Sparse Reconstruction of the Merging A520 Cluster System

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Abstract

Merging galaxy clusters present a unique opportunity to study the properties of dark matter in an astrophysical context. These are rare and extreme cosmic events in which the bulk of the baryonic matter becomes displaced from the dark matter halos of the colliding subclusters. Since all mass bends light, weak gravitational lensing is a primary tool to study the total mass distribution in such systems. Combined with X-ray and optical analyses, mass maps of cluster mergers reconstructed from weak-lensing observations have been used to constrain the self-interaction cross-section of dark matter. The dynamically complex Abell 520 (A520) cluster is an exceptional case, even among merging systems: multi-wavelength observations have revealed a surprising high mass-to-light concentration of dark mass, the interpretation of which is difficult under the standard assumption of effectively collisionless dark matter. We revisit A520 using a new sparsity-based mass-mapping algorithm to independently assess the presence of the puzzling dark core. We obtain high-resolution mass reconstructions from two separate galaxy shape catalogs derived from Hubble Space Telescope observations of the system. Our mass maps agree well overall with the results of previous studies, but we find important differences. In particular, although we are able to identify the dark core at a certain level in both data sets, it is at much lower significance than has been reported before using the same data. As we cannot confirm the detection in our analysis, we do not consider A520 as posing a significant challenge to the collisionless dark matter scenario.

Key words: dark matter – galaxies: clusters: individual (Abell 520) – gravitational lensing: weak

1. Introduction

As the largest gravitationally bound objects in the universe, galaxy clusters represent the most recent phase in the hierarchical formation of cosmic structure. Understanding their properties and evolution is crucial to the progress of cosmology. Multi-wavelength studies have revealed that the majority of the mass in clusters resides in cold dark matter (CDM), while the bulk of the baryonic matter is contained in the hot intracluster gas. The galaxies themselves constitute only a few percent of the total mass. The often extreme characteristics of merging cluster systems make them a unique astrophysical laboratory in which to test the paradigm of collisionless dark matter.

The primary signature of a merger between two (or more) clusters is the dissociation of the intracluster gas from the dark matter and the galaxies, the latter two of which remain spatially coincident. This is because the galaxies interact principally via the tidal gravitational fields and thus essentially pass through each other. In contrast, the ionized intracluster plasma clouds experience ram pressure that slows them down during crossing, leaving an overdensity of X-ray-emitting gas between the luminous subclusters along the merger axis. The fact that the dark mass component, inferred by, for example, weak-lensing analysis, remains separate from the bulk of the baryons has been seen as direct proof of the existence of dark matter (Clowe et al. 2004, 2006). Furthermore, the relative positions of the dark matter and galaxy centroids have led to an upper limit on the the self-interaction cross-section of dark matter; see, for example, Markevitch et al. (2004), Randall et al. (2008), Bradač et al. (2008), Kahlhoefer et al. (2014), Harvey et al. (2015), and Robertson et al. (2017).

The Abell 520 system (MS 0451+02, z = 0.2, Abell et al. 1989), first studied using weak lensing by Mahdavi et al. (2007, hereafter M07), exhibits complex structure and offers a possible counterexample to the collisionless dark matter scenario. Like the Bullet Cluster (1E 0657-558) (Markevitch et al. 2002), the galaxies and dark matter in A520 are offset from the intracluster gas distribution, indicating that significant ram-pressure stripping has occurred from merging. It is our fortunate viewing angle with respect to the orientation of the merger axis, which lies essentially in the plane of the sky, that allows us to observe these offsets. A recent X-ray study using deep Chandra4 data has elucidated details of the history of the merger using structure-rich temperature maps (Wang et al. 2016). However, the authors of M07 also detected a dark core, labeled as P3 in the figures below, using data from the Canada–France–Hawaii Telescope5 (CFHT) and Subaru6. The unexpected dark structure was found to coincide spatially with the peak of the X-ray emission but, unlike the other detected mass peaks, the dark core region did not appear to contain any luminous cluster galaxies. The presence of such a high mass-to-light-ratio peak challenges the current understanding of dark matter and, if real, could help to significantly reduce the parameter space of possible dark matter particle candidates.

Okabe & Umetsu (2008) performed a reanalysis of the data of M07 and found a consistent mass peak at the dark core location in their reconstruction. Two further follow-up studies of A520 were carried out in 2012 with weak-lensing analyses presented in Jee et al. (2012, hereafter J12) and Clowe et al. (2012, hereafter C12). J12 confirmed the dark peak detection at higher than 10σ significance using mosaic images in a single passband from the Hubble Space Telescope (HST) Wide Field

4 http://chandra.harvard.edu/
5 http://www.cfht.hawaii.edu/
6 http://subarutelescope.org/
Planetary Camera $^2$ (WFPC2). The higher-resolution data afforded a number density of galaxies more than three times higher than from the CFHT. The reconstructed mass map of J12 agreed overall with that of M07, both in the positions of the most significant mass peaks as well as their aperture mass estimates. Two new peaks were detected in J12, labeled as P5 and P6, the former of which resolved a discrepancy from M07, where the peak was expected but curiously absent from the previous reconstruction. The other new peak emerged due to the higher resolution of the data at a location consistent with some of the bright cluster members.

Contrary to the three previous studies, C12 did not detect a dark core in their data, which consisted of independent ground-based Magellan$^6$ observations combined with mosaic images from the HST Advanced Camera for Surveys$^9$ (ACS). The locations, morphologies, and aperture mass measurements of the primary cluster substructures were mostly consistent with those of J12, although a few significant differences were found. These included larger uncertainties in mass estimates for all peaks, as well as measuring a larger luminosity and a lower column mass at the dark peak location. C12 concluded that the gross mass distribution of A520 is consistent with a constant mass-to-light ratio and that both M07 and J12 overstated the significance of their dark peak detections.

More recently, Jee et al. (2014, hereafter J14) revisited A520 with an updated weak-lensing analysis using ACS data and also provided a detailed comparison with J12 and C12. The study claimed again to find a dark peak region characterized by a very high mass-to-light ratio, although not at the same location as in M07 and J12. The position of the new peak P3$'$ was offset from the former by about 1 arcmin southwest toward the largest mass substructure P4. In contrast to C12, a $\chi^2$ test led the authors to reject the constant mass-to-light ratio hypothesis at a level of at least $\sim$6$\sigma$. Comparing catalogs and mass reconstructions with C12 indicated that the discrepancies were likely caused by differences in the charge transfer inefficiency (CTI) correction methods and the shape measurement pipelines. It is not clear what the origin of a true dark peak in the A520 data would be, although a number of scenarios were suggested in M07, J12, and J14. The most intriguing possibility is that dark matter particles could possess a non-negligible self-interaction cross-section.

