The Journal of Open Source Software

Synthesizer: Synthetic Observables For Modern Astronomy

Will J. Roper [1*¶], **Christopher C. Lovell** [2*], **Aswin Vijayan** [1*], **Stephen Wilkins** [1*], **Hollis Akins** [3], **Sabrina Berger** [4], **Connor Sant Fournier** [5], **Thomas Harvey** [6], **Kartheik Iyer** [7], **Marco Leonardi** [8], **Sophie Newman** [2], **Borja Pautasso** [1], **Ashley Perry** [1], **Louise Seeyave** [1], and **Laura Sommovigo** [9]

1 Astronomy Centre, University of Sussex, Falmer, Brighton BN1 9QH, UK **2** Kavli Institute for Cosmology, University of Cambridge, Madingley Road, Cambridge CB3 0HA, UK **3** Institute of Astronomy, University of Cambridge, Madingley Road, Cambridge CB3 0HA, UK **4** Institute of Cosmology and Gravitation, University of Portsmouth, Burnaby Road, Portsmouth, PO1 3FX, UK **5** Department of Astronomy, The University of Texas at Austin, Austin, TX 78712, USA **6** School of Physics, University of Melbourne, Parkville, VIC 3010, Australia **7** Institute of Space Sciences and Astronomy, University of Malta, Msida MSD 2080, Malta **8** Jodrell Bank Centre for Astrophysics, University of Manchester, Oxford Road, Manchester M13 9PL, UK **9** Columbia Astrophysics Laboratory, Columbia University, 550 West 120th Street, New York, NY 10027, USA **10** Leiden Observatory, Leiden University, PO Box 9513, NL-2300 RA Leiden, The Netherlands **11** Center for Computational Astrophysics, Flatiron Institute, 162 5th Ave, New York, NY 10010, USA ¶ Corresponding author * These authors contributed equally.

DOI: 10.xxxxxx/draft

Software

- Review
- Repository
- Archive

Editor: Tobias Buck

Reviewers:

- @steven-murray
- @ConnorStoneAstro

Submitted: 17 June 2025
Published: unpublished

Summary

Synthesizer is a fast, flexible, modular, and extensible Python package that empowers astronomers to turn theoretical galaxy models into realistic synthetic observations - including spectra, photometry, images, and spectral cubes - with a focus on interchangeable modelling assumptions. By offloading computationally intensive tasks to threaded C++ extensions, Synthesizer delivers both simplicity and speed, enabling rapid forward-modelling workflows without requiring users to manage low-level data processing and computational details.

Statement of need

Producing synthetic observations from simulations has a long history in astronomy (e.g. Torrey et al., 2015), but the availability of public, general-purpose tools for this task has only recently grown. Comparing theoretical models of galaxy formation with observations traditionally relies on two main approaches, both translating theoretical models into the observer space (a technique known as forward modelling). The first uses computationally expensive dust radiative transfer codes (e.g. Camps & Baes, 2015; Jonsson, 2006; Narayanan et al., 2021); these codes are typically computationally expensive, prioritising fidelity. The second uses simpler, bespoke pipelines that sacrifice some physical fidelity to generate observables rapidly from large datasets (e.g. Fortuni et al., 2023; Marshall et al., 2025; Roper et al., 2022; Vijayan et al., 2020; Wilkins et al., 2020). Synthesizer is neither. It instead provides the tools to construct standardized, flexible pipelines that prioritize performance and modularity while enabling exploration of modelling assumptions.

Simplified inverse modelling approaches, such as SED fitting (e.g. Brammer et al., 2008; Carnall et al., 2018; Johnson et al., 2021) work in the opposite direction, translating observables into intrinsic physical quantities. However, these methods can introduce biases and uncertainties from both observational effects and model assumptions. Compounding these uncertainties is the fact that converged inverse modelling techniques are costly in their own right, necessitating a simplified parameter space to ensure convergence in a reasonable time. Forward modelling is therefore becoming increasingly important not only for probing the validity of theoretical models, but also for quantifying the uncertainties in the modelling assumptions themselves.

