Tidal Features at 0.05 < z < 0.45 in the Hyper Suprime-Cam Subaru Strategic Program: Properties and Formation Channels

E. Kado-Fong1, J. E. Greene1, D. Hendel2, A. M. Price-Whelan1, J. P. Greco1, A. D. Goulding1, S. Huang3,4, K. V. Johnston2, Y. Komiyama2, C.-H. Lee3, N. B. Lust1, M. A. Strauss1, and M. Tanaka4

Department of Astrophysical Sciences, Princeton University, Princeton, NJ 08544, USA

2 Department of Astronomy, Columbia University, 550 W. 120th Street, New York, NY 10027, USA

3 Kavli-IPMU, The University of Tokyo Institutes for Advanced Study, The University of Tokyo, Kashiwa 277-8583, Japan

4 Department of Astronomy and Astrophysics, University of California Santa Cruz, 1156 High Street, Santa Cruz, CA 95064, USA

5 National Astronomical Observatory of Japan, 2-21-1 Osawa, Mitaka, Tokyo 181-8588, Japan

6 Graduate University for Advanced Studies (SOKENDAI), 2-21-1 Osawa, Mitaka, Tokyo 181-8588, Japan

7 Subaru Telescope, NAOJ, 650 North A’ohoku Place, Hilo, HI 96720, USA

Received 2018 May 15; revised 2018 September 7; accepted 2018 September 10; published 2018 October 17

Abstract

We present 1201 galaxies at 0.05 < z < 0.45 that host tidal features in the first ~200 deg² of imaging from the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP). We select these galaxies from a sample of 21,208 galaxies with spectroscopic redshifts drawn from the Sloan Digital Sky Survey (SDSS) spectroscopic campaigns. Of these galaxies, we identify 214 shell systems and 987 stream systems. For 575 of these systems, we are additionally able to measure the (g−i) colors of the tidal features. We find evidence for star formation in a subset of the streams, with the exception of streams around massive ellipticals, and find that stream host galaxies span the full range of stellar masses in our sample. Galaxies that host shells are predominantly red and massive: we find that observable shells form more frequently around ellipticals than around disk galaxies of the same stellar mass. Although the majority of the shells in our sample are consistent with being formed by minor mergers, 15% ± 4.4% of shell host galaxies have (g−i) colors as red as their host galaxy, consistent with being formed by major mergers. These “red shell” galaxies are preferentially aligned with the major axis of the host galaxy, as previously predicted from simulations. We suggest that although the bulk of the observable shell population originates from fairly minor mergers, which preferentially form shells that are not aligned with the major axis of the galaxy, major mergers produce a significant number of observable shells.

Key words: catalogs – galaxies: interactions – galaxies: statistics – galaxies: structure – techniques: image processing

1. Introduction

In the hierarchical merging model of galaxy formation, galaxy mergers are a crucial mechanism through which galaxies grow in size and mass (Toomre 1977; White & Rees 1978; White & Frenk 1991). This picture of galaxy formation has received strong support from modern cosmological simulations and semianalytical models. A general consensus has emerged that for the highest masses the growth of galaxies is dominated by matter accreted from other systems, with the ex situ (accreted) stellar mass fraction reaching ~0.80 (Oser et al. 2010; Lee & Yi 2013; Rodriguez-Gomez et al. 2016), suggesting that mergers are necessary to produce galaxies of \( \log(M_*/M_\odot) \gtrsim 11.0 \) (Lee & Yi 2017).

The idea that mergers can generate extended features is well established, having been shown first by Pfleiderer (1963) and Toomre & Toomre (1972) for ongoing mergers between two equal-mass disks. It is now also widely accepted that the extended, low surface brightness features found around low-redshift galaxies are the product of past merging events (Malin & Carter 1983; Quinn 1983; Dupraz & Combes 1986; Fort et al. 1986; Mihos et al. 1998; Bartošková et al. 2011; Pop et al. 2017b), and that the structure and characteristics of these features hold a substantial amount of information regarding the dynamics and assembly history of their hosts (e.g., Johnston et al. 2008; Belokurov et al. 2017).

These tidal features can be separated into two broad classes: “shells,” which are characterized by umbrella-like fans and caustics of stars whose radius of curvature points toward the host galaxy, and “streams,” which are extended ribbon-like structures near the host galaxy. The boundary between these two classes is intrinsically soft, as stream-like features can, owing to line-of-sight projection effects, appear shell-like (Foster et al. 2014; Greco et al. 2018a) and have been shown to evolve into shell-like systems (Hendel & Johnston 2015). Nevertheless, the ensemble characteristics of these shells and streams are distinct —shells tend to be found around massive ellipticals and do not appear to host significant star formation (Malin & Carter 1983; Tal et al. 2009; Atkinson et al. 2013), while streams can be quite blue and often appear around disk galaxies (Adamo et al. 2012; Knierman et al. 2012; Atkinson et al. 2013; Higdon et al. 2014).

The nature of the mergers that formed these tidal features, however, is still debated. In the minor merger picture of shell formation, a low-mass satellite falls radially into the potential of a more massive host, and the stars of the satellite form the resultant tidal feature (see, e.g., Johnston et al. 2001; Kawata et al. 2006; Sanderson & Helmi 2013; Hendel & Johnston 2015). This mechanism of tidal feature formation has been successfully used to model many nearby systems (e.g., the Umbrella galaxy by Foster et al. 2014, the Ophiuchus Stream by Price-Whelan et al. 2016, Sumo Puff by Greco et al. 2018a), and the inferred merger mass ratios for most known tidal features that have been modeled are in agreement with this picture (Kawata et al. 2006; Feldmann et al. 2008; Gu et al. 2013; Foster et al. 2014).
However, a separate formation channel has been proposed wherein the shells are formed by major mergers. Following Hernquist & Spergel (1992), it was recently reported by Pop et al. (2017b) that the shells found around the most massive galaxies in the Illustris simulation (Vogelsberger et al. 2014) are generated by major mergers, with the distribution of shell-forming events peaking at mergers between galaxies of approximately equal stellar mass. Observations of three dwarf galaxies in the Virgo Cluster (Paudel et al. 2017) and of nine nearby early-type galaxies (ETGs) taken from the Malin & Carter (1983) sample (Carlsten et al. 2017) show signs of shells that are thought to be generated by major mergers. Unlike tidal features formed from minor mergers between a quiescent host and quiescent satellite, where the tidal feature is bluer than the core of its host galaxy owing to the color–mass relation along the red sequence, these major merger shells should show metallicities close to those at the core of the galaxy (Pop et al. 2017a), implying colors close to that of the core of the host (see, e.g., Gallazzi et al. 2006). This provides an observationally accessible difference between the minor and major merger scenarios.

The picture for stream formation is somewhat clearer: they are generally accepted to originate from infalling satellites with relatively high angular momentum, although there is a smooth transition from stream to shell in the minor merger picture (see, e.g., Hernquist & Quinn 1988; Hendel & Johnston 2015). Blue, low surface brightness tidal streams can, however, be caused by both recent minor (Knierman et al. 2012, 2013) and older major mergers (Rodruck et al. 2016). We additionally observe red, quiescent streams which show no active star formation. These could be either the result of a dry merger or from quenching of a gas-rich satellite upon infall (Feldmann et al. 2008).

The majority of observational work on tidal features in external galaxies to date has been based on targeted observations of a relatively small number of galaxies (see, e.g., Schweizer & Seitzer 1988; Martínez-Delgado et al. 2009, 2010; Kim et al. 2012; Knierman et al. 2012, 2013; Beaton et al. 2014; Martínez-Delgado et al. 2015; Rodruck et al. 2016; Greco et al. 2018a). Among those works that are able to derive tidal feature occurrence fractions, where \( f_{\text{tidal}} \) is the fraction of all galaxies that host tidal features, inferred values of \( f_{\text{tidal}} \) vary by a factor of 7, from \( f_{\text{tidal}} < 0.10 \) to \( f_{\text{tidal}} > 0.70 \) (Malin & Carter 1983; van Dokkum 2005; Tal et al. 2009; Nair & Abraham 2010; Atkinson et al. 2013; Hood et al. 2018). This is due in part to variations in targeting strategy and detection methods, as well as from differences in imaging depth. Moreover, the vast majority of the existing samples of tidal features are created via visual inspection.

Large variations in \( f_{\text{tidal}} \) as a function of survey depth are expected owing to a steep dependence of tidal feature number density on peak surface brightness. Simulations predict that the majority of tidal features, having been formed from minor accretion events, have a peak surface brightness of \( \gtrsim 30 \text{ mag arcsec}^{-2} \) in optical bands (Johnston et al. 2008). Though some surveys approach this benchmark—for example, the Next Generation Virgo Survey reaches surface brightnesses of \( \mu_v \sim 29 \text{ mag arcsec}^{-2} \) (Ferrarese et al. 2012)—we note that wide-field imaging campaigns do not yet routinely reach these surface brightnesses. However, these wide-field campaigns continue to characterize the observable tidal feature population at progressively lower surface brightnesses.