Given the disagreement in the literature and the scientific impact that detecting a real dark substructure would have, we perform new mass map reconstructions of A520 using a completely different algorithm from those of the previous studies. The software is called Glimpse2D (Lanusse et al. 2016), and it approaches the mass-mapping problem as an ill-posed inverse problem, regularized by a multi-scale wavelet prior on the reconstructed surface mass density map. The algorithm is able to retain all available small-scale information by avoiding the need to bin the irregularly sampled shear field. It has also been shown to perform beautifully on ACS-like weak-lensing simulations, reproducing the input maps at high resolution and fidelity. The goal of this work is therefore twofold: to test Glimpse2D on real data, and to determine whether we detect a significant dark peak in accordance with J14.

The remainder of the paper is organized as follows. In Section 2 we describe the two galaxy catalogs we use in our weak-lensing analysis, which correspond to those of C12 and J14. We review some basics of weak-lensing theory and describe our sparsity-based approach to mass mapping in Section 3. In Section 4 we present our mass map reconstructions of A520, along with uncertainty and significance analyses. We summarize and conclude in Section 5.

2. Data

We obtained both weak-lensing catalogs used in C12 and J14 (D. Clowes 2016, private communication; J. Jee 2015, private communication) to carry out our sparsity-based surface mass reconstructions of A520. We give brief descriptions of these data sets here and refer to their respective papers for more complete details. As an illustration of the data field and its primary features, we show mass map contours derived from Glimpse2D using typical parameters overlaid on the science image of J14 in Figure 1 (compare Figure 5 of their paper). Contours on the left and right plots were obtained using the C12 and J14 data, respectively. Details of the algorithm and analysis results are presented fully in the following sections.

2.1. C12: Magellan + HST/ACS

The catalog used for the weak-lensing analysis in C12 was derived from a combination of images from the Magellan telescope along with an HST/ACS mosaic of four pointings (P: D. Clowes). Magellan imaged A520 in Bessell B, V, and R passbands with a field of view of 15.4 arcmin. These images were cleaned of defects, corrected for smearing by the point-spread function, and co-added to produce a final image. The ACS data cover a smaller area near the center of the Magellan field and consist of four partially overlapping fields, each imaged in the filters F435W, F606W, and F814W. An important step in reducing these data was correcting for the effect of CTI caused by the degradation of the CCD detectors due to prolonged radiation exposure of the instrument outside Earth’s atmosphere. CTI induces spurious distortions in the shapes of galaxies in a way that can substantially contaminate the weak-lensing signal. C12 obtained consistent results from two independent CTI correction procedures and concluded that CTI did not significantly impact their final weak-lensing analysis.

Shape measurements were made separately on galaxies in the Magellan and ACS images and then combined for a total of 5903 objects in the final lensing catalog. To be compatible with the ACS galaxies, the Magellan set of observed ellipticities was scaled by a small factor to account for the difference in the redshift distributions between the two populations. A map of the source galaxy density is shown the left plot of Figure 2. The outer circle marks the boundary of the Magellan field, and its inner polygonal area indicates the ACS footprint. The central ACS region, which contains the majority of the cluster mass, shows a higher source density than its surroundings, as expected from space-based observations.

2.2. J14: CFHT + HST/ACS

The J14 catalog was derived from the same raw ACS images that were used in C12 combined with the ground-based CFHT catalog that was used in J12. Different reduction procedures of the ACS images led to a different set of galaxies in the final catalog. Notably, the J14 catalog contains approximately twice
the number of galaxies as that of C12, the difference arising partly due to the inclusion of more faint galaxies by J14. One reason for this could stem from the different drizzling kernels used to create the mosaics. J14 used an approximate sinc interpolation kernel, whereas C12 used a square kernel that may not perform as well in measuring the shapes of small galaxies. Perhaps more importantly, the CTI correction method used by J14 was updated with improved performance in the low-flux regime (Ubeda & Anderson 2012) compared to what was available to C12. A comparison between the catalogs of C12 and J14 revealed no significant difference between the the (independently) calibrated ellipticity components for their common galaxies (Jee et al. 2014).

J14 used the F814W image for their primary weak-lensing analysis, although the other filters were used for identifying and removing foreground/cluster galaxies. It is worth noting that J14 claim that, although both studies supplement their ACS data with (different) ground-based observations, the difference between their mass reconstructions comes from the treatment of the ACS data.

The J14 source galaxy density is shown in the right panel of Figure 2 using the same color scale as the left panel to indicate pixel number counts. The map is visually consistent with the ACS region of C12, but the higher number density of the J14 catalog of 4953 galaxies is clearly seen. We note that the pixelization in Figure 2 has been chosen simply for visualization purposes; we use a much higher resolution in our mass reconstructions.

3. Method

Different mass-mapping techniques were used in the C12 and J14 analyses. C12 used an improved version of Kaiser–Squires inversion (Kaiser & Squires 1993) that accounts for the reduced shear (Seitz & Schneider 1995). On the other hand, J14 used an implementation (Jee et al. 2007) of the entropy-regularized maximum likelihood method introduced by Seitz et al. (1998). Our mass reconstruction technique is completely independent of these two methods. We present a summary of Glimpse2D in this section after briefly recalling some basics of weak-lensing theory.

3.1. Weak-lensing and Mass Maps

Galaxy shape distortions caused by gravitational lensing can be characterized by a transformation between the lensed image coordinates $\theta$ and the source coordinates $\beta$. In the linear regime, the mapping between $\theta$ and $\beta$ is given by the amplification matrix $A = \partial \beta / \partial \theta$, which is parameterized by a scalar part $\kappa(\theta)$ and a complex (spin-two) field $\gamma(\theta)$ as

$$A = \begin{pmatrix}
1 - \kappa & -\gamma_1 \\
-\gamma_2 & 1 - \kappa + \gamma_1
\end{pmatrix}$$

(1)

The function $\kappa$ is called *convergence* and quantifies an isotropic change in the size of the source image, while the shear $\gamma$ describes anisotropic stretching. In the context of lensing by large-scale structures, both $\kappa$ and $\gamma$ are much smaller than 1. The convergence can also be interpreted directly as the projected mass density of the matter field between the observer and the source. As such, it is often convenient to express $\kappa$ as

$$\kappa = \frac{\Sigma}{\Sigma_{\text{crit}}},$$

(2)

where $\Sigma(\theta)$ is the surface mass density of the lens, and $\Sigma_{\text{crit}}$ is the critical surface mass density given by

$$\Sigma_{\text{crit}} = \frac{c^2}{4\pi G} \frac{D_S}{D_L D_{LS}}.$$  

(3)

In the above equation, $D_S$, $D_L$, and $D_{LS}$ are the angular diameter distances from observer to source, observer to lens, and from lens to source, respectively.