However, existing forward modelling tools often lack the flexibility to explore modelling uncertainties, the usability and modularity to explore a wide range of modelling assumptions, and the performance necessary to explore a large parameter space and process modern-day large datasets. Furthermore, they frequently lack comprehensive documentation, hindering consistency, and reproducibility across a range of datasets.

Synthesizer addresses these shortcomings by offering:

- Flexibility: Anything that could be changed by the user is explicitly designed to be variable (for a quantitative model parameter) or exchangeable (for a qualitative modelling choice). This means that users can easily vary everything in a reproducible way, without needing to modify the core code.
- Performance: Computationally intensive operations are optimised by employing C extensions with OpenMP threading. Without this performance, the aforementioned flexibility is moot; only by coupling flexibility with the performance to utilise it can we explore large, high-dimensional parameter spaces in a reasonable time.
- Modularity: Synthesizer is object-oriented, with a focus on decoupled classes that can be specialised and then swapped out at will. This modularity, in conjunction with a reliance on templating and dependency injection (see Emission Models below), is what enables Synthesizer's flexibility, as well as its application to a diverse range of astrophysical problems in both forward and inverse modelling
- Extensibility: Extensive documentation and a clear API enable users to extend the package with their own calculations, parameterisations and subclasses. From the beginning, Synthesizer has been designed to be expanded to fit the needs of all users, even as astronomy and astrophysics evolve.

Synthesizer's design facilitates apples-to-apples comparisons between simulations and observations (e.g. Wilkins et al., 2025), permits exhaustive tests of the impact of parameter choices (e.g. Ho et al., 2024), enables the forward modelling of large datasets previously considered impractical (e.g. Lovell et al., 2024), and promotes open and reproducible science. Synthesizer's combination of modularity and performance is also critical for emerging inference techniques such as simulation-based inference (SBI), which require large training datasets of forward-modelled observables generated rapidly under flexible modelling assumptions, a regime where neither flexibility nor performance alone suffices. For example, Harvey et al. (2025) use Synthesizer to inexpensively generate the training data needed for SBI-based SED fitting of galaxy photometry.

Package overview

Synthesizer is structured around a set of core abstractions. Here we give a brief outline of these abstractions and a link to the documentation for each.

- **Components**: Represent stars, gas, and black holes, encapsulating physical properties, and emission and emission generation methods. For more details, see the components documentation.
- **Galaxies**: Combine multiple components into a single object, allowing for cohesive calculations with all components, taking account of their interdependencies. For more details, see the galaxies documentation.

- **Emission Grids**: N-dimensional lookup tables of precomputed spectra and lines. Precomputed grids are available for stellar population synthesis models, including BC03 (Bruzual & Charlot, 2003), BPASS (Stanway & Eldridge, 2018), FSPS (Conroy et al. (2009), Conroy & Gunn (2010)), Maraston (Maraston (2005), Newman et al. (2025)), all reprocessed using Cloudy (Ferland et al., 1998). Grids of AGN emission can also be calculated and explored. Users can generate custom grids via the accompanying grid-generation package. For more details, see the grids documentation.
- **Emission Models**: Modular templates defining the process of producing emissions from components. These models can be used to extract, generate, transform, or combine emissions. These are the backbone of Synthesizer's flexibility and modularity. For more details, see the emission models documentation.
- **Emissions**: The output of combining components with an emission model. These emissions are either spectra stored in `Sed` objects, or line emissions stored in `LineCollection` objects.
- **Instruments**: Definitions of filters, resolutions, PSFs, and noise models to convert emissions into photometry, spectroscopy, images, and data cubes. For more details, see the instruments documentation and filters documentation.
- **Observables**: Containers for the output spectra with observational effects (`Sed` objects), photometry (`PhotometryCollection` objects), images (`Image` and `ImageCollection` objects), and spectral data cubes (`SpectralDataCube` objects).

