

¹ Shear Mapping in Python (SMPy): Modular, ² Extensible, and Accessible Dark Matter Mapping

³ **Georgios N. Vassilakis**    , **Jacqueline E. McCleary**    , **Maya Amit**    ,
⁴ **Sayan Saha** 

⁵ 1 Department of Physics, Northeastern University, Boston, MA, USA 2 Institute of Astronomy,
⁶ University of Cambridge, Cambridge, UK 3 Department of Applied Mathematics and Theoretical Physics,
⁷ University of Cambridge, Cambridge, UK 4 Kavli Institute for Cosmology, University of Cambridge,
⁸ Cambridge, UK ¶ Corresponding author

DOI: [10.xxxxxx/draft](https://doi.org/10.xxxxxx/draft)

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Submitted: 01 January 1970

Published: unpublished

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⁹ Summary

¹⁰ Understanding the universe's large-scale distribution of dark matter is a central objective in the
¹¹ era of precision cosmology. A key technique for the study of dark matter is weak gravitational
¹² lensing: a phenomenon where light from distant galaxies is sheared as it passes through the
¹³ gravitational field of a massive object, like a galaxy cluster. This shear, which manifests as a
¹⁴ slight (weak) distortion of shapes over thousands of galaxies, allows astrophysicists to infer the
¹⁵ distribution of total matter, including both luminous and dark matter.

¹⁶ Obtaining a mass distribution from a catalog of galaxy shears requires an intermediate step.
¹⁷ A common tool for this step is the mapping of convergence (κ), which quantifies how much
¹⁸ a gravitational lens converges the light from distant galaxies, resulting in a magnification of
¹⁹ their shapes. This value is directly proportional to the projected mass density, enabling easy
²⁰ visualization of the overall mass distribution. For a comprehensive review of weak gravitational
²¹ lensing, refer to ([Umetsu, 2020](#)).

²² The **Shear Mapping in Python (SMPy)** package provides a standardized, well-documented,
²³ and open-source solution for creating convergence maps from weak lensing galaxy shear
²⁴ measurements. SMPy was initially developed to support the Superpressure Balloon-borne
²⁵ Imaging Telescope (SuperBIT), a stratospheric, near-UV to near-IR observing platform which
²⁶ completed its 45-night observing run in spring 2023 with over 30 galaxy cluster observations
²⁷ ([Gill et al., 2024](#); [Sirks et al., 2023](#)). SMPy has since evolved into a general-purpose tool suitable
²⁸ for analyzing the weak lensing data from cosmological surveys.

²⁹ Statement of need

³⁰ While mass maps are a key deliverable of many cosmological analyses ([Jeffrey et al., 2021](#);
³¹ [Madhavacheril et al., 2024](#); [Oguri et al., 2017](#)), scientists are often left to make these maps
³² from scratch. SMPy addresses an outstanding need for the lensing community: an accessible,
³³ well-documented, and extensible tool to construct publication-quality mass maps from galaxy
³⁴ shear data. Built on standard scientific Python packages, it provides an easy entry point for
³⁵ researchers new to mass mapping, while also being robust for more senior scientific use. There
³⁶ are currently three separate mapping methods implemented into SMPy: the classic Kaiser-Squires
³⁷ inversion ([Kaiser & Squires, 1993](#)), aperture mass mapping ([Leonard et al., 2012](#); [McCleary et
38 al., 2020](#)), and notably, to our knowledge, the first publicly available implementation of the
39 KS+ algorithm ([Pires, 2020](#)). KS+ improves reconstruction quality by correcting for systematic
40 effects including missing data, field borders, and reduced shear. SMPy also offers specialized
41 and unique features valuable for mass mapping, such as flexible coordinate system support

42 (both celestial and pixel space) and comprehensive signal-to-noise analysis with multiple noise
43 randomization techniques. An example convergence map, created from simulated SuperBIT
44 galaxy cluster observations (McCleary et al., 2023), is shown in Figure 1. SMPy is, to our
45 knowledge, the first convergence mapping software to prioritize both accessibility and advanced
46 features.

47 State of the field

48 The weak lensing community is served by publicly available mapping tools like `lenspack`
49 and `jax-lensing` (Remy et al., 2022), each with their own strengths. `jax-lensing` excels
50 at neural network-based approaches and deep learning methods, but applying it to survey-
51 specific data products requires substantial additional development by the end user. `lenspack`
52 provides well-documented, stand-alone mass-mapping functions, but does not provide an end-
53 to-end convergence-mapping workflow (e.g., configuration management, coordinate handling,
54 noise/SNR analysis, and plotting). In practice, many mass-mapping analyses still rely on
55 bespoke codes built for a specific survey or science case. These gaps, combined with the
56 need for a flexible, configuration-driven, and modular mapping framework, motivated the
57 development of SMPy as an accessible and extensible alternative.