The convergence and shear are both expressible as derivatives of a scalar lensing potential $\psi$. This leads to an integral relation between $\kappa$ and $\gamma$ (Kaiser & Squires 1993),

$$\kappa(\theta) - \kappa_0 = \frac{1}{\pi} \int d^2\theta' D^k(\theta - \theta') \gamma(\theta'),$$

(4)
where $\kappa_0$ is a constant of integration corresponding to the mass-sheet degeneracy, and the kernel $D$ is given by

$$D(\theta) = -\frac{\theta_1^2 - \theta_2^2 + 2i\theta_1\theta_2}{|\theta|^4}. \quad (5)$$

The reconstruction of a convergence map is hindered in practice by several considerations. First, the shear field is not directly observable; lensing surveys measure instead the reduced shear $g = \gamma/(1 - \kappa)$. Second, Equation (4) assumes knowledge of the shear field over an infinite domain; in practice the reduced shear is only sampled at discrete points over a limited survey area. Finally, in most situations, the shear signal is dominated by shape noise; some sort of filtering is therefore required to recover a meaningful map. In this work, we reconstruct the convergence map using the Glimpse2D algorithm (Lanusse et al. 2016) which aims at addressing all three issues simultaneously.

3.2. Glimpse2D: Sparsity-based Mass Mapping

For the reasons stated in the previous section, mass-mapping is in practice a non-trivial inverse problem. Glimpse2D aims at solving this inverse problem using sparse recovery, a powerful framework for solving ill-posed inverse problems with many successful applications in image processing, medical imaging, radio-interferometry, and astrophysics. This approach relies on the so-called sparse prior, the idea that, when expressed in an appropriate basis or dictionary, most signals are sparse (i.e., have only a few non-zero coefficients) or at least compressible (i.e., can be represented to a very good approximation by a sparse signal). More formally, a signal $x$ is said to be sparse in a dictionary $\Phi$ if only a small number of its coefficients $\alpha = \Phi^*x$ are non-zero. Consider a generic linear inverse problem of the form:

$$y = Ax + n, \quad (6)$$

where $y$ are the measurements, $A$ is a linear operator, $x$ is the signal we want to recover, and $n$ is an additive noise term. Under the assumption that the signal to recover $x$ is sparse in dictionary $\Phi$, the solution can be robustly estimated by solving an optimization problem of the form:

$$x = \arg\min_x \frac{1}{2}||y - Ax||^2 + \lambda||\Phi^*x||_1, \quad (7)$$

where $\lambda$ is a regularization parameter. The objective function in Equation (7) seeks a solution that balances data fidelity via the first (quadratic) term against the sparsity of the analysis coefficients $\alpha = \Phi^*x$ via the sparsity inducing $\ell_1$ norm of the second term. Glimpse2D adopts this framework to treat the full mass-mapping problem, from noisy and discretely sampled noisy reduced shear measurements to a non-parametric mass-map. In this situation, the inverse problem that we aim to solve takes the following form:

$$g = \frac{ZTPF^*\kappa}{1 - ZTF^*\kappa} + n, \quad (8)$$

where $F$ is the discrete Fourier operator, $P$ is the Fourier-based lensing operator, yielding $\gamma$ from $\kappa$, $T$ is the non-equispaced discrete Fourier transform operator evaluating the Fourier transform at the positions of the galaxies in the catalog, and $Z$ is a cosmological weight function depending on the redshifts of the lens and background sources. Here $\kappa$ is understood to be the convergence for sources at infinite redshift and $Z$ rescales the convergence based on the redshift of each individual galaxy in the survey. We refer to Lanusse et al. (2016) for more details on the definition of these operators. Equation (8) relates the convergence map $\kappa$ to the reduced shear $g$ measured at each galaxy position, Glimpse2D aims at recovering $\kappa$ by solving...
the following optimization problem:

\[
\arg \min_{\kappa} \frac{1}{2} \| C^{-1} \kappa (1 - ZTF^* \kappa) g - ZTPF^* \kappa \|_2^2 + \lambda \| w \circ \Phi^* \kappa \|_1 + i_{\ell_1=0}(\kappa). \tag{9}
\]

where the matrix 

\( C^{-1} = \Sigma^{-1}/(1 - ZTF^* \kappa) \)

accounts for a diagonal covariance matrix of the lensing measurements \( \Sigma \), \( \lambda \) is our regularization parameter, \( w \) is a sparsity scaling factor based on the level of noise in the data, and \( i_{\ell_1=0}(\cdot) \) is an indicator function ensuring that the reconstructed convergence map has no imaginary part, i.e., enforcing a zero B-mode constraint. Again, we refer the reader to Lanusse et al. (2016) for the details of the algorithm solving this problem; see in particular Section 4 of that paper.

One of the keys to sparse regularization is the choice of the dictionary and proper tuning of the sparsity constraint. Glimpse2D adopts a wavelet-based dictionary for \( \Phi \), combining a multi-scale starlet dictionary (Starck et al. 2007) along with a Battle–Lemarié wavelet to help constrain the smallest scales. We find this combination of dictionaries very well suited to the convergence signal at the cluster scale, and this prior can lead to near-perfect reconstruction in the absence of noise. To tune the sparsity constraint based on the level of noise on different scales and at different locations in the field, Glimpse2D adopts a weighted \( \ell_1 \) norm, through the weight factor \( w \) in Equation (9). This factor is computed empirically by propagating randomized galaxy ellipticities through to wavelet coefficients and estimating the resulting scale- and position-dependent noise standard deviation. Using this scheme, the sparsity constraint in Glimpse2D is tuned by a single parameter \( \lambda \).

The regularization parameter \( \lambda \) controls the trade-off between fitting the observed data and enforcing sparse solutions. A large value will provide a solution containing features that can be considered as real with a very high probability, but faint features may be lost. A small value preserves the smallest features, but some of them may be due to the noise. There are empirical motivations, however, which guide our choices in this work and that we describe further in Section 4. See also the Appendix, where we present numerical experiments testing the Glimpse2D algorithm on the simple case of a known halo mass profile in the context of A520-like noise. We find that a typical value of \( \lambda \) to obtain a good mass reconstruction is \( \sim 3 \) for noisy data.

Compared to other approaches, Glimpse2D is better able to preserve small-scale information by avoiding the need to bin the shear measurements before solving for convergence. Another benefit is that the algorithm is able to incorporate flexion measurements of the individual galaxies into the reconstruction when available, which significantly improves the recoverability of small-scale features. As there are no flexion measurements for A520, we do not use this feature in the present work. However, even without flexion, Glimpse2D is still an extremely powerful reconstruction technique due to its sparsity-based regularization scheme. A good illustration of this is Figure 6 in Lanusse et al. (2016), where sparse regularization yields a near-perfect reconstruction on a noiseless inversion problem, despite 93% missing pixels in the input shear field.