Synthesizer is hosted on GitHub and is available on PyPI. The documentation is available through GitHub Pages. A comprehensive description of Synthesizer's methodology and science validation is presented in the companion paper (Lovell et al., 2025).

Related packages

Several packages either overlap with Synthesizer's functionality or complement it in end-to-end workflows. Some already interface with Synthesizer as plugins (e.g. SPS grids, PSF tools), while others are fully independent codes with conceptually similar goals:

- **Synthetic observation codes**: A number of codes produce synthetic observables from simulated galaxies, each targeting specific use cases. **FORECAST** (Fortuni et al., 2023) and **GalaxyGenius** (Zhou et al., 2025) generate mock images from hydrodynamical simulations for specific telescopes; **RealSim-IFS** (Bottrell & Hani, 2022) and **SimSpin** (Harborne et al., 2023) produce synthetic IFU datacubes; **py-ananke** (Thob et al., 2024) creates stellar catalogs for Milky Way-like simulations; **pyMGal** (Janulewicz et al., 2025) generates mock optical observations; **popkinmocks** (Jethwa, 2023) produces mock IFU datacubes for stellar population and kinematic modelling; and **synphot** (Lim & STScI development team, 2023) provides synthetic photometry utilities. While these share conceptual overlap with Synthesizer, they each target narrower use cases; Synthesizer aims to provide a general-purpose, modular framework spanning the full pipeline from theoretical models to multi-wavelength observables.
- **SPS & photoionisation**: Libraries for stellar spectra—**BC03** (Bruzual & Charlot, 2003), **FSPS** (Conroy et al., 2009; Conroy & Gunn, 2010), **Maraston** (Maraston, 2005), **BPASS** (Stanway & Eldridge, 2018)—paired with dust/nebular models, plus **Cloudy** (Ferland et al., 1998) or **MAPPINGS** (Dopita & Sutherland, 1996) for reprocessing. These serve as inputs to Synthesizer's emission grids.
- **Monte Carlo RT**: Photon–dust/gas simulators like **SKIRT** (Camps & Baes, 2015), **Powderday** (Narayanan et al., 2021), **Hyperion** (Robitaille, 2011). These produce SEDs and images that can be ingested by Synthesizer.
- **PSF & instrument tools**: **STPSF** (Perrin et al., 2014) (JWST, Roman, HST) and **GalSim** (Rowe et al., 2015) model telescope optics, detector effects, and noise. These integrate directly with Synthesizer's instrument pipeline.
- **Pre/post-processing**: **YT** (Turk et al., 2011) for volumetric data analysis and visualization of simulation outputs; **Astroquery** (Ginsburg et al., 2019) for automated querying of

astronomical archives and catalogs; **Dense Basis** (Iyer et al., 2019) offers SED-/SFH-tailored basis functions.

- **Inverse modeling & SED fitting**: **EAZY** (Brammer et al., 2008), **BAGPIPES** (Carnall et al., 2018), **PROSPECTOR** (Johnson et al., 2021) extract galaxy properties from SEDs.

Acknowledgements

We acknowledge the use of the following software packages in this work: Astropy (Astropy Collaboration et al., 2022), unyt (Goldbaum et al., 2018), Matplotlib (Hunter, 2007), NumPy (Harris et al., 2020), SciPy (Virtanen et al., 2020), and OpenMP (Dagum & Menon, 1998).

WJR, APV, and SMW acknowledge support from the Sussex Astronomy Centre STFC Consolidated Grant (ST/X001040/1). CCL acknowledges support from a Dennis Sciama fellowship funded by the University of Portsmouth for the Institute of Cosmology and Gravitation. APV acknowledges support from the Carlsberg Foundation (grant no CF20-0534). SB is supported by the Melbourne Research Scholarship and N D Goldsworthy Scholarship. LS and SN are supported by an STFC studentship. This work was supported by the Simons Collaboration on "Learning the Universe".

