can be rewritten as follows:

\[ a^2 b^2 = f^2 = (C \sin \theta \cos \phi)^2 + (BC \sin \theta \sin \phi)^2 + (B \cos \theta)^2, \]  
\[ a^2 + b^2 = g = \cos^2 \phi + \cos^2 \theta \sin^2 \phi + B^2(\sin^2 \phi + \cos^2 \theta \cos^2 \phi) + (C \sin \theta)^2. \]  

We now define the quantity \( h \) to be

\[ h = \sqrt{\frac{g - 2f}{g + 2f}}, \]  

such that it may be shown that

\[ \frac{b}{a} = \frac{1 - h}{1 + h}. \]  

Because the distribution of viewing angles is known to be isotropic on the surface of the sphere, we can predict the projected distribution of \( q \) given a choice of intrinsic shape distribution characterized by \( \alpha \) by sampling \( \phi \) and \( \theta \) as follows:

\[ \phi \sim U[0, 2\pi] \]
\[ \nu \sim U[0, 1] \]
\[ \theta = \cos^{-1}(2\nu - 1). \]  

For simplicity, we first consider a normal distribution over both \( B \) and \( C \), such that the 3D shape distribution can be described by the parameters \( \alpha = \{\mu_B, \mu_C, \sigma_B, \sigma_C\} \). We find that the data are well described by this relatively simple model and that the fit is not significantly changed or improved by a more complex model (as motivated by Zhang et al. 2019; see Appendix C).

Armed with this framework, we are able to quickly estimate the distribution of the projected axis ratios for a given choice of \( \alpha \). This can then be compared cheaply to the observed distribution of \( q \) by adopting a Poisson likelihood,

\[ \ln p(q|\mu_B, \mu_C, \sigma_B, \sigma_C) = \sum_i n_i \ln m_i - m_i - \ln n_i!, \]  

where \( n_i \) is the observed count where \( 0.04i < q \leq 0.04(i + 1) \) and \( m_i \) is the predicted count in the same range. Though this likelihood is, in principle, sensitive to the adopted bin size, for our sample, we find that the results are not significantly

Figure 5. Distribution of errors in recovered effective radius (left), ellipticity at 1\( R_{\text{eff}} \) (middle), and ellipticity at 3\( R_{\text{eff}} \) (right) for an injected population of disk \((A, B, C) = [1., 0.9, 0.1]; \) blue), spheroid \((A, B, C) = [1., 0.9, 0.9]; \) red), and prolate \((A, B, C) = [1., 0.1, 0.1]; \) green) galaxies. Each mock galaxy is assigned a viewing angle drawn isotropically over the sphere, injected into the HSC data with an \( n = 1 \) Sérsic profile, and recovered with our pipeline.

Figure 6. Left: observed distribution of projected axis ratio, \( q = b/a \), for the HSC nonparametric measurements (filled teal histogram), HSC Sérsic measurements (open green histogram), and SDSS catalog measurements (derived from exponential fits; open brown histogram). All three measurements are in good agreement; we find that the mean difference in the measured \( q \) \((\Delta q)\) and the standard deviation of this difference \((\sigma_{\Delta q})\) are \((\Delta q) = 0.017, 0.71)\) and \((\sigma_{\Delta q}) = \{-0.01, 0.10\}\) for the HSC Sérsic measurements and SDSS catalog exponential measurements, respectively. In the middle panel, we plot the nonparametric measurements at 1\( R_{\text{eff}} \) against the HSC Sérsic measurements, while in the right panel, we show the same nonparametric measurements at 1\( R_{\text{eff}} \) against the SDSS exponential measurements for galaxies in the SDSS catalog.
affected by reasonable choices for the bin width. For each step, we choose the bin size from a uniform distribution bounded by $[0.03, 0.1]$. The minimum width is chosen such that for the minimum sample size that we consider ($N = 700$; see Section 5.1), for a uniform distribution of projected axis ratio, the standard deviation of the counts in a given bin is expected to be $\sim 20\%$ of the mean bin count.

We adopt a flat prior for all model parameters. The prior over $\mu_B$ and $\mu_C$ is set purely by the physical boundaries,

$$p(\mu_B) = \begin{cases} 1 & \text{if } 0 < \mu_B < 1; \\ 0 & \text{otherwise} \end{cases}$$

we constrain $\mu_C \leq \mu_B$ to maintain the order of axes,

$$p(\mu_C) = \begin{cases} 1 & \text{if } 0 < \mu_C < 1 \text{ and } \mu_C \leq \mu_B; \\ 0 & \text{otherwise} \end{cases}$$

and, when sampling from a given $\alpha$, we disregard cases where $C > B$.

We implement the same flat prior over $\sigma_B$ and $\sigma_C$,

$$p(\sigma_X) = \begin{cases} 1 & \text{if } 0 < \sigma_X < 0.5; \\ 0 & \text{otherwise} \end{cases}$$

where $X \in (B, C)$. Here the upper limit is set so that the distribution is contained largely within the physically admissible region.\(^8\)

We can then write the posterior probability distribution as

$$p(\alpha | \text{data}) \propto p(\text{data} | \alpha) p(\mu_B)p(\mu_C)p(\sigma_B)p(\sigma_C).$$

to sample efficiently from this distribution, we use the Markov Chain Monte Carlo (MCMC) ensemble sampler implemented in emcee (Foreman-Mackey et al. 2013). For each case discussed in this work, we run the sampler with 32 walkers and 3000 moves. We verify that the walkers have converged and discard the first 150 moves of each.

\(^8\) We furthermore find that none of our data suggest $\sigma_X$ near 0.5, indicating that this choice of boundary does not affect our results.