\( \text{10} \) The Glimpse2D software is publicly available at \( \text{http://www.cosmostat.org/software/glimpse.} \)

4. Results

In this section we present the Glimpse2D mass reconstructions of A520 from the weak-lensing catalogs of C12 and J14. To make meaningful comparisons between our results and the previously published maps, we perform the reconstructions for each data set assuming the cosmology used in its respective paper. Both papers assumed a flat \( \Lambda \)CDM cosmological model with a present-day Hubble constant of \( H_0 = 70 \text{ km s}^{-1} \text{ Mpc}^{-1} \). As for the matter density, C12 used \( \Omega_m = 0.27 \), while J14 used \( \Omega_m = 0.3 \). This difference is unimportant for our purposes, as it only slightly scales the amplitude of the lensing signal between the two analyses.

For all of the results that follow, we run Glimpse2D using the same configuration parameters. The resolution of the reconstructed mass maps can be as high as we wish, since we are not limited by a prior binning of the data. The cost of smaller pixels, however, is increased computation time. We set the pixel size to 0.033 arcmin as a balance between resolution and speed.

We choose to use eight wavelet scales, since this is the maximum number allowed by the size of our output images. In the multi-scale regularization step of the algorithm, the wavelet function is dilated by a factor of 2 at each new resolution level. For our 256 \( \times \) 256 pixel maps, this corresponds to a maximum of \( \log_2 256 = 8 \) possible scales. The noise of the coarsest resolution scale can affect the solution in principle, since it does not have zero mean and is therefore not thresholded like the smaller scales. On large enough scales, however, the noise is typically negligible, so we should achieve the best solution by using the largest number of wavelet scales permitted by the image size. Using a smaller number could negatively impact the results by allowing the potentially higher noise level on smaller scales to enter the reconstructions.

As Glimpse2D is an iterative solver, we must also specify the number of iterations. We set this to 500, since we have verified that the algorithm converges by this point for the range of \( \lambda \) values of interest for both data sets. Following Lanusse et al. (2016), we use five re-weightings (see Section 3.2) in order to help correct for the possible bias induced by the \( \ell_1 \) sparsity constraint. Finally, the code is run with a positivity constraint on the reconstructed \( \kappa \) in order to focus only on the overdense peaks. While this effectively adds a mass sheet to the reconstructions, since we do not compute (aperture) masses of the substructures, the results we present are not affected by this choice.

4.1. C12: Magellan + HST/ACS

Figure 3 shows three reconstructions of the C12 data corresponding to regularization parameters \( \lambda = 2.0, 3.0, \) and \( 4.0 \). Recall that a higher \( \lambda \) value promotes a sparser solution and thus more effectively suppresses the noise and lower significance features. From left to right, the maps visually exhibit the expected trend in terms of the number and amplitudes of mass peaks. We label the locations of structures identified in C12 and J14 by the same numbering scheme used in those studies. It is clear that structures P1, P2, and P4 are the most prominent, as they appear in all three reconstructions, while the other peaks that show up at \( \lambda = 2.0 \) have disappeared at \( \lambda = 3.0 \) and above. P4 has the highest amplitude, followed by P2, which is consistent with the column mass estimates given in C12 (see their Tables 1 and 2).
Figure 3. Surface mass reconstructions from C12 data for regularization parameters $\lambda = 2.0, 3.0, \text{and} 4.0$. Labels P1–P6 indicate the approximate locations of the relevant structures reported in C12 and J14. From left to right, one can see that noise and low-amplitude features are better suppressed with increasing $\lambda$. The presence of a dark core at P3$'$ claimed by J14 is visible in the $\lambda = 2.0$ map, but not in the $\lambda = 3.0, 4.0$ maps.

Of particular interest are the locations P3 and P3$'$, the previous and updated detection positions, respectively, of the dark peak. In agreement with C12, the P3 region shows no indication of the dark core reported by M07 and J12. On the other hand, there is indeed a visible peak near P3$'$ in the $\lambda = 2.0$ map. It has a smaller size and lower amplitude compared to the other structures, apart from P6. It is also not immediately clear that this constitutes a true mass concentration rather than simply a noise fluctuation. A similarly sized peak appears just south of P3$'$ in the direction of P6, as do two others in the outskirts of the cluster. Among these, however, only P3$'$ is still visible up to $\lambda = 2.3$. The others disappear between $\lambda = 2.1$ and 2.2, suggesting that they are likely spurious noise peaks, whereas P3$'$ is a potentially real, albeit low-amplitude feature. We return to the issue of quantifying the significance of the P3$'$ detection in Section 4.4.

Another interesting aspect of the reconstructions is in the morphologies of P2 and P4. Each region shows multiple connected peaks at $\lambda = 2.0$ that essentially converge into a single peak by $\lambda = 4.0$. Some indication of substructure is still apparent at P4 for $\lambda = 4.0$, however. The fact that the P2 centroid remains stable as a single peak between $\lambda = 3.0$ and $\lambda = 2.0$ is caused by noise, even though it appears at higher relative amplitude in that map. On the other hand, the presence of the pair of peaks at P4 even in the higher-$\lambda$ maps could reflect the ability of Glimpse2D to recover small-scale information afforded by the high resolution of the reconstructions.

4.2. J14: CFHT + HST/ACS

In Figure 4 we show three reconstructions of the J14 data for the same $\lambda$ values as in Figure 3, with the relevant substructures again labeled P1–P6. The maps agree well overall with the entropy-regularized maximum likelihood reconstruction presented in J14 (see their Figure 5). For $\lambda = 2.0$ it is easiest to see the correspondence between the shapes and relative positions of the Glimpse2D substructures and those of J14. In terms of size and amplitude, the most prominent features in both are P2 and P4, followed by P1 and P3$'$.

Table 1

| Substructure | C12 $\lambda_{\text{max}}$ | J14 $\lambda_{\text{max}}$ |
|--------------|---------------------------|---------------------------|
| P1           | 4.5                       | 3.0                       |
| P2           | $>5.0$                    | $>5.0$                    |
| P3           | ND                        | 2.5                       |
| P3$'$        | 2.3                       | 3.6                       |
| P4           | $>5.0$                    | $>5.0$                    |
| P5           | 2.3                       | ND                        |
| P6           | 2.0                       | 3.0                       |

Note. ND stands for no detection.

Table 2

| Substructure | R.A. (h:m:s) | Decl. ($^\circ$:"\") | $\Delta$R.A. ($^\circ$) | $\Delta$Decl. ($^\circ$) |
|--------------|--------------|-----------------------|-------------------------|-------------------------|
| P1           | 04:54:19.94  | +02:57:42.66          | +5.16                   | −6.43                   |
| P2           | 04:54:14.71  | +02:57:10.19          | −1.92                   | +3.94                   |
| P3$'$        | 04:54:07.58  | +02:54:46.87          | ...                     | ...                     |
| P4           | 04:54:04.08  | +02:53:44.48          | −7.35                   | −14.1                   |
| P5           | 04:54:16.90  | +02:55:34.75          | −3.21                   | +4.66                   |

Note. Differences $\Delta$ are computed by subtracting the published C12 values from the local maxima of our mean bootstrap map. C12 did not study the P3$'$ location, so we give only our determined centroid position.