This work used the DiRAC@Durham facility managed by the Institute for Computational Cosmology on behalf of the STFC DiRAC HPC Facility (www.dirac.ac.uk). The equipment was funded by BEIS capital funding via STFC capital grants ST/K00042X/1, ST/P002293/1, ST/R002371/1 and ST/S002502/1, Durham University and STFC operations grant ST/R000832/1. DiRAC is part of the National e-Infrastructure.

References

Astropy Collaboration, Price-Whelan, A. M., Lim, P. L., Earl, N., Starkman, N., Bradley, L., Shupe, D. L., Patil, A. A., Corrales, L., Brasseur, C. E., Nöthe, M., Donath, A., Tollerud, E., Morris, B. M., Ginsburg, A., Vaher, E., Weaver, B. A., Tocknell, J., Jamieson, W., … Astropy Project Contributors. (2022). The Astropy Project: Sustaining and Growing a Community-oriented Open-source Project and the Latest Major Release (v5.0) of the Core Package. *935*(2), 167. https://doi.org/10.3847/1538-4357/ac7c74

Bottrell, C., & Hani, M. H. (2022). Realistic synthetic integral field spectroscopy with RealSim-IFS. *514*(2), 2821–2838. https://doi.org/10.1093/mnras/stac1532

Brammer, G. B., van Dokkum, P. G., & Coppi, P. (2008). EAZY: A Fast, Public Photometric Redshift Code. *686*(2), 1503–1513. https://doi.org/10.1086/591786

Bruzual, G., & Charlot, S. (2003). Stellar population synthesis at the resolution of 2003. *344*(4), 1000–1028. https://doi.org/10.1046/j.1365-8711.2003.06897.x

Camps, P., & Baes, M. (2015). SKIRT: An advanced dust radiative transfer code with a user-friendly architecture. *Astronomy and Computing*, *9*, 20–33. https://doi.org/10.1016/j.ascom.2014.10.004

Carnall, A. C., McLure, R. J., Dunlop, J. S., & Davé, R. (2018). Inferring the star formation histories of massive quiescent galaxies with BAGPIPES: evidence for multiple quenching mechanisms. *480*(4), 4379–4401. https://doi.org/10.1093/mnras/sty2169

Conroy, C., & Gunn, J. E. (2010). The Propagation of Uncertainties in Stellar Population Synthesis Modeling. III. Model Calibration, Comparison, and Evaluation. *712*(2), 833–857. https://doi.org/10.1088/0004-637X/712/2/833

Conroy, C., Gunn, J. E., & White, M. (2009). The Propagation of Uncertainties in Stellar Population Synthesis Modeling. I. The Relevance of Uncertain Aspects of Stellar Evolution

The Journal of Open Source Software

and the Initial Mass Function to the Derived Physical Properties of Galaxies. *699*(1), 486–506. https://doi.org/10.1088/0004-637X/699/1/486

Dagum, L., & Menon, R. (1998). OpenMP: An industry standard API for shared-memory programming. *Computational Science & Engineering, IEEE*, *5*(1), 46–55. https://doi.org/10.1109/99.660313

Dopita, M. A., & Sutherland, R. S. (1996). Spectral Signatures of Fast Shocks. I. Low-Density Model Grid. *102*, 161. https://doi.org/10.1086/192255

Ferland, G. J., Korista, K. T., Verner, D. A., Ferguson, J. W., Kingdon, J. B., & Verner, E. M. (1998). CLOUDY 90: Numerical Simulation of Plasmas and Their Spectra. *110*(749), 761–778. https://doi.org/10.1086/316190

Fortuni, F., Merlin, E., Fontana, A., Giocoli, C., Romelli, E., Graziani, L., Santini, P., Castellano, M., Charlot, S., & Chevallard, J. (2023). FORECAST: A flexible software to forward model cosmological hydrodynamical simulations mimicking real observations. *677*, A102. https://doi.org/10.1051/0004-6361/202346725