Figure 7. For the injected ellipsoid populations described in Figure 5, we infer the 3D shape distribution of the population from the recovered projected axis ratios. The panels labeled prolate, disk, and spheroid show the $b/a$ distribution recovered for the mock observations by our 1D profile measurement pipeline as filled histograms, and the posterior $b/a$ sample as open black histograms. In the bottom-right panel, we show the inference results for our injected populations of disk ($[A, B, C] = [1., 0.9, 0.1]$; blue), spheroid ($[A, B, C] = [1., 0.9, 0.9]$; red), and prolate ($[A, B, C] = [1., 0.1, 0.1]$; green) galaxies. The black circles shows the true values of the intrinsic axis ratios. For physical context, we show the $C/A$ values measured for the Milky Way (MW) disk–halo system as measured by Schönrich & Binney (2009) and Iorio & Belokurov (2019). The dashed black line shows the definitional boundary of $B = C$. 

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4.1. Validation: Comparison to Sérsic Populations

In order to test our 3D inference framework, we return to the injected Sérsic populations of Section 3.3.1. These tests have the advantage of incorporating both major sources of uncertainty in the final 3D shape inference: the uncertainties in the 1D profile measurement (due to, e.g., neighboring galaxies and residual sky background) and 3D shape inversion problem.

In Figure 7, we show the recovered distribution of projected axis ratios with colored histograms: blue for the disk population, red for spheroidal, and green for prolate. The distribution of projected axis ratios generated by sampling the posterior is shown by the thick black line in each panel (the thin black lines show individual draws from the posterior). The lower right panel of Figure 7 shows the distribution of this posterior sample in the intrinsic B–C axis space; the colored contours show the regions that contain 0.34^2, 0.68^2, 0.95^2, and 0.99^2 of the distribution (corresponding to the 0.5σ, 1σ, 2σ, and 3σ regions for a multivariate normal distribution). The black circles show the true value of μB and μC.

When the true values of μB and μC are sufficiently distant from the boundary, we find that we are able to recover their values very well, as seen for the disk population in blue. However, we find that our inferred values are biased when the true value is close to the imposed boundary (B/A = C/A) of the problem, as is the case for the spheroidal and prolate populations. Based on the shape distributions inferred by studies at higher masses (see, e.g., Padilla & Strauss 2008; van der Wel et al. 2014) and of ultradiffuse galaxies (UDGs) in clusters (Burkert 2017; Rong et al. 2020), as well as the shape distributions measured from cosmological simulations (Pillepich et al. 2019), it is unlikely that real galaxies are characterized by extreme distributions at the B = C boundary.

All of our injected Sérsic galaxies are drawn from a 3D shape distribution where σB and σC = 0; the inferred σB and σC in these test cases should then provide a lower limit on the intrinsic dispersion to which we are sensitive.9

4.2. Validation: Comparison to Padilla & Strauss (2008)

Before applying this shape inference framework to our sample of HSC dwarfs, we want to confirm that our method can reproduce published 3D shape distributions of higher-mass galaxies. Toward this end, we use SDSS catalog shape measurements to infer 3D shape distributions from data that are analogous to those of Padilla & Strauss (2008), who used SDSS catalog measurements to estimate the 3D shape distribution of galaxies with stellar masses of \( M_\ast \gtrsim 10^9 \, M_\odot \).

For a linear combination of an exponential profile (i.e., a Sérsic profile with index \( n = 1 \)) and a de Vaucouleurs profile (i.e., a Sérsic profile with index \( n = 4 \)), the SDSS photometric catalog provides the weight assigned to the \( n = 4 \) component as \( f_{\text{deV}} \) (Abazajian et al. 2004). Padilla & Strauss (2008) separated their sample into a subset of spiral galaxies, wherein \( f_{\text{deV}} < 0.8 \), and elliptical galaxies, wherein \( f_{\text{deV}} > 0.8 \), and evaluated their 3D shape distributions independently. Using the SDSS DR16 catalog, we divide the sample of galaxies with \( z < 0.05 \) and \( M_\ast \gtrsim 10^9 \, M_\odot \) in the same manner (Ahumada et al. 2020).

We then use the 3D shape inference method described above to estimate the distribution over intrinsic axes B and C for bins of approximately 0.5 dex in stellar mass (the first mass cut is set at \( \log_{10}(M_\ast/M_\odot) = 9.6 \) so that the lowest mass bin considered is equivalent to the highest mass bin of our sample). The results of this inference, with the roughly equivalent SDSS-band absolute magnitude bins of Padilla & Strauss (2008) overlaid, are shown in Figure 8. Each panel inset shows the observed distribution of \( b/a \), measured via the

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9 Because the Sérsic profiles are quite different from real galaxies, we do not attempt to deconvolve the error in \( \sigma_B \) and \( \sigma_C \) for the real sample using these test cases in this work.
nonparametric profile construction described in Section 3, with filled teal histograms. We then overplot the distribution of the projected $b/a$ generated from sampling the MCMC chain in gray, i.e., $\alpha_i \sim P(\mu_\alpha, \sigma_\alpha, \alpha_i | b/a)$. The distribution of $b/a$ over all of these samples is shown by the thick orange curve. In the main panel, we show the analogous distribution in the intrinsic axis ($B–C$) plane. Here the same samples from the posterior are shown by the orange filled contour. The dashed colored curves are the contours of the pure disk, prolate, and spheroid Sérsic populations shown in the lower right panel of Figure 7.

Due to the differences in the data used and the imperfect mapping between stellar mass and absolute magnitude, we do not expect that the inferences will be statistically identical. However, we find good agreement between our results and those of Padilla & Strauss (2008) for all but their brightest bin at $-21 < M_\star < -24$, which includes a significantly wider mass range than our most similar bin. Having reproduced the 3D shape distribution of this literature sample and the mock galaxies injected into HSC imaging, we proceed to apply the shape inference technique to the dwarf sample at hand.

5. Results

The HSC-SSP imaging has both the surface brightness sensitivity to reliably measure the ellipticity profile of individual galaxies out to $3R_{\text{eff}}$ and the on-sky area necessary to build a sample large enough to infer the 3D shape distribution.