P5 is curiously missing from all of our reconstructions, whereas J14 found it to have a projected mass larger than that of P1. Given differences in the sharpness of the two peaks, seen both in our $\lambda = 2.0$ map of Figure 3 as well as the mass map of J14, we have explored the possibility that our choice of the number of wavelet scales might be influencing the result. We have verified that decreasing the number of scales from eight to five, where now the size of the broadest wavelet function corresponds to an angular scale of $\sim$1 arcmin, does not produce a peak at P5. If indeed there is a significant mass peak in the data at this location, our algorithm appears to be insensitive to it. This would indeed be surprising, however, as we have not seen such behavior in tests on simulations.
With the J14 data, the dark core at P3' appears as a distinct peak comparable in size to P1. It is still detectable at $\lambda = 3.0$, unlike for the C12 data, where instead P1 remains as the third prominent substructure at that level. Some possible fragmentation of P2 and P4 is noticeable at $\lambda = 2.0$ in the J14 data, although it is less apparent than in C12. Finally, there does appear to be a peak at the location of P3 at $\lambda = 2.0$, but it is not distinguishable from the many other low-amplitude noise peaks scattered across the field at that level, which all vanish for $\lambda \approx 2.5$ and above. We therefore confirm the conclusion of C12 and J14 that there is no significant dark mass concentration at the P3 location.

We summarize the detectability of the various labeled peaks in Table 1 for the two data sets. Reconstructions were made for $\lambda \in [2.0, 5.0]$ in increments of $\Delta \lambda = 0.1$. Substructures not detected within this range are marked as ND.

4.3. Peak Position Uncertainties

To study the uncertainties of our mass reconstructions, we perform a bootstrap analysis by generating $N = 1000$ re-sampled (with replacement) catalogs from both data sets and running Glimpse2D on each to obtain $N$ mass maps. We can study the positional uncertainties of the primary substructures for a given $\lambda$ by examining the distributions of their detected locations in a large number of bootstrapped reconstructions.

We compute these uncertainties by considering a circle of radius 150 kpc centered on each structure and taking the closest peak to the centroid in each bootstrap detected within the interior. This circular search area coincides with the aperture size used in both C12 and J14 and also corresponds approximately to the typical positional variability of a P4-like structure in the noise simulations studied in the Appendix. We then determine three contour levels surrounding each mass peak that enclose 68%, 95%, and 99.7% of the detections from the $N$ resampled maps. For both data sets, we have verified that the contours do not change whether we take the reference centroid positions (centers of the circles) to be the peaks from the original catalog reconstruction or as the local maxima of the bootstrap mean.

To fix the $\lambda$ value for each data set, we seek a level high enough that the frequency of false detections due to noise does not strongly impact the resulting uncertainty contours. This will occur if many noise peaks appearing within the centroid search areas are mistaken for the true centroid. We also want to be able to detect the primary substructures of interest in each bootstrap map, meaning $\lambda$ should not be so high as to suppress reconstruction of the lower-amplitude centroids. We therefore set $\lambda$ to be the highest value in which P1, P2, P3', and P4 are all detectable based on the original data reconstructions (see Table 1). This is $\lambda = 2.3$ for the C12 data and $\lambda = 3.0$ for the J14 data.

We show results from the C12 bootstraps in Figure 5. In panel (a) we plot the centroid uncertainty contours for substructures P1, P2, P3', P4, and P5, which are overlaid on the original catalog reconstruction for reference. The tighter contours of the P1 and P2 substructures indicate that their positions are the most stable, whereas P3' and P4 show more variability. This is not too surprising considering the relative strengths of these peaks as seen in the $\lambda = 2.0$ map of Figure 3. The uncertainty areas we derive are comparable to, but slightly smaller than, those obtained by C12 in a similar bootstrap analysis (see their Figure 4). The most notable aspect of the contours is that the positional variations of P3' and P4 are large enough that their $3\sigma$ regions almost overlap. Although the 1 and $2\sigma$ regions remain clearly distinct between the centroids, their outer contours are approaching the 150 kpc limit and thus approaching each other. We contrast this to the J14 results in Figure 6.

Shown in panel (b) of Figure 5 is the mean of the bootstrap reconstructions. Comparing to the original reconstruction in (a) and to those of Figure 3, the bootstrap mean exhibits significantly more structure overall due to shifting of the primary centroid positions as well as the appearance of noise peaks. The variability of the centroid locations is reflected in the contours in panel (a) and depends on the strength of the lensing signal. The standard error on the mean (pixel-wise) is shown in panel (c). The variability is around 10% the amplitude of the mean, and a clear correlation with panel (b) can be seen. We attribute the numerous additional noise features appearing in (b) primarily to the low value of regularization parameter used.
the features seen in λ. The largest discrepancy, which occurs for P4, is an angular separation smaller than 16″.

Finally, we compare our measured centroid positions (marked by filled circles) with those reported in C12 (marked by × symbols) in panel (c) as well. There is no × at P3′, since the updated dark core position was not available to C12 when they performed their analysis. Our centroid locations are in excellent agreement with those of C12. Right ascension (R.A.) and declination (decl.) values for each are given in Table 2, along with the differences between our coordinates and theirs. The largest discrepancy, which occurs for P4, is an angular separation smaller than 16″.

For the J14 data, we carry out an analogous bootstrap analysis to the one we did for C12 described above. Results are presented in Figure 6. Panel (a) shows the uncertainty contours computed from the N = 1000 bootstraps overlaid on the original λ = 3.0 reconstruction. In this case we focus only on P1–P4, since we do not detect P5 as a prominent feature. The contours are well localized on their respective centroids and have overall smaller sizes than those in Figure 5. In contrast to our results with C12 data, however, the P3′ is clearly seen as a substructure distinct from P4. This agrees with expectations based on the reconstructions in Figure 4.

In panel (b), we see again that the bootstrap mean exhibits more features than its counterpart in (a), although it is not as noisy compared to panel (b) of Figure 5. The primary reason for this is the higher λ value used. Another contributing factor is also likely the higher source number density of the J14 catalog. It is interesting to notice the multiple peaks visible within the P4 region. These coincide with the hints of additional low-amplitude peaks seen in the λ = 2.0 map of Figure 4 but not for λ = 3.0.

As was the case in Figure 5, the overall error structure shown in panel (c) correlates well with the bootstrap mean. We mark the centroid positions from our bootstraps as filled circles and compare to the reported locations in J14, which are marked by an ×. Our centroids are again in good agreement with the published locations, in particular P1, P2, and P3′, which are all within an angular separation of 14″. The largest discrepancy is now P4 with a separation of ∼26″, similar to that of P4 in the C12 analysis. Centroid coordinates and differences with the J14 values are given in Table 3.

