King Ghidorah Supercluster: Mapping the light and dark matter in a new supercluster at $z = 0.55$ using the Subaru Hyper Suprime-Cam

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ABSTRACT
This paper reports our discovery of the most massive supercluster, termed the King Ghidorah Supercluster (KGSc), at $z = 0.50 - 0.64$ in the Third Public Data Release of the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP PDR3) over 690 deg$^2$, as well as an initial result for a galaxy and dark matter mapping. The primary structure of the KGSc comprises triple broad weak-lensing (WL) peaks over 70 comoving Mpc. Such extensive WL detection at $z > 0.5$ can only currently be achieved using the wide-field high-quality images produced by the HSC-SSP. The structure is also contiguous with multiple large-scale structures across a ~ 400 comoving Mpc scale. The entire field has a notable overdensity ($\delta = 14.7 \pm 4.5$) of red-sequence clusters. Additionally, large-scale underdensities can be found in the foreground along the line of sight. We confirmed the overdensities in stellar mass and dark matter distributions to be tightly coupled and estimated the total mass of the main structure to be $1 \times 10^{16}$ solar masses, according to the mock data analyses based on large-volume cosmological simulations. Further, upcoming wide-field multi-object spectrographs such as the Subaru Prime Focus Spectrograph may aid in providing additional insights into distant superclusters beyond the 100 Mpc scale.

Key words: galaxies: clusters: general – gravitational lensing: weak – cosmology: large-scale structure of Universe

1 INTRODUCTION
Superclusters are known to be the largest coherent structures in the universe. They contain numerous galaxy clusters with sizes greater than ~ 100 $h^{-1}$Mpc, which are deemed to have originated from the initial density perturbations on a large scale (de Vaucouleurs 1953; Gregory & Thompson 1978; Kirshner et al. 1981; Oort 1983). They may provide useful clues regarding the nature of the density fluctuations in the early universe (Zel’dovich 1970; White & Silk 1979; Einasto et al. 2021) and the hierarchical evolution of galaxies and large-scale structures (see, e.g., Einasto et al. 2014; Galametz et al. 2018; Paulino-Afonso et al. 2020 for galaxy properties and also Busha et al. 2003; Nagamine & Loeb 2003; Einasto et al. 2019 for large-scale structures). Hence, investigating the mass distributions of both galaxies and the underlying dark matter in superclusters is crucial to better comprehend the mass assembly history of baryonic matter and dark matter in the universe.

Past spectroscopic campaigns and weak lensing (WL) studies have successfully constrained the masses and dynamical states of superclusters at low redshifts. These studies have resolved complex matter structures in superclusters to be $\sim 10^{15} - 10^{17}$ $M_{\odot}$ and have revealed their close correlations with galaxy number densities (Geller et al. 1999; Reisenegger et al. 2000; Bardelli et al. 2000; Heymans et al. 2008; O’Mill et al. 2015; Higuchi et al. 2020). They have also discovered morphological diversities among superclusters, further suggesting the varying evolutionary histories (Shandarin et al. 2004; Einasto et al. 2011, 2014). Given the recent development of gigapixel-level prime focus cameras for use in large ground-based telescopes (Miyazaki et al. 2018; Ivezic et al. 2019), the next step involves extending such analyses to more distant superclusters. However, to date, the number of distant supercluster discoveries remains limited (Gunn et al. 1986; Lubin et al. 2000; Nakata et al. 2005; Gal et al. 2008; Tanaka et al. 2009; Mei et al. 2012; Galametz et al. 2018; Paulino-Afonso et al. 2018).

In this context, we are currently conducting a systematic supercluster (and void) search at $z > 0.3$ based on the Hyper Suprime-Cam Subaru Strategic Program (HSC-SSP; Aihara et al. 2018), and this paper reports an initial result focusing on the most massive supercluster found at $z = 0.55$ within the samples considered in our previous study (Shimakawa et al. 2021b, §2). This research is particularly motivated by the desire to investigate galaxy and dark matter overdensities and their spatial relations in the supercluster based on WL analysis (§3). Combined with cosmological simulations, we also estimate the total mass of the supercluster (§4).