Ginsburg, A., Sipőcz, B. M., Brasseur, C. E., Cowperthwaite, P. S., Craig, M. W., Deil, C., Guillochon, J., Guzman, G., Liedtke, S., Lian Lim, P., Lockhart, K. E., Mommert, M., Morris, B. M., Norman, H., Parikh, M., Persson, M. V., Robitaille, T. P., Segovia, J.-C., Singer, L. P., … a subset of the astropy collaboration. (2019). astroquery: An Astronomical Web-querying Package in Python. *157*, 98. https://doi.org/10.3847/1538-3881/aafc33

Goldbaum, N. J., ZuHone, J. A., Turk, M. J., Kowalik, K., & Rosen, A. L. (2018). Unyt: Handle, manipulate, and convert data with units in python. *Journal of Open Source Software*, *3*(28), 809. https://doi.org/10.21105/joss.00809

Harborne, K. E., Serene, A., Davies, E. J. A., Derkenne, C., Vaughan, S., Burdon, A. I., Lagos, C. del P., McDermid, R., O'Toole, S., Power, C., Robotham, A. S. G., Santucci, G., & Tobar, R. (2023). SimSpin v2.6.0 – constructing synthetic spectral IFU cubes for comparison with observational surveys. *Publications of the Astronomical Society of Australia*, *40*, e048. https://doi.org/10.1017/pasa.2023.47

Harris, C. R., Millman, K. J., Walt, S. J. van der, Gommers, R., Virtanen, P., Cournapeau, D., Wieser, E., Taylor, J., Berg, S., Smith, N. J., Kern, R., Picus, M., Hoyer, S., Kerkwijk, M. H. van, Brett, M., Haldane, A., Río, J. F. del, Wiebe, M., Peterson, P., … Oliphant, T. E. (2020). Array programming with NumPy. *Nature*, *585*(7825), 357–362. https://doi.org/10.1038/s41586-020-2649-2

Harvey, T., Lovell, C. C., Newman, S., Conselice, C. J., Austin, D., Roper, W. J., Vijayan, A. P., Wilkins, S. M., Iglesias-Navarro, P., Rusakov, V., Li, Q., Adams, N., Magdwick, K., Goolsby, C. M., Huertas-Company, M., & Ho, M. (2025). Flexible Simulation Based Inference for Galaxy Photometric Fitting with Synthesizer. *arXiv e-Prints*, arXiv:2511.10640. https://doi.org/10.48550/arXiv.2511.10640

Ho, M., Bartlett, D. J., Chartier, N., Cuesta-Lazaro, C., Ding, S., Lapel, A., Lemos, P., Lovell, C. C., Makinen, T. L., Modi, C., Pandya, V., Pandey, S., Perez, L. A., Wandelt, B., & Bryan, G. L. (2024). LtU-ILI: An All-in-One Framework for Implicit Inference in Astrophysics and Cosmology. *The Open Journal of Astrophysics*, *7*, 54. https://doi.org/10.33232/001c.120559

Hunter, J. D. (2007). Matplotlib: A 2D graphics environment. *Computing in Science & Engineering*, *9*(3), 90–95. https://doi.org/10.1109/MCSE.2007.55

Iyer, K. G., Gawiser, E., Faber, S. M., Ferguson, H. C., Kartaltepe, J., Koekemoer, A. M., Pacifici, C., & Somerville, R. S. (2019). Nonparametric star formation history reconstruction with gaussian processes. I. Counting major episodes of star formation. *The Astrophysical Journal*, *879*(2), 116. https://doi.org/10.3847/1538-4357/ab2052

Janulewicz, P., Torrey, P., Trayford, J. W., & Wilkinson, M. J. (2025). PyMGal: A Python Package for Generating Optical Mock Observations from Hydrodynamical Simulations. *arXiv e-Prints*, arXiv:2507.00123. https://doi.org/10.48550/arXiv.2507.00123

Jethwa, P. (2023). popkinmocks: mock IFU datacubes for modelling stellar populations and kinematics. *Journal of Open Source Software*, *8*(85), 5225. https://doi.org/10.21105/joss.05225