An important difference between our analysis and that of J14 is that we do not use the bootstraps to determine the significance of the detected structures. This can usually be done, for example, by considering the number of times a particular peak is detected above a given threshold out of the N re-sampled maps. One problem with this approach for Glimpse2D lies in setting the detection threshold in a meaningful way. Using a global kσ, k = 1,2,3... level, where σ is the standard deviation of the bootstrap map, does not work, since the interpretation of this σ is not clear. Furthermore, our maps are generated for a chosen value of λ, which essentially imposes a prior threshold on the result, below which structures are not reconstructed and which varies depending on the properties of the particular realization. Instead, we have set the threshold for detection low enough that a peak within the circle of radius 150 kpc is found in all of the bootstrap maps. We address the question of significance in the following section.

4.4. Significance of the Dark Core

The results of the previous sections indicate that there is indeed a peak visible at P3′ in the HST/ACS A520 data, at least for some levels of the regularization parameter. We now address the question of quantifying the significance of this detection.

As discussed above, the regularization parameter functions as a detection threshold in such a way that, at a given λ, only features above a particular amplitude relative to the local noise level are reconstructed. The higher the λ value, the more effectively the algorithm removes low significance features. We can therefore think of λ as providing a natural significance scale in the following sense. We interpret features appearing in a λ = λ1 map but not in a λ = λ2 map, where λ1 < λ2, as being less significant than features appearing in both maps. We can say, then, that P2 and P4 are the most significant cluster substructures in both data sets we have studied, in agreement with the C12 and J14 analyses. Furthermore, the peak at P1 appears at higher significance in the C12 data than in the J14 data, whereas the reverse is true for P3′.

To make this intuition more quantitative, we aim to associate the presence of a peak in a particular λ map to a kσ detection level based on noise simulations of the data. We first generate

Figure 5. Bootstrap analysis of C12 data with λ = 2.3. (a) Position uncertainties are computed from N = 1000 bootstrap reconstructions and are indicated by contour lines surrounding each centroid. Outward from the centers, the contours enclose 68%, 95%, and 99.7% of the centroid detections. The background image is the λ = 2.3 Glimpse2D reconstruction of the original catalog for reference. (b) Mean map of the bootstrap reconstructions. Many more features are present here than in (a), both due to noise peaks as well as shifting of the primary centroid positions. (c) Pixel-wise standard error on the bootstrap mean. The highest error regions track the features seen in (b), although the overall amplitude is low. Locations of the major substructures determined as maxima of the mean bootstrap map are marked as filled circles. Centroids reported in C12 are shown with an × for comparison.
Note. Differences from the local maxima of our mean bootstrap map.

N Monte Carlo simulations of the original data sets in which both the positions and orientations of the galaxies are randomized. Each resulting noise simulation occupies the same footprint on the sky as the catalog it derives from (see Figure 2) and contains the same number of galaxies. For the C12 data, the Magellan and ACS galaxies are initially treated separately and then combined into a single catalog in order to respect the original galaxy number density.

We run Glimpse2D on $N = 1000$ such noise simulations and consider the number and amplitudes of peaks detected in each reconstructed map. As an example visualization, we show in the upper panel of Figure 7 the mean of the noise maps for J14 data with $\lambda = 3.0$. The polygonal pattern filling the central region reflects the shape of the ACS field. The fact that this region has higher amplitude with respect to its surroundings indicates that the majority of the noise peaks reconstructed in each simulation fall within the boundary of the source galaxy field. Compared with the data reconstruction (lower panel), the overall noise level is about two orders of magnitude lower than the amplitudes of the P2 and P4 mass peaks. Since we have randomized galaxy positions as well as their orientations, spatial fluctuations seen in the mean noise map are merely statistical.

The mass reconstruction of the original catalog is shown in the lower panel of Figure 7, again for $\lambda = 3.0$. The highest peaks detected in the map are marked with numbers indicating rank ordering by amplitude, where 1 is the highest. After numbers 1 and 2, which correspond to substructures P4 and P2 (see Figure 4), the remaining peaks are difficult to discern by eye given their low relative amplitudes. The third highest peak, corresponding to the dark core location at P3', is about 24% the amplitude of the highest.

An interesting feature of the P3' region is that two peaks in fact appear at comparable amplitude, numbers 3 and 5. This is apparent as well in the position uncertainties in Figure 6, where the contours centered on the third peak extend to enclose the fifth highest peak toward the southeast. The two peaks remain at similar relative amplitudes up to $\lambda = 3.5$, near the level where they vanish from the reconstructions. This could be a hint that the peaks are in fact connected, i.e., that the region actually contains an elongated mass structure. If this is the case, it is possible that a different wavelet dictionary from the isotropic starlet we have used in Glimpse2D might be better at revealing its morphology. Finally, we note that, unlike P2 and P4, whose rank ordering remains the same for all $\lambda$ values we have considered, the secondary peak associated with P3' (number 5) switches places with P1 (number 4) in the ordering for $\lambda = 3.5$, meaning that its detectability actually increases slightly relative to the primary P3' peak with increasing $\lambda$.

For this $\lambda$, we can assign a significance level to the peaks by determining the probability $p$ of a pure noise peak to occur at or above the true peak amplitude in the data reconstruction. We can then convert $p$ into a $k \sigma$ value by finding the $k$ satisfying $1 - p = \text{erf}(k/\sqrt{2})$, as the right-hand side represents the fraction of a Gaussian distribution lying within $k \sigma$ of the mean. We focus on the primary subclusters P2 and P4, since they constitute the strongest isolated detections in the field that also remain consistent across the various $\lambda$ values. Considering first the highest peak P4, the number of noise maps in which a peak appears at or above the P4 height is 37, corresponding to a significance of 2.1$\sigma$. For P2, we find 50 such false detections, corresponding to 2.0$\sigma$. Given the low amplitudes and inconsistent ordering of the remaining peaks, the interpretation of their associated false detection rates is not as straightforward. We can conclude, however, that their significance must be less than that of P2, or 2.0$\sigma$.

We can update the detection significance values by repeating the analysis for larger $\lambda$. For structures with amplitudes that are still high enough to be detected (i.e., P2 and P4) the values represent a new lower bound on their significance. For example, with $\lambda = 3.5$, P4 and P2 appear now at 3.0$\sigma$ and 2.5$\sigma$, respectively. At $\lambda = 5.0$, no noise peaks appear above either the P4 or P2 amplitudes out of 1000 realizations, implying that their detection significances are at least 3.3$\sigma$. We expect this trend to continue at still larger $\lambda$ values, but the computation would require more than the number of noise realizations we have at hand.