Before proceeding, we note that the transition from thin disk to thick disk to spheroid does not have a well-defined boundary. To put our results into context, we provide the intrinsic axis ratios of the MW disk and halo system. Assuming an exponentially declining disk, the MW has a disk scale length of 2.5 kpc, a thin disk scale height of 270 pc, and a thick disk scale height of 820 pc. This corresponds to an axis ratio of $C/A = 0.11$ for the MW thin disk and $C/A = 0.33$ for the MW thick disk (Schönrich & Binney 2009). The MW stellar halo

| $R_{\text{eff}}$ | $N$ | $10^{9.0} < M_\star < 10^{10.5}$ |
|-----------------|-----|----------------------------------|
| $1R_{\text{eff}}$ | 4596 | 0.0 0.5 1.0 |
| $2R_{\text{eff}}$ | 4455 | 0.0 0.5 1.0 |
| $3R_{\text{eff}}$ | 4139 | 0.0 0.5 1.0 |
| $4R_{\text{eff}}$ | 2783 | 0.0 0.5 1.0 |

Figure 9. For bins in increasing stellar mass (rows) and measurement radius (columns), we show the distribution of inferred axis ratios $B/A$ and $C/A$ for the dwarf sample. Each panel shows the distribution of intrinsic axis ratios in orange. The black ellipses show the 1σ region of the maximum a posteriori estimate, $\alpha_{\text{max}} P(\alpha | b/a)$. We also show the same contours for the pure disk, prolate, and spheroid Sérsic population presented in Figure 7 by the dashed blue, green, and red curves. The black line shows the $B/A = C/A$ definitional boundary. Each inset panel shows the observed axis ratio distribution, $b/a = 1 - e$, as a filled teal histogram. The distribution of $b/a$ produced by the posterior sample in $B/A$ and $C/A$ is shown by the open orange histogram; individual samples from the posterior are shown by the open gray histograms.
becomes increasingly spheroidal as a function of radius in the range of $0.57 \leq C/A \leq 0.75$ (Iorio & Belokurov 2019).

5.1. 3D Shape as a Function of Stellar Mass and Radius

We first consider the change in the galaxy 3D shape as a function of stellar mass and radius. Previous studies have found that the high-mass end of our sample ($10^9 < M_*/M_\odot < 10^{10.5}$) is composed largely of (thick) disks (Padilla & Strauss 2008; Sánchez-Janssen et al. 2010; van der Wel et al. 2014); 3D shapes beyond $1R_{\text{eff}}$ or at lower masses have not been measured for general dwarf samples.

First, we consider the distribution of observed $b/a$ as measured at $1R_{\text{eff}}$, $2R_{\text{eff}}$, $3R_{\text{eff}}$, and $4R_{\text{eff}}$ for bins of stellar mass in Figure 9. Each panel shows the number of measurements made for each slice in radius and stellar mass. From tests with Sérsic populations, we find that the recovered values of $\sigma_B$ and $\sigma_C$ increase significantly at $N \lesssim 700$; we therefore do not consider subsets where $N < 700$ (see Appendix D).

From the observed distribution alone, we see first that the distribution of projected axis ratios becomes increasingly more concentrated at large values of $b/a$ as we consider larger radii. This is consistent with a shift toward more spheroidal shapes; indeed, in Figure 9, we see that the high-mass dwarfs are consistent with a thick disk at $1R_{\text{eff}}$ and shift toward the spheroidal extreme at $3R_{\text{eff}}$ and $4R_{\text{eff}}$. We note that a minority of the galaxies in the sample have bars at $1R_{\text{eff}}$; though these bars clearly do not dominate the signal (bars are intrinsically prolate, with $\mu_B \sim \mu_C \sim 0.3$; Compère et al. 2014; Méndez-Abreu et al. 2018), it is likely that they contribute to the recovered triaxiality of the sample. Indeed, though the dwarfs are only slightly triaxial ($\mu_B \sim 0.75$ at all masses and radii), we find that a purely oblate model is a significantly worse fit to the data.

We see relatively little change in the intrinsic shape distribution of galaxies at $10^{9.5} < M_*/M_\odot < 10^{10.0}$ and $10^{9.0} < M_*/M_\odot < 10^{9.5}$. Both show $\mu_C(1R_{\text{eff}}) \sim 0.3$ and shift toward progressively larger $\mu_C$ with increasing radius. In our lowest mass bin, we see a hint that the shape distribution shifts dramatically, toward lower $\mu_B$ and $\mu_C$ (i.e., away from the pure disk region). Though this behavior is not unexpected, as lower-mass galaxies are expected to be increasingly dispersion-dominated (see, e.g., Wheeler et al. 2017; Pillepich et al. 2019) and consistent with a previous study of Virgo dwarfs at somewhat lower stellar masses by Sánchez-Janssen et al. (2016), we caution that we are not complete at this mass bin, and that the number of galaxies in our lowest mass bin is significantly lower ($N \sim 700$), which may lead to an over-estimate of $\sigma_B$ and/or $\sigma_C$ (see Appendix D).

5.2. 3D Shape and Galaxy Color

At higher masses, we reproduce in Figure 8 the divergence in 3D shape distribution of spiral and elliptical galaxies seen in Padilla & Strauss (2008). One can then reasonably expect to see a similar trend at $\approx 1R_{\text{eff}}$ when our sample is divided between red and blue galaxies. We divide our sample at $(g-i)_{\text{SDSS}} \approx 0.9$, chosen as the midpoint between the blue sequence and red cloud for this choice of color and stellar mass range.\footnote{Because the red sequence is relatively unpopulated at this mass range, we choose the division using the SDSS catalog and a somewhat broader range in stellar mass, $M_* \lesssim 10^{10.5} M_\odot$.}
We show the 3D shape distribution for the highest mass bin in Figure 10 as a function of radius, again at 1$R_{\text{eff}}$, 2$R_{\text{eff}}$, 3$R_{\text{eff}}$, and 4$R_{\text{eff}}$ from left to right. The left column shows the results at 1$R_{\text{eff}}$. Indeed, in the left column, we see that the red galaxies are at preferentially larger C/A with respect to the blue galaxies, similar to Figure 8 when the sample is split between spiral and elliptical galaxies.

At larger radii, however, we find that the blue and red galaxies occupy the same region in the B–C plane. While the red galaxies show little shape change with radius, the distribution of blue galaxies increases in σ_C and shifts toward the spheroidal corner (red dashed curve) of parameter space.