58 Software design

59 SMPy was built with the following design principles in mind:

- 60 1. **Accessibility:** SMPy is written entirely in Python and deliberately relies only on widely-used
61 scientific Python packages (NumPy, SciPy, Pandas, Astropy, Matplotlib, and PyYAML).
62 This choice of standard dependencies ensures that users can easily install the packages
63 without complex dependency chains, and that the codebase is maintainable and familiar
64 to the scientific Python community.
 - 65 2. **Extensibility:** SMPy's modular architecture enables seamless addition of new mass mapping
66 techniques, encouraging open-source contribution. The framework's standardized abstract
67 base class architecture allows for the integration of different mapping methods with
68 minimal effort.
 - 69 3. **Usability:** Creating convergence maps with SMPy requires minimal input—users need to
70 only provide a catalog of galaxies with their associated shear components and coordinates.
71 This straightforward input requirement makes the tool accessible to researchers at all
72 levels. A flexible configuration system is integrated via a single YAML file that defines
73 file paths, convergence map algorithm settings, plotting parameters, and more. With
74 this configuration file, the user can create convergence and SNR maps with one line,
75 either via terminal or within code.
 - 76 4. **Robustness:** SMPy is designed to be mathematically and algorithmically accurate, allowing
77 the user to create convergence maps with any galaxy shear data. The coordinate
78 system abstraction handles both celestial coordinates (with proper spherical geometry
79 approximations) or pixel-based coordinates through a unified interface. To quantify the
80 significance of the weak lensing detection, multiple noise realizations can be generated
81 using either spatial shuffling (randomizing galaxy positions while preserving shear values)
82 or orientation shuffling (randomizing shear orientations while preserving positions). These
83 noise realizations are used to create a signal-to-noise map with the observed convergence.
- 84 These design decisions are reflected in SMPy's overall workflow: users provide a shear catalog
85 and a single YAML configuration file, and SMPy produces convergence maps, signal-to-noise
86 maps, and publication-quality plots with minimal boilerplate. The mapping framework is
87 implemented through standardized abstract base classes, allowing different reconstruction

⁸⁸ methods to be interchanged while preserving a consistent interface and coordinate-system
⁸⁹ handling.

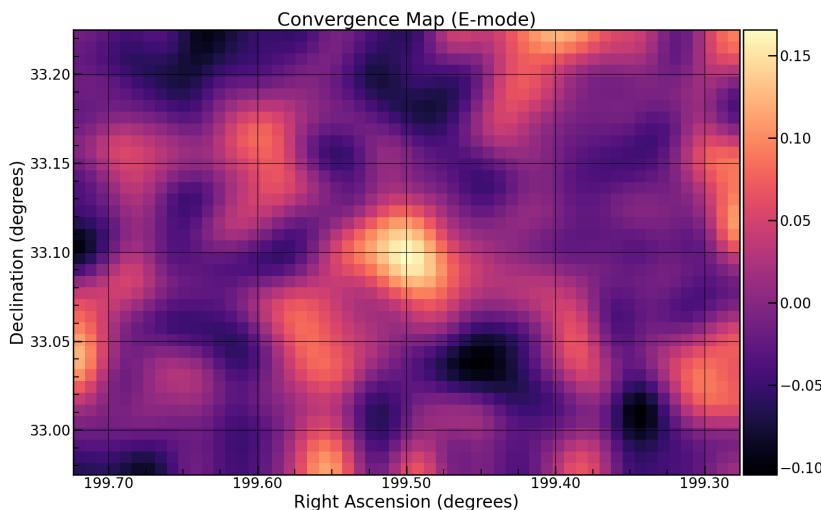


Figure 1: Example convergence map created with SMPy showing the mass distribution of a simulated galaxy cluster. The map was generated using the Kaiser-Squires inversion method on simulated weak lensing data from SuperBIT. The color scale represents the dimensionless surface mass density (convergence), with brighter regions indicating higher mass concentrations.

⁹⁰ Research impact statement

⁹¹ SMPy was initially developed as part of the weak lensing analysis pipeline for SuperBIT, and it
⁹² is currently being used to create the first convergence maps measured from the stratosphere,
⁹³ derived from SuperBIT's 2023 science flight imaging. These convergence maps will be presented
⁹⁴ in a forthcoming SuperBIT weak-lensing analysis (Saha et al., in preparation, 2026; "Lensing
⁹⁵ in the Blue IV"). In addition, SMPy has been presented at the Jet Propulsion Laboratory, and
⁹⁶ we have received interest in exploring integration into Euclid weak-lensing analysis workflows.

⁹⁷ AI usage disclosure

⁹⁸ Generative AI was used in three ways in this work. First, Claude Sonnet 4 (with Extended
⁹⁹ Thinking enabled via the Claude.ai web interface) was used to assist in implementing the KS+
¹⁰⁰ algorithm in SMPy. The author reviewed all AI-assisted code line-by-line against the Algorithm
¹⁰¹ 1 description in Appendix A of (Pires, 2020) and validated the implementation by injecting
¹⁰² fiducial star masks into data and confirming that the reconstruction behaved as expected.
¹⁰³ Second, OpenAI's ChatGPT (5.0-Thinking and 5.2-Thinking) models have been used for
¹⁰⁴ generating unit tests for the codebase via the Codex CLI. Lastly, both OpenAI's ChatGPT
¹⁰⁵ models and Anthropic's Claude models have been used in the GitHub App harness to review
¹⁰⁶ pull requests and catch bugs. An example use case of this would include making a comment
¹⁰⁷ on an open pull request along the lines of '(?)/(?) review this PR'.

¹⁰⁸ Software references

¹⁰⁹ SMPy is written in Python 3.8+ and uses the following packages:

- ¹¹⁰ ▪ NumPy ([Harris et al., 2020](#))
- ¹¹¹ ▪ SciPy ([Virtanen et al., 2020](#))
- ¹¹² ▪ Pandas ([team, 2024](#))

- ¹¹³ ■ Astropy ([Astropy Collaboration et al., 2013, 2018, 2022](#))
- ¹¹⁴ ■ Matplotlib ([Hunter, 2007](#))
- ¹¹⁵ ■ PyYAML ([Simonov, 2024](#))

¹¹⁶ Acknowledgements

¹¹⁷ This material is based upon work supported by a Northeastern University Undergraduate
¹¹⁸ Research and Fellowships PEAK Summit Award.

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