For this study, we adopt the AB magnitude system (Oke & Gunn 1983) and the Chabrier (2003) initial mass function. In line with relevant previous studies (Takahashi et al. 2017; Shirasaki et al. 2017; Shimakawa et al. 2021b,a), we assume the following values for cosmological parameters, $\Omega_M = 0.279$, $\Omega_k = 0.721$, and $h = 0.7$, in a flat lambda cold dark matter model, which are consistent with those obtained from the WMAP nine-year data (Hinshaw et al. 2013).
2 DATA AND TARGET SELECTION

This study was based on the data from the Third Public Data Release of the HSC-SSP (HSC-SSP PDR3; Aihara et al. 2022). The data were collected over 278 nights and reduced using the hscPipe software (version 8; Bosch et al. 2018). This research focused on the data covering 690 deg$^2$ in the grizY bands at complete depth (e.g., $i > 26$ mag at 5σ limiting magnitudes). We employed a projected density map to obtain magnitude limited samples of galaxies (Shimakawa et al. 2021b), along with the red-sequence cluster catalogue (Oguri et al. 2018); however, we used updated versions for the HSC-SSP PDR3\(^1\). As complete descriptions of these databases are available in their respective papers, this section only presents a summary.

Shimakawa et al. (2021b) obtained the number densities of i-band magnitude limited galaxies ($i < 23$) in the projected space of the following redshift interval $\Delta z = 0.1$ from $z = 0.3$ to $z = 1$ within circular apertures of three different radii (10 arcmin, 30 arcmin, and 10 comoving Mpc (cMpc)), to identify superclusters and voids. The grid size of the density map was 1.5 x 1.5 arcmin\(^2\), which was adopted for computing angular cross-correlations (§3). This study used density measurements based on an aperture size of $r = 10$ cMpc. We derived photometric redshifts and stellar masses of the targets based on the Chizu SED fitting code (Tanaka 2015; Tanaka et al. 2018), where we set a chi-square limit of $\chi^2 < 5$, following suggestions by Tanaka et al. (2018, §7). Although the original density map was prepared for the HSC-SSP PDR2 over 360 deg$^2$, our study employed the updated catalogue for the HSC-SSP PDR3, which extended the survey area to 690 deg$^2$. Consequently, 14.4 million objects were used for the density estimation. Moreover, we adopted the CAMIRA red-sequence cluster catalogue (Oguri et al. 2018) for further validations of the obtained density map. Oguri et al. (2018) estimated the 3D richness ($N_{mem}$) of red-sequence galaxies with $M_\star > 10^{10.2}$ $M_\odot$ within 1$h^{-1}$ proper Mpc using the cluster-finding algorithm, CAMIRA (Oguri 2014). We selected the CAMIRA cluster samples above a richness of $N_{mem} = 15$, approximately corresponding to a cluster virial mass $> 10^{14}$ $h^{-1}$M$_\odot$ (Oguri et al. 2018).

This study focused on the densest region at $z = [0.5 : 0.6]$ in the projected density map. The three reasons behind our choice of this redshift slice for $z = 0.3–1.0$ are as follows. (1) The survey area can adequately capture large-scale structures on the $\sim 100$ cMpc scale. (2) We can reasonably estimate the stellar masses of galaxies (Shimakawa et al. 2021a). (3) The approach is expected to detect WL signals with acceptable signal-to-noise ratios (SNRs), as reported by Shimakawa et al. (2021b). Following this, we searched for the most massive overdensity in the density map by measuring the surface area beyond a density excess of $\sigma = 3$ (Area$_{\sigma > 3}$). Here, we applied a density-based clustering algorithm, DBSCAN (Ester et al. 1996), from a Python-based machine learning library, scikit-learn (version 0.24.2; Pedregosa et al. 2012), to automate the selection process of overdense regions.

Consequently, we identified the largest supercluster at RA=216.2° and Dec=-0.34° with an Area$_{\sigma > 3} = 1321$ cMpc$^2$, referred to as the King Ghidorah Supercluster (KGSc), which is more than three times larger than any other overdense regions at the same redshift. Figure 1 depicts the projected density map around the KGSc in three redshift slices from $z = 0.4$ to $z = 0.7$. Surprisingly, the KGSc appears to be associated with 15 red-sequence clusters and multiple large-scale structures outside it. Two large filamentous structures are present toward the northeast and southeast, and each system involves more than ten red-sequence clusters in the same redshift slice. While additional overdensity peaks can be observed backwards along the line of sight, large-scale underdensities appear to spread in the foreground.