5.3. 3D Shape and Environment

Star formation in dwarfs is thought to be quenched by almost entirely environmental means (Geha et al. 2012); it is of interest, then, to ask whether populations of field and satellite dwarfs display the same change in 3D shapes as blue and red dwarfs. For this exercise, we search massive companions ($M_\star > 10^{10} M_\odot$) in the NASA Sloan Atlas (NSA) within Δv < 1000 km s$^{-1}$ and 1 Mpc projected distance. We choose the projected distance cut $d_{\text{NN}} > 1$ Mpc to coincide with the distance at which the dwarf quenched fraction, $f_{\text{quench}}(d_{\text{NN}})$, approaches its field limit $f_{\text{quench}}(d_{\text{NN}} \to \infty)$ for the mass range considered in Geha et al. (2012, their Figure 4). We additionally consider only galaxies at z < 0.10. Though the NSA contains galaxies up to z = 0.15, at z > 0.1, the satellite fraction begins to drop, indicating that the massive galaxy sample is not sufficiently complete to characterize the environment of the dwarfs in our sample. In Figure 11, we show the 3D shape distribution for field (top row) and satellite (bottom row) dwarfs at $M_\star > 10^9 M_\odot$. Unlike the dwarfs separated by color, the satellite and field dwarf samples show roughly the same 3D shape distribution as a function of radius. It is important to note that the difference in σ_B at large radius between the field and satellite dwarfs is likely unphysical, as the inferred σ_B for these populations is close to or below the estimated σ_B for our zero-scatter disk and spheroid populations (shown in Figure 11 by the dashed contours).

We find that at 1$R_{\text{eff}}$, the satellite galaxies scatter toward marginally more spheroidal shapes than do the field galaxies. This effect is similar to the trend seen in Section 5.2 between red and blue dwarfs, but the separation between field and satellite galaxies is relatively small. Though the projected axis ratio distribution of field and satellite galaxies is significantly different (Kolmogorov–Smirnov (K-S) p-value ≈ 0.001), we do not see a significant difference between the $b/a$ distribution of field galaxies and blue satellites (K-S p-value ≈ 0.29). This is likely due to fact that, for our sample, nearly all red galaxies are satellites of more massive galaxies (Geha et al. 2012). Blue galaxies, on the other hand, are found both as satellites and in the field. It is likely that making a cut on color produces, in effect, a selection of satellite galaxies that have been more processed by the host central.

Finally, to facilitate an easier comparison to future work, we note that maximum a posteriori estimates and 1σ standard deviations for all subsamples considered in this section are tabulated in Appendix B.

6. Discussion

6.1. The Emergence of Round Outskirts around Low-mass Galaxies

At higher masses, stellar halos are generally thought to be the product of a series of minor mergers that deposit stars at
large radii (Amorisco 2017). However, because the stellar-to-halo mass ratio tends to increase as galaxy mass decreases, the dwarfs in our sample are unlikely to accrete a sufficient mass in stars to build a stellar halo via minor mergers alone (Purcell et al. 2007; Moster et al. 2013).

Even though it appears unlikely that dwarfs can accrete a stellar halo via conventional means, it has long been known that dwarfs in the Local Group and M81 group host a smooth intermediate/old stellar population in their outskirts (see Stinson et al. 2009; Hargis et al. 2020, and references therein). These observations hint at the existence of an in situ halo formation mechanism at low masses, but this conclusion is obfuscated for two reasons. First, the sample is comprised almost entirely of galaxies that are interacting with a more massive companion. Second, such stellar halos have been confirmed for only a few tens of galaxies. In this work, we have presented the first large sample where a clear transition to a round stellar component is detected in the outskirts of dwarfs that are not Local Group members.

In Section 5.1, we presented a set of inferred 3D shapes for a sample of dwarf galaxies as a function of stellar mass and radius. Due to the depth of the HSC-SSP imaging, we are able to measure ellipticity profiles out to 4\(R_{\text{eff}}\) for the most massive dwarfs in our sample. Indeed, we see that the structure of the dwarfs is characterized by thick disks at 1\(R_{\text{eff}}\) and becomes increasingly spheroidal at large radii, as shown in the top row of Figure 9. For clarity, we also show the C/A distribution as a function of radius for the 10\(^9\) \(M_\odot\) < \(M_*\) < 10\(^9.6\) \(M_\odot\) and 10\(^8.5\) \(M_\odot\) < \(M_*\) < 10\(^8\) \(M_\odot\) stellar mass bins in Figure 12. At 1\(R_{\text{eff}}\), the dwarfs have C/A axis ratios consistent with the MW thick disk and significantly thicker than the MW thin disk (Schönrich & Binney 2009). This thick disk morphology is in rough agreement with previous measurements for dwarfs in SDSS and the Local Group (Padilla & Strauss 2008; Sánchez-Janssen et al. 2010; Roychowdhury et al. 2013). At 4\(R_{\text{eff}}\), the dwarf shapes are of comparable thickness to the inner stellar halo of the MW as measured by Iorio & Belokurov (2019). These results indicate that the dwarf disk–halo interface is similar in structure, if not origin, to more massive galaxies.

Though they are not expected to form through minor mergers, the existence of round stellar outskirts around dwarfs is not unexpected theoretically. Dwarf galaxies sit in shallow potential wells and are thus more sensitive to the effects of star formation feedback than their more massive analogs. Stinson et al. (2009) proposed that dwarf galaxies would generically form stellar halos through stellar radial migration, star formation in outflows, and a contraction of the central star-forming region. Similarly, Maxwell et al. (2012) found that stellar feedback could drive sufficient quantities of dense gas to produce a fluctuation in the overall potential and thus build a stellar spheroid through migration (see also El-Badry et al. 2016). The concordance in 3D shape at large radii for blue and red dwarfs, as shown in Figure 10, and at all measured radii in field and satellite dwarfs, as shown in Figure 11, also suggests that the creation of round outskirts is not driven by an interaction with a more massive halo.