Johnson, B. D., Leja, J., Conroy, C., & Speagle, J. S. (2021). Stellar Population Inference with Prospector. *254*(2), 22. https://doi.org/10.3847/1538-4365/abef67

Jonsson, P. (2006). SUNRISE: polychromatic dust radiative transfer in arbitrary geometries. *372*(1), 2–20. https://doi.org/10.1111/j.1365-2966.2006.10884.x

Lim, P. L., & STScI development team. (2023). *synphot: Synthetic Photometry Using Astropy*. Zenodo. https://doi.org/10.5281/zenodo.3673988

Lovell, C. C., Roper, W. J., Vijayan, A. P., Wilkins, S. M., Newman, S., & Seeyave, L. (2025). Synthesizer: a Software Package for Synthetic Astronomical Observables. *The Open Journal of Astrophysics*, *8*, 152. https://doi.org/10.33232/001c.145766

Lovell, C. C., Starkenburg, T., Ho, M., Anglés-Alcázar, D., Davé, R., Gabrielpillai, A., Iyer, K., Matthews, A. E., Roper, W. J., Somerville, R., Sommovigo, L., & Villaescusa-Navarro, F. (2024). Learning the Universe: Cosmological and Astrophysical Parameter Inference with Galaxy Luminosity Functions and Colours. *arXiv e-Prints*, arXiv:2411.13960. https://doi.org/10.48550/arXiv.2411.13960

Maraston, C. (2005). Evolutionary population synthesis: models, analysis of the ingredients and application to high-z galaxies. *362*(3), 799–825. https://doi.org/10.1111/j.1365-2966.2005.09270.x

Marshall, M. A., Amen, L., Woods, T. E., Côté, P., Yung, L. Y. A., Amenouche, M., Pass, E. K., Balogh, M. L., Salim, S., & Moutard, T. (2025). FORECASTOR - II. Simulating galaxy surveys with the Cosmological Advanced Survey Telescope for Optical and UV Research. *537*(2), 1703–1719. https://doi.org/10.1093/mnras/staf065

Narayanan, D., Turk, M. J., Robitaille, T., Kelly, A. J., McClellan, B. C., Sharma, R. S., Garg, P., Abruzzo, M., Choi, E., Conroy, C., Johnson, B. D., Kimock, B., Li, Q., Lovell, C. C., Lower, S., Privon, G. C., Roberts, J., Sethuram, S., Snyder, G. F., … Wise, J. H. (2021). POWDERDAY: Dust Radiative Transfer for Galaxy Simulations. *252*(1), 12. https://doi.org/10.3847/1538-4365/abc487

Newman, S. L., Lovell, C. C., Maraston, C., Giavalisco, M., Roper, W. J., Saxena, A., Vijayan, A. P., & Wilkins, S. M. (2025). Cloudy-Maraston: Integrating nebular continuum and line emission with the Maraston stellar population synthesis models. *arXiv e-Prints*, arXiv:2501.03133. https://doi.org/10.48550/arXiv.2501.03133

Perrin, M. D., Sivaramakrishnan, A., Lajoie, C.-P., Elliott, E., Pueyo, L., Ravindranath, S., & Albert, Loïc. (2014). Updated point spread function simulations for JWST with WebbPSF. In J. M. Oschmann Jr., M. Clampin, G. G. Fazio, & H. A. MacEwen (Eds.), *Space telescopes and instrumentation 2014: Optical, infrared, and millimeter wave* (Vol. 9143, p. 91433X). https://doi.org/10.1117/12.2056689

Robitaille, T. P. (2011). HYPERION: an open-source parallelized three-dimensional dust continuum radiative transfer code. *536*, A79. https://doi.org/10.1051/0004-6361/201117150

Roper, W. J., Lovell, C. C., Vijayan, A. P., Marshall, M. A., Irodotou, D., Kuusisto, J. K., Thomas, P. A., & Wilkins, S. M. (2022). First light and reionisation epoch simulations (flares) – IV. The size evolution of galaxies at z 5. *Monthly Notices of the Royal Astronomical Society*, *514*(2), 1921–1939. https://doi.org/10.1093/mnras/stac1368