We estimated the number densities of red-sequence clusters in the KGSc and neighbouring overdense structures compared to those in general fields. The upper panel of figure 2 illustrates the redshift distributions of the CAMIRA clusters and the brightest cluster galaxies (BCGs) within figure 1, which suggests that the entire system of the KGSc may spread out to $z \sim 0.64$ (see also figure 1). Following this, we obtained the number densities of red-sequence clusters located in overdense areas above $\sigma = 2$ within figure 1 and compared them with those within 50,000 random points from the entire survey field, except the KGSc region. The obtained number densities demonstrated a notable excess at $z = [0.5 : 0.6]$ in the KGSc and approached $\delta = 14.7 \pm 4.5$ compared to the mean density in random fields (figure 2). We also observed underdensities of the red-sequence clusters ($\delta = -0.75 \pm 0.26$) in the foreground at $z = [0.4 : 0.5]$. We note that this number excess seen in low redshifts would be partially attributed to the Abell 1882 supergroup (RA=213.6° and Dec=−0.4° at $z = 0.14$, Abell et al. 1989).

3 STELLAR MASS AND DARK MATTER MAPS

In this section, we map and compare the stellar mass and dark matter distributions in and around the KGSc. Notably, mapping the mass densities based on two independent measurements may help us validate massive structures and investigate the spatial correlations between the galaxies and dark matter in the supercluster. The latter can be examined by analysing the WL signals and the colloquially named E-modes and B-modes, which are decomposed from the shear field (Kaiser 1992). In particular, the E-mode map is treated as a gravitational overdensity map in WL studies.

The WL analysis follows the analysis conducted by Okabe et al. (2019, 2021), who employed galaxy shape measurements based on the re-Gaussianization method (Hirata & Seljak 2003), which was implemented in the HSC-SSP pipeline. The basis of such shape

\footnote{https://hsc-release.mtk.nao.ac.jp/doc}
Figure 2. (Top) Distributions of photometric redshifts of the CAMIRA red-sequence clusters (shown in red) and the spectroscopic redshifts of the BCGs therein (shown in cyan hatch), as reported by Oguri et al. (2018). (Bottom) Number densities of the CAMIRA clusters in the KGSc \((\sigma > 2 \text{ in figure } 1, \text{ shown as red bars}) \) and 50,000 random fields (grey bars). The black vertical lines indicate Poisson noises in each redshift bin.

measurements is a Gaussian fitting with elliptical isophotes, which considers the profiles of both the point-spread function and the galaxy surface brightness (see Rowe et al. 2015; Mandelbaum et al. 2018 for details). Herein, we reconstructed a dimensional mass map \(\Sigma(\theta) \approx \kappa(\theta) (\Sigma_{\text{crt}})\) using a smoothing scale with a beam size of \(\approx 10 \text{ cMpc}\) following Okabe & Umetsu (2008). This reconstruction was performed with calculation modifications to interpret the dimensional unit of \(\Sigma_{\text{crt}}\) based on its dimensionless counterpart (Okabe et al. 2019, 2021). Here, \(\kappa\) denotes a dimensionless surface mass density, and \(\Sigma(\theta)\) denotes an average critical surface mass density for background galaxies. We assume a mean lens redshift \(z = 0.55\) to suit the KGSc region. The background galaxies are selected based on \(p = \int_{\delta \omega} \frac{1}{\Sigma_{\text{crt}}} (\delta \omega) \frac{d\omega}{p(\omega)} \). The noise maps are computed based on 500 realisations of the random orientations of galaxy ellipticities with fixed positions. The resulting map of the SNR (\(\Sigma_{\text{E,SNR}}\)) is depicted in figure 3. Note that the SNR of the imaginary component of the weak-mass reconstruction is referred to as \(\Sigma_{\text{B,SNR}}\).

Subsequently, we calculated the total stellar mass \(\Sigma_{M_{*}}\) and its variation \(\delta M_{*}\) for massive galaxies with \(M_{*} > 2.5 \times 10^{10} \text{ M}_{\odot}\) in the KGSc based on the outputs obtained from the \(\text{Hi}z\)uki SED fitting (Tanaka et al. 2018, see also §2). We set the mass threshold to the original \(i\)-band magnitude limited samples \((i < 23)\) in consideration of the increasing systematic error at lower masses (Shimakawa et al. 2021a). This decreased the sample size to 0.9 million in the entire field. Here, we emphasise that we used the same Gaussian kernel with a beam size of 10 cMpc for the WL map to ensure a fair comparison between the stellar mass and dark matter distributions.