It has also been suggested that dwarf halos could be formed as a result of major mergers between dwarfs (Bekki 2008). However, the detection of an increasingly spheroidal component in the outskirts of our dwarf sample is at odds with this formation mechanism; the major-merger rate of dwarfs is likely not high enough to generate enough stellar halos to produce such a population. Simulations suggest that approximately 30% of dwarfs in our stellar mass range outside of the virial radius of an MW–like object have undergone a dwarf–dwarf major merger in the past 10 Gyr (Deason et al. 2014). Though dwarf–dwarf major mergers were more common in the early universe, due to fading via passive evolution, it is unlikely that we would be able to detect such ancient halos. Though the \(z = 0\) surface brightness of any given merger-driven stellar halo is dependent on its assembly history, Bekki (2008) found that their simulated stellar halo reaches \(\sim 30\) mag arcsec\(^{-2}\) at \(R \sim 2\) kpc. If the stellar halo population had a uniform age of 1 Gyr at the time of halo creation and was created at a look-back time of 10 Gyr, the stellar halo will have dimmed by 1–2 mag arcsec\(^{-2}\) by \(z = 0\) from the evolution of the mass-to-light ratio alone (as computed from the FSPS models of Conroy et al. 2009), well below the surface brightness sensitivity of our imaging. Moreover, the intermediate-age stellar component often observed at large radii in resolved star studies requires a relatively recent

![Figure 12](https://example.com/figure12.png)

**Figure 12.** Change in galaxy thickness (C/A) as a function of radius for 10\(^7\) \(M_\odot\)/\(M_\odot\) < 10\(^6.8\) (top) and 10\(^8.5\) \(M_\odot\)/\(M_\odot\) < 10\(^8\) (bottom). In both cases, the dwarfs become systematically more spherical (C ∝ A, B/A ⩾ 0.8 for all cases) at large radii. For physical context, we also show the C/A axis ratio of the MW thin and thick disks (Schönrich & Binney 2009) and the stellar halo at \(R = 0\) and 6\(R_{\text{eff}}\) (Iorio & Belokurov 2019). The MW axis ratios are shown by vertical black lines and labeled in the bottom panel.
deposition of stars in the outskirts (see, e.g., Zaritsky et al. 2000; Stinson et al. 2009, and references therein). We thus find it unlikely that major mergers are the sole formation mechanism of low-mass stellar halo formation, though we note that some individual cases are consistent with both star formation feedback and accretion driving stellar halo formation (Puchta et al. 2019). The apparent ubiquity of round stellar outskirts in this work is instead consistent with the proposal that stellar outskirts are formed primarily through in situ processes.

6.2. Morphological Transformation and Quenching

It has long been observed that the cessation of star formation in dwarfs, their morphological transformation from a disk-dominated to a dispersion-dominated structure, and their proximity to more massive galaxies are all strongly correlated (see, for example, Dressler 1980; Lin & Faber 1983; Postman & Geller 1984; Weimann et al. 2006; Geha et al. 2012; Kormendy & Bender 2012; Ann 2017).

As shown in the left column of Figure 10, we find that the blue dwarfs in our sample tend toward lower values of C/A than red dwarfs—that is, the blue dwarfs are more consistent with a thick disk, while red dwarfs scatter toward more spheroidal shapes. This is in concordance with the familiar morphology–color dichotomy and follows the same trend seen in intrinsic shape studies of satellite dwarfs in the nearby universe (Sánchez-Janssen et al. 2019) and at higher masses (see, e.g., Padilla & Strauss 2008; Rodríguez et al. 2016; and Figure 8). We see a similar trend when separating dwarfs by the projected nearest-neighbor distance (within 1000 km s⁻¹), though the shift between satellite and field galaxies is relatively marginal (see left column of Figure 11). This finding is in good agreement with the results of Sánchez-Janssen et al. (2019), who found that for a sample of quiescent satellite dwarfs, intrinsic shape correlates strongly with galaxy morphology and luminosity but is largely insensitive to the specific environment of the dwarf.

We do not detect a significant difference in the intrinsic shapes of blue satellites and dwarfs in the field. This is in contrast with the shift toward rounder shapes seen in the red galaxy subset (Figure 10) and satellite galaxies (without a color cut; Figure 11). This suggests that morphological transformation operates on a longer timescale than star formation quenching, or that quenching is a prerequisite to the morphological transformation. However, it is important to note our choice of model (a singly peaked multivariate Gaussian) will necessarily only recover the dominant shape population.

6.3. Comparison with Simulations

Due again to their increased sensitivity to star formation feedback, the 3D shapes of dwarfs are a strong constraint on the feedback prescription of cosmological simulations.

Pillepich et al. (2019) gave the distribution of dwarf 3D shapes as measured at twice the stellar half-mass radius. First, we note that our results are in broad agreement with those of Pillepich et al. (2019) in that our 3D shapes are in the disky/spheroidal regime, with essentially no galaxies in the prolate regime (defined by van der Wel et al. 2014 as B/A < 1 − C/A). At R eff, the change in our 3D shape distribution is also qualitatively similar to that of Pillepich et al. (2019); as stellar mass decreases, σC increases, and the distribution shifts toward more spheroidal shapes (as shown in the left column of Figure 9).

However, under the assumption of centrally concentrated star formation, we would expect the half-mass radius to be larger than the half-light radius, implying that a comparison at the same physical radius should occur at >2R eff. Moreover, the conversion between the i HSC-band surface brightness and the stellar mass distribution is a function of the galaxy’s stellar populations.

Clearly, to make a quantitative comparison will require significant effort to put the simulations and observations on equal footing. Nevertheless, the broad agreement in the shape distribution of dwarfs and their evolution with stellar mass is a promising step.

7. Conclusions

In this work, we have measured the surface brightness and ellipticity profiles of a sample of spectroscopically confirmed dwarfs using imaging from the HSC-SSP (Section 3). We then extended the framework commonly used to infer 3D galaxy shapes (see, e.g., Padilla & Strauss 2008; Roychowdhury et al. 2013; van der Wel et al. 2014; Putko et al. 2019; Zhang et al. 2019) to measure the change in dwarf galaxy shape as a function of radius.