The Hyper Suprime-Cam Subaru Strategic Program (hereafter HSC-SSP) is an ongoing wide-field survey executed by the Hyper Suprime-Cam mounted on the 8.2 m Subaru Telescope (Miyazaki et al. 2012; Furusawa et al. 2018; Komiyama et al. 2018; Kawanomoto et al. 2018; Miyazaki et al. 2018). HSC-SSP is planning to cover over 1400 deg\(^2\) of the sky in five bands (grizY) to \( i_{\text{HSC}} \sim 26 \) (5σ point source depth; see Aihara et al. 2018a, 2018b). The survey boasts a median \( \Omega_z = 0.56 \) seeing in the \( i_{\text{HSC}} \) band (Aihara et al. 2018a), making it an optimal imaging campaign in which to detect extended, low surface brightness features around galaxies out to intermediate redshifts (see Greco et al. 2018a, 2018b; Huang et al. 2018a, 2018b). Such a survey will be able to search for low surface brightness tidal features across a much larger area of the sky than previous campaigns at similar depths (e.g., Atkinson et al. 2013), and to much lower surface brightnesses than previous surveys such as the Sloan Digital Sky Survey (SDSS).

In this paper, we consider 21,208 galaxies with spectroscopic observations from the SDSS DR12 (Alam et al. 2015) in the footprint of the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP) Wide layer (Aihara et al. 2018a). The HSC Wide layer covers the largest on-sky area at a relatively shallow depth (\( i \sim 26 \)) relative to the Deep and UltraDeep Layers (\( i \sim 27 \) and \( i \sim 28 \), respectively). We describe the survey and sample selection in Section 2. Our aims are as follows. First, for a survey as large as HSC-SSP, it is necessary to construct an algorithm that is capable of producing a homogeneously selected sample of galaxies with tidal features. In Section 3, we create an algorithm for automatic detection, and, because there does not exist a suitable training set, we classify the morphologies of detected tidal features through visual inspection. In Section 4, we compare the results of our method to previous, purely visual samples and compare the nature of the stream and shell host galaxies to each other, as well as to the noninteracting galaxies in our sample. We present the results of measurements of the color of the tidal features in Section 4.3. Finally, we discuss the demographics of the tidal feature hosts and typical origins of the features in our sample.

In this work, we adopt a cosmology of \( \Omega_m = 0.3, \Omega_b = 0.7 \), and \( H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1} \).

### 2. Sample Selection

#### 2.1. HSC-SSP

In this work, we use the co-added images produced by the HSC software pipeline hscPipe (Bosch et al. 2018). For extended, low surface brightness structure, accurate sky subtraction is crucial. hscPipe performs sky subtraction via fitting a sixth-order 2D Chebyshev polynomial to a binned average of the image (with a bin size of 128 × 128 pixels, or \( 21^\prime 5 \times 21^\prime 5 \)). Sky subtraction is performed prior to source detection, after initial source detection, and after final (per-visit) source detection during CCD processing. During co-addition, a constant background is measured and subtracted from the images. For a detailed description of the HSC-SSP data reduction process, see Bosch et al. (2018). Because the \( i_{\text{HSC}} \) band has the best seeing on average across HSC-SSP, we use the \( i_{\text{HSC}} \)-band images as our detection images.

We set our redshift limits at \( 0.05 < z < 0.45 \), selecting from cross matches between the HSC Wide catalog from hscPipe (internal data release S16A, ~200 deg\(^2\)) and the SDSS...
spectroscopic surveys. At the lowest redshifts, we are currently unable to accurately detect tidal features. This is due to issues in background subtraction around very extended galaxies that become important when the size of the target galaxy becomes comparable to the area over which the background is subtracted (however, we note that the background subtraction has been improved for future data releases). At the high redshift cut of our window, we lose the ability to detect tidal features owing to cosmological surface brightness dimming and a loss of spatial resolution; a negligible number of galaxies at $z > 0.45$ have automatically detected tidal features using our algorithm (see Figure 6 and Section 3.4 for details regarding our surface brightness limits and sample completeness). In Section 3.4, we investigate our surface brightness limits by injecting simulated tidal features at various spatial extents into noninteracting galaxies from our sample.

2.2. SDSS Spectra

All of the galaxies in the present sample are selected to have spectra from SDSS DR12 and thus have known spectroscopic redshifts (Alam et al. 2015). We additionally use stellar masses derived by Chen et al. (2012) by fitting the SDSS spectra to principal components constructed from the models of Bruzual & Charlot (2003). We use the stellar masses calculated by Kauffmann et al. (2003) when a stellar mass measurement from Chen et al. (2012) is not available, where an offset calibrated from the galaxies where a stellar mass was available from both methods is applied to the stellar masses from Kauffmann et al. (2003). Both stellar mass estimates adopt a Kroupa (2001) initial mass function.

We include galaxies from both the SDSS Legacy catalog (complete to $r < 17.77$ mag; Strauss et al. 2002) and the Baryon Oscillation Spectroscopic Survey of SDSS-III (BOSS, color-selected and roughly stellar mass complete; Dawson et al. 2013; Reid et al. 2016). This generates a sample composed primarily of massive, low-$z$ galaxies with a bias toward elliptical galaxies. To avoid concerns about inhomogeneity of the SDSS samples, we consider our sample in bins of stellar mass and redshift. We additionally note that for $z < 0.15$ (which we will consider as a low-$z$ subset of the full spectroscopic sample), the sample is dominated by galaxies from the SDSS Legacy catalog. We use the HSC catalog associated with the internal data release S16A to cross-match HSC objects to their SDSS spectroscopic counterparts, resulting in 21,208 galaxies.

3. Identification and Characterization of Tidal Features

3.1. Detection

Visually classifying every nearby galaxy in the HSC footprint is neither scalable nor feasible. It is therefore of interest to use this initial spectroscopic sample to develop a more automated detection method that can be applied to the full HSC-SSP survey area. However, an automated method for detecting tidal features should be

1. able to operate in a single band (both to maximize the area over which the algorithm can function and so that the algorithm can be applied to any arbitrary bandpass);
2. agnostic to the global morphological characteristics of both the tidal features and host; and
3. functional in the low surface brightness regime.

To this end, we have developed a method that separates high spatial frequency features (e.g., streams, shell caustics) from low spatial frequency features (e.g., host galaxy light) in a single-band image.

Our algorithm is represented schematically in Figure 1. We iteratively separate low and high spatial frequency features, using the $h_{\text{HSC}}$-band image output by hscPipe. We take our initial image as a $512 \times 512$ pixel cutout (approximately 86" on a side) around a galaxy of interest in our parent sample ($I_0$). The nth image is then given by the convolution of the previous image and the kernel, $K$ (left-most column, Figure 1):

$$ I_n = I_{n-1} * K, $$

where $K(x, y) = h_{1D} h_{1D}^T$. We choose $\phi$ to be the 1D B3-spline

$$ \phi(x) = \frac{1}{12}(|x - 2|^3 - 4|x - 1|^3 $$

$$ + 6|x|^3 - 4|x + 1|^3 + |x + 2|^3), $$

which results in the convolution mask $h_{1D}^T = \begin{pmatrix} \frac{1}{16} & 1 & \frac{3}{4} & \frac{1}{4} & 1 \end{pmatrix}$ pixels (where each pixel spans 0"168, following Starck et al. 2007). We then isolate the high spatial frequency features in the image by constructing a high spatial frequency image, $e^{(n)}$, from the difference of the smoothed and unsmoothed images. This is shown in the middle column of Figure 1 as

$$ e^{(n)} = I_{n-1} - I_n. $$

Thus, those features that have spatial frequencies that are present in $I_{n-1}$ but removed in $I_n$ have positive values in $e^{(n)}$. $e^{(n)}$ is essentially the output of the well-known unsharp masking algorithm on image $I_{n-1}$ (for astronomical applications, see, e.g., Malin 1977; Meaburn 1980).

We then construct a detection image of the high spatial frequency components in the image by stacking the positive components of each $e^{(n)}$:

$$ C_{ik} = \sum_{n=2}^{N} \max \{0, c_{ik}^{(n)}\}, $$

where $C_{ik}$ is the pixel at $(i, k)$ in the stacked image, $c_{ik}^{(n)}$ is the pixel at $(i, k)$ in $e^{(n)}$, and $J$ is the number of layers in the filter bank (right-most column, Figure 1). We exclude the first component, $c^{(1)}$, as it is dominated by noise features.

For high $J$, the spatial frequencies probed by $c^{(J)}$ become low and can encompass the host galaxy. Similarly, the spatial frequencies associated with the host galaxy are strongly dependent on the physical size and redshift of the galaxy. The value of $J$ is therefore tuned to the sample at hand. The range of on-sky sizes for the galaxies in our sample, which tend to be massive and low redshift (our sample has a mean redshift of $z = 0.260$ and a mean stellar mass of $\log(M_*/M_\odot) = 11.19$), allows us to adopt a static value for $J$. Here, we set $J = 36$ (i.e., where the signal from one pixel can spread over at most a square with sides of 145 pixels).

3.2. Contaminant Removal

This method to produce the detection image $C$ generates high pixel values at the locations of tidal features, the cores of sources, spiral arms, and imaging artifacts. To remove contaminants from imaging artifacts, we reject detections
where a saturated star is located within the image cutout, when greater than 20% of the pixels in the cutout are flagged as missing data, or when greater than 95% of the pixels in the cutout are flagged as being near a bright star. These cuts are tuned to the pipeline used to process the HSC-SSP S16A imaging data, removing imaging artifacts that produce high spatial frequency features.

We take the following approach to remove contamination from spiral arms and neighboring galaxies. First, a flux threshold is applied to identify the cores of the brightest objects. The core of the target galaxy is excluded from this flux thresholding. The threshold is then iteratively lowered: at each iteration, the detected regions (i.e., a group of contiguous pixels) that are either connected to a previously detected source or are considered circular ($p < 0.25 \text{obj}^2$, where $\text{R}_{\text{obj}}$ and $A_{\text{obj}}$ are half the extent of the object and the area of the object in pixels, respectively) are flagged as nontarget objects. This cut is designed to remove faint point-source-like objects, which are circular in the detection image owing to the axisymmetric and monotonically decreasing radial profile of the convolution mask used. For an application of this technique to low surface brightness galaxies, see Greco et al. (2018b).

