

¹ SolarWindPy: A Heliophysics Data Analysis Tool Set

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⁴ Summary

The region of space within the Sun's envelope of influence is called the heliosphere (the bubble of solar influence extending beyond the planets). The field of heliophysics (the study of the Sun and its influence throughout the solar system) starts in the solar interior and extends out to the very local interstellar medium, just beyond the heliosphere. The solar wind is a stream of charged particles that continuously flows away from the Sun, carrying mass, energy, and momentum along with an embedded magnetic field. In short, it mediates the interaction of the Sun with the heliosphere and this is a feature shared by stars and their astrospheres more broadly. Changes in the solar wind are one source of space weather, which is a critical threat to our technological infrastructure on Earth and in space. SolarWindPy provides a unified framework for analyzing the solar wind and related space weather data, filling the gap between packages targeting astronomy, remote observations of the Sun, and general timeseries analysis of spacecraft based data. The package is available via PyPI¹ and conda-forge² and can be installed using `pip install solarwindpy` or `conda install -c conda-forge solarwindpy`.

¹⁸ Statement of Need

There is a growing ecosystem of python libraries to enable astrophysics, solar physics, plasma physics, and space physics. The table below cites key examples. Notably, there are several packages that support different elements of space physics, including magnetospheric data analysis (Pysat), integration of magnetospheric observations (SpacePy), and the retrieval and analysis of heliophysics timeseries data (pySpedas and PyTplot). Tools for the dedicated analysis of solar wind observations are noticeably absent. SolarWindPy fills this gap by providing a unified framework for analyzing solar wind observations in combination with relevant information about the spacecraft from which the observations were made. The package targets heliophysics researchers analyzing spacecraft observations, from graduate students learning plasma analysis to experienced scientists conducting multi-mission data studies.

Library	Purpose	Citation
AstroPy	Astronomical observations.	Astropy Collaboration et al. (2022)
SunPy	Remote sensing observations of the Sun.	Barnes et al. (2020)
PlasmaPy	Theoretical plasma physics.	(PlasmaPy Community, 2025)
SpacePy	Timeseries analysis and magnetospheric modeling.	Morley et al. (n.d.)
Pysat	Magnetospheric mission data analysis.	Stoneback et al. (2023)
pySpedas	Retrieval and plotting of heliophysics timeseries.	(Grimes et al., 2022)

¹<https://pypi.org/project/solarwindpy/>

²<https://anaconda.org/conda-forge/solarwindpy>

Library	Purpose	Citation
PyTplot	Timeseries and spectrograph data visualization.	(Harter & MAVENSDC Team, 2019)

29 The SolarWindPy framework utilizes a pythonic, class-based architecture that combines ion
 30 and magnetic field objects into a single, unified plasma. It is designed for both experienced
 31 researchers and to provide an intuitive scaffold for students learning to analyze spacecraft
 32 data. SolarWindPy's primary functionality (core, fitfunctions, plotting, instabilities, and
 33 solar_activity submodules) was written by the author and developed or utilized in support
 34 of multiple publications B. L. Altermann, Rivera, Lepri, & Raines (2025). The transformation
 35 from thesis research code to a production package deployable via PyPI and conda-forge was
 36 accomplished using AI-assisted development with specialized quality assurance infrastructure
 37 for the supporting infrastructure (test suites, documentation, and deployment workflows), while
 38 the core scientific functionality remains human-authored.

39 The package builds on well-established libraries including NumPy van der Walt et al. (2011),
 40 SciPy (Virtanen et al., 2020), Matplotlib (Hunter, 2007), and Pandas Mckinney (2013) to
 41 ensure that the dependencies are stable. The plotting functionality retains the mapping
 42 between timeseries and aggregated observations to enable researchers to easily extract subsets
 43 of their observations for detailed analysis. The plot labeling functionality maps the quantities
 44 plotted to their file names, improving the mapping from the user's analysis to the saved
 45 output. The non-linear fitting libraries (utilizing scipy optimize) are designed for multi-step
 46 fitting in which the user performs nested regression of one variable on parameters derived
 47 from fitting other quantities. Submodules for the analysis of magnetohydrodynamic turbulence
 48 parameters and kinetic instabilities are also provided. The solar_activity submodule provides
 49 the user with seamless access to solar activity indicators provided by the LASP Interactive
 50 Solar IRRadiance Datacenter (LISIRD) (Leise et al., 2019) and the Solar Information Data
 51 Center (SIDC) at the Royal Observatory of Belgium (?). This tool enables easy comparison
 52 of solar wind parameters across different phases of the solar cycle and different solar cycles,
 53 which is an essential component of solar wind data analysis. SolarWindPy currently stores data
 54 in pandas DataFrames and Timeseries objects. However, there is a clear separation between
 55 the two libraries such that future development could transition to using more nuanced and
 56 scientifically-targeted data structures, for example those provided by xarray (Hoyer & Hamman,
 57 2017), SunPy, or AstroPy.

58 AI-Assisted Development Workflow

59 SolarWindPy's evolution from thesis research code (B. L. Altermann et al., 2018; Benjamin L.
 60 Altermann, 2019; B. L. Altermann & Kasper, 2019) to a production software package required
 61 comprehensive testing, documentation, and deployment infrastructure. To be explicit about
 62 the scope of AI assistance: the core scientific modules (core/, fitfunctions/, plotting/,
 63 instabilities/, solar_activity/) containing the physics algorithms and analysis methods
 64 were developed by the author without AI assistance and represent the scholarly contribution of
 65 this work, validated through eight peer-reviewed publications B. L. Altermann, Rivera, Lepri,
 66 & Raines (2025). AI-assisted development was used exclusively for supporting infrastructure:
 67 test suites, continuous integration pipelines, package deployment workflows, and completion of
 68 docstring documentation.

69 This was accomplished using Claude Code (Anthropic, 2024) with custom AI development
 70 infrastructure designed for scientific computing quality assurance.

71 The implementation includes specialized domain-specific agents and automated validation
 72 workflows using pre-commit hooks for physics validation, test execution, and coverage monitoring.
 73 This systematic approach enabled rapid development of test suites for modules outside
 74 the original core implementation, completion of documentation including missing docstrings,

and creation of continuous integration and deployment pipelines for PyPI, conda-forge, and ReadTheDocs. The current agent system contains 7 specialized agents with an extensible architecture designed for integration with Claude Code's skills system. The infrastructure incorporates git commit integration, GitHub Issues planning workflows, and comprehensive audit trails to ensure traceability of all AI-generated modifications, establishing an infrastructure for trustworthy AI-assisted scientific software.

The project targets 95% test coverage, with core physics and plasma functionality currently achieving comprehensive coverage (95%), while tests for advanced features such as fitfunctions and plotting capabilities remain in active development, bringing overall coverage to 78%. All code generated or modified by AI in the supporting infrastructure (representing the test suites, CI/CD pipelines, and packaging tooling) undergoes expert review to ensure correctness, while the scientific algorithms themselves remain entirely human-authored as evidenced by their multi-year publication history. The complete AI-assisted development infrastructure, including agent specifications, validation hooks, and workflow automation, is publicly available in the .claude/ directory of the repository.

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