We show that the population of dwarfs in our sample tends to host thick, disk-like structures at R eff and evolve toward more spheroidal shapes in their outskirts (see Figure 9). This finding is in agreement with the predicted quasi-spherical shapes of in situ stellar halos (Stinson et al. 2009).

At M* > 10⁸.5 M⊙, blue dwarfs tend to be diskier than red dwarfs near their centers (i.e., at R = 1R eff; left panels of Figure 10). This divergence as a function of color mirrors the same dichotomy seen at higher masses, where blue galaxies are preferentially diskier and red galaxies relatively thicker and spheroidal (see Figure 8). However, the outskirts of both red and blue dwarfs move toward more spheroidal shapes, suggestive of an in situ formation mechanism for the extended stellar outskirts. This interpretation is also supported by a uniform trend toward more spheroidal outskirts in both field and satellite galaxies (see Figure 11).

The sample considered in this work is based on spectroscopic surveys; we are thus missing low surface brightness and UDGs. In particular, simulations suggest that the effective surface brightness cuts implemented in the SDSS and GAMA spectroscopic surveys bias dwarf samples toward more compact objects (Wright et al. 2020). Previous works have focused on samples of cluster UDGs; Burkert (2017) found that, for a sample of Coma UDGs, μR = μ C ≈ 0.67 (for a model with the assumption C = B ≤ A). Similarly, Rong et al. (2020) found that for a triaxial model, μR = 0.86 and μ C = 0.49. These results imply that cluster UDGs are typically rounder than high surface brightness dwarfs, with an intrinsic minor axis ratio (C/A) comparable to the outskirts of dwarfs in our sample.

However, samples of cluster UDGs are in highly overdense environments compared to the typical dwarf galaxy in our sample. To more fairly compare the structural composition of low and high surface brightness dwarfs and better understand the nature of the relationship between these two populations, we must instead look to build a sufficiently large sample of UDGs in the field (e.g., Bellazzini et al. 2017; Leisman et al. 2017;
Román & Trujillo 2017; Greco et al. 2018; Tanoglidis et al. 2020) such that the deprojection problem is tractable.

Our analysis also suggests that at $M_\star < 10^{6.5} M_\odot$, dwarfs become increasingly round (larger $\mu_C$). However, our spectroscopic sample is far from mass-complete at $M_\star < 10^8 M_\odot$. In order to more comprehensively understand the properties of the dwarf population, it is necessary to construct a large and mass-complete sample of dwarfs at stellar masses lower than what is accessible with the spectroscopic surveys currently in hand. As has been shown theoretically, star formation feedback is expected to play an increasingly dramatic role in the stellar structure of increasingly low-mass dwarfs; extending the observational lever arm to lower stellar masses will provide an important constraint on prescriptions for star formation feedback and novel insights into the stellar structure of such systems.

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GAMA is a joint European-Australasian project based around a spectroscopic campaign using the Anglo-Australian Telescope. The GAMA input catalog is based on data taken from the Sloan Digital Sky Survey and the UKIRT Infrared Deep Sky Survey. Complementary imaging of the GAMA regions is being obtained by a number of independent survey programs, including GALEX MIS, VST KiDS, VISTA VIKING, WISE, Herschel-ATLAS, GMRT, and ASKAP, providing UV to radio coverage. GAMA is funded by the STFC (UK), the ARC (Australia), the AAO, and the participating institutions. The GAMA website is http://www.gama-survey.org/.

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Software: Astropy (Astropy Collaboration et al. 2013; Price-Whelan et al. 2018), matplotlib (Hunter 2007), SciPy (Virtanen et al. 2020), the IPython package (Pérez & Granger 2007), NumPy (Van Der Walt et al. 2011).

Appendix A
Tests of the Background Subtraction

The fidelity of the background subtraction is of key importance for two aspects of our analysis. First, background subtraction schemes that measure the sky background on scales comparable to the size of the target galaxies are liable to attribute diffuse light in the target outskirts to the sky background. This causes oversubtracted “dark rings” around galaxies that are large on the sky. Second, a uniform under- or oversubtraction of the background could affect our measurement of $R_{\text{eff}}$ as well as the estimate of our surface brightness limit.

Dark rings were a significant problem for nearby massive galaxies in the first data release of the HSC-SSP, prompting a change in the background estimation algorithm used for S18A (and the second data release). The updated algorithm is described in detail in Section 4.1 of Aihara et al. (2019); here we summarize the changes that most strongly affect the performance for our sample.

The most pertinent change to the sky subtraction algorithm of S18A (or, equivalently, PDR2) is that the sky is now...
estimated over the full focal plane, rather than individual CCDs. In both cases, the sky is estimated by fitting a sixth-order 2D Chebyshev polynomial to “superpixels,” which are themselves defined as the clipped mean of nondetection pixels within an $N \times N$ pixel grid. However, because the S18A pipeline fits a sky background over the entire focal plane of the HSC, the superpixels can be much larger ($N = 1024$ pixels, $2' 52''$; $2.8$ arcmin) than is possible with individual CCD sky estimation ($N = 256$ pixels, $43''$). The maximum radial range at which we measure the 1D surface brightness profiles in this work is 500 pixels ($84''$), significantly smaller than the S18A superpixels. Oversubtracted dark rings should thus not occur around our target galaxies in S18A; indeed, the galaxies are sufficiently small on the sky that the dark-ring oversubtraction was not likely to be present even in the PDR1 pipeline.

To quantitatively test this statement, as well as to estimate the overall residual sky background in the vicinity of our targets, we follow the approach of J. Li et al. (2020, in preparation), who tested the performance of the surface brightness sensitivity and S18A background subtraction for a set of low-$z$ ($z \sim 0.02$) and intermediate-$z$ ($z \sim 0.40$) massive galaxies in HSC. From tests on mock galaxies and comparisons to imaging from the Dragonfly Wide Field Survey (Danieli et al. 2020) and the Dark Energy Camera Legacy Survey (DECaLS; Dey et al. 2019), they concluded that the intermediate-redshift massive galaxies are slightly uniformly undersubtracted, while the low-redshift massive galaxies are slightly uniformly oversubtracted. They moreover find that nearby “sky objects” (SkyObj), can be used to estimate and correct for the residual over- or undersubtraction of the sky background to reach surface brightness sensitivities of $\mu_r \sim 29.5$ mag arcsec$^{-2}$. These sky objects are identified by the HSC data reduction pipeline (see Section 6.6.8 of Aihara et al. 2019) to be locations in which no objects are detected. Sky-object photometry is measured in apertures ranging from $20''$ to $118''$ in diameter.