In total, we detect candidate tidal features around 1561 of the galaxies in our sample. For this initial application, we take the additional step of visually classifying the morphology of the tidal features in the automated sample (i.e., the 1561 galaxies around which tidal features have been detected), as well as removing contamination from tidal features that are likely associated with projected neighbors.

In Figure 2, we show the result of the algorithm on a synthetic case. Here, the signal that we wish to isolate is a simulated shell system from Hendel & Johnston (2015) with a mean surface brightness of $\bar{\mu} = 25.4 \text{mag arcsec}^{-2}$, where the mean is taken over pixels that have at least one count after the simulation is convolved with the HSC point-spread function (PSF; see Section 3.4). We add this signal to an $i_{\text{HSC}}$-band image of a noninteracting galaxy from the parent sample (left panel). The detection image, $C$, that we derive for the raw image, $I_0$, is shown in the middle panel; the two bright caustics in the system are visible in the middle of the detection image. The detected tidal features output by the algorithm are shown by the orange outline in the right-most panel.

### 3.3. Visual Morphological Classification

While all of the tidal features in our sample were detected in an automated fashion, using the methodology described above, we additionally visually classified tidal feature morphologies and removed neighbors from the automated sample. In order to build a classification algorithm that can differentiate shells from streams, it is necessary to have a sufficiently representative sample of known shells and streams from which an algorithm can be trained. A possible approach is to employ a supervised
learning algorithm where some known set of tidal features is used as the training set. There do exist simulated tidal features from which mock observations could be created for training (e.g., Kawata et al. 2006; Johnston et al. 2008; Hendel & Johnston 2015; Amorisco 2017; Pop et al. 2017b) and tidal feature catalogs that overlap with the HSC Wide footprint (e.g., Nair & Abraham 2010; Atkinson et al. 2013). However, training solely from simulations would risk propagating biases due to the parameter space explored by the simulation. The latter approach, training from known tidal feature hosts, is likely to yield large numbers of false negatives in the training set where HSC-SSP data reveal tidal features around a galaxy that was not identified previously, as HSC-SSP data reach significantly lower surface brightnesses than previous surveys at similar areas. A training set from only those works that reach significantly lower surface brightnesses than HSC-SSP (e.g., van Dokkum 2005; Martínez-Delgado et al. 2009; Tal et al. 2009) would neither have the necessary size nor be representative of the distribution of host galaxies in the sample at hand.

Additionally, identifying the host of a tidal feature is in some cases a nontrivial problem (see, e.g., Greco et al. 2018a). For nearby galaxies with extended tidal features, the host galaxy is often not the source that is closest to the tidal feature. Future work will address automatic classification of such cases; for the sample at hand, we identify these cases visually.

We visually classify each galaxy in the automated sample using three possible classes: stream, shell, and neighbor contaminant. Shells are characterized by their caustics, and the center of curvature is located near the center of the host galaxy. Streams are long, thin features wherein the curvature is not globally oriented toward the center of the host galaxy (though streams are not necessarily radial features). Neighbor contaminants are classified either as background galaxies (an example can be seen in the bottom right panel of Figure 5) or as tidal features that are associated with a neighboring galaxy, rather than the target. A small number of imaging artifacts from HSC (e.g., missing data, satellite trails, and imaging defects around saturated stars) also passed our automatic cuts and were removed at this stage.

In cases where the detected tidal features are not visible to the human classifier, our visual classification is primarily governed by the shape of the detected regions (see, e.g., the bottom left panel of Figure 5). The visual classification produces a final sample of 214 shell hosts and 987 stream hosts between 0.05 < z < 0.45.

We also consider the effect of astrophysical contaminants that could have passed both automatic and visual cuts on our sample selection. First, strong lenses could be mistaken for shell caustics and propagated to the final sample. However, from a comparison between the redshift distribution of our final tidal feature sample galaxies and the redshift distribution of known HSC strong lenses from Sonnenfeld et al. (2018), it is highly unlikely that strong lenses are a significant contaminant. Second, it is possible that some identified tidal features are in fact low surface brightness galaxies (hereafter LSBGs) that are not associated with the target galaxy. There are some notably ambiguous cases (see Merritt et al. 2016; Greco et al. 2018a), and it is possible that there are LSBGs misidentified as tidal features in our final sample owing to chance alignment. However, because of the low on-sky density of LSBGs, we expect <3 chance-aligned LSBGs in our final sample (here we define chance-aligned as an LSBG anywhere within the 512 × 512 cutout made around each galaxy, so this contamination rate should also be seen as an upper limit). We estimate this contamination based on the detection of 781 LSBGs in ~200 deg² of HSC Wide data by Greco et al. (2018b).

In Figure 3, we compare the redshift versus stellar mass distribution of our visually classified tidal feature sample (black) and visually identified contaminant sample (orange). We note that there is no apparent bias in the distribution of the visually classified neighbor contaminants with respect to our final sample.

We summarize the number of galaxies in our sample in Table 1. In particular, we note that the automatic detection step removes ≈93% of the parent sample from consideration during visual inspection, such that the main function of the visual classification is to differentiate shells from streams in our sample and to remove 23% of objects as contaminants. We further note that because the false positives are driven by imaging artifacts and background sources, the analysis herein
After automatic cut 1561 0.073

Initial SDSS sample 21208 1.00

Note.

N inspection does not introduce significant bias into the characteristics of our final tidal feature sample. In these panels, the orange bars show the neighbor contaminant sample, while the black bars show the tidal feature sample. The neighbor contaminants are not offset from the main tidal feature population, indicating that removing candidates via visual inspection does not introduce significant bias into the characteristics of our final tidal feature sample.

Figure 3. Redshift vs. stellar mass for the galaxies in the parent spectroscopic sample (small gray points), the tidal feature sample (black), and the neighbor contaminant sample (orange). The 1D histograms over redshift and stellar mass are shown in the top and right panels, respectively. In each case, the black bars show the distribution of the final, visually classified sample. In these panels, the orange bars show the neighbor contaminant sample, while the black bars show the tidal feature sample. The neighbor contaminants are not offset from the main tidal feature population, indicating that removing candidates via visual inspection does not introduce significant bias into the characteristics of our final tidal feature sample.

### Table 1

| Cut Type                  | $N_{\text{gal}}$ | Frac. of Initial Sample |
|---------------------------|------------------|-------------------------|
| Initial SDSS sample       | 21208            | 1.00                    |
| After automatic cut       | 1561             | 0.073                   |
| After visual classification| 1201             | 0.057                   |

Note. The number of galaxies surviving each stage of sample selection. Note that the automatic detection step removes ≈93% of the parent sample from consideration for the visual morphological classification.

3.4. Detection Recovery Efficiency

In previous work, the surface brightness limits of tidal feature searches have normally been estimated from the variations in fluxes from random sky apertures (Atkinson et al. 2013; Hood et al. 2018; Morales et al. 2018). If we were to use the methods described in Atkinson et al. (2013) and Morales et al. (2018), we would derive nominal surface brightness limits for the Wide layer of HSC-SSP of $\mu_i \sim 27.9$ mag arcsec$^{-2}$ and $\mu_i \sim 28.4$ mag arcsec$^{-2}$ from each method, respectively.

However, the detection of tidal features is also strongly dependent on the apparent size and morphology of the tidal feature. We find that the surface brightness limits derived from the methods from prior work are significantly deeper than practical limits for both automatic and visual inspection (for more details, see Appendix B). Moreover, our automated algorithm allows us to run through the detection process many times without a proportionate increase in the required human time. Thus, in order to understand the surface brightness and angular size limits of our detection method as applied to the HSC wide layer, we use the simulated tidal features of Hendel & Johnston (2015) to create mock HSC-like tidal feature systems.

Taking $h_{\text{HSC}}$-band cutouts of six galaxies (four elliptical and two disk galaxies) in which no candidate tidal features were originally detected, we insert nine mock tidal features into each galaxy. We inject all tidal features such that the line of sight runs perpendicular to the orbital plane; the recovery fractions should therefore be taken as upper limits with respect to tidal feature orientation. The tidal features are scaled to a grid of mean surface brightnesses and sizes (normalized to the effective radius of the host) over $24.5 < \bar{\mu}_i < 27.0$ mag arcsec$^{-2}$ and $1 < d/R_{e,\text{host}} < 5$, and convolved with the local HSC PSF. Here $d$ refers to the maximum radial extent of the tidal feature, and $\bar{\mu}_i$ refers to the mean surface brightness of the convolved tidal feature system, averaged over the pixels in the cutout that have at least one count after convolution with the HSC PSF. Simulations of four streams and five shells are used for this test.

For each simulated system, we define the recovery fraction as

$$f_{\text{rec}} = \frac{N_{\text{pix,rec}}}{N_{\text{pix,sim}}}$$

where $N_{\text{pix,rec}}$ is the total number of pixels flagged as part of a detected tidal feature and $N_{\text{pix,sim}}$ is the total number of pixels in the PSF-convolved simulation that have at least one count. Although the detection algorithm is never successful in recovering 100% of the pixels with some flux associated with the simulated tidal feature, the value of $f_{\text{rec}}$ is a useful measure of the algorithm performance. The definition of $N_{\text{pix,sim}}$ is a convenient normalization that excludes pixels that, while technically associated with the simulated tidal feature, are at surface brightnesses much fainter than what would be feasibly detectable.