### Table 3

| Substructure | R.A. (h:m:s) | Decl. (°′″) | $\Delta$R.A. (°) | $\Delta$Decl. (°) |
|--------------|-------------|-------------|-----------------|------------------|
| P1           | 04:54:19.82 | +02:57:41.54 | -14.1           | +3.14            |
| P2           | 04:54:15.13 | +02:57:09.26 | +1.58           | +0.06            |
| P3'          | 04:54:07.19 | +02:54:42.42 | -4.82           | +1.12            |
| P4           | 04:54:03.99 | +02:53:25.53 | -4.90           | -25.5            |

Note. Differences $\Delta$ are computed by subtracting the published J14 values from the local maxima of our mean bootstrap map.

An interesting feature of the P3' region is that two peaks in fact appear at comparable amplitude, numbers 3 and 5. This is apparent as well in the position uncertainties in Figure 6, where the contours centered on the third peak extend to enclose the fifth highest peak toward the southeast. The two peaks remain at similar relative amplitudes up to $\lambda = 3.5$, near the level where they vanish from the reconstructions. This could be a hint that the peaks are in fact connected, i.e., that the region actually contains an elongated mass structure. If this is the case, it is possible that a different wavelet dictionary from the isotropic starlet we have used in Glimpse2D might be better at revealing its morphology. Finally, we note that, unlike P2 and P4, whose rank ordering remains the same for all $\lambda$ values we have considered, the secondary peak associated with P3' (number 5) switches places with P1 (number 4) in the ordering for $\lambda = 3.5$, meaning that its detectability actually increases slightly relative to the primary P3' peak with increasing $\lambda$.

For this $\lambda$, we can assign a significance level to the peaks by determining the probability $p$ of a pure noise peak to occur at or above the true peak amplitude in the data reconstruction. We can then convert $p$ into a $k \sigma$ value by finding the $k$ satisfying $1 - p = \text{erf}(k/\sqrt{2})$, as the right-hand side represents the fraction of a Gaussian distribution lying within $k \sigma$ of the mean. We focus on the primary subclusters P2 and P4, since they constitute the strongest isolated detections in the field that also remain consistent across the various $\lambda$ values. Considering first the highest peak P4, the number of noise maps in which a peak appears at or above the P4 height is 37, corresponding to a significance of 2.1$\sigma$. For P2, we find 50 such false detections, corresponding to 2.0$\sigma$. Given the low amplitudes and inconsistent ordering of the remaining peaks, the interpretation of their associated false detection rates is not as straightforward. We can conclude, however, that their significance must be less than that of P2, or 2.0$\sigma$.

We can update the detection significance values by repeating the analysis for larger $\lambda$. For structures with amplitudes that are still high enough to be detected (i.e., P2 and P4) the values represent a new lower bound on their significance. For example, with $\lambda = 3.5$, P4 and P2 appear now at 3.0$\sigma$ and 2.5$\sigma$, respectively. At $\lambda = 5.0$, no noise peaks appear above either the P4 or P2 amplitudes out of 1000 realizations, implying that their detection significances are at least 3.3$\sigma$. We expect this trend to continue at still larger $\lambda$ values, but the computation would require more than the number of noise realizations we have at hand.
Carrying out the analogous process on the C12 data with \( \lambda = 3.0 \), we find that the most significant substructures are P1, P2, and P4, with corresponding significance levels of 1.6\( \sigma \), 1.5\( \sigma \), and 1.4\( \sigma \) for this \( \lambda \). This could be anticipated from the data reconstructions shown in Figure 3 and from Table 1. While these limits would certainly increase by analyzing simulations at higher \( \lambda \), it is clear already at this level that the significance of the other peaks must be less than the minimum of the highest three, or 1.4\( \sigma \). This includes the dark peak region, which does not appear for \( \lambda = 3.0 \).

The ordering of peak amplitudes in the C12 data represents an interesting departure from the J14 data. In particular, the significance of P1 is elevated relative to P2 and P4 at this \( \lambda \), but this would not remain the case at \( \lambda = 4.0 \) and above based on the Figure 3 reconstructions. The prevalence of P1 here compared to in the J14 data could be due to a dilution of the lensing signal at this location by the numerous faint galaxies included in the J14 catalog but not in the C12 catalog.

Finally, it is important to point out some relevant considerations in our determination of peak significance levels from pure noise simulations. The first is that, in our calculation, we have assumed that all locations in the reconstructed field are equally probable. For high-amplitude peaks that are clearly detected, such as P2 and P4, we expect this assumption to hold well. However, there is likely some degree of dependence on the probability of reconstructing P3 due to the presence of P4, given their proximity. Another caveat is that we have performed only a weak-lensing analysis in this work. We have not considered, for example, peaks in the X-ray gas map that are known to coincide with the P3 location (Wang et al. 2016). A joint study could be useful here to determine the probability of obtaining a peak simultaneously in both X-ray and weak-lensing maps.

5. Summary and Conclusion

We have analyzed the A520 merging cluster using a novel sparsity-based mass-mapping code called Glimpse2D. The goal of the re-analysis was twofold. The first objective was to test the Glimpse2D algorithm on real data, since it has been shown to perform well on simulations of Hubble ACS-like data, but has not been applied to real observations until now. Second, given the reported detection of a significant but anomalously high mass-to-light ratio structure in the A520 system, we sought to carry out a separate study using an independent mass inversion technique to assess the presence of the peculiar dark core.

We obtained the source galaxy catalogs with shape measurements from two different groups who have studied the cluster. The first catalog is that of C12, which consists of galaxies derived from a combination of Magellan images and HST/ACS mosaics. The second catalog is from J14, which derives from the same HST/ACS images that were used in C12. The resulting catalogs are different, namely in the number density of galaxies in their common regions of sky coverage due to different reduction pipelines. The J14 catalog contains nearly twice the number of galaxies as that of C12.

Our mass reconstructions obtained from running Glimpse2D on both data sets were in good agreement overall with those presented in their respective papers. The two main subcluster components were reconstructed along the same merger axis inferred by the previous studies. In particular, for the C12 reconstructions, we found the substructures labeled P1, P2, and P4 to be the most prominent, as they were detectable up to the highest value of regularization parameter (\( \lambda = 4.0 \)) used. A peak was visible at the P3 position in the \( \lambda = 2.0 \) reconstruction, but not above \( \lambda = 2.3 \). In contrast, for the J14 reconstructions, P3 was undetectable only in the maps with \( \lambda > 3.5 \), indicating its higher likelihood of being a real structure. The P1 peak, however, appeared much less prominent than P2 and P4, and somewhat less than P3 as well.