We estimate the residual background around our dwarf sample by taking the mean flux in sky objects in the vicinity of our sample, as was done by J. Li et al. (2020, in preparation) for their more massive galaxy sample. We expect that the sky around our dwarf galaxies will be better estimated than the sky around the low-$z$ massive galaxy for two reasons. First, our sample is characterized by nearly exponential profiles (Sérsic indices close to $n = 1$), meaning that their surface brightness profiles drop more steeply with distance than do the higher-$n$ massive galaxies in J. Li et al. (2020, in preparation). Second, the massive galaxies are much more physically extended than our sample and thus appear larger on-sky at fixed redshift.

Indeed, we find that the background around our galaxies tends to be slightly undersubtracted to a similar degree as in the intermediate-redshift sample of J. Li et al. (2020, in preparation). In Figure A1, we show the estimate of the sky background as a function of sky-object aperture size for sky objects within 100$''$ (green) and 200$''$ (purple) of our target galaxies. For context, we reiterate that the maximum distance at which we measure profiles is 84$''$. We note that the two largest sky objects (of size 84$''$ and 118$''$) are as large as or larger than the extent over which we measure 1D profiles. Sky objects with increasingly large apertures are more likely to include contributions from background objects. The increase in the background level as a function of aperture size can be partially attributed to this effect. Regardless, we find that in all cases, the additive background residual is $\lesssim 0.004$ counts pixel$^{-1}$. This corresponds to a change in surface brightness of $\lesssim 0.02$ mag arcsec$^{-2}$ for an object with a surface brightness of 28.5 mag arcsec$^{-2}$. The impact of the sky residual is small down to our nominal surface brightness limit of 28.5 mag arcsec$^{-2}$.

**Appendix B**

**Tabulation of Inferred Parameters**

For ease of comparison to future studies, in Table B1, we provide the maximum a posteriori estimates and 1σ standard deviations of the intrinsic shape parameters inferred for the samples presented in Figures 9–11. In each row, we list the figure, sample selection criterion, and measurement radius associated with the inferred parameters.
### Appendix C

#### Model Selection: Allowing for Shape–Size Covariance

For a sample of galaxies at higher stellar mass and redshift, Zhang et al. (2019) showed that the inferred 3D shape distribution changes significantly when allowing a nonzero covariance between galaxy size and ellipticity.

To test whether this model is necessary for our sample of dwarfs, we fit a multivariate normal described by $\alpha = \{\mu_A, \mu_B, \mu_C, \sigma_{AA}, \sigma_{BB}, \sigma_{CC}, \sigma_{AC}\}$. As in Zhang et al. (2019), we only allow for a nonzero covariance between A and C. In order to understand whether the $(R_{\text{eff}}, b/a)$ data demand a nonzero shape–size covariance, we initiate walkers normally distributed about the best-fit values inferred for the fiducial models. For each parameter $X$, the initial values for the walkers are drawn from a normal distribution $\mathcal{N}(X, 0.25X)$, where $X$ is the best-fit value from the fiducial model.

The results of this test are shown in Figure C1. Though the data are well described by a slightly negative shape–size covariance $\sigma_{AC} \sim -0.16$, we find that this model yields a small shift toward lower $B/A$ and a negligible shift in $C/A$. Therefore, because the model of Zhang et al. (2019) adds three additional degrees of freedom to the model ($\mu_A, \sigma_{AA}$, and $\sigma_{AC}$), we choose to fit the marginalized $b/a$ distribution, rather than $(R_{\text{eff}}, b/a)$.