The results of these tests are shown in Figure 4. The left column (blue) shows the results for the simulated stream systems, while the right column (red) shows the results for the simulated shell systems. The top row shows, for a given radial extent and mean surface brightness, the average $f_{\text{rec}}$ of the simulated systems. The bottom row shows, again for a given radial extent and mean surface brightness, the fraction of systems wherein $f_{\text{rec}} > 0.05$ (approximately the threshold at which a visual morphological classification can be made).

As expected, tidal features that extend farther from the center of the host galaxy are more easily detectable owing to reduced host light contamination. For a given surface brightness and tidal feature extent, the simulated streams have a higher $f_{\text{rec}}$ than shells (top row) and are more likely to be detected at visually classifiable levels than shells (bottom row); this is a product of the fact that a significant number of the particles in the simulated shells are contained within diffuse stellar fans (for reference, see the low surface brightness fans in the right panel of Figure 2).
There is also a drop in detection recovery at very high mean surface brightnesses; the detection fraction of both streams and shells drops from \(>80\%\) to \(<65\%\) between injected features with a mean surface brightness of \(25.125\) and \(24.5\) mag arcsec\(^{-2}\). This occurs when the tidal feature enters a regime in which its associated signal in the detection map becomes comparable to that of spiral arms and neighboring sources. These tidal features are therefore removed as a likely contaminant (i.e., misidentified as a neighboring source or spiral arm). However, such features are in practice typically associated with ongoing major mergers with mass ratios close to 1:1, which are not the focus of this work. In these cases, the material in the tidal features can be from the disruption of either the host or the interloper; here, we focus on those cases in which the material in the tidal features is drawn primarily from the satellite. Ongoing major mergers are also significantly less common than tidal features and are therefore not a significant contaminant in our sample. We note that there are more effective means for finding merger samples with HSC (Goulding et al. 2018), and ultimately it will be productive to think about both types of samples together. It should also be noted that the parameters that we choose in the detection step are tuned to our primarily low-z, massive sample. If applied to a different set of galaxies (e.g., higher redshift), it is likely that the thresholds used would need to be adjusted.

As shown in Figure 4, the algorithm can identify tidal features down to \(\approx 27\) mag arcsec\(^{-2}\) at an extent of \(d \approx 4R_{e,\text{host}}\). We note, however, that we are significantly incomplete at these surface brightnesses (e.g., although we detect, on average, 2.6\% of the pixels of our simulated streams at 27 mag arcsec\(^{-2}\), only 25\% of simulated cases yield a detection). Our approximate 50\% completeness for tidal features with \(d \approx 3R_{e,\text{host}}\) is \(\mu_i \approx 26.4\) mag arcsec\(^{-2}\).

3.5. Measuring Tidal Feature Color

For a subset of the galaxies with detected tidal features, the features are sufficiently far from the galaxy to allow for a clean measurement of color. We rerun our detection algorithm in the \(g\)-band and measure the color of the detected tidal features by using the union of the detected regions in \(g\)-band and \(i\)-band as the apertures (e.g., in Figure 2 the orange outlines in the rightmost panel would be used as an aperture).
To determine where the color of the tidal feature will be significantly impacted by flux from the host galaxy, we measure the tidal feature contrast ratio, $c_{tf}$, as the observed flux of the system and expected flux from the host via surface brightness profiles where the tidal features have been masked from the image, i.e., $c_{tf} = \frac{f_{observed}}{f_{host}}$. We measure $f_{observed}$ by simple aperture photometry, where the aperture is the detected region associated with the tidal feature. We estimate $f_{host}$ by measuring the surface brightness profiles of our sample in the $g_{HSC}$ and $r_{HSC}$ bands in elliptical annuli. Here, the position angle and ellipticity are obtained from fits to the host galaxy using imfit (Erwin 2015), where neighboring galaxies and the tidal feature system are masked from the fit. $f_{host}$ is then the flux expected in the region of the tidal feature as estimated by the surface brightness profile in that region.

To calibrate and test the ability of $c_{tf}$ to trace the accuracy in measurements of colors for extended tidal features, we inject tidal feature simulations (presented in Section 3.4) of known colors into noninteracting HSC galaxies. The data from the $N$-body simulations of Hendel & Johnston (2015) are also convolved with the HSC PSFs in each band. The simulated systems are then run through our full detection and color measurement algorithm. We find that a $c_{tf}$ threshold of 2.5 produces tidal feature colors that are accurate to 0.06 mag, which includes the effect from band-dependent PSF size.

For a given tidal feature system, it is possible that a number of the detected regions are contaminants that have been detected along with the true tidal features; see Section 3.3 for a description of the expected types of contaminants. At this stage, we only flag contaminated regions within a tidal feature system and do not remove galaxies from the sample. However, when we estimate the average color of the tidal feature system, we use color as a filter to remove regions that are unlikely to be associated with the target galaxy.

The color of the candidate tidal feature with respect to the host also acts as a flag for potential neighbor contamination for individual detected regions. When comparing tidal feature color to host color, we consider $\Delta(g - i)$, where $\Delta(g - i)$ is defined as the difference between the $(g - i)$ color of the tidal feature and the host (i.e., larger values correspond to a tidal feature that is redder with respect to its host). In the case of shells, we keep only those tidal feature candidates with $-0.5 \text{mag} < \Delta(g - i) < 0.2 \text{mag}$. For this initial sample, we verify visually that this color cut does not remove potentially interesting tidal features from the sample. Streams have been observed to host significant star formation (Knieerman et al. 2012; Higdon et al. 2014), and so we impose only the red cut, i.e., we keep those color measurements for which $\Delta(g - i) < 0.2 \text{mag}$.

After removing likely neighbors (i.e., those detected regions that are removed owing to the cuts in color), we estimate an average color of the tidal feature system by taking the mean of the colors measured for the individual detected regions. We estimate the uncertainty on the measurement of the average color ($\sigma_{\overline{TF}}$) as follows:

$$\sigma_{\overline{TF}} = \left( \frac{1}{N} \sum_{i} \sigma_{TF,i}^2 + \sigma_{sim}^2 \right)^{1/2},$$

where $\sigma_{TF,i}$ is the uncertainty on the color of the $i$th-detected tidal feature region (as propagated from the variance maps output by hscPipe) in a system of $N$ tidal feature regions (defined as a group of contiguous pixels that are flagged by the detection algorithm; e.g., Figure 2 shows an $N = 2$ system), and $\sigma_{sim}$ is the uncertainty due to PSF differences and host galaxy contamination ($\sigma_{sim} \sim 0.06$, from above).

Finally, we estimate the color of the host galaxy core from simple aperture photometry with an aperture diameter of $2R_{e,host}$. We do not perform PSF matching for this measurement, as the impact of doing so is negligible.

4. Results

Here, we present a sample of 214 shells and 987 streams found semiautomatically in the S16A internal release of the HSC-SSP Wide layer (covering $\sim 200 \text{deg}^2$). The tidal feature morphologies are visually classified as either streams or shells and cover a redshift range of $0.05 < z < 0.45$. In Figure 5, we show a sample of shell galaxies (left), stream galaxies (middle), and galaxies without tidal features (right) as identified by this method.

4.1. Observed Tidal Feature Occurrence Fractions

We first consider the tidal feature occurrence fractions for our sample, which we define to be the fraction of galaxies in the sample within a given range of redshift and stellar mass in which a stream or shell was detected, divided by the total number of galaxies in the sample that occupy that area of parameter space. As shown in Section 3.4, the observed occurrence fraction will reflect both the astrophysical occurrence fraction and our ability to recover the tidal feature signal from HSC data.

Many factors affect the observed surface brightness of a tidal feature system. The tidal feature grows increasingly faint with time since its creation owing to phase mixing (Hendel & Johnston 2015) and stellar population fading (e.g., Conroy et al. 2009), while the orbital parameters of the encounter influence the morphology of the resultant tidal feature (see, e.g., Johnston et al. 2008; Sanderson & Helmi 2013; Hendel & Johnston 2015; Pop et al. 2017b). The surface brightness and angular size of the tidal feature are also dependent on the redshift of the source owing to changes in the angular diameter distance and surface brightness dimming. Lower-mass galaxies should also host tidal features from lower-mass satellites, which produce tidal features of lower surface brightnesses. Figure 6 shows our observed occurrence fractions as a function of host redshift and stellar mass. As expected, our observed occurrence fractions fall as redshift is increased or stellar mass is decreased. The observed occurrence fractions of shells fall more steeply as a function of redshift than those of streams, which we expect from our lower recovery fractions for simulated shells in Figure 4. At low redshift ($z < 0.15$), we find a number of low-mass systems with $\log(M_*/M_\odot) < 9.7$ that are apparent stream hosts. From a visual inspection of these objects, we find that these systems are either dwarf galaxies undergoing major mergers (because of the mass of the galaxies involved, the surface brightness of the extended features is low enough to avoid being thrown out as spiral arms) or close neighbors of larger galaxies that host tidal features. Though ongoing major mergers in dwarf galaxies are not the focus of this paper, we note that our method could also generate samples of such ongoing mergers if a different parent sample were used (see, e.g., Paudel et al. 2018).
The fraction of galaxies that host observable tidal features has been measured by many authors, who find a wide range of values, from 7% as derived from SDSS (Nair & Abraham 2010) to 71% from a deep imaging campaign of local ETGs (van Dokkum 2005). It is likely that a majority of faint substructures have peak surface brightnesses of $>30$ mag arcsec$^{-2}$ in the optical (Johnston et al. 2008) and that the occurrence and morphology of tidal features are dependent on the mass and merging history of the host (Wang et al. 2005; Hendel & Johnston 2015; Jiang et al. 2015). Thus, tidal feature detection is highly sensitive to the type of host galaxy examined and to the surface brightness limits of the relevant observations, leading to a large variance in the observed tidal feature occurrence fractions.