Rowe, B. T. P., Jarvis, M., Mandelbaum, R., Bernstein, G. M., Bosch, J., Simet, M., Meyers, J. E., Kacprzak, T., Nakajima, R., Zuntz, J., Miyatake, H., Dietrich, J. P., Armstrong, R., Melchior, P., & Gill, M. S. S. (2015). GALSIM: The modular galaxy image simulation toolkit. *Astronomy and Computing*, *10*, 121–150. https://doi.org/10.1016/j.ascom.2015.02.002

Stanway, E. R., & Eldridge, J. J. (2018). Re-evaluating old stellar populations. *479*(1), 75–93. https://doi.org/10.1093/mnras/sty1353

Thob, A. C. R., Sanderson, R. E., Wetzel, A., Cunningham, E. C., Segovia Otero, A., Eden, N., & Panithanpaisal, N. (2024). Generating synthetic star catalogs from simulated data for next-gen observatories with py-ananke. *Journal of Open Source Software*, *9*(102), 6234. https://doi.org/10.21105/joss.06234

Torrey, P., Snyder, G. F., Vogelsberger, M., Hayward, C. C., Genel, S., Sijacki, D., Springel, V., Hernquist, L., Nelson, D., Kriek, M., Pillepich, A., Sales, L. V., & McBride, C. K. (2015). Synthetic galaxy images and spectra from the Illustris simulation. *447*(3), 2753–2771. https://doi.org/10.1093/mnras/stu2592

Turk, M. J., Smith, B. D., Oishi, J. S., Skory, S., Skillman, S. W., Abel, T., & Norman, M. L. (2011). yt: A Multi-code Analysis Toolkit for Astrophysical Simulation Data. *192*(1), 9. https://doi.org/10.1088/0067-0049/192/1/9

Vijayan, A. P., Lovell, C. C., Wilkins, S. M., Thomas, P. A., Barnes, D. J., Irodotou, D., Kuusisto, J., & Roper, W. J. (2020). First Light And Reionization Epoch Simulations (FLARES) – II: The photometric properties of high-redshift galaxies. *Monthly Notices of the Royal Astronomical Society*, *501*(3), 3289–3308. https://doi.org/10.1093/mnras/staa3715

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., van der Walt, S. J., Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., … SciPy 1.0 Contributors. (2020). SciPy 1.0: Fundamental Algorithms for Scientific Computing in Python. *Nature Methods*, *17*, 261–272. https://doi.org/10.1038/s41592-019-0686-2

Wilkins, S. M., Lovell, C. C., Fairhurst, C., Feng, Y., Matteo, T. D., Croft, R., Kuusisto, J., Vijayan, A. P., & Thomas, P. (2020). Nebular-line emission during the Epoch of Reionization. *Monthly Notices of the Royal Astronomical Society*, *493*(4), 6079–6094. https://doi.org/10.1093/mnras/staa649

Wilkins, S. M., Vijayan, A. P., Hagen, S., Caruana, J., Conselice, C. J., Done, C., Hirschmann, M., Irodotou, D., Lovell, C. C., Matthee, J., Plat, A., Roper, W. J., & Taylor, A. J. (2025). First Light and Reionization Epoch Simulations (FLARES) – XVIII: the ionising emissivities and hydrogen recombination line properties of early AGN. *arXiv e-Prints*, arXiv:2505.05257. https://doi.org/10.48550/arXiv.2505.05257

Zhou, X., Nagai, D., Guan, Y., Vogelsberger, M., Genel, S., Hernández-Aguayo, C., Kannan, R., Marinacci, F., Pakmor, R., & Springel, V. (2025). GalaxyGenius: Mock galaxy image generator for various telescopes from hydrodynamical simulations. *700*, A120. https://doi.org/10.1051/0004-6361/202554287