To study the positional uncertainties on the mass centroids, we performed bootstrap analyses on both data sets. We examined the variability in the detected locations of P1–P5 for the C12 data and P1–P4 for the J14 data, finding that the peaks were well localized in nearly all cases. The 68%, 95%, and 99.7% confidence contours around each centroid remained separate from the others, except those for P3 and P4 in the C12.
data, which exhibited an overlap of their outer regions. It is thus reasonable to interpret the P3' peak as a distinct structure (whether as a spurious noise peak or indeed as a real concentration of mass) in the J14 data, but not in the C12 data.

We established the significance of the peak detections by generating Monte Carlo noise simulations of the two catalogs at various λ values. Assuming independence of the peaks, i.e., that all locations in the field are equally likely, we placed an upper limit on the significance of the P3' dark peak at 2.0σ using the J14 data and 1.4σ using the C12 data. This is substantially less than the >6σ rejection of the constant mass-to-light ratio hypothesis that was reported by J14. We showed then that in neither case can we confirm the detection of a dark peak, the reality of which would be problematic within the current understanding of dark matter as an effectively collisionless particle.

We finally note that we have not carried out a full mass-to-light ratio analysis of the A520 data, since we are currently unable to do this independently with Glimpse2D. The issue of measuring a peak mass in excess of what is expected—based on, for example, a hypothesis of constant mass to light—is related to, though logically distinct from, assessing the significance of a peak appearing at that location. However, J14 reported a projected mass for P3' consistent with that of P2 and only about 7% smaller than that of P4. Given that we have detected both P2 and P4, but not P3', with Glimpse2D at high confidence, we cannot confirm by our analysis that there is indeed such an anomalous peak at the purported location.

In the spirit of presenting reproducible research, we have made the galaxy catalogs used in this work to produce our mass reconstructions available on the CosmoStat website at http://www.cosmostat.org/software/glimpse/ . Configuration files, output maps, and instructions for running Glimpse2D on the catalogs have also been included.

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Appendix

We present here the results of numerical experiments carried out on the A520 data to test Glimpse2D in the current setting. As discussed in Section 3.2, the regularization parameter λ controls the sparsity constraint on the mass map reconstructed by Glimpse2D. Since we need to fix the trade-off between smoothness and sensitivity through the choice of λ, we aim to guide our intuition empirically by testing the algorithm on simulations representative of the data. Algorithm configuration parameters here are the same as those used to obtain the main text results.

We generate simulated data by injecting a Navarro–Frenk–White (NFW) (Navarro et al. 1997) halo mass profile into the ACS footprint at z = 0.2, the redshift of the A520 cluster. We place it at the position of P4 based on the original data reconstructions (see Figure 4) with size and concentration parameters of $r_{200} = 0.85$ Mpc and $c = 3.5$, respectively. This results in a mass $M_{200} = 4.9 \times 10^{13}$ $M_{\odot}$ corresponding approximately to the average of the column masses derived for P4 in C12 and J14. We compute the (reduced) shear field analytically (Wright & Brainerd 2000) and carry out Glimpse2D reconstructions without shape noise for $\lambda \in \{1.0, 5.0\}$ in steps of $\Delta \lambda = 0.1$. Source galaxies are placed randomly within the field with a number density matching that of the J14 data. The results for $\lambda = 2.0$, 3.0, and 4.0 are shown in the top row of Figure 8. The three maps are representative of all the reconstructions in that they are hardly distinguishable in terms of the morphology and position of the mass peak. The primary difference among the results shown is that the $\lambda = 3.0$ and 4.0 peak amplitude is about 4% lower than for $\lambda = 2.0$. This example shows that Glimpse2D is able to accurately recover mass peaks in a noise-free setting even for relatively low values of $\lambda$. This is also consistent with the results of Lanusse et al. (2016), in particular their experiment in Section 3.5.

We next test the impact of noise by assigning intrinsic shapes to the source galaxies drawn from the J14 catalog. Our goal is to study the statistical behavior of Glimpse2D in simulations with a similar noise context to that of the original data. Note that using the galaxy ellipticities from the data in this way does not perfectly capture the true noise properties for two reasons. The first is that the spatial variation of the galaxy density across a simulation field will not match that of the original data, and the second is that the shear produced by the A520 cluster is still contained within the ellipticities. We do not expect the effect of the latter to be significant, as the shear remains weak throughout most of the field and is further diluted by our random sampling of the catalog ellipticities. Furthermore, because we are aiming merely for a guide to setting $\lambda$ in the real data reconstructions, the galaxy distribution need not match exactly—we can establish the expected behavior on average by carrying out a large number realizations of the noise where the ellipticity distributions still match the data well. We have generated 1000 such noise simulations.

A typical example of a noise simulation with the same NFW profile described above is shown in the second row of Figure 8. From left to right, the maps represent Glimpse2D reconstructions for $\lambda = 2.0$, 3.0, and 4.0. With $\lambda = 2.0$, the input halo is clearly recovered at the correct location; at this level, however, many spurious noise peaks appear as well. As discussed in Section 3, this reflects the fact that lower $\lambda$ values are better at preserving smaller features but at the expense of signal to noise, i.e., our confidence that they are real. Looking closer at the region containing the true mass peak, we see that false peaks can arise close enough to the true peak that one might mistake them for extensions of it. Importantly, raising $\lambda$ to 3.0 (center panel) effectively suppresses this as well as all other noise peaks in the field. For this particular realization, raising $\lambda$ further does not improve the quality of the reconstruction in terms of eliminating false detections.

Finally, we examine the mean of the 1000 noise simulations for the same three $\lambda$ values as above, which are shown in the bottom row of Figure 8. As expected, the $\lambda = 2.0$ map exhibits significantly more variation across the field due to noise.
compared to higher values. In all three cases, the true mass peak is smoothed out (and isotropized), which we also expect due to small variations in the reconstructed peak amplitude and position based on the particular noise realization. Overlaid are contours indicating the 1 and 2σ levels of the distribution of the highest-amplitude peak position in each map for a given $\lambda$. As such, the contours are not showing specifically the dispersion of the true peak position, since the highest peak in a given map might be due to noise. This is apparent in the $\lambda = 2.0$ case, where clearly many false peaks appear with higher amplitude than the true peak. Instead, this is a simple test to verify our expectation that the features detected in higher $\lambda$ reconstructions can be interpreted as being part of the real signal. By $\lambda = 4.0$, the contours have closed in on the true peak location. Note that in this case, since essentially all noise peaks are suppressed at this level, the contours indeed approximate the scatter in the recoverability of the true peak position.

The results described in this Appendix motivate the range of $\lambda$ values used in the various mass reconstructions of the main text. Furthermore, we can take the size of the contours on the $\lambda = 4.0$ map as an estimate of the typical variability of a peak. The 1 and 2σ regions correspond to a radius of approximately
80 and 200 kpc, respectively, at the redshift of the cluster. The 150 kpc search radius about each peak in the bootstrap analysis of Section 4.3 seems therefore reasonable.

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