

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

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⁸ Summary

⁹ Understanding the universe's large-scale distribution of dark matter is a central objective in the
¹⁰ era of precision cosmology. A key technique for the study of dark matter is weak gravitational
¹¹ lensing: a phenomenon where light from distant galaxies is sheared as it passes through the
¹² gravitational field of a massive object, like a galaxy cluster. This shear, which manifests as a
¹³ slight (weak) distortion of shapes over thousands of galaxies, allows astrophysicists to infer the
¹⁴ distribution of total matter, including both luminous and dark matter.

¹⁵ Obtaining a mass distribution from a catalog of galaxy shears requires an intermediate step.
¹⁶ A common tool for this step is the mapping of convergence (κ), which quantifies how much
¹⁷ a gravitational lens converges the light from distant galaxies, resulting in a magnification of
¹⁸ their shapes. This value is directly proportional to the projected mass density, enabling easy
¹⁹ visualization of the overall mass distribution. For a comprehensive review of weak gravitational
²⁰ lensing, refer to ([Umetsu, 2020](#)).

²¹ The **Shear Mapping in Python (SMPy)** package provides a standardized, well-documented,
²² and open-source solution for creating convergence maps from weak lensing galaxy shear
²³ measurements. SMPy was initially developed to support the Superpressure Balloon-borne
²⁴ Imaging Telescope (SuperBIT), a stratospheric, near-UV to near-IR observing platform which
²⁵ completed its 45-night observing run in spring 2023 with over 30 galaxy cluster observations
²⁶ ([Gill et al., 2024; Sirks et al., 2023](#)). SMPy has since evolved into a general-purpose tool suitable
²⁷ for analyzing the weak lensing data from cosmological surveys.

²⁸ Statement of need

²⁹ While mass maps are a key deliverable of many cosmological analyses ([Jeffrey et al., 2021](#);
³⁰ [Madhavacheril et al., 2024](#); [Oguri et al., 2017](#)), scientists are often left to make these maps
³¹ from scratch.

³² SMPy addresses an outstanding need for the lensing community: an accessible, well-documented,
³³ and extensible tool to construct publication-quality mass maps from galaxy shear data. Built
³⁴ on standard scientific Python packages, it provides an easy entry point for researchers new to
³⁵ mass mapping, while also being robust for more senior scientific use. There are currently three
³⁶ separate mapping methods implemented into SMPy: the classic Kaiser-Squires inversion ([Kaiser
37 & Squires, 1993](#)), aperture mass mapping ([Leonard et al., 2012; McCleary et al., 2020](#)), and
³⁸ notably, to our knowledge, the first publicly available implementation of the KS+ algorithm
³⁹ ([Pires, 2020](#)). KS+ improves reconstruction quality by correcting for systematic effects including
⁴⁰ missing data, field borders, and reduced shear. SMPy also offers specialized and unique features

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

46 State of the field

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

57 Software design

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

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

83 These design decisions are reflected in SMPy's overall workflow: users provide a shear catalog
84 and a single YAML configuration file, and SMPy produces convergence maps, signal-to-noise
85 maps, and publication-quality plots with minimal boilerplate. The mapping framework is
86 implemented through standardized abstract base classes, allowing different reconstruction

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

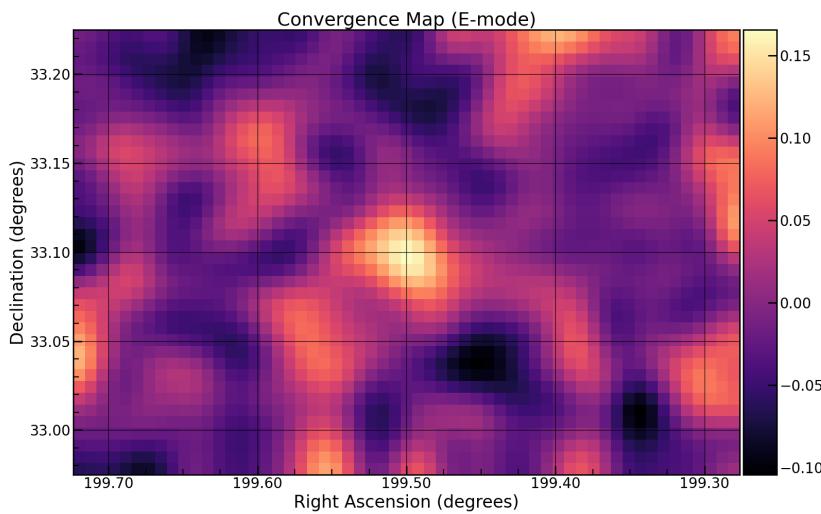


Figure 1: Example convergence map created with SMPy showing the mass distribution of a simulated galaxy cluster. The map was generated using the Kaiser-Squires inversion method on simulated weak lensing data from SuperBIT. The color scale represents the dimensionless surface mass density (convergence),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

89 Research impact statement

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

96 AI usage disclosure

97 Generative AI was used in three ways in this work. First, Claude Sonnet 4 (via the Claude.ai
 98 web interface) was used to assist in implementing the KS+ algorithm in SMPy. The author
 99 reviewed all AI-assisted code line-by-line against the Algorithm 1 description in Appendix A of
 100 (Pires, 2020) and validated the implementation by injecting fiducial star masks into data and
 101 confirming that the reconstruction behaved as expected. Second, OpenAI's ChatGPT (5.0
 102 and 5.2) models have been used for generating unit tests for the codebase. Lastly, OpenAI's
 103 ChatGPT models (5.2) in the Codex harness have been used to review pull requests and catch
 104 bugs.

105 Software references

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

- 107 ■ NumPy ([Harris et al., 2020](#))
- 108 ■ SciPy ([Virtanen et al., 2020](#))
- 109 ■ Pandas ([team, 2024](#))
- 110 ■ Astropy ([Astropy Collaboration et al., 2013, 2018, 2022](#))
- 111 ■ Matplotlib ([Hunter, 2007](#))

¹¹² ▪ PyYAML ([Simonov, 2024](#))

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