In campaigns where a smaller area on the sky is observed to large depths, the limiting surface brightness is significantly deeper than that which is accessible from the HSC wide layer (e.g., van Dokkum 2005; Tal et al. 2009; Martínez-Delgado et al. 2010). Although we are unable to construct a matching sample against which to compare our observations, we note that the systematically higher occurrence fractions that are often found by such studies point to the minor merger picture, in which increasingly more numerous and minor mergers leave behind increasingly fainter tidal features (Johnston et al. 2008).
Other studies present samples that we have no clean method of emulating. For example, Schweizer & Seitzer (1988) consider S0, S0/Sa, and Sa NGC galaxies and derive an occurrence fraction of 16%, while Adams et al. (2012) observe a 3% tidal feature occurrence fraction for cluster ETGs.

However, it is valuable to consider whether the tidal feature occurrence rate that we observe from our semiautomatic method is consistent with those samples derived from visual classification alone. Here, we compare our observed occurrence fractions to literature results where it is possible to account for differences in sample selection.

4.1.1. Comparison with Atkinson et al. (2013)

The catalog of tidal feature hosts in the Canada–France–Hawaii Telescope Legacy Survey (hereafter CFHTLS) assembled by Atkinson et al. (2013) is perhaps the clearest benchmark against which we can evaluate our observed tidal feature occurrence fractions. The CFHTLS data are similar to the HSC Wide layer in terms of depth and spatial resolution; the deepest band that Atkinson et al. (2013) consider, the CFHT g band, has a roughly equivalent 5σ point-source depth to $i_{HSC}$ in the Wide layer of HSC-SSP (Boulade et al. 2003; Aihara et al. 2018a). The catalog was constructed entirely from visual inspection and thus serves to test the efficiency of our method against pure visual inspection.

To compare our tidal feature detection fractions with those of Atkinson et al. (2013), we consider the 2113 galaxies in our sample for which 15.5 mag $< r_{SDSS} < 17$ mag, $M_r < -19.3$ (derived from SDSS; Alam et al. 2015), and 0.05 $< z < 0.2$, following the sample selection cuts used by Atkinson et al. (2013). We find a tidal feature occurrence fraction of 13.30% ± 0.79%, where the uncertainty reflects only counting uncertainty assuming a Poisson distribution. This fraction is significantly higher than those in Figure 6 because of the additional cuts for bright galaxies imposed in the Atkinson et al. (2013) sample.

Within the Atkinson et al. (2013) sample (hereafter the CFHTLS sample), we consider only the galaxies for which the authors were able to make a morphological classification of the tidal feature. We furthermore exclude any galaxies for which the only feature morphology tags belong to the classes “diffuse” and “fun,” which are observed in 4.6% of their galaxies, as the nature of our method biases us significantly against the detection of tidal features that are diffuse (i.e., of spatial frequency similar to or lower than their host galaxy). Given these cuts, the fraction of galaxies that host morphologically classifiable tidal features of Atkinson et al. (2013) is, at 12.98% ± 0.85%, in agreement with our observed tidal feature occurrence fraction.

Given that the Atkinson et al. (2013) sample was constructed via purely visual classification from a data set with a similar limiting depth and spatial resolution to HSC-SSP, this agreement is encouraging and implies that our detection method is able to detect tidal features as well as visual inspection methods can for tidal features with high spatial frequency features.

4.1.2. Comparison with Malin & Carter (1983)

As one of the earliest papers to report the occurrence rates of shells around elliptical galaxies, it is informative to compare our shell occurrence fraction with that of Malin & Carter (1983). However, we caution that it is not straightforward to compare the data of Malin & Carter (1983), taken with photographic plates, with HSC-SSP data; we use this comparison only as an order-of-magnitude estimate. The authors consider a sample of NGC ellipticals from the ESO/SRC (IIIa-J) Southern Sky Survey and find that 5.8% of the galaxies therein show signs of stellar shells. The authors cite their surface brightness limit as $B = 26.5$ mag arcsec$^{-2}$ on photographic plates.

Although the galaxies considered by Malin & Carter (1983) are at significantly lower redshifts, we do not expect the true shell occurrence fraction to change significantly out to $z \lesssim 0.1$ (Pop et al. 2017b). We use concentration as a proxy for morphology, wherein high-concentration galaxies are likely ellipticals and low-concentration galaxies are likely disks. $C$ is defined as the ratio between the radii containing 90% and 50% of the Petrosian $i$-band luminosity as measured in SDSS. We consider only high-concentration ($C > 3.1$) galaxies at the

Figure 6. Tidal feature occurrence fractions as a function of stellar mass (y-axis) and redshift (x-axis) for the visually identified stream (top) and shell (bottom) samples. Each bin in the top (bottom) panel is annotated with the fraction of galaxies tagged as a stream (shell) host from the full spectroscopic sample. Blank regions indicate bins for which no tidal feature systems were identified.
4.2. Host Galaxy Properties

We first review the properties of the galaxies that host shells and streams in the context of the full SDSS spectroscopic sample. Relative to the noninteracting sample (i.e., galaxies for which no tidal features were detected), shell hosts tend to have higher stellar masses and redder \((g−i)\) colors at a given redshift (left and middle panels of Figure 7). Stream hosts span the full range of stellar masses and colors present in the noninteracting sample at a given redshift.

At \(z < 0.15\), stream host galaxies in our sample have higher concentrations on average than do the noninteracting sample. The shell host galaxies have higher average concentrations than do either the stream hosts or the noninteracting sample (Figure 7, right panel). These offsets imply that the shell hosts tend to be massive, red ETGs (since high concentration is correlated with an elliptical morphology).

We find no significant differences between the color gradients of the tidal feature host galaxies and a noninteracting sample matched in mass, redshift, and color—this implies either that the average tidal feature is generated by a minor merger that does not significantly alter the color gradient of the host, or that the tidal feature was created sufficiently long ago that the host is fully relaxed. This is in agreement with the findings of Kim et al. (2012), who find that the bulk structural properties of tidal feature hosts are not significantly different from those of noninteracting galaxies.

4.2.1. A Dearth of Low-concentration Galaxies Hosting Shells

From a visual inspection of our sample, we find only three instances in which a low-concentration (disk) galaxy hosts a shell (these three cases are shown in Figure 8). Here, we investigate possible selection or completeness effects that could produce this dearth of observed low-concentration galaxies that host shells at a fixed stellar mass.

In a paradigm where satellites falling into more massive hosts tend to be on more radial infall trajectories (see, e.g., Benson 2005; Jiang et al. 2015), we expect somewhat fewer spiral galaxies to host shells owing to the differences in the stellar mass range occupied by elliptical and spiral galaxies. To gauge whether the low number of shells observed around disks is purely a mass effect, Figure 9 shows the fraction of tidal features that are identified as shells in our sample as a function of stellar mass at \(z < 0.15\).

To estimate the effect of differential completeness in shell and stream detection on the trend apparent in Figure 9, we take the naive null hypothesis that shells and streams appear equally often, independent of stellar mass, and have radial extents that are distributed uniformly from \(3R_e\) to \(5R_e\). We here disregard the effect of passive stellar population fading and assume that the shells and streams have the same distribution in time since interaction. We also assume that the events all have the same mass ratio. Using the simulations presented in Section 3.4, this scenario would predict that the fraction of observed shells would remain roughly constant as a function of host stellar mass and rise at low masses (\(\log(M_*/M_\odot) < 10.5\)). Thus, we expect that the trend seen in Figure 9 is not a completeness effect.

As a second experiment, if we take the naive assumption that the morphology of the tidal feature is independent of the morphology of the host, we would expect \(\approx 15\%\) of detectable tidal features around low-concentration galaxies to be shell-like at \(\log(M_*/M_\odot) \sim 10.5\), near the peak of the distribution of stellar mass for a sample of low-concentration galaxies in our sample. However, we find that only \(4\% \pm 3\%\) (6\% ± 4\%) of the tidal features around \(C < 2.8\) (\(C < 2.6\)) galaxies at \(10.2 < \log(M_*/M_\odot) < 10.7\) are shell-like.

We repeat this exercise using morphological classifications from the citizen science project Galaxy Zoo (Lintott et al. 2011). Here, we consider only those galaxies where one class accounts for >80\% of the votes. Here, we again find a dearth of late-type galaxies hosting shells. We thus conclude that indeed there is a significant deficit of shells around late-type galaxies.
We now consider whether this deficit is due to our detection method, which may be biased against finding shells around face-on disks, where bright substructure (e.g., spiral arms) may obscure tidal features. Broadly speaking, contamination by spiral arms should affect the detection of shells and streams equally, rather than preferentially affecting the fraction of observed shells. We used the method outlined in Section 3.4 to compare the detection recovery efficiency of shell-like tidal features around a face-on spiral with that of an elliptical host with similar on-sky size. We did not find significant differences in detection recovery for the automatic stage in these two cases. However, it is probable that human classifiers are biased against shell-like tidal features around face-on disk galaxies, as the curvature of shell caustics is similar to that of spiral arms.

To test whether a human bias could account for the difference in shell fraction at fixed stellar mass, we consider only shells that are substantially separated from their host galaxy (i.e., where contamination by host light is low, or with high values of $c_f$; see Section 3.5) and find that we again observe relatively more ellipticals that host shell systems at fixed stellar mass. We therefore conclude that the relative dearth of shell systems around disk galaxies in our sample is not due to a bias in our sample selection method. We return to interpret this result in Section 5.3.

**Figure 8.** Top: gri-composite images (Lupton et al. 2004) of the three disk galaxies that host shells in our sample. Both caustics and diffuse stellar fans are visible in all cases. In the middle panel, two umbrella-like shell structures are visible to the left of the galaxy. Bottom: same galaxies in the $i_{	ext{HSC}}$ band, with the features detected by the algorithm shown in orange. A diffuse trail is also visible in the top right of the right-most panels, which is not detected owing to its overlap with the cutout edge.

**Figure 9.** Stellar mass vs. the fraction of tidal features that are shells for the $z < 0.15$ galaxies in our final tidal feature sample. Shells are found more frequently around more massive galaxies, growing from $\approx 20\%$ at $\log(M_*/M_\odot) = 10.5$ to $\approx 50\%$ at $\log(M_*/M_\odot) = 11.5$. A larger shell fraction around massive galaxies is expected owing to an increase in the number of radially biased satellite infall trajectories around such galaxies (Hendel & Johnston 2015; Jiang et al. 2015).
4.3. Tidal Feature Colors

We are able to measure colors for 78 shell systems and 497 stream systems in our sample. Below, we present the average $(g-i)$ colors of tidal feature systems. Here, we specifically consider the difference in the average color of the tidal feature system and the core of its host galaxy (hereafter $\Delta (g-i)$). In the case of a non-star-forming satellite, $\Delta (g-i)$ is a probe of the mass ratio of the merging event that formed the shells: if one assumes that the tidal feature progenitor satellites sat on the red sequence during their infall, the mass of the satellite may be estimated by finding the mass on the red sequence that corresponds to the measured satellite color (Gu et al. 2013; Huang et al. 2016). We find this assumption to be reasonable, as the red colors measured for the shells are too red to plausibly host significant star formation. In the case of blue tidal features, $\Delta (g-i)$ does not yield mass information.

4.3.1. Shell Colors

We find that the shells are, on average, slightly bluer than their hosts, with a mean color offset of $-0.15 \pm 0.02$ mag (see top panel of Figure 10). The observed $\Delta (g-i)$ does not have a strong dependence on the mass of the host galaxy. This finding is in agreement with the majority of individual systems in the literature for which the colors of the shells have been measured (Quinn 1983; Gu et al. 2013; Foster et al. 2014). The color difference between the shells and their hosts then suggests that our sample is dominated by mergers where the infalling satellite is significantly less massive than the host.

However, we also find that for $15\% \pm 4.4\%$ of shell galaxies the colors of the shells are consistent, within errors, with those of the core of their host galaxy. We will hereafter refer to these galaxies as “red shell” galaxies. This lack of a color difference has been suggested by Pop et al. (2017a) to be a signature of shells produced by major mergers, wherein the shell caustics of the system within $\approx 50$ kpc from the host center approach the metallicity of the core of the host galaxy. Though the shell caustics in Pop et al. (2017a) have slightly lower metallicities than the host core, we estimate that their optical colors will be consistent within the errors to the core of the host within $1R_{e, host}$.

Though there are relatively few “red shell” galaxies, we find there to be a morphological difference between these shells and the bulk of the shell population. Relative to the other galaxies that host shells, “red shell” galaxies tend to host more Type I shells, wherein the axis of symmetry of the shells is aligned with the major axis of the galaxies (see the left-most panel of the second row in Figure 11 for an example). The caustics of Type II shells, on the other hand, are arranged randomly around the galaxy (see the middle panel of the bottom row in Figure 11 for an example). The Type I shell occurrence fraction in our “red shell” sample is $86\%^{+35}\%_{-30}\%$, significantly higher than the Type I shell occurrence fraction for the rest of the shell hosts, $30\% \pm 14\%$. Considering both the “red shell” galaxies and minor merger-like shell hosts together gives a Type I host fraction of $43\% \pm 12\%$. This is in agreement with the same quantity estimated by Prieur (1990) for the catalog of Malin & Carter (1983). The uncertainties listed are those derived from counting statistics only and reflect the significant uncertainty that we face as a result of low numbers of “red shell” galaxies present in the sample.

4.3.2. Stream Colors

The streams in our sample are bluer with respect to their hosts than the shells are, with a mean offset of $-0.38 \pm 0.02$ mag (see bottom row of Figure 10). There are also a number of very blue streams around less massive galaxies. We bound the rest-frame colors of these streams by calculating $K$-corrections for three SSPs from Bruzual & Charlot (2003) with a Chabrier (2003) initial mass function for a young (0.5 Gyr), intermediate-age (5 Gyr), and old (12 Gyr) population (see Figure 12). The $(g-i)$ rest-frame colors of the SSPs are shown by the dashed vertical lines. Based on the rest-frame $(g-i)$ colors of the streams relative to those of the SSPs, a subset of streams in our sample are blue enough to suggest that they likely host active star formation.

We do a visual search for UV counterparts to our stream sample in Galaxy Evolution Explorer (GALEX; Martin et al. 2005; Morrissey et al. 2007) imaging surveys (i.e., the
Figure 11. Left: iHSC-band imaging of a sample of shells where the color of the shell caustics (boundaries defined by the orange outlines) is consistent with the color of the host galaxy within $1R_{e,\text{host}}$. Right: sample of shells for which the color of the shell caustics is bluer ($\Delta m < -0.25$ mag) than the color of the host galaxy within $1R_{e,\text{host}}$. All panels use a logarithmic stretch to increase contrast at low surface brightness. The shells that are as red as their host galaxy cores display a higher incidence of Type I shells (86.1$^{+14.6}_{-13.3}$%) than their blue counterparts (30% ± 14%).
Figure 12. Distribution of (g − i) rest-frame colors for our stream sample, using the K-correction computed for a 0.5 Gyr (purple), 5 Gyr (green), and 12 Gyr (red) SSP from Bruzual & Charlot (2003). The dashed vertical lines show the rest-frame colors for, from left to right, the 0.5 Gyr (purple), 5 Gyr (green), and 12 Gyr (red) populations. The existence of streams with rest-frame colors bluer than the youngest SSP considered implies that a subset of the streams are not on the red sequence and host star formation.

5. Discussion

For decades, astronomers have used tidal features to probe the merger histories and potentials of the Milky Way and external galaxies (Quinn 1983, 1984; Dupraz & Combes 1986; Hernquist & Quinn 1987, 1988, 1989; Hernquist & Spergel 1992; van Dokkum 2005; Kawata et al. 2006; Johnston et al. 2008; Sanderson & Helmi 2013; Hendel & Johnston 2015; Price-Whelan et al. 2016). But disentangling the relative importance of merger mass ratio, orbital angular momentum, and galaxy potential shape is nontrivial from both an observational and a theoretical standpoint.

HSC-SSP provides the on-sky area and surface brightness sensitivity to generate an unprecedentedly large sample of shells and streams around external galaxies, giving us the numbers necessary to consider, on a statistical level, the questions of tidal feature formation. With a sample of 1201 tidal feature hosts from the ongoing survey, we are able to compare the characteristics of the observed shell and stream samples. We find that shells are more commonly associated with massive, high-concentration galaxies (see Figure 7); although streams are more common (214 shell and 987 stream hosts), the fraction of tidal features that are classified as shells rises steeply with host stellar mass (see Figure 9). We additionally measure the colors of a subset of extended tidal features; this allows us to estimate the mass ratio of the merger event in the case of the red sequence progenitors (see Figure 10) and gives insight into the prevalence of star formation in tidal features for nonquiescent progenitors (see Figure 12). Here, we consider probable formation scenarios and physical characteristics of a typical tidal feature system in our sample.

5.1. The Mass Ratio of Shell-forming Events

First, we consider the mass ratios of the mergers that formed the shells in our sample. We have observed a bias in host galaxies toward massive ellipticals (see Figures 9 and 7). In the canonical theoretical picture of tidal feature formation, streams and shells are created from the stars in a satellite galaxy as it falls into a more massive halo; shells are formed from satellites on orbits with low angular momentum, and the debris morphology gradually transitions from “shell-like” to “stream-like” with increasing angular momentum (Johnston et al. 2008; Sanderson & Helmi 2013; Amorisco 2015; Hendel & Johnston 2015). The idea that shells could form from major mergers was introduced several decades ago (Hernquist & Spergel 1992), and recent theoretical work using cosmological simulations has suggested that the shell population is dominated by mergers more major than 10:1 (and that the distribution peaks at ≈1:1; Pop et al. 2017a, 2017b).

In the minor merger picture of tidal feature formation, as host mass rises, the fraction of red sequence satellites also rises (Hansen et al. 2009; Skelton et al. 2009; Wetzel et al. 2012; Wang et al. 2014; Sales et al. 2015). In the two-stage model of galaxy formation (Oser et al. 2010), the outskirts of such hosts are built up via dry mergers since ε ≈ 2 of, on average, mass ratios of ≈5:1 (Gabor & Davé 2012; Oser et al. 2012; Hilz et al. 2013). Observations of such galaxies in SDSS also indicate that the satellite population is dominated by red sequence galaxies both in the field (Wang et al. 2014) and in high-density environments (Hansen et al. 2009).

The dominance of red sequence satellites is generally understood to originate from interactions between the host and satellite. Cold gas reservoirs in infalling satellites are thought to be drained via environmental effects: the satellites’ gas reservoirs experience ram pressure stripping (Gunn et al. 1972; Simonsen et al. 2018), are unable to accrete new gas, and, in halos with $M_{\text{halo}} > 10^{13} M_\odot$, undergo shock heating (Dekel & Birnboim 2006). At lower host masses, these effects are expected to be significantly weaker, allowing the blue satellite fraction to rise as the host mass decreases (Prescott et al. 2011; Wang et al. 2014; Sales et al. 2015). The characteristics of the observed tidal feature population are then intrinsically linked to the progenitor population from which they were formed.

For shells with a major merger origin, where the observed host light contains a significant contribution from the interloper, the shells should be at similar metallicities to the host galaxy core (Pop et al. 2017a). This leads to shell colors that are consistent with those of the host core, to within our measurement error. Thus, we expect that the majority of shell-forming progenitors are red sequence galaxies for which $\Delta(g-i)$ provides a probe of the merger mass ratio.
5.1.1. Signatures of Major and Minor Shell-forming Mergers

We find that the majority of shell galaxies have colors that are consistent with a minor merger origin; from our measured mean value of $\Delta(g-i) = -0.15 \pm 0.02$, we place an upper limit on our mean mass ratio of $\approx 4:1$ via the stellar mass--$(g-i)_{\text{HSC}}$ relation for our SDSS parent sample, though the spread and flattening in the mass--color relation prevent us from inferring a precise mass ratio from the colors of any given individual tidal feature system. It should be noted that this procedure has large error bars, especially at high host masses, as a result of the flattening of the color--mass relation---previous studies that find color differences close to our mean color difference cite mass ratios as small as 90:1 for a host galaxy of $M_1 \approx -18.7$ mag (Gu et al. 2013).

The detection of shells that are as red as their hosts is suggestive of a major merger origin for some of the shell systems. The observed correlation between shell morphology and shell color (and therefore mass ratio) in Section 4.3 is in good agreement with predictions from Amorisco (2017), who shows that progressively larger satellites (in terms of merger mass ratio) are dragged into more radial orbits via dynamical friction. This morphology--color relation is also in agreement with the visual morphology of the shells presented in Pop et al. (2017b). In the picture presented by Amorisco (2017), the more major shell-forming mergers in our sample should form the classical Type I shells; indeed, we observed that 86$^{+14}_{-15}$% of our “red shell” galaxies are Type I shells. Meanwhile, the shells formed from more minor mergers may retain increasingly more angular momentum at the point at which the stars were stripped. This results in shell morphologies suggestive of higher angular momenta where the shell caustics are distributed randomly in azimuth about the host core (Sanderson & Helmi 2013; Hendel & Johnston 2015) and a lower fraction of Type I shells (30% ± 14%). Cosmological studies also suggest that more major mergers are preferentially accreted along the major axis of the galaxy (Wang et al. 2005); major merger shells are also expected to form preferentially as Type I shells (Hernquist & Spergel 1992).

We therefore suggest that the majority of observable shells are generated from intermediate and minor mergers, while major mergers play an important but subordinate role in shell formation. This picture is in agreement with the current state of the literature, in which the majority of observations point to a minor merger origin (Malin et al. 1983; Quinn 1983; Fort et al. 1986; Gu et al. 2013; Foster et al. 2014), but there exists some evidence for shells with a major merger origin (see, e.g., Carlsten et al. 2017; Paudel et al. 2017). Our main tension with the results of Pop et al. (2017b) is in the mass ratio distribution of shell-forming events; whereas Pop et al. (2017b) find a distribution dominated by relatively major mergers that peaks at $\approx 1:1$ mergers, we find that shells are primarily formed by mergers with mass ratios more minor than $\approx 4:1$, with a tail toward major mergers.

Both our sample and the results of Pop et al. (2017a), however, indicate that major mergers tend to form Type I shells. Our observations are also in agreement with the predictions of Hendel & Johnston (2015) and Pop et al. (2017b), which predict that the expected number of shell galaxies should increase with the mass of the host. Further work is necessary to explore possible technical, observational, or physical explanations for the discrepancies in the nature of HSC and Illustris shell galaxies of Pop et al. (2017b). In particular, the appearance and characteristics of specific shell morphologies should be compared across theoretical and observational work.

5.1.2. Other Influences on Shell Morphology and Color

It has also been proposed that, for minor mergers, the morphology of the resulting shell system is governed by the shape of the dark matter halo. Using N-body simulations of shell-forming mergers, Dupraz & Combes (1986) propose that halos preferentially form Type I shells and that oblate halos preferentially form Type II shells. The authors further-state that shells around prolate halos are more common. However, it has also been argued by Hernquist & Quinn (1989) that other characteristics of the merging event (such as orbital parameters, satellite mass, etc.) play a significant role in the morphology of the resultant tidal feature and thus obfuscate any relationship between the form of the host potential and the tidal feature morphology.

In the minor merger picture of shell formation, the outskirts of the satellite are the first material to be stripped from the infalling satellite and form the outermost shells (Hernquist & Quinn 1987). The color of these shells is then expected to be bluer than that of the host core. To consider whether this effect poses a significant problem for our analysis, we refer to the color gradients measured by D’Souza et al. (2014) for ellipticals. We consider here whether the color difference caused by stripping material from the outskirts of the infalling satellite is of similar magnitude to the color difference caused by the luminosity--color relation of ellipticals. Material stripped from the half-light radius of an elliptical satellite would be $\sim 0.05-0.1$ mag bluer in $(g-r)_{\text{SDSS}}$ than at the core of the satellite. Using the same color gradients to compare a host galaxy of $11 < \log(M_*/M_\odot) < 11.4$ and a satellite of $10.2 < \log(M_*/M_\odot) < 10.4$, D’Souza et al. (2014) yield a color difference of $\Delta(g-r)_{\text{SDSS}} \sim 0.19$. The color difference between this hypothetical host and satellite is almost a factor of 4 larger than the color difference between the satellite host and outskirts. Therefore, we conclude that the color gradient of the satellite galaxies cannot mimic the full color difference originating from the mass ratio between the satellite and host galaxy.

5.2. Star Formation in Tidal Features

We now consider the characteristics of streams in our sample, which occur across the full host stellar mass range of our sample. In particular, we consider the evidence for star formation in the streams in our samples.

At $\log(M_*/M_\odot) \lesssim 11$, the majority of infalling satellites are blue (Wang et al. 2014; Sales et al. 2015). Thus, we expect some tidal features that host star formation around such galaxies. As expected, we find no evidence for tidal features that host star formation around massive early-type galaxies (see previous section). Outside of our high-mass, high-concentration sample, however, there are a significant number of streams with colors suggestive of active star formation (see Figure 12). The detection of UV emission in a subset of streams in GALEX imaging also suggests that the streams are capable of
hosting star formation. Such star-forming streams have previously been observed (see, e.g., Adamo et al. 2012; Knierman et al. 2012; Atkinson et al. 2013) and are thought to represent star-forming environments that are significantly different from star formation in the disk of a galaxy. It is thus of interest to further study the star-forming properties of these extended features, though a more detailed analysis of their composition and star-forming history is inaccessible from optical imaging alone.

5.3. Host Galaxy Morphologies

Finally, we consider the connection between host galaxy morphology and tidal feature morphology. In Section 4.2.1, we showed that the dearth of observed shells around low-concentration galaxies is not an effect of our detection methods. Here, we consider possible astrophysical origins of this phenomenon. At fixed stellar mass, ellipticals are far more likely to host observable shells than disk galaxies; we find that out of the 214 shell hosts, only 3 are late-type galaxies.

Both early-type and late-type galaxies should undergo a significant number of minor mergers throughout their assembly history. However, at fixed stellar mass, late-type galaxies generally possess a lower fraction of ex situ stellar mass (i.e., stars that were formed external to the galaxy and accreted after formation), as shown in Rodriguez-Gomez et al. (2016) and D’Souza et al. (2014).

If it is assumed that there is no correlation between the morphology of the host galaxy and the morphology of the tidal features, we should be able to see a significantly higher number of shells around disk galaxies than are currently identified in the sample. We exclude the possibility that this is a manifestation of morphology-dependent completeness effects in Section 4.2, and here we consider astrophysical explanations for the lack of shells around low-concentration galaxies in our sample.

Two possible explanations for this phenomenon are as follows. First, the tidal feature morphology is likely more sensitive to the total mass of the system than the stellar mass alone. Mandelbaum et al. (2006) showed that for more massive galaxies (log(M_s/M_☉) ≥ 11.0) elliptical galaxies tend to have larger halo masses than do disk galaxies at a fixed stellar mass. Because shells also preferentially form in more massive systems (see Figure 9), this picture would lead to a smaller fraction of disk galaxies with shells. The interpretation is complicated, however, by the fact that more massive ellipticals are also more likely than a massive disk to be at the center of a group or cluster; in this case, the derived halo mass would reflect the total group or cluster halo, rather than the halo of the individual galaxy alone. Furthermore, the detectable lifetime of a shell system as a function of environment is not well known, though there is evidence that the tidal feature occurrence fraction is suppressed in clusters (Adams et al. 2012; Sheen et al. 2012).

Additionally, it is probable that elliptical galaxies can host shells generated by more major mergers than can a disk galaxy. We have shown that there is a subset of shells that appear to have been created during a major merger; such events would not be able to form shells around a disk galaxy without disrupting the disk of the host (Hernquist & Spergel 1992).

It is also likely that the most minor mass ratio at which we can detect streams is higher than for shells. Based on the analysis in Section 3.4, we are able to recover streams at lower mean surface brightnesses than we are able to recover shells. Holding the time of satellite infall fixed to control for passive stellar population fading, which also affects surface brightness (see, e.g., Conroy et al. 2009), and using the surface brightness of the feature as a crude proxy for the mass ratio of the event, we would be able to detect stream-forming events at more extreme mass ratios than shell-forming events because of the difference in our completeness in streams and shells (see Figure 4). If the disk galaxies are unable to host a shell-forming major merger (while maintaining their disk), and if streams are more easily detectable in more minor mergers, we would expect a lower number of shells around disk galaxies relative to ellipticals and a lower number of shells relative to streams around disk galaxies, as observed. This interpretation is also supported by the detections of shells in a small sample of disk galaxies observed at surface brightness significantly fainter than what is attainable in the Wide Layer of HSC-SSP (μ_V ≤ 28.5 mag arcsec^-2) by Martínez-Delgado et al. (2010).

Aside from the observed dearth of shells around spirals, we also note an apparent bias for shells around disk galaxies to be oriented such that the axis of symmetry of the shell lies in the plane of the disk (see Figure 8). Though this observation hinges on extremely small numbers (face-on disks cannot be considered in this analysis, as shells oriented perpendicular to the disk would lie on top of the disk), it is of interest to note that the disk galaxies that host shells in Morales et al. (2018), NGC 681 and NGC 4762, are aligned in the same manner as those in our sample.

However, because this sample targeted primarily massive, red galaxies, it would be informative to explore this morphological difference further using a sample that includes more late-type galaxies.

6. Summary and Conclusions

In this work, we have presented observations of 1201 systems that host tidal features in the redshift range 0.05 < z < 0.45 in the HSC-SSP Wide Layer with accompanying spectroscopic observations from SDSS. Of these systems, we find that 214 host shells and 987 host streams. For 78 shell systems and 497 stream systems, we are additionally able to measure the average (g−i) color of the tidal features.

In our sample, streams appear around galaxies with a range of masses, colors, and concentrations. We find evidence for star formation in streams around low-mass host galaxies, but no evidence for star formation around massive ETGs, suggesting that satellites are quickly quenched upon infall into a massive elliptical. Shells appear to form preferentially around massive, red ETGs, with only three examples of shell systems around disk galaxies in our sample.

Although the majority of the shells in our sample appear to be generated from a minor merger, there exist a non-negligible number of shells that appear to have originated from a major merger. These “red shell” galaxies are furthermore predominantly Type I, wherein the shell caustics are roughly symmetric about the major axis of the galaxy; this morphological dependence has been predicted in simulations (Hernquist & Spergel 1992; Pop et al. 2017b).

Based on the performance of the automatic detection method presented in this work, future investigations will focus on fully automating the detection and morphological classification of tidal features such that the technique may be autonomously applied to the full HSC data set and future wide-field imaging.
campaigns (e.g., LSST, Euclid), as well as extending our analysis to existing data sets. Because the majority of tidal features are expected to lie at $\gtrsim$30 mag arcsec$^{-2}$ (Johnston et al. 2008), efforts using future generations of deep wide-field imaging will greatly increase the number of detected tidal features around galaxies and provide a new window into the impact of minor mergers on galaxy growth.

We thank Vasily Belokurov, Rachael Beaton, and Scott Carlsten for insightful discussions regarding this work.

This research was supported in part by NSF AST-1613744, PI Greene. D.H.’s and K.V.J.’s contributions to this paper were supported by NSF grant AST 1614743.

This research made use of Astropy, a community-developed core Python package for Astronomy (The Astropy Collaboration et al. 2018).

The Hyper Suprime-Cam (HSC) Collaboration includes the astronomical communities of Japan and Taiwan, as well as Princeton University. The HSC instrumentation and software were developed by the National Astronomical Observatory of Japan (NAOJ), the Kavli Institute for the Physics and Mathematics of the Universe (Kavli IPMU), the University of Tokyo, the High Energy Accelerator Research Organization (KEK), the Academia Sinica Institute for Astronomy and Astrophysics in Taiwan (ASIAA), and Princeton University. Funding was contributed by the FIRST program from the Japanese Cabinet Of Science, the Japan Society for the Promotion of Science. The SDSS-III website is http://www.sdss3.org/.

SDSS-III is managed by the Astrophysical Research Consortium for the Participating Institutions of the SDSS-III Collaboration, including the University of Arizona, the Brazilian Participation Group, Brookhaven National Laboratory, Carnegie Mellon University, University of Florida, the French Participation Group, the German Participation Group, Harvard University, the Instituto de Astrofísica de Canarias, the Michigan State/Notre Dame/JINA Participation Group, Johns Hopkins University, Lawrence Berkeley National Laboratory, Max Planck Institute for Astrophysics, Max Planck Institute for Extraterrestrial Physics, New Mexico State University, New York University, Ohio State University, Pennsylvania State University, University of Portsmouth, Princeton University, the Spanish Participation Group, University of Tokyo, University of Utah, Vanderbilt University, University of Virginia, and Yale University.

Appendix A
Image Decomposition

To illustrate our method of image decomposition, we consider the case of a galaxy hosting a stream in Figure 13. The top three rows show the $n = 5$ and $n = 31$ components of the decomposition (middle and right columns, respectively) and the input image (left column). As can be seen from the size of the bright objects’ cores, the spatial frequencies that the nth coefficient probes decrease as $n$ grows large. The stream itself has red observed colors, detected clearly in the $i_{HSC}$ and $z_{HSC}$ bands and less so in $r_{HSC}$. We show multiband observations of this stream in order to show the change in algorithm performance as a function of the contrast in surface brightness between the tidal feature and the host galaxy. In practice, to cover the largest amount of area possible while keeping the application of our method consistent, we consider only the $i_{HSC}$ band during detection.

The effect of noise on our decomposition is also visible in the middle column of Figure 13. The $z_{HSC}$-band imaging has significantly more noise than the $i_{HSC}$ image, which corresponds to higher noise in the $c^{(5)}$ image. Because the noise is largely uncorrelated on large scales, however, there is relatively little difference between the $c^{(31)}$ image of the $i_{HSC}$ band and that of its counterpart in the $z_{HSC}$ band.

Finally, we show the effect of cleaning the detection image in the bottom row of Figure 13. The left panel shows the initial detection image, $C$, as obtained from Equation (4). The middle panel shows the detection image after the cleaning steps outlined in Section 3.1 are applied. The right panel shows the output of the detection algorithm on the $i_{HSC}$-band image. As noted in Section 3.1, features in the detection map that overlap significantly with neighboring sources are not included in the final detection.
Figure 13. Example decompositions following the algorithm presented in Section 3.1. Top row, left to right: $r_{\text{HSC}}$-band input image, $c^s$ component, and $c^{31}$ component. Second row: same as the top row, but for $i_{\text{HSC}}$. Third row: same as the top row, but for $z_{\text{HSC}}$. Bottom row, left to right: initial detection image (C) for the $i_{\text{HSC}}$ band, the cleaned detection image (wherein the cores of sources and spiral arms are removed), and the detection map (red) overlaid on the $i_{\text{HSC}}$-band input image.
Appendix B
Surface Brightness Limits

Here, we consider the surface brightness limits that we would have derived following examples in the literature. The nominal surface brightness limits that we calculate from the methods in Atkinson et al. (2013) and Morales et al. (2018) are comparable to the values generated for the Atkinson et al. (2013) and Morales et al. (2018) data sets, who give surface brightness limits of $\mu \sim 27.7$ mag arcsec$^{-2}$ (stacked gri images) and $\mu \sim 28.1$ mag arcsec$^{-2}$ (r SDSS imaging). However, our tidal feature injections indicate that we are highly incomplete at these surface brightnesses (see Figure 4).

Figure 14 shows the result of injecting a simulated stream at the HSC nominal surface brightness limits (not including the bound remnant visible in the top right panel) of 26.375 mag arcsec$^{-2}$, where we measure a completeness of $\approx 75\%$ (bottom left), and 28.4 mag arcsec$^{-2}$ (bottom right). Though 28.4 mag arcsec$^{-2}$ is the nominal surface brightness of the HSC i band when derived in the same way as estimates for other surveys in the literature (Atkinson et al. 2013; Hoo et al. 2018; Morales et al. 2018), a stream at this surface brightness is not detectable through either human or automatic means. We do note that Huang et al. (2018b) measured surface brightness profiles of massive galaxies down to $\mu_i \sim 28.5$ mag arcsec$^{-2}$—this measurement was performed by leveraging the information provided by the shape and location of the galaxy isophotes at smaller radii. In our case, in order to assess the completeness of our automated search, it is necessary to run the full suite of injected simulations as detailed in Section 3.4.

Furthermore, the surface brightness limit of a tidal feature search is an intrinsically difficult quantity to measure, as the detectability of a tidal feature is dependent on both its surface brightness and the area of the feature, which is naturally different for each system. One may consider the limiting case in which there are two tidal features with the same peak surface brightness $\mu_0$. The first tidal feature has only one pixel with a value corresponding to $\mu_0$, while the second has many pixels with values approximately $\mu_0$. Though the two tidal features have the same peak surface brightness, the second instance will be significantly easier to detect. In visual inspection methods, the human hours needed to quantify completeness as a function of these factors are prohibitive. In our automatic detection method, however, simulations can be run easily. Thus, in Section 3.4, we consider both the mean surface brightness and the extendedness of the tidal feature in describing our completeness.