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#### Table B1

Maximum a Posteriori Estimates and 1σ Standard Deviations of Inferred Parameters

| Associated Figure | Selection | $R$ | $\mu_A$ | $\mu_B$ | $\mu_C$ | $\sigma_B$ | $\sigma_C$ |
|-------------------|-----------|-----|---------|---------|---------|-----------|-----------|
| Figure 9          | 10$^{9.0}$ M$_{\odot}$ < $M_*$ < 10$^{9.6}$ M$_{\odot}$ | 1R$_{\text{eff}}$ | 0.84 ± 0.01 | 0.30 ± 0.01 | 0.09 ± 0.01 | 0.11 ± 0.01 |
|                   |           | 2R$_{\text{eff}}$ | 0.93 ± 0.02 | 0.35 ± 0.02 | 0.04 ± 0.02 | 0.15 ± 0.02 |
|                   |           | 3R$_{\text{eff}}$ | 0.94 ± 0.01 | 0.43 ± 0.01 | 0.05 ± 0.01 | 0.14 ± 0.01 |
|                   |           | 4R$_{\text{eff}}$ | 0.82 ± 0.04 | 0.55 ± 0.02 | 0.21 ± 0.02 | 0.19 ± 0.03 |
|                   | 10$^{8.5}$ M$_{\odot}$ < $M_*$ < 10$^{9.0}$ M$_{\odot}$ | 1R$_{\text{eff}}$ | 0.75 ± 0.03 | 0.47 ± 0.03 | 0.02 ± 0.04 | 0.19 ± 0.02 |
|                   |           | 2R$_{\text{eff}}$ | 0.79 ± 0.03 | 0.46 ± 0.03 | 0.05 ± 0.04 | 0.20 ± 0.05 |
|                   |           | 3R$_{\text{eff}}$ | 0.81 ± 0.05 | 0.47 ± 0.03 | 0.18 ± 0.03 | 0.17 ± 0.03 |
|                   |           | 4R$_{\text{eff}}$ | 0.80 ± 0.10 | 0.44 ± 0.04 | 0.30 ± 0.06 | 0.10 ± 0.05 |
|                   | 10$^{7.0}$ M$_{\odot}$ < $M_*$ < 10$^{8.5}$ M$_{\odot}$ | 1R$_{\text{eff}}$ | 0.86 ± 0.02 | 0.32 ± 0.02 | 0.02 ± 0.02 | 0.11 ± 0.02 |
|                   |           | 2R$_{\text{eff}}$ | 0.91 ± 0.03 | 0.38 ± 0.02 | 0.05 ± 0.02 | 0.17 ± 0.02 |
|                   |           | 3R$_{\text{eff}}$ | 0.93 ± 0.06 | 0.41 ± 0.02 | 0.06 ± 0.05 | 0.11 ± 0.04 |
|                   |           | 4R$_{\text{eff}}$ | 0.79 ± 0.07 | 0.50 ± 0.03 | 0.27 ± 0.03 | 0.18 ± 0.03 |
| Figure 10         | $(g-i) < 0.90$ | 1R$_{\text{eff}}$ | 0.84 ± 0.01 | 0.30 ± 0.01 | 0.08 ± 0.01 | 0.10 ± 0.01 |
|                   |           | 2R$_{\text{eff}}$ | 0.90 ± 0.02 | 0.34 ± 0.01 | 0.02 ± 0.02 | 0.14 ± 0.02 |
|                   |           | 3R$_{\text{eff}}$ | 0.94 ± 0.04 | 0.42 ± 0.01 | 0.04 ± 0.03 | 0.12 ± 0.02 |
|                   |           | 4R$_{\text{eff}}$ | 0.77 ± 0.04 | 0.54 ± 0.02 | 0.26 ± 0.02 | 0.20 ± 0.02 |
|                   | $(g-i) > 0.90$ | 1R$_{\text{eff}}$ | 0.93 ± 0.03 | 0.40 ± 0.02 | 0.01 ± 0.03 | 0.17 ± 0.03 |
|                   |           | 2R$_{\text{eff}}$ | 0.89 ± 0.05 | 0.43 ± 0.03 | 0.07 ± 0.04 | 0.17 ± 0.04 |
|                   |           | 3R$_{\text{eff}}$ | 0.96 ± 0.07 | 0.46 ± 0.04 | 0.04 ± 0.05 | 0.12 ± 0.06 |
| Figure 11         | $d_{\text{SN}} > 1$ Mpc | 1R$_{\text{eff}}$ | 0.89 ± 0.01 | 0.29 ± 0.01 | 0.04 ± 0.01 | 0.08 ± 0.01 |
|                   |           | 2R$_{\text{eff}}$ | 0.90 ± 0.02 | 0.35 ± 0.01 | 0.05 ± 0.02 | 0.11 ± 0.02 |
|                   |           | 3R$_{\text{eff}}$ | 0.93 ± 0.03 | 0.39 ± 0.01 | 0.05 ± 0.02 | 0.13 ± 0.02 |
|                   |           | 4R$_{\text{eff}}$ | 0.85 ± 0.05 | 0.48 ± 0.03 | 0.23 ± 0.02 | 0.20 ± 0.03 |
|                   | $d_{\text{SN}} \leq 1$ Mpc | 1R$_{\text{eff}}$ | 0.86 ± 0.03 | 0.36 ± 0.02 | 0.04 ± 0.02 | 0.17 ± 0.02 |
|                   |           | 2R$_{\text{eff}}$ | 0.91 ± 0.03 | 0.40 ± 0.02 | 0.06 ± 0.02 | 0.16 ± 0.02 |
|                   |           | 3R$_{\text{eff}}$ | 0.95 ± 0.06 | 0.44 ± 0.03 | 0.04 ± 0.05 | 0.14 ± 0.04 |
|                   |           | 4R$_{\text{eff}}$ | 0.76 ± 0.04 | 0.59 ± 0.04 | 0.25 ± 0.04 | 0.17 ± 0.04 |

Note. For the inferred parameters associated with Figures 10 and 11, only galaxies with stellar masses >10$^{9.5}$ $M_\odot$ are considered.

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11 Here A is in kpc, whereas B and C are defined as normalized lengths relative to A.
Appendix D

Parameter Recovery and Sample Size

As sample size decreases, the precision of our inferred model parameters $\alpha = \{\mu_B, \mu_C, \sigma_B, \sigma_C\}$ decreases in kind. In Figure D1, we show the distribution of intrinsic axis ratios inferred for a sample of $N = \{100, 200, 1500, 2500\}$ galaxies. We find that at $N \sim 200$ galaxies, though $\mu_B$ and $\mu_C$ are well recovered, $\sigma_B$ and $\sigma_C$ are increasingly overestimated.\(^{12}\) We thus choose to only consider subsets of galaxies where $N > 700$.

\(^{12}\) We note that $\sigma_B$ and $\sigma_C$ are always overestimated when $\sigma_B = \sigma_C = 0$ due to the uncertainty in measuring 1D surface brightness profiles.

Figure C1. Left: distribution of effective radius and projected axis ratio for a sample drawn from the posterior distribution for a model where we allow for a nonzero covariance between $C/A$ and $R_{\text{eff}}$. Middle: distribution over $R_{\text{eff}}$ and projected axis ratio $(b/a)$ for the observed galaxies. Right: inferred distribution over intrinsic axis ratios for the fiducial model (orange filled contours) and the model at left (green open contours).

Figure D1. For a population of mock disk galaxies described by $\alpha = \{\mu_B, \mu_C, \sigma_B, \sigma_C\} = \{0.9, 0.1, 0., 0\}$, we investigate the precision at which the model parameters $\alpha$ may be recovered as a function of sample size $N$. The top row shows, in each panel, the true distribution of the projected axis ratio $b/a$ in teal and the posterior sample in orange. Individual draws from the posterior are shown in gray. The bottom row shows the distribution of intrinsic axis ratios $(B/A$ and $C/A$) from the posterior sample in orange. The maximum a posteriori estimate is shown by the black ellipse. The pure disk, prolate, and spheroidal populations are shown by dashed contours (see Figure 7). A successful recovery is one in which the orange contours of the posterior samples coincide with the dashed blue contours of the pure disk population.

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