The obtained WL and total stellar mass maps present triple density peaks associated with the KGSc and also other peaks in the massive filament along the southeast (figure 3). While each of the two WL peaks along the south, among the three peaks associated with the main structure, involves three or four red-sequence clusters, the northeast peak has only one cluster with a richness of \(N_{\text{mem}} = 23\), implying that blue galaxies and clusters may be missing. In the entire filed, the lack of WL signals in the northeast overdensities suggests that this structure is less massive (or less concentrated) than the two others. We note a WL peak at RA=213.6° and Dec=−0.4° is attributed to the Abell 1882 supergroup at \(z = 0.14\). (bottom) Angular cross-correlations between \(\Sigma_{\text{E,SNR}}\) and \(\delta M_{*} > 1\) (light blue squares), \(\Sigma_{\text{E,SNR}}\) and \(\delta M_{*} > 2\) (dark blue triangles), \(\Sigma_{\text{B,SNR}}\) and \(\delta M_{*} > 1\) (light yellow triangles), and \(\Sigma_{\text{B,SNR}}\) and \(\delta M_{*} > 2\) (dark yellow triangles). Refer to the text for a description of the calculation procedure.

4 DISCUSSION AND CONCLUSIONS

In this section, we present an analysis of the total masses of associated haloes using the mock catalogue dedicated to the HSC-SSP based on the ray-tracing cosmological simulation (Takahashi et al. 2017; Shirasaki et al. 2017). Here, we should note that the mock catalogue covers the HSC-SSP PDR2 field over 430 deg\(^2\), as it was originally established for our previous study (Shimakawa et al. 2021b). Nevertheless, we consider that the survey area is sufficient for predicting the
The best-fit line considered by the curve fitting code, (Newville et al. 2021), suggests that the KGSc and the southeast (SE) region have the same redshift space. Consequently, the derived total masses are found to have a total mass of $(1.09 \pm 0.15) \times 10^{16} \, M_\odot$.

This supercluster not only hosts 15 red-sequence clusters but also one of the most massive structures in the universe, accounting for $1 \times 10^{16} \, M_\odot$ of the total mass of the associated dark matter haloes already present at $z = 0.55$. Further, precise measurements of halo masses of the member clusters and cross-correlations between galaxies and dark matter require a wide-field multi-object spectrograph such as the Subaru Prime Focus Spectrograph (Takada et al. 2014). However, understanding the entire picture even with spectroscopic data still remains a challenge to overcome, given the difficulty in resolving the fingers-of-god effect. A novel solution is thus required to scrutinise the mass assembly histories around superclusters.

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DATA AVAILABILITY

The catalogue and data underlying this article are available on the public data release site of Hyper Suprime-Cam Subaru Strategic Program (https://hsc.mtk.nao.ac.jp/ssp/data-release/).
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APPENDIX A: SUPERCLUSTERS IN THE MOCK DATA

This appendix provides a supplementary explanation on the most massive structures in the mock data (figure 4). For further details on the cosmological simulation and the mock catalogue, readers may refer to Takahashi et al. (2017); Shimakawa et al. (2021b).

We determined that the abundance of supercluster candidates with an Area$_{vir}$ > 100 cMpc$^2$ in the mock sample is (4.0 ± 1.0) × 10$^{-2}$ deg$^{-2}$ (figure 4), which is consistent with that in HSC-SGP PDR3 (4.8 ± 0.8) × 10$^{-2}$ deg$^{-2}$. This implies that a field coverage of more than 20–30 deg$^{-2}$ is generally required to locate at least one of these massive structures in this redshift slice based on a blind survey. However, we note that the uncertainty in the number density may be underestimated owing to the lack of independent N-body realisations, as it only provides a sense of typical statistical fluctuations. For more precise error estimates, more N-body simulations may be required in future research. Figure A1 presents a projected 2D density map around the most massive structure at z = 0.5, which is consistent with that in HSC-SGP PDR3 (4.8 ± 0.8) × 10$^{-2}$ deg$^{-2}$. This implies that a field coverage of more than 20–30 deg$^{-2}$ is generally required to locate at least one of these massive structures in this redshift slice based on a blind survey. However, we note that the uncertainty in the number density may be underestimated owing to the lack of independent N-body realisations, as it only provides a sense of typical statistical fluctuations. For more precise error estimates, more N-body simulations may be required in future research. Figure A1 presents a projected 2D density map around the most massive structure at z = 0.5, which is consistent with that in HSC-SGP PDR3 (4.8 ± 0.8) × 10$^{-2}$ deg$^{-2}$.

Figure A1. (Top) Same as figure 1 but for the most massive supercluster in the mock data at z = 0.5, 0.6. The red cross symbols indicate the positions of cluster haloes with M$_{vir}$ ≥ 10$^{14}$ M$_{⊙}$ (Bottom) Projected 2D distribution of massive dark matter haloes with M$_{vir}$ ≥ 10$^{13}$ M$_{⊙}$ (and up to 7 × 10$^{14}$ M$_{⊙}$) in the same redshift slice. The marker sizes and colours are scaled by their halo masses as indicated in the inset colour